telco_churn_model

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1 Final Project Submission

Student name: David Boyd

Student pace: Self paced

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Instructor name: Abhineet

1.1 Business Objective

A telecommunications company wants to identify the leading factors of why a customer cancels their service. By understanding the factors which most strongly contribute to their churn rate they can set up work streams to help mitigate and reduce this effect over time, which will increase the LTV and overall ROI for the company.

1.2 Importing packages & EDA

[44]:
```
# Packages that I'm using to create the classification
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪StratifiedKFold
from sklearn.metrics import classification_report, precision_score,␣
 ↪recall_score, accuracy_score, f1_score
from sklearn.metrics import plot_confusion_matrix, confusion_matrix,␣
 ↪plot_roc_curve
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
 ↪GradientBoostingClassifier
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
 ↪FunctionTransformer
from sklearn.compose import ColumnTransformer
```

```python
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.linear_model import LogisticRegression


from xgboost import XGBClassifier

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImPipeline

import warnings
warnings.filterwarnings('ignore')
```

[45]:
```python
# Loads data into a DataFrame for investigation
df = pd.read_csv('data/telco_churn_data.csv')

df.head()
```

[45]:
```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day calls  \
0             yes                     25              265.1              110
1             yes                     26              161.6              123
2              no                      0              243.4              114
3              no                      0              299.4               71
4              no                      0              166.7              113

   total day charge  …  total eve calls  total eve charge  \
0             45.07  …               99             16.78
1             27.47  …              103             16.62
2             41.38  …              110             10.30
3             50.90  …               88              5.26
4             28.34  …              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
```

```
1             13.7                 3              3.70
2             12.2                 5              3.29
3              6.6                 7              1.78
4             10.1                 3              2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

[46]:
```python
# Checking what datatypes each column consists of
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

[47]:
```
# Converting target variable into an integer for ease of use later
df['churn'] = df['churn'].astype('int')
```

[48]:
```
#
df.describe()
```

[48]:
```
       account length    area code  number vmail messages  total day minutes  \
count     3333.000000  3333.000000            3333.000000        3333.000000
mean       101.064806   437.182418               8.099010         179.775098
std         39.822106    42.371290              13.688365          54.467389
min          1.000000   408.000000               0.000000           0.000000
25%         74.000000   408.000000               0.000000         143.700000
50%        101.000000   415.000000               0.000000         179.400000
75%        127.000000   510.000000              20.000000         216.400000
max        243.000000   510.000000              51.000000         350.800000

       total day calls  total day charge  total eve minutes  total eve calls  \
count      3333.000000       3333.000000        3333.000000      3333.000000
mean        100.435644         30.562307         200.980348       100.114311
std          20.069084          9.259435          50.713844        19.922625
min           0.000000          0.000000           0.000000         0.000000
25%          87.000000         24.430000         166.600000        87.000000
50%         101.000000         30.500000         201.400000       100.000000
75%         114.000000         36.790000         235.300000       114.000000
max         165.000000         59.640000         363.700000       170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls        churn
```

```
count      3333.000000            3333.000000  3333.000000
mean          2.764581               1.562856     0.144914
std           0.753773               1.315491     0.352067
min           0.000000               0.000000     0.000000
25%           2.300000               1.000000     0.000000
50%           2.780000               1.000000     0.000000
75%           3.270000               2.000000     0.000000
max           5.400000               9.000000     1.000000
```

[49]:
```
df.isna().sum()
```

[49]:
```
state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

[50]:
```
# Creating area code into a categorical variable, instead of int as it's more␣
↪applicable
df['area code'] = df['area code'].astype('str')
```

[51]:
```
df.churn.value_counts()
```

[51]:
```
0    2850
1     483
Name: churn, dtype: int64
```

Looking at the above we can see that this dataset is imbalanced, therefore in the process to maximise the model performance on unseen data we'll have to utilise a resampling method on the training set.

[52]:
```
# observing how many and what different options are available for the␣
↪categorical features
df_obj_cols = df.select_dtypes(include='object')

for col in df_obj_cols:
    print(f'{col.title()} has the following different values: {df[col].
↪unique()}')
    print(f'There are {df[col].nunique()} options for the {col.title()} feature')
```

