Currency Crises Prediction with Rough Set Theory

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ABSTRACT
Currency crises remain to be an important problem for economies around the world. Especially emerging markets are vulnerable to this type of crises. The complex nature of currency crises result in disappointment in out-of-sample experiments of traditional methods. In this study we used rough set theory for predicting possible currency crises and tested our model with macroeconomic data from Turkey.

General Terms
Set Theory, Rough Set Theory, Currency crises prediction, Data mining.

Keywords
Currency crises, currency crisis prediction, rough set theory, data mining.

1. INTRODUCTION
Currency crisis is one of the most devastating economic situations for a country's economy. The damage can be an increase of debts which were loaned in foreign currency or loss of value of a life time savings done by average citizens. But there is also great potential of profit during the chaos of the impact for money market investors. Because of all this reasons many researchers study and work to predict currency crisis for last decades.

Currency crises have a very sophisticated nature and various reasons [1] so predicting currency crises is very difficult and also vulnerable to error.

The pioneers of currency crises prediction researchers generally used simple linear logit models to predict crisis periods. Then as it is seen that currency crisis is not behaving linearly, researchers began to use more complex logistic models and artificial intelligence.

In this study we build a model based on rough set theory. And we tested our model by using different macroeconomic data from Turkey which had many currency crises in late 1990's and early 2000's.

In the following sections, first we review the literature of currency crises and currency crises prediction in the second section, than in the third section we will explain our models theatrical back ground and rough set theory. After third section we continue with the data we used in this study and the empirical experiment. Fourth and fifth sections we will review our results and discuss them in conclusion. In the last section we will share our ideas for the future studies.

2. LITERATURE REVIEW
Currency crises and currency crises predictions are are remain to be hot topics of research for the last decades. Many researchers from economy, mathematics and computer science back ground studied on this topic. So for a better understanding of the literature we choose to review literature in two parts, first studies mostly done by economy back grounded researchers and second computer scientists and artificial intelligence researchers.

2.1 Currency Crises and Currency Crisis Prediction Literature From Economy Background
One of the most important studies is the Kaminsky, Lizanda and Reinhart's "Leading Indicators of Currency Crises". In that study, they try to figure out the main indicators of currency crises and analysed the behaviors of that indicators for producing signals than build an early warning system based on this signals. They tested this model on a very large set of data consist of different countries in different regions and a large set of indicators [1].

Many researchers continued to work on KLR's signals approach to evaluate the model, they used probit-based models and logit models, and some try to find better indicators that can be helpful in crisis prediction [2].

There is also a set of literature that critizing KLR's signals approach with empirical studies, especially in out-of-sample experiments [3].

Another approach in currency crises prediction is composed of logit and multi-nominal logit models [4, 5, 6], those approaches generally can't get meaningful results in out-of-sample experiments.

And as another group of prediction models is that using the stock market or option market data for prediction proposes [7].

2.2 Computer Science Literature of Currency Crises and Currency Crisis Prediction
This part of the literature is relatively recent. Main method computer scientist use for predicting currency crisis is the artificial neural networks, [8] the main reason is the good learning potential of neural networks and their ability to handle non-linear situation like economy.

Some researchers extend neural networks approach and added a fuzzy interface to get a better interaction between real world and the neural network systems [9, 10]. Both studies with neural networks and neural networks with fuzzy logic get many good results in their prediction tests. And as a further extension to fuzzy neural networks, some researchers include granular methods [11].

An example of rough set theory in financial and economic issues is done by Tay and Shen. They made a very useful survey and study on most of the rough set theory's problems [12].

3. MATERIALS AND METHOD

In this section we will first explain our data set and then the model we used for predicting currency crisis.

3.1 Data Set

We used macroeconomic data of Turkey. The main reason behind this decision is the nature of macroeconomic data. Macroeconomic data are the summary of one country's economy, both past, present and future knowledge are included in different macroeconomic variables. The reason of choosing Turkey is that Turkey is an emerging market with memories of currency crises and Turkey also done very well in the past two years financial crises of USA and EU.

In our data set, we used volume of gold market, volume of stock market, interbank money market transactions, domestic loans, foreign trade export volume index, interest rates on deposits, inflation rate, reserves of central bank, deposits with deposit money banks and construction statistics according to construction permits. Our data time scope is from 01.2003 to 01.2010 in a monthly basis. We got our test data from the web site of Central Bank of the Republic of Turkey [13].

Another important point is the decision of definition of currency crises. In this paper we consider a monthly 4.5% drop in the value of currency as a currency crisis.

3.2 Rough Set Theory

Now let's focus on the theoretical back ground of rough set theory.

Rough Set theory is one of the recent areas of data mining. Rough set theory is developed by Zdzislaw Pawlak in the early 80's.[14] In general it is an extension to set theory. The main idea of rough set analysis is induction of approximations of concepts. In other words, if we consider every member of a set has some knowledge about the set by decreasing the crispiness of one set we can increase our ability to find out patterns hidden in the set [15, 16].

