Exploring Differential Topic Models for Comparative Summarization of Scientific Papers

Lei He*, Wei Li*, Hai Zhuge*

* System Analytics Research Institute, Aston University, Birmingham, UK
# Key Lab of Intelligent Information Processing, ICT, CAS, University of Chinese Academy of Sciences, Beijing, China

hel2@aston.ac.uk, weili.ict.kg@gmail.com, zhuge@ict.ac.cn

Abstract

This paper investigates differential topic models (dTM) for summarizing the differences among document groups. Starting from a simple probabilistic generative model, we propose dTM-SAGE that explicitly models the deviations on group-specific word distributions to indicate how words are used differentially across different document groups from a background word distribution. It is more effective to capture unique characteristics for comparing document groups. To generate dTM-based comparative summaries, we propose two sentence scoring methods for measuring the sentence discriminative capacity. Experimental results on scientific papers dataset show that our dTM-based comparative summarization methods significantly outperform the generic baselines and the state-of-the-art comparative summarization methods under ROUGE metrics.

1 Introduction

Today, the interconnected nature of real-world applications brings more cross-field research problems leading to a much closer relationship between research areas. Real-world challenges require researchers to quickly get acquainted with knowledge in other areas. For example, imagine a researcher who is familiar with topic models wants to extend her research to opinion summarization. She would be more interested in finding out the current development of sentiment analysis and how topic models can be used in sentiment analysis, rather than the common background knowledge such as topic models and basic NLP technologies. Such a real-world demand encourages the study of multi-document comparative summarization for scientific papers in multiple subject areas. This paper presents the initial study on this problem.

Comparative summarization aims at summarizing the differences among document groups (Wang et al., 2012). The core is to compare different topics and find unique characteristics for each document group. The main motivation of this paper is to apply dTM to comparative summarization and to model the group-specific topics to capture the unique word usage for characterising documents in the same group. To our best knowledge, there is no previous study providing in-depth model analysis and detailed experimental results on dTM applied for comparative summarization.

We first propose a probabilistic generative model dTM-Dirichlet to model the group-specific word distributions to capture the unique word usage for each document group. However, dTM-Dirichlet is not a truly differential topic model and it suffers from the problems of high inference cost, over-parameterization and lack of sparsity. Evolving from the idea of SAGE (Eisenstein et al., 2011), we develop dTM-SAGE to make the word probability distributions for each document group to share a common background word distribution and explicitly models how words are used differently in each group from the background word distribution.

Our main contributions include the following two points: (1) we propose dTM to capture unique characteristics of each document group in the application background of comparative summarization for cross-area scientific papers; and (2) we propose two sentence scoring methods to measure the sen-
sentence discriminative capacity and a greedy sentence selection method to automatically generate summary for dTM-based comparative summarization.

2 Related Work

Multi-document Summarization. Existing multi-document summarization can be either extractive or abstractive (Sekine and Nobata, 2003). Our work focuses on the extractive techniques which involve in assigning saliency scores to sentences and extracting high-scored sentences in a greedy manner to construct a summary (Wan et al., 2007; Cai et al., 2010; Gupta and Lehal, 2010; Celikyilmaz and Hakkani-Tur, 2011). Graph-based ranking techniques such as TextRank (Mihalcea and Tarau, 2004) and LexPageRank (ErKan and Radev, 2004) have been widely used in extractive summarization. A bigram based supervised method was proposed for extractive summarization in ILP framework (Li et al., 2013; Li, 2015). Jha et al. (2015) proposed an extractive algorithm that combines a content model with a discourse model to generate coherent summaries for scientific articles. A multi-dimensional summarization methodology was proposed to transform the paradigm of traditional summarization research through multi-disciplinary fundamental exploration on semantics, dimension, knowledge, computing and cyber-physical society (Zhuge, 2016).

Comparative Summarization. Unlike the generic summarization that summarizes the common information in document collection, the comparative summarization aims to summarize the differences among document groups. Wang et al. (2012) proposed a discriminative sentence selection method to generate summary by selecting sentences in a greedy manner to minimize the generalized variance of a covariance matrix using a multivariate normal model. Shen and Li (2010) proposed a method by building the sentence graph for each document group and extracting a complementary minimum dominating set on each graph to form a discriminative summary.

Update Summarization. The most similar task to comparative summarization is update summarization, which aims to detect and summarize novel information in a document set B under the assumption that users have already learnt the documents in set A, where documents in A chronologically precede the documents in B. The update summarization has been well studied. Most existing methods solve it as a redundancy removal problem by adding functionality to remove redundant sentences using filtering rules (Fisher and Roark, 2008), Maximal Marginal Relevance (Boudin et al., 2008), or graph-based algorithms (Shen and Li, 2010; Li et al., 2008).

More related to this paper is the work of a topic-model based update summarization approach DualSum (Delort and Alfonseca, 2012), which learns a general background distribution across the corpus and a document-specific distribution for each document, but also learns two collection-specific distributions for each pair of update collection and base collection: the joint topic distribution and the update topic distribution. This paper revises DualSum as a baseline for evaluation in Section 5.2.

Topic Models for Documents Comparison. The other type of related work is the comparison of documents. Most existing studies for this goal focus on topic models to discover common and specific themes among document collections, referred to as cross-collection topic models (Paul, 2009). This idea was first explored with an initial topic model PLSI (Zhai et al., 2004), and later improved with LDA topic model (Blei, 2012; Paul, 2009) which inspires our dTM-Dirichlet. There are a number of real-world applications extending cross-collection topic models in different scenarios (Ahmed and Xing, 2010; Li et al., 2011). For example, Paul and Girju (2009) employed cross-collection LDA (cc-LDA) for cross-cultural analysis of blogs and forums and later they proposed a two-dimensional topic-aspect model (TAM) to jointly discover topics and aspects in scientific literature (Paul and Girju, 2010). The common idea behind these cross-collection topic models is that using latent topics capture the common and unique word usage among document collections. Cross-collection topic models neglect the correlations between each collection-specific topic and the common background topic, thus make it insufficient to capture differential word usage. More importantly, the correlations are the essence of the differential topic models.

3 Differential Topic Models

In this section, the differential topic models are explored for comparative summarization. We first develop a simple probabilistic generative model, dTM-Dirichlet. Evolved from dTM-Dirichlet, dTM-SAGE is developed by modelling the correlations as additive relation between the group-specific devi-
ations and a background word distribution, which enables to capture more salient group-specific words and bypass the problems of high inference cost, over-parameterization and lack of sparsity.

To illustrate $dTM$, we first define some notations to express a document corpus $C$. Let $G$ be the number of groups in the corpus, $M_g$ be the number of papers in group $g$ and $N_g, m$ be the number of words in paper $m$. A word $w_{g,m,n}$ representing the $n^{th}$ word in paper $m$ of group $g$ is a discrete observed variable, defined to be an item in the vocabulary list of the whole corpus.

### 3.1 $dTM$-Dirichlet Model

$dTM$-Dirichlet model is a simplified version of cross-collection LDA (ccLDA) (Paul and Girju, 2009) for comparing multiple text collections. $dTM$-Dirichlet builds two types of word model. One is for each document group $g$, in which there is a group-specific content word model $\theta_g$ that emits discriminative words for the group. The other type is a superset of group-independent word models $\phi_k$ that generates either background words shared by all document groups or salient words occurring in several documents of different groups. Reconsidering the example in section 1, the group-independent word model represents two classes of words, i.e. the background words like topic model that are shared by almost all papers; and the salient words like NP chunk and dependency parsing that only occur in several papers of different groups.

We focus on the group-specific word model for comparative summarization. Since background words and salient words provide no group-specific knowledge, they are not distinguished in $dTM$-Dirichlet. Following probabilistic topic models, we assume that word models $\phi_k$ and $\theta_g$ are multinomial distributions over words, drawn from uniform Dirichlet distribution ($\text{Dir}$) with priors $\alpha_\phi$ and $\alpha_\theta$.

As shown in Fig. 1, $dTM$-Dirichlet associates each document a topic distribution $\gamma \sim \text{Dir}(\alpha_\gamma)$, and the topic assignment variable $z$ for each word in the document thus can be multinomially sampled from $\gamma$. Besides a topic variable $z$, each word is also assigned with a binary variable $s$ that indicates whether the word is a group-independent topic word ($s=1$) or a group-specific content word ($s=0$). Each document has a group-specific word controller $\lambda \sim \text{Beta}(\alpha_\lambda)$, which reflects the proportion of group-specific content in a document. $s$ is sampled from a Bernoulli test with the probability of $\lambda$.

Formally, the generative process of $dTM$-Dirichlet model for a corpus $C$ divided into $G$ document groups is shown in Table 1. When $s_{g,m,n} = 1$, the sample of the group-independent topic word is identical to $LDA$. When $s_{g,m,n} = 0$, the sample of the word $w_{g,m,n}$ is independent from the document’s topic distribution $\gamma_{g,m}$ and directly drawn from the group-specific content word distribution $\theta_g$.

$dTM$-Dirichlet models group-specific word distributions to capture the differential lexicon usage of document groups. However, $dTM$-Dirichlet is not a truly differential topic model, which requires the development of $dTM$-SAGE for comparative summarization.

### 3.2 $dTM$-SAGE Model

When generating topics for multiple document collections, $LDA$-style generative models associate a multinomial distribution with each document group, which is the same as how we model the group-specific content words in $dTM$-Dirichlet model.

In contrast, SAGE (Sparse Additive Generative model) (Eisenstein et al., 2011) provides an alternative way to $LDA$ by endowing each document group with a model of the deviation in log-frequency
from a constant background distribution, which brings three advantages: First, a sparsity-inducing prior can be applied to limit the number of terms whose probability diverges from the background term frequencies. Second, multi-facets latent variables can be easily combined by adding each facet component together to reduce the inference cost. Third, it is redundant to learn unique probabilities for high-frequency background words of each group. Modelling the deviation of each group-specific word distribution cancels the relearn process for the background words.

We propose dTM-SAGE which explicitly models the deviation in log-frequency of each group-specific word distribution from a background lexical distribution. dTM-SAGE also builds word models for group-independent topic words and group-specific content words. The group-independent topic words consist of background topic words and salient topic words.

dTM-SAGE models two types of group-independent words separately: as shown in Fig. 2, the salient topic words captured by \( \varphi_k \) and the background topic words captured by \( \vartheta_0 \). The word models \( \varphi_k \) and \( \vartheta_0 \) are multinomial distributions drawn from uniform Dirichlet prior with parameter \( \alpha_g \) and \( \alpha_B \). To enable \( \vartheta_0 \) to capture real background topic words shared by all document groups, we replace the constant background distribution in SAGE with a latent distribution learnt by MAP estimation using a Newton optimization.

The major difference between dTM-SAGE and dTM-Dirichlet is how the group-specific topics are generated. In Fig.2, each document group \( g \) has a group component vector \( \eta_g \), representing the deviations in log-frequencies from the background distribution \( \vartheta_0 \). The group-specific topic is represented by log frequency deviations rather than word probabilities. Given the background distribution \( \vartheta_0 \) and the group component vector \( \eta_g \), the group-specific topic distribution \( \vartheta_g \) for each word in a document in the group \( g \), denoted by \( \vartheta_g \propto \exp(\vartheta_0 + \eta_g) \), is computed by Equation (1):

\[
p(w \mid \vartheta_g, \eta_g) / \sum_v \exp(\vartheta_0, \eta_v) = \frac{\exp(\vartheta_0 + \eta_g)}{\sum_v \exp(\vartheta_0 + \eta_v)} = \frac{1}{\sum_v \exp(\vartheta_0 + \eta_v)} \exp(\vartheta_0 + \eta_g)
\]

In Equation (1), \( g \) indexes the group component vector and \( v \) indexes the term in the corpus vocabulary. Following SAGE, we ignore covariance between terms. For each term \( v \), \( \eta_{g,v} \) is drawn from a zero-mean Gaussian distribution \( N(0, \sigma_{g,v}) \), where the variance \( \sigma_{g,v} \) is drawn from the Exponential distribution parameterized by \( \alpha_g \). The compound model \( \int N(\eta; 0, \sigma) \exp(\vartheta_0 + \eta_g) d\sigma \) is equivalent to a zero-mean Laplace prior on \( \eta \) inducing sparsity and meanwhile permitting large degrees of deviations. In dTM-SAGE, we treat the variance \( \sigma \) as a latent variable and develop variational inference on it, which is the same as SAGE. The remaining part of dTM-SAGE is the same as dTM-Dirichlet model. Formally, the generative process of dTM-SAGE is shown in Table 1. See Appendix A for inference details of \( \vartheta_0 \) and \( \eta_g \).

### Table 1: The generation process of dTM-Dirichlet and dTM-SAGE

| dTM-Dirichlet | dTM-SAGE |
|---------------|----------|
| 1. For each topic \( k \), where \( 1 \leq k \leq K \) | 1. Draw \( \vartheta_0 \sim \text{Dir}(\alpha_0) \) |
| a. Draw \( \varphi_k \sim \text{Dir}(\alpha_k) \) | 2. For each topic \( k \), where \( 1 \leq k \leq K \) |
| 2. For each document group \( g \), where \( 1 \leq g \leq G \) | a. Draw \( \vartheta_0 \sim \text{Dir}(\alpha_0) \) |
| a. Draw \( \vartheta_k \sim \text{Dir}(\alpha_k) \) | 3. For each document group \( g \), where \( 1 \leq g \leq G \) |
| b. For each document \( m \) in group \( g \), where \( 1 \leq m \leq M_g \) | a. For each term \( v \), where \( 1 \leq v \leq V \) |
| 1) Draw \( \lambda_{g,m} \sim \beta(\alpha_g) \) | 1) Draw \( \sigma_v \sim \text{Exponential}(\alpha_v) \) |
| 2) Draw \( \gamma_{g,m} \sim \text{Dir}(\alpha_g) \) | b. Set \( \eta_g = \exp(\vartheta_0 + \eta_g) \) |
| 3) For each word \( n \), where \( 1 \leq n \leq N_{g,m} \) | c. For each document \( m \) in group \( g \), where \( 1 \leq m \leq M_g \) |
| a) Draw \( \eta_{g,m,n} \sim \text{Bern}(\eta_g) \) | 1) Draw \( \lambda_{g,m} \sim \text{Dir}(\alpha_g) \) |
| b) Draw a word \( w_{g,m,n} \sim \varphi_{g,m,n} \) | 2) Draw \( \gamma_{g,m} \sim \text{Dir}(\alpha_g) \) |
| c) If \( \eta_{g,m,n} = 0 \) (a group-specific content word) | 3) For each word \( n \), where \( 1 \leq n \leq N_{g,m} \) |
| A. Draw \( w_{g,m,n} \sim \varphi_{g,m,n} \) | a) Draw \( \eta_{g,m,n} \sim \text{Bern}(\eta_g) \) |
| b) If \( \eta_{g,m,n} = 1 \), Draw \( \gamma_{g,m,n} \sim \lambda_{g,m} \) |
| A. Draw \( w_{g,m,n} \sim \varphi_{g,m,n} \) |
| c) If \( \eta_{g,m,n} = 0 \), Draw \( w_{g,m,n} \sim \vartheta_0 \) |

4. **Comparative Summary Generation**

To summarize differences among document groups, we rely on group-specific topics \( \vartheta_k \) to select most discriminative sentences for summary generation. This section introduces the sentence scoring and the sentence selection techniques developed for dTM-based comparative summarization.
4.1 Sentence Scoring

Both dTM-Dirichlet and dTM-SAGE model the group-specific word distributions $\theta_g$ to capture the unique content in each document group. For dTM-SAGE, we can also get a corpus background topic distribution $\theta_0$ that reflects the common themes shared by all groups. To measure the sentence discriminative capacity, we develop two sentence scoring methods: one is based on the word discriminative scores and the other is measured by the difference of the probabilities that a sentence is generated from a group-specific topic distribution and the background topic distribution.

First, given a set of group-specific word distributions $\theta_g (1 \leq g \leq G)$, we define the word discriminative score $DSW(v, g)$ of a term $v$ to a group $g$ as $DSW(v, g) = \sum_{w \in S} \frac{\theta_g(w) - \theta_g(w)}{\sum_{g'} \theta_{g'}(w)} + \epsilon$, where $\epsilon$ is a small number (set to 0.05) to avoid the error of division by zero. Larger value of the word discriminative score indicates more discriminative ability the word has. The intuition is that a word more likely to occur in a particular group and less likely to occur in other groups tends to be more discriminative.

The discriminative capacity of a sentence $s$ to a group $g$ $DCS_{dsw}(s, g)$ is the average over the word discriminative scores:

$$DCS_{dsw}(s, g) = \frac{\sum_{w \in s} DSW(w, g)}{|s|}$$

The other method to measure the discriminative capacity of a sentence relies on the likelihood that the sentence is generated from a group-specific distribution and the background topic distribution. Its design is motivated by the idea that a word is more discriminative if it occurs more often in a group-specific topic and occurs rarely in the shared background topic. Given a topic-word distribution $\theta$, the probability of a sentence $s$ generated from $\theta$:

$$\log P(s \mid \theta) = \sum_{w \in s} \log \theta_w$$

Given a set of group-specific word distributions $\theta_g (1 \leq g \leq G)$ and the background topic distribution $\theta_0$, the discriminative capacity of a sentence $s$ to a group $g$ is defined as the difference of sentence generative probabilities $DCS_{dgp}(s, g)$:

$$DCS_{dgp}(s, g) = u \log P(s \mid \theta_g) - (1 - u) \log P(s \mid \theta_0)$$

where $u$ is a balance factor trading off between group-specific words and background words.

4.2 Sentence Selection

To select discriminative sentences to form group summary, we use different sentence selection methods according to sentence scoring techniques.

For the sentence scoring based on the word discriminative scores, we first rank the sentences according to the sentence discriminative capacity score $DCS_{dsw}$. Then we select a sentence with the highest score if it satisfies the redundancy constraint that indicated by a cosine similarity threshold (empirically set to 0.8). For the scoring based on difference sentences generative probabilities, suppose we have a set of candidate sentences $S$ to form a summary for group $g$ and we want to select $k$ sentences denoted as $S_k$. A greedy sentence selection schema is proposed to build $S_k$ by iteratively choosing a $j$th sentence that currently has the maximum sentence discriminative capacity score $DCS_{dgp}$:

$$s^*_{j} = \arg \max_{s_j \in S \setminus S_{j-1}} DCS_{dgp}(s, g)$$

In order to discourage redundancy, after select one sentence, we update the group-specific topic distribution $\theta_g$ by setting $\theta_{g,w} \propto \theta_{g,w}$ for each word $w$ in the selected sentence $s^*_j$. Sentences are selected in this manner until reaching the summary limit.

5 Experiments and Results

5.1 Data Collection and Annotation

Comparative summarization is not a new task. However, to our best knowledge there is no public benchmark data set available. For collecting experiment data, we choose three tasks in NLP: summarization (SUMMA), sentiment analysis (SA) and geographical NLP tasks (GEO) to form three document groups. To make different groups share more salient themes, we focus on papers using probabilistic
topic models. We collect 129 papers in total for the three groups from ACL Anthology Searchbench providing full-text search for 28,000 papers in the ACL Anthology. For each group, we search with two types of keyword filters: plain text filter and title filter. Table 2 shows the general information of each document group, including the keywords, the number of documents |D| and the number of sentences |S|. To pre-process the dataset, we exclude all tables, figures and formulas, remove stop words, perform stemming with Porter Stemmer, and prune words less than 5 times across the corpus. There are 3720 tokens after pre-processing.

We hire three PhD students in Aston University to annotate the dataset. After reading papers in each group, each annotator is asked to first pick out all discriminative sentences in each paper and then write reference summaries delivering the major differences for each group. Additional instructions are given to annotators: Each reference summary should be no more than 300 words; and the discriminative sentences should enable the judgment of which group the paper belongs to. Equipped with the annotated dataset, two parts of evaluations are performed: evaluation of differential topic models and evaluation of the summarization methods.

### 5.2 Evaluations on dTM

In this section, we compare dTM-Dirichlet and dTM-SAGE with other three topic models in terms of model perplexity and topic coherences: (1) the standard LDA topic model, which we run across the corpus and perform Newton optimization to update hyper-parameters; (2) SAGE, which a sparse additive generative model proposed in (Eisenstein et al., 2011), and the non-parametric Jeffrey’s prior make it parameter-free; (3) the variant of DualSum, which is proposed for update summarization (Detlor and Alfonseca, 2012) and revised to perform comparative summarization by replacing pairs of collection-specific distributions with group-specific distributions. We implement the variant of DualSum, dTM-Dirichlet and dTM-SAGE models. Experimental settings are detailed below.

**Settings for the variant of DualSum.** The dirichlet priors for word distributions are empirically set to 0.1 and \( \alpha_2 = (2.0, 2.0, 1.0) \) to encourage more words generated from the group-specific distributions and document-specific distributions.

**Settings for dTM-Dirichlet.** The dirichlet priors for word distributions \( \alpha_\phi \) and \( \alpha_\theta \) are set to 0.1. For other parameters, we set the number of group-independent topics \( K = 20 \), the prior for the topic distribution \( \alpha_\nu = 50/K \), and the prior for the group-specific word controller \( \alpha_\lambda = 2.0 \). \( \text{Beta}(2.0, 2.0) \) yields equal probabilities that words sampling from the group-specific distribution and the group-independent distributions.

**Settings for dTM-SAGE.** Parameters are set the same as those in dTM-Dirichlet: \( \alpha_\phi = \alpha_\theta = 0.1, K = 20, \alpha_\nu = 50/K \) and \( \alpha_\lambda = 2.0 \). The variational distribution of the variance \( \sigma \) is \( \text{Gamma}(\tilde{\alpha}, \tilde{\beta}) \) which is initialized as \( \tilde{\alpha} = 10.0 \) and \( \tilde{\beta} = 5.0 \). The initialization for \( \theta_\phi \) and \( \eta \) are from the Uniform distribution \( U(0, 1) \) and the Normal distribution \( N(0, 0.5) \) respectively.

First, we investigate the model perplexity. Perplexity is a general measure for evaluating the generative ability of a probabilistic topic model. We compute the perplexity on a held-out test set, 20% of the original dataset. Note that we calculate the perplexity for all models except the variant of DualSum, since it models the document-specific distribution for each document and thus there is no natural way to assign probability to new document. For the variant of DualSum, we train the model on the whole dataset and report the results on the test set, though it by no means can reflect the generalization capacity of the model.

Perplexity results are shown in the first row in Table 3, from which we can see that the perplexity scores decrease by 7% and 13% respectively between dTM-Dirichlet and standard LDA and between dTM-SAGE and standard SAGE. The better results of differential topic models over the standard ones are due to the discrimination between group-specific topics and group-independent topics. Both SAGE methods outperform their counterparts of the Dirichlet-multinomial, because the sparsity-inducing prior enables SAGE to control sparsity adaptively without over-fitting (Eisenstein et al., 2011).

| Group     | Keywords          | | | | |
|-----------|-------------------|---|---|---|---|
| SUMMA     | summarization     | topic model | 35 | 6636 | |
| SA        | Sentiment         | topic model | 45 | 10239 | |
| GEO       | N/A               | topic model, geographical | 49 | 8249 | |
| **Table 2:** General Information of the Dataset | | | | | |

| Measures | LDA | SAGE | Variant of DualSum | dTM-Dirichlet | dTM-SAGE |
|----------|-----|------|---------------------|---------------|----------|
| Perplexity | 2218.37 | 2177.29 | 1564.04 | 2052.78 | 1891.10 |
| C_A(Wiki) | 0.098 | 0.143 | 0.139 | 0.138 | 0.147 |
| C_V(Wiki) | 0.321 | 0.334 | 0.344 | 0.360 | 0.355 |
| C_UCI(Wiki) | -2.116 | -1.917 | -1.272 | -1.495 | -0.905 |
| C.UCI(Intra) | -0.895 | -0.849 | -0.662 | -0.661 | -0.668 |
| **Table 3:** Comparisons of Perplexity and Topic Coherences for Different Topic Models | | | | | |
To check the quality of the generated group-specific topics, we investigate various topic coherence measures. The intuition behind the topic coherence measures is that words clustering into a single topic tend to co-occur in the same document. It has been previously verified that topic coherence score is highly correlated with human-judged topic coherence in many works. We rely on Palmetto library (Röder et al., 2015), an online open source implementation, which offers a framework to calculate many coherence measures within a reference corpus of the English Wikipedia.

In our experiment, we compare three widely-used coherence scores over the five topic models: (1) $C_A$, which is the pairwise comparison of the top words based on a context window of size 5, and proposed in (Aletras and Stevenson, 2013); (2) $C_V$, which is a one-set segmentation of the top words based on a sliding window of size 110, and proposed in (Röder et al., 2015); (3) $C_UCI$, which is the pointwise mutual information (PMI) of all word pairs of the top words based on a sliding window of size 10, and proposed in (Newman et al., 2010).

We focus on the group-specific topics. For each group-specific topic-word distribution we get a word list containing the top-20 words and calculate the coherence scores for each word list. The topic coherence results shown in Table 3 are the average coherence scores of the three group word lists. The coherence scores are calculated within two reference corpus: the English Wikipedia (Wiki) and the original dataset (Intra). Table 4 shows the top 10 words selected by $SAGE$, $dTM$-$SAGE$ and $dTM$-$Dirichlet$ for the group SUMMA. Main observations found in Table 3 include:

1. The three differential topic models generally perform much better than the standard LDA and $SAGE$ models on all coherence measures, which shows the superiority of our $dTM$ models by distinguishing group-specific words and group-independent words;

2. $dTM$-$SAGE$ consistently performs the best among all the five models in terms of $C_A$ and $C_UCI$ with the significant increase at least by 6.5% over $dTM$-$Dirichlet$ and 8.2% over the variant of DualSum, which shows the advantage of $dTM$-$SAGE$ in accurately ranking the group-specific words due to the essence of the differential word model;

3. $dTM$-$Dirichlet$ outperforms the variant of DualSum with $C_A$ and $C_V$, however, it performs nearly the same or even worse when measured with $C_UCI$.

As shown in Table 4, words selected by $dTM$-$SAGE$ (like rouge, lexrank, redundant) are more informative and discriminative than words selected by $SAGE$ and $dTM$-$Dirichlet$.

### 5.3 Evaluations on Summarization

To evaluate the quality of the generated summaries, we compare our $dTM$-based comparative summarization methods with five other typical methods under ROUGE metrics (Lin and Hovy, 2003). Further, to check the discriminative ability of the comparative summaries, following the evaluation method of (Wang et al., 2012), we investigate the precision of the discriminative sentence selection.

In our experiment, we implement three types of summarization methods: (1) Generic baseline methods, including the centroid-based method (Radev et al., 2004), the graph-based method LexPage-
eRank (Radev et al., 2004) and the MMR-based method (Carbonell and Goldstein, 1998); (2) State-of-the-art comparative summarization methods, including the discriminative sentence selection (DSS) method (Wang et al., 2012) and the complementary dominating set (CDS) method (Shen and Li, 2010); (3) TM-based comparative summarization methods, which combine four different TMs with two sentence scoring strategies $DCS_{ds}$ and $DCS_{dgp}$ defined in section 4.1, including the basic LDA (ds), the variant of DualSum (ds), $dTM$-Dirichlet (ds), $dTM$-SAGE (ds) and $dTM$-SAGE (dgp). For each group, we select 20 sentences to form the final summary.

First, we examine the precision of the discriminative sentence selection. For each group we have 20 sentences in a summary and count how many sentences belong to the annotated discriminative sentence set. Comparisons of the precision results of discriminative sentence selection by different methods are shown at the last column in Table 5. From the precision results, we find that (1) our $dTM$-based comparative summarization methods can select over $70\%$ discriminative sentences, which significantly outperform the state-of-the-art methods with a nearly $20\%$ increase on the precision score; (2) All generic summarization methods perform rather worse due to different concerns on summarization resulting in the lack of discriminative ability of summaries.

We use ROUGE-1.5.5 toolkit to evaluate the quality of generated summaries by comparing them with human-written reference summaries. In our experiment, we limit the length of all summaries to 250 words and report the average ROUGE scores (F-Scores) on various summarization methods in Table 5. According to the results, we observe that: (1) our $dTMB$-based comparative summarization methods perform much better (paired t-test with $p<0.05$) than all the baselines, which demonstrates that targeting at a different goal for summarizing the general information among document groups, generic summarization methods are less applicable for comparative summarization, though by removing redundancy, MMR performs better than the other two baselines but still lags behind other summarization methods specifically proposed for comparative summarization; (2) our $dTMB$-based comparative summarization methods significantly outperform (paired t-test with $p<0.05$) the other two state-of-the-art comparative summarization methods, which shows that summarizing differences by extracting group-specific topics is more effective than directly summarizing at the sentence level; (3) Both $dTM$-SAGE methods achieve better ROUGE scores than $dTM$-Dirichlet, which is ascribe to the advantage of a differential word model contributing to more informative and discriminative group-specific topics (discussed in section 5.2); and, (4) For $dTM$-SAGE, the greedy sentence selection schema based on $DCS_{dgp}$ is more effective than simply ranking sentence with $DCS_{ds}$.

5.4 Summary Example

We show an example of the summary generated for the group SUMMA by our $dTM$-SAGE and $dTM$-Dirichlet in Table 6. Looking into the summaries, we find that all sentences in both summaries are related to summarization but different in the degree of their discriminative ability. Apparently, the summary generated by $dTM$-SAGE is more specific and unique to summarization, while the summary generated by $dTM$-Dirichlet still contains some general information about topic models in sentence ② and ⑤. Another observation is that the summary of $dTM$-SAGE tends to contain more salient group-specific terms that may not occur in most of group documents but still possess high discrimination, like ‘query-focused’, ‘MMR’ and ‘HierSUM’. In contrast, the summary by $dTM$-Dirichlet covers more background group-specific words, like ‘summarization’ and ‘MDS’. Although these background group-specific terms are discriminative for the group, they are relatively less informative than the salient terms for the purpose of summarization.

6 Conclusions

This paper studies the differential topic models for comparative summarization on cross-area scientific papers. A differential topic model $dTM$-SAGE is proposed to capture the unique characteristics of each document group and generate coherent group-specific topics. A greedy sentence selection method with two sentence discriminative capacity scoring schemas is designed to automatically generate summary for $dTM$-based comparative summarization methods, which achieve significant improvements with various ROUGE metrics. The analysis on experiment results shows that the summaries generated by our $dTM$-SAGE method can cover major differences for each group.
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Appendix A. Variational Inference of $\theta_0$ and $\eta_g$

Generally, we take MAP (maximum a posteriori) estimation for the background word distribution $\theta_0$ and the group component vectors $\eta$ and develop variational inference techniques for all other variables.

In dTM-SAGE, the lower bound $L$ with regarding to $\theta_0$, $\eta$, and $\sigma$ is:

$$L = \log P(\theta_0 | a_0) + \sum_g \sum_m \sum_n \log P(w_{g,m,n} | s_{g,m,n} = 0, \theta_0, \eta_g)$$

Maximize L with respect to $\theta_0$:

$$L(\theta_0) = \sum_v (\alpha^v_g - 1) \log \theta_0^v + \sum_g \sum_m \sum_n \lambda^0_{g,m,n} * (\theta_0^w_{g,m,n} - \log(\sum_{v'} \exp(\eta^v_g + \phi_{v'})))$$

By Assuming $T(v) = \frac{\exp(\phi^v_{\{g\}+\phi^v_{\|=0\}})}{\sum \exp(\phi^v_{\{g\}+\phi^v_{\|=0\}})}$, taking derivatives with respect to $\theta_0^v$:

$$\frac{\partial L}{\partial \theta_0^v} = \frac{\alpha^v_g - 1}{\theta_0^v} + \sum_g \sum_m \sum_n \lambda^0_{g,m,n} * [I(w_{g,m,n} = v) * (1 - T(v)) + I(w_{g,m,n} \neq v) * (-T(v))]$$

We use Newton-Raphson method to optimize $\theta_0$. First, we derive the Hessian matrix by setting:
After getting Hessian matrix, we invert it with Sherman-Morrison formula and compute the Newton step: \( \Delta \theta_0 = H^{-1}(\theta_0) \nabla_L \nabla_L (\theta_0) \). Same procedure on \( \eta \):

\[
\frac{\partial^2 L}{\partial \eta^2} = -\eta \{ \left[ (a g - 1) b g \right]^{-1} + \sum g \sum m \sum n \lambda_{gmn}^0 \} \{ I(w_{g,m,n} = v) \} (1 - T(v)) + I(w_{g,m,n} \neq v) \} (-T(v))
\]

\[
H_{\eta \eta}(\theta_0) = \frac{\partial^2 L}{\partial \eta \partial \eta} = -\left[ (a g - 1) b g \right]^{-1} + \sum g \sum m \sum n \lambda_{gmn}^0 \cdot (T(v))^2 - T(v)
\]