# Attrition rate prediction in an organization

In [38]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set_style("dark")
```

In [40]:
```
df = pd.read_csv('../Data/HR_comma_sep.csv")
df.head()
```

Out[40]:

| | satisfaction_level | last_evaluation | number_project | average_montly_hours | time_spend_company | Work_accident | left | prom |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.38 | 0.53 | 2 | 157 | 3 | 0 | 1 | |
| 1 | 0.80 | 0.86 | 5 | 262 | 6 | 0 | 1 | |
| 2 | 0.11 | 0.88 | 7 | 272 | 4 | 0 | 1 | |
| 3 | 0.72 | 0.87 | 5 | 223 | 5 | 0 | 1 | |
| 4 | 0.37 | 0.52 | 2 | 159 | 3 | 0 | 1 | |

In [41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
satisfaction_level       14999 non-null float64
last_evaluation          14999 non-null float64
number_project           14999 non-null int64
average_montly_hours     14999 non-null int64
time_spend_company       14999 non-null int64
Work_accident            14999 non-null int64
left                     14999 non-null int64
promotion_last_5years    14999 non-null int64
Department               14999 non-null object
salary                   14999 non-null object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

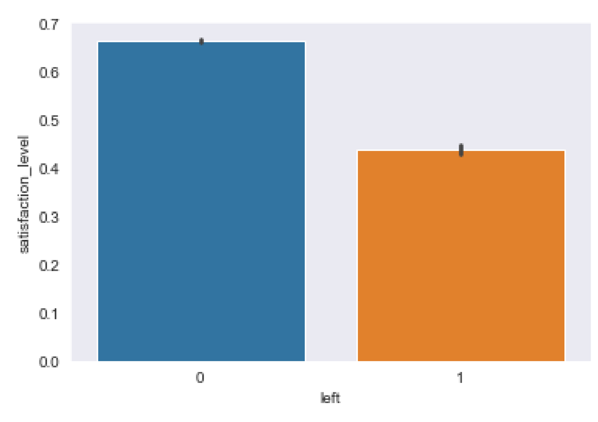
In [42]:
```
df.head()
```

Out[42]:

| | satisfaction_level | last_evaluation | number_project | average_montly_hours | time_spend_company | Work_accident | left | prom |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.38 | 0.53 | 2 | 157 | 3 | 0 | 1 | |
| 1 | 0.80 | 0.86 | 5 | 262 | 6 | 0 | 1 | |
| 2 | 0.11 | 0.88 | 7 | 272 | 4 | 0 | 1 | |
| 3 | 0.72 | 0.87 | 5 | 223 | 5 | 0 | 1 | |
| 4 | 0.37 | 0.52 | 2 | 159 | 3 | 0 | 1 | |

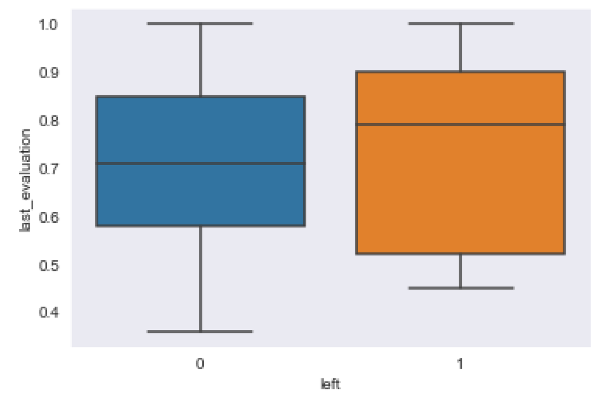
**Employee satisfaction vs employee attrition. Lower the satisfaction level higher chances of employee leaving**

In [43]:
```
sns.barplot(x="left", y= "satisfaction_level", data=df)
plt.show()
```



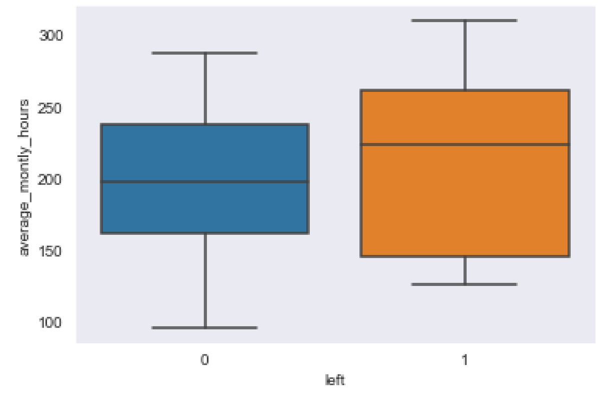

**Effect of last performance evaluation on employee attrition**

In [44]:
```
