Partially Labeled Topic Models for Interpretable Text Mining

Daniel Ramage  
Computer Science Dept.  
Stanford University  
Stanford, California  
dramage@cs.stanford.edu

Christopher D. Manning  
Computer Science Dept.  
Stanford University  
Stanford, California  
manning@cs.stanford.edu

Susan Dumais  
Microsoft Research  
Redmond, Washington  
sdumais@microsoft.com

ABSTRACT

Much of the world’s electronic text is annotated with human-interpretable labels, such as tags on web pages and subject codes on academic publications. Effective text mining in this setting requires models that can flexibly account for the textual patterns that underlie the observed labels while still discovering unlabeled topics. Neither supervised classification, with its focus on label prediction, nor purely unsupervised learning, which does not model the labels explicitly, is appropriate. In this paper, we present two new partially supervised generative models of labeled text, Partially Labeled Dirichlet Allocation (PLDA) and the Partially Labeled Dirichlet Process (PLDP). These models make use of the unsupervised learning machinery of topic models to discover the hidden topics within each label, as well as unlabeled, corpus-wide latent topics. We explore applications with qualitative case studies of tagged web pages from del.icio.us and PhD dissertation abstracts, demonstrating improved model interpretability over traditional topic models. We use the many tags present in our del.icio.us dataset to quantitatively demonstrate the new models’ higher correlation with human relatedness scores over several strong baselines.

Categories and Subject Descriptors

H.2.8 [Database Applications]: Data mining; I.2.7 [Natural Language Processing]: Text analysis

General Terms

Algorithms, Experimentation

1. INTRODUCTION

The world’s text is increasingly created and consumed electronically, providing opportunities for tools to help make sense of that text. As web technologies have evolved, the amount of human-provided annotations on that text has grown, too, becoming a source of information our text mining tools should not ignore. In this paper, we address a set of related challenges presented by such datasets. How can we understand and interpret the meaning of labels and the different ways they are used? Can we model the labels while simultaneously uncovering topics in the dataset that are not labeled? Can we discover which words in documents should be attributed to which of the documents’ labels? Or to none at all? We take these challenges as examples of partially supervised text mining, in which models discover textual topics in a corpus that contains some labels, although those labels may not be the primary object of study.

This form of partially supervised learning straddles the boundary between unsupervised learning, in which models discover unmarked statistical relationships in the data, and supervised learning, which emphasizes the relationship between word features and a given space of labels for the purpose of classifying new documents. Popular unsupervised approaches like Latent Dirichlet Allocation [5], Latent Semantic Indexing [11] and related methods [20, 3] are well suited for exploratory text analysis—e.g. [13]—but most of these models do not account for the label space. When they do, it is usually to improve the quality of a shared set of latent topics—such as in [19, 4, 16, 17, 34, 23]—rather than to directly model the contents of the provided labels. As a result, practitioners face challenges in interpreting what these topics really mean, how they should be named, and to what extent trends based on them can be trusted in qualitative applications. While unsupervised topics are successful in capturing broad patterns in a document collection, the learned topics do not, in general, align with human provided labels.

In contrast, supervised learning and (multi-) label prediction explicitly model the label space for the purpose of prediction (such as in [12, 18]), but by design do not discover latent sub-structure or other latent patterns. Other learning formulations exist in the space between supervised learning and unsupervised learning, most notably semi-supervised learning [10], in which the goal is to improve label classification performance by making use of unsupervised data [35]. Another, similar learning paradigm is semi-supervised clustering—such as [2, 33]—in which some supervised information is used to improve an unsupervised task. Usually this information comes in the form of human-provided pair-wise similarity/dissimilarity scores or constraints. As a result, these approaches can be used effectively for label prediction or document clustering, but do not lend themselves to more fine-grained questions about how the terms and label space interact. By contrast, the partially supervised approach pursued here is explicitly designed to im-
prove upon the exploratory and descriptive analyses that draw practitioners to unsupervised topic models to begin with—i.e. to discover and characterize the relationships between patterns, but with the added ability to constrain those patterns to align with label classes that are meaningful to people.

