Topic Modeling with Network Regularization

Qiaozhu Mei, Deng Cai, Duo Zhang, ChengXiang Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign
{qmei2, dengcai, dzhang22, czhai}@uiuc.edu

ABSTRACT

In this paper, we formally define the problem of topic modeling with network structure (TMN). We propose a novel solution to this problem, which regularizes a statistical topic model with a harmonic regularizer based on a graph structure in the data. The proposed method combines topic modeling and social network analysis, and leverages the power of both statistical topic models and discrete regularization. The output of this model can summarize well topics in text, map a topic onto the network, and discover topical communities. With appropriate instantiations of the topic model and the graph-based regularizer, our model can be applied to a wide range of text mining problems such as author-topic analysis, community discovery, and spatial text mining. Empirical experiments on two data sets with different genres show that our approach is effective and outperforms both text-oriented methods and network-oriented methods alone. The proposed model is general; it can be applied to any text collections with a mixture of topics and an associated network structure.

Categories and Subject Descriptors: H.3.3 [Information Search and Retrieval]: Text Mining

General Terms: Algorithms

Keywords: statistical topic models, social networks, graph-based regularization

1. INTRODUCTION

With the prevailing of Web 2.0 applications, more and more web users are actively publishing text information online. These users also often form social networks in various ways, leading to simultaneous growth of both text information and network structures such as social networks. Taking weblogs (i.e., blogs) as an example, one can find a wide coverage of topics and diversified discussions in the blog posts, as well as a fast evolving friendship network among the bloggers. In another scenario, as researchers are regularly publishing papers, we not only obtain text information, but also naturally have available co-authorship networks of authors. In yet another scenario, as email users produce many text messages, they also form networks through the relation of sending or replying to messages. One can easily imagine many other examples of text accompanied by network structures such as webpages accompanied by links and literature accompanied by citations. Figure 1 presents an example coauthor network from SIGIR proceedings, where each author is associated with the papers he/she published.

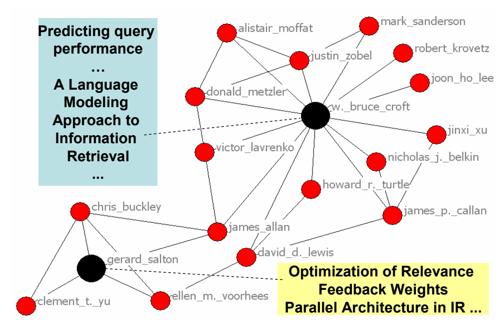


Figure 1: A sample network structure with text

These examples show that in many web mining tasks, we are often dealing with collections of text with a network structure attached, making it interesting to study how we can leverage the associated network structure to discover interesting topic and/or network patterns.

Statistical topic models have recently been successfully applied to multiple text mining tasks [10, 4, 28, 26, 20, 15, 27] to discover a number of topics from text. Some recent work has incorporated into topic modeling context information [20], such as time [27], geographic location [19], and authorship [26, 23, 19], to facilitate contextual text mining. Topics discovered in this way can be used to infer research communities [26, 23] or information diffusion over geographic locations [19]. However, they do not consider the natural network structure among authors, or geographic locations. Intuitively, these network structures are quite useful for refining and structuring topics, and are sometimes essential for discovering network-associated topics. For example, two researchers who often coauthor with each other are likely to be working on the same topics, thus are likely to be in the same research community. For geographically sensitive events (e.g., hurricane Katrina), bloggers living at adjacent locations tend to write about similar topics. The lack of consideration of network structures is also a deficiency in some other text mining techniques such as document clustering.

On the other hand, social network analysis (SNA) focuses on the topology structure of a network [11, 13, 1, 12], addressing questions such as "what the diameter of a network is [13]", "how a network evolves [13, 1]", "how information diffuses on the network [9, 14]", and "what are the communities on a network [11, 1]." However, these techniques usually do not leverage the rich text information. In many

WWW 2008, April 21–25, 2008, Beijing, China.
ACM 978-1-60558-085-2/08/04.

scenarios, text information is very helpful for SNA tasks. For example, Newton and Einstein had never collaborated on a paper (i.e., *social network*), but we still consider them in the same research (physics) community because they made research contributions on related research topics (i.e., *text*). Similarly, to attract Bruce Willis to take a role in a movie, "the script is interesting (i.e., *text*)" is as important as "the director is a trustable friend (i.e., *social network*)."

Is there a way to leverage the power of both the textual topics and the network structure in text mining? Can the two successful complementary mining techniques (i.e., probabilistic topic modeling and social network analysis) be combined to help each other? To the best of our knowledge, these questions have never been seriously studied before. As a result, there is no principled way to combine the mining process of topics in text and social networks (e.g., combining topic modeling with network analysis). Although methods have been proposed to combine page contents and links in web search [22], none of them is tuned for text mining.

In this paper, we formally define the major tasks of **Topic Modeling with Network Structure (TMN)**, and propose a unified framework to combine statistical topic modeling with network analysis by regularizing the topic model with a discrete regularizer defined based on the network structure. The framework makes it possible to cast our mining problem as an optimization problem with an explicit objective function. Experiment results on different genres of real world data show that our model can effectively extract topics, generat topic maps on a network, and discover topical communities. The results also show that our model improves over both pure text mining methods and pure network analysis methods, suggesting the necessity of combining them.

The proposed framework of regularized topic modeling is general; one can choose any topic model and a corresponding regularizer on the network. Variations of the general model are effective for solving real world text mining problems, such as author-topic analysis and spatial topic analysis.

The rest of this paper is organized as follows. In Section 2, we formally define the problem of topic modeling with network structure. In Section 3, we propose the unified regularization framework as well as two general methods to solve the optimization problem. We discuss the variations and applications of our model in Section 4 and present empirical experiments in Section 5. Finally, we discuss the related work in Section 6 and conclude in Section 7.

2. PROBLEM FORMULATION

We assume that the data to be analyzed consists of both a collection of text documents and an associated network structure. This setup is quite general: The text documents can be a set of web pages, blog articles, scientific literature, emails, or profiles of web users. The network structure can be any social networks on the web, co-author/citation graphs, geographic networks, or even latent networks that can be inferred from the text (e.g., entity-relation graph, document nearest-neighbor graph, etc). We now formally define the related concepts and the general tasks of topic modeling with network structure.

Definition 1 (Document): A text ***document*** d in a text collection $\mathcal{C}$ is a sequence of words $w_1 w_2 ... w_{|d|}$, where w_i is a word from a fixed vocabulary. Following a common simplification in most work in information retrieval and topic modeling [10, 4], we represent a document with a bag of words, i.e., $d = \{w_1, w_2, ..., w_{|d|}\}$. We use $c(w, d)$ to denote the occurrences of word w in d.

Definition 2 (Network): A ***network*** associated with a text collection $\mathcal{C}$ is a graph $G = \langle V, E\rangle$, where V is a set of vertices and E is a set of edges. Without losing generality, we define a ***vertex*** $u \in V$ as a subset of documents $\mathcal{D}_v \subset \mathcal{C}$. For example, a vertex in a coauthor graph can be a single author associated with all papers he/she published. An ***edge*** $\langle u, v\rangle$ is a binary relation between vertices u and v, where we use $w(u, v)$ to denote the weight of $\langle u, v\rangle$. An edge can be either **undirected** or **directed**. In this work, we only consider the undirected case, i.e., $\langle u, v\rangle = \langle v, u\rangle$.

Definition 3 (Topic): A semantically coherent ***topic*** in a text collection $\mathcal{C}$ is represented by a ***topic model*** θ , which is a probabilistic distribution of words $\{p(w|\theta)\}_{w\in V}$. Clearly, we have $\sum_{w\in V} p(w|\theta) = 1$. We assume that there are all together k topics in $\mathcal{C}$.

