Identifying Uncertain Words within an Utterance via Prosodic Features

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The Importance of Sub-Utterance Prosody in Predicting Level of Certainty

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Abstract
We present an experiment aimed at understanding how to optimally use acoustic and prosodic information to predict a speaker’s level of certainty. With a corpus of utterances where we can isolate a single word or phrase that is responsible for the speaker’s level of certainty we use different sets of sub-utterance prosodic features to train models for predicting an utterance’s perceived level of certainty. Our results suggest that using prosodic features of the word or phrase responsible for the level of certainty and of its surrounding context improves the prediction accuracy without increasing the total number of features when compared to using only features taken from the utterance as a whole.

1 Introduction
Prosody is a fundamental part of human-to-human spoken communication; it can affect the syntactic and semantic interpretation of an utterance (Hirschberg, 2003) and it can be used by speakers to convey their emotional state. In recent years, researchers have found prosodic features to be useful in automatically detecting emotions such as annoyance and frustration (Ang et al., 2002) and in distinguishing positive from negative emotional states (Lee and Narayanan, 2005).

In this paper, we address the problem of predicting the perceived level of certainty of a spoken utterance. Specifically, we have a corpus of utterances where it is possible to isolate a single word or phrase responsible for the speaker’s level of certainty. With this corpus we investigate whether using prosodic features of the word or phrase causing uncertainty and of its surrounding context improves the prediction accuracy when compared to using features taken only from the utterance as a whole.

This work goes beyond existing research by looking at the predictive power of prosodic features extracted from salient sub-utterance segments. Previous work on uncertainty has examined the predictive power of utterance- and intonational phrase-level prosodic features (Liscombe et al., 2005) as well as the relative strengths of correlations between level of certainty and sub-utterance prosodic features (Pon-Barry, 2008). Our results suggest that we can do a better job at predicting an utterance’s perceived level of certainty by using prosodic features extracted from the whole utterance plus ones extracted from salient pieces of the utterance, without increasing the total number of features, than by using only features from the whole utterance.

This work is relevant to spoken language applications in which the system knows specific words or phrases that are likely to cause uncertainty. For example, this would occur in a tutorial dialogue system when the speaker answers a direct question (Pon-Barry et al., 2006; Forbes-Riley et al., 2008), or in language (foreign or ESL) learning systems and literacy systems (Alwan et al., 2007) when new vocabulary is being introduced.

2 Previous Work
Researchers have examined certainty in spoken language using data from tutorial dialogue systems (Liscombe et al., 2005) and data from an uncertainty corpus (Pon-Barry, 2008).

Liscombe et al. (2005) trained a decision tree
classifier on utterance-level and intonational phrase-
level prosodic features to distinguish between cer-
tain, uncertain, and neutral utterances. They
achieved 76% accuracy, compared to a 66% accu-
readiness baseline (choosing the most common class).

We have collected a corpus of utterances spoken
under varying levels of certainty (Pon-Barry, 2008).
The utterances were elicited by giving adult native
English speakers a written sentence containing one
or more gaps, then displaying multiple options for
filling in the gaps and telling the speakers to read
the sentence aloud with the gaps filled in according
to domain-specific criteria. We elicited utterances
in two domains: (1) using public transportation in
Boston, and (2) choosing vocabulary words to com-
plete a sentence. An example is shown below.

Q: How can I get from Harvard to the Silver Line?
A: Take the red line to ______
   a. South Station
   b. Downtown Crossing

The term ‘context’ refers to the fixed part of the re-
sponse (“Take the red line to ______”, in this exam-
ple) and the term ‘target word’ refers to the word or
phrase chosen to fill in the gap.

The corpus contains 600 utterances from 20
speakers. Each utterance was annotated for level
of certainty, on a 5-point scale, by five human
judges who listened to the utterances out of context.
The average inter-annotator agreement (Kappa) was
0.45. We refer to the average of the five ratings as
the ‘perceived level of certainty’ (the quantity we at-
ttempt to predict in this paper).

