APS Failure at Scania Trucks Data Set

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The task is to analyze data collected from heavy Scania trucks in everyday usage which might be correlated to Air Pressure System (APS) and to find a method to obtimize a cost given a formula based on miss classification

For this assigment I used the following supervised learning methods:

- Random Forest
- Extreme Gradient Boosting (XGBoost)

Dataset

Abstract

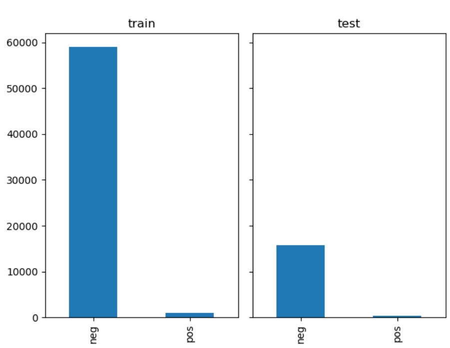
From dataset's description:

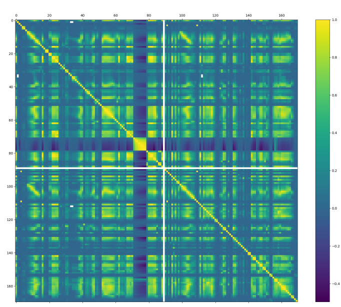
> According to the datasets' description, positive class consists of component failures for a specific component of the APS system. The negative class consists of trucks with failures for components not related to the APS. The attribute names of the data have been anonymized for proprietary reasons
>
> The dataset contains 170 features and 60000 samples for the training set

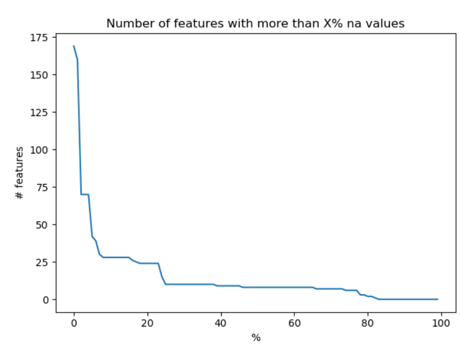
Exploratory Data Analysis

During EDA the followings things were observed:

- I had to skip some lines from the csv files because it contained description
- classes are strong imbalanced (98.3% are negative, only 1.6% positive)
- a lot of `NA` values
- a lot of 0 values
- some of the features tend to correlated beteen them (see the correlatioin matrix)
- one column has 0 standard variation (cd_000)
- all features are numeric







RandomForest Classifier

Description

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes or mean prediction of the individual

Basic model

Applying a simple model of RandomForestClassifier has a result of 52670$ applying a mean .

Tuning hyperparameters

To find the optimal hyperparameters, its commont to think of set of candidate hyper parameters, train models and compare their performance via cross validation. Where there are many parameters `Randomized Search Cross Validation` is recommended ^{[1]}(#ref1)

We're doing a RandomSearchCV to find best parameters for the model

```
{
'n_estimators': [100, 311, 522, 733, 944, 1155, 1366, 1577, 1788, 2000],
'max_features': ['auto', 'sqrt'],
'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 4],
'bootstrap': [True, False]
}
```

One problem was the time it took 14 hours to find these parameters

```
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 795.3min finished
```

Best parameters

```
{
'n_estimators': 311,
'min_samples_split': 2,
'min_samples_leaf': 1,
'max_features': 'sqrt',
'max_depth': None,
'bootstrap': False
}
```

Having in mind the costs function for FP and FN, I runned RandomSearch with a custom scoring function getting different parameterd and I got different parameters optimized for my model: `max_depth=30, n_estimators=600`.

Using different imputation methods and parameters obtained after RandomSearch

name	cost	accuracy	neg_precision	neg_f1_score	pos_precision	pos_f1_score
mean__basic	52670	0.9924	0.9933	0.9961	0.9408	0.8157
mean__tuned	48210	0.9927	0.9939	0.9963	0.93	0.8267
mean__tuned-scoring	49220	0.9925	0.9938	0.9962	0.9264	0.822
median__basic	56630	0.9921	0.9928	0.996	0.9527	0.8062
median__tuned	51710	0.9922	0.9934	0.996	0.9283	0.8144
median__tuned-scoring	51220	0.9922	0.9935	0.996	0.9254	0.8149
most__frequent__basic	50690	0.9925	0.9936	0.9962	0.9352	0.8204
most__frequent__tuned	48190	0.9928	0.9939	0.9963	0.9362	0.8291
most__frequent__tuned-scoring	51190	0.9924	0.9935	0.9961	0.9349	0.8186
smote-median	35220	na	na	na	na	na

Oversampling

One of the problem of the data is the fact that classes are highly unblanced. Apply SMOTE (SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE) added a big improovement to our results (see the above table)

Reducing dimensionality

One way of reducing dimensionality is by applying Principal Component Analysis (PCA). In this way we can see that we can have 80 featyre

I tried different number of components to be retained with PCA and results got better results for cost reduction

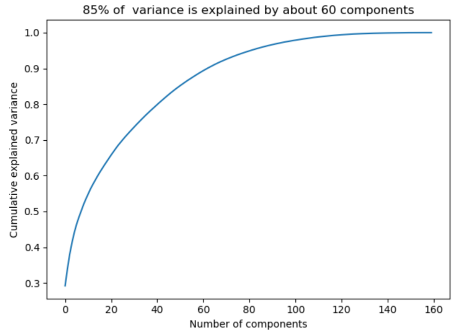


Figure 1: explained variance

name	cost	accuracy	neg_precision	neg_f1_score	pos_precision	pos_f1_score
pca50	55100	0.9772	0.9933	0.9884	0.3067	0.3866
pca100	45830	0.9769	0.9945	0.9883	0.2453	0.3327
pca150	**31940**	0.978	0.9963	0.9888	0.216	0.3152
pca160	39330	0.9778	0.9953	0.9887	0.2453	0.3407

Adjust the decision threshold

The model is able to return probabilities for each class, so we can try to fit the right threshold that will balance one class or another

```
Y_prob = model.predict_proba(X_test_pca)

t_values = [0.05, 0.6, 0.07, 0.08, 0.09, 0.1, 0.14, 0.2, 0.3]
t_costs = []
for t in t_values:
    predicted = (Y_prob[:, 1] >= t).astype('int')
    t_costs.append(cost_confusion_matrix(confusion_matrix(Y_test, predicted)))
```

And we'll get this plot and find the value `t_values[np.argmin(t_costs)]` of 0.07 getting a cost of 17920

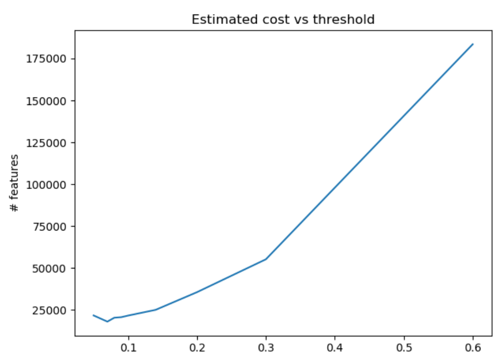


Figure 2: threshold

Extreme Gradient Boosting (XGBoost)

The model

Extreme Gradient Boosting is also known as XGBoost. XGBoost is also an ensemble learning method that favor trees with small depth. This model is preferred due to its execution speed and learning performance.

Running against the data

Using the same methods of RandomizedSearchCV we get better these results on un original data, with a cost og 44150$ vs 48190%. This time the model with parameters found using the custom score methods gave a better result

name	cost	accuracy	neg_precision	neg_f1_score	pos_precision	pos_f1_score

we can see that cost is 25050 for n=129

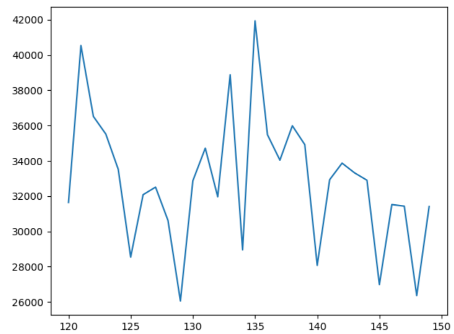


Figure 3: cost per PCA n of components

Comparing results

XGBoost performed better than RandomForest from the begging and also after applying different enhancements.

In order to achieve better results data processing is necessary and PCA was a good method to achieve an improvement of 35% for XGBoost and 40% for Random Forest method

Conclusions

Comparing to baseline model that would classify all trucks Ok which would have a cost of 187500$ for the test samples we obtained a cost of 26050$

In order to speed development a developer should build a small library to be able to compare results against different parameters

Dimensionality should be reduced at first in order to take less time in tunning hyper-parameters

Further workk should be made combining RandomizedSearchCV over processed dataset with feature reduction (PCA) and oversampling (SMOTE)

Files in the project

- eda.py - analyze data: na values, heatmap
- rf_compare.py - different combinations of parameters for Random Forest
- rf_threshold .py- applying threshold + PCA and finding best value for threshold
- rf_hyper_tune.py - finding best params for RandormForest
- xgboost_compare.py - different combination of parameters for XGBoost
- xgboost_hyper_tune.py - finding best params for RandomForest.

Referencess

1. Géron, A. (2017), Hands-on machine learning with Scikit-Learn and TensorFlow : concepts, tools, and techniques to build intelligent systems , O'Reilly Media , Sebastopol, CA . @book{géron aurélien_2019, place={Beijing ; Boston ; Farnham ; Sebastopol ; Tokyo}, title={Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems}, publisher={OReilly}, author={Géron Aurélien}, year={2019}}