IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

FUZZY PETRI NETS CONSTRUCTION FOR PREDICTING THE BANK-DEPOSIT PROFILES

S. Meher Taj*, A. Kumaravel
Department of Mathematics, AMET University, Chennai, Tamil Nadu, India.
School of Computing, Bharath University, Chennai, Tamil Nadu, India.

ABSTRACT
Fuzzy Petri nets are powerful specifications as they cover concurrency and control of impreciseness of any real time application domain .Researchers use this tool for interpreting the results obtained in data mining. Data mining helps marketing professionals improve their understanding of customer behavior. In turn, this better understanding allows them to target marketing campaigns more accurately and to align campaigns more closely with the needs, wants and attitudes of customers and prospects. In this paper, fuzzy Petri nets and classification mining techniques have been implemented using a real marketing data obtained from Portuguese marketing campaign related to bank deposit subscription The aim of this study is to predict whether a client will subscribe a term deposit.

KEYWORDS: Data mining, high level fuzzy Petri nets, classifications, selected attributes, search methods, WEKA, Marketing Data set.

INTRODUCTION
In deposit terminology, the term Bank Deposit refers to an amount of money in cash or checks form or sent via a wire transfer that is placed into a bank account. The target bank account for the Bank Deposit can be any kind of account that accepts deposits. For example, a Bank Deposit is generally made when opening an account or in the course of routine business or personal transactions that involve placing funds with the bank for future use.

Data mining is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and review the relationships identified. Data mining is developing into an intentionally important dimension for many business organizations including banking sector. It is a method of analyzing the data from different viewpoints and summarizing it into valuable information. Data mining assists the banks to look for hidden pattern in a group and discover unknown relationship in the data [1]. Accordingly, DM can be used to aid decision makers in banking sector to meet the economical pretense by avoiding risky transactions that cause bank attrition and increasing the customer retention incentives to raise the bank revenues [2, 3].

Data mining techniques are very useful to the banking sector for

- Better targeting and acquiring new customers
- Most valuable customer retention
- Analysis of the customers,
- Transaction patterns over time for better retention and relationship
- Risk management and marketing.

MATERIALS AND METHODS
2.1 Fuzzy Petri Nets (FPN): Petri Nets (PN) are a graphical and mathematical modeling tool applicable to many systems. There are promising tools for describing and studying information processing systems that are characterized as being concurrent, asynchronous, distributed, parallel, nondeterministic and/or stochastic [7]. Fuzzy Petri nets containing two types of nodes: places and transitions, where circles represent places and rectangle represent transitions. Each place represents an antecedent or consequent and may or may not contain a token associated with a

truth degree between zero and one which speaks for the amount of trust in the validity of the antecedent or consequent. Each transition representing a rule is associated with a certainty factor value between zero and one. The certainty factor represents the strength of the belief in the rule [8, 9]

2.1.2 Mapping the Rule Base to FPN:
Throughout this mapping technique, all principle is represented as transitions with its relating certainty factor and each antecedent is displayed by an input place and therefore the consequents are incontestable by an output place with scrutiny truth degrees. During this displaying a transition here a suggestion is enabled to be fired if its entire input place have a truth degree resembling or over a predefined limit esteem. After firing the rule, the output place can have a truth degree resembling the input place truth degree multiplied by the transition certainty factor.

2.1.1 Confidence factor:
The confidence factor used for pruning (smaller values incur more pruning). It determines the confidence value when the tree is pruned. Pruning is a way of reducing the size of the decision tree. This will reduce the accuracy on the training data, but (in general) increase the accuracy on unseen data. It is used to mitigate over fitting, where you would achieve perfect accuracy on training data.

2.2 DATA SET:
In this research, we use a real dataset which was collected from a Portuguese bank that used its own contact-center to do direct marketing campaigns in order to motivate and attract the deposit clients. The dataset is related to 17 marketing campaigns and corresponding to 79354 contacts [4,5].

There are two datasets:
1. Bank-full.csv that contains various examples corresponding to 45211records and ordered by date.
2. Bank.csv with 10%of the examples (4521record), randomly selected from bank-full.csv. However, it contains almost the all possible varieties for the attributes, values and objects instances.

