Optimization of Vague Association Rule Mining: A Survey

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Abstract- *In this article, we survey measures of interestingness for vague association rule . Data mining can be regarded as an algorithmic process that takes data as input and yields patterns such as classification rules, association rules, or summaries as output. An association rule is an implication of the form X → Y, where X and Y are nonintersecting sets of items. For example, {milk, eggs} → {bread} is an association rule that says that when milk and eggs are purchased, bread is likely to be purchased as well. The traditional association rule mining approach has limitations as it fails to capture some of the information in the applications that involve uncertain data. One such application is the scenario of online shopping. In many cases, it is observed that a customer puts some items in his shopping cart, but eventually removes some of those items at the time of checkout. Those items, which can be considered as "almost sold" items carry hesitation information [4], since customers are hesitating to buy them. The hesitation information of items is valuable knowledge for the design of good selling strategies. In this paper we surveyed various optimization techniques which extract this vague or hesitant information.*

Keywords- Optimization technique, vague rule, hesitant information, ACO, Genetic algorithm.

I. BASIC TERMINOLOGY

Measuring the interestingness of discovered patterns is an active and important area of data mining research. Although much work has been conducted in this area, so far there is no widespread agreement on a formal definition of interestingness in this context. Based on the diversity of definitions presented to-date, interestingness is per-haps best treated as a broad concept that emphasizes conciseness, coverage, reliability, peculiarity, diversity, novelty, surprisingness, utility, and actionability. These specific criteria are used to determine whether or not a pattern is interesting. They are as follow:

(i) Conciseness: A pattern is concise if it contains relatively few attribute-value pairs, while a set of patterns is concise if it contains relatively few patterns. A concise pattern or set of patterns is relatively easy to understand and remember and thus is added more easily to the user's knowledge (set of beliefs). Accordingly, much research has been conducted to find a "minimum set of patterns," using properties such as mono-tonicity and confidence invariance.

(ii) Generality/Coverage: A pattern is general if it covers a relatively large subset of a dataset. Generality (or coverage) measures the comprehensiveness of a pattern, that is, the fraction of all records in the dataset that matches the pattern. If a pattern characterizes more information in the dataset, it tends to be more interesting [1]. Frequent itemsets are the most studied general patterns in the data mining literature. An itemset is a set of items, such as some items from a grocery basket. An itemset is frequent if its support, the fraction of records in the dataset containing the itemset, is above a given threshold [1]. The best known algorithm for finding frequent itemsets is the Apriori algorithm [1]. Some generality measures can form the bases for pruning strategies; for example, the support measure is used in the Apriori algorithm as the basis for pruning itemsets. For classification rules, [12] gave an empirical evaluation showing how generality affects classification results. Generality frequently coincides with conciseness because concise patterns tend to have greater coverage.

(iii) Reliability: A pattern is reliable if the relationship described by the pattern occurs in a high percentage of applicable cases. For example, a classification rule is reliable if its predictions are highly accurate, and an association rule is reliable if it has high confidence. Many measures from probability, statistics, and information retrieval have been proposed to measure the reliability of association rules [4].

(iv) Peculiarity: A pattern is peculiar if it is far away from other discovered patterns according to some distance measure. Peculiar patterns are generated from peculiar data (or outliers), which are relatively few in number and significantly different from the rest of the data [6]. Peculiar patterns may be unknown to the user, hence interesting.

(v) Diversity: A pattern is diverse if its elements differ significantly from each other, while a set of patterns is diverse if the patterns in the set differ significantly from each other.

Diversity is a common factor for measuring the interestingness of summaries [3]. According to a simple point of view, a summary can be considered diverse if its probability distribution is far from the uniform distribution. A diverse summary may be interesting because in the absence of any relevant knowl-edge, a user commonly assumes that the uniform distribution will hold in a summary. According to this reasoning, the more diverse the summary is, the more interesting it is. We are unaware of any existing research on using diversity to measure the interestingness of classification or association rules.

