Amazon.com - Employee Access Challenge

Data Description

The data consists of real historical data collected from 2010 & 2011. Employees are manually allowed or denied access to resources over time. You must create an algorithm capable of learning from this historical data to predict approval/denial for an unseen set of employees.

File Descriptions

train.csv - The training set. Each row has the ACTION (ground truth), RESOURCE, and information about the employee's role at the time of approval

test.csv - The test set for which predictions should be made. Each row asks whether an employee having the listed characteristics should have access to the listed resource.

Column Descriptions

Column Name	Description
ACTION	ACTION is 1 if the resource was approved, 0 if the resource was not
RESOURCE	An ID for each resource
MGR_ID	The EMPLOYEE ID of the manager of the current EMPLOYEE ID record; an employee may have only one manager at a time
ROLE_ROLLUP_1	Company role grouping category id 1 (e.g. US Engineering)
ROLE_ROLLUP_2	Company role grouping category id 2 (e.g. US Retail)
ROLE_DEPTNAME	Company role department description (e.g. Retail)
ROLE_TITLE	Company role business title description (e.g. Senior Engineering Retail Manager)
ROLE_FAMILY_DESC	Company role family extended description (e.g. Retail Manager, Software Engineering)
ROLE_FAMILY	Company role family description (e.g. Retail Manager)
ROLE_CODE	Company role code; this code is unique to each role (e.g. Manager)

In [ ]:
```
from pyforest import*
lazy_imports()
```

Out[ ]:
```
['from dask import dataframe as dd',
 'import plotly.express as px',
 'import tensorflow as tf',
 'import spacy',
 'import re',
 'import os',
 'from sklearn import svm',
 'import pickle',
 'from pyspark import SparkContext',
 'import glob',
 'import altair as alt',
 'import tqdm',
 'from sklearn.ensemble import RandomForestRegressor',
 'import plotly as py',
 'import sklearn',
 'import nltk',
 'from sklearn.model_selection import train_test_split',
 'from pathlib import Path',
 'from sklearn.manifold import TSNE',
 'import bokeh',
 'from openpyxl import load_workbook',
 'from sklearn.preprocessing import OneHotEncoder',
 'from sklearn.ensemble import GradientBoostingRegressor',
 'import sys',
 'from sklearn.feature_extraction.text import TfidfVectorizer',
 'import datetime as dt',
 'import keras',
 'import statistics',
 'import plotly.graph_objs as go',
 'from sklearn.ensemble import GradientBoostingClassifier',
 'import gensim',
 'import dash',
 'import pydot',
 'import matplotlib as mpl',
 'from sklearn.ensemble import RandomForestClassifier']
```

In [ ]:
```
train=pd.read_csv("amazontrain.csv")
```

In [ ]:
```
test=pd.read_csv("amazontest.csv")
```

In [ ]:
```
train.head()
```

Out[ ]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPT
0	1	39353	85475	117961	118300	1
1	1	17183	1540	117961	118343	1
2	1	36724	14457	118219	118220	1
3	1	36135	5396	117961	118343	1
4	1	42680	5905	117929	117930	1

In [ ]:
```
train.shape
```

Out[ ]: (32769, 10)

In [ ]:
```
test.shape
```

Out[ ]: (58921, 10)

In [ ]:
```
test.head()
```

Out[ ]:

	id	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME
0	1	78766	72734	118079	118080	117878
1	2	40644	4378	117961	118327	118507
2	3	75443	2395	117961	118300	119488
3	4	43219	19986	117961	118225	118403
4	5	42093	50015	117961	118343	119598

CatBoost

CatBoost is an algorithm for gradient boosting on decision trees. It is developed by Yandex researchers and engineers, and is used for search, recommendation systems, personal assistant, self-driving cars, weather prediction and many other tasks at Yandex and in other companies, including CERN, Cloudflare, Careem taxi. It is in open-source and can be used by anyone.

Procedure for other gradient boosting algorithms (XG boost, Light GBM) Step 1: Consider all (or a sample) the data points to train a highly biased model.

Step 2: Calculate residuals (errors) for each data point.

Step 3: Train another model with the same data points and corresponding residuals (errors) as class labels.

Step 4: Repeat Step 2 & Step 3 (for n iterations).

This procedure is prone to overfitting, because we are calculating residuals of each data point by using the model that has already been trained on same set of data points.

Advantages of CatBoost Library

Performance:

CatBoost provides state of the art results and it is competitive with any leading machine learning algorithm on the performance front.

Handling Categorical features automatically:

We can use CatBoost without any explicit pre-processing to convert categories into numbers. CatBoost converts categorical values into numbers using various statistics on combinations of categorical features and combinations of categorical and numerical features. You can read more about it here.

Robust:

It reduces the need for extensive hyper-parameter tuning and lower the chances of overfitting also which leads to more generalized models. Although, CatBoost has multiple parameters to tune and it contains parameters like the number of trees, learning rate, regularization, tree depth, fold size, bagging temperature and others. You can read about all these parameters here.

Easy-to-use: You can use CatBoost from the command line, using an user-friendly API for both Python and R.

