# TagLDA: Bringing document structure knowledge into topic models

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**Abstract**

Latent Dirichlet Allocation models a document by a mixture of topics, where each topic itself is typically modeled by a unigram word distribution. Documents however often have known structures, and the same topic can exhibit different word distributions under different parts of the structure. We extend latent Dirichlet allocation model by replacing the unigram word distributions with a factored representation conditioned on both the topic and the structure. In the resultant model each topic is equivalent to a set of unigrams, reflecting the structure a word is in. The proposed model is more flexible in modeling the corpus. The factored representation prevents combinatorial explosion and leads to efficient parameterization. We derive the variational optimization algorithm for the new model. The model shows improved perplexity on text and image data, but not significant accuracy improvement when used for classification.

## 1 Introduction

Latent Dirichlet Allocation (LDA) is a powerful topic model [1] [2]. LDA model is completely data driven. But sometimes there are certain domain knowledge one wishes

to incorporate into an LDA model. In this paper we consider domain knowledge in the form of tags on words. The tags can be quite general. For example in text documents each word can be tagged with its part-of-speech (POS), obtained from a POS tagger. In HTML web pages each word can be tagged as whether it appears on a hyperlink (anchor text), or body text. For scholarly papers there is usually a fixed structure (abstract, body, references, etc.), and each word can be tagged by the section it is in. We assume the set of tags are pre-defined and known. We also assume for each word in the corpus, its corresponding tag is given. Therefore the tags constitute domain knowledge. In this paper we do not consider higher order tags that apply to a pair or a group of words.

How should tags affect a topic model? Tags and topics can be thought of as orthogonal to each other. It is important to note that in LDA the same unigram is used throughout the document whenever a given topic is about to generate a word. But the same topic can have different word distribution under different tags. Knowing the tags should allow us to build a better model than using the topic model alone.

However the interaction between tags and topics can be subtle. On one hand, for the same topic the word distributions under different tags may be different. For instance if the tags represent part-of-speech, on a *space* topic the high probability words with a *noun* tag might be "space, shuttle, mission, launch, . . .", while those with a *verb* tag might be " make, launch, plan, schedule, . . .". On the other hand, these distributions may also be similar, depending on the nature of the tags. Consider the case where tags are section information in scholarly papers. On a *neural network chip* topic, the high probability words with an *abstract* tag might be "neural, network, chip, system, parallel, . . .", and those with a *body* tag might be "network, neural, time, chip, system, . . .".

One naive way to incorporate tags is to treat different tags separately. If we were to build a $k$-topic model without the tags, we can now build one $k$-topic model for each tag by ignoring all words in a document with other tags. Simple as it is, this approach has several shortcomings: 1. It fragments the corpus so that rare tags cannot be trained well. 2. It ignores the similarity between tags like *abstract* and *body*. 3. It results in a large number of parameters. With $k$ topics, $N_t$ different tag types and a vocabulary of size $V$, the number of parameters is $k \times N_t \times V$.

In this paper we propose *tagLDA*, a topic model which combines latent Dirichlet allocation (LDA) and tag knowledge using a factored representation. tagLDA addresses all three shortcomings above at the same time.

## 2 Representation

tagLDA model assumes the following generative process for each document $\mathbf{w}$ in a corpus $D$, given the tags $\mathbf{t}$ of the words:

1. Choose $\theta \sim \text{Dir}(\alpha)$. $\theta$ is the topic multinomial with $k$ outcomes for the document. $\text{Dir}(\alpha)$ is a Dirichlet distribution with hyperparameter $\alpha$.

2. For word positions $n = 1 \ldots N$, with tag $t_n$:

   (a) Choose a topic $z_n \sim \text{Multinomial}(\theta)$.

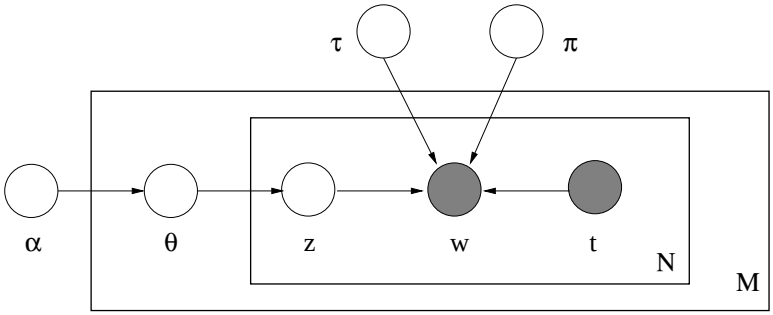



Figure 1: Graphical model representation of tagLDA. The outer plate represents documents, the inner plate represents words. The dark nodes are observed variables.

(b) Choose a word $w_n \sim P(w_n|z_n, t_n, \tau, \pi)$, a word multinomial with $V$ outcomes.

As in standard LDA, the dimensionality $k$ of the Dirichlet distribution (i.e. the number of topics) is assumed given and fixed.

The key difference between the standard LDA model and the tagLDA model is how words are generated. The word probabilities are parameterized by a factored representation. $\tau$ is a $k \times V$ topic-word matrix which corresponds to the logarithm of the word multinomial parameters $\beta$ in [1]. $\pi$ is a $N_t \times V$ tag-word matrix, where $N_t$ is the number of unique tags. Given that $w_n$ is from topic $z_n$ and has tag $t_n$, the word probability is

$$P(w_n = v|z_n, t_n, \tau, \pi) \propto \exp\left(\tau_{z_n,v} + \pi_{t_n,v}\right). \tag{1}$$

The factored representation has only $(k + N_t) \times V$ parameters.

Given the set of $N$ tags $\mathbf{t}$ and parameters $\alpha, \tau, \pi$, the joint distribution of a topic mixture $\theta$, a set of $N$ topics $\mathbf{z}$, and a set of $N$ words $\mathbf{w}$ is given by:

$$p(\theta, \mathbf{z}, \mathbf{w}|\mathbf{t}, \alpha, \tau, \pi) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) p(w_n|z_n, t_n, \tau, \pi). \tag{2}$$

The marginal probability of a document is

$$p(\mathbf{w}|\mathbf{t}, \alpha, \tau, \pi) = \int p(\theta|\alpha) \left( \prod_{n=1}^{N} \sum_{z_n=1}^{k} p(z_n|\theta) p(w_n|z_n, t_n, \tau, \pi) \right) d\theta. \tag{3}$$

The marginal probability of a corpus $D$ with $M$ documents is

$$p(D|\mathbf{t}_1, \ldots, \mathbf{t}_M, \alpha, \tau, \pi) = \prod_{d=1}^{M} \int p(\theta_d|\alpha) \left( \prod_{n=1}^{N_d} \sum_{z_{dn}=1}^{k} p(z_{dn}|\theta_d) p(w_{dn}|z_{dn}, t_{dn}, \tau, \pi) \right) d\theta_d. \tag{4}$$

