Spoken Lecture Summarization by Random Walk over a Graph Constructed with Automatically Extracted Key Terms

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Abstract

This paper proposes an improved approach for spoken lecture summarization, in which random walk is performed on a graph constructed with automatically extracted key terms and probabilistic latent semantic analysis (PLSA). Each sentence of the document is represented as a node of the graph and the edge between two nodes is weighted by the topical similarity between the two sentences. The basic idea is that sentences topically similar to more important sentences should be more important. In this way all sentences in the document can be jointly considered more globally rather than individually. Experimental results showed significant improvement in terms of ROUGE evaluation.

Index Terms: summarization, course lecture, probabilistic latent semantic analysis (PLSA), random walk, key term

1. Introduction

In the Internet era, digital content over the network includes all the information and activities of human life. The most attractive form of network content is multimedia that may include speech. Such speech information usually tells the subjects, topics, and core concepts of the content. However, multimedia/spoken documents are just video/audio signals, usually much more difficult to retrieve and browse, because they cannot be easily displayed on the screen, and the user cannot simply "skim through" each of them from the beginning to the end. Hence, spoken document summarization becomes very important [1].

Automatic summarization of spoken documents have been actively investigated. While most work was focused primarily on news content, recent effort has been increasingly directed to new domains such as lectures and meeting recordings [2, 3]. This paper takes course lecture as an example in the experiments. Many approaches selected a number of indicative sentences or passages from the original spoken documents according to a target summarization ratio, and sequenced them to form a summary. Some approaches tried to identify sentences carrying concepts closer to the complete documents [4]. The spoken document summarization actually carry intrinsic difficulties such as the recognition errors, problems with spontaneous speech, and lack of correct sentence or paragraph boundaries. A general approach has been found very successful [5, 6], in which each sentence in the document d, $S = t_1 t_2 ... t_i ... t_n$, represented as a sequence of terms t_i, is given an importance score:

$$I(S,d) = \frac{1}{n}\sum_{i=1}^{n}[\lambda_1 s(t_i,d) + \lambda_2 l(t_i) + \lambda_3 c(t_i) + \lambda_4 g(t_i)] + \lambda_5 b(S), \quad (1)$$

where $s(t_i,d)$, $l(t_i)$, $c(t_i)$, $g(t_i)$ are respectively some statistical measure (such as TF-IDF), linguistic measure (e.g., different parts-of-speech (PoSs) are given different weights), confidence score and N-gram score for the term t_i, and $b(S)$ is calculated from the grammatical structure of the sentence S, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ and λ_5 are weighting parameters. For each document d, sentences used in the summary is then selected based on this importance score $I(S,d)$.

Prior work showed that the topical information obtained by probabilistic latent semantic analysis (PLSA) was very useful in estimating the statistical measure $s(t_i,d)$ in (1) above to identify the important sentences [7, 8]. Such topical information from PLSA is also used in this paper. We further rescore $I(S,d)$ above in (1) by random walk over a graph to consider not only the importance of terms but the similarity between sentences in the whole document, so that sentences topically similar to more important sentences are given higher scores.

2. Proposed Approach

2.1. Probabilistic Latent Semantic Analysis (PLSA)

PLSA [10] has been widely used to analyze the semantics of documents based on a set of latent topics. Given a set of documents $\{d_j, j = 1,2,...,J\}$ and all terms $\{t_i, i = 1,2,...,M\}$ they include, PLSA uses a set of latent topic variables, $\{T_k, k = 1,2,...,K\}$, to characterize the "term-document" co-occurrence relationships. The probability of observing a term t_i given a document d_j can be parameterized by

$$P(t_i \mid d_j) = \sum_{k=1}^{K} P(t_i \mid T_k) P(T_k \mid d_j). \quad (2)$$

The PLSA model can be optimized with EM algorithm by maximizing a likelihood function [10].

