Neutrosophic Sets and Systems

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Review of Recommender Systems Algorithms Utilized in Social Networks based e-Learning Systems & Neutrosophic System

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Abstract. In this paper, we present a review of different recommender system algorithms that are utilized in social networks based e-Learning systems. Future research will include our proposed our e-Learning system that utilizes Recommender System and Social Network. Since the world is full of indeterminacy, the neutrosophics found their place into contemporary research. The fundamental concepts of neutrosophic set, introduced by Smarandache in [21, 22, 23] and Salama et al. in [24-66].The purpose of this paper is to utilize a neutrosophic set to analyze social networks data conducted through learning activities.

Keywords: e-Learning , Social Networks , Recommender System , Neutrosophic System.

1 Introduction

The Internet shows great potential for enhancing collaboration between people and the role of social software has become increasingly relevant in recent years. A vast array of systems exist which employ users' stored profile data, identifying matches for collaboration. Social interaction within an online framework can help university students share experiences and collaborate on relevant topics. As such, social networks can act as a pedagogical agent, for example, with problem-based learning [1].Social networking websites are virtual communities which allow people to connect and interact with each other on a particular subject or to just ''hang out'' together online. Membership of online social networks has recently exploded at an exponential rate [2]. Recommender systems cover an important field within collaborative services that are developed in the Web 2.0 environment and enable user-generated opinions to be exploited in a sophisticated and powerful way. Recommender Systems can be considered as social networking tools that provide dynamic and collaborative communication, interaction and knowledge [3].

Course management systems (CMSs) can offer a great variety of channels and workspaces to facilitate information sharing and communication among participants in a course. They let educators distribute information to students, produce content material, prepare assignments and tests, engage in discussions, manage distance classes and enable collaborative learning with forums, chats, file storage areas, news services, etc. Some examples of commercial systems are Blackboard, WebCT and Top Class while some examples of free systems are Moodle, Ilias and Claroline. Nowadays, one of the most commonly used is Moodle (modular object oriented developmental learning environment), a free learning management system enabling the creation of powerful, flexible and engaging online courses and experiences [4,30].

The new era of e-Learning services is mainly based on ubiquitous learning, mobile technologies, social networks (communities) and personalized knowledge management. "The convergence of e-Learning and knowledge management fosters a constructive, open, dynamic, interconnected, distributed, adaptive, user friendly, socially concerned, and accessible wealth of knowledge". The

knowledge management tools such as community, social software, peer-to-peer and personalized knowledge management and are now commonly are being used in ubiquitous learning. Learners use these tools to generate and share ideas, explore their thinking, and acquire knowledge from other learners. Learners search and navigate the learning objects in this knowledge filled environment. However, due to the failure of indexing methods to provide the anticipated, ubiquitous learning grid for them, learners often fail to reach their desired learning objects [5]. The fundamental concepts of neutrosophic set, introduced by Smarandache [21, 22, 23] and Salama et al. in [24-66], provides a natural foundation for treating mathematically the
neutrosophic phenomena which exist pervasively in our real world and for building new branches of neutrosophic mathematics and computer applications.

This paper goes as follows: Section Two presents different Recommender Systems algorithms that can be utilized in e-Learning. Section three presents the C4.5 algorithm. Section four presents the K-means algorithm. Section five introduces the Support Vector Machines algorithm. Section six highlights the Apriori algorithm. Section seven presents the conclusion and future work.the notion of neutrosophics crisp set.

2 Recommender Systems

There is a need for Personal Recommender Systems in Learning Networks in order to provide learners with advice on the suitable learning activities to follow. Learning Networks target lifelong learners in any learning situation, at all educational levels and in all national contexts. They are community-driven because every member is able to contribute to the learning material. Existing Recommender Systems and recommendation techniques used for consumer products and other contexts are assessed on their suitability for providing navigational support in a Learner Networks..

3 C4.5

Systems that construct classifiers are one of the commonly used tools in data mining. Such systems take as input a collection of cases, each belonging to one of a small number of classes and described by its values for a fixed set of attributes, and output a classifier that can accurately predict the class to which a new case belongs.Like CLS and ID3, C4.5 generates classifiers expressed as decision trees, but it can also construct classifiers in more comprehensible ruleset form.

A. *Decision Trees*

Given a set S of cases, C4.5 first grows an initial tree using the divide-and-conquer algorithms follows:

- If all the cases in S belong to the same class or S is small, the tree is a leaf labeled with the most frequent class in S.

