High Utility Itemsets Identification in Big Data

Ashish Tamrakar
University of Nevada, Las Vegas

HIGH UTILITY ITEMSETS IDENTIFICATION IN BIG DATA

by

Ashish Tamrakar

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Ashish Tamrakar

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Master of Science in Computer Science
Department of Computer Science

Justin Zhan, Ph.D.,
Examination Committee Chair

Laxmi Gewali, Ph.D.,
Examination Committee Member

Fatma Nasoz, Ph.D.,
Examination Committee Member

Ge Lin Kan, Ph.D.,
Graduate College Faculty Representative

Kathryn Hausbeck Korgan, Ph.D.
Graduate College Interim Dean

Abstract

High utility itemset mining is an important data mining problem which considers profit factors besides quantity from the transactional database. It helps find the most valuable products/items that are difficult to track using only the frequent data mining set. An item that has a high-profit value might be rare in the transactional database despite its tremendous importance. While there are many existing algorithms which generate comparatively large candidate sets while finding high utility itemsets, the major focus is to reduce the computational time significantly with the introduction of pruning strategies. Another aspect of high utility itemset mining is to compute the large dataset. There are very few algorithms that can handle a large dataset to find high utility itemset mining in a parallel (distributed) system.

In this thesis, there are two proposed methods: 1) High utility itemset mining using pruning strategies approach (HUI-PR) and 2) Parallel EFIM (EFIM-Par). In the method I, the proposed algorithm constructs the candidate sets in the form of a tree structure, which traverses the itemsets with High Transaction-Weighted Utility (HTWUIs). It uses a pruning strategies to reduce the computational time by refraining the visit to unnecessary nodes of an itemset to reduce the search space. It significantly minimizes the transaction database generated on each node. In the method II, the distributed approach is proposed dividing the search space among different worker nodes to compute high utility itemsets which are aggregated to find the result. The experimental results for both methods show that they significantly improve the execution time for computing the high utility itemsets.

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Ashish Tamrakar

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List of Algorithms

List of Acronyms

1-HTWUI First-level High Transaction-Weighted Utility Itemset

ARM Associative Rule Mining

EFIM EFIM: a highly EFficient algorithm for high-utility Itemset Mining

EFIM-Par Parallel EFIM

FIM Frequent Itemset Mining

HDFS Hadoop Distributed File System

HTWUI High Transaction-Weighted Utility Itemset

HUI-PR High Utility Itemset mining using Pruning Strategies Approach

HUIM High Utility Itemset Mining

PHUI-Miner Approximate Parallel High Utility Itemset Mining

RDD Resilient Distributed Dataset

TD Transactional Database

TU Total Utility

TWU Transaction-Weighted Utility

Chapter 1

Introduction

The challenge in big data mining has been finding the meaningful information in large datasets. A technique in data mining to discover interesting, unexpected and useful patterns of data from a large database is called pattern mining. For example, if the customer buys a mobile phone then he/she is most likely to buy phone cover and screen protector as well. These patterns are found based on the mining of large database transactions. It can also be used in the recommendation systems by accessing the history of customers and arrangement of goods in the departmental stores. In the past, most research in pattern mining focuses on Frequent Itemset Mining (FIM) and Associative Rule Mining (ARM), which are the traditional ways to find the frequent set of itemset patterns which are higher than the minimum support threshold[1]. These mining patterns occur frequently within a huge transaction database. Apriori algorithm was proposed for frequent itemset mining which scans database in multiple scans and large candidate sets were generated [2]. To overcome the limitation of Apriori algorithm, FP-Growth was then proposed which discovers all the frequent patterns with only two scans of the transactional database [3]. Although FIM was a great discovery to mine frequently occurring itemsets, it gives equal importance to all items in the transactional database. It only gives importance to quantity however the importance of profit was lacking. For example, the sale of milk and bread occurrence is frequent in the transactions of the dataset while the sale of diamond seems to be rare and it might not be reflected in the outcome of the FIM and ARM. Therefore, it is necessary to consider both profit and quantity of the itemsets. Consequently, the concept of utility mining was introduced.

Utility pattern mining has been one of the most significant research works proposed to discover the useful and profitable itemsets from the large transactional datasets[4]. Utility mining includes both internal utility and external utility to compute the itemset where internal utility is represented by the quantity of an item and external utility is represented by the profit of an item[5]. A minimum utility threshold is used to discover whether an itemset is a high utility itemset or not. Recently, many types of research have been carried out in the field of high utility itemset mining [6, 5, 7, 8]. Liu et al. proposed a two-phase model which computes transaction-weighted utility (TWU) and considers the transaction-weighted download closure property to find high utility itemsets [9]. Downward closure property defines that every sub-pattern of itemsets must also be frequent. However, this algorithm by Liu et al. generates a large number of candidates in order to find the high utility itemsets. Therefore, the performance is not optimized even for the smaller datasets. It takes a lot of computational time and memory to process a large number of candidates. Different methods were proposed to reduce the possible number of candidate sets [10, 11]. Liu et al. [12] proposed an approach to find the high utility mining without candidate generation. And, Zida et al. [13] proposed different upper-bound pruning to reduce candidate sets. Different pruning approaches have been introduced so far to reduce the number of candidate sets generation. However, these state-of-the-art algorithms perform well when the dataset is small. When the size of the dataset increases, the performance degrades. Therefore with the current era of big data, there is a need to compute datasets in multiple machines, which is possible through distributed computing.

One of the methods of distributed computing is to implement Map-Reduce framework [14] with Hadoop. This framework is highly scalable and fault-tolerant system and can process large datasets on multiple clusters. Hadoop framework can be implemented on less powerful and cheap machines. However, this popular framework is a disk-based paradigm and is heavily dependent on its Hadoop Distributed File System (HDFS). Another framework named Spark [15] was introduced to overcome its heavy dependency with HDFS by allowing in-memory computation. Spark framework can perform up to 100 times faster than Hadoop. Spark uses Resilient Distributed Datasets (RDD) which is an immutable data structure allowing efficient reuse of data for in-memory computation.

1.1 Objective

The objective of this thesis is to extend the state-of-the-art algorithm named EFIM: A Highly Efficient Algorithm for High-Utility Itemset Mining (EFIM) [13] with a novel pruning strategies approach for smaller datasets. In this thesis, an algorithm named High Utility Itemset mining using Pruning Strategies Approach (HUI-PR) is proposed which uses a pruning hash table to reduce the searching area in EFIM algorithm and another utility bound named transaction-weighted utility (TWU) is also considered. These proposed pruning strategies reduce the number of candidate sets generated reducing the computational time to find the high utility itemsets. Another contribution of this thesis is to build the distributed system using Apache Spark^{TM} (The Apache Software Foundation) Framework from the EFIM algorithm named EFIM parallel computing (EFIM-Par) for larger datasets.

1.2 Outline

In Chapter 1, the brief topic of itemset mining, its application in real world and the proposed method was described.

In Chapter 2, we will discuss the related works with our proposed methods and the background information required to understand the itemset mining. It will also cover the distributed system and the most popular distributed computing frameworks.

In Chapter 3, we will propose two methods to find the high utility itemsets. One method will be based on the pruning strategies approach which is suitable for the smaller datasets while another method will be based on the distributed computing approach for the very large datasets. The detailed description will be provided along with the examples of these methods.

In Chapter 4, we will present the experimental results showing the difference between our methods and the state-of-the-art algorithms based on the time, accuracy and efficiency. The characteristics of datasets used for these methods will also be described.

In Chapter 5, we will summarize the proposed methods and their results along with the possible extension of this thesis.

Chapter 2

Background and Preliminaries

2.1 Related Work

Many researchers have been focusing their efforts in the field of high utility itemset mining (HUIM). HUIM started with the pattern mining concepts [1, 16, 17, 3] such as Frequent Itemset Mining (FIM) and Associative Rule Mining. The initial breakthrough came when Agrawal and Srikant [2] proposed a method named Apriori. However, Han et al. [3] proposed the FP-Growth algorithm, with a tree-structure named FP-tree to improve performance than Apriori algorithm. FIM does not emphasize the importance of items and quantities of items. Therefore, there is the need for weighted FIM (WTI-FWI) [18, 8]. These methods that focus on weight gives importance to items.

High utility itemset mining (HUIM) [19, 5, 20, 7, 21, 22, 6, 11] gives the importance to the item quantities and profit value (external utility). This concept was firstly proposed by Yao et al. [6]. Liu et al. [9] proposed a Two-Phase algorithm based on Apriori to find high utility itemsets using multiple database scans. The initial scan generates the high transaction-weighted utility items (1-HTWUIs) for the first level which accepts only items that have transaction-weighted utility (TWU) higher than the threshold value. The second scan generates the candidate sets based on the 1-HTWUIs and considers only those itemsets with TWU higher than the minimum threshold. The next scan selects the high utility itemsets (HUIs) with higher utility value than the minimum threshold value. This maintains the downward closure property. However, for each level of the tree, this algorithm generates a large number of candidate sets.

To reduce the overestimated utilities, different pruning approaches have been proposed [23, 12, 24, 25, 13, 11, 26, 27, 28]. Liu et al. [12] proposed the mining of high utility itemsets without candidate generation. A utility-list was used to store the information about utilities for itemsets.

These utility-lists also helped to prune unnecessary candidates. However, this algorithm uses a large amount of memory for utility list for each itemset. Zida et al. [13] also use the concept of utility-lists and proposed two upper bounds named sub-tree utility and local utility for pruning the search space. These bounds are described in the following sections. It also uses the fast utility counting technique to reduce the memory usage. Fournier-Viger et al. [28] introduced the pruning strategy of length upper bound reduction by constraining the generation of candidate sets up to given maximum length of itemsets.

Since the advent of Big Data, many research works have been on computing the very large datasets using parallel computing. Initially, simple approaches for map-reduce framework have been used for frequent itemset mining[29, 30]. There are very few algorithms proposed so far for both the frequent itemset mining and high utility itemset mining. Li et.al [31] proposed the Parallel FP-Growth algorithm to find the frequent itemsets in a distributed approach with multiple map-reduce stages. For the parallel high utility itemset mining, Lin et.al [32] proposed the parallel UP-Growth (PHUI-Growth) algorithm with counting map-reduce phase and mining phase using Hadoop framework [14]. Another algorithm proposed by Chen et.al [33] implemented the distributed approach (PHUI-Miner) on HUI-Miner algorithm [12] to perform better than PHUI-Growth. PHUI-Miner replaces the Hadoop framework [14] with more efficient Spark framework [15]. Spark performs much better because of its ability to perform an in-memory computation.

Hence, the number of candidate sets reduction by applying pruning rule for smaller datasets and parallel computing for high utility itemsets in large datasets play a significant role in improving the performance in the identification of high utility itemsets. Therefore, our thesis aims to construct a novel approach to generate candidate sets efficiently and to apply proposed pruning strategies to reduce the unnecessary candidate sets. The distributed approach can be used with Spark framework on state-of-the-art algorithm EFIM [13] to improve the computational time for finding the high utility itemsets.

