Scalable Probabilistic Entity-Topic Modeling

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Abstract

We present an LDA approach to entity disambiguation. Each topic is associated with a Wikipedia article and topics generate either content words or entity mentions. Training such models is challenging because of the topic and vocabulary size, both in the millions. We tackle these problems using a novel distributed inference and representation framework based on a parallel Gibbs sampler guided by the Wikipedia link graph, and pipelines of MapReduce allowing fast and memory-frugal processing of large datasets. We report state-of-the-art performance on a public dataset.

1 Introduction

Popular data-driven unsupervised learning techniques such as topic modeling can reveal useful structures in document collections. However, they yield no inherent interpretability in the structures revealed. The interpretation is often left to a post-hoc inspection of the output or parameters of the learned model. In recent years an increasing amount of work has focused on the task of annotating phrases, also known as mentions, with unambiguous identifiers, referring to topics, concepts or entities, drawn from large repositories such as Wikipedia. Mapping text to unambiguous references provides a first scalable handle on long-standing problems such as language polysemy and synonymy, and more generally on the task of semantic grounding for language understanding. Resources such as Wikipedia, Freebase and YAGO provide enough coverage to support the investigation of Web-scale applications such search results clustering [29].

By using such a notion of topic one gains the advantage over pure data-driven clustering, in that the topics have an identifiable transparent semantics, be it a person or location, an event such as earthquakes or the “financial crisis of 2007-2008”, or more abstract concepts such as friendship, expressionism etc. Hence, one not only gets human-interpretable insights into the documents directly from the model, but also....

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from a ‘grounded interpretation’ which allows the system’s output to be interfaced with downstream systems or structured knowledge bases for further inference. The discovery of such topics in documents is known as entity annotation.

The task of annotating entities in documents typically involves two phases. First, in a segmentation step, entity mentions are identified. Secondly, in the disambiguation or linking step, the mention phrases are assigned one Wikipedia identifier (alternatively from Freebase, YAGO etc.). In this paper we focus upon the latter task which is challenging due to the enormous space of possible entities that mentions could refer to. Thus, we assume that the segmentation step has already been performed, for example via pre-processing the text with a named entity tagger. We then take a probabilistic topic modeling approach to the mention disambiguation/linking task.

Probabilistic topic models, such as Latent Dirichlet Allocation (LDA) [2], although they do not normally address the interpretability issue, provide a principled, flexible and extensible framework for modeling latent structure in high-dimensional data. We propose an approach, based upon LDA, to model Wikipedia topics in documents. Each topic is associated with a Wikipedia article and can generate either content words or explicit entity mentions. Inference in such a model is challenging because of the topic and vocabulary size, both in the millions; furthermore, training and applications require the ability to process very large datasets.

To perform inference at this scale we propose a solution based on stochastic variational inference (SVI) and distributed learning. We build upon the hybrid inference scheme of [23] which combines document-level Gibbs sampling with variational Bayesian learning of the global topics, resulting in an online algorithm that yields parameter-sparsity and a manageable resource overhead. We propose a new learning framework that combines online inference with parallelization, whilst avoiding the complexity of asynchronous training architectures. The framework uses a novel, conceptually simple, MapReduce pipeline for learning; all data necessary for inference (documents, model, metadata) is serialized via join operations so that each document defines a self-contained packet for inference purposes. Additionally, to better identify document-level consistent topic assignments, local inference is guided by the Wikipedia link graph.

The original contributions of this work include:

1. A large scale topic modeling approach to the entity disambiguation task that can handle millions of topics as necessary.

2. A hybrid inference scheme that exploits the advantages of both stochastic inference and distributed processing to achieve computational and statistical efficiency.

3. A fast Gibbs sampler that exploits model sparsity and incorporates knowledge from the Wikipedia graph directly.

4. A novel, simple, processing pipeline that yields resource efficiency and fast processing that can be applied to other problems involving very large models.

5. We report state-of-the-art results in terms of scalability of LDA models and in disambiguation accuracy on the Aida-CoNLL dataset [12].
The paper is organized as follows: Background on the problem and related work is discussed in the following section. Section 3 introduces our model. Section 4 describes the inference scheme, and Section 5 the distributed framework. Experimental setup and findings, are presented in Section 6. Follow conclusions.

2 Related Work

Much recent work has focused on associating textual mentions with Wikipedia topics [20, 22, 16, 9, 12, 27, 11]. The task is known as topic annotation, entity linking or entity disambiguation. Most of the proposed solutions exploit two sources of information compiled from Wikipedia: the link graph, used to infer similarity measures between topics, and anchor text, to estimate how likely a string is to refer to a given topic.

Figure 1 illustrates the main intuitions behind most annotators’ designs. The figure depicts a few words and names from a news article about cricket. Connections between strings and Wikipedia topics are represented by arrows whose line weight represents the likelihood of that string being used to mention the topic. In this example, a priori, it is more likely that “Croft” refers to the fictional character rather than the cricket player. However, a similarity graph induced from Wikipedia would reveal that the cricket player topic is actually densely connected to several of the candidate topics on the page, those related to cricket (line weight represents again the connection strength). Virtually all topic annotators propose different ways of exploiting these ingredients.

A few topic model-inspired approaches have been proposed for modeling entities

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The similarity measure is typically symmetric.
Early work [24] presents extensions to LDA to model both words and entities; however, they treat entities as strings, not linked to a knowledge base. [15] model a document as a collection of topic mentions, materializing as words or phrases, with topics being identified with Wikipedia articles. Kataria et al. in particular investigate the use of the Wikipedia category graph as the topology of a hierarchical topic model. The main drawback of this proposal is its scalability both in terms of efficiency and topic coverage; they prune Wikipedia to a subset of approximately 60k entities, reporting training times of 2.6 days. Han & Sun carried out the largest experiment of this kind, training on 3M Wikipedia documents (and no graph), reporting training times of one week with a memory footprint of 20GB on one machine. Our goal is to provide full Wikipedia coverage and high annotation accuracy with reasonable training/processing efficiency.

Scalable inference for topic models is the focus of much recent work. Broadly, the main approaches divide into two classes: those that parallelize inference e.g., via distributed sampling methods [35, 31], and stochastic optimization methods [13]. Computing infrastructures like MapReduce [7] allow processing of huge amounts of data across thousands of machines. Unlike in previous work, we deal with an enormous topic space as well as large datasets and vocabularies. Very high dimensional models, that can also grow as new data is presented, impose additional constraints such as a large memory footprint, limiting the resources available for distributed processing. One solution is to store a model in scalable distributed storage systems such as Bigtables [4], and allow individual processes to read the parameters needed to process subsets of the data from the global model. This approach allows individual workers to send back model updates thus supporting asynchronous training. The downside is the cost of the worker-model communication which can become prohibitive and difficult to optimize. Sophisticated asynchronous training strategies and/or dedicated control architectures are necessary to address these issues [31, 10, 19, 18]. Recent work on SVI provides an online alternative to parallelization [13]. This approach can yield memory efficient inference and good empirical convergence. In this paper we combine a sparse SVI approach with a distributed processing framework that gives us massive scalability with our models.

3 Wikipedia-Topic Modeling

3.1 Problem statement

We follow the task formulation, and evaluation framework, of [12]. Given an input text where entity mentions have been identified by a pre-processor, e.g., a named entity tagger, the goal of a system is to disambiguate (link) the entity mentions with respect to a Wikipedia page. Thus, given a snippet of text such as “[Moin Khan] returns to lead [Pakistan]” where the NER tagger has identified the entity mentions “Moin Khan” and “Pakistan”, the goal is to assign the cricketer id to the former, and the national cricket team id to the latter. We refer to the words outside entity mentions, e.g., “returns” and

\[ \text{Respectively, en.wikipedia.org/wiki/Moin_Khan} \quad \text{and} \quad \text{http://en.wikipedia.org/wiki/Pakistan_national_cricket_team} \]


“lead”, as content words.

### 3.2 Notation

Throughout the paper we use the following notation conventions.

#### 3.2.1 Data

The training data consists of a collection of $D$ documents, $D = \{w_d\}_{d=1}^D$. Note that this data can be any corpus of documents, e.g., news, web pages or Wikipedia itself. Each document is represented by a set of $L_d^c$ content words $w_d^c = \{w_1^c, \ldots, w_{L_d^c}^c\}$ and $L_d^m$ entity mentions $w_d^m = \{w_1^m, \ldots, w_{L_d^m}^m\}$.

Each word is either a ‘content word’ or an ‘entity mention’, these two types are distinguished with a superscript $w^c, w^m$ respectively; when unambiguous, this superscript is dropped for readability. Content words consist of all words occurring in the English Wikipedia articles. Mentions are phrases (i.e., possibly consisting of several words) that can be used to refer directly to particular entities e.g. “JFK Airport”, “Boeing 747”. Mention phrases are collected from Wikipedia titles, redirect pages and anchor text of links to other Wikipedia pages. The vocabularies of words and mentions have size $V^c, V^m$ respectively. More details on the data pre-processing step are provided in Section 6.1.

#### 3.2.2 Parameters

Associated with each document are two sets of latent variables, referred to as ‘local’ parameters because they model only the particular document in question. The first is the topic assignments for each content word in the document $z_d^c = \{z_1, \ldots, z_{L_d^c}\}$, and the topic assignments for each entity mention $z_d^m = \{z_1, \ldots, z_{L_d^m}\}$. Thus, content words and entity mentions are generated from the same topic space, each $z_i$ indicates which topic the word $w_i$ (content or mention) is assigned to, where the topic represents a single Wikipedia entity. For example, if $w_i^m = “Bush”$, then $z_i$ could label this word with the topic “George Bush Sn.”, or “George Bush Jn.”, or “bush (the shrub)” etc. The model must decide on the assignment based upon the context in which $w_i^m$ is observed.

The second type of local parameter is the document-topic distribution $\theta_d$. There is one such distribution per document, and it represents the topic mixture over the $K$ possible topics that characterize the document. Formally, $\theta_d$ is a parameter vector for a $K$-dimensional multinomial distribution over the topics in document $d$. For example, in an article about The Ashes\footnote{http://en.wikipedia.org/wiki/The_Ashes} $\theta_d$ would put large mass upon topics such as “Australian cricket team”, “bat (cricket)” and “Lords Cricket Ground”. Note that, although mention and content word’s topic assignments are generated independently, conditioned on the topic mixture $\theta_d$, they become dependent when we marginalize out $\theta_d$, as explained in Section 4 in more detail.

There are two vectors of ‘global’ parameters per topic, the ‘topic-word’ and ‘topic-mention’ distributions $\phi_k^c, \phi_k^m$ respectively. These distributions represent a probabilis-
Figure 2: LDA with content words (superscript $c$) and mentions (superscript $m$).

tic ‘dictionary’ of content words/mentions associated with the Wikipedia entity represented by the topic. The content and mention distributions are essentially treated identically, the only difference being that they are distributions over different dictionaries of words. Therefore, for clarity we omit the superscript and the following discussion applies to both types. For, each topic $k$, $\phi_k$ is the parameter vector of a multinomial distribution over the words, and will put high mass on words associated with the entity represented by topic $k$. Because each topic corresponds to a Wikipedia entity, the number of topic-word distributions, $K$, is large ($\approx 4 \cdot 10^6$); this provides additional computational challenges not normally encountered by LDA models.

3.2.3 Variational Parameters

When training the probabilistic model, we learn the topic distributions $\phi_k$ from the training data $D$; again, note that training is unsupervised and $D$ is any collection of documents. Rather than learn a fixed set of topic distributions, we represent statistical uncertainty by learning a probability distribution over these global parameters. Using variational Bayesian inference (detailed in Section 4.2) we learn a Dirichlet distribution over each topic distribution, $\phi_k \sim \text{Dir}(\lambda_k)$, and learn the parameters of the Dirichlet, $\lambda_k \in \mathbb{R}^V$, called the ‘variational parameters’. The set of all vectors $\lambda_k$ represents our model. Intuitively, each element $\lambda_{kv}$ governs the prevalence of vocabulary word $v$ in topic $k$; for example, for the topic “Apple Inc.” $\lambda_{kv}$ will be large for words such as “phone” and “tablet”. Most topics will only have a small subset of words from the large vocabulary associated with them i.e. the topic distributions are sparse. However, the model would not be robust if we ruled out all possibility of a new word being associated with a particular topic - this would correspond to having $\lambda_{kv} = 0$. Therefore, each variational parameter takes at least a small minimum value $\beta$ (defined by a prior, details to follow). Due to the sparsity, most $\lambda_{kv}$ will take this minimum value $\beta$. Therefore, in practice, to save memory we represent the model using ‘centered’ variational parameters, $\hat{\lambda}_{kv} = \lambda_{kv} - \beta$, most of which will take value zero, and need not be explicitly stored.
3.3 Latent Dirichlet Allocation

The underlying framework for our model is based upon LDA, a Bayesian generative probabilistic model, commonly used to model text collections [2]. We review the generative process of our model below. The only difference to vanilla LDA is that both mentions and content words are generated (in the same manner), whereas LDA just considers words.

1. For each topic \( k \) (corresponding to a Wikipedia article), sample a distribution over the vocabulary of words from a Dirichlet prior \( \phi_k \sim \text{Dir}(\beta) \).

2. For each document \( d \) sample a distribution over the topics from a Dirichlet prior \( \theta_d \sim \text{Dir}(\alpha) \).

3. For each content word \( i \) in the document:
   
   (a) Sample a topic assignment from the multinomial: \( z_i \sim \text{Multi}(\theta_d) \).
   
   (b) Sample the word from the corresponding topic’s word distribution \( w_i^c \sim \text{Multi}(\phi_z^c) \).

4. For each mention phrase \( j \) in the document:
   
   (a) Sample a topic assignment from the multinomial: \( z_j \sim \text{Multi}(\theta_d) \).
   
   (b) Sample the word from the corresponding topic’s mention distribution \( w_j^m \sim \text{Multi}(\phi_z^m) \).

Since topics are identified with Wikipedia articles, we can use the topic assignments to annotate entity mentions. \( \alpha, \beta \) are scalar hyperparameters for the symmetric Dirichlet priors; they may be interpreted as topic and word ‘pseudo-counts’ respectively. By setting them greater than zero, we allow some residual probability that any word can be assigned to any topic during training.

Documents can be seen as referring to topics either with content words, e.g., the topic “Barack Obama” is likely to be relevant in a document mentioning words like “election” “2012”, “debate” and “U.S.”, but also via explicit mentions of the entity names such as “President Obama” or “the 44th President of the United States”. It is important to notice that mentions, although to a less degree than words, can be highly ambiguous; e.g., there at least seven different “Michael Jordan”s in the English Wikipedia – including two basketball players.

Mentions in text can be detected by running a named entity tagger on the text, or by heuristic means [11]. Here we adopt the former approach which is consistent with the evaluation data used in our experiments [1]. Thus, a mention is a portion of text identified as an entity by a named entity tagger [1].

However, it is not known to which entity a particular mention refers and the resolution of this ambiguity is the disambiguation/ linking task. Assuming the segmentation of the document is known, the simplest possible extension to LDA to include topic

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4 Off-the-shelf taggers run typically in linear time with respect to the document length, thus do not add complexity.
5 We disregard the label predicted by the tagger.
mentions, derived from Link-LDA [8], is depicted in Figure 2 and the generative process corresponding to this graph is outlined above.

Importantly, note that although the topics for each word type are sampled independently, their occurrence is coupled across words and mentions via the document’s topic distribution $\theta_d$. During inference, topics appearing in a document that correspond to content words and those corresponding to mentions will influence each other. Therefore, during training, the parameters of the topics $\phi_k^c, \phi_k^m$ can learn to capture word-mention co-occurrence. This enables our model to use the content words for disambiguating annotations of the mentions. This sets our approach apart from many current approaches to entity-disambiguation, which often ignore the content words.

Because the locations of the mentions in a document are observed, the inference process is virtually identical to LDA. For ease of exposition, throughout the paper we present our framework using vanilla LDA, but extension to the model in Figure 2 is straightforward.

### 4 Inference and Learning

The model is trained in an unsupervised manner on a corpus of unlabeled text, e.g. news articles, web-pages, or the Wikipedia articles themselves. Only during initialization of the model do we use supervised information from Wikipedia articles, which by construction of our model, are each labeled with a single topic.

The English Wikipedia contains around 4M articles (topics). The vocabulary size for content words and mention strings is, respectively, around 2M and 10M. Given the vast potential size of the parameter space (topic-word, and topic-mention matrix), learning a sparse set of parameters is essential, and large corpora are required, necessitating a highly scalable framework.

#### 4.1 Hybrid inference

We build upon a hybrid variational inference and Gibbs sampling framework [23]. The key advantages of this method are statistical efficiency from the online variational inference (the parameters are updated online, before waiting for all the data to be processed), and parameter sparsity from taking finite samples. Here we present the key equations, together with reformulations that yield a fast implementation of the sampler. For notational brevity we present the equations in this section for content word modeling only (i.e. omitting $w_{di}^m, \phi_k^m, \beta^m$ nodes and the superscript $c$. from Figure 2); given the conditional independence assumptions the equations are easily extensible to the model in Figure 2.

#### 4.2 Variational Bayes

The goal of learning in LDA is to infer the posterior distribution of topics $\phi_k$. When performing inference on documents we seek the ‘local’ topic assignments $z_d$. We integrate/collapse out $\theta_d$, which is found to improve convergence [32]. Bayes rule is employed to compute the joint posterior...
$p(\mathbf{z}_1, \ldots, \mathbf{z}_D, \phi_1, \ldots, \phi_K | \mathcal{D}, \alpha, \beta)$. This computation is not tractable, and hence approximate variational Bayesian inference is used. Variational inference involves approximating a complex posterior distribution with a simpler one, $q(\mathbf{z}_1, \ldots, \mathbf{z}_D, \phi_1, \ldots, \phi_K)$. The latter is fitted to the true posterior so as to maximize the ‘Evidence Lower Bound’ (ELBO), a lower bound on the log marginal probability of the data $p(\mathcal{D}|\text{model})$ \[\square\].

We use the following approximation to the posterior:

$$p(\mathbf{z}_1, \ldots, \mathbf{z}_D, \phi_1, \ldots, \phi_K | \mathcal{D}, \alpha, \beta) \approx q(\mathbf{z}_1, \ldots, \mathbf{z}_D)q(\phi_1, \ldots, \phi_K) = \prod_d q(\mathbf{z}_d) \prod_k q(\phi_k; \lambda_k).$$

In [\square] we assume statistical independence in the $K$ topics and $D$ topic-assignment vectors. Importantly, however, independence is not assumed between the elements of each document’s assignment vector, $\mathbf{z}_d$. The correlations between the topics are key to modeling topic consistency in the document, and the sparse computations that follow.

