Abstract
The Pachinko Allocation Machine (PAM) is a deep topic model that allows representing rich correlation structures among topics by a directed acyclic graph over topics. Because of the flexibility of the model, however, approximate inference is very difficult. Perhaps for this reason, only a small number of potential PAM architectures have been explored in the literature. In this paper we present an efficient and flexible amortized variational inference method for PAM, using a deep inference network to parameterize the approximate posterior distribution in a manner similar to the variational autoencoder. Our inference method produces more coherent topics than state-of-art inference methods for PAM while being an order of magnitude faster, which allows exploration of a wider range of PAM architectures than have previously been studied.

1 Introduction
Topic models are widely used tools for exploring and visualizing document collections. Simpler topic models, like latent Dirichlet allocation (LDA) (Blei et al., 2003), capture correlations among words but do not capture correlations among topics. This limits the model’s ability to discover finer-grained hierarchical latent structure in the data. For example, we expect that very specific topics, such as those pertaining to individual sports teams, are likely to co-occur more often than more general topics, such as a generic “politics” topic with a generic “sports” topic.

A popular extension to LDA that captures topic correlations is the Pachinko Allocation Machine (PAM) (Li and McCallum, 2006). PAM is essentially “deep LDA”. It is defined by a directed acyclic graph (DAG) in which each leaf node denotes a word in the vocabulary, and each internal node is associated with a distribution over its children. The document is generated by sampling, for each word, a path from the root of the DAG to a leaf. Thus the internal nodes can represent distributions over topics, so-called “super-topics” that represent correlations among topics.

Unfortunately PAM introduces many latent variables — for each word in the document, the path in the DAG that generated the word is latent. Therefore, traditional inference methods, such as Gibbs sampling and decoupled mean-field variational inference, become significantly more expensive. This not only affects the scale of data sets that can be considered, but more fundamentally the computational cost of inference makes it difficult to explore the space of possible architectures for PAM. As a result, to date only relatively simple architectures have been studied in the literature (Li and McCallum, 2006; Mimno et al., 2007; Li et al., 2012).

We present what is, to the best of our knowledge, the first variational inference method for PAM, which we call Amortized Variational Inference for PAM (aviPAM). Unlike collapsed Gibbs, aviPAM can be generically applied to any PAM architecture without the need to derive a new inference algorithm, allowing much more rapid exploration of the space of possible model architectures.

aviPAM is an amortized inference method that follows the learning principle of variational autoencoders (VAE) (Kingma and Welling, 2013; Rezende et al., 2014), which means that all the variational distributions are parameterized by deep neural networks (encoder/inference-network) that are trained to perform inference. The actual observation model in such a framework is often referred to as the decoder. aviPAM introduces a novel structured VAE since the existing VAE architectures cannot deal with the highly complicated latent spaces of PAMs. We find that aviPAM is not only an order of magnitude faster than collapsed Gibbs, but even returns topics with greater or com-
parable coherence. The dramatic speedup in inference time comes from the complete amortization of the learning cost via our highly structured encoder architecture (neural network) that directly outputs all the variational parameters of the approximate posterior over all the latent variables in PAM, instead of learning them separately for each training instance. This efficiency in inference enables exploration of more complex and deeper PAM models than have previously been possible.

As a demonstration of this, as our second contribution we introduce a mixture of PAMs model. By mixing PAMs with varying numbers of topics, this model captures the latent structure in the data at many different levels of granularity that decouples general broad topics from the more specific ones.

Like other variational autoencoders, our model also suffers from the problem of posterior collapse (van den Oord et al., 2017), which is sometimes also called component collapse (Dinh and Dumoulin, 2016). We present an analysis of these issues in the context of topic modeling and propose a normalization based solution to alleviate them.

2 Latent Dirichlet Allocation

LDA represents each document \( w \) in a collection as an admixture of topics. Each topic vector \( \beta_k \) is a distribution over the vocabulary, that is, a vector of probabilities, and \( \beta = (\beta_1 \ldots \beta_K) \) is the matrix of the \( K \) topics. Every document is then generated under the model by first sampling a proportion vector \( \theta \sim \text{Dirichlet}(\alpha) \), and then for each word at position \( n \), sampling a topic indicator \( z_n \sim \text{Categorical}(\theta) \), and finally sampling the word index \( w_n \sim \text{Categorical}(\beta_{z_n}) \).

