Final Project Submission

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- Student pace: Self paced
- Scheduled project review date/time: 1/31/2023 0930
- Instructor name: Mark Barbour
- Blog post URL: https://medium.com/@heathlikethecandybar/

Introduction

Business Case/ Summary

SyriaTel, a telecommunications company wants to identify the leading factors of why a customer cancels their service. This is also referred to as 'Churn.' If they understand the factors that lead to churn, the company can implement programs to reduce the risk of churn, and increase the lifetime value of and for their customers.

My goal is to build a classifer to predict whether a customer will stop doing business with SyriaTel. I will be using information such as usage, interactions with SyriaTel, and certain features that the customer has purchased. I am mostly focused on reducing the rate of false negatives so the metric in which I will be evaluating my models is called Recall.

Core Field Names and Definitions from Data Source

- `state` - The state in which the account owner resides.
- `account length` -
- `area code` - Primary 3 digit area of the line for the account.
- `phone number` - Primary 7 digit area of the line for the account.
- `international plan` - Indicator denoting whether or not the account has an international feature.
- `voice mail plan` - Indicator denoting whether or not the account has an voice mail feature.
- `number vmail messages` - Usage metric counting the total number of voicemails for the phone number in question.
- `total day minutes` - Usage metric indicating how many minutes (call time) were used between 6:00am and 5:00pm.
- `total day calls` - Usage metric indicating how many calls were used between 6:00am and 5:00pm.

- `total day charge` - Usage metric indicating how much the user was charged for their usage between 6:00am and 5:00pm.
- `total eve minutes` - Usage metric indicating how many minutes (call time) were used between 5:01pm and 8:00pm.
- `total eve calls` - Usage metric indicating how many calls were used between 5:01pm and 8:00pm.
- `total eve charge` - Usage metric indicating how much the user was charged for their usage between 5:01pm and 8:00pm.
- `total night minutes` - Usage metric indicating how many minutes (call time) were used between 8:01pm and 5:59am.
- `total night calls` - Usage metric indicating how many calls were used between 8:01pm and 5:59am.
- `total night charge` - Usage metric indicating how much the user was charged for their usage between 8:01pm and 5:59a.
- `total intl minutes` - Usage metric indicating how many minutes (call time) were used internationally.
- `total intl calls` - Usage metric indicating how many calls were made internationally.
- `total intl charge` - Usage metric indicating how much the user was charged for their international call usage.
- `customer service calls` - The total number of customer service calls made by the user to the Skyvia Customer Service line.
- `churn` - Our target category indicating whether or not the customer churned/ cancelled their plan.

Additional information about the dataset can be found here: https://www.kaggle.com/datasets/becksddf/churn-in-telecoms-dataset

Data Load, Cleaning

Importing Packages

In [81]:
```
# Importing packages for analysis

import pandas as pd
import numpy as np
import seaborn as sns
import statsmodels.api as sm

from matplotlib import pyplot as plt
import matplotlib.ticker as mtick
from matplotlib.colors import ListedColormap
%matplotlib inline

from sklearn.linear_model import LinearRegression, LogisticRegression, RidgeClassifier
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV, StratifiedKFold
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler, FunctionTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import MissingIndicator, SimpleImputer
```

```python
from sklearn.compose import ColumnTransformer
from sklearn.dummy import DummyClassifier
from sklearn.metrics import plot_confusion_matrix, confusion_matrix, plot_roc_curve, classification_report, plc
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score, precision_recall_curve, rc
from sklearn.neighbors import KNeighborsClassifier, NearestNeighbors
from sklearn.ensemble import AdaBoostRegressor, GradientBoostingRegressor, AdaBoostClassifier, GradientBoosting
from sklearn.feature_selection import RFECV
import xgboost as xgb
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier, plot_tree
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImPipeline

plt.style.use('seaborn-talk')
```

Choosing Colors & Templates

In [82]:

```python
# Choosing standard colors for project

pal = sns.color_palette("viridis")

color_codes = ['purple', 'darkblue', 'blue', 'bluegreen', 'green', 'lime']

my_cmap = ListedColormap(sns.color_palette(pal).as_hex())

pal.as_hex()
```

Out[82]:

Import data

In [83]:

```python
# Importing data and viewing the first 5 rows

df = pd.read_csv('data/data.csv')

df.head()
```

Out[83]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls	total night charge	m
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	11.01	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	11.45	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	7.32	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	8.86	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	8.41	

5 rows × 21 columns

In [84]:

```
# Updating column names to have an _ vs a space

df.columns = [c.replace(' ', '_') for c in df.columns]
```

In [85]:

```
# Taking a quick peak at our datatypes for any transformations needed.

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
```

Looks like we have a few categorical variables in which we will need to encode. We'll look at that here in a bit. First I want to make sure our dataset is complete. Moving on to checking to see if we need to remove or impute any data before any transformations.

In [86]:
```python
# Checking for missing values.

df.isna().sum()
```

Out[86]:
```
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
```

No missing values. Going to create some columns to add together all of our minutes, calls, and charges. We might be able to reduce the number of dimensions we have if the customer is not using the plan at all. We may drop these later, but let's add them while we are in the mood.

In [87]:
```python
# Adding column for total calls
```

```python
df['total_calls'] = (df['total_day_calls'] +
                     df['total_eve_calls'] +
                     df['total_night_calls'] +
                     df['total_intl_calls']
                     )
```

In [88]:

```python
# Adding column for total minutes

df['total_charges'] = (df['total_day_charge'] +
                     df['total_eve_charge'] +
                     df['total_night_charge'] +
                     df['total_intl_charge']
                       )
```

In [89]:

```python
# Adding column for total charges

df['total_minutes'] = (df['total_day_minutes'] +
                     df['total_eve_minutes'] +
                     df['total_night_minutes'] +
                     df['total_intl_minutes']
                       )
```

In [90]:

```python
# Adding column for price per minute

df['price_per_minute'] = df['total_day_charge']/df['total_minutes']
```

In [91]:

```python
# Quick check to make sure our columns were added correctly and math checks out

df.head()
```

Out[91]:

	state	account_length	area_code	phone_number	international_plan	voice_mail_plan	number_vmail_messages	total_day_minutes
0	KS	128	415	382-4657	no	yes	25	265.1
1	OH	107	415	371-7191	no	yes	26	161.6
2	NJ	137	415	358-1921	no	no	0	243.4
3	OH	84	408	375-9999	yes	no	0	299.4
4	OK	75	415	330-6626	yes	no	0	166.7

5 rows × 25 columns

Calculations are looking good. These will primarily serve as EDA helper stats. Since they are formulas based on existing fields, I would assume that we will see a high level of colinearity within these added metrics.

In [92]:
```
df.describe()
```

Out[92]:

	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

Across the board we can already tell that our data is pretty well distributed. We can see this by a quick glance at the relationship between our mean and our median (50%) values. This will reduce the amount of data cleaning, and imputation that we will need to complete later. Roughly looks like our daytime minutes are more expensive than our evening, and night time minutes. Looks like customers interact with customer service on average 1.6 times. Customers pay on average $60 in total, and on average .05 cents a minute. What is difficult to discern from this data set is if this is across one month, or a different time period. That would help us determine how we institute our strategy from a timing perspective. However, we will just discuss the strategies in general, and think of the time as an arbitrary component.

Features of the cell phone plan EDA

Since we know that our target variable is imbalanced (churn accounts for roughly 15% of the total dataset). There are only a few other features that are tied to the account besides the usage, and those are voice_mail_plan, international_plan, and customer_service_calls. Let's dig into those next!

There are 323 accounts that purchased a international plan (roughly 10% of customers.). Going to take a look to see if churn within the international accounts is similar to those accounts that did not purchase international plans.

In [93]:
```
# Checking our target/ dataset for balance before creating our baseline classifcation model.
```

```python
pd.pivot_table(df,
               values='account_length',
               index='international_plan',
               columns='churn',
               aggfunc='count'
              )
```

Out[93]:

churn	False	True
international_plan		
no	2664	346
yes	186	137

As we can see, churn within our customer segment that has the international_plan feature, churn at a higher rate than those without the feature. Going to visualize this relationship next.

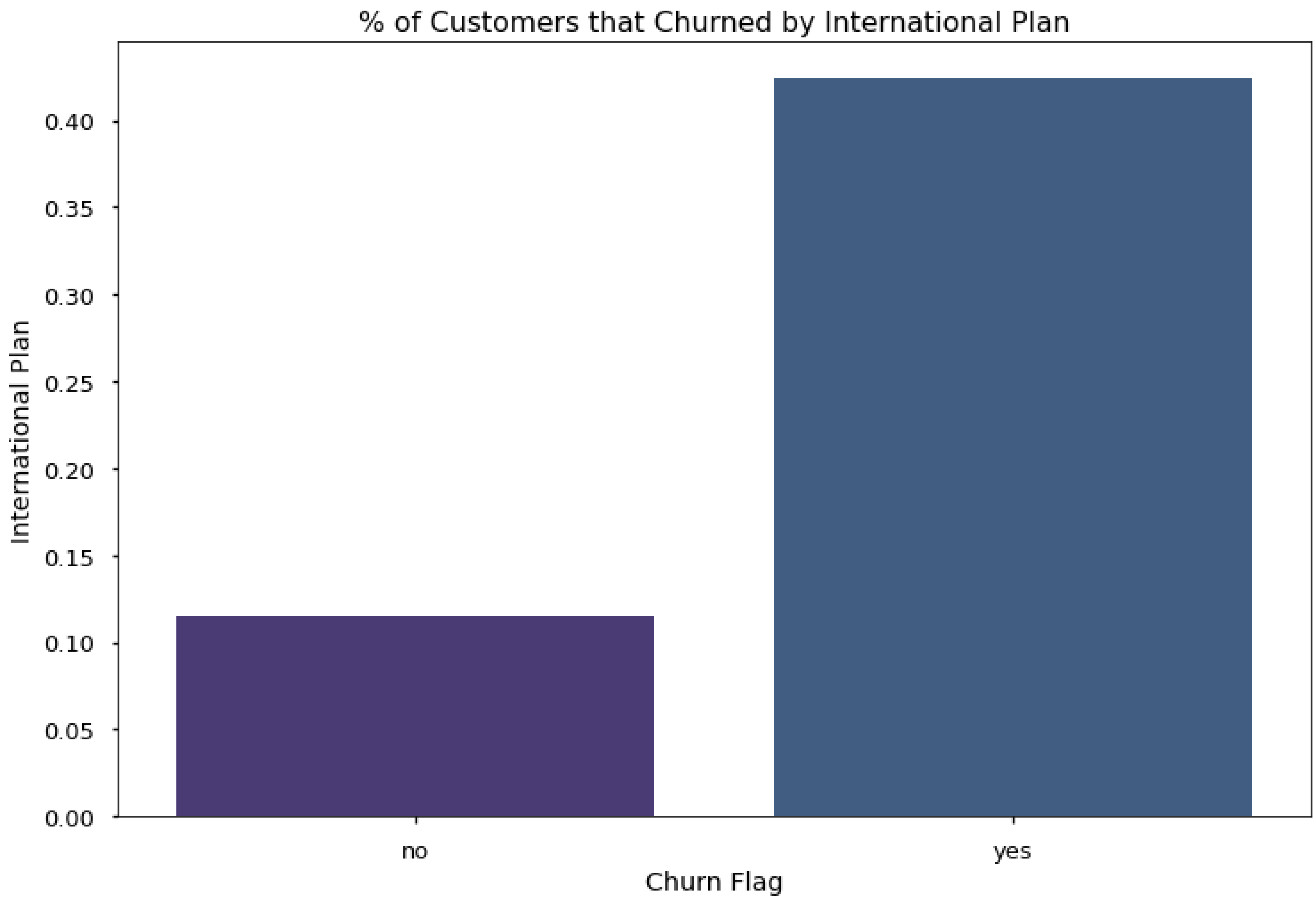
In [94]:

```python
# Credit for this little function belongs to Eva Mizer :) Leveraging to make my charts
# easier as I get through my EDA process.

def mini_bar(x, y, y_title, x_title, plot_title):
    mean_df = df[[x, y]].groupby(x, as_index=False).mean()
    print(mean_df)

    #Bar plot to visualize!
    ax = sns.barplot(x=x, y=y, data=mean_df, palette=pal)
    ax.figure.set_size_inches(12,8)
    ax.set_ylabel(y_title)
    ax.set_xlabel(x_title)
    ax.set_title(plot_title)
```

In [95]:

```python
# Visualizing the relationship

mini_bar('international_plan', 'churn', 'International Plan', 'Churn Flag', '% of Customers that Churned by Int
```

```
  international_plan     churn
0                 no  0.114950
1                yes  0.424149
```



As we mentioned above, the customers with an International plan experience a higher churn percentage than those without; just over 40% of those that had the interntational plan, and about 10% for those without. About 1/3 of the total churn that was experienced were customers that had purchased the international plan. Moving on to the Voice Mail Plan feature next.

In [96]:
```
# Creating pivot table for voice mail plan vs churn.

pd.pivot_table(df,
               values='account_length',
               index='voice_mail_plan',
               columns='churn',
               aggfunc='count'
              )
```

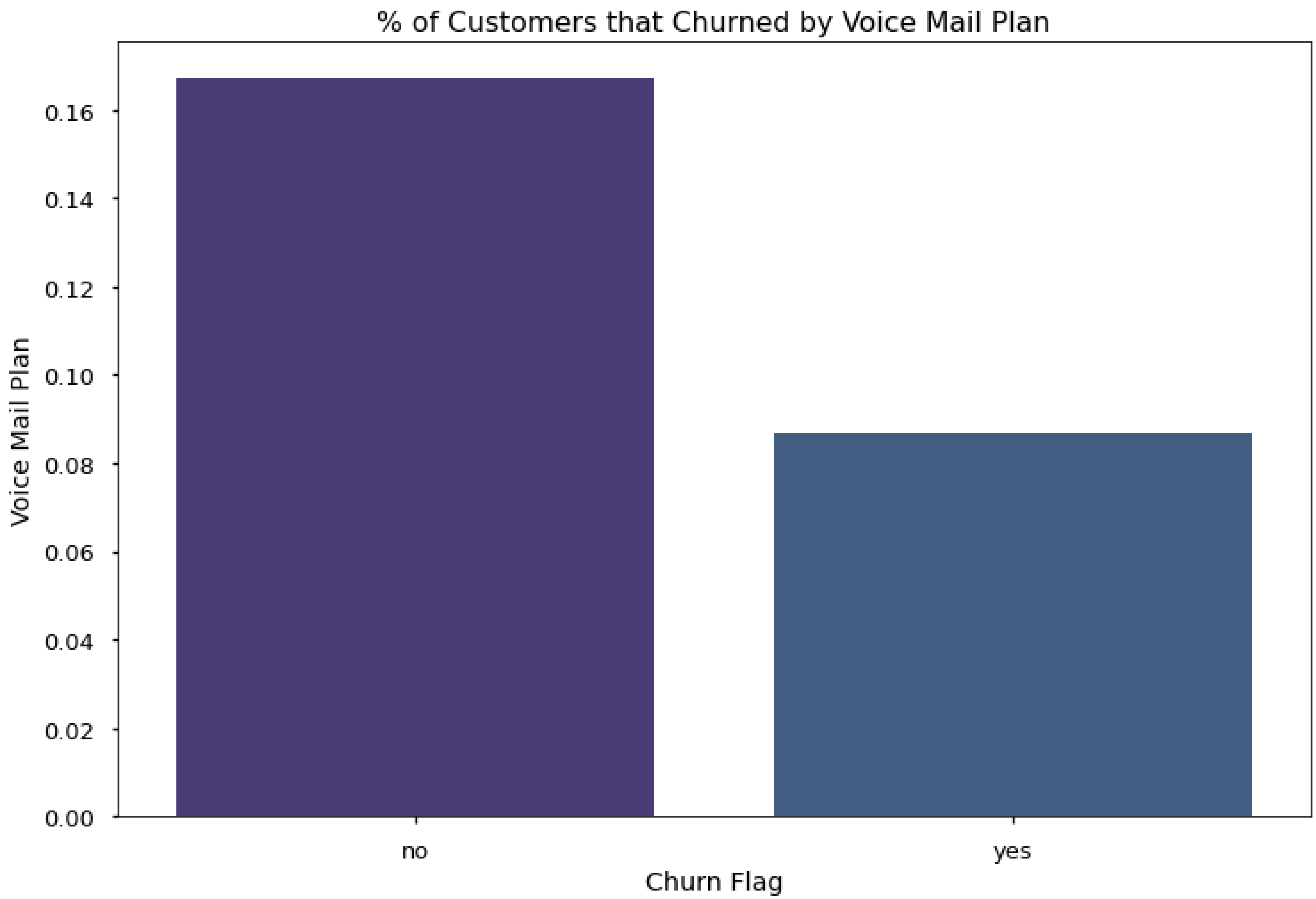
Out[96]:

churn	False	True
voice_mail_plan		
no	2008	403
yes	842	80

In [97]:

```
# Visualizing relationship

mini_bar('voice_mail_plan', 'churn', 'Voice Mail Plan', 'Churn Flag', '% of Customers that Churned by Voice Mai
```

```
  voice_mail_plan     churn
0              no  0.167151
1             yes  0.086768
```



Looks like those plans with a voice mail plan have a lower churn percentage than those without. 9% of those with the voice mail plan vs 17% of those without a voice mail plan churn. We will keep this in mind as we complete our analyses. So as of right now, it would suffice us to say that customers with the voicemail plan were more satisfied than those customers without that feature.

In [98]:

```
# Now looking at the relationship of churn between the 2 product features we listed
# above.  Looking for any uniqueness within the feature combinations.

pd.pivot_table(df,
               values='account_length',
               index=['voice_mail_plan', 'international_plan'],
               columns='churn',
```

```
                aggfunc='count'
```

Out[98]:

	churn	False	True
voice_mail_plan	international_plan		
no	no	1878	302
	yes	130	101
yes	no	786	44
	yes	56	36

So between our two features above, it looks like:

- `No voice mail plan & no interntational plan Churn -` **14%**
- `No voice mail plan & interntational plan Churn -` **44%**
- `Voice mail plan & no international plan Churn -` **5%**
- `Voice mail plan & international plan Churn -` **39%**

So customers that had the voice mail plan & no international plan, or no features at all performed be best (5%, and 14% respectively). Again, this could mean that the service of the international plan does meet the expectations of the customers. With that being said, the voice mail feature/ functionality does generally pretty well, and customers see the value in that feature. The same cannot be said for the international feature. This is typically bringing down the experience overall.

In [99]:

```
# Now that we know customers generally are not satisfied with the international plan
# we are going to dig into whether they pay more per minute to have those features
# enabled.

pd.pivot_table(df,
               values='price_per_minute',
               index=['voice_mail_plan', 'international_plan'],
               columns='churn',
               aggfunc=np.mean
              )
```

Out[99]:

	churn	False	True
voice_mail_plan	international_plan		
no	no	0.050518	0.055644
	yes	0.053261	0.053121

	churn	False	True
voice_mail_plan	international_plan		
yes	no	0.051141	0.049108
	yes	0.051807	0.053927

Now taking a look at the average price paid per minute between the same feature diagram we looked at above, it looks like those plans with the international plan pay more on average than those without.

Here is the comparison of price between the churn, and non-churn groups that we looked at above:

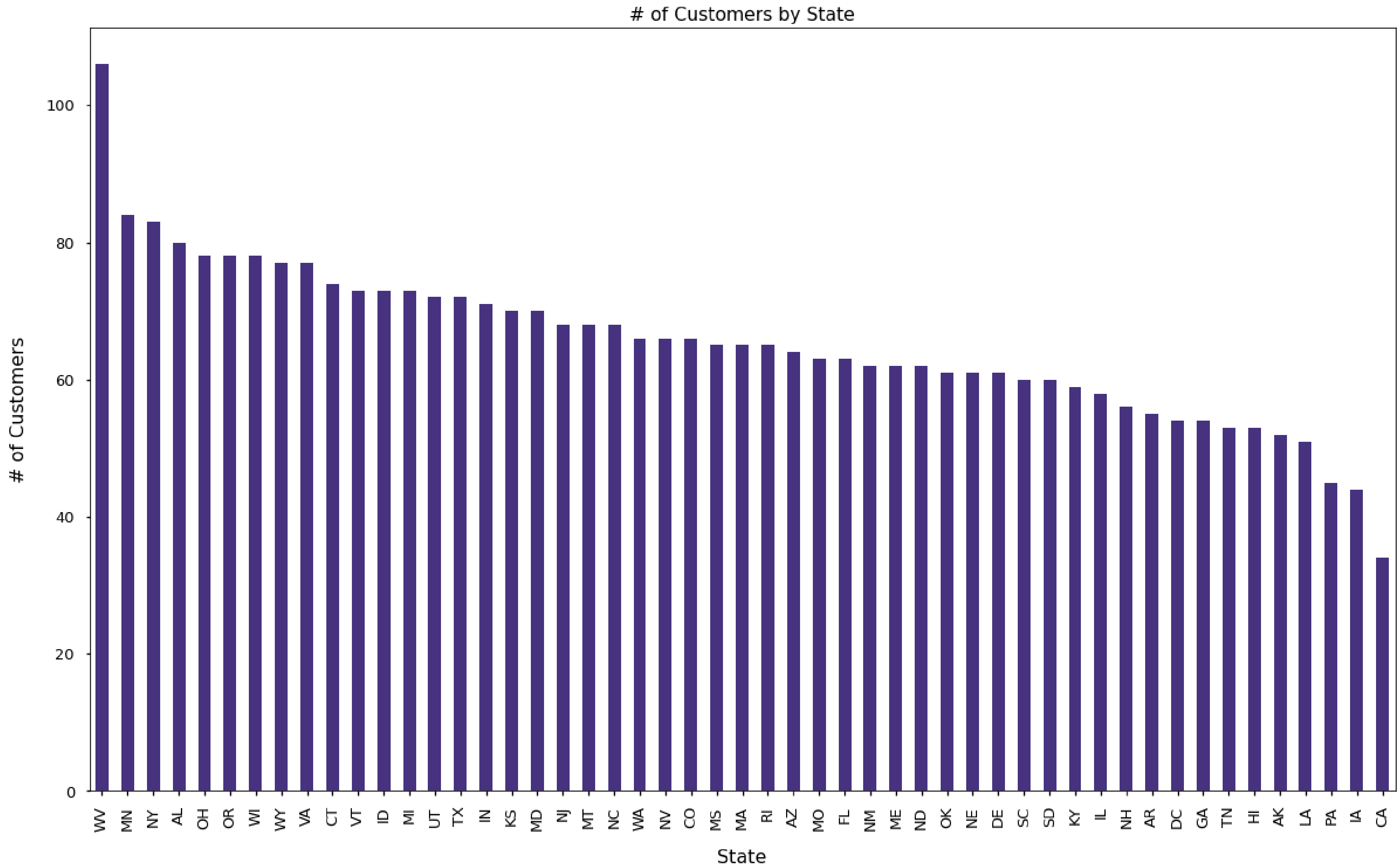
- `No voice mail plan & no interntational plan Churn -` **10% higher in Churn price per minute vs Non Churn price per minute**
- `No voice mail plan & interntational plan Churn -` **0% difference in Churn price per minute vs Non Churn price per minute**
- `Voice mail plan & no international plan Churn -` **-4% difference in Churn price per minute vs Non Churn price per minute**
- `Voice mail plan & international plan Churn -` **4% higher cost in Churn price per minute vs Non Churn price per minute**

This would indicate that there really isn't much price difference when looking at the per minute costs for these additional features. Or at least the customers that churned weren't paying that much more than the customers that were retained, providing support for the fact that those features value were really based on if they met the expectations of functionality or not.