2.1.1. Latent Topic Significance (LTS)

Latent Topic Significance (LTS) for a given term t_i with respect to a topic T_k can be defined [7, 8] as

$$\mathrm{LTS}_{t_i}(T_k) = \frac{\sum_{d_j \in D} n(t_i,d_j) P(T_k \mid d_j)}{\sum_{d_j \in D} n(t_i,d_j)[1 - P(T_k \mid d_j)]}, \quad (3)$$

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where $n(t_i, d_j)$ is the occurrence count of term t_i in a document d_j. In the numerator of (3), the count of the given term t_i in each document d_j, $n(t_i, d_j)$, is weighted by the likelihood that the given topic T_k is addressed by the document d_j, $P(T_k \mid d_j)$, and then summed over all documents d_j in the training corpus $\mathcal{D}$. Therefore the numerator is the total count of the given term t_i used for the given topic T_k over the whole training corpus, as estimated by PLSA model. The denominator is very similar except for latent topics other than T_k, so $P(T_k \mid d_j)$ is replaced by $[1 - P(T_k \mid d_j)]$. Thus, a higher $\mathrm{LTS}_{t_i}(T_k)$ indicates the term t_i is more significant for the latent topic T_k.

2.1.2. Latent Topic Entropy (LTE)

Latent Topic Entropy (LTE), $\mathrm{LTE}(t_i)$, for a given term t_i can be calculated as (4) from the topic distribution $P(T_k \mid t_i)$ for each term t_i,

$$\mathrm{LTE}(t_i) = -\sum_{k=1}^{K} P(T_k \mid t_i) \log P(T_k \mid t_i), \tag{4}$$

where the topic distribution $P(T_k \mid t_i)$ can be estimated as follows [7, 8],

$$P(T_k \mid t_i) = \frac{P(t_i \mid T_k) \cdot P(T_k)}{P(t_i)}, \tag{5}$$

where the probability $P(T_k)$ is left out because a good approach to estimate it is not yet available, while $P(t_i)$ can be obtained from a large corpus. $\mathrm{LTE}(t_i)$ is a measure of how the term t_i is focused on a few topics, so a lower latent topic entropy implies the term carries more topical information.

2.2. Automatic Key Term Extraction

Key terms are the terms used in the documents carrying core concepts of the content. They are useful for indexing, retrieving, and browsing. There are in general two types of key terms: keywords (single words) and key phrases (such as "hidden Markov model"). Automatically extracting key terms from spoken content is still a difficult problem, but some initial approaches have been shown to be successful in recent experiments [9]. Such approaches include use of right/left branching entropy derived from PAT-Trees to extract frequently occurring patterns including two or more words, and identifying or verifying key terms (including key phrases) by prosodic (pitch, duration, energy), lexical, and semantic (from PLSA) features with unsupervised techniques or supervised training [9]. Here well show such automatically extracted key terms are very helpful in summarization.

2.3. Statistical Measures of a Term

Here in this work, the statistical measure of a term t_i, $s(t_i, d)$ in (1) can be defined in two different ways below.

2.3.1. LTE-Based Statistical Measure

The statistical measure $s(t_i, d)$ in (1) can be defined based on $\mathrm{LTE}(t_i)$ in (4) as

$$s_{\mathrm{LTE}}(t_i, d) = \frac{\beta n(t_i, d)}{\mathrm{LTE}(t_i)}, \tag{6}$$

where β is a scaling factor, so the score $s_{\mathrm{LTE}}(t_i, d)$ is inversely proportion to the latent topic entropy $\mathrm{LTE}(t_i)$. Some previous works [7, 8] showed that this measure outperformed the very successful "significance score" in speech summarization [6], and here we use $s_{\mathrm{LTE}}(t_i, d)$ as the baseline.

2.3.2. Key-Term-Based Statistical Measure

With automatically extracted key terms (with some errors) as mentioned above, we can estimate a new latent topic probability $P_{\mathrm{KEY}}(T_k \mid d)$ hopefully better than $P(T_k \mid d)$ directly from PLSA,

$$P_{\mathrm{KEY}}(T_k \mid d) = \frac{\sum_{t_i \in key} n(t_i, d) P(T_k \mid t_i)}{\sum_{k=1}^{K} \sum_{t_i \in key} n(t_i, d) P(T_k \mid t_i)}, \tag{7}$$

where key is the set of automatically extracted key terms, and $P(T_k \mid t_i)$ is in (5). Therefore only the automatically extracted key terms t_i in d are considered, avoiding the influence from other insignificant terms. We can then define the statistical measure $s(t_i, d)$ as

$$s_{\mathrm{KEY}}(t_i, d) = \sum_{k=1}^{K} \mathrm{LTS}_{t_i}(T_k) P_{\mathrm{KEY}}(T_k \mid d), \tag{8}$$

where the information of $\mathrm{LTS}_{t_i}(T_k)$ in (3) is used here.

2.4. Random Walk on a Graph

We formulate the sentence selection problem as random walk on a directed graph, in which each sentence is a node and the edges between them are weighted by topical similarity. The basic idea is that a sentence similar to more important sentences should be more important [12, 13]. In this way all sentences in the document can be jointly considered more globally rather than individually. We define two directed edges between each pair of nodes with two directions, weighted by an asymmetric topical similarity between them, We then keep only the top N outgoing edges with the highest weights from each node, while consider incoming edges to each node for importance propagation in the graph. A simplified example for such a graph is in Figure 1, in which A_i and B_i are the sets of neighbors of the node S_i connected respectively by outgoing and incoming edges.

2.4.1. Topical Similarity between Sentences

Within a document d, we can first compute the probability that the topic T_k is addressed by a sentence S_i,

$$P(T_k \mid S_i) = \frac{\sum_{t \in S_i} n(t, S_i) P(T_k \mid t)}{\sum_{t \in S_i} n(t, S_i)}. \tag{9}$$

Then an asymmetric topical similarity $sim(S_i, S_j)$ for sentences S_i to S_j (with direction $S_i \rightarrow S_j$) can be defined by accumulating $\mathrm{LTS}_t(T_k)$ in (3) weighted by $P(T_k \mid S_i)$ for all terms t in S_j over all latent topics,

$$sim(S_i, S_j) = \sum_{t \in S_j} \sum_{k=1}^{K} \mathrm{LTS}_t(T_k) P(T_k \mid S_i), \tag{10}$$

We normalize this similarity by the total similarity summed over the top N sentences S_k with edges outgoing from S_i, or the set A_i, to produce the weight $p(i, j)$ for the edge from S_i to S_j on the graph,

$$p(i, j) = \frac{sim(S_i, S_j)}{\sum_{S_k \in A_i} sim(S_i, S_k)}. \tag{11}$$

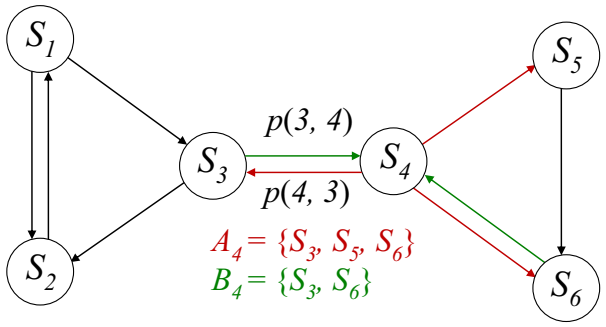

Figure 1: *A simplified example of the graph considered. Each sentence is represented as a node on the graph. A_i and B_i are the neighbors of the node S_i connected respectively by outgoing and incoming edges.*

2.4.2. Random Walk

Random walk [12, 13] is now performed over the graph obtained above. $v(i)$ is the new score for node S_i, which is the interpolation of two scores, the normalized initial importance $r(i)$ for node S_i and the score contributed by all neighboring nodes S_j of node S_i weighted by $p(j,i)$,

$$v(i) = (1-\alpha)r(i) + \alpha \sum_{S_j \in B_i} p(j,i)v(j), \qquad (12)$$

where α is the interpolation weight, B_i is the set of neighbors connected to node S_i via incoming edges, and

$$r(i) = \frac{I(S_i,d)}{\sum_{S_j} I(S_j,d)} \qquad (13)$$

is the importance score of sentence S_i, $I(S_i,d)$, defined in (1), but normalized by the sum of such scores for all sentences S_j in the document d. (12) can be solved with the approach very similar to that for the PageRank problem [11]. Let $\mathbf{v} = [v(i), i = 1,2,...,L]^{\mathbf{T}}$ and $\mathbf{r} = [r(i), i = 1,2,...,L]^{\mathbf{T}}$ be the column vectors for $v(i)$ and $r(i)$ for all sentences in the document, where L is the total number of sentences in the document d and $\mathbf{T}$ represents transpose. (12) then has a vector from below,

$$\begin{aligned} \mathbf{v} &= (1-\alpha)\mathbf{r} + \alpha\mathbf{P}\mathbf{v} \\ &= ((1-\alpha)\mathbf{r}\mathbf{e}^{\mathbf{T}} + \alpha\mathbf{P})\mathbf{v} = \mathbf{P}'\mathbf{v}, \end{aligned} \qquad (14)$$

where $\mathbf{P}$ is an $L \times L$ matrix of $p(j,i)$, and $\mathbf{e} = [1,1,...,1]^{\mathbf{T}}$ is an L-dimensional vector with all components being 1. Because $\sum_i v(i) = 1$ from (12) and (13), $\mathbf{e}^{\mathbf{T}}\mathbf{v} = 1$.

