- Team Member:
  Jiayue Chen, USC ID: 1010470489
  Zhengan Pan, USC ID: 3134818448
  Jiahe Zhang, USC ID: 4321317535
- Kaggle Project Name: Don't Overfit!II
- Kaggle Score: 0.903
- Kaggle Team Name : ABCCC
- Date of uploading result: 12/10/2019
- Section: Wednesday

### Larger dataset for test set but extremely small dataset for the trainning set.

In this project, we have 250 rows of data with 300 features as our train set but 19.8k rows of data for our test set. Thus, we need to find a way to avoid overfitting and try to pull up the accuracy rate of predicting the target value for the test set.

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
import numpy as np
import pandas as pd
```

In [4]:
```
import matplotlib.pyplot as plt
```

In [5]:
```
from xgboost import XGBClassifier
```

In [6]:
```
from sklearn.feature_selection import SelectFromModel
```

In [7]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

In [8]:
```
from sklearn.preprocessing import StandardScaler
```

# Retrieving the trainning data.

In [13]:
```
trainset = pd.read_csv('train.csv')
```

In [14]:
```
trainset.head()
```

Out[14]:

| | id | target | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | ... | 290 | 291 | 2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 1.0 | -0.098 | 2.165 | 0.681 | -0.614 | 1.309 | -0.455 | -0.236 | 0.276 | ... | 0.867 | 1.347 | 0.5 |
| **1** | 1 | 0.0 | 1.081 | -0.973 | -0.383 | 0.326 | -0.428 | 0.317 | 1.172 | 0.352 | ... | -0.165 | -1.695 | -1.2 |
| **2** | 2 | 1.0 | -0.523 | -0.089 | -0.348 | 0.148 | -0.022 | 0.404 | -0.023 | -0.172 | ... | 0.013 | 0.263 | -1.2 |
| **3** | 3 | 1.0 | 0.067 | -0.021 | 0.392 | -1.637 | -0.446 | -0.725 | -1.035 | 0.834 | ... | -0.404 | 0.640 | -0.5 |
| **4** | 4 | 1.0 | 2.347 | -0.831 | 0.511 | -0.021 | 1.225 | 1.594 | 0.585 | 1.509 | ... | 0.898 | 0.134 | 2.4 |

5 rows × 302 columns

In [15]:
```
y = trainset['target']
```

In [16]:
```
y.head()
```

Out[16]:
```
0    1.0
1    0.0
2    1.0
3    1.0
4    1.0
Name: target, dtype: float64
```

In [17]:
```
X = trainset.drop(columns = ['target', 'id'])
```

In [18]:
```
X.head()
```

Out[18]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 290 | 291 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | -0.098 | 2.165 | 0.681 | -0.614 | 1.309 | -0.455 | -0.236 | 0.276 | -2.246 | 1.825 | ... | 0.867 | 1.347 |
| **1** | 1.081 | -0.973 | -0.383 | 0.326 | -0.428 | 0.317 | 1.172 | 0.352 | 0.004 | -0.291 | ... | -0.165 | -1.695 |
| **2** | -0.523 | -0.089 | -0.348 | 0.148 | -0.022 | 0.404 | -0.023 | -0.172 | 0.137 | 0.183 | ... | 0.013 | 0.263 |
| **3** | 0.067 | -0.021 | 0.392 | -1.637 | -0.446 | -0.725 | -1.035 | 0.834 | 0.503 | 0.274 | ... | -0.404 | 0.640 |
| **4** | 2.347 | -0.831 | 0.511 | -0.021 | 1.225 | 1.594 | 0.585 | 1.509 | -0.012 | 2.198 | ... | 0.898 | 0.134 |

5 rows × 300 columns

### Randomly split the trainning set into new train set and test set to test the models

In [14]:
```
X_train, X_test, y_train,y_test = train_test_split(X,y, test_size = 0.20
, random_state = 1)
```

In [15]:
```
X_train.shape
```
Out[15]:
```
(200, 300)
```

In [16]:
```
X_test.shape
```
Out[16]:
```
(50, 300)
```

# Using XGBoosting and select the most important features

In [17]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import StratifiedKFold
```

In [18]:
```
from xgboost import XGBClassifier
```

In [19]:
```
XGBmodel = XGBClassifier(n_estimators = 100, learning_rate = 0.10)
XGBmodel.fit(X_train, y_train)
```
Out[19]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=100, n_job
s=1,
              nthread=None, objective='binary:logistic', random_state=
0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

#### Using XGBmodel to find the critical features (whose importance is not equal to 0 )

In [20]:
```
acc_train_XGB = round(100*XGBmodel.score(X_train,y_train),2)
acc_train_XGB
```
Out[20]:
```
100.0
```

In [21]:
```
acc_test_XGB = round(100*XGBmodel.score(X_test,y_test),2)
acc_test_XGB
```
Out[21]:
```
68.0
```

we can see that XGB model is still overfitting since the test score is only 68.0 while the train score is 100.

In [22]:
```
importance = XGBmodel.feature_importances_*100
```

In [23]:
```
importances = pd.DataFrame({'Importance':importance}, index = X_train.co
lumns)
importances[:5]
```

Out[23]:

| | Importance |
|---|---|
| **0** | 0.540294 |
| **1** | 0.462361 |
| **2** | 0.000000 |
| **3** | 0.260296 |
| **4** | 0.992477 |

In [24]:
```
thresholds = importances.sort_values(by='Importance', axis = 0, ascendin
g = True)
thresholds[-6:-1]
```

Out[24]:

| | Importance |
|---|---|
| **215** | 2.104079 |
| **119** | 2.118968 |
| **266** | 2.167058 |
| **287** | 2.251271 |
| **222** | 2.556155 |

As we can see that these are 5 most important features gotten by XGB model.

In [25]:
```
selected_features = thresholds.loc[~(thresholds<=0.5).all(axis=1)]
selected_features.shape
```

Out[25]: (73, 1)

For the features whose importance is less than 0.5, we just ignore these features and only use other features to build the model

In [26]:
```
selected_features.head()
```

Out[26]:

| | Importance |
|---|---|
| **259** | 0.501513 |
| **241** | 0.503999 |
| **127** | 0.516164 |
| **0** | 0.540294 |
| **165** | 0.541194 |

In [27]:
```
indexarray = selected_features.index
```

In [28]:
```
indexlist = []
for i in indexarray:
    temp = int(i)
    indexlist.append(temp)
```

In [29]:
```
indexlist[:5]
```

Out[29]:
```
[259, 241, 127, 0, 165]
```

In [30]:
```
selected_X_train = X_train.iloc[:, indexlist]
selected_X_test = X_test.iloc[:,indexlist]
```

We created a new train and test set only use the selected features.