(vi) Novelty: A pattern is novel to a person if he or she did not know it before and is not able to infer it from other known patterns. No known data mining system represents everything that a user knows, and thus, novelty cannot be measured explicitly with reference to the user's knowledge. Similarly, no known data mining system represents what the user does not know, and therefore, novelty cannot be measured explicitly with reference to the user's ignorance. Instead, novelty is detected by having the user either explicitly identify a pattern as novel [9] or notice that a pattern cannot be deduced from and doesnot contradict previously discovered patterns. In the latter case, the discovered patterns are being used as an approximation to the user's knowledge.

(vii) Actionability/Applicability: A pattern is actionable (or applicable) in some domain if it enables decision making about future actions in this domain [3]. Actionability is sometimes associated with a pattern selection strategy. So far, no general method for measuring actionability has been devised. Existing measures depend on the applications. For example, [5], measured accountability as the cost of changing the customer's current condition to match the objectives, whereas Wang et al. [7], measured accountability as the profit that an association rules can bring.

II. INTRODUCTION

A typical example is an online shopping scenario, such as "Amazon.com", for which it is possible to collect huge amount of data from the Web log that can be modeled to mine hesitation information. From Web logs, we can infer a customer's browsing pattern in a trail, say how many times and how much time s/he spends on a Web page, at which steps s/he quits the browsing, what and how many items are put in the basket when a trail ends, and so on. Therefore, we can further identify and Categorize different browsing patterns into different hesitation information with respect to different applications. The hesitation information can then be used to design and implement selling strategies that can potentially turn those "interesting" items into "under consideration" items and "under consideration" items into "sold" items. From the literature [4], it is evident that very little attention has been paid for mining hesitation information .In this paper an attempt has been made to develop a vague set model for mining hesitation information within given time period .It is illustrated with the help of problem of choosing a course in an educational institute. Here we are employ the vague set theory [3,4,5] to model the hesitation status of the course attended by the students. The main benefit of this approach is that the theory addresses the drawback of a single membership value in fuzzy set theory [6] by using interval-based membership that captures three types of evidence with respect to an object in a universe of discourse: support, against and hesitation. Thus, we naturally model the hesitation information of a course in the mining context as the evidence of hesitation. The information of the "attended the class" and the "not attended the class" (without any hesitation information) in the traditional setting of association rule mining correspond to the evidence of support and against with respect to the class. To study the relationship between the support evidence and the hesitation evidence with respect to topics, the concepts of attractiveness and hesitation are used, which are derived from the vague membership in vague sets. A topic with high attractiveness means that the topic is well attended and has a high possibility to be attended again next time. A topic with high hesitation means that the student is always hesitating to attend the topic due to some reason but has a high possibility to attend it next time if the reason is identified and resolved. For example, given the vague membership value, [0.5, 0.7], of a topic, the attractiveness is 0.6 (the median of 0.5 and 0.7) and the hesitation is 0.2 (the difference between 0.7 and 0.5), which implies that the student may attend the topic next time with a possibility of 60% and hesitate to attend the topic with a possibility of 20%.Using the attractiveness and hesitation of topics, we model a database with hesitation information as an AH-pair[4] database that consists of AH-pair transactions, where A stands for attractiveness and H stands for hesitation. Based on the AH-pair database, we then employed the notion of Vague Association Rules, which capture four types of relationships between two sets of items: the implication of the attractiveness/ hesitation of one set of items on the attractiveness/hesitation of the other set of items. For example, if we find an AH-rule like "People always buy quilts and pillows (A) but quit the process of buying beds at the step of choosing delivery method (H)". Thus, there might be something wrong with the delivery method for beds (for example, no home delivery service provided) which causes people hesitate to buy beds.

