FINAL PROJECT - Customer Churn Machine Learning

```
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ikhail Nepomnyaschy
```

In [3]:
```
# Load Required Libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from sklearn.naive_bayes import GaussianNB # Gaussian Naive Bayes
from sklearn import tree #Look at documentation: http://scikit-learn.org/stable/m
from sklearn import model_selection
from sklearn import metrics
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn import cross_validation
from sklearn import tree
from sklearn import svm
from sklearn import ensemble
from sklearn import neighbors
from sklearn import linear_model
from sklearn import metrics
from sklearn import preprocessing
from sklearn.naive_bayes import GaussianNB

from sklearn.model_selection import train_test_split # Helping you divide your da
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
```

In [25]:
```
# Load the csv file and display first few entries
churn_df=pd.read_csv('customer_churn.csv')
churn_df.head()
```

Out[25]:

	State	Account Length	Area Code	Phone	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	...	Eve Calls	Eve Charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61

5 rows × 21 columns

In [26]:
```
# Before we can use the data we need to rename the columns to remove spaces and s
col_names = churn_df.columns.tolist()
print (col_names)
```

```
['State', 'Account Length', 'Area Code', 'Phone', "Int'l Plan", 'VMail Plan',
'VMail Message', 'Day Mins', 'Day Calls', 'Day Charge', 'Eve Mins', 'Eve Call
s', 'Eve Charge', 'Night Mins', 'Night Calls', 'Night Charge', 'Intl Mins', 'In
tl Calls', 'Intl Charge', 'CustServ Calls', 'Churn?']
```

In [27]:
```
# Rename columns
column_names = ['State','Acct_Len','Area_Code','Ph_Num','Int_Plan','Vmail','Vmail
                'Day_Calls','Day_Chrg','Evng_Mins','Evng_Calls','Evng_Chrg','Nigh
                'Night_Chrg','Intl_Mins','Intl_Calls','Intl_Chrg','CustServ_Calls
churn_df = pd.read_csv('customer_churn.csv', header = 0, names = column_names )
churn_df.head(5)
```

Out[27]:

	State	Acct_Len	Area_Code	Ph_Num	Int_Plan	Vmail	Vmail_Msg	Day_Mins	Day_Calls	Day_
0	KS	128	415	382-4657	no	yes	25	265.1	110	4
1	OH	107	415	371-7191	no	yes	26	161.6	123	2
2	NJ	137	415	358-1921	no	no	0	243.4	114	4
3	OH	84	408	375-9999	yes	no	0	299.4	71	5
4	OK	75	415	330-6626	yes	no	0	166.7	113	2

5 rows × 21 columns

In [28]:
```python
# Look to see what types of data we have and if there are any missing data
churn_df.info()
churn_df.describe(include='all')
#churn_df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
State            3333 non-null object
Acct_Len         3333 non-null int64
Area_Code        3333 non-null int64
Ph_Num           3333 non-null object
Int_Plan         3333 non-null object
Vmail            3333 non-null object
Vmail_Msg        3333 non-null int64
Day_Mins         3333 non-null float64
Day_Calls        3333 non-null int64
Day_Chrg         3333 non-null float64
Evng_Mins        3333 non-null float64
Evng_Calls       3333 non-null int64
Evng_Chrg        3333 non-null float64
Night_Mins       3333 non-null float64
Night_Calls      3333 non-null int64
Night_Chrg       3333 non-null float64
Intl_Mins        3333 non-null float64
Intl_Calls       3333 non-null int64
Intl_Chrg        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
```

Out[28]:

	State	Acct_Len	Area_Code	Ph_Num	Int_Plan	Vmail	Vmail_Msg	Day_Mins	D
count	3333	3333.000000	3333.000000	3333	3333	3333	3333.000000	3333.000000	333
unique	51	NaN	NaN	3333	2	2	NaN	NaN	
top	WV	NaN	NaN	398-2138	no	no	NaN	NaN	
freq	106	NaN	NaN	1	3010	2411	NaN	NaN	
mean	NaN	101.064806	437.182418	NaN	NaN	NaN	8.099010	179.775098	10
std	NaN	39.822106	42.371290	NaN	NaN	NaN	13.688365	54.467389	2
min	NaN	1.000000	408.000000	NaN	NaN	NaN	0.000000	0.000000	(
25%	NaN	74.000000	408.000000	NaN	NaN	NaN	0.000000	143.700000	8
50%	NaN	101.000000	415.000000	NaN	NaN	NaN	0.000000	179.400000	10
75%	NaN	127.000000	510.000000	NaN	NaN	NaN	20.000000	216.400000	11
max	NaN	243.000000	510.000000	NaN	NaN	NaN	51.000000	350.800000	16

11 rows × 21 columns

In [29]:
```
# We have some columns with categorical information
# Convert categorical values (Churn, Internation Calls and Voicemail options) to i
churn_df['Churn'] = churn_df['Churn'].map({'True.': 1, 'False.': 0})
churn_df['Int_Plan'] = churn_df['Int_Plan'].map({'yes': 1, 'no': 0})
churn_df['Vmail'] = churn_df['Vmail'].map({'yes': 1, 'no': 0})
churn_df.head(5)
```

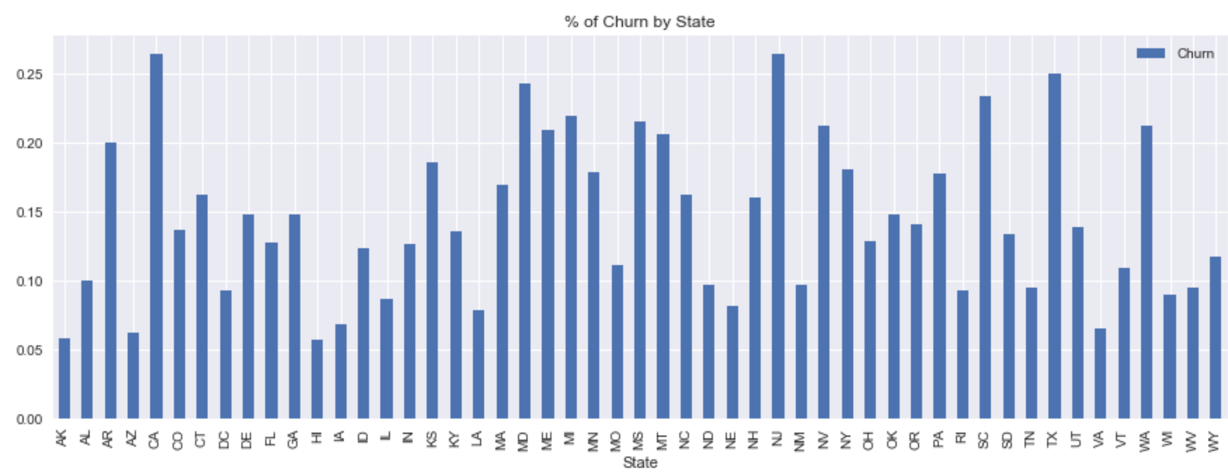
Out[29]:

	State	Acct_Len	Area_Code	Ph_Num	Int_Plan	Vmail	Vmail_Msg	Day_Mins	Day_Calls	Day_(
0	KS	128	415	382-4657	0	1	25	265.1	110	4
1	OH	107	415	371-7191	0	1	26	161.6	123	2
2	NJ	137	415	358-1921	0	0	0	243.4	114	4
3	OH	84	408	375-9999	1	0	0	299.4	71	5
4	OK	75	415	330-6626	1	0	0	166.7	113	2

5 rows × 21 columns

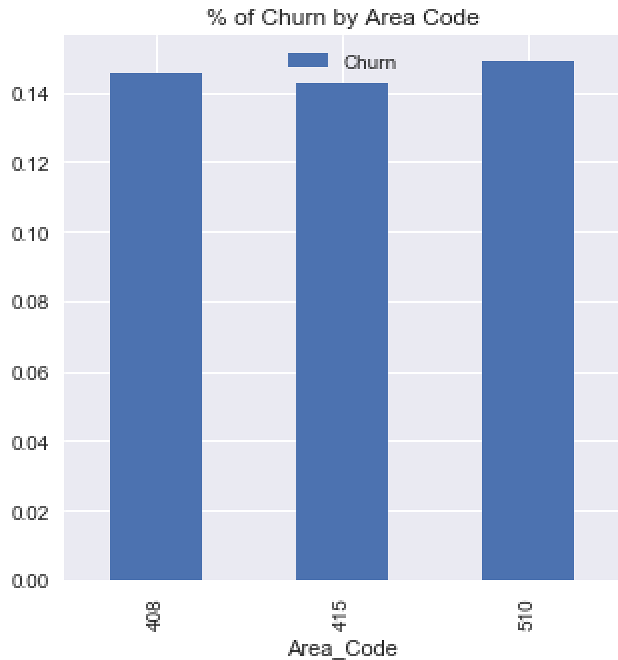
In [9]:
```
# Remove columns with little to no predictive power
# Right off the bat, we see that there are 3333 unique phone numbers meaning one 
# So Ph_Num will definitely not be helpful for this modelling
# Let us look to see if State or Area_Code have any correlation to Churn
```

In [30]:
```
# Churn by State
churn_by_state = pd.pivot_table(churn_df, values='Churn', index=['State'],aggfunc
churn_by_state.sort_values(by='Churn', ascending=False)
churn_by_state.plot.bar(title='% of Churn by State',figsize=(15,5));
```



