Keyword Assisted Embedded Topic Model

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ABSTRACT

By illuminating latent structures in a corpus of text, topic models are an essential tool for categorizing, summarizing, and exploring large collections of documents. Probabilistic topic models, such as latent Dirichlet allocation (LDA), describe how words in documents are generated via a set of latent distributions called topics. Recently, the Embedded Topic Model (ETM) has extended LDA to utilize the semantic information in word embeddings to derive semantically richer topics. As LDA and its extensions are unsupervised models, they aren’t defined to make efficient use of a user’s prior knowledge of the domain. To this end, we propose the Keyword Assisted Embedded Topic Model (KeyETM), which equips ETM with the ability to incorporate user knowledge in the form of informative topic-level priors over the vocabulary. Using both quantitative metrics and human responses on a topic intrusion task, we demonstrate that KeyETM produces better topics than other guided, generative models in the literature.

KEYWORDS

Topic models, Guided Topic Modeling, Embedded Topic Modeling, prior knowledge, Clustering, Human-in-the-Loop and Collaborative

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1 INTRODUCTION

Topic models illuminate latent semantic themes within a large collection of documents. These approaches have gained mass appreciation, with applications spanning from industry to computer science research [4], as well as into the humanities [20]. Despite their efficiency in exploring major themes of a corpus, topic models usually tend to retrieve the most general and prominent topics in the corpus, which may not necessarily align with the topics a user is interested in, and may occlude important nuance in a dataset.

Table 1: LDA retrieved topics on part of AYLIEN COVID-19. The retrieved topics have overlapped semantically.

| Topic 1 | Topic 2 | Topic 3 | Topic 4 |
|---------|---------|---------|---------|
| president | coronavirus | death | democrat |
| trump | country | covid | campaign |
| vote | state | coronavirus | black |
| | | state | elect |

As a result, fully automated topic models (either classical or neural) are susceptible to create multiple topics with similar semantic themes that are difficult to interpret. To understand the issues better, consider retrieved topics from subset of AYLIEN COVID-19 dataset via LDA in Table 1. This real-world example lays bare this important shortcoming of topic models. As is shown here, it is hard to interpret topics 1 and 4 due to coherence issues (e.g., topic 1 might related to the election or Covid). Furthermore, the topics are not diverse (e.g., topics 2 and 3 mostly refer to the same subject).

It is not surprising that automated topic models suffer from these setbacks, as they are not exposed to information regarding the topics of interest. In these cases, experts need to wait until the model is fit and then make post-hoc decisions about substantive topics of interest [8]. Even then, topics pertaining to niche concepts are often missing.

One way to tackle the issue is to incorporate user knowledge in deriving topics by leveraging informative topic-level priors over the vocabulary. Building off the success of ETM which blends the strengths of neural topic models and word embeddings, we propose Keyword Assisted Embedded Topic Model (KeyETM), an embedded topic model guided by a user’s knowledge of the corpus. The user supplies the model with a set of seed word lists associated with topics of interest, effectively placing informative topic-level priors over the vocabulary to guide statistical inference. We demonstrate the power of this approach by comparing our model to other guided topic models on the basis of quantitative measures and human responses on an intrusion task [5]. Our contributions are as follows:

(1) Propose KeyETM, a new algorithm which equips the powerful ETM topic modeling algorithm with keyword priors.

(2) Extensively test KeyETM against several state-of-the-art baselines and show how it outperforms in terms of quantitative and qualitative topic measures.

2 RELATED WORK

Traditional topic models have been studied extensively. The widely-used latent Dirichlet allocation (LDA) model specifies how words
Figure 1: KeyETM Schematic: middle blue boxes represent flow of computational processing in the ETM. Remainder of figure (yellow and pink boxes), demonstrates how the model is guided by seed words. KeyETM uses document-topic distribution $\theta$ and word-topic distribution $\beta$ to estimate the marginal likelihood of a document. While $\beta$ is calculated using model parameters $\rho$ and $\alpha$ (the bottom blue boxes), $\theta$ is inferred from the variational parameters (the top blue boxes). The prior matrix (the pink box) then is defined to control these two sets of parameters independently.

are generated in documents given latent variables, or topics [3]. However, LDA suffers from limitations such as struggling to produce semantically coherent topics when fit to a large, heavy-tailed vocabulary [7]. LDA is also computationally inefficient as it relies on Gibbs Sampling to estimate posterior densities [21]. To overcome these issues, recent models, such as neural topic models have been suggested which employ autoencoding variational inference (e.g., Autoencoded Variational Inference For Topic Model (AVITM) [21] or Embedded Topic Model (ETM) [7]).

