A Method for Reducing Repetitive items on Weighted Data using the WIT-WFI Algorithm

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Abstract

Trying and mining frequent item sets plays an important role in the mining of association rules in a dataset that stored with items and transactions an items can used for various significance. Association rules is a important and considerable ways in data mining without presidency. one of discussion that today investigate is mining and finding frequent weighted item set and reduce run time of algorithm and reduce production frequent item set is one of problem for research. at this paper we purpose present some method and ways for reduce run time of algorithm and reduce production frequent item set. all methods and ways applying on WIT algorithm and WIT-Tree structure. In first section we express and description classic association rule method (Apriori) and then WIT and then WIT-Diff algorithm and finally explain my proposed ways and experimental results.

Keywords: Data mining – Frequent items – Weighted item sets – WIT-Tree – Association rules.

1. Introduction

Association Rules Mining (ARM) is an important part in the domain of knowledge discovery in data (KDD) [1,2]. Association rule mining is used for finding and mining frequent patterns and relationship between transactions in a database or dataset. Association rules used of presidency learning principle, that purpose this principle is obvious and we understand that research what knowledge unlike without presidency way than result and purpose the mining not clear. Given a set of items $I = \{i_1, i_2, \ldots, i_n\}$, a transaction is defined as a subset of $I$. The input to an ARM algorithm is a dataset $D$ comprising a set of transactions. Given an item set $X \subseteq I$, the support of $X$ in $D$, denoted as $\sigma(X)$, is the number of transactions in $D$ which contain $X$ [18]. An item set is described as being frequent if its support is larger...
than or equal to a user supplied minimum support threshold (min Sup). A ‘classical’ Association Rule (AR) is an expression of the form \( X \rightarrow Y \) (sup, conf), where \( X, Y \subseteq I \) and \( X \cap Y = \emptyset \). The support of this rule is \( \text{sup} = \sigma(XY) \) and the confidence is \( \text{conf} = \frac{\sigma(XY)}{\sigma(X)} \). Given a specific min Sup and a minimum confidence threshold (min Conf), we want to mine all association rules whose support and confidence exceeds min Sup and min Conf respectively [3, 6].

However, Classical association rule have some problem that very great run time and many scan of database for finding item sets. If we add computation time of items with weight as time of algorithm raising purpose the this paper is expansion WIT algorithm for mining frequent items in view run time and reduce product item set. The rest of this paper is organized as follows. Section 2 presents some related work about the mining of frequent weighted items and weighted association rules and some terms and equations. Section 3 we explain WIT-Tree structure and in Section 4 explain WIT algorithm. In Section 5 explain and descript WIT-DIFF algorithm. In Section 6 explain and descript my proposal methods. Some experimental results are present in Section 7 and my conclusion in Section 8.

2. Related works

This section presents some related works. The section begins with a formal definition of weighted transaction databases. A weighted transaction database (D) is defined as follows: D comprises a set of transactions \( T=\{t_1,t_2,..,t_n\} \), a set of items \( I=\{i_1,i_2,..,i_n\} \) and a set of positive weights \( W=\{w_1,w_2,..,w_n\} \) corresponding to each item in I. For example, consider the data presented in Tables 1 and 2. Table 1 presents a data set comprising six transactions \( T=\{t_1,t_2,..,t_6\} \) and five items \( I=\{A,B,C,D,E\} \). The weights of these items are presented in Table 2, \( W=\{0.6,0.1,0.3,0.9,0.2\} \). [4,5].

<table>
<thead>
<tr>
<th>Transactions</th>
<th>Bought items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A, B, D, E</td>
</tr>
<tr>
<td>2</td>
<td>B, C, E</td>
</tr>
<tr>
<td>3</td>
<td>A, B, D, E</td>
</tr>
<tr>
<td>4</td>
<td>A, B, C, E</td>
</tr>
<tr>
<td>5</td>
<td>A, B, C, D, E</td>
</tr>
<tr>
<td>6</td>
<td>B, C, D</td>
</tr>
</tbody>
</table>

Table 1: The transaction database

<table>
<thead>
<tr>
<th>Items weight</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.6</td>
</tr>
<tr>
<td>B</td>
<td>0.1</td>
</tr>
<tr>
<td>C</td>
<td>0.3</td>
</tr>
<tr>
<td>D</td>
<td>0.9</td>
</tr>
<tr>
<td>E</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 2: Items weight

The equations that we used in this paper consist:

- Calculation weight of transaction \( (tw^1) \).

