

Personal Stock Forecaster

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Abstract-Frequent weighted itemsets represent correlations frequently holding in data in which items may weight differently. However, in some contexts, when the need is to minimize a certain cost function, discovering rare data correlations is more interesting than mining frequent ones. This paper tackles the issue of discovering rare and weighted itemsets, the infrequent weighted itemset (IWI) mining problem. Two novel quality measures are proposed to drive the IWI mining process. Furthermore, two algorithms that perform IWI and Minimal IWI mining efficiently, driven by the proposed measures, are presented. Experimental results show efficiency and effectiveness of the proposed approach.

I. INTRODUCTION

The purpose of this project to help the investors to make decisions on stock markets based on the analysis of the stock price levels and to market profitable investments on a long term as well as short term basis. With the aim of choosing a subset of good features with respect to the target concepts, feature subset selection is an effective way for reducing dimensionality, removing irrelevant data, increasing learning accuracy, and improving result comprehensibility.

This project completely deals with prediction

The first attempt to perform itemset mining

Discovering rare data correlations is more interesting than mining frequent ones

This paper tackles the issue of discovering rare and weighted itemsets, i.e., the infrequent weighted itemset (IWI) mining problem

Personal stock forecasting is a prediction that is done using data items in a tool Rapid Miner. In this paper we are going to follow IWI mining method.

A. Existing System

This paper tackles the issue of discovering rare and weighted itemsets, i.e., the infrequent weighted itemset (IWI) mining problem. In recent years, the attention of the research community has also been focused on the infrequent itemset mining problem, i.e., discovering itemsets whose frequency of occurrence in the analysed data is less than or equal to a maximum threshold. When dealing with optimization problems, minimum and maximum are the most commonly used cost functions. Hence, they are deemed suitable for driving the selection of a worthwhile subset of infrequent weighted data correlations. The problem of mining itemsets by considering weights associated with each item is known as the weighted itemset mining problem. IWI and Minimal IWI mining driven by a maximum IWI-support-min threshold

B. Problem with Existing System

This paper differs from the above-mentioned approaches because it focuses on mining infrequent item sets from weighted data instead of frequent ones.

Different pruning techniques are exploited.

A parallel effort has been devoted to discovering rare correlations among data, i.e., the infrequent itemset mining problem.

II. PROPOSED SYSTEM

In different approaches to incorporating item weights in the itemset support computation have been proposed. Infrequent itemset discovery is applicable to data coming from different real-life application contexts such as (i) statistical disclosure risk assessment from census data and (ii) fraud detection. This section presents two algorithms, namely Infrequent Weighted Itemset Miner and Minimal Infrequent Weighted Itemset Miner, which address tasks, stated, respectively. The proposed algorithms are FPGrowth-like miners whose main characteristics may be summarized as follows: (i) The use of the equivalence property, stated in, to adapt weighted transactional data to traditional FP-tree-based itemset mining, and (ii) the exploitation of a novel FP-tree pruning strategy to prune part of the search space early.

A. Advantage

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Easily Find the Today's Sales of the product.

The attention of the research community has also been focused on the infrequent itemset mining problem, i.e., discovering item sets whose frequency of occurrence in the analyzed data is less than or equal to a maximum threshold.

Frequent item is easily found out the cluster of the item.

III. ALGORITHM

Algorithm that are used to map the itemset provided as input to predict the future sale and profit are IWI miner and Minimal IWT miner.

Infrequent Weighted Itemset Miner

Algorithm 1 IWI-Miner(T, ξ)

Input: T , a weighted transactional dataset

Input: ξ , a maximum IWI-support threshold

Output: \mathcal{F} , the set of IWIs satisfying ξ

1: $\mathcal{F} = \emptyset$ /* Initialization */

 /* Scan T and count the IWI-support of each item */

2: countItemIWI-support(T)

3: $Tree \leftarrow$ a new empty FP-tree; /* Create the initial FP-tree from T */

4: for all weighted transaction t_q in T do

5: $TE_q \leftarrow$ equivalentTransactionSet(t_q)

6: for all transaction te_j in TE_q do

7: insert te_j in $Tree$

8: end for

9: end for

10: $\mathcal{F} \leftarrow$ IWIMining($Tree, \xi, \text{null}$)

11: return \mathcal{F}

Minimal Infrequent Weighted Itemset Miner

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Algorithm 2 IWIMining(*Tree*, ξ , *prefix*)

Input: *Tree*, a FP-tree
Input: ξ , a maximum IWI-support threshold
Input: *prefix*, the set of items/projection patterns with respect to which *Tree* has been generated
Output: \mathcal{F} , the set of IWIs extending *prefix*

- 1: $\mathcal{F} = \emptyset$
- 2: **for all** item *i* in the header table of *Tree* **do**
- 3: $I = \text{prefix} \cup \{i\}$ /* Generate a new itemset *I* by joining *prefix* and *i* with IWI-support set to the IWI-support of item *i* */
/* If *I* is infrequent store it */
- 4: **if** IWI-support(*I*) $\leq \xi$ **then**
- 5: $\mathcal{F} \leftarrow \mathcal{F} \cup \{I\}$
- 6: **end if**
/* Build *I*'s conditional pattern base and *I*'s conditional FP-tree */
- 7: *condPatterns* \leftarrow generateConditionalPatterns(*Tree*, *I*)
- 8: *Tree_I* = createFP-tree(*condPatterns*)
/* Select the items that will never be part of any infrequent itemset */
- 9: *prunableItems* \leftarrow identifyPrunableItems(*Tree_I*, ξ)
/* Remove from *Tree_I* the nodes associated with prunable items */
- 10: *Tree_I* \leftarrow pruneItems(*Tree_I*, *prunableItems*)
- 11: **if** *Tree_I* $\neq \emptyset$ **then**
- 12: $\mathcal{F} \leftarrow \mathcal{F} \cup \text{IWIMining}(\text{Tree}_I, \xi, I)$ /* Recursive mining */
- 13: **end if**
- 14: **end for**
- 15: **return** \mathcal{F}

IV. CONCLUSION

This paper faces the issue of discovering infrequent itemsets by using weights for differentiating between relevant items and not within each transaction. Two FPGrowth-like algorithms that accomplish IWI and MIWI mining efficiently are also proposed. The usefulness of the discovered patterns has been validated on data coming from a real-life context with the help of a domain expert.

V. FUTURE SCOPE

As future work, we plan to integrate the proposed approach in an advanced decision-making system that supports domain expert's targeted actions based on the characteristics of the discovered IWIs. Furthermore, the application of different aggregation functions besides minimum and maximum will be studied.

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