IJCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Volume-2, Issue-11 E-ISSN: 2347-2693

Decision Models for Record Linkage Using OCCT-One Class Clustering Tree

D. Angelin Ponrani

Dept. of CSE, Kongunadu College Of Engineering &Technology, Trichy, Tamilnadu, India

www.ijcseonline.org

Received: 04 Nov 2014 Revised: 12 Nov 2014 Accepted: 20 Nov 2014 Published: 30 Nov 2014

Abstract— Record linkage is traditionally performed among the entities of same type. It can be done based on entities that may or may not share a common identifier. In this paper we propose a new linkage method that performs linkage between matching entities of different data types as well. The proposed technique is based on one-class clustering tree that characterizes the entities which are to be linked. The tree is built in such a way that it is easy to understand and can be transformed into association rules. The inner nodes of the tree consist of features of the first set of entities. The leaves of the tree represent features of the second set that are matching. The data is split using two splitting criteria. Also two pruning methods are used for creating one-class clustering tree. The proposed system results better in performance of precision and recall.

Keywords— Linkage, Clustering, Splitting, Decision Tree

I. INTRODUCTION

Record linkage is a process of identifying different data items that refer to the same entity among different data sources. The main goal of record linkage is to join datasets that do not share a foreign key or a common identifier. Record linkage is usually performed to reduce the large data into smaller data. It also helps in removing duplicate records in the datasets. This technique is known as data deduplication. The record linkage can be divided into two types: deterministic record linkage and probabilistic record linkage. Deterministic record linkage is the simplest record linkage and it is also known as rules-based record linkage. Probabilistic record linkage is also known as fuzzy matching.

Record linkage can also be divided into: one-to-one and one-to-many record linkage. In one-to-one record linkage, an entity from one dataset has a single matching entity in another dataset. In one-to-many record linkage, an entity from first dataset has a group of matching entities from another dataset. Most of the previous works focuses on one-to-one record linkage.

In this paper, a new record linkage method which performs one-to-many linkage is proposed. This method links the entities using a One-Class Clustering Tree (OCCT) [1]. A clustering tree is a tree in which each of the leaves contains a cluster whereas a normal tree consists of a single classification. Each cluster in the clustering tree is generalized by a set of rules. The OCCT can used in different domains like fraud detection, recommender systems and data leakage prevention. In fraud detection domain, the main aim is to find the fraudulent users. In recommender systems domain, the proposed system can be used for matching new users with their product expectations. In data leakage prevention domain, the main aim is to detect the abnormal access to the database records that indicates data leakage or data misuse.

Corresponding Author: D. Angelin Ponrani

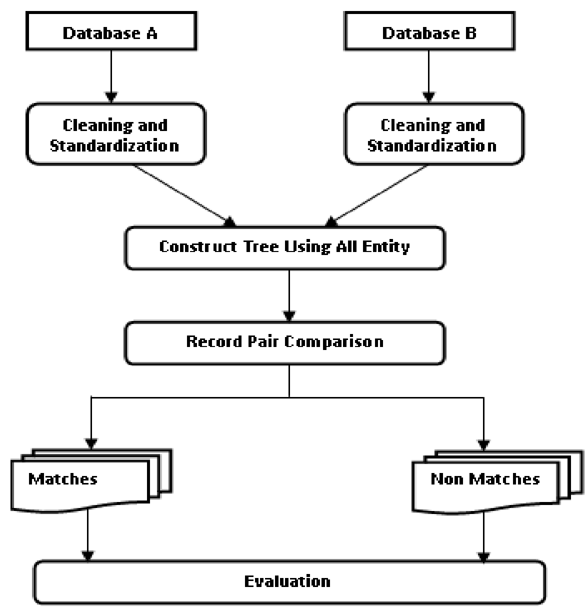


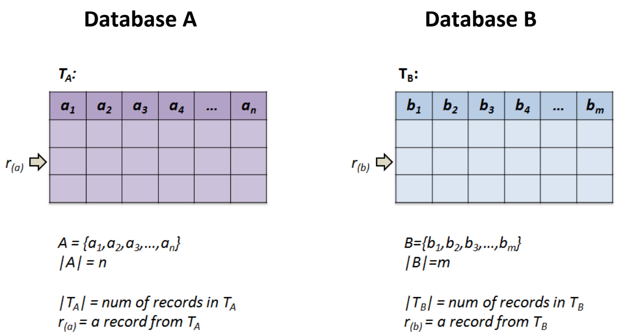
Fig 1: Outline of general record linkage process

The contribution of the proposed work is it allows performing one-to-many linkage between entities of same or different types. Another main advantage of the proposed system is using a one-class approach. Fig 1 describes the general outline of the record linkage process.