2.1 Deep LDA: Pachinko Allocation Machine

PAM is a class of topic models that extends LDA by modeling correlations among topics. A particular instance of a PAM represents the correlation structure among topics by a DAG in which the leaf nodes represent words in the vocabulary and the internal nodes represent topics. Each node \( s \) in the DAG is associated with a distribution \( \theta_s \) over its children, which has a Dirichlet prior. There is no need to differentiate between nodes in the graph and the distributions \( \theta_s \), so we will simply take \( \{\theta_s\} \cup \{1 \ldots V\} \) to be the node set of the graph, where \( V \) is the size of the vocabulary. To generate a document in PAM, for each word we sample a path from the root to a leaf, and output the word associated with that leaf.

More formally, we present the special case of 4-PAM, in which the DAG is a 4-partite graph.\(^1\) It will be clear how to generalize this discussion to arbitrary DAGs. In 4-PAM, the DAG consists of a root node \( \theta_r \) which is connected to children \( \theta_1 \ldots \theta_S \) called super-topics. Each super-topic \( \theta_s \) is connected to the same set of children \( \beta_1 \ldots \beta_K \) called subtopics, each of which are fully connected to the vocabulary items \( 1 \ldots V \) in the leaves.

A document is generated in 4-PAM as follows. First, a single matrix of subtopics \( \beta \) are generated for the entire corpus as \( \beta_k \sim \text{Dirichlet}(\alpha_0) \). Then, to sample a document \( w \), we sample child distributions for each remaining internal node in the DAG. For the root node, \( \theta_r \) is drawn from a Dirichlet prior \( \theta_r \sim \text{Dirichlet}(\alpha_r) \), and similarly for each super-topic \( s \in \{1 \ldots S\} \), the super-topic \( \theta_s \) is drawn as \( \theta_s \sim \text{Dirichlet}(\alpha_s) \). Finally, for each word \( w_n \), a path is sampled from the root to the leaf. From the root, we sample the index of a supertopic \( z_{n0} \in \{1 \ldots S\} \) as \( z_{n0} \sim \text{Categorical}(\theta_r) \), followed by a subtopic index \( z_{n2} \in \{1 \ldots K\} \) sampled as \( z_{n2} \sim \text{Categorical}(\beta_{z_{n1}}) \), and finally the word is sampled as \( w_n \sim \text{Categorical}(\beta_{z_{n1}}) \). This process can be written as a density

\[
P(w, z, \theta \mid \alpha, \beta) = P(\theta_r \mid \alpha_r) \prod_{s=1}^{S} P(\theta_s \mid \alpha_s) \times \prod_{n} p(z_{n1} \mid \theta_r)p(z_{n2} \mid \theta_{z_{n1}})p(w_n \mid \beta_{z_{n2}}).
\]

It should be easily seen how this process can be extended to arbitrary \( \ell \)-partite graphs, yielding the \( \ell \)-PAM model, and also to arbitrary DAGs. Observe also that in this nomenclature, LDA exactly corresponds to 3-PAM.

3 Mixture of PAMs

The main advantage of the inference framework we propose is that it allows easily exploring the design space of possible structures for PAM. As a demonstration of this, we present a word-level mixture of PAMs that allows learning finer grained topics than a single PAM, as some mixture components learn topics that capture the more general,

\(^1\)An \( \ell \)-partite graph is the natural generalization of a bipartite graph.
global topics so that other mixture components can focus on finer-grained topics.

We describe a word-level mixture of $M$ PAMs $P_1 \ldots P_M$, each of which can have a different number of topics or even a completely different DAG structure. To generate a document under this model, first we sample an $M$-dimensional document level mixing proportion $\theta_r \sim \text{Dirichlet}(\alpha_r)$. Then, for each word $w_n$ in the document, we choose one of the PAM models by sampling $m \sim \text{Categorical}(\theta_r)$ and then finally sample a word by sampling a path through $P_m$ as described in the previous section. This model can be expressed as a general PAM model in which the root node $\theta_r$ is connected to the root nodes of each of the $M$ mixture components. If each of the mixture components are 3-PAM models, that is LDA, then we call the resulting model a mixture of LDA models (MoLDA).

