Stacey Patrick Ken Ben - Customer Churn Version 5

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1 Customer Churn Dataset

Group 4 - Patrick Codrington, Stacey Jovcic, Ben Polasek, Kenneth Brandt The intial work surrounded loading the data, analyzing the data and preparing the attibiutes that would be used for modeling.

2 PART 1 - Data Preparation and Pre-prediction Analysis

2.1 A) Initial data load

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

#numpy and pandas for data investigation and cleanup
import numpy as np
import pandas as pd

#pprint
import pprint

#matplotlib and seaborn for visuals
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
plt.style.use('seaborn-whitegrid')

#sklearn for machine learning
from sklearn import tree
#from c.linear_model import LogisticRegression
#from sklearn.svm import SVC, LinearSVC
#from sklearn.ensemble import RandomForestClassifier
#from sklearn.neighbors import KNeighborsClassifier
#from sklearn.naive_bayes import GaussianNB
#from sklearn.linear_model import Perceptron
#from sklearn.linear_model import SGDClassifier
#from sklearn.tree import DecisionTreeClassifier
```

```
In [2]: #Import the customer_churn.csv dataset
        df = pd.read_csv('customer_churn.csv')

        #Verify import was successful and check for missing values
        #Confirmed and there is no missing data
        df.info()

        #See column names
        #print(df.columns.values)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
State              3333 non-null object
Account Length     3333 non-null int64
Area Code          3333 non-null int64
Phone              3333 non-null object
Int'l Plan         3333 non-null object
VMail Plan         3333 non-null object
VMail Message      3333 non-null int64
Day Mins           3333 non-null float64
Day Calls          3333 non-null int64
Day Charge         3333 non-null float64
Eve Mins           3333 non-null float64
Eve Calls          3333 non-null int64
Eve Charge         3333 non-null float64
Night Mins         3333 non-null float64
Night Calls        3333 non-null int64
Night Charge       3333 non-null float64
Intl Mins          3333 non-null float64
Intl Calls         3333 non-null int64
Intl Charge        3333 non-null float64
CustServ Calls     3333 non-null int64
Churn?             3333 non-null object
dtypes: float64(8), int64(8), object(5)
memory usage: 546.9+ KB
```

2.2 B) What are the attribute type? (e.g. categorical, ordinal or quantitative)

```
In [3]: #Preview the data, to determine types
        df.head()
```

```
Out[3]:   State  Account Length  Area Code     Phone Int'l Plan VMail Plan  \
        0    KS             128        415  382-4657         no        yes
        1    OH             107        415  371-7191         no        yes
        2    NJ             137        415  358-1921         no         no
        3    OH              84        408  375-9999        yes         no
```

```
4    OK               75         415   330-6626        yes          no

   VMail Message  Day Mins  Day Calls  Day Charge   ...    Eve Calls  \
0             25     265.1        110       45.07   ...           99
1             26     161.6        123       27.47   ...          103
2              0     243.4        114       41.38   ...          110
3              0     299.4         71       50.90   ...           88
4              0     166.7        113       28.34   ...          122

   Eve Charge  Night Mins  Night Calls  Night Charge  Intl Mins  Intl Calls  \
0       16.78       244.7           91         11.01       10.0           3
1       16.62       254.4          103         11.45       13.7           3
2       10.30       162.6          104          7.32       12.2           5
3        5.26       196.9           89          8.86        6.6           7
4       12.61       186.9          121          8.41       10.1           3

   Intl Charge  CustServ Calls  Churn?
0         2.70               1  False.
1         3.70               1  False.
2         3.29               0  False.
3         1.78               2  False.
4         2.73               3  False.

[5 rows x 21 columns]
```

What are the categorical attributes?

Categorical: State, Area Code, Phone, Int'l Plan (binary), VMail Message (binary), Churn (class variable).

What are the numerical attributes?

Continous: Account Length, Day Mins, Day Charge, Eve Mins, Eve Charge, Night Mins, Night Charge, Intl Mins, Intl Charge Discrete: VMail Message, Day Calls, Eve Calls, Night Calls, Intl Calls, CustServ Calls

3 C) Find the max, min, mean and standard deviation of each attribute

Use describe to first gather this data for the categorical values and convert area code to object as this field is not numeric.

In [4]:
```
df['Area Code'] = df['Area Code'].astype(object)
df.describe(include=['O'])
```

Out[4]:

	State	Area Code	Phone	Int'l Plan	VMail Plan	Churn?
count	3333	3333	3333	3333	3333	3333
unique	51	3	3333	2	2	2
top	WV	415	381-2745	no	no	False.
freq	106	1655	1	3010	2411	2850

Use describe again to this time gather the data for numerical values.

In [5]:
```
df.describe()
```

Out[5]:

	Account Length	VMail Message	Day Mins	Day Calls	Day Charge	\
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	
mean	101.064806	8.099010	179.775098	100.435644	30.562307	
std	39.822106	13.688365	54.467389	20.069084	9.259435	
min	1.000000	0.000000	0.000000	0.000000	0.000000	
25%	74.000000	0.000000	143.700000	87.000000	24.430000	
50%	101.000000	0.000000	179.400000	101.000000	30.500000	
75%	127.000000	20.000000	216.400000	114.000000	36.790000	
max	243.000000	51.000000	350.800000	165.000000	59.640000	

	Eve Mins	Eve Calls	Eve Charge	Night Mins	Night Calls	\
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	
mean	200.980348	100.114311	17.083540	200.872037	100.107711	
std	50.713844	19.922625	4.310668	50.573847	19.568609	
min	0.000000	0.000000	0.000000	23.200000	33.000000	
25%	166.600000	87.000000	14.160000	167.000000	87.000000	
50%	201.400000	100.000000	17.120000	201.200000	100.000000	
75%	235.300000	114.000000	20.000000	235.300000	113.000000	
max	363.700000	170.000000	30.910000	395.000000	175.000000	

	Night Charge	Intl Mins	Intl Calls	Intl Charge	CustServ Calls
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	9.039325	10.237294	4.479448	2.764581	1.562856
std	2.275873	2.791840	2.461214	0.753773	1.315491
min	1.040000	0.000000	0.000000	0.000000	0.000000
25%	7.520000	8.500000	3.000000	2.300000	1.000000
50%	9.050000	10.300000	4.000000	2.780000	1.000000
75%	10.590000	12.100000	6.000000	3.270000	2.000000
max	17.770000	20.000000	20.000000	5.400000	9.000000

As was shown phone is all unique values and can be removed from the data frame. Also decided to create dummy variables for the binary attributes.

In [6]:
```
df.drop('Phone', axis=1, inplace=True)
#df.drop('VMail Message', axis=1, inplace=True)
```

In [7]:
```
df['Int\'l Plan'] = df['Int\'l Plan'].map( {'yes': 1, 'no': 0} ).astype(int)
df['VMail Plan'] = df['VMail Plan'].map( {'yes': 1, 'no': 0} ).astype(int)
df['Churn?'] = df['Churn?'].map( {'True.': 1, 'False.': 0} ).astype(int)
df.head()
```

Out[7]:

	State	Account Length	Area Code	Int'l Plan	VMail Plan	VMail Message	\
0	KS	128	415	0	1	25	
1	OH	107	415	0	1	26	
2	NJ	137	415	0	0	0	
3	OH	84	408	1	0	0	
4	OK	75	415	1	0	0	

```
   Day Mins  Day Calls  Day Charge  Eve Mins  Eve Calls  Eve Charge  \
0     265.1        110       45.07     197.4         99       16.78
1     161.6        123       27.47     195.5        103       16.62
2     243.4        114       41.38     121.2        110       10.30
3     299.4         71       50.90      61.9         88        5.26
4     166.7        113       28.34     148.3        122       12.61

   Night Mins  Night Calls  Night Charge  Intl Mins  Intl Calls  Intl Charge  \
0       244.7           91         11.01       10.0           3         2.70
1       254.4          103         11.45       13.7           3         3.70
2       162.6          104          7.32       12.2           5         3.29
3       196.9           89          8.86        6.6           7         1.78
4       186.9          121          8.41       10.1           3         2.73

   CustServ Calls  Churn?
0               1       0
1               1       0
2               0       0
3               2       0
4               3       0
```

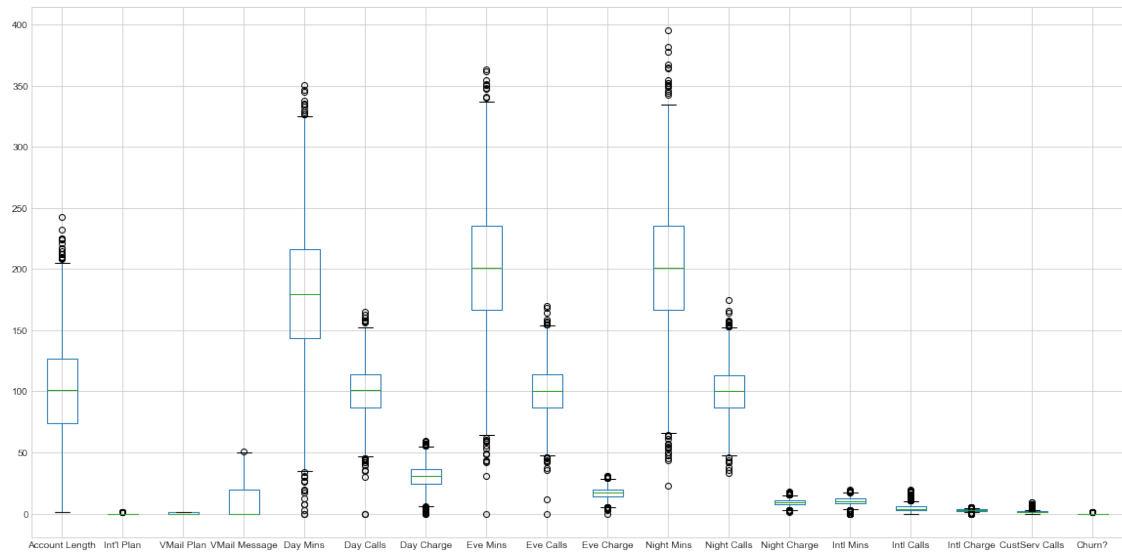
4 D) Are there any outlier values (records) for each of the attributes ?

The box plot shows that some attributes (acc len, calls, mins, charges) have a quite a few outliers. This is most likely due to this data not being a full dataset and the nature of this data is most likely influenced by the pareto principle.

In this case it makes sense to consolidate the fields calls, mins, charges. Also makes sense to bin the data and then see if there is any relation to the class variable.

```
In [8]: #Use boxplot to see if there are any outlier values
        df.boxplot(figsize=(20,10))
```

```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x24a57f338d0>
```



4.1 E) Analyze the distribution of numeric attributes (normal or other)

As noted above it made sense to consolidate min, calls, and charges. This was done before plotting the distributions

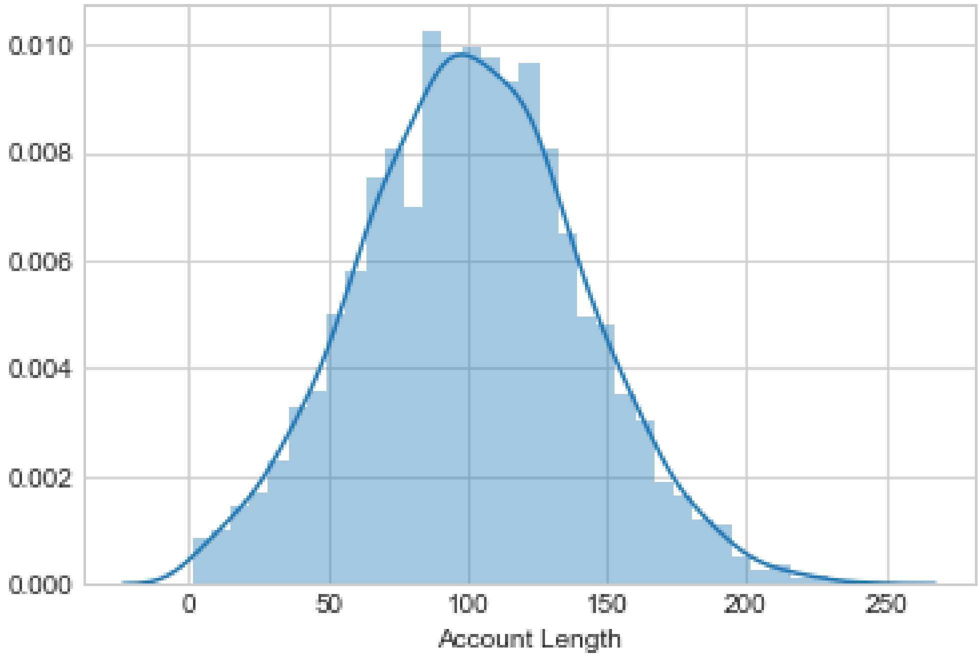
```
In [9]: #Group the day, eve, night data into total calls, total charges and total mins to simp
        df['Total Mins Non-Intl'] = df['Day Mins'] + df['Eve Mins'] + df['Night Mins']
        df['Total Calls Non-Intl'] = df['Day Calls'] + df['Eve Calls'] + df['Night Calls']
        df['Total Charge Non-Intl'] = df['Day Charge'] + df['Eve Charge'] + df['Night Charge']

        #Create a new columns for combined totals  (non-intl and intl)
        df['Total Mins'] = df['Total Mins Non-Intl'] + df['Intl Mins']
        df['Total Calls'] = df['Total Calls Non-Intl'] + df['Intl Calls']
        df['Total Charge'] = df['Total Charge Non-Intl'] + df['Intl Charge']
        #df.head()
```

Account Length - Normally distributed

```
In [10]: #Account Length, Day Mins, Day Charge, Eve Mins, Eve Charge, Night Mins, Night Charge
         sns.distplot(df["Account Length"])
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5deacda0>
```

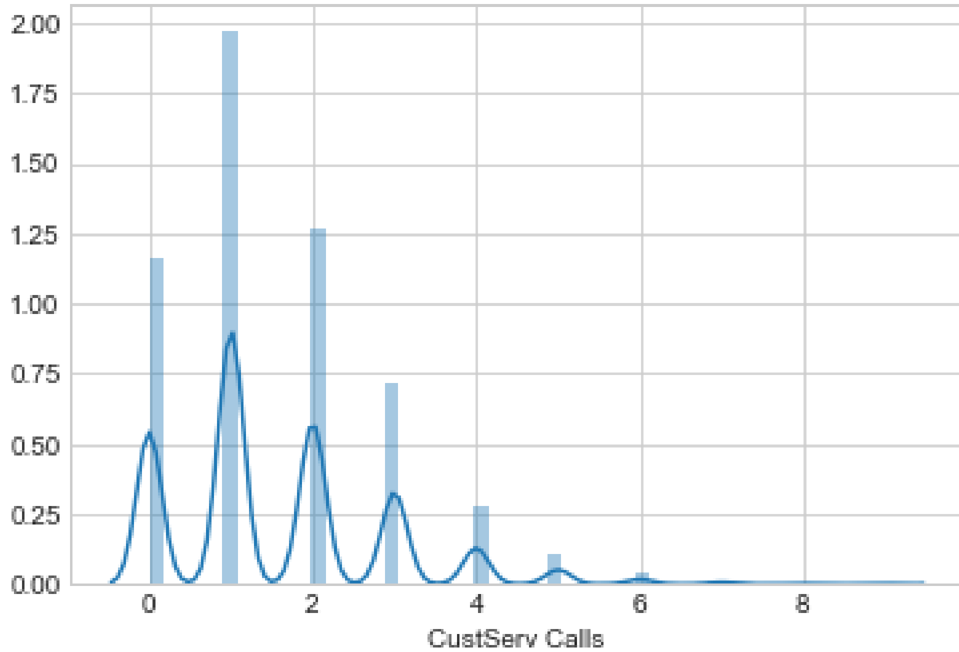


CustServ Calls - Not normally dist and should be converted to a binary value

In [11]:
```
sns.distplot(df["CustServ Calls"])
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a5db27748>
```



VMail Message - Was not normally dist and should be converted to a binary value. Basically the same as VMail Plan so it was dropped.

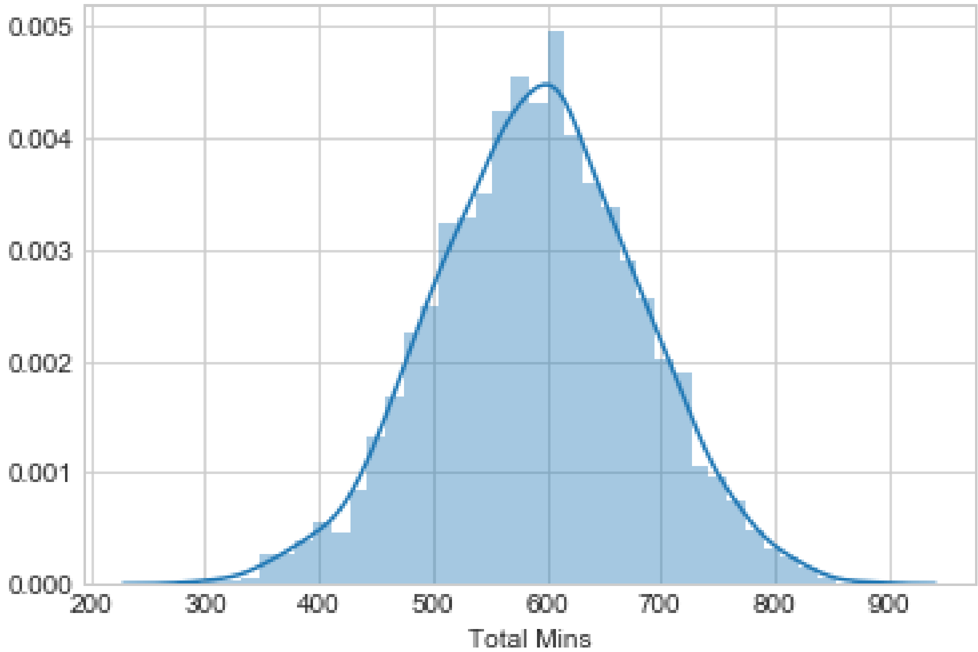
```
In [12]: #sns.distplot(df["VMail Message"])
```

Mins - Normally distributed

```
In [13]: sns.distplot(df["Total Mins"])
```

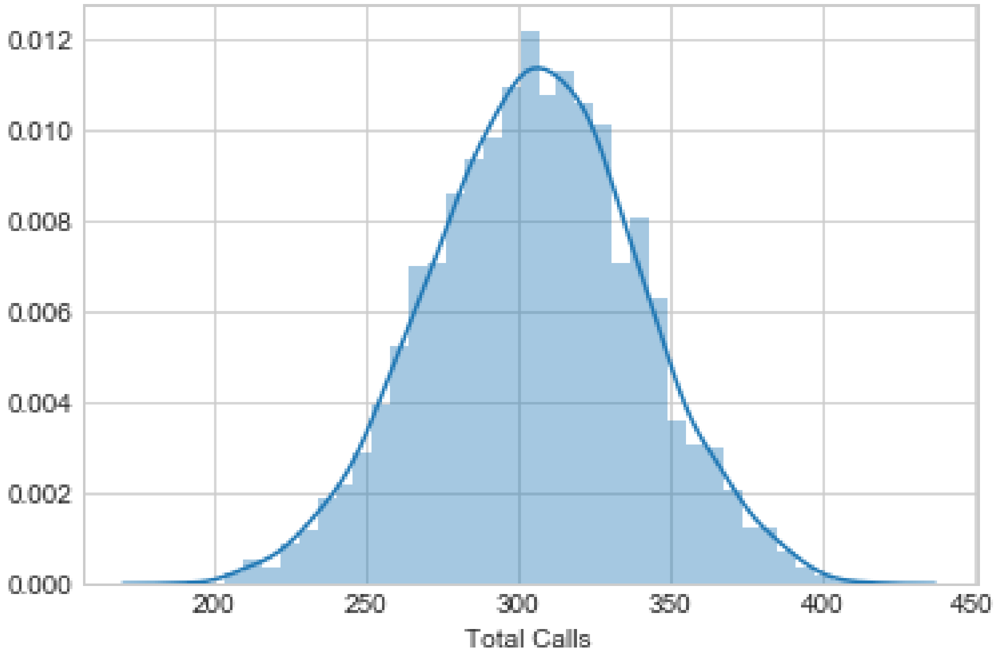
```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5dc16b38>
```



Calls - Normally distributed

```
In [14]: sns.distplot(df["Total Calls"])

C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval


Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5dcd3828>
```

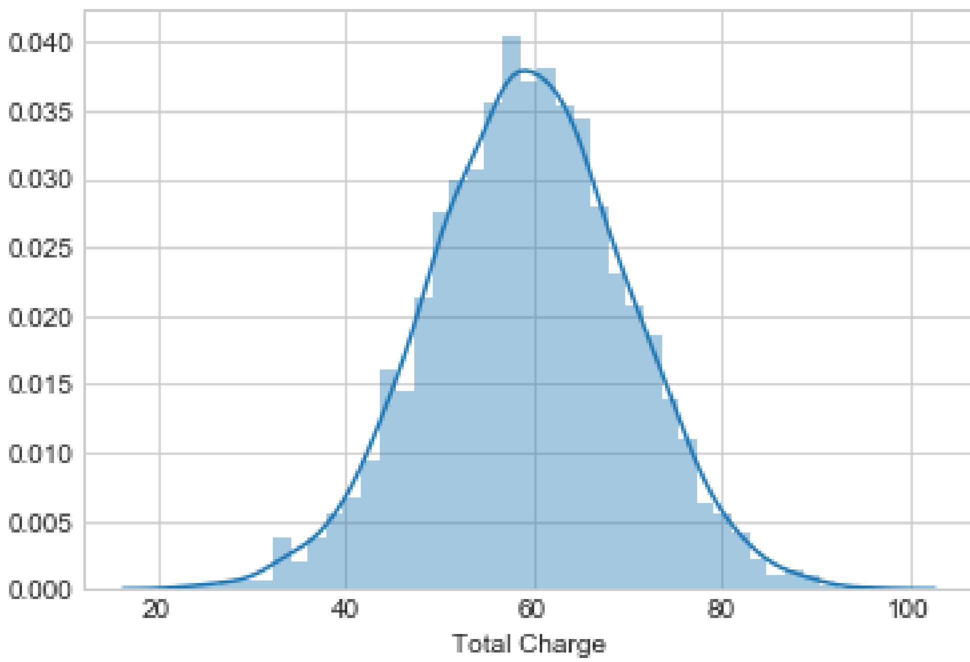


Charge - Normally distributed

```
In [15]: sns.distplot(df["Total Charge"])
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5dd7f978>
```



4.2 F) Analyze attributes and determine if they have any influence on the class

Before starting this analysis the account length was binned. Skipped binning each individual min, call, charge coloumn and focused on the the overall totals.

In [16]:
```
#Bin account length
binwidth_al = int((max(df['Account Length'])-min(df['Account Length']))/5)
bins_al = range(min(df['Account Length']), max(df['Account Length']), binwidth_al)
al_names = ['Newest', 'Avg', "Oldest"]
df['Acc Length Binned'] = pd.cut(df['Account Length'], bins_al)

#Convert total mins to int so it can be binned
df['Total Mins'] = df['Total Mins'].astype(np.int64)
#Bin Total Mins
binwidth_tm = int((max(df['Total Mins'])-min(df['Total Mins']))/6)
bins_tm = range(min(df['Total Mins']), max(df['Total Mins']), binwidth_tm)

df['Total Mins Binned'] = pd.cut(df['Total Mins'], bins_tm)

#Convert total Calls to int so it can be binned
df['Total Calls'] = df['Total Calls'].astype(np.int64)
#Bin Total Calls
binwidth_tc = int((max(df['Total Calls'])-min(df['Total Calls']))/6)
bins_tc = range(min(df['Total Calls']), max(df['Total Calls']), binwidth_tc)
df['Total Calls Binned'] = pd.cut(df['Total Calls'], bins_tc)
```

```python
#Convert total Calls to int so it can be binned
df['Total Charge'] = df['Total Charge'].astype(np.int64)
#Bin Total Calls
binwidth_tch = int((max(df['Total Charge'])-min(df['Total Charge']))/6)
bins_tch = range(min(df['Total Charge']), max(df['Total Charge']), binwidth_tch)
df['Total Charge Binned'] = pd.cut(df['Total Charge'], bins_tch)

df.head()
```

```
Out[16]:   State  Account Length  Area Code  Int'l Plan  VMail Plan  VMail Message  \
         0    KS             128        415           0           1             25
         1    OH             107        415           0           1             26
         2    NJ             137        415           0           0              0
         3    OH              84        408           1           0              0
         4    OK              75        415           1           0              0

            Day Mins  Day Calls  Day Charge  Eve Mins          ...          \
         0     265.1        110       45.07     197.4          ...
         1     161.6        123       27.47     195.5          ...
         2     243.4        114       41.38     121.2          ...
         3     299.4         71       50.90      61.9          ...
         4     166.7        113       28.34     148.3          ...

            Total Mins Non-Intl  Total Calls Non-Intl  Total Charge Non-Intl  \
         0                707.2                   300                  72.86
         1                611.5                   329                  55.54
         2                527.2                   328                  59.00
         3                558.2                   248                  65.02
         4                501.9                   356                  49.36

            Total Mins  Total Calls  Total Charge  Acc Length Binned  \
         0         717          303            75          (97, 145]
         1         625          332            59          (97, 145]
         2         539          333            62          (97, 145]
         3         564          255            66           (49, 97]
         4         512          359            52           (49, 97]

            Total Mins Binned  Total Calls Binned  Total Charge Binned
         0         (684, 784]          (302, 339]             (70, 82]
         1         (584, 684]          (302, 339]             (58, 70]
         2         (484, 584]          (302, 339]             (58, 70]
         3         (484, 584]          (228, 265]             (58, 70]
         4         (484, 584]          (339, 376]             (46, 58]

         [5 rows x 30 columns]
```

State - Some states are more likely to result in churn but there is no strong correlation visible . It can be dropped.

```
In [17]: df[['State', 'Churn?']].groupby(['State'], as_index=False).mean().sort_values(by='Chu
```

Out[17]:

	State	Churn?
31	NJ	0.264706
4	CA	0.264706
43	TX	0.250000
20	MD	0.242857
40	SC	0.233333
22	MI	0.219178
25	MS	0.215385
33	NV	0.212121
47	WA	0.212121
21	ME	0.209677
26	MT	0.205882
2	AR	0.200000
16	KS	0.185714
34	NY	0.180723
23	MN	0.178571
38	PA	0.177778
19	MA	0.169231
6	CT	0.162162
27	NC	0.161765
30	NH	0.160714
10	GA	0.148148
8	DE	0.147541
36	OK	0.147541
37	OR	0.141026
44	UT	0.138889
5	CO	0.136364
17	KY	0.135593
41	SD	0.133333
35	OH	0.128205
9	FL	0.126984
15	IN	0.126761
13	ID	0.123288
50	WY	0.116883
24	MO	0.111111
46	VT	0.109589
1	AL	0.100000
32	NM	0.096774
28	ND	0.096774
49	WV	0.094340
42	TN	0.094340
7	DC	0.092593
39	RI	0.092308
48	WI	0.089744
14	IL	0.086207
29	NE	0.081967

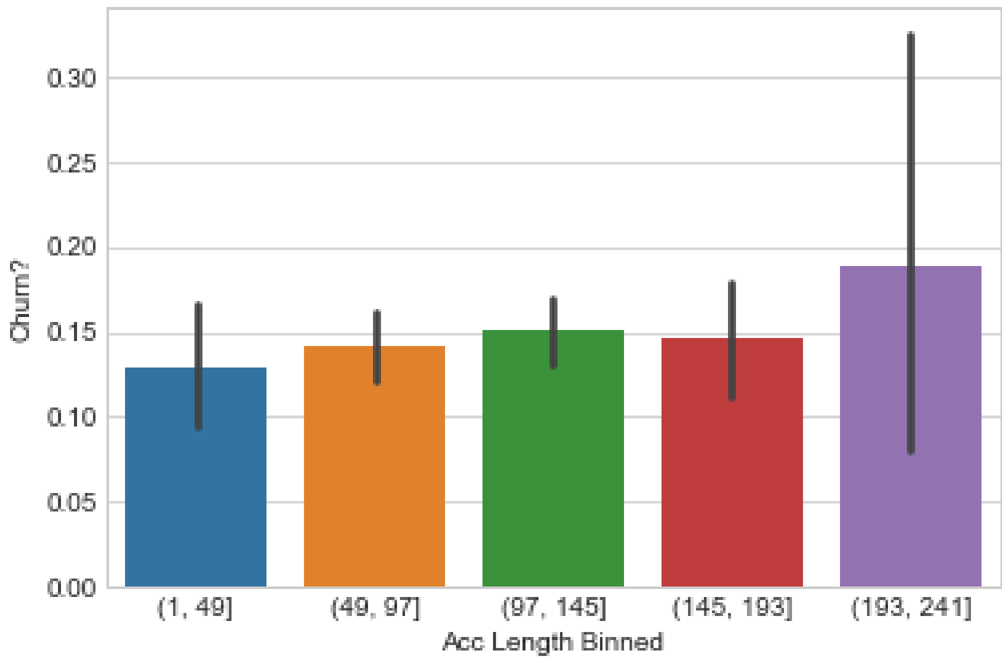
```
18     LA   0.078431
12     IA   0.068182
45     VA   0.064935
3      AZ   0.062500
0      AK   0.057692
11     HI   0.056604
```

Acc Length Binned - No real difference shown. It can be dropped.

In [18]:
```
sns.barplot(x='Acc Length Binned', y='Churn?', data=df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[18]: `<matplotlib.axes._subplots.AxesSubplot at 0x24a5e1c3be0>`

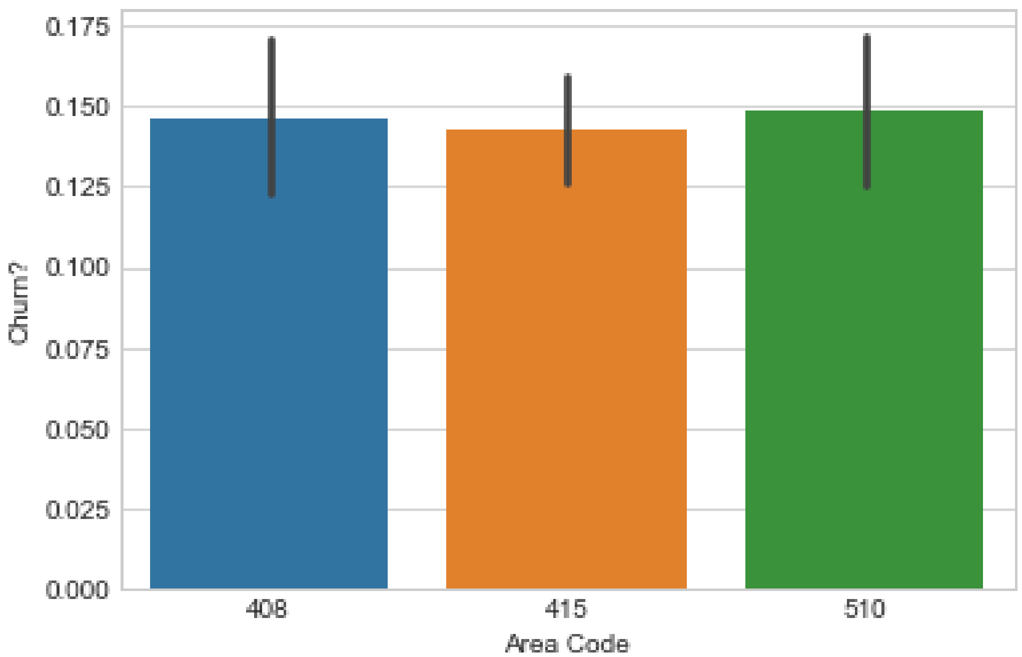


Area Code - No predictive power. It can be dropped

In [19]:
```
#df[['Area Code', 'Churn?']].groupby(['Area Code'], as_index=False).mean().sort_value
sns.barplot(x='Area Code', y='Churn?', data=df)
```

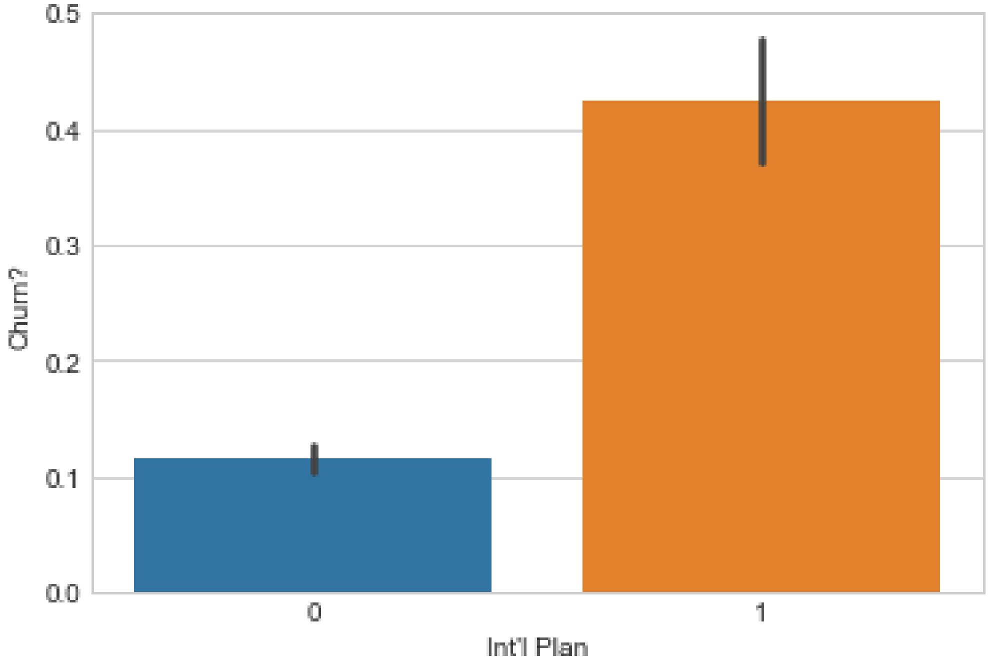
```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[19]: `<matplotlib.axes._subplots.AxesSubplot at 0x24a5e19e6a0>`



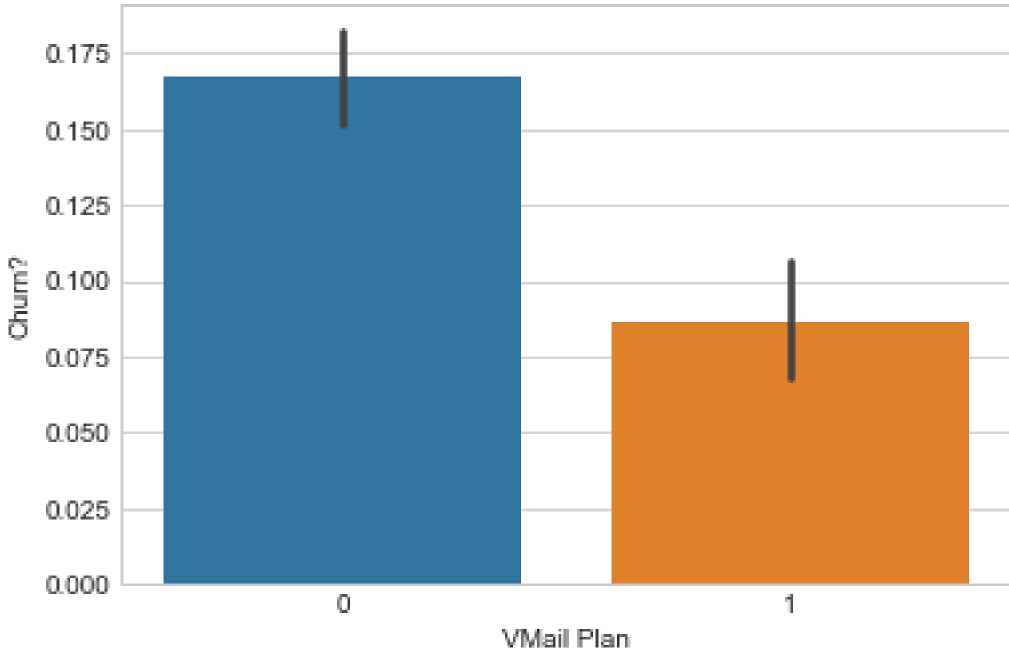
Intl Plan - If customer has international plan, they are more likely to churn. Keep attribute.

```
In [20]: sns.barplot(x='Int\'l Plan', y='Churn?', data=df)

C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval


Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5e2b1550>
```



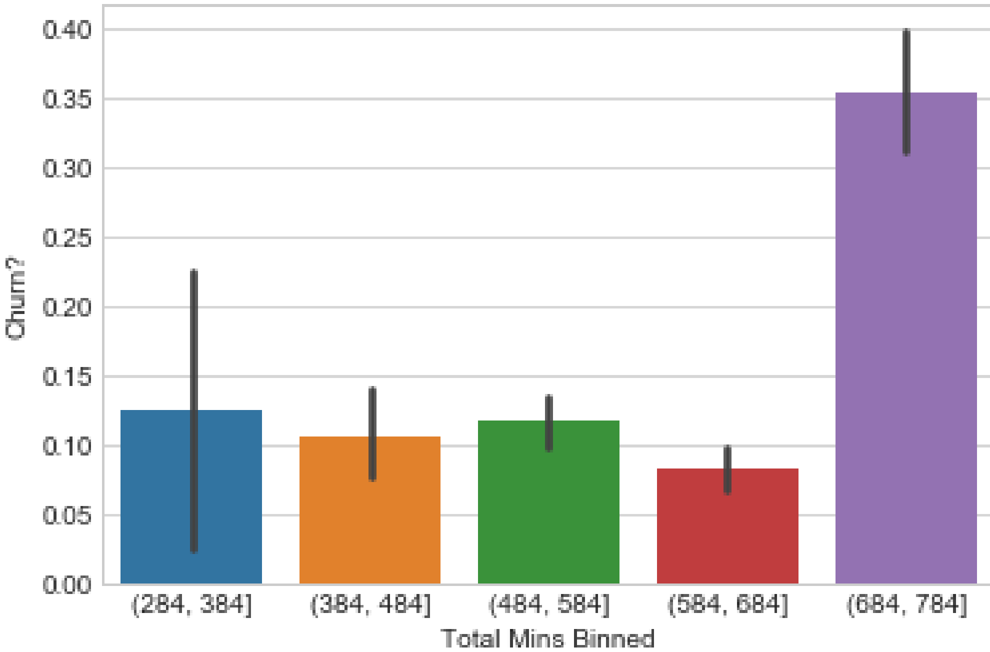
VMail Plan - No Voicemail plan does increase chance of churn slightly. Keep for now, but it can be removed later on from model.

```
In [21]: sns.barplot(x='VMail Plan', y='Churn?', data=df)

C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval


Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5e2fa828>
```



Total Mins Binned - Minutes don't appear to influence churn as the outcome is fairly random. Will drop field based on this and fact there are a high number of outliers previously identified for this attribute.

```
In [22]: sns.barplot(x='Total Mins Binned', y='Churn?', data=df)

C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval


Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5e35b358>
```

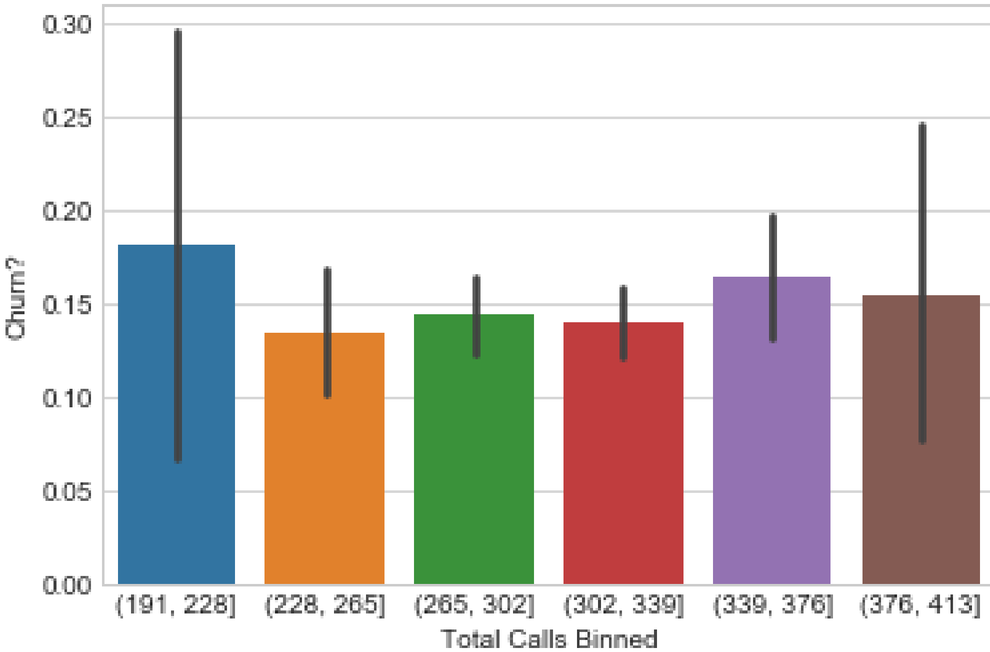


Total Calls Binned - Total Calls doesn't appear to influence the class attribute. Will drop field based on this and fact there are a high number of outliers previously identified for this attribute.

```
In [23]: sns.barplot(x='Total Calls Binned', y='Churn?', data=df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5e3c0898>
```

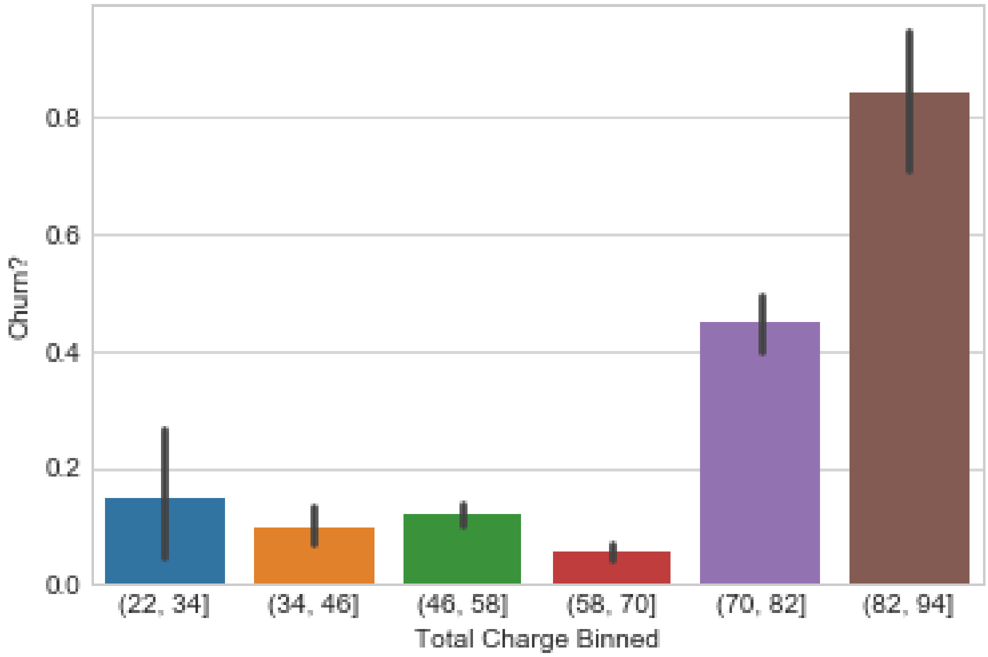


Total Charge Binned - Customer is more likely to churn if their charge is high. Create a feature if charge >80 (y/n)

```
In [24]: sns.barplot(x='Total Charge Binned', y='Churn?', data=df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5e4304a8>
```



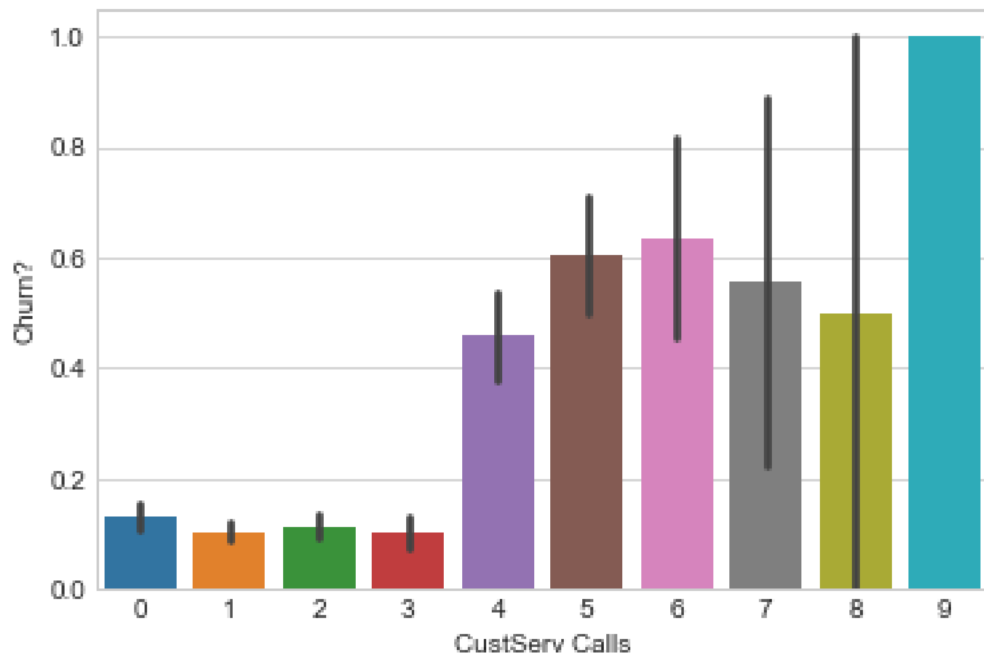
In [25]:
```
#Create new feature
df['Total Charge > 80'] = df['Total Charge'].apply(lambda x: 1 if x >80 else 0)
```

CustServ Calls - The more calls equals a much greater chance of churn. Greater than 3 looks like a strong indicator. Create new feature based on this.

In [26]:
```
sns.barplot(x='CustServ Calls', y='Churn?', data=df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24a5f4399e8>
```



In [27]:
```
#Create new feature
df['CustServ Calls >3'] = df['CustServ Calls'].apply(lambda x: 1 if x >3 else 0)
#df.info()
```

4.3 G) Final Clean-up

Above there has already been some data clean up such as removing attributes not needed and coverting categorical data to numerical values. In this section anything remaining before data is used for modeling is completed

Remove columns that are not needed (identified in part f)

In [28]:
```
#df.drop('State', axis=1, inplace=True)
df.drop('Account Length', axis=1, inplace=True)
df.drop('Area Code', axis=1, inplace=True)
df.drop('Day Mins', axis=1, inplace=True)
df.drop('Day Calls', axis=1, inplace=True)
df.drop('Day Charge', axis=1, inplace=True)
df.drop('Eve Mins', axis=1, inplace=True)
df.drop('Eve Calls', axis=1, inplace=True)
df.drop('Eve Charge', axis=1, inplace=True)
df.drop('Night Mins', axis=1, inplace=True)
df.drop('Night Calls', axis=1, inplace=True)
df.drop('Night Charge', axis=1, inplace=True)
df.drop('Intl Mins', axis=1, inplace=True)
df.drop('Intl Calls', axis=1, inplace=True)
```

```
df.drop('Intl Charge', axis=1, inplace=True)
df.drop('Total Mins Non-Intl', axis=1, inplace=True)
df.drop('Total Calls Non-Intl', axis=1, inplace=True)
df.drop('Total Charge Non-Intl', axis=1, inplace=True)
df.drop('Total Mins', axis=1, inplace=True)
df.drop('Total Calls', axis=1, inplace=True)
#df.drop('Total Charge', axis=1, inplace=True)
df.drop('Acc Length Binned', axis=1, inplace=True)
df.drop('Total Mins Binned', axis=1, inplace=True)
df.drop('Total Calls Binned', axis=1, inplace=True)
df.drop('Total Charge Binned', axis=1, inplace=True)
df.drop('CustServ Calls', axis=1, inplace=True)
```

There are now 7 features to use for modeling after investigating which attributes can influence the class variable and then removing the ones are unrelated.