Reference for Gradient Boosting : https://bit.ly/2LOJQYD

In [ ]:
```
!pip install catboost
```

```
Requirement already satisfied: catboost in /Users/mybeast/anaconda3/lib/pyth
on3.7/site-packages (0.23.1)
Requirement already satisfied: six in /Users/mybeast/anaconda3/lib/python3.
7/site-packages (from catboost) (1.12.0)
Requirement already satisfied: scipy in /Users/mybeast/anaconda3/lib/python
3.7/site-packages (from catboost) (1.4.1)
Requirement already satisfied: graphviz in /Users/mybeast/anaconda3/lib/pyth
on3.7/site-packages (from catboost) (0.13.2)
Requirement already satisfied: matplotlib in /Users/mybeast/anaconda3/lib/py
thon3.7/site-packages (from catboost) (3.1.0)
Requirement already satisfied: pandas>=0.24.0 in /Users/mybeast/anaconda3/li
b/python3.7/site-packages (from catboost) (0.24.2)
Requirement already satisfied: plotly in /Users/mybeast/anaconda3/lib/python
3.7/site-packages (from catboost) (4.6.0)
Requirement already satisfied: numpy>=1.16.0 in /Users/mybeast/anaconda3/li
b/python3.7/site-packages (from catboost) (1.16.4)
Requirement already satisfied: cycler>=0.10 in /Users/mybeast/anaconda3/lib/
python3.7/site-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /Users/mybeast/anaconda
3/lib/python3.7/site-packages (from matplotlib->catboost) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /
Users/mybeast/anaconda3/lib/python3.7/site-packages (from matplotlib->catboo
st) (2.4.0)
Requirement already satisfied: python-dateutil>=2.1 in /Users/mybeast/anacon
da3/lib/python3.7/site-packages (from matplotlib->catboost) (2.8.0)
Requirement already satisfied: pytz>=2011k in /Users/mybeast/anaconda3/lib/p
ython3.7/site-packages (from pandas>=0.24.0->catboost) (2019.1)
Requirement already satisfied: retrying>=1.3.3 in /Users/mybeast/anaconda3/l
ib/python3.7/site-packages (from plotly->catboost) (1.3.3)
Requirement already satisfied: setuptools in /Users/mybeast/anaconda3/lib/py
thon3.7/site-packages (from kiwisolver>=1.0.1->matplotlib->catboost) (41.0.
1)
```

In [ ]:

In [ ]:
```
# Loading data directly from CatBoost
from catboost.datasets import amazon

traindf, testdf = amazon()
```

In [ ]:
```
traindf.shape
```

Out[ ]: (32769, 10)

In [ ]:
```
testdf.shape
```

Out[ ]: (58921, 10)

In [ ]:
```
traindf.head()
```

Out[ ]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPT
0	1	39353	85475	117961	118300	1
1	1	17183	1540	117961	118343	1
2	1	36724	14457	118219	118220	1
3	1	36135	5396	117961	118343	1
4	1	42680	5905	117929	117930	1

ACTION is our target column

In [ ]:
```
testdf.head()
```

Out[ ]:

	id	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME
0	1	78766	72734	118079	118080	117878
1	2	40644	4378	117961	118327	118507
2	3	75443	2395	117961	118300	119488
3	4	43219	19986	117961	118225	118403
4	5	42093	50015	117961	118343	119598

In [ ]:
```

```

In [ ]:
```
traindf.apply(lambda x: len(x.unique()))
```

Out[ ]:
```
ACTION                2
RESOURCE           7518
MGR_ID             4243
ROLE_ROLLUP_1       128
ROLE_ROLLUP_2       177
ROLE_DEPTNAME       449
ROLE_TITLE          343
ROLE_FAMILY_DESC   2358
ROLE_FAMILY          67
ROLE_CODE           343
dtype: int64
```

In [ ]:
```
traindf['MGR_ID'].value_counts()
```

Out[ ]:
```
770       152
2270       99
2594       82
1350       71
2014       67
16850      66
3966       64
7807       64
5244       62
5396       62
3526       62
4659       61
7411       61
54618      61
18686      60
7578       58
7389       58
3281       57
70062      57
18213      57
6982       56
1475       56
71189      55
85475      55
1334       54
3838       54
46254      54
1903       53
1755       53
7553       53
           ...
50605       1
93720       1
55662       1
53519       1
28225       1
6358        1
20421       1
3285        1
17628       1
64779       1
6030        1
5542        1
311597      1
8047        1
5526        1
5966        1
50604       1
142801      1
7639        1
15651       1
97915       1
58648       1
44633       1
1908        1
73591       1
```

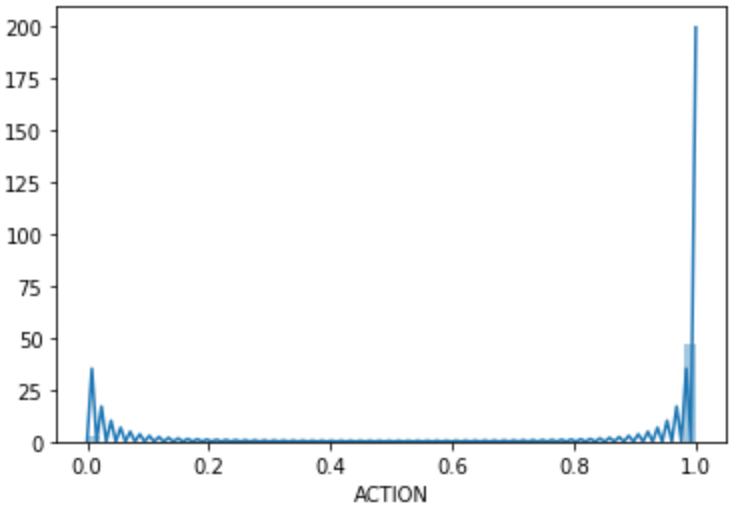
```
1940        1
8087        1
22526       1
34948       1
58677       1
Name: MGR_ID, Length: 4243, dtype: int64
```

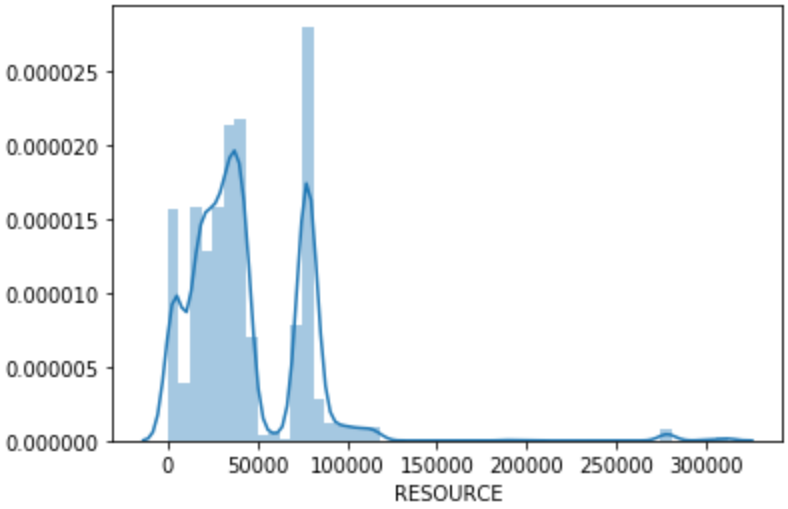
In [ ]:

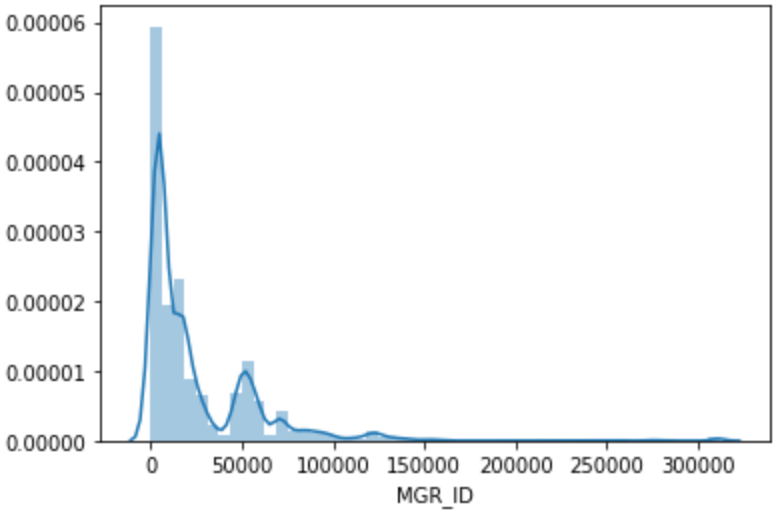
Distribution of Features

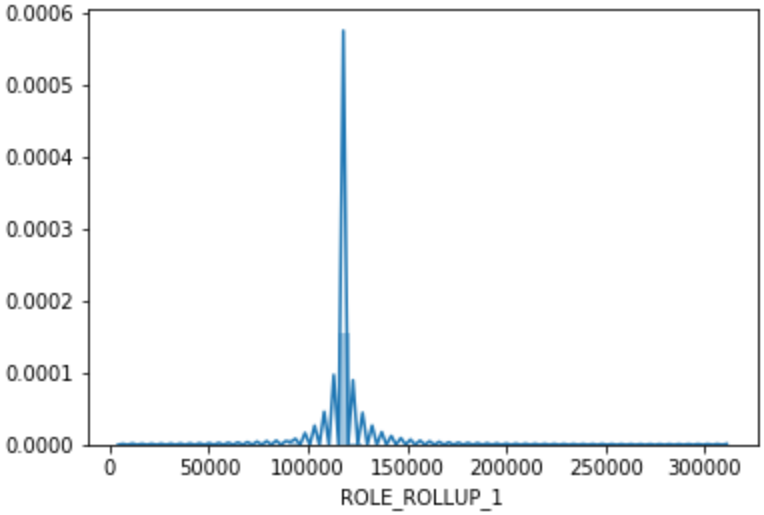
Distplot

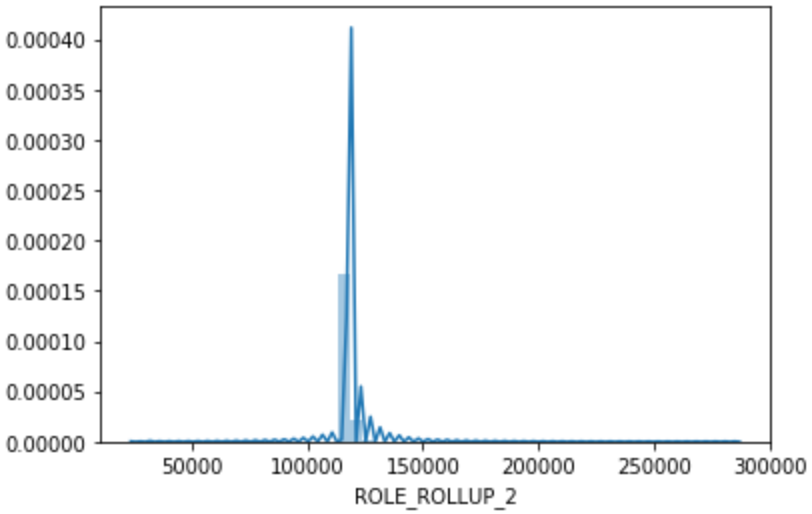
In [ ]:
```
for i in traindf.describe().columns:
    sns.distplot(traindf[i].dropna())
    plt.show()
```

