

Case Study 7:

Economizing the Prediction of Class 0 and 1

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Introduction

In this study, the customer presents private, anonymous data to create a model that will most accurately predict class 0 or 1. The goal is to minimize monetary loss, where every incorrect prediction loses either \$100 or \$250 depending on whether it was predicted as class 1 or class 0. Different binary classification models will be explored and tuned to find the one that best minimizes financial loss.

Methods

Data Preparation

The provided dataset has a shape of 160,000 rows and is 136MB in file size. There are 50 attributes and 1 target variable, 'y', which is a binary integer of 0 and 1. Fortyfive of the attributes were floats, with 5 categorical columns.

Looking further into these 5 attributes, column x37 represents some monetary value as seen by the dollar sign label. The '\$' character was removed from the column and it was converted to a float. The remaining four columns including 'x24', 'x29', 'x30', and 'x32' were categorical, and were one-hot encoded into dummy variables. By looking into the actual columns, these categorical attributes represented country, month, day, and percentages. The percentages column was kept as categorical because there were only 13 unique values in this column, however it could have been converted to numerical also.

The numerical attributes were all scaled with the StandardScaler from sklearn. This was done only to the numerical variables and not the dummy variables as they are already binary entries or 0 and 1 and it would over inflate their values.

There were 1,608 rows with missing data. Because these entries only comprised 1% of the overall data, they were dropped from the dataset.

Lastly, the data was split into 80% training dataset and 20% test data set. The training set will be used to train and tune the models, while the test set will be used solely for model performance evaluation.

Model Development

Accuracy was used to tune and optimize each model, and final evaluation for the models was based on minimizing monetary loss.

Feature Creation

In order to explore feature creation, the PolynomialFeatures function from sklearn was used on the attributes, creating over 1,000 features. Logistic regression was attempted to be used to narrow down these features, but the large size of the dataset alongside the increased number of features crashed the kernel and the computer when trying to narrow down which of these features was important through L1 regression. The ram of the system could not handle the memory of the large amount of columns. Since the huge amount of the interaction terms could not be narrowed down, they were not used in the models.

To reduce the number of added features introduced to the model, only the squared attributes were added to the dataset to see if this would increase performance of the models. These features were added to the dataset, then L1 was used to narrow down the most important features. Only the most important attributes were used in the data. This larger dataset was used to train and test all the models, however across the board the models increased monetary loss. Because of this, the squared features were not used in the final models, and instead only the original 79 attributes were used.

Random Forest Development

The first model created for this task was a Random Forest binary classification model. In order to optimize the model on the train data, 5-fold cross validation was used in a random search to find the model with the highest accuracy. The parameters tuned included max_depth, max_features, min_samples_leaf, min_samples_split, class_weight, and criterion. When the optimal parameter chosen for the model was the maximum value possible from the search, the parameter range was expanded to ensure no better value existed outside of the range. For the random search, n_estimators was set at 100, then scaled to 1,000 for the final model to minimize runtime.

XGBoost Development

For XGBoost, the train datasets were first converted to dmatrices in order to use the XGBoost package. In order to optimize the model on the train data, 5-fold cross validation was used in a manual random search to find the model with the lowest log loss for the validation data. The

parameters tuned included subsample, colsample_bytree, max_depth, min_child_weight, and gamma. Early stopping for the XGBoost model was set to two rounds, with num_round set to 1,000 but usually stopping around 750.

Neural Network Development

The neural network is built out of 7 layers, 1 input and 6 dense. Since the data has already been scaled with the standard scaler, BatchNormalization is not necessary. BatchNormalization was tested to see if accuracy would increase but it turned out that it did not help. The use of BatchNormalization caused the train and test loss to behave poorly. For early stopping, the monitored statistic was validation loss and patience was set to three. The validation set was created by splitting the training set into an 80% train and 20% validation set. Batch size and epochs were both set to 1,000, and early stopping usually only ran the neural net for about 10-15 epochs.

Ensemble Development

Many different forms of ensembles were tested, including different two level and three level ensembles. Models included in these levels were Random Forest, Logistic Regression, Neural Networks, and XGBoost Classifiers. The final level was tested between Linear Regressors and XGBoost Classifiers. The main issue with testing different ensembles is the extremely long runtimes. This greatly limited the number and variety of models that could be tested. The individual models within the layers were also tested to see if optimization would improve the overall ensemble, but in each case little to no improvement was seen for a cost of much runtime.

Results

Random Forest Final Model

The final Random Forest model scaled n_estimators up to 1,000, and its parameters can be seen below:

```
RandomForestClassifier(class_weight='balanced', criterion='entropy', max_depth=50,  
max_features=35, min_samples_leaf=4, min_samples_split=8, n_estimators=1000)
```

XGBoost Classifier Final Model

The final XGBoost Classifier model used the following parameters:

```
final_params = {'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,  
'subsample': 0.5792877172818175, 'colsample_bytree': 0.7680400747721351, 'max_depth': 20,  
'min_child_weight': 5, 'gamma': 1.5}
```

For the final model, num_round was set to 1,000 and early stopping set to two. The model usually stops running at num_round 743.

Neural Network Final Model

The final Neural Network model uses the adam optimizer, binary cross entropy loss, a batch size and epochs set to 1,000, and early stopping patience set to 3 and monitor set to validation loss. The layers of the network can be seen below:

Layer	Neurons	Activation
Input	79	relu
Dense	500	relu
Dense	400	relu
Dense	300	relu
Dense	200	relu
Dense	100	relu
Dense (Output)	1	sigmoid

Ensemble Final Model

The best ensemble model was built with tuned Random Forest and tuned Logistic Regression models in layer 1, Random Forest and Logistic Regression models in layer 2, and an XGBoost Classifier for the final layer.

Model Performance Evaluation

Model	Monetary Loss per Prediction
Random Forest	12.8856
XGBoost	10.1866
Neural Network	8.4522
Ensemble	12.715

Conclusion

In conclusion, a collection of models (Random Forest, XGBoost, Neural Network, and an Ensemble of all previous) were built to minimize the incorrect predictions of the 2 given classes or to maximize the correct prediction of the 2 given classes. Monetary loss for the customer was minimized by optimizing the models to correctly predict the target classes. The model that successfully minimized the monetary loss the most was the Neural Network, with a loss of \$8.45 per prediction.

