



# Prominence based scoring of speech segments for automatic speech-to-speech summarization

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## Abstract

In order to perform speech summarization it is necessary to identify important segments in speech signal. The importance of a speech segment can be effectively determined by using information from lexical and prosodic features. Standard speech summarization systems depend on ASR transcripts or gold standard human reference summaries to train a supervised system which combines lexical and prosodic features to choose a segment into summary. We propose a method which uses prominence values of syllables in a speech segment to rank the segment for summarization. The proposed method does not depend on ASR transcripts or gold standard human summaries. Evaluation results showed that summaries generated by the proposed method are as good as the summaries generated using tf\*idf scores and supervised system trained on gold standard summaries.

**Index Terms:** speech summarization, prominence measure

## 1. Introduction

Speech summarization systems produce extractive summaries where important segments from the speech signal are identified, ranked and concatenated without any alterations to form a summary. One of the crucial steps in extractive summarization is determining the important segments and ranking the segments for inclusion in a summary. Initial approaches to speech summarization used automatic speech recognition (ASR) output of speech files and applied methods based on tf\*idf, maximum marginal relevance (MMR), and latent semantic analysis (LSA) to rank the segments for summarization. Methods were proposed to reduce the effect of disfluencies present in speech and ASR errors to improve the quality of summaries [1, 2, 3, 4]. Recent methods used acoustic features in combination with lexical and structural features derived from ASR transcripts of speech signals to perform summarization. In this type of approaches a supervised system is trained with the help of gold standard human reference summaries to classify a segment as belonging to summary or not. [5] combines lexical and acoustic features to train a supervised system to classify a segment as belonging to summary or not. [6] attempts to summarize speech without lexical features, using only acoustic features in a HMM frame work.

All the above mentioned methods depend on the availability of human/ASR transcribed speech, or gold standard human reference summaries for training. However, ASR systems may not be available for all languages, and it involves considerable amount of resources and effort in building an ASR system for a new language. Also, constructing gold standard human reference summaries is a tedious job and they are not easily available for all speech files. In this work, we propose a method to rank

speech segments based on prominence features. The proposed method does not require an ASR system or a gold standard human summary as it uses prominence values of syllables in a speech segment to rank the speech segment for summarization.

## 2. Data-set

The studies described in the current work are carried out on two different speech corpora.

1) A subset of Boston university radio news corpus (BU-RNC) which contains read style speech. The data subset used in current work contains 40 news stories on different topics spoken by a female speaker (f2b). The corpus consists of orthographic text transcript for each news story.

2) A subset of switchboard data corpus released by ICSI which contains spontaneous telephone conversations. The data subset used consists of 40 conversations on the issue of credit cards. It contains 38 female and 42 male speakers coming from wide range of dialectal patterns of American English. The corpus contains orthographic text transcript and speaker turn information.

### 2.1. Construction of human reference summaries

The text transcripts of the speech files are presented to 4 human annotators along with corresponding audio files for constructing a summary. Each annotator was instructed to generate a summary for 30% compression ratio. They were instructed to pick meaningful phrases or sentences present in original story without altering them. The number of reference summaries and speech files is decided following the standard evaluation setup for text summarization at document understanding conference (DUC) [7] which uses 40 topics and 4 human reference summaries for each topic.

## 3. Significance of prominence for speech summarization

### 3.1. Prominence

Prominence is defined as perceptual salience of a language unit. It is the property by which linguistic units are perceived as standing out from their environment. Prominence is also described in terms of distribution of accents. The first corpus (f2b) contains hand labelled pitch accent markings by experienced human labelers. These pitch accent markings are treated as prominence markers. In this section we describe experiments done using these manual prominence markings.

### 3.2. Content and Function words

Previous studies [8, 9] have shown that content words are made prominent than function words in continuous speech. In order to validate these observations, we analyzed the nature of words that are marked as prominent by human labellers in f2b corpus. Out of 9090 words in the corpus 2852 words are marked as

prominent, of which 2614 (91.6%) are content words and 238 (8.3%) are function words. This observation shows that prominence can be used to distinguish content and function words. The content and function words classification was based on POS tags given in the corpus.

