A DNN-HMM Approach to Story Segmentation

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Abstract

Hidden Markov model (HMM) is one of the popular techniques for story segmentation, where hidden Markov states represent the topics, and the emission distributions of n-gram language model (LM) are dependent on the states. Given a text document, a Viterbi decoder finds the hidden story sequence, with a change of topic indicating a story boundary. In this paper, we propose a discriminative approach to story boundary detection. In the HMM framework, we use deep neural network (DNN) to estimate the posterior probability of topics given the bag-of-words in the local context. We call it the DNN-HMM approach. We consider the topic dependent LM as a generative modeling technique, and the DNN-HMM as the discriminative solution. Experiments on topic detection and tracking (TDT2) task show that DNN-HMM outperforms traditional n-gram LM approach significantly and achieves state-of-the-art performance.

Index Terms: Deep neural network, Hidden Markov Model, story segmentation

1. Introduction

Story segmentation is a task to partition a stream of text, audio or video into a sequence of topically coherent segments named as stories [1, 2, 3, 4]. The task serves as a necessary precursor for subsequent tasks such as topic detection and tracking [1, 5], summarization [6], information extraction [7], indexing and retrieval [8]. Automatic story segmentation has gained ever-increasingly interests with the explosive growth of multimedia data. Specifically, this paper addresses the task of segmenting a speech recognition transcript (i.e., from broadcast news) to a sequence of stories by a hybrid deep neural network (DNN) - hidden Markov model (HMM) approach that has achieved tremendous success in speech recognition [9].

Story segmentation has been historically studied through different media types (audio/prosodic [10, 11, 12], video [13] and text [14, 2, 15, 16, 4, 17]) and genres (broadcast news [18], meeting recordings [17] and lectures [19, 10]). With recent progress in large vocabulary continuous speech recognition (LVCSR), lexical cohesion based methods have drawn much attention for story segmentation of spoken documents [4, 20, 21]. These methods work on a sequence of words and reveal story transitions that manifest semantic topic shifts. As one of the earliest approaches, TextTiling [4, 20] measures the lexical similarity (i.e. via cosine) between adjacent sentences and story boundaries are discovered at the local similarity minima, where sentences are represented by bag-of-words (BOW) or term frequency – inverted document frequency (*tf-idf*) vectors. TextTiling is one of the methods focusing on identifying boundaries through local lexical comparison, while other lexical methods aims to find an optimal segmentation under some global criteria [22, 23]. Popular approaches include dynamic programing (DP) [22, 23, 24], Ncuts [25], BayesSeg [26] and dd-CRP [27].

The lexical cohesion based approaches mentioned above mostly rely on the *tf-idf* representation of a sentence, which is not necessarily attached to topics of stories. Instead, probabilistic topic models, e.g., probabilistic latent semantic analysis (pLSA) [28], latent Dirichlet allocation (LDA) [29] and LapPLSA [28], learn from a training corpus, to map a *tf-idf* representation to a topic representation [25]. These generative topic models assume documents are comprised of topics following certain distributions and words are generated from these topics. Significant performance improvements have been observed when a *tf-idf* representation is substituted by a topic representation in both TextTiling and DP approaches [30, 31].

As another generative model, hidden Markov model (HMM) [32] has been successfully introduced to automatically infer story boundaries [15, 16, 14]. A story is treated as an instance of an underlying topic (a hidden state) and words are generated from the distribution of the topic. The transition from one topic to another indicates a story boundary. Transition and emission probabilities of the hidden states can be inferred from a training corpus. Specifically, the emission probability of a state is inferred by a topic-dependent language model (LM), which is calculated by word counting. In the decoding process, the Viterbi algorithm is used to label the input sequences. The position of topic change is regarded as a story boundary.

In this paper, we introduce the DNN-HMM hybrid model to the story segmentation task. Unlike the topic-dependent LM used in traditional HMM-based approach [15, 16, 14], which is a generative model of the word sequence, we use a *DNN* to directly map the word observation into topic posterior probabilities. The input features of the DNN is the BOW computed from a local context of every candidate story boundary. DNN is known to be able to learn meaningful continuous features for words and hence has better discriminative and generalization capability than n-gram models [33, 34].

