In [36]:

```python
import pandas as pd
import numpy as np
import matplotlib as mlp
import matplotlib.pyplot as plt
pd.set_option('display.max_rows', None)
%matplotlib inline
import seaborn as sns
import sklearn
from IPython.display import Image
from IPython.display import Markdown, display

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score, m
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, plot_confusion_m
from imblearn.over_sampling import SMOTE
from sklearn.pipeline import Pipeline

# from scipy.stats import uniform
# from sklearn import ensemble
import warnings
pd.set_option('display.max_columns', None)
import pickle
```

Table of Contents

In [37]:

```
# Load Data From Pickel
with open('./data/df_wD.pickle', 'rb') as file:
    df_wD = pickle.load(file)

with open('./data/df_wD_all.pickle', 'rb') as file:
    df_wD_all = pickle.load(file)
df_CleanCol_Names = pd.read_excel("./data/CleanColumnNames.xlsx")
```

Support Functions

In [38]:

```
def get_Scaled_TrainTestSplit_W_orWO_Smote(X, y, SmoteYorN):
    '''Returns Scaled, train-test split data, and either SMOTE or No SMOTE, takes in X

    # Split data between train and test
    X_train_wo_Scaling_Or_Smote, X_test_wo_Scaling, y_train, y_test = train_test_split
    #scale using min max
    df_X_train_sc, df_X_test_sc = scaleData(X_train_wo_Scaling_Or_Smote,X_test_wo_Sca

    if SmoteYorN =="Y":
        smote = SMOTE(random_state=41, sampling_strategy=1)
        X_train, y_train = smote.fit_sample(df_X_train_sc, y_train)
        print(f'SMOTED\n: {y_train.value_counts()}')
    elif SmoteYorN =="N":
        X_train = df_X_train_sc
        y_train = y_train
        print(f'Not SMOTED\n: {y_train.value_counts()}')

    return  X_train, y_train, df_X_test_sc, y_test

def scaleData(X_train_wo_Scaling_Or_Smote,X_test_wo_Scaling):
    '''Scaler, takes in X_train and X_test, returns scaled data'''
    scaler = MinMaxScaler(feature_range = (0,1))

    #Fit
    scaler.fit(X_train_wo_Scaling_Or_Smote)

    #Transform
    X_train_sc = scaler.transform(X_train_wo_Scaling_Or_Smote)
    X_test_sc = scaler.transform(X_test_wo_Scaling)
    #convert back to dataframe
    df_X_train_sc = pd.DataFrame(X_train_sc, columns=X_train_wo_Scaling_Or_Smote.colum
    df_X_test_sc = pd.DataFrame(X_test_sc, columns=X_train_wo_Scaling_Or_Smote.columns
    return df_X_train_sc, df_X_test_sc


# -----------------------Classification Metrics Functions

def createAUCReport(model, X_, y_, RsgName = None):
    '''Creates and plots ROC, called by createConfusionMatrix2() function'''
    print(RsgName)
    y_scores = model.predict_proba(X_)
    y_score =  y_scores[:, 1]
    fpr, tpr, thresholds = roc_curve(y_, y_score)
    AUC = auc(fpr, tpr)
    rndAuC = round(AUC,2)
    return rndAuC ,fpr, tpr, thresholds


def createROCCurve(result_table):
    '''Creates and plots multiple ROC, takes in a df of classifiers along with results
    fig = plt.figure(figsize=(8,6))

    for i in result_table.index:
        plt.plot(result_table.loc[i]['fpr'],
                 result_table.loc[i]['tpr'],
                 label="{},-{}:, AUC={:.3f},R={:.3f}".format(result_table.loc[i]['clf_
                                                                  result_table.loc[i][
                                                                  result_table.loc[i][
                )

    plt.plot([0,1], [0,1], color='orange', linestyle='--')
```

```python

    plt.xticks(np.arange(0.0, 1.1, step=0.1))
    plt.xlabel("Flase Positive Rate", fontsize=15)

    plt.yticks(np.arange(0.0, 1.1, step=0.1))
    plt.ylabel("True Positive Rate", fontsize=15)

    plt.title('ROC Curve Analysis', fontweight='bold', fontsize=15)
    plt.legend(prop={'size':10}, loc='lower right')

    plt.show()

def createClassificationReport(y_test, y_hat_test, name):
    '''Creates classification report, takes in actual y and predicted y along with nam
    returns a df of results'''
    report = classification_report(y_test, y_hat_test, output_dict=True)
    df = pd.DataFrame(report).transpose()
    df["SMOTE"] = name
    return df


def createConfusionMatrix2(model, X_train, y_train, y_hat_train, X_test,y_test, y_hat_
    '''Creates confusion matrix takes in results from classifer along with the actual
    plots 2 matrix, one with acutal #'s other normalized'''
    fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15,10))
    model_name = type(model).__name__

    #Plot Training Matrix
    plot_confusion_matrix(model, X_train, y_train, ax=axes[0,0], cmap='Blues', display
                          colorbar = False)
    cm_train = confusion_matrix(y_train, y_hat_train)
    #normalized
    plot_confusion_matrix(model, X_train, y_train, ax=axes[1,0],
                          cmap='Blues', display_labels=["Loyal","Churn"], normalize='t


    #Plot Training Matrix
    plot_confusion_matrix(model, X_test, y_test, ax=axes[0,1], cmap='Blues', display_
                          colorbar = False)
    cm_test = confusion_matrix(y_test, y_hat_test)
    #normalized
    plot_confusion_matrix(model, X_test, y_test, ax=axes[1,1],
                          cmap='Blues', display_labels=["Loyal","Churn"],normalize='tr

    axes[0,0].title.set_text(f'{model_name} Train')
    axes[0,1].title.set_text(f'{model_name} Test')
    axes[1,0].title.set_text(f'{model_name} Train')
    axes[1,1].title.set_text(f'{model_name} Test')


    plt.tight_layout()
    plt.show()

def createvisuals(df_classifiers,X_train,y_train,X_test,y_test, df_classifier_scores)
    '''Creates confusion matrix takes in results from classifer along with the actual
    plots all results from multiple classifiers and plots'''

    df_Reports = pd.DataFrame(columns=['precision', 'recall', 'f1-score', 'support',

    df_DataForPloting_ROC = pd.DataFrame(columns=['clf_name','modifiers' ,'dataset','
                                                  "SMOTE", 'recall', 'precision','df'