In [11]:
```
# Doesn't seem like State plays a role in predicting Churn
```

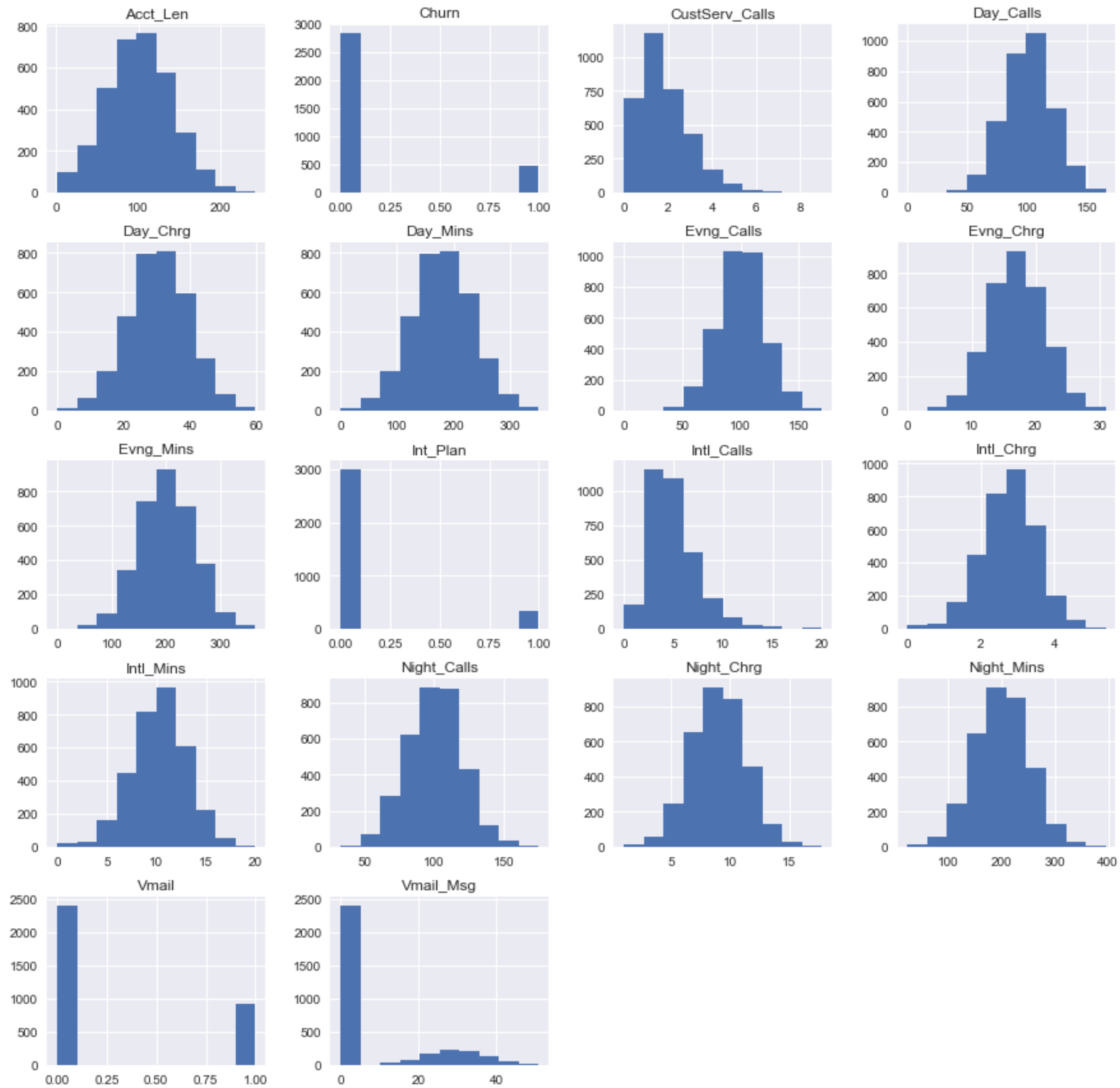
In [31]:
```
# Churn by Area_Code
churn_by_area_code = pd.pivot_table(churn_df, values='Churn', index=['Area_Code']
churn_by_area_code.sort_values(by='Churn', ascending=False)
churn_by_area_code.plot.bar(title='% of Churn by Area Code',figsize=(5,5));
```



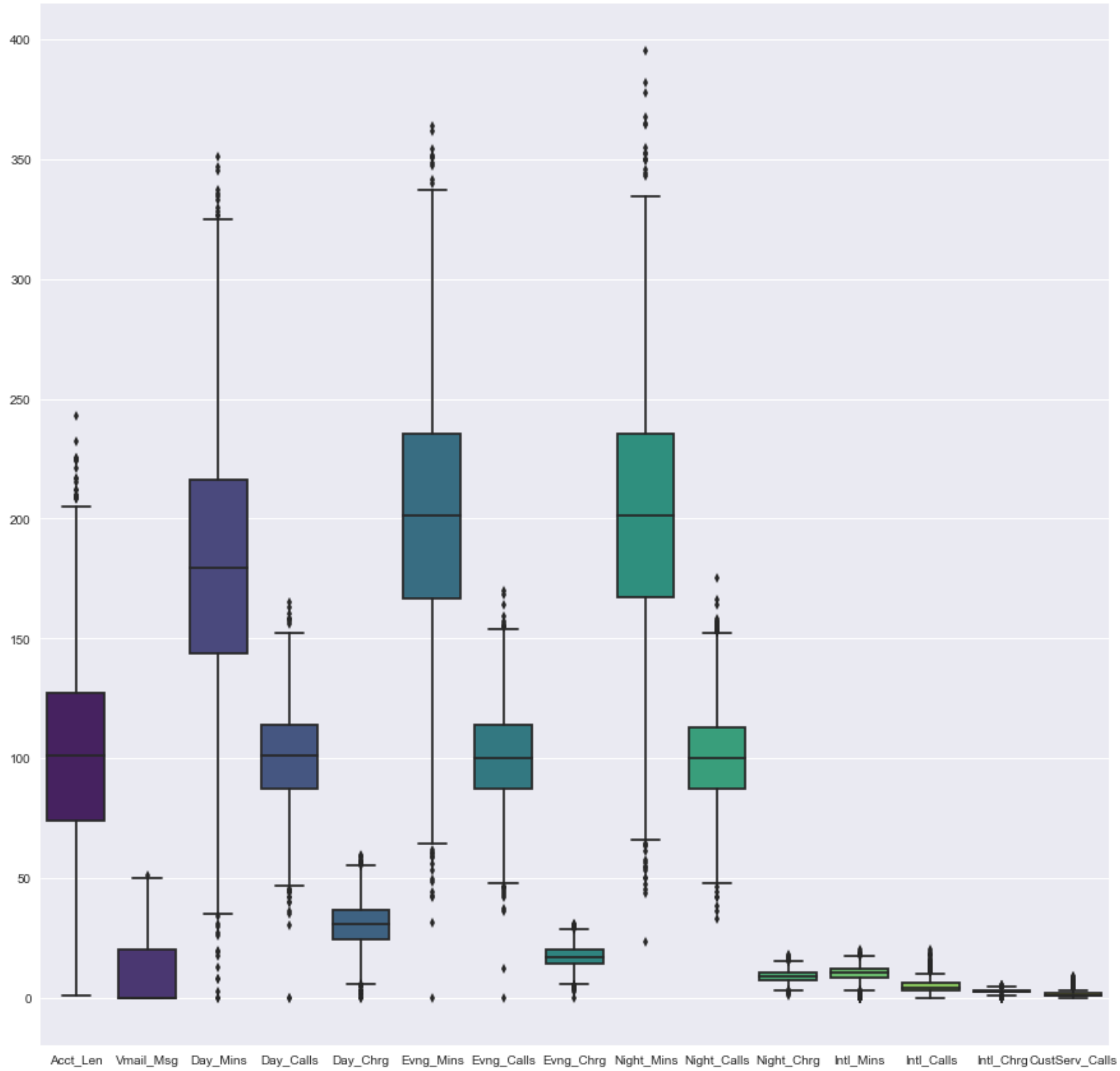
In [13]:
```
# Doesn't seem like Area_Code plays a role in predicting Churn either
```

In [32]:
```
# For now let us remove State, Area_Code and Ph_Num from our dataframe
churn_df = churn_df.drop(['State', 'Area_Code','Ph_Num'], axis=1)
churn_df.head();
```

In [33]:
```
#Visualizing the distribution the data
churn_df.hist();
```



In [20]:
```
# Make boxplots for the data to see if any of them have large outliers
# Removing the categorical attributes for graphing purposes since values are alway
# Creating a new dataframe without the categorical data
churn_stats_df = churn_df.drop(['Int_Plan','Vmail','Churn'],axis = 1)
sns.boxplot(data=churn_stats_df, palette='viridis')
sns.set(rc={'figure.figsize':(15,15)})
```



In [35]:
```
# From both the histogram and the boxplots we see that some of these numerical ca
# Whereas others have a large enough distribution
# Need to create a dataframe without skewed distribution before we can remove the
# This is done so as to not remove valuable data from the skewed attributes
non_skew_churn = churn_stats_df.drop(['Intl_Mins','Night_Chrg','Intl_Calls','Intl_
non_skew_churn.head()
```

Out[35]:

	Acct_Len	Vmail_Msg	Day_Mins	Day_Calls	Day_Chrg	Evng_Mins	Evng_Calls	Evng_Chrg	Nig
0	128	25	265.1	110	45.07	197.4	99	16.78	
1	107	26	161.6	123	27.47	195.5	103	16.62	
2	137	0	243.4	114	41.38	121.2	110	10.30	
3	84	0	299.4	71	50.90	61.9	88	5.26	
4	75	0	166.7	113	28.34	148.3	122	12.61	

In [36]:
```
# Removing outliers that are more than 3 standard deviations from the mean
clean_churn_df = non_skew_churn[non_skew_churn.apply(lambda x: np.abs(x - x.mean(
```

In [37]:
```
# Now lets add back all the skewed and non numerical columns to this dataframe wi
# After we concate them we remove the rows with NaN (the ones that were outliers)
clean_churn_df = pd.concat([churn_df.loc[:,'Intl_Mins',], clean_churn_df], axis=1
clean_churn_df = pd.concat([churn_df.loc[:,'Night_Chrg',], clean_churn_df], axis=
clean_churn_df = pd.concat([churn_df.loc[:,'Intl_Calls',], clean_churn_df], axis=
clean_churn_df = pd.concat([churn_df.loc[:,'Intl_Chrg',], clean_churn_df], axis=1
clean_churn_df = pd.concat([churn_df.loc[:,'CustServ_Calls',], clean_churn_df], a
clean_churn_df = pd.concat([churn_df.loc[:,'Int_Plan',], clean_churn_df], axis=1)
clean_churn_df = pd.concat([churn_df.loc[:,'Vmail',], clean_churn_df], axis=1)
clean_churn_df = pd.concat([churn_df.loc[:,'Churn',], clean_churn_df], axis=1)
clean_churn_df.dropna(inplace = True)
```

In [38]:
```
clean_churn_df.info()
```

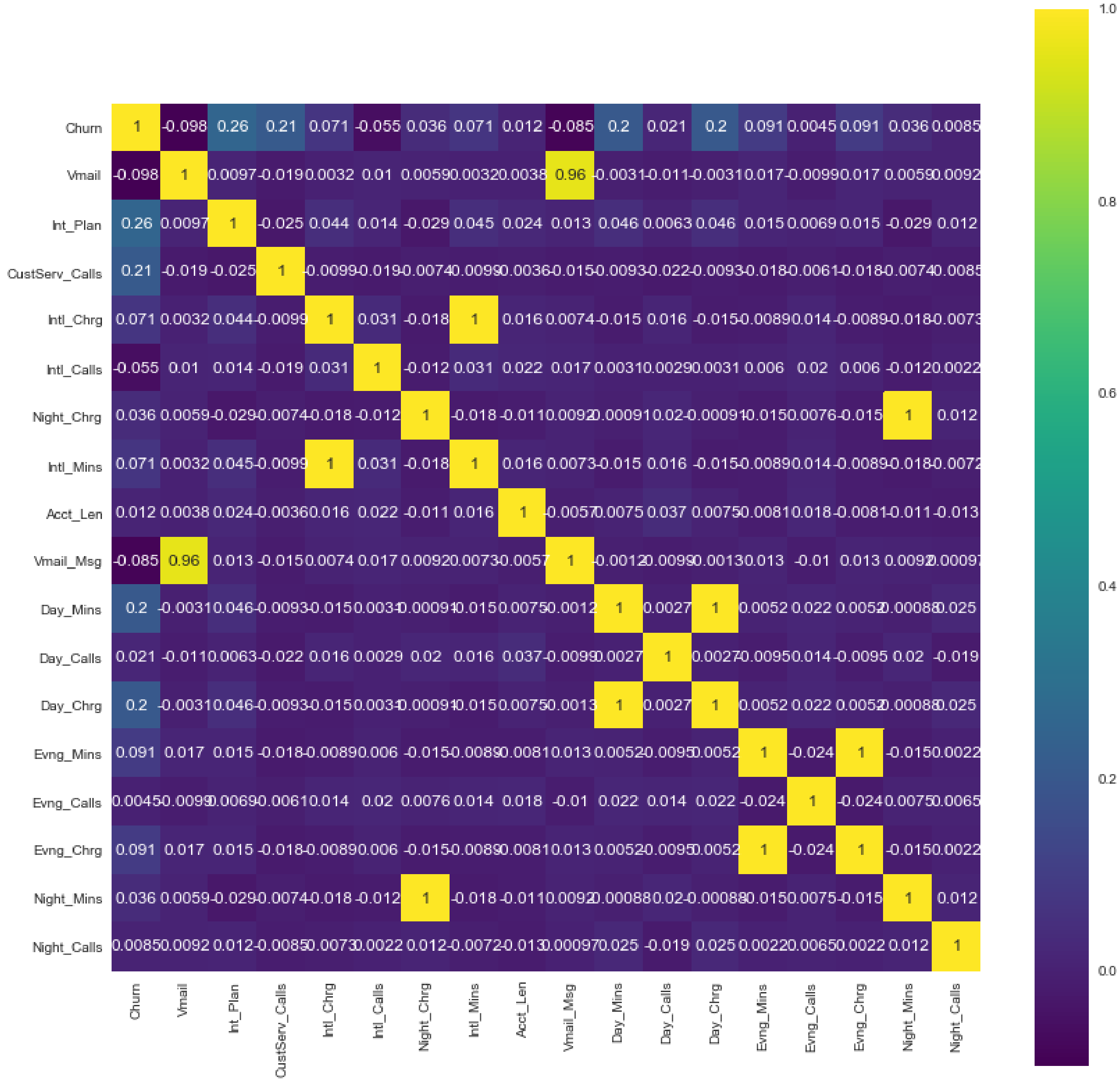
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3275 entries, 0 to 3332
Data columns (total 18 columns):
Churn             3275 non-null int64
Vmail             3275 non-null int64
Int_Plan          3275 non-null int64
CustServ_Calls    3275 non-null int64
Intl_Chrg         3275 non-null float64
Intl_Calls        3275 non-null int64
Night_Chrg        3275 non-null float64
Intl_Mins         3275 non-null float64
Acct_Len          3275 non-null float64
Vmail_Msg         3275 non-null float64
Day_Mins          3275 non-null float64
Day_Calls         3275 non-null float64
Day_Chrg          3275 non-null float64
Evng_Mins         3275 non-null float64
Evng_Calls        3275 non-null float64
Evng_Chrg         3275 non-null float64
Night_Mins        3275 non-null float64
Night_Calls       3275 non-null float64
dtypes: float64(13), int64(5)
memory usage: 486.1 KB
```

In [40]:
```
# We see that the data has dropped from 3332 records to 3275 records after removi
# Calculate the total number and percent of Churn in this new dataset
churn_sum = clean_churn_df['Churn'].sum()
churn_mean = clean_churn_df['Churn'].mean()
print("Total Churn for this data set is", np.round(churn_sum,decimals = 2))
print("Churn rate for this data set is ", np.round(churn_mean*100,decimals = 2),"
```