# 3 Variational Inference and Parameter Learning

The inference problem is to compute the posterior distribution of hidden variables $\theta, \mathbf{z}$ given *a single* document and its tags:

$$p(\theta, \mathbf{z}|\mathbf{w}, \mathbf{t}, \alpha, \tau, \pi). \tag{5}$$

Unfortunately this distribution is intractable just as in standard LDA. Like [1] we use variational inference to approximate the above posterior. We first lower bound the document marginal log likelihood with Jensen's inequality using an auxiliary distribution $q(\theta, \mathbf{z}|\gamma, \phi)$:

$$\begin{aligned}
& \log p(\mathbf{w}|\mathbf{t}, \alpha, \tau, \pi) && (6)\\
= \quad & \log \int_\theta \sum_{\mathbf{z}} p(\mathbf{w}, \theta, \mathbf{z}|\mathbf{t}, \alpha, \tau, \pi) d\theta && (7)\\
= \quad & \log \int_\theta \sum_{\mathbf{z}} \frac{q(\theta, \mathbf{z}|\gamma, \phi) p(\mathbf{w}, \theta, \mathbf{z}|\mathbf{t}, \alpha, \tau, \pi)}{q(\theta, \mathbf{z}|\gamma, \phi)} d\theta && (8)\\
\geq \quad & \int_\theta \sum_{\mathbf{z}} q(\theta, \mathbf{z}|\gamma, \phi) \left(\log p(\mathbf{w}, \theta, \mathbf{z}|\mathbf{t}, \alpha, \tau, \pi) - \log q(\theta, \mathbf{z}|\gamma, \phi)\right) d\theta && (9)\\
\equiv \quad & L(\gamma, \phi; \alpha, \tau, \pi). && (10)
\end{aligned}$$

We choose a particular form for the auxiliary distribution

$$q(\theta, \mathbf{z}|\gamma, \phi) = q(\theta|\gamma) \prod_{n=1}^{N} q(z_n|\phi_n), \tag{11}$$

where $\gamma$ is a Dirichlet parameter vector of length $k$, and $\phi$ is a $N \times k$ matrix whose rows are topic multinomials.

## 3.1 The variational distribution

The lower bound (10) can be written as

$$\begin{aligned}
& L(\gamma, \phi; \alpha, \tau, \pi) && (12)\\
= \quad & \mathrm{E}_q[\log p(\mathbf{w}, \theta, \mathbf{z}|\mathbf{t}, \alpha, \tau, \pi)] - \mathrm{E}_q[\log q(\theta, \mathbf{z}|\gamma, \phi)] && (13)\\
= \quad & \mathrm{E}_q[\log p(\theta|\alpha)] + \mathrm{E}_q[\log p(\mathbf{z}|\theta)] + \mathrm{E}_q[\log p(\mathbf{w}|\mathbf{z}, \tau, \pi)] \\
& -\mathrm{E}_q[\log q(\theta)] - \mathrm{E}_q[\log q(\mathbf{z})], && (14)
\end{aligned}$$

which is the same as eq (14) in [1] except the third term. The third term is:

$$
\begin{aligned}
& \mathrm{E}_q \left[\log p(\mathbf{w}|\mathbf{z}, \tau, \pi)\right] && (15)\\
= \; & \mathrm{E}_q \left[\log \prod_{n=1}^{N} p(w_n|z_n, \tau_{z_n}, \pi_{t_n})\right] && (16)\\
= \; & \mathrm{E}_q \left[\sum_{n=1}^{N} \log \frac{\exp(\tau_{z_n,w_n} + \pi_{t_n,w_n})}{\sum_{v=1}^{V} \exp(\tau_{z_n,v} + \pi_{t_n,v})}\right] && (17)\\
= \; & \mathrm{E}_q \left[\sum_{n=1}^{N} \left(\tau_{z_n,w_n} + \pi_{t_n,w_n} - \log \sum_{v=1}^{V} \exp(\tau_{z_n,v} + \pi_{t_n,v})\right)\right] && (18)\\
= \; & \sum_{n=1}^{N} \mathrm{E}_q \left[\tau_{z_n,w_n} + \pi_{t_n,w_n}\right] - \sum_{n=1}^{N} \mathrm{E}_q \left[\log \sum_{v=1}^{V} \exp(\tau_{z_n,v} + \pi_{t_n,v})\right]. && (19)
\end{aligned}
$$

Because of the log-sum-exp in the second term of (19), parameter learning for $\tau, \pi$ is difficult. Following the technique used in [3], we upper bound the second term of (19) with $N$ more variational parameters $\zeta_n$. We make use of the inequality

$$\log(x) \leq \zeta^{-1} x + \log(\zeta) - 1, \forall \zeta > 0, \tag{20}$$

which gives

$$
\begin{aligned}
& \sum_{n=1}^{N} \mathrm{E}_q \left[\log \sum_{v=1}^{V} \exp(\tau_{z_n,v} + \pi_{t_n,v})\right] && (21)\\
\leq \; & \sum_{n=1}^{N} \mathrm{E}_q \left[\zeta_n^{-1} \left(\sum_{v=1}^{V} \exp(\tau_{z_n,v} + \pi_{t_n,v})\right) + \log \zeta_n - 1\right] && (22)\\
= \; & \sum_{n=1}^{N} \left[\zeta_n^{-1} \left(\sum_{v=1}^{V} \mathrm{E}_{q(z_n)} \left[\exp(\tau_{z_n,v} + \pi_{t_n,v})\right]\right) + \log \zeta_n - 1\right] && (23)\\
= \; & \sum_{n=1}^{N} \left[\zeta_n^{-1} \left(\sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{ni} \exp(\tau_{i,v} + \pi_{t_n,v})\right) + \log \zeta_n - 1\right]. && (24)
\end{aligned}
$$

Putting everything together, we obtain a lower bound $L2$ on the original lower bound $L$:

$$
\begin{aligned}
& L(\gamma, \phi; \alpha, \tau, \pi) && (25)\\
= \; & \mathrm{E}_q[\log p(\theta|\alpha)] + \mathrm{E}_q[\log p(\mathbf{z}|\theta)] \\
& + \mathrm{E}_q[\log p(\mathbf{w}|\mathbf{z}, \tau, \pi)] \\
& - \mathrm{E}_q[\log q(\theta)] - \mathrm{E}_q[\log q(\mathbf{z})] && (26)\\
\geq \; & \mathrm{E}_q[\log p(\theta|\alpha)] + \mathrm{E}_q[\log p(\mathbf{z}|\theta)] \\
& + \sum_{n=1}^{N} \mathrm{E}_q\left[\tau_{z_n, w_n} + \pi_{t_n, w_n}\right] - \sum_{n=1}^{N} \left[ \zeta_n^{-1} \left( \sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{ni} \exp(\tau_{i,v} + \pi_{t_n,v}) \right) + \log \zeta_n - 1 \right] \\
& - \mathrm{E}_q[\log q(\theta)] - \mathrm{E}_q[\log q(\mathbf{z})] && (27)\\
= \; & \log \Gamma(\sum_{j=1}^{k} \alpha_j) - \sum_{i=1}^{k} \log \Gamma(\alpha_i) + \sum_{i=1}^{k} (\alpha_i - 1)(\Psi(\gamma_i) - \Psi(\sum_{j=1}^{k} \gamma_j)) \\
& + \sum_{n=1}^{N} \sum_{i=1}^{k} \phi_{ni} (\Psi(\gamma_i) - \Psi(\sum_{j=1}^{k} \gamma_j)) \\
& + \sum_{n=1}^{N} \sum_{i=1}^{k} \phi_{ni} (\tau_{i, w_n} + \pi_{t_n, w_n}) - \sum_{n=1}^{N} \left[ \zeta_n^{-1} \left( \sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{ni} \exp(\tau_{i,v} + \pi_{t_n,v}) \right) + \log \zeta_n - 1 \right] \\
& - \log \Gamma(\sum_{j=1}^{k} \gamma_j) + \sum_{i=1}^{k} \log \Gamma(\gamma_i) - \sum_{i=1}^{k} (\gamma_i - 1)(\Psi(\gamma_i) - \Psi(\sum_{j=1}^{k} \gamma_j)) \\
& - \sum_{n=1}^{N} \sum_{i=1}^{k} \phi_{ni} \log \phi_{ni} && (28)\\
\equiv \; & L2(\gamma, \phi, \zeta; \alpha, \tau, \pi). && (29)
\end{aligned}
$$

