

# Diversity-Aware Coherence Loss for Improving Neural Topic Models

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## Abstract

The standard approach for neural topic modeling uses a variational autoencoder (VAE) framework that jointly minimizes the KL divergence between the estimated posterior and prior, in addition to the reconstruction loss. Since neural topic models are trained by recreating individual input documents, they do not explicitly capture the coherence between topic words on the corpus level. In this work, we propose a novel diversity-aware coherence loss that encourages the model to learn corpus-level coherence scores while maintaining a high diversity between topics. Experimental results on multiple datasets show that our method significantly improves the performance of neural topic models without requiring any pretraining or additional parameters.

## 1 Introduction

The main goal of topic modeling is to discover latent topics that best explain the observed documents in the corpus. The topics, conceptualized as a multidimensional distribution over the vocabulary, are useful for many downstream applications, including summarization (Wang et al., 2020; Xiao et al., 2022), text generation (Wang et al., 2019; Nevezhin et al., 2020), dialogue modeling (Xu et al., 2021; Zhu et al., 2021), as well as analyzing the data used for pretraining large language models (Chowdhery et al., 2022). When presented to humans, they are often represented as lists of the most probable words to assist the users in exploring and understanding the underlying themes in a large collection of documents. While the extrinsic quality of topics can be quantified by the performance of their downstream tasks, the intrinsic interpretability of topics appears to be strongly correlated with two important factors, namely *coherence* and *diversity* (Dieng et al., 2020).

The topic *coherence* measures to what extent the words within a topic are related to each other in a

meaningful way. Although human studies provide a direct method for evaluation, they can be costly, especially when a large number of models are waiting to be assessed. Therefore, various automatic metrics have been developed to measure topic coherence (Newman et al., 2010; Mimno et al., 2011; Xing et al., 2019; Terragni et al., 2021). For instance, the well-established Normalized Pointwise Mutual Information (NPMI) metric (Lau et al., 2014), based on word co-occurrence within a fixed window, has been found to have a strong correlation with human judgment (Röder et al., 2015). On the other hand, topic *diversity* measures to what extent the topics are able to capture different aspects of the corpus based on the uniqueness of the topic words (Nan et al., 2019). Importantly, studies have shown that optimizing for coherence can come at the expense of diversity (Burkhardt and Kramer, 2019). Even without accounting for topic diversity, directly optimizing for topic coherence by itself is a non-trivial task, due to the computational overhead and non-differentiability of the score matrix (Ding et al., 2018).

While traditional topic modeling algorithms are in the form of statistical models such as the Latent Dirichlet Allocation (LDA) (Blei et al., 2003), advancements in variational inference methods (Kingma and Welling, 2014; Rezende et al., 2014) have led to the rapid development of neural topic model (NTM) architectures (Miao et al., 2016, 2017; Srivastava and Sutton, 2017). More recently, follow-up works have focused on the integration of additional knowledge to improve the coherence of NTMs. Their attempts include the incorporation of external embeddings (Ding et al., 2018; Card et al., 2018; Dieng et al., 2020; Bianchi et al., 2021a,b), knowledge distillation (Hoyle et al., 2020), and model pretraining (Zhang et al., 2022). However, as the model is designed to operate on a document-level input, one significant limitation of NTMs is their inability to explicitly capture the corpus-

level coherence score, which assesses the extent to which words within specific topics tend to occur together in a comparable context within a given corpus. For example, semantically irrelevant words such as “*politics*” and “*sports*” might be contextually relevant in a given corpus (e.g., government funding for the national sports body). Recently, one closely related work addresses this gap by reinterpreting topic modeling as a coherence optimization task with diversity as a constraint (Lim and Lauw, 2022).

While traditional topic models tend to directly use corpus-level coherence signals, such as factorizing the document-term matrix (Steinberger and Griffiths, 2007), and topic segment labeling with random walks on co-occurrence graphs (Mihalcea and Radev, 2011; Joty et al., 2013), to the best of our knowledge, no existing work have explicitly integrated corpus-level coherence scores into the training of NTMs without sacrificing topic diversity. To address this gap, we propose a novel **coherence-aware diversity loss**, which is effective to improve both the coherence and diversity of NTMs by adding as an auxiliary loss during training. Experimental results show that this method can significantly improve baseline models without any pretraining or additional parameters<sup>1</sup>.