### 3.3. Acoustic measure for prominence

The hand labelled prominence markings in the corpus provide information about whether a syllable is prominent or not, but does not provide a measure of prominence. In order to obtain prominence values of syllables in a speech segment, we followed the method described in [10]. This method computes prominence value of a syllable based on acoustic features like syllable duration, subband energy(300-2200 Hz) and pitch variation. A brief description of this method is presented below.

Prominence value ( $p_i$ ) of  $i^{th}$  syllable in a speech segment is given by  $p_i = \max(F1_i, F2_i)$  where,  $F1_i = dur^i \times en_{300-2200}^i$ . Here,  $dur^i$  is the syllable duration and  $en_{300-2200}^i$  is the energy in frequency band 300 – 2200 Hz.  $F2_i = en_{ov}^i \times (A_{event}^i \times D_{event}^i \times R_{event}^i)$  where,  $en_{ov}^i$  is the overall syllable energy,  $A_{event}^i$  and  $D_{event}^i$  are amplitude and duration of an intonational event respectively and  $R_{event}^i$  is normalizing factor. The intonational events considered here are those events that contain a rise followed by a fall in the pitch profile. These type of intonation events were shown to correlate well with human prominence judgements [10].

Fig. 1 shows the distribution of prominence values for prominent and not prominent syllables in the corpus.

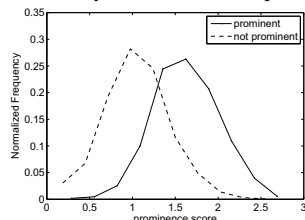


Figure 1: Distributions of prominence values for prominent and non prominent syllables.

It can be observed from Fig.1 that prominence values for syllables marked as prominent are higher than values of non prominent syllables. Therefore, the computed prominence value for a syllable ( $p_i$ ) can be treated as a measure of its prominence.

### 3.4. Usefulness of prominence for speech summarization

In order to investigate usefulness of prominence for summarization, we use hand labelled prominence markings for automatic summarization. The prominence scores of syllables that are hand-labelled as prominent are obtained by the method described in Sec. 3.3. Acoustic score of a speech segment used for its ranking is obtained by taking the mean of prominence values of syllables that are hand marked as prominent. Speech segments are ranked in decreasing order of acoustic scores and top ranking segments are concatenated in chronological order of their occurrence in the news show until desired summary length is achieved.

The distribution of acoustic scores for speech segments belonging to summary class and non summary class is shown in Fig. 2. It can be observed from the Fig. 2 that segments belonging to summary class tend to have high prominence score than segments not in summary. This shows that prominence based scoring of speech segments helps in automatic summarization. In order to formally evaluate the usefulness of prominence for summarization, we compare the summaries generated by prominence based scoring with summaries generated by tf\*idf based scoring of manual transcripts (Sec. 3.5) and

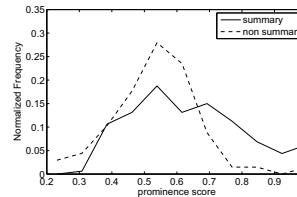


Figure 2: Distributions of acoustic scores for segments belonging to summary and non summary classes.

summaries generated by a supervised system trained on gold standard human reference summaries (Sec. 3.6).

### 3.5. Summaries based on tf\*idf scores

The tf\*idf scores are computed from manual transcripts provided along with the corpus. The tf\*idf based score of a segment is computed as similarity measure between the segment and the whole document. Sentences are ranked in decreasing order of their similarity scores. The similarity between a segment and the document is computed by the dot product between corresponding vectors with terms as dimensions and tf\*idf scores of the terms as magnitudes of corresponding dimensions.

### 3.6. Supervised system trained on gold standard summaries

An artificial neural network classifier is trained on gold standard human labelled summaries. A gold standard summary for a given speech file is obtained by combining all segments present in four human reference summaries of the speech file. The corpus is divided randomly into two non overlapping halves. Classifier was trained on one half and tested on the other. The classifier is trained with class labels -1 for class ‘non summary’ and 1 for class ‘summary’. While testing, the classifier outputs a score between -1 and 1 for a given speech segment. This score is used for ranking the speech segments to generate audio summaries for desired length. The features on which the classifier is trained consist of minimum, maximum, mean, standard deviation of RMS intensity ( $I$ ),  $\Delta I$ ,  $F_0$ ,  $\Delta F_0$  over each segment and duration of the segment. The  $F_0$  and  $I$  contours are normalized using z-score normalization.