By combining text topics and a network structure, we can discover new types of interesting patterns. For example, we can explore who first brought the topic "language modeling" into the IR community, and who have been diffusing this topic on the research network. A topic could also define a latent community on the network (e.g., the machine learning community, the SNA community, etc). The following patterns are unique to topic modeling with network structure, and cannot be discovered solely from text or social networks.

Definition 4 (Topic Map): A ***topic map*** of a topic θ on network G, M_θ, is represented by a vector of weights $\langle f(\theta, v_1), f(\theta, v_2), ..., f(\theta, v_m)\rangle$, where $v_i \in V$, and $f(\theta, v)$ is a weighting function of a topic on a vertex. For example, we may define f as $f(\theta, v_i) = p(\theta|v_i)$, where $\sum_\theta p(\theta|v_i) = 1$ for all v_i. From a topic map, we can learn how a topic is distributed on the network. Intuitively, we expect that the adjacent vertices be associated with similar topics and the weights of topics on adjacent vertices are similar.

Definition 5 (Topical Community): A ***topical community*** on network G is represented by a subset of vertices $\mathcal{V}_\theta \subset V$. We can assign a vertex v to $\mathcal{V}_\theta$ with any reasonable criterion, e.g. $f(\theta, v) > \epsilon$, or $\forall\theta', f(\theta, v) > f(\theta', v)$. The topic model θ is then a natural summary of the semantics of the topical community $\mathcal{V}_\theta$. Intuitively we expect that the vertices within the same topical community are tightly connected and all have a large $f(\theta, v)$; vertices from different topical communities are loosely connected and have different $f(\theta, v)$. A *topical community* is different from a *community* in the SNA literature in that it must have coherent semantics, and can be summarized with a coherent *topic* in text.

Based on the definitions of these concepts, we can formalize the major tasks of **topic modeling with network structure (TMN)** as follows:

Task 1: (Topic Extraction) Given a collection $\mathcal{C}$ and a network structure G, the task of *Topic Extraction* is to model and extract k major topic models, $\{\theta_1, ..., \theta_k\}$, where k is a user specified parameter.

Task 2: (Topic Map Extraction) Given a collection $\mathcal{C}$ and a network structure G, the task of *Topic Map Extraction* is to model and extract the k weight vectors $\{M_{\theta_1}, ..., M_{\theta_k}\}$, where each vector M_θ is a map of topic θ on network G.

Task 3: (Topical Community Discovery) Given a collection $\mathcal{C}$ and a network structure G, the task of *Topical Community Discovery* is to extract k topical communities $\{\mathcal{V}_1, ..., \mathcal{V}_k\}$, where each $\mathcal{V}_i$ has a coherent semantic summary θ_i, which is one of the k major topics in $\mathcal{C}$.

These tasks are challenging in many ways. First, there is no existing unified model that can embed a network structure in a topic model. Indeed, whether a social network structure can help extracting topics is an open question. Second, in existing community discovery methods, there is no guarantee that the semantics of a community is coherent. It is rather unclear how to satisfy the topical coherency and the connectivity coherency at the same time. Moreover, since it is usually hard to create training examples to this problem, the solution has to be unsupervised.

The three major tasks above are by no means the only tasks of topic modeling with network structure. With the output of such basic tasks, more in-depth analysis can be done. For example, one can compare topic maps over time and analyze how topics are propagating over the network. One can also track the evolution of topical communities.

3. REGULARIZING TOPIC MODELS WITH NETWORK STRUCTURE

In this section, we propose a novel and general framework of regularizing statistical topic models with the network structure.

3.1 Statistical Topic Models

We first discuss the basic statistical topic models, which have been applied to many text mining tasks [10, 4, 26, 19, 15, 27, 20]. The basic idea of these models is to model documents with a finite mixture model of k topics and estimate the model parameters by fitting the data with the model. Two basic statistical topic models are the Probabilistic Latent Semantic Analysis (PLSA) [10] and the Latent Dirichlet Allocation (LDA) [4]. For example, the log likelihood of a collection $\mathcal{C}$ to be generated with PLSA is given as follows:

$$L(\mathcal{C}) = \sum_d \sum_w c(w,d) \log \sum_{j=1}^{k} p(\theta_j|d) p(w|\theta_j) \quad (1)$$

The parameters in PLSA are $\Psi = \{p(\theta_j|d), p(w|\theta_j)\}_{d,w,j}$. Naturally, we can use $\{p(\theta_j|v)\}_j$ as the weights of topics on vertex v, and compute $p(\theta_j|v)$ by

$$p(\theta_j|v) = \sum_{d \in \mathcal{D}_v} p(\theta_j|d) p(d|v) \quad (2)$$

PLSA thus provides an over-simplified solution to the problem of TMN by ignoring the network structure. There is no guarantee that vertices in the same topical community are well connected, or adjacent vertices are associated with similar topics. Indeed, a limitation of PLSA is that there is no constraint on the parameters $\{p(\theta_j|d)\}$ for different d, the number of which grows linearly with the data. Therefore, the parameters $\{p(\theta_j|d)\}_{d,j}$ would overfit the data. To alleviate this overfitting problem, LDA assumes that the document-topic distributions $\{p(\theta_j|d)\}_j$ of each document d are all generated from the same Dirichlet distribution.

3.2 The Regularization Framework

We propose a new framework to model topics with a network structure, by regularizing a statistical topic model with a regularizer on the network. The criterion of this regularization is succinct and natural: vertices which are connected to each other should have similar weights of topics ($f(\theta_j, v)$).

Formally, we define a regularized data likelihood as

$$O(\mathcal{C}, G) = -(1-\lambda) L(\mathcal{C}) + \lambda R(\mathcal{C}, G) \quad (3)$$

where $L(\mathcal{C})$ is the log likelihood of the collection $\mathcal{C}$ to be generated by the statistical topic model, and $R(\mathcal{C}, G)$ is a harmonic regularizer defined on the network structure G.

This regularization framework is quite general. We can use any statistical topic model to refine $L(\mathcal{C})$, and use any graph based regularizer $R(\mathcal{C}, G)$ as long as it can smooth the topics among adjacent vertices. We abbreviate the network regularized statistical topic model as **NetSTM**.

To illustrate this framework, in this paper we use PLSA as the statistical topic model and a regularizer similar to the graph harmonic function in [33], i.e.,

$$R(\mathcal{C}, G) = \frac{1}{2} \sum_{\langle u,v \rangle \in E} w(u,v) \sum_{j=1}^{k} (f(\theta_j, u) - f(\theta_j, v))^2 \quad (4)$$

Correspondingly, we call this model **NetPLSA**.

Note that the regularizer in Equation 4 is an extension of the graph harmonic function in [33] to multiple classes (topics). It can be rewritten as

$$R(\mathcal{C}, G) = \frac{1}{2} \sum_{j=1}^{k} f_j^T \Delta f_j \quad (5)$$

where f_j is a $|V|$ dimensional vector of the weights of the j-th topic on each vertex (e.g., $\{p(\theta_j|v)\}_v$). Δ is the graph Laplacian matrix [33, 32]. We have $\Delta = D - W$, where W is the matrix of edge weights, and D is a diagonal matrix where $d(u,u) = \sum_v w(u,v)$.

This framework is a general one that can leverage the power of both the topic model and the graph Laplacian regularization. Intuitively, the $L(\mathcal{C})$ in Equation 6 measures how likely the data is generated from this topic model. By minimizing $-L(\mathcal{C})$, we will find $\{p(\theta_j|d)\}$ and $\{p(w|\theta_j)\}$ which fits the text data as much as possible. By minimizing $R(\mathcal{C})$, we smooth the topic distributions on the network structure, where adjacent vertices have similar topic distributions.

