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Apache Mahout: Machine Learning on Distributed Dataflow Systems

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Abstract

Apache Mahout is a library for scalable machine learning (ML) on distributed dataflow systems, offering various implementations of classification, clustering, dimensionality reduction and recommendation algorithms. Mahout was a pioneer in large-scale machine learning in 2008, when it started and targeted MapReduce, which was the predominant abstraction for scalable computing in industry at that time. Mahout has been widely used by leading web companies and is part of several commercial cloud offerings.

In recent years, Mahout migrated to a general framework enabling a mix of dataflow programming and linear algebraic computations on backends such as Apache Spark and Apache Flink. This design allows users to execute data preprocessing and model training in a single, unified dataflow system, instead of requiring a complex integration of several specialized systems. Mahout is maintained as a community-driven open source project at the Apache Software Foundation, and is available under `https://mahout.apache.org`.

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1. Introduction

Apache Mahout was started in 2008 as a subproject of the open source search engine Apache Lucene (Owen et al. (2012)), when the search community encountered a growing need for applying ML techniques to large text corpora. In 2010, Mahout became its own top-level Apache project. At the time when Mahout emerged, *Apache Hadoop* was the dominant open platform for storing and processing large datasets using the MapReduce paradigm (Dean and Ghemawat (2008)) and was initially developed to build indexes for web-scale search engines. Due to the prevalence of Hadoop in industry, as well as research which indicated that a large family of popular ML algorithms can be reformulated under the MapReduce paradigm (Chu et al. (2007)), Mahout initially focused on MapReduce-based algorithm implementations. These implementations have been widely used by leading web companies[1] including Twitter, LinkedIn and Foursquare and are available in major commercial cloud offerings such as Amazon's *Elastic MapReduce* service[2] and Microsoft's *Azure HDInsight*[3].

The platforms and paradigms used to process ML-related data have changed tremendously over the past decade, due to a range of performance and programmability issues with MapReduce-based systems and the need to execute ML workloads on modern hardware like GPUs. In response to these factors, Mahout has evolved to leverage a domain-specific language (DSL) called Samsara for algorithm implementations, which can be executed on a variety of different platforms. In the remainder of this paper, we will provide a brief overview of Mahout's 'legacy' algorithms implemented on MapReduce in Section 2, and afterwards describe the Samsara language in Section 3.

2. Legacy: MapReduce-based Algorithms

Collaborative Filtering. Mahout features various collaborative filtering algorithms for recommendation scenarios. A simple and widely deployed nearest-neighbor-based approach is item-based collaborative filtering (Sarwar et al. (2001)). Another popular technique to analyze interactions between users and items are so-called latent factor models (Koren et al. (2009)). Mahout features distributed and non-distributed implementations of item-based approaches (Dunning (1993); Schelter et al. (2012)), as well as different variants of latent factor models (Zhou et al. (2008); Schelter et al. (2013)).

Classification. Mahout contains a distributed implementation of Naive Bayes with preprocessing steps tailored for textual data (Rennie et al. (2003)). This algorithm fits the MapReduce paradigm particularly well as it only requires a fixed number of passes over the data, which compute easy-to-parallelize aggregates. Additionally, Mahout features a single machine implementation of logistic regression learned with SGD, which includes a library to encode different types of features. Furthermore, Mahout contains a MapReduce-based implementation of Random Forests (Breiman (2001)).

1. `https://mahout.apache.org/general/powered-by-mahout.html`
2. `https://docs.aws.amazon.com/emr/latest/ReleaseGuide/emr-mahout.html`
3. `https://docs.microsoft.com/en-us/azure/hdinsight/hdinsight-component-versioning`

Clustering. Mahout includes MapReduce-based implementations of k-Means clustering and canopy clustering (McCallum et al. (2000)), as well as a streaming version of k-Means (Shindler et al. (2011)).

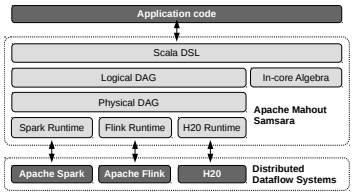
Dimensionality Reduction. Mahout contains implementations of two algorithms to compute the singular value decomposition (SVD) of large matrices: MapReduce-based versions of the Lanczos algorithm (Golub and Van Loan (2012)) and of Stochastic SVD (Halko (2012)). Furthermore, Mahout features MapReduce-based implementations for computing embeddings of textual data such as Latent Semantic Analysis (Deerwester et al. (1990)) and Latent Dirichlet Allocation (Blei et al. (2003)).

3. Mahout Samsara

Over time, it became apparent that the MapReduce paradigm is suboptimal for the distributed execution of ML algorithms, both for reasons of usability and performance. At the same time, the underlying Hadoop platform had been rewritten to expose resource management and job scheduling capabilities[4] to allow systems with parallel processing paradigms different from MapReduce to operate on data stored in the distributed filesystem. Examples of such systems are Apache Spark (Zaharia et al. (2012)) and Apache Flink (Alexandrov et al. (2014)). Unfortunately, these systems are still difficult to program, as their programming model is heavily influenced by the underlying data-parallel execution scheme. Furthermore, the available programming abstractions typically rely on partitioned, unordered bags; this is a mismatch for ML applications that mostly operate on tensors, matrices and vectors. Therefore, implementing ML algorithms on dataflow systems is still a tedious and difficult task. While ML systems such as Tensorflow (Abadi et al. (2016)) excel at efficiently executing programs built from linear algebra operations, they are not designed to execute general dataflow programs and have to rely on complicated integrations with other systems for such operations, e.g., Apache Beam[5] in the case of the Tensorflow Extended Platform (Baylor et al. (2017)).

As a consequence, Mahout has been rebuilt on top of Samsara (Lyubimov and Palumbo (2016)), a domain-specific language for declarative machine learning in cluster environments. Samsara allows its users to specify programs using a set of common matrix abstractions and linear algebraic operations, which at the same time integrate with existing dataflow operators. Samsara then optimizes and executes these programs on distributed dataflow systems (Schelter et al. (2016)). The aim of Samsara is to allow mathematicians and data scientists to easily integrate their algorithms into ML workloads running on distributed dataflow systems via common declarative abstractions. Figure 1a illustrates the architecture of Samsara. Applications are written using the Scala DSL, and developers have to choose between an in-memory and a distributed representation of matrices used in the program (Figure 1b). Operations on in-memory matrices are executed eagerly, while operations on distributed matrices (which are partitioned among the machines in the cluster) are deferred. The system records the actions to perform on these distributed matrices as a directed acyclic graph (DAG) of logical operations, where vertices refer to matrices and edges correspond to transformations between them. Materialization barriers (e.g., persist-

4. `https://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/YARN.html`
5. `https://www.tensorflow.org/tfx/guide/beam`

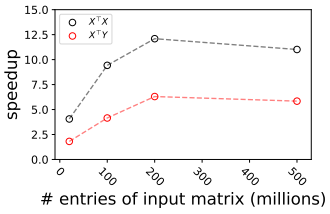


(a) Samsara architecture.

```
def dridge(
    drmX: DrmLike[Int],
    drmY: DrmLike[Int],
    lambda: Double
  ): Matrix {

  val XtX = (drmX.t %*% drmX).collect
  val XtY = (drmX.t %*% drmY).collect
  XtX.diagv += lambda
  solve(XtX, XtY)
}
```

(b) Distributed regression.



(c) Optimisation benefits.

Figure 1: System architecture, code example and optimisation benefits of Mahout Samsara.

ing a result or collecting a matrix into local memory) implicitly trigger execution. Upon execution, the DAG of logical operators is optimized, e.g., by removing redundant transpose operations and by choosing execution strategies for matrix multiplications based on the shape and sparsity of the operands. The program is then transformed into a DAG of physical operators to execute, which are specific to one of the backends that Samsara supports, and its distributed parts are executed by the respective backend. Figure 1c illustrates the benefits of these optimizations for solving a large regression problem (Schelter et al. (2016)), where the automatic rewrites and specialized operators provide a significant speedup compared to execution without optimizations. A current effort is underway to support the native execution of costly matrix operations on GPUs via an integration of the ViennaCL (Rupp et al. (2010)) framework.

Relationship to the Python ML ecosystem: The majority of recent ML research relies on implementations in Python (e.g., NUMPY, SCIKIT-LEARN (Pedregosa et al. (2011)) or JUPYTER), and often operates on single, static and relatively well understood datasets. In contrast to that, production systems typically include complex data integration and preprocessing pipelines, which continuously ingest new data. Such systems are often built on top of the JVM and deployed in the cloud, for reasons of reliability, scalability and ease of operations. Python-based solutions are typically very difficult to integrate into such setups (Schelter et al. (2018)), and therefore JVM-based solutions that only require a single system and code base for the whole pipeline (such as APACHE SPARK) are often preferred, even though the model training performance might be sub-par in many cases (Boden et al. (2017)). Samsara thereby targets the same set of use cases as the SPARKML library (Meng et al. (2016)), which however only exposes a collection of pre-made algorithms and lacks the flexibility offered by a linear algebra DSL such as SAMSARA, (e.g., to allow users to easily implement their own algorithms or to adjust existing ones).

4. Availability and Requirements

Mahout is run as a top-level project under the umbrella of the Apache Software Foundation, and developed in a community-driven, meritocratic fashion according to the *Apache Way*[6]. Mahout is available under the Apache License at `https://mahout.apache.org`. The latest version v0.14 requires at least Java 8 and Scala 2.11 for Samsara. The legacy algorithms require Hadoop 2.4, while Samsara programs can be executed on Spark 2.x and Flink 1.1.

6. `https://www.apache.org/foundation/how-it-works.html`

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