```
In [29]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 8 columns):
State                   3333 non-null object
Int'l Plan              3333 non-null int32
VMail Plan              3333 non-null int32
VMail Message           3333 non-null int64
Churn?                  3333 non-null int32
Total Charge            3333 non-null int64
Total Charge > 80       3333 non-null int64
CustServ Calls >3       3333 non-null int64
dtypes: int32(3), int64(4), object(1)
memory usage: 169.3+ KB
```

Finally for each newly created attibute used determine churn, group by and take a count of no churn.churn to see size of each influencer and confirm it should still be included. Would have exluded if attributes were highly weighted to either no churn or churn.

```
In [30]: df_groupby2 = (df.groupby(['Int\'l Plan'])['Churn?'].agg('count'))
         df_groupby2

Out[30]: Int'l Plan
         0    3010
         1     323
         Name: Churn?, dtype: int64

In [31]: df_groupby2 = (df.groupby(['VMail Plan'])['Churn?'].agg('count'))
         df_groupby2
```

```
Out[31]: VMail Plan
         0    2411
         1     922
         Name: Churn?, dtype: int64
```

```
In [32]: df_groupby2 = (df.groupby(['Total Charge > 80'])['Churn?'].agg('count'))
         df_groupby2
```

```
Out[32]: Total Charge > 80
         0    3266
         1      67
         Name: Churn?, dtype: int64
```

```
In [33]: df_groupby2 = (df.groupby(['CustServ Calls >3'])['Churn?'].agg('count'))
         df_groupby2
```

```
Out[33]: CustServ Calls >3
         0    3066
         1     267
         Name: Churn?, dtype: int64
```

4.4 H) Three way data split (training 60%, validation 20%, test 20%)

The function below takes the dataframe and does a three way split based on provided percentges. It also randomizes the index so that the output is a random sample.

```
In [34]: def train_validate_test_split(df, train_percent=.6, validate_percent=.2, seed=None):
             np.random.seed(seed)
             perm = np.random.permutation(df.index)
             m = len(df.index)
             train_end = int(train_percent * m)
             validate_end = int(validate_percent * m) + train_end
             train = df.ix[perm[:train_end]]
             validate = df.ix[perm[train_end:validate_end]]
             test = df.ix[perm[validate_end:]]
             return train, validate, test

         np.random.seed([3,1415])

         train, validate, test = train_validate_test_split(df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  import sys
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:8: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated

C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:9: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  if __name__ == '__main__':
```

```
In [35]: test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 668 entries, 373 to 2237
Data columns (total 8 columns):
State                668 non-null object
Int'l Plan           668 non-null int32
VMail Plan           668 non-null int32
VMail Message        668 non-null int64
Churn?               668 non-null int32
Total Charge         668 non-null int64
Total Charge > 80    668 non-null int64
CustServ Calls >3    668 non-null int64
dtypes: int32(3), int64(4), object(1)
memory usage: 39.1+ KB
```

```
In [36]: df.to_csv("customer _churn_processed.csv", sep=',', encoding='utf-8')
```

5 PART 2 - Predictive Modeling (Classification)

6 DECISION TREE

6.1 A) Read partially processed file from earlier analysis and review included variables

```
In [37]: # import dataset

         df = pd.read_csv("customer _churn_processed.csv")
```

```
#Verify import was successful and check for missing values
#Confirmed and there is no missing data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 9 columns):
Unnamed: 0           3333 non-null int64
State                3333 non-null object
Int'l Plan           3333 non-null int64
VMail Plan           3333 non-null int64
VMail Message        3333 non-null int64
Churn?               3333 non-null int64
Total Charge         3333 non-null int64
Total Charge > 80    3333 non-null int64
CustServ Calls >3    3333 non-null int64
dtypes: int64(8), object(1)
memory usage: 234.4+ KB
```

6.2 B) Confirm relative frequency of churn in the dataset

The results of the analysis show an imbalance of churn versus non-churn

```
In [38]: df_groupby = (df.groupby(['Churn?'])['Churn?'].agg('count'))

         print (df_groupby)
         print ("Churn rate - ",483/(2850+483))
```

```
Churn?
0    2850
1     483
Name: Churn?, dtype: int64
Churn rate -  0.14491449144914492
```

6.3 C) List the names of columns for easy later reference

```
In [39]: # create list with column names

         col_nm = list(df.columns.values)

         print (col_nm)
```

```
['Unnamed: 0', 'State', "Int'l Plan", 'VMail Plan', 'VMail Message', 'Churn?', 'Total Charge',
```

In [40]:
```
## Create dummy variables for state to feed into decision tree

s = df['State']
state_dummies = pd.get_dummies(s)
```

6.4 D) Concatenate state_dummies with main df and drop original state variable

In [41]:
```
df = pd.concat([df,state_dummies], axis=1, sort=False)
df.drop('State',  axis=1, inplace=True)
df.drop('Unnamed: 0',  axis=1, inplace=True)
```

In [42]:
```
# Create train, test and validation data sets (60,20,20)
# note generates and error but works fine

def train_validate_test_split(df, train_percent=.6, validate_percent=.2, seed=None):
    np.random.seed(seed)
    perm = np.random.permutation(df.index)
    m = len(df.index)
    train_end = int(train_percent * m)
    validate_end = int(validate_percent * m) + train_end
    train = df.ix[perm[:train_end]]
    validate = df.ix[perm[train_end:validate_end]]
    test = df.ix[perm[validate_end:]]
    return train, validate, test

np.random.seed([3,1415])

train, validate, test = train_validate_test_split(df)
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  # Remove the CWD from sys.path while we load stuff.
C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  # This is added back by InteractiveShellApp.init_path()
C:\Users\benpo\Anaconda3\lib\site-packages\ipykernel_launcher.py:12: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
```

```
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  if sys.path[0] == '':
```

6.5 E) Confirm the split took place correctly.

```
In [43]: # confirm split
         print(test.describe())
         print(train.describe())
         print(validate.describe())
```

```
       Int'l Plan  VMail Plan  VMail Message      Churn?  Total Charge  \
count  668.000000  668.000000     668.000000  668.000000    668.000000
mean     0.109281    0.255988       7.492515    0.149701     59.008982
std      0.312226    0.436742      13.220819    0.357045     10.372951
min      0.000000    0.000000       0.000000    0.000000     25.000000
25%      0.000000    0.000000       0.000000    0.000000     52.000000
50%      0.000000    0.000000       0.000000    0.000000     58.000000
75%      0.000000    1.000000      15.000000    0.000000     66.000000
max      1.000000    1.000000      45.000000    1.000000     92.000000

       Total Charge > 80  CustServ Calls >3          AK          AL  \
count         668.000000         668.000000  668.000000  668.000000
mean            0.016467           0.062874    0.014970    0.023952
std             0.127358           0.242919    0.121524    0.153015
min             0.000000           0.000000    0.000000    0.000000
25%             0.000000           0.000000    0.000000    0.000000
50%             0.000000           0.000000    0.000000    0.000000
75%             0.000000           0.000000    0.000000    0.000000
max             1.000000           1.000000    1.000000    1.000000

               AR     ...              SD          TN          TX          UT  \
count  668.000000     ...      668.000000  668.000000  668.000000  668.000000
mean     0.019461     ...        0.023952    0.008982    0.022455    0.025449
std      0.138242     ...        0.153015    0.094418    0.148269    0.157603
min      0.000000     ...        0.000000    0.000000    0.000000    0.000000
25%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
50%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
75%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
max      1.000000     ...        1.000000    1.000000    1.000000    1.000000

               VA          VT          WA          WI          WV          WY
count  668.000000  668.000000  668.000000  668.000000  668.000000  668.000000
mean     0.017964    0.017964    0.019461    0.026946    0.031437    0.025449
std      0.132920    0.132920    0.138242    0.162047    0.174627    0.157603
```

```
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
50%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
75%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
max      1.000000    1.000000    1.000000    1.000000    1.000000    1.000000

[8 rows x 58 columns]
        Int'l Plan   VMail Plan  VMail Message       Churn?  Total Charge  \
count  1999.000000  1999.000000    1999.000000  1999.000000   1999.000000
mean      0.100050     0.273137       8.034017     0.147074     58.882441
std       0.300142     0.445682      13.724912     0.354268     10.554245
min       0.000000     0.000000       0.000000     0.000000     25.000000
25%       0.000000     0.000000       0.000000     0.000000     52.000000
50%       0.000000     0.000000       0.000000     0.000000     59.000000
75%       0.000000     1.000000      19.000000     0.000000     66.000000
max       1.000000     1.000000      50.000000     1.000000     96.000000

       Total Charge > 80  CustServ Calls >3           AK           AL  \
count        1999.000000        1999.000000  1999.000000  1999.000000
mean            0.020510           0.086043     0.014507     0.022511
std             0.141773           0.280498     0.119599     0.148376
min             0.000000           0.000000     0.000000     0.000000
25%             0.000000           0.000000     0.000000     0.000000
50%             0.000000           0.000000     0.000000     0.000000
75%             0.000000           0.000000     0.000000     0.000000
max             1.000000           1.000000     1.000000     1.000000

                AR     ...               SD           TN           TX  \
count  1999.000000     ...      1999.000000  1999.000000  1999.000000
mean      0.014007     ...         0.015508     0.018009     0.024012
std       0.117549     ...         0.123592     0.133017     0.153125
min       0.000000     ...         0.000000     0.000000     0.000000
25%       0.000000     ...         0.000000     0.000000     0.000000
50%       0.000000     ...         0.000000     0.000000     0.000000
75%       0.000000     ...         0.000000     0.000000     0.000000
max       1.000000     ...         1.000000     1.000000     1.000000

                UT           VA           VT           WA           WI  \
count  1999.000000  1999.000000  1999.000000  1999.000000  1999.000000
mean      0.020510     0.024512     0.020510     0.019010     0.020510
std       0.141773     0.154672     0.141773     0.136592     0.141773
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

                WV           WY
```

```
count  1999.000000  1999.000000
mean      0.031516     0.020010
std       0.174751     0.140069
min       0.000000     0.000000
25%       0.000000     0.000000
50%       0.000000     0.000000
75%       0.000000     0.000000
max       1.000000     1.000000

[8 rows x 58 columns]
       Int'l Plan  VMail Plan  VMail Message      Churn?  Total Charge  \
count  666.000000  666.000000     666.000000  666.000000    666.000000
mean     0.075075    0.307808       8.902402    0.133634     59.147147
std      0.263710    0.461933      14.018391    0.340514     10.489349
min      0.000000    0.000000       0.000000    0.000000     22.000000
25%      0.000000    0.000000       0.000000    0.000000     53.000000
50%      0.000000    0.000000       0.000000    0.000000     59.000000
75%      0.000000    1.000000      22.000000    0.000000     66.000000
max      1.000000    1.000000      51.000000    1.000000     89.000000

       Total Charge > 80  CustServ Calls >3          AK          AL  \
count         666.000000         666.000000  666.000000  666.000000
mean            0.022523           0.079580    0.019520    0.028529
std             0.148487           0.270845    0.138446    0.166602
min             0.000000           0.000000    0.000000    0.000000
25%             0.000000           0.000000    0.000000    0.000000
50%             0.000000           0.000000    0.000000    0.000000
75%             0.000000           0.000000    0.000000    0.000000
max             1.000000           1.000000    1.000000    1.000000

               AR     ...              SD          TN          TX          UT  \
count  666.000000     ...      666.000000  666.000000  666.000000  666.000000
mean     0.021021     ...        0.019520    0.016517    0.013514    0.021021
std      0.143562     ...        0.138446    0.127547    0.115546    0.143562
min      0.000000     ...        0.000000    0.000000    0.000000    0.000000
25%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
50%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
75%      0.000000     ...        0.000000    0.000000    0.000000    0.000000
max      1.000000     ...        1.000000    1.000000    1.000000    1.000000

               VA          VT          WA          WI          WV          WY
count  666.000000  666.000000  666.000000  666.000000  666.000000  666.000000
mean     0.024024    0.030030    0.022523    0.028529    0.033033    0.030030
std      0.153239    0.170798    0.148487    0.166602    0.178857    0.170798
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
50%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
75%      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
```

```
max       1.000000     1.000000     1.000000     1.000000     1.000000     1.000000

[8 rows x 58 columns]
```

6.6 F) Create separate target vector to feed into the algorithm.

```
In [44]: # create separate arrays for target variable


         train_target = train['Churn?']
         test_target = test['Churn?']
         validate_target = validate['Churn?']


         # delete target variable from train and test  dataframes

         train = train.drop('Churn?',1)
         test = test.drop('Churn?',1)
         validate = validate.drop('Churn?',1)
```

6.7 G) Import decision tree and fit model

#importing other algorithms is very similar

```
In [45]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.tree import tree
         from sklearn.model_selection import train_test_split


         tree = DecisionTreeClassifier(criterion = 'gini', splitter='best', max_depth=None, mi
                                       min_samples_leaf=10, min_weight_fraction_leaf=0.0,  ranc
                                       max_leaf_nodes=None, min_impurity_decrease=0.0, min_impu
                                       presort=False)

         tree.fit (train,train_target)

Out[45]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=10, min_samples_split=5,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=0,
                     splitter='best')

In [46]: # Score train data set

In [47]: # Output model scores for test

         test_pred =  tree.predict(test)
```

In [48]:
```
# Calculate model evaluation metrics


from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import accuracy_score
precision, recall, fscore, support = score(test_target, test_pred)


precision = ('precision: {}'.format(precision))
recall = ('recall: {}'.format(recall))
fscore = ('fscore: {}'.format(fscore))
support = ('support: {}'.format(support))
accuracy = accuracy_score(test_target, test_pred, normalize=True)

output = {accuracy, precision, recall, fscore, support}
output
```

Out[48]:
```
{0.938622754491018,
 'fscore: [0.96480687 0.76023392]',
 'precision: [0.94137353 0.91549296]',
 'recall: [0.98943662 0.65      ]',
 'support: [568 100]'}
```

In [49]:
```
# Create confusion matrix
```

In [50]:
```
df_confusion = pd.crosstab(test_target, test_pred)
print (df_confusion)
```

```
col_0     0   1
Churn?
0       562   6
1        35  65
```

In [51]:
```
# Use grid search to improve performance
```

In [52]:
```
from sklearn.model_selection import GridSearchCV
#from sklearn.model_selection import GridSearchCV


parameters = {'min_samples_split':np.arange(2, 80), 'max_depth': np.arange(2,10), 'cr
tree = DecisionTreeClassifier()
grid = GridSearchCV(tree, parameters,scoring='accuracy', cv=8)

grid.fit(train, train_target)
print('The parameters combination that would give best accuracy is : ')
print(grid.best_params_)
print('The best accuracy achieved after parameter tuning via grid search is : ', grid
```

```
The parameters combination that would give best accuracy is :
{'criterion': 'gini', 'max_depth': 3, 'min_samples_split': 37}
The best accuracy achieved after parameter tuning via grid search is :  0.9464732366183092
```

In [53]:
```python
# enter optimized hyperparameters
```

In [54]:
```python
tree2 = DecisionTreeClassifier(criterion = 'gini', splitter='best', max_depth=3, min_s
                               min_samples_leaf=5, min_weight_fraction_leaf=0.0,  rando
                               max_leaf_nodes=None, min_impurity_decrease=0.0, min_impu
                               presort=False)

tree2.fit (train,train_target)
```

Out[54]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=5, min_samples_split=5,
            min_weight_fraction_leaf=0.0, presort=False, random_state=0,
            splitter='best')
```

In [55]:
```python
#rescore test with updated hyperparameters


test_pred2 =  tree2.predict(test)
```

In [56]:
```python
#recheck metrics based on grid search based hyperparameter settings

precision, recall, fscore, support = score(test_target, test_pred2)

precision = ('precision: {}'.format(precision))
recall = ('recall: {}'.format(recall))
fscore = ('fscore: {}'.format(fscore))
support = ('support: {}'.format(support))
accuracy = accuracy_score(test_target, test_pred2, normalize=True)

output = {accuracy, precision, recall, fscore, support}
output
```

Out[56]:
```
{0.9446107784431138,
 'fscore: [0.96834902 0.77844311]',
 'precision: [0.94176373 0.97014925]',
 'recall: [0.99647887 0.65      ]',
 'support: [568 100]'}
```

In [57]:
```python
# create confusion matrix for optimized algorithm

df_confusion = pd.crosstab(test_target, test_pred2)
print (df_confusion)
```

```
col_0      0   1
Churn?
0        566   2
1         35  65
```

```
In [58]: # code below to check model performance on validate - not currently working
```

```
In [59]: estimator = tree2.fit (train,train_target)
         validate_pred2 =  tree2.predict(validate)
         precision, recall, fscore, support = score(validate_target, validate_pred2)

         precision = ('precision: {}'.format(precision))
         recall = ('recall: {}'.format(recall))
         fscore = ('fscore: {}'.format(fscore))
         support = ('support: {}'.format(support))
         accuracy = accuracy_score(test_target, test_pred2, normalize=True)

         final_output = {accuracy, precision, recall, fscore, support}
         final_output
```

```
Out[59]: {0.9446107784431138,
          'fscore: [0.97792869 0.83116883]',
          'precision: [0.95840266 0.98461538]',
          'recall: [0.9982669  0.71910112]',
          'support: [577  89]'}
```

7 NAIVE BAYES

Now on to the second classification model naive bayes

```
In [60]: #verify categorical data converted to numeric
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 58 columns):
Int'l Plan           3333 non-null int64
VMail Plan           3333 non-null int64
VMail Message        3333 non-null int64
Churn?               3333 non-null int64
Total Charge         3333 non-null int64
Total Charge > 80    3333 non-null int64
CustServ Calls >3    3333 non-null int64
AK                   3333 non-null uint8
AL                   3333 non-null uint8
AR                   3333 non-null uint8
AZ                   3333 non-null uint8
```

```
CA                     3333 non-null uint8
CO                     3333 non-null uint8
CT                     3333 non-null uint8
DC                     3333 non-null uint8
DE                     3333 non-null uint8
FL                     3333 non-null uint8
GA                     3333 non-null uint8
HI                     3333 non-null uint8
IA                     3333 non-null uint8
ID                     3333 non-null uint8
IL                     3333 non-null uint8
IN                     3333 non-null uint8
KS                     3333 non-null uint8
KY                     3333 non-null uint8
LA                     3333 non-null uint8
MA                     3333 non-null uint8
MD                     3333 non-null uint8
ME                     3333 non-null uint8
MI                     3333 non-null uint8
MN                     3333 non-null uint8
MO                     3333 non-null uint8
MS                     3333 non-null uint8
MT                     3333 non-null uint8
NC                     3333 non-null uint8
ND                     3333 non-null uint8
NE                     3333 non-null uint8
NH                     3333 non-null uint8
NJ                     3333 non-null uint8
NM                     3333 non-null uint8
NV                     3333 non-null uint8
NY                     3333 non-null uint8
OH                     3333 non-null uint8
OK                     3333 non-null uint8
OR                     3333 non-null uint8
PA                     3333 non-null uint8
RI                     3333 non-null uint8
SC                     3333 non-null uint8
SD                     3333 non-null uint8
TN                     3333 non-null uint8
TX                     3333 non-null uint8
UT                     3333 non-null uint8
VA                     3333 non-null uint8
VT                     3333 non-null uint8
WA                     3333 non-null uint8
WI                     3333 non-null uint8
WV                     3333 non-null uint8
WY                     3333 non-null uint8
dtypes: int64(7), uint8(51)
```

```
memory usage: 348.4 KB
```

7.1 A) Gaussian Model

```
In [61]: #import library for Gaussian Naive Bayes
         from sklearn.naive_bayes import GaussianNB, BernoulliNB

         #set the classifier
         gnb = GaussianNB()

         #set features
         used_features = ["Int'l Plan", "VMail Plan", "Total Charge > 80", "CustServ Calls >3"]
```

```
In [62]: #train classifier
         gnb.fit(train[used_features].values, train_target)

         response_var = gnb.predict(validate[used_features])

         #print results

         print("Number of mislabeled points out of a total {} points : {}, performance {:05.2f}
               .format(
                   test.shape[0],
                   (validate_target != response_var).sum(),
                   100*(1-(validate_target != response_var).sum()/test.shape[0])))
```

```
Number of mislabeled points out of a total 668 points : 91, performance 86.38%.
```

```
In [63]: #import libraries for model evaluation
         from sklearn.metrics import classification_report
         from sklearn.metrics import confusion_matrix
         from sklearn.metrics import accuracy_score
         from sklearn import metrics
```

```
In [64]: #model evaluation
         print(metrics.classification_report(validate_target, response_var))
```

```
              precision    recall  f1-score   support

           0       0.94      0.90      0.92       577
           1       0.49      0.61      0.54        89

   micro avg       0.86      0.86      0.86       666
   macro avg       0.71      0.75      0.73       666
weighted avg       0.88      0.86      0.87       666
```

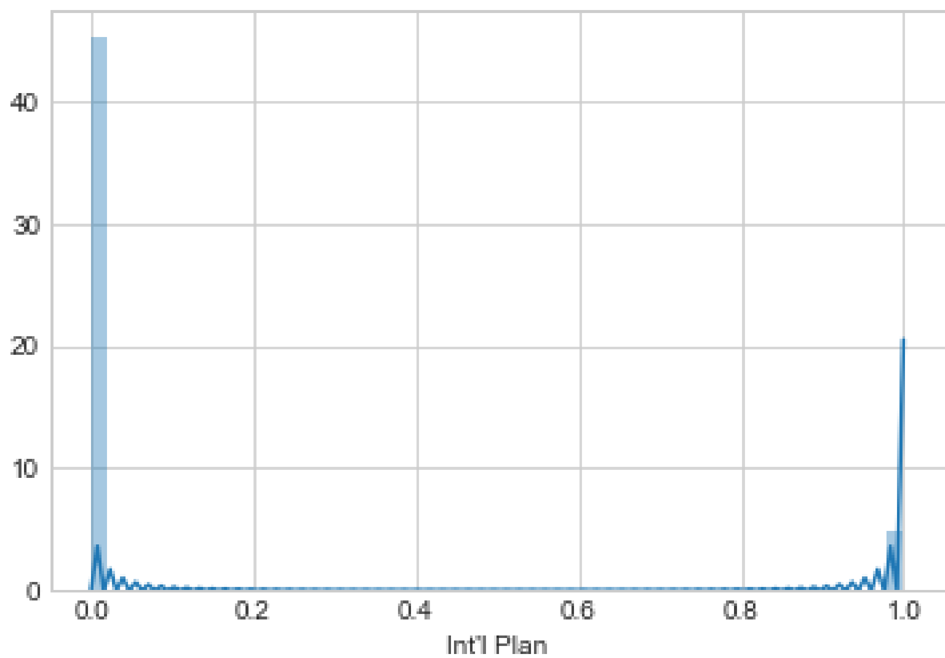
In [65]: #confusion matrix
```
print(metrics.confusion_matrix(validate_target, response_var))
```

```
[[521  56]
 [ 35  54]]
```

In [66]: # consider the distribution of the features
```
sns.distplot(df["Int'l Plan"])
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

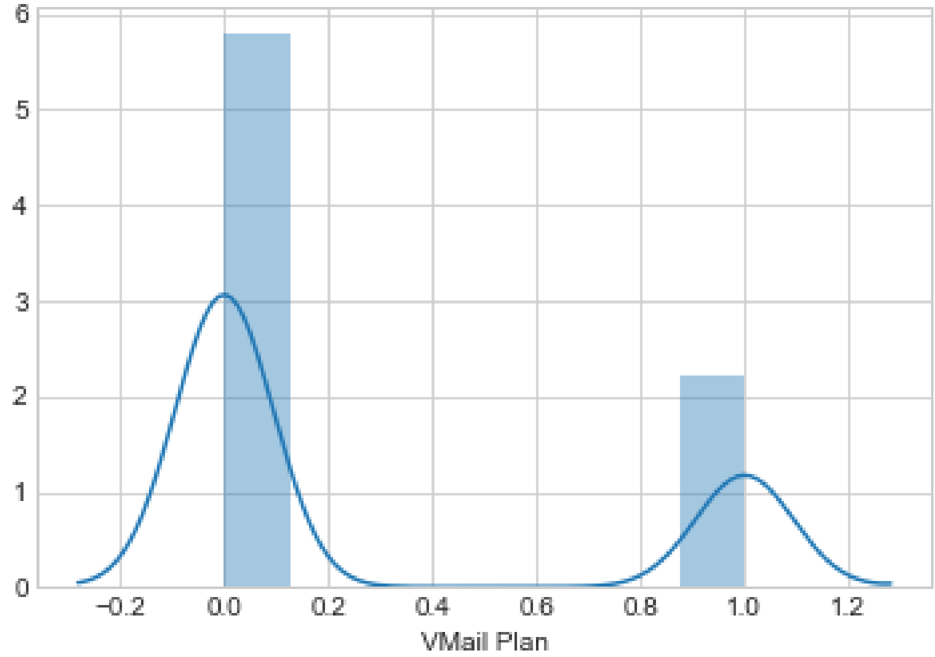
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5f66afd0>



In [67]: sns.distplot(df["VMail Plan"])

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

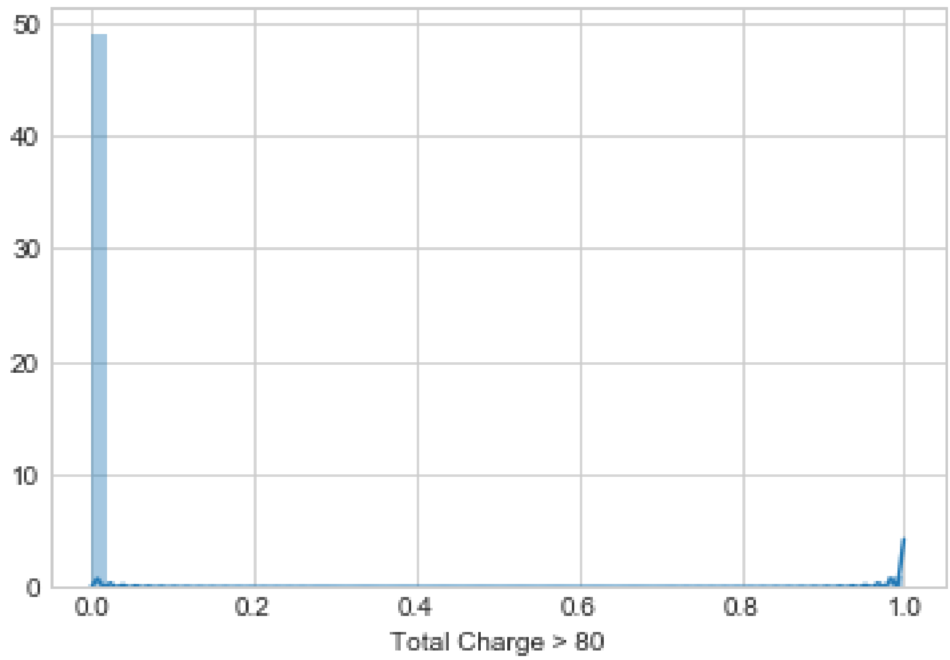
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5f640438>



In [68]: sns.distplot(df["Total Charge > 80"])

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

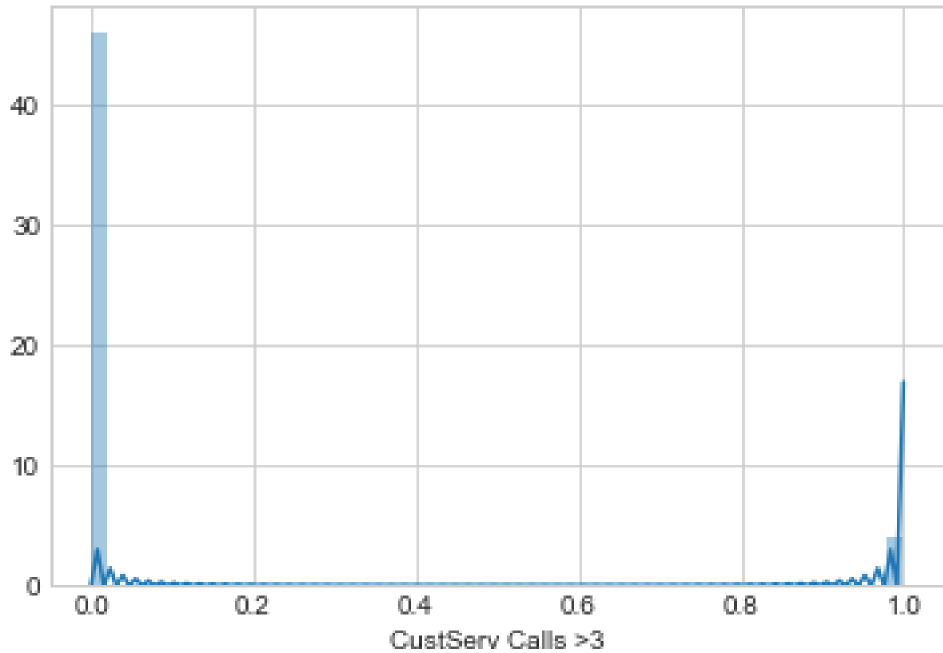
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5f4f8f60>



```
In [69]: sns.distplot(df["CustServ Calls >3"])
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x24a5f6f0630>
```



7.2 B) Bernoulli

Our selected features are 1s and 0s. Lets try the Bernoulli model.

```
In [70]: #set the classifier
         bnb = BernoulliNB()

         bnb.fit(train[used_features].values, train_target)

         bnb_response_var = bnb.predict(validate[used_features])

         #print results
         print("Number of mislabeled points out of a total {} points : {}, performance {:05.2f
               .format(
                   test.shape[0],
```

```
                    (validate_target != bnb_response_var).sum(),
                    100*(1-(validate_target != bnb_response_var).sum()/test.shape[0])))
```

```
Number of mislabeled points out of a total 668 points : 80, performance 88.02%.
```

```
In [71]: #model evaluation
         print(metrics.classification_report(validate_target, bnb_response_var))
```

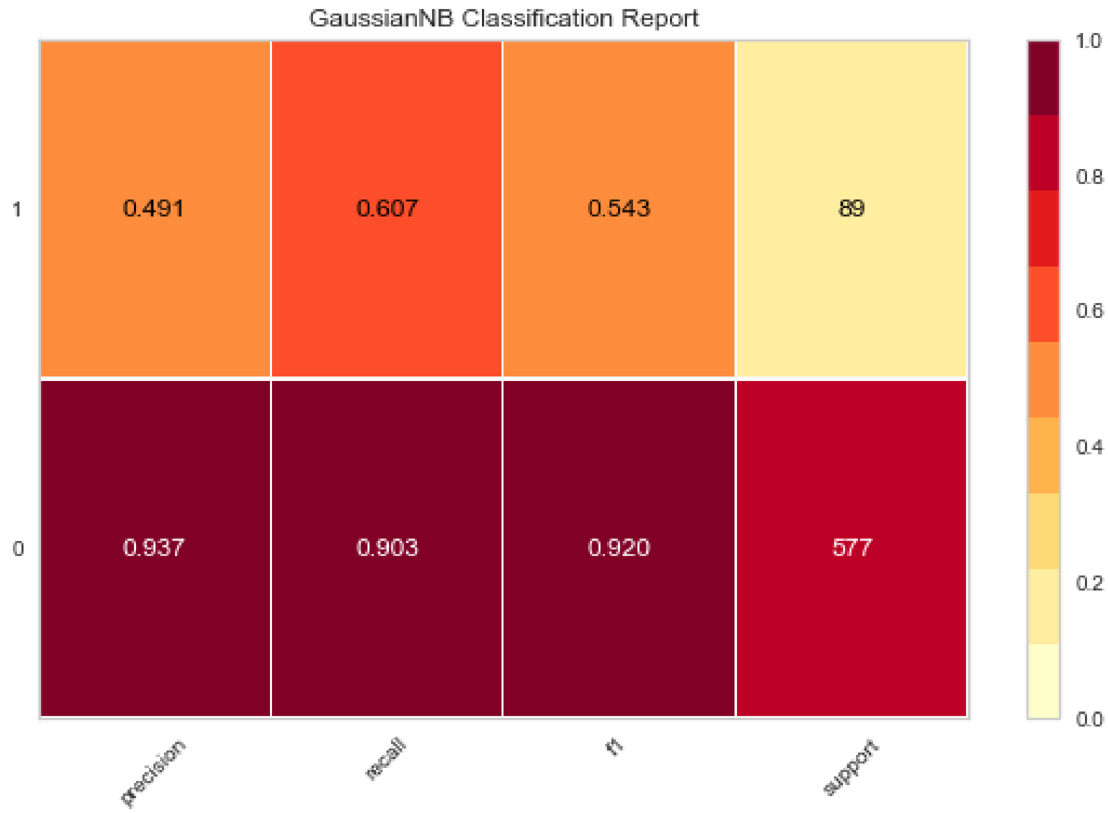
```
              precision    recall  f1-score   support

           0       0.88      0.99      0.93       577
           1       0.74      0.16      0.26        89

   micro avg       0.88      0.88      0.88       666
   macro avg       0.81      0.57      0.60       666
weighted avg       0.86      0.88      0.84       666
```

```
In [72]: #confusion matrix
         print(metrics.confusion_matrix(validate_target, bnb_response_var))
```

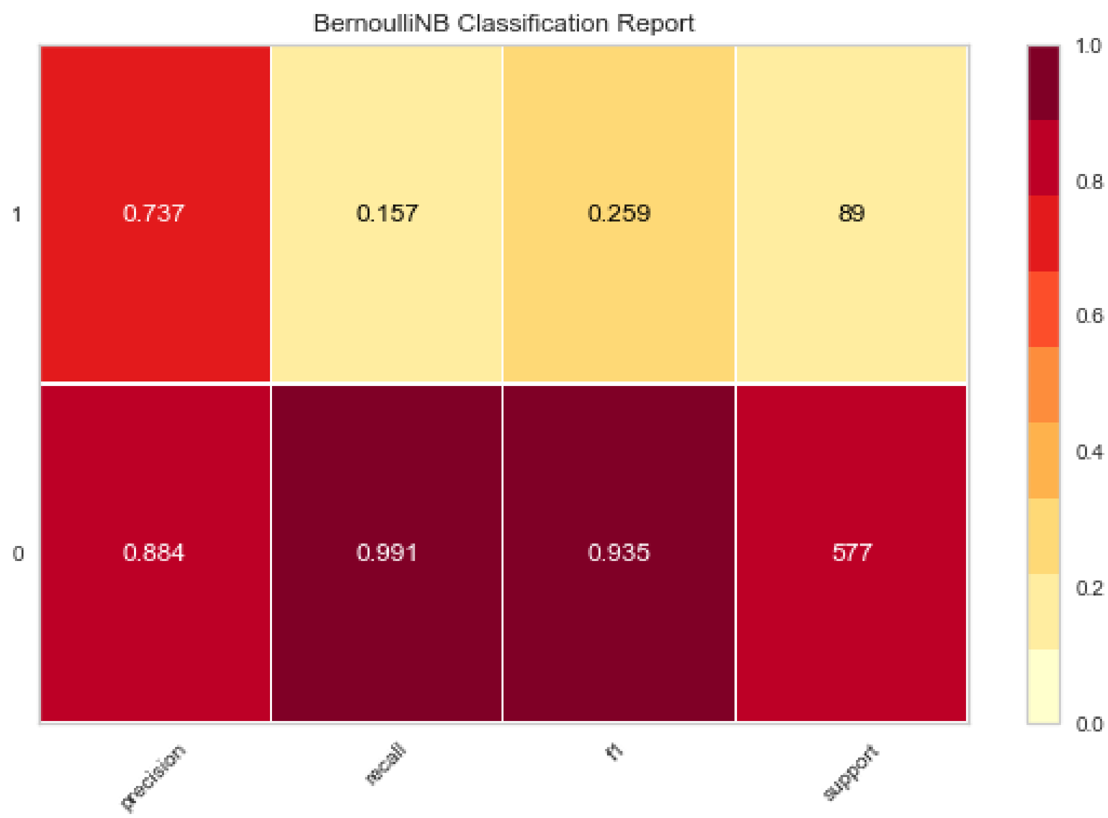
```
[[572   5]
 [ 75  14]]
```

7.3 C) Model Selection