The lower bound $L2$ is a function of the variational parameters $\gamma, \phi, \zeta$ – one finds the optimal $\gamma, \phi, \zeta$ to maximize it. The combined lower bound $L2$ on the whole corpus $D$ is then viewed as a function of the model parameters $\alpha, \tau, \pi$, which are optimized holding the variational parameters fixed. Variational parameter learning and model parameter learning proceed alternatively to improve $L2$.

We use the variational distribution $q(\theta, \mathbf{z}|\gamma, \phi)$ to approximate the true posterior distribution $p(\theta, \mathbf{z}|\mathbf{w}, \mathbf{t}, \tau, \pi)$ for inference. Notice the variational distribution is w.r.t. the maximizing variational parameters $\gamma, \phi, \zeta$ explicitly, and model parameters $\alpha, \tau, \pi$ implicitly.

## 3.2 Variational parameter Learning

We maximize $L2$ w.r.t. the variational parameters $\gamma, \phi, \zeta$ by coordinate ascend. First we maximize $L2$ with respect to $\zeta$:

$$
\frac{\partial L2}{\partial \zeta_n} = \zeta_n^{-2} \left( \sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{ni} \exp(\tau_{i,v} + \pi_{t_n,v}) \right) - \zeta_n^{-1}. \qquad (30)
$$

Setting it to zero and we find

$$\hat{\zeta}_n = \sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{ni} \exp(\tau_{i,v} + \pi_{t_n,v}), \tag{31}$$

which is the maximum by verifying the second derivative.

Second we maximize $L2$ with respect to $\phi$. With the constraint $\sum_{j=1}^{k} \phi_{nj} = 1$ we form the Lagrangian, and take the derivative:

$$\begin{aligned} & \frac{\partial L2 + \lambda \left( \left( \sum_{j=1}^{k} \phi_{nj} \right) - 1 \right)}{\partial \phi_{ni}} \qquad (32) \\ = \quad & \Psi(\gamma_i) - \Psi(\sum_{j=1}^{k} \gamma_j) \\ & + (\tau_{i,w_n} + \pi_{t_n,w_n}) - \sum_{v=1}^{V} \zeta_n^{-1} \exp(\tau_{i,v} + \pi_{t_n,v}) \\ & - \log \phi_{ni} - 1 \\ & + \lambda. \qquad (33) \end{aligned}$$

Setting it to zero, the maximizing value is

$$\hat{\phi}_{ni} \propto \exp\left( \Psi(\gamma_i) - \Psi(\sum_{j=1}^{k} \gamma_j) + (\tau_{i,w_n} + \pi_{t_n,w_n}) - \sum_{v=1}^{V} \zeta_n^{-1} \exp(\tau_{i,v} + \pi_{t_n,v}) \right). \tag{34}$$

Finally we maximize $L2$ with respect to $\gamma$. It can be shown the maximum is at

$$\hat{\gamma}_i = \alpha_i + \sum_{n=1}^{N} \phi_{ni} \tag{35}$$

Notice the maximizing values of $\zeta, \phi, \gamma$ depend on each other. Therefore we need to iteratively optimize the three until $L2$ converges.

## 3.3 Model parameter Learning

Fixing the variational parameters $\zeta, \phi, \gamma$, the variational marginal likelihood of the corpus $D$ as a function of $\alpha, \tau, \pi$ is $L2_D = \sum_{d=1}^{M} L2_d$.

First the maximizing model parameter $\alpha$ can be found with the same linear-time Newton-Raphson algorithm in [1] A.4.2.

Then we maximize $L2_D$ with respect to $\tau$. The relevant terms in $L_D$ are:

$$\begin{aligned} & L2_{D[\tau,\pi]} \\ = \quad & \sum_{d=1}^{M} \sum_{n=1}^{N_d} \sum_{i=1}^{k} \phi_{dn,i} (\tau_{i,w_{dn}} + \pi_{t_{dn},w_{dn}}) \\ & - \sum_{d=1}^{M} \sum_{n=1}^{N_d} \left[ \zeta_{dn}^{-1} \left( \sum_{v=1}^{V} \sum_{i=1}^{k} \phi_{dn,i} \exp(\tau_{i,v} + \pi_{t_{dn},v}) \right) + \log \zeta_{dn} - 1 \right]. \qquad (36) \end{aligned}$$

The derivative with respect to $\tau_{i,v}$ is:

$$\frac{\partial L2_D}{\partial \tau_{i,v}} = \sum_{d=1}^{M}\sum_{n=1}^{N_d} \phi_{dn,i}\delta(w_{dn}, v) - \left(\sum_{d=1}^{M}\sum_{n=1}^{N_d} \zeta_{dn}^{-1}\phi_{dn,i}\exp(\pi_{t_{dn},v})\right)\exp(\tau_{i,v}), \quad (37)$$

where $\delta(x, x') = 1$ if $x = x'$, and 0 otherwise. For $v = 1 \ldots V$, setting the derivative to zero we find

$$\tau_{i,v} = \log\left(\sum_{d=1}^{M}\sum_{n=1}^{N_d} \phi_{dn,i}\delta(w_{dn}, v)\right) - \log\left(\sum_{d=1}^{M}\sum_{n=1}^{N_d} \zeta_{dn}^{-1}\phi_{dn,i}\exp(\pi_{t_{dn},v})\right). \quad (38)$$

Finally we maximize $L2_D$ with respect to $\pi$. The derivative with respect to $\pi t, v$ is:

$$\frac{\partial L2_D}{\partial \pi_{t,v}} = \sum_{d=1}^{M}\sum_{n=1}^{N_d}\sum_{i=1}^{k} \phi_{dn,i}\delta(t_{dn}, t)\delta(w_{dn}, v) - \left(\sum_{d=1}^{M}\sum_{n=1}^{N_d}\sum_{i=1}^{k} \zeta_{dn}^{-1}\phi_{dn,i}\exp(\tau_{i,v})\delta(t_{dn}, t)\right)\exp(\pi_{t,v}). \quad (39)$$

For $v = 1 \ldots V$, setting the derivative to zero we find

$$\pi_{t,v} = \log\left(\sum_{d=1}^{M}\sum_{n=1}^{N_d}\sum_{i=1}^{k} \phi_{dn,i}\delta(t_{dn}, t)\delta(w_{dn}, v)\right) - \log\left(\sum_{d=1}^{M}\sum_{n=1}^{N_d}\sum_{i=1}^{k} \zeta_{dn}^{-1}\phi_{dn,i}\exp(\tau_{i,v})\delta(t_{dn}, t)\right). \quad (40)$$

Notice $\tau$ appears in $\pi$'s maximum solution and vice versa. Therefore we iterate (38) and (40) until $\tau$ and $\pi$ converge, which happens quickly in practice.

