Final Project Submission

Please fill out:

- Student name:
- Student pace: self paced / part time / full time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

In [1]:
```
#Importing Required Libraries

import numpy as np
import pandas as pd

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import precision_score, recall_score, accuracy_sco


import matplotlib.pyplot as plt

```

In [2]:
```
#Create initial DF

df = pd.read_csv('ChurnData.csv')
```

In [3]:
```
#Checking Info

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
```

In [4]:
```
#Get data set dimnensions

df.shape
```

Out[4]: (3333, 21)

In [5]:
```
#Get data set

df.describe()
```

Out[5]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000

In [6]:
```
#Famliarizing with Target Variable

df['churn'].value_counts()
```

Out[6]:
```
False    2850
True      483
Name: churn, dtype: int64
```

In [7]:
```
#Further investigation of target variable

df['churn'].value_counts(normalize = True)
```

Out[7]:
```
False    0.855086
True     0.144914
Name: churn, dtype: float64
```

In [8]:
```
from sklearn.model_selection import train_test_split

#Define X & Y

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

#Train Test Split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1
```

In [9]:
```
#Get numeric cols, categorical cols, and cols to frequency

#taken from: https://github.com/flatiron-school/Online-DS-PT-022221/blob/

num_cols = []
cols_to_ohe = []
cols_to_freq = []

for c in X_train.columns:
    # Want to grab numeric columns
    if X_train[c].dtype in ['float64', 'int64']:
        # same as if X_train[c].dtype == 'float64'
        num_cols.append(c)

    # Then grab columns with fewer than 10 unique values
    elif len(X_train[c].unique()) < 10:
        cols_to_ohe.append(c)

    # Then grab columns with more than 10, since we won't OHE those
    else:
        cols_to_freq.append(c)

print(f'Numeric Columns: ')
print(num_cols)
print(f'==')

print(f'OHE Columns: ')
print(cols_to_ohe)
print(f'==')

print(f'Categorical Columns that will not OHE: ')
print(cols_to_freq)
```

```
Numeric Columns:
['account length', 'area code', 'number vmail messages', 'total day minut
es', 'total day calls', 'total day charge', 'total eve minutes', 'total e
ve calls', 'total eve charge', 'total night minutes', 'total night call
s', 'total night charge', 'total intl minutes', 'total intl calls', 'tota
l intl charge', 'customer service calls']
==
OHE Columns:
['international plan', 'voice mail plan']
==
Categorical Columns that will not OHE:
['state', 'phone number']
```

In [10]:
```
Creating Pre Processing Pipeline

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
import category_encoders as ce


Sourced From: https://github.com/flatiron-school/Online-DS-PT-022221/blob/ma

Numerical Pre Processing Steps:

num_transformer = Pipeline(steps=[
('num_imputer', SimpleImputer(strategy='mean')),
('scaler', MinMaxScaler())])

OHE Pre processing Steps:

ohe_transformer = Pipeline(steps=[
('ohe_imputer', SimpleImputer(strategy='constant', fill_value='Unknown'))
('ohencoder', OneHotEncoder(handle_unknown='ignore'))])

Frequency Columns Pre processing Steps:

freq_transformer = Pipeline(steps=[
('freq_imputer', SimpleImputer(strategy='constant', fill_value='Unknown')
('freq_enc', ce.count.CountEncoder(normalize=True,
                                   handle_unknown=0,
                                   min_group_size=0.001,
                                   min_group_name='Other'))])

Put all Processing Steps together in Columntransformer

preprocessor = ColumnTransformer(
transformers=[
    ('num', num_transformer, num_cols),
    ('ohe', ohe_transformer, cols_to_ohe),
    ('freq', freq_transformer, cols_to_freq)])
```

In [11]:
```
#Fit preprocessor to X_Train data

X_train_proc = pd.DataFrame(preprocessor.fit_transform(X_train))
```