## 2 Background

Latent Dirichlet Allocation (LDA) (Blei et al., 2003) is a simple yet effective probabilistic generative model trained on a collection of documents. It is based on the assumption that each document  $w$  in the corpus is described by a random mixture of latent topics  $z$  sampled from a distribution parameterized by  $\theta$ , where the topics  $\beta$  are represented as a multidimensional distribution over the vocabulary  $V$ . The formal algorithm describing the generative process is presented in Appendix A. Under this assumption, the marginal likelihood of the document  $p(w|\alpha, \beta)$  is described as:

$$\int_{\theta} \left( \prod_i \sum_{z_i} p(w_i|z_i, \beta) p(z_i|\theta) \right) p(\theta|\alpha) d\theta \quad (1)$$

However, since the posterior distribution  $p(z_i|\theta)$  is intractable for exact inference, a wide variety of approximate inference algorithms have been used for LDA (e.g., Hoffman et al. (2010)).

<sup>1</sup>The implementation of our work is available at: <https://github.com/raymondzmc/Topic-Model-Diversity-Aware-Coherence-Loss>

A common strategy to approximate such posterior is employing the variational auto-encoder (VAE) (Kingma and Welling, 2014). In particular, NTMs use an encoder network to compress the document representation into a continuous latent distribution and pass it to a generative decoder to reconstruct the bag-of-words (BoW) representation of the documents. The model is trained to minimize the evidence lower bound (ELBO) of the marginal log-likelihood described by the LDA generative process:

$$L_{\text{ELBO}} = -D_{\text{KL}}[q(\theta, z|w)||p(\theta, z|\alpha)] + \mathbb{E}_{q(\theta, z|w)}[\log p(w|z, \theta, \alpha, \beta)] \quad (2)$$

In Equation 2, the first term attempts to match the variational posterior over latent variables to the prior, and the second term ensures that the variational posterior favors values of the latent variables that are good at explaining the data (i.e., reconstruction loss). While standard Gaussian prior has typically been used in VAEs, **ProdLDA** (Srivastava and Sutton, 2017) showed that using a Laplace approximation of the Dirichlet prior achieved superior performance. To further improve topic coherence, **CombinedTM** (Bianchi et al., 2021a) concatenated the BoW input with contextualized SBERT embeddings (Reimers and Gurevych, 2019), while **ZeroshotTM** (Bianchi et al., 2021b) used only contextualized embeddings as input. These are the three baselines included in our experiments.

## 3 Proposed Methodology

Despite the recent advancements, one significant limitation of the NTM is that since the model is trained on document-level input, it does not have direct access to corpus-level coherence information (i.e., word co-occurrence). Specifically, the topic-word distribution  $\beta$  is optimized on the document-level reconstruction loss, which may not be an accurate estimate of the true corpus distribution due to the inherent stochasticity of gradient-descent algorithms. We address this problem by explicitly integrating a corpus-level coherence metric into the training process of NTMs using an auxiliary loss.

### 3.1 Optimizing Corpus Coherence

To improve the topic-word distribution  $\beta$ , we maximize the corpus-level coherence through the well-established NPMI metric<sup>2</sup> (Bouma, 2009; Lau et al.,

<sup>2</sup>Detailed definition of NPMI is presented in Appendix B.

2014). After computing the pairwise NPMI matrix  $N \in \mathbb{R}^{|V| \times |V|}$  on the corpus, we use the negative  $\beta$ -weighted NPMI scores of the top- $n$  words within each topic as the weight for the coherence penalty of  $\beta$ , where  $n$  is a hyperparameter that equals to the number of topic words to use. Specifically, we apply a mask  $M_c$  to keep the top- $n$  words of each topic and apply the row-wise softmax operation  $\sigma$  to ensure the value of the penalty is always positive. We define the coherence weight  $W_C$  in Equation 3.

$$W_C = 1 - \text{normalize}(\sigma(\beta \odot M_c)N) \quad (3)$$

Intuitively, each value in  $\sigma(\beta \odot M_k)N$  represents the  $\beta$ -weighted average NPMI score with other words in the topic. Then we use row-wise normalization to scale the values, so  $W_C \in [0, 1]$ .

### 3.2 Improving Topic Diversity

One problem with the coherence weight  $W_C$  is that it does not consider the diversity across topics. To account for this, we propose an additional method to simultaneously improve topic diversity by encouraging words unused by other topics to have higher probabilities. To achieve this, we bin the words within each topic into two groups, where the words in the first group consist of those that already have a high probability in other topics (i.e., appear within top- $n$  words), while the second group does not. The intuition is that we want to penalize the words in the first group more than the words in the second group. In practice, we use a mask  $M_d \in \mathbb{R}^{K \times V}$  for selecting  $\beta$  logits in the first group, where hyperparameter  $\lambda_d \in [0.5, 1]$  is a balancing constant between the two groups and  $n$  is the number of topic words to use. We then compute the diversity-aware coherence weight  $W_D$  as the  $\lambda_d$ -weighted sum of  $W_C$ :

$$W_D = \lambda_d M_d \odot W_C + (1 - \lambda_d)(\neg M_d) \odot W_C \quad (4)$$

From Equation 4, we see that when  $\lambda_d = 0.5$ , there are no constraints on diversity since the two groups are penalized equally ( $2W_D = W_C$ ).