And then we fit the XGB model with the selected features

In [31]:
```
XGBmodel_new = XGBClassifier(n_estimators = 600, learning_rate = 0.10)
XGBmodel_new.fit(selected_X_train, y_train)
```

Out[31]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=600, n_job
s=1,
              nthread=None, objective='binary:logistic', random_state=
0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [32]:
```
acc_train_XGB_new = round(100*XGBmodel_new.score(selected_X_train,y_trai
n),2)
acc_train_XGB_new
```

Out[32]:
```
100.0
```

In [33]:
```
acc_test_XGB_new = round(100*XGBmodel_new.score(selected_X_test,y_test),
2)
acc_test_XGB_new
```

Out[33]:
```
66.0
```

After using the selected features as our predictors, we still overfit the model and get lower accuracy rate for the test set.

So maybe we should try other methods and models to find out which features we should choose as our predictors rater than XGBmodels.

# Using Shap and XGBoost model to select the features

In [34]:
```
pip install shap
```

```
Requirement already satisfied: shap in /Users/jiayuechen/anaconda3/lib/
python3.7/site-packages (0.33.0)
Requirement already satisfied: scikit-learn in /Users/jiayuechen/anacon
da3/lib/python3.7/site-packages (from shap) (0.21.2)
Requirement already satisfied: pandas in /Users/jiayuechen/anaconda3/li
b/python3.7/site-packages (from shap) (0.24.2)
Requirement already satisfied: tqdm>4.25.0 in /Users/jiayuechen/anacond
a3/lib/python3.7/site-packages (from shap) (4.32.1)
Requirement already satisfied: numpy in /Users/jiayuechen/anaconda3/li
b/python3.7/site-packages (from shap) (1.16.4)
Requirement already satisfied: scipy in /Users/jiayuechen/anaconda3/li
b/python3.7/site-packages (from shap) (1.3.0)
Requirement already satisfied: joblib>=0.11 in /Users/jiayuechen/anacon
da3/lib/python3.7/site-packages (from scikit-learn->shap) (0.13.2)
Requirement already satisfied: python-dateutil>=2.5.0 in /Users/jiayuec
hen/anaconda3/lib/python3.7/site-packages (from pandas->shap) (2.8.0)
Requirement already satisfied: pytz>=2011k in /Users/jiayuechen/anacond
a3/lib/python3.7/site-packages (from pandas->shap) (2019.1)
Requirement already satisfied: six>=1.5 in /Users/jiayuechen/anaconda3/
lib/python3.7/site-packages (from python-dateutil>=2.5.0->pandas->shap)
(1.12.0)
Note: you may need to restart the kernel to use updated packages.
```

In [35]:
```
import shap
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size = 0.2
, random_state = 0)
```

In [37]:
```
modelg =  XGBClassifier(n_estimators=1000, learning_rate=0.1,max_depth =
2)
```

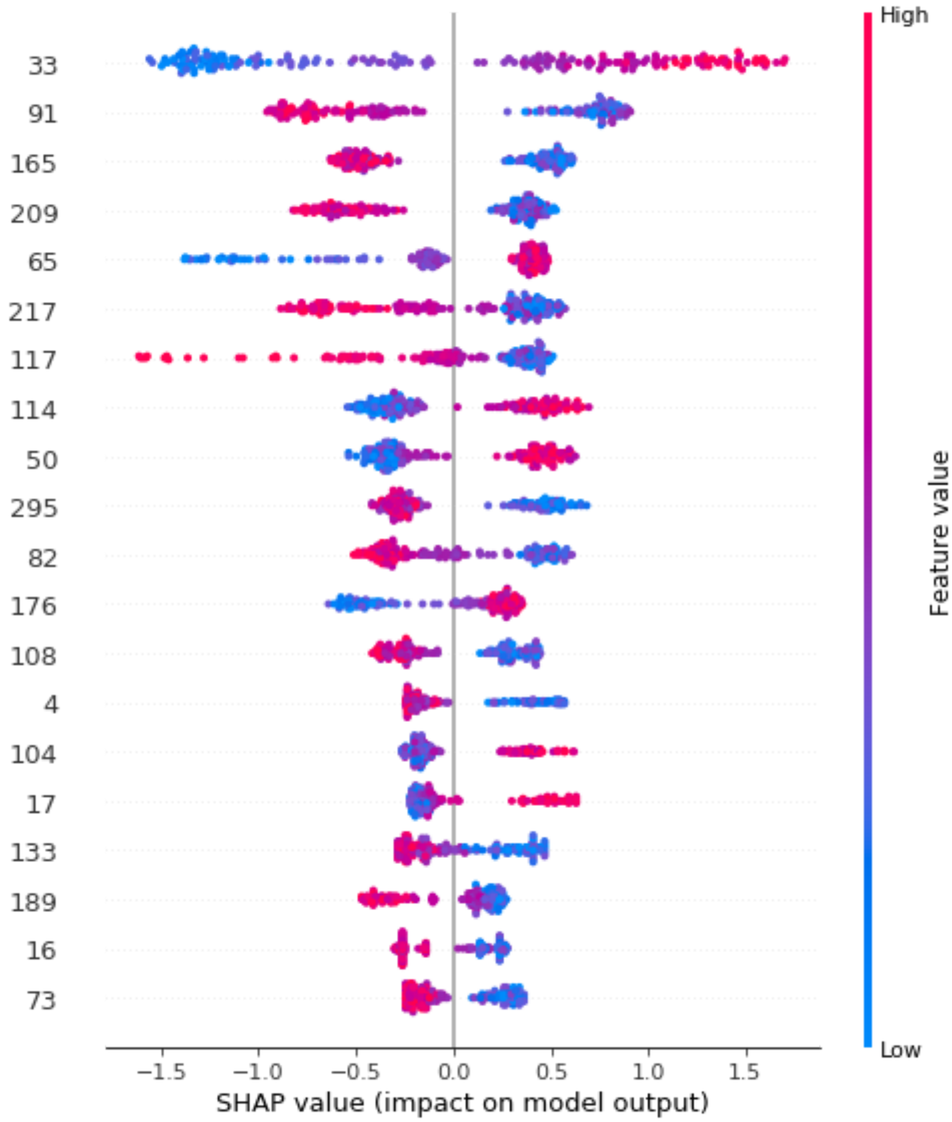
In [38]:
```
modelg.fit(X_train,y_train)
```

Out[38]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=2,
              min_child_weight=1, missing=None, n_estimators=1000, n_jo
bs=1,
              nthread=None, objective='binary:logistic', random_state=
0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [39]:
```
explainer = shap.TreeExplainer(modelg, X_train)
```

In [40]:
```
shap_values = explainer.shap_values(X_train)
```

In [41]:
```
shap.summary_plot(shap_values, X_train)
```



In [42]:
```
Xs_train = X_train[['33','91','165','209','65','217','117','114','50','2
95','82','176','108','4','104','17','133','189','16','73']]
```

In [43]:
```
Xs_test = X_test[['33','91','165','209','65','217','117','114','50','29
5','82','176','108','4','104','17','133','189','16','73']]
```

In [44]:
```
scaler = StandardScaler()
```

In [45]:
```
Xs_train_trans = scaler.fit_transform(Xs_train)
Xs_test_trans = scaler.transform(Xs_test)
```

## tuning parameters for XBGoost

In [46]:
```
param_dist = {
        'n_estimators':[500,1000,1500,2000],
        'learning_rate':[0.001,0.01,0.1,1],
        'max_depth':[1,2,3]
        }
```

In [47]:
```
grid = GridSearchCV(XGBClassifier(),param_dist,cv = 10,scoring = 'neg_lo
g_loss')
```

In [48]:
```
grid.fit(Xs_train_trans,y_train)
```

```
The default of the `iid` parameter will change from True to False in ve
rsion 0.22 and will be removed in 0.24. This will change numeric result
s when test-set sizes are unequal.
```

Out[48]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_byn
ode=1,
                                     colsample_bytree=1, gamma=0,
                                     learning_rate=0.1, max_delta_step=
0,
                                     max_depth=3, min_child_weight=1,
                                     missing=None, n_estimators=100, n_
jobs=1,
                                     nthread=None, objective='binary:lo
gistic',
                                     random_state=0, reg_alpha=0, reg_l
ambda=1,
                                     scale_pos_weight=1, seed=None, sil
ent=None,
                                     subsample=1, verbosity=1),
             iid='warn', n_jobs=None,
             param_grid={'learning_rate': [0.001, 0.01, 0.1, 1],
                         'max_depth': [1, 2, 3],
                         'n_estimators': [500, 1000, 1500, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring='neg_log_loss', verbose=0)
```

In [49]:
```
best_estimator1 = grid.best_params_
print(best_estimator1)
```

```
{'learning_rate': 0.1, 'max_depth': 1, 'n_estimators': 500}
```

In [50]:
```
modelgs =  XGBClassifier(n_estimators=500, learning_rate=0.1,max_depth =
1)
```

In [51]:
```
modelgs.fit(Xs_train_trans,y_train)
```

Out[51]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=1,
              min_child_weight=1, missing=None, n_estimators=500, n_job
s=1,
              nthread=None, objective='binary:logistic', random_state=
0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [52]:
```
preds = modelgs.predict(Xs_test_trans)
```

In [53]:
```
accuracy2 = round(modelgs.score(Xs_test_trans,y_test)*100,2)
```

In [54]:
```
accuracy2
```

Out[54]:
```
74.0
```

In [55]:
```
accuracy3 = round(modelgs.score(Xs_train_trans,y_train)*100,2)
```

In [56]:
```
accuracy3
```

Out[56]:
```
100.0
```

Although the accuracy rate for test set has been improved a little, it still overfits and have a low test accuracy

# Using Random Forest Model

In [57]:
```
from sklearn.ensemble import RandomForestClassifier
```

### feature selection using shap

In [58]:
```
modelR =  RandomForestClassifier(n_estimators=3000,max_depth = 3,random_
state = 42)
```

In [59]:
```
modelR.fit(X_train,y_train)
```

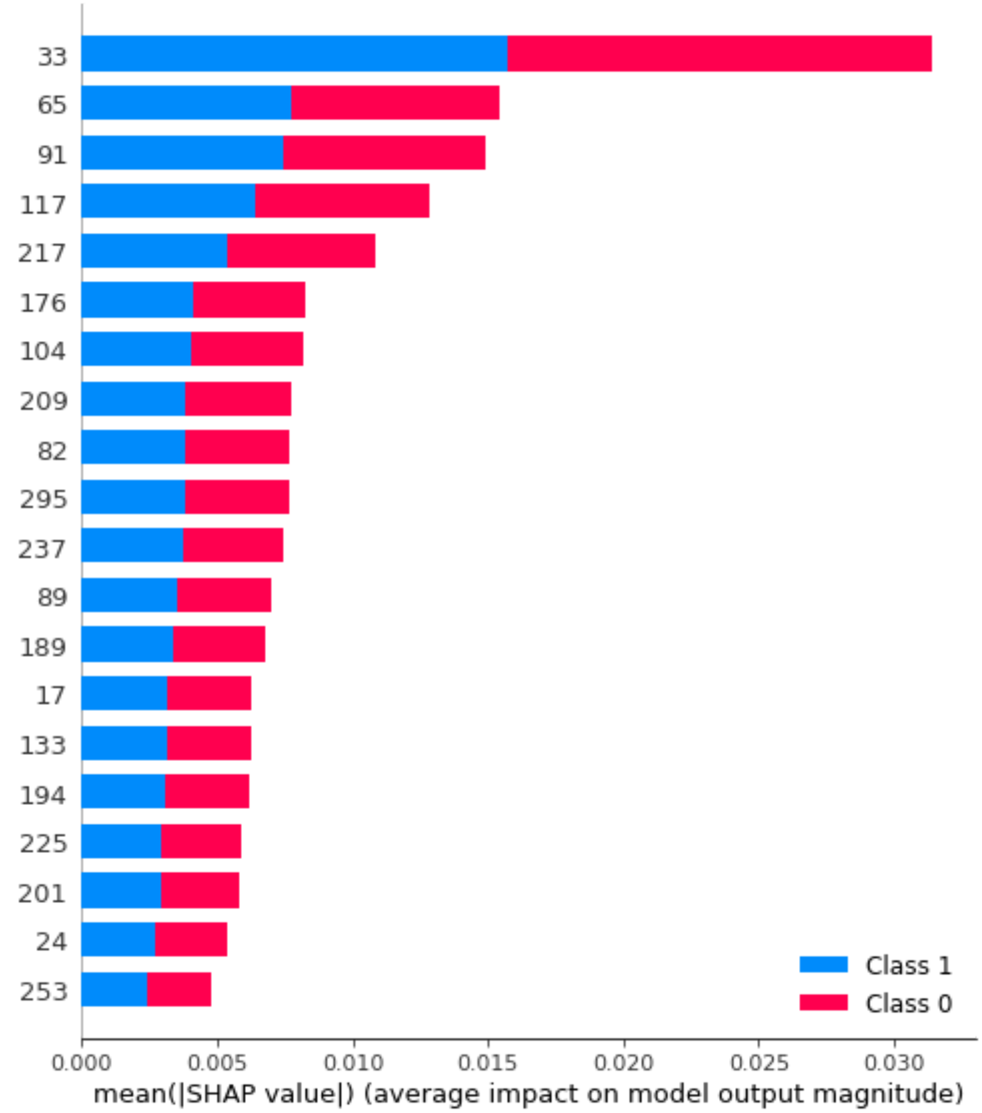
Out[59]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gi
ni',
                       max_depth=3, max_features='auto', max_leaf_nodes
=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=3000,
                       n_jobs=None, oob_score=False, random_state=42, v
erbose=0,
                       warm_start=False)
```