The advantage of this model is that if we choose to incorporate different mixture components with different numbers of topics, we find that the components with fewer topics explain the coarse-grained structure in the data, freeing up the other components to learn finer grained topics. For example, the Omniglot dataset contains 28x28 images of handwritten alphabets from artificial scripts. In Figure 1, panels (C) and (D) are visualization of the latent topics that are generated using vanilla LDA with 10 and 50 topics, respectively. Because we are modelling image data, each topic can also be visualized as an image. Panels (A) and (B) show the topics from a single MoLDA with two components, one with 10 topics and one with 50 topics. It is apparent that the MoLDA topics are sharper, indicating that each individual topic is capturing more detailed information about the data. The mixture model allows the two LDAs being mixed to focus exclusively on higher (for 10 topics) and lower (for 50 topics) level features while modeling the images. Since the final image is modeled by mixing these topics, such a mixture model with extremely sharp topics will lead to a sharper image with detailed features. On the other hand, the topics in the vanilla LDA need to account for all the variability in the dataset using just 10 (or 50) topics and therefore are fuzzier. This in turn leads to blurry images when the topics (from (c) or (d)) are mixed to generate the images.

4 Inference

Probabilistic inference in topic models is the task of computing posterior distributions $p(z|w, \alpha, \beta)$ over the topic assignments for words, or over the posterior $p(\theta|w, \alpha, \beta)$ of topic proportions for documents. For all practical topic models, this task is intractable. Commonly used methods include Gibbs sampling (Li and McCallum, 2006; Blei et al., 2004), which can be slow to converge, and variational inference methods such as mean field (Blei et al., 2003; Blei and Lafferty, 2006), which sometimes sacrifice topic quality for computational efficiency. More fundamentally, these families of approximate inference algorithms tend to be model specific and require extensive mathematical sophistication on the practitioner’s part since even the slightest changes in model assumptions may require substantial adjustments to the inference. The time required to derive new approximate inference algorithms dramatically slows explorations through the space of possible models.

In this work we describe a generic, amortized approximate inference method avPAM for learning in the PAM family of models, that is extremely fast, flexible and accurate. The inference method is flexible in the sense that it can be generically applied to any DAG structure for PAM, without the
need to derive a new variational update. The main
idea is that we will approximate the posterior dis-
tribution \( p(\theta_s|w, \alpha, \beta) \) for each super-topic \( \theta_s \) by a
variational distribution \( q(\theta_s|w) \). Unlike stan-
ard mean field approaches, in which \( q(\theta_s|w) \) has
an independent set of variational parameters for
each document in the corpus, the parameters of
\( q(\theta_s|w) \) will be computed by an inference net-
work, which is a neural network that takes the doc-
ument \( w \) as input, and outputs the parameters of
the variational distribution. This is motivated by
the observation that similar documents can be de-
scribed well by similar posterior parameters.

In aviPAM, we seek to approximate the poste-
rior distribution \( P(\theta|w, \alpha, \beta) \), that is, the, the paths \( z_{n,}\)
for each word are integrated out. Note that this is
in contrast to previous collapsed Gibbs methods
for PAM (Li and McCallum, 2006), which inte-
grate out \( \theta \) using conjugacy. To simplify notation,
we will describe aviPAM for the special case of
4-PAM, but it will be clear how to generalize this
discussion to arbitrary DAGs. So for 4-PAM, we
have \( \theta = (\theta_1, \theta_2, \ldots, \theta_S) \).

We introduce a variational distribution
\( q(\theta|w) = q(\theta_1|w)q(\theta_2|w)\ldots q(\theta_S|w) \).

To choose the best approximation \( q(\theta|w) \), we
construct a lower bound to the evidence (ELBO)
using Jensen’s inequality, as is standard in varia-
tional inference. For example, the log-likelihood
function \( \log p(w|\alpha, \beta) \) for the 4-PAM model (1)
can be lower bounded by

\[
\mathcal{L} = -\text{KL}[q(\theta_1|w)||p(\theta_1|\alpha_1)] - \sum_{s=1}^{S} \text{KL}[q(\theta_s|w)||p(\theta_s|\alpha_s)] + \mathbb{E}\left[\sum_n \log p(w_n|\theta_i, \beta)\right]
\]

where the expectation is with respect to the vari-
tional posterior \( q(\theta|w) \).

 aviPAM uses stochastic gradient descent to
maximize this ELBO to infer the variational pa-
rameters and learn the model parameters. To finish
describing the method, we must describe how \( q \) is
parameterized, which we do next. For the subtopic
parameters \( \beta \), we learn these using variational EM,
that is, we maximize \( \mathcal{L} \) with respect to \( \beta \). It would
be a simple extension to add a variational distribu-
tion over \( \beta \) if this was desired.

**Re-parameterizing Dirichlet Distribution:**
The expectation over the second term in equation
(2) is in general intractable and therefore we
approximate it using a special type of Monte-
Carlo (MC) method (Kingma and Welling, 2013;
Rezende and Mohamed, 2015) that employs the
re-parametrization-trick (Williams, 1992) for
sampling from the variational posterior. But this
MC-estimate requires \( q(\theta|w) \) to belong to the
location-scale family which excludes Dirichlet
distribution. Recently, some progress has been
made in the re-parametrization of distributions
like Dirichlet (Ruiz et al., 2016) but in this
work, following Srivastava and Sutton (2017)
we approximate the posterior with a logistic
normal distribution. First, we construct a Laplace
approximation of the Dirichlet prior in the soft-
max basis, which allows us to approximate the
posterior distribution using a Gaussian that is
in the location-scale family. Then in order to
sample \( \theta \) from the posterior in the simplex basis
we apply the softmax transform to the Gaussian
samples. Using this Laplace approximation trick
also allows handling different prior assump-
tions, including other non-location-scale family
distributions.

**Amortizing Super-Topics:** As mentioned
above, in PAM the super topics need to be
sampled for each document in the corpus. This
presents a bottleneck in speeding up posterior
inference via Gibbs sampling or DMFVI as the
number of variables to be sampled increases with
the amount of data. Our use of an amortized in-
ference method allow us to tackle this bottleneck
such that the number of posterior parameters to be
learned does not directly depend on the number of
documents in the corpus.

**aviPAM Inference Network** Recently Sri-
vastava and Sutton (2017) amortized the cost
of learning posterior parameter in LDA with a
VAE-type model where they used a feedforward
Multi-layer Perceptron (MLP) as the encoder net-
work to generate the parameters for the poste-
rior distribution over the topic proportion vector
\( \theta \). Like them, we model the posterior \( q(\theta_1|w) \) as
LN(\( \theta; f_{\mu}(w), f_{\alpha}(w) \)) where \( f_{\mu} \) and \( f_{\alpha} \) are
neural networks that generate the parameters for
the logistic normal distribution. But their simple enc-
coder cannot be used to learn super-topics be-
cause they need to be sampled separately per doc-
ument, in fact this is one of the reasons Srivas-
tava and Sutton (2017) assumed the topics to be
fixed model parameters. We now describe our novel structured encoder (inference-network) that can efficiently sample super-topics on-the-fly from a Dirichlet prior per document and use them as network weights to generate all the posterior parameters that need to be inferred in PAMs.

PAM requires a set of variational parameters (topic vectors) per document at each level of the DAG. These topic vectors need to be sampled from a Dirichlet prior $\alpha$ of that level. To generate these parameters, we use one MLP per level which samples the specified number of topic vectors per document for its level.

Then in order to generate the mixing proportions for the nodes in the lower level, we first note that the Dirichlet distribution is a conjugate prior to the multinomial distribution. This fact can be used to leverage the modern GPU-based computation to generate these mixing proportions since it only involves a dot-product between the mixing proportion from the previous level and the matrix of the topics of the current level.

Therefore we first stack all the topic vectors of the current level in a 3-D tensor and using a custom implementation for the dot-product we generate the mixing proportions for the next lower level. This amortization scheme of our structured encoder gains us significant reduction in training time. We want to point out that the result of above process can also be seen as construction of MLPs on the fly by sampling Dirichlet vectors from our inference networks and stacking them to form weight matrices of the MLPs. This maybe useful in other tasks that require efficient fully Bayesian treatment of the latent variables.

The decoder in the case of PAM is similarly just a dot product between the sample from the output distribution of the inference network, the mixing proportions $\theta$ and the sub-topic matrix $\beta$. The only difference is that topics matrix $\beta$ is a global latent variable/model parameter that is sampled only once for the entire corpus.

This framework can be readily extended in several different ways. Although in our experiments we always use MLPs to encode the posterior and decode the output, if required other architectures like CNNs and RNNs can be easily used to replace the MLPs. As mentioned before, aviTAM can work with non-Dirichlet priors by using the Laplace approximation trick. It can also handle full-covariance Gaussian as well as logistic Normals by simply using the Cholesky decomposition and can therefore be used to learn Correlated Topic Model (CTM) (Blei and Lafferty, 2006).

At first, the use of an inference network seems strange, as coupling the variational parameters across documents guarantees that the variational bound will not be as tight. But the advantage of an inference network is that after the weights of the inference network have been learned on training documents, we can obtain an approximate posterior distribution for a new test document simply by evaluating the inference network, without needing to carry out any variational optimization. This is the reason for the term amortized inference, i.e., the computational cost of training the inference network is amortized across future test documents.

4.1 Learning Issues in VAE

Trained with stochastic variational inference, like VAEs, our PAM models suffer from primarily two learning problems: slow learning and component collapse. In this section, we describe each of those problems in more detail and how we address them.

Slow Learning

Training PAM models even on the recommended learning rate of 0.001 for the ADAM optimizer (Kingma and Ba, 2014) generally causes the gradients to diverge early on in training. Therefore in practice, fairly low learning rates have been used in VAE-based generative models of text, which significantly slows down learning. In this section we first explain one of the reasons for the diverging behavior of the gradients and then propose a solution that stabilizes them, which allows train-
ing VAEs with high learning rates, making learning much faster.

Consider a VAE for a model \( p(x, z) \) where \( z \) is a latent Gaussian variable, \( x \) is a categorical variable distributed as \( p_{\Theta_d}(x|z) = \text{Multinomial}(f_d(z, \Theta_d)) \), and the function \( f_d() \) is a decoder MLP with parameters \( \Theta_d \). BN transformation for an incoming mini-batch of \( \Theta \) demands an adaptive learning rate for encoder \( \Theta_e \), which makes it difficult to optimize it with respect to \( \Theta_e \) in high learning rates.

The instability of the gradient w.r.t. to \( u \) demands an adaptive learning rate for encoder parameters \( \Theta_u \) that can adapt to sudden large changes in \( \nabla_u L \).

We now propose that this adaptive learning rate can be achieved by applying BatchNorm (BN) (Ioffe and Szegedy, 2015) transformation to \( f_u \). BN transformation for an incoming mini-batch of activations \( \{ u_{i=1}^m \} \) (we overload the notion on purpose here, in general \( u \) can come from any layer) is,

\[
u_{BN} = \frac{\gamma (u - \mu_{\text{batch}})}{\sqrt{\sigma_{\text{batch}}^2 + \epsilon}} + b.
\]

Here, \( \mu_{\text{batch}} = \frac{1}{m} \sum_{i=1}^m u_i, \sigma_{\text{batch}}^2 = \frac{1}{m} \sum_{i=1}^m (u_i - \mu_{\text{batch}})^2 \), \( \gamma \) is the gain parameter and finally \( b \) is the shift parameter. We are specifically interested in the scaling factor \( \frac{\gamma}{\sqrt{\sigma_{\text{batch}}^2}} \), because the sample variance grows and shrinks with large changes in the norm of the mini-batch therefore allowing the scaling factor to approximately dictate the norm of the activations. Let \( L \) be defined as before, the posterior \( q \) is now a function of \( u_{BN} \). The gradients w.r.t. \( u \) and the gain parameter \( \gamma \) are

\[
\nabla_u L = \frac{\gamma}{\sqrt{\sigma_{\text{batch}}^2 + \epsilon}} P_u \nabla_{u_{BN}} L
\]

\[
\nabla_\gamma L = \frac{(u - \mu_{\text{batch}})}{\sqrt{\sigma_{\text{batch}}^2 + \epsilon}} \nabla_{u_{BN}} L,
\]

where \( P_u \) is a projection matrix. If \( \nabla_{u_{BN}} L \) is large with respect to the out-going \( u_{BN} \), the scaling term brings it down. Therefore, the scaling term works like an adaptive learning rate that grows and shrinks in response to the change in norm of the batch of \( u \)’s due to large gradient updates to the weights, thus resolving the issue with the diverging gradients. As shown in Figure 3, after applying BN to one of the outputs \( u \) encoder of the prodLDA model on 20newsgroup dataset (Srivastava and Sutton, 2017), the KL term minimizes fairly slowly (red) compared to the case (blue) when no BN is applied to \( u \). We experimentally found that at this point the topics start to improve when the learning rate is \( \geq 0.001 \).

In order to establish that the improvement in training comes from the adaptive learning rate property of the gain parameter we replace the divider in the BN transformation with the \( \ell_2 \) norm of the activation. We neither center the activations nor apply any shift to them. This normalization performs equivalently and occasionally better than BN, therefore confirming our hypothesis. It also removes any dependency on batch-level statistics that might be a requirement in models that make i.i.d assumptions.