# 4 A Toy Example

To illustrate the benefit of tagLDA, we create a toy example as follows. On a vocabulary of 9 words, we specify 3 topic parameters $\tau$ which are the upper three rows in Figure 2. We also specify 3 tag parameters $\pi$ which are the lower three rows in the same figure. These parameters are smoothed and do not contain zero.

With these parameters, we generate a corpus of 300 documents. All documents are 40 words long. For each word position, a tag is chosen with probability 0.6, 0.3, 0.1 for tags 1, 2, 3 respectively. All words in a document share the same topic, which is chosen uniformly from topics 1, 2, 3. Given tag $t$ and topic $i$, a word is generated according to the multinomial proportional to $\exp(\tau_i + \pi_t)$. Since there are three topics and three tags, nine word multinomials are possible; They are plotted in Figure 3.

For tagLDA, the input is the corpus and the tags. That is, for each word in the corpus we give the corresponding tag (1, 2, or 3) as domain knowledge to tagLDA. Therefore there are three tag parameters $\pi$ to learn. We ask tagLDA to learn three topics parameters $\tau$. tagLDA optimizes the lower bound $L2$ (29), which converges to -20816. We plot the learned parameters $\tau$ and $\pi$ in Figure 4. tagLDA is able to approximate the intended factored representation. With the learned parameters $\tau$ and $\pi$, the word posterior given a topic $i$ and tag $t$ in tagLDA is the multinomial proportional

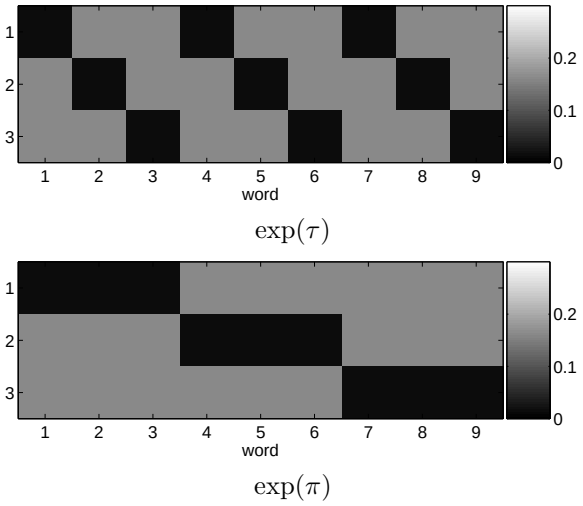



Figure 2: The original parameters $\tau$, $\pi$ used to generate the toy corpus

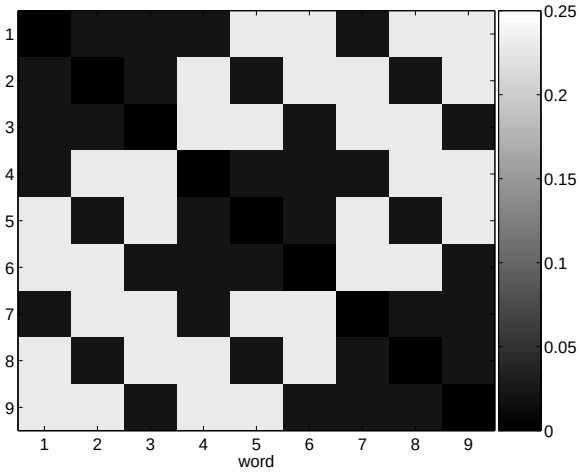



Figure 3: The nine word multinomials out of the combination of $\tau$ and $\pi$

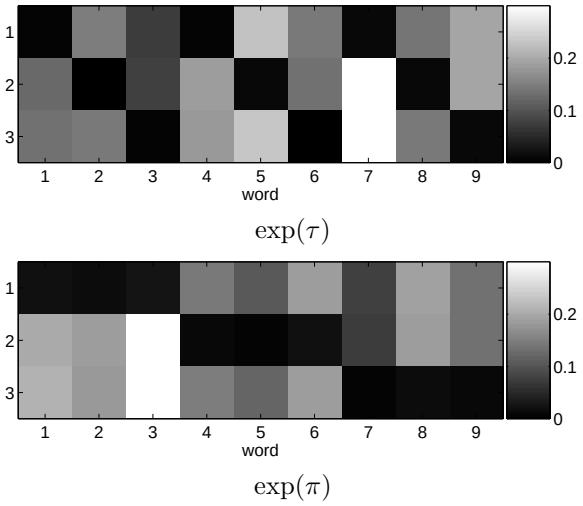



Figure 4: The parameters $\tau$, $\pi$ learned by tagLDA

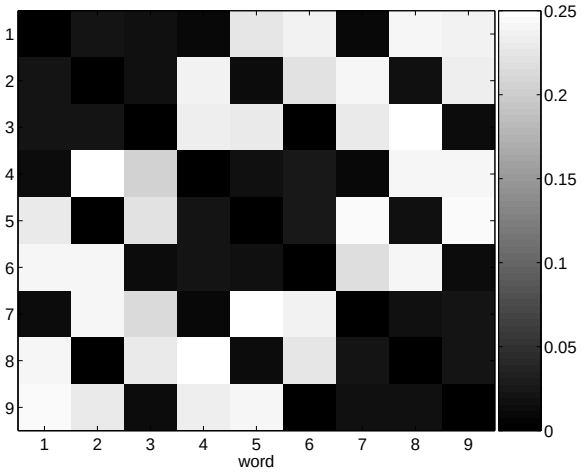



Figure 5: The nine multinomial distributions of tagLDA.

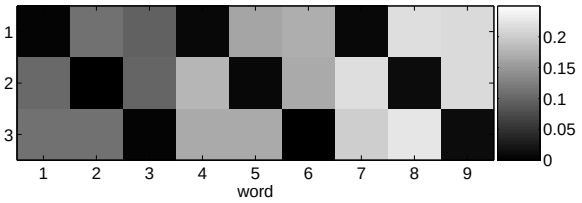



Figure 6: Topics learned by standard LDA

to $\exp(\tau_i + \pi_t)$. We show the nine multinomials in Figure 5, which are similar to Figure 3 as they should be.

We ran standard LDA on the toy example for comparison. We ask LDA to learn three topics too. LDA optimizes a variational lower bound on the log likelihood, which converges to -23414. The log likelihood bound is worse than tagLDA. We plot the topics learned by LDA in Figure 6. The topic probabilities are not uniform as those in the upper panel of Figure 2. This is because LDA attempts to explain the asymmetry introduced by uneven tag distributions.

# 5 A Small Text Corpus

We selected 45 documents from AP news [1] to form a small corpus. 15 of the documents are about politics, 15 about finance, and the remaining 15 about war. We converted all words into lower case, used a stop list of 300 words, and a frequency cutoff of 5 on the whole AP data, to obtain a vocabulary of about 10,000 words. No other preprocessing was carried out. We then ran a link parser on the documents. For this experiment, the parser was used as a part-of-speech tagger. Each word is tagged as 'noun' (n), 'verb' (v) or 'other' (o).