```
State has the following different values: ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO'
'LA' 'WV' 'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']
There are 51 options for the State feature
Area Code has the following different values: ['415' '408' '510']
There are 3 options for the Area Code feature
Phone Number has the following different values: ['382-4657' '371-7191'
'358-1921' … '328-8230' '364-6381' '400-4344']
There are 3333 options for the Phone Number feature
International Plan has the following different values: ['no' 'yes']
There are 2 options for the International Plan feature
Voice Mail Plan has the following different values: ['yes' 'no']
There are 2 options for the Voice Mail Plan feature
```

Looking at the above columns, it is clear that while we have been give a phone number, since these are all unique, this isn't going to have any influence over whether a customer has churned or not, therefore the next steps will be to drop this column.

After this, looking at our brief exploratory data above there are a few different steps to complete before the data is ready to be passed into a model. These are: - One hot encode all of the categorical columns - Normalize all of the numerical columns - Account for the class imbalance within the target data by using SMOTE

Once these steps have been completed the data should be ready to pass into our proposed models

1.3 Setting up datasets for model testing

[53]:
```
# Removing phone number as it'll lead to overfitting given each number is unique
X = df.drop(columns=['churn', 'phone number'], axis=1)

# Selecting target variable
y = df.churn
```

[54]:
```
# Splitting the data for model testing
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪stratify=y, random_state=42)
```

1.4 Useful Functions

Below I've created a few functions that are useful when it comes to building out the model. The first is focused on adding additional features through feature engineering to enrich the dataset

[55]:
```
def additional_churn_features(X):

    X['total_calls'] = X['total day calls'] + X['total eve calls'] + X['total␣
↪night calls'] + X['total intl calls']
    X['total_charges'] = X['total day charge'] + X['total eve charge'] +␣
↪X['total night charge'] + X['total intl charge']
    X['total_minutes'] = X['total day minutes'] + X['total eve minutes'] +␣
↪X['total night minutes'] + X['total intl minutes']
    X['pct_intl_calls'] = X['total intl calls'] / X['total_calls']
    X['pct_domestic_calls'] = 1 - X['pct_intl_calls']
    X['pct_intl_minutes'] = X['total intl minutes'] / X['total_minutes']
    X['pct_intl_charges'] = X['total intl charge'] / X['total_charges']
    X['avg_mins_per_call_day'] = X['total day minutes'] / X['total day calls']
    X['avg_mins_per_call_eve'] = X['total eve minutes'] / X['total eve calls']
    X['avg_mins_per_call_night'] = X['total night minutes'] / X['total night␣
↪calls']

    X.fillna(method='bfill', inplace=True)

    return X
```

[56]:
```
def preparing_model_pipeline(X, model=DecisionTreeClassifier, grid=None,␣
↪score='f1', booster=None):
     '''
     This function takes a dataset, a model to instantiate if provided and a grid
     which then creates a sklearn pipeline to perform the following steps:
     - Adding additional features to the dataset
     - OHE all categorical features
     - Scaling all numeric columns
     - performing SMOTE to account for class imbalance
     - Instantiating the model

     If grid is provided, it then performs the relevant gridsearch function
     '''
      # feature engineering
     feat_eng_transformer = FunctionTransformer(additional_churn_features,␣
↪validate=False)
```

```
    # OHE
    cat_features = X.select_dtypes(exclude=[np.number]).columns.tolist()
    cat_col_transformer = ColumnTransformer(transformers=[
     ("ohe", OneHotEncoder(handle_unknown='ignore', sparse=True),␣
↪cat_features)], remainder="passthrough")


    # SMOTE & StandardScaler
    if booster == None:
        imb_pipe = ImPipeline(steps=[('feat_eng', feat_eng_transformer),
                              ('cat_ohe', cat_col_transformer),
                              ('sscaler', StandardScaler(with_mean=False)),
                              ('smote', SMOTE(random_state=42)),
                              ('model', model(random_state=42))
                              ])
    else:
        imb_pipe = ImPipeline(steps=[('feat_eng', feat_eng_transformer),
                              ('cat_ohe', cat_col_transformer),
                              ('sscaler', StandardScaler(with_mean=False)),
                              ('smote', SMOTE(random_state=42)),
                             ('model', model(random_state=42, booster=booster))
                              ])


    if grid == None:
       return imb_pipe

    else:

        stratified_kfold = StratifiedKFold(n_splits=3,
                                           shuffle=True,
                                           random_state=42)

        gridsearch = GridSearchCV(estimator=imb_pipe,
                         param_grid=grid,
                         scoring=score,
                         cv=stratified_kfold)

