SenGen: Sentence Generating Neural Variational Topic Model

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Abstract

We present a new topic model that generates documents by sampling a topic for one whole sentence at a time, and generating the words in the sentence using an RNN decoder that is conditioned on the topic of the sentence. We argue that this novel formalism will help us not only visualize and model the topical discourse structure in a document better, but also potentially lead to more interpretable topics since we can now illustrate topics by sampling representative sentences instead of bag of words or phrases. We present a variational auto-encoder approach for learning in which we use a factorized variational encoder that independently models the posterior over top-ic mixture vectors of documents using a feed-forward network, and the posterior over topic assignments to sentences using an RNN. Our preliminary experiments on two different datasets indicate early promise, but also expose many challenges that remain to be addressed.

1. Introduction

One of the most popular approaches for fully generative modeling of documents is the Latent Dirichlet Allocation (Blei et al., 2003) model. This model that assumes a discrete mixture distribution over topics for each document that is sampled from a Dirichlet prior shared by all documents. A topic is sampled for each word position in the document from this mixture and then the word itself is generated from another multinomial indexed by the corresponding topic. Although very successful in various tasks, one of the shortcomings of this model is its bag-of-words approach where dependencies between words are not explicitly modeled. Several extensions of LDA have been proposed to relax the bag-of-words assumption and capture longer term relationships between words (Hsu & Glass, 2006; Wang et al., 2007; Du et al., 2012), segments (Eisenstein & Barzilay, 2008), and discourse elements in documents (Lazaridou et al., 2013; Louis & Cohen, 2015).

Recently, Kingma and Welling proposed a Variational Auto-Encoder (VAE) based approach for learning complex generative distributions where the generative model as well as the approximate variational posterior are based on deep neural networks (Kingma & Welling, 2013). This approach has been recently applied to topic modeling of documents by several researchers. One of the first VAE-based approaches for document modeling is called the Neural Variational Document Model (NVDM) (Miao et al., 2015), which reports impressive gains over LDA and other models on perplexity. However the topic mixture vector in this model, h, being a real-valued vector generated from a multivariate Gaussian, is not very interpretable unlike multinomial mixture in the standard LDA model. Motivated by this weakness of NVDM, the authors of (Srivastava & Sutton, 2017) propose the NVLDA model that employs a Logistic Normal distribution to replace the Dirichlet prior and a variational Logistic Normal posterior to bring the h vector into the multinomial space. However, the perplexity values from the new NVLDA model on unseen data are worse than those from the NVDM model. Although both the models mentioned above employ sophisticated VAE approach, they still use the same bag-of-words formalism of LDA in modeling the document. Further, their VAE approach focuses only on modeling the posteriors over the document-level topic mixtures vector, and ignores modeling the posteriors over the local topic assignment to words and sentences.

With the advent of neural networks, RNN-based language models have emerged as de facto choice to capture short and long range dependencies between words (Mikolov et al., 2010) and have been used for language modeling in speech (Chung et al., 2015), and dialogue (Serban et al., 2016). However, these models do not capture the topical structure of the larger document context. A recent work that integrates topic modeling with RNNs is that of (Dieng et al., 2016), where a Gaussian based topic vector, similar to the one used in NVDM, is used to model topic strengths for each document, but an RNN is used to generate words conditioned on the topic vector. The Topic RNN model marginalizes the topic assignments to words, without explicitly modeling their posteriors.
2. **SenGen: Sentence Generating Topic Model**

Similar to the work of (Dieng et al., 2016), we are interested in modeling dependencies between words in a document and also capturing the larger topical context jointly. In addition, we are also interested in capturing the topical discourse structure in a document including notions such as topical drift and topical switch. To capture such phenomena, we argue that sentences are the ideal smallest units for modeling instead of individual words or phrases, since sentences tend to be topically cohesive while topical drift or switch usually occur across sentence or paragraph boundaries. We therefore make topical assignments to whole sentences, unlike traditional topic models that assign them to each individual word position in the document. We use RNNs to generate the words in each sentence conditioned on its assigned topic, so as to capture within-sentence dependencies between words. We believe our modeling choice not only allows us to better visualize topical discourse structure in a document (say, by analyzing the changes in the posterior over the topic assignment variables for sentences as move from start to end of the document), but may also potentially lend topics better interpretability since we can visualize them by generating representative sentences from the learned topic-specific RNN word generators.

In this work, we will also present a VAE framework to model the posteriors over the topic assignment variables at sentence-level explicitly through an encoder based on another RNN. Previous work on VAE-based learning approach for topic models such as (Dieng et al., 2016), (Miao et al., 2015) and (Srivastava & Sutton, 2017) focus on modeling the posterior of the topical mixture at document-level, but ignore the issue of modeling the posterior of topic assignments. We hope that our work on explicit modeling of the posteriors of the topic assignment variables will pave the way for future work on more sophisticated posteriors that can also capture topical correlations across neighboring sentences.

### 2.1. Generative Process

The **SenGen** model first samples the document-level topic strengths $\theta_d$ from a $K$-dimensional multivariate Gaussian $\mathcal{N}(\cdot|\mathbf{0}, \mathbf{I})$. Topic indices $z_s$ are sampled from the mixture distribution $\text{softmax} (\theta_d)$ for each sentence $s$ in the document. Conditioned on the topic-id $z_s$, a topic-specific GRU-RNN (Chung et al., 2014) based decoder is run to generate all the words $w_s$ in the sentence. The conditioning on topic is done via a topic-embedding vector $\text{Emb}\mathbf{Z}$ which is also learned automatically.

In effect, our model relaxes the bag-of-words assumption of LDA, and instead assumes the document to be a bag of independent sentences, each of which can assume its own topic. The words in each sentence share the same topic, and are generated jointly using the decoder RNN.

The steps in Algorithm 1 describe the generative process of the model in more detail. A graphical representation of the model is also presented in Figure 1. Note that there is a separate decoder RNN for each topic, but they all share the same parameters except for the word-generating softmax layer.

![Figure 1. Graphical representation of the SenGen Model.](image)

### 2.2. Likelihood and Parameter Learning

The observed data log likelihood of a document corpus $C = \{d_1, \cdots, d_N\}$ from this model is given by:

$$
P(w|\beta) = \prod_{d=1}^{N} \int \mathcal{N}(\theta_d|\mathbf{0}, \mathbf{I}) \left( \sum_{s=1}^{N_d} \prod_{z_s=1}^K P(z_s|\theta_d)P(w_s|z_s, \beta) \right) d\theta_d$$

(1)

where

$$P(z = k|\theta_d) = \text{softmax}(\theta_{dk}),$$

(2)

and $\beta$ are the parameters of the word-generating RNN decoder and $\text{softmax}(x_k) = \frac{\exp(x_k)}{\sum_{k'} \exp(x_{k'})}$ is an operator that maps the topic strengths vector $\theta_d$ into a multinomial simplex, and $K$ is a hyperparameter indicating the number of topics in the model, and $N_s^{(d)}$ is the number of sentences in document $d$.

The likelihood of the words $w_s$ in each sentence using the RNN is given by:

$$P(w_s|z_s, \beta) = \prod_{i=1}^{N_s^{(s)}} P(w_i|w_{-i}, z_s, \beta)$$

(3)

where each term in the RHS of the equation above is computed using step (11) in the generative process displayed in Algorithm 1.
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Algorithm 1 Generative process for SenGen Model

1. For each document \( d \) in \( \{1, \cdots, N\} \):
   2. Generate un-normalized topic mixture of the document \( \theta_d \sim \mathcal{N}(\cdot; \mathbf{0}, \mathbf{I}) \)
   3. For each sentence \( s \) in \( \{1, \cdots, N_w^{(d)}\} \):
      4. Sample topic \( z_s \sim \text{Mult}(\text{softmax}(\theta_d)) \)
      5. Initialize the hidden state of the RNN as \( h_0^s = \text{zeros}(|\mathbf{h}|) \)
      6. Set the embeddings of the zeroth word in the RNN as \( \text{Emb}[w_0] = \text{zeros}(|\text{Emb}|) \)
      7. Select context vector for the RNN from topic embeddings: \( c_s = \text{Emb}[z_s] \)
      8. For each word position in the sentence \( i \) in \( \{1, \cdots, N_w^{(d)}\} \):
         9. Update the hidden state of RNN \( h_i = \tanh(W_h h_{i-1} + W_c \text{Emb}[w_{i-1}] + W_r c_s + b) \)
      10. Compute the readout layer \( r_i = \tanh(W_h^r h_i + W_c^r \text{Emb}[w_{i-1}] + W_r^r c_s + b^r) \)
      11. Generate word using \( P(w_i = w^o) = \text{softmax}(W_s r_i + b^r) \)

2.3. Learning using VAE

We consider the following factorized variational encoders to model the posteriors for the latent variables \( \theta \) for documents and \( z \) for sentences.

\[
q(\theta_1, z_1, \cdots, \theta_N, z_N|w) = \prod_{d=1}^{N} q(\theta_d|w_d) \prod_{s=1}^{N_w^{(d)}} q(z_s|w_s) \tag{4}
\]

where \( w_d \) is the vector of words in the document \( d \) and \( w_s \) is the vector of words in the sentence \( s \). In other words, the posteriors over the topic indicators for each sentence are assumed to be independent from the posteriors of the topic vector for the entire document. This is clearly a simplifying assumption that makes inference tractable, and may need to be relaxed in the future.

Note that the encoders are amortized over all the documents unlike mean-field approaches where each latent variable is assumed to have its own independent posterior (Blei et al., 2003). The document-level encoder \( q(\theta_d|w_d) \) is a simple feed forward network that estimates the mean and covariance of the posterior for \( \theta_d \) as given by the following series of steps:

\[
\gamma_d = \tanh(W_\gamma \sum_{i=1}^{N_w^{(d)}} \text{Emb}[w_i]) + b_\gamma
\]

\[
\mu_d = W_\mu \gamma_d + b_\mu
\]

\[
\sigma_d = \exp(W_\sigma \gamma_d + b_\sigma)
\]

\[
\hat{\theta}_d = \mu_d + \sigma_d \odot \epsilon
\]

where \( N_w^{(d)} \) is the number of words in the document and \( W_\gamma, b_\gamma, W_\mu, b_\mu, W_\sigma, b_\sigma \) are the parameters of the encoder. \( \epsilon \) is a \( K \)-dimensional Gaussian noise vector generated from \( \mathcal{N}(\mathbf{0}, \mathbf{I}) \). In the last equation above, we used the reparametrization trick to sample \( \hat{\theta}_d \) from the encoder’s posterior \( q(\theta_d|w_d) \) while maintaining end-to-end differentiability of the model.

The sentence-level encoder is another GRU-RNN that outputs the posterior over topics given the words in the sentence \( w_s \) as follows.

\[
q(z_s = k|w_s) = \text{softmax}(W_k^{(s)} h^{(s)}_{k} + b_k),
\]

where \( h^{(s)}_{k} = \text{GRU}(h^{(s)}_{k-1}, \text{Emb}[w_i]) \) \tag{5}

Thus, the encoder RNN consumes all the words in the sentence as input, one at every time step, and emits the posterior probabilities over topics at the last time step \( N_w^{(s)} \). The graphical representation of both the variational encoders is displayed in Figure 2.

Given the two encoders, the variational lowerbound for the log-likelihood of the observed data in the VAE approach can be written as:

\[
\log P(w_d|\beta) \geq -KL(q(\theta_d)||P(\theta_d)) + \sum_{s=1}^{N_w^{(d)}} (E_q log P(z_s|\theta_d) + H(q(z_s|w_s))) + E_q \log P(w_s|z_s, \beta) \tag{7}
\]

Further, each term on the RHS of Eq. (7) can be factorized.
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Figure 2. Graphical representation of the encoder architecture: the posteriors for sentence-level topic assignments $z_s$ and for document level topical strengths $\theta_d$ are modeled as independent of each other.

\[
KL(q(\theta_d)\|P(\theta_d)) = \frac{1}{2} \sum_{k=1}^{K} (1 + \log(\sigma_j^2) - \mu_j^2 - \sigma_j^2)
\]

\[
E_q \log P(z_s|\theta_d) \approx \sum_k \log \frac{\exp(\theta_{dk})}{\sum_k \exp(\theta_{dk})}
\]

\[
H(q(z_s|w_s)) = \sum_k q(k|w_s) \log q(k|w_s)
\]

\[
E_q \log P(w_s|z_s, \beta) = \sum_k q(k|w_s) \log P(w_s|\beta, k)
\]

where the first term above, involving KL-divergence between two Gaussians, is computed analytically as described in (Kingma & Welling, 2013). The second term above, consisting of the expectation of $P(z_s|\theta_d)$ is computed using a sample based estimate. For computing the other terms, we took advantage of the clear separation of $z_s$ and $\theta_d$ in the posterior to compute the expectations exactly, and involves summation over all topics.

3. Experiments

3.1. Datasets

In our experiments, we used the ‘by-date’ version of the 20 Newsgroups dataset downloadable from http://qwone.com/~jason/20Newsgroups/ as well as the CNN/Daily Mail corpus available at http://cs.nyu.edu/~kcho/DMQA/.

Although preprocessed versions of the 20 Newsgroups datasets are available where the text is tokenized and words converted to integer ids, we preprocessed the text on our own since we needed to preserve sentence boundary information. We did not remove any stopwords since we want the model to produce meaningful sentences. We used the official training and test splits defined in the by-date version of the dataset. We further sub-divided training set into training and validation sets, so that the validation loss could be used for early stopping of the training process. In all, we had 10,000 training documents, 1,314 validation documents and 7,532 test documents. There are about 18 sentences per document and 20 words per sentence on average.

We pruned our vocabulary to 60,359 most frequent words, which is very close to that reported in other experiments (Srivastava & Sutton, 2017). However, it is not clear to us if the vocabulary we used in our experiments is identical to the vocabulary in the preprocessed versions, since we had to do many clean-up operations such as removing email-headers and signatures from the documents to reduce noise.

The CNN/Daily Mail corpus is a large corpus consisting of more than 300,000 documents. This documents in this corpus are well formatted with sentence boundaries, which is required in our model. We randomly subsampled 10,000 documents for training, 1,000 documents for validation and 2,000 documents for testing. On average, this dataset has 29 sentences per document, and 26 words per sentence. The vocabulary size is pruned to 55,226 top most frequent words. We ran the other baselines on this corpus using their open source code.

The authors of (Miao et al., 2015) and (Srivastava & Sutton, 2017) use the RCV1 corpus as an additional corpus, but the free version of this corpus is already tokenized with no sentence boundary information, hence we ignored it in our experiments.

3.2. Model settings

For runs on both datasets, we used word embeddings of dimension 100, pre-trained using word2vec on the full CNN/Daily Mail corpus. We set the hidden state of both the encoder and decoder RNNs to 200, the dimension of the readout layer to 100. Each topic has its own decoder but they all share the same parameters except in the softmax layer where the parameters are distinct. Since the softmax layer is of size $|V| \times |r|$ where $|V|$ is the training vocabulary size, and $|r|$ is the size of the readout layer (see steps 10 and 11 in Table 1), training the model is very challenging both in terms of space and time computational requirements. Therefore, we limited our number of topics to 25, and also fixed our batch size to 1.

To save GPU memory, we implemented a variant of the large vocabulary trick (Jean et al., 2014) where for each batch we sampled a subset of 4,000 words from the training corpus distribution to be used as the vocabulary in the softmax layer, in addition to the words that occurred in
Table 1. Perplexity comparison of various models on two different datasets. All models are configured to use 25 topics. Lower is better.

| Model                        | 20 Newsgroups | CNN/Daily Mail |
|------------------------------|---------------|----------------|
| LDA (Blei et al., 2003)      | 1247          | 776            |
| NVDM (Miao et al., 2015)     | 757           | 435            |
| NVLDA (Srivastava & Sutton, 2017) | 1213     | 592            |
| ProdLDA (Srivastava & Sutton, 2017) | 1695       | 735            |
| SenGen (Our Model)           | 2354          | 671            |

3.3. Perplexity results

We compute perplexity of the test dataset using the trained SenGen model as follows:

\[
\text{Perplexity} = \frac{1}{N} \sum_{d=1}^{N} \exp\left(-\frac{\log P(w_d|\beta)}{N_d}\right)
\]  

where the log probability is computed using the lower-bound estimate in Eq. (7). In the above equation, \(N\) is the number of test documents, and \(N_d\) is the number of words in document \(d\). We compared the perplexity of our model with models from (Blei et al., 2003), (Miao et al., 2015) and (Srivastava & Sutton, 2017). We could not compare our results with (Dieng et al., 2016) since they reported their numbers on different datasets, and their code is not yet publicly released either. The results in Table 1 indicate that the new SenGen model does not achieve better perplexity than any of the models we compared with on the 20 Newsgroups dataset. On CNN/Daily Mail, our model achieves better perplexity than LDA as well as ProdLDA variant of (Srivastava & Sutton, 2017), but is not as good as the other VAE-based models. On 20 Newsgroups datasets, we suspect the main reason is due to the differences in preprocessing between our work and that of others – we noticed that there are many non-dictionary terms in our vocabulary that originated from email signatures and headers. Another potential reason is that the model may be overfitting the training set due to the extremely large number of parameters.

3.4. Qualitative results

One advantage of assigning topics to whole sentences is that the decoder RNN learns to generate sentences for each topic, which could be potentially more interpretable than representing topics merely by top ranking words. In Table 2, we displayed the best sequences generated by beam search of width 5 on the decoder’s softmax layer for three randomly chosen topics on the CNN/Daily Mail data set. We also displayed two different stochastic samples for the same topics where we greedily sample words from the distribution defined by the softmax layer of the RNN decoder for each time-step.

The table shows that the best sequences tend to be very generic, non-informative sentences. Although they are grammatically well formed in the beginning, they tend to repeat the generated phrases after a few time-steps. The stochastic samples, on the other hand, are not grammatically well formed, but do contain topical words. However the learned topics are certainly not as coherent as those learned by bag-of-words approaches such as LDA.

Clearly, more work needs to be done before we get these models learn more interpretable topics. To address the issue of non-informative best sequences, we may need to handle stop words and other frequent words in a special manner as done in the (Dieng et al., 2016) work which used a separate class for these words which are then mixed with topics. Also, since the SenGen model has very large number of parameters, it may be desirable to initialize the model’s parameters to those learned by a bag-of-words model, so that there is less chance it gets stuck at arbitrary local minima.
| Topic 1                                                                 |
|------------------------------------------------------------------------|
| Best sequence                                                          |
| he said that he had not been made with the case and that he had not been made with the case |
| bestsellers we positives hollywood-walk-of-fame dribbled in the association wilmington-10 horyn |
| timberlake united-lincolnshire-hospitals-trust enrolled snowballed helipad advertiser |
| Stochastic sample 1                                                   |
| Stochastic sample 2                                                   |

| Topic 2                                                                 |
|------------------------------------------------------------------------|
| Best sequence                                                          |
| it is one of the world in the world of the world                      |
| leader nasser chhattisgarh stroked arrogance debra-nelson impossibly fingers funding |
| waterboarding pele will be compulsory to nh1 as department-of-defense darren-sammy scott-brown |
| Stochastic sample 1                                                   |
| Stochastic sample 2                                                   |

| Topic 3                                                                 |
|------------------------------------------------------------------------|
| Best sequence                                                          |
| but it is not a lot of people who have to be able to be able to make  |
| catania ralph-lauren some0 impressionable re-interview texas-department-of-public-safety characters |
| lucy-jones breakwater chats david-laws fanciful dyke gustafson said |
| Stochastic sample 1                                                   |
| Stochastic sample 2                                                   |

Table 2. Example sequences of words generated by our model trained on the CNN / Daily Mail corpus, conditioned on various topics. Best sequence is obtained by performing a beam search on the softmax layer of the decoder RNN. Stochastic samples are obtained by greedy sampling from the softmax layer of the RNN, one word at a time.

4. Discussion and Conclusion

The main contributions of this work are (i) assigning topics to whole sentences instead of words, so that the resulting topics have the potential to be more interpretable since we can generate representative sentences for each topic; (ii) presenting a VAE approach that not only models posteriors of topic mixtures at document-level but also of topic assignments at sentence-level.

Preliminary qualitative and quantitative results indicate some promise, but deeper investigation needs to be conducted to overcome some of the existing deficiencies of the current model such as handling frequent words, preventing overfitting, learning better topics and improving computational efficiency.

Although one of our motivations is to capture topical discourse structure including the phenomena of topic drift and topic switch, this work addresses this issue only partially through the posteriors over topics for each sentence, which can be visualized graphically. We believe the framework proposed in this work can be extended to construct more sophisticated models that can capture dependencies between topics of adjacent sentences. Another direction we are interested in exploring is to provide the decoder with not only topical context but also the context from previous sentences in the document. Finally, we also need to relax the assumption of fully factorized posteriors of the document’s topic vector and those of the sentence topics.

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