Given these three kinds of tags we ran tagLDA on the 45 documents, asking for three topics. The lower bound on log likelihood, $L2$, converges to -43916. tagLDA learned topic parameters $\tau_1, \tau_2, \tau_3$ and tag parameters $\pi_n, \pi_v, \pi_o$, each is a vocabulary-sized vector. Given topic $t$ and tag $p$ the word probability is $P(w|\tau_t, \pi_p) \propto \exp(\tau_{tw} + \pi_{pw})$. We show the top 10 words with the largest probabilities in each $\tau, \pi$ combination in Figure 7. Not surprisingly, tagLDA learned to separate nouns, verbs and other words according to the tag.

As a comparison we also ran standard LDA on the 45 documents, asking for three topics. The lower bound on log likelihood converges to -51264. We show the top 10 words in each topic in Figure 8. The distinction of noun, verb, other is not present since this information is not available to standard LDA. We could have trained a three-topic LDA model separately for noun, verb and other words. This would achieve similar word distributions as tagLDA, but the number of parameters would be nine for LDA, while tagLDA uses only six parameters.

[1] The same AP corpus in the LDA distribution at http://www.cs.berkeley.edu/∼blei/lda-c/ap.tgz

| tag=n, topic=politics | | tag=n, topic=finance | | tag=n, topic=war | |
|---|---|---|---|---|---|
| 0.020710 | campaign | 0.054672 | market | 0.018956 | army |
| 0.015500 | state | 0.035832 | index | 0.015796 | hostages |
| 0.015302 | poll | 0.032898 | trading | 0.014217 | government |
| 0.014452 | convention | 0.027564 | prices | 0.014217 | gunmen |
| 0.014118 | support | 0.026186 | volume | 0.009478 | attack |
| 0.013945 | primary | 0.026184 | stock | 0.009478 | soldiers |
| 0.011902 | sen | 0.024808 | shares | 0.008760 | forces |
| 0.011052 | delegates | 0.022024 | stocks | 0.008688 | miles |
| 0.010925 | president | 0.017917 | session | 0.008688 | troops |
| 0.010201 | voters | 0.017917 | average | 0.008688 | israeli |
| tag=v, topic=politics | | tag=v, topic=finance | | tag=v, topic=war | |
| 0.027641 | going | 0.051953 | rose | 0.048936 | killed |
| 0.022763 | think | 0.033524 | came | 0.016312 | freed |
| 0.014633 | vote | 0.031971 | outnumbered | 0.014022 | told |
| 0.011381 | asked | 0.027975 | fell | 0.011845 | fighting |
| 0.011381 | brokered | 0.023978 | listed | 0.011263 | shot |
| 0.010295 | made | 0.017555 | reported | 0.010875 | opened |
| 0.009755 | see | 0.015986 | totaled | 0.010875 | died |
| 0.009755 | got | 0.015986 | traded | 0.010875 | wounded |
| 0.009755 | campaigning | 0.011989 | go | 0.009062 | go |
| 0.008650 | added | 0.011989 | led | 0.009062 | kidnapped |
| tag=o, topic=politics | | tag=o, topic=finance | | tag=o, topic=war | |
| 0.030569 | i | 0.034266 | million | 0.025995 | police |
| 0.029899 | dukakis | 0.029793 | stock | 0.019496 | two |
| 0.023104 | south | 0.026817 | dow | 0.018568 | people |
| 0.021745 | jackson | 0.026788 | exchange | 0.017639 | south |
| 0.020386 | percent | 0.022347 | unchanged | 0.013926 | red |
| 0.018133 | bush | 0.019368 | jones | 0.011141 | thursday |
| 0.017667 | gephardt | 0.017878 | big | 0.010212 | new |
| 0.016988 | dole | 0.017873 | nyse | 0.010212 | 15 |
| 0.016308 | democratic | 0.016658 | new | 0.008798 | military |
| 0.016185 | new | 0.016443 | wall | 0.008355 | i |

Figure 7: The top 10 words and their probabilities in each topic / tag combination learned by tagLDA on the small AP corpus.

| topic=politics | | topic=finance | | topic=war | |
|---|---|---|---|---|---|
| 0.013957 | i | 0.024101 | market | 0.009347 | police |
| 0.013922 | dukakis | 0.023651 | stock | 0.009347 | army |
| 0.012024 | bush | 0.015768 | index | 0.009013 | killed |
| 0.010758 | south | 0.014531 | trading | 0.007891 | two |
| 0.010441 | dole | 0.013948 | million | 0.006677 | people |
| 0.010045 | jackson | 0.012129 | prices | 0.006677 | hostages |
| 0.009492 | percent | 0.012126 | exchange | 0.006343 | south |
| 0.009492 | primary | 0.011523 | volume | 0.006009 | government |
| 0.009475 | gore | 0.010916 | shares | 0.006009 | gunmen |
| 0.008752 | campaign | 0.010916 | dow | 0.005341 | bank |

Figure 8: The top 10 words learned by standard LDA on the small AP corpus.

# 6 AP: A Larger Text Corpus

We ran tagLDA on 2243 AP news articles [2]. Again each word is tagged as noun, verb or other. The corpus has 434979 words. The vocabulary size is 10174. We asked for 50 topics. tagLDA converged in 25 iterations with log likelihood bound -2799598. We show the top 10 words from selected topics learned with tagLDA in Figure 9.

We also ran standard LDA under the same settings. LDA converged in 30 iterations with log likelihood bound -3158008. Figure 10 shows the top 10 words in the corresponding topics.

# 7 The WebKB Corpus

For the WebKB corpus [3] we used two tags: b='body text' for words in the body text of an html page, and a='anchor text' for words in a hyperlink. The corpus has 8099 html pages. Each page is treated as a document. We kept words that consists of more than one letter, converted them into lower case, and used a stopword list. The processed corpus has 1.3 million words. The vocabulary size is 9898 with a frequency cutoff. We ran tagLDA with 30 topics. tagLDA converged in 30 iterations, with a lower bound of -9674409 on log likelihood.

In Figure 11 we show the top 10 words in six selected topics, separately with the two tags. For the anchor text tag, tagLDA learns the words that frequently appear on hyperlinks, such as *postscript*, *publications*, *resume*, *tar.gz*, *slide*, *solution*, etc.

[2] The same AP corpus in the LDA distribution at http://www.cs.berkeley.edu/∼blei/lda-c/ap.tgz

[3] http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-20/www/data/webkb-data.gtar.gz

| tag=o, topic=health | | tag=n, topic=health | | tag=v, topic=health | |
|---|---|---|---|---|---|
| 0.016932 | fda | 0.017016 | patients | 0.011801 | say |
| 0.016657 | medical | 0.015987 | drug | 0.010072 | think |
| 0.016476 | dr | 0.011704 | heart | 0.009529 | done |
| 0.015216 | new | 0.010520 | health | 0.009292 | approved |
| 0.010832 | i | 0.009013 | research | 0.008741 | treated |
| 0.009916 | people | 0.008909 | children | 0.008541 | says |
| 0.009315 | last | 0.008291 | researchers | 0.008359 | tested |
| 0.008834 | federal | 0.007752 | company | 0.007660 | take |
| 0.008361 | two | 0.007538 | officials | 0.006936 | produce |
| 0.007884 | year | 0.007335 | aspirin | 0.006456 | make |
| tag=o, topic=space | | tag=n, topic=space | | tag=v, topic=space | |
| 0.025630 | nasa | 0.033668 | space | 0.018064 | made |
| 0.017886 | earth | 0.030260 | shuttle | 0.017410 | make |
| 0.014641 | two | 0.015557 | mission | 0.014456 | launch |
| 0.014353 | venus | 0.012612 | launch | 0.011008 | launched |
| 0.013671 | spacecraft | 0.010747 | time | 0.009746 | planned |
| 0.011961 | magellan | 0.009480 | rocket | 0.009159 | take |
| 0.010080 | first | 0.008723 | planet | 0.008764 | go |
| 0.009874 | mars | 0.008507 | telescope | 0.008667 | released |
| 0.009604 | space | 0.007826 | astronauts | 0.008078 | scheduled |
| 0.009204 | soviet | 0.007532 | system | 0.008002 | manned |
| tag=o, topic=iraq | | tag=n, topic=iraq | | tag=v, topic=iraq | |
| 0.053580 | iraq | 0.034619 | iraqi | 0.014466 | asked |
| 0.034202 | kuwait | 0.021629 | troops | 0.012714 | sent |
| 0.028902 | military | 0.017273 | american | 0.011458 | go |
| 0.024496 | saudi | 0.015365 | war | 0.011372 | made |
| 0.020978 | united | 0.013507 | forces | 0.010901 | held |
| 0.018748 | gulf | 0.012611 | president | 0.008841 | say |
| 0.018244 | arabia | 0.011997 | invasion | 0.008632 | invaded |
| 0.016660 | bush | 0.011673 | oil | 0.008474 | leave |
| 0.015744 | saddam | 0.011476 | defense | 0.008038 | told |
| 0.014341 | persian | 0.011141 | officials | 0.007746 | take |

Figure 9: The top 10 words and their probabilities in selected topic / tag combinations learned by tagLDA on the large AP corpus.

| topic=health | | topic=iraq | | topic=space | |
|---|---|---|---|---|---|
| 0.008081 | drug | 0.024015 | iraq | 0.016574 | space |
| 0.007592 | patients | 0.015315 | kuwait | 0.011573 | shuttle |
| 0.006566 | health | 0.014820 | iraqi | 0.009906 | nasa |
| 0.005777 | fda | 0.014201 | military | 0.008528 | earth |
| 0.005624 | heart | 0.012394 | saudi | 0.007515 | launch |
| 0.005415 | dr | 0.011004 | gulf | 0.006466 | mission |
| 0.005250 | medical | 0.009460 | united | 0.006079 | two |
| 0.005168 | new | 0.009104 | war | 0.005547 | venus |
| 0.005025 | research | 0.008582 | arabia | 0.005283 | spacecraft |
| 0.004526 | children | 0.008456 | bush | 0.005123 | time |

Figure 10: The top 10 words (and their probabilities) in selected topics learned by standard LDA on the large AP corpus.

# 8 The NIPS Corpus

We manually tagged 1602 papers from Neural Information Processing Systems (NIPS) vol. 0 – 12 [4]. We tagged each word with the section it is in. There are seven tag types:

| | |
|---|---|
| h | header, anything before abstract: title, authors, address |
| a | the abstract |
| i | the introduction section of the paper |
| b | main body of the paper |
| c | the conclusion / discussion / summary section of the paper |
| k | the acknowledgments |
| r | the references |

We kept words that consists of more than one letters, converted them into lower case, and used a stopword list. The processed corpus has 2.3 million words. The vocabulary size is 8100 with a frequency cutoff. We ran tagLDA with 30 topics. tagLDA converged in 20 iterations with a lower bound of -16099655 on log likelihood. In Figure 12 we show the top 10 words in three selected topics, with all tag combinations.

It is interesting to see the interaction between the 30 topic parameter vectors $\tau$ and 7 tag parameter vectors $\pi$ in the factored representation. First of all, some tags seem to be dominated by the topic parameter. This effect is especially prominent for tags a, i, b, c. Intuitively it is what one would expect, as the abstract, introduction, body and conclusion sections are about the same topic. Meanwhile some tags have its distinct word distribution that overwhelms the topic parameter, most noticeably tag k. All topics with tag k exhibits common acknowledgment words like 'grant, supported, thank'. Finally the tags h and r are in the middle: their word distribution is roughly a half-half combination of the topic and tag parameters. Tag h contains both topic-specific words 'neural, networks, speech, recognition' from the titles, and tag-specific words 'university, department' from the affiliations. Tag r contains similar topic-specific words, and tag-specific words 'journal, press, proc, vol'. We conclude that the factored represen-

[4] The un-tagged corpus comes from Sam Roweis at http://www.cs.toronto.edu/∼roweis/data.html

| tag=b, topic 1 | | tag=a, topic 1 | | tag=b, topic 2 | | tag=a, topic 2 | |
|---|---|---|---|---|---|---|---|
| 0.027352 | pp | 0.043408 | postscript | 0.042366 | file | 0.360304 | ps |
| 0.025519 | proceedings | 0.023498 | acm | 0.033877 | ps | 0.031480 | ftp |
| 0.025408 | conference | 0.016093 | ieee | 0.032590 | hello | 0.028412 | gz |
| 0.022164 | ieee | 0.014476 | real | 0.028990 | files | 0.027834 | tar |
| 0.019816 | acm | 0.014272 | report | 0.020195 | ftp | 0.027094 | pub |
| 0.016230 | international | 0.013964 | publications | 0.019446 | directory | 0.024495 | file |
| 0.014353 | symposium | 0.013829 | conference | 0.011910 | window | 0.022174 | directory |
| 0.014010 | vol | 0.013779 | computing | 0.011171 | public | 0.018556 | readme |
| 0.013411 | time | 0.012498 | abstract | 0.010971 | seed | 0.017426 | latex |
| 0.011079 | th | 0.012086 | technical | 0.010481 | version | 0.015414 | tex |
| tag=b, topic 3 | | tag=a, topic 3 | | tag=b, topic 4 | | tag=a, topic 4 | |
| 0.038483 | home | 0.090302 | cs | 0.044209 | lecture | 0.110431 | slide |
| 0.034131 | am | 0.065067 | edu | 0.018009 | logic | 0.105939 | lecture |
| 0.028080 | cs | 0.059314 | home | 0.016922 | tree | 0.025189 | format |
| 0.020557 | interests | 0.014164 | resume | 0.014621 | data | 0.024708 | notes |
| 0.018242 | student | 0.011802 | columbia | 0.013322 | structures | 0.024291 | slides |
| 0.017917 | edu | 0.011165 | student | 0.013154 | notes | 0.022500 | gif |
| 0.016436 | phone | 0.010680 | homepage | 0.011297 | trees | 0.016721 | logic |
| 0.014113 | fax | 0.010626 | graduate | 0.010682 | chapter | 0.015202 | cs |
| 0.012872 | office | 0.009934 | new | 0.009741 | format | 0.014314 | postscript |
| 0.012539 | last | 0.009767 | publications | 0.009087 | functions | 0.012711 | tree |
| tag=b, topic 5 | | tag=a, topic 5 | | tag=b, topic 6 | | tag=a, topic 6 | |
| 0.030285 | due | 0.080319 | postscript | 0.047212 | programming | 0.050997 | programming |
| 0.026808 | program | 0.071853 | assignment | 0.024635 | languages | 0.022725 | languages |
| 0.026076 | assignment | 0.071069 | homework | 0.019574 | language | 0.020991 | language |
| 0.015785 | homework | 0.032510 | solution | 0.015835 | design | 0.014813 | software |
| 0.011901 | problem | 0.026703 | program | 0.015237 | software | 0.013375 | program |
| 0.011669 | code | 0.025780 | solutions | 0.012700 | program | 0.012944 | design |
| 0.010428 | project | 0.023100 | cs | 0.010638 | compiler | 0.012457 | ece |
| 0.009513 | class | 0.018283 | project | 0.010404 | programs | 0.011931 | compiler |
| 0.009420 | file | 0.016141 | due | 0.010088 | object | 0.011874 | object |
| 0.009191 | assignments | 0.014712 | problem | 0.009591 | oriented | 0.011028 | cs |

Figure 11: The top 10 words (and their probabilities) in six selected topics, with b='body text' and a='anchor text' tags respectively, learned by tagLDA on WebKB corpus.

tation is appropriate for the corpus.

