This is an Accepted Manuscript of an article published by Taylor & Francis in **Cybernetics and Systems** 46(1/2) : 19-34 (2015) on 24 Mar 2015, available at: https://doi.org/10.1080/01969722.2015.1007725.

Experiments of Trust Prediction in Social Networks by Artificial Neural Networks

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Social network online services are growing at an exponential pace, both in quantity of users and diversity of services; thus, the evaluation of trust in the interaction between users and towards the system is a central issue from the user point of view. Trust can be grounded in past direct experience or in the indirect information provided by trusted third party users shaping the trustee reputation. When there is no previous history of interactions, the truster must resort to some form of prediction to establish Trust or Distrust on a potential trustee. In this paper we deal with the prediction of trust relationships on the basis of reputation information. Trust can be positive or negative (Distrust), hence, we have a two class problem. Feature vectors for the classification have binary valued components. Artificial Neural Network and Statistical classifiers provide state-of-the-art results with these features on a benchmarking trust database. In this paper we propose the application of a sample generation method for the minority class in order to reduce some of the effect of class imbalance among Trust and Distrust classes. Specifically, the approach shows high resiliency to system growth.

KEYWORDS Trust, Social Networks, Artificial Neural Networks, Epinions, Wikipedia

1 INTRODUCTION

Trust prediction is becoming a central issue in many computational problems involving the interaction of agents through online services. These agents can be humans or autonomous computational entities. The Internet of Things is supported on trusted interactions (Artz and Gil 2007) (Chen et al. 2013) (Grieco 2013). We are specifically concerned with trust relations in social networks, where trust is a property of the relation among human agents, at the basis of community detection (Rebollo-Ruiz, Graña 2013). Trust can be built from a history of interactions between a pair of agents, but still the question of the cold start remains. What is the basic attitude of a truster regarding a trustee when there is no previous history of interactions? It can be inferred indirectly from user attributes, i.e. following some homophily reasoning (alike users like similar things), or it can be predicted from the trustee reputation. We have followed in this paper this later approach, formulating the problem as a two class (Trust, Distrust) classification problem, where the feature vectors are built from the Trust values communicated by trusted users about the trustee. Artificial Neural Network (ANN) and Support Vector Machine (SVM) approaches have been used for classification. The prediction performance achieved with approach suffers from the strong imbalance of the classes, because people are much more reluctant to define Distrust relations than Trust relations. We have dealt with this problem applying a sample generation technique, achieving some improvement of the results. The extensive experimentation reported gives some answers to the generality of the approach, as well as its resiliency to a difficult issue in current social networks: scalability to system growth.

The contents of the paper are as follows: Section 2 describes some related works. Section 3 describes summarily the classifier building techniques validated in the experiments. Section 4 describes the feature extraction process and the specific dataset built for the experiments. Section 5 describes the experimental design. Section 6 reports experimental results on the selected datasets. Section 7 provides our conclusions.

2 RELATED WORKS

In this section we give state of the art reviews of trust prediction and imbalance class problems.

2.1 Trust prediction in social networks

Trust is a central issue for users seeking online reliable interaction, whether it consists of information to make some decision, or simply social interaction (Jøsang 2007). However, user specified trust relations are very sparse, only a very small fraction of users do provide explicit trust information. Usually, social webservices allow users to specify publicly or to keep track in private of the trust or distrust on another users, thus creating to a Web of Trust (WoT) embedded in the social service. Examples of trust-aware services are online recommendation systems, or crowd-sourcing systems, such as Wikipedia. For instance, trust has been proposed to filter out controversial reviews (Victor et al. 2011), and to improve collaborative filtering in social networks (Chen et al. 2010) (Dang and Viennet 2013).