- Otherwise, choose a test based on a single attribute with two or more outcomes. Make this test the root of the tree with one branch for each outcome of the test, partition S into corresponding subsets according to the outcome for each case, and apply the same procedure recursively to each subset.

There are usually many tests that could be chosen in this last step. C4.5 uses two heuristic criteria to rank possible tests: information gain, which minimizes the total entropy of the subsets (but is heavily biased towards tests with numerous outcomes), and the default gain ratio that divides information gain by the information provided by the test outcomes.

B. *Ruleset Classifier*

Complex decision trees can be difficult to understand, for instance because information about one class is usually distributed throughout the tree. C4.5 introduced an alternative formalism consisting of a list of rules of the form "if A and B and C and ... then class X", where rules for each class are grouped together. A case is classified by finding the first rule whose conditions are satisfied by the case; if no rule is satisfied, the case is assigned to a default class.C4.5 rulesets are formed from the initial (unpruned) decision tree. Each path from the root of the tree to a leaf becomes a prototype rule whose conditions are the outcomes along the path and whose class is the label of the leaf. This rule is then simplified by determining the effect of discarding each condition in turn. Dropping a condition may increase the number N of cases covered by the rule, and also the number E of cases that do not belong to the class nominated by the rule, and may lower the pessimistic error rate determined as above. A hill-climbing algorithm is used to drop conditions until the lowest pessimistic error rate is found.To complete the process, a subset of simplified rules is selected for each class in turn. These class subsets are ordered to minimize the error on the training cases and a default class is chosen. The final ruleset usually has far fewer rules than the number of leaves on the pruned decision tree.The principal disadvantage of C4.5's rulesets is the amount of CPU time and memory that they require.

4 K-Means Algorithm

The k-means algorithm is a simple iterative method to partition a given dataset into a user specified number of clusters, k. This algorithm has been discovered by several researchers across different disciplines, most notably Lloyd [6], Forgey, Friedman and Rubin, and McQueen. A detailed history of k-means along with descriptions of several variations are given in [7]. Gray and Neuhoff [8] provide a nice historical background for k-means placed in the larger context of hill-climbing algorithms.The algorithm is initialized by picking k points in as the initial k cluster representatives or "centroids". Techniques for selecting these initial seeds include sampling at random from the dataset, setting them as the solution of clustering a small subset of the data or perturbing the global mean of the data k times. Then the algorithm iterates between two steps till convergence:

- Step 1: Data Assignment. Each data point is assigned to its closest centroid, with ties broken arbitrarily. This results in a partitioning of the data.
- Step 2: Relocation of "means". Each cluster representative is relocated to the center (mean) of all data points assigned to it. If the data points come with a probability measure (weights), then the relocation is to the expectations (weighted mean) of the data partitions.

The algorithm converges when the assignments (and hence the   values) no longer change.One issue to resolve is how to quantify "closest" in the assignment step. The default measure of closeness is the Euclidean distance, in which case one can readily show that the non-negative cost function

$$\sum_{i=1}^{n} \left(\arg\min_{j} \left\| x_i - c_j \right\|_2^2 \right)$$

,will decrease whenever there is a change in the assignment or the relocation steps, and hence convergence is guaranteed in a finite number of iterations. The greedy-descent nature of k-means on a non-convex cost also implies that the convergence is only to a local optimum, and indeed the algorithm is typically quite sensitive to the initial centroid locations.

A. Limitations
In addition to being sensitive to initialization, the k-means algorithm suffers from several other problems. First, observe that k-means is a limiting case of fitting data by a mixture of k Gaussians with identical, isotropic covariance matrices,

when the soft assignments of data points to mixture components are hardened to allocate each data point solely to the most likely component. So, it will falter whenever the data is not well described by reasonably separated spherical balls, for example, if there are non-covex shaped clusters in the data. This problem may be alleviated by rescaling the data to "whiten" it before clustering, or by using a different distance measure that is more appropriate for the dataset. For example, information-theoretic clustering uses the KL-divergence to measure the distance between two data points representing two discrete probability distributions. It has been recently shown that if one measures distance by selecting any member of a very large class of divergences called Bregman divergences during the assignment step and makes no other changes, the essential properties of k-means, including guaranteed convergence, linear separation boundaries and scalability, are retained [9]. This result makes k-means effective for a much larger class of datasets so long as an appropriate divergence is used.