In [12]:

```
#Get feature names from processor

#Sourced from: https://johaupt.github.io/scikit-learn/tutorial/python/d

import warnings
import sklearn
import pandas as pd

def get_feature_names(column_transformer):
    """Get feature names from all transformers.
    Returns
    -------
    feature_names : list of strings
        Names of the features produced by transform.
    """
    # Remove the internal helper function
    #check_is_fitted(column_transformer)

    # Turn loopkup into function for better handling with pipeline late
    def get_names(trans):
        # >> Original get_feature_names() method
        if trans == 'drop' or (
                hasattr(column, '__len__') and not len(column)):
            return []
        if trans == 'passthrough':
            if hasattr(column_transformer, '_df_columns'):
                if ((not isinstance(column, slice))
                        and all(isinstance(col, str) for col in column)
                    return column
                else:
                    return column_transformer._df_columns[column]
            else:
                indices = np.arange(column_transformer._n_features)
                return ['x%d' % i for i in indices[column]]
        if not hasattr(trans, 'get_feature_names'):
        # >>> Change: Return input column names if no method avaiable
            # Turn error into a warning
            warnings.warn("Transformer %s (type %s) does not "
                                  "provide get_feature_names. "
                                  "Will return input column names if ava
                                  % (str(name), type(trans).__name__))
            # For transformers without a get_features_names method, use
            # names to the column transformer
            if column is None:
                return []
            else:
                return [name + "__" + f for f in column]

        return [name + "__" + f for f in trans.get_feature_names()]

    ### Start of processing
    feature_names = []

    # Allow transformers to be pipelines. Pipeline steps are named diff
    if type(column_transformer) == sklearn.pipeline.Pipeline:
        l_transformers = [(name, trans, None, None) for step, name, tra
```

```
    else:
        # For column transformers, follow the original method
        l_transformers = list(column_transformer._iter(fitted=True))


    for name, trans, column, _ in l_transformers:
        if type(trans) == sklearn.pipeline.Pipeline:
            # Recursive call on pipeline
            _names = get_feature_names(trans)
            # if pipeline has no transformer that returns names
            if len(_names)==0:
                _names = [name + "__" + f for f in column]
            feature_names.extend(_names)
        else:
            feature_names.extend(get_names(trans))

    return feature_names
```

In [13]:

```
#Get feature names of preprocessor

processed_feature_names = get_feature_names(preprocessor)

#Assign column names to preprocessed X_train_cols

X_train_proc.columns = processed_feature_names

#transform X_test

X_test_proc = pd.DataFrame(preprocessor.transform(X_test))
```

```
<ipython-input-12-0d499a1f2f22>:38: UserWarning: Transformer num_imputer
(type SimpleImputer) does not provide get_feature_names. Will return inpu
t column names if available
  warnings.warn("Transformer %s (type %s) does not "
<ipython-input-12-0d499a1f2f22>:38: UserWarning: Transformer scaler (type
MinMaxScaler) does not provide get_feature_names. Will return input colum
n names if available
  warnings.warn("Transformer %s (type %s) does not "
<ipython-input-12-0d499a1f2f22>:38: UserWarning: Transformer ohe_imputer
(type SimpleImputer) does not provide get_feature_names. Will return inpu
t column names if available
  warnings.warn("Transformer %s (type %s) does not "
<ipython-input-12-0d499a1f2f22>:38: UserWarning: Transformer freq_imputer
(type SimpleImputer) does not provide get_feature_names. Will return inpu
t column names if available
  warnings.warn("Transformer %s (type %s) does not "
<ipython-input-12-0d499a1f2f22>:38: UserWarning: Transformer freq_enc (ty
pe CountEncoder) does not provide get_feature_names. Will return input co
lumn names if available
  warnings.warn("Transformer %s (type %s) does not "
```

In [14]:

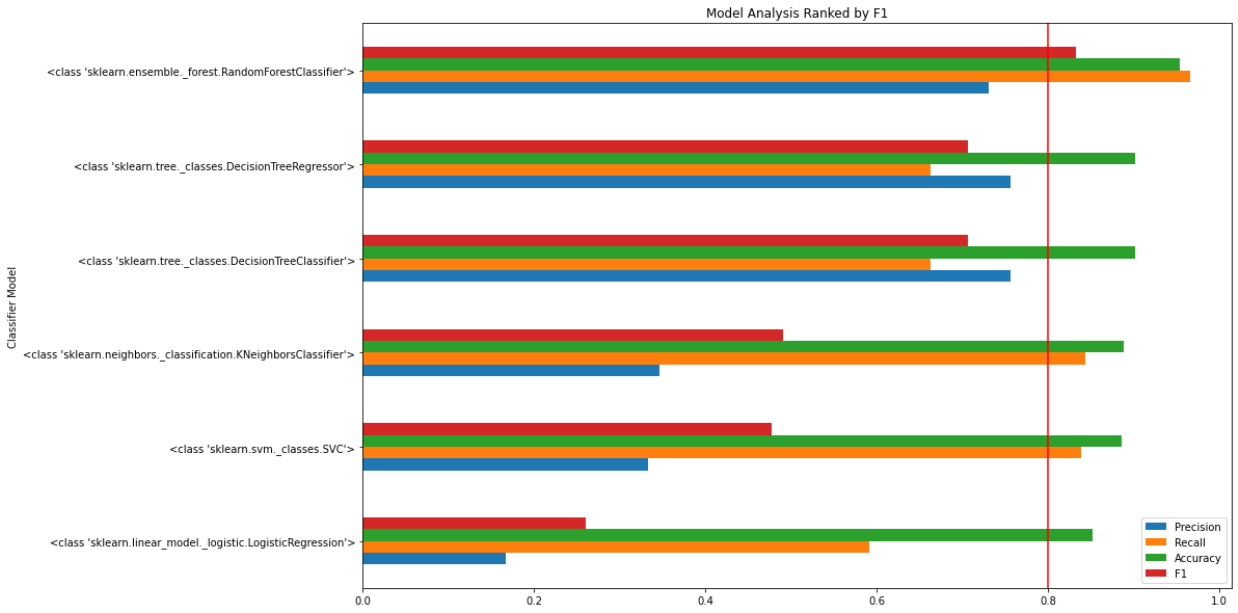
```
#Get Metrics for Classifier Model Types:

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

def multi_model_analysis(models, weight):

    classifier = []
    precision = []
    recall = []
    accuracy = []
    f1 = []

    # Class Weight Models

    def get_weighted_model_metrics(reg, weight, X_train_proc, y_train,

        from sklearn.metrics import precision_score, recall_score, accu

        model = reg(class_weight = weight)

        model.fit(X_train_proc, y_train)

        model_pred_train = model.predict(X_train_proc)

        model_pred_test = model.predict(X_test_proc)

        #Get Evaluation Metrics for DTC Train Set:

        model_train_precision = precision_score(model_pred_train, y_tra
        model_train_recall = recall_score(model_pred_train, y_train)
        model_train_accuracy = accuracy_score(model_pred_train, y_train
        model_train_f1 = f1_score(model_pred_train, y_train)

        #Get Evaluation Metrics for DTC Test Set:

        model_test_precision = precision_score(model_pred_test, y_test)
        model_test_recall = recall_score(model_pred_test, y_test)
        model_test_accuracy = accuracy_score(model_pred_test, y_test)
        model_test_f1 = f1_score(model_pred_test, y_test)

        classifier.append(reg)
        precision.append(model_test_precision)
        recall.append(model_test_recall)
        accuracy.append(model_test_accuracy)
        f1.append(model_test_f1)

    #Non Class Weight Models

    def get_model_metrics(reg, X_train_proc, y_train, X_test_proc, y_te

        from sklearn.metrics import precision_score, recall_score, accu
```

```
57
58          model = reg()
59
60          model.fit(X_train_proc, y_train)
61
62          model_pred_train = model.predict(X_train_proc)
63
64          model_pred_test = model.predict(X_test_proc)
65
66          #Get Evaluation Metrics for DTC Train Set:
67
68          model_train_precision = precision_score(model_pred_train, y_tra
69          model_train_recall = recall_score(model_pred_train, y_train)
70          model_train_accuracy = accuracy_score(model_pred_train, y_trai
71          model_train_f1 = f1_score(model_pred_train, y_train)
72
73          #Get Evaluation Metrics for DTC Test Set:
74
75          model_test_precision = precision_score(model_pred_test, y_test
76          model_test_recall = recall_score(model_pred_test, y_test)
77          model_test_accuracy = accuracy_score(model_pred_test, y_test)
78          model_test_f1 = f1_score(model_pred_test, y_test)
79
80          classifier.append(reg)
81          precision.append(model_test_precision)
82          recall.append(model_test_recall)
83          accuracy.append(model_test_accuracy)
84          f1.append(model_test_f1)
85
86      for item in models:
87          if item in [DecisionTreeClassifier, RandomForestClassifier, Log
88              get_weighted_model_metrics(item, weight, X_train_proc, y_t
89          else:
90              get_model_metrics(item, X_train_proc, y_train, X_test_proc,
91
92      metrics_df = pd.concat([pd.DataFrame(classifier), pd.DataFrame(prec
93                pd.DataFrame(f1)], axis = 1)
94
95      metrics_df.columns = ['Classifier Model', 'Precision', 'Recall', 'A
96
97      metrics_df.sort_values(by = 'F1', inplace = True, ascending = True)
98
99      metrics_df.plot(x ='Classifier Model', y=['Precision', 'Recall', 'A
100                     figsize = (15, 10))
101
102     plt.axvline(0.8, 0, 1, color = 'red')
103     plt.title('Model Analysis Ranked by F1')
104
105
106     return metrics_df
```