# 9 Perplexity

Both tagLDA and LDA models are trained unsupervised. The natural measure of performance is the log likelihood on some unseen held-out corpus. Equivalently we compute the *perplexity* on the held-out set, a conventional measure in language modeling. The perplexity is a monotonically decreasing function of the log likelihood, and can be understood as the predicted number of equally likely words for a word position on average. For a held-out set $D$ of $M$ documents the perplexity is defined as

$$\text{perplexity}(D) = \exp\left(-\frac{\sum_{d=1}^{M} \log p(\mathbf{w}_d|\mathbf{t}_d)}{\sum_{d=1}^{M} N_d}\right), \tag{41}$$

where $N_d$ is the number of words in document $d$. Note (41) computes the conditional perplexity given the tags $\mathbf{t}_d$. For LDA it reverts to $p(\mathbf{w}_d|\mathbf{t}_d) = p(\mathbf{w}_d)$ since the tag information is not used. Also note we can only compute an upper bound of the perplexity, because we lower-bound the log likelihood with variational methods for both tagLDA and LDA.

We compute and compare the perplexity of tagLDA and LDA on the AP, WebKB and NIPS corpora with aforementioned tags respectively. For each corpus we run 5 trials in which we randomly hold out 20% of the document for test, and train on the remaining 80%. We train tagLDA and LDA with the same stopping criteria. The number of topics in both models is systematically varied.

We plot the average perplexity on held-out data in Figure 13. By utilizing the tag information tagLDA has lower perplexity on all three corpora. That is, tagLDA is a better model by assigning higher likelihood to held-out documents than LDA. We also note that the reduction in perplexity strongly depends on the type of tags. Intuitively when different tags tend to mark distinctive words, perplexity reduction is large. For example the part-of-speech tags in the AP corpus mark nouns, verbs etc., and tagLDA has a 50% perplexity reduction. On the other hand when different tags mark similar words the perplexity reduction is small, as in the anchor-text / body-text tags for WebKB corpus.

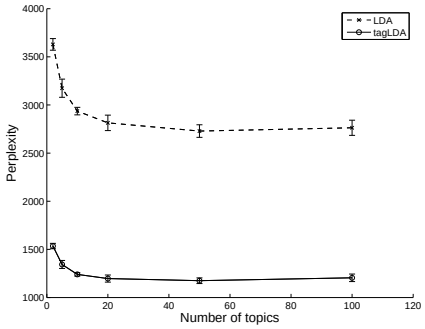
# 10 Document Classification

The 'topics' learned by tagLDA and LDA can be viewed as a concise representation of the original document. Here the topics are represented by the variational posterior vector $P(\gamma|\mathbf{w})$. One can perform document classification in a discriminative framework, by using $\gamma$ as feature vectors in a support vector machine (SVM). It should be emphasized that both tagLDA and LDA are trained with unsupervised learning, and are therefore not geared towards classification.

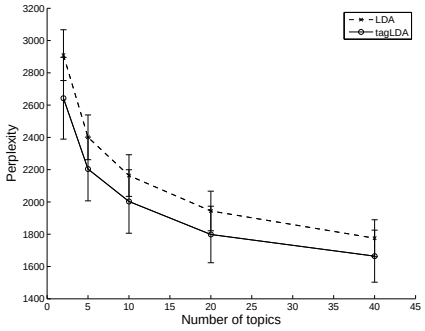
We are interested in whether the topics learned with tagLDA or LDA perform differently in classification. It is important to note that the tag information is what makes

| tag=h | a | i | b | c | k | r |
|---|---|---|---|---|---|---|
| university | eye | eye | eye | model | supported | neural |
| institute | model | head | model | system | grant | eye |
| department | system | model | head | cells | acknowledgments | visual |
| edu | abstract | system | system | head | research | journal |
| salk | head | cells | figure | eye | acknowledgements | brain |
| electrical | visual | visual | cells | direction | thank | press |
| science | cells | motor | direction | visual | foundation | motor |
| brain | motor | direction | position | motor | project | neuroscience |
| neurobiology | vor | neurons | velocity | neurons | work | movements |
| ca | neurons | sensory | map | target | eye | auditory |
| university | abstract | function | function | functions | grant | neural |
| department | networks | functions | theorem | networks | supported | networks |
| neural | functions | networks | let | function | research | pp |
| networks | neural | neural | functions | bounds | acknowledgement | theory |
| edu | function | number | bound | theorem | work | ieee |
| engineering | network | network | threshold | bound | gratefully | computation |
| science | bounds | bounds | number | results | afosr | proc |
| computer | show | paper | proof | number | thank | vol |
| ca | bound | class | case | neural | nsf | bounds |
| australia | paper | threshold | size | complexity | discussions | functions |
| recognition | recognition | recognition | training | recognition | darpa | recognition |
| speech | speech | speech | hmm | speech | work | speech |
| university | system | hmm | word | hmm | acknowledgements | neural |
| neural | hmm | system | system | system | arpa | morgan |
| street | network | training | recognition | training | research | ieee |
| department | abstract | models | network | context | thank | systems |
| systems | speaker | context | context | models | acknowledgments | networks |
| technology | context | network | speech | model | steve | pp |
| ca | models | neural | probabilities | hybrid | acknowledgement | proc |
| networks | word | model | model | network | authors | processing |

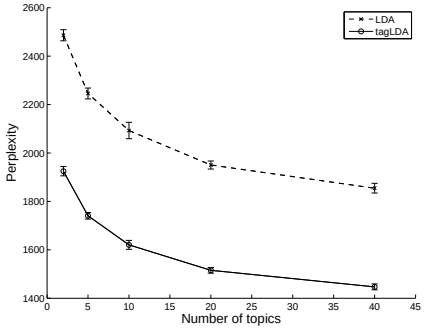
Figure 12: The top 10 words in three selected topics (the top, middle and bottom panel respectively), and with all tag combinations (the columns), learned by tagLDA on NIPS corpus.




(a) the AP corpus




(b) the WebKB corpus




(c) the NIPS corpus

Figure 13: Held-out set perplexity

tagLDA different from LDA. The tags however may or may not have direct correlation with the classification goal.

