ABSTRACT

This paper presents our recent efforts, ZenLDA, an efficient and scalable collapsed Gibbs Sampling (CGS) system for Latent Dirichlet Allocation (LDA) training, which is thought to be challenging that both data parallelism and model parallelism are required because of the Big sampling data with up to billions of documents and Big model size with up to trillions of parameters. ZenLDA combines both algorithm level improvements and system level optimizations. It first presents a novel CGS algorithm that balances the time complexity, model accuracy and parallelization flexibility. The input corpus in ZenLDA is represented as a directed graph and model parameters are annotated as the corresponding vertex attributes. The distributed training is parallelized by partitioning the graph that in each iteration it first applies CGS step for all partitions in parallel, followed by synchronizing the computed model each other. In this way, both data parallelism and model parallelism are achieved by converting them to graph parallelism. We revisited the tradeoff between system efficiency and model accuracy and presented approximations such as unsynchronized model, sparse model initialization and “converged” token exclusion. To better fit in distributed data-parallel framework and achieve comparable performance with contemporary systems, we also presented several system level optimizations to push the performance limit. ZenLDA was evaluated against web-scale corpus, and the result indicates that ZenLDA can achieve about much better performance than other CGS algorithm we implemented, and simultaneously achieve better model accuracy. The experiments also demonstrates the effectiveness of presented techniques.

1. INTRODUCTION

Topic models provide a way to aggregate vocabulary from a document corpus to form latent “topics”. In particular, Latent Dirichlet Allocation (LDA) \( O(K) \) is one of the most popular models [4, 13] that has rich applications in web mining, from News clustering, hot topics mining, search intent mining even to user interests profiling. Collapsed Gibbs Sampling (CGS) is the most commonly used algorithm in LDA that samples the latent variables for a word occurrence (token) by integrating out the Dirichlet priors. However, the training with massive corpus is challenging because of high time and space complexity. Consider a typical topic modelling system that in each iteration it first applies CGS step for all partitions in parallel, followed by synchronizing the computed model each other. In this way, both data parallelism and model parallelism are achieved by converting them to graph parallelism. We revisited the tradeoff between system efficiency and model accuracy and presented approximations such as unsynchronized model, sparse model initialization and “converged” token exclusion. To better reflect our latest efforts that builds an efficient and scalable CGS system on distributed data-parallel platform. ZenLDA combines both algorithm level improvements and system level optimizations. It first presents a novel CGS algorithm that balances the time complexity, model accuracy and parallelization flexibility. The input corpus in ZenLDA is represented as a directed graph and model parameters are annotated as the corresponding vertex attributes. The distributed training is parallelized by partitioning the graph that in each iteration it first applies CGS step for all partitions in parallel, followed by synchronizing the computed model each other. In this way, both data parallelism and model parallelism are achieved by converting them to graph parallelism. We further revisited the tradeoff between system efficiency and model accuracy and presented approximations such as unsynchronized model, sparse model initialization and “converged” token exclusion. To better fit in distributed data-parallel framework and achieve comparable performance with contemporary systems, we also presented several system level optimizations to push the performance limit. ZenLDA reflects our latest efforts that builds an efficient and scalable CGS system on distributed data-parallel platform. ZenLDA combines both algorithm level improvements and system level optimizations. It first presents a novel CGS algorithm that balances the time complexity, model accuracy and parallelization flexibility. The input corpus in ZenLDA is represented as a directed graph and model parameters are annotated as the corresponding vertex attributes. The distributed training is parallelized by partitioning the graph that in each iteration it first applies CGS step for all partitions in parallel, followed by synchronizing the computed model each other. In this way, both data parallelism and model parallelism are achieved by converting them to graph parallelism.
fit in distributed data-parallel framework, we also presented several system level optimizations to push the performance limit. ZenLDA is built on GraphX in Spark that provides distributed data abstraction (RDD) and expressive APIs to simplify the programming efforts and simultaneously hides the system complexities. Such generalization approach enables us to implement other CGS algorithms with only a few lines of code change, specifically, SparseLDA and LightLDA are implemented as evaluation baseline. The comparison with them against NYTones and one real web-scale dataset with about 3 billions tokens shows that ZenLDA can achieve about 2X-6X better performance than LightLDA and about 14X speedup than SparseLDA, and simultaneously achieve better model accuracy. The effectiveness of presented techniques is also evaluated. And we also conduct scalability experiment against another bigger Bing web chunk data with about 50 billions tokens and run it a multi-tenancy production environment, the result indicates ZenLDA has good scalability and industry-strength quality.

2. BACKGROUND AND RELATED WORK

This section describes the necessary background, including LDA and the corresponding Collapsed Gibbs Sampling (CGS) training algorithm, as well as the description of state-of-art distributed data-parallel system, Apache Spark and its library GraphX where ZenLDA is built.

2.1 LDA

In LDA, each of D documents is modeled as a mixture over K latent topics, each being a multi-nomial distribution over W vocabulary words. In order to generate a new document d, LDA first draw a mixing proportion \( \theta_{id} \) from a Dirichlet parameter \( \alpha \). For the \( w \)th word in a document, a topic assignment \( z_{dw} \) is drawn with topic \( k \) chosen with probability \( \theta_{id} \). Then word \( x_{dw} \) is drawn from the \( z_{dw} \)th topic, with \( x_{dw} \) taking on value \( w \) with probability \( \phi_{wk} \), where \( \phi_{wk} \) is drawn from a Dirichlet prior with parameter \( \beta \). Finally, the generative process is below:

\[
\theta_{id} \sim \text{Dir}(\alpha), \quad \phi_{wk} \sim \text{Dir}(\beta), \quad z_{dw} \sim \theta_{id}, \quad x_{dw} \sim \phi_{wk} \tag{1}
\]

where \( \text{Dir}(\alpha) \) represents the Dirichlet distribution.

2.2 Collapsed Gibbs Sampling Algorithm

Given the observed words \( x = x_{dw} \), the task of Bayesian inference for LDA is to compute the posterior distribution over the latent topic assignments \( z = z_{dw} \), the mixing proportions \( \theta_{id} \) and the topics \( \phi_{wk} \). Approximate inference for LDA can be performed either using variational methods or Markov chain Monte Carlo (MCMC) methods. In the MCMC context, the usual procedure is to integrate out the mixtures \( \theta \) and topics \( \phi \) in Formula and just sample the latent variables \( z \) which exhibits fast convergence. This procedure is called Collapsed Gibbs Sampling (CGS), where the conditional probability of \( z_{dw} \) is computed as follows:

\[
p(z_{dw} = k | z_{-dw}, x_{-dw}, \alpha, \beta) \propto \frac{N_{dk}^{w} + \beta}{W \beta + \sum N_{dw}^{k} (N_{dk}^{w} + \alpha)} \tag{2}
\]

where the superscript \(-dw\) means the corresponding topic sampled last time is excluded in the count values, \( N_{dw}^{k} \) denotes the number of tokens in document \( d \) assigned to topic \( k \), \( N_{wk} \) denotes the number of tokens with word \( w \) assigned to topic \( k \), and \( N_k = \sum N_{wk} \). Note that \( p_k \geq 0 \) is unnormalized.