Our approach to the challenges of partially supervised text mining is through methods that make use of the unsupervised learning machinery of topic modeling, but with constraints that align some learned topics with a human-provided label. In this paper, we introduce two models, unifying and generalizing the popular unsupervised topic model, Latent Dirichlet Allocation (LDA) [5] as well as the multinomial naive Bayes supervised text classifier’s event model [28] and the more recent multi-label generative model Labeled LDA [27]. As in LDA, Partially Labeled Dirichlet Allocation (PLDA), assumes that each document’s words are drawn from a document-specific mixture of latent topics, where each topic is represented as a distribution over words. Unlike LDA, PLDA assumes that each document can use only those topics that are in a topic class associated with one or more of the document’s labels. In particular, we introduce one class (consisting of multiple topics) for each label in the label set, as well as one latent class that applies to all documents. This construction allows PLDA to discover large-scale patterns in language usage associated with each individual label, variations of linguistic usage within a label, and background topics not associated with any label. A parallel learning and inference algorithm for PLDA allows it to scale to large document collections. Our second model, the Partially Labeled Dirichlet Process (PLDP), extends PLDA by incorporating a non-parametric Dirichlet process prior over each class’s topic set, allowing the model to adaptively discover how many topics belong to each label, at the expense of parallelizability. We evaluate our approach qualitatively on PhD dissertation abstracts and quantitatively on a document-similarity task derived from tagged web pages on del.icio.us.

Related work

Recently, researchers in the topic modeling community have begun to explore new ways of incorporating meta-data and hierarchy into their models, which is the approach to partially supervised text mining that we take here. For instance, Markov Random Topic Fields [16] and Markov Topic Models [32] both allow information about document groups to influence the learned topics. There has also been a great amount of work on simultaneously modeling relationships among several variables, such as authors and topics in the Author-Topic model [28], tags and words in [29], and topics sentiment in [21]. All of these models assume a latent topic space that is influenced by external label information of some form. By contrast, we use topics to model the substructure of labels and unlabeled structure around them. Other ways to constrain and exploit topic models for text mining tasks include recent work in mining product reviews [8] or lead and sentiment in [21].

In our formalization of partially supervised text mining, we are given a collection of documents D, each containing a multi-set of words \( w_d \) from a vocabulary \( V \) of size \( V \) and a set of labels \( L_d \) from a space of labels \( L \). We would like to recover a set of topics \( \Phi \) that fit the observed distribution of words in the multi-labeled documents, where each topic is a multinomial distribution over words \( V \) that tend to co-occur with each other and some label \( l \in L \). Latent topics that have no associated label are optionally modeled by assuming the existence of a background latent label \( l \), that is applied to all documents in the collection.

In the sections below, we define PLDA and PLDP, both of which assume that the word \( w \) at position \( i \) in each document \( d \) is generated by first picking a label \( l \) from \( L_d \) and then a topic \( z \) from the topic indexed \( \Phi_{l,z} \). In this way, both PLDA and PLDP can be used for \textit{credit attribution} of words to labels by examining the posterior probability over labels for a particular word instance. Both PLDA and PLDP are generative probabilistic graphical models, and so for each we will use an approximate inference algorithm to re-construct the per-document mixtures over labels and topics, as well as the set of words associated with each label. By incorporating the latent class of topics in addition to the label classes, the model effectively forces each word to decide if it is better modeled by a broad, latent topic, or a topic that applies specifically to one of its document’s labels.

2. PARTIALLY SUPERVISED MODELS

In our formalization of partially supervised text mining, we are given a collection of documents \( D \), each containing a multi-set of words \( w_d \) from a vocabulary \( V \) of size \( V \) and a set of labels \( L_d \) from a space of labels \( L \). We would like to recover a set of topics \( \Phi \) that fit the observed distribution of words in the multi-labeled documents, where each topic is a multinomial distribution over words \( V \) that tend to co-occur with each other and some label \( l \in L \). Latent topics that have no associated label are optionally modeled by assuming the existence of a background latent label \( l \), that is applied to all documents in the collection.

In the sections below, we define PLDA and PLDP, both of which assume that the word \( w \) at position \( i \) in each document \( d \) is generated by first picking a label \( l \) from \( L_d \) and then a topic \( z \) from the topic indexed \( \Phi_{l,z} \). In this way, both PLDA and PLDP can be used for \textit{credit attribution} of words to labels by examining the posterior probability over labels for a particular word instance. Both PLDA and PLDP are generative probabilistic graphical models, and so for each we will use an approximate inference algorithm to re-construct the per-document mixtures over labels and topics, as well as the set of words associated with each label. By incorporating the latent class of topics in addition to the label classes, the model effectively forces each word to decide if it is better modeled by a broad, latent topic, or a topic that applies specifically to one of its document’s labels.
2.1 Partially Labeled Dirichlet Allocation

Partially Labeled Dirichlet Allocation (PLDA) is a generative model for a collection of labeled documents, extending the generative story of LDA [5] to incorporate labels, and of Labeled LDA [27] to incorporate per-label latent topics. Formally, PLDA assumes the existence of a set of $L$ labels (indexed by $1..L$), each of which has been assigned some number of topics $K_l$ (indexed by $1..K_l$) and where each topic $\psi_{l,k}$ is represented as a multinomial distribution over all terms in the vocabulary $\mathcal{V}$ drawn from a symmetric Dirichlet prior $\eta$. One of these labels may optionally denote a latent topic for each word. For derivational simplicity, we define the element at position $\ell$ of $\psi_{l,k}$ is represented as a multinomial distribution because each label has its own distinct subset of topics, the topic assignment alone is sufficient to determine which label was assigned, so there is no need to represent $\ell$ explicitly in order to compute $n_{d,j,k}$.

