Data Dogs Group Project

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In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import model_selection

from sklearn.model_selection import cross_val_score
from sklearn.model_selection import learning_curve
from sklearn.model_selection import train_test_split # Helping you divid
e your datasets to train/test(validation)

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import r2_score


%matplotlib inline
fg_width = 20
fg_height = 10
plt.figure(figsize=(fg_width, fg_height))
```

Out[1]:
```
<matplotlib.figure.Figure at 0x109a88198>
```

```
<matplotlib.figure.Figure at 0x109a88198>
```

Data Preparation and Pre-prediction Analysis

In [2]:
```
# Read customer churn data into a pandas DataFrame
customer_churn_data = pd.read_csv("../datasets/customer_churn.csv")
customer_churn_data.head()
```

Out[2]:

	State	Account Length	Area Code	Phone	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	...	Eve Calls	Cl
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12

5 rows × 21 columns

Initial Observations

- 3333 datasets in total
- People spend about 100-120 mins on average during day, evening and night calls
- Area Code, State or Phone doesn't seem that important vis-à-vis customer churn
- Customer service calls might be important as people usually call more when they have complaints
- International calls are the most expensive, than day > evening > night in the following order

In [3]:
```
customer_churn_data.describe()
```

Out[3]:

	Account Length	Area Code	VMail Message	Day Mins	Day Calls	Day Charge	
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	2
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	5
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	1
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	2
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	2
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	3

In [4]:
```
customer_churn_data.describe(include=['O'])
