

Topic modeling

Literature overview

The input

- **22.287** abstracts - 15676 journal, 3086 papers, 2418 conference, 241 book chapters
- Average document length ranging from **140** to **200** words

Potential issues:

- Heavy tailed word distribution
- Sparse document-topic distribution (i.e. 1 topic per document)
- Correlated documents and topics (e.g. follow-up works,...)
- Evolving topics over time evolving vocabulary
- Considering abstracts as short texts?

Our goals

Desiderata of the final topic model (in order of priority):

- High performance (topic coherence, perplexity, qualitative assessment)
- Hierarchical model
- Automatic topic name inference
- Lifelong learning model, i.e. the ability to incorporate new knowledge into the model while retaining the old knowledge
- Exploiting the information contained in the metadata
- Modeling temporal evolution

The papers

[Topic modeling literature](#)

The nested chinese restaurant process and bayesian nonparametric inference of topic hierarchies

[DM Blei](#), [TL Griffiths](#), [MI Jordan](#) - Journal of the ACM (JACM), 2010 - [dl.acm.org](#)

[HTML] **Atm: Adversarial-neural topic model**

[R Wang](#), [D Zhou](#), [Y He](#) - Information Processing & Management, **2019** - Elsevier

Building a PubMed knowledge graph

Jian Xu, Sunkyu Kim, Min Song, Minbyul Jeong, Donghyeon Kim, Jaewoo Kang, Justin F. Rousseau, Xin Li,

Weijia Xu, Vetle I. Torvik, Yi Bu, Chongyan Chen, Islam Akef Ebeid, Daifeng Li ✉ & Ying Ding ✉

Scientific Data **7**, Article number: 205 (2020) | [Cite this article](#)

4437 Accesses | **34** Altmetric | [Metrics](#)

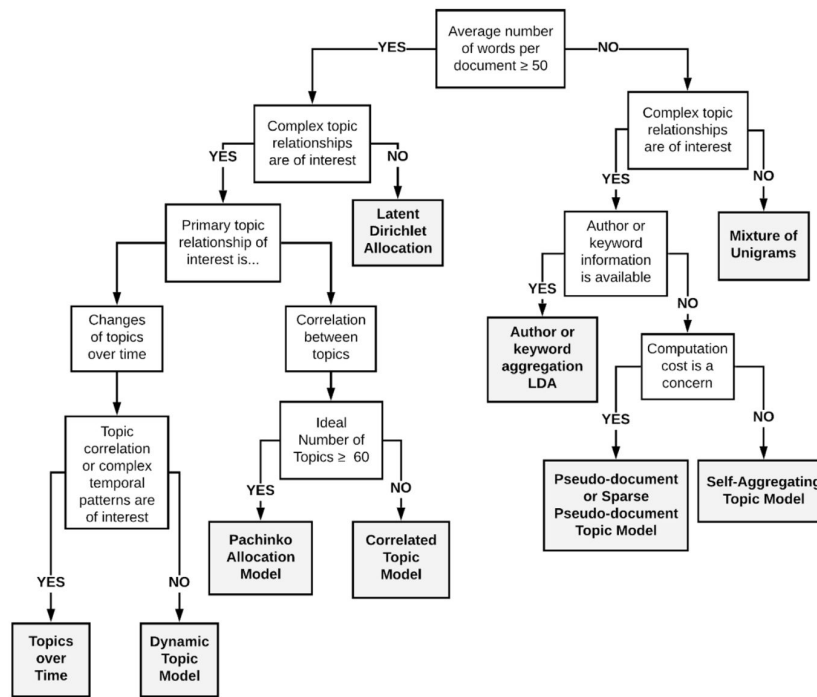
Autoencoding variational inference for topic models

[A Srivastava](#), [C Sutton](#) - arXiv preprint arXiv:1703.01488, 2017 - [arxiv.org](#)

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The baseline

- Latent Dirichlet Allocation (LDA)
- Correlated Topic Model (CTM)
- Pachinko Allocation Model



Adversarial-neural Topic Model (ATM)

- Outperforms common topic modelling approaches
- No hierarchy/lifelong learning/metadata

Lifelong Neural Topic Modeling (LNTM)

- Modular: can be applied to other topic models
- Lifelong learning
- Memory/computation requirements
- Static number of topics

Hierarchical LDA (hLDA)

- Hierarchical model
- Flexible number of topics
- Outperforms baseline
- Cannot model interdisciplinary texts

Embedded Topic Model (ETM)

- Automatic topic name inference
- Modular approach
- No hierarchy/lifelong learning/metadata

Questions?