```
Total Churn for this data set is 472
Churn rate for this data set is 14.41%
```

In [41]:

```
# Look to see the correlation amongst the attributes
corrmat=clean_churn_df.corr(method='pearson')
f, ax = plt.subplots(figsize=(14, 14))
# Draw the heatmap using seaborn
sns.heatmap(corrmat, vmax=1, square=True, cmap="viridis", annot=True)
plt.show()
```



In [42]:
```
# Figure out which categories show the strongest correlation with Churn
churn_corellation = churn_df[clean_churn_df.columns].corr()['Churn'][1:]
churn_corellation.sort_values(ascending=False)
```

Out[42]:
```
Int_Plan          0.259852
CustServ_Calls    0.208750
Day_Mins          0.205151
Day_Chrg          0.205151
Evng_Mins         0.092796
Evng_Chrg         0.092786
Intl_Chrg         0.068259
Intl_Mins         0.068239
Night_Chrg        0.035496
Night_Mins        0.035493
Day_Calls         0.018459
Acct_Len          0.016541
Evng_Calls        0.009233
Night_Calls       0.006141
Intl_Calls       -0.052844
Vmail_Msg        -0.089728
Vmail            -0.102148
Name: Churn, dtype: float64
```

Based on this it seems like the strongest attributes are whether or not the customer has an international plan, number of times they have called customer service, number of Daytime mins and Daytime mins charge

Modelling of the Churn Data

We have established that the dataset is not balanced given that amount of Churn is only about 14.4%. This means that the sample data available would not be ideal for a simple split of data into test and train for machine learning. We should train the model on a large portion of the dataset. Otherwise we'll fail to read and recognise the underlying trend in the data. This will eventually result in a higher bias.

Instead what we should do is a k-fold cross validation, more specifically a stratified k-fold cross validation. This method allows the whole data set to be used for both training and validation. Stratification is the process of rearranging the data so as to ensure that each fold is a good representative of the whole.It is generally a better approach when dealing with both bias and variance. A randomly selected fold might not adequately represent the minor class, particularly in cases where there is a huge class imbalance. Simply put the number of folds (e.g k = 10) would split the data into 10 subsamples and the cross validation process is repeated 10 times with each subsample being used as the test sample and the remaining 9 being used as the training. Then the average accuracy of all the validations can be used to produce a single value of estimation.

In [43]:
```
# Remove the Churn values from the data set and store it as the response value
y = clean_churn_df['Churn'].as_matrix().astype(np.int)
clean_churn_df = clean_churn_df.drop(['Churn'], axis=1)
clean_churn_df.head()
```

Out[43]:

	Vmail	Int_Plan	CustServ_Calls	Intl_Chrg	Intl_Calls	Night_Chrg	Intl_Mins	Acct_Len	Vmail_M
0	1	0	1	2.70	3	11.01	10.0	128.0	2
1	1	0	1	3.70	3	11.45	13.7	107.0	2
2	0	0	0	3.29	5	7.32	12.2	137.0	(
3	0	1	2	1.78	7	8.86	6.6	84.0	(
4	0	1	3	2.73	3	8.41	10.1	75.0	(

In [44]:
```
#Convert the dataframe into a numpy matrix for cross validation
X = clean_churn_df.as_matrix().astype(np.float)
X
```

Out[44]:
```
array([[  1.  ,   0.  ,   1.  , ...,  16.78, 244.7 ,  91.  ],
       [  1.  ,   0.  ,   1.  , ...,  16.62, 254.4 , 103.  ],
       [  0.  ,   0.  ,   0.  , ...,  10.3 , 162.6 , 104.  ],
       ...,
       [  0.  ,   0.  ,   2.  , ...,  24.55, 191.9 ,  91.  ],
       [  0.  ,   1.  ,   2.  , ...,  13.57, 139.2 , 137.  ],
       [  1.  ,   0.  ,   0.  , ...,  22.6 , 241.4 ,  77.  ]])
```

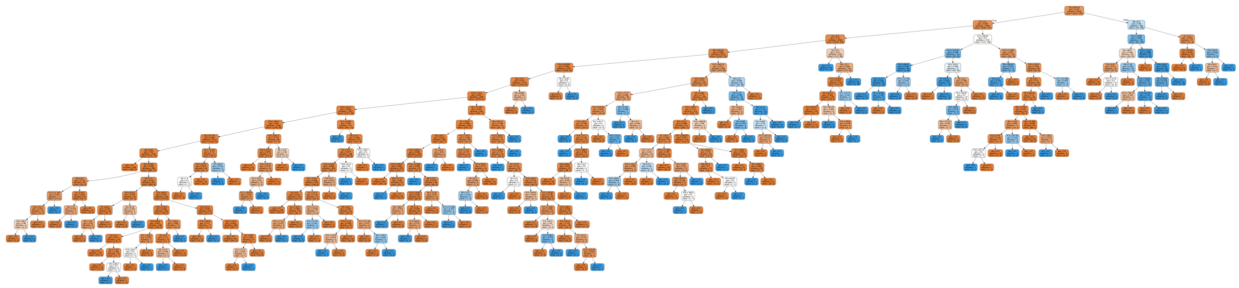
In [45]:
```
# Model 1
# Stratified K Fold modelling for Decision Tree
skf = cross_validation.StratifiedKFold(y, n_folds = 10, shuffle=True)
y_predicted = y.copy()
for train, test in skf:
    X_train, X_test = X[train], X[test]
    y_train = y[train]
    clf = tree.DecisionTreeClassifier()
    clf.fit(X_train,y_train)
    y_predicted[test] = clf.predict(X_test)

print('Accuracy with Decision Tree:{:.2f}' .format(metrics.accuracy_score(y, y_pr
```

```
Accuracy with Decision Tree:0.92
```

In [47]:
```
d_data = StringIO()
export_graphviz(clf, out_file=d_data,
                filled=True, rounded=True,
                special_characters=True)
graph = pydotplus.graph_from_dot_data(d_data.getvalue())
Image(graph.create_png())
```

Out[47]:



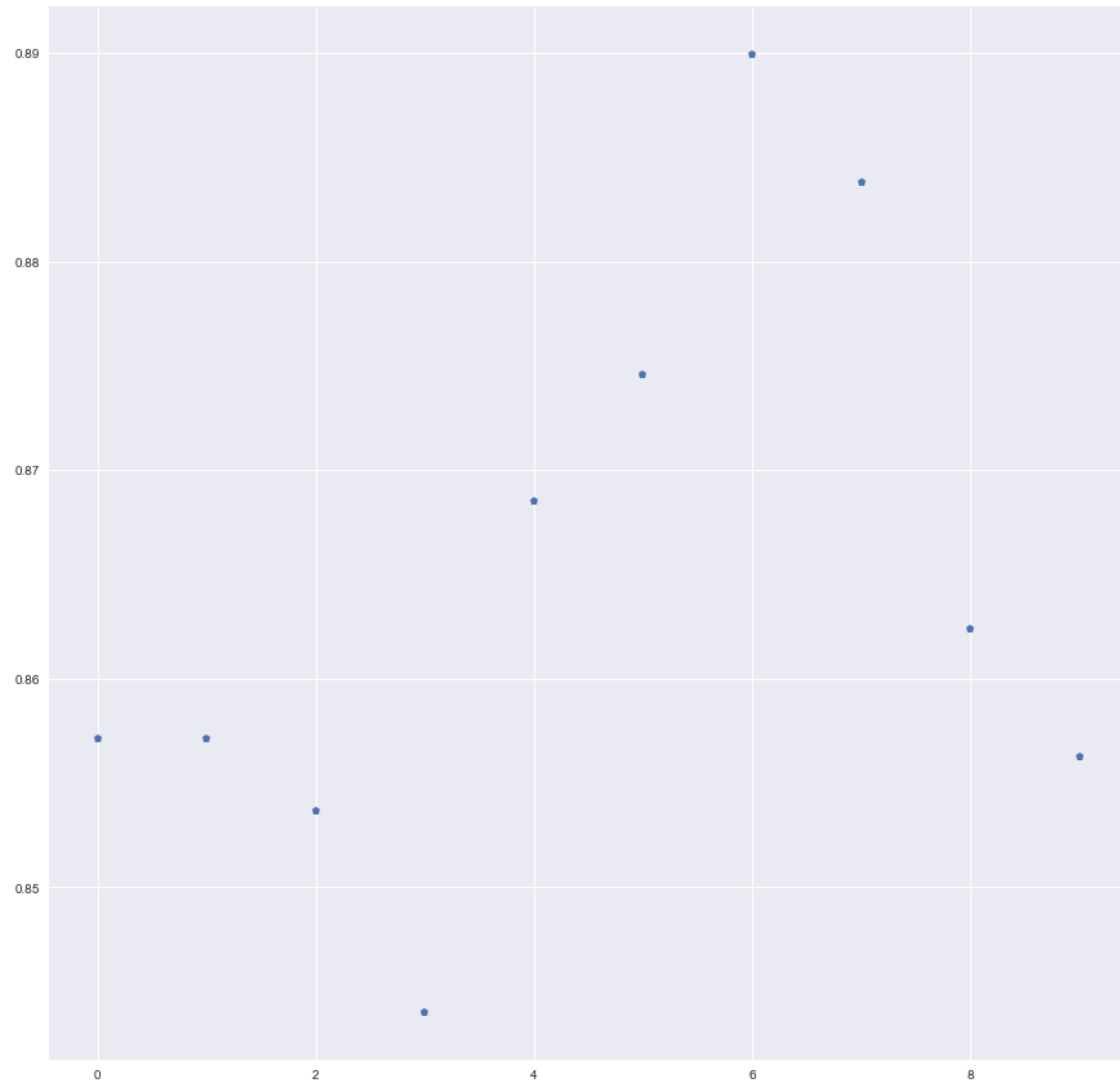
In [53]:
```
# Model 2
# Stratified K Fold modelling for Naive Bayes
skf = cross_validation.StratifiedKFold(y, n_folds = 10, shuffle=True)
y_predicted = y.copy()
for train, test in skf:
    X_train, X_test = X[train], X[test]
    y_train = y[train]
    clf = GaussianNB()
    clf.fit(X_train,y_train)
    y_predicted[test] = clf.predict(X_test)