### 3.3 Auxiliary Loss

From the two definitions of coherence weight ( $W_C, W_D$ ), we propose an auxiliary loss that can be directly combined with the ELBO loss (Equation 2) when training the NTM. Since  $\beta$  are unnormalized logits containing negative values, we

apply the softmax operation  $\sigma(\beta)$  to avoid unbound optimization.

$$L_{AUX} = \frac{1}{2} [\sigma(\beta)]^2 \odot W_D \quad (5)$$

In Equation 5, the topic probabilities are penalized by their negative weighted coherence score with the top- $n$  words. The square operation ensures that words with very high probability are penalized to avoid the global minima, we justify this decision based on its partial derivatives in the next subsection.

The final objective function is the multitask loss consisting of the ELBO and our defined auxiliary loss:

$$L = L_{ELBO} + \lambda_a L_{AUX} \quad (6)$$

During training, we employ a linear warm-up schedule to increase  $\lambda_a$  gradually, so the model can learn to reconstruct the BoW representation based on the topic distribution  $\alpha$  before optimizing for coherence and diversity.

### 3.4 Derivatives

We justify our auxiliary loss defined in Equation 5 using the derivatives w.r.t. the  $\beta$  parameters. For simplicity, we define  $p_{k,i} = \sigma(\beta_k)_i$  as the softmax probability for word  $i$  in topic  $k$ . Since we detach the gradients when computing  $W$ , it can be treated as a constant  $w$  in the derivatives.

$$\begin{aligned} \frac{\partial L_{AUX}}{\partial \beta_{k,i}} &= w \cdot p_{k,i} \cdot p_{k,i} (1 - p_{k,i}) + \\ &w \cdot \sum_{j \neq i} p_{k,j} (-p_{k,j} p_{k,i}) \end{aligned} \quad (7)$$

In Equation 7, the partial derivatives w.r.t.  $\beta_{k,i}$  can be broken down into two terms. In the first term, the softmax derivative  $p_{k,i}(1 - p_{k,i})$  is zero when  $p_{k,i}$  is either 0 or 1 (really small or really large). The additional  $p_{k,i}$  (from the square operation) penalizes over-confident logits and leads to better topics. Similarly for the second term, since  $\sum_i p_{k,i} = 1$ ,  $\sum_{j \neq i} (p_{k,j} p_{k,i})$  is zero (global minima) when one logit dominates the others. Therefore, the additional  $p_{k,j}$  has the same penalizing effect on the over-confident logits.

## 4 Experiments

In this section, we describe the experimental settings and present the quantitative results to assess the benefits of our proposed loss.

Dataset	20NewsGroup				Wiki20K				GoogleNews			
Metrics	NPMI	WE	I-RBO	TU	NPMI	WE	I-RBO	TU	NPMI	WE	I-RBO	TU
LDA	.0426	.1624	<b>.9880</b>	<b>.8077</b>	-.0470	.1329	.9934	<b>.8664</b>	-.2030	.0989	.9973	<b>.9065</b>
ProdLDA	.0730	.1626	.9923	.7739	.1712	.1883	<b>.9948</b>	.7674	.0919	.1240	.9974	.8460
CombinedTM	.0855	.1643	.9922	.7705	.1764	.1893	.9941	.7509	.1062	.1316	.9943	.7498
ZeroshotTM	.1008	.1749	.9910	.7214	.1783	.1896	.9916	.6999	.1218	.1321	.9967	.8200
ProdLDA + $W_C$	.1233	.1775	.9916	.7526	.2386	.2094	.9905	.6933	.1236	.1262	.9973	.8400
CombinedTM + $W_C$	.1301	.1781	.9910	.7477	.2392	.2113	.9890	.6748	.1378	.1339	.9938	.7421
ZeroshotTM + $W_C$	.1456	.1882	.9895	.6975	.2455	.2147	.9862	.6350	.1562	.1349	.9964	.8131
ProdLDA + $W_D$	.1235	.1786	.9940	.7901	.2367	.2101	.9929	.7556	.1275	.1274	<b>.9975</b>	.8504
CombinedTM + $W_D$	.1309	.1790	.9935	.7833	.2404	.2137	.9918	.7366	.1429	.1354	.9942	.7541
ZeroshotTM + $W_D$	<b>.1482</b>	<b>.1899</b>	.9919	.7343	<b>.2460</b>	<b>.2156</b>	.9890	.6904	<b>.1569</b>	<b>.1350</b>	.9967	.8228

Table 1: Average results over 5 number of topics ( $K = 25, 50, 75, 100, 150$ ), where the results for each  $K$  are averaged over 10 random seeds. The results are reported for  $\lambda_d = 0.7$ , a mid-range value in the  $[0.5, 1]$  interval.

#### 4.1 Datasets and Evaluation Metrics

To test the generality of our approach, we train and evaluate our models on three publicly available datasets: 20NewsGroups, Wiki20K (Bianchi et al., 2021b), and GoogleNews (Qiang et al., 2022). We provide the statistics of the three datasets in Table 2<sup>3</sup>.

Dataset	Domain	Docs	Vocabulary
20Newsgroups	Email	18,173	2,000
Wiki20K	Article	20,000	2,000
Google News	News	11,108	8,110

Table 2: Statistics of the three datasets used in our experiments.

We use automatic evaluation metrics to measure the topic coherence and diversity of the models. For coherence, we use the NPMI and Word Embedding (WE) (Fang et al., 2016) metrics, which measure the pairwise NPMI score and word embedding similarity, respectively, between the top-10 words of each topic. For diversity, we use Topic Uniqueness (TU) (Dieng et al., 2020), which measures the proportion of unique topic words, and Inversed Rank-Biased Overlap (I-RBO) (Terragni et al., 2021; Bianchi et al., 2021a), measuring the rank-aware difference between all combinations of topic pairs.

#### 4.2 Baselines

We plug our proposed auxiliary loss to three baseline NTMs’ training process to demonstrate the benefits of our approach across different settings. Specifically, the three models are (1) ProdLDA

<sup>3</sup>Detailed description of the three datasets is provided in Appendix C.

(Srivastava and Sutton, 2017), (2) CombinedTM (Bianchi et al., 2021a), and (3) ZeroshotTM (Bianchi et al., 2021b). For comparison, we also include the results of the standard LDA algorithm (Blei et al., 2003).

#### 4.3 Hyperparameter Settings

We follow the training settings reported by Bianchi et al. (2021a), with 100 epochs and a batch size of 100. The models are optimized using the ADAM optimizer (Kingma and Ba, 2015) with the momentum set to 0.99 and a fixed learning rate of 0.002. We do not modify the architecture of the models, where the inference network is composed of a single hidden layer and 100 dimensions of softplus activation units (Zheng et al., 2015). The priors over the topic and document distributions are learnable parameters. A 20% Dropout (Srivastava et al., 2014) is applied to the document representations. During our evaluation, we follow the same setup and used the top-10 words of each topic for the coherence and diversity metrics.

For the hyperparameters introduced in the diversity-aware coherence loss, both  $M_c$  and  $M_d$  are computed using the top-20 words of each topic. The scaling factor  $\lambda_a$  is linearly increased for the first 50 epochs and kept constant for the last 50 epochs, we set  $\lambda_a$  to be **100** in order to balance the loss magnitude of  $L_{ELBO}$  and  $L_{AUX}$ . The  $\lambda_d$  in the diversity loss is set by taking a mid-range value of **0.7** in the  $[0.5, 1]$  range. We do not perform any searches over our defined hyperparameters; we believe that additional experiments will yield better results (i.e., by using a validation set).

#### 4.4 Results

Table 1 shows improvements across all settings. However, with the basic coherence loss ( $W_C$ ), the

significant coherence increase comes at the expense of topic diversity, where a slight decrease can be observed in the I-RBO and TU scores. In contrast, with the diversity-aware coherence loss ( $W_D$ ), we observe that the model improves in coherence while having a significantly higher diversity over the basic loss ( $W_C$ ). The further coherence improvements can be attributed to the regularization effects, where words with a high probability of belonging to another topic are less likely to be related to words in the current topic. Lastly, it is worth noting that due to the gradual increase in  $\lambda_d$ , our proposed loss has a negligible effect on the original document-topic distribution  $\theta$ , and only modifies the word distribution within the established topics. We provide some sample model outputs in [Appendix D](#).

