Final Code

In [1]:
```
# Default Loads
import pandas as pd
import numpy as np
import os
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:85% !important; }</style>"))
pd.options.display.float_format = '{:.4f}'.format

#No SK-Learn Loads
from hyperopt import STATUS_OK, Trials, fmin, hp, tpe
import lightgbm as lg

#SK Learn Loads
from sklearn.model_selection import train_test_split, ShuffleSplit, cross
_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.preprocessing import OneHotEncoder, Imputer, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.base import TransformerMixin, BaseEstimator
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import roc_auc_score, accuracy_score

#Plotting Loads
import matplotlib.pyplot as plt
import seaborn as sb

#Deep Learning Loads
from keras.models import Sequential
from keras.layers import Dense, BatchNormalization, Activation
from keras.layers import Dropout
from keras.wrappers.scikit_learn import KerasClassifier
import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping

# IGNORE Warnings
import warnings
warnings.filterwarnings("ignore")
```

```
Using TensorFlow backend.
```

The below functions and classes will be used later in the notebook

The below class was borrowed from the sample notebook

In [2]:
```
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.attribute_names].values
```

The following function will help us load the train dataset.

- We have engineered 6 features here

In [3]:
```
def load_main_files(filename =""):
        df_train = pd.read_csv(filename)
        df_train.index = df_train['SK_ID_CURR']

        # Converting days to years and removing outliers
        df_train[df_train.columns[df_train.columns.str.contains('DAYS')]]
= abs(
            df_train[df_train.columns[df_train.columns.str.contains('DAY
S')]]).replace(365243, np.nan)/365

        # Naimesh Features
        df_train['income_credit_percen'] = (
            df_train.AMT_INCOME_TOTAL / df_train.AMT_CREDIT).replace(np.i
nf, 0)
        df_train['fam_member_income'] = (
            df_train.AMT_INCOME_TOTAL / df_train.CNT_FAM_MEMBERS).replace
(np.inf, 0)
        df_train['ann_incom_percen'] = (
            df_train.AMT_ANNUITY / df_train.AMT_INCOME_TOTAL).replace(np.
inf, 0)

        # Nishad Features
        df_train['new_employ_to_birth_ratio'] = (
            df_train.DAYS_EMPLOYED / df_train.DAYS_BIRTH).replace(np.inf,
0)
        df_train['new_credit_to_annuity'] = (
            df_train['AMT_CREDIT'] / df_train['AMT_ANNUITY']).replace(np.
inf, 0)
        df_train['new_credit_to_goods_ratio'] = (
            df_train['AMT_CREDIT'] / df_train['AMT_GOODS_PRICE']).replace
(np.inf, 0)
        df_train['new_car_to_birth_ratio'] = (
            df_train['OWN_CAR_AGE'] / df_train['DAYS_BIRTH']).replace(np.
inf, 0)
        df_train['new_car_to_emp_ratio'] = (
            df_train['OWN_CAR_AGE'] / df_train['DAYS_EMPLOYED']).replace(
np.inf, 0)
        df_train['new_inc_per_child'] = (
            df_train['AMT_INCOME_TOTAL'] / (1 + df_train['CNT_CHILDREN'
])).replace(np.inf, 0)

        selected_features = ['SK_ID_CURR', 'AMT_INCOME_TOTAL',  'AMT_CRED
IT', 'DAYS_EMPLOYED', 'DAYS_BIRTH', 'EXT_SOURCE_1',
                             'EXT_SOURCE_2', 'EXT_SOURCE_3', 'CODE_GENDE
R', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR',
                             'NAME_CONTRACT_TYPE', 'NAME_EDUCATION_TYPE',
'OCCUPATION_TYPE', 'NAME_INCOME_TYPE',
                             'income_credit_percen', 'fam_member_income',
'ann_incom_percen', 'new_employ_to_birth_ratio',
                             'new_credit_to_annuity', 'new_credit_to_good
s_ratio', 'new_car_to_birth_ratio', 'new_car_to_emp_ratio',
                             'new_inc_per_child']

        X_train = df_train[selected_features]


        if filename == 'application_train.csv':
            y_train = df_train['TARGET']

            X_train, X_valid, y_train, y_valid = train_test_split(
                X_train, y_train, test_size=0.15, random_state=42, strati
fy=y_train)
            X_train, X_test, y_train, y_test = train_test_split(
```

```
                X_train, y_train, test_size=0.15, random_state=42, strati
fy=y_train)

            X_valid.index = X_valid['SK_ID_CURR']

            X_train.index = X_train['SK_ID_CURR']
            X_test.index = X_test['SK_ID_CURR']
            X_valid.drop('SK_ID_CURR', inplace=True, axis=1)
            X_test.drop('SK_ID_CURR', inplace=True, axis=1)
            X_train.drop('SK_ID_CURR', inplace=True, axis=1)
            return  X_train, y_train, X_valid, y_valid, X_test, y_test

        else:
            X_train.index = X_train['SK_ID_CURR']
            X_train.drop('SK_ID_CURR', inplace=True, axis=1)
            return X_train
```

The following class will help us merge all auxilary files

In [4]:
```
class merge_df(BaseEstimator, TransformerMixin):
    def __init__(self, dflist):
        self.dflist = dflist

    def fit(self, X, y=None):

        return self

    def transform(self,X, y = None):
        for f in self.dflist:
            X = X.merge(f, how='left', on='SK_ID_CURR')
        X.fillna(0, inplace=True)

        return X
```

The following function will help us transform the train dataset

In [5]:
```
class transform_train(BaseEstimator, TransformerMixin):
    def __init__(self, num_attribs, cat_attribs):
        self.Nattrib = num_attribs
        self.Cattrib = cat_attribs
        self.num_pipeline = Pipeline([
            ('selector', DataFrameSelector(self.Nattrib)),
            ('imputer', SimpleImputer(strategy='mean')),
            ('std_scaler', StandardScaler()),
        ])
        self.cat_pipeline = Pipeline([
            ('selector', DataFrameSelector(self.Cattrib)),
            ('imputer', SimpleImputer(strategy='constant')),
            ('ohe', OneHotEncoder(
                sparse=False, handle_unknown="ignore"))
        ])
        self.data_prep_pipeline = FeatureUnion(transformer_list=[
            ("num_pipeline", self.num_pipeline),
            ("cat_pipeline", self.cat_pipeline),
        ])

        self.full_pipeline = Pipeline(
            [("preparation", self.data_prep_pipeline)])

    def fit(self, X, y=None):
        self.full_pipeline.fit(X)
        return self

    def transform(self, X, y=None):
        X_trans = pd.DataFrame(self.full_pipeline.transform(X), index=X.i
ndex)

        cat_cols = list(self.full_pipeline.named_steps['preparation'].tra
nsformer_list[1]
                        [1].named_steps['ohe'].get_feature_names(self.Cat
trib))

        X_trans.columns = self.Nattrib + cat_cols

        return X_trans

    def fit_transform(self, X, y=None):
        self.full_pipeline.fit(X)

        X_ftrans = pd.DataFrame(self.full_pipeline.transform(X), index=X.
index)

        cat_cols = list(self.full_pipeline.named_steps['preparation'].tra
nsformer_list[1]
                        [1].named_steps['ohe'].get_feature_names(self.Cat
trib))

        X_ftrans.columns = self.Nattrib + cat_cols

        return X_ftrans

    def get_features(self):
            cat_cols = list(self.full_pipeline.named_steps['preparation']
.transformer_list[1]
                    [1].named_steps['ohe'].get_feature_names(self.Cattrib
))
            final = self.Nattrib + cat_cols
            return final
```

The Following function will help us update our expirement Log

In [6]:
```
def update_log(expLog, exp_name, model, X_train, y_train, X_test, y_test
, X_valid, y_valid):
    p_value = 0
    expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
        [accuracy_score(y_train, model.predict(X_train)),
         accuracy_score(y_valid, model.predict(X_valid)),
         accuracy_score(y_test, model.predict(X_test)),
         roc_auc_score(y_train, model.predict_proba(X_train)[:, 1]),
         roc_auc_score(y_valid, model.predict_proba(X_valid)[:, 1]),
         roc_auc_score(y_test, model.predict_proba(X_test)[:, 1]), p_valu
e],
        4))
    return expLog
```

The bellow function will help us aggregate all auxiliary file except the ones related to bureau.

- We have engineered two manual features here. There is potential to add many more for the different files
- Rest of the features are engineered via automated programming. For each field we will take the mean, sum, and count

In [7]:
```
def agg_files_set(file="", pre=""):
    if file != "":
        df_pa = pd.read_csv(file)
        df_pa.index = df_pa['SK_ID_CURR']
        df_pa.drop(['SK_ID_PREV', 'SK_ID_CURR'], axis=1, inplace=True)

        # Individual File Feature Will Go Here
        if file == 'previous_application.csv':
            df_pa['AppToCredit'] = (
                df_pa.AMT_APPLICATION/df_pa.AMT_CREDIT).replace(np.inf, 0
)
            df_pa['DownToCredit'] = (
                df_pa.AMT_DOWN_PAYMENT/df_pa.AMT_CREDIT).replace(np.inf,
0)

        numcols = df_pa.select_dtypes(exclude='object').columns
        catcols = df_pa.select_dtypes(include='object').columns

        num = df_pa[numcols]
        cat = df_pa[catcols]

        num = num.groupby('SK_ID_CURR').agg([np.sum, np.mean, 'count'])
        num.columns = num.columns.map('_'.join)
        mdl = StandardScaler().fit(num)
        num = pd.DataFrame(mdl.transform(
            num), index=num.index, columns=num.columns)

        if len(catcols) != 0:

            catt = SimpleImputer(strategy='constant').fit_transform(cat)
            mdl = OneHotEncoder().fit(catt)
            cat = pd.DataFrame(mdl.transform(catt).toarray(
            ), index=cat.index, columns=list(mdl.get_feature_names(catcol
s)))
            cat = cat.groupby('SK_ID_CURR').agg(np.mean)
            final = num.merge(cat, how='left', on='SK_ID_CURR')
        else:
            final = num

        final = final.add_prefix(pre)
        return final
    return "No File"
```

The below function will help us aggregate the bureau files

In [8]:
```
def bur_balance():
    bur_bal = pd.read_csv('bureau_balance.csv')
    bur_bal.index = bur_bal['SK_ID_BUREAU']
    bur_bal.drop('SK_ID_BUREAU', inplace = True, axis = 1)
    numcols = bur_bal.select_dtypes(exclude='object').columns
    catcols = bur_bal.select_dtypes(include='object').columns

    num = bur_bal[numcols]
    cat = bur_bal[catcols]


    num = pd.DataFrame(SimpleImputer(strategy = 'mean').fit_transform(num
), columns = num.columns, index = num.index)
    num = num.groupby('SK_ID_BUREAU').agg([np.sum, np.mean, 'count'])
    num.columns = num.columns.map('_'.join)

    if len(catcols) != 0:
        catt = SimpleImputer(strategy='constant').fit_transform(cat)
        mdl = OneHotEncoder().fit(catt)
        cat = pd.DataFrame(mdl.transform(catt).toarray(
        ), index=cat.index, columns=list(mdl.get_feature_names(catcols)))
        cat = cat.groupby('SK_ID_BUREAU').agg(np.mean)
        bur_final = num.merge(cat, how='left', on='SK_ID_BUREAU')
    else:
        bur_final = num

    bur_final = bur_final.add_prefix("bu_bal_")
    return bur_final
```

```
In [9]: def bureau():
            bur = pd.read_csv('bureau.csv')
            bur_final =  bur_balance()
            bur = bur.merge(bur_final , how='left', on='SK_ID_BUREAU')
            bur.index = bur['SK_ID_CURR']
            bur.drop(['SK_ID_CURR','SK_ID_BUREAU'], axis = 1, inplace = True)

            numcols = bur.select_dtypes(exclude='object').columns
            catcols = bur.select_dtypes(include='object').columns

            num = bur[numcols]
            cat = bur[catcols]

            num = pd.DataFrame(SimpleImputer(strategy = 'mean').fit_transform(num
        ), columns = num.columns, index = num.index)
            num = num.groupby('SK_ID_CURR').agg([np.sum, np.mean, 'count'])
            num.columns = num.columns.map('_'.join)
            mdl = StandardScaler().fit(num)
            num = pd.DataFrame(mdl.transform(
                num), index=num.index, columns=num.columns)

            if len(catcols) != 0:

                catt = SimpleImputer(strategy='constant').fit_transform(cat)
                mdl = OneHotEncoder().fit(catt)
                cat = pd.DataFrame(mdl.transform(catt).toarray(
                ), index=cat.index, columns=list(mdl.get_feature_names(catcols)))
                cat = cat.groupby('SK_ID_CURR').agg(np.mean)
                final = num.merge(cat, how='left', on='SK_ID_CURR')
            else:
                final = num

            final = final.add_prefix("BU_")
            return final
```

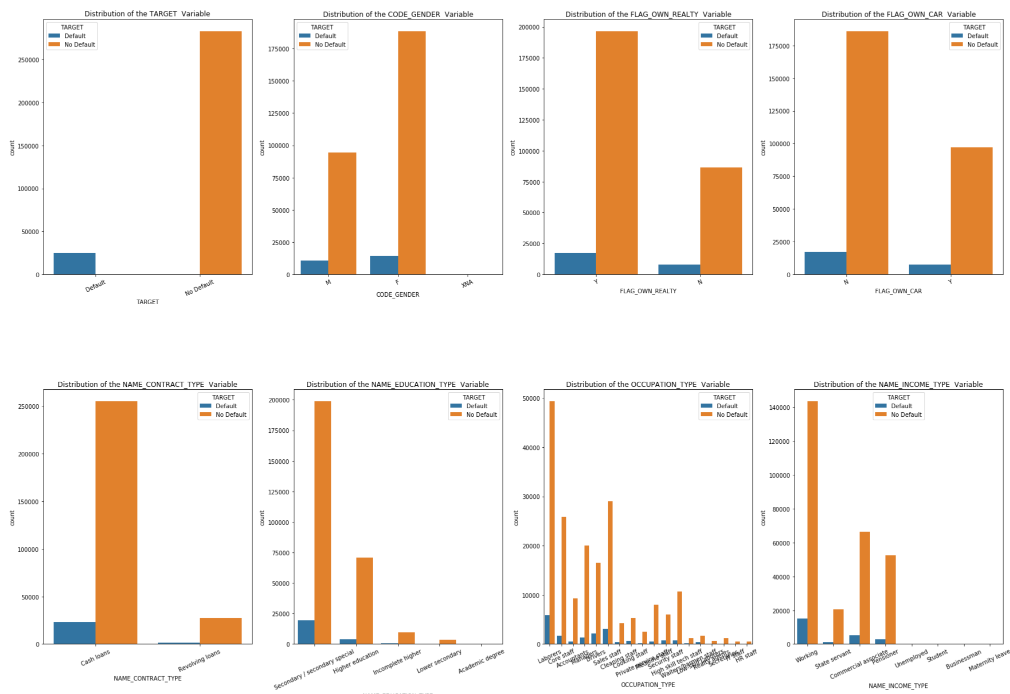
Exploratory Data Analysis

```
In [10]: df = pd.read_csv('application_train.csv')
         df['DAYS_BIRTH'] = round(abs(df['DAYS_BIRTH'])/365).astype(int)
         df['DAYS_EMPLOYED'] = round(abs(df['DAYS_EMPLOYED'])/365).astype(int)
         df['TARGET'].replace(0, "No Default", inplace=True)
         df['TARGET'].replace(1, "Default", inplace=True)
```

Categorical Variables

- Imbalanced Dataset
- More Females then Males
- Most people own realty but not cars
- Most of the loan request were cash loans
- Most people had some sort of secondary or higher education
- Occupation type is wide spread but laborers are the highest.
- Highest income type is working

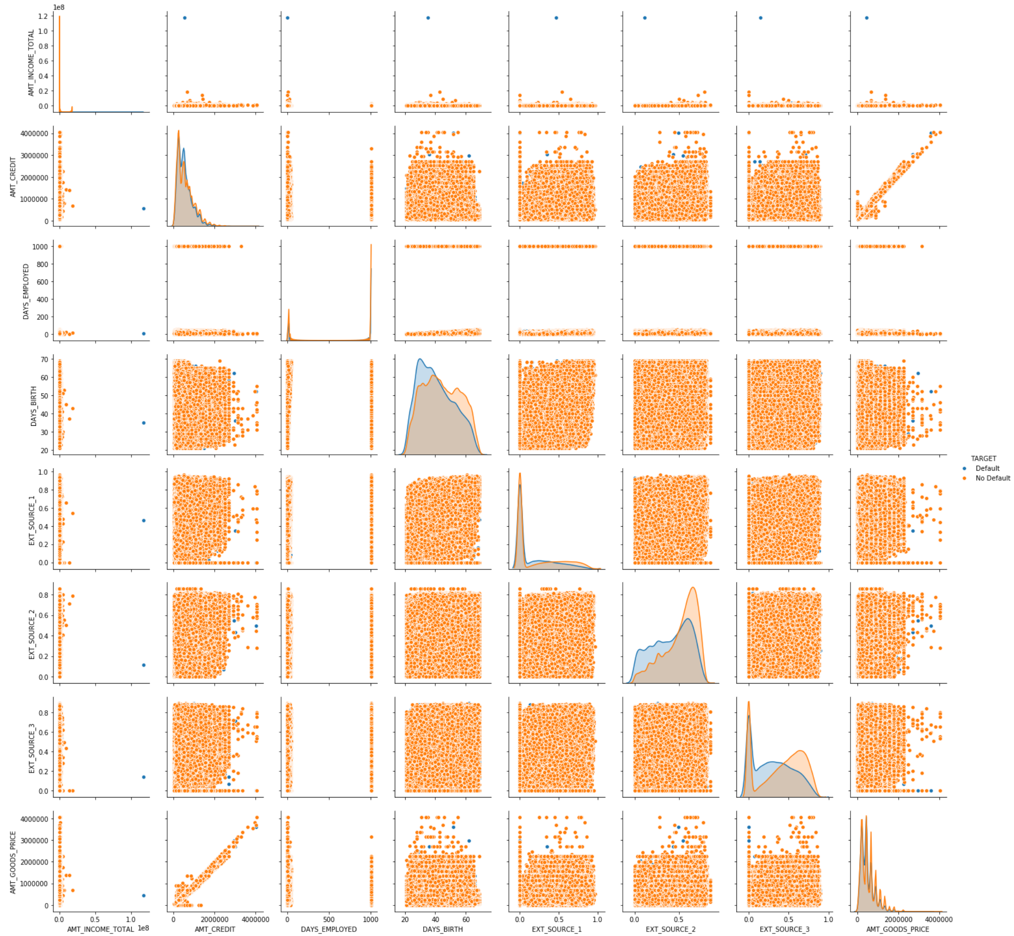
In [11]:
```python
cat_attribs = ['TARGET', 'CODE_GENDER', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR'
, 'NAME_CONTRACT_TYPE',
               'NAME_EDUCATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYP
E']
fig, ax = plt.subplots(2, 4, figsize=(30, 20))
plt.subplots_adjust(left=None, bottom=None, right=None,
                    top=None, wspace=None, hspace=0.45)
num = 0
for i in range(0, 2):
    for j in range(0, 4):
        tst = sb.countplot(x=cat_attribs[num],
                           data=df, hue='TARGET', ax=ax[i][j])
        tst.set_title(f"Distribution of the {cat_attribs[num]}  Variable"
)
        tst.set_xticklabels(tst.get_xticklabels(), rotation=25)
        num = num + 1
```



Numerical Variables

- Highest income value defaulted
- People in 60's/70's tend to default more
- Need to clean up days employed, no one is aged 1001 years old
- Non-Defaulters tend to have a higher EXT-Source 2 & 3
- No Strong variable correlation
- Amount Good Price and Amount Credit have a very strong linear relationship

In [12]:
```
run = True  # Set this to true if you would ike to run, else just leave i
t. Take 5 mins to run
if run == True:
    num_attribs = ['TARGET', 'AMT_INCOME_TOTAL',  'AMT_CREDIT', 'DAYS_EMP
LOYED',
                   'DAYS_BIRTH', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOU
RCE_3', 'AMT_GOODS_PRICE']
    df2 = df[num_attribs]
    df2['TARGET'].replace(0, "No Default", inplace=True)
    df2['TARGET'].replace(1, "Default", inplace=True)
    df2.fillna(0, inplace=True)
    sb.pairplot(df2, hue="TARGET")
```



Correlation Map of Numerical Variables

- Strong correlation between amount credit and amount goods price
- Strong correlation between days birth and days employed
- strong correlation between ext source 1 and days birth

These might be good candidates to do some feature engineering in.

In [13]:
```
num_attribs = ['TARGET', 'AMT_INCOME_TOTAL',  'AMT_CREDIT', 'DAYS_EMPLOYE
D',
               'DAYS_BIRTH', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_
3', 'AMT_GOODS_PRICE']
df2 = df[num_attribs]
corr = df2.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

Out[13]:

	AMT_INCOME_TOTAL	AMT_CREDIT	DAYS_EMPLOYED	DAYS_BIRTH
AMT_INCOME_TOTAL	1	0.16	-0.064	-0.027
AMT_CREDIT	0.16	1	-0.064	0.055
DAYS_EMPLOYED	-0.064	-0.064	1	0.62
DAYS_BIRTH	-0.027	0.055	0.62	1
EXT_SOURCE_1	0.026	0.17	0.3	0.6
EXT_SOURCE_2	0.061	0.13	-0.018	0.092
EXT_SOURCE_3	-0.03	0.044	0.12	0.21
AMT_GOODS_PRICE	0.16	0.99	-0.062	0.053

Loading Train Dataset & Splitting Into Train Valid & Test

In [14]:
```
expLog = pd.DataFrame(columns=["exp_name",
                               "Train Acc",
                               "Valid Acc",
                               "Test  Acc",
                               "Train AUC",
                               "Valid AUC",
                               "Test  AUC",
                               "P_Value"
                               ])

X_train, y_train, X_valid, y_valid, X_test, y_test = load_main_files(file
name = "application_train.csv")
```

Getting Baseline Score Logistic Regression

In [15]:
```
num_attribs = ['AMT_INCOME_TOTAL',  'AMT_CREDIT', 'DAYS_EMPLOYED', 'DAYS_
BIRTH', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
                'income_credit_percen', 'fam_member_income', 'ann_incom_pe
rcen', 'new_employ_to_birth_ratio',
                'new_credit_to_annuity', 'new_credit_to_goods_ratio', 'new
_car_to_birth_ratio', 'new_car_to_emp_ratio',
                'new_inc_per_child']

cat_attribs = ['CODE_GENDER', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR', 'NAME_CO
NTRACT_TYPE',
                'NAME_EDUCATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYP
E']

basepipe = Pipeline([
    ('tran', transform_train(num_attribs,cat_attribs))
   ,('mdl', LogisticRegression(n_jobs=-1, solver='lbfgs') )
])

basepipe.fit(X_train,y_train)
expLog = update_log(expLog, 'LogisticBase',basepipe, X_train, y_train, X_
test, y_test, X_valid, y_valid)
expLog
```

Out[15]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000

Getting Baseline Score LightGBM

In [16]:
```
params = {
    'n_estimators': 1000, 'learning_rate': 0.1, 'n_jobs': -1
}

lgbmbase = Pipeline([
    ('tran', transform_train(num_attribs,cat_attribs))
   ,('mdl',  lg.LGBMClassifier(**params))
])

lgbmbase.fit(X_train,y_train)
expLog = update_log(expLog, 'LightGBM - No Additional Files- ',lgbmbase,
X_train, y_train, X_test, y_test, X_valid, y_valid)
expLog
```

Out[16]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000

Loading all auxiliary files to the train test & valid set

```
In [17]: df_pv_app = agg_files_set('previous_application.csv', 'PA_')
df_pos_app = agg_files_set('POS_CASH_balance.csv', 'POS_')
df_ins_pay = agg_files_set('installments_payments.csv', 'IP_')
df_credit_pay = agg_files_set('credit_card_balance.csv', 'CC_')
df_bureau = bureau()
lst = [df_pv_app, df_pos_app, df_ins_pay, df_credit_pay, df_bureau]
```

Auxiliary files have been aggregate with metrics [Mean, Count, SUM]

Adding all auxiliary files to the train test & valid set & training LightGBM model

```
In [18]: #Had to split pipeline because we needed validation set to be transformed
#so that we can use it under eval metrics

params = {
    'n_estimators': 1000, 'learning_rate': 0.1, 'n_jobs': -1
}
TransPipe = Pipeline([
    ('tran', transform_train(num_attribs,cat_attribs))
   ,('merge', merge_df(lst))])

TransPipe.fit(X_train,y_train)


X_train_t = TransPipe.transform(X_train)
X_valid_t = TransPipe.transform(X_valid)
X_test_t = TransPipe.transform(X_test)


mdl = lg.LGBMClassifier(**params)
mdl.fit(X_train_t , y_train
        ,eval_set=[(X_train_t , y_train),(X_test_t, y_test),(X_valid_t ,
y_valid)]
        ,eval_metric=['logloss', 'auc']
        ,early_stopping_rounds=100
        ,verbose=False)


expLog = update_log(expLog, 'LightGBM - All Files- ',mdl, X_train_t, y_tr
ain, X_test_t, y_test, X_valid_t, y_valid)

expLog
```

Out[18]:

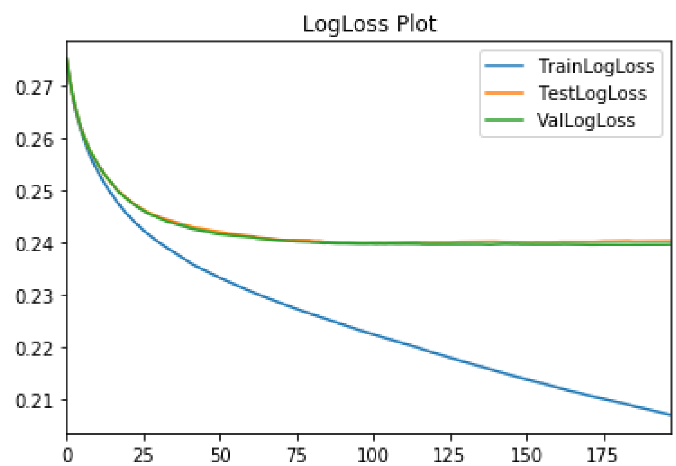
	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000
2	LightGBM - All Files-	0.9221	0.9200	0.9200	0.8280	0.7792	0.7781	0.0000

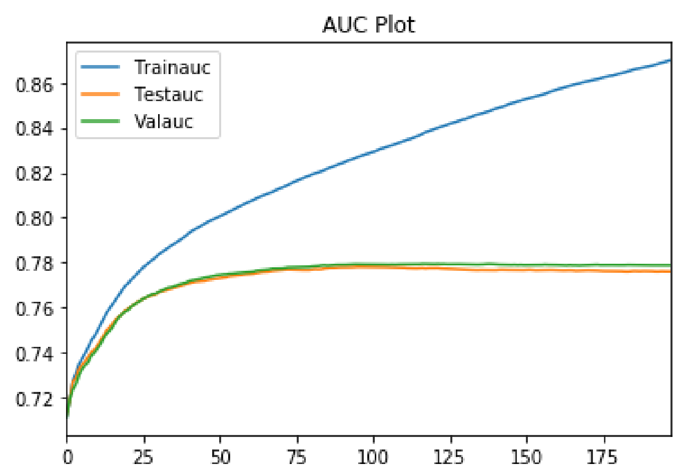
77% Valid & Test AUC Not Bad

In [19]:
```
lg_model = mdl
evals_result = lg_model.evals_result_
evals = pd.DataFrame(evals_result['training']
                     ['binary_logloss'], columns=['TrainLogLoss'])
evals['TestLogLoss'] = evals_result['valid_1']['binary_logloss']
evals['ValLogLoss'] = evals_result['valid_2']['binary_logloss']
evals.plot(title="LogLoss Plot")


auc = pd.DataFrame(evals_result['training']['auc'], columns=['Trainauc'])
auc['Testauc'] = evals_result['valid_1']['auc']
auc['Valauc'] = evals_result['valid_2']['auc']
auc.plot(title="AUC Plot")
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x16a39d8aa20>

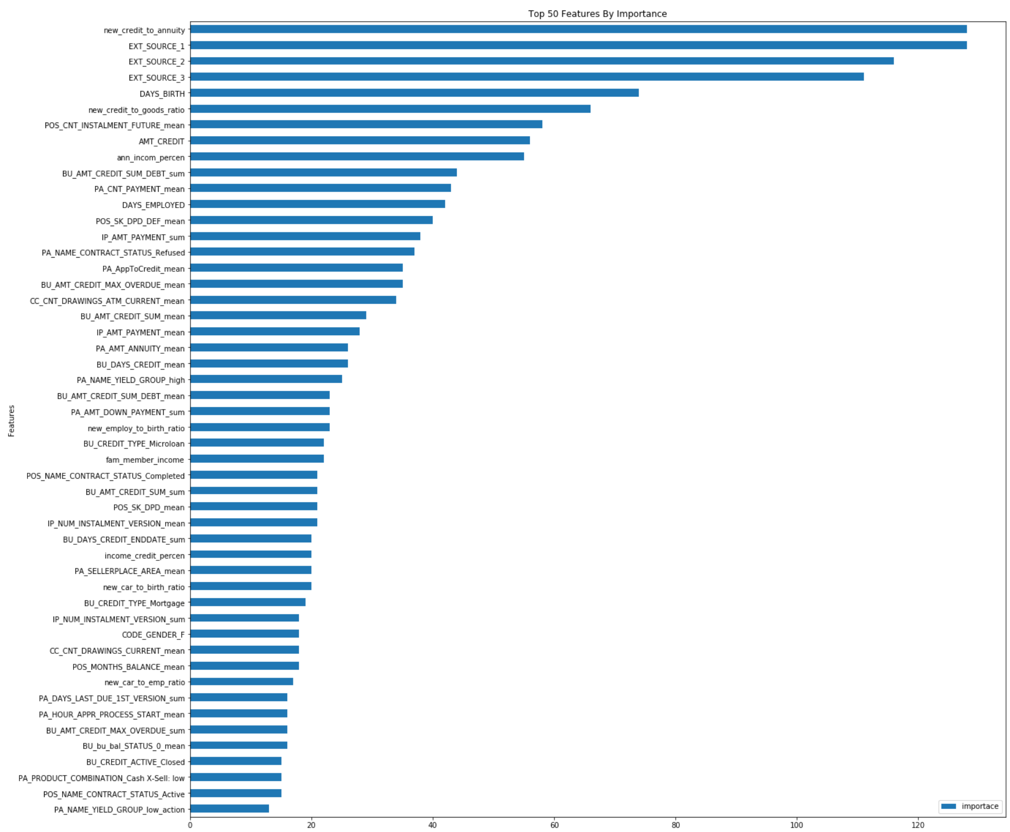




Lets see if we can improve accuracy by selecting an lower set of features

In [21]:
```
imp = pd.DataFrame(X_train_t.columns, columns=['Features'])
imp['importace'] = lg_model.feature_importances_
imp = imp.sort_values(by='importace', ascending=False)
imp[imp['importace'] > 0][0:50].sort_values(by='importace', ascending=Tru
e).plot(
    kind='barh', x='Features', y='importace', figsize=(20, 20), title="To
p 50 Features By Importance")
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x16a1cf3e748>
```



There are lots of features, lets try a feature selection model

In [22]:
```
feamodel = SelectFromModel(mdl, prefit=True, threshold="median")
X_train_new = feamodel.transform(X_train_t)
X_valid_new = feamodel.transform(X_valid_t)
X_test_new = feamodel.transform(X_test_t)

mdl = lg.LGBMClassifier(**params)
mdl.fit(X_train_new , y_train
        ,eval_set=[(X_train_new , y_train),(X_test_new, y_test),(X_valid_
new , y_valid)]
        ,eval_metric=['logloss', 'auc']
        ,early_stopping_rounds=100
        ,verbose=False)
expLog = update_log(expLog, 'LightGBM - With Features Selected - ',mdl, X
_train_new, y_train, X_test_new, y_test, X_valid_new, y_valid)
expLog
```

Out[22]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000
2	LightGBM - All Files-	0.9221	0.9200	0.9200	0.8280	0.7792	0.7781	0.0000
3	LightGBM - With Features Selected -	0.9216	0.9201	0.9199	0.8206	0.7782	0.7787	0.0000

We reduced about half the feature and kept the same level of accuracy. That is a win!

In [24]:
```
print(f" The Original Shape was {X_train_t.shape}")
print(f" The New Shape is {X_train_new.shape}")
print(f" A Reduction of {X_train_t.shape[1] - X_train_new.shape[1]} featu
res")
```

```
The Original Shape was (222176, 466)
The New Shape is (222176, 243)
A Reduction of 223 features
```

Lets see if we can improve the score by hyper parameter tuning

- We did not want to use grid search as that would take a very long time. So we opted for Bayesian hyper parameter optimization via the hyperopt package

```
In [16]: def objective(params):
    params = {
        'max_depth': int(params['max_depth']),
        'reg_alpha': "{:.3f}".format(params['reg_alpha']),
        'reg_lambda': "{:.3f}".format(params['reg_lambda']),
        'colsample_bytree': '{:.3f}'.format(params['colsample_bytree']),
        'learning_rate': '{:.3f}'.format(params['learning_rate']),
        'min_child_weight': int(params['min_child_weight']),
        'subsample': '{:.3f}'.format(params['subsample']),
    }

    clf = lg.LGBMClassifier(
        n_estimators=500,
        n_jobs=-1,
        **params
    )

    gbm_model = clf.fit(X_train_new, y_train
                        ,eval_set=[(X_valid_new, y_valid)]
                        ,eval_metric=['logloss', 'auc']
                        ,early_stopping_rounds=50, verbose=False)

    predictions = gbm_model.predict_proba(X_valid_new)[:, 1]
    score = roc_auc_score(y_valid, predictions)

    return {'loss': 1-score, 'status': STATUS_OK}


space = {
    'max_depth': hp.quniform('max_depth', 2, 8, 1),
    'colsample_bytree': hp.quniform('colsample_bytree', 0.3, 1.0, 0.1),
    'learning_rate': hp.quniform('learning_rate', 0.025, 0.1, 0.025),
    'min_child_weight': hp.quniform('min_child_weight', 1, 6, 1),
    'subsample': hp.quniform('subsample', 0.5, 1, 0.05),
    'reg_alpha': hp.quniform('reg_alpha', 0.0, 1, 0.1),
    'reg_lambda': hp.quniform('reg_lambda', 0.0, 1, 0.1),

}

best = fmin(fn=objective,
            space=space,
            algo=tpe.suggest,
            max_evals=30)
print(best)
```

```
100%|██████████████████████████████████████████████████| 30/30 [09:13<0
0:00, 15.20s/it, best loss: 0.21485193362152166]
{'colsample_bytree': 0.30000000000000004, 'learning_rate': 0.07500000000
000001, 'max_depth': 6.0, 'min_child_weight': 6.0, 'reg_alpha': 0.2, 're
g_lambda': 0.9, 'subsample': 0.8}
```

Retraining with best parameter & optimal feature

We good better results with the optimal hyperparameters!

In [25]:
```
#Score Stopps getting better after about 600 itteration.
best = {'colsample_bytree': 0.30000000000000004
        ,'learning_rate': 0.075000000000000001
        ,'max_depth': 4
        ,'min_child_weight': 3.0
        ,'reg_alpha': 0.8
        ,'reg_lambda': 0.6000000000000001
        ,'subsample': 0.5}


best['max_depth'] = int(best['max_depth'])
mdl = lg.LGBMClassifier(n_estimators=1000, n_jobs = -1, **best)
mdl.fit(X_train_new , y_train
        ,eval_set=[(X_train_new , y_train),(X_test_new, y_test),(X_valid_
new , y_valid)]
        ,eval_metric=['logloss', 'auc']
        ,early_stopping_rounds=100
        ,verbose=False)
expLog = update_log(expLog, 'LightGBM - With Features Selected- Parameter
s Optimized ',mdl, X_train_new, y_train, X_test_new, y_test, X_valid_new,
y_valid)
expLog
```

Out[25]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000
2	LightGBM - All Files-	0.9221	0.9200	0.9200	0.8280	0.7792	0.7781	0.0000
3	LightGBM - With Features Selected -	0.9216	0.9201	0.9199	0.8206	0.7782	0.7787	0.0000
4	LightGBM - With Features Selected- Parameters ...	0.9226	0.9198	0.9206	0.8351	0.7838	0.7841	0.0000

Below is a final pipeline implementation of all of the above steps!

In [26]:
```
params = {
    'n_estimators': 600, 'learning_rate': 0.1, 'n_jobs': -1
}

best = {'colsample_bytree': 0.30000000000000004
        ,'learning_rate': 0.07500000000000001
        ,'max_depth': 4
        ,'min_child_weight': 3.0
        ,'reg_alpha': 0.8
        ,'reg_lambda': 0.6000000000000001
        ,'subsample': 0.5}

finalpipe =Pipeline([
    ('tran', transform_train(num_attribs,cat_attribs))
   ,('merge', merge_df(lst))
   ,('S_features',SelectFromModel(lg.LGBMClassifier(**params) ,prefit=Fal
se, threshold="median") )
   ,('f_model', lg.LGBMClassifier(n_estimators=600, n_jobs = -1, **best)
)
])


finalpipe.fit(X_train,y_train)
expLog = update_log(expLog, 'LightGBM - Final Pipeline ',finalpipe, X_tra
in, y_train, X_test, y_test, X_valid, y_valid)
expLog
```

Out[26]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000
2	LightGBM - All Files-	0.9221	0.9200	0.9200	0.8280	0.7792	0.7781	0.0000
3	LightGBM - With Features Selected -	0.9216	0.9201	0.9199	0.8206	0.7782	0.7787	0.0000
4	LightGBM - With Features Selected- Parameters ...	0.9226	0.9198	0.9206	0.8351	0.7838	0.7841	0.0000
5	LightGBM - Final Pipeline	0.9231	0.9198	0.9203	0.8388	0.7843	0.7830	0.0000

Testing our model on the application_test data.

In [27]:
```
load = True
if load:
    x_test  = load_main_files('application_test.csv')
    tst_ind = x_test.index
    pred = finalpipe.predict_proba(x_test)[:,1]
    sub = pd.DataFrame(tst_ind)
    sub['TARGET'] = pred
    sub.to_csv('submission.csv', index=False)
```

In [28]:
```
!kaggle competitions submissions home-credit-default-risk
```

```
fileName        date                 description
status    publicScore  privateScore
--------------  -------------------  ----------------------------------
-------------------------------------------------------  ---------  -----
------  ------------
submission.csv  2019-04-27 17:30:27  Deep Learning Model- With Feature S
electio  - 30 epoc - 10 batchsize                        complete  0.766
06      0.76237
submission.csv  2019-04-27 15:36:36  Deep Learning Model- With Feature S
electio  - 30 epoc                                       complete  0.762
12      0.75667
submission.csv  2019-04-23 01:01:27  Keras Attempt 1 with Opt Features 3
13 start                                                 complete  0.551
07      0.53958
submission.csv  2019-04-22 22:07:24  LightGBM - Final Pipeline - Will AL
L Test Data                                              complete  0.783
16      0.78141
submission.csv  2019-04-22 21:13:44  LightGBM - With Features Selected-
Parameters Optimized (Using Select From Model & Median)  complete  0.783
61      0.77773
submission.csv  2019-04-18 05:59:53  LightGBM - All Files - 300 Features
With Opt Parameters & Nishad Features v2               complete  0.7787
1      0.77851
submission.csv  2019-04-18 04:12:52  LightGBM - All Files - 300 Features
With Opt Parameters & Nishad Features v2               complete  0.7794
4      0.77962
submission.csv  2019-04-18 03:39:34  LightGBM - All Files - 250 Features
With Opt Parameters & Nishad Features v2               complete  0.7811
1      0.77847
submission.csv  2019-04-18 02:42:39  LightGBM - All Files - 250 Features
With Opt Parameters & Nishad Features v2               complete  0.7795
1      0.77692
submission.csv  2019-04-18 01:02:07  LightGBM - All Files - 300 Features
With Opt Parameters v1                                 complete  0.7631
6      0.76709
submission.csv  2019-04-18 01:01:38  XGBOOST - All Files - No Features S
election                                                 complete  0.763
16      0.76709
submission.csv  2019-04-17 04:29:44  XGBOOST - All Files - No Features S
election                                                 complete  0.764
42      0.76688
submission.csv  2019-04-17 02:37:46  XGBOOST - Previous Application w/be
st features & POS                                        complete  0.748
85      0.75171
submission.csv  2019-04-16 05:17:15  XGBoost - Hist - TunedHP - 100 Impo
rtant features with previous app                         complete  0.750
34      0.75570
submission.csv  2019-04-13 15:15:13  XGBoost - Hist - TunedHP
complete  0.74813      0.75039
submission.csv  2019-04-07 19:47:17  XGBoost - Hist - TunedHP
complete  0.75162      0.75435
submission.csv  2019-04-07 06:05:35  LightGBM - TunedHP
complete  0.74094      0.74544
submission.csv  2019-04-07 05:30:19  XGBoost - Hist - TunedHP
complete  0.75011      0.75439
submission.csv  2019-04-06 22:05:28  XGBoost - Hist
complete  0.74886      0.75185
submission.csv  2019-04-06 08:47:56  LogR - With Previous APP Data(actua
l2)                                                      complete  0.743
40      0.74151
```

Attempting a Deep Learning Model!

In [36]:
```
def create_model():
    md2 = Sequential()

    sha = 233

    md2.add(Dense(sha, input_dim=sha, kernel_initializer="uniform"))
    md2.add(BatchNormalization())
    md2.add(Activation('relu'))
    md2.add(Dropout(0.2))

    md2.add(Dense(200, kernel_initializer="uniform"))
    md2.add(BatchNormalization())
    md2.add(Activation('relu'))
    md2.add(Dropout(0.2))

    md2.add(Dense(100, kernel_initializer="uniform"))
    md2.add(BatchNormalization())
    md2.add(Activation('relu'))
    md2.add(Dropout(0.2))

    md2.add(Dense(100, kernel_initializer="uniform"))
    md2.add(BatchNormalization())
    md2.add(Activation('relu'))
    md2.add(Dropout(0.2))


    md2.add(Dense(1,  kernel_initializer="uniform"))
    md2.add(BatchNormalization())
    md2.add(Activation('sigmoid'))

    md2.compile(loss='binary_crossentropy', optimizer='adagrad', metrics=
['accuracy'])
    return md2

md3 =KerasClassifier(build_fn=create_model, epochs=30, batch_size=10, ver
bose=0)
```

In [37]:

```
lst = [df_pv_app, df_pos_app, df_ins_pay, df_credit_pay, df_bureau]

finalpipe =Pipeline([
    ('tran', transform_train(num_attribs,cat_attribs))
   ,('merge', merge_df(lst))
   ,('S_features',SelectFromModel(lg.LGBMClassifier(**params) ,prefit=Fal
se, threshold="median"))
   ,('model',md3)])

finalpipe.fit(X_train,y_train)
```

```
WARNING:tensorflow:From C:\Anaconda3\envs\tf_gpu\lib\site-packages\tenso
rflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.ops.
math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
```

Out[37]:

```
Pipeline(memory=None,
     steps=[('tran', transform_train(cat_attribs=None, num_attribs=Non
e)), ('merge', merge_df(dflist=[            PA_AMT_ANNUITY_sum  PA_AMT_A
NNUITY_mean  PA_AMT_ANNUITY_count  \
SK_ID_CURR
100001                 -0.7748             -1.0606              -0.927
3
100002                 -0.7030          ...d='median')), ('model', <ker
as.wrappers.scikit_learn.KerasClassifier object at 0x0000016A3993F518
>)])
```

In [38]:

```
expLog = update_log(expLog, 'Deep Learning Model- With Feature Selection
 - pipeline  - 30 epoc - 10 batchsize ',finalpipe, X_train, y_train, X_te
st, y_test, X_valid, y_valid)
expLog
```

Out[38]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	LogisticBase	0.9191	0.9193	0.9197	0.7411	0.7447	0.7487	0.0000
1	LightGBM - No Additional Files-	0.9318	0.9188	0.9187	0.9408	0.7547	0.7529	0.0000
2	LightGBM - All Files-	0.9221	0.9200	0.9200	0.8280	0.7792	0.7781	0.0000
3	LightGBM - With Features Selected -	0.9216	0.9201	0.9199	0.8206	0.7782	0.7787	0.0000
4	LightGBM - With Features Selected- Parameters ...	0.9226	0.9198	0.9206	0.8351	0.7838	0.7841	0.0000
5	LightGBM - Final Pipeline	0.9231	0.9198	0.9203	0.8388	0.7843	0.7830	0.0000
6	Deep Learning Model- With Feature Selection - ...	0.9193	0.9193	0.9193	0.8054	0.7719	0.7717	0.0000

Deep Learning Submission

In [ ]:

```
load = True
if load:
    x_test  = load_main_files('application_test.csv')
    tst_ind = x_test.index
    pred = finalpipe.predict_proba(x_test)[:,1]
    sub = pd.DataFrame(tst_ind)
    sub['TARGET'] = pred
    sub.to_csv('submission.csv', index=False)
```

In [79]:

```
!kaggle competitions submit -c home-credit-default-risk -f submission.csv
-m "Deep Learning Model- With Feature Selectio  - 30 epoc - 10 batchsize"
```

```
Successfully submitted to Home Credit Default Risk

  0%|          | 0.00/919k [00:00<?, ?B/s]
 10%|#         | 96.0k/919k [00:00<00:00, 902kB/s]
100%|##########| 919k/919k [00:02<00:00, 414kB/s]
```

In [80]:
```
!kaggle competitions submissions home-credit-default-risk
```

```
fileName        date                 description
status    publicScore  privateScore
--------------  -------------------  ----------------------------------
------------------------------------------------------  --------  -----
------  ------------
submission.csv  2019-04-27 17:30:27  Deep Learning Model- With Feature S
electio  - 30 epoc - 10 batchsize                         complete  0.766
06      0.76237
submission.csv  2019-04-27 15:36:36  Deep Learning Model- With Feature S
electio  - 30 epoc                                        complete  0.762
12      0.75667
submission.csv  2019-04-23 01:01:27  Keras Attempt 1 with Opt Features 3
13 start                                                  complete  0.551
07      0.53958
submission.csv  2019-04-22 22:07:24  LightGBM - Final Pipeline - Will AL
L Test Data                                               complete  0.783
16      0.78141
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Parameters Optimized (Using Select From Model & Median)  complete  0.783
61      0.77773
submission.csv  2019-04-18 05:59:53  LightGBM - All Files - 300 Features
With Opt Parameters & Nishad Features v2                complete  0.7787
1      0.77851
submission.csv  2019-04-18 04:12:52  LightGBM - All Files - 300 Features
With Opt Parameters & Nishad Features v2                complete  0.7794
4      0.77962
submission.csv  2019-04-18 03:39:34  LightGBM - All Files - 250 Features
With Opt Parameters & Nishad Features v2                complete  0.7811
1      0.77847
submission.csv  2019-04-18 02:42:39  LightGBM - All Files - 250 Features
With Opt Parameters & Nishad Features v2                complete  0.7795
1      0.77692
submission.csv  2019-04-18 01:02:07  LightGBM - All Files - 300 Features
With Opt Parameters v1                                  complete  0.7631
6      0.76709
submission.csv  2019-04-18 01:01:38  XGBOOST - All Files - No Features S
election                                                  complete  0.763
16      0.76709
submission.csv  2019-04-17 04:29:44  XGBOOST - All Files - No Features S
election                                                  complete  0.764
42      0.76688
submission.csv  2019-04-17 02:37:46  XGBOOST - Previous Application w/be
st features & POS                                         complete  0.748
85      0.75171
submission.csv  2019-04-16 05:17:15  XGBoost - Hist - TunedHP - 100 Impo
rtant features with previous app                          complete  0.750
34      0.75570
submission.csv  2019-04-13 15:15:13  XGBoost - Hist - TunedHP
complete  0.74813      0.75039
submission.csv  2019-04-07 19:47:17  XGBoost - Hist - TunedHP
complete  0.75162      0.75435
submission.csv  2019-04-07 06:05:35  LightGBM - TunedHP
complete  0.74094      0.74544
submission.csv  2019-04-07 05:30:19  XGBoost - Hist - TunedHP
complete  0.75011      0.75439
submission.csv  2019-04-06 22:05:28  XGBoost - Hist
complete  0.74886      0.75185
submission.csv  2019-04-06 08:47:56  LogR - With Previous APP Data(actua
l2)                                                       complete  0.743
40      0.74151
```

Project Report

Title

Assessing Risk For Home Credit Applications

Abstract

Assessing risk when providing credit to an individual is a significant problem all lenders face. It is crucial to know how likely a person is to repay the borrowed money in an agreed upon time. There are many factors in a person's life lenders can use to assess this risk such as previous credit history, occupation, age, location, credit card usage, and others. We will be studying these factors when trying to assess a loan application. The dataset we will be using is provided from Home Credit which contains samples of over 600K credit application. We will use all the factors provided in the dataset to understand which factors are the most important in predicting a person's default risk. In this study, we will focus on creating a machine learning model that is well optimized and performs efficiently to asses this risk for leaders and provides them with decision-making guidance to maximize their profits.

Introduction

Many people apply for the loan but struggle to get due to insufficient or non-existent credit histories. The Home Credit Group is primarily lending to people with little or no credit history. The Home Credit Group is an international consumer finance provider with operations in 10 countries. The company has helped financially over 111 million customers. With the increase loan applications, the importance of risk management in credit has increased for both borrowers and lenders. The credit risk can be defined as the possibility that a borrower party will fail to repay loans with the agreed terms. The Home Credit is using various statistical and machine learning methods to predict credit risk. The Home Credit is also looking to improve their predictions on whether applicants will default on their loans or not. The goal of this project is to develop a model that will demonstrate a better understanding of which loan applications are capable of repayment. The Home Credit project dataset has information about each loan application, previous credits, previous applications, point of sale or cash loans and monthly credit card balance. The aim of the project to develop "LGBMClassifier" model that effectively measures the credit risk associated with the applications from clients.

Feature Engineering

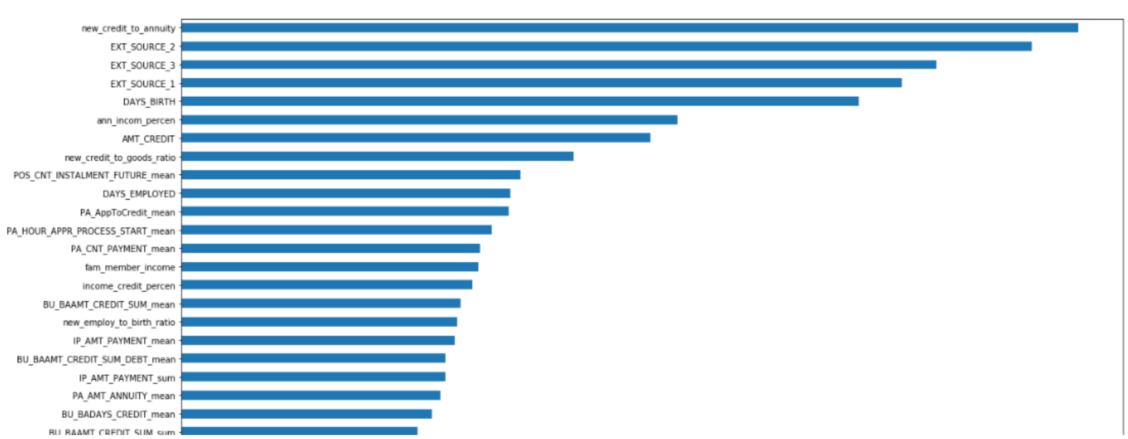
As we have substantial features in our dataset, it was essential to force our algorithms to focus on superior features. The high dimensionality we observed in phase 1 was not only time consuming but also not contributing much to the improvement of the model. With limited domain knowledge, we created numerical features such as aggregations from auxiliary files along with simple numerical custom features available from train dataset. During phase 1, we observed a significant increase in the accuracy from 74% to 75% on the Kaggle website after addition of previous applications table. The breakthrough also encouraged us to get the basic statistics from other files especially the ones which represents client past activity such as count of previous loans, Previous term from other Bureau's, Term of installments, Hour at which clients made the application, etc.

Below are some of the custom features that stood out when we checked our feature importance scores. new_credit_to_annuity – This ratio would tell how much the loan annuity client is paying with the credit loan approved. new*credit* goods_ratio – The Loan to Good Value ratio, this compares the loan value to the client's property. Ann_income_percen – Amount of annuity to the amount of income of the client. Employ_to_birth_ratio – This ratio tells us the employment history of our client, having higher ratio indeed a positive sign. Cnt_fam_members – Income spends across the family members per client.

In [3]:
```
from IPython.display import Image
```

```
# Naimesh Features
df_train['income_credit_percen'] = (
    df_train.AMT_INCOME_TOTAL / df_train.AMT_CREDIT).replace(np.inf, 0)
df_train['fam_member_income'] = (
    df_train.AMT_INCOME_TOTAL / df_train.CNT_FAM_MEMBERS).replace(np.inf, 0)
df_train['ann_incom_percen'] = (
    df_train.AMT_ANNUITY / df_train.AMT_INCOME_TOTAL).replace(np.inf, 0)

# Nishad Features
df_train['new_employ_to_birth_ratio'] = (
    df_train.DAYS_EMPLOYED / df_train.DAYS_BIRTH).replace(np.inf, 0)
df_train['new_credit_to_annuity'] = (
    df_train['AMT_CREDIT'] / df_train['AMT_ANNUITY']).replace(np.inf, 0)
df_train['new_credit_to_goods_ratio'] = (
    df_train['AMT_CREDIT'] / df_train['AMT_GOODS_PRICE']).replace(np.inf, 0)
df_train['new_car_to_birth_ratio'] = (
    df_train['OWN_CAR_AGE'] / df_train['DAYS_BIRTH']).replace(np.inf, 0)
df_train['new_car_to_emp_ratio'] = (
    df_train['OWN_CAR_AGE'] / df_train['DAYS_EMPLOYED']).replace(np.inf, 0)
df_train['new_inc_per_child'] = (
    df_train['AMT_INCOME_TOTAL'] / (1 + df_train['CNT_CHILDREN'])).replace(np.inf, 0)
```



We created standard data frame selector Transformer taught in AML class to select the numerical and categorical columns, which we pass on to our “FeatureUnion” pipeline object to concatenate our transformer objects to single transformer object.

```
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.attribute_names].values
```

Pipelines

A pipeline is an object that has an inlet and an outlet and transports a liquid from a location to another. The pipeline helps to automate machine learning workflows. It operates by enabling a sequence of data to be transformed and correlated together in a model. The transformed data can be tested and evaluated to achieve an outcome. There are two pipeline approaches as supervised learning and unsupervised learning. In supervised learning, a model is built and datasets are provided to solve a particular problem using classification algorithms and is the most common use of machine learning. The second approach is unsupervised learning, where a model is built to discover structures within the given datasets. The initial data captured is not necessarily labeled so clustering algorithms are used to group the unlabeled data together. In the project, we applied numerical pipeline on numerical features and categorical pipeline on categorical features. The numerical pipeline has DataFrameSelector, SimpleImputer with mean and StandardScaler transformations. The DataframeSelector is to select specific attributes from the DataFrame. The SimpleImputer is completing missing values with attribute mean. The StandardScaler is standardized features by removing the mean and scaling to unit variance. The categorical pipeline has DataFrameSelector, SimpleImputer with constant and OneHotEncoder transformations. The SimpleImputer is completing missing values with constant strategy. The OneHotEncoder transformation is used to encode categorical integer features as a one-hot numeric array. The input to this transformer should be an array-like of integers or strings and creates a binary column for each category and returns a sparse matrix or dense array. The full pipeline is generated by combining numerical and categorical pipelines. The full pipeline is used on training data to transform it for model input.

```
num_pipeline = Pipeline([
                        ('selector', DataFrameSelector(num_attribs)),
                        ('imputer', SimpleImputer(strategy='mean')),
                        ('std_scaler', StandardScaler()),
                       ])

cat_pipeline = Pipeline([
                        ('selector', DataFrameSelector(cat_attribs)),
                        ('imputer', SimpleImputer(strategy='constant')),
                        ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"))
                        ])

data_prep_pipeline = FeatureUnion(transformer_list=[
                                                    ("num_pipeline", num_pipeline),
                                                    ("cat_pipeline", cat_pipeline),
                                                   ])

full_pipeline = Pipeline([("preparation", data_prep_pipeline)])
```

Experiments

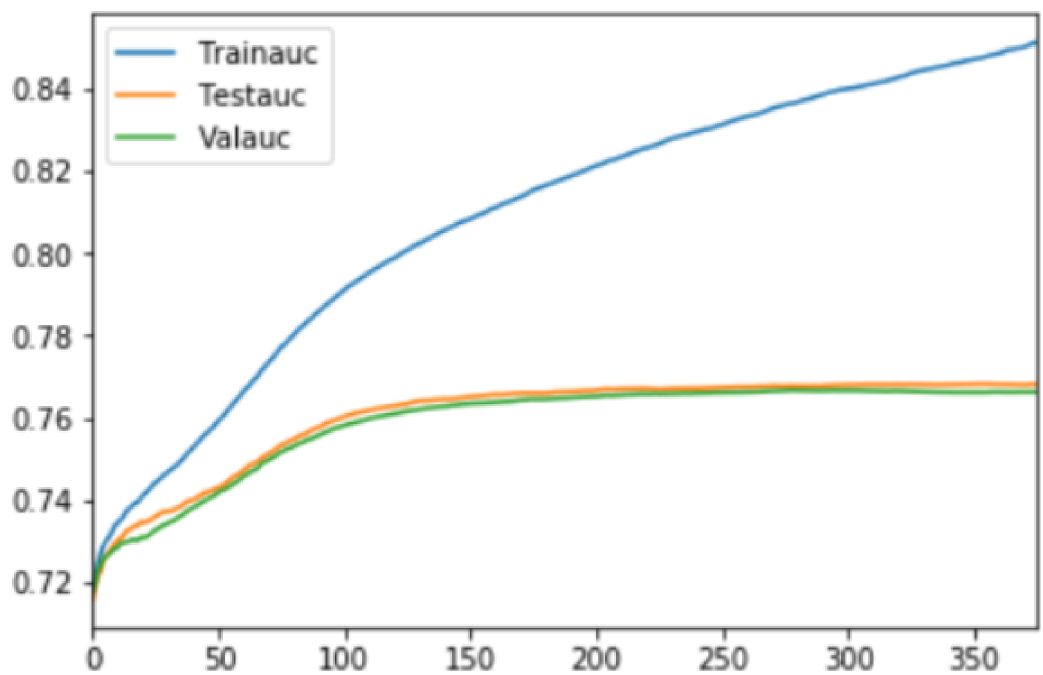
Phase -1

We spend time in phase one to understand the data, prepare it to remove anomalies and explore the different models. Tracking our results through tables (Pandas Dataframes) was one of many best things we learned in through the AML class, we created Dataframe that keeps track of experiment name, accuracy and AUC scores of from train, test and validation data.

Using the P-Values we can also check the statistical significance and compare it to our base model. The table below shows results from Phase-0 (Baseline model) and BaselinePlus model. The initial models we started with the 48 features and then extended to 269 features with aggregates from previous application table, we did not track the time but overall this we observed slow progress while training the data.

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	Model_Logistic_features_48	0.9191	0.9192	0.9196	0.7357	0.7407	0.7450	0.0000
1	Model_RandomForest_features_48	0.9999	0.9194	0.9194	1.0000	0.7100	0.7169	0.1024
2	Model_Logistic_Prev_app_features_269	0.9193	0.9194	0.9196	0.7567	0.7584	0.7601	0.0068
3	Model_RandomForest_prev_app_features_269	1.0000	0.9194	0.9195	1.0000	0.7168	0.7197	0.0000

Kaggle submissions from Phase 1 and AUC score and Log loss plots, we can see a plateau after 150 epochs this output is plotted through eval_results features of XGBOOST, we were successful bump the accuracy by 2% in our Kaggle submissions from the baseline model. AUC plot phase I

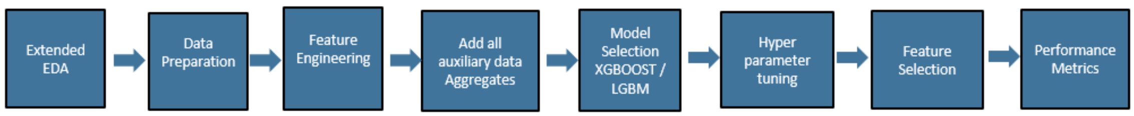



```
#test_sub(full_pipeline,df_pv_app,fitted_models)
#!kaggle competitions submit -c home-credit-default-risk -f submission.csv -m "XGBoost - Hist"
!kaggle competitions submissions home-credit-default-risk
```

```
fileName           date                 description
status     publicScore  privateScore
-----------------  -------------------  -----------------------------------------------------------------
-----------  --------  -----------  ------------
submission.csv     2019-04-06 22:05:28  XGBoost - Hist
complete  0.74886      0.75185
submission.csv     2019-04-06 08:47:56  LogR - With Previous APP Data(actual2)
complete  0.74340      0.74151
submission.csv     2019-04-06 08:47:22  LogR - With Previous APP Data(actual)
```

Phase-2

During the phase -2 we continued our approach XGBOOST and LightGBM however this time we added all the auxiliary data files along with aggregates, we also introduced the custom features derived from the application train dataset. To handle the dimensionality we used LightGBM's feature importance and carried out experiments iterating over stages containing a different number of with unique features.



We did not want to use the grid search as that would take a very long time. So we opted for Bayesian hyperparameter tuning via the hyper opt package. Most of the custom features we introduced helped us to improve the model accuracy below chart shows our best features by their importance. Model submission using the optimal features and parameters, great we are able to improve our accuracy by almost 3% by the end of phase-2

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	Model_Logistic_features_57	0.92	0.92	0.92	0.74	0.74	0.75	0.00
1	LGBM - All Files - No Feature Selection - No p...	0.92	0.92	0.92	0.89	0.78	0.78	0.00
2	LGBM - All Files - 300 Feature - No parameter ...	0.92	0.92	0.92	0.89	0.78	0.78	0.00
3	LGBM - All Files - 300 Feature - Parameter Tun...	0.93	0.92	0.92	0.88	0.79	0.78	0.00

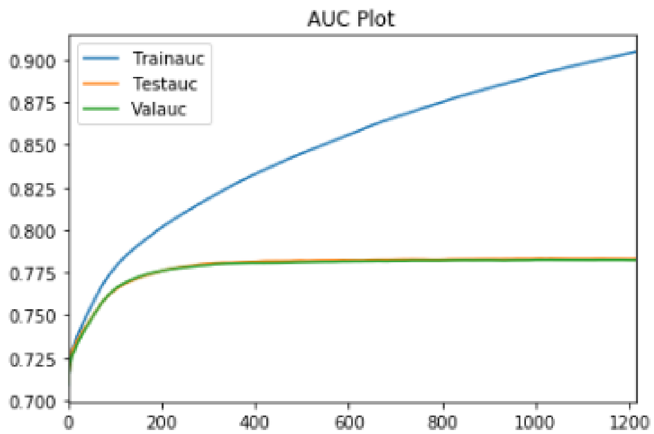
Kaggle Submission Phase II

```
!kaggle competitions submissions home-credit-default-risk
```

executed in 595ms, finished 00:13:11 2019-04-18

```
fileName         date                 description                                                          status    publicScore  privateScore
---------------  -------------------  -------------------------------------------------------------------  --------  -----------  ------------
submission.csv   2019-04-18 04:12:52  LightGBM - All Files - 300 Features With Opt Parameters & Nishad Features v2  complete  0.77944      0.77962
submission.csv   2019-04-18 03:39:34  LightGBM - All Files - 250 Features With Opt Parameters & Nishad Features v2  complete  0.78111      0.77847
submission.csv   2019-04-18 02:42:39  LightGBM - All Files - 250 Features With Opt Parameters & Nishad Features v2  complete  0.77951      0.77692
submission.csv   2019-04-18 01:02:07  LightGBM - All Files - 300 Features With Opt Parameters v1                    complete  0.76316      0.76709
submission.csv   2019-04-18 01:01:38  XGBOOST - All Files - No Features Selection                                   complete  0.76316      0.76709
submission.csv   2019-04-17 04:29:44  XGBOOST - All Files - No Features Selection                                   complete  0.76442      0.76688
submission.csv   2019-04-17 02:37:46  XGBOOST - Previous Application w/best features & POS                          complete  0.74885      0.75171
```

AUC PLOT - phase II



Discussion and Analysis

Extended EDA and Feature Engineering

During our extended EDA, we figured out, A strong correlation between amount credit and amount of goods price, days birth and days employed, ext source 1 and days birth this helped us in feature engineering to derive custom features around these variables.

	AMT_INCOME_TOTAL	AMT_CREDIT	DAYS_EMPLOYED	DAYS_BIRTH	EXT_SOURCE_1	EXT_SOURCE_2	EXT_SOURCE_3	AMT_GOODS_PRICE
AMT_INCOME_TOTAL	1	0.16	-0.064	-0.027	0.026	0.061	-0.03	0.16
AMT_CREDIT	0.16	1	-0.064	0.055	0.17	0.13	0.044	0.99
DAYS_EMPLOYED	-0.064	-0.064	1	0.62	0.3	-0.018	0.12	-0.062
DAYS_BIRTH	-0.027	0.055	0.62	1	0.6	0.092	0.21	0.053
EXT_SOURCE_1	0.026	0.17	0.3	0.6	1	0.21	0.19	0.18
EXT_SOURCE_2	0.061	0.13	-0.018	0.092	0.21	1	0.11	0.14
EXT_SOURCE_3	-0.03	0.044	0.12	0.21	0.19	0.11	1	0.048
AMT_GOODS_PRICE	0.16	0.99	-0.062	0.053	0.18	0.14	0.048	1

Most of the custom features we introduced helped us to improve the model accuracy below chart shows our best features by their importance.

LightGBM Breakthrough

So during phase 1 while working on professor's notebook we realized that the random forest was too slow and not helping much in terms of accuracy, hence in parallel, we started exploring the Light GBM model without tuning the hyperparameters. We found the algorithm works really fast and we were hitting accuracy approximately 76.49% during the start of phase 2 with the same amount of features and without tuning. This was the main trigger point that we decided to switch on lightGBM instead of XGBOOST.

```
x_train, x_val, y_train, y_val = train_test_split(trainX, Y, test_size=0.2, random_state=18)
lgb_train = lgb.Dataset(data=x_train, label=y_train)
lgb_eval = lgb.Dataset(data=x_val, label=y_val)
```

```
model = lgb.train(params, lgb_train, valid_sets=lgb_eval, early_stopping_rounds=100, verbose_eval=200)
```

Bayesian Hyper-Parameter tuning

During phase-2 timely completion of code was crucial; hence we did not use a grid search as that would take a very long time and opted for Bayesian hyperparameter tuning via the "Hyperopt" package.

```
features = imp['Features'][0:300].values
train  = X_train[features]
valid = X_valid[features]
test = X_test[features]
def objective(params):
    params = {
        'max_depth': int(params['max_depth']),
        'reg_alpha': "{:.3f}".format(params['reg_alpha']),
        'reg_lambda': "{:.3f}".format(params['reg_lambda']),
        'colsample_bytree': '{:.3f}'.format(params['colsample_bytree']),
        'learning_rate' : '{:.3f}'.format(params['learning_rate']),
        'min_child_weight' : int(params['min_child_weight']),
        'subsample' : '{:.3f}'.format(params['subsample']),
           }

    clf =lg.LGBMClassifier(
        n_estimators=500,
        n_jobs=-1,
        **params
    )

    gbm_model = clf.fit(train , y_train
                ,eval_set=[(valid, y_valid)]
                ,eval_metric=['logloss','auc']
                ,early_stopping_rounds = 50
                ,verbose=False)

    predictions = gbm_model.predict_proba(valid)[:, 1]
    score = roc_auc_score(y_valid, predictions)

    return {'loss': 1-score, 'status': STATUS_OK}

space = {
    'max_depth': hp.quniform('max_depth', 2, 8, 1),
    'colsample_bytree': hp.quniform('colsample_bytree', 0.3, 1.0,0.1),
    'learning_rate': hp.quniform('learning_rate', 0.025, 0.1, 0.025),
     'min_child_weight': hp.quniform('min_child_weight', 1, 6, 1),
    'subsample': hp.quniform('subsample', 0.5, 1, 0.05),
    'reg_alpha': hp.quniform('reg_alpha', 0.0, 1, 0.1),
    'reg_lambda': hp.quniform('reg_lambda', 0.0, 1, 0.1),

}

best = fmin(fn=objective,
            space=space,
            algo=tpe.suggest,
            max_evals=30)
print(best)
```

100%|██████████| 30/30 [24:21<00:00, 48.10s/it, best loss: 0.21581935929436535]

{'colsample_bytree': 0.6000000000000001, 'learning_rate': 0.07500000000000001, 'max_depth': 4.0, 'min_child_weight': 6.0, 'reg_alpha': 0.6000000000000001, 'reg_lambda': 0.8, 'subsample': 0.9}

Model submission using the optimal features and parameters, we are able to improve our accuracy by almost 3% by the end of phase-2

```
!kaggle competitions submissions home-credit-default-risk
```

executed in 595ms, finished 00:13:11 2019-04-18

```
fileName          date                 description                                                              status    publicScore  privateScore
----------------  -------------------  ------------------------------------------------------------------------  --------  -----------  ------------
submission.csv    2019-04-18 04:12:52  LightGBM - All Files - 300 Features With Opt Parameters & Nishad Features v2  complete  0.77944      0.77962
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submission.csv    2019-04-18 01:02:07  LightGBM - All Files - 300 Features With Opt Parameters v1                 complete  0.76316      0.76709
submission.csv    2019-04-18 01:01:38  XGBOOST - All Files - No Features Selection                                complete  0.76316      0.76709
submission.csv    2019-04-17 04:29:44  XGBOOST - All Files - No Features Selection                                complete  0.76442      0.76688
submission.csv    2019-04-17 02:37:46  XGBOOST - Previous Application w/best features & POS                       complete  0.74885      0.75171
```

conlcusion

In our study, we were able to find that Machine learning models effectively measure credit risk exposure based on clients application. The model we built can analyze current, and past activity records of the client acquired through various financial institutions.

During the several experiments carried with various algorithms, feature set, and data subsets we observed adding the right features to the data helps a lot in terms of improving prediction accuracy. During **phase 1**, we submitted the Kaggle score of **75.18** using **XGBOOST**

During **phase 2** we observed XGBOOST has good accuracy, but it performs poorly in comparison **LightGBM** that has similar accuracy with faster performance. We preferred **Bayesian hyperparameter tuning** over the grid search for faster optimization of parameters. Throughout the project tracking results through the table of experiments helped us to compare our results with the baseline models. By the end of phase 2, we submitted the score of **77.96** with total 300 features including the custom features developed by us.

During **phase 3**, although we see good potential in **Deep learning**, with observed high training time, we did not focus much on hyperparameter tuning with the deep learning model. In the end, we tried multiple models to help analyze default risk, but **LightGBM** ended up being the model we choose for our final submission being fastest and accurate with Kaggle score **78.14%** We want to thank Professor Shanahan, Amil, and Mariem for the guidance provided throughout the semester; it has been a great learning experience for us.

Final Score Table

Model	Train AUC(%)	Test AUC(%)	Number of Features	Train Time(Min)	Kaggle Accuracy(%)
Logistic Regression	75.67	76.01	269	5	74.34
XGBoost	84.92	76.77	269	5	74.88
LightGBM	**88.00**	**78.00**	**300**	**2**	**78.14**
Deep Learning	83.18	77.05	253	90	75.66