```
In [74]: #Gaussian Classification Report
         from yellowbrick.classifier import ClassificationReport

         visualizer = ClassificationReport(gnb,support=True)

         visualizer.fit(train[used_features], train_target)  # Fit the visualizer and the mode
         visualizer.score(validate[used_features], validate_target)  # Evaluate the model on t
         g = visualizer.poof()
```

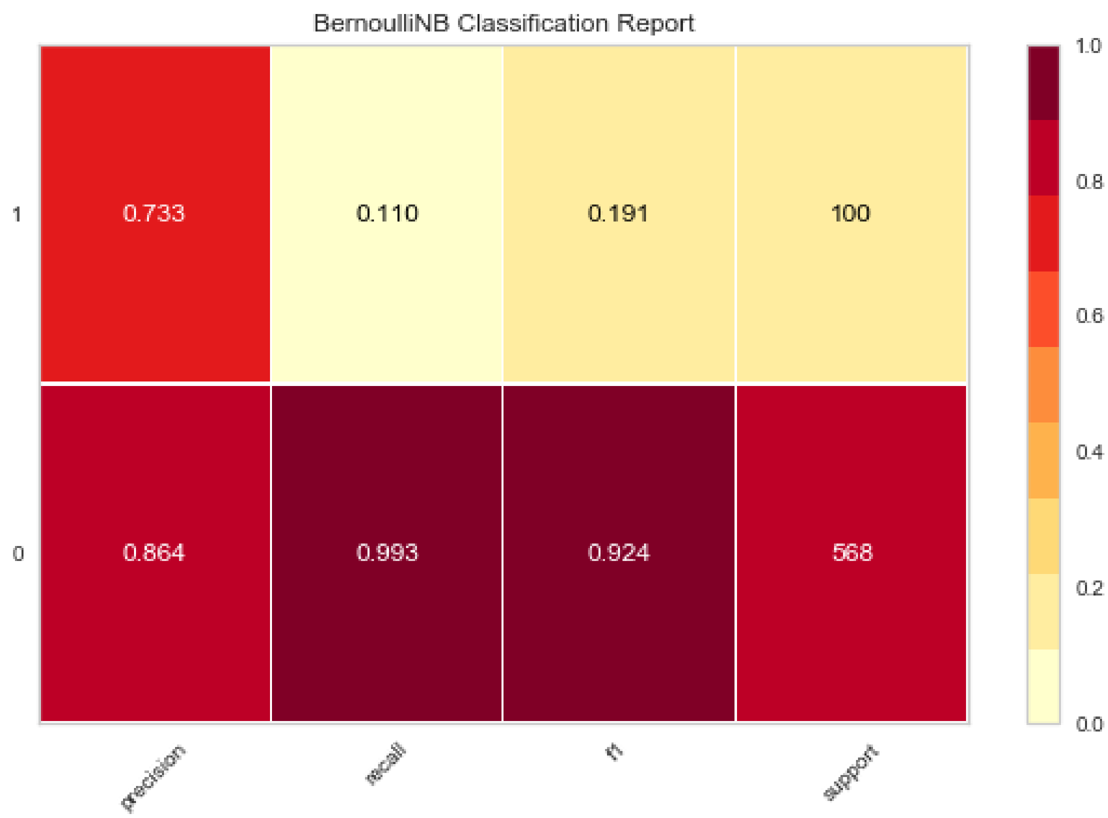


In [75]:
```
#Bernoulli Classification Report
from yellowbrick.classifier import ClassificationReport

visualizer = ClassificationReport(bnb,support=True)

visualizer.fit(train[used_features], train_target)  # Fit the visualizer and the mode
visualizer.score(validate[used_features], validate_target)  # Evaluate the model on th
g = visualizer.poof()
```



7.4 D) Bernoulli and the Test Set

```
In [76]: #Classification Report
         from yellowbrick.classifier import ClassificationReport

         visualizer = ClassificationReport(bnb,support=True)

         visualizer.fit(train[used_features], train_target)  # Fit the visualizer and the mode
         visualizer.score(test[used_features], test_target)  # Evaluate the model on the test
         g = visualizer.poof()
```




```
In [77]: bnb.fit(train[used_features].values, train_target)

         bnb_predicted_test = bnb.predict(test[used_features])

         #print results
         print("Number of mislabeled points out of a total {} points : {}, performance {:05.2f
               .format(
                   test.shape[0],
                   (test_target != bnb_predicted_test).sum(),
                   100*(1-(test_target != bnb_predicted_test).sum()/test.shape[0])))
```

```
Number of mislabeled points out of a total 668 points : 93, performance 86.08%.
```

8 RANDOM FOREST

The third and final model considered was random forest.

```
In [78]: from sklearn.ensemble import RandomForestClassifier
```

8.1 A) Initilize Random Forest Classifier & Initial fit

```
In [79]: rf = RandomForestClassifier(n_estimators=100, criterion='gini', max_depth=3, min_sampl
                    min_samples_leaf=50, min_weight_fraction_leaf=0.0, max_features='auto', max_lea
                    min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=F
                    n_jobs=None, random_state=42, verbose=0, warm_start=False, class_weight=None)

In [80]: rf.fit(train, train_target)

Out[80]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                            max_depth=3, max_features='auto', max_leaf_nodes=None,
                            min_impurity_decrease=0.0, min_impurity_split=None,
                            min_samples_leaf=50, min_samples_split=19,
                            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
                            oob_score=False, random_state=42, verbose=0, warm_start=False)

In [81]: test_pred = rf.predict(test)
```

8.2 B) Instantiate performace metrics

```
In [82]: precision, recall, fscore, support = score(test_target, test_pred)
         precision = ('precision: {}'.format(precision)),
         recall = ('recall: {}'.format(recall)),
         fscore = ('fscore: {}'.format(fscore)),
         support = ('support: {}'.format(support)),
         accuracy = accuracy_score(test_target, test_pred, normalize=True)
         output = {accuracy, precision, recall, fscore, support}
         output

C:\Users\benpo\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1143: UndefinedMet
  'precision', 'predicted', average, warn_for)


Out[82]: {('fscore: [0.91909385 0.        ]',),
          ('precision: [0.8502994 0.       ]',),
          ('recall: [1. 0.]',),
          ('support: [568 100]',),
          0.8502994011976048}

In [83]: df_confusion = pd.crosstab(test_target, test_pred)
         print (df_confusion)

col_0     0
Churn?
0       568
1       100


In [84]: from sklearn.model_selection import GridSearchCV
```

In [85]:
```
precision, recall, fscore, support = score(test_target, test_pred)
precision = ('precision: {}'.format(precision))
recall = ('recall: {}'.format(recall))
fscore = ('fscore: {}'.format(fscore))
support = ('support: {}'.format(support))
accuracy = accuracy_score(test_target, test_pred, normalize=True)

output = {accuracy, precision, recall, fscore, support}
output
```

```
C:\Users\benpo\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1143: UndefinedMe
  'precision', 'predicted', average, warn_for)
```

Out[85]:
```
{0.8502994011976048,
 'fscore: [0.91909385 0.        ]',
 'precision: [0.8502994 0.       ]',
 'recall: [1. 0.]',
 'support: [568 100]'}
```

In [86]:
```
print(df_confusion)
```

```
col_0     0
Churn?
0       568
1       100
```

8.3 C) Grid Search for optimized parameters

In [87]:
```
parameters = {#'n_estimators': [500,1000,1500,2000],
              'max_features': ['auto', 'sqrt', 'log2', .9, .2],
              'max_depth': [2,4,6,8,10],
              'criterion':['gini','entropy'],
              # 'boostrap': [True, False],
               'min_samples_leaf':[1,2,3]
              }
rand_for = RandomForestClassifier()
grid = GridSearchCV(rf, parameters, scoring='accuracy', cv=4)
grid.fit(train, train_target)
```

Out[87]:
```
GridSearchCV(cv=4, error_score='raise-deprecating',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion=
            max_depth=3, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=50, min_samples_split=19,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
            oob_score=False, random_state=42, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
```

```
            param_grid={'max_features': ['auto', 'sqrt', 'log2', 0.9, 0.2], 'max_depth': [2
            pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
            scoring='accuracy', verbose=0)
```

The optimized parameters are:

```
In [88]: print(grid.best_params_)
         print(grid.best_score_)

{'criterion': 'gini', 'max_depth': 4, 'max_features': 0.9, 'min_samples_leaf': 1}
0.9449724862431216
```

8.4 D) Insert new parameters. Fit & Train Model

```
In [102]: rf = RandomForestClassifier(n_estimators=2000, criterion='gini', max_depth=6, min_sam
                 min_samples_leaf=2, min_weight_fraction_leaf=0.0, max_features=0.9, max_leaf_n
                 min_impurity_decrease=0.0, min_impurity_split=None, bootstrap='auto', oob_scor
                 n_jobs=None, random_state=42, verbose=0, warm_start=False, class_weight=None)
          rf.fit(train,train_target)

Out[102]: RandomForestClassifier(bootstrap='auto', class_weight=None, criterion='gini',
                      max_depth=6, max_features=0.9, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=2, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=2000, n_jobs=None,
                      oob_score=False, random_state=42, verbose=0, warm_start=False)

In [103]: rf_pred = rf.predict(test)
```

8.5 E) Re-test performance metrics

```
In [104]: precision, recall, fscore, support = score(test_target, rf_pred)

          precision = ('precision: {}'.format(precision))
          recall = ('recall: {}'.format(recall))
          fscore = ('fscore: {}'.format(fscore))
          support = ('support: {}'.format(support))
          accuracy = accuracy_score(test_target, rf_pred, normalize=True)

          output = {accuracy, precision, recall, fscore, support}
          output

Out[104]: {0.9446107784431138,
           'fscore: [0.96829477 0.78106509]',
           'precision: [0.94323873 0.95652174]',
           'recall: [0.99471831 0.66      ]',
           'support: [568 100]'}
```

```
In [105]: df_confusion = pd.crosstab(test_target, rf_pred)
          print (df_confusion)

col_0     0   1
Churn?
0       565   3
1        34  66
```

8.6 F) Evaluate performance on validation set

```
In [106]: rf_pred = rf.predict(validate)
          precision, recall, fscore, support = score(validate_target, rf_pred)
          precision = ('precision: {}'.format(precision))
          recall = ('recall: {}'.format(recall))
          fscore = ('fscore: {}'.format(fscore))
          support = ('support: {}'.format(support))
          accuracy = accuracy_score(validate_target, rf_pred, normalize=True)
          output = {accuracy, precision, recall, fscore, support}
          output

Out[106]: {0.960960960960961,
           'fscore: [0.97792869 0.83116883]',
           'precision: [0.95840266 0.98461538]',
           'recall: [0.9982669  0.71910112]',
           'support: [577  89]'}

In [107]: df_confusion = pd.crosstab(validate_target, rf_pred)
          print (df_confusion)

col_0     0   1
Churn?
0       576   1
1        25  64
```

8.7 G) Determine most important features

```
In [108]: importances = rf.feature_importances_
          std = np.std([tree.feature_importances_ for tree in rf.estimators_],
                       axis=0)
          indices = np.argsort(importances)[::-1]

          print("Feature ranking:")

          for f in range (5):
              print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))
```

```
Feature ranking:
1. feature 3 (0.555415)
2. feature 5 (0.153025)
3. feature 0 (0.105762)
4. feature 2 (0.084555)
5. feature 1 (0.062942)
```

```
In [109]: train.columns
```

```
Out[109]: Index(['Int'l Plan', 'VMail Plan', 'VMail Message', 'Total Charge',
                 'Total Charge > 80', 'CustServ Calls >3', 'AK', 'AL', 'AR', 'AZ', 'CA',
                 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'HI', 'IA', 'ID', 'IL', 'IN', 'KS',
                 'KY', 'LA', 'MA', 'MD', 'ME', 'MI', 'MN', 'MO', 'MS', 'MT', 'NC', 'ND',
                 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC',
                 'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY'],
                dtype='object')
```

We see that the following feature ranking of importance for the Random Forest: 1. Total Charge (55.54%) 2. CustServ Calls >3 (15.30%) 3. Int'l Plan (10.58%) 4. VMail Messages (8.45%) 5. VMail Plan (6.29)