Although theoretically $f(\theta, u)$ can be defined as any weighting function of a topic θ on u, in practice it must be a function of the parameters in PLSA (i.e., $\{p(\theta_j|d)\}$ and $\{p(w|\theta_j)\}$). When a vertex have multiple documents, an example choice is $f(\theta, u) = p(\theta|u) \propto \sum_{d \in \mathcal{D}_u} p(\theta|d) p(d|u)$.

The parameter λ can then be set between 0 to 1 to control the balance between the data likelihood and the smoothness of topic distributions over the network. It is easy to show that if $\lambda = 0$, the objective function boils down to the log likelihood of PLSA. Minimizing $O(\mathcal{C}, G)$ will give us the topics which best fit the content of the collection. When $\lambda = 1$, this objective function boils down to $\frac{1}{2} \sum_{j=1}^{k} f_j^T \Delta f_j$. Embedded with additional constraints, this is related to the objective of spectral clustering (i.e., ratio cut [6]). By minimizing $O(\mathcal{C}, G)$, we will extract document clusters solely based on the network structure.

An interesting simplified case is when every vertex only contains one document (thus substitute u, v with d_u, d_v) and $f(\theta, u) = p(\theta|d_u)$. Then we have

$$\begin{aligned} O(\mathcal{C}, G) &= -(1-\lambda) * \sum_d \sum_w c(w,d) \log \sum_{j=1}^{k} p(\theta_j|d) p(w|\theta_j) \\ &+ \frac{\lambda}{2} \sum_{\langle u,v \rangle \in E} w(u,v) \sum_{j=1}^{k} (p(\theta_j|d_u) - p(\theta_j|d_v))^2. \quad (6) \end{aligned}$$

In the following section, we discuss parameter estimation of the NetPLSA model in such a simplified case. The estimation for more complex cases can be done similarly.

3.3 Parameter Estimation

Let us first consider the special case when $\lambda = 0$. In such a case, the objective function degenerates to the log-likelihood function of PLSA with no regularization.

The standard way of parameter estimation for PLSA is to apply the Expectation Maximization (EM) algorithm [8] which iteratively computes a local maximum of $L(\mathcal{C})$. Specifically, in the E-step, it computes the expectation of the complete likelihood $Q(\Psi;\Psi_n)$, where Ψ denotes all the parameters, and Ψ_n denotes the value of Ψ estimated in the last (n-th) EM iteration. In the M-step, the algorithm finds a better estimate of parameters, Ψ_{n+1}, by maximizing $Q(\Psi;\Psi_n)$:

$$\Psi_{n+1} = \arg\max_{\Psi} Q(\Psi;\Psi_n) \tag{7}$$

Computationally, the E-step boils down to computing the conditional distribution of the hidden variables given the data and Ψ_n. The hidden variables in PLSA correspond to the events that a term w in document d is generated from the j-th topic. Formally, we have the **E-Step:**

$$\begin{aligned} z(w,d,j) &= p(\theta_j|w,d,\Psi_n) \\ &= \frac{p_n(\theta_j|d)p_n(w|\theta_j)}{\sum_{j'=1}^{k} p_n(\theta_{j'}|d)p_n(w|\theta_{j'})} \end{aligned} \tag{8}$$

$$Q(\Psi;\Psi_n) = \sum_d \sum_w c(w,d) \sum_j z(w,d,j) \log p(\theta_j|d)p(w|\theta_j) \tag{9}$$

The maximization problem in the **M-Step** (i.e., Equation 7) has a closed form solution:

$$p_{n+1}(\theta_j|d) = \frac{\sum_w c(w,d)z(w,d,j)}{\sum_w \sum_{j'} c(w,d)z(w,d,j')} \tag{10}$$

$$p_{n+1}(w|\theta_j) = \frac{\sum_d c(w,d)z(w,d,j)}{\sum_d \sum_w c(w,d)z(w,d,j)}. \tag{11}$$

We now discuss how we can extend this standard EM algorithm to handle the case $\lambda \neq 0$. Using a similar derivation to that of the EM algorithm, we have the following expected complete likelihood function for NetPLSA, where for convenience of discussion, we also added the Lagrange multipliers corresponding to the constraints on our parameters:

$$\begin{aligned} Q(\Psi;\Psi_n) &= (1-\lambda)\sum_d \sum_w c(w,d) \sum_j z(w,d,j) \log p(\theta_j|d)p(w|\theta_j) \\ &+ \sum_d \alpha_d(\sum_j p(\theta_j|d) - 1) + \sum_j \alpha_j(\sum_w p(w|\theta_j) - 1) \\ &- \frac{\lambda}{2} \sum_{\langle u,v\rangle \in E} w(u,v) \sum_{j=1}^{k} (p(\theta_j|d_u) - p(\theta_j|d_v))^2 \end{aligned} \tag{12}$$

where $\alpha_d(\sum_j p(\theta_j|d)-1)$ and $\alpha_j(\sum_w p(w|\theta_j)-1)$ are Lagrange multipliers corresponding to the constraints that $\sum_j p(\theta_j|d) = 1$ and $\sum_w p(w|\theta_j) = 1$.

Thus in general, we can still use the EM algorithm to estimate the parameters when $\lambda > 0$ in Equation 6 by maximizing $-O(\mathcal{C}, G)$. It is easy to see that NetPLSA shares the same hidden variables with PLSA, and the conditional distribution of the hidden variables can still be computed using Equation 8. Thus the E-step remains the same.

The M-step is more complicated due to the introduction of the regularizer. The estimation of $P(w|\theta_j)$ does not rely on the regularizer, thus can still be computed using Equation 10. Unfortunately, we do not have a closed form solution to re-estimate the parameters $\{P(\theta_j|d)\}_{j,d}$ through maximizing $Q(\Psi;\Psi_n)$.

To solve this problem, we can apply a Newton-Raphson method to update Ψ_{n+1} by finding a local maximum of $Q(\Psi;\Psi_n)$ in the M step. Specifically, let X be the vector of variables to be updated with the Newton-Raphson method (i.e., $\{P(\theta_j|d)\}_{j,d}$ and $\{\alpha_d\}_d$). The updating formula of the Newton-Raphson's method is as follows:

$$X^{(t+1)} = X^{(t)} - \gamma[HQ(X^{(t)};\Psi_n)]^{-1} \bigtriangledown Q(X^{(t)};\Psi_n) \tag{13}$$

where $X^{(t)}$ is the new estimation of parameters at the t-th inner iteration of the M step. $\bigtriangledown Q(X;\Psi_n)$ is the gradient of $Q(X;\Psi_n)$. $HQ(X;\Psi_n)$ is the Hessian matrix of $Q(X;\Psi_n)$. γ is a small step size to ensure the satisfaction of the Wolfe conditions [1]. A good selection of γ guarantees that $p(\theta|d) \geq 0$. It is easy to evaluate all the elements in $HQ(X^{(t)};\Psi_n)$ and $\bigtriangledown Q(X^{(t)};\Psi_n)$. We omit the details due to the limit of space. Instead of computing $[HQ(X^{(t)};\Psi_n)]^{-1}$, it is more efficient to find $X^{(t+1)}$ directly by solving the linear system

$$HQ(X^{(t)};\Psi_n)(X^{(t)} - X^{(t+1)}) = \gamma \bigtriangledown Q(X^{(t)};\Psi_n) \tag{14}$$

We want to set the start point of $X^{(0)}$ corresponding to Ψ_n. This is because, to guarantee that the generalized EM algorithm will converge, we need to assure $Q(\Psi_{n+1};\Psi_n) \geq Q(\Psi_n;\Psi_n)$. By setting the start point of Newton-Raphson method at Ψ_n, we ensure that Q would not drop.

3.4 An Efficient Algorithm

In the previous section, we give a way to gradually approach the local maximum of $Q(\Psi;\Psi_n)$ at M step. However, this involves multiple iterations of Newton-Raphson updating, in each of which we need to solve a linear system of $|d| * (k+1)$ variables. This significantly increases the cost of parameter estimation of NetPLSA.

