MACHINE LEARNING - 3 - Assignment

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Problem Statement

I decided to treat this as a classification problem by creating a new binary variable affair (did the woman have at least one affair?) and trying to predict the classification for each woman.

Dataset:

The dataset I chose is the affairs dataset that comes with Statsmodels. It was derived from a survey of women in 1974 by Redbook magazine, in which married women were asked about their participation in extramarital affairs. More information about the study is available in a 1978 paper from the Journal of Political Economy.

Description of Variables

The dataset contains 6366 observations of 9 variables:

- rate_marriage: woman's rating of her marriage (1 = very poor, 5 = very good)
- age: woman's age
- yrs_married: number of years married
- children: number of children
- religious: woman's rating of how religious she is (1 = not religious, 4 = strongly religious)
- educ: level of education (9 = grade school, 12 = high school, 14 = some college, 16 = college graduate, 17 = some graduate school, 20 = advanced degree)
- occupation: woman's occupation (1 = student, 2 = farming/semi-skilled/unskilled, 3 = "white collar", 4 = teacher/nurse/writer/technician/skilled, 5 = managerial/business, 6 = * professional with advanced degree)
- occupation_husb: husband's occupation (same coding as above)
- affairs: time spent in extra-marital affairs

In [2]:

```
# Code to Loading data and modules
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
from patsy import dmatrices
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import train_test_split
from sklearn import metrics
from sklearn.cross_validation import cross_val_score
dta = sm.datasets.fair.load_pandas().data
dta.head(4)
```

Out[2]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs
0	3.0	32.0	9.0	3.0	3.0	17.0	2.0	5.0	0.111111
1	3.0	27.0	13.0	3.0	1.0	14.0	3.0	4.0	3.230769
2	4.0	22.0	2.5	0.0	1.0	16.0	3.0	5.0	1.400000
3	4.0	37.0	16.5	4.0	3.0	16.0	5.0	5.0	0.727273

In [3]:

```
# add "affair" column: 1 represents having affairs, 0 represents not
dta['affair'] = (dta.affairs > 0).astype(int)
dta.head(4)
```

Out[3]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs	affair
0	3.0	32.0	9.0	3.0	3.0	17.0	2.0	5.0	0.111111	1
1	3.0	27.0	13.0	3.0	1.0	14.0	3.0	4.0	3.230769	1
2	4.0	22.0	2.5	0.0	1.0	16.0	3.0	5.0	1.400000	1
3	4.0	37.0	16.5	4.0	3.0	16.0	5.0	5.0	0.727273	1

- Explore Data

In [4]:
```
# Statistical Analysis of the Dataset
dta.describe()
```

Out[4]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs
count	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000
mean	4.109645	29.082862	9.009425	1.396874	2.426170	14.209865	3.424128	3.850141	0.705374
std	0.961430	6.847882	7.280120	1.433471	0.878369	2.178003	0.942399	1.346435	2.203374
min	1.000000	17.500000	0.500000	0.000000	1.000000	9.000000	1.000000	1.000000	0.000000
25%	4.000000	22.000000	2.500000	0.000000	2.000000	12.000000	3.000000	3.000000	0.000000
50%	4.000000	27.000000	6.000000	1.000000	2.000000	14.000000	3.000000	4.000000	0.000000
75%	5.000000	32.000000	16.500000	2.000000	3.000000	16.000000	4.000000	5.000000	0.484848
max	5.000000	42.000000	23.000000	5.500000	4.000000	20.000000	6.000000	6.000000	57.599991

In [5]:
```
# Group the Data with respect to average of affair
dta.groupby('affair').mean()
```

Out[5]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs
affair									
0	4.329701	28.390679	7.989335	1.238813	2.504521	14.322977	3.405286	3.833758	0.000000
1	3.647345	30.537019	11.152460	1.728933	2.261568	13.972236	3.463712	3.884559	2.187243

In [6]:
```
# Group the Data with respect to average of affair
dta.groupby('affair').count()
```

Out[6]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs
affair									
0	4313	4313	4313	4313	4313	4313	4313	4313	4313
1	2053	2053	2053	2053	2053	2053	2053	2053	2053

In [7]:
```
# Check how many women have affair (1 - having affair)
dta['affair'].value_counts()
```