Supervised approaches Supervised systems perform feature extraction to train binary classifiers (Nguyen et al. 2009), (Liu et al. 2008)) for trust prediction. Feature extraction can include ancillary information (Liu et al. 2008) trying to cover all possible influences between users leading to trust. Specifically, in recommendations systems the information about ratings and review evaluations is used to complement the WoT graph features. Some works (Nguyen et al. 2009) elaborate on basic philosophical arguments (i.e. trust antecedent framework for ability, benevolence and integrity) to derive feature extraction procedures in recommendation systems. The classification data is strongly imbalanced, so that research into the effect of strategies to cope with this issue is an open research problem. It is also unclear whether the ancillary information is useful or a source of noise in the classification.

Unsupervised approaches The unsupervised approaches are either graph based methods of trust propagation or try to derive user similarity measures from ancillary information. An instance of graph based trust prediction (Al-Oufi et al. 2012) applies a capacity-first maximal flow algorithm to identify strong paths leading to trusted user groups. Also, (Bachi et al. 2012) performs graph mining to detect patterns that allow to derive rules for the completion of the ego-graph of one user with trusted users. Homophily is proposed (Tang et al 2013b) to regularize previous unsupervised approaches. Low rank matrix factorization searches for small dimension decompositions of the trust graph adjacency matrix, in fact looking for compact (trust) communities with early applications in collaborative filtering. Global and local information effect in matrix factorization approaches is examined in (Tang et al 2013). Generative models (Chua et al. 2013) try to discover the underlying communities by latent variable analysis. Finally, the Ant Colony Optimization approach is used in (Bedi and Sharma 2012) to perform trust propagation, including popularity modeling by pheromone accumulation.

2.2 Imbalanced classification problems

Classification problems are often imbalanced, that is, some classes are inherently more frequent than others, resulting in datasets with significantly more samples for some classes. Conventional classifier building approaches have the problem of bias towards the most frequent classes. In a Bayesian formulation, classifiers guided by the maximization of the overall accuracy are biased towards classes with the higher a priori probability. This implies that minority classes are underestimated. In many real life situations the minority classes are the interesting ones, such as in target detection, or anomaly detection problems.

Two ways of dealing with the issue of class imbalance have been developed in the machine learning community. One assigns different costs to training examples. Assuming that the minority class has a greater cost associated to error committed to it allows to drive the learning process towards its more accurate modeling. The other pre-processes the original dataset, either by over- sampling the minority class and/or under-sampling the majority class, such as the SMOTE process that will presented below (Chawla et al. 2002). Empirical studies on specific domains, such as software quality, are curried out nowadays (Seiffert et al. 2014).

A recent cost sensitive approach is (Krawczyk 2014) proposing a new cost-sensititive ensemble of decision trees. The approach performs an evolution based search for the optimal classifier selection and fusion. Base classifiers are cost-sensitive trees, performing local sequential search at each node. Another evolutionary algorithm approach to develop cost sensitive Boosted SVM (Zieba et al. 2014) are ensembles of SVM which are trained in a procedure alternating two steps: solving the optimal SVM problem for fixed weights of the data samples, and updating these weights in an external loop. Along these lines, (Maratea et al. 2014) propose the adjustment of the F-measure for the evaluation of the classification results while performing fine tuning of the kernel scaling in SVM based approaches. On the other hand, works on data resampling are less abundant. Recent evolutionary sampling techniques have been proposed (Garcia et al. 2012) in order to select the best representatives for generalized sample representation by hyper- rectangles. A heuristic method for selection of balanced datasets minimizing the majority class while maximizing the minority class is provided in (Wang et al. 2012).

3 CLASSIFIER BUILDING METHODS

In this section we give a short review of the classifier building methods, which are very well known in the literature, that have been applied in the experiments below. We have applied two ANN approaches, the Multi-Layer Perceptron (MLP) and the Radial Basis Function Network (RBFN), and a statistical classifier, the well-known SVM. We also describe the SMOTE data preprocessing aim to cope with imbalanced classification problems.