2. DNN-HMM Model for Story Segmentation

Fig. 1 depicts the architecture of the proposed DNN-HMM approach for story segmentation. Each HMM state represents a topic and a transition matrix is used to model the probabilities of switching between stories. The DNN produces topic posteri-

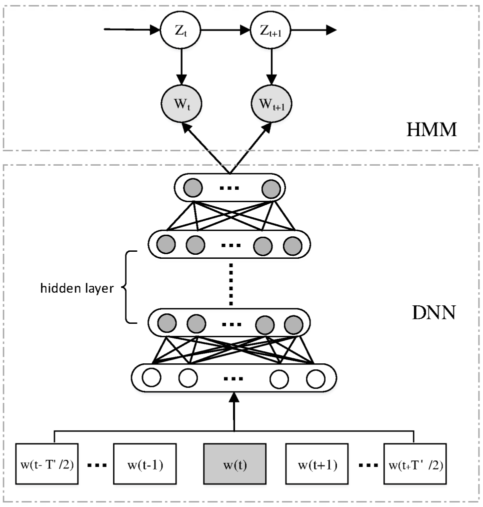


Figure 1: *The DNN-HMM approach for story segmentation.*

or probabilities given the BOW computed from the local context of candidate story boundaries. The posterior is converted to the likelihood score for Viterbi decoding (i.e. the emission probability of the states) using the Bayesian rule in a similar way as in the DNN-HMM acoustic model for speech recognition [9].

2.1. HMM based Story Segmentation

HMM is a generative model for sequence data and has been applied to the text segmentation task [14]. An HMM contains a set of N states, each representing a topic. The transition between the states can be modeled by a $N \times N$ matrix, which can be learnt from segmented and labeled training data. Each state is associated with an emission probability distribution function (PDF) that models the n-gram word distribution for the topic represented by the state. For example, in [15], a topic-dependent unigram language model is used as the emission probability of each HMM state.

Given a sequence of words and the trained HMM, we can infer the topic sequence by solving the following optimization problem:

$$\hat{\mathbf{z}} = \arg\max_{\mathbf{z}} p(\mathbf{z}|\mathbf{w};\theta) \tag{1}$$

where $\mathbf{w} = [w_1, ..., w_T]$ is a sequence of T words observed, $\mathbf{z} = [z_1, ..., z_T]$ is the topic sequence to be inferred, and θ represent the HMM parameters including the transition probabilities and the state emission PDFs. Here we assume that each word is an observation. By applying the Bayesian's rule, the above optimization problem is equivalent to:

$$\hat{\mathbf{z}} = \arg\max_{\mathbf{z}} p(\mathbf{w}|\mathbf{z};\theta)p(\mathbf{z})/p(\mathbf{w}) \tag{2}$$

$$= \arg\max_{\mathbf{z}} p(\mathbf{w}|\mathbf{z};\theta)p(\mathbf{z}) \tag{3}$$

where $p(\mathbf{w})$ does not depend on z and hence ignored in the optimization problem. $p(z)$ is the transition probabilities between states

$$p(\mathbf{z}) = p(z_1)\prod_{t=2}^{T} p(z_t|z_{t-1}) \tag{4}$$

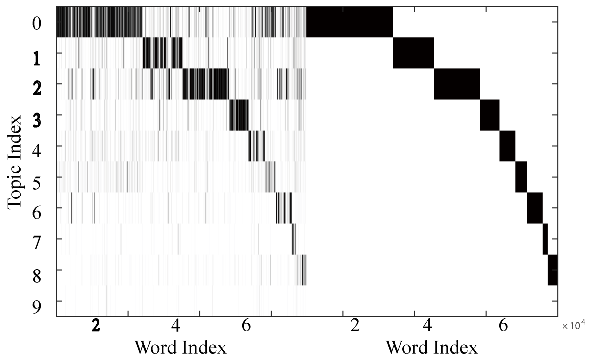
where $p(z_t|z_{t-1})$ is the transition probability from state z_{t-1} to z_t. The words in neighboring time steps are assumed to be independent given the state sequence, hence

$$p(\mathbf{w}|\mathbf{z}) = \prod_{t=1}^{T} p(w_t|z_t) \tag{5}$$

where $p(w_t|z_t)$ is the conditional distribution of the word given the topic, i.e. topic-dependent LM. Note that the formulation in (5) only allows unigram topic LM to be used. To use higher order ngram for topic LM, we can use a fixed window of words [35] or sentence [15] as the basic observation unit.