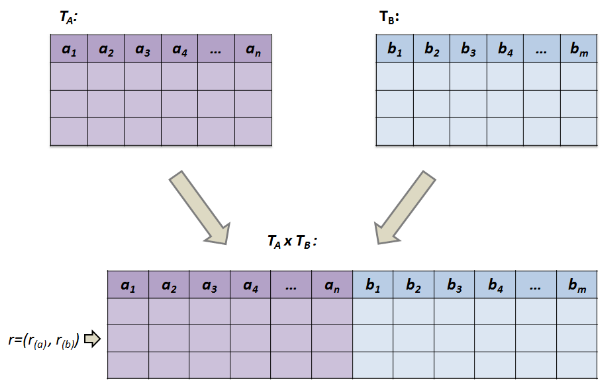
II. RELATED WORK

Record linkage is a process of matching entities from two different data sources that may or may not share a common identifier (i.e., foreign key). One-to-one record linkage was implemented using algorithms like SVM classifier, Maximum Likelihood Expectation and performing behavior analysis [2]. These methods assume that entities in the datasets are linked and try to match records that refer to the same entity.

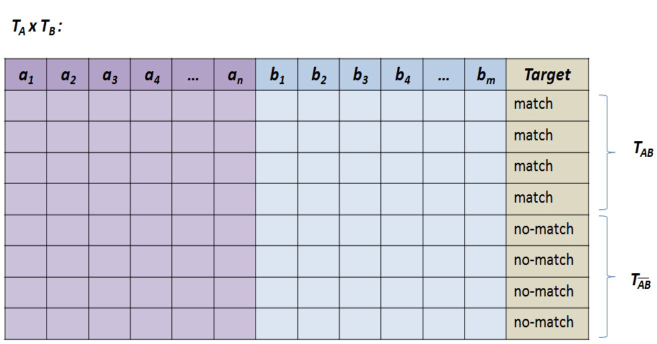
Only a few previous works have dealt about one-to-many record linkage. Storkey et al. [3] used the Expectation Maximization algorithm for two purposes. They are, calculating the probability of a given record pair that is matched and to learn the characteristics of the matched records. A Gaussian mixture model was used to model the conditional magnitude distribution. The drawback in this system is no evaluation was conducted on this work.



Merging of Database A and B

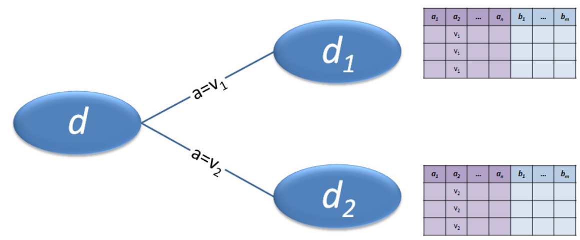


To find Matching and Non-matching Entities



Splitting the root of the tree

$$Split_a\left(T_{AB}^{(d)}\right) = T_{AB}^{(d)(a)}$$



Ivie et al. [4] used one-to-many linkage for genealogical research. In that work, data linkage was performed using five attributes: a person's name, gender, date of birth, location and the relationships between the persons. Using these five attributes a decision tree was induced. The drawback of this approach is that it performs matching using specific attributes and therefore it is very hard to generalize.

Christen and Goiser [5] used a C4.5 decision tree to determine which records must be matched to one another. In their work, different string comparisons methods are built and compared using different decision trees. However, their method performs the matching of attributes that are only predefined. Moreover only one or two attributes are usually used. In this paper, we propose a new record linkage method that performs one-to-many linkage that match entities of different data types along with the time calculation for the linkage process. The inner nodes of the tree consist of attributes that are in both of the tables being matched (TA and TB). The leaves of the tree will determine whether a pair of records described in the end of the tree with the current leaf as a match or non-match.

Decision trees are used for regression tasks and for classification. However, the training set used for the induction of tree must not be unlabeled. Yet, acquiring a labeled dataset is a costly work. Therefore, we thought that using examples of one class in a decision model is highly preferable than using training set with labeled dataset.

