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Text Segmentation with Topic Models

This article presents a general method to use information retrieved from the Latent Dirichlet Allocation (LDA) topic model for Text Segmentation: Using topic assignments instead of words in two well-known Text Segmentation algorithms, namely TextTiling and C99, leads to significant improvements. Further, we introduce our own algorithm called TopicTiling, which is a simplified version of TextTiling (Hearst, 1997). In our study, we evaluate and optimize parameters of LDA and TopicTiling. A further contribution to improve the segmentation accuracy is obtained through stabilizing topic assignments by using information from all LDA inference iterations. Finally, we show that TopicTiling outperforms previous Text Segmentation algorithms on two widely used datasets, while being computationally less expensive than other algorithms.

1 Introduction

Text Segmentation (TS) is concerned with "automatically break[ing] down documents into smaller semantically coherent chunks" (Jurafsky and Martin, 2009). We assume that semantically coherent chunks are also similar in a topical sense. Thus, we view a document as a sequence of topics. This semantic information can be modeled using Topic Models (TMs). TS is realized by an algorithm that identifies topical changes in the sequence of topics.

TS is an important task, needed in Natural Language Processing (NLP) tasks, e.g. information retrieval and text summarization. In information retrieval tasks, TS can be used to extract segments of the document that are topically interesting. In text summarization, segmentation results are important to ensure that the summarization covers all themes a document contains. Another application could be a writing aid to assist authors with possible positions for subsections.

In this article, we use the Latent Dirichlet Allocation (LDA) topic model (Blei et al., 2003). We show that topic IDs, assigned to each word in the last iteration of the Bayesian inference method of LDA, can be used to improve TS significantly in comparison to methods using word-based features. This is demonstrated on three algorithms: TextTiling (Hearst, 1997), C99 (Choi, 2000) and a newly introduced algorithm called TopicTiling. TopicTiling resembles TextTiling, but is conceptually simpler since it does not have to account for the sparsity of word-based features.

In a sweep over parameters of LDA and TopicTiling, we find that using topic IDs of a single last inference iteration leads to enormous instabilities with respect to TS error rates. These instabilities can be alleviated by two modifications: (i) repeating the inference iterations several times and selecting the most frequently assigned topic ID for each word across several inference runs, (ii) storing the topic IDs assigned to each word for each iteration during the Bayesian inference and selecting most frequently assigned topic ID (the mode) per word. Both modifications lead to similar stabilization, however (ii) needs less computational resources. Furthermore, we can also show that the standard parameters recommended by Griffiths and Steyvers (2004) do not always lead to optimal results.

Using what we have learned in these series of experiments, we evaluate the performance of an optimized version of TopicTiling on two datasets: The Choi dataset (Choi, 2000) and a more challenging Wall Street Journal (WSJ) corpus provided by Galley et al. (2003). Not only does TopicTiling deliver state-of-the-art segmentation results, it also performs the segmentation in linear time, as opposed to most other recent TS algorithms.

The paper is organized as follows: The next section gives an overview of TS algorithms. Then we introduce the method of replacing words by topic IDs, lay out three algorithms using these topic IDs in detail, and show improvements for the topic-based variants. Section 5 evaluates parameters of LDA in combination with parameters of our TopicTiling algorithm. In Section 6, we apply the method to various datasets and end with a conclusion and a discussion.

2 Related Work

Topic segmentation can be divided into two sub-fields: (i) linear topic segmentation and (ii) hierarchical topic segmentation. Whereas linear topic segmentation deals with the sequential analysis of topical changes, hierarchical segmentation concerns with finding more fine grained subtopic structures in texts.

One of the first unsupervised linear topic segmentation algorithms was introduced by Hearst (1997): TextTiling segments texts in linear time by calculating the similarity between two blocks of words based on the cosine similarity. The calculation is accomplished by two vectors containing the number of occurring terms of each block. LcSeg, a TextTiling-based algorithm, was published by Galley et al. (2003). In comparison to TextTiling, it uses *tf-idf* term weights, which improves TS results. Choi (2000) introduced an algorithm called C99, that uses a matrix-based ranking and a clustering approach in order to relate the most similar textual units. Similar to the previous introduced algorithms, C99 uses words. Utiyama and Isahara (2001) introduced one of the first probabilistic approaches using Dynamic Programming (DP) called U00. DP is a paradigm that can be used to efficiently find paths of minimum cost in a graph. Text Segmentation algorithms using DP, represent each possible segment (e.g. every sentence boundary) as an edge. Providing a cost function that penalizes common vocabulary across segment boundaries, DP can be applied to find the segments with minimal cost.

Related to our work are a modified C99 algorithm, introduced by Choi et al. (2001) that uses the term-representation matrix in latent space of LSA in combination with a term frequency matrix to calculate the similarity between sentences and two DP approaches described in Misra et al. (2009) and Sun et al. (2008): here, topic modeling is used to alleviate the sparsity of word vectors. The algorithm of Sun et al. (2008) follows the approach described in Fragkou et al. (2004), but uses a combination of topic distributions and term frequencies. A Fisher kernel is used to measure the similarity between two blocks, where each block is represented as a sequence of sentences. The kernel uses a measure that indicates how much topics two blocks share, combined with the term frequency, which is weighted by a factor that indicates how likely the terms belong to the same topic. They use entire documents as blocks and generate the topic model using the test data. This method is evaluated using an artificially garbled Chinese corpus. In a similar fashion, Misra et al. (2009) extended the DP algorithm U00 from Utiyama and Isahara (2001) using topic models. Instead of using the probability of word co-occurrences, they use the probability of co-occurring topics. Segments with many different topics have a low topic-probability, which is used as a cost function in their DP approach. (Misra et al., 2009) trained the topic model on a collection of the Reuters corpus and a subset of the Choi dataset, and tested on the remaining Choi dataset. The topics for this test set have to be generated for each possible segment using Bayesian inference methods, resulting in high computational cost. In contrast to these previous DP approaches, we present a computationally more efficient solution. Another approach would be to use an extended topic model that also considers segments within documents, as proposed by Du et al. (2010). A further approach for text segmentation is the usage of Hidden Markov Model (HMM), first introduced by Mulbregt et al. (1998). Blei and Moreno (2001) introduced an Aspect Hidden Markov Model (AHMM) which combines an aspect model (Hofmann, 1999) with a HMM. The limiting factor of both approaches is that a segment is assumed to have only one topic. This problem has been solved by Gruber et al. (2007) who extends LDA to consider the word and topic ordering using a Markov Chain. In contrast to LDA, not a word is assigned to a topic, but a sentence, so the segmentation can be performed sentence-wise.

In early TS evaluations, Hearst (1994) measured the fitting of the estimated segments using precision and recall. But these measures are considered inappropriate for the task, since the distance of a falsely estimated boundary to the correct one is not considered at all. With P_k (Beeferman et al., 1999), a measure was introduced that regulates this problem. But there are issues concerning the P_k measure, as it uses an unbalanced penalizing between false negatives and false positives. WindowDiff (WD) (Pevzner and Hearst, 2002) solves this problem, but most published algorithms still use the P_k measure. In practice, both measures are highly correlated. While there are newer published metrics (see Georgescul et al. (2006), Lamprier et al. (2007) and Scaiano and Inkpen (2012)), in practice still the two metrics P_k and WD are commonly used.

To handle near misses, P_k uses a sliding window with a length of k tokens, which is moved over the text to calculate the segmentation penalties. This leads to following pairs: $(1, k), (2, k + 1), ..., (n - k, n)$, with n denoting the length of the document. For each pair (i, j) it is checked whether positions i and j belong to the same segment or to different segments. This is done separately for the gold standard boundaries and the estimated segment boundaries. If the gold standard and the estimated segments do not match, a penalty of 1 is added. Finally, the error rate is computed by normalizing the penalty by the number of pairs $(n - k)$, leading to a value between 0 and 1. A value of 0 denotes a perfect match between the gold standard and the estimated segments. The value of parameter k is assigned to half of the number of tokens in the document divided by the number of segments, given by the gold standard.

According to Pevzner and Hearst (2002), a drawback of the P_k measure is its unawareness of the number of segments between the pair (i, j). WD is an enhancement of P_k: the number of segments between position i and j are counted, where again the distance between the positions is parameterized by k. Then the number of segments is compared between the gold standard and the estimated segments. If the number of segments are not equal, 1 is added to the penalty, which is again normalized by the number of pairs to get an error rate between 0 and 1.

The first hierarchical algorithm was proposed by Yaari (1997), using the cosine similarity and agglomerative clustering approaches. A hierarchical Bayesian algorithm based on LDA is introduced by Eisenstein (2009). In our work, however, we focus on linear topic segmentation.

LDA was introduced by Blei et al. (2003) and is a generative model that discovers topics based on a training corpus. Model training estimates two distributions: A topic-word distribution and a topic-document distribution. As LDA is a generative probabilistic model, the creation process follows a generative story: First, for each document a topic distribution is sampled. Then, for each document, words are randomly chosen, following the previously sampled topic distribution. Using the Gibbs inference method, LDA is used to apply a trained model for unseen documents. Here, words are annotated by topic IDs by assigning the most probable topic ID on the basis of the two distributions. Note that the inference procedure, in particular, marks the difference between LDA and earlier dimensionality reduction techniques such as Latent Semantic Analysis.

3 Text Segmentation Datasets

In this paper we use two datasets: A document collection generated based on the Brown corpus and a more challenging corpus generated using WSJ documents.

3.1 Choi Dataset

The Choi dataset (Choi, 2000) is commonly used in the field of TS (see e.g. Misra et al. (2009); Sun et al. (2008); Galley et al. (2003)). It is an artificially generated corpus generated from the Brown corpus and consists of 700 documents. Each document consists of ten segments. The document generation was performed extracting consecutive snippets of 3-11 sentences from different documents from the Brown corpus. 400 documents consist of segments with a sentence length of 3-11 sentences and there are 100 documents each with sentence counts of 3-5, 6-8 and 9-11.

3.2 Galley Dataset

Galley et al. (2003) present two corpora for written language, each having 500 documents, which are also generated artificially. In comparison to Choi's dataset, the segments in its 'documents' vary from 4 to 22 segments, and are composed by concatenating full source documents. Use of full documents make this corpus a more realistic one in comparison to the one provided by Choi. One dataset is generated based on WSJ documents of the Penn Treebank (PTB) project (Marcus et al., 1994) and the other is based on Topic Detection Track (TDT) documents (Wayne, 1998). As the WSJ dataset seems to be harder (consistently higher error rates across several works), we use this dataset for experimentation.

4 From Words to Topics

4.1 Method to Represent Words with Topic IDs

The method (see also Misra et al., 2009; Sun et al., 2008) for using information gained by topic models is conceptually simple: Instead of using words directly as features to characterize textual units, we use their topic IDs as assigned by Bayesian inference. LDA inference assigns a topic ID to each word in the test document in each inference iteration step, based on a TM trained on a training corpus. The first series of experiments use the topic IDs assigned to each word in the last inference iteration. Figure 1 depicts the general setup.

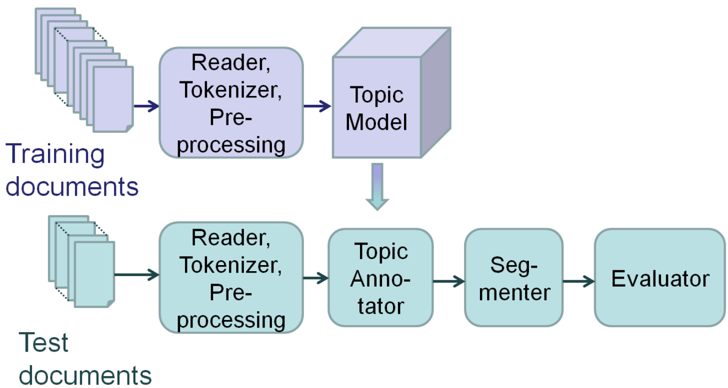


Figure 1: Basic concept of text segmentation using Topic Models

First, preprocessing steps[1] like tokenizing, sentence segmentation, part-of-speech tagging or filtering are applied to the training and test documents.

[1] we use the DKPro framework, `http://code.google.com/p/dkpro-core-asl/`

The training data used to estimate the topic models should ideally be from the same domain as the test documents. Since no information about the test data should inform the training, no test documents should be used for the topic model estimation, even though topic models belong to the unsupervised learning paradigm. The topic model is estimated once in advance and can then be used for inference on the test documents: LDA inference assigns a topic ID to each word in the test document and generates a document topic distribution.

An example of a text annotated with topic IDs, taken from the WSJ test data, is presented in Figure 2. One can clearly see the boundary by looking at the most probable topic IDs. The first text is about a telecommunication company, having mostly topic ID 2 assigned to words. The second segment is about an anti-government rally in South Africa. Most words of this segment are annotated with topic ID 37. The topic IDs are not assigned statically per word, but converge from Gibbs Sampling inference, which iterates over the words and re-samples topic IDs according to the per-document topic distribution and the per-topic word probabilities from the previous inference step. For example, the word *people* (marked bold in Figure 2) is marked with topic 37 since this topic is highly probable in the document. Using this word in a different context would most likely lead to a different topic ID.

Mr:62 .:97 Pohs:2 ,:2 previously:4 executive:2 vice:2 president:2 and:17 chief:2 operating:2 officer:2 ,:72 was:2 named:2 interim:2 president:2 and:73 chief:2 executive:2 officer:2 after:17 David:2 M:27 .:36 Harrold:65 ,:2 a:84 company:2 founder:2 ,:26 resigned:2 from:91 the:34 posts:2 for:62 personal:61 reasons:2 in:84 August:2 .:58 Cellular:70 said:54 Robert:2 J:61 .:42 Lunday:2 Jr:18 .:31 ,:44 its:57 chairman:2 and:73 another:25 founder:2 ,:31 resigned:2 from:91 the:57 company:2 's:24 board:2 to:10 pursue:2 the:10 sale:55 of:67 his:28 telephone:31 company:42 ,:74 Big:10 Sandy:50 Telecommunications:31 Inc:2 .:74

APARTHEID:37 FOES:37 STAGED:41 a:37 massive:37 anti-government:37 rally:37 in:40 South:37 Africa:37 .:19 More:29 than:34 70:45 ,:26 000 **people:37** *filled:17 a:22 soccer:37 stadium:88 on:46 the:34 outskirts:37 of:93 the:24 black:37 township:37 of:45 Soweto:37 and:37 welcomed:11 freed:37 leaders:37 of:98 the:57 outlawed:37 African:37 National:45 Congress:87 .:72 It:79 was:55 considered:37 South:37 Africa:37 's:33 largest:90 opposition:67 rally:37 .:37*

Figure 2: Excerpt from a test document, taken from Galley's WSJ corpus. Each word is followed by a colon and a number, which represents the topic ID.

In the example, all tokens are used for topic model estimation — it is also possible to filter tokens by parts-of-speech or very short sentences for the purpose of model estimation and inference. This is expected to lead to even sparser topic distributions.

Once the topic IDs are assigned, most previous segmentation algorithm can be applied, using the topic ID of each word instead of the word itself.

In this work, we implement topic-based versions of C99 (Choi, 2000), TextTiling (Hearst, 1994) and develop a new TextTiling-based method called TopicTiling. Our aim is to find a simplified algorithm that could solve the segmentation problem using topic IDs.

4.2 Text Segmentation Algorithms using Topic Models

4.2.1 C99 using Topic Models

The topic-based version of the C99 algorithm (Choi, 2000), called C99LDA, divides the input text into minimal units on sentence boundaries. A similarity matrix $S_{m \times m}$ is computed, where m denotes the number of units (sentences). Every element s_{ij} is calculated using the cosine similarity (e.g. Manning and Schütze, 1999) between unit i and j. For these calculations, each unit i is represented as a T-dimensional vector, where T denotes the number of topics selected for the topic model. Each element t_k of this vector contains the number of times topic ID k occurs in unit i. Next, a rank matrix R is computed to improve the contrast of S: Each element r_{ij} contains the number of neighbors of s_{ij} that have lower similarity scores then s_{ij} itself. This step increases the contrast between regions in comparison to matrix S. In a final step, a top-down hierarchical clustering algorithm is performed to split the document into m segments. This algorithm starts with the whole document considered as one segment and splits off segments until the stop criteria are met, e.g. the number of segments or a similarity threshold. At this, the ranking matrix is split at indices i, j that maximize the inside density function D.

$$D = \sum_{k=1}^{m} \frac{\text{sum of ranks within segment } k}{\text{area within segment } k} \tag{1}$$

As a threshold-based criterion, the gradient δD is introduced as $\delta D^{(n)} = D^{(n)} - D^{(n-1)}$. The threshold can then be calculated by $\mu + c \times \sigma$, where mean μ and the standard deviation σ are calculated from the gradients[2].

4.2.2 TextTiling using Topic Models

In TTLDA, the topic-based version of TextTiling (TT) (Hearst, 1994), documents are represented as a sequence of n topic IDs instead of words. TTLDA splits the document into *topic-sequences*, instead of sentences, where each sequence consists of w topic IDs. To calculate the similarity between two topic-sequences, called *sequence-gap*, TTLDA uses k topic-sequences, named *block*, to the left and to the right of the sequence gap. This parameter k defines the so-called *blocksize*. The cosine similarity is applied to compute a similarity score based on the topic frequency vectors of the adjacent blocks at each sequence-gap. A value close to 1 indicates a high similarity among two blocks, a value close to zero denotes a low similarity. Then for each sequence-gap a *depth score* d_i is calculated for describing the sharpness of a gap, given by

$$d_i = 1/2(hl(i) - s_i + hr(i) - s_i).$$

[2] $c = 1.2$ as in Choi (2000).

The function $hl(i)$ returns the highest similarity score on the left side of the sequence-gap index i that does not increase and $hr(i)$ returns the highest score on the right side. Then all local maxima positions are searched based on the depth scores.

In the next step, these obtained maxima scores are sorted. If the number of segments n is given as input parameter, the n highest depth scores are used, otherwise a cut-off function is used that applies a segment only if the depth score is larger than $\mu - \sigma/2$, where mean μ and the standard deviation σ are calculated based on the entirety of depth scores. As TTLDA calculates the depth on every topic-sequence using the highest gap, this could lead to a segmentation in the middle of a sentence. To avoid this, a final step ensures that the segmentation is positioned at the nearest sentence boundary.

4.2.3 TopicTiling

This section introduces our own Text Segmentation algorithm called TopicTiling which is based on TextTiling, but conceptually simpler. TopicTiling assumes a sentence s_i as the smallest basic unit. Between each position p between two adjacent sentences, a *coherence score* c_p is calculated. To calculate the coherence score, we exclusively use the topic IDs assigned to the words by inference: Assuming an LDA model with T topics, each block is represented as a T-dimensional vector. The t-th element of each vector contains the frequency of the topic ID t obtained from the respective block. The coherence score is calculated by cosine similarity for each adjacent "topic vector". Values close to zero indicate marginal relatedness between two adjacent blocks,

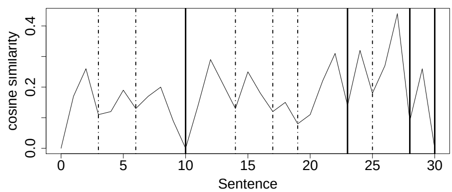


Figure 3: Similarity scores plotted for a document. The vertical lines indicate all possible segment boundaries. The solid lines indicate segments chosen by the threshold criterion, when the number of segments is not given in advance.

whereas values close to one denote a substantial connectivity. Next, the coherence scores are plotted to trace the local minima (see Figure 3). These minima are utilized as possible segmentation boundaries. But rather using the c_p values itself, a *depth score* d_p is calculated for each minimum (cf. TextTiling, Hearst (1997)). In comparison to TopicTiling, TextTiling calculates the depth score for each position and than searches for maxima. The depth score measures the deepness of a minimum by looking at the highest coherence scores on the left and on the right and is calculated using this formula (cf. depth score formula in the previous section):

$$d_p = 1/2 * (hl(p) - c_p + hr(p) - c_p)$$

The functionality of the function hl (highest peak on the left side) and hr (highest peak on the right side) is illustrated in Figure 4. The function $hl(p)$ iterates to the

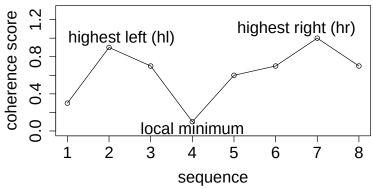


Figure 4: Illustration of the highest left and the highest right peak according to a local minimum.

left as long as the score increases and returns the highest coherence score value. The same is done, iterating in the other direction with the $hr(p)$ function. According to the illustration, $hl(4) = 0.93$, the score value at position 2, and $hr(4) = 0.99$ from the value at position 7.

If the number of segments n is given as input, the n highest depth scores are used as segment boundaries. Otherwise, a threshold is applied (cf. TextTiling). This threshold predicts a segmentation if the depth score is larger than $\mu - \sigma/2$, with μ being the mean and σ being the standard variation calculated on the depth scores.

The algorithm runtime is linear in the number of possible segmentation points, i.e. the number of sentences: for each segmentation point, the two adjacent blocks are sampled separately and combined into the coherence score. This is the main differences to the dynamic programming approaches for TS described in (Utiyama and Isahara, 2001; Misra et al., 2009).

4.3 Experiment: Word-based vs. Topic-based Methods

To show the impact of the topic-based representation introduced in Section 4.1, we show results for TT and C99 using words and topic IDs, and for TopicTiling.

4.3.1 Experimental Setup

As laid out in Section 4.1, an LDA Model is estimated on a training dataset and used for inference on the test set. To ensure that we do not use information from the test set, we perform a 10-fold Cross Validation (CV) for all reported results. To reduce the variance stemming from the random nature of sampling and inference, the results for each fold are calculated 30 times using different LDA models.

While we aim at not using the same *documents* for training and testing by using a folded CV scheme, it is not guaranteed that all testing data is unseen, since the same source *sentences* can find their way in several artificially crafted *documents*. We could detect that all *sentences* from the training subset also occur in the test subset, but not in the same combinations. This makes the Choi data set artificially easy for supervised approaches. This problem, however, affects all evaluations on this dataset that use any kind of training, be it LDA models in Misra et al. (2009) or *tf-idf* values in Fragkou et al. (2004) and Galley et al. (2003).

The LDA model is trained with $T = 100$ topics, 500 sampling iterations and symmetric hyperparameters as recommended by Griffiths and Steyvers (2004)($\alpha = 50/N$ and $\beta = 0.01$), using the JGibbsLda implementation of Phan and Nguyen (2007). Unseen data is annotated with topic information, using LDA inference, sampling $i = 100$ iterations. Inference is executed sentence-wise, since sentences form the minimal unit of our segmentation algorithms and we cannot use document information in the test setting. The performance of the algorithms is measured using P_k and WindowDiff (WD) metrics, cf. Section 2. The C99 algorithm is initialized with a 11×11 ranking mask, as recommended in Choi (2000). TT is configured according to Choi (2000) with sequence length $w = 20$ and block size $k = 6$.

4.3.2 Results

The experiments are executed in two settings using the C99 and TT implementations[3]: using words (C99, TT) and using topics (C99LDA, TTLDA). TT and C99 use stemmed words and filter out words using a stopword list. C99 additional removes words using predefined regular expressions. In the case of topic-based variants, no stopword filtering or stemming was deemed necessary. Table 1 shows the result of the different algorithms with segments provided and unprovided.

Method	**Segments provided**		**Segments unprovided**	
	P_k	WD	P_k	WD
C99	11.20	12.07	12.73	14.57
C99LDA	4.16	4.89	8.69	10.52
TT	44.48	47.11	49.51	66.16
TTLDA	1.85	2.10	16.41	21.40
TopicTiling	2.65	3.02	4.12	5.75
TopicTiling (filtered)	**1.50**	**1.72**	**3.24**	**4.58**

Table 1: Results by segment length for TT with words and topics (TTLDA), C99 with words and topics (C99LDA) and TopicTiling using all sentences and using only sentences with more than 5 word tokens (filtered).

We note that WD values are always higher than the appropriate P_k values. But we also observe that these measures are highly correlated. First we discuss results for the setting with number of segments provided (see column 2-3 of Table 1). A significant improvement for C99 and TT can be achieved when using topic IDs. In case

[3]We use the implementations by Choi available at `http://code.google.com/p/uima-text-segmenter/`.

of C99LDA, the error rate is at least halved and for TTLDA the error rate is reduced by a factor of 20. The newly introduced algorithm TopicTiling as described above does not improve over TTLDA. Analysis revealed that the Choi corpus includes also captions and other "non-sentences" that are marked as sentences, which causes TopicTiling to introduce false positive segments since the topic vectors are too sparse for these short "non-sentences". We therefore filter out "sentences" with less than 5 words (see bottom line in Table 1). This leads to smaller errors values in comparison to the results achieved with TTLDA. Without the number of segments given in advance (see columns 3-4 in Table 1), we again observe significantly better results, comparing topic-based methods to word-based methods. But the error rates of TTLDA are unexpectedly high. We discovered in data analysis that TTLDA estimates too many segments, as the topic ID distributions between adjacent sentences within a segment are often too diverse, especially in face of random fluctuations from the topic assignments. Estimating the number of segments is better achieved using TopicTiling instead of TTLDA even without any additional sentence filtering. As we aimed to find a simple algorithm that can cope with the topic-based approach, we will use TopicTiling for the next series of experiments.

5 Sweeping the Parameter Space of LDA

Aside from the main parameter, the number of topics or dimensions T, surprisingly little attention has been spent to understand the interactions of hyperparameters, the number of sampling iterations in model estimation and interference, and the stability of topic assignments across runs using different random seeds in the LDA topic model. While progress in the field of topic modeling is mainly made by adjusting prior distributions (e.g. Sato and Nakagawa, 2010; Wallach et al., 2009), or defining more complex mixture models (Heinrich, 2011), it seems unclear whether improvements, reached on intrinsic measures like perplexity or on application-based evaluations, are due to an improved model structure or could originate from sub-optimal parameter settings or due to the randomized nature of the sampling process.

These subsections address these issues by systematically sweeping the parameter space and evaluating LDA parameters with respect to text segmentation results achieved by TopicTiling.

5.1 Experimental Setup

Again, the Choi dataset (see Section 3.1) is used, applying a 10-fold CV as described in Section 4.3.1. To assess the robustness of the TM, we sweep over varying configurations of the LDA model, and plot the results using Box-and-Whiskers plots: the box indicates the quartiles and the whiskers are maximally 1.5 times Interquartile Range (IQR) or equal to the data point that has not a distance larger than 1.5 times IQR. The following parameters are subject to our exploration:

- T: Number of topics used in the LDA model. Common values vary between 50 and 500.
- α : Hyperparameter that regulates the sparseness topic-per-document distribution. Lower values result in documents being represented by fewer topics (Heinrich, 2004). Recommended: $\alpha = 50/T$ (Griffiths and Steyvers, 2004)
- β : Reducing β increases the sparsity of topics, by assigning fewer terms to each topic, which is correlated to how related words need to be, to be assigned to a topic (Heinrich, 2004). Recommended: $\beta = \{0.1, 0.01\}$ (Griffiths and Steyvers, 2004; Misra et al., 2009)
- m Model estimation iterations. Recommended / common settings: $m = 500 - 5000$ (Griffiths and Steyvers, 2004; Wallach et al., 2009; Phan and Nguyen, 2007)
- i Inference iterations. Recommended / common settings: 100 (Phan and Nguyen, 2007)
- d Mode of topic assignments. At each inference iteration step, a topic ID is assigned to each word within a document (represented as a sentence in our application). With this option ($d = true$), we count these topic assignments for each single word in each iteration. After all i inference iterations, the most frequent topic ID is chosen for each word in a document.
- r Number of inference runs: We repeat the inference r times and assign the most frequently assigned topic per word at the final inference iteration for the segmentation algorithm. High r values might reduce fluctuations due to the randomized process and lead to a more stable word-to-topic assignment.
- w Window: We introduce a so-called *window parameter* that specifies the number of sentences to the left and to the right of position p that define two *blocks*: $s_{p-w}, s_{p-w+1}, \ldots, s_p$ and $s_{p+1}, \ldots, s_{p+w}, s_{p+w+1}$.

All introduced parameters parameterize the TM. Other works stabilize topic assignments by averaging assignments probed from every 50-100th iteration. Examining this effect more closely, we look at the mechanisms of using several inference runs r to find the correct segments and the mode of topic assignments d. Further, we did not find previous work that systematically varies TM parameters in combination with measures other than perplexity.

5.2 Parameter Sweeping Evaluation

5.2.1 Number of Topics T

To provide a first impression of the data, a 10-fold CV is calculated and the segmentation results are visualized in Figure 5. Each box plot is generated from the P_k values of 700

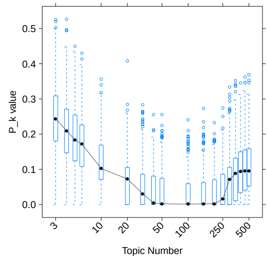


Figure 5: Box plots for different number of topics T. Each box plot is generated from the average P_k value of 700 documents, $\alpha = 50/T$, $\beta = 0.1$, $m = 1000$, $i = 100, r = 1$.

documents. As expected, there is a continuous range of topic numbers, namely between 50 and 150 topics, where we observe the lowest P_k values. Using too many topics leads to overfitting of the data and too few topics result in too general distinctions to grasp text segment information. This general picture is in line with other studies that determine an optimum for T, (cf. Griffiths and Steyvers, 2004), which is specific to the application and the data set.

5.2.2 Estimation and Inference iterations

The next step examines the robustness of the model estimation iterations m needed to achieve stable results. 600 documents are used for training an LDA model and the remaining 100 documents are segmented using this model. This evaluation is performed using 100 topics (as this number leads to stable results according to Figure 5) and performed using 20 and 250 topics. To assess stability across different model estimation runs, we trained 30 LDA models using different random seeds. Each box plot in Figures 6 is generated from 30 mean values, calculated from the P_k values of the 100 documents. The variation indicates the score variance for the 30 different models.

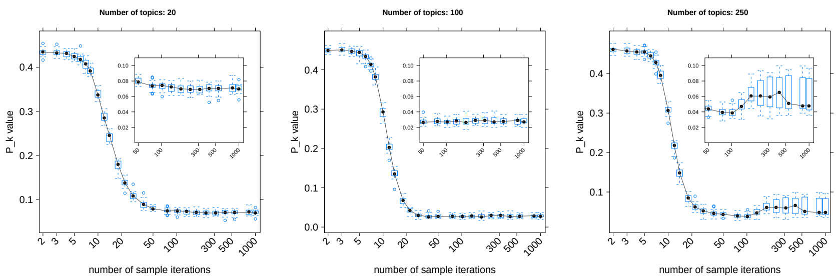
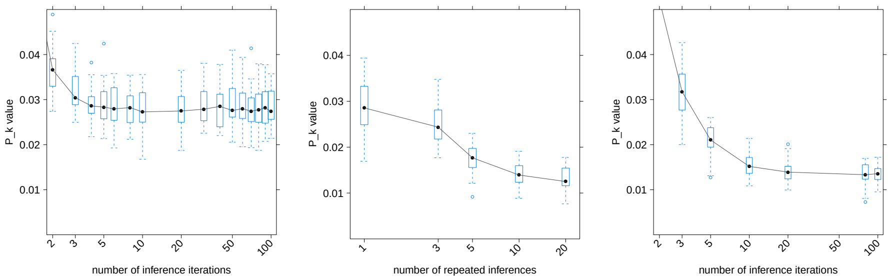


Figure 6: Box plots with different model estimation iterations m, with T=20,100,250 (from left to right), $\alpha = 50/T$, $\beta = 0.1$, $i = 100$, $r = 1$. Each box plot is generated from 30 mean values calculated from 100 documents.

Using 100 topics (see Figure 6), the burn-in phase starts with 8–10 iterations and the mean P_k values stabilize after 40 iterations. But looking at the inset for large m values, significant variations between the different models can be observed: note that the P_k error rates are between 0.021 - 0.037. As expected using 20 and 250 topics leads to worse results as with 100 topics. Looking at the plot with 250 topics, a robust range for the error rates can be found between 20 and 100 sample iterations. With more iterations m, the results get both worse and unstable: as the 'natural' topics of the collection have to be split in too many topics in the model, perplexity reduction that drives the estimation process leads to random fluctuations, which the TopicTiling algorithm is sensitive to. Manual inspection of models for $T = 250$ revealed that in fact many topics do not stay stable across estimation iterations. In the next step we sweep over several inference iterations i using 100 topics. Starting from 5 iterations, error rates do not change much, see Figure 7a. But there is still substantial variance, between about 0.019 - 0.038 for inference on sentence units.



(a) number of inferences i **(b)** repeated inference runs r **(c)** mode method d = true

Figure 7: Figure a) shows the box plots for different inference iterations i, Figure b) shows the box plots for several inference runs r and Figure c) presents the usage of the mode method $d = true$. All remaining parameters are set to the default values.

5.2.3 Repeat the inference r times

To decrease this variance, we assign the topic not only from a singe inference run, but repeat the inference calculations several times, denoted by the parameter r. Then the frequency of assigned topic IDs per token is counted across the r single runs, and we assign the most frequent topic ID (frequency ties are broken randomly). The box plot for several evaluated values of r is shown in Figure 7b. This log-scaled plot shows that both variance and P_k error rate can be substantially decreased. Already for $r = 3$, we observe a significant improvement in comparison to the default setting of $r = 1$ and with increasing r values, the error rates are reduced even more: for $r = 20$, variance and error rates are cut in less than half of their original values using this simple operation.

5.2.4 Mode of topic assignment d

In the previous experiment, we use the topic IDs that have been assigned most frequently at the last inference iteration step. Now, we examine something similar, but for all i inference steps of a single inference run: we select the mode of topic ID assignments for each word across all inference steps. The impact of this method on error and variance is illustrated in Figure 7c. Using a single inference iteration, the topic IDs are almost assigned randomly. After 20 inference iterations P_k values below 0.02 are achieved. Using further iterations, the decrease of the error rate is only marginal. In comparison to the repeated inference method, the additional computational costs of this method are much lower as the inference iterations have to be carried out anyway in the default application setting. Note that this is different from using the overall topic distribution as determined by the inference step, since this winner-takes-it-all approach reduces noise from random fluctuations. As this parameter stabilizes the topic IDs at low computational costs, we recommend using this option in all setups where subsequent steps rely on single topic assignments.

5.2.5 Hyperparameters α and β

In many previous works, hyperparameter settings $\alpha = 50/T$ and $\beta = \{0.1, 0.01\}$ are commonly used. In the next series of experiments we investigate how different parameters of these both parameters can change the TS task. Analyzing the α values, shown in Figure 8, we can see that the recommended values for $T = 100$, $\alpha = 0.5$ lead to sub-optimal settings, and an error rate reduction of about 40% can be achieved by setting $\alpha = 0.1$. Regarding values of β, we find that P_k rates and their variance are

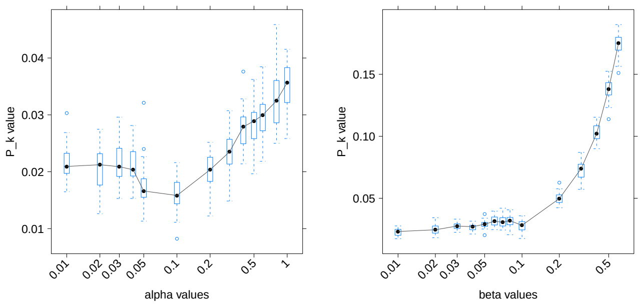
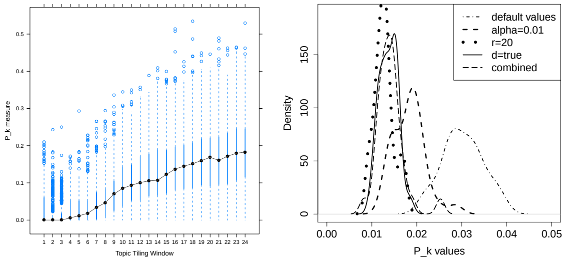


Figure 8: Box plot for several alpha (left) and beta (right) values with $m = 500$, $i = 100$, $T = 100$, $r = 1$ and $\beta = 0.1$ (left image) and $\alpha = 0.5$ (right image).

relatively stable between the recommended settings of 0.1 and 0.01. Values larger than 0.1 lead to much worse performance. Regarding variance, no patterns within the stable range emerge, see Figure 8.

5.2.6 Window Parameter w

The optimal window parameter has to be specified according to the documents that are segmented.



(a) window parameter **(b)** Error distributions

Figure 9: Figure a) represents the box plots for varying window parameter w with $m = 500$, $i = 100$, $T = 100$, $\alpha = 50/T$, $\beta = 0.1$, $r = 1$. The Density of the error distribution for the system according to Table 2 is shown in Figure b).

Using the Choi corpus we observe that the window parameter could be increased to a size of 3 before the error rate increases. Since the segment sizes vary from 3-11 sentences we expect a decline for $w > 3$, which is confirmed by the results shown in Figure 9a.

5.3 Putting it all together

Until this point, we have examined different parameters with respect to stability and error rates one at the time. Now, we combine what we have learned from this and strive at optimal system performance. Table 2 shows P_k error rates for the different systems. At this, we fixed the following parameters: $T = 100$, $m = 500$, $i = 100$, $\beta = 0.1$. For the computations we use 600 documents for the LDA model estimation, apply TopicTiling to the 100 remaining documents and repeat this 30 times with different random seeds.

System	P_k	error red.	σ^2	var. red.
default	0.0302	0.00%	2.02e-5	0.00%
$\alpha = 0.1$	0.0183	39.53%	1.22e-5	39.77%
$r = 20$	0.0127	57.86%	4.65e-6	76.97%
$d = true$	0.0137	54.62%	3.99e-6	80.21%
combined	0.0141	53.45%	9.17e-6	54.55%

Table 2: Comparison of single parameter optimizations, and combined system. P_k averages and variance are computed over 30 runs, together with reductions relative to the default setting. Default: $\alpha = 0.5$, $r = 1$, $d = false$. combined: $\alpha = 0.1$, $r = 20$, $d = true$

We observe massive improvements for optimized single parameters. The α-tuning results in an error rate reduction of 39.77% in comparison to the default configurations. Using $r = 20$, the error rate is cut in less than half its original value. Also for the mode mechanism ($d = true$) the error rate is halved but slightly worse than when using the repeated inference. Regarding the practice to assign the most frequent topic ID selected from every 50-100th iteration, we conclude that – at least in our application – a much smaller number of iterations suffices when taking assignments from all iterations. Here, allowing long inference periods to account for possible topic drifts seems not required. Using combined optimized parameters does not result to additional error decreases. We attribute the slight decline of the combined method in both the error rate P_k and the variance to complex parameter interactions that shall be examined in further work. In Figure 9b, we visualize these results in a density plot. It becomes clear that repeated inference leads to slightly better and more robust performance (higher peak) than the mode method. We attribute the difference to situations, where there are several highly probable topics in our sampling units, and by chance the same one is picked for adjacent sentences that belong to different segments, resulting in failure to recognize the segmentation point. However, since the differences are miniscule, only using the mode method might be more suitable for practical purposes since its computational cost is lower.

6 Comparison to other Algorithms

In a last series of experiments, we compare the performance of TopicTiling to other TS algorithms on several datasets. All LDA models for these series were created using $T = 100$, $\alpha = 50/T$, $\beta = 0.01$, $m = 500$, $i = 100$.

6.1 Evaluation on the Choi Dataset

The evaluation uses the 10-fold CV setting as described in Section 4.3.1. For this dataset, no word filtering based on parts of speech was deemed necessary. The results for different parameter settings are listed in Table 3. Using only the window parameter

seg. size	**3-5**		**6-8**		**9-11**		**3-11**	
	P_k	WD	P_k	WD	P_k	WD	P_k	WD
d=false,w=1	2.71	3.00	3.64	4.14	5.90	7.05	3.81	4.32
d=true,w=1	3.71	4.16	1.97	2.23	2.42	2.92	2.00	2.30
d=false,w=2	1.46	1.51	1.05	1.20	1.13	1.31	1.00	1.15
d=true,w=2	**1.24**	**1.27**	**0.76**	**0.85**	**0.56**	**0.71**	**0.95**	**1.08**
d=false,w=5	2.78	3.04	1.71	2.11	4.47	4.76	3.80	4.46
d=true,w=5	2.34	2.65	1.17	1.35	4.39	4.56	3.20	3.54

Table 3: Results based on the Choi dataset with varying parameters.

without the mode ($d = false$), the results demonstrate a significant error reduction with a window of 2 sentences. An impairment is observed when using a too large window (w=5) (cmp. Section 5.2.6). We can also see that the mode method improves the results when using a window of 1, except for the documents having small segments ranging from 3-5 sentences. The lowest error rates are obtained with the mode method and a window size of 2. As described in Section 4.2.3, the algorithm is also able to automatically estimate the number of segments using a threshold value (see Table 4).

	3-5		**6-8**		**9-11**		**3-11**	
	P_k	WD	P_k	WD	P_k	WD	P_k	WD
d=false,w=1	**2.39**	**2.45**	4.09	5.85	9.20	15.44	4.87	6.74
d=true,w=1	3.54	3.59	1.98	2.57	3.01	5.15	2.04	2.62
d=false,w=2	15.53	15.55	0.79	0.88	1.98	3.23	1.03	1.36
d=true,w=2	14.65	14.69	**0.62**	**0.62**	**0.67**	**0.88**	**0.66**	**0.78**
d=false,w=5	21.47	21.62	16.30	16.30	6.01	6.14	14.31	14.65
d=true,w=5	21.57	21.67	17.24	17.24	6.44	6.44	15.51	15.74

Table 4: Results on the Choi dataset without providing the number of segments

As can be seen the optimized parameters leads to worse results for segments of length 3-5. This is caused by the smoothing effect of the window parameter which leads to less detected boundaries. But the results of the other documents are comparable to the ones shown in Table 3. Some results (see segment length 6-8 and 3-11 with parameter d=true and w=2) are even better than the results with segments provided which is attributed to the remaining variance in the probabilistic inference computations. The threshold method can outperform the setup with a given number of segments, since not recognizing a segment produces less error in the measures than predicting a wrong segment. Table 5 presents a comparison of the performance of TopicTiling compared to different algorithms in the literature.

Method	**3-5**	**6-8**	**9-11**	**3-11**
TT (Choi, 2000)	44	43	48	46
C99 (Choi, 2000)	12	9	9	12
U00 (Utiyama and Isahara, 2001)	9	7	5	10
LCseg (Galley et al., 2003)	8.69			
F04 (Fragkou et al., 2004)	5.5	3.0	1.3	7.0
M09 (Misra et al., 2009)	2.2	2.3	4.1	2.3
TopicTiling (d=true, w=2)	**1.24**	**0.76**	**0.56**	**0.95**

Table 5: Lowest P_k values for the Choi data set for various algorithms in the literature with provided segment number.

It is obvious that the results are far better than current state-of-the-art results. Using a one-sample t-test with $\alpha = 0.05$ we can state significant improvements in comparison to all other algorithms. With error rates below the 1% range, TS on the Choi dataset can be considered as solved. However, since the dataset is comparatively easy, and test data has probably been seen during model training (cf. Section 4.3), we assess the performance of our algorithm on a second dataset.

6.2 Evaluation on Galley's WSJ Dataset

The evaluation on Galley's WSJ dataset is performed, using a topic model created from the WSJ collection of the PTB. The dataset for model estimation consists of 2499 WSJ articles, and is the same dataset Galley used as a source corpus. The evaluation generally leads to higher error rates than in the evaluation for the Choi dataset, as shown in Table 6.

Parameters	All words		Filtered	
	P_k	WD	P_k	WD
d=false,w=1	37.31	43.20	37.01	43.26
d=true,w=1	35.31	41.27	33.52	39.86
d=false,w=2	22.76	28.69	21.35	27.28
d=true,w=2	21.79	27.35	19.75	25.42
d=false,w=5	14.29	19.89	12.90	18.87
d=true,w=5	**13.59**	**19.61**	**11.89**	**17.41**
d=false,w=10	14.08	22.60	14.09	22.22
d=true,w=10	13.61	21.00	13.48	20.59

Table 6: Results for Galley's WSJ dataset using different parameters with using unfiltered documents (column 2-3) and with filtered documents using only verbs, nouns (proper and common) and adjectives (column 3-4).

This table shows results of the WSJ data when using all words of the documents for training a topic model and assigning topic IDs to new documents. It also shows results using only nouns (proper and common), verbs and adjectives[4]. Considering the unfiltered results, we observe that performance benefits from using the mode assigned topic ID and a window larger than one. In case of the WSJ dataset, we find the optimal setting for the window parameter to be 5. As the test documents contain whole articles, which consist of at least 4 sentences, a larger window is advantageous here, yet a value of 10 is too large. Filtering the documents for parts of speech leads to $\sim$ 1% absolute error rate reduction, as can be seen in the last two columns of Table 6. Again, we observe that the mode assignment always leads to better results, gaining at least 0.6%. Especially the window size of 5 helps TopicTiling to decrease the error rate to a third of the value observed with d=false and w=1. Table 7 shows the results we achieve with the threshold-based estimation of segment boundaries for the unfiltered and filtered data.

In contrast to the results obtained with the Choi dataset (see Table 4) no decline occurs, when using the threshold approach in combination with the window method. We attribute this due to the small segments and documents in the Choi dataset. Part-of-speech-based filtering is always advantageous over using all words here. Also a decrease of both error rates, P_k and WD, is detected when using the mode and using a larger window size. An improvement is even gained for a window of size 10. This can be attributed to the fact that using small window sizes, too many boundaries are detected.

[4] as identified by the Treetagger `http://code.google.com/p/tt4j/`

Parameters	All words		Filtered	
	P_k	WD	P_k	WD
d=false,w=1	53.07	72.78	52.63	72.66
d=true,w=1	53.42	74.12	51.84	72.57
d=false,w=2	46.68	65.01	44.81	63.09
d=true,w=2	46.08	64.41	43.54	61.18
d=false,w=5	30.68	43.73	28.31	40.36
d=true,w=5	28.29	38.90	26.96	36.98
d=false,w=10	19.93	32.98	18.29	29.29
d=true,w=10	**17.50**	**26.36**	**16.32**	**24.75**

Table 7: Table with results the WSJ dataset without providing the number of segments. Columns 2 and 3 show the results when using all words of the documents. Columns 4 and 5 show the results with part-of-speech-based filtering.

As the window approach smooths the similarity scores, this leads to less segmentation boundaries and improved results.

Table 8 presents the results of other algorithms, as published in Galley et al. (2003), in comparison to TopicTiling. Again, TopicTiling improves over the state of the art.

Method	P_k	WD
C99 Choi (2000)	19.61	26.42
U00 Utiyama and Isahara (2001)	15.18	21.54
LCseg Galley et al. (2003)	12.21	18.25
TopicTiling (d=true,w=5)	**11.89**	**17.41**

Table 8: List of results based on the WSJ dataset. Values for C99, U00 and LCseg as stated in Galley et al. (2003).

The improvements with respect to LCseg are significant using a one-sample t-test with $\alpha = 0.05$.

7 Conclusion

In this article we showed that replacing words in documents by topic IDs, as assigned by the Bayesian inference method of LDA, leads to better results in the Text Segmentation task. This technique is applied in the TT and C99 algorithms. Additionally, we introduced a simplified algorithm based on TT called TopicTiling that outperforms the topic-based versions of TT and C99. In contrast to other TS algorithms using topic models (Misra et al. (2009); Sun et al. (2008)), the runtime of TopicTiling is linear in the number of sentences. This makes TopicTiling a fast algorithm with complexity of $O(n)$ (n denoting the number of sentences) as opposed to $O(n^2)$ of the dynamic programming approach as discussed in Fragkou et al. (2004).

During sweeping the parameter space of LDA and TopicTiling (see Section 5) we show that repeating the Bayesian inference several times and using the most frequently assigned topic IDs in the last iteration not only reduces the variance, but also improves overall results. We obtain almost equal performance, when selecting the most frequent topic ID (mode) assigned per word across each inference step. Although the error rates are slightly higher in our experiments, this method is preferred, as the computational cost is much lower than repeating the inference step several times. This method is not only applicable to Text Segmentation, but in all applications where performance crucially depends on stable topic ID assignments per token. Using the Choi dataset and the Galleys WSJ dataset we can show significant improved results in comparison to actual state-of-the-art algorithms.

For further work, we would like to devise a method to detect the optimal setting for the window parameter w automatically, especially in a setting where the number of target segments is not known in advance. This is an issue that is shared with the original TextTiling algorithm. Moreover, we will extend the usage of our algorithm to more realistic corpora.

More interesting is the perspective on possible applications. Equipped with a highly reliable segmentation mechanism, we would like to apply text segmentation as a writing aid to assist authors with feasible segmentation boundaries. This could be applied in an interactive manner by giving feedback about the coherence during the writing process. As the author is responsible for accepting such segmentation, the need for automatically determining the number of segments would be dispensable, and subject to tuning to the author's preferences.

Another direction of research that is more generic for approaches based on topic models is the question of how to automatically select appropriate data for topic model estimation, given only a small target collection. Since topic model estimation is computationally expensive, and topic models for generic collections (think Wikipedia) might not suit the needs of a specialized domain (such as with the WSJ data), it is a promising direction to look at target-domain-driven automatic corpus synthesis.

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References

Beeferman, D., Berger, A., and Lafferty, J. (1999). Statistical models for text segmentation. *Machine learning*, 34(1):177–210.

Blei, D. M. and Moreno, P. J. (2001). Topic segmentation with an aspect hidden markov model. In *Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval*, SIGIR '01, pages 343–348, New Orleans, Louisiana, USA.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 3:993–1022.

Choi, F. Y. Y. (2000). Advances in domain independent linear text segmentation. In *Proceedings of the 1st North American chapter of the Association for Computational Linguistics conference*, pages 26–33, Seattle, WA, USA.

Choi, F. Y. Y., Wiemer-Hastings, P., and Moore, J. (2001). Latent semantic analysis for text segmentation. In *Proceedings of EMNLP*, pages 109–117, Pittsburgh, PA, USA.

Du, L., Buntine, W., and Jin, H. (2010). A segmented topic model based on the two-parameter poisson-dirichlet process. *Machine Learning*, 81(1):5–19.

Eisenstein, J. (2009). Hierarchical text segmentation from multi-scale lexical cohesion. In *Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 353–361, Boulder, CO, USA.

Fragkou, P., Petridis, V., and Kehagias, A. (2004). A Dynamic Programming Algorithm for Linear Text Segmentation. *Journal of Intelligent Information Systems*, 23(2):179–197.

Galley, M., McKeown, K., Fosler-Lussier, E., and Jing, H. (2003). Discourse segmentation of multi-party conversation. In *Proceedings of the 41st Annual Meeting on Association for Computational Linguistics*, volume 1, pages 562–569, Sapporo, Japan.

Georgescul, M., Clark, A., and Armstrong, S. (2006). An analysis of quantitative aspects in the evaluation of thematic segmentation algorithms. In *Proceedings of the 7th SIGdial Workshop on Discourse and Dialogue*, pages 144–151, Sydney, Australia.

Griffiths, T. L. and Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101:5228–5235.

Gruber, A., Rosen-Zvi, M., and Weiss, Y. (2007). Hidden topic markov models. In *In Proceedings of Artificial Intelligence and Statistics*, San Juan, Puerto Rico.

Hearst, M. A. (1994). Multi-paragraph segmentation of expository text. In *Proceedings of the 32nd annual meeting on Association for Computational Linguistics*, pages 9–16, Las Cruces, NM, USA.

Hearst, M. A. (1997). TextTiling : Segmenting Text into Multi-paragraph Subtopic Passages. *Computational Linguistics*, 23(1):33–64.

Heinrich, G. (2004). Parameter estimation for text analysis. Technical report, University of Leipzig, http://www.arbylon.net/publications/text-est.pdf.

Heinrich, G. (2011). Typology of mixed-membership models: Towards a design method. In *Machine Learning and Knowledge Discovery in Databases*, volume 6912 of *Lecture Notes in Computer Science*, pages 32–47. Springer Berlin / Heidelberg. 10.1007/978-3-642-23783-6 3.

Hofmann, T. (1999). Probabilistic Latent Semantic Analysis. In *Proceedings of Uncertainty in Artificial Intelligence, UAI'99*, pages 289–296, Stockholm, Sweden.

Jurafsky, D. and Martin, J. H. (2009). *Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics*. Pearson International Edition.

Lamprier, S., Amghar, T., Levrat, B., and Saubion, F. (2007). ClassStruggle. In *Proceedings of the 2007 ACM symposium on Applied computing - SAC '07*, page 600, New York, New York, USA. ACM Press.

Manning, C. and Schütze, H. (1999). *Foundations of statistical natural language processing*. MIT Press, Cambridge, MA.

Marcus, M., Kim, G., Marcinkiewicz, M. A., Macintyre, R., Bies, A., Ferguson, M., Katz, K., and Schasberger, B. (1994). The Penn Treebank: Annotating predicate argument structure. In *Proceedings of the workshop on Human Language Technology*, pages 114–119, Plainsboro, NJ, USA.

Misra, H., Yvon, F., Jose, J. M., and Cappe, O. (2009). Text Segmentation via Topic Modeling: An Analytical Study. In *Proceeding of the 18th ACM Conference on Information and Knowledge Management*, pages 1553–1556, Hong Kong.

Mulbregt, P. v., Carp, I., Gillick, L., Lowe, S., and Yamron, J. (1998). Text segmentation and topic tracking on broadcast news via a hidden markov model approach. In *Proceedings of 5th International Conference on Spoken Language Processing*, Sydney, Australia.

Pevzner, L. and Hearst, M. A. (2002). A Critique and Improvement of an Evaluation Metric for Text Segmentation. *Computational Linguistics*, 28(1):19–36.

Phan, X.-H. and Nguyen, C.-T. (2007). GibbsLDA++: A C/C++ implementation of latent Dirichlet allocation (LDA). http://jgibblda.sourceforge.net/.

Sato, I. and Nakagawa, H. (2010). Topic Models with Power-Law Using Pitman-Yor Process Categories and Subject Descriptors. *Science And Technology*, (1):673–681.

Scaiano, M. and Inkpen, D. (2012). Getting more from segmentation evaluation. In *Proceedings Conference of North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 362–366, Montreal, Canada.

Sun, Q., Li, R., Luo, D., and Wu, X. (2008). Text segmentation with LDA-based Fisher kernel. *Proceedings of the 46th Annual Meeting of the Association for Computational Linguistics on Human Language Technologies*, pages 269–272.

Utiyama, M. and Isahara, H. (2001). A statistical model for domain-independent text segmentation. In *Proceedings of the 39th Annual Meeting on Association for Computational Linguistics*, pages 499–506, Toulouse, France.

Wallach, H., Mimno, D., and McCallum, A. (2009). Rethinking LDA: Why priors matter. In *NIPS*, Vancouver, B.C., Canada.

Wayne, C. (1998). Topic detection and tracking (TDT): Overview & perspective. In *Proceedings of the Broadcast News Transcription and Understanding Workshop*, Lansdowne, Virginia.

Yaari, Y. (1997). Segmentation of expository texts by hierarchical agglomerative clustering. In *Proceedings of the Conference on Recent Advances in Natural Language Processing*, Tzigov Chark, Bulgaria.