Method of Forming a Training Sample for Segmentation of Tender Organizers on Machine Learning Basis

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Abstract

Paper develops the method of a training sample forming for training the segmentation of tender organizers on the basis of machine learning. To segment the tender's organizers on the machine learning basis, it is necessary to form an ideal training sample. This will allow segmenting tender organizers into the following groups: The best tenders organizers, Loyal tenders organizers, Large consumers, Seldom tenders organizer, but for a large sum, and Weak tender organizers. The method is based on RTF analysis and K-means clustering. Completed agreements of tender participants in Ukraine from the ProZorro Sales site were used as input data. The sample is 93,336 values relative to 10 parameters. The result was tested using Logistic Regression and Naive Bayes, which demonstrated 100% accuracy.

Keywords 1

Segmentation, tender, training set, machine learning

1. Introduction

Tenders are an important tool in the modern mechanism of the market economy: they promote the domestic trade development, which, in turn, is a means of ensuring higher growth rates of the national economy. A tender is an indicator of the country economic civilization, because through the degree of development of public procurement mechanism is possible determination the level of entire economic system development. Tender [15] is a competitive form of an order placing for goods purchasing, services provision or works performance in accordance with the conditions specified in the documentation in an agreed time on the principles of generality, fairness and efficiency.

It is important for the tenderer to know complete information about the organizer, how many auctions the organizer has conducted, how many of them were successful and their amount. Therefore, this requires an automated system for selecting tender organizers based on machine learning, which will also allow to automate the participation process in the tender. To do this, it is needed a training sample forming that can teach the system to recognize the tender's organizers without additional calculations.

In this regard, it can be considered that the development of a method of training sample forming for machine learning base for tender organizers' segmentation is an important area in e-tenders.

The paper is distributed as follows: Section 2 discusses the analysis of related work. Section 3 presents a method of a training sample forming for tender organizers segmentation machine learning base. Section 4 presents the method implementation. Section 5 summarizes results.

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2. Related Work

Many authors conduct research on public tender procurement [21] in the areas of: health care [16]; renewable energy sources [17]; food industry [18]; construction industry [19]; mining industry [22] and by some countries [20, 23-25].

Paper [2] considers the methods of classified training sample forming, which is generated only by active interference, to adapt spatial filters weights under the conditions of interference combined presence.

In paper [3] the adaptive method of classified educational sample forming on the basis of using a correlation coefficient of threshold estimation for of inter-channels obstacles combination is offered.

In [4] the problem of representative sample effective formation for neural network training on Multilayer Perceptron Type (MLP) is considered.

Paper [5] proposes an algorithm for training set developing for better description of objects recognition.

The study [6] evaluates the effectiveness of different approaches to data clustering for finding profitable consumer segments in the UK hospitality industry.

The study [7] is based on the RFM model (Recency, Frequency and Monetary) and uses the principles of data set segmentation using the K-Means algorithm. The obtained sales results are compared with such parameters, as recent sales, sales frequency and sales volume.

Research [8] develops a new approach by integrating "Recency, Frequency and Monetary" with rare K-means clustering algorithm proposed by Witten and Tibshirani. The proposed approach is suitable for processing of large, great and sparse consumers data.

Paper [9] provides an example of the data science methods using to classify online store buyers by their purchasing activities.

Paper [10] combines the radiation values of the community relationship with the RFM model and improves the M index algorithm to form the RFMC model, for making it more suitable for e-commerce organizations with community promotion nature.

In [11], investigated solving of enterprise real problems using RFM models and K-means clustering algorithm, which are used for consumer segmentation and cost analysis by online sales data. Here, various CRM strategies are put forward to achieve a customer satisfaction.

In paper [12] by analyzing the evaluation index of clustering algorithm and analysis of visualization experiment, and its results show that the model and algorithm of consumer classification satisfy the consumer value.

In [13] the peculiarities of clients' behavior during clients clustering are considered. Also were investigated method of optimal clusters number and initial cluster centers values to obtain better results.

Researches [14, 27] improve research on the digital marketing strategies development based on recommendations, providing forecast model, for data science usage, especially machine learning techniques and big data, for better financial impacts for users on the base of new customers quality, which are redirected to the cash-back website.

