index

October 23, 2020

[1]:
```
from my_funct import confusion_matrix_info, load_clean_data,␣
↪create_plot_of_feature_importances
```

0.1 Data Cleaning

[2]:
```
import pandas as pd
import numpy as np
```

[3]:
```
df = pd.read_csv('../data/churn_data.csv')
```

[4]:
```
df.head()
```

[4]:
```
  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]
```

[5]:
```
#we need to convert our yes/no and true/false into 0's and 1's

churn_dict = {False: 0, True: 1}
yes_no_dict = {'no': 0, 'yes': 1}
df['churn'].replace(churn_dict, inplace=True)
df['international plan'].replace(yes_no_dict, inplace=True)
df['voice mail plan'].replace(yes_no_dict, inplace=True)
```

[6]:
```
df.head()
```

[6]:
```
  state  account length  area code phone number  international plan  \
0    KS             128        415     382-4657                   0
1    OH             107        415     371-7191                   0
2    NJ             137        415     358-1921                   0
3    OH              84        408     375-9999                   1
4    OK              75        415     330-6626                   1

   voice mail plan  number vmail messages  total day minutes  total day calls  \
0                1                     25              265.1              110
1                1                     26              161.6              123
2                0                      0              243.4              114
3                0                      0              299.4               71
4                0                      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      0
1                       1      0
2                       0      0
3                       2      0
4                       3      0

[5 rows x 21 columns]
```

[7]:

```
#pop off uneeded columns

df = df.drop(['phone number', 'area code'], axis=1)

df.head()
```

[7]:

```
  state  account length  international plan  voice mail plan  \
0    KS             128                   0                1
1    OH             107                   0                1
2    NJ             137                   0                0
3    OH              84                   1                0
4    OK              75                   1                0

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total day charge  total eve minutes  total eve calls  total eve charge  \
0             45.07              197.4               99             16.78
```

```
1              27.47              195.5              103              16.62
2              41.38              121.2              110              10.30
3              50.90               61.9               88               5.26
4              28.34              148.3              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      0
1                       1      0
2                       0      0
3                       2      0
4                       3      0
```

[8]:
```python
#lets check our target variables value count for balance

df.churn.value_counts()

#looks like we have a large imbalance, this is something we can fix using SMOTE
```

[8]:
```
0    2850
1     483
Name: churn, dtype: int64
```

[9]:
```python
#let's now prepare our data for the train_test_split

X = df.drop('churn', axis=1)
y = df.churn
```

[10]:
```python
#we must import the proper packages to perform train_test_split

from sklearn.model_selection import train_test_split, cross_val_score

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=2021,␣
 ↪test_size=0.20)
```

0.2 Making Pipelines

[11]:
```
#let's create a pipeline to do all of our preprocessing for us

from imblearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import make_column_selector, make_column_transformer
from sklearn.model_selection import GridSearchCV
from imblearn.over_sampling import SMOTE
```

[12]:
```
preprocessing = make_column_transformer((OneHotEncoder(),␣
 ↪make_column_selector(dtype_include=object)),
                                        (StandardScaler(),␣
 ↪make_column_selector(dtype_include=np.number),
                                         SMOTE()))

preprocessing
```

[12]:
```
ColumnTransformer(transformers=[('onehotencoder', OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
                                ('standardscaler', StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])
```

[13]:
```
#fit and transform our preprocessing pipeline to our training data

preprocessing.fit_transform(X_train)
```

[13]:
```
<2666x68 sparse matrix of type '<class 'numpy.float64'>'
        with 47988 stored elements in Compressed Sparse Row format>
```

[14]:
```
#the next thing we'll do is make separate pipelines for each model we want to␣
 ↪test
#each of these pipelines will contain our preprocessing pipeline

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.neighbors import KNeighborsClassifier

dt_pipeline = make_pipeline(preprocessing,␣
 ↪DecisionTreeClassifier(random_state=2021))
rf_pipeline = make_pipeline(preprocessing,␣
 ↪RandomForestClassifier(random_state=2021))
```

```
lr_pipeline = make_pipeline(preprocessing,␣
 ↪LogisticRegression(random_state=2021))
et_pipeline = make_pipeline(preprocessing,␣
 ↪ExtraTreesClassifier(random_state=2021))
kn_pipeline = make_pipeline(preprocessing, KNeighborsClassifier())
```

The purpose for the creation of various pipelines is to find the best performing model using our training data that can then be used to perform reliably on unseen data. In this context, we can use our best model to predict churn patterns for SyriaTel.