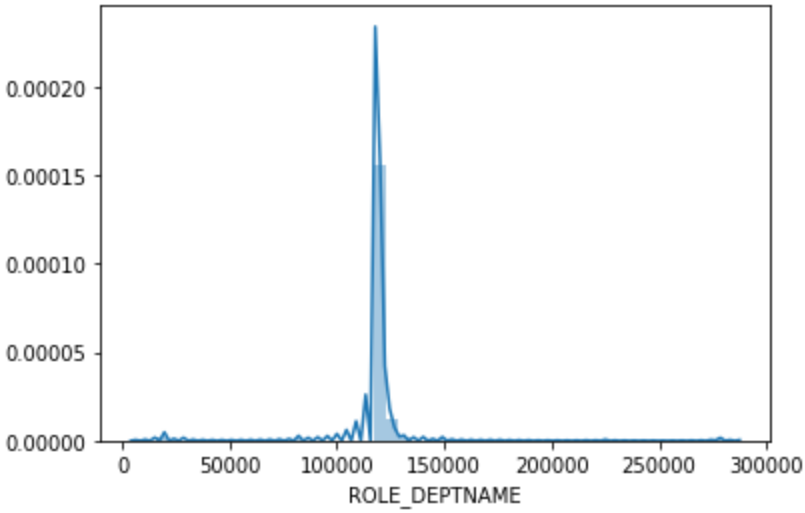


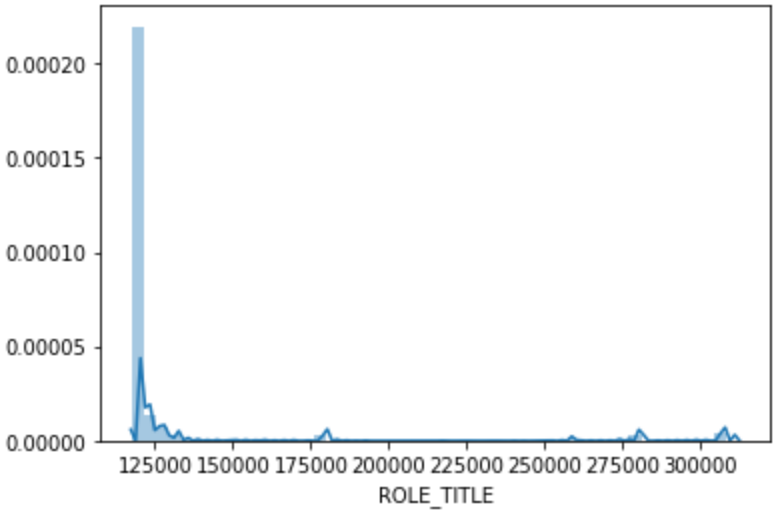


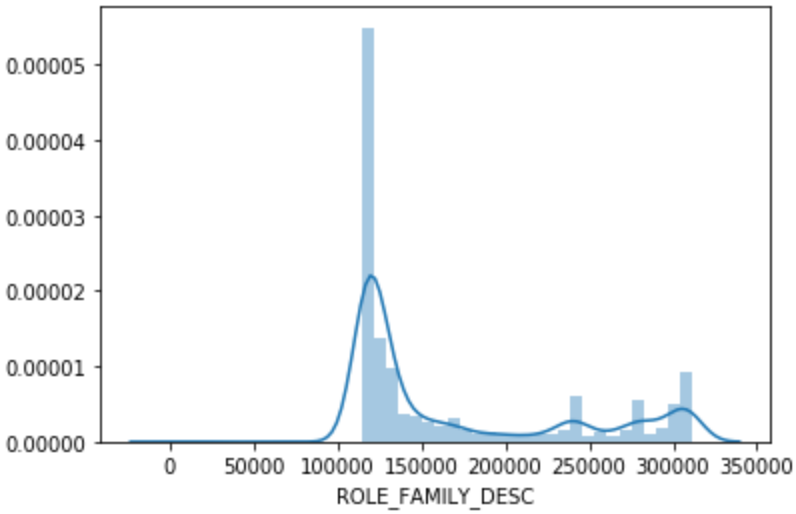

0.00006
0.00005
0.00004
0.00003
0.00002
0.00001
0.00000
0
50000
100000
150000
200000
250000
300000
MGR_ID

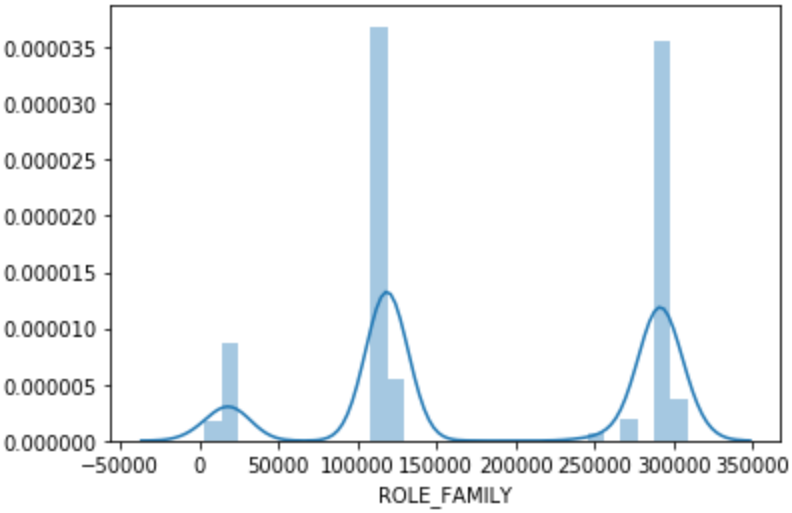

0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
0
50000
100000
150000
200000
250000
300000
ROLE_ROLLUP_1

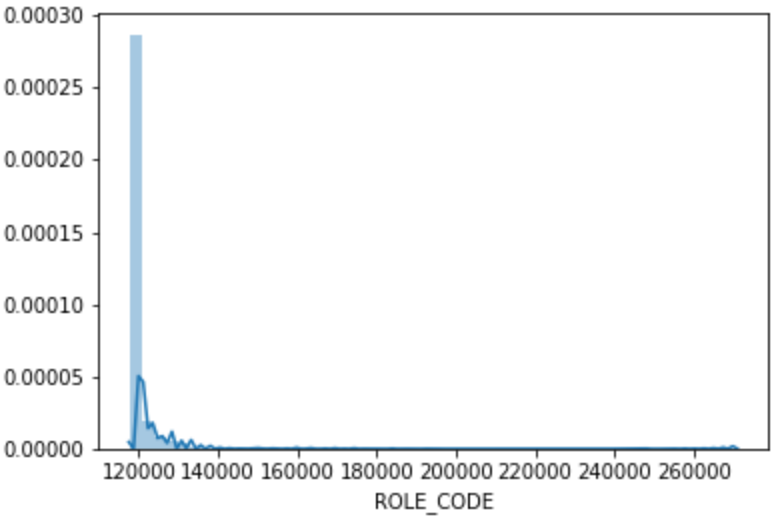

0.00040
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
50000
100000
150000
200000
250000
300000
ROLE_ROLLUP_2