Implementations of topic models typically use symmetric Dirichlet priors with fixed concentration parameters. However, Wallach, et al. found that an asymmetric Dirichlet prior over the document-topic distributions \( \alpha \) has substantial advantages over a symmetric prior, and introduce another hyper-parameter \( \alpha' \) to approximate that asymmetric prior as \( K \alpha + K = \sum N_{wk} / \sum N_{dw}^{k} \) by that CGS sampling formula can be rewritten as:

\[
p(z_{dw} = k | ...) \propto \frac{N_{dk}^{w} + \beta}{W \beta + \sum N_{dw}^{k} (N_{dk}^{w} + \alpha') (N_{dk}^{w} + K \alpha + K \sum N_{wk} / \sum N_{dw}^{k})} \tag{3}
\]

Algorithm 1 Serial standard CGS algorithm.

91: procedure STANDARDCGS
92: for each epoch e do
93: for each document d do
94: for each word w do
95: for each topic k do
96: \( p(k) = \frac{N_{dk}^{w} + \beta}{W \beta + \sum N_{dw}^{k}} \) \( (N_{dk}^{w} + \alpha_k) \) \( \sum N_{wk} / \sum N_{dw}^{k} \) \( \alpha + \)
97: \( \text{end for} \)
98: \( t = \text{TopicSampling}(p(k)) \)
99: update \( N_{dk}^{w}, N_{wk} \) and \( N_k \) accordingly
100: \( \text{end for} \)
101: \( \text{end for} \)
102: \( \text{end for} \)
103: \( \text{end procedure} \)

Algorithm describes the standard CGS algorithm. Note that the processing order of for-loops in line 3 and line 4 can be interchanged. There are two steps in CGS sampling, first is constructing step that computes the sampling probability of each topic \( k \) (K-dimensional discrete distribution in total), followed by sampling step that draws a sample z of topic such that \( P(z = t) \sim p_t \). The time complexity is \( O(D \cdot W \cdot K) \). Similarly, the space complexity is also extremely high that the storage of input corpus would be \( O(D \cdot W) \), and with \( O(W \cdot K) \) for word-topic matrix, \( O(D \cdot K) \) for document-topic matrix.

2.3 Spark

Spark is a fast and general engine for large-scale data processing, which was open-sourced as a top-level Apache project at 2013. It grew fast with a mature community, and is becoming the de-facto big computing engine that has been widely adopted by industry. Two types of applications that current computing frameworks handle inefficiently can be benefited from RDDs: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude.

RDD abstraction. Spark improves the distributed data-parallel systems such as MapReduce, Hadoop, Dryad by providing a Resilient Distributed Datasets (RDDs) abstraction, which is an efficient, general-purpose and fault-tolerant abstraction for sharing data in cluster applications. Essentially, RDD represents an immutable, partitioned collection of elements that can be operated on in parallel. The RDD element can be any type, from primitive types to complex classes. RDDs is immutable, and is offered with APIs that support coarse-grained transformations that transform RDDs and actions that return result. lets them recover data efficiently using lineage that tracks how to re-compute lost data from previous RDDs. Users can explicitly cache an RDD in memory or disk across machines and reuse it in successive computing. In addition, Spark supports two restricted types of shared variables, accumulator that works can only “add” to using an associative operation and only the driver can read, and broadcast variable that create a “broadcast variable” object that wraps the value and ensures that it is only copied to each worker once. Spark core itself is written in Scala language, and each RDD is represented by a Scala object. High-level languages such as Java, Python and R are also supported in SparkR as a light-weight frontend. Therefore, developer can easily write learning applications like single-box environments.

To use Spark, developers write a driver program that implements the high-level control flow of their application and launches various RDD operations in parallel. These operations are invoked by passing a function to apply on a RDD. Driver is responsible for scheduling the tasks and coordinating the worker execution.

Machine learning. It is unsurprised that there are already progresses on learning in Spark. MLlib is Spark’s machine learning (ML) library. Its goal is to simplify practical machine learning programming, by provides high-level representations Vector/Matrix/DataFrame on top of RDDs. MLlib consists of common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, as well as lower-level optimization primitives and higher-level pipeline APIs. It is noteworthy that there already are

91We skipped the for-each-occurrence loop between line 4 and line 5.
two LDA implementations, including expectation-maximization (EM)\(^5\) on the likelihood function and variational inference based online training.

Besides data/model parallelism, graph parallelism is also inherent to learning algorithm and is widely used to parallelize the training process. GraphX extends the Spark RDD by introducing a new Graph abstraction: a directed graph with properties attached to each vertex and edge. To support graph computation, GraphX exposes a set of fundamental operators (e.g., subgraph, joinVertices, and aggregateMessages) as well as an optimized variant of the Pregel API. In addition, GraphX includes a growing collection of graph algorithms and builders to simplify graph analytics tasks.

3. ZenLDA DESIGN

In this section, we first describe the serial CGS algorithm in ZenLDA that has different formula decomposition, then followed by the comparison with existing approaches.

3.1 Sampling approach.

Another dimension in design space is the choice of decomposition of Formula\(^3\) which costs large proportion of execution time in one iteration. Different formula decompositions have different sampling characteristics. There are three major considerations in ZenLDA: 1). whether the decomposed part is loop invariant or with negligible change? For example, \(a_{vk}β^k\) is loop invariant while \(N_{zk}α_k\) changes significantly.

2). whether the decomposed part is sparse with respect to topic \(k\)? Sparse part has less computing complexity as well as less memory consumption. For example, \(N_{zk}α_k\) is sparse since \(N_{zk}\) is sparse, and the computing complexity is \(O(K_u)\). 3). whether or not the approximation is permitted in computing topic probability that does not compromise sampling accuracy? It is reasonable to the approximation on formula parts with less value proportion would have less deviation errors in total. For instance, \(N_{zk}α_k\) is the smallest. It is thus unnecessary to compute the less important part every time, including \(N_{zk}α_k\) and \(N_{zk}α_k\).

ZenLDA decomposition. ZenLDA chooses a different decomposition with \(a_{vk}β^kN_{zk}α_k + N_{zk}α_kN_{zk}α_kβ^k\), which has the following benefits compared with other approaches:

- \(\frac{a_{vk}β^k}{N_{zk}α_k}\) is only computed once and reused afterwards in an iteration. And an alias table\(^15\), \(gTable\), is created accordingly, thus \(O(1)\) sampling complexity is achieved. Approximation happens here since \(N_z\) changes for each sampling, that is why SparseLDA adopts linear search based sampler which has \(O(K)\) sampling complexity.

- \(\frac{N_{zk}α_kN_{zk}α_kβ^k}{N_{zk}α_k}\) is also approximated it is pre-computed and reused for the same word \(w\). Similarly, the alias table \(wSparse\) is created accordingly. The lifecycle of this alias table in ZenLDA is reduced with word-by-word process order, that all tokens of the same word are grouped and sampled together. Recall that the corresponding topic \(k\) sampled last time should be excluded in the count values \(N_{wk}\) for current sampling, i.e. \(N_{wk}\) should be subtracted by one for that \(k\). However, such subtraction is skipped since there is no information on which topic should be subtracted during the preprocessing. We apply remedy by resampling with a probability of \(\frac{1}{N_z}\) if the sampled topic is equal to the topic sampled last time. This is especially useful when \(N_{wk}\) is small that is close to 1.

- Only \(\frac{N_{zk}α_kN_{zk}α_kβ^k}{N_{zk}α_k}\) is computed for each token with \(O(K_u)\) time complexity. And a cumulative distribution function (CDF) is created and the corresponding sampling complexity is \(O(\log K_u)\). It is noteworthy that it is only computed once for different occurrences of the same word in the same document. Thereby similarly, this did not subtract 1 for \(N_{zd}\) and \(N_{zk}\), thus the \(1∗β^k\) should be excluded from \(N_{zd}\) and \(N_{zk}\) and \(N_{zd}β^k + N_{zk}β^k\) should be excluded from \(N_{zd}\) and \(N_{zk}\). Therefore, resampling is applied for remedy with probability of \(\frac{1}{N_z}\) if the sampled topic is equal to the topic sampled last time\(^9\).}

\[\text{Algorithm 2} \text{ The single-box CGS training algorithm in ZenLDA.}\]

9\(^9\)We actually compute this decomposed part with \(1\) is subtracted if only

\\[\begin{array} {l}
91: & \text{Input: The set of edges } E; \text{ the set of words } W \text{ and documents } D \text{ in a partition } P.
\\92: & \text{Output: Sample new topic for each edge and update the model state.}
\\93: & \text{procedure CGSTRAINING}
\\94: & \text{for each epoch } e \text{ do}
\\95: & \text{for each topic } k \in K \text{ do}
\\96: & gDense ← a_{vk}β^kN_{zk}α_k
\\97: & \text{end for}
\\98: & gTable ← createAliasTable(gDense)
\\99: & \text{for each word } w \in D \text{ do}
\\100: & \text{for each topic } k \in K \text{ do}
\\101: & wSparse ← N_{zk}α_kN_{zk}α_kβ^k
\\102: & \text{end for}
\\103: & wTable ← createAliasTable(wSparse)
\\104: & \text{for each edge } e \in E, di \in D \text{ do}
\\105: & \text{for each topic } k \in K \text{ do}
\\106: & dSparse ← N_{zk}α_kN_{zk}α_kβ^k
\\107: & \text{end for}
\\108: & dTable ← createAliasTable(dSparse)
\\109: & \text{for each token } t \in di \text{ do}
\\110: & z_t \leftarrow \text{sample}(gTable, wTable, dSparse)
\\111: & N_{zk}α_kN_{zk}α_kβ^k \leftarrow \text{Update } N_{zk}α_kN_{zk}α_kβ^k \text{ and } N_k
\\112: & \text{end for}
\\113: & \text{end for}
\\114: & \text{end for}
\\115: & \text{end for}
\\116: & \text{end procedure}
\\\end{array}\]

ZenLDAHybrid decomposition. \(\frac{a_{vk}β^kN_{zk}α_k + N_{zk}α_kβ^k + N_{zk}α_kβ^k}{N_{zk}α_k}\) is better than \(\frac{a_{vk}β^k}{N_{zk}α_k} + \frac{N_{zk}α_kβ^k}{N_{zk}α_k}\) (used in SparseLDA\(^31\), \(^27\)) since decomposed part \(\frac{N_{zk}α_kβ^k}{N_{zk}α_k}\) in latter one has complexity of \(O(K_u)\), which is worse than \(O(K_d)\) in former one. Consider that word-topic array is generally more dense than document-topic array. However, the long-tail words may have less occurrences than the document length, thus the corresponding word-topic array may be more sparse that \(K_u < K_d\). We further provide a hybrid sampling approach, ZenLDAHybrid\(^1\), that alternates the formula decomposition between them, that we choose the former one for tokens with more sparse document-topic array; otherwise, we choose the latter one for tokens with more sparse document-topic array. Note that if \(N_{zk}α_kβ^k\) would have significant change, we adopt F+ tree based sampler that has \(O(\log K_d)\) complexity. To minimize the lifecycle of alias table that corresponds to the second decomposed part, the tokens should be grouped according to vertex that has larger degree, and tokens in a group are processed together.

3.2 Algorithm

ZenLDA algorithm. The specific serial algorithm of CGS training in ZenLDA is described in Algorithm\(^2\). We skipped the algorithm for ZenLDAHybrid that is with a natural extension. Compared with standard CGS that has \(O(K)\) complexity, ZenLDA significantly reduces the complexity into \(O(\min(K_d,K_u))\).

There are multiple factors that constitute large design space when consider to parallelize the CGS across multiple machines.

3.3 Related work in CGS algorithm

Table\(^\text{I}\) depicts the detailed summary on comparison among different CGS approaches. Besides the difference in decomposition, this table also list the difference on which sampler is used, whether it is fresh that the formula is computed for each token, whether approximation is applied, the corresponding computing complexity if computing is needed, the sampling complexity, and the process order applied in CGS step. SparseLDA\(^31\) is the first sampling method which considered decomposition occurrence for the same (word, document) pair.
ZenLDA

| Decomposition | ZenLDAHybrid | AliasLDA |
|---------------|--------------|----------|
| $\alpha + \beta \frac{n_k + \alpha}{n_k + n_d}$ | $\alpha + \beta \frac{n_k + \alpha}{n_k + n_d} + \frac{n_d(n_k + \alpha)}{n_k + n_d}$ | $\alpha + \beta \frac{n_k + \alpha}{n_k + n_d} + \frac{n_d(n_k + \alpha)}{n_k + n_d}$ |

| Sampler | Alias | Alias | CDF |
|---------|-------|-------|-----|
| Fresh | no    | no    | yes |
| Computing | $O(1)$ | $O(1)$ | $O(K_d)$ |
| Sampling | $O(1)$ | $O(1)$ | $O(\log K_d)$ |
| Process Order | Word-by-Word | Doc-by-Doc | Doc-by-Doc |
| Approximation | yes | yes | no |

Table 1: Comparison of different LDA sampling approaches. Note that two decompositions are alternately used in ZenLDAHybrid, another one is listed in ZenLDA.

composing $p_k$ into a sum of sparse vectors and a dense vector. In particular, it considers a three-term decomposition as:

$$\frac{\alpha + \beta}{N_k + \alpha} + \frac{n_d + \alpha}{N_k + \alpha} + \frac{n_d(n_k + \alpha)}{N_k + \alpha}.$$ 

where the first term is dense, the second term is sparse with $K_d$ non-zeros, and the third term is sparse with $K_w$ non-zeros. As SparseLDA follows the document-by-document sequence, very few elements will be changed for the first two terms at each CGS step. Linear search [32] (LSearch) is applied to all of these three terms in both SparseLDA implementations (Yahoo!LDA [1] and Mallet LDA [31]), which makes the sampling complexity with $O(K_d)$, $O(K_w)$ and $O(K)$ for these three terms, respectively.