```

Out[4]:

	State	Phone	Int'l Plan	VMail Plan	Churn?
count	3333	3333	3333	3333	3333
unique	51	3333	2	2	2
top	WV	421-6694	no	no	False.
freq	106	1	3010	2411	2850

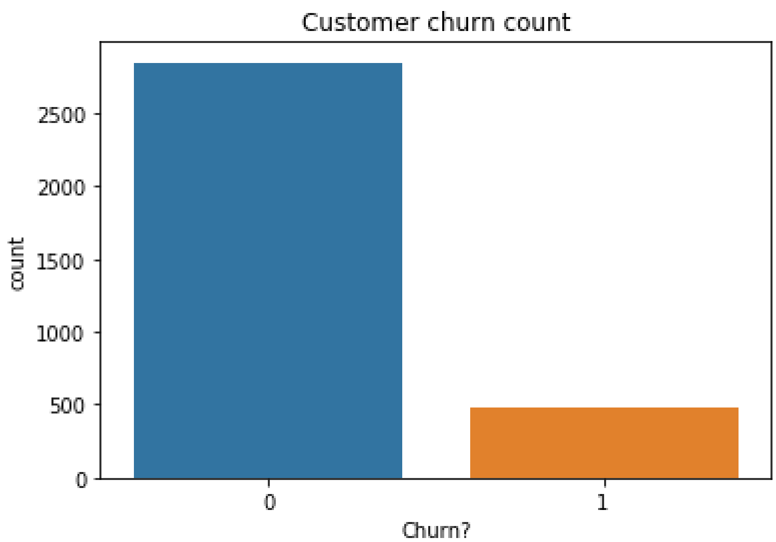
In [5]:
```
# Eliminate columns that do not affect the class
list_of_col_to_drop = ['State','Area Code', 'Phone']
customer_churn_data.drop(list_of_col_to_drop, axis=1, inplace=True)
```

In [6]:
```
# Replace categorical data to be numerical, so that it can be used for predictive modelling
customer_churn_data["Churn?"].replace({'True.': 1,'False.':0}, inplace=True)
customer_churn_data["Int'l Plan"].replace({'yes': 1,'no':0}, inplace=True)
customer_churn_data["VMail Plan"].replace({'yes': 1,'no':0}, inplace=True)
```

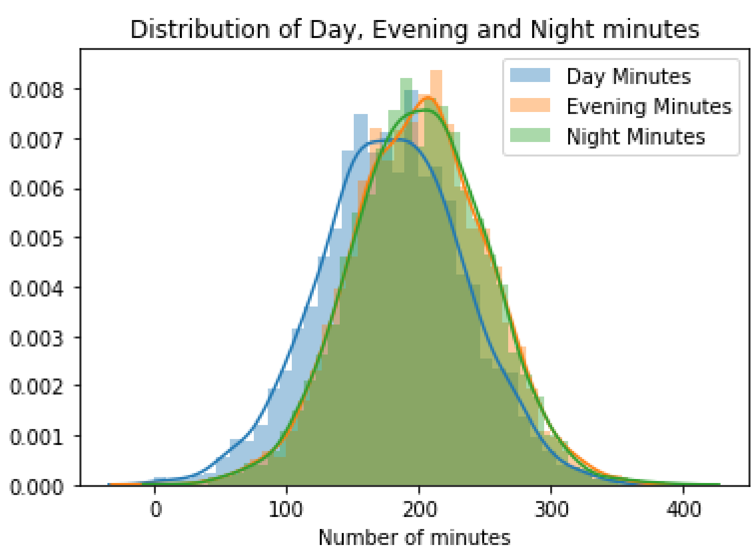
In [7]:
```
# Add new columns that calculate total mins, charge, calls
customer_churn_data['Total Mins'] = customer_churn_data['Day Mins'] + customer_churn_data['Eve Mins'] + customer_churn_data['Night Mins']
customer_churn_data['Total Charge'] = customer_churn_data['Day Charge'] + customer_churn_data['Eve Charge'] + customer_churn_data['Night Charge']
customer_churn_data['Total Calls'] = customer_churn_data['Day Calls'] + customer_churn_data['Eve Calls'] + customer_churn_data['Night Calls']
```

In [8]:
```
# Get data frame for no churn vs churn customers
churn_customers = customer_churn_data.loc[customer_churn_data['Churn?']
== 1]
no_churn_customers = customer_churn_data.loc[customer_churn_data['Chur
n?'] == 0]
```

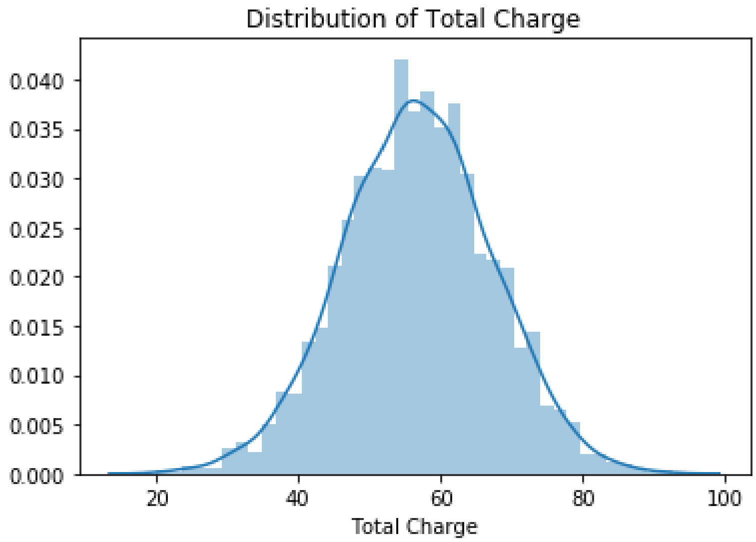
In [9]:
```
# See how many churns there are
sns.countplot(x="Churn?", data=customer_churn_data)
plt.title('Customer churn count')
plt.show()
```



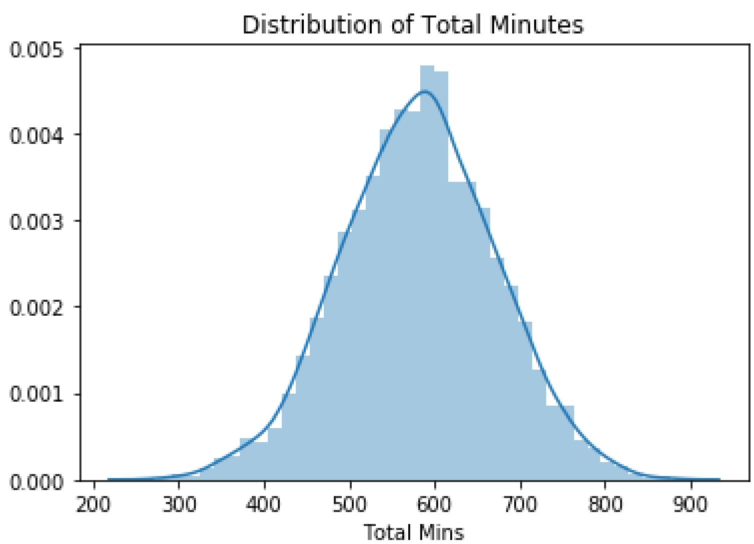
In [29]:
```
sns.distplot(customer_churn_data['Day Mins'], label='Day Minutes')
sns.distplot(customer_churn_data['Eve Mins'], label='Evening Minutes')
sns.distplot(customer_churn_data['Night Mins'], label='Night Minutes')