Customer segmentation research is an extremely popular topic, as confirmed by the analysis above. However, none of them considers the tender auction organizers segmentation, as this will allow auction participants to analyze: new markets for their products; transparency and honesty of the e-trading system – the best wins; choosing the most attractive organizer, which will allow to follow the best deals. Also, on the received data basis, it is possible to develop system for a tenders' organizers choice on the machine learning basis that will give the chance to automate process of tender participation.

Therefore, the goal of the paper is developing of method for training sample forming for tender organizers segmentation on machine learning base.

Unlike analogues [4, 5] the developed method of educational sample forming for tenders' organizers segmentation on the machine learning basis, will allow to form the educational sample, which become the part of system for tenders' organizers selection on the machine learning basis.

3. Proposed method

To determine the tenderers organizers who conduct the largest number of auctions and those who spend the most money on the agreement completion, the authors have developed a method of training sample forming for segmentation of tender organizers on machine learning base.

The proposed method is represented by the following steps (Fig. 1):

1. Data input (Block 1): completed bidding agreements.
2. RFM analysis. It is a consumer segmentation technique that uses the behavior of past transactions to divide customers into groups. This method of analysis can also be used well to tender organizers segmentation.

2.1. RFM-analysis for the tender organizer's segmentation will be based on three indicators.

- Recency – the period of time since the last transaction.
- Frequency – the number of transactions for relevant period.
- Monetary – sum of all completed transactions for the relevant period.

3. Quartiles Formation. Quartiles divide the number of data points into four parts, or quarters, of more or less the same size. Data should be sorted from smallest to largest to calculate quartiles.
4. Grouping by the quartiles amount (Block 4). Grouping of tender organizers according to the following criteria: The best tenders' organizers, Loyal tenders' organizers, Large consumers, seldom Tenders holders, but for a large sum, and Weak tender organizers.