3.1 Multilayer Perceptron

The MLP architecture (Haykin 1998) consists of multiple layers, this allows solving problems that are not linearly separable, overcoming the main limitation of the original perceptron (also called single layer perceptron). The MLP can be totally or locally connected. In the first case each output of a neuron of layer "i" is input to all neurons of layer "i + 1" while every neuron in the second layer "i" is a number of input neurons (region) layer "i + 1". Each neuron unit performs the sum of its inputs and output is the application of a non-linear filter, usually a sigmoid function, to this value. Weight training minimizing the output error is performed by backpropagation of the error, which is well defined because of the shape of the activation function at each neuron. This backpropagation is analytically derived from the classical Chain Rule of derivation.

3.2 Radial Basis Function

The RBFN (Chen et al. 1991) are an ANN architecture whose input units activation functions are unnormalized Gaussian function, i.e. an exponential function of the distance of the input to a representative of data. The RBFN implies a clustering performed in the data space, resulting in a Voronoi tesselation, whose centers are the RBF units representatives. RBFs have been shown to be universal approximators, such as the MLP. The RBFN is composed of two layers, the RBF units at the input, and the output unit which is a linear combination of the activations at the input layer. Training of the input unit weights often is performed by clustering, while the output units weights are found by least squares solution of the linear equations posed by the training data fitting. We denote below as RBFC a gradient descent version of the RBFN.

3.3 Support Vector Machines

The SVM (Vapnik 1998) training looks for the set of support vectors that provide the greatest margin discriminant surface, i.e. SVM separates a given set of binary labeled training data with a hyperplane that is maximally distant from the two classes (known as the maximal margin hyperplane). When no linear separation of the training data is possible, SVMs can work effectively in combination with kernel techniques using the kernel trick, so that the hyperplane defining the SVMs corresponds to a non-linear decision boundary in the input space that is mapped to a linearized higher-dimensional space (Vapnik 1998). The kernel function chosen results in different kinds of SVM with different performance levels, and the choice of the appropriate kernel for a specific application is a difficult task. In this study two different kernels were tested: the linear and the radial basis function (RBF) kernel. This kernel is best suited to deal with data that have a class-conditional probability distribution function approaching the Gaussian distribution (Burges 1998). The RBF kernel is largely used in the literature because it corresponds to the mapping into an infinite dimension feature space, and it can be tuned by its variance parameter σ.

3.4 SMOTE

Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al. 2002) consists in the generation of new samples of the minority (less frequent) class in order to obtain a more balanced representation of the classes. Instead of performing a re-sampling with replacement from the original database, which only introduces repetitions of the already sampled points in the feature space, SMOTE performs a random linear interpolation processes in order to generate new sampling points in feature space. Mere replication of sampling points do not alter the decision boundary. This process can be tuned specifying the number of nearest neighbors. SMOTE can be used in combination with majority class under-sampling (removing samples). Notice that SMOTE may “fill the gaps” in data distributions that show disperse connected regions.

4 REPUTATION FEATURES

4.1 Epinions database

Epinions is a webservice where users provide reviews of products of any kind, from music and perfumes to construction hardware. The relations between users on these reviews conform a social network of recommenders, which is endowed with a Web of Trust (WoT) where users can specify whether they trust or distrust a reviewer. The aim of trust prediction would be to predict these trust/distrust relations.

Trust is a binary variable taking values in $\{-1,1\}$: a user can choose to trust (1) another or not (-1). Negative trust values are not published in the web service, but the anonymized dataset provided for computational experimentation, which is available to the public, contains also negative Trust values. This dataset has $841{,}372$ data samples. Each sample is a triplet (A,B,t_{AB}) composed of two user indexing numbers (no personal data of any form is included) and a binary Trust value: $t_{AB}=1$ if A trusts B, $t_{AB}=-1$ if A distrusts B. Therefore, the Trust relation defines a directed graph with weighted edges. The Epinions dataset is highly imbalanced: 85.3% of instances are positive trust (717,667 triplets), versus 14.7% negative trust instances (123,705 triplets). Also, the graph is very sparse. Epinions dataset has been used previously to perform computational experiments on Trust models (Massa and Avesani 2005), recommendation systems (Victor et al. 2011), and Trust prediction (Nguyen et al. 2009).