The ELBO is optimized with respect to the variational distributions $q(\mathbf{z}_1, \ldots, \mathbf{z}_D)$, $q(\phi_1, \ldots, \phi_K)$ in an alternating manner; one distribution is held fixed, while the other is optimized. The variational distribution over topics $q(\phi_k; \lambda_k)$ is a Dirichlet distribution, with $V$-dimensional parameter vector $\lambda_k$, one for each topic. The elements of the topic’s variational parameter vector $\lambda_{kv}$ give the importance of word $v$ in topic $k$. This can be observed from the mean of the Dirichlet, which is the multinomial: $E_q(\phi_k | \lambda_k) = p(v|k) = \text{Multi}(\lambda_{kv} / \sum_k \lambda_{kv})$. The variational parameters $\lambda_k$ are optimized during learning, with $\{q(\mathbf{z}_d)\}_{d=1}^D$ fixed. The optimal variational parameters are given by:

$$\lambda_{kv} = \beta + \sum_{d=1}^D \sum_{i=1}^{L_d} E_q(\mathbf{z}_d) [\mathbb{I}_{z_{di} = k} \mathbb{I}_{w_{di} = v}].$$

For brevity we shall henceforth refer to these variational parameters simply as the ‘parameters’ of the model.

The optimal $q(\mathbf{z}_d)$ given $\{q(\phi_k; \lambda_k)\}_{k=1}^K$ is given by

$$q(\mathbf{z}_d) \propto \exp\{E_{q_i}(\mathbf{z}_1:D \setminus \mathbf{z}_d) \log p(\mathbf{z}_d|\alpha)p(\mathbf{w}_d|\mathbf{z}_d, \beta)\},$$

where $q(\mathbf{z}_{1:D} \setminus \mathbf{z}_d)$ is the variational distribution over all assignment vectors for all documents excluding $d$. However, in stead of parameterizing $q(\mathbf{z})$ and performing variational inference we Gibbs sample from $q(\mathbf{z})$. This involves sequentially visiting each topic and sampling that topic conditioned on all other assignments and the other parameters of the (variational) posterior and word $w_i$: $z_i \sim p(z_i | \mathbf{z}^{i-1}, \lambda_1, \ldots, \lambda_K, w_i)$.

The key advantage of sampling the assignments is that one can retain sparsity. Most improbable word-topic assignments will not be sampled, the result being that many of the elements $\lambda_k$ remain constant.

### 4.3 Stochastic variational inference

The key insight behind SVI is that one can update the model parameters $\lambda_k$ from just a subset of the data, $\mathcal{B}$ \[[14]\]. This enables one to discard the local variables (sampled
topic assignments) after each update is performed. Having performed inference on only a subset of the data, one achieves only a noisy estimate of the full batch update step; but, provided that the noisy estimates are unbiased (averaging over the data sub-sampling process), one can guarantee convergence to an optima of the full batch solution. The correct update scheme is achieved by interpolating the noisy updated parameters from the subset with the old ones:

$$\lambda_{kv} = (1 - \rho)\lambda_{kv}^{\text{old}} + \rho \frac{|D|}{|B|}\lambda_{kv}^{\text{new}}$$  \hspace{1cm} (3)

The scaling of the update by $|D|/|B|$ ensures that the expected value of the update is equal to the batch update that uses all of the data, as required.

The stochastic approach has two key advantages. Firstly, one does not have to wait until the entire dataset is observed before performing even a single update to the parameters (as in the batch approach, Eq. (2)), which yields improved convergence. Secondly, by discarding the local samples after each mini-batch $B$ one can save vast amounts of memory. The requirement to store and communicate all of the local samples can be prohibitive in approaches based purely upon Gibbs sampling [35]. Section 5 details how the hybrid scheme is incorporated into a distributed framework.

4.4 Implementation of sparse sampling

Beyond sparsity, when working with a very large topic space it is important to perform efficient Gibbs sampling. For each word in each document (and for each sweep) we must sample $z_i$ from a $K$ dimensional multinomial. Naive sampling would require $O(K)$ operations. However, if one judiciously visits the high probability topics first, the number of computations can be vastly reduced, and any $O(K)$ operations can be pre-computed. The sampling distribution for $z_i$ is given by (for brevity we omit the parameters):

$$q(z_i = k|z^{\setminus i}, w_i = v) \propto \alpha \exp\{\Psi(\beta + \hat{\lambda}_{kv}) - \Psi(\beta + \hat{\lambda}_k)\} \cdot \kappa'_{kv} \cdot \mu^{(d)}_k + \frac{\alpha \kappa_{kv}}{\kappa'_{kv}} + \frac{\alpha \kappa_{kv}}{\kappa'_{kv}} + \frac{\alpha \kappa_{kv}}{\kappa'_{kv}}$$  \hspace{1cm} (5)

where $\kappa_{kv} = \exp\{\Psi(\beta + \hat{\lambda}_{kv})\} - \exp\{\Psi(\beta)\}$ and $\kappa'_{k} = \exp\{\Psi(V\beta + \hat{\lambda}_k)\}$ are transformed versions of the variational parameters. $\mu^{(d)}_k$ is dense, but it can be
precomputed. For each word $\mu^{(c)}_k$ has mass only for the topics for which $\hat{\kappa}_{kv} \neq 0$; for each word in the document this can be precomputed. $\mu^{(v)}_k$ has mass only for the topics for which $\hat{\kappa}_{kv} \neq 0$; for each word in the document this can be precomputed. $\mu^{(c)}_k$ has mass only for currently observed topics in the document, i.e. those for which $N_k^i \neq 0$; this term must be updated every time we sample, but it can be done incrementally. $\mu^{(c,v)}_k$ is non-zero only for topics which have non zero parameters and counts, but must be recomputed for every update and new word. If most of the topic-mass is in the smaller components (which can be achieved via appropriate choices of $\alpha, \beta$), visiting these topics first when performing sampling will require much fewer than $O(K)$ operations. To compute the normalizing constant of (4), the rearrangement (5) is exploited with $O(K)$ sums in the initialization, followed by sparse online updates. Algorithm 1 summarizes the processing of a single document.