### 3.7. Evaluation

The evaluation of summaries generated by the three techniques explained in sections 3.4, 3.5 and 3.6 was done by estimating how close they are with human reference summaries. Audio summaries are transcribed into text by picking corresponding text segments from the manual transcripts provided with the corpus. The summaries are evaluated using standard text summarization evaluation system ROUGE[11]. ROUGE measures n-gram overlap between human reference summaries and automatic summaries. Four human reference summaries are provided as model reference summaries for each news story. ROUGE-1, ROUGE-2 and ROUGE-SU4 scores for these summaries are reported in Tab. 1. ROUGE-N measures N-gram overlap between human reference summaries and automatic summary. ROUGE-SU4 measures the skip bi-gram overlap within a window of four.

Table 1:  $F$ -measure values and 95% confidence intervals for ROUGE-1 (R-1), ROUGE-2 (R-2), ROUGE-SU4 (R-SU4) metrics for prominence based summaries and summaries generated by supervised system and tf\*idf scores.

system	R-1	R-2	R-SU4
prominence	0.515[0.49 0.53]	0.351[0.33 0.37]	0.345[0.32 0.36]
supervised	0.478[0.45 0.49]	0.340[0.32 0.36]	0.337[0.31 0.35]
tf*idf	0.514[0.49 0.53]	0.337[0.31 0.35]	0.344[0.32 0.36]

From Tab. 1 it can be seen that prominence based features

generate summaries as good as summaries generated by supervised system trained on standard acoustic features and summaries based on tf\*idf scores of manual transcripts. The advantage of prominence based summaries is, they do not depend on ASR output or gold standard human labelled summary for training. In this experiment, we have made use of prominence markings provided by human experts. This was done primarily to demonstrate that explicit modelling of prominence helps in ranking speech segments for automatic summarization in an unsupervised framework. In the next section we propose a speech-to-speech summarization method where syllable boundaries of a speech segment are automatically computed and the segment is ranked using prominence scores of syllables in the segment.

#### 4. Speech summarization using automatic prominence scoring

The speech files are first segmented by extracting speech segments based on pause duration. A segment boundary is assumed whenever a pause greater than 250 ms is encountered. In order to rank the speech segments automatically by their acoustic score, syllable boundaries are required. Syllable boundaries are identified by modified convex hull algorithm [10]. The errors in syllable segmentation on the present data set is reported in terms of missed detection rate (MDR) and false alarm rate (FAR). The MDR and FAR values on the current data set are 12.3% and 9.4% respectively. Prominence value of each syllable in the segment is computed as described in Sec.3.3. To obtain acoustic score of a segment from prominence values of syllables present in it, four types of scoring functions are experimented. First function calculates mean prominence score (mp) of a segment by taking mean of prominence values of syllables present in it.

$$mp = \frac{\sum_{i=1}^N p_i}{N}, \quad (1)$$

where  $p_i$  is prominence value of  $i^{th}$  syllable and  $N$  is total number of syllables in the segment. Second function scores a segment by maximum prominence value (Mp) of syllables present in it.

Third function assigns mean value of absolute difference between prominence values of consecutive syllables (mdp) in a segment as its score. The use of difference between prominence values serves to normalize data against variation between speakers, but preserves variations produced by prosody.

$$mdp = \frac{\sum_{i=1}^{N-1} |p_{i+1} - p_i|}{N-1}, \quad (2)$$

Fourth function assigns maximum of absolute difference (Mdp) between prominence values of consecutive syllables in a segment as its score. Segments are ranked in decreasing order of their acoustic score and top ranking segments are concatenated in chronological order of their occurrence in the news story until the desired summary length is achieved.

##### 4.1. Evaluation

Evaluation of the summaries generated by automatic prominence detection was done in two ways, using ROUGE [11] and task based evaluation by humans. Task based evaluation was done to evaluate the quality of the audio summaries.