In [15]:
```
#Test All Models

models = [DecisionTreeClassifier, RandomForestClassifier, LogisticRegre
          KNeighborsClassifier]

multi_model_analysis(models, None)
```

Out[15]:

	Classifier Model	Precision	Recall	Accuracy	F1
2	<class 'sklearn.linear_model._logistic.Logisti...	0.166667	0.590909	0.852	0.260000
3	<class 'sklearn.svm._classes.SVC'>	0.333333	0.838710	0.886	0.477064
5	<class 'sklearn.neighbors._classification.KNei...	0.346154	0.843750	0.888	0.490909
0	<class 'sklearn.tree._classes.DecisionTreeClas...	0.756410	0.662921	0.902	0.706587
4	<class 'sklearn.tree._classes.DecisionTreeRegr...	0.756410	0.662921	0.902	0.706587
1	<class 'sklearn.ensemble._forest.RandomForestC...	0.730769	0.966102	0.954	0.832117



Initial Multi Model Findings

1. The highest F1 scores come from Decision Tree Classifiers and Decission Tree Regression
2. Random Forest Metrics are showing very promising Accuracy and Recall, however Precision is very low
3. Scores may be improved accross all models by first solving for the Class Imbalance

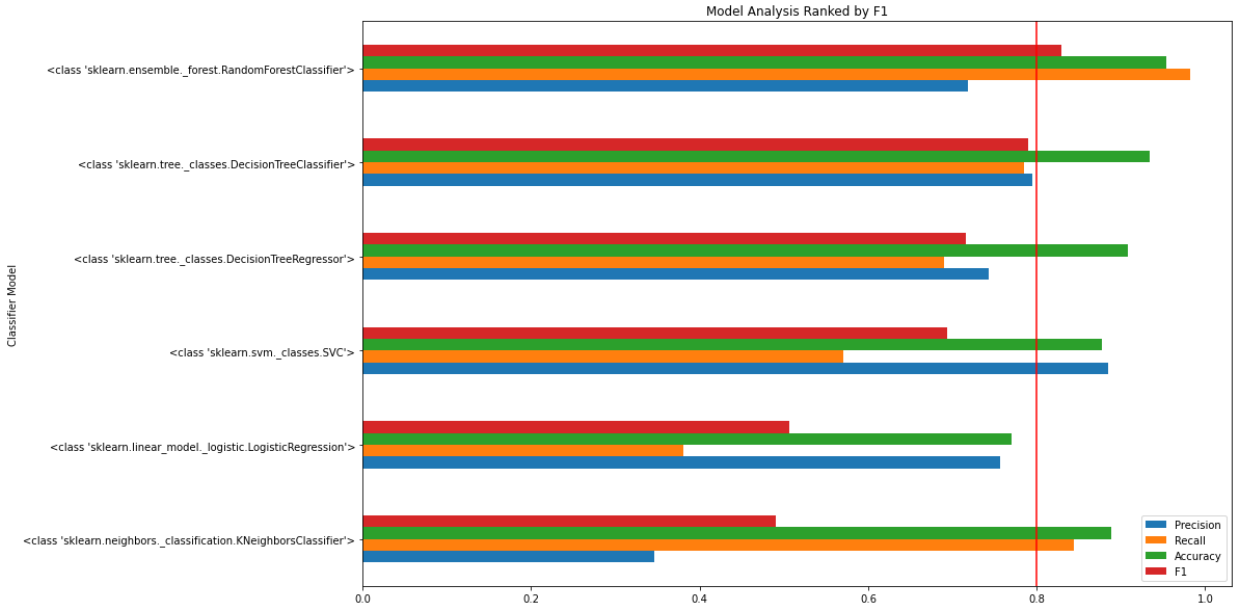
Check Class Weight Imbalance

1. Multi Model Check will be run with Class Weight Imbalanced rectified

In [16]:
```
multi_model_analysis(models, 'balanced')
```

Out[16]:

	Classifier Model	Precision	Recall	Accuracy	F1
5	<class 'sklearn.neighbors._classification.KNei...	0.346154	0.843750	0.888	0.490909
2	<class 'sklearn.linear_model._logistic.Logisti...	0.756410	0.380645	0.770	0.506438
3	<class 'sklearn.svm._classes.SVC'>	0.884615	0.570248	0.878	0.693467
4	<class 'sklearn.tree._classes.DecisionTreeRegr...	0.743590	0.690476	0.908	0.716049
0	<class 'sklearn.tree._classes.DecisionTreeClas...	0.794872	0.784810	0.934	0.789809
1	<class 'sklearn.ensemble._forest.RandomForestC...	0.717949	0.982456	0.954	0.829630



Class Weight Analysis

1. Random Forests yielded the greatest improvement in total F1
2. Deision Tree Classifiers came in a close second
3. Logistic Regression maintained a relatively low score

Next Steps:

1. Run CV/Grid Search on Random Forest Classifier
2. Determine feature importance

In [17]:
```
# #Grid Search Parameters

# # dt_param_grid = {
# #     'criterion': ['gini', 'entropy'],
# #     'max_depth': [None, 2, 3, 4, 5, 6],
# #     'min_samples_split': [2, 5, 10],
# #     'min_samples_leaf': [1, 2, 3, 4, 5, 6]
# # }

# dt_param_grid = {
#     'criterion': ['gini', 'entropy'],
#     'max_depth': [None, 2, 3, 4, 5, 6],
#     'min_samples_split': [ 2, 5, 10],
#     'min_samples_leaf': [1, 2, 3, 4, 5, 6]
# }

# #Instantiate Grid Search CV

# from sklearn.model_selection import GridSearchCV

# grid = GridSearchCV(model, dt_param_grid, cv = 3, scoring = 'f1')

# grid.fit(X_train_proc, y_train)


```

In [18]:
```
# #Evaluating Metrics from Gridsearch CV:

# print(f'Best Score: {grid.best_score_}')

# #Evaluating best

# print(f'Best Parameters: {grid.best_params_}')

print(f'Best Metrics: criterion: entropy, max_depth: None, min_samples_
```

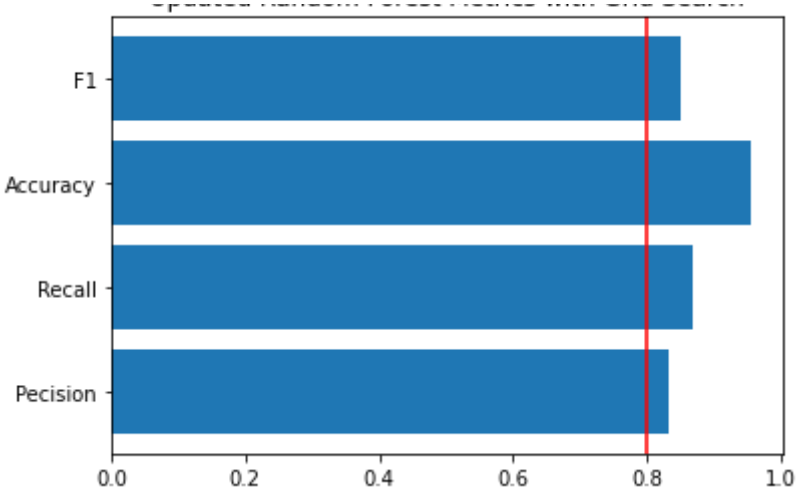
```
Best Metrics: criterion: entropy, max_depth: None, min_samples_leaf: 5, m
in_samples_split: 2
```