```

```
    for i in df_classifiers.index:

        clf = df_classifiers.loc[i]['clf']
        clf_name = df_classifiers.loc[i]['clf_name']

        print(clf_name)

        y_hat_train = clf.predict(X_train)
        y_hat_test = clf.predict(X_test)

        #Create Dataframe of results________________________________
        yhat_test_probs = clf.predict_proba(X_test)

        preds = clf.predict_proba(X_test)
        preds = pd.DataFrame(preds)
        preds.columns = ["Loyal_Prob", "Churn_Prob"]

        y_test.reset_index(drop=True, inplace=True)
        preds['churn'] = y_test
        preds['churn_Pred'] = y_hat_test
        preds['wrong'] = preds.apply(lambda x: 1 if x.churn - x.churn_Pred !=0 else 0
        preds['Correct?'] = preds['churn'] == preds['churn_Pred']

        preds.reset_index(drop=True, inplace=True)
        X_test.reset_index(drop=True, inplace=True)

        df_results = pd.concat([preds,X_test],axis=1)
        df_results
    #     ______________________________

        #Create Confusion Matrix
        createConfusionMatrix2(clf, X_train, y_train, y_hat_train, X_test,y_test, y_ha

        #Get ROC Datapoints, Store In Dataframe, One Rows for each classifier - Train

        # Train AUC #'s
        Auc_Train, fpr_Train, tpr_Train, thresholds_Train = createAUCReport(clf, X_tra

        # Train recall & precision #'s
        recall_train = round(recall_score(y_train, y_hat_train),2)
        precision_train = round(precision_score(y_train, y_hat_train),2)


        #insert training classifier#'s' into dataframe
        df_DataForPloting_ROC = df_DataForPloting_ROC.append({'fpr':fpr_Train, 'tpr':t
                                                              'dataset':"Train",'clf_n
                                                              'recall':recall_train,"p
                                                             'modifiers':"None"}, igno

        #Testing AUC #'s
        Auc_Test, fpr_Test, tpr_Test, thresholds_Test = createAUCReport(clf, X_test, y

        #Test recall & precision #'s
        recall_test = round(recall_score(y_test, y_hat_test),2)
        precision_test = round(precision_score(y_test, y_hat_test),2)


        #Insert Testing classifier#'s' into dataframe
        df_DataForPloting_ROC = df_DataForPloting_ROC.append({'fpr':fpr_Test, 'tpr':tp
                                                              'dataset':"Test", 'clf_n
                                                              'recall':recall_test,"pr
                                                             'modifiers':"None",'df':d
```

```
        df_DataForPloting_ROC_Current = df_DataForPloting_ROC[df_DataForPloting_ROC["c
        createROCCurve(df_DataForPloting_ROC_Current)

        #Create Classification Detail Report
        report = createClassificationReport(y_test, y_hat_test,"test")
        report["C"] = i
        df_Reports = df_Reports.append(report)

        display(Markdown('---'))

    df_DataForPloting_ROC.rename(columns={"clf_name": "clf_name1"}, inplace = True)

    # combine raw data with results
    df_All_classifierData = pd.concat([df_DataForPloting_ROC, df_classifier_scores], a

    # get just the test data
    df_All_classifierData_Test = df_All_classifierData[df_All_classifierData.dataset =

    #Get just the "Scores for test data"
    df_All_classifierScores_Test = df_All_classifierData_Test.drop(
        columns=['fpr', 'tpr', 'SMOTE', 'set', 'clf_name1'])
    #reorder Columns for the"Scores dataframe
    df_All_classifierScores_Test = df_All_classifierScores_Test[['clf_name', 'dataset
                                                                 'recall', 'prec
    return df_All_classifierData , df_All_classifierData_Test, df_All_classifierScores

def createDfsOFClassifiers(dictOfHyperParams):
    '''Creates a dict of classifier params and returns a data frame containing classif
    warnings.filterwarnings("ignore")
    classifiers = []


    pipe_knn = Pipeline([('clf',KNeighborsClassifier())])
    pipe_dt = Pipeline([('clf',DecisionTreeClassifier())])
    pipe_rf = Pipeline([('clf',RandomForestClassifier(random_state=0))])
    jobs = -1
    cv = 10

    Rgs_knn = GridSearchCV(estimator=pipe_knn,param_grid=dictOfHyperParams["hyp_params
    classifiers.append(("knn",Rgs_knn))

    Rgs_dt = GridSearchCV(estimator=pipe_dt,param_grid=dictOfHyperParams["hyp_params_d
    classifiers.append(("dt",Rgs_dt))

    Rgs_rf = GridSearchCV(estimator=pipe_rf,param_grid=dictOfHyperParams["hyp_params_r
    classifiers.append(("rf",Rgs_rf))
    return classifiers


def adjusted_classes(y_scores, t):
    """
    This function adjusts class predictions based on the prediction threshold (t).
    """
    # playing with thresholds to reduce recall
    #https://towardsdatascience.com/fine-tuning-a-classifier-in-scikit-learn-66e048c21

    return [1 if y >= t else 0 for y in y_scores]
```

Hyperparameter Grid

In [39]:

```
def paramScenarios(parmsNumber,dataNumber):
    dictOfHyperParams ={}
    '''Contains all the hyper params and columns to be used for each classifer by iter

# Initial iteration no tuning, select basic parameters for start
    if parmsNumber ==1:

        # Knn Params For Gridsearch
        hyp_params_knn = [{
            'clf__n_neighbors': [3]}]
        dictOfHyperParams.update({"hyp_params_knn":hyp_params_knn})

        # DT Params For Gridsearch
        hyp_params_dt = [{
            'clf__max_depth': [5],
            'clf__max_features': ["sqrt"],
            'clf__criterion': ['gini'],
            'clf__min_samples_split': [10]}]
        dictOfHyperParams.update( {"hyp_params_dt":hyp_params_dt})

        # RF Params For Gridsearch
        hyp_params_rf = [{'clf__criterion': ['entropy'],
          'clf__max_depth': [5],
          'clf__n_estimators': [150],
          'clf__min_samples_leaf':[50],
         'clf__max_features': ["sqrt"],
         'clf__random_state':[0]}]
        dictOfHyperParams.update( {"hyp_params_rf":hyp_params_rf})

# Still no changes in parameters, as changing SMOTE and features
    if parmsNumber ==2:

        # Knn Params For Gridsearch
        hyp_params_knn = [{
            'clf__n_neighbors': [3]}]
        dictOfHyperParams.update({"hyp_params_knn":hyp_params_knn})

        # DT Params For Gridsearch
        hyp_params_dt = [{
            'clf__max_depth': [5],
            'clf__max_features': ["sqrt"],
            'clf__criterion': ['gini'],
            'clf__min_samples_split': [10]}]
        dictOfHyperParams.update( {"hyp_params_dt":hyp_params_dt})

        # RF Params For Gridsearch
        hyp_params_rf = [{'clf__criterion': ['entropy'],
          'clf__max_depth': [5],
          'clf__n_estimators': [150],
          'clf__min_samples_leaf':[50],
         'clf__max_features': ["sqrt"],
         'clf__random_state':[0]}]
        dictOfHyperParams.update( {"hyp_params_rf":hyp_params_rf})

# Final tuning with SMOTE
    if parmsNumber ==3:
        # Knn Params For Gridsearch
        hyp_params_knn = [{
            'clf__metric': ['euclidean', 'manhattan'],
            'clf__n_neighbors': list(range(1,15)),
            'clf__weights': ['uniform', 'distance'],
```

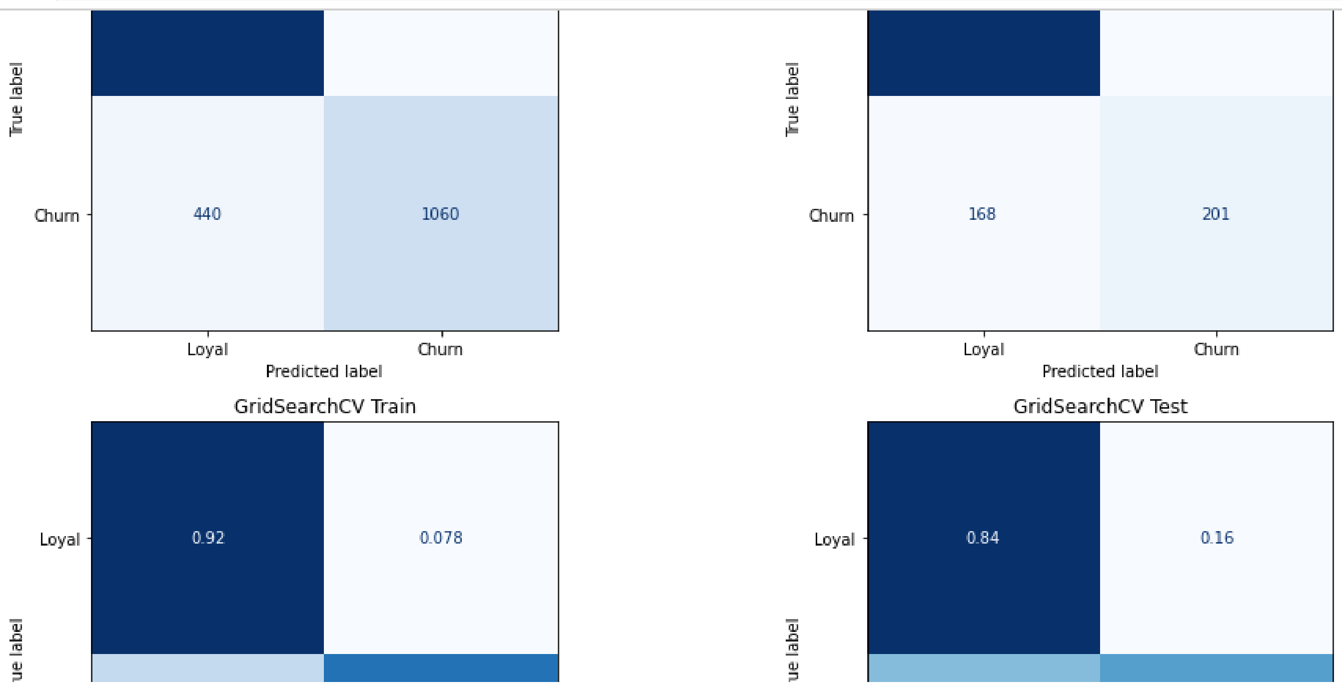
```
                'clf__p': [1, 2, 10]}]
        dictOfHyperParams.update({"hyp_params_knn":hyp_params_knn})

        # DT Params For Gridsearch
        hyp_params_dt = [{
            'clf__max_depth': [25, 50, 75],
            'clf__max_features': ["sqrt", "auto"],
            'clf__criterion': ['gini', 'entropy'],
            'clf__min_samples_split': [6, 10, 14]}]
        dictOfHyperParams.update({"hyp_params_dt":hyp_params_dt})

        # Rf Params For Gridsearch
        hyp_params_rf = [{
            'clf__criterion': ['gini'],
            'clf__max_depth': [1],
            'clf__n_estimators': [700],
            'clf__min_samples_split': [2, 3, 5],
            'clf__min_samples_leaf':[600],
            'clf__max_features': [.2],
            'clf__oob_score':[True],
            'clf__bootstrap': [True],
            'clf__random_state':[0]}]

        dictOfHyperParams.update({"hyp_params_rf":hyp_params_rf})


#___________________Setting Data Parameters


    if dataNumber == 1:
        #All data to start with
        colsToInclude = X.columns

    if dataNumber == 2:
        colsToInclude = ['tenure','PyM_Chk_E','IsrvcType_FO','Cntrct_M2M','ChrgTtls',
         'tenureSeg_>= 29M','TS_Y','StrTV_Y','StrMvs_Y','Sex_M','PlB_Y','PhSrv_Y','Ol
         'IsrvcType_No','Cntrct_2Yr','ChrgTtlsSeg_>= $1397M','65p_Y','tenureSeg_>= 55M
                         'ServCntSeg_>= 2Srvc','PyM_Chk_M']


    if dataNumber == 3:
        colsToInclude = ['tenure','PyM_Chk_E','IsrvcType_FO','Cntrct_M2M','ChrgTtls',
                         'tenureSeg_>= 29M','servCnt','TS_Y','StrTV_Y','StrMvs_Y','Se
                         'OlSec_Y','MLns_Y','Isrvc_Y','IsrvcType_No','Cntrct_2Yr','Ch
                         'tenureSeg_>= 55M','ServCntSeg_>= 4Srvc','ServCntSeg_>= 2Srv
    return dictOfHyperParams, colsToInclude