0.00020
0.00015
0.00010
0.00005
0.00000
0
50000
100000
150000
200000
250000
300000
ROLE_DEPTNAME


0.00020
0.00015
0.00010
0.00005
0.00000
125000 150000 175000 200000 225000 250000 275000 300000
ROLE_TITLE


0.00005
0.00004
0.00003
0.00002
0.00001
0.00000
0
50000
100000
150000
200000
250000
300000
350000
ROLE_FAMILY_DESC



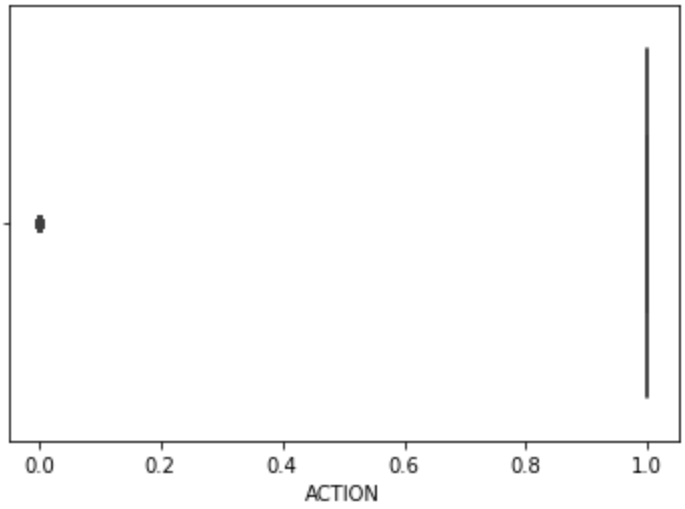


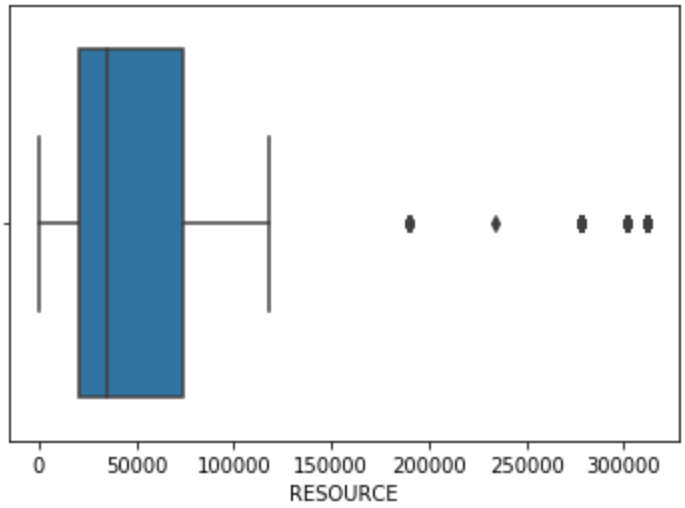
Boxplot

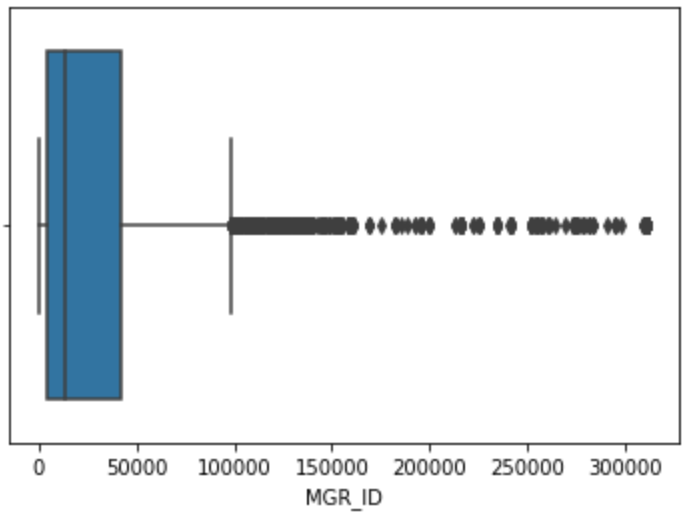
In [ ]:
```
traindf['ACTION'].value_counts()
```

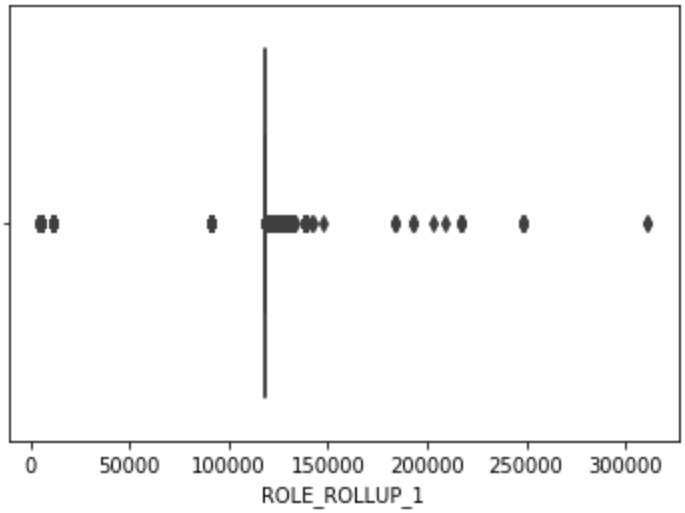
Out[ ]:
```
1    30872
0     1897
Name: ACTION, dtype: int64
```

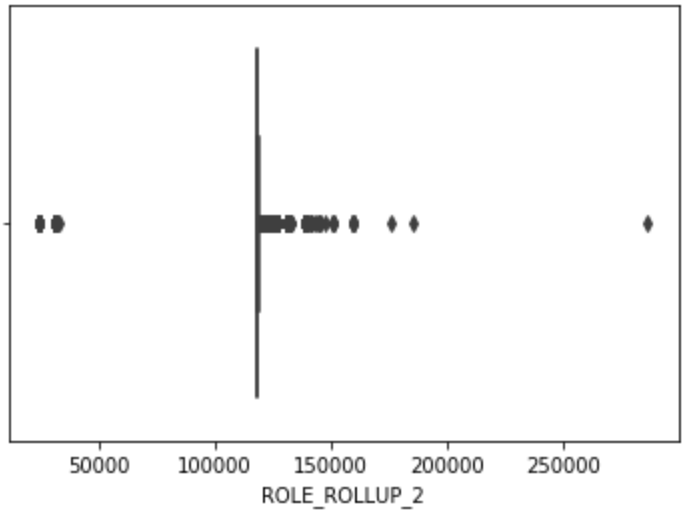
In [ ]:
```
for i in traindf.describe().columns:
    sns.boxplot(traindf[i].dropna())
    plt.show()
```