We computed correlations between perceived
level of certainty and prosodic features extracted
from the whole utterance, the context, and the tar-
get word. Pauses preceding the target word were
considered part of the target word; all segmen-
tation was done manually. Because the speakers had
unlimited time to read over the context before see-
ing the target words, the target word is considered
to be the source of the speaker’s confidence or un-
certainty; it corresponds to the decision that the
speaker had to make. Our correlation results sug-
gest that while some prosodic cues to level of cer-
tainty were strongest in the whole utterance, others
were strongest in the context or the target word. In
this paper, we extend this past work by testing the
prediction accuracy of models trained on different
subsets of these prosodic features.

3 Prediction Experiments

In our experiments we used 480 of the 600 utter-
ances in the corpus, those which contained exactly
one gap. (Some had two or three gaps.) We ex-
tracted the following 20 prosodic feature-types from
each whole utterance, context, and target word (a to-
tal of 60 features) using WaveSurfer\(^1\) and Praat\(^2\).

**Pitch:** minf, maxf, meanf, stddevf, rangef, rela-
tive position minf, relative position maxf, absolute slope (Hz), absolute slope (semitones)

**Intensity:** minRMS, maxRMS, meanRMS, stdde-
RMS, relative position minRMS, relative position maxRMS

**Temporal:** total silence, percent silence, total dura-
tion, speaking duration, speaking rate

These features are comparable to those used in Lis-
combe et al.’s (2005) prediction experiments. The
pitch and intensity features were represented as
z-scores normalized by speaker; the temporal fea-
tures were not normalized.

Next, we created a ‘combination’ set of 20 fea-
tures based on our correlation results. Figure 1 il-
lustrates how the combination set was created: for
each prosodic feature-type (each row in the table) we
chose either the whole utterance feature, the context
feature, or the target word feature, whichever one
had the strongest correlation with perceived level of
certainty. The selected features (highlighted in Fig-
ure 1) are listed below.

**Whole Utterance:** total silence, total duration,
speaking duration, relative position maxf, rela-
tive position maxRMS, absolute slope (Hz),
absolute slope (semitones)

**Context:** minf, maxf, meanf, stddevf, rangef,
minRMS, maxRMS, meanRMS, relative position
minRMS

**Target Word:** percent silence, speaking rate, rela-
tive position minf, stdevRMS

\(^1\)http://www.speech.kth.se/wavesurfer/
\(^2\)http://www.fon.hum.uva.nl/praat/
ble5 was produced by selecting either the whole utterance or the most common class. The accuracies that would be achieved by always selecting the whole utterance features only are reported as a baseline. The naive baseline numbers were obtained by computing the prediction accuracy over five classes rather than a cross-validation on unseen speakers. Others they ran one experiment using data from 19 speakers and tests on the remaining speaker. Thus, when we test our models, we are testing the ability to classify utterances of an unseen speaker.

Table 1 shows the accuracies of the models trained on the five subsets of features. The numbers reported are averages of the 20 cross-validation accuracies. We report results for two cases: 5 prediction classes and 3 prediction classes. We first computed the prediction accuracy over five classes (the regression output was rounded to the nearest integer). Next, in order to compare our results to those of Liscombe et al. (2005), we redrew the 5-class results into 3-class results, following Pon-Barry (2008), in the way that maximized inter-annotator agreement. The naive baseline numbers are the accuracies that would be achieved by always choosing the most common class.

<table>
<thead>
<tr>
<th>Feature-type</th>
<th>Whole Utterance</th>
<th>Context</th>
<th>Target Word</th>
</tr>
</thead>
<tbody>
<tr>
<td>min f0</td>
<td>0.107</td>
<td>0.119</td>
<td>0.041</td>
</tr>
<tr>
<td>max f0</td>
<td>−0.073</td>
<td>−0.153</td>
<td>−0.045</td>
</tr>
<tr>
<td>mean f0</td>
<td>0.033</td>
<td>0.070</td>
<td>−0.004</td>
</tr>
<tr>
<td>stdev f0</td>
<td>−0.047</td>
<td>−0.047</td>
<td>−0.047</td>
</tr>
<tr>
<td>range f0</td>
<td>−0.128</td>
<td>−0.211</td>
<td>−0.075</td>
</tr>
<tr>
<td>rel. position min f0</td>
<td>0.042</td>
<td>0.022</td>
<td>0.046</td>
</tr>
<tr>
<td>rel. position max f0</td>
<td>0.015</td>
<td>0.008</td>
<td>0.001</td>
</tr>
<tr>
<td>abs. slope f0 (Hz)</td>
<td>0.275</td>
<td>0.180</td>
<td>0.191</td>
</tr>
<tr>
<td>abs. slope f0 (Semi)</td>
<td>0.160</td>
<td>0.147</td>
<td>0.002</td>
</tr>
<tr>
<td>min RMS</td>
<td>0.101</td>
<td>0.172</td>
<td>0.027</td>
</tr>
<tr>
<td>max RMS</td>
<td>−0.091</td>
<td>−0.110</td>
<td>−0.034</td>
</tr>
<tr>
<td>mean RMS</td>
<td>−0.012</td>
<td>0.039</td>
<td>−0.031</td>
</tr>
<tr>
<td>stdev RMS</td>
<td>−0.002</td>
<td>−0.003</td>
<td>−0.019</td>
</tr>
<tr>
<td>rel. position min RMS</td>
<td>0.101</td>
<td>0.172</td>
<td>0.027</td>
</tr>
<tr>
<td>rel. position max RMS</td>
<td>−0.039</td>
<td>−0.028</td>
<td>−0.007</td>
</tr>
<tr>
<td>total silence</td>
<td>−0.643</td>
<td>−0.507</td>
<td>−0.495</td>
</tr>
<tr>
<td>percent silence</td>
<td>−0.455</td>
<td>−0.225</td>
<td>−0.532</td>
</tr>
<tr>
<td>total duration</td>
<td>−0.592</td>
<td>−0.502</td>
<td>−0.590</td>
</tr>
<tr>
<td>speaking duration</td>
<td>−0.430</td>
<td>−0.390</td>
<td>−0.386</td>
</tr>
<tr>
<td>speaking rate</td>
<td>0.050</td>
<td>0.014</td>
<td>0.136</td>
</tr>
</tbody>
</table>

Figure 1: The Combination feature set (highlighted in table) was produced by selecting either the whole utterance feature, the context feature, or the target word feature for each prosodic feature-type, whichever one was most strongly correlated with perceived level of certainty.

To compare the prediction accuracies of different subsets of features, we fit five linear regression models to the feature sets. The five subsets are: (A) whole utterance features only, (B) target word features only, (C) context features only, (D) all features, and (E) the combination feature set. We divided the data into 20 folds (one fold per speaker) and performed a 20-fold cross-validation for each set of features. Each experiment fits a model using data from 19 speakers and tests on the remaining speaker. Thus, when we test our models, we are testing the ability to classify utterances of an unseen speaker.

Table 1 shows the accuracies of the models trained on the five subsets of features. The numbers reported are averages of the 20 cross-validation accuracies. We report results for two cases: 5 prediction classes and 3 prediction classes. We first computed the prediction accuracy over five classes (the regression output was rounded to the nearest integer). Next, in order to compare our results to those of Liscombe et al. (2005), we redrew the 5-class results into 3-class results, following Pon-Barry (2008), in the way that maximized inter-annotator agreement. The naive baseline numbers are the accuracies that would be achieved by always choosing the most common class.

4 Discussion

Assuming that the target word is responsible for the speaker’s level of certainty, it is not surprising that the target word feature set (B) yields higher accuracies than the context feature set (C). It is also not surprising that the set of all features (D) yields higher accuracies than sets (A), (B), and (C).

