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

```
import numpy as np
import pandas as pd
#using pandas.tseries instead of statsmodels.api
import statsmodels.api as sm
import pandas.tseries as pdt
import matplotlib.pyplot as plt
from patsy import dmatrices
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.model_selection import cross_val_score
#To avoid warnings
import warnings
warnings.filterwarnings('ignore')
dta = sm.datasets.fair.load_pandas().data
df_affair = dta.copy()


#  add "affair" column: 1 represents having affairs, 0 represents not
dta['affair'] = (dta.affairs > 0).astype(int)
y, X = dmatrices('affair ~ rate_marriage + age + yrs_married + children + \
religious + educ + C(occupation) + C(occupation_husb)',
dta, return_type="dataframe")
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)
```

```
dta.head()
```

	rate_marriage	age	yrs_married	children	religious	educ	occupation	occupation_hu
0	3.0	32.0	9.0	3.0	3.0	17.0	2.0	
1	3.0	27.0	13.0	3.0	1.0	14.0	3.0	
2	4.0	22.0	2.5	0.0	1.0	16.0	3.0	
3	4.0	37.0	16.5	4.0	3.0	16.0	5.0	
4	5.0	27.0	9.0	1.0	1.0	14.0	3.0	

```
X.head()
```

	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_marr
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	

```
X.describe()
```

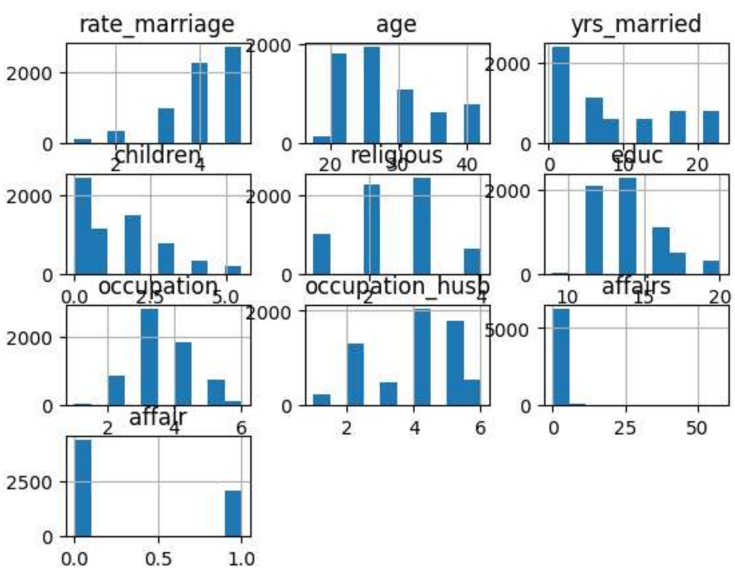
	Intercept	occ_2	occ_3	occ_4	occ_5	occ_6	occ_husb_2	occ_husb_3	occ_husb_4	occ_husb_5	occ_l
count	6366.0	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.000000	6366.(
mean	1.0	0.134936	0.437166	0.288093	0.116243	0.017122	0.205467	0.076971	0.318882	0.279453	0.(
std	0.0	0.341682	0.496075	0.452910	0.320541	0.129737	0.404074	0.266567	0.466080	0.448766	0.2
min	1.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
25%	1.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
50%	1.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
75%	1.0	0.000000	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000	0.(
max	1.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.(

```
y
```

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

```
dta.hist()
```

```
array([[<Axes: title={'center': 'rate_marriage'}>,
        <Axes: title={'center': 'age'}>,
        <Axes: title={'center': 'yrs_married'}>],
       [<Axes: title={'center': 'children'}>,
        <Axes: title={'center': 'religious'}>,
        <Axes: title={'center': 'educ'}>],
       [<Axes: title={'center': 'occupation'}>,
        <Axes: title={'center': 'occupation_husb'}>,
        <Axes: title={'center': 'affairs'}>],
       [<Axes: title={'center': 'affair'}>, <Axes: >, <Axes: >]],
      dtype=object)
```




```
print("Model Evaluation Using a Validation Set")
from sklearn.model_selection import train_test_split
# evaluate the model by splitting into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=32)
print(X_train.shape)
print(y_train