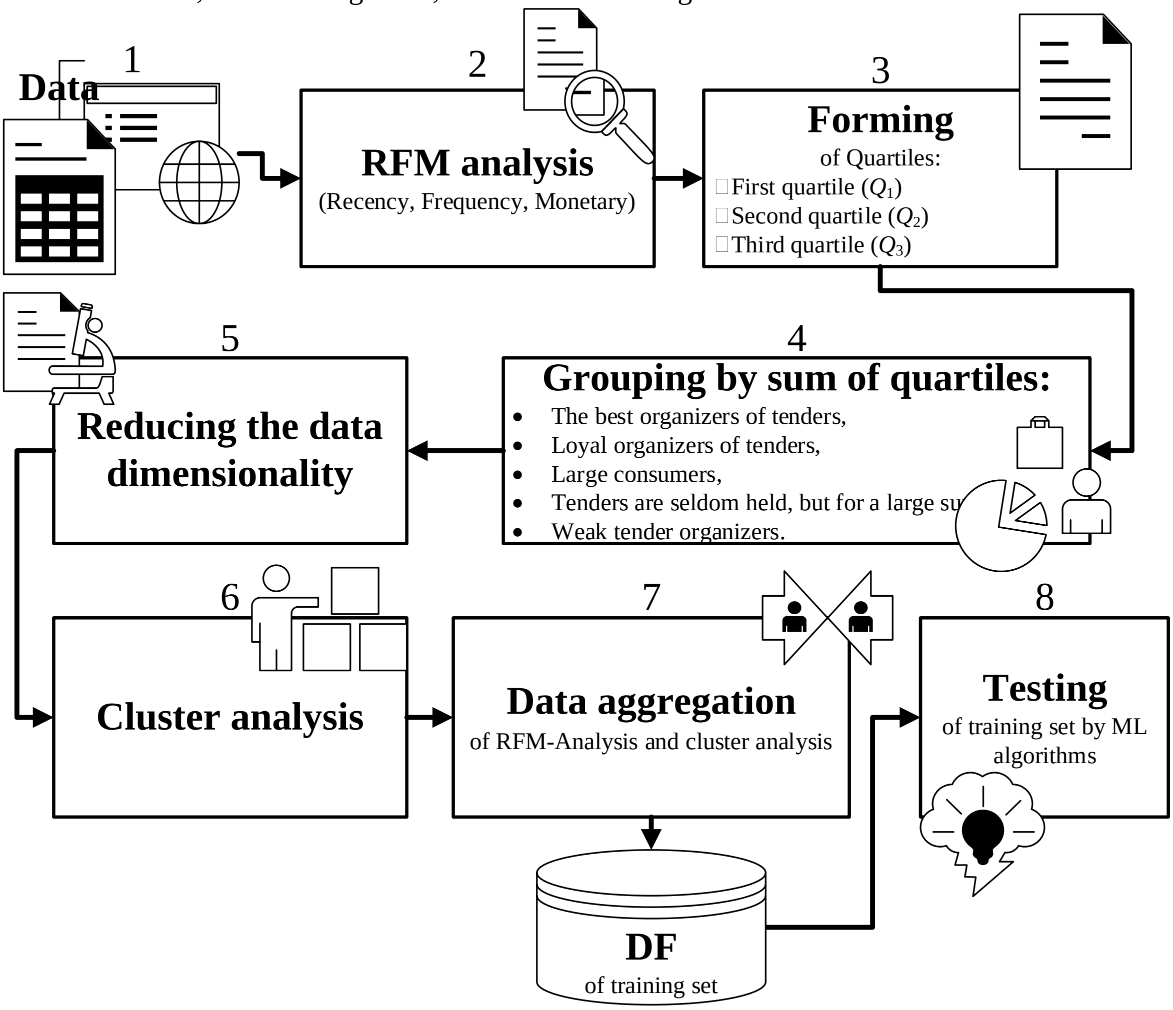


Figure 1. The structure of the training sample formation for the tender organizer's segmentation based on machine learning

5. Reducing the dimensionality of data (Block 5). Dimension reduction means reducing the number of random variables by obtaining a main variable set. The separation of features and

reduction of dimensionality can be combined in one stage using the method of principal components (MPC), linear separation analysis (LSA), canonical correlation analysis (CCA) or non-negative matrix factorization (RNM). Data on tender agreements are very scattered, so reducing the dimension is an important step for further clustering of data.

6. Clustering (Block 6). Cluster analysis is used for dividing a given set into clusters (subsets) and each cluster haves similar objects, and they are significantly different for different clusters. Cluster analysis is a deeper analysis for the segmentation of tender organizers, so it is important for the training sample. This analysis is divided into the following stages:

- Research conducting.
- Data preparation for cluster analysis.
- Choosing of cluster analysis method.
- Choosing a distance measure between objects and its calculation.
- Choosing of clustering strategy.
- Application of the chosen strategy for the clusters forming.
- Checking the results of cluster analysis for meaningfulness and their interpretation.

7. Combining of RFM-analysis data, cluster analysis and entering into database (Block 7). Based on these data, it is possible to train segmentation classification of tender organizers.

8. Training sample testing (Block 8) on the algorithm's basis of machine learning classification.

4. Experimental Results and Discussion

Python language was selected to form a training sample for segmentation of tender organizers on machine learning base. The following libraries were employed: pandas, numpy, train_test_split, KMeans, PCA.

Completed agreements of tenderers in Ukraine from the ProZorro Sales website were used as input data [1]. The sample (Fig. 2) after cleaning is 93,336 values relative to 10 parameters.

```
RangeIndex: 93336 entries, 0 to 93335
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Bid Date             93336 non-null  object
 1   Organizer            93336 non-null  object
 2   ID_Orzanizer         93336 non-null  int64
 3   Auction ID           93336 non-null  object
 4   Auction Status       93336 non-null  object
 5   Final Bid Value      93336 non-null  int64
 6   Tenderer             93335 non-null  object
 7   ID_Tenderer          93334 non-null  float64
 8   Bid Marketplace      93334 non-null  object
 9   ID_Bid Marketplace   93334 non-null  object
```

Figure 2. Sample structure

When estimating the quantitative indicators (Fig. 3), 92638 auctions were identified, 29164 unique auctions and 39747 unique organizers.

	Organizer
Number of auctions	92638
Number of unique auctions	29164
Number of Unique Organizers	39747

Figure 3. Quantitative indicators of the sample

Next, we will conduct an RFM analysis. RFM will help divide organizers into different categories or clusters to determine which organizers are more likely to hold auctions with the largest amounts. These 3 attributes of the client for each organizer (Fig. 4).

To calculate the Recency, it is needed to choose the date from which the evaluation will be conducted, and how many days ago the last transaction was made.

Frequency of transactions will allow to find out how many times the organizer has made transactions. To do this, was checked how many accounts were registered by the same organizer.

The Monetary attribute determines how much money is earned on organizer transactions.

ID_Orzanizer	Recency	Frequency	Monetary
1	952	2	1134546
2	412	1	23414
3	154	1	7
4	421	14	8625230
5	1214	1	24225
6	122	9	27834555
7	1	1	16368
8	1086	17	5746360
9	436	4	307177
10	647	4	209575

Figure 4. RFM-analysis (head(10))

The easiest way to segment organizers is to use Quartiles, namely assigning scores from 1 to 4 Recency, Frequency and Monetary (Figure 5). Four is the highest value and one is the lowest value.

ID_Orzanizer	Recency	Frequency	Monetary	Rank	R_Quartile	F_Quartile	M_Quartile	RFMScore
1745	374	21	15920922384	1.0	3	4	4	344
453	353	52	9056844144	2.0	3	4	4	344
408	275	33	5848400325	3.0	4	4	4	444
1290	426	48	4465808177	4.0	2	4	4	244
1632	31	24	3856853376	5.0	4	4	4	444

Figure 5. RFM-Quartiles

Figure 5 shows that the organizers with ID 408 and 1632, received the highest score, i.e.: R_Quartile = 4: recent transaction, F_Quartile = 4: the largest number of transactions; M_Quartile = 4: Earned the most money. Accordingly, RFMScore = 444 for these tender organizers.

The evaluation of the general sample (Fig. 6) was carried out according to the following criteria: The best organizers of tenders (RFMScore = 444), Loyal organizers of tenders (F_Quartile = 4), Large consumers (M_Quartile = 4), Tenders are seldom held, but for a large sum (RFMScore = 114) and Weak tender organizers (RFMScore = 111).

Now, when there is a segmentation of tender organizers, it is possible to evaluate each group individually and analyze how money is spent and which organizers conduct tenders most often.

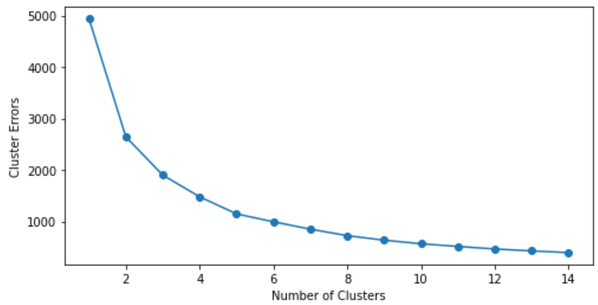
To gain an even greater understanding of the tender organizer behavior, it is necessary to further study the relationship between RFM variables. Therefore, it is necessary to combine the obtained results with certain predictive models, such as clustering K-means clustering, logistic regression or recommendation system to obtain better informative results on the behavior of tender organizers.

```
The best organizers of tenders:  119
Loyal organizers of tenders:  385
Large consumers:  455
Tenders are seldom held, but for a large sum:  15
Weak tender organizers:  48
```

Figure 6. RFM evaluation of tender organizers

K-means clustering is chosen for grouping, as this method is widely used for market segmentation, and it offers the advantage of ease of implementation. Before clustering, the dimensionality of the data was reduced by PCA with 2 dimensions vectors (components).

From the area (Fig. 7) of the elbow there is a sharp bend after increasing the number of values on the 2nd cluster. The Silhouette score is also the highest for cluster 2. There is also a significant reduction in cluster error from 2 to 5, and after 6 the reduction is not large. Accordingly, n_clusters = 5 is selected to properly segment the tender organizers.




```
For 2 clusters, average silhoutte score = 0.4234
For 3 clusters, average silhoutte score = 0.3859
For 4 clusters, average silhoutte score = 0.3906
For 5 clusters, average silhoutte score = 0.3884
For 6 clusters, average silhoutte score = 0.3515
For 7 clusters, average silhoutte score = 0.3717
For 8 clusters, average silhoutte score = 0.3821
For 9 clusters, average silhoutte score = 0.3833
For 10 clusters, average silhoutte score = 0.378
For 11 clusters, average silhoutte score = 0.379
For 12 clusters, average silhoutte score = 0.372
For 13 clusters, average silhoutte score = 0.376
```

Figure 7. Determining the clusters number

Figure 8 shows the clustering of K-means of tender organizers, where the number of clusters is 5. The graph is presented for the 2-component PCA method. The boxplot diagram shows the emissions to each cluster, also in the context of the 2-component PCA method. The following number of values is assigned to each cluster: clusters number 0 – 494; clusters number 3 – 475; clusters number 2 – 352; clusters number 1 – 345; clusters number 4 – 155.

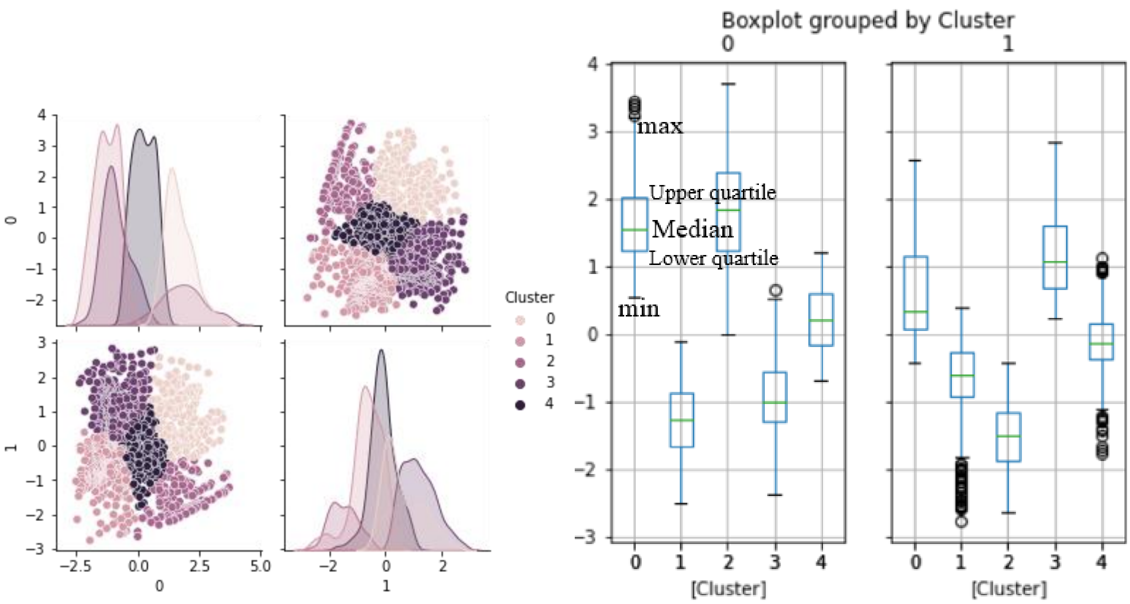


Figure 8. K-means clustering of tender organizers

The boxplot analysis shows that for the first component (number 0) the clusters have the lowest emissions, which confirms a more detailed distribution by clusters, so a more detailed analysis of this cluster analysis was performed.

The first cluster (number 0): the minimum value is 0.6; lower quartile (25% of the sample) – 1.2; median (50% of the sample) – 1.5; upper quartile (25% of the sample) – 2; the maximum result is 3.2. Also, there are several ejection values.

Second cluster (number 1): minimum value – -2.5; lower quartile – -1.5; median – -1.4; upper quartile – -0.9; the maximum result is -0.1. There are no ejections.

Third cluster (number 2): minimum value – 0; lower quartile – 1.3; median – 1.8; upper quartile – 2.4; the maximum result is 3.8. There are no ejections.

Fourth cluster (number 3): minimum value – -2.5; lower quartile – -1.3; median– -1; upper quartile – -0.5; the maximum result is 0.6. There is one ejection value.

Fifth cluster (number 4): minimum value – -0.6; lower quartile – -0.2; median – 0.3; upper quartile – 0.5; the maximum result is 1.2. There are no ejections.

When comparing RTF estimates and K-means groups with trend organizers (Fig. 9), who organize tenders the most and for the largest amount of money, the group with organizers who hold tenders a little, but not for significant amounts, coincided. Other groups of tender organizers partially coincided.

ID_Orzanizer	Recency	Frequency	Monetary	Cluster	RFMScore
1551	30.0	1.0	3060000.0	3	413
695	309.0	1.0	2598260.0	3	413
954	1.0	1.0	1401975.0	4	413
598	309.0	1.0	1140000.0	3	413
579	30.0	1.0	1070856.0	3	413
...	...	...	...	...	...
1349	317.0	1.0	43.0	0	411
1754	30.0	1.0	36.0	0	411
1214	317.0	1.0	32.0	0	411
300	290.0	1.0	24.0	0	411
3	154.0	1.0	7.0	0	411

Figure 9. The result of RTF estimates clustering and K-means

Based on these data, it is possible to predict clusters using machine learning methods. To do this, it is used the method of Logistic Regression and Naive Bayes, because these methods have the simplest logic of qualification and good results of modeling evaluation.

70% of the sample was taken for training. Training was performed by Logistic Regression and Naive Bayes algorithms. After testing, the evaluation results are, for both methods (Fig. 10):

```
Train Set Accuracy for Power Transformed Data: 100.0 %
Test Set Accuracy for Power Transformed Data: 100.0 %
Bias Error: 0.0
Variance Error: 0.0
```

Figure 10. Evaluation results for both methods

The simulation results show that RTF estimates and K-means give 100% grouping accuracy, according to these data to further classify the organizers of tender projects, which makes it possible to identify more attractive tender organizers.

Thus, the sample contains 92638 auctions, 29164 unique auctions and unique organizers – 39747. Based on RFM-analysis, the following groups were formed: The best tenders' organizers – 119; Loyal tenders' organizers – 385; Large consumers – 455; Seldom tenders organizer, but for a large sum – 15; Weak tender organizers – 48. Based on clustering by the K-means method, the following values number is assigned: cluster number 0 – 494; cluster number 3 – 475; cluster number 2 – 352; cluster number 1 – 345; cluster number 4 – 155. After testing by algorithms of Logistic Regression та Naive Bayes, the evaluation results are for both methods: Train Set Accuracy for Power Transformed Data – 100.0%; Test Set Accuracy for Power Transformed Data – 100.0%.

5. Conclusions

There was developed the method of training sample forming for tender organizers segmentation on machine learning base. On its basis the tenderer can make management decisions regarding the favorable proposal placement, and that can reduce the risks of non-profit transactions. Also, the proposed method reduces the time spent for searching of the most attractive organizers.

The developed method enables forming a sample based on combination of RFM-analysis data and cluster analysis. The method is implemented on the basis of input data on tenderers completed agreements in Ukraine from the ProZorro Sales website. The sample contains 92638 auctions, 29164 unique auctions and unique organizers – 39747. Based on RFM-analysis, the following groups were formed: The best tenders' organizers – 119; Loyal tenders' organizers – 385; Large consumers – 455; Seldom tenders organizer, but for a large sum – 15; Weak tender organizers – 48. Based on clustering by the K-means method, the following values number is assigned: cluster number 0 – 494; cluster number 3 – 475; cluster number 2 – 352; cluster number 1 – 345; cluster number 4 – 155. When comparing RTF estimates and K-means groups with the tender's organizers who organize the most tenders and for the largest amount, the group with the organizers who hold few tenders coincided, but not for significant amounts. Data testing was performed by Logistic Regression and Naive Bayes algorithms. After testing, the evaluation results are for both methods: Train Set Accuracy for Power Transformed Data – 100.0%; Test Set Accuracy for Power Transformed Data – 100.0%.

One of further research directions should be the development of an information system for the tender organizers selection based on machine learning and ontology approach [29].

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