2.2 Preliminaries

2.2.1 High Utility Itemset Mining

Let us suppose the transactional database with set of transactions $D = T_1, T_2, ..., T_n$ which has the finite set of m unique items $I = i_1, i_2, ..., i_m$. Each transaction in database, $T_q \in D$ where $1 \leq q \leq n$ has a unique identifier, called its Transaction ID (TID). Each item i_j is associated with

Table 2.1: A Transactional Database D

TID	**Transaction (item:quantity)**	**TU**
T_1	A:3, B:2, D:2	17
T_2	A:4, C:1, D:3, E:2	15
T_3	A:2, B:1, E:3, F:5, G:2	22
T_4	B:2, C:1, E:3	16
T_5	B:1, C:1, E:1, F:1	11

Table 2.2: A Profit Table

Item	**Profit Value**
A	1
B	5
C	3
D	2
E	1
F	2
G	1

quantity, which is internal utility, and with its associated profit value, which is external utility. Internal utility is denoted by $q(i_j, T_q)$ and external utility by $pft(i_j)$. A set of k unique items $X = i_1, i_2, ..., i_k$ where $X \subseteq I$ is said to be a k-itemset, where k is the length of an itemset and an itemset X is in transaction T_q if $X \subseteq T_q$ and a minimum threshold ratio δ is defined.

An illustrative example is shown in Table 2.1 which represents the quantitative (transactional) database. There are five transactions with seven distinct items in the quantitative database. Table 2.2 represents the profit table which contains profit value for each item. The user specified threshold ratio δ is taken as 30.86% which will be threshold value of $25(TU \times \delta)$.

Definition 2.2.1 *The utility of an item i_j denoted by $u(i_j, T_q)$ in a transaction T_q is defined as,*

$$u(i_j, T_q) = q(i_j, T_q) \times pft(i_j) \tag{2.1}$$

The utility of items A, B and D in transaction T_1 are calculated using the Equation 2.1 as,

$u(A, T_1) = q(A, T_1) \times pft(A) = 3 \times 1 = 3$

$u(B, T_1) = q(B, T_1) \times pft(B) = 2 \times 5 = 10$

$u(D, T_1) = q(D, T_1) \times pft(D) = 2 \times 2 = 4$

Definition 2.2.2 *The utility of an itemset X denoted by $u(X, T_q)$ in a transaction T_q is defined as,*

$$u(X, T_q) = \sum_{i_j \subseteq X \cap X \subseteq T_q} u(i_j, T_q) \tag{2.2}$$

The utility of itemsets in transaction T_1 is calculated from Equation 2.2 as,

$u(AB, T_1) = u(A, T_1) + u(B, T_1) = 3 + 10 = 13$

$u(ABD, T_1) = u(A, T_1) + u(B, T_1) + u(D, T_1) = 3 + 10 + 4 = 17$

Definition 2.2.3 *The utility of an itemset X denoted by $u(X)$ in database D is defined as,*

$$u(X) = \sum_{X \subseteq T_q \cap T_q \in D} u(X, T_q) \tag{2.3}$$

The utility of itemsets C and D in database D is calculated from Equation 2.3 as,

$u(AB) = u(AB, T_1) + u(AB, T_3) = 13 + 7 = 20.$

Definition 2.2.4 *The transaction utility of a transaction T_q denoted by $TU(T_q)$ is defined as,*

$$TU(T_q) = \sum_{X \subseteq T_q} u(X, T_q) \tag{2.4}$$

The transaction utility of a transaction T_1 is calculated from Equation 2.4 as,

$TU(T_1) = u(A, T_1) + u(B, T_1) + u(D, T_1) = 3 + 10 + 4 = 17.$

Similarly, the total utility for other transactions are $T_2 = 15, T_3 = 22, T_4 = 16$ and $T_5 = 11$ as shown in Table 2.1.

Definition 2.2.5 *The total utility denoted by TU in database D is defined as,*

$$TU = \sum_{T_q \in D} TU(T_q) \tag{2.5}$$

The total utility is calculated from Equation 2.5 as,

$TU = 17 + 15 + 22 + 16 + 11 = 81.$

Definition 2.2.6 *The transaction-weighted utility of an itemset X denoted by $TWU(X)$ in database D is defined as,*

$$TWU(X) = \sum_{X \subseteq T_q \in D} TU(T_q) \tag{2.6}$$

The transaction-weighted utility for an itemset {A,B} is calculated from Equation 2.6 as,

$TWU(AB) = TU(T_1) + TU(T_3) = 17 + 22 = 39.$

Table 2.3: Transaction-Weighted Utility of 1-TWU Items

Itemset	**{A}**	**{B}**	**{C}**	**{D}**	**{E}**	**{F}**	**{G}**
TWU	54	66	42	32	64	33	22

Table 2.4: Revised Transactional Database

TID	**Transaction (item:utility)**
T_1	D:4, A:3, B:10
T_2	D:6, C:3, A:4, E:2
T_3	F:10, A:2, E:3, B:5
T_4	C:3, E:3, B:10
T_5	F:2, C:3, E:1, B:5

Definition 2.2.7 *An itemset X in a database D is a high transaction-weighted utility itemset (HTWUI) if its TWU is greater than or equal to the minimum threshold, where minimum threshold is TU multiplied by user specified threshold ratio δ as,*

$$HTWUI \leftarrow \{X|TWU(X) \geq TU \times \delta\} \tag{2.7}$$

Since an itemset $\{A, B\}$ has $TWU(AB) \geq TU \times \delta(81 \times 30.86 = 25)$, it is therefore a high transaction-weighted utility itemset.

Definition 2.2.8 *An itemset X in a database D is a high utility itemset (HUI) if its utility is greater than or equal to the minimum threshold, where minimum threshold is TU multiplied by user specified threshold ratio δ as,*

$$HUI \leftarrow \{X|u(X) \geq TU \times \delta\} \tag{2.8}$$

An itemset $\{A, B\}$ has $u(AB) \leq TU \times \delta$, it is not a high utility itemset (HUI). Similarly, an itemset $\{B, E\}$ has $u(BE) \geq TU \times \delta$, it is a HUI.

Definition 2.2.9 *The total ordering denoted by → is the ordering of items in the increasing order of transaction-weighted utility in the transaction.*

The transaction-weighted utility for each item is as shown in the Table 2.3. The increasing order of items in terms of TWU is: G, D, F, C, A, E, B ($G \rightarrow D \rightarrow F \rightarrow C \rightarrow A \rightarrow E \rightarrow B$).

Definition 2.2.10 *The revised transaction (RT) is said to be a transaction in which all the items which have $TWU \leq TU \times \delta$ are removed and the items remaining are sorted in increasing order of TWU. The items that are removed from the transactions are said to be unpromising items.*

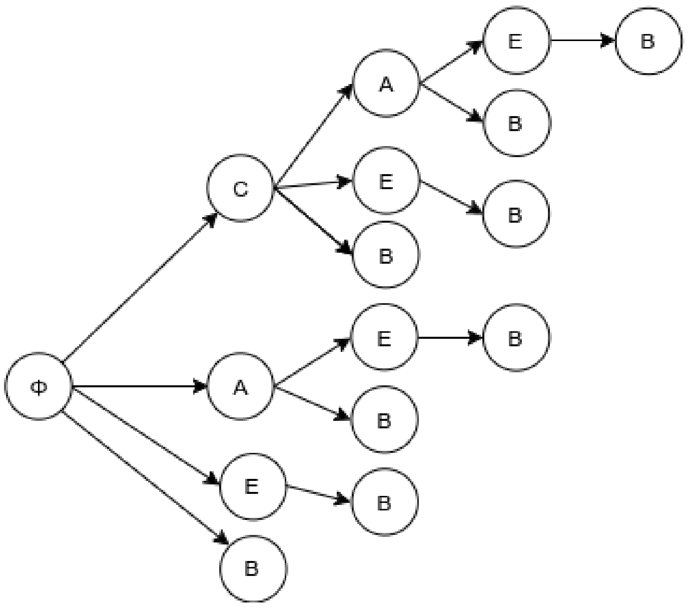


Figure 2.1: Construction of Tree Structure of Itemsets.

From the given illustrative example in Table 2.1 and Table 2.2, the revised transactional database after removing the unpromising items and the items arranged in increasing order of TWU are as shown in Table 2.4.

Definition 2.2.11 *The remaining utility denoted by $rem(X, T)$ in the transaction T with total ordering ($\rightarrow$) of items on itemset X is defined as,*

$$rem(X, T) = \sum_{i_j \in T \cap i_j \rightarrow z \forall z \in X} u(i_j, T) \tag{2.9}$$

From the Table 2.4, the remaining utility for the itemset $\{D, C\}$ in transaction T_2 is,

$rem(DC, T_2) = u(A, T_2) + u(E, T_2) = 4 + 2 = 6.$

Definition 2.2.12 *The extension of an itemset γ denoted by $Ex(\gamma)$ is the possible following items for the given itemset γ.*

From Figure 2.1, the extension of an itemset {A} is {B,E} and similarly, for itemset {C} is {A, E,B}.

Definition 2.2.13 *The projected database of a revised transactional database D denoted by γD of an itemset γ is as,*

$$\gamma D = \{\gamma T | T \in D \cap \gamma T \neq \phi\} \tag{2.10}$$

where, $\gamma T = \{i_j | i_j \in T \cap i_j \in Ex(\gamma)\}$ is the projection of a transaction T of an itemset γ.

Table 2.5: Projected Database for Itemset D of 1-HTWUIs

TID	**Transaction (item:utility)**
T_1	A:3, B:10
T_2	C:3, A:4, E:2

The projected database for the itemset D of 1-HTWUIs is as shown in the Table 2.5.

Definition 2.2.14 *The projected transaction merging is the method of merging the identical projected transactions (γT) and the utility from each transaction is merged into one as,*

$$u(i, T_m) = \sum q(i, T_k) \tag{2.11}$$

where, k is the number of identical projected transactions.

From the illustrative example from Table 2.4, considering $\gamma = \{C\}$, γD gets projected transactions of $\{A, E\}$ from T_2, $\{E, B\}$ from T_4 and $\{E, B\}$ from T_5. The projected transactions from T_4 and T_5 are merged to form a single projected transaction in the γD database. As a result, the new projected database will have $\{A, E\}$ and $\{E, B\}$ transactions.

Definition 2.2.15 *The utility-bin denoted by Ub is an array with length equal to the number of items I in the database D. For each itemset $x \in I$, the utility bin is denoted as $Ub[x]$.*

Definition 2.2.16 *The sub-tree utility denoted by $subU(\gamma, x)$ of an itemset γ and an item x which can have extension of γ is as,*

$$\begin{aligned} subU(\gamma, x) = & \textstyle\sum_{T \in (\gamma \cup \{x\})} [u(\gamma, T) + u(x, T) \\ & + \textstyle\sum_{i_j \in T \cap E(\gamma \cup \{x\})} u(i_j, T)] \end{aligned} \tag{2.12}$$

This sub-tree utility is one of the pruning strategies to reduce the search space. If $subU(\gamma, x) < TU \times \delta$ then, an itemset $\gamma \cup \{x\}$ can be pruned.