0.3 Creating Our Param_Grids

[15]:
```
#we need to create different param_grids for each pipeline

dt_param_grid = {
    'decisiontreeclassifier__criterion': ['entropy', 'gini'],
    'decisiontreeclassifier__splitter': ['best', 'random'],
    'decisiontreeclassifier__max_depth': [2, 5, 10],
    'decisiontreeclassifier__max_features': ['auto', 'sqrt', 'log2'],
    'decisiontreeclassifier__class_weight': ['none', 'balanced']

}

rf_param_grid = {
    'randomforestclassifier__n_estimators': [100, 1000, 2000],
    'randomforestclassifier__max_depth': [2, 5, 10]

}

lr_param_grid = {
    'logisticregression__penalty': ['l1', 'l2', 'elasticnet', 'none'],
    'logisticregression__dual': [True, False],
    'logisticregression__solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag',␣
 ↪'saga'],
    'logisticregression__multi_class': ['auto', 'ovr', 'multinomial'],
    'logisticregression__n_jobs': [10, 20, 30],
    'logisticregression__C': [0.01, 0.1, 0.5]

}

et_param_grid = {
    'extratreesclassifier__criterion': ['entropy', 'gini'],
    'extratreesclassifier__max_depth': [2, 5, 10],
    'extratreesclassifier__n_estimators': [100, 250, 500],
    'extratreesclassifier__max_features': ['auto', 'sqrt', 'log2'],
    'extratreesclassifier__class_weight': ['none', 'balanced']
```

```
}

kn_param_grid = {
    'kneighborsclassifier__n_neighbors': [5, 10, 20],
    'kneighborsclassifier__weights': ['uniform', 'distance'],
    'kneighborsclassifier__algorithm': ['auto', 'ball_tree', 'kd_tree',␣
 ↪'brute'],
    'kneighborsclassifier__leaf_size': [25, 50, 100],
    'kneighborsclassifier__p': [1, 2],
    'kneighborsclassifier__metric': ['minkowski', 'manhattan']

}
```

[16]:
```
#we can now use each param_grid in our GridSearchCV alongside its coinciding␣
 ↪model
```

0.4 DecisionTree

[17]:
```
search_dt = GridSearchCV(dt_pipeline, dt_param_grid, n_jobs=-1)

search_dt.fit(X_train, y_train)
```

[17]:
```
GridSearchCV(estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('onehotencoder',
OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
('standardscaler',
StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])),
                                       ('decisiontreeclassifier',
DecisionTreeClassifier(random_state=2021))]),
             n_jobs=-1,
             param_grid={'decisiontreeclassifier__class_weight': ['none',
                                                                   'balanced'],
                         'decisiontreeclassifier__criterion': ['entropy',
                                                               'gini'],
                         'decisiontreeclassifier__max_depth': [2, 5, 10],
                         'decisiontreeclassifier__max_features': ['auto',
                                                                  'sqrt',
                                                                  'log2'],
                         'decisiontreeclassifier__splitter': ['best',
                                                              'random']})
```

[18]:
```
#we can check out its best parameters
```

```
search_dt.best_params_
```

[18]:
```
{'decisiontreeclassifier__class_weight': 'balanced',
 'decisiontreeclassifier__criterion': 'entropy',
 'decisiontreeclassifier__max_depth': 10,
 'decisiontreeclassifier__max_features': 'auto',
 'decisiontreeclassifier__splitter': 'best'}
```

[19]:
```
#then assign that best model using best_estimator_ to a variable

best_dt_pipeline = search_dt.best_estimator_
```

[20]:
```
#then check its f1 score using the training data

best_dt_cross_val = cross_val_score(best_dt_pipeline, X_train, y_train,␣
 ↪scoring='f1')
```

0.5 RandomForest

[21]:
```
search_rf = GridSearchCV(rf_pipeline, rf_param_grid, n_jobs=-1)

search_rf.fit(X_train, y_train)
```