Now let's return to the computation of $P(\bar{\ell}|\bar{\alpha},\gamma,\alpha)$, which, because $\bar{\alpha}$ is considered observed, can be factorized into:

$$P(\bar{\ell}|\bar{\alpha},\gamma,\alpha) = \prod_{\ell=1}^{\bar{l}} \prod_{j=1}^{\bar{j}} P(\psi_{d,j}|\alpha,\Lambda) \prod_{d=1}^{D} \prod_{i=1}^{n_d} P(\phi_{d,i}|\alpha,\psi_d)$$

By re-indexing over label types, and applying the standard Dirichlet prior and Dirichlet-multinomial integral to get our final probability $P(\bar{\ell}|\bar{\alpha},\gamma,\alpha) = \prod_{\ell=1}^{\bar{l}} \prod_{j=1}^{\bar{j}} \frac{\Delta(\bar{\alpha},\gamma)}{\Delta(\bar{\alpha},\gamma)}$.

Observing that the actual values of $\bar{\ell}$ are never used explicitly, and because every topic takes part in only a single label, we can represent the model using a Gibbs sampler tracking only the topic assignments $\bar{z}$. We do not need to allocate memory to represent which label $\bar{l}$ is assigned to each token. After combining terms, applying Bayes rule, and folding terms into the proportionality constant, the sampling update formula for assigning a new label and topic to a word token is defined as follows:

$$P(\bar{l}_d, \bar{z}_d, k | \bar{l}_{-d,i}, \bar{z}_{-d,i}, w_{d,i} = t; \alpha, \eta)$$

$$\propto \prod_{j \in \Lambda_d} \prod_{k \in 1..K_j} \left( \begin{array}{c} n_{d,j,k} + \eta \left( n_{d,-j,k} + \frac{1}{\alpha} \right) + \alpha \left( n_{d,-j,k} + \sum_{j' \in \Lambda_d} \alpha_{j'} \right) \end{array} \right)$$

The notation $n_{d,j,k}$ refers to the corresponding count excluding the current assignment of topic $z$ and label $l$ in document $d$ position $i$. Here we have used the definition of $\alpha_{j,k}$ at position $j$ is $K_j$, which allows the numerator in the second fraction to cancel the denominator in the last term. Because the denominator in the second fraction is independent of the topic and label assignment, it is folded into the proportion-
EQUATION 3. Efficient computation of the counts algorithm can be developed for estimating the hidden param-
tritional approximation to the LDA objective as described in and inference algorithm for PLDA based on the CVB0 vari-
histograms. However, Gibbs sampling is inherently sequen-
ting the development of the models in this paper.

Learning and Inference. An efficient Gibbs sampling al-
gorithm can be developed for estimating the hidden param-
eters in PLDA based on the collapsed sampling formula in Equation 3. Efficient computation of the counts n can be
done by keeping histograms over the number of times each
term has been associated with each topic within each doc-
ument and how often each topic has been associated with
each term. The sampler loops over the corpus, re-assigning
topic assignment variables z and updating the corresponding
histograms. However, Gibbs sampling is inherently sequen-
tial and we would like this model scale to the size of modern
web collections, so we developed a parallelizable learning and inference algorithm for PLDA based on the CVB0 vari-
ational approximation to the LDA objective as described in
[1]. For each word at position i in each post d, we store a dis-
tribution γd,i over the likelihood that each label and topic
generated that word in that document using the normal-
ized probabilities from the Gibbs sampling update formula in
Equation 3. These distributions are summed into frac-
tional counts of how often each word is paired with each
topic and label globally, denoted #d,j,k and how often each label appears in an each document, denoted #d,j,k. The
algorithm alternates between assigning values to γd,i,j,k and
then summing assignments in a counts phase. The update
equations are listed below. Initially, we use small random
values to initialize #d,j,k,w and #d,j,k.

