AUTOMATICALLY SELECTING USEFUL PHRASES FOR DIALOGUE ACT TAGGING

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We present an empirical investigation of various ways to *automatically* identify phrases in a tagged corpus that are useful for dialogue act tagging. We found that a new method (which measures a phrase's deviation from an optimally-predictive phrase), enhanced with a lexical filtering mechanism, produces significantly better cues than manually-selected cue phrases, the exhaustive set of phrases in a training corpus, and phrases chosen by traditional metrics, like mutual information and information gain.

1. INTRODUCTION

Although machine learning approaches have achieved success in many areas of Natural Language Processing, researchers have only recently begun to investigate applying machine learning methods to discourse-level problems (Litman 1994, Andernach 1996, Reithinger & Klesen 1997, Wiebe et al. 1997, DiEugenio, Moore, & Paolucci 1997). An important task in discourse understanding is to interpret an utterance's **dialogue act**, which is a concise abstraction of the speaker's intention; Figure 1 presents a hypothetical dialogue that has been labeled with dialogue acts. Recognizing dialogue acts is critical for discourse-level understanding and can also be useful for other applications, such as resolving ambiguity in speech recognition. However, computing dialogue acts is a challenging task, because often a dialogue act cannot be directly inferred from a literal interpretation of an utterance.

#	Speaker	Utterance	Dialogue Act
1	John	Hello.	Greet
2	John	I'd like to meet with you on Tuesday at 2:00.	Suggest
3	Mary	That's no good for me,	Reject
4	Mary	but I'm free at 3:00.	Suggest
5	John	That sounds fine to me.	Accept
6	John	I'll see you then.	Bye

FIGURE 1. A sample dialogue labeled with dialogue acts

We have investigated applying Transformation-Based Learning (Brill 1995) to the task of computing dialogue acts. Transformation-Based learning is a symbolic supervised machine learning method that generates a sequence of rules. This method, which has not been applied previously to discourse-level problems, has a number of attractive characteristics for our task, such as its intuitive learned model and its resistance to overfitting. (Brill 1995)

Our machine learning algorithm makes use of several abstract features extracted from utterances (Samuel et al. 1998a). In particular, one of the most effective features is the phrases[1] in an utterance that provide useful information for dialogue act tagging, which we

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[1]In this paper, the term **phrase** refers to any sequence of one of more words that may be found in a dialogue, such as "by the way" or "how about the".

will call **dialogue act cues**. This paper presents our investigation of methods for identifying dialogue act cues.

We experimentally compared the effectiveness of various *automatic* methods for selecting phrases, by applying them to a VerbMobil tagged corpus (Reithinger & Klesen 1997). This corpus consists of appointment-scheduling dialogues in which each utterance has been manually labeled with one of eighteen dialogue acts, such as Greet, Suggest, and Accept. Although we understand that there may be problems[2,3] with the dialogue acts in this corpus, we will assume that they are correct, because these issues are beyond the scope of this project. In any event, if another tagged corpus were to become available, the methods presented here should be directly applicable.

Our results showed that a *new* metric (which measures how far a phrase deviates from an optimally-predictive phrase) enhanced with a simple lexical filtering mechanism can select phrases that are more effective for dialogue act tagging than phrases chosen by human intuitive approaches or traditional metrics (like mutual information and information gain).

2.   RELATED WORK

Several researchers (Cohen 1987, Fraser 1990, Grosz & Sidner 1986, Halliday & Hasan 1976, Heeman, Byron, & Allen 1998, Hirschberg & Litman 1993, Knott 1996, Marcu 1997, Reichman 1985, Schiffrin 1987, Warner 1985, Zukerman & Pearl 1986) identified **cue phrases** that are useful for discourse processing, such as "but", "so", and "by the way". In most cases, their research focused on selecting phrases that might be *generally* useful; however, we have found that many of the phrases that appear to be useful for our purposes were *not* included in the previous literature. By analyzing the phrases and tags in a corpus, automatic methods directly address three important factors:

1. The domain of discourse affects which phrases are useful. In the appointment-scheduling dialogues of the VerbMobil corpus, phrases such as "what time" and "I'm busy" could be effective.
2. The desired task of the system (dialogue act tagging, utterance segmentation, etc.) has a significant impact. For dialogue act tagging, "how about" and "sounds great" might serve as dialogue act cues.
3. The specific dialogue acts that we want to identify can affect the usefulness of phrases. For example, one of the VerbMobil dialogue acts is Thank, so this motivates a need for phrases like "thank you" and "thanks".