Referring to the Table 2.4, assuming the items are in total ordering as G, D, F, C, A, E, B, let us assume $\rho = \{\phi\}$, then the sub utility from Equation 2.12 for the following items i_j - E, D can be shown as,

$subU(\rho, \{E\}) = \sum_{T \in (\rho \cup \{E\})} [u(\rho, T) + u(\{E\}, T) + \sum_{i_j \in T \cap E(\rho \cup \{E\})} u(i_j, T)]$, where $T = T_2, T_3, T_4, T_5$

$= (0 + 2 + (0))_{T_2} + (0 + 3 + (5))_{T_3} + (0 + 3 + (10))_{T_4} + (0 + 1 + (5))_{T_5} = 29$

$subU(\rho, \{D\}) = (0 + 4 + (3 + 10))_{T_1} + (0 + 6 + (3 + 4 + 2))_{T_2} = 32$

Similarly, let us assume $\rho = \{D\}$, referring to the Table 2.5 the sub utility for items A and E are as,

$subU(\rho, \{A\}) = (4 + 3 + (10))_{T_1} + (6 + 4 + (2))_{T_2} = 29$

$subU(\rho, \{E\}) = (6 + 2 + (0))_{T_2} = 8$

Definition 2.2.17 *The local utility denoted by $locU(\gamma, x)$ for an itemset is as,*

$$locU(\gamma, x) = \sum_{T \in (\gamma \cup \{x\})} [u(\gamma, T) + re(\gamma, T)] \tag{2.13}$$

The local utility from Equation 2.13 for some of the following items i_j - E, A with $\rho = \{D\}$ can be shown as,

$locU(\rho, \{E\}) = [u(\rho, T_2) + re(\rho, T_2)]$ where T_2 is from projected transaction of ρ,

$= (6 + (3 + 4 + 2)) = 15$

$locU(\rho, \{A\}) = (4 + (3 + 10))_{T_1} + (6 + (3 + 4 + 2))_{T_2} = 32$

Definition 2.2.18 *The items are said to be itemsToKeep or follower items of an itemset if the items of 1-HTWUIs or follower items of previous itemset have the local utility value greater than threshold value.*

$$itemsToKeep(\rho) = followerItems(\rho) = \{x \in followerItems(\gamma) \mid locU(\rho, x) \geq \delta \times TU\} \tag{2.14}$$

Items to keep are computed from 1-HTWUIs for the case of root node only, and for remaining sub-trees, items to keep are computed from follower node of its parent node.

Definition 2.2.19 *The items are said to be itemsToExplore or next nodes of an itemset if the items of itemsToKeep or followerNodes have the sub-tree utility value greater than the threshold value.*

$$itemsToExplore(\rho) = nextNodes(\rho) = \{x \in followerItems(\gamma) \mid subU(\rho, x) \geq \delta \times TU\} \tag{2.15}$$

2.2.2 Distributed Systems

With the advent of big data, there is a need for large and parallel computations to find the solution in short time. Therefore, parallel computation is used to take advantage of solving the tasks by computing in parallel using cheap resources. The parallel computation is categorized into different types, but according to the hardware level parallelism, there are generally two types: shared memory and non-shared memory (distributed systems) [14]. In shared memory computation, there are multiple processors which concurrently access the shared memory. This model is very efficient and easy to develop. However, this model requires large memory and suffers the problem of need of large memory. In non-shared memory computation, there are different processors which have their own local memories and each processor communicates with other by passing a message through an interconnected network. This model is usually scalable and very efficient than shared memory model.

In the field of big data mining, there is a need to analyze, process and extract the information from the large data. However, there is a restriction on data because of the computation limitation by the single machine. This limitation affects the scalability of the algorithm implemented. Therefore, to process the huge amount of data and extract meaningful information, distributed systems are used. There are different distributed computing frameworks available to take advantage of scalability.

2.2.2.1 Apache Hadoop

A Java-based framework, Apache$^{\text{TM}}$ Hadoop® [34], is a popular framework at present. This framework is highly scalable, reliable and fault-tolerant. There are two main components of Apache Hadoop. One is the Hadoop Distributed File System (HDFS), which is designed to store large datasets in a reliable manner. It stores data in different nodes by splitting as a block of the large file and it is distributed among different clusters. It is highly fault-tolerant and reliable as it replicates the file from another node even in the case of failure. Another part of Hadoop system is map-reduce which can process a large amount of data in terms of key-value pairs. There are two stages: map and reduce. The map is used to process block of data to produce the key-value pairs which are then reduced or aggregated by Reducer based on its keys.

However, there is a limitation with Hadoop system as it is based on key-value pair paradigm. Every problem needs to be formulated in terms of key-value pair solution which might be difficult for all the problems. Each map-reduce pairs are read from the disks, processed and write back into the disk. This model restricts the flexibility and performance of the Hadoop system.

2.2.2.2 Apache Spark

To overcome the limitation of Hadoop system, Apache Spark [15] was introduced which does an in-memory computation. Unlike Hadoop system, which depends upon HDFS. Spark introduced the Resilient Distributed Datasets (RDD) abstraction which is a read-only collection of objects. These read-only objects are created by reading the disk or by transformation of other previously created RDDs. Those RDD objects created if lost can be built again, and RDDs are loaded in the memory of multiple nodes so that it can be re-used again and again in Map-reduce operations. In Apache Spark, there are one driver node (Master) and many worker nodes (Slaves) which do map-reduce operations similar to Hadoop system. However, Spark framework can operate any number of the map or reduce operations independently. In Spark framework, it is not necessary that Map operation is followed by Reduce operation unlike in Hadoop framework. These feature of Spark provides much more flexibility.

Chapter 3

Proposed System

3.1 Method I - Pruning Strategies Approach

This section describes our proposed algorithm High Utility Itemset mining using Pruning Strategies Approach (HUI-PR). This section consists of the construction of First-level High Transaction-Weighted Utility Itemsets (1-HTWUIs) of the given items, the node selection rule in the subsequent tree structure, construction of sub-trees of itemsets and pruning strategies to reduce search space by skipping unnecessary visitation of nodes.

3.1.1 Construction of 1-HTWUIs Tree of Items

1-HTWUIs are constructed from a tree-structured graph. The items of the transactional database are considered for forming itemsets at level one of the tree, and these itemsets are arranged in increasing order of the Transaction-Weighted Utility (TWU). Based on the transaction-weighted downward closure property[9], the transaction-weighted utility of a superset itemset is low. Therefore, the itemsets with TWU less than a threshold value are removed, and these removed items are known as unpromising items.

Let us take an example from the Table 2.3. There are 7 items in the transactional database D in which there is one item, $ItemG$, with TWU less than a threshold. $ItemG$ is removed for the construction of 1-HTWUIs. This pruning of items in the initial stage reduces the searching space. The remaining items with TWU, $ItemA = 54, ItemB = 66, ItemC = 42, ItemD = 32, ItemE = 64, ItemF = 33$ are arranged in the ascending order of TWU. Therefore, 1-HTWUIs have the items D, F, C, A, E, B which is shown in the Figure 3.1.

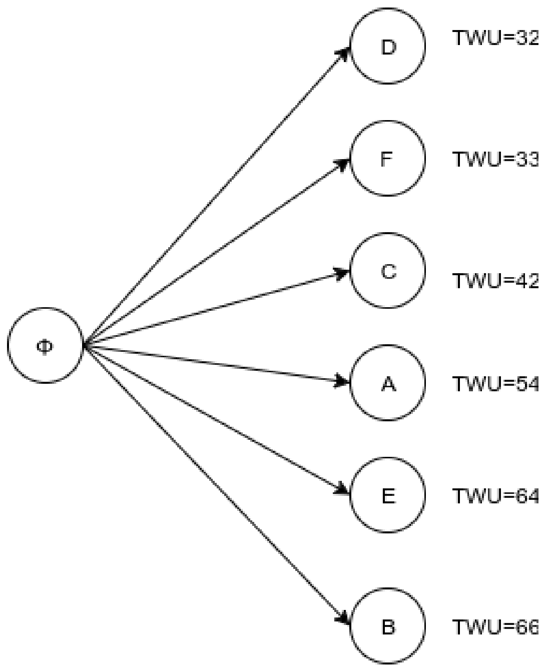


Figure 3.1: Construction of 1-HTWUI Tree of Items.

3.1.2 Node Selection Rule

According to the Node Selection Rule, the node with highest TWU is traversed first. From the Figure 2.1, the highest TWU item, $ItemB$, is traversed and then next item $ItemE$ is traversed along with its child nodes. The case is same when traversing inside the child of child nodes. For example, the child nodes of $ItemA$ are $ItemE$ and $ItemB$. The node with $ItemB$ is traversed first and then $ItemE$ is traversed. Therefore, some of the itemsets formed by traversing the tree are as $\{B\}, \{E\}, \{E, B\}, \{A\}, \{A, B\}, \{A, E\}, \{A, E, B\}$

3.1.3 Construction of Sub-tree of Itemsets

For the construction of a sub-tree of itemsets, a recursive approach is used in which traversing of node starts from the node with higher TWU itemset and the next subsequent node is taken and traversed. It utilizes depth-first search strategy to traverse every node.

Different computation undergoes in the algorithm as shown in Algorithm 1 which includes the computation of projected database, checking the pruning table to prune the transactions, calculation of utility of an itemset, calculation of sub-tree utilities, local utilities and transaction-weighted utilities for all its following items, next child nodes of a current itemset and follower nodes of the child node is computed and the insertion of an itemset to pruning table is also carried out in this process.

Algorithm 1: Build Sub-tree to determine Itemsets

```
Input: Transactional Database $D$, ThresholdRatio $\delta$, Total Utility $TU$
1  Function constructSubTree($\gamma$, $D$, nextNodes($\gamma$), followerItems($\gamma$), $\delta$, $TU$)
2      for each item $i_j$ in nextNodes($\gamma$) do
3          $\rho \leftarrow \gamma \cup \{i_j\}$;
4          while scan each $T_j$ in $D$ do
5              if checkPruningTable($T_j$) then
6                  continue from while loop;
7              Compute $\rho D$;
8              Calculate $u(\rho)$;
9          end
10         if $u(\rho) \geq \delta \times TU$ then
11             $HUIs \leftarrow \rho$;
12         Calculate $subU(\rho, x), locU(\rho, x)$ and $TWU(\rho, x)$ for all the items $i_j$ in
             $followerItems(\gamma)$ by scanning $\rho D$;
13         $nextNodes(\rho) = \{x \in followerItems(\gamma) | subU(\rho, x) \geq \delta \times TU\}$;
14         $followerItems(\rho) = \{x \in followerItems(\gamma) | locU(\rho, x) \geq \delta \times TU\}$;
15         while scan each item $i_k$ in $followerItems(\gamma)$ do
16             $i_s \leftarrow \rho \cup i_k$;
17             if $TWU(i_s) < \delta \times TU$ then
18                 $insertToPruningTable(i_s)$;
19         end
20         $constructSubTree(\rho, \rho D, nextnodes(\rho), followerItems(\rho), \delta, TU)$;
21     end
```

3.1.4 Pruning Strategies

The proposed algorithm explains the concept of a pruning hash table implemented. The detail of the pruning hash table is explained in the Transaction Pruning Strategy section. Different utility-bounds such as sub-tree utility, local utility and transaction-weighted utility are used to prune the branches.

