STCS 6701: Foundations of Graphical Models: Reading 12

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1 Topic Modeling in Embedding Spaces - Dieng et al. (2019)

LDA relies solely on the counts of occurrences of words in documents, and therefore struggles to account for the least frequent words. In large datasets, these words are pruned which is problematic if rare terms are important.

This paper combines LDA and word embeddings to form Embedded Topic Models (ETM). ETMs ensure the performance of LDA improves when the vocabulary size increases.

The ETM data generative process is the following, and the posterior parameters are approximated using Variational Inference.

1. Draw a topic proportion θ_d
2. For each word index i:
a. Draw topic assignment z_{di}
b. Draw word w_{di} $\sim$softmax$(\rho^T \alpha_{z_{di}})$

with ρ the $L \times V$ the matrix containing the embeddings of the vocabulary, and α_{di} the embedding vector of the words surrounding w_{di} (context embedding).

This paper has an invaluable results section which describes quantitative metrics to evaluate the quality of topic models. Topic coherence (Mimno et al., 2011) measures topic interpretability using mutual information (probability of words in the same topics appearing in the same document). Topic predictive quality is measured using the log-likelihood in a document completion task (observe part of a sentence, measure likelihood on the rest of the sentence). Held-out perplexity for document completion and topic coherence is also used to evaluate the scalability of topic models.

2 Structural Topic Models for Open-Ended Survey Responses - Roberts et al. (2014)

Polls and survey analysts usually prefer close-ended questions, which are easy to process. Ppen-ended responses give better insight into a subject's thought process. This paper proposes a topic model approach to summarize open-ended responses. Instead of having survey-makers make assumptions about the answers a responder should make and topics they can address, this approach infers the responder's beliefs from their responses with minimal assumptions.

The structural Topic Model (STM) builds on LDA and includes additional metadata such as covariates relating to the topics (X), and to the users (U) (e.g. democrats may be more likely to use certain words) to inform the prior distributions for topic proportions and distributions. Notably, it allows topics to be correlated, gives each document its individual prior distribution over topics (defined by X, related to how much the respondent might discuss a topic), allows words within a topic to vary by U (related to which respondent might discuss a topic). The U and X sets of covariates can overlap.

This approach closely resembles a hierarchical model. The STM framework allows analysts to quickly infer treatment effects (relative to gender, income, party affiliation) while also inferring topics.

Alongside usual LDA properties, STM allows analysts to infer: - degrees of association between a document covariate X and the topic proportions (e.g. treatment assignment subjects devote twice as many words to a topic as control subjects).

- degrees of association between a document covariate U and the rate of word use within a topic (e.g. treatment subjects are twice as likely to use a specific word when writing about a given topic).

An interesting mention of this paper is the Chang et al. (2009) paper which finds that model diagnostics based on likelihoods maximize the model fit, but do not necessarily generate more informative or interpretable topics. The authors of this paper insist that *exclusivity* is important for topic models: top words for a topic should be unlikely to appear as top words for another topic. This paper also mentions the limitation of LDA's prioritization of high frequency words, regardless of their semantic importance.

To evaluate the performance of their method, researchers recover a true ATE using STM. They also evaluate differences in topic proportions for treatment and control groups, differences in vocabulary for treatment and control groups, and differences in topics addressed for treatment and control groups.

A fascinating read.