CS388 NLP Project Report

Text Mining for Hidden Relations and Trending

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***Abstract*—The main contribution of this paper has two folds. First, we formalized an illustration method to visualize topic trending on a bidirectional spanning tree, which gives a meaningful intuition to discover how hidden thematic structures in large archive of text documents change, merge and split over time. Second, we proposed an algorithm, Thematic Particle Clustering, that combines probabilistic sampling, clustering and gradient descent methods to predict upcoming topics based on a sequence of history topics. The effectiveness of our methods is demonstrated through a collection of 10,000 patent data in the field of robotics spanning over 30 years.**

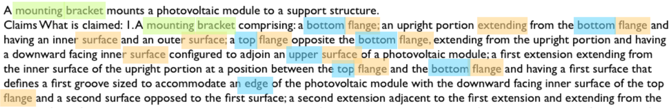
I. Introduction

II. Background

Given a collection of text-based patent documents, one intuitive idea to find out knowledge spillovers is to look at some underlying thematic structures hidden in the text. Based on the word usages and terminology distributions, we need to know what are the intrinsic topics implied in the relevant context, and one common way to do exactly that is called Probabilistic Topic Models formalized by Blei et al. [1]

A. Probabilistic Topic Models

The main objective of topic modeling is to automatically discover the unobserved hidden structures–the topics, per-document topic distributions, and the per-document per-word topic assignments, with a collection of text documents as the only observable variables.



A mounting bracket mounts a photovoltaic module to a support structure.
Claims What is claimed: 1.A mounting bracket comprising: a bottom flange; an upright portion extending from the bottom flange and having an inner surface and an outer surface; a top flange opposite the bottom flange, extending from the upright portion and having a downward facing inner surface configured to adjoin an upper surface of a photovoltaic module; a first extension extending from the inner surface of the upright portion at a position between the top flange and the bottom flange and having a first surface that defines a first groove sized to accommodate an edge of the photovoltaic module with the downward facing inner surface of the top flange and a second surface opposed to the first surface; a second extension adjacent to the first extension and extending from the

Fig. 1: A sample patent document (partial)

For example, given a sample patent text, we assume that there exists a set of topics associated with this patent. In Fig. 1, we have annotated a selection of words, with topics distinguished by colors. For the orange topic, we get words like flange, surface and extending, which could be interpreted as having something to do with attachment of hardware components such as pipes and cylinders. Similarly, the blue and green topics could be interpreted as installation and mounting respectively. By looking at the text, any human being with common comprehensive ability can easily tell what a document similar to Fig. 1 is about, and highlight the associated keywords that defines such topics.

Nonetheless, when we scale up the size and complexity of these patent documents, using human labor to do such tasks suddenly becomes erroneous and expensive. The goal of probabilistic topic modeling is to automate this process and to provide hidden insights and meaningful intelligence of big data. If we can successfully construct a reasonable thematic structure from our patent data, we can presumably infer influences or spillovers of patent authors within the same topics.

B. Latent Dirichlet Allocation

Latent Dirichlet allocation, or LDA, is the simplest topic model [2] that assigns each word in the documents a distribution over a fixed number of topics. Instead of having a hard boundary between topic collections, LDA provides a distribution of topics per document, giving the likelihood of a mixed proportion of topic assignments. Namely, all patent documents share the same set of topic collection but with different proportions to each topic. For instance in Fig. 2, although there are $K = 100$ topics overall, only a few topics were actually activated.

To build the generative probabilistic model, we compute the joint distribution and use it to estimate the posterior probability. Before jumping into the actual calculation, let's formalize our notations:

$\beta_k,\ k = 1 \cdots K$ the K topics, represented by a distribution over words

$\theta_d,\ d = 1 \cdots D$ topic proportions for document d, where $\theta_{d,k}$ is the topic proportion of topic k for document d

$z_d,\ d = 1 \cdots D$ topic assignments for document d, where $z_{d,n}$ is

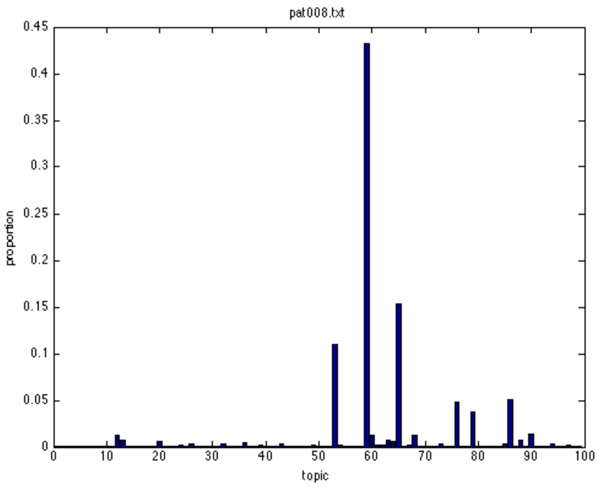


Fig. 2: A sample topic proportion of a patent

the topic assignment for the n-th word in document d

$w_d,\ d = 1:D$ observed words for document d, where $w_{d,n}$ is the n-th word in document d

With the above notation, the LDA generative process can be formalized as the following joint probability of both hidden and observed random variables:

$$p(\beta_{1:K},\theta_{1:D},z_{1:D},w_{1:D}) \\ = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

which can alternatively be expressed as a graphical model:

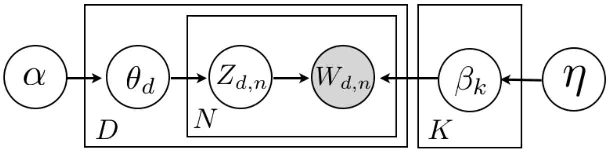


Fig. 3: LDA graphical model. Nodes represent variables, while edges indicate the dependency relations. The shaded node is the only observed variable (document words), and all others are the hidden variables. The D plate denotes the replicated variables product over D documents, while the N plate denotes replication over N words in each document.

Note that there are several conditional dependencies implied in the graphical models, which reflects the main principles of how LDA "think" the documents are generated:

1) Randomly pick a distribution θ_d over topics.

2) For each word in the document

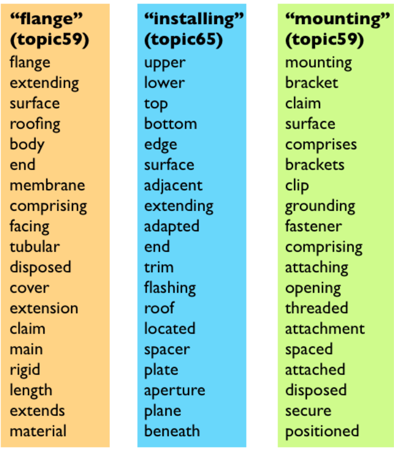
   a) Randomly choose a topic from the previously-chosen distribution $\theta_{d,n}$.

   b) Randomly choose a word from the corresponding distribution $Z_{d,n}$.

Assuming this generative process is how our documents are created, now LDA uses the graphical model in Fig. 3 to infer the posterior probability of the hidden structures given our observable:

$$p(\beta_{1:K},\theta_{1:D},z_{1:D}|w_{1:D}) = \frac{p(\beta_{1:K},\theta_{1:D},z_{1:D},w_{1:D})}{p(w_{1:D})}$$

The computation of possible topic structures is often intractable and the posterior distribution can only be approximated in most cases. To form an approximation algorithm, topic modeling can generally be categorized as sampling-based algorithms and variational algorithms. The most popular sampling method for topic modeling is Gibbs sampling, which introduces a sequence of random variables to construct a Markov chain and collects samples from the limiting distribution to estimate the posterior. Instead of using samples to approximate the posterior, variational methods find the closest parameterized distribution candidate by solving optimization problems [2] [3].



"flange" (topic59)	**"installing" (topic65)**	**"mounting" (topic59)**
flange	upper	mounting
extending	lower	bracket
surface	top	claim
roofing	bottom	surface
body	edge	comprises
end	surface	brackets
membrane	adjacent	clip
comprising	extending	grounding
facing	adapted	fastener
tubular	end	comprising
disposed	trim	attaching
cover	flashing	opening
extension	roof	threaded
claim	located	attachment
main	spacer	spaced
rigid	plate	attached
length	aperture	disposed
extends	plane	secure
material	beneath	positioned

Fig. 4: The top 3 topics of a sample patent

C. Limitations & Potential Improvements

Although LDA provides a powerful perspective to browsing and interpreting the implicit topic structures in our patent corpus, there are a few limitations it imposes against further discoveries. An extensive amount of research has been focused on relaxing some of the assumptions made by LDA to make it more flexible and suitable for various adaptations in more sophisticated context.

Bag of Words LDA is essentially a bag-of-words probabilistic model. Namely, it constructs a word-frequency vector for each document but disregards the word ordering and the neighboring context. Although this assumption looses the syntactic information and sometimes seems unrealistic when processing natural language, it is usually good enough when capturing the document semantics and simplifying hidden structural inferences. Nonetheless, for more sophisticated tasks such as language generation or writing style modeling, the bag-of-words assumption is apparently insufficient and needs to be relaxed. In these cases, there are variants of topic models that generate topic words conditioned on the previous word [4], or switches between LDA and hidden Markov models (HMM) [5].

Document Ordering The LDA graphical model in Fig. 3 is invariant to the ordering of our patent documents, which could be inappropriate if the hidden thematic structure is actually dependent on sequential information such as years published, which is typical in document collections spanning years, decades or centuries. To discover how the topics change over time, the dynamic topic model [6] treats topics as a sequence of distributions over words and tracks how they change over time.

Fixed Number of Topics In either LDA or more sophisticated dynamic topic models [6], the number of topics $\beta_{1:K}$ is determined manually and assumed to be fixed. One elegant approach provided by the Bayesian nonparametric topic model [7] is to find a hierarchical tree of topics, in which new documents can now imply previously undiscovered topics.

Meta-data To include additional attribute information associated with the documents such as authorships, titles, geolocation, citations and many others, an active branch of research has been performed to incorporate meta-data in topic models. The author-topic model [8] associates author similarity based on their topic proportions, the relational topic model [9] assumes document links are dependent on their topic proportion distances, and more general purpose methods such as Dirichlet-multinomial regression models [10] and supervised topic models [11].

Others Many other extensions of LDA are available, including the correlated topic model [12], pachinko allocation machine, [13], spherical topic model [14], sparse topic models [15] and bursty topic models [16].

III. Problem Definition and Algorithm

A. *Task Definition*

B. *Algorithm Definition*

1) Assign K topics to N particles uniformly
2) Add Gaussian noise to particles
3) Cluster particles into K groups (TF-IDF weights with cosine/Euclidean distances)
4) Compare the clusters with topics from the next year, apply discounts to current weights, and adjust to new weights
5) repeat

IV. Experimental Evaluation

A. *Methodology*

B. *Results*

C. *Discussion*

V. Related Work

VI. Future Work

VII. Conclusion

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