In [19]:

```
model = RandomForestClassifier(class_weight = 'balanced',
                               criterion = 'entropy',
                               max_depth = None,
                               min_samples_leaf = 5,
                               min_samples_split = 2)

model.fit(X_train_proc, y_train)

model_pred_train = model.predict(X_train_proc)

model_pred_test = model.predict(X_test_proc)

#Get Evaluation Metrics for DTC Train Set:

model_train_precision = precision_score(model_pred_train, y_train)
model_train_recall = recall_score(model_pred_train, y_train)
model_train_accuracy = accuracy_score(model_pred_train, y_train)
model_train_f1 = f1_score(model_pred_train, y_train)

#Get Evaluation Metrics for DTC Test Set:

model_test_precision = precision_score(model_pred_test, y_test)
model_test_recall = recall_score(model_pred_test, y_test)
model_test_accuracy = accuracy_score(model_pred_test, y_test)
model_test_f1 = f1_score(model_pred_test, y_test)

print(f'Random Forest Model Metrics:')
print(f'')
print(f'Model Test Precision: {model_test_precision}')
print(f'Model Test Recall: {model_test_recall}')
print(f'Model Test Accuracy: {model_test_accuracy}')
print(f'Model Test F1: {model_test_f1}')
print(f'---')
print(f'---')

metrics = ['Pecision', 'Recall', 'Accuracy', 'F1']
scores = [model_test_precision, model_test_recall, model_test_accuracy,

plt.barh(metrics, scores)
plt.title('Updated Random Forest Metrics with Grid Search')
plt.axvline(0.8, 0, 1, color = 'red')


```

```
Random Forest Model Metrics:

Model Test Precision: 0.8333333333333334
Model Test Recall: 0.8666666666666667
Model Test Accuracy: 0.954
Model Test F1: 0.8496732026143791
---
---
```

Out[19]: <matplotlib.lines.Line2D at 0x7fc28893ee20>



Grid Search CV Results

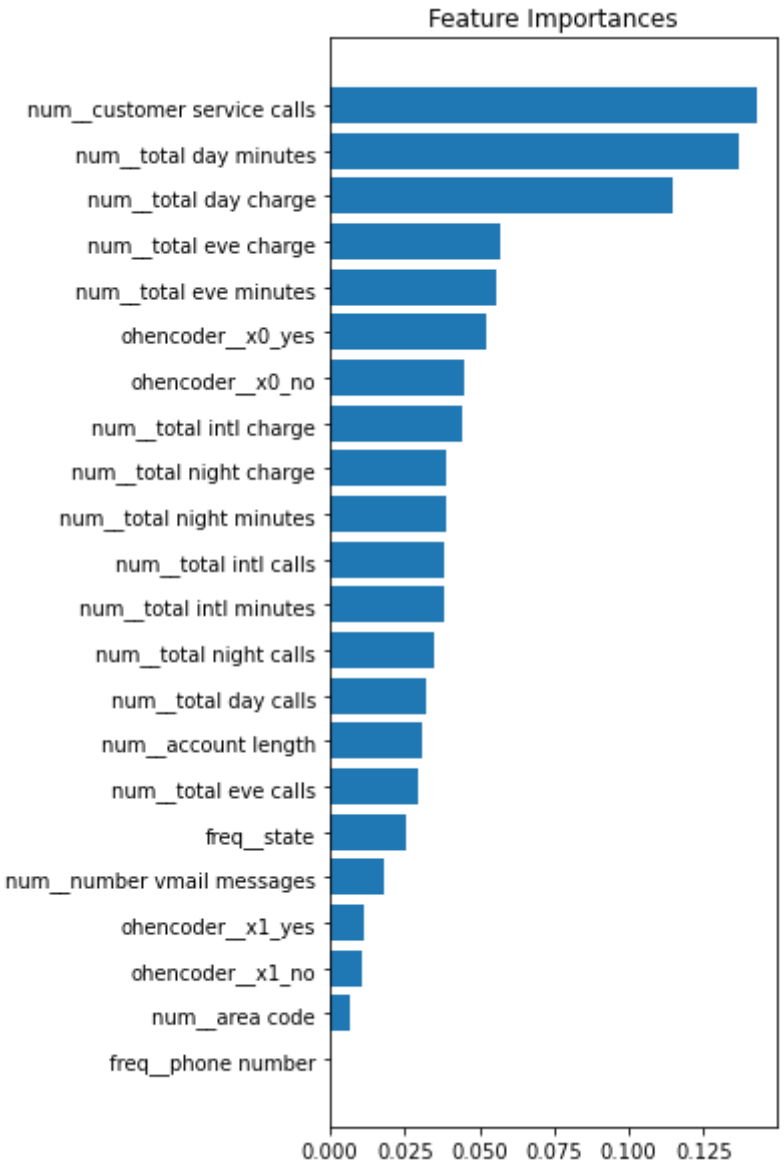
Overall scoring has gone up significantly, with Accuracy hitting 95% and F1 increasing to 85%