III. BASIC/ GENERAL APPROACH TO IDENTIFY VAGUE RULE

Having considered above criteria for determining whether a pattern is interesting, let us now consider three methods for performing this determination, which we call interestingness determination. First, we can classify each pattern as either interesting or uninteresting. For example, we use the chi-square test to distinguish between inter-esting and uninteresting patterns. Secondly, we can determine a preference relation to represent that one pattern is more interesting than another. This method produces a partial ordering. Thirdly, we can rank the patterns. For the first or third approach, we can define an interestingness measure based on the aforementioned nine criteria and use this measure to distinguish between interesting and uninteresting patterns in the first approach or to rank patterns in the third approach. Thus, using interestingness measures facilitates a general and practical approach to automatically identifying interesting patterns. In the remainder of this survey, we concentrate on this approach. The attempt to compare patterns classified as interesting by the interestingness measures to those classified as interesting by human subjects has rarely been tackled. Two recent studies have compared the ranking of rules by human experts to the ranking of rules by various interestingness measures, and suggested choosing the measure that produces the ranking which most resembles the ranking of experts [8, 9].

During the data mining process, interestingness measures can be used in three ways, which we call the roles of interestingness measures. Figure 1 shows these three roles

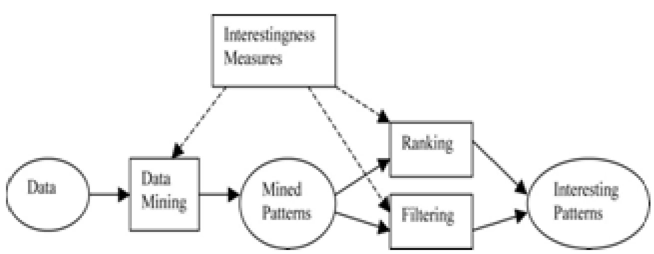


Figure 1: Interestingness measure

First, measures can be used to prune uninteresting patterns during the mining process so as to narrow the search space and thus improve mining efficiency. For example, a threshold for support can be used to filter out patterns with low support during the mining process and thus improve efficiency [1]. Similarly, for some utility-based measures, a utility threshold can be defined and used for pruning.

IV.MEASURES FOR ASSOCIATION AND CLASSIFICATION RULES

(i) Hesitation and Overall Hesitation

Given an item $x \in I$ and a set of HSs S=*$s1,s2,...,sn$+with a partial order ≤, the hesitation of x with respect to a hesitation status HS $si \in S$ is a function $hi(x)$:I→[0,1] such that $\alpha(x)$+$\beta(x)$+ $hini$=1(x)=1 where $hi(x)$ represents the evidence for the HS si of x. The overall hesitation of x with respect to S is given by H(x)= $hini$=1(x). This is directly implied from the above definition that (x)=1−$\alpha(x)$−$\beta(x)$.

(ii) Intent and Overall Intent

Given a set of HSs (S, ≤), the intent of an item x with respect to an HS si ∈ S, denoted as $int(x,si)$ is a vague value [$\alpha i(x)$,1− $\beta i(x)$] which is sub interval of [$\alpha(x)$,1−$\beta(x)$]. The overall intent of x denoted as (x) is the interval[$\alpha(x)$,1−$\beta(x)$].

(iii) Attractiveness and Overall Attractiveness

The attractiveness of x with respect to a HS si, denoted as $att(x,si)$ is defined as the median membership of x with respect to Si that is 12 .$\alpha i(x)$+ 1−$\beta i(x)$ /. The overall attractiveness of x is a function (x):I→,0,1- such that $ATT(x)$=12 .$\alpha(x)$+ 1−$\beta(x)$ /.
Given the intent [αV(x); 1- βV(x)] of an item x for an HS si, we have a one-to-one corresponding pair of the attractiveness and hesitation, known as AH-pair, denoted as [att(x; si); h(x)]. Attractiveness and hesitation are two significant ideas, since one might be interested in gaining ARs with the items having high hesitation or high attractiveness.

(iv) Weighted Attributes

The variables selected to calculate weight are known as weighted attributes (a1,2,…,an). Depending on the domain, it could be any kind of variable such as the item weight in case of supermarket domain.

(v) Item Weight

Item weight is the value attached to each item representing its significance. In case of supermarket transactions, it can represent the profit associated with the sale of a certain item. The item weight is a function of the weighted attribute. If item weight is represented as (i) then (i)=$f(a)$.

(vi) Itemset Weight

Weight of an itemset is the weight of the enclosing items. It can be denoted as (is). The item weight is a special case of the itemset weight, when the itemset has only one item. The average value of the item weight is given by (is)= $w(ik)Nk$=1N

(vii) Transaction Weight

Transaction weight is a type of an itemset weight that is attached to all transactions. Higher the transaction weight, larger is the contribution of the transaction in mining results.
3.8 AH-pair Transaction and Database
An AH-pair database is a sequence of AH-pair transactions. An AH-pair transaction T is a tuple <v1,2 ,…,vm> on an itemset IT={x1,x2,…,xm} where IT⊆I and vj=<MA xj ,MH xj > is an AH-pair of the item xj with respect to a given HS or the overall hesitation for 1≤ j ≤ m.

Although association and classification rules are both represented as if-then rules, we see five differences between them.

First, they have different purposes. Association rules are ordinarily used as descrip-tive tools. Classification rules, on the other hand, are used as a means of predicting classifications for unseen data.

Second, different techniques are used to mine these two types of rules. Association rule mining typically consists of two steps: (1) Finding frequent itemsets, that is, all itemsets with support greater than or equal to a threshold, and (2) generating association rules based on the frequent itemsets. Classification rule mining often consists of two different steps: (1) Using heuristics to select attribute-value pairs to use to form the conditions of rules, and (2) using pruning methods to avoid small disjuncts, that is, rules with antecedents that are too specific. The second pruning step is performed because although more specific rules tend to have higher accuracy on training data, they may not be reliable on unseen data, which is called overfitting. In some cases, classification rules are found by first constructing a tree (commonly called a decision tree), then pruning the tree, and finally generating the classification rules [Quinlan 1986].

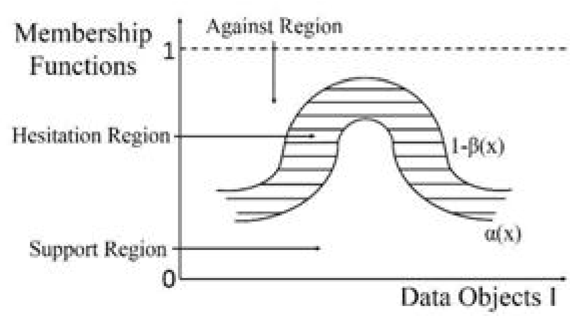
Third, association rule mining algorithms often find many more rules than classification rule mining algorithms. An algorithm for association rule mining finds all rules that satisfy support and confidence requirements. Without postpruning and ranking, different algorithms for association rule mining find the same results. In contrast, most algorithms for classification rule mining find rules that together are sufficient to cover the training data, rather than finding all the rules that could be found for the dataset. Therefore, various algorithms for classification rules often find different rulesets.

Fourth, the algorithms for generating the two types of rules are evaluated differently. Since the results of association rule mining algorithms are the same, the running time and main memory used are the foremost issues for comparison. For classification rules, the comparison is based primarily on the predictive accuracy of the ruleset on testing data.
Fifth, the two types of rules are evaluated in different ways. Association rules are commonly evaluated by users, while classification rules are customarily evaluated by applying them to testing data.

IV. VAGUE ASSOCIATION RULE MINING

(i) Vague set Theory

Gau and Buehrer [7] introduced the notion of vague sets. A vague set V in a universe of discourse I is characterized by a true membership function αv, and a false membership function βv,. where
αv : I → [0, 1],
βv : I → [0, 1], and
αv (x) + βv(x) ≤ 1.
Here αV(x) is a lower bound on the grade of membership of x derived from the evidence for x, and βV(x) is a lower bound on negation of grade of membership of x derived from the evidence against x. Suppose I = {x1, x2, …, xn }.
Let I be a set of objects, called the universe of discourse, where an element of I is denoted by x.