Assign:

(\gamma_{d,i,j,k} \propto I[j \in \Lambda_d, k \in 1..K] \cdot \frac{\#d,j,k,w + \gamma_{d,i,j,k} + \eta}{\#d,j,k - \gamma_{d,i,j,k} + \alpha})

Count:

\#d,j,k = \sum_{w} \gamma_{d,i,j,k}
\#j,k,w = \sum_{d,i} \gamma_{d,i,j,k} \cdot I[w_{d,i} = w]
\#j,k = \sum_w \#j,k,w

The references to \gamma_{d,i,j,k} on the right side of the propor-
tionality in the assignment phase refer to the value at
the previous iteration. This formulation allows for a data-
parallel implementation, by distributing documents across a
cluster of compute nodes. Assignments are done in parallel
on all nodes based on the previous counts #d,j,k, #j,k,w and
#j,k (initially small random values). The resulting assign-
ments \gamma_{d,i,j,k} are then summed in parallel across all compute
nodes in a tree sum, before being distributed to all compute
nodes for a new assignments phase. The process repeats
until convergence. Like in [1], we find that the CVB0 learn-
ing and inference algorithm converges more quickly than
the Gibbs sampler to a solution of comparable quality. In
practice, we find that this algorithm scales to very large
datasets—experiments on a corpus of one million PhD dis-
sertation abstracts resulted in models that trained in less
than a day on a cluster of twelve 4-core machines.

2.2 Partially Labeled Dirichlet Process

PLDA provides a great deal of flexibility in defining the
space of latent topics to effectively learn latent topics both
within labels and in a common background space. Unfortu-
nately, PLDA introduces an important new parameter for
each label, \kappa_1, representing the number of topics available
within each label’s topic class. Fortunately, non-parametric
statistical techniques can help estimate an appropriate size
for each per-label topic set automatically. Concretely, we
replace PLDA’s per-label topic mixture \theta_i with a Dirichlet
process mixture model [24], which can be seen as the in-
finite limit of the finite mixture of topics per label used in
PLDA. Formally, PLDP assumes a generative process simi-
lar to PLDA, with a multi-set of words \omega_d for each document
and an observed set of labels \Lambda_d. Like in PLDA, each word
\omega_d.i has an associated label variable l_d,i and topic variable
z_d,i. Here, the label l_d,i is drawn from a document-specific
multinomial over labels, which for efficiency we assume is
drawn from a symmetric Dirichlet prior with parameter \alpha.
To generate a topic assignment z_d,i, PLDP picks an exist-
ting topic within label l_d,i for word \omega_d.i in proportion to
how often it is used, or generates a new topic with held-out
mass parameter \alpha (the same as the Dirichlet prior for the
document-specific multinomial over labels). The word \omega_d.i,
is then generated according to the topic distribution \phi_{l_d,i,z_d,i},
as in PLDA. The Gibbs sampling formula for updating the
joint label and topic assignment l_d,i and z_d,i in PLDP is:

\begin{align}
P(l_d,i = j, z_d,i = k | l_d,i_z, w_{d,i}) & \propto \frac{\frac{n_{(d,i),j,k}}{n_{(d,i),j,k} + V\eta} \frac{n_{(d,i),w_{d,i}}}{n_{(d,i),w_{d,i}} + \alpha | \Lambda_d}}{n_{(d,i),j,k} + V\eta} \\
& \quad \quad \times \begin{cases} \frac{\gamma_{d,j,k}}{\alpha} & \text{for } k \text{ existing} \\ 1 & \text{for } k \text{ new} \end{cases} \\
& \quad \quad \times \begin{cases} \frac{\gamma_{d,j,k}}{\alpha} & \text{for } k \text{ existing} \\ 1 & \text{for } k \text{ new} \end{cases}
\end{align}

As in the Gibbs expression for PLDA in Equation 3, we
cancel the numerator in the second fraction with the de-
nominator in both versions of the final term. Again, the
denominator in the second fraction is independent of label
and topic assignments, so it is folded into the proportionality
constant. The Gibbs re-assignment parameters in Equation
4, paired with data structures updated to reflect the
appropriate counts of interest at reassignment, can be used to
to create an efficient Gibbs sampling algorithm for the Par-
tially Labeled Dirichlet Process. Unfortunately, the embed-
ded Dirichlet process mixture model complicates the paral-
lelizability of learning and inference in this model.