AliasLDA [15] considers the following decomposition of $p$:

$$\frac{\alpha + \beta}{N_k + \alpha} + n_d + \frac{n_d(n_k + \alpha)}{N_k + \alpha}.$$ 

Instead of the exact multinomial sampling, AliasLDA considers a proposal distribution $q_k$ with a very efficient generation routine and performs a series of Metropolis-Hastings (MH) steps using this proposal to simulate the true distribution $p_k$. In particular, the proposal distribution is constructed using the latest second term and a stale version of the first term. For both terms, Alias method is applied. #MH steps decide the quality of the sampling results. The overall amortized cost for each CGS step is $O(K_d + #MH)$. Note the initialization cost $O(K)$ for the first term can be amortized. Therefore, AliasLDA reduces the amortized cost of each step to $O(K_d)$.

LightLDA [33] is a recently proposed approach that develops an Metropolis Hastings sampler with different constructed proposals that combines the document-proposal ($N_{id} + \alpha$) and word-proposal ($N_{id} + \beta$) into a “cycle proposal”. The word-proposal is pre-computed and Alias method is applied, thus the $O(K)$ complexity is amortized to $O(1)$. And $O(1)$ complexity is also achieved by a lookup table with document length that stores the corresponding topic for its word occurrences.

F+LDA [32] has two variants that differ with different decompositions. The document-by-document process order has the decomposition as:

$$\beta\left(\frac{N_{id} + \alpha}{N_k + \alpha}\right) + N_{wk}\left(\frac{N_{id} + \beta}{N_k + \beta}\right).$$

For each document, a sample step only changes two topic counter for $N_{id}$ in the first term, so they adopt F+tree sampling for the first term that with $O(\log K)$ complexity for both updating and sampling. Correspondingly, different word in the same document has different $N_{wk}$ for the second term, and the complexity is $O(K_w)$. Similarly, the word-by-word process order has opposite decomposition and properties:

$$\alpha\left(\frac{N_{wk} + \beta}{N_k + \beta}\right) + N_{id}\left(\frac{N_{wk} + \alpha}{N_k + \alpha}\right).$$

It is worth to compare with LightLDA, since the complexity of ZenLDA is better than other alternatives but could be worse than LightLDA [33]. First, LightLDA needs an extra lookup table that stores the correspondence of a token and its sampled topic (analogous to edge and its attribute in ZenLDA). Instead of directly read $N_{id}$, LightLDA samples the lookup table to simulate $N_{id}$, thus the complexity is reduced from $O(K_d)$ to $O(1)$. However, it requires data is partitioned in a document-wise way, otherwise the sample result would be inaccurate. This limits the exploration of better partition approaches (Section 4.2). Second, a MH-step will compute the true probability (Formula [10]) of the sampled topic, $O(1)$ complexity can only be achieved when dense vector or hash table is used, this will result in high memory consumption. Otherwise, MH-step could result in $O(\max(K_w, K_d))$ complexity to get value from $N_{wk}$. Note that both sparse and model are sparse.

4. ZenLDA PARALLELIZATION

In this section, we first discuss the parallelization design in ZenLDA, followed by other useful utilities ZenLDA provided.

4.1 Parallelization design in ZenLDA

Consider a typical web-scale application with 100 millions of documents and words, and with a large number of topics (typically on the order of thousands), where there are almost trillions of parameters. No single machine can hold the entire Big corpus data nor the Big model size. This made single machine solution impossible, which motivates a scalable and efficient way of distributing the computation across multiple machines. However, the design is challenging that a typical web-scale LDA training requires both data parallelism and model parallelism and involves hundreds of machines. In this section, we will discuss multiple design dimensions to parallelize the ZenLDA across multiple machines.

Graph based data and model representation. In stead of represented the data (input corpus) and model (word-topic and document-topic) as matrix, ZenLDA represents data as a directed bipartite graph that is the dual representation of sparse matrix. Figure [1] depicts the graph representation of a corpus with three words ($w_1, w_2, w_3$) and documents ($d_1, d_2, d_3$). The graph has two kinds of vertices, word vertices and document vertices. An edge exists from word vertex to document vertex only if that word is occurred in the document. This corpus in LDA is a natural graph [10] like many other natural language processing problems, where the graph have highly skewed power-law degree distributions. This graph representation can be naturally mapped to Graph in GraphX. Note that the corpus graph is treated as directed graph just because Graph in GraphX is directed, the direction is actually meaningless.
The edges in GraphX is grouped in a partition according to the source vertex ID (word vertex).

The model parameter word-topic matrix is split in a word-wise fashion that each word vertex is attached with the corresponding word-topic array \((N_{w|d})\) as attributes. Similarly, the document-topic matrix is also split in a document-wise fashion and each document vertex is attached with the corresponding document-topic array \((N_{d|w})\). Both word-topic and document-topic array are sparse that not all topics are sampled, and they are becoming more and more sparse as the training converged. Relationally speaking, a long-tail word may have more sparse word-topic array than a hot word; and document-topic array maybe more sparse than word-topic array since a word may have more occurred tokens than the average document length. The current topic \((Z_{d|w})\) of a word occurrence \((d|w)\) is annotated as the corresponding edge attribute. It is noteworthy that the edge attribute is an array since there may be multiple occurrences of the same word in one document. And the global state \(N_k = \sum_{i} N_{k|d_{i}} = \sum_{i} N_{k|w_{i}}\) records the total number of tokens (edges) been sampled as topic \(k\), which is computed by aggregating the \(N_{k|d_{i}}\) from all document vertices (or \(N_{k|w_{i}}\) from all word vertices).

**Partition approach.** The distributed parallelism is achieved by partitioning the graph into multiple partitions (described in next paragraph), and workers apply CGS process in Algorithm 2 for all partitions in parallel, followed by synchronizing the model state at the end of iteration. In this way, data parallelism and model parallelism are achieved [27], where the model is also partitioned and distributed across workers.

Partition strategy that determines how to partition the corpus and model plays crucial impact on system performance. The improper partition would result in load imbalance and large network communication. Compared with (sparse)-matrix based representation that can only be partitioned in a “rectangle” way, graph has more freedom for partitioning choice. There are two partition strategies, edge-cut that tries to evenly assign the vertices to machines by cutting the edges. vertex-cut [10] that tries to evenly assign the edges to machines by cutting the vertices. PowerGraph [10] pointed out that vertex-cut can achieve better performance than edge-cut, especially for power-law graphs. And the workload of a machine in vertex-cut is determined by the number of edges located in that machine, and the total communication cost is proportional to the number of mirrors of the vertices. However, the power-law distributions in corpus graph makes the partitioning challenging [29].