In [60]:
```
explainer = shap.TreeExplainer(modelR, X_train)
```

In [61]:
```
shap_values = explainer.shap_values(X_train)
```

```
 98%|===================| 394/400 [00:31<00:00]
```

In [62]:
```
shap.summary_plot(shap_values, X_train)
```




### Doing feature selection and scaling

In [63]:
```
Xs_trainR = X_train[['33','65','91','117','217','176','104','209','82',
'295','237','89','189','17','133','194','225','201','24','253']]
Xs_testR = X_test[['33','65','91','117','217','176','104','209','82','29
5','237','89','189','17','133','194','225','201','24','253']]
Xs_train_transR = scaler.fit_transform(Xs_trainR)
Xs_test_transR = scaler.transform(Xs_testR)
```

### Tuining parameters for getting better results

In [64]:
```
param_distRs = {'n_estimators': [500,1000,1500,2000],
                          'max_depth':[None,1,2,3]
                }
```

In [65]:
```
gridRs = GridSearchCV(RandomForestClassifier(), param_grid=param_distRs,
cv=10, scoring='roc_auc', n_jobs=-1)
```

In [66]:
```
gridRs.fit(Xs_train_transR, y_train)
```

```
The default of the `iid` parameter will change from True to False in ve
rsion 0.22 and will be removed in 0.24. This will change numeric result
s when test-set sizes are unequal.
```

Out[66]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True, class_wei
ght=None,
                                              criterion='gini', max_dep
th=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.
0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=
0.0,
                                              n_estimators='warn', n_jo
bs=None,
                                              oob_score=False,
                                              random_state=None, verbos
e=0,
                                              warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_depth': [None, 1, 2, 3],
                         'n_estimators': [500, 1000, 1500, 2000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring='roc_auc', verbose=0)
```

In [67]:
```
best_estimatorR = gridRs.best_params_
print(best_estimatorR)
```

```
{'max_depth': None, 'n_estimators': 1000}
```

Fit model and get accuracy score

In [68]:
```
modelRs = RandomForestClassifier(n_estimators=1500, max_depth = None)
```

In [69]:
```
modelRs.fit(Xs_train_transR,y_train)
```

Out[69]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gi
ni',
                       max_depth=None, max_features='auto', max_leaf_no
des=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=1500,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [70]:
```
predsR = modelRs.predict(Xs_test_transR)
```

In [71]:
```
accuracy2R = round(modelRs.score(Xs_test_transR,y_test)*100,2)
accuracy2R
```

Out[71]:
```
78.0
```

In [72]:
```
accuracy3R = round(modelRs.score(Xs_train_transR,y_train)*100,2)
accuracy3R
```

Out[72]:
```
100.0
```

We got a decent test score but the train score is still 100, which indicates we are still overfitting the model

# Building SVC Model

In [73]:
```
from sklearn.svm import SVC
```

In [74]:
```
modelV =  SVC(C = 1,kernel = 'linear')
```

In [75]:
```
modelV.fit(X_train,y_train)
```

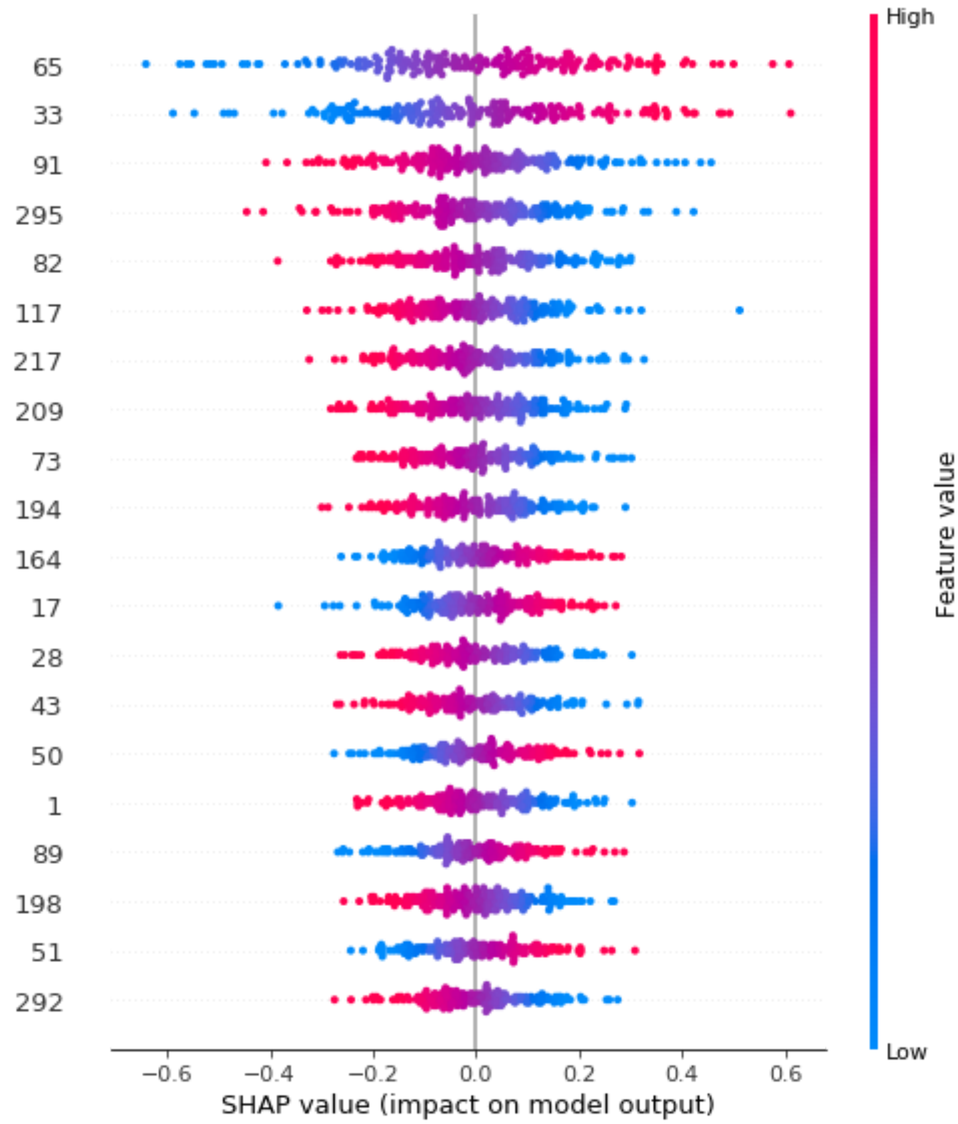
Out[75]:
```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
```

### Using Shap to select features

In [76]:
```
explainer = shap.LinearExplainer(modelV, X_train)
```

In [77]:
```
shap_values = explainer.shap_values(X_train)
```

In [78]:
```
shap.summary_plot(shap_values, X_train)
```




In [79]:
```
# Scaling and select features
```

In [80]:
```
Xs_trainV = X_train[['33','65','91','295','82','117','209','217','73','1
94','164','17','28','43','50','1','89','198','51','292']]
Xs_testV = X_test[['33','65','91','295','82','117','209','217','73','19
4','164','17','28','43','50','1','89','198','51','292']]
Xs_train_transV = scaler.transform(Xs_trainV)
Xs_test_transV = scaler.transform(Xs_testV)
```

#### Tuning the model to improve the accuracy rate

In [81]:
```
param_distV = {'C': [0.001, 0.01, 0.1, 1.0, 10.0],
                  'kernel': ['linear', 'poly', 'rbf'],
                 }
```

In [82]:
```
svc = SVC(probability=True, gamma='scale')
```

In [83]:
```
gridV = GridSearchCV(svc, param_grid=param_distV, cv=10, scoring='roc_au
c', n_jobs=-1)
```

In [84]:
```
gridV.fit(Xs_train_transV, y_train)
```