3.1.4.1 Transaction Pruning Strategy

The algorithm uses a transaction pruning rule to avoid the transactions which contain the itemsets in the pruning hash table to generate the projected transaction ρD.

A hash table is implemented to insert itemsets that are to be pruned. The hash table stores the itemsets with low-utility value. While traversing the different nodes, the itemset is inserted into the pruning hash table if the current itemset has transaction-weighted utility lower than the threshold value. For example, if an itemset $\{A, B, C\}$ is to be inserted into the pruning table, our proposed algorithm first checks whether there is already a superset of that itemset in the hash table. If pruning hash table does not contain any superset, it then stores an $ItemA$ in the map with key as A and $null$ as value. Then, another map with $ItemB$ will be inserted as the value in A and so on until all the items are stored in the pruning hash table.

The algorithm to check whether the superset of an itemset is present or not is shown in Algorithm 2 and to insert an itemset in the pruning hash table is shown in Algorithm 3.

Algorithm 2: Checking in Pruning Hash Table for Transaction Pruning

```
   Input: Pruning Hash Table $pTable$, transaction $T_j$
1  Function checkPruningTable($T_j$)
2      $pr \leftarrow pTable$;
3      if $pTable.size() > 0$ then
4          for each item $i_k \in T_j$ do
5              //check item in pruning table
                if $i_k$ not in $pr$ then
6                  return false;
7              $pr \leftarrow pr(i_k)$;
8              if $pr$ is null then
9                  return true;
10         end
11     return false;
```

Algorithm 3: Insertion in Pruning Hash Table

```
   Input: Itemset itemset, Maximum limit of pruning table $\phi$
1  Function insertIntoPruningTable(itemset)
2      if checkPruningTable(itemset) is null then
3          if $pTable.size() < \phi$ then
4              Insert into pruning table recursively;
5              pTablesize++;
6              return true;
7      return false;
```

3.1.4.2 Utility-Based Pruning

Utility-based pruning prunes the branches with itemsets that are not feasible. Utility-based pruning includes sub-tree utility, local utility and transaction-weighted utility. The transaction-weighted utility of an itemset prunes the itemset that is less than the minimum threshold by inserting into the pruning hash table which is used for reducing the search space. During the generation of projected transaction, while traversing on each node, calculation of sub-tree utility and local utility are done for each of the possible follower items of that node. If any of the possible follower items have sub-tree utility less than the minimum threshold, then that item cannot be the next possible node but still has a chance to be the follower item for the next nodes of the current itemset. If those possible follower items of a node have local utility less than the minimum threshold, it cannot be the next node as well as a follower item for that node.

Let us consider a node as $ItemA$ and suppose, there are 3 possible follower items $ItemB, ItemC$ and $ItemD$. The sub-tree utility is calculated for all its follower items B, C and D and if B has sub-tree utility greater than threshold value and C and D have sub-tree utility value less than threshold then, $ItemB$ is the next node as well as the follower item for $ItemA$ but the local utility is calculated for $ItemC$ and $ItemD$ and suppose if $ItemC$ has local utility greater than threshold value and $ItemD$ has local utility less than threshold, then $ItemC$ can be the follower item of node $ItemA$. Therefore, next node of $ItemA$ is $\{B\}$ and follower items is $\{B, C\}$.

3.1.5 HUI-PR Algorithm

Algorithm 4 starts with reading the transactional database (TD) and threshold ratio (δ). The total utility (TU), transaction-weighted utility (TWU) of items and local utility ($locU$) of all the items of a database is computed by scanning the whole transactional database. Total utility of an database, transaction-weighted utility of items and local utility of items are calculated as defined in Equation 2.5, 2.4 and 2.13. 1-HTWUIs are calculated based on the transaction-weighted utility obtained as described in Section 3.1.1. The follower items are 1-HTWUIs for the initial node and these items are sorted in increasing order in total ordering ($\rightarrow$) as described in Definition 2.2.9. From the list of 1-HTWUIs, those itemsets with transaction-weighted utility values less than the threshold are known as unpromising items. Moreover, those unpromising items are removed from the transactions of the whole transactional database. After removing the unpromising items from the database, if there are empty transactions created, then those transactions are removed. The items of each transaction in the transactional database are sorted based on the total ordering. Calculation of sub-tree utility for each item that follows, termed *followerItems*, is done by scanning the whole database and based on the sub-tree utility values, next nodes termed, *nextNodes*, of the initial root node are defined where the items must have sub-tree utility greater than the threshold. Sub-tree is constructed recursively with taking the parameters as transactional database, nextNodes, followerItems, thresholdRatio and total utility. The algorithm to find the sub-tree of itemsets is defined in detail in Section 3.1.3.

```
Algorithm 4: Algorithm to find HUIs
  Input  : Transactional Database $TD$, ThresholdRatio $\delta$
  Output: High Utility Itemsets $HUIs$
1 Initial itemset, $\gamma = \phi$;
2 Calculate Total Utility $TU$, $TWU(\gamma, i_j)$ and local utility $locU(\gamma, i_j)$ for all $i_j \in I$ by
   scanning whole database $TD$;
3 Compute 1-HTWUIs itemsets,
   $followerItems(\gamma) = \{i_j | i_j \in I \cap TWU(\gamma, i_j) \geq \delta \times TU\}$
   Sort the items in $followerItems(\gamma)$ in total ordering $(\rightarrow)$;
4 Remove the unpromising items $j$ from the transactions $T_j$;
5 Remove the empty transaction after removing unpromising items;
6 Sort the items in each transaction in total ordering $(\rightarrow)$;
7 Calculate sub-tree utility $subU(\gamma, i_j)$ for all $i_j \in followerItems(\gamma)$ by scanning database
   $TD$;
8 Compute next nodes to visit in reverse order,
   $nextNodes(\gamma) = \{i_j | i_j \in reverse(followerItems(\gamma)) \cap subU(\gamma, i_j) \geq \delta \times TU\}$;
9 $constructSubTree(\gamma, TD, nextNodes(\gamma), followerItems(\gamma), \delta, TU)$;
```

3.2 Method II - Distributed EFIM

In the EFIM Parallel (EFIM-Par) algorithm, Apache Spark was used to find high utility itemsets with computation in parallel. This algorithm is the parallel (distributed) implementation of the algorithm EFIM [13]. This section consists of generating 1-HTWUIs, generating revised transactions, finding the sub-tree utility and the local utility, assigning the sub-tree to worker nodes, node data generation, mining high utility itemsets by individual worker nodes and explanation of the overall flow of EFIM Parallel algorithm.

3.2.1 Generating 1-HTWUIs with their corresponding TWU

The Transactional Database (TD) was scanned to find out the 1-HTWUIs of items along with their transaction-weighted utility. First of all, the transactional database was divided into different blocks which were computed by different worker nodes using $flatMap$ operation. The result obtained from worker nodes were reduced using *reduceByKey* operation to get the itemTWU of items which contained items with their corresponding TWU.

3.2.2 Generating Revised Transactional Database

In this process, the Transactional Database (TD) was mapped to generate the revised transactional database using map operation. Firstly, TD was split into different blocks to distribute among worker nodes in which pruning of unpromising items were done, and then for each items of the transaction, they were sorted in the ascending order of their transaction-weighted values. Besides pruning of unpromising items and sorting, the removal of empty transactions were done by using filter operation. The generated revised transactions used the functionality provided by Spark to persist the RDD so that it could be used again later. It was used later to find out the sub-tree utility of items and assignment of items to worker nodes which will be described in the later sections.

Algorithm 5: Revised Transactional Database Generation

```
  Input  : Transactional Database $TD$, ThresholdRatio $\delta$, Total Utility $TU$
  Output: Revised Transactional Database
1 Function map()
2     for $k = 0$ to $len(TD)-1$ do
3         // Removing unpromising items from the transaction
          $TD_k = \sum_{j=0}^{len(TD_k)-1}\{i_j | i_j \in TD_k \cap TWU(i_j) \geq \delta \times TU\}$;
4         // Sort items in transaction in total ordering
5         $SortItems(TD_k)$;
6         if $len(TD_k) == 0$ then
7             Remove $TD_k$;
8         end
9     end
```

3.2.3 Finding Local Utility and Sub-tree Utility of 1-HTWUIs

There are two utilities in this algorithm which prunes the unnecessary visitation of the nodes. It reduces the search space significantly. It needs to be calculated in the first level of the tree in order to compute the next nodes of each item and the follower nodes of those items. The local utility was calculated using the Equation 2.13. For the initial case, it was computed same as transaction-weighted utility, therefore, it used TWU of 1-HTWUIs as described in Section 3.2.1. Another utility, sub-tree utility which was calculated using the Equation 2.12. It scanned the revised transaction to generate the sub-tree utility for each item of 1-HTWUIs. It used flatMap and Reduce operations to get the sub-tree utility values for each item.

3.2.4 Sub-tree Assignment to Worker Nodes

The algorithm uses grouping strategy to assign the *itemsToExplore* and their respective sub-trees to the worker nodes. The *itemsToExplore* was computed by using the Equation 2.15. Grouping of 1-HTWUIs is as shown in the Algorithm 6. This grouping approach helps to divide our tasks among the worker nodes to be executed in distributed environment properly. The grouping was done based on the number of items to explore. Items to explore is defined in the Equation 2.14.

Referring to the example in Table 2.1 and 2.2, we have 7 items in which there are 6 1-HTWUI items. From the definition of 2.2.19, we have D, F, C, A, E, B as items to explore. Let us suppose we have 3 worker nodes as $Node$ 1, $Node$ 2 and $Node$ 3. According to the Algorithm 6, the worker nodes are assigned as $D \rightarrow Node$ 1, $F \rightarrow Node$ 2, $C \rightarrow Node$ 3, $A \rightarrow Node$ 3, $E \rightarrow Node$ 2 and $B \rightarrow Node$ 1. The worker nodes are assigned to the sub-tree nodes along with their respective node data which is described in Section 3.2.5.