plt.title('Distribution of Day, Evening and Night minutes')
plt.xlabel('Number of minutes')
plt.legend()
plt.show()
```



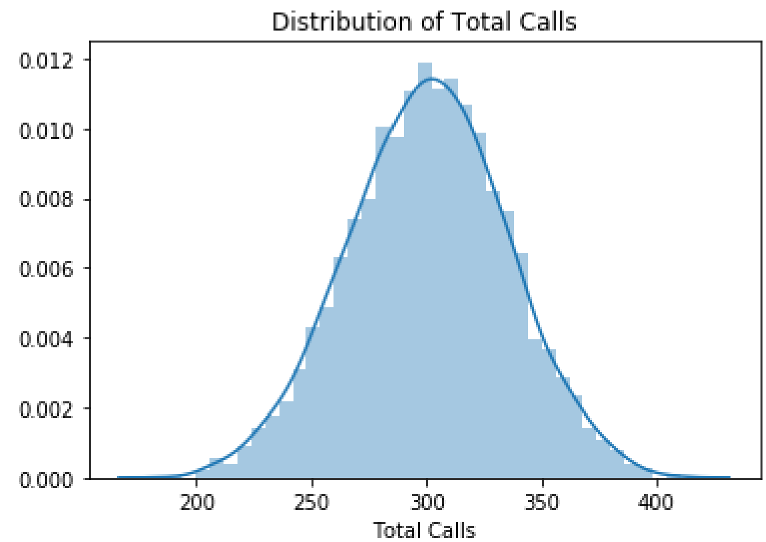
In [11]:
```
sns.distplot(customer_churn_data['Total Charge'])
plt.title('Distribution of Total Charge')
plt.show()
```



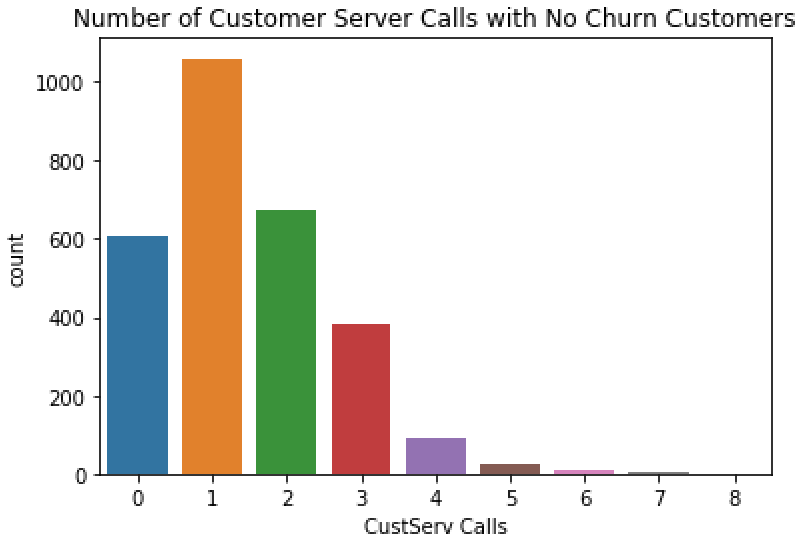
In [12]:
```
sns.distplot(customer_churn_data['Total Mins'])
plt.title('Distribution of Total Minutes')
plt.show()
```

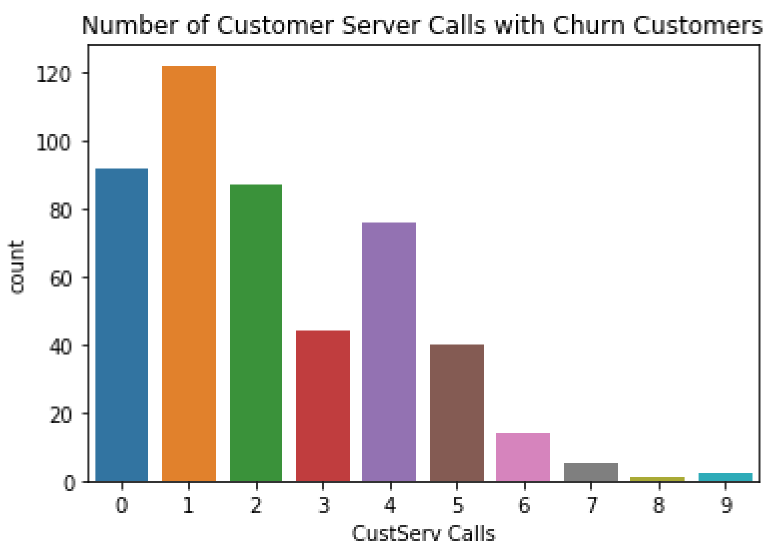


In [13]:
```
sns.distplot(customer_churn_data['Total Calls'])
plt.title('Distribution of Total Calls')
plt.show()
```

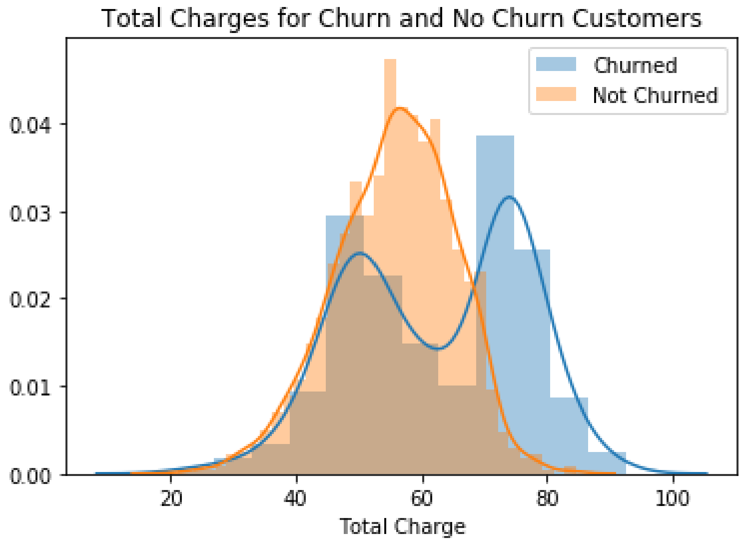


In [14]:
```
sns.countplot(x='CustServ Calls', data=no_churn_customers)
plt.title('Number of Customer Server Calls with No Churn Customers')
plt.show()