Demographics/ Customer Categorical Features EDA

In [100…

```
fix, ax = plt.subplots(figsize=(20,12))

df['state'].value_counts().plot(kind='bar', color=pal[0])

ax.set_title('# of Customers by State')
ax.set_xlabel('State', labelpad=15, fontsize=16)
ax.set_ylabel('# of Customers', labelpad= 15, fontsize=16)

plt.show()
```



Overall the distribution of states is pretty good! No concerns here, however we will need to encode this categorical column if we want to retain this information. I am not sure if this will help us or if it will cause us to over fit on our training model. I say that because of the account specificity that we will introduce by maintaining this feature.

Since we are thinking about dropping our state column, we still have area_code, and our phone_number_prefix, to give us an idea of where the users are located. Going to split those columns out from the line_number, which won't really help us. We may need to drop the prefix and the area code for the same reasons I mentioned for state above. For now, we will prep the data in case we do want to keep it in.

In [101…

```python
# Adjusting out our phone number prefix and line number information to make it easier to work with.

df[['phone_number_prefix','line_number']] = df.phone_number.str.split("-",expand=True,).astype(int)
df
```

Out[101…

	state	account_length	area_code	phone_number	international_plan	voice_mail_plan	number_vmail_messages	total_day_minut
0	KS	128	415	382-4657	no	yes	25	265
1	OH	107	415	371-7191	no	yes	26	161
2	NJ	137	415	358-1921	no	no	0	243
3	OH	84	408	375-9999	yes	no	0	299
4	OK	75	415	330-6626	yes	no	0	166
...	...	...	...	...	...	...	...	
3328	AZ	192	415	414-4276	no	yes	36	156
3329	WV	68	415	370-3271	no	no	0	23
3330	RI	28	510	328-8230	no	no	0	180
3331	CT	184	510	364-6381	yes	no	0	213
3332	TN	74	415	400-4344	no	yes	25	234

3333 rows × 27 columns

In [102…

```python
# dropping state, and phone number

df = df.drop(['phone_number',
              'line_number',
              'state'
             ],
             axis=1
            )
```

In [103…

```python
# Going back to look at our columns that need transformed from string to integer // international plan

df = df.replace({'international_plan':
                  {'yes': 1,
                   'no': 0
                  }
```

```
    }
    )
```

In [104…

```
# Going back to look at our columns that need transformed from string to integer // voice mail plan

df = df.replace({'voice_mail_plan':
                  {'yes': 1,
                   'no': 0
                  }
                 }
                )
```

In [105…

```
# Going back to look at our columns that need transformed from string to integer // voice mail plan

df['churn'] = df['churn'].astype(int)
```

In [106…

```
# Quick look at our data set to see how we are evolving.

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 24 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account_length          3333 non-null   int64  
 1   area_code               3333 non-null   int64  
 2   international_plan      3333 non-null   int64  
 3   voice_mail_plan         3333 non-null   int64  
 4   number_vmail_messages   3333 non-null   int64  
 5   total_day_minutes       3333 non-null   float64
 6   total_day_calls         3333 non-null   int64  
 7   total_day_charge        3333 non-null   float64
 8   total_eve_minutes       3333 non-null   float64
 9   total_eve_calls         3333 non-null   int64  
 10  total_eve_charge        3333 non-null   float64
 11  total_night_minutes     3333 non-null   float64
 12  total_night_calls       3333 non-null   int64  
 13  total_night_charge      3333 non-null   float64
 14  total_intl_minutes      3333 non-null   float64
 15  total_intl_calls        3333 non-null   int64  
 16  total_intl_charge       3333 non-null   float64
 17  customer_service_calls  3333 non-null   int64  
 18  churn                   3333 non-null   int64  
 19  total_calls             3333 non-null   int64  
 20  total_charges           3333 non-null   float64
 21  total_minutes           3333 non-null   float64
```

```
 22  price_per_minute        3333 non-null   float64
 23  phone_number_prefix     3333 non-null   int64
dtypes: float64(11), int64(13)
memory usage: 625.1 KB
```

Usage EDA

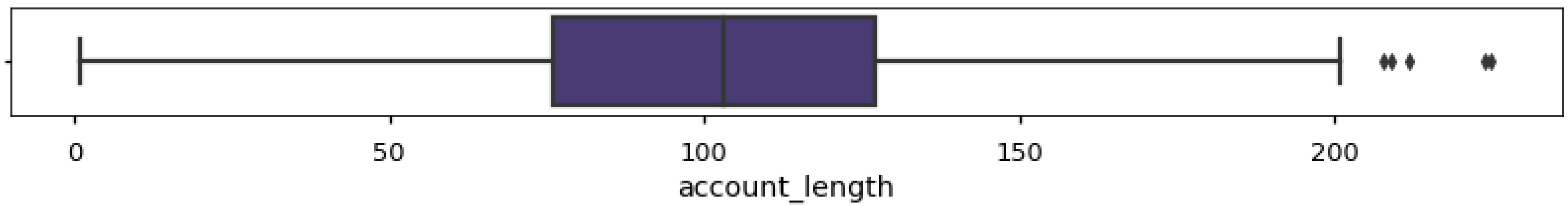
Now that we have looked at some of our categorical/ demogrphic based features, next we are going to dig into some of our usage based features to note any outliers, and any patterns between our target, churn vs non-churn customer segments.

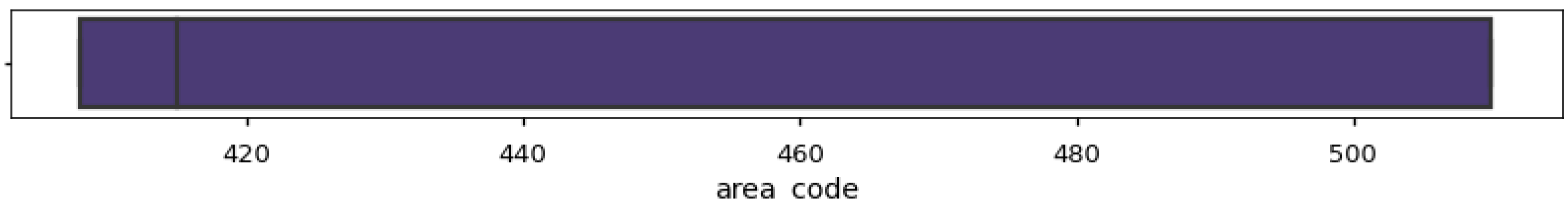
In [107…

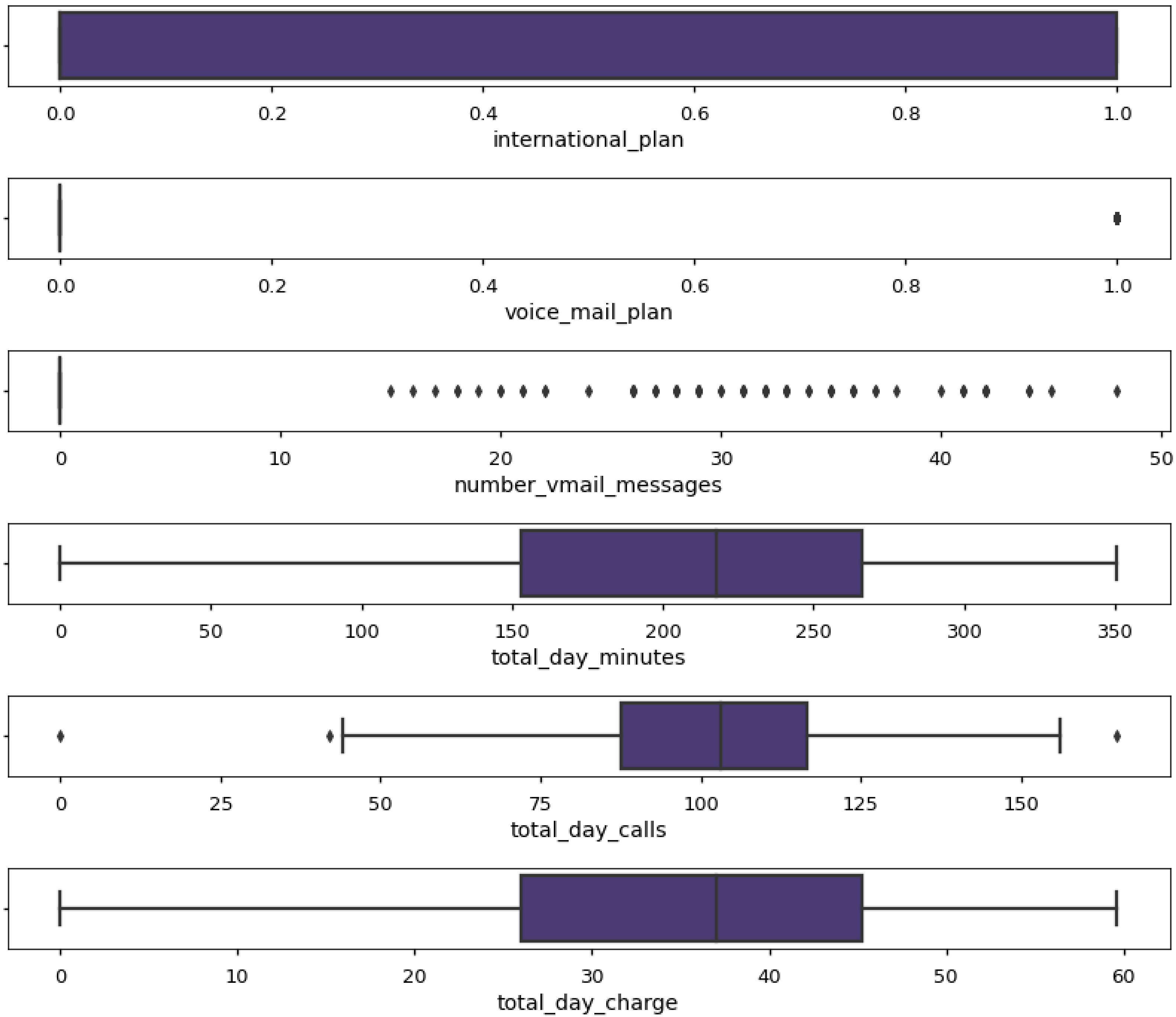
```
# Creating a few filtered data sets to make some visuals/ grouping easier if needed.

df_churn = df[df['churn'] == True]
df_active = df[df['churn'] == False]
```

In [108…

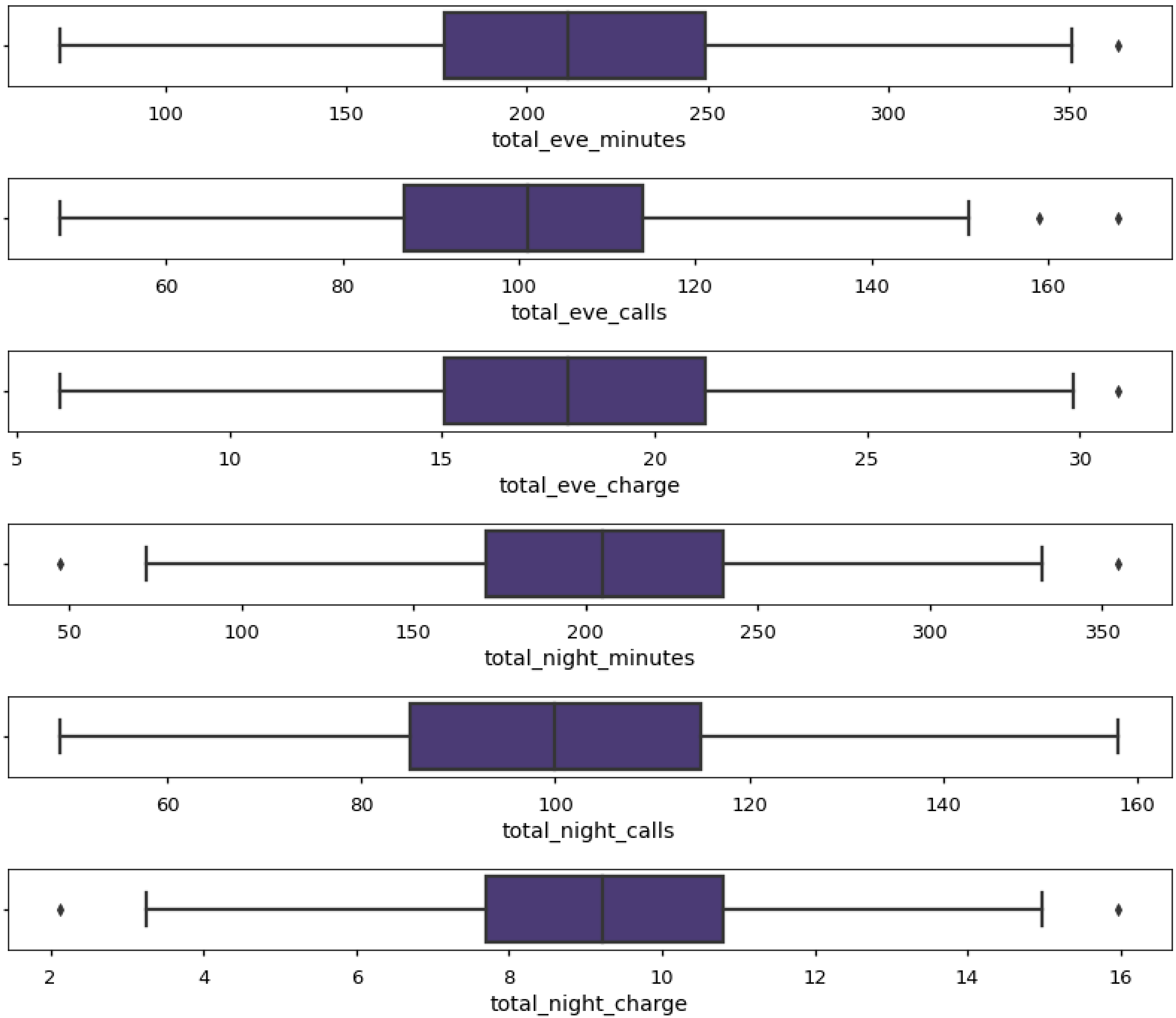
```
# Quick look at distribution across our numerical values.  Looking for outliers, even though
# our data seems to be pretty evenly distributed across our feature sets.

plt.rcParams['figure.max_open_warning'] = 0;

for column in df:
        plt.figure(figsize=(14,1))
        sns.boxplot(data=df_churn, x=column, color=pal[0])
```

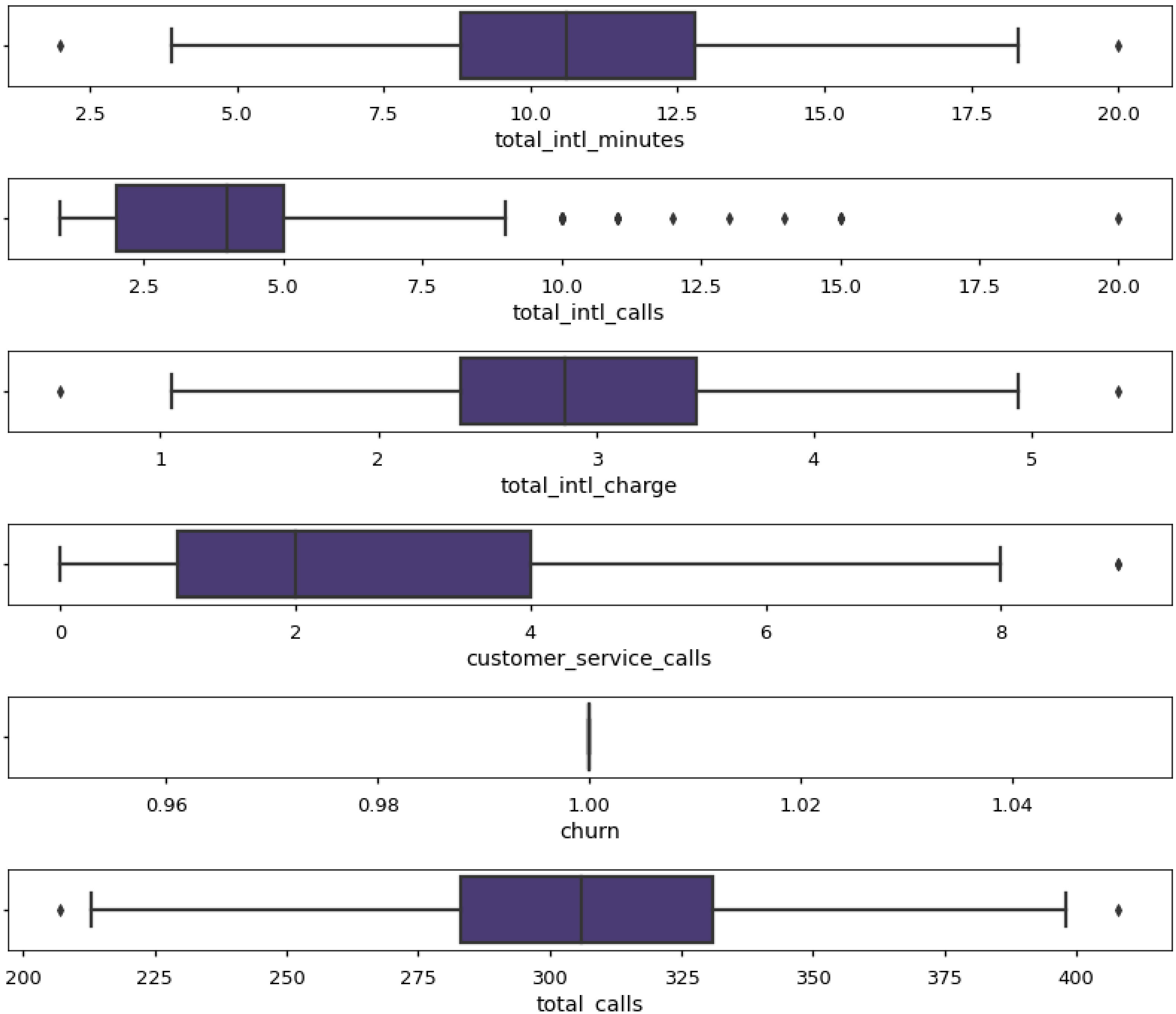


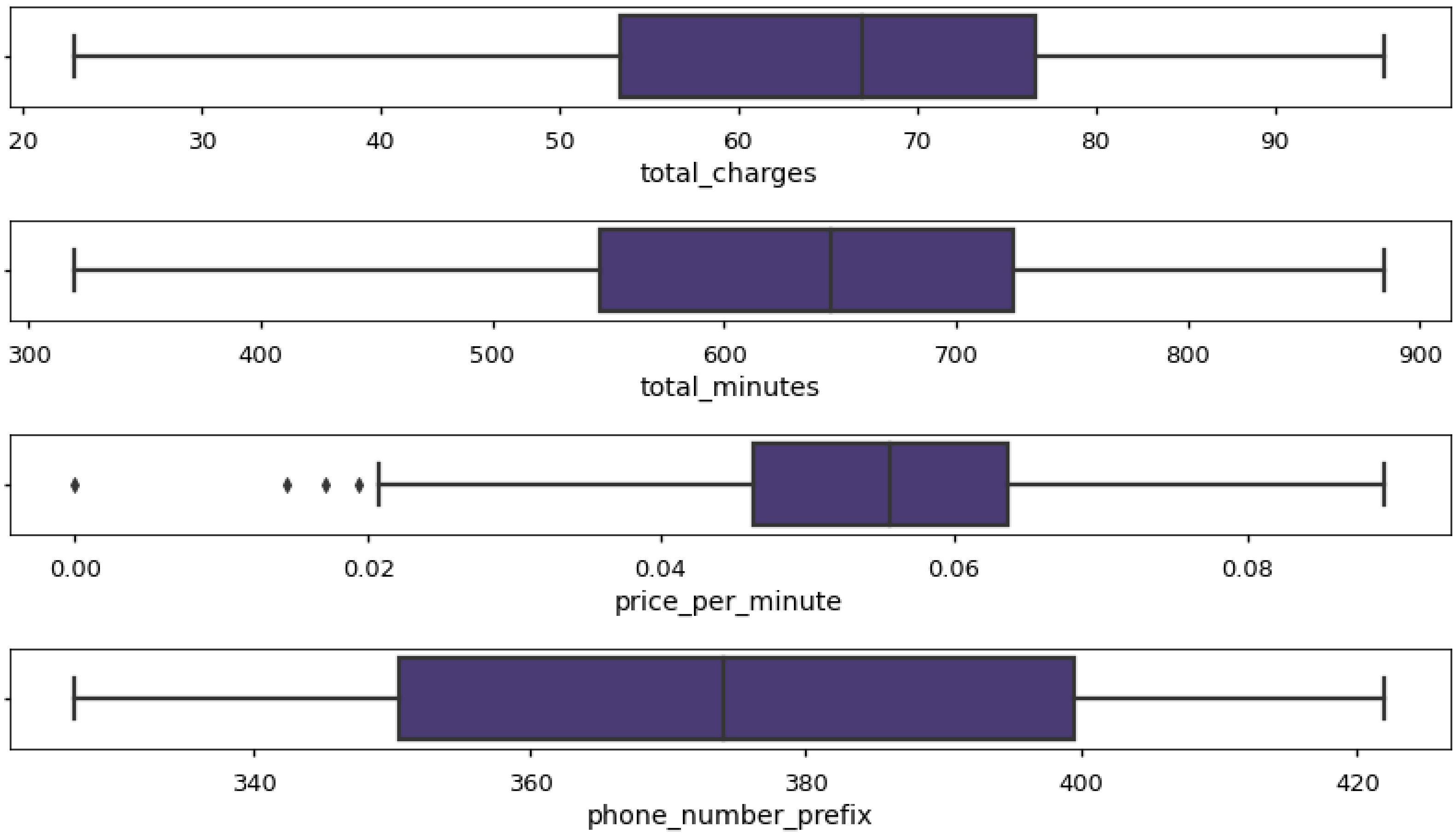




0.0
0.2
0.4
0.6
0.8
1.0
international_plan
0.0
0.2
0.4
0.6
0.8
1.0
voice_mail_plan
0
10
20
30
40
50
number_vmail_messages
0
50
100
150
200
250
300
350
total_day_minutes
0
25
50
75
100
125
150
total_day_calls
0
10
20
30
40
50
60
total_day_charge


100 150 200 250 300 350
total_eve_minutes
60 80 100 120 140 160
total_eve_calls
5 10 15 20 25 30
total_eve_charge
50 100 150 200 250 300 350
total_night_minutes
60 80 100 120 140 160
total_night_calls
2 4 6 8 10 12 14 16
total_night_charge


2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
total_intl_minutes
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
total_intl_calls
1
2
3
4
5
total_intl_charge
0
2
4
6
8
customer_service_calls
0.96
0.98
1.00
1.02
1.04
churn
200
225
250
275
300
325
350
375
400
total_calls

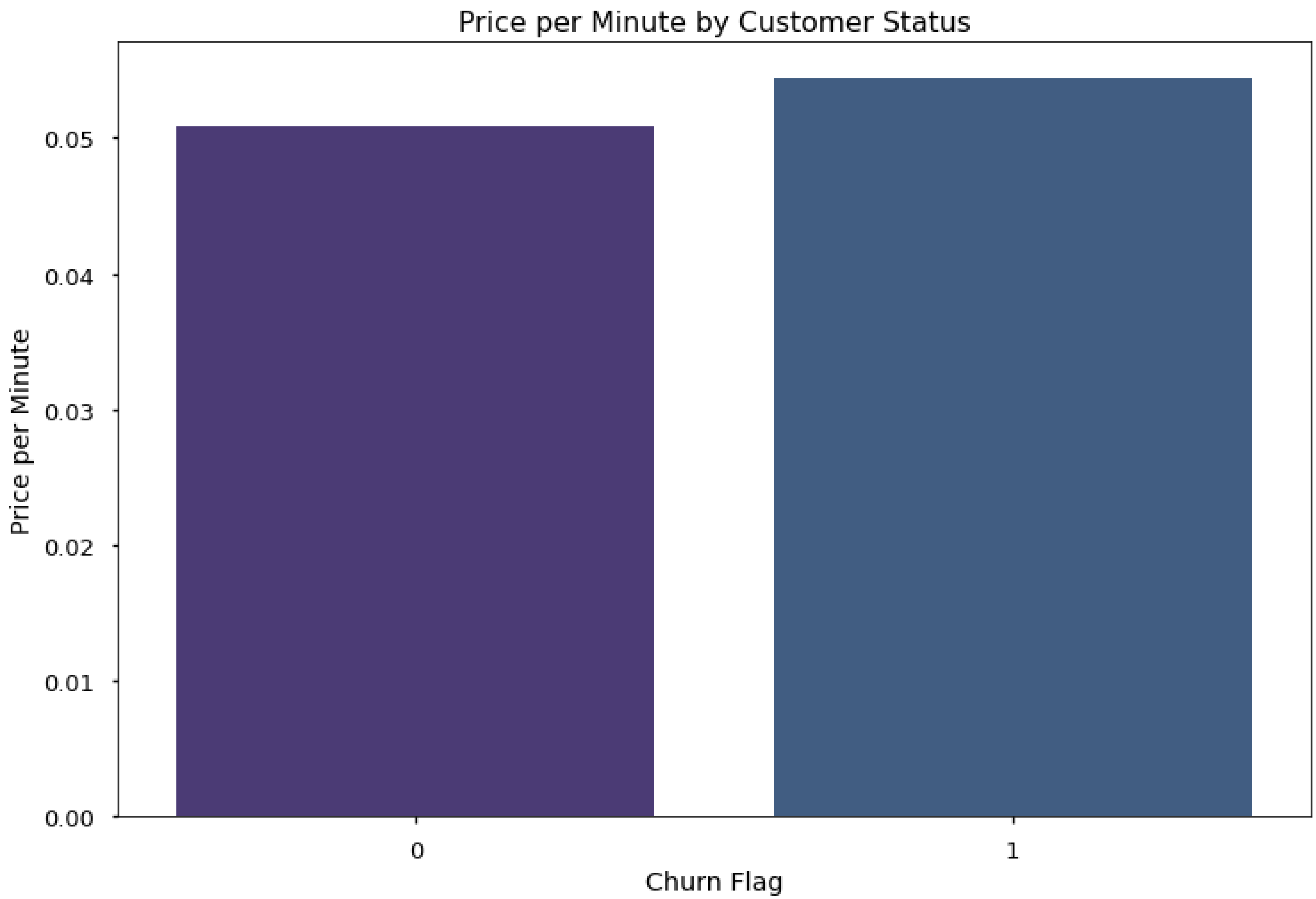


Not a ton of outliers within our numerical features, at least in aggregate. The voice mail messages seems to have the hgiher number of outliers, but that could be for a number of reasons. The sample is smaller, and we will have the impact between the groups that actually have the feature, vs those that don't have the feature impacting the distribution (since our charts are naive).

In [109…

```
# Going to visualize our price per minute feature between churn and non- churn accounts.

mini_bar('churn', 'price_per_minute', 'Price per Minute', 'Churn Flag', 'Price per Minute by Customer Status');
```

```
   churn  price_per_minute
0      0          0.050840
1      1          0.054393
```

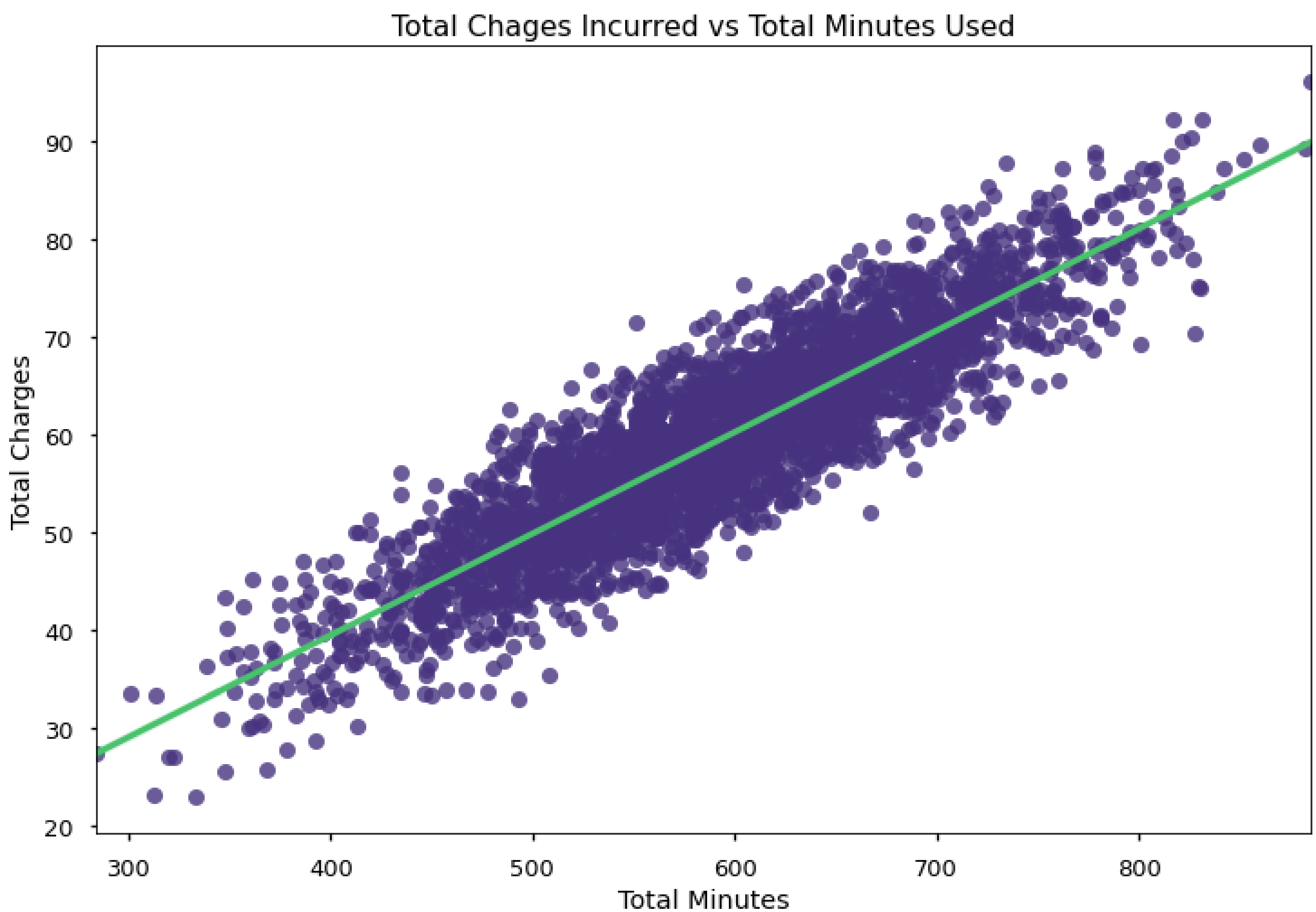


Churned customers paid **7% more** per minute than customers that were retained. Not sure why that might be the case, but could be a result of customers with the international plan included.

In [110…

```
# Creating a scatter plot to look at the relationship between price, and usage.

plt.figure(figsize = (12,8))

rp = sns.regplot(x='total_minutes',
                y='total_charges',
                data=df,
                scatter_kws={"color": pal[0]},
                line_kws={"color": pal[4]})
```

```
rp.set_ylabel('Total Charges')
rp.set_xlabel('Total Minutes')
rp.set_title('Total Chages Incurred vs Total Minutes Used');
```

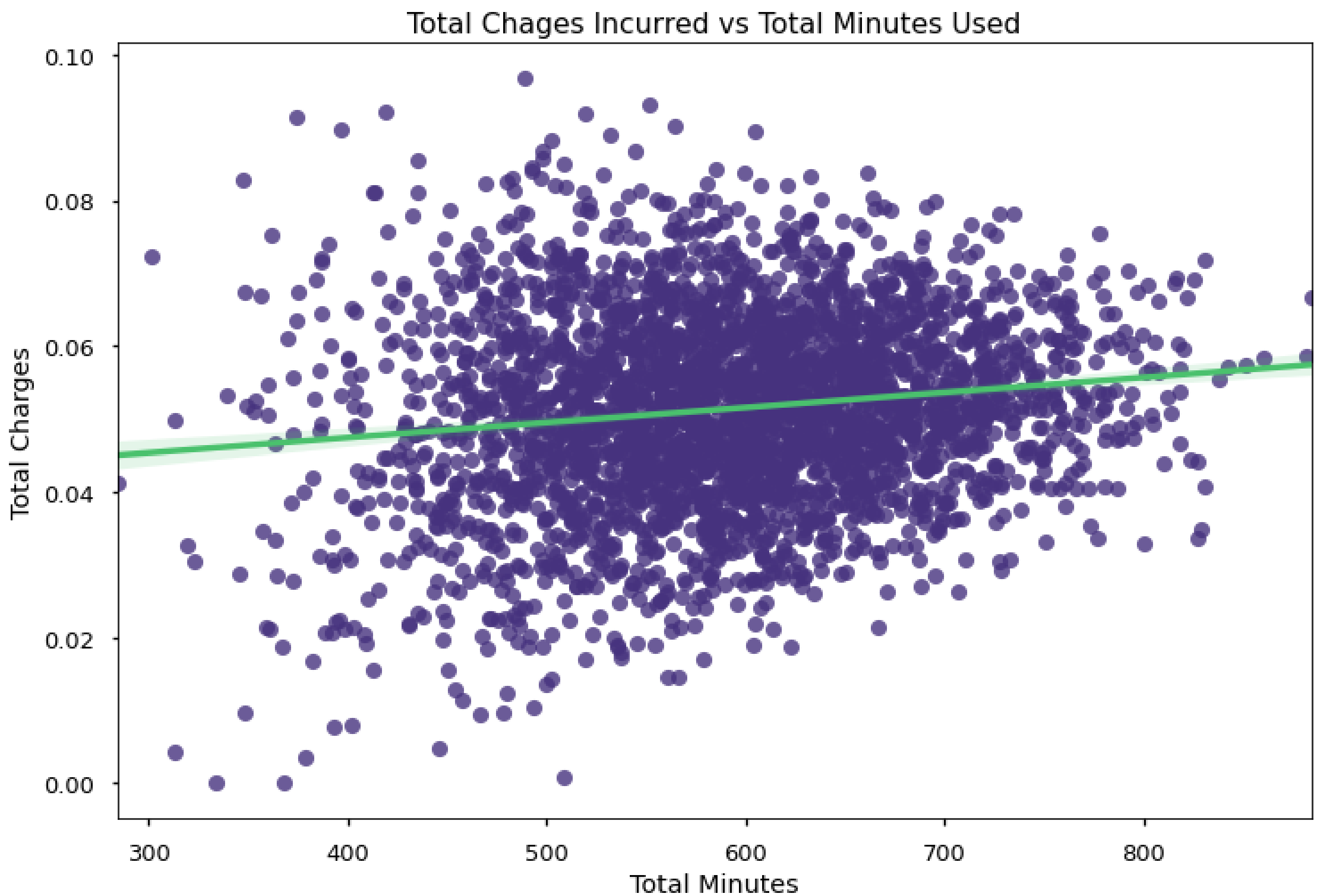


This makes sense to me. As the product is used, charges are increasing. What we really want to investigate though is if the price per minute is going down, as the the total minutes go up. If there was a strategic pricing, I think we would want to see the price per minute go down, but the charges stay flat because of the increase in minutes used.

In [111…

```
# Creating a scatter plot to look at the relationship between price, and usage.

plt.figure(figsize = (12,8))
```

```
rp = sns.regplot(x='total_minutes',
                 y='price_per_minute',
                 data=df,
                 scatter_kws={"color": pal[0]},
                 line_kws={"color": pal[4]})

rp.set_ylabel('Total Charges')
rp.set_xlabel('Total Minutes')
rp.set_title('Total Chages Incurred vs Total Minutes Used');
```

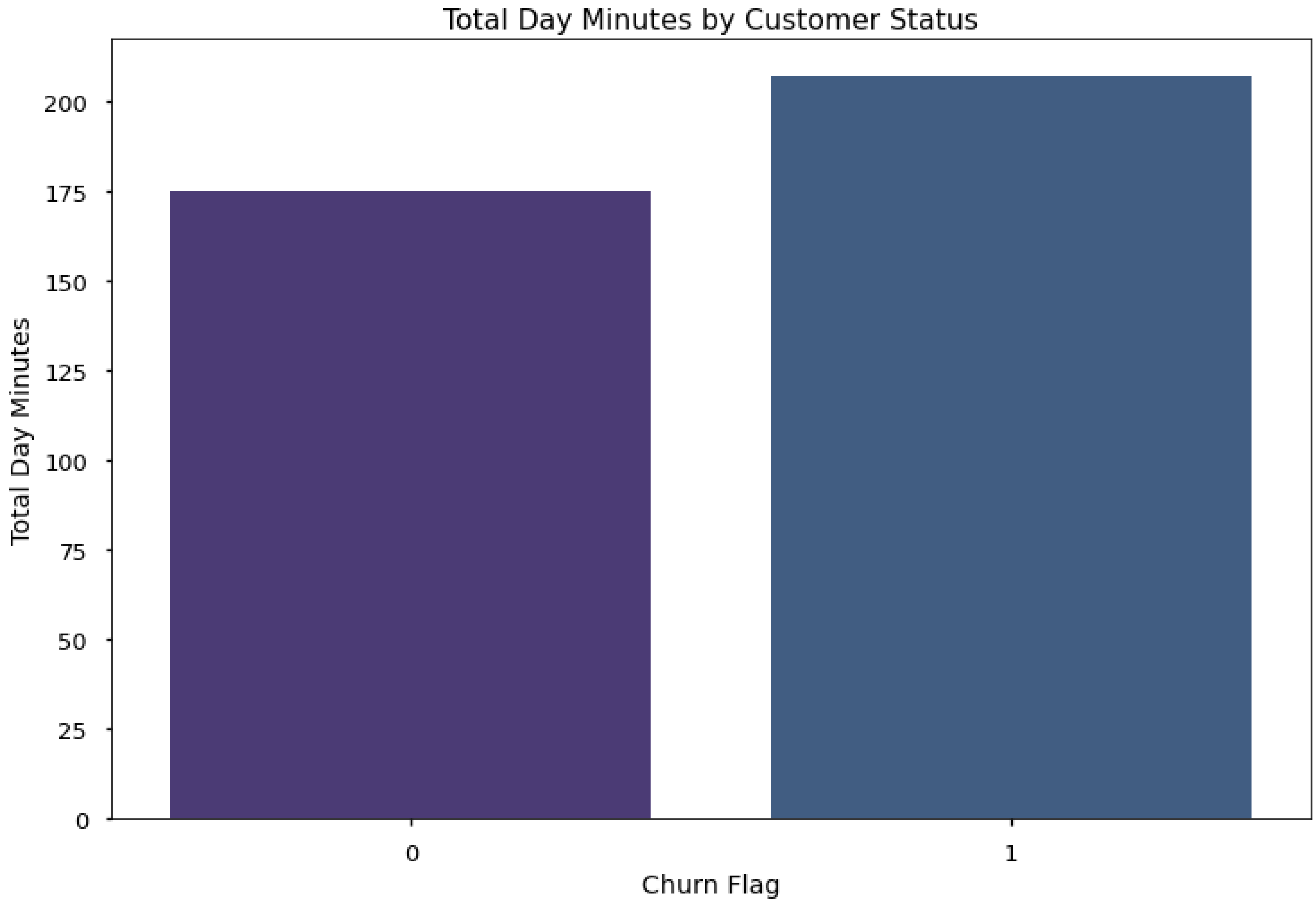


This is still showing a positive correlation between our two variables. I think we would actually want to see a negative slope here indicating that the customers that use the product the most, would be getting a slight discount on pricing as usage increases.