It is worth noting that PLDP’s embedding of the Dirichlet
Process is, in some ways, an even more natural fit than in
standard topic modeling applications such as the Hierarchi-
cal Dirichlet Process [30]. HDPs and related models discover
a global set of latent topics within a corpus as a function of
both the concentration parameter \( \alpha \) and the corpus being
analyzed. So for a known corpus of interest, text mining
practitioners still have a single parameter to choose—instead
of picking the number of topics, they pick a concentration
parameter. In practice, this is often no easier than picking
the number of topics directly. In contrast, for PLDP, a single
DP concentration parameter \( \alpha \) selects the number of topics
for each label in \( L \), effectively reducing the number of model
parameters related to topic cardinality from \( |L| \) to one, \( \alpha \).

3. CASE STUDIES

We illustrate applications of PLDA and PLDP to partially
supervised text mining tasks on two kinds of labeled corpora
with very different distributional properties: PhD disserta-
tion abstracts annotated with subject code designations and
tagged web pages from del.icio.us. Our PhD dissertation
data set contains over 1 million United States PhD disserta-
tion abstracts from the ProQuest UMI database\(^1\), averaging
about just over 2 subject codes from a controlled vocabulary
of roughly 260 codes curated by ProQuest staff. These sub-
ject codes correspond to high-level field designations such as
biochemistry, public administration, cultural anthropology,
etc. Each document contains 179 non-stop words on aver-
age, corresponding to about two paragraphs of text from
each abstract. Our del.icio.us dataset is a subset of 3,200
popular, heavily tagged documents from the Stanford Tag
Crawl Dataset [15] collected in the Summer of 2007, with
an average length of 1263 words from a word vocabulary
of 321,062 terms, and an average of 122 distinct tags out of a
vocabulary of 344,540 tags.

These datasets have very different distributional statistics,
both in terms of the underlying texts and the label spaces.
The del.icio.us documents are longer and have high overlap
in common tags, whereas the dissertations tend to be shorter
and carefully filed in a small number of subjects. In the
following subsections, we examine these datasets from the
partially supervised text mining perspective, finding that,
despite their differences, both datasets can be effectively
modeled. Because of the size of the dissertation dataset
in the case study below, we focus on qualitative results that
can be achieved through our parallelized PLDA model. Be-
cause of the smaller size of the del.icio.us data, we use the
del.icio.us case study to quantify our intuitions about the
model’s ability to approach text mining challenges and com-
pare PLDA with PLDP. Where not otherwise specified, we
used fixed hyperparameters of 0.1 for \( \alpha \) and \( \eta \).

3.1 PhD Dissertation Abstracts

Traditional digital libraries often annotate documents with
a controlled vocabulary maintained by domain experts to
ease indexing, searching, and browsing. While these collec-
tions represent a shrinking fraction of all the world’s elec-
tronic text, they do contain some of the most focused and
important content within a limited domain. One such col-
lection is the UMI database of PhD dissertation abstracts
maintained by ProQuest, the official archival agency for dis-
sertations written in the United States as designated by
the US Library of Congress. In collaboration with social
scientists at Stanford’s School of Education, we collected
1,023,084 PhD dissertation abstracts from the Proquest UMI
data base filed by US students since 1980 from any of 151
schools classified as research-intensive by the Carnegie Foun-
dation since 1994.\(^2\) These dissertations are an excellent basis
for the study of the history academia because they reflect
the entire academic output of universities, as seen through
their graduating students, and do not reflect the coverage
biases toward scientific or engineering publications found in
most databases of academic publications, such as ISI (with
a biomedicine) and CiteSeer (with computer science). A
more complete study of this dataset can be found in [25]
and warrants more space than is available here, so we use
the PhD dissertation database as a concrete illustration of
the advantages of partially supervised topic models in an
active computational social science collaboration.

While the subject codes in our data cover the full range
of academic fields, they are not evenly distributed in usage,
reflecting real differences in field sizes. Indeed, the most
common subject code in our dataset (electrical engineering)
has 44,551 instances, whereas the least common (African
literature) has only 1,041. Models like PLDA are a natural
fit for analyzing these controlled-vocabulary document col-
lections due to their ability to model both the text content
in terms of latent usages of the known indexing vocabulary.
By contrast, latent topics on this dataset collapse distinc-
tions between small fields (folding them into a single topic)
and overly emphasize the importance of larger ones, just
based on the amount of support in the data. For example,
one run of LDA on this dataset—using 100 latent topics—
associated topics to fields in proportion to their prevalence
in the data: electrical engineering was assigned three top-
ics, whereas African literature was split between one topic
related to all forms of race culture in America (“american,
black, white, ethnic, african”) and another on all forms of lit-
erature (“literari, novel, narr, text, writer”). By seeing which
subject codes appeared in each topic, we can see that these
two topics are themselves dominated by larger subjects: an-
thropology and political science for the former and modern
and classical literature for the latter. This result is reason-
able from the perspective of how much support there is for
topics in the dataset. But by losing smaller subject codes in
the tails of larger topics, we lose the ability to describe topic
dimensions in terms of the known, human interpretable ob-
jects of study (fields) while simultaneously losing all latent
sub-structure within each field.