Intuitively, all of the phrases in the above examples seem to be perfectly reasonable indicators of dialogue acts. However, to our knowledge, no one has previously identified these phrases as cue phrases. This leads us to suspect that the domain, task, and tags need to be considered when selecting phrases.

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[2]It may be relatively difficult for human coders to label utterances with dialogue acts in a consistent manner. Traditionally, intercoder reliability and intracoder reliability have been significant problems for dialogue act tagging.

[3]There is substantial disagreement about how to select an effective set of dialogue acts. Although several researchers are currently addressing this problem (DRI 1997, MATE 1998, JDTWG 1999), the research community still lacks a standardized set of dialogue acts.

Method	Abbreviation
Previous Literature	LIT
All Phrases	ALL
Cooccurrences	COOC
Conditional Probability	CP
Entropy	ENT
T Test	TTEST
Mutual Information	MI
Selectional Preference Strength	S
Information Gain	IG
Deviation	D
Deviation Conditional Probability	DCP

FIGURE 2.   The various phrase-selection methods

3.   PHRASE-SELECTION METHODS

The goal of our research is to devise a method that automatically identifies dialogue act cues. This section discusses two baseline approaches and several automatic methods, listed in Figure 2.

3.1.   Baseline Approaches

We used two sets of phrases as baselines for comparison. 1) The LIT set consists of the 687 different cue phrases proposed in twelve papers, dissertations, and books (Cohen 1987, Fraser 1990, Grosz & Sidner 1986, Halliday & Hasan 1976, Heeman, Byron, & Allen 1998, Hirschberg & Litman 1993, Knott 1996, Marcu 1997, Reichman 1985, Schiffrin 1987, Warner 1985, Zukerman & Pearl 1986). 2) The ALL set represents an extreme approach, selecting *all* sequences of up to three words found in a training corpus. Although this set is likely to include all of the useful phrases, it also includes many extraneous phrases, and we hypothesize that these irrelevant phrases can overwhelm a machine learning algorithm.

3.2.   Automatic Methods

Our general approach is to use *some metric* that estimates how useful a phrase is for dialogue act tagging by analyzing the dialogue acts of the utterances containing that phrase in a training corpus. In this section, we will discuss the motivations and limitations of several different metrics that we considered.

Counting cooccurrences.   It is reasonable to expect that a dialogue act cue would cooccur frequently with a specific dialogue act. For example, in the VERBMOBIL corpus, the phrase "see you" is found in 106 utterances that are labeled Bye, suggesting that "see you" is a dialogue act cue. A straightforward way to rank phrases is to count how often each phrase occurs in utterances labeled with each dialogue act. The **cooccurence** method sorts phrases in decreasing order by their COOC scores:

$$\text{COOC(p)} = \max_{d} \#(p\&d)$$

where p is a phrase, d is a dialogue act, and #(x) is the frequency (in the training corpus) of an event x. This metric maximizes over dialogue acts in order to base the score on the best dialogue act for the phrase.

Considering dialogue act distribution. The simple COOC metric does not take into account the *a priori* distribution of dialogue acts. Unless each dialogue act is equally likely, the most frequently-occurring dialogue acts will generate many high-scoring phrases, even though that may be inappropriate. It might be better to replace the joint frequency in COOC with the **conditional probability** of a phrase given a dialogue act. The conditional probability method sorts phrases in decreasing order by their CP scores:

$$\mathrm{CP(p)} = \max_{\mathrm{d}} \mathrm{P(p|d)}$$

where $\mathrm{P(x|y)}$ is the probability of x given y.

Since COOC and CP maximize over dialogue acts, these scores only account for one dialogue act for each phrase. But we might expect that a dialogue act cue should cooccur frequently with a few dialogue acts and infrequently with the others; a theoretically optimal dialogue act cue would correlate *perfectly* with a single dialogue act, as represented by the dashed line in Figure 3. So it might be worthwhile to consider how skewed the distribution of dialogue acts cooccurring with a phrase is. This criterion is captured by the **entropy** of the dialogue acts given a phrase. The entropy method[4] sorts phrases in increasing order by their ENT scores:

$$\mathrm{ENT(p)} = -\sum_{\mathrm{d}} \mathrm{P(d|p)} \log_2 \mathrm{P(d|p)}$$

However, like COOC, ENT does not account for the *a priori* distribution of dialogue acts. Suppose the original dialogue act distribution has relatively low entropy, and a phrase p is completely independent[5] of the dialogue acts. Then ENT(p) is also relatively low (since the dialogue act distribution is unaffected by the existence of p), incorrectly signifying that p conveys useful information. To account for the a priori dialogue act distribution, we examined four different metrics, which are based on the Kullback-Liebler distance, mutual information, the t test, and information gain.

The **selectional preference strength** method considers the difference between the distribution of dialogue acts given a particular phrase and the a priori distribution of dialogue acts to estimate the amount of information a phrase carries about the dialogue acts it cooccurs with.[6] This is a special case of the **Kullback-Liebler distance** (also known as **relative entropy** or **divergence**),[7] which measures how much information about a dialogue act would be lost by failing to recognize a specific phrase. The selectional preference strength method sorts phrases in decreasing order by their S scores:

$$\mathrm{S(p)} = \sum_{\mathrm{d}} \mathrm{P(d|p)}[\log_2 \mathrm{P(d|p)} - \log_2 \mathrm{P(d)}]$$

where $\mathrm{P(x)}$ is the probability of x.

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[4]Our previous work (Samuel et al. 1998b) did not consider any metrics except for entropy.

[5]P(p|d) is constant for all d.

[6]Resnik (1996) introduced the selectional preference strength metric to measure how much information about an argument of a verb would be lost by not taking into account the verb itself.

[7]These metrics are related to the **L1 norm** and **information radius** (also known as **divergence from the average**).
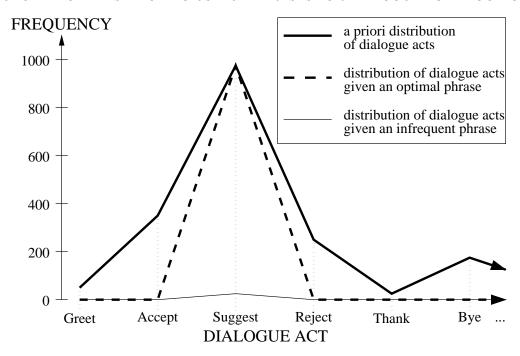
FIGURE 3.   Dialogue act distributions

Mutual information has been used to measure the reduction of uncertainty in one factor that results from the introduction of another factor. We consider the mutual information between the dialogue acts and a phrase, to compute the reduction of uncertainty in an utterance's dialogue act when the utterance contains the phrase. The mutual information method sorts phrases in decreasing order by their MI scores:

$$\mathrm{MI(p)} = \mathrm{P(p)} \sum_{\mathrm{d}} \mathrm{P(d|p)}[\log_2 \mathrm{P(d|p)} - \log_2 \mathrm{P(d)}]$$

We note that, in this context, mutual information is closely related to selectional preference strength.

The **t test** is used to measure the statistical difference between two distributions. We ran a t test between the a priori distribution of dialogue acts and the distribution of dialogue acts given a phrase. The t test method sorts phrases in decreasing order by their TTEST scores:

$$\mathrm{TTEST(p)} = \#(\overline{\mathrm{p}})\sqrt{\sum_{\mathrm{d}} \frac{\mathrm{D}^2 - \mathrm{D}}{[\mathrm{D}\#(\mathrm{p\&d}) - \#(\mathrm{p})]^2 + [\mathrm{D}\#(\mathrm{d}) - \mathrm{U}]^2}}$$

where D is the number of different dialogue acts, U is the total number of utterances, and $\overline{\mathrm{p}}$ refers to the utterances where p does not appear.

Information gain is typically utilized to estimate the usefulness of a feature. For example, information gain has been used to determine how to split a node in a decision tree, by considering the distributions of data that fall along each branch. For our task, we are testing for the existence of a phrase, so we use information gain to measure the reduction in

entropy of the dialogue acts resulting from partitioning utterances based on whether or not they contain the phrase. The information gain method sorts phrases in decreasing order by their IG scores:

$$\text{IG(p)} = \sum_d [\text{P(p)P(d\&p)}\log_2\text{P(d\&p)} + \text{P}(\overline{\text{p}})\text{P(d\&}\overline{\text{p}})\log_2\text{P(d\&}\overline{\text{p}}) - \text{P(d)}\log_2\text{P(d)}]$$

Measuring deviation from optimal. In addition to adapting existing metrics, we also designed some new metrics, which evaluate phrases based on their estimated effectiveness in the hypothetical rule[8] `p IFF d`. Recall that, if p is an optimal dialogue act cue, it correlates perfectly with a single dialogue act (like the dashed line in Figure 3). And, if d^* is that dialogue act,[9] then the rule `p IFF d`* is *valid*. Therefore, this hypothetical dialogue act cue would be a *perfect* indicator for the dialogue act d^*. Our new metrics measure how much each phrase deviates from this optimal design by assigning a penalty point for each utterance where the rule fails.