Algorithm 6: Assignment of Sub-tree to Worker Nodes

```
Input  : Number of worker nodes $N$, Follower nodes $itemsToExplore$
Output: Hashmap($nodeId$, $itemsToExplore$) $workerNodeMap$
Function grouping()
    $workerNodeMap \leftarrow map()$;
    $nodeId \leftarrow 1$;
    $incr \leftarrow 1$;
    $flag \leftarrow false$;
    for $i$ in $itemsToExplore$ do
        $workerNodeMap[i] \leftarrow nodeId$;
        $nodeId \leftarrow nodeId + 1$;
        if ($nodeId == 0 \mid\mid nodeId == N - 1$) then
            if ($flag == false$) then
                $incr \leftarrow 0$;
                $flag \leftarrow true$;
            else
                if ($nodeId == 0$) then
                    $incr \leftarrow 1$;
                else
                    $incr \leftarrow -1$;
                end
                $flag \leftarrow false$;
            end
        end
    end
    return $workerNodeMap$;
```

3.2.5 Node Data Generation

Each worker node was assigned with a sub-tree which needed to be traversed. Each node traversal indicates the candidate generation which is needed to generate projected transaction at each node. Therefore, each worker node gets the refined transactions including the items it needs to visit which was computed using flatMap operation. Algorithm 7 shows the steps to generate the node data for the specific items assigned to the worker nodes. Each transaction was checked by the binary search to find the item assigned to worker node was present or not. If items assigned were not in the transaction, then that transaction was not added to the nodeMap. After scanning all the nodes, nodeMap was grouped by a key which was then used to mine high utility itemsets which are explained in Section 3.2.6 later.

Algorithm 7: Node Data Generation

```
   Input  : Revised Transactions $T$, $workerNodeMap$
   Output: Hashmap($nodeId$, $T_r$) $nodeMap$
 1 Function flatMap
 2     $nodeMap = map()$;
 3     for $i \leftarrow 0$ to $len(T) - 1$ do
 4         for $(nodeId, item) \leftarrow workerNodeMap$ do
 5             $check = binarySearchIterative(T.itemset, item)$;
 6             if $check == true$ then
 7                 $nodeMap \leftarrow (nodeId, T_i)$;
 8             end
 9         end
10     end
11     return $nodeMap$;
12 Function binarySearchIterative(list, target)
13     $left \leftarrow 0$; $right \leftarrow len(list) - 1$;
14     while $(left \leq right)$ do
15         $mid = left + (right - left)\ /\ 2$;
16         if $(list(mid) == target)$ then
17             return $true$;
18         else if $list(mid) \geq target$ then
19             $right = mid - 1$;
20         else
21             $left = mid + 1$;
22         end
23     end
24     return $false$;
```

3.2.6 Mining High Utility Itemsets

This section describes the mining of high utility itemsets that are computed by worker nodes using generated Node data. The detailed algorithm is shown in Algorithm 8. Each worker processed to compute the high utility itemsets (HUIs) for the assigned sub-tree of items. It used a recursive algorithm to find HUIs which generated the possible candidate sets assigned to them.

Let us consider the example from the Figure 2.1 in which each item of 1st level is assigned to one worker node. Let us assume that there are 3 worker nodes, then we know from the previous Section 3.2.4, $ItemD$ is assigned to $Node1$. All the possible candidate sets for $ItemD$ are processed by $Node1$. Similarly, for the $ItemF$, possible candidate sets are processed by $Node2$ and so on.

Algorithm 8: Mining HUIs in Parallel

```
Input  : Database $d$, ThresholdRatio $\delta$, Total Utility $TU$, $nodeMap$, $nodeId$
Output: High Utility Itemsets $HUIs$
1  Function $mineHUIs(\gamma, d, itemsToExplore(\gamma), itemsToKeep(\gamma), \delta, TU, flagFirst = true)$
2      for $each\ item\ i_j\ in\ itemsToExplore(\gamma)$ do
3          if $(flag \neq true \mid\mid nodeId == nodeMap(i))$ then
4              $\rho \leftarrow \gamma \cup \{i_j\}$;
5              while $scan\ each\ T_j\ in\ \gamma D$ do
6                  Compute $\rho D$;
7                  Calculate $u(\rho)$;
8              end
9              if $u(\rho) \geq \delta \times TU$ then
10                 $HUIs \leftarrow \rho$;
11             Calculate $subU(\rho, x)$ and $locU(\rho, x)$ for all the items $i_j$ in $itemsToKeep(\gamma)$ by
                scanning $\gamma D$;
12             $itemsToExplore(\rho) = \{x \in itemsToKeep(\gamma) | subU(\rho, x) \geq \delta \times TU\}$;
13             $itemsToKeep(\rho) = \{x \in itemsToKeep(\gamma) | locU(\rho, x) \geq \delta \times TU\}$;
14             $mineHUIs(\rho, d, itemsToExplore(\rho), itemsToKeep(\rho), \delta, TU, false)$;
15         end
16     end
```

3.2.7 Overall Flow of EFIM Parallel Algorithm

The overall flow diagram of EFIM Parallel Algorithm is shown in Figure 3.2. It started with a reading of dataset from the file which is split into different blocks to be distributed among the worker nodes. The worker nodes worked on the block of the file using $flatMap$ operation to generate the key-value pairs of items and its corresponding TWU which was then combined using $ReduceByKey$ operation to get the final $itemTWU$. The generation of 1-HTWUIs was explained in detail in the previous Section 3.2.1.

The split dataset was also used to find the total utility of the transactional database to find the threshold value. This threshold value was used to find the $itemsToKeep$ by filtering out the items in 1-HTWUIs having TWU values less than the threshold value. Only those items remaining in the $itemsToKeep$ were kept in the transactions of the database. Therefore, other items not in $itemsToKeep$ known as unpromising items, were removed from the transactions, sorted the items in a transaction in the total ordering and removal of empty transactions were done to get the sorted revised transactions which were described in detail in Section 3.2.2.

In the next step, the sorted revised transactions were used to find the *utilityBinSU* for each item by using $flatMap$ and $ReduceByKey$ operations. The *utilityBinSU* contained the sub-tree utility for all the items of $itemsToKeep$. The *utilityBinLU* contained the local utility for all the items which was same as the $itemTWU$. Using the *utilityBinSU*, the list containing all the items for $itemsToExplore$ was created. A sub-tree was created from the items in $itemsToExplore$.

Assignment of items of $itemsToExplore$ was done using the grouping mechanism as described in detail in Section 3.2.4. In this process, the worker node identified the sub-tree it needed to generate. Each worker node processed to filter the transactions to produce the Node Data. Using these node data, each worker node computed the high utility itemsets forming sub-trees to generate the candidate sets. In the mining process, the nodes were pruned based on the sub-tree utility and the local utility as given in Equation 2.12 and Equation 2.13 respectively. Finally, the results obtained from the worker nodes were combined to give the aggregated high utility itemsets.

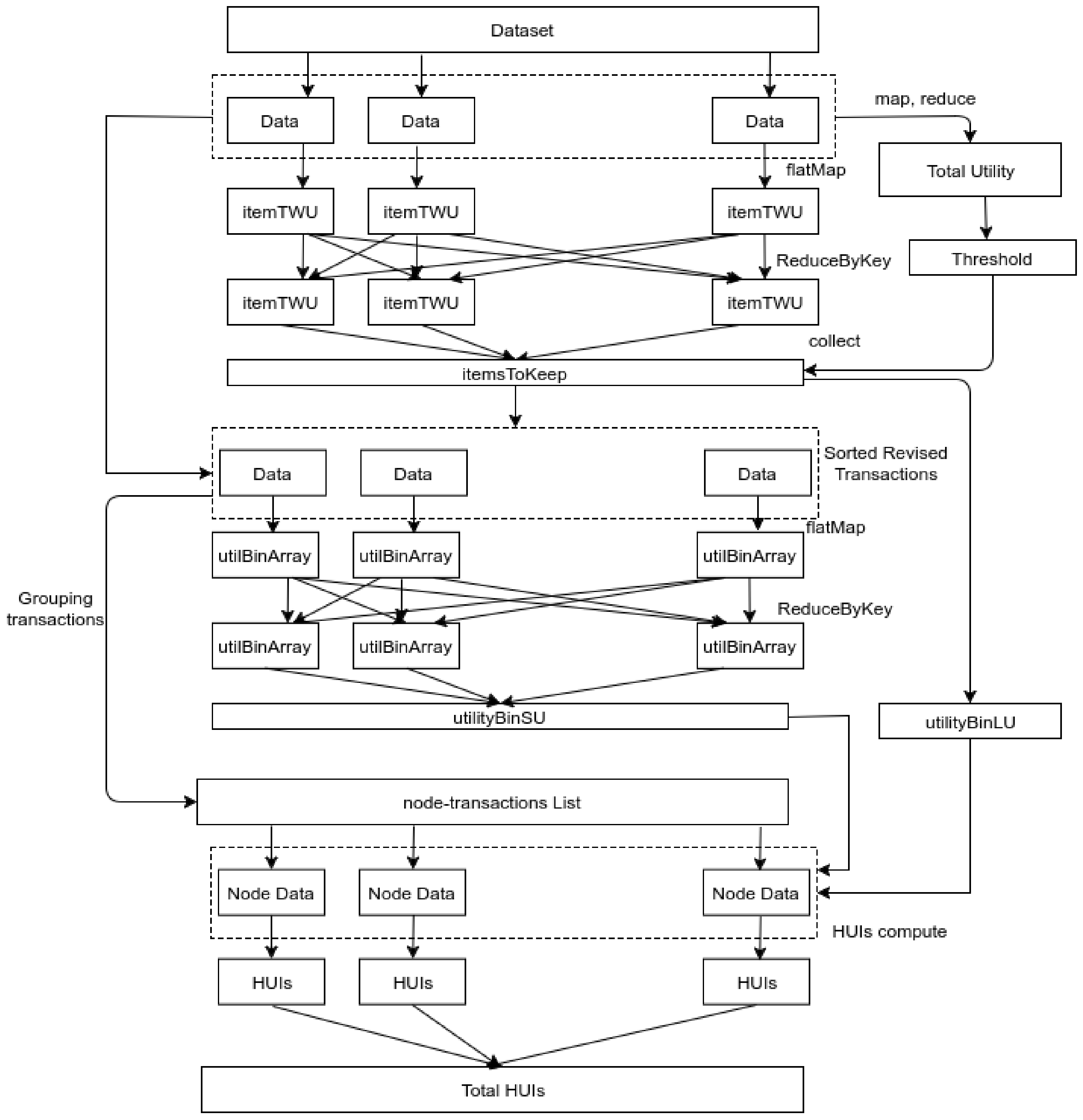


Figure 3.2: Overall Flow Diagram of EFIM Parallel Algorithm.

Chapter 4

Experimental Results

The experiments were performed for our Method I with our proposed algorithm (HUI-PR) and EFIM algorithm [13] to find high utility itemsets on 16GB main memory in Intel Xeon(R) CPU E5-1607 0 @ 3.00 GHz x 4 on an Ubuntu 16.04 Linux Operating system. The language used to write these algorithms was Oracle Java 1.8.

For the Method II, the experiments were performed on Spark clusters with Master and all Slave nodes with 16GB main memory and Intel Xeon(R) CPU E5-2695 v4 @ 2.10 GHz x 4 with an Ubuntu 16.04 Linux Operating system. The language used to write the spark application was Scala version 2.12.1 with Spark framework version 2.0.2 to run an experiment for our proposed algorithm EFIM-Par and PHUI-Miner [33].

4.1 Datasets

The experiments were performed on multiple real-world datasets [35, 36]. For the method I, our experiments were conducted on relatively smaller datasets such as Chess, Connect and Retail. For the method II, our experiments were conducted on relatively large datasets such as Connect20x, Chess30x, BMS4x, Mushroom20x. For relatively large datasets, the small datasets such as Connect, Chess, BMS and Mushroom were multiplied to get the larger dataset. The characteristics of the datasets are shown in the Table 4.1 where $\#|D|$, $\#|I|$, $AvgLen$, $MaxLen$, $Type$ and $Scale$ represent the total number of transactions, the number of distinct items, the average size of a transaction, maximum size of a transaction, type of dataset and size of dataset respectively. For each threshold ratio of a dataset, the experimental results were executed 10 times and the average was taken.

Table 4.1: Datasets Characteristics

Dataset	$\#\lvert D\rvert$	$\#\lvert I\rvert$	**AvgLen**	**MaxLen**	**Type**	**Scale**
chess	3196	76	37	37	dense	Small
connect	67557	129	43	43	dense	Small
retail	88162	16470	10	76	sparse	Medium
$connect2x$	135114	129	43	43	dense	Large
$chess30x$	95880	76	37	37	dense	Large
$BMS4x$	238408	497	3	267	sparse	Large
$Mushroom20x$	162400	119	23	23	dense	Large

4.2 HUI-PR vs. EFIM

HUI-PR algorithm was compared with EFIM algorithm [13] with comparisons on the computational time, the number of high utility itemsets (HUIs) found and the number of Candidate Sets generated. These algorithms were performed on the smaller datasets.

4.2.1 Comparison of Computational Time

In this section, we compared our algorithm (HUI-PR) with the EFIM algorithm [13] with the real datasets (Connect, Chess, Retail). Experiments were conducted to show the effectiveness of our algorithm with the real datasets and the approach that was taken to improve the performance of an experiment. The pruning rule proposed in our algorithm HUI-PR helped to improve computational time significantly for the datasets with a large number of transactions. HUI-PR generated the projected transaction which reduced the number of transactions in each level. It not only reduced the number of transactions based on utility calculations but it also used the pruning hash table to eliminate the transactions in which the itemsets in the pruning table might have been a subset of items in a transaction. Therefore, it helped to check whether the items in a transaction were a superset or not in very quick time.

From the Figure 4.1, we see that HUI-PR can perform better than the EFIM algorithm. From the Figure 4.1a, for the "Connect" dataset, the threshold ratio was set from 28.90% to 29.70% as shown. When the threshold ratio was 28.90%, our algorithm HUI-PR took 1830.87 seconds while the EFIM algorithm took 1927.95 seconds. The proposed algorithms showed significant improvement in Figure 4.1c on threshold ratio 0.03%, the running time for HUI-PR was 5718.36 seconds while for EFIM algorithm, the running time was 7370.33 seconds.

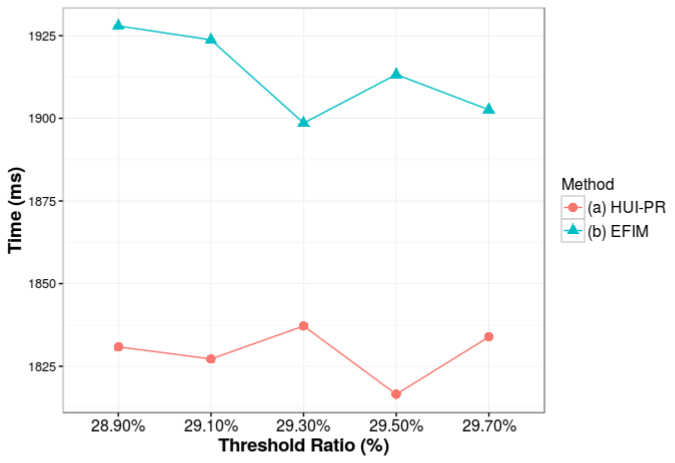
We also conducted our experiment against the other state-of-the-art algorithms: HUI-Miner [12], HUP-Miner [25], FHM [26], FHM+ [28], d^{2}HUP [25, 12]. The algorithm HUI-PR performs better than these state-of-the-art algorithms as shown in Figure 4.2. For the “Connect” dataset, HUI-PR performed better by more than 100 times than HUI-Miner, HUP-Miner and FHM algorithms while it performed better by almost 50 times than d^{2}HUP. Similarly, for the “Chess” dataset, HUI-PR performed better by 20 times than HUI-Miner, HUP-Miner and FHM algorithms while it performed better than 7 times than d^{2}HUP. Since the time performed by FHM+ was significantly higher when it was executed with parameter $MaxLength = 15$ for the “Chess” dataset and $MaxLength = 21$ for the “Connect” dataset. Therefore, it is not shown in the graph.

4.2.2 Comparison of HUIs

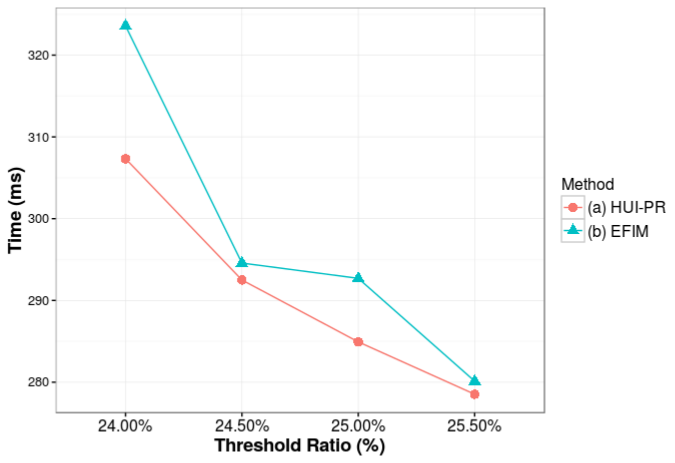
From the experiments conducted on the real-world datasets (Connect, Chess, and Retail), the number of HUIs found by both the experiments were same. We recorded the number of HUIs found for the range of threshold ratio for different datasets which are shown in Table 4.2. For the “Connect” database, we got 81 HUIs for 28.90% and 4 HUIs for 29.70%. Similarly, for the “Chess” dataset, we got 342 HUIs for 24.00% and 16 HUIs for 26.00% threshold ratio. From the results obtained, we can verify that all the high utility itemsets have been found from the algorithm HUI-PR.

4.2.3 Comparison of Candidate Sets

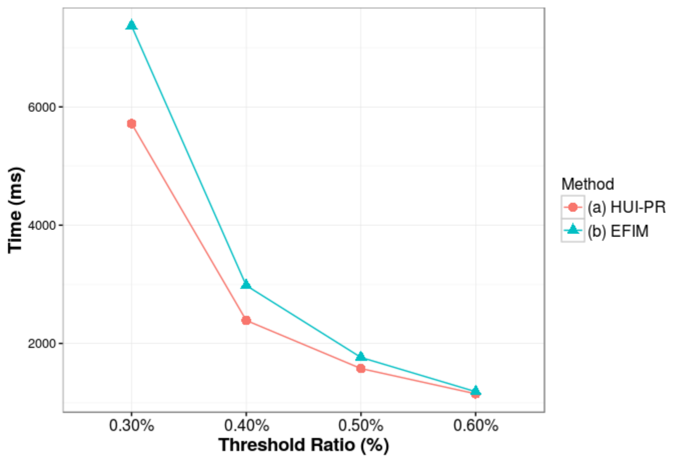
From the Figure 4.3, we compared the candidate sets obtained from HUI-PR and EFIM algorithms. The candidate sets generated in HUI-PR are lower in number than that in EFIM algorithm. The candidate sets were minimized in the HUI-PR using transaction pruning strategies with pruning hash table and utility-based pruning. For the “Connect” dataset for threshold ratio 28.90%, HUI-PR generated 3007 candidate sets while the EFIM algorithm generated 3132 candidate sets. HUI-PR could generate fewer candidate sets in the “Chess” dataset. For 24.00% threshold ratio, HUI-PR generated 2933 candidate itemsets while EFIM generated 2965 number of candidate itemsets. We also compared the candidate sets obtained from state-of-the-art algorithms: HUIMiner, FHM, and FHM+ as shown in Figure 4.4. The number of candidate sets generated by our algorithm HUI-PR is 8 times less than HUIMiner and FHM for the “Chess” dataset while HUI-PR generates 10 times less than HUIMiner and FHM for the “Connect” dataset.



(a) Connect Dataset

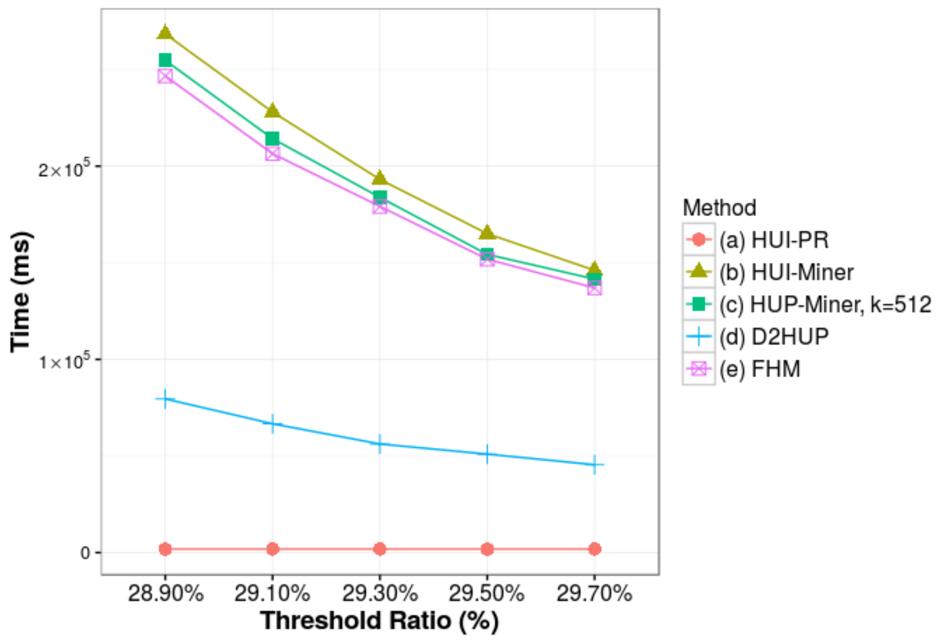


(b) Chess Dataset

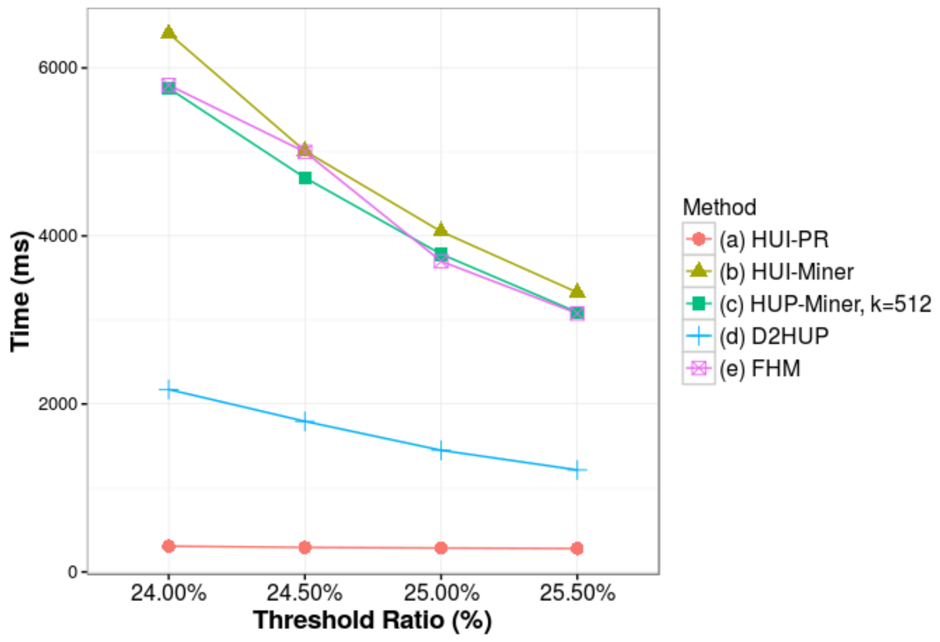


(c) Retail Dataset

Figure 4.1: Comparison of computational time between HUI-PR and EFIM w.r.t. variants of minimum threshold for different datasets.



