Probabilistic Topic Modeling

CS5340 Project

Yannis Montreuil Anand Subramanian Yijie Hu Tiana Chen
Rahul Gupta

School of Computing
National University of Singapore

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Modeling Topics in AI Research

- Artificial intelligence (AI) has undergone substantial changes in the past few decades.
- AI research has also gained popularity.
  - Number of AI-related papers on arXiv has increased more than sixfold in the past six years.
- We aim to analyze and track the evolution of research over time, and seek to explore some of following use cases.
  - Tracking research trends
  - Identifying key researchers
  - Tracking author-specific topics
  - Identifying related fields
  - Evaluating impact of research
  - Discovering new research directions

Latent Dirichlet allocation

- Topic modeling with Latent Dirichlet allocation (LDA)
- *Topics*: $k = 1, \ldots, K$
  - Dirichlet distribution $p(\beta_k|\eta) = \text{Dir}_{\beta_k}[\eta]$, shared prior η
- *Documents*: $d = 1, \ldots, D$
  - Categorical distribution $p(\theta_d|\alpha) = \text{Cat}_{\theta_d}[\alpha]$
  - Proportions $\theta_d = [\theta_{d,a}, \ldots, \theta_{d,K}]$ is latent
  - Shared prior $\alpha = [\alpha_1, \ldots, \alpha_K]^T$
- *Words*: $n = 1, \ldots, N$
  - Word n of document d assigned to (unobserved) topic $z_{d,n} \sim p(z_{d,n}|\theta_d) = \text{Cat}_{z_{d,n}}[\theta_d]$
  - (observed) word $w_{d,n} \sim p(w_{d,n}|\beta_k, z_{d,n}) = p(\beta_{z_{d,n}})$

Latent Dirichlet allocation

- "Bag-of-words" model: mutually independent assumption of word-generating process

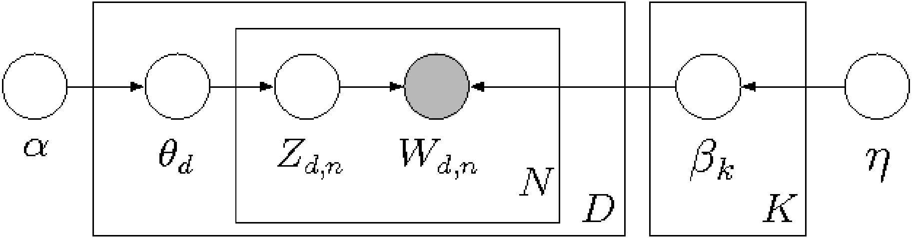
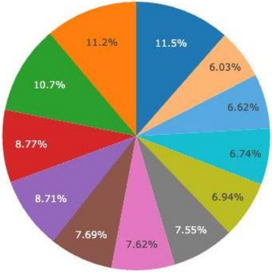


Figure 1: The graphical model for LDA, taken from [1]

- Observed words $W_{d,n}$ from latent $Z_{d,n}$ and β_k.
- $Z_{d,n}$ from latent θ_d
- Shared parameters: α and η.

Results Demonstration



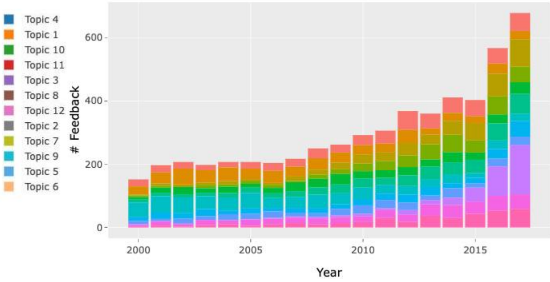


Figure 2: Overall and per year distribution of topics.

Results Demonstration

Extensions

- We extend our work to incorporate lexical priors into our base LDA model.
- *Guided LDA:* Provide relevant seed words to guide topic exploration.
- Select set of keywords related to the research question of interest.
- We implement this by biasing the prior assigned towards the seed keywords for its corresponding topic
- More targeted exploration of corpora
- Preliminary results are promising.

Initial Exploration of LDA with Lexical Priors

(a) Topic without CV priors.

(b) Topic with CV lexical priors

Figure 3: Initial Exploration of LDA with lexical priors. In the initial case, on exploration of the topic most similar to computer vision, CV keywords were weighted very less by the topic. Explicitly introducing CV lexical priors improved the topic formation.

Blei, David M. (2010). Introduction to Probabilistic Topic Models.