When compared with traditional decision trees, clustering trees are different based on their structure [6]. In traditional decision trees, each node represents a single classification. Whereas, in clustering trees, each node represents a cluster or a concept. The tree on the whole can be considered as a hierarchy. Then, each leaf of the tree is characterized by a logical expression, which represents the instances that belongs to it. The OCCT is a decision model which resembles to a clustering tree. It is a one-class model that learns and represents only positive examples. This method differs from other clustering trees by linking two different data types.

III. LINKAGE MODEL INDUCTION

In the proposed method, linkage model induction is the first step. The linkage model gets the knowledge about records that are expected to match each other. The process includes deriving the structure of the tree. The tree building requires the decision of which attributes must be selected at each level of the tree. The inner nodes of the tree consist of attributes from table TA. The selection of attributes is actually done by using any one of the splitting criteria. The splitting criteria ranks the attributes based on their clustering of matching examples.

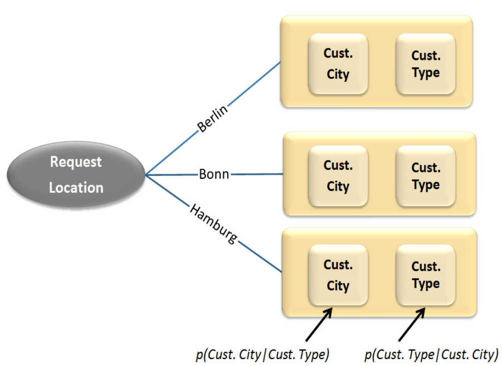
A pre-pruning approach is implemented in this proposed method. When using this approach, the algorithm stops expanding a branch whenever the sub-branch does not improve the accuracy of the given model. The inducer is actually trained with matching examples only.

The OCCT can be derived using any one of the splitting criteria. The splitting criterion is used to determine which attribute must be used in each step of constructing the tree. Our main goal is to achieve a tree that contains less number of nodes, as smaller trees easily generalize the data by avoiding over fitting. It will also be simpler for the human eyes to understand the tree structure [7].The two types of splitting criteria used in this system are: Maximum Likelihood Estimation (MLE) and Least Probable Intersections (LPI).

A. Maximum Likelihood Estimation (MLE):

This particular splitting criterion uses the Maximum Likelihood Estimation (MLE) [8] for choosing the attribute that is most appropriate to serve as the next splitting attribute for the forthcoming attributes that are yet to be split. We aim to choose the split that achieves the maximum likelihood and hence we choose the attribute that has the highest likelihood score as the next splitting criterion in the tree.

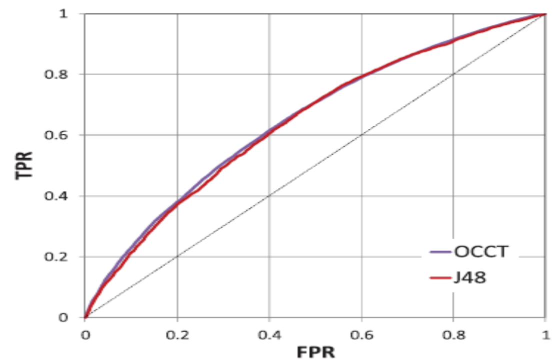
The computational complexity of building a decision model using the MLE method is dependent on the complexity of building the model and time taken to calculate the likelihood. The complexity varies according to the method chosen for representing the model, size of the input dataset and to the number of attributes.



MLE Splitting the root of the tree

B. Least Probable Intersections (LPI):

Gershman et al. [9] proposed an optimal splitting criterion which relies on cumulative distribution function (CDF). In this method, the main aim is to find a splitting attribute which has least amount of identifiers that are shared. That splitting attribute must be least probable to generate the subsets randomly. Hence, the splitting attribute with highest score is chosen as the next attribute for the split. The consecutive splitting attribute of the tree would be the attribute which has achieved the highest score.