There are two ways that the rule may fail. First, the rule may be **unsound**, meaning that the left-to-right rule, `IF p THEN d`*, applies incorrectly. For each utterance that contains p but is not labeled d^*, we assign a penalty point to the phrase, for a total of $\sum_{d \neq d^*}\#(\text{p\&d})$ points. However, unsoundness alone is not sufficient. A phrase may produce a perfect unsoundness score of 0, and yet still not be optimal. In the extreme case, any phrase that appears only once in the training corpus has an unsoundness score of 0.

One possible way to address this problem is to consider the thin line in Figure 3, which represents a phrase that only occurs in 25 utterances, where all 25 of those utterances are labeled Suggest. Although this is certainly a useful phrase, since it is as sound as the optimal phrase, we notice that there are 942 other Suggest utterances, which do not include the phrase. We expect that another equally-sound phrase that occurs more frequently should be ranked higher, and so we are considering the case where the rule `p IFF d`* is **incomplete**, meaning that `IF d`* `THEN p` applies incorrectly. For each utterance that is labeled d^* but does not contain p, we assign one penalty point to the phrase, for a total of $\#(\overline{\text{p}}\&d^*)$ points.

It is unclear how to combine unsoundness and incompleteness in a general metric. Certainly, when choosing between two equally sound phrases, one would prefer the phrase that is more complete, and vice versa. (See the next section for a qualitative analysis of empirical results.) So, as an initial approach, we considered adding incompleteness and unsoundness together. The **deviation** method sorts phrases in decreasing order by their D scores:

$$\text{D(p)} = \min_{d^*}[\#(\overline{\text{p}}\&d^*) + \sum_{d \neq d^*}\#(\text{p\&d})]$$

We minimize over dialogue acts, in order to base the score on the best d^* for p.

Like COOC and ENT, the D metric does not account for the a priori distribution of dialogue acts. So, we considered replacing the joint frequencies in D with conditional probabilities. The **deviation conditional probability** method sorts phrases in increasing order by their DCP scores:

$$\text{DCP(p)} = \min_{d^*}[\text{P}(\overline{\text{p}}|d^*) + \sum_{d \neq d^*}\text{P(p|d)}]$$

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[8]In other words, the rule states that phrase p appears in an utterance if and only if that utterance is assigned the dialogue act d.

[9]In Figure 3, d* = Suggest.

Phrase	Unsoundness rank	Incompleteness rank
we could meet	3	1883
how does the	14	2825
yeah that	20	1174
see you	8421	13
hi	8285	20
thanks	6813	26

FIGURE 4.   The tradeoff between unsoundness and incompleteness

4.   QUALITATIVE ANALYSIS

We conducted some experiments to evaluate the merits of the various metrics discussed in the last section. First, we used each metric to order the phrases in the ALL set (all of the phrases in the VERBMOBIL corpus). Then, we manually examined the highest-ranking phrases to intuitively compare the methods. This qualitative analysis immediately revealed some problems.

Several methods suffer from an undesirable bias based on frequency. Many methods are susceptible to *infrequent* phrases; if a phrase appears only once or twice in the corpus, we cannot really draw any reliable conclusions about its usefulness. On the other hand, a number of methods are biased toward phrases that appear *very frequently* (such as "the"). These phrases may be cooccurring frequently with several (or all) of the dialogue acts, making them poor discriminators of dialogue acts. To address a frequency bias, we might want to remove any phrase with a frequency outside of some arbitrary range. However, we believe it may be difficult (or even impossible) to find an appropriate range, and so we would prefer to address this problem by developing some *automatic* mechanism.

In addition, we analyzed the tradeoffs between unsoundness and incompleteness. Figure 4 lists some phrases that we believe to be dialogue act cues, specifying how they would be ranked based on unsoundness or incompleteness alone.[10] For example, the phrase "thanks" occurs in eleven utterances in the training corpus, and ten of these utterances are labeled with the Thank dialogue act. As a result, it is assigned a very good (though not perfect) unsoundness score. However, since every phrase that occurs only once in the training corpus gets a perfect unsoundness score, they all outrank "thanks" if only unsoundness is considered. Alternatively, using incompleteness, "thanks" is ranked 26th, and the DCP method ranks it fifth.

The problem is that unsoundness is biased toward low-frequency phrases, while incompleteness is biased toward high-frequency phrases. It is not clear how to combine these two factors in order to balance their biases. The D and DCP methods simply sum them, although we have also considered weighting incompleteness and unsoundness in different ways.

Another potential problem is that, for several methods, many of the highest-ranking phrases appear to address the same goal. For example, all of the top eight ENT phrases ("how 'bout the", "'bout the", "okay how", etc.) signal the Suggest dialogue act in basically the same way. This is not surprising since, if one of these phrases receives a good score, then they all should. However, we hypothesize that the repetitions should be eliminated in

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[10]For this figure, we used the conditional probability scoring method discussed above.

order to produce a more concise set of phrases, since this may increase the effectiveness of the machine learning method in tagging dialogue acts. Furthermore, if we want to select a predetermined number of phrases, then a set with a wide variety of different phrases is probably more useful than a set with many redundant phrases.

As a starting point, we can easily eliminate some of the redundant phrases with a simple, lexical filtering mechanism, introduced in Samuel et al. (1998b). If one phrase contains another phrase as a subsequence, and the second phrase is ranked higher, then the first phrase is probably repetitious, and so it is unlikely to contribute anything useful. For example, suppose the phrase "see you" is ranked higher than "will see you", indicating that "see you" is more informative. Since "see you" appears in every utterance where "will see you" appears (and perhaps more), there is no good reason to keep the phrase "will see you". The phrase "see you" has better coverage and a better score, so it should always serve as a better feature for dialogue act tagging. The **lexical filter** removes a phrase if one of its subsequences is ranked higher.

5.   EXPERIMENTAL RESULTS

We ran several experiments to compare the methods in Figure 2 on the task of labeling utterances with dialogue acts. For all of these experiments, we applied Transformation-Based Learning (Brill 1995) using three classes of features that we have experimentally found to be particularly effective:

- Applying one of the methods described above to rank the phrases, the system used the best-rated phrases as features of utterances.
- An attractive characteristic of Transformation-Based Learning is that it generates preliminary tags during training. These tags can then be used as features to further refine the learned model. Ramshaw and Marcus (1994) referred to this as "leveraged learning". So, to help determine the dialogue act of a given utterance, our system used the preliminary dialogue act assigned to the *preceding* utterance as a feature.
- Our system utilized a "change-of-speaker" feature that represented information about the speaker of a given utterance. This boolean feature is True for an utterance if the speaker of that utterance differs from the speaker of the preceding utterance, and False otherwise.

An effective heuristic is to cluster certain words into semantic classes, which can collapse several dialogue act cues into a single dialogue act cue. For example, in the appointment-scheduling corpora, there is a strong correlation between utterances that mention weekdays and the Suggest dialogue act, but to express this fact, it is necessary to consider five separate dialogue act cues, such as: "on Monday the", "on Tuesday the", "on Wednesday the", "on Thursday the", and "on Friday the". However, if the five weekdays are combined under one label, "$weekday$", then the same information can be captured by a single dialogue act cue that has five times as much data supporting it. The experiments presented in this paper use the following semantic clusters: "$weekday$", "$month$", "$number$", "$ordinal-number$", and "$proper-name$".

All of our experimental results were derived from a set of held-out data (328 utterances), which was completely disjoint from the training data (2701 utterances) that we used to select phrases.
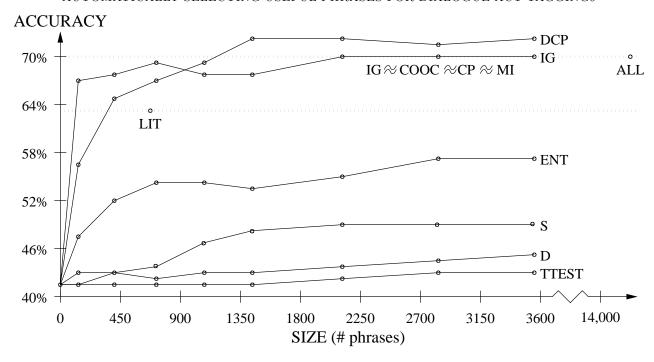
ACCURACY

FIGURE 5.   Size versus accuracy without the filter

5.1.   The Cutoff Points

Since the methods are supposed to rank dialogue act cues higher than other phrases, we should be able to separate the dialogue act cues from the other phrases. To test this, we applied various cutoff points to each method to determine how many lower-ranking phrases may be removed before accuracy begins to decrease. We wanted to investigate the cutoff points in isolation, so the lexical filter was not used in this set of experiments. Figure 5 presents the accuracy of each method as a function of the number of phrases used. The ALL and LIT sets are also included in the figure, for comparison. (For clarity, COOC, CP, and MI are not shown in the figure, because their curves are similar to IG's curve.)