k-means can be paired with another algorithm to describe non-convex clusters. One first clusters the data into a large number of groups using k-means. These groups are then agglomerated into larger clusters using single link hierarchical clustering, which can detect complex shapes. This approach also makes the solution less sensitive to initialization, and since the hierarchical method provides results at multiple resolutions, one does not need to pre-specify k either.The cost of the optimal solution decreases with increasing k till it hits zero when the number of clusters equals the number of distinct data-points. This makes it more difficult to (a) directly compare solutions with different numbers of clusters and (b) to find the optimum value of k. If the desired k is not known in advance, one will typically run k-means with different values of k, and then use a suitable criterion to select one of the results. For example, SAS uses the cube-clustering-criterion, while X-means adds a complexity term (which increases with k) to the original cost function (Eq. 1) and then identifies the k which minimizes this adjusted cost. Alternatively, one can progressively increase the number of clusters, in conjunction with a suitable stopping criterion. Bisecting k-means [10] achieves this by first putting all the data into a single cluster, and then recursively splitting the least compact cluster into two using 2-means. The celebrated LBG algorithm [8] used for vector quantization doubles the number of clusters till a suitable code-book size is obtained. Both these approaches thus alleviate the need to know k before-

hand.The algorithm is also sensitive to the presence of outliers, since "mean" is not a robust statistic. A preprocessing step to remove outliers can be helpful. Post-processing the results, for example to eliminate small clusters, or to merge close clusters into a large cluster, is also desirable. Ball and Hall's ISODATA algorithm from 1967 effectively used both pre- and post-processing on k-means.

5 Support Vector Machines

In today's machine learning applications, support vector machines (SVM) [11] are considered amust try—it offers one of the most robust and accurate methods among all well-known algorithms. It has a sound theoretical foundation, requires only a dozen examples for training, and is insensitive to the number of dimensions. In addition, efficient methods for training SVM are also being developed at a fast pace. In a two-class learning task, the aim of SVM is to find the best classification function to distinguish between members of the two classes in the training data. The metric for the concept of the "best" classification function can be realized geometrically.

Because there are many such linear hyperplanes, what SVM additionally guarantee is that the best such function is found by maximizing the margin between the two classes. Intuitively, the margin is defined as the amount of space, or separation between the two classes as defined by the hyperplane. Geometrically, the margin corresponds to the shortest distance between the closest data points to a point on the hyperplane. Having this geometric definition allows us to explore how to maximize the margin, so that even though there are an infinite number of hyperplanes, only a few qualify as the solution to SVM.The reason why SVM insists on finding the maximum margin hyperplanes is that it offers the best generalization ability. It allows not only the best classification performance (e.g., accuracy) on the training data, but also leaves much room for the correct classification of the future data.

There are several important questions and related extensions on the above basic formulation of support vector machines. SVM can be easily extended to perform numerical calculations. The first is to extend SVM to perform regression analysis, where the goal is to produce a linear function that can approximate that target function. Careful consideration goes into the choice of the error models; in support vector regression, or SVR, the error is defined to be zero when the difference between actual and predicted values is within an epsilon amount. Otherwise, the epsilon insensitive error will grow linearly. The support vectors can then be learned through the minimization of the Lagrangian. An advantage of support vector regression is reported to be its insensitivity to outliers.

Another extension is to learn to rank elements rather than producing a classification for individual elements [12]. Ranking can be reduced to comparing pairs of instances and producing a +1 estimate if the pair is in the correct ranking order, and −1 otherwise. Thus, a way to reduce this task to SVM learning is to construct new instances for each pair of ranked instance in the training data, and to learn a hyperplane on this new training data. This method can be applied to many areas where ranking is important, such as in document ranking in information retrieval areas.

6 The Apriori algorithm

One of the most popular data mining approaches is to find frequent itemsets from a transaction dataset and derive association rules. Finding frequent itemsets (itemsets with frequency larger than or equal to a user specified minimum support) is not trivial because of its combinatorial explosion. Once frequent itemsets are obtained, it is straightforward to generate association rules with confidence larger than or equal to a user specified minimum confidence.Apriori is a seminal algorithm for finding frequent itemsets using candidate generation [13]. It is characterized as a level-wise complete search algorithm using anti-monotonicity of itemsets, "if an itemset is not frequent, any of its superset is never frequent". By convention, Apriori assumes that items within a transaction or itemset are sorted in lexicographic order. Apriori first scans the database and searches for frequent itemsets of size 1 by accumulating the count for each item and collecting those that satisfy the minimum support requirement. It then iterates on the following three steps and extracts all the frequent itemsets.

Many of the pattern finding algorithms such as decision tree, classification rules and clustering techniques that are frequently used in data mining have been developed in machine learning research community. Frequent pattern and association rule mining is one of the few exceptions to this tradition. The introduction of this technique boosted data mining research and its impact is tremendous. The algorithm is quite simple and easy to implement. Experimenting with Apriori-like algorithm is the first thing that data miners try to do.

Since Apriori algorithm was first introduced and as experience was accumulated, there have been many attempts to devise more efficient algorithms of frequent itemset mining. Many of them share the same idea with Apriori in that they generate candidates. These include hash-based technique, partitioning, sampling and using vertical data format. Hash-based technique can reduce the size of candidate itemsets. Each itemset is hashed into a

corresponding bucket by using an appropriate hash function. Since a bucket can contain different itemsets, if its count is less than a minimum support, these itemsets in the bucket can be removed from the candidate sets. A partitioning can be used to divide the entire mining problem into n smaller problems. The dataset is divided into n non-overlapping partitions such that each partition fits into main memory and each partition is mined separately. Since any itemset that is potentially frequent with respect to the entire dataset must occur as a frequent itemset in at least one of the partitions, all the frequent itemsets found this way are candidates, which can be checked by accessing the entire dataset only once. Sampling is simply to mine a random sampled small subset of the entire data. Since there is no guarantee that we can find all the frequent itemsets, normal practice is to use a lower support threshold. Trade off has to be made between accuracy and efficiency. Apriori uses a horizontal data format, i.e. frequent itemsets are associated with each transaction. Using vertical data format is to use a different format in which transaction IDs (TIDs) are associated with each itemset. With this format,taking the intersection of TIDs can perform mining. The support count is simply the length of the TID set for the itemset. There is no need to scan the database because TID set carries the complete information required for computing support.

The most outstanding improvement over Apriori would be a method called FP-growth (frequent pattern growth) that succeeded in eliminating candidate generation [14]. It adopts a divide and conquer strategy by (1) compressing the database representing frequent items into a structure called FP-tree (frequent pattern tree) that retains all the essential information and (2) dividing the compressed database into a set of conditional databases, each associated with one frequent itemset and mining each one separately. It scans the database only twice. In the first scan, all the frequent items and their support counts (frequencies) are derived and they are sorted in the order of descending support count in each transaction. In the second scan, items in each transaction are merged into a prefix tree and items (nodes) that appear in common in different transactions are counted. Each node is associated with an item and its count. Nodes with the same label are linked by a pointer called node-link. Since items are sorted in the descending order of frequency, nodes closer to the root of the prefix tree are shared by more transactions, thus resulting in a very compact representation that stores all the necessary information. Pattern growth algorithm works on FP-tree by choosing an item in the order of increasing frequency and extracting frequent itemsets that contain the chosen item by recursively calling itself on the conditional FP-tree. FP-growth is an order of magnitude faster than the original Apriori algorithm.There are several other

dimensions regarding the extensions of frequent pattern mining. The major ones include the followings:

(1) incorporating taxonomy in items [15]: Use of Taxonomy makes it possible to extract frequent itemsets that are expressed by higher concepts even when use of the base level concepts produces only infrequent itemsets.

(2) incremental mining: In this setting, it is assumed that the database is not stationary and a new instance of transaction keeps added. The algorithm in [16] updates the frequent itemsets without restarting from scratch.

(3) using numeric valuable for item: When the item corresponds to a continuous numeric value, current frequent itemset mining algorithm is not applicable unless the values are discretized. A method of subspace clustering can be used to obtain an optimal value interval for each item in each itemset [17].

(4) using other measures than frequency, such as information gain or value: These measures are useful in finding discriminative patterns but unfortunately do not satisfy anti-monotonicity property. However, these measures have a nice property of being convex with respect to their arguments and it is possible to estimate their upperbound for supersets of a pattern and thus prune unpromising patterns efficiently. Apriori SMP uses this principle [18].

(5) using richer expressions than itemset:Many algorithms have been proposed for sequences, tree and graphs to enable mining from more complex data structure [19].

Closed itemsets: A frequent itemset is closed if it is not included in any other frequent itemsets. Thus, once the closed itemsets are found, all the frequent itemsets can be derived from them. LCM is the most efficient algorithm to find the closed itemsets [20].

7 Neutrosophic System

The first input parameter to the neutrosophic variable "the number Clusters" has three membership function (Y) , non-membership(N) and indeterminacy(I) of n is illustrated in Figure 1.
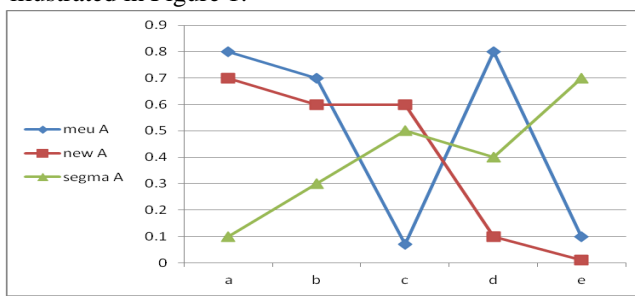
Figure 1: Membership function, non-membership and indeterminacy of neutrosophic set with variable n.

The input neutrosophic variable "the frequency of Subject Items" has the membership functions , non-membership and indeterminacy of f is showed in formulation (1)

$$f = \begin{cases} \text{yes} & \text{the key item is constant} \\ \text{no} & \text{the subject item is variable} \\ \text{Indeterminacy} & \text{non(yes, no)} \end{cases}$$

Formula 1

The output neutrosophic variable "Subject Items" has neutrosophic sets. It should be noted that modifying the membership functions, non-membership and indeterminacy will change the sensitivity of the neutrosophic logic system's output to its inputs. Also increasing the number of neutrosophic sets of the variables will provide better sensitivity control but also increases computational complexity of the system. Table 1 and Figure 2 show the rules used in the neutrosophic system.

Table 1: The neutrosophic system rules

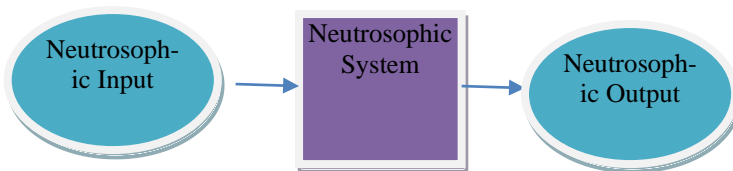| Cluster	membership functions	non-membership	indeterminacy
1	Y	N	I
2	N	I	Y
3	I	Y	N
4	Y	N	I

Figure 2: show the graph neutrosophic system.

The Neutrosophic System Equation Given by :

$$A \circ R = B \text{ Such That}$$

A : Represent Neutrosophic Data input for e-Learning System .

R : Represent Processing Neutrosophic System Data .

A :Represent Recommendation Subject for Students .

The output of that system determines the number of Subject Items Recommended. This determination is based on the NS analysis whish passes the three   parameters of $A = \langle \mu_A(x), \sigma_A(x), \nu_A(x) \rangle$ where $\mu_A(x), \sigma_A(x)$ and $\nu_A(x)$ which represent the degree of membership function (namely $\mu_A(x)$), the degree of indeterminacy (namely $\sigma_A(x)$), and the degree of non-member ship (namely $\nu_A(x)$) respectively of each element $x \in X$ to the set A where

$$0^- \leq \mu_A(x), \sigma_A(x), \nu_A(x) \leq 1^+ \qquad \text{and}$$

$0^- \leq \mu_A(x) + \sigma_A(x) + \nu_A(x) \leq 3^+$, then based on that analysis the system decides the accurate key size in each situation.

8 Conclusion and Future Work

In this paper, we presented the importance of social networks in e-Learning systems. Recommender systems play important roles in e-Learning as they help students to chose among different learning objects to study and activities to participate in. Among the different objects and activities available, recommender systems can chose between different algorithms. Presented algorithms in this paper are: C4.5, K-Means, Support Vector Machine, and Apriori algorithms. Each of those algorithms fit into a certain functionality of the recommender system. Future work will include comparison between other important machine learning algorithms, and our proposed e-Learning model that utilizes different machine learning algorithms for social network supported e-Learning. We have presented a proposed effective e-Learning system that utilizes a newly presented neutrosophic data set in analyzing social network data integrated in e-Learning. Identifying relationships between students is important for learning. Future work include incorporating the results we have achieved in customizing course contents to students, and recommending new learning objects more suitable for personalized learning.

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