In this section, we are discussing about vague set theory and the concept of Hesitation Statuses (HSs) is shown and modeling of hesitation information is discussed.

(ii) Hesitation Information Modeling

While purchasing an item during a transaction, a particular state between two different situations of “buying” and “not buying” is termed as a Hesitation Status (HS).

In order to capture the hesitation evidence, a subinterval of [αv(x); 1- βv(x)] is used to represent the customer‟s intent for each item with respect to various HSs.

To find the intent value, the linear extensions concept of a partial order is used.

(iii) Vague Association Rule

A Vague Association Rule (VAR), r = (X =>Y), is an association rule obtained from an AH-pair database.
Based on attractiveness and hesitation of an item with respect to a hesitation status (HS), various types of confidence and support of a VAR can be described. Attractiveness-Hesitation confidence and Attractiveness-Hesitation support of a VAR have been defined in order to evaluate the quality of the VAR. Accordingly, four kinds of support and confidence have been described to evaluate the VARs as follows.

(iv) Support

The support of the rule is the fraction of the transactions in T that satisfy the union of items in X and Y.

In other words, it is an evidence of how frequently the items show up in the database. Support Correspond to statistical significance.

(v) Confidence

The probability, measured as the fraction of the transactions containing X also containing Y, is called the confidence of the rule.

IV. LITERATURE SURVEY

An Lu, Yiping Ke et al. [8] activated the approach of ambiguous sets in the ambience of AR mining as to cover the averseness advice into ARs. Concepts like affability and averseness accept been introduced, which characterize the all-embracing advice of a customer‟s absorbed on an item. Depending on these two concepts, the angle of ambiguous affiliation rules (VARs) has been proposed and an algorithm to abundance the VARs has been designed. Experiments authenticate that the algorithm is able and the VARs abduction added exact and bigger advice as compared to accepted ARs

Bernecker et al. [9], and Q. Zhang et al. [10] advised that employing anticipated abutment may conceivably could cause the accident of some important patterns. For accretion the anticipation that a arrangement is frequent, they presented the angle of Probabilistic Common Itemsets (PFI). Activating programming based solutions were ahead getting acclimated to achieve PFIs from ambiguous databases. This algorithm computed probabilities, and accurate that an itemset was a PFI in O(n2) time. However, the proposed algorithm avoids the use of activating programming, and is able of acceptance a PFI abundant faster, i.e. in O(n) time

An Lu et al. [12, 13] aid in acceptance of what is bigger aural Fuzzy Sets, Intuitionistic Fuzzy Sets and Ambiguous Sets aswell accouterment angle of ambiguous affiliation rules (VARs) by utilizing two added measures: affability and averseness of a abstracts account permits interval-based associates to abduction added evidences to an article in the cosmos of discourse. Ambiguous set approach has been activated to apprenticeship acreage for mining affiliation rules.

Priya Bajaj et al. [14] proposed an algorithm that enhances the ability of web admission by utilizing the next accepted web page above-mentioned to the user requests. It is an able predictive mining that examines the user‟ web admission history and predicts the next page. Here ambiguous added Markov archetypal is devised to assassinate the prediction. Suggestions accept been fabricated for ambiguous rules to backpack out the pruning at audible levels of Markov model. When the anticipation table is formed, the affiliation mining will be implemented to ascertain the able next page. This archetypal enhances the definiteness and ability of the prediction.

Vivek Badhe et al. [15] proposed a archetypal for accumulation arrangement mining. They accept approved the adversity in authoritative decisions, decidedly in banking problems which is a analytical job in industry. Although accumulation arrangement mining serves the purpose, this arrangement relies on the inaccurate and ambiguous surroundings. Most of the approaches to affiliation aphorism mining apply on answer rules by agency of associations amid abstracts and analytic common patterns that abide in the data. The key action makes use of abutment and aplomb measures for basic rules. But as the abstracts has angry out to be added blended today, it is all-important to seek solutions which aid in ambidextrous with these issues.

An Lu et al. [17] devised an algorithm for the issue, accustomed a ambiguous affiliation r over a action R and FDs F over R set, what is"best" approximation with annual to F if demography into average associates (m) and the blunder associates (i) thresholds account. Employing these two ambiguous set thresholds, authentic mi-overlap a part of ambiguous sets angle and a absorb operation on r. FD achievement in r is authentic in ethics agreement getting mi-overlapping. Presenting Lien's and Atzeni's adage arrangement is complete and complete for FDs getting annoyed in the ambiguous relations. Chase action is advised for a ambiguous affiliation r over R, called VChase(r, F), as a agency to advance bendability of r with annual to F. The capital outcomes is that the achievement of the action is the a lot of object-precise approximation of r with annual to F. The complication of VChase(r, F) is polynomial time in the sizes of r and F.

B. Y. Chilakalapudi et al. [19] presented an algorithm for extracting common itemsets from a huge ambiguous database, interpreted beneath PWS. They accept appropriate that the mining action can be modeled as a Poisson binomial distribution, and accept advised an algorithm is implemented which can finer and accurately actuate common itemsets in a ample ambiguous database. The devised mining algorithm facilitate PFI outcomes to be re-energized. This lessens the claim of re-executing the absolute mining algorithm over the beginning database, which is generally added cher and redundant. The devised algorithm can advance incremental mining and provides absolute outcomes on mining the ambiguous database. A ample admiration on absolute datasets has been performed in adjustment to prove the capability of the proposed algorithm.

A. Pandey et al. in “A Model for Mining Course Advice application Ambiguous Affiliation Rules” [25] accept proposed an algorithm for mining ambiguous affiliation aphorism that discovers the averseness advice of items. The algorithm was devised to abundance the courses and the averseness of acceptance to appear the courses. Application abstracts on absolute datasets they accept accepted their algorithm to be able in mining ambiguous affiliation rules. In adverse to the accepted affiliation rules mined from transactional databases, ambiguous affiliation rules mined from the AH-pair databases accept been begin to be added abundant and accurate, and are able of capturing bigger information. Later in their work, “A Model for Ambiguous Affiliation Aphorism Mining in Banausic Databases”, [26] A. Pandey et al. accept proposed an addendum of their algorithm for mining banausic affiliation rules and allegory the acquired averseness advice which can be activated in authoritative the courses added able and attractive.

The contempo abstract analysis indicates that there is a claim of optimizing the extracted after-effects further, so that the final outcomes are added bigger and accurate. Several enhancement techniques accept already been auspiciously activated in assorted fields of abstracts mining such as allocation and clustering. Some of these techniques accept been discussed in the afterward section..

VI. VARIOUS OPTIMIZATION TECHNIQUES FOR VAGUE RULE MINING

(i) Genetic algorithm (GA)

A Vague Association Rule (VAR) r = (X ⇒ Y),is an association rule obtained from an AH-pair database. An AH-pair database is a sequence of AH-pair transactions[22]. An AH-pair transaction T is a tuple <$v1,2$,…,vm> on an itemset $IT=\{x1,x2,\ldots,xm\}$ where $IT\subseteq I$ and vj=<$MA\ xj$,$MH\ xj$ > is an AH-pair of the item xj with respect to a given HS or the overall hesitation for 1≤ j ≤ m.

GA has been used to mine Vague Association Rules from temporal database. We first mine the set of all A,H, AH and HA frequent itemset (FI) from the input AH pair database with respect to certain HS or the overall hesitation. Then, we generate the Vague Association Rules from the set of FIs.

To generate the A,H, AH and HApair from the database first module is developed to calculate the Intent of an item .The intent of an item x , denoted as intent(x), is a vague value [α(x), 1 − β(x)]. The vague value of intent is calculated using the Algorithm CalIntent().

The calIntent() Algorithm which is first module is a nested iterative method to calculate the intent. This algorithm takes a Data-set (D) as input. This Data-set consists of rows and column as student ID (S_ID) and topic ID (T_ID) of the course. Therefore, data set D is considered as a two dimensional array. Step 1 initializes the intent array (having size as no. of topics) while Step 2 and Step 4 are used to navigate in the Data-set array. In Step 3 favor (α) and against (β) are initialized to store overall favor and against which is finally stored in the intent array in the Step 8. This algorithm returns an intent array.

Algorithm CalIntent(D)
1. Initialize intent array to store intent;
2. For each i=0,1,2…..where i<no. of tpID, do
3. Initialize favor(α) & against(β) variable with value zero;
4. For each j=0,1,2…..where j<no. of stID, do
5. Increment favor(α) by one when D[i][j] is equal to one;
6. Increment against(β) by one when D[i][j] is equal to zero;
7. End of for ;
8. Generate intent using favor and against as [α,1-β] ;
9. End of for;
10. return all intent;

The CalAHPair Algorithm which is the second module is a simple iterative method to calculate the

AH pair. This algorithm takes a Intent as input as given by algorithm 3.1.Step 1 initialize the AH pair array having size as no. of tpID. Step 2 is used to traverse the intent array while

Step 3, 4, 5 are used to calculate attractiveness and hesitation to finally calculate the AH pair.

(ii) Artificial Bee Colony (ABC) Algorithm

Artificial Bee Colony (ABC) algorithm is a problem solving method, developed based on the behaviors of honey bee colony, searching and sharing the information with other colony members in the hive, to be able to find out richest food sources in shortest possible time [18, 19, 20, 21].
A possible solution in the problem is represented by a position of a food source in nature. The amount of nectar in that food source represents the fitness value of that solution.

(iii) Particle Swarm Optimization (PSO)

PSO is an optimization technique based on the stochastic optimization method developed by Dr. Eberhart and Dr. Kennedy. PSO is based on the social behavior of a fish school or bird flock [20].

PSO shares numerous similarities with evolutionary computing methods such as genetic algorithm. An initial random population of possible solutions is taken and the system searches the population for an optimal solution by updating generations. However, in contrast with GA, PSO does not involve any evolution operators, for example mutation and crossover. In PSO, potential solutions, or particles, fly through the problem space following the present optimum particles.

Every particle updates itself by following two “best” values.

The particle keeps track of its coordinates in the problem.

(iv) Ant Colony Optimization (ACO)

ACO is a technique that simulates the behavior of ants as social insects that work together to accomplish a general aim with the use of crowd wisdom. ACO algorithms put swarm intelligence into particular action. Swarm intelligence, which is based on the concept of collective behavior, has occupied ACO in numerous fields and domains of problem solving. ACO has been applied successfully in several domains of data mining, such as classification and clustering, and has provided scalable solutions.

ACO is a collection of algorithms of Artificial Intelligence that rely on imitation of social insects‟ behavior, especially ants‟. These algorithms use agents, that we call “ants”, for investigation of the best solution to a problem, such as shortest path between few places that might be food for colony, just like the case with real world ant colonies. These agents are iteratively construct problem solutions. The probability for an ant to visit a town is depends upon the quantity of pheromone that all agents detect at the time of its exploration. Pheromone is a substance that ants create and deposit along paths that they have traversed, creating those paths more attractive for the next ones that might pass through the same point, while previously existent pheromones vapourize as time passes. At the time of algorithm improvement, artificial pheromone is placed after complete tour-solution construction on each and every town that was selected and visited for its construction. In this way, the pheromone amount is the heuristic data at a given point of time, reflecting colony experience about feasible solutions of the problem.

VII. CONCLUSION

Interestingness measures play an important role in data mining, regardless of the kind of patterns being mined. These measures are intended for various optimization technique for mining vague rule association. Good measures also allow the time and space costs of the mining process to be reduced. This survey reviews the interestingness measures for rules and summaries, classifies them from several perspectives, compares their properties, identifies their roles in the data mining process, gives strategies for selecting appropriate measures for applications, and identifies opportunities for future research in this area.

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