Information System (IS) can be shown as a pair (U, A) where U is a non-empty finite set of objects and A is a non-empty set of Attributes such that in Eq. (3.1).

$$a : U \rightarrow V_a \text{ for every } a \in A . \qquad (3.1)$$

Va is called the value set of a. A decision system (DS) is presented like Eq. (3.2).

$$T = (U, A \cup \{d\}) \text{ and } d \notin A \qquad (3.2)$$

In Eq. (3.2) d is not an element of attributes but a decision attribute. A result for the attributes and the elements of A are called conditional attributes.

One of the most important properties of rough set theory is the indiscernibility. IND (P) exists where Eq. (3.3) is supported. IND (P) is called P- indiscernility relation and is defined as in Eq. (3.4).

$$P \subseteq A . \qquad (3.3)$$

$$IND(P) = \{(x, y) \in U^2 \mid V_a \in P, a(x) = a(y)\} . \qquad (3.4)$$

The partition of U is a group of all equivalence classes of IND (P) and is denoted by Eq. (3.5).

$$U/IND(P) . \qquad (3.5)$$

If (x, y), IND (P) then x and y are indiscernible objects may be represented several times.

Let T = (U, A) and let $B \in A$ and $X \subseteq A$. We can approximate X using the only information contained in B by constructing the B-lower and B-upper approximation of X, denoted as in Eq. (3.6) and defined in Eq. (3.7) and Eq. (3.8).

$$\underline{B}X \text{ And } \overline{B}X . \qquad (3.6)$$

Where

$$\underline{B}X = \{X \mid [X]_B \subseteq X\} \qquad (3.7)$$

$$\overline{B}X = \{X \mid [X]_B \cap X \neq Ø\} \qquad (3.8)$$

B-boundary region of X is formulated in Eq. (3.9).

$$BNB(X) = \overline{B}X \neg \underline{B}X \qquad (3.9)$$

B-boundary region consist of object that we can't classify X in B for sure.

B-outside region of X is shown in Eq. (3.10), consist of objects that certainly classified as not belong to X.

$$B\text{-outside} = U - \overline{B}X \qquad (3.10)$$

A set is said to be rough if its boundary region is non-empty, otherwise the set is crisp.

In figure 1 we summarize the basic elements in rough sets.

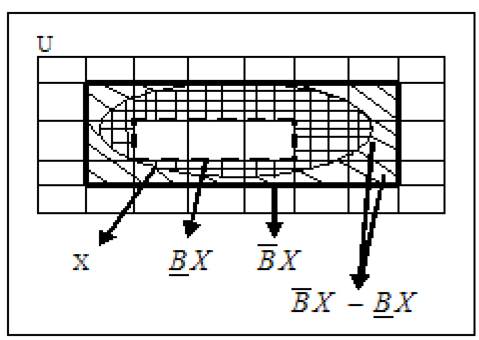

Figure 1: Basic concepts of rough sets

3.3 Method

We have used an integrated approach of rough set theory and signal approach.

The main idea is to find the patterns of crises in the chosen macro-economic variables with the help of rough set theory and our model decides if the pattern is producing any crises.

Here is a basic example of our methods;

First we use rough set theory to reduce our information system with finding reducts and core. Than we mine decision rules that will help us to classify our test instances. Our rules are if-then-else rules like the formula in Eq. (3.11).

$$\text{if}(X \wedge Y) \rightarrow a\,. \qquad (3.11)$$

We use RSES2 [17] tool to discretize our data and to build decision rules from reducts. In this step RSES2 tool uses genetic algorithms.

After finding our results, we continue to study on the data set. In order to evaluate our results, we also tested our data with 2 more widely known data mining methods, BayesNet [18] and Logistic [19], with WEKA [20] tool.

Let $c \in C$. Attribute c is dispensable if the equation Eq. (3.12) exists; otherwise attribute c is indispensable in T.

$$POS_C(D) = POS_{(C\text{-}\{c\})}(D)\,. \qquad (3.12)$$

T= (U, C, D) is independent if all are indispensible in T.

The set of attributes is called a reduct of C, if T= (U, R, D) is independent and the Eq. (3.13) is valid.

$$POS_R(D) = POS_C(D)\,. \qquad (3.13)$$

The set of all condition attributes in dispensable in T is denoted by CORE (C)

$$CORE(C) = \cap RED(C)\,. \qquad (3.14)$$

Where RED(C) is he set of all reducts of C as seen in Eq. (3.14).

4. EMPIRICAL EXPERIMENT AND FINDINGS

In this section we will explain details of our empirical experiment and then review the results of our experiment.

4.1 Empirical Experiment

In our empirical experiment we used RSES2, a free rough set analysis tool. RSES2 is a power tool and support many different formats. Another important issue is the ratio of our training and test data. We choose to take 70% of the data for training and the remaining 30% for test purposes.

We preprocessed our data sets in order to discrete our data so the rough set theory can be implemented to our dataset. We used RSES2's discretization function, in order to achieve this purpose. After discretizing our data by using RSES2, some variables became same for all data so we reduced the number of variables in our data set. So the reduction of the variables in the data set let us to concentrate the most essential variable that our model suggests that those macroeconomic variables affect the most. In our experiment five of our ten macro macroeconomic variables showed up as not affecting the out coming rules so they are removed. The remaining variables are central bank reserves, cost of living, and volume of gold exchange market, ISE value and deposits in bank accounts. The rules created by our model use those five variables.

4.2 Analysis of Generated Rules

Our model generated seven rules to classify a data set either a crisis or non-crisis period. Those rules vary in strength, some rules matching 37 out of 54 tuples of our data set while some other rules match only 1 or 2 tuples. This number of matching tuples may seem low but as we discussed in earlier sections this number is depending on the number of crisis periods, and the number of crisis periods are about 10% of our data so the model can have much tuple for crisis periods.

Rules generated by our model and some information about them;

Rule 1 (37 out of 54 matches) indicates that if cost of living is lower than a certain threshold there won't be any currency crisis.

Rule 2 (24 out of 54 matches) indicates that if central bank reserves are more than a certain threshold there won't be any currency crisis.

Rule 3 (23 out of 54 matches) indicates that if the stock exchange in increasing than a certain threshold there won't be any curreny crisis.

Rule 4 (18 out of 54 matches) indicates that if the volume of gold exchange market is lower than a certain threshold there won't be any currency crisis.

Rule 5 (2 out of 54 matches) indicates that if value of ISE and central bank reserves are lower, and cost of living and volume of the gold exchange market is higher than a certain threshold there will be a currency crisis.

Rule 6 (1 out of 54 matches) indicates that if value of ISE and central bank reserves are lower is lower, and cost of living and deposit money in bank accounts are higher than a certain threshold there will be a currency crisis.

Rule 7 (1 out of 54 matches) indicates that if cost of living and volume of gold market and deposit money in bank accounts are higher, and central bank reserves are lower than a certain threshold there will be a currency crisis.

4.3 Other Methods

In our experiment we used two other methods to compare the results of our rough set theory model. These methods are BayesNet and Logistic Regression, the reason for choosing these algorithms are that they are widely known and popular in data mining world. In order to use these methods we used WEKA.

4.3.1 BayesNet
A Bayesian network is a probabilistic graphic model that represents a set of random variables and their conditional dependences via a directed acyclic graph [18].

4.3.2 Logistic regression
Logistic regression is a centralistic linear model used for binominal regression, it makes use of several predictor variables that may be either numerical or categorical [19].

4.4 Findings
The results for our experiment can be seen in table 1 and the comparison of our result with two different data mining methods can be seen in table 2.

Table 1: Result of the rough set implementation

	0	1	# of obj.	Accuracy	Coverage
0	19	0	19	1	1
1	1	4	5	0,8	1
TP rate	0,95	1			

In table 1, we can see the non-crises periods as "0" and crises periods as "1", there are 5 crises periods and 20 non-crises periods in our data set, the accuracy of our rough set implementation is 80%, we have managed to find out four out of five crises period in our data while one of the crises periods is mislabeled as non-crises period. And we have also managed to label 23 periods successfully, only failing at one period. We can also see that the true positive (TP) rate of non-crises periods are 95 % and crises periods are 100 %, so this shows that we only mislabeled a crises period as non-crises but we didn't labeled any non-crises period as crises.

Table 2: Comparing results

	Accuracy (%)	crisis period found	non-crisis periods found
BayesNet	79.166	0 %	100%
Logistic	83.333	60%	89.4%
Rough Set	95.8	80%	100%

If we compare the results of rough set theory application, as we can see from table 2, BayesNet had spotted all the non-crisis periods successfully but failed in finding crisis periods. One of the main reasons of this outcome is the over fitting of BayesNet to non-crisis periods, as they are about 90% of all data while logistic regression spotted 60% of crisis periods but labeled some crisis periods as non-crisis which decreased its precision to 83%, and it is certain that logistic regression performed much better than BayesNet in finding crisis periods in the expense of some false positives. On the other hand rough set theory performed very well, our model predicted 80% of crisis periods which is 30% better than logistic regression model.

5. CONCLUSION
In this study we proposed to use rough set theory in predicting currency crises. We also compared the results of rough set implementation with two other popular algorithms.

The results of our empirical experiment are very successful and promising for the rough set theory. Further researches with larger data sets and more careful variable selection will surely increase the success of rough set theory implementation.

In summary our contribution to currency crises prediction and rough set theory literatures are giving us a better look to rough set theory as a tool for prediction and giving rough set theory another field to study.

6. FURTHER STUDY
This research can be used as a base line in currency crisis prediction with rough set theory. The following researches may use different variables and use more complicated models to select their variables. Other aspects of rough set theory can be used while hybrid rough set models like fuzzy rough set are very promising research options.

The results of the model can be more precise with the usage of a larger time scope, with the larger time line the rules we produce for prediction will be stronger.

Following researches may also use the model we produce in this research as an early warning system and build a simulation model or a decision support system over it to help policy makers and monetary authorities if a currency crisis is approaching and in what particular way they can handle this crisis and even evade it.

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