#### 4.5 Coherence and Diversity Trade-off

To study the effects of  $\lambda_d$  on the trade-off between coherence and diversity, we perform experiments with different values of  $\lambda_d$  with the ZeroshotTM baseline, which has the best overall performance. Note that when  $\lambda_d = 0.5$ , the objective is equivalent to the basic coherence loss. From results on the 20NewsGroups Dataset ([Table 3](#)), we see that coherence peaks at  $\lambda_d = 0.7$  before the diversity penalty begins to dominate the loss. Further, while a higher value of  $\lambda_d$  leads to a lower coherency score, both coherency and diversity are still improved over the baselines for all values of  $\lambda_d$ , demonstrating the effectiveness of our method without the need for extensive hyperparameter tuning. We observe an identical trend in other datasets.

	NPMI	WE	I-RBO	TU
ZeroshotTM	.1008	.1749	.9910	.7214
$\lambda_d = 0.5$	.1456	.1882	.9895	.6975
$\lambda_d = 0.6$	.1428	.1875	.9908	.7198
$\lambda_d = 0.7$	<b>.1482</b>	<b>.1899</b>	.9919	.7343
$\lambda_d = 0.8$	.1443	.1890	.9925	.7499
$\lambda_d = 0.9$	.1369	.1867	.9933	.7724
$\lambda_d = 1.0$	.1193	.1816	<b>.9951</b>	<b>.8086</b>

Table 3: Results on the 20NewsGroups dataset for different values of  $\lambda_d$  with ZeroshotTM.

#### 4.6 Comparison with Composite Activation

The recent work by [Lim and Lauw \(2022\)](#) proposed a model-free technique to refine topics based on the parameters of the trained model. Specifically, they solve an optimization problem (with the NPMI score as the objective) using a pool of candidates while setting the diversity score as a constraint.

Since their goal is similar to ours, we run further evaluations to compare the respective approaches. In particular, we experiment with ZeroshotTM on the 20NewsGroups dataset for  $K = 25, 50$ . For comparison, we use their Multi-Dimensional Knapsack Problem (MDKP) formulation, since it achieved the best overall performance. Regrettably, considering larger topic numbers was not possible due to the NP-hard runtime complexity of MDKP. From the results in [Table 4](#), we see that while our methods have similar coherence scores, MDKP archives higher topic diversity due to its selectivity of less-redundant topics. However, when combining MDKP with our proposed loss ( $+ W_D + \text{MDKP}$ ), we achieve the highest overall performance across all metrics. This is expected since the pool of potential topic candidates is generated based on the trained model, and better-performing models lead to superior candidates.

$K = 25$	NPMI	WE	I-RBO	TU
ZeroshotTM	.1059	.1791	.9927	.9152
+ MDKP	.1481	.1895	<b>.9991</b>	.9804
+ $W_D$	.1433	.1921	.9981	.9688
+ $W_D + \text{MDKP}$	<b>.1657</b>	<b>.2043</b>	.9989	<b>.9808</b>
$K = 50$	NPMI	WE	I-RBO	TU
ZeroshotTM	.1109	.1746	.9937	.8498
+ MDKP	.1578	.1903	.9983	.9452
+ $W_D$	.1581	.1921	.9963	.8840
+ $W_D + \text{MDKP}$	<b>.1783</b>	<b>.1932</b>	<b>.9985</b>	<b>.9500</b>

Table 4: Results for comparing our approach with Composite Activation on the 20NewsGroups dataset.

## 5 Conclusion and Future Work

In this work, we present a novel diversity-aware coherence loss to simultaneously improve the coherence and diversity of neural topic models. In contrast to previous methods, our approach directly integrates corpus-level coherence scores into the training of Neural Topic Models. The extensive experiments show that our proposal significantly improves the performance across all settings without requiring any pretraining or additional parameters.

For future work, we plan to perform extensive user studies to examine the extent to which improvements in quantitative metrics affect human preference. Further, we would like to extend our approach to other quantitative metrics (e.g., semantic similarity), and perform extrinsic evaluation to study the effects of our approach when the topics are used for downstream tasks (e.g., summarization, dialogue modeling, text generation).

## Limitations

We address several limitations with regard to our work. First, the publicly available datasets used in our experiments are limited to English. Documents in different languages (i.e., Chinese) might require different segmentation techniques and may contain unique characteristics in terms of vocabulary size, data sparsity, and ambiguity. Secondly, we only evaluate the quality of the topic models in terms of coherence and diversity. Future work should explore how our method impacts other characteristics, such as document coverage (i.e., how well documents match their assigned topics) and topic model comprehensiveness (i.e., how thoroughly the model covers the topics appearing in the corpus).