```

Create Models

Iteration 1 - Base Models

In [40]:

```python
# Get Data
X = df_wD.drop(columns=["Churn"])
y = df_wD["Churn"]


# paramScenarios(parmsNumber,dataNumber)
dictOfHyperParams, colsToInclude = paramScenarios(1,1)
classifiers = createDfsOFClassifiers(dictOfHyperParams)

#Create Line Between Printouts
display(Markdown('---'))

X1 = X[colsToInclude]

X_train, y_train, X_test, y_test = get_Scaled_TrainTestSplit_W_orWO_Smote(X1,y,"N")
display(Markdown('---'))

warnings.filterwarnings("ignore")
df_classifiers_I1 = pd.DataFrame(columns=['clf_name','clf'])
df_classifier_scores = pd.DataFrame(columns=['clf_name','set','mscore'])

for clf_name, classifier in classifiers:
    pipe = classifier
    pipe.fit(X_train, y_train)
    modelscore_Train = round(pipe.score(X_train, y_train),2)
    modelscore_Test = round(pipe.score(X_test, y_test),2)

    # Store classifiers and scoring into a dataframe for future use
    df_classifiers_I1 = df_classifiers_I1.append({'clf_name':clf_name, 'clf':classifie
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Tr
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Te

df_All_classifierData_I1 , df_All_classifierData_Test_I1, df_All_classifierScores_Test
```



Create/ Fit Classifiers using Pipeline/ Create Visuals

Review Train vs. Test Accuracy Scores For Overfitting </a

In [41]:
```python
df_All_classifierData_I1["Rnd"] = 1
df_All_classifierData_I1[["Rnd","clf_name","set","mscore","recall","precision"]]
```

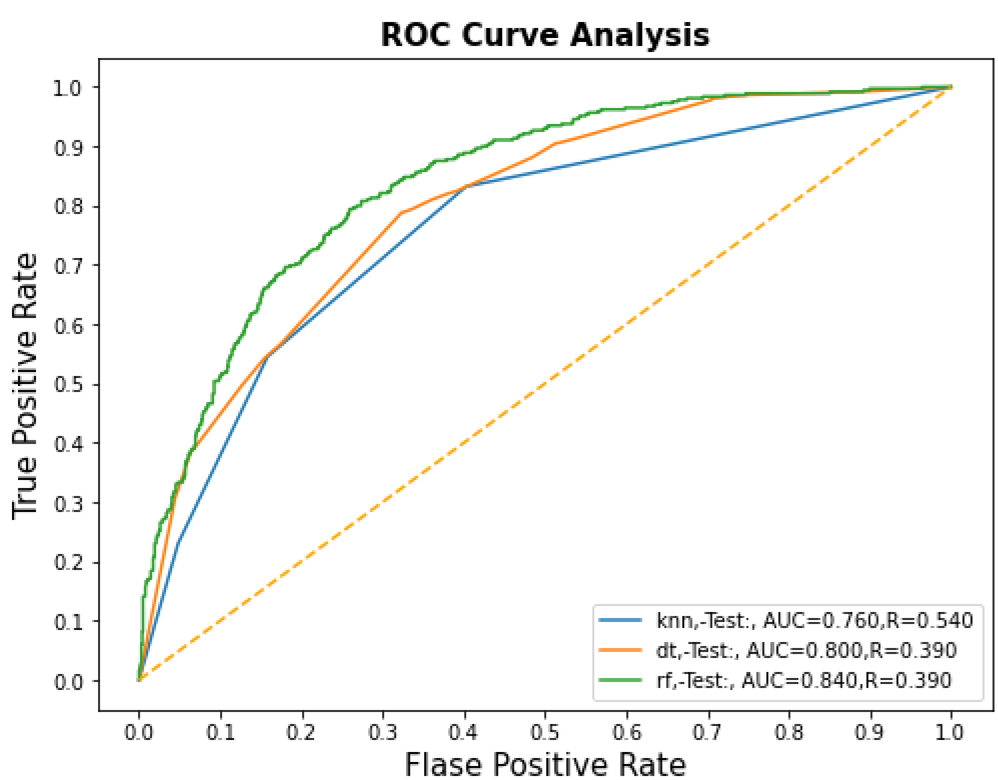
Out[41]:

	Rnd	clf_name	set	mscore	recall	precision
0	1	knn	Train	0.71	0.71	0.77
1	1	knn	Test	0.54	0.54	0.55
2	1	dt	Train	0.41	0.41	0.67
3	1	dt	Test	0.39	0.39	0.68
4	1	rf	Train	0.43	0.43	0.71
5	1	rf	Test	0.39	0.39	0.67

Veiw Test results only

In [42]:
```python
#sort both dataframes by recall for presentation
# View Scores
df_All_classifierScores_Test_I1 = df_All_classifierScores_Test_I1.sort_values(by="reca
print(df_All_classifierScores_Test_I1)

#View ROC
df_All_classifierData_Test_I1 = df_All_classifierData_Test_I1.sort_values(by="recall",
df_All_classifierData_Test_I1 = df_All_classifierData_Test_I1.reset_index(drop=True)
print()
createROCCurve(df_All_classifierData_Test_I1)
```

```
  clf_name dataset   auc  recall  precision  mscore modifiers
1      knn    Test  0.76    0.54       0.55    0.54      None
3       dt    Test  0.80    0.39       0.68    0.39      None
5       rf    Test  0.84    0.39       0.67    0.39      None
```



OBSERVATIONS:

- Inital Models Performing poorly (still without tuning or SMOTE), Recall Scores Range from 50-67
- Bigger problem is overfitting for all models, big gap between train and test mscores

Save all Iteration 1 Data

In [43]:

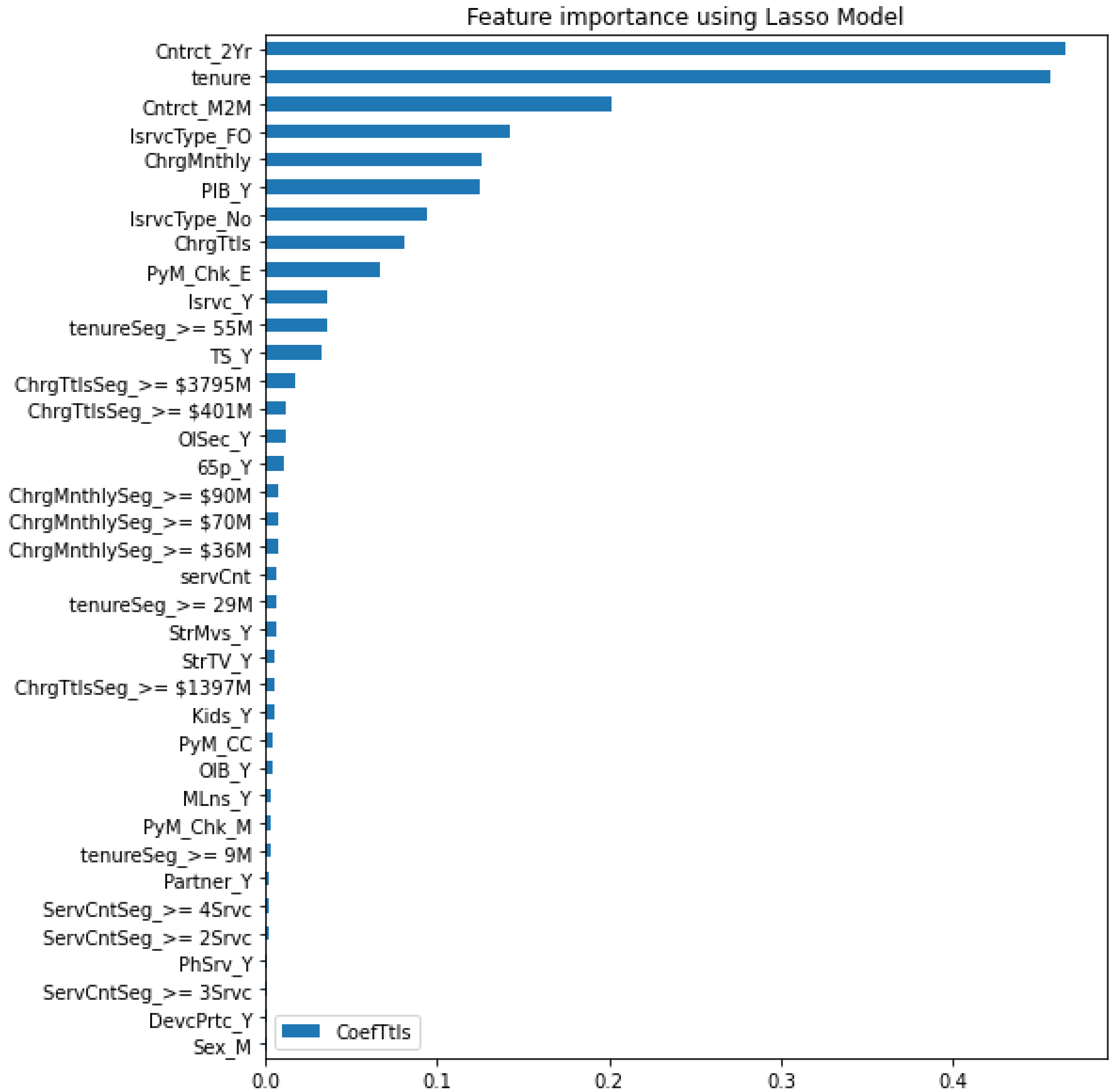
```
with open('./data/df_classifiers1.pickle', 'wb') as f:
    pickle.dump(df_classifiers_I1, f)

with open('./data/df_All_classifierData_I1.pickle', 'wb') as f:
    pickle.dump(df_All_classifierData_I1, f)

with open('./data/df_All_classifierScores_Test_I1.pickle', 'wb') as f:
    pickle.dump(df_All_classifierScores_Test_I1, f)
```

Iteration 2 - SMOTE & Feature Selection

Feature Selection using Iteration 1 Models (Feature_importance)

In [44]:

```python
# Get get and store important features from classifiers where possible
dictOfDfs_Importantfeatures = {}
for index, row in df_classifiers_I1.iterrows():
    clf = row['clf']
    xtest = row['X_test']
    clf_name = row['clf_name']
    if clf_name != "knn":
        df_feature_importances = pd.concat([pd.DataFrame(xtest.columns, columns = ["fe
                                            pd.DataFrame(np.transpose(clf.best_estimat
        df_feature_importances["coef"] = round(df_feature_importances["coef"],3)
        dfname = "df_{}".format(clf_name)
        dictOfDfs_Importantfeatures[dfname] = df_feature_importances

# Load Important features into dict then into dataframe
df_dt = dictOfDfs_Importantfeatures.get("df_dt")
df_dt.rename(columns={"coef": "dt"},inplace=True)
df_rf = dictOfDfs_Importantfeatures.get("df_rf")
df_rf.rename(columns={"coef": "rf"}, inplace=True)
df_All_ImportanceScores_I1 = df_dt.merge(df_rf, on="features")

# Get ranking of each coef from relevant models to aid in selecting "Top" features
df_All_ImportanceScores_I1['dt_rk'] = df_All_ImportanceScores_I1['dt'].rank(ascending=
df_All_ImportanceScores_I1['rf_rk'] = df_All_ImportanceScores_I1['rf'].rank(ascending=
df_All_ImportanceScores_I1['rk_avg'] = round(df_All_ImportanceScores_I1[['dt_rk', 'rf_


#select top x features
df_All_ImportanceScores_I1 = df_All_ImportanceScores_I1.sort_values(by="rk_avg", ascen
df_All_ImportanceScores_I1["CoefTtls"] = df_All_ImportanceScores_I1["dt"]+df_All_Impor
df_All_ImportanceScores_I1 = df_All_ImportanceScores_I1.reset_index(drop=True)
# df_All_ImportanceScores_I1

imp_coef = df_All_ImportanceScores_I1[['features','CoefTtls']]
imp_coef = imp_coef.sort_values(by="CoefTtls")
import matplotlib
matplotlib.rcParams['figure.figsize'] = (8.0, 10.0)
ax = imp_coef.plot(kind = "barh")
plt.title("Feature importance using Lasso Model")

# ax = freq_series.plot(kind='bar')
# ax.set_title('Amount Frequency')
# ax.set_xlabel('Amount ($)')
# ax.set_ylabel('Frequency')
ax.set_yticklabels(imp_coef['features']);
plt.show();
```


Feature importance using Lasso Model
Cntrct_2Yr
tenure
Cntrct_M2M
IsrvcType_FO
ChrgMnthly
PIB_Y
IsrvcType_No
ChrgTtls
PyM_Chk_E
Isrvc_Y
tenureSeg_>= 55M
TS_Y
ChrgTtlsSeg_>= $3795M
ChrgTtlsSeg_>= $401M
OlSec_Y
65p_Y
ChrgMnthlySeg_>= $90M
ChrgMnthlySeg_>= $70M
ChrgMnthlySeg_>= $36M
servCnt
tenureSeg_>= 29M
StrMvs_Y
StrTV_Y
ChrgTtlsSeg_>= $1397M
Kids_Y
PyM_CC
OlB_Y
MLns_Y
PyM_Chk_M
tenureSeg_>= 9M
Partner_Y
ServCntSeg_>= 4Srvc
ServCntSeg_>= 2Srvc
PhSrv_Y
ServCntSeg_>= 3Srvc
DevcPrtc_Y
Sex_M
CoefTtls
0.0
0.1
0.2
0.3
0.4

In [45]:

```
#Veiw Scores in df
df_All_ImportanceScores_I1
```

Out[45]:

	features	dt	rf	dt_rk	rf_rk	rk_avg	CoefTtls
0	tenure	0.297	0.160	2.0	2.0	2.00	0.457
1	Cntrct_2Yr	0.353	0.113	1.0	3.0	2.00	0.466
2	Cntrct_M2M	0.010	0.192	8.0	1.0	4.50	0.202
3	IsrvcType_FO	0.056	0.086	5.0	4.0	4.50	0.142
4	ChrgMnthly	0.069	0.057	4.0	7.0	5.50	0.126
5	PIB_Y	0.107	0.018	3.0	11.0	7.00	0.125
6	IsrvcType_No	0.055	0.039	6.0	8.0	7.00	0.094
7	ChrgTtls	0.005	0.076	10.5	5.0	7.75	0.081
8	PyM_Chk_E	0.001	0.066	16.0	6.0	11.00	0.067
9	TS_Y	0.026	0.007	7.0	16.0	11.50	0.033
10	65p_Y	0.005	0.006	10.5	19.0	14.75	0.011
11	ChrgTtlsSeg_>= $401M	0.007	0.005	9.0	21.5	15.25	0.012
12	Isrvc_Y	0.000	0.036	28.0	9.5	18.75	0.036
13	tenureSeg_>= 55M	0.000	0.036	28.0	9.5	18.75	0.036
14	servCnt	0.003	0.003	12.0	27.5	19.75	0.006
15	ChrgTtlsSeg_>= $1397M	0.001	0.004	16.0	23.5	19.75	0.005
16	ChrgTtlsSeg_>= $3795M	0.000	0.017	28.0	12.0	20.00	0.017
17	StrTV_Y	0.002	0.003	13.0	27.5	20.25	0.005
18	OlSec_Y	0.000	0.012	28.0	13.0	20.50	0.012
19	ChrgMnthlySeg_>= $90M	0.000	0.008	28.0	14.0	21.00	0.008
20	PyM_CC	0.001	0.003	16.0	27.5	21.75	0.004
21	ChrgMnthlySeg_>= $36M	0.000	0.007	28.0	16.0	22.00	0.007
22	ChrgMnthlySeg_>= $70M	0.000	0.007	28.0	16.0	22.00	0.007
23	tenureSeg_>= 29M	0.000	0.006	28.0	19.0	23.50	0.006
24	StrMvs_Y	0.000	0.006	28.0	19.0	23.50	0.006
25	Kids_Y	0.000	0.005	28.0	21.5	24.75	0.005
26	ServCntSeg_>= 2Srvc	0.001	0.001	16.0	34.5	25.25	0.002
27	ServCntSeg_>= 4Srvc	0.001	0.001	16.0	34.5	25.25	0.002
28	OIB_Y	0.000	0.004	28.0	23.5	25.75	0.004
29	tenureSeg_>= 9M	0.000	0.003	28.0	27.5	27.75	0.003
30	MLns_Y	0.000	0.003	28.0	27.5	27.75	0.003
31	PyM_Chk_M	0.000	0.003	28.0	27.5	27.75	0.003
32	Partner_Y	0.000	0.002	28.0	31.0	29.50	0.002
33	ServCntSeg_>= 3Srvc	0.000	0.001	28.0	34.5	31.25	0.001
34	DevcPrtc_Y	0.000	0.001	28.0	34.5	31.25	0.001
35	PhSrv_Y	0.000	0.001	28.0	34.5	31.25	0.001

	features	dt	rf	dt_rk	rf_rk	rk_avg	CoefTtls
36	Sex_M	0.000	0.001	28.0	34.5	31.25	0.001

