LEARNING PROBABILISTIC MODELS
OF WORD SENSE DISAMBIGUATION

Approved by:

Dr. Dan Moldovan

Dr. Rebecca Bruce

Dr. Weidong Chen

Dr. Frank Coyle

Dr. Margaret Dunham

Dr. Mandyam Srinath

LEARNING PROBABILISTIC MODELS OF WORD SENSE DISAMBIGUATION

A Dissertation Presented to the Graduate Faculty of the

School of Engineering and Applied Science

Southern Methodist University

in

Partial Fulfillment of the Requirements

for the degree of

Doctor of Philosophy

with a

Major in Computer Science

by

Ted Pedersen

(B.A., Drake University)
(M.S., University of Arkansas)

May 16, 1998

ACKNOWLEDGMENTS

I am indebted to Dr. Rebecca Bruce for sharing freely of her time, knowledge, and insights throughout this research. Certainly none of this would have been possible without her.

Dr. Weidong Chen, Dr. Frank Coyle, Dr. Maggie Dunham, Dr. Dan Moldovan, and Dr. Mandyam Srinath have all made important contributions to this dissertation. They are also among the main reasons why my time at SMU has been both happy and productive.

I am also grateful to Dr. Janyce Wiebe, Lei Duan, Mehmet Kayaalp, Ken McKeever, and Tom O'Hara for many valuable comments and suggestions that influenced the direction of this research.

This work was supported by the Office of Naval Research under grant number N00014-95-1-0776.

Pedersen, Ted

B.A., Drake University
M.S., University of Arkansas

Learning Probabilistic Models
of Word Sense Disambiguation

Advisor: Professor Dan Moldovan
Doctor of Philosophy degree conferred May 16, 1998
Dissertation completed May 16, 1998

Selecting the most appropriate sense for an ambiguous word is a common problem in natural language processing. This dissertation pursues corpus–based approaches that learn probabilistic models of word sense disambiguation from large amounts of text. These models consist of a parametric form and parameter estimates. The parametric form characterizes the interactions among the contextual features and the sense of the ambiguous word. Parameter estimates describe the probability of observing different combinations of feature values. These models disambiguate by determining the most probable sense of an ambiguous word given the context in which it occurs.

This dissertation presents several enhancements to existing supervised methods of learning probabilistic models of disambiguation from sense–tagged text. A new search strategy, forward sequential, guides the selection process through the space of possible models. Each model considered for selection is judged by a new class of evaluation metric, the information criteria. The combination of forward sequential search and Akaike's Information Criteria is shown to consistently select highly accurate models of disambiguation. The same search strategy and evaluation criterion also serve as the basis of the Naive Mix, a new supervised learning algorithm that is shown to be competitive with leading machine learning methodologies. In these comparisons the Naive Bayesian classifier also fares well which seems surprising since it is based on a model where the parametric form is simply assumed. However, an

explanation for this success is presented in terms of learning rates and bias–variance decompositions of classification error.

Unfortunately, sense–tagged text only exists in small quantities and is expensive to create. This substantially limits the portability of supervised learning approaches to word sense disambiguation. This bottleneck is addressed by developing unsupervised methods that learn probabilistic models from raw untagged text. However, such text does not contain enough information to automatically select a parametric form. Instead, one must simply be assumed. Given a form, the senses of ambiguous words are treated as missing data and their values are imputed via the Expectation Maximization algorithm and Gibbs Sampling. Here the parametric form of the Naive Bayesian classifier is employed. However, this methodology is appropriate for any parametric form in the class of decomposable models. Several local–context, frequency–based feature sets are also developed and shown to be appropriate for unsupervised learning of word senses from raw untagged text.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

This dissertation is about computational methods that resolve the meanings of ambiguous words in natural language text. Here, disambiguation is defined as the selection of the intended sense of an ambiguous word from a known and finite set of possible meanings. This choice is based upon a probabilistic model that tells which member of the set of possible meanings is the most likely given the context in which the ambiguous word occurs.

Resolving ambiguity is a routine process for a human; it requires little conscious effort since a broad understanding of both language and the real–world are utilized to make decisions about the intended sense of a word. For a human, the context in which an ambiguous word occurs includes a wealth of knowledge beyond that which is contained in the text. Modeling this vast amount of information in a representation a computer program can access and make inferences from is an, as yet, unachieved goal of Artificial Intelligence. Given the lack of such resources, this dissertation does not attempt to duplicate the process a human uses to resolve ambiguity.

Instead, *corpus–based* methods are employed which make disambiguation decisions based on probabilistic models learned from large quantities of naturally occurring text. In these approaches, context is defined in a very limited way and consists of information that can easily be extracted from the sentence in which an ambiguous word occurs; no deep understanding of the linguistic structure or real–world underpinnings of a text is required. This results in methods that take advantage of the abundance of text available online and do not require the availability of rich sources of real–world knowledge.

1.1. Word Sense Disambiguation

Most words have multiple possible senses, each of which is appropriate in certain contexts. Such ambiguity can result in the misunderstanding of a sentence. For example, the newspaper headline *Drunk Gets 9 Years in Violin Case* causes momentary confusion due to word sense ambiguity. Does this imply that someone has been sentenced to spend 9 years in a box used to store a musical instrument? Or has someone has been sentenced to prison for 9 years for a crime involving a violin? Clearly the latter interpretation is intended. The key to making this determination is resolving the intended sense of *case*. This is not terribly difficult for a human since it is widely known that people are not imprisoned in violin cases. However, a computer program that attempts to resolve this same ambiguity will have a more challenging task since it is not likely to have this particular piece of knowledge available.

The difficulty of resolving word sense ambiguity with a computer program was first noted by Yehoshua Bar–Hillel, an early researcher in machine translation. In [3] he presented the following example:

> Little John was looking for his toy box. Finally, he found it. The box was in the pen. John was very happy.

Bar-Hillel assumed that *pen* can have two senses: a writing instrument or an enclosure where small children can play. He concluded that:

> . . . no existing or imaginable program will enable an electronic computer to determine that the word *pen* in the given sentence within the given context has the second of the above meanings.

Disambiguating *pen* using a knowledge–based approach requires rather esoteric pieces of information; "toy boxes are smaller than play pens" and "toy boxes are larger than writing pens," plus some mechanism for making inferences given these facts. To have this available for all potential ambiguities is indeed an impossibility. In that regard Bar–Hillel is correct. However, while such approaches require an

impractical amount of real–world knowledge, corpus–based methods that learn from large amounts of naturally occurring text offer a viable alternative.

Computational approaches that automatically perform word sense disambiguation have potentially wide application. Resolving ambiguity is an important issue in machine translation, document categorization, information retrieval, and language understanding.

Consider an example from machine translation. The noun *bill* can refer to a piece of legislation that is not yet law or to a statement requesting payment for services rendered. However, in Spanish these two senses of *bill* have two distinct translations; *proyecto de ley* and *cuenta*. To translate *The Senate bill is being voted on tomorrow* from English to Spanish, the intended sense of *bill* must be resolved. Even a simple word by word translation to Spanish is not possible without resolving this ambiguity.

Document classification can also hinge upon the interpretation of an ambiguous word. Suppose that there are two documents where the word *bill* occurs a large number of times. If a classification decision is made based on this fact and the sense of *bill* is not known, it is possible that *Peterson's Field Guide to North American Birds* and the *Federal Register* will be considered the same type of document as both contain frequent usages of *bill*.

1.2. Learning from Text

This dissertation focuses on corpus–based approaches to learning probabilistic models that resolve the meaning of ambiguous words. These models indicate which sense of an ambiguous word is most probable given the context in which it occurs. In this framework disambiguation consists of classifying an ambiguous word into one of several predetermined senses.

These probabilistic models are learned via supervised and unsupervised approaches. If manually disambiguated examples are available to serve as *training data* then supervised learning is most effective. These examples take the form of *sense–tagged text* which is created by collecting a large number of sentences that contain

a particular ambiguous word. Each instance of the ambiguous word is manually annotated to indicate the most appropriate sense for that usage. Supervised learning builds a generalized model from this set of examples and uses this model to disambiguate instances of the ambiguous word found in *test data* that is separate from the training data.

If there are no training examples available then learning is unsupervised and is based upon *raw* or *untagged* text. An unsupervised algorithm divides all the usages of an ambiguous word into a specified number of groups based upon the context in which each instance of the word occurs. There is no separation of the data into a training and test sample.

Before either kind of learning can take place, a feature set must be developed. This defines the context of the ambiguous word and consists of those properties of both the ambiguous word and the sentence in which it occurs that are relevant to making a sense distinction. These properties are generally referred to as *contextual features* or simply *features*. Human intuition and linguistic insight are certainly desirable at this stage. The development of a feature set is a subjective process; given the complexity of human language there are a huge number of possible contextual features and it is not possible to empirically examine even a fraction of them. This dissertation uses an existing feature set for supervised learning and develops several new feature sets appropriate for unsupervised learning.

Regardless of whether a probabilistic model is learned via supervised or unsupervised techniques, the nature of the resulting model is the same. These models consist of a *parametric form* and *parameter estimates*. The parametric form shows which contextual features affect the values of other contextual features as well as which contextual features affect the sense of the ambiguous word. The parameter estimates tell how likely certain combinations of values for the contextual features are to occur with a particular sense of an ambiguous word.

Thus, there are two steps to learning a probabilistic model of disambiguation. First, the parametric form must either be specified by the user or learned from sense–

tagged text. Second, parameter estimates are made based upon evidence in the text. The following sections summarize how each of these steps is performed during supervised and unsupervised learning. More details of the learning processes are contained in Chapters 3 and 4. Empirical evaluation of these methods is presented in Chapters 6 and 7.

1.2.1. Supervised Learning

The supervised approaches in this dissertation generally follow the model selection method introduced by Bruce and Wiebe (e.g, [10], [11], and [12]). Their method learns both the parametric form and parameter estimates of a special class of probabilistic models, *decomposable log–linear models*. This dissertation extends their approach by identifying alternative criteria for evaluating the suitability of a model for disambiguation and also identifies an alternative strategy for searching the space of possible models.

The approach of Bruce and Wiebe and the extensions described in this dissertation all have the objective of learning a single probabilistic model that adequately characterizes a training sample for a given ambiguous word. However, this dissertation shows that different models selected by different methodologies often result in similar levels of disambiguation performance. This suggests that model selection is somewhat uncertain and that a single "best" model may not exist for a particular word. A new variation on the sequential model selection methodology, the *Naive Mix*, is introduced and addresses this type of uncertainly. The Naive Mix is an averaged probabilistic model that is based on an entire sequence of models found during a selection process rather than just a single model. Empirical comparison shows that the Naive Mix improves on the disambiguation performance of a single selected model and is competitive with leading machine learning algorithms.

The *Naive Bayesian classifier* is a supervised learning method where the parametric form is assumed and only parameter estimates are learned from sense–tagged text. Despite some history of success in word sense disambiguation and other appli-

cations, the behavior of Naive Bayes has been poorly understood. This dissertation includes an analysis that offers an explanation for its ability to perform at relatively high levels of accuracy.

1.2.2. Unsupervised Learning

A general limitation of supervised learning approaches to word sense disambiguation is that sense–tagged text is not available for most domains. While sense–tagged text is not as complicated to create as more elaborate representations of real–world knowledge, it is still a time–consuming activity and limits the portability of methods that require it. In order to overcome this difficulty, this dissertation develops *knowledge–lean* approaches that learn probabilistic models from raw untagged text.

Raw text only consists of the words and punctuation that normally appear in a document; there are no manually attached sense distinctions to ambiguous words nor is any other kind of information augmented to the raw text. Even without sense–tagged text it is still possible to learn a probabilistic model using an unsupervised approach. In this case the parametric form must be specified by the user and then parameter estimates can be made from the text. Based on its success in supervised learning, this dissertation uses the parametric form of the Naive Bayesian classifier when performing unsupervised learning of probabilistic models. However, estimating parameters is more complicated in unsupervised learning than in the supervised case.

The parametric form of any probabilistic model of disambiguation must include a feature representing the sense of the ambiguous word; however, raw text contains no values for this feature. The sense is treated as a *latent* or *missing* feature. Two different approaches to estimating parameters given missing data are evaluated; the EM algorithm and Gibbs Sampling. The probabilistic models that result are also compared to two well–known agglomerative clustering algorithms, Ward's minimum–variance method and McQuitty's similarity analysis. The application of these methodologies to word sense sense disambiguation is an important development since it eliminates the requirement for sense–tagged text made by supervised learning algorithms.

1.3. Basic Assumptions

There are several assumptions that underly both the supervised and unsupervised approaches to word sense disambiguation presented in this dissertation:

1. A separate probabilistic model is learned for each ambiguous word.

2. Any part–of–speech ambiguity is resolved prior to sense disambiguation.[1]

3. Contextual features are only defined within the boundaries of the sentence in which an ambiguous word occurs. In other words, only information that occurs in the same sentence is used to resolve the meaning of an ambiguous word.

4. The possible senses of a word are defined by a dictionary and are known prior to disambiguation. In this dissertation Longman's Dictionary of Contemporary English [75] and WordNet [60] are the sources of word meanings.

The relaxation or elimination of any of these assumptions presents opportunities for future work that will be discussed further in Chapter 9.

1.4. Chapter Summaries

Chapter 2 develops background material regarding probabilistic models and their use as classifiers. Particular emphasis is placed on the class of decomposable models since they are used throughout this dissertation.

Chapter 3 discusses supervised learning approaches to word sense disambiguation. The statistical model selection method of Bruce and Wiebe is outlined here and alternatives to their model evaluation criteria and search strategy are presented. The Naive Mix is introduced. This is a new supervised learning algorithm that extends model selection from a process that selects a single probabilistic model to one that finds an averaged model based on a sequence of probabilistic models. Each succeeding

[1]For example, *share* can be used as a noun, *I have a share of stock*, or as a verb, *It would be nice to share your stock*.

model in the sequence characterizes the training data increasingly well. The Naive Bayesian classifier is also presented.

Chapter 4 addresses unsupervised learning of word senses from raw, untagged text. This chapter shows how the EM algorithm and Gibbs Sampling can be employed to estimate the parameters of a model given the parametric form and the systematic absence of data; in this case the sense of an ambiguous word is treated as missing data. Two agglomerative clustering algorithms, Ward's minimum–variance method and McQuitty's similarity analysis, are also presented and used as points of comparison.

Chapter 5 describes the words that are disambiguated as part of the empirical evaluation of the methods described in Chapters 3 and 4. The possible senses for each word are defined and an empirical study of the distributional characteristics of each word is presented. Four feature sets are also discussed. The feature set for supervised learning is due to Bruce and Wiebe. There are three new feature sets introduced for unsupervised learning.

Chapter 6 presents an empirical evaluation of the supervised learning algorithms described in Chapter 3. There are four principal experiments. The first compares the overall accuracy of a range of sequential model selection methods. The second compares the accuracy of the Naive Mix to several leading machine learning algorithms. The third determines the learning rate of the most accurate methods from the first two experiments. The fourth decomposes the classification errors of the most accurate methods into more fundamental components.

Chapter 7 makes several comparisons among the unsupervised learning methods presented in Chapter 5. The first is between the accuracy of probabilistic models where the parametric form is assumed and parameter estimates are made via the EM algorithm and Gibbs Sampling. The second employs two agglomerative clustering algorithms, Ward's minimum–variance method and McQuitty's similarity analysis, and determines which is the more accurate. Finally, the two most accurate approaches, Gibbs Sampling and McQuitty's similarity analysis, are compared.

Chapter 8 reviews related work in word sense disambiguation. Methodologies are grouped together based upon the type of knowledge source or data they require to perform disambiguation. There are discussions of work based on semantic networks, machine readable dictionaries, parallel translations of text, sense–tagged text, and raw untagged text.

Chapter 9 summarizes the contributions of this dissertation and provides a discussion of future research directions.

CHAPTER 2

PROBABILISTIC MODELS

This chapter introduces the basics of probabilistic models and shows how such models can be used as classifiers to perform word sense disambiguation. Particular attention is paid to a special class of probabilistic model known as *decomposable log–linear models* [26] since they are well suited for use with the supervised and unsupervised learning methodologies described in Chapters 3 and 4.

2.1. Inferential Statistics

The purpose of inferential statistics is to learn something about a population of interest. The characteristics of a population are described by *parameters*. Since it is generally not possible to exhaustively study a population, estimated values for parameters are learned from randomly selected samples of data from the population.

Each parameter is associated with a distinct *event* that can occur in the population. An event is the state of a process at a particular moment in time. A common example is coin tossing. This is a *binomial* process since there are only two possible events; the coin toss comes up heads or tails. A process with more than two possible events is *multinomial*. Tossing a die is an example since there are 6 possible events.

The events in this dissertation are sentences in which an ambiguous word occurs. Each sentence is represented by a combination of discrete values for a set of *random variables*. Each random variable represents a property or *feature* of the sentence. The dependencies among these features are characterized by the *parametric form* of a probabilistic model.

A *feature vector* is a particular instantiation of the random variables. Each feature vector represents an observation or an instance of an event, i.e., a sentence

with an ambiguous word. The exhaustive collection of all possible events given a set of feature variables defines the *event space*.

The *joint probability distribution* of a set of feature variables indicates how likely each event in the event space is to occur. The probability of observing a particular event is described by a parameter. In addition to the parametric form, a probabilistic model also includes estimated values for all of these parameters.

Suppose that in a random sample of events from a population there are N observations of q distinct events, i.e., feature vectors, where each observation is described by n discrete feature variables $(F_1, F_2, \ldots, F_{n-1}, F_n)$. Let f_i and θ_i be the frequency and probability of the i^{th} feature vector, respectively. Then the data sample $D = (f_1, f_2, \ldots, f_q)$ has a multinomial distribution with parameters $(N; \Theta)$, where $\Theta = (\theta_1, \theta_2, \ldots, \theta_q)$ defines the joint probability distribution of the feature variables $(F_1, F_2, \ldots, F_{n-1}, F_n)$.

The parameters of a probabilistic model can be estimated using a number of approaches; maximum likelihood and Bayesian estimation are described in the following sections. The model selection methodologies described in Chapter 3 and the EM algorithm from Chapter 4 employ maximum likelihood estimates. Gibbs Sampling, also described in Chapter 4, makes use of Bayesian estimates.

2.1.1. Maximum Likelihood Estimation

Values for the parameters of a probabilistic model can be estimated using maximum likelihood estimates such that $\hat{\theta}_i = \frac{f_i}{N}$. In this framework, a parameter can only be estimated if the associated event is observed in a sample of data.

A maximum likelihood estimate maximizes the probability of obtaining the data sample that was observed, D, by maximizing the likelihood function, $p(D|\Theta)$. The likelihood function for a multinomial distribution is defined as follows:[1]

[1]Other distributions will have different formulations of the likelihood function.

$$p(D|\Theta) = \frac{N!}{\prod_{i=1}^{q} f_i!} \prod_{i=1}^{q} \hat{\theta}_i^{f_i} \tag{2.1}$$

Implicit in the multinomial distribution is the assumption that all the features of an event are *dependent*. When this is the case the value of any single feature variable is directly affected by the values of all the other feature variables. A probabilistic model where all features are dependent is considered *saturated*.

The danger of relying on a saturated probabilistic model is that reliable parameter estimates may be difficult to obtain. When using maximum likelihood estimates, any event that is not observed in the data sample will have a zero–valued parameter estimate associated with it. This is undesirable since the model regards the associated event as an impossibility. It is more likely that the event is simply unusual and that the sample is not large enough to gather adequate information regarding rare events when using a saturated model.

However, if the event space is very small it may be reasonable to assume that all feature variables are dependent on one another and that every possible event can be observed in a data sample. For example, if an event space is defined by two binary feature variables, (F_1, F_2), then the saturated model has four parameters, each representing the probability of observing one of the four possible events. Table 2.1 shows a scenario where a sample consists of $N = 150$ events. The frequency counts of these events are shown in column $freq(F_1, F_2)$, and the resulting maximum likelihood estimates are calculated and displayed in column MLE.

It is more often the case in real world problems that the number of possible events is somewhat larger than four. The number of parameters needed to represent these events in a probabilistic model is determined by the number of dependencies among the feature variables. If the model is saturated then all of the features are dependent on one another and the number of parameters in the probabilistic model is equal to the number of possible events in the event space.

Table 2.1. Maximum Likelihood Estimates

F_1	F_2	$freq(F_1, F_2)$	MLE
0	0	21	$\hat{\theta}_1 = \frac{21}{150} = .14$
0	1	38	$\hat{\theta}_2 = \frac{38}{150} = .25$
1	0	60	$\hat{\theta}_3 = \frac{60}{150} = .40$
1	1	31	$\hat{\theta}_4 = \frac{31}{150} = .21$

Suppose that an event space is defined by a set of 20 binary feature variables $(F_1, F_2, \cdots, F_{20})$. The joint probability distribution of this feature set consists of 2^{20} parameters. Unless the number of observations in the data sample is greater than 2^{20}, it is inevitable that there will be a great many parameter estimates with zero values. If $q < 2^{20}$, where q represents the number of distinct events in a sample, then $2^{20} - q$ events will have zero estimates. This situation is exacerbated if the distribution of events in the data sample is *skewed*, i.e., $q \ll N$. Unfortunately, it is often the case in natural language that the distribution of events is quite skewed (e.g. [74], [101]).

An alternative to using a saturated model is to find a probabilistic model with fewer dependencies among the feature variables that still maintains a good *fit* to the data sample. Such a model is more parsimonious and yet retains a reasonably close characterization of the data. Given such a model, the joint probability distribution can be expressed in terms of a smaller number of parameters.

Dependencies among feature variables can be eliminated if a pair of variables are identified as *conditionally independent*. Feature variables F_1 and F_2 are conditionally independent given S if:

$$p(F_1 = f_1 | F_2 = f_2, S = s) \quad = \quad p(F_1 = f_1 | S = s) \tag{2.2}$$

or:

$$p(F_2 = f_2|F_1 = f_1, S = s) \quad = \quad p(F_2 = f_2|S = s) \tag{2.3}$$

In Equation 2.2, the probability of observing feature variable F_1 with value f_1 is not affected by the value of feature variable F_2 if it is already known that feature variable S has value s. A similar interpretation applies to Equation 2.3.[2]

An automatic method for selecting probabilistic models with fewer dependencies among the feature variables is described by Bruce and Wiebe (e.g., [10], [11], [12]). This method selects models from the class of decomposable log–linear models and will be described in greater detail in Chapter 3.

2.1.2. Bayesian Estimation

Bayesian estimation of parameters is an alternative to maximum likelihood estimation. Such an estimate is the product of the likelihood function, $p(D|\Theta)$, and the prior probability, $p(\Theta)$. This product defines the *posterior probability function*, $p(\Theta|D)$, defined by Bayes Rule as:

$$p(\Theta|D) = \frac{p(D|\Theta)p(\Theta)}{p(D)} \tag{2.4}$$

The posterior function represents the probability of estimating the parameters, Θ, given the observed sample, D. The likelihood function, $p(D|\Theta)$, represents the probability of observing the sample, D, given that it comes from the population characterized by the parameters, Θ. The prior probability function, $p(\Theta)$, represents the unconditional probability that the parameters have values Θ. This is a subjective probability that is estimated prior to sampling. Finally, $p(D)$ is the probability of observing a sample, D, regardless of the actual value of the parameters, Θ.

[2]In the remainder of this dissertation, a simplified notation will be employed where feature variable names are not specified when they can be inferred from the feature values. For example, in $p(f_1|f_2, s) = p(f_1|s)$ it is understood that the lower case letters refer to particular values for a feature variable of the same name.

When making a Bayesian estimate some care must be taken in specifying the distribution of the prior probability $p(\Theta)$. The nature of the likelihood function must be taken into account, otherwise the product of the likelihood function and the prior function may lead to invalid results. Prior probabilities whose distributions lend themselves to fundamentally sound computation of the posterior probability from the likelihood function are known as *conjugate priors*. A prior probability is a conjugate prior if it is related to the events represented by the likelihood function in such a way that both the posterior and prior probabilities are members of the same family of distributions.

For example, suppose a binomial process such as coin tossing is being modeled, where the observations in a sample are classified into two mutually exclusive categories; heads or tails. The beta distribution is known to be conjugate to observations in a binomial process. If the prior probability of observing a heads or tails is assigned via a beta distribution, then the posterior probability will also be a member of the beta family.

The multinomial distribution is the n–event generalization of the 2–event binomial distribution. The Dirichlet distribution is the n–event generalization of the 2–event beta distribution. Since the beta distribution is the conjugate prior of the binomial distribution, it follows that the Dirichlet distribution is the conjugate prior of the multinomial distribution. When the likelihood function is multinomial and the prior function is specified using the Dirichlet distribution, the resulting posterior probability function is expressed in terms of the Dirichlet distribution.

2.2. Decomposable Models

Decomposable models [26] are a subset of the class of Graphical Models [93] which is in turn a subset of the class of log-linear models [5]. Decomposable models can also be categorized as the class of models that are both Bayesian Networks [67] and Graphical Models. They were first applied to natural language processing and word sense disambiguation by Bruce and Wiebe (e.g., [10], [11], [12]).

In any Graphical Model, feature variables are either dependent or conditionally independent of one another. The parametric form of these models have a graphical representation such that each feature variable in the model is represented by a node in the graph, and there is an undirected edge between each pair of nodes corresponding to dependent feature variables. Any two nodes that are not directly connected by an edge are conditionally independent given the values of the nodes on the path that connects them.

The graphical representation of a decomposable model corresponds to an undirected chordal graph whose set of maximal cliques defines the joint probability distribution of the model. A graph is chordal if every cycle of length four or more has a shortcut, i.e., a chord. A maximal clique is the largest set of nodes that are completely connected, i.e., dependent.

In general, parameter estimates are based on *sufficient statistics*. These provide all the information from the data sample that is needed to estimate the value of a parameter. The sufficient statistics of the parameters of a decomposable model are the *marginal frequencies* of the events represented by the feature variables that form maximal cliques in the graphical representation. Each maximal clique is made up of a subset of the feature variables that are all dependent. Together these features define a *marginal event space*. The probability of observing any specific instantiation of these features, i.e., a *marginal event*, is defined by the *marginal probability distribution*.

The joint probability distribution of a decomposable model is expressed as the product of the marginal distributions of the variables in the maximal cliques of the graphical representation, scaled by the marginal probability distributions of feature variables common to two or more of these maximal sets. Because their joint distributions have such closed–form expressions, the parameters of a decomposable model can be estimated directly from the data sample without the need for an iterative fitting procedure as is required, for example, to estimate the parameters of maximum entropy models (e.g., [4]).

Table 2.2. Sense–tagged text for *bill*

Sense–tagged sentences	Feature vectors				
	C	V	R	T	S
I paid the bill/pay at the restaurant.	no	no	yes	no	pay
Congress overrode the veto of that bill/law.	yes	yes	no	no	law
Congress passed a new bill/law today.	yes	no	no	no	law
The restaurant bill/pay does not include the tip.	no	no	yes	yes	pay
The bill/law was killed in committee.	no	no	no	no	law

2.2.1. Examples

To clarify these concepts, both the graphical representation and parameter estimates associated with several examples of decomposable models are presented in terms of a simple word sense disambiguation example. The task is to disambiguate various instances of *bill* by selecting one of two possible senses; a piece of pending legislation or a statement requesting payment for services rendered.

Each sentence containing *bill* is represented using five binary feature variables. The classification variable S represents the sense of *bill*. Four contextual feature variables indicate whether or not a given word has occurred in the sentence with the ambiguous use of *bill*. The presence or absence of *Congress, veto*, *restaurant* and *tip*, are represented by binary variables C, V, R and T, respectively. These variables have a value of *yes* if the word occurs in the sentence and *no* if it does not.

A sample of N sentences that contain *bill* is collected. The instances of *bill* are manually annotated with sense values by a human judge. These sense–tagged sentences are converted by a *feature extractor* into the feature vectors shown in Table 2.2.

Given five binary feature variables, there are 32 possible events in the event space. If the parametric form is the saturated model then there are also 32 parameters to estimate. For this example the saturated model is notated $(CVRTS)$ and its

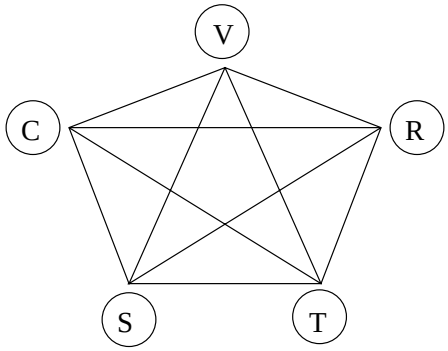


Figure 2.1. Saturated Model ($CVRTS$)

graphical representation is shown in Figure 2.1. This model is decomposable as there is a path of length one between any two feature variables in the graphical representation.

In order to estimate values for all the parameters of the saturated model, every possible event must be observed in the sample data. Let the parameter estimate $\hat{\theta}^{F_1,F_2,\ldots,F_{n-1},S}_{f_1,f_2,\ldots,f_{n-1},s}$ represent the probability that a feature vector $(f_1, f_2, \ldots, f_{n-1}, s)$ is observed in the data sample where each sentence is represented by the random variables $(F_1, F_2, \ldots, F_{n-1}, S)$. The parameter estimates of the saturated model are calculated as follows:

$$\hat{\theta}^{C,V,R,T,S}_{c,v,r,t,s} \quad = \quad \hat{p}(c, v, r, t, s) \quad = \quad \frac{freq(c, v, r, t, s)}{N} \tag{2.5}$$

However, an alternative to the saturated model is to use the model selection process described in Chapter 3 to find a more parsimonious probabilistic model that contains only the most important dependencies among the feature variables. This model can then be used as a classifier to disambiguate subsequent occurrences of the ambiguous word.

Suppose that the model selection process finds that the model $(CSV)(RST)$, shown in Figure 2.2, is an adequate characterization of the data sample. There are a number of properties of the model revealed in the graphical representation.

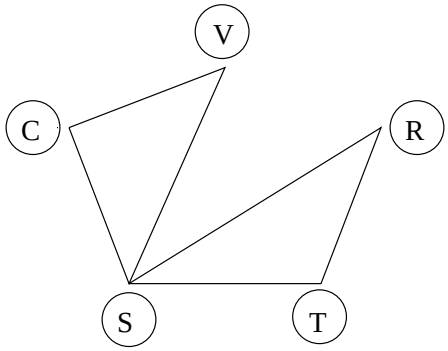


Figure 2.2. Decomposable Model $(CSV)(RST)$

First, it is a decomposable model since all cycles of length four or more have a chord. Second, conditional independence relationships can be read off the graph. For example, the values of features R and V are conditionally independent given the value of S; $p(r|v,s) = p(r|s)$, or $p(v|r,s) = p(v|s)$. Third, (CSV) and (RST) are the maximal cliques. The variables in each clique are all dependent and each clique defines a marginal distribution. Each marginal distribution defines a marginal event space with eight possible events. Thus the total number of parameters needed to define the joint probability distribution reduces from 32 to 16 when using this model rather than the saturated model.

The maximum likelihood estimates for the parameters of the joint probability distribution are expressed in terms of the parameters of the decomposable model. The sufficient statistics of a decomposable model are the marginal frequencies of the variables represented in the maximal cliques of the graphical representation. Given the parametric form $(CSV)(RST)$, the sufficient statistics are the marginal frequencies $freq(c,s,v)$ and $freq(r,s,t)$. The parameters of the decomposable model are $\hat{\theta}^{C,S,V}_{c,s,v}$ and $\hat{\theta}^{R,S,T}_{r,s,t}$. These represent the probability that the marginal events (c,s,v) and (r,s,t) will be observed in a data sample. These estimates are made by normalizing the marginal frequencies by the sample size N:

$$\hat{\theta}^{CSV}_{c,s,v} = \hat{p}(c,s,v) = \frac{freq(c,s,v)}{N} \tag{2.6}$$

and

$$\hat{\theta}^{RST}_{r,s,t} = \hat{p}(r,s,t) = \frac{freq(r,s,t)}{N} \tag{2.7}$$

Each parameter of the joint probability distribution can be expressed in terms of these decomposable model parameters. The joint probability of observing the event (c,v,r,t,s) is expressed as the product of the marginal probabilities of observing marginal events (c,s,v) and (r,s,t):

$$\hat{\theta}^{CVRTS}_{c,v,r,t,s} = \frac{\hat{\theta}^{CSV}_{c,s,v} \times \hat{\theta}^{RST}_{r,s,t}}{\hat{\theta}^{S}_{s}} \tag{2.8}$$

While the denominator $\hat{\theta}^{S}_{s}$ represents an estimate of a marginal distribution, it is not technically a parameter since it is completely determined by the numerator. The denominator does not add any new information to the model, it simply factors out any marginal distributions that occur in more than one of the marginal distributions found in the numerator.

In contrast to the saturated model, the model of independence assumes that there are no dependencies among any of the feature variables. For this example the model of independence is notated $(C)(V)(R)(T)(S)$ and the graphical representation is shown in Figure 2.3. This model has five maximal cliques, each containing one node and no dependencies. This defines five marginal distributions, each of which has two possible values. The number of parameters needed to define the joint probability distribution is reduced to 10. These parameters are estimated as follows:

$$\hat{\theta}^{C,V,R,T,S}_{c,v,r,t,s} = \hat{\theta}^{C}_{c} \times \hat{\theta}^{V}_{v} \times \hat{\theta}^{R}_{r} \times \hat{\theta}^{T}_{t} \times \hat{\theta}^{S}_{s} \tag{2.9}$$

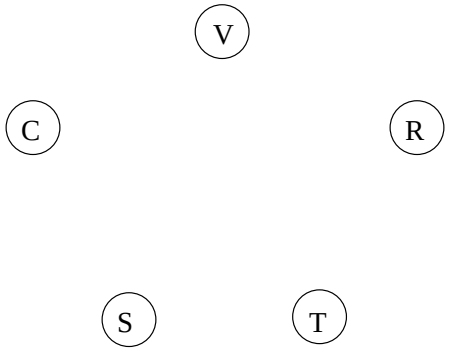


Figure 2.3. Model of Independence $(C)(V)(R)(T)(S)$

This model indicates that the probability of observing a particular value for a feature variable is not influenced by the values of any of the other feature variables. No features affect the values of any other features. The model of independence is trivially decomposable as there are no cycles in the graphical representation of the model. Despite its simplicity, the model of independence is used throughout the experimental evaluation described in Chapter 6. It serves as the basis of the *majority classifier*, a probabilistic model that assigns the most frequent sense of an ambiguous word in a sample of data to every instance of the ambiguous word it subsequently encounters.

The Naive Bayesian classifier [33] also plays a role later in this dissertation. This is a decomposable model that has a significant history in natural language processing and a range of other applications. This model assumes that all of the contextual features are conditionally independent given the value of the classification variable.

For the example in this chapter, the parametric form of Naive Bayes is notated $(CS)(RS)(TS)(VS)$ and has a graphical representation as shown in Figure 2.4. In this model there are four maximal cliques, each with two nodes and one dependency. The variables are binary so each of the four marginal distributions represents four possible events. The parameter estimates for Naive Bayes are computed as follows:

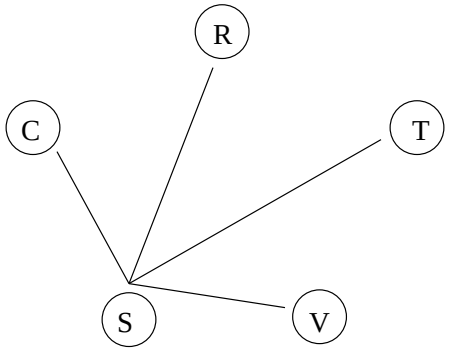


Figure 2.4. Naive Bayes Model $(CS)(RS)(TS)(VS)$

$$\hat{\theta}^{C,V,R,T,S}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S}_{c,s} \times \hat{\theta}^{V,S}_{v,s} \times \hat{\theta}^{R,S}_{r,s} \times \hat{\theta}^{T,S}_{t,s}}{\hat{\theta}^{S}_{s} \times \hat{\theta}^{S}_{s} \times \hat{\theta}^{S}_{s}} \tag{2.10}$$

By applying the following identities,

$$\hat{\theta}^{X,S}_{x,s} \;=\; \hat{p}(x,s) \;=\; \hat{p}(x|s) \times \hat{p}(s) \quad \textit{and} \quad \hat{\theta}^{S}_{s} \;=\; \hat{p}(s) \tag{2.11}$$

the Naive Bayesian classifier can also be expressed in its more traditional representation:

$$\hat{p}(c,v,r,t,s) = \hat{p}(s) \times \hat{p}(c|s) \times \hat{p}(v|s) \times \hat{p}(r|s) \times \hat{p}(t|s) \tag{2.12}$$

2.2.2. Decomposable Models as Classifiers

A probabilistic model consists of a parametric form that describes the dependencies among the features and parameter estimates that tell how likely each possible event is to occur. Such a model can be used as a classifier to identify the most probable sense of an ambiguous word given the context in which it appears.

