Applying hLDA to Practical Topic Modeling

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Outline

1. Introduction
   - HLDA
   - Discussion
2. Bayesian Clue
   - the nested CRP
   - GEM Distribution
   - Dirichlet Distribution
   - Posterior Inference

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Background

♣ **The Goal in Our Paper.**
HLDA has been proved to be a powerful tool. One of the bottlenecks which prevent its large-scale application is that we cannot find a quick and effective approach to modeling new data properly. There exist lots of factors, eg. hyper-parameter settings, uncertainty of random algorithms and features of different corpus.

♣ **Probabilistic Topic Models**
Topic models are algorithms for discovering the main themes that pervade a large and otherwise unstructured collection of documents. Topic models can organize the collection according to the discovered themes.

♣ **LDA-related Introduction**
LDA and other topic models are part of the larger field of probabilistic modeling. In generative probabilistic modeling, we treat our data as arising from a generative process that includes hidden variables.

Merits of HLDA

1. Generative process for documents [2]
2. Posterior approximate inference with Gibbs sampling [1]

$$p(z_{d,n}|z_{-(d,n)}, c, w, \pi, \eta) \propto p(z_{d,n}|z_{-d,-n}, m, \pi) p(z_{d,n}|z, c, w_{-(d,n)}, \eta) \quad (1)$$

$$p(c_d|w, c_{-d}, z, \eta, \gamma) \propto p(c_d|c_{-d}, \gamma) p(w_d|c, w_{-d}, z, \eta) \quad (2)$$

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3. Assessing convergence and approximating the mode.

$$L^{(t)} = \log p(c_{1:D}^{(t)}, z_{1:D}^{(t)}, z_{1:D}|\eta, \gamma, m, \pi) \quad (3)$$

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Practical Difficulty

- ♣ **What's practical problem [3] when using hDLA to topic modeling?**
- ♣ **Why unified framework?**

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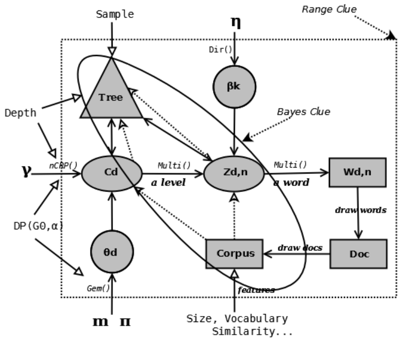

Figure : unified analysis framework with two clues

Generative Process

Document are assumed to be drawn from the following process.

- For each node k $\in$ T in the infinite tree, draw a topic $\beta_k \sim Dirichlet(\gamma)$.
- For each document, d $\in$ 1,2,...,D
  - Draw $C_d \in nCRP(\gamma)$ to choose the path
  - Draw a distribution over levels in the tree, $\theta_d|m, \pi \in GEM(m, \pi)$.
  - For each word,
    - Choose level $Z_{d,n}|\theta \in Mult(\theta_d)$.
    - Choose word $W_{d,n}|Z_{d,n}, C_d, \beta \in Mult(\beta_{c_d}, [Z_{d,n})$.

nCRP

- Introduction to CRP algorithm
- γ parameters
- Experiments with γ
- Comparision

GEM

- The Different View of DP
- Parameters m and π
- Experiments with m and π

Dirichlet Process

1. Experiment with parameter
2. Relationship with Three above.

Iterator Convergency

- ♣ Monte Carlo Markov Chain
- ♣ (Collapsed) Gibbs Sampling Algorithm

Global Modeling Strategy

- **Tree Depth**

Global Modeling Strategy

- **Tree Depth**

theme\depth	3	4	5
XTUS	4.9	59.7	78.7
IRSA	3.6	35.8	46.5
LTFC	7.1	54.2	74.8
EUDC	4.1	59.2	83.5
GBAB	3.1	47	66.2

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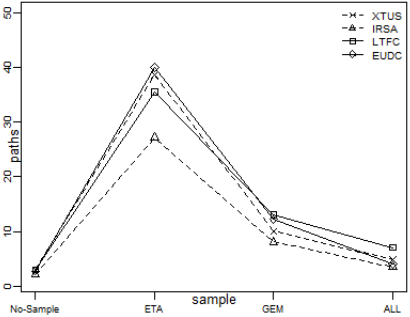

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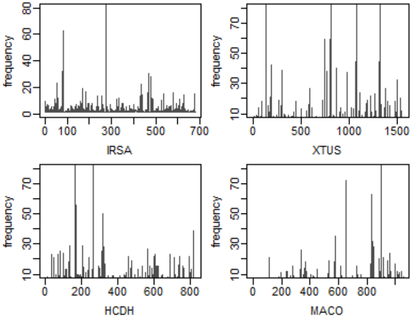

Manual Modeling Procedure

- *Generate hLDA input and extract features from corpus.*
- *Approximate depth of tree.*
- *Topic parameter for each level.*
- *nCRP parameter for non-leaf levels.*
- *m*, π *parameter for words allocations.*
- *Sampling for hyper-parameters or not.*

Empirical Results

Experiments have been conducted with the guide of modeling procedure above with only three modifications to the settings.

theme	level#1	level#2	hLDA#1	hLDA#2	score
XTUS	4	9	5.3	10	4
EUDC	4	5	5.2	9	3
IRSA	2	5	3.9	8	4
HCDH	5	7	4.8	10	4
CQWF	4	9	5.3	10	5
SBAG	4	10	6	10	5
GBAB	6	8	4.8	11	3
LTFC	6	14	7.2	12	5
MACO	4	7	6.7	8	4
NOHN	5	9	7	9	4

Reference

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