As a modeling alternative, we could train an independent
topic model on all dissertations in each subject code. How-
ever, almost all dissertations have more than one subject
code. As a result, many words in the corpus will be double-
counted whereas PLDA will attribute each word in each dis-
sertation to the appropriate subject code’s latent topics. As
a modeling framework, PLDA further allows for the auto-
matic construction of shared latent background topics that
\(^1\)http://www.proquest.com/en-US/products/dissertations/

\(^2\)http://classifications.carnegiefoundation.org/resources/
### PhD Dissertation Subjects

<table>
<thead>
<tr>
<th>Computer Science</th>
<th>Linguistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>algorithm, problem, network, design, system, method, applic, gener, comput, techniq, present, approach, model, program, prov, props, implement, set, struct, effic</td>
<td>language, english, struct, linguist, word, chap, verb, semant, speaker, theori, examin, present, form, subject, discours, gener, phonolog differ, construct, syntact</td>
</tr>
<tr>
<td>databas queri web file access retriev storag user search document system relat process</td>
<td>vocabl speech phonet</td>
</tr>
<tr>
<td>algorithm problem graph comput optin solv solut number effici complex bound</td>
<td>parallel memori processor schedul comput execut architect appli cach</td>
</tr>
<tr>
<td>design software user system appli environ interfac tool provid support implement</td>
<td>learn secur detect attack approach techniqu classif propos feature knowledge</td>
</tr>
<tr>
<td>network protocol rout servic commun distribut node props applic mobil wireless</td>
<td>program languag gener logic specif formal semant code implement system</td>
</tr>
<tr>
<td>increas rate level decreas higher lower low size valu number compar reduc averag show</td>
<td>chapter theori discuss present concept theori literatur approach examin question</td>
</tr>
<tr>
<td>abstract avaii shortn librari exclud copi author umi permiio la cambri mit ang felax</td>
<td>method model simul predict techniq estim</td>
</tr>
<tr>
<td>variabl measur relationship test correl factor</td>
<td>structur type pattern function differ</td>
</tr>
<tr>
<td>level sampl scale statis score differ determin</td>
<td>influenc factor affect plai phase import condit</td>
</tr>
</tbody>
</table>

### del.icio.us tags

| pm posted blog comments april post june | great march january february comment |
| file files download version click page text | virus windows window menu search make |
| web read privacy information email page | version page support using available file other |
| web page del.icio.us tags string class object | system data which files source here features |
| file line text command string search match | table database data sql mysql select query |
| number files character emacs characters | index column create tables set rows null row |
| ask javascript page function object code | css style elements c. visual inherit layout |
| asp net element event method script var class | section sheets sheet table property |
| python function returns string class object | file line text command string search match |
| module functions return type list file int | number files character emacs characters |
| engl ish languag spanish french nt greek learn | pdf german bible chinese languages |
| languag german scottish scottland english | languag unicode code logo which irish code |
| languag sign semiotics sign words | which languag sign semiotics signs words |
| spell word british e.g. say english american | film movie films cinemati mexxhoo |
| user comic tray ad. after caption stewart | fashion manolo shoes style june bag |
| comments dress posted vintage bags london | class code int function line const file files |
| header statements names type variables | class code int function line const file files |

Figure 2: PLDA output on dissertation abstracts (left) and del.icio.us tags (right). Computer Science and Linguistics are two subject codes. “NB” (upper, left) refers to the naive Bayes term estimates associated with each respective code, contrasted with the latent topics learned within each. The “(background)” class (of del.icio.us in upper right, dissertations in lower-left) is the latent topic class shared by all documents in the respective collection.

extract common words found in most abstracts across all per-field topics. The background topics in PLDA are explicitly labeled as such by the model and do not need to be manually identified as they would if each subject code had an independently trained model.

Examples of the topics learned by PLDA are in Figure 2. At the top, we see the most common words associated with each subject code by the simple count-and-divide multinomial naive Bayes estimate, as well as latent sub-topics discovered for each subject code. We used a distributed implementation of PLDA to learn a model with eight global latent background topics and eight latent topics per subject code, resulting in a total of 2,080 latent topics. The results shown are representative of the quality of discovered topics across all academic disciplines. Note that the major distinctions within each subject code roughly correspond to the broad areas of study within computer science and linguistics. The latent topics capture shared common structure in PhD dissertations, including basic things such as variables that increase or decrease, rates of change, and structural starting points about needs, problems, and goals.

A high quality topic space with labeled groups of latent dimensions, as output by PLDA, can be used to ask and answer questions about the nature of academia. For example, we can re-run inference on any given dissertation (while allowing it to use all subject labels) in order to compute a per-dissertation distribution over fields of study—which words might the dissertation have borrowed from which other fields. This can tell us which dissertations within an area of interest are more or less interdisciplinary. Did computational biology get an earlier head start at public or private institutions? Or, at a larger-scale, we can ask which schools tend to have the most inter-disciplinary research in general, or even whether interdisciplinary dissertations are more likely to result in productive future research careers. As always, external, dataset-specific validation metrics need to be in place in order to trust the output of such analyses.

Although this section is merely descriptive, we hope it serves to illustrate the practical impact that human-interpretable topic dimensions can bring to text mining practitioners and computational social scientists. In the next section, we examine content from the social bookmarking website del.icio.us, and use that dataset’s abundance of tags as the basis for extrinsic comparison between models.

### 3.2 Tagged web pages

Users of social bookmarking websites like del.icio.us bookmark the pages they encounter with single word tags [7]. In contrast to more traditional supervised learning problems, user-generated tags are not predetermined nor applied uniformly to all items. For example, the tag language on the social bookmarking site http://del.icio.us/ might be applied to web pages about human languages or programming languages. We call these variations in usage of the same tag sub-tags. The right half of Figure 2 summarizes some of the types of trends discovered within each tag on del.icio.us.

The model was run on a randomly selected 3,200 tagged
Table 1: HTJS within a tag (left) and within sub-tags (right). % change is relative to the .0183 score for randomly selected documents.

<table>
<thead>
<tr>
<th>Tag</th>
<th>Docs by tag HTJS</th>
<th>Docs by sub-tag HTJS</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>books</td>
<td>.0264 39%</td>
<td>.1292 605%</td>
<td></td>
</tr>
<tr>
<td>computer</td>
<td>.0362 97%</td>
<td>.1609 777%</td>
<td></td>
</tr>
<tr>
<td>culture</td>
<td>.0259 41%</td>
<td>.0780 326%</td>
<td></td>
</tr>
<tr>
<td>design</td>
<td>.0269 47%</td>
<td>.0510 178%</td>
<td></td>
</tr>
<tr>
<td>education</td>
<td>.0206 12%</td>
<td>.1784 873%</td>
<td></td>
</tr>
<tr>
<td>english</td>
<td>.0263 44%</td>
<td>.0531 189%</td>
<td></td>
</tr>
<tr>
<td>language</td>
<td>.0314 71%</td>
<td>.1996 988%</td>
<td></td>
</tr>
<tr>
<td>style</td>
<td>.0290 58%</td>
<td>.2244 1124%</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>.0273 49%</td>
<td>.1191 550%</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3: Correlation with HTJS for varying numbers of topic dimensions (PLDA, LDA) or as decided by model form (PLDP, Labeled LDA). Higher is better.

Figure 4: Average training time per iteration (in minutes) while varying the total number of latent topics for LDA (top) and PLDA (bottom) on tagged web pages. PLDA is substantially faster than LDA at a comparable number of topics because of the sparsity inherent to PLDA’s sampling distribution.
3.3 Model comparison by HTJS Correlation

In this section we use HTJS to compare PLDA and PLDP to several strong baselines. Better performing models should have better agreement with HTJS similarity scores across a wide range of document pairs. We quantify this intuition with Pearson’s correlation coefficient: for any given model, we compute the correlation of similarity scores generated by the model with HTJS scores over 5,000 randomly selected document pairs. Higher correlations mean that the similarity score implied by the model better aligns with our surrogate human judgments.

Figure 3 shows the correlation of PLDP, PLDA, LDA, Labeled LDA, and tf-idf cosine similarity with HTJS scores as the total number of latent topics changes. The way we compute similarity scores depends on the model form: the partially supervised models introduced here, like other topic models, project documents into a lower dimensional topic space through their per-document topic loadings. In the case of standard topic models such as LDA, this loading is just the per-document topic distribution \( \theta \). For PLDA and PLDP, we take a document’s “\( \theta \)” to be the concatenation of the documents’ topic loading on all labels (even those not present in the document), resulting in a vector that is dense for topics corresponding to the document’s labels and zero elsewhere. Values of these signature vectors are compared using cosine similarity, which we have found to be a stable and high performing metric in this context.