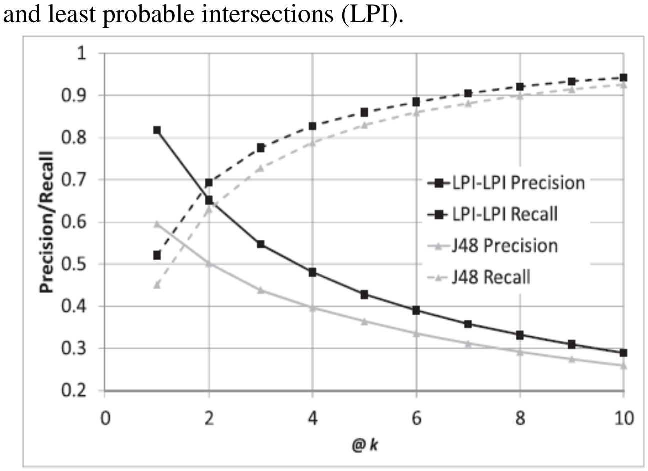
ROC graphs of the OCCT (when using MLE as the splitting criteria and MLE for pruning) and the J48 algorithms.

In terms of computational complexity, building a tree using the LPI method is found to be cheap when compared with other methods.

C. Pruning:

In a tree induction process, pruning is considered to be an important task. The necessity of using pruning is to build a tree with accuracy and also to avoid overfitting. Pruning can be done in two ways: pre-pruning and post-pruning. In pre-pruning, the branches are pruned during the induction process if there are no possible splits found. In post-pruning, the tree is built completely followed by a bottom-up approach to determine which branches are not beneficial.

In our system we have followed a pre-pruning approach. It was chosen for the reason that it reduces the time complexity of the algorithm. The decision to prune the branch or not is taken once the next attribute for split is chosen. In this proposed system, two pre-pruning methods are used. They are maximum likelihood estimation (MLE) and least probable intersections (LPI).



IV. LINKAGE USING OCCT

Linkage is a process in which a pair is determined match or not. During this phase, each possible pair of test records is tested against the linkage model to determine if the pair is a match or not.

Summary of the Splitting Criteria

Method	Advantages	Disadvantages
Coarse-grained Jaccard coefficient	- Low computational complexity	- Can only handle binary splits - Produces bias results when the attributes are not distributed uniformly
Fine-grained Jaccard coefficient	- Takes partial intersections into consideration - In some domains produces results which are significantly better than other criteria	- Can only handle binary splits - High computational complexity
Least probable intersections	- Can be used as a criterion for pruning - Can handle non-uniformly distributed attributes - Most durable to noise in the data	- Can only handle binary splits
Maximum Likelihood estimation	- Can handle multiple way splits - Can be used as a criterion for pruning	- Assumes that the attributes are independent with one another - High computational complexity (dependent on the type of probability model used)

This process results in calculating a score which represents the probability of the record pair if it is a true match. The initial score is calculated using maximum likelihood estimation [10].

The input to the algorithm is an instance from table A i.e., TA and an instance from table B i.e., TB. The output of this algorithm is a Boolean value determining whether the instances should be matched or not.

The likelihood score for a match between the records is calculated by using the probability of each value, given all other values and appropriate model.

Eventually, the determination of the given records is found match or not by comparing the likelihood score which was calculated earlier with the threshold value. The pair is found to be matched if the pair's score is greater than the threshold value. It is considered as a non-match if the pair's score is less than the threshold value.

Finally, the pairs that are found to be matched are listed in the output. Also the time taken for the linkage process is calculated and displayed in the output.

Overall Execution Time for the Fraud Detection Scenario (Millisecond)

Pruning \ Splitting	CGJ	FGJ	LPI	MLE
No pruning	137,908	682,303 7,537,885 (no clustering)	145,989	297,829
LPI	91,294	633,396	107,222	157,760
MLE	120,482	565,659	123,587	107,004

Executed on 64-bit Windows Server 2008 Enterprise ed., Intel Xeon CPU 1.6 Ghz, 2-Gb memory (RAM).

V. CONCLUSIONS AND FUTURE WORK

In this system we have represented a one class clustering tree approach which performs one-to-many record linkage. This method is based on a one class decision tree model which sums up the knowledge of which records to be linked together.

To summarize, this method allows performing one-to-many linkage while the traditional methods followed one-to-one linkage. Then, we have used a one-class approach which results in matching pairs are only required in the training set, as more number of non-matching (negative) pairs will confuse the model and it will lead to a less accurate model. Another advantage of using OCCT modle is that the solution can be easily transformed to rules.

The future work may include comparing the OCCT with the other data linkage methods. Also it can be extended to perform many-to-many linkage.

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