Data Mining versus Statistical Tools for Value at Risk Estimation

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ABSTRACT: *Financial crises are perceived as shocking events, several researchers concentrated on the identification of stressed and stable periods in order to take strategic decisions on time. In this paper, for one hand we propose a new hybrid approach to deal with the prediction of the Value at Risk (VaR). Based on financial variables from bank's balance sheets as input data , this approach integrate Rough Set Theory (RST), Gaussian Case Based Reasoning- clustering (GCBR-Clustering), Real valued Genetic Algorithm (RGA) with Support Vector Machines (SVM) in order to classify stressed and non stressed periods and therefore determine the VaR . The RST-GCBR Clustering-RGA-SVM combination is justified by a high accuracy rate which reaches 96.551% in cluster 1and 100% in cluster 2. In another hand we attempt to highlight the usefulness of our proposed model versus the existing one based on the extreme value theory. Based on a Kupiec backtest it is proved that our proposed approach is more performant at different confidence level.*

Keywords: Component, Rough Set Theory, Gaussian Case Based Reasoning- clustering, Real Valued Genetic Algorithm, Support Vector Machine, Financial stress index, Value at Risk

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1. Introduction

Recently, stressful events have been occurring with alarming regularity and with severe impacts. In the last 15 years alone there have been about 12 stress events, some examples of which are the Gulf War, the Asian Crisis, the Russian Default, September 11, 2001, and the Argentine default. In the literature on financial crises, many procedures have been developed to tackle the problem of risk prediction and many researchers have questioned the predictability of crises and the appropriateness of early warning indicators. In order to meet catastrophic unexpected risks, in the late 1980's regulators and financial industry advisory groups, developed the value at risk (VaR). Theoretically, VaR measures the maximum possible loss adverse market movement for a given position or a portfolio within a known confidence interval over a certain holding period. Since there is no predefined method that helps in identifying stress periods in the banking sector, a new hybrid method is developed in this paper for the purpose cited above, based on financial stress index (FSI) and finally calculate appropriately the VaR. in the hybrid approach we attempt to integrate Rough Set Theory (RST), the Gaussian Case Based Reasoning clustering (GCBR-clustering), and Real Valued Genetic Algorithm (RGA) with the Support Vector Machines (SVM). This combination is used to reckon if there is a stressed period or not via analyzing deriving information from variables collected from balance sheet data which are also used to build the FSI that will be used in the classification process.

A performance analysis is conducted to identify stressed periods and to show the effectiveness of this new hybrid approach. The remainder of this paper is organized as follows, in Section 2, Business intelligence tools are presented. Section 3 outlines the

FSI. Section 4 develops the new proposed model. The experimental study is conducted in Section 5. Section 6 discusses the conclusion and future research issues.

2. Business Intelligence Tools

In the recent literature [1], commented that combining classifiers system tends to minimize the disadvantages of single classifiers and maximize their advantages. Thus more attention should be paid on the new content of risk measures prediction based on multiple classifiers system to generate more promising performance than single classifiers. Single classifiers come out with ineffective results. Thus, it is crucial to follow different steps before doing classification based SVM, such as preprocessing using RST, clustering using GCBR-Clustering and optimization using RGA. The application of business intelligence tools is newly developed in the area of VaR calculation.

2.1 Support Vector Machines

Reference [2] developed the SVM technique. SVM has a high performance of generalization [3], and it minimizes the misclassification error. The SVM embody the principle of structural risk minimization. In SVM process generally they search the optimal hyper plane by maximizing the margin of the separating hyper plane while ensuring the accuracy of correct classification. There is a linear and non linear case, where the treatment will differs. To deal with non linear cases the kernel function should be introduced such as the radial basis function, where according to [4] any symmetric positive semi-definite function, which satisfies Mercer's conditions, can be used as a kernel function in the SVMs context. In the non linear case, data may be not separable, for this reason a slack variable ξ_i , i = 1, 2, …, N can be introduced which indicate the distance between the margin when x_i lying in the wrong side of the margin [5]. The problem is experimented as follow:

$$min\ \phi(\omega\ \xi) = 1/2\ \omega^T\omega + X\ \Sigma\iota^N_{=1}\ \xi_\iota\ .\quad \iota = 1, 2,..., N \tag{1}$$

Subject to

$$y_i\,[\omega^T\varphi\,(x_i) + b] \geq 1 - \xi_i\ . \qquad i = 1, 2,\ldots, N \tag{2}$$

$$\xi_i \geq 0. \qquad i = 1, 2,\ldots, N \tag{3}$$

Where, ω is the normal vector of the hyper plane, $\varphi\,(x_i)$ is the transformation function, b is the bias value, $X = \{x_1, x_2,\ldots, x_N\}$ is the training data set, $y_i = \pm 1$ is the label associated to case (i), N is the number of samples, the regularization parameter C is the tradeoff between minimizing fitting errors and minimizing model complexity and ξ is the slack variable. To solve this equation we can use the Lagrange formulation and Krauch- Khun- Tucker condition:

$$Max\ L_D = \Sigma^N_{i=1}\ \alpha_i - ½\ \Sigma^N_{i=1}\ \Sigma^N_{j=1}\ \alpha_i\ \alpha_j\ y_i\ y_j\ \varphi^T(x_i)\ \varphi(x_j). \tag{4}$$

Subject to:

$$\Sigma^N_{i=1}\ \alpha_i\ y_i = 0. \qquad i= 1, 2,\ldots., N \tag{5}$$

$$0 \leq \alpha_i \leq C. \qquad i= 1, 2,\ldots., N \tag{6}$$

$$\alpha_i\ [y_i\ (\omega^T\varphi(x_i) + b) - 1 + \xi_i\ ] = 0. \tag{7}$$

$$\mu_i\ \xi_i = 0. \tag{8}$$

where, the term $\varphi^T(x_i)\ \varphi\ (x_j)$ tends to be replaced by the radial basis function

$$K(x, y) = \exp\,(-\,|x-y|^2/\sigma^2). \tag{9}$$

where α_i is the Lagrange multiplier.

In reference [6] they have done extensive work to identify which kernel function that gives a good result in classification with low expected error bound they proved that the radial basis function is the most useful one.

2.2 Rough Set Theory

Many researchers have focused on developing methods for feature or variable selection. Reference [7] and [8] developed a new mathematical tool which is the RST to discover data dependencies and deal with vagueness and uncertainty. The main advantage

of RST is the fact that it does not need any preliminary or additional information about data. Recently, RST has been successfully applied in the real world classification problem (see for example [9]; [10]; [11]; [12]; [13]; etc).

The process of RST is easy to understand, where the main step is the extraction of the key attributes out of a huge data set. There are three basic concepts in this technique which are the information system, data reduction and decision table. Through these concepts a rough set can be extracted. The basic concept occurring in the knowledge base is the reducts which may be derived in the reduction process, once the reducts are found; researchers are interested on their intersection, the core which represents the set of important variables. RST can serve for a decision making, this appear when we transfer the information system into a decision table {U, C *U* D} where U is the universe, C is the condition attribute and D is the decision attributes. The reduction of the decision table is the reduction of condition attributes with respect to decision attributes.

2.3 GCBR- Clustering

The GCBR- Clustering is a new developed methodology, it is a combination of two main steps, similarity calculation and the clustering step based on similarity information. The GCBR algorithm given by Reference [14] is as follow:

Step 1: Obtain data related to mining task.

Step 2: Get the number of features.

Step 3: Calculate distance between two cases on each feature.

Step 4: Obtain Gaussian indicators.

Step 5: Obtain similarities.

In reference [5], they have applied the clustering method based on similarity information in the area of financial time series prediction. Thus, in our case a clustering method can be used in order to ameliorate the prediction performance of the model.The detailed procedure of the clustering algorithm is as below:

Step1: Determine the similarity matrix SM= (SIM_{ab}) based on equation

$$SIM_{ab} = \Sigma_{s=1}^{s} \omega_s . g_{abs}. \qquad (10)$$

where, SIM_{ab} is the similarity between case (a) and case (b), ω_s is the weight, $\omega_s \in [0, 1]$ and $\Sigma\omega_s=1$, and g_{abs} is the Gaussian indicator of the sth feature.

Step2: Fix two centroid X and Y representing stressed and nonstressed periods respectively.

Step3: Determine clusters according to the rule "case i" belong to the cluster 1 if and only if $SIM_{Xi} > SIM_{Yi}$ and belong to cluster 2 otherwise, i= 1,…, N. Where SIM is defined in step1 and N is the number of years.

2.4 Real Valued Genetic Algorithm

Parameter optimization procedure is considered as main step in order to ameliorate the prediction performance. In order to reach this target, the genetic algorithm (GA) has been widely and successfully applied to various optimization problems. Few studies have dealt with the Real Valued Genetic Algorithm (RGA) which is considered faster, straightforward and more efficient than the binary genetic algorithm. It uses real value as parameter of chromosomes in the population [15] which is advantageous for finding optimal parameters and avoids convergence to local optima. In reference [16] they have developed the algorithm of RGA-SVM seeking the optimization of SVM parameters *C* and σ^2.

3. Financial Stress Index

Stress is the product of a vulnerable structure and some exogenous shock. Financial fragility describes weaknesses in financial conditions and in the structure of the system. The stress level is measured on a scale ranging from tranquil situations, where stress is quasi-absent, to extreme distress, where the system goes through a severe crisis. It is important to distinguish the system's stress from its fragility.

One relevant measure of the latter is the FSI. To compute the FSI, we use a widely used technique namely variance-equal weight method (see [17], [18]). It consists first to standardize the variables, and then we aggregate those using identical weights. By using the standardized values, we equalize the variance of the components, and thus avoid the possibility that any one, of the components dominates the stress index. The index formula is the following:

$$I_t = \sum_{i=1}^{k} \frac{(x_{i,t} - \overline{x_i})}{S_i}, \tag{11}$$

where k is the number of variables in the index, x' is the mean of the variable X_i and S_i its standard deviation.

4. Extreme Value Theory

EVT has been widely used in all areas of quantitative risk management, insurance, finance (see [19]). The main virtue of EVT is that it gives a critical view for issues like skewness, rare events. It is generally acknowledge that the generalized Pareto distribution (GPD) uses data more efficiently, and it is therefore considered the most useful for practical applications. The main advantage of GPD is that it focuses directly on the tail of the distribution and it is based on iid residuals. GPD is considered as equally important as the normal distribution (see [20]). This approach, consist of an appropriate selection of a threshold level μ and estimating the unknown distribution function F of a strictly white noise. Let $z_1, z_2, ..., z_n$ representing an iid strictly white noise process supposed to be heavy tailed. The GPD is defined as follow:

$$G_{\xi,\beta} = \begin{cases} 1-(1+\frac{\xi}{\beta}z_t)^{-\frac{1}{\xi}}, if\ \xi \neq 0 \\ 1-\exp(-\frac{z_t}{\beta}), if\ \xi = 0 \end{cases} \tag{12}$$

Where ξ and β are the shape and scaling parameters of the distribution respectively.

Where, $\beta > 0$; $z_t > 0$when $\xi \geq 0$ and for $\xi < 0$ the iid process satisfy this condition $0 \leq z_t \leq \frac{-\beta}{\xi}$.

The most relevant case of risk management purpose is where $\xi > 0$ since in this case the GPD distribution is heavy tailed (see [21]).

With reference to the literature, the α quantile of the residual process can be estimated by VaR_α defined by:

$$VaR_\alpha = \mu + \frac{\hat{\beta}(\mu)}{\hat{\xi}} \left\{ \left[\frac{n}{N_\mu}(1-\alpha) \right]^{-\hat{\xi}} - 1 \right\} \tag{13}$$

Where, μ is the threshold, $\hat{\beta}(\mu)$ is the estimated scale parameter, $\hat{\xi}$ is the estimated shape parameter.

5. Bactesting For Performance Evaluation

In this section, we review one of the existing back-tests. Originally, reference [22] recommends back-testing VaR models to assess forecast accuracy. Back-testing is a statistical procedure where actual profits and losses are systematically compared to corresponding VaR estimates. With reference to the literature, the earliest proposed VaR back-tests is the unconditional coverage (UC) test of Kupiec (see [23]) known also as the POF test (Proportion of Failure) that focuses on whether or not the reported VaR is violated. Since the late 1990's, several backtests have been proposed in order to gauge the accuracy of any VaR model. For instance, [23] focused on the property of unconditional coverage. This kind of backtests are concerned with whether or not the reported VaR is violated more than á of the time.

Because an accurate VaR measure should hold for any level of α, in this section we backtest our proposed VaR, Empirical VaR and EVT-VaR using the Kupiec test based on multiple VaR levels. In cases where the VaR has been underestimated and thus when the FSI has experienced a value greater than VaR, we say that VaR has been violated, and such an event is called a violation of VaR. If there have been too many violations, then the VaR model may not be adequate for the instruments composing the sample.

If we observe a time series of past ex-ante VaR forecasts and past ex-post FSI, a hit sequence function cause defined as

(14)

Then, we have a sequence $\{I_{t+1}\}_{t=1}^{T}$ across T months indicating when the past violations occurred. If we could predict the VaR violations, then that information could be used to construct a better model. The hit sequence of violations is distributed as Bernouilli variable.

In order to test if π, the fraction of violations obtained is significantly different from the promised fraction α.

Based on unconditional coverage hypothesis and under H_0, the likelihood of an iid Bernouilli (π) hit sequence is:

$$L(\pi)=\prod_{t=1}^{T}(1-\pi)^{1-I_{t+1}}\pi^{I_{t+1}} = (1-\pi)^{T_0}\pi^{T_1} = (1-\alpha)^{T_0}\alpha^{T_1} \qquad (15)$$

where T_0 is the number of 0 and T_1 is the number of 1 in the sample. Therefore, $\hat{\pi} = \frac{T_1}{T}$.

The likelihood ratio test is

$$LR = -2\ln\left[\frac{L(\alpha)}{L(\hat{\pi})}\right] = -2\ln\left[\frac{(1-\alpha)^{T_0}\alpha^{T_1}}{(1-\frac{T_1}{T})^{T_0}(\frac{T_1}{T})^{T_1}}\right] \sim \chi^2 \qquad (16)$$

If the p-value is below the desired significance level, we will reject the null hypothesis. Results will be presented in the real case study.

6. Proposed Model

Following the idea that combined classifiers are more efficient than single ones, the proposed approach combine classifiers system by integrating RST, GCBR- clustering, RGA with SVM for estimating VaR. Our proposed work is based on the algorithm developed in [24]:

Step 1: Obtain data related to predictive task based on RST algorithm.

Step 2: Determine the FSI based data generated using RST.

Step 3: Train GCBR-Clustering.

Step 4: Based on GCBR-Clustering output prepare a training sample of RGA-SVM

Step 5: Based on the selected sample train RGA-SVM

Step 6: Generate clusters by GCBR-Clustering

Step 7: Generate the final prediction of GCBR-Clustering based RGA-SVM.

Step 8: Determine the VaR.

7. Real Case Study

In this part we aim to highlight the usefulness of the proposed VaR estimation method based on the conjunction of RST, GCBR-clustering and SVM. We attempt, firstly to estimate the VaR based on the benchmark model VaR-EVT at different confidence levels. A performance evaluation study is conducted based on Kupiec backtest.

7.1 Data

We use aggregate Tunisian balance sheet data. Our choice is limited mainly to deposit banks and development banks for two reasons. First, we have a regular set of data and second, leasing companies and off-shore banks do not have the right to collect deposits and have access to refinancing from the Tunisian central bank. The data span from 1970 to 2006.

7.2 VaR-EVT model

The EVT was widely used for quantile estimation since it takes in account tail behavior. The yearly FSI using 14 initial variables was computed based on equation (11), thereby; we attempt to apply the EVT to this new series. Table I summarizes the founded VaR at 95%, 97%, and 99%.

Based on EVT-VaR, we found 18 stress periods form 1989 to 2006. This method is able to detect confirmed stress periods as 1989 and 2004 but we cannot classify stress periods in order to distinguish between fairly and highly stressed periods.

	95%	97%	99%
ξ	-0, 2482	-0, 2482	-0, 2482
σ	5, 1118	5, 1118	5, 1118
VaR-EVT	-0, 00936	-0, 00907	-0, 00877

Table 1. VaR-EVT Model Results

7.3 RST for data preprocessing

Based on RST reduction process, we have found 7 key attribute out of 14 initial variables extracted from the IMF statistics CD-ROM (the whole variables are shown in the Appendix). As it is known financial variables are continuous attributes. For this reason we have use the ROSETTA software [25].

7.4 FSI Computation

Due to the annual frequency of some series, we compute a yearly FSI using (11) for the Tunisian banking sector from 1970 to 2006. For our case study, the seven chosen variables by RST are reserves, foreign assets, total deposits, claims on Central Government, loans to the private sector; bank capital and credit from Monetary Authorities. We have 37 observations for each variable from 1970 to 2006.

Following Table II the FSI distribution has a negative excess kurtosis (platykurtic). In terms of shape, the distribution has a lower, wider peak around the mean and thinner tails (lower probability than a normally distributed variable of extreme values). Furthermore, the distribution has a positive skew (right-skewed), the right tail is longer, and the mass of the distribution is concentrated on the left. The Jarque–Bera test shows that the data are not normally distributed.

Mean	Std.	Skewness	Kurtosis	Jarque-Bera	Probability
3.84E-16	4.8947	0.74	2.8623	3.4064	0.000

Table 2. Descriptive Statics for Tunisian Banks FSI

7.5 GCBR-Clustering

After assessing the key attributes from RST, these variables were used as input data of the GCBR clustering process to achieve the aimed output which is a set of subclusters where we find this clusters using the software Matlab software.

We fix two centroid randomly, 1970 as non-stressed period and 2006 as stressed periods. Using the GCBR-Clustering the first cluster contains 28 FSI from 1970 to 1998; the first years are non stressed. Since we are not interested on non stressed periods, we eliminate their corresponding FSI from 1970 to 1988. Thereby, cluster 1 become sized 10 FSIs from 1989 to 1998. This cluster presents fairly stressed periods. The most stressed year for this cluster is 1997 essentially due to increased loans to private sector. As for the second cluster, it is sized 8 FSIs from 1999 to 2006 and contains highly stressed periods. We notice essentially three remarkable periods in this cluster namely 2004 due in part to the increase of non-performing loans and difficult economic conditions in certain sectors such as in tourism. 2005 and 2006 are also identified stressed because of an increased rate of the claims to the private sector.

7.6 RGA-SVM

In the final step, using SVM based RGA those two clusters form two new databases will be used in the process. The results of the proposed diagnosis model are given in Table III. The accuracy rate is the average of cluster's accuracy rate; it is about 98.275%; in cluster 1it is about 96.551% and 100% in cluster 2.

	Overall error Rate%	Accuracy rate %
Cluster 1	3.449	96.551
Cluster 2	0	100
Average	1.749	98.275

Table 3. Diagnosis Results RST-GCBR-Clustering Based RGA- SVM

7.7 VaR Estimation

To obtain the final prediction result we use MATLAB software precisely LIBSVM in order to estimate the $VaR_{99\%}$, $VaR_{97\%}$ and $VaR_{95\%}$.

Results are summarized in Table 4.

α	95%	97%	99%
VaR	10,7732	11,5465	12,4533

Table 4. VaR For Tunisian Banks

Those VaRs identifies 2006 as the most stressful period for Tunisian banks. This result is confirmed by the IMF report [26]. In fact, inflation spikes in 2006 due essentially to rising oil international prices and other raw materials and declining terms of trade.

7.8 Backtesting results

For VaR accuracy test a Kupiec POF test was performed for all candidate models. Table A summarize the founded p-value for different confidence level (99%, 97%, and 95%).

	1-α	p-value
VaR-EVT	95.00	00.002
	97.00	00.0005
	99.00	00.00
Proposed Model	95.00	00.00
	97.00	00.00
	99.00	00.00

Table 5. Backtest Results

Through Table 5 our model estimate accurately the VaR. In all cases for different confidence levels, we can reject the null hypothesis. Backtesting ensured that the proposed VaR model achieve consistent results.

8. Conclusion

In this framework, we propose a combined classifier model where we integrate RST, GCBR clustering, RGA with SVM in order to compute an FSI for the Tunisian banking system, to identify stress periods and to estimate the VaR. First, RST method is applied for data preprocessing. The outputs of the RST process are used as input data for the FSI computation. Therefore, the variables selection based on RST is more objective than those given by literature. Then we proceed with the GCBR clustering process, this method serve to retrieve similarity between cases and employ these similarity information's in the process of clustering. The GCBR clustering output is two clusters namely fairly stressed cluster and high stressed cluster which are transferred as input data of SVM aiming to estimate VaR. This framework shows that 2006 is the most stressed period, a result confirmed by the IMF. Moreover, based on Kupiec back-testing, our proposed VaR model outperforms the VaR-EVT.

The innovation is that we have an objective performing FSI that can be very useful to risk managers in order to identify different stressed periods namely fairly and highly stressed ones and therefore to know the system's weaknesses in order to avoid eventual crisis.

Foreign Assets	Counterpart Funds
Claims on Central Government	Central Govt. Lending Funds
Claims on Private Sector	Credit from Monetary Authorities
Demand Deposits	Capital Accounts
Quasi-Monetary Liabilities	Other Items (Net)
Foreign Liabilities	Post Office: Checking Deposits
Long-Term Foreign Liabilities	Reserves

Appendix-Financial Variables

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