Algorithm 1 receives as input the document $w_d$, initial topic assignment vector $z_d^{(0)}$, and transformed parameters $\kappa'_k, \kappa_{kv}$. Firstly, the components of the sampling distribution in (5) that are independent of the topic counts $\mu^{(d)}, \mu^{(v)}$ and their corresponding normalizing constants $Z^{(d)}, Z^{(v)}$ are pre-computed (lines 2-3). This is the only stage at which the full dense $K$-dimensional vector $\mu^{(d)}$ needs to be computed. Note that one only computes $\mu^{(v)}_k$ for the words in the current document, not for the entire vocabulary. Next, at the beginning of each Gibbs sweep, $s$, the counts for each word-topic pair $N_{kv}$ and overall topic-counts $N_k$ are computed from the initial vector of samples $z^{(0)}$ (lines 5-6). During each iteration of sampling the first operation is to subtract the current topic from the counts in line 8. Now that the topic count has changed, the two count-dependent components of the sampling distribution are computed (note that $\mu^{(c)}_k$ can be updated from the previous sample, but $\mu^{(c,v)}_k$ must be recomputed for the new word). The four components of the sampling distribution and their normalizing constants are summed in lines 13-14 and a single topic is drawn for the word at location $i$ (line 15). The topic-word counter for the current sweep is updated in line 16, and if the topic has changed since the previous sweep the total topic count is updated accordingly (line 18).

The key to efficient sampling from the multinomial in line 15 is to visit $\mu_k$ in order $\{k \in \mu^{(c,s)}_k, k \in \mu^{(c)}_k, k \in \mu^{(v)}_k, k \in \mu^{(d)}_k\}$. A random schedule would require on average $K/2$ evaluations of $\mu_k$. However, if the distribution is skewed, with most of the mass in the sparse components, then much fewer evaluations are required if these topics are visited first. The degree of skewness in the distribution is governed by the initialization of the parameters, and the priors $\alpha, \beta$. Because the latter act as pseudo-counts, setting them to small values favors sparsity.

After completion of all of the Gibbs sweeps the topic-word counts from each sweep $N_{kv}$ are averaged (discarding an initial burn in period of length $B$) to yield updated parameter values $\hat{\lambda}^{d}_{kv}$.

After completion of Algorithm 1 the parameter updates from the processing of each document $\hat{\lambda}^{d}_{kv}$ are interpolated with the current values on the shard using (3) to complete the local SVI procedure. In practice, we found a baseline local minibatch size $|B|$ of one, and a small local update weight $\rho_{loc}$ already worked well.
Algorithm 1 Inner Gibbs Sampling Loop

1: **input**: $(w_d, z_d^{(0)}, \{\kappa_{kv}\}, \{\kappa'_k\})$
2: $\mu_k^{(d)} \leftarrow \alpha e^{\psi(\beta)}/\kappa'_k$, $Z(d) \leftarrow \sum_k \mu_k^{(d)}$
3: $\mu_k^{(v)} \leftarrow \alpha \kappa_{kv}/\kappa'_k$, $Z(v) \leftarrow \sum_k \mu_k^{(v)} \forall v \in D$
4: **for** $s \in 1 \ldots S$ **do**
5: $N_{kv}^{(s)} \leftarrow \sum_{i=1}^{L_d} I_{z_i^{(s-1)}=k} \land I_{w_i^{(s-1)}=v}$ **▷** Initial counts
6: $N_{k} \leftarrow \sum_v |N_{kv}^{(s)}|$ **▷** Loop over words.
7: **for** $i \in 1 \ldots L_d$ **do**
8: $N_{k}^{i} \leftarrow N_{k} - I_{z_i=k}$ **▷** Remove topic $z_i$ from counts.
9: $\mu_k^{(c)} \leftarrow N_{k}^{i} e^{\psi(\beta)/\kappa'_k}$
10: $Z(c) \leftarrow \sum_k \mu_k^{(c)}$
11: $\mu_k^{(c,v)} \leftarrow N_{kv}^{i} / \kappa'_k$ **▷** Sample topic.
12: $Z(c,v) \leftarrow \sum_k \mu_k^{(c,v)}$
13: $\mu_k \leftarrow \mu_k^{(d)} + \mu_k^{(v)} + \mu_k^{(c)} + \mu_k^{(c,v)}$
14: $Z \leftarrow Z^{(d)} + Z^{(v)} + Z^{(c)} + Z^{(c,v)}$
15: $z_i^{(s)} \sim \text{Multi}(\{\mu_k/Z\}_{k=1}^{K})$
16: $N_{z_i^{(s)}w_i}^{(s)} \leftarrow N_{z_i^{(s)}w_i} + 1$ **▷** Update counts.
17: **if** $z_i^{(s)} \neq z_i^{(s-1)}$ **then**
18: **update** $N_{k}$
19: **end if**
20: **end for**
21: **end for**
22: $\lambda_{kv}^{d} \leftarrow \frac{1}{\alpha - B} \sum_{s > B} N_{kv}^{(s)}$ **▷** Compute updated parameters.
23: **return**: $\hat{\lambda}_{kv}^{d}$
4.5 Incorporating the graph

Most non-probabilistic approaches to entity disambiguation achieve good performance by using the Wikipedia in-link graph. We exploit the Wikipedia-interpretability of the topics to readily include the graph into our sampler. Intuitively, we would like to weight the probability of a topic, not only by the presence of other topics in the document, but by a measure of its consistency with these topics. This is in line with the Gibbs sampling approach where, by construction, all topics assignments, except the one being considered, are known. For this purpose we introduce the following coherence score:

$$
\text{coh}(z_k|w_i) = \frac{1}{|\{z_d\}| - 1} \sum_{k' \in \{z_d\}} \text{sim}(z_k, z_{k'}). 
$$

(6)

where \(\{z_d\}\) is the set of topics induced by assignment \(z_d\) for document \(d\), and \(\text{sim}(z_k, z_{k'})\) is the ‘Google similarity’ \([5, 21]\) between the corresponding Wikipedia pages.

We include the coherence score by augmenting \(N_{ki}\) in Eqn. 5 as \(N_{ki} = (N_{ki} - \mathbb{I}_{z_i = k})\text{coh}(z_k|w_i)\). Thus, the coherence contributions is appropriately incorporated into the computation of the normalizing constant. Adding coherence will change the convergence of the model, however, we perform a relatively small numbers of Gibbs sweeps; full convergence is not desired anyway because it would yield an impractical dense solution. In practice, the addition of coherence to the sampler proves effective.

Previous work has extended LDA to learn topic correlations, for example, by using a more sophisticated prior \([17]\). Learning the correlations in such a manner, using the Wikipedia graph for guidance, could provide an effective alternative solution. However, extending the model in this direction and maintaining scalability is a challenging problem, and an opportunity for future research. Alternatively, our simple approach, that incorporates the graph directly into the sampler, provides an effective solution that does not increase the complexity of inference.

