Automatic Detection of Discourse Structure for Speech Recognition and Understanding

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We describe a new approach for statistical modeling and detection of discourse structure for natural conversational speech. Our model is based on 42 'Dialog Acts' (DAs), (question, answer, backchannel, agreement, disagreement, apology, etc). We labeled 1155 conversations from the Switchboard (SWBD) database (Godfrey *et al.* 1992) of human-to-human telephone conversations with these 42 types and trained a Dialog Act detector based on three distinct knowledge sources: sequences of words which characterize a dialog act, prosodic features which characterize a dialog act, and a statistical Discourse Grammar. Our combined detector, although still in preliminary stages, already achieves a 65% Dialog Act detection rate based on acoustic waveforms, and 72% accuracy based on word transcripts. Using this detector to switch among the 42 Dialog-Act-Specific trigram LMs also gave us an encouraging but not statistically significant reduction in SWBD word error.

1 Introduction

The ability to model and automatically detect discourse structure is essential as we address problems like *understanding spontaneous dialog* (a meeting summarizer needs to know who said what to who), *building human-computer dialog systems* (a conversational agent needs to know whether it just got asked a question or ordered to do something), and *transcription of conversational speech* (utterances with different discourse function also have very different words). This paper describes our preliminary work (as part of the 1997 Summer Workshop on Innovative Techniques in LVCSR) on automatically detecting discourse structure for speech recognition and understanding tasks.

Table 1 shows a sample of the kind of discourse structure we are modeling and detecting. Besides the usefulness of discourse structure detection for speech understanding, discourse structure can be directly relevant for speech recognition tasks. For example in the state-of-the-art HTK recognizer we used, the word **do** has an error rate of 72%. But **do** is in almost every **Yes-No-Question**; if we could detect **Yes-No-Question**s (for example by looking for utterances with rising intonation) we could increase the probability of **do** and hence decrease the error rate.

There are many excellent previous attempts to build predictive, stochastic models of dialog structure (Kita *et al.* 1996; Mast *et al.* 1996; Nagata and Morimoto 1994; Reithinger *et al.* 1996; Suhm and Waibel 1994; Taylor *et al.* 1998; Woszczyna and Waibel 1994; Yamaoka and Iida 1991), and our effort is in many ways inspired by

Spkr	Dialog Act	Utterance
A	**Wh-Question**	What kind do you have now?
B	**Statement**	*Uh, we have a, a Mazda nine twenty nine and a Ford Crown Victoria and a little two seater CRX.*
A	**Acknowledge-Answer**	Oh, okay.
B	**Opinion**	*Uh, it's rather difficult to, to project what kind of, uh, -*
A	**Statement**	we'd, look, always look into, uh, consumer reports to see what kind of, uh, report, or, uh, repair records that the various cars have –
B	**Turn-Exit**	*So, uh, -*
A	**Yes-No-Quest**	And did you find that you like the foreign cars better than the domestic?
B	**Answer-Yes**	*Uh, yeah,*
B	**Statement**	*We've been extremely pleased with our Mazdas.*
A	**Backchannel-Quest**	Oh, really?
B	**Answer-Yes**	*Yeah.*

Table 1: *A fragment of a labeled switchboard conversation.*

this work, and indeed our group overlaps in personnel with some of these projects. Our project extends these earlier efforts particularly in its scale (our models were trained on 1155 dialog-annotated conversations comprising 205,000 utterances and 1.4 million words; an order of magnitude larger than any previous system) and in focusing on longer, less task-oriented dialogs.