In [112…

```
# Looking at usage between total day minutes within our target customer segments

mini_bar('churn', 'total_day_minutes', 'Total Day Minutes', 'Churn Flag', 'Total Day Minutes by Customer Status
```

```
   churn  total_day_minutes
0      0         175.175754
1      1         206.914079
```

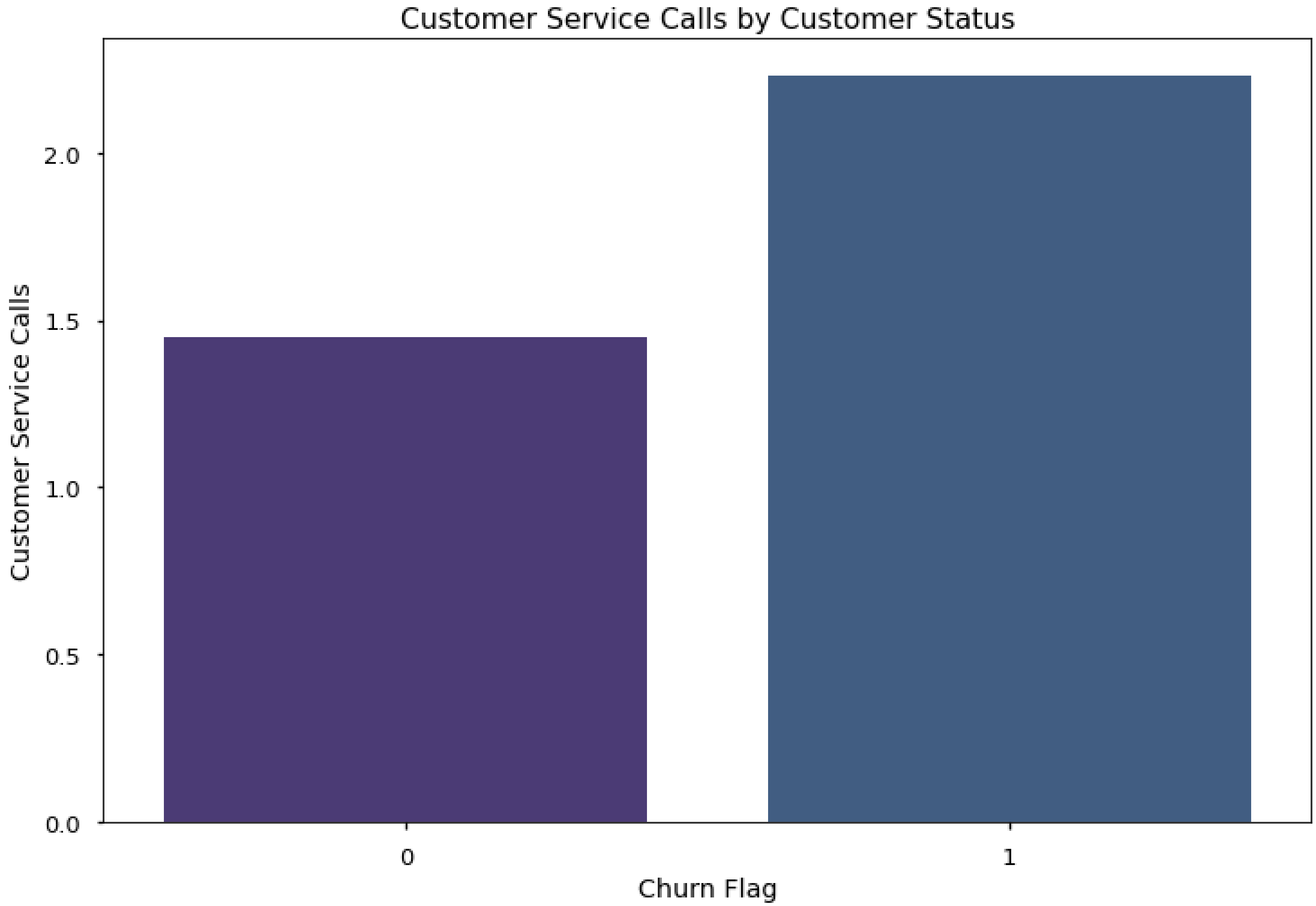


Customers that churn use the plan during the day **18% more** than the customers that were retained.

In [113…

```
# Looking at averag customer service calls between our target customer segements.

mini_bar('churn', 'customer_service_calls', 'Customer Service Calls', 'Churn Flag', 'Customer Service Calls by
```

```
   churn  customer_service_calls
0      0                1.449825
1      1                2.229814
```



Customers that churned contacted customer service **54% more** than customers that were retained. Going to take a quick look at the % of churn as customer service calls increase.

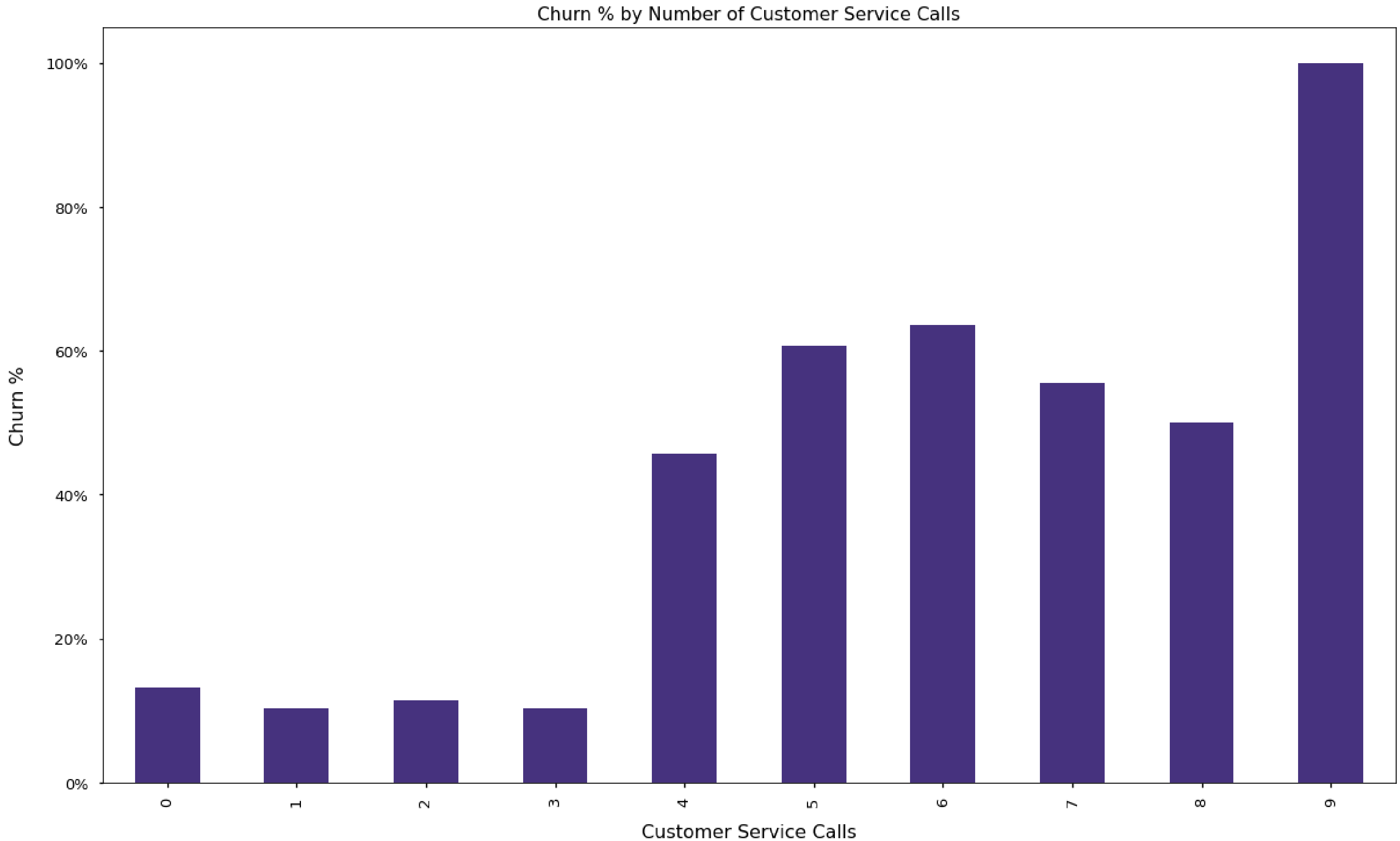
In [114…

```
# Create an object to chart

cs_churn_percent = df['churn'].groupby(df['customer_service_calls']).mean()*100
```

In [115…

```
# Create a charge looking at the customer service calls and churn percentage within each.
```

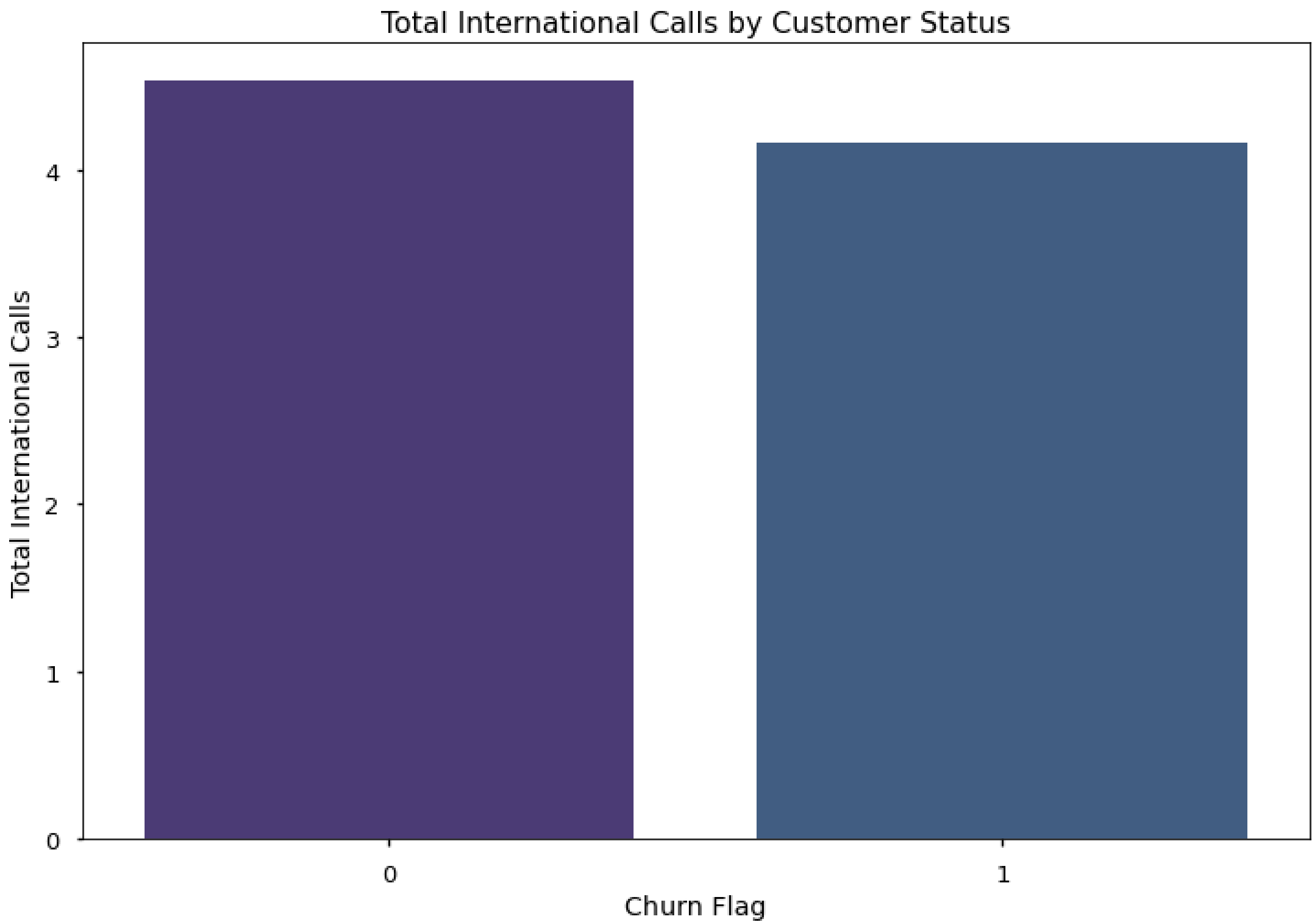
```
fix, ax = plt.subplots(figsize=(20,12))

cs_churn_percent.plot(kind='bar', color=pal[0])


ax.set_title('Churn % by Number of Customer Service Calls')
ax.set_xlabel('Customer Service Calls', labelpad=15, fontsize=16)
ax.set_ylabel('Churn %', labelpad= 15, fontsize=16)

fmt = '%.0f%%' # Format you want the ticks, e.g. '40%'
yticks = mtick.FormatStrFormatter(fmt)
ax.yaxis.set_major_formatter(yticks)

plt.show()
```



In [116…

```
# Total international calls by target customer segment

mini_bar('churn', 'total_intl_calls', 'Total International Calls', 'Churn Flag', 'Total International Calls by
```

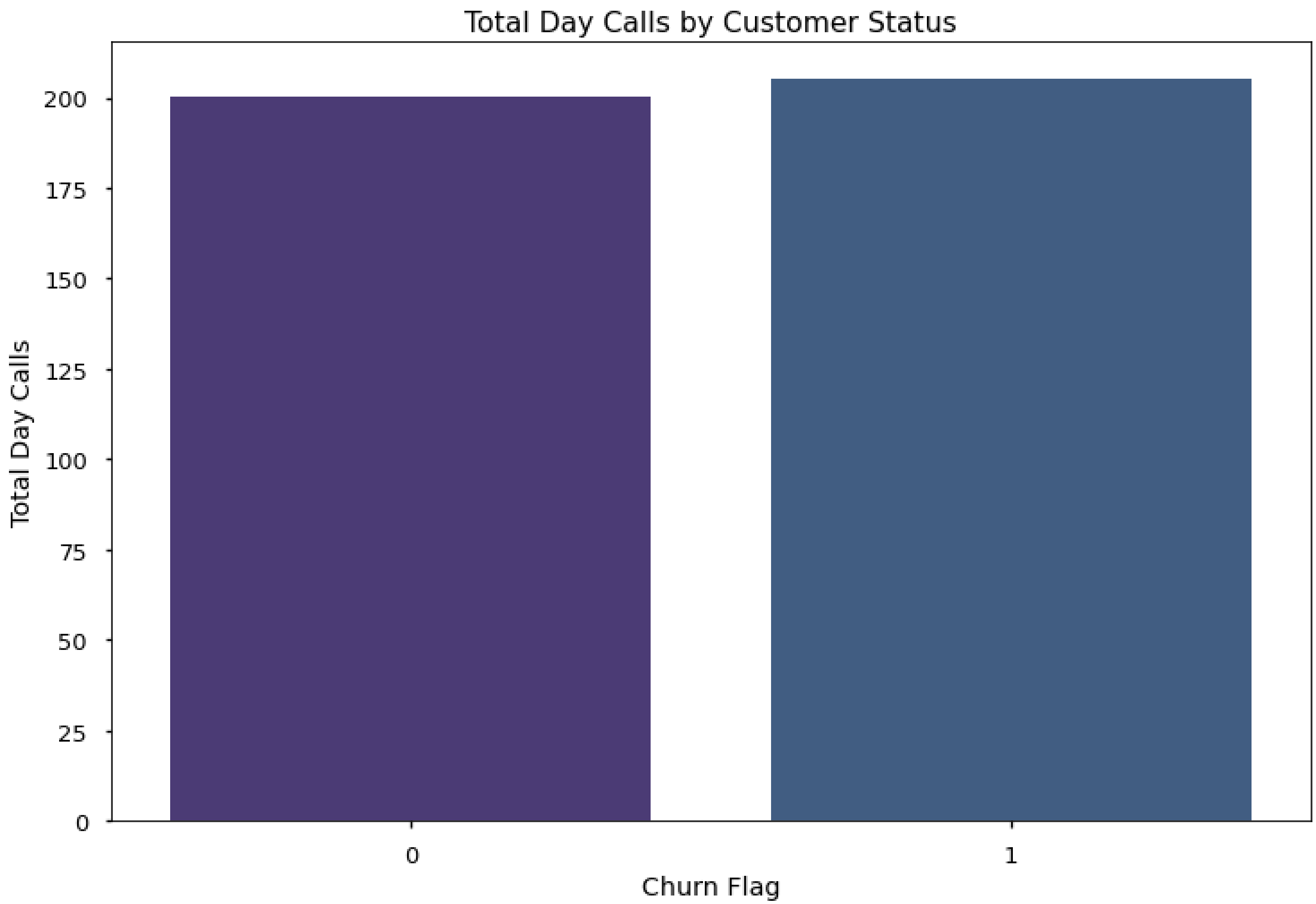
```
   churn  total_intl_calls
0      0          4.532982
1      1          4.163561
```



In [117…

```
# Total night minutes between target customer segments

mini_bar('churn', 'total_night_minutes', 'Total Day Calls', 'Churn Flag', 'Total Day Calls by Customer Status')
```

```
   churn  total_night_minutes
0      0           200.133193
1      1           205.231677
```

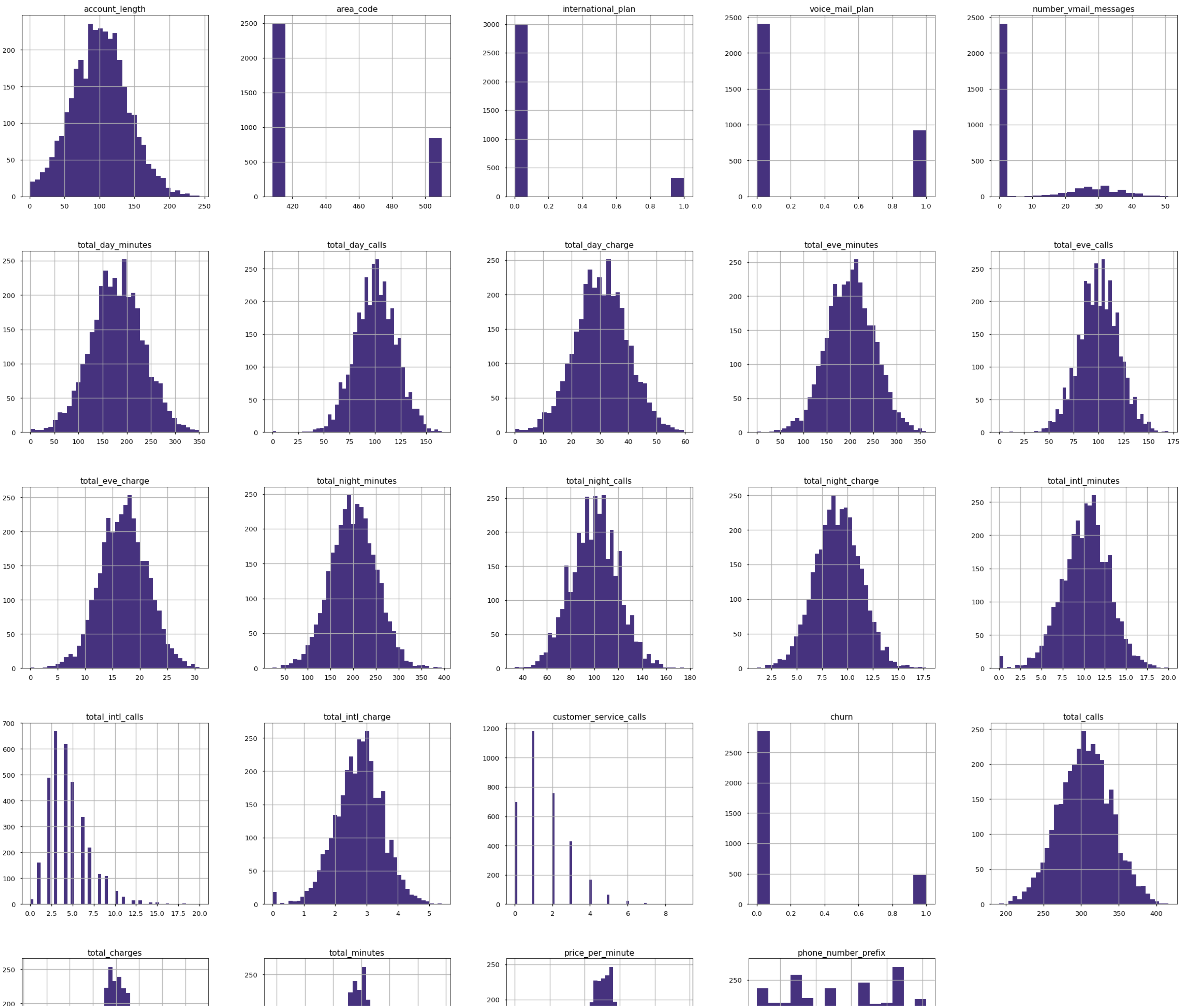


Nothing to really write home about with the last two charts. The difference in usage between our target segments is negligible. Moving on to collinearity before we get into our classification modeling.

Distribution, Linearity, Correlation EDA

In [118…

```
# Going to look at overall distribution and histograms to visually inspect our data

df.hist(bins='auto',
        figsize=(40,40),
        color=pal[0]
       );
```


account_length
area_code
international_plan
voice_mail_plan
number_vmail_messages
total_day_minutes
total_day_calls
total_day_charge
total_eve_minutes
total_eve_calls
total_eve_charge
total_night_minutes
total_night_calls
total_night_charge
total_intl_minutes
total_intl_calls
total_intl_charge
customer_service_calls
churn
total_calls
total_charges
total_minutes
price_per_minute
phone_number_prefix

These look great. Reminds me of why I choose this dataset in the first place!

In [119…

```python
# Before summarizing the table above, I am going to take a peek at the area code column vs the prefix columns.

df['area_code'].value_counts()


pd.pivot_table(df,
               values='account_length',
               index='area_code',
               columns='phone_number_prefix',
               aggfunc='count'
              )
```

Out[119…

phone_number_prefix	327	328	329	330	331	332	333	334	335	336	...	413	414	415	416	417	418	419	420	421	422
area_code																					
408	3	9	9	5	6	12	13	11	10	14	...	6	4	10	10	15	6	6	9	5	7
415	10	12	17	20	10	21	25	20	16	20	...	12	15	21	22	21	21	13	18	13	9
510	6	11	11	9	9	11	8	7	8	7	...	10	10	5	5	10	5	8	8	6	3

3 rows × 96 columns

We only have 3 area codes for the all the prefixes that we see. We may want to encode this category since it is categorical feature. I will also encode the phone number prefix, and the state columns before running any models. Going to continue to review.