        return gridsearch
```

1.5 Set up baseline performance for all models

In the code below we create a dataframe to show what performance looks like across a range of different classifier models at a baseline level, this will allow us to select a few to look at hypertuning using the GridSearchCV method

[57]:
```python
model_list = [DecisionTreeClassifier, RandomForestClassifier,␣
 ↪LogisticRegression,
              AdaBoostClassifier, GradientBoostingClassifier, XGBClassifier]
model_performance = []
for model in model_list:
    inner_list = []
    inner_list.append(f'{str(model).split(".")[-1][:-2]}')

    result = preparing_model_pipeline(X_train, model)

    fitted_model = result.fit(X_train, y_train)

    recall_train = recall_score(y_train, fitted_model.predict(X_train))
    recall_test = recall_score(y_test, fitted_model.predict(X_test))
    inner_list.append(recall_train)
    inner_list.append(recall_test)

    f1_train = f1_score(y_train, fitted_model.predict(X_train))
    f1_test = f1_score(y_test, fitted_model.predict(X_test))
    inner_list.append(f1_train)
    inner_list.append(f1_test)

    model_performance.append(inner_list)

    #print(f'This is a {model} model')
   #print(classification_report(y_test, fitted_model.predict(X_test), digits=3))

base_model_df = pd.DataFrame(model_performance, columns= ['model_name',␣
 ↪'recall_train', 'recall_test', 'f1_train', 'f1_test'])

base_model_df
```

[57]:

	model_name	recall_train	recall_test	f1_train	f1_test
0	DecisionTreeClassifier	1.000000	0.820690	1.000000	0.725610
1	RandomForestClassifier	1.000000	0.744828	1.000000	0.791209
2	LogisticRegression	0.766272	0.662069	0.516451	0.446512
3	AdaBoostClassifier	0.730769	0.648276	0.704708	0.620462
4	GradientBoostingClassifier	0.875740	0.813793	0.933754	0.877323
5	XGBClassifier	1.000000	0.834483	1.000000	0.886447

Looking at the above, we'll select the following models to tune further: - DecisionTreeClassifier - RandomForestClassifier - XGBClassifier

These will run through a grid search and return both the best parameters for performance metrics, targetting the f1 metric

[15]:
```
grid_dt =[{'model__criterion': ['gini', 'entropy'],
    'model__max_depth': [None, 5, 10, 15, 20],
    'model__max_features': [None, 10,  5, 15],
    'model__min_samples_split': [2, 5, 10],
    'model__min_samples_leaf': [1, 2, 5]}]

tuned_decision_model = preparing_model_pipeline(X_train, grid=grid_dt)

fitted_tuned_dt = tuned_decision_model.fit(X_train, y_train)

fitted_tuned_dt.best_params_
```

[15]:
```
{'model__criterion': 'gini',
 'model__max_depth': 5,
 'model__max_features': None,
 'model__min_samples_leaf': 1,
 'model__min_samples_split': 2}
```

[16]:
```
pd.DataFrame(classification_report(y_test, fitted_tuned_dt.predict(X_test),␣
 ↪digits=3, output_dict=True)).transpose()
```

[16]:

	precision	recall	f1-score	support
0	0.953462	0.982456	0.967742	855.000
1	0.873950	0.717241	0.787879	145.000
accuracy	0.944000	0.944000	0.944000	0.944
macro avg	0.913706	0.849849	0.877810	1000.000
weighted avg	0.941933	0.944000	0.941662	1000.000

[17]:
```
grid_rf ={
    'model__n_estimators': [100, 150],
    'model__criterion': ['entropy', 'gini'],
    'model__max_depth': [3, 7],
    'model__max_features': [5, 10, 15],
    'model__min_samples_split': [10, 20, 50],
    'model__min_samples_leaf': [1, 2, 4]
            }
tuned_rforest_model = preparing_model_pipeline(X_train,␣
 ↪model=RandomForestClassifier, grid=grid_rf)

fitted_tuned_rf = tuned_rforest_model.fit(X_train, y_train)

fitted_tuned_rf.best_params_
```

[17]:
```
{'model__criterion': 'entropy',
 'model__max_depth': 7,
 'model__max_features': 15,
 'model__min_samples_leaf': 4,
```

```
 'model__min_samples_split': 10,
 'model__n_estimators': 100}
```

[18]:
```
pd.DataFrame(classification_report(y_test, fitted_tuned_rf.predict(X_test),␣
 ↪digits=3, output_dict=True)).transpose()
```

[18]:

	precision	recall	f1-score	support
0	0.968531	0.971930	0.970228	855.000
1	0.830986	0.813793	0.822300	145.000
accuracy	0.949000	0.949000	0.949000	0.949
macro avg	0.899759	0.892861	0.896264	1000.000
weighted avg	0.948587	0.949000	0.948778	1000.000

[58]:
```
grid_xgb = {
    'model__learning_rate': [0.1, 0.2],
    'model__max_depth': [6],
    'model__min_child_weight': [1, 2],
    'model__subsample': [0.5, 0.7],
    'model__n_estimators': [100],
}

tuned_xgboost_model = preparing_model_pipeline(X_train, model=XGBClassifier,␣
 ↪grid=grid_xgb, score='recall', booster='gbtree')

tuned_xgboost_model.fit(X_train, y_train)

tuned_xgboost_model.best_params_
```

[58]:
```
{'model__learning_rate': 0.1,
 'model__max_depth': 6,
 'model__min_child_weight': 1,
 'model__n_estimators': 100,
 'model__subsample': 0.7}
```

[59]:
```
pd.DataFrame(classification_report(y_test, tuned_xgboost_model.predict(X_test),␣
 ↪digits=3, output_dict=True)).transpose()
```

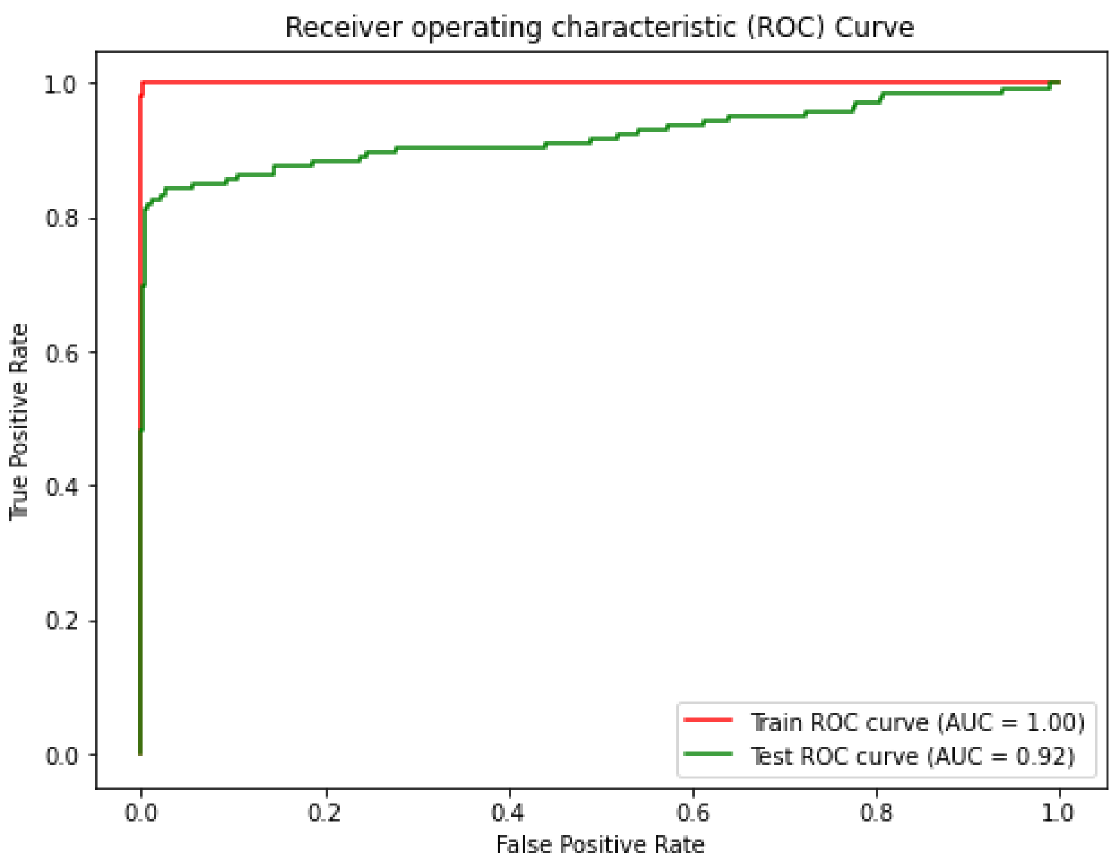
[59]:

	precision	recall	f1-score	support
0	0.969213	0.994152	0.981524	855.000
1	0.959350	0.813793	0.880597	145.000
accuracy	0.968000	0.968000	0.968000	0.968
macro avg	0.964281	0.903973	0.931061	1000.000
weighted avg	0.967783	0.968000	0.966890	1000.000

Now we've performed the tuning on each model, it appears that the best tradeoff between recall and f1-score is with our XGBoostClassifier model. As a result, below we'll produce a few different plots.

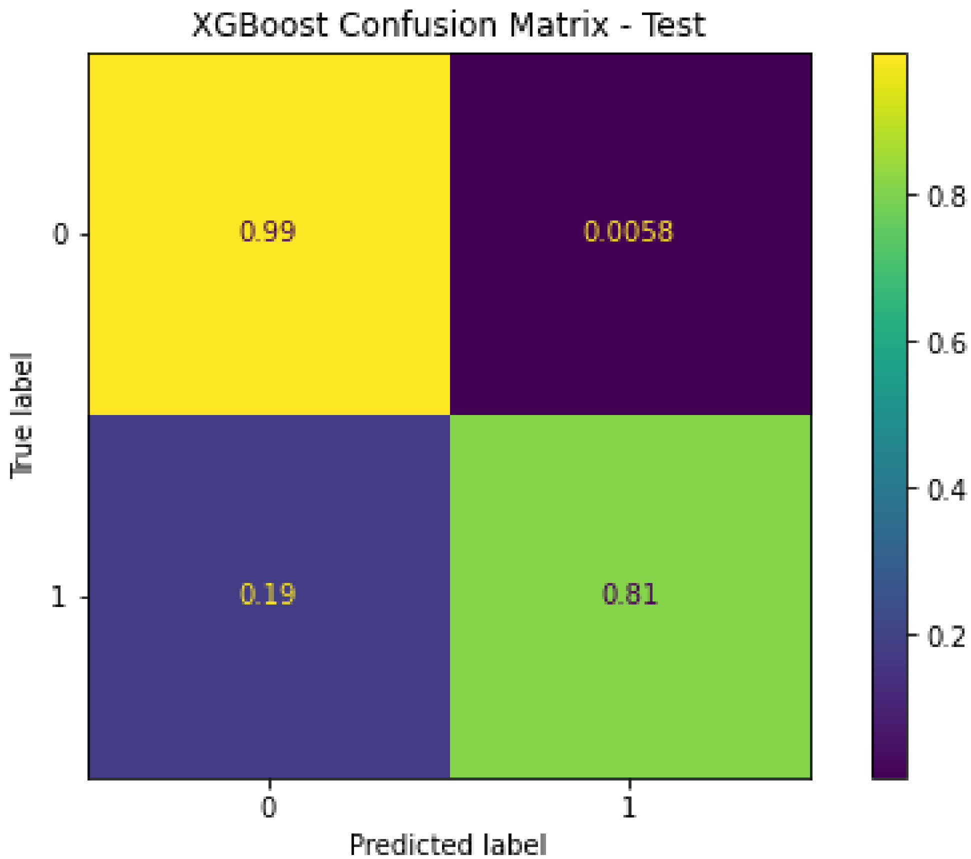
The first will be plotting our AUC-ROC curve After that we want to plot the confusion matrix on our test dataset

[60]:
```
fig, ax2 = plt.subplots(figsize=(8,6))
plot_roc_curve(tuned_xgboost_model, X_train, y_train, ax=ax2, name ='Train ROC␣
 ↪curve', color='r')
plot_roc_curve(tuned_xgboost_model, X_test, y_test, ax=ax2, name ='Test ROC␣
 ↪curve', color='g')
ax2.set_xlabel('False Positive Rate')
ax2.set_ylabel('True Positive Rate')
ax2.set_title('Receiver operating characteristic (ROC) Curve')
plt.show();
```



[61]:
```
fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(tuned_xgboost_model, X_test, y_test, ax=ax,␣
 ↪normalize='true')
ax.set_title("XGBoost Confusion Matrix - Test");
```



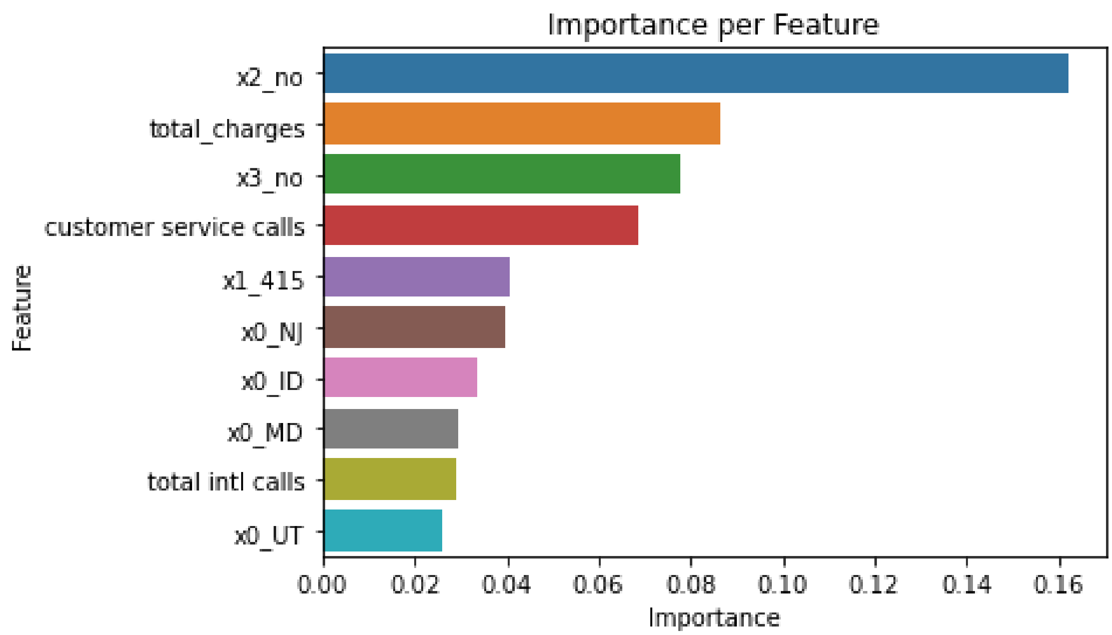
Below we look to extract the name of the features which have the highest importance in the selected model, to highlight these back to our stakeholders for areas that need further investigation

[62]:
```
# Identifying which features have the highest level of importance