We also included two baselines: tf-idf cosine similarity (in word space) and the Jaccard score of the modeled (i.e. not held-out) tags. For all models, we used fixed hyperparameters of \( \alpha = .01 \) and \( \eta = .01 \). Along the x-axis is the total number of latent topics used by PLDA (varying the number of topics allocated per class from 1 to 16) and of LDA. Labeled LDA has a horizontal line corresponding to using 20 topics, one per class (and no latent class) and performs substantially worse than the other models because of its inability to model the sub-structure of each tag. PLDP demonstrates a higher correlation with the HTJS scores across the whole dataset by adapting to the label and word distributions in the data. PLDP’s embedded Dirichlet process allows it to allocate different numbers of topics to each tag as a function of its concentration parameter \( \alpha \). Here, our PLDP model allocated 293 topics with substantial probability mass (and several hundred more occurring with very low frequency). These topics were allocated differentially according to the frequency of each tag and the variety of ways in which it is used—most were given to the latent class and common tags such as design, politics, and internet. Only four topics were allocated to the least common tag in the dataset (grammar). We experimented with several values of \( \alpha \) for PLDP, resulting in more or fewer topics, but with similar ratios of topics allocated to each tag and similar (but not always superior) overall performance results.

As the number of topics grows, the performance of PLDA approaches that of PLDP, but with substantial computational advantages. In particular, our PLDA implementation can be parallelized in a straightforward manner and PLDA does not have the additional overhead of constructing (and possibly pruning) new topics. On average, our PLDA implementation is between 5 and 20 times faster per iteration than our (much less optimized) PLDP implementation, and takes fewer iterations to converge.

4. SCALABILITY

The expense of adding more label classes is directly proportional to how many documents each label participates in, and is always faster than modeling more global latent topics. Indeed, the impact of a label \( l \)’s topics on running time appears only in computing the sampling proportions in documents with \( l \in \Lambda_d \). This allows PLDA models such as those trained on the PhD dissertation dataset to scale to very large topic spaces and in an appreciably shorter period of time—indeed, training our 8 topics-per-subject PLDA model on one million abstracts ran in under a day on a small cluster of multi-core computers. Training a comparable number of latent topics (2,080) on this dataset took, on average 82 times longer per iteration and more iterations to converge. Like LDA, the running time of PLDA (for a fixed number of iterations) is linear in the size of the input data.

On collections with more common labels that have a higher degree of overlap, such as del.icio.us, incorporating more label classes or topics per class increases the computational load, but at a rate much slower than the cost of adding more global shared latent topics, as most tags are not applied to most documents. Figure 4 shows the running time per iteration (in minutes) for the collapsed variational Bayes learning algorithm on roughly twelve thousand documents from del.icio.us as the effective number of topics increases (using the same schedule of topics as in Figure 3). PLDA is substantially faster to train, and also results in a better correspondence with human similarity judgments. We note, however, that practitioners should use models like PLDA with care, choosing the set of labels modeled and topics per label depending on the statistics of the dataset. PLDP can help by automatically determining an appropriate number of topics per label class, but its flexibility comes at the expense of speed, as the model takes substantially longer to train than the Gibbs sampler for PLDA, and does not yet have a data parallel implementation.

5. CONCLUSION

This work proposes two topic models that incorporate label supervision in novel ways: PLDA and PLDP, which learn latent topic structure within the scope of observed, human-interpretable labels. The models introduce high-level constraints on latent topics that cause them to align with human provided labels, essentially “filling in the details” with the use of unsupervised machine learning. The addition of these constraints improves interpretability of the resulting topics, shortens running time, and improves correlation with similarity judgments. And because these models fit into the Bayesian framework, they can be extended to incorporate other features, such as time or sequence information.

PLDA and PLDP provide a direct solution to the problem of label ambiguity: as in linguistic word usage, labels on tagging sites like del.icio.us and social media sites like Twitter are used with different meanings in different contexts. PLDA and PLDA can tease these meanings apart into separate latent topics within each label. However, the models do not directly address the inverse problem of synonymy, where several labels may refer to the same thing. Future work could look at recognizing (partially-) synonymous labels via a post-processing step or with explicit topic sharing. However, the independence of topics across labels is central to the favorable scalability of the models, as dis-
cussed in Section 4, so care must be taken when relaxing this constraint. We believe that PLDA, PLDP, and similar future models hold promise for addressing the challenges of partially supervised learning for more interpretable text mining, where human provided labels are present but do not always align with the needs of text mining practitioners.

Acknowledgments

This work was supported by the National Science Foundation under Grant No. 0835614.

6. REFERENCES