In [120…

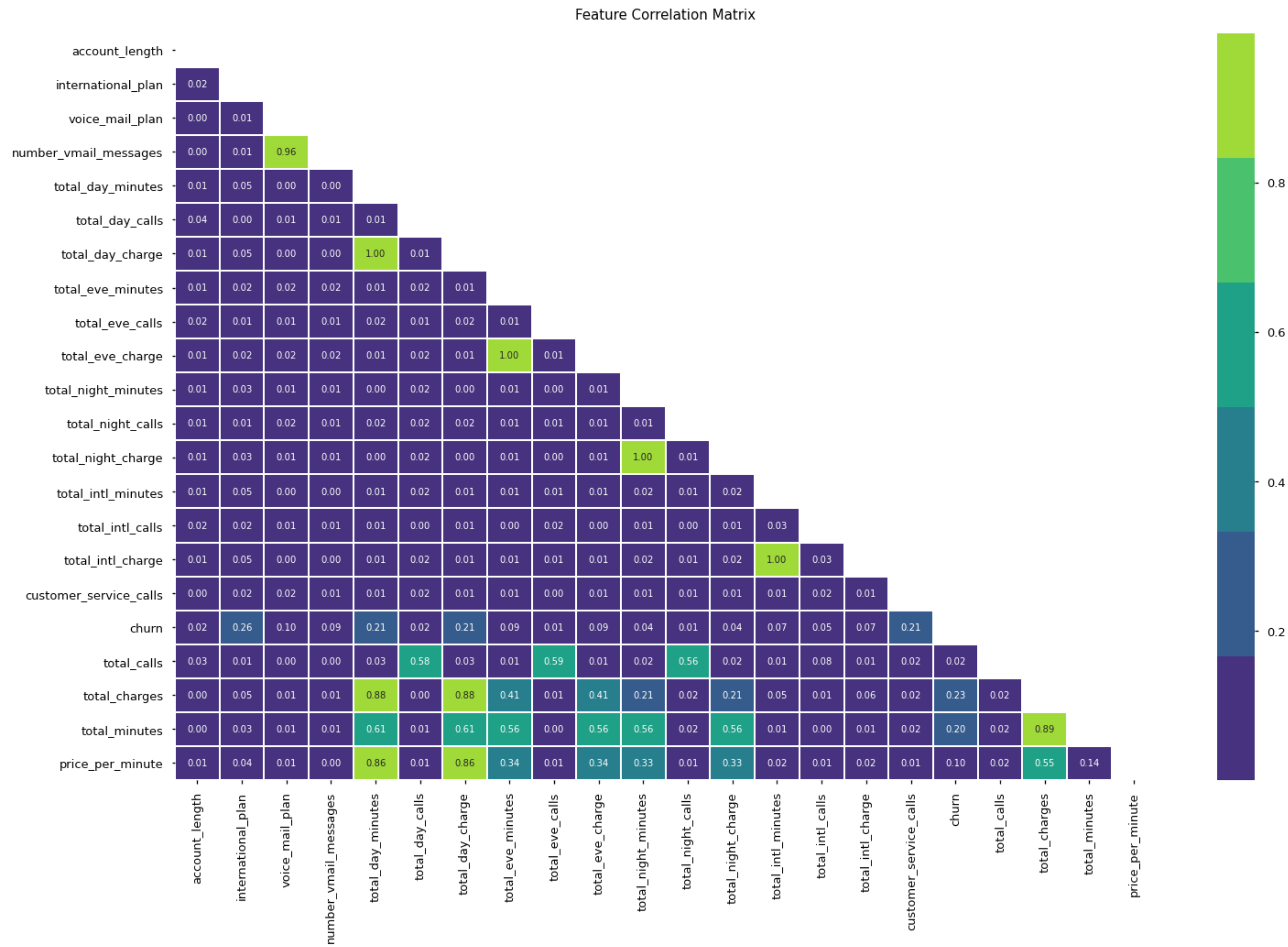
```python
# Updating international and voicemail indicators to boolean, and area code and phone_num prefix to strings

df['area_code'] = df['area_code'].astype(str)
df['phone_number_prefix'] = df['phone_number_prefix'].astype(str)


df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 24 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   account_length          3333 non-null   int64 
 1   area_code               3333 non-null   object
 2   international_plan      3333 non-null   int64 
```

```
 3   voice_mail_plan         3333 non-null   int64
 4   number_vmail_messages   3333 non-null   int64
 5   total_day_minutes       3333 non-null   float64
 6   total_day_calls         3333 non-null   int64
 7   total_day_charge        3333 non-null   float64
 8   total_eve_minutes       3333 non-null   float64
 9   total_eve_calls         3333 non-null   int64
 10  total_eve_charge        3333 non-null   float64
 11  total_night_minutes     3333 non-null   float64
 12  total_night_calls       3333 non-null   int64
 13  total_night_charge      3333 non-null   float64
 14  total_intl_minutes      3333 non-null   float64
 15  total_intl_calls        3333 non-null   int64
 16  total_intl_charge       3333 non-null   float64
 17  customer_service_calls  3333 non-null   int64
 18  churn                   3333 non-null   int64
 19  total_calls             3333 non-null   int64
 20  total_charges           3333 non-null   float64
 21  total_minutes           3333 non-null   float64
 22  price_per_minute        3333 non-null   float64
 23  phone_number_prefix     3333 non-null   object
dtypes: float64(11), int64(11), object(2)
memory usage: 625.1+ KB
```

In [121…

```
# Creating a heatmap to look at colinearity and potential categories that will lead to churn prediction.

corr = df.corr().abs()

fix, ax = plt.subplots(figsize = (24,15))
matrix = np.triu(corr)
ax.set_title('Feature Correlation Matrix', pad=15, fontsize=15)
heatmap = sns.heatmap(corr, annot=True, cmap=pal, fmt='.2f', mask=matrix, linewidths=1)
plt.show()
```



Charges and total minutes are perfectly correlated, which makes sense. Also the number of voicemail messages, and the voice mail plan category are also highly correlated. Meaning if they purchased the plan, it is highly likely that they used it. Day minutes were highly correlated with the total minutes vs evening minutes. It looks like churn had the highest correlation with the international plan (which we identified as a possibility earlier). Total day minutes, total day charges, and customer service calls. Customer service calls could be related to the actual service that the customer experienced, or could be the fact that the customer had to call in to cancel their plan, thus driving that columns correlation higher.

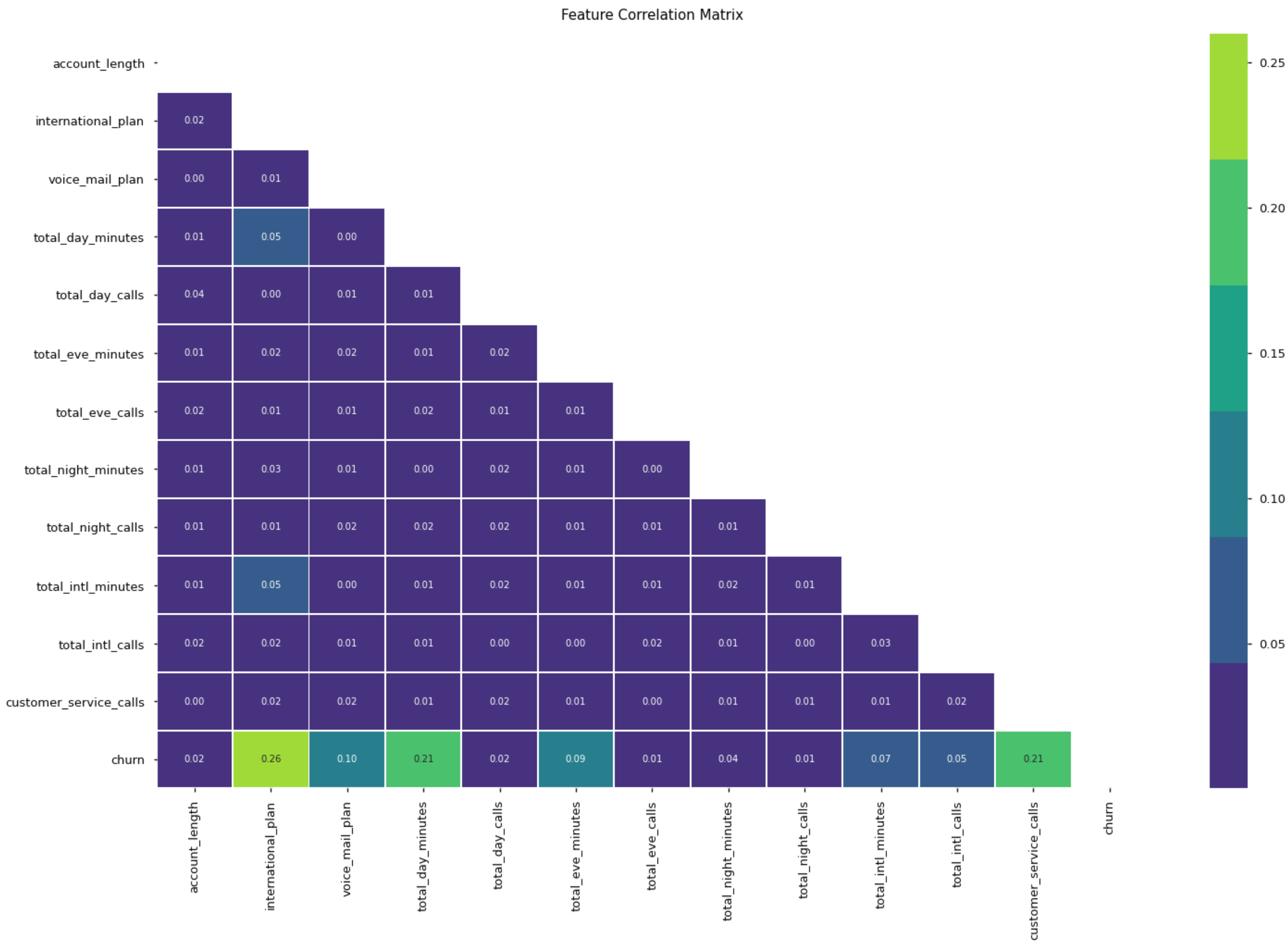
Going to drop the columns we added earlier, and columns that are dependent on another for its calculation (i.e. charges). They are too dependent on the source features.

In [122…

```
df = df.drop(['total_charges',
         'total_intl_charge',
         'total_eve_charge',
         'total_day_charge',
         'total_night_charge',
         'number_vmail_messages',
         'total_calls',
         'total_minutes',
         'price_per_minute'
        ],
         axis=1)
```

In [123…

```
# Creating a heatmap to look at colinearity and potential categories that will lead to churn prediction.

corr = df.corr().abs()

fix, ax = plt.subplots(figsize = (24,15))
matrix = np.triu(corr)
ax.set_title('Feature Correlation Matrix', pad=15, fontsize=15)
heatmap = sns.heatmap(corr, annot=True, cmap=pal, fmt='.2f', mask=matrix, linewidths=1)
plt.show()
```



Looking much better. Looks liek that international plan, the total day minutes, and customer serivce calls are all showing some correlation to our target variable of churn. I would expect these to manifest again at the end when we are looking at feature importances of our model.

In [124…

```
# Checking our target/ dataset for balance before creating our baseline classifcation model.

print('Raw Counts')
print(df['churn'].value_counts())
print()
print('Percentages')
print(df['churn'].value_counts(normalize=True))
```

```
Raw Counts
0    2850
1     483
Name: churn, dtype: int64

Percentages
0    0.855086
1    0.144914
Name: churn, dtype: float64
```

A baseline model that always chose the majority class would have an accuracy of over 85%. Therefore we will want to report additional metrics at the end.

Classfication Modeling

Now we are going to get into our classification modeling. We are going to first try and create a psuedo pipeline to do some of the lifting as we move between our models. In addition, we will be doing some oversampling in order to account for our target imbalance.

In [125…

```
# Quick look at our dataframe

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account_length          3333 non-null   int64  
 1   area_code               3333 non-null   object 
 2   international_plan      3333 non-null   int64  
 3   voice_mail_plan         3333 non-null   int64  
 4   total_day_minutes       3333 non-null   float64
 5   total_day_calls         3333 non-null   int64  
 6   total_eve_minutes       3333 non-null   float64
 7   total_eve_calls         3333 non-null   int64  
 8   total_night_minutes     3333 non-null   float64
 9   total_night_calls       3333 non-null   int64  
```

```
 10   total_intl_minutes      3333 non-null   float64
 11   total_intl_calls        3333 non-null   int64
 12   customer_service_calls  3333 non-null   int64
 13   churn                   3333 non-null   int64
 14   phone_number_prefix     3333 non-null   object
dtypes: float64(4), int64(9), object(2)
memory usage: 390.7+ KB
```

In [126…

```
# Dropping out superfulous columns here before we do our X, y splits for test/ train.

df = df.drop(['area_code', 'phone_number_prefix'], axis=1)
```

In [127…

```
# Situate target and non-target features

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

# Create splits

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

In [128…

```
# Also looking at a dummy model with 5 cross validation folds.  Mean accuracy is about
# 86%.  This aligns with our assumption above with the imbalance of our churned
# customer count.

dummy_model = DummyClassifier(strategy='most_frequent')

cv_results = cross_val_score(dummy_model,
                             X_train,
                             y_train,
                             cv=5)

dummy_model.fit(X_train, y_train)

np.mean(cv_results)
```

Out[128…

```
0.8567430861723446
```

Case and point from our statement earlier, a most frequent model could capture around 86% of the correct cases. With that being said, the metric we will be evaluating is recall. Recall is calculated by taking the number of True Positives divided by the True Positives and the False Negative classes. Recall is typically good when we want to limit false negatives. For our use case, false negatives would be a customer that churned, and we didn't predict them to churn, thus never giving our partners in Customer Success the opportunity to "save" the client.

Pipeline

In [129…
```
# Labeling columns for different preprocessing steps

categorical_columns = []

numerical_columns = ['account_length', 'total_day_minutes',
                     'total_day_calls', 'total_eve_minutes', 'total_eve_calls',
                     'total_night_calls', 'total_intl_minutes', 'total_intl_calls',
                     'customer_service_calls', 'total_night_minutes'
                    ]

binary_columns = ['international_plan', 'voice_mail_plan']
```

In [130…
```
df.columns
```

Out[130…
```
Index(['account_length', 'international_plan', 'voice_mail_plan',
       'total_day_minutes', 'total_day_calls', 'total_eve_minutes',
       'total_eve_calls', 'total_night_minutes', 'total_night_calls',
       'total_intl_minutes', 'total_intl_calls', 'customer_service_calls',
       'churn'],
      dtype='object')
```

In [131…
```
# Check to make sure we have all our columns accounted for

(len(categorical_columns)+len(numerical_columns)+len(binary_columns)) == (df.shape[1]-1)
```

Out[131…
```
True
```

In [132…
```
# One Hot Encoding out categorical variables on our training data

categorical_Xtr_df = pd.DataFrame(X_train, columns=categorical_columns)

ohe = OneHotEncoder(drop='first',
                    sparse = False)

ohe_data = ohe.fit_transform(categorical_Xtr_df)


# Dum dums

ohe_data_df = pd.DataFrame(ohe_data,
                     columns=ohe.get_feature_names(),
```

```
                    index=categorical_Xtr_df.index)#make sure to pass an index

clean_df = X_train.drop(categorical_Xtr_df, axis=1)


# Putting humpty back together again

X_train = pd.concat([clean_df, ohe_data_df], axis=1)


# Quick peek

X_train.head()
```

Out[132…

	account_length	international_plan	voice_mail_plan	total_day_minutes	total_day_calls	total_eve_minutes	total_eve_calls	total_
367	45	0	0	78.2	127	253.4	108	
3103	115	0	0	195.9	111	227.0	108	
549	121	0	1	237.1	63	205.6	117	
2531	180	0	0	143.3	134	180.5	113	
2378	112	0	0	206.2	122	164.5	94	

In [133…

```
# One Hot Encoding out categorical variables on our testing data

categorical_Xts_df = pd.DataFrame(X_test, columns=categorical_columns)

ohe = OneHotEncoder(drop='first',
                    sparse = False)

ohe_data = ohe.fit_transform(categorical_Xts_df)

# Dum dums

ohe_data_df = pd.DataFrame(ohe_data,
                     columns=ohe.get_feature_names(),
                     index=categorical_Xts_df.index)#make sure to pass an index

clean_df = X_test.drop(categorical_Xts_df, axis=1)

# Putting humpty back together again

X_test = pd.concat([clean_df, ohe_data_df], axis=1)
```

```
# Quick peek
X_test.head()
```

Out[133…

	account_length	international_plan	voice_mail_plan	total_day_minutes	total_day_calls	total_eve_minutes	total_eve_calls	total_
438	113	0	0	155.0	93	330.6	106	
2674	67	0	0	109.1	117	217.4	124	
1345	98	0	0	0.0	0	159.6	130	
1957	147	0	0	212.8	79	204.1	91	
2148	96	0	0	144.0	102	224.7	73	

In [134…

```
# Saving a copy of our data frame to reference columns later.

df_X_train_copy = X_train.iloc[:10]

df_X_test_copy = X_test.iloc[:10]
```

In [135…

```
# Scaling our data to prevent features from outweight others

SC = StandardScaler()
X_train = SC.fit_transform(X_train)
X_test = SC.transform(X_test)
```

SMOTE Work

In [136…

```
# Let's take a quick look at that imbalance once more.

y_train.value_counts()
```

Out[136…

```
0    2141
1     358
Name: churn, dtype: int64
```

In [137…

```
# Instantiating SMOTE

sm = SMOTE(sampling_strategy='auto', random_state=42)
```

In [138…

```
# Another look at our data post resample

X_train, y_train = sm.fit_resample(X_train, y_train)
```

```python
y_train.value_counts()
```

Out[138…

```
1    2141
0    2141
Name: churn, dtype: int64
```

Logistic Regression Model

Baseline Log Reg

In [139…

```python
# Baseline Logistic Regression model

baseline_logreg = ImPipeline(steps=[('sm', SMOTE(random_state=42)),
                            ('estimator', LogisticRegression(random_state=42))])

# Train model

baseline_logreg.fit(X_train, y_train);
```

In [143…

```python
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

divider = ('-----' * 10)
# Capture roc_auc for test, and train

baseline_logreg_roc_score_train = roc_auc_score(y_train, baseline_logreg.predict_proba(X_train)[:, 1])
baseline_logreg_roc_score_test = roc_auc_score(y_test, baseline_logreg.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

baseline_logreg_recall_score_train_cv = cross_val_score(estimator=baseline_logreg, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


baseline_logreg_recall_score_train = recall_score(y_train, baseline_logreg.predict(X_train))
baseline_logreg_recall_score_test = recall_score(y_test, baseline_logreg.predict(X_test))


# Capture f1 scores for test and train

baseline_logreg_f1_score_train = f1_score(y_train, baseline_logreg.predict(X_train))
baseline_logreg_f1_score_test = f1_score(y_test, baseline_logreg.predict(X_test))
```

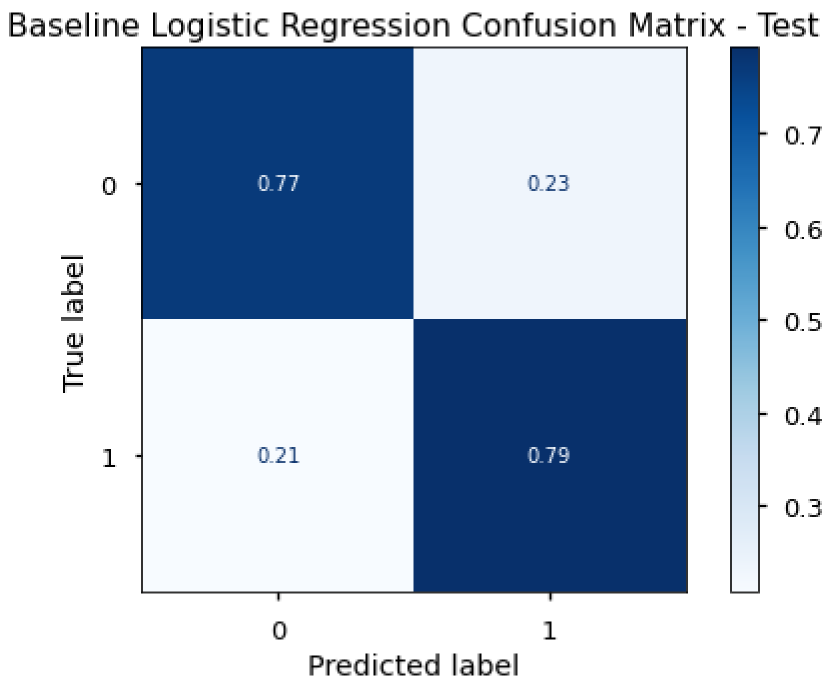
```python
# Capture precision scores for test and train

baseline_logreg_precision_score_train = precision_score(y_train, baseline_logreg.predict(X_train))
baseline_logreg_precision_score_test = precision_score(y_test, baseline_logreg.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {baseline_logreg_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {baseline_logreg_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {baseline_logreg_recall_score_train :.2%}")
print(f" Test Recall score: {baseline_logreg_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {baseline_logreg_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {baseline_logreg_f1_score_train :.2%}")
print(f" Test F1 score: {baseline_logreg_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {baseline_logreg_precision_score_train :.2%}")
print(f" Test Precision score: {baseline_logreg_precision_score_test :.2%}")
print(divider, '\n')
```

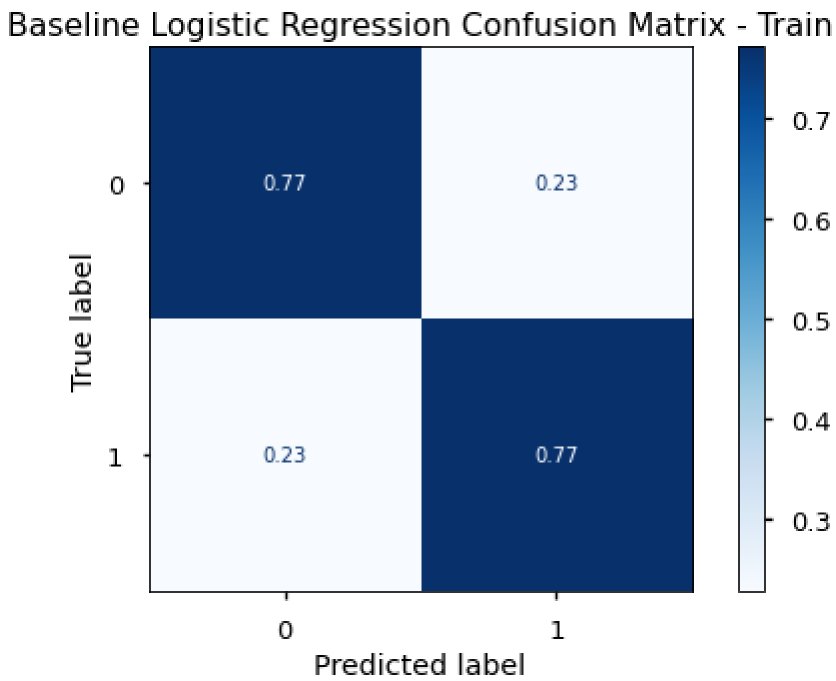
```
 Performance Comparison 