sns.countplot(x='CustServ Calls', data=churn_customers)
plt.title('Number of Customer Server Calls with Churn Customers')
plt.show()
```

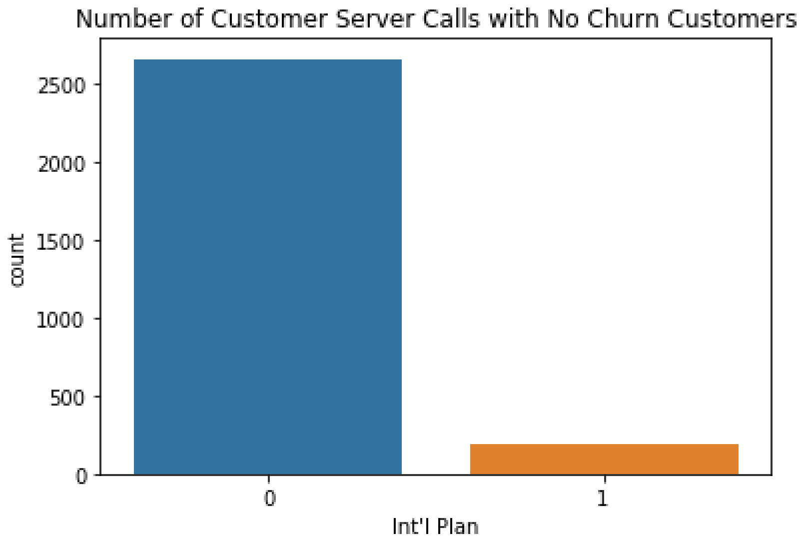


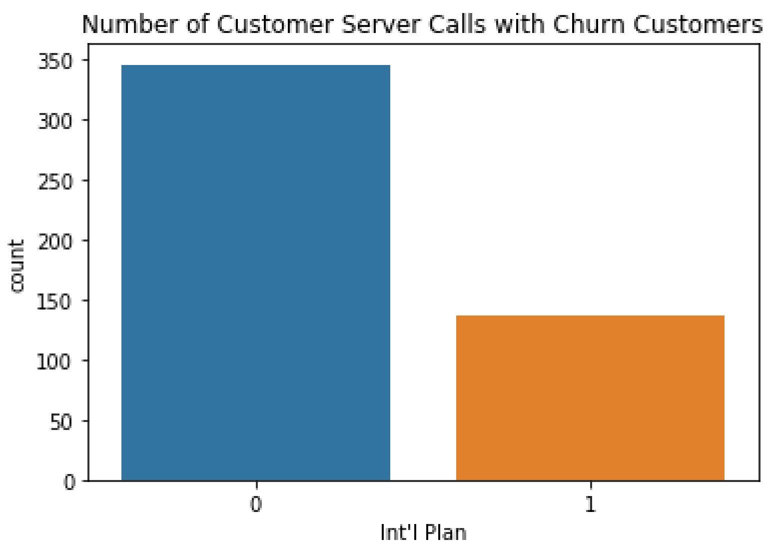


In [15]:
```
sns.distplot(churn_customers['Total Charge'], label='Churned')