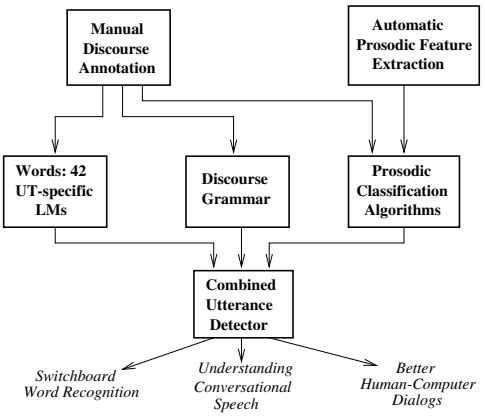

Figure 1: *Outline of Paper and Project*

Figure 1 outlines the major stages of our work and of this paper. We begin by discussing how we manually annotated 1155 conversations with hand-labeled discourse-tags. We then describe the 3 knowledge sources for dialog act detection (word-sequences, discourse grammar, and prosody), show how these knowledge sources can be combined, and finally apply the detector to help improve word recognition of SWBD.

2 Manual Discourse Tagging

In order to tag the 1155 SWBD conversations, we first designed the SWBD-DAMSL tagset (Jurafsky *et al.* 1997b) by augmenting the DAMSL tag-set (Core and Allen 1997). Our SWBD-DAMSL tagset consists of approximately 60 groupable labels in

orthogonal dimensions which the labelers combined to produce 220 unique tags for the 205,000 SWBD utterances. The SWBD conversations had already been hand-segmented into utterances by the Linguistic Data Consortium ((Meteer *et al.* 1995); an utterance roughly corresponds to a sentence). Each utterance thus received exactly one of these 220 tags. The average conversation consisted of 144 turns, 271 utterances, and took 28 minutes for trained CU Boulder grad students to label. The labeling agreement was 84% (κ = .80; (Carletta 1996)). We then clustered these 220 tags into 42 final tags. All of our experiments were run with this 42-tag tagset. Table 2 shows the most common tags. [1]

Tag	Example	Count	%
Statement	*Me, I'm in the legal department.*	72,824	36%
Backchannel	*Uh-huh.*	37,096	19%
Opinion	*I think it's great*	25,197	13%
Agree/Accept	*That's exactly it.*	10,820	5%
Abandoned/Turn-Exit	*So, -/*	10,569	5%
Appreciation	*I can imagine.*	4,633	2%
Yes-No-Question	*Do you have to have any special training*	4,624	2%
Non-verbal	*<Laughter>,<Throat_clearing>*	3,548	2%
Yes answers	*Yes.*	2,934	1%
Conventional-closing	*Well, it's been nice talking to you.*	2,486	1%
Uninterpretable	*But, uh, yeah*	2,158	1%
Wh-Question	*Well, how old are you?*	1,911	1%
No answers	*No.*	1,340	1%
Response Ack	*Oh, okay.*	1,277	1%
Hedge	*I don't know if I'm making any sense or not.*	1,182	1%
Declarative Question	*So you can afford to get a house?*	1,174	1%
Other	*Well give me a break, you know.*	1,074	1%
Backchannel-Question	*Is that right?*	1,019	1%

Table 2: *18 most frequent tags (of 42)*

3 Dialog Act Detection

The goal of our dialog act (DA) detection algorithms is to automatically assign the correct tag from our 42 DA set to each of the presegmented utterance wavefiles. We achieved a 65% detection accuracy, based on automatic word recognition and prosodic analysis. This compares with a baseline of 35% if we simply chose the most frequent dialog act each time. Human labelers were able to do significantly better (84%). However, note that the human labeling was based purely on word transcripts. Using actual, rather than recognized words, our DA detection algorithm achieved 72% accuracy, so we can expect substantially improved automatic detection simple as a result of continually improving recognition accuracy.

Our algorithm is based on combining three sources of knowledge:

[1] For many of our experiments we combined the **Statement** and **Opinion** classes; these two classes together comprise 49% of the utterances, but a full **83%** of the words in the corpus. As we will see, this limits the affect our tagging had on word-related metrics like word error.

Prosodic Information: Using prosodic features such as pitch and speaking rate to choose DA. For example based on the literature we predicted that **Yes-No-Questions** would be detectable from their final F0 rise.

Words and Word Grammar: Pick the most likely DA given the word string. For example, **88.4%** of the trigrams **"<start> do you"** occur in **Yes-No-Questions**.