The key comparison to notice is that the combination feature set (E), with only 20 features, yields higher average accuracies than the utterance feature set (A): a difference of 6.42% for 5 classes and 5.83% for 3 classes. This suggests that using a combination of features from the context and target word in addition to features from the whole utterance leads to better prediction of the perceived level of certainty than using features from only the whole utterance.

One might argue that these differences are just due to noise. To address this issue, we compared the prediction accuracies of sets (A) and (E) per fold. This is illustrated in Figure 2. Each fold in our cross-validation corresponds to a different speaker, so the folds are not identically distributed and we do not expect each fold to yield the same prediction accuracy. That means that we should compare predictions of the two feature sets within folds rather than between folds. Figure 2 shows the correlations between the predicted and perceived levels of certainty for the models trained on sets (A) and (E). The combination set (E) predictions were more strongly correlated than whole utterance set (A) predictions in 16 out of 20 folds. This result supports our claim that using a combination of features from the context and target word in addition to features from the whole utterance leads to better prediction of level of certainty.

Our best prediction accuracy for the 3 class case, 74.79%, was slightly lower than the accuracy reported by Liscombe et al. (2005), 76.42%. However, our difference from the naive baseline was 18.54% where Liscombe et al.’s was 10.42%. Liscombe et al. randomly divided their data into training and test sets, so it is unclear whether they tested on seen or unseen speakers. Further, they ran one experiment rather than a cross-validation, so their reported accuracy may not be indicative of the entire data set.

We also trained support vector models on these subsets of features. The main result was the same:
Fold the for the In “6 of the -” experiments9 the correlation coefficients feature set predictions, sorted by the size of the difference.

The results of our experiments suggest a better prediction models of the speaker’s self-reported level of certainty than using features from the whole utterance leads to better prediction of words or phrases likely to cause uncertainty are known ahead of time. Without increasing the total number of features, combining select prosodic features from the target word, the surrounding context and the whole utterance leads to better prediction of level of certainty than using features from the whole utterance only. In the near future, we plan to experiment with prediction models of the speaker’s self-reported level of certainty.

5 Conclusion and Future Work

The results of our experiments suggest a better predictive model of level of certainty for systems where words or phrases likely to cause uncertainty are known ahead of time. Without increasing the total number of features, combining select prosodic features from the target word, the surrounding context and the whole utterance leads to better prediction of level of certainty than using features from the whole utterance only. In the near future, we plan to experiment with prediction models of the speaker’s self-reported level of certainty.

Table 1: Average prediction accuracies for the linear regression models trained on five subsets of prosodic features. The models trained on the Combination feature set and the All feature set perform better than the other three models in both the 3- and 5-class settings.

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>Num Features</th>
<th>Accuracy (5 classes)</th>
<th>Accuracy (3 classes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Baseline</td>
<td>N/A</td>
<td>31.46%</td>
<td>56.25%</td>
</tr>
<tr>
<td>(A) Utterance</td>
<td>20</td>
<td>39.00%</td>
<td>68.96%</td>
</tr>
<tr>
<td>(B) Target Word</td>
<td>20</td>
<td>43.13%</td>
<td>68.96%</td>
</tr>
<tr>
<td>(C) Context</td>
<td>20</td>
<td>37.71%</td>
<td>67.50%</td>
</tr>
<tr>
<td>(D) All</td>
<td>60</td>
<td>48.54%</td>
<td>74.58%</td>
</tr>
<tr>
<td>(E) Combination</td>
<td>20</td>
<td>45.42%</td>
<td>74.79%</td>
</tr>
</tbody>
</table>

The set of all features (D) and the combination set (E) had better prediction accuracies than the utterance feature set (A). In addition, the combination set (E) had the best prediction accuracies (of all models) in both the 3- and 5-class settings. The raw accuracies were approximately 5% lower than those of the linear regression models.

Acknowledgments

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References