Data Prep

```
In [ ]: from google.colab import drive
drive.mount('/content/drive')
```

```
In [ ]: # Import necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import cross_val_score, StratifiedKFold, KFold, cross_val_predict
from sklearn.metrics import precision_score, recall_score, confusion_matrix, accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import plot_confusion_matrix

import random

import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import KFold
from sklearn.metrics import precision_score, recall_score, accuracy_score
import pandas as pd
from scipy.io import arff
from sklearn.ensemble import RandomForestClassifier
import missingno as msno
from numpy import nan
from numpy import isnan
from sklearn.impute import SimpleImputer
from xgboost import XGBClassifier
import xgboost as xgb

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import LinearRegression

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import GradientBoostingClassifier

from sklearn.metrics import accuracy_score
```

```
In [ ]: data = pd.read_csv("/content/drive/MyDrive/SMU Work/Quantifying the World/Case S
# data = pd.read_csv("/Users/hallepurdor/Desktop/SMU/Classes/Quantifying the Wor
data.head()
```

```
In [ ]:
```

```
data.shape
```

```
In [ ]: data.duplicated().value_counts()
```

```
In [ ]: # Visualization function for the columns
def visualize_counts(col_name, df, f_height = 15, f_width=10, title= "", f_rotati
plt.figure(figsize=(f_height, f_width))
axis_font = {'fontname': 'Arial', 'size': '24'}
ax = sns.countplot(x=col_name, data=df)
plt.xlabel(col_name, **axis_font)
plt.ylabel("count", **axis_font)
plt.title(title, **axis_font)
plt.xticks(rotation = f_rotation)

for label in (ax.get_xticklabels() + ax.get_yticklabels()):
    label.set_fontname('Arial')
    label.set_fontsize(18)

plt.show()

visualize_counts('y', data, title='Target Distribution')
```

```
In [ ]: # Missing Values, Column types
data_types = data.dtypes
missing_value_stats = ((data.isnull().sum()/len(data)*100))
unique_values = data.apply(lambda column: column.unique().shape[0])

basic_stats = pd.concat([data_types, unique_values, missing_value_stats], axis =
basic_stats.columns = ['type', 'unique values', 'missing percent']
basic_stats = basic_stats.sort_values('missing percent', ascending = False)
print(basic_stats)
```

```
In [ ]: msno.matrix(data)
```

```
In [ ]: data = data.dropna()
data.shape
```

```
In [ ]: #Convert column x37 to numeric
data['x37'] = data['x37'].str[1:]
data['x37'] = data['x37'].astype('float')
data['x37']
```

```
In [ ]: # reindex because concat function was combining incorrectly after missing values
data = data.reset_index()
data
```

```
In [ ]: numerical_cols = data._get_numeric_data().columns
categorical_cols= [i for i in data.columns if data.dtypes[i]!='object' ]
```

```
print(f"numerical columns: \n {numerical_cols}")
print(f"categorical columns: \n {categorical_cols}")
```

```
In [ ]: # Normalize numeric variables with StandardScaler() -- W/OUT FEATURE CREATION
y = data['y']

numerical_cols_df = data[numerical_cols].copy().drop('y', axis=1)
scaler = StandardScaler()

numerical_cols_standard = scaler.fit_transform(numerical_cols_df)
numerical_cols_standard = pd.DataFrame(data = numerical_cols_standard, columns =

### FEATURE CREATION - squared features (no interaction terms bc ram limit)
# y = data['y']

# numerical_cols_df = data[numerical_cols].copy().drop('y', axis=1)

# for col in numerical_cols_df.columns:
#     numerical_cols_df[col + "_2"] = numerical_cols_df[col]*numerical_cols_df[c

# scaler = StandardScaler()

# numerical_cols_standard = scaler.fit_transform(numerical_cols_df)
# numerical_cols_standard = pd.DataFrame(data = numerical_cols_standard, columns
```

```
In [ ]: # Create dummy variables for categorical features - One hot encoding
categorical_features = pd.get_dummies(data[categorical_cols])
```

```
In [ ]: # Recombine dataset
data_processed = pd.concat([numerical_cols_standard, categorical_features], axis
```

```
In [ ]: data_processed.shape
```

```
In [ ]: # train test split
X_train, X_test, y_train, y_test = train_test_split(data_processed, y, test_size
```

Feature Creation and Logistic Regression

```
In [ ]: # param = {'C': [10**-2, 10**-1, 10**0, 10**1, 10**2]}

# lr_model = LogisticRegression(penalty='l1', solver='liblinear')
# gs_model = GridSearchCV(estimator=lr_model, param_grid=param)
# gs_model.fit(X_train, y_train)

# # Train a LR model with best parameters
# model = LogisticRegression(**gs_model.best_params_, penalty='l1', solver='libl
# model.fit(X_train, y_train)
```

```
Out[ ]: LogisticRegression(C=1, penalty='l1', solver='liblinear')
```



```
In [ ]: # Train a LR model with best parameters
# model = LogisticRegression(**gs_model.best_params_, penalty='l1', solver='libl
# model.fit(X_train, y_train)
```

```
Out[ ]: LogisticRegression(C=1, penalty='l1', solver='liblinear')
```

```
In [ ]: # set new relevant features for train/test

# coef = model.coef_[0]
# imp_features = pd.Series(data_processed.columns)[list(coef!=0)]
# X_train = X_train[imp_features]
# X_test = X_test[imp_features]
```

Random Forest

```
In [ ]: # Random Forest Parameter tuning
split = KFold(n_splits = 5, shuffle = True)

param_grid = {
    'max_depth': [35, 40, 50], # [9,10, 15, 20, 25, 30 , 35],
    'max_features': [25, 35, 50], # [10,15, 20, 25],
    'min_samples_leaf': [3, 4, 7], # [3, 4, 5, 7],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100],
    'class_weight': ['balanced', 'balanced_subsample'],
    'criterion': ['gini', 'entropy']
}
# Create a based model
rf = RandomForestClassifier()
# Instantiate the grid search model
grid_search = RandomizedSearchCV(estimator = rf, param_distributions = param_gri
                                cv = split, n_jobs = 6, verbose = 2, scoring='accuracy
```

```
In [ ]: # Uncomment to run random search
# grid_search.fit(X_train, y_train)
```

Fitting 5 folds for each of 30 candidates, totalling 150 fits

```
Out[ ]: RandomizedSearchCV(cv=KFold(n_splits=5, random_state=None, shuffle=True),
                           estimator=RandomForestClassifier(), n_iter=30, n_jobs=6,
                           param_distributions={'class_weight': ['balanced',
                                                                    'balanced_subsample'],
                                                'criterion': ['gini', 'entropy'],
                                                'max_depth': [35, 40, 50],
                                                'max_features': [25, 35, 50],
                                                'min_samples_leaf': [3, 4, 7],
                                                'min_samples_split': [8, 10, 12],
                                                'n_estimators': [100]},
                           scoring='accuracy', verbose=2)
```

```
In [ ]: # Uncomment if running random search
# Best parameters
# print(grid_search.best_estimator_)
# print(grid_search.best_score_)
```

```
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                        max_depth=50, max_features=35, min_samples_leaf=4,
                        min_samples_split=8)
0.9275686192494458
```

```
In [ ]: # Add best params from above, make n_estimators greater=1000
rf = RandomForestClassifier(class_weight='balanced', criterion='entropy', max_dep
rf.fit(X_train, y_train)
```

```
Out[ ]: RandomForestClassifier(class_weight='balanced', criterion='entropy',
                               max_depth=50, max_features=35, min_samples_leaf=4,
                               min_samples_split=8, n_estimators=1000)
```

```
In [ ]: # Performance statistics 0.93172 accuracy
preds = rf.predict(X_test)

precision = precision_score(y_true=y_test, y_pred=preds)
recall = recall_score(y_true=y_test, y_pred=preds)
accuracy = accuracy_score(y_true=y_test, y_pred=preds)

print(f"Accuracy: {accuracy:.5f}")
print(f"Precision: {precision:.5f}")
print(f"Recall: {recall:.5f}")
```

```
Accuracy: 0.93150
Precision: 0.92826
Recall: 0.90031
```

```
In [ ]: confusion_matrix_rf = confusion_matrix(y_test, preds)
print(confusion_matrix_rf)
print((confusion_matrix_rf[0,1]*100 + confusion_matrix_rf[1,0]*250)/len(y_test))
```

```
[[17967   892]
 [ 1278 11542]]
12.901291076107201
```

```
RandomForestClassifier(class_weight='balanced_subsample',
criterion='entropy', max_depth=35, max_features=25,
min_samples_leaf=4, min_samples_split=10, n_estimators=1000)
```

```
Accuracy: 0.93077
```

```
Precision: 0.92696
```

```
Recall: 0.89984
```

```
RandomForestClassifier(class_weight='balanced', criterion='entropy', max_depth=50,
max_features=35, min_samples_leaf=4, min_samples_split=8, n_estimators=1000)
```

```
Accuracy: 0.93178
```

```
Precision: 0.92811
```

```
Recall: 0.90125
```