\(^1\) Transaction weight
Calculation weight of items or weighted support (ws).

For acquire weight of a transaction we must sum of all items weight in transaction and then calculate average of items with divide sum of items in count of items in each transactions. See definition 2.1, we can compute the transaction weight [7, 8].

\[ T_{w(t_k)} = \frac{\sum_{i j \in t_k} W_j}{|t_k|} \]  \hspace{1cm} 2.1

\( t_k \): Transaction k.

\( i_j \): j th items in transaction.

\( |t_k| \): Size of transaction k, count of items .

\( w_j \): Weight of j th item.

For compute weighted support must compute sum of transaction weight (table 3) and divide to sum of transaction. See definition 2.2, we can compute the transaction weight.

\[ WS(X) = \frac{\sum_{k \in T} T_{w(t_k)}}{\sum_{k \in T} T_{w(t_k)}} \]  \hspace{1cm} 2.2

\( X \): The item.

\( t_w(t_k) \): Weight of transaction \( t_k \).

\( t(X) \): Transaction consist item (X).

\( T \): total of dataset.

<table>
<thead>
<tr>
<th>Table 3: Transaction weight for transaction in table 1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transactions</strong></td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td><strong>Sum</strong></td>
</tr>
</tbody>
</table>

Example for calculation transaction weight and weighted Support. For transaction weight used of table 1, table 2 and definition 2.1, we can compute the transaction weight:

\[ t_w = \frac{0.6 + 0.1 + 0.9 + 0.2}{4} = 0.45 \]
And Table 3 shows all tw values of transactions in Table 1.

From Tables 1 and 3, and Definition 2.2, we can compute the \( ws(BD) \) value as follows: Because BD appears in transactions \{1, 3, 5, 6\}, \( ws(BD) \) is computed:

\[
WS(BD) = \frac{0.45 + 0.45 + 0.42 + 0.43}{2.25} \approx 0.78
\]

From equation 2.1 and 2.2 using in all algorithm and my proposal methods, in all methods a input value (threshold) used for filter algorithm input, we used this value for comparison and evaluation run time of algorithm and methods. The mining of FWI requires identification all item sets whose weighted support satisfies a user specified minimum weighted support threshold (\( \text{minws}^2 \)).

\[
\text{FWI} = \{X \subseteq I | WS(X) \geq \text{minWS} \}
\] 2.3

3. WIT-Tree structure

The structure that we used to explain my methods is WIT structure. For description this structure we first explain some terms [9].

- **X**: set of items.
- **t(X)**: Set of transaction contain item(X).
- **ws**: Value of weighted support for item(X).

For show a node of my tree used \( <X, T(x), ws> \) style. In this style \( x \) is my item and \( T(x) \) is transactions id which item X member of them. And ws is value of weighted support. For more description see Figure 1.

![WIT-Tree structure example](image)

In fig 1 level \( \emptyset \) or root display with two accolade \{ \}. If items member of a transaction consist same prefix they are called equivalence class items and display them with \[ \]. For example if item X is prefix item in some items we illustrate it with \[X\]. In root level my prefix item is \( \emptyset \) and equivalence class is

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2 Minimum weighted support
In this figure we see for all levels and items we compute transaction weight and weighted support. For compute number of all items in dataset used of $2^k-1$ equation that variable $k$ is all items in dataset and too for number of items in each level we used of combination equation $\binom{4}{i}$. Variable $k$ is number of items and variable $L$ is level numeral [2,19]. In this structure for create next level must used of two top level items or parent item. For example level 1 on fig 1 consist $\{A,B,C,D,E\}$ items and a part of level 2 consist items with equivalence class $[A]$, $\{AB,AC,AD,AE\}$ this process resume for all items. Inspection of Fig. 1 suggests that all item sets satisfy the downward closure property. So, we can prune an equivalence class in the WIT-tree if its $ws$ value does not satisfy the $minws$. For example, suppose that $minws = 0.4$, because $ws(ABC) = 0.32 < minws$ we can prune the equivalence class with the prefix ABC, i.e., all child nodes of ABC can be pruned. In nest sections explain WIT and WIT-Diff methods.

4. WIT algorithm

In classic association rule (Apriori) for mining frequent weighted items we must for all items compute transaction weight and $ws$ and too scan dataset for transaction id and location of each item in dataset. But in WIT we proceed to reduce repetitive calculation and whereupon reducing run time of my algorithm and methods. For this purpose we explain some theorems. we propose algorithms for mining FWI from weighted transaction databases [11,12]. First an algorithm for directly mining FWI from WIT-trees is presented. It uses a $minws$ threshold and the downward closure property to prune nodes that are not frequent. Some theorems are then derived and based on these theorems, an improved algorithm is proposed. Finally, the algorithm is further developed, by adopting a Diffset strategy to allow for fast computing the weighted support of item sets in a memory efficient way. If we have two item set $X$, $Y$ that transaction id of item set $X$ equal item set $Y$, otherwise $t(X)=t(Y)$. in result can deduction for two item set $X$ and $Y$, value of Weighted support is equal. Or otherwise $WS(X)=WS(Y)$.

$$\text{If } t(X)=t(Y) \text{ Then } WS(X)=WS(Y) \quad 4.1$$

If item set $X$ member of collection $Y$ and too number of transaction common together equal, in result weighted support value of two item set $X$ and $Y$ is unify.

$$\text{if } X \subseteq Y \text{ and } |t(X)|=|t(Y)| \quad 4.2$$

then $WS(X)=WS(Y)$

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Figure 2: Example of WIT

For more description can see figures 2 and 3.

In Fig 2, first selection all items that satisfy min ws and then sort them with increasing by their weighted support and set them in frequent weighted items (FWI) list. In line 4 of WIT algorithm Fig 3 call extend function for produce next item set from combination top level items. Too equation 4.1 and 4.2 used in 9, 10, 11 lines. With inspection In fig 2 for item <A, 1345, 0.72> and that combination with item set <B, 123456, 1> and item set <AB, 1345, ?> value of weighted support of item set AB with definition 4.1 and 4.2 equal with item A weighted support and not require for computing ws for item set AB. this process continue for next level and item sets to pending remain one item set in level.

| Input: Database D and minimum weighted support threshold minws. |
| Output: FWI contains all frequent weighted Item sets that satisfy minws from D. |

| Method: |
| WIT () |
| 1. \( L_r = \) All items that their ws satisfy minws. |
| 2. sort Nodes in \( L_r \) increasing by their ws. |
| 3. \( FWI = \emptyset \). |
| 4. call Function FWI-Extend with the parameter is \( L_r \). |
| FWI-Extend (\( L_r \)) |
| 5. Consider each node \( l_i \) in \( L_1 \) DO \ |
| 6. Add(\( l_i, itemset, l_i, ws \)) to FWI. |
| 7. Create a new set \( L_i \) by join \( l_i \) with all \( l_j \) following it in \( L_1 \)by: |
| 8. Set \( X = l_i, itemset \cup l_j, itemset \) and \( Y = t(l_i) \cap t(l_j) \) |
| 9. if \( |t(l_i)| = |Y| \) then ws(X)=ws(l_j) |
| 10. Else if \( |t(l_j)| = |Y| \) then ws(X)=ws(l_j) |
| 11. if \( Y = \emptyset \) then \( ws(X) = ws(l_i) \) |
| 12. Else \( ws(X) = COMPUTE - WS(Y) \) |
| 13. if ws(X) satisfies minws then |

---

3 Weighted Support
14. Add new Node $<X,Y,ws(X)>$ into $L_i$
15. if number of nodes in $L_i \geq 2$ then
16. Call recursive the function FWI-Extend with the parameter is $L_i$

**Figure 3: WIT algorithm**

5. **WIT-Diff algorithm**

Proposed the Diffset\(^4\) strategy for fast computing the support of item sets and saving memory to store Tidsets\(^5\). We recognize that it can be used for fast computing the ws values of item sets (1). Diffset computes the difference set between two Tidsets in the same equivalence class. In a dense database, the size of Diffset is smaller than the Tidset. Thus, using Diffset will consume less storage and allow for the fast computing of weighted support values. In this algorithm difference between PX and PY illustrated d(PXY) that X and Y are my items and P is prefix that illustrated equivalence class of items [13,15].(Fig 4)

$$d(pxy) = \frac{t(px)}{t(py)} \quad 5.1$$

If have values of d(PX) and d(PY) and I will compute d(PXY), can used bellow equation:

$$d(pxy) = \frac{d(py)}{d(px)} \quad 5.2$$

Beneficial of equation 5.1 and 5.2 can reach an equation for calculate weighted support in this method:

$$WS(pxy) = ws(px) \cdot \frac{\sum_{t \in d(pxy)} tw(t)}{\sum_{t \in T} tw(t)} \quad 5.3$$

If value of d(PXY)=∅ then value of ws(PXY)=ws(PX), this denote if d(PXY)=∅ then value of ws is equal parent ws value.

---

| **Input:** Database D and minimum weighted support threshold minws.  
**Output:** FWI contains all frequent weighted Itemsets that satisfy minws from D.  
**Method:** WIT-Diff()  
1. $L_{rm}$ All items that their ws satisfy minws.  
2. sort Nodes in $L_r$ increasing by their tid.  
3. FWI = ∅.  
4. call Function FWI-Extend-Diff with the parameter is $L_r$.  
**FWI-Extend-Diff ($L_r$)**  
5. Consider each node $l_i$ in $L_r$, DO.  
6. Add($l_i, itemset, l_i.ws$) to FWI.  
7. Create a new set $L_i$ by join $l_i$ with all $l_j$ following it in $L_r$ by:  
8. Set $X = l_i.itemset \cup l_j.itemset$ |
9. If \( L_r \) is the first Level Then \( Y = \frac{t(l_i)}{t(l_j)} \)

10. Else \( Y = \frac{d(l_i)}{d(l_j)} \)

11. If \( Y = \emptyset \) then \( ws(X) = ws(l_i) \)

12. Else \( ws(X) = \text{COMPUTE} - WS - \text{DIFF}(Y) \)

13. If \( ws(X) \) satisfies minws then

14. Add new Node \(< X, Y, ws(X) >\) into \( L_i \)

15. If number of nodes in \( L_i \) \( \geq 2 \) then

16. Call recursive the function FWI-Extend-Diff with the parameter is \( L_i \)

Figure 4: WIT-Diff algorithm

For description example of this algorithm used of table 1, table 2 and fig 5, for compute difference between item B and D we must compute \( d(BD) \):

\[
d(BD) = \frac{t(B)}{t(D)}
\]

That \( t(B)=123456 \) and \( t(D)=1356 \) then difference of two items is 24, while that result of unlike combination of item B and item D is null.

Using the example data presented in Tables 1 and 3, and the algorithm in Fig. 5, we illustrate the WIT-DIFF algorithm with minws = 0.4 as follows. Level 1 of the WIT-tree contains single items, their tids\(^6\), and their ws. They are sorted in increasing order by their \(|\text{tids}|\). The purpose of this work is to compute Diffset faster [16,17].

A join D:

\[
d(AD) = \frac{t(A)}{t(D)} = \frac{1345}{1356} = 4 = \text{ws}(AD)
\]

\(^6\) Transaction identity number
\[\text{ws}(A) = \frac{\sum_{t \in \text{AD}} \text{tw}(t)}{\sum_{t \in T} \text{tw}(t)} = 0.72\]

A join B:

\[d(AB) = \frac{t(A)}{t(B)} = \frac{1345}{123456} = 0\]

\[\Rightarrow \text{ws}(AB) = \text{ws}(A) = 0.72\]

6. The proposed methods:

In explained ways and methods we used of datasets that cleaned and removed the duplicate items and preprocessing with other tools such as Microsoft excel, Clementine, Weka or with other tools. We modified WIT-Diff algorithm at first remove duplicate items in each transactions and reduce transactions weight computations for similar transactions.

6.1. WIT-Odd or Even method:

In this way at first scanning dataset and selection all items that not repetitive and unique then classify all items in two group, odd items and even items. In continue of process the algorithm done individually for even items and odd items. And at the end we have two run times, one for even items and other run time for odd items. And have compounds of only odd and even items. In result we reducing run time and produce frequent item sets. (Fig 6)

| Input: Database D and minimum weighted support threshold minws. |
| Output: FWI contains all frequent weighted Itemsets that satisfy minws from D and Even and odd weight. |

Method:

1. \[\text{WIT-Diff-even and odd()}\]
   \[\text{IF } w_i \ MOD \ 2 \neq 0 \text{ then } \] // odd items.
   \[\text{Else if } w_i \ MOD \ 2 = 0 \text{ then } \] //even items.
   1. \(L_r\) All items that their ws satisfy minws.
   2. sort Nodes in \(L_r\) increasing by their ws.
   3. \(FWI = \emptyset\).
   4. call Function FWI-Extend-Diff –even and odd with the parameter is \(L_r\).
   5. FWI-Extend-Diff-even and odd\((L_r)\)
   6. Consider each node \(l_i\) in \(L_I\) DO.
   7. Add \((l_i, itemset, l_i, ws)\) to FWI.
   8. Set X = \(l_i, itemset \cup l_j, itemset\)
   9. If \(L_r\) is the first Level then \(Y = \frac{t(l_i)}{t(l_j)}\)
10. Else \( Y = \frac{d(l_i)}{d(l_j)} \)
11. If \( Y = \emptyset \) then \( ws(X) = ws(l_i) \)
12. Else \( ws(X) = COMPUTE - WS - DIFF - even \) and odd(\( Y \))
13. If \( ws(X) \) satisfies minws then
14. Add new Node \( <X,Y,ws(X)> \) into \( L_i \)
15. If number of nodes in \( L_i \) \( \geq 2 \) then
16. Call recursive the function FWI-Extend-Diff –even and odd with the parameter is \( L_i \)

**Figure 6: WIT-Diff-even and odd algorithm**

### 6.2. WIT-Max of Even or odd method:

The previous method ,we use of two variables for keeping count of even and odd items then at the end counting down count of two variables and then each of have maximum count and value ,my algorithm run with it. In this way purpose is reduce more calculations. (Fig 7)

**Input:** Database D and minimum weighted support threshold minws.
**Output:** FWI contains all frequent weighted Item sets that satisfy minws from D With Max.
**Method:**
WIT-Diff-MAX()
1. For All items of Dataset Do
2. \( IF \ item_{Weight} = \text{ODD} \) DO
3. \( \text{max}_{odd} + + \)
4. Else if \( \text{item}_{weight} = \text{EVEN} \) Do
5. \( \text{max}_{even} + + \)
6. \( IF \ max_{odd} > max_{even} \) then
7. FWI-Extend-Diff-ODD()
8. Else if \( max_{even} > max_{odd} \) then
9. FWI-Extend-Diff-EVEN()

**Figure 7: WIT-Diff-max of even or odd algorithm**

### 6.3. WIT-Percent method:

In third method , In first counting each of items in total dataset and then compute percent of each item in all items. And then run method with specified percent of items. (Fig 8)

**Input:** Database D and minimum weighted support threshold minws.
**Output:** FWI contains all frequent weighted Item sets that satisfy minws from D.
**Method:**
WIT-Diff-Percent ( )
Array 1[ ][ ]= count of all items.
Array 2[ ][ ]=percent of each items in dataset.
**Computing** Percent of each item in dataset.
Input user threshold for percent of items.
1. \( L_r \)-All items that their ws satisfy minws.
2. sort Nodes in \( L_r \) increasing by their ws.
3. $FWI = \emptyset$.
4. call Function FWI-Extend-Diff-Percen with the parameter is $L_r$.
FWI-Extend-Diff-Percen ($L_r$)
5. Consider each node $l_i$ in $L_I$ DO.
6. Add ($l_i$, itemset, $l_i$, ws) to FWI.
7. Create a new set $L_i$ by join $l_i$ with all $l_j$ following it in $L_I$ by:
8. Set $X=l_i$, itemset $\cup l_j$, itemset
9. If $L_r$ is the first Level Then $Y = \frac{t(l_i)}{t(l_j)}$
10. Else $Y = \frac{d(l_i)}{d(l_j)}$
11. If $Y = \emptyset$ then $ws(X) = ws(l_i)$
12. Else $ws(X) = COMPUTE - WS - DIFF - Percen(Y)$
13. if $ws(X)$ satisfies minws then
14. Add new Node $<X, Y, ws(X)>$ into $L_i$
15. if number of nodes in $L_i \geq 2$ then
16. Call recursive the function FWI-Extend-Diff-Percen with the parameter is $L_i$

We can use data mining tools (such as Clementine software) for acquire count of items and percent of items in total of datasets. (See Fig 9 and Fig 10)
6.4. WIT-Scope of weight method:

In fourth method, use of domain for weight of items as respects we assign for each item a value for weight with a random function. we can filter items with their weight and then running algorithm for selected items. In all method we purpose reducing the input of algorithm and as a result reduce run time and produce item sets. (Fig 11)

| Input: | Database D and minimum weighted support threshold minws. |
| Output: | FWI contains all frequent weighted Item sets that satisfy minws from D. |

**Method:**

WIT-Diff-Scope ()

Input two Scope for weight Domains

From scope₁ to scope₂ Do

1. \( L_r = \) All items that their ws satisfy minws.
2. sort Nodes in \( L_r \) increasing by their ws.
3. \( FWI = \) ∅.
4. call Function FWI-Extend-Diff-Scope with the parameter is \( L_r \).

FWI-Extend-Diff-Scope (\( L_r \))

5. Consider each node \( l_i \) in \( L_i \) DO.
6. Add \((l_i.itemset, l_i.ws)\) to FWI.
7. Create a new set \( L_i \) by join \( l_i \) with all \( l_j \) following it in \( L_i \) by:
8. Set \( X = l_i.itemset \cup l_j.itemset \)
9. If \( L_r \) is the first Level Then \( Y = \frac{\sigma(l_i)}{\sigma(l_j)} \)
10. Else \( Y = \frac{d(l_i)}{d(l_j)} \)
11. If \( Y = \) ∅ then \( ws(X) = ws(l_i) \)
12. Else \( ws(X) = COMPUTE − WS − DIFF − SCOPE(Y) \)
13. if \( ws(X) \) satisfies minws then
14. Add new Node \( < X, Y, ws(X) > \) into \( L_i \)
15. if number of nodes in \( L_i \) ≥ 2 then
16. Call recursive the function FWI-Extend-Diff-Scope with the parameter is \( L_i \)

**Figure 11:** WIT-Diff-Domain of weight algorithm

7. Experimental results

All experimental described below were performed on a Intel(R) Core ™ i5 2.2 GHz .4GB RAM memory, Windows 7, using visual studio C# 2010. the experimental datasets used for the experimentation were downloaded from [http://finin.cs.helsinki.fi/data][14]. we add a value for weight each of items with random function (values in the range of (1 to 10) for each datasets). In table 4 see more information of experimental datasets.

In table 4 view databases name and number of items and transactions, and in table 5 view result of run time of algorithms and methods. View number of FWI(Frequent weighted items) based MinWs threshold.
Table 4: Information of datasets

<table>
<thead>
<tr>
<th>Database (DB)</th>
<th># Transactions</th>
<th>#Items</th>
<th>Modified</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chess</td>
<td>3196</td>
<td>75</td>
<td>Insert duplicate items on each transaction</td>
</tr>
<tr>
<td>Mushroom</td>
<td>8124</td>
<td>120</td>
<td>Insert duplicate items on each transaction</td>
</tr>
</tbody>
</table>

Table 5: Number of FWI from databases

<table>
<thead>
<tr>
<th>Database</th>
<th>MinWs</th>
<th>#FWI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chess</td>
<td>80</td>
<td>8063</td>
</tr>
<tr>
<td>Chess</td>
<td>70</td>
<td>16039</td>
</tr>
<tr>
<td>Chess</td>
<td>60</td>
<td>23208</td>
</tr>
<tr>
<td>Chess</td>
<td>50</td>
<td>29431</td>
</tr>
<tr>
<td>Mushroom</td>
<td>50</td>
<td>436</td>
</tr>
<tr>
<td>Mushroom</td>
<td>40</td>
<td>3038</td>
</tr>
<tr>
<td>Mushroom</td>
<td>30</td>
<td>5347</td>
</tr>
<tr>
<td>Mushroom</td>
<td>20</td>
<td>11634</td>
</tr>
</tbody>
</table>

Table 6: Number of FWI with methods

<table>
<thead>
<tr>
<th>Database</th>
<th>MinWs</th>
<th>Even</th>
<th>Odd</th>
<th>Percent</th>
<th>Max</th>
<th>Domain of Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chess</td>
<td>80</td>
<td>150</td>
<td>996</td>
<td>70% → 5900</td>
<td>996</td>
<td>(20.90) → 315</td>
</tr>
<tr>
<td>Chess</td>
<td>70</td>
<td>450</td>
<td>9376</td>
<td>60% → 12912</td>
<td>9376</td>
<td>(20.90) → 2955</td>
</tr>
<tr>
<td>Chess</td>
<td>60</td>
<td>3730</td>
<td>13815</td>
<td>50% → 18126</td>
<td>13815</td>
<td>(20.90) → 1043</td>
</tr>
<tr>
<td>Chess</td>
<td>50</td>
<td>5216</td>
<td>16057</td>
<td>40% → 28422</td>
<td>16057</td>
<td>(20.90) → 13817</td>
</tr>
<tr>
<td>Mushroom</td>
<td>50</td>
<td>18</td>
<td>17</td>
<td>80% → 31</td>
<td>18</td>
<td>(20.90) → 25</td>
</tr>
<tr>
<td>Mushroom</td>
<td>40</td>
<td>112</td>
<td>54</td>
<td>70% → 31</td>
<td>112</td>
<td>(20.90) → 42</td>
</tr>
<tr>
<td>Mushroom</td>
<td>30</td>
<td>133</td>
<td>71</td>
<td>40% → 5331</td>
<td>133</td>
<td>(20.90) → 91</td>
</tr>
<tr>
<td>Mushroom</td>
<td>20</td>
<td>689</td>
<td>134</td>
<td>30% → 9452</td>
<td>134</td>
<td>(20.90) → 336</td>
</tr>
</tbody>
</table>

Figure 12: Run time for the eight methods in Chess dataset
8. Conclusion

This paper has presented some method for mining frequent weighted item sets from weighted item transaction databases with reduce run time and reduce produce frequent item sets. And several efficient algorithms proposed. We use of WIT-Tree structure and apply my method to WIT-Diff algorithm that have less than run time from other algorithm. In this paper, we have concentrated only on the on the mining of FWIs using the proposed WIT-Tree data structure. And in my proposed methods at the first remove duplicated items in a transaction because they not efficacy in computations and not compute similar transactions weight since used weight transaction of previous similar transaction.

9. References


[17]. Weighted association rule mining via a graph based connectivity model. **Russel Pears, Yun Sing Koh,Gillian Dobbie,Wai Yeap.** s.l. : Information Sciences, 2012.