(a) Connect Dataset



(b) Chess Dataset

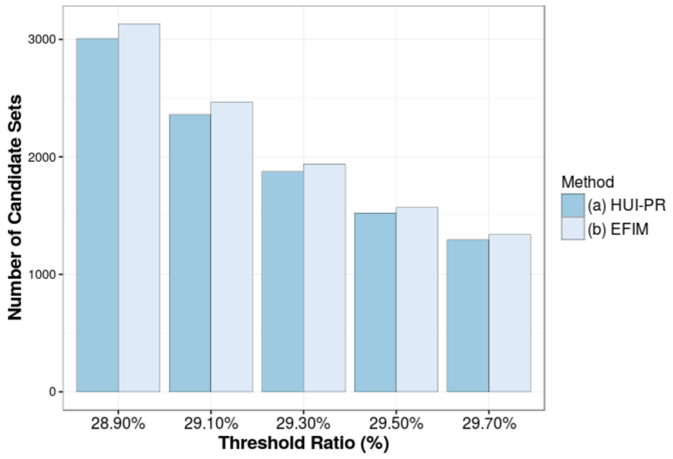
Figure 4.2: Comparison of computational time with state-of-the-art algorithms w.r.t. variants of minimum threshold.

Table 4.2: Total Number of HUIs found in HUI-PR and EFIM

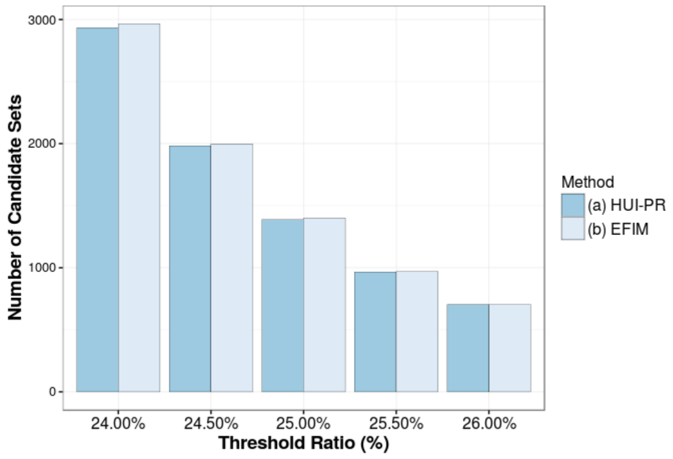
Dataset	**ThresholdRatio δ**	**# of HUIs**
Connect	28.90%	81
Connect	29.10%	40
Connect	29.30%	20
Connect	29.50%	8
Connect	29.70%	4
Chess	24.00%	342
Chess	24.50%	177
Chess	25.00%	98
Chess	25.50%	41
Chess	26.00%	16
Retail	0.30%	92
Retail	0.40%	58
Retail	0.50%	41
Retail	0.60%	30

Table 4.3: Total Number of Transactions Pruned in HUI-PR

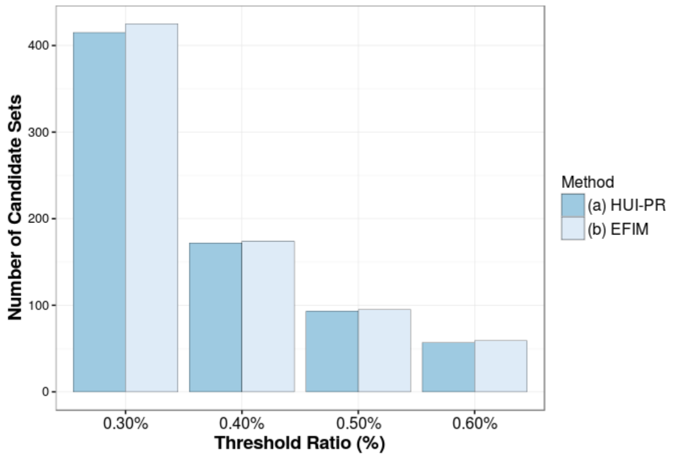
Dataset	**ThresholdRatio δ**	**# Transactions Pruned**
Connect	28.90%	556831
Connect	29.10%	550630
Connect	29.30%	550630
Connect	29.50%	550630
Connect	29.70%	550630
Chess	24.00%	24878
Chess	24.50%	30779
Chess	25.00%	27829
Chess	25.50%	26265
Chess	26.00%	26304
Retail	0.30%	670018
Retail	0.40%	245342
Retail	0.50%	117453
Retail	0.60%	61939



(a) Connect Dataset

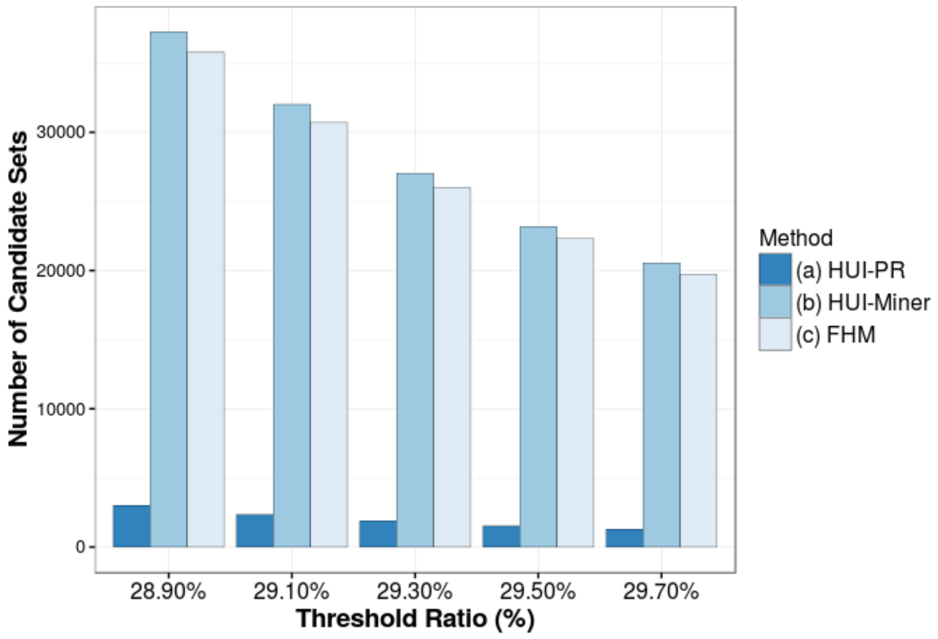


(b) Chess Dataset

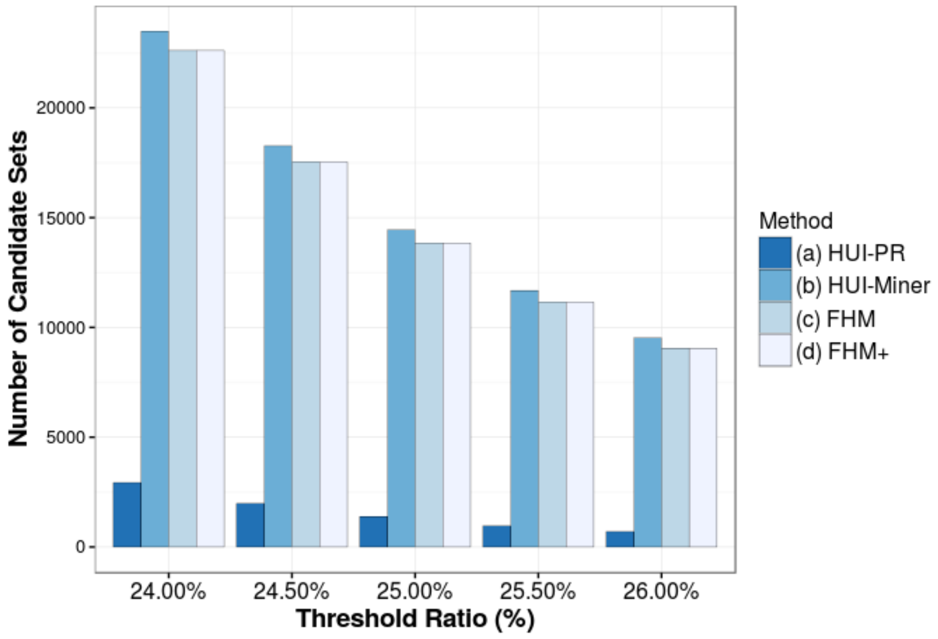


(c) Retail Dataset

Figure 4.3: Comparison of candidate sets between HUI-PR and EFIM w.r.t. variants of minimum threshold.



(a) Connect Dataset



(b) Chess Dataset

Figure 4.4: Comparison of candidate sets with state-of-the-art algorithms w.r.t. variants of minimum threshold.

4.3 EFIM-Par vs EFIM

We compared our distributed algorithm Parallel EFIM (EFIM-Par) with Approximate parallel high utility itemset mining (PHUI-Miner) [33]. The computational time was recorded for the different datasets as shown in the Figure 4.5. These algorithms were performed on the larger datasets. Both algorithms were conducted on one master node and ten slave nodes in the Spark Framework.