XGBoost

```
In [ ]: # Create dmatrices for xgboost
dtrain = xgb.DMatrix(X_train, label=y_train)
```

```
dtest = xgb.DMatrix(X_test, label=y_test)
evallist = [(dtest,'eval'), (dtrain,'train')]
num_round = 1000
```

In []:

```
# Uncomment to run random search
# params = {
#     'booster':'gbtree',
#     'objective':'multi:softmax',
#     'num_class':2,
#     'eta':0.05,
#     'subsample':0.5,
#     'colsample_bytree':0.5,
#     'max_depth':3,
#     'min_child_weight':1,
#     'gamma': 0.5,
# }

# max_depth = [3,5,10,15,20,40]
# sub_s = np.random.random(10)
# cols = np.random.random(10)
# md = np.random.randint(0,6,10)
# m_child = [1, 5, 10]
# mc = np.random.randint(0,3,10)
# gam = [0.5, 1, 1.5, 2, 5]
# g = np.random.randint(0,5,10)

# for i in range(10):
#     params['subsample']=sub_s[i]
#     params['colsample_bytree']=cols[i]
#     params['max_depth']=max_depth[md[i]]
#     params['min_child_weight']=m_child[mc[i]]
#     params['gamma']=gam[g[i]]
#     tmp = xgb.cv(params, dtrain, num_boost_round=2000, nfold=5, stratified=False)
#     print('_____done_____')
#     print(params)
#     print(tmp.loc[tmp.shape[0]-1:,:])
#     print("=====")
#     tmp=0
```

```
_____done_____
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.5629982928352992, 'colsample_bytree': 0.03643859527751492, 'max_d
epth': 3, 'min_child_weight': 5, 'gamma': 0.5}
      train-mlogloss-mean  train-mlogloss-std  test-mlogloss-mean  \
1999          0.45507          0.002683          0.475331

      test-mlogloss-std
1999          0.003982
=====
_____done_____
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.6254736809223108, 'colsample_bytree': 0.03169912253713203, 'max_d
epth': 10, 'min_child_weight': 10, 'gamma': 2}
      train-mlogloss-mean  train-mlogloss-std  test-mlogloss-mean  \
1313          0.390581          0.003215          0.485198

      test-mlogloss-std
1313          0.005623
=====
_____done_____
```

```

{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.5792877172818175, 'colsample_bytree': 0.7680400747721351, 'max_de
pth': 20, 'min_child_weight': 5, 'gamma': 1.5}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
507          0.050257          0.000344          0.156774

test-mlogloss-std
507          0.002705
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.2154988709032628, 'colsample_bytree': 0.35378532017795794, 'max_d
epth': 15, 'min_child_weight': 10, 'gamma': 1}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
645          0.082731          0.000448          0.197044

test-mlogloss-std
645          0.002947
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.4380425538499748, 'colsample_bytree': 0.6255799676269455, 'max_de
pth': 40, 'min_child_weight': 5, 'gamma': 1}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
447          0.04278          0.000155          0.162993

test-mlogloss-std
447          0.00327
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.67426081615934, 'colsample_bytree': 0.6695681612228545, 'max_dept
h': 5, 'min_child_weight': 10, 'gamma': 1.5}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
1031         0.172172          0.000798          0.214375

test-mlogloss-std
1031         0.003184
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.44028850038384393, 'colsample_bytree': 0.7428093558620357, 'max_d
epth': 40, 'min_child_weight': 10, 'gamma': 2}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
465          0.073296          0.000212          0.164742

test-mlogloss-std
465          0.002814
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.4169617908893525, 'colsample_bytree': 0.1256871684760852, 'max_de
pth': 3, 'min_child_weight': 5, 'gamma': 0.5}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
1999         0.297244          0.000528          0.319033

test-mlogloss-std
1999         0.004782
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.6087373301330863, 'colsample_bytree': 0.3344551174016209, 'max_de
pth': 3, 'min_child_weight': 10, 'gamma': 0.5}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
1999         0.246245          0.001452          0.270635

```

```

test-mlogloss-std
1999          0.002735
=====
done
{'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05,
'subsample': 0.3272549518122969, 'colsample_bytree': 0.14665633169460623, 'max_d
epth': 5, 'min_child_weight': 1, 'gamma': 5}
train-mlogloss-mean train-mlogloss-std test-mlogloss-mean \
1999          0.25014          0.001454          0.265591

test-mlogloss-std
1999          0.004463
=====

```

In []:

```

#Best model test-mlogloss-mean: 0.156774
final_params = {'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class':

# Final model
model_rs = xgb.train(final_params, dtrain, num_round, evallist, early_stopping_r
preds = model_rs.predict(dtest)

#32 min
# round 743