Out[7]:
```
0    4313
1    2053
Name: affair, dtype: int64
```

In [8]:
```
# Check how many women have affair in % (1 - having affair)
dta['affair'].value_counts(normalize=True)*100
```

Out[8]:
```
0    67.75055
1    32.24945
Name: affair, dtype: float64
```

Data Visualisation

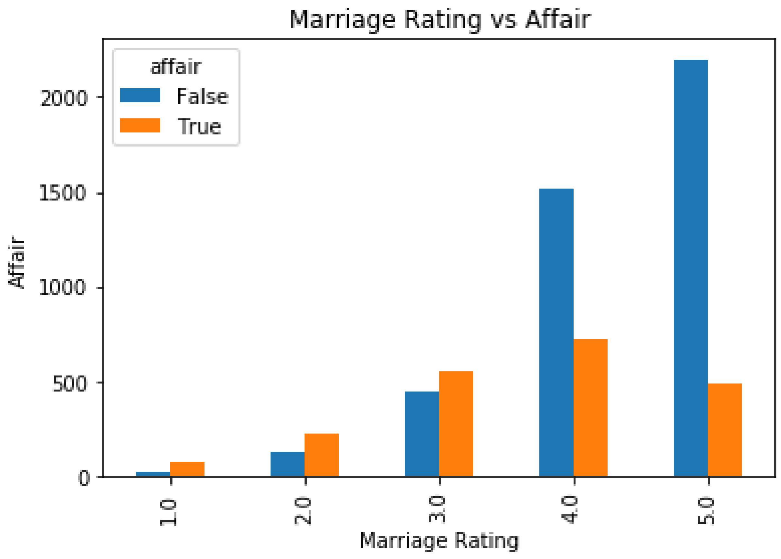
- histograms

In [9]:

```
# barplot of Marriage Rating vs Affair
pd.crosstab(dta['rate_marriage'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title('Marriage Rating vs Affair')
plt.xlabel('Marriage Rating')
plt.ylabel('Affair')
```

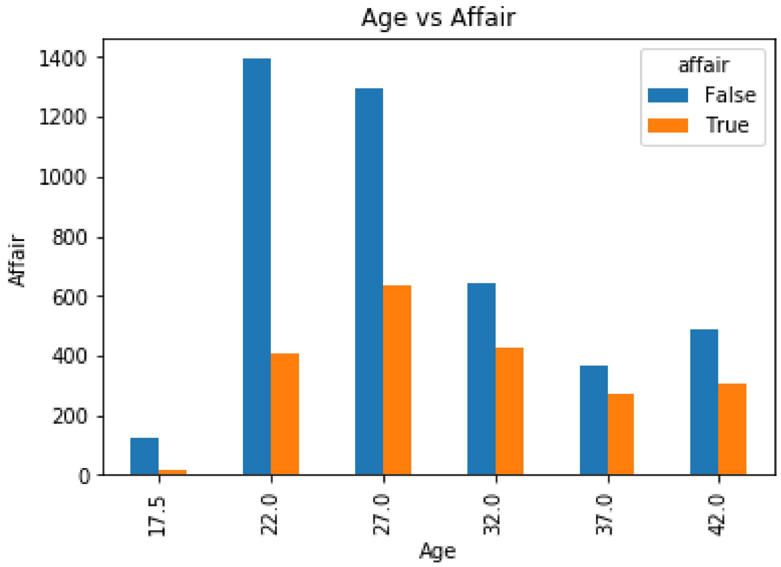
Out[9]:

```
Text(0,0.5,'Affair')
```



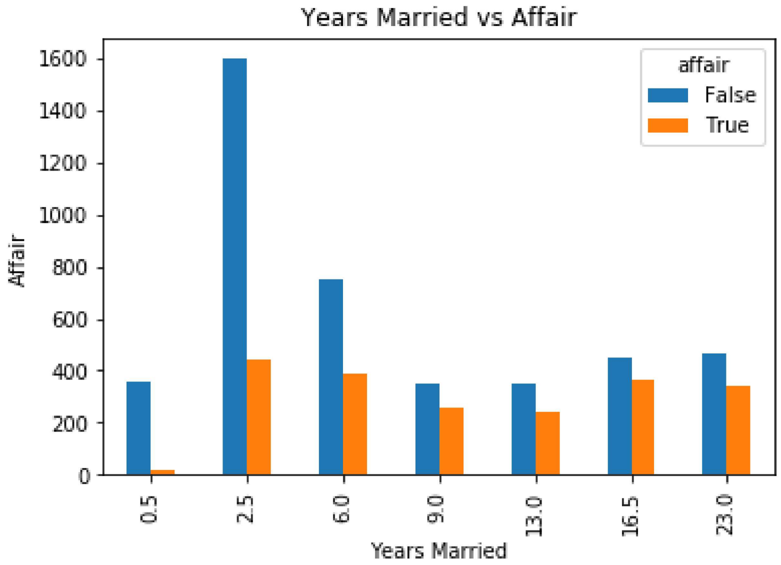
In [10]:
```
# barplot of Age vs Affair
pd.crosstab(dta['age'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title('Age vs Affair')
plt.xlabel('Age')
plt.ylabel('Affair')
```

Out[10]:
```
Text(0,0.5,'Affair')
```



```
In [11]: # barplot of Years Married vs Affair
         pd.crosstab(dta['yrs_married'], dta['affair'].astype(bool)).plot(kind='bar')
         plt.title('Years Married vs Affair')
         plt.xlabel('Years Married')
         plt.ylabel('Affair')
```

```
Out[11]: Text(0,0.5,'Affair')
```

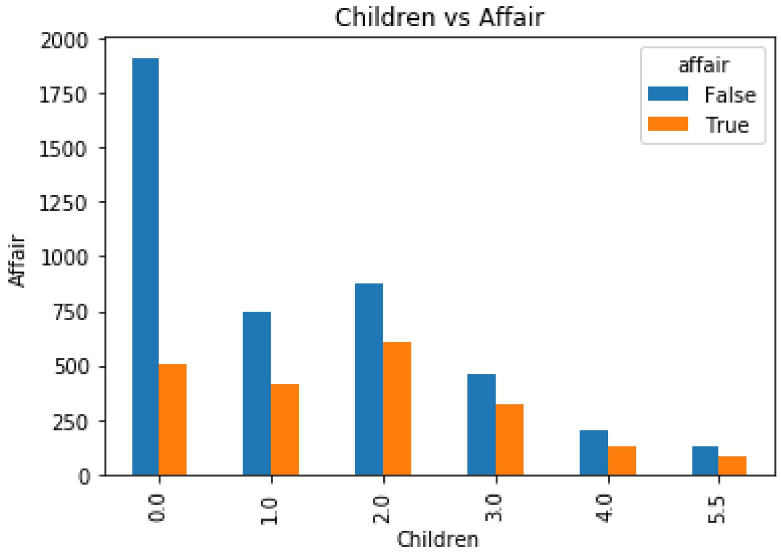


In [12]:

```
# barplot of Children vs Affair
pd.crosstab(dta['children'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title('Children vs Affair')
plt.xlabel('Children')
plt.ylabel('Affair')
```