In this section, we propose a simpler algorithm for parameter estimation based on the generalized EM algorithm (GEM) [21]. According to GEM, we do not have to find the local maximum of $Q(\Psi_{n+1};\Psi_n)$ at every M step; instead, we only need to find a better value of Ψ in the M-step, i.e., to ensure $Q(\Psi_{n+1};\Psi_n) \geq Q(\Psi_n;\Psi_n)$.

Thus our idea is to optimize the likelihood part and the regularizer part of the objective function separately in hope of finding an improvement of the current Ψ. Specifically, let us write $Q(\Psi;\Psi_n) = (1-\lambda)L'(\mathcal{C}) - \lambda R(\mathcal{C}, G)$, where $L'(\mathcal{C})$ denotes the expectation of the complete likelihood of the topic model. Clearly, $Q(\Psi;\Psi_n) \geq Q(\Psi_n;\Psi_n)$ holds if $\Psi = \Psi_n$. We introduce $\Psi_{n+1}^{(0)} = \Psi_n$, which is the first eligible set of parameter values that assure $Q(\Psi;\Psi_n) \geq Q(\Psi_n;\Psi_n)$.

At every M-step, we would first attempt to find $\Psi_{n+1}^{(1)}$ to maximize $L'(\mathcal{C})$ instead of the whole $Q(\Psi;\Psi_n)$. This can be done by simply applying Equation 11 and 10. Clearly, $Q(\Psi_{n+1}^{(1)};\Psi_n) \geq Q(\Psi_n;\Psi_n)$ does not necessarily hold as the regularizer part may have been decreased. Thus we further start from $\Psi_{n+1}^{(1)}$ and attempt to increase $-R(\mathcal{C}, G)$.

The Hessian matrix of $2R(\mathcal{C}, G)$ is the graph Laplacian matrix (i.e., $\Delta = D - W$). By applying one Newton-Raphson step on $R(\mathcal{C}, G)$, we propose a closed form solution for $\Psi_{n+1}^{(2)}$;

[1] http://en.wikipedia.org/wiki/Newton%27s_method_in_optimization

we then repeatedly obtain $\Psi_{n+1}^{(3)}$, ..., $\Psi_{n+1}^{(m)}$ using the Equation 15 until the value of the Q-function starts to drop:

$$p_{n+1}^{(t+1)}(\theta_j|d_u) = (1-\gamma)p_{n+1}^{(t)}(\theta_j|d_u)+\gamma\frac{\sum_{\langle u,v\rangle\in E} w(u,v)p_{n+1}^{(t)}(\theta_j|d_v)}{\sum_{\langle u,v\rangle\in E} w(u,v)} \quad (15)$$

Clearly, $\sum_j p_{n+1}^{(t+1)}(\theta_j|d) = 1$ and $p_{n+1}^{(t+1)}(\theta_j|d) \geq 0$ always hold in Equation 15. When the step parameter γ is set to 1, it means that the new topic distribution of a document is the average of the old distributions from its neighbors. This is related to the random-walk interpretation in [33]. Every iteration of Equation 15 makes the topic distributions smoother on the network. Note that an inner iteration does not affect the estimation of $\{p(w|\theta)\}_{w,\theta}$ in $\Psi_{n+1}^{(1)}$.

The stepping parameter γ can be interpreted as a controlling factor of smoothing the topic distribution among the neighbors. Once we have found $Q(\Psi_{n+1}^{(t)};\Psi_n) \geq Q(\Psi_n;\Psi_n)$, we can limit the further iterations of processing of Equation 15, so that Ψ_{n+1} would not be too far away from $\Psi_{n+1}^{(0)}$.

4. APPLICATIONS OF NETSTM

The framework defined in Equation 3 is quite general. Actually, one can use any topic models for $L(\mathcal{C})$ and a related regularizer for $R(\mathcal{C}, G)$. The choice of the topic model and the regularizer should be task dependent. In this section, we show that with difference choices of L and R, this framework can be applied to different mining tasks.

4.1 Author-Topic Analysis and Community Discovery

Author-topic analysis has been proposed in text mining literature [26, 23, 20]. One major task of author-topic analysis is to extract research topics from scientific literature and to measure the associations between topics and authors. This can be regarded as modeling topic maps and discovering research communities solely based on textual contents, where the authors in the same community works on the same topic. With a topic model, one can find a summary for a topical community, e.g., using the distribution $p(w|\theta)$.

On the other hand, many methods have been proposed to discover communities from social networks [11, 1], which solely explore the network structure. One concrete example is to discover research communities based on the coauthor relationship between researchers, where authors with collaborations are likely to lie in the same community.

However, both directions have their own limitations. In author-topic analysis, the associations between authors are indirectly modeled through the content. A professor and his fellow student may be assigned to two different communities, if they have different flavor of topics. On the other hand, solely relying on the network structure is at risk of assigning a biologist and a computer scientist into the same community, even if they just coauthored one paper of bioinformatics. Moreover, it is difficult to summarize the semantics of a community (i.e., to explain why they form a community).

To leverage the information in the text and the network, we can apply the NetPLSA model to extract topical communities. Specifically, for each author a, we may concatenate all his/her publications to form a virtual document of a. Then a coauthor social network G is constructed where there is an edge between author a and a' if they coauthored at least one paper.

We can define $w(a, a')$ as the number of papers that a and a' coauthored. Equation 6 can be rewritten as

$$\begin{aligned} O(\mathcal{C}, G) &= -(1-\lambda) * \sum_a \sum_w c(w,a) \log \sum_{j=1}^{k} p(\theta_j|a)p(w|\theta_j) \\ &+ \frac{\lambda}{2} \sum_{\langle a,a'\rangle\in E} w(a,a') \sum_{j=1}^{k} (p(\theta_j|a) - p(\theta_j|a'))^2 \quad (16) \end{aligned}$$

By minimizing $O(\mathcal{C}, G)$, we can estimate $p(\theta_j|a)$, which denotes the probability that the author a belongs to the j-th topical community. The estimated distribution $p(w|\theta_j)$ can be used as a semantic summary of the j-th community.

4.2 Spatial Topic Analysis

A general task in spatial text mining [20] is to extract topics from text with location labels and model their distribution over different geographic locations. Some natural topics, like public reaction to an event (e.g., hurricane Katrina), are geographic correlated. Intuitively we can expect that people live at nearby locations express similar topics.

Let L be a set of geographic locations and $l, l' \in L$. We denote $d \in \mathcal{D}_l$ if document d has a location label of l. By introducing a vertex for every location and an edge between two adjacent locations, we construct a geographic location network $G = \langle L, E\rangle$. We can then model the geographic topic distribution with a variation of the NetPLSA, where

$$\begin{aligned} O(\mathcal{C}, G) &= -(1-\lambda) * \sum_d \sum_w c(w,d) \log \sum_{j=1}^{k} p(\theta_j|d)p(w|\theta_j) \quad (17) \\ &+ \frac{\lambda}{2} \sum_{\langle l,l'\rangle\in E} w(l,l') \sum_{j=1}^{k} (\sum_{d\in\mathcal{D}_l} \frac{p(\theta_j|d)}{|l|} - \sum_{d'\in\mathcal{D}_{l'}} \frac{p(\theta_j|d')}{|l'|})^2 \end{aligned}$$

where $|l|$ is the number of documents in l. Specifically, we modify the regularizer by replacing $p(\theta_j|d)$ with $\sum_{d\in\mathcal{D}_l} \frac{p(\theta_j|d)}{|l|}$, which is the topic distribution over a location, instead of a single document (we assume a uniform $p(d|l)$).