For example, suppose a sentence that contains an ambiguous word is represented by the following feature vector:

$$(C = c, V = v, R = r, T = t, S = ?) \tag{2.13}$$

The variable S represents the sense of an ambiguous word. Variables C, V, R, and T are the features that represent the context in which the ambiguous word occurs. The values of the feature variables are known while the value of S is unknown. Given x possible values of S, where each possible sense is notated s_x, there are x possible events associated with the incomplete feature vector in Equation 2.13. A probabilistic classifier determines which of these possible events has the highest associated probability according to the probabilistic model, i.e., it maximizes the probability of S conditioned on the values of the observed feature variables.

Thus, disambiguation is performed via a simple maximization function. Given values for the observed contextual features, a probabilistic classifier determines which value of S is associated with the most probable event:

$$S = \overset{argmax}{s_x}\ p(s_x|c, v, r, t) = \overset{argmax}{s_x}\ \frac{p(c, v, r, t, s_x)}{p(c, v, r, t)} \tag{2.14}$$

The denominator in Equation 2.14 acts as a constant since it does not include S. As such it can be dropped and the maximization operation is simplified to finding the value of S that maximizes the joint probability distribution of the feature variables C, V, R, T, and S:

$$S = \overset{argmax}{s_x}\ p(c, v, r, t, s_x) = \overset{argmax}{s_x}\ \hat{\theta}^{C,V,R,T,S}_{c,v,r,t,s_x} \tag{2.15}$$

This chapter has shown how estimates of the joint probability distribution can be expressed in terms of more parsimonious decomposable models. The following chapter shows how decomposable models can be automatically selected from sense–tagged text.

CHAPTER 3

SUPERVISED LEARNING FROM SENSE–TAGGED TEXT

When applied to classification problems, supervised learning is a methodology where examples of properly classified events are used to train an algorithm that will classify subsequent instances of similar events. For word sense disambiguation, manually disambiguated usages of an ambiguous word serve as training examples. This sense–tagged text is used to learn a probabilistic model that determines the most probable sense of an ambiguous word, given the context in which it occurs.

In this dissertation, the objective of supervised learning is to select the parametric form of a decomposable model that represents the important dependencies among a set of feature variables exhibited in a particular sample of sense–tagged text. Given this form, the joint probability distribution of this set of feature variables can be expressed in terms of the marginal probability distributions of the decomposable model. Once the values of these parameters are estimated, the probabilistic model is complete and can be used as a classifier to perform disambiguation.

The challenge in learning probabilistic models is to locate a parametric form that is both a specific representation of the important dependencies in the training sample and yet general enough to successfully disambiguate previously unobserved instances of the ambiguous word. A model is too complex if a substantial number of parameters in the joint probability distribution have zero–valued estimates; this indicates that the available data sample simply does not contain enough information to support the estimates required by the model. However, a model is too simple if relevant dependencies among features are not represented. In other words, the model should achieve an appropriate balance between model complexity and model fit.

There are several supervised learning methodologies discussed in this chapter. *Sequential model selection* learns a single parametric form that is judged to achieve the best balance between model complexity and fit for a given sample of sense–tagged text. This methodology is extended by the *Naive Mix*, which learns an averaged probabilistic model from the sequence of parametric forms generated during a sequential model selection process. An alternative to learning the parametric form is to simply assume one. In this case no search of parametric forms is conducted; the form is specified by the user and the sense–tagged text is only utilized to make parameter estimates. This is the methodology of the *Naive Bayesian classifier* [33], often simply referred to as Naive Bayes.

The degree to which a probabilistic model successfully balances complexity and fit is determined by its accuracy in disambiguating previously unobserved instances of an ambiguous word. The methods discussed in this chapter are subjected to such an evaluation in Chapter 6.

3.1. Sequential Model Selection

Sequential model selection integrates a *search strategy* and an *evaluation criterion*. Since the number of possible parametric forms is exponential in the number of features, an exhaustive search of the possible forms is usually not tractable. A search strategy determines which parametric forms, from the set of all possible parametric forms, will be considered during the model selection process. The evaluation criterion is the ultimate judge of which parametric form achieves the most appropriate balance between complexity and fit, where complexity is defined by the number of dependencies in the model, i.e., the number of edges in its graphical representation.

The search strategies employed here are greedy and result in the evaluation of models of steadily increasing or decreasing levels of complexity. A number of *candidate models* are generated at each level of complexity. The evaluation criterion determines which candidate model results in the best fit to the training sample; this model is designated as the *current model*. Another set of candidate models is generated by

increasing or decreasing the complexity of the current model by one dependency. The process of evaluating candidates, selecting a current model, and generating new candidate models from the current model is iterative and continues until a model is found that achieves the best overall balance of complexity and fit. This is the *selected model* and is the ultimate result of the sequential model selection process.

A selected model is parsimonious in that it has as few dependencies as are necessary to characterize or fit the training sample. When using maximum likelihood estimates, the saturated model exactly fits the distribution of the observed events in the training sample. However, the number of parameters is equal to the number of events in the event space and obtaining non–zero estimates for large numbers of parameters is usually difficult. A parsimonious model should capture the important dependencies among the features in a training sample and yet allow the joint probability distribution to be expressed relatively simply in terms of a smaller number of decomposable model parameters.

As formulated in this dissertation, the model selection process also performs feature selection. If a model is selected where there is no dependency between a feature variable and the sense variable, then that feature is removed from the model and will not impact disambiguation.

3.1.1. Search Strategy

Two sequential search strategies are employed in this dissertation: *backward sequential search* [92] and *forward sequential search* [28]. These methods are also known as *backward elimination* and *forward inclusion*.

Backward sequential search for probabilistic models of word sense disambiguation was introduced by Bruce and Wiebe (e.g., [10], [11], [12]). This dissertation introduces forward sequential search. Forward searches evaluate models of increasing complexity based on how much candidate models improve upon the fit of the current model, while backward searches evaluate candidate models based on how much they degrade the fit of the current model.

A forward sequential search begins by designating the model of independence as the current model. The level of complexity is zero since there are no edges in the graphical representation of this model. The set of candidate models is generated from the model of independence and consists of all possible one edge decomposable models. These are individually evaluated for fit by an evaluation criterion. The one edge model that exhibits the greatest improvement in fit over the model of independence is designated as the new current model. A new set of candidate models is generated by adding an edge to the current model and consists of all possible two edge decomposable models. These models are evaluated for fit and the two edge decomposable model that most improves on the fit of the one edge current model becomes the new current model. A new set of three edge candidate models is generated by adding one edge at a time to the two edge current model. This sequential search continues until:

1. none of the candidate decomposable models of complexity level $i+1$ results in an appreciable improvement in fit over the current model of complexity level i, as defined by the evaluation criterion, or

2. the current model is the saturated model.

In either case the current model becomes the selected model and the search ends.

In general then, during a forward search the current model is reset to the decomposable model of complexity level i that most improves on the fit of the current decomposable model of complexity level $i-1$. All possible decomposable models of complexity level $i+1$ that are generated from the current model of complexity level i are considered as candidate models and then evaluated for fit. The candidate model that most improves on the fit of the current model of complexity level i is designated the new current model. This process continues until either there is no decomposable model of complexity level $i+1$ that results in an appreciable improvement in fit over the current model or the current model of complexity level i is the saturated model. In either case the current model is selected and the search ends.

For the sparse and skewed samples typical of natural language data [101], forward sequential search is a natural choice. Early in the search the models are of low complexity and the number of parameters in the model is relatively small. This results in few zero–valued estimates and ensures that the model selection process is based upon the best available information from the training sample.

A backwards sequential search begins by designating the saturated model as the current model. If there are n feature variables then the number of edges in the saturated model is $\frac{n(n-1)}{2}$. As an example, given 10 feature variables there are 45 edges in a saturated model. The set of candidate models consists of each possible decomposable model with 44 edges generated by removing a single edge from the saturated model. These candidates are evaluated for fit and the 44 edge model that results in the least degradation in fit from the saturated model becomes the new current model. Each possible 43 edge candidate decomposable model is generated by removing a single edge from the 44 edge current model and then evaluated for fit. The 43 edge decomposable candidate model that results in the least degradation in fit from the 44 edge current model becomes the new current model. Each possible 42 edge candidate decomposable model is generated by removing a single edge from the current 43 edge model and then evaluated for fit. This sequential search continues until:

1. every candidate decomposable model of complexity level $i-1$ results in an appreciable degradation in fit from the current model of complexity level i, as defined by the evaluation criterion, or

2. the current model is the model of independence.

In either case the current model is selected and the search ends.

In general then, during a backward search the current model is reset to the decomposable model of complexity level i that results in the least degradation in fit from the current model of complexity level $i+1$. Each possible decomposable model of complexity level $i-1$ is generated by removing a single edge from the current model

of complexity level i and evaluated for fit. This process continues until either every decomposable model of complexity level $i-1$ results in an appreciable degradation in fit from the current model of complexity level i or the current model has complexity level zero, i.e., the model of independence. In either case the current model is selected and the search ends.

The backward search in this dissertation differs slightly from that of Bruce and Wiebe. Their backward search begins with the saturated model and generates a series of models of steadily decreasingly complexity where the minimal or concluding model is Naive Bayes. All models in this sequence are evaluated via a test of predictive accuracy; the model that achieves the best balance between complexity and fit is the model that achieves the highest disambiguation accuracy. Here, backward sequential search begins with the saturated model and generates a series of models that concludes with the one that best balances complexity and fit, as judged by an evaluation criterion. If no such model is found then the model of independence is the concluding model in the sequence.

For sparse and skewed data samples, backward sequential search should be used with care. Backward search begins with the saturated model where the number of parameters equals the number of events in the event space. Early in the search the models are of high complexity. Parameter estimates based on the saturated model or other complex models are often unreliable since many of the marginal events required to make maximum likelihood estimates are not observed in the training sample.

3.1.2. Evaluation Criteria

The degradation and improvement in fit of candidate models relative to the current model is assessed by an evaluation criterion. Two different varieties of evaluation criteria are employed in this dissertation; significance tests and information criteria.

The use of significance tests as evaluation criteria during sequential searches for probabilistic models of word sense disambiguation was introduced by Bruce and Wiebe (e.g., [10], [11], [12]). They employ the log–likelihood ratio G^2 and assign

significance values to this test statistic using an asymptotic distribution and an exact conditional distribution. This dissertation expands the range of evaluation criteria available for model selection by introducing two information criteria, Akaike's Information Criterion (AIC) [1] and the Bayesian Information Criterion (BIC) [86].

3.1.2.1. Significance Testing

In significance testing, a model is a hypothesized representation of the population from which a training sample was drawn. The adequacy of this model is evaluated via a test statistic that measures the fit of the model to the training sample.[1] The fit of the hypothesized model is judged acceptable if it differs from the training sample by an amount that is consistent with sampling error, where that error is defined by the distribution of the test statistic.

The log–likelihood ratio G^2 is a frequently used test statistic:

$$G^2 = 2 \times \sum_{i=1}^{q} f_i \times log \frac{f_i}{e_i} \tag{3.1}$$

where f_i and e_i are the observed and expected counts of the i^{th} feature vector. The observed count f_i is calculated directly from the training sample while the expected count e_i is calculated assuming that the model under evaluation fits the sample, i.e., that the null hypothesis is true. This statistic measures the deviation between what is observed in the training sample and what would be expected in that sample if the hypothesized model is an accurate representation of the population.

The distribution of G^2 is asymptotically approximated by the χ^2 distribution [94] with adjusted degrees of freedom (dof) equal to the number of parameters that have non–zero estimates given the data in the sample. The degrees of freedom are adjusted to remove those parameters in the hypothesized model that can not be

[1] When using maximum likelihood estimates, the training sample is exactly characterized by the saturated model. Thus the fit of the hypothesized model to the training sample is assessed by measuring the fit of the model to the saturated model.

estimated from the training sample. These are parameters whose sufficient statistics have a value of zero since the marginal events they are associated with do not occur in the training sample. The statistical significance of a model is equal to the probability of observing its associated G^2 value in the χ^2 distribution with appropriate degrees of freedom. If this probability is less than a pre–defined cutoff value, α, then the deviance of the hypothesized model from the training sample is less than would be expected due to sampling error. This suggests that the hypothesized model is a reasonable representation of the population from which the training sample was taken.

During backward sequential search a significance test determines if a candidate model results in a significantly worse fit than the current model. During forward search a significance test determines if a candidate model results in a significantly better fit than the current model. This is a different formulation than the significance test described above, where the hypothesized or candidate model is always fitted to the saturated model. This dissertation treats sequential search as a series of local evaluations, where the fit of candidate models is made relative to current models that have one more or one less dependency, depending on the direction of the search. This is in contrast to a global evaluation where the fit of candidate models is always relative to the saturated model or some other fixed model.

The degree to which a candidate model improves upon or degrades the fit of the current model is measured by the difference between the G^2 values for the candidate and current model, ΔG^2. Like G^2, the distribution of ΔG^2 is approximated by a χ^2 distribution with adjusted degrees of freedom equal to the difference in the adjusted degrees of freedom of the candidate and current model, Δdof [5].

During backward search a candidate model does not result in a significant degradation in fit from the current model if the probability, i.e., significance, of its ΔG^2 value is above a pre–determined cutoff, α, that defines the allowable sampling error. This error is defined by the asymptotic distribution of ΔG^2, which is in turn defined by the χ^2 distribution with degrees of freedom equal to Δdof. If the error is small then the candidate model is an adequate representations of the population.

A candidate model of complexity level $i-1$ inevitably results in a degradation in fit from the current model of complexity level i. The objective of backward search is to select the candidate model that results in the least degradation in fit from the current model. Thus, the candidate model of complexity level $i-1$ with the lowest significance value less than α is selected as the current model of complexity level $i-1$. The degradation in fit is judged acceptable if the value of ΔG^2 is statistically insignificant, according to a χ^2 distribution with degrees of freedom equal to Δdof. If the significance of ΔG^2 is unacceptably large for all candidate models the selection process stops and the current model becomes the ultimately selected model.

During forward search the candidate model has one more edge than the current model. A candidate model of complexity level $i+1$ inevitably improves upon the fit of the current model of complexity level i. The objective of forward search is to select the candidate model that results in the greatest increase in fit from the current model. The candidate model of complexity level $i+1$ with the largest significance value greater than α is selected as the current model of complexity level $i+1$. This is the model that results in the largest improvement in fit when moving from a model of complexity level i to one of $i+1$. The improvement in fit is judged acceptable if a significance test shows that the value of ΔG^2 is statistically significant. If all candidate models result in insignificant levels of improvement in fit then model selection stops and selects the current model of complexity level i.

While it is standard to use a χ^2 distribution to assess the significance of G^2 or ΔG^2, it is known that this approximation may not hold when the data is sparse and skewed [80]. An alternative to using an asymptotic approximation to the distribution of test statistics such as G^2 and ΔG^2 is to define their exact distribution. There are two ways to define the exact distribution of a test statistic:

1. enumerate all elements of that distribution as in Fisher's Exact Test [35] or
2. sample from that distribution using a Monte Carlo sampling scheme [81].

The significance of G^2 and ΔG^2 based on the exact conditional distribution does not rely on an asymptotic approximation and is accurate for sparse and skewed data samples. Sequential model selection using the exact conditional test is developed for word sense disambiguation in [10]. The exact conditional test is also applied to the identification of significant lexical relationships in [74].

This dissertation employs sequential model selection using both the asymptotic approximation of the significance of G^2 values as well as the exact conditional distribution. The forward and backward sequential search procedures remain the same for both methods; the distinction is in how significance is assigned. The asymptotic assumption results in the assignment of significance values from a χ^2 distribution while the exact conditional test assigns significance based upon a Monte Carlo sampling scheme.[2]

3.1.2.2. Information Criteria

Two information criteria are employed as evaluation criteria in this dissertation; Akaike's Information Criteria (AIC) and the Bayesian Information Criteria (BIC). These criteria are formulated as follows for use during sequential model selection:

$$AIC = \Delta G^2 - 2 \times \Delta dof \tag{3.2}$$

$$BIC = \Delta G^2 - log(N) \times \Delta dof \tag{3.3}$$

where ΔG^2 again measures the deviation in fit between the candidate model and the current model. However, here ΔG^2 is treated as a raw score and not assigned significance. Δdof represents the difference between the adjusted degrees of freedom for the current and candidate models. Like ΔG^2, it is treated as a raw score and is not

[2]The freely available software package CoCo [2] implements the Monte Carlo sampling scheme described in [48].

used to assign significance. In Equation 3.3, N represents the number of observations in the training sample.

The information criteria are alternatives to using a pre–defined significance level, α, to judge the acceptability of a model. AIC and BIC explicitly balance model fit and complexity; fit is determined by the value of ΔG^2 while complexity is expressed in terms of the difference in the adjusted degrees of freedom of the two models, Δdof. Small values of ΔG^2 imply that the fit of the candidate model to the training data does not deviate greatly from the fit obtained by the current model. Likewise, small values for the adjusted degrees of freedom, Δdof, suggest that the candidate and current models do not differ greatly in regards to complexity.

During backward search the candidate model with the lowest negative AIC value is selected as the current model of complexity level $i-1$. This is the model that results in the least degradation in fit when moving from a model of complexity level i to one of $i-1$. This degradation is judged acceptable if the AIC value for the candidate model of complexity level $i-1$ is negative. If there are no such candidate models then the degradation in fit is unacceptably large and model selection stops and the current model of complexity level i becomes the selected model.

During forward search the candidate model with the largest positive AIC value is selected as the current model of complexity level $i+1$. This is the model that results in the largest improvement in fit when moving from a model of complexity level i to one of $i+1$. This improvement is judged acceptable if the AIC value for the model of complexity level $i+1$ is positive. If there are no such models then the improvement in fit is unacceptably small and model selection stops and the current model of complexity level i becomes the selected model.

The information criteria have a number of appealing properties that make them particularly well suited for sequential model selection. First, they do not require that a pre–determined cutoff point be specified to stop the model selection process; a mechanism to stop model selection is inherent in the formulation of the statistic. Second, the balance between model complexity and fit is explicit in the statistic and

Table 3.1. Model Selection Example Data

A	B	C	$freq(A, B, C)$
0	0	0	0
0	0	1	1
0	1	0	5
0	1	1	12
1	0	0	0
1	0	1	3
1	1	0	2
1	1	1	1

can be directly controlled by adjusting the constant that precedes Δdof. As this value increases the selection process results in models of decreasing complexity.[3]

3.1.3. Examples

For clarity, the sequential model selection process is illustrated with two simple examples; one using forward search in combination with AIC and the other using backward search and AIC. These methodologies are abbreviated as FSS AIC and BSS AIC, respectively. Both examples learn a parametric form from the 24 observation training sample shown in Table 3.1, where the feature set consists of three binary variables, A, B, and C. There are eight possible events in the event space. The frequency with which each event occurs in the sample is shown by $freq(A, B, C)$.

3.1.3.1. FSS AIC

During forward search, the candidate models are evaluated relative to how much they improve upon the fit of the current model. Such an improvement is expected since the candidate model has one more dependency than the current model.

[3]In general, BIC selects models of lower complexity than does AIC. This is discussed further in Chapter 6.

The value of ΔG^2 measures the amount of deviance between the candidate model and the current model; a large value implies that the candidate model greatly increases the fit of the model. Only candidate models that have positive AIC values improve upon the fit of the current model sufficiently to merit designation as the new current model. A negative value for AIC during forward search indicates that the increase in fit is outweighed by the resulting increase in complexity and will not result in a model that attains an appropriate balance of complexity and fit.

The steps in sequential model selection using FSS AIC are shown in Table 3.2. The G^2 values for the current and candidate models are shown, as is their difference, ΔG^2. The steps of the sequential search using forward search and AIC are shown in Table 3.2. The value of ΔG^2 measures the improvement in the fit when a dependency is added to the current model. During forward search, ΔG^2 is calculated by subtracting the G^2 value associated with the candidate model from the G^2 associated with the current model:

$$\Delta G^2 = G^2_{current} - G^2_{candidate} \tag{3.4}$$

This difference shows the degree to which the candidate model improves upon the fit of the current model. A large value of ΔG^2 shows that the fit of the candidate model to the training sample is considerably better than that of the current model.

The degree to which complexity is increased by the addition of a dependency to the candidate model is measured by the difference in the adjusted degrees of freedom for the two models, Δdof:

$$\Delta dof = dof_{candidate} - dof_{current} \tag{3.5}$$

Step 1: Forward search begins with the model of independence, $(A)(B)(C)$, as the current model. The set of one edge decomposable candidate models is generated by adding an edge to the model of independence. The candidate models include $(AC)(B)$, $(A)(BC)$, and $(AB)(C)$. These are all evaluated via AIC with the result

Table 3.2. Model Selection Example: FSS AIC

	Current	G^2	Candidate	G^2	ΔG^2	Δdof	AIC
Step 1	(A)(B)(C)	10.14	(AC)(B)	10.08	0.06	1	-1.94
	(A)(B)(C)	10.14	(A)(BC)	7.07	3.07	1	1.07
	(A)(B)(C)	10.14	(AB)(C)	4.56	5.58	1	3.58
Step 2	(AB)(C)	4.56	(AB)(AC)	4.50	0.06	1	-1.94
	(AB)(C)	4.56	(AB)(BC)	1.48	3.08	1	1.08
Step 3	(AB)(BC)	1.48	(ABC)	0.00	1.48	1	-0.52
Selected: **(AB)(BC)**							

that $(AB)(C)$ has the greatest positive AIC value. This candidate model exhibits the greatest deviance from the current model and therefore most increases the fit. Thus, $(AB)(C)$ becomes the new current model.

Step 2: A new set of candidate models is generated by adding an edge to the current model, $(AB)(C)$. The candidate models are $(AB)(AC)$ and $(AB)(BC)$. These are each evaluated relative to the current model $(AB)(C)$. The model $(AB)(BC)$ has the greatest positive AIC value associated with it and thus most increases the fit over the current model. The new current model is now $(AB)(BC)$.

Step 3: The set of candidate models is generated by adding an edge to the current model $(AB)(BC)$. The only resulting candidate is (ABC), the saturated model. However, when evaluated relative to the current model it has a negative AIC value associated with it; this suggests that the increase in fit is not sufficient to merit further increases in the complexity of the model. Thus, the current model $(AB)(BC)$ becomes the selected model and is the ultimate result of the selection process.

3.1.3.2. BSS AIC

During backward search, candidate models are evaluated based upon how much they degrade the fit of the current model. Since the candidate models have one

Table 3.3. Model Selection Example: BSS AIC

	Candidate	G^2	Current	G^2	ΔG^2	Δdof	AIC
Step 1	(AC)(BC)	7.00	(ABC)	0.00	7.00	1	5.00
	(AB)(AC)	4.49	(ABC)	0.00	4.49	1	2.49
	(AB)(BC)	1.48	(ABC)	0.00	1.48	1	-0.52
Step 2	(A)(BC)	7.07	(AB)(BC)	1.48	5.59	1	3.59
	(AB)(C)	4.56	(AB)(BC)	1.48	3.08	1	1.08
Selected: **(AB)(BC)**							

fewer dependency than the current model, it is inevitable that there will be some degradation in fit.

During backward search only candidate models that have negative AIC values are eligible to be designated current models. A positive AIC suggests that the degradation in model fit that occurs due to removal of a dependency is too large and offsets the benefits of reducing the complexity of the current model.

The steps of the sequential search using backward search and AIC are shown in Table 3.3. The value of ΔG^2 measures the degradation in fit when a dependency is removed from the current model:

$$\Delta G^2 = G^2_{candidate} - G^2_{current} \tag{3.6}$$

The degree to which complexity is decreased by the removal of a dependency from the candidate model is shown by the difference in the degrees of freedom for the two models, Δdof:

$$\Delta dof = dof_{current} - dof_{candidate} \tag{3.7}$$

Step 1: A backward search begins with the saturated model, (ABC), as the current model. The set of candidate models consists of all two edge models that

are generated by removing a single edge from the saturated model. The models $(AC)(BC)$, $(AB)(AC)$, and $(AB)(BC)$ are evaluated relative to the saturated model. $(AC)(BC)$ has the lowest negative AIC value and becomes the current model.

Step 2: The candidate models are all the one edge models generated by removing a single edge from the current model. The models $(A)(BC)$ and $(AB)(C)$ are evaluated and both have positive AIC values. Both result in a degradation in fit that is not offset by an appropriate reduction in model complexity. Thus, model selection stops and the current model, $(AB)(BC)$, becomes the selected model.

3.2. Naive Mix

This dissertation introduces the Naive Mix, a new supervised learning algorithm that extends the sequential model selection methodology. The usual objective of model selection is to find a single model that achieves the best representation of the training sample both in terms of complexity and fit. However, empirical results described in Chapter 6 show that it is often the case that very different models can result in nearly identical levels of disambiguation accuracy. This suggests that there is an element of uncertainty in model selection and that a single best model may not always exist.

The Naive Mix is based on the premise that each of the models that serve as a current model during a sequential search have important information that can be exploited for word sense disambiguation. The Naive Mix is an averaged probabilistic model based upon the average of the parameter estimates for all of the current models generated during a sequential model selection process.

Sequential methods of model selection result in a sequence of decomposable models $(m_1, m_2, \ldots, m_{r-1}, m_r)$ where m_1 is the initial current model and m_r is the selected model. Each model m_i is designated as the current model at the i^{th} step in the search process. During forward search m_1 is the model of independence and during backward search m_1 is the saturated model.

Each model m_i has a parametric form that expresses the dependencies among the feature variables $(F_1, F_2, \ldots, F_{n-1}, S)$, where the sense of the ambiguous word is represented by S and $(F_1, F_2, \ldots, F_{n-1})$ represent the feature variables. The joint probability distribution of this set of feature variables can be expressed in terms of the marginal probability distributions defined by each decomposable model m_i.

Given a sequence of current models found during a sequential search, the parameters of the joint probability distribution of the set of feature variables are estimated based upon the marginal distributions of each of these models. In other words, r different estimates for the joint probability distribution of a set of feature variables are made. These r estimates are averaged and the resulting joint probability distribution is a Naive Mix:

$$\hat{\theta}^{(F_1,F_2,\ldots,F_{n-1},S)_{average}} \quad = \quad \frac{1}{r} \times \sum_{i=1}^{r} \hat{\theta}^{(F_1,F_2,\ldots,F_{n-1},S)_{m_i}} \tag{3.8}$$

where $\hat{\theta}^{(F_1,F_2,\ldots,F_{n-1},S)_{m_i}}$ represents the parameter estimates given that the parametric form is m_i.

A Naive Mix can be created using either forward or backward search. However, there are a number of advantages to formulating a Naive Mix with a forward search. First, the inclusion of very simple models in the mix eliminates the problem of zero–valued parameter estimates in the averaged probabilistic model. The first model in the Naive Mix is the model of independence which acts as a majority classifier and has estimates associated with it for for every event in the event space. Second, forward search incrementally builds on the strongest dependencies among features while backward search incrementally removes the weakest dependencies. Thus a Naive Mix formulated with backward search can potentially contain many irrelevant dependencies while a forward search only includes the most important dependencies.

Consider an example that formulates a Naive Mix with a forward search; this example follows the notation of the earlier *bill* example. Suppose that the sequence of models shown in Table 3.4 are found to be the best fitting models by some evaluation

Table 3.4. Sequence of Models for Naive Mix created with FSS

	current model	mixed model
m_1	(C)(V)(R)(T)(S)	(S)
m_2	(CS)(V)(R)(T)	(CS)
m_3	(CS)(ST)(V)(R)	(CS)(ST)
m_4	(CS)(ST)(SV)(R)	(CS)(ST)(SV)
m_5	(CSV)(ST)(R)	(CSV)(ST)
m_6	(CSV)(ST)(TR)	(CSV)(ST)
m_7	(CSV)(RST)	(CSV)(RST)

criterion at each step of the forward search. These represent the set of current models.

Any marginal distributions of the current models that do not include S, the sense variable, can be eliminated from the model included in the mix. Such marginal distributions simply act as constants in a probabilistic classifier and can be removed from the mix without affecting the final result. In Table 3.4, the models in the column *mixed model* are used to make the parameter estimates of the joint probability distributions that are included in the Naive Mix.

The parameters of the joint probability distribution of each decomposable model m_i are expressed as the product of the marginal distributions of each current model. The parameters of the joint distributions are averaged across all of the models to create the Naive Mix. For example, the averaged parameter $\theta_{c,v,r,t,s}^{(C,V,R,T,S)_{average}}$ is estimated as follows:

$$\begin{aligned}\theta_{c,v,r,t,s}^{(C,V,R,T,S)_{average}} &= \frac{1}{7}(\hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_1}} + \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_2}} + \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_3}} + \\ &\quad \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_4}} + \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_5}} + \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_6}} + \hat{\theta}_{c,v,r,t,s}^{(C,V,R,T,S)_{m_7}}) \qquad (3.9)\end{aligned}$$

where

$$\hat{\theta}^{(C,V,R,T,S)_{m_1}}_{c,v,r,t,s} = \hat{\theta}^{S}_{s} \;,\; \hat{\theta}^{(C,V,R,T,S)_{m_2}}_{c,v,r,t,s} = \hat{\theta}^{C,S}_{c,s} \quad , \quad \hat{\theta}^{(C,V,R,T,S)_{m_3}}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S}_{c,s} \times \hat{\theta}^{S,T}_{s,t}}{\hat{\theta}^{S}_{s}}$$

$$\theta^{(C,V,R,T,S)_{m_4}}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S}_{c,s} \times \hat{\theta}^{S,T}_{s,t} \times \hat{\theta}^{S,V}_{s,V}}{\hat{\theta}^{S}_{s} \times \hat{\theta}^{S}_{s}} \quad , \quad \hat{\theta}^{(C,V,R,T,S)_{m_5}}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S,V}_{c,s,v} \times \hat{\theta}^{S,T}_{s,t}}{\hat{\theta}^{S}_{s}}$$

$$\hat{\theta}^{(C,V,R,T,S)_{m_6}}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S,V}_{c,s,v} \times \hat{\theta}^{S,T}_{s,t}}{\hat{\theta}^{S}_{s}} \quad , \quad \theta^{(C,V,R,T,S)_{m_7}}_{c,v,r,t,s} = \frac{\hat{\theta}^{C,S,V}_{c,s,v} \times \hat{\theta}^{R,S,T}_{r,s,t}}{\hat{\theta}^{S}_{s}}$$

Once the parameter estimates are made and averaged, the resulting probabilistic model can be used as a classifier to perform disambiguation. Suppose that the following feature vector represents a sentence containing an ambiguous use of *bill*. S represents the sense of the ambiguous word and the other variables represent observed features in the sentence:

$$(C = c, V = v, R = r, T = t, S = ?) \tag{3.10}$$

The value of S that maximizes $\hat{\theta}^{(C,V,R,T,S)_{average}}_{c,v,r,t,s_x}$ is determined to be the sense of *bill*. Here again disambiguation reduces to finding the value of S that is most probable in a particular context as defined by the observed values of the feature variables.

$$S = \underset{s_x}{^{argmax}} \; \hat{\theta}^{(C,V,R,T,S)_{average}}_{c,v,r,t,s_x} = \underset{s_x}{^{argmax}} \; p(s_x|c,v,r,t) \tag{3.11}$$

The Naive Mix addresses the uncertainty that exists in model selection. Similar difficulties in selecting single best models have been noted elsewhere; in fact, there is a general trend in model selection research away from the selection of such models (e.g., [53]). A similar movement exists in machine learning, based on the premise that no learning algorithm is superior for all tasks [83]. This has lead to hybrid approaches

that combine diverse learning paradigms (e.g., [31]) and approaches that select the most appropriate learning algorithm based on the characteristics of the training data (e.g., [8]).

3.3. Naive Bayes

Naive Bayes differs from the models learned via sequential model selection and the Naive Mix since the parametric form of Naive Bayes is always the same and does not have to be learned. Naive Bayes assumes that all feature variables are conditionally independent given the value of the classification variable. Examples of both the graphical representation of this parametric form and the associated parameter estimates are shown in Chapter 2.

In disambiguation, feature variables represent contextual properties of the sentence in which an ambiguous word occurs. The classification variable represents the sense of the ambiguous word. Thus, Naive Bayes assumes that the values of any two contextual features in a sentence do not directly affect each other. In general this is not a likely representation of the dependencies among features in language. For example, one kind of feature used in this dissertation represents the part–of–speech of words that surround the ambiguous word. It is typically the case that the part–of–speech of the $i + 1^{th}$ word in a sentence is dependent on the part–of–speech of the i^{th} word. When an article occurs in the i^{th} position, one can predict that a noun or adjective is more likely to occur at the $i + 1^{th}$ position than is a verb, for example. However, despite the fact that Naive Bayes does not correspond to intuitions regarding the dependencies among features, experimental results in Chapter 6 show that Naive Bayes performs at levels comparable to models with learned parametric forms.

If the contextual features of a sentence are represented by variables ($F_1, F_2, \ldots, F_{n-1}$) and the sense of the ambiguous word is represented by S, then the parameter estimates of Naive Bayes are calculated as follows:

$$\hat{\theta}^{F_1,F_2,\ldots,F_{n-1},S}_{f_1,f_2,\ldots,f_{n-1},s} = \theta^S_s \times \prod_{i=1}^{n-1} \frac{\hat{\theta}^{F_i,S}_{f_i,s}}{\hat{\theta}^S_s} \tag{3.12}$$

Several alternative but equivalent formulations are shown in Chapter 2.

Even with a large number of features, the number of parameters in Naive Bayes is relatively small. For a problem with n feature variables, each having l possible values, and a classification variable with s possible values, the number of parameters in Naive Bayes is $n * l * s$. More complicated models often require that an exponential number of parameters be learned. For example, a saturated model given the same scenario will have $n^l * s$ parameters.

CHAPTER 4

UNSUPERVISED LEARNING FROM RAW TEXT

The main limitation of the supervised learning methods presented in Chapter 3 is the need for sense–tagged text to serve as training examples. The creation of such text is time–consuming and proves to be a significant bottleneck in porting and scaling the supervised approaches to new and larger domains of text.

Unsupervised learning presents an alternative that eliminates this dependence on sense–tagged text. The object of unsupervised learning is to determine the classification of each instance in a sample without using training examples. In word sense disambiguation, this corresponds to grouping instances of an ambiguous word into some pre–specified number of sense groups, where each group corresponds to a distinct sense of the ambiguous word. This is done strictly based on information obtained from raw untagged text; no external knowledge sources are employed. While this increases the portability of these approaches, it also imposes an important limitation. Since no knowledge beyond the raw text is employed, the unsupervised learning algorithms do not have access to the sense inventory for a word. Thus, while they create sense groups based on the features observed in the text, these groups are not labeled with a definition or any other meaningful tag. If such labels are desired, they must be attached after unsupervised learning has created the sense groups. One means of attaching such labels is discussed in Chapter 7.

This chapter describes a methodology by which probabilistic models can be learned from raw text. It requires that the variable values associated with the sense of an ambiguous word be treated as missing or unobserved data in the sample. Given that these values are never present in the data sample, it is not possible to conduct a systematic search for the parametric form of a model; one must simply be assumed.

In this framework, the Expectation Maximization (EM) algorithm [29] and Gibbs Sampling [39] are used to estimate the parameters of a probabilistic model. As a part of this process, values are imputed, i.e., filled–in, for the sense variable. This effectively assigns instances of an ambiguous word to a particular sense group.

An alternative to this probabilistic methodology is to use an agglomerative clustering algorithm that forms sense groups of untagged instances of an ambiguous word by minimizing a distance measure between the instances of an ambiguous word in each sense group. Two agglomerative algorithms are explored here, McQuitty's similarity analysis [55] and Ward's minimum–variance method [91].

4.1. Probabilistic Models

In supervised learning, given the parametric form of a decomposable model, maximum likelihood estimates of parameters are simple to compute. The sufficient statistics of these parameters are the frequency counts of marginal events that are defined by the marginal distributions of the model. These counts are obtained directly from the training data. However, in unsupervised learning, parameter estimation is more difficult since direct estimates from the sample are not possible given that data is missing.

To illustrate the problem, the *bill* example from the previous chapter is recast as a problem in unsupervised learning. Suppose that $(CVS)(RTS)$ is the parametric form of a decomposable model. In supervised learning, maximum likelihood estimates of the parameters of the joint distribution are made by observing the frequency of the marginal events (CVS) and (RTS). However, when sense–tagged text is not available this estimate can not be computed directly since the value of S is unknown. There is no way, for example, to directly count the occurrences of the marginal events $(C = yes, S = 1, V = no)$ and $(C = yes, S = 2, V = no)$ in an untagged sample of text; the only observed marginal event is $(C = yes, S = ?, V = no)$. However, both the EM algorithm and Gibbs Sampling impute values for this missing data and thereby make parameter estimation possible.

Here the assumption is made that the parametric form of the model is Naive Bayes. In this model, all features are conditionally independent given the value of the classification feature, i.e., the sense of the ambiguous word. This assumption is based on the success of the Naive Bayes model when applied to supervised word–sense disambiguation (e.g. [11], [37], [51], [62], [70], [73]).

In these discussions, the sense of an ambiguous word is represented by a feature variable, S, whose value is missing. The observed contextual features are represented by $Y = (F_1, F_2, \ldots, F_n)$. The complete data sample is then $D = (Y, S)$ and the parameters of the model are represented by the vector Θ.

4.1.1. EM Algorithm

The EM algorithm is an iterative estimation procedure in which a problem with missing data is recast to make use of complete data estimation techniques. The EM algorithm formalizes a long–standing method of making estimates for the parameters of a model, Θ, when data is missing. A high–level description of the algorithm is as follows:

1. Randomly estimate initial values for the parameters Θ. Call this set of estimates Θ^{old}.

2. Replace the missing values of S by their expected values given the parameter estimates Θ^{old}.

3. Re–estimate parameters based on the filled–in values for the missing variable S. Call these parameter estimates Θ^{new}.

4. Have Θ^{old} and Θ^{new} converged? If not, rename Θ^{new} as Θ^{old} and go to step 2.

4.1.1.1. General Description

At the heart of the EM Algorithm lies the *Q-function*. This is the expected value of the log of the likelihood function for the complete data sample, $D = (Y, S)$,

where Y is the observed data and S is the missing sense value:

$$Q(\Theta^{new}|\Theta^{old}) \quad = \quad E[\ln p(Y, S|\Theta^{new})|\Theta^{old}, Y)] \tag{4.1}$$

Here, Θ^{old} is the previous value of the maximum likelihood estimates of the parameters and Θ^{new} is the improved estimate; $p(Y, S|\Theta^{new})$ is the likelihood of observing the complete data given the improved estimate of the model parameters.

When approximating the maximum of the likelihood function, the EM algorithm starts from a randomly generated initial estimate of the model parameters and then replaces Θ^{old} by the Θ^{new} which maximizes $Q(\Theta^{new}|\Theta^{old})$. This is a two step process, where the first step is known as the expectation step, i.e., the E–step, and the second is the maximization step, i.e., the M–step. The E–step finds the expected values of the sufficient statistics of the complete model using the current estimates of the model parameters. For decomposable models these sufficient statistics are the frequency counts of events defined by the marginal distributions of the model. The M–step makes maximum likelihood estimates of the model parameters using the sufficient statistics from the E–step. These steps iterate until the parameter estimates Θ^{old} and Θ^{new} converge.

The M–step is usually easy, assuming it is easy for the complete data problem. As shown in Chapter 2, making parameter estimates for decomposable models is straightforward. In the general case the E–step may be complex. However, for decomposable models the E–step simplifies to the calculation of the expected marginal event counts defined by a decomposable model, where the expectation is with respect to Θ^{old}. The M–step simplifies to the calculation of new parameter estimates from these counts. Further, these expected counts can be calculated by multiplying the sample size N by the probability of the complete data within each marginal distribution, given Θ^{old} and the observed data within each marginal Y_m. This simplifies to:

$$freq^{new}(S_m, Y_m) = p(S_m|Y_m) \times freq(Y_m) \tag{4.2}$$

where $freq^{new}$ is the current estimate of the expected count and $p(S_m|Y_m)$ is formulated using Θ^{old}.

4.1.1.2. Naive Bayes description

The expectation and maximization steps of the EM algorithm are outlined here. It is assumed that the parametric form is Naive Bayes, although this discussion extends easily to any decomposable model [50]. Given that the parametric form is Naive Bayes, it follows that:

$$p(F_1, F_2, \ldots, F_n, S) = p(S) \times \prod_{i=1}^{n} p(F_i|S) \tag{4.3}$$

where $p(S)$ and $p(F_i|S)$ are the model parameters. This is equivalent to treating $p(F_i, S)$ as the model parameters since $p(F_i, S) = \frac{p(F_i|S)}{p(S)}$. However, the conditional representation lends itself to developing certain analogies between the EM algorithm and Gibbs Sampling.

E–step: The expected values of the sufficient statistics of the Naive Bayes model are computed. These are the frequency counts of marginal events of the form (F_i, S) and are notated $freq(F_i, S)$. Since S is unobserved, values for it must be imputed before the marginal events can be counted. During the first iteration of the EM algorithm, values for S are imputed by random initialization. Thereafter, S is imputed with values that maximize the probability of observing a particular sense for an ambiguous word in a given context:

$$S = \overset{argmax}{s_x} \hat{p}(S|f_1, f_2, \ldots, f_{n-1}, f_n) \tag{4.4}$$

From $p(a|b) = \frac{p(a,b)}{p(b)}$ it follows that:

$$\hat{p}(S|f_1, f_2, \ldots, f_{n-1}, f_n) = \frac{\hat{p}(f_1, f_2, \ldots, f_{n-1}, f_n, S)}{\hat{p}(f_1, f_2, \ldots, f_{n-1}, f_n)} \tag{4.5}$$

And from $p(a, b) = \sum_c p(a, b, c)$ it follows that:

$$\hat{p}(f_1, f_2, \ldots, f_{n-1}, f_n) = \sum_S \hat{p}(f_1, f_2, \ldots, f_n, S) \tag{4.6}$$

Thus,

$$S = \underset{s_x}{^{argmax}} \frac{\hat{p}(S) \times \prod_{i=1}^{n} \hat{p}(f_i|S)}{\sum_S \hat{p}(f_1, f_2, \ldots, f_n, S)} \tag{4.7}$$

This calculation determines the value of S to impute for each possible combination of observed feature values. Given imputed values for S, the expected values of the marginal event counts, $freq(F_i, S)$, are determined directly from the data sample following Equation 4.2. These counts are the sufficient statistics for the Naive Bayes model.

M–Step: The sufficient statistics from the E–step are used to re–estimate the model parameters. This new set of estimates is designated Θ^{new} while the previous set of parameter estimates is called Θ^{old}. The model parameters $p(S)$ and $p(F_i|S)$ are estimated as follows:

$$\hat{p}(S) = \frac{freq(S)}{N} \qquad \hat{p}(F_i|S) = \frac{freq(F_i, S)}{freq(S)} \tag{4.8}$$

Convergence?: If the difference between the parameter estimates obtained in the previous and current iteration is less than some pre–specified value ϵ, i.e.,:

$$||\Theta^{old} - \Theta^{new}|| < \epsilon \tag{4.9}$$

then the parameter estimates have converged and the EM algorithm stops. If this difference is greater than ϵ, Θ^{new} is renamed Θ^{old} and the EM algorithm continues.

Table 4.1. Unsupervised Learning Example Data

F_1	F_2	S
1	2	?
1	2	?
2	2	?
2	2	?
1	2	?
1	1	?
1	1	?
1	1	?
1	2	?
2	2	?

The EM algorithm is guaranteed to converge [29], however if the likelihood function is very irregular it may converge to a local maxima and not find the global maximum. In this case, an alternative is to use the more computationally expensive method of Gibbs Sampling which is guaranteed to converge to a global maximum.

4.1.1.3. Naive Bayes example

The step by step operation of the EM algorithm is illustrated with a simple example where the parametric form is assumed to be Naive Bayes. Suppose that there is a data sample where events are described by 3 random variables. The variables F_1 and F_2 are observed and have two possible values. The variable S represents the class of the event but is unobserved. Given this formulation, the model parameters are $p(S)$, $p(F_1|S)$ and $p(F_2|S)$, following Equation 4.3. The data sample used in this example has ten observations and is shown in Table 4.1.

E–Step Iteration 1: The EM algorithm begins by randomly assigning values to S. Such an assignment is shown on the left side of Figure 4.1. Given these random assignments, expected values for the sufficient statistics of the Naive Bayes model are

F_1	F_2	S
1	2	1
1	2	3
2	2	2
2	2	2
1	2	1
1	1	3
1	1	1
1	1	2
1	2	2
2	2	1

		F_1		
		1	2	
S	1	3	1	4
	2	2	2	4
	3	2	0	2
		7	3	10

		F_2		
		1	2	
S	1	1	3	4
	2	1	3	4
	3	1	1	2
		7	3	10

Figure 4.1. E–Step Iteration 1

determined by counting the marginal events defined by Naive Bayes, i.e., $freq(F_1, S)$ and $freq(F_2, S)$. These marginal event counts are conveniently represented in a cross–classification or contingency table, as appears in the center and right of Figure 4.1. For example, the center table shows that:

$$freq(F_1 = 1, S = 1) = 3 \qquad freq(F_1 = 2, S = 1) = 1$$
$$freq(F_1 = 1, S = 2) = 2 \qquad freq(F_1 = 2, S = 2) = 2$$
$$freq(F_1 = 1, S = 3) = 2 \qquad freq(F_1 = 2, S = 3) = 0$$

M–Step Iteration 1: Maximum likelihood estimates for the parameters of Naive Bayes are made from the marginal event counts found during the E–step. Given the marginal event counts in Figure 4.1, the parameter estimates are computed following Equation 4.8. The values for these estimates found during iteration 1 are shown in the contingency tables in Figure 4.2. For example, the center table shows that:

1	0.4	
S 2	0.4	
3	0.2	

F_1

	1	2	
1	0.75	0.25	1.0
S 2	0.50	0.50	1.0
3	1.00	0.00	1.0

F_2

	1	2	
1	0.25	0.75	1.0
S 2	0.25	0.75	1.0
3	0.50	0.50	1.0

Figure 4.2. M–Step Iteration 1: $\hat{p}(S)$, $\hat{p}(F_1|S)$, $\hat{p}(F_2|S)$

$$\hat{p}(F_1 = 1|S = 1) = 0.75 \qquad \hat{p}(F_1 = 2|S = 1) = 0.25$$
$$\hat{p}(F_1 = 1|S = 2) = 0.50 \qquad \hat{p}(F_1 = 2|S = 2) = 0.50$$
$$\hat{p}(F_1 = 1|S = 3) = 1.00 \qquad \hat{p}(F_1 = 2|S = 3) = 0.00$$

E–Step Iteration 2: After the first iteration of the EM algorithm, all subsequent iterations find the expected values of the marginal event counts by imputing new values for S that maximize the following conditional distribution:

$$S = \overset{argmax}{s}\ \hat{p}(S|F_1, F_2) = \frac{\hat{p}(S) \times \hat{p}(F_1|S) \times \hat{p}(F_2|S)}{\hat{p}(F_1, F_2)} \tag{4.10}$$

The estimates of the parameters required by Equation 4.10 are the estimates made in the M–step of the previous iteration, shown in Figure 4.2. The computation in Equation 4.10 results in the value of S that maximize the conditional probability distribution where S is conditioned on the values of the observed features F_1 and F_2. The values of $\hat{p}(S|F_1, F_2)$ are shown in Figure 4.3. The maximum estimate for each given pair of values for the features (F_1, F_2) are shown in bold face. The value of S associated with each of these maximum probabilities is imputed for each observation in the data sample that shares the same values for the observed feature values. For

F_1	F_2	S	$\hat{p}(S\|F_1, F_2)$
1	1	1	.333
1	1	2	.222
1	1	3	**.444**
1	2	1	**.474**
1	2	2	.316
1	2	3	.211
2	1	1	.333
2	1	2	**.667**
2	1	3	.000
2	2	1	.333
2	2	2	**.667**
2	2	3	.000

Figure 4.3. E–Step Iteration 2

example, if $(F_1 = 1, F_2 = 1, S = ?)$ is an observation in the data sample, then the value of 3 is imputed for S since $\hat{p}(S = 3|F_1 = 1, F_2 = 1)$ is greater than both $\hat{p}(S = 2|F_1 = 1, F_2 = 1)$ and $\hat{p}(S = 1|F_1 = 1, F_2 = 1)$.

The data sample that results from these imputations for S is shown on the left of Figure 4.4. The expected counts of the marginal events in that updated data sample are shown in contingency table form in the center and right of this same figure.

M–Step Iteration 2: Given the expected values of the marginal event counts from the previous E–step, values for the model parameters are re–estimated. Figure 4.5 shows the values for the parameter estimates $\hat{p}(S)$, $\hat{p}(F_1|S)$, and $\hat{p}(F_2|S)$.

At this point, two iterations of the EM algorithm have been performed. From this point forward, at the conclusion of each iteration a check for convergence is made. The parameters estimated during the previous iteration are Θ^{old} and those estimated during the current iteration are Θ^{new}. For example, during iterations 1 and 2 the following estimates have been made:

F_1	F_2	S
1	2	1
1	2	1
2	2	2
2	2	2
1	2	1
1	1	3
1	1	3
1	1	3
1	2	1
2	2	2

F_1

		1	2	
	1	4	0	4
S	2	0	3	3
	3	3	0	3
		7	3	10

F_2

		1	2	
	1	0	4	4
S	2	0	3	3
	3	3	0	3
		3	7	10

Figure 4.4. E–Step Iteration 2

	1	0.4	
S	2	0.3	
	3	0.3	

F_1

		1	2	
	1	1.0	0.0	1.0
S	2	0.0	1.0	1.0
	3	1.0	0.0	1.0

F_2

		1	2	
	1	0.0	1.0	1.0
S	2	0.0	1.0	1.0
	3	1.0	0.0	1.0

Figure 4.5. M–Step Iteration 2: $\hat{p}(S)$, $\hat{p}(F_1|S)$, $\hat{p}(F_2|S)$

F_1	F_2	S	$\hat{p}(S\|F_1, F_2)$
1	1	1	0.0
1	1	2	0.0
1	1	3	**1.0**
1	2	1	**1.0**
1	2	2	0.0
1	2	3	0.0
2	1	1	0.0
2	1	2	0.0
2	1	3	0.0
2	2	1	0.0
2	2	2	**1.0**
2	2	3	0.0

Figure 4.6. E–Step Iteration 3

$$\Theta^{old} = \{.4, .4, .2, .75, .25, .5, .5, 1.0, 0.0, .25, .75, .25, .75, .5, .5\}$$

$$\Theta^{new} = \{.4, .3, .3, 1.0, 0.0, 0.0, 1.0, 1.0, 0.0, 0.0, 1.0, 0.0, 1.0, 1.0, 0.0\}$$

The difference between Θ^{old} and Θ^{old} is considerable and certainly more than a typical value of ϵ, i.e., .01 or .001. Thus, the EM algorithm continues for at least one more iteration.

E–step Iteration 3: The expected values for the marginal event counts are determined as in the previous iteration. First, the values of S that maximize the conditional probability distribution of $\hat{p}(S|F_1, F_2)$ are determined. This maximization is based on the parameter estimates, shown in Figure 4.5, which were determined during the M–step of the previous iteration.

Figure 4.6 shows the estimated values for $\hat{p}(S|F_1, F_2)$, the conditional distribution of S given the values of the observed feature values. The maximum probability for each given pair of feature values is shown in bold face. The values of S that

F_1	F_2	S
1	2	1
1	2	1
2	2	2
2	2	2
1	2	1
1	1	3
1	1	3
1	1	3
1	2	1
2	2	2

Figure 4.7. E–Step Iteration 3

result in this maximized conditional distribution are imputed for the missing data of observations in the sample that share the same observed feature values. The data set that results from this imputation is shown in Figure 4.7. However, note that the values found during the third iteration prove to be identical to those found during the second iteration.

The expected counts of marginal events and the parameter estimates found during iteration 3 are identical to those found during iteration 2. Given this, the difference between Θ^{old} and Θ^{new} is zero and the parameter estimates have converged. The values for the missing variable S are assigned as shown in Figure 4.7. This is an intuitively appealing result that can be interpreted in terms of assigning events to classes. The event $(F_1 = 1, F_2 = 1)$ belongs to class 3, event $(F_1 = 2, F_2 = 2)$ belongs to class 2, and event $(F_1 = 1, F_2 = 2)$ belongs to class 1.

4.1.2. Gibbs Sampling

Gibbs Sampling is a more general tool than the EM algorithm in that it is not restricted to handling missing data; it is a special case of Markov Chain Monte

Carlo methods for approximate inference. These methods were first used for applications in statistical physics in the 1950's; perhaps the most notable example being the Metropolis algorithm [58]. Gibbs Sampling was originally presented in the context of an image restoration problem but has since been applied to a wide range of applications.

In general, Gibbs Sampling provides a means of approximating complex probabilistic models. In unsupervised learning probabilistic models are complex because there is missing data, i.e., the sense of the ambiguous word is unknown. Gibbs Sampling approximates the distribution of the parameters of a model as if the missing data were observed. By contrast, the EM algorithm simply maximizes the estimated values for the parameters of a model, again by acting as if the missing data were observed.

4.1.2.1. General Description

Gibbs Sampling has a Bayesian orientation in that it naturally incorporates prior distributions, $p(\Theta)$, into the sampling process. When a prior distribution is specified in conjunction with an observed data sample, Gibbs Sampling approximates the posterior probability function, $p(\Theta|D)$, by taking a large number of samples from it. If a prior distribution is not utilized then Gibbs Sampling still takes a large number of samples, however, they are drawn from the likelihood function $p(D|\Theta)$. In this dissertation, non–informative prior distributions are employed and the sampling is from the posterior distribution function.

A Gibbs Sampler creates Markov Chains of parameter estimates and values for missing data whose stationary distributions approximate the posterior distribution, $p(\Theta|D)$, by simulating a random walk in the space of Θ. A Markov Chain is a series of random variables $(X^0, X^1, \ldots)$ in which the influence of the values of $(X^0, \ldots, X^n)$ on the distribution of X^{n+1} is mediated entirely by the value of X^n.

Let the values of the observed contextual feature variables be represented by $Y = (F_1, F_2, \cdots, F_{n-1}, F_n)$ and let S represent the unknown sense of an ambiguous

word. Given that the parametric form of the model is known, random initial values are generated for the missing data $S^0 = (S_1^0, S_2^0, \ldots, S_N^0)$ and the unknown parameter estimates of the assumed model $\Theta^0 = (\theta_1^0, \theta_2^0, \ldots, \theta_q^0)$. S^0 is a vector containing a value for each instance of the missing sense data, Θ^0 is a vector containing the parameters of the model, N is the number of observations in the data sample, and q is the number of parameters in the model.

A Gibbs Sampler performs the following loop, where j is the iteration counter, until convergence is detected:

$$\begin{aligned}
S^{j+1} &\sim p(S|\theta_1^j, \theta_2^j, \cdots, \theta_q^j, Y) \\
\theta_1^{j+1} &\sim p(\theta_1|\theta_2^j, \cdots, \theta_q^j, Y, S^{j+1}) \\
\theta_2^{j+1} &\sim p(\theta_2|\theta_1^{j+1}, \theta_3^j, \cdots, \theta_q^j, Y, S^{j+1}) \\
&\vdots \\
\theta_q^{j+1} &\sim p(\theta_q|\theta_1^{j+1}, \cdots, \theta_{q-1}^{j+1}, Y, S^{j+1})
\end{aligned}$$

Each iteration of the Gibbs Sampler samples values for the missing data and for the unknown parameter estimates. The values for the missing data are conditioned on the values of the parameters and the observed data. The parameter estimates are conditioned on the previously estimated values of the other parameters and the missing data as well as the observed data.

A chain of values is constructed for each missing value and parameter estimate via this sampling loop. Each chain is monitored for convergence. A range of techniques for monitoring convergence are discussed in [88]; this dissertation uses Geweke's method [40]. In this approach, a chain is divided into two windows, one at the beginning and the other at the end. Each window contains about 10% of the total number of iterations in the chain. If the entire chain has reached a stationary distribution, then these two windows, one early in the chain and the other late, will

have approximately the same mean values. If they do not then the parameters have not yet converged to a stationary distribution.

The early iterations of Gibbs Sampling produce chains of values with very high variance. It is standard to discard some portion of the early iterations; this process is commonly known as a *burn–in*. The general procedure followed here is to have a 500 iteration burn–in followed by 1000 iterations that are monitored for convergence. If the chains do not converge after 1000 iterations then additional iterations in increments of 500 are performed until they do. This procedure was designed following recommendations by [79].

A proof that convergence on the posterior probability distribution is guaranteed during Gibbs Sampling is given in [39]. Once convergence occurs, the approximation to the posterior probability function can be summarized like any other probability function. Also, the median value in each chain of sampled values for missing data becomes the sense group to which an instance of an ambiguous word is ultimately assigned.

4.1.2.2. Naive Bayes description

Gibbs Sampling is developed in further detail, given the assumption that the parametric form is Naive Bayes. However, this discussion is easily extended to any decomposable model. As in the previous example, the parameters of the model are $p(S)$ and $p(F_i|S)$, following Equation 4.3.

A Gibbs Sampler generates chains of values for each missing instance of S in the data sample and also for each of the parameters $\hat{p}(S)$ and $\hat{p}(F_i|S)$. Each of these chains will eventually converge to a stationary distribution.

In this dissertation the observed data sample is multinomial, i.e., each instance in the data sample is described by a combination of discrete feature values. As was shown in Chapter 2, such a sample can be formally defined by a multinomial distribution with parameters $(N; \theta_1, \theta_2, \ldots, \theta_q)$. However, here the distribution of multinomial data is represented by the frequency counts for each possible event. This

is notated as $M(f_1, f_2, \ldots, f_q)$, where q is the number of possible events and f_i is the frequency of the i^{th} event. For example, $M(f_1, f_2, \ldots, f_q)$ represents a multinomial distribution with q possible events where the i^{th} event occurs f_i times.

The conjugate prior to the multinomial distribution is the Dirichlet distribution, described by $D(\alpha_1, \alpha_2, \ldots, \alpha_q)$, where α_i represents the prior frequency of the i^{th} event. If all α_i are set to 1 then a non–informative prior has been properly specified [38]. For example, if $q = 3$, $D(1, 1, 1)$ describes a non–informative Dirichlet prior distribution.

Following Bayes Rule, the product of a prior distribution and the likelihood distribution results in a posterior probability distribution. If the prior distribution and the likelihood function are conjugate, then the posterior distribution has the same distribution as the prior. Here, since the observed data is described by a multinomial distribution and the prior is specified in terms of a Dirichlet distribution, the resulting posterior distribution is Dirichlet.

A multinomial distribution and a Dirichlet distribution are multiplied by adding the frequency counts associated with each possible event in the multinomial with the prior frequency count as specified by the Dirichlet. The resulting sums specify the parameters that describe a posterior Dirichlet distribution [38].

$$D(f_1 + g_1, \ldots, f_{q-1} + g_{q-1}, f_q + g_q) = M(f_1, \ldots, f_{q-1}, f_q) + D(g_1, \ldots, g_{q-1}, g_q)$$

This defines a distribution from which values can be sampled to approximate the posterior distribution of the parameter estimates.

In this discussion, Gibbs Sampling is cast as a non–deterministic version of the EM algorithm. This treatment is similar in spirit to that of [15], where the EM algorithm is treated as a deterministic version of Gibbs Sampling.

1. **Stochastic E–Step**: The expected values of the sufficient statistics are calculated. These are the counts of the marginal events defined by the marginal

distributions of the Naive Bayes model, (F_i, S). However, before the marginal events can be counted, values for S must be imputed for each instance in the data sample. In the EM algorithm these values are obtained by finding the value of S that maximizes $\hat{p}(S|F_1, F_2, \ldots, F_{n-1}, F_n)$. In Gibbs Sampling, these values are imputed via sampling from that same conditional distribution:

$$S \sim \hat{p}(S|f_1, f_2, \ldots, f_{n-1}, f_n) = \frac{\hat{p}(S) \times \prod_i^n \hat{p}(F_i|S)}{\hat{p}(f_1, f_2, \ldots, f_{n-1}, f_n)} \tag{4.11}$$

This conditional distribution is based upon values for $\hat{p}(S)$ and $\hat{p}(F_i|S)$ that are arrived at via sampling during the previous iteration of the stochastic M–step. If this is the first iteration of the Gibbs Sampler, then these values come about as the result of random initialization. After values for S are imputed via sampling, the marginal events are counted and the stochastic E–step concludes.

2. **Stochastic M–Step**: The expected values of the sufficient statistics found during the stochastic E-step are now used to re–estimate the parameters of the model. The EM algorithm makes maximum likelihood estimates directly from these marginal event counts. However, in Gibbs Sampling these marginal event counts are used to describe a multinomial distribution that is multiplied by a Dirichlet prior distribution to create a Dirichlet posterior distribution from which values of the model parameters are sampled.

   The observed frequency counts of marginal events are used to describe a multinomial distribution from which samples for the model parameters can be drawn. To approximate the conditional distribution of $\hat{p}(F_i|S)$ via sampling, suppose there are 2 possible events when the value of S is fixed. The frequency count of each event is represented by f_1 and f_2 and the multinomial distribution of this data can be described by $M(f_1, f_2)$. Further suppose that a non–information prior Dirichlet distribution is specified, i.e., $D(1, 1)$. These two distributions

are multiplied to create a posterior Dirichlet distribution from which values for $\hat{p}(F_i|S)$ are sampled:

$$\hat{p}(F_i|S) \sim D(f_1 + 1, f_2 + 1) = M(f_1, f_2) \times D(1, 1) \tag{4.12}$$

Values for $\hat{p}(S)$ are sampled along similar lines. After values for the model parameters have been sampled, the stochastic M–step concludes.

3. **Convergence?**: After j iterations there are chains of length j for both the sampled values for each model parameter and for each of the N missing sense values in the data sample. After some set number of iterations, these chains are checked for convergence.

   Once convergence is detected, the median values in the chains created during sampling are regarded as the estimates of parameters and missing data. For example, suppose that (1, 1, 1, 2, 2, 2, 2, 2, 2, 3) is a chain that represents the values for a missing sense value sampled for a particular instance in the data sample. The median sense value is 2 and this value is imputed for S for that observation in the sample.

4.1.2.3. Naive Bayes example

The same example used to demonstrate the EM algorithm is employed here with Gibbs Sampling. The data sample is shown in Table 4.1 and the parametric form of the model is Naive Bayes with model parameters $p(S)$, $p(F_1|S)$, and $p(F_2|S)$.

Stochastic E–Step Iteration 1: Like the EM algorithm, Gibbs Sampling begins by randomly assigning values to S. Assume that the random assignment of values to S is as shown on the left of Figure 4.8 and the expected counts of marginal events, as represented in the contingency tables, are as shown in the center and right of that figure.

F_1	F_2	S
1	2	1
1	2	3
2	2	2
2	2	2
1	2	1
1	1	3
1	1	1
1	1	2
1	2	2
2	2	1

F_1

S	1	2	
1	3	1	4
2	2	2	4
3	2	0	2
	7	3	10

F_2

S	1	2	
1	1	3	4
2	1	3	4
3	1	1	2
	7	3	10

Figure 4.8. Stochastic E–Step Iteration 1

Stochastic M–Step Iteration 1: In the EM algorithm the marginal event counts are used directly to make maximum likelihood estimates for the model parameters. However, in Gibbs Sampling no maximum likelihood estimates are computed; instead, the frequency counts of observed marginal events combine with a specified prior distribution to describe a posterior distribution from which values for the model parameters are sampled.

Each row in the contingency tables shown in Figure 4.8 represents counts of marginal events where the value of S is fixed. These counts can be thought of as describing a multinomial distribution that represents a conditional probability of the form $\hat{p}(F_i|S)$. This conditional distribution is multiplied by a prior distribution to define a posterior distribution from which estimated values for the model parameters are sampled. For example, given that S has a fixed value of 1, the distribution of $\hat{p}(F_1|S = 1)$ is described by $M(3, 1)$. Thus, based on the expected counts of the marginal events in Figure 4.8 and the assumption that all priors are non–informative, the following sampling scheme is devised:

S	1	0.03
	2	0.51
	3	0.47

		F_1		
		1	2	
S	1	0.64	0.36	1.0
	2	0.54	0.46	1.0
	3	0.76	0.24	1.0

		F_2		
		1	2	
S	1	0.37	0.63	1.0
	2	0.09	0.91	1.0
	3	0.73	0.27	1.0

Figure 4.9. Stochastic M–step Iteration 1: $\hat{p}(S)$, $\hat{p}(F_1|S)$, $\hat{p}(F_2|S)$

$$\hat{p}(F_1|S=1) \sim D(4,2) = M(3,1) \times D(1,1)$$
$$\hat{p}(F_1|S=2) \sim D(3,3) = M(2,2) \times D(1,1)$$
$$\hat{p}(F_1|S=3) \sim D(3,1) = M(2,0) \times D(1,1)$$
$$\hat{p}(F_2|S=1) \sim D(2,4) = M(1,3) \times D(1,1)$$
$$\hat{p}(F_2|S=2) \sim D(2,4) = M(1,3) \times D(1,1)$$
$$\hat{p}(F_2|S=3) \sim D(2,2) = M(1,1) \times D(1,1)$$
$$\hat{p}(S) \sim D(5,5,3) = M(4,4,2) \times D(1,1,1)$$

The parameter estimates shown in Figure 4.9 are the result of this sampling plan.

Stochastic E–Step Iteration 2: After the first iteration of Gibbs Sampling, all subsequent iterations arrive at new values for the marginal event counts by sampling new values for S from the following conditional distribution:

$$S \sim \hat{p}(S|F_1, F_2) = \frac{\hat{p}(S) \times \hat{p}(F_1|S) \times \hat{p}(F_2|S)}{\hat{p}(F_1, F_2)} \tag{4.13}$$

The estimates of this conditional distribution are based upon the estimates of the model parameters shown in Figure 4.9; these were obtained via sampling during

F_1	F_2	S	$\hat{p}(S\|F_1, F_2)$
1	1	1	.024
1	1	2	.085
1	1	3	.891
1	2	1	.033
1	2	2	.699
1	2	3	.267
2	1	1	.100
2	1	2	.525
2	1	3	.375
2	2	1	.028
2	2	2	.852
2	2	3	.120

Figure 4.10. E–Step Iteration 2

the stochastic M–step of the previous iteration. The estimated values of $\hat{p}(S|F_1, F_2)$ are shown in Figure 4.10.

Rather than simply imputing the value of S that maximizes $\hat{p}(S|F_1, F_2)$, as is the case in the EM algorithm, values of S are sampled from the conditional distributions $\hat{p}(S|F_1, F_2)$. The result of this sampling process is an imputed value for S for a given pair of feature values. The resulting data sample after imputation of S is shown on the left in Figure 4.11. As an example of how Gibbs Sampling differs from the EM algorithm, note that the first two observations in the data sample have the same observed feature values, $(F_1 = 1, F_2 = 2)$. However, the stochastic E–step imputes different values of S for these observations. This occurs because a value of 2 is imputed for S with a probability of 70% while a value of 1 is imputed with a probability of 27%. In the E–step of the EM algorithm, only the value of S that maximizes the conditional probability is imputed.

Figure 4.11 shows the contingency tables of marginal event counts that result after values for S are imputed.

F_1	F_2	S
1	2	2
1	2	3
2	2	2
2	2	2
1	2	3
1	1	3
1	1	3
1	1	3
1	2	2
2	2	2

F_1

		1	2	
	1	0	0	0
S	2	2	3	5
	3	5	0	5
		7	3	10

F_2

		1	2	
	1	0	0	0
S	2	0	5	5
	3	3	2	5
		3	7	10

Figure 4.11. Stochastic E–Step Iteration 2

Stochastic M–Step Iteration 2 Given the marginal event counts found during the stochastic E–step, shown in Figure 4.11, sampling from the Dirichlet posterior of the model parameters is performed according to the following scheme:

$$\hat{p}(F_1|S=1) \sim D(1,1) = M(0,0) \times D(1,1)$$
$$\hat{p}(F_1|S=2) \sim D(3,4) = M(2,3) \times D(1,1)$$
$$\hat{p}(F_1|S=3) \sim D(6,1) = M(5,0) \times D(1,1)$$
$$\hat{p}(F_2|S=1) \sim D(1,1) = M(0,0) \times D(1,1)$$
$$\hat{p}(F_2|S=2) \sim D(1,6) = M(0,5) \times D(1,1)$$
$$\hat{p}(F_2|S=3) \sim D(4,3) = M(3,2) \times D(1,1)$$
$$\hat{p}(S) \sim D(1,6,6) = M(0,5,5) \times D(1,1,1)$$

Figure 4.12 shows the sampled estimates for $\hat{p}(S)$, $\hat{p}(F_1|S)$, and $\hat{p}(F_2|S)$. This concludes the second iteration of the Gibbs Sampler.

1	0.06	
S 2	0.54	
3	0.40	

	F_1		
	1	2	
1	0.25	0.75	1.0
S 2	0.68	0.32	1.0
3	0.93	0.06	1.0

	F_2		
	1	2	
1	0.16	0.84	1.0
S 2	0.05	0.95	1.0
3	0.52	0.48	1.0

Figure 4.12. Stochastic M–step Iteration 2: $\hat{p}(S)$, $\hat{p}(F_1|S)$, $\hat{p}(F_2|S)$

Stochastic E–step Iteration 3 Given the parameter estimates from the previous stochastic M–step, shown in Figure 4.12, conditional distributions for S given the values of the observed features are defined, per Equation 4.13.

The resulting distributions are shown in Figure 4.13. From those distributions imputed values for S are obtained via sampling. The updated data sample is shown in Figure 4.14.

Once again, the expected counts of marginal events are represented in contingency tables. These will be used to describe multinomial distributions that will be used in conjunction with a non–informative prior to create the posterior distributions from which new estimates of the model parameters will be sampled.

Normally Gibbs Sampling performs hundreds of iterations before it is checked for convergence. However, in the interest of brevity no further calculations or sampling operations will be shown. Unlike the EM algorithm, Gibbs Sampling does not stop itself. It must be told how many iterations to perform and then the resulting chains of parameter estimates and chains of missing values are checked for convergence. If convergence does not occur then some fixed number of additional iterations must be performed and then, once again, the resulting chains must be checked for convergence.

F_1	F_2	S	$\hat{p}(S\|F_1, F_2)$
1	1	1	0.009
1	1	2	0.085
1	1	3	0.906
1	2	1	0.024
1	2	2	0.645
1	2	3	0.331
2	1	1	0.250
2	1	2	0.321
2	1	3	0.429
2	2	1	0.181
2	2	2	0.759
2	2	3	0.056

Figure 4.13. Stochastic E–Step Iteration 3

F_1	F_2	S
1	2	2
1	2	2
2	2	2
2	2	2
1	2	3
1	1	3
1	1	3
1	1	3
1	2	2
2	2	2

Figure 4.14. Stochastic E–Step Iteration 3

4.2. Agglomerative Clustering

In general, clustering methods rely on the assumption that classes of events occupy distinct regions in a feature space. The distance between two points in a multi–dimensional space can be measured using any of a wide variety of metrics (see, e.g. [30]). Observations are grouped in the manner that minimizes the distance between the members of each cluster. When applied to word sense disambiguation, each cluster represents a particular sense group of an ambiguous word.

Ward's minimum–variance clustering and McQuitty's similarity analysis are agglomerative clustering algorithms that only differ in regards to their distance measures. All agglomerative algorithms begin by placing each observation in a unique cluster, i.e. a cluster of one. The two closest clusters are merged to form a new cluster that replaces the two merged clusters. Merging of the two closest clusters continues until some pre–specified number of clusters remain.

However, natural language data does not immediately lend itself to a distance–based interpretation. Typical features represent part–of–speech tags, morphological characteristics, and word co-occurrence; such features are nominal and their values do not have scale. However, suppose that the values of a part–of–speech feature are represented numerically such that $noun = 1$, $verb = 2$, $adjective = 3$, and $adverb = 4$. While distance measures could be computed using this representation, they would be meaningless since the fact that a noun has a smaller value than an adverb is purely arbitrary and reflects nothing about the relationship between nouns and adverbs.

Thus, before a clustering algorithm is employed, the data must be converted into a form where spatial distances actually convey a meaningful relationship between observations. In this dissertation this is done by representing the data sample as a *dissimilarity matrix*. Given N observations in a data sample, this can be represented in a $N \times N$ dissimilarity matrix such that the value in cell (i, j), where i represents the row number and j represents the column, is equal to the number of features in observations i and j that do not match.

noun	verb	car	0	2	1	0
adjective	verb	defeat	2	0	2	2
adverb	verb	car	1	2	0	1
noun	verb	car	0	2	1	0

Figure 4.15. Matrix of Feature Values, Dissimilarity Matrix

For example, in Figure 4.15 the matrix on the left represents a data sample consisting of four observations, where each observation has three nominal features. This sample is converted into a 4×4 dissimilarity matrix that is shown on the left in this figure. In the dissimilarity matrix, cells $(1, 2)$ and $(2, 1)$ have the value 2, indicating that the first and second observations in the matrix of feature values have different values for two of the three features. A value of 0 indicates that observations i and j are identical.

When clustering this data, each observation is represented by its corresponding row (or column) in the dissimilarity matrix. Using this representation, observations that fall close together in feature space are likely to belong to the same class and are grouped together into clusters. In this dissertation, Ward's and McQuitty's methods are used to form clusters of observations; each cluster corresponds to a sense group of related instances of an ambiguous word.

4.2.1. Ward's minimum–variance method

In Ward's method, the internal variance of a cluster is the sum of squared distances between each observation in the cluster and the mean observation for that cluster, i.e., the average of all the observations in the cluster. At each step in Ward's method, a new cluster, C_{KL}, with the smallest possible internal variance, is created by merging the two clusters, C_K and C_L, that have the minimum variance between them. The variance between C_K and C_L is computed as follows:

$$V_{KL} = \frac{||\overline{x}_K - \overline{x}_L||^2}{\frac{1}{N_K} + \frac{1}{N_L}} \tag{4.14}$$

where $\overline{x}_K$ is the mean observation for cluster C_K, N_K is the number of observations in C_K, and $\overline{x}_L$ and N_L are defined similarly for C_L.

Implicit in Ward's method is the assumption that the sample comes from a mixture of normal distributions [91]. Natural language data is typically not well characterized by a normal distribution. However, when such data is converted into a dissimilarity matrix there is reason to believe that a normal approximation is adequate. The number of features employed here is relatively small, thus the number of possible feature mismatches between observations is limited. This tends to have a smoothing effect on data that may be quite sparse and skewed when represented strictly as a matrix of feature values.

4.2.2. McQuitty's similarity analysis

In McQuitty's method, clusters are based on a simple averaging of the number of dissimilar features as represented in the dissimilarity matrix.

At each step in McQuitty's method, a new cluster, C_{KL}, is formed by merging the clusters C_K and C_L that have the fewest number of dissimilar features between them. Put another way, these are the clusters that have the most number of features in common. The clusters to be merged, C_K and C_L, are identified by finding the cell (l, k) (or (k, l)), where $k \neq l$, that has the minimum value in the dissimilarity matrix.

Once the new cluster C_{KL} is created, the dissimilarity matrix is updated to reflect the number of dissimilar features between C_{KL} and all other existing clusters. The dissimilarity between any existing cluster C_I and C_{KL} is computed as:

$$D_{KL-I} = \frac{D_{KI} + D_{LI}}{2} \tag{4.15}$$

where D_{KI} is the number of dissimilar features between clusters C_K and C_I and D_{LI} is similarly defined for clusters C_L and C_I. This is simply the average number of

mismatches between each component of the new cluster and the components of the existing cluster.

Unlike Ward's method, McQuitty's method makes no assumptions concerning the underlying distribution of the data sample [55].

CHAPTER 5

EXPERIMENTAL DATA

5.1. Words

In addition to having many possible meanings, words are also ambiguous syntactically in that they can serve as multiple possible parts–of–speech. For instance, *line* can be used as a noun, *Cut the telephone line*, or as a verb, *I line my pockets with cash.* This dissertation does not address syntactic ambiguity; it is assumed that this has been resolved for each of the 13 words studied here. Those words and their part–of–speech are as follows:

- Adjectives: *chief*, *common*, *last*, and *public*.
- Nouns: *bill*, *concern*, *drug*, *interest*, and *line*.
- Verbs: *agree*, *close*, *help*, and *include*.

The *line* data [51] is from the ACL/DCI Wall Street Journal corpus [54] and the American Printing House for the Blind corpus and tagged with WordNet [59] senses. The remaining twelve words [13] are from the ACL/DCI Wall Street Journal corpus and tagged with senses from the Longman Dictionary of Contemporary English [75]. The text that occurs with these twelve words is tagged with part–of–speech information using the Penn TreeBank tag set[1].

The possible senses for each word are shown in Tables 5.1, 5.2, and 5.3. The distribution of senses in the supervised and unsupervised learning experiments is also

[1]The *line* data is excluded from the supervised experiments since the text from the American Printing House for the Blind is not part–of–speech tagged.

shown. The sense inventories for the latter are reduced in order to eliminate very small minority senses. Making fine grained sense distinctions using unsupervised techniques is not considered in this dissertation and remains a challenging problem for future work.

In the supervised and unsupervised experiments a separate model is learned for each word. Only sentences that contain the ambiguous word for which a model is being constructed are included in the learning process. This group of sentences is referred to as a "word–corpus". The number of sentences in each word–corpus is shown in Table 5.1, 5.2, and 5.3 in the row "total count".

5.2. Feature Sets

Each sentence containing an ambiguous word is reduced to a vector of feature values. One set of features is employed in the supervised learning experiments and three are used in the unsupervised. All of these features occur within the sentence in which the ambiguous word occurs. Extending the features beyond sentence boundaries is a potential area for future work.

5.2.1. Supervised Learning Feature Set

The feature set used in the supervised experiments was developed by Bruce and Wiebe and is described in [10], [11], [12], and [13]. In subsequent discussion this is referred to as feature set BW. This feature set has one morphological feature describing the ambiguous word, four part–of-speech features describing the surrounding words, and three co–occurrence features that indicate if certain key words occur anywhere within the sentence.

Morphology: This feature represents the morphology of the ambiguous word. It is binary for an ambiguous noun and indicates if it is singular or plural. It shows the tense of an ambiguous verb and has up to 7 possible values. This feature is not used for adjectives. It is represented by variable M.

Table 5.1. Adjective Senses

	supervised	unsupervised
chief:		
highest in rank:	86%	86%
most important; main:	14%	14%
total count:	1048	1048
common:		
as in the phrase 'common stock':	80%	84%
belonging to or shared by 2 or more:	7%	8%
happening often; usual:	8%	8%
widely known; general; ordinary:	3%	
of no special quality; ordinary:	1%	
same relationship to 2 more or quantities:	$< 1\%$	
total count:	1113	1060
last:		
on the occasion nearest in the past:	93%	94%
after all others:	6%	6%
least desirable:	$< 1\%$	
total count:	3187	3154
public:		
concerning people in general:	56%	68%
concerning the government and people:	16%	19%
not secret or private:	11%	13%
for the use of everyone:	8%	
to become a company:	6%	
known to all or many:	3%	
as in public TV or public radio	1%	
total count:	871	715

Table 5.2. Noun Senses

	supervised	unsupervised
bill:		
a proposed law under consideration:	68%	68%
a piece of paper money or treasury bill:	22%	22%
a list of things bought and their price:	10%	10%
total count:	1341	1341
concern:		
a business; firm:	64%	67%
worry; anxiety:	32%	33%
a matter of interest or importance	3%	
serious care or interest	2%	
total count:	1490	1429
drug:		
a medicine; used to make medicine:	57%	57%
a habit-forming substance:	43%	43%
total count:	1217	1217
interest:		
money paid for the use of money:	53%	59%
a share in a company or business:	21%	24%
readiness to give attention:	15%	17%
advantage, advancement or favor:	8%	
activity, etc. that one gives attention to:	3%	
quality of causing attention to be given to:	$< 1\%$	
total count:	2367	2113
line:		
a wire connecting telephones:		37%
a cord; cable:		32%
an orderly series:		30%
total count:	0	1149

Table 5.3. Verb Senses

	supervised	unsupervised
agree:		
to concede after disagreement:	74%	74%
to share the same opinion:	26%	26%
to be happy together; get on well together:	< 1%	
total count:	1115	1109
close:		
to (cause to) end:	68%	77%
to (cause to) stop operation:	20%	23%
to close a deal:	6%	
to (cause to) shut:	2%	
to (cause to) be not open to the public:	2%	
to come together by making less space between:	2%	
total count:	1535	1354
help:		
to enhance - inanimate object:	75%	79%
to assist - human object:	20%	21%
to make better - human object:	4%	
to avoid; prevent; change - inanimate object:	1%	
total count:	1398	1328
include:		
to contain in addition to other parts:	91%	91%
to be a part of - human subject:	9%	9%
total count:	1526	1526

Table 5.4. Supervised Co–occurrence features

	C_1	C_2	C_3
agree	million	that	to
bill	auction	discount	treasury
chief	economist	executive	officer
close	at	cents	trading
common	million	sense	share
concern	about	million	that
drug	company	FDA	generic
help	him	not	then
include	are	be	in
interest	in	percent	rate
last	month	week	year
public	going	offering	school

Part of Speech: These features represent the part–of–speech of words within $\pm i$ positions of the ambiguous word. Feature set BW contains features that indicate the part of speech of words 1 and 2 positions to the left (–) and right (+) of the ambiguous word. Each feature has one of 25 possible values which are derived from the first letter of the Penn TreeBank tag contained in the ACL/DCI WSJ corpus. These features are represented by variables P_{-2}, P_{-1}, P_{+1}, and P_{+2}.

Co–occurrences: These are binary features that indicate whether or not a particular word occurs in the sentence with the ambiguous word. The values of these features are selected from among the 400 words that occur most frequently in each word–corpus. The three words chosen are most indicative of the sense of the ambiguous word as judged by a test for independence. These features are represented by variables C_1, C_2, and C_3 and the words whose occurrence they represent are shown in Table 5.4.

5.2.2. Unsupervised Learning Feature Sets

There are three different feature sets employed in the unsupervised experiments. This dissertation evaluates the effect that different types of features have on the accuracy of unsupervised learning algorithms; particular attention is paid to features that occur in close proximity to the ambiguous word, i.e., "local context" features. As the amount of context is increased the size of the associated event space grows and unsupervised methods require increasing amounts of computational time and space.

The unsupervised learning feature sets are designated A, B, and C. They are composed of combinations of the following five types of features.

Morphology: This feature represents the morphology of ambiguous nouns and verbs. It is the same as the morphology feature in set BW.

Part of Speech: As in feature set BW, these features represent the part–of–speech of words that occur within 1 and 2 positions of the ambiguous word. However, in the unsupervised experiments the range of possible values for these features is reduced to five: noun, verb, adjective, adverb, or other. These crude distinctions are made with the rule–based part–of–speech tagger incorporated in the Unix command `style` [19]. The tags available in the ACL/DCI WSJ corpus are not used since such high–quality, detailed tagging is not generally available for raw text. These features are represented by variables $P5_{-2}$, $P5_{-1}$, $P5_{+1}$, and $P5_{+2}$.

Co–occurrences: These binary features represent whether or not certain high frequency words in the sentence with the ambiguous word. These features differ from the co–occurrence features in set BW since sense–tagged text is not available to select their values via a test of independence. Rather, the words whose occurrences are represented are determined by the most frequent content words[2] that occur in each word–corpus. Three such features are used. CF_1 represents the most frequent content word, CF_2 the second most frequent, and CF_3 the third. The words represented by these features are shown in Table 5.5.

[2]Content words are defined here to include nouns, pronouns, verbs, adjectives and adverbs.

Table 5.5. Unsupervised Co–occurrence Features

word	CF_1	CF_2	CF_3
chief	officer	executive	president
common	share	million	stock
last	year	week	million
public	offering	million	company
bill	treasury	billion	house
concern	million	company	market
drug	fda	company	generic
interest	rate	million	company
line	he	it	telephone
agree	million	company	pay
close	trading	exchange	stock
help	it	say	he
include	million	company	year

Unrestricted Collocations: These features represent the most frequent words that occur within ± 2 positions of the ambiguous word. These features have 21 possible values. Nineteen correspond to the 19 most frequent words that occur in that fixed position in the word–corpus. There is also a value, (none), that indicates when the position i to the left or right is occupied by a word that is not among the 19 most frequent, and a value, (null), indicating that the position $\pm i$ falls outside the sentence boundary. These features are represented by variables UC_{-2}, UC_{-1}, UC_{+1}, and UC_{+2}. For example, the values of the unrestricted collocation features for *concern* are as follows:

- UC_{-2}: and, the, a, of, to, financial, have, because, an, 's, real, cause, calif., york, u.s., other, mass., german, jersey, (null), (none)

- UC_{-1} : the, services, of, products, banking, 's, pharmaceutical, energy, their, expressed, electronics, some, biotechnology, aerospace, environmental, such,

japanese, gas, investment, (null), (none)

- UC_{+1}: about, said, that, over, 's, in, with, had, are, based, and, is, has, was, to, for, among, will, did, (null), (none)

- UC_{+2}: the, said, a, it, in, that, to, n't, is, which, by, and, was, has, its, possible, net, but, annual, (null), (none)

Content Collocations: These features represent high frequency content words that occur within 1 position of the ambiguous word. The values of these features are determined by the most frequent content words that occur on either side of the ambiguous word in the word–corpus. These features are represented by variables CC_{-1} and CC_{+1}. The content collocations associated with *concern* are as follows:

- CC_{-1}: services, products, banking, pharmaceutical, energy, expressed, electronics, biotechnology, aerospace, environmental, japanese, gas, investment, food, chemical, broadcasting, u.s., industrial, growing, (null), (none)

- CC_{+1}: said, had, are, based, has, was, did, owned, were, regarding, have, declined, expressed, currently, controlled, bought, announced, reported, posted, (null), (none)

There is a limitation to frequency based features such as the co–occurrences and collocations previously described; they contain little information about low frequency minority senses and are skewed towards the majority sense. Consider the values of the co–occurrence features associated with *chief*: *officer*, *executive* and *president*. *Chief* has a majority class distribution of 86% and, not surprisingly, these three content words are all indicative of "highest in rank", the majority sense. However, when using raw text it isn't clear how features that are indicative of minority senses can be identified. This remains an interesting question for future work.

5.2.3. Feature Sets and Event Distributions

The 4 feature sets used in this dissertation are designated BW, A, B, and C. The supervised experiments are conducted with feature set BW and the unsupervised with A, B, and C. Each of these feature sets results in a different event space, i.e., the set of possible marginal events. The formulation of each feature set as well as the maximum size of the event spaces associated with the saturated model and the Naive Bayes model are as follows:

- BW: $M, P_{-2}, P_{-1}, P_{+1}, P_{+2}, C_1, C_2, C_3$
  Saturated Event Space: 15,857,856
  Naive Bayes Event Space: 534

- A: $M, P5_{-2}, P5_{-1}, P5_{+1}, P5_{+2}, CF_1, CF_2, CF_3$
  Saturated Event Space: 105,000
  Naive Bayes Event Space: 99

- B: $M, UC_{-2}, UC_{-1}, UC_{+1}, UC_{+2}$
  Saturated Event Space: 4,084,101
  Naive Bayes Event Space: 273

- C: $M, P5_{-2}, P5_{-1}, P5_{+1}, P5_{+2}, CC_{-1}, CC_{+1}$
  Saturated Event Space: 5,788,125
  Naive Bayes Event Space: 207

The minimum size of the event space depends on the number of possible senses and the value of the morphological feature. It also varies if possible values of a feature variable do not occur in the training data. For example, if there are 20 possible values for a feature and only 5 are observed in the training data the parameter estimates associated with the 15 non–occurring events will be zero. The degrees of freedom of models are adjusted to eliminate zero estimates and reduce the size of the event space further.

Tables 5.6 through 5.18 contrast the size of the event spaces associated with the saturated model and the Naive Bayes model. This illustrates that event distributions are very skewed under the saturated model and that this skewness is reduced, but not eliminated, with the Naive Bayes model. The reduction in model complexity results in a smaller number of marginal events that must be observed to make parameter estimates. The number of marginal events given the saturated model and Naive Bayes are shown in the row "total events".

For example, as shown in Table 5.13, the number of marginal events for *interest* under the saturated model and feature set BW is approximately 16,000,000 while under Naive Bayes it is 534. Given such a large number of marginal events under the saturated model it is inevitable that most of these will not be observed and parameter estimates will be zero since the training sample sizes are so small by comparison. However, when the model is simplified the number of marginal events is reduced and the percentage of marginal events that are observed in the training data increases. For *interest*, 99.9% of the marginal events under the saturated model for feature set BW are unobserved while under Naive Bayes only 36.9% are never observed. The distribution of the event space for all words is smoothed and results in more reliable parameter estimates since the majority of possible marginal events are observed in the training data.

Table 5.6. Event Distribution for Adjective *chief*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.1	99.9	99.9	19.4	13.0	29.5	26.3
1–5	$\ll$0.1	0.8	0.1	0.1	32.7	22.2	39.2	36.8
6–10	$\ll$0.1	0.1	0.0	0.0	7.1	5.6	9.0	6.1
11–50	$\ll$0.1	0.1	0.0	0.0	16.3	14.8	11.4	11.4
51–100	$\ll$0.1	0.0	0.0	0.0	9.2	5.6	4.2	6.1
101–1000	0.0	0.0	0.0	0.0	15.3	38.9	6.6	13.2
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	1.4×10^5	1.6×10^4	6.7×10^5	6.4×10^5	98	54	166	114

Table 5.7. Event Distribution for Adjective *common*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.1	99.9	99.9	42.1	7.1	40.5	42.2
1–5	$\ll$0.1	0.8	$\ll$0.1	$\ll$0.1	30.6	28.6	27.8	25.5
6–10	$\ll$0.1	0.1	0.0	0.0	8.5	6.0	10.7	4.7
11–50	$\ll$0.1	0.1	0.0	0.0	11.7	26.2	12.3	15.1
51–100	0.0	0.0	0.0	0.0	2.7	15.5	5.2	6.3
101–1000	0.0	0.0	0.0	0.0	4.4	16.7	3.6	6.3
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	1.6×10^6	3.0×10^4	1.1×10^6	1.7×10^6	366	84	252	192

Table 5.8. Event Distribution for Adjective *last*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	95.5	99.8	99.9	33.3	1.9	27.9	30.5
1–5	$\ll$0.1	3.3	0.2	0.1	23.4	17.3	12.2	10.2
6–10	$\ll$0.1	0.4	0.0	0.0	4.7	3.8	6.4	7.8
11–50	$\ll$0.1	0.7	0.0	0.0	16.7	11.5	35.5	22.7
51–100	0.0	0.1	0.0	0.0	4.2	15.4	7.0	10.2
101–1000	0.0	0.0	0.0	0.0	14.1	32.7	8.7	14.1
1000+	0.0	0.0	0.0	0.0	3.6	17.3	2.3	4.7
total events	1.0×10^6	8.0×10^3	4.1×10^5	4.8×10^5	192	52	172	128

Table 5.9. Event Distribution for Adjective *public*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.2	99.9	99.9	38.3	8.3	28.5	38.3
1–5	$\ll$0.1	0.8	$\ll$0.1	$\ll$0.1	32.0	20.2	37.8	25.9
6–10	$\ll$0.1	0.0	0.0	0.0	10.7	9.5	15.7	9.0
11–50	$\ll$0.1	0.0	0.0	0.0	12.9	25.0	10.8	13.9
51–100	0.0	0.0	0.0	0.0	3.2	17.9	4.8	6.5
101–1000	0.0	0.0	0.0	0.0	2.9	19.0	2.4	6.5
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	2.3×10^6	3.0×10^4	1.0×10^6	1.9×10^6	441	84	249	201

Table 5.10. Event Distribution for Noun *bill*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.2	99.9	99.9	15.4	10.0	30.3	38.3
1–5	$\ll$0.1	0.8	$\ll$0.1	$\ll$0.1	24.4	12.2	25.7	13.4
6–10	$\ll$0.1	0.0	0.0	0.0	9.5	6.7	10.7	10.9
11–50	$\ll$0.1	0.0	0.0	0.0	27.4	21.1	23.4	17.9
51–100	0.0	0.0	0.0	0.0	11.4	17.8	5.7	8.0
101–1000	0.0	0.0	0.0	0.0	11.9	32.2	4.2	11.4
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	2.2×10^6	6.0×10^4	2.6×10^6	3.5×10^6	201	90	261	201

Table 5.11. Event Distribution for Noun *concern*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	97.7	99.9	99.9	25.4	3.6	22.8	29.0
1–5	$\ll$0.1	2.1	0.1	$\ll$0.1	30.6	3.6	19.1	13.7
6–10	$\ll$0.1	0.1	0.0	0.0	8.6	7.1	17.9	16.1
11–50	$\ll$0.1	0.1	0.0	0.0	19.4	25.0	27.8	17.7
51–100	0.0	0.0	0.0	0.0	4.1	7.1	2.5	2.4
101–1000	0.0	0.0	0.0	0.0	11.9	53.6	9.9	21.0
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	2.9×10^6	2.0×10^4	6.1×10^5	1.0×10^6	268	56	162	124

Table 5.12. Event Distribution for Noun *drug*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	98.6	99.9	99.9	6.6	3.4	15.1	25.8
1–5	$\ll$0.1	1.3	0.1	$\ll$0.1	17.6	10.3	21.1	18.0
6–10	$\ll$0.1	0.1	0.0	0.0	11.0	5.2	19.9	12.5
11–50	$\ll$0.1	0.1	0.0	0.0	33.1	19.0	34.3	19.5
51–100	0.0	0.0	0.0	0.0	14.0	15.5	1.8	5.5
101–1000	0.0	0.0	0.0	0.0	17.6	46.6	7.8	18.8
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	2.3×10^6	3.0×10^4	9.6×10^5	1.6×10^6	136	58	166	128

Table 5.13. Event Distribution for Noun *interest*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	98.7	99.9	99.9	36.9	6.9	22.5	33.3
1–5	$\ll$0.1	1.1	$\ll$0.1	0.1	26.2	8.0	25.7	5.2
6–10	$\ll$0.1	0.1	0.0	0.0	6.0	4.6	11.6	3.0
11–50	$\ll$0.1	0.1	0.0	0.0	16.7	16.1	26.1	20.0
51–100	0.0	0.0	0.0	0.0	6.2	17.2	5.6	11.1
101–1000	0.0	0.0	0.0	0.0	7.5	42.5	8.0	25.9
1000+	0.0	0.0	0.0	0.0	0.6	4.6	0.4	1.5
total events	1.6×10^7	4.5×10^4	1.4×10^6	6.8×10^5	534	87	249	135

Table 5.14. Event Distribution for Noun *line*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	na	97.9	99.9	99.9	na	2.4	22.4	34.4
1–5	na	2.0	0.1	$\ll$0.1	na	9.5	34.6	20.4
6–10	na	0.1	0.0	0.0	na	4.8	14.2	7.5
11–50	na	0.0	0.0	0.0	na	19.0	18.7	12.9
51–100	na	0.0	0.0	0.0	na	22.6	2.0	9.7
101–1000	na	0.0	0.0	0.0	na	41.7	8.1	15.1
1000+	na	0.0	0.0	0.0	na	0.0	0.0	0.0
total events	na	3.0×10^4	9.6×10^5	1.5×10^6	na	84	246	186

Table 5.15. Event Distribution for Verb *agree*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.4	99.9	99.9	36.2	3.1	16.5	12.3
1–5	$\ll$0.1	0.5	$\ll$0.1	$\ll$0.1	23.2	10.9	29.4	34.6
6–10	$\ll$0.1	0.1	0.0	0.0	6.8	6.3	16.5	7.7
11–50	$\ll$0.1	0.0	0.0	0.0	18.4	28.1	24.7	21.5
51–100	0.0	0.0	0.0	0.0	3.9	14.1	7.1	8.5
101–1000	0.0	0.0	0.0	0.0	11.1	37.5	5.9	15.4
1000+	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0
total events	5.1×10^6	2.8×10^6	1.8×10^6	2.8×10^6	207	64	170	130

Table 5.16. Event Distribution for Verb *close*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	99.4	99.9	99.9	28.6	1.5	25.3	22.8
1–5	$\ll$0.1	0.6	$\ll$0.1	$\ll$0.1	36.2	16.7	23.0	17.6
6–10	$\ll$0.1	0.0	0.0	0.0	7.4	6.1	9.6	11.0
11–50	$\ll$0.1	0.0	0.0	0.0	18.6	24.2	29.8	25.0
51–100	0.0	0.0	0.0	0.0	3.6	15.2	4.5	8.8
101–1000	0.0	0.0	0.0	0.0	5.7	36.4	7.9	14.7
1000+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
total events	9.5×10^6	7.0×10^4	2.5×10^6	3.7×10^6	420	66	178	136

Table 5.17. Event Distribution for Verb *help*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	98.6	99.9	99.9	28.7	0.0	8.6	11.2
1–5	$\ll$0.1	1.4	$\ll$0.1	$\ll$0.1	27.6	1.6	31.6	28.4
6–10	$\ll$0.1	0.0	0.0	0.0	8.1	3.2	23.0	13.4
11–50	$\ll$0.1	0.0	0.0	0.0	21.3	33.9	25.9	23.1
51–100	0.0	0.0	0.0	0.0	6.6	17.7	3.4	7.5
101–1000	0.0	0.0	0.0	0.0	7.0	43.5	7.5	16.4
1000+	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0
total events	6.9×10^6	4.8×10^4	2.0×10^6	2.6×10^6	272	62	174	134

Table 5.18. Event Distribution for Verb *include*

event	Saturated				Naive Bayes			
count	BW	A	B	C	BW	A	B	C
0	99.9	98.8	99.9	99.9	13.7	1.6	25.9	23.1
1–5	$\ll$0.1	1.1	$\ll$0.1	$\ll$0.1	26.0	12.5	18.4	23.1
6–10	$\ll$0.1	0.1	0.0	0.0	6.8	6.3	15.5	14.9
11–50	0.0	0.0	0.0	0.0	26.7	28.1	26.4	17.9
51–100	0.0	0.0	0.0	0.0	10.3	7.8	5.2	3.7
101–1000	0.0	0.0	0.0	0.0	15.1	39.1	8.0	15.7
1000+	0.0	0.0	0.0	0.0	1.4	0.0	0.6	1.5
total events	3.9×10^6	6.0×10^4	2.0×10^6	3.2×10^6	146	61	174	134

CHAPTER 6

SUPERVISED LEARNING EXPERIMENTAL RESULTS

The theoretical foundations of sequential model selection and the Naive Mix are introduced in Chapter 3. This chapter discusses four experiments that evaluate these methods.[1] The principal measure is disambiguation accuracy, the percentage of ambiguous words in a held–out test sample that are disambiguated correctly.

The first experiment measures the accuracy of models selected using various combinations of search strategy and evaluation criterion. The second compares the accuracy of the Naive Mix to several leading machine learning algorithms. The third experiment studies the learning rate of the most accurate methods from the first two experiments. The final experiment decomposes the overall classification error of two of the most accurate methods into more fundamental components.

6.1. Experiment 1: Sequential Model Selection

In the first experiment, each of the eight possible combinations of search strategy and evaluation criterion as described in Chapter 3 are utilized to select a probabilistic model of disambiguation for each word.

The accuracy of each model is evaluated via *10–fold cross validation*. All of the sense–tagged examples for a word are randomly shuffled and divided into 10 equal folds. Nine folds are used as the training sample and the remaining fold acts as a held–out test set. This process is repeated 10 times so that each fold serves as the test set once. The disambiguation accuracy for each word is the average accuracy across all 10 test sets.

[1] The freely available software package CoCo [2] was used in conjunction with the Class.3.0 classifier [68] for all the model selection experiments.

Within this first experiment there are four separate analyses performed. The first examines the overall disambiguation accuracy of the selected models for each word. The second evaluates model complexity by comparing the number of interactions in the various models. The third assesses the robustness of the selection process relative to changes in the search strategy. The fourth and final analysis is a case study of the model selection process for a single word.

All of these evaluations assume that the overall objective of sequential model selection is to automatically stop the search process at an accurate model of disambiguation. However, there are alternatives to this orientation. For example, Bruce and Wiebe (e.g., [10], [11], and [12]) use backward search and the exact conditional test to generate a sequence of models beginning with the saturated model and concluding with Naive Bayes. The most accurate model is selected from this sequence using a test of predictive accuracy.

6.1.1. Overall Accuracy

Table 6.1 shows the accuracy and standard deviation of models selected using each evaluation criterion with forward (F) and backward (S) sequential search. The accuracy of Naive Bayes and the majority classifier are also reported since they serve as simple benchmarks; neither performs a model search but rather rely upon assumed parametric forms. When averaged over all twelve words, Naive Bayes and FSS AIC are the most accurate approaches.[2] However, the differences between Naive Bayes, FSS AIC, and BSS AIC are not statistically significant for any word. Throughout this evaluation, judgments regarding the significance of differences are made using a two–sided pairwise t–test where $p = .01$.

A reasonable lower bound on supervised disambiguation algorithms is the accuracy attained by the majority classifier. The majority classifier is based on the

[2]Each combination of strategy and criterion is sometimes referred to in an abbreviated form. For example, the combination of a forward sequential search and Akaike's Information Criteria is called FSS AIC.

Table 6.1. Sequential Model Selection Accuracy

	Majority	Naive Bayes		$G^2 \sim \chi^2$	exact	AIC	BIC
agree	.777 .032	.930 .026	B	.914 .018	.915 .019	.909 .026	.924 .023
			F	.916 .026	.896 .030	.911 .026	.921 .024
bill	.681 .044	.865 .026	B	*.634 .073*	*.612 .022*	.836 .036	.850 .034
			F	.778 .048	*.625 .039*	.851 .029	.851 .041
chief	.862 .026	.943 .015	B	.945 .020	.895 .033	.945 .020	.936 .020
			F	.926 .027	.891 .043	.939 .020	.943 .021
close	.680 .033	.817 .023	B	.687 .039	.739 .029	.806 .029	.742 .031
			F	.773 .035	.646 .037	.810 .040	.763 .040
common	.802 .029	.832 .034	B	.843 .030	.802 .058	.850 .019	.815 .030
			F	.848 .023	.747 .066	.846 .023	.815 .030
concern	.639 .054	.859 .037	B	.565 .055	.753 .033	.838 .038	.767 .031
			F	.820 .044	.618 .106	.830 .025	.864 .038
drug	.575 .033	.807 .036	B	.695 .091	.806 .040	.792 .043	.784 .041
			F	.790 .052	.527 .048	.800 .037	.784 .041
help	.753 .032	.780 .033	B	.770 .049	.769 .037	.777 .036	.797 .030
			F	.793 .035	.779 .037	.798 .033	.797 .030
include	.912 .024	.944 .021	B	.922 .019	.938 .020	.912 .030	.949 .016
			F	.953 .014	*.735 .142*	.950 .012	.950 .019
interest	.529 .026	.763 .016	B	*.476 .040*	.498 .034	.751 .018	.676 .025
			F	.713 .037	*.441 .032*	.757 .026	.734 .020
last	.933 .014	.919 .011	B	.895 .023	*.849 .018*	.931 .015	.920 .011
			F	*.898 .021*	*.849 .021*	.927 .021	.915 .012
public	.560 .055	.593 .054	B	.610 .048	.551 .042	.600 .047	.597 .053
			F	.616 .049	.472 .095	.614 .053	.602 .050
average	.725	.838	B	.746	.761	.829	.813
			F	.819	.712	.836	.828

model of independence and classifies each instance of an ambiguous word with the most frequent sense in the training data.

Neither AIC nor BIC ever selects a model that results in accuracy significantly less than the lower bound. This is true for both forward and backward searches. However, FSS exact conditional has accuracy significantly less than the lower bound for four words and BSS exact conditional has accuracy below the lower bound for two words. FSS $G^2 \sim \chi^2$ and BSS $G^2 \sim \chi^2$ are significantly less accurate than the lower bound for one and two words respectively. These cases are italicized in Table 6.1.

This behavior is suggestive of a difficulty in using significance tests as evaluation criteria when the objective of model selection is to automatically stop the search process at an accurate model of disambiguation. The value of α determines when the selection process will stop; unfortunately there is no single value of α that leads to consistent results. In this experiment the α values .01, .05, .001, and .0001 are evaluated and .0001 is found to select the most accurate models overall. However, there is considerable variation from word to word and improved results are likely if α is adjusted for each word.

It is generally expected that the accuracy of the majority classifier will be improved upon by more sophisticated models. The majority classifier does not take into account any of the available contextual information when performing disambiguation; presumably a model that does will prove to be more accurate.

However, there are four words where no method ever significantly improves upon the majority classifier; *help*, *include*, *last*, and *public*. Two of these words, *last* and *include*, have majority senses of over 90% so significant improvement over the lower bound is not likely. But the majority senses of *public* and *help* are 56% and 75% so there is certainly room for improvement. However, the most accurate models for these words have 4 and 6 interactions and disregard most of the features in set BW. For these two words the set of features may need to be modified to disambiguate at higher levels of accuracy.

6.1.2. Model Complexity

The number of interactions in a model is a general indicator of the complexity of the model. Given n features, the saturated model has $\frac{n^2-n}{2}$ interactions, Naive Bayes has n interactions, and the model of independence has 0. Table 6.2 shows the number of interactions in the models selected by each combination of evaluation criterion and search strategy. The number of interactions in Naive Bayes is included as a point of comparison although this is not a selected model.

This table shows that BIC and $G^2 \sim \chi^2$ often select models with fewer interactions than either AIC or the exact conditional test. However, these models also result in reduced accuracy when compared to AIC. Since BIC assesses a greater penalty on complexity than AIC, it has a stronger bias towards less complex models. As a result, BSS BIC is more aggressive in removing interactions than BSS AIC; similarly FSS BIC is more conservative than FSS AIC in adding them.

The comparable levels of accuracy among models selected with the information criteria and Naive Bayes are curious since Table 6.2 shows that these methods select models of differing complexity. For example, the model selected for *bill* by FSS AIC has 20 interactions, the model selected by FSS BIC has 11, and Naive Bayes has only 9. However, the accuracy of these 3 models is nearly identical.

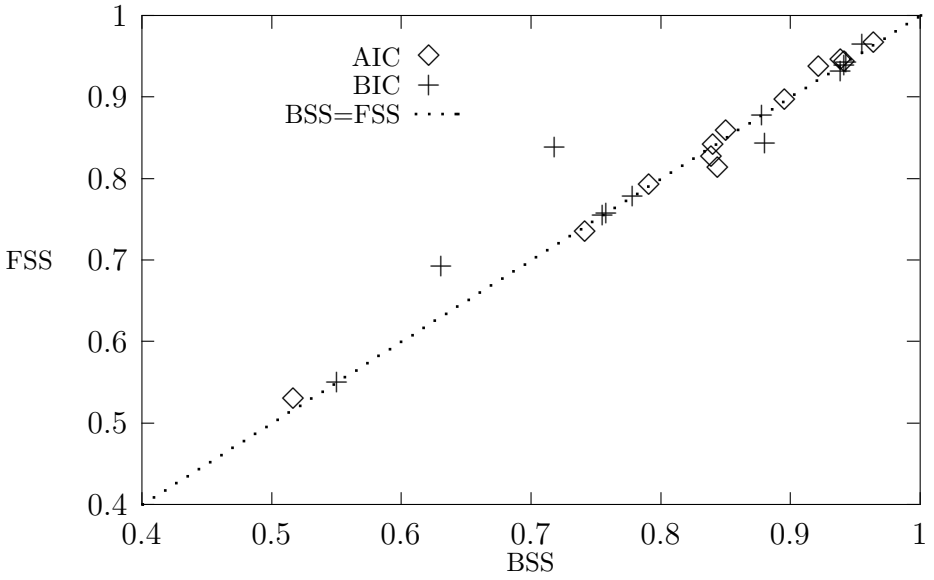
The fact that models of differing levels of complexity yield similar levels of accuracy demonstrates that model selection is an uncertain enterprise. In other words, there is not a single model for a word that will result in overall superior disambiguation accuracy. This motivates the development of the Naive Mix, an extension to the sequential model selection process that is evaluated later in this chapter.

6.1.3. Model Selection as a Robust Process

A model selection process is robust when models of similar accuracy are selected as a result of both a forward and a backward search using the same evaluation criterion. In general the information criteria result in a robust selection process while the significance tests do not.

Table 6.2. Complexity of Selected Models

	Naive Bayes		$G^2 \sim \chi^2$ .0001	exact .0001	AIC	BIC
agree	9	B	8	10	15	9
		F	12	15	13	7
bill	9	B	22	25	26	7
		F	20	28	20	11
chief	8	B	6	17	14	6
		F	6	18	14	7
close	9	B	12	13	13	3
		F	13	19	10	3
common	8	B	4	10	7	2
		F	4	16	7	2
concern	9	B	5	15	16	6
		F	17	24	13	9
drug	9	B	10	7	14	9
		F	10	19	12	9
help	9	B	7	6	6	4
		F	3	9	4	4
include	9	B	6	3	16	8
		F	6	22	9	9
interest	9	B	24	24	21	6
		F	22	32	15	4
last	8	B	8	9	14	9
		F	15	18	14	2
public	8	B	7	9	8	3
		F	6	11	6	3
average	9	B	10	12	14	6
		F	11	19	11	6



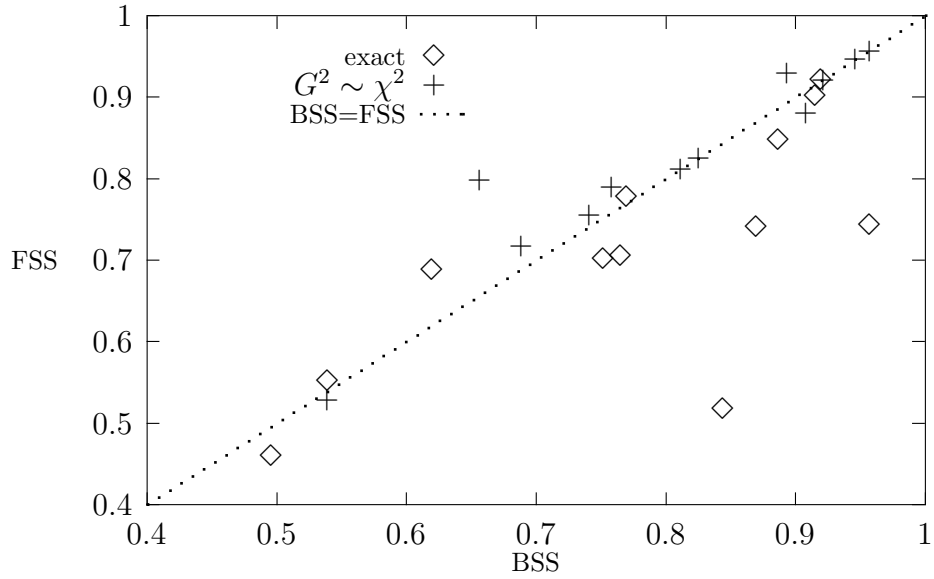


Figure 6.1. Robustness of Selection Process

In Figure 6.1 each point represents the accuracy of models selected using the specified evaluation criterion with backward and forward search. The BSS coordinate is the accuracy attained by the model selected during backward search while the FSS coordinate is the accuracy resulting from forward search. Points that fall close to the line $BSS = FSS$ represent an evaluation criterion that selects models of similar accuracy regardless of search strategy. Figure 6.1 (top) shows that, in general, the information criteria select models of similar accuracy using either forward or backward search.

However, Figure 6.1 (bottom) shows that the significance tests are sensitive to changes in search strategy. For example, BSS exact conditional is more accurate than FSS exact conditional. FSS $G^2 \sim \chi^2$ is slightly more accurate than BSS $G^2 \sim \chi^2$. This suggests that the value of α may need to be adjusted depending on the direction of the search strategy. The following section shows that this is due to changes in the bias of the evaluation criteria that are caused by changing the search strategy.

6.1.4. Model selection for Noun *interest*

The model selection process for *interest* is discussed in some detail here. Figures 6.2 and 6.3 show the accuracy and recall[3] of the model at each level of complexity during the selection process. The rightmost point on each plot is the measure associated with the model ultimately selected by the evaluation criterion and search strategy.

As shown in Table 6.2, BIC selects models that have fewer interactions than the other criteria. Table 6.1 indicates that this often results in less accurate classification than AIC. In Figure 6.2, BSS BIC (top) removes too many interactions and goes past the more accurate model selected by AIC, while FSS BIC (bottom) does not add enough interactions and stops short of selecting a highly accurate model. For

[3]The percentage of ambiguous words in a held out test sample that are disambiguated, correctly or not. A word is not disambiguated if any of the model parameters needed to assign a sense tag cannot be estimated from the training sample.

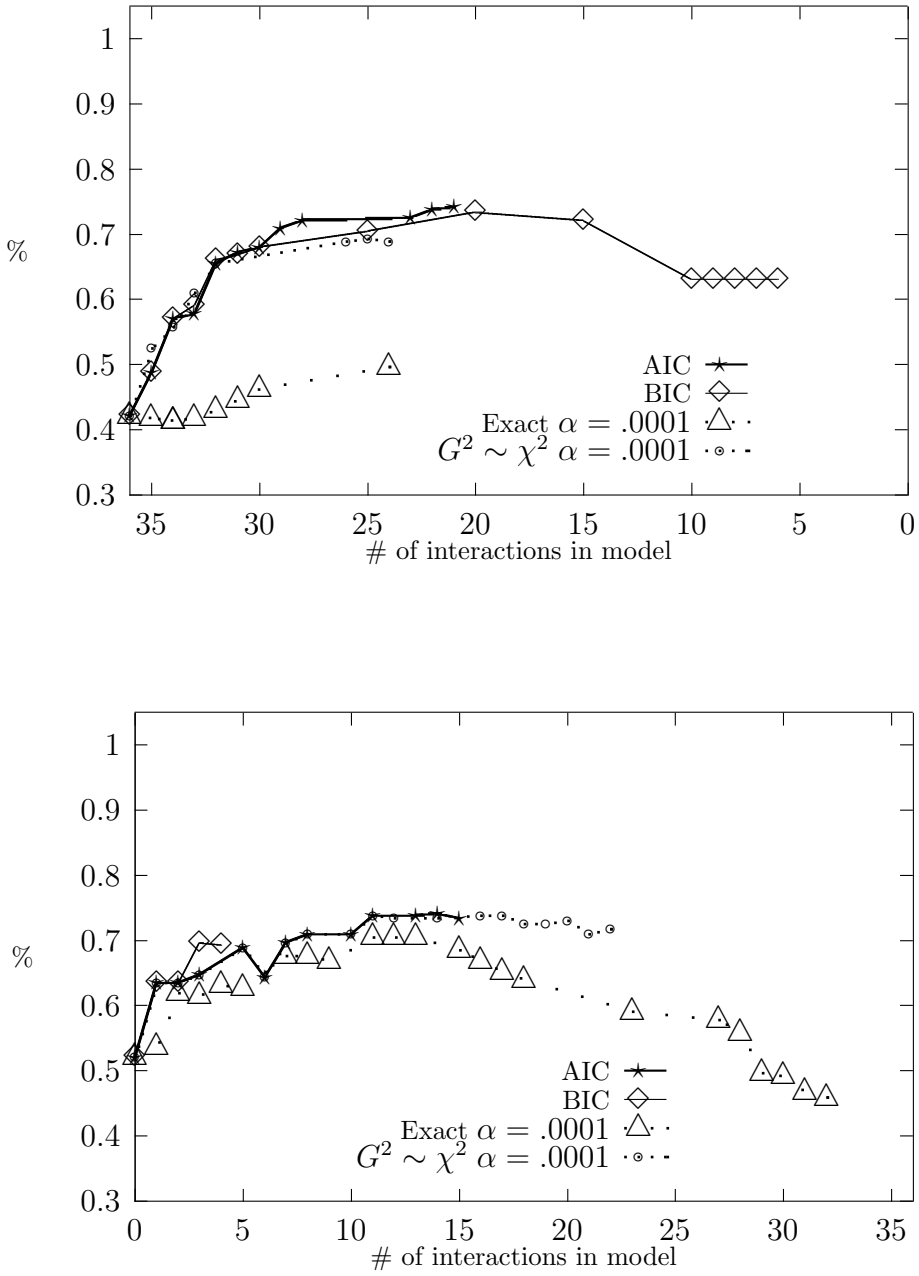


Figure 6.2. BSS (top) and FSS (bottom) accuracy for Noun *interest*

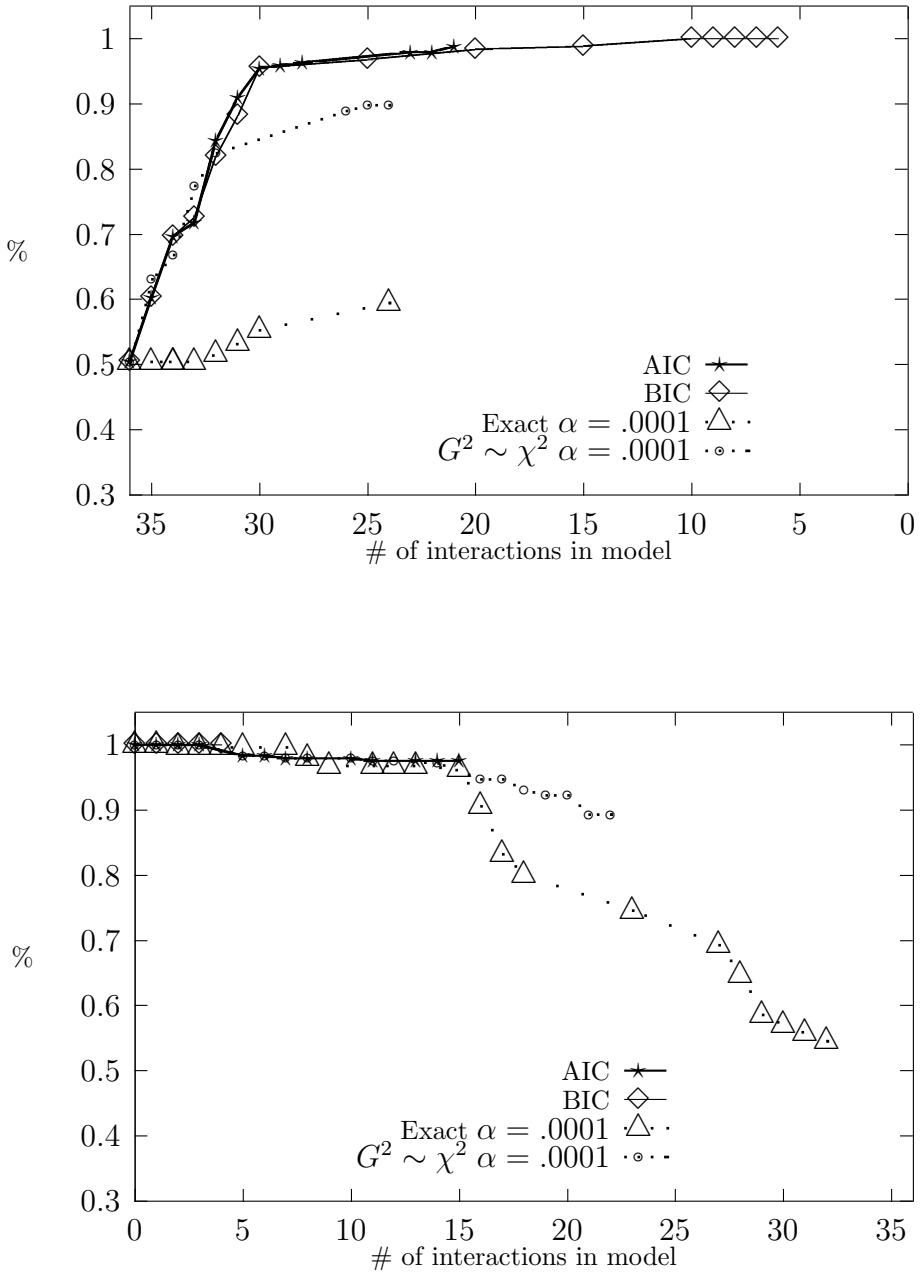


Figure 6.3. BSS (top) and FSS (bottom) recall for Noun *interest*

interest, BSS BIC selects a model of 6 interactions while FSS BIC selects a model of 4 interactions. The other combinations of strategy and criterion select models with between 15 and 32 interactions and result in higher levels of accuracy. As mentioned previously, the bias of BIC towards models with small numbers of interactions is not surprising given the large penalty that it assesses to complexity.

The exact conditional test suffers from the reverse problem in that it selects models with too many interactions. BSS exact conditional removes a small number of interactions while FSS exact conditional adds a great many; in both cases the resulting models have lower accuracy than the other approaches.

Figure 6.3 shows that for both forward and backward search, models of relatively low recall are selected by the exact conditional test. This suggests that the selected models are overly complex and contain many parameters that can not be estimated from the training data.

The contrast between the exact conditional test and the other criteria is stark during backward search. Figures 6.2 (top) and 6.3 (top) show that the exact conditional test remains at low levels of accuracy and recall while the other criteria rapidly increase both recall and accuracy. However, during forward search Figures 6.2 (bottom) and 6.3 (bottom) show there is little difference among the criteria; all select high recall models that achieve high accuracy early in the search.

A backward search begins with the saturated model. For feature set BW saturated models have millions of parameters to estimate. The information criteria remove the interactions that result in models with the highest degrees of freedom in the early stages of the search. This is a consequence of the complexity penalty that both AIC and BIC assess. The significance test $G^2 \sim \chi^2$ also targets interactions with high degrees of freedom for removal. When G^2 values are assigned significance there is an implicit weighting for complexity. Larger degrees of freedom result in smaller significance values due to the nature of the χ^2 distribution. Interactions that result in models with very high degrees of freedom and are more likely to be removed early in the course of a backward search since they have smaller significance values.

The bias of the information criteria and $G^2 \sim \chi^2$ towards removing interactions with high degrees of freedom results in a rapid reduction in the number of model parameters to estimate. This in turn increases the percentage of model parameters that can be estimated from the training data. In Figure 6.3 (top), recall increases rapidly as interactions with high degrees of freedom are removed by the information criteria. Most of the model parameters can be estimated from the training data early in the search process and this results in a rapid increase in accuracy.

On the other hand, the exact conditional test does not take degrees of freedom into account when evaluating models. Interactions are removed or added via significance values that are based upon the distribution of randomly generated values of G^2 relative to the observed value of G^2. Thus, the exact conditional test may result in the removal of interactions with relatively small degrees of freedom in cases where the information criteria and $G^2 \sim \chi^2$ would remove interactions with higher degrees of freedom. During a backward search the exact conditional test has a different bias; the other criteria tend to remove interactions that result in models with large degrees of freedom while the exact conditional test removes interactions that maintain the fit of the model to the training data.

However, during forward search the exact conditional test achieves approximately the same levels of recall and accuracy as do the other criteria. Forward search begins with the model of independence. The information criteria add those interactions that most increase the fit of the model; in the early stages of forward search this results in a bias towards interactions that have lower degrees of freedom. The same occurs with $G^2 \sim \chi^2$ since it seeks to add those interactions that have the largest significance value. Interactions with smaller degrees of freedom will tend to have higher significance values due to the nature of the χ^2 distribution. Thus, during a forward search all of the criteria are biased towards the inclusion of interactions with lower degrees of freedom. This results in models that have relatively small numbers of model parameters; both recall and accuracy are likely to be high.

The only difference among the criteria during forward search is that the significance tests tend to add too many interactions to the model. During a forward search where the evaluation criteria is a significance test, the value of α should be larger than in the backward search in order to stop the selection process sooner. This has the added benefit of reducing the computational complexity of the exact conditional test since the number of random tables that must be generated to assess the significance of each interaction is $1/\alpha$ [48].

6.2. Experiment 2: Naive Mix

The Naive Mix is defined in Section 3.2 and extends sequential model selection methods by allowing for the incorporation of uncertainty in the development of the model. Rather than attempting to find a single most accurate model, the Naive Mix forms an averaged probabilistic model from the sequence of models generated during FSS AIC. In this experiment the Naive Mix is compared to the following machine learning algorithms:

PEBLS [23]: A k nearest–neighbor algorithm where classification is performed by assigning an ambiguous word to the majority class of the k–nearest training examples. In these experiments each ambiguous word is assigned the sense of the single most similar training example, i.e., $k = 1$.

C4.5 [78]: A decision tree learner in which classification rules are formulated by recursively partitioning the training sample. Each nested partition is based on the feature value that provides the greatest increase in the information gain ratio for the current partition.

CN2 [22]: A rule induction algorithm that selects classification rules that cover the largest possible subsets of the training sample as measured by the Laplace error estimate.

The Naive Mix, C4.5, CN2, and any model selection method using forward sequential search all perform general–to–specific searches that add features to the learned representation of the training sample based on some measure of information

content increase. These methods all perform feature selection and have a bias towards simpler models. All of these methods can suffer from *fragmentation* when learning from sparse training data. Fragmentation occurs when the model is complex, incorporating a large number of feature values to describe a small number of training instances. When this occurs, there is inadequate support in the training data for the inference being specified by the model. The Naive Mix is designed to reduce the effects of fragmentation in a general–to–specific search by averaging the distributions of high complexity models with those of low complexity models that include only the most relevant features.

The nearest–neighbor algorithm PEBLS shares a number of traits with Naive Bayes. Neither perform a search to create a representation of the training sample. Naive Bayes assumes the form of a model in which all features are regarded as relevant to disambiguation but, as in PEBLS, their interdependencies are not considered. Weights are assigned to features via parameter estimates from the training sample. These weights allow some discounting of less relevant features. Here, PEBLS stores all instances of the training sample and treats each feature independently and equally, making it susceptible to irrelevant features.

Table 6.3 shows the accuracy of the Naive Mix, Naive Bayes, the majority classifier, C4.5, CN2, and PEBLS. The accuracies of the sequential model selection methods from the first experiment are directly comparable to these since both are evaluated via 10–fold cross validation using all of the sense–tagged examples for each word.

Based on a word by word comparison, this experiment shows that the Naive Mix improves upon the accuracy of models selected by FSS AIC. However, in general there prove to be few significant differences between the accuracy of the Naive Mix, Naive Bayes, C4.5, PEBLS, and CN2.

The success of Naive Bayes in the first two experiments is a bit surprising since it neither performs feature selection nor a model search. Despite this, it is among the most accurate of the methods considered in this study.

Table 6.3. Naive Mix and Machine Learning Accuracy

	Majority classifier	Naive Bayes	PEBLS k=1	C4.5	CN2	Naive Mix
agree	.777 .032	.930 .026	.928 .030	.947 .031	.947 .031	.948 .017
bill	.681 .044	.865 .026	.855 .034	.878 .029	.873 .035	**.897 .026**
chief	.862 .026	.943 .015	.945 .018	.947 .020	.945 .013	.951 .016
close	.680 .033	.817 .023	.843 .042	**.853 .021**	.834 .036	.831 .033
common	.802 .029	.832 .034	.853 .019	.871 .030	.803 .029	.853 .024
concern	.639 .054	.859 .037	.840 .036	.852 .042	.859 .033	.846 .039
drug	.575 .033	.807 .036	.778 .034	.798 .038	.777 .069	.815 .041
help	.753 .032	.780 .033	.710 .047	.790 .039	.779 .045	.796 .038
include	.912 .024	.944 .021	.939 .015	.954 .019	.951 .018	.956 .018
interest	.529 .026	.763 .016	.768 .020	**.793 .019**	.729 .034	**.800 .019**
last	.933 .014	.919 .011	**.947 .012**	**.945 .008**	.935 .013	**.940 .016**
public	.560 .055	.593 .054	.536 .039	.598 .047	.579 .057	.615 .055
average	.725	.838	.829	.852	.834	.854

Table 6.4. Naive Bayes Comparison

	Average Accuracy	win–tie–loss
Naive Mix	.854	0–9–3
C4.5	.852	0–9–3
Naive Bayes	.838	
FSS AIC	.836	0–12–0
BSS AIC	.829	0–12–0
PEBLS	.829	1–10–1
FSS BIC	.828	1–11–0
FSS G^2	.819	1–11–0
BSS BIC	.813	3–9–0
BSS exact	.761	6–6–0
BSS G^2	.746	5–7–0
Majority	.725	8–4–0
FSS exact	.712	9–3–0

Table 6.4 summarizes the accuracy of Naive Bayes relative to the other methods employed in the first two experiments. The accuracy reported is based on 10–fold cross validation. The *win–tie–loss* measure is also shown; this indicates the number of times Naive Bayes is significantly more–equally–less accurate than the competing method. The win–tie–loss record 1–10–1 associated with PEBLS means that Naive Bayes is significantly more accurate than PEBLS for 1 word, not significantly different than PEBLS for 10 words, and significantly less accurate than PEBLS for 1 word. This measure shows that there are only 7 out of a possible 144 cases where Naive Bayes is significantly less accurate than a competing method. The cases where a competing method is significantly more accurate than Naive Bayes are shown in Table 6.3 in bold face. There is no such case in Table 6.1; Naive Bayes is never significantly less accurate than a sequential model selection method in the first experiment.

The success of Naive Bayes in these experiments confirms the results of previous studies of disambiguation. For instance, [51] compares a neural network, Naive Bayes, and a content vector when disambiguating six senses of *line*.[4] They report that all three methods are equally accurate. The *line* data is utilized again in [62] with an even wider range of methods. Naive Bayes, a perceptron, a decision tree learner, a nearest–neighbor classifier, a logic based disjunctive normal form learner, a logic based conjunctive normal form learner, and a decision list learner are compared. Naive Bayes and the perceptron are found to be the most accurate approaches. Finally, [63] compare PEBLS and Naive Bayes and finds them to be of comparable accuracy when disambiguating the Defence Science Organization sense–tagged corpus [64]. However, all of these studies differ from this dissertation in that they employ a feature set that consists of thousands of binary co–occurrence features, each of which represents the occurrence of a particular word within some fixed distance of the ambiguous word. This feature set is commonly known as *bag–of–words*.

The relatively high accuracy achieved by Naive Bayes in disambiguation is sometimes explained as a consequence of the bag–of–words feature set, e.g., [70]. Given so many features, the assumptions of conditional independence made by Naive Bayes are potentially valid and may result in a model that fits the training data reasonably well. However, this explanation does not apply to feature set BW since a previous study [13] shows that all of these features are good indicators of the sense of the ambiguous word. In addition, Naive Bayes is successful in a number of other domains where the bag–of–words explanation is not relevant.

For example, [22] compare Naive Bayes, a rule induction system, and a decision tree learner. They find that Naive Bayes performs as accurately as these more sophisticated methods in various medical diagnosis problems.

A more extensive study of Naive Bayes appears in [49]. They compare Naive Bayes and a decision tree learner using data from the University of California at

[4]This data is described in Chapter 5, Experimental Data.

Irvine (UCI) Machine Learning repository [57]. For 4 of 5 naturally occurring data sets they report that Naive Bayes is the more accurate. They also present an average case analysis of Naive Bayes that is verified empirically using artificial data.

Naive Bayes and more elaborate Bayesian networks that diagnose the cause of acute abdominal pain are compared in [76]. They argue that simple classification models will often outperform more detailed ones if the domain is complex and the amount of data available is relatively small. Their experiment consists of 1270 cases, each of which has 169 features. They find that the Naive Bayes model with 169 interactions is more accurate than a Bayesian network that has 590 interactions.

A software agent that learns to rate Web pages according to a user's level of interest is discussed in [66]. They construct a profile using examples of pages that a user likes and dislikes. They compare Naive Bayes, a nearest–neighbor algorithm, a term–weighting method from information retrieval, a perceptron, and a multi–layer neural network and find that Naive Bayes is most accurate at predicting Web pages a user will find interesting.

Finally, [32] compare the accuracy of Naive Bayes with a decision tree learner, a nearest–neighbor algorithm, and a rule induction system. They report that Naive Bayes is at least as accurate as the rule induction system and nearest–neighbor algorithm for 22 of 28 UCI data sets and at least as accurate as the decision tree learner for 20 of 28 data sets. They also present an extensive analysis of the conditions under which Naive Bayes is an optimal classifier even when the conditional independence assumptions are not valid.

6.3. Experiment 3: Learning Rate

The first two experiments suggest that Naive Bayes may be an effective general purpose method of disambiguation. However, these experiments only study the disambiguation accuracy of models that are learned from relatively large amounts of training data, i.e, 90% of the total available sense–tagged text for a word.

The third experiment differentiates among the most accurate methods in the first two experiments by training each algorithm with steadily increasing amounts of training data and studying the *learning rate*. This shows the relationship between accuracy and the number of training examples. A "slow" learning rate implies that accuracy gradually increases with the number of training examples. A "fast" learning rate suggests an algorithm that attains high accuracy with a very small number of examples. This experiment compares the learning rates of the Naive Mix, Naive Bayes, C4.5, and FSS AIC.

A variant of 10–fold cross validation is employed. Each word–corpus is divided into 10 folds; the desired number of training examples are sampled from 9 folds and the remaining fold is held out as the test set. Each algorithm learns a model from the training data and uses this to disambiguate the test set. This is repeated until each fold serves as the test set once. The accuracy reported is averaged over all 10 folds.

This procedure is repeated with increasing quantities of training data. In this experiment the number of training examples is first 10, then 50, and then 100. Thereafter the number of examples is incremented 100 at a time until all the available training data is used. For each amount of training data the accuracy attained for all the words belonging to a particular part–of–speech are averaged. These values are plotted in Figures 6.4 through 6.6 and show the learning rate for each method for each part–of–speech. Also included is the learning rate of the majority classifier. This proves to be constant since it classifies every held–out instance of an ambiguous word with the most frequent sense in the training data. This is easy to correctly identify even with very small amounts of training data due to the skewed sense distributions.

Adjectives C4.5, FSS AIC, and the Naive Mix achieve nearly the same level of accuracy learning from 10 examples as they do 900 examples. Naive Bayes has a slower learning rate; accuracy is low with a small number of examples but improves with the addition of training data. Naive Bayes achieves approximately the same accuracy as C4.5, FSS AIC, and the Naive Mix after 300 training examples. However, none of the methods significantly exceeds the accuracy of the majority classifier.

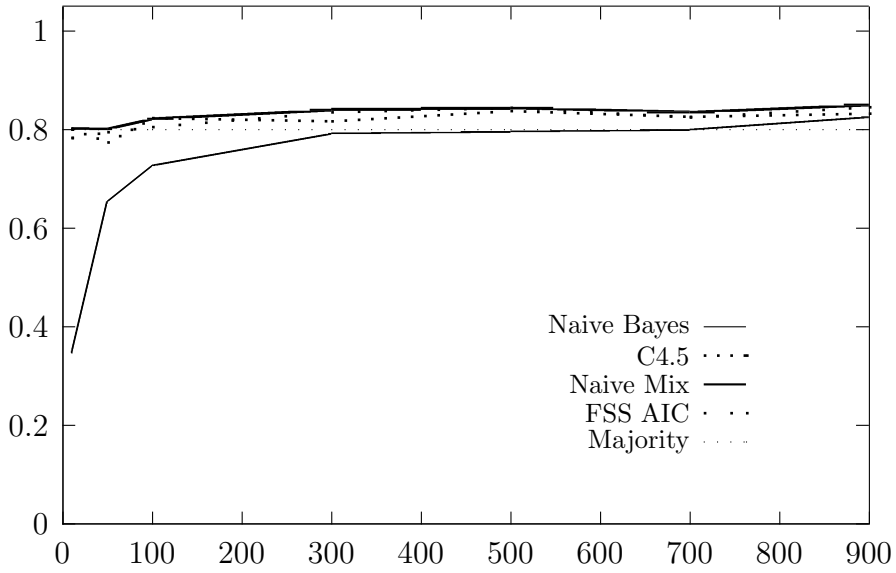


Figure 6.4. Learning Rate for Adjectives

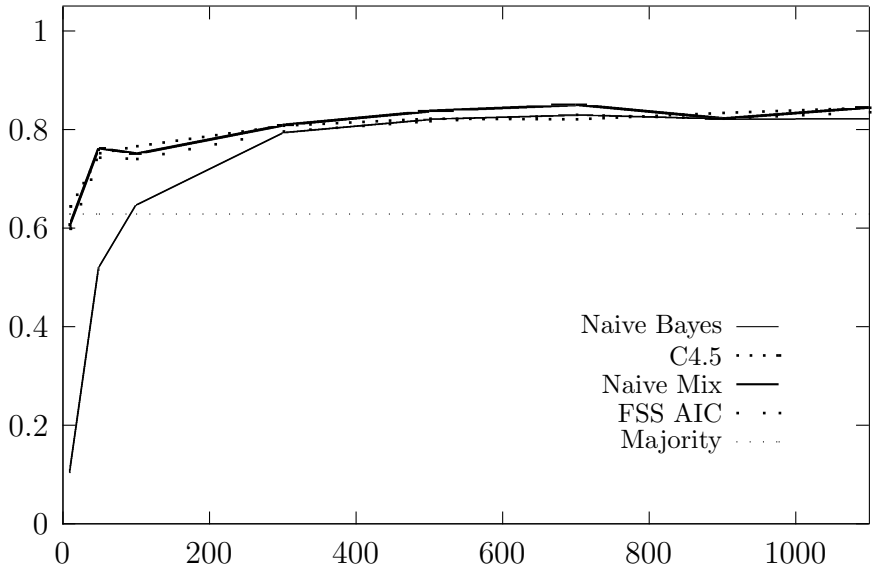


Figure 6.5. Learning Rate for Nouns

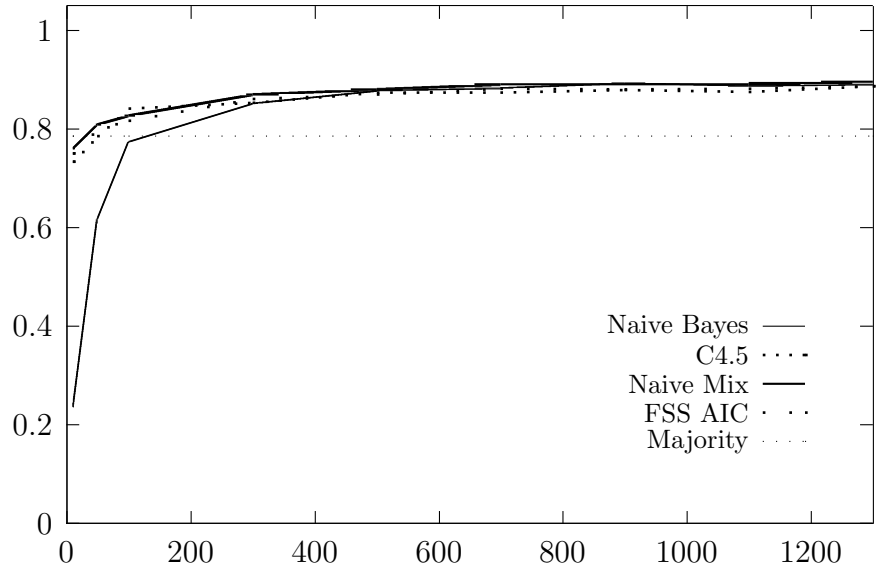


Figure 6.6. Learning Rate for Verbs

Nouns C4.5, FSS AIC, and the Naive Mix are nearly as accurate as the majority classifier after only learning from 10 training examples. However, unlike the adjectives, accuracy increases with additional training data and significantly exceeds the majority classifier. Like the adjectives, Naive Bayes begins at very low accuracy but reaches the same level as C4.5, FSS AIC, and the Naive Mix when approximately 300 training examples are available.

Verbs As is the case with adjectives and nouns, Naive Bayes begins at a very low level of accuracy while C4.5, FSS AIC, and the Naive Mix nearly match the accuracy of the majority classifier after only 10 training examples. All methods exceed the majority classifier and perform at nearly exactly the same level of accuracy after learning from approximately 600 examples.

The main distinction among these approaches is that Naive Bayes has a slower learning rate; C4.5, FSS AIC, and the Naive Mix achieve at least the accuracy of the majority classifier after just 10 or 50 examples. However, after 300–600 examples

all of the methods perform at roughly the same level of accuracy and no method shows significant improvement in accuracy when given more training examples. This suggests that high levels of accuracy in word sense disambiguation are attainable with relatively small quantities of training data.

The fast learning rates of C4.5, FSS AIC, and the Naive Mix are largely due to skewed sense distributions, especially for adjectives and verbs. A small number of examples is sufficient to correctly determine the majority sense. With only 10 or 50 examples to learn from, a decision tree or probabilistic model consists of a few features and relies upon knowledge of the majority sense to perform disambiguation. Given the large majority senses that exist, most models are able to attain high levels of accuracy with very small numbers of examples. However, Naive Bayes estimates model parameters that involve all of the contextual features even when there is only a very small amount of training data. In these cases it becomes an inaccurate classifier since it is easily mislead by spurious relationships in the data that do not hold true in larger samples.

6.4. Experiment 4: Bias Variance Decomposition

The success of Naive Bayes may seem a bit mysterious. It is a simple approach that does not perform feature selection nor does it engage in a systematic search for a model. It simply assumes a parametric form that is usually not an accurate representation of the interactions among contextual features. Despite this, it performs as accurately as any other method except when the amount of training data is small.

The decomposition of classification error, i.e., $(1 - accuracy)$, into bias and variance components offers an explanation for this behavior. This experiment shows that different representations of the same training data attain similar levels of accuracy due to the differing degrees with which bias and variance contribute to overall classification error.[5]

[5]There are two different senses of *bias* used in this dissertation. One indicates a preference exhibited by a learning algorithm. The other refers to a component of classification error. Hopefully,

The estimated bias of an algorithm reflects how often the average classifications, across multiple training samples, of a learned model fail to correspond to the actual classifications in the held–out test data. Variance estimates the degree to which the classifications predicted by the learned model vary across multiple training samples. An algorithm that always makes the same classification regardless of the training data will have variance of 0.

Decision tree learners are inherently unstable in that they produce very different models across multiple samples of training data, even if there are only minor differences in the samples [7]. These models result in different levels of accuracy when applied to a held–out test set. Such algorithms are said to have low bias and high variance.

Naive Bayes is more robust in that it is relatively unaffected by minor changes in the training data. Naive Bayes is not particularly representative of the training data since the parametric form is assumed rather than learned. Naive Bayes is an example of a high bias and low variance algorithm.

This experiment estimates the degree to which bias and variance contribute to the classification error made by Naive Bayes and the decision tree learner MC4[6]. Naive Bayes represents a high bias and low variance approach while MC4 represents a low bias and high variance algorithm. The estimates of bias and variance reported here are made following the sampling procedure described in [47]:

1. Randomly divide the data into two sets, D and E. D serves as a super–set of the training sample while E is the held–out test set.

2. Generate T samples of size m from D. Let the size of $D = 2m$ so that there are $\left(\begin{smallmatrix} 2m \\ m \end{smallmatrix} \right)$ possible training sets. For even a small value of m this will ensure that there are relatively few duplicate training sets sampled from D.

---

the context will be sufficient to allow for immediate disambiguation.

[6]The MLC++[46] version of C4.5.

3. Run a learning algorithm on the T training samples. Classify each observation in the test–set E using each of the T learned models. Store these results in an array called R.

4. Array R and the correct classifications of E serve as the input to the procedure described in [47] that estimates bias and variance.

As discussed in [47], the reliability of the bias and variance estimates depends upon having as large a test set as possible. Therefore, a training sample size of $m = 400$ is employed since this is generally the lowest number of examples where the decision tree learner and Naive Bayes perform at comparable levels of accuracy. The size of the D is set to 800 and $T = 1000$ different training samples are randomly selected.

Table 6.5 shows the bias and variance estimates for MC4 and Naive Bayes using a training sample size of 400. The size of the test set is also listed. The results in this table are divided into three groups. In the first group, Naive Bayes has higher bias and lower variance than MC4. This corresponds to what would be expected; a decision tree learner should have lower bias since it learns a more representative model of the training data than Naive Bayes. The second group has very similar bias and variance for Naive Bayes and MC4. Only *drug* falls into this group; for this word both Naive Bayes and a learned decision tree have approximately the same representational power. In the third group of results MC4 has higher bias and lower variance than Naive Bayes. This is the reverse of what is expected and initially appears somewhat counter–intuitive.

However, the words in this third group have appeared together in a previous experiment; they are the same words where no supervised learning method significantly improves upon the accuracy of the majority classifier: *help*, *last*, *include*, and *public*. For these words disambiguation accuracy is based almost entirely on knowledge of the majority sense; the contextual features provide little information helpful in disambiguation. However, Naive Bayes assumes a parametric form that includes all of

Table 6.5. Bias Variance Estimates, m = 400

word	test size	Naive Bayes			MC4		
		bias	var	error	bias	var	error
agree	550	.063	.014	.077	.048	.021	.069
bill	540	.133	.027	.160	.110	.039	.149
chief	240	.060	.004	.064	.037	.020	.057
close	730	.137	.028	.165	.110	.054	.164
common	310	.140	.027	.167	.116	.027	.143
concern	790	.112	.027	.139	.101	.035	.136
interest	1560	.212	.051	.263	.189	.089	.278
drug	420	.192	.027	.219	.192	.017	.208
help	590	.182	.037	.219	.207	.028	.235
last	2380	.044	.013	.057	.051	.006	.057
include	760	.055	.010	.065	.086	.007	.093
public	70	.359	.071	.430	.381	.024	.405

the contextual features. This accounts for the higher amounts of variance since these irrelevant features are included in the model and affect disambiguation. However, the decision tree learner disregards features that are not relevant and essentially becomes a majority classifier where variance is very low and bias is the main source of error.

The data in Table 6.5 is presented again as correlation plots in Figures 6.7, 6.8, and 6.9. The classification error, bias, and variance for each word are represented by a point in each plot. The x coordinate represents the estimate associated with Naive Bayes and the y coordinate is associated with MC4. Thus, points on or near $x = y$ are associated with measures that have nearly identical estimates for Naive Bayes and MC4 for a particular word.

Figure 6.7 confirms that the two methods result in approximately the same level of classification error. Figure 6.8 shows that the bias error of Naive Bayes is at least slightly higher for 8 of 12 words. And Figure 6.9 confirms that the variance error tends to be greater for MC4.

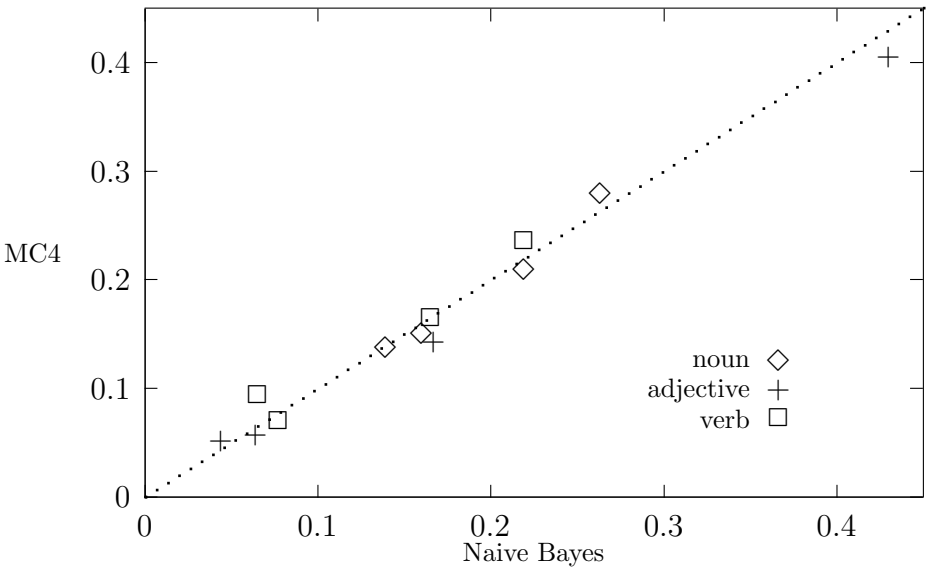


Figure 6.7. Classification Error Correlation, m=400

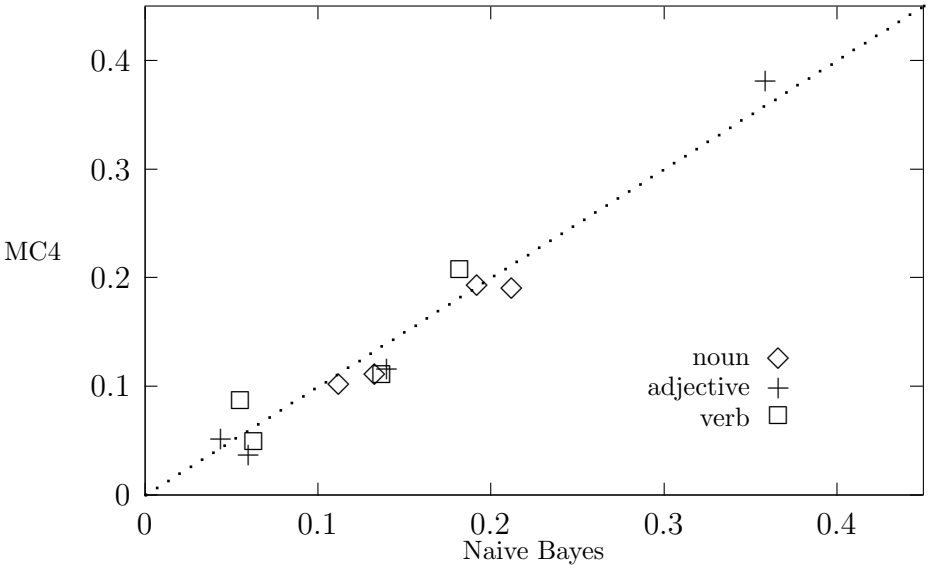


Figure 6.8. Bias Correlation, m=400

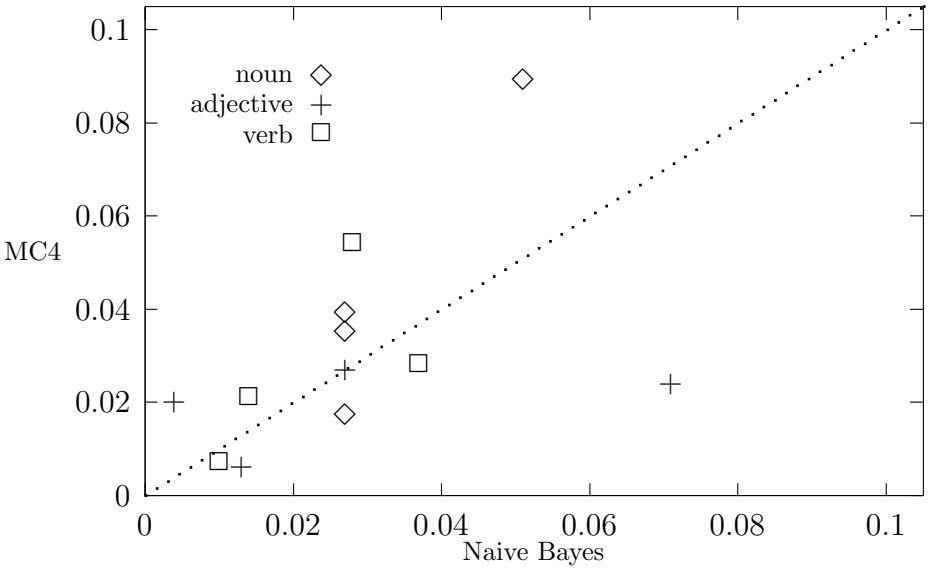


Figure 6.9. Variance Correlation, m=400

CHAPTER 7

UNSUPERVISED LEARNING EXPERIMENTAL RESULTS

This chapter contains an experimental evaluation of the unsupervised learning methodologies described in Chapter 4. These approaches differ from the supervised learning methods in that no sense–tagged text is required; only raw untagged text is used to perform disambiguation.

A probabilistic model of disambiguation is learned from raw text by treating the sense of an ambiguous word as missing data. As discussed in Chapter 4, the learning is restricted to parameter estimation since the parametric form must be specified rather than learned. These experiments assume that the parametric form is Naive Bayes and use two different methods to estimate parameter values; the EM algorithm and Gibbs Sampling. Two agglomerative clustering algorithms are also considered, Ward's minimum–variance method and McQuitty's similarity analysis. As discussed in Chapter 4, these methods perform disambiguation based upon measures of distance that are derived from a dissimilarity matrix representation of the raw untagged text.[1]

There is one experiment discussed in this chapter. Thirteen words are disambiguated using four unsupervised methodologies where the context in which the ambiguous word occurs is represented by three different feature sets. This results in disambiguation by 156 possible combinations of word, method, and feature set. Each possible combination is repeated 25 times in order to measure the deviation introduced by randomly selecting initial parameter estimates for the EM algorithm and

[1]The freely available software package Bugs [41] was used for all Gibbs Sampling experiments. Various freely available implementations of the EM algorithm were employed; AutoClass [18], GAMES [89], and CoCo [2]. The commercial software package SAS [82], was used to perform the agglomerative clustering methods.

Gibbs Sampling, and randomly selecting among equally distant clusters when using Ward's and McQuitty's algorithms. The results of this experiment are evaluated in terms of disambiguation accuracy. However, as will be outlined in Section 7.1, the evaluation methodology for unsupervised learning is somewhat different than in the supervised case.

There are three pairwise analyses of the four unsupervised algorithms presented. First, the accuracy of the probabilistic models where the parameter estimates are learned with the EM algorithm and Gibbs Sampling are compared. Second, the accuracy of agglomerative clustering performed by Ward's and McQuitty's methods are compared. The final analysis compares the two most accurate methods from the first two pairwise comparisons, McQuitty's similarity analysis and Gibbs Sampling.

Each analysis contains two discussions. First, a methodological comparison is made that highlights any significant differences in accuracy between two unsupervised learning algorithms when both use the same feature set. Second, a feature set comparison is made that focuses on the variations in accuracy for an unsupervised learner as different feature sets are used.

7.1. Assessing Accuracy in Unsupervised Learning

In the supervised learning experiments, accuracy is the rate of agreement between the sense tags automatically assigned by a learned model and the sense tags assigned by a human judge. This definition of accuracy is also employed in the unsupervised experiment. However, the means of arriving at that evaluation measure are different and in fact point to some important differences between supervised and unsupervised learning.

In supervised learning accuracy is fairly easy to measure. The supervised algorithm learns from examples where a human judge has assigned sense tags to ambiguous words that refer to specific entries in the sense inventory of a word. For example, given multiple instances of *line* and the sense inventory *(telephone, series, cable)*, a human judge tags some instances with the *telephone* sense, others with the *cable*

sense, and still others with the *series* sense. From these examples, the supervised algorithm learns how to assign these same meaningful tags to other instances of the ambiguous word.

In the supervised framework, the act of sense–tagging richly augments the knowledge contained in a text by creating a link from the manually disambiguated instances of a word to a sense inventory provided by a dictionary or other lexical resource. These links are critical for evaluation relative to a human judge since they connect the text to the same sense inventory that the human tagger used. However, in unsupervised learning no such links exist. The text is disconnected from the sense inventory. No human tagger is involved and the only information available to the unsupervised learner is the raw text which has no links to a sense inventory or any other external knowledge source.

An unsupervised algorithm is limited to creating *sense groups*. A sense group is simply a number of instances of an ambiguous word that are considered to belong to the same sense. However, there is no link from the members of the sense group to a sense inventory. The sense group is labeled by the unsupervised learner but this label has no relation to the sense inventory nor does it describe the contents of the group; it essentially meaningless.

In order to evaluate the accuracy of the unsupervised algorithm relative to a human judge, a mapping between the uninformative labels attached to sense groups and the sense inventory for a word must be established. In supervised learning these mappings are automatic since the human tagger provides the link between the text and the sense inventory. In unsupervised learning this mapping must be made as a second step after the sense groups are learned.[2]

Consider the following example. Suppose there are 10 instances of *line* to be disambiguated. A human tagger is told that there are three entries in the sense

[2]The separation of disambiguation into a two step process is discussed in [85]. There the act of creating sense groups is termed *sense discrimination* and the process of attaching meaningful labels to these groups is called *sense labeling*.

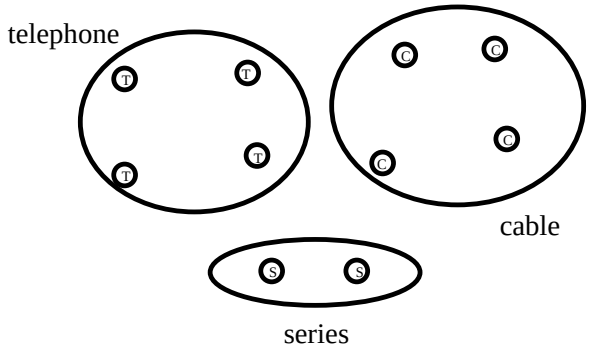


Figure 7.1. Human Labeled Senses for *line*

inventory, *(telephone, series, cable)*. The human assigns these sense tags as shown in Figure 7.1. An unsupervised learner is given these same 10 instances and told that there are three possible senses. It divides the usages of the ambiguous word into the 3 sense groups shown in Figure 7.2.

At this point there is not an immediately apparent means to assess the agreement between the sense group assignments made by the unsupervised learner and the sense tags assigned by the human judge. In order to determine accuracy, the sense groups must be linked to the entries in the sense inventory. For this example there are 6 possible mappings between *(1,2,3)* and *(telephone, series, cable)*.[3] Each possible mapping is examined to determine which results in the closest agreement with the human judge.

One possible mapping is shown in Figure 7.3. Sense group 1 is assigned sense tag *series*, sense group 2 is assigned *cable*, and sense group 3 is assigned *telephone*. The shaded instances show where the sense group label matches the sense tag assigned by the human judge. In this figure, 3 of 10 instances agree and result in unsupervised accuracy of 30%.

A second possible mapping is shown in Figure 7.4. Sense group 1 is assigned *series*, 2 is assigned *telephone*, and 3 is assigned *cable*. Here 7 of 10 instances agree

[3]Given n sense groups to be assigned n meaningful sense tags, there are $n!$ possible mappings to be considered.

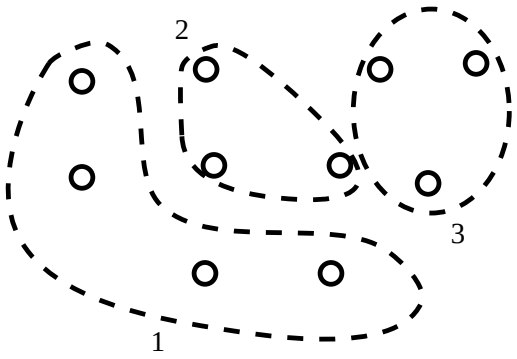


Figure 7.2. Unlabeled Sense Groups for *line*

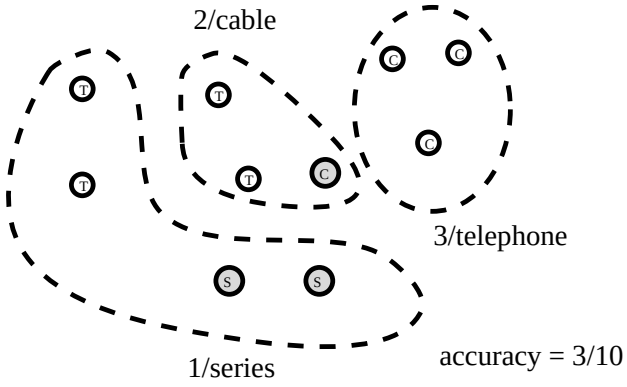


Figure 7.3. Thirty Percent Accuracy Mapping of *line*

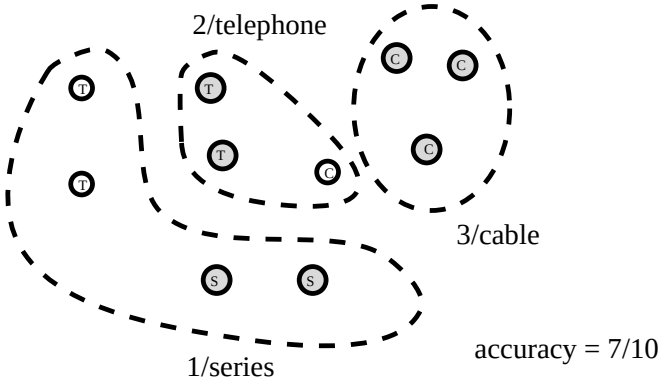


Figure 7.4. Seventy Percent Accuracy Mapping of *line*

with the human judge so accuracy is 70%. The other four possible mappings are evaluated and the maximum accuracy is reported as the unsupervised accuracy.

Given this evaluation methodology, a convenient means of determining a lower bound for unsupervised disambiguation accuracy emerges. An unsupervised learner can achieve accuracy equal to the percentage of the majority sense by not performing any disambiguation at all. In other words, a lower bound classifier for unsupervised learning simply assigns every instance of an ambiguous word to the same sense group. This is somewhat analogous to supervised learning where the lower bound is established by assigning every instance of an ambiguous word to the most frequent sense in the training data, i.e., the majority sense. However, in supervised learning it is relatively easy to exceed this lower bound. The same does not prove to be true for unsupervised learning.

7.2. Analysis 1: Probabilistic Models

The first analysis of this experiment compares the accuracy of a probabilistic model where the parametric form is assumed to be Naive Bayes and the parameter estimates are learned by the EM algorithm and Gibbs Sampling. Table 7.1 shows the average unsupervised disambiguation accuracy and standard deviation for each combination of word, feature set, and parameter estimation method over 25 trials, where each trial begins with a different random initialization of the parameter estimates.

In this table, significant differences in the disambiguation accuracy of a word using the EM algorithm and Gibbs Sampling for a given feature set are shown in bold face. These differences are discussed in Section 7.2.1, the methodological comparison. The highest overall accuracy for a word using either the EM algorithm or Gibbs Sampling and any of the three feature sets is shown in parenthesis. Any other values that are not significantly less than the maximum accuracy are underlined. These results are discussed in Section 7.2.2, the feature set comparison.[4]

[4]As in the supervised learning experiments, judgments as to the significance of differences in accuracy are made by a two tailed t–test where $p = .01$.

Table 7.1. Unsupervised Accuracy of EM and Gibbs

		Feature Set A		Feature Set B		Feature Set C	
	Maj.	Gibbs	EM	Gibbs	EM	Gibbs	EM
chief	.861	.719 .01	(.729 .06)	.648 .00	.646 .01	.728 .04	.697 .06
common	.842	.522 .00	.521 .00	.507 .07	.464 .06	**(.670 .01)**	.543 .09
last	.940	.900 .00	.903 .00	(.912 .00)	.909 .00	.908 .00	.874 .07
public	.683	**.514 .00**	.473 .03	**.478 .04**	.411 .03	**(.578 .00)**	.507 .03
adjectives	.832	.663	.657	.636	.608	.721	.655
bill	.681	.590 .04	.537 .05	(.705 .10)	.624 .08	.592 .04	.569 .04
concern	.638	(.842 .00)	(.842 .00)	.819 .01	.840 .02	.785 .01	.758 .09
drug	.567	(.676 .00)	.658 .03	.543 .04	.551 .05	.674 .06	.652 .04
interest	.593	.627 .08	.616 .06	(.652 .04)	.615 .05	.617 .05	.649 .09
line	.373	.446 .02	.457 .01	(.477 .03)	.474 .03	.457 .01	.458 .01
nouns	.570	.636	.622	.639	.621	.625	.617
agree	.740	.609 .07	.631 .08	(.714 .14)	.683 .14	.685 .14	.685 .14
close	.771	.564 .09	.560 .08	(.714 .05)	.672 .06	.636 .05	.648 .05
help	.780	**.658 .04**	.586 .05	.524 .00	.526 .00	**(.696 .05)**	.602 .03
include	.910	.734 .08	.725 .02	**(.833 .03)**	.783 .07	.551 .06	.535 .00
verbs	.800	.641	.626	.696	.666	.632	.618
overall	.734	.646	.634	.657	.631	.659	.629

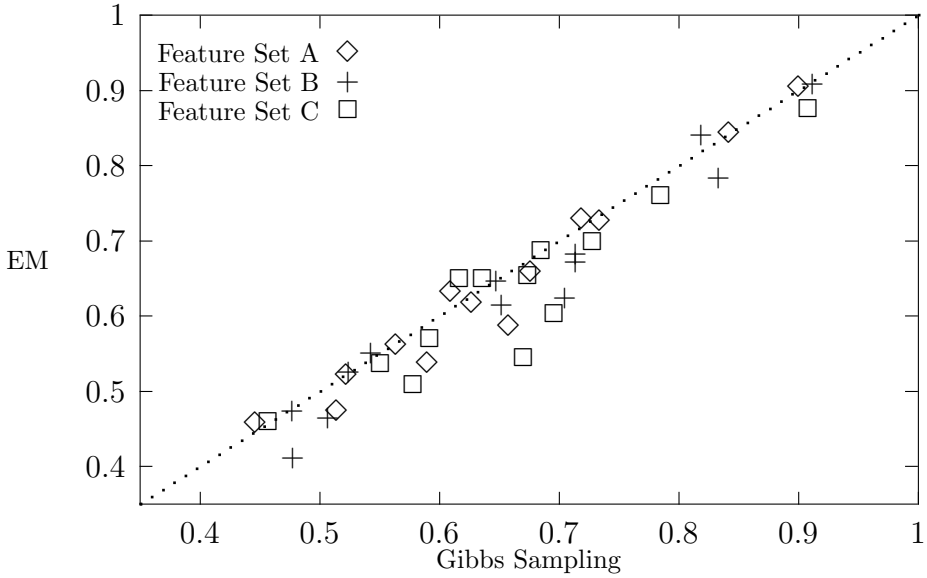


Figure 7.5. Probabilistic Model Correlation of Accuracy for all words

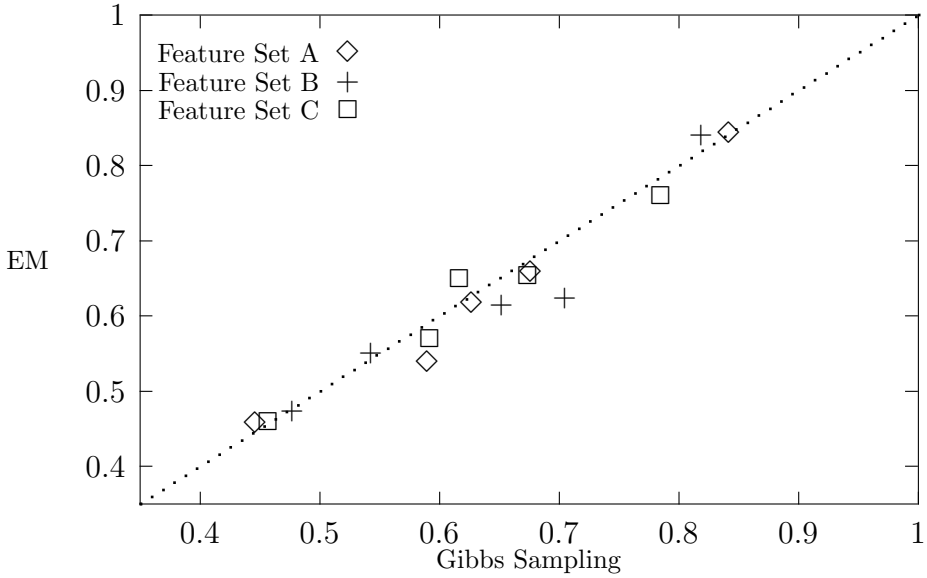


Figure 7.6. Probabilistic Model Correlation of Accuracy for Nouns

7.2.1. Methodological Comparison

This comparison studies the effect on disambiguation accuracy of learning parameter estimates for a probabilistic model using Gibbs Sampling and the EM algorithm. The motivation for the comparison is that while the EM algorithm is easy to implement and generally quick to converge, it is also prone to converging at local maxima rather than a global maximum. However, while Gibbs Sampling is guaranteed to converge at the global maximum, it does so at greater computational expense.

This experiment shows that there are only a few cases where a probabilistic model with parameter estimates learned by Gibbs Sampling results in significantly different disambiguation than the model arrived at with the EM algorithm. Of the 39 possible pairwise comparisons (13 words $\times$ 3 feature sets) between the EM algorithm and Gibbs Sampling, only 7 result in significant differences. Of those, all favor Gibbs Sampling. Those cases are shown in bold face in Table 7.1.

The lack of significant differences between the EM algorithm and Gibbs Sampling is somewhat surprising given that the EM algorithm can converge to local maxima when the distribution of the likelihood function is not well approximated by the normal distribution. However, in this experiment the EM algorithm does not appear to have great difficulty with local maxima, often converging within 20 iterations to essentially the same estimates obtained by Gibbs Sampling.

The use of Naive Bayes as the parametric form of the probabilistic model provides at least a partial explanation for the comparable results obtained with the EM algorithm and Gibbs Sampling. Chapter 5 presents the distribution of the event counts in the experimental data when the parametric form of the model is Naive Bayes. These distributions prove to be relatively smooth for the three unsupervised feature sets and are not dominated by events that are never observed in the data; in fact, a majority of the possible events for each word are observed. If the parametric form of the model were more complex than Naive Bayes, it would certainly be the case that the distribution of event counts would be more skewed and that the EM algorithm would be more susceptible to becoming trapped at a local maxima. How-

ever, the specification of Naive Bayes as the parametric form of the model seems to avoid this difficulty.

While the number of significant differences between the EM algorithm and Gibbs Sampling is small, the correlation plot comparing the accuracy of the two methods in Figure 7.5 reveals a consistent increase in the accuracy of Gibbs Sampling relative to the EM algorithm. Each point on this plot shows the accuracy attained by the probabilistic model where parameter estimates are learned by the EM algorithm and Gibbs Sampling for a given word and feature set. Figure 7.6 again shows the correlation of accuracy, but only for the nouns. This shows the comparable performance of both methods and suggests that Gibbs Sampling has a particular advantage over the EM algorithm for the adjectives and verbs. This is not surprising since the adjectives and verbs have the most skewed distributions of senses and are more likely to cause difficulty for the EM algorithm than are the nouns.

The standard deviations associated with the two approaches also prove to be similar, generally falling between .03 and .10. A standard deviation of .00 indicates that the exact same sense group is created by each of the 25 trials of the algorithm. The larger the deviation the more variation there is in the sense groups created from trial to trial. The standard deviation observed is somewhat larger than expected, particularly since neither method has substantial difficulties with local maxima. This suggests that there is some degree of noise in the data that is obscuring sense distinctions and causing the variance in the results from trial to trial.

There are several possible sources of noise in this data. The very crude part–of–speech distinctions made in feature sets A and C may not provide sufficient information to distinguish among senses. In addition, this tagging was performed without the benefit of training data and is likely to contain inaccuracies.

The frequency based co–occurrences in feature sets B and C include a value that signifies that the word at a specified position relative to the ambiguous word is not among the 19 most frequent words that occur at this position with all instances of the ambiguous word; this lumps together a great many words into a single feature

value and may further blur the ability of the learning algorithm to accurately make sense distinctions.

The difficulty in unsupervised learning is that features must be selected from raw untagged text. The availability of accurately part–of–speech tagged text can not be assumed, nor can the ability to select feature values that are indicative of minority senses. Raw untagged text generally does not lend itself to fine grained feature values that are able to identify particular senses; generally speaking features must be selected simply based on frequency counts and lead to a certain amount of noise in the data.

A noteworthy result is that only the nouns are disambiguated with accuracy greater than the discussed lower bound for unsupervised learning. The accuracy of the probabilistic models is less than the lower bound when the percentage of the majority sense exceeds 68%. However, even in cases where the accuracy of the EM algorithm and Gibbs Sampling is less than the lower bound, these methods are often still providing high accuracy disambiguation. For example, Gibbs Sampling is able to achieve 91% accuracy for *last* and 83% accuracy for *include*.

The relative success of noun disambiguation is at least partially explained by the fact that, as a class, the nouns have the most uniform distribution of senses. However, the distribution of senses is not the only factor affecting disambiguation accuracy; the performance of the EM algorithm and Gibbs Sampling is quite different for *bill* and *public* despite having roughly the same sense distributions.

It is difficult to quantify the effect of the distribution of senses on a learning algorithm, particularly when using naturally occurring data. In previous unsupervised experiments with *interest*, using a feature set similar to A, an increase of 36 percentage points over the accuracy of the lower bound was achieved when the 3 senses were evenly distributed in the training data [71]. Here, the most accurate performance using larger samples and a natural distribution of senses is only an increase of 20 percentage points over the accuracy of the lower bound.

The actual distribution of senses does not closely correspond to the distribution of senses discovered by either method. As examples, the distribution of senses discovered by the EM algorithm and Gibbs Sampling relative to the known distribution of senses is illustrated in Figures 7.7, 7.8 and 7.9. These show the confusion matrices associated with the disambiguation of *concern*, *interest*, and *help*, using feature sets A, B, and C, respectively. A confusion matrix shows the number of cases where the sense discovered by the algorithm agrees with the manually assigned sense along the main diagonal; disagreements are shown in the rest of the matrix. The row totals show the actual distribution of senses while the column totals show the discovered distributions.

In general, these matrices show that the EM algorithm and Gibbs Sampling result in distributions of senses that are more balanced than those of the actual distribution. This is at least partially due to the assumption made prior to learning by the unsupervised methods that each possible sense is equally likely. Adjusting this prior assumption could result in the discovery of less balanced distributions of senses and is an interesting direction for future research.

The fact that the EM algorithm and Gibbs Sampling often arrive at similar results suggests that a combination of the these methods might be appropriate for this data. It is proposed in [56] that the Gibbs Sampler be initialized with the parameters that the EM algorithm converges upon rather than with randomly selected values. If the EM algorithm has found a local maxima then the Gibbs Sampler can escape it and find the global maximum. However, if the EM algorithm has already found the global maximum then the Gibbs Sampler will converge quickly and confirm this result.

7.2.2. Feature Set Comparison

While there is little variation between the EM algorithm and Gibbs Sampling given a particular word and feature set, there are differences in the accuracy attained for each method as they are used with different feature sets. In general, variation

	Discovered		
Actual	worry	business	
worry	384	63	447
business	132	656	788
	516	719	1235

EM - 1040 correct

	Discovered		
Actual	worry	business	
worry	384	63	447
business	132	656	788
	516	719	1235

Gibbs - 1040 correct

Figure 7.7. concern - Feature Set A

	Discovered			
Actual	attention	share	money	
attention	127	230	4	361
share	134	364	2	500
money	320	124	808	1252
	581	718	814	2113

EM - 1299 correct

	Discovered			
Actual	attention	share	money	
attention	152	205	4	361
share	134	364	2	500
money	297	94	861	1252
	583	663	867	2113

Gibbs - 1377 correct

Figure 7.8. interest - Feature Set B

	Discovered		
Actual	assist	enhance	
assist	119	160	279
enhance	344	644	988
	463	804	1267

EM - 763 correct

	Discovered		
Actual	assist	enhance	
assist	169	110	279
enhance	276	712	988
	445	822	1267

Gibbs - 881 correct

Figure 7.9. help - Feature Set C

in the accuracy of a method when using different feature sets suggests that certain types of features are more or less appropriate for particular words. Table 7.1 shows the maximum accuracy for each word in parenthesis. Any accuracies that are not significantly less than this are underlined.

There are a number of cases where the same method attains very different levels of accuracy when used with different feature sets. For example, the accuracies of the EM algorithm and Gibbs Sampling for *bill* and *include* are much higher with feature set B than with A or C. Less extreme examples of the same behavior are shown by *agree* and *close*. However, the accuracies for *drug* and *help* are much lower with feature set B than with A or C. A less extreme example is *chief*.

The separation of behavior between feature sets A and C and feature set B is due to the nature of the features in these sets. A and C both include part–of–speech features while feature set B does not. It appears that the usefulness of part–of–speech features for disambiguation varies considerably from word to word. The fact that 3 of 4 verbs perform at higher levels of accuracy with feature set B suggests that part–of–speech features may not be helpful when disambiguating verbs.

When using either the EM algorithm or Gibbs Sampling, *line*, *interest*, and *last* result in very similar disambiguation accuracy regardless of the feature set. In fact, for *interest* and *line* there are no significant differences among any combination of method and feature set. This lack of variation shows that the different feature sets are not able to make sufficient distinctions among all words. It may also point to limitations in Naive Bayes. While it performs well in general, there may be certain words and feature sets for which the assumptions it makes are not appropriate.

The performance of *concern* is slightly unusual; it disambiguates most accurately with feature sets A and B. However, the only feature in common between sets A and B is the morphological feature; it seems unlikely that this accounts for the high disambiguation accuracy achieved using both sets. A more likely explanation is that the part–of–speech features from set A somewhat duplicate the information contained in the unrestricted co–occurrences of set B. Unrestricted co–occurrences

can be largely dominated by non–content words that provide more syntactic rather than semantic information. This same explanation may apply in cases such as *line* and *interest* where the results for feature sets A, B, and C are very similar. Feature sets A and C rely heavily upon part–of–speech features which largely convey syntactic information. If the co–occurrences in feature set B are also essentially representing syntactic information, then similar performance across all feature sets is possible.

The highest average accuracy achieved for adjectives occurs when Gibbs Sampling is used in combination with feature set C. The adjectives have the most skewed sense distributions and set C has the largest dimensionality of the feature sets. Given this combination of circumstances, it appears that the EM algorithm gets trapped at local maxima for *common* and *public*; Gibbs Sampling finds a global maximum and results in significantly better accuracy in these cases.

Feature set B appears to be well suited for *bill* but fares poorly with *drug*. Otherwise there is not a clear pattern as to which feature set is most accurate for the nouns. The relatively similar behavior across the feature sets suggests that certain features are either essentially duplicating one another or that there are features included in these sets that are simply not useful for the disambiguation of nouns. While it is clear that the part–of–speech and co–occurrence features are contributing to disambiguation accuracy, it is less certain that the morphological and collocation features make significant contributions.

7.3. Analysis 2: Agglomerative Clustering

The second analysis of this experiment compares the accuracy of two agglomerative clustering algorithms, Ward's minimum variance method and McQuitty's similarity analysis. Table 7.2 shows the average accuracy and standard deviation of disambiguation over 25 random trials for each combination of word, method, and feature set. The repeated trials are necessary to determine the impact of randomly breaking ties during clustering. As in the first analysis, both methodological and feature set comparisons are presented.

Table 7.2. Unsupervised Accuracy of Agglomerative Clustering

		Feature Set A		Feature Set B		Feature Set C	
	Maj.	McQuitty	Ward	McQuitty	Ward	McQuitty	Ward
chief	.861	**.844 .05**	.721 .01	**.831 .06**	.611 .01	**(.856 .00)**	.673 .03
common	.842	.648 .12	.513 .08	**.797 .04**	.444 .04	**(.799 .06)**	.561 .05
last	.940	(.791 .12)	.598 .09	.541 .11	.659 .03	.636 .07	.601 .08
public	.683	.560 .08	.450 .05	**.558 .07**	.461 .03	**(.628 .05)**	.488 .04
adjectives	.832	.711	.571	.682	.544	.730	.581
bill	.681	.669 .08	.647 .11	**(.753 .05)**	.600 .04	.561 .10	.515 .04
concern	.638	.629 .07	**.741 .04**	.679 .04	.697 .02	.614 .08	**(.758 .04)**
drug	.567	.530 .03	.557 .06	.521 .01	.528 .00	.573 .06	(.632 .06)
interest	.593	.601 .04	.619 .04	(.653 .06)	.552 .06	.651 .02	.615 .04
line	.373	.420 .03	(.441 .03)	.403 .02	.428 .03	.410 .02	.427 .02
nouns	.570	.570	.601	.602	.561	.562	.589
agree	.740	**.610 .08**	.547 .03	.678 .08	.613 .04	**(.685 .07)**	.601 .00
close	.771	**.616 .09**	.531 .02	.667 .07	.664 .00	(.720 .11)	.645 .04
help	.780	**(.713 .05)**	.591 .05	**.636 .11**	.519 .01	**.700 .06**	.570 .03
include	.910	**(.880 .06)**	.707 .08	.767 .09	.770 .06	.768 .17	.558 .04
verbs	.800	.705	.594	.687	.642	.718	.593
overall	.734	.655	.589	.653	.580	.662	.588

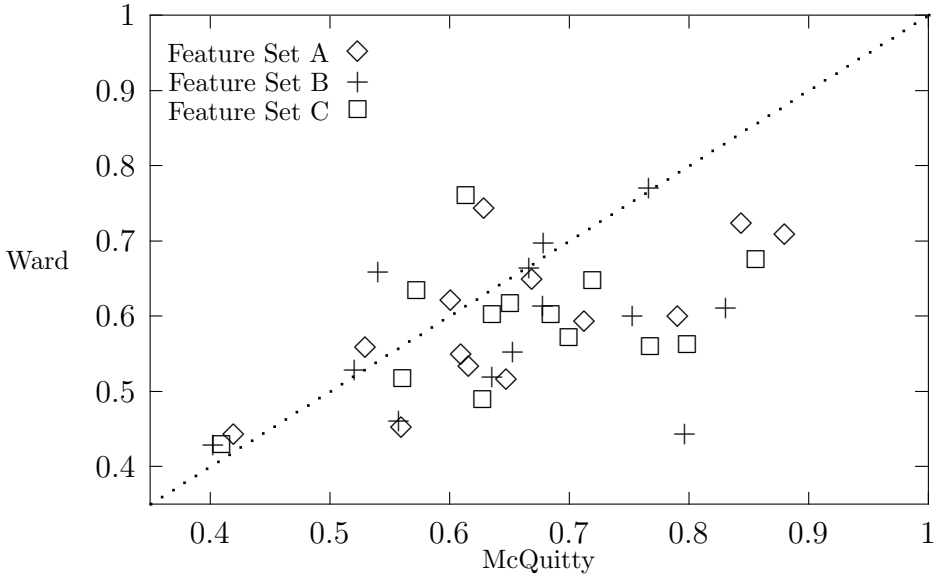


Figure 7.10. Agglomerative Clustering Correlation of Accuracy for all words

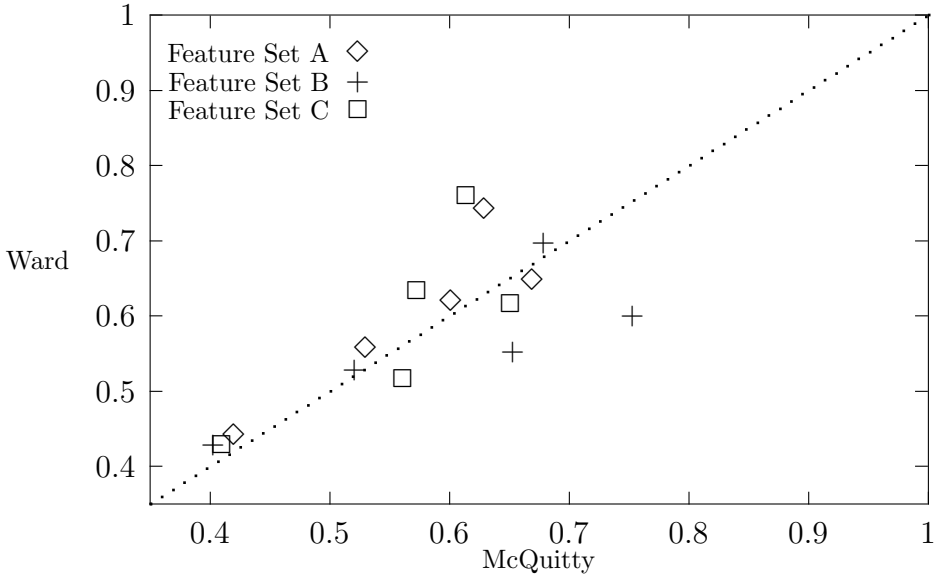


Figure 7.11. Agglomerative Clustering Correlation of Accuracy for Nouns

7.3.1. Methodological Comparison

Ward's and McQuitty's methods are both agglomerative clustering algorithms and differ only in the distance measure each uses to determine if an instance of an ambiguous word belongs in a particular sense group. Since distance is not implicit in the features used in this experiment, the data representing the instances of an ambiguous word must be converted into a form where distance can be measured. In this dissertation that representation is a dissimilarity matrix.

Ward's method is based on a classical measure, Euclidean distance, while McQuitty's method employs a simple count of the number of dissimilar features to establish group membership. The dramatic difference in the nature of these distance measures motivates their inclusion in this study.

Unlike the probabilistic models, there are significant differences in the accuracy of the two agglomerative clustering algorithms given a particular feature set. Of the 39 possible pairwise comparisons, 17 result in significant differences. There are 2 cases where Ward's method is significantly more accurate and 15 favoring McQuitty's similarity analysis. The significant differences are shown in bold face in Table 7.2.

The plot of the correlation of accuracy between Ward's and McQuitty's methods in Figure 7.10 shows that McQuitty's method generally is the more accurate. However, in Figure 7.11 the correlation plot is restricted to the nouns and Ward's method is shown to be slightly more accurate. This is also illustrated in Table 7.2, where there are only three significant differences among the nouns; in two of those cases Ward's method is the most accurate. Thus, it is only for verbs and adjectives that McQuitty's method shows a decisive advantage.

As is the case with the probabilistic models, only the nouns are consistently disambiguated with accuracy greater than the majority sense. However, McQuitty's method achieves accuracy comparable to the majority sense for a few of the adjectives and verbs when the standard deviation is taken into account. This occurs for *chief* with all feature sets, *common* for sets B and C, *close* for set C, and *include* for set A.

There appears to be significant relationships among the actual sense distributions of the ambiguous words, the inherent biases of the agglomerative clustering algorithms, and the accuracy attained by each method. Ward's method has a well–known bias towards finding balanced distributions of sense groups [91]. However, McQuitty's method has no such bias since there are no underlying parametric models or distributional assumptions that influence the algorithm.[5] The tendencies of both agglomerative methods are illustrated in Figures 7.12, 7.13, and 7.14. These show the confusion matrices for the same word and feature set combinations that are discussed in the first analysis. These illustrate the bias of Ward's method towards the discovery of balanced sense distributions while also showing that McQuitty's similarity analysis tends to find more skewed distributions.

The bias of Ward's method towards balanced distributions of senses results in accurate disambiguation of the nouns but also leads to rather poor performance with adjectives and verbs. As the actual distribution of senses grows more skewed, Ward's method becomes less accurate. By contrast, McQuitty's method performs fairly well with words that have skewed distributions of senses. It has no bias regarding the distribution of senses it discovers and is able to learn very unbalanced distributions.

The standard deviations in Table 7.2 measure the impact of randomly breaking ties during the clustering process. A standard deviation of .00 indicates that no ties occurred during clustering; in this case the agglomerative algorithm is deterministic and the sense groups discovered from trial to trial are identical. As clustering becomes more influenced by random breaking of ties, the standard deviation will increase since the sense groups created will vary from trial to trial.

Overall, the standard deviation for McQuitty's similarity analysis is greater than that of Ward's method. This is not surprising given the simplicity of McQuitty's approach; distances are based on a count of the dissimilar features between two

[5]In this regard McQuitty's method is unique among the four unsupervised approaches discussed in this dissertation. Recall that both the EM algorithm and Gibbs Sampling also tend to find balanced distributions of senses.

	Discovered		
Actual	worry	business	
worry	166	281	447
business	181	607	788
	347	888	1235

McQuitty - 773 correct

	Discovered		
Actual	worry	business	
worry	288	159	447
business	155	633	788
	443	792	1235

Ward - 921 correct

Figure 7.12. concern - Feature Set A

	Discovered			
Actual	attention	share	money	
attention	53	6	302	361
share	58	187	255	500
money	108	4	1140	1252
	219	197	1697	2113

McQuitty - 1380 correct

	Discovered			
Actual	attention	share	money	
attention	280	3	78	361
share	240	197	63	500
money	559	0	693	1252
	1079	200	834	2113

Ward - 1170 correct

Figure 7.13. interest - Feature Set B

Actual	Discovered assist	enhance	
assist	45	234	279
enhance	146	842	988
	191	1076	1267

McQuitty - 887 correct

Actual	Discovered assist	enhance	
assist	88	191	279
enhance	354	634	988
	442	825	1267

Ward - 722 correct

Figure 7.14. help - Feature Set C

instances of an ambiguous word. Ties are common given these sets since they contain relatively small numbers of features; A has 8, B has 5, and C has 7.

However, Ward's method computes Euclidean distances in n–space. While this more detailed measure results in fewer ties, there are still enough to cause relatively large amounts of deviation for some words. This suggests that the conversion of raw text into a dissimilarity matrix representation results in a reduction in the discriminating power of the feature set to the point where ties are still common.

In general, these standard deviations suggest that the feature sets need to be expanded to provide more distinctions between instances of an ambiguous word when using the agglomerative clustering algorithms.

7.3.2. Feature Set Comparison

When using probabilistic models, feature sets A and C result in similar performance and often have an inverse relationship to the accuracy attained with feature set B. For example, if set B results in high accuracy then A and C may not. When feature set A and C result in high accuracy then set B often does not. These patterns hold for 7 of 13 words when disambiguating with probabilistic models. This suggests that the features common to sets A and C, the part–of–speech of surrounding words, are a main contributor to disambiguation accuracy when using probabilistic models.

However, when an agglomerative approach is employed these patterns are much less pronounced. The only cases where results from set A and set C are more accurate than those from set B are when McQuitty's method is used to disambiguate *help* and when Ward's method is used for *concern*. The only case where feature set B is most accurate is when McQuitty's method is used to disambiguate *bill*.

This change in behavior suggests that the data representation employed by the agglomerative methods blurs some distinctions that are present in the frequency count data used by the probabilistic models. While both the probabilistic models and agglomerative methods use the same feature sets, the agglomerative methods convert the data into a dissimilarity matrix representation that shows how many features

differ between instances of an ambiguous word; however, it makes no distinctions as to which features differ. Thus the part–of–speech distinctions that appear to have significant impact on disambiguation accuracy when using probabilistic models are not distinguishable from other features in the dissimilarity matrix representation.

Overall the combination of McQuitty's similarity analysis with feature set C results in consistently high accuracy for the adjectives and verbs. Feature set C has the highest dimensionality of the three feature sets. Thus, the number of dissimilar features between two instances of an ambiguous word will likely be fairly high most of the time since there are a large number of possible values for the features. This results in the creation of a large sense group where all members have fairly high dissimilarity counts. The distribution of discovered senses in this case will be skewed and likely correspond fairly well with the actual distributions.

The only cases where McQuitty's method and feature set C fares poorly for the verbs and adjectives are for *last* and *include*. These are interesting exceptions in that these two words have the largest majority senses, .94% and .91% respectively. They are both most accurately disambiguated with feature set A; no other combination of feature set and method results in comparable performance. Agglomerative clustering based on dissimilarity counts of the features in set A is particularly effective with these words. This suggests that the combination of a low dimensional feature set with a word that has an extremely skewed distribution of senses may be appropriate.

There is not a clear pattern as to which feature sets lead to accurate disambiguation of nouns. For *concern*, Ward's method in conjunction with feature sets A and C achieves the highest accuracy. Ward's method is also most accurate for *drug* when used with feature set C. The success of Ward's method for these two nouns is related to the general tendency of Ward's method to find balanced distributions of senses. As is the case in the probabilistic models, *interest* and *line* do not show great variation from one feature set to the next. This again suggests that the dissimilarity matrix may be reducing the granularity of the information available to the clustering algorithm by reducing the distinctions that the feature sets are able to represent.

7.4. Analysis 3: Gibbs Sampling and McQuitty's Similarity Analysis

The first analysis in Section 7.2 shows that Gibbs Sampling offers some improvement over the EM algorithm, particularly for adjectives and verbs. The second analysis in Section 7.3 shows that McQuitty's similarity analysis is often more accurate than Ward's method; primarily when disambiguating adjectives and verbs. This final analysis compares McQuitty's method and Gibbs Sampling. This section only contains a methodological comparison since the feature set comparisons for McQuitty's method and Gibbs Sampling are included in the first two analyses.

Table 7.3 reformats the accuracies reported in the previous two analyses for easy comparison. As before, significant differences between the two methods for a particular word and feature set are shown in bold face. The maximum accuracy for a word is in parenthesis and any accuracies that are not significantly less than this maximum are underlined.

There are a relatively large number of significant differences between Gibbs Sampling and McQuitty's similarity analysis given a particular feature set. Of the 39 pairwise comparisons, 19 show significant differences. Gibbs Sampling is more accurate in 10 of those cases and McQuitty's method is more accurate in 9. These significant differences are shown in bold face in Table 7.3.

The correlation of accuracy between Gibbs Sampling and McQuitty's method is shown in Figure 7.15. Since there is not a clear pattern associated with the performance of the methods, this data is broken down into separate correlation plots for adjectives, nouns, and verbs in Figures 7.16, 7.17, and 7.18.

Figure 7.16 shows that McQuitty's method is generally more accurate for adjectives, the exception being *last* for all three feature sets. Figure 7.17 suggests that Gibbs Sampling is more accurate for the nouns. Figure 7.18 shows that McQuitty's method is generally more accurate for the verbs, although not so dramatically as is the case with the adjectives.

Table 7.3. Unsupervised Accuracy of Gibbs and McQuitty's

		Feature Set A		Feature Set B		Feature Set C	
	Maj.	Gibbs	McQuitty	Gibbs	McQuitty	Gibbs	McQuitty
chief	.861	.719 .01	**.844 .05**	.648 .00	**.831 .06**	.728 .04	**(.856 .00)**
common	.842	.522 .00	**.648 .12**	.507 .07	**.797 .04**	.670 .11	**(.799 .06)**
last	.940	**.900 .00**	.791 .12	**(.912 .00)**	.541 .11	**.908 .00**	.636 .07
public	.683	.514 .00	.560 .08	.478 .04	.558 .07	.578 .00	**(.628 .05)**
adjectives	.832	.663	.711	.636	.682	.721	.730
bill	.681	.590 .04	.669 .08	.705 .10	(.753 .05)	.592 .04	.561 .10
concern	.638	**(.842 .00)**	.629 .07	**.819 .01**	.679 .04	**.785 .01**	.614 .08
drug	.567	**(.676 .00)**	.530 .03	.543 .04	.521 .01	**.674 .06**	.573 .06
interest	.593	.627 .08	.601 .04	.652 .04	(.653 .06)	.617 .05	.651 .02
line	.373	.446 .02	.420 .03	**(.477 .03)**	.403 .02	**.457 .01**	.410 .02
nouns	.570	.636	.570	.639	.602	.625	.562
agree	.740	.609 .07	.610 .08	(.714 .14)	.678 .08	.685 .14	.685 .07
close	.771	.564 .09	.616 .09	.714 .05	.667 .07	.636 .05	(.720 .11)
help	.780	.658 .04	(.713 .05)	.524 .00	**.636 .11**	.696 .05	.700 .06
include	.910	.734 .08	**(.880 .06)**	.833 .03	.767 .09	.551 .06	.768 .17
verbs	.800	.641	.705	.696	.687	.632	.718
average	.734	.646	.655	.657	.653	.659	.662

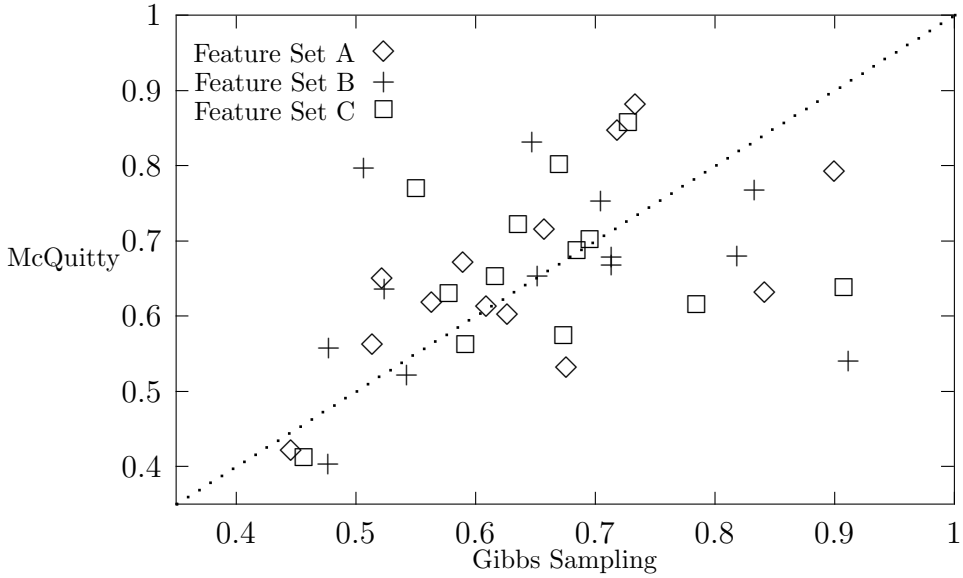


Figure 7.15. Gibbs and McQuitty's Correlation of Accuracy for all words

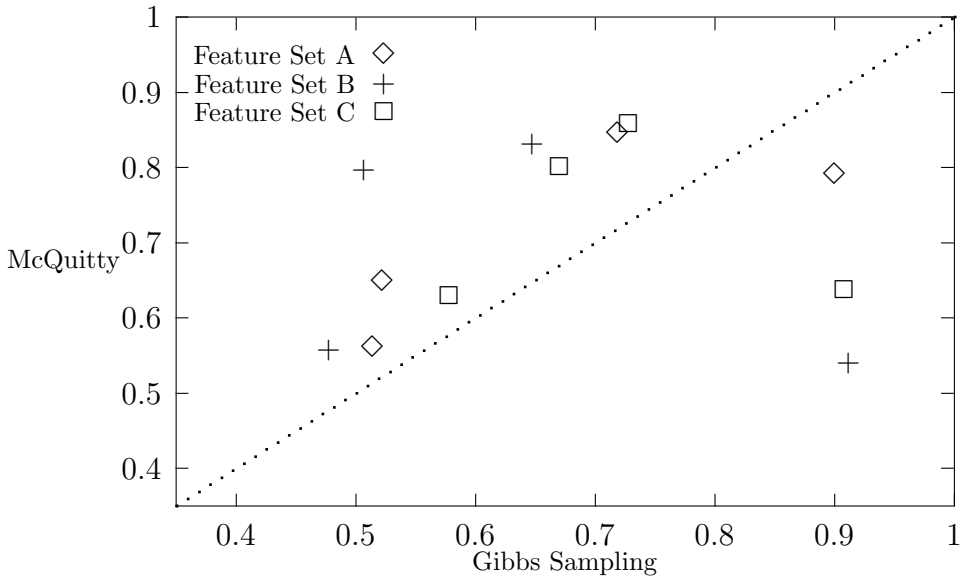


Figure 7.16. Gibbs and McQuitty's Correlation of Accuracy for Adjectives

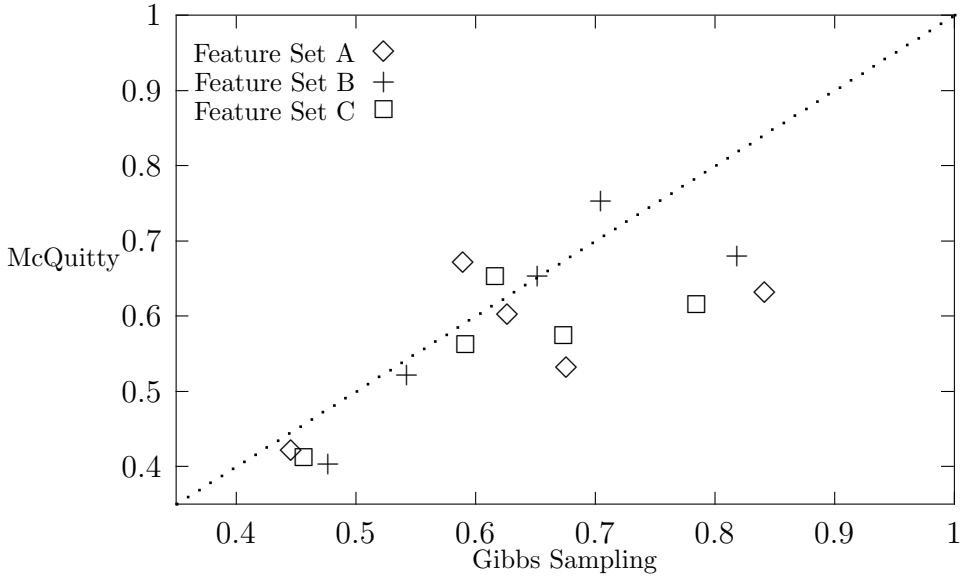


Figure 7.17. Gibbs and McQuitty's Correlation of Accuracy for Nouns

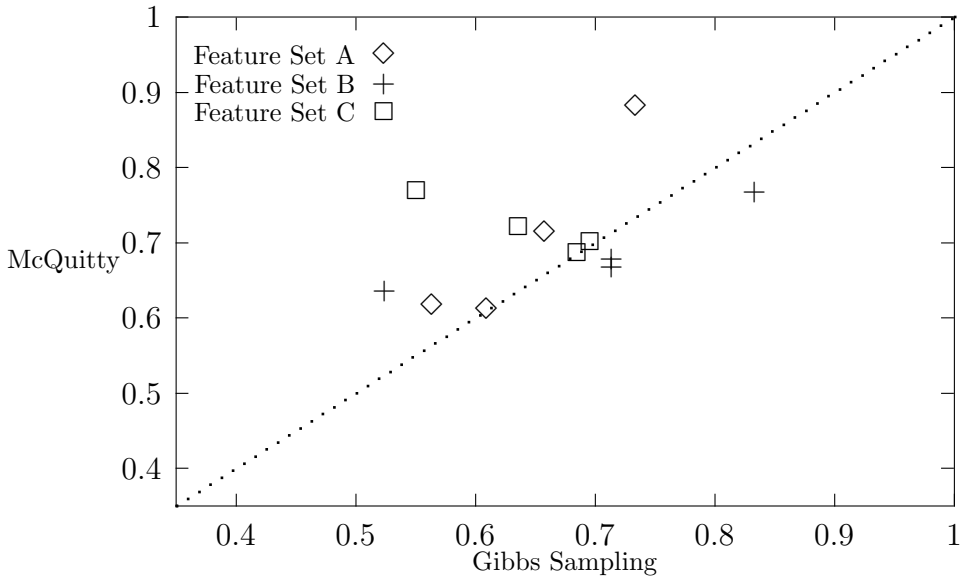


Figure 7.18. Gibbs and McQuitty's Correlation of Accuracy for Verbs

Of the 19 significant differences, 10 occur among the adjectives, 7 occur among the nouns, and 2 occur among the verbs. The distribution of senses plays a role in these results, particularly for the adjectives. Of the 10 significant differences among the adjectives, 7 favor McQuitty's method. Given the tendency of McQuitty's method to discover skewed sense distributions this is not surprising. Of the 7 significant differences observed among the nouns, all favor Gibbs Sampling. Again, this is somewhat expected given the bias of Gibbs Sampling towards discovering balanced distributions of senses. Finally, the two significant differences in the verbs favor McQuitty's method. Despite having rather skewed sense distributions, McQuitty's method and Gibbs Sampling perform at comparable levels of accuracy for the verbs. This indicates that the greater granularity of the data representation used by Gibbs Sampling is sometimes sufficient to offset the bias of McQuitty's method towards discovering skewed sense distributions.

Direct comparison of McQuitty's method and Gibbs Sampling must take into account the differences in the data representations employed. McQuitty's similarity analysis is based upon counts of the number of dissimilar features between multiple instances of the ambiguous word. A probabilistic model is based upon frequency counts of the marginal events as defined by its parametric form. Given these rather different representations, it is not surprising that the accuracies for the two methods for a given word and feature set are often quite different. However, this makes the few cases where the two methods achieve nearly identical results all the more intriguing. For example, *agree* with feature sets A and C, *interest* with feature set B, and *help* with feature set C, all achieve very similar levels of accuracy despite the differences in representation. Understanding the conditions that lead to these results is an interesting area for future work.

In general, these results suggest that the characteristics of a feature set must be compatible with the learning algorithm in order to achieve good results. Gibbs Sampling benefits from feature sets that contain a small number of features that each have a limited number of possible values. This allows for accurate parameter

estimation, particularly when the parametric form is a simple model such as Naive Bayes. For example, the ability learn reliable parameter estimates contributes to the high accuracy that Gibbs Sampling achieves with feature set A for the nouns. By contrast, McQuitty's method generally benefits from larger numbers of features and higher dimensional spaces. Given such data, a dissimilarity matrix becomes a richer source of information that can be used to make more fine grained distinctions than is the case with a small number of features. This data representation contributes to the overall high accuracy attained with feature set C for adjectives and verbs.

CHAPTER 8

RELATED WORK

Much of the early work in word sense disambiguation relied on the use of rich, manually–crafted knowledge sources such as semantic networks and concept hierarchies (e.g., [43], [87], [95]). While these systems were very successful in limited domains, they tended to be difficult to scale up or port to new domains.

As the difficulty in creating knowledge–rich resources for larger domains became apparent, research shifted to exploiting online lexical resources that were already constructed such as dictionaries, thesaruses, and encyclopedias (e.g., [52], [97]). While these are rich sources of knowledge that offer relatively broad coverage of both language and topic, they are not designed for use with a mechanical inferencing algorithm. Rather, these resources are intended for a human user who will apply their own inferencing methods to find and understand the information in the lexical resource.

Recent work in disambiguation has been geared towards corpus–based, statistical methods (e.g., [11], [12], [64], [63], [70], [73], [96]). These approaches often employ supervised learning algorithms and require the availability of manually created training examples from which to learn. However, sense–tagged generally does not exist in large quantities and it proves expensive to create.

The difficulties in building semantic networks, the lack of automatic inferencing algorithms appropriate for lexical resources designed for human use, and the time consuming nature of manually sense–tagging text; all these factors lead to the realization that the only truly broad–coverage knowledge resource currently available for word sense disambiguation is raw untagged text. However, the lack of any systematic structure and the absence of points of reference to external knowledge sources makes untagged text a very challenging resource from which to learn.

It is difficult to precisely quantify the degree of structure and richness in a knowledge source for word sense disambiguation. The following is an approximate and subjective ranking, beginning with the richest and most structured sources of knowledge and ending with raw untagged text, the most impoverished and unstructured source considered here.

1. semantic networks, concept hierarchies
2. machine readable dictionaries, thesaruses
3. parallel translations
4. sense–tagged corpora
5. raw untagged corpora

This chapter discusses representative approaches to word sense disambiguation that employ each of these different kinds of knowledge resources.

8.1. Semantic Networks

A semantic network is a highly structured knowledge source where nodes represent concepts and related concepts are connected by links of various types. Common examples of links include *is–a*, *has–part*, and *is–made–of*.

Semantic networks are often used to model and enforce selectional restrictions, a concept that finds its roots in Case Grammar [34]. This is a lexically based linguistic formalism where verbs are defined based on the roles, i.e, case frames, of the words that they may be validly used with. As a simple example, suppose that the verb *hit* is defined as follows:

hit :: [AGENT:human] [OBJECT:projectile] [INSTRUMENT:club]

AGENT, OBJECT and INSTRUMENT are just a few examples of possible case frames. The selectional restrictions on these frames are specified in lower case letters.

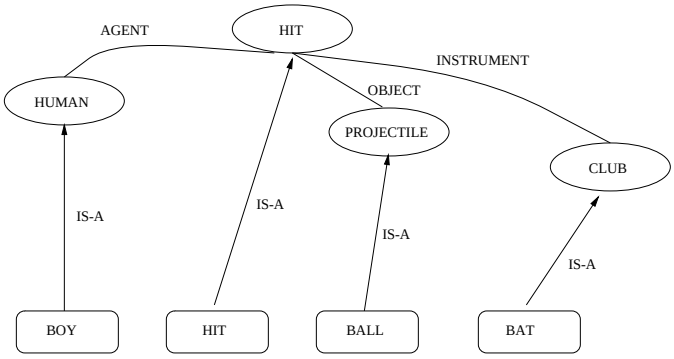


Figure 8.1. Simple Semantic Network

This definition tells us that the verb *hit* expects that the AGENT who performs the hitting is a human, that the OBJECT that AGENT hits is a projectile, and that the INSTRUMENT the AGENT uses to hit the OBJECT with is a club.

In these approaches nouns are often defined in terms of subsuming relations as shown in a IS-A hierarchy. A *bat* is a club, a *boy* is a human, and a *ball* is a projectile. A Case Grammar parser will accept the sentence *The boy hit the ball with a bat* since all of the selectional restrictions imposed by the verb are honored.

Case Grammar and selectional restrictions are conveniently mapped onto a semantic network. The nodes of the network represent concepts and the links between nodes enforce the selectional restrictions. A semantic network representation of the Case Grammar for *hit* appears in Figure 8.1. Here the nouns and verbs in the sentence are shown in boxes, the concepts are in ovals, and the links are labeled appropriately.

Once a semantic network is constructed, word sense disambiguation can be performed using marker passing as an inference mechanism. Marker passing was introduced in [77] as a means of spreading activation on semantic memory. Marker passing was extended to serve as an inferencing mechanism by [17].

Markers are able to travel through the semantic network, visiting the nodes and moving along the links. Markers are restricted as to what types of links they may travel along. Inferencing is achieved by propagating markers from the concepts

of interest and determining at what concepts they intersect in the network. These points of intersection will reveal some kind of relationship between the two concepts that may not have been previously realized.

Marker passing has been widely used in language processing for various inferencing problems, including word sense disambiguation (e.g. [21], [43], [61], [65], and [100]). Generally the words in a sentence activate the concepts that they are linked to by passing a marker. The activated concepts continue to propagate markers to other concepts until the network eventually stabilizes. This stabilized network represents the disambiguated sentence.

Marker passing offers tremendous opportunities to exploit parallel computer architectures. It is also an intuitively appealing approach that may ultimately allow for the development of reasonable cognitive models of disambiguation. However, the question of how to construct the underlying representations remains problematic. One approach that has proven successful is to learn selectional constraints via interactive training with a user (e.g. [16], [45]). Another option is to automatically construct these representations from existing resources such as a machine readable dictionary (e.g. [14], [20], [90]).

8.2. Machine Readable Dictionaries

Machine readable dictionaries were first applied to word sense disambiguation in [52]. There, *pine cone* was disambiguated based on the dictionary definitions of *pine* and *cone*. It was noted that the definitions of *pine* and *cone* both contained references to the concept of a tree:

> **pine:** any of a genus of coniferous evergreen *trees* which have slender elongated needles and some of which are valuable timber *trees* or ornamentals
> **cone:** a mass of ovule-bearing or pollen-bearing scales or bracts in *trees* of the pine family or in cycads that are arranged usually on a somewhat elongated axis

By unifying these references to *tree* a computer program inferred that *pine cone* is the fruit of a tree rather than an edible receptacle for a pine tree. Experimental results for this approach are reported at 50%–70% accuracy for short passages from *Pride and Prejudice* and an Associated Press news story.

[97] presents an approach where ambiguous words that occur in encyclopedia entries are disambiguated with respect to categories defined in Roget's Thesaurus. A Naive Bayes model is developed that contains 100 feature variables and a single variable representing the sense of the ambiguous word. The feature variables are the 50 words to the left and right of the ambiguous word. The parameter estimates for this model are made using category information from Roget's Thesaurus. There are 1042 categories in Roget's. Typical examples of categories include *tools–machinery* or *animal–insect*, and each category is described by a broad set of relations (similar to those represented by links in a semantic network) that typically consist of over 3,000 words. After the parameter estimates are made from the entries describing Roget's categories, this probabilistic model is used to disambiguate instances of twelve ambiguous words found in the June 1991 version of Grolier's Encyclopedia. Accuracy is reported at above 90% for 11 of 12 words with between 2 and 6 possible senses.

While machine readable dictionaries are a promising resource for disambiguation, it can sometimes be the case that dictionary entries are too brief to provide all of the salient collocations or other clues that might identify the sense of an ambiguous word. However, as online dictionaries grow more extensive their usefulness as a knowledge source in corpus–based language processing will likewise increase.

8.3. Parallel Translations

Given the expense of manually tagging ambiguous words with senses, it is natural to ask if there are clever means of obtaining sense–tagged text that avoid the need for manual intervention. In fact, the use of parallel translations is such an approach. This methodology relies upon the premise that while a word may be ambiguous in one language, the various senses may have distinct word forms in another language.

Consider the word *bill* in English. It has many possible senses, among them pending legislation and statement requesting payment. In Spanish these two senses have distinct word forms, *proyecto de ley* and *cuenta*. Suppose the following usages of *bill* are found in parallel English and Spanish text:

1E) The bill is too much.

1S) La cuenta es demasiado.

2E) The bill to save the banks is good.

2S) El proyecto de ley para salvar los bancos es bueno.

From the Spanish text it is clear that usage of *bill* in sentence 1E) refers to a statement requesting payment while the usage in sentence 2E) refers to pending legislation. Thus, the sense distinction made in Spanish is utilized to assign the appropriate sense–tags to *bill* in English.

This approach to creating sense–tagged text has been pursued mainly in French and English due to the availability of parallel translations of the Canadian Parliamentary Proceedings, i.e., the Hansards, (e.g. [9], [37]). Once the sense–tags are obtained from a parallel translation, supervised learning methods can be employed as if the tagging had been performed manually. Naive Bayes with a large window of context is employed in [37] while [9] identify a single binary feature that makes the sense distinction.

However, given the nature of the Hansards, it is in fact rather difficult to locate many words that are truly ambiguous within that domain. For example,[37] point out that while *bank* is highly ambiguous in general text, in the Hansards it nearly always is used to refer to a financial institution. Indeed, the location of more diverse parallel bilingual texts remains the main obstacle to wider use of this approach.

A related method described in [24] finds translations between Hebrew and English using co–occurrence statistics from independent Hebrew and English corpora. This approach is somewhat more flexible in that it does not require the availability of diverse parallel bilingual corpora.

An unanswered question is key to determining the viability of parallel corpora approaches; how large is the set of words that are ambiguous in both languages? If it is small then this approach is certainly viable. If not, then it may suffer from scaling problems much like other resources.

8.4. Sense–Tagged Corpora

The earliest use of sense–tagged text to create models of word sense disambiguation may have been that of [44]. They built 1,815 models of disambiguation manually, focusing on words that occur at least 20 times in a corpus of 510,976 words. Their models consist of sets of rules and use features that are found within four positions of the ambiguous word. These features include the part–of–speech of surrounding words, the morphology of the ambiguous word, and membership of surrounding words into one of sixteen possible semantic categories: Animate, Human, Collective, Abstract Noun, Social Place, Body Part, Political, Economic, Color, Communications, Emotions, Frequency, Evaluative Adjective, Dimensionality Adjective, Position Adjective, and Degree Adverb.

An early automatic approach where models are learned from sense–tagged text is presented in [6]. Two–thousand sense–tagged instances for each of five words were created, where each word had three or four possible senses. A decision tree learner was provided with 1,500 training examples for each word, where each example was characterized by 81 binary features representing the presence or absence of certain "contextual categories". There are three varieties of contextual category; subject categories from Longman's Dictionary of Contemporary English, the 41 words that occur most frequently within two positions of the ambiguous word, and the 40 content words that occur most frequently in the sentence with an ambiguous word. It was found that the dictionary categories resulted in 47% accuracy, the 41 most frequent words resulted in 72% accuracy, and the 40 most frequent content words resulted in 75% accuracy.

Early probabilistic approaches typically attempted to identify and exploit a single very powerful contextual feature to perform disambiguation. For example [9], [25], and [98] all present methods for identifying a single feature that is sufficient to make highly accurate disambiguation decisions. In [98] for example, it is reported that a single collocation feature, *content–word–to–the–right*, results in accuracy well over 90% for binary sense distinctions.

In order to utilize probabilistic models with more complicated interactions among feature variables, [12] introduced the use of sequential model selection and decomposable models for word sense disambiguation. Prior to this, statistical analysis of natural language data was often limited to the application of standard models, such as n-grams and Naive Bayes. They developed a sequential model selection procedure using backward search and the exact conditional test in combination with a test for model predictive power. In their procedure, the exact conditional test is used to guide the generation of new models and a test of model predictive power was used to select the final model from among those generated during the search.

The supervised learning portion of this dissertation largely consists of extensions to the work of Bruce and Wiebe. As such, their methods are discussed rather extensively in Chapter 3 and their feature set and sense–tagged text is described in Chapter 5.

What emerges throughout the literature of corpus–based approaches to word sense disambiguation is considerable variation in the methodologies, a wide range of feature sets, and a great variety in the types of text that have been disambiguated. Unfortunately, comparative studies of these approaches have been relatively rare.

As mentioned in Chapter 6, [51] compare a neural network, a Naive Bayes classifier, and a content vector when disambiguating six senses of *line*. It is reported that all three methods are equally accurate. This same data is utilized by [62] and applied to an even wider range of approaches; a Naive Bayes classifier, a perceptron, a decision–tree, a nearest–neighbor classifier, a logic based Disjunctive Normal Form learner, a logic based Conjunctive Normal Form learner, and a decision list learner

are all compared. It is found that the Naive Bayes classifier and the perceptron prove to be the most accurate of these approaches.

Both studies employ the same feature set for the *line* data. It consists of binary features that represent the occurrence of all words within approximately a 50 word window of the ambiguous word, resulting in nearly 3,000 binary features. Given the vast size of the event space, representations of training data created by simple approaches such as Naive Bayes and the perceptron capture the same information as those created by more sophisticated methods.

A comparative study of the nearest neighbor classifier PEBLS and the backward sequential model selection method of [12] is presented by [64]. They compare the performance of the two methods at disambiguating 6 senses of *interest*. They report that PEBLS achieves accuracy of 87% while [12] report accuracy of 78%.[1] They expand upon the feature set used in [12] (feature set BW) by including collocation features and verb–object relationships. Their feature set consists of the following:

1. collocations that occur within one word of the ambiguous word
2. part–of–speech of words ± 3 positions of ambiguous word
3. morphology of the ambiguous word
4. unordered set of surrounding key–words, i.e., co–occurrences
5. verb–object syntactic relations

[64] evaluate the relative contribution of each type of feature to the overall disambiguation accuracy. They report that the collocations provide nearly all of the disambiguation accuracy, while the part–of–speech and morphological information also prove useful. The unordered sets of surrounding key–words and verb–object syntactic relations tended to contribute very little to disambiguation accuracy. Thus,

[1]The same data is employed in this dissertation and the highest accuracy attained is 76±2%.

the improvement in accuracy that they report may be due to their use of collocations features.

The fundamental limitation of supervised learning approaches to word sense disambiguation is the availability of sense–tagged text. The largest available source of sense–tagged text is the Defense System Organization 192,800 sense–tagged word corpus [64]. There are 191 different nouns and verbs that are sense–tagged. The average number of senses per noun is 7.8 and 12.0 senses per verb. The only other large source of sense–tagged text that is widely available is a 100,000 word subset of the Brown Corpus [36]. Both of these corpora are tagged with WordNet senses. By way of speculation, if all of the "privately held" sense–tagged text was added to the 300,000 words provided by the two corpora above, it seems unlikely that the total number of sense–tagged instances would exceed one–million words.

8.5. Raw Untagged Corpora

There are in fact relatively few "pure" unsupervised methodologies for word sense disambiguation that rely strictly on raw untagged text (e.g., [69], [72], [84], [85]). More typically, *bootstrapping* approaches have been employed. The first such example is described in [42]. There a supervised learning algorithm is trained with a small amount of manually sense–tagged text and applied to a held out test set. Those examples in the test set that are most confidently disambiguated are added to the training sample and the supervised learning algorithm is re–trained with this larger collection of examples.

[99] describes a more recent bootstrapping approach. This method takes advantage of the *one sense per collocation* hypothesis put forth in [98], where it is observed that words have a strong tendency to be used only in one sense in a given collocation. This is an extension of the observation made in [37] that words tend to be used only in one sense in a given discourse or document, i.e., the *one sense per discourse* hypothesis.

This algorithm requires a small number of training examples to serve as a seed. There are a variety of options discussed for automatically selecting seeds; one is to identify collocations that uniquely distinguish between senses. For *plant*, the collocations *manufacturing plant* and *living plant* make such a distinction. Based on 106 examples of *manufacturing plant* and 82 examples of *living plant* this algorithm is able to distinguish between two senses of *plant* for 7,350 examples with 97 percent accuracy. Experiments with 11 other words using collocation seeds result in an average accuracy of 96 percent where each word had two possible senses.

There are relatively few approaches that attempt to perform disambiguation only using information found in raw untagged text. One of the first such efforts is described [84]. There words are represented in terms of the co-occurrence statistics of four letter sequences. This representation uses 97 features to characterize a word, where each feature is a linear combination of letter four-grams formulated by a singular value decomposition of a 5000 by 5000 matrix of letter four-gram co-occurrence frequencies. The weight associated with each feature reflects all usages of the word in the sample. A context vector is formed for each occurrence of an ambiguous word by summing the vectors of the contextual words. The set of context vectors for the word to be disambiguated are then clustered, and the clusters are manually sense-tagged.

A related method is described in [85]. However, here ambiguous words are clustered into sense groups based on second–order co–occurrences; two instances of an ambiguous word are assigned to the same sense if the words that they co–occur with likewise co–occur with similar words in the training data. In the previous approach the assignment to sense groups was based on first–order co–occurrences where an ambiguous word was represented by the four–grams it directly occurs with. It is reported that second–order co–occurrences reduce sparsity and allow for the use of smaller matrices of co–occurrence frequencies. In this approach the evaluation is performed relative to information retrieval tasks that utilize the sense group and do not require sense–tags. This results in a fully automatic approach where no manual intervention is required.

While similar in spirit, the unsupervised work in this dissertation and that of Schütze are somewhat distinct. The features employed in this dissertation occupy a much smaller event space and rely mainly on collocations, part–of–speech and morphological information. While he also employs agglomerative clustering to form sense groups, the data is represented in terms of context vectors while the data here is represented in terms of dissimilarity matrices.

CHAPTER 9

CONCLUSIONS

This dissertation presents methods of learning probabilistic models of word sense disambiguation that use both supervised and unsupervised techniques. This chapter summarizes the contributions of this research and outlines directions for future work.

9.1. Supervised Learning

Supervised learning approaches to word sense disambiguation depend upon the availability of sense–tagged text. While the amount of such text is still limited, there has been a definite increase in quantity in recent years. The largest contribution to this has been the release of the DSO corpus, discussed in the previous chapter. Given the likelihood that even larger amounts of sense–tagged text will become available, continuing to develop and improve supervised learning approaches for word sense disambiguation is an important issue.

Indeed, while the cost of manually tagging text with senses is high, it is still a less expensive enterprise than creating the resources utilized by knowledge–intensive approaches to disambiguation. These more elaborate representations of knowledge bring with them an additional problem; suitable inferencing mechanisms must also be developed to reason from this data. When viewed against these alternatives, the cost of manually annotating text is actually quite modest.

9.1.1. Contributions

This dissertation advances the state of supervised learning as applied to word sense disambiguation in the following ways:

The information criteria are introduced as evaluation criteria for sequential model selection as applied to word sense disambiguation. These are alternatives to significance tests that result in a fully automatic selection process. The information criteria do not require manually tuned values to stop the model selection process; such a mechanism is inherent in their formulation.

In particular, Akaike's Information Criteria is shown to result in a model selection process that automatically selects accurate models of disambiguation using either backward or forward search.

Forward sequential search is introduced as a search strategy for sequential model selection as applied to word sense disambiguation. This is an alternative to backward search that is especially well suited for the sparse data typical in language processing. Forward sequential search has the advantage that the search process starts with models of very low complexity. This results in candidate models that have a small number of parameters whose estimates are well supported even in relatively small quantities of training data. This ensures that the selection process makes decisions based upon the best available information at the time.

This dissertation also introduces the Naive Mix, a new supervised learning algorithm for word sense disambiguation. The Naive Mix averages an entire sequence of decomposable models generated during a sequential selection process to create a probabilistic model. It is more typical that model selection methods only find a single best model. However, this dissertation shows that there are usually several different models that result in similar levels of accuracy; this suggests a degree of uncertainly in model selection that is accommodated by the Naive Mix.

Empirically, the Naive Mix is shown to result in improved accuracy over single best selected models and also proves to be competitive with leading machine learning algorithms. It is also observed that the learning rate of the Naive Mix is very fast. It often learns models of high accuracy using small amounts of training data, sometimes with as few as 10 or 50 sense–tagged examples.

Despite making rather broad assumptions about the dependencies among features in models of disambiguation, Naive Bayes consistently results in accuracy that is competitive with a host of other methods. *This dissertation presents an analysis of Naive Bayes that includes a study of the learning rate as well as a bias–variance decomposition of classification error.*

The learning rate reveals that Naive Bayes has poor accuracy when the training sample sizes are small. Given its fixed parametric form it is easily mislead by spurious patterns in very small amounts of sense–tagged text. However, as the amount of training data is increased, it quickly achieves levels of accuracy comparable to methods that build more representative models of the training data.

This behavior is analyzed via a bias variance decomposition and reveals that the nature of the errors made by the Naive Bayes model are substantially different than those made by a more representative model of the training data, here represented as a decision tree. The bulk of classification errors made by Naive Bayes are due to the assumptions conveyed in the parametric form of the model. However, it also tends to be very robust to differences between the test and training data. By contrast, the errors made by a decision tree learner are largely due to a failure to generalize well enough to accommodate differences between test and training instances. However, despite these different sources of error, the total level of classification accuracy achieved by both methods is comparable.

9.1.2. Future Work

The continued viability of supervised learning for word sense disambiguation is largely dependent on the availability of sense–tagged text. Thus, the creation of such text at relatively low cost must be a high priority; future improvments in supervised learning methodologies will be of little interest if sufficient quantities of training data are not readily available.

In general, supervised learning is a well developed area of research. However, natural language poses peculiar problems that have not necessarily been accounted

for in previous work. Continued refinement of supervised learning methodologies as applied to natural language processing problems is an important area of future work.

Creation of Sense–Tagged Text: The manual annotation of text with sense tags is the clearest route to expanding the current pool of sense–tagged text. Results from this dissertation suggest that even relatively small amounts of sense–tagged text can result in high levels of disambiguation accuracy. This is encouraging news, suggesting that even small additions to the available quantity of sense–tagged text will prove to be a valuable resource for word sense disambiguation.

Traditional manual annotation efforts will benefit greatly from the development of tools that provide some degree automated assistance. As an example, the Alembic workbench [27], provides support for discourse process tagging tasks. A similar tool devoted to word sense disambiguation would considerably ease the burden of manual annotation. If a human tagger noticed a particularly salient co–occurrence or collocation, such a tool could allow for the rapid tagging of a large number of similar instances. For example, suppose that a human tagger notes that any time *interest rate* occurs, it is nearly certain that *interest* refers to the cost of borrowing money. After the first such instance is manually sense–tagged, an annotation tool locates all the sentences in a corpus where *interest rate* occurs and applies that same sense tag automatically.

When a commitment is made to manual annotation, there are related questions that arise. Which sense inventory should be used for a particular domain? Are the sense distinctions in any dictionary clear enough so that only one sense can be assigned to a particular word in a particular context? How can tagger uncertainty be incorporated into sense tagging? How large a factor is human error in manual annotation efforts? All of these questions open up new areas of future research.

As an alternative to manual sense–tagging, the large amount of text linked together via the World Wide Web can be viewed as a source of alternative sources of knowledge to apply to language processing problems. A hyperlink connecting a word or a phrase to a related web page is not nearly as precise a source of information

as is the link from a word to a sense inventory, i.e., a sense tag. However, this diversity brings richness; hyperlinks from *mallard* could lead to photos, stories from duck watching expeditions, or maps showing migratory patterns. Short summaries generated from these various resources (or provided by the web page creator by way of a title or introductory comment) can then serve as definitions or descriptions of the word or phrase in the referring web page. This process ultimately results in an abstracted and simplified version of the relevant portion of the Web that can then be treated as a knowledge representation structure from which inferences about other bodies of text can be made.

Varying Search Strategies: To date only backward and forward search strategies have been utilized with sequential model selection for word sense disambiguation. However, these are greedy approaches that conduct very focused searches that can bypass models that are worthy of consideration. Developing approaches that combine backward and forward search is a potential solution to this problem.

Given the success of Naive Bayes, an alternative strategy is to begin forward searches at Naive Bayes rather than the model of independence. However, this strategy presumes that all the features are relevant to disambiguation and disables the ability to perform feature selection. In order to allow model selection to disregard irrelevant features, the process could begin at Naive Bayes and perform a backward search to determine if any dependencies can safely be removed. The model that results from this backward search then serves as the starting point for a forward search. At various intervals the strategy could be reversed from forward to backward, backward to forward, and so on, before arriving at a selected model.

An alternative to starting the forward searches at Naive Bayes is to generate a model of moderate complexity randomly and then search backward for some number of steps, then forward, and so on until until a model is selected. This entire process is repeated some number of times so that a variety of random starting models are employed. The models that are ultimately selected presumably differ somewhat and could be averaged together in a randomized variant of the Naive Mix.

If a reversible search strategy is adopted then the information criteria present certain advantages over the significance tests as evaluation criteria. The information criteria perform at roughly the same levels of accuracy during backward and forward search and do not require any adjustment when changing search direction. However, the significance tests are somewhat sensitive and require that the pre–determined cutoff value, α, be reset as the direction of the search changes.

Extending Feature Sets: The feature set employed for supervised learning in this dissertation relies upon part–of–speech of the surrounding words, morphology of the ambiguous word, and collocations that occur anywhere in the sentence. A potential extension to this feature set is to incorporate co–occurrence features. Preliminary experimental results with feature sets made up entirely of co–occurrences that occur within 1 or 2 positions of an ambiguous word result in disambiguation accuracy that is at least comparable to that of the supervised learning feature set. This result, mentioned briefly in [71], largely inspired the use of co–occurrence features in the unsupervised learning experiments.

The feature set could also be extended beyond the sentence boundary to include features that occur in the same paragraph or even the same document as the ambiguous word. This would allow for the inclusion of features that provide information about earlier occurrences of a word and the sense it was determined to have in that previous context. For example, if an instance of *bill* is being disambiguated and it is known that two sentences earlier *bill* refers to a bird jaw then it seems unlikely that the current occurrence is being used in the sense of pending legislation.

9.2. Unsupervised Learning

The development and improvement of unsupervised learning techniques is an important issue in natural language processing given the difficulty in obtaining training data for supervised learning. The lack of sense–tagged text poses a considerable bottleneck when porting supervised learning methods to new domains and unsupervised methods offer a way to eliminate this need for sense–tagged text.

9.2.1. Contributions

The contributions of this dissertation to unsupervised learning of word senses are as follows:

Several feature sets appropriate for unsupervised learning of word senses from raw text are developed. Feature sets designed for use with supervised approaches are not directly applicable in an unsupervised setting since they often contain features whose values are based on information only available in sense–tagged text.

The local context features developed for unsupervised learning are co–occurrences that occur within a few positions of the ambiguous word. It is more common for unsupervised approaches learning from raw text to rely upon a much wider window of context. However, such approaches result in high dimensional event spaces that can press the limits of computing resources. The use of local context features in this dissertation has led to acceptable levels of disambiguation accuracy while still maintaining a relatively modest event space.

This dissertation develops probabilistic models for word sense disambiguation without utilizing sense–tagged text. The EM algorithm and Gibbs Sampling are used to estimate the parameters of probabilistic models of disambiguation based strictly upon information available in raw untagged text.

Empirical comparison shows that Gibbs Sampling results in limited improvement over the accuracy of models learned via the EM algorithm. The similar results are somewhat surprising given the tendency of the EM algorithm to find local maxima. However, the combination of local context features and the parametric form of Naive Bayes results in relatively small event spaces where parameter estimation is still fairly reliable.

Despite its widespread popularly in a wide range of other applications, Gibbs Sampling has not previously been applied to word sense disambiguation. The introduction of this technique is an important contribution since it is a general purpose methodology that can be used in a variety of language processing problems.

Finally, the comparable accuracy of the EM algorithm and Gibbs Sampling suggests that rather than competing methodologies these should be treated as complimentary. The EM algorithm appears to provide a reasonably good and very efficient first pass through untagged data. It may be reasonable to approach unsupervised learning using the EM algorithm first and then allowing Gibbs Sampling to continue from there. A similar suggestion is made in [56].

McQuitty's similarity analysis has not been applied to word sense disambiguation previously. It is a simple agglomerative clustering algorithm that makes no assumptions about the nature of the data it is processing and yet results in accurate disambiguation in an unsupervised setting. This approach requires that the data to be disambiguated be converted into a dissimilarity matrix representation that shows the number of mismatched features between observations.

Despite the simplicity of both the algorithm and the data representation, McQuitty's method is shown to consistently result in more accurate disambiguation than a well–known agglomerative clustering algorithm, Ward's minimum–variance method. It also outperforms the EM algorithm and Gibbs Sampling when disambiguating words with very skewed sense distributions such as the adjectives and verbs in these experiments.

9.2.2. Future Work

Unsupervised approaches to word sense disambiguation are of interest because they eliminate the need for sense–tagged text. Disambiguation can be performed based solely on information found in raw untagged text. However, the lack of sense–tagged text impacts much more than the learning algorithm itself. Both the feature sets and the evaluation methodology must be formulated somewhat differently than in the case of supervised learning.

Meaningful Labeling of Sense Groups: In the process of eliminating the need for sense–tagged text to learn probabilistic models of disambiguation, unsupervised approaches also remove the link between the text and a sense inventory established

by a dictionary or some other lexical resource. Thus, the sense groups that are created by an unsupervised learner do not have meaningful sense labels or definitions automatically attached to them; the sense groups are tagged with meaningless names. This poses a problem if the evaluation of the unsupervised learner is relative to human sense judgments which are in turn based on knowledge of an established sense inventory.

This dissertation addresses this problem by developing an evaluation methodology where a post–processing step is performed that maps sense groups to entries in a sense inventory via sense–tagged text. While this allows for very exact measurements of the agreement between the unsupervised learner and a human judge, it also imposes a requirement for sense–tagged text on the evaluation methodology.

A more automatic alternative is to generate some form of sense descriptions from the sense groups themselves. It is unlikely that definitions as precise as those found in a dictionary could be created. However, some meaningful labeling of the sense groups based on the content of the sentences assigned to the sense group is possible and might provide enough additional information to make a link to a known entry in a sense inventory.

This is perhaps best viewed as another manifestation of a text summarization problem. Given the sentences that make up a sense group, generate a statement that summarizes those sentences. Suppose the following usages of the ambiguous word *bank* are found in a sense group:

I went to the *bank* to deposit the money.

The *bank* extended a loan to the Martinez family.

Chase Manhattan bought my *bank*.

The Federal Reserve *Bank* controls the money supply.

While it seems improbable that a formal dictionary definition could be generated from these examples, it is possible to imagine the creation of a generalized description such as *An entity concerned with financial matters*. This description can then be used

to choose from the entries in a sense inventory for *bank*, resulting in the selection of an entry that includes some mention of finances, for example.

There are several potential problems in this approach. First, creating these generalized descriptions implies that some external knowledge source is available. It is possible that this sort of external knowledge will be just as difficult to acquire as sense–tagged text. Second, incorrectly grouped instances could cause a description to become overly general, i.e., *An entity concerned with objects.*

Feature Selection: The frequency based features developed for unsupervised learning of word senses result in reasonably accurate performance, however they do not tend to provide much information about minority senses.

When using raw text features, values are usually selected based on frequency of occurrence. This results in features that are often skewed towards the majority sense, particularly if the majority sense is a large one. The development of feature selection methods that pick out values indicative of minority senses is a key issue for improving the performance of unsupervised approaches.

Part–of–Speech Ambiguity: Since the early work of Kelly and Stone, sense disambiguation has been detached from the problem of part–of–speech ambiguity. It has generally been assumed that part–of–speech ambiguity is resolved before sense disambiguation is performed. In supervised learning this is a reasonable assumption since a human tagger must make a part–of–speech judgment before assigning a sense–tag. However, in unsupervised learning where no such examples are employed, the decoupling of sense and part–of–speech ambiguity may in fact gloss over the fact that reliable part–of–speech information may not be available in a truly unsupervised setting.

There are two alternatives. In this dissertation part–of–speech ambiguity is resolved by a rule based part–of–speech tagger that is applied to the text before unsupervised learning begins. However, the quality of this tagging is dubious, even though the part–of–speech distinctions are rather coarse. The second option is to simply assume that part–of–speech information will not be available for unsupervised

learning problems. This requires disambiguation using a wider range of possible senses that will cross over multiple parts–of–speech. This assumption would also suggest that unsupervised disambiguation be based only on collocations, co–occurrences, and any other immediately apparent lexical feature. In fact, one of the feature sets in this dissertation (B) takes this approach and performs as well as those features sets that rely more heavily on syntactic information.

REFERENCES

[1] Akaike, H. A new look at the statistical model identification. *IEEE Transactions on Automatic Control AC-19*, 6 (1974), 716–723.

[2] Badsberg, J. *An Environment for Graphical Models.* PhD thesis, Aalborg University, 1995.

[3] Bar-Hillel, Y. The present status of automatic translation of languages. In *Advances in Computers. Vol. 1.*, F. Alt, Ed. Academic Press, New York, NY, 1960, pp. 91–163.

[4] Berger, A., Della Pietra, S., and Della Pietra, V. A maximum entropy approach to natural language processing. *Computational Linguistics 22*, 1 (1996), 39–71.

[5] Bishop, Y., Fienberg, S., and Holland, P. *Discrete Multivariate Analysis.* The MIT Press, Cambridge, MA, 1975.

[6] Black, E. An experiment in computational discrimination of English word senses. *IBM Journal of Research and Development 32*, 2 (1988), 185–194.

[7] Breiman, L. The heuristics of instability in model selection. *Annals of Statistics 24* (1996), 2350–2383.

[8] Brodley, C. Recursive automatic bias selection for classifier construction. *Machine Learning 20* (1995), 63–94.

[9] Brown, P., Della Pietra, S., and Mercer, R. Word sense disambiguation using statistical methods. In *Proceedings of the 29th Annual Meeting of the Association for Computational Linguistics* (1991), pp. 264–304.

[10] Bruce, R. *A Statistical Method for Word-Sense Disambiguation.* PhD thesis, Dept. of Computer Science, New Mexico State University, 1995.

[11] Bruce, R., and Wiebe, J. A new approach to word sense disambiguation. In *Proceedings of the ARPA Workshop on Human Language Technology* (1994), pp. 244–249.

[12] Bruce, R., and Wiebe, J. Word-sense disambiguation using decomposable models. In *Proceedings of the 32nd Annual Meeting of the Association for Computational Linguistics* (1994), pp. 139–146.

[13] Bruce, R., Wiebe, J., and Pedersen, T. The measure of a model. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (1996), pp. 101–112.

[14] Bruce, R., Wilks, Y., Guthrie, L., Slator, B., and Dunning, T. Nounsense - a disambiguated noun taxonomy with a sense of humour. Tech. Rep. MCCS-92-246, New Mexico State University - Computing Research Laboratory, August 1992.

[15] Buntine, W. Operations for learning with graphical models. *Journal of Artificial Intelligence Research 2* (1994), 159–225.

[16] Cardie, C. A case-based approach to knowledge acquisition for domain-specific sentence analysis. In *Proceedings of the 11th National Conference on Artificial Intelligence (AAAI-93)* (1993), pp. 798–803.

[17] Charniak, E. Passing markers: A theory of contextual influence in language comprehension. *Cognitive Science 7* (1983).

[18] Cheeseman, P., and Stutz, J. Bayesian classification (AutoClass): Theory and results. In *Advances in Knowledge Discovery and Data Mining*, U. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, Eds. AAAI Press/MIT Press, 1996.

[19] Cherry, L. PARTS - a system for assigning word classes to English text. Tech. rep., AT &T Bell Laboratories, June 1978.

[20] Chodorow, M., Byrd, R., and Heidorn. Extracting semantic hierarchies from a large on-line dictionary. In *Proceedings of the 23rd Annual Meeting of the Association for Computational Linguistics* (Chicago, IL, 1993), pp. 299–304.

[21] Chung, M., and Moldovan, D. Parallel memory-based parsing on a marker-passing computer. Tech. Rep. PKPL 93-4, University of Southern California, August 1993.

[22] Clark, P., and Niblett, T. The CN2 induction algorithm. *Machine Learning 3*, 4 (1989), 261–283.

[23] Cost, S., and Salzberg, S. A weighted nearest neighbor algorithm for learning with symbolic features. *Machine Learning 10*, 1 (1993), 57–78.

[24] Dagan, I., and Itai, A. Word sense disambiguation using a second language monolingual corpus. *Computational Linguistics 20* (1994), 563–596.

[25] Dagan, I., Itai, A., and Schwall, U. Two languages are more informative than one. In *Proceedings of the 29th Annual Meeting of the Association for Computational Linguistics* (1991), pp. 130–137.

[26] Darroch, J., Lauritzen, S., and Speed, T. Markov fields and log-linear interaction models for contingency tables. *The Annals of Statistics 8*, 3 (1980), 522–539.

[27] Day, D., Aberdeen, J., Hirschman, L., Kozierok, R., Robinson, P., and Vilain, M. Mixed initiative development of language processing systems. In *Proceedings of the Fifth Conference on Applied Natural Language Processing Systems* (Washington, DC, April 1997), pp. 348–355.

[28] Dempster, A. Covariance selection. *Biometricka 28* (1972), 157–175.

[29] Dempster, A., Laird, N., and Rubin, D. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society B 39* (1977), 1–38.

[30] Devijver, P., and Kittler, J. *Pattern Classification: A Statistical Approach*. Prentice Hall, Englewood Cliffs, NJ, 1982.

[31] Domingos, P. Unifying instance–based and rule–based induction. *Machine Learning 24* (1996), 141–168.

[32] Domingos, P., and Pazzani, M. On the optimality of the simple Bayesian classifier under zero–one loss. *Machine Learning* (forthcoming).

[33] Duda, R., and Hart, P. *Pattern Classification and Scene Analysis*. Wiley, New York, NY, 1973.

[34] Fillmore, C. The case for case. In *Universals in Linguistic Theory*, E. Bach and R. Harms, Eds. Holt, New York, NY, 1968.

[35] Fisher, R. *The Design of Experiments*. Oliver and Boyd, London, 1935.

[36] Francis, W. N., and Kucera, H. *Frequency Analysis of English Usage: Lexicon and Grammar*. Houghton Mifflin, 1982.

[37] Gale, W., Church, K., and Yarowsky, D. A method for disambiguating word senses in a large corpus. *Computers and the Humanities 26* (1992), 415–439.

[38] Gelman, A., Carlin, J., Stern, H., and Rubin, D. *Bayesian Data Analysis*. Chapman & Hall, New York, 1995.

[39] Geman, S., and Geman, D. Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence 6* (1984), 721–741.

[40] Geweke, J. Evaluating the accuracy of sampling–based approaches to calculating posterior moments. In *Bayesian Statistics 4*, J. Bernardo, J. Berger, A. Dawid, and A. Smith, Eds. Oxford University Press, Oxford, 1992.

[41] Gilks, W., Thomas, A., and Spiegelhalter, D. A language and program for complex Bayesian modeling. *The Statistician 43*, 1 (1994), 169–177.

[42] Hearst, M. Noun homograph disambiguation using local context in large text corpora. In *Proceedings of the 7th Annual Conference of the UW Centre for the New OED and Text Research: Using Corpora* (Oxford, 1991).

[43] Hirst, G. *Semantic Interpretation and the Resolution of Ambiguity*. Cambridge University Press, 1987.

[44] Kelly, E., and Stone, P. *Computer Recognition of English Word Senses*. North–Holland, Amsterdam, 1975.

[45] Kim, J., and Moldovan, D. PALKA: A system for linguistic knowledge acquisition. Tech. Rep. PKPL 92-8, Dept. of Electrical Engineering-Systems, University of Southern California, 1992.

[46] Kohavi, R., Sommerfield, D., and Dougherty, J. Data mining using MLC++: A machine learning library in C++. In *Tools with Artificial Intelligence* (1996), pp. 234–245. http://www.sgi.com/Technology/mlc.

[47] Kohavi, R., and Wolpert, D. Bias plus variance decomposition for zero–one loss functions. In *Proceedings of the Thirteenth International Conference on Machine Learning* (Bari, Italy, July 1996), pp. 275–283.

[48] Kreiner, S. Analysis of multidimensional contingency tables by exact conditional tests: Techniques and strategies. *Scandinavian Journal of Statistics 14* (1987), 97–112.

[49] Langley, P., Iba, W., and Thompson, K. An analysis of Bayesian classifiers. In *Proceedings of the 10th National Conference on Artificial Intelligence* (San Jose, CA, 1992), pp. 223–228.

[50] Lauritzen, S. The EM algorithm for graphical association models with missing data. *Computational Statistics and Data Analysis 19* (1995), 191–201.

[51] Leacock, C., Towell, G., and Voorhees, E. Corpus-based statistical sense resolution. In *Proceedings of the ARPA Workshop on Human Language Technology* (March 1993), pp. 260–265.

[52] Lesk, M. Automatic sense disambiguation using machine readable dictionaries: How to tell a pine cone from a ice cream cone. In *Proceedings of SIGDOC '86* (1986).

[53] Madigan, D., and Raftery, A. Model selection and accounting for model uncertainty in graphical models using Occam's Window. *Journal of American Statistical Association 89* (1994), 1535–1546.

[54] Marcus, M., Santorini, B., and Marcinkiewicz, M. Building a large annotated corpus of English: The Penn Treebank. *Computational Linguistics 19*, 2 (1993), 313–330.

[55] McQuitty, L. Similarity analysis by reciprocal pairs for discrete and continuous data. *Educational and Psychological Measurement 26* (1966), 825–831.

[56] Meng, X., and van Dyk, D. The EM algorithm – an old folk–song sung to a new fast tune (with discussion). *Journal of Royal Statistics Society, Series B 59*, 3 (1997), 511—567.

[57] Merz, C., Murphy, P., and Aha, D. UCI Repository of Machine Learning Databases, 1997. http://www.ics.uci.edu/mlearn/MLRepository.html.

[58] Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., and Teller, E. Equations of state calculations by fast computing machines. *Journal of Chemical Physics 21* (1953), 1087–1091.

[59] Miller, G. WordNet: A lexical database. *Communications of the ACM 38*, 11 (November 1995), 39–41.

[60] Miller, G., Beckwith, R., Fellbaum, C., Gross, D., and Miller, K. Five papers on WordNet, March 1993. CSL Report 43, Princeton, NJ.

[61] Moldovan, D., Lee, W., Lin, C., and Chung, M. SNAP: parallel processing applied to AI. *Computer* (May 1992).

[62] Mooney, R. Comparative experiments on disambiguating word senses: An illustration of the role of bias in machine learning. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (May 1996), pp. 82–91.

[63] Ng, H. Exemplar–based word sense disambiguation: Some recent improvements. In *Proceedings of the Second Conference on Empirical Methods in Natural Language Processing* (Providence, RI, August 1997), pp. 208–213.

[64] Ng, H., and Lee, H. Integrating multiple knowledge sources to disambiguate word sense: An exemplar-based approach. In *Proceedings of the 34th Annual Meeting of the Society for Computational Linguistics* (1996), pp. 40–47.

[65] Norvig, P. Marker passing as a weak method for text inferencing. *Cognitive Science 13* (1989).

[66] Pazzani, M., Muramatsu, J., and Billsus, D. Syskill & Webert: Identifying interesting web sites. In *Proceedings of the Thirteenth National Conference on Artificial Intelligence* (Portland, OR, 1996), pp. 54–61.

[67] Pearl, J. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Mateo, CA, Morgan Kaufmann, 1988.

[68] Pedersen, T. Class.3.0: A probabilistic classifier using decomposable models. Tech. Rep. 97-CSE-14, Southern Methodist University, August 1997.

[69] Pedersen, T., and Bruce, R. Distinguishing word senses in untagged text. In *Proceedings of the Second Conference on Empirical Methods in Natural Language Processing* (Providence, RI, August 1997), pp. 197–207.

[70] Pedersen, T., and Bruce, R. A new supervised learning algorithm for word sense disambiguation. In *Proceedings of the Fourteenth National Conference on Artificial Intelligence* (Providence, RI, July 1997), pp. 604–609.

[71] Pedersen, T., and Bruce, R. Unsupervised text mining. Tech. Rep. 97-CSE-9, Southern Methodist University, June 1997.

[72] Pedersen, T., and Bruce, R. Knowledge lean word sense disambiguation. In *Proceedings of the Fifteenth National Conference on Artificial Intelligence* (Madison, WI, July 1998).

[73] Pedersen, T., Bruce, R., and Wiebe, J. Sequential model selection for word sense disambiguation. In *Proceedings of the Fifth Conference on Applied Natural Language Processing* (Washington, DC, April 1997), pp. 388–395.

[74] Pedersen, T., Kayaalp, M., and Bruce, R. Significant lexical relationships. In *Proceedings of the Thirteenth National Conference on Artificial Intelligence* (Portland, OR, August 1996), pp. 455–460.

[75] Procter, P., Ed. *Longman Dictionary of Contemporary English*. Longman Group Ltd., Essex, UK, 1978.

[76] Provan, G., and Singh, M. Data mining and model simplicity: A case study in diagnosis. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining* (Portland, OR, 1996).

[77] Quillian, M. The teachable language comprehender: A simulation program and theory of language. *Communications of the ACM 12*, 8 (August 1969), 459–476.

[78] Quinlan, J. *C4.5: Programs for Machine Learning*. Morgan Kaufmann, San Mateo, CA, 1992.

[79] Raftery, A., and Lewis, S. How many iterations in the Gibbs Sampler? In *Bayesian Statistics 4*, J. Bernardo, J. Berger, A. Dawid, and A. Smith, Eds. Oxford University Press, Oxford, 1992, pp. 763–773.

[80] Read, T., and Cressie, N. *Goodness of fit Statistics for Discrete Multivariate Data*. Springer-Verlag, New York, NY, 1988.

[81] Ripley, B. *Stochastic Simulation*. John Wiley, New York, NY, 1987.

[82] SAS Institute, I. *SAS/STAT User's Guide, Version 6*. SAS Institute Inc., Cary, NC, 1990.

[83] Schaffer, C. A conservation law for generalization performance. In *Proceedings of the Eleventh International Machine Learning Conference* (1994).

[84] Schutze, H. Dimensions of meaning. In *Proceedings of Supercomputing '92* (Minneapolis, MN, 1992), pp. 787–796.

[85] Schutze, H. Automatic word sense discrimination. *Computational Linguistics 24*, 1 (1998), 97–123.

[86] Schwarz, G. Estimating the dimension of a model. *The Annals of Statistics 6*, 2 (1978), 461–464.

[87] Small, S., and Rieger, C. Parsing and comprehending with word experts (a theory and its realizations. In *Strategies for Natural Language Processing*, W. Lehnert and M. Ringle, Eds. Lawrence Erlbaum Associates, Hillsdale, NJ, 1982.

[88] Tanner, M. *Tools for Statistical Inference: Methods for the Exploration of Posterior Distributions and Likelihood Functions*. Springer–Verlag, New York, NY, 1993.

[89] Thiesson, B. Users's guide to GAMES, ver. 1.0. Tech. rep., Department of Mathematics and Computer Science, Aalborg University, Denmark, 1996.

[90] Veronis, J., and Ide, N. Word sense disambiguation with very large neural networks extracted from machine readable dictionaries. In *Proceedings of the 13th International Conference on Computational Linguistics (COLING-90)* (Helsinki, Finland, 1990), pp. 389–394.

[91] Ward, J. Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association 58* (1963), 236–244.

[92] Wermuth, N. Model search among multiplicative models. *Biometrics 32* (June 1976), 253–263.

[93] Whittaker, J. *Graphical Models in Applied Multivariate Statistics*. John Wiley, New York, 1990.

[94] Wilks, S. The large–sample distribution of the likelihood ratio for testing composite hypotheses. *The Annals of Mathematical Statistics 9* (1938), 60–62.

[95] Wilks, Y. An intelligent analyzer and understander of English. *Communications of the ACM 18*, 5 (1975), 264–274.

[96] Wilks, Y., and Stevenson, M. The grammar of sense: Using part–of–speech tags as a first step in semantic disambiguation. *Natural Language Engineering 1* (1997).

[97] Yarowsky, D. Word-sense disambiguation using statistical models of Roget's categories trained on large corpora. In *Proceedings of the 14th International Conference on Computational Linguistics* (Nantes, France, July 1992), pp. 454–460.

[98] Yarowsky, D. One sense per collocation. In *Proceedings of the ARPA Workshop on Human Language Technology* (1993), pp. 266–271.

[99] Yarowsky, D. Unsupervised word sense disambiguation rivaling supervised methods. In *Proceedings of the 33rd Annual Meeting of the Association for Computational Linguistics* (Cambridge, MA, 1995), pp. 189–196.

[100] Yu, Y., and Simmons, R. Truly parallel understanding of text. In *Proceedings of the 8th National Conference on Artificial Intelligence (AAAI-90)* (1990).

[101] Zipf, G. *The Psycho-Biology of Language*. Houghton Mifflin, Boston, MA, 1935.