MULTI-CLASS CLASSIFICATION FOR COMPLICATED TECHNICAL SYSTEMS' OPERATION DIAGNOSTICS

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Introduction

Technical systems operation diagnostics is realized to provide safety and reliability. But it is always limited by the object state division into several classes: serviceable status class and different types of malfunctions classes.

The task is to apply multi-class classification with the use of machine learning tools. Based on the available set of reference data the classifying system is realized, and it helps diagnose the object state for the new set of indices.

With a big number of indices it is reasonable to select the most significant ones among them, and define the sample size, (or learning-to-test samples size ratio), to choose the classification method ensuring the required accuracy. To avoid overfitting, cross validation is used. These are the problems, solved in any task of machine learning.

The specific feature of complicated technical systems diagnostics is a comparatively small size of observations and classes imbalance: as a rule the observations of unserviceable systems are fewer than those of the serviceable ones.

Multiclass classification program

The program is developed in Python language. The reference data file is entered, then at random it is divided into test and training sets with a certain ratio, and stratified, the cross-validation is done with a number of units preset by the user.

The program provides the selection of the object operation significant indices in two ways: indices correlation and predictor variable significance in linear regression model of the object class dependence on its indices.

Sklearn library is applied hereto, as it imports ready-made constructors for base classification lists, the modules to calculate the scores of multi-class classification: accuracy_score; f1_score – F-measure (main characteristics of classification fidelity for imbalanced classes), and confusion_matrix, as well as cross validation score and training and test sets division.

To realize the average value aggregation, Python functions are used to predict the probability of each object belonging to a certain class. The application of classifiers aggregation stems from the fact that binary classification approach ensures significant classification accuracy increase.

The result of the program is the calculation of three measures of classification fidelity, applying a test sample for each base classification list, ensemble classifier and aggregated classifier.

The user chooses the best classifier, depending on this or that criteria. This classifier is to be used in future to diagnose the object state. Taking into consideration the newly determined indices of object operation the object state class is predicted.

Computational investigation

To monitor the computer operation, there was done a test of its characteristics with application of AIDA64. Extreme software integrated functions together with parallel load from other programs within a certain period of time.
The effect of different indices of the computer operation (processor load, dynamic memory components heating, voltage, power, etc. Totally there are nine indices: x1…x9) on its state was investigated: 1 is serviceable, 2 is hanging, 3 is image distortion, 4 is the cursor dormancy, 5 is sound jamming.
There were 715 observation results totally, with 143 abnormalities found (20%). This distribution testifies to the data imbalance, so the main feature of model classification fidelity should be F-measure.

The selection of significant factors and their remoteness in the experiment did not contribute to the classification quality. All nine indices of the computer operation were applied to the further computations.

During the investigation the program was launched several times with different test-to-training sets ratios in reference data divisions (9:1, 85:15, 8:2, 75:25, and 7:3).
F-measure calculation results for different base classification lists and ensemble classifiers with test sample size 10% are presented in Tables 1-2. The best result was given by the Decision Tree: F-measure was 0.972 , this was the result of the test set not used during modelling.

Table 1.
F-measure values for 10% test sample base classification list and ensemble classifiers

Classifier	Acronym	F1-score
Decision Tree	DT	0.972
Random Forest	RF	0.944
Support Vector Machine	SVM	0.877
K-Nearest Neighbors	KNN	0.928
AdaBoost (Adaptive Boosting)	AB	0.815
Logistic Regression	LR	0.931
Linear Discriminant Analysis	LDA	0.886

This experiment aggregation (Table 2) did not have any effect.

Table 2. F-measure values for 10% test sample aggregated classifiers

Aggregation	F1-score
RF + SVM	0.944
RF + KNN	0.958
RF + AB	0.944
RF + LR	0.944
RF + LDA	0.944
SVM + KNN	0.917
SVM + AB	0.877
SVM + LR	0.889
SVM + LDA	0.873
KNN + AB	0.928
KNN + LR	0.928
KNN + LDA	0.928
AB + LR	0.931
AB+ LDA	0.886
LR + LDA	0.889

So, the test sample size variation did not increase the computer state prediction quality significantly (the error is 2-3%). Such error is available in the repated experiment (due to random selection of data for the test and trainig samples).
But it is worth highlighting that in two experiments out of five experiments the aggregated classifiers increased the diagnostics qiality.

Conclusion

The developed program of multi-class classification for complicated technical systems operation diagnostics with machine learning tools provides rather high accuracy as per preliminary built sample of reference data based on the results of the object preceding operation. The best classifier can be applied to predict the system state as per the preset indices of its operation.

In the considered example of computer system operation diagnostics it was revealed that the selection of significant factors and variation of test sample fraction did not contribute to classification quality significant improvement, however, for other technical systems this effect can be essential.