Next Steps

1. Determine Feature Importance
2. Establish final steps of qualitative analysis

In [20]:
```
#Establish Feature Importance in a Dta Frame

feature_by_importance = pd.concat([pd.DataFrame(X_train_proc.columns),
                                   axis = 1)

feature_by_importance.columns = ['Feature', 'Importance']

feature_by_importance.sort_values(by='Importance', ascending = True, in

plot = plt.figure()
plot.set_figwidth(4)
plot.set_figheight(10)

plt.title('Feature Importances')

plt.barh(feature_by_importance['Feature'],
         feature_by_importance['Importance'])
```

Out[20]: <BarContainer object of 22 artists>



Feature Importance Results

1. Top features include Customer Service Calls, Total Day Minutes, Total Day Charge, Total Night Minutes, Total Night Charge
2. It appears that the most active, high frequency users are most likely to churn out

Next Steps

1. Establish average usage and point in which users are most likely to churn

In [21]:
```
#Service Calls Analysis

cust_service_calls_mean = np.mean(df['customer service calls'])

cust_service_calls_sd = np.std(df['customer service calls'])

non_churn_cust_service_calls_mean = np.mean(df[df['churn'] == 0]['custo

churn_cust_service_calls_mean = np.mean(df[df['churn'] == 1]['customer

print(f'Mean of Customer Service Calls For Non Churners: {non_churn_cus
print(f'Standard Deviation of Customer Service Calls: {cust_service_cal
print(f'Mean of Customer Service Calls for Churners: {churn_cust_servic
```

```
Mean of Customer Service Calls For Non Churners: 1.4498245614035088
Standard Deviation of Customer Service Calls: 1.3152936866709521
Mean of Customer Service Calls for Churners: 2.229813664596273
```

In [22]:
```
#Day Time Minutes Analysis

day_miniutes_mean = np.mean(df['total day minutes'])

day_minutes_sd = np.std(df['total day minutes'])

non_churn_day_minutes_mean = np.mean(df[df['churn'] == 0]['total day mi

churn_day_minutes_mean = np.mean(df[df['churn'] == 1]['total day minute

print(f'Mean of total day minutes Non Churners: {non_churn_day_minutes_
print(f'Standard Deviation of total day minutes: {day_minutes_sd}')
print(f'Mean of total day minutes for Churners: {churn_day_minutes_mean
```