## Ethics Statement

The datasets used in this work are publicly available and selected from recent literature. There could exist biased views in their content, and should be viewed with discretion.

Our proposed method can be applied to extract topics from a large collection of documents. Researchers wishing to apply our method should ensure that the input corpora are adequately collected and do not violate any copyright infringements.

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## A LDA Generative Process

The formal generative process of a corpus under the LDA assumption can be described by the following algorithm.

---

**Algorithm 1** Generative process of LDA

---

```
for each document  $w$  do
  Sample topic distribution  $\theta \sim \text{Dirichlet}(\alpha)$ 
  for each word  $w_i$  do
    Sample topic  $z_i \sim \text{Multinomial}(\theta)$ 
    Sample word  $w_i \sim \text{Multinomial}(\beta_{z_i})$ 
  end for
end for
```

---

## B Normalized Pointwise Mutual Information

Normalized Pointwise Mutual Information (NPMI) (Lau et al., 2014) measures how much more likely the most representative terms of a topic co-occur than if they were independent. The method for computing the NPMI score between word  $w_i$  and  $w_j$  is described in Equation 8, where  $P(w_i, w_j)$  is computed using a window size of 10. This metric ranges from  $-1$  to  $1$ .

$$\text{NPMI}(w_i, w_j) = \frac{\log \frac{P(w_i, w_j)}{P(w_i)P(w_j)}}{-\log P(w_i, w_j)} \quad (8)$$

In practice, the pairwise NPMI matrix is computed by first counting the word co-occurrence of all words in the corpus and then calculating the pairwise score following Equation 8. In summary, the NPMI matrix can be computed in  $\mathcal{O}(|W| + |V|^2)$  for a corpus of  $|W|$  words and vocab size  $|V|$ . Since the matrix is computed only once for each corpus prior to training, it does not increase the runtime complexity of training time.

## C Datasets

This section provides details regarding the datasets we used. The 20NewsGroup<sup>4</sup> dataset is a collection of email documents partitioned evenly across 20 categories (e.g., electronics, space), we use the same filtered subset provided by Bianchi et al. (2021a). The Wiki20K dataset<sup>5</sup> contains randomly sampled subsets from the English Wikipedia abstracts from DBpedia<sup>6</sup>. GoogleNews<sup>7</sup> (Qiang et al., 2022) is downloaded from the Google news site by crawling the titles and snippets. We do not perform any additional pre-processing and directly use the data provided by the sources to create contextualized and BoW representation.

## D Sample Output

Table 5 provides a qualitative comparison of the topics generated by our proposed method using ZeroshotTM on the 20NewsGroups dataset.

## E Implementation Details

We base our implementation using the code provided by the authors of ZeroshotTM and CombinedTM (Bianchi et al., 2021a,b). Their repository<sup>8</sup> also provides the evaluation metrics used in our experiments. Our Python code base includes external open-source libraries including NumPy<sup>9</sup>, SciPy<sup>10</sup>, PyTorch<sup>11</sup>, SentenceTransformers<sup>12</sup>, Pandas<sup>13</sup>, Gensim<sup>14</sup> and scikit-learn<sup>15</sup>.

## F Computing Details

All our experiments are run on Linux machines with single 1080Ti GPU (CUDA version 11.4). Each epoch with 100 batch size on the most computationally intensive setting (GoogleNews with  $K = 150$ ) takes on average 3 seconds to run for the baselines models and 8 and 15 seconds, for  $W_C$  and  $W_D$ , respectively. Under this setting, a maximum VRAM usage of 800MB was recorded.

<sup>4</sup><http://qwone.com/~jason/20Newsgroups>

<sup>5</sup><https://github.com/vinid/data>

<sup>6</sup><https://wiki.dbpedia.org/downloads-2016-10>

<sup>7</sup><https://github.com/qiang2100/STTM/tree/master/dataset>

<sup>8</sup><https://github.com/MilaNLProc/contextualized-topic-models>

<sup>9</sup><https://numpy.org/>

<sup>10</sup><https://scipy.org/>

<sup>11</sup><https://pytorch.org/>

<sup>12</sup><https://www.sbert.net/>

<sup>13</sup><https://pandas.pydata.org/>

<sup>14</sup><https://radimrehurek.com/gensim/>

<sup>15</sup><https://scikit-learn.org/stable/>

Table 5: Sample model output  $K = 25$  by running ZeroshotTM ( $Z$ ) with our proposed method ( $+W_C$  and  $+W_D$ ) on the 20NewsGroups dataset. We visualize the top-10 keywords of each topic with unique keywords in **bold**.