Prior knowledge of a corpus can guide models to produce better topics [6]. A variety of guided topic models have been proposed which turn LDA into a supervised model, such as Supervised LDA [2], DiscLDA [12], and Labeled LDA [19]. A critical shortcoming of these models is that they require massive collections of annotated documents to be effective. An alternative approach for guiding topic models is to supply them with topic-specific sets of seed words, operating as informative topic-level priors over the vocabulary. Popular models leveraging this form of weak supervision are Guided LDA [11] and KeyATM [8]).

A similar thread of research is aspect discovery, which requires initial seed words relating to aspects of the corpus, and oftentimes can be jointly applied for sentiment analysis [1, 9, 10]. With the development of word embeddings [16, 18], several studies have been conducted to extend topic modeling to incorporate word embeddings in deriving topics. CatE [14] is among these models which employs user knowledge to build a discriminative embedding space to derive topics. However, strict discrimination assumptions make them fragile when applied to a corpus with a dominating topic. Embedded Topic Model (ETM)[7] employs variational autoencoders to learn topic posteriors and benefits from word embeddings, however, it does not incorporate user’s prior knowledge in deriving topics.

3 KEYWORD ASSISTED EMBEDDED TOPIC MODEL

We are given a corpus of $D$ documents $\{W_1, W_2, ..., W_D\}$, such that $W_d$ is a collection of $N_d$ words belonging to our vocabulary $V$. Suppose that we have a total of $K$ topics and for each topic $k$, a user provides a set of $L_k$ seed words: $\omega_k = \{s_{k1}, s_{k2}, ..., s_{kL_k}\}$. The remainder of this section details how to fit an ETM using these keyword sets.

3.1 Embedded Topic Model

The ETM is a topic model that employs embedding representations of both words and topics. Therefore, the model contains two notions of latent dimensions: a word embedding matrix, $\rho \in \mathbb{R}^{V \times L}$, that embeds the vocabulary $V$ in an $L$-dimensional space (similar to the idea of classical word embeddings), and a topic embedding matrix, $\alpha \in \mathbb{R}^{K \times L}$, that each topic $\alpha_k$ (each row of the matrix) is a distributed representation of the $k^{th}$ topic in the semantic space of words. This is unlike the idea of classical topic modeling approaches such as LDA where each topic is a full distribution over the vocabulary.

The generative process of the $d^{th}$ document within a corpus $D$ under the ETM assumption is then defined as the following:

1. Draw topic proportions: $\theta_d \sim \mathcal{LN}(0, I)$, where $\mathcal{LN}(\cdot)$ denotes a logistic-normal distribution that transforms a standard Gaussian random variable: $\delta_d \sim \mathcal{N}(0, I)$ to the simplex: $\theta_d = \text{softmax}(\delta_d)$. Consequently, $\delta_d$ and $\theta_d$ are called untransformed and transformed topic proportions respectively.
Figure 2: An example of how the square loss terms work in Equations 9 and 10. The prior in the middle is defined based on seed word sets, then in each iteration, the algorithm will try to decrease the Euclidean distance between this prior and $\gamma^\alpha$ (topic-word distribution), and also $\gamma^\mu$ (topic-word distribution for documents). As a result of these changes, not only the injected words, but also the similar words to them will gradually converge to the true topics.

(2) For each word $n$ in the $d^{th}$ document, draw topic assignment $z_{dn}$ ~ $\text{Cat}(\theta_d)$, then draw the word $w_{dn}$ ~ $\text{softmax}(\rho^T \alpha z_{dn})$, where $\rho$ is the word embedding matrix and $\alpha z_{dn}$ is the $z_{dn}$’s topic embeddings. The $\text{Cat}(\cdot)$ also denotes the categorical distribution.

The inference process in ETM is the estimation of its two sets of model parameters: word embeddings $\rho$ and topic embeddings $\alpha$. To achieve the goal, the marginal likelihood of documents is maximized:

$$L(\alpha, \rho) = \sum_{d=1}^{D} \log p(W_d | \alpha, \rho).$$  \hspace{1cm} (1)

Under ETM’s generative model, the marginal likelihood of a document $W_d$, after marginalizing out each word topic assignment $z_{dn}$, is equal to:

$$p(W_d | \rho, \alpha) = \int p(\delta_d) \prod_{d=1}^{N_d} p(w_{dn} | \delta_d, \alpha, \rho) d\delta_d,$$  \hspace{1cm} (2)

where the distribution of $w_{dn} | \delta_d, \alpha, \rho$ can be estimated as:

$$p(w_{dn} | \delta_d, \rho, \alpha) = \sum_{k=1}^{K} \theta_{dk} \beta_{k, w_{dn}}.$$  \hspace{1cm} (3)

So one only needs to evaluate the distributions of $\theta$ and $\beta$ to calculate this probability. Similar to LDA, $\theta_{dk}$ in Equation 3 denotes topic proportions for each document, and $\beta_{k, w}$ shows a topic distribution over vocabulary ($V$), but unlike LDA, $\theta$ is calculated based on step 1 in ETM’s generative process and $\beta$, inspired by the continuous bag-of-words (CBOW) [15] model, is induced using: $\text{softmax}(\rho^T \alpha_k)$ (see step 2 in ETM’s generative process).

Finally, Equations 3 and 2 can flesh out the likelihood in Equation 1 and the solution seems to be obtained completely. However, the calculation of marginal likelihood of each document in Equation 2 is hard to compute due to the existence of an intractable integral over the topic proportions. To tackle the issue, ETM uses the evidence lower bound (ELBO) function that includes both the model parameters ($\rho, \alpha$), and the variational parameters ($\nu$):

$$L(\Theta) = \sum_{d=1}^{D} \sum_{n=1}^{N_d} \mathbb{E}_q[\log p(w_{dn} | \delta_d, \alpha, \rho)] - \sum_{d=1}^{D} K_L(q(\delta_d; w_d, \nu) || p(\delta_d)),$$  \hspace{1cm} (4)

where $\Theta$ represents the set of all the model and variational parameters and $q(\cdot)$ is a Gaussian whose mean and variance come from a neural network, parameterized by variational parameters ($NN(x; \nu)$).

As a function of the model parameters, the objective function in Equation 4 tries to maximize the expected complete log-likelihood. As a function of the variational parameters, the first term pushes parameters to place mass on topic proportions, which explains the observed words better, and the second term forces them to be as close as possible to the prior. For more information, see the blue boxes in Figure 1, the top blue boxes show how $\theta$ is obtained and the bottom blue boxes show $\beta$ calculation.
Now we describe how ETM can be modified to utilize a user’s prior knowledge about the corpus to infer desired topics.

3.2 KeyETM Description

KeyETM extends ETM to incorporate user-defined seed words \((ω_k)\) when inferring topics. First, since ETM with pre-fit word embeddings (i.e., labeled ETM) is considered as the base model, \(ρ\) is trained on the given corpus \(D\) using skip-gram embeddings [17] and is considered fixed during KeyETM training. Then, for each topic \(k\), its corresponding semantic vector \(ω_k\) is defined as a mean of all word embedding vectors in \(ω_k\):

\[
ω_k = \frac{\sum_{v \in ω_k} \rho(s_{vk})}{|k|}
\]  

(5)

and based on that, each element of the prior knowledge matrix \(y^\text{prior} \in \mathbb{R}^{V \times K}\) is defined as follows:

\[
y^\text{prior}_{vk} = \begin{cases} 
1, & \text{if } ((v \in ω_k) \land (\cosSim(ρ(v), ω_k) \geq \text{thr})) \\
0, & \text{else}.
\end{cases}
\]  

(6)

In Equation 6, for all words \(v \in V\) and in each topic \(k\), if \(v\) is a member of topic \(k\)’s seed words \((v \in ω_k)\) or \(v\) not in topic \(k\)’s seed words, but its similarity to topic \(k\)’s semantic vector \((ω_k)\) is greater than a threshold, the prior value is set to one. Otherwise, the prior is assigned to zero \((y^\text{prior}\) is shown with the pink box in Figure 1).

Using matrix \(y^\text{prior}\), set \(S\) is defined as a union of all words with at least one value greater than zero in their corresponding rows in \(y^\text{prior}\) matrix:

\[
S = \{v | \exists k, y^\text{prior}_{vk} = 1\}
\]

In other words, \(S\) is a union of all seed words for all topics plus similar words to them.

After the definition of primitive variables, the ETM’s objective function needs to be changed. As mentioned in section 3.1, the ELBO function in Equation 4 is optimized with respect to both the model parameters and variational parameters. Consequently, we need to penalize both sets of parameters to force the model to infer the desired topics.

To penalize variational parameters, inspired by AVIAD model[9], \(y^\mu \in \mathbb{R}^{V \times K}\) is defined as the topic distribution over vocabularies \(V\) corresponding to document \(d\). \(y^\mu\) is shown in the top yellow box in Figure 1. As you see in this box, we have three linear layers: let \(W_1 \in \mathbb{R}^{H_1 \times V}\) and \(b_1 \in \mathbb{R}^{H_1}\) be the parameters in the first layer, \(W_2 \in \mathbb{R}^{H_2 \times H_1}\) and \(b_2 \in \mathbb{R}^{H_2}\) be the parameters in the second layer, and \(W_3 \in \mathbb{R}^{H_3 \times K}\) and \(b_3 \in \mathbb{R}^{K}\) be the parameters for the third one. To estimate \(y^\mu\) for each document, we first calculate the following steps:

\[
M = \text{SoftPlus}(W_1^T + b_1)
\]

\[
N = \text{SoftPlus}(M.W_2^T + b_2)
\]

\[
W_{dr} = \text{dropout}(N, \text{dropout_rate})
\]

\[
W_{mean} = \text{Softmax}(W_{dr}.W_3^T + b_3),
\]

where \(W_{mean} \in \mathbb{R}^{V \times K}\). Then, each element of \(W_{mean}\) is multiplied with scalar value 0 if the word corresponding to that row is not available in document \(d\) and 1 otherwise.

To penalize model parameters, as word embedding \(ρ\) is considered fixed, we need to force topic embedding \(α\) to be as close as possible to the desired topics. Therefore, \(y^\alpha\) is defined as the output of this transformation:

\[
y^\alpha = \text{Softmax}(ρ.α^T),
\]

(8)

which is shown using the bottom yellow box in Figure 1. In fact, \(y^\alpha\) is equal to \(β\) and shows the distribution of topics over words, but we choose another name to make it more consistent.

By using the prior matrix \(y^\text{prior}\), the variational regularization term \(L_μ\) is defined as:

\[
L_μ = \sum_d \sum_{v \in S} \|y^μ_d - y^\text{prior}_v\|^2
\]

(9)

and the model regularization term is defined as:

\[
L_α = \sum_{v \in S} \|y^α_v - y^\text{prior}\|^2
\]

(10)

Both losses are just applied for each word \(v\) that exist in set \(S\). The square loss in Equation 9 will penalize the variational parameters to make the inference neural network produce the distribution \(y^μ\) as similar to the prior distribution \(y^\text{prior}\) as possible, and the square loss in Equation 10 penalizes the topic embedding \(α\) to produce topics near the selected themes.

Finally, the loss function in Equation 4 is modified by adding these two new regularization terms:

\[
\mathcal{L}(θ) = \text{ELBO} - λ_1 L_μ - λ_2 L_α
\]

(11)

To better demonstrate the process, consider the example that is shown in Figure 2. Given the three topics, namely Election, BLM and Covid, we chose three seed words for each topic and showed them in the top middle table. Then, \(y^\text{prior}\) was constructed based on this table, such that each element of the matrix \(y^\text{prior}\) is set to 1 if \(v \in ω_k\) and 0 otherwise (e.g., the word “vote” is received prior 1 for Election topic and 0 for the rest). Moreover, the similar words to topic \(k\)’s semantic vectors \(ω_k\), also receive the prior of 1 for the corresponding topic (e.g., mask for topic Covid).

Assume at the \(k^{th}\) iteration of the training process, the general topic-word distribution \(y^μ\) is in the state that is displayed in the left matrix and \(y^μ\) is the topic distribution for each word corresponding to a document \(d\) that is shown in the right matrix. Then minimizing the Euclidean distance between \(y^μ\) and \(y^\text{prior}\ for v \in S\) (e.g., vote, black, poll, etc.) encourages topic embedding \(α_{1,K}\) gradually generate topics near to the selected themes, and minimizing the Euclidean distance between \(y^μ\) and \(y^\text{prior}\ forces the variational parameters to place mass on topic proportions that explain the injected words and the similar words to them better. As a result of these changes, not only do the seed words receive high topic posterior, but other related words define the topic as well. In effect, shedding light on the broader topics in which the seed words are related to. The complete procedure is shown in Algorithm 1, when \(NN(x; v)\) is used to represent a neural network with input \(x\) and parameters \(v\).

4 EVALUATION OF KEYETM

In this section, we first discuss the role of some hyper-parameters in KeyETM, then the model’s performance will be studied and compared to other guided topic models. In particular, topics coherency
Algorithm 1 KeyETM topic modeling

1. Choose K and define $\omega_{1:K}$
2. Create word2vec embedding from dataset and define $\rho$
3. Define the semantic vector $\omega_{1:L}$, for $\omega_{1:K}$ based on $\rho$
4. Initialize prior matrix $\gamma_{prior}$ using $\omega_{1:K}$ and $\omega_{(1:K)}$
5. Initialize model and variational parameters
6. for iteration $i = 1, 2, \ldots$ do
7. Compute $\beta_k = \text{softmax}(\rho^T z_d)$ for each topic $k$
8. Choose a minibatch $N$ of documents
9. for each document $d$ in $N$ do
10. Get normalized bag-of-word $x_d$
11. Compute $\mu_d = N(x_d, v)$
12. Compute $\Sigma_d = N(x_d, v)$
13. Sample $z_d \sim \mathcal{N}(\mu_d, \Sigma_d)$
14. for each word in the document $d$ do
15. Compute $p(w_{dn}|\theta_d) = \theta_d^T \beta_k w_{dn}$
16. end for
17. end for
18. set $y^a = \beta$
19. Compute $L_y = \sum_d \sum_{w \in S} ||y_d^a - y_d^{|prior}||^2$
20. Compute $L_x = \sum_{w \in S} ||y_d^a - y_d^{|prior}||^2$
21. Estimate ELBO ($kl_d$ - reconstruction loss)
22. Estimate the total loss: $L = \text{ELBO} - \lambda_1 L_y - \lambda_2 L_x$
23. Estimate gradient (backprop.)
24. Update model parameters
25. end for

and diversity will be examined by designing quantitative and qualitative experiments, and classification performance will be reported to analyze document representations.

Dataset: We used the AYLIEN COVID-19 dataset\(^3\) which consists of over 1.5M news articles about the Covid-19 pandemic, with articles spanning from November 2019 to July 2020. We then limited the articles to the ones that were published in the Huffington Post, CNN, Breitbart and, Fox News. To ease model fitting, we extracted a subset of 9, 663 posts which had one of the following IPTC Subject Codes\(^4\): medical procedure, disease, election, social issues, unemployment, employment, media, business and economy. This selection criteria resulted in a corpus with imbalanced topic representation. For instance, there are nearly 3, 200 articles discussing disease and 457 about racism. Also as the name of the dataset suggests, Covid is a dominant theme, which implies, in addition to documents that talk about Covid directly (e.g., disease), other documents may also relate to an aspect of Covid (e.g., election or employment). This imbalance captures the ecological conditions in which practitioners often apply topic models, and we believe provides a verdant assessment of how the evaluated models will fair in the field.

To have a more balanced dataset, without a dominant theme, the 20Newsgroups corpus was also used which is a collection of news-group posts. We extracted a subset of 6, 000 articles from religion, politics and science subjects. Both datasets were preprocessed by filtering stop words, and words with document frequency above

\(^3\)https://aylien.com/blog/free-coronavirus-news-dataset
\(^4\)https://docs.aylien.com/newapi/search-taxonomies/#search-labels-for-iptc-subject-codes
As it shows in Figure 2, the seed words proportions highlight the imbalanced representation of topics in the AYLIEN COVID-19 (e.g., the rate of terms related to Covid-19 dwarfs the rate of terms about the Black Lives Matter movement), while these proportions seem more balanced for 20Newsgroups and only medical documents are less representative. Guided topic models should be able to effectively recover dwarfed topics given when provided with the proper set of keywords.

4.1 Finding a Balance Point
As it is shown in Section 3, KeyETM uses ELBO function to approximate a posterior over the document representation \( \theta_d \) and the model parameter \( \beta \); while \( \beta \) is calculated using model parameters \((\rho, \alpha, \theta)\) is inferred from the variational ones. Two additional regularization terms \((L_\mu, L_\nu)\) are then applied to the ELBO to control \( \theta \) and \( \beta \) independently (see Equation 11).

One important question that is left to answer is how these additional losses work with respect to each other and how they will effect the final outputs. To address this, in Figure 4, for a fixed value of \( \lambda_1 \) (weight of \( L_\mu \)), that is identified with the different colors in each subplot, we change the value of \( \lambda_2 \) (weight of \( L_\nu \)) to see their effects on F1 score and Topic Quality. Here, F1 is considered as a index of a document representation quality(\( \theta_d \)), and the Topics Quality\(^6\) is used to analyze \( \beta \) (to get more information about Topic Quality see section 4.4).

As you see in Figure 4, while the \( \lambda_2 \) is increased, at some point, the F1 decreases but the Topic Quality increases. The reason is, when we put so much weight on model regularization \( (L_\nu) \), \( \gamma^\nu \) will gradually converge to prior matrix, consequently, a higher quality in topic-word distribution matrix \( (\beta) \) is obtained. However, as the weight for variational regularization \( (L_\mu) \) is fixed, the model’s reconstruction loss from ELBO will dominate the changes of the variational parameters (to minimize the distance between input and output), and as a result, the documents representation \( (\theta) \) will shift towards the dominant topics. The more the dataset is unbalanced or having a dominant theme, the more stronger this effect will be emerged.

For instance, in AYLIEN COVID-19 (shown in the left side of Figure 4) with a dominant theme in all documents (Covid) and also an imbalance issue, the F1 scores drop almost 60%, when we change \( \lambda_2 \) from 5 to 20, while the Topic Quality is increased from 0.14 to 0.22. Whereas, in the 20Newsgroups dataset without dominant theme and less unbalancing issue, the F1 drop less than 10% and the topic quality also is changed in the shorter range. The reason of sudden drop in F1 for the AYLIEN dataset is that the documents representations \( \theta \), is converged to the dominant topics (topic 3 and 4), while in 20Newsgroups we just observe less accurate results for the less representative topic (medical).

As a consequence, we need to find a balance point between Topic Quality and document representation (specifically when we are using unbalanced dataset), and adjust these two parameters based on our needs to avoid the model overfitting.

4.2 Baseline Methods
We compared KeyETM to three other key-words guided models (GuidedLDA [11], AVIAD [9], and KeyATM [8]) using identical sets of seed words we listed in Figure 3. Like KeyETM, all these models are generative, making them easy for comparison.

GuidedLDA\(^6\) implements latent Dirichlet allocation (LDA) by placing topic-level priors over vocabulary informed by the seed words. Seed_confidence is the parameter that controls how much extra boost should be given to a word and it can be range between 0 and 1. We set this parameter to 0.6 and number of epochs to 250.

AVIAD [9] extends the Autoencoding Variational Inference for Topic Models (AVITM) approach [21] to embed prior knowledge by rewriting loss function to infer desired topics. It uses a variational autoencoder with the reparameterization trick to simulate the sampling task, while it does not consider word embedding. To train the model, we set learning rate to 0.001, Dirichlet parameter \( \alpha = 1.0 \), \( \lambda = 20.0 \), hidden_size in encoder 1 and 2 to 150 and run the model for 150 epochs.

KeyATM(Base)\(^7\) extends GuidedLDA to use term weights to penalize highly frequent words in the corpus, to avoid dominate the resulting topics, but like GuidedLDA uses collapsed Gibbs sampling to sample from the posterior distribution. The model allows topics to have empty seed words sets, which are called no_keywords topics.

\(^6\)https://guidedlda.readthedocs.io/en/latest/
\(^7\)https://keyatm.github.io/keyATM/
As shown here, GuidedLDA has the worst performance among others specifically in the less dominant topic (BLM). KeyETM, shows impressive performance in topic 1 and topic 4, but it is still unsuccessful in the less dominant topic (BLM). KeyATM shows better performance in topic 1 and topic 4, and the middle one talks about financial issues. Consequently, the model fails to represent the BLM and social issues topic.

4.3 Qualitative Measures

As the AYLIEN dataset is more complicated, to analyze results qualitatively we used this dataset and compared the learned topics by all models. Table 2 displays the top 5 words of 3 topics we defined in Figure 3, respectively. Topic sequence is matched across topic models and semantically irrelevant words are marked with (X). As suggested in [7] the overall metric for measuring qualitative measures to assess topic quality:

\[ TC = \frac{1}{K \binom{m}{2}} \sum_{k=1}^{K} \sum_{i=1}^{m} \sum_{j=i+1}^{m} f(w_i^{(k)}, w_j^{(k)}) \]

where \( P(w_i, w_j) \) is the probability of two words co-occurring in a document and \( P(w_i) \) is the marginal probability of word \( w_i \). Then the topic coherence (TC) is calculated on the top-\( m \) (\( m=10 \) in our experiments) words as:

\[ f(w_i, w_j) = \log \frac{P(w_i, w_j)}{-\log P(w_i) P(w_j)} \]

The intuition behind the TC is that the top words of a topic should co-occur often, therefore the higher coherency, the more interpretable topics are.

4.4 Measures of Topic Quality

A good topic model in general should provide both coherent patterns of language and diversity. In other words, the inferred topics not only should be interpretable, but also include a range of aspects. Therefore, we used the following quantitative and behavioral measures to assess topic quality:

**Coherence:** Coherence is a widely-used measure of topic interpretability based on the point-wise mutual information between words in each document [13]. For any two words drawn randomly from the same document, the normalized point-wise mutual information is defined as:

\[ f(w_i, w_j) = \log \frac{P(w_i, w_j)}{-\log P(w_i) P(w_j)} \]

Table 2: Resulting Topics for Four Guided Topic Models

| Guided LDA | AVIAD |
|------------|-------|
| fraud      | suprem |
| voter      | paid   |
| speak      | contest|
| year       | labor  |
| maintain   | ballot |
| encourag   | payment|
| therapi    | nurs   |
| constitui  | respiratori |
| suspect    | nurs   |
| minneapolis| respect|
| KeyATM Base | KeyETM |
| biden      | campaign |
| worker     | job     |
| coronavirus| coronaviru |
| mask       | trump(x) |
| state      | health  |
| coronavirus| state   |
| peopl      | blanc   |
| order      | white   |
| hous       | black   |
| ETM        |         |
| trump      | state   |
| worker     | peopl   |
| coronaviru | health  |
| mask       | case    |
| campaign   | voter   |
| week       | live    |
| democrat   | job     |
| covid      | black   |

up the learning. Both hidden sizes are set to 800, learning rate to 0.005, and the batch size to 40. For 20Newsgroups dataset based on our discussion in the section 4.1, the \( \lambda_1 = 15 \) and the \( \lambda_2 = 10 \), and for the AYLIEN the \( \lambda_1 = 25 \) and the \( \lambda_2 = 10 \).
were correctly identified. We refer to this probability value as the intrusion score. To ensure reliable measurement, an intrusion was selected from the highly probable words in other topics. As eight workers responded to each hit, we collected a total of 160 intrusion measurements (3 topics \times 4 intruders \times 8 workers) for each model. As the AYLIE dataset is more complicated, we applied the Intrusion task just for this dataset.

The results for both datasets are shown in Table 3 and for all three measures (coherence, diversity, quality). They suggest the KeyETM model produces the most coherent and interpretable topics.

The result of the intrusion task is also showed in Table 3 for the four guided topic models. The probability that an intruder was correctly selected (averaged across participants and topics) captures how semantically interpretable the model was to human raters, with a value of 1 indicating that all subjects correctly identified all the intruders for each topic and a value of 0 indicating no intruders were correctly identified. We refer to this probability value as the intrusion score of the model. For AYLIE dataset, KeyETM received the highest intrusion score, with a value over 6% higher than the second ranking model. These results suggest that KeyETM produced the most semantically interpretable topics as judged by human raters.

### 4.5 Experimental Results for Classification Performance

Although generative topic models such as KeyETM are proposed as an unsupervised model, we can also use them to analyze the document representation \( \theta_d \) and consider its maximum probability as a label. Therefore, the classification performance of all models are evaluated in Table 4 via precision, recall and F1 metrics.

For the AYLIE dataset, as KeyETM has a better performance to capture the less representative topics (e.g., BLM), it has a better performance to represent documents eventually. As a result, it achieves the highest numbers for all metrics. However, for 20News-groups dataset, although KeyATM shows slightly better results compared to our proposed model, but as KeyETM uses VAE instead of sampling, the document representations that are generated by the KeyETM are more robust.

### 5 DISCUSSION AND CONCLUSION

Automated topic models tend to retrieve the most general and prominent topics in the corpus as they are not exposed to information regarding the topics of interest. One way to tackle the issue is to incorporate user knowledge in deriving topics by leveraging informative topic-level priors over the vocabulary. Building off the success of ETM which blends the advantages of neural topic models and word embeddings, in this work we propose Keyword Assisted Embedded Topic Model (KeyETM), an embedded topic model guided by a user’s knowledge of the corpus.

Through quantitative and qualitative results, we demonstrate that KeyETM retrieves reasonably good topics, relevant to category names we selected earlier. Specifically, it has the best performance in revealing less dominant themes. When compared to baselines which utilize sampling methods, the model has acceptable performance in document representation and classification. This is because it benefits from neural topics modeling and word embeddings. KeyETM can arm researchers with a tool for extracting desired semantic themes from noisy corpora.

One avenue of future work is to extend KeyETM to enable it to generate robust guided and unguided topics. One approach may be to set the number of topics (K) to a larger value than the number of seed word lists. However, further analysis is needed to validate this approach.