print('Accuracy with Naive Bayes: {:.2f}' .format(metrics.accuracy_score(y, y_pre
```

```
Accuracy with Naive Bayes: 86.23%
```

In [54]:
```
clfCV= cross_validation.cross_val_score(clf,X,y,cv=10)
plt.plot(clfCV,"p")
```

Out[54]:
```
[<matplotlib.lines.Line2D at 0x113f592e8>]
```



In [56]:
```
# Model 3
# Stratified K Fold modelling for Gradient Boosting Classifier
skf = cross_validation.StratifiedKFold(y, n_folds = 10, shuffle=True)
y_predicted = y.copy()
for train, test in skf:
    X_train, X_test = X[train], X[test]
    y_train = y[train]
    clf = ensemble.GradientBoostingClassifier()
    clf.fit(X_train,y_train)
    y_predicted[test] = clf.predict(X_test)

print('Accuracy with Gradient Boosting Classifier: {:.2f}' .format(metrics.accura
```

```
Accuracy with Gradient Boosting Classifier: 95.45%
```

In [57]:
```
# Model 4
# Stratified K Fold modelling for Random Forest Classifier
skf = cross_validation.StratifiedKFold(y, n_folds = 10, shuffle=True)
y_predicted = y.copy()
for train, test in skf:
    X_train, X_test = X[train], X[test]
    y_train = y[train]
    clf = ensemble.RandomForestClassifier()
    clf.fit(X_train,y_train)
    y_predicted[test] = clf.predict(X_test)

print('Accuracy with Random Forest Classifier: {:.2f}' .format(metrics.accuracy_s
```

```
Accuracy with Random Forest Classifier: 94.75%
```

In [58]:
```
# Model 5
# Stratified K Fold modelling for Logistic Regression
skf = cross_validation.StratifiedKFold(y, n_folds = 10, shuffle=True)
y_predicted = y.copy()
for train, test in skf:
    X_train, X_test = X[train], X[test]
    y_train = y[train]
    clf = linear_model.LogisticRegression()
    clf.fit(X_train,y_train)
    y_predicted[test] = clf.predict(X_test)

print('Accuracy with Logistic Regression: {:.2f}' .format(metrics.accuracy_score(
```

```
Accuracy with Logistic Regression: 86.02%
```

Summary of Results

Accuracy with Logistic Regression: 0.86

Accuracy with Naive Bayes: 0.86

Accuracy with Decision Tree: 0.91

Accuracy with Random Forest Classifier: 0.95

Accuracy with Gradient Boosting Classifier: 0.95

Conclusion

Random Forest Classifier or Gradient Boosting Classifier gives the best predictions and hence are the preferred predictive model for this analysis.

In [ ]: