FINDING PARAPHRASES USING PNRULE

by

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Abstract

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In this thesis, we attempt to use a machine-learning algorithm, PNrule, along with simple lexical and syntactic measures to detect paraphrases in cases where their existence is rare. We choose PNrule because it was specifically developed for classification in instances where the target class is rare compared to other classes within the data. We test our system both on a dataset we develop based on movie reviews, and on the PASCAL RTE dataset; we obtain poor results on the former, and moderately good results on the latter. We examine why this is the case, and suggest improvements for future research.

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Chapter 1

Introduction

Merriam-Webster's dictionary defines a paraphrase as "a restatement of a text, passage, or work giving the meaning in another form." Recently, there has been a lot of work in computational linguistics towards developing systems that can automatically detect paraphrases. There are a number of ways in which such a system could be useful; some examples include: as part of an automatic summarization system, removing multiple instances of the same information; looking for the recurrence of an idea within a particular body of work; detecting political talking points in a body of news articles; or creating a dataset that can be used by a system that automatically learns how to generate paraphrases, in the same way that aligned sentences are used in systems that learn how to translate between two languages.

Most of the work up to this point has dealt primarily with paraphrases that occur within parallel corpora—situations in which paraphrases occur relatively frequently, and are often lexically similar to the text unit they paraphrase. While this has led to useful systems, we feel the next obvious step is to attempt to detect paraphrases in situations where they occur rarely, and are not necessarily lexically similar to the text unit they paraphrase. In this thesis, we attempt to do just that, using a machine learning technique in combination with a set of simple lexical and syntactic measures.

Chapter 2

Background

2.1 Paraphrases

Given two texts, T and P, we say that P is a *paraphrase* of T if the semantic meaning of P is found entirely in T, with the possible aid of world knowledge (e.g., that a German shepherd is a breed of dog). Some loss of information is acceptable; for instance, "A dog went to the store." is an acceptable paraphrase of "A German shepherd ran to the store." The latter is more specific than the former—we know the breed of the dog, and have some sense of the rate at which it traveled—but both convey the same *basic meaning*. However, in a case where information loss occurs, the paraphrase relationship is asymmetric; it would not be accurate to state that "A German shepherd ran to the store." is a paraphrase of "A dog went to the store."

2.2 Why use machine learning to detect paraphrases?

There are several reasons to use machine learning to detect paraphrases. First, there's the fact that machine-learning approaches have been used successfully to solve many other natural-language-processing problems. Màrquez (2000) lists many of these problems, including: sense discrimination, word sense disambiguation, text classification, speech recognition, part-of-speech tagging, text summarization, dialog act tagging, co-reference resolution, cue phrase

a. *An OH-58 helicopter, carrying a crew of two, was on a routine training orientation when contact was lost at about 11:30 a.m. Saturday (9:30 p.m. EST Friday).*

b. *"There were two people on board," said Bacon. "We lost radar contact with the helicopter about 9:15 EST (0215 GMT)."*

Figure 2.1: Example of two text units that are *similar*, but where neither is a paraphrase of the other. From Hatzivassliloglou et al. (1999).

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identification, machine translation, homograph disambiguation in speech synthesis, accent restoration, PP-attachment disambiguation, phonology, morphology, and spelling correction.

Second, and more importantly, machine learning has been used, with some success, to solve a very similar problem: Hatzivassliloglou et al. (1999) use it to match *similar* pairs of small textual units (in particular, paragraphs, although in theory their technique could be applied to sentences as well). They consider two textual units to be similar if they share the same focus on a common concept, actor, object, or action, and if that common actor or concept either performs or is the subject of the same action. This definition includes paraphrases, but it includes other sorts of relationships as well. Hatzivassliloglou et al. (1999) focused on news stories about the same event, in which such similar text units are likely to arise; we're hoping to detect paraphrases in corpora where they are much less likely to arise.

So far we have shown that a machine-learning approach *could* potentially be used to solve the problem of classifying paraphrases. But we still have not explained why it *should* be used. Our reasoning is basically this: while ideally, we'd like to simply look at the semantics of two textual units (in our case, clauses) and decide whether or not they are the same; however, building semantical forms of sentences and rules that encode world knowledge is very difficult. Instead, we rely on syntactic and lexical clues to decide whether or not one textual unit is a paraphrase of another. While some clues may be the same across the English language, others

likely vary depending upon the corpus, both due to different styles of writing, and due to different contexts. In addition, even if a clue does exist across the entire language, it may be more important within some corpora than within others. Because we don't believe that it is currently possible to develop a system that can, out of the box, detect paraphrases in any corpus, we feel that it is best to develop a system that can be easily trained to deal with a new situation.

This leads us to our final point: simplicity. Machine-learning algorithms are much easier to adapt to new situations than are finely-tailored solutions. While the latter may be preferable in some cases, what we'd like to see is a machine-learning algorithm combined with a toolbox of syntactic and lexical features which could easily be trained on new corpora. This has the added benefit of allowing people to easily add new features to the toolbox (there are any number of features we have not tried yet, some of which could prove quite useful). There is, of course, one weakness to our approach: because it's a supervised method, we need annotated corpora, the production of which can be quite time consuming. This could potentially be overcome using an unsupervised approach, however because such an approach would require us to devise a heuristic to generate examples, we were concerned that the resulting model would not accurately reflect human judgment about paraphrases. A supervised method would avoid this problem.[1]

2.3 Machine learning and rare classes

2.3.1 What is a rare class?

A class is *rare* when the number of examples of that class is proportionally very small compared to the number of examples of other classes in the training and testing data. While it is difficult to quantify this precisely, Joshi (2002) states that, while it's possible for a class covering up

[1] However, an unsupervised method may well be worth researching in the future.

to 35% of a training set to be considered rare, a rare class is generally one that covers at most 10% of the training examples. Unless we are considering two highly similar corpora, it's likely that paraphrases will be a rare class under this definition.

As we are concerned only with binary classification—either a pair of sentences contains clauses that are paraphrases of one another, or they do not—for further discussion, borrowing from Joshi (2002), we will use *C* to refer to the rare class, and *NC* to refer to its complement.

2.3.2 What makes learning rare classes difficult?

Joshi (2002) lists three issues that arise in the context of a rare class that make learning difficult (note that we have simply borrowed Joshi's terms for these problems):

Low Separability Occasionally, one encounters a case where the data are noise-free and the examples can be classified using only one or two attributes. In this case, the data have a high degree of *separability*, and only a very simple classification model is needed. Usually, however, the records of class *C* are distributed in small clusters throughout various subspaces of the attribute space. This makes it difficult to find a large cluster containing records of class *C* that does not also contain a number of examples of class *NC*. This low degree of separability makes classification more difficult, and thus a more complicated model is required.

Multi-modality of the classes Related to separability is the fact that *C* and, in particular, *NC* may consist of different subclasses with different characteristics. It may be easy to separate *C* from some of those subclasses, but very difficult to separate it from others. We will see an example of this later in the chapter.

Rarity The rarity of the class is itself a problem. In particular, it's very difficult to avoid overfitting the model to *C*: since the set of records in *C* is so much smaller than the set of records in *NC*, it's easy to find a model that fits those few positive examples exactly, but

then doesn't generalize well. Thus, it performs well on the training data, but not on the testing data.

2.4 Rule-based machine learning

One set of commonly-used methods in machine learning falls into a group that we will call "rule-based machine learning". Given as data a set of records made up of attribute-value pairs, a *rule* is a set of conditions that a record must meet in order to be placed into a particular class. Each rule can thus be described as a conjunction within propositional logic (Mitchell, 1997).[2] Ideally, then, the model would consist of a single rule for each class. However, recall that we earlier mentioned the multi-modality of the classes. This means that it's likely that each class will be made up of subclasses, each with its own *signature*—that is, its own set of values that indicate its existence. In order to handle this, the model must instead be a set of rules; if a record satisfies any single rule that indicates it belongs to a particular class, it is placed into that class. It is those machine-learning approaches that build as their models disjunctions of rules that we are referring to as rule-based machine-learning algorithms.

2.4.1 Why rule-based?

The main reason we feel that rule-based machine learning should be used for this task is that, as mentioned by Mitchell (1997) and Joshi (2002), a rule-based method is easily interpretable by humans. We believe this to be particularly important in the domain of paraphrase identification. Human beings have some intuition as to what attributes are likely to indicate the occurrence of paraphrases. Using a rule-based approach, they can see how well their intuition fits with what's discovered by the machine learning algorithm. This is advantageous for several reasons: first, we are more likely to catch errors in the software we use to obtain the attribute-value pairs, since such errors will cause situations where the results do not match our expectations. For example,

[2]There are also methods for learning first-order logic models, but we are not concerned with these.

if we find that the presence of matching trigrams between two sentences indicates that they are not paraphrases of one another, we know that we should take a second look at our trigram-matching algorithm. Second, in the case where the differences are not caused by an error, we may learn something new about the problem. Finally, because we can associate a record with the rule that classified it, we can look at false positives and discover both what attributes are indicating that these examples are positive, and, by looking at the sentences themselves, what additional attributes might allow us to distinguish between false and true positives. These are opportunities that less easily understood classification methods might not afford us.

A second reason for focusing on rule-based machine learning is that, compared to some other approaches, the parameters to the algorithm are relatively intuitive. One has a sense of what it means to have an upper bound on the length of a rule, or a lower bound on its accuracy. Compare this with, for example, support vector machines, where one has to decide between using a radial or an exponential kernel space. It's much more difficult to understand what the latter "means" in terms of the problem one is trying to solve.

2.4.2 Methods for rule-based machine learning

While there are a number of methods for building rule-based models, the two most common are to build a decision tree, in which case each path through the tree can be considered a rule[3], or to attempt to discover the rules directly (Mitchell, 1997). We will refer to the former as the "decision-tree-construction" method or approach, and the latter as the "rule-induction" method or approach. We will describe both of these approaches, will explain why a rule-induction approach is better suited to cases in which the target class is rare, and will then explain where the rule-induction approach falls short in such cases.

[3]C4.5rules actually explicitly transforms the tree into rules, with consequences that will be described later. Any decision tree can be viewed as a conjunction of disjunctive rules, however.

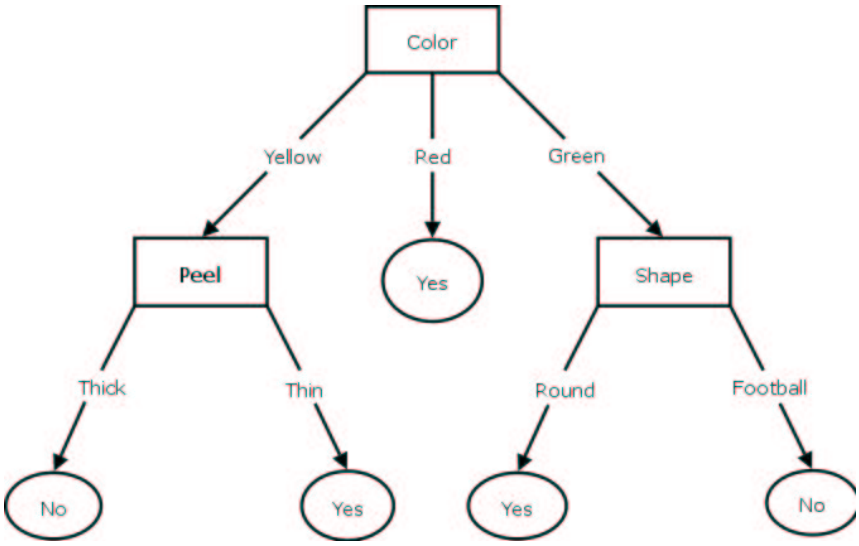


Figure 2.2: An example of a decision tree, for the class IS-AN-APPLE.

Decision-tree-construction methods

In order to understand decision-tree-construction methods, it is first helpful to understand how a decision tree is used to classify a record. A decision tree is made up of leaf nodes, each of which has a class associated with it, and inner or decision nodes, each of which has an attribute associated with it. There are branches from each decision node corresponding to the possible values of its associated attribute. In order to classify a record, one simply starts at the root node, and for each attribute picks the path that corresponds to the value of that attribute in the record, until one reaches a leaf node. The record is labeled with the class associated with the leaf node. Note that an attribute may only appear once in a given path; to appear more than once would simply be redundant, as the attribute value for the record has already been determined.[4]

An example of a decision tree can be seen in Figure 2.2. This tree tries to determine whether a fruit is an apple by means of three attributes: **color**, **peel**, and **shape**. **Color** can take on the value *yellow*, *red*, or *green*; **peel** can take on the value *thick* or *thin*; and **shape** can take on

[4]One reader brought up the question of whether this would be true if the tree were required to be binary. The answer is a qualified yes: each attribute would have to be replaced with a set of attributes that took binary values, and each of these new attributes could only appear once in each path.

the value *round* or *football*. Each path through the tree is distinguished by the values these attributes take on; the final node in the path describes whether the fruit is in the target class or not. This is, of course, a fairly silly example, but nevertheless, demonstrates how a decision tree works.

There are a number of efficient decision-tree-construction algorithms, but they are all variations of an algorithm that does a top-down greedy search through the hypothesis space of all possible decision trees. Mitchell (1997), from whom we draw much of this information, states that the two algorithms that most exemplify this approach are ID3 (Quinlan, 1986) and its descendant, C4.5 (Quinlan, 1993). Certainly the latter is one of the most, if not the most widely-used decision-tree-construction algorithms. In general, the algorithm operates as follows, beginning at the root node of a single-node tree: The algorithm must use some fitness measure, such as *information gain* or *gain ratio*[5], to decide what attribute best separates the instances by class. This attribute is then used as the test for the current node, a branch is created for each possible value of that attribute, and at the end of each branch a new leaf node is created. The process is then repeated for each of these descendant nodes, using only those training examples covered by the attribute value associated with the branch leading to the descendant node and only those attributes not already selected. This continues until each potential path through the tree either has only one class associated with it, or has every possible attribute in it.

One thing to note is that the algorithm, as described so far, works only if the attributes can only take on discrete values. However, it is possible for decision-tree-construction methods to handle continuous attributes. The idea is that instead of using the values of the attribute directly, the algorithm creates a new attribute A_c, which for each record has as its value the truth value of $A < c$, where A is the continuous attribute, and c is some threshold. To find this threshold, the algorithm sorts the training examples by the values of A. Then, the algorithm iteratively sets c to the halfway point between two adjacent examples, and tests this threshold

[5]We won't describe these measures here, as we don't use them in our method.

using information gain. Whichever *c* scores highest is used as the threshold (Mitchell, 1997).

One serious weakness of this approach is that it is prone to over-fitting. Two approaches have been taken to combat this problem:

1. stopping the growth of the tree before it over-fits; or

2. allowing the tree to over-fit, and then pruning it.

The latter of the two approaches has been shown to be more effective (Mitchell, 1997), so we will examine it further.

One possible implementation of this approach, called *reduced-error pruning* (Quinlan, 1987), begins by splitting the training data into a training set and a validation set. For each decision node, the method creates a pruned tree by removing the subtree rooted at that decision node, making it a leaf node. It then assigns the most-frequently-appearing class of training examples covered by the pruned node to that node. For example, if the pruned node covered 5 examples of class *A*, and 7 examples of class *B*, then the pruned node would be labeled with class *B*. If the pruned tree does no worse than the current tree, it is used; otherwise, the current tree is kept. At any iteration there could be several possible pruned trees that do no worse than the current tree; in this case, the method picks the pruned tree that most increases the accuracy over the validation set. The idea behind this implementation is that while the algorithm may be fooled by noise in the training set, that same noise is unlikely to be present in the validation set. As Mitchell (1997) notes, this method works well with large amounts of training data, but will further reduce already small training sets. As we're dealing with a very rare class, splitting the training data might eliminate vital positive examples; it would be too easy to eliminate a subclass of the target class by removing just a few examples. Thus, we can eliminate this approach from our consideration.

Another implementation is that used in C4.5 (Quinlan, 1993), called *rule post-pruning*. Instead of pruning the decision tree, Quinlan first converts the decision tree into a conjunction of rules; as we mentioned earlier, any decision-tree model can be represented as such a

conjunction; however, Quinlan makes this transformation explicit. He does so by creating a conjunctive rule for every path through the tree. From each rule, he removes any condition whose removal does not reduce the accuracy of the rule set. As above, if there's more than one possible pruning, the one that causes the highest increase in accuracy is chosen. Once the rules have been pruned, they are sorted by their estimated accuracy, and are then applied in this order during classification (Mitchell, 1997).

There are two advantages to this pruning method. First, transforming the decision tree into a conjunction of rules allows the algorithm to take into consideration the context within which a particular decision node is used. Within one path, a decision node could be vital, whereas within another path, the same decision node could be utterly irrelevant. Because the paths are converted into rules, the algorithm can remove the node within the context in which it is irrelevant, while leaving it in the context in which it is vital. Reduced-error pruning could only distinguish whether a node was relevant to the tree as a whole, and can only decide to remove it from all paths that go through it, or from none. Second, by converting the paths to rules, this method removes the distinction between decisions that occur near the root of the tree, and those that occur near the leaves of the tree. This has two consequences: while within a tree, one would almost never remove a node near the root, because it has a large effect on the tree as a whole, within a rule one might remove such a node, because it may have little or no effect within the context of that rule; and bookkeeping is made much easier, because one no longer has to remove all the nodes below a removed node.

Aside from pruning rules instead of the decision tree, another difference between rule post-pruning and reduced-error pruning is the method by which accuracy is estimated. Instead of using a validation set, rule post-pruning uses the training data with a pessimistic estimate of accuracy. It calculates the accuracy of a rule over the training examples, and the standard deviation of that accuracy, assuming a binomial distribution. It then subtracts the latter from the former. Because of this, for large data sets, the estimated accuracy will be close to the observed accuracy; but, for smaller data sets, the estimated accuracy will be further from the

observed accuracy. Thus, rules that cover only a few positive examples will have a very low estimated accuracy and are more likely to be pruned. While normally this is precisely the behavior that you'd want—pruning rules that cover only a few examples with high accuracy in favor of rules that cover a number of examples with somewhat less accuracy—in a case with rare classes, any good rule is likely to cover only a few examples with high accuracy. A model with several low-coverage, high-accuracy rules might be precisely what we'd want in such a case.

Thus, while rule post-pruning might work, at least in some situations, it seems that we might be better served by modeling the rule set directly. With that in mind, let's take a look at rule induction.

Rule-induction methods

As mentioned previously, both decision-tree-construction methods and rule-induction methods build models which can be described by a set of conjunctive rules. A decision-tree-construction method does so by searching the hypothesis space of decision trees. In contrast, a rule-induction method does so by directly searching the hypothesis space of sets of conjunctive rules (Mitchell, 1997).

There are two methods for rule induction: specific-to-general, and general-to-specific. The former isn't tractable for high-dimension datasets, and so most algorithms use the latter (Agarwal and Joshi, 2000). The most common method for general-to-specific rule induction is a method called *sequential covering* (Agarwal and Joshi, 2000; Mitchell, 1997), which we will now describe.

Borrowing from Mitchell (1997), we will first describe a subroutine called LEARN-ONE-RULE. This subroutine accepts a set of positive and negative training examples, and outputs a rule that covers many of the positive examples while covering few of the negative examples. This rule must have high accuracy—most of the examples it covers must be positive—but not necessarily high coverage—it is allowed to cover only a small number of examples.

One possible implementation of LEARN-ONE-RULE, again taken from Mitchell (1997), is as follows: begin with a trivial rule that classifies all examples as positive. At each iteration, try all of the possible attribute tests, and pick whichever one most improves the performance measure over the training data. Repeat this until the rule has reached an acceptably high level of accuracy. Note that this is a greedy general-to-specific search through the space of possible conjunctive rules. There is no backtracking, so it is possible that a suboptimal choice will be made during the search. Most rule-induction methods use some variation of this approach.

Sequential covering is the method by which the hypothesis space is searched. It works as follows: first, the training set is fed into LEARN-ONE-RULE, which returns a single high-accuracy rule. Next, the examples covered by this rule are removed from the training set, and the new training set is again fed into LEARN-ONE-RULE. This process is repeated until the model has achieved a satisfactory overall accuracy, or until there remain no positive examples not covered by an existing rule. This is one of the most widespread approaches to learning a set of rules (Mitchell, 1997).

So why is a rule-induction approach superior to a decision-tree-construction approach? One might expect, given Mitchell's statement that decision trees may be more effective when data is scarce, that a decision-tree-construction method would be a better approach. However, as Joshi (2002) points out, a decision-tree-construction method is evaluated by how well it separates the two classes, the target class and the non-target class. This is fine if the signature for the target class is very pure, but this is often not the case for rare classes. Rule-induction methods, on the other hand, are able to simply focus in on the target class. This gives us the ability to control the recall and precision of the algorithm in a way that is not possible with decision-tree-construction approaches. This is particularly important in the case of rare classes.

Rare classes are still hard

While sequential covering is a better approach to building a model to classify rare classes than constructing a decision tree, it is still far from ideal. Joshi (2002) cites two significant

problems with this approach. The first is a fairly well-known problem called the *problem of small disjuncts* (Holte et al., 1989).

A small disjunct is one that correctly classifies only a few training cases. They are much more error-prone than large disjuncts (Holte et al., 1989). However, they collectively cover a significant percentage of examples, and thus cannot simply be ignored (Weiss, 1995). This is particularly true when dealing with rare classes, where even a few missed examples can lead to a far lower recall for a particular class. Unfortunately, because there are few positive training examples, a rare class tends to engender small disjuncts—because there aren't that many examples to begin with, a rule targeting a rare class probably will correctly classify only a few training cases, even if it is highly accurate. For example, if there are only 10 records in class *A*, out of perhaps a total of 1000 records, a rule *R* which predicts *A* and covers 4 of those examples and no other examples is highly accurate and covers a significant percentage of the examples of class *A*, but is still a small disjunct. To make matters worse, sequential covering removes some of those already-few examples at each iteration (Weiss, 1995; Joshi, 2002).

We should take a moment to distinguish between errors in a model, and errors in a disjunct. In both cases, an *error* is a misclassified record. However, while in a model this refers to both false positives and false negatives, in a disjunct it refers only to false positives. This is because a disjunct claims only that if a record satisfies it, that record will be in the class it predicts. It makes no claim about records that do not satisfy it.

Weiss (1995) gives several reasons why small disjuncts are prone to errors:

Bias *Inductive bias* is the policy by which a machine learning algorithm generalizes beyond the training examples it is given (Mitchell, 1997). Holte et al. (1989) found that biases that work well for large disjuncts do not work well for small disjuncts. In particular, the "maximum generality" bias, which states that an algorithm should find the maximally-general disjunct that matches a particular set of training examples and no others, works very poorly for small disjuncts. Holte instead suggests a "selective specificity" bias, which, after deciding to create a disjunct that matches a set of examples, would then de-

cide what sort of bias to use to pick between possible disjuncts matching these examples. Unlike the other four problems, which we mention below, bias is not a problem inherent to data containing rare classes, but instead is a consequence of using methods designed to learn models that classify frequently-occurring classes to attempt to learn models that classify rare classes.

Attribute noise Attribute noise changes the values of the attributes of the records. This can have different effects, depending on whether it is introduced into the testing set or the training set. If it is introduced into the testing set, it can cause records to be misclassified. With rare classes, even a few such misclassifications can have a large effect on the accuracy of the model. Worse, if it's introduced into the training set, it can cause the wrong model to be learned. This is particularly problematic when dealing with rare classes; since there are only a small number of examples of a rare class in the first place, even a few such transformations can cause the target class to be overwhelmed. For example, imagine there are two classes, M and N, which differ on a single binary attribute: M has the value 0 for attribute A, and N has the value 1. If the two classes are approximately the same size, then a bit of attribute noise changes things very little. However, imagine that examples of class N occur over one hundred times more frequently than examples of class M. Even if just a small percentage of the N examples have their value for A transformed into 0 by noise, there could well end up being more N-class examples with that value than M-class examples. In such a case, a machine learning algorithm would learn to classify examples with M's signature as N. Generalization can exacerbate this problem, since they often work by removing the distinction between two signatures and then classifying both as whichever class occurs more frequently in the records with the now-indistinguishable signatures. While we do not have to deal with noise being introduced into our system, the attributes we use are noisy by the nature of our data; thus, this will be a problem for us.

Missing attributes When an attribute is missing, two records that would normally be easily placed into two different classes may instead appear to be the same. If this happens during testing, the system will have to guess somehow. If it happens during training, the model will learn to classify such records by whichever class appears more frequently; in the case where the target class is rare, this likely will be the non-target class. We encounter this in our latent semantic indexing measure: some of the textual units contain no indexing terms, and thus cannot be compared to other textual units. We'll discuss this further when we describe our experiments.

Class noise Class noise causes a record to be mislabeled. The problems in this situation are similar to those caused by attribute noise. In our particular case, this could arise if an annotator missed a paraphrase.

Training set size Weiss (1995) states:

> Training set size also has an impact on learning. Rare cases will have a higher error rate than common cases since they are less likely to be found in the training set. The small disjuncts will tend to be more error prone because they cover fewer correct cases than large disjuncts.

We are uncertain as to why Weiss believes this will necessarily cause small disjuncts to be more error-prone (although one reader suggested bias). However, we'd like to add that this certainly makes the model containing the small disjuncts more error-prone. Because small disjuncts cover only a few positive examples, if there are a lot of positive examples in the population that aren't in your sample (or if you stop the learning algorithm early, although this is not a concern in our case), it's far more likely that there will be positive examples in the testing set that are not covered by any of the small disjuncts. This leads to a higher error rate in a model with small disjuncts than in one with large disjuncts. There could even be positive examples that appear in the testing data that do not have a

similar signature to anything in the training data, and, because the class is rare, just a few such examples would lead to a dramatically higher error rate.

The second potential problem is identified by Agarwal and Joshi (2000) and Joshi (2002) as the *problem of splintered positives*. This problem arises when the signature for the target class is a composite of attributes that indicate the presence of the target class, and attributes that indicate the absence of the non-target class. Since we're dealing with paraphrases in this thesis, let us consider an example in that domain: imagine that we have a number of pairs of sentences, most of which have nothing to do with one another. On the other hand, a few pairs of sentences will look like this:

a. *The elephant sitting on the dock was very large.*

b. *The elephant sitting on the dock was huge.*

It would thus seem that a high lexical similarity between a pair of sentences would be a good indication of the presence of our target class. However, remember that earlier we mentioned the multi-modality of classes. Although pairs of unrelated sentences make up a large subclass of the non-target class, there also could be a subclass that contains pairs of sentences with opposite meanings. This subclass might contain such pairs as:

a. *The horse ran past the barn was very large.*

b. *The horse ran past the barn was very small.*

Like the first pair, this pair would have a very high lexical similarity. However, clearly it is not a paraphrase. Instead, we need some other attribute, such as the presence of an antonym, to indicate the presence of the non-target class.

We should emphasize that the problem is not that an algorithm using sequential covering couldn't create a model that accounted for the presence of such an attribute; the problem is with how it would do so. Because of its high accuracy constraints, a sequential covering approach would refine its current rule, adding another conjunctive condition to it (in the case

of our example, it might refine the rule "HIGHLEXICALSIMILARITY $\Longrightarrow$ PARAPHRASE" to "HIGHLEXICALSIMILARITY $\wedge$ $\neg$ANTONYM $\Longrightarrow$ PARAPHRASE"). However, if the current rule didn't cover very many negative examples, the algorithm might not correctly learn the signature of the non-target class—the additional condition might only apply to the few negative examples covered by the rule, instead of to the non-target class as a whole—and again we'd end up with generalization error (Joshi, 2002).

For prevalent classes, these two problems are not very likely to arise. During its early iterations, the algorithm is likely to discover rules that cover large numbers of positive examples, which means that the problem of small disjuncts will only arise in later iterations, when less-significant rules are discovered; these can simply be dropped. In addition, because the early-discovered rules would cover many positive examples, the rules which had to be refined to account for the presence of a non-target class would cover a large number of negative examples as well; if they did not, their accuracy would be high enough that they would not need to be refined. Thus the problem described in the previous paragraph would be avoided.

However, for rare classes, it is incredibly likely that both problems will occur. For one thing, there aren't very many positive examples to begin with, so the problem of small disjuncts will pop up very early, even in the most significant rules. For another, the signatures of rare classes tend to be very impure, and because of the high accuracy constraints, the sequential covering method is likely to create a large number of very detailed rules that cover very few examples.

Because in most situations paraphrases will be rare phenomena, sequential-covering rule-induction machine-learning algorithms are not very useful to us. Fortunately, Agarwal and Joshi have developed a rule-induction machine-learning algorithm called PNrule (Joshi, 2002; Agarwal and Joshi, 2000; Joshi et al., 2001) meant specifically to model cases where the target class is rare. Although they had in mind more systems-oriented uses such as data mining for network-intrusion detection (Joshi et al., 2001), we believe PNrule could be equally useful for cases within computational linguistics where one is trying to model rare phenomena, such as

paraphrases. We describe PNrule below.

2.5 PNrule

PNrule uses two innovations to deal with the problem of modeling rare classes: two-phase rule induction, and a scoring mechanism. Two-phase rule induction takes the place of sequential covering as the method by which the model is built, while the scoring mechanism is a post-processing step that adds additional flexibility to the model. We will discuss both of these innovations, beginning with two-phase rule induction.

2.5.1 Two-phase rule induction

Agarwal and Joshi's hypothesis is that sequential-covering algorithms have the problems mentioned above because they attempt to achieve both high recall and high precision at the same time. While this works well when the target class is prevalent, it does not work as well in situations where the target class is rare, for the reasons mentioned previously. Their solution is to model the class in two stages: in the first stage, they attempt to obtain high recall, and in the second, they attempt to obtain high precision (Joshi, 2002).

In order to understand these stages, it's important to understand two concepts: *rule-accuracy* and *support*. Let us say we have a rule R. A rule, as mentioned above, has a set of conditions on some set of attributes. If the attributes of a particular record meet the conditions of that rule, then we can say that the record satisfies those conditions. Each rule predicts that the records that satisfy its conditions will be of a particular class. Now, let there be some training set T, let $S \subseteq T$ be the set of records that satisfy R's conditions, and let $S' \subseteq S$ be the set of records in S that are from the class that R is trying to predict. Then the support of R is $|S|$, and the rule-accuracy of R is $|S'|/|S|$. In other words, support is the number of records that a rule covers, whereas rule-accuracy is the percentage of the records covered by the rule's conditions that are in the class that the rule predicts (Joshi, 2002).

Now that we've defined these two terms, we can explain the two stages. The first stage is called the P-stage, and the rules discovered within it are called P-rules. In some ways, it works much the same way as sequential covering: at each iteration, a rule is formed, and the records covered by that rule are then removed from consideration. However, instead of simply using a high-accuracy constraint, P-rules are discovered using a fitness function that balances accuracy with support. This leaves us with more false positives (and thus lower accuracy) than in a sequential-covering algorithm, but without rules that cover only a tiny number of examples. The idea is that in this stage, the algorithm should maximize recall at the expense of precision, up to a certain point.

The second stage is called the N-stage, and the rules discovered within it are called N-rules. This stage operates on the union of the sets of records covered by the P-rules. The point of this stage is to learn rules that will remove some of the false positives from the last stage; that is, the N-rules predict the absence of the target class. The problem is that these rules can also remove true positives; Agarwal and Joshi call this *introducing false negatives* (Joshi, 2002; Agarwal and Joshi, 2000). Aside from the fact that the training data are now the records covered by the P-rules, and that the target class is now in effect the non-target class, the N-stage works basically the same way the P-stage did. The idea is that in this stage, the algorithm should attempt to maximize precision.

Each stage can be thought of as an outer and inner loop. The inner loop finds the best rule it can, according to some evaluation measure and input parameters. The outer loop looks at the rule produced by the inner loop, and, again according to certain parameters, decides whether or not to add it to the set of rules in the model. Each of the four loops has its own criteria for stopping. We'll refer to the inner loop as "refining rules", and the outer as "adding rules."

Refining rules

First we should describe what, precisely, a rule looks like in PNrule. PNrule allows for two types of attributes: categorical and continuous. Given a categorical attribute A_{cat} and a value v,

PNrule allows for two conditions: $A_{cat} = v$ and $A_{cat} \neq v$. For a continuous attribute A_{cont} and two values, vl and vr, where $vl \leq vr$, PNrule allows for three conditions: $A_{cont} > vl$, $A_{cont} \leq vr$, and $vl < A_{cont} \leq vr$. A rule is a conjunction of these conditions.

The refinement step works much like the function LEARN-ONE-RULE described in the section on rule-induction methods: it is fed a training set of examples, and returns the best rule it can find according to some evaluation metric. In both the P-stage and the N-stage, refinement works the same way, with the exception of the stopping conditions. Beginning with the empty rule, at each iteration the algorithm creates a set of potential refinements by, for each possible condition, conjoining the current best rule to that condition. Each of these potential refinements is scored by the evaluation metric, and then the algorithm decides whether to replace the current best rule with the best of the refinements according to certain criteria, which we discuss below.

Any evaluation metric will be calculated using the training data. However, in order to improve the reliability of the evaluation metric, the training data can be split randomly into two sets—in this case, the metric is calculated on each of the sets, and the minimum of the two values is used. The criterion for whether or not this happens relies on the input parameter **MinCExamplesToSplit**. If the number of target class examples in the original training set is greater than this parameter, the metric is calculated in this fashion. The idea is that if the rule really does do a good job of discriminating between the classes, it should do so in any large sample of the data, and that thus, testing on two random sets of the data will help avoid the problem of fitting to noise. If there are not enough target class examples in the original training set, the evaluation metric is simply calculated over all of the training data.

For each stage, there are different criteria for accepting the refined rule. These also function as stopping criteria: once a potential refinement is not accepted, the algorithm stops looking for new refinements and returns the current best rule. The stopping criteria are determined by parameters input by the user.

For the P-stage, the relevant input parameter is **MinSupFractionP**, which is some value between 0 and 1, inclusive. To understand how this stage works, let us look at Figure 2.3. The

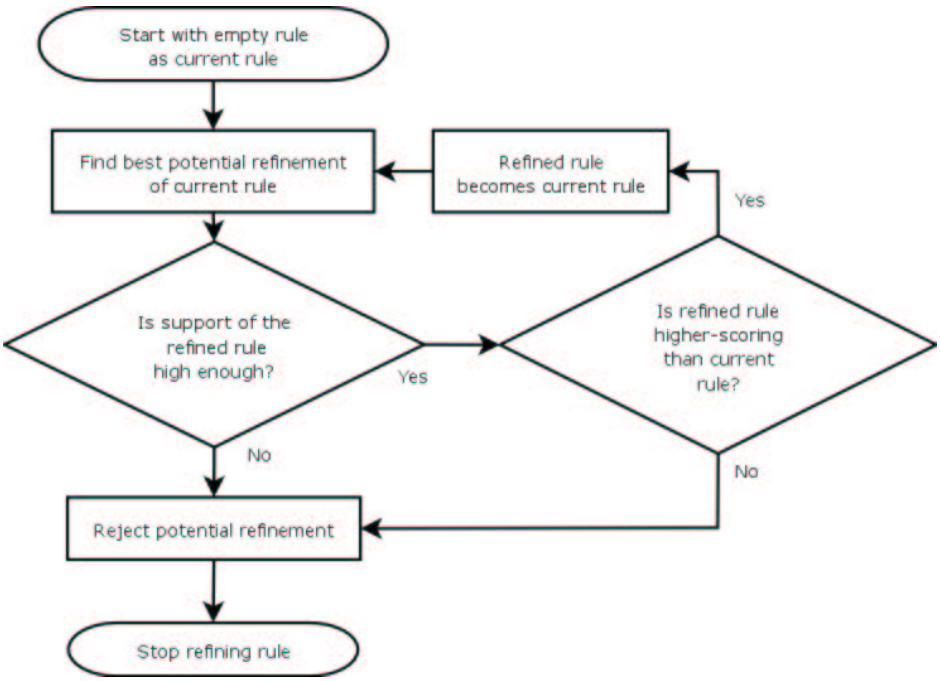


Figure 2.3: Rule refinement during the P-stage

algorithm begins with the empty rule. It creates a set of potential refinements and finds the best one, as described above. It then checks to see whether the refined rule has high-enough support—the rule must have a support value of at least **MinSupFractionP** $\cdot$ *ntc*, where *ntc* is the number of training examples that are in the target class. If the support is not high enough, the potential refinement is rejected, and the algorithm stops refining the rule. Otherwise, the algorithm checks to see whether the refined rule is higher scoring, according to the evaluation metric, than the current best rule. If it is not, the refined rule is rejected, and refinement stops. Otherwise, the refined rule becomes the current best rule, and the process begins again.

For the N-stage, the relevant input parameter is **MinRecallN**.[6] Figure 2.4 is an illustration of rule-refinement in this stage. As we can see from the illustration, it is very similar to the rule-refinement process in the P-stage. To see the difference, look at the diamond just beneath the step where the best refinement is found. In Figure 2.3, this was the point at which the algorithm

[6]This parameter is not listed in Joshi (2002). However, the description of the N-stage in Joshi (2002) suggests that this parameter is necessary.

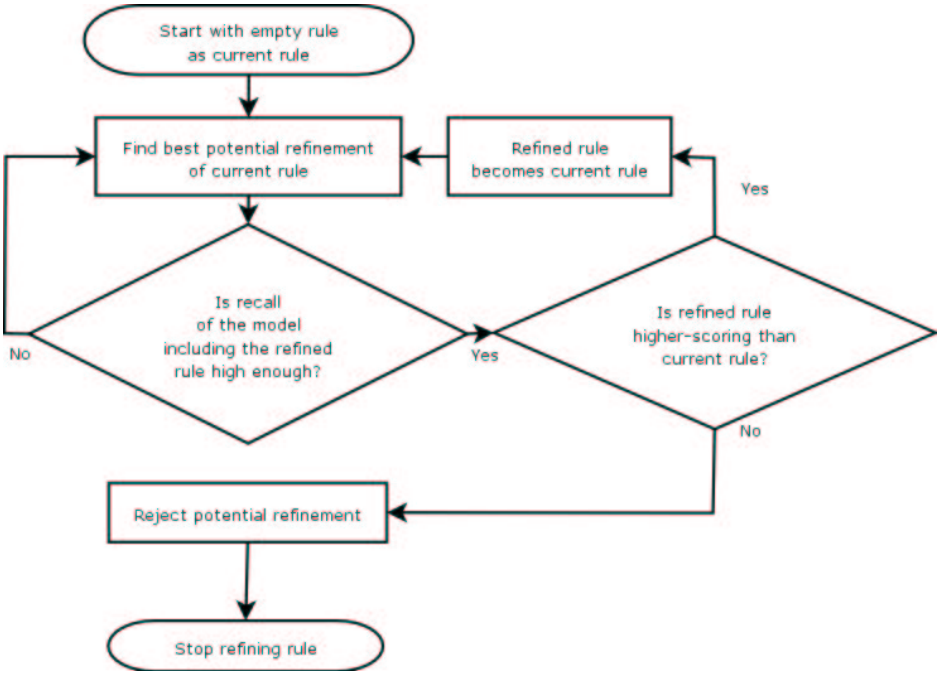


Figure 2.4: Rule refinement during the N-stage

checked to see whether the support of the refined rule was high enough; if this criterion was not met, the refinement was rejected, while if it was met, the algorithm then checked to see if the refined rule was higher scoring than the current best rule. In this stage, the algorithm checks to see whether the model including the refined rule has a high-enough recall—higher than **MinRecallN**. If this criterion is met, then, like in the P-stage, the algorithm goes on to see whether the refined rule is higher scoring than the current best rule. However, if it is not met, the refinement is *accepted*, and, setting the current best rule to the refined rule, the process starts again.

To understand this difference, remember that an example covered by an N-rule is *not* covered by the model. If the recall of the model drops too low in the N-stage, it means the current N-rule covers too many positive examples. The more conditions one adds to a rule, the fewer examples that rule will cover. Thus, by refining an N-rule, the algorithm can increase the recall of the model.

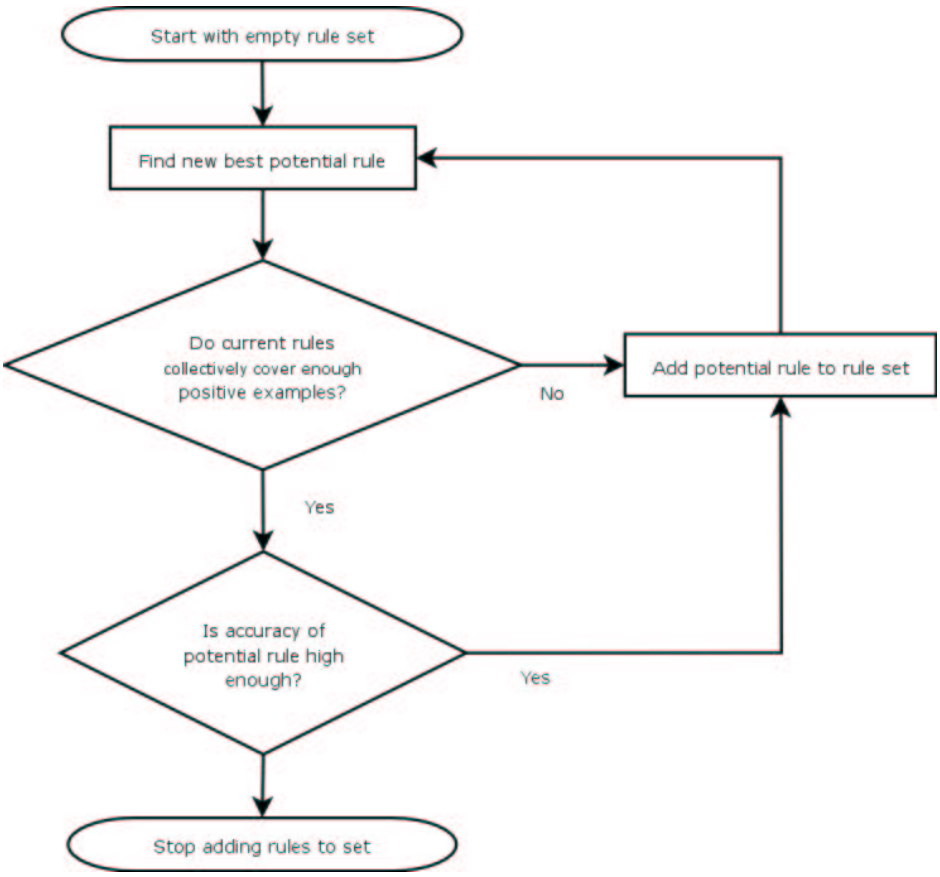


Figure 2.5: Adding new P-rules

Adding rules

Like rule-refinement, this process is virtually identical for the P-stage and the N-stage, but with different stopping conditions. Starting with no rules, at each iteration a new rule is obtained from the refinement function. Depending on the stage, different input parameters determine whether the new rule is added to the model, or whether the current stage should end. As with sequential covering, whenever a rule is added to the model, all records covered by that rule are removed from the training set.

For the P-stage, there are two relevant input parameters: **MinCoverageP** and **MinAccuracyP**. The process is illustrated in Figure 2.5. The algorithm begins with an empty rule set, and, using the rule-refinement function, finds the highest-scoring potential rule. It first checks to see

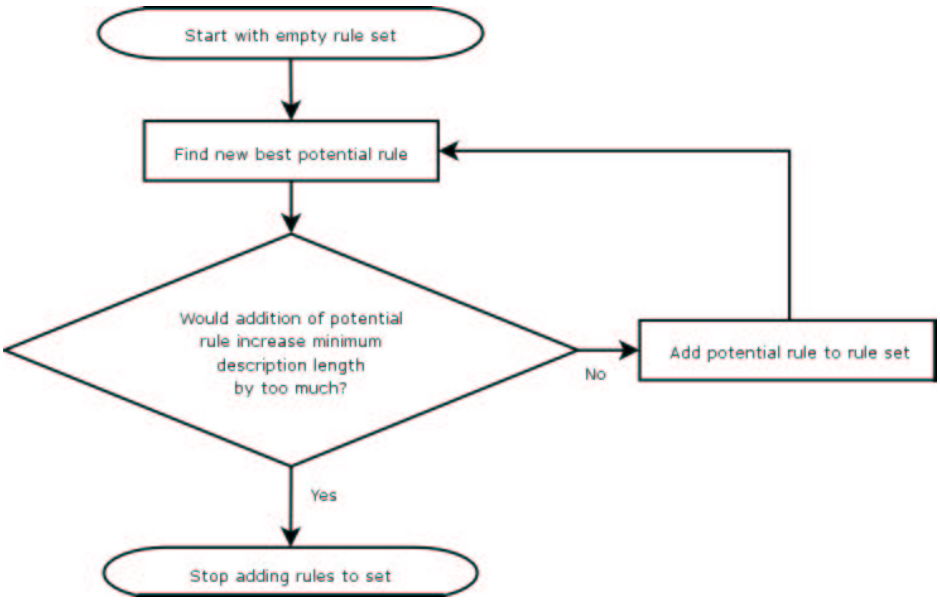


Figure 2.6: Adding N-rules

whether the current set of rules cover at least **MinCoverageP** examples. If they do not, it adds the potential rule to the rule set and goes on to find the next best-scoring potential rule. This allows the user to choose the minimum recall for the P-stage. If the rules do cover at least **MinCoverageP** examples, the algorithm checks to see whether the accuracy of the potential rule is greater than **MinAccuracyP**. If it is, it adds the potential rule to the rule set, and goes on to find the next best-scoring potential rule. If it does not, it stops adding rules to the set and exits the P-stage. Thus, in this stage, the algorithm adds P-rules until a minimum recall is met, and then only adds further P-rules if they meet a particular accuracy constraint.

For the N-stage, there's only one input parameter: **MaximumLengthIncrease**[7]. As can be seen in Figure 2.6, the process of adding N-rules is very similar to that of adding P-rules. The difference is that instead of having two conditions which could lead to a potential rule being added to the set, there is only one condition: would the addition of the potential N-rule increase the minimum description length of the model by more than **MaximumLengthIncrease**? If it

[7] Again, this parameter was not listed in Joshi (2002), but seemed necessary to the algorithm.

would not, the potential rule is added to the rule set. Otherwise, the algorithm stops adding rules to the set and exits the N-stage. The minimum description length of the model is the number of bits it would take to encode the model, plus the number of bits it would take to encode the errors made by the model. Using this as a stopping criterion allows the algorithm to trade off between the model complexity and the number of errors. A high value for this parameter means that the algorithm is allowed to add a lot of complexity in order to remove a small number of errors; a low value means the algorithm can only add complexity if in doing so it removes a large number of errors. Note that too high a value would lead to over-fitting.

Evaluation metric

As mentioned above, rule refinement in both stages relies on some evaluation metric to determine whether a refinement is an improvement over a current rule or not. According to Joshi (2002), this metric should capture three things: the ability of a rule to distinguish members of the target class from those records not in the target class, the support of that rule, and the accuracy of that rule. Naturally, a rule with high support and high accuracy should be given a high score by the metric. Joshi (2002) notes that there are several possible metrics, including Gini index, information gain, gain-ratio, and chi-square statistics. However, the one that Agarwal and Joshi define, and that we implement, is called Z-number, and is based on the z-test in statistics.

Let there be some rule R, with accuracy a_R and support s_R. Let S be the current training data (which, as mentioned earlier, change over each iteration) and let $S' \subseteq S$ be the examples in S that are in the target class. Then $a_C = \frac{|S'|}{|S|}$ would be the mean of the target class were it normally distributed and centered at the rate achieved by random guessing. Since this is a binary problem, $\sigma_C = \sqrt{a_C(1-a_C)}$ gives us the standard deviation of the target class. Using this, the Z-number is:

$$Z_R = \frac{\sqrt{s_R}(a_R - a_C)}{\sigma_C}$$

There are two things going on in this measure. First, it's measuring the number of standard

deviations the mean of the rule is away from the mean of the target class. A large positive Z-number indicates that the rule predicts the presence of the target class with high confidence, while a large negative Z-number indicates the rule predicts the absence of the target class with high confidence. Second, the Z-number is weighted by the square root of the rule's support. This gives preference to rules with high support, and also allows for the accuracy/support trade-off mentioned earlier in this thesis.

2.5.2 Scoring mechanism

The second important innovation in PNrule is the scoring mechanism. Without the scoring mechanism, the model would simply predict that a record is in the target class if it satisfies the conditions of some P-rule while satisfying none of the N-rule conditions. However, recall that the N-rules were trained on the union of the examples covered by the P-rules. Thus, while we have a good sense of the effect an N-rule has on the overall number of false positives, we do not have any sense on how well it works towards removing the false positives caused by a particular P-rule. Let's assume we have a P-rule and two N-rules. One N-rule does an excellent job of removing the types of false positives the P-rule causes; the other does not. It stands to reason that a record that is covered by the conditions of the P-rule and the first N-rule is less likely to be in the target class than one that is covered by the conditions of the P-rule and the second N-rule.

Furthermore, it's possible that for a particular P-rule, a particular N-rule introduces a large number of false negatives. If one could give such a P-rule/N-rule combination a low score, one could recover those false negatives.

Thus, Agarwal and Joshi develop a scoring mechanism that estimates the posterior probability of a record belonging to the target class given the particular P-rule and the particular N-rule it satisfies the conditions of, and assigns a score to each record accordingly. The algorithm then determines a threshold th, where a record is in the target class if its score is $\geq th$, that maximizes the F_1 score.

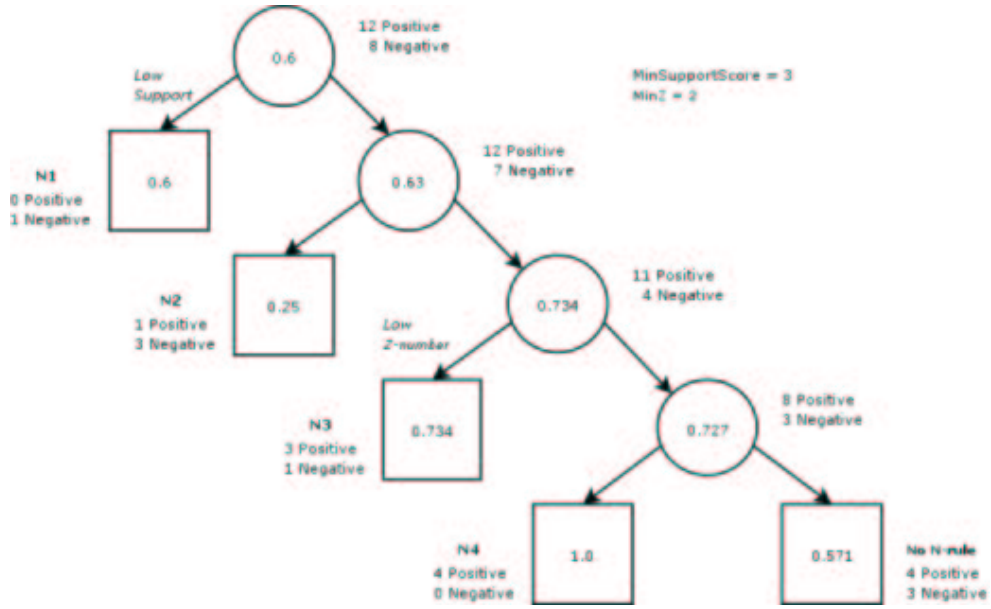


Figure 2.7: Assignment of accuracy scores to P-rule/N-rule combinations.

In order to understand the scoring mechanism, it's best to think of the original model as a forest of trees, with each tree corresponding to a P-rule. These trees are ordered in the same order the P-rules were originally discovered, from most to least significant. Given a record, we attempt to apply each P-rule to it in order. If none of the P-rule conditions can be successfully matched, then the record does not belong to the target class.

Let's assume there exists a P-rule for which the conditions can be, however, and look at the corresponding tree, illustrated in Figure 2.7. This figure requires a bit of explanation. The root of the tree is labeled with the accuracy of the P-rule before any N-rules are applied, and with the number of positive and negative examples it covers. Like the P-rules, the N-rules are ordered from most to least significant. The circle nodes represent the accuracy of the examples that have not had their classifications determined: they are covered by the conditions of the current P-rule, but it is unknown whether an the conditions of an N-rule will also cover some of them. The square nodes represent the scores assigned to examples that are covered by the conditions of a particular P-rule/N-rule combination, or, in the case of the bottom right-most

node, the conditions of a P-rule and not of any N-rule. We use two different shapes for these nodes to highlight the fact that the values in the inner nodes represent the *accuracy* of the records covered by that node, while the values in the leaf nodes represent the *scores* assigned to those leaf nodes; we will explain the distinction further below. The square nodes are also labeled with an N-rule and the number of positive and negative examples that the conditions of both the P-rule and the N-rule cover.

Our eventual goal is to assign a score, within the range of $[0,1]$, to each of the leaf nodes. This score reflects the model's confidence that the record that reaches that node is within the target class. In order to calculate this confidence measure, we first have to find the accuracy at each of the inner nodes. In order to understand how this is done, it is important to first understand what happens as we descend the tree. We can think of each level of the tree as the application of a particular N-rule. We begin with all of the records covered by the P-rule. We apply each N-rule in turn, removing some of the records, while others remain. In Figure 2.7, the removed records end up in the left branches of the tree, while those that remain end up in the right.

Thus, we label the root node with the initial accuracy of the P-rule, $|S'|/|S|$—in other words, the number of true positives covered by the conditions of the P-rule over the number of records covered by the conditions of the P-rule. Every time an N-rule is applied, some of the false positives are removed, along with some of the true positives. This changes the accuracy of the set of records that remain covered—we record this accuracy in the right-branching child node of the current inner node. We simply repeat this process until all of the N-rules have been applied.

In order to assign a score to each of the leaf nodes, we want to take into account the accuracy, not of all the N-rules, but instead of only those N-rules *that are significant with regard to the current P-rule*. In order to determine significance, we use two input parameters, **MinSupportScore** and **MinZ** (for the example in Figure 2.7, **MinSupportScore** is set to 3, and **MinZ** is set to 2). If an N-rule passes these two criteria, we use its accuracy as the score

for the leaf node. This is what occurs for both **N2** and **N4** in Figure 2.7. If it does not pass these two criteria, we use the accuracy of its parent inner node.

The idea behind **MinSupportScore** is fairly simple. Basically, in order for an N-rule to cause a significant difference in the accuracy of a P-rule, its conditions must cover some minimum number of records. For instance, in most cases, an N-rule whose conditions covered a single record would not make much difference one way or the other in the accuracy of the P-rule. This minimum number is set through **MinSupportScore**. We can see this in Figure 2.7: **N1** covers one negative example and no positive examples, and thus has a support of 1, which is less than the **MinSupportScore** of 3. Thus, instead of using its own accuracy, which would be 0, as the score, we use the accuracy of its parent, which is 0.6. In addition to this parameter's effects on individual leaf nodes, if at any point the support of one of the inner nodes drops below $2 \cdot$ **MinSupportScore**, all leaf nodes below it are assigned the accuracy of its parent node. This helps to prevent the scoring mechanism from fitting to noise.

The use of the second parameter, **MinZ**, is a little more complicated. In order to understand it, we have to introduce a slightly different version of the Z-number: $Z_n = \frac{\sqrt{n_P}(a_N - a_P)}{\sigma_P}$. a_N is the accuracy of the current N-rule, a_P is the accuracy of its parent decision node, n_P is the support of its parent node, and $\sigma_p = \sqrt{a_P(1-a_P)}$ is the standard deviation of the records covered by the parent node. If the absolute value of the leaf node's Z-number is at least **MinZ**, then it is significant with regard to the current P-rule, and thus its accuracy should be used. For an example where the Z-number is too low, however, look at **N3** in Figure 2.7. It covers 3 positive examples and 1 negative example, so its support is high enough to satisfy the **MinSupportScore** requirement. However, its accuracy is 0.75, which is fairly close to its parent node's accuracy of approximately 0.734. In fact, its Z-number is $\frac{\sqrt{15}(0.75-0.734)}{\sqrt{0.734(1-0.734)}} \approx 0.14$, considerably less than the **MinZ** requirement of 2.

Now that we have taken a look at examples where the N-rule does not meet one of the two requirements, let us look at an example where both of the requirements are met: that of **N2**. **N2** covers 1 positive and 3 negative examples, which gives it a support of 4, so it passes the

MinSupportScore requirement. Its Z-number is $\frac{\sqrt{19}(0.25-0.63)}{\sqrt{0.63(1-0.63)}} \approx -3.43$, the absolute value of which is higher than our **MinZ** requirement of 2. Thus, **N2** is assigned the accuracy of the examples it covers.

We should also take a moment to clarify a point that may be confusing: for a node corresponding to an N-rule, we are hoping that the accuracy *will be low*—after all, accuracy is based on the ratio of the number of positive examples covered by the rule to the total number of records covered by the rule, and for N-rules we want the former to be low. Thus, we want a large, negative Z-number here; it means that the accuracy of the N-rule node is much lower than that of its parent node. The low score that the node will then be accorded reflects the low confidence that the model has that the records covered by that node will be in the target class. This is also why, if an N-rule fails the **MinSupportScore** or **MinZ** test, the accuracy of its parent is taken; if the N-rule isn't significant with regard to a specific P-rule, a record covered by the conditions of that P-rule is as likely to be in the target class when covered by the conditions of that N-rule as it is when not covered.

However, there is no guarantee that the accuracy of a P-rule/N-rule combination will be very low. While every N-rule should do a reasonable job of removing false positives from the records covered by the union of all P-rules, for a particular P-rule, a particular N-rule may not only fail to remove many false positives, but instead may remove mostly *true* positives. This could lead to a situation where if a record is covered by the conditions of a specific P-rule/N-rule combination, it will have a higher chance of being in the target class than if it were covered by the conditions of the P-rule alone! This is why we care about the *absolute value* of the Z-number. While we are hoping for a large, negative Z-number, it is important to recognize instances where we find a large, positive Z-number, too. For an example of such a situation, look at **N4** in Figure 2.7. While under the union of all P-rules **N4** must have covered a number of negative examples, under this particular P-rule it covers none; instead, it covers 4 positive examples, giving it a support of 4—higher than the requirement—and an accuracy of 1.0, higher than that of its parent (approximately 0.727). This gives it a Z-number

of $\frac{\sqrt{11}(1.0-0.727)}{\sqrt{0.727(1-0.727)}} \approx 2.03$, higher than the **MinZ** requirement. While the final result of this—rules covered by **N4**'s conditions end up with a higher score than those covered by those of no N-rules—seems contrary to the expected behavior of P-rules and N-rules, it's clear from this example that it's important to record these scores nonetheless.

One detail that's been left out so far, both in the explanation and in the example, is that we don't actually use the accuracy measure mentioned above, but instead adjust it using add-one smoothing, giving us an accuracy measure of $\frac{|S'|+1}{|S|+2}$. In order to illustrate why, let's imagine there are two rules, R_1 and R_2, both with perfect accuracy. However, R_1 covers 5 records, while R_2 covers 100 records. Clearly, our model should be more confident of the latter than the former. Without add-one smoothing, both rules would get a score of 1, but with add-one smoothing, the former gets a score of approximately 0.857, while the second gets a score of around 0.99. In addition, if at any point the pre-smoothing accuracy of an inner node is perfect, all of the leaf nodes below it are given the same accuracy as it. The reason for this is obvious: if the P-rule at that point is perfect, applying any further N-rules would lead to a worse, or at best the same, result.

The resulting scoring mechanism consists of the threshold th mentioned above, and a ScoreMatrix, which represents the leaf nodes of the trees mentioned previously. Let $P = \{P_0, \ldots, P_{|P|}\}$ be the set of all P-rules, and let $N = \{N_0, \ldots, N_{|N|}\}$ be the set of all N-rules. Then entry (i, j) in the ScoreMatrix holds the score assigned to the combination of rules P_i and N_j. Entry $(i, |N|)$ holds the score assigned to rule P_i when no N-rule applies.

Classification

At this point we have a set of P-rules, $(P_0, \ldots, P_i)$, a set of N-rules, $(N_0, \ldots, N_j)$, the ScoreMatrix, and a threshold th that maximizes F_1. We will explain, in brief, how a record is classified.

First, remember that the P-rules and the N-rules are ordered in terms of their significance. That is, P_0 is a better predictor than P_1, which is a better predictor than P_2, and so forth. Given a record, we first try to apply each P-rule, in order, to the record. If the record fails to satisfy any

of the P-rules, it's classified as not being in the target class. If it does match one of the P-rules, P_i, the algorithm then checks to see if it satisfies any of the N-rules. If it satisfies one of the N-rules, N_j, it's assigned the proper score from the ScoreMatrix, at entry (i, j). If it does not satisfy any of the N-rules, it is assigned the score at entry $(i, |N|+1)$ in the ScoreMatrix. Either way, its score is then compared to the threshold th. If its score is at least th, then the record is classified as being in the target class; otherwise, it is classified as being in the non-target class.

What if the target class isn't rare?

Joshi (2002), Agarwal and Joshi (2000), and Joshi et al. (2001) have shown that PNrule is competitive with other approaches in the normal classification case. Thus, if for some reason paraphrases were not rare in the corpora we were using, we'd lose nothing by using PNrule.

Chapter 3

Related Work

In this section, we review several systems, both supervised and unsupervised, that detect paraphrases as part of their operation. Most of them (Shinyama et al. (2002), Barzilay and Lee (2003), Quirk et al. (2004)) do so in order to discover rules for rewriting text units; one of them (Barzilay and Elhadad (2003)) detects them as its main function. We also review the PASCAL Recognizing Textual Entailment Challenge; as paraphrasing is a type of entailment, the systems submitted to this challenge are also worth reviewing.

3.1 Shinyama, Sekine, and Sudo 2002

Shinyama et al. developed a method to automatically build paraphrases for a particular domain using news articles from that domain. Their idea was that if two news articles described the same event, then if a sentence from one article had the same named entities as a sentence in the other article, one of those sentences was likely to be a paraphrase of the other. They were looking at news articles written in Japanese.

Their algorithm worked as follows. They used two newspapers. First, they used a stochastic information-retrieval system developed by Murata et al. (1999) to find articles for a particular domain written for a single newspaper. Then, they took the top 300 relevant articles, and tried to find articles about the same event in another newspaper. They did so, for each relevant

article, by finding the similarity between it and every article available from the other newspaper. Then they took the article with the highest similarity, assuming its similarity passed a certain threshold, and paired it with the relevant article.

To obtain this similarity value, they first tagged the named entities in each article, using a simple tagger that tagged any word not found in a dictionary of common nouns. They then used a similarity measure developed by Papka et al. (1999) for the purpose of Topic Detection and Tracking:

$$\begin{aligned} S_a(a_1, a_2) &= \cos(W_1, W_2) \\ W_k^i &= TF_k(w_i) \times IDF(w_i) \\ TF_k(w_i) &= \frac{f_k(w_i)}{f_k(w_i) + 0.5 + 1.5 \times \frac{length(k)}{avgdl}} \\ IDF(w_i) &= \frac{\log(\frac{C+0.5}{df(w_i)})}{\log(C+1)} \end{aligned}$$

W_1 and W_2 are vectors containing elements W_1^i and W_2^i, for articles a_1 and a_2 respectively. Each w_i represents a named entity. $f_k(w_i)$ is the number of times w_i appears in article a_k. $df(w_i)$ is the number of articles w_i appears in at least once. $length(a_k)$ is the length of article a_k, $avgdl$ is the average document length, and C is the number of articles.

Once they had the article pairs, they ran an IE pattern acquisition system, developed by Sudo and Sekine (2001), on each of the articles. This system performed named entity tagging and dependency analysis. This gave it a dependency tree, which it then picked paths from to create IE patterns. Shinyama et al. used the patterns that are created more than once, and that contained at least one named entity. An example of four IE patterns can be seen in Figure 3.1.

Next, they looked at each pair of articles and again tagged the named entities, this time using a statistical tagging system developed by Uchimoto et al. (2000). They then applied a morphological analyzer, Juman (Kurohashi and Nagao, 1999), and a dependency analyzer, KNP (Kurohashi and Nagao, 1994), to each of the sentences. This output a set of dependency trees, with the named entities tagged. They then applied the IE patterns to each of the sentences,

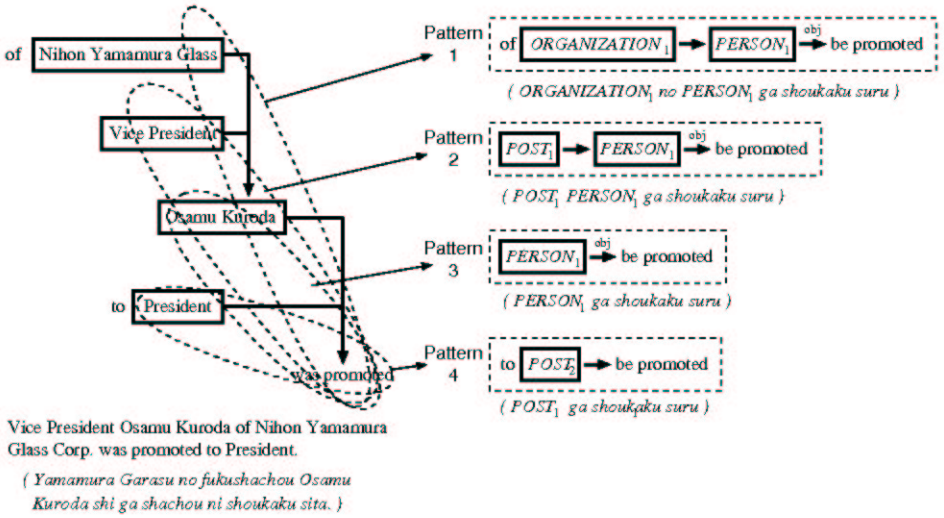


Figure 3.1: An example of four IE patterns, obtained from a single sentence. This example was taken from Shinyama et al. (2002).

dropping the sentences if there was no match, and filling the variables of the matching pattern with the appropriate named entities if there was a match.

Now that they had pairs of similar articles, the authors wanted to find those sentences in one article that were similar to sentences in the other article. Again, they based their similarity measure on named entities, penalizing frequently occurring ones using $tf \cdot idf$. This time, however, instead of looking for exact matches, they looked for *comparable* named entities. When looking at the similarity between articles, it makes sense to use exact matches between named entities, as it's highly likely that the same entity will be named in the same way at least once in both articles. However, this is not the case with sentences: it's highly likely that even if the same entity is named, it will not be named in the same manner. For instance, one sentence may refer to a "Mr. Suzuki," while another sentence may refer to the same person as "Wataru Suzuki." The authors defined two named entities as comparable if one entity began with at least half of the beginning string of the other (this makes sense in Japanese, where last names are printed before any first names, titles, etc.—in a Japanese article, our two sentences would've

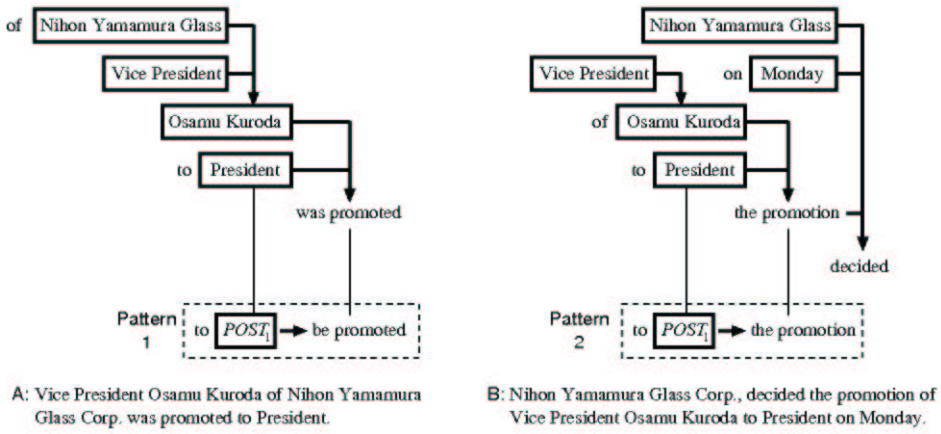


Figure 3.2: An example of paraphrase extraction, taken from Shinyama et al. (2002).

referred to the same person as "Suzuki-san" and "Suzuki Wataru"). Given a sentence s_1 from article a_1, and a sentence s_2 from article a_2, their sentence similarity measure was as follows:

$$\begin{aligned} S_s(s_1, s_2) &= \cos(W_1, W_2) \\ W_k^i &= TF_k(w_i) \times IDF_k(w_i) \\ TF_k(w_i) &= f_k(w_i) \\ IDF_k(w_i) &= \log(\frac{C_k}{df_k(w_i)}) \end{aligned}$$

W_1 and W_2 are vectors containing elements W_1^i and W_2^i, for sentences s_1 and s_2, respectively. w_i is, again, a named entity. $f_k(w_i)$ is the number of named entities comparable to w_i that appear in sentence s_k. $df_k(w_i)$ is the number of sentences in article a_k that contain at least one named entity that is comparable to w_i. C_k is the number of named entities in article a_k.

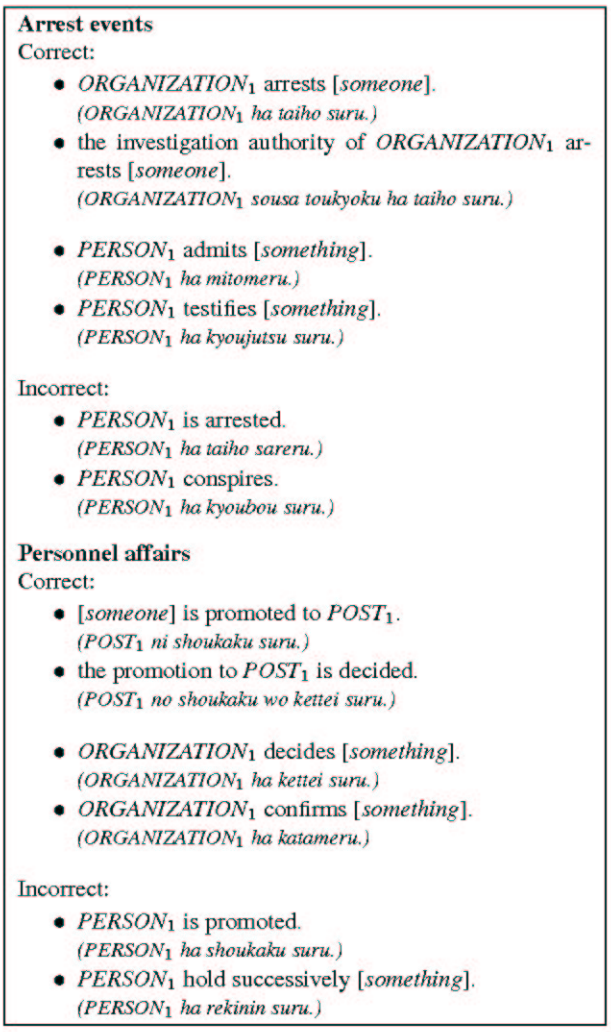
The authors picked as pairs any two sentences with similarity above a certain threshold. Recall that each sentence had at least one IE pattern associated with it. If a pattern associated with one sentence had the same number of comparable named entities as a pattern associated with the other sentence, the two patterns were linked as paraphrases. An example of this process can be found in Figure 3.2.

In order to test their algorithm, the authors used one year's worth of articles from two

Japanese papers, Mainichi and Nikkei. They looked at two domains: arrest events, which they defined as articles about arresting robbery suspects, and personnel affairs, which they defined as articles about the hiring and firing of executives. They managed to obtain 294 pairs of articles in the arrest events domain, and 289 in the personnel affairs domain. They then ran the pattern acquisition system, and obtained 725 patterns in the arrest events domain and 157 in the personnel affairs domain. Using these patterns, they obtained 53 arrest-events-domain paraphrase pairs and 83 personnel-affairs-domain pairs.

In order to evaluate the precision and coverage of their method, the authors first split the IE patterns into clusters. Each cluster contained patterns that described the same event and that captured the same information. If a cluster contained only a single pattern, that pattern was dropped. This left the authors with 393 patterns in 111 clusters for the arrest events domain, and 129 patterns in 20 clusters for the personnel affairs domain. Recall that at this point, some of the patterns had been paired with others, and were considered paraphrases of one another. In order to determine precision, a pairing was considered correct if both patterns were in the same cluster. For the arrest events domain, this was true for 26 out of the 53 pairs, giving a precision of 49%. For personnel affairs, it was true for 78 out of 83 pairs, which gave a precision of 94%.

In order to determine coverage, the authors first represented each of these clusters as a graph, with the patterns as nodes and their pairings as edges. Ideally, each graph should have been connected; there should have been a path between any two nodes in the cluster. The authors were able to get an estimation of coverage by looking at the number of edges necessary to make the graphs connected. They defined $L = \sum_{i=1}^{n}(s_i - 1)$ as the additional links necessary to make the graphs connected, where s_i is the number of connected components in cluster i. Let p_i be the number of patterns in a cluster i. Then $M = \sum_{i=1}^{n}(p_i - 1)$ is the total number of necessary edges to make each cluster a complete graph. The authors thus defined coverage as $C = 1 - \frac{L}{M}$. For the arrest events domain, the authors needed to add 230 new edges to obtain the necessary 252 edges to make each cluster a complete graph, which gave them a coverage of 9%. For the personnel domain, the authors needed 57 new edges to obtain a total of 109 edges,



Arrest events
Correct:

- *ORGANIZATION*$_1$ arrests [*someone*].
  (ORGANIZATION$_1$ *ha taiho suru.)*
- the investigation authority of *ORGANIZATION*$_1$ arrests [*someone*].
  (ORGANIZATION$_1$ *sousa toukyoku ha taiho suru.)*
- *PERSON*$_1$ admits [*something*].
  (PERSON$_1$ *ha mitomeru.)*
- *PERSON*$_1$ testifies [*something*].
  (PERSON$_1$ *ha kyoujutsu suru.)*

Incorrect:

- *PERSON*$_1$ is arrested.
  (PERSON$_1$ *ha taiho sareru.)*
- *PERSON*$_1$ conspires.
  (PERSON$_1$ *ha kyoubou suru.)*

Personnel affairs
Correct:

- [*someone*] is promoted to *POST*$_1$.
  (POST$_1$ *ni shoukaku suru.)*
- the promotion to *POST*$_1$ is decided.
  (POST$_1$ *no shoukaku wo kettei suru.)*
- *ORGANIZATION*$_1$ decides [*something*].
  (ORGANIZATION$_1$ *ha kettei suru.)*
- *ORGANIZATION*$_1$ confirms [*something*].
  (ORGANIZATION$_1$ *ha katameru.)*

Incorrect:

- *PERSON*$_1$ is promoted.
  (PERSON$_1$ *ha shoukaku suru.)*
- *PERSON*$_1$ hold successively [*something*].
  (PERSON$_1$ *ha rekinin suru.)*

Figure 3.3: Example of paraphrase patterns obtained by Shinyama et al. (2002), taken from that paper.

which gave them a coverage of 47%.

3.2 Barzilay and Lee 2003

Barzilay and Lee developed a method to extract automatically paraphrase patterns from an unannotated corpus, and then to use those patterns to create new paraphrases. Specifically,

they looked at sentence-level paraphrases, which, as they state, cannot be constructed by simply combining lexical paraphrases. As with Shinyama et al., they were looking at news articles about the same event, although they drew their articles from two newswire agencies instead of two newspapers. They claim that their method allowed them to extract paraphrases that bear little surface resemblance to one another. In addition, their method allowed them to acquire some paraphrases from each individual corpus, although these paraphrases had to be very similar in structure.

The first step in their algorithm was to cluster the sentences in the corpora. They began by preprocessing the sentences, replacing all dates, proper names, and numbers with generic tokens. Next, they did a hierarchical complete-link clustering, using a similarity measure based on the word n-gram overlap of the sentences. The idea was that within a cluster, the sentences should describe similar events and should have similar structures.

The next step was to induce patterns that could be used to build paraphrases. First, the authors created a word lattice by using *iterative pairwise alignment* on the sentences. There is a method known as *pairwise multiple-sequence alignment* that takes two sentences and a scoring function that gives a similarity measure between two words, and determines the highest scoring way to transform one sentence into the other, using insertions, deletions, and transformations. Iterative pairwise alignment is an extension of this method to multiple sentences. Figure 3.4 contains an example of a word lattice.

Each path through a word lattice corresponds to a sentence. Thus, using this lattice, the authors could create as many sentences as the lattice had paths through it, including some sentences that they had not necessarily seen before. For example, look at Figure 3.4. Two of the paths through this lattice might correspond to sentences found in the corpus, for instance:

a. *A suicide bomber blew himself up in the coastal resort of NAME on DATE killing NUM other people as well as himself and wounding NUM more.*

b. *A Palestinian suicide bomber blew himself up in a garden cafe on DATE killing himself and injuring NUM people.*

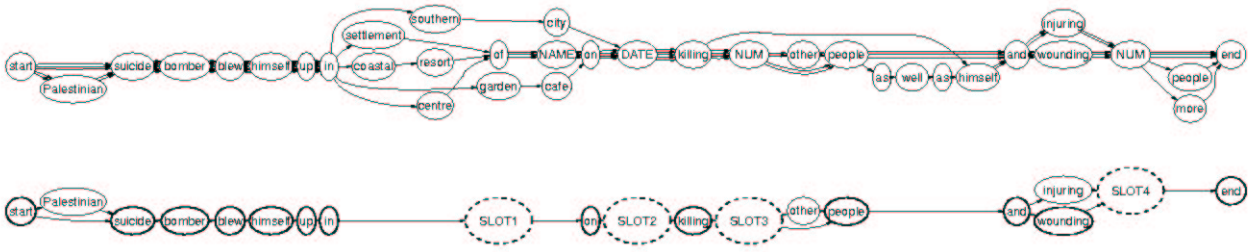


Figure 3.4: An example of a a word lattice obtained using pairwise multiple-sequence alignment, and the same lattice after parts of it have been replaced by slots. This example was taken from Barzilay and Lee (2003).

By following parts of each of these two paths, we can get a sentence such as: *A Palestinian suicide bomber blew himself up in a garden cafe on DATE killing NUM people as well as himself and injuring NUM more.*

However, there was still no way to use this lattice to paraphrase a sentence that contained words not in the lattice, even if the structure and meaning of the sentence was close to those of the sentences represented by the lattice. The authors needed some way to determine which words were not vital to the structure of the lattice, but were instead instances of arguments. The authors hypothesized that areas of large variability within the lattice corresponded to arguments, and should be replaced with *slots*, which could be filled by any instance of an argument.

In order to identify what parts of the lattice ought to be replaced by slots, the authors first identified those nodes that were clearly not arbitrary. They called these *backbone nodes*, and defined them as those nodes shared by at least 50% of the sentences from which the lattice was induced. If one of the backbone nodes contained one of the generic markers they used to replace proper names, dates, and numbers, it was replaced with a slot.

Now that they had identified the backbone nodes, the authors wanted to distinguish between variations caused by synonyms, and those caused by arguments. They wanted to preserve those parts of the lattice caused by the former, while replacing those caused by the latter with slots. To achieve this, they tuned a threshold s (in this case, it was tuned to 30): if less than s% of

the edges out of a backbone node led to the same node, a slot node was inserted after that backbone node. Also, any node that had less than s edges leading into it was dropped, under the assumption that it was probably an idiosyncrasy.

At this point, the authors paired the lattices by comparing the slot values of cross-corpus sentence pairs that appeared in articles written on the same topic on the same day. The lattices were paired if the degree of matching was over a tuned threshold. The similarity measure was based on word overlap. It gave double weight to proper names and numbers, and ignored auxiliaries.

Given a sentence, the authors would first find the lattice to which the sentence was best aligned. First, "insert" nodes were added between backbone nodes; these could match any word sequence, which allowed the system to handle previously unseen words. Then, they performed multiple-sequence alignment where insertions were scored as -0.1 and all other node assignments were scored as 1. After this was accomplished, the authors could generate paraphrases by filling in the slots of the best-aligning lattice's pair with the arguments from the sentence. This gave as many paraphrases as there were paths through the paired lattice.

In order to evaluate their algorithm, the authors used articles written between September 2000 and August 2002 from Agent France-Presse and Reuters. Using a document-clustering system, they collected 9MB of articles on acts of violence in Israel and army raids on Palestinian territory. Of these articles, 120 were held out for parameter training.

The algorithm extracted 43 slotted lattices from the AFP corpus, and 32 from Reuters. It found 25 cross-corpus matching pairs of lattices. A path through a lattice can be considered a paraphrase *template*: it consists of backbone nodes and nodes where arguments can be placed. Since each lattice contains multiple paths, the 25 lattice pairs yielded a total of 6,534 template pairs. These templates were judged by four native speakers of English who were unfamiliar with the system. Given a pair of templates, the judges were told to mark them as paraphrases if, for many instantiations of the variables, the resulting text units were paraphrases of one another. The authors randomly extracted 250 template pairs. 50 of those pairs were evaluated

Original (1)	*The caller identified the bomber as Yussef Attala, 20, from the Balata refugee camp near Nablus.*
MSA	The caller named the bomber as 20-year old Yussef Attala from the Balata refugee camp near Nablus.
Baseline	The company placed the bomber as Yussef Attala, 20, from the Balata refugee camp near Nablus.
Original (2)	*A spokesman for the group claimed responsibility for the attack in a phone call to AFP in this northern West Bank town.*
MSA	The attack in a phone call to AFP in this northern West Bank town was claimed by a spokesman of the group.
Baseline	A spokesman for the grouping laid claim responsibility for the onslaught in a phone call to AFP in this northern West Bank town.

Table 3.1: Two example sentences and generated paraphrases taken from Barzilay and Lee (2003). Baseline was achieved by simply replacing words with randomly-chosen WordNet synonyms. The judges felt that the MSA algorithm preserved meaning for example 1, but not 2, and that the baseline did not preserve meaning in either case.

by all 4 judges; the other 200 were split into 4 groups of 50 pairs, and each judge was given a different group of 50. The Kappa score on the 50 common pairs was 0.54. Each judge gave a different validity score: 68%, 74%, 76%, and 96%.

The authors also evaluated the quality of the resulting paraphrases. They randomly selected 20 AFP articles about violence in the Middle East. Out of the 484 sentences contained in these articles, they found they were able to paraphrase 59 (12.2%) of them. The authors noted that once proper-names were substituted back in, only seven of the paraphrasable sentences were found in the training set, which indicates that generalization did occur. Interestingly, the authors found that they were more likely to find paraphrasable sentences in shorter articles, as longer articles were more likely to contain unique information. This time, two judges were used to evaluate the quality of the paraphrase pairs. They had a Kappa score of 0.6, with one judge evaluating 81.4% of the pairs as correct, and the other 78%.

3.3 Barzilay and Elhadad 2003

Like us, Barzilay and Elhadad wanted to identify pairs of sentences that contain clauses conveying the same information. In order to do so, they developed a method of sentence alignment for monolingual comparable corpora. Sentence alignment works by first computing the local

(A)	· Petersburg served as the capital of Russia for 200 years. · For two centuries Petersburg was the capital of the Russian Empire.
(B)	· The city is also the country's leading port and center of commerce. · And yet, as with so much of the city, the port facilities are old and inefficient.

Figure 3.5: While both of these sentence pairs have the same similarity value, the first pair are paraphrases of one another, while the second pair are not. This example was taken from Barzilay and Elhadad (2003).

similarity for each sentence, and then finding an overall sequence of mapped sentences, using the local similarity of the sentences as well as other attributes. To illustrate why a local similarity value alone is not sufficient, Barzilay and Elhadad (2003) give the example in Figure 3.5. Despite the fact that both pairs of sentences have the same number of matching word pairs, the first pair are paraphrases of one another, while the second pair are not.

Traditionally, sentence alignment has been used on parallel multilingual corpora. In such corpora, there are minimal insertions and deletions, and the information appears in roughly the same order in the two texts. In contrast, comparable corpora tend to contain a lot of noise. There may be a great deal of information appearing in one text that does not appear in the other, and there is no guarantee as to what order that information will appear in. Thus, the authors had to develop a new method of sentence alignment, specifically designed for monolingual comparable corpora.

The authors based their approach on a theory called *Domain Communication Knowledge*. This theory states that within a particular domain and genre, texts draw from a limited set of topics. Texts also have a topical structure: roughly speaking, the sentences within a particular paragraph will tend to be on the same topic. Thus, one can look at the context of two sentences to help determine whether or not they should be aligned. If two sentences appear within contexts that fall within the same topic, they are more likely to be aligned than if they fall within

unrelated topics.

With this in mind, the first thing the authors had to do was find some way to decide whether a paragraph in one corpus fell within the same topic as a paragraph in the other corpus. They decided to use a two-step process: first, they placed the paragraphs of each corpus into topic clusters; then, informed by these clusters, they found a mapping between the paragraphs of one corpus and those of the other. To accomplish the first step, they began by replacing proper names, dates, and numbers with generic tags. This was important, because they were trying to cluster by the type of information provided, not by the subject of that information. Next, they did a hierarchical complete-link clustering of the paragraphs, using the cosine similarity measure based on the matching of content words. This gave them their topic clusters for each corpus.

For the purposes of training, they considered two paragraphs to map to one another if they contained at least one aligned sentence pair. To map the paragraphs, the authors used a supervised approach. For their training set, they used a set of manually aligned text pairs from the corpora. They then used BoosTexter (Singer and Schapire, 1998), iterating 200 times, to train a model to classify two paragraphs, *P* and *Q* as mapping or not mapping based on their lexical similarity (again, cosine similarity based on word overlap), the cluster number of *P*, and the cluster number of *Q*. An example of two paragraphs that mapped to one another can be seen in Figure 3.6.

Given this model, sentence alignment worked as follows: given two texts, sentences with high lexical similarity ($> .5$) were aligned. Then, for each paragraph, the cluster it was closest to was found. Each paragraph in one text was mapped to the other text's paragraphs using the classification scheme mentioned above. Within each pair of mapped paragraphs, dynamic programming was then used to compute local alignments. The idea was that given two sentence pairs with moderate lexical similarity, whether or not they should be aligned could be determined by looking at whether they were near to other sentence pairs with high lexical similarity.

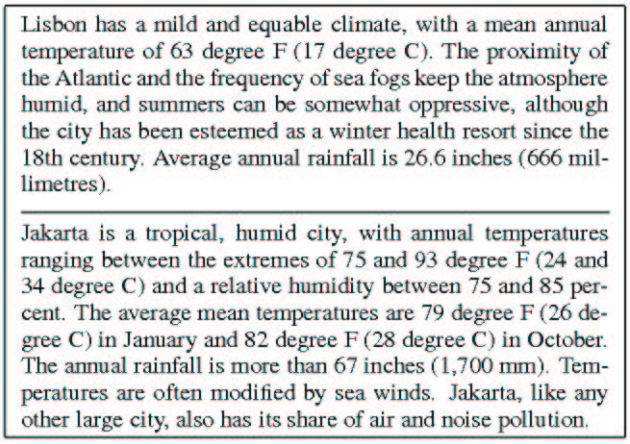


Figure 3.6: An example of two paragraphs that mapped to one another, taken from Barzilay and Elhadad (2003).

Thus, given two sentences, i and j, their local similarity value was:

$$sim(i,j) = cos(i,j) - mismatch\_penalty$$

The mismatch penalty was used to further penalize sentence pairs with low similarity measures. The weight of the optimal alignment between two sentences was computed as:

$$s(i,j) = \max \begin{cases} s(i,j-1) - skip\_penalty \\ s(i-1,j) - skip\_penalty \\ s(i-1,j-1) + sim(i,j) \\ s(i-1,j-2) + sim(i,j) + sim(i,j-1) \\ s(i-2,j-1) + sim(i,j) + sim(i-1,j) \\ s(i-2,j-2) + sim(i,j-1) + sim(i-1,j) \end{cases}$$

The skip penalty was used to stop only those sentence pairs with high similarity from being aligned. Unfortunately, this weight measure appears to be a recursion without a halting condition; however, we have printed it exactly as it appears in Barzilay and Elhadad (2003).

In order to evaluate their method, Barzilay et al. used as corpora the Encyclopedia Britannica and the Britannica Elementary. They picked 103 pairs of city descriptions, held out

(*)	Gradually the German culture and language became more widespread in the city.
	Capping Prague's rebirth, it was designated a European City of Culture in 2000.
	Prague is a centuries-old city with a wealth of historic landmarks.
	The physical attractions and landmarks of Prague are many.

Figure 3.7: An example of two alignments found by this method, taken from Barzilay and Elhadad (2003). The first alignment is incorrect, while the second is correct.

11 for testing, used the other 92 for vertical clustering into 20 clusters, and then of those 92 pairs, used 9 for training. They had each pair in the training and testing set annotated by two annotators. The sentences in each pair were considered to be aligned if they both contained at least one clause that expressed the same information. Many-to-many alignments were allowed. Once the two annotators were finished, a third annotator judged any contested pairs. 320 pairs were aligned in the training set, out of a total of 4192 sentence pairs, and 281 were aligned in the testing set, out of a total of 3884 pairs.

By varying the mismatch penalty from 0 to 0.45, and using a skip penalty of 0.001, the authors were able to get a range of recall from 25% to 65%. At 55.8% recall, they obtained 76.9% precision.

One point we'd like to address is Barzilay and Elhadad's (2003) criticism of Hatzivassiloglou et al. (2001). Like us, Hatzivassiloglou et al. (2001) use a machine-learning algorithm with various lexical features, although they use it to find similar text passages (where similarity includes, but is not limited to, paraphrasing) instead of clause-level paraphrases. Barzilay and Elhadad claim that their results, and the fact that Hatzivassiloglou et al.'s system, SIMFINDER, does not perform as well on the same test data, proves that it is better to use an approach with a simple local similarity combined with a simple global similarity, instead of an approach with a set of complex lexical features and a machine-learning algorithm. There are two problems with this conclusion: first, SIMFINDER was trained on news articles, not encyclopedia entries,

so it's hardly surprising that it wouldn't perform as well on the test data; second, Barzilay and Elhadad are able to obtain 55.8% recall and 57.9% precision on their test data by doing nothing more than seeing if the cosine similarity of two sentences is over a particular threshold. While this does not dismiss their results—they obtain a precision of 76.9% at the same level of recall using their system—we do question whether it's fair to dismiss more complicated methods based on results using a corpus where such an incredibly simple method works so well.

3.4 Quirk, Brockett, and Dolan 2004

Quirk et al. (2004) tried to infer rules for the generation of phrasal-level paraphrases from comparable corpora. Instead of attempting to extract patterns like Shinyama et al. (2002) or Barzilay and Lee (2003), they treated paraphrasing as a statistical machine translation problem. Specifically, they used the noisy channel model developed by Brown et al. (1993). Given a sentence S to be paraphrased, they wanted to find:

$$\begin{aligned} T^* &= \underset{T}{\operatorname{argmax}}\{\Pr(T|S)\} \\ &= \underset{T}{\operatorname{argmax}}\{\Pr(S|T)\Pr(T)\} \end{aligned}$$

where T^* is the optimal paraphrase of S, T is a sentence in the same language as S, $\Pr(S|T)$ is the channel model, and $\Pr(T)$ is the target language model.

Like Shinyama et al. (2002) and Barzilay and Lee (2003), Quirk et al.'s corpus was drawn from news articles on the same event. However, instead of drawing the articles from two newspapers, they used online news gatherers, such as Yahoo News and Google News, to locate clusters of articles from a variety of newspapers on the same event. Using a Hidden Markov Model to distinguish between article content and various types of noise such as ads, they collected these clusters over a period of about eight months, eventually gathering 11,162 in all, containing a total of 117,095 articles, with an average of 15.8 articles per cluster.

In order to find pairs of sentences containing potential paraphrases of one another, they first

set all of the words in the sentences to lowercase, and then found the Levenshtein edit distance[1] between each pair of sentences within a cluster. They rejected duplicate pairs, pairs that were identical or differed only in punctuation, pairs with significantly different lengths, and pairs where the edit distance was greater than 12.0. This gave them a total of 139,000 non-identical pairs.

At this point, they aligned the words of each pair of sentences using GIZA++ (Och and Ney, 2000), which is a free implementation of IBM Models 1–5 (Brown et al., 1993) and HMM alignment (Vogel et al., 1996). In machine translation, one would align the target text to the source text. However, in order to capture many-to-many alignments between sentences, the authors both aligned the target text to the source text, and aligned the source text to the target text. They then heuristically recombined the unidirectional word alignments into a single bidirectional alignment.

Next, they adapted a phrasal decoder patterned after that of Vogel et al. (1996) to identify what they refer to as *phrasal replacements*. The decoder worked as follows: think of two sentences, S and T, where S is the source sentence and T is the target sentence, as sequences of words $s_1, \ldots, s_m$ and $t_1, \ldots, t_n$, respectively. Then a word alignment A of S and T can be expressed as a function from each token of S and T to a unique *cept* (Brown et al., 1993). A cept is a minimal mapping between words and their positions in one sentence to words and their positions in the other, where the two sets of words refer to the same concept. In order to understand what we mean by "minimal", let's look at two sentences:

a. Four humans saw the large cat.

b. Four people saw the tiger.

In this case, (four(1)|four(1)) and (humans(2)|people(2)) would both be cepts, but (four(1) humans(2)|four(1) people(2)) would not be. This is not to say that each component of the cept

[1]The Levenshtein edit distance between two strings is the number of insertions, deletions, and substitutions required to transform one string into the other. For further explanation, see http://www.merriampark.com/ld.htm.

can only consist of a single word: (large(5) cat(6)|tiger(5)) would also be a cept in this sentence, since "large cat" and "tiger" are both the minimal representations of the same conceptual entity. Note that it is possible for one word to be in multiple cepts, as well as for a word to be in no cepts.

For a given sentence pair (S,T) and word alignment A, the authors define a *phrase pair* as the subset of the cepts in which both the tokens of S and those of T are contiguous. They collected these pairs, excluding those with greater than 5 cepts for computational reasons, into a replacement database. It is these pairs that the authors refer to as *phrasal replacements*.

The authors then assigned a probability to each phrasal replacement using IBM Model 1 (Brown et al., 1993). They first gathered lexical translation probabilities $\Pr(s|t)$ by running 5 iterations of the expectation-maximization algorithm of IBM Model 1 on the training corpus. Then, they assigned probability as follows:

$$\begin{aligned}\Pr(S|T) &= \sum_{A}\Pr(S,A|T)\\ &= \prod_{t\in T}\sum_{s\in S}\Pr(s|t)\end{aligned}$$

$\Pr(S|T)$ is referred to by the authors as the *replacement model*. For the target language model, $\Pr(T)$, the authors used a trigram model using interpolated Kneser-Ney smoothing (Kneser and Ney, 1995) trained over 1.4 million sentences.

In order to generate paraphrases, the authors first preprocessed the sentences: the text was lowercased and tokenized, and a few types of named entities were identified using regular expressions. The authors then used statistical phrase-based decoding. Given a sentence, they first constructed a lattice of all possible paraphrases based on the phrasal translation database. The lattice had a set of $|S|+1$ vertices, with edges labeled with sequences of words and probabilities drawn from the database. The idea was that an edge e between a vertex v_i and v_j represented the chance that the words $s_i+1,\ldots,s_j$ would be replaced with the sequence of words labeling e with the probability associated with it. The authors also added an identity mapping from S to T, by, for each s_i, adding an edge from v_{i-1} to v_i labeled with s_i and a uniform probability u.

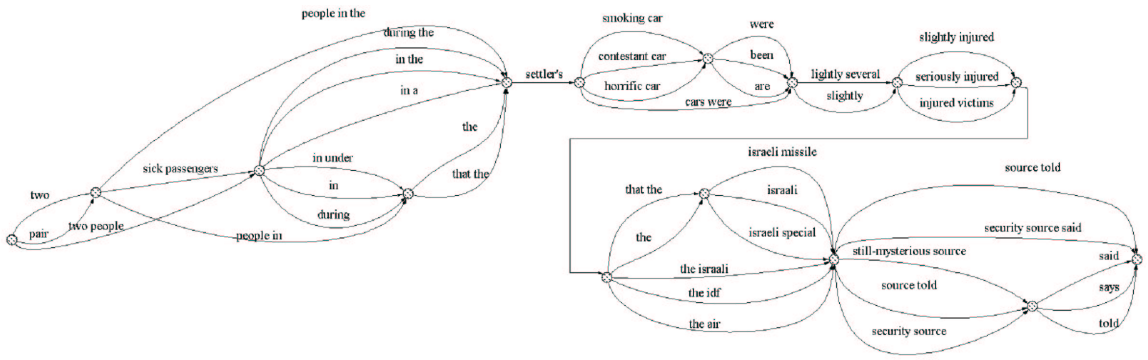


Figure 3.8: An example of a translation lattice, without the assigned probabilities, taken from Quirk et al. (2004).

This has two effects: it allowed the method to handle unseen words, by simply keeping those words, and, if *u* was set to a high value, it encouraged conservative paraphrases.

Once this had been accomplished, the optimal paraphrase could be found by finding the optimal path through the lattice, scored by the product of the replacement model and the language model. This was accomplished using the Viterbi algorithm. Finally, there was some post-processing done on the paraphrase, which restored named entities and casing.

The authors noted that as this model relied on simply replacing a sequence of words with another sequence of words, it could not handle intra-phrasal reordering. Thus, it could not capture, for instance, active-passive alternation. However, it was able to capture synonymy (e.g., *injured/wounded*), phrasal replacements (e.g., *Bush administration/White House*), and intra-phrasal re-orderings (e.g., *margin of error/error margin*).

Quirk et al. evaluated two things: first, how well GIZA++ did word alignment between sentence pairs, and second, how acceptable the paraphrases their method produced were. To evaluate the former, they followed the method of Och and Ney (2003). First, they held out a set of news clusters from their training set. From these clusters, they randomly extracted 250 sentence pairs with edit distances between 5 and 20 for evaluation. Each pair was checked by an independent evaluator to make certain they contained paraphrases. Then, two evaluators

created annotations for the sentence pairs. They marked alignments as either SURE, meaning those words must be aligned, or POSSIBLE, meaning that it is preferable, but not necessary that those words be aligned. Given that A is the set of all alignments, S is the set of SURE alignments, and P is the union of the set of all SURE alignments with the set of all POSSIBLE alignments, precision, recall, and alignment error rate (AER) are determined as follows:

$$\text{precision} = \frac{|A \cap P|}{|A|}$$

$$\text{recall} = \frac{|A \cap S|}{|S|}$$

$$\text{AER} = \frac{|A \cap P| + |A \cap S|}{|A| + |S|}$$

Measured by AER, the agreement between the two annotators was 93.1%. Overall, AER was 11.58%, with an AER of 10.57% on identical words and an AER of 20.88% on non-identical words.

In order to judge the quality of the paraphrases generated by their method, the authors used as a test set the 59 sentences used in Barzilay and Elhadad (2003), and 141 randomly selected sentences from the held-out part of their corpus. For each sentence, two judges decided whether the sentence generated by the algorithm was indeed a paraphrase of the original sentence. The first time, the judges had an agreement rating of 84%. The authors decided this was too low, so they had the two judges look at any examples upon which they disagreed. This led to an agreement of 96.9%. The system was able to generate a paraphrase for all 200 sentences; the best-scoring paraphrases received a 91.5% acceptance rate for the 59 sentences from Barzilay and Lee (2003), and an 89.5% acceptance rate for all 200 sentences. It's worth noting that while this method achieved excellent coverage and acceptability, the changes were often relatively minor, such as replacing a word or a phrase will a similar word or phrase. The average edit distance of the paraphrases produced by this system was 2.9, as opposed to 25.8 for Barzilay and Lee (2003).

3.5 The PASCAL Recognizing Textual Entailment Challenge

3.5.1 The challenge

Since we began this project, there has been a considerable amount of publication on a related topic: textual entailment. Textual entailment is a directional relationship between two units of text: given two text units, t_1 and t_2, we say that t_1 *entails* t_2 if we can infer t_2 from the information given to us by t_1. This is relevant to us because, by the definition of entailment, if a text t_2 is a paraphrase of a text t_1, it must also be entailed by t_1. Note that the reverse is not true: *The man murdered Bob* entails *Bob is dead*, but *Bob is dead* is *not* a paraphrase of *The man murdered Bob*.

Much of the recent work on entailment has come about due to the Recognizing Textual Entailment Challenge, put out by the PASCAL Network of Excellence (Dagan et al., 2005). This challenge consists of a dataset of 567 development examples and 800 test examples that has been designed to reflect the occurrence of entailment within several common NLP tasks. These tasks are: question answering, information extraction, machine translation, paraphrase acquisition, information retrieval, comparable documents (this was the authors' term; "sentence alignment of comparable documents" might be more accurate), and reading comprehension. An example consists of a text unit *t* and a hypothesis unit *h*; the text is one or two sentences (usually one), while the hypothesis is a shorter sentence. Each example was annotated by two annotators, who were told to label an example as true if it was *very probable* that *h* could be inferred from *t*. An example of a very probable positive example given in Dagan et al. (2005) is as follows:

Text: The two suspects belong to the 30th Street gang which became embroiled in one of the most notorious recent crimes in Mexico: a shootout at the Guadalajara airport in May, 1993, that killed Cardinal Juan Jesus Posadas Ocampo and six others.

Hypothesis: Cardinal Juan Jesus Posadas Ocampo died in 1993.

As Dagan et al. (2005) explain, it's possible that Ocampo died months later, in 1994, from the wounds he sustained in 1993, but it's very likely that he died in the same year that the shootout occurred.

The annotators were told to ignore tense, due to the fact that the text and hypothesis were sometimes drawn from different documents, which could have been written at different times. Any examples upon which the two annotators disagreed were discarded, as were some examples that one of the organizers thought might be too controversial. The final corpus was built in such a way as to have an even number of positive and negative examples. Other annotators, who were not involved in the original annotation, also replaced anaphora with appropriate references, and shortened some of the hypotheses and texts to reduce complexity.

Here's a brief run-down of how examples were obtained for each of the various tasks:

Information Retrieval: Hypotheses look like IR queries, and were selected by examining prominent sentences in news stories; texts were selected by putting hypothesis into search engine and selecting from retrieved documents.

Comparable Documents: Pairs were selected by examining aligned sentences from clusters of similar news stories found in Google news; they were also drawn from an existing corpus of aligned sentences (probably that of Barzilay and Elhadad (2003), although it's a bit unclear from the paper).

Reading Comprehension: Texts were selected from news stories; hypotheses were written by annotators, with the instruction that they should be like reading comprehension examples found in high school tests (or, for that matter, the SATs).

Question Answering: Questions were mostly drawn from the CLEF-QA (Magnini et al., 2003) and TREC (Voorhees, 2004) datasets, although annotators could write their own; they inserted the questions into the TextMap Web-Based Question Answering system (Echihabi et al., 2003) and used the results as the texts; they then rewrote the questions as affirmative statements and used these as the hypotheses.

Information Extraction: Examples were drawn from a dataset produced by Roth and Yih (2002) and from news stories; texts were sentences in which particular relations held, and hypotheses were the relations with their slots filled in.

Machine Translation: Examples were drawn from two translations of the same text, one automatic and the other done by a human; half of the time the hypothesis was taken from the automatic translation and the text from the human translation, and the other half of the time the reverse was done. Some of the automatic translations were rewritten so as to be grammatically correct.

Paraphrase Acquisition: Texts were drawn from news stories that contained particular relations; hypotheses were created by drawing paraphrases from a paraphrase-acquisition system (probably Lin and Pantel (2001), although again, it's a little unclear) and by then applying those paraphrases to the original text.

So how does the goal of this challenge differ from that of our thesis? First, as stated above, entailment includes relationships other than paraphrases. Second, systems designed for the RTE challenge only have to do one-way matching: they know ahead of time which text unit is the text and which is the hypothesis. Our system, on the other hand, does not know which of the sentences in a given pair may contain the paraphrase (if either), and which is the "original" text. Also, in the RTE challenge, there can be no information in the hypothesis that is not included in the text; for us, there may be clauses in either of the sentences that have no correlating clause in the other sentence. Finally, the RTE challenge uses a corpus primarily drawn from newspaper stories; this allows the systems designed for the challenge to use a number of tools, such as parsers and chunkers, that have been trained on newspaper corpora.

All of that said, the goal of the PASCAL RTE challenge is still close enough to our own that we can learn from the various systems submitted for it. Below, we give a brief overview of these systems.

3.5.2 The systems

Roughly speaking, the systems submitted to the PASCAL RTE challenge can be placed into two groups: those that attempt to logically infer the hypothesis from the text, and those that use some other method to detect entailment. The systems in the former group include those of Akhmatova (2005), Bayer et al. (2005) (system 1), Bos and Markert (2005) (system 2), de Salvo Braz et al. (2005), Fowler et al. (2005), and Raina et al. (2005) (system 2).

Akhmatova (2005)'s system works by first transforming the text and the hypothesis into a series of atomic propositions, and then for each of the hypothesis propositions, attempting to find a text proposition that entails it. In order to do the transformation, the system uses a link parser and then a semantic analyzer. To find entailment between propositions, it uses an automated deduction system called OTTER (McCune, 2004). It is aided in this by some hand-coded logic rules—including representations of equivalence, hypernymy, lexical relations, and syntactical equivalence, among other relations—and by a WordNet relatedness algorithm, which is used if no exact entailment can be found for a proposition (presumably some sort of threshold is used, although the author doesn't describe this). Entailment holds for the text/hypothesis pair if all of the hypothesis propositions are entailed by text propositions.

Bayer et al. (2005) (system 1) transform the text and the hypothesis into logic propositions, and then use the EPILOG event-oriented probabilistic inference engine (Schubert and Hwang, 2000), aided by a few hand-crafted inference rules and by simple word lists, to determine whether the hypothesis is entailed by the text. To transform the text and the hypothesis, they do a lot of pre-processing: the text and the hypothesis are tokenized, segmented, tagged with parts-of-speech, morphologically analyzed, and parsed with a link parser. They are then processed by a dependency analyzer and by a Davidsonian logic generator, which outputs them in propositional form.

Bos and Markert (2005) (system 2) also transform the text and the hypothesis into propositions, and use these along with background-knowledge axioms (*bk*) to attempt to prove entailment. An example can be marked positive one of three ways: a theorem prover, Vampire

(Riazanov and Voronkov, 2002), finds entailment; a model builder, Paradox (Claessen and Sorensson, 2003) finds a model for the negation of entailment; or the difference in the sizes of the model of $(bk \wedge t)$ and the model of $(bk \wedge t \wedge h)$ is under some threshold. The authors use a CCG-parser to parse the text and the hypothesis into propositions, and use three sources for the background knowledge: the semantics of certain types of words and relationships; lexical knowledge created using WordNet hypernyms; and geographic knowledge from the CIA factbook. They combine these features with those of system 1 (described below) by training a decision tree classifier over them.

De Salvo Braz et al. (2005), Fowler et al. (2005), and Raina et al. (2005) (system 2) all use a method known as "extended unification": if two terms cannot be unified, the rules governing unification are relaxed. Each type of relaxation that can occur is assigned a cost, and at the end the total cost of unification is compared against some threshold; if the cost is below that threshold, the example is marked as positive (this is how both de Salvo Braz et al. (2005) and Raina et al. (2005) work; Fowler et al. (2005) actually assigns *higher* scores to those examples which require less relaxation of terms, and then checks to see if the total score is *over* a threshold, but the basic idea is still the same).

De Salvo Braz et al. (2005) use Extended Feature Description Logic to represent the text and hypothesis (augmented with syntactic and semantic parses), as well as a series of syntactic and semantic rewrite rules. The representations of the text and of the hypothesis are hierarchical—this allows the rewrite rules to depend on levels higher than lexical—and are created using a tokenizer, a lemmatizer, a part-of-speech tagger, a syntactic parser, a semantic parser, a named entity recognizer, and a name coreference system. Some of the rewrite rules are taken from Lin and Pantel (2001); others have been manually generated. The system uses these rewrite rules to create several alternative representations of the text. For each of these representations, it attempts to unify the hypothesis into the representation, using extended unification. The unification process is a bit complicated, but the idea is basically this: first, they make sure that for each verb in the hypothesis, there is a verb in the text with the same attribute

set and arguments at both the semantic role and syntactic parse levels. If every verb in the hypothesis has a matching verb in the text, then the cost is set to zero; otherwise, the cost is set to infinity. Assuming the cost has not been set to infinity, the system goes on to recursively match phrase-level nodes, penalizing nodes that do not match by assigning them a uniform cost, and then to match word-level nodes, again penalizing nodes that do not match by assigning them a uniform cost; this gives the system the total unification cost.

Fowler et al. (2005) use part-of-speech tagging, parse-tree generation, word-sense disambiguation, and semantic-relations detection to convert the text and the hypothesis into logical forms—although they ultimately remove the word senses from the predicates, as it turns out that the disambiguator is rather inaccurate. To prove entailment, they use COGEX (Moldovan et al., 2003), a modified version of OTTER (McCune (2004); the prover used by Akhmatova (2005)). COGEX is fed the negated form of the hypothesis, the text, and a set of axioms that include world knowledge, knowledge of syntactic equivalence, and lexical chains. In order to successfully complete unification, COGEX is allowed to use these axioms, to relax predicate arguments, and to drop predicates. The example is then scored depending on how many of these actions take place during the proof process—the more that take place, the lower the score. The score is normalized by calculating the maximum penalty that can be assigned and then dividing by this number.

Raina et al. (2005) (system 2) transforms the text and the hypothesis into logical formulas that capture their respective syntactic dependencies. In order to unify each term of the hypothesis with a term of the text, the system can relax unification in the following ways: allowing terms with different predicates to be unified (with cost determined by a similarity measure), allowing terms with different numbers of arguments to unify (with cost based on the annotation of those arguments), and allowing constants to unify (the cost is uniform over an example, although it is lowered if there's a possible coreference or appositive reference); they use a learning algorithm to determine the costs of these relaxations. This system outputs a confidence score for each example; this is combined with a similar confidence score output by

Raina et al. (2005) (system 1) using logistic regression. The authors try training the weights for the regression in two ways: one set of weights trained over all of the examples, and a separate sets of weights trained over the examples from each of the tasks.

The rest of the systems used a variety of approaches to the entailment problem. Pazienza et al. (2005), Raina et al. (2005) (system 1), and Herrera et al. (2005) use dependency parsers to transform the text and the hypothesis into graphs, then use approaches based on graph matching. The goal of these systems is to maximize the similarity value between the two graphs; this similarity value is then compared against a threshold, and if it's greater than or equal to that threshold, the example is marked positive. Pazienza et al. (2005) create syntactic graph representations of the text and the hypothesis (the nodes are words or phrases, and the edges are syntactic relationships), and then attempts to find the maximal subgraph of the hypothesis that is in an isomorphic relationship with a subgraph of the text. An isomorphic relationship exists between two graphs, G and H, if every node and edge in G can be subsumed by the nodes and edges in H, and vice versa. In this system, when a node is subsumed by another node, it is assigned a similarity value based on the semantic similarity between the two nodes; similarly, when an edge is subsumed by another edge, it is assigned a similarity value based on the syntactic similarity between the two edges. The calculation of the similarity between the two graphs is based on these similarities. There are two versions of this system: in one, the parameters used in the similarity measures are set manually; in the other, these parameters are tuned using a support vector machine.

Raina et al. (2005) (system 1) also use graph isomorphisms, only instead of trying to find a maximal subgraph of the hypothesis, they add a *nil* node to each graph and allow the nodes of the other graph to match to it if necessary. Each node or edge subsumption is assigned a particular cost, depending on the properties of the nodes or edges involved in the subsumption. For node subsumption, the properties the system checks for are as follows, in order of increasing cost: whether the stems of the hypothesis node and the subsumption node and their parts of speech match; whether the stems of the two nodes match, but having different parts of speech;

whether the hypothesis node is a synonym of the subsuming node; whether the hypothesis node is a hypernym of the subsuming node; and, finally, whether the two nodes are similar according to a word similarity module developed by the authors. Each cost is weighted by the importance of the hypothesis node it applies to, as determined by the part-of-speech tag of the node or the type of named entity it is; the cost is then normalized by dividing it by the total weight of the nodes. For edges, the cost of the subsumption is determined solely by looking at the properties of the nodes of the subsuming edge. These properties, again in order of increasing cost, are: whether one of the nodes is a parent of the other; whether one of the nodes is an ancestor of the other; whether the two nodes share a parent; and, whether the two nodes share an ancestor. Again, the costs of the edge subsumptions are weighed by the importance of the edges being substituted for, as determined by the relations those edges represent (such as subject or object). The overall edge- and node-subsumption costs are then combined using a convex mixture; the algorithm approximates the lowest-cost match using a combination of the Hungarian method (Kuhn, 1955) and a greedy hill-climbing search. This system outputs a confidence score for each of the examples, which is them combined with the output of Raina et al. (2005) (system 1), as detailed earlier.

Herrera et al. (2005) take a somewhat different approach. Their system begins by trying to find nodes in the hypothesis that are entailed by nodes in the text: using WordNet, a hypothesis node is entailed by a text node if the two nodes are in the same synset, or if, using the hypernymy and entailment relations, a path can be found between a synset of the hypothesis node and a synset of the text node. The system also checks for negation: in such a case, the antonym of the node (as determined by WordNet) is used in its place in determining entailment between nodes. Once this is accomplished, a simple matching algorithm is used, that matches the branches of the hypothesis tree with branches in the text tree. Two branches match if each of the nodes in the text branch entails a node in the hypothesis branch. The similarity value between the two trees is then simply the percentage of nodes in the hypothesis tree that are part of a branch that is matched to a branch in the text tree. The threshold used by this system is

50%.

Wu (2005) uses a measure based on the Inversion Transduction Grammar Hypothesis. Previously, ITGs had been used in machine translation and alignment. Given two languages, an input language and an output language, the ITG grammar is used to transform sentences from the input language into sentences in the output language; in the case of this system, of course, the input and output languages are the same. ITGs have two types of rules: straight and inverted. In a straight rule, the symbols on the right-hand side of the rule must be in the same order for both languages. In an inverted rule, the symbols on the right-hand side of the rule must be left-to-right for the input language and right-to-left for the output language. Wu (2005) uses a special type of ITG, a Bracketing ITG. It uses only a single "dummy" non-terminal, and thus, unlike other ITGs, it does not requiring any language-specific information; the only operation it allows for is transposition of words and phrases. The examples are assigned scores using a biparsing algorithm described in Wu and Fung (2005); we won't get into the details of that algorithm, but the basic idea is that those pairs of sentences that have fewer transpositions between them are assigned a higher score. There are two runs of this system: one where the system is run after removing words in a stoplist from the example, and one where no such removal is performed.

Following a similar idea as Wu (2005), Bayer et al. (2005) also use a method originally developed for machine translation—in this case, a statistical machine translation model. Like Quirk et al. (2004), this system uses GIZA++ for its alignment models. In this case, the models were trained on the Gigaword (Graff, 2003) corpus, using the lead paragraphs of the articles as "texts" and their headlines as "hypotheses". They combine the alignment model with a series of string similarity metrics by placing the examples in a vector space and using a *k*-nearest-neighbor classifier to classify them.

Glickman et al. (2005) use a generative probability model to determine the probability that a given text entails a given hypothesis. In order to do this, they make several simplifying assumptions: first, that the content words in a hypothesis can be assigned truth values; second,

that a hypothesis is true if and only if all of its content words are true; third, that the probability of a content word being *true* is independent of the truth of the other content words in the hypothesis; and fourth, that the probability that a content word in the hypothesis is true is primarily dependent upon a single content word in the text. The basic idea, then, is to find an alignment between the text and the hypothesis in such a way as to maximize the probability of entailment. In order to do this, of course, the authors need to come up with the probability that a given content word entails another content word. To do this, they use a search engine and maximum likelihood: given two words, *n* and *m*, the probability that *n* entails *m* is estimated as the number of documents in which both *n* and *m* appear over the number of documents in which *n* appears. Once they've found the best alignment and calculated its probability, the authors compare the probability to a threshold; if it's over that threshold, the example is marked as positive.

Delmonte et al. (2005) use a rather complicated approach to the problem. Their system involves two subsystems, with the output of the first subsystem piped into the second subsystem. The first subsystem is relatively straightforward: it takes the text and the hypothesis as input, and outputs a list of head-dependent structures labeled with their grammatical relations and their semantic roles. The second subsystem either assigns a score to an example, where a lower score is better than a higher one, or simply labels the example as *false*. The latter occurs if the example fails a consistency check; these checks look for things such as the presence of antonyms, differing time values (e.g. 1992 vs 2003), and differing locations (e.g. England vs France). This subsystem consists of two modules. The first module consists of five subcalls based in linguistics; and the second module scores an example based on the number of matching heads, dependents, grammatical relations, and semantic roles between the text and the hypothesis. Each subcall of the first module requires certain aspects of the text and of the hypothesis to match. The idea is to first try to find obvious cases of entailment (for example, when only word order has been changed), and to then work down to situations where the system has little more than a rough estimate of semantic similarity to work with. Thus, they

are ordered in such a way that the earlier subcalls give lower (and thus better) costs than the later ones, as those subcalls are also more likely to be indicative of entailment. We won't go into detail about all five of these subcalls, but, for example, the first subcall requires the main predicates of the text and hypothesis to match, as well as their core arguments, although certain semantic roles may be changed (a pair such as *I killed Bob* and *Bob was killed by me.* would fit the requirements of this subcall). By contrast, the fifth subcall allows the main predicates to be different, but the core arguments must be synonyms of one another, and another non-argument head-driven structure must also be matched. For later subcalls, the second module is used to supplement the decision. Unfortunately, the authors don't go into detail about precisely how the examples are scored, but ultimately they are compared against some threshold; if they score below that threshold, they are classified as positive.

We now detail three very simple systems: Andreevskaia et al. (2005), Bos and Markert (2005) (system 1), and Jijkoun and de Rijke (2005). Andreevskaia et al. (2005) compare Predicate Argument Structures; a PAS contains a verb, its subject, and its object (if any). They transform the hypothesis and the text into PASs by extracting the noun phrases and the verb groups from them, and then parsing them using either the Link parser (Sleator and Temperley, 1993) or the RASP parser (Briscoe and Carroll (2002), whichever creates more PASs). They also find coreference chains for the text and for the hypothesis, both separately and together. Once it has the PASs, their system checks to whether a numerical value exists in the hypothesis that does not exist in the text; if it does, it classifies the example as negative. Next, it transforms any passive PASs into active ones, and uses WordNet to compute the distance between verbs in the text and in the hypothesis. If this distance is below some threshold, and both verbs have subjects and/or arguments, and if the corresponding subjects and/or arguments share coreferences, then the example is classified as positive. Finally, the system checks whether the hypothesis contains the pattern *X is Y*; if it does, and there exists some X' and some Y' in the text such that X' is in the same coreference chain as X and that Y' is in the same coreference chain as Y, the example is marked as positive. Otherwise, the example is classified as negative.

Bos and Markert (2005) (system 1) is particularly simple. It first tokenizes and lemmatizes the text and the hypothesis. Using the Web as a corpus, it assigns each lemma in the hypothesis an IDF value. It then initializes the similarity score of the text/hypothesis pair to zero, and looks at the word overlap between them: if a lemma in the hypothesis exists in the text, its IDF value is added to the score; otherwise, its IDF value is subtracted from the score. The score is then normalized by dividing it by the sum of the IDF values of the lemmatize in the hypothesis. This normalized score, which has a value between -1 and 1 (inclusive), is then compared against a threshold. If it's greater than the threshold, the example is classified as positive; otherwise, it's classified as negative.

Jijkoun and de Rijke (2005) use a bag-of-words approach. First, they assign each word a weight; for this they use its normalized inverse document frequency, as calculated over a corpus of newspaper texts. Then, for each word in the hypothesis, they use a similarity measure to find the most similar word in the text. They try two different similarity measures: a dependency-based measure (Lin, 1998) and a measure based on lexical chains (Hirst and St-Onge, 1998). Starting with a total similarity score of zero, for each word in the hypothesis, they add its weight multiplied by the similarity value of its most-similar word to the total score. If no similar word could be found (that is, all the words in the text gave a similarity score of zero), then the weight of the word is subtracted from the total score. The total similarity score is then normalized by dividing it by the total weight of the words in the hypothesis. It's then compared to a threshold, and if it's greater or equal to that threshold, the example is classified as positive; otherwise, it's classified as negative.

The final system we describe here is that of Newman et al. (2005). We left this for last, as it is the most similar to our own system (albeit, as mentioned earlier, designed for a somewhat different purpose). Newman et al. (2005) use a decision-tree classifier trained on the development data. The features it uses to classify examples include the ROUGE metrics (Lin and Hovy, 2004), cosine similarity, synonym matching using WordNet, Latent Semantic Indexing, and the antonym and similar-to relationships for verbs from VerbOcean (Chklovski and Pantel,

2004). They also use several features based on the longest common subsequence between the text and the hypothesis; these include a feature that indicates whether the subsequence contains a synonym, another that indicates whether the subsequence contains an antonym, another that handles both of these cases, and yet another that handles both of these cases and also looks for the presence of the word *not*. The authors also try using the task (comparable documents, machine translation, etc.) as a feature: this leads to better results on certain tasks, but slightly worse performance overall.

3.5.3 Discussion of results

Looking at Table 3.2, we can see that that none of these systems do particularly well. Recall that the data set is split evenly between positive and negative examples. This means that a classifier that simply labeled all of the examples positive, or labeled all of them negative, would have an accuracy of 0.5. The systems that cover all of the examples (as opposed to those with only partial coverage) really don't do much better than this. Furthermore, what improvement the systems do show over the baseline comes almost entirely from a single source: the comparable documents task. This may explain why the two systems that do the best are Bayer et al. (2005) (system 2) and Glickman et al. (2005): both systems use a form of statistical sentence alignment.

One exception to this is Delmonte et al. (2005): their system does best on the paraphrase acquisition task. Their impressive results on the testing data (0.8 accuracy) may be misleading, as their system only had an accuracy of 0.671 for the same task over the training data. Still, their system does far better at this task than any of the other systems. This may be due to the organization of their system: as mentioned earlier, it works to classify exceptional cases, such as where there are obvious paraphrases, before dealing with standard cases. Since some of the examples in this task category are such obvious paraphrases, this could explain this system's performance on that task.

All told, it's a bit discouraging that even the most complex of methods don't do much better

System	Coverage	Accuracy							
		By Task							Overall
		IR	CD	RC	QA	IE	MT	PP	
Akhmatova	100%	0.511	0.587	0.521	0.477	0.508	0.492	0.520	0.519
Andreevskaia, et al. (thresh=1)	100%	0.52	0.64	0.51	0.45	0.51	0.47	0.50	0.52
Andreevskaia, et al. (thresh=3)	100%	0.53	0.63	0.48	0.45	0.52	0.47	0.50	0.52
Bayer, et al. (system 1)	73%								0.516
Bayer, et al. (system 2)	100%								0.586
Bos, et al. (system 1)	100%								0.555
Bos, et al. (system 2)	100%								0.563
Braz, et al.	100%	0.522	0.773	0.514	0.500	0.500	0.533	0.500	0.561
Delmonte, et al.	100%	**0.622**	0.687	0.521	**0.585**	**0.583**	0.467	**0.800**	**0.593**
Fowler, et al.	100%	0.478	0.780	0.514	0.485	0.483	0.542	0.450	0.551
Glickman, et al.	100%	0.500	0.833	0.529	0.492	0.558	**0.567**	0.520	0.586
Herrera, et al.	100%	≤ 0.558	0.787	≤ 0.558	≤ 0.558	≤ 0.558	≤ 0.558	≤ 0.558	0.548
Jijkoun, et al.	100%	0.533	**0.847**	0.493	0.423	0.550	0.467	0.420	0.553
Newman, et al. (w/ task)	100%	0.446	0.747	**0.571**	0.515	0.558	0.475	0.520	0.563
Newman, et al. (w/out task)	100%	0.544	0.740	0.529	0.539	0.492	0.508	0.560	0.565
Pazienza, et al. (manual params)	100%	0.444	0.765	0.486	0.395	0.467	0.521	0.540	0.525
Pazienza, et al. (SVM-tuned params)	100%	0.489	0.644	0.521	0.457	0.492	0.479	0.500	0.518
Raina, et al. (single weight)	100%	0.567	0.793	0.529	0.485	0.475	0.467	0.580	0.562
Raina, et al. (multiple weights)	100%	0.556	0.840	0.507	0.439	0.550	0.475	0.540	0.552
Wu (w/ stoplist)	100%	0.478	0.700	0.450	0.446	0.517	0.392	0.520	0.505
Wu (w/out stoplist)	100%	0.467	0.713	0.471	0.408	0.550	0.400	0.560	0.513

Table 3.2: The performance of the various systems submitted for the PASCAL RTE challenge. Where results were unavailable, we have left the cells blank. Best scores in each category are marked in bold.

(if at all) than simple word overlap. To make matters worse, according to Dagan et al. (2005), *none* of the systems had a significantly better F-score than a classifier that labels all of the examples true (0.67).

3.6 What makes our method different?

We've already discussed the ways in which the goal of this thesis is different from that of the systems submitted for the PASCAL RTE challenge. But what makes our system different from the other systems we described—those that detect paraphrases?

As opposed to the unsupervised methods (Shinyama et al. (2002), Barzilay and Lee (2003), and Quirk et al. (2004)), our method tries to maximize recall. Because they are mainly concerned with obtaining paraphrases for use in rewriting rules from a large, unannotated corpus, these methods may be missing large numbers of less-than-obvious paraphrases in favor of obvious ones. It would, of course, be possible to test these methods on an annotated corpus, but that wasn't the main concern of the authors of these approaches.

Of course, Barzilay and Elhadad (2003) *are* concerned with recall, in the same way we are. The main difference between our approach and theirs, then, is that we assume that paraphrases are a *very rare* class—and use a corpus that reflects this assumption—while they do not.

Finally, and related to this assumption, all of these approaches use comparable documents for their corpora. As we have seen in the PASCAL RTE challenge, something about comparable corpora makes entailment—and thus paraphrases—easier to detect; most likely, there's more lexical overlap between paraphrases in comparable corpora than is the case in other corpora. Our corpus does not contain comparable documents: while the reviews we use are of the same film, they deal with totally different aspects of said film, and in fact say completely different (or even opposite) things about the film.

Chapter 4

Finding Paraphrases Using PNrule

4.1 Our goal

Our goal in this thesis is to use the PNrule algorithm in combination with a set of simple measures to detect paraphrases in corpora containing documents about the same subject within which:

- paraphrases are extremely rare; and
- a single simple measure, such as cosine similarity, cannot be used effectively to detect paraphrases.

Within our corpus, paraphrases are, for the most part, found only at the clause level. Ideally, we'd like to match pairs of clauses, where one member of the pair is a paraphrase of the other member. However, we felt that attempting to automatically extract clauses from sentences would introduce error into a system that, due to the nature of the data, cannot handle much error, and extracting them by hand would be impractical. Instead, we attempt to match sentences where one sentence contains a clause that is a paraphrase of a clause in the other sentence. This is basically what Barzilay and Elhadad (2003) attempted to do, albeit with a very different data set.

		Annotator 1		
		Yes	No	Totals
	Yes	33	29	62
Annotator 2	No	75	74067	74142
	Totals	108	74096	74204

Table 4.1: The original agreement matrix.

4.2 Our corpus

For our corpus, we used a set of reviews from Epinions.com (`www.epinions.com`). In particular, we used reviews of the movie *Spider-Man 2*. While we used all 99 reviews available for latent semantic indexing (which we'll get to later), we used five of these articles to create our training and testing sets. First, we paired the articles with each other, giving us a total of 10 pairs of articles, with a total of 74,204 pairs of sentences. Then, we had two judges annotate each article pair, marking those sentence pairs that had a clause-paraphrase relationship. We can see a quantitative summary of the results of this annotation in the agreement matrix of Table 4.1.

If we simply looked at the percentage of examples upon which our annotators agreed, we'd come up with an agreement value of $\frac{33+74067}{74204} \approx 0.99$. However, this measure would ignore the fact that it's far more likely for the annotators to agree on a negative example than a positive one. There are several reasons for this:

1. the number of negative examples far exceeds the number of positive examples. This may cause the annotators to prefer to mark a difficult-to-classify example as negative; this is exacerbated by the fact that

2. all of the examples are marked as negative by default—the annotators then search out and mark the examples that are positive (this also means that if both annotators simply

fail to find a positive example, it will be agreed upon as negative—an entirely plausible scenario); and also by the fact that

3. most of the negative examples are obviously negative (that is, the two sentences have absolutely nothing in common), while the positive examples are not necessarily as easy to identify.

The fact that the two annotators are more likely to agree on a negative example than on a positive one is reflected in the *expected agreement* of the annotation. The expected agreement is the proportion of examples expected to be agreed on by chance. A measure known as *kappa* has been developed to measure agreement while taking into account expected agreement.

Originally, kappa was only 0.388. According to Landis and Koch (1977), this indicates only fair agreement. However, due to the annotation method we used, it was entirely possible that some of the "disagreement" was actually caused by one annotator spotting a paraphrase that the other had missed. Because paraphrases are very rare in our corpus, it would both be easy to overlook them, and severely affect the kappa score if a few were to be overlooked. To distinguish between actual disagreement and overlooked paraphrases, we had the annotators take a second look at the pairs upon which they disagreed. The resulting agreement matrix can be seen in Table 4.2. Using these new totals, the kappa value is 0.792, which indicates substantial agreement. This indicates that much of the original disagreement was indeed due to overlooked paraphrases, as opposed to actual disagreement over what constitutes a paraphrase.

Discarding the examples the annotators disagreed on, this gave us a total of 90 positive examples and 74,067 negative examples: we are indeed dealing with a very rare class.

The rareness of this class made determining our testing and training sets somewhat difficult. We wanted to keep the article pairs either entirely in the training set, or entirely in the testing set; this way, it would be as though the system were seeing entirely new pairs of articles during training.[1] There were two reasons for this: first, we use information about the paragraphs

[1]Although our system would've seen both of these articles before individually, we don't see this as an issue,

		Annotator 1		
		Yes	No	Totals
	Yes	90	8	98
Annotator 2	No	39	74067	74106
	Totals	129	74075	74204

Table 4.2: The agreement matrix after disagreements had been re-examined.

in which the sentences are embedded in our system, and thus it's more realistic to assume the system is looking at pairs of articles; second, and more importantly, it may be that several types of paraphrasing occur within an article, and thus, we want a sample that would include all such types. In theory, were we simply to treat all of the pairs as one big bag, it might be possible that we'd only end up with one type of paraphrasing in our test set—particularly since there are so few positive examples. We ended up with approximately 79% of the positive examples in the training set, and 21% of the positive examples in the testing set.

4.3 Measuring the signature clarity of a model

Throughout this thesis, we have discussed class signatures. The signature of a class is the combination of measure-values that indicate the presence of that class. The point of a machine-learning algorithm is to develop a model that imitates that signature; the clearer the signature, the easier this task is.

There are, of course, many signatures within a particular hypothesis space, all of which can be considered to be an approximation of the class signature. We wanted to be able to measure how well a particular signature approximated the class signature of the target class. We call this

as our method looks at each pair of sentences individually, without retaining any information about a particular article. Thus, whether the system has trained on a particular article is not an issue; it's whether the system has trained on a particular *pair* of articles that matters.

measure *signature clarity*, because it reflects the amount of noise added to the class signature to create the hypothesis signature. A clear signature (which would have a value of 1 with this measure) would be one that 1) covered all of the target class examples, and 2) covered none of the non-target class examples. Thus, we felt our measure should reflect two things: 1) how strongly the presence of the target class indicates the presence of the signature, and 2) to what degree the signature has been polluted by the signature of the non-target class (less pollution should lead to a higher score). We refer to 1) as the signature's *strength*, and to 2) as the signature's *purity*. Recall is an excellent measure of the former. But how do we measure the latter? It seems to us that this should be determined by how well the signature covers the target class, versus how well it covers the non-target class. Thus, we arrive at the following measure for purity:

$$P_S = \frac{R_C}{R_C + R_{NC}}$$

where R_C is the recall of the target class, and R_{NC} is the recall of the non-target class. A signature's clarity is the product of its purity and its recall; thus

$$Cl_S = R_C \cdot \frac{R_C}{R_C + R_{NC}} = \frac{R_C^2}{R_C + R_{NC}}$$

Since in effect a model is simply a hypothesis signature, we can measure the signature clarity of a model.

So what distinguishes this measure from the F_1 measure? The difference is that the F_1 measure only focuses on how well the model identifies examples of the target class, without taking into account the nature of the non-target class. This means that, for instance, in a data set where there are 99 positive examples and 1 negative example, simply picking a trivial hypothesis that covers all of the examples gives a very high F_1 measure; whereas in a data set with 99 negative examples and 1 positive example, the same hypothesis gives a very low F_1 measure. Our clarity measure, on the other hand, will always give this trivial hypothesis a score of 0.5, regardless of the relative sizes of the classes. This is because the target class perfectly predicts the presence of the signature (i.e., the trivial hypothesis), but so does the non-target

class.

4.4 Changes to PNrule

During development, we noticed that, despite its focus on rare cases, PNrule was vastly overfitting its model to the training data: during the rule-refinement stage, it would often discover rules that covered only a single positive example. The problem was that, despite their low support, these rules would often have a higher Z-number than the alternatives. We also noticed that these rules usually consisted of a single range condition. In order to combat this overfitting problem, we made two changes to PNrule.

First, we removed PNrule's ability to treat a range as a single condition of a rule. You'll recall that in its original formation, PNrule was capable of discovering conditions such as $0 \leq v_1 < 1$, where v_1 is some attribute. However, we noticed that this allowed PNrule to discover highly accurate rules by using range conditions to cover a very small number of examples. It was our hypothesis that the problem was that, because ranges were treated as a single condition, PNrule was examining these before it could find potentially better combinations of conditions. Note that we did *not* remove the ability of PNrule to discover ranges—only that now a range is treated as two conditions of a rule instead of a single condition (i.e., $0 \leq v_1 < 1$ becomes $v_1 \geq 0 \wedge v_1 < 1$). Thus, PNrule compares a given range to all other possible pairs of conditions, instead of comparing it to unary conditions.

Second, we added add-one smoothing during the calculation of the Z-number. The advantage of using add-one smoothing in this manner is that it significantly lessens the accuracy value assigned to rules with low coverage without significantly affecting the accuracy value assigned to rules with high coverage. For instance, if a rule covered one positive example and no negative examples, its accuracy value would be reduced from 1.0 to $\frac{1+1}{1+2} = 0.66$, whereas if a rule covered 100 positive examples and no negative examples, its accuracy value would only be reduced to $\frac{100+1}{100+2} = 0.99$.

Although, as we will see in the results, PNrule was still unable to find a particularly good model, it did begin to make reasonable choices given the training data, and ceased to drastically overfit the data. Note that this reflects one of the great advantages of rule-based machine learning: because we were able to understand the model that PNrule was outputting, we were able to make adjustments to improve its performance.

In addition to these changes, we also created a second version of PNrule, wherein we substituted signature clarity for the Z-number during the rule-building stage, and changed the stopping condition for rule building during both the P-stage and the N-stage to a less than 0.05 increase in the clarity value of the rule. Why did we do this? Originally, we had conceived of signature clarity in order to aid discussion during the analysis of our results. However, it occurred to us that signature clarity has a property that makes it useful for PNrule. When the target class is significantly smaller than the non-target class, the purity of the rule quickly approaches 1. Thus, in order to obtain a high clarity in this situation, an algorithm will focus on maximizing recall. By contrast, if the target class is significantly larger than the non-target class, covering only a few of the non-target examples will cause the purity value—and thus the clarity value—to be very low; in such a situation, an algorithm will focus more on precision. This is precisely the behavior we'd like to see in PNrule. Note, however, that while a large disparity between the sizes of the target and non-target class can cause the purity value to approach 1 very quickly, the same is *not* true for recall. Thus, at the very least, PNrule must always balance recall with precision, while in some cases it can nearly ignore the latter in favor of the former. This asymmetry is important; if it were possibly to nearly ignore recall, we'd end up with a model containing a large number of rules, each of which would cover only a small number of examples; this would mean the model was overfitting the data.

4.5 Preprocessing

Our preprocessing consists of the following steps:

1. Expanding contractions
2. Part-of-speech tagging
3. Removing auxiliary verbs
4. Removing certain parts of speech

We detail these steps below.

4.5.1 Expanding contractions

We use a small set of heuristics to expand contractions back into their component words. For instance, we replace *can't* with *can not*, and *won't* with *will not*. We do this so that phrases such as *can't go* will match with phrases such as *cannot go*.

4.5.2 Part-of-speech tagging

In order to tag our data, we use the rule-based part-of-speech tagger developed by Eric Brill (Brill, 1994), and trained on the Brown corpus. Although it would've been preferable to retrain the tagger on data more similar to our own, we simply did not have a large enough tagged corpus available to do so. We examined our data after it had been tagged, however, and the Brill tagger seemed to do a reasonable job; its most common mistake was to mis-tag adjectives as nouns. We felt it was better to try measures based on imperfect tagging than to leave out tagging altogether. A possibility for the future would be to train a tagger that learns in an unsupervised fashion; we'll return to this idea in Chapter 5.

4.5.3 Removing extra verbs

It's possible for auxiliary verbs to cause a pair of sentences to have a higher similarity measure than that pair ought to have. For example, the pair of sentences *I am running* and *I am dancing* will have a higher similarity measure than the pair of sentences *I dance* and *I run*. We thus

want to remove any auxiliary verbs from our corpus. We do this as best we can by removing any form of the verbs *to have* or *to be* that is followed by another verb. The reason we don't simply remove all *to have* or *to be* verbs is because in cases where they are not auxiliary, they are potentially important indicators of paraphrasing.

4.5.4 Removing certain parts of speech

In many applications similar to this one, function words are removed from the corpus. *Function words* are those words that carry little lexical meaning (Strazny, 2005). However, we found that in many lists of function words, words that were useful to our measures (such as forms of the verb *to be*) were included. Thus, instead of removing function words, we decided to try to remove words with certain parts of speech that seemed to indicate that they did not carry much semantic meaning. With that in mind, we remove words with the following parts of speech from the tagged versions of our corpus: determiner (*all*, *an*, etc.), preposition or subordinating conjunction (*astride*, *among*, etc.), modal auxiliary (*can*, *cannot*, etc.), pre-determiner (*all*, *both*, etc.), and interjection (*golly*, *gosh*, *jeepers*, etc.). We believe that this serves the same purpose as removing function words, while allowing us to be more precise by allowing us to distinguish between multiple syntactic uses of the same word. For instance, while *that* may not be useful to our system as a determiner, it may well be useful as a WH-pronoun.

4.6 Measures

There were two overarching, and conflicting, concerns when we were developing these measures. The first was that for any measure we might use that relies on matching lexical units, two long sentences are much more likely to have a number of matches, regardless of what we are trying to match, than are two shorter sentences. Thus, it would appear that regularization is key. However, we are interested in matching *clauses*, not sentences. So, for instance, take two pairs of sentences:

1. a. *The boy jumped the fence.*

   b. *The boy hopped the barrier.*

2. a. *Susan walked to the store, and the boy jumped the fence.*

   b. *As impossible as it may seem, the boy hopped the barrier.*

Both of these should be positive examples, as they both contain clauses with a paraphrase relationship. However, due to regularization, the latter pair would score lower than the former.

We thus use a series of measures, of two types: continuous and binary. We try to combine measures that look at the whole sentence with others that we hope will help to pinpoint clauses with a paraphrase relationship. We'll explain the reasoning behind each measure as we proceed.

Note that for all of our measures, a word can only be matched to once. For computational reasons, we end up using a greedy matching algorithm for these measures. Thus, it's possible that for some of our measures, particularly those using WordNet, we end up with sub-optimal measures.

4.6.1 Regularization of continuous measures

We have to regularize most of our continuous measures (LSI and cosine similarity being the exceptions). We tried two different regularization methods. The first we took from Hatzivassiloglou et al. (2001). Given two textual units, A and B, where A contains $|A|$ features and B contains $|B|$ features, we divide our measure by $\sqrt{|A| \cdot |B|}$. For word matching, this means we use the number of words in A and B; for bigrams, it means we use the number of bigrams in A and B; etc.

The second method we tried was simply to divide the measure by the number of features in the shorter of the two sentences. Since we are looking for clause-level paraphrases, it's possible that a long sentence could contain a clause that was a paraphrase of a shorter sentence. This method would give much higher scores in such cases than would the first method.

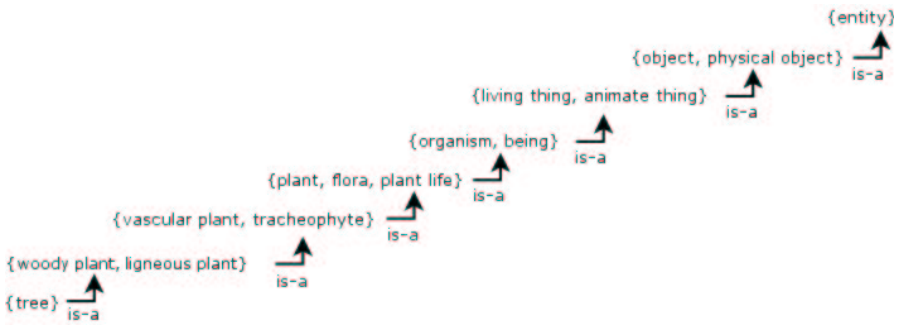


Figure 4.1: The hypernyms of the synset {tree}.

After testing both methods during development, we settled on the one from Hatzivassiloglou et al. (2001), as it appeared to lead to more accurate results.

4.6.2 Word-stem matching

Our simplest measure is word-stem matching. First we use the Lingua::Stem::Snowball module (Potencier, 2005), a Perl implementation of the Porter stemming algorithm (Porter, 1980), to stem the two words we are comparing, and then we see if they match. We count the number of matching word-stems, and then regularize the results as detailed above.

Porter stemming algorithm

The Porter stemming algorithm is a widely-used algorithm, for the reasons that it is small, fast, reasonably simple, and has been shown to effectively improve the performance of information retrieval systems (Porter, 1980). While ours is not an information retrieval system, Porter's point that "terms with a common stem will usually have similar meanings" (Porter, 1980) holds equally well in this domain, and is at least as important.

4.6.3 Using WordNet

All of the measures using WordNet (Fellbaum, 1998) are continuous, and are regularized as described above. In order to access WordNet's database, we used the WordNet::QueryData Perl module (Rennie, 2005).

Matching immediate hypernyms

First, we should describe what we mean by an "immediate" hypernym. By this, we mean the synset that is the parent of the synset we are concerned with. Thus, for our earlier example, the immediate hypernym of {tree} is {woody plant, ligneous plant}. Naturally this is a flawed measure: in reality, there may be times when replacing {tree} with {plant, flora, plant life}, or even with {entity}, would make sense. Nevertheless, we hope that this will provide our method with information lacking in our simple word-matching measure.

We match two word senses if any of the following hold:

1. The two words are the same; or

2. The synset of one word is the same as the immediate hypernym of the other word; or

3. The immediate hypernyms of the synsets of the two words are the same.

We actually gather four measures here. First, we ignore the part-of-speech of each word. This means that we could in effect be looking at several words: for instance, since *knife* can be either a noun or a verb, we'd look at both the senses of knife (noun) and the senses of knife (verb). We compute one measure where we try to match for any sense of the two words, and another measure where we try to match for only the most frequent senses of the words. We do this because using the less frequent senses can lead to some strange results. For example, during development, we found that the word *son* was being matched with the word *father*. As it turned out, both *son* and *father* had a sense corresponding to the Christian Trinity, and thus both had the hypernym *hypostasis*, which refers to any of the three aspects of the Trinity. The

most frequent senses of *father* and *son* were, however, the senses we had in mind. On the other hand, we don't want to discount the less frequent senses entirely: using only the most frequent sense should increase precision, while matching for any sense should increase recall. By including both, we hope that PNrule will find a happy medium.

We then compute these two measures a second time, only this time we do take the part-of-speech tag into account, matching only for senses of the word that match the part-of-speech tag. Relying on a measure that matches any part of speech should lead to higher recall, while relying on a measure that matches specific parts of speech should lead to higher precision; again, this reflects the balance between recall and precision we hope to achieve. This is a common theme throughout our measures.

Matching synsets

This measure is much like the hypernym measure, except that we simply check whether two words belong to the same synset. Like the hypernym matching, we do this four times: ignoring and taking into account the part-of-speech tag, and allowing any or only the most frequent senses to match.

4.6.4 Using VerbNet

In our examination of our results during development, we found that while WordNet worked fairly well for nouns, adverbs, and adjectives, it would often fail to match verbs that seemed as though they ought to have been matched. For instance, given the two phrases *the chip was shattered* and *the chip was destroyed*, it failed to match *shattered* with *destroyed*. This was, of course, not a fault with WordNet—*shatter* and *destroy* are not synonyms of one another. Nevertheless, we felt that such verbs ought to be matched in our system. Thus, we took the data from VerbNet (Kipper et al., 2000), and associated each verb with its Levin class (Levin, 1993). There are 193 Levin classes, and verbs are grouped into these classes based upon their argument syntax; while not perfect, these classes do give a rough indication of semantic

similarity.

Unlike with WordNet, where we used a Perl module to access a database, with VerbNet we simply took an XML file and parsed it into a hash table, with the verbs as the keys and the Levin classes as the values. We then altered our WordNet measures so that if two words could both be considered verbs, they would be matched if they were in the same Levin class.

In addition, we created a new binary measure, which is set to **true** if the two sentences contain verbs that share the same Levin class. We chose this as a binary measure because we are looking for pairs of clauses that share a paraphrase relationship, and we thought that a matching pair of verbs might indicate the presence of such a clause regardless of the lengths of the two sentences.

4.6.5 Bigram and trigram matching

An *n*-gram is a sequence of tokens. Two *n*-grams match if, for each position in the first *n*-gram, the token occupying the same position in the second *n*-gram matches the token in the first *n*-gram. We matched bigrams and trigrams of word-stems and of most frequent synsets. For the most frequent synsets, we also took part-of-speech tags taken into account. Because it is unlikely that such bigrams and trigrams would appear in entirely unrelated sentences, the idea behind these measures is to increase precision by finding a small number of pairs of sentences that are highly likely to share a clause-paraphrase relationship. These measures are continuous, and are regularized using the method described earlier.

4.6.6 Skip-one bigram matching

Related to our measure above, for these measures we created bigrams and *skip-one bigrams*. The latter is created by using one word-stem or synset as the first position in the bigram, and the word-stem or synset two words to the right of that word for the second position. Thus, whereas using regular bigrams the sentences: *The dog ran* and *The fat dog ran* would have

only one matching bigram ($\langle dog, ran \rangle$), with these measures, these same sentences would have one matching bigram and one matching skip-one bigram ($\langle the, dog \rangle$, and $\langle dog, ran \rangle$). Note, however, that this does change the number of potential matches, and thus the regularization: for traditional bigrams, the first sentence contains two potential matches ($\langle the, dog \rangle$, $\langle dog, ran \rangle$), and the second contains three ($\langle the, fat \rangle$, $\langle fat, dog \rangle$, $\langle dog, ran \rangle$); under this measure, the first sentence contains three possible matches ($\langle the, dog \rangle$, $\langle the, ran \rangle$, $\langle dog, ran \rangle$), and the second sentence contains five ($\langle the, fat \rangle$, $\langle the, dog \rangle$, $\langle fat, dog \rangle$, $\langle fat, ran \rangle$, $\langle dog, ran \rangle$). It may thus seem like there's no advantage to using these measures instead of measures using standard bigrams; after all, under a standard bigram measure, using our first regularization method, the similarity between these two sentences is approximately $\frac{1}{\sqrt{2 \cdot 3}} \approx 0.577$, whereas under this measure the similarity is only $\frac{2}{\sqrt{3 \cdot 5}} \approx 0.516$. However, a value of a particular measure should be judged only relative to other values of the same measure. For example, consider a third sentence, *No dog ran*. Using a traditional bigram measure, this would have the same similarity to the sentence *The fat dog ran* as does the sentence *The dog ran*. However, using this measure, it would have a similarity measure of only $\frac{1}{\sqrt{3 \cdot 5}} \approx 0.258$, less than the 0.516 similarity measure of the first two sentences. It's our hope that this measure could thus capture something measures based on simple bigrams cannot.

4.6.7 Matching within a window

The problem with the above measures is that while we are looking for clauses with a paraphrase relationship, they are all measures on sentences. It occurred to us that simple clauses often consist of a small sequence of contiguous words, and thus it might make sense to use the measures listed above on small "windows" of words within each pair of sentences. We thus collect the word-stem, hypernym, and synset measures on windows containing 4–7 words, and take the highest values.

As an example, let's look at the sentences *Betty walked the dog, while Bob prepared dinner* and *Later that afternoon, Betty walked the dog*. For the sake of simplicity, assume we don't

remove any words. Then four words are the same in both sentences: *Betty*, *walked*, *the*, and *dog*. Our normal word-stem measure would return a value of $\frac{4}{\sqrt{8 \cdot 7}} \approx 0.53$. However, if we use a window of size 4, we'll end up with a value of 1, because four consecutive words match in each sentence. On the other hand, if we had two sentences, *Bob walked the dog, while Betty prepared dinner* and *Later that afternoon, Bob prepared dinner*, the value of the word-stem measure would still be approximately 0.53, since four words still match, but the windows-of-size-4 measure would've been reduced to 0.5, since the highest-scoring windows would now be *while Betty prepared dinner* and *afternoon, Bob prepared dinner*.

4.6.8 Latent semantic indexing

For this measure, we trained Telcordia's LSI program (Chen et al., 2001) using the sentences of the 99 reviews of *Spider-Man 2* found on Epinions.com. We used log entropy term weighting, and 100 factors. We used the same program to find the similarity values between the sentences. There was no need for us to regularize this measure, as regularization is built into cosine similarity (and thus LSI).

4.6.9 Using the similarity of containing paragraphs

As mentioned in Chapter 3, Barzilay and Elhadad (2003) found that using the cosine similarity of the paragraphs containing two potentially matching sentences could increase the accuracy of the results. We thus include two measures: the cosine similarity of the paragraphs, and the cosine similarity of the paragraphs without any proper nouns[2]. In order to gather the cosine similarity, we used Paul Clough's overlap program (Clough, 2001), which gives a number of similarity measures including cosine similarity.

In addition, we trained the LSI program using the paragraphs found in the 99 reviews of *Spider-Man 2* and then took the LSI values of the containing paragraphs, once with 100 factors

[2]We roughly estimate the latter by removing any capitalized word that does not occur at the beginning of a sentence.

and again with 25 factors. This of course serves the same purpose as the cosine similarity, but we thought that perhaps LSI would prove to be a better measure.

4.6.10 Complex measures

In order to further help us detect pairs of clauses sharing a paraphrase relation, we decided to use a series of binary measures based on a combination of lexical and syntactic features that we thought might indicate the presence of matching clauses within a pair of sentences. These features are a combination of three things: a pair of parts-of-speech that the matching words must conform to, whether or not these parts-of-speech must occur in a particular order, and whether these parts-of-speech must occur within a particular range of one another (separated by only a certain number of words or less). Two words match if their most frequent senses are in the same synset, or if they are both verbs in the same Levin class. We used this as our matching criteria because we expect these measures to increase recall, and thus wanted them to be as precise as possible. The features are as follows:

noun-verb ordered Each sentence must contain a matching noun-verb pair, in that order. This roughly corresponds to a subject-verb pair, where the verb follows something like a conjunction; for instance, *The boy went to the store and bought a pear* would match *The boy bought a pear*.

noun-verb ordered ranged Each sentence must contain a matching noun-verb pair, in that order, within a range, which varies from 1–5 words. This roughly corresponds to a subject-verb pair.

verb-noun ordered ranged Each sentence must contain a matching verb-noun pair, in that order, within a range, which varies from 1–5 words. This roughly corresponds to a verb-object pair.

verb-adverb ranged Each sentence must contain a matching verb-adverb pair, where the verb cannot be a form of *to be*, and where the matching words must be within a range of each

other. The range varies from 1–5 words. This allows us to match such phrase pairs as *quickly ran* and *ran quickly*.

be-adj ordered ranged Each sentence must contain a form of the verb *to be* followed by a matching adjective within a particular range, which varies from 1–5. We use this measure because a fairly commonly occurring clause is one of the sort ⟨*noun*⟩ is ⟨*adj*⟩. For example, this would help our system match *The ball is big* with *The ball is large*.

noun-noun ranged Each sentence must contain two matching nouns, which occur within a particular range of one another. This range varies from 1–5 words. This could be indicative of a number of relationships; it mainly reflects the fact that two clauses with a paraphrase relationship will often contain the synonymous pairs of nouns within close proximity to one another.

noun-adjective ranged Each sentence must contain a matching noun and a matching adjective, each within a particular range of one another. The range varies from 1–5. We include this measure because we are dealing with opinions, and thus a large amount of the meaning of a clause is likely to be found in pairs of nouns and adjectives (*excellent performance, exciting movie,* etc.).

4.6.11 Matching words with different parts of speech

One common method of paraphrasing is to transform a word with one part of speech into a related word with a different part of speech. For example, *Bob was responsible for the murder of Joe* and *Bob murdered Joe*; or, *The man was a giant* and *He was a giant man*. With this in mind, we created binary measures that reflected whether two words with different parts of speech shared the same stem. The matches we attempted were noun-to-verb, noun-to-adjective, verb-to-adjective, and adjective-to-adverb. For each of these measures, the result was **true** if such a match occurred in the sentence, and **false** if it did not.

4.7 Results

First, we had to create a baseline against which our results could be compared. Since Barzilay and Elhadad (2003) were also looking for sentences sharing clause-paraphrase relationships, we decided that, like them, we would use a cosine similarity threshold to create our baseline.[3] To do so, we found the cosine similarity of all of our examples, then took the threshold that gave us the best F_1 value on the training data and applied it to the testing data. The results can be seen in Table 4.4 (for the training data) and Table 4.5 (for the testing data).

We then collected the measures listed in the previous section. We ran PNrule on these measures, using the parameters that can be seen in Table 4.3. We picked these parameters partly on the suggestions of Joshi (2002), and partly on our judgment of what seemed reasonable. Note that due to our choice of **MinCExamplesToSplit** (which we took from Joshi (2002)), PNrule does not split the data; this is probably reasonable given the paucity of positive training examples.

As we can see from Table 4.4, the model found by PNrule over our lexical measures performed better during training than the model developed using a cosine threshold. It's worth discussing the model that PNrule came up with, as it has some interesting qualities. An example is potentially labeled as positive if one of two P-rules apply to it, and none of the N-rules do. The two P-rules were:

1. The skip-one-bigram word-matching measure is greater than 0.115 and the latent-semantic-indexing measure is greater than 0.586.

2. The latent-semantic-indexing measure is greater than 0.949.

There were other P-rules, but none of them had a confidence score over the threshold, so in effect we can ignore them. The N-rules that could apply to the two P-rules are listed in Figure 4.2. The N-rules are complicated and do not show any clear pattern, which demonstrates

[3]We thought of using Barzilay and Elhadad (2003), but during early development we had tried the method without much success. We chose cosine because we did not have any notion of how it might perform.

Parameter	Value
MinZ	3
MinSupportScore	1
MinCExamplesToSplit	100
MinCoverageP	0.5
MinSupFractionP	0.25
MinAccuracyP	0.25
MinRecallN	0.2
MaximumLengthIncrease	64

Table 4.3: Parameter values for PNrule.

that there isn't any obvious way to divide the true positives from the false positives.

The confidence levels for rules covered by one of the two P-rules, and by none of the N-rules, were 0.421 and 0.428, respectively. This is clearly what gives us our precision: if one of these two rules covers an example, there's a nearly 50% chance that the example will be positive (not bad, given the difficulty of our problem). Also interesting to note: even when covered by an N-rule, an example covered by the first P-rule would still have a confidence level of 0.4; by contrast, one covered by the second P-rule could have a confidence level of as low as 0.182. This demonstrates that a combination of measures is (perhaps unsurprisingly) likely to lead to a better result than use of a single measure.

Unfortunately, in the training set, P-rule 1 covered only 7 positive examples, and P-rule 2 covered only 4—even worse, as we can see in Table 4.5, they covered no positive examples in the testing data, which means that our method did no better than cosine threshold. Thus while we have a couple of rules that appear to be reasonable indicators, relatively speaking, of a clause-paraphrase relationship, they cover far too few examples to be useful in and of themselves.

Method	Recall	Precision	F_1
Cosine Threshold	0.042	0.1	0.059
PNrule	0.211	0.268	0.236
PNrule (clarity)	0.253	0.122	0.165
PNrule (3 measures)	0.127	0.130	0.129

Table 4.4: Precision, recall, and F_1 of the models learned on the training data.

We include the results of our clarity-measure-based version of PNrule as well. As we can see, it unfortunately doesn't perform any better than PNrule. However, the model it arrived at was far simpler. This model consisted of a single one-condition P-rule, and two one-condition N-rules. In fact, the entire model can be summed up in one line:

$$\texttt{F\_HYP\_PoS} > 0.137 \wedge \neg(\texttt{LSI} \leq 0.531) \wedge \neg(\texttt{F\_HYP\_WIN}_5 \leq 0.5)$$

where F_HYP_PoS is the regularized most-frequent hypernym count, where the hypernyms must have the tagged part-of-speech; LSI is the latent semantic indexing measure; and $\texttt{F\_HYP\_WIN}_5$ is the regularized most-frequent hypernym count taken within a 5-word window. The P-rule covers 63 out of 90 of the positive examples, giving it a fairly high recall, but it also covers 15674 negative examples, giving it a terrible precision. The N-rules remove 24 and 12 positive examples, respectively, but also remove 14248 and 1292 negative examples. This gives us 18 out of 90 positive examples, and 134 negative examples, which, while not a stunning result, is the sort of behavior we'd want to see in PNrule. In particular, the use of the LSI measure, which in our data has low coverage but is highly precise, as an N-rule instead of a P-rule makes considerably more sense. Thus, while the performance of this version of PNrule on our data is not ultimately any better than the performance of the original version, it does leave us with a much simpler model, and behaves in a manner closer to what we'd expect in PNrule.

Method	Recall	Precision	F_1
Cosine Threshold	0	0	0
PNrule	0	0	0
PNrule (clarity)	0.053	0.045	0.049
PNrule (3 measures)	0.210	0.235	0.222

Table 4.5: Precision, recall, and F_1 of the models applied to the testing data.

As an experiment for further analysis, we decided to try running PNrule with small subsets of the measures. Of these, the best performance on the testing data was obtained by training on three measures: the cosine similarity of the containing paragraphs (ignoring proper nouns), the noun-noun ranged measure with a range of 3, and noun-adjective ranged measure with a range of 4. We label this "PNrule (3 measures)" in Table 4.4 and Table 4.5. As we can see, despite doing better on the testing data, it's still not a strong result—in fact, because it does no better on the training data, it's likely that it does better on the testing data due purely to chance.

4.8 Results on RTE dataset

Because its goal was similar to ours, we decided to also try our method on the first PASCAL RTE challenge dataset. In order to do so, we dropped all paragraph similarity measures (since the data didn't contain paragraphs), retrained the LSI model on the Reuters-21578 corpus (Lewis, 1999) (since we're now dealing with news articles, not movie reviews), and added a *task* category to our measures. In addition, we set **MinRecallN** to 0.02—since we're not dealing with a rare class (there are an equal number of positive and negative examples), there's no real need to worry about minimum recall. For the purpose of comparison, we've included the results of the systems submitted to the challenge, along with our own results, in Table 4.6.

As we can see, our results are in line with those of the other systems, with the comparable

1. $\texttt{F\_HYP\_PoS} \leq 0.137 \wedge \texttt{SYN\_PoS} \leq 0.213 \wedge \texttt{MATCH\_N\_ADJ} = false \wedge \texttt{ORDERED\_N\_V} = false \wedge \texttt{WORD} \leq 0.133 \wedge \texttt{PCOS} \leq 0.181$
2. $\texttt{SYN} \leq 0.26 \wedge \texttt{WORD\_WIN}_4 \leq 0.25 \wedge \texttt{HYP\_POS} > 0.146 \wedge \texttt{F\_HYP} > 0.118 \wedge \texttt{LSI} \leq 0.789 \wedge \texttt{PCOS} > 0$
3. $\texttt{F\_HYP\_PoS} \leq 0.166 \wedge \texttt{F\_SYN\_WIN}_7 \leq 0.286 \wedge \texttt{RANGED}_3\texttt{\_BE\_ADJ} = false \wedge \texttt{SYN\_PoS\_WIN}_7 \leq 0.429 \wedge \texttt{F\_HYP} \leq 0.218 \wedge \texttt{F\_SYN\_PoS} \leq 0.144$
4. $\texttt{PCOS} \leq 0.081 \wedge \texttt{ORDERED\_N\_V} = false \wedge \texttt{LSI} \leq 0.991 \wedge \texttt{HYP} > 0.171$
5. $\texttt{BISKIP\_SYN} \leq 0.02 \wedge \texttt{PCOS\_NOPROP} > 0.072 \wedge \texttt{ORDERED\_RANGED}_5\texttt{\_N\_V} = false \wedge \texttt{F\_HYP\_PoS} > 0.141 \wedge \texttt{PCOS} \leq 0.225$
6. $\texttt{PCOS} \leq 0.122 \wedge \texttt{HYP} \leq 0.476 \wedge \texttt{ORDERED\_RANGED}_5\texttt{\_V\_N} = false \wedge \texttt{SYN\_PoS} > 0.178 \wedge \texttt{PCOS\_NOPROP} > 0 \wedge \texttt{HYP\_PoS} \leq 0.6 \wedge \texttt{PCOS} > 0.056$

Figure 4.2: The N-rules discovered by PNrule over our measures. SYN is the regularized synonym count, HYP is the regularized hypernym count, and WORD is the regularized word count. If preceded by F_, only the most-frequent synonyms or hypernyms are matched. If followed by _PoS, only synonyms or hypernyms with the tagged part of speech are matched. If followed by $\texttt{\_WIN}_{\#}$, the count was obtained within a window of size #. If preceded by BI_, TRI_, or BISKIP_, the measure is of regularized bigrams, trigrams, or skip-one bigrams, respectively. PCOS is the cosine similarity of the containing paragraphs, PCOS_NOPROP is the same measure without proper nouns, and LSI is the latent semantic indexing measure. MATCH_, ORDERED_, and $\texttt{RANGED}_{\#}$ followed by two parts of speech indicate our stem-matching, ordered-matching, and ranged-matching measures, along with the parts-of-speech that have to be matched.

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documents task causing most of the overall accuracy improvement. The F_1 score we obtained was 0.67, a basically insignificant improvement over simply labeling every example as positive, which obtains a score of 0.666. We don't know precisely what the F_1 scores of the other systems were, but we do know from Dagan et al. (2005) that none of them do significantly better than this.

System	Coverage	Accuracy							
		By Task							Overall
		IR	CD	RC	QA	IE	MT	PP	
Akhmatova	100%	0.511	0.587	0.521	0.477	0.508	0.492	0.520	0.519
Andreevskaia, et al. (thresh=1)	100%	0.52	0.64	0.51	0.45	0.51	0.47	0.50	0.52
Andreevskaia, et al. (thresh=3)	100%	0.53	0.63	0.48	0.45	0.52	0.47	0.50	0.52
Bayer, et al. (system 1)	73%								0.516
Bayer, et al. (system 2)	100%								0.586
Bos, et al. (system 1)	100%								0.555
Bos, et al. (system 2)	100%								0.563
Braz, et al.	100%	0.522	0.773	0.514	0.500	0.500	0.533	0.500	0.561
Delmonte, et al.	100%	0.622	0.687	0.521	0.585	0.583	0.467	0.800	0.593
Fowler, et al.	100%	0.478	0.780	0.514	0.485	0.483	0.542	0.450	0.551
Glickman, et al.	100%	0.500	0.833	0.529	0.492	0.558	0.567	0.520	0.586
Herrera, et al.	100%	≤ 0.558	0.787	≤ 0.558	≤ 0.558	≤ 0.558	≤ 0.558	≤ 0.558	0.548
Jijkoun, et al.	100%	0.533	0.847	0.493	0.423	0.550	0.467	0.420	0.553
Newman, et al. (w/ task)	100%	0.446	0.747	0.571	0.515	0.558	0.475	0.520	0.563
Newman, et al. (w/out task)	100%	0.544	0.740	0.529	0.539	0.492	0.508	0.560	0.565
Pazienza, et al. (manual params)	100%	0.444	0.765	0.486	0.395	0.467	0.521	0.540	0.525
Pazienza, et al. (SVM-tuned params)	100%	0.489	0.644	0.521	0.457	0.492	0.479	0.500	0.518
Raina, et al. (single weight)	100%	0.567	0.793	0.529	0.485	0.475	0.467	0.580	0.562
Raina, et al. (multiple weights)	100%	0.556	0.840	0.507	0.439	0.550	0.475	0.540	0.552
Wu (w/ stoplist)	100%	0.478	0.700	0.450	0.446	0.517	0.392	0.520	0.505
Wu (w/out stoplist)	100%	0.467	0.713	0.471	0.408	0.550	0.400	0.560	0.513
PNrule	**100%**	**0.511**	**0.793**	**0.507**	**0.500**	**0.500**	**0.533**	**0.500**	**0.563**

Table 4.6: The performance of the various systems submitted for the PASCAL RTE challenge, plus PNrule's performance, included in bold. Where results were unavailable, we have left the cells blank.

4.9 Analysis

Now that we have discussed our results, we are left with two questions: how reliable are these results, and, if they are reliable, why didn't our approach work?

We anticipate that one criticism of these results might be the small number of positive examples in our training and testing data. While it's true that the number of positive examples

is small, given the proportion of positive to negative examples, we'd need a very clear signature to achieve reasonable results—clear enough that it should be obvious even given those few positive examples. Our method is clearly unable to find such a clear signature.

The question that remains, then, is why our method was unable to find a clear signature. Two possibilities exist, and the answer may in fact be a combination of these: our measures are inadequate, or rule-based models are inadequate.

Barzilay and Elhadad (2003) demonstrate that when using comparable corpora, it is possible to classify such sentence pairs with a good deal of success, using simple lexical measures. Assuming, as we did, that the paraphrases within our corpus were like those found in comparable corpora, the problem is that lexical measures at best provide only an approximation of semantic measures. In cases where the two classes are close in size, a reasonably good approximation will suffice. However, in rare cases, the approximation must be nearly perfect, because, as we discussed earlier, even a small amount of noise can lead to a large amount of error. It is probably not a coincidence that the most accurate rules were those using the LSI measure—of all our measures, this comes closest to approximating the underlying semantics of the sentences. Unfortunately, those rules do not have a particularly high recall.

All of that said, our results both on our own corpus and on the RTE dataset, in combination with the results of the other systems, suggest two things: first, that the paraphrases found in our corpus are *not* necessarily of the same sort found in comparable corpora, and second, that simple lexical measures are not sufficient when dealing with paraphrases outside of the comparable documents domain. To see why this is so, let's look at a few examples. First, here's an example of the sort of paraphrase we anticipated would be prevalent:

a. The red dog ran across the street.

b. The dog ran across the street.

As we can see, the only difference is that an adjective, *red*, has been dropped; this does not fundamentally change the meaning of the sentence. However, let us look at another example:

a. Osaka is the gastronomic capital of Japan.

b. Osaka is the capital of Japan.

Like the first example, the two sentences are lexically and syntactically very similar, and only an adjective, *gastronomic* has been dropped; however, this has *fundamentally altered* the meaning of the sentence. The difference is that *gastronomic* completely changes the meaning of the word *capital*, whereas *red* is an intersective adjective. In cases such as this, measures such as mutual information may be able to help.

However, let's look at another pair of examples. In the first example, the text unit is both lexically and syntactically similar to the first:

a. The event was a gastronomic delight.

b. The event was a delight.

Now let's compare that to a second example:

a. The event was a gastronomic delight.

b. The food at the event was absolutely delicious.

The second sentence in this example is far less similar both lexically and, particularly, syntactically to the first sentence than is the second sentence in the previous example; however, it's a much better paraphrase of the first sentence. What's more, outside of the comparable document domain, there are likely to be a number of negative examples that are equally or more lexically and syntactically similar to this first sentence than is our paraphrase. This turns out to be a far more prevalent problem than we had anticipated, particularly in our own corpus—due to the prevalence of negative examples—but also in the RTE corpus, where due to the annotation approach, it's more immediately obvious.[4] We hypothesize that due to the fact that two com-

[4]Due to the annotation process, many of the negative hypotheses in the RTE corpus are still very lexically similar to the texts.

parable documents are, in effect, descriptions of the same object or event, lexical similarity has a far higher correspondence with paraphrasing than in other domains.

This is not to say that lexical measures are entirely useless—in fact, when detecting paraphrases in cases where they are rare, most negative examples *can* be weeded out using simple lexical measures. For example, using our testing set, if we use a model where examples are labeled as *positive* if their LSI values are greater than or equal to 0.4, over half of the positive examples (57%) are marked as true, whereas only around 900 of the negative examples (less than 10%) are marked as true. However, that still leaves us with a 90-to-1 ratio of negative to positive examples, and the remaining negative examples cannot be easily distinguished from the positive ones using simple lexical measures. Thus it's clear that, whatever the weaknesses of PNrule, we need more sophisticated measures for this task.

The other possibility as to why PNrule couldn't find a clear signature in the hypothesis space is the limits of using this rule-based model: it has a difficult time discovering relationships between measures. For example, imagine we have two measures, $\mathtt{m}_1$ and $\mathtt{m}_2$, as well as a target class *C*. The signature for the target class could be something like $\mathtt{m}_1 + \mathtt{m}_2 > 1$. While a number of statistical machine-learning techniques could model this signature directly, a rule-based approach using the same class of rules as PNrule can only approximate it. For instance, it could come up with the following series of rules:

1. $\mathtt{m}_1 > 1$
2. $\mathtt{m}_2 > 1$
3. $\mathtt{m}_2 > 0.75 \wedge \mathtt{m}_1 > 0.25$
4. $\mathtt{m}_1 > 0.5 \wedge \mathtt{m}_2 > 0.5$
5. $\mathtt{m}_1 > 0.75 \wedge \mathtt{m}_2 > 0.25$

Even in cases where the target class was not rare, there's a difficulty in finding this approximation: in order to find one of the rules with two conditions, the first condition must do

better than all other possible first conditions. If, for instance, there was some measure, $\mathtt{m}_3$, and $\mathtt{m}_3 > 0.3$ gave better results than $\mathtt{m}_2 > 0.75$, rule 2 would not be discovered. This problem arises because the rule-refinement stage uses a greedy search; replacing it with, for example, a beam search might ameliorate this problem, but there's no computationally-friendly way to eliminate it entirely.

In addition, there is another difficulty that is specific to cases in which the target class is rare. By approximating the signature using several different rules, we split up an already-small pool of positive examples; each rule will, at best, cover only a tiny number of these examples. What's worse, we almost inevitably add error, either because the rules cover examples they shouldn't, or because they miss examples.

So, then, we are attempting to detect a semantic relationship with a set of measures that can at best only approximate semantics, and with a model that, in all likelihood, is only able to approximate the target-class signature. This, combined with the fact that, when dealing with a rare target class, even a few errors can lead to terrible results, likely explains why our method failed. The only question that remains is to what degree each of the two problems contributed to our method's failure—a question that will have to be answered in future work.

Chapter 5

Future Work

Clearly, a lot of work still has to be done toward solving this problem. Roughly speaking, we can separate future work into four groups: preprocessing, method, machine learning, and measures.

5.1 Preprocessing

One obvious thing to try is to use a partial parser (Abney, 1996, 1997) to split the sentences in our corpus into clauses, and then attempting to match those clauses. The danger here is that misparsing sentences might add an unacceptable amount of error; on the other hand, if the parsing is good, it would reduce noise.

Another preprocessing step that would be worth trying would be to identify any multiword WordNet entries that might appear in the corpus (e.g., *German shepherd*. Of course, then one might want to deal with such multiword entries both as a single unit and as separate words (since, in theory, a *German shepherd* could refer to a German who herds sheep).

5.2 Method

In hindsight, and in particular after reviewing the systems submitted for the RTE challenge, it has become clear to us that one mistake we have made in our method is to treat an asymmetric relationship as though it were a symmetric one. Imagine we have two sentences, s_1 and s_2. Currently, we use symmetric measures in an attempt to detect whether one sentence contains a paraphrase of the other. It would be better if instead we dealt with each pair twice: first check to see if s_1 contained a paraphrase of a clause in s_2, and then vice versa. This would allow us to use asymmetric measures: for example, if s_1 contains a hypernym of a word in s_2, that increases its chance of containing a paraphrase—however, it does *not* increase the chance that s_2 contains a paraphrase of a clause in s_1, and in fact may *decrease* that chance. Currently, our measures cannot reflect that distinction; this change would fix that.

5.3 Machine Learning

As we can see from the submissions to the Pascal RTE challenge, there are a number of potential approaches to the problem of entailment (and thus paraphrasing). Limiting ourselves to approaches using machine learning, there are several things that could be tried. First, we could attempt to make changes to PNrule that might improve its performance. For example, we could try fitness functions other than Z-number or signature clarity. Another idea would be to start with a pseudo N-stage: this stage would find strong indications that examples were *negative*, and then create N-rules accordingly. Why focus on negative examples first? Three reasons:

1. because there's a large number of negative examples, noise is less likely to be a factor;

2. the strongest indicator that an example is negative is not necessarily the complement of the strongest indicator that an example is positive; and

3. it's possible that the strongest indicator that an example is negative in the full data set will not be the strongest indicator in the set of examples covered by the P-rules.

Of course, the pseudo N-stage would be required to keep recall at or near one: the idea would be to remove *obvious* negative examples; less obviously labeled examples would be dealt with in the normal P- and N-stages.

Second, we could adapt a different machine-learning technique to deal with rare classes, either by redesigning the technique, or by penalizing false negatives much more severely than false positives. We could pick a method that does not have the weaknesses of a rule-based system mentioned earlier, or alter PNrule to automatically learn rules that allowed, for example, attributes to be added together. Alternatively, if we gathered far more data, we might be able to use something like *k*-nearest-neighbor unaltered; one advantage of that method is that it can handle small "clusters" of positive examples surrounded by negative examples within a vector space.

Finally, related to this second option, we could combine multiple learners, using a method such as a *mixture of experts*. These learners could be different machine-learning systems trained on the same measures, copies of the same machine-learning system trained on different measures, or different systems trained on different measures. We'd want each system to obtain near-perfect recall, but not necessarily good precision. The idea would be that each system would cover the same true positives, but *different* false positives. Assuming this is, in fact, the case, the combination of systems will outperform the individual systems.

In addition, any future system should be modified to handle negation and numbers; some of the systems submitted to the Pascal RTE provide ideas as to how this can be done.

5.4 Measures

The Pascal RTE challenge has provided a number of other measures to try; in particular, we feel that measures based on lexical chains might be helpful, given that this would allows us to add more contextual information to our measures. Another measure we'd like to try is one based on latent Dirichlet allocation (Blei et al., 2002), since it is similar in some ways to LSI (which

was one of our strongest measures), but may offer some advantages over the former. That said, given the results of both our and other systems on the Pascal RTE data, it seems as though paraphrase detection (as well as entailment detection) will require innovative new measures; a major part of any future work will be finding these measures—for example, using the mutual information between a noun and and adjective to decide whether that adjective has a large or small effect on the meaning of the noun phrase (and thus, whether any potential paraphrase will be more likely to include the adjective). In addition, it would be worthwhile to investigate those machine learning techniques that incorporate feature selection, since including some measures does nothing more than introduce noise.

Clearly, there's still a great deal of work to be done, both on our specific task, and on detecting entailment in general. We hope that this thesis contributes some ideas to that future research, as well as perhaps highlighting some pitfalls to avoid.

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