--------------------------------------------------
 Train Roc_Auc Score: 83.13%
 Test Roc_Auc Score: 83.59%
--------------------------------------------------
 Train Recall score: 77.16%
 Test Recall score: 79.20%
 Mean Cross Validated Recall Score: 77.16%
--------------------------------------------------
 Train F1 score: 77.12%
 Test F1 score: 50.90%
--------------------------------------------------
 Train Precision score: 77.09%
 Test Precision score: 37.50%
--------------------------------------------------
```

Our model is performing ok. The fact that our scores are so close means that we probably have some slight underfitting going on (since our test is higher than our train). In addition, our precision is pretty poor meaning that we have a high number of false positives. As we mentioned that probably isn't the end of the world but something. we want to keep in mind as we complete additional models.

In [144…

```
# Plotting confusion matrix for our baseline logistic regression - Test

fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(baseline_logreg, X_test, y_test, ax=ax, cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Test");


# Plotting confusion matrix for our baseline logistic regression - Train

fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(baseline_logreg, X_train, y_train, ax=ax,  cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Train");
```





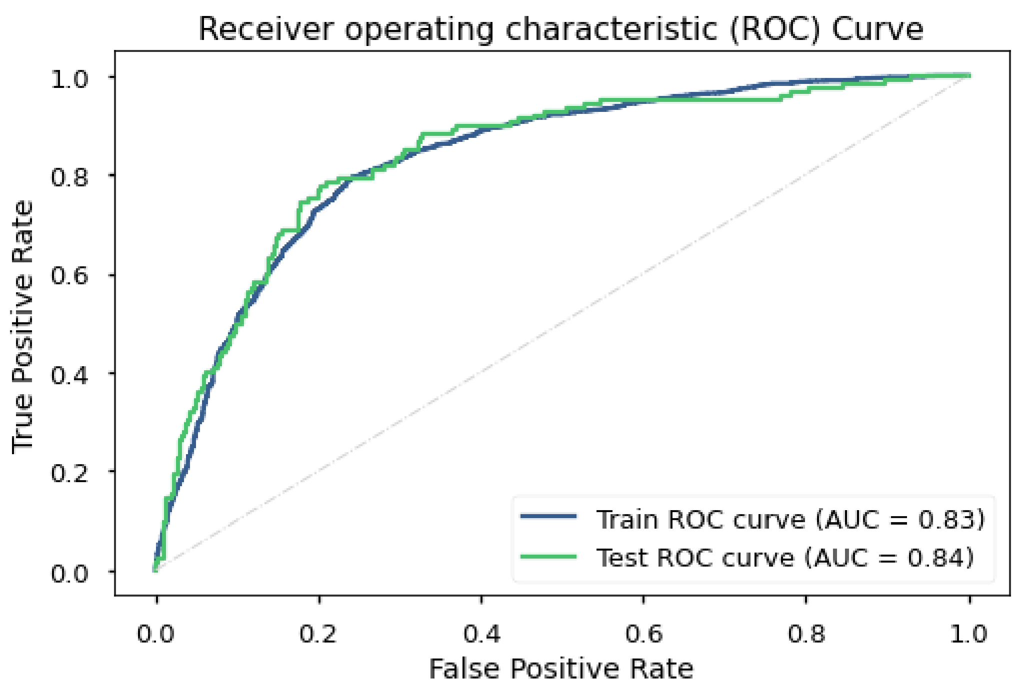
In [145…

```
# Print classification Scores for the test set

y_pred = baseline_logreg.predict(X_test)
divider = ('-' * 60)
table = classification_report(y_test, y_pred, digits=3)

print('\n', 'Classification Report - Test', '\n')
print(divider)
print(table)
```

```
 Classification Report - Test

------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.954     0.767     0.851       709
           1      0.375     0.792     0.509       125

    accuracy                          0.771       834
   macro avg      0.665     0.780     0.680       834
weighted avg      0.868     0.771     0.799       834
```

In [146…

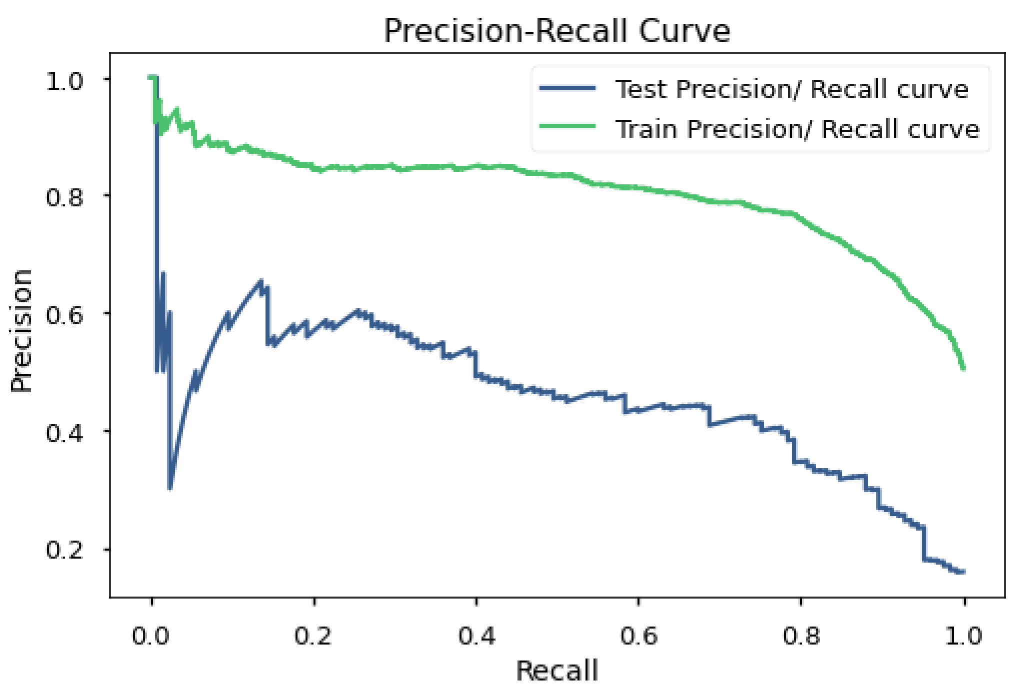
```python
# Quick look at the performance of our baseline model.  We'll take a peek
# at the ROC curve first, even though our metric of interest is recall, and F1.

fig, ax2 = plt.subplots(figsize=(8,5))
plot_roc_curve(baseline_logreg, X_train, y_train, ax=ax2, name ='Train ROC curve', color=pal[1])
plot_roc_curve(baseline_logreg, X_test, y_test, ax=ax2, name ='Test ROC curve', color=pal[4])
ax2.plot([0, 1], [0, 1], color='lightgray', lw=1, linestyle='-.')
ax2.set_xlabel('False Positive Rate')
ax2.set_ylabel('True Positive Rate')
ax2.set_title('Receiver operating characteristic (ROC) Curve')
plt.show();
```



In [147…

```python
# Since we are more focused on our precision and recall we are going to look at the precision/ recall curve as

y_train_score = baseline_logreg.predict_proba(X_train)[:, 1]
y_test_score = baseline_logreg.predict_proba(X_test)[:, 1]


# Calculate precision and recall

precision, recall, thresholds = precision_recall_curve(y_test, y_test_score)
precision_train, recall_train, thresholds_train = precision_recall_curve(y_train, y_train_score)
```

```
# Create precision recall curve

fig, ax = plt.subplots(figsize=(8,5))
ax.plot(recall, precision, color=pal[1], label='Test Precision/ Recall curve')
ax.plot(recall_train, precision_train, color=pal[4], label='Train Precision/ Recall curve')


# Add axis labels to plot

ax.set_title('Precision-Recall Curve')
ax.set_ylabel('Precision')
ax.set_xlabel('Recall')
ax.legend()

plt.show()
```



Our model seems to be peforming better on our training data set vs our test data set. This would suggest some overfitting happening. We will try and penalize our model and look into some hyperparameter tuning.

Tuned Logisitic Regression model

Next we will look at tuning our baseline model with some hyperparameters. We will select some random parameters in addition to the default values to see if we can improve the recall score, and ultimately the F1 score of our model.

In [148…

```
# Parameters for our gridsearch, model optimization

parameters = {
    'estimator__penalty' : ['l1', 'l2', 'elasticnet'],
    'estimator__fit_intercept':[True, False],
    'estimator__C'       : [0.001, 0.01, 0.1, 0.5, 1, 10],
    'estimator__solver'  : ['newton-cg', 'lbfgs', 'liblinear'],
    'estimator__max_iter'  : [50, 100, 200, 300]
}


# Create the grid, with "logreg_pipeline" as the estimator

best_logreg = GridSearchCV(estimator=baseline_logreg,
                          param_grid=parameters,
                          scoring='recall',
                          cv=5,
                          n_jobs=-1
)
```

In [149…

```
# Train the pipeline (tranformations & predictor)

best_logreg.fit(X_train, y_train);


# Let's take a look at our best parameters

best_logreg.best_params_
```

Out[149…

```
{'estimator__C': 0.1,
 'estimator__fit_intercept': False,
 'estimator__max_iter': 50,
 'estimator__penalty': 'l1',
 'estimator__solver': 'liblinear'}
```

In [150…

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train

best_logreg_roc_score_train = roc_auc_score(y_train, best_logreg.predict_proba(X_train)[:, 1])
best_logreg_roc_score_test = roc_auc_score(y_test, best_logreg.predict_proba(X_test)[:, 1])
```

```python
# Capture recall scores for test and train

best_logreg_recall_score_train_cv = cross_val_score(estimator=best_logreg, X=X_train,  y=y_train,
                                        cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


best_logreg_recall_score_train = recall_score(y_train, best_logreg.predict(X_train))
best_logreg_recall_score_test = recall_score(y_test, best_logreg.predict(X_test))


# Capture f1 scores for test and train

best_logreg_f1_score_train = f1_score(y_train, best_logreg.predict(X_train))
best_logreg_f1_score_test = f1_score(y_test, best_logreg.predict(X_test))


# Capture precision scores for test and train

best_logreg_precision_score_train = precision_score(y_train, best_logreg.predict(X_train))
best_logreg_precision_score_test = precision_score(y_test, best_logreg.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {best_logreg_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {best_logreg_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {best_logreg_recall_score_train :.2%}")
print(f" Test Recall score: {best_logreg_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_logreg_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_logreg_f1_score_train :.2%}")
print(f" Test F1 score: {best_logreg_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {best_logreg_precision_score_train :.2%}")
print(f" Test Precision score: {best_logreg_precision_score_test :.2%}")
print(divider, '\n')
```

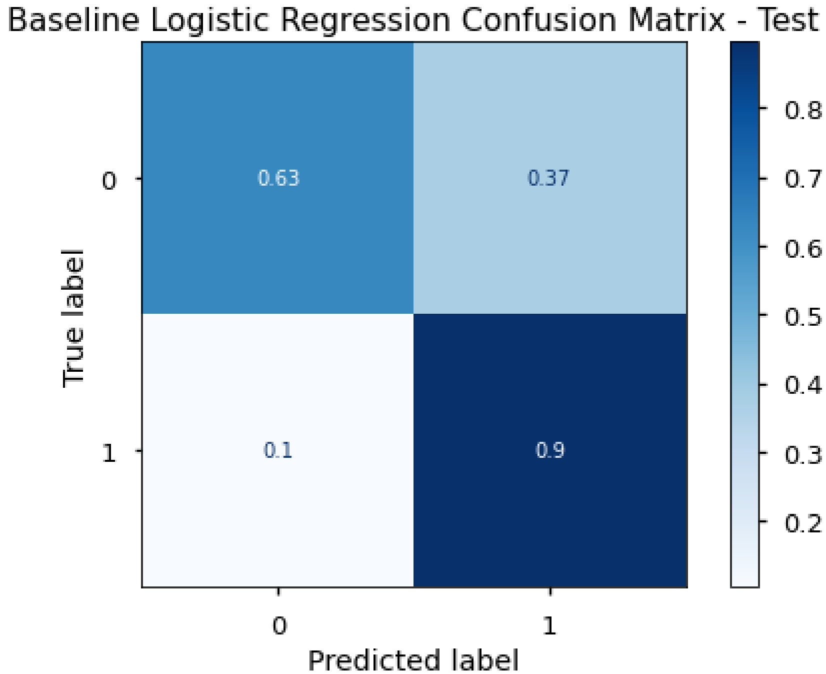
```
 Performance Comparison 

------------------------------------------------------------
 Train Roc_Auc Score: 83.17%
 Test Roc_Auc Score: 83.52%
```

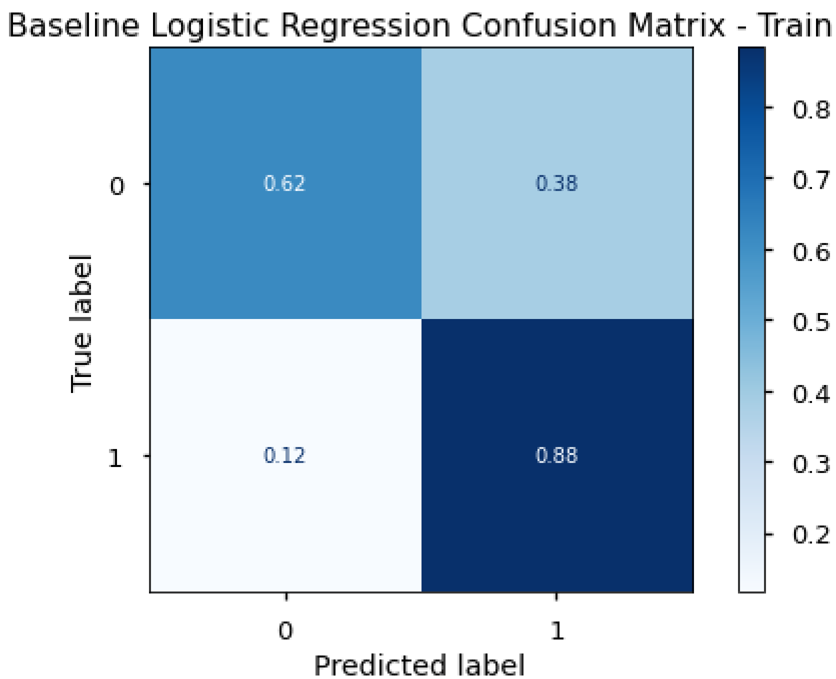
```
--------------------------------------------------------------
 Train Recall score: 88.37%
 Test Recall score: 89.60%
 Mean Cross Validated Recall Score: 88.09%
--------------------------------------------------------------
 Train F1 score: 78.04%
 Test F1 score: 44.71%
--------------------------------------------------------------
 Train Precision score: 69.87%
 Test Precision score: 29.79%
--------------------------------------------------------------
```

Looks like our recall metric is performing better by a few points. Up to 88 on the training set and 90 on the test set. We are probably under fitting a little but not sure if that is a big deal since we are already beating our most frequent baseline of 85%.

In [151…

```
# plotting confusion matrix for our tuned logistic regression - Test

fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(best_logreg, X_test, y_test, ax=ax,  cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Test");

# plotting confusion matrix for our tuned logistic regression - Train

fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(best_logreg, X_train, y_train, ax=ax,  cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Train");
```


Baseline Logistic Regression Confusion Matrix - Test
True label
Predicted label
0
1
0
1
0.63
0.37
0.1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2


Baseline Logistic Regression Confusion Matrix - Train
True label
Predicted label
0
1
0
1
0.62
0.38
0.12
0.88
0.8
0.7
0.6
0.5
0.4
0.3
0.2

In [152…

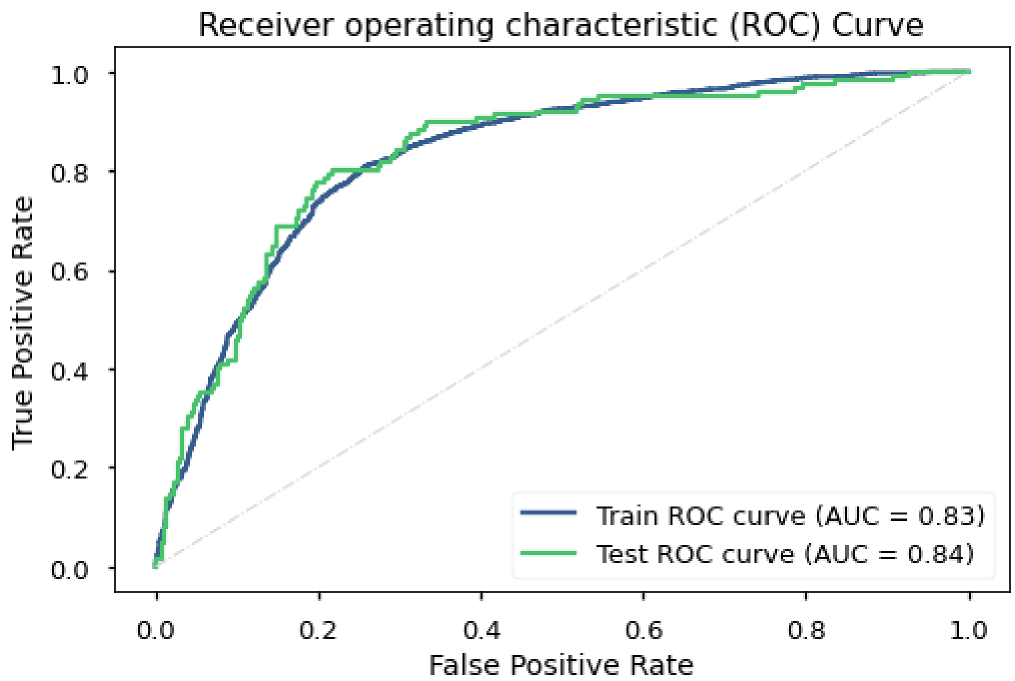
```
# Print classification scores for the test set

y_pred = best_logreg.predict(X_test)
divider = ('-' * 60)
table = classification_report(y_test, y_pred, digits=3)

print('\n', 'Classification Report - Test', '\n')
print(divider)
print(table)
```

```
 Classification Report - Test

------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.972     0.628     0.763       709
           1      0.298     0.896     0.447       125

    accuracy                          0.668       834
   macro avg      0.635     0.762     0.605       834
weighted avg      0.871     0.668     0.715       834
```

Again peforming better on our recall scores -- however our f1 score is lagging behind our baseline model. Primarily because we aren't as concerned with the false positives as we mentioned before.

In [153…

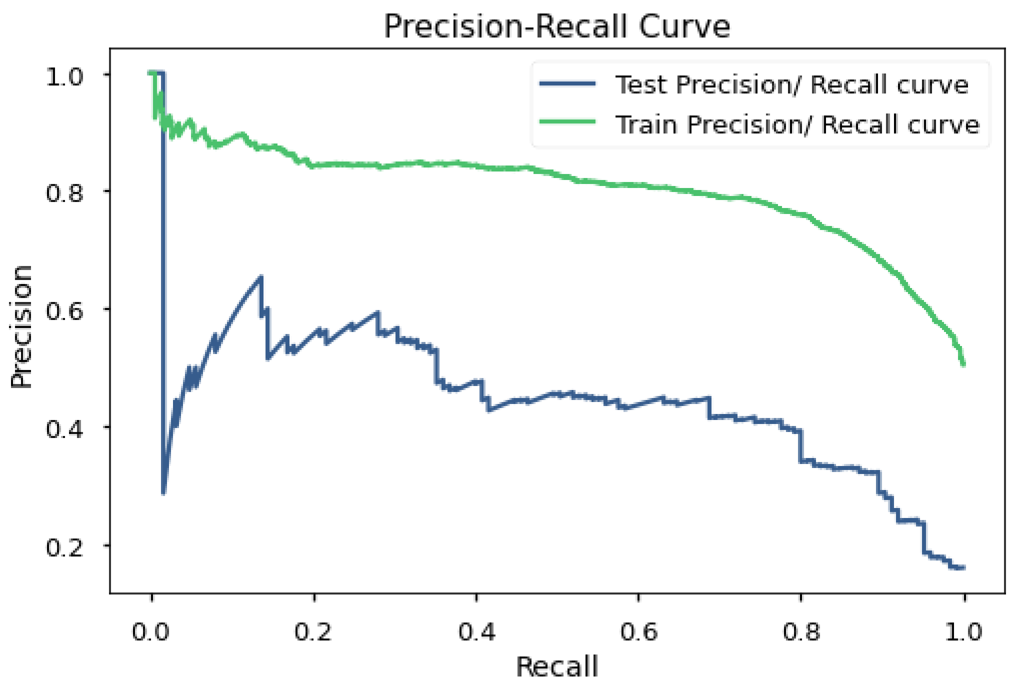
```
# Checking in on our ROC curve on our tuned model.

fig, ax2 = plt.subplots(figsize=(8,5))
plot_roc_curve(best_logreg, X_train, y_train, ax=ax2, name ='Train ROC curve', color=pal[1])
plot_roc_curve(best_logreg, X_test, y_test, ax=ax2, name ='Test ROC curve', color=pal[4])
ax2.plot([0, 1], [0, 1], color='lightgray', lw=1, linestyle='-.')
ax2.set_xlabel('False Positive Rate')
ax2.set_ylabel('True Positive Rate')
ax2.set_title('Receiver operating characteristic (ROC) Curve')
plt.show();
```



In [154…

```
# Since we are more focused on our precision and recall we are going to look at the precision/ recall curve as

y_train_score = best_logreg.predict_proba(X_train)[:, 1]
y_test_score = best_logreg.predict_proba(X_test)[:, 1]


# Calculate precision and recall

precision, recall, thresholds = precision_recall_curve(y_test, y_test_score)
precision_train, recall_train, thresholds_train = precision_recall_curve(y_train, y_train_score)


# Create precision recall curve

fig, ax = plt.subplots(figsize=(8,5))
ax.plot(recall, precision, color=pal[1], label='Test Precision/ Recall curve')
ax.plot(recall_train, precision_train, color=pal[4], label='Train Precision/ Recall curve')


# Add axis labels to plot

ax.set_title('Precision-Recall Curve')
ax.set_ylabel('Precision')
```

```
ax.set_xlabel('Recall')
ax.legend()

plt.show()
```



Build Ridge Model

Baseline Ridge Model

First we will start with our baseline model. See if we can out perform out logistic regression baseline and tuned models.