We then use the following formula instead of Equation 15:

$$\begin{aligned} p_{n+1}^{(t+1)}(\theta_j|d) &= (1-\gamma)p_{n+1}^{(t)}(\theta_j|d) \quad (18) \\ &+ \gamma\frac{\sum_{\langle l_d,l'\rangle\in E} w(l_d,l') \sum_{d'\in\mathcal{D}_{l'}} \frac{p_{n+1}^{(t)}(\theta_j|d')}{|l'|}}{\sum_{\langle d,d'\rangle\in E} w(l_d,l')}. \end{aligned}$$

where l_d denotes the location which d belongs to.

5. EXPERIMENTS

In the previous sections, we introduced the novel framework of topic modeling with network regularization, and discussed how it could be applied to solve real world text mining problems. In this section, we show the effectiveness of our model with experiments on two genres of data. We show how NetPLSA works for the author-topic analysis in Section 5.1 and for spatial topic analysis in Section 5.2.

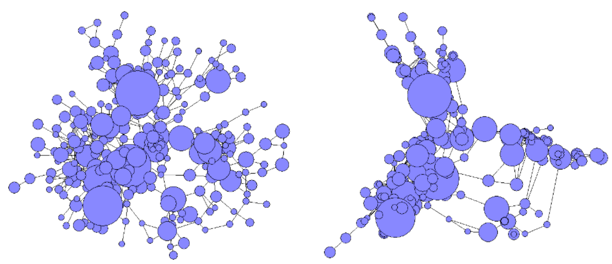
5.1 DBLP Author-Topic Analysis

Data Collection

The Digital Bibliography and Library Project (DBLP) is a database which contains the basic bibliographic information of computer science publications [2]. In this experiment, we

[2] http://www.informatik.uni-trier.de/~ley/db/

create our testing data set (4-CONF) from a subset of the DBLP records. We first extract all the papers published at four different conferences, WWW, SIGIR, KDD, and NIPS. For each paper, we extract the title in text and all its authors. We then construct the coauthor network, by making a vertex for every unique author a and an edge $\langle a, a' \rangle$ between two authors if they have coauthored at least one paper. We weight each edge in this network, by the number of papers that the two researchers have coauthored, $w(a, a')$. Finally, we concatenate the titles of all papers of an author to create a document d_a associated with this author. Our dataset has 9041 authors, and 16902 unique edges (without self links); the average weight for an edge is 1.2.



(a) View I (b) View II

* In this figure, we only show the authors who have more than 7 publications in the four conference(s). We do not show singletons.

Figure 2: Coauthor network in DBLP dataset

In Figure 2, we visualize the coauthor network structure of the 4-CONF dataset using the NetDraw software[3]. We only show the authors with more than five publications. The two views are "*Spring Embedder*" and "*Gower Metric Scaling*" provided by NetDarw. Basically, *Spring Embedder* is a standard graph layout algorithm which tries to put two vertices which are connected by an edge closer, and *Gower Metric Scaling* will locate two vertices closer if they are intensely connected directly or through other vertices [5]. Therefore, in both layout views (Figure 2 (a) and (b)), authors closer to each other are more likely to be in the same community. Clearly, from Figure 2 (b), we can guess that there are 3 to 4 major communities in the 4-CONF dataset, and such major communities are connected.

Topic Extraction

Once we created the testing datasets, we extract topics from the data using both PLSA and NetPLSA. Since the testing data is a mixture of four conferences, it is interesting to see whether the extracted topics could automatically reveal this mixture. Therefore, in both PLSA and NetPLSA, we set the number of topics to be 4. Following [28, 19], we introduce an extra background topic model to absorb the common words in English. We run the EM algorithm multiple times with random starting points to improve the local maximum of the EM estimates. To make the comparison fair, we use the same starting points for PLSA and NetPLSA. We summarize each topic θ with terms having the highest $p(w|\theta)$.

From Table 1, we see that PLSA extracts reasonable topics. However, in terms of representing research communities, all four topics have their limitations. The first topic is somewhat related to information retrieval, but it is mixed with some heterogenous topic like "*protein*". Although the third column is a very coherent NIPS topic (i.e., analog VLSI of neural networks), it is not broad enough to represent the general community of NIPS.

[3]http://www.analytictech.com/Netdraw/netdraw.htm

Table 1: Topics extracted from 4-CONF with PLSA

Topic 1		Topic 2		Topic 3		Topic 4	
term	0.02	peer	0.02	visual	0.02	interface	0.02
question	0.02	patterns	0.01	analog	0.02	towards	0.02
protein	0.01	mining	0.01	neurons	0.02	browsing	0.02
training	0.01	clusters	0.01	vlsi	0.01	xml	0.01
weighting	0.01	streams	0.01	motion	0.01	generation	0.01
multiple	0.01	frequent	0.01	chip	0.01	design	0.01
recognition	0.01	e	0.01	natural	0.01	engine	0.01
relations	0.01	page	0.01	cortex	0.01	service	0.01
library	0.01	gene	0.01	spike	0.01	social	0.01

Table 2: NetPLSA extracts cleaner topics

Topic 1		Topic 2		Topic 3		Topic 4	
retrieval	0.13	mining	0.11	neural	0.06	web	0.05
information	0.05	data	0.06	learning	0.02	services	0.03
document	0.03	discovery	0.03	networks	0.02	semantic	0.03
query	0.03	databases	0.02	recognit.	0.02	service	0.03
text	0.03	rules	0.02	analog	0.01	peer	0.02
search	0.03	association	0.02	vlsi	0.01	ontologi.	0.02
evaluation	0.02	patterns	0.02	neurons	0.01	rdf	0.02
user	0.02	frequent	0.01	gaussian	0.01	manage.	0.01
relevance	0.02	streams	0.01	network	0.01	ontology	0.01

As a comparison with PLSA, we present the topics extracted with NetPLSA in Table 2. It is easy to see that the four topics regularized with the coauthor network are much cleaner. They are coherent enough to convey certain semantics, and general enough to cover the natural "topical communities". Specifically, Topic 1 well corresponds to the information retrieval (SIGIR) community, Topic 2 is closely related to the data mining (KDD) community, Topic 3 covers the machine learning (NIPS) community, and Topic 4 well covers the topic that is unique to the conference of WWW.

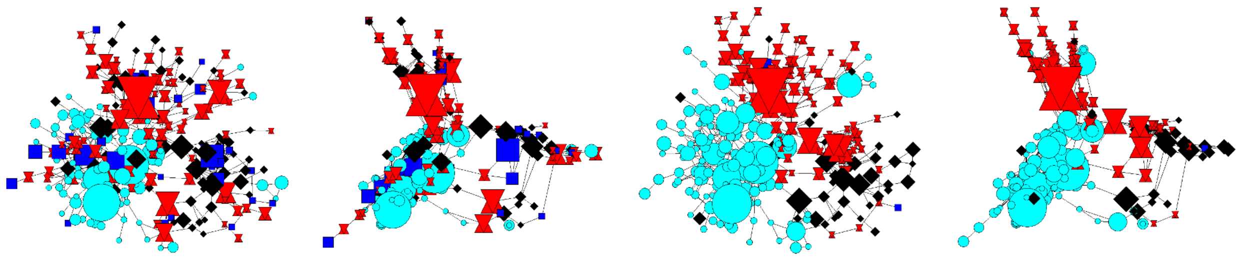
Topical Communities

We see that the quality of the topic models extracted with network regularization are better than those extracted without considering the network structure. However, could the regularized topic model really extract better topical communities? Are the topics in Table 2 really corresponding to coherent communities? We compare the topical communities identified by PLSA and NetPLSA.

Specifically, we assign each author to one of the topics, by $c_a = \arg\max_j p(\theta_j|a)$. We then visualize the authors assigned to different topics with different shapes and colors. The authors with the same shape thus form a topical community summarized by the corresponding topic model. As discussed in Section 2, the authors in the same topical community are expected to be well connected.

Figure 3 (a) and (b) present the topical communities extracted with the basic PLSA model, and Figure 3 (c) and (d) present the topical communities extracted with NetPLSA. With PLSA, although we can still see that lots of vertices in the same community are located closely, there aren't clear boundaries between communities. A considerable number of community members are scattered freely on the network (geometrically far from each other). On the other hand, when we regularize PLSA with the coauthor network, we see that the different communities can be identified clearly. Most authors assigned to the same topical community are well connected and closely located, which presents a much "smoother" pattern than Figure 3 (a) and (b).

Can we quantitatively prove that NetPLSA extracts better communities than PLSA? We have shown that network



(a) PLSA (b) PLSA: View II (c) NetPLSA (d) NetPLSA: View II

* Red: information retrieval; Black: data mining; Blue: machine learning; Grey: Web; $\lambda = 0.7$, $\gamma = 0.3$

Figure 3: Topical Communities in 4-CONF dataset

structure can help extracting topics. What about the reverse? Can a topic model of text help the network analysis?

Table 3: Quantitative Comparison of PLSA, NetPLSA, and Normalized Cut in Community Finding

Methods	Cut Edge weights	R. Cut/ N. Cut	Community Size ($\|V\|$)			
			C1*	C2	C3	C4
PLSA	4831	2.14/1.25	2280	2178	2326	2257
NetPLSA	**662**	0.29/0.13	2636	1989	3069	1347
NCut	855	**0.23/0.12**	2699	6323	**8**	**11**

*Ck means the k-th topical community, as in Table 1 and 2.
*Avg author weight: C1: 2.5; C2: 2.4; C3: 2.3; C4: **1.8**; All: 2.2

In Table 3, we quantitatively compare the performance of PLSA, NetPLSA, and a pure graph-based community extraction algorithm. We present the total weight of edges across different communities in column 2, and number of authors in each community in the rightmost 4 columns. Intuitively, if the communities are coherent, there should be many inner edges within each community and few cut edges across different communities. Clearly, there is significantly fewer cross community edges, and more inner community conductorships in the communities extracted by NetPLSA than PLSA. This means that NetPLSA indeed extracts more coherence topical communities than PLSA. Interestingly, we see that although Topic 4 (Web) in Table 2 is a coherent topic (more than 1300 authors are assigned to that topic), we cannot see a comparable number of members of this topical community from Figure 3, where we removed low degree authors and singletons (especially from Figure 3 (c) and (d)). This is because unlike IR, data mining and machine learning, "Web" is more an application field to the researchers than a focused research community, where many authors are from external communities and applying their techniques to the Web domain, and publishing papers to WWW. People purely assigned to the "WWW" topic either didn't publish many papers, or are not well connected.

One may argue that in terms of inner/inter-community links alone, a community discovery algorithm which purely relies on the network structure may achieve a better performance. Indeed, what if we use the graph-based regularizer alone (by setting the $\lambda = 1$ in Equation 3 and including some constraints)? A quick answer maybe "*you can get intensively connected communities but you may not get semantically coherent ones*". To verify this, we compare our results with a pure graph-based clustering method. Specifically, we compare with the Normalized Cut (NC) clustering algorithm [24], which is one of the standard spectral clustering algorithms. By feeding the algorithm[4] with the coauthor matrix, we also extract four clusters (communities).

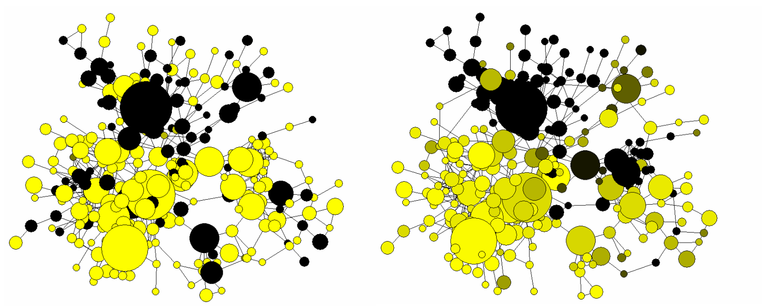
[4] http://www.cis.upenn.edu/~jshi/software/

We present two other objectives of graph segmentation in the third column of Table 3, namely the "normalized cut [24]" and "ratio cut [6]". They respectively normalize the cross edges between two communities with the number of inner edges and the size of vertices in each community. If we solely consider the cut edges, it is hard to tell whether Normalized Cut or NetPLSA segments the network better, since one has a smaller "minimum cut" and the other has a smaller "normalized cut". However, in terms of topical communities, we see that our results are more reasonable. Community 3 and 4 of NC are extremely small. There is no way that they could represent a real research community, or any of the 4 conferences. Indeed, graph-based clustering algorithms are often trapped with small communities when the graph structure is highly skewed (or disconnected). In the network, we find that both cluster 3 and 4 are isolated components in the network (no out edges). They are both very coherent "*topological communities*", but not good *topical communities*, since the semantic information they represent is too narrow to cover a general topic. The involving of a topic model alleviates this sensitivity by bridging disconnected components with implicit topical correlations. This also guarantees semantical coherency within communities.

Even when a pure graph-based method extracts a perfect community, without the help of the topic model, it's hard to get a good topical summary of such a community. Community 1 of Normalized Cut well overlaps with the "information retrieval" community we got by NetPLSA. However, if we estimate a language model from the authors assigned to this community, we ends up with top probability words like "*web*", "*information*", "*retrieval*", "*neural*", "*learning*", "*search*", "*document*", etc (with MLE, and removing stop words). The semantics looks like a mixture and not as coherent as the NetPLSA results in Table 2. This is because in reality, an author usually works on more than one topics. Even when she is assigned to one community (even if assigned softly), we still need to exclude her work on other areas from the summary of this community, which cannot be achieved with just the network structure. This problem is naturally solved with the involvement of a topic model, which assumes that a document covers multiple topics, and treats different words in a document differently.

Topic Mapping

Another basic task of TMN is to generate a map on the network for every topic. We use the probability $p(\theta|a)$ as the weighting function $f(v, \theta)$. We use the shades of a vertex to visualize the probability $p(\theta|a)$, where a darker vertex has a larger $p(\theta|a)$. As in Section 2, in a good topic map, the shades of adjacent vertices should be smooth.



(a) Topic Map with PLSA (b) With NetPLSA: Smoothed

Figure 4: Topic Map of "information retrieval" in 4-CONF dataset

In Figure 4, we visualize the topic map of "information retrieval" with the spring embedded view of the 4-CONF network. The darker a vertex is, the more likely the author belongs to the information retrieval community. From Figure 4 (a), we see that although a topic map could also be constructed with PLSA alone, the distribution of the topic on the network is desultory. It is hard to see where the topic origins, and how it is propagated on the network. We also see that PLSA likes to make extreme decisions, where an author is likely to be assigned an extremely large or small $p(\theta|a)$. In Figure 4 (b), however, we see that through the regularization with the coauthor network, the topic map is much smoother. We can easily identify the densest region of the topic "IR", and see it gradually propagates to the farther areas. Transitions between IR and non-IR communities are smooth, where the color of nodes changes from the darkest to the lightest in a gradational manner.

5.2 Geographic Topic Analysis

The other application we discussed in Section 4 is spatial topic analysis, more specifically, to model the geographic topic distributions. With this, we can analyze how a topic is propagating over the geographic locations. We create a collection of documents where each document is associated with a geographic location. All the geographic locations will then form a network structure based on their adjacency.

As discussed in [19, 20, 9], the weblog/blog data is a new genre of text data which is associated with rich demographic information. It is thus a suitable test bed for text mining problems with spatial analysis. Following [19], we collect weblog articles about a focused topic, by submitting a focused query to Google Blog Search[5], and crawling the content and geographic information of returned blog posts from their original websites. In this experiment, we use one of the data sets in [19], the Hurricane Katrina dataset. We also create a new dataset, with blog articles which contains the word "weather" in their titles. The basic statistics of the datasets are shown in Table 4.