For these experiments we used the WebKB corpus with 8106 documents. We train a tagLDA and a LDA model respectively, both with 60 topics. The tags for tagLDA are 'anchor text' vs. 'body text' as mentioned before. Each document therefore is represented by a 60-dimensional $\gamma$ vector under tagLDA model, and a different 60-dimensional vector under LDA. The classification goals are the set of natural categories of WebKB data, namely whether the document is a *course*, *faculty*, *student*, or *other* web page. For simplicity we create four binary classification tasks of one category vs. the rest. We use the $SVM^{light}$ software [4] with exactly the same settings for tagLDA and LDA. We vary the proportion of training data from 10% to 70%. Figure 14 compares the classification accuracy. Each point is an average of 30 random trials (the same random split is applied to both tagLDA and LDA). For completeness we also include the accuracy where individual words are used as SVM features.

The tag of anchor/body text is not directly related to any of the classification tasks. Therefore it is interesting to note that in three out of four experiments (a – c), the tagLDA topic representation gives a small improvement over the LDA representation; but on (d) tagLDA is worse than LDA.

# 11 Image Categorization

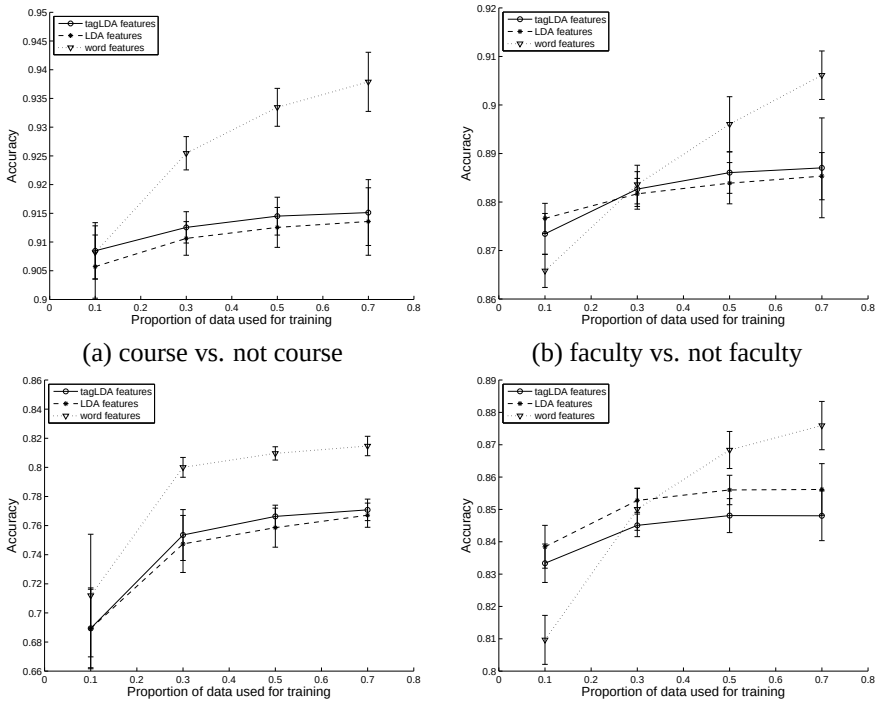
We use the image dataset from [5], which contains 13 categories of natural scenes and a total of 3859 images. Each image is gray-scale. The average size of an image is about $250 \times 300$ pixels. Image patches are sampled at an evenly spaced grid of $10 \times 10$ pixels. The patches have side lengths randomly between 10 to 30 pixels. Each patch is then resized to $11 \times 11$ pixels. The histogram of each patch is stretched over the whole range.

We randomly split the images into a training set and a test set. Each scene category has 100 training images and the rest are test images. In total there are 1300 training images and 2559 test images.

We learn a codebook by randomly sampling 2% of the patches from a random half of the training set. We run k-means algorithm on the sampled patches to generate $V$ clusters. We use the Euclidean distance between patches. The $V$ cluster centers are then used as codewords. In the experiments we used $V = 200$ and 1600 respectively. With the codebook, all images are converted into a bag-of-patch representation, where each patch is quantized to its closest codeword.

For tagLDA we tag each patch by its vertical position in the image. This is motivated by the intuition that many images show vertical inhomogeneity. Specifically we divide an image evenly into four parts along its height. A patch is tagged by the part its top-left corner falls into.

We note that both LDA and tagLDA are unsupervised learning models. They are used only to generate feature vectors. We separately train a LDA and a tagLDA model on the 1300 training images *without using the labels*. This is different from [5], who use a supervised variant of the LDA model that incorporates the labels. In all experiments we use 40 topics. We then perform inference on the test images. Table 1 lists the test set




(a) course vs. not course

(b) faculty vs. not faculty

(c) other vs. not other

(d) student vs. not student

Figure 14: Classification accuracy on WebKB data with different proportions of training data.

| codebook $V$ | LDA | tagLDA |
|---|---|---|
| 200 | 130.0 | 126.0 |
| 1600 | 575.1 | 555.5 |

Table 1: Perplexity on test images for LDA and tagLDA

| codebook $V$ | kernel | bag-of-patch | LDA $\gamma$ | tagLDA $\gamma$ |
|---|---|---|---|---|
| 200 | linear | 58.8% | 53.0% | 53.0% |
| | poly3 | 63.0% | 57.3% | 55.4% |
| 1600 | linear | 60.9% | 56.2% | 56.8% |
| | poly3 | 66.1% | 58.6% | 58.0% |

Table 2: Accuracies on test images using $SVM^{light}$

perplexity. Similar to text tasks, tagLDA gives lower perplexity (i.e. higher predicted probability) on test images than LDA.

We use the inferred posterior variational Dirichlet parameters $\gamma$ (a $40$-vector) as a reduced feature representation for each image. Note the original bag-of-patch representation has $V = 200$ or $1600$ features. Thus the $\gamma$ representation achieves 80% and 97.5% feature reduction.

For classification, we compare the performance of $SVM^{light}$ under the three feature representations: bag-of-patch raw counts (200 or 1600 dimensions), LDA $\gamma$ vector (40 dimensions), and tagLDA $\gamma$ vector (40 dimensions). We train the SVMs on the training set and test them on the test set with one-vs-all for 13-class classification. For each feature representation, we use a linear kernel and a cubic (poly3) kernel $K(x, y) = (x^\top y + 1)^3$ respectively. Table 2 lists the test set accuracies. We observe that:

- A larger codebook is better.
- Raw bag-of-patch features are better than the reduced LDA and tagLDA $\gamma$ features when using SVM. This is consistent with the text classification experiments in the previous section.
- LDA and tagLDA $\gamma$ features perform similarly for classification. This is disappointing, but also consistent with previous text classification experiments.
- We achieve 66.1% accuracy with 1600 codewords, simple bag-of-patch features, and SVM poly3 kernel. This is comparable to the 64.0% accuracy reported in [5] with a LDA-like theme model. We suspect the fact that SVM is a discriminative model while theme model is generative might have played a role, since it is known that discriminative models tend to yield better classification accuracies.

## 12 Discussions

We introduced tagLDA model, a factored representation that models the structure of a document. In experiments tagLDA is better than LDA in terms of test set perplexity. But there is no significant advantage when tagLDA is used for classification.

TagLDA is only the first step towards incorporating domain knowledge into topic models. There are several future directions:

- Allowing unknown tags for some of the words.
- Allowing multiple tags per word.
- Extending tagLDA to express higher order domain knowledge. The tags describe knowledge on individual words. An obvious extension is to use links that describe knowledge on pairs of words, for example those obtained using a link parser.

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