

Mining Frequent Sequential Patterns and Top Rules from Large Uncertain Database

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Abstract - Data mining play very important role in mining useful knowledge from Wireless Sensor Network. In Today's real world environment, most of the databases such as weather database, RFID, stock market analysis are uncertain as it may contain random and noisy values because of some faulty nodes. The uncertainty in database can be handle with the help of U-PrefixSpan algorithm. This algorithm is applied on the database for finding out the frequent sequential patterns by providing the minimum support. As Database is very large, the number of frequent sequential patterns is also large which is difficult to study. Hence there is need to apply the Top K Rule Mining algorithm on the generated frequent sequential patterns to obtain the top K rules. According to the generated rules the prediction can be done. The result and analysis show that the U-PrefixSpan takes more time for execution than Top K rule mining algorithm.

Key Words: Wireless Sensor Network, U-PrefixSpan, Top K Rule mining.

1. INTRODUCTION

Data Mining is the process of mining the useful knowledge from the database. The Data mining concepts useful for uncovering the interesting patterns hidden in large data sets. Nowadays data uncertainty is inherent in many real time application like wireless sensor network, RFID, Scientific experiments and web access pattern. Uncertain databases contains random values which are subtly different from each other. Consider the wireless sensor network in the lab where 54 sensors are deployed to collect the reading. The sensors nodes collect the reading having attributes such as date, time, temperature, light, humidity, voltage. The problem of finding the frequent sequential patterns from uncertain databases has attracted a lot of attention in the research area. For example, in biological research, FSP mining is helpful in determining the association among gene sequence and also useful in the grouping of moving objects.

Consider the sequence level uncertainty where the expected support is used to measure the frequentness of patterns such as frequent item sets [2] and frequent subsequences on uncertain data. The sequence level uncertain model is fundamental for a lot of real-life application of expected support unable to reflect pattern frequentness. An RFID location tracking system taking as example, where a set of RF reader are organized in an indoor Environment, and a user may be sensed by several near-by

readers. In such application, user locations are uncertain. In Uncertain databases, the expected support unable to identify frequent patterns. In fact expected support may give rise to many infrequent patterns. Therefore, the evaluation of frequentness of sequential pattern observing to probability theory which gives idea of probabilistic frequentness.

In this paper, the frequent sequential patterns is generated by U-PrefixSpan [5] algorithm. The output of U-PrefixSpan is given to TopKRules algorithm which generate rules showing association among different attributes. There are four stages required for finding frequent sequential patterns such as conversion of text dataset into CSV format, pre-processing the dataset, creating the batches of ten thousand each and then finally applying the U-PrefixSpan algorithm. The Rules showing association among them is obtained using TopKRules algorithm.

The remaining part of this paper are organized as follows. Section II describes the literature review, the working of system model and proposed plan are discussed in section III, results and analysis are shown in section IV and paper is concluded in section V.

2. LITERATURE REVIEW

In [1], the author proposed the concept of applying U-Prefix Span for mining probabilistically frequent sequential patterns in large uncertain databases in which two uncertainty models are used such as sequence-level and element-level uncertainty model to handle the data uncertainty in real world application. The drawback of this system is to use expected support as the measurement of frequentness of pattern. It effectively avoids the problem of possible world explosion this is advantage of this system.

In [2], the author proposed the concept of mining of frequent itemsets on large uncertain databases, since an uncertain database consist an exponential number of possible worlds. To overcome this problem the incremental mining algorithm is used and poisson binomial distribution model is applied for mining. As it the frequent itemset mining, the tuple and attribute uncertainty models are used. Incremental mining algorithm enables the results to be revitalized by reducing the need of re-executing the mining algorithm on novel database which is more expensive and unnecessary.

Author proposed the system in [3], to reduce the search space and avoid redundant computation by applying efficient mining algorithm based on depth-first search method to obtain all probabilistic frequent closed itemsets.