```
The default of the `iid` parameter will change from True to False in ve
rsion 0.22 and will be removed in 0.24. This will change numeric result
s when test-set sizes are unequal.
```

Out[84]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=SVC(C=1.0, cache_size=200, class_weight=None, co
ef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='rbf', max_iter=-1,
                           probability=True, random_state=None, shrinki
ng=True,
                           tol=0.001, verbose=False),
             iid='warn', n_jobs=-1,
             param_grid={'C': [0.001, 0.01, 0.1, 1.0, 10.0],
                         'kernel': ['linear', 'poly', 'rbf']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring='roc_auc', verbose=0)
```

In [85]:
```
best_estimatorV = gridV.best_params_
print(best_estimatorV)
```

```
{'C': 0.1, 'kernel': 'linear'}
```

In [86]:
```
# Fit model and get accuracy score
```

In [87]:
```
modelVs = SVC(C = 0.1,kernel = 'linear')
```

In [88]:
```
modelVs.fit(Xs_train_transV,y_train)
```

Out[88]:
```
SVC(C=0.1, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
```

In [89]:
```
predsV = modelVs.predict(Xs_test_transV)
```

In [90]:
```
accuracy2V = round(modelVs.score(Xs_test_transV,y_test)*100,2)
accuracy2V
```

Out[90]:
```
72.0
```

In [91]:
```
accuracy3V = round(modelVs.score(Xs_train_transV,y_train)*100,2)
accuracy3V
```

Out[91]:
```
84.5
```

As a result, we can see that even though our model is not overfitting, the test score for SVC model is pretty low

# Building SGD Model

In [92]:
```
from sklearn.linear_model import SGDClassifier
```

In [93]:
```
sgd = SGDClassifier(eta0=1, max_iter=1000, tol=0.0001)
```

In [94]:
```
modelG =  SGDClassifier(eta0=1, tol=0.0001, alpha = 0.01, l1_ratio = 1.0
, learning_rate='adaptive',loss='log',penalty='elasticnet',random_state
= 42)
```

In [95]:
```
modelG.fit(X_train,y_train)
```

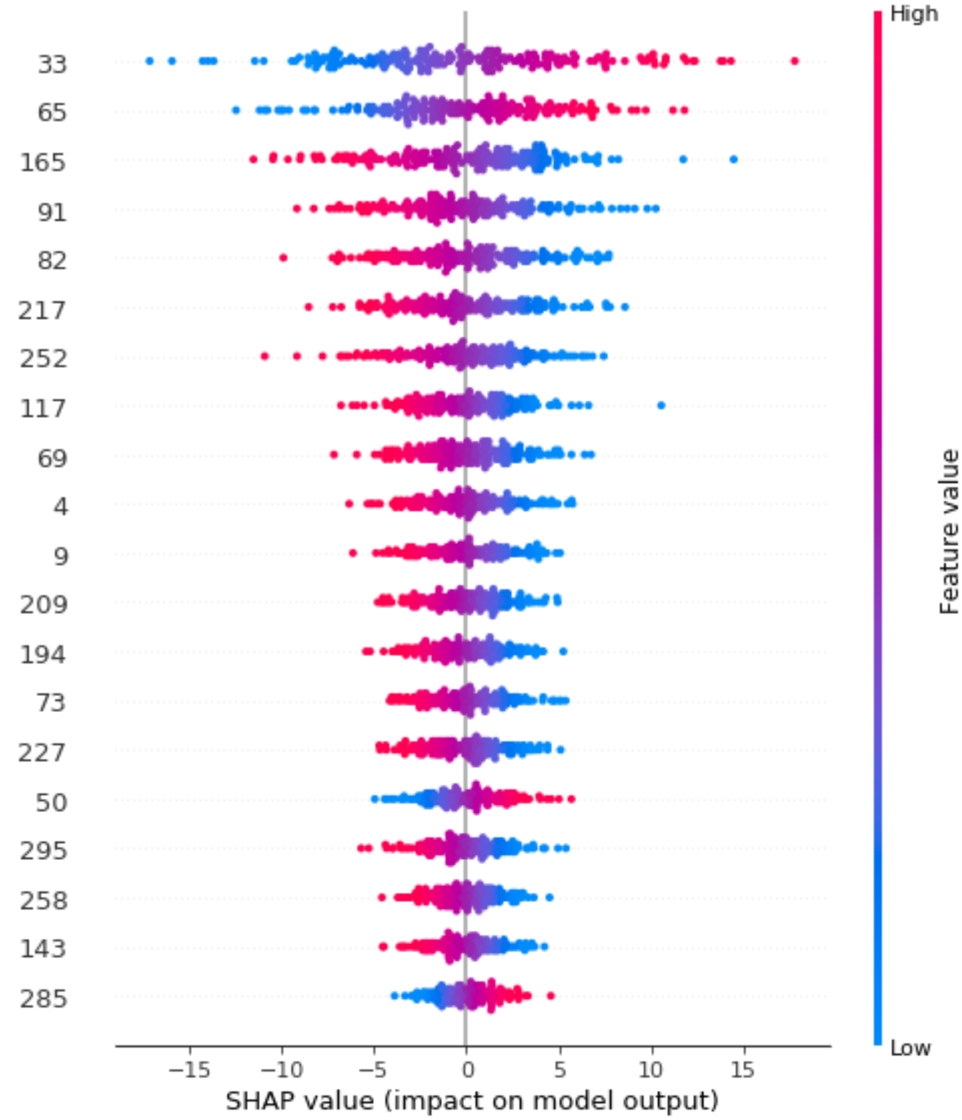
Out[95]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=1, fit_intercept=
True,
              l1_ratio=1.0, learning_rate='adaptive', loss='log', max_i
ter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='elasticnet',
              power_t=0.5, random_state=42, shuffle=True, tol=0.0001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