In [155…

```
# Baseline model
baseline_ridge = ImPipeline(steps=[('sm', SMOTE(random_state=42)),
                            ('estimator', RidgeClassifier(random_state=42))])

# Train model
baseline_ridge.fit(X_train, y_train);
```

In [156…

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.
```

```python
# There is no predict probablities for ridge.  So we will exclude those scores for this model.  That
# will primarily impact the roc_auc scoring.


# Capture recall scores for test and train

baseline_ridge_recall_score_train_cv = cross_val_score(estimator=baseline_ridge, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()

baseline_ridge_recall_score_train = recall_score(y_train, baseline_ridge.predict(X_train))
baseline_ridge_recall_score_test = recall_score(y_test, baseline_ridge.predict(X_test))


# Capture f1 scores for test and train

baseline_ridge_f1_score_train = f1_score(y_train, baseline_ridge.predict(X_train))
baseline_ridge_f1_score_test = f1_score(y_test, baseline_ridge.predict(X_test))


# Capture precision scores for test and train

baseline_ridge_precision_score_train = precision_score(y_train, baseline_ridge.predict(X_train))
baseline_ridge_precision_score_test = precision_score(y_test, baseline_ridge.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)

print(f" Train Recall score: {baseline_ridge_recall_score_train :.2%}")
print(f" Test Recall score: {baseline_ridge_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {baseline_ridge_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {baseline_ridge_f1_score_train :.2%}")
print(f" Test F1 score: {baseline_ridge_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {baseline_ridge_precision_score_train :.2%}")
print(f" Test Precision score: {baseline_ridge_precision_score_test :.2%}")
print(divider, '\n')
```

```
 Performance Comparison 

------------------------------------------------------------
 Train Recall score: 77.07%
 Test Recall score: 79.20%
 Mean Cross Validated Recall Score: 76.88%
------------------------------------------------------------
```

```
 Train F1 score: 77.14%
 Test F1 score: 51.43%
------------------------------------------------------------
 Train Precision score: 77.21%
 Test Precision score: 38.08%
------------------------------------------------------------
```

Very similar results as our logistic regression which isn't super suprising. We will continue to move forward with this model to see if the tuned version can perform any better than our baseline or hyper tuned logistic regressions.

Tuned Ridge Model

In [157…

```
# Parameters for our gridsearch, model optimization

parameters = {
    'estimator__alpha' : ['1', '10', '20', '50'],
    'estimator__fit_intercept':[True, False],
    'estimator__solver'  : ['auto', 'lsqr', 'svd', 'sag', 'saga'],
    'estimator__max_iter'  : [None, 50, 100, 200, 300]
}

# Create the grid, with "logreg_pipeline" as the estimator
best_ridge = GridSearchCV(estimator=baseline_ridge,   # model
                          param_grid=parameters,
                          scoring='recall',             # my metric for scoring
                          cv=5,                         # default folds
                          n_jobs=-1
)
```

In [158…

```
# Train the pipeline (tranformations & predictor)

best_ridge.fit(X_train, y_train)

# Let's take a look at our best parameters

best_ridge.best_params_
```

Out[158…

```
{'estimator__alpha': '1',
 'estimator__fit_intercept': False,
 'estimator__max_iter': None,
 'estimator__solver': 'auto'}
```

In [159…

```python
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# There is no predict probablities for ridge.  So we will exclude those scores for this model.  That
# will primarily impact the roc_auc scoring.


# Capture recall scores for test and train

best_ridge_recall_score_train_cv = cross_val_score(estimator=best_ridge, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()

best_ridge_recall_score_train = recall_score(y_train, best_ridge.predict(X_train))
best_ridge_recall_score_test = recall_score(y_test, best_ridge.predict(X_test))


# Capture f1 scores for test and train

best_ridge_f1_score_train = f1_score(y_train, best_ridge.predict(X_train))
best_ridge_f1_score_test = f1_score(y_test, best_ridge.predict(X_test))


# Capture precision scores for test and train

best_ridge_precision_score_train = precision_score(y_train, best_ridge.predict(X_train))
best_ridge_precision_score_test = precision_score(y_test, best_ridge.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)

print(f" Train Recall score: {best_ridge_recall_score_train :.2%}")
print(f" Test Recall score: {best_ridge_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_ridge_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_ridge_f1_score_train :.2%}")
print(f" Test F1 score: {best_ridge_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {best_ridge_precision_score_train :.2%}")
print(f" Test Precision score: {best_ridge_precision_score_test :.2%}")
print(divider, '\n')
```

```
 Performance Comparison

------------------------------------------------------------
```

```
Train Recall score: 88.32%
Test Recall score: 88.80%
Mean Cross Validated Recall Score: 87.95%
------------------------------------------------------------
Train F1 score: 77.64%
Test F1 score: 44.31%
------------------------------------------------------------
Train Precision score: 69.27%
Test Precision score: 29.52%
------------------------------------------------------------
```

Our tuned ridge model although performing better than it's respective baseline, the tuned results are similar to the baseline and tuned logistic regression models. If it were a choice at this point we would still entertain our core logistic regression model for classification.

Decision Tree Model

Baseline Decision Tree

In [160…

```
# Baseline model
baseline_tree = ImPipeline(steps=[('sm', SMOTE(random_state=42)),
                            ('estimator', DecisionTreeClassifier(random_state=42))])

# Train model
baseline_tree.fit(X_train, y_train);
```

In [161…

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train

baseline_tree_roc_score_train = roc_auc_score(y_train, baseline_tree.predict_proba(X_train)[:, 1])
baseline_tree_roc_score_test = roc_auc_score(y_test, baseline_tree.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

baseline_tree_recall_score_train_cv = cross_val_score(estimator=baseline_tree, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


baseline_tree_recall_score_train = recall_score(y_train, baseline_tree.predict(X_train))
baseline_tree_recall_score_test = recall_score(y_test, baseline_tree.predict(X_test))
```

```python
# Capture f1 scores for test and train

baseline_tree_f1_score_train = f1_score(y_train, baseline_tree.predict(X_train))
baseline_tree_f1_score_test = f1_score(y_test, baseline_tree.predict(X_test))


# Capture precision scores for test and train

baseline_tree_precision_score_train = precision_score(y_train, baseline_tree.predict(X_train))
baseline_tree_precision_score_test = precision_score(y_test, baseline_tree.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {baseline_tree_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {baseline_tree_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {baseline_tree_recall_score_train :.2%}")
print(f" Test Recall score: {baseline_tree_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {baseline_tree_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {baseline_tree_f1_score_train :.2%}")
print(f" Test F1 score: {baseline_tree_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {baseline_tree_precision_score_train :.2%}")
print(f" Test Precision score: {baseline_tree_precision_score_test :.2%}")
print(divider, '\n')
```

```
 Performance Comparison 

------------------------------------------------------------
 Train Roc_Auc Score: 100.00%
 Test Roc_Auc Score: 81.56%
------------------------------------------------------------
 Train Recall score: 100.00%
 Test Recall score: 72.00%
 Mean Cross Validated Recall Score: 91.36%
------------------------------------------------------------
 Train F1 score: 100.00%
 Test F1 score: 64.75%
------------------------------------------------------------
 Train Precision score: 100.00%
 Test Precision score: 58.82%
```

Holy over fitting batman. As you can see with our training data being at 100% there is some clear over fitting happening within our baseline Decision Tree model. This should get better with our tuning. It is worth noting however, that this is the highest F1 score we have seen thus far. Hopefully we can close the gap between our train and test sets since we are seeing a better F1 and a comparable recall score out of the gate.

Tuned Decision Tree Model

In [162…

```
# Let's tune this model!

parameters = {
    'estimator__criterion': ['gini', 'entropy'],
    'estimator__max_depth': [None, 3, 5, 10, 15, 20],
    'estimator__max_features': [None, 15,  5],
    'estimator__min_samples_split': [2, 5, 7, 10],
    'estimator__min_samples_leaf': [1, 2, 5]
            }


# Grid with our baseline tree as our estimator

best_tree = GridSearchCV(estimator=baseline_tree,
                          param_grid=parameters,
                          scoring='recall',
                          cv=5,
                          n_jobs=-1
                        )
```

In [163…

```
# Train the pipeline based on our most appropriate parameters

best_tree.fit(X_train, y_train);
best_tree.best_params_
```

Out[163…

```
{'estimator__criterion': 'entropy',
 'estimator__max_depth': None,
 'estimator__max_features': None,
 'estimator__min_samples_leaf': 1,
 'estimator__min_samples_split': 2}
```

In [164…

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.
```

```
# Capture roc_auc for test, and train

best_tree_roc_score_train = roc_auc_score(y_train, best_tree.predict_proba(X_train)[:, 1])
best_tree_roc_score_test = roc_auc_score(y_test, best_tree.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

best_tree_recall_score_train_cv = cross_val_score(estimator=best_tree, X=X_train,  y=y_train,
                                          cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


best_tree_recall_score_train = recall_score(y_train, best_tree.predict(X_train))
best_tree_recall_score_test = recall_score(y_test, best_tree.predict(X_test))


# Capture f1 scores for test and train

best_tree_f1_score_train = f1_score(y_train, best_tree.predict(X_train))
best_tree_f1_score_test = f1_score(y_test, best_tree.predict(X_test))


# Capture precision scores for test and train

best_tree_precision_score_train = precision_score(y_train, best_tree.predict(X_train))
best_tree_precision_score_test = precision_score(y_test, best_tree.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {best_tree_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {best_tree_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {best_tree_recall_score_train :.2%}")
print(f" Test Recall score: {best_tree_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_tree_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_tree_f1_score_train :.2%}")
print(f" Test F1 score: {best_tree_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {best_tree_precision_score_train :.2%}")
print(f" Test Precision score: {best_tree_precision_score_test :.2%}")
print(divider, '\n')
```

```
Performance Comparison

-------------------------------------------------------------
Train Roc_Auc Score: 100.00%
Test Roc_Auc Score: 79.84%
-------------------------------------------------------------
Train Recall score: 100.00%
Test Recall score: 70.40%
Mean Cross Validated Recall Score: 92.06%
-------------------------------------------------------------
Train F1 score: 100.00%
Test F1 score: 60.90%
-------------------------------------------------------------
Train Precision score: 100.00%
Test Precision score: 53.66%
-------------------------------------------------------------
```

Not much improvement on our tuned model. Going to move on to our next model.

Random Forest

Baseline Forest

In [165…

```
# Moving along to our next model

baseline_RF = ImPipeline(steps=[('sm', SMOTE(random_state=42)),
                               ('estimator', RandomForestClassifier(random_state=42))])


# Train model

baseline_RF.fit(X_train, y_train);
```

In [166…

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train

baseline_RF_roc_score_train = roc_auc_score(y_train, baseline_RF.predict_proba(X_train)[:, 1])
baseline_RF_roc_score_test = roc_auc_score(y_test, baseline_RF.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train
```

```python
baseline_RF_recall_score_train_cv = cross_val_score(estimator=baseline_RF, X=X_train,  y=y_train,
                                                     cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


baseline_RF_recall_score_train = recall_score(y_train, baseline_RF.predict(X_train))
baseline_RF_recall_score_test = recall_score(y_test, baseline_RF.predict(X_test))


# Capture f1 scores for test and train

baseline_RF_f1_score_train = f1_score(y_train, baseline_RF.predict(X_train))
baseline_RF_f1_score_test = f1_score(y_test, baseline_RF.predict(X_test))


# Capture precision scores for test and train

baseline_RF_precision_score_train = precision_score(y_train, baseline_RF.predict(X_train))
baseline_RF_precision_score_test = precision_score(y_test, baseline_RF.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {baseline_RF_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {baseline_RF_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {baseline_RF_recall_score_train :.2%}")
print(f" Test Recall score: {baseline_RF_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {baseline_RF_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {baseline_RF_f1_score_train :.2%}")
print(f" Test F1 score: {baseline_RF_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {baseline_RF_precision_score_train :.2%}")
print(f" Test Precision score: {baseline_RF_precision_score_test :.2%}")
print(divider, '\n')
```

```
 Performance Comparison 

------------------------------------------------------------
 Train Roc_Auc Score: 100.00%
 Test Roc_Auc Score: 94.06%
------------------------------------------------------------
 Train Recall score: 100.00%
 Test Recall score: 77.60%
```

```
 Mean Cross Validated Recall Score: 94.91%
------------------------------------------------------------
 Train F1 score: 100.00%
 Test F1 score: 80.83%
------------------------------------------------------------
 Train Precision score: 100.00%
 Test Precision score: 84.35%
------------------------------------------------------------
```

Again, some serious over fitting on our training data however we do see some life now in our F1 score. Our recall is also holding strong in a range that we have seen in our previous models.

Tuned Forest

In [167...

```
# Parameters for our gridsearch, model optimization

parameters = {
    #'estimator__n_estimators': [100, 150, 200],
    #'estimator__criterion': ['entropy', 'gini'],
    'estimator__max_depth': [2, 5],
    #'estimator__max_features': [2, 5, 10],
    'estimator__min_samples_split': [10, 20, 50],
    'estimator__min_samples_leaf': [1, 2, 4]
            }

best_RF = GridSearchCV(estimator=baseline_RF,
                        param_grid=parameters,
                        scoring='recall',
                        cv=5,
                        n_jobs=-1
                      )
```

In [168...

```
# Train the pipeline based on our most appropriate parameters

best_RF.fit(X_train, y_train)
best_RF.best_params_
```

Out[168...

```
{'estimator__max_depth': 5,
 'estimator__min_samples_leaf': 2,
 'estimator__min_samples_split': 10}
```

In [169...

```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train
```

```
best_RF_roc_score_train = roc_auc_score(y_train, best_RF.predict_proba(X_train)[:, 1])
best_RF_roc_score_test = roc_auc_score(y_test, best_RF.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

best_RF_recall_score_train_cv = cross_val_score(estimator=best_RF, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


best_RF_recall_score_train = recall_score(y_train, best_RF.predict(X_train))
best_RF_recall_score_test = recall_score(y_test, best_RF.predict(X_test))


# Capture f1 scores for test and train

best_RF_f1_score_train = f1_score(y_train, best_RF.predict(X_train))
best_RF_f1_score_test = f1_score(y_test, best_RF.predict(X_test))


# Capture precision scores for test and train

best_RF_precision_score_train = precision_score(y_train, best_RF.predict(X_train))
best_RF_precision_score_test = precision_score(y_test, best_RF.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {best_RF_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {best_RF_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {best_RF_recall_score_train :.2%}")
print(f" Test Recall score: {best_RF_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_RF_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_RF_f1_score_train :.2%}")
print(f" Test F1 score: {best_RF_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {best_RF_precision_score_train :.2%}")
print(f" Test Precision score: {best_RF_precision_score_test :.2%}")
print(divider, '\n')
```

```
 Performance Comparison

-------------------------------------------------------------
 Train Roc_Auc Score: 95.78%
 Test Roc_Auc Score: 91.79%
-------------------------------------------------------------
 Train Recall score: 84.49%
 Test Recall score: 78.40%
 Mean Cross Validated Recall Score: 84.03%
-------------------------------------------------------------
 Train F1 score: 88.89%
 Test F1 score: 70.50%
-------------------------------------------------------------
 Train Precision score: 93.78%
 Test Precision score: 64.05%
-------------------------------------------------------------
```

This model is looking much better now that we tuned out some of the noise from our baseline model. So far this is the best performing model from both a Recall, and from an F1 perspective.

XG Boost Model

Baseline XGBoost

In [170…
```
baseline_xgb = ImPipeline(steps=[('sm', SMOTE(random_state=42)),
                             ('estimator', xgb.XGBClassifier(objective="binary:logistic", random_state=42))])

# Train model
baseline_xgb.fit(X_train, y_train);
```

In [171…
```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train

baseline_xgb_roc_score_train = roc_auc_score(y_train, baseline_xgb.predict_proba(X_train)[:, 1])
baseline_xgb_roc_score_test = roc_auc_score(y_test, baseline_xgb.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

baseline_xgb_recall_score_train_cv = cross_val_score(estimator=baseline_xgb, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()
```

```
baseline_xgb_recall_score_train = recall_score(y_train, baseline_xgb.predict(X_train))
baseline_xgb_recall_score_test = recall_score(y_test, baseline_xgb.predict(X_test))


# Capture f1 scores for test and train

baseline_xgb_f1_score_train = f1_score(y_train, baseline_xgb.predict(X_train))
baseline_xgb_f1_score_test = f1_score(y_test, baseline_xgb.predict(X_test))


# Capture precision scores for test and train

baseline_xgb_precision_score_train = precision_score(y_train, baseline_xgb.predict(X_train))
baseline_xgb_precision_score_test = precision_score(y_test, baseline_xgb.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {baseline_xgb_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {baseline_xgb_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {baseline_xgb_recall_score_train :.2%}")
print(f" Test Recall score: {baseline_xgb_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {baseline_xgb_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {baseline_xgb_f1_score_train :.2%}")
print(f" Test F1 score: {baseline_xgb_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {baseline_xgb_precision_score_train :.2%}")
print(f" Test Precision score: {baseline_xgb_precision_score_test :.2%}")
```

```
 Performance Comparison

------------------------------------------------------------
 Train Roc_Auc Score: 100.00%
 Test Roc_Auc Score: 92.54%
------------------------------------------------------------
 Train Recall score: 100.00%
 Test Recall score: 76.00%
 Mean Cross Validated Recall Score: 96.12%
------------------------------------------------------------
 Train F1 score: 100.00%
```

```
 Test F1 score: 83.33%
------------------------------------------------------------
 Train Precision score: 100.00%
 Test Precision score: 92.23%
------------------------------------------------------------
```

Clear over fitting again, but positive measurements on our F1 test score. Going to tune our parameters again and see if we can create a nice fitting model to predict our customer churn!

Tuned XGBoost

In [172…

```
# Tuning our XGB model.

parameters = {
    "estimator__n_estimators": [50, 75],
    "estimator__learning_rate": [0.05, 0.1, 0.2],
    "estimator__max_depth": [4, 5, 6],
    'estimator__gamma': [0.5, 1],
    'estimator__min_child_weight': [3, 4, 5],
    'estimator__subsample': [0.5, 0.75],
    'estimator__colsample_bytree':[0.5, 0.75]
            }

best_xgb = GridSearchCV(estimator=baseline_xgb,
                        param_grid=parameters,
                        scoring='recall',
                        cv=5,
                        n_jobs=-1
                       )
```

In [173…

```
# Train the pipeline based on our most appropriate parameters

best_xgb.fit(X_train, y_train)
best_xgb.best_params_
```

Out[173…

```
{'estimator__colsample_bytree': 0.75,
 'estimator__gamma': 0.5,
 'estimator__learning_rate': 0.2,
 'estimator__max_depth': 6,
 'estimator__min_child_weight': 3,
 'estimator__n_estimators': 75,
 'estimator__subsample': 0.75}
```

In [174…

```python
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

# Capture roc_auc for test, and train

best_xgb_roc_score_train = roc_auc_score(y_train, best_xgb.predict_proba(X_train)[:, 1])
best_xgb_roc_score_test = roc_auc_score(y_test, best_xgb.predict_proba(X_test)[:, 1])


# Capture recall scores for test and train

best_xgb_recall_score_train_cv = cross_val_score(estimator=best_xgb, X=X_train,  y=y_train,
                                         cv=StratifiedKFold(shuffle=True), scoring='recall').mean()


best_xgb_recall_score_train = recall_score(y_train, best_xgb.predict(X_train))
best_xgb_recall_score_test = recall_score(y_test, best_xgb.predict(X_test))


# Capture f1 scores for test and train

best_xgb_f1_score_train = f1_score(y_train, best_xgb.predict(X_train))
best_xgb_f1_score_test = f1_score(y_test, best_xgb.predict(X_test))


# Capture precision scores for test and train

best_xgb_precision_score_train = precision_score(y_train, best_xgb.predict(X_train))
best_xgb_precision_score_test = precision_score(y_test, best_xgb.predict(X_test))

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {best_xgb_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {best_xgb_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {best_xgb_recall_score_train :.2%}")
print(f" Test Recall score: {best_xgb_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_xgb_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_xgb_f1_score_train :.2%}")
print(f" Test F1 score: {best_xgb_f1_score_test :.2%}")
print(divider)
```

```
print(f" Train Precision score: {best_xgb_precision_score_train :.2%}")
print(f" Test Precision score: {best_xgb_precision_score_test :.2%}")
```

```
 Performance Comparison

------------------------------------------------------------
 Train Roc_Auc Score: 99.99%
 Test Roc_Auc Score: 93.80%
------------------------------------------------------------
 Train Recall score: 98.65%
 Test Recall score: 78.40%
 Mean Cross Validated Recall Score: 95.89%
------------------------------------------------------------
 Train F1 score: 99.22%
 Test F1 score: 83.40%
------------------------------------------------------------
 Train Precision score: 99.81%
 Test Precision score: 89.09%
------------------------------------------------------------
```

The model still seems to be overfitting. However, the performance within our Recall and our F1 score really shows the balance that we were looking for within our classification model.

Model Evalution

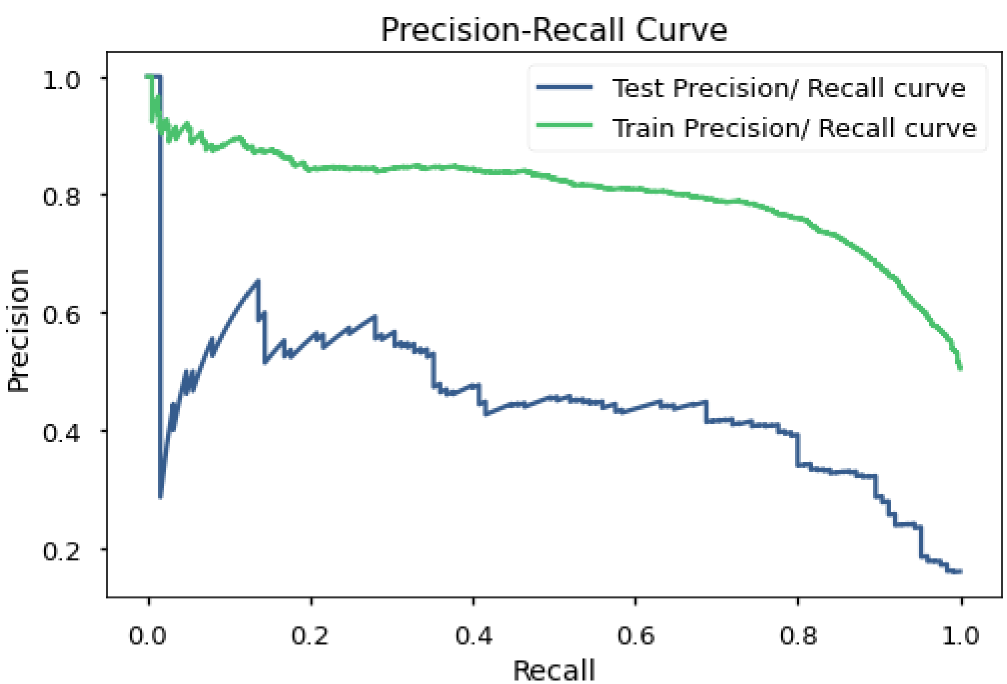
Comparison between Models

Although the best performing model based on recall only was our tuned logistic regression, and our tuned ridge model, the best performing model from both a Recall and a F1 perspective was our tuned XGBoost model. This model was able to predict our positive cases at a rate of 78%, and our negative cases of churn at 98% within the test data sets. We will go back and visualize some of these metrics below.

In [175…

```
# Since we are more focused on our precision and recall we are going to look at the precision/ recall curve as


y_test_score_best_logreg = best_logreg.predict_proba(X_test)[:, 1]
y_test_score_best_logreg = best_logreg.predict_proba(X_test)[:, 1]

# Calculate precision and recall

precision, recall, thresholds = precision_recall_curve(y_test, y_test_score_best_logreg)
precision_train, recall_train, thresholds_train = precision_recall_curve(y_train, y_train_score)
```

```python
# Create precision recall curve

fig, ax = plt.subplots(figsize=(8,5))
ax.plot(recall, precision, color=pal[1], label='Test Precision/ Recall curve')
ax.plot(recall_train, precision_train, color=pal[4], label='Train Precision/ Recall curve')


# Add axis labels to plot

ax.set_title('Precision-Recall Curve')
ax.set_ylabel('Precision')
ax.set_xlabel('Recall')
ax.legend()

plt.show()
```



Final Model

So in Summary, our best performing model according to the best recall, and F1 score is our Tuned XGBoost model. As mentioned above, we are able to successfully predict our groups for churn approximately 78% of the time, without sacrificing groups that we are not able to successfully predict, and they churn (false negatives).

Let's first start by taking a look back at our summary metrics and performance of our best performing model.

In [176…

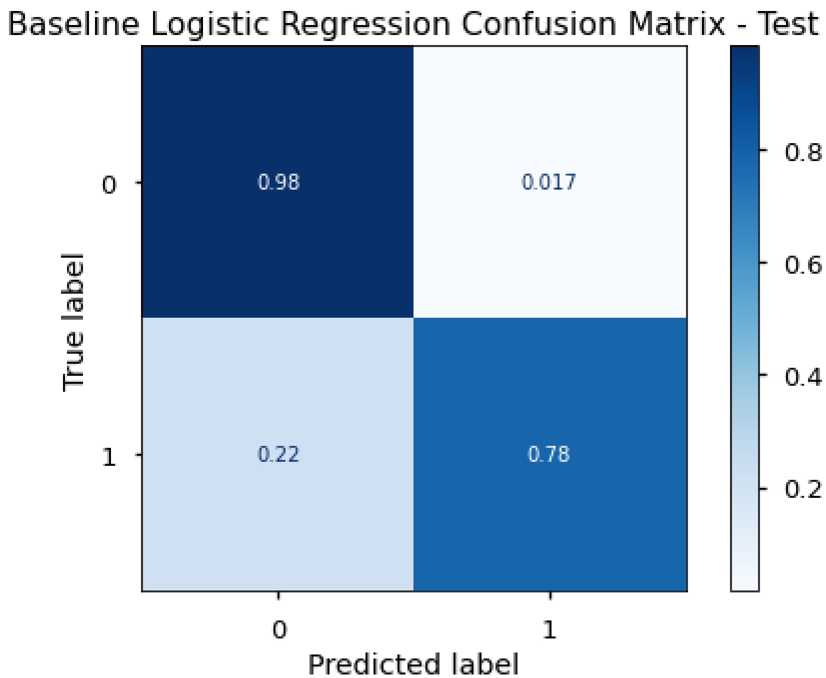
```
# Scoring print out adapted from others -- Eva Mizer, and Aysu Erdemir.

print('\n', "Performance Comparison", '\n')
print(divider)
print(f" Train Roc_Auc Score: {best_xgb_roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {best_xgb_roc_score_test :.2%}")
print(divider)

print(f" Train Recall score: {best_xgb_recall_score_train :.2%}")
print(f" Test Recall score: {best_xgb_recall_score_test :.2%}")
print(f" Mean Cross Validated Recall Score: {best_xgb_recall_score_train_cv :.2%}")
print(divider)

print(f" Train F1 score: {best_xgb_f1_score_train :.2%}")
print(f" Test F1 score: {best_xgb_f1_score_test :.2%}")
print(divider)

print(f" Train Precision score: {best_xgb_precision_score_train :.2%}")
print(f" Test Precision score: {best_xgb_precision_score_test :.2%}")
print(divider, '\n')
```

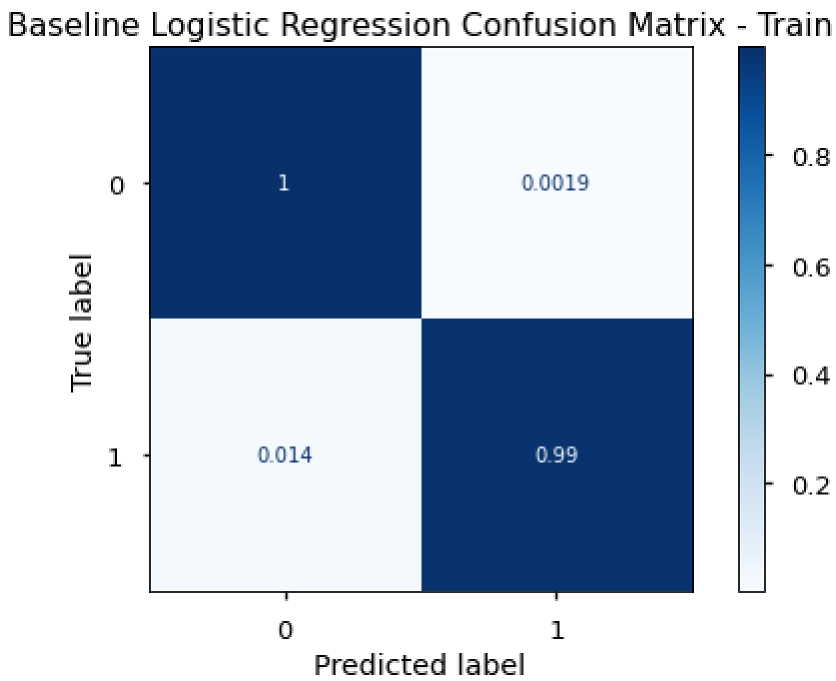
```
 Performance Comparison 

------------------------------------------------------------
 Train Roc_Auc Score: 99.99%
 Test Roc_Auc Score: 93.80%
------------------------------------------------------------
 Train Recall score: 98.65%
 Test Recall score: 78.40%
 Mean Cross Validated Recall Score: 95.89%
------------------------------------------------------------
 Train F1 score: 99.22%
 Test F1 score: 83.40%
------------------------------------------------------------
 Train Precision score: 99.81%
 Test Precision score: 89.09%
------------------------------------------------------------
```

In [177…

```
# Confusion matrix for our best performing model

fig, ax = plt.subplots(figsize=(8,5))
```

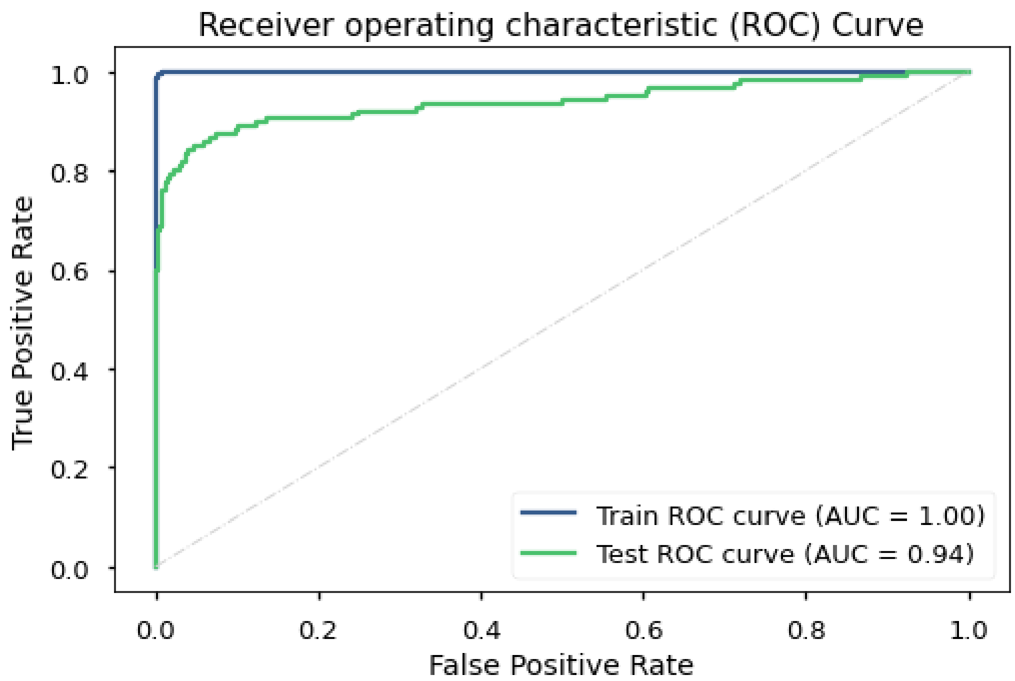
```
plot_confusion_matrix(best_xgb, X_test, y_test, ax=ax,  cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Test");

# plotting confusion matrix for our tuned logistic regression - Train

fig, ax = plt.subplots(figsize=(8,5))

plot_confusion_matrix(best_xgb, X_train, y_train, ax=ax,  cmap='Blues', normalize='true')
ax.set_title("Baseline Logistic Regression Confusion Matrix - Train");
```





In [178…

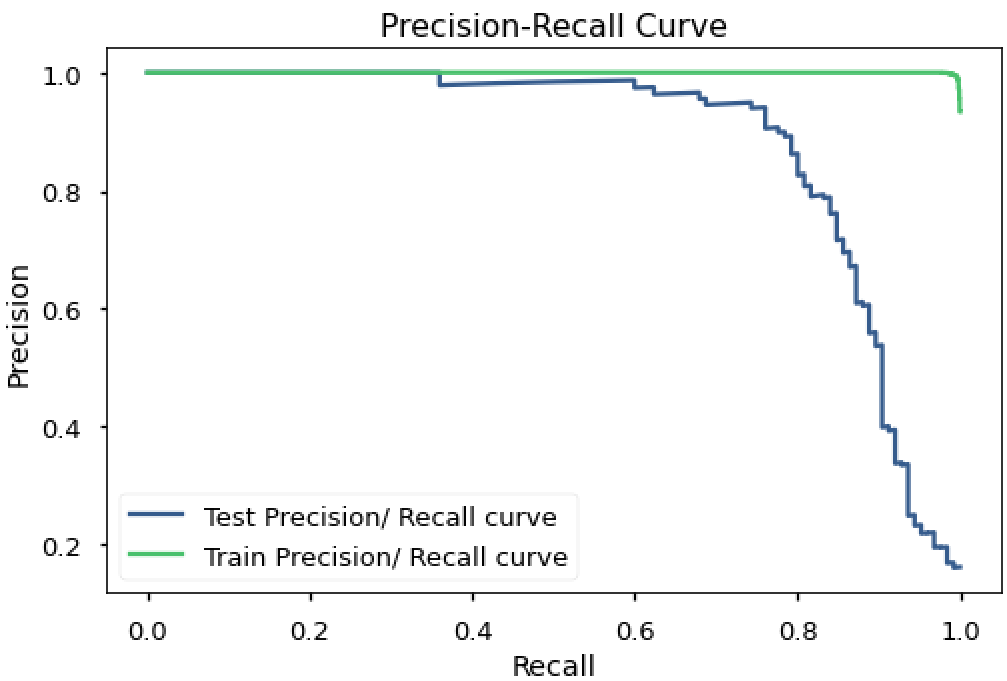
```
# ROC_AUC curve for our best performing model

fig, ax2 = plt.subplots(figsize=(8,5))
plot_roc_curve(best_xgb, X_train, y_train, ax=ax2, name ='Train ROC curve', color=pal[1])
plot_roc_curve(best_xgb, X_test, y_test, ax=ax2, name ='Test ROC curve', color=pal[4])
ax2.plot([0, 1], [0, 1], color='lightgray', lw=1, linestyle='-.')
ax2.set_xlabel('False Positive Rate')
ax2.set_ylabel('True Positive Rate')
ax2.set_title('Receiver operating characteristic (ROC) Curve')
plt.show();
```



In [179…

```
# Precision Recall curve for our best performing model

y_train_score = best_xgb.predict_proba(X_train)[:, 1]
y_test_score = best_xgb.predict_proba(X_test)[:, 1]


# Calculate precision and recall

precision, recall, thresholds = precision_recall_curve(y_test, y_test_score)
precision_train, recall_train, thresholds_train = precision_recall_curve(y_train, y_train_score)


# Create precision recall curve

fig, ax = plt.subplots(figsize=(8,5))
ax.plot(recall, precision, color=pal[1], label='Test Precision/ Recall curve')
ax.plot(recall_train, precision_train, color=pal[4], label='Train Precision/ Recall curve')


# Add axis labels to plot

ax.set_title('Precision-Recall Curve')
ax.set_ylabel('Precision')
```

```
ax.set_xlabel('Recall')
ax.legend()

plt.show()
```



In [180…

```
# Taking a look at our feature importances

best_xgb.estimator.steps[1][1].feature_importances_
```

Out[180…

```
array([0.01843614, 0.31464106, 0.1297837 , 0.10481425, 0.02072486,
       0.0432858 , 0.0139287 , 0.02530239, 0.01932141, 0.05191775,
       0.06407015, 0.19377384], dtype=float32)
```

In [181…

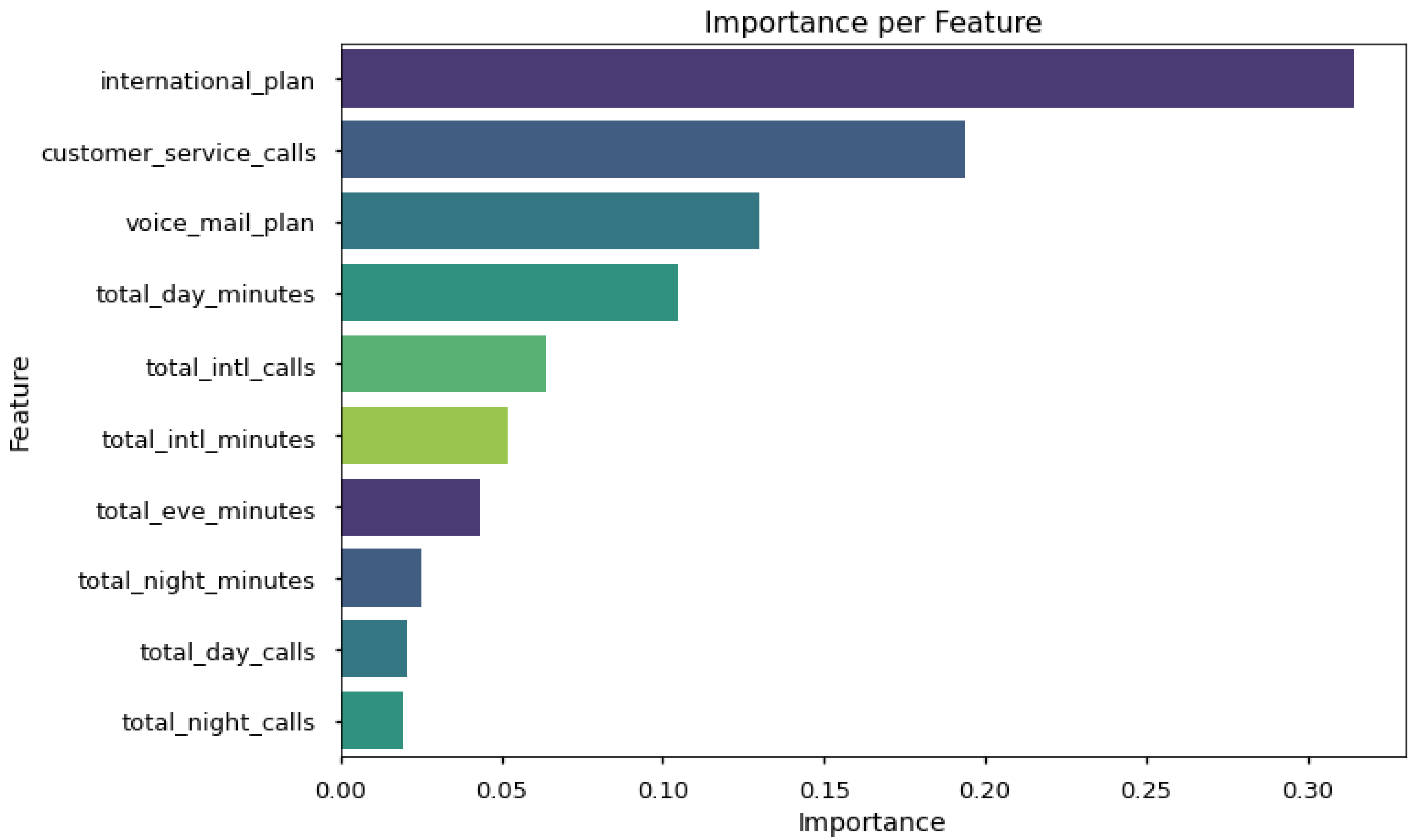
```
# Columns on our dataframe

df_X_train_copy.columns
```

Out[181…

```
Index(['account_length', 'international_plan', 'voice_mail_plan',
       'total_day_minutes', 'total_day_calls', 'total_eve_minutes',
       'total_eve_calls', 'total_night_minutes', 'total_night_calls',
       'total_intl_minutes', 'total_intl_calls', 'customer_service_calls'],
      dtype='object')
```

In [182…

```python
# Visualize our Feature importances

feature_imp_xgb = pd.DataFrame(pd.Series(best_xgb.estimator.steps[1][1].feature_importances_, index=df_X_train_
feature_imp_xgb = feature_imp_xgb.head(10)
feature_imp_xgb['index'] = feature_imp_xgb.index
feature_imp_xgb.head()

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



Recommendations & Summary

The top 3 features that lead to churn are customers that have the international plan, folks that engage with customer service frequently, and those with the voice mail plan. Those that are engaging with customer service already, most likely have some other questions or concern about the value that the features/ service are providing. These would be good indicators of risk, and information to understand what issues customers are experiencing.

Having customer service calls on this list, actually will make it easier to identify risk within the customer base. Thus making the outbound efforts to engage with customers with the international plan and the voice mail plan that aren't engaging frequently with customer service.

1. Once a customer reaches 3 customer service calls, flag the account as at risk. Once the account reaches 4 calls, the probability of canceling goes from 10% to 45%.

2. Customers that have the international plan and the voice mail plan should be surveyed to understand product performance and value. Although the voice mail plan performances better when paired with the international plan, it should be noted still that no international plan, and no voice mail plan performs the worst of the possible feature combinations (with those products).

3. Scale pricing to offer some relief for customers that use the plan more often. The pricing scale doesn't incentivize more usage of the product. Another option would be to look at unlimited usage based pricing, to give customers that use the plan more, the relief knowing that if they use the plan more, they won't necessarily be charged more for that usage.

In [ ]:

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