Discourse Grammar: Pick the Dialog Act which is most likely given the surrounding DAs. For example a **Command** will be **Agreed** to with probability **.23**, a **Yes-No-Question** will receive a **Yes** answer with probability **.30**.

The utterance detection algorithm we describe is based on hand-segmented utterance boundaries. That is, both our training and test sets were segmented by hand into turns and utterances.

3.1 Prosodic Dialog Act Detection

Extending earlier work by others on the use of prosodic knowledge for dialog act prediction (Mast *et al.* 1996; Taylor *et al.* 1997; Terry *et al.* 1994; Waibel 1988), we automatically extracted prosodic features for each utterance, performed various normalizing and postprocessing, and trained CART decision trees to predict the dialog act of an utterance. Our goal was to discriminate classes that were particularly confusable given only words, and also to understand prosodic feature usage so as to build future prosodic detectors. We used no word information in extracting or computing features, other than the location of utterance boundaries which were assumed for all knowledge sources. Features included duration, pause, F0, energy (RMS and signal-to-noise-ratio), and speaking rate (using a signal processing measure 'enrate' (Morgan *et al.* 1997)) measures. Because the distribution of DAs was highly skewed,we downsampled our data to uniform priors (train and test) to train more discriminate trees.

We built trees to detect specifically confusable dialog acts including **Yes-No-Questions**, and **Abandoned/Turn Exits**. For **Yes-No-Question**s, for example, a word-based detector for all 42 types only achieved 32% accuracy. But **Yes-No-Questions** are strongly prosodically marked: they generally have a rising F0 contour. Table 3 shows our accuracy for a single prosodic tree for distinguishing **Yes-No-Question** from all other dialog acts. We achieved an accuracy (# of correct classifications / all data) of 70.3% (where chance is 50%).

Test	Count	Accuracy	Perp	Entropy$_e$	Efficiency
Prior		50.0	2	0.693	
Cond. HLD	618	70.3	1.80	0.589	15.0%

Table 3: *Results of Yes-No-Question Detection Tree*

This **Yes-No-Question** tree relied mainly on the F0 rise, but also on other features; nearly all the main feature types played a role in the trees. For details of the decision trees, see Shriberg *et al.* (submitted) and Jurafsky *et al.* (1997a). In a number of focussed analyses assuming uniform DA priors, prosody alone allowed classification significantly above chance. In addition, although space does not permit discussion, adding prosody to word information significantly improved classification for the majority of the analyses.

3.2 Word-sequence-based Dialog Act Detection

Word-based DA detection is based on separate trigram language models for each of the 42 dialog acts, (i.e. one LM for **Statements**, another for **Yes-No-Questions**, another for **Backchannels**, etc). and choosing the dialog act that assigns the highest likelihood to the word string (Garner *et al.* 1996; Peskin *et al.* 1996). The resulting LMs were quite distinct from each other, and had a significantly lower perplexity (66.9) on the test set than the baseline LM (76.8) indicating that the 42 LMs do in fact capture the lexical distinctions among the 42 dialog acts (see Table 6).

We then used the 42 language models to choose the most likely DA given the word string, by maximizing over likelihoods of the utterance-words given the utterance (e.g. $P(\text{I lived in Chicago}|\text{Statement})$) for each utterance in a conversation and for each DA. Table 5 in §3.4 shows that by using the bigram Discourse Grammar described below we achieve 64.6% utterance detection accuracy using the likelihoods computed via the 2500-best word strings from each utterance (where 35% is chance). (Using the correct (reference, i.e. cheating) word strings, we achieved 70.6% accuracy).

3.3 Discourse Grammar

Our discourse grammar is a backoff N-gram (Katz 1987) with Witten-Bell discounting (Witten and Bell 1991) which predicts the sequence of dialog acts given the previous types; the use of N-gram discourse grammars was motivated by previous work by Kita *et al.* (1996); Mast *et al.* (1996); Nagata and Morimoto (1994); Suhm and Waibel (1994); Taylor *et al.* (1997); Taylor *et al.* (1998); Woszczyna and Waibel (1994); Yamaoka and Iida (1991). For example, in the sample conversation in Table 1, the grammar gives the probability of the utterance in Channel A being an **Acknowledge-Answer** given that the previous utterance was a **Statement** on Channel B and before that was a **Wh-Question** on Channel A.

