Hierarchical Latent Word Clustering

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Abstract

This paper presents a new Bayesian non-parametric model by extending the usage of Hierarchical Latent Dirichlet Allocation to extract tree structured word clusters from text data. The inference algorithm of the model collects words in a cluster if they share similar distribution over documents. In our experiments, we observed meaningful hierarchical structures on NIPS corpus and radiology reports collected from public repositories.

1 Introduction

Extracting relationships between words plays an important role on information retrieval, document summarization, and document classification. One way to extract hidden relationships is creating clusters on words. Creating hierarchy within these clusters is further useful to enhance abstraction level. For example, the terms “brain” and “skull” are more related as compared to “brain” and “kidney” in the medical domain. We have discovered that modifying the data generation model of Hierarchical Latent Dirichlet Allocation (HLDA) [1] creates a model that is able to capture hidden hierarchical word clusters from text. We named the algorithm as “Hierarchical Latent Word Clustering” (HLWC). HLWC merges generative topic models with entropy-based agglomerative word clustering methods.

Topic modeling literature models word relationships using multinomial distributions on words. Documents are represented as mixtures of extracted topics. Latent Dirichlet Allocation (LDA) [2] is an important milestone in this area. LDA uses a Dirichlet prior on Probabilistic Latent Semantic Indexing (PLSI) [3] to avoid overfitting. Later, Hierarchical Dirichlet Process (HDP) [8] is extended from LDA to achieve a non-parametric structure. HDP allows to grow number of topics with incoming data. However, in these models interesting hierarchical relations are not captured. Extension studies considered hierarchical versions of topic models. Authors of [1] proposed HLDA model to get tree structured topic relations from a corpus. Moreover, Pachinko Allocation Machine (PAM) allows DAG-structured hierarchy [5]. As opposed to these models, we utilized multinomial on documents. As a result, HLWC creates word clusters instead of multinomial distributions on words.

An alternative to get clustering of words is representing words in an embedding space as in Word2Vec [7], then obtaining clustering with standard clustering algorithms. However, hierarchical extraction is a more challenging problem. Recently, REBUS algorithm is introduced using the projection entropy value to obtain agglomerative hierarchical clustering on words. This algorithm merges clusters pairwise to obtain final hierarchy. However, extracted relationships do not define
abstract representations of documents because of the unbalanced binary tree structure. Liu et al. [6] presented another greedy agglomerative procedure to create word clusters based on mutual information. In their study, a node can have multiple branches. Our study differentiates from agglomerative methods by using Bayesian formalism on clustering. A top-down approach divides words into clusters with a Bayesian non-parametric prior.

Specifically, we modified the generative model of HLDA using the document generation model of PLSI [4]. Whereas, topic model studies followed the word generation branch of PLSI. Our model shares the same non-parametric prior, nested Chinese Restaurant Process (nCRP), with HLDA. However, it produces hierarchical non-parametric word clusters like REBUS [3] instead of document clusters as in HLDA. Relations with existing methods are illustrated in Figure 1a.

In the following section, we describe our model and inference. We have given experimental results on section 3. The last section concludes the text and gives future directions.

2 Hierarchical Latent Word Clustering

nCRP prior used in HLWC was first presented in [1]. nCRP is an exchangeable distribution on tree structures with unbounded depth and branching factor. A sample tree structure is shown in Figure 1b. The observed nodes are shown in dark color. Light nodes are potential new branches providing non-parametric behavior for incoming data. The path model is the model that describes the conditional distribution of data given the path. Parameters associated with each node are used in path model to generate data. The difference between HLDA and HLWC comes in the path model. In each path of HLDA, documents follow LDA distribution as shown in Figure 1c. Each document has its own distribution across levels $\theta_d$ and level allocation variable $z_{di}$ is sampled from that distribution. Then, the word $w_{di}$ is sampled from selected multinomial topic $\beta_{z_{di}}$. In this notation, $D$ is used for a number of documents and $N_d$ is used for the number of words in that document. Although it is not explicitly shown, the document ids along with words are observed variables of the model.

We modified path model using document generation model of PLSI [4] as shown in Figure 1d. The generative model for HLWC is according to Equation (1). In this model, each word $w$ chooses its path $c_w$ according to nCRP prior. Then, document ids are generated from the path model. In other words, each word generates distribution over levels $\theta_w$ from a Dirichlet distribution parameterized with $\alpha$. Then, level allocations for word observation $z_{wi}$ are sampled from $\theta_w$ and document ids.
$d_{wi}$ are sampled from multinomial distributions $\beta_{z_{wi}}$. Topic $\beta_i$'s are distributed i.i.d. according to Dirichlet prior with parameter $\eta$. In HLWC $N_w$ represents total number of observation of a word in the whole corpus. Also, $N_d$ represents number of documents in the corpus.

\[ \begin{align*}
    c_w &\sim \text{nCRP}(\gamma) \\
    \theta_w &\sim \text{Dirichlet}(\alpha) \\
    \beta_i &\sim \text{Dirichlet}(\eta) \\
    z_{wi} &\sim \text{Multinomial}(\theta_w) \\
    d_{wi} &\sim \text{Multinomial}(\beta_{z_{wi}})
\end{align*} \]

The parameters of the model are $\gamma$, $\eta$, $L$ and $\alpha$. $\gamma$ is nCRP prior parameter affecting the probability of new branches. Higher values of $\gamma$ tend to create wider trees. The parameter $\eta$ controls the sparseness of document distributions. For smaller values of $\eta$, model tends to create smaller clusters. Number of levels $L$ changes the depth of the tree. More levels could slow down inference and may create noisy clusters because the nodes may not have enough data to reliably estimate the parameter. The depth is restricted to $L=3$ levels in this study. $\alpha$ controls the sparseness of distribution over levels. If the level distribution is sparse words tend to belong only one level.