feat_import_array = tuned_xgboost_model.estimator.fit(X_train, y_train).
↪steps[4][1].feature_importances_
```

[67]:
```
imp_features = pd.DataFrame(pd.Series(feat_import_array, index=X_train_df.
↪columns).sort_values(ascending=False))
imp_features = imp_features.head(10)
imp_features['index'] = imp_features.index
imp_features.head()

ax = sns.barplot(x=imp_features[0], y=imp_features['index'], data=imp_features)
ax.set_xlabel('Importance')
ax.set_ylabel('Feature')
ax.set_title('Importance per Feature');
```



1.6 Section to be removed (Code used to preprocess without a pipeline)

The below code is used in the section above to extract the correct column names for feature importance. As we've combined our model into the pipeline, it doesn't currently extract the DataFrame with the preprocessed features for more efficient code.

[63]:
```
X_train_cat = X_train.select_dtypes(include='object')

ohe = OneHotEncoder(handle_unknown='ignore', sparse=False)

X_train_cat_encoded = ohe.fit_transform(X_train_cat)
X_train_cat_encoded_df = pd.DataFrame(X_train_cat_encoded,
                        columns=ohe.get_feature_names(),
                        index=X_train_cat.index)
X_train_cat_encoded_df.shape
```

[63]: (2333, 58)

[64]:
```
X_train_cat_encoded_df
```

[64]:

	x0_AK	x0_AL	x0_AR	x0_AZ	x0_CA	x0_CO	x0_CT	x0_DC	x0_DE	x0_FL	\
606	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2468	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1844	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3187	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

```
3083    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
…     …    …    …    …    …    …    …    …    …    …
2670    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2165    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2988    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
179     0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2762    0.0    0.0    0.0    0.0    0.0    0.0    0.0    1.0    0.0    0.0