[21]:
```
GridSearchCV(estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('onehotencoder',
OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
('standardscaler',
StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])),
                                       ('randomforestclassifier',
RandomForestClassifier(random_state=2021))]),
             n_jobs=-1,
             param_grid={'randomforestclassifier__max_depth': [2, 5, 10],
                         'randomforestclassifier__n_estimators': [100, 1000,
                                                                   2000]})
```

[22]:
```
#we can check out its best parameters

search_rf.best_params_
```

[22]:
```
{'randomforestclassifier__max_depth': 10,
 'randomforestclassifier__n_estimators': 2000}
```

[23]:
```
#then assign that best model using best_estimator_ to a variable

best_rf_pipeline = search_rf.best_estimator_
```

[24]:
```
#then check its f1 score using the training data

best_rf_cross_val = cross_val_score(best_rf_pipeline, X_train, y_train,␣
↪scoring='f1')
```

0.6 LogisticRegression

[25]:
```
search_lr = GridSearchCV(lr_pipeline, lr_param_grid, n_jobs=-1)

search_lr.fit(X_train, y_train)
```

[25]:
```
GridSearchCV(estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('onehotencoder',
OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
('standardscaler',
StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])),
                                       ('logisticregre…
LogisticRegression(random_state=2021))]),
             n_jobs=-1,
             param_grid={'logisticregression__C': [0.01, 0.1, 0.5],
                         'logisticregression__dual': [True, False],
                         'logisticregression__multi_class': ['auto', 'ovr',
                                                             'multinomial'],
                         'logisticregression__n_jobs': [10, 20, 30],
                         'logisticregression__penalty': ['l1', 'l2',
                                                         'elasticnet', 'none'],
                         'logisticregression__solver': ['newton-cg', 'lbfgs',
                                                        'liblinear', 'sag',
                                                        'saga']})
```

[26]:
```
#we can check out its best parameters

search_lr.best_params_
```

[26]:
```
{'logisticregression__C': 0.01,
 'logisticregression__dual': False,
 'logisticregression__multi_class': 'auto',
 'logisticregression__n_jobs': 10,
 'logisticregression__penalty': 'l2',
```

```
 'logisticregression__solver': 'newton-cg'}
```

[27]:
```
#then assign that best model using best_estimator_ to a variable

best_lr_pipeline = search_lr.best_estimator_
```

[28]:
```
#then check its f1 score using the training data

best_lr_cross_val = cross_val_score(best_lr_pipeline, X_train, y_train,␣
 ↪scoring='f1')
```

0.7 ExtraTrees

[29]:
```
search_et = GridSearchCV(et_pipeline, et_param_grid, n_jobs=-1)

search_et.fit(X_train, y_train)
```

[29]:
```
GridSearchCV(estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('onehotencoder',
OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
('standardscaler',
StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])),
                                       ('extratreesclassifier',
ExtraTreesClassifier(random_state=2021))]),
             n_jobs=-1,
             param_grid={'extratreesclassifier__class_weight': ['none',
                                                                'balanced'],
                         'extratreesclassifier__criterion': ['entropy', 'gini'],
                         'extratreesclassifier__max_depth': [2, 5, 10],
                         'extratreesclassifier__max_features': ['auto', 'sqrt',
                                                                'log2'],
                         'extratreesclassifier__n_estimators': [100, 250, 500]})
```

[30]:
```
#we can check out its best parameters

search_et.best_params_
```

[30]:
```
{'extratreesclassifier__class_weight': 'balanced',
 'extratreesclassifier__criterion': 'gini',
 'extratreesclassifier__max_depth': 10,
 'extratreesclassifier__max_features': 'auto',
 'extratreesclassifier__n_estimators': 500}
```

[31]:
```
#then assign that best model using best_estimator_ to a variable

best_et_pipeline = search_et.best_estimator_
```

[32]:
```
#then check its f1 score using the training data

best_et_cross_val = cross_val_score(best_et_pipeline, X_train, y_train,␣
 ↪scoring='f1')
```

0.8 KNeighbors

[33]:
```
search_kn = GridSearchCV(kn_pipeline, kn_param_grid, n_jobs=-1)

search_kn.fit(X_train, y_train)
```

[33]:
```
GridSearchCV(estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('onehotencoder',
OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FC9D0>),
('standardscaler',
StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x00000243491FCB50>)])),
                                       ('kneighborscla…
                                        KNeighborsClassifier())]),
             n_jobs=-1,
             param_grid={'kneighborsclassifier__algorithm': ['auto',
                                                               'ball_tree',
                                                               'kd_tree',
                                                               'brute'],
                         'kneighborsclassifier__leaf_size': [25, 50, 100],
                         'kneighborsclassifier__metric': ['minkowski',
                                                          'manhattan'],
                         'kneighborsclassifier__n_neighbors': [5, 10, 20],
                         'kneighborsclassifier__p': [1, 2],
                         'kneighborsclassifier__weights': ['uniform',
                                                           'distance']})
```

[34]:
```
#we can check out its best parameters

search_kn.best_params_
```

[34]:
```
{'kneighborsclassifier__algorithm': 'auto',
 'kneighborsclassifier__leaf_size': 25,
 'kneighborsclassifier__metric': 'minkowski',
 'kneighborsclassifier__n_neighbors': 5,
```

```
 'kneighborsclassifier__p': 1,
 'kneighborsclassifier__weights': 'uniform'}
```

[35]:
```
#then assign that best model using best_estimator_ to a variable

best_kn_pipeline = search_kn.best_estimator_
```

[36]:
```
#then check its f1 score using the training data

best_kn_cross_val = cross_val_score(best_kn_pipeline, X_train, y_train,␣
↪scoring='f1')
```

0.9 Model F1 Score Means

[37]:
```
print(f"RandomForest: {best_rf_cross_val.mean()}\n DecisionTree:␣
↪{best_dt_cross_val.mean()}\n KNeighbors: {best_kn_cross_val.mean()}\n␣
↪LogisticRegression: {best_lr_cross_val.mean()}\n ExtraTrees:␣
↪{best_et_cross_val.mean()}")
```

```
RandomForest: 0.6162381988178686
 DecisionTree: 0.49161777125440886
 KNeighbors: 0.48455377627943996
 LogisticRegression: 0.2248114677359882
 ExtraTrees: 0.6481831855744898
```

[38]:
```
#based on this information, we chose to proceed with ExtraTrees
```

0.10 Final Model

[39]:
```
#refit training data onto best model

best_et_pipeline.fit(X_train, y_train)
```

[39]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('onehotencoder',
                                                  OneHotEncoder(),
<sklearn.compose._column_transformer.make_column_selector object at
0x0000024343E2A160>),
                                                 ('standardscaler',
                                                  StandardScaler(),
<sklearn.compose._column_transformer.make_column_selector object at
0x000002434D65B790>)])),
                ('extratreesclassifier',
                 ExtraTreesClassifier(class_weight='balanced', max_depth=10,
                                      n_estimators=500, random_state=2021))])
```

[40]:
```
#checking the f1 score of best model using the training and testing data
#similar for both indicating that we have a reliable model
```

```
f1_score_train_mean = best_et_cross_val.mean()
f1_score_test_mean = cross_val_score(best_et_pipeline, X_test, y_test,␣
 ↪scoring='f1').mean()

print(f'Training F1 Score: {f1_score_train_mean}')
print(f'Testing F1 Score: {f1_score_test_mean}')
```

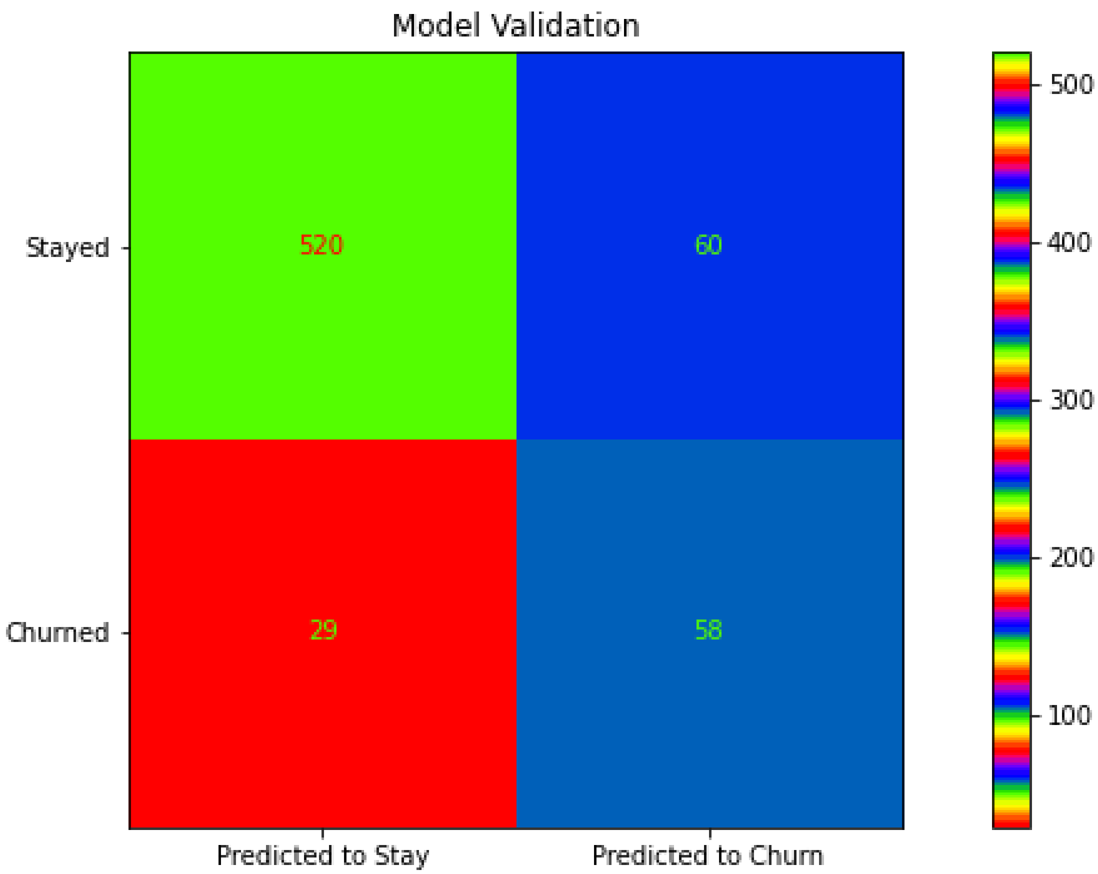
```
Training F1 Score: 0.6481831855744898
Testing F1 Score: 0.6179055216206919
```

[41]:
```
from sklearn.metrics import accuracy_score

#checking the accuracy of best model using the training and testing data
#similar for both indicating that we have a reliable model

train_preds = best_et_pipeline.predict(X_train)
test_preds = best_et_pipeline.predict(X_test)

print(f'Training Accuracy: {accuracy_score(y_train, train_preds)}')
print(f'Testing Accuracy: {accuracy_score(y_test, test_preds)}')
```

```
Training Accuracy: 0.9253563390847712
Testing Accuracy: 0.8665667166416792
```

0.11 Final Model Confusion Matrix

[42]:
```
confusion_matrix_info(best_et_pipeline, X_test, y_test, save_path='images/
 ↪final_confusion_matrix.png')
```



[42]: (None, <Figure size 720x360 with 2 Axes>)

<Figure size 432x288 with 0 Axes>

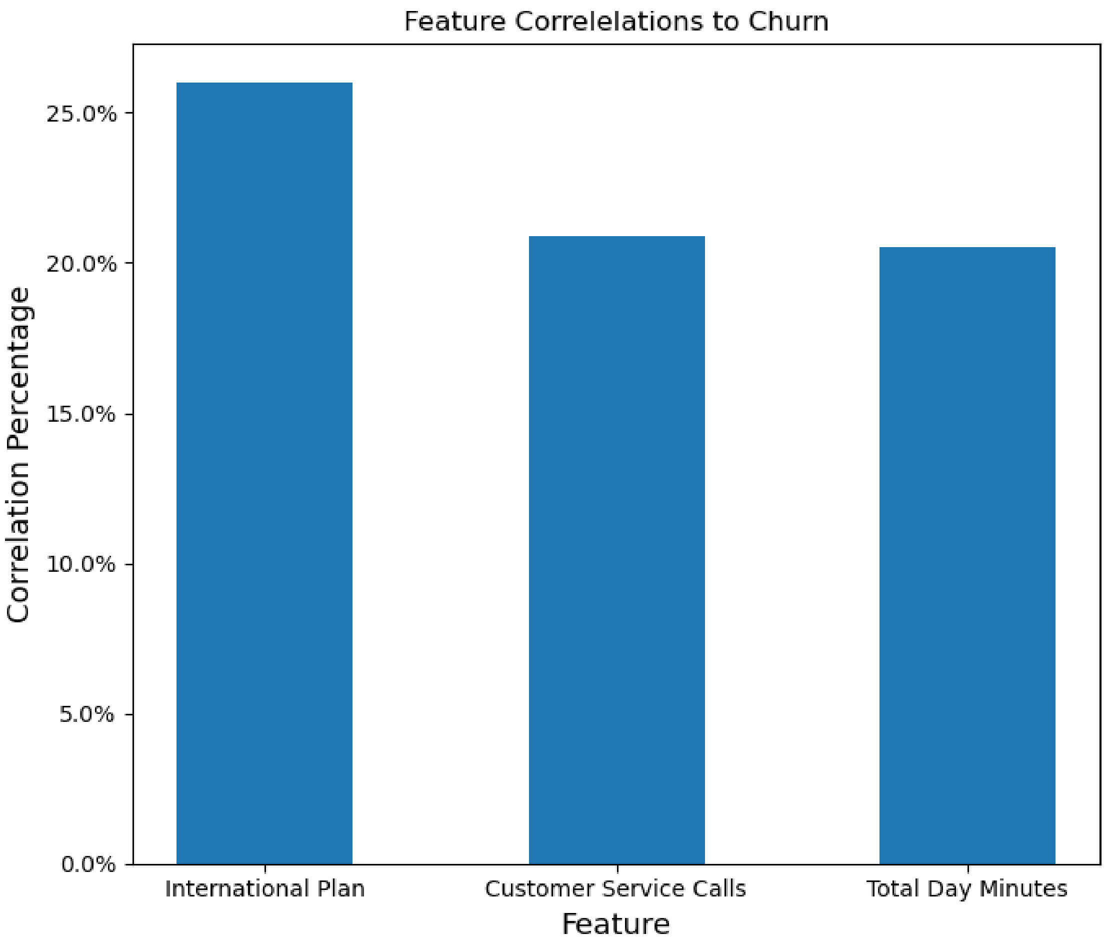
0.12 Other Visualizations

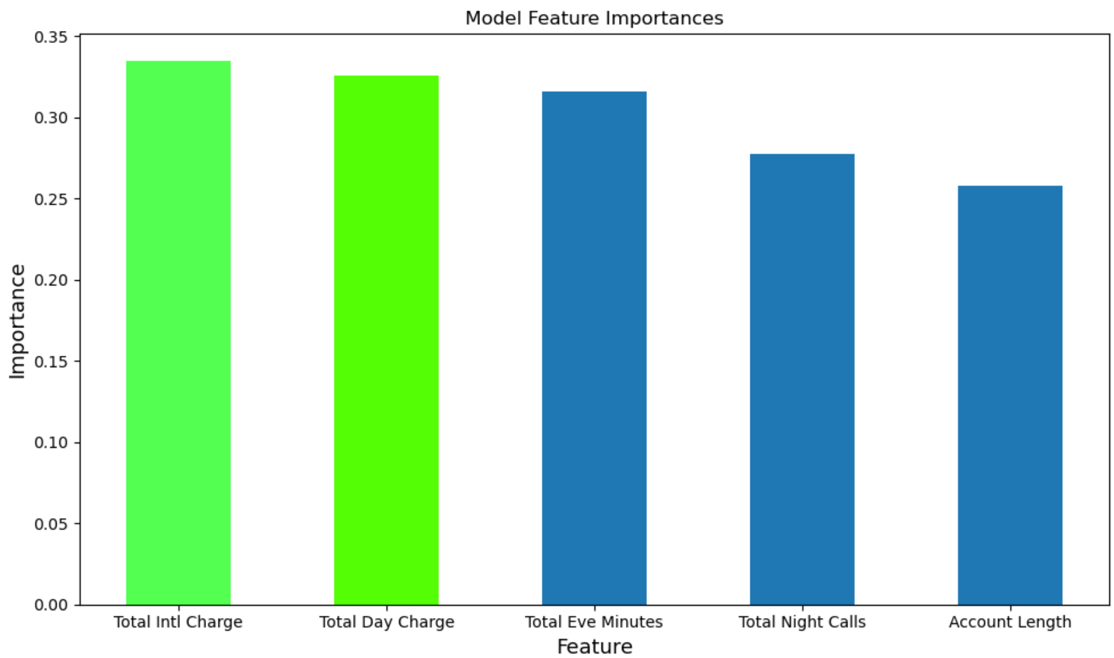
[43]:
```
top_17 = [('total intl calls', 0.007662110949917248),
 ('total intl charge', 0.003347009100443020 4),
 ('total day charge', 0.003259961859933837),
 ('total eve minutes', 0.003162403246382117),
 ('total night calls', 0.002774496742 39552),
 ('account length', 0.002581535009061759),
 ('international plan', 0.002109226781666918),
 ('voice mail plan', 0.002103748904989105),
 ('total intl minutes', 0.001871168018434775 3),
 ('total eve charge', 0.001747497700507767 9),
 ('total day calls', 0.001710128439101434 2),
 ('total night charge', 0.001615454532337387),
 ('number vmail messages', 0.0015464521017542058),
```

```
('customer service calls', 0.0012120735471571925),
('total eve calls', 0.001163035733859368),
('total night minutes', 0.000949022695754378),
('total day minutes', 0.0009380786304271744)]
```

[44]:
```
min_percent = 0.12
corr = df.corr().churn
corr=dict(corr)
create_plot_of_feature_importances(corr, title='Feature Correlelations to␣
↪Churn', top_num=3, width=0.5, percent=True)
create_plot_of_feature_importances(dict(top_17), figsize=(10, 6),␣
↪bar_colors=['#53FF50', '#54FE04', '#1F77B4', '#1F77B4',␣
↪'#1F77B4','#54FE00'], top_num=5, width=0.5, title='Model Feature␣
↪Importances', ylabel='Importance')
```

```
['International Plan', 'Customer Service Calls', 'Total Day Minutes']
[25.985184734548415, 20.874999878379207, 20.515082926138778]
['Total Intl Charge', 'Total Day Charge', 'Total Eve Minutes', 'Total Night
Calls', 'Account Length']
[0.334700910044302, 0.3259961859933837, 0.31624032463821167, 0.277449674239552,
0.2581535009061759]
```


Feature Correlelations to Churn
Correlation Percentage
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
International Plan
Customer Service Calls
Total Day Minutes
Feature



[45]:
```
train_f1_scores_dict = {
    "F1 Score": [
        cross_val_score(best_kn_pipeline, X_train, y_train, scoring='f1').
 ↪mean(),
        cross_val_score(best_rf_pipeline, X_train, y_train, scoring='f1').
 ↪mean(),
        cross_val_score(best_et_pipeline, X_train, y_train, scoring='f1').
 ↪mean(),
        cross_val_score(best_dt_pipeline, X_train, y_train, scoring='f1').mean()
    ]
}
train_f1_scores_df = pd.DataFrame(train_f1_scores_dict, index=["KNeighbors",␣
 ↪"RandomForest", "ExtraTrees", "DecisionTree"])
train_f1_scores_df
```

[45]:

	F1 Score
KNeighbors	0.484554
RandomForest	0.616238
ExtraTrees	0.648183
DecisionTree	0.491618

[46]:
```
test_f1_scores_dict = {
    "F1 Score": [
        cross_val_score(best_kn_pipeline, X_test, y_test, scoring='f1').mean(),
        cross_val_score(best_rf_pipeline, X_test, y_test, scoring='f1').mean(),
```

```
        cross_val_score(best_et_pipeline, X_test, y_test, scoring='f1').mean(),
        cross_val_score(best_dt_pipeline, X_test, y_test, scoring='f1').mean()
    ]
}
test_f1_scores_df = pd.DataFrame(test_f1_scores_dict, index=["KNeighbors",␣
 ↪"RandomForest", "ExtraTrees", "DecisionTree"])
test_f1_scores_df
```

[46]:

	F1 Score
KNeighbors	0.355152
RandomForest	0.298128
ExtraTrees	0.617906
DecisionTree	0.414153