Model	Top-10 Topic Keywords
$Z$	newsletter, aids, hiv, medical, cancer, disease, page, health, volume, patients
$Z + W_C$	newsletter, aids, hiv, medical, cancer, disease, page, health, volume, patients
$Z + W_D$	newsletter, hiv, aids, medical, cancer, disease, health, page, volume, patients
$Z$	mary, sin, god, heaven, lord, christ, jesus, grace, spirit, <b>matthew</b>
$Z + W_C$	mary, sin, heaven, god, christ, lord, jesus, spirit, grace, <b>matthew</b>
$Z + W_D$	mary, heaven, sin, christ, god, spirit, lord, jesus, <b>holy</b> , grace
$Z$	engine, car, bike, cars, oil, ride, road, dealer, <b>miles</b> , riding
$Z + W_C$	engine, bike, car, cars, oil, ride, dealer, road, riding, <b>driving</b>
$Z + W_D$	engine, bike, car, cars, oil, ride, dealer, riding, road, <b>driving</b>
$Z$	game, baseball, ball, season, fans, team, year, playing, players, <b>winning</b>
$Z + W_C$	game, baseball, fans, ball, season, team, playing, <b>teams</b> , players, year
$Z + W_D$	baseball, game, fans, season, <b>teams</b> , ball, team, playing, players, year
$Z$	fbi, koresh, batf, trial, compound, gas, investigation, <b>media</b> , branch, agents
$Z + W_C$	fbi, batf, koresh, compound, gas, agents, trial, branch, investigation, <b>waco</b>
$Z + W_D$	fbi, koresh, batf, compound, gas, agents, trial, branch, <b>waco</b> , investigation
$Z$	entry, rules, entries, email, build, info, file, char, program, section
$Z + W_C$	entry, rules, entries, email, info, build, file, char, section, program
$Z + W_D$	entry, rules, entries, email, build, info, file, char, program, section
$Z$	army, turkey, muslim, jews, greek, jewish, genocide, <b>professor</b> , ottoman, greece
$Z + W_C$	army, muslim, turkey, ottoman, jews, greek, genocide, jewish, greece, <b>muslims</b>
$Z + W_D$	muslim, turkey, ottoman, genocide, army, jews, greek, jewish, greece, <b>muslims</b>
$Z$	board, driver, video, cards, card, monitor, windows, drivers, screen, <b>resolution</b>
$Z + W_C$	board, video, driver, cards, monitor, card, windows, drivers, screen, <b>printer</b>
$Z + W_D$	video, board, driver, cards, monitor, card, drivers, <b>printer</b> , screen, windows
$Z$	frequently, previously, suggested, <b>announced</b> , <b>foundation</b> , <b>spent</b> , <b>contain</b> , <b>grant</b> , <b>consistent</b> , authors
$Z + W_C$	<b>basically</b> , frequently, frequently, <b>generally</b> , suggested, <b>primary</b> , authors, <b>appropriate</b> , <b>kinds</b> , <b>greater</b>
$Z + W_D$	<b>essentially</b> , <b>basically</b> , <b>kinds</b> , <b>consistent</b> , frequently, authors, previously, <b>primary</b> , <b>equivalent</b> , suggested
$Z$	sale, condition, offer, asking, offers, shipping, items, price, <b>email</b> , sell
$Z + W_C$	sale, condition, offer, shipping, asking, items, offers, sell, <b>email</b> , price
$Z + W_D$	sale, condition, shipping, offer, asking, items, offers, sell, price, <b>excellent</b>
$Z$	application, window, xterm, motif, font, manager, widget, <b>root</b> , event, server
$Z + W_C$	xterm, application, window, motif, font, widget, manager, <b>x11r5</b> , server, event
$Z + W_D$	xterm, motif, font, application, window, widget, manager, <b>x11r5</b> , event, server
$Z$	gun, amendment, constitution, firearms, right, militia, guns, weapon, bear, weapons
$Z + W_C$	amendment, constitution, firearms, gun, militia, right, guns, weapon, bear, weapons
$Z + W_D$	amendment, firearms, constitution, gun, militia, guns, right, weapon, bear, weapons
$Z$	<b>suggested</b> , <b>frequently</b> , previously, <b>authors</b> , <b>foundation</b> , <b>consistent</b> , <b>spent</b> , <b>join</b> , <b>et</b> , <b>announced</b>
$Z + W_C$	<b>suggested</b> , previously, <b>frequently</b> , <b>greater</b> , <b>requirements</b> , <b>consistent</b> , <b>opportunity</b> , <b>authors</b> , <b>particularly</b> , <b>appropriate</b>
$Z + W_D$	<b>spent</b> , <b>greater</b> , <b>association</b> , <b>appropriate</b> , <b>opportunity</b> , <b>requirements</b> , <b>posts</b> , previously, <b>success</b> , <b>training</b>
$Z$	objective, atheist, atheism, morality, exists, belief, does, exist, atheists, existence
$Z + W_C$	objective, atheist, atheism, morality, exists, belief, atheists, does, exist, existence
$Z + W_D$	atheist, objective, atheism, belief, morality, exists, atheists, existence, exist, does
$Z$	think, president, people, Stephanopoulos, dont, jobs, just, know, mr, myers
$Z + W_C$	think, president, Stephanopoulos, people, dont, jobs, just, know mr, myers
$Z + W_D$	think, president, Stephanopoulos, people, dont, jobs, just, know, mr, myers
$Z$	board, drive, ide, scsi, bus, isa, mhz, motherboard, <b>internal</b> , <b>pin</b>
$Z + W_C$	board, drive, ide, scsi, motherboard, bus, isa, mhz, <b>hd</b> , <b>controller</b>
$Z + W_D$	board, drive, ide, motherboard, scsi, mhz, bus, <b>hd</b> , isa, <b>controller</b>
$Z$	jpeg, images, image, formats, gif, format, software, conversion, quality, color
$Z + W_C$	jpeg, images, formats, image, gif, format, conversion, software, quality, color
$Z + W_D$	jpeg, images, formats, gif, image, format, conversion, software, quality, color
$Z$	msg, food, doctor, vitamin, doctors, medicine, diet, <b>insurance</b> , treatment, studies
$Z + W_C$	msg, food, doctor, medicine, doctors, vitamin, diet, studies, <b>insurance</b>
$Z + W_D$	msg, food, doctor, medicine, doctors, vitamin, diet, studies, <b>patients</b> , treatment
$Z$	agencies, encryption, keys, secure, algorithm, <b>chip</b> , enforcement, nsa, <b>clipper</b> , <b>secret</b>
$Z + W_C$	agencies, encryption, secure, keys, algorithm, nsa, enforcement, <b>encrypted</b> , <b>escrow</b> , <b>chip</b>
$Z + W_D$	secure, encryption, keys, agencies, algorithm, <b>escrow</b> , <b>encrypted</b> , enforcement, nsa, <b>clipper</b>
$Z$	windows, dos, nt, network, card, disk, pc, software, modem, operating
$Z + W_C$	windows, dos, nt, card, network, disk, pc, modem, software, operating
$Z + W_D$	windows, dos, nt, card, network, disk, pc, modem, software, operating
$Z$	address, site, thanks, looking, newsgroup, appreciate, advance, mailing, <b>obtain</b> , <b>domain</b>
$Z + W_C$	address, thanks, newsgroup, site, appreciate, advance, looking, mailing, <b>thank</b> , <b>reply</b>
$Z + W_D$	address, appreciate, site, thanks, advance, newsgroup, looking, mailing, <b>thank</b> , <b>obtain</b>