It has been shown that the solution $\mathbf{v}$ of (14) is the dominant eigenvector of $\mathbf{P}'$ [14], or the eigenvector corresponding to the largest absolute eigenvalue (which is 1) of $\mathbf{P}'$. The solution $v(i)$ can then be integrated with the original importance score $I(S_i,d)$ using LTE-based statistical measure (6) or key-term-based statistical measure (8),

$$\hat{I}(S_i,d) = I(S_i,d)(v(i))^{\delta}, \qquad (15)$$

where δ is a weighting parameter.

3. Experimental Setup

3.1. Corpus

The corpus used in this research is the lectures for a course offered in National Taiwan University. The lectures were given in the host language of Mandarin Chinese but with almost all terminologies produced in the guest language of English and embedded in the Mandarin utterances. There is a total of 17 chapters, while the lecture is 45.2 hours long. We segmented the whole lecture into 155 documents by topic segmentation [15], and extracted the summary for each document.

34 documents out of the 155 were tested. The average length of each document was about 17.5 minutes, and manual transcriptions without word errors and ASR results were both used. For ASR, the acoustic models were trained with the AST-MIC corpus for Mandarin and the Sinica Taiwan English corpus for English respectively, and then adapted by 25.2 minutes bilingual corpus from the target speaker (the course instructor) [16]. The language model was trained by two other courses offered by the same instructor and adapted by the course slides. The accuracies for the ASR transcriptions are 78.15% for Mandarin characters, 53.44% for English words, and 76.26% for overall.

The automatically key term extraction approach mentioned in Section 2.2 was used and both keywords and key phrases were extracted [9]. The F-measures for key terms were 62.70% and 67.31% for ASR and manual transcriptions respectively. We set the number of topics for PLSA as 32, considering the course of 17 chapters. The value of α is set to 0.9, which is empirically better choice [12, 13]. Two human subjects (students at National Taiwan University) were requested to produce two reference summaries for each document by ranking the importance of the sentences in each document from "the most important" to "of average importance."

3.2. Evaluation Metrics

The well-known evaluation package called ROUGE [17] was used in this research, including ROUGE-N ($N = 1,2,3$) and ROUGE-L scores. ROUGE$_{\text{r}}$-N is an N-gram recall between the automatically generated summary and a set of manually generated reference summaries calculated as

$$\text{ROUGE}_{\text{r}}\text{-N} = \frac{\sum_{\mathcal{S}\in\mathbb{S}} \sum_{\text{gram}_N \in \mathcal{S}} \text{Count}_{\text{match}}(\text{gram}_N)}{\sum_{\mathcal{S}\in\mathbb{S}} \sum_{\text{gram}_N \in \mathcal{S}} \text{Count}(\text{gram}_N)}, \qquad (16)$$

where N stands for the length of N-gram considered, gram_N; $\mathcal{S}$ is an individual reference summary, and $\mathbb{S}$ is a set of reference summaries. $\text{Count}_{\text{match}}(\text{gram}_N)$ is the maximum number of N-grams co-occurring in the automatically generated summary and the reference summary. $\text{Count}(\text{gram}_N)$ is then the total number of N-grams in the reference summary. ROUGE-L is similarly obtained but counting the "longest common subsequence" (LCS) between the automatically generated summary and the reference summary. F-measures for ROUGE-N ($N = 1,2,3$) and ROUGE-L can be evaluated in exactly the same way, which are used in the following results.

4. Results and Discussion

In the experiments to be presented below, the summarization ratio was set to be 10%, 20%, and 30% respectively. The key phrases (with more than one word) automatically extracted were taken as individual terms in PLSA modeling and all following processes.