The topic-dependent LM and state transition probabilities can be trained from a set of text documents, with story boundary and topic label annotated. If the topic label is not available, we can cluster the segmented stories into a set of topics. With these models and the definition of the optimization problem from (3) to (5), we can use the Viterbi algorithm [36] to find the optimal topic sequence for test data efficiently.

The HMM approach to story segmentation is a generative approach, i.e. it models the generation process of the stories and words, and reverse the generative process at test phase to infer the topic sequence. Motivated by the recent success of DNN-HMM approach in ASR, we propose to use a discriminative approach for the story segmentation task. Specifically, we propose to replace the topic-dependent LM with a DNN that predicts the posterior probabilities of the topics directly given a window of observed words.



(a) Posteriors and Topics (b) Original Words and Topics

Figure 2: *Predicted topic posterior probabilities versus true topic label. Darker means higher probability. (a) is the topic posteriors of words predicted by DNN with BOW input. (b) is the true topic class label of the words. The data used to generate the plot are stories taken from TDT2 corpus.*

2.2. DNN based Topic Posterior Prediction

A DNN is actually a multi-layer perception (MLP), i.e., a feedforward neural network model that maps sets of input data onto a set of outputs. It can be considered as a hierarchical feature learner with a nonlinear transformation refining the input representation to a better one, which is topic posterior in our case.

As different topics usually have different word distributions, the input of DNN at word w_t is the BOW computed from the local context of the current word, defined by

$$\mathbf{x}_t = \frac{1}{T'+1}\sum_{\tau=-T'/2}^{T'/2} \tilde{w}_{t-\tau} \tag{6}$$

where $\tilde{w}_t$ is the 1-hot vector representation of the word w_t, and $T'+1$ is the context window size. At the beginning and ending of the input word sequence, we won't be able to get the full context, and the normalization term $T' + 1$ is replaced by the actual number of words used in the sum. In this way, we normalize $\mathbf{x}_t$ independent of its position in the input sequence. The BOW vector $\mathbf{x}_t$ is sparse and has a dimension of $|V|$, i.e. the size of the vocabulary. It captures the unigram statistics around the current word w_t, and hence contains information to predict the topic class for w_t.

The BOW feature vector is nonlinearly transformed by the DNN to generate the topic posteriors. The hidden layers of the DNN produces their output as follows:

$$\mathbf{h}_l = f_l(\mathbf{W}_l \mathbf{h}_{l-1} + \mathbf{b}_l) \tag{7}$$

where $\mathbf{h}_l$, f_l, $\mathbf{W}_l$, and $\mathbf{b}_l$ are the output, activation function, transform matrix, and bias vector at layer l, respectively. In this study, we use the sigmoid activation function for hidden layers. Note that the input of the first hidden layer $\mathbf{h}_0 = \mathbf{x}_t$. The posterior probability of the i^{th} topics given the input is

$$p(z_t = i|\mathbf{x}_t) = \frac{e^{h_L(i)}}{\sum_{j=1}^{J} e^{h_L(j)}} \tag{8}$$

where $h_L(i)$ is the i^{th} element of the last hidden layer's output vector, and J is the total number of topic classes. In equation (8), we used the softmax activation function.

From (5), what we need for Viterbi decoding is the likelihood $p(w_t|z = i)$. We first assume that $p(z_t = i|w_t) = p(z_t = i|\mathbf{x}_t)$, i.e. the topic posterior given a word is the same as the topic posterior given the word's local context. Then, the likelihood can be obtained from the Bayesian rule

$$p(w_t|z_t = i) \quad = \quad \frac{p(z_t = i|\mathbf{x}_t)p(w_t)}{p(z_t = i)} \tag{9}$$

where $p(w_t)$ can be ignored in the decoding as it does not depend on the topic class. $p(z_t = i)$ is the prior probability of the topic class i. Note that the way of converting class posteriors to observation likelihood in equation (9) has been used widely in hybrid DNN-HMM ASR systems [9, 37].

Fig. 2 shows the quality of the DNN predicted topic posterior and compare it against true topic label. Horizontal axis is the index of words while vertical axis is the topic class. From the figure, the predicted topic posterior follows the true topic label reasonably well. This shows that it is suitable to use BOW features of a word to predict its topic class.

2.3. Generating Training Class Label Using Clustering

In order to get topic labels of words for the training of DNN, we cluster training text segments into a predefined number of clusters using the CLUTO [38] tool. The clustering objective is to minimize the inter-cluster similarity and maximize the intra-cluster similarity.

The unigram probabilities of words are usually different in different clusters (topics). For example, there is high probability of appearance of words like football, basketball, tennis in a sports news, while bank, stock market and bond appears frequently in economic news. Fig. 3 shows the distribution of most frequently appeared words in some selected clusters. From this figure, we can observe that the most frequent words used usually depends on the topic. Such information can be captured by the BOW feature vector used in this study and used to predict the topic by using a DNN.

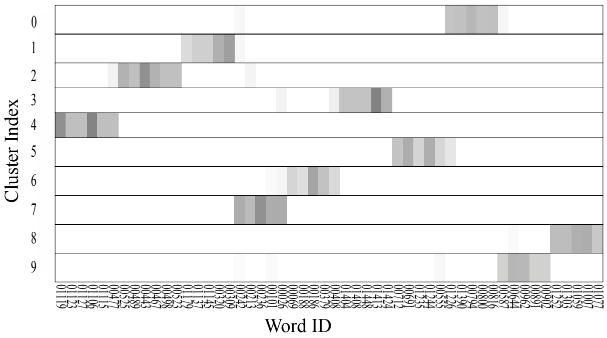


Figure 3: *The distribution of most frequent words in 10 clusters. X-axis is the index of frequent words in the 10 clusters, while y-axis is the index of clusters. Darker color means higher probability of occurrence.*

3. Experiments

3.1. Experimental Setup

We carried out experiments on Topic Detection and Tracking (TDT2) [5] corpus, which contains 2,280 English broadcast news programs. Our testing set includes 240 programs, chosen as subset of the whole corpus, with the remaining 1,800 programs as training set and 240 programs as development set. All texts were preprocessed by a Porter stemmer and stop words were removed. The size of vocabulary is 57,817. In the test set, each of the out-of-vocabulary words is replaced by its prior word. In the unsupervised clustering process, a k-way clustering solution was used and the distance metric used in CLUTO toolkit was cosine.

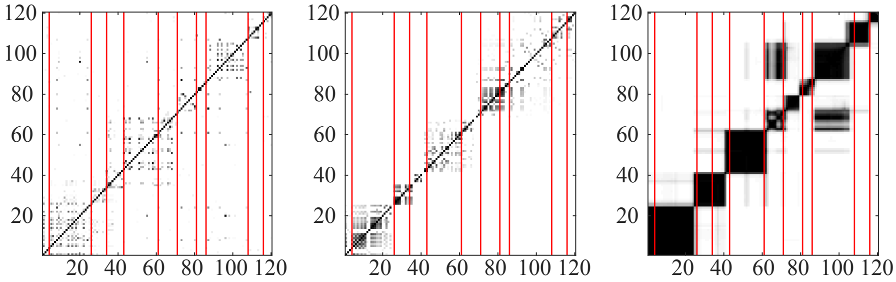
We trained a DNN with 2 hidden layers, each of which contains 256 nodes. We used 60 words as context to construct BOW vector. A diagonal transform and bias vector is used to make the BOW feature vectors have zero mean and unit variance for the training corpus (global mean and variance normalization). The same transform and bias are also used to normalize the test BOW feature vectors. Sentence boundary is used to construct sentence unit for the decoding process. According to [15], for each HMM state, the probability of staying at the state is 0.8 (tuned on the development set), while the remaining 0.2 probability is evenly assigned to the switching from the current state to other states.

Performance was evaluated by precision, recall and F1-measure with a tolerance window of 50 words according to the TDT2 standard [5]. In this approach the discovered boundaries of the topic segments were compared to the manually segmented reference boundaries. Recall is the fraction of reference boundaries that are retrieved. Precision is the fraction of declared boundaries that coincide with reference boundaries. A single numeric score is referred to as the F1-measure and defined as:

$$F1\text{-}measure = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{10}$$

3.2. Results of the DNN-HMM approach

We first investigate the effect of the number of clusters in the DNN-HMM approach. Table 1 shows the F1-measure with different numbers of clusters. We observe that the F1-measures are above 0.7 for all numbers of clusters tested, from 50 to 200. We got the highest F1-measure when the number of clusters is



(a) TF-IDF

(b) LDA

(c) DNN Posterior

Figure 4: *Sentence similarity matrix dotplots for an episode of broadcast news program from the TDT2 corpus, in which the similarities are calculated based on (a) TF-IDF, (b) LDA and (c) DNN Posteriors,respectively. x-axis and y-axis are index of sentences. High similarity values are represented by dark pixels. The vertical lines indicate the real topic boundaries.*

Table 1: F1-measure with different numbers of clusters.

Cluster	50	100	150	170	200
F1-measure	0.719	0.725	0.742	**0.765**	0.730

Table 2: F1-measure with different size of context.

Size	40	50	60	70	80
F1-measure	0.753	0.761	**0.765**	0.758	0.752

170. The results show that the proposed method is quite stable at different numbers of clusters. Table 2 shows the relationship between the size of context and F1-measure. We got highest F1-measure when the size of context is 60. The results show that the F1-measure is not very sensitive to the size of context.

We compared the proposed DNN-HMM approach with the traditional HMM approach in which the emission probability is calculated from topic-dependant unigram LMs [15] in Table 3. The F1 measure is improved by 20% from 0.637 to 0.765 by the proposed DNN-HMM approach (the differences are significant at $p < 0.01$ [39]).

3.3. Different representations in TextTiling and DP

We applied the topic posteriors generated by the DNN to TextTiling and DP approaches and compared it with *tf-idf* and LDA representation. Fig. 4 illustrates the sentence similarity matrix dot plots for an episode of broadcast news program, in which the similarity is calculated based on *tf-idf*, LDA and the topic posteriors, respectively. The red line indicates the real topic boundaries. We can see that all dotplot figures contain dark square regions along the diagonal delimited by topic boundaries. These regions indicate cohesive topic segments with high sentence similarities. We can see more salient blocks on the posterior based dot plot on figure (c) generated by DNN , which indicates more promise in topic segmentation result.

We use DP and TextTiling approaches to segment broadcast news stories with different representations. Cosine distance is used to calculate similarity between sentences in the TextTiling approach. Table 4 shows the segmentation results of DP and TextTiling approach. The systems with DNN generated topic posteriors get the highest F1-measure (significant at $p < 0.05$), which suggests that the posteriors contain more discriminative topic information.

3.4. Comparison with the state-of-the-art methods

We also compare the proposed DNN-HMM method with the state-of-the-art methods in Table 5. From the results, we observe that the proposed DNN-HMM approach obtains the best result. Please note that all results are reported using the same TDT2 data configurations.

Table 3: F1-measure with different ways to generate the emission probabilities of the HMM states.

Approach	F1-measure
Topic-dependent n-gram LM [15]	0.637
DNN + BOW (this study)	**0.765**

Table 4: F1-measure of TextTiling and DP approaches on different representations

Representation	TextTiling	DP
tf-idf	0.553	0.421
LDA	0.574	0.682
Topic posteriors by DNN	**0.663**	**0.726**

Table 5: F1-measure with different features and approaches

Approach	F1-measure
TextTiling [4]	0.553
PLSA-DP-CE [25]	0.682
BayesSeg [26]	0.710
DD-CRP [27]	0.730
DNN-TextTiling	0.663
DNN-HMM	**0.765**

4. Conclusions and Future Work

This paper proposes a DNN-HMM approach for story segmentation in broadcast news. In our approach, we use a DNN to predict topic posterior from BOW feature vector and a HMM to model the transition between topics. Then a Viterbi search is used for decoding the word sequence into topic sequence, from which the story boundary can be identified when the topic changes. As the topic posteriors contains discriminative topic information, we also apply it to DP and TextTiling approaches. Experimental results on the TDT2 task shows that the proposed DNN-HMM approach has achieved state-of-art performance. In addition, the DNN predicted topic posteriors can be used as features in DP and TextTiling methods to improve story segmentation performance compared to previous features such as *tf-idf* and LDA derived features. Future work goes in two directions, first, we plan to include more information such as prosodic and ngram as input to train the DNN. Second, we plan to test different neural networks, e.g., convolution neural networks (CNN) [40] and recurrent neural networks (RNN) [41] in story segmentation.

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6. References

[1] A. James, "Introduction to topic detection and tracking," *Topic detection and tracking*, pp. 1–16, 2002.

[2] D. Beeferman, A. Berger, and J. Lafferty, "Statistical models for text segmentation," *Machine learning*, vol. 34, no. 1-3, pp. 177–210, 1999.

[3] J. C. Reynar, "An automatic method of finding topic boundaries," in *Proc. ACL*, 1994, pp. 331–333.

[4] M. A. Hearst, "Texttiling: Segmenting text into multi-paragraph subtopic passages," *Computational linguistics*, vol. 23, no. 1, pp. 33–64, 1997.

[5] J. Fiscus, G. Doddington, J. Garofolo, and A. Martin, "Nists 1998 topic detection and tracking evaluation (tdt2)," *Proceedings of the 1999 DARPA Broadcast News Workshop*, pp. 19–24, 1999.

[6] L. F. Rau, P. S. Jacobs, and U. Zernik, "Information extraction and text summarization using linguistic knowledge acquisition," *Information Processing & Management*, vol. 25, no. 4, pp. 419–428, 1989.

[7] S. Soderland, "Learning information extraction rules for semi-structured and free text," *Machine learning*, vol. 34, no. 1-3, pp. 233–272, 1999.

[8] L.-s. Lee and B. Chen, "Spoken document understanding and organization," *Signal Processing Magazine, IEEE*, vol. 22, no. 5, pp. 42–60, 2005.

[9] D. Yu and L. Deng, *Automatic Speech Recognition - A Deep Learning Approach*. Springer, 2015.

[10] I. Malioutov, A. Parkand, R. Barzilay, and J. Glass, "Making sense of sound: Unsupervised topic segmentation over acoustic input," in *Proc. ACL*, 2007, p. 504.

[11] E. Shriberg, A. Stolcke, D. Hakkani-Tur, and G. Tür, "Prosody-based automatic segmentation of speech into sentences and topics," *Speech Communication*, vol. 32, no. 1-2, pp. 127–154, 2000.

[12] D. Charlet, G. Damnati, A. Bouchekif, and A. Douib, "Fusion of speaker and lexical information for topic segmentation: A co-segmentation approach," in *Proc. ICASSP*, 2015, pp. 5261–5265.

[13] L. Chaisorn, T. S. Chua, and C. H. Lee, "A multi-modal approach to story segmentation for news video," *World Wide Web-internet and Web Information Systems*, vol. 6, no. 2, pp. 187–208, 2003.

[14] J. P. Yamron, I. Carp, L. Gillick, S. Lowe, and P. van Mulbregt, "A hidden markov model approach to text segmentation and event tracking," in *Proc. ICASSP*, 1998, pp. 333–336.

[15] M. Sherman and Y. Liu, "Using hidden markov models for topic segmentation of meeting transcripts," in *Proc. SLT*, 2008, pp. 185–188.

[16] P. Van Mulbregt, I. Carp, L. Gillick, S. Lowe, and J. Yamron, "Text segmentation and topic tracking on broadcast news via a hidden markov model approach." in *Proc. ICSLP*, 1998.

[17] S. Banerjee and A. I. Rudnicky, "A texttiling based approach to topic boundary detection in meetings," in *Proc. ICSLP*, 2006.

[18] A. Rosenberg and J. Hirschberg, "Story segmentation of brodcast news in english, mandarin and arabic," in *Proc. HLT*, 2006, pp. 125–128.

[19] I. Malioutov and R. Barzilay, "Minimum cut model for spoken lecture segmentation," in *Proc. ACL*, 1998, pp. 25–32.

[20] L. Xie, Y.-L. Yang, and Z.-Q. Liu, "On the effectiveness of subwords for lexical cohesion based story segmentation of chinese broadcast news," *Information Sciences*, vol. 181, no. 13, pp. 2873–2891, 2011.

[21] A. Bouchekif, G. Damnati, and D. Charlet, "Intra-content term weighting for topic segmentation," *in Proc. ICASSP*, pp. 7113–7117, 2014.

[22] P. Fragkou, V. Petridis, and A. Kehagias, "A dynamic programming algorithm for linear text segmentation," *Journal of Intelligent Information Systems*, vol. 23, no. 2, pp. 179–197, 2004.

[23] O. Heinonen, "Optimal multi-paragraph text segmentation by dynamic programming," in *Proc. ACL*, 1998, pp. 1484–1486.

[24] L. Xie, L. Zheng, Z. Liu, and Y. Zhang, "Laplacian eigenmaps for automatic story segmentation of broadcast news," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 20, no. 1, pp. 276–289, 2012.

[25] M. Lu, L. Zheng, C.-C. Leung, L. Xie, B. Ma, and H. Li, "Broadcast news story segmentation using probabilistic latent semantic analysis and laplacian eigenmaps," *in Proc. APSIPA ASC 2011*, pp. 356–360, 2011.

[26] J. Eisenstein and R. Barzilay, "Bayesian unsupervised topic segmentation," in *Proc. EMNLP*, 2008, pp. 334–343.

[27] C. Yang, L. Xie, and X. Zhou, "Unsupervised broadcast news story segmentation using distance dependent chinese restaurant processes," in *Proc. ICASSP*, 2014, pp. 4062–4066.

[28] Hofmann and Thomas, "Probabilistic latent semantic indexing," in *Proc. SIGIR*, 1999, pp. 50–57.

[29] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *the Journal of machine Learning research*, vol. 3, pp. 993–1022, 2003.

[30] Y. Yang and L. Xie, "Subword latent semantic analysis for texttiling-based automatic story segmentation of chinese broadcast news," in *Proc. ISCLP*, 2008, pp. 1–4.

[31] X. Lu, C.-C. Leung, L. Xie, B. Ma, and H. Li, "Broadcast news story segmentation using latent topics on data manifold," in *Proc. ICASSP*, 2013, pp. 8465–8469.

[32] L. R. Rabiner and B.-H. Juang, "An introduction to hidden markov models," *ASSP Magazine, IEEE*, vol. 3, no. 1, pp. 4–16, 1986.

[33] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Advances in neural information processing systems*, 2013, pp. 3111–3119.

[34] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," *arXiv preprint arXiv:1301.3781*, 2013.

[35] D. M. Blei and P. J. Moreno, "Topic segmentation with an aspect hidden markov model," in *Proc. SIGIR*, 2001, pp. 343–348.

[36] G. D. Forney Jr, "The viterbi algorithm," *Proceedings of the IEEE*, vol. 61, no. 3, pp. 268–278, 1973.

[37] H. A. Bourlard and N. Morgan, *Connectionist speech recognition: a hybrid approach*. Springer Science & Business Media, 2012, vol. 247.

[38] G. Karypis, "Cluto-a clustering toolkit," DTIC Document, Tech. Rep., 2002.

[39] P.Koehn, "Statistical significance tests for machine translation e-valuation." in *Proc. EMNLP*, 2004, pp. 388–395.

[40] O. Abdel-Hamid, L. Deng, and D. Yu, "Exploring convolutional neural network structures and optimization techniques for speech recognition." in *Proc. INTERSPEECH*, 2013, pp. 3366–3370.

[41] M. Ryo, A. Taichi, O. Takanobu, M. Hirokazu, S. Sumitaka, and I. Akinori, "Latent words recurrent neural network language models," in *Proc. INTERSPEECH*, 2015.