Four methods, TTEST, D, S, and ENT, produced accuracies significantly[11] below LIT when 25% (3558) of the 14,231 phrases were selected. This implies that many dialogue act cues were ranked in the bottom 75% by these methods, suggesting that there may be a problem with these phrase orderings. On the other hand, for four methods, IG, COOC, CP, and MI, we could remove more than 13,000 phrases without significantly affecting the accuracy. These methods also produced significantly higher accuracy scores than the LIT set. Therefore, automatic methods can select phrases that are better for dialogue act tagging than the cue phrases found in the literature.

However, DCP was the only method that produced a significant *rise* in accuracy over ALL. With cutoff points from 10% (1423) to 25% (3558), DCP's accuracy was significantly

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[11]In all of the experiments in this paper, the differences were analyzed for statistical significance with the t test (Levine 1981) or the Tukey "honest significant differences" test, which is an extension of the t test that is appropriate for comparing more than two distributions. (Masterson 1997)
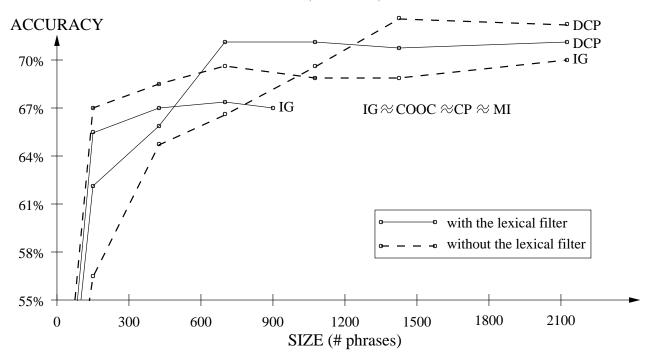
ACCURACY

Figure 6.   Size and filter versus accuracy

higher than ALL's accuracy. As we hypothesized above, it appears that the irrelevant phrases in ALL limit the accuracy of the machine learning method. And we expect that this effect would be more pronounced for a larger training corpus (with more phrases) or another machine learning method (that is more susceptible to irrelevant features).

However, for cutoff points of 5% (712) and lower, DCP is significantly worse than ALL. We believe that this is because DCP is susceptible to repetitive phrases. Since DCP assigns high scores to many redundant phrases, we require a relatively large set of phrases in order to capture the full variety of dialogue act cues. This is precisely the problem that the lexical filter was designed to address.

5.2.   The Lexical Filter

Our next set of experiments tested the lexical filter. If the phrases are ordered properly, then the filter should eliminate some redundant phrases without compromising accuracy in labeling dialogue acts. First, we ordered the phrases with each method and applied the filter. Then, we used various cutoff points to select the top-ranked phrases for training and testing our dialogue act tagger.

This produced some unexpected results, as shown in Figure 6.[12] We found that, in some cases, the filter significantly *decreased* the accuracy on the dialogue act tagging task. Since we

[12]In this figure, three methods, COOC, CP, and MI, are again omitted for clarity, because their results were similar to IG's results. Also, with the lexical filter, these four curves don't extend beyond 900 phrases, because the lexical filter removes 94% (13,342-13,347) of the phrases in each case.

Method	Size
LIT	687
COOC	3994
MI	4291
IG	5202
CP	5515
DCP	8509
ENT	9610
S	9635
TTEST	10,189
D	11,007
ALL	14,231

FIGURE 7.   Experimental results with the modified filter

expected the filter to remove phrases *without* compromising accuracy, this result prompted us to analyze the filter's design more carefully.

We now believe that it is important for the filter to consider *why* a phrase is being selected. For example, while the phrase "hi" tends to signal the Greet dialogue act, an utterance with "hi I" is more likely to be an Init. Our filter would erroneously remove the phrase "hi I", losing some relevant information. So, we modified our filter to follow this new rule:

> IF a phrase p has a subsequence p' that is ranked higher
> *AND both p and p' were selected for the same dialogue act*
> THEN remove p

The second condition requires further explanation. For the COOC, CP, D, and DCP methods, the metrics maximize (or minimize) over dialogue acts. So, for a given phrase, we determine which dialogue act is producing the maximum (or minimum) value, and define that to be the dialogue act referred to in the second condition. For the other methods, the metrics sum over dialogue acts. In these cases, we follow Resnik (1996) by selecting the dialogue act that produces the greatest contribution to the sum.[13]

The effect of this modified filter varies dramatically, removing 23% (3224) to 72% (10,237) of the 14,231 phrases, as shown in Figure 7. However, Figure 8 shows that, as expected, using the filter does not cause the accuracy to decrease. In addition, it allows the system to maintain a high accuracy with fewer phrases. In particular, DCP's accuracy is significantly higher than ALL's accuracy when using only 5% (712) of the phrases in ALL. This suggests that the filter is effectively removing redundant phrases, to produce a more parsimonious set of phrases.

[13]For TTEST, the sum is not located on the outside of the formula. However, since the square root function is monotonic and $\#(\overline{p})$ is constant for a given phrase, we can use the same approach for selecting a dialogue act with the TTEST method.
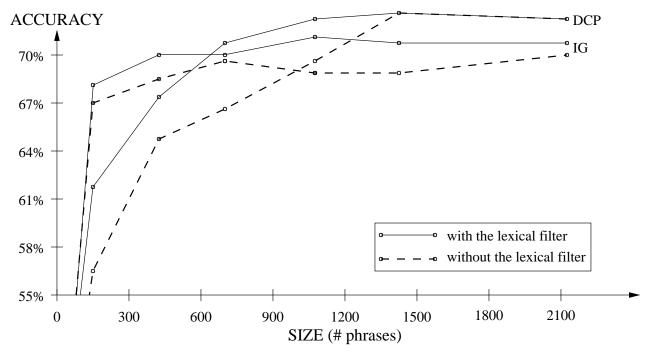
FIGURE 8.   Size and modified filter versus accuracy

6. DISCUSSION

This paper presented an investigation of various methods for selecting useful phrases. We argued that the traditional method of selecting phrases, in which a human researcher analyzes discourse and chooses general cue phrases by intuition, could miss useful phrases. To address this problem, we introduced *automatic* methods that use a tagged training corpus to select phrases, and our experimental results demonstrated that these methods can outperform the manual approach. Another advantage of automatic methods is that they can be easily transferred to another tagged corpus.

Our experiments also showed that the effectiveness of different methods on the dialogue act tagging task varied significantly, when using relatively small sets of phrases. The method that used our new metric, DCP, produced significantly higher accuracy scores than any of the baselines or traditional metrics that we analyzed. In addition, we hypothesized that repetitive phrases should be eliminated in order to produce a more concise set of phrases. Our experimental results showed that our modified lexical filter can eliminate many redundant phrases without compromising accuracy, enabling the system to label dialogue acts effectively using only 5% of the phrases.

There are a number of research areas that we would like to investigate in the future, including the following: We intend to experiment with different weightings of unsoundness and incompleteness in the DCP metric; we believe that the simple lexical filter presented in this paper can be enhanced to improve it; we would like to study the merits of enforcing frequency thresholds for methods that have a frequency bias; for the semantic-clustering technique, we selected the clusters of words by hand, but it would be interesting to see

how a taxonomy, such as WordNet, could be used to automate this process; since all of the experiments in this paper were run on a single corpus, in order to show that these results may generalize to other tasks and domains, it would be necessary to run the experiments on different corpora.

7.   ACKNOWLEDGMENTS

REFERENCES

ANDERNACH, T. 1996. A Machine Learning Approach to the Classification of Dialogue Utterances. In *Proceedings of NeMLaP-2*. Ankara, Turkey.

BRILL, E. 1995. Transformation-Based Error-Driven Learning and Natural Language Processing: A Case Study in Part-of-Speech Tagging. *Computational Linguistics.* **21(4)**:543–566.

COHEN, R. 1987. Analyzing the Structure of Argumentative Discourse. *Computational Linguistics.* **13(1-2)**:11–24.

DI EUGENIO, B., J. MOORE, and M. PAOLUCCI. 1997. Learning Features that Predict Cue Usage. In *Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics and the 8th Conference of the European Chapter of the Association for Computational Linguistics.* 80–87. Madrid, Spain.

