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Latent Dirichlet Allocation

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Abstract

We describe *latent Dirichlet allocation* (LDA), a generative probabilistic model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. We present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. We report results in document modeling, text classification, and collaborative filtering, comparing to a mixture of unigrams model and the probabilistic LSI model.

1. Introduction

In this paper we consider the problem of modeling text corpora and other collections of discrete data. The goal is to find short descriptions of the members of a collection that enable efficient processing of large collections while preserving the essential statistical relationships that are useful for basic tasks such as classification, novelty detection, summarization, and similarity and relevance judgments.

Significant progress has been made on this problem by researchers in the field of information retrieval (IR) (Baeza-Yates and Ribeiro-Neto, 1999). The basic methodology proposed by IR researchers for text corpora—a methodology successfully deployed in modern Internet search engines—reduces each document in the corpus to a vector of real numbers, each of which represents ratios of counts. In the popular *tf-idf* scheme (Salton and McGill, 1983), a basic vocabulary of "words" or "terms" is chosen, and, for each document in the corpus, a count is formed of the number of occurrences of each word. After suitable normalization, this term frequency count is compared to an inverse document frequency count, which measures the number of occurrences of a