5 Distributed Processing

We use MapReduce \([7]\) for distributed processing of the input data. A dataset is partitioned in shards which are processed independently by multiple workers. Documents, model parameters and all other data used for inference are stored in SSTables \([4]\), immutable key-value maps where both keys and values are arbitrary strings. Keys are sorted by lexicographic order, allowing efficient joins over multiple tables with the same key types. Values hold serialized structured data encoded as protocol buffers\([6]\). We denote such tables as \(<K, V>\), where \(K\) is a key type and \(V\) a value type, when the value is a collection of objects we use the notation \(<K, <V>>\).

5.1 Pipelines of MapReduce

Each worker needs the current model to perform inference. The model is typically large to start with and can grow larger as new explicit parameters can be added after each
iteration. Storing huge models in memory on many machines is impractical. One solution is to store the model in a distributed data structure, e.g., a Bigtable. A shortcoming of using a centralized model is the latency introduced due to concurrent worker-model communication [31, 10, 19, 18].

We propose a novel, conceptually simple, and practical alternative. Documents are stored in \( <I,D> \) tables where the key is a document identifier and the value holds the document content. The current model is stored in a table \( <V,<T>> \) keyed by a symbol (a mention or content word) while the value is a collection of the symbol’s topic parameters. Before inference we process the data and generate tables re-keyed by symbols, whose values are the document identifiers of the documents where the symbol occurred. Then a join \( ^7 \) is performed of the new table with the model table, which outputs a table \( <I,<T>> \) keyed by document id, whose values are all model parameters appearing in the corresponding document. A document and its parameters can now be streamed in the inference step, by-passing the issue of representing the full model anywhere, either in local memory or in distributed storage.

Additional meta-data, e.g. the Wikipedia graph, can be passed to the document-level sampler in a similar fashion by generating a table \( <I,<E>> \) keyed by document identifiers, whose values are the edges of the Wikipedia graph connecting the topics in that document. Thus, document-model-metadata tuples which define self-contained blocks with all information needed to perform inference on one document are streamed together. After inference, the topic assignments are outputted. While training, updates are computed, streamed out and aggregated over the full dataset by reducers. Updates are stored in a table \( <V,<T>> \) keyed by a symbol which can finally be joined with the original model table for interpolation with old values (as defined by the SVI procedure \( ^5 \)), to generate a new model.

Figure 3 illustrates the flow graph for the process corresponding to one iteration. Rounded boxes with continuous lines denote input or output tables, dashed-line boxes denote intermediate outputs. Although apparently complex, this procedure is efficient since the join and data re-keying operations are faster than the inference step which dominates computation time. The procedure can produce large intermediate outputs, however, these are only temporary and are deleted immediately after being consumed.

We implement the pipeline using Flume \( ^8 \) which greatly simplifies coding and execution, and takes care of the clean-up of intermediate outputs and optimization of the flow of operations. The proposed architecture is significantly simpler to replicate using public software than complex asynchronous solutions e.g. [31, 6]. Open source implementations of Flume and other MapReduce pipelines (e.g., Pig [25]) are becoming increasingly popular and are publicly available, opening up new opportunities for machine learning at web scale.\(^8\)

### 5.2 Combined procedure

The overall procedure for parameter re-estimation takes the following pathway which is summarized in Algorithm 2. Globally we store (on disk, not in memory) just the

---

\(^7\) With the term join we always mean an outer join.

\(^8\) E.g., see [http://flume.apache.org/](http://flume.apache.org/).
sparse set of parameters, and their sum over words for each topic (lines 1-2). We perform \( T \) global iterations of Stochastic Variational Inference. Using the pipeline described in Section 5.1 parameters (and meta-data) corresponding to the words in each shard of data (i.e. only those \( \lambda_{kv} \) for which word \( v \) appears at least once in \( D^m \)) are copied to an individual worker, along with relevant pre-computed quantities, \( \lambda_k \). In lines 6,7 the transformed parameters \( \kappa_{kv}, \kappa'_k \) are computed using Eqn. (5) once at the initialization stage of each worker. The initial topic assignments are set in line 8. In each worker we loop sequentially over the documents, performing Gibbs sampling (algorithm 1). We run an ‘inner loop’ of SVI on each shard; after sampling a single document, the local copy of the model parameters \( \hat{\lambda}_{kv} \) is updated using weighted interpolation in line 10. In line 11, the dense vector \( \lambda_k \) is updated incrementally, i.e. its values corresponding to topics that have not been observed in the current document do not change. After processing all of the documents in the shard, the updates from each document are averaged (line 13), and the global parameter updates are aggregated and interpolated with the previous model (line 15). This completes the ‘outer loop’ of SVI. The minibatch size for the outer loop SVI is equal to the number of documents per shard. We use a minibatch size of one in the inner loop SVI, as presented in Algorithm 2, extension to arbitrary minibatches is straightforward.

For simplicity we set the interpolation \( \rho_{loc}, \rho_{global} \) to be constant. It is straightforward to extend the algorithm to use a Robbins-Monroe schedule [28]. Recent work has developed methods for automatic setting of this parameter [30, 26], investigating an optimal update schedule within our framework is a subject for future work.
**Algorithm 2**: Distributed inference for LDA

1: initialize $\hat{\lambda}_{kv} \leftarrow$ Wikipedia initialization (Section 6.1).
2: $\hat{\lambda}_k = \sum_v \hat{\lambda}_{kv}$ → Dense $K$-dim vector.
3: for $t = 1 \ldots T$ do → Global SVI iterations.
4: parfor $m = 1, \ldots, M; D^m \subset D$ do → MapReduce.
5: for $d \in D^m$ do
6: $\kappa_{kv} \leftarrow \exp\{\Psi(\beta + \hat{\lambda}_{kv})\} - \exp\{\Psi(\beta)\}$ → Sparse.
7: $\kappa'_k \leftarrow \exp\{\Psi(V\beta + \hat{\lambda}_k)\}$ → Dense $K$-dim vector.
8: $z_d^{(t)} \leftarrow$ TagMe initialization (Section 6.2)
9: $\hat{\lambda}_{kv} \leftarrow (1 - \rho_{loc})\hat{\lambda}_{kv} + \rho_{loc}\sum_{d \in D^m} \hat{\lambda}_{d}^{(t)}$ → Update locally.
10: $\hat{\lambda}_k \leftarrow \sum_v \hat{\lambda}_{kv}$ → Update incrementally (sparse).
11: $\hat{\lambda}_m \leftarrow \sum_{d \in D^m} \hat{\lambda}_{d}^{(t)}$
12: end parfor
13: end for
14: $\hat{\lambda}_k^{(t+1)} \leftarrow (1 - \rho_{global})\hat{\lambda}_k^{(t)} + \frac{\rho_{global}}{M} \sum_m \hat{\lambda}_m$
15: $\hat{\lambda}_{kv} \leftarrow$ TagMe initialization (Section 6.2)
16: end for

### 6 Experiments

For statistical models with a very large parameter space, and many local optima, such as the proposed Wikipedia-LDA model, the initialization of the parameters has a significant impact upon performance (deep neural networks are another classical example where this is the case). Empirically, we found that in this vast topic space, random initializations results in models with poor performance. We describe firstly how we initialize the global parameters of the model $\lambda_{kv}$, and secondly, the initialization of topic assignments $z_d^{(0)}$ when performing Gibbs sampling on a document.

We test the performance of our model on the CoNLL 2003 NER dataset [12], a large public dataset for evaluation of entity annotation systems, and compare to the current best performing annotation algorithm.

#### 6.1 Model initialization and training

An English Wikipedia article is an admissible topic if it is not a disambiguation, redirect, category or list page, and its main content section is longer than 50 characters. Out of the initial 4.1M pages this step selects 3.8M articles, each one defining a topic in the model. Initial candidate mention strings for a topic are generated from its title, the titles of all Wikipedia pages that redirect to it, and the anchor text of all its incoming links (within Wikipedia). All mention strings are lower-cased, single-character mentions are ignored. This amounts to roughly 11M mention types and 13M mention-topic parameters. Note, that although this initialization is highly sparse - for most mention-topic pairs, the initial variational parameter $\hat{\lambda}_{kv}$ is initialized to zero, this does not mean that topics cannot be associated with new mentions during training, due to the inclusion of the prior pseudo-count $\beta$. 
We carry out a minimal filtering of infrequent and stop words. We compile a list of 600 stop words: all lower-cased single tokens that occur in more than 5% of Wikipedia. We discard all words that occur in less than 3 articles. This procedure defines a vocabulary of 1.8M different (lowercased) words. The total number of topic-word parameters is approximately 70M.

Let \( v \) be a symbol denoting a word or a mention. We initialize the corresponding parameter \( \hat{\lambda}_{kv} \) for topic \( k \) as \( \hat{\lambda}_{kv} = P(k|v) = \frac{\text{count}(v,k)}{\text{count}(v)} \). For the content words, counts are collected from Wikipedia articles and for mentions, from titles (including redirects) and anchors. For each word we retain in the initial model the top 500 scoring topics, according to \( P(k|v) \). We don’t limit the number of topics associated with mentions. Notice that parameters not explicitly represented in the initial model are still eligible for sampling via the pseudocount \( \beta \), thus the full model is given by the cross-product of the vocabularies and the topics.

We train model on the English Gigaword Corpus\(^9\), a collection of news-wire text consisting of 4.8M documents, containing a total of 2 billion tokens. We annotate the text with an off-the-shelf CoNLL-style named entity recognizer which identifies mentions of organizations, people and location names. We ignore the label and simply use the entity boundaries to identify mention spans. Before evaluating in terms of entity disambiguation, as an objective measure of model quality, we compute the log likelihood on a held-out set with a ‘left-to-right’ approximation \([34]\). Figure 4 shows that the model behaves as expected and appears not to overfit: both train and held-out likelihood increase with each iteration, levelling out over time.

### 6.2 Sampler initialization

A naive initialization of the Gibbs sampler could use the topic with the greatest parameter value for a word \( z_i^{(0)} = \arg \max_k \lambda_{kv} \), or even random assignments. We find that these are not good solutions. Poor performance arises because the distribution of

\(^9\)LDC Catalogue: 2003T05
topics for a mention is typically long-tailed. If the true topic for a mention is not the most likely one, its parameter value could be several orders of magnitude smaller than the primary topic. The problem is that topics have extremely fine granularity and even with sparse priors it is unlikely that the right patterns of topic mixtures will emerge by brute-force sampling in a reasonable amount of time.

To improve the initialization we use a simpler, and faster, heuristic disambiguation algorithm derived from TagMe’s annotator [9]. The score for topic $z_k$ being assigned to mention $w_i$ is defined as the edge-weighted contribution from all other mentions in the document:

$$\text{rel}(z_k|w_i) = \sum_{j \neq i} \text{votes}_j(z_k),$$

where the edge-weighted votes are defined as:

$$\text{votes}_j(z_k) = \frac{\sum_{k' \in z(w_j)} \text{sim}(z_k, z_{k'}) \lambda_{k'w_j}}{|z(w_j)|},$$

and $z(v)$ indexes the set of topics $k$ with $\hat{\lambda}_{kv} > 0$. The similarity measure is that used in Equation (6). Given hyperparameters $\epsilon$ and $\tau$ TagMe excludes from the set of candidates for mention $w_i$ topics with score lower than $\max_k \text{rel}(z_{w_i}, k) \times \epsilon$, and $P(k|w_i) < \tau$. Within this set the candidate $\arg \max_k \lambda_{kw_i}$ is selected. Intuitively, this method first selects a set of topics that are closely related according to the graph, then picks the one with the highest prior.

### 6.3 Evaluation data and metrics

A well-studied dataset for named entity recognition is the English CoNLL 2003 NER dataset [33], a corpus of Reuters news annotated with person, location, organization and miscellaneous tags. It is divided in three partitions: train (946 documents), test-a (216 documents, used for development) and test-b (231 documents, used for blind evaluation). The dataset was augmented with identifiers from YAGO, Wikipedia and Freebase to evaluate entity disambiguation systems [12]. We refer to this dataset as CoNLL-Aida. In our experiments on this data we report micro-accuracy: the fraction of mentions whose predicted topic is the same as the gold-standard annotation. There are 4,788 mentions in test-a and 4,483 mentions in test-b. We also report macro-accuracy, where document-level accuracy is averaged by the total number of documents.

### 6.4 Hyper-parameters

Since we don’t train on the CoNLL-Aida data, we set the hyper-parameters of the model by carrying out a greedy search that optimizes the sum of the micro and macro scores on both the train and test-a partitions.

Our model has a few hyperparameters, $\alpha$, $\beta^e$, $\beta^m$, the number of Gibbs sweeps and the number of iterations. We find that comparable performance can be achieved using a wide range of values. The priors control the degree of exploration of the sampler. $\alpha$ acts as a pseudo-count for each topic in a document. If this parameter is set to zero
the sampler can visit only topics that have already been observed in the document; although this ensures a high degree of consistency in the topics, preventing any exploration in this manner is detrimental to performance. We find that any $\alpha \in [10^{-5}, 10^{-1}]$ works well. $\beta$ provides a residual probability that any word/mention can be associated with a topic, thus controlling exploration in sampling and vocabulary growth. $\beta$ also regularizes the sampling distribution; the denominator $\kappa_{z_i}$ in Equation (5) is a function of $\beta$. If $V \beta$ is too small, the topics with very small parameters $\lambda$ can be sampled with high probability. For our model the vocabulary is in the order of $10^6$, thus in practice we find $\beta \in [10^{-7}, 10^{-3}]$ works well for both words and mentions.

The robustness of the model’s performance to these wide range of hyperparameter settings advocates the use of our probabilistic approach. Conversely, we find that approaches built upon heuristic scoring metrics, such as our TagMe-like algorithm for sampler initialization require much more careful tuning. We found that $\epsilon$ and $\tau$, values around 0.25 and 0.02, respectively, worked well.

We obtain the best results after one training iteration, this is probably because Wikipedia essentially provides a (noisy) labeled dataset to fix the initial parameters, which yields a strong initialization. Indeed, a number of approaches just use a Wikipedia initialization like ours alone, along with the graph. Note, however, that without running inference in model, the initial model alone, even with the guidance of the Wikipedia in-link graph, e.g., as in the TagMe tagging algorithm, does not yield optimal performance (see Table 1 column ‘TagMe’). It is the fast Gibbs sampler used in combination with the Wikipedia in-link graph which greatly improves the annotation accuracy.

In terms of Gibbs sweeps the best results are achieved with 800 sweeps but the improvement over 50 (which we use for training) is marginal.

### 6.5 Results

Table 1 summarizes the disambiguation evaluation results. The Baseline predicts for mention $m$ the topic $k$ maximizing $P(k|m)$. The baseline is quite high, this is due to the skewed distribution of topics – which makes the problem challenging. The second column reports the accuracy of our implementation of TagMe (TagMe*), used to initialize the sampler. Finally, we compare against the best of the Aida systems, extensively benchmarked in [12] where they proved superior to all the best currently published systems. We report figures for the latest best model (“r-prior sim-k r-coh”), periodically

|            | Test-a | Test-b |
|------------|--------|--------|
| Base       | 0.707  | 0.698  |
| TagMe*     | 0.768  | 0.786  |
| Aida       | 0.793  | 0.825  |
| Wiki-LDA   | 0.809  | 0.837  |

Table 1: Accuracy on the CoNLL-Aida corpus.
The proposed method, Wiki-LDA, has the best results on both development (test-a) and blind evaluation (test-b). For completeness, we report micro and macro figures for the train partition: 83.04% and 82.84% respectively. We report standard deviations on the micro accuracy scores of our model obtained via bootstrap re-sampling of the system’s predictions.

Inspection of errors on the development partitions revealed at least one clear issue. In some documents, a mention can appear multiple times with different gold annotations. E.g., in one article, ‘Washington’ appears multiple times, sometimes annotated as the city, and sometimes as USA (country); in another, ‘Wigan’ is annotated both as the UK town, and its rugby club. Due to the ‘bag-of-words’ assumption, the Wiki-LDA model is not able to discriminate such cases and naturally tends to commit to one assignment per string per document. Local context could help disambiguate these cases. It would be relatively straightforward to up-weight this context in our sampler; e.g., by weighting the influence of assignments by a distance function. This extension is left for future work.

6.6 Efficiency remarks

The goal of this work is not simply provide a new scalable inference framework for LDA, but to produce a system sufficiently scalable to address the entity-disambiguation task effectively, hence achieving state-of-the-art performance in this domain. Indeed, direct comparison to other scalable LDA algorithms is impossible due to the different regimes in which the models operate – typical LDA models seek to ‘compress’ the documents, representing them with a small set of topics, but our model addresses annotation with a very large number of topics. However, we attempt to roughly compare approximate computation times and memory requirements with the current state-of-the-art scalable LDA frameworks.

The time needed to train on 5M documents with 50 Gibbs sweeps per document on 1,000 machines is approximately one hour. The memory footprint is negligible (a few hundred Mb). As noted, one cannot compare directly to the current distributed LDA systems which use far fewer topics and run different inference algorithms (usually pure Gibbs sampling), however, some of the fastest systems to date are reported in [31]. This work reports a maximum throughput of around 16k-30k documents/machine per hour on different corpora, using 100 machines, beyond this number they run out of memory. They use a complex architecture and vanilla LDA, with our simple architecture and a much (5000 times) larger topic space our training rates are certainly comparable. In addition, in our architecture based on pipelines of MapReduce speed should, in principle at least, correlate linearly with the number of machines as the processes run independently of each other. We plan to investigate these issues further in the future.

The LDA model proposed in [11] is somewhat comparable, they report a training time of over a week with 20G memory, on a single machine.

http://www.mpi-inf.mpg.de/yago-naga/aida/ as of May 2013. We thank Johannes Hoffart for providing us with the latest best results on the test-a partition in personal communications.
7 Conclusion and Future Work

Topic models provide a principled, flexible framework for analyzing latent structure in text. These are desirable properties for a whole new area of work that is beginning to systematically explore semantic grounding with respect to web-scale knowledge bases such as Wikipedia and Freebase. We have proposed a conceptually simple, highly scalable, and reproducible, distributed inference framework built upon pipelines of MapReduces for scaling topic models for the entity disambiguation task, and beyond. We extended the hybrid SVI/Gibbs sampling framework to a distributed setting and incorporated crucial metadata such as the Wikipedia link graph into the sampler. The model produced, to the authors’ best knowledge, the best results to date on the CoNLL-Aida evaluation dataset. Although we address a different task to the usual applications of LDA (exploratory analysis and structure discovery in text) and work in a very different parameter domain, this system is comparable to, or even faster than state of the art learning systems for vanilla LDA. The topic space and parallelization degree are the largest to date. Further lines of investigation include implementing more advanced local/global update schedules, investigating their interaction with sharding and batching schemes, and the effect on computational efficiency and performance. On the modeling side our first priority is the inclusion of the segmentation task directly into the model, and exploring hierarchical variants, which could provide an alternative way to incorporate information from the Wikipedia graph. The graphical structure could even be further refined from data.

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