      …  x0_WI  x0_WV  x0_WY  x1_408  x1_415  x1_510  x2_no  x2_yes  x3_no  \
606   …    0.0    0.0    0.0     0.0     1.0     0.0    1.0     0.0    1.0
2468  …    0.0    1.0    0.0     0.0     0.0     1.0    0.0     1.0    0.0
1844  …    0.0    0.0    0.0     0.0     0.0     1.0    1.0     0.0    0.0
3187  …    0.0    1.0    0.0     1.0     0.0     0.0    1.0     0.0    0.0
3083  …    0.0    0.0    0.0     0.0     0.0     1.0    1.0     0.0    1.0
…    …    …    …    …    …    …    …    …    …    …
2670  …    0.0    0.0    1.0     0.0     0.0     1.0    1.0     0.0    0.0
2165  …    0.0    0.0    0.0     0.0     1.0     0.0    1.0     0.0    1.0
2988  …    0.0    0.0    0.0     0.0     1.0     0.0    1.0     0.0    1.0
179   …    0.0    0.0    0.0     1.0     0.0     0.0    1.0     0.0    1.0
2762  …    0.0    0.0    0.0     1.0     0.0     0.0    1.0     0.0    1.0

      x3_yes
606      0.0
2468     1.0
1844     1.0
3187     1.0
3083     0.0
…       …
2670     1.0
2165     0.0
2988     0.0
179      0.0
2762     0.0

[2333 rows x 58 columns]
```

[65]:

```
X_train_clean = X_train.drop(columns=X_train_cat.columns.values, axis=1)
X_train_df = pd.concat([X_train_cat_encoded_df, X_train_clean], axis=1)

X_train_df
```

[65]:

```
      x0_AK  x0_AL  x0_AR  x0_AZ  x0_CA  x0_CO  x0_CT  x0_DC  x0_DE  x0_FL  \
606     0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2468    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
1844    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
3187    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
3083    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
```

```
…     …    …    …    …    …    …    …    …    …    …
2670    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2165    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2988    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
179     0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
2762    0.0    0.0    0.0    0.0    0.0    0.0    0.0    1.0    0.0    0.0

      …  total_calls  total_charges  total_minutes  pct_intl_calls  \
606   …          329          57.67          571.3        0.024316
2468  …          306          60.01          650.3        0.006536
1844  …          296          56.33          599.4        0.010135
3187  …          259          70.27          702.2        0.015444
3083  …          387          69.77          707.0        0.012920
…   …            …              …              …               …
2670  …          312          60.90          560.0        0.019231
2165  …          319          61.33          605.9        0.009404
2988  …          234          72.22          668.9        0.021368
179   …          346          73.36          725.6        0.000000
2762  …          272          32.89          394.4        0.014706

      pct_domestic_calls  pct_intl_minutes  pct_intl_charges  \
606             0.975684          0.022930          0.061384
2468            0.993464          0.006612          0.019330
1844            0.989865          0.019186          0.055210
3187            0.984556          0.007690          0.020777
3083            0.987080          0.017680          0.048445
…                    …                 …                 …
2670            0.980769          0.016071          0.039901
2165            0.990596          0.021456          0.057231
2988            0.978632          0.017940          0.044863
179             1.000000          0.000000          0.000000
2762            0.985294          0.024087          0.078139

      avg_mins_per_call_day  avg_mins_per_call_eve  avg_mins_per_call_night
606                1.172269               2.755238                 1.334021
2468               1.146875               2.975000                 2.670000
1844               1.161538               2.397059                 2.804054
3187               5.297500               3.610526                 1.514388
3083               2.180556               0.995105                 2.417557
…                       …                      …                        …
2670               2.046296               1.279661                 2.237500
2165               1.662136               2.012397                 1.936957
2988               2.701042               1.806186                 6.177778
179                1.902459               2.609821                 1.796429
2762               0.572222               1.673469                 2.117500

[2333 rows x 83 columns]
```

1.7 Summary & Main results

From the feature importance chart above, we can see the areas that have the biggest influence on customer churn are: - Not having an international plan in their account - Not having a voice mail plan in their account - The total charges per account - The number of contacts being made to customer services

To set up a clear list of actions for the company, it is now worth performing a more thorough and in depth EDA around those features to identify what thresholds the business wants to set for their operations teams to try and achieve with the goal of reducing overall customer churn.

After these features, we can also see from the dataset that specific area codes and states have a higher influence than others. While it might be worth investigating this aspect, it is worth having caution what actions can be made around this discovery.