	N-gram model			
n	0	1	2	3
perplexity	42.0	9.0	5.1	4.8

Table 4: *DA Perplexity (conditioned on turns).*

As Table 4 shows, the discourse grammar does in fact progressively reduce the perplexity of the utterance detection task as a larger dialog act history is added. We also explored alternative models for discourse grammar, including maximum entropy models and cache models. See Jurafsky *et al.* (1997a) for further details.

3.4 The Combined Dialog Act Detector

We then ran a number of different experiments combining our three knowledge sources (words, prosody, discourse) for DA detection. The prosodic component of these combined detection results is still preliminary, because we only had a very preliminary prosodic detection tree at this point (distinguishing **Statements**, **Questions**, **Backchannels**, **Agreements**, and **Abandoned** from each other and from other DAs), and also because we are still studying the optimal way to combine different

prosodic classifiers. See Stolcke *et al.* (submitted) and Jurafsky *et al.* (1997a) for the mathematical foundation of our combinations; Table 5 simply shows our final detection results.

Discourse Grammar	Accuracy (%)		
	Prosody only	Rec. Words only	Combined
None	38.9	42.8	56.5
Unigram	48.3	61.9	62.6
Bigram	50.2	64.6	**65.0**

Table 5: *Combined utterance detection accuracies.*

Using the recognized words together with the bigram discourse grammar accounts for the bulk of our accuracy, although we expect more help from the prosody as we train more trees.

4 Word Recognition Experiments

We applied our detection algorithm to the SWBD word-recognition task by using a mixture of the 42 DA-specific LMs to rescore each test-set utterance, and using the combined detector to set the mixture weights. Table 6 shows word error and perplexities obtained for the DA-conditioned mixture LM. Also shown are the results for the baseline LM, and for the 'cheating' LM, conditioned on the true DA labels. WER is reduced by only 0.3% over the baseline, a non-significant change ($0.3 > p > 0.2$).

Model	WER (%)	Perplexity
Baseline	**41.2**	76.8
Mixture LM	**40.9**	66.9
Cheating LM	40.3	66.8

Table 6: *Non-significant reduction in SWBD word error.*

It is encouraging that the perplexity of the DA-conditioned mixture model is virtually the same as that of the cheating LM. But the cheating experiment shows that even perfect knowledge of the dialog acts can only be expected to give about a 1 percent reduction in WER. This is mainly because **Statements** (non-opinion plus opinion) account for 83% of the words in our corpus (since e.g. backchannels and answers tend to be short). Table 7 shows, however, that using utterance-specific language models can significantly improve WER for some dialog acts, and hence this approach could prove useful for tasks with a different distribution of utterance types.

5 Conclusions

We have described a new approach for statistical modeling and detection of discourse structure for natural conversational speech. Our algorithm has possibilities for reducing word error in speech recognition. Although the skewed dialog act distribution limited our maximum word error improvement for the Switchboard task, improvements for WER of individual dialog acts suggests that the algorithm has

Dialog Act	WER	Oracle WER	Improvement with Oracle
Answer No	29.4	11.8	-17.6%
Backchannel	25.9	18.6	-7.3%
Backchannel Questions	15.2	9.1	-6.1%
Abandoned/Turn-Exit	48.9	45.2	-3.7%
Wh-Questions	38.4	34.9	-3.5%
Yes-No-Questions	55.5	52.3	-3.2%
Statement	42.0	41.5	-0.5%

Table 7: *Cheating Error Rates on Specific Dialog Acts*

potential to improve recognition on other tasks (like conversational agents) where questions and other non-statements are more common. Furthermore, by combining our three knowledge sources, we achieved significant improvements in our ability to automatically detect dialog acts, which will help address tasks like understanding spontaneous dialog and building human-computer dialog systems.

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