#### feature selection using shap

In [96]:
```
explainer = shap.LinearExplainer(modelG, X_train)
```

In [97]:
```
shap_values = explainer.shap_values(X_train)
```

In [98]:
```
shap.summary_plot(shap_values, X_train)
```




In [99]:
```
# feature selection and scaling
```

In [100]:
```
Xs_trainG = X_train[['33','65','165','91','82','217','252','117','69',
'4','9','209','194','73','227','50','295','258','143','285']]
Xs_testG = X_test[['33','65','165','91','82','217','252','117','69','4',
'9','209','194','73','227','50','295','258','143','285']]
Xs_train_transG = scaler.transform(Xs_trainG)
Xs_test_transG = scaler.transform(Xs_testG)
```

**Tuning the model and get better accuracy**

In [101]:
```
param_distG = {'loss': ['log', 'modified_huber'],
               'penalty': ['l1', 'l2', 'elasticnet'],
               'alpha': [0.001, 0.01],
               'l1_ratio': [0, 0.15, 0.5, 1.0],
               'learning_rate': ['optimal', 'invscaling', 'adaptive']
              }
```

In [102]:
```
gridG = GridSearchCV(sgd, param_grid=param_distG, cv=10, scoring='roc_au
c', n_jobs=-1)
```

In [103]:
```
gridG.fit(Xs_train_transG, y_train)
```

```
The default of the `iid` parameter will change from True to False in ve
rsion 0.22 and will be removed in 0.24. This will change numeric result
s when test-set sizes are unequal.
```

Out[103]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=
False,
                                     epsilon=0.1, eta0=1, fit_intercept
=True,
                                     l1_ratio=0.15, learning_rate='opti
mal',
                                     loss='hinge', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True,
                                     tol=0.0001, validation_fraction=0.
1,
                                     verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': [0.001, 0.01],
                         'l1_ratio': [0, 0.15, 0.5, 1.0],
                         'learning_rate': ['optimal', 'invscaling', 'ad
aptive'],
                         'loss': ['log', 'modified_huber'],
                         'penalty': ['l1', 'l2', 'elasticnet']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring='roc_auc', verbose=0)
```

In [104]:
```
best_estimatorGs = gridG.best_params_
print(best_estimatorGs)
```

```
{'alpha': 0.01, 'l1_ratio': 0, 'learning_rate': 'invscaling', 'loss':
'modified_huber', 'penalty': 'elasticnet'}
```

In [105]:
```
modelGs =  SGDClassifier(eta0=1, tol=0.0001, alpha = 0.01, l1_ratio = 1.
0, learning_rate='invscaling',loss='modified_huber',penalty='l2')
```

In [106]:
```
modelGs.fit(Xs_train_transG,y_train)
```

Out[106]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=1, fit_intercept=
True,
              l1_ratio=1.0, learning_rate='invscaling', loss='modified_
huber',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty
='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.0001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [107]:
```
accuracyG2 = round(modelGs.score(Xs_test_transG,y_test)*100,2)
accuracyG2
```

Out[107]:
```
74.0
```

In [108]:
```
accuracyG3 = round(modelGs.score(Xs_train_transG,y_train)*100,2)
accuracyG3
```

Out[108]:
```
89.5
```

This SGD model looks decent, but still, the test score is too low for large test size

# Logsitc Regression and Tuning

In [109]:
```
!pip install eli5
```

```
Requirement already satisfied: eli5 in /Users/jiayuechen/anaconda3/lib/
python3.7/site-packages (0.10.1)
Requirement already satisfied: scipy in /Users/jiayuechen/anaconda3/li
b/python3.7/site-packages (from eli5) (1.3.0)
Requirement already satisfied: six in /Users/jiayuechen/anaconda3/lib/p
ython3.7/site-packages (from eli5) (1.12.0)
Requirement already satisfied: attrs>16.0.0 in /Users/jiayuechen/anacon
da3/lib/python3.7/site-packages (from eli5) (19.1.0)
Requirement already satisfied: jinja2 in /Users/jiayuechen/anaconda3/li
b/python3.7/site-packages (from eli5) (2.10.1)
Requirement already satisfied: tabulate>=0.7.7 in /Users/jiayuechen/ana
conda3/lib/python3.7/site-packages (from eli5) (0.8.6)
Requirement already satisfied: graphviz in /Users/jiayuechen/anaconda3/
lib/python3.7/site-packages (from eli5) (0.13.2)
Requirement already satisfied: scikit-learn>=0.18 in /Users/jiayuechen/
anaconda3/lib/python3.7/site-packages (from eli5) (0.21.2)
Requirement already satisfied: numpy>=1.9.0 in /Users/jiayuechen/anacon
da3/lib/python3.7/site-packages (from eli5) (1.16.4)
Requirement already satisfied: MarkupSafe>=0.23 in /Users/jiayuechen/an
aconda3/lib/python3.7/site-packages (from jinja2->eli5) (1.1.1)
Requirement already satisfied: joblib>=0.11 in /Users/jiayuechen/anacon
da3/lib/python3.7/site-packages (from scikit-learn>=0.18->eli5) (0.13.
2)
```

In [110]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

In [111]:
```
import eli5
```

```
Using TensorFlow backend.
```

In [112]:
```
model_log = LogisticRegression(solver = 'lbfgs')
```

## Tuning the logistic model and try to find out the best C value to see if it helps avoid overfitting

In [113]:
```
kfold = StratifiedKFold(shuffle = True, random_state = 1, n_splits = 17)
param_grid_log = [{'C':np.linspace(0.001,1,1000)}]
```

In [114]:
```
grid_search_log = GridSearchCV(model_log,param_grid_log,scoring = 'neg_l
og_loss',cv=kfold)
grid_result_log = grid_search_log.fit(selected_X_train,y_train)
```

