

# Using Gradient Boosting Tree algorithms on Porto-Seguro's safe drive competition

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# Overview

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# Introduction

- Hosted on Kaggle, by Porto Seguro - a car insurance company.
- Objective: build a model that predicts the probability that a driver will initiate an auto insurance claim in the next year.
- Done on Python & Google Cloud Platform

# Problem settings

- Supervised learning
- Binary classification.
- Performance metrics: Normalized Gini Index.

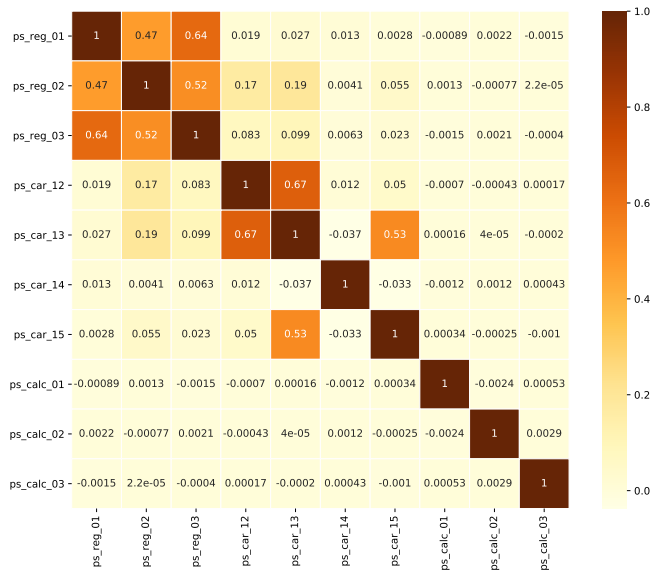
## General info

- `train.csv` & `test.csv`
- For train:  $n = 595212$ ;  $p = 59$ . For test:  $n = 892816$

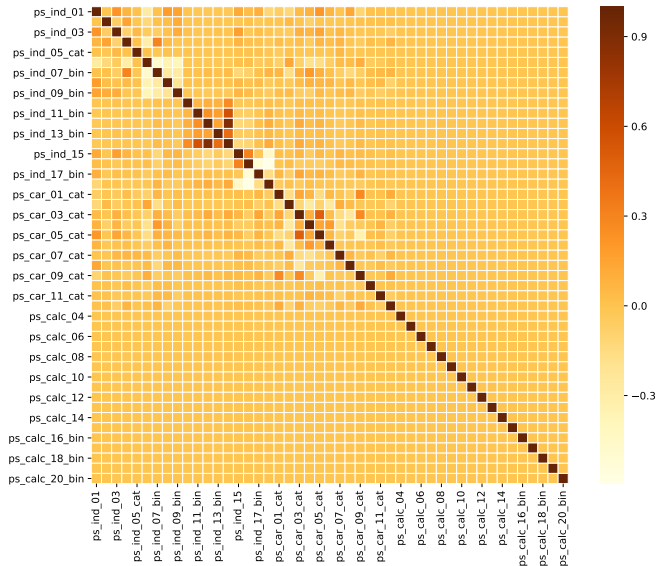
## Interesting findings

- Number of  $n$  in test is much larger than train.
- Features are encoded under generic names (for example `ps_car_01`, `ps_reg_02`) that give no specific indication on the meaning.
- There are 3 types: continuous features, categorical features and binary features.
- Values of -1 indicate that the feature was missing from the observation, or NaN value as normally seen in many datasets.

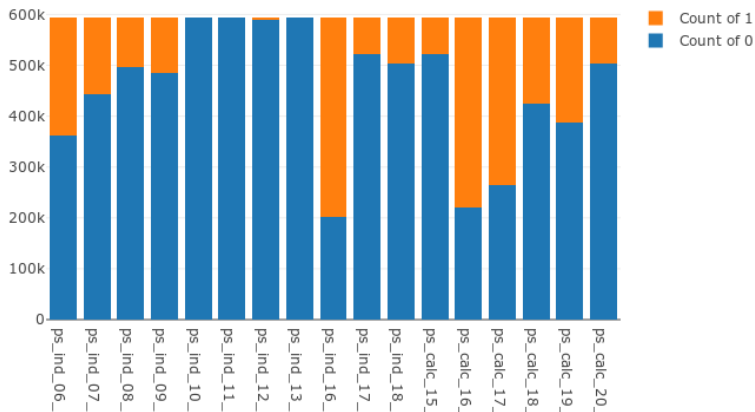
# Correlation matrix of continuous features (float64)



# Correlation matrix of continuous features (int32)

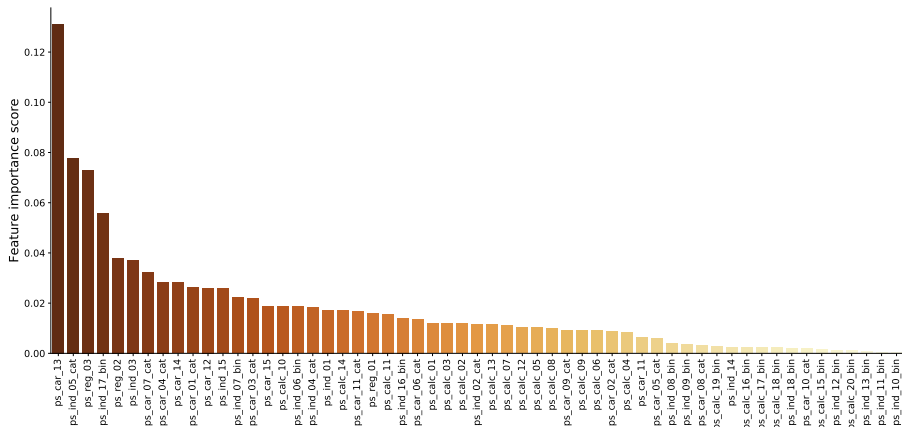


# Count of number of 0 and 1 in binary features





# Variable important ranking using Random Forest Classifier



# Feature Engineering

## Eliminating unimportant features

Top 35 variables which have highest feature important score are kept.

## Dealing with missing values

One could possibly either set NaN to some extreme value (e.g.  $10^6$ ) or use the value that represented the property of the particular variable ( $\max(X_i)$ ,  $\text{median}(X_i)$ ). In this case, we choose to keep the default value  $-1$  to represent NaN.

## Likelihood encoding

The central idea behind likelihood (or target) encoding technique is to estimate likelihood target variable given a particular value of a categorical variable:

$$Pr(y = 1 \mid x = \text{catValue}) = \frac{\sum \mathbb{1}_{y=1|x=\text{catValue}}(y)}{n_{\text{observation}}}$$

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**Algorithm 1** Target encoding categorical variables

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**Input:** categoricalArray, labelArray,  $k$ ,  $l$

```
1: data  $\leftarrow$  join (categoricalArray, labelArray)
2: targetEncodedArray  $\leftarrow$  Empty Array
3: categoricalValue  $\leftarrow$  unique values of categoricalArray
4: split data into  $k$  parts
5: for each fold[i] in  $k$  folds do
6:   valueEncoded  $\leftarrow$  0
7:   fold[-i]  $\leftarrow$  join remaining  $k - 1$  folds except  $i$ 
8:   split fold[-i] into  $l$  parts
9:   for each fold[j] in new  $l$  parts do
10:    for each value in categoricalValue do
11:      valueEncoded  $\leftarrow$  valueEncoded +  $\frac{Pr(label \mid value)}{l}$ 
12:    end for
13:  end for
14:  valueEncodedFold[i]  $\leftarrow$  join all valueEncoded
15: end for
16: targetEncodedArray  $\leftarrow$  join  $k$  parts of valueEncodedFold[i]
17: return targetEncodedArray
```

# Implementation

## Model Selection

- Gradient Boosting Tree: XGBoost<sup>a</sup> & LightGBM<sup>b</sup>
- Extremely fast, can also be used with GPU

<sup>a</sup><https://github.com/dmlc/xgboost>

<sup>b</sup><https://github.com/Microsoft/LightGBM>

## Ensembling technique

- 5-fold cross-validation
- Using `sklearn.model_selection.GridSearchCV` to find best `learning_rate`, `max_depth` parameters
- Prediction data from these 2 models was fitted by a Logistic Classifier acted as the ensembler to produce final prediction
- Google Cloud cluster with 16 CPU cores and 12GB RAM takes over 2 hours

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## Algorithm 2 Ensemble classifier (XGBoost + LightGBM + Logistic Regression)

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**Input:** trainData, testData,  $k$

```
1: objective  $\leftarrow$  Normalized Gini Index
2: split trainData, testData to  $k$  folds
3: for each fold[i] in  $k$  folds do
4:   run Algorithm 1
5:   fit XGBoost on fold[-i] using fold[i] to maximize objective
6:   fit lightGBM on fold[-i] using fold[i] to maximize objective
7:   predictXGB  $\leftarrow$  XGBoost(testData)
8:   predictLGBM  $\leftarrow$  lightGBM(testData)
9: end for
10: predictXGB  $\leftarrow \frac{\text{predictXGB}}{k}$ 
11: predictLGBM  $\leftarrow \frac{\text{predictLGBM}}{k}$ 
12: ensemblePrediction  $\leftarrow$  logisticRegression(predictXGB, predictLGBM)
13: return ensemblePrediction
```

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# Results

Model	Public Leaderboard	Final Leaderboard
XGBoost only	0.27477	0.27756
XGBoost + target encode	0.28204	0.28598
Ensemble + target encode	<b>0.28365</b>	0.28763
<b>Best result</b>	0.28332	<b>0.28849</b>

1800	▼ 960	Regis		0.28764	26	2mo
1801	▼ 257	AntiLippasaar		0.28764	23	2mo
1802	▲ 544	scut_430	 	0.28763	3	3mo
1803	▼ 2	idc man		0.28763	68	3mo
1804	▲ 606	LightR		0.28763	1	3mo
1805	▼ 29	Rafael Ladeira		0.28762	9	3mo

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0.28849

0.28332



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10 fold cv

[submission-171022-004132.csv](#)

0.28838

0.28225



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Upload Submission File submission-171022-004132 stack of 3 including gradient boosting tree with max\_depth=5 all other default. No feature elimination.

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0.28820

0.28321



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submission-lgb-only-impact-encoding-5fold-notps13square-171025-193323.csv not create ps13square, not drop ps 13

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0.28806

0.28287



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submission-lgb-only-impact-encoding-joinbin-dropcalonly-171024-171759.csv - create new impact join bin 06-09, maxdepth 6 on lgb learning rate 0.01

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0.28806

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# The End.