Development of a machine learning software system for customer churn predictions

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OBJECTIVES AND WORK TASKS

Target:

- Creating models for predicting customer churn in the banking sector using classification methods
- Comparative analysis of the accuracy of results using visualization of quality metrics

Tasks:

- Searching and processing large number of data (Big Data)
- Determining possible customer loyalty in the analysis of input data
- Algorithm adaptation and modeling
- Comparative analysis of results
- Interpretation of results using visual metrics representation of output data

WHY DO YOU NEED PREDICTIONS?

The customer churn prediction allows:

- Analyze the current state of the organization
- Receive recommendations regarding customer segmentation, banking products

The ratio of clients in banks

Bank A

Bank B

TASK SETTINGS

- The formal setting of the classification task represents an unknown target dependency

$$y^*: X \to Y, \quad (1)$$

where X – many object descriptions, Y – finite number of class numbers.

The display values (1) are only known in the teaching sample objects:

$$X^n = \{(x_1, y_1), \dots, (x_n, y_n)\},$$

where n – number of rows of objects.

In a binary classification task, a number of class numbers $Y = \{f_1, f_2\}$. Usually $f_1 = 0, f_2 = 1$.

SELECTED METHODS OF SOLUTION

All selected methods are based on decision trees. Trees are a set of nodes that can be divided into two types:

- Decision nodes - signs on which the tree is built.
- Probabilistic (closing) nodes are leaves of trees in which subtotals or final values of characters are calculated.

1. Boosting – technology consistent building composition of machine learning algorithms, where each subsequent algorithm tries to compensate for the shortcomings of the composition of all previous algorithms.

Methods: XGBoost (Extreme Gradient Boosting), CatBoost (Categorical Boosting).

2. Bagging – classification technology, where all elementary classifiers are calculated in parallel before building decision trees.

Method: Random Forest.

INPUT DATA

The input data is given by a matrix $N \times M$, where N – bank clients, M – their indicative description.

Bank A: 45211 clients.

age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

Bank B: 10000 clients.

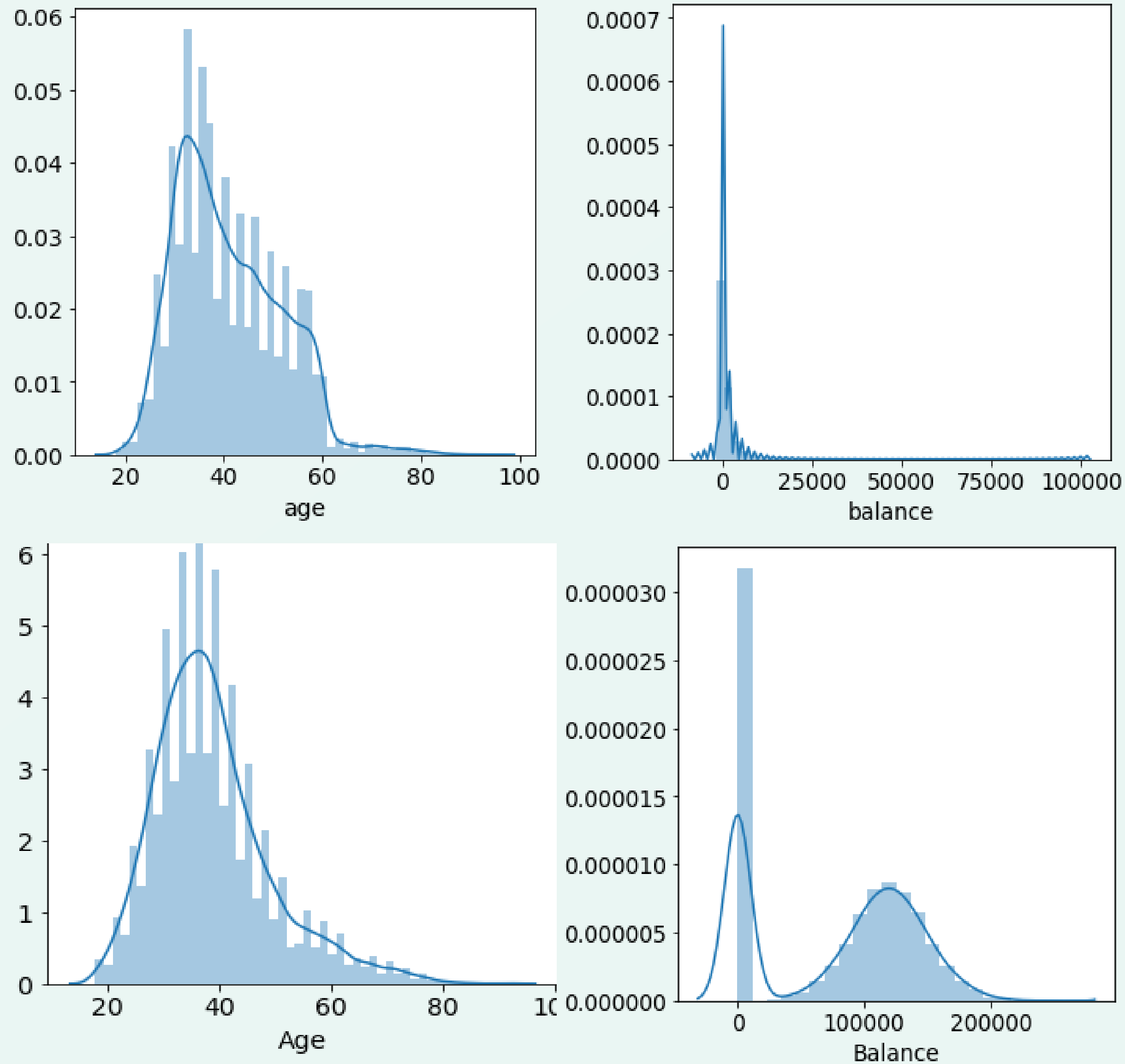
CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

Characters are numeric and categorical data. The target mark for bank A is column "y", for bank B - "Exited".