The inference task is getting a representative sample tree from the posterior distribution. That is, finding level allocations of document observations and paths of the words. It is possible to utilize similar inference methods with HLDA since transpose operation on dataset (changing rows with columns in bag of words representation) creates the desired model. In a similar manner, intermediate parameters are integrated out in collapsed Gibbs sampler. The resulting distribution of integration in a node becomes Dirichlet-multinomial compound distribution that is denoted by DM. We sampled path of each word according to the distribution (2). Then, for each observation of word in a document, the level allocation is sampled according to the distribution (3).

In our notation, we have used capital bold letters for collection of variables (i.e. $C = \{c_w\}_{w=1}^{V}$, $D_w = \{d_{wi}\}_{i=1}^{N_w}$, $Z_w = \{z_{wi}\}_{i=1}^{N_w}$). Minus sign (-) in power represents the exclusion of variables which is common in collapsed Gibbs sampling. To represent the frequencies, we have used symbol ‘#’. For example $\#[D_{c_w,z_{wi}}] = d_{wi} | c_w, z_{wi}$ represents how many times the document id $d_{wi}$ appears in selected topic indexed by path $c_w$ and level $z_{wi}$.

\[ \begin{align*}
    P(c_w|\gamma, C^{-w}, Z, D) &\propto \text{nCRP}(c_w|\gamma, C^{-w})DM(D_w|Z, D^{-w}, \eta, c_w) \\
    P(z_{wi}|\alpha, Z^{-wi}_{c_w}, c_w, d_{wi}) &\propto (\#[Z^{-wi}_{c_w} = z_{wi}|c_w] + \alpha) \times \frac{\#[D_{c_w,z_{wi}} = d_{wi}|c_w, z_{wi}] + \eta}{\#[D_{c_w,z_{wi}}|c_w, z_{wi}] + N_d \eta}
\end{align*} \]

3 Results

We performed our inference on two datasets. First one is NIPS dataset, a widely used text corpus used in topic modeling literature. Also, we have collected radiology reports from publicly available data sources. The collection included IDash radiology reports, OpenI chest x-ray reports and Medical NLP Challenge dataset.

In NIPS dataset, top 50 most frequent words were removed. We chose following 4k words for clustering without applying stemming on the vocabulary. We restricted number of levels to 3 in nCRP prior. Parameters of the model was $\eta = [1, 1, 1]$, $\gamma = 1$ and $\alpha = [1, 1, 1]$ for NIPS dataset. This setting corresponds to less informative prior.Collapsed Gibbs sampler ran for 2.5k iterations. Part of the resulting hierarchy is shown in Figure 2. Top node was not drawn since it is shared by all words. Rest of the tree can be found in the supplementary material. It could be seen that the model is able to group related words in the same cluster. Thanks to common distribution on documents, related word clusters were combined in the upper level.

We collected 8452 documents to conduct experiments on radiology reports. Vocabulary size for this corpus was 5046. We used parameters $\eta = [1, 1, 1]$, $\gamma = 1$ and $\alpha = [0.5, 0.5, 0.5]$. After 5000

\footnote{http://www-users.cs.umn.edu/~bthomson/medicalchallenge/index.html}
4 Conclusion

We presented Hierarchical Latent Word Clustering as a non-parametric hierarchical clustering structure on words. Proposed algorithm defines topics as multinomial distributions over documents and words those are sharing similar document distributions are clustered in a tree. We conducted experiments on two real-world datasets: NIPS and radiology reports. Results indicate that word clusters could be identified with proposed inference algorithm. This study suggests a potentially fruitful new direction in text analysis. It is possible to extend this study with more informative features like Word2Vec skip-gram features. Also, it could be possible to obtain more coherent clusters with allowing some degree of polysemy.

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References

[1] David M. Blei, Thomas L. Griffiths, Michael I. Jordan, and Joshua B. Tenenbaum. Hierarchical
topic models and the nested chinese restaurant process. In Advances in Neural Information
Processing Systems, page 2003. MIT Press, 2004.

[2] David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. the Journal of
machine Learning research, 3:993–1022, 2003.

[3] İsk Bağış Fidaner and Ali Taylan Cemgil. Clustering words by projection entropy. arXiv
preprint arXiv:1410.6830, 2014.

[4] Thomas Hofmann. Probabilistic latent semantic indexing. In Proceedings of the 22nd annual
international ACM SIGIR conference on Research and development in information retrieval,
pages 50–57. ACM, 1999.

[5] Wei Li and Andrew McCallum. Pachinko allocation: Dag-structured mixture models of topic
correlations. In Proceedings of the 23rd international conference on Machine learning, pages
577–584. ACM, 2006.

[6] Tengfei Liu, Nevin L Zhang, and Peixian Chen. Hierarchical latent tree analysis for topic detec-
tion. In Machine Learning and Knowledge Discovery in Databases, pages 256–272. Springer,
2014.

[7] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word rep-
resentations in vector space. arXiv preprint arXiv:1301.3781, 2013.

[8] Yee Whye Teh, Michael I Jordan, Matthew J Beal, and David M Blei. Hierarchical dirichlet
processes. Journal of the american statistical association, 101(476), 2006.