4.2 Reputation features

We extract reputation features from database. From the original database of trust triplets obtained from the Epinions WoT, we build experimental Reputation feature databases consisting on the observation of the Trust values of related users. Each database is made of samples composed of a feature vector of specific dimension and the desired trust value to be predicted. Figure 1 illustrates the construction of the feature vector for a given (A,B) pair.

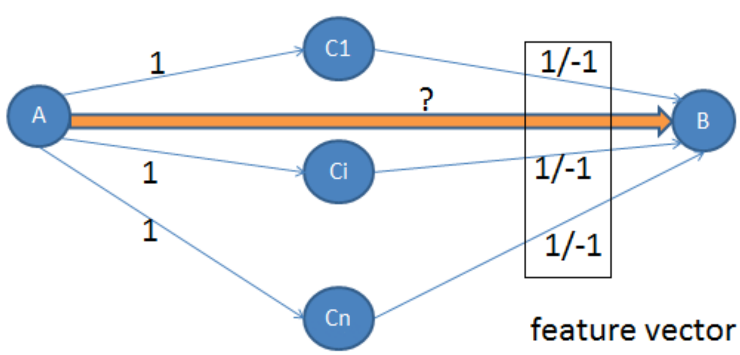

Figure 1: Trust reputation feature vector construction

The node A queries its trusted peers C_i about their trust on target trustee B. Construction of the experimental database is formalized as follows: For each triplet (A,B,t_{AB}) we construct a list of witness users $L_{AB}=\{C|(A,C,t_{AC})\in D\wedge(C,B,t_{CB})\in D\}$, where D denotes the original database of triplets. For a fixed feature vector dimension, i.e. d, we discard the triplet if $|L_{AB}|<d$. If $|L_{AB}|>d$, we perform a random selection of d witness nodes C obtaining L^{*}_{AB} such that $L^{*}_{AB}=d$. The reputation feature input/output pair (X,Y) corresponding to triplet (A,B,t_{AB}) is constructed such as $X=\{t_{CB}|C\in L^{*}_{AB}\}$ and $Y=t_{AB}$. For $d=10$,the Epinions reputation feature database has 210,999 samples with 9.98% of class "-1" and 90.02% of class "1". We build from this dataset another of reduced dimension $d=3$ by selecting randomly the components of this reputation vector.

5 EXPERIMENTAL DESIGN

The computational experiments have been designed trying to answer the following questions:

- How well the ANN classifiers would generalize trust prediction? This question is addressed by the application of cross-validation methodology, ensuring that the test set is fully independent of the training set.
- How sensitive are ANN to the future growth of the social database? To answer this question, we have applied several partitions of the data into folds. The smaller partitions, such as 2-fold cross-validation, correspond to the situation where the size of the database is expected to double. On the other hand, the larger number of folds, i.e. 20-fold cross-validation, correspond to the situation where database size increase is marginal. Specifically, we make a 2, 5, 10, 15 and 20-fold cross

validation experiments.

- What is the influence of pre-processing procedures, such as SMOTE, on the generalization results, especially in the minority class of distrusted relations? For this question, we have repeated all the experiments with and without SMOTE preprocessing.

Performance measures reported in the experimental results section are the Precision and Recall measures, defined as PRECISION =TP/(TP+FP) and RECALL =TP/(TP+FN), respectively. Recall is the classifier true positive prediction ratio relative to the entire positive class data, while Precision is the classifier true positive prediction ratio relative to the total positive predictions. Minority classes suffer from small recall and precision values in imbalanced classification problems.

6 EXPERIMENTAL RESULTS

The figures in this section contain plots of average Precision and Recall for varying number of folders in the cross-validation process. As said before, small number of folds can be interpreted as expecting a greater growth of the database between training and operational phases. A crucial question, because we want to assess whether predictors built at one moment in time will remain valid in the future. Plots refer to different classifiers (MP=Multi-Layer Perceptron, SVM=Support Vector Machine, RBFC=Radial Basis Function Conjugate training, RBFN=k-means plus LSE) and feature vector dimension (d=3 or d=10). Notice that the range of values changes from one plot to another. We have restricted them in order to highlight the differences between classifiers.

The first collection of experiments is carried out without any balancing preprocessing of the dataset. Figures 2 and 3 provide plots of the Precision of the Trust and Distrust classes, respectively, while figures 4 and 5 provide plots of the Recall of the Trust and Distrust classes, respectively. The second collection of experiments is carried out performing a SMOTE preprocessing of the dataset to improve imbalanced classes. Figures 6 and 7 provide plots of the Precision of the Trust and Distrust classes, respectively, while figures 8 and 9 provide plots of the Recall of the Trust and Distrust classes, respectively.

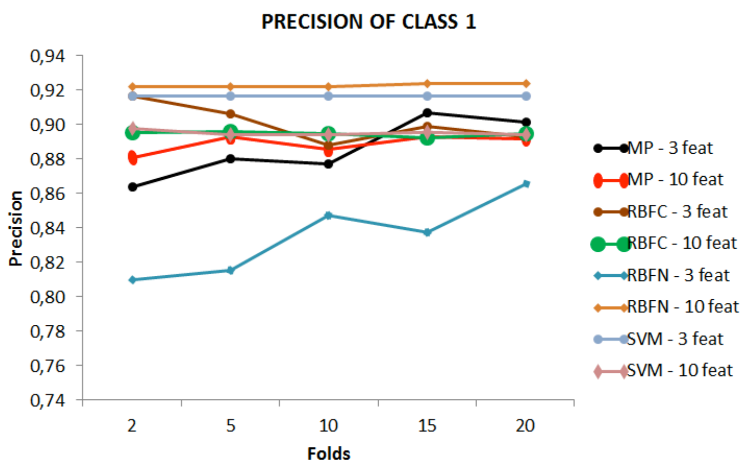

Figure 2: Average Precision of Trust prediction for diverse numbers of folders.

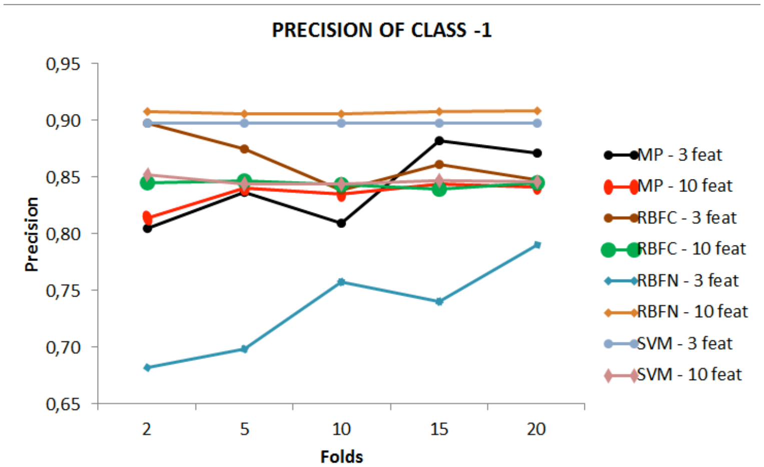

Figure 3: Average Precision of Distrust prediction for diverse numbers of folders.

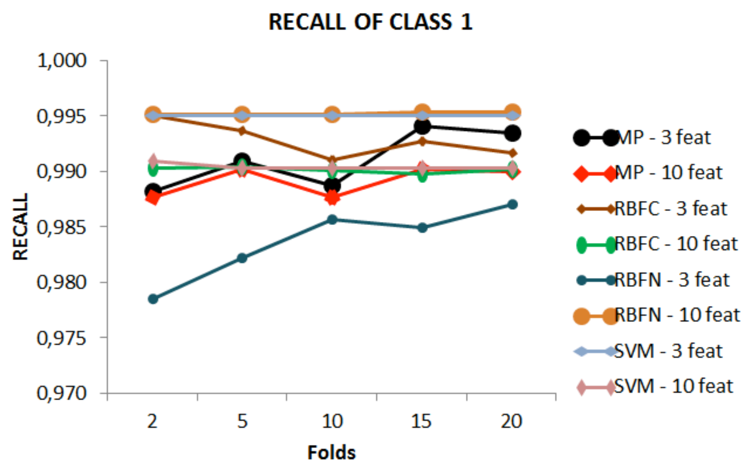

Figure 4: Average Recall of Trust prediction for diverse numbers of folders.

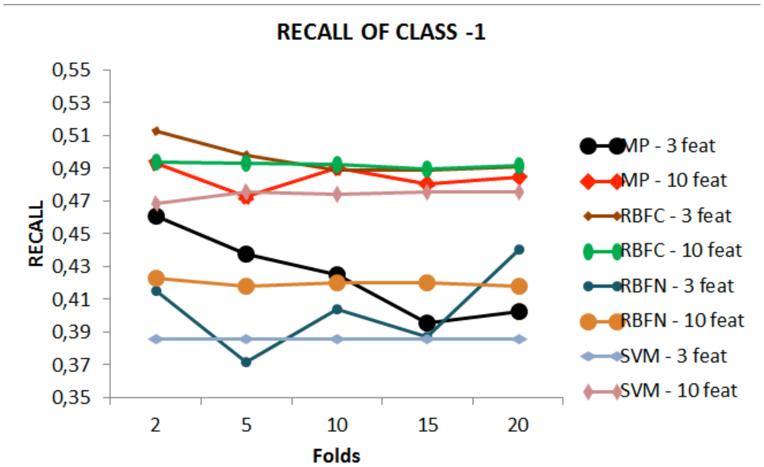

Figure 5: Average Recall of Distrust prediction for diverse numbers of folders.

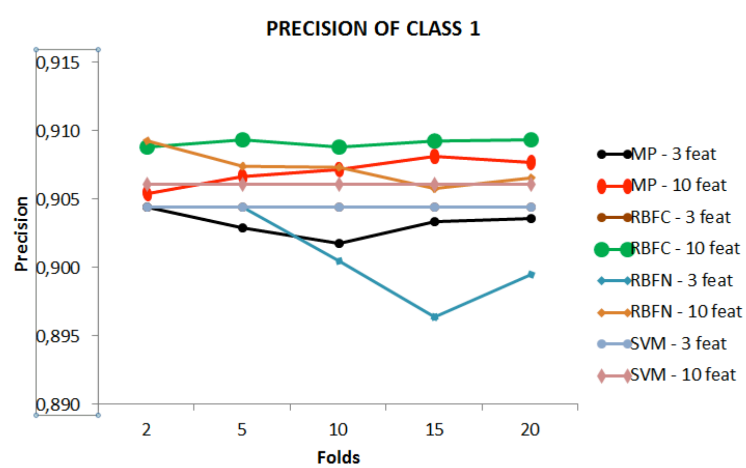

Figure 6: Average Precision of Trust prediction for diverse numbers of folders after

SMOTE preprocessing of the datasets.

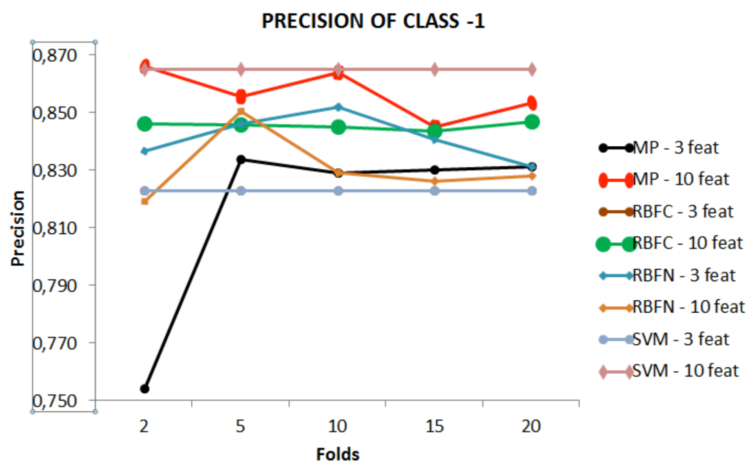

Figure 7: Average Precision of Distrust prediction for diverse numbers of folders after SMOTE preprocessing of the datasets.

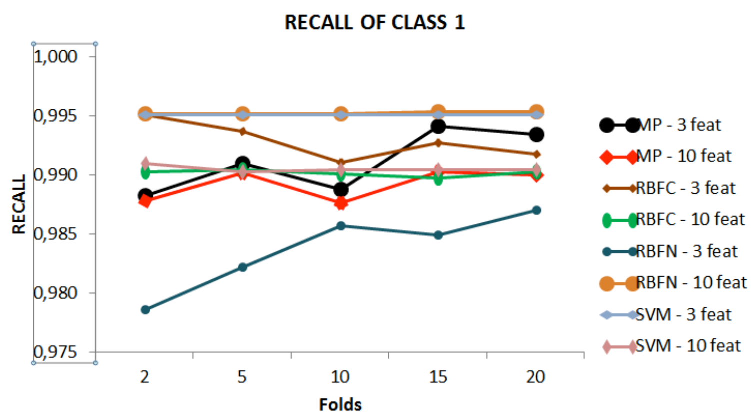

Figure 8: Average Recall of Trust prediction for diverse numbers of folders after SMOTE preprocessing of the datasets.

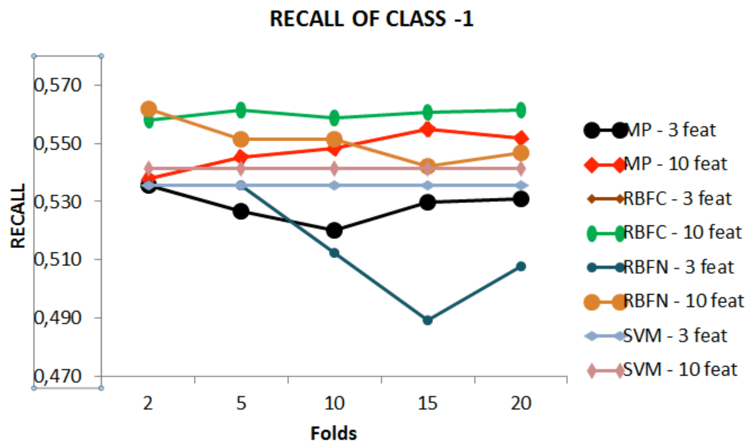

Figure 9: Average Recall of Distrust prediction for diverse numbers of folders after SMOTE preprocessing of the datasets.

Effect of class imbalance It is quite notorious comparing the Recall plots of class Trust with those of the class Distrust. Best Recall results for Distrust are below 60% while for Trust are above 97% in all cases, sometimes quite close to 100%. The difference in Precision between Trust and Distrust classes is not so dramatic, both are very high. Trust Precision is above 90% for many classifiers, while the Distrust Precision is 2% down in the best cases, and 10% in the worst cases.

Effect of SMOTE preprocessing Comparison of results with and without SMOTE preprocessing show that there is a small decrease in Precision for both Trust and Distrust classes, though at the same time there is an effect of compression of the classifier Precision results. Without SMOTE the interval between best and worst Precision results (removing some outliers) is about 6% for the Trust class and 10% for the Distrust class, while after SMOTE this interval is reduced to 2% for the Trust class and 4% for the Distrust class. SMOTE has almost no effect on the Recall of Trust class, but there is relatively strong effect on the Recall of the Distrust class: there is an increase of 7% of the best classifiers, and a big reduction of the interval between the best and worst classifiers, from more than 10% down to 3%. Therefore, SMOTE increases the robustness of both classifier and feature vector size. However, the effect of SMOTE is not uniform on all the classifiers. For instance, focusing in the MLP classifier with feature vectors of size 10 (red line), its ranking among the classifiers changes if SMOTE is applied in almost all plots. Another example of this variable effect is the change of ranking of the RBFN classifier in the plots of Distrust Recall.

Effect of feature vector size The comparison of plots for feature vector sizes 3 an 10 shows that there is a big effect of the number of features, in general towards worse results with the smaller set of features. However, there are some paradoxical results, such as the plots for Recall of the Trust class (with and without SMOTE) that show the reverse effect. This may be due a stronger bias towards the majority class with smaller feature vector. It seems that the SVM is the classifier less affected by this change of feature size. In general, it seems that 10 features is enough to obtain good results on the Trust class. However, the observation of the big performance gaps in the performance measures of the Distrust class suggest that increasing the feature size would improve results on this class.

Effect of classifier Regarding Precision of both classes and Trust Recall, the SVM provides the best results (with some exception in the Trust Precision after SMOTE). The SVM is quite robust to the number of features and cross- validation folders. Interestingly, in the most difficult issue of Distrust Recall the RBF and MLP provide better results and are more robust. This may point out to some kind of overfitting to the most frequent class by the SVM. However, this is not a general assessment of the performance of SVM as we are using linear kernel SVM.

Effect of the number of folders The number of folders in the cross-validation process is the way we have to pose the question: the classifier remains valid after the growth of the system? The smaller number of folders is 2, meaning that we expect the system to double in size for testing. It can be appreciated a general trend to improved results as the number of folders increases, meaning that most classifiers can cope with small additions to the system. In fact, for some plots this parameter seems to have the greatest effect. A very interesting result is the resiliency of SVM to this parameter: they show almost a flat response in all plots. In general, this is a very encouraging result, because it allows to expect that current studies will remain useful in the future. Interestingly, the MLP and RBF architectures also show this resiliency in the difficult Distrust Recall case, with and without SMOTE preprocessing.

Comparison with results in the literature Though a rigorous meta-analysis on the results found in the literature is difficult due to the diversity of approaches, performance measures and experimental details, we can refer some comparative results found on the Epinions database which show that the proposed approach is state-of-the-art. In (Tang et al 2013) the Accuracy reported for various sizes of training sets is in the order of 80% to 90%, which is roughly improved by the mean of Trust and Distrust Precisions reported here. Most of our results improve over the Precision reported in (Bachi et al. 2012) for Epinions dataset, which is below 90%. In the works of (Al-Oufi et al. 2012) the goal is to recover groups of trusted people, hence the definition of Precision and Recall is somewhat different because they refer to the percentage of the collection of *n* peers tested that are trustworthy, however their results are quite low compared with ours (maximum 20% Precision, 30% Recall). Best Precision reported in (Bedi and Sharma 2012) is below 90%.

7 CONCLUSIONS

In this paper we present the application of several ANN classifiers to the prediction of trust in social network systems. The approach is rather straightforward compared with other works in the literature: feature vectors are built as reputation vectors from the trustworthiness assertions of trusted users on the target trustee. Then, trust prediction becomes a two-class classification problem that can be directly solved by training on the feature dataset. The approach gives good results, though the problem suffers from the extreme imbalance of the classes. On a benchmark study on the Epinions data, we achieve good Precision results for both classes and encouraging results for the Recall of the less frequent Distrust class. Distrust Recall improves when applying SMOTE preprocessing. Interestingly, we found that classical ANN classifiers (MLP and RBF) achieved better results on the most difficult issue of Distrust Recall, pointing to some bias of the SVM. A rough comparison with state-of-the-art approaches is favorable to our definition of reputation features. Further work will involve testing new approaches to cope with imbalanced datasets, as well as other feature definitions. Also, other knowledge modeling approaches based on experience may be tested on this data such as (Artetxe et al. 2013), (Toro, Sanchez et al. 2012), (Toro, Vaquero et al. 2012), (Zhang et al. 2013).

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