```
The default of the `iid` parameter will change from True to False in ve
rsion 0.22 and will be removed in 0.24. This will change numeric result
s when test-set sizes are unequal.
```

In [115]:
```
grid_result_log.best_params_
```

Out[115]:
```
{'C': 0.001}
```

The best C for the logistic model is 0.001

In [116]:
```
logreg = LogisticRegression(C = 0.001, solver = 'lbfgs')
logreg.fit(X_train, y_train)
```

Out[116]:
```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercep
t=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbo
se=0,
                   warm_start=False)
```

In [117]:
```
acc_train_logreg = round(100*logreg.score(X_train,y_train),2)
acc_train_logreg
```

Out[117]:
```
64.5
```

In [118]:
```
acc_test_logreg = round(100*logreg.score(X_test, y_test))
acc_test_logreg
```

Out[118]:
```
62.0
```

We can see that both the train score and the test score are extremely low

## Now let's try to use KFold validation and see if we can avoid overfittng.

In [119]:
```
mspe = cross_val_score(logreg,X_train,y_train,cv = kfold)
mspe
```

Out[119]:
```
array([0.61538462, 0.61538462, 0.61538462, 0.66666667, 0.66666667,
       0.66666667, 0.66666667, 0.66666667, 0.66666667, 0.66666667,
       0.63636364, 0.63636364, 0.63636364, 0.63636364, 0.63636364,
       0.63636364, 0.63636364])
```

In [120]:
```
mspe_list = []
```

In [121]:
```
for nsplits in range (2,21):
    mspe = (cross_val_score(logreg, X_train, y_train,cv = KFold(n_splits
= nsplits, random_state = 42)))
    mspe_list.append(mspe.mean())
```

In [122]:
```
mspe_list
```

Out[122]: [0.645, 0.645258555706317, 0.645, 0.645, 0.6452762923351157, 0.6453201970443351, 0.645, 0.644927536231884, 0.645, 0.644869750132908, 0.6458333333333334, 0.6455128205128204, 0.6448979591836734, 0.6454212454212453, 0.6458333333333334, 0.6466131907308378, 0.6452020202020202, 0.6464114832535884, 0.6449999999999999]

In [123]:
```
optimal_nsplits = mspe_list.index(max(mspe_list)) + 2
optimal_nsplits
```

Out[123]: 17

As we can see, the best n_splits for kfold is when n_splits = 17

## Next, try to use ELI5 for feature selectoin based on the Logistic Regerssion model

In [124]:
```
eli5.show_weights(logreg, top=20)
```

Out[124]: **y=1.0** top features

| Weight? | Feature |
|---|---|
| +0.612 | <BIAS> |
| +0.029 | x33 |
| +0.024 | x65 |
| +0.015 | x89 |
| +0.013 | x30 |
| +0.013 | x226 |
| +0.013 | x272 |
| *… 128 more positive …* | |
| *… 153 more negative …* | |
| -0.013 | x82 |
| -0.014 | x16 |
| -0.014 | x73 |
| -0.014 | x39 |
| -0.014 | x4 |
| -0.014 | x189 |
| -0.014 | x133 |
| -0.014 | x194 |
| -0.015 | x209 |
| -0.015 | x217 |
| -0.016 | x117 |
| -0.017 | x295 |
| -0.019 | x91 |

Here, we only choose 20 features as our predictors and try to see if it helps avoid overfitting

In [125]:
```
X_train_eli = X_train.iloc[:, [33,65,89,30,226,272,82,16,73,39,4,189,133
,194,209,217,117,295,91]]
X_test_eli = X_test.iloc[:, [33,65,89,30,226,272,82,16,73,39,4,189,133,1
94,209,217,117,295,91]]
```

In [126]:
```
X_train_eli.shape
```
Out[126]:
```
(200, 19)
```

We build the new model only use top 19 features

In [127]:
```
logreg_new = LogisticRegression(solver = 'lbfgs', C = 0.001)
logreg_new.fit(X_train_eli, y_train)
```
Out[127]:
```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercep
t=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbo
se=0,
                   warm_start=False)
```

In [128]:
```
acc_train_logreg_new = round(100*logreg_new.score(X_train_eli,y_train),2
)
acc_train_logreg_new
```
Out[128]:
```
64.5
```

In [129]:
```
acc_test_logreg_new = round(100*logreg_new.score(X_test_eli,y_test),2)
acc_test_logreg_new
```
Out[129]:
```
62.0
```

For Logistic Regression model, the test score is getting lower and thus ELI5 does not give us a good feature selection

# Neural Network

In [130]:
```
from keras.models import Sequential
from keras.layers import Dense
```

In [131]:
```
scaler = StandardScaler()
scaler.fit(X_train)
```
Out[131]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [132]:
```
Xtrain_trans = scaler.transform(X_train)
Xtest_trans = scaler.transform(X_test)
```

In [133]:
```
NW = Sequential()
NW.add(Dense(64,activation = 'relu', input_shape=(300,)))
NW.add(Dense(64,activation = 'relu'))
NW.add(Dense(1))
NW.compile(optimizer = 'rmsprop', loss = 'mse', metrics=['mae'])
NW.fit(Xtrain_trans,y_train,epochs =10, batch_size = 1)
```

```
Epoch 1/10
200/200 [==============================] - 0s 2ms/step - loss: 0.6009 -
mae: 0.6404
Epoch 2/10
200/200 [==============================] - 0s 1ms/step - loss: 0.1227 -
mae: 0.2695
Epoch 3/10
200/200 [==============================] - 0s 1ms/step - loss: 0.2198 -
mae: 0.3722
Epoch 4/10
200/200 [==============================] - 0s 1ms/step - loss: 0.1136 -
mae: 0.2696
Epoch 5/10
200/200 [==============================] - 0s 1ms/step - loss: 0.1285 -
mae: 0.2868
Epoch 6/10
200/200 [==============================] - 0s 1ms/step - loss: 0.0945 -
mae: 0.2417
Epoch 7/10
200/200 [==============================] - 0s 1ms/step - loss: 0.0815 -
mae: 0.2329
Epoch 8/10
200/200 [==============================] - 0s 1ms/step - loss: 0.0773 -
mae: 0.2254
Epoch 9/10
200/200 [==============================] - 0s 1ms/step - loss: 0.0738 -
mae: 0.2246
Epoch 10/10
200/200 [==============================] - 0s 1ms/step - loss: 0.0587 -
mae: 0.1967
```

Out[133]: <keras.callbacks.callbacks.History at 0x1a3c2d9668>

# LB probing

After trying these models, we think all of the models will overfit the trainning data. Thus, we decide to use another approach which excludes the models and directly predict the target value by getting the coefficients for each feature.

### Brief Introduction to LB Probing

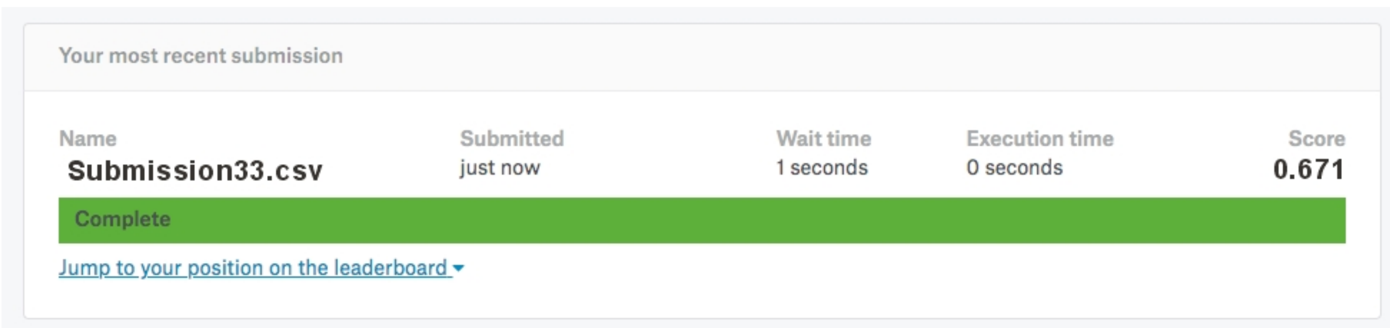
To apply LB Probing to this kaggle project, we assume that each coefficient $a_i$ is independent to other coefficients. Then, since we have 300 features in this project, the target value will just be:

$$\text{target} = \text{Heaviside}(a_0 x_0 + a_1 x_1 + ... a_{298} x_{298} + a_{299} x_{299} + \text{noise})$$

But how would we get the coefficients for $a_i$?

Now, let's say we want the coefficient $a_{33}$ for the feature variable $x_{33}$. We just simply fill out the target value according to $x_{33}$. Since we have 19.8k rows of target value to predict, and we also have 19.8k rows of $x_{33}$ values in the test set, we just fill out the target value using $x_{33}$ values in the test set. For example:

```
var = 33
test = pd.read_csv('test.csv')
sub = pd.read_csv('sample_submission.csv')
sub['target'] = test[str(var)]
sub.to_csv('submission'+str(var)+'.csv',index=False)
```




When we submit this result to kaggle, we will get the score for $x_{33}$ and the $a_{33}$ will just be

$$a_{33} = \text{LB\_SCORE}_{33} - 0.500 = 0.671 - 0.500 = 0.171$$

A better way to calculate $a_{33}$ will be:

$$a_{33} = \frac{8}{9} * \text{LB\_SCORE}_{33} + \frac{1}{9} * \text{CV\_SCORE}_{33} - 0.500 = \frac{8}{9} * 0.671 + \frac{1}{9} * 0.7317 - 0.500 = 0.171$$

Therefore, we just need to get all 300 $a_i$ from the public LeaderBoard of Kaggle and we can avoid overfitting problem and get a decent target value using these coefficients. Fortunately, the first place solution has provided us with LB_SCORE for all 300 features.

In [9]:
```
dfLB = pd.read_csv('probed_aucs.csv')
dfLB[:5]
```

Out[9]:

| | variable | public_auc |
|---|---|---|
| **0** | X33 | 0.671 |
| **1** | X65 | 0.671 |
| **2** | X217 | 0.382 |
| **3** | X67 | 0.501 |
| **4** | X117 | 0.405 |

Thus, we can just utilize these LB_SCORE and easily calculate each coefficient $a_i$. But first, we also need to calculate the CV_SCORE using roc_auc_score

In [10]:
```
from sklearn.metrics import roc_auc_score
```

We first build the dataframe to store variables $x_i$, CV_score, diff and LB_score

In [11]:
```
df = pd.DataFrame({'var':np.arange(300),'CV':np.zeros(300),'diff':np.zer
os(300),'LB':0.5*np.ones(300)})
```

In [19]:
```
for i in range(300):
    df.loc[i,'CV'] = roc_auc_score(trainset['target'],trainset[str(i)])
    df.loc[i,'diff'] = abs(df.loc[i,'CV']-0.5)
```

In [20]:
```
df.head()
```

Out[20]:

| | var | CV | diff | LB |
|---|---|---|---|---|
| **0** | 0 | 0.560278 | 0.060278 | 0.5 |
| **1** | 1 | 0.468889 | 0.031111 | 0.5 |
| **2** | 2 | 0.514722 | 0.014722 | 0.5 |
| **3** | 3 | 0.501840 | 0.001840 | 0.5 |
| **4** | 4 | 0.432014 | 0.067986 | 0.5 |

We first calculate CV_SCORE using the target value in train_set, and get the difference by

$$\text{Diff} = CV - 0.5$$

Then, we introduce the LB_SCORE from probed_aucs.csv file

In [21]:
```
for i in range(300):
    dfLB.iloc[i,0] = dfLB.iloc[i,0][1:]
```

In [22]:
```
for i in range(300):
    index = int(dfLB.iloc[i,0])
    df.loc[ df['var']==index, 'LB' ] = dfLB.iloc[i,1]
```

In [23]:
```
df.head()
```

Out[23]:

| | var | CV | diff | LB |
|---|---|---|---|---|
| **0** | 0 | 0.560278 | 0.060278 | 0.500 |
| **1** | 1 | 0.468889 | 0.031111 | 0.484 |
| **2** | 2 | 0.514722 | 0.014722 | 0.508 |
| **3** | 3 | 0.501840 | 0.001840 | 0.500 |
| **4** | 4 | 0.432014 | 0.067986 | 0.516 |

Finally, we calculate the coefficient $a_i$ for each feature using the formula mentioned above

In [24]:
```
df['A'] = 0
df['A'] = (8/9)*df['LB'] + (1/9)*df['CV'] - 0.500
keep_threshold = 0.04 # YIELDS 15 NON-ZEROS A'S
df.loc[ abs(df['A'])<keep_threshold , 'A' ] = 0
df.sort_values('var',inplace=True)
for i in range(300):
    if df.loc[i,'LB'] != 0.500:
        if(df.loc[i,'A'] != 0):
            print('A_'+str(i)+' = ',round(df.loc[i,'A'],6))
```

```
A_16 =  -0.0661
A_29 =  -0.044931
A_33 =  0.177745
A_45 =  -0.052594
A_63 =  -0.07363
A_65 =  0.170951
A_70 =  -0.059018
A_73 =  -0.104708
A_91 =  -0.117979
A_106 =  -0.042198
A_108 =  -0.044608
A_117 =  -0.098418
A_132 =  -0.044833
A_164 =  0.046188
A_189 =  -0.051302
A_199 =  0.111729
A_209 =  -0.07035
A_217 =  -0.119819
A_239 =  -0.045545
```

In [25]:
```
test = pd.read_csv('test.csv')
```

We try to calculate the predicted target value using the formula

$$\text{target} = \text{Heaviside}(a_0 x_0 + a_1 x_1 + \ldots a_{298} x_{298} + a_{299} x_{299})$$

In [26]:
```
pred = test.iloc[:,1:].values.dot(df['A'].values)
```

In [27]:
```
pred.shape
```

Out[27]: (19750,)

In [28]:
```
sub = pd.read_csv('sample_submission.csv')
```

In [29]:
```
sub.target = pred
```

In [30]:
```
sub[:5]
```

Out[30]:

| | id | target |
|---|---|---|
| **0** | 250 | 0.035338 |
| **1** | 251 | -0.097590 |
| **2** | 252 | 0.314809 |
| **3** | 253 | 0.313386 |
| **4** | 254 | -0.353095 |

In [31]:
```
sub.to_csv('submission.csv',index=False)
```

# Result

| Submission and Description | Private Score | Public Score | Use for Final Score |
|---|---|---|---|
| **submission.csv**<br>2 days ago by Jiayue Chen95<br>test 1 | 0.877 | 0.903 | ☐ |

Using LB Probing made us get a pretty high public score on Kaggle LeaderBoard, which is 90.3