Author proposed the system in [4], where sequential pattern mining is one of the challenging task since explosive number of possible subsequence patterns are generated. The Apriori reduce the number of combination but rises the problem when sequence database is large. To overcome this problem PrefixSpan algorithm is proposed which mines complete set of patterns but reduces the efforts of candidate sequence generation which leads to efficient processing.

In [5], author discusses about the concept of dynamic programming algorithm which embedded into candidate-generate and test approach and explore the pattern into breadth-First search and depth first search manner. In this system, the elimination of candidate sequences without calculating their support through probabilistic pruning.

In [6], author discusses about mining top k association rules which chooses the top k rules only and has advantage that the user can control the number of rules. The drawback of this system is that it generate so many results or too few results eliminating valuable data.

3. PROPOSED PLAN

Basically proposed work consist of mainly 4 stages:

- 1) Weather Dataset taken as input
- 2) Data Pre-processing.
- 3) FSPs generation using U- PrefixSpan algorithm
- 4) Applying the top k association Rule mining algorithm.
- 1) Weather Dataset taken as input:

The collection of dataset is very essential step in the process of data mining because the data mining techniques are applied over the databases which is chosen. The dataset may be of different type such as wireless sensor network data, e-commerce data, web log etc. The data collected from Intel Research Lab where 54 sensors are deployed. The dataset having the attribute like date, time, epoch, mote id, temperature, humidity, light, voltage. The dataset consist of 2.3 million entries where epoch is increasing series number from each mote. At the same time two readings from the same epoch number were produced. There are few missing epoch in the dataset. The range of mote changes from 1 to

54; there may be the chance that some data is missing. Temperature is measured in degrees Celsius. Humidity ranges from 0-100%. Light is measured in the Lux. Voltage is expressed in volts, ranging from 2-3.

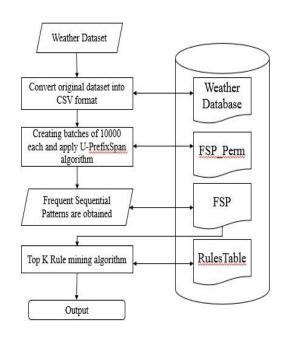


Fig. 1 Working of System Model

2) Data Pre-processing:

In Today's real-world databases are highly affected by noise. Missing and inconsistent data obtained due to their typically huge size and in fact data is collected from heterogeneous sources. It may happen that Low-quality data will lead to improper mining results hence there is need to apply the pre-processing techniques. There are many pre-processing techniques such as data cleaning, data transformation as well as integration of data etc. Among these pre-processing techniques, Data cleaning is most suitable for weather dataset to eliminate noise and correct irregularities in the data. Data cleaning helps to clean the records by filling in missing values.

3) Mining frequent sequential pattern using U-Prefixspan algorithm:

The mining of frequent sequential pattern (FSPs) from probabilistic databases using U-PrefixSpan algorithm possess the model called Seq-UPrefixSpan which effectively solves the problem of possible world explosion. The various pattern mining algorithm like GSP, SPADE, FreeSpan and PrefixSpan having interestingness measure



as expected support that unable to find some probabilistically frequent pattern. Expected support may give rise to some probabilistically infrequent patterns as a result. The U-PrefixSpan algorithm uses the idea of probabilistic frequentness which is able to capture the complex relationship between uncertain sequences.

4) Mining Rules using TopKRules algorithm:

The mining of frequent sequential patterns is not enough as large number of patterns are obtained because large uncertain database is taken as input. It is essential to obtain the top K rules by applying Top K association Rule mining algorithm. Since frequent sequential patterns consumes more memory. TopKRules algorithm added after U-PrefixSpan gives precise result based on which prediction can be done.