DRI. 1997. Discourse Resource Initiative. Retrieved June 15, 1999 from the World Wide Web: http://www.georgetown.edu/luperfoy/Discourse-Treebank/

FRASER, B. 1990. An Approach to Discourse Markers. *Journal of Pragmatics.* **14**:383–395.

GROSZ, B. and C. SIDNER. 1986. Attention, Intentions, and the Structure of Discourse. *Computational Linguistics.* **12(3)**:175–204.

HALLIDAY, M. and R. HASAN. 1976. *Cohesion in English.* Longman Group Limited, London, England.

HEEMAN, P., D. BYRON, and J. ALLEN. 1998. Identifying Discourse Markers in Spoken Dialog. In *Applying Machine Learning to Discourse Processing: Papers from the 1998 American Association for Artificial Intelligence Spring Symposium.* 44–51. Stanford, California.

HIRSCHBERG, J. and D. LITMAN. 1993. Empirical Studies on the Disambiguation of Cue Phrases. *Computational Linguistics.* **19(3)**:501–530.

JDTWG. 1999. Japanese Discourse Tagging Working Group. Retrieved June 15, 1999 from the World Wide Web: http://www.slp.cs.ritsumei.ac.jp/dtag/

KNOTT, A. 1996. *A Data-Driven Methodology for Motivating a Set of Coherence Relations.* Ph.D. thesis. University of Edinburgh, Edinburgh, Scotland.

LEVINE, G. 1981. *Introductory Statistics for Psychology: The Logic and the Methods.* Academic Press, New York, New York.

LITMAN, D. 1994. Classifying Cue Phrases in Text and Speech Using Machine Learning. In *Proceedings of the Twelfth National Conference of the American Association for Artificial Intelligence.* 806–813. Seattle, Washington.

MARCU, D. 1997. *The Rhetorical Parsing, Summarization, and Generation of Natural Language Texts.* Ph.D. thesis. University of Toronto, Toronto, Canada. Tech Report #CSRG-371.

MASTERSON, F. 1997. *Introduction to Statistical Data Analysis.* Draft copy, Department of Psychology, University of Delaware.

MATE. 1998. Multilevel Annotation, Tools Engineering Telematics Project LE4-8370. Retrieved June 15, 1999 from the World Wide Web: http://mate.nis.sdu.dk/

Ramshaw, L. and M. Marcus. 1994. Exploring the Statistical Derivation of Transformation Rule Sequences for Part-of-Speech Tagging. In *Proceedings of the 32nd Annual Meeting of the Association for Computational Linguistics.* 86–95. Las Cruces, New Mexico. Balancing Act Workshop.

Reichman, R. 1985. *Getting Computers to Talk Like You and Me: Discourse Context, Focus, and Semantics.* MIT Press, Cambridge, Massachusetts.

Reithinger, N. and M. Klesen. 1997. Dialogue Act Classification using Language Models. In *Proceedings of EuroSpeech-97.* 2235–2238. Rhodes, Greece.

Resnik, P. 1996. Selectional Constraints: An Information-Theoretic Model and its Computational Realization. *Cognition.* **61**:127–159.

Samuel, K., S. Carberry, and K. Vijay-Shanker. 1998a. Computing Dialogue Acts from Features with Transformation-Based Learning. In *Applying Machine Learning to Discourse Processing: Papers from the 1998 American Association for Artificial Intelligence Spring Symposium.* 90–97. Stanford, California.

Samuel, K., S. Carberry, and K. Vijay-Shanker. 1998b. Dialogue Act Tagging with Transformation-Based Learning. In *Proceedings of the 17th International Conference on Computational Linguistics and the 36th Annual Meeting of the Association for Computational Linguistics.* 1150–1156. Montréal, Québec, Canada.

Schiffrin, D. 1987. *Discourse Markers.* Cambridge University Press, London, England.

Warner, R. 1985. *Discourse Connectives in English.* Garland Publications, New York, New York.

Wiebe, J., T. O'Hara, K. McKeever, and T. Öhrstroem-Sandgren. 1997. An Empirical Approach to Temporal Reference Resolution. In *Proceedings of the Second Conference on Empirical Methods in Natural Language Processing.* 174–186. Providence, Rhode Island.

Zukerman, I. and J. Pearl. 1986. Comprehension-Driven Generation of Meta-Technical Utterances in Math Tutoring. In *Proceedings of the Sixth National Conference of the American Association for Artificial Intelligence.* Philadelphia, Pennsylvania.