**Component Collapse**

Another well known issue in VAEs such as aviPAM is the problem of component collapsing (Dinh and Dumoulin, 2016; van den Oord et al., 2017). In the context of topic models, component collapsing is a bad local minimum of VAEs in which the model only learns a small number of topics out of \( K \) (Srivastava and Sutton, 2017). For example, suppose we train a 3-PAM model on the Omniglot dataset (Lake et al., 2015) using the stochastic variational inference from Kingma and Welling (2013). Figure 2 shows nine randomly sampled topics for from this model which have been reshaped to Omniglot image dimensions. All the topics look exactly the same, with a few exceptions. This is clearly not a useful set of topics.
In optimization without any BatchNorm, the average KL gets minimized fairly early in the training. With BatchNorm applied to the encoder unit that produces $\log \sigma^2$, the KL minimization is slow and slower if BatchNorm is also applied to each of the topics in the decoder.

When trained without applying BN to the $\log \sigma^2$ output of the encoder, the KL terms across most of the latent dimensions (components of $z$) vanish to zero. We call them collapsed dimensions, since the posterior along them has collapsed to the prior. As a result, the decoder only receives the sampling noise along such collapsed dimensions and in order to minimize the noise in the output, it makes the weights corresponding to these collapsed components very small. In practice this means that these weights do not participate in learning and therefore do not represent any meaningful topic.

Following Srivastava and Sutton (2017), we also found that the topic coherence increases drastically when BN is also applied to the topic matrix $\beta$ prior to the application of the softmax non-linearity. Besides preventing the softmax units to saturate, this slows down the KL minimization further as shown by the green curve in figure 3.

5 Experiments and Results

We evaluate how aviPAM inference performs for different architectures of PAM models when compared to the state-of-art collapsed Gibbs inference. To this end we evaluate three different PAM architectures, 4-PAM, 5-PAM and MoLDA, on two different datasets, 20 Newsgroups and NIPS abstracts (Lichman, 2013). We use these two data sets because they represent two extreme settings. 20 Newsgroups is a large dataset (12,000 documents) but with a more restricted vocabulary (2000 words) whereas the NIPS dataset is smaller in size (1500 abstracts) dataset but has a considerably larger vocabulary (12419 words). We compare inference methods both on time required for training as well as topic quality. As a measure of topic quality, we use the topic coherence metric (normalized point-wise mutual information), which as shown in Lau et al. (2014) corresponds very well with human judgment on the quality of topics. We do not report perplexity of the models because it has been repeatedly shown to not be a good measure of topic coherence and even to be negatively correlated with the topic quality in some cases (Lau et al., 2014; Chang et al., 2009; Srivastava and Sutton, 2017).

We start by comparing the topic coherence across the different topic models on the 20 Newsgroup dataset. We train an LDA model using both collapsed Gibbs sampling4 (Griffiths and Steyvers, 2004) and Decoupled Mean-Field Variational Inference (DMFVI)5 (Blei et al., 2003). Using Mallet, we train a 4-PAM model using 10000 iterations of collapsed Gibbs sampling and using aviPAM we train a 4-PAM, a 5-PAM, a MoLDA and a correlated topic model (CTM). In this experiment we use 50 sub-topics for all models. For MoLDA we use two mixture components with 10 and 50 topics. For 4-PAM and 5-PAM, we use two super-topics following Li and McCallum (2006), and two additional super-duper-topics for 5-PAM. Results are shown in Table 1. All PAM models perform better than LDA-type models, showing that more complex PAM architectures do improve the quality of the topics. Additionally 4-PAM and 5-PAM models trained on aviPAM beat all the LDA models for topic quality. MoLDA and CTM trained using aviPAM also perform competitively with the LDA models but the CTM model falls significantly behind PAM models on topic coherence.

Next, to study the effect of increasing the number of PAM supertopics, we increase the number of super-duper-topics to 10, super-topics to 50 and sub-topics to 100. Table 2 shows the topic coherence for each of these models and also the training time. Not only our inference method produces better topics it also is an order of magnitude faster than the state-of-art Gibbs sampling based inference for 4-PAM. Note that we run the sampler for a total of 3000 iterations with the burn-in parameter set to 2000 iterations.

4We used the Mallet implementation (McCallum, 2002).
5We used the scikit-learn implementation (Pedregosa et al., 2011).
Table 1: Topic coherence on 20 Newsgroups for 50 topics. PAM models use two super-topics at each level. For MoLDA, we report separate the coherence for each component in the admixture.

|           | aviPAM | LDA | LDA | 4-PAM | 4-PAM | 5-PAM | CTM | MoLDA |
|-----------|--------|-----|-----|-------|-------|-------|-----|-------|
|           | GIBBS  | GMB | DMFV1 | GIBBS | 4-PAM | 5-PAM |     |       |
| Topic Coherence | 0.17  | 0.11 | 0.20 | 0.24 | 0.24 | 0.14 | 0.29 | 0.21 |

Table 2: Topic coherence for models trained on 20 Newsgroups dataset for 100 topics with 50 super-topics.

|           | aviPAM | 4-PAM | 5-PAM | MoLDA |
|-----------|--------|-------|-------|-------|
|           | GIBBS  | 4-PAM | 5-PAM |       |
| Topic Coherence | 0.19  | 0.22  | 0.21  | 0.24  | 0.21 |
| Training Time (Min.) | 594 | 11 | 16 | 16 |

Table 3: Topic coherence for models trained on NIPS dataset for 50 topics with 2 super-topics.

|           | aviPAM | 4-PAM | 5-PAM | MoLDA |
|-----------|--------|-------|-------|-------|
|           | GIBBS  | 4-PAM | 5-PAM |       |
| Topic Coherence | 0.033 | 0.042 | 0.039 | 0.036 | 0.024 |

Table 4: Topic coherence for models trained on NIPS dataset for 100 topics with 50 super-topics.

|           | aviPAM | 4-PAM | 5-PAM | MoLDA |
|-----------|--------|-------|-------|-------|
|           | GIBBS  | 4-PAM | 5-PAM |       |
| Topic Coherence | 0.047 | 0.041 | 0.045 | 0.025 | 0.024 |
| Training Time (Min.) | 892 | 19 | 26 | 11 |

For the NIPS dataset, we repeat the same experiments only for the PAM models again under the same exact settings as described above. Reported in Table 3 are the topic coherence for smaller PAM models with 50 sub-topics. Again, we allowed 10,000 Gibbs iterations which took more than a day to finish but did not beat aviPAM-trained models on topic quality. For the bigger PAM models we replicated the experiments from the original paper. As reported in Table 4, we found that while the collapsed Gibbs based 4-PAM model produced the best topics, it did so in 15 hours. On the other hand, aviPAM-trained models produced topics with comparable quality with a fraction of the inference time, because this method is able to leverage the GPU architecture for computing dot-products very efficiently. We are not aware of GPU-based implementations of other inference method for PAMs.

5.1 Hyper-Parameter Tuning

For the experiments in this section we did not conduct extensive hyper-parameter tuning. We used a grid search for setting the encoder capacity according to the dataset. As a general guideline for PAM models, the encoder capacity should grow with the vocabulary size. For the learning rate, we used the default setting of $1e^{-3}$ for the Adam optimizer for all the models. We used a batch size of 200 for 20 Newsgroups as used in (Srivastava and Sutton, 2017) and 50 for the NIPS dataset. We found that the topic coherence, especially for the smaller NIPS dataset, is sensitive to the batch size setting and initialization. For certain settings we were able to achieve higher topic coherence than the average topic coherence reported in this section.

6 Related Work

Topic models have been explored extensively via directed (Blei et al., 2003; Li and McCallum, 2006; Blei and Lafferty, 2006; Blei et al., 2004)
as well as undirected models or restricted Boltzmann machines (Larochelle and Lauly, 2012; Hinton and Salakhutdinov, 2009). Hierarchical extensions to these models have received special attention since they allow capturing the correlations between the topics and provide meaningful interpretation to the latent structures in the data.

Recent advancements in blackbox-type inference method (Kucukelbir et al., 2016; Ranganath et al., 2014; Mnih and Gregor, 2014; Khan and Lin, 2017) have made it easier to try newer models without the need of deriving model-specific inference algorithms.

7 Conclusion
In this work we introduced aviPAM, which extends the idea of variational inference in topic models via structured VAEs. We found that the combination of amortized inference and modern GPU software allows for an order of magnitude improvement in training time compared to standard inference mechanisms in such models. We hope that this will allow future work to explore new and more complex architectures for deep topic models.

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