4. RESULT AND ANALYSIS

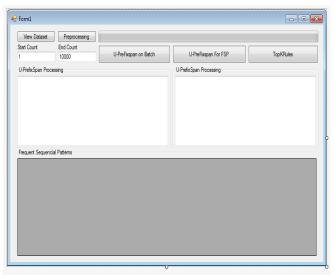


Fig. 2 GUI showing main window

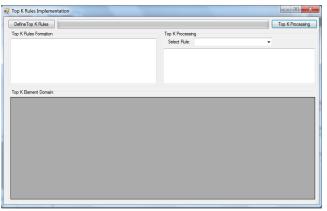


Fig. 3 GUI obtained after Top K Rule Mining Button

Defi	neTop K Rules					Top K Proc	essing
Top K	Rules Formation		T	op K Processing			
Start empe humid ight-> voltag empe	ssing Time: 12/03/2016 arature->humidty Ji ty->temperature, Ji temperature, humi p=>temperature, humi arature, Jught->humi & Bement, Domain	ght.voltage: dity.voltage; umidity.light: ght.voltage; dity.voltage;		Select Rule:		•	
TOP I	RuleID	Rule	RuleDescription	Support	Confidence	CreatedDate	
Þ	1481	1	temperature->humidity.light.voltage	0.005555556	0.005649718	12/03/2016 11:49 AM	
	1482	2	humidity->temperature.light.voltage	0.005555556	0.006329114	12/03/2016 11:49 AM	-
	1483	3	light->temperature.humidity.voltage	0.005555556	0.1	12/03/2016 11:49 AM	
	1483 1484	3 4	light->temperature.humidity.voltage voltage->temperature.humidity.light	0.005555556	0.1 0.03448276	12/03/2016 11:49 AM 12/03/2016 11:49 AM	
							_
	1484	4	voltage->temperature.humidity.light	0.005555556	0.03448276	12/03/2016 11:49 AM	_
	1484 1485	4 5	voltage->temperature.humidity.light temperature.humidity->light.voltage	0.005555556	0.03448276	12/03/2016 11:49 AM 12/03/2016 11:49 AM	_
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	1484 1485 1486 1487	4 5 6 7	voltage->temperature humidty light temperature humidty->light,voltage temperature light->humidty,voltage temperature,voltage->humidty.light	0.005555556 0.005555556 0.005555556 0.005555556	0.03448276 0.006410256 0.2 0.03448276	12/03/2016 11:49 AM 12/03/2016 11:49 AM 12/03/2016 11:49 AM 12/03/2016 11:49 AM	

Fig. 4 GUI obtained after Clicking Define Top K Rules button

DefineTo	op K Rules						Top K Processin	
Top K Ru	les Formation			Top K Processing				
temperatu humidity-> ight->temp voltage->t temperatu temperatu	12/03/2016 11:49:23 re->humidty.light.voltage temperature.light.voltage perature.humidity.voltage rentere.humidity.voltage re.light.>humidity.voltage re.light.>humidity.voltage			Select Rule:	temperature->humid	ty.light,voltage •		
TOP K Ele	ment Domain: temperature	humidity	light	voltage	WeatherAnalysis	StartTime	EndTime	
۶.	122.153	-3.91901	68.08	2.18353	Office Hall Light	12/03/2016 11:5	12/03/2016 11:5	
	122.153	-3.91901	136.16	2.18353	Very Dark Overc	12/03/2016 11:5	12/03/2016 11:5	
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	122.153	-3.91901	128.8	2.18353	Very Dark Overc	12/03/2016 11:5	12/03/2016 11:5	
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Fig. 5 GUI obtained after clicking Top K Processing button





Fig. 6 Graph Showing execution time required for FSP generation

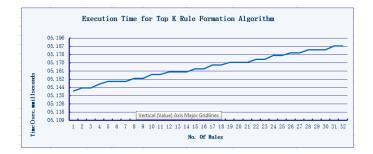


Fig. 7 Graph displaying execution time (in milliseconds) for generation of Top K Rules.

5. CONCLUSION

The research work include combining the two different algorithms to improve the efficiency of system in terms of time and iteration. The U-PrefixSpan algorithm applied on large uncertain database to obtain frequent sequential patterns. Since database is large uncertain, the large number of patterns are generated which is difficult to study hence there is need of top k rule mining algorithm for obtaining precise results. TopKRules algorithm generate 32 rules based upon that the prediction of weather can be done which help to know the climate based on the ranges of attributes.

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