Fuzzy kernel k-medoids application with fisher score feature selection for predicting bank financial failure

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Abstract. The bank financial failure has a huge impact on the real sector, households and can even cause knock-on effects for other banks, therefore is important to predict bank financial failure. Prediction bank financial failure is like an early warning system for bank, because a bankruptcy doesn’t happen suddenly but there are indications that can be detected that is financial statement. Financial statement will be extracted to 6 components of CAMELS. The 2019, we had predicted bank financial failures using random forest with the data that used in Boyacioglu, Kara and Baykan paper (2009), however in this research we will make novelty by using fuzzy kernel k-medoids. Based on our results, fuzzy kernel k-medoids using RBF kernel with $\sigma = 0.1$ and 60% composition of training data has 100% for accuracy, sensitivity, precision, specificity, and f-score with 0.9 sec running time. If we compare to our previous research by random forest, fuzzy kernel k-medoids gives the highest accuracy prediction, but if we compare to Boyacioglu, Kara and Baykan research (2009), it’s has the same accuracy but with fuzzy kernel k-medoids, we can use only 60% of training data to learn.

1. Introduction
In January 24, 1980, Government Turkey declared their reformation in Turkish economy. Their inward-oriented closed economy replaced by liberal economy. The reformation has a good impact to Turkish economy which has an export-oriented sector economy. However, the reformation has another impact which is make political competition increasing and large fiscal imbalance. The bad impact forced the government to compromise the stabilization program and pursue a populist economic policy. Economic stabilization and liberalization at the same time was characteristic of a period under military rule in 1980-83 [1], resulting in the beginning of 1994, there are crisis in Turkey. After the crisis, Turkey’s economy so unstable. First thing that happened after the crisis is Turkey’s economy improving. The economic construction is 6% and this is the highest level ever that happen on the Republic of Turkey. But after that, Turkish Lira --Turkey’s money-- depreciated against the US Dollar more than 50%, the inflation rate reached a number within the three digits degree, interest rates skyrocketed, and half reserves were lost by the Central Bank [1]. Of course, because of that the banking sector in Turkey experienced a highly negative impact. The banking sector remains tested and still continues to weaken, so to solve that problem the State Deposit Insurance Fund (SDIF) transferred money to 6 banks in 1999 to help their financial. But not every bank has a chance to survive, in 2001 some banks have been declared bankrupt or financially failed.
According to Arena (2005), bank or financial institution have failed (bankrupt) if they received external support or directly closed [2]. There are several characteristics of bankruptcy: first, the central bank or an agency particularly made to cite the crisis is the one who recapitalized the financial institution and/or demanded a liquidity injection from monetary authorities; the government tentatively stopped or ‘frozen’ the operations of the financial institution; financial institution was closed by the government; another financial institution absorbed the financial institution [3]. Bank failures not only happen in Turkey, but also in other countries such as America and some parts of the Organization for Economic Co-operation and Development (OECD). In 2008 until 2014, more than 500 banks on United States of America declared bankrupt, this phenomenon stated by Federal Deposit Insurance Corporation (FDIC). If the cost of failure per dollar is considered as failed bank asset, then it is already high and may continue to rise [4].

In Turkey, during 1994’s crisis, some banks bankrupt, the consequences are real sector and the households were deeply affected by that in 1997 to 2003 [5]. In some cases, bank failure can be like a chain which is if one bank failed it can affect the other bank as well. So, it is important to detect bank failures before they occur as in to preventing bankruptcy and keeping the public’s confidence in the banking industry. In anticipation of bankruptcy of a bank, it is an optimal necessity as a self-warning, because with early detection it is possible to take necessary action to avoid bankruptcy. One of the indicators is to predict bankruptcy is financial statements of bank. The financial statements are not only draw the condition of the bank in the past but also in the future. Based on financial statements, we can calculate the financial ratios as the basic to evaluate the banking performance. In this research, we used CAMELS as variable predictor to predict bank financial failure.

Statistical method is standard approach to predict bank financial failure but low accuracy has been obtained by some standpoints of statistical techniques [6], then by development of computational method, many researchers used machine learning to predict bank financial failure because the numerous studies machine learning is more effective and accurate than statistical techniques [7]. The implementation of machine learning is not only for predicting bank financial failure but also insolvency of another company, for example insurance companies [8]. Another sector that also used machine learning is the medical sector, they used machine learning as a classification technique such as for predicting cancer [9][10][11]. So, based on many researches before, machine learning’s performance has been proven in many sectors.

There are various machine learning method that have been used for predict bank financial failures, such as random forest [7] neural network, support vector machine and multivariate statistical methods [5][12], and fuzzy support vector machine [13], in this research we try to find another method that never use for Boyacioglu, Kara and Baykan paper’s data, that is fuzzy kernel k-medoids. The previous studies, fuzzy kernel k-medoids has been applied for anomaly detection problems [14], cancer classification [15], and multiclass multidimensional data classification [16]. Therefore, we know that fuzzy kernel k-medoid will be a great tool for building classification model. Furthermore, we will also use fisher score feature selection to filter any redundant ratios, so we can compare each of performance model and find the best model for bank financial failure classification.

2. Data and methodology
2.1. Data
Data in this research provide by Prof. Melek Acar that collected from annual publication of banks in Turkey by the Banks Association of Turkey (BAT) over the period 1997 – 2004 [5]. This dataset has 65 Turkish bank, 43 insolvent banks and 22 banks that transferred to Saving Deposit Insurance Fund (SDIF) which is solvent banks. There are 20 financial ratios used as variables to classify the solvent and the insolvent banks, 20 variables came from the financial statement of the bank. Financial ratios are grouped into six components of CAMELS: Capital adequacy (CA1, CA2, CA3), Asset quality (AQ1, AQ2, AQ3, AQ4, AQ5), Management (M1), Earnings (E1, E2, E3, E4, E5), Liquidity (L1, L2) and Sensitivity to market risk (SMR1, SMR2, SMR3, SMR4), where the description each of financial ratios has written in Boyacioglu, Kara and Baykan paper (2009). CAMELS developed with the purpose of
monitoring and classifying the overall condition of the bank, mean as a supervisory rating system based on ratio analysis of the financial statements [17]. As a predictor variable for future and relative risk of performance evaluation in the bank, CAMELS has been proven that gives the best results [7], that’s why we use CAMELS.

2.2. Fisher score

Fisher score future selection is one of many ways to reduce the dimension of the dataset, the aim of reducing is to filter any redundant ratios by calculating Fisher score for every ratio. The main idea of Fisher's score is to find a subset of features, so that in the data space spanned by the selected feature, the distance between data points in different classes is as large as possible, while the distance between data points in the same class is as small as possible [18]. Given the selected $m$ features, then $X \in \mathbb{R}^{d \times n}$ reduces to $Z \in \mathbb{R}^{m \times n}$. Then the Fisher score can derive as follows,

$$F(Z) = tr\left\{ (\bar{S}_b)(\bar{S}_t + \gamma I)^{-1} \right\}$$  \hspace{1cm} (1)

where $\bar{S}_b$ is between-class scatter matrix, $\bar{S}_t$ is total scatter matrix and $\gamma$ is positive regularization parameter. $\bar{S}_b$ and $\bar{S}_t$ are defined as

$$\bar{S}_b = \sum_{k=1}^{c} n_k (\bar{\mu}_k - \bar{\mu})(\bar{\mu}_k - \bar{\mu})^T$$  \hspace{1cm} (2)
$$\bar{S}_t = \sum_{i=1}^{n} n_i (z_i - \bar{\mu})(z_i - \bar{\mu})^T$$  \hspace{1cm} (3)

where $n_k$ is the size of the $k$th and $\bar{\mu}_k$ is the mean vector in the reduced data space, because $\bar{S}_t$ is usually singular, the perturbation term $\gamma I$ is added to make it possible semi-definite. Because a lot of candidate of $Z$, we used heuristic strategy to compute a score for each feature independently according to the criterion of $F$, which is we will only consider $x_j$ element. So, there are only $d$ candidates. Let $\mu_j$ and $\sigma_j$ denote the mean and standard deviation of the data set corresponding to the $j$th feature, then the Fisher score of the $j$th feature can derive as follows,

$$F(x_j) = \sum_{k=1}^{c} n_k (\mu_k - \mu)^2 \left( \sigma_j \right)^2$$  \hspace{1cm} (4)

where $(\sigma_j)^2 = \sum_{k=1}^{c} n_k (\sigma_k)^2$. After calculating the Fisher score for each feature, let choose the top $m$ -ranking feature with a large score [18].

2.3. Fuzzy k-medoids

Fuzzy k-medoids is technique that execute fuzzy clustering in the first to produce the membership degree of each cluster and then use k-medoids to find the cluster center [19]. The difference between Fuzzy k-medoids and fuzzy c-means is while choosing the centroid, fuzzy c-means uses means [9] and k-medoids uses median. Given a set of data $X = \{x_1, x_2, ..., x_n\}$, where $x_j \in \mathbb{R}^d, j = 1, 2, ..., n$. The dissimilarity between object $x_j$ and $x_j$ is denoted by $r(x_i, x_j)$. Let $V = \{v_1, v_2, ..., v_c\}$ as medoid set, $v_i \subset \mathbb{R}^d$ and $v_i \in X$ represent a subset of $X$ with cardinality $c$. Let $X^c$ represent the set of all $c$-subsets $V$ of $X$. The dissimilarity between data points $x_j$ and medoid $v_i$, where $v_i \in V$ is denoted $r(x_j, v_i)$. Let $U = [u_{ij}]$, where $1 \leq j \leq n, 1 \leq i \leq c$. $u_{ij}$ represents the fuzzy or membership of $x_j$ in cluster $i$. The membership model is calculated as follows,

$$u_{ij} = \frac{r^m(x_j, v_i)}{\sum_{k=1}^{c} r^m(x_j, v_k)}$$  \hspace{1cm} (5)

where $1 \leq j \leq n, 1 \leq i \leq c$ and fuzziness degree is denoted by $m$ where $b = -\frac{1}{m-1}$. The fuzzy k-medoids algorithm minimizes:

$$J(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m r(x_j, v_i)$$  \hspace{1cm} (6)

where the minimization is performed over all $V$ in $X^c$.

Algorithm of fuzzy k-medoids [20]

Step 1. Fix the number of clusters $c$ ;

Step 2. Pick the initial set of medoids $V = \{v_1, v_2, ..., v_c\}, \forall v_i, 1 \leq i \leq c$ from in $X^c$;
Step 3  **Repeat**
Compute value of memberships \( u_{ij}(6) \).
Identify \( X_{(p)i}, i = 1,2, ..., c \). \( X_{(p)i} \) is the subset where the set of \( p \) objects in \( X \) that correspond to the top \( p \) highest membership values in cluster \( i \).
Store the current medoids \( V^{old} = V \).
Compute the new value of \( v_i \) in \( V \) by \( v_i = x_q \) where \( 1 \leq i \leq c \),
\[
q = \arg\min_{x_kX_{(p)i}} \sum_{i=1}^{n} \sum_{i=1}^{c} u_{ij} \| r(x_k, x_j) \|
\]
\[
\text{iter} = \text{iter} + 1
\]
**Until** \( V^{old} = V \) or \( \text{iter} = \text{MAX ITER} \)

2.4. **Fuzzy kernel k-medoids**
In this research we used kernel method into fuzzy k-medoids to overcome the possibility of linear data inseparability, the main idea of kernel method is transforming the data set into another space (feature space) that the dimension is much higher than the data space [21]. However, learning is very hard in high dimensional data and will impact to the computational cost and also make overfitting, but the kernel method using “connector” between data space and feature space can help to solve that issues then the classification will have the good performance without directly working in the feature space [12]. Let \( \phi \) is a non-linear mapping from input data space \( \mathbb{R}^d \) to feature space \( F \). Next step is find the distance between transformed data \( \phi(x) \) and \( \phi(y) \), where \( x, y \) are objects at data space without knowing explicit form of \( \phi \) with the kernel function \( K \) [22]:
\[
d^2(\phi(x), \phi(y)) = \| \phi(x) - \phi(y) \|^2
= \phi(x)^t \phi(x) - 2\phi(x)^t \phi(y) + \phi(y)^t - \phi(y)
= K(x, x) - 2K(x, y) + K(y, y)
\]
Kernel used for this research are RBF kernel function \( K(x, y) = \exp\left(-\frac{\|x-y\|^2}{\sigma^2}\right) \) and \( p_0 \) th degree polynomial kernel function \( K(x, y) = (x^ty + 1)^{p_0} \). Let \( K_{ij} = K(x_j, v_i) = d(x_j, v_i) \) is used to calculate the distance between \( x_j \) and \( v_i \) this function will replace the dissimilarity function of fuzzy k-medoids.

Fuzzy kernel k-medoids is method with combining fuzzy k-medoids, kernel method, and fuzziness degree. Fuzziness degree \( (m) \) at each iteration is calculated as follows
\[
m = m_i + \frac{t}{T}(m_f - m_i)
\]
where \( m_f \) is initial value and \( m_i \) end value of \( m \), \( t \) is the counter of iteration and \( T \) is the maximum number of iteration.

Algorithm of fuzzy kernel k-medoids [23]
Step 1  **Input** \( X, c, m_i, m_f, e, T; \)
Step 2  **Pick** the initial set of medoids \( V = \{v_1, v_2, ..., v_c\}, \forall v_i, 1 \leq i \leq c \) from in \( X^c; \)
Step 3  **For** \( t = 1 \) to \( T \)
  Compute value of fuzziness degree \( m \) (8)
  Compute value of memberships \( u_{ij} \) (6)
  Compute value of medoid of \( v_i \) in \( V \) by \( v_i = x_q \) where \( 1 \leq i \leq c \),
  \[
  q = \arg\min_{x_kX_{(p)i}} \sum_{i=1}^{n} \sum_{i=1}^{c} u_{ij} \| r(x_k, x_j) \|
  \]
  If \( \sum_{k=1}^{N} K^2(v_i t, v_{it-1}) \leq e \) then stop
  Else \( t = t + 1 \)
3. Result and Analysis

Experimental method that used in this research is representative in Figure 1. Then, there are several metrics used to evaluate the performance of classification: accuracy, sensitivity, precision, specificity, f-score and running time.

Based on fisher score for every ratio that we’ve measured using Equation (4), the result is order from the top ranking feature with the large score: M1, SMR2, L2, AQ5, CA3, CA2, E5, CA1, SMR1, AQ1, AQ4, L1, E3, E4, AQ3, E2, AQ2, SMR3, SMR4, E1. Table 1 and Table 2 below show us the performance of fuzzy kernel k-medoids using RBF kernel (σ = 0.05) and polynomial kernel (d = 4) with k-fold: 3, 5, 7, 10 for predicting bank financial failure with ranking of feature based on the result of fisher score. Then, we have tried to use several parameter values and found that highest f-score achieved while using RBF kernel with σ = 0.05 and polynomial kernel with d = 4.

Table 1. The performance of prediction using fuzzy kernel k-medoids using RBF kernel

| Number of features | K Fold | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-score (%) | Running Time (sec) |
|--------------------|--------|--------------|----------------|--------------|---------------|-------------|-------------------|
| 5                  | 3      | 74.07407407  | 97.61904762    | 72.78106509  | 26.98412698   | 83.38983051  | 0.1875            |
| 10                 | 3      | 69.84126984  | 90.47619048    | 71.69811321  | 28.57142857   | 80          | 0.796875          |
| 15                 | 3      | 66.13756614  | 84.12698413    | 70.66666667  | 30.15873016   | 76.8115942  | 0.5              |
| 5                  | 5      | 75           | 97.5           | 73.58490566  | 30            | 83.87096774  | 0.171875          |
| 10                 | 5      | 66.66666667  | 90             | 69.23076923  | 20            | 78.26086957  | 0.78125           |
| 15                 | 5      | 65.55555556  | 80             | 71.64179104  | 36.66666667   | 75.59055118  | 0.796875          |
| 5                  | 7      | 74.6031746   | 97.61904762    | 73.21428571  | 28.57142857   | 83.67346939  | 1.046875          |
| 10                 | 7      | 67.72486772  | 92.06349206    | 69.46107784  | 19.04761905   | 79.18088737  | 0.78125           |
| 15                 | 7      | 66.13756614  | 86.50793651    | 69.87179487  | 25.3968254    | 77.30496454  | 0.84375           |
| 5                  | 10     | 75           | 97.5           | 73.58490566  | 30            | 83.87096774  | 0.671875          |
| 10                 | 10     | 67.77777778  | 91.66666667    | 69.62025316  | 20            | 79.13669065  | 0.6875            |
| 15                 | 10     | 67.77777778  | 82.5           | 72.79411765  | 38.33333333   | 77.34375    | 0.765625          |
Table 2. The performance of prediction using fuzzy kernel k-medoids using polynomial kernel

| Number of features | K Fold | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-score (%) | Running Time (sec) |
|-------------------|--------|--------------|----------------|--------------|----------------|-------------|-------------------|
| 5                 | 3      | 74.07407407  | 97.61904762    | 72.78106509  | 26.98412698    | 83.38983051 | 0.390625         |
| 10                | 3      | 67.1957672   | 92.85714286    | 68.82352941  | 15.87301587    | 79.05405405 | 0.734375         |
| 15                | 3      | 66.66666667  | 85.71428571    | 70.58823529  | 28.57142857    | 77.41935484 | 0.703125         |
| 5                 | 5      | 75.55555556  | 98.33333333    | 73.75        | 30             | 84.28571429 | 0.890625         |
| 10                | 5      | 67.22222222  | 90.83333333    | 69.42675159  | 20             | 78.70036101 | 0.96875          |
| 15                | 5      | 67.77777778  | 85             | 71.83098592  | 33.33333333    | 77.86259542 | 0.890625         |
| 5                 | 10     | 75.55555556  | 98.33333333    | 73.75        | 30             | 84.28571429 | 1.078125         |
| 10                | 10     | 68.33333333  | 92.5           | 69.81132075  | 20             | 79.56989247 | 0.375            |
| 15                | 10     | 67.77777778  | 87.5           | 70.94594595  | 28.33333333    | 78.35820896 | 0.84375          |

It can be seen from Table 1 and Table 2 that the best performance for classification bank failures by fuzzy kernel k-medoids is while using polynomial kernel with 5 features and number of k-fold is 10. The performance of classifier is 75.5% accuracy, 98.3% sensitivity, 73.7% precision, 30% specificity, 84.2% f-score and 0.375 sec running time.

Table 3. The performance of prediction using fuzzy kernel k-medoids with all features

| K Fold | Kernel | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-score (%) | Running Time (sec) |
|--------|--------|--------------|----------------|--------------|----------------|-------------|-------------------|
| 3      | RBF    | 96.2962963   | 99.20634921    | 95.41984733  | 90.47619048    | 97.27626459 | 0.765625         |
| 5      | RBF    | 95.55555556  | 98.33333333    | 95.16129032  | 90             | 96.72131148 | 0.078125         |
| 7      | RBF    | 95.76719577  | 97.61904762    | 96.09375     | 92.06349206    | 96.8503937  | 0.859375         |
| 10     | RBF    | 96.1111111   | 97.5           | 96.69421488  | 93.33333333    | 97.09543568 | 0.21875          |
| 3      | Polynomial | 94.70899471  | 97.61904762    | 94.61538462  | 88.88888888    | 96.09375    | 0.8125           |
| 5      | Polynomial | 96.82539683  | 97.61904762    | 95.23809524  | 97.61904762    | 97.09543568 | 0.9375           |
| 7      | Polynomial | 96.1111111   | 97.5           | 96.69421488  | 93.33333333    | 97.09543568 | 1.203125         |
| 10     | Polynomial | 96.1111111   | 97.5           | 96.69421488  | 93.33333333    | 97.09543568 | 1               |

It can be seen from Table 3 that the best performance for predicting bank failures by fuzzy kernel k-medoids with all features and no ranking the features gives the better performance result than with fisher score feature selection, this means the sequence of features is impactful to the result of classification. The best performance of prediction is while using polynomial and number of k-fold is 7. The performance of classifier is 96.8% accuracy, 97.6% sensitivity, 97.6% precision, 95.2% specificity, 97.6% f-score and 1.2 sec running time. Table 4 and Table 5 shows us the performance of prediction using RBF and polynomial kernel with the parameter who gives the best result when σ =
0.1 and \(d = 6\), in this experiment we tried to make models with a different composition of training data.

**Table 4.** The performance of prediction using fuzzy kernel k-medoids using RBF kernel

| %Data Train | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-score (%) | Running Time (sec) |
|-------------|--------------|-----------------|---------------|-----------------|-------------|-------------------|
| 10          | 96.49122807  | 97.43589744     | 97.43589744   | 94.44444444     | 97.43589744 | 0.078125          |
| 20          | 96.07843137  | 97.14285714     | 97.14285714   | 93.75           | 97.14285714 | 0.046875          |
| 30          | 97.72727273  | 100             | 96.77419355   | 92.85714286     | 98.36065574 | **0.0625**        |
| 40          | 94.73684211  | 100             | 92.85714286   | 83.33333333     | 96.2962963  | 0.1875            |
| 50          | 96.875       | 100             | 95.65217391   | 90              | 97.77777778 | 0.765625          |
| 60          | **100**      | **100**         | **100**       | **100**         | **100**     | **0.90625**       |
| 70          | **100**      | **100**         | **100**       | **100**         | **100**     | **0.09375**       |
| 80          | **100**      | **100**         | **100**       | **100**         | **100**     | **0.140625**      |
| 90          | **100**      | **100**         | **100**       | **100**         | **100**     | **0.984375**      |

**Table 5.** The performance of prediction using fuzzy kernel k-medoids using Polynomial kernel

| %Data Train | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-score (%) | Running Time (sec) |
|-------------|--------------|-----------------|---------------|-----------------|-------------|-------------------|
| 10          | 98.24561404  | 100             | 97.5          | 94.44444444     | 98.73417722 | **0.09375**       |
| 20          | 98.03921569  | 100             | 97.22222222   | 93.75           | 98.5915493  | 0.109375          |
| 30          | 97.72727273  | 100             | 96.77419355   | 92.85714286     | 98.36065574 | 0.125             |
| 40          | 94.73684211  | 100             | 92.85714286   | 83.33333333     | 96.2962963  | 0.515625          |
| 50          | 93.75        | 95.45454545     | 95.45454545   | 90              | 95.45454545 | 0.65625           |
| 60          | 96           | 94.11764706     | **100**       | **100**         | **100**     | **0.796875**      |
| 70          | **100**      | **100**         | **100**       | **100**         | **100**     | **0.875**         |
| 80          | **100**      | **100**         | **100**       | **100**         | **100**     | **1.015625**      |
| 90          | **100**      | **100**         | **100**       | **100**         | **100**     | **1.078125**      |

From Table 4 and Table 5, we know that while using RBF, the classifier can correctly classify the data into 100% of accuracy, sensitivity, precision, specificity, and f-score for 60 – 90% composition of training data, while polynomial start from 70 – 90% composition training data.

4. **Conclusion**

This research aimed to apply fuzzy kernel k-medoids to classify bank financial failures data. As we can see from the result and analysis section, the best performance of fuzzy kernel k-medoids shows when we are using RBF kernel with \(\sigma = 0.1\) and all features in 60% composition of training data, the result is 100% for accuracy, sensitivity, precision, specificity, and f-score with 0.9 sec running time. However, if we used fisher score feature selection, the result of prediction is not giving the best performance of model. Then, if we compare the result with our previous research with random forest [7], fuzzy kernel k-medoids gives the highest accuracy than random forest. However, another research Boyacioglu, Kara and Baykan (2009) while using learning vector quantization is resulting 100% accuracy, same as our result [5]. For the next research, we suggest use another feature selection method that can give the highest performance than fisher score and also try to apply fuzzy kernel k-medoids in another dataset that updated and bigger dimension.
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