Model	Top-10 Topic Keywords
Z	launch, nasa, shuttle, mission, satellite, energy, mass, moon, orbit, lunar
Z + $W_C$	launch, shuttle, nasa, mission, moon, satellite, orbit, energy, mass, lunar
Z + $W_D$	shuttle, launch, nasa, mission, orbit, moon, satellite, lunar, mass, energy
Z	floor, door, said, people, azerbaijani, neighbors, apartment, like, saw, <b>dont</b>
Z + $W_C$	floor, azerbaijani, door, said, people, apartment, neighbors, like, saw, <b>dont</b>
Z + $W_D$	azerbaijani, floor, apartment, door, said, people, neighbors, saw, like, <b>building</b>
Z	join, <b>grant, foundation, suggested, previously</b> , discussions, <b>frequently, authors, positions, announced</b>
Z + $W_C$	discussions, <b>topic, suggested</b> , join, <b>mailing, responses, robert, lists, summary, received</b>
Z + $W_D$	join, discussions, <b>foundation, robert, mailing, lists, topic, grant, received, responses</b>
Z	pts, boston, van, pittsburgh, pp, san, <b>vancouver</b> , chicago, <b>la, st</b>
Z + $W_C$	pts, boston, van, pittsburgh, pp, san, <b>vancouver</b> , chicago, <b>buf, tor</b>
Z + $W_D$	pts, pittsburgh, van, boston, pp, chicago, <b>buf, tor</b> , san, <b>det</b>