GraphX currently only supports vertex-cut method, and provides three partitioning approaches: RandomVertexCut that assigns edges to partitions by hashing the source and destination vertex IDs; EdgePartition1D that assigns edges to partitions using only the source/destination vertex ID, collocating edges with the same source/destination; and EdgePartition2D that assigns edges to partitions using a 2D (“rectangle”) partitioning of the sparse edge adjacency matrix, guaranteeing a \(2 + \sqrt{\text{numParts}}\) bound on the number of vertex replication.

Xie, et al. [29] presented degree-based hashing (DBH) partition method that can achieve lower communication cost than existing methods and can simultaneously guarantee good workload balance. The theoretical bounds on the communication cost and workload balance can also be derived. DBH is also vertex-cut that it first applies randomized hash function to evenly assign vertices to partitions, then assigns an edge \((v_i, v_j)\) to partition that contains its source or destination whose degree is less. In other words, the vertex with larger degree is cut that it would have multiple replicas. DBH shares the same insights with PowerLyra [6] that locality matters for low-degree vertex thus it places all edges related to this vertex together, while parallelism matters for high-degree vertex thus it favors to cut high-degree vertex. However, DBH only considers the relative size between source degree and destination degree, without considering their absolute value. Consider the case where both source and destination degree are small (smaller than a threshold value), it is not reasonable to still correspond the edge to vertex with lower degree, but should be the vertex with higher degree. In ZenLDA, we improved DBH as DBHP, and the algorithm is listed in Algorithm 3.

We actually explored many other partitioning strategies, such as different greedy algorithms [6] and iterative algorithm [9].

**Synchronization approach.** After partitioning and distributing the data/model, the remaining thing to consider is the synchronization among machines. In theory, the update of topic assignment \(Z_{d|w}\) cannot be performed concurrently with the update of any other topic assignment \(Z_{d|w'}\), with conflicts on \(N_k\) and possible conflicts on \(N_{k|d}\) or \(N_{k|w}\). The conflicts must be guaranteed using locks [3] which is costly and is hardly implemented in distributed environment. The good news is that this dependence is weak, given the typically large number of word tokens compared to the number of machines. If two processors are concurrently sampling, but sampling different words in different documents (i.e., \(w_{d|w'} \neq w'_{d|w'}\), then concurrent sampling will be very close to sequential sampling that the only affected state is \(N_k\). This means that we can still achieve convergence by relaxing these locks. There are three possible design choices, either only \(N_{k|d}\) or \(N_{k|w}\) is strictly synchronized, or none of them are not synchronized. This is more suitable for distributed data-parallel processing that communication happens only across the stage boundary. The first two can be achieved by choosing EdgePartition1D method that either all edges corresponding to a word or a document are located in the same partition, where \(N_{k|d}\) or \(N_{k|w}\) is not synchronized. However, EdgePartition1D would result in data severely skew, that even the number of documents is even distributed but the number of words is not, or vice versa. Therefore, ZenLDA further aggressively relaxes the dependency that both model states are updated independently, this asynchronization approach enables us to choose any possible partition methods that has better load balance with less network communication, such as DBHPlus presented above. Furthermore, even inside a partition, the CGS process result is only used to update the edge attribute \((Z_{d|w})\), and only update the vertex attribute \((N_{k|d_{i}}, N_{k|w_{i}})\) at the end procedure.

### Algorithm 3 DBH: an improved Degree-based hashing (DBH) algorithm

```plaintext
91: Input: The set of edges E; the set of vertices V; the number of machines p.
92: Output: The assignment \(P(e) \in \{p\}\) partitions for each edge e.
93: procedure DBHPlus
94: for each \(v \in V\) do
95: \(P(v) = \text{hash}(v)\)
96: end for
97: count the degree \(d_i\) for each \(i \in V\) in parallel
98: for each \(e = (v_i, v_j) \in E\) do
99: if \(\max(d_i, d_j) < \text{threshold}\) then
100: \(P(e) = P(d_i)\)
101: end if
102: else
103: \(P(e) = P(d_j)\)
104: end if
105: end for
106: end procedure
```

9^Topic level parallelism exists that the topic probability computing for each topic \(p(k)\) can be parallelized without any locks.
Figure 2: ZenLDA workflow in an iteration.

end, i.e., line 21 in Algorithm 2 is moved to at the epoch. This will largely reduce the lock cost if multi-threaded is enabled inside a partition. The side effect is that \(N_{k|d}, N_{w|k}\) and \(N_k\) are stale with value computed in last iteration.

**ZenLDA workflow.** In conclusion, the CGS workflow of one iteration in ZenLDA is illustrated in Figure 2. There are five steps: 1). driver broadcasts \(N_k\) to all workers. 2). the vertex master ships the model state \((N_{k|d}, N_{w|k})\) to all of the corresponding vertex slaves. 3). workers apply Algorithm 2 in parallel and update the \(N_{k|d}\) or \(N_{w|k}\) locally at the end. 4). at the end of an iteration, vertex master aggregates \(N_{k|d}\) or \(N_{w|k}\) all local updates from workers. 5). driver aggregates \(N_k = \sum N_{k|d}\) from all word master vertices. Note that we do not aggregate \(N_t = \sum N_{k|d}\) since the number of documents may be 100+ times larger than word number.

### 4.2 Related work in parallelization

Recently, there are many efforts towards to build distributed topic modelling system. They have different partition approaches and synchronization approaches. Almost all works \([21][33][12]\) partition the corpus in a document-wise way. Instead, ZenLDA permits any kind of partition methods. No parallelization work is found to have strictly synchronization semantic that at least \(N_t\) is not synchronized. The above works all achieve the synchronization on \(N_{t|d}\) since they choose document-wise partitioning. They further processes one document partition in a word-by-word order, and synchronization cross-machine happens once a mini-batch with certain workload is completed. However, SparkLDA and F+LDA schedule the tasks that only one task is working on a word mini-batch that they have no conflict on \(N_{w|k}\).

### 4.3 Utilities

ZenLDA supports both log likelihood and perplexity as the metric to evaluate the model convergence. ZenLDA also supports flexible termination condition, which can be based on a given number of training iteration or the perplexity value. Besides the core of model training, ZenLDA provides useful utilities in entire lifecycle.

**Incremental training.** Model can be saved in the middle of training rather than waiting the end of the training. In this way, users can terminate the training if they think the model is converged. Incremental training that the model can be initialized by a pre-trained model is also supported. This is useful when users are not satisfied the trained model and continue the model training. The model re-training could be equipped with better hyper-parameters, or new training data, etc.