```

[21:35:12] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softmax' was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.

```

[0]    eval-mlogloss:0.66345    train-mlogloss:0.66021
[1]    eval-mlogloss:0.63752    train-mlogloss:0.63079
[2]    eval-mlogloss:0.61255    train-mlogloss:0.60273
[3]    eval-mlogloss:0.58881    train-mlogloss:0.57636
[4]    eval-mlogloss:0.56908    train-mlogloss:0.55382
[5]    eval-mlogloss:0.54854    train-mlogloss:0.53092
[6]    eval-mlogloss:0.52963    train-mlogloss:0.50957
[7]    eval-mlogloss:0.51269    train-mlogloss:0.49019
[8]    eval-mlogloss:0.49507    train-mlogloss:0.47066
[9]    eval-mlogloss:0.48001    train-mlogloss:0.45351
[10]   eval-mlogloss:0.46456    train-mlogloss:0.43627
[11]   eval-mlogloss:0.45111    train-mlogloss:0.42087
[12]   eval-mlogloss:0.43836    train-mlogloss:0.40625
[13]   eval-mlogloss:0.42625    train-mlogloss:0.39245
[14]   eval-mlogloss:0.41441    train-mlogloss:0.37908
[15]   eval-mlogloss:0.40356    train-mlogloss:0.36671
[16]   eval-mlogloss:0.39291    train-mlogloss:0.35472
[17]   eval-mlogloss:0.38381    train-mlogloss:0.34401
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[617]	eval-mlogloss:0.15261	train-mlogloss:0.04559

[618]	eval-mlogloss:0.15260	train-mlogloss:0.04558
[619]	eval-mlogloss:0.15258	train-mlogloss:0.04555
[620]	eval-mlogloss:0.15257	train-mlogloss:0.04554
[621]	eval-mlogloss:0.15256	train-mlogloss:0.04552
[622]	eval-mlogloss:0.15256	train-mlogloss:0.04550
[623]	eval-mlogloss:0.15255	train-mlogloss:0.04549
[624]	eval-mlogloss:0.15256	train-mlogloss:0.04547
[625]	eval-mlogloss:0.15257	train-mlogloss:0.04546
[626]	eval-mlogloss:0.15257	train-mlogloss:0.04544
[627]	eval-mlogloss:0.15257	train-mlogloss:0.04544
[628]	eval-mlogloss:0.15257	train-mlogloss:0.04543
[629]	eval-mlogloss:0.15258	train-mlogloss:0.04541
[630]	eval-mlogloss:0.15258	train-mlogloss:0.04539
[631]	eval-mlogloss:0.15258	train-mlogloss:0.04539
[632]	eval-mlogloss:0.15257	train-mlogloss:0.04536
[633]	eval-mlogloss:0.15258	train-mlogloss:0.04534
[634]	eval-mlogloss:0.15257	train-mlogloss:0.04533
[635]	eval-mlogloss:0.15257	train-mlogloss:0.04531
[636]	eval-mlogloss:0.15258	train-mlogloss:0.04529
[637]	eval-mlogloss:0.15256	train-mlogloss:0.04527
[638]	eval-mlogloss:0.15257	train-mlogloss:0.04526
[639]	eval-mlogloss:0.15257	train-mlogloss:0.04524
[640]	eval-mlogloss:0.15258	train-mlogloss:0.04522
[641]	eval-mlogloss:0.15257	train-mlogloss:0.04521
[642]	eval-mlogloss:0.15255	train-mlogloss:0.04519
[643]	eval-mlogloss:0.15256	train-mlogloss:0.04516
[644]	eval-mlogloss:0.15256	train-mlogloss:0.04514
[645]	eval-mlogloss:0.15255	train-mlogloss:0.04513
[646]	eval-mlogloss:0.15254	train-mlogloss:0.04511
[647]	eval-mlogloss:0.15254	train-mlogloss:0.04510
[648]	eval-mlogloss:0.15255	train-mlogloss:0.04509
[649]	eval-mlogloss:0.15255	train-mlogloss:0.04507
[650]	eval-mlogloss:0.15255	train-mlogloss:0.04506
[651]	eval-mlogloss:0.15255	train-mlogloss:0.04503
[652]	eval-mlogloss:0.15249	train-mlogloss:0.04498
[653]	eval-mlogloss:0.15249	train-mlogloss:0.04497
[654]	eval-mlogloss:0.15249	train-mlogloss:0.04497
[655]	eval-mlogloss:0.15249	train-mlogloss:0.04494
[656]	eval-mlogloss:0.15249	train-mlogloss:0.04491
[657]	eval-mlogloss:0.15250	train-mlogloss:0.04489
[658]	eval-mlogloss:0.15248	train-mlogloss:0.04486
[659]	eval-mlogloss:0.15247	train-mlogloss:0.04484
[660]	eval-mlogloss:0.15246	train-mlogloss:0.04482
[661]	eval-mlogloss:0.15246	train-mlogloss:0.04481
[662]	eval-mlogloss:0.15246	train-mlogloss:0.04480
[663]	eval-mlogloss:0.15247	train-mlogloss:0.04480
[664]	eval-mlogloss:0.15246	train-mlogloss:0.04478
[665]	eval-mlogloss:0.15246	train-mlogloss:0.04476
[666]	eval-mlogloss:0.15246	train-mlogloss:0.04474
[667]	eval-mlogloss:0.15247	train-mlogloss:0.04472
[668]	eval-mlogloss:0.15246	train-mlogloss:0.04471
[669]	eval-mlogloss:0.15244	train-mlogloss:0.04467
[670]	eval-mlogloss:0.15244	train-mlogloss:0.04466
[671]	eval-mlogloss:0.15244	train-mlogloss:0.04464
[672]	eval-mlogloss:0.15242	train-mlogloss:0.04462
[673]	eval-mlogloss:0.15243	train-mlogloss:0.04460
[674]	eval-mlogloss:0.15241	train-mlogloss:0.04458
[675]	eval-mlogloss:0.15241	train-mlogloss:0.04457
[676]	eval-mlogloss:0.15241	train-mlogloss:0.04457
[677]	eval-mlogloss:0.15238	train-mlogloss:0.04453
[678]	eval-mlogloss:0.15238	train-mlogloss:0.04452
[679]	eval-mlogloss:0.15238	train-mlogloss:0.04451
[680]	eval-mlogloss:0.15238	train-mlogloss:0.04449
[681]	eval-mlogloss:0.15238	train-mlogloss:0.04447
[682]	eval-mlogloss:0.15238	train-mlogloss:0.04446

[683]	eval-mlogloss:0.15238	train-mlogloss:0.04444
[684]	eval-mlogloss:0.15238	train-mlogloss:0.04442
[685]	eval-mlogloss:0.15238	train-mlogloss:0.04441
[686]	eval-mlogloss:0.15238	train-mlogloss:0.04439
[687]	eval-mlogloss:0.15238	train-mlogloss:0.04439
[688]	eval-mlogloss:0.15239	train-mlogloss:0.04437
[689]	eval-mlogloss:0.15239	train-mlogloss:0.04435
[690]	eval-mlogloss:0.15238	train-mlogloss:0.04433
[691]	eval-mlogloss:0.15238	train-mlogloss:0.04432
[692]	eval-mlogloss:0.15239	train-mlogloss:0.04430
[693]	eval-mlogloss:0.15239	train-mlogloss:0.04429
[694]	eval-mlogloss:0.15239	train-mlogloss:0.04428
[695]	eval-mlogloss:0.15238	train-mlogloss:0.04426
[696]	eval-mlogloss:0.15238	train-mlogloss:0.04423
[697]	eval-mlogloss:0.15235	train-mlogloss:0.04419
[698]	eval-mlogloss:0.15235	train-mlogloss:0.04417
[699]	eval-mlogloss:0.15233	train-mlogloss:0.04416
[700]	eval-mlogloss:0.15233	train-mlogloss:0.04414
[701]	eval-mlogloss:0.15229	train-mlogloss:0.04411
[702]	eval-mlogloss:0.15230	train-mlogloss:0.04410
[703]	eval-mlogloss:0.15230	train-mlogloss:0.04407
[704]	eval-mlogloss:0.15229	train-mlogloss:0.04407
[705]	eval-mlogloss:0.15229	train-mlogloss:0.04405
[706]	eval-mlogloss:0.15230	train-mlogloss:0.04404
[707]	eval-mlogloss:0.15230	train-mlogloss:0.04403
[708]	eval-mlogloss:0.15231	train-mlogloss:0.04402
[709]	eval-mlogloss:0.15231	train-mlogloss:0.04401
[710]	eval-mlogloss:0.15230	train-mlogloss:0.04399
[711]	eval-mlogloss:0.15228	train-mlogloss:0.04395
[712]	eval-mlogloss:0.15227	train-mlogloss:0.04394
[713]	eval-mlogloss:0.15226	train-mlogloss:0.04393
[714]	eval-mlogloss:0.15226	train-mlogloss:0.04391
[715]	eval-mlogloss:0.15226	train-mlogloss:0.04390
[716]	eval-mlogloss:0.15224	train-mlogloss:0.04387
[717]	eval-mlogloss:0.15224	train-mlogloss:0.04386
[718]	eval-mlogloss:0.15224	train-mlogloss:0.04385
[719]	eval-mlogloss:0.15222	train-mlogloss:0.04382
[720]	eval-mlogloss:0.15222	train-mlogloss:0.04381
[721]	eval-mlogloss:0.15222	train-mlogloss:0.04381
[722]	eval-mlogloss:0.15222	train-mlogloss:0.04380
[723]	eval-mlogloss:0.15221	train-mlogloss:0.04378
[724]	eval-mlogloss:0.15221	train-mlogloss:0.04377
[725]	eval-mlogloss:0.15221	train-mlogloss:0.04376
[726]	eval-mlogloss:0.15222	train-mlogloss:0.04375
[727]	eval-mlogloss:0.15222	train-mlogloss:0.04374
[728]	eval-mlogloss:0.15222	train-mlogloss:0.04373
[729]	eval-mlogloss:0.15219	train-mlogloss:0.04370
[730]	eval-mlogloss:0.15220	train-mlogloss:0.04369
[731]	eval-mlogloss:0.15220	train-mlogloss:0.04368
[732]	eval-mlogloss:0.15220	train-mlogloss:0.04367
[733]	eval-mlogloss:0.15220	train-mlogloss:0.04366
[734]	eval-mlogloss:0.15220	train-mlogloss:0.04365
[735]	eval-mlogloss:0.15220	train-mlogloss:0.04364
[736]	eval-mlogloss:0.15220	train-mlogloss:0.04364
[737]	eval-mlogloss:0.15220	train-mlogloss:0.04364
[738]	eval-mlogloss:0.15220	train-mlogloss:0.04363
[739]	eval-mlogloss:0.15219	train-mlogloss:0.04362
[740]	eval-mlogloss:0.15219	train-mlogloss:0.04360
[741]	eval-mlogloss:0.15219	train-mlogloss:0.04358
[742]	eval-mlogloss:0.15219	train-mlogloss:0.04357
[743]	eval-mlogloss:0.15219	train-mlogloss:0.04357
[744]	eval-mlogloss:0.15219	train-mlogloss:0.04357

In []:

```
# Performance metrics
```



```
precision = precision_score(y_true=y_test, y_pred=preds)
recall = recall_score(y_true=y_test, y_pred=preds)
accuracy = accuracy_score(y_true=y_test, y_pred=preds)

print(f"Accuracy: {accuracy:.5f}")
print(f"Precision: {precision:.5f}")
print(f"Recall: {recall:.5f}")
```

Accuracy: 0.94567
Precision: 0.94279
Recall: 0.92168

```
In [ ]: confusion_matrix_xgb = confusion_matrix(y_test, preds)
print(confusion_matrix_xgb)
print((confusion_matrix_xgb[0,1]*100 + confusion_matrix_xgb[1,0]*250)/len(y_test
```

```
[[18142  717]
 [ 1004 11816]]
10.186558919157802
```

```
In [ ]: print(model_rs)
```

<xgboost.core.Booster object at 0x7faf2c64a4c0>
Best model test-mlogloss-mean: 0.156774
final_params = {'booster': 'gbtree', 'objective': 'multi:softmax', 'num_class': 2, 'eta': 0.05, 'subsample': 0.5792877172818175, 'colsample_bytree': 0.7680400747721351, 'max_depth': 20, 'min_child_weight': 5, 'gamma': 1.5}
xgb.train(final_params, dtrain, num_round, evallist, early_stopping_rounds=2)

Accuracy: 0.94567
Precision: 0.94279
Recall: 0.92168

NN

```
In [ ]: import tensorflow as tf

from tensorflow.keras import datasets, layers, models

from time import time
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import TensorBoard
```

```
In [ ]: X_train_nn, X_val_nn, y_train_nn, y_val_nn = train_test_split(X_train, y_train,
```

```
In [ ]: X_train_nn.columns
```

```
Out[ ]: Index(['index', 'x0', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9',
              'x10', 'x11', 'x12', 'x13', 'x14', 'x15', 'x16', 'x17', 'x18', 'x19',
```

```
'x20', 'x21', 'x22', 'x23', 'x25', 'x26', 'x27', 'x28', 'x31', 'x33',
'x34', 'x35', 'x36', 'x37', 'x38', 'x39', 'x40', 'x41', 'x42', 'x43',
'x44', 'x45', 'x46', 'x47', 'x48', 'x49', 'x24_america', 'x24_asia',
'x24_euorpe', 'x29_Apr', 'x29_Aug', 'x29_Dev', 'x29_Feb', 'x29_January',
'x29_July', 'x29_Jun', 'x29_Mar', 'x29_May', 'x29_Nov', 'x29_Oct',
'x29_sept.', 'x30_friday', 'x30_monday', 'x30_thursday', 'x30_tuesday',
'x30_wednesday', 'x32_-0.0%', 'x32_-0.01%', 'x32_-0.02%', 'x32_-0.03%',
'x32_-0.04%', 'x32_-0.05%', 'x32_0.0%', 'x32_0.01%', 'x32_0.02%',
'x32_0.03%', 'x32_0.04%', 'x32_0.05%'],
dtype='object')
```

```
In [ ]: X_train_nn.shape
```

```
Out[ ]: (101370, 79)
```

```
In [ ]: from tensorflow.keras.layers import BatchNormalization
model_nn = Sequential()
model_nn.add(tf.keras.Input(shape=(79,)))
model_nn.add(tf.keras.layers.Dense(500, activation='relu'))
model_nn.add(tf.keras.layers.Dense(400, activation='relu'))
model_nn.add(tf.keras.layers.Dense(300, activation='relu'))
model_nn.add(tf.keras.layers.Dense(200, activation='relu'))
model_nn.add(tf.keras.layers.Dense(100, activation='relu'))
model_nn.add(tf.keras.layers.Dense(1, activation='sigmoid'))
```

```
In [ ]: from tensorflow.keras.callbacks import EarlyStopping

safety = EarlyStopping(patience = 3, monitor='val_loss')
```

```
In [ ]: # from tensorflow.keras.optimizers import SGD
# opt = SGD()
model_nn.compile(optimizer='adam', loss = tf.keras.losses.BinaryCrossentropy() ,
```

```
In [ ]: # X_train, X_test, y_train, y_test
history = model_nn.fit(X_train_nn, y_train_nn, validation_data=(X_val_nn, y_val_nn),
```

```
Epoch 1/1000
102/102 [=====] - 9s 72ms/step - loss: 0.3498 - accurac
y: 0.8418 - false_negatives_1: 9513.0000 - false_positives_1: 6528.0000 - auc_1:
0.9204 - precision_1: 0.8265 - recall_1: 0.7657 - val_loss: 0.2541 - val_accurac
y: 0.8944 - val_false_negatives_1: 999.0000 - val_false_positives_1: 1677.0000 -
val_auc_1: 0.9611 - val_precision_1: 0.8447 - val_recall_1: 0.9013
Epoch 2/1000
102/102 [=====] - 7s 65ms/step - loss: 0.2005 - accurac
y: 0.9211 - false_negatives_1: 4199.0000 - false_positives_1: 3799.0000 - auc_1:
0.9740 - precision_1: 0.9055 - recall_1: 0.8966 - val_loss: 0.1820 - val_accurac
y: 0.9299 - val_false_negatives_1: 1158.0000 - val_false_positives_1: 619.0000 -
val_auc_1: 0.9789 - val_precision_1: 0.9354 - val_recall_1: 0.8856
Epoch 3/1000
102/102 [=====] - 7s 65ms/step - loss: 0.1464 - accurac
y: 0.9462 - false_negatives_1: 2897.0000 - false_positives_1: 2553.0000 - auc_1:
0.9853 - precision_1: 0.9366 - recall_1: 0.9287 - val_loss: 0.1598 - val_accurac
y: 0.9407 - val_false_negatives_1: 618.0000 - val_false_positives_1: 885.0000 -
val_auc_1: 0.9832 - val_precision_1: 0.9148 - val_recall_1: 0.9389
Epoch 4/1000
102/102 [=====] - 7s 65ms/step - loss: 0.1193 - accurac
```

```

y: 0.9581 - false_negatives_1: 2244.0000 - false_positives_1: 1999.0000 - auc_1:
0.9895 - precision_1: 0.9505 - recall_1: 0.9447 - val_loss: 0.1494 - val_accurac
y: 0.9463 - val_false_negatives_1: 871.0000 - val_false_positives_1: 489.0000 -
val_auc_1: 0.9848 - val_precision_1: 0.9498 - val_recall_1: 0.9139
Epoch 5/1000
102/102 [=====] - 7s 65ms/step - loss: 0.0988 - accurac
y: 0.9673 - false_negatives_1: 1731.0000 - false_positives_1: 1579.0000 - auc_1:
0.9921 - precision_1: 0.9610 - recall_1: 0.9574 - val_loss: 0.1501 - val_accurac
y: 0.9469 - val_false_negatives_1: 789.0000 - val_false_positives_1: 556.0000 -
val_auc_1: 0.9849 - val_precision_1: 0.9438 - val_recall_1: 0.9220
Epoch 6/1000
102/102 [=====] - 7s 65ms/step - loss: 0.0848 - accurac
y: 0.9729 - false_negatives_1: 1459.0000 - false_positives_1: 1288.0000 - auc_1:
0.9937 - precision_1: 0.9681 - recall_1: 0.9641 - val_loss: 0.1484 - val_accurac
y: 0.9484 - val_false_negatives_1: 644.0000 - val_false_positives_1: 664.0000 -
val_auc_1: 0.9848 - val_precision_1: 0.9345 - val_recall_1: 0.9364
Epoch 7/1000
102/102 [=====] - 7s 64ms/step - loss: 0.0729 - accurac
y: 0.9771 - false_negatives_1: 1221.0000 - false_positives_1: 1098.0000 - auc_1:
0.9949 - precision_1: 0.9729 - recall_1: 0.9699 - val_loss: 0.1532 - val_accurac
y: 0.9477 - val_false_negatives_1: 801.0000 - val_false_positives_1: 524.0000 -
val_auc_1: 0.9846 - val_precision_1: 0.9468 - val_recall_1: 0.9209
Epoch 8/1000
102/102 [=====] - 7s 64ms/step - loss: 0.0609 - accurac
y: 0.9813 - false_negatives_1: 1001.0000 - false_positives_1: 894.0000 - auc_1:
0.9961 - precision_1: 0.9779 - recall_1: 0.9753 - val_loss: 0.1548 - val_accurac
y: 0.9518 - val_false_negatives_1: 758.0000 - val_false_positives_1: 463.0000 -
val_auc_1: 0.9850 - val_precision_1: 0.9529 - val_recall_1: 0.9251
Epoch 9/1000
102/102 [=====] - 7s 64ms/step - loss: 0.0514 - accurac
y: 0.9842 - false_negatives_1: 860.0000 - false_positives_1: 743.0000 - auc_1:
0.9970 - precision_1: 0.9816 - recall_1: 0.9788 - val_loss: 0.1644 - val_accurac
y: 0.9482 - val_false_negatives_1: 695.0000 - val_false_positives_1: 617.0000 -
val_auc_1: 0.9831 - val_precision_1: 0.9386 - val_recall_1: 0.9313

```

In []:

```

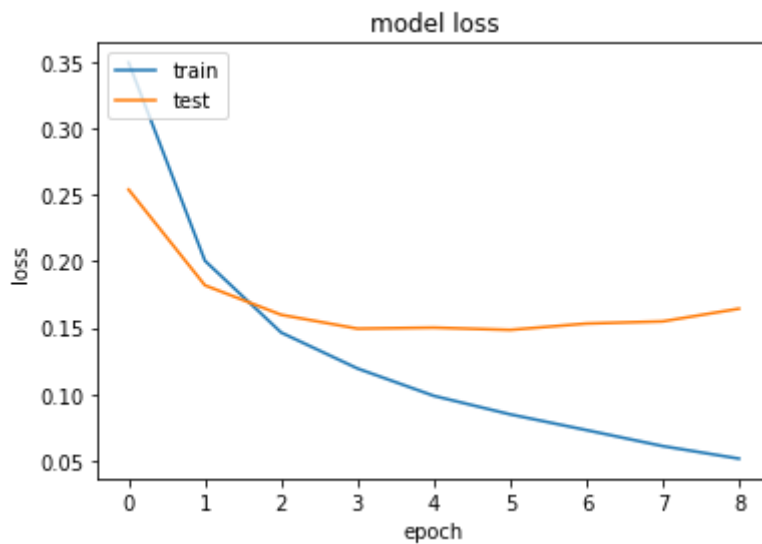
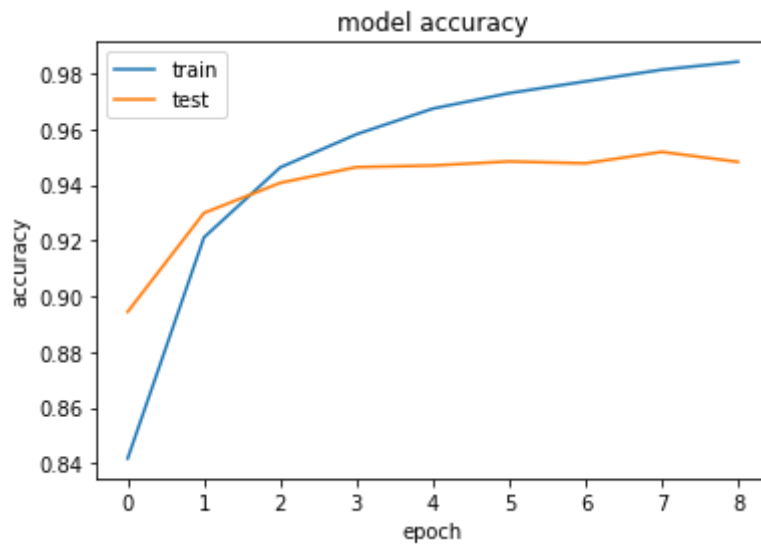
print(history.history.keys())
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

```

```

dict_keys(['loss', 'accuracy', 'false_negatives_1', 'false_positives_1', 'auc_
1', 'precision_1', 'recall_1', 'val_loss', 'val_accuracy', 'val_false_negatives_
1', 'val_false_positives_1', 'val_auc_1', 'val_precision_1', 'val_recall_1'])

```



```
In [ ]: nn_preds = model_nn.predict(X_test)
```

```
In [ ]: nn_preds
```

```
Out[ ]: array([[2.9492378e-04],
               [9.9992323e-01],
               [9.9677444e-01],
               ...,
               [1.1721969e-02],
               [1.3581514e-03],
               [7.9426467e-03]], dtype=float32)
```

```
In [ ]: test_guess_nn = pd.DataFrame(nn_preds)
test_guess_nn['predict'] = 0
test_guess_nn.loc[test_guess_nn[0]>0.221,"predict"]=1
```

```
In [ ]: precision = precision_score(test_guess_nn['predict'],y_test)
recall = recall_score(test_guess_nn['predict'],y_test)
accuracy = accuracy_score(test_guess_nn['predict'],y_test)

print(f"Accuracy: {accuracy:.5f}")
```

```
print(f"Precision: {precision:.5f}")
print(f"Recall: {recall:.5f}")
```

Accuracy: 0.94346
Precision: 0.95000
Recall: 0.91372

```
In [ ]: confusion_matrix_nn = confusion_matrix(y_test, test_guess_nn['predict'])
print(confusion_matrix_nn)
print((confusion_matrix_nn[0,1]*100 + confusion_matrix_nn[1,0]*250)/len(y_test))