sns.distplot(no_churn_customers['Total Charge'], label='Not Churned')
plt.title('Total Charges for Churn and No Churn Customers')
plt.legend()
plt.show()
```



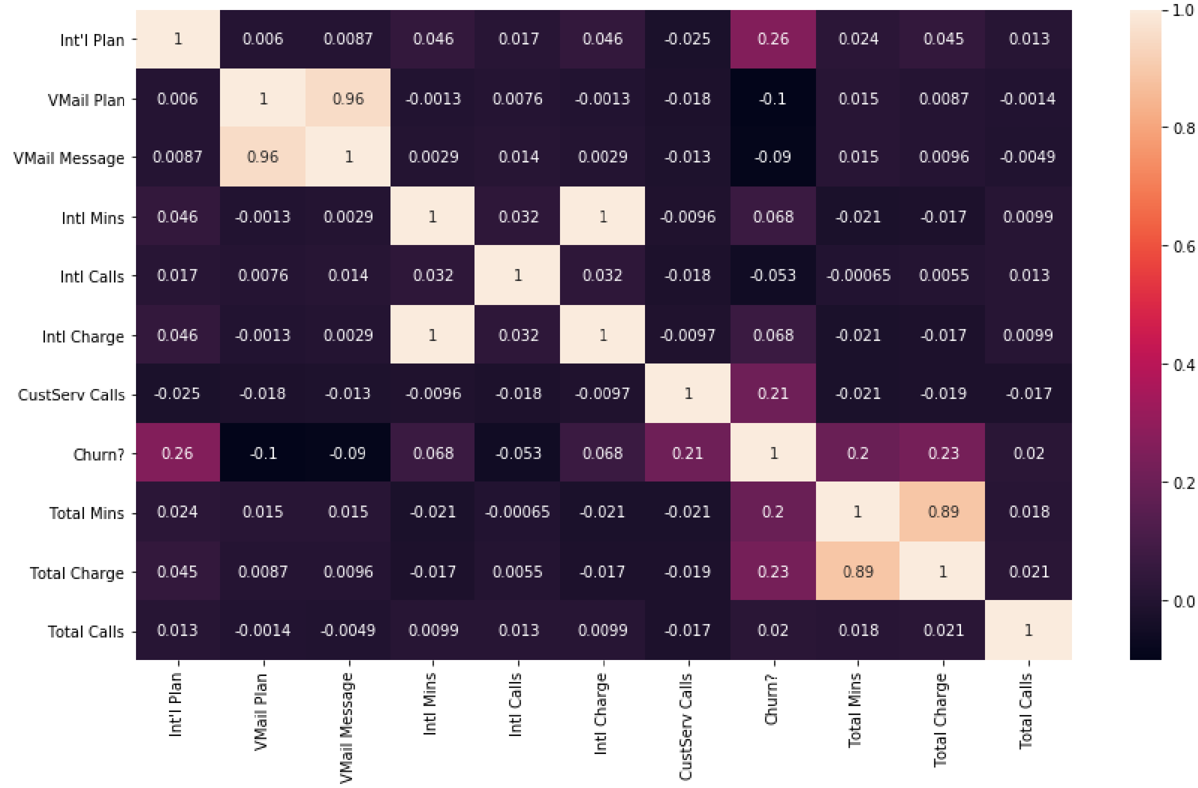
In [69]:
```
sns.countplot(x='Int\'l Plan', data=no_churn_customers)
plt.title('Number of Customer Server Calls with No Churn Customers')
plt.show()

sns.countplot(x='Int\'l Plan', data=churn_customers)
plt.title('Number of Customer Server Calls with Churn Customers')
plt.show()
```





In [16]:
```
# Create a new pandas data frame that takes the most relevant columns by
 dropping redundant data
dropped = ['Day Mins', 'Day Calls', 'Day Charge', 'Eve Mins', 'Eve Charg
e', 'Eve Calls',
           'Night Mins', 'Night Calls', 'Night Charge', 'Account Length']
correlation_pd = customer_churn_data.drop(dropped, axis=1)
```

In [48]:
```
plt.figure(figsize=(14, 8))
# Take the relevant variables and see their correlation with class
sns.heatmap(correlation_pd.corr(), annot=True)
plt.show()
```



Predictive Modelling (Classification)

In [18]:
```
# Prepare independent and dependent variable and split test in 0.25
X = customer_churn_data.drop('Churn?', axis=1)
y = customer_churn_data['Churn?']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25
)
```

In [19]:
```
# Naive Bayes
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
nb_predict = nb_model.predict(X_test)
nb_score = nb_model.score(X_test, y_test)
```

In [20]:
```
# Decision Tree
tree_model = DecisionTreeClassifier()
tree_model.fit(X_train, y_train)
tree_predict = tree_model.predict(X_test)
tree_score = tree_model.score(X_test, y_test)
```

In [21]:
```
# Random Forest
forest_model = RandomForestClassifier()
forest_model.fit(X_train, y_train)
forest_predict = forest_model.predict(X_test)
forest_score = forest_model.score(X_test, y_test)
```

In [22]:
```
predictions = [{'name': 'Naive Baynes', 'predict': nb_predict, 'model':
nb_model },
               {'name': 'Decision Tree', 'predict': tree_predict, 'mode
l': tree_model },
               {'name': 'Random Forest', 'predict': forest_predict, 'mod
el': forest_model }]

def get_results(fn):
    for p in predictions:
        fn(p)
```

In [23]:
```
# Get classification report
def get_classification_report(prediction):
    report = classification_report(y_test, prediction['predict'])
    print(prediction['name'], '\n', report)

get_results(get_classification_report)
```

```
Naive Baynes
              precision    recall  f1-score   support

          0       0.93      0.92      0.93       708
          1       0.58      0.63      0.61       126

avg / total       0.88      0.88      0.88       834

Decision Tree
              precision    recall  f1-score   support

          0       0.97      0.97      0.97       708
          1       0.82      0.86      0.84       126

avg / total       0.95      0.95      0.95       834

Random Forest
              precision    recall  f1-score   support

          0       0.96      0.99      0.98       708
          1       0.96      0.79      0.86       126

avg / total       0.96      0.96      0.96       834
```

image.png

In [24]:
```
# Calculate confusion matrix
def get_confusion_matrix(model):
    cm = confusion_matrix(y_test, model['predict'])
    print('Confusion matrix: \n', model['name'], '\n', cm)

get_results(get_confusion_matrix)
```

```
Confusion matrix:
 Naive Baynes
 [[650  58]
 [ 46  80]]
Confusion matrix:
 Decision Tree
 [[685  23]
 [ 18 108]]
Confusion matrix:
 Random Forest
 [[704   4]
 [ 27  99]]
```

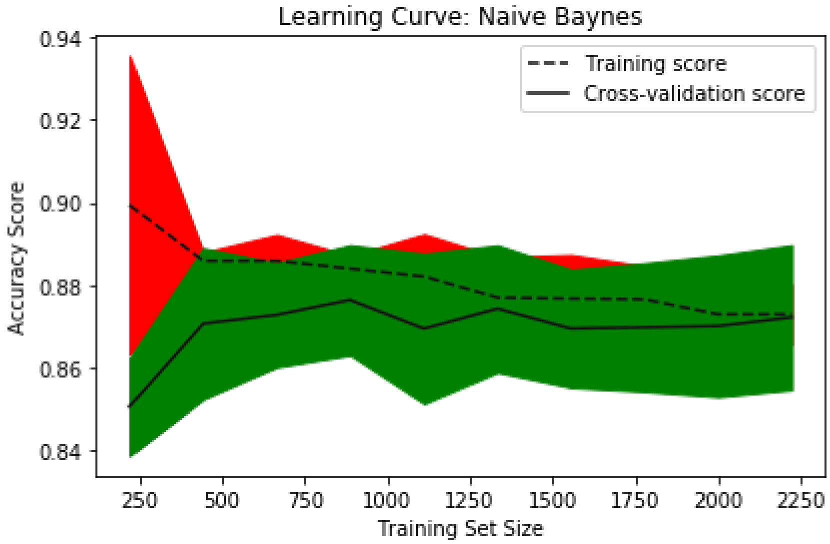
In [25]:
```
# Calculate Logarithmic Loss of model
scoring = 'neg_log_loss'

def get_log_loss(model):
    loss = cross_val_score(model['model'], X, y, cv=6, scoring=scoring )
    print('Cross-validated losses in 6 fold:\n', model['name'], loss)

get_results(get_log_loss)
```

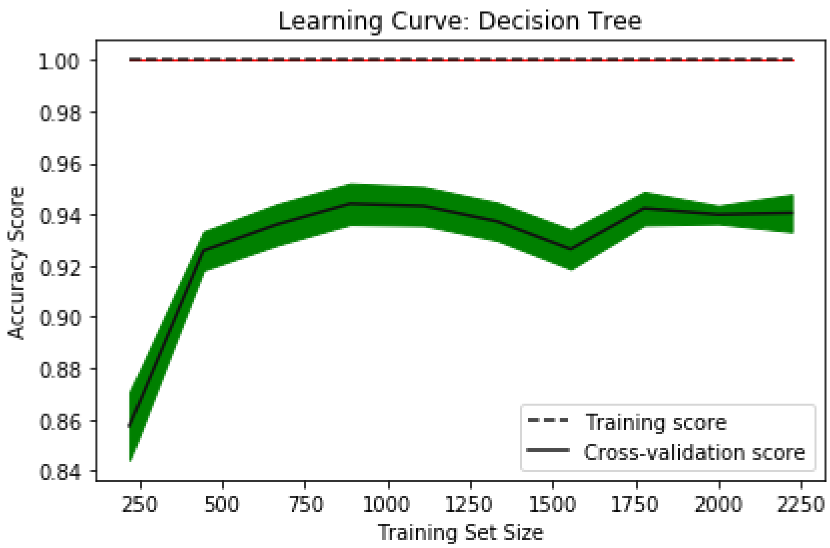
```
Cross-validated losses in 6 fold:
 Naive Baynes [-0.49809376 -0.45029937 -0.45924449 -0.29136882 -0.44007
926 -0.38739724]
Cross-validated losses in 6 fold:
 Decision Tree [-2.17420355 -1.98784325 -1.73936284 -1.86696089 -2.3025
8509 -1.43133668]
Cross-validated losses in 6 fold:
 Random Forest [-0.48992974 -0.48732101 -0.76925763 -0.35612072 -0.7243
8682 -0.39788344]
```

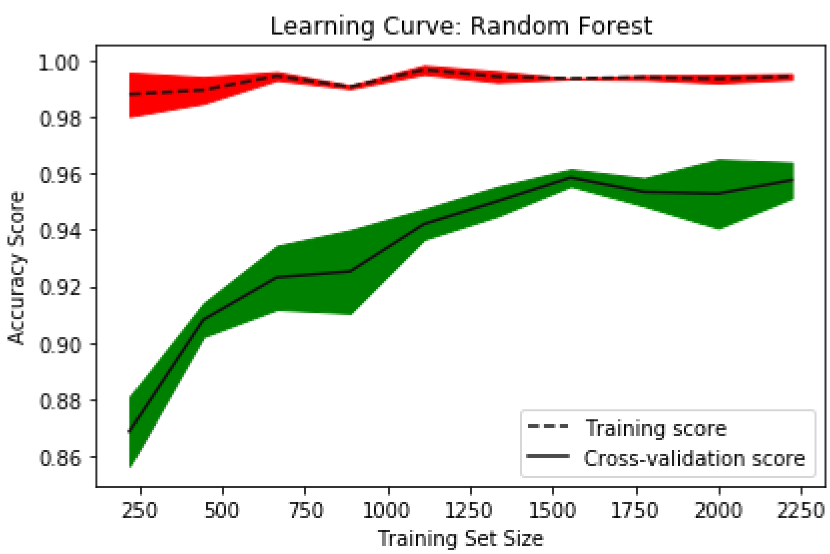
In [26]:
```
# Calculate R^2 score of model
def get_r2_score(model):
    score = r2_score(y_test, model['predict'])
    print('Cross-predicted accuracy: \n', model['name'], score)

get_results(get_r2_score)
```

```
Cross-predicted accuracy:
 Naive Baynes 0.027710519235943143
Cross-predicted accuracy:
 Decision Tree 0.6166935700834006
Cross-predicted accuracy:
 Random Forest 0.7101829432337907
```

In [27]:
```
# Calculate learning curve of model
# http://scikit-learn.org/stable/modules/learning_curve.html
def get_learning_curve(model):
    train_sizes, train_scores, valid_scores = learning_curve(
        model['model'], X, y, train_sizes=np.linspace(0.1, 1.0, 10),
                   exploit_incremental_learning=False,
                   n_jobs=1, pre_dispatch="all", verbose=0)
    # Create means and standard deviations of training set scores
    train_mean = np.mean(train_scores, axis=1)
    train_std = np.std(train_scores, axis=1)

    # Create means and standard deviations of test set scores
    test_mean = np.mean(valid_scores, axis=1)
    test_std = np.std(valid_scores, axis=1)

    # Draw lines
    plt.plot(train_sizes, train_mean, '--', color="#111111",  label="Tra
ining score")
    plt.plot(train_sizes, test_mean, color="#111111", label="Cross-valid
ation score")

    # Draw bands
    plt.fill_between(train_sizes, train_mean - train_std, train_mean + t
rain_std, color="r")
    plt.fill_between(train_sizes, test_mean - test_std, test_mean + test
_std, color="g")

    # Create plot
    model_name = 'Learning Curve: ' + model['name']
    plt.title(model_name)
    plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.l
egend(loc="best")
    plt.tight_layout()
    plt.show()


get_results(get_learning_curve)
```


Learning Curve: Naive Baynes
Training score
Cross-validation score
Accuracy Score
0.94
0.92
0.90
0.88
0.86
0.84
250 500 750 1000 1250 1500 1750 2000 2250
Training Set Size


Learning Curve: Decision Tree
Training score
Cross-validation score
Accuracy Score
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0.84
250 500 750 1000 1250 1500 1750 2000 2250
Training Set Size


Learning Curve: Random Forest
Training score
Cross-validation score
Accuracy Score
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
250 500 750 1000 1250 1500 1750 2000 2250
Training Set Size