Figure 2 shows the results for ROUGE-N and ROUGE-L for ASR (Figure 2 (a)-(d)) and manual transcriptions (Figure 2 (e)-(h)). In each case the three groups of bars are for 10%, 20%, and 30% summarization ratios, and in each group the four bars

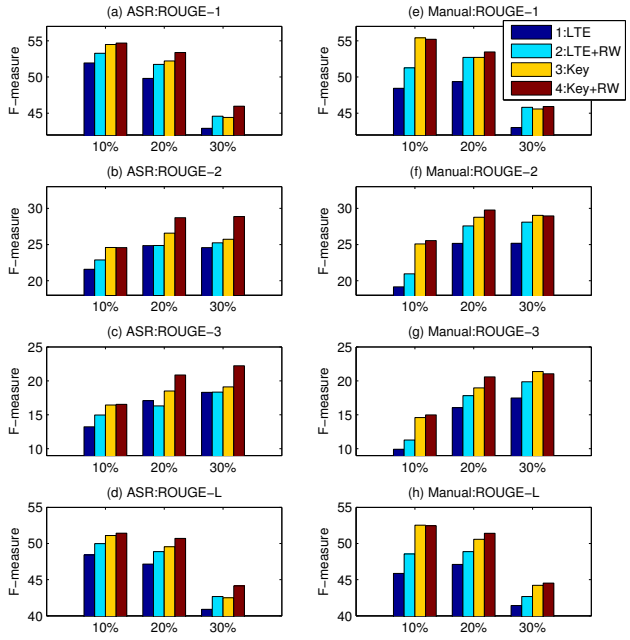

Figure 2: *The results of different choices of parameters: LTE-based (1, 2) or key-term-based (3, 4), without (1, 3) or with (2, 4) random walk, for ASR ((a)-(d)) or manual ((e)-(h)) transcriptions at summarization ratios of* 10%, 20%, *and* 30%.

are respectively for LTE-based statistical measure $s_{\text{LTE}}(t_i, d)$ in (6) (LTE, the baseline), that followed by random walk (LTE + RW), key-term-based statistical measure in (8) (Key) and that followed by random walk (Key + RW). In all cases, the key-term-based statistical measure (bar 3) always outperformed the baseline (bar 1), or the LTE-based statistical measure. Clearly the key term knowledge is very helpful, especially for manual transcriptions. This is probably because in manual transcriptions all key terms are correctly transcribed (although may be incorrectly extracted) so that the key-term-based statistical measures were much more accurately estimated. Similar improvements can also be observed for ASR transcriptions, but slightly less significant.

In all cases, random walk based on topical similarity always helped the LTE-based statistical measure (bar 2 vs bar 1) For ASR transcriptions (Figure 2 (a)-(d)), random walk also improved the performance of key-term-based statistical measure (bar 4 vs bar 3). However, with 10% summarization ratio for manual transcriptions (Figure 2 (e)-(h)), random walk wasn't able to similarly help the key-term-based statistical measure (bar 4 vs bar 3). The reason is probably that for manual transcriptions the important sentences within 10% were already very well selected by the key-term-based statistical measure, so adding extra topical similarity among many sentences cannot further improve the performance. However, the important sentences ranked between top 10% to 30% are less clear and therefore random walk can help the key term knowledge (bar 4 vs bar 3) for 20% and 30% of summarization ratio (Figure 2 (e)-(h)).

Table 1 lists the maximum relative improvement (RI) achievable with respect to the baseline in all cases discussed above. For ASR transcriptions, the RI with different summarization ratios are similar, and the results are all from key-term-based statistical measure with random walk, probably because the topical similarity can compensate recognition errors and help include important sentences. For manual transcriptions, on the other hand, the results are from LTE-based statistical measure with or without random walk, probably because without recognition errors the key terms can accurately include important sentences so that topical similarity cannot improve the performance in all cases; also, the RI with 10% summarization ratio is highest, probably because key terms are very helpful to identify top 10% important sentences; but with roughly 67% of F-measure of key terms, the top 20% or 30% important sentences selected did include some noisy sentences.

Table 1: *Maximum relative improvement (RI) with respect to the baseline achievable in all cases (%).*

MAX RI	ASR Transcriptions			Manual Transcriptions		
	10%	20%	30%	10%	20%	30%
ROUGE-1	5.30	7.19	7.13	14.37	8.27	6.74
ROUGE-2	13.94	15.48	17.45	33.31	18.33	15.33
ROUGE-3	24.98	22.23	21.33	50.98	28.21	22.25
ROUGE-L	6.23	7.51	7.92	14.52	9.12	7.49

5. Conclusions

Extensive experiments and evaluation with ROUGE metrics showed key-term-based statistical measure is good for speech summarization, and random walk also improves the performance. The random walk approach helps give higher scores to sentences topically similar to more important sentences, and thus consider all sentences in the document more globally.

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