General Electric Customer Churn Problem

GE has partnered with a cellular carrier–SmartAppCellular–that provides dedicated bandwidth and configuration services for cell phone applications. GE is beginning to experience a small amount of attrition, and based on customer feedback, it is related to the cellular service and not the application. GE Healthcare recognizes that other vendors are beginning to compete in this space and is attempting to identify ways to retain its customers.

The Customer Account Management team would like to determine if this data can be used to identify subscribers that may churn. It is important to be able to understand churn default drivers for metadata like longevity, cell usage, and other pertinent groupings which come from the analysis.

-Genesis Taylor

Import Modules

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import time
#import timeit
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('dark_background')

#stats
from scipy import stats
from scipy.stats import chi2_contingency

#sklearn modeling and metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, log_loss
from sklearn.metrics import classification_report
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.model_selection  import train_test_split
from sklearn.model_selection import cross_val_score, GridSearchCV, train_test_split, RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.utils import resample

#warning ignorer
import warnings
warnings.filterwarnings("ignore")

#for imbalance
from imblearn.over_sampling import SMOTE
from collections import Counter
```

Import and Explore Data Set

In [2]:
```
#import data set into datafream
df = pd.read_csv(r'DAT690_Churn Data_Training.csv')
```

In [3]:
```
#Get columns names and data shape and general look
print('Column Names:\n',df.columns)
print('\n')
print("Dataframe Shape:", df.shape)

df.head()
```

```
Column Names:
 Index(['REVENUE', 'MOU', 'RECCHRGE', 'DIRECTAS', 'OVERAGE', 'ROAM', 'CHANGEM',
       'CHANGER', 'DROPVCE', 'BLCKVCE', 'UNANSVCE', 'CUSTCARE', 'THREEWAY',
       'MOUREC', 'OUTCALLS', 'INCALLS', 'PEAKVCE', 'OPEAKVCE', 'DROPBLK',
       'CALLFWDV', 'CALLWAIT', 'CHURN', 'MONTHS', 'UNIQSUBS', 'ACTVSUBS',
       'CSA', 'PHONES', 'MODELS', 'EQPDAYS', 'CUSTOMER', 'AGE1', 'AGE2',
       'CHILDREN', 'CREDITA', 'CREDITAA', 'CREDITB', 'CREDITC', 'CREDITDE',
       'CREDITGY', 'CREDITZ', 'CREDIT_RATING', 'PRIZMRUR', 'PRIZMUB',
       'PRIZMTWN', 'Column 45', 'REFURB', 'WEBCAP', 'TRUCK', 'RV', 'OCCPROF',
       'OCCCLER', 'OCCCRFT', 'OCCSTUD', 'OCCHMKR', 'OCCRET', 'OCCSELF', 'OCC',
       'OCC_LABEL', 'OWNRENT', 'MARRYUN', 'MARRYYES', 'MARRYNO', 'MARRY',
       'MARRY_LABEL', 'MAILORD', 'MAILRES', 'MAILFLAG', 'TRAVEL', 'PCOWN',
       'CREDITCD', 'RETCALLS', 'RETACCPT', 'NEWCELLY', 'NEWCELLN', 'REFER',
       'INCMISS', 'INCOME', 'MCYCLE', 'CREDITAD', 'SETPRCM', 'SETPRC',
       'RETCALL', 'CALIBRAT', 'CHURNDEP'],
      dtype='object')


Dataframe Shape: (1000, 84)
```

Out[3]:

	REVENUE	MOU	RECCHRGE	DIRECTAS	OVERAGE	ROAM	CHANGEM	CHANGER	DROPVCE	BLCKVCE	...	REFER	INCMISS	INCOME	M
0	342.86	2961.25	139.96	11.14	1444.75	62.34	203.75	6.88	10.00	9.33	...	0	1	0	

	REVENUE	MOU	RECCHRGE	DIRECTAS	OVERAGE	ROAM	CHANGEM	CHANGER	DROPVCE	BLCKVCE	...	REFER	INCMISS	INCOME	M
1	35.31	307.00	34.99	0.00	0.00	0.00	204.00	-0.32	1.00	2.33	...	0	0	6	
2	84.66	1642.75	80.00	1.49	0.00	0.00	0.25	-2.47	9.33	9.00	...	0	1	0	
3	65.62	321.50	50.00	0.25	2.25	0.00	-117.50	-13.63	12.67	2.67	...	0	0	7	
4	86.48	807.00	75.00	0.00	0.00	0.26	110.00	-5.25	13.67	0.33	...	0	0	2	

5 rows × 84 columns

In [4]:
```
#data type count
df.dtypes.value_counts()
```

Out[4]:
```
int64      56
float64    25
object      3
dtype: int64
```

In [5]:
```
#descriptive statistics about the data
df.describe()
```

Out[5]:

	REVENUE	MOU	RECCHRGE	DIRECTAS	OVERAGE	ROAM	CHANGEM	CHANGER	DROPVCE	BLCKVCE	...	
count	997.000000	997.000000	997.000000	997.000000	997.000000	997.000000	991.000000	991.000000	1000.000000	1000.000000	...	1000
mean	59.662939	537.777503	47.186058	0.892106	41.523390	1.475938	-3.490585	-1.394097	6.131680	3.538140	...	0
std	48.110161	538.751303	24.436293	2.013783	109.214544	8.477650	254.537147	47.718943	9.044241	7.421263	...	0
min	4.840000	0.000000	0.000000	0.000000	0.000000	0.000000	-1345.500000	-341.800000	0.000000	0.000000	...	0
25%	32.900000	165.750000	30.000000	0.000000	0.000000	0.000000	-77.250000	-6.560000	0.670000	0.000000	...	0
50%	47.240000	364.750000	44.990000	0.250000	1.750000	0.000000	-3.500000	-0.300000	3.000000	1.000000	...	0
75%	70.500000	730.250000	59.990000	0.990000	36.500000	0.170000	62.875000	1.325000	8.000000	3.670000	...	0
max	526.560000	3656.250000	232.490000	22.770000	1444.750000	147.160000	1295.750000	895.570000	130.670000	77.000000	...	6

8 rows × 81 columns

In [6]:
```
#unique values
```

```python
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df.nunique().sort_values(ascending=False))
```

```
CUSTOMER         1000
MOU               876
REVENUE           846
MOUREC            843
CHANGEM           768
CHANGER           722
EQPDAYS           583
PEAKVCE           497
OPEAKVCE          442
OVERAGE           339
CSA               277
UNANSVCE          264
OUTCALLS          258
RECCHRGE          244
ROAM              171
INCALLS           148
DROPBLK           137
DROPVCE            98
BLCKVCE            81
CALLWAIT           55
CUSTCARE           55
MONTHS             48
DIRECTAS           48
AGE1               37
AGE2               36
THREEWAY           24
PHONES             13
SETPRC             11
INCOME             10
OCC_LABEL           8
OCC                 8
MODELS              8
UNIQSUBS            7
CREDIT_RATING       7
REFER               7
ACTVSUBS            6
CREDITAD            6
Column 45           4
MARRY               3
CALLFWDV            3
RETACCPT            3
RETCALLS            3
CHILDREN            2
CREDITA             2
CHURN               2
CREDITB             2
```

```
CREDITAA         2
CHURNDEP         2
CREDITC          2
CREDITDE         2
MARRYYES         2
MARRYNO          2
MARRY_LABEL      2
MAILORD          2
MAILRES          2
MAILFLAG         2
TRAVEL           2
PCOWN            2
CREDITCD         2
NEWCELLY         2
NEWCELLN         2
INCMISS          2
MCYCLE           2
SETPRCM          2
RETCALL          2
MARRYUN          2
OWNRENT          2
OCCSELF          2
WEBCAP           2
CREDITGY         2
CREDITZ          2
CALIBRAT         2
PRIZMUB          2
PRIZMTWN         2
REFURB           2
TRUCK            2
OCCRET           2
RV               2
OCCPROF          2
OCCCLER          2
OCCCRFT          2
OCCSTUD          2
OCCHMKR          2
PRIZMRUR         2
dtype: int64
```

In [7]:

```
#Check Missing/null data
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df.isnull().sum().sort_values(ascending=False))
```

```
CHURNDEP       437
AGE2            14
AGE1            14
CHANGEM          9
CHANGER          9
```

MOU	3
RECCHRGE	3
DIRECTAS	3
OVERAGE	3
ROAM	3
REVENUE	3
NEWCELLY	0
CREDITB	0
CALLFWDV	0
CALLWAIT	0
CHURN	0
MONTHS	0
UNIQSUBS	0
ACTVSUBS	0
CSA	0
PHONES	0
MODELS	0
EQPDAYS	0
CUSTOMER	0
REFER	0
NEWCELLN	0
CHILDREN	0
CREDITA	0
DROPBLK	0
OPEAKVCE	0
PEAKVCE	0
INCMISS	0
RETCALL	0
SETPRC	0
SETPRCM	0
CREDITAD	0
MCYCLE	0
INCOME	0
DROPVCE	0
INCALLS	0
BLCKVCE	0
UNANSVCE	0
CUSTCARE	0
THREEWAY	0
MOUREC	0
OUTCALLS	0
CREDITAA	0
CREDITC	0
RETACCPT	0
CREDITDE	0
OCC	0
OCC_LABEL	0
OWNRENT	0
MARRYUN	0

```
MARRYYES           0
MARRYNO            0
MARRY              0
MARRY_LABEL        0
MAILORD            0
MAILRES            0
MAILFLAG           0
TRAVEL             0
PCOWN              0
CREDITCD           0
RETCALLS           0
OCCSELF            0
OCCRET             0
OCCHMKR            0
Column 45          0
CREDITGY           0
CREDITZ            0
CREDIT_RATING      0
CALIBRAT           0
PRIZMUB            0
PRIZMTWN           0
REFURB             0
OCCSTUD            0
WEBCAP             0
TRUCK              0
RV                 0
OCCPROF            0
OCCCLER            0
OCCCRFT            0
PRIZMRUR           0
dtype: int64
```

In [8]:

```
#predicited variable
df['CHURN'].value_counts(ascending=True)
```

Out[8]:

```
1    297
0    703
Name: CHURN, dtype: int64
```

Data Cleansing

In [9]:

```
#standardize all columns to lowercase for ease of use in querying
df.columns = map(str.lower, df.columns)
#verify
print('Columns:\n',df.columns)
```

```
Columns:
 Index(['revenue', 'mou', 'recchrge', 'directas', 'overage', 'roam', 'changem',
```

```
       'changer', 'dropvce', 'blckvce', 'unansvce', 'custcare', 'threeway',
       'mourec', 'outcalls', 'incalls', 'peakvce', 'opeakvce', 'dropblk',
       'callfwdv', 'callwait', 'churn', 'months', 'uniqsubs', 'actvsubs',
       'csa', 'phones', 'models', 'eqpdays', 'customer', 'age1', 'age2',
       'children', 'credita', 'creditaa', 'creditb', 'creditc', 'creditde',
       'creditgy', 'creditz', 'credit_rating', 'prizmrur', 'prizmub',
       'prizmtwn', 'column 45', 'refurb', 'webcap', 'truck', 'rv', 'occprof',
       'occcler', 'occcrft', 'occstud', 'occhmkr', 'occret', 'occself', 'occ',
       'occ_label', 'ownrent', 'marryun', 'marryyes', 'marryno', 'marry',
       'marry_label', 'mailord', 'mailres', 'mailflag', 'travel', 'pcown',
       'creditcd', 'retcalls', 'retaccpt', 'newcelly', 'newcelln', 'refer',
       'incmiss', 'income', 'mcycle', 'creditad', 'setprcm', 'setprc',
       'retcall', 'calibrat', 'churndep'],
      dtype='object')
```

In [10]:

```
#fixing mislabeled column according to data descriptipn file
df.rename(columns={'column 45':'przm_num'}, inplace=True)

#verify
print('Columns:\n',df.columns)
```

```
Columns:
 Index(['revenue', 'mou', 'recchrge', 'directas', 'overage', 'roam', 'changem',
       'changer', 'dropvce', 'blckvce', 'unansvce', 'custcare', 'threeway',
       'mourec', 'outcalls', 'incalls', 'peakvce', 'opeakvce', 'dropblk',
       'callfwdv', 'callwait', 'churn', 'months', 'uniqsubs', 'actvsubs',
       'csa', 'phones', 'models', 'eqpdays', 'customer', 'age1', 'age2',
       'children', 'credita', 'creditaa', 'creditb', 'creditc', 'creditde',
       'creditgy', 'creditz', 'credit_rating', 'prizmrur', 'prizmub',
       'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv', 'occprof',
       'occcler', 'occcrft', 'occstud', 'occhmkr', 'occret', 'occself', 'occ',
       'occ_label', 'ownrent', 'marryun', 'marryyes', 'marryno', 'marry',
       'marry_label', 'mailord', 'mailres', 'mailflag', 'travel', 'pcown',
       'creditcd', 'retcalls', 'retaccpt', 'newcelly', 'newcelln', 'refer',
       'incmiss', 'income', 'mcycle', 'creditad', 'setprcm', 'setprc',
       'retcall', 'calibrat', 'churndep'],
      dtype='object')
```

In [11]:

```
#predicited variable
df['churn'].value_counts(ascending=True)
```

Out[11]:

```
1    297
0    703
Name: churn, dtype: int64
```

In [12]:

```
#drop churndep because it is just a field set up for logreg
#drop calibrat bc I want to do my own separation
```

```
df = df.drop(['churndep'], axis=1)
df = df.drop(['calibrat'], axis=1)
```

Changing Data Types

In [13]:
```
'''
    Using data dictionary to fix some data types to string/objects.
    So that they won't be misrepresented in any cleaning and calculations.
    They're not actually numbers.
    This is mostly done for analysis purposes in Tableau.
    It is also done to properly handle null values.

'''

df['children'] = df['children'].apply(str)
df['churn'] = df['churn'].apply(str)
df['credit_rating'] = df['credit_rating'].apply(str)
df['credita'] = df['credita'].apply(str)
df['creditaa'] = df['creditaa'].apply(str)
df['creditad'] = df['creditad'].apply(str)
df['creditb'] = df['creditb'].apply(str)
df['creditc'] = df['creditc'].apply(str)
df['creditcd'] = df['creditcd'].apply(str)
df['creditde'] = df['creditde'].apply(str)
df['creditgy'] = df['creditgy'].apply(str)
df['creditz'] = df['creditz'].apply(str)
df['incmiss'] = df['incmiss'].apply(str)
df['income'] = df['income'].apply(str)
df['mailflag'] = df['mailflag'].apply(str)
df['mailord'] = df['mailord'].apply(str)
df['mailres'] = df['mailres'].apply(str)
df['marry'] = df['marry'].apply(str)
df['marryno'] = df['marryno'].apply(str)
df['marryun'] = df['marryun'].apply(str)
df['marryyes'] = df['marryyes'].apply(str)
df['mcycle'] = df['mcycle'].apply(str)
df['newcelln'] = df['newcelln'].apply(str)
df['newcelly'] = df['newcelly'].apply(str)
df['mailflag'] = df['mailflag'].apply(str)
df['mailord'] = df['mailord'].apply(str)
df['mailres'] = df['mailres'].apply(str)
df['marryno'] = df['marryno'].apply(str)
df['marryun'] = df['marryun'].apply(str)
df['marryyes'] = df['marryyes'].apply(str)
df['mcycle'] = df['mcycle'].apply(str)
```

```
df['newcelln'] = df['newcelln'].apply(str)
df['newcelly'] = df['newcelly'].apply(str)
df['occ'] = df['occ'].apply(str)
df['occ_label'] = df['occ_label'].apply(str)
df['occcler'] = df['occcler'].apply(str)
df['occcrft'] = df['occcrft'].apply(str)
df['occhmkr'] = df['occhmkr'].apply(str)
df['occprof'] = df['occprof'].apply(str)
df['occret'] = df['occret'].apply(str)
df['occself'] = df['occself'].apply(str)
df['occstud'] = df['occstud'].apply(str)
df['ownrent'] = df['ownrent'].apply(str)
df['pcown'] = df['pcown'].apply(str)
df['prizmrur'] = df['prizmrur'].apply(str)
df['prizmtwn'] = df['prizmtwn'].apply(str)
df['prizmub'] = df['prizmub'].apply(str)
df['przm_num'] = df['przm_num'].apply(str)
df['refurb'] = df['refurb'].apply(str)
df['retcall'] = df['retcall'].apply(str)
df['rv'] = df['rv'].apply(str)
df['setprcm'] = df['setprcm'].apply(str)
df['travel'] = df['travel'].apply(str)
df['truck'] = df['truck'].apply(str)
df['webcap'] = df['webcap'].apply(str)
```

In [14]:

```
#datatype count
df.dtypes.value_counts()
```

Out[14]:

```
object     48
float64    24
int64      10
dtype: int64
```

Missing Values

In [15]:

```
#Check Missing/null data
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df.isnull().sum().sort_values(ascending=False))
```

```
age2               14
age1               14
changem             9
changer             9
revenue             3
mou                 3
recchrge            3
```

```
directas        3
overage         3
roam            3
csa             0
phones          0
models          0
eqpdays         0
customer        0
creditb         0
children        0
credita         0
creditaa        0
uniqsubs        0
creditc         0
creditde        0
creditgy        0
actvsubs        0
callfwdv        0
months          0
churn           0
callwait        0
setprc          0
dropblk         0
opeakvce        0
peakvce         0
incalls         0
outcalls        0
mourec          0
threeway        0
custcare        0
unansvce        0
blckvce         0
dropvce         0
creditz         0
retcall         0
prizmrur        0
prizmub         0
marry_label     0
mailord         0
mailres         0
mailflag        0
travel          0
pcown           0
creditcd        0
retcalls        0
retaccpt        0
newcelly        0
newcelln        0
refer           0
```

```
incmiss          0
income           0
mcycle           0
creditad         0
setprcm          0
marry            0
marryno          0
marryyes         0
occcler          0
prizmtwn         0
przm_num         0
refurb           0
webcap           0
truck            0
rv               0
occprof          0
occcrft          0
marryun          0
occstud          0
occhmkr          0
occret           0
occself          0
occ              0
occ_label        0
ownrent          0
credit_rating    0
dtype: int64
```

Age1

In [16]:

```
#check values of age1

print("Age1 Values:")
print("Average Age1 w/o Zeroes: ", round(df['age1'].loc[df['age1']!=0].mean(),0))
print("Average Age1: ", round(df['age1'].mean(),0))
print("Minimum Age1 WITH Zeroes: ", df['age1'].min())
print("Minimum Age1 w/o Zeroes: ", df['age1'].loc[df['age1']!=0].min())
print("Maximum Age1: ", df['age1'].max())
print("Null values for Age1: ", pd.isnull(df['age1']).sum())

#check # 0s in age1
print("Number of Age1 Zeroes: ",(df['age1'] ==0).sum())
```

```
Age1 Values:
Average Age1 w/o Zeroes:  43.0
Average Age1:  31.0
Minimum Age1 WITH Zeroes:  0.0
Minimum Age1 w/o Zeroes:  18.0
```

```
Maximum Age1:  94.0
Null values for Age1:  14
Number of Age1 Zeroes:  266
```

In [17]:
```
''' Fill null age values to 0 to match the other ages that are missing AS 0.
    Will also create a "Missing" group for ages out of those groups later. '''

df['age1'].fillna(value=0, inplace=True)
```

In [18]:
```
#recheck values of age1

print("Age1 Values")
print("Average Age1: ", round(df['age1'].mean(),0))
print("Minimum Age1: ", df['age1'].min())
print("Maximum Age1: ", df['age1'].max())
print("Null values for Age1: ", pd.isnull(df['age1']).sum())
#check # 0s in age1
print("Number of Age1 Zeroes: ",(df['age1'] ==0).sum())
```

```
Age1 Values
Average Age1:  31.0
Minimum Age1:  0.0
Maximum Age1:  94.0
Null values for Age1:  0
Number of Age1 Zeroes:  280
```

Age2

In [19]:
```
#check values of age2

print("Age2 Values:")
print("Average Age2 w/o Zeroes: ", round(df['age2'].loc[df['age2']!=0].mean(),0))
print("Average Age2: ", round(df['age2'].mean(),0))
print("Minimum Age2 WITH Zeroes: ", df['age2'].min())
print("Minimum Age2 w/o Zeroes: ", df['age2'].loc[df['age2']!=0].min())
print("Maximum Age2: ", df['age2'].max())
print("Null values for Age2: ", pd.isnull(df['age2']).sum())

#check # 0s in age2
print("Number of Age2 Zeroes: ",(df['age2'] ==0).sum())
```

```
Age2 Values:
Average Age2 w/o Zeroes:  44.0
Average Age2:  21.0
Minimum Age2 WITH Zeroes:  0.0
Minimum Age2 w/o Zeroes:  18.0
Maximum Age2:  90.0
```

```
Null values for Age2:  14
Number of Age2 Zeroes:  521
```

In [20]:
```
''' Fill null age values to 0 to match the other ages that are missing As 0.
    Will also create a "Missing" group for ages out of those groups later. '''

df['age2'].fillna(value=0, inplace=True)
```

In [21]:
```
#recheck values of age2

print("Age2 Values")
print("Average Age2: ", round(df['age2'].mean(),0))
print("Minimum Age2: ", df['age2'].min())
print("Maximum Age2: ", df['age2'].max())
print("Null values for Age2: ", pd.isnull(df['age2']).sum())
#check # 0s in age2
print("Number of Age2 Zeroes: ",(df['age2'] ==0).sum())
```

```
Age2 Values
Average Age2:  21.0
Minimum Age2:  0.0
Maximum Age2:  90.0
Null values for Age2:  0
Number of Age2 Zeroes:  535
```

Because the values for the remaining null columns can legitimately have a zero value, and are numerical and discrete, I am going to fill the rest of those with their mean. I think that it is a safe choice being that the highest null is 9/1000.

In [22]:
```
'''
Because the values for the remaining null columns can legitimately have a zero value,
and are numerical and discrete, I am going to fill the rest of those with their mean.
I think that it is a safe choice being that the highest null is 9/1000.'''

#fill rest of nulls with their averages
df= df.fillna(df.mean())
```

In [23]:
```
#recheck nulls
df.isnull().sum().sort_values(ascending=False)
```

Out[23]:
```
retcall      0
callwait     0
months       0
uniqsubs     0
actvsubs     0
            ..
occself      0
```

```
occ          0
occ_label    0
ownrent      0
revenue      0
Length: 82, dtype: int64
```

Outliers

In [24]:
```python
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df.describe(include='all'))
```

```
            revenue          mou     recchrge     directas      overage  \
count   1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean      59.662939   537.777503    47.186058     0.892106    41.523390
std       48.037869   537.941759    24.399574     2.010757   109.050435
min        4.840000     0.000000     0.000000     0.000000     0.000000
25%       32.930000   166.312500    30.000000     0.000000     0.000000
50%       47.335000   366.000000    44.990000     0.250000     1.875000
75%       70.110000   729.875000    59.990000     0.990000    37.000000
max      526.560000  3656.250000   232.490000    22.770000  1444.750000

               roam      changem      changer      dropvce      blckvce  \
count   1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean       1.475938    -3.490585    -1.394097     6.131680     3.538140
std        8.464911   253.387989    47.503507     9.044241     7.421263
min        0.000000 -1345.500000  -341.800000     0.000000     0.000000
25%        0.000000   -77.000000    -6.397500     0.670000     0.000000
50%        0.000000    -3.490585    -0.320000     3.000000     1.000000
75%        0.175000    61.687500     1.295000     8.000000     3.670000
max      147.160000  1295.750000   895.570000   130.670000    77.000000

           unansvce     custcare     threeway       mourec     outcalls  \
count   1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean      28.854610     1.696210     0.338700   116.669540    27.140610
std       44.665855     5.040183     1.163631   163.026685    43.787284
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        5.670000     0.000000     0.000000     9.177500     3.330000
50%       15.670000     0.000000     0.000000    52.985000    13.670000
75%       37.330000     1.330000     0.330000   154.757500    34.415000
```

```
max      814.330000    93.000000    19.670000  1141.990000   644.330000

            incalls      peakvce      opeakvce      dropblk     callfwdv  \
count   1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean       9.058980    93.167050    69.881530     9.696300     0.003330
std       21.936599   115.834207    97.385312    12.683301     0.080151
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        0.000000    21.000000    10.330000     1.670000     0.000000
50%        2.000000    61.670000    38.165000     5.670000     0.000000
75%        9.000000   120.415000    89.415000    12.330000     0.000000
max      404.000000  1018.670000  1052.330000   148.670000     2.330000

           callwait churn       months     uniqsubs     actvsubs        csa  \
count   1000.000000  1000  1000.000000  1000.000000  1000.000000       1000
unique          NaN     2          NaN          NaN          NaN        277
top             NaN     0          NaN          NaN          NaN  NYCBRO917
freq            NaN   703          NaN          NaN          NaN         37
mean       1.915810   NaN    18.802000     1.529000     1.346000        NaN
std        5.597785   NaN     9.919031     0.828158     0.605517        NaN
min        0.000000   NaN     6.000000     1.000000     1.000000        NaN
25%        0.000000   NaN    11.000000     1.000000     1.000000        NaN
50%        0.330000   NaN    16.000000     1.000000     1.000000        NaN
75%        1.670000   NaN    24.250000     2.000000     2.000000        NaN
max      101.000000   NaN    59.000000     8.000000     6.000000        NaN

             phones       models      eqpdays      customer        age1  \
count   1000.000000  1000.000000  1000.000000  1.000000e+03  1000.00000
unique          NaN          NaN          NaN           NaN         NaN
top             NaN          NaN          NaN           NaN         NaN
freq            NaN          NaN          NaN           NaN         NaN
mean       1.815000     1.581000   380.558000  1.050803e+06    30.98600
std        1.400977     0.957265   250.540258  2.904940e+04    22.15045
min        1.000000     1.000000    -1.000000  1.000057e+06     0.00000
25%        1.000000     1.000000   202.000000  1.025528e+06     0.00000
50%        1.000000     1.000000   332.000000  1.051723e+06    36.00000
75%        2.000000     2.000000   514.250000  1.075226e+06    48.00000
max       13.000000     9.000000  1344.000000  1.099979e+06    94.00000

               age2 children credita creditaa creditb creditc creditde  \
count   1000.000000     1000    1000     1000    1000    1000     1000
unique          NaN        2       2        2       2       2        2
top             NaN        0       0        0       0       0        0
freq            NaN      754     829      628     822     910      865
mean      20.664000      NaN     NaN      NaN     NaN     NaN      NaN
std       24.077101      NaN     NaN      NaN     NaN     NaN      NaN
min        0.000000      NaN     NaN      NaN     NaN     NaN      NaN
```

```
25%         0.000000      NaN     NaN      NaN     NaN     NaN      NaN
50%         0.000000      NaN     NaN      NaN     NaN     NaN      NaN
75%        42.000000      NaN     NaN      NaN     NaN     NaN      NaN
max        90.000000      NaN     NaN      NaN     NaN     NaN      NaN

       creditgy creditz credit_rating prizmrur prizmub prizmtwn przm_num  \
count      1000    1000          1000     1000    1000     1000     1000
unique        2       2             7        2       2        2        4
top           0       0             2        0       0        0        0
freq        983     963           372      953     684      850      542
mean        NaN     NaN           NaN      NaN     NaN      NaN      NaN
std         NaN     NaN           NaN      NaN     NaN      NaN      NaN
min         NaN     NaN           NaN      NaN     NaN      NaN      NaN
25%         NaN     NaN           NaN      NaN     NaN      NaN      NaN
50%         NaN     NaN           NaN      NaN     NaN      NaN      NaN
75%         NaN     NaN           NaN      NaN     NaN      NaN      NaN
max         NaN     NaN           NaN      NaN     NaN      NaN      NaN

       refurb webcap truck    rv occprof occcler occcrft occstud occhmkr  \
count    1000   1000  1000  1000    1000    1000    1000    1000    1000
unique      2      2     2     2       2       2       2       2       2
top         0      1     0     0       0       0       0       0       0
freq      870    900   805   924     832     977     971     997     999
mean      NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
std       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
min       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
25%       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
50%       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
75%       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN
max       NaN    NaN   NaN   NaN     NaN     NaN     NaN     NaN     NaN

       occret occself   occ occ_label ownrent marryun marryyes marryno marry  \
count    1000    1000  1000      1000    1000    1000     1000    1000  1000
unique      2       2     8         8       2       2        2       2     3
top         0       0     0      NONE       0       0        0       0     3
freq      983     986   745       745     669     616      645     739   384
mean      NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
std       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
min       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
25%       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
50%       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
75%       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN
max       NaN     NaN   NaN       NaN     NaN     NaN      NaN     NaN   NaN

       marry_label mailord mailres mailflag travel pcown creditcd  \
count         1000    1000    1000     1000   1000  1000     1000
unique           2       2       2        2      2     2        2
top        UNKNOWN       0       0        0      0     0        1
freq           739     655     642      981    952   822      675
```

```
mean           NaN     NaN     NaN      NaN     NaN    NaN       NaN
std            NaN     NaN     NaN      NaN     NaN    NaN       NaN
min            NaN     NaN     NaN      NaN     NaN    NaN       NaN
25%            NaN     NaN     NaN      NaN     NaN    NaN       NaN
50%            NaN     NaN     NaN      NaN     NaN    NaN       NaN
75%            NaN     NaN     NaN      NaN     NaN    NaN       NaN
max            NaN     NaN     NaN      NaN     NaN    NaN       NaN

           retcalls     retaccpt newcelly newcelln       refer incmiss  \
count   1000.000000  1000.000000     1000     1000 1000.000000    1000
unique          NaN          NaN        2        2         NaN       2
top             NaN          NaN        0        0         NaN       0
freq            NaN          NaN      801      883         NaN     762
mean       0.037000     0.021000      NaN      NaN    0.059000     NaN
std        0.199175     0.150272      NaN      NaN    0.354464     NaN
min        0.000000     0.000000      NaN      NaN    0.000000     NaN
25%        0.000000     0.000000      NaN      NaN    0.000000     NaN
50%        0.000000     0.000000      NaN      NaN    0.000000     NaN
75%        0.000000     0.000000      NaN      NaN    0.000000     NaN
max        2.000000     2.000000      NaN      NaN    6.000000     NaN

       income mcycle creditad setprcm       setprc retcall
count    1000   1000     1000    1000  1000.000000    1000
unique     10      2        6       2          NaN       2
top         0      0        0       1          NaN       0
freq      238    989      962     569          NaN     965
mean      NaN    NaN      NaN     NaN    36.935690     NaN
std       NaN    NaN      NaN     NaN    58.053305     NaN
min       NaN    NaN      NaN     NaN     0.000000     NaN
25%       NaN    NaN      NaN     NaN     0.000000     NaN
50%       NaN    NaN      NaN     NaN     0.000000     NaN
75%       NaN    NaN      NaN     NaN    59.990000     NaN
max       NaN    NaN      NaN     NaN   399.990000     NaN
```

In [25]:

```
#creating a backup dataframe before removing outliers using IQR
df3 = df
```

In [26]:

```
#outlier detection
Q1 = df.quantile(0.05)
Q3 = df.quantile(0.95)
IQR = Q3 - Q1
```

In [27]:

```
#new dataframe with outliers removed
df=df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
```

In [28]:

```
#new dataframe shape
df.shape
```

Out[28]:
```
(822, 82)
```

In [29]:
```
#predicited variable count
df['churn'].value_counts(ascending=True)
```

Out[29]:
```
1    247
0    575
Name: churn, dtype: int64
```

Grouping

age1

In [30]:
```
#value counts
df['age1'].value_counts(ascending=True)
```

Out[30]:
```
90.0     1
18.0     1
74.0     1
88.0     1
86.0     1
78.0     2
20.0     2
80.0     3
76.0     3
64.0     4
70.0     5
66.0     5
72.0     6
62.0     6
22.0     7
68.0     7
60.0     9
24.0    19
56.0    22
26.0    22
50.0    23
58.0    24
48.0    25
30.0    27
54.0    29
38.0    31
32.0    31
44.0    32
36.0    33
34.0    34
```

```
52.0     35
28.0     36
42.0     36
40.0     37
46.0     40
0.0     222
Name: age1, dtype: int64
```

In [31]:
```
#Group the ages into groups
binsage=[0,17, 25, 35, 45, 55, 65, 99]
labelsage=['Missing','18-24','25-34','35-44','45-54', '55-64', '65+']
df['age_group'] = pd.cut(df['age1'], binsage, labels=labelsage, include_lowest=True)
```

In [32]:
```
#Age
print("Distinct values for age:\n", set(df['age_group']))
```

```
Distinct values for age:
 {'35-44', '45-54', '65+', 'Missing', '25-34', '55-64', '18-24'}
```

In [33]:
```
df['age_group'].value_counts(ascending=True)
```

Out[33]:
```
18-24       29
65+         35
55-64       65
25-34      150
45-54      152
35-44      169
Missing    222
Name: age_group, dtype: int64
```

age2

In [34]:
```
#Group the ages for age2 into groups using same labels from age1
df['age_group2'] = pd.cut(df['age2'], binsage, labels=labelsage, include_lowest=True)

#Age
print("Distinct values for age:\n", set(df['age_group2']))
df['age_group2'].value_counts(ascending=True)
```

```
Distinct values for age:
 {'35-44', '45-54', '65+', 'Missing', '25-34', '55-64', '18-24'}
```

Out[34]:
```
65+         28
18-24       30
55-64       44
25-34       77
35-44      101
45-54      106
```

```
Missing    436
Name: age_group2, dtype: int64
```

roam

In [35]:
```python
print("roam Values")
print("Average roam: ", df['roam'].mean())
print("Minimum roam: ", df['roam'].min())
print("Maximum roam: ", df['roam'].max())
print("Null values: ", pd.isnull(df['roam']).sum())
print("Roam Value Counts:", df['roam'].value_counts(ascending=True))
#check # 0s in Roam
print("Number of Roam Zeroes: ",(df['roam'] ==0).sum())
```

```
roam Values
Average roam:  0.41072726695902795
Minimum roam:  0.0
Maximum roam:  10.54
Null values:  0
Roam Value Counts: 1.73       1
4.27       1
3.49       1
10.54      1
6.91       1
        ...
0.32       8
0.20      15
0.16      17
0.10      21
0.00     593
Name: roam, Length: 126, dtype: int64
Number of Roam Zeroes:  593
```

In [36]:
```python
#create groups for roaming
binsroam=[0,0.000000000001,1,2,3,4,5,6,7,8,9,10,11]
labelsroam=['Not_Roaming','1','2','3','4','5','6','7','8','9','10','over 10']
df['roaming_range'] = pd.cut(df['roam'], bins=binsroam, labels=labelsroam, include_lowest=True)
```

In [37]:
```python
print("Distinct values for roam range:\n", set(df['roaming_range']))
print("Value counts for roaming range", df['roaming_range'].value_counts(ascending=True))
```

```
Distinct values for roam range:
 {'6', '7', 'Not_Roaming', '9', '4', '2', '5', 'over 10', '1', '3', '8'}
Value counts for roaming range 10               0
over 10          1
9                2
8                4
7                5
```

```
6                6
5                9
3               11
4               11
2               42
1              138
Not_Roaming    593
Name: roaming_range, dtype: int64
```

In [38]:

```
#Make sure the datatype for these new grouped columns are strings/objects
df['age_group'] = df['age_group'].astype(str)
df['age_group2'] = df['age_group2'].astype(str)
df['roaming_range'] = df['roaming_range'].astype(str)

df.dtypes
```

Out[38]:

```
revenue          float64
mou              float64
recchrge         float64
directas         float64
overage          float64
                  ...
setprc           float64
retcall           object
age_group         object
age_group2        object
roaming_range     object
Length: 85, dtype: object
```

In [39]:

```
#did they churn (this was done for visualization but not necessary)
df['churn_status'] = df.churn.replace(to_replace=[0,1], value=['no','yes'])
```

Correlation and importance checks

In [40]:

```
#checking which columns are objects/strings
print("Object Columns:\n",list(df.select_dtypes(['object'])))
```

```
Object Columns:
 ['churn', 'csa', 'children', 'credita', 'creditaa', 'creditb', 'creditc', 'creditde', 'creditgy', 'creditz', 'credit_rat
ing', 'prizmrur', 'prizmub', 'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv', 'occprof', 'occcler', 'occcrft',
'occstud', 'occhmkr', 'occret', 'occself', 'occ', 'occ_label', 'ownrent', 'marryun', 'marryyes', 'marryno', 'marry', 'mar
ry_label', 'mailord', 'mailres', 'mailflag', 'travel', 'pcown', 'creditcd', 'newcelly', 'newcelln', 'incmiss', 'income',
'mcycle', 'creditad', 'setprcm', 'retcall', 'age_group', 'age_group2', 'roaming_range', 'churn_status']
```

In [41]:

```
#checking which columns are floats
print("Float Columns:\n",list(df.select_dtypes(['float64'])))
```

```
Float Columns:
 ['revenue', 'mou', 'recchrge', 'directas', 'overage', 'roam', 'changem', 'changer', 'dropvce', 'blckvce', 'unansvce', 'c
ustcare', 'threeway', 'mourec', 'outcalls', 'incalls', 'peakvce', 'opeakvce', 'dropblk', 'callfwdv', 'callwait', 'age1',
'age2', 'setprc']
```

In [42]:
```
#checking which columns are integers
print("Int Columns:\n",list(df.select_dtypes(['int64'])))
```

```
Int Columns:
 ['months', 'uniqsubs', 'actvsubs', 'phones', 'models', 'eqpdays', 'customer', 'retcalls', 'retaccpt', 'refer']
```

In [43]:
```
#separate the data into object vs nonobjects
notif=df.select_dtypes(exclude=['int','float','int64'])
intfldtypes = df.select_dtypes(include=['int','float','int64'])
print(df.shape)
print(notif.shape)
print(intfldtypes.shape)
```

```
(822, 86)
(822, 52)
(822, 34)
```

In [44]:
```
#label encode objects for correlaton/importance checking
obj_le= notif.apply(LabelEncoder().fit_transform)


#re-add with non-objects to df_ml
df_ml= pd.concat([obj_le,intfldtypes], axis=1, sort=False)
df_ml=df_ml.drop(['churn_status'], axis=1)


#check shape
print(df_ml.shape)
```

```
(822, 85)
```

Spearman's Correlation

In [45]:
```
#check correlation
#Spearman's correlation
print("Spearman's Correlation:")
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df_ml.corr(method='spearman')['churn'].sort_values(ascending=False))
#corr[np.argsort(corr,axis=0)[::-1]]
```

```
Spearman's Correlation:
churn            1.000000
eqpdays          0.108040
```

refurb	0.100411
roam	0.081060
prizmub	0.056727
months	0.050740
setprcm	0.044384
uniqsubs	0.042080
creditc	0.041131
marry	0.034076
actvsubs	0.032985
marryun	0.031545
age_group	0.027069
prizmrur	0.024777
creditaa	0.024714
age_group2	0.022143
credita	0.016881
overage	0.015045
incmiss	0.011450
ownrent	0.010160
occ_label	0.009215
creditz	0.007538
income	0.007518
mailflag	0.005134
occstud	0.004336
csa	0.003830
occret	0.003692
age2	0.003310
occprof	0.001567
newcelln	-0.004534
pcown	-0.004606
przm_num	-0.005845
threeway	-0.007253
marryyes	-0.007435
creditb	-0.009634
creditad	-0.012910
occcrft	-0.014661
age1	-0.017232
newcelly	-0.021112
occhmkr	-0.022874
truck	-0.024540
marryno	-0.026379
marry_label	-0.026379
rv	-0.026428
creditcd	-0.026854
prizmtwn	-0.028339
changer	-0.031916
occ	-0.032862
revenue	-0.032905
setprc	-0.032945
occself	-0.035527

```
mcycle          -0.037946
children        -0.042250
directas        -0.043221
blckvce         -0.043543
occcler         -0.043674
phones          -0.044333
credit_rating   -0.044515
mailres         -0.045252
callwait        -0.049148
models          -0.050591
creditde        -0.053595
customer        -0.057741
mailord         -0.060496
travel          -0.064411
creditgy        -0.069531
dropblk         -0.071918
peakvce         -0.074349
roaming_range   -0.074933
unansvce        -0.077226
dropvce         -0.077544
changem         -0.077685
webcap          -0.079049
custcare        -0.088075
recchrge        -0.090420
incalls         -0.097669
mourec          -0.097822
outcalls        -0.100629
mou             -0.120161
opeakvce        -0.129500
retcall               NaN
callfwdv              NaN
retcalls              NaN
retaccpt              NaN
refer                 NaN
Name: churn, dtype: float64
```

Kendall's Correlation

In [46]:

```
print("Kendall's Correlation")
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(df_ml.corr(method ='kendall')['churn'].sort_values(ascending=False))
```

```
Kendall's Correlation
churn            1.000000
refurb           0.100411
eqpdays          0.088326
roam             0.075685
prizmub          0.056727
setprcm          0.044384
```

months	0.042228
creditc	0.041131
uniqsubs	0.040625
actvsubs	0.032551
marry	0.032169
marryun	0.031545
prizmrur	0.024777
creditaa	0.024714
age_group	0.024073
age_group2	0.020270
credita	0.016881
overage	0.013141
incmiss	0.011450
ownrent	0.010160
occ_label	0.008900
creditz	0.007538
income	0.006536
mailflag	0.005134
occstud	0.004336
occret	0.003692
csa	0.003142
age2	0.002960
occprof	0.001567
newcelln	-0.004534
pcown	-0.004606
przm_num	-0.005547
threeway	-0.006963
marryyes	-0.007435
creditb	-0.009634
creditad	-0.012863
occcrft	-0.014661
age1	-0.014661
newcelly	-0.021112
occhmkr	-0.022874
truck	-0.024540
changer	-0.026277
marry_label	-0.026379
marryno	-0.026379
rv	-0.026428
creditcd	-0.026854
revenue	-0.026901
prizmtwn	-0.028339
setprc	-0.030509
occ	-0.031738
occself	-0.035527
blckvce	-0.037401
mcycle	-0.037946
directas	-0.039044
credit_rating	-0.040060

```
children        -0.042250
phones          -0.042291
occcler         -0.043674
callwait        -0.044371
mailres         -0.045252
customer        -0.047174
models          -0.049018
creditde        -0.053595
dropblk         -0.059662
mailord         -0.060496
peakvce         -0.061004
changem         -0.063497
unansvce        -0.063568
travel          -0.064411
dropvce         -0.064866
creditgy        -0.069531
roaming_range   -0.071943
recchrge        -0.075686
webcap          -0.079049
custcare        -0.080379
mourec          -0.080610
outcalls        -0.083098
incalls         -0.083561
mou             -0.098193
opeakvce        -0.106335
retcall               NaN
callfwdv              NaN
retcalls              NaN
retaccpt              NaN
refer                 NaN
Name: churn, dtype: float64
```

In [47]:

```
df_ml.columns
```

Out[47]:

```
Index(['churn', 'csa', 'children', 'credita', 'creditaa', 'creditb', 'creditc',
       'creditde', 'creditgy', 'creditz', 'credit_rating', 'prizmrur',
       'prizmub', 'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv',
       'occprof', 'occcler', 'occcrft', 'occstud', 'occhmkr', 'occret',
       'occself', 'occ', 'occ_label', 'ownrent', 'marryun', 'marryyes',
       'marryno', 'marry', 'marry_label', 'mailord', 'mailres', 'mailflag',
       'travel', 'pcown', 'creditcd', 'newcelly', 'newcelln', 'incmiss',
       'income', 'mcycle', 'creditad', 'setprcm', 'retcall', 'age_group',
       'age_group2', 'roaming_range', 'revenue', 'mou', 'recchrge', 'directas',
       'overage', 'roam', 'changem', 'changer', 'dropvce', 'blckvce',
       'unansvce', 'custcare', 'threeway', 'mourec', 'outcalls', 'incalls',
       'peakvce', 'opeakvce', 'dropblk', 'callfwdv', 'callwait', 'months',
       'uniqsubs', 'actvsubs', 'phones', 'models', 'eqpdays', 'customer',
       'age1', 'age2', 'retcalls', 'retaccpt', 'refer', 'setprc'],
      dtype='object')
```

Chi-Square for importance

In [48]:
```
class ChiSquare:
    def __init__(self, dataframe):
        self.df_ml = dataframe
        self.p = None #P-Value
        self.chi2 = None #Chi Test Statistic
        self.dof = None

        self.df_mlObserved = None
        self.df_mlExpected = None

    def _print_chisquare_result(self, colX, alpha):
        result = ""
        if self.p<alpha:
            result="\n~~~~The column {0} is IMPORTANT for Prediction.~~~~\n".format(colX)
        else:
            result="The column {0} is NOT an important predictor.".format(colX)

        print(result)

    def TestIndependence(self,colX,colY, alpha=0.10):
        X = self.df_ml[colX].astype(str)
        Y = self.df_ml[colY].astype(str)

        self.df_mlObserved = pd.crosstab(Y,X)
        chi2, p, dof, expected = stats.chi2_contingency(self.df_mlObserved.values)
        self.p = p
        self.chi2 = chi2
        self.dof = dof

        self.df_mlExpected = pd.DataFrame(expected, columns=self.df_mlObserved.columns,
                                          index = self.df_mlObserved.index)

        self._print_chisquare_result(colX,alpha)

#Initialize ChiSquare Class
cT = ChiSquare(df_ml)

#Feature Selection
testColumns = ['age_group2','csa', 'occ_label', 'marry_label', 'age_group', 'roaming_range',
               'revenue', 'mou', 'recchrge', 'directas', 'overage', 'roam', 'changem',
               'changer', 'dropvce', 'blckvce', 'unansvce', 'custcare', 'threeway',
               'mourec', 'outcalls', 'incalls', 'peakvce', 'opeakvce', 'dropblk',
               'callfwdv', 'callwait', 'months', 'uniqsubs', 'actvsubs',
```

```
                'phones', 'models', 'eqpdays', 'customer', 'age1','age2', 'children',
                'credita', 'creditaa', 'creditb', 'creditc', 'creditde', 'creditgy',
                'creditz', 'credit_rating', 'prizmrur', 'prizmub', 'prizmtwn',
                'przm_num', 'refurb', 'webcap', 'truck', 'rv', 'occprof', 'occcler',
                'occcrft', 'occstud', 'occhmkr', 'occret', 'occself', 'occ', 'ownrent',
                'marryun', 'marryyes', 'marryno', 'marry', 'mailord', 'mailres',
                'mailflag', 'travel', 'pcown', 'creditcd', 'retcalls', 'retaccpt',
                'newcelly', 'newcelln', 'refer', 'incmiss', 'income', 'mcycle',
                'creditad', 'setprcm', 'setprc', 'retcall']
for var in testColumns:
    cT.TestIndependence(colX=var,colY="churn" )
```

```
The column age_group2 is NOT an important predictor.
The column csa is NOT an important predictor.
The column occ_label is NOT an important predictor.
The column marry_label is NOT an important predictor.
The column age_group is NOT an important predictor.
The column roaming_range is NOT an important predictor.
The column revenue is NOT an important predictor.
The column mou is NOT an important predictor.
The column recchrge is NOT an important predictor.
The column directas is NOT an important predictor.
The column overage is NOT an important predictor.
The column roam is NOT an important predictor.
The column changem is NOT an important predictor.
The column changer is NOT an important predictor.
The column dropvce is NOT an important predictor.
The column blckvce is NOT an important predictor.
The column unansvce is NOT an important predictor.
The column custcare is NOT an important predictor.
The column threeway is NOT an important predictor.
The column mourec is NOT an important predictor.
The column outcalls is NOT an important predictor.
The column incalls is NOT an important predictor.
The column peakvce is NOT an important predictor.
The column opeakvce is NOT an important predictor.
The column dropblk is NOT an important predictor.
The column callfwdv is NOT an important predictor.
The column callwait is NOT an important predictor.

~~~~The column months is IMPORTANT for Prediction.~~~~

The column uniqsubs is NOT an important predictor.
The column actvsubs is NOT an important predictor.
The column phones is NOT an important predictor.
The column models is NOT an important predictor.
The column eqpdays is NOT an important predictor.
The column customer is NOT an important predictor.
```

```
The column age1 is NOT an important predictor.
The column age2 is NOT an important predictor.
The column children is NOT an important predictor.
The column credita is NOT an important predictor.
The column creditaa is NOT an important predictor.
The column creditb is NOT an important predictor.
The column creditc is NOT an important predictor.
The column creditde is NOT an important predictor.

~~~~The column creditgy is IMPORTANT for Prediction.~~~~

The column creditz is NOT an important predictor.
The column credit_rating is NOT an important predictor.
The column prizmrur is NOT an important predictor.
The column prizmub is NOT an important predictor.
The column prizmtwn is NOT an important predictor.

~~~~The column przm_num is IMPORTANT for Prediction.~~~~


~~~~The column refurb is IMPORTANT for Prediction.~~~~


~~~~The column webcap is IMPORTANT for Prediction.~~~~

The column truck is NOT an important predictor.
The column rv is NOT an important predictor.
The column occprof is NOT an important predictor.
The column occcler is NOT an important predictor.
The column occcrft is NOT an important predictor.
The column occstud is NOT an important predictor.
The column occhmkr is NOT an important predictor.
The column occret is NOT an important predictor.
The column occself is NOT an important predictor.
The column occ is NOT an important predictor.
The column ownrent is NOT an important predictor.
The column marryun is NOT an important predictor.
The column marryyes is NOT an important predictor.
The column marryno is NOT an important predictor.
The column marry is NOT an important predictor.

~~~~The column mailord is IMPORTANT for Prediction.~~~~

The column mailres is NOT an important predictor.
The column mailflag is NOT an important predictor.

~~~~The column travel is IMPORTANT for Prediction.~~~~

The column pcown is NOT an important predictor.
```

```
The column creditcd is NOT an important predictor.
The column retcalls is NOT an important predictor.
The column retaccpt is NOT an important predictor.
The column newcelly is NOT an important predictor.
The column newcelln is NOT an important predictor.
The column refer is NOT an important predictor.
The column incmiss is NOT an important predictor.
The column income is NOT an important predictor.
The column mcycle is NOT an important predictor.
The column creditad is NOT an important predictor.
The column setprcm is NOT an important predictor.
The column setprc is NOT an important predictor.
The column retcall is NOT an important predictor.
```

In [49]:
```
df = df_ml
```

In [50]:
```
#new columns
"""
We will be making new columns out of the important columns from the Chi-Squared test above.

The important columns are as follows:
                            months, creditgy, przm_num, refurb, webcap, mailord, and travel.

Some will be columns that I think would match well with the important column
and others will be a combination of important columns.

"""

#months
df['months_mou'] = df['months'].astype(str) + '_' + df['mou'].astype(str)
df['months_creditgy'] = df['months'].astype(str) + '_' + df['creditgy'].astype(str)
df['months_przm_num'] = df['months'].astype(str) + '_' + df['przm_num'].astype(str)
df['months_refurb'] = df['months'].astype(str) + '_' + df['refurb'].astype(str)
df['months_webcap'] = df['months'].astype(str) + '_' + df['webcap'].astype(str)
df['months_mailord'] = df['months'].astype(str) + '_' + df['mailord'].astype(str)
df['months_travel'] = df['months'].astype(str) + '_' + df['travel'].astype(str)
df['months_models'] = df['months'].astype(str) + '_' + df['models'].astype(str)
df['months_agegroup'] = df['months'].astype(str) + '_' + df['age_group'].astype(str)
df['months_agegroup2'] = df['months'].astype(str) + '_' + df['age_group2'].astype(str)

#creditgy
df['creditgy_przm_num'] = df['creditgy'].astype(str) + '_' + df['przm_num'].astype(str)
df['creditgy_refurb'] = df['creditgy'].astype(str) + '_' + df['refurb'].astype(str)
df['creditgy_webcap'] = df['creditgy'].astype(str) + '_' + df['webcap'].astype(str)
df['creditgy_mailord'] = df['creditgy'].astype(str) + '_' + df['mailord'].astype(str)
df['creditgy_travel'] = df['creditgy'].astype(str) + '_' + df['travel'].astype(str)
```

```python
df['creditgy_income'] = df['creditgy'].astype(str) + '_' + df['income'].astype(str)
df['creditgy_agegroup'] = df['creditgy'].astype(str) + '_' + df['age_group'].astype(str)
df['creditgy_agegroup2'] = df['creditgy'].astype(str) + '_' + df['age_group2'].astype(str)
df['creditgy_occ'] = df['creditgy'].astype(str) + '_' + df['occ'].astype(str)

#przm_num
df['przm_num_refurb'] = df['przm_num'].astype(str) + '_' + df['refurb'].astype(str)
df['przm_num_webcap'] = df['przm_num'].astype(str) + '_' + df['webcap'].astype(str)
df['przm_num_mailord'] = df['przm_num'].astype(str) + '_' + df['mailord'].astype(str)
df['przm_num_travel'] = df['przm_num'].astype(str) + '_' + df['travel'].astype(str)
df['przm_num_dropblk'] = df['przm_num'].astype(str) + '_' + df['dropblk'].astype(str)
df['przm_num_dropvce'] = df['przm_num'].astype(str) + '_' + df['dropvce'].astype(str)
df['przm_num_roam_range'] = df['przm_num'].astype(str) + '_' + df['roaming_range'].astype(str)


#refurb
df['refurb_webcap'] = df['refurb'].astype(str) + '_' + df['webcap'].astype(str)
df['refurb_mailord'] = df['refurb'].astype(str) + '_' + df['mailord'].astype(str)
df['refurb_travel'] = df['refurb'].astype(str) + '_' + df['travel'].astype(str)
df['refurb_models'] = df['refurb'].astype(str) + '_' + df['models'].astype(str)
df['refurb_dropblk'] = df['refurb'].astype(str) + '_' + df['dropblk'].astype(str)
df['refurb_dropvce'] = df['refurb'].astype(str) + '_' + df['dropvce'].astype(str)
df['refurb_custcare'] = df['refurb'].astype(str) + '_' + df['custcare'].astype(str)
df['refurb_retcalls'] = df['refurb'].astype(str) + '_' + df['retcalls'].astype(str)
df['refurb_retcall'] = df['refurb'].astype(str) + '_' + df['retcall'].astype(str)

#webcap
df['webcap_mailord'] = df['webcap'].astype(str) + '_' + df['mailord'].astype(str)
df['webcap_travel'] = df['webcap'].astype(str) + '_' + df['travel'].astype(str)
df['webcap_agegroup'] = df['webcap'].astype(str) + '_' + df['age_group'].astype(str)
df['webcap_agegroup2'] = df['webcap'].astype(str) + '_' + df['age_group2'].astype(str)
df['webcap_income'] = df['webcap'].astype(str) + '_' + df['income'].astype(str)
df['webcap_setprc'] = df['webcap'].astype(str) + '_' + df['setprc'].astype(str)
df['webcap_retcall'] = df['webcap'].astype(str) + '_' + df['retcall'].astype(str)

#mailord
df['mailord_travel'] = df['mailord'].astype(str) + '_' + df['travel'].astype(str)
df['mailord_mailres'] = df['mailord'].astype(str) + '_' + df['mailres'].astype(str)
df['mailord_mailflag'] = df['mailord'].astype(str) + '_' + df['mailflag'].astype(str)
df['mailord_agegroup'] = df['mailord'].astype(str) + '_' + df['age_group'].astype(str)
df['mailord_agegroup2'] = df['mailord'].astype(str) + '_' + df['age_group2'].astype(str)

#travel
df['travel_roaming_range'] =df['travel'].astype(str) + '_' + df['roaming_range'].astype(str)
df['travel_income'] =df['travel'].astype(str) + '_' + df['income'].astype(str)
```

```
df['travel_occ'] =df['travel'].astype(str) + '_' + df['occ'].astype(str)
df['travel_marry'] =df['travel'].astype(str) + '_' + df['marry'].astype(str)
```

In [51]:
```
#re_separate the data into object vs nonobjects
notif2=df.select_dtypes(exclude=['int','float','int64'])
intfldtypes2 = df.select_dtypes(include=['int','float','int64'])
print(df.shape)
print(notif2.shape)
print(intfldtypes2.shape)
```

```
(822, 136)
(822, 51)
(822, 85)
```

In [52]:
```
#label encode objects
obj_le2= notif2.apply(LabelEncoder().fit_transform)
#re-add with non-objects
df_ml2= pd.concat([obj_le2,intfldtypes2], axis=1, sort=False)
#df_ml2=df_ml2.drop(['churn_status'], axis=1)
#check shape
print(df_ml2.shape)
```

```
(822, 136)
```

In [53]:
```
pd.options.display.max_columns = None
pd.options.display.max_rows = None
print(df_ml2.columns.tolist())
```

```
['months_mou', 'months_creditgy', 'months_przm_num', 'months_refurb', 'months_webcap', 'months_mailord', 'months_travel',
'months_models', 'months_agegroup', 'months_agegroup2', 'creditgy_przm_num', 'creditgy_refurb', 'creditgy_webcap', 'credi
tgy_mailord', 'creditgy_travel', 'creditgy_income', 'creditgy_agegroup', 'creditgy_agegroup2', 'creditgy_occ', 'przm_num_
refurb', 'przm_num_webcap', 'przm_num_mailord', 'przm_num_travel', 'przm_num_dropblk', 'przm_num_dropvce', 'przm_num_roam
_range', 'refurb_webcap', 'refurb_mailord', 'refurb_travel', 'refurb_models', 'refurb_dropblk', 'refurb_dropvce', 'refurb
_custcare', 'refurb_retcalls', 'refurb_retcall', 'webcap_mailord', 'webcap_travel', 'webcap_agegroup', 'webcap_agegroup
2', 'webcap_income', 'webcap_setprc', 'webcap_retcall', 'mailord_travel', 'mailord_mailres', 'mailord_mailflag', 'mailord
_agegroup', 'mailord_agegroup2', 'travel_roaming_range', 'travel_income', 'travel_occ', 'travel_marry', 'churn', 'csa',
'children', 'credita', 'creditaa', 'creditb', 'creditc', 'creditde', 'creditgy', 'creditz', 'credit_rating', 'prizmrur',
'prizmub', 'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv', 'occprof', 'occcler', 'occcrft', 'occstud', 'occhmk
r', 'occret', 'occself', 'occ', 'occ_label', 'ownrent', 'marryun', 'marryyes', 'marryno', 'marry', 'marry_label', 'mailor
d', 'mailres', 'mailflag', 'travel', 'pcown', 'creditcd', 'newcelly', 'newcelln', 'incmiss', 'income', 'mcycle', 'credita
d', 'setprcm', 'retcall', 'age_group', 'age_group2', 'roaming_range', 'revenue', 'mou', 'recchrge', 'directas', 'overag
e', 'roam', 'changem', 'changer', 'dropvce', 'blckvce', 'unansvce', 'custcare', 'threeway', 'mourec', 'outcalls', 'incall
s', 'peakvce', 'opeakvce', 'dropblk', 'callfwdv', 'callwait', 'months', 'uniqsubs', 'actvsubs', 'phones', 'models', 'eqpd
ays', 'customer', 'age1', 'age2', 'retcalls', 'retaccpt', 'refer', 'setprc']
```

In [54]:
```
#chisquared #2 to check the importance with newly created columns added
class ChiSquare:
```

```
    def __init__(self, dataframe):
        self.df_ml2 = dataframe
        self.p = None #P-Value
        self.chi2 = None #Chi Test Statistic
        self.dof = None

        self.df_ml2Observed = None
        self.df_ml2Expected = None

    def _print_chisquare_result(self, colX, alpha):
        result = ""
        if self.p<alpha:
            result="\n~~~~The column {0} is IMPORTANT for Prediction.~~~~\n".format(colX)
        else:
            result="The column {0} is NOT an important predictor.".format(colX)

        print(result)

    def TestIndependence(self,colX,colY, alpha=0.10):
        X = self.df_ml2[colX].astype(str)
        Y = self.df_ml2[colY].astype(str)

        self.df_ml2Observed = pd.crosstab(Y,X)
        chi2, p, dof, expected = stats.chi2_contingency(self.df_ml2Observed.values)
        self.p = p
        self.chi2 = chi2
        self.dof = dof

        self.df_ml2Expected = pd.DataFrame(expected, columns=self.df_ml2Observed.columns,
                                           index = self.df_ml2Observed.index)

        self._print_chisquare_result(colX,alpha)

#Initialize ChiSquare Class
cT = ChiSquare(df_ml2)

#Feature Selection
testColumns = ['months_mou', 'months_creditgy', 'months_przm_num', 'months_refurb', 'months_webcap',
               'months_mailord', 'months_travel', 'months_models', 'months_agegroup',
               'months_agegroup2', 'creditgy_przm_num', 'creditgy_refurb', 'creditgy_webcap',
               'creditgy_mailord', 'creditgy_travel', 'creditgy_income', 'creditgy_agegroup',
               'creditgy_agegroup2', 'creditgy_occ', 'przm_num_refurb', 'przm_num_webcap',
               'przm_num_mailord', 'przm_num_travel', 'przm_num_dropblk', 'przm_num_dropvce',
               'przm_num_roam_range', 'refurb_webcap', 'refurb_mailord', 'refurb_travel',
               'refurb_models', 'refurb_dropblk', 'refurb_dropvce', 'refurb_custcare',
               'refurb_retcalls', 'refurb_retcall', 'webcap_mailord', 'webcap_travel',
```

```
                'webcap_agegroup', 'webcap_agegroup2', 'webcap_income', 'webcap_setprc',
                'webcap_retcall', 'mailord_travel', 'mailord_mailres', 'mailord_mailflag',
                'mailord_agegroup', 'mailord_agegroup2', 'travel_roaming_range', 'travel_income',
                'travel_occ', 'travel_marry', 'csa', 'children', 'credita', 'creditaa', 'creditb',
                'creditc', 'creditde', 'creditgy', 'creditz', 'credit_rating', 'prizmrur', 'prizmub',
                'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv', 'occprof', 'occcler',
                'occcrft', 'occstud', 'occhmkr', 'occret', 'occself', 'occ', 'occ_label', 'ownrent',
                'marryun', 'marryyes', 'marryno', 'marry', 'marry_label', 'mailord', 'mailres',
                'mailflag', 'travel', 'pcown', 'creditcd', 'newcelly', 'newcelln', 'incmiss',
                'income', 'mcycle', 'creditad', 'setprcm', 'retcall', 'age_group',
                'age_group2', 'roaming_range', 'revenue', 'mou', 'recchrge', 'directas',
                'overage', 'roam', 'changem', 'changer', 'dropvce', 'blckvce', 'unansvce',
                'custcare', 'threeway', 'mourec', 'outcalls', 'incalls', 'peakvce', 'opeakvce',
                'dropblk', 'callfwdv', 'callwait', 'months', 'uniqsubs', 'actvsubs', 'phones',
                'models', 'eqpdays', 'customer', 'age1', 'age2', 'retcalls', 'retaccpt', 'refer',
                'setprc']
for var in testColumns:
    cT.TestIndependence(colX=var,colY="churn" )
```

```
The column months_mou is NOT an important predictor.

~~~~The column months_creditgy is IMPORTANT for Prediction.~~~~


~~~~The column months_przm_num is IMPORTANT for Prediction.~~~~


~~~~The column months_refurb is IMPORTANT for Prediction.~~~~


~~~~The column months_webcap is IMPORTANT for Prediction.~~~~

The column months_mailord is NOT an important predictor.
The column months_travel is NOT an important predictor.

~~~~The column months_models is IMPORTANT for Prediction.~~~~

The column months_agegroup is NOT an important predictor.
The column months_agegroup2 is NOT an important predictor.

~~~~The column creditgy_przm_num is IMPORTANT for Prediction.~~~~


~~~~The column creditgy_refurb is IMPORTANT for Prediction.~~~~


~~~~The column creditgy_webcap is IMPORTANT for Prediction.~~~~
```

```
~~~~The column creditgy_mailord is IMPORTANT for Prediction.~~~~


~~~~The column creditgy_travel is IMPORTANT for Prediction.~~~~

The column creditgy_income is NOT an important predictor.
The column creditgy_agegroup is NOT an important predictor.
The column creditgy_agegroup2 is NOT an important predictor.
The column creditgy_occ is NOT an important predictor.

~~~~The column przm_num_refurb is IMPORTANT for Prediction.~~~~


~~~~The column przm_num_webcap is IMPORTANT for Prediction.~~~~


~~~~The column przm_num_mailord is IMPORTANT for Prediction.~~~~

The column przm_num_travel is NOT an important predictor.
The column przm_num_dropblk is NOT an important predictor.
The column przm_num_dropvce is NOT an important predictor.
The column przm_num_roam_range is NOT an important predictor.

~~~~The column refurb_webcap is IMPORTANT for Prediction.~~~~


~~~~The column refurb_mailord is IMPORTANT for Prediction.~~~~


~~~~The column refurb_travel is IMPORTANT for Prediction.~~~~


~~~~The column refurb_models is IMPORTANT for Prediction.~~~~

The column refurb_dropblk is NOT an important predictor.
The column refurb_dropvce is NOT an important predictor.
The column refurb_custcare is NOT an important predictor.

~~~~The column refurb_retcalls is IMPORTANT for Prediction.~~~~


~~~~The column refurb_retcall is IMPORTANT for Prediction.~~~~


~~~~The column webcap_mailord is IMPORTANT for Prediction.~~~~


~~~~The column webcap_travel is IMPORTANT for Prediction.~~~~
```

```
The column webcap_agegroup is NOT an important predictor.
The column webcap_agegroup2 is NOT an important predictor.
The column webcap_income is NOT an important predictor.

~~~~The column webcap_setprc is IMPORTANT for Prediction.~~~~


~~~~The column webcap_retcall is IMPORTANT for Prediction.~~~~

The column mailord_travel is NOT an important predictor.

~~~~The column mailord_mailres is IMPORTANT for Prediction.~~~~

The column mailord_mailflag is NOT an important predictor.
The column mailord_agegroup is NOT an important predictor.
The column mailord_agegroup2 is NOT an important predictor.
The column travel_roaming_range is NOT an important predictor.
The column travel_income is NOT an important predictor.
The column travel_occ is NOT an important predictor.
The column travel_marry is NOT an important predictor.
The column csa is NOT an important predictor.
The column children is NOT an important predictor.
The column credita is NOT an important predictor.
The column creditaa is NOT an important predictor.
The column creditb is NOT an important predictor.
The column creditc is NOT an important predictor.
The column creditde is NOT an important predictor.

~~~~The column creditgy is IMPORTANT for Prediction.~~~~

The column creditz is NOT an important predictor.
The column credit_rating is NOT an important predictor.
The column prizmrur is NOT an important predictor.
The column prizmub is NOT an important predictor.
The column prizmtwn is NOT an important predictor.

~~~~The column przm_num is IMPORTANT for Prediction.~~~~


~~~~The column refurb is IMPORTANT for Prediction.~~~~


~~~~The column webcap is IMPORTANT for Prediction.~~~~

The column truck is NOT an important predictor.
The column rv is NOT an important predictor.
The column occprof is NOT an important predictor.
The column occcler is NOT an important predictor.
```

```
The column occcrft is NOT an important predictor.
The column occstud is NOT an important predictor.
The column occhmkr is NOT an important predictor.
The column occret is NOT an important predictor.
The column occself is NOT an important predictor.
The column occ is NOT an important predictor.
The column occ_label is NOT an important predictor.
The column ownrent is NOT an important predictor.
The column marryun is NOT an important predictor.
The column marryyes is NOT an important predictor.
The column marryno is NOT an important predictor.
The column marry is NOT an important predictor.
The column marry_label is NOT an important predictor.

~~~~The column mailord is IMPORTANT for Prediction.~~~~

The column mailres is NOT an important predictor.
The column mailflag is NOT an important predictor.

~~~~The column travel is IMPORTANT for Prediction.~~~~

The column pcown is NOT an important predictor.
The column creditcd is NOT an important predictor.
The column newcelly is NOT an important predictor.
The column newcelln is NOT an important predictor.
The column incmiss is NOT an important predictor.
The column income is NOT an important predictor.
The column mcycle is NOT an important predictor.
The column creditad is NOT an important predictor.
The column setprcm is NOT an important predictor.
The column retcall is NOT an important predictor.
The column age_group is NOT an important predictor.
The column age_group2 is NOT an important predictor.
The column roaming_range is NOT an important predictor.
The column revenue is NOT an important predictor.
The column mou is NOT an important predictor.
The column recchrge is NOT an important predictor.
The column directas is NOT an important predictor.
The column overage is NOT an important predictor.
The column roam is NOT an important predictor.
The column changem is NOT an important predictor.
The column changer is NOT an important predictor.
The column dropvce is NOT an important predictor.
The column blckvce is NOT an important predictor.
The column unansvce is NOT an important predictor.
The column custcare is NOT an important predictor.
The column threeway is NOT an important predictor.
The column mourec is NOT an important predictor.
The column outcalls is NOT an important predictor.
```

```
The column incalls is NOT an important predictor.
The column peakvce is NOT an important predictor.
The column opeakvce is NOT an important predictor.
The column dropblk is NOT an important predictor.
The column callfwdv is NOT an important predictor.
The column callwait is NOT an important predictor.

~~~~The column months is IMPORTANT for Prediction.~~~~

The column uniqsubs is NOT an important predictor.
The column actvsubs is NOT an important predictor.
The column phones is NOT an important predictor.
The column models is NOT an important predictor.
The column eqpdays is NOT an important predictor.
The column customer is NOT an important predictor.
The column age1 is NOT an important predictor.
The column age2 is NOT an important predictor.
The column retcalls is NOT an important predictor.
The column retaccpt is NOT an important predictor.
The column refer is NOT an important predictor.
The column setprc is NOT an important predictor.
```

In [55]:

```
#Creating a dataframe with important columns for visualizations later
df1 = df[['age_group', 'months_creditgy', 'months_przm_num', 'months_refurb', 'months_webcap',
          'months_models', 'creditgy_przm_num', 'creditgy_refurb', 'creditgy_webcap',
          'creditgy_mailord', 'creditgy_travel', 'przm_num_refurb', 'przm_num_webcap',
          'przm_num_mailord', 'refurb_webcap', 'refurb_mailord', 'refurb_travel',
          'refurb_models', 'refurb_retcalls', 'refurb_retcall', 'webcap_mailord',
          'webcap_travel', 'webcap_setprc', 'webcap_retcall', 'mailord_mailres',
          'creditgy', 'przm_num', 'refurb', 'webcap', 'mailord', 'travel',
          'months','churn']]
```

In [56]:

```
#saving previously mentions dataframe to a csv for visualizations
df1.to_csv(r'celldata_to_visualize.csv', index=False)
```

Model Preparation

In [57]:

```
#separate dtypes to do label encoding to actual df dataframe
notif=df.select_dtypes(exclude=['int','float','int64'])
intfldtypes = df.select_dtypes(include=['int','float','int64'])
print('Objects',notif.columns)
print("\nNonObjects",intfldtypes.columns)

#checking to make sure all are accounted for
print(df.shape)
```

```
print(notif.shape)
print(intfldtypes.shape)
```

```
Objects Index(['months_mou', 'months_creditgy', 'months_przm_num', 'months_refurb',
       'months_webcap', 'months_mailord', 'months_travel', 'months_models',
       'months_agegroup', 'months_agegroup2', 'creditgy_przm_num',
       'creditgy_refurb', 'creditgy_webcap', 'creditgy_mailord',
       'creditgy_travel', 'creditgy_income', 'creditgy_agegroup',
       'creditgy_agegroup2', 'creditgy_occ', 'przm_num_refurb',
       'przm_num_webcap', 'przm_num_mailord', 'przm_num_travel',
       'przm_num_dropblk', 'przm_num_dropvce', 'przm_num_roam_range',
       'refurb_webcap', 'refurb_mailord', 'refurb_travel', 'refurb_models',
       'refurb_dropblk', 'refurb_dropvce', 'refurb_custcare',
       'refurb_retcalls', 'refurb_retcall', 'webcap_mailord', 'webcap_travel',
       'webcap_agegroup', 'webcap_agegroup2', 'webcap_income', 'webcap_setprc',
       'webcap_retcall', 'mailord_travel', 'mailord_mailres',
       'mailord_mailflag', 'mailord_agegroup', 'mailord_agegroup2',
       'travel_roaming_range', 'travel_income', 'travel_occ', 'travel_marry'],
      dtype='object')

NonObjects Index(['churn', 'csa', 'children', 'credita', 'creditaa', 'creditb', 'creditc',
       'creditde', 'creditgy', 'creditz', 'credit_rating', 'prizmrur',
       'prizmub', 'prizmtwn', 'przm_num', 'refurb', 'webcap', 'truck', 'rv',
       'occprof', 'occcler', 'occcrft', 'occstud', 'occhmkr', 'occret',
       'occself', 'occ', 'occ_label', 'ownrent', 'marryun', 'marryyes',
       'marryno', 'marry', 'marry_label', 'mailord', 'mailres', 'mailflag',
       'travel', 'pcown', 'creditcd', 'newcelly', 'newcelln', 'incmiss',
       'income', 'mcycle', 'creditad', 'setprcm', 'retcall', 'age_group',
       'age_group2', 'roaming_range', 'revenue', 'mou', 'recchrge', 'directas',
       'overage', 'roam', 'changem', 'changer', 'dropvce', 'blckvce',
       'unansvce', 'custcare', 'threeway', 'mourec', 'outcalls', 'incalls',
       'peakvce', 'opeakvce', 'dropblk', 'callfwdv', 'callwait', 'months',
       'uniqsubs', 'actvsubs', 'phones', 'models', 'eqpdays', 'customer',
       'age1', 'age2', 'retcalls', 'retaccpt', 'refer', 'setprc'],
      dtype='object')
(822, 136)
(822, 51)
(822, 85)
```

In [58]:

```
#label encode objects
obj_le= notif.apply(LabelEncoder().fit_transform)

#re-add with non-objects
df_pred= pd.concat([obj_le,intfldtypes], axis=1, sort=False)
#check shape
print(df_pred.shape)
```

```
(822, 136)
```

Resampling imbalanced data

In [59]:
```
#set X and y for modeling
X=df_pred.drop(['churn'],axis=1)
y=df_pred['churn']
```

In [60]:
```
#checking value count of churn
df_pred.churn.value_counts()
```

Out[60]:
```
0    575
1    247
Name: churn, dtype: int64
```

In [61]:
```
# SMOTE oversampling method from imblearn used to resample data
oversample = SMOTE(random_state=42)
X, y = oversample.fit_resample(X, y)


# summarize the new class distribution
counter = Counter(y)
print(counter)
```

```
Counter({0: 575, 1: 575})
```

In [62]:
```
# setting up testing and training sets
res_X_train, res_X_test, res_y_train, res_y_test = train_test_split(X, y,
                                                    test_size=0.25, random_state=42)
```

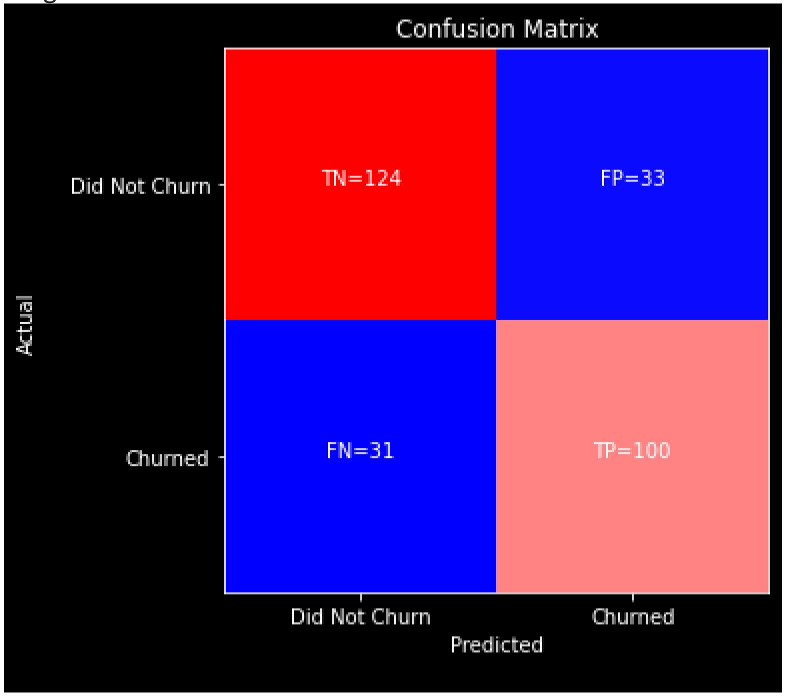
In [63]:
```
#scale X variable data
scaler = StandardScaler()

#fit training set
scaler.fit(res_X_train)

# Apply transform to both the training set and the test set
res_X_train = scaler.transform(res_X_train)
res_X_test = scaler.transform(res_X_test)
```

In [64]:
```
#confusion matrix plot function
def cm_plot(var):
    plt.figure(figsize=(15,5))
    plt.clf()
    plt.imshow(var, interpolation='nearest', cmap='bwr')
    classNames = ['Did Not Churn','Churned']
    plt.title('Confusion Matrix')
```

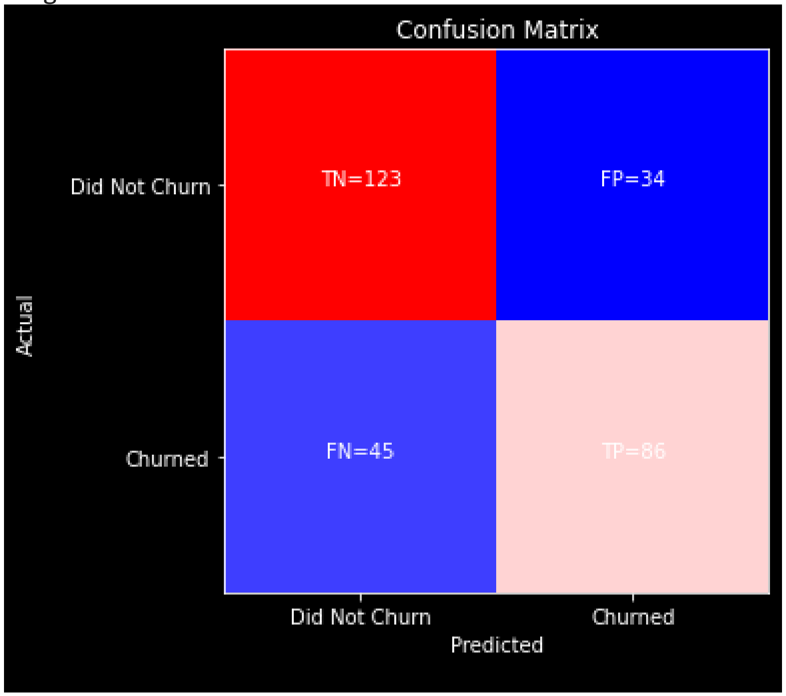
```python
    plt.ylabel('Actual\n')
    plt.xlabel('Predicted\n')
    tick_marks = np.arange(len(classNames))
    plt.xticks(tick_marks, classNames)
    plt.yticks(tick_marks, classNames)
    s = [['TN','FP'], ['FN', 'TP']]

    for i in range(2):
        for j in range(2):
            plt.text(j,i, str(s[i][j])+"="+str(var[i][j]),horizontalalignment='center')
    plt.show()

#Modeling to compare Random Forest and Logistic Regression
classifiers = [
    RandomForestClassifier(random_state=42, n_estimators=100),
    LogisticRegression(random_state=42)]

#putting performance measure results in df
res_cols=["Classifier", "Accuracy", "Log Loss", "Cross Val", "Recall", "Roc Auc","F1",
          "False Positive Rate", "Error Rate"]
results = pd.DataFrame(columns=res_cols)

#measure specifications
for clf in classifiers:
    clf.fit(res_X_train, res_y_train)
    name = clf.__class__.__name__

    print("\n"*3)
    print(name,"Results:")

    print('~'*40)
    res_y_pred = clf.predict(res_X_test)
    acc = accuracy_score(res_y_test, res_y_pred)
    print("Accuracy: {:.4%}".format(acc))

    cv= np.mean(cross_val_score(clf, res_X_train, res_y_train, cv=10))
    print("Cross validation scores:",cv)


    train_predictions = clf.predict_proba(res_X_test)
    logloss = log_loss(res_y_test, train_predictions)
    print("Log Loss: {}".format(logloss))

    cm = confusion_matrix(res_y_test, res_y_pred)

    cm_plot(cm)
```

```python
    #FPR and Error Rate setup
    tn, fp, fn, tp = confusion_matrix(res_y_test,res_y_pred).ravel()

    fpr = fp/(tn+fp)
    ers = 1-acc
    rec= recall_score(res_y_test, res_y_pred)
    roc=roc_auc_score(res_y_test, res_y_pred, average='weighted')
    f1s=f1_score(res_y_test, res_y_pred, average='weighted')
    results_final = pd.DataFrame([[name, round(acc*100,3), round(logloss,3),
                                   round(cv*100,3), round(rec*100,3), round(roc*100,3),
                                   round(f1s*100,3),round(fpr*100,3),round(ers*100,3)]],
                                 columns=res_cols)
    results = results.append(results_final)

print("*"*40)
```

```
RandomForestClassifier Results:
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Accuracy: 77.7778%
Cross validation scores: 0.7656642608928095
Log Loss: 0.48431632387361134
```



```
LogisticRegression Results:
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Accuracy: 72.5694%
Cross validation scores: 0.742381716118685
Log Loss: 0.5025600393212577
```




```
****************************************
```

In [65]:
```
#checking scores of rf and lr
print("Shape",results.shape)
results.head(10)
```

```
Shape (2, 9)
```

Out[65]:

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate
0	RandomForestClassifier	77.778	0.484	76.566	76.336	77.658	77.791	21.019	22.222
0	LogisticRegression	72.569	0.503	74.238	65.649	71.996	72.433	21.656	27.431

In [ ]:
```
'''AFTER EVALUATING THE ALGORITHMS AND THEIR PERFORMANCE
RANDOM FOREST PERFORMED THE BEST SO PARAMETER TUNING WILL BE DONE TO IT
FOR THE BEST SET OF PARAMETERS'''
```

```python
#not necessary to re-run unless you want to parameter tune again (timely)

#Get tuning parameter of  random forest
#random forest

# timing to see how long it takes

#start
tune_start_rfc = time.time()
rfc = RandomForestClassifier()
print('\n')
param_grid = {
    'bootstrap': [True, False],
    'n_estimators': [400, 1000],
    'criterion': ['entropy','gini'],
    'max_depth': [100,150],
    'min_samples_split': [0, 2, 4],
    'max_features': ['auto', 2, 3],
    'n_jobs':[None, 2],
    'warm_start': [True],
    'random_state':[42]}



grid_rfc = GridSearchCV(rfc, param_grid = param_grid, scoring='accuracy', cv = 10)
grid_rfc.fit(res_X_train,res_y_train)
rfcbest_estimator = grid_rfc.best_estimator_
print("Random Forest:\n",grid_rfc.best_params_)
print('\n')
tune_end_rfc = time.time()
print("\nTuning Random Forest Time (in minutes): ", (tune_end_rfc - tune_start_rfc)/60)
```

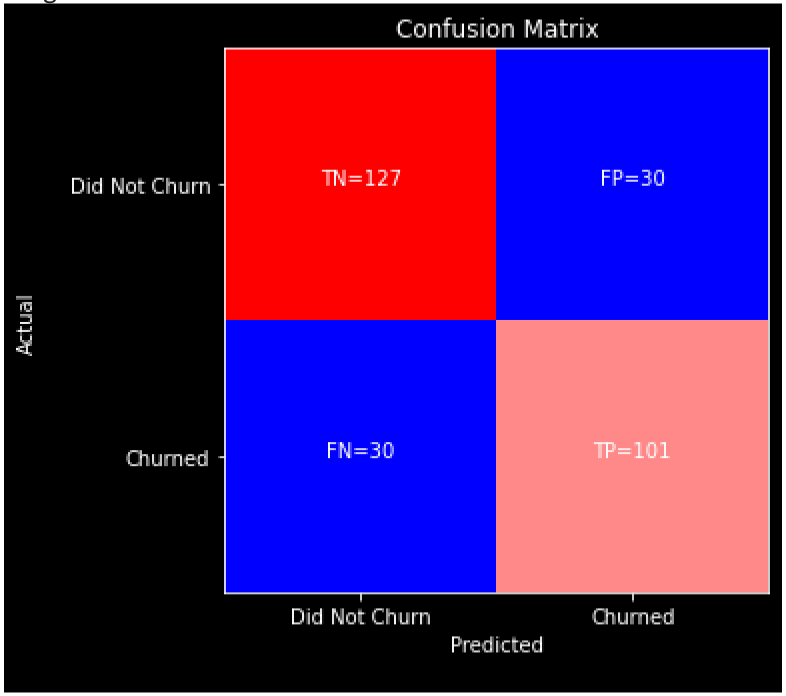
In [66]:

```python
#Final Random Forest Modelling
classifiers = [
    RandomForestClassifier(bootstrap=False, criterion='gini', max_depth=100,
                           min_samples_split=2, n_estimators=1000, max_features=3,
                           class_weight='balanced', warm_start=True, n_jobs=None,
                           random_state=42)]

#putting results2 in df
res_cols=["Classifier", "Accuracy", "Log Loss", "Cross Val", "Recall", "Roc Auc","F1",
          "False Positive Rate", "Error Rate"]
results2 = pd.DataFrame(columns=res_cols)
```

```python
for clf in classifiers:
    clf.fit(res_X_train, res_y_train)
    name = clf.__class__.__name__

    print("\n"*3)
    print(name,"results2:")

    print('~'*40)
    res_y_pred = clf.predict(res_X_test)
    acc = accuracy_score(res_y_test, res_y_pred)
    print("Accuracy: {:.4%}".format(acc))

    cv= np.mean(cross_val_score(clf, res_X_train, res_y_train, cv=10))
    print("Cross validation scores:",cv)


    train_predictions = clf.predict_proba(res_X_test)
    logloss = log_loss(res_y_test, train_predictions)
    print("Log Loss: {}".format(logloss))

    cm = confusion_matrix(res_y_test, res_y_pred)

    cm_plot(cm)

    #FPR and Error Rate setup
    tn, fp, fn, tp = confusion_matrix(res_y_test,res_y_pred).ravel()

    fpr = fp/(tn+fp)
    ers = 1-acc
    rec= recall_score(res_y_test, res_y_pred)
    roc=roc_auc_score(res_y_test, res_y_pred, average='weighted')
    f1s=f1_score(res_y_test, res_y_pred, average='weighted')
    results2_final = pd.DataFrame([[name, round(acc*100,3), round(logloss,3),
                                   round(cv*100,3), round(rec*100,3), round(roc*100,3),
                                   round(f1s*100,3),round(fpr*100,3),round(ers*100,3)]],
                                 columns=res_cols)
    results2 = results2.append(results2_final)

print("*"*40)
```

```
RandomForestClassifier results2:
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Accuracy: 79.1667%
```

```
Cross validation scores: 0.7667602245388934
Log Loss: 0.46563905510980913
```




```
****************************************
```

In [ ]:

```
#checking feature importance just in case
start_time = time.time()

importances = clf.feature_importances_

feature_names = X.columns

forest_importances = pd.Series(importances, index=feature_names)

elapsed_time = time.time() - start_time

print(f"Elapsed time to compute the importances: "
      f"{elapsed_time:.3f} seconds")
```

In [ ]:

```
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    print(forest_importances.sort_values(ascending=False))
```

In [67]:

```
results2['Classifier'] = results2['Classifier'].replace(['RandomForestClassifier'],
                                                        'RetunedRandomForestClassifier')
```

```
results2.head()
```

Out[67]:

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate
0	RetunedRandomForestClassifier	79.167	0.466	76.676	77.099	78.995	79.167	19.108	20.833

In [68]:

```
ml_results = pd.concat([results,results2])
ml_results.reset_index(drop=True, inplace=True)
print("Shape",ml_results.shape)
ml_results.head(10)
```

```
Shape (3, 9)
```

Out[68]:

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate
0	RandomForestClassifier	77.778	0.484	76.566	76.336	77.658	77.791	21.019	22.222
1	LogisticRegression	72.569	0.503	74.238	65.649	71.996	72.433	21.656	27.431
2	RetunedRandomForestClassifier	79.167	0.466	76.676	77.099	78.995	79.167	19.108	20.833

In [69]:

```
'''
    testing model on another set of data
    importing cleaned dataset (verificationdataset.csv) from another notebook to be tested.'''

#import data set into datafream
ver_df= pd.read_csv(r'verificationdataset.csv')

#Create X an y test sets
ver_X_test = ver_df.drop(['churn'],axis=1)
ver_y_test = ver_df['churn']
```

In [70]:

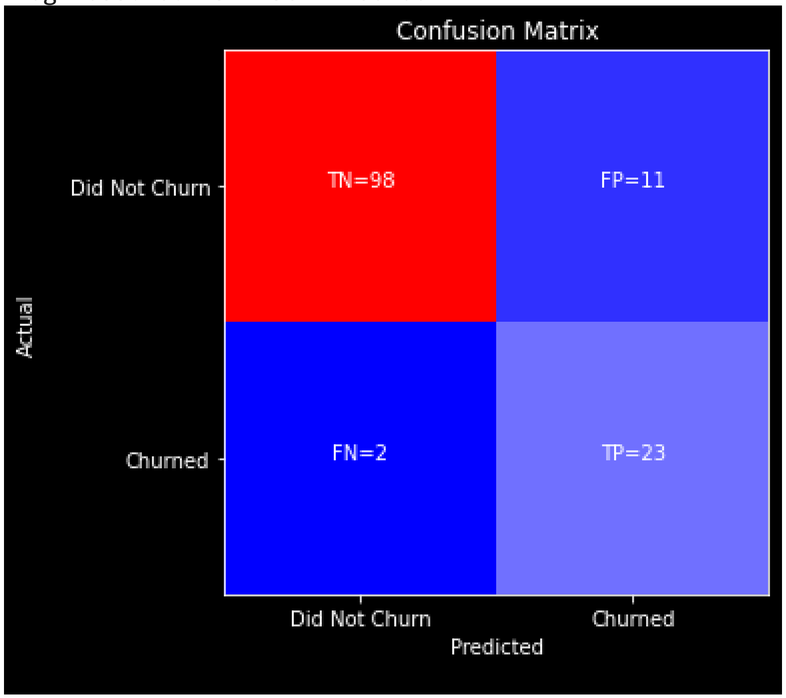
```
#scale verification X set
ver_X_test = scaler.transform(ver_X_test)
```

In [71]:

```
#Final Random Forest Modelling
classifiers = [
    RandomForestClassifier(bootstrap=False, criterion='gini', max_depth=100,
                           min_samples_split=2, n_estimators=1000, max_features=3,
                           class_weight='balanced', warm_start=True, n_jobs=None,
                           random_state=42)]

#putting results3 in df
res_cols=["Classifier", "Accuracy", "Log Loss", "Cross Val", "Recall", "Roc Auc","F1",
```

```
            "False Positive Rate", "Error Rate"]
results3 = pd.DataFrame(columns=res_cols)

for clf in classifiers:
    clf.fit(res_X_train, res_y_train)
    name = clf.__class__.__name__

    print("\n"*3)
    print(name,"results3:")

    print('~'*40)
    ver_y_pred = clf.predict(ver_X_test)
    acc = accuracy_score(ver_y_test, ver_y_pred)
    print("Accuracy: {:.4%}".format(acc))

    cv= np.mean(cross_val_score(clf, res_X_train, res_y_train, cv=10))
    print("Cross validation scores:",cv)


    train_predictions = clf.predict_proba(ver_X_test)
    logloss = log_loss(ver_y_test, train_predictions)
    print("Log Loss: {}".format(logloss))

    cm = confusion_matrix(ver_y_test, ver_y_pred)

    cm_plot(cm)

    #FPR and Error Rate setup
    tn, fp, fn, tp = confusion_matrix(ver_y_test,ver_y_pred).ravel()

    fpr = fp/(tn+fp)
    ers = 1-acc
    rec= recall_score(ver_y_test, ver_y_pred)
    roc=roc_auc_score(ver_y_test, ver_y_pred, average='weighted')
    f1s=f1_score(ver_y_test, ver_y_pred, average='weighted')
    results3_final = pd.DataFrame([[name, round(acc*100,3), round(logloss,3),
                                    round(cv*100,3), round(rec*100,3), round(roc*100,3),
                                    round(f1s*100,3),round(fpr*100,3),round(ers*100,3)]],
                                  columns=res_cols)
    results3 = results3.append(results3_final)

print("*"*40)
```

```
RandomForestClassifier results3:
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Accuracy: 90.2985%
Cross validation scores: 0.7667602245388934
Log Loss: 0.42397438171986906
```




```
****************************************
```

In [72]:

```python
results3['Classifier'] = results3['Classifier'].replace(['RandomForestClassifier'],
                                                        'VerificationRandomForestClassifier')
results3.head()
```

Out[72]:

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate
0	VerificationRandomForestClassifier	90.299	0.424	76.676	92.0	90.954	90.83	10.092	9.701

In [73]:

```python
ml_results = pd.concat([results,results2,results3])
ml_results.reset_index(drop=True, inplace=True)
print("Shape",ml_results.shape)
ml_results.head(10)
```

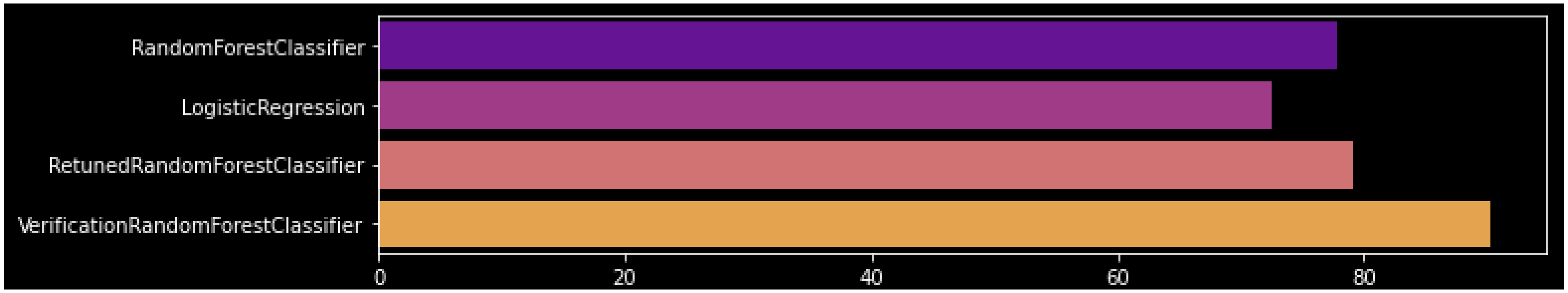
```
Shape (4, 9)
```

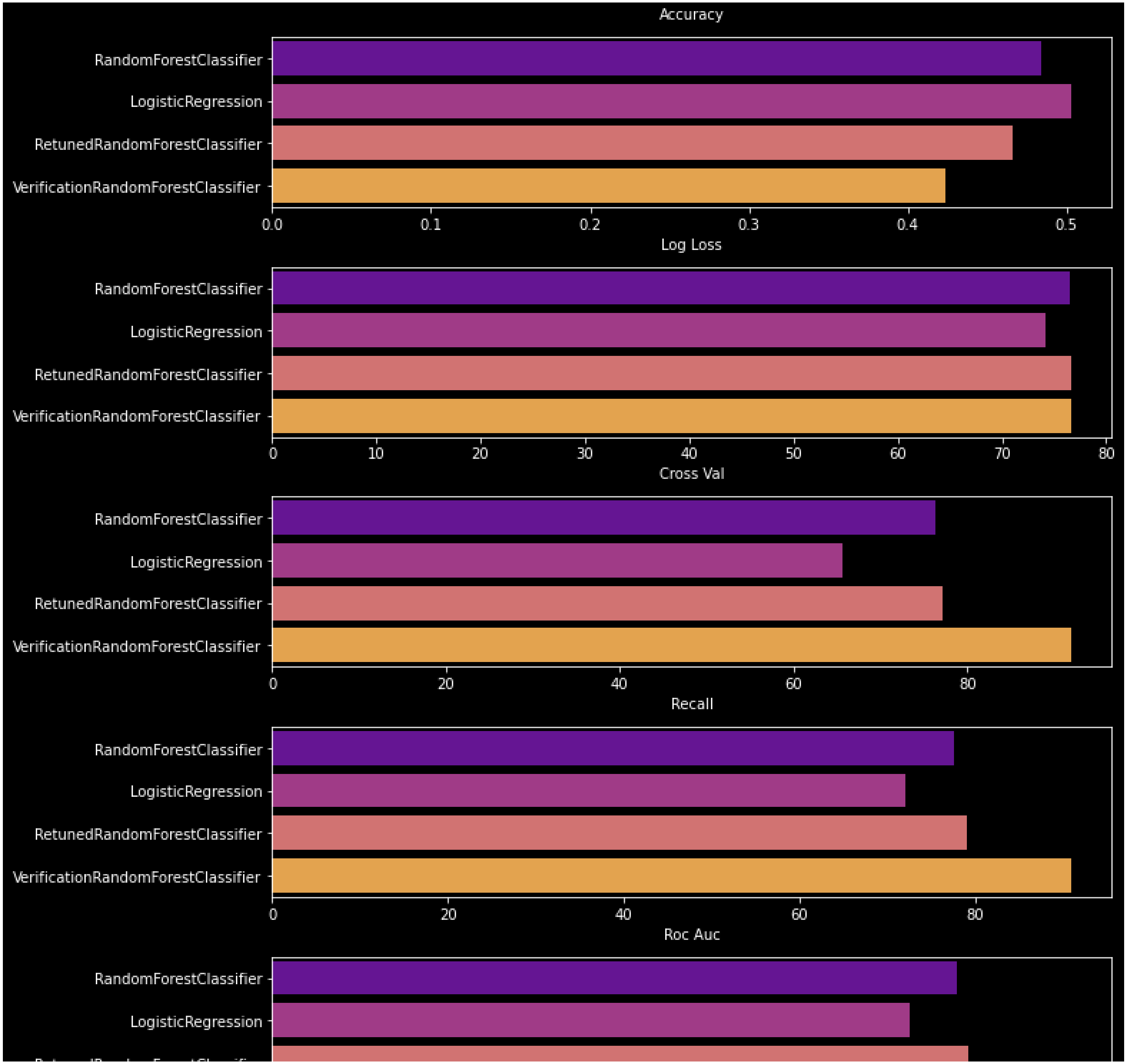
Out[73]:

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate

	Classifier	Accuracy	Log Loss	Cross Val	Recall	Roc Auc	F1	False Positive Rate	Error Rate
0	RandomForestClassifier	77.778	0.484	76.566	76.336	77.658	77.791	21.019	22.222
1	LogisticRegression	72.569	0.503	74.238	65.649	71.996	72.433	21.656	27.431
2	RetunedRandomForestClassifier	79.167	0.466	76.676	77.099	78.995	79.167	19.108	20.833
3	VerificationRandomForestClassifier	90.299	0.424	76.676	92.000	90.954	90.830	10.092	9.701

In [74]:
```
#Visualize scores for all models

fig, ax =plt.subplots(nrows=8, ncols=1, figsize = (11,18))

sns.barplot(x='Accuracy', y='Classifier', data=ml_results, palette='plasma', ax=ax[0])
sns.barplot(x='Log Loss', y='Classifier', data=ml_results, palette='plasma', ax=ax[1])
sns.barplot(x='Cross Val', y='Classifier', data=ml_results, palette='plasma', ax=ax[2])
sns.barplot(x='Recall', y='Classifier', data=ml_results, palette='plasma', ax=ax[3])
sns.barplot(x='Roc Auc', y='Classifier', data=ml_results, palette='plasma', ax=ax[4])
sns.barplot(x='F1', y='Classifier', data=ml_results, palette='plasma', ax=ax[5])
sns.barplot(x='False Positive Rate', y='Classifier', data=ml_results, palette='plasma', ax=ax[6])
sns.barplot(x='Error Rate', y='Classifier', data=ml_results, palette='plasma', ax=ax[7])

#remove classifier label from y
ax[0].set(ylabel = '')
ax[1].set(ylabel = '')
ax[2].set(ylabel = '')
ax[3].set(ylabel = '')
ax[4].set(ylabel = '')
ax[5].set(ylabel = '')
ax[6].set(ylabel = '')
ax[7].set(ylabel = '')

plt.tight_layout()
plt.savefig('machinelearningresults.png')
plt.show()
```





Accuracy
RandomForestClassifier
LogisticRegression
RetunedRandomForestClassifier
VerificationRandomForestClassifier
0.0
0.1
0.2
0.3
0.4
0.5
Log Loss
RandomForestClassifier
LogisticRegression
RetunedRandomForestClassifier
VerificationRandomForestClassifier
0
10
20
30
40
50
60
70
80
Cross Val
RandomForestClassifier
LogisticRegression
RetunedRandomForestClassifier
VerificationRandomForestClassifier
0
20
40
60
80
Recall
RandomForestClassifier
LogisticRegression
RetunedRandomForestClassifier
VerificationRandomForestClassifier
0
20
40
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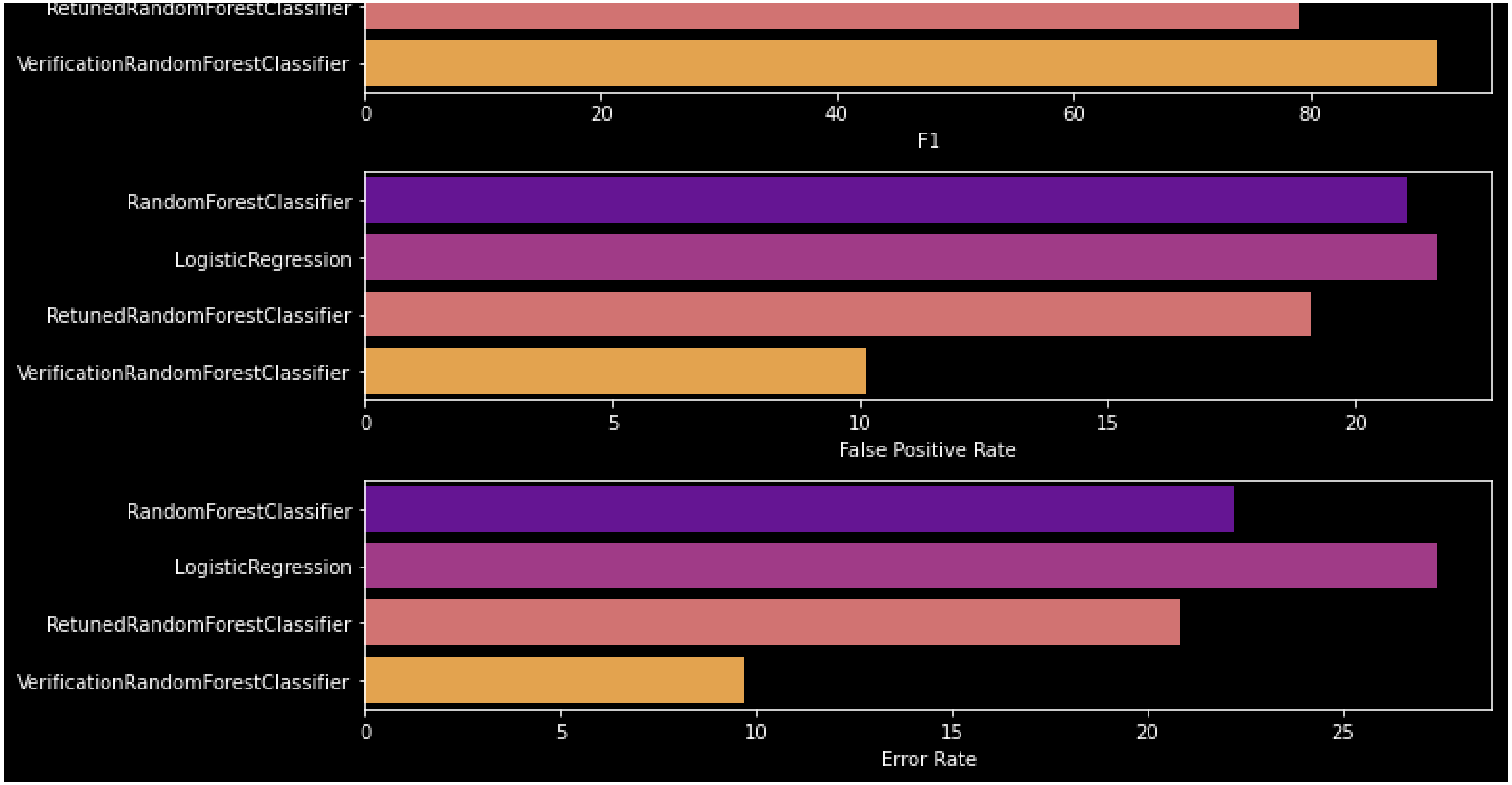
Roc Auc
RandomForestClassifier
LogisticRegression



In [75]:
```
ml_results.to_csv(r'ml_results.csv', index=False)
```