Mount Dataset

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, c
all drive.mount("/content/drive", force_remount=True).
```

In [2]:

```
import os
ROOT = r'/content/drive/MyDrive/MEA'
os.chdir(ROOT)
assert os.getcwd() == ROOT
```

Importing Libraries

In [3]:

```
import time
import pandas as pd
import numpy as np
import pickle

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_roc_curve, accuracy_score, classification_report
from datetime import datetime

#Suppressing warnings
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Importing Dataset

In [4]:

```
df = pd.read_csv('Employee-Attrition.csv')
```

Data Source

Reading file from folder locations

In [5]:

```
print("Shape of Data: ",df.shape)
print('The missing columns in the dataset are: ',df.columns[df.isnull().any()].values)
df.head()
```

```
Shape of Data:  (1470, 35)
The missing columns in the dataset are:  []
```

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Ed
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	

In [6]:

```
#View some basic statistical details like percentile, mean, standard deviation etc.
df.describe()
```

Out[6]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	Employee
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	147(
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024
std	9.135373	403.509100	8.106864	1.024165	0.0	602
min	18.000000	102.000000	1.000000	1.000000	1.0	1
25%	30.000000	465.000000	2.000000	2.000000	1.0	491
50%	36.000000	802.000000	7.000000	3.000000	1.0	102(
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068

EDA

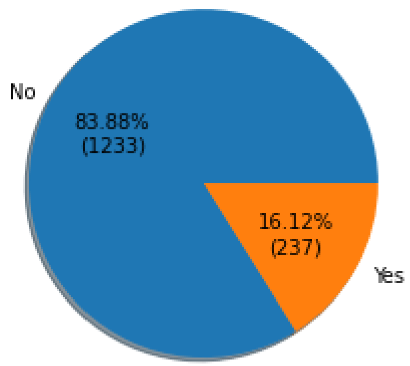
Number of employee oberall left or stayed in company

In [7]:

```
def per_val(x):
    print(x)
    return '{:.2f}%\n({:.0f})'.format(x, total*x/100)

v_counts = df['Attrition'].value_counts()
total = len(df['Attrition'])
fig = plt.figure()
plt.pie(v_counts, labels=v_counts.index, autopct=per_val, shadow=True);
```

```
83.87755155563354
16.122448444366455
```

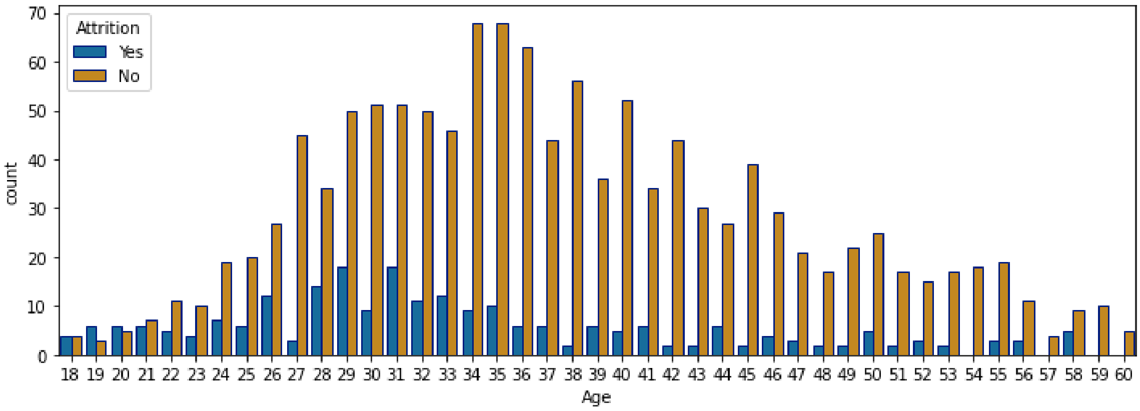


Number of employees that left and stayed by age

In [8]:

```
import matplotlib.pyplot as plt
fig_dims = (12, 4)
fig, ax = plt.subplots(figsize=fig_dims)

sns.countplot(x='Age', hue='Attrition', data = df, palette="colorblind", ax = ax,
              edgecolor=sns.color_palette("dark", n_colors = 1))
plt.show()
```

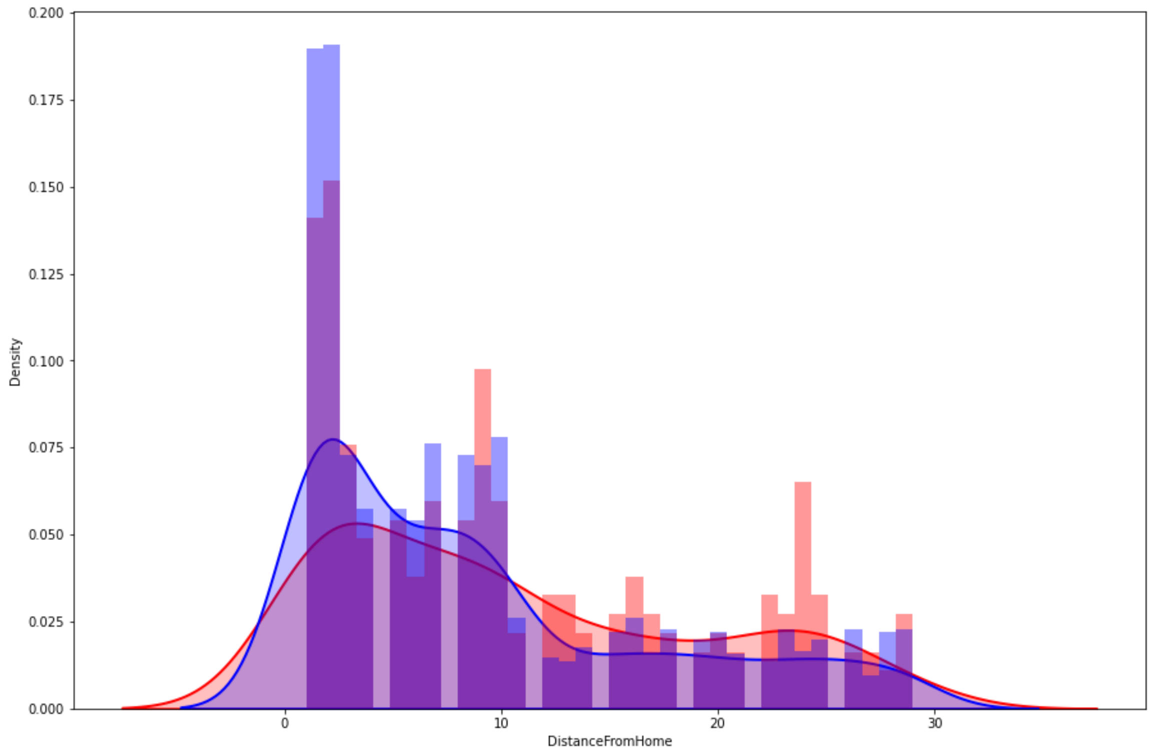


In [9]:

```
yes_attrition_df = (df[df['Attrition']=='Yes']).copy()
no_attrition_df = (df[df['Attrition']=='No']).copy()
plt.figure(figsize=(15,10))
sns.distplot(yes_attrition_df['DistanceFromHome'], hist=True, kde=True,
             bins=int(180/5), color = 'red',
             kde_kws = {'shade': True, 'linewidth': 2},
             label = "Left the Organization")

sns.distplot(no_attrition_df['DistanceFromHome'], hist=True, kde=True,
             bins=int(180/5), color = 'blue',
             kde_kws = {'shade': True, 'linewidth': 2},
             label = "Stayed back organization")

plt.show()
```

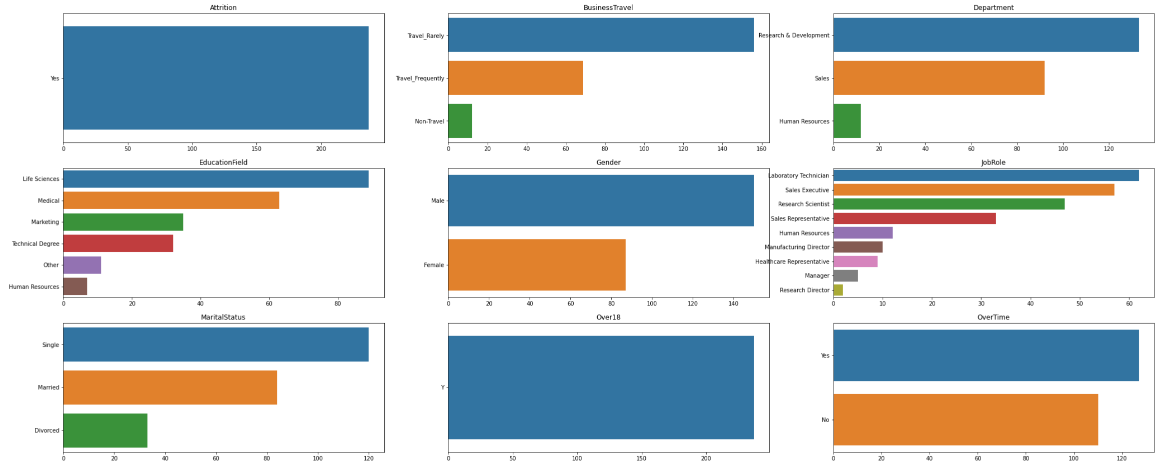


In [10]:

```
attrition_df = (df[df['Attrition']=='Yes']).copy()
def bar_plt(df):
    plt.figure(figsize=(len(df.columns),len(df.columns)+10), facecolor='white')
    cat_col = (df.select_dtypes(include = "object")).columns
    plotnum=1
    for i in cat_col:
        ax=plt.subplot(len(cat_col),3,plotnum)
        sns.barplot(df[i].value_counts().values, df[i].value_counts().index)
        plt.title(i)
        plotnum+=1
    plt.show(block=False)
```

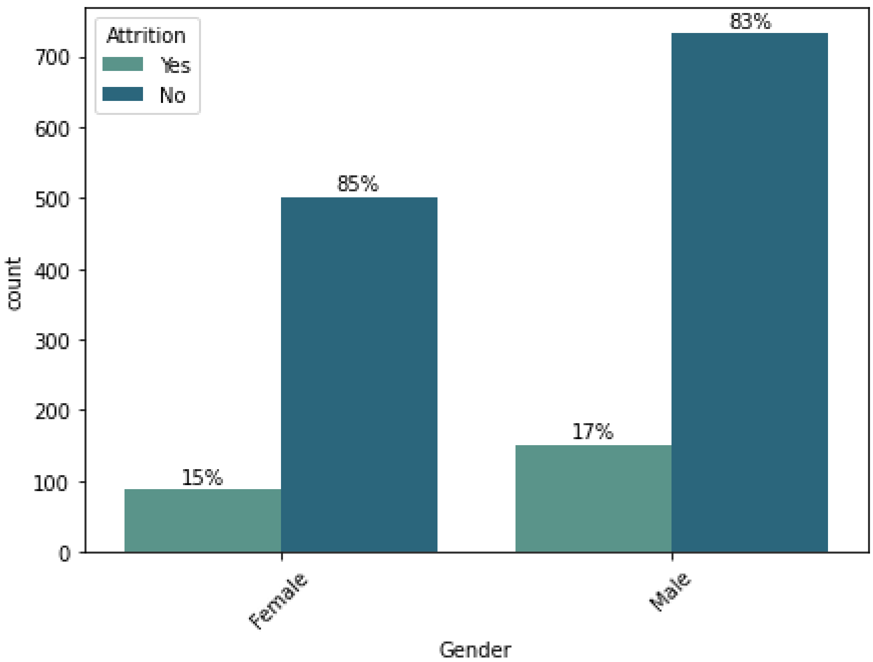
In [11]:

```
bar_plt(attrition_df)
```



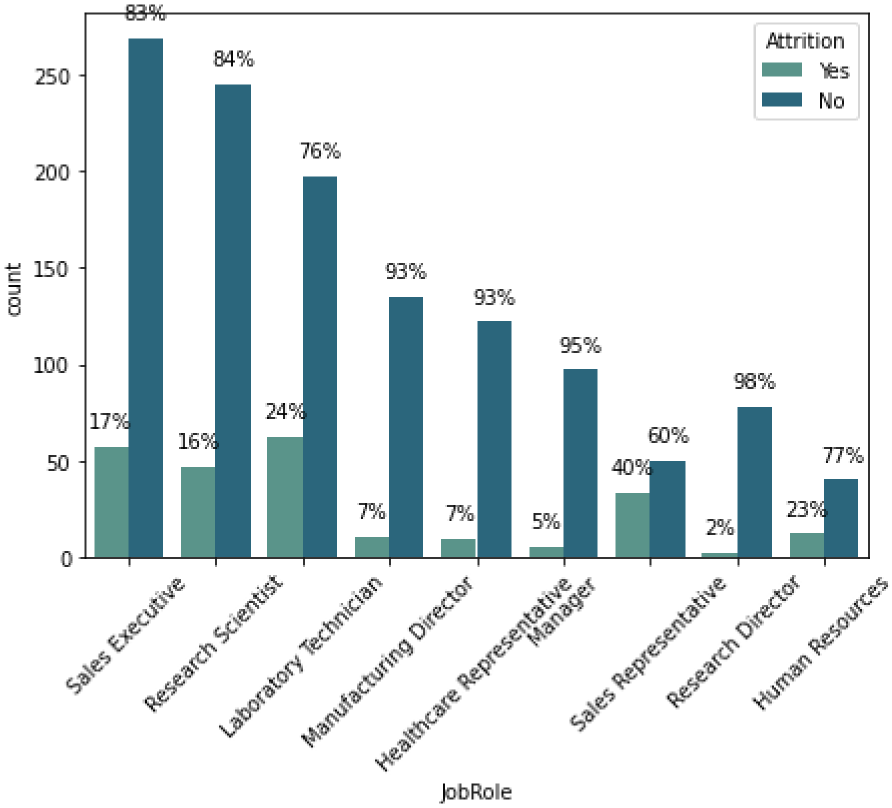
In [12]:

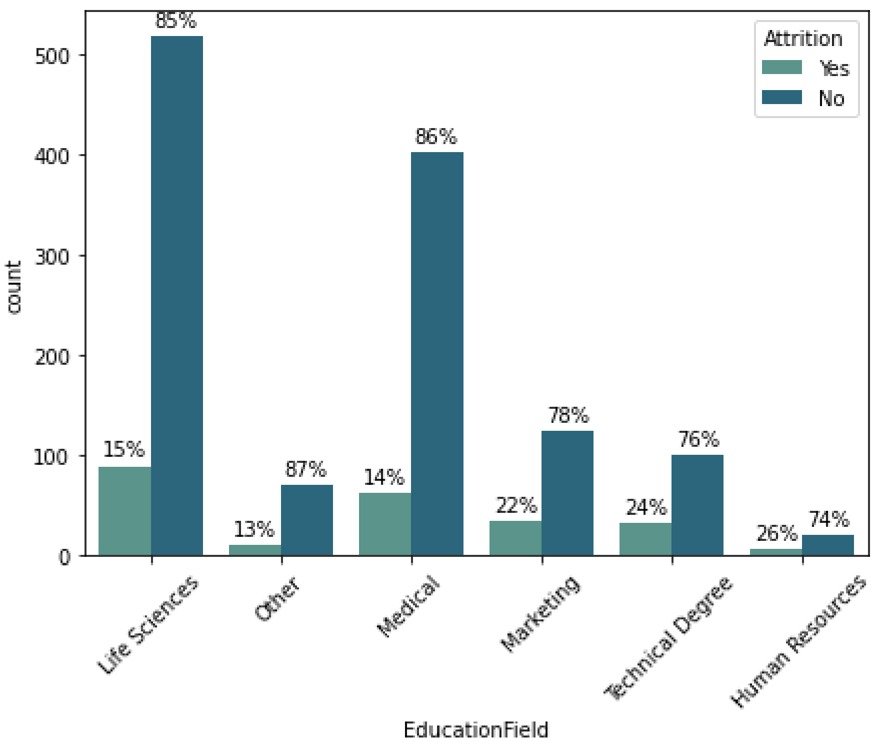
```
def plt_bar(i):
    plt.figure(figsize=(7,5))
    ax=sns.countplot(x=df[i], hue="Attrition", data=df,palette='crest')
    bars = ax.patches
    half = int(len(bars)/2)
    left_bars = bars[:half]
    right_bars = bars[half:]
    for left, right in zip(left_bars, right_bars):
            height_l = left.get_height()
            height_r = right.get_height()
            total = height_l + height_r
            ax.text(left.get_x() + left.get_width()/2., height_l + 10, '{0:.0%}'.format(height_l/total), ha="center")
            ax.text(right.get_x() + right.get_width()/2., height_r + 10, '{0:.0%}'.format(height_r/total), ha="center")
    plt.xticks(rotation=45)
    plt.show()
plt_bar('Gender')
```



In [13]:

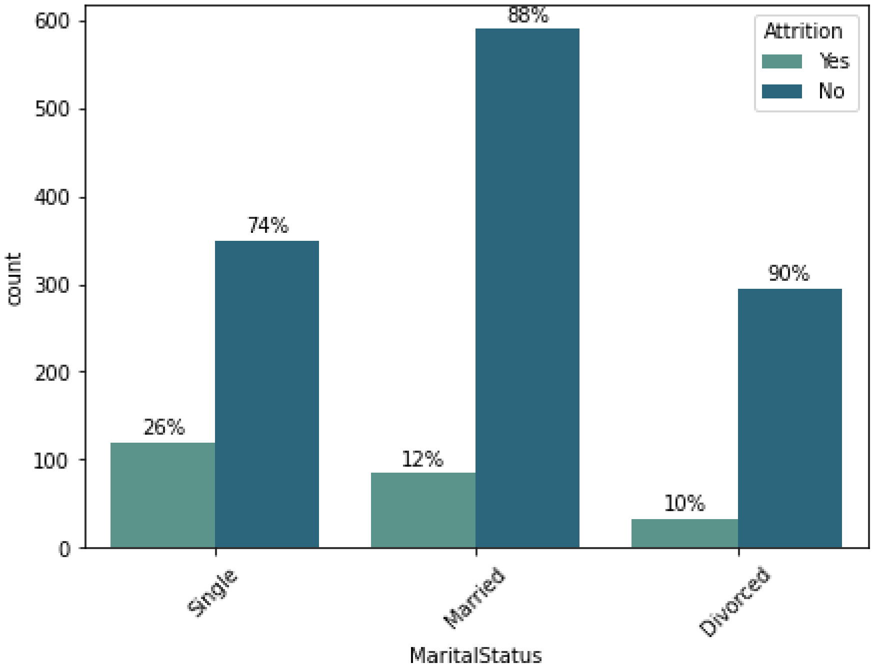
```
plt_bar('JobRole')
plt_bar('EducationField')
```

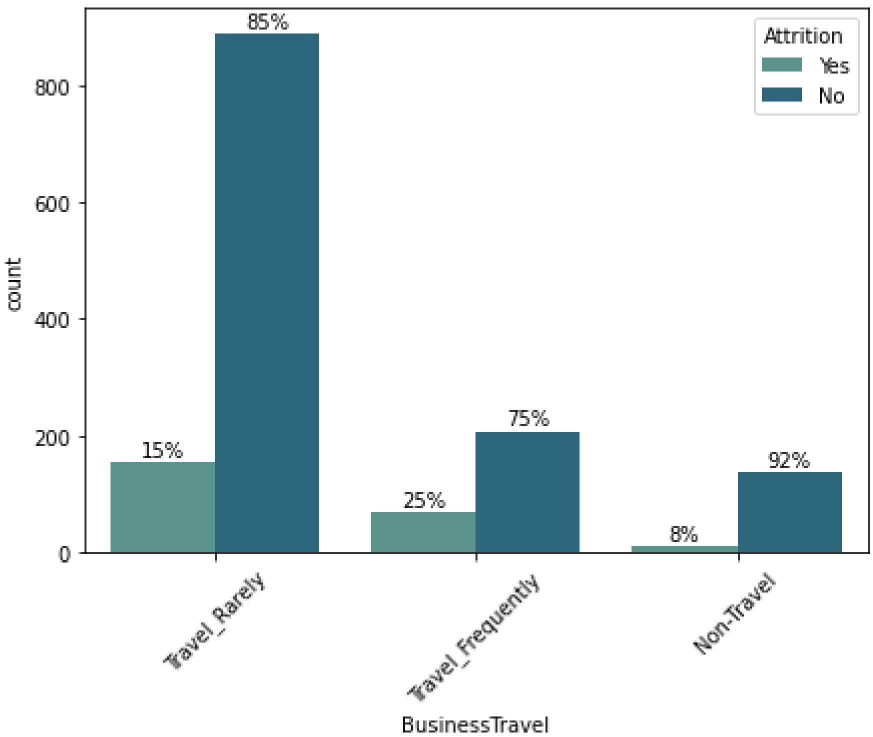




In [14]:

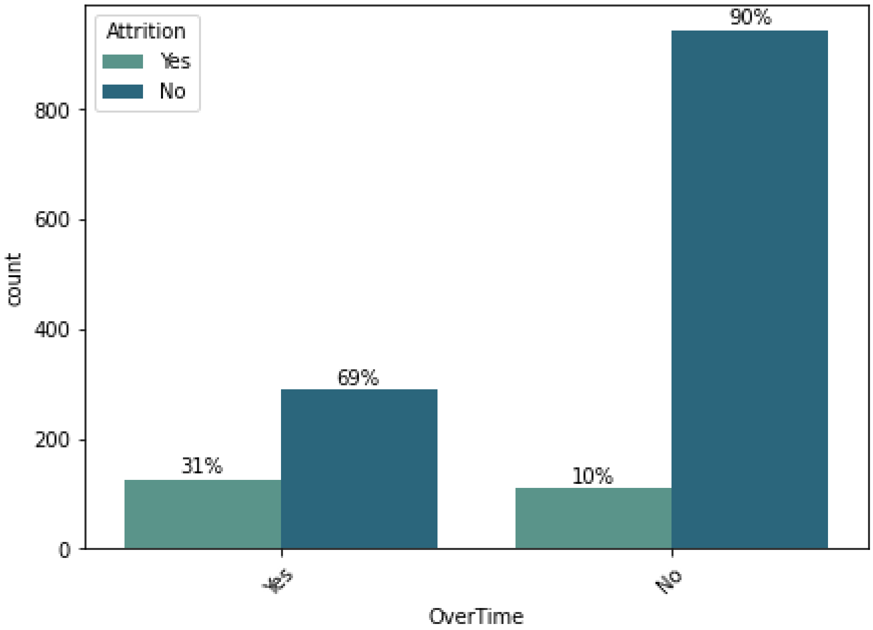
```
plt_bar('MaritalStatus')
plt_bar('BusinessTravel')
```

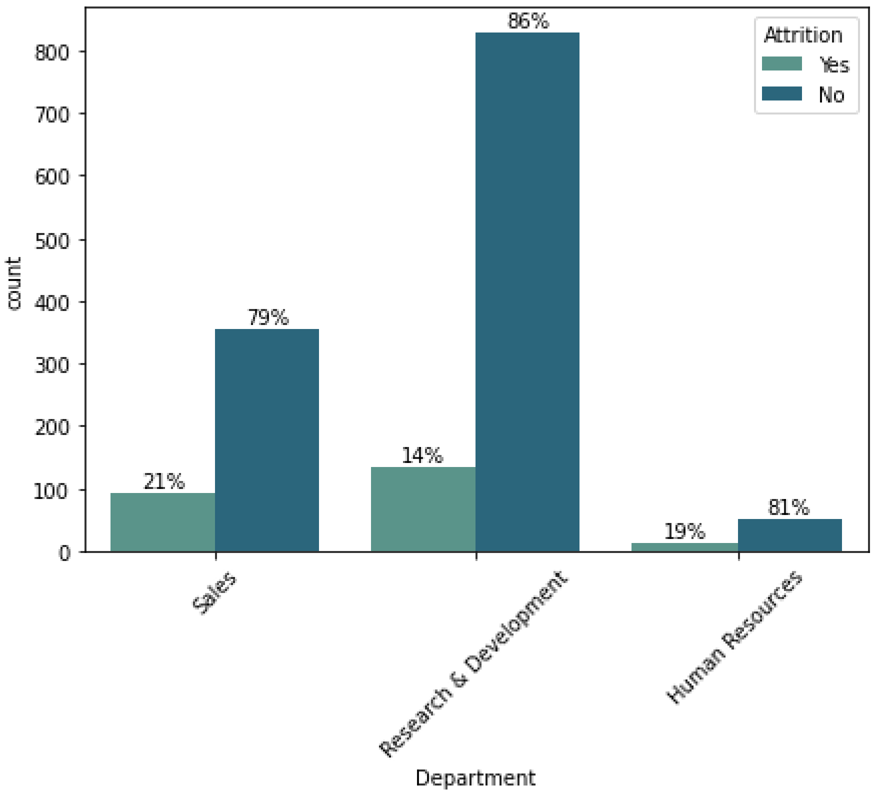




In [15]:

```
plt_bar('OverTime')
plt_bar('Department')
```





Features and their unique values

In [16]:

```
for column in df.columns:
    if df[column].dtype == object:
        print(str(column) + ' : ' + str(df[column].unique()))
        print(df[column].value_counts())
        print("_________________________________________________________________")
```

```
Attrition : ['Yes' 'No']
No     1233
Yes     237
Name: Attrition, dtype: int64
```

```
BusinessTravel : ['Travel_Rarely' 'Travel_Frequently' 'Non-Travel']
Travel_Rarely        1043
Travel_Frequently     277
Non-Travel            150
Name: BusinessTravel, dtype: int64
```

```
Department : ['Sales' 'Research & Development' 'Human Resources']
Research & Development    961
Sales                     446
Human Resources            63
Name: Department, dtype: int64
```

```
EducationField : ['Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree'
 'Human Resources']
Life Sciences       606
Medical             464
Marketing           159
Technical Degree    132
Other                82
Human Resources      27
Name: EducationField, dtype: int64
```

```
Gender : ['Female' 'Male']
Male      882
Female    588
Name: Gender, dtype: int64
```

```
JobRole : ['Sales Executive' 'Research Scientist' 'Laboratory Technician'
 'Manufacturing Director' 'Healthcare Representative' 'Manager'
 'Sales Representative' 'Research Director' 'Human Resources']
Sales Executive              326
Research Scientist           292
Laboratory Technician        259
Manufacturing Director       145
Healthcare Representative    131
Manager                      102
Sales Representative          83
Research Director             80
Human Resources               52
Name: JobRole, dtype: int64
```

```
MaritalStatus : ['Single' 'Married' 'Divorced']
Married     673
Single      470
Divorced    327
Name: MaritalStatus, dtype: int64
```

```
Over18 : ['Y']
Y    1470
Name: Over18, dtype: int64
```

```
OverTime : ['Yes' 'No']
No     1054
Yes     416
```

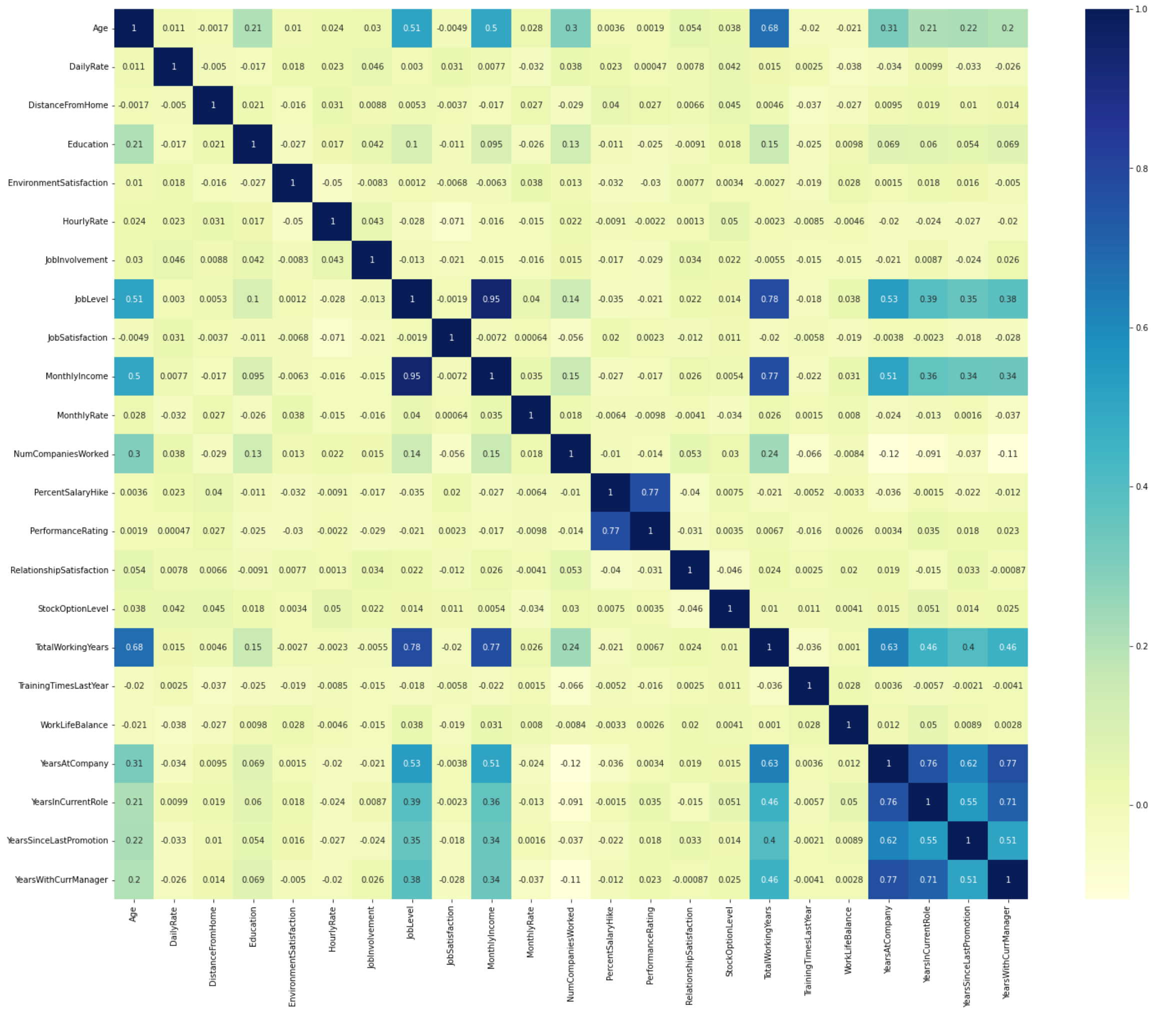
```
Name: OverTime, dtype: int64
```

In [17]:

```python
#droping some of the unwanted columns
df=df.drop(['EmployeeCount','EmployeeNumber','StandardHours','Over18'], axis=1)
```

In [18]:

```python
plt.figure(figsize=(25,20))
sns.heatmap(df.corr(),annot=True,cmap='YlGnBu')
plt.show()
```



Number of Attrition : Out of 1470 nos. of employee 237 Employees left the Job and are the reason of attrition employees

Cleary dat we have got is unbalanced to make prediction, hence we have to consider it at the time of model prediction and creating Model Training and Model Testing

Feature Engineering

The numeric and categorical fields need to be treated separately and the target field needs to be separated from the training dataset. The following few steps separate the numeric and categorical fields and drops the target field 'Attrition' from the feature set.

In [19]:

```
#Extracting the Numeric and Categorical features
df_num = pd.DataFrame(data = df.select_dtypes(include = ['int64']))
df_cat = pd.DataFrame(data = df.select_dtypes(include = ['object']))
print("Shape of Numeric: ",df_num.shape)
print("Shape of Categorical: ",df_cat.shape)
```

```
Shape of Numeric:  (1470, 23)
Shape of Categorical:  (1470, 8)
```

Encoding Categorical Fields

The categorical fields have been encoded using the get_dummies() function of Pandas.

In [20]:

```
#Dropping 'Attrition' from df_cat before encoding
df_cat = df_cat.drop(['Attrition'], axis=1)

#Encoding using Pandas' get_dummies
df_cat_encoded = pd.get_dummies(df_cat)
df_cat_encoded.head(5)
```

Out[20]:

	BusinessTravel_Non-Travel	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Depa
0	0	0	1	
1	0	1	0	
2	0	0	1	
3	0	1	0	
4	0	0	1	

Scaling Numeric Fields

The numeric fields have been scaled next for best results. StandardScaler() has been used for the same. Post scaling of the numeric features, they are merged with the categorical ones.

In [21]:

```
#Using StandardScaler to scale the numeric features
standard_scaler = StandardScaler()
df_num_scaled = standard_scaler.fit_transform(df_num)
df_num_scaled = pd.DataFrame(data = df_num_scaled, columns = df_num.columns, index = df
_num.index)
print("Shape of Numeric After Scaling: ",df_num_scaled.shape)
print("Shape of categorical after Encoding: ",df_cat_encoded.shape)
```

```
Shape of Numeric After Scaling:  (1470, 23)
Shape of categorical after Encoding:  (1470, 28)
```

In [22]:

```
#Combining the Categorical and Numeric features
df_transformed_final = pd.concat([df_num_scaled,df_cat_encoded], axis = 1)
print("Shape of final dataframe: ",df_transformed_final.shape)
```

```
Shape of final dataframe:  (1470, 51)
```

In [23]:

```
#Extracting the target variable - 'Attrition'
target = df['Attrition']

#Mapping 'Yes' to 1 and 'No' to 0
map = {'Yes':1, 'No':0}
target = target.apply(lambda x: map[x])

print("Shape of target: ",target.shape)

#Copying into commonly used fields for simplicity
X = df_transformed_final #Features
Y = target #Target
```

```
Shape of target:  (1470,)
```

Spliting data for Model Training and Testing

In [24]:

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, stratify=Y,ran
dom_state=50)
print("Shape of Train Dataset: ",x_train.shape)
print("Shape of Test Dataset: ",x_test.shape)
```

```
Shape of Train Dataset:  (1176, 51)
Shape of Test Dataset:  (294, 51)
```

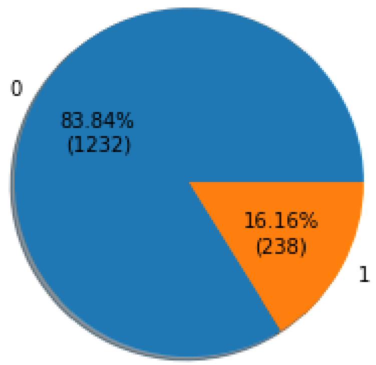
In [25]:

```
print('******Count of attrition and no_attrition employee in Train Dataset:******\n')
def per_val(x):
    print(x)
    return '{:.2f}%\n({:.0f})'.format(x, total*x/100)

v_counts = y_train.value_counts()
total = len(df['Attrition'])
fig = plt.figure()
plt.pie(v_counts, labels=v_counts.index, autopct=per_val, shadow=True);
```

```
******Count of attrition and no_attrition employee in Train Dataset:******

83.84353518486023
16.15646332502365
```



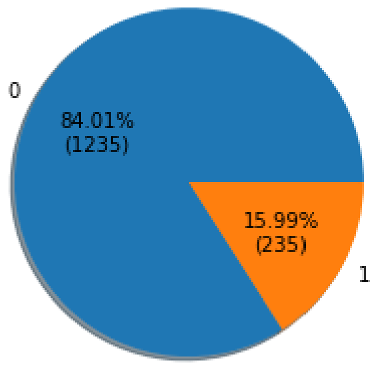
In [26]:

```
print("******Count of attrition and no_attrition employee in Test Dataset:******\n")
def per_val(x):
    print(x)
    return '{:.2f}%\n({:.0f})'.format(x, total*x/100)

v_counts = y_test.value_counts()
total = len(df['Attrition'])
fig = plt.figure()
plt.pie(v_counts, labels=v_counts.index, autopct=per_val, shadow=True);
```

```
******Count of attrition and no_attrition employee in Test Dataset:******

84.01360511779785
15.986394882202148
```



Creating few Functions for further Evaluation

In [27]:

```
def plot_confusion_matrix(cm,target_names,title='Confusion matrix',cmap=None,normalize=
True):
        import matplotlib.pyplot as plt
        import numpy as np
        import itertools
        accuracy = np.trace(cm) / np.sum(cm).astype('float')
        misclass = 1 - accuracy
        if cmap is None:
            cmap = plt.get_cmap('Blues')
        plt.figure(figsize=(8, 6))
        plt.imshow(cm, interpolation='nearest', cmap=cmap)
        plt.title(title)
        plt.colorbar()

        if target_names is not None:
            tick_marks = np.arange(len(target_names))
            plt.xticks(tick_marks, target_names, rotation=45)
            plt.yticks(tick_marks, target_names)

        if normalize:
            cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

        thresh = cm.max() / 1.5 if normalize else cm.max() / 2
        for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
            if normalize:
                plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                         horizontalalignment="center",
                         color="white" if cm[i, j] > thresh else "black")
            else:
                plt.text(j, i, "{:,}".format(cm[i, j]),
                         horizontalalignment="center",
                         color="white" if cm[i, j] > thresh else "black")


        plt.tight_layout()
        plt.ylabel('True label')
        plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accurac
y, misclass))
        plt.show()

def evaluate(model, test_features, test_labels):
    predictions = model.predict(test_features)
    accuracy = accuracy_score(test_labels, predictions)
    print('_________________________Model Performance_________________________\n\n')
#     print('Accuracy = {:0.2f}%.'.format(accuracy * 100))
    print(classification_report(test_labels, predictions))
    return accuracy
```

Base Model

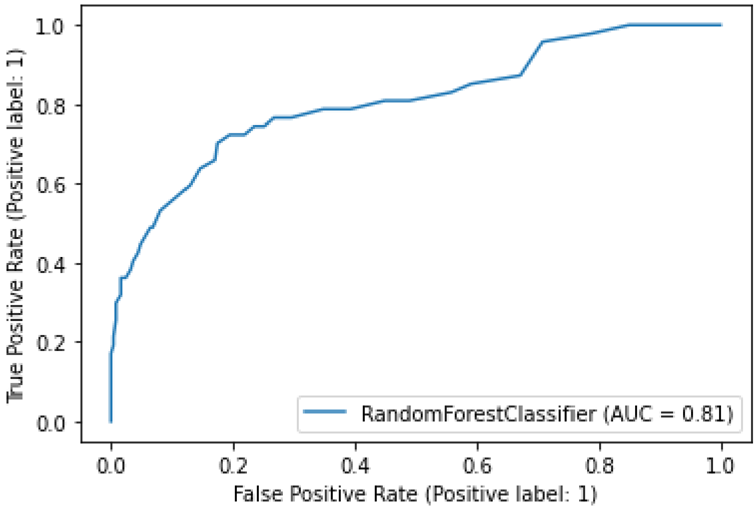
In [28]:

```
start = time.process_time()
rf = RandomForestClassifier(random_state=42, oob_score=True)
model=rf.fit(x_train, y_train)
print("RF Train Model Score :{:0.2f}%.".format( 100 * model.oob_score_))

y_pred = model.predict(x_test)
plot_roc_curve(rf, x_test, y_test)
plt.show()

print('Time elapsed {}'.format(time.process_time() - start))
```

```
RF Train Model Score :85.54%.
```

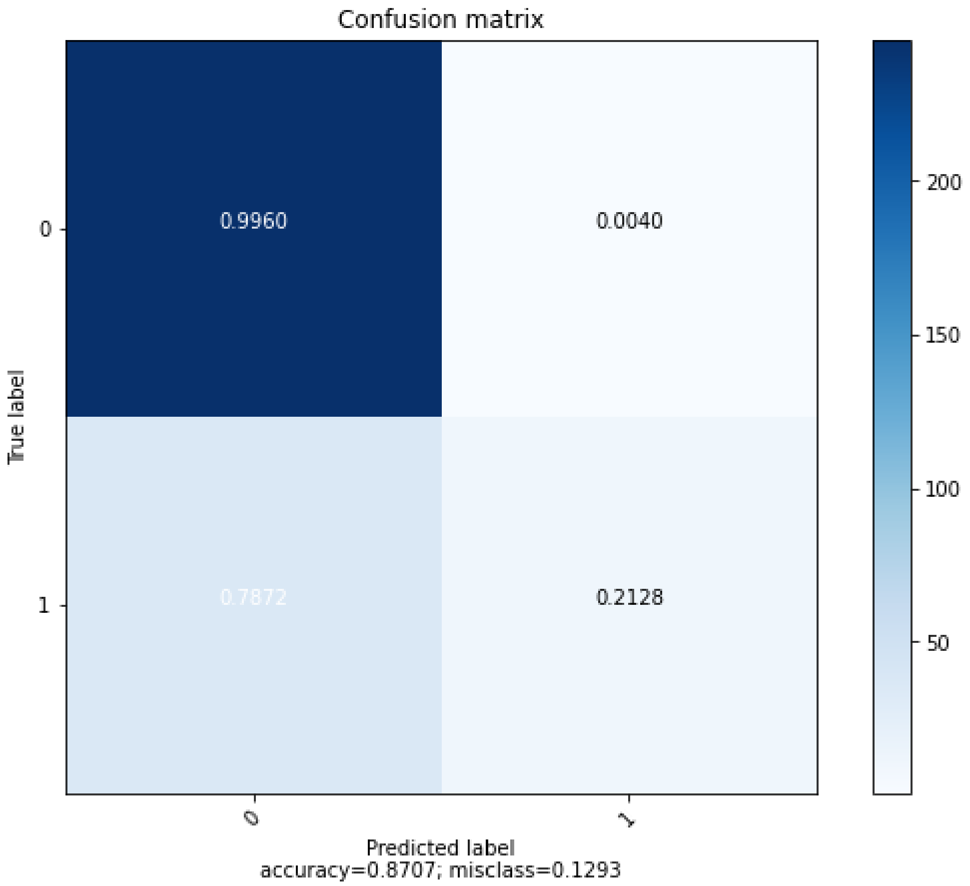



```
Time elapsed 0.8767707530000006
```

Model Evaluation

In [29]:

```
labels = ['Attrition_Yes', 'Attrition_No']
cm=confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cm,[0,1])
```



In [30]:

```
base_accuracy= evaluate(model, x_test, y_test)
print("\n\nBase Model Accuracy: {:0.2f}%." .format(base_accuracy * 100))
```

```
_________________________Model Performance_________________________


              precision    recall  f1-score   support

           0       0.87      1.00      0.93       247
           1       0.91      0.21      0.34        47

    accuracy                           0.87       294
   macro avg       0.89      0.60      0.64       294
weighted avg       0.88      0.87      0.84       294



Base Model Accuracy: 87.07%.
```

Hyper-parameter tuning for the Random Forest¶

In [31]:

```
from sklearn.ensemble import GradientBoostingClassifier
start = time.process_time()
rf = GradientBoostingClassifier(max_features = 0.7, learning_rate = 0.3)

params = {
    'max_depth': [3,5,6,8,10,12],
    'min_samples_leaf': [2,5,10,20],
    'n_estimators': [2,5,10,15,25]
}

from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv =2,
                           verbose=1, scoring="accuracy")

grid_model=grid_search.fit(x_train, y_train)
rf_best = grid_search.best_estimator_

print("\nBest Model: ",rf_best)

print("\nGridSerchCV Model Score: {:0.2f}%." .format(grid_search.best_score_*100))

grid_accuracy = evaluate(rf_best,  x_test, y_test)

print('Time elapsed {}'.format(time.process_time() - start))
```

```
Fitting 2 folds for each of 120 candidates, totalling 240 fits

Best Model:  GradientBoostingClassifier(learning_rate=0.3, max_features=0.
7,
                           min_samples_leaf=20, n_estimators=15)

GridSerchCV Model Score: 86.82%.
_________________________Model Performance_________________________


              precision    recall  f1-score   support

           0       0.88      0.98      0.93       247
           1       0.76      0.28      0.41        47

    accuracy                           0.87       294
   macro avg       0.82      0.63      0.67       294
weighted avg       0.86      0.87      0.84       294

Time elapsed 15.616130409000002
```

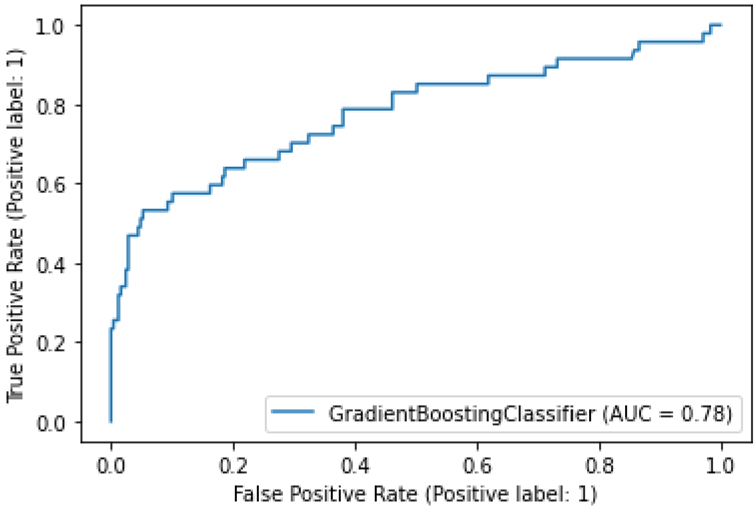
In [32]:

```
final_model=rf_best.fit(x_train, y_train)
```

In [33]:

```
print('Improvement of {:0.2f}%.'.format( 100 * (grid_accuracy - base_accuracy) ))
plot_roc_curve(final_model, x_test, y_test)
plt.show()
```

```
Improvement of 0.00%.
```



In [34]:

```
# Return the feature importances (the higher, the more important the feature).
importances = pd.DataFrame({"Varname": x_train.columns,"Imp": rf_best.feature_importanc
es_})
importances = importances.sort_values('Imp',ascending=False)
importances
print("\n\n**-------------------Top 5 Important Features------------------**\n",importa
nces.head(6))
```

```
**-------------------Top 5 Important Features------------------**
                Varname       Imp
49         OverTime_No  0.150406
0                  Age  0.078165
9        MonthlyIncome  0.071732
15    StockOptionLevel  0.066066
16   TotalWorkingYears  0.061439
1            DailyRate  0.061074
```

In [35]:

```
# Import statements required for Plotly
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
trace = go.Scatter(
    y = rf_best.feature_importances_,
    x = x_train.columns.values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 13,
        #size= rf.feature_importances_,
        #color = np.random.randn(500), #set color equal to a variable
        color = rf_best.feature_importances_,
        colorscale='Portland',
        showscale=True
    ),
    text = x_train.columns.values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Random Forest Feature Importance',
    hovermode= 'closest',
     xaxis= dict(
         ticklen= 5,
         showgrid=False,
        zeroline=False,
        showline=False
     ),
    yaxis=dict(
        title= 'Feature Importance',
        showgrid=False,
        zeroline=False,
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')
```

In [36]:

```
y_pred = final_model.predict(x_test)
print("Train Model Score:{:0.2f}%.".format( 100 * model.score(x_train, y_train)))
print("Test Model Score:{:0.2f}%.".format( 100 * model.score(x_test, y_test)))
print("\nTrain Model Score after Hyper Parameter Tunning: {:0.2f}%.".format( 100 * fina
l_model.score(x_train, y_train)))
print("Test Model Score after Hyper Parameter Tunning:{:0.2f}%.".format( 100 * final_mo
del.score(x_test, y_test)))
predication_output = pd.DataFrame({'Id': x_test.index ,'Target': y_pred })
```

```
Train Model Score:100.00%.
Test Model Score:87.07%.

Train Model Score after Hyper Parameter Tunning: 91.07%.
Test Model Score after Hyper Parameter Tunning:87.41%.
```

In [37]:

```
predication_output.head(15)
```

Out[37]:

	Id	Target
0	78	0
1	623	0
2	787	0
3	529	0
4	195	0
5	109	0
6	365	0
7	931	0
8	62	0
9	299	0
10	960	0
11	875	0
12	1002	0
13	601	0
14	1394	0

In [37]:

```
```