All the summaries are generated for 30% compression ratio (same as model summaries). 4 human summaries are provided as model reference summaries for each story. ROUGE scores for different prominence scoring functions are reported in Tab. 2. It can be observed that mdp performs better than other scoring functions. The summaries generated by automatic prominence scoring using mdp (Tab. 2) have less ROUGE scores than summaries generated by manual prominence markings and

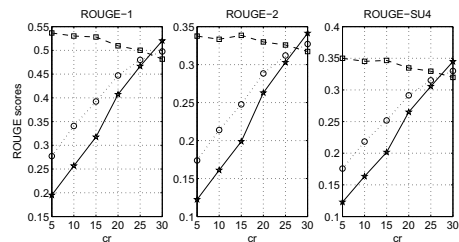


Figure 3: Figure showing recall (solid line), precision (dashed line) and f-measure (dotted line) values of different ROUGE metrics for different compression ratios (5, 10, 15, 20, 25, 30) of audio summaries generated by mdp scoring function.

tf\*idf based scores (Tab. 1). But the difference is not statistically significant as the 95% confidence intervals of these systems overlap significantly. In order to evaluate the summarization capability of the proposed technique for different compression ratios, ROUGE scores for summaries of different compression ratios (5, 10, 15, 20, 25, 30) with mdp as scoring function are reported in Fig. 3. It can be observed from Fig. 3 that precision values do not drop much with increase in compression ratio. This shows that system is capable of generating summaries of different lengths without compromising on the quality of summaries.

Table 2: F-measure values and 95% confidence intervals of ROUGE-1 (R-1), ROUGE-2 (R-2), ROUGE-SU4 (R-SU4) metrics for various scoring functions.

system	R-1	R-2	R-SU4
mp	0.496[0.47 0.51]	0.316[0.29 0.33]	0.322[0.29 0.34]
Mp	0.474[0.45 0.49]	0.297[0.27 0.31]	0.305[0.28 0.32]
mdp	0.508[0.48 0.52]	0.341[0.32 0.36]	0.343[0.32 0.36]
Mdp	0.489[0.46 0.50]	0.323[0.30 0.34]	0.328[0.30 0.34]

In task based evaluation, five human subjects are asked to listen to a summary of a given compression rate and answer a questionnaire given to them. All the subjects are in the age group of 20-23 and are graduate students who can understand and speak English. The questionnaire consisted of simple questions based on facts of the news story. The questions are of type what, when, who, where etc. The subjects were given strict instructions not to use their prior knowledge on the news stories in answering the questions. They answered the questions based on the information present in the summary. The subjects were not restricted from listening to a summary multiple times. The percentage of the questions answered correctly for each compression ratio is presented in Tab. 3.

Table 3: Percentage of questions answered correctly for different compression ratios (CR)

cr	5	10	15	20	25
correct(%)	32.4%	41.5%	45.6%	51.3%	56.8%

The results of task based evaluation (Tab. 3) show that humans are able to understand the audio summaries and are able to get some useful information from these audio summaries. The number of questions answered correctly increased with the compression ratio which agrees with the ROUGE based evaluation (Fig. 3).

##### 4.2. Correlation between tf\*idf based summaries and prominence based summaries

Fig. 4 shows scatter plot between tf\*idf scores and prominence score (mdp) for phrases picked in prominence (mdp) based summaries (a) and tf\*idf based summaries (b) for two news stories 1 and 2. In Fig. 4 it can be observed from 1(a) and 2(a) that some phrases picked in prominence based summaries have low tf\*idf scores, where as it can be observed from 1(b) and 2(b) (tf\*idf