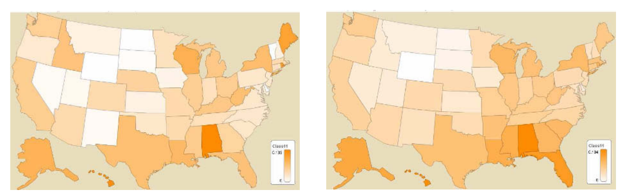
Table 4: The basic statistics of blog datasets

Dataset	# docs	Time Span	Query
Katrina	4341*	8/16/05 - 10/04/05	"hurricane katrina"
Weather	493	10/01/06 - 9/30/07	"weather" in Title

* Unlike [19], we only use the documents containing state labels. We restrict the domain in Live Spaces (http://spaces.live.com).

For both datasets, we create a vertex for every state in the U.S. and an edge between two adjacent states.

We use the model in Section 4.2 to extract topics with the context of geographic network structure. We then use the Many Eye visualization service[6] to visualize the spatial topic distribution of the one subtopic in hurricane Katrina. The subtopic discusses about the storms in Katrina, and in its successor hurricane Rita. Comparing Figure 5 (a) with Figure 5 (b), we see that the geographic distribution of topic is not dramatically different. This is reasonable, since the topic plotted in both figures is the same topic. However, we can still feel the difference between the figures: the topic distribution of Figure 5 (b) is much smoother than that in Figure 5 (a). Assume that a user does not know about hurricane Katrina or hurricane Rita, it is hard for her to guess where the events occurred from Figure 5 (a). People in Maine, Michigan, and Rhode Island seem to particularly focus on this topic, even more than people in Florida, Louisiana, and Mississippi (because of the sparsity of data in those states). From Figure 5 (b), however, we clearly see that the topic is densest along the Golf of Mexico, and gradually dilutes when it goes north and west. It is also clear that the discussion on this topic is denser in the west US than in the east. This is consistent with the reality, where the topic origins in the southeast coast, and gradually propagates to other states. In Figure 5 (b), we also see that the topic propagates smoothly between adjacent states. This also shows that our model could alleviate the overfitting problem of PLSA.



(a) With PLSA (b) With NetPLSA

Figure 5: Geographic Topic Distributions

Let us show the results with another dataset, the Weather dataset in Table 4. Intuitively, when a user was discussing about weather in her blogs, the topics she chose to write about would be affected by where she lived. Since the topic "weather" is very broad, we guide the mixture model with some prior knowledge, so that it could extract several topics which we expect to see. Following [18], this is done by changing the MLE estimation of $p(w|\theta)$ in M step (Equation 11) into a maximum a posterior (MAP) estimation. We extract 7 topics from the Weather dataset. We use "wind" and "hurricane" as the prior for two of the topics, so that one of the output topic will be about the windy weather, and another will be about hurricanes. Table 5 compares the prior-guided topic models extracted from the Weather dataset. We see

[5] http://blogsearch.google.com

[6] http://services.alphaworks.ibm.com/manyeyes/home

that with the network based regularizer, we indeed extract more coherent topics.

Table 5: Topic models: the Weather dataset

PLSA		NetPLSA	
"wind"	**"hurricane"**	**"wind"**	**"hurricane"**
windy	dean	windy	hurricanes
severe	storm	f	storms
pm	mexico	hi	tropical
thunderstorm	texas	cloudy	atlantic
hail	category	lo	season
watch	jamaica	lows	erin
blah	oil	highs	houston
probability	tourists	mph	louisiana

In Figure 6, we visualize the geographic distributions of two weather topics over the US states. Comparing to the distributions computed with PLSA, we see that with NetPLSA, we can get much smoother distributions. PLSA assigns extremely large (close to 1) $p(\theta|d)$ of the topic "windy" to Delaware, and "hurricane" to Hawaii. On the other hand, it assigns surprisingly low probability of "windy" to Texas. It also assigns extremely low probability of "hurricane" to Mississippi, Alabama and Georgia, although they are among the most vulnerable states to hurricanes. Through the regularization with states network, we see that this problem is alleviated. Northern midwest states and Texas are identified as windy states, especially Illinois (where the "windy city" Chicago locates). The southeast coasts, especially the states alone the Golf of Mexico (Florida as a representative), are identified as "hurricane" states.

In this section, we showed that with network based regularization, the NetPLSA model outperforms PLSA. It also extracts more robust topical communities than solely graph-based methods. NetPLSA generates coherent topics, topologically and semantically coherent communities, smoothed topic maps, and meaningful geographic topic distributions.

6. RELATED WORK

Statistical topic modeling and social network analysis have little overlap in existing literature. Statistical topic modeling [10, 4, 28, 26, 19, 20, 15] uses a multinomial word distribution to represent a topic, and explains the generation of the text collection with a mixture of such topics. However, none of these existing models considers the natural network structure in the data. In the basic models such as PLSA [10] and LDA [4], there is no constraint other than "sum-to-one" on the topic-document distributions. [25] uses a regularizer based on KL divergence, by discouraging the topic distribution of a document from deviating the average topic distribution in the collection. We propose a different method, by regularizing a statistical topic model (e.g., PLSA) with the network structure associated with the data.

Contextual text mining [28, 26, 19, 20] is concerned with modeling topics and discovering other textual patterns with the consideration of contextual information, such as time, geographic location, and authorship. Our work is the first attempt where a network structure is considered as the context in topic models.

Social network analysis has been a hot topic for quite a few years. Many techniques have been proposed to discover communities [11, 1], model the evolution of the graph [13], and understand the diffusion of social networks [9, 14]. However, the rich textual information associated with the social network is ignored in most cases.

Although there has been some existing explorations [7, 17, 16, 2], there has not been a unified way to combine textual contents with social networks. Indeed, [31] proposes a probabilistic model to extract e-communities based on the content of communication documents, but they leave aside the network structure in their model. Cohn and Hofmann proposed a model which combines PLSA and PHITS on the web graph [7]. Both topic and link are modeled as generated from a probabilistic mixture model. Their model, however, assumes a directed graph and does not directly optimize the smoothness of topics on the graph. To the best of our knowledge, combining topic modeling with graph-based harmonic regularization is a novel approach.

The graph-based regularizer is related to existing work in machine learning, especially graph-based semi-supervised learning [33, 29, 3, 32] and spectral clustering [6, 24]. The optimization framework we propose is closely related to [34], which is probably the first work combining a generative model with graph-based regularizer. Our work is different from theirs, as their task is semi-supervised classification, while we focus on unsupervised text mining problems such as topic modeling. NetSTM is a generalization of harmonic mixture to multiple topics and unsupervised learning.

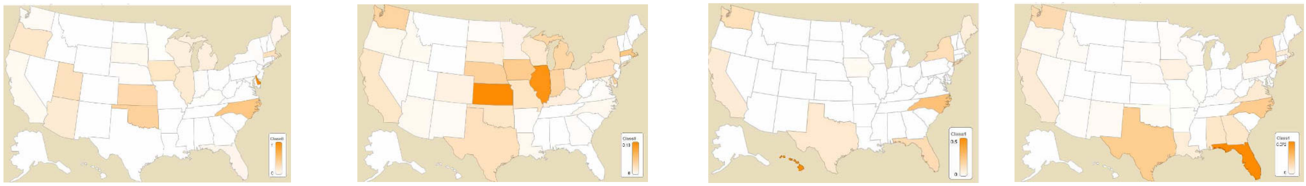
The concrete applications we introduced in Section 4 are also related to existing work on author-topic analysis [26, 20], spatiotemporal text mining [19, 20], and blog mining [9, 19]. [30] explores co-author network to estimate the Markov transition probabilities between topics, which uses the network structure as a post processing step of topic modeling. Our work leverages the generative topic modeling and discriminative regularization in a unified framework.

7. CONCLUSIONS

In many knowledge discovery tasks, we encounter a data collection with both abundant textual information and a network structure. Statistical topic models extract coherent topics from the text, while usually ignoring the network structure. Social network analysis on the other hand, tends to focus on the topological network structure, while leaving aside the textual information. In this work, we formally define the major tasks of topic modeling with network structure. We propose a general solution of text mining with network structure, which optimizes the likelihood of topic generation and the topic smoothness on the graph in a unified way. Specifically, we propose a regularization framework for statistical topic models, with a harmonic regularizer based on the network structure. The general framework allows arbitrary choices of the topic model and the graph based regularizer. We show that with concrete choices, the model can be applied to tackle real world text mining problems such as author-topic analysis, topical community discovery, and spatial topic analysis.

Empirical experiments on two different genres of data show that our proposed method is effective to extract topics, discover topical communities, build topic maps, and model geographic topic distributions. It improves both pure topic modeling, and pure graph-based method.

There are many potential future directions of this work. It is interesting to see how other topic models and regularizers can be adopted (e.g., LDA, normalized cut, etc). It is also interesting to study how the special properties of social networks can be considered in this framework, such as the small world property. Utilizing such a model to model



(a) "Windy" states with PLSA (b) "Windy" states with NetPLSA (c) "Hurricane" with PLSA (d) "Hurricane" with NetPLSA

Figure 6: Geographic distribution of topics in Weather

the evolution of topics and community is also a promising direction, which requires the modeling of time dimension.

8. ACKNOWLEDGEMENTS

We sincerely thank the three anonymous reviewers for their very comprehensive and constructive comments. Although some of them are difficult to be addressed in this paper, they provide nice suggestions for our future work. This work was in part supported by the National Science Foundation under award numbers 0713571 and 0713581. The first author was supported by the Yahoo! Ph.D Fellowship.

9. REFERENCES

[1] L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group formation in large social networks: membership, growth, and evolution. In *Proceedings of KDD '06*, pages 44–54, 2006.

[2] R. Bekkerman, R. El-Yaniv, and A. McCallum. Multi-way distributional clustering via pairwise interactions. In *Proceedings of ICML*, pages 41–48, 2005.

[3] M. Belkin and P. Niyogi. Laplacian eigenmaps for dimensionality reduction and data representation. *Neural Comput.*, 15(6):1373–1396, 2003.

[4] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3:993–1022, 2003.

[5] S. Borgatti, M. Everett, and L. Freeman. Ucinet for windows: Software for social network analysis. *Harvard: Analytic Technologies*, 2002.

[6] P. K. Chan, M. D. F. Schlag, and J. Y. Zien. Spectral k-way ratio-cut partitioning and clustering. In *Proceedings of the 30th international conference on Design automation*, pages 749–754, 1993.

[7] D. A. Cohn and T. Hofmann. The missing link - a probabilistic model of document content and hypertext connectivity. In *NIPS*, 2000.

[8] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of Royal Statist. Soc. B*, 39:1–38, 1977.

[9] D. Gruhl, R. Guha, D. Liben-Nowell, and A. Tomkins. Information diffusion through blogspace. In *Proceedings of the 13th International Conference on World Wide Web*, pages 491–501, 2004.

[10] T. Hofmann. Probabilistic latent semantic indexing. In *Proceedings of SIGIR '99*, pages 50–57, 1999.

[11] J. Kleinberg. The small-world phenomenon: an algorithm perspective. In *Proceedings of the thirty-second annual ACM symposium on Theory of computing*, pages 163–170, 2000.

[12] R. Kumar, P. Raghavan, S. Rajagopalan, and A. Tomkins. Trawling the web for emerging cyber-communities. In *Proceeding of the eighth international conference on World Wide Web*, pages 1481–1493, 1999.

[13] J. Leskovec, J. Kleinberg, and C. Faloutsos. Graphs over time: densification laws, shrinking diameters and possible explanations. In *Proceeding of KDD '05*, pages 177–187, 2005.

[14] J. Leskovec, M. McGlohon, C. Faloutsos, N. Glance, and M. Hurst. Cascading behavior in large blog graphs. In *Proceeding of SDM' 07*, 2007.

[15] W. Li and A. McCallum. Pachinko allocation: Dag-structured mixture models of topic correlations. In *Proceedings of ICML*, pages 577–584, 2006.

[16] B. Long, Z. M. Zhang, X. Wu, and P. S. Yu. Spectral clustering for multi-type relational data. In *ICML*, pages 585–592, 2006.

[17] A. McCallum, A. Corrada-Emmanuel, and X. Wang. Topic and role discovery in social networks. In *IJCAI*, pages 786–791, 2005.

[18] G. J. McLachlan and T. Krishnan. *The EM Algorithm and Extensions*. Wiley, 1997.

[19] Q. Mei, C. Liu, H. Su, and C. Zhai. A probabilistic approach to spatiotemporal theme pattern mining on weblogs. In *Proceedings of the 15th international conference on World Wide Web*, pages 533–542, 2006.

[20] Q. Mei and C. Zhai. A mixture model for contextual text mining. In *Proceedings of KDD '06*, pages 649–655, 2006.

[21] R. M. Neal and G. E. Hinton. A view of the em algorithm that justifies incremental, sparse, and other variants. pages 355–368, 1999.

[22] M. Richardson and P. Domingos. The intelligent surfer: Probabilistic combination of link and content information in pagerank. In *NIPS*, pages 1441–1448, 2002.

[23] M. Rosen-Zvi, T. Griffiths, M. Steyvers, and P. Smyth. The author-topic model for authors and documents. In *Proceedings of the 20th conference on Uncertainty in artificial intelligence*, pages 487–494, 2004.

[24] J. Shi and J. Malik. Normalized cuts and image segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.*, 22(8):888–905, 2000.

[25] L. Si and R. Jin. Adjusting mixture weights of gaussian mixture model via regularized probabilistic latent semantic analysis. In *PAKDD*, pages 622–631, 2005.

[26] M. Steyvers, P. Smyth, M. Rosen-Zvi, and T. Griffiths. Probabilistic author-topic models for information discovery. In *Proceedings of KDD '04*, pages 306–315, 2004.

[27] X. Wang and A. McCallum. Topics over time: a non-markov continuous-time model of topical trends. In *Proceedings of KDD '06*, pages 424–433, 2006.

[28] C. Zhai, A. Velivelli, and B. Yu. A cross-collection mixture model for comparative text mining. In *Proceedings of KDD '04*, pages 743–748, 2004.

[29] D. Zhou, O. Bousquet, T. N. Lal, J. Weston, and B. Schölkopf. Learning with local and global consistency. In *NIPS*, 2004.

[30] D. Zhou, X. Ji, H. Zha, and C. L. Giles. Topic evolution and social interactions: how authors effect research. In *Proceedings of CIKM '06*, pages 248–257, 2006.

[31] D. Zhou, E. Manavoglu, J. Li, C. L. Giles, and H. Zha. Probabilistic models for discovering e-communities. In *Proceedings of WWW '06*, pages 173–182, 2006.

[32] D. Zhou and B. Schölkopf. Discrete regularization. *Semi-supervised learning*, pages 221–232, 2006.

[33] X. Zhu, Z. Ghahramani, and J. D. Lafferty. Semi-supervised learning using gaussian fields and harmonic functions. In *ICML*, pages 912–919, 2003.

[34] X. Zhu and J. D. Lafferty. Harmonic mixtures: combining mixture models and graph-based methods for inductive and scalable semi-supervised learning. In *ICML*, pages 1052–1059, 2005.