The bank.csv data set was firstly used in the implementation phase as a test database; however it has been implemented in the form of relation database as seen below in the database implementation subsection.

2.2. 1 Data set Description
The data set consists of 16 non- empty conditional attributes and one decision attribute, where:

- age : age of the customer (Numeric)
- job : type of the job (categorical : admin, un employed, unknown, management, house maid, entrepreneur , student, blue - collar, self employed, retired, technician, services.
- marital : marital status(Categorical :married, divorced (means divorced or widowed), single)
- education : (Categorical: secondary, primary, and tertiary).
- default : has credit in default ?(binary :yes, no
- balance : Average yearly balance (numeric)
- housing : has housing loan ? (binary : yes, no)
- loan : has personal loan ? (binary : yes, no)
- contact : last contact of the current (Categorical :unknown, telephone, cellular
- day : last contact day of the month (numeric)
- month : last contact month of the year(Categorical : jan,feb,mar,……nov,dec)
- duration : last contact duration in seconds (numeric)
- campaign : number of contacts performed during this campaign for this client includes last contact (numeric).
- pdays : number of days that passed by after the client was last contacted from a previous campaign (numeric,-1 means client was not previously contacted)
- previous : number of contacts performed before this campaign for this client (numeric)
- poutcome : outcome of the previous marketing campaign (Categorical: unknown other, failure,success)
- Output attribute (desired target):

y – has the client subscribed a term deposit ? (binary: yes or no)

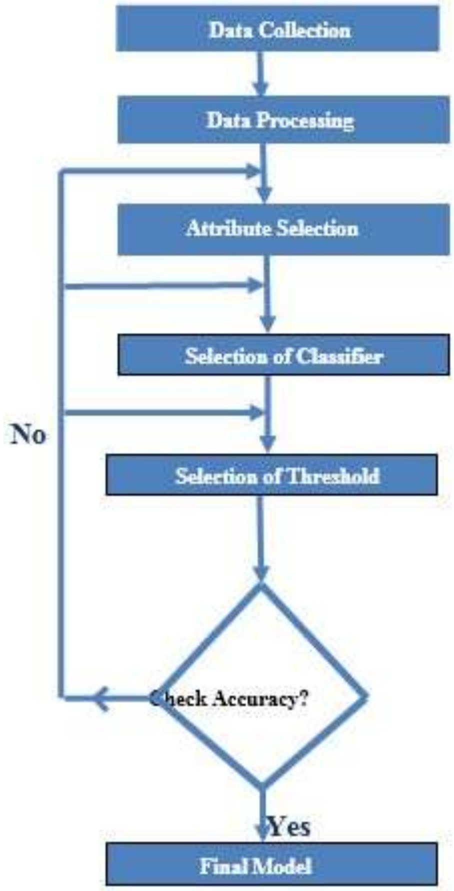

Fig 1: Main method Proposed

2.3 METHODOLOGY

We use different search methods; attribute evaluators, and classifier techniques in this paper.

Attribute evaluators [6]: The Attribute Evaluator is the method by which subsets of attributes are assessed. Various attribute evaluators are available in WEKA. We used (Weka, 3.7.11) a learning machine tool in this work which includes Cfs Subset Evaluator, Info Gain Attribute Evaluator, Correlation Attribute Evaluator, Gain ratio Attribute Evaluator, Relief F Attribute Evaluator, Symmetrical Uncert Attribute Evaluator.

(a)Cfs Subset Evaluator: Evaluates the worth of a subset of attributes by considering the individual analytical ability of each feature along with the degree of redundancy between them. Values subsets that correlate highly with the class value and low correlation with each other.

(b)Info Gain Attribute Evaluator: Evaluates the worth of an attribute by measuring the information gain with respect to the class.

InfoGain(Class, Attribute) = H(Class) – H(Class | Attribute).

(c)Correlation Attribute Evaluator: Evaluates the worth of an attribute by measuring the correlation (Pearson's) between it and the class. Nominal attributes are considered on a value by value basis by treating each value as an indicator. An overall correlation for a nominal attribute is arrived at via a weighted average.

(d)Gain ratio Attribute Evaluator: Evaluates the worth of an attribute by measuring the gain ratio with respect to the class.
GainR (Class, Attribute) = (H(Class) - H(Class|Attribute))/ H(Attribute).

(e)Relief F Attribute Evaluator: Evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. Can operate on both discrete and continuous class data.

(f)Symmetrical Uncert Attribute Evaluator:
Evaluates the worth of an attribute bymeasuring the symmetrical uncertainty with respect to the class.
SymmU(Class, Attribute) = 2 * (H(Class) - H(Class |Attribute)) / H(Class) + H(Attribute).

Search Method [6]: The Search Method is the structured way in which the search space of possible attribute subsets is navigated based on the subset evaluation.

(a)Best First: Searches the space of attribute subsets by greedy hill climbing augmented with a backtracking facility. Setting the number of consecutive non-improving nodes allowed controls the level of backtracking done. Best first may start with the empty set of attributes and search forward, or start with the full set of attributes and search backward, or start at any point and search in both directions (by considering all possible single attribute additions and deletions at a given point).

(b)Greedy Stepwise: Uses a forward (additive) or backward (subtractive) step-wise strategy to navigate attribute subsets. May start with no/all attributes or from an arbitrary point in the space. Stops when the addition/deletion of any remaining attributes results in a decrease in evaluation. Can also produce a ranked list of attributes by traversing the space from one side to the other and recording the order that attributes are selected.

(c)Ranker : It ranks attributes by their individual evaluations. Use in conjunction with attribute evaluators (Chi square, Gain Ratio, Info Gain etc).It's a kind of dummy search algorithm. It calls an attribute evaluator to evaluate each attribute not included in the start Set and then sorts them to produce a ranked list of attribute

Classifier: [6] All schemes for numeric or nominal prediction in Weka implement this interface.
(a)J Rip : This class implements a single rule that predicts specified class. A rule consists of antecedents "AND"ed together and the consequent (class value) for the classification. In this class, the Information Gain (p*[log(p/t) - log(P/T)]) is used to select an antecedent and Reduced Error Prunning (REP) with the metric of accuracy rate p/(p+n) or (TP+TN)/(P+N) is used to prune the rule.

(b)PART : Class for generating a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule.

EXPEREIMENTAL RESULT

The following tables show that we need to identify suitable combination of classifier attribute selection with accuracy level, mean absolute error ,AUC of ROC as maximum ,minimum, high respectively .Based on this optimal solution we choose two combination of classifier attribute selection. Firstly, the high accuracy 89.85%,low error 0.1605 and high ROC 0.694.Second one being the high accuracy 89.90%, low error 0.1615 and high ROC 0.685.The above two combinations generate the j rip rules .

Using CPN tool to show the below two combinations rules.

The first combination generate the following rules,

R1. (duration >= 251) and (duration >= 646) and (duration >= 796) => y=yes (203.0/87.0)
R2. (duration >= 213) and (poutcome = success) => y=yes (84.0/21.0)

R3.(duration >= 223) and (duration >= 384) and (duration >= 641) and (contact = cellular) and (duration <= 709) and (age = Low) => y=yes (26.0/9.0)
R4. => y=no (4208.0/325.0).

The second combination generate the following rules,

R1. (duration >= 344) and (duration >= 646) and (duration >= 775) => y=yes (214.0/93.0)
R2. (duration >= 222) and (poutcome = success) and (duration <= 633) => y=yes (71.0/15.0)
R3.(duration >= 213) and (duration >= 458) and (duration >= 639) and (duration <= 671) and (day <=18)=> y=yes (27.0/9.0)
R4. (duration >= 213) and (housing = no) and (month = oct) and (duration >= 251) => y=yes (21.0/4.0)
R5. (duration >= 213) and (housing = no) and (month = apr) and (day >= 21) and (duration >= 243) => y=yes (15.0/1.0)
R6. (duration >= 212) and (contact = cellular) and (month = jun) => y=yes (31.0/11.0)
R7. => y=no (4142.0/275.0)

The corresponding Petri net model is illustrated in Fig. 2. In the Petri net model [9,10], according to the proportions dedicated to each place, transitions 1 to 3 respectively represent rules 1 to 4 .In Fig.3 the Petri net model, according to the proportions dedicated to each place, transitions 1 to 6 respectively represent rules 1 to 7 in the introduced rule base above and firing each transition means the corresponding rule is fulfilled.

S.No	Search method	Attribute Evaluator	Classifier	Thrust hold value(if any)	Accuracy	No of Rules generated	Mean absolute Error	ROC Area
1.	Best First	Cfs Subset Evaluator	J Rip	-	89.76%	7	0.1678	0.666
2.	Greedy Stepwise	Cfs Subset Evaluator	J Rip	-	89.76%	7	0.1678	0.666
3.	Ranker	Info Gain Attribute Evaluator	J Rip	0.003	89.63%	8	0.1646	0.666
				0.004	89.43%	5	0.1631	0.687
				0.007	89.72%	6	0.1611	0.676
				-	89.94%	4	0.1600	0.436
4.	Ranker	Correlation Attribute Evaluator	J Rip	0.05	89.72%	8	0.1628	0.679
				0.06	89.72%	4	0.1655	0.673
				0.07	89.67%	7	0.1668	0.658
				-	89.12%	8	0.1674	0.668
5.	Ranker	Gain ratio Attribute Evaluator	J Rip	0.04	89.85%	4	0.1605	0.694
				0.05	89.34%	8	0.1674	0.673
				0.07	89.78%	7	0.1623	0.703
				-	89.83%	9	0.1630	0.682
6.	Ranker	Relief F Attribute Evaluator	J Rip	0.03	89.80 %	7	0.1615	0.685
				0.04	89.63 %	4	0.1641	0.673
				0.05	89.09%	8	0.1727	0.658
				-	89.50%	8	0.1641	0.665
7.	Ranker	Symmetrical Uncert Attribute Evaluator	J Rip	0.004	89.78%	6	0.1625	0.680
				0.006	89.60%	5	0.164	0.688
				0.007	89.52%	5	0.1622	0.677
				-	89.25%	6	0.1683	0.657

Table I - Evaluation of different feature selection methods based on J Rip Classifier

S.No	Search method	Attribute Evaluator	Classifier	Thrust hold value(if any)	Accuracy	No of Rules generated	Mean absolute Error	ROC Area
1.	Best First	Cfs Subset Evaluator	PART	-	89.36%	37	0.1507	0.813
2.	Greedy Stepwise	Cfs Subset Evaluator	PART	-	89.36%	37	0.1507	0.813
3.	Ranker	Info Gain Attribute Evaluator	PART	0.003	87.84%	133	0.1414	0.815
				0.004	87.79%	148	0.1455	0.811
				0.007	87.84%	143	0.1447	0.830
				-	88.21%	152	0.1343	0.811
4.	Ranker	Correlation Attribute Evaluator	PART	0.05	88.27%	157	0.1373	0.808
				0.06	88.63%	90	0.1485	0.795
				0.07	89.60%	46	0.1454	0.813
				-	88.50%	152	0.1333	0.806
5.	Ranker	Gain ratio Attribute Evaluator	PART	0.04	88.08%	135	0.1365	0.805
				0.05	88.32%	123	0.1392	0.806
				0.07	89.36%	106	0.1356	0.832
				-	88.21%	152	0.1342	0.812
6.	Ranker	Relief F Attribute Evaluator	PART	0.03	88.48%	144	0.1326	0.811
				0.04	88.72%	139	0.1325	0.829
				0.05	87.68%	133	0.1442	0.788
				-	87.81%	150	0.137	0.804
7.	Ranker	Symmetrical Uncert Attribute Evaluator	PART	0.004	87.28%	154	0.1454	0.780
				0.006	87.75%	185	0.1416	0.818
				0.007	89.36%	106	0.1356	0.832

Table II - Evaluation of different feature selection methods based on PART Classifier

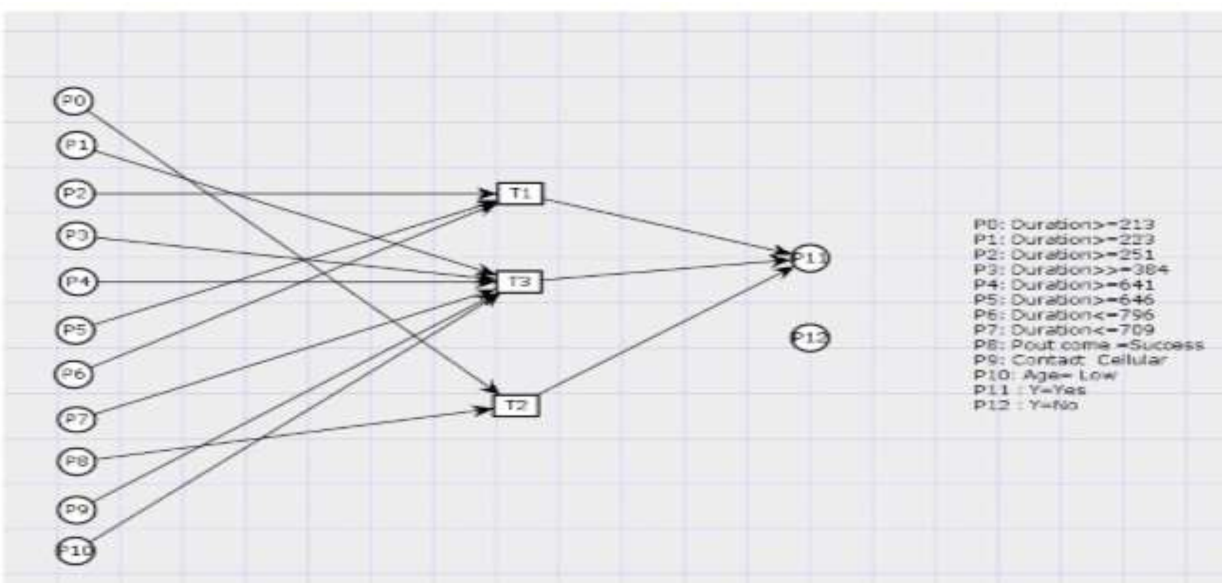

Fig : 1 CPN Tool Snapshot for bank deposit profiles

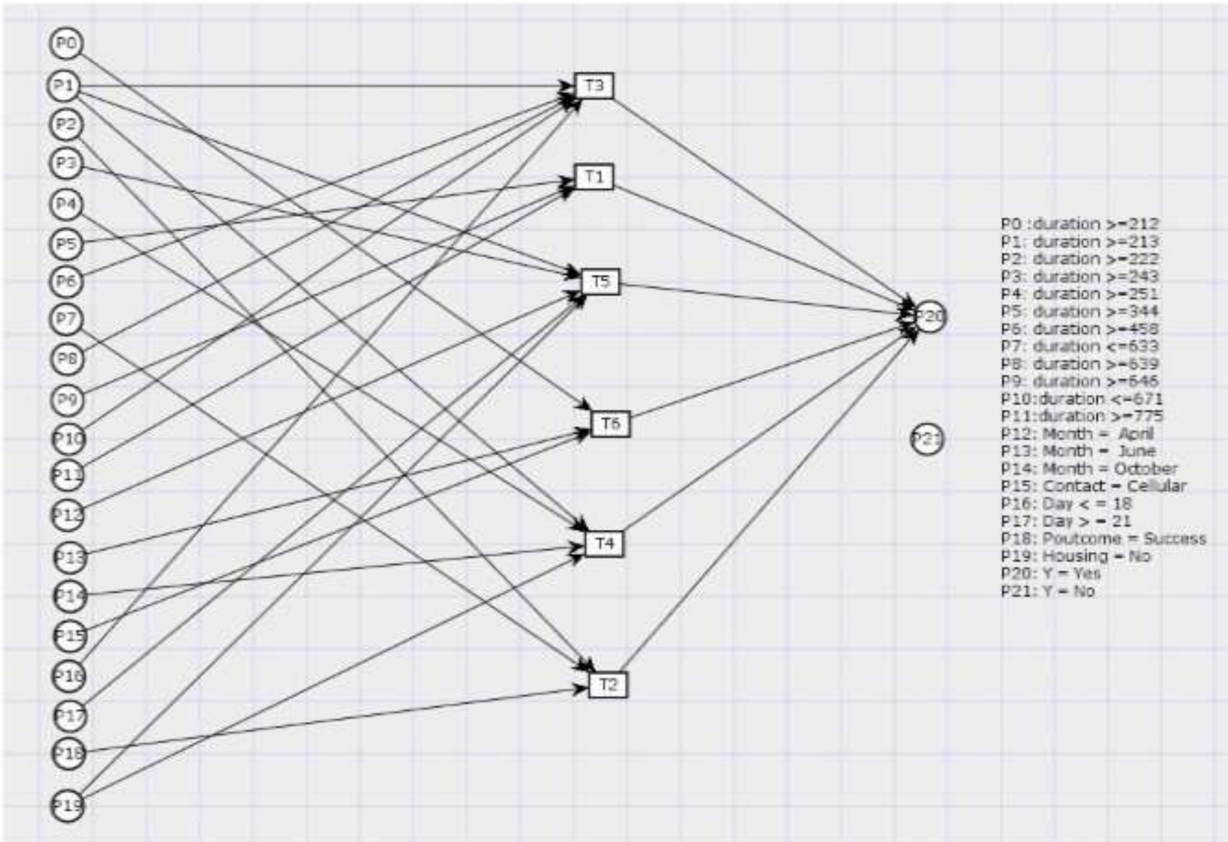

Fig.2: CPN Tool Snapshot for bank deposit profiles

CONCLUSION

We establish the connection of Petri net's behavior for implementing the decision rules. The context of bank services is selected for this purpose and obtained the results for potential customers for deposits. The specification of generated rules based on the data set gathered is not by colored Petri nets and the clarity is improved. Data mining tool like Weka is used to fit the appropriate set of rules with metrics in terms of support and confidence factors. Maximum accuracy around 89% is achieved by tuning parameters as well the attribute selection. For future one may go for different data size with more attributes of significance.

ACKNOWLEDGMENT

The first author would like to thank the management of AMET University for their support and encouragement for this research study.

REFERENCES

[1] Fathimathabasum (2006) Data Mining in Banks,Indiastudychannel.com, http://www.indiastudychannels.com/serve.php.
[2] Serhat Ö., A.Yilimza, Classification and predication in a data mining application , Journal of Marmara for Pure and Applied Sciences, 18 159-174 ,Marmara University, Printed in Turkey, 2002.
[3] BinhThanh Luong, Salvatore Ruggieri, Franco Turini, k-NN as an Implementation of Situation Testing for Discrimination Discovery and Prevention, KDD'11, San Diego, California, USA, 2011.
[4] S. Moro, R. Laureano and P. Cortez. Using Data Mining for Bank Direct Marketing: An Application of the CRISP-DM Methodology. In P. Novais et al. (Eds.), Proceedings of the European Simulation and Modelling Conference - ESM'2011, pp. 117-121, Guimarães, Portugal, October, 2011.
[5] http://hdl.handle.net/1822/14838.

[6] http://weka.sourceforge.net/doc.dev/weka/attribute Selection.
[7] Murata, T., 1989. Petri nets: Properties, analysis and applications. Proceeding of the IEEE, l7 (4) pp. 541-580.
[8] Fei Liu, Ming Yang and Peng Shi, "Verification and Validation of Fuzzy Rules-Based Human Behavior Models", 7th International Conference on System Simulation and Scientific Computing, 2008 pp. 813 – 819
[9] Kouzehgar,M.,M.A.Badamchizadeh and S. Khanmohammadi, 2011. Fuzzy Petri nets for human behavior verification and validation. Int. J. Adv. Comput. Sci. Appl., 2(12): 106-114.
[10] Meher Taj.S and Dr.Kumaravel.A,2015.Measuring Employee performance key indicators by Fuzzy Petri Nets.
[11] Research journal of Applied Sciences, Engineering and Technology.,9(7) : 485-490.