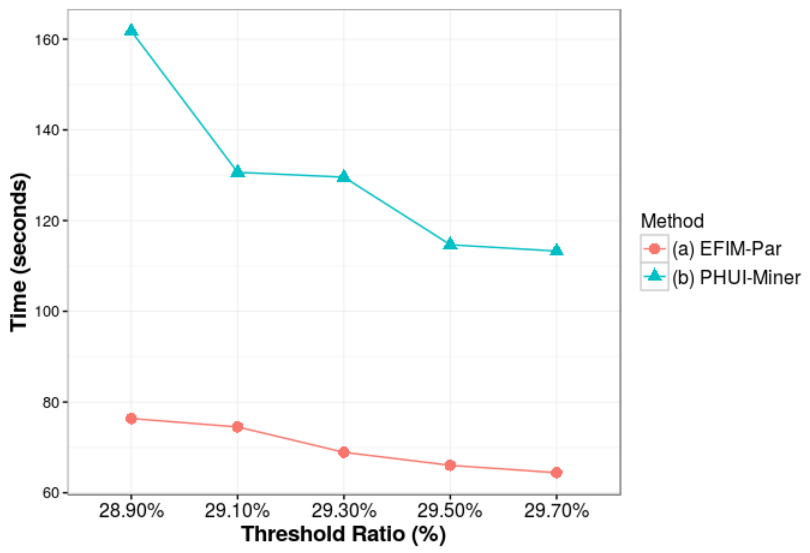
4.3.1 Comparison of Computational Time

The experiments were conducted on the real-world datasets (Connect, Chess, BMS, and Mushroom). However, in order to make the dataset sufficiently large, we multiplied the "Connect" dataset by a factor of 2, "Chess" dataset by a factor of 30, "BMS" dataset by a factor of 4 and "Mushroom" dataset by a factor of 20. The experiments were conducted on these algorithms, EFIM-Par and PHUI-Miner.

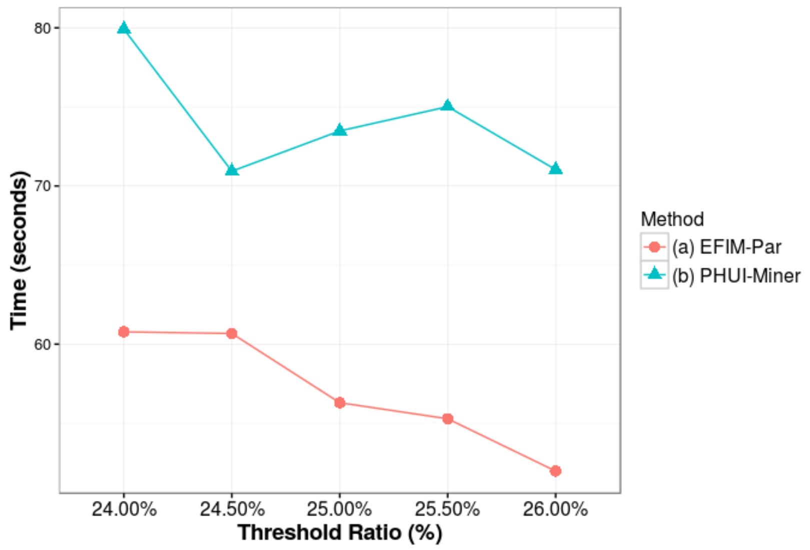
From the Figure 4.5a, EFIM-Par algorithm took 76.36 seconds while PHUI-Miner took 161.76 seconds for the threshold ratio 28.90% for the "Connect" dataset. Similarly, for the threshold ratio 29.70%, EFIM-Par took 64.42 seconds while PHUI-Miner took 113.27 seconds. The algorithm, EFIM-Par was able to perform around 2 times better than PHUI-Miner for the "Connect" dataset for different threshold ratio taken. From the Figure 4.5b, for the "Chess30x" dataset, EFIM-Par algorithm took 60.77 seconds for the threshold ratio 24.00% while PHUI-Miner took 79.19 seconds. Similarly, for the threshold ratio 26.00%, EFIM-Par took 51.97 seconds while PHUI-Miner took 71.03 seconds. The algorithm, EFIM-Par performed almost 1.5 times better than PHUI-Miner for the "Chess30x" dataset. Similarly for the "BMS4x" dataset, EFIM-Par algorithm performed better for the lower threshold and almost similar for the higher threshold values. EFIM-Par performed better than 1.2 times the PHUI-Miner algorithm for "Mushroom20x" dataset.

4.3.2 Comparison of HUIs

From the Table 4.4, EFIM-Par algorithm found the same number of HUIs as found by PHUI-Miner. Therefore, we can conclude EFIM-Par algorithm is as accurate as PHUI-Miner.

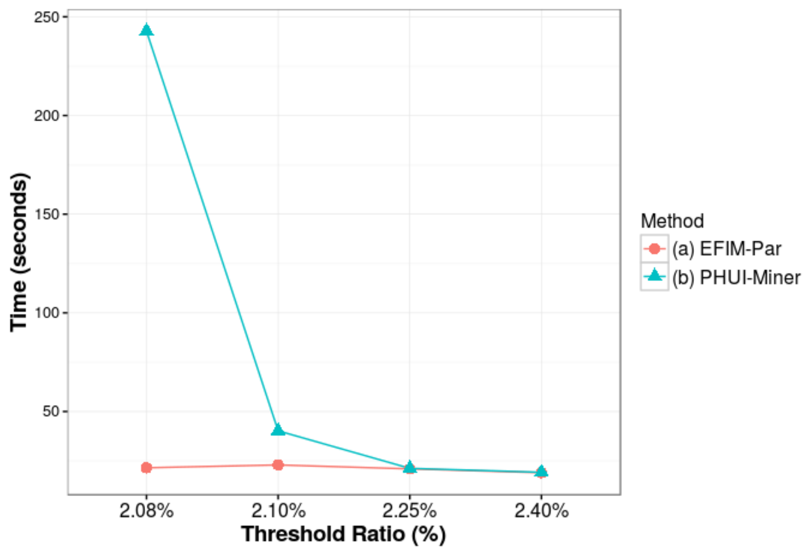


(a) Connect2x Dataset

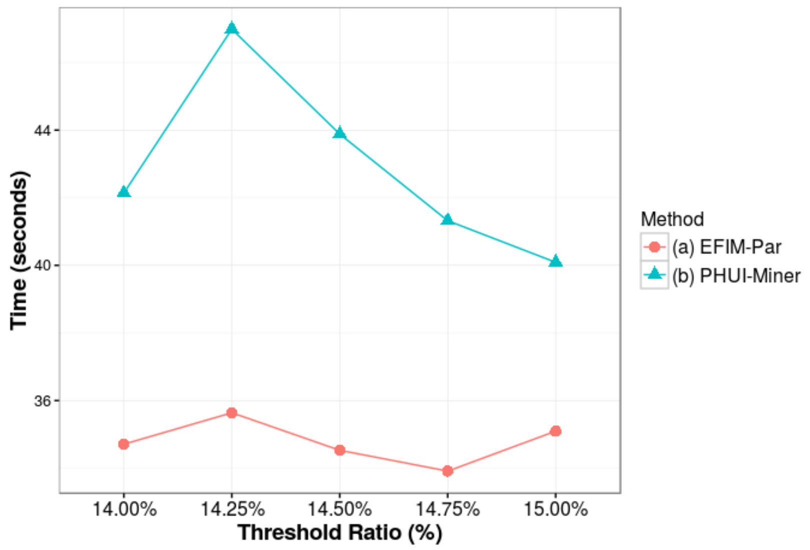


(b) Chess30x Dataset

Figure 4.5: Comparison of computational time between EFIM-Par and PHUI-Miner w.r.t. variants of minimum threshold for different datasets.



(c) BMS4x Dataset



(d) Mushroom20x Dataset

Figure 4.5: Comparison of computational time between EFIM-Par and PHUI-Miner w.r.t. variants of minimum threshold for different datasets.

Table 4.4: Total Number of HUIs found in EFIM-Par and PHUI-Miner

Dataset	**ThresholdRatio** δ	**# of HUIs**
$Connect2x$	28.90%	81
$Connect2x$	29.10%	40
$Connect2x$	29.30%	20
$Connect2x$	29.50%	8
$Connect2x$	29.70%	4
$Chess30x$	24.00%	342
$Chess30x$	24.50%	177
$Chess30x$	25.00%	98
$Chess30x$	25.50%	41
$Chess30x$	26.00%	16
BMS	2.08%	7
BMS	2.10%	7
BMS	2.40%	5
BMS	2.80%	3
BMS	3.00%	2
$Mushroom20x$	14.00%	67
$Mushroom20x$	14.25%	38
$Mushroom20x$	14.50%	19
$Mushroom20x$	14.75%	10
$Mushroom20x$	15.00%	2

Chapter 5

Conclusion and Future Work

In this thesis, two methods HUI-PR and EFIM-Par was proposed. The proposed algorithm, HUI-PR is a novel approach to pruning transactions to reduce the search space while finding high utility itemsets. HUI-PR could reduce the search space by eliminating the number of candidate sets which avoided the computation of unnecessary itemsets. HUI-PR used a pruning hash table, which stores low-utility itemsets that were checked while generating the projected transaction in each node. This elimination helped reduce the candidate sets in HUI-PR besides different utilities such as sub-tree utility, local utility and transaction-weighted utility for pruning. This approach was highly suited for relatively smaller datasets.

Another proposed algorithm, EFIM-Par is a novel approach to mine high utility itemsets using distributed approach. Spark framework was used for the distributed computing because of its advantage over the Hadoop framework. Spark framework uses in-memory computation which is much faster than disk dependent Hadoop framework. The algorithm, EFIM-Par divided the computation into multiple stages such that each task was divided into multiple worker nodes. In the mining stage, each work was assigned the task using the grouping mechanism which computed the high utility itemsets that were aggregated to find the overall high utility itemsets.

An extensive experiment in various datasets with the state-of-the-art algorithm was conducted for both methods. Our experiments showed that HUI-PR could perform more efficiently than other existing algorithms. HUI-PR improved the computational time for finding the high utility itemsets as it reduced the number of candidate sets. HUI-PR gained significant performance improvement in terms of computational time and a number of candidates sets generated. Our experiments for EFIM-Par showed that it performed better than PHUI-Miner. Our algorithm performed much better in terms of computation time than PHUI-Miner. EFIM-Par divided the search space in an efficient way so that each worker node computed in faster time.

Although our proposed methods perform much better than other algorithms, these methods could be enhanced to perform at optimum level. Our algorithm (HUI-PR) finds the high utility itemsets efficiently for small datasets. However, it has lessened improvement when the datasets are very small. Therefore, an improvement could be done for very small datasets. Also, different tree construction mechanisms could be studied so that the proposed pruning strategies can work best. Our other algorithm (EFIM-Par) could be enhanced with much better grouping mechanism to divide the tasks to each worker node in an optimum manner.

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Curriculum Vitae

Graduate College

University of Nevada, Las Vegas

Ashish Tamrakar

Degrees:

Bachelor Degree in Computer Engineering 2012

Tribhuvan University, Institute of Engineering, Pulchwok Campus, Nepal

Thesis Title: High Utility Itemsets Identification in Big Data

Thesis Examination Committee:

Chairperson, Dr. Justin Zhan, Ph.D.

Committee Member, Dr. Laxmi Gewali, Ph.D.

Committee Member, Dr. Fatma Nasoz, Ph.D.

Graduate Faculty Representative, Dr. Ge Lin Kan, Ph.D.