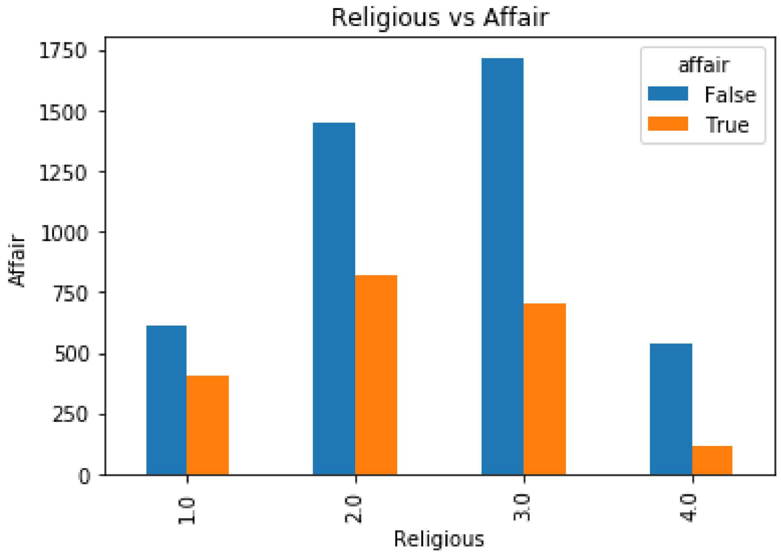
Out[12]:

```
Text(0,0.5,'Affair')
```



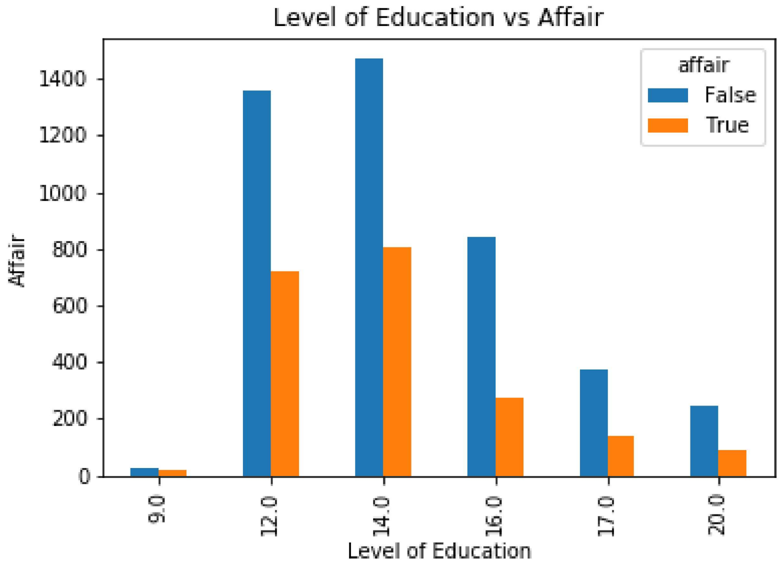
```
In [13]: # barplot of Religious vs Affair
         pd.crosstab(dta['religious'], dta['affair'].astype(bool)).plot(kind='bar')
         plt.title('Religious vs Affair')
         plt.xlabel('Religious')
         plt.ylabel('Affair')

Out[13]: Text(0,0.5,'Affair')
```



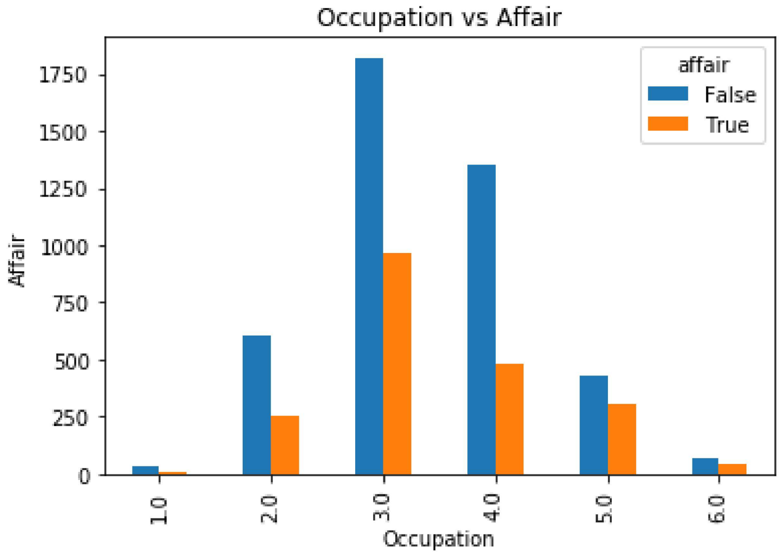
In [14]:
```
# barplot of Level of Education vs Affair
pd.crosstab(dta['educ'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title('Level of Education vs Affair')
plt.xlabel('Level of Education')
plt.ylabel('Affair')
```

Out[14]:
```
Text(0,0.5,'Affair')
```



In [15]:
```
# barplot of Occupation vs Affair
pd.crosstab(dta['occupation'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title('Occupation vs Affair')
plt.xlabel('Occupation')
plt.ylabel('Affair')
```

Out[15]:
```
Text(0,0.5,'Affair')
```

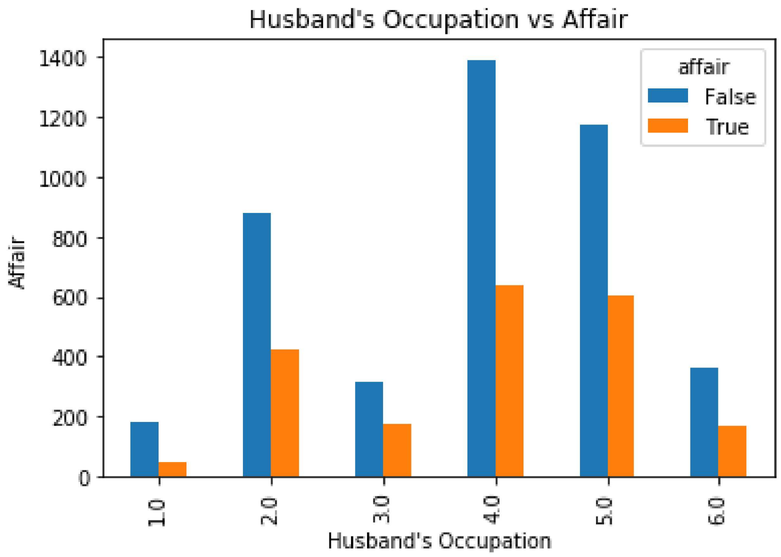


In [16]:

```
# barplot of Husband's Occupation  vs Affair
pd.crosstab(dta['occupation_husb'], dta['affair'].astype(bool)).plot(kind='bar')
plt.title("Husband's Occupation vs Affair")
plt.xlabel("Husband's Occupation")
plt.ylabel('Affair')
```

Out[16]:

```
Text(0,0.5,'Affair')
```



Logistic Regression

- Prepare Data for Logistic Regression

In [17]:

```
#The dmatrices function
y, X = dmatrices('affair ~ rate_marriage + age + yrs_married + children + \
religious + educ + C(occupation) + C(occupation_husb)', dta, return_type="dataframe")

# fix column names of X
X = X.rename(columns = {'C(occupation)[T.2.0]':'occ_2',
                        'C(occupation)[T.3.0]':'occ_3',
                        'C(occupation)[T.4.0]':'occ_4',
                        'C(occupation)[T.5.0]':'occ_5',
                        'C(occupation)[T.6.0]':'occ_6',
                        'C(occupation_husb)[T.2.0]':'occ_husb_2',
                        'C(occupation_husb)[T.3.0]':'occ_husb_3',
                        'C(occupation_husb)[T.4.0]':'occ_husb_4',
                        'C(occupation_husb)[T.5.0]':'occ_husb_5',
                        'C(occupation_husb)[T.6.0]':'occ_husb_6'})
y = np.ravel(y)

#Print Target Variable i.e Affair
y
```

Out[17]:

```
array([1., 1., 1., ..., 0., 0., 0.])
```

In [18]:

```
#Print Independant Variables
X.head(4)
```

Out[18]:

	Intercept	occ_2	occ_3	occ_4	occ_5	occ_6	occ_husb_2	occ_husb_3	occ_husb_4	occ_husb_5	occ_husb_6	rate_marriage	ag
0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	3.0	32.0
1	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	3.0	27.0
2	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	4.0	22.0
3	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	4.0	37.0

In [19]:

```
lr = LogisticRegression()
lr = lr.fit(X, y)

# check the accuracy on the training set
lr.score(X, y)
```

Out[19]:

```
0.7258875274897895
```

In [20]:

```
# Predict the affair and add to the dataframe
dta['Predict_Affair']=lr.predict(X)
dta.head(5)
```

Out[20]:

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs	affair	Predict_Affair
0	3.0	32.0	9.0	3.0	3.0	17.0	2.0	5.0	0.111111	1	0.0
1	3.0	27.0	13.0	3.0	1.0	14.0	3.0	4.0	3.230769	1	1.0
2	4.0	22.0	2.5	0.0	1.0	16.0	3.0	5.0	1.400000	1	0.0
3	4.0	37.0	16.5	4.0	3.0	16.0	5.0	5.0	0.727273	1	0.0
4	5.0	27.0	9.0	1.0	1.0	14.0	3.0	4.0	4.666666	1	0.0

In [ ]:

```
print('% of Affairs - based on raw data:\t', round((y.mean()*100),2),'%')
```

```
In [21]: # Now we will check our learning based on the analysis
         # examine the coefficients
         X.columns, np.transpose(lr.coef_)
```

```
Out[21]: (Index(['Intercept', 'occ_2', 'occ_3', 'occ_4', 'occ_5', 'occ_6', 'occ_husb_2',
                 'occ_husb_3', 'occ_husb_4', 'occ_husb_5', 'occ_husb_6', 'rate_marriage',
                 'age', 'yrs_married', 'children', 'religious', 'educ'],
                dtype='object'), array([[ 1.48983589],
                 [ 0.18806639],
                 [ 0.49894787],
                 [ 0.25066856],
                 [ 0.83900806],
                 [ 0.83390843],
                 [ 0.19063594],
                 [ 0.29783271],
                 [ 0.16140885],
                 [ 0.18777091],
                 [ 0.19401637],
                 [-0.70312336],
                 [-0.05841777],
                 [ 0.10567654],
                 [ 0.01691927],
                 [-0.37113627],
                 [ 0.0040165 ]]))
```

Evaluate the model by splitting dataset into train and test sets

```
In [22]: # evaluate the model by splitting dataset into train and test sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
         lr2 = LogisticRegression()
         lr2.fit(X_train, y_train)
```

```
Out[22]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False)
```

```
In [23]: # predict class labels for the test set
         predict = lr2.predict(X_test)
         predict

Out[23]: array([1., 0., 0., ..., 0., 0., 0.])
```

```
In [24]: # generate class probabilities
         y_probs = lr2.predict_proba(X_test)
         y_probs

Out[24]: array([[0.3514634 , 0.6485366 ],
                [0.90955084, 0.09044916],
                [0.72567333, 0.27432667],
                ...,
                [0.55727385, 0.44272615],
                [0.81207043, 0.18792957],
                [0.74734601, 0.25265399]])
```

- Confusion matrix

```
In [25]: from sklearn import metrics
         confusion_matrix = metrics.confusion_matrix(y_test, predict)
         confusion_matrix

Out[25]: array([[1169,  134],
                [ 382,  225]], dtype=int64)
```

- Classification Report

In [26]:
```
classification_report= metrics.classification_report(y_test,predict)
print(classification_report)
```

```
             precision    recall  f1-score   support

        0.0       0.75      0.90      0.82      1303
        1.0       0.63      0.37      0.47       607

avg / total       0.71      0.73      0.71      1910
```

- Model Accuracy

In [27]:
```
model_accuracy = lr2.score(X_test,y_test)
print(model_accuracy)
```

```
0.7298429319371728
```

- Evaluation metrics

In [28]:
```
print(metrics.accuracy_score(y_test, predict))
print(metrics.roc_auc_score(y_test, y_probs[:, 1]))

#The accuracy is 73%, which is the same as we experienced when training and predicting on the same data.
```

```
0.7298429319371728
0.745950606950631
```

- Model Evaluation Using Cross-Validation

In [30]:
```
# evaluate the model using 10-fold cross-validation
scores = cross_val_score(LogisticRegression(), X, np.ravel(y), scoring='accuracy', cv=10)
scores
```

Out[30]:
```
array([0.72100313, 0.70219436, 0.73824451, 0.70597484, 0.70597484,
       0.72955975, 0.7327044 , 0.70440252, 0.75157233, 0.75      ])
```

```
In [31]: print(scores.mean())

         0.7241630685514876
```

above results slated that , It's still performing at 73% accuracy.

Predicting the Probability of an Affair

Example: A women who is manager by profession, is college degree having somewhat religious, have 2 children from her marriage which is longer than 6 years. she is 30 years old women and rate her marriage is fair and her husband worked as a teacher:

As per affair dataset
rate_marriage = 3 for fair marriage rating
age = 30
yrs_married = 6
children =2
relegious values : 2 for somewhat religious
edu= 14 for some college
women's occupation = 5 for managerial/business (1 in occ_5)
husband occupation = 4 for teacher/nurse/writer/technician/skilled (1 in occ_husb_4)

```
In [32]: # Create array with the above value
         col_array=np.array([[1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 3, 30, 6, 2, 2, 14]])
```

```
In [37]: predict_affair=lr2.predict_proba(col_array)
         predict_affair

Out[37]: array([[0.46401118, 0.53598882]])
```

```
In [41]: print('The predicted probability of having an affair is:',round((predict_affair[0,1]*100),2) ,'%')

         The predicted probability of having an affair is: 53.6 %
```

- i.e For an women aged 30 years, married more than 6 years with a teacher, having 2 children and who is doing a managerial job after completing a college degree and who is somewhat religious and rate her marriage as fair, the predicted probability of having an affair is: 53.6 %