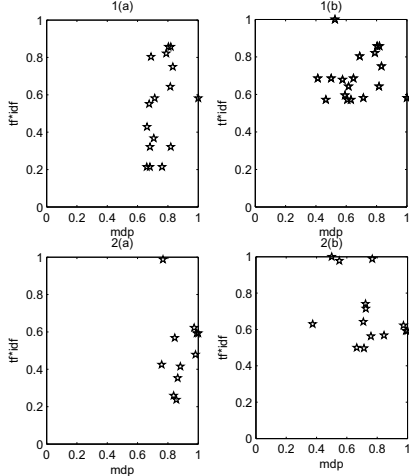


Figure 4: Scatter plots between  $tf*idf$  scores and prominence score ( $mdp$ ) for summaries of two news stories 1 and 2. (a) shows the scatter plot of scores for phrases picked in summaries based on prominence ( $mdp$ ) scores. (b) shows the scatter plot of scores for phrases picked in summaries based on  $tf*idf$  scores.

based summaries) that phrases having high  $tf*idf$  scores also have high prominence ( $mdp$ ) scores. This shows that prominence based ranking provides some complementary information to  $tf*idf$  based ranking. In order to capture this complementary information, segments are ranked by a combined score computed from prominence score and  $tf*idf$  score of segments. The scores obtained from prominence scoring and  $tf*idf$  scoring for a document are normalized between 0 and 1 and a combined score is obtained by adding these two scores. Summaries are generated for 30% cr. The ROUGE scores for these summaries are reported in Tab. 4.

Table 4:  $F$ -measure values and 95% confidence intervals of ROUGE-1 (R-1), ROUGE-2 (R-2), ROUGE-SU4 (R-SU4) metrics for summaries generated by combined score.

system	R-1	R-2	R-SU4
$mdp + tf*idf$	0.520[0.50 0.54]	0.350[0.33 0.37]	0.356[0.33 0.37]

The ROUGE scores in Tab. 4 show that summaries generated by combined scores based on prominence and  $tf*idf$  scores are better than summaries generated by the individual systems ( $tf*idf$  in Tab. 1,  $mdp$  in Tab. 2).

#### 4.3. Experiments on switchboard data

The evaluation of the proposed method is also done on switchboard data which contains spontaneous telephone dialogues. A conversation is segmented at speaker turns that are provided with the corpus. These speaker turns are treated as basic units while performing extractive summarization. Each speaker turn is assigned an acoustic score as described in Sec. 4. Top scoring speaker turns are concatenated until desired summary length is reached. Evaluation of these summaries was carried out using ROUGE package. Similar to the results obtained on f2b corpus  $mdp$  scoring function performed better than other scoring functions. The performance of the proposed method along with  $tf*idf$  based scores and supervised system trained on switchboard data is reported in terms of ROUGE scores in Tab. 5.

It can be observed from Tab. 5 that the prominence based ranking ( $mdp$ ) performs as good as  $tf*idf$  scores and supervised system even on spontaneous speech data. The ROUGE scores for switchboard corpus are higher than ROUGE scores for f2b corpus. This might be because of the choice of the extraction unit. In the case of switchboard data speaker turns which are

Table 5:  $F$ -measure values and 95% confidence intervals of ROUGE-1 (R-1), ROUGE-2 (R-2), ROUGE-SU4 (R-SU4) metrics for prominence based summaries,  $tf*idf$  based summaries and supervised system on switchboard data.

system	R-1	R-2	R-SU4
$mdp$	0.666[0.64 0.68]	0.464[0.41 0.49]	0.491[0.45 0.52]
$tf*idf$	0.653[0.62 0.68]	0.461[0.40 0.49]	0.490[0.42 0.53]
supervised	0.628[0.59 0.65]	0.456[0.40 0.48]	0.474[0.40 0.52]

linguistically and semantically meaningful segments are considered, where as in the case of f2b corpus segments were based on pause.

## 5. Summary and Conclusions

In this paper, we have demonstrated the significance of prominence for speech summarization. We have shown that explicit modelling of prominence captures the prosodic information relevant to summarization in an unsupervised framework. The proposed method scores speech segments from the prominence values of syllables in the segment. The proposed technique generates summaries that are as good as summaries based on  $tf*idf$  scores and summaries generated by a supervised system trained using gold standard summaries. It was also shown that the proposed prominence based scoring captures complimentary information to  $tf*idf$  based scoring and their combined scores generate summaries of better quality than the individual systems. The output summaries are presented in form of speech by preserving characteristics of the input speech signal.

## 6. References

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