In [46]:
```
#Place Top 15 importnat scores into a list
ls_Top_features_I1 = df_All_ImportanceScores_I1['features'][0:15].tolist()
ls_Top_features_I1
```

Out[46]:
```
['tenure',
 'Cntrct_2Yr',
 'Cntrct_M2M',
 'IsrvcType_FO',
 'ChrgMnthly',
 'PlB_Y',
 'IsrvcType_No',
 'ChrgTtls',
 'PyM_Chk_E',
 'TS_Y',
 '65p_Y',
 'ChrgTtlsSeg_>= $401M',
 'Isrvc_Y',
 'tenureSeg_>= 55M',
 'servCnt']
```

Feature Selection - Sk Learn

In [47]:
```
X = df_wD.drop(columns=["Churn"])
y = df_wD["Churn"]
```

Chi2

In [48]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
chi_selector = SelectKBest(chi2)
chi_selector.fit(X, y)
chi_support = chi_selector.get_support()
chi_feature = X.loc[:,chi_support].columns.tolist()
print(str(len(chi_feature)), 'selected features')
```

```
10 selected features
```

RFE

In [49]:
```
warnings.filterwarnings("ignore")
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
rfe_selector = RFE(estimator=LogisticRegression())
rfe_selector.fit(X, y)
rfe_support = rfe_selector.get_support()
rfe_feature = X.loc[:,rfe_support].columns.tolist()
print(str(len(rfe_feature)), 'selected features')
```

```
18 selected features
```

Embedded Log

In [50]:
```python
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import LogisticRegression

embeded_lr_selector = SelectFromModel(LogisticRegression(solver='liblinear',penalty="l
embeded_lr_selector.fit(X, y)

embeded_lr_support = embeded_lr_selector.get_support()
embeded_lr_feature = X.loc[:,embeded_lr_support].columns.tolist()
print(str(len(embeded_lr_feature)), 'selected features')
```

```
34 selected features
```

Embedded RF

In [51]:
```python
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestClassifier

embeded_rf_selector = SelectFromModel(RandomForestClassifier(n_estimators=100))
embeded_rf_selector.fit(X, y)

embeded_rf_support = embeded_rf_selector.get_support()
embeded_rf_feature = X.loc[:,embeded_rf_support].columns.tolist()
print(str(len(embeded_rf_feature)), 'selected features')
```

```
7 selected features
```

LGBM

In [52]:
```python
from sklearn.feature_selection import SelectFromModel
from lightgbm import LGBMClassifier

lgbc=LGBMClassifier(n_estimators=500, learning_rate=0.05, num_leaves=32, colsample_byt
            reg_alpha=3, reg_lambda=1, min_split_gain=0.01, min_child_weight=40)

embeded_lgb_selector = SelectFromModel(lgbc)
embeded_lgb_selector.fit(X, y)

embeded_lgb_support = embeded_lgb_selector.get_support()
embeded_lgb_feature = X.loc[:,embeded_lgb_support].columns.tolist()
print(str(len(embeded_lgb_feature)), 'selected features')
```

```
4 selected features
```

Summary Of Feature Selectors

In [53]:

```
# put all selection together
feature_name = X.columns

feature_selection_df = pd.DataFrame({'Feature':feature_name, 'RFE':rfe_support, 'Logis
                                     'Random Forest':embeded_rf_support, 'LightGBM':emb
feature_selection_df['Total'] = np.sum(feature_selection_df, axis=1)

feature_selection_df = feature_selection_df.sort_values(['Total','Feature'] , ascendin
feature_selection_df.index = range(1, len(feature_selection_df)+1)
feature_selection_df

# Select Top 15 Features
ColsToModel = feature_selection_df[:25]["Feature"].to_list()
# ColsToModel = feature_selection_df[:20]["Feature"].to_list()
```

In [54]:

```
# Columns to use in Rnd 2 and 3
ColsToModel
```

Out[54]:

```
['tenure',
 'PyM_Chk_E',
 'IsrvcType_FO',
 'Cntrct_M2M',
 'ChrgTtls',
 'ChrgMnthly',
 'tenureSeg_>= 9M',
 'tenureSeg_>= 29M',
 'servCnt',
 'TS_Y',
 'StrTV_Y',
 'StrMvs_Y',
 'Sex_M',
 'PlB_Y',
 'PhSrv_Y',
 'OlSec_Y',
 'MLns_Y',
 'IsrvcType_No',
 'Cntrct_2Yr',
 'ChrgTtlsSeg_>= $1397M',
 '65p_Y',
 'tenureSeg_>= 55M',
 'ServCntSeg_>= 4Srvc',
 'ServCntSeg_>= 2Srvc',
 'PyM_Chk_M']
```

*NOTE:

- Need To Manually Review Features and Cut and Paste Into Params Above

Create/ Fit Classifiers using Pipeline/ Create Visuals

In [55]:

```
# Get Data
X = df_wD.drop(columns=["Churn"])
y = df_wD["Churn"]


# paramScenarios(parmsNumber,dataNumber)
dictOfHyperParams, colsToInclude = paramScenarios(2,2)
classifiers = createDfsOFClassifiers(dictOfHyperParams)

#Create Line Between Printouts
display(Markdown('---'))

X1 = X[colsToInclude]

X_train, y_train, X_test, y_test = get_Scaled_TrainTestSplit_W_orWO_Smote(X1,y,"Y")
display(Markdown('---'))

warnings.filterwarnings("ignore")
df_classifiers_I2 = pd.DataFrame(columns=['clf_name','clf'])
df_classifier_scores = pd.DataFrame(columns=['clf_name','set','mscore'])

for clf_name, classifier in classifiers:
    pipe = classifier
    pipe.fit(X_train, y_train)
    modelscore_Train = round(pipe.score(X_train, y_train),2)
    modelscore_Test = round(pipe.score(X_test, y_test),2)

    # Store classifiers and scoring into a dataframe for future use
    df_classifiers_I2 = df_classifiers_I2.append({'clf_name':clf_name, 'clf':classifie
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Tr
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Te

df_All_classifierData_I2 , df_All_classifierData_Test_I2, df_All_classifierScores_Test
```

```
SMOTED
: 1    4125
0    4125
Name: Churn, dtype: int64
```

---

knn

Review Train vs. Test Accuracy Scores For Overfitting

In [56]:
```
df_All_classifierData_I2["Rnd"] = 2
df_All_classifierData_I2[["Rnd","clf_name","set","mscore","recall","precision"]]
```

Out[56]:

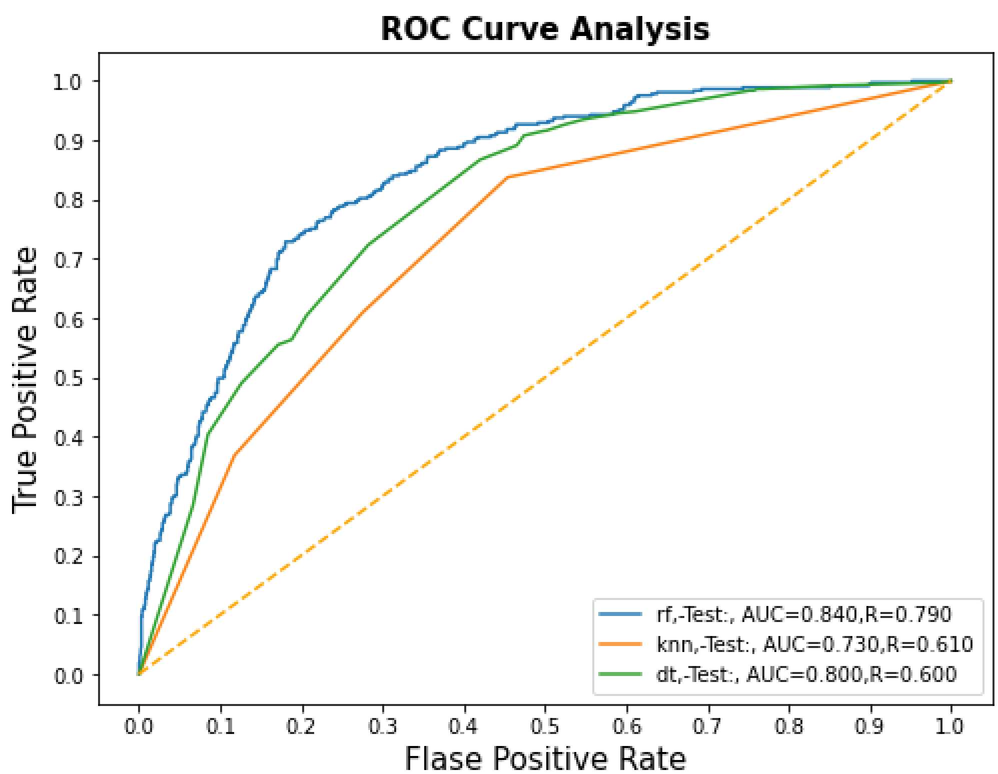
	Rnd	clf_name	set	mscore	recall	precision
0	2	knn	Train	0.97	0.97	0.86
1	2	knn	Test	0.61	0.61	0.44
2	2	dt	Train	0.71	0.71	0.77
3	2	dt	Test	0.60	0.60	0.51
4	2	rf	Train	0.86	0.86	0.77
5	2	rf	Test	0.79	0.79	0.52

Veiw Test results only

In [57]:

```
#sort both dataframes by recall for presentation
# View Scores
df_All_classifierScores_Test_I2 = df_All_classifierScores_Test_I2.sort_values(by="reca
print(df_All_classifierScores_Test_I2)

#View ROC
df_All_classifierData_Test_I2 = df_All_classifierData_Test_I2.sort_values(by="recall",
df_All_classifierData_Test_I2 = df_All_classifierData_Test_I2.reset_index(drop=True)
print()
createROCCurve(df_All_classifierData_Test_I2)
```

```
  clf_name dataset   auc  recall  precision  mscore modifiers
5       rf    Test  0.84    0.79       0.52    0.79      None
1      knn    Test  0.73    0.61       0.44    0.61      None
3       dt    Test  0.80    0.60       0.51    0.60      None
```



Review Train vs. Test Accuracy Scores For Overfitting, Side By Side with Round 1

In [58]:
```
df_Rnd1 = df_All_classifierData_I1[["Rnd","clf_name","set","mscore","recall","precisio
# df_Rnd1["Rnd"] = 1
df_Rnd2 = df_All_classifierData_I2[["Rnd","clf_name","set","mscore","recall","precisio

df_Rnd_12 = df_Rnd1.merge(df_Rnd2,on=["clf_name","set"])
df_Rnd_12
```

Out[58]:

	Rnd_x	clf_name	set	mscore_x	recall_x	precision_x	Rnd_y	mscore_y	recall_y	precision_y
0	1	knn	Train	0.71	0.71	0.77	2	0.97	0.97	0.86
1	1	knn	Test	0.54	0.54	0.55	2	0.61	0.61	0.44
2	1	dt	Train	0.41	0.41	0.67	2	0.71	0.71	0.77
3	1	dt	Test	0.39	0.39	0.68	2	0.60	0.60	0.51
4	1	rf	Train	0.43	0.43	0.71	2	0.86	0.86	0.77
5	1	rf	Test	0.39	0.39	0.67	2	0.79	0.79	0.52

OBSERVATIONS:

- After SMOTE and narrowing parametets, getting better scores than previous round of models (still without tuning), Recall Scores Range from 61-80
- However, overfitting for all models still a big issue

Observations:

Save all Iteration 2 Data

In [59]:
```
with open('./data/df_classifiers_I2.pickle', 'wb') as f:
    pickle.dump(df_classifiers_I2, f)

with open('./data/df_All_classifierData_I2.pickle', 'wb') as f:
    pickle.dump(df_All_classifierData_I2, f)

with open('./data/df_All_classifierScores_Test_I2.pickle', 'wb') as f:
    pickle.dump(df_All_classifierScores_Test_I2, f)
```

Iteration 3

Create/ Fit Classifiers using Pipeline/ Create Visuals

In [60]:

```
# Get Data
X = df_wD.drop(columns=["Churn"])
y = df_wD["Churn"]


# paramScenarios(parmsNumber,dataNumber)
dictOfHyperParams, colsToInclude = paramScenarios(3,3)
classifiers = createDfsOFClassifiers(dictOfHyperParams)

#Create Line Between Printouts
display(Markdown('---'))

X1 = X[colsToInclude]

X_train, y_train, X_test, y_test = get_Scaled_TrainTestSplit_W_orWO_Smote(X1,y,"Y")
display(Markdown('---'))

warnings.filterwarnings("ignore")
df_classifiers_I3 = pd.DataFrame(columns=['clf_name','clf'])
df_classifier_scores = pd.DataFrame(columns=['clf_name','set','mscore'])

for clf_name, classifier in classifiers:
    pipe = classifier
    pipe.fit(X_train, y_train)
    modelscore_Train = round(pipe.score(X_train, y_train),2)
    modelscore_Test = round(pipe.score(X_test, y_test),2)

    # Store classifiers and scoring into a dataframe for future use
    df_classifiers_I3 = df_classifiers_I3.append({'clf_name':clf_name, 'clf':classifie
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Tr
    df_classifier_scores = df_classifier_scores.append({'clf_name':clf_name, "set":"Te

df_All_classifierData_I3 , df_All_classifierData_Test_I3, df_All_classifierScores_Test
```

```
SMOTED
: 1    4125
0    4125
Name: Churn, dtype: int64
```

```
knn
```

Review Train vs. Test Accuracy Scores For Overfitting

In [61]:
```python
df_All_classifierData_I3["Rnd"] = 3
df_All_classifierData_I3[["Rnd","clf_name","set","mscore","recall","precision"]]
```

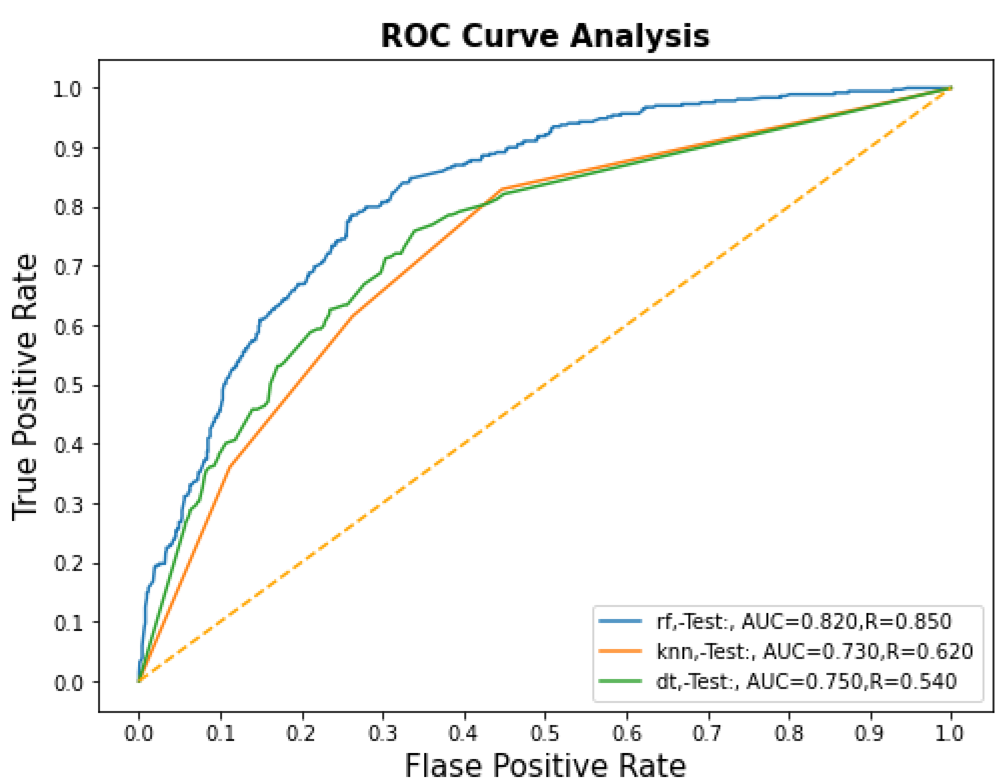
Out[61]:

	Rnd	clf_name	set	mscore	recall	precision
0	3	knn	Train	0.96	0.96	0.86
1	3	knn	Test	0.62	0.62	0.45
2	3	dt	Train	0.89	0.89	0.90
3	3	dt	Test	0.54	0.54	0.52
4	3	rf	Train	0.86	0.86	0.72
5	3	rf	Test	0.85	0.85	0.47

Veiw Test results only

In [62]:
```python
#sort both dataframes by recall for presentation
# View Scores
df_All_classifierScores_Test_I3 = df_All_classifierScores_Test_I3.sort_values(by="reca
print(df_All_classifierScores_Test_I3)

#View ROC
df_All_classifierData_Test_I3 = df_All_classifierData_Test_I3.sort_values(by="recall",
df_All_classifierData_Test_I3 = df_All_classifierData_Test_I3.reset_index(drop=True)
print()
createROCCurve(df_All_classifierData_Test_I3)
```

```
  clf_name dataset   auc  recall  precision  mscore modifiers
5       rf    Test  0.82    0.85       0.47    0.85      None
1      knn    Test  0.73    0.62       0.45    0.62      None
3       dt    Test  0.75    0.54       0.52    0.54      None
```



Review Train vs. Test Accuracy Scores For Overfitting, Side By Side with Round 1&2

In [63]:

```
df_Rnd3 = df_All_classifierData_I3[["Rnd","clf_name","set","mscore","recall","precisio

df_Rnd_123 = df_Rnd1.merge(df_Rnd2,on=["clf_name","set"]).merge(df_Rnd3,on=["clf_name"
df_Rnd_123
```

Out[63]:

	Rnd_x	clf_name	set	mscore_x	recall_x	precision_x	Rnd_y	mscore_y	recall_y	precision_y	Rnd	msc
0	1	knn	Train	0.71	0.71	0.77	2	0.97	0.97	0.86	3	(
1	1	knn	Test	0.54	0.54	0.55	2	0.61	0.61	0.44	3	(
2	1	dt	Train	0.41	0.41	0.67	2	0.71	0.71	0.77	3	(
3	1	dt	Test	0.39	0.39	0.68	2	0.60	0.60	0.51	3	(
4	1	rf	Train	0.43	0.43	0.71	2	0.86	0.86	0.77	3	(
5	1	rf	Test	0.39	0.39	0.67	2	0.79	0.79	0.52	3	(

Save all Iteration 3 Data

In [64]:

```
with open('./data/df_classifiers_I3.pickle', 'wb') as f:
    pickle.dump(df_classifiers_I3, f)

with open('./data/df_All_classifierData_I3.pickle', 'wb') as f:
    pickle.dump(df_All_classifierData_I3, f)

with open('./data/df_All_classifierScores_Test_I3.pickle', 'wb') as f:
    pickle.dump(df_All_classifierScores_Test_I3, f)
```

Final Results & Observations

In [65]:

```
df_Rnd_123a = df_Rnd_123[df_Rnd_123["clf_name"]=="rf"][["Rnd","clf_name","set","mscore
df_Rnd_123a
```

Out[65]:

	Rnd	clf_name	set	mscore	recall	precision
4	3	rf	Train	0.86	0.86	0.72
5	3	rf	Test	0.85	0.85	0.47

OBSERVATIONS:

- `Given past results, focused on tuning rf classifier, as you can see acheived a 84% recall score without overfitting.  mscores between train and test within a point`

Feature Importance

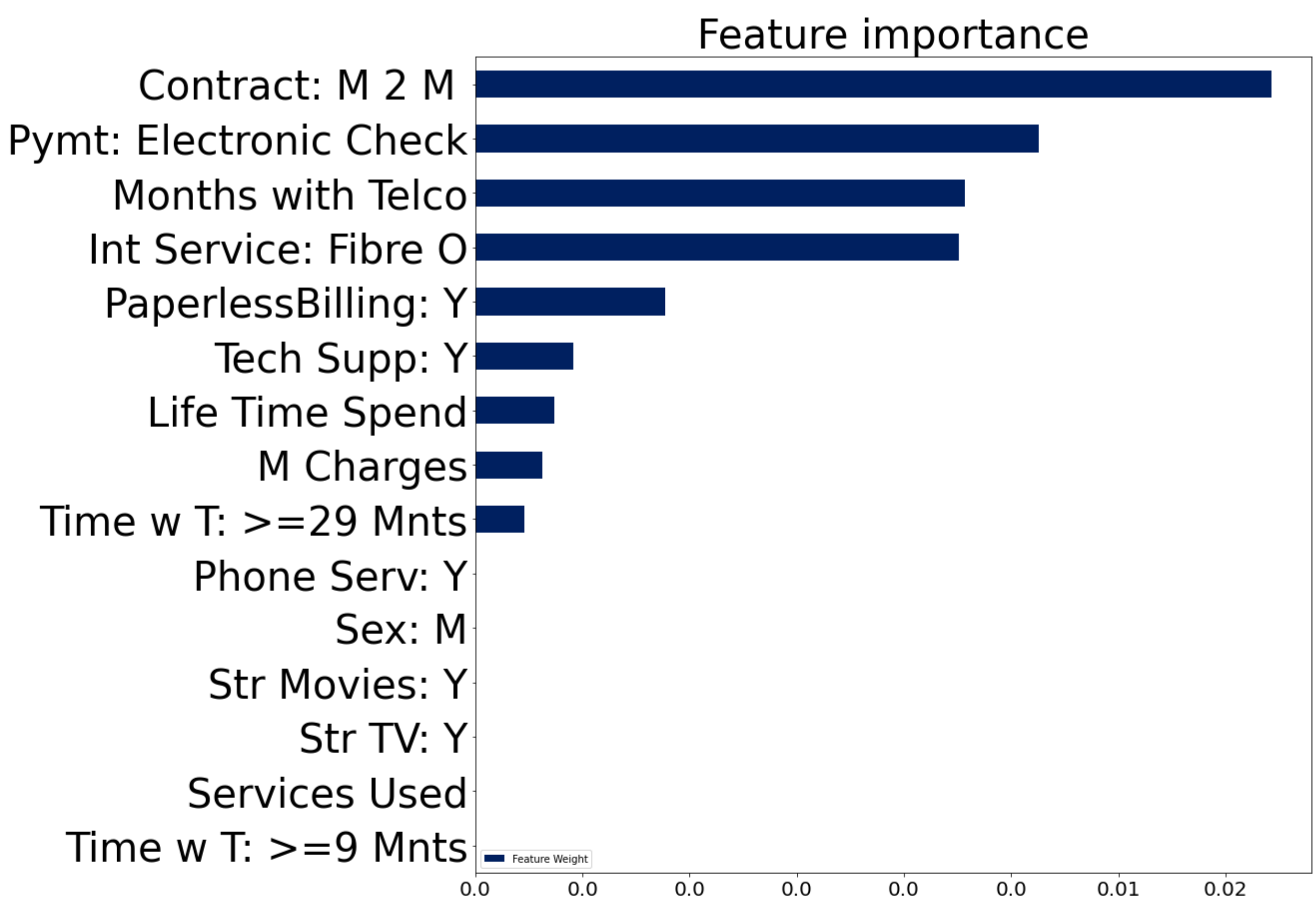
In [66]:

```
#get classifier from dataframe, stored above
clf = df_classifiers_I3.iloc[2]["clf"]
clf_name = df_classifiers_I3.iloc[2]["clf_name"]
xtest = df_classifiers_I3.iloc[2]["X_test"]
ytest = df_classifiers_I3.iloc[2]["y_test"]
print(clf_name)
```

```
rf
```

In [67]:

```
# Get and Print most important features
pipe = clf

# clf.best_estimator_.named_steps['clf'].feature_importances_


feature_importances = pd.concat([pd.DataFrame(xtest.columns, columns = ["features"]),
pd.DataFrame(np.transpose(pipe.best_estimator_.named_steps['clf'].feature_importances_
columns = ["coef"])],axis = 1)

feature_importances = feature_importances.merge(df_CleanCol_Names, on="features", how=
feature_importances_clean = feature_importances[["Name", "coef"]]
feature_importances_clean.sort_values("coef", ascending = False)
feature_importances_clean_shrt = feature_importances_clean[:15]
feature_importances_clean_shrt = feature_importances_clean_shrt.sort_values("coef", as

# import matplotlib
matplotlib.rcParams['figure.figsize'] = (15, 15)

ax = feature_importances_clean_shrt.plot(kind = "barh", color='#002060')
plt.title("Feature importance", size=40)
# ax = freq_series.plot(kind='bar')
# ax.set_title('Amount Frequency')
# ax.set_xlabel('Amount ($)')
# ax.set_ylabel('Frequency')
ax.set_yticklabels(feature_importances_clean_shrt['Name'], size=40);
ax.set_xticklabels(round(feature_importances_clean_shrt['coef'],2), size=20);
ax.legend(['Feature Weight'])
plt.show();
```



X Factor

- Visualizing Recall (TP) vs. Precision (FP) vs. Undetected Tradeoffs (FN)
- Also review impact of adjusting Tresholds on recall, precision metrics

In [68]:
```
with open('./data/df_classifiers_I3.pickle', 'rb') as f:
    df_classifiers_I3 = pickle.load(f)

with open('./data/df_All_classifierData_I3.pickle', 'rb') as f:
    df_All_classifierData_I3 = pickle.load(f)
```

In [69]:
```
#get classifier from dataframe, stored above
clf = df_classifiers_I3.iloc[2]["clf"]
clf_name = df_classifiers_I3.iloc[2]["clf_name"]
print(clf_name)
```

```
rf
```

In [71]:

```python
#get original dataset from train_test split associated with  clf above
df_Classifier_Data_specified = df_All_classifierData_I3[(df_All_classifierData_I3["clf
                                                        (df_All_classifierData_I3["dat

df_Preds_And_X_test_I3 = df_Classifier_Data_specified.iloc[0]["df"]
X_test_I3= df_Preds_And_X_test_I3.drop(columns=['Loyal_Prob', 'Churn_Prob', 'churn', '

y_test_I3 = df_Preds_And_X_test_I3["churn"]
y_hat_test_I3 = df_Preds_And_X_test_I3["churn_Pred"]


df_conf_Matrix_O = pd.DataFrame(confusion_matrix(y_test_I3, y_hat_test_I3), columns=['
df_conf_Matrix_ON = pd.DataFrame(confusion_matrix(y_test_I3, y_hat_test_I3,normalize='

print("Confusion Matrix with .5  Treshhold\n")
print(df_conf_Matrix_O)
print()
print(df_conf_Matrix_ON)
tn, fp, fn, tp = confusion_matrix(y_test_I3, y_hat_test_I3).ravel()

predictedChurnCnt = tp + fp

recall_test_I3 = round(recall_score(y_test_I3, y_hat_test_I3),2)
precision_test_I3 = round(precision_score(y_test_I3, y_hat_test_I3),2)
accuracy_test_I3 = round(accuracy_score(y_test_I3, y_hat_test_I3),2)

#adjust treshhold to in
y_score_I3 = clf.predict_proba(X_test_I3)[:, 1]

newthreshold = .47
y_hat_test_NewThreshold = adjusted_classes(y_score_I3, newthreshold)

df_conf_Matrix_th = pd.DataFrame(confusion_matrix(y_test_I3, y_hat_test_NewThreshold),
df_conf_Matrix_thN = pd.DataFrame(confusion_matrix(y_test_I3, y_hat_test_NewThreshold,

display(Markdown('---'))
print(f'Confusion Matrix with {newthreshold} Treshhold\n')
print(df_conf_Matrix_th)
print()
print(df_conf_Matrix_thN)
tn, fp, fn, tp = confusion_matrix(y_test_I3, y_hat_test_NewThreshold).ravel()

recall_test_Th = round(recall_score(y_test_I3, y_hat_test_NewThreshold),2)
precision_test_Th = round(precision_score(y_test_I3, y_hat_test_NewThreshold),2)
accuracy_test_Th = round(accuracy_score(y_test, y_hat_test_NewThreshold),2)
```

```
Confusion Matrix with .5  Treshhold

     pred_neg  pred_pos
neg       688       350
pos        56       313

     pred_neg  pred_pos
neg  0.662813  0.337187
pos  0.151762  0.848238
```

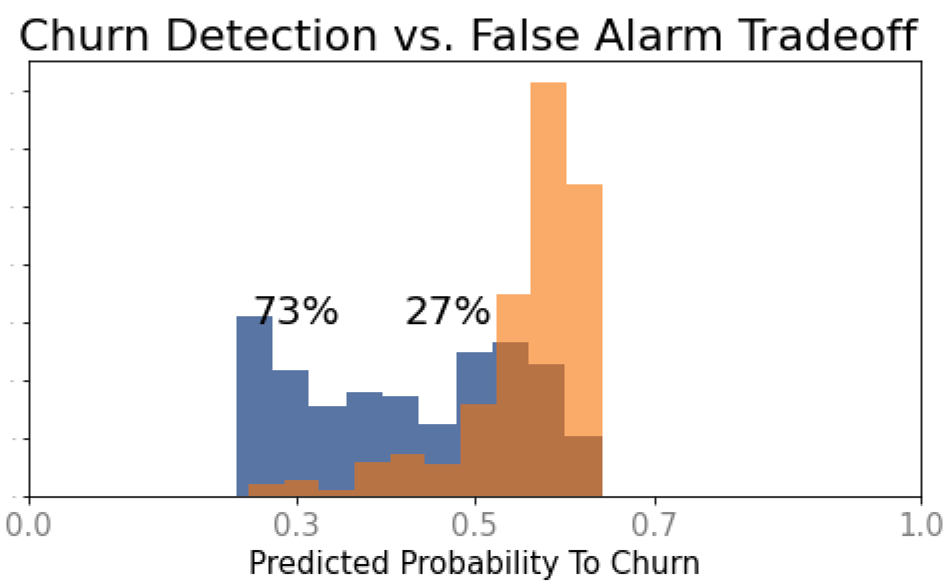
```
Confusion Matrix with 0.47 Treshhold

     pred_neg  pred_pos
neg       589       449
pos        41       328
```

In [72]:

```
df_Loyal = df_Preds_And_X_test_I3[df_Preds_And_X_test_I3["churn"]==0][["churn","Churn_
df_churn = df_Preds_And_X_test_I3[df_Preds_And_X_test_I3["churn"]==1][["churn","Churn_
```

In [73]:

```python
from matplotlib.ticker import PercentFormatter
plt.figure(figsize=(8,4))

ax = plt.gca()
ax.set_facecolor('w')

ax.grid(which='major', axis='y', linestyle='-', color='white', linewidth=0)
ax.grid(which='major', axis='x', linestyle='-', color='white', linewidth=0)

plt.rcParams['axes.facecolor'] = "w"
df_Loyal["Churn_Prob"].hist(bins=10, weights=np.ones_like(df_Loyal["Churn_Prob"]) / le
                             color='#5975A4', alpha=1, linewidth=2)
df_churn["Churn_Prob"].hist(bins=10, weights=np.ones_like(df_churn["Churn_Prob"]) / le
                             color='xkcd:Orange', alpha=0.6)
# organge #CC8963
#DD8452
# 'xkcd:Orange'
# red, green and blue + the transparency and it returns a color
# plt.xticks([.5], weight = 'bold')
#'xkcd:Orange'

plt.xticks([0,.3,.5,.7,1], size=15, color="grey")
plt.yticks(size=0)
plt.gca().yaxis.set_major_formatter(PercentFormatter(1, decimals=0))
# plt.legend(("Loyal", "Churn"),fontsize=20)
# ax.get_legend().remove()

ax.text(.25, .15, "73%",fontsize=20)
ax.text(.42 ,.15, "27%",fontsize=20)


# plt.ylabel('Percent Customers')
plt.xlabel('Predicted Probability To Churn', size=15);
plt.title('Churn Detection vs. False Alarm Tradeoff ', size=22)
plt.show();
```



Concluding Summary Observations

Business Comments

TOP 4 FEATURES PREDICTING CHURN:

- **1. Type Of Contract -** Month-Month contracts is single most predictive feature, this alings with previous analysis showing 89% of churners are in month-month contracts vs. longer term contracts
- **2. Type of Payment -** Using Electronic Payments is the second my significant feature, this aligns with previous reseach show 66% of churners pay electronically.
- **3. Months with Company -** The thrid most significant feature is Months with Telco. 75% of churn is occurring within 29 months of becoming a Telco customer.
- **4. Type of Internet Service -** The last of the top 4 , but equally as significate is being enrolled in the Fiber Optics program. 66% Churners are using Telcos Fiber Optics

Modeling Comments

OBSERVATIONS/ FUTURE STEPS:

- **1. Data Imbalance** Given imbalance, decided to SMOTE(Synthetic Minority Oversampling Technique) to improve classification.
- **2. Selection of Supervised Learning Classifiers** Initially I tried several different types of classifiers, ranging from Logistic Regression, Naive Bayes, Gradient Boost, Ada, and XGBoost. Ultimately, I decided to use **Knn, Decision Trees and Random Forest** , as these classifiers are non-parametric and are highly interpretable. Interpretability, the disproportionate number of categorical features, along with being able to avoid addressing multicollinearity were the most influential factors in selecting which classifiers to implement for this project.
- **3. Business Drivers: Churn Detection > False Alarms** Recommendations on model development were based on secondary research along with working knowledge on the disparity between the cost to acquire vs the cost to retain customers. In this hypothetical scenario, the CEO of Telco has asked me to place a particular focus on detection at the potential expense of unnecessary outreach activities.

- **3. Next Steps** Look to develop additional classifiers, ultimately place model into production.

In [ ]:

```
1
```