Spherical Topic Models

Joseph Reisinger, Austin Waters, Bryan Silverthorn & Raymond Mooney
Department of Computer Science
The University of Texas at Austin
{joeraii, austin, bsilvert, mooney}@cs.utexas.edu

Abstract

We introduce the Spherical Admixture Model (SAM), a Bayesian topic model over arbitrary $\ell_2$ normalized data. SAM models documents as points on a high-dimensional spherical manifold, and is capable of representing negative word-topic correlations and word presence/absence, unlike models with multinomial document likelihood, such as LDA. In this paper, we evaluate SAM as a topic browser, focusing on its ability to model “negative” topic features, and also as a dimensionality reduction method, using topic proportions as features for difficult classification tasks in natural language processing and computer vision.

1 Introduction

Unsupervised admixture, or topic models, such as Latent Dirichlet Allocation (LDA) [3] build compact descriptions of document collections in terms of a small set of semantically coherent topics. This paper introduces the Spherical Admixture Model (SAM), a topic models that represent documents using distributions on the unit hypersphere [8], modeling both word frequency and word presence/absence. Specifically, we derive a variant of LDA, replacing the multinomial document likelihood with the von Mises-Fisher (vMF) distribution, which has been found to often model sparse data such as text more accurately [2, 1].

SAM offers several major benefits over LDA: documents can be represented as arbitrary unit vectors; document-topic similarity is measured in terms of weighted cosine distance in the generative model; and, by exploiting the entire support of the von Mises-Fisher distribution, topics can model negative correlations between words within each topic.

2 The Spherical Admixture Model

2.1 Mixtures of von Mises-Fisher Distributions

The vMF distribution has its support on $S^{d-1}$, the $(d - 1)$-dimensional unit hypersphere embedded in $\mathbb{R}^d$. Its density is $f(x; \mu, \kappa) = c_d(\kappa) \exp (\kappa \mu^\top x)$, where $\mu$ is the mean direction with $||\mu|| = 1$, $\kappa \geq 0$ is the concentration parameter, $c_d(\kappa) = \frac{\kappa^{d/2 - 1}}{(2\pi)^{d/2} I_{d/2 - 1}(\kappa)}$, and $I_r(\cdot)$ is the modified Bessel function of the first kind and order $r$ [8].

Motivated by the success of cosine distance in information retrieval, Banerjee et al. introduce the mixture of von Mises-Fisher distributions (movMF) [2], which treats each normalized document tf or tf-idf vector as drawn from a vMF distribution centered on a one topic mean. Although movMF outperforms mixture models with multinomial likelihood in several clustering benchmarks [2], the single-topic mixture-model assumption is too restrictive for document modeling.
2.2 SAM Definition

SAM is a Bayesian admixture model that operates on normalized vectors on \( \mathbb{S}^{|V|-1} \). It is not therefore possible to define the admixture in terms of topic indicators for individual words in each document, as is done by LDA. SAM instead uses a weighted directional average to achieve the same goal. Representing the \( T \) topics as columns of matrix \( \phi \) and \( \beta_d \) as a column vector, the weighted directional average is written as: \( \hat{\phi}_d = \frac{\phi \beta_d}{||\phi \beta_d||} \). The generative model for SAM is given by

\[
\begin{align*}
\mu_t | \kappa_0 & \sim \text{vMF}(m, \kappa_0), \quad t \in T, \quad \text{(topic means)} \\
\phi_t | \mu_t, \xi & \sim \text{vMF}(\mu_t, \xi), \quad t \in T, \quad \text{(topics)} \\
\beta_d | \phi, \beta & \sim \text{Dirichlet}(\alpha), \quad d \in D, \quad \text{(topic proportions)} \\
\hat{\phi}_d | \phi, \beta_d & = \text{Avg}(\phi, \beta_d), \quad d \in D, \quad \text{(spherical average)} \\
v_d | \phi_d, \kappa & \sim \text{vMF}(\phi_d, \kappa), \quad d \in D, \quad \text{(documents)}
\end{align*}
\]

where \( \mu \) is the corpus mean direction, \( \xi \) controls the concentration of topics around \( \mu \), the elements of \( \beta_d \) are the mixing proportions for document \( d \), \( \phi_t \) is the mean of topic \( t \), and \( v_d \) is the observed vector for document \( d \).

Each topic \( \phi_d \) is vector on the unit hypersphere \( \mathbb{S}^{|V|-1} \). Negative entries in a topic mean vector reduce the frequency of corresponding words in the resulting mean. This expressive power does not exist in admixture models with multinomial likelihood, and the empirical results in Section 3 demonstrate that this flexibility captures useful structure in real data.

2.3 Variational Approximation

We employ a variational mean-field method to perform approximate inference on SAM [7]. The posterior is approximated as the factored distribution \( q(\phi|\mu, \xi)q(\beta|\alpha)q(\mu|m, \kappa_0) \) and the factors are assumed to have the parametric forms \( q(\phi_t) = \text{vMF}(\phi_t|\mu_t, \xi) \), \( q(\beta_d) = \text{Dir}(\beta_d|\alpha) \), and \( q(\mu) = \text{vMF}(\mu|m, \kappa_0) \). Here, \( \mu, \hat{\mu}, \hat{m}, \) and \( \alpha \) are the free variational parameters. Given this factorization, it can be shown that a lower bound on the log likelihood is given by the expression

\[
L(\mu, \alpha, \hat{m}) = E_q[\log p(v, \phi, \beta, \mu)] - E_q[\log q(\phi, \beta, \mu; \alpha, \hat{m})]
\]

(1)

In the variational EM procedure, we use gradient ascent to update the variational topic means \( \hat{\mu} \) and per-document topic proportions \( \hat{\alpha}_d \). For convenience, we define \( \hat{\alpha}_{d,0} = \sum_{j=1}^{k} \hat{\alpha}_{d,j} \) and \( \rho_d = E_q[\text{Avg}(\phi, \beta_d)] \uparrow v_d \), where \( d \in \{1 \ldots D\} \) ranges over the documents. Taking gradients of eq. (1) with respect to the variational parameters, we have

\[
\frac{dL}{d\hat{\alpha}_{d,i}} = \kappa \left( \frac{d}{d\hat{\alpha}_{d,i}} \rho_d \right) + \Psi'(\hat{\alpha}_{d,0} - \alpha_0) - \Psi'(\hat{\alpha}_{d,i} - \alpha_i)
\]

\[
\nabla_{\hat{\mu}_t} L = AV(\xi)A_V(\kappa_0)\xi \hat{m}_t + \kappa \sum_{d=1}^{D} \nabla_{\hat{\mu}_t} (\rho_d)
\]
### Table

<table>
<thead>
<tr>
<th>Model</th>
<th>different</th>
<th>similar</th>
<th>same</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bag-of-words</td>
<td>75.1 ± 3.2</td>
<td>68.7 ± 2.1</td>
<td>57.2 ± 2.6</td>
</tr>
<tr>
<td>LDA</td>
<td>75.1 ± 2.4</td>
<td>67.5 ± 1.3</td>
<td>52.2 ± 1.3</td>
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<tr>
<td>movMF</td>
<td>65.3 ± 0.8</td>
<td>62.0 ± 3.2</td>
<td>49.1 ± 0.4</td>
</tr>
<tr>
<td>MH SAM [S]</td>
<td>80.9 ± 1.1</td>
<td>69.5 ± 1.3</td>
<td>62.2 ± 1.6</td>
</tr>
<tr>
<td>VEM SAM [S⁺]</td>
<td>72.0 ± 1.3</td>
<td>69.6 ± 0.9</td>
<td>62.2 ± 0.5</td>
</tr>
<tr>
<td>VEM SAM [S]</td>
<td>80.2 ± 1.0</td>
<td>72.4 ± 0.9</td>
<td>65.5 ± 0.4</td>
</tr>
</tbody>
</table>

### 3 Experiments

SAM’s performance is evaluated empirically on Usenet post and natural scene image classification. Four models are compared: (i) **LDA**: the mixture of von-Mises Fisher clustering algorithm with soft assignments [2]; (ii) **movMF**, the mixture of von-Mises Fisher clustering algorithm with soft assignments [2]; (iii) **SAM [S]**, SAM with topic means in $S^{11}[-1]$; and (iv) **SAM [S⁺]**, SAM with topic means in $S^{11}[-1]$. SAM with topic means in $S^{11}[-1]$ also has negative correlations between word and topics.

Figure 2 summarizes the results. SAM finds better features than the other models, and more meaningful distinctions between finer-grained topics (20% reduction in relative error for **different**; 27.8% reduction for **same**). The differences between SAM [S⁺] and SAM [S] highlight the utility of allowing topics to encode negative correlations between terms and topics, and the differences between SAM [S] and LDA suggest that generative models based on vMF distributions are a better match for text than multinomial models.
3.2 13 Natural Scene Categories

We divide the image recognition task of [6] into separate 4-class problems: \textbf{13-scene-different}, \textbf{13-scene-similar}, \textbf{13-scene-outdoor}, and \textbf{13-scene-indoor}, ordered by their classification difficulty. We follow Fei-Fei and Perona’s preprocessing steps, representing each image with counts of its \textit{visual words}. Note that this task differs fundamentally from the textual tasks in terms of sparsity: most visual words tend to occur in most scenes. Thus the comparative results obtained in this domain can be considered an ablation of SAM’s ability to model the lack of features.

Using 200 visual words, we find that SAM outperforms LDA across all scene recognition tasks (Table 3.2); 10% of the data is used for training a Logistic Regression classifier. As more training data is used, the performance of LDA and SAM converge.

4 Discussion

SAM opens up a new class of admixture models based on spherical distributions. Unlike previous spherical mixtures, SAM is a fully Bayesian admixture model that allows multiple component vMFs to explain different aspects of the data; unlike previous admixture models, SAM uses directional distributions that are parameterized by cosine distance and is therefore capable of modeling negative correlations between features as well as word absence/presence.

Using classification performance for evaluation, SAM was found to produce more relevant topic features than the movMF spherical mixture model and LDA, particularly on data where fine-grained topic distinctions are important. Two properties of SAM—its use of directional distributions, and ability to model negative correlations—were found to contribute to its performance. It is an important step in improving generative topic models.

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References


\footnote{Collapsed Gibbs sampler with full hyperparameter estimation, implemented in HBC [4]}