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### REFERENCES

[1] Stefanos Angelidis and Mirella Lapata. 2018. Summarizing Opinions: Aspect Extraction Meets Sentiment Prediction and They Are Both Weakly Supervised. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Brussels, Belgium, 3675–3686. https://doi.org/10.18653/v1/D18-1403

[2] David M. Blei and Jon D. McAuliffe. 2007. Supervised Topic Models. In Proceedings of the 20th International Conference on Neural Information Processing Systems (Vancouver, British Columbia, Canada) (NIPS’07). Curran Associates Inc., Red Hook, NY, USA, 1211?1218.

[3] David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. The Journal of machine Learning research 3 (2003), 993–1022.

[4] Jordan L Boyd-Graber, Yueming Hu, David Mimno, et al. 2017. Applications of topic models. Vol. 11. now Publishers Incorporated.

[5] Jonathan Chang, Sean Gerrish, Chong Wang, Jordan Boyd-graber, and David Blei. 2009. Reading Tea Leaves: How Humans Interpret Topic Models. In Advances in Neural Information Processing Systems, Y. Bengio, D. Schuurmans, J. Lafferty, C. Williams, and A. Culotta (Eds.), Vol. 22.
[6] Zhiyuan Chen, Arjun Mukherjee, Bing Liu, Mei{-}chun Hsu, Malu Castellanos, and Riddhiman Ghosh. 2013. Leveraging Multi{-}Domain Prior Knowledge in Topic Models. In IJCAI, Vol. 13. Citeseer, 2071–77.

[7] Adji B Dieng, Francisco JR Ruiz, and David M Blei. 2020. Topic modeling in embedding spaces. Transactions of the Association for Computational Linguistics 8 (2020), 439–453.

[8] Shusei Eshima, Kosuke Imai, and Tomoya Sasaki. 2020. Keyword assisted topic models. arXiv preprint arXiv:2004.05964 (2020).

[9] Tai Hoang, Huy Le, and Thi Quan. 2019. Towards autoencoding variational inference for aspect-based opinion summary. Applied Artificial Intelligence 33, 9 (2019), 796–816.

[10] Jiaxin Huang, Yu Meng, Fang Guo, Heng Ji, and Jiawei Han. 2020. Weakly-supervised aspect-based sentiment analysis via joint aspect-sentiment topic embedding. arXiv preprint arXiv:2010.06705 (2020).

[11] Jagadeesh Jagarlamudi, Hal Daumé III, and Raghavendra Udupa. 2012. Incorporating Lexical Priors into Topic Models. In Proceedings of the 13th Conference of the Association for Computational Linguistics. Association for Computational Linguistics, Avignon, France, 204–213. https://www.aclweb.org/anthology/E12-1021

[12] Simon Lacoste{-}Julien, Fei Sha, and Michael I Jordan. 2008. DiscLDA: Discriminative learning for dimensionality reduction and classification. In Advances in neural information processing systems. 897–904.

[13] Jey Han Lau, David Newman, and Timothy Baldwin. 2014. Machine Reading Tea Leaves: Automatically Evaluating Topic Coherence and Topic Model Quality. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, Gothenburg, Sweden, 530–539. https://doi.org/10.3115/v1/E14-1056

[14] Yu Meng, Jiaxin Huang, Guangyuan Wang, Zihan Wang, Chao Zhang, Yu Zhang, and Jiawei Han. 2020. Discriminative Topic Mining via Category-Name Guided Text Embedding. In Proceedings of The Web Conference 2020 (Taipei, Taiwan) (WWW ’20). Association for Computing Machinery, New York, NY, USA, 2121–2132. https://doi.org/10.1145/3366423.3380278

[15] Tomás Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient Estimation of Word Representations in Vector Space. In 1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings, Yoshua Bengio and Yann LeCun (Eds.). http://arxiv.org/abs/1301.3784

[16] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Distributed Representations of Words and Phrases and Their Compositionality. In Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2 (Lake Tahoe, Nevada) (NIPS’13). Curran Associates Inc., Red Hook, NY, USA, 3111–3119.

[17] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Distributed representations of words and phrases and their compositionality. arXiv preprint arXiv:1310.4546 (2013).

[18] Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. GloVe: Global Vectors for Word Representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, Doha, Qatar, 1532–1543. https://doi.org/10.3115/v1/D14-1162

[19] Daniel Ramage, David Hall, Ramesh Nallapati, and Christopher D. Manning. 2009. Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Singapore, 248–256. https://www.aclweb.org/anthology/D09-1026

[20] Benjamin M Schmidt. 2012. Words alone: Dismantling topic models in the humanities. Journal of Digital Humanities 2, 1 (2012), 49–65.

[21] Akash Srivastava and Charles Sutton. 2017. Autoencoding Variational Inference for Topic Models. In 5th International Conference on Learning Representations.