sns.boxplot(x="left", y= "last_evaluation", data=df)
plt.show()
```



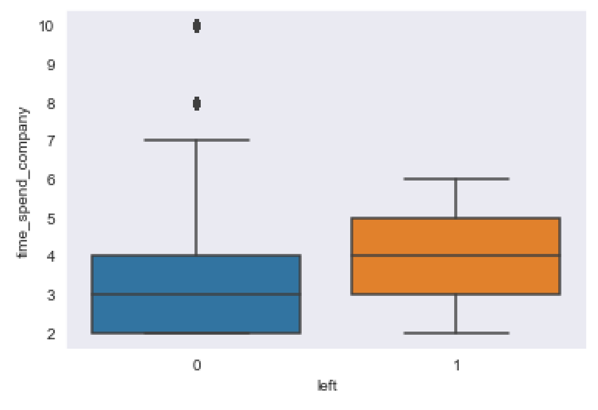

**Do employees spending more hours tends to leave organization?**

In [45]:
```
sns.boxplot(x="left", y= "average_montly_hours", data=df)
plt.show()
```



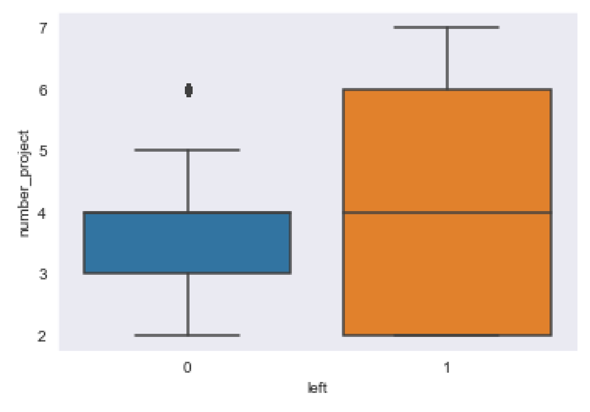

**Does years spent in the organization influence employees to leave?**

In [46]:
```
sns.boxplot(x="left", y="time_spend_company", data=df)
plt.show()
```




**Do number of projects changes cause attrition? Seems employees who worked on between 3 to 4 projects stayed on than people with very less changes or very high changes**

In [47]:
```
sns.boxplot(x="left", y="number_project", data=df)
plt.show()
```




In [48]:
```
#Convert salary into numerical type by Dummification
df = pd.get_dummies(df, columns=['salary'], drop_first=True)
df.head()
```

Out[48]:

| | satisfaction_level | last_evaluation | number_project | average_montly_hours | time_spend_company | Work_accident | left | prom |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.38 | 0.53 | 2 | 157 | 3 | 0 | 1 | |
| 1 | 0.80 | 0.86 | 5 | 262 | 6 | 0 | 1 | |
| 2 | 0.11 | 0.88 | 7 | 272 | 4 | 0 | 1 | |
| 3 | 0.72 | 0.87 | 5 | 223 | 5 | 0 | 1 | |
| 4 | 0.37 | 0.52 | 2 | 159 | 3 | 0 | 1 | |

In [49]:
```
#Split the data set into train and test
y = df["left"]
#drop department & left
columns = ['Department', 'left']
df = df.drop(columns, axis=1)
col = df.columns
x = df[col]
x.head()
```

Out[49]:

| | satisfaction_level | last_evaluation | number_project | average_montly_hours | time_spend_company | Work_accident | promotion_ |
|---|---|---|---|---|---|---|---|
| 0 | 0.38 | 0.53 | 2 | 157 | 3 | 0 | |
| 1 | 0.80 | 0.86 | 5 | 262 | 6 | 0 | |
| 2 | 0.11 | 0.88 | 7 | 272 | 4 | 0 | |
| 3 | 0.72 | 0.87 | 5 | 223 | 5 | 0 | |
| 4 | 0.37 | 0.52 | 2 | 159 | 3 | 0 | |

### Build model and import logistic regression

In [50]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

#Split the data intorain and test
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.20,  random_state = 1)
```