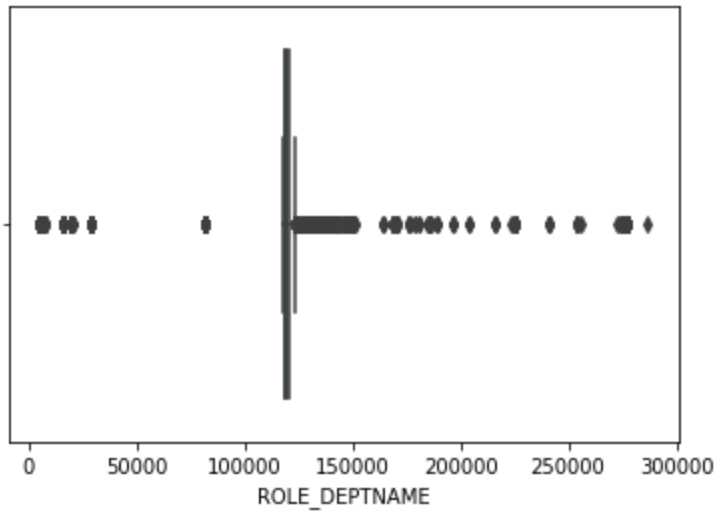

0.0
0.2
0.4
0.6
0.8
1.0
ACTION

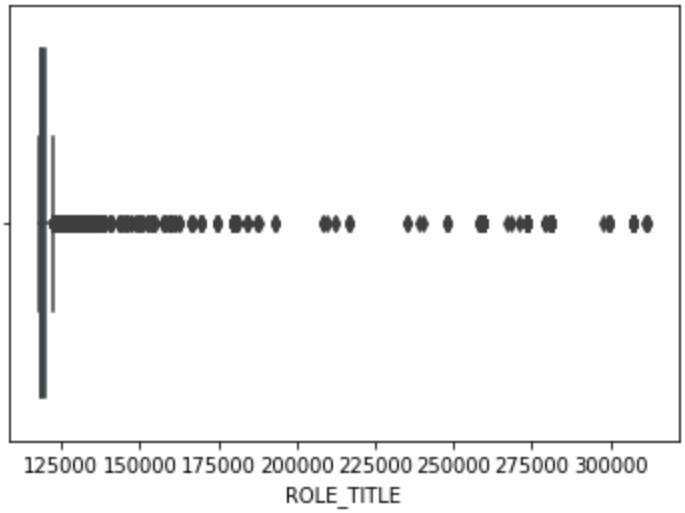

0
50000
100000
150000
200000
250000
300000
RESOURCE

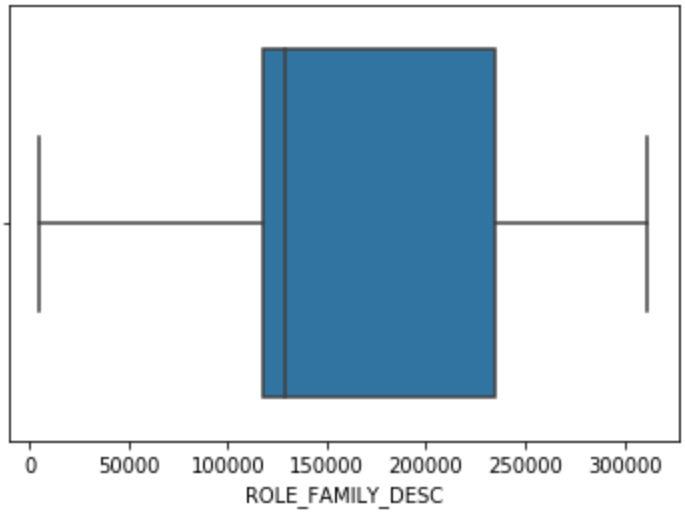

0
50000
100000
150000
200000
250000
300000
MGR_ID

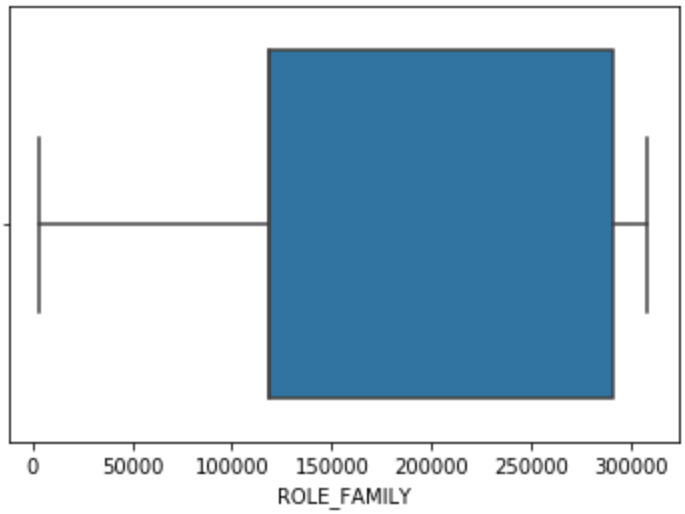

0
50000
100000
150000
200000
250000
300000
ROLE_ROLLUP_1

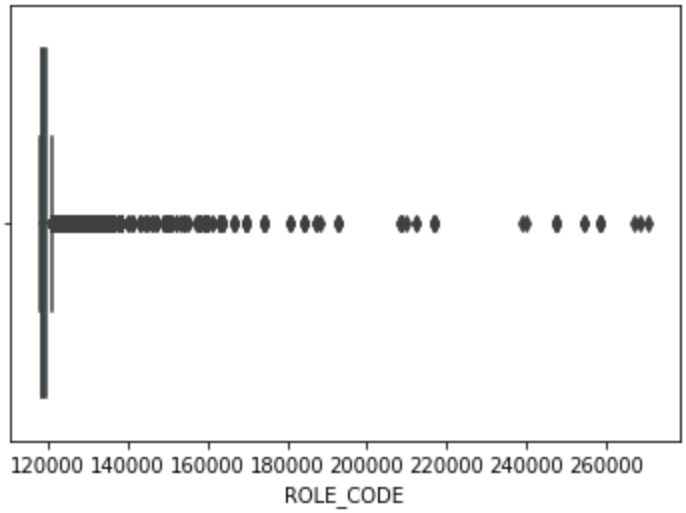

50000
100000
150000
200000
250000
ROLE_ROLLUP_2


0
50000
100000
150000
200000
250000
300000
ROLE_DEPTNAME


125000 150000 175000 200000 225000 250000 275000 300000
ROLE_TITLE

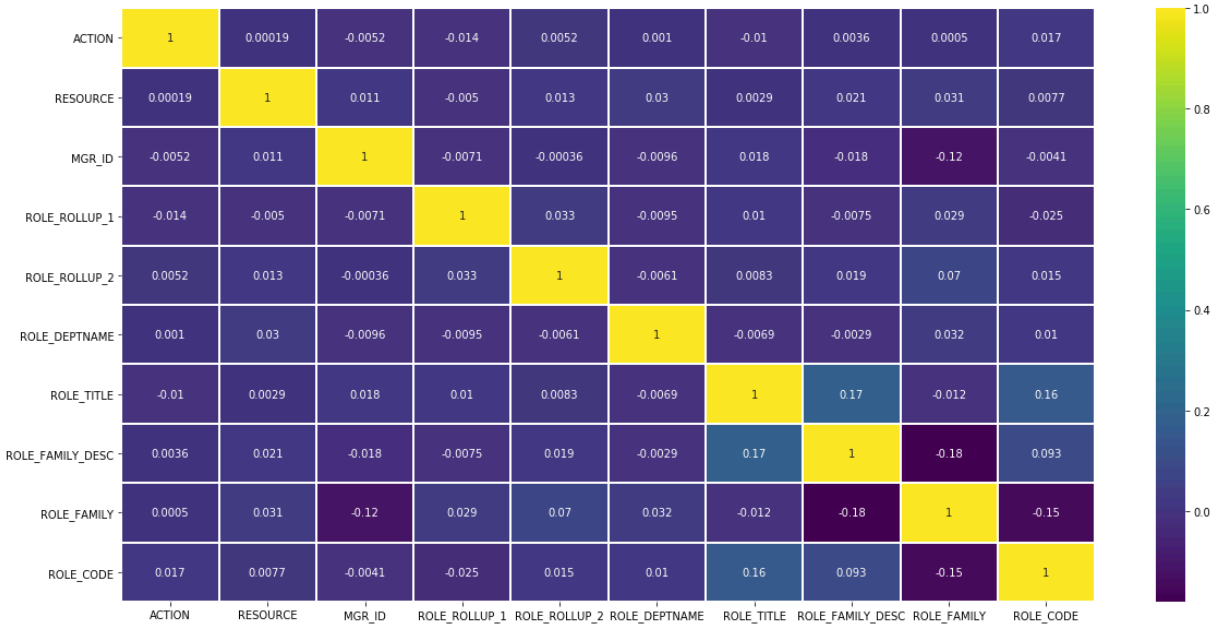

0 50000 100000 150000 200000 250000 300000
ROLE_FAMILY_DESC


0 50000 100000 150000 200000 250000 300000
ROLE_FAMILY



In [ ]:
```
plt.figure(figsize=(20,10))
sns.heatmap(traindf.corr(),annot=True,cmap='viridis',linewidth=1)
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x160f3ec88>



In [ ]:
```
traindf.head()
```

Out[ ]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPT
0	1	39353	85475	117961	118300	1
1	1	17183	1540	117961	118343	1
2	1	36724	14457	118219	118220	1
3	1	36135	5396	117961	118343	1
4	1	42680	5905	117929	117930	1

In [ ]:
```
testdf.head()
```

Out[ ]:

	id	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME
0	1	78766	72734	118079	118080	117878
1	2	40644	4378	117961	118327	118507
2	3	75443	2395	117961	118300	119488
3	4	43219	19986	117961	118225	118403
4	5	42093	50015	117961	118343	119598

In [ ]:

Model Building

In [ ]:
```
y = traindf['ACTION']

X = traindf.drop('ACTION',axis=1)

X_test = testdf.drop('id',axis=1)
```

In [ ]:

In [ ]:
```
from sklearn.model_selection import train_test_split

X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.25,
```

In [ ]:
```
from catboost import CatBoostClassifier
```

In [ ]:
```
%%time

params = {'loss_function':'Logloss', # objective function
          'eval_metric':'AUC', # metric
          'verbose': 200, # output to stdout info about training process eve
          'random_seed': 1
         }
catmodel_1 = CatBoostClassifier(**params)
catmodel_1.fit(X_train, y_train, # data to train on (required parameters, ur
          eval_set=(X_valid, y_valid), # data to validate on
          use_best_model=True, # True if we don't want to save trees created
         );
```

```
Learning rate set to 0.069882
0:      test: 0.5400959 best: 0.5400959 (0)     total: 100ms    remaining: 1
m 40s
200:    test: 0.8016667 best: 0.8017826 (196)   total: 4.98s    remaining: 1
9.8s
400:    test: 0.8234442 best: 0.8234442 (400)   total: 8.81s    remaining: 1
3.2s
600:    test: 0.8323016 best: 0.8323806 (596)   total: 15.4s    remaining: 1
0.2s
800:    test: 0.8358278 best: 0.8361184 (795)   total: 21.4s    remaining:
5.33s
999:    test: 0.8391131 best: 0.8393621 (997)   total: 26.7s    remaining: 0
us

bestTest = 0.8393620826
bestIteration = 997

Shrink model to first 998 iterations.
CPU times: user 48.7 s, sys: 8.9 s, total: 57.6 s
Wall time: 28.4 s
```

Out[ ]: <catboost.core.CatBoostClassifier at 0x15d99d550>

In [ ]:
```
#catmodel_1.plot_tree(tree_idx=0)

# https://catboost.ai/docs/concepts/python-reference_catboostclassifier_plot
```

In [ ]:
```
X.head()
```

Out[ ]:

	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME	R
0	39353	85475	117961	118300	123472	
1	17183	1540	117961	118343	123125	
2	36724	14457	118219	118220	117884	
3	36135	5396	117961	118343	119993	
4	42680	5905	117929	117930	119569	

In [ ]:
```
#In the above model CatBoost treated categorical features as numerical ones.

categorical_features= list(range(X.shape[1]))
print(categorical_features)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8]
```

In [ ]:
```

```

In [ ]:
```
%%time

params = {'loss_function':'Logloss',
          'eval_metric':'AUC',
          'cat_features': categorical_features,
          'verbose': 200,
          'random_seed': 1
```

```
        }
catmodel = CatBoostClassifier(**params)
catmodel.fit(X_train, y_train,
          eval_set=(X_valid, y_valid),
          use_best_model=True);
```

```
Learning rate set to 0.069882
0:      test: 0.5637606 best: 0.5637606 (0)     total: 197ms    remaining: 3
m 17s
200:    test: 0.8955617 best: 0.8955872 (198)   total: 15.6s    remaining: 1
m 1s
400:    test: 0.8973364 best: 0.8979162 (365)   total: 28.7s    remaining: 4
2.8s
600:    test: 0.8972380 best: 0.8979162 (365)   total: 42.8s    remaining: 2
8.4s
800:    test: 0.8967943 best: 0.8979162 (365)   total: 59s      remaining: 1
4.7s
999:    test: 0.8958776 best: 0.8979162 (365)   total: 1m 13s   remaining: 0
us

bestTest = 0.8979161719
bestIteration = 365

Shrink model to first 366 iterations.
CPU times: user 2min 52s, sys: 29.9 s, total: 3min 22s
Wall time: 1min 15s
```

Out[ ]: <catboost.core.CatBoostClassifier at 0x161497198>

Cross Validation

In [ ]:
```
from catboost import cv



params = {'loss_function':'Logloss',
          'eval_metric':'AUC',
          'verbose': 200,
          'random_seed':1
         }

# pool for Dataset processing.

total_train_data = Pool(data=X,
                        label=y,
                        cat_features= categorical_features
                       )

scores = cv(pool=total_train_data,
            params=params,
            fold_count=4,
            seed=1,
            shuffle=True,
```

```
            stratified=True, # if True the folds are made by preserving the
           )
```

```
0:      test: 0.5381441 best: 0.5381441 (0)     total: 503ms    remaining: 8
m 22s
200:    test: 0.8855009 best: 0.8855191 (198)   total: 1m 14s   remaining: 4
m 54s
400:    test: 0.8890032 best: 0.8890032 (400)   total: 2m 49s   remaining: 4
m 13s
600:    test: 0.8908147 best: 0.8908147 (600)   total: 3m 58s   remaining: 2
m 38s
800:    test: 0.8919210 best: 0.8919526 (797)   total: 5m 4s    remaining: 1
m 15s
999:    test: 0.8924165 best: 0.8924269 (995)   total: 6m 37s   remaining: 0
us
```

In [ ]:
```
feature_imp=catmodel.get_feature_importance(prettified=True)
feature_imp
```

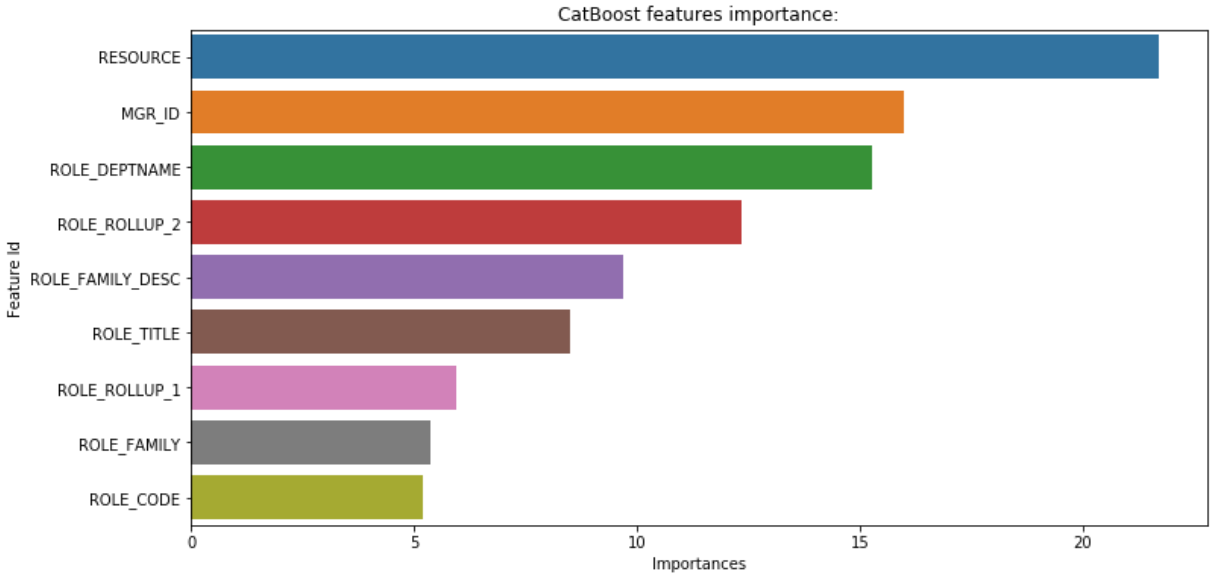
Out[ ]:

	Feature Id	Importances
0	RESOURCE	21.710100
1	MGR_ID	15.975161
2	ROLE_DEPTNAME	15.268135
3	ROLE_ROLLUP_2	12.338805
4	ROLE_FAMILY_DESC	9.690491
5	ROLE_TITLE	8.505203
6	ROLE_ROLLUP_1	5.953400
7	ROLE_FAMILY	5.361993
8	ROLE_CODE	5.196712

In [ ]:
```
```

In [ ]:
```
from matplotlib import pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6));
sns.barplot(x="Importances", y="Feature Id", data=feature_imp, orient='V');
plt.title('CatBoost features importance:');
```



In [ ]:
```
predictions=catmodel.predict_proba(X_test)
```

In [ ]:
```
predictions
```

Out[ ]:
```
array([[0.29867231, 0.70132769],
       [0.01846929, 0.98153071],
       [0.00779143, 0.99220857],
       ...,
       [0.00983214, 0.99016786],
       [0.06395067, 0.93604933],
       [0.01295259, 0.98704741]])
```

In [ ]:
```
predictions=catmodel.predict(X_test)
predictions
```

Out[ ]:
```
array([1, 1, 1, ..., 1, 1, 1])
```

In [ ]:
```

```

In [ ]:
```
catmodel.score(X_valid, y_valid)
```

Out[ ]:
```
0.9564262175027463
```

In [ ]:
```
traindf['ACTION'].value_counts()
```

Out[ ]:
```
1    30872
0     1897
Name: ACTION, dtype: int64
```

IMPORTANT

Note that our target column (**ACTION**) contains **30872** 1s and only **1897** 0s. This is an indication of data imbalance. You can deal with this and use the same steps above to build the algorithm.

If you are not familiar with how to deal with **data imbalance**, watch the **Credit Card Fraud Detection** project video to get to know how to solve this.

Alternatively

Consider building a **Logistic Regression** on same dataset to compare the results

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
```