**Merge duplicated topics.** Frequent words often dominate more than one topics, and the learned topics are similar to each other. These similar topics are duplicated \([25][27]\). ZenLDA adopts the asymmetric Dirichlet prior \([25]\) that automatically combine similar topics into one large topic, rather than splitting topics more uniformly by symmetric priors. This is especially useful when the number of topic number is large (\(\leq 10^6\)). Besides, we also cluster topic duplicates if their L1-distance is below a threshold. The lower L1-distance threshold means that we would remove more duplicates from large number of topics.

**Model inference.** ZenLDA also supports model inference besides model training, that ZenLDA infers the topic distribution over the given document with the same CGS process. The inference process can use the same tricks presented in ZenLDA (Section 3.1). To accelerate the model inference in online applications like search engine and online advertising systems to predict latent semantics of new user queries in realtime (usually in milliseconds) from large number of topics, we adopts RT-LDA \([27]\) that replace the sampling operation in Equation 5 by the max operation, which makes RT-LDA significantly faster than standard inference equation, but still with similar perplexity.

### 5. OPTIMIZATIONS

Data-parallel system helps ZenLDA to simplify the programming efforts, hide the system complexity and integrate with entire training pipeline. However, it would result in sub-optimal performance compared with customized approaches. In this section, we describe the techniques that help ZenLDA to achieve comparable performance and scalability, including approximated training, network I/O reduction and several low-level optimizations.

#### 5.1 Approximated training

As proved in asynchronous update that sampling can work on staled model state, CGS training could tolerate a certain degree of approximation. In this section, we will present two important approximations to make better tradeoffs on efficiency and model accuracy, including sparse model initialization and “converge” edges exclusion from sampling.

**Sparse model initialization.** It is well known that the execution time per iteration decreases by degrees as training makes progress, and the first several iterations are always the performance and scalability bottleneck, i.e., the training would succeed if it passes the first iteration.

Usually, CGS training is initialized by first randomly sampling a topic for each token with equal topic probability, and initiating the model state \((N_{k|d}, N_{w|k})\) by aggregating the topic distribution for each word and document, respectively. However, such random initialization would result in relatively dense topic distribution for word, especially for hot words that occurred in most of the documents. As a consequence, this dense word-topic distribution takes more memory consumption, network I/O (step 2 in Figure 2) and more computing complexity. Can we initialize the model with a sparse word-topic distribution but still achieve the similar convergence speed and accuracy? To validate the assumption, ZenLDA presents two sparse initialization approaches that demonstrate much better performance in the first several iterations and comparable or even better convergence and accuracy (See Figure 3).

1. **Sparse word-topic array.** The first approaches is to directly sparsify word-topic array \((N_{w|k})\). Assume that there are \(T\) tokens of word \(w\) in the corpus. Given total topics \(K\) and the sparsity degree \(deg \ll 1\), it first randomly samples \(deg * K\) topic set \(S\) from \(K\) topics, then randomly samples a topic from \(k \in S\) for each token of that word with equal probability, and updates \(N_{k|d}\) and \(N_{w|k}\) such that \(\sum N_{w|k} = T\). Such sparse initialization would largely relieve the convergence burden in the first iteration. However, it has side effects on model accuracy. The good side is that it reduces the possibility to allocate the same topic for two words that should be with different topic, since their topic overlapping probability is reduced due to sparse initialization; on the contrary, the bad side is that this also reduces the possibility if the two words should be with the same topic. Our evaluation indicates that the CGS process still converges and gradually recovers the side effect of sparse initialization. This optimization is essentially to gradually amortize the cost of first iteration to the following iterations. We further neutralize the side effect by increasing the \(\beta\) value in decomposed part \(N_{k|d} \ast (N_{w|k} + \beta)\) for those topics that are not assigned during initialization.

2. **Sparse document-topic array.** The second approach is to sparsify document-topic array \((N_{k|d})\) with the same method, that thus indirectly results in sparse word-topic array.

“Converged” token exclusion. We observed that different tokens are with different convergence rate. However, the CGS process still be applied normally without differentiation. We present “converged” token exclusion that excludes tokens from CGS process that have been converged, which will largely reduce the workload per iteration, especially as for later iterations that almost tokens are converged (See Figure 4).
The question is how to identify a token is converged, and how to neutralize the possible side effect? We treat a token is converged if current sampled topic is the same as topic sampled in last iteration. To reduce the side effect, we do not exclude the converged token directly, instead, they are still sampled with a probability. Such probability considers how many iterations a token has not been processed (i) and how many times it was processed but with the same sampled topic (t). Both i and t are zeroed for clearing once the sampled topic is different. Thereby, the probability is $2^{-i}$ if the probability has positive correlation with i but has negative correlation with t. We also support user to configure this optimization to be enabled only after certain iterations.

5.2 Network I/O reduction via delta aggregation

Network I/O still matters that a significant portion of time is spent in average, especially for large scale execution with large number of partitions. As shown in Figure 2, there are only four steps (except step 3) involved with network I/O, where the size of $N_t$ in step 1 is negligible, and the size of $N_{id}$ and $N_{wik}$ (step 2, 3 and 5) has already been reduced by sparse initialization. In this section, we describe techniques to further reduce the network I/O in step 4 that each vertex slaves sends its locally aggregated $N_{id}$ and $N_{wik}$ to master. The $N_{id}$ to be transferred are locally aggregated from $Z_{dv}$ from all tokens of document $d$, and the same is for $N_{wik}$. Obviously, they are positively correlated with the number of tokens per document and per word, respectively. With the same insight as “converged” token exclusion, high proportion of tokens are converged without topic change, we present delta aggregation that only the topic of changed tokens is aggregated in local and transferred to master. Thereby, the network I/O would be largely reduced as the model becomes converged. This requires to store the old topic sampled last time, other than new topic sampled currently, which doubles the attribute size in edge. Moreover, the effectiveness would be offset by “converged” token exclusion. Thereby, we will disable this optimization if token exclusion is enabled. However, it is worth noting that unlike token exclusion, this optimization would not affect the model accuracy.

5.3 Low-level optimizations

Besides the design principle, the performance also lies in the detail. In this section, we introduce several low-level optimizations that are proved to be generally effective, including efficient data structure that exploits the sparsity and redundant computing elimination.

Sparse data structure. The right choice on data structure is crucial for performance. Here we discuss three different choices that exploits the inherent sparsity in word-topic array $N_{wik}$ and document-topic array $N_{id}$, including DenseVector and SparseVector that provided in MLlib, as well as our new proposed CompactVector. DenseVector is represented as an array, and SparseVector is represented by an index array that records the indices of non-empty elements and a value array that records the corresponding values. For instance, a vector $(1, 0, 0, 0, 0, 3)$ can be represented in dense format as $[1, 0, 0, 0, 0, 3]$ in sparse format as $(6, [0, 5], [1, 3])$, where 6 is the size of the vector. Compared with dense vector, it is more memory efficient if vector has large sparsity, but with increased cost for operations such as search that the complexity is increased from $O(1)$ to $O(log(length))$. Note that it would result in more memory space for vector with less sparsity. The tipping point is when the sparsity is 0.5 that only half of the elements are empty, where the total length of index and value array is equal to the original vector length. Instead, we provide a new sparse vector representation, called CompactVector, that also includes a value array as SparseVector and a different index array. The index array is composed of $(s, n)$ pairs where s records the starting index of an empty sequence and n records the number of non-empty elements before position s. For example, $(1, 0, 0, 0, 0, 3)$ is represented as $(6, [(1, 1), [1, 3])]$. Figure 4 describes how to get value from CompactVector, given the original index $x$. The time complexity is $OlogN$ where N is the number of empty sequences, i.e., N is the number of non-empty sequences, thus N is less than the number of non-empty elements E, since sequence is composed of at least one element. Thereby, the time complexity is lower than it in SparseLDA that is with $O(logE)$. In addition, the size of CompactVector could be smaller specifically when $\frac{E}{N} \geq 2$, consider that CompactVector represents a sequence with two (both s and n) data element. The disadvantage of CompactVector is that the insertion is much costly with $O(N)$ complexity.

The right choice should tradeoff between the space requirement and computing cost. Generally, CompactVector is more suitable for scenarios where space is critical and almost operations are read; SparseVector is suitable for vectors with large sparsity; and DenseVector is suitable for dense vector with many write operations, since array in Scala can be updated in place while the others are immutable that a new operation is required each time the value is changed or a new value is inserted. The probability of $N_{wik}$ is the same as sampled in last iteration. To reduce the creation cost, we further refine the algorithm presented in AliasLDA [15]. First, we only maintain the H queue that keeps the topic information in a sequential way. Second, when create alias table for $N_{id}$ (used in LightLDA), the probability (count) is integer, but the average probability would be float that is the result of dividing the sum by $K_d$. Consequently, the split probability in a bin should be float. Instead, we first multiply $K_d$ for each individual probability, therefore, both the average and the split probability are integer. In this way, we avoid the costly divide operation, and simultaneously save the space.

Redundant computing elimination. There are many redundant computing in CGS formula. For instance, $\frac{1}{K_d}$ will be used many times during entire iteration, thus we can pre-compute it first and re-use the result later. The following code snippet (Algorithm 5) depicts how we avoid re-computation cost and save the sampling complexity for $O(1)$. However, the time complexity to build alias table is $O(K)$ and $O(\log K)$, respectively. Moreover, Each word vector has a wTable , which requires more memory space. We reduce the memory consumption by processing the tokens in word-by-word fashion that reduces the lifecycle of wTable thus unused wTable would be freed (GC). To reduce the creation cost, we further refine the algorithm presented in AliasLDA [15]. First, we only maintain the H queue that keeps the topic information in a sequential way. Second, when create alias table for $N_{id}$ (used in LightLDA), the probability (count) is integer, but the average probability would be float that is the result of dividing the sum by $K_d$. Consequently, the split probability in a bin should be float. Instead, we first multiply $K_d$ for each individual probability, therefore, both the average and the split probability are integer. In this way, we avoid the costly divide operation, and simultaneously save the space.

Algorithm 4 Get value from CompactVector.

```
91: Input: CV = (len, index, value), original index x.
92: Output: the value indexed at x.
93: procedure GetValue(CV, x)
94:  (s, n) = (x, n) ← BSearch(x, CV)
95:  assert(s ≤ x ≤ s + n)
96:  if x < s then
97:     if s < x < s + n then
98:         d = x − (s + n)
99:         return value[n + d]
100:     end if
101:     end if
102:     end if
103: end procedure
```

9Note that $N_t$ is constant with value computed in last iteration.

Others. ZenLDA also implements several other optimizations that are generally beneficial. First, ZenLDA tries to reuse the same generated random number as far as possible to avoid cost of random number generation. For example, there are three random number generations, the first is used to locate gTable, wTable or gSparse, the second is for locating the specific bin in alias table, and the last one is to locate the high or low region in a bin. Apparently, the last two can use the same random number. Second, we can pre-generate $n$ random numbers for $n$ different tokens in the same $(d, w)$ pair, in this way, the CDF sampling cost is reduced from $O(n \ast \log K_d)$ to $\log n \ast \log K_d$ that only logn passes of CDF binary search are required. Lastly, ZenLDA also implements op-
timization to exploit the difference between hot and long-tail word, as described in LightLDA [33].

6. IMPLEMENTATION

We encountered scalability issues due to the inherent inefficiency of managed language (Scala) and framework cost of GraphX. The implementation must balance resource (CPU, network and memory) usage that no resource is the bottleneck and all are fully utilized.

Memory. Memory is the major bottleneck to when we first try to scale out ZenLDA. Data-parallel system like Spark is designed to process one partition per core and the whole partition must be loaded in memory. “Out of memory” occurs frequently if many partitions (we have 16-32 cores per machine) loaded at the same time. The dilemma lies in that if too many partitions would reduce the memory consumption but with the increased network I/O. We observed that these partitions in a machine may share common data, such as the same word or document may exist in multiple partitions, thus the same as the corresponding word-topic or document-topic array. Instead, we load less partitions at one time and use multi-thread computing in a partition to fully utilize the CPU cores.

More specifically, edges is sorted queued in word-by-word order in a partition (already done by GraphX), and work-stealing with word granularity is adopted among multiple threads that once a thread completed all edges of one word, it will get all edges of the first word from edge queue. This achieve relative good load balance. The more fine-grained edge granularity is also feasible that the edges of the same word are processed in parallel, where $N_{w|k}$ is further shared among threads. Besides CGS processing (step 3 in Figure 2), we re-implement some GraphX APIs (except shuffling operator) to make them multi-threaded, such as ShipVertexAttributes (step 2) and aggregateMessages (step 4).

Actually, we abandon aggregateMessages that updates vertex attribute with value aggregated from edges, and constraints that the edge attribute type must be the same as with vertex attribute, thus costly type conversion happened. Instead, we directly operate on the Graph data structures (e.g., edge array and vertex index array in EdgePartition, vertex array and routing table in VertexPartition). This will significantly reduce memory costs and scale 10X up than original GraphX implementation.

Many GraphX APIs would create many intermediate objects that raise higher memory costs and the overhead of garbage collection. For example, to represent the bin of alias table $(i, h, p_h)$, we use three arrays with primitive type instead of one array with Scala Tuple1 to avoid the boxing/unboxing overhead.

CPU. Once we fixed the memory limitation via multi-threading, we found that high CPU cost on RDD decompression and deserialization that is processed by a single thread. Therefore, we prefer to configure RDD in uncompressed and deserialized format. Besides the optimizations presented in Section 5.3, the avoid of boxing/unboxing and generation of closures can also reduce the CPU cost.

Network. The relax on memory burden can enable more partitions, but this will increase the network I/O. We adopt Kryo serialization library in Spark that is significantly faster and more compact than default Java serialization. Shuffling cost is largely reduced when Kryo is enabled for serializing shuffling data.

7. EVALUATION

This section describes the evaluation to demonstrate the effectiveness and efficiency of ZenLDA.

7.1 Evaluation design

Datasets. We use 3 different datasets, including a small sized NYTimes [7] (about 520MB), a medium sized one month web chunk data indexed by Bing News (about 17GB), and a large scale Bing web chunk data (320G). They are all pre-processed and saved as 1\%bam format. The detailed information is listed in Table 2.

| Dataset       | Tokens  | Words  | Docs | T/D |
|---------------|---------|--------|------|-----|
| NYTimes       | 99,542,125 | 101,636 | 299,752 | 332 |
| BingWebC1Mon  | 3,150,765,984 | 302,098 | 16,422,424 | 192 |
| BingWebC320G  | 54,059,670,863 | 4,780,428 | 406,038,204 | 133 |

Figure 3: Execution time comparison between ZenLDA and LightLDA.
are compared, and the result is shown in Figure 3 and Figure 4 respectively. Note that it excludes the log-likelihood computing time, and the spikes in Figure 3 stems from full GC in JVM. We can see significant execution reduction (2-6X speedup) and better model accuracy than LightLDA for all experiments. Different datasets have different speedup, the larger the dataset is, the more speedup achieved (2X in NYTimes and about 4-6X in BingWebC1Mon). There is no obvious speedup difference when topics varies from 1,000 to 10,000. The experiments also show that as the number of topics increased, the performance is still almost the same in ZenLDA but increases a little (about from 13s to 17s in NYTimes and from 220s to 250s) in LightLDA. Performance is slowdown with sub-linearity if dataset is increased.

The performance result is a little bit “surprising”, consider that LightLDA has \( O(1) \) perplexity. As discussed in Section 3.3, the MH-step in LightLDA would be more costly due to the computation of true probability, which requires \( O(\text{max}(\log \alpha, \log K)) \) complexity since \( N_{kw} \) and \( N_{dk} \) in our implementation is sparse thus with \( O(\log \alpha) \) or \( O(\log K) \) complexity to read the value. And there are \#MH (8 in our implementation) MH-steps. As a comparison, the complexity in ZenLDA can be as low as \( \text{min}(K, \alpha) \). With respect to log-likelihood, ZenLDA outperforms LightLDA, and even more significant as the number of topics increased. This may be due to facts that the asymmetric prior is used in ZenLDA and the proposal distribution in LightLDA is an approximation of the true probability.

We also compared with other algorithms such as SparseLDA (we implemented in the same framework), and the EM based implementation in MLLib. SparseLDA is much slower that we did not run full length of SparseLDA but only with the first 15 iterations. It spends about 27,707 seconds (10,000) while ZenLDA only needs 1,907 seconds. And the EM algorithm in MLLib even cannot finish the first iteration against BingWebC1Mon dataset with errors reported 1 hour later.

### 7.3 Scalability

The scalability experiments are conducted against the largest dataset and run on our multi-tenancy data center. Figures 5 indicates that ZenLDA can support super large dataset in acceptable time. When 2X more executors (containers in Yarn) joined in (240 VS 120), the performance is almost linearly speedup. As we continue to add more executors (360), the performance can be improved, but with less speedup due to the network I/O becomes larger.

We also evaluated the performance when topic number varies. The experiment is conducted against BingWebC1Mon with 1,000, 10,000 and 100,000 topics, respectively. Their training time of first 50 iterations is shown in Figure 6. When \( K = 10,000 \), the average time per iteration is only increased a little bit compared with \( K = 1,000 \). Even with 100X more topics (\( K = 100,000 \)), the time is only increased by about 3X.

### 7.4 Optimization evaluation

**Sparse initialization.** Figure 7 shows the log-likelihood of different initialization strategies. Specially, we further split log-likelihood into word log-likelihood and doc log-likelihood. With respect to accuracy, sparse initialization of word-topic distribution (SparseWord) can achieve better total and word log-likelihood, but with worse document log-likelihood. In contrast, sparsifying document-topic distribution (SparseDoc) only achieves better doc log-likelihood in the first several iterations, and is “dragged” to normal distribution as random initialization. With respect to performance, Figure 8 shows that both SparseWord and SparseDoc make the sampling time faster than random initialization at the first several iterations. This is helpful to reduce the scalability bottleneck. However, it gradually increases to normal performance as random initialization as we expected, and even higher in SparseWord because of the increased \( K_d \) (the worse document log-likelihood, the dense document-topic distribution).

**“Converged” token exclusion.** ZenLDA chooses to turn on this optimization after the 30th iteration. Both sampling time (exclude time on shuffling) and log-likelihood are compared. The result shown in Figure 9 and Figure 10 indicates that “converged” token exclusion techniques can achieve about 50% faster in later iterations, without hurting the log-likelihood much. Figure 11 explains the underlying reason that the changing rate of topic assignment decreases as the iteration increases, with only about 22% remained at the end. This figures also demonstrates that delta aggregation (Section 5.2) can largely reduce the network I/O. The speedup is not strictly align with the change rate since the sample rate also considers the other factors.

**Redundant computing elimination.** We only evaluate the effectiveness of “redundant computing elimination” and skip other low-level optimizations that are hard to separated out. The result in Figure 12 shows that the sampling is faster with about 11% improvements.

### 8. DISCUSSION AND FUTURE WORK

This section describes several points that has crucial impacts on model accuracy and system performance, and they are out of the scope of this
cuts that vertex may introduce more the network I/O in step 2 and 4 of word-topic and document-topic distribution, the partition strategy that training. For example, Given a vertex with less degrees but more dense is the same. However, this assumption does not remain true in LDA. Ally assume that the network I/O introduced by cutting different vertices is the same. However, this assumption does not remain true in LDA.

Graph partitioning. Conventional graph partitioning algorithms usually assume that the network I/O introduced by cutting different vertices is the same. However, this assumption does not remain true in LDA training. For example, Given a vertex with less degrees but more dense word-topic and document-topic distribution, the partition strategy that cuts that vertex may introduce more the network I/O in step 2 and 4 of ZenLDA (Figure 2). Besides, consider the situation where “converged” edge exclusion is enabled, the number of active edges would gradually decrease. This will conversely affect the partitioning approach that an approach may get good load balance at first, but it gradually becomes imbalance as training proceeds.

Others. Currently, GraphX does not permit different typed attributes for different vertices. This prohibits us to efficiently exploit the difference between hot words and long tail words. It would also be interesting to theoretically analyze the impact of sparse initialization and “converged” token exclusion, and how to systematically neutralize their side effect remains future work.

9. CONCLUSION

In this paper, we present ZenLDA that proves to be an efficient and scalable collapsed Gibbs sampling system for LDA model on distributed data-parallel platform. This reflects our belief that build distributed machine learning system is not only feasible and beneficial, but also efficient and scalable. ZenLDA comes from combined innovations from both algorithm side and system side, and both are indispensable to achieve the goal. A clear abstraction like RDD in Spark can accelerate the research on both sides, respectively. We will continue this methodology and add more and more models in the future.
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