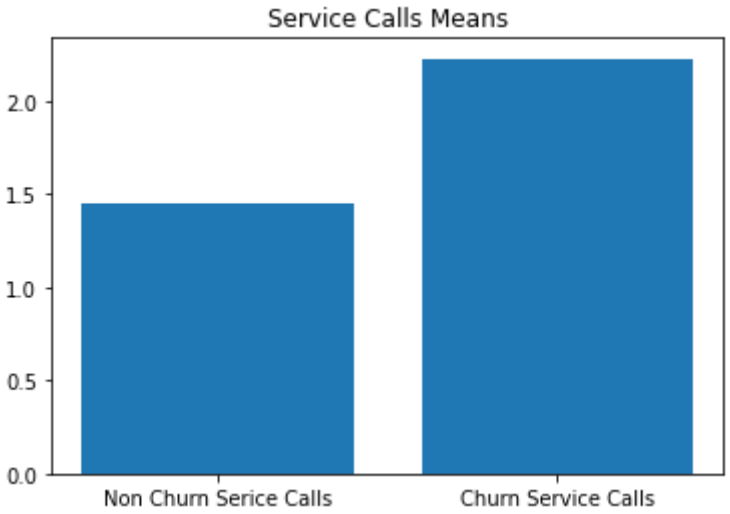
```
Mean of total day minutes Non Churners: 175.1757543859649
Standard Deviation of total day minutes: 54.45921766392581
Mean of total day minutes for Churners: 206.91407867494823
```

In [23]:
```
#Day Time Minutes Analysis

day_charge_mean = np.mean(df['total day charge'])

day_charge_sd = np.std(df['total day charge'])

non_churn_day_charge_mean = np.mean(df[df['churn'] == 0]['total day cha

churn_day_charge_mean = np.mean(df[df['churn'] == 1]['total day charge'

print(f'Mean of total day minutes Non Churners: {non_churn_day_charge_m
print(f'Standard Deviation of total day minutes: {day_charge_sd}')
print(f'Mean of total day minutes for Churners: {churn_day_charge_mean}
```

```
Mean of total day minutes Non Churners: 29.780421052631578
Standard Deviation of total day minutes: 9.258045395636893
Mean of total day minutes for Churners: 35.17592132505176
```

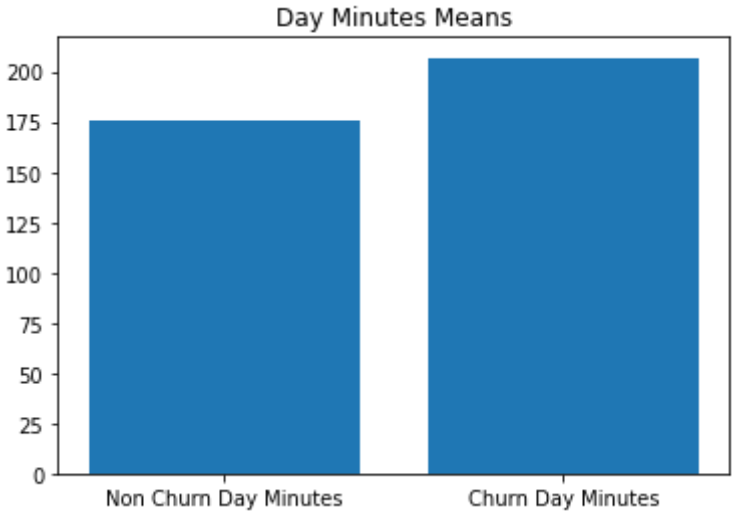
In [24]:
```
import matplotlib.pyplot as plt

#Service Calls Metrics

plt.bar(['Non Churn Serice Calls', 'Churn Service Calls'], [
        non_churn_cust_service_calls_mean, churn_cust_service_calls_mea

plt.title('Service Calls Means')
```

Out[24]: Text(0.5, 1.0, 'Service Calls Means')



In [25]:
```
#Day Minutes Metrics

plt.bar(['Non Churn Day Minutes', 'Churn Day Minutes'], [
        non_churn_day_minutes_mean, churn_day_minutes_mean])

plt.title('Day Minutes Means')
```

Out[25]: Text(0.5, 1.0, 'Day Minutes Means')



Usage Results

1. Users with higher usage during the day / charges are clearly more inclined to churn
2. This clearly shows that heavy usage users are not experiencing a satisfactory service

Proposition

1. Provide a service that scales with usage in order to save 15% of the business
2. Specifically when a user starts exceeding 170 / 175 minutes per week offer reduce costs and a higher level of service