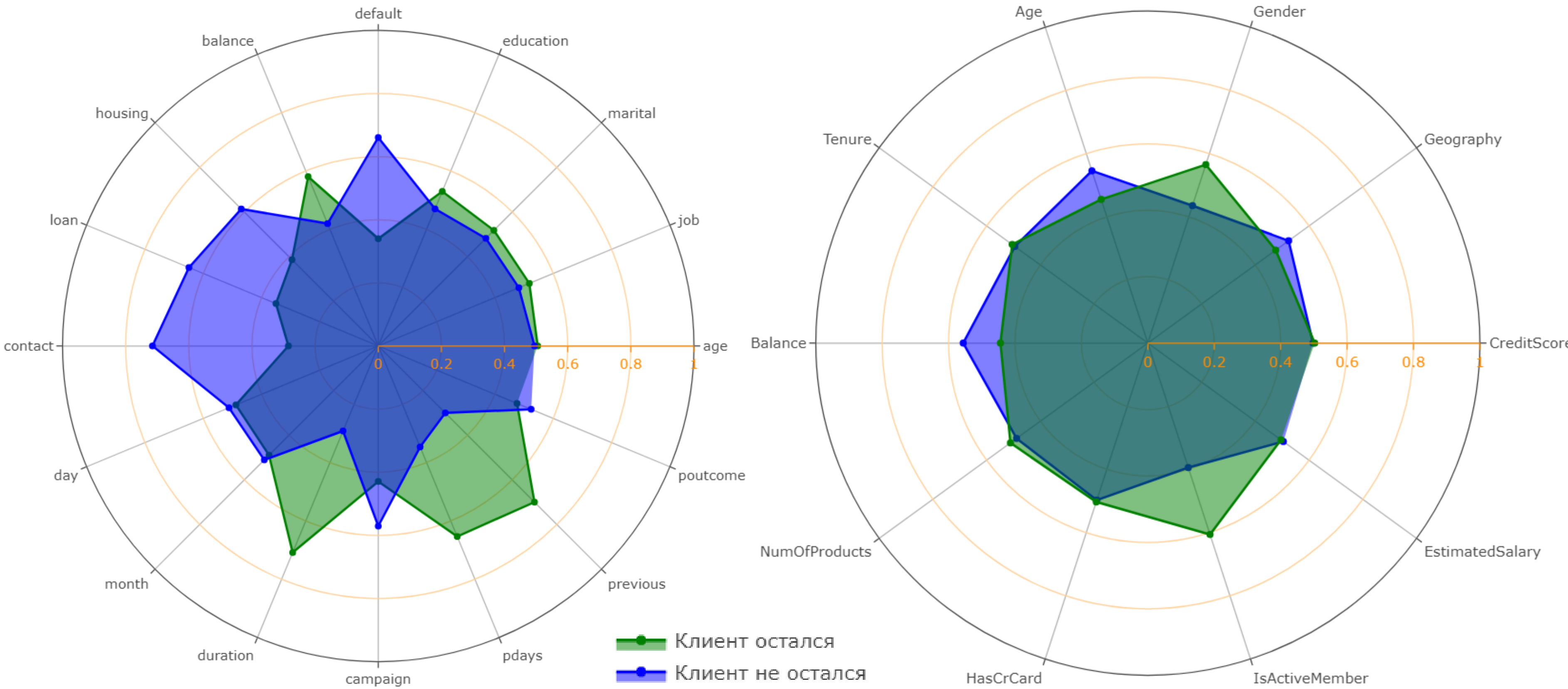
CHARACTER LAYOUT

The character layout shows the proportion of each unique hint value in the datasets and is a visual indicator of balance.
In axis **OX** the character is deferred, in the axis **OY** is the distribution of characters in the sample.
$\sum_{i=1}^{N} Feature_p = 1, p \in \overline{1,M}.$

Features:
Age – client's age,
Balance – client's balance.



AVERAGE FEATURE VALUES

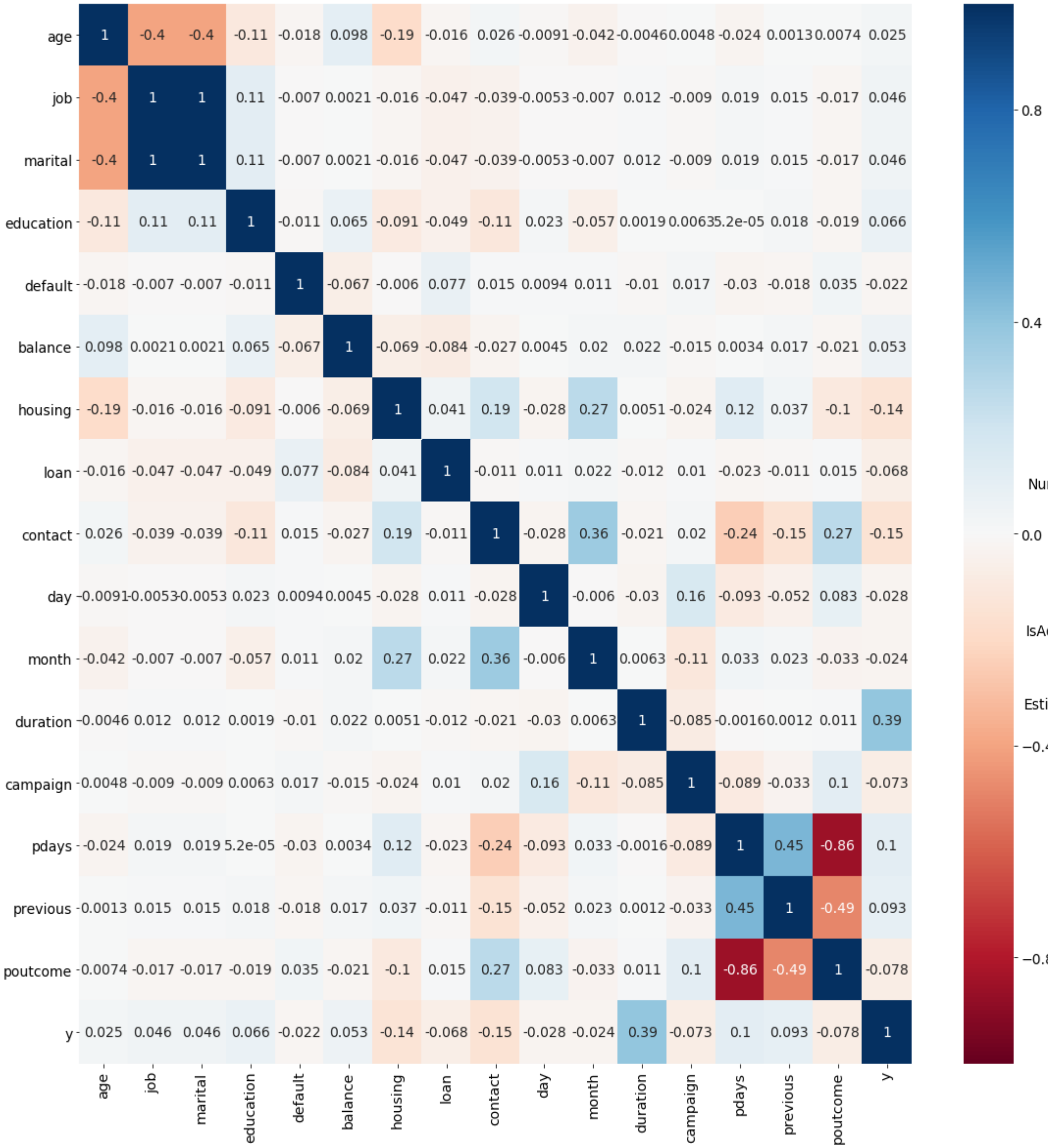


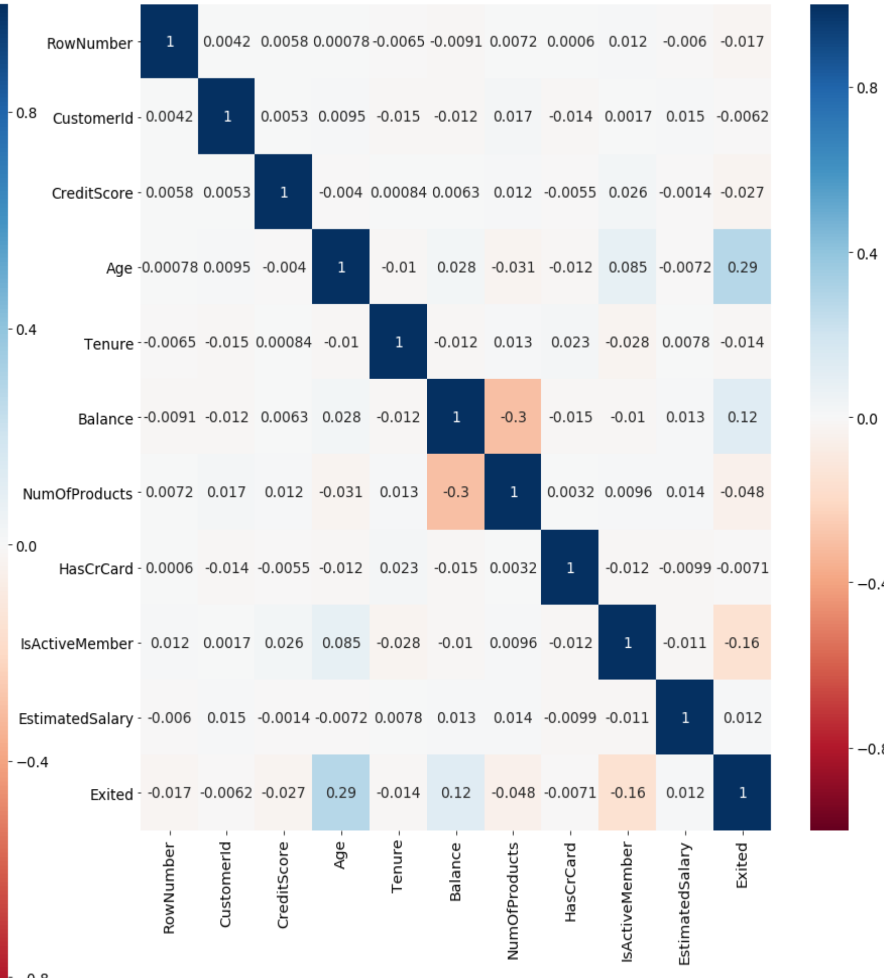
Feature values can be calculated according to the formula:

$$Feature_{mean_p} = \frac{Feature_{mean_i}}{Feature_{mean_0} + Feature_{mean_1}}, i = \{0,1\}, p = \overline{1, M}.$$

The graphs show that it differs more in bank A and it is easier to choose it's threshold.

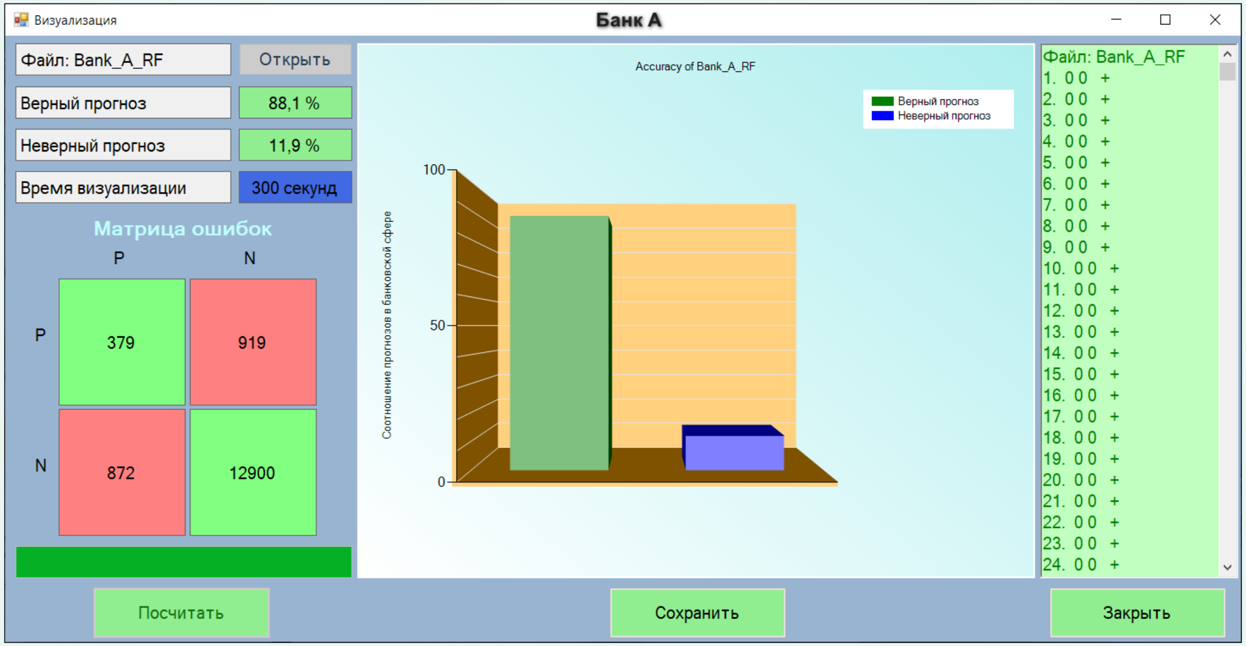
CORRELATION MATRICES

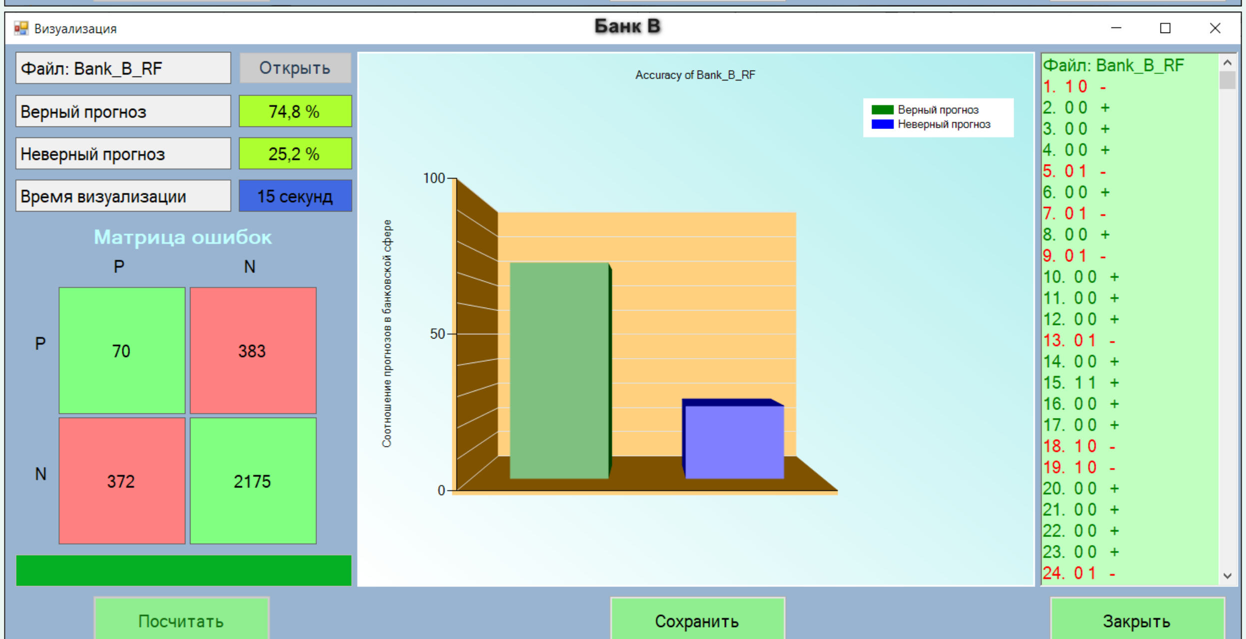




Blue color means strict direct relation, white - no relation, red - strict reverse relation.

VISUALIZATION

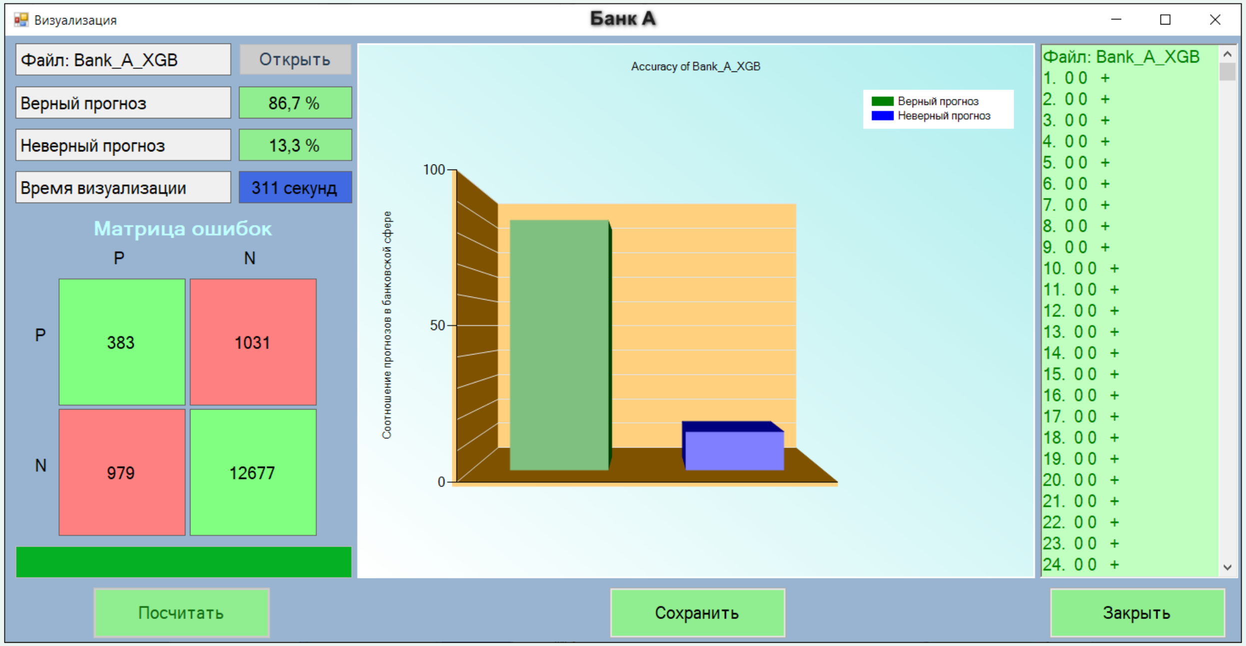


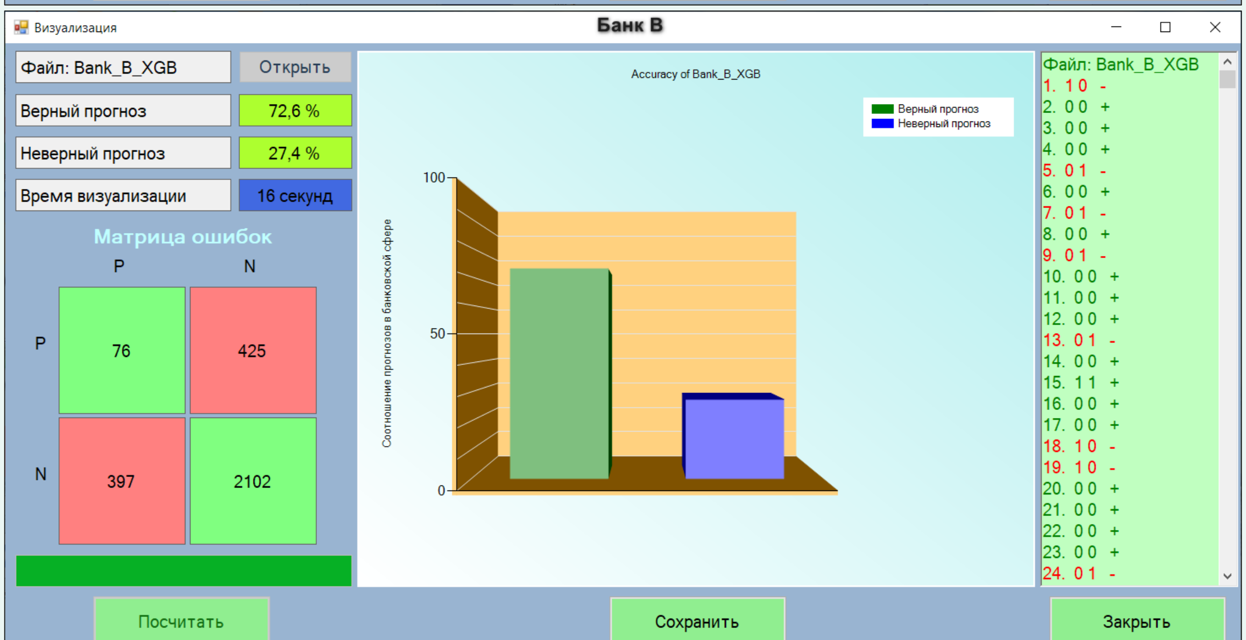


Visualization results of models trained by the Random Forest method. Accuracy metric value (correct prediction):
Bank A: 88,1%,
Bank B: 74,8%.

$$Accuracy = \frac{TP+TN}{P+N} \bullet 100\% .$$

VISUALIZATION

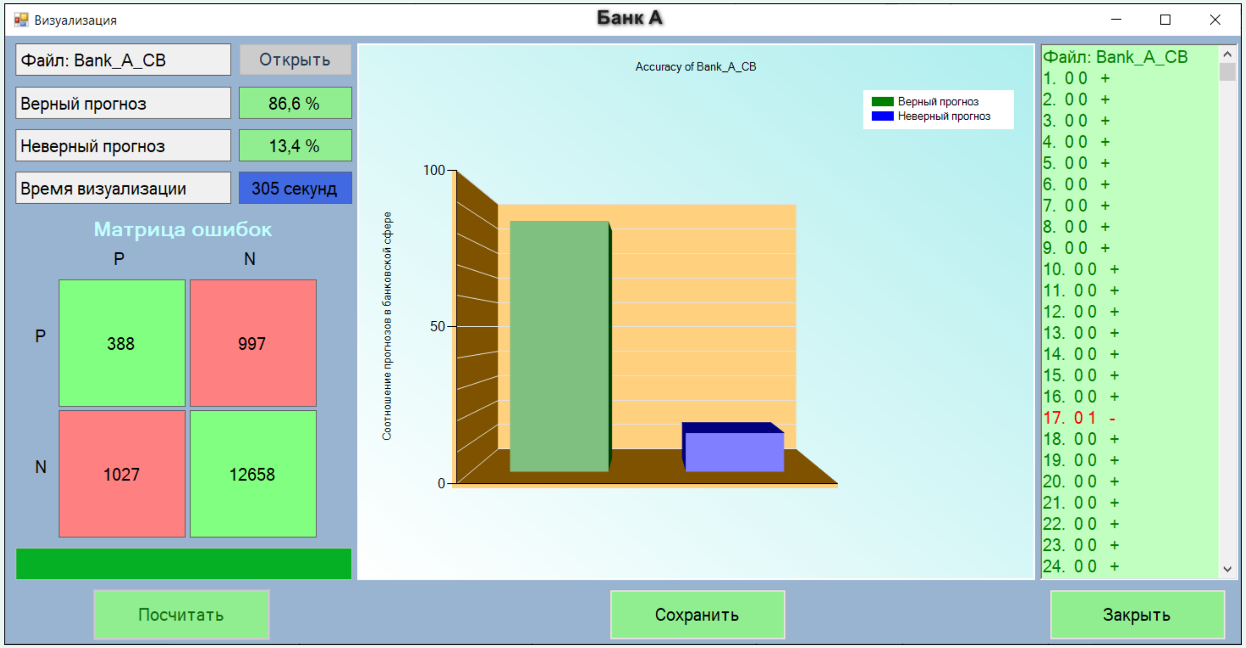


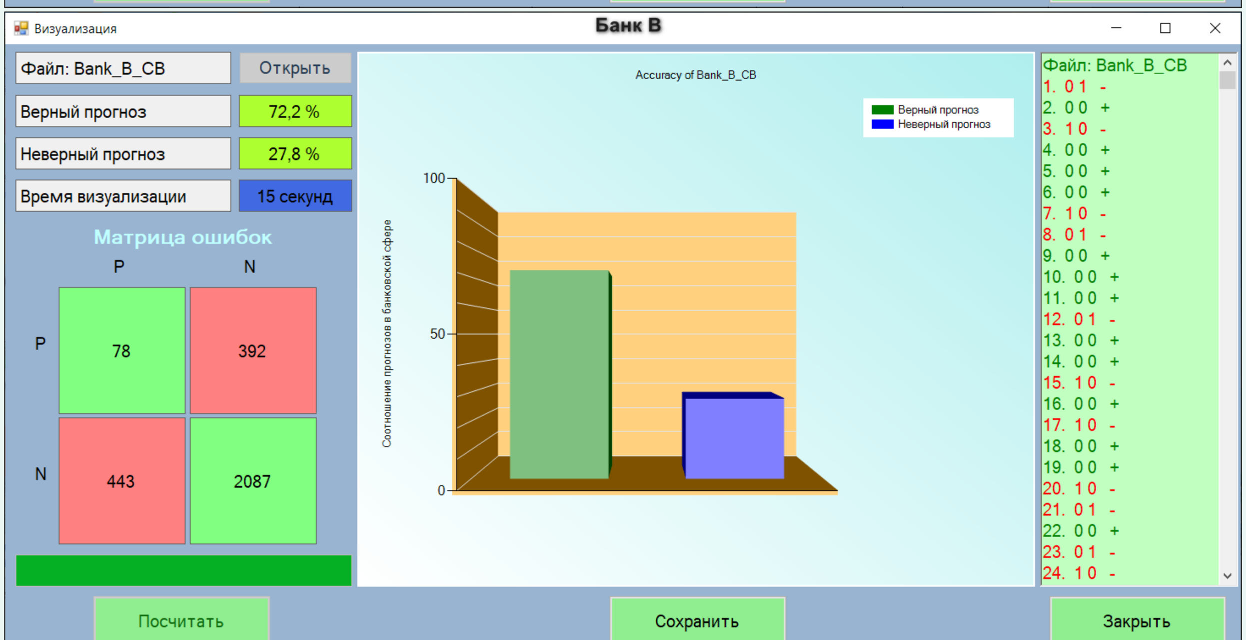


Visualization results of models trained by the XGBoost method. Accuracy metric value (correct prediction): Bank A: 86,7%, Bank B: 72,6%.

$$\text{Accuracy} = \frac{TP+TN}{P+N} \bullet 100\% .$$

VISUALIZATION





Visualization results of models trained by the CatBoost method. Accuracy metric value (correct prediction): Bank A: 86,6%, Bank B: 72,2%.

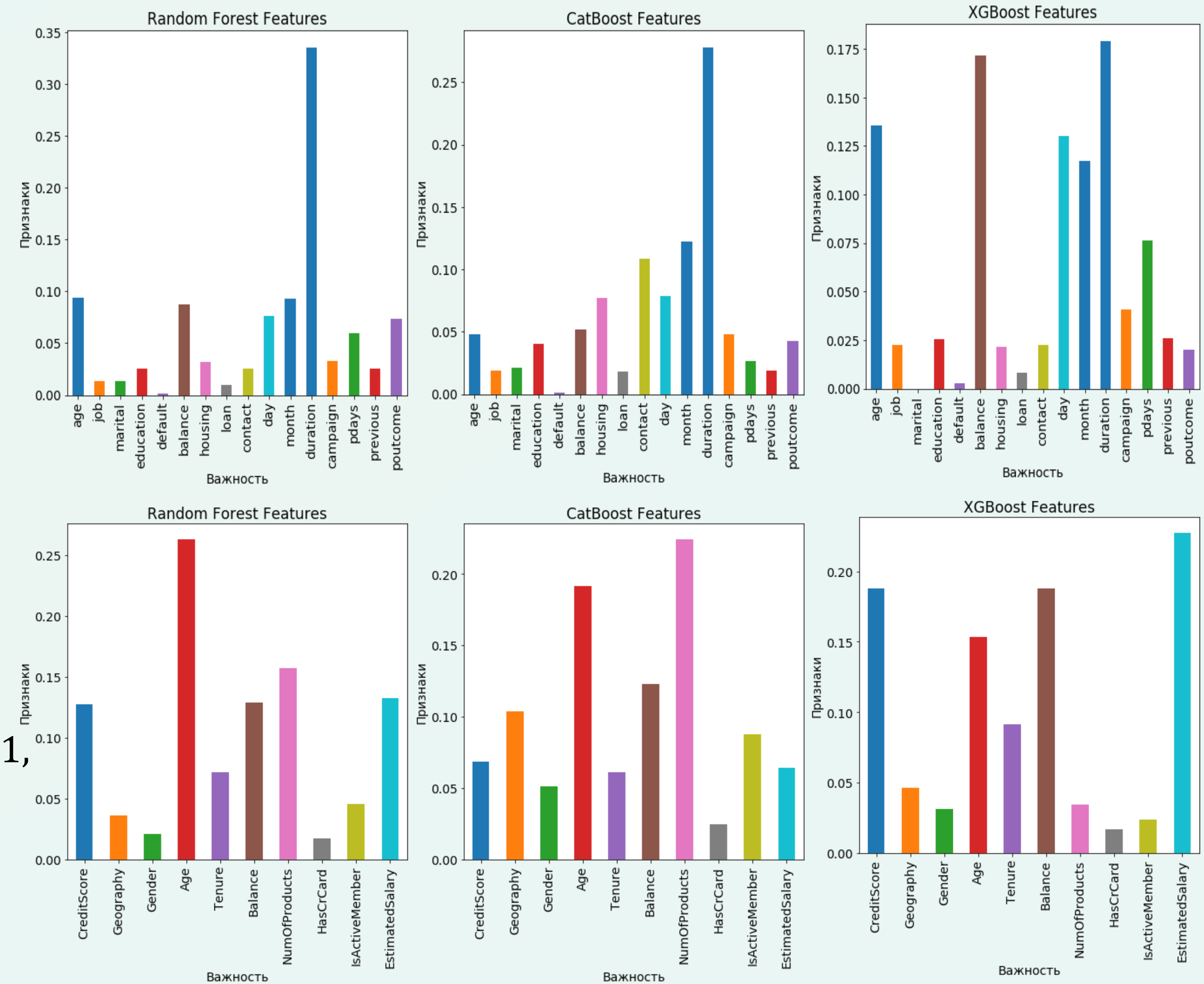
$$\text{Accuracy} = \frac{TP+TN}{P+N} \bullet 100\% .$$

CONCLUSION

- A comparative analysis of the methods show that all classifiers have good accuracy in the range of 72.2% to 88.1%, which proves their effectiveness in solving the problem of machine learning classification. The best results on the test sample were shown by the Random Forest method (88.1%), in second place - XGBoost and in third place - the CatBoost classifier
- The running time of the Random Forest method proved to be the shortest due to the possibility of building solution trees in parallel
- The Random Forest method can be used in all areas of customer outflow forecasting

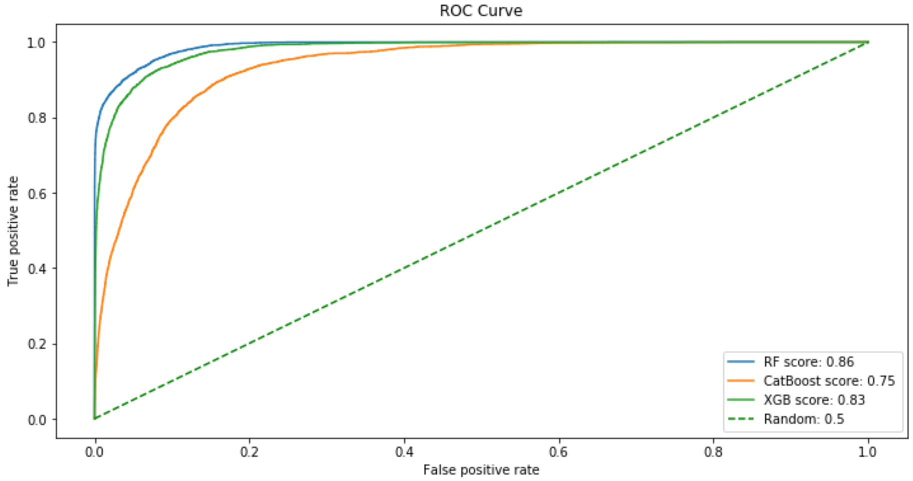
CHARACTER MEANING GRAPHS

The graph of the meaning of the characters shows their influence on the construction of the model.
In axis **OX** features appear, along axis **OY** – the probability value of the feature.
$\sum_{i=1}^{N} feature_p = 1,$
where $p \in \overline{1, M}$.

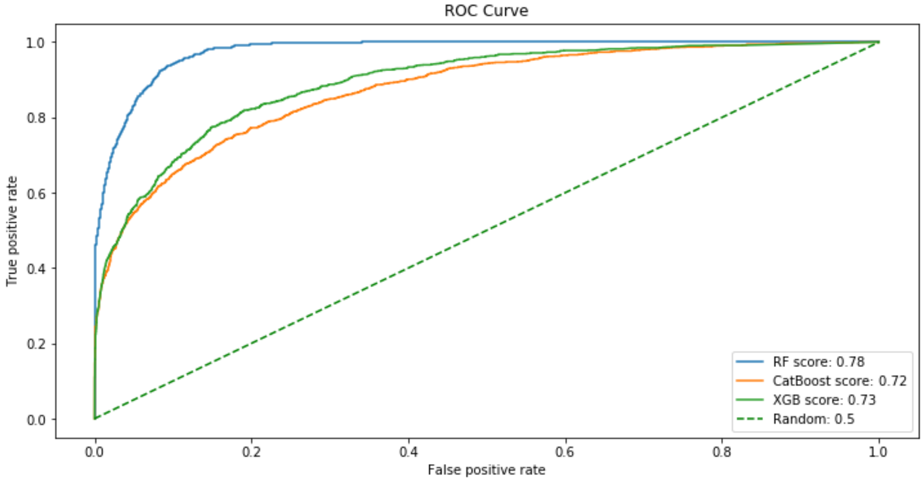


METRICS

Bank A



Bank B



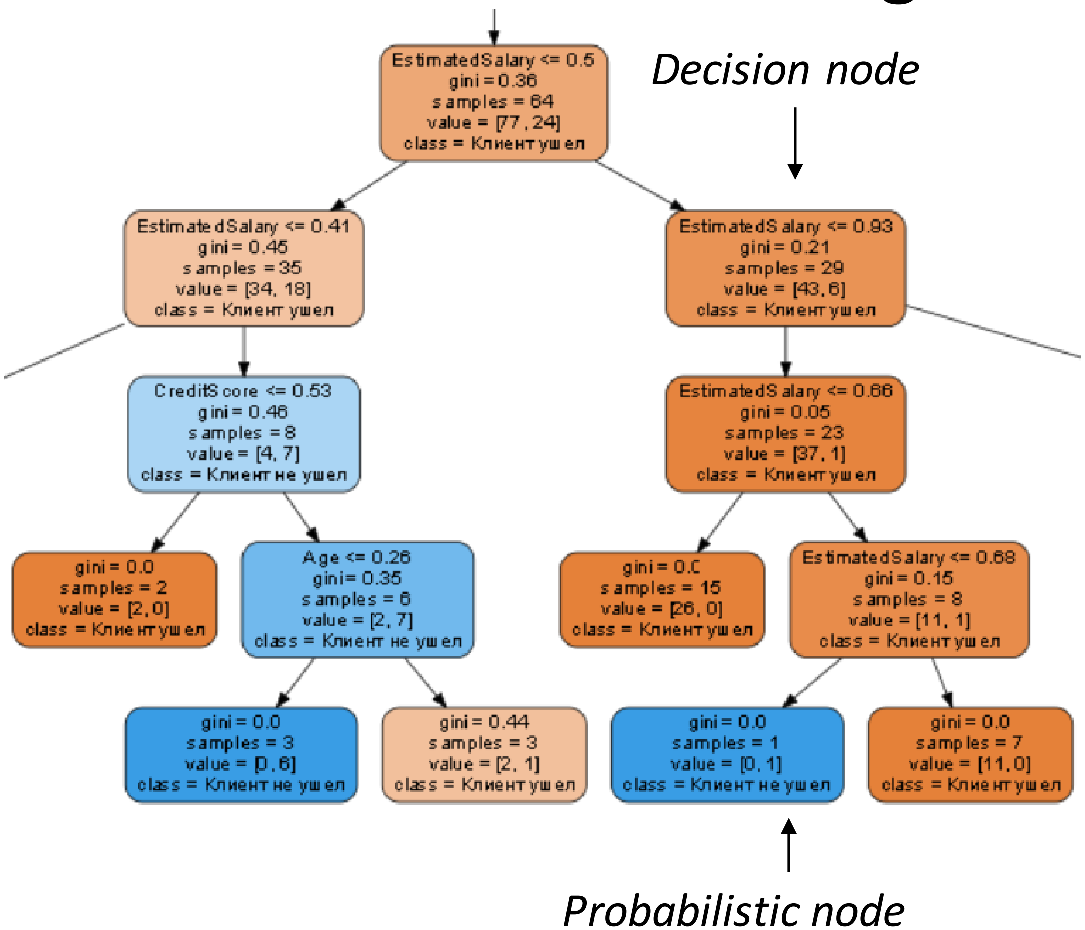
$$FPR = \frac{FP}{N}, \mathrm{TPR} = \frac{TP}{P}$$

The ROC-curve construction algorithm is built on the grid points $m \times n$, where m – number of "1", n – number of "0" on the following conditions. If the values of the target attributes are matched (true prediction), then there will be a shift up one division of the test sample, if the values of the target attributes are mismatched (false prediction), then there will be a shift to the right of one division. The overall execution of m steps up and n steps on the right will allow you to come to point (1,1).

Target: $S_{max} \to 1.$

Smoother lines on the bank chart are caused by the test sample having a large size matrix for constructing AUC ROC metrics.

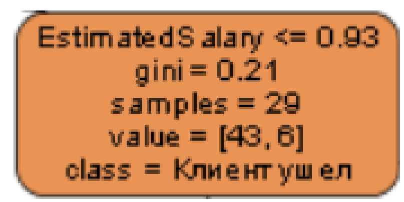
Solution tree fragment visualization



The purpose of building trees is to minimize the criterion of probability of incorrect classification:

$$Gini = 1 - \sum_{1}^{j} k_j^2 ,$$

$where\ k_j - probability$ of j class. There are two classes in binary classification = > j = 2.



Example of Gini calculation for solution node "$EstimatedSalary$ <= 0.93":

$$Gini = 1 - (k_1^2 + k_2^2) = 1 - \left(\left(\frac{43}{49}\right)^2 + \left(\frac{6}{49}\right)^2\right) = 1 - \frac{1849 + 36}{2401} \sim 1 - 0{,}785 \sim 0{,}21.$$

Total building and visualization time