[[17709  1150]
 [   641 12179]]
8.688721234887465
```

Ensembling

```
In [ ]: # Neural Net Wrapper Scikitlearn KerasClassifier
```

```
In [ ]: from keras.wrappers.scikit_learn import KerasClassifier
```

```
In [ ]: def create_model_3():
    my_model = Sequential()
    my_model.add(tf.keras.Input(shape=(3,)))
    my_model.add(tf.keras.layers.Dense(500, activation='relu'))
    my_model.add(tf.keras.layers.Dense(400, activation='relu'))
    my_model.add(tf.keras.layers.Dense(300, activation='relu'))
    my_model.add(tf.keras.layers.Dense(200, activation='relu'))
    my_model.add(tf.keras.layers.Dense(100, activation='relu'))
    my_model.add(tf.keras.layers.Dense(1, activation='sigmoid'))

    # safety = EarlyStopping(patience = 3, monitor='val_loss')

    my_model.compile(optimizer='adam', loss = tf.keras.losses.BinaryCrossentropy())

    return my_model
```

```
In [ ]: def create_model_79():
    my_model = Sequential()
    my_model.add(tf.keras.Input(shape=(79,)))
    my_model.add(tf.keras.layers.Dense(500, activation='relu'))
    my_model.add(tf.keras.layers.Dense(400, activation='relu'))
    my_model.add(tf.keras.layers.Dense(300, activation='relu'))
    my_model.add(tf.keras.layers.Dense(200, activation='relu'))
    my_model.add(tf.keras.layers.Dense(100, activation='relu'))
    my_model.add(tf.keras.layers.Dense(1, activation='sigmoid'))

    # safety = EarlyStopping(patience = 3, monitor='val_loss')

    my_model.compile(optimizer='adam', loss = tf.keras.losses.BinaryCrossentropy())

    return my_model
```

```
In [ ]: # my_model = KerasClassifier(build_fn=create_model, epochs=10, batch_size=1000,
```

Ensemble: 1

Level 1 - Random Forest and Logistic Regression

Level 2 - XGBoost

91.8% Train Accuracy

```
In [ ]: rf_level1 = RandomForestClassifier()
lr_level1 = LogisticRegression(max_iter=500)

# Uncomment when you need test preds
# rf_level1.fit(X_train, y_train)
# lr_level1.fit(X_train, y_train)

rf1 = cross_val_predict(rf_level1, X_train, y_train, cv=3, method='predict_proba')
lr1 = cross_val_predict(lr_level1, X_train, y_train, cv=3, method='predict_proba')
```

```
In [ ]: level2_data = pd.DataFrame(rf1[:,1])
level2_data['lr'] = lr1[:,1]
level2_data
```

```
Out[ ]:
```

	0	lr
0	0.28	0.374970
1	0.10	0.099207
2	0.74	0.515404
3	0.36	0.438831
4	0.83	0.595021
...
126708	0.39	0.780199
126709	0.17	0.071159
126710	0.14	0.166706
126711	0.38	0.569869
126712	0.37	0.619805

126713 rows × 2 columns

```
In [ ]: final_model = GradientBoostingClassifier()

# Uncomment when you need test preds
# final_model.fit(level2_data, y_train)

final_preds = cross_val_predict(final_model, level2_data, y_train, cv=5)
```

```
In [ ]: guess = pd.DataFrame(final_preds)
```

```
guess['predict'] = 0
guess.loc[guess[0]>0.5,"predict"]=1

accuracy_score(guess['predict'],y_train)
```

Out[]: 0.918074704252918

Ensemble 2

Level 1 - Tuned Random Forest, Tuned Logistic Regression

Level 2 - Random Forest, Logistic Regression

Level 3 - XGBoost

92.5% Train Accuracy

```
In [ ]: rf_level1 = RandomForestClassifier(class_weight='balanced', criterion='entropy',
lr_level1 = LogisticRegression(C=0.01, max_iter=500)

# Uncomment when you need test predictions
rf_level1.fit(X_train, y_train)
lr_level1.fit(X_train, y_train)
```

```
rf1 = cross_val_predict(rf_level1, X_train, y_train, cv=3, method='predict_proba')
lr1 = cross_val_predict(lr_level1, X_train, y_train, cv=4, method='predict_proba')
```

```
In [ ]: level2_data = pd.DataFrame(rf1[:,1])
level2_data['lr'] = lr1[:,1]
level2_data
```

```
Out[ ]:
```

	0	lr
0	0.329193	0.374303
1	0.084028	0.095674
2	0.717596	0.470001
3	0.518386	0.432468
4	0.921238	0.593786
...
126708	0.320996	0.773343
126709	0.032964	0.078576
126710	0.090867	0.170910
126711	0.430979	0.569288
126712	0.223400	0.616765

126713 rows × 2 columns

```
In [ ]: rf_level2 = RandomForestClassifier()
lr_level2 = LogisticRegression()
```

```
# Uncomment when you need test predictions
rf_level2.fit(level2_data, y_train)
lr_level2.fit(level2_data, y_train)

rf2 = cross_val_predict(rf_level2, level2_data, y_train, cv=3, method='predict_p
lr2 = cross_val_predict(lr_level2, level2_data, y_train, cv=3, method='predict_p
```

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,


```
level3_data = pd.DataFrame(rf2[:,1])
level3_data['lr'] = lr2[:,1]
level3_data
```

	0	lr
0	0.44	0.161453
1	0.00	0.024415
2	0.75	0.908471
3	0.50	0.561996
4	1.00	0.985386
...
126708	0.09	0.075824
126709	0.00	0.014855
126710	0.03	0.022748
126711	0.54	0.284001
126712	0.15	0.038034

126713 rows x 2 columns

```
final_model = GradientBoostingClassifier()

# Uncomment when you need test predictions
final_model.fit(level3_data, y_train)

final_preds = cross_val_predict(final_model, level3_data, y_train, cv=5)
```

[illegible]

```

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,

```

```

In [ ]: guess = pd.DataFrame(final_preds)
guess['predict'] = 0
guess.loc[guess[0]>0.5,"predict"]=1

accuracy_score(guess['predict'],y_train)

```

Out[]: 0.925098450829828

Ensemble 3

Level 1 - Random Forest, Logistic Regression, Neural Network

Level 2 - Random Forest, Logistic Regression, Neural Network

Level 3 - XGBoost

91.8% Train Accuracy

```

In [ ]: rf_level1 = RandomForestClassifier()
lr_level1 = LogisticRegression(max_iter=500)
nn_level1 = KerasClassifier(build_fn=create_model_79, epochs=9, batch_size=1000,

# Uncomment when you need test predictions
# rf_level1.fit(X_train, y_train)
# lr_level1.fit(X_train, y_train)
# nn_level1.fit(X_train, y_train)

rf1 = cross_val_predict(rf_level1, X_train, y_train, cv=3, method='predict_proba')
lr1 = cross_val_predict(lr_level1, X_train, y_train, cv=4, method='predict_proba')
nn1 = cross_val_predict(nn_level1, X_train, y_train, cv=4, method='predict_proba')

level2_data = pd.DataFrame(rf1[:,1])
level2_data['lr'] = lr1[:,1]
level2_data['nn'] = nn1[:,1]
level2_data

```

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras (https://github.com/adriangb/scikeras) instead. See https://www.adriangb.com/scikeras/stable/migration.html for

```

help migrating.

This is separate from the ipykernel package so we can avoid doing imports until

```
Out[ ]:
```

	0	lr	nn
0	0.44	0.373100	0.373100
1	0.16	0.097436	0.097436
2	0.73	0.513791	0.513791
3	0.42	0.431478	0.431478
4	0.74	0.587620	0.587620
...
126708	0.46	0.777981	0.777981
126709	0.12	0.073421	0.073421
126710	0.14	0.167913	0.167913
126711	0.51	0.576890	0.576890
126712	0.29	0.620542	0.620542

126713 rows × 3 columns

```
In [ ]:
```

```
rf_level2 = RandomForestClassifier()
lr_level2 = LogisticRegression()
nn_level2 = KerasClassifier(build_fn=create_model_3, epochs=15, batch_size=1000,

# Uncomment when you need test predictions
# rf_level2.fit(level2_data, y_train)
# lr_level2.fit(level2_data, y_train)
# nn_level2.fit(level2_data, y_train)

rf2 = cross_val_predict(rf_level2, level2_data, y_train, cv=3, method='predict_p
lr2 = cross_val_predict(lr_level2, level2_data, y_train, cv=3, method='predict_p
nn2 = cross_val_predict(nn_level2, level2_data, y_train, cv=3, method='predict_p

level3_data = pd.DataFrame(rf2[:,1])
level3_data['lr'] = lr2[:,1]
level3_data['nn'] = nn2[:,1]
level3_data
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras (<https://github.com/adriangb/scikeras>) instead. See <https://www.adriangb.com/scikeras/stable/migration.html> for help migrating.

This is separate from the ipykernel package so we can avoid doing imports until

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning:

arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureW
arning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

Out[]:

	0	lr	nn
0	0.43	0.445174	0.478795
1	0.00	0.040444	0.044240
2	0.99	0.961405	0.953613
3	0.66	0.345794	0.391266
4	0.99	0.958944	0.954714
...
126708	0.72	0.271237	0.316899
126709	0.00	0.025896	0.023975
126710	0.00	0.026349	0.022788
126711	0.22	0.547167	0.605917
126712	0.05	0.056640	0.072156

126713 rows x 3 columns

```
In [ ]: final_model = GradientBoostingClassifier()
```

```
# Uncomment when you need test predictions  
# final_model.fit(level3_data, y_train)
```

```
final_preds = cross_val_predict(final_model, level3_data, y_train, cv=5)
```

```
guess = pd.DataFrame(final_preds)  
guess['predict'] = 0  
guess.loc[guess[0]>0.5, "predict"] = 1
```

```
accuracy_score(guess['predict'], y_train)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
```

```
FutureWarning,
```

```
Out[ ]: 0.9178537324504984
```

Ensemble 4

Level 1 - Random Forest, Logistic Regression, Neural Network, Neural Network, XGBoost Classifier

Level 2 - XGBoost Classifier

91.8% Train Accuracy

In []:

```
rf_level1 = RandomForestClassifier()
lr_level1 = LogisticRegression(max_iter=500)
nn_level1 = KerasClassifier(build_fn=create_model_79, epochs=9, batch_size=1000,
nn_level1_2 = KerasClassifier(build_fn=create_model_79, epochs=30, batch_size=10
xgb_level1 = GradientBoostingClassifier()

## Uncomment when test evaluation is needed
# rf_level1.fit(X_train, y_train)
# lr_level1.fit(X_train, y_train)
# nn_level1.fit(X_train, y_train)
# nn_level1_2.fit(X_train, y_train)
# xgb_level1.fit(X_train, y_train)

rf1 = cross_val_predict(rf_level1, X_train, y_train, cv=3, method='predict_proba
lr1 = cross_val_predict(lr_level1, X_train, y_train, cv=3, method='predict_proba
nn1 = cross_val_predict(lr_level1, X_train, y_train, cv=3, method='predict_proba
nn1_2 = cross_val_predict(nn_level1_2, X_train, y_train, cv=3, method='predict_p
xgb1 = cross_val_predict(xgb_level1, X_train, y_train, cv=3, method='predict_pro

level2_data = pd.DataFrame(rf1[:,1])
level2_data['lr'] = lr1[:,1]
level2_data['nn'] = nn1[:,1]
level2_data['nn_2'] = nn1_2[:,1]
level2_data['xgb'] = xgb1[:,1]
level2_data
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras (<https://github.com/adriangb/scikeras>) instead. See <https://www.adriangb.com/scikeras/stable/migration.html> for help migrating.

This is separate from the ipykernel package so we can avoid doing imports until

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras (<https://github.com/adriangb/scikeras>) instead. See <https://www.adriangb.com/scikeras/stable/migration.html> for help migrating.

after removing the cwd from sys.path.

Out[]:

	0	lr	nn	nn_2	xgb
0	0.48	0.374840	0.374840	1.887556e-07	0.444457
1	0.15	0.099180	0.099180	5.177485e-06	0.072695
2	0.73	0.515659	0.515659	9.999931e-01	0.528277
3	0.36	0.438907	0.438907	9.998369e-01	0.342214
4	0.84	0.595057	0.595057	9.998915e-01	0.681795
...
126708	0.34	0.780217	0.780217	3.338272e-05	0.636786
126709	0.16	0.071169	0.071169	8.145187e-06	0.061157
126710	0.26	0.166705	0.166705	8.583481e-11	0.143517
126711	0.45	0.569767	0.569767	4.715800e-03	0.396046

	0	lr	nn	nn_2	xgb
126712	0.31	0.619666	0.619666	9.001749e-10	0.449983

126713 rows x 5 columns

In []:

```
final_model = GradientBoostingClassifier()

# Uncomment when you need test predictions
# final_model.fit(level3_data, y_train)

final_preds = cross_val_predict(final_model, level3_data, y_train, cv=5)

guess = pd.DataFrame(final_preds)
guess['predict'] = 0
guess.loc[guess[0]>0.5,"predict"]=1

accuracy_score(guess['predict'],y_train)
```

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,

Out[]: 0.9178379487503255

Test Eval

```
In [ ]: test_rf = rf_level1.predict_proba(X_test)
        test_lr = lr_level1.predict_proba(X_test)

        test_level2_data = pd.DataFrame(test_rf[:,1])
        test_level2_data['lr'] = test_lr[:,1]
```

```
In [ ]: test_rf_2 = rf_level2.predict_proba(test_level2_data)
        test_lr_2 = lr_level2.predict_proba(test_level2_data)

        test_final_data = pd.DataFrame(test_rf_2[:,1])
        test_final_data['lr'] = test_lr_2[:,1]
```

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.

FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,

```
In [ ]: test_preds = final_model.predict(test_final_data)
```

/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:1692: FutureWarning: Feature names only support names that are all strings. Got feature names with dtypes: ['int', 'str']. An error will be raised in 1.2.
FutureWarning,

```
In [ ]: test_guess = pd.DataFrame(test_preds)
        test_guess['predict'] = 0
        test_guess.loc[test_guess[0]>0.5, "predict"] = 1
```

```
In [ ]: precision = precision_score(test_guess['predict'], y_test)
        recall = recall_score(test_guess['predict'], y_test)
        accuracy = accuracy_score(test_guess['predict'], y_test)

        print(f"Accuracy: {accuracy:.5f}")
        print(f"Precision: {precision:.5f}")
        print(f"Recall: {recall:.5f}")
```

Accuracy: 0.92999
Precision: 0.90577
Recall: 0.91998

```
In [ ]: confusion_matrix_ens = confusion_matrix(y_test, test_guess['predict'])
        print(confusion_matrix_ens)
        print((confusion_matrix_ens[0,1]*100 + confusion_matrix_ens[1,0]*250)/len(y_test))

[[17849  1010]
 [ 1208 11612]]
12.721361154076833
```