In [51]:
```
x_train.shape
```

Out[51]: (11999, 9)

In [52]:
```
x_test.shape
```

Out[52]: (3000, 9)

In [53]:
```
y_train.shape
```

Out[53]: (11999,)

In [54]:
```
y_test.shape
```

Out[54]: (3000,)

### Train the data

In [55]:
```
logisticRegr = LogisticRegression()
logisticRegr.fit(x_train, y_train)
```

```
e:\Anaconda\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning: Default solve
r will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[55]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

### Predict the test data

In [56]:
```
pred = logisticRegr.predict(x_test)
pred
```

Out[56]: array([0, 0, 0, ..., 0, 1, 0], dtype=int64)

### Model Evaluation using accuracy classification score

In [57]:
```
from sklearn import metrics
ac = metrics.accuracy_score(y_test, pred)
print('Accuracy score for test data is:', ac)
```

```
Accuracy score for test data is: 0.7886666666666666
```

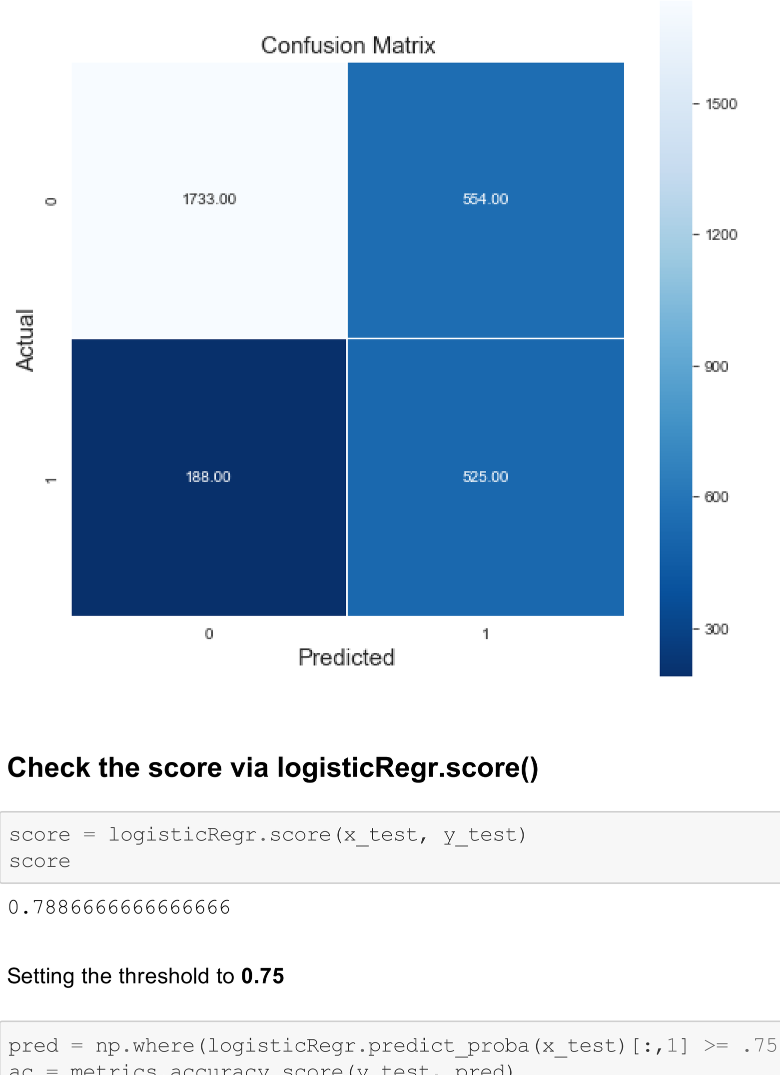
### Model Evaluation using confusion matrix

In [58]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = pd.DataFrame(confusion_matrix(y_test, pred))
print(confusion_matrix)
```

```
      0    1
0  2107  180
1   454  259
```

In [37]:
```
def plot_confusion_matrix(df_confusion):
    plt.figure(figsize=(8,8))
    sns.heatmap(df_confusion, linewidth=.2, fmt='.2f', annot=True, square = True, cmap = 'Blues_r')
    plt.title('Confusion Matrix',size = 15)
    plt.ylabel('Actual', fontsize = 15)
    plt.xlabel('Predicted', fontsize = 15)

plot_confusion_matrix(confusion_matrix)
```




### Check the score via logisticRegr.score()

In [59]:
```
score = logisticRegr.score(x_test, y_test)
score
```

Out[59]: 0.7886666666666666

Setting the threshold to **0.75**

In [60]:
```
pred = np.where(logisticRegr.predict_proba(x_test)[:,1] >= .75, 1, 0)
ac = metrics.accuracy_score(y_test, pred)
print('Accuracy score fo test data is:', ac)
```

```
Accuracy score fo test data is: 0.7573333333333333
```

The accuracy has been **reduced** from **0.78 to 0.75**. Hence, 0.75 is **not a good threshold** for our model.

Setting the threshold to **0.25**

In [61]:
```
pred = np.where(logisticRegr.predict_proba(x_test)[:,1] >= .25, 1, 0)
ac = metrics.accuracy_score(y_test, pred)
print('Accuracy score fo test data is:', ac)
```

```
Accuracy score fo test data is: 0.7526666666666667
```

The accuracy has been **reduced** from **0.78 to 0.75**. Hence, 0.25 is also **not a good threshold** for our model.

In [ ]: