



Cairo University

ASCF: Apriori Algorithm on Spark Based on Cuckoo Filter Structure

By

Bana Ahmad Alrahwan

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
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In
Computer Engineering

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ASCF: Apriori Algorithm on Spark Based on Cuckoo Filter Structure

Key Words:

Data mining, Big Data, Apache Spark, Apriori algorithm, Cuckoo filter.

Summary:

The Apriori algorithm is one of the most basic techniques that are used to discover frequent patterns in dataset. Apriori is iterative and works sequentially. It generates candidate sets having all possible combinations for frequent itemsets that are generated from the previous iteration and comparing each combination of items with every transaction record in every iteration. Thus, Apriori algorithm is not efficient and gets computationally more expensive as the data size is increased. The rapid growth of data necessitates running the data intensive algorithms in parallel distributed environment to achieve convenient performance. Many approaches have been proposed to solve the Apriori major drawbacks that severely degrade the performance as the datasets get larger which is a common feature in Today's data. In this thesis, Apriori Algorithm on Spark based on Cuckoo Filter structure (ASCF) is introduced. ASCF succeeds in removing the candidate generation step from Apriori algorithm to reduce computational complexity and avoid costly comparisons. The proposed algorithm is implemented on spark in-memory processing distributed environment to reduce processing time. The ASCF offers great improvement in performance over other implementation approaches of Apriori algorithm based on spark.

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List of Acronyms

Acronym	Definition
ARM	Association Rule Mining
ASCF	Apriori Algorithm on Spark based on Cuckoo Filter structure
HDFS	Hadoop Distributed File System
HFIM	a Spark-based Hybrid Frequent Itemset Mining algorithm for big data processing
KDD	Knowledge Discovery in Databases
LHS	Left Hand Side
R-Apriori	An Efficient Apriori based Algorithm on Spark
RDD	Resilient Distributed Dataset
RHS	Right Hand Side
YAFIM	(Yet Another Frequent Itemset Mining) A Parallel Frequent Itemset Mining Algorithm with Spark

Abstract

Data mining is the process that is used for extracting interesting patterns from large amount of data using a variety of techniques. One of the techniques that help to discover important relations between variables in large dataset is Association rule mining (ARM). It is used to identify strong rules discovered in databases. To build the association rules for all itemsets this requires large memory and processing resources. So, only frequent itemsets are considered to reduce the number of itemsets. There are many frequent itemset mining algorithms; the most popular algorithm is the Apriori algorithm. The Apriori algorithm is iterative and works sequentially, its normal execution is on a single machine. Nowadays, there is a great explosion of data; the rapid growth of data necessitates running the data intensive algorithms in parallel distributed environment to achieve convenient performance. The major drawbacks of the Apriori algorithm concerning its computational complexity make the algorithm inefficient to use when the data size is getting larger. In this thesis, Apriori Algorithm on Spark based on Cuckoo Filter structure (ASCF) is introduced. The ASCF algorithm solves the inherent drawbacks in the original Apriori algorithm. It succeeds in removing the candidate generation step from Apriori algorithm to reduce computational complexity and avoid costly comparisons, and uses cuckoo filter to further enhance the performance. The proposed algorithm is implemented on spark in-memory processing distributed environment to reduce processing time. It offers great improvement in performance over other previous approaches of Apriori algorithm implementation based on spark. The ASCF on a cluster of 4 nodes achieves a time of only 5.8% of the competing approach on the Retail dataset with minimum support of 0.75% , 25.6% on Chess dataset with minimum support of 85% and 37.3% on T10I4D100K with minimum support of 0.25%.

Chapter 1 : Introduction

We live in the data age, this data is being generated by everything around us at all times: from social sites, sensors, search engine, medical reports, etc. This huge amount of data is known as 'Big Data'. It is as a collection of large, diverse, complex dataset that comes at high speed. There is an urgent need to assist humans in extracting useful information (knowledge) from this data. It requires new architecture, techniques, algorithms, and analytic methods to manage it and extract value and hidden knowledge from it. Big Data mining is the process of discovering patterns from large datasets that have those mentioned properties.

1.1. Problem Statement

The problem can be formally stated as:

Let D be a set of transactions in large transactional data where each transaction T is a set of items such that $T \subseteq I$, where $I = \{i_1, i_2, \dots, i_m\}$ is a set of items. Each transaction has a unique identifier TID . Let X and Y be two different sets of items, where $X \subseteq I$, $Y \subseteq I$ are subset of I and $X \cap Y = \emptyset$. IF $X \subseteq T$ then the transaction T is said to contain X .

Each itemset appears a number of times in D so there are a percentage of transactions that contain all items in X , which is called $\text{support}(X)$. The itemsets X and Y appear together in D if there are S percentage transactions that contain $X \cup Y$, where S is the $\text{support}(X \cup Y)$, we say there is association between itemsets X and Y .

The problem is discovering important association rules between variables (items) in large transactional dataset. These rules are called strong rules if they have support and confidence greater than or equal predefined minimum support and confidence thresholds.

Mining association rule task consist of two steps:

- Finding all frequent itemsets which have support greater than or equal a predefined minimum support
- Generating confident rules from the frequent itemsets discovered.

The performance of an algorithm for mining association rules is determined by the first step, while the second step is straightforward. Most of the algorithms are inefficient and take a lot of time when working with large datasets because they are designed to work with a single machine in an iterative manner with no natural way for distribution. So, new technologies are required to store and process large data sets in a distributed computing environment like Hadoop Mapreduce and Spark.

1.2. Motivation

The Apriori algorithm is iterative and works sequentially. Its normal execution is on a single machine whose speed leads to severe performance degradation when working with big data so multiple machines and a parallel algorithm are needed where issues like data replication and synchronization must be addressed. The major drawbacks of the Apriori algorithm concerning its computational complexity make the algorithm inefficient to use when the data size get larger. It generates candidate sets having all possible pairs from frequent itemsets that are generated from previous iteration and compares each pair with every transaction record in every iteration.

In this thesis, we apply Apriori Algorithm on Spark based on Cuckoo Filter structure (ASCF) to solve these problems. We propose a parallel Apriori implementation on Spark distributed environment to reduce processing time, and use cuckoo filter structure to further enhance the performance. We focus on the step that is the most time consuming in the whole algorithm, which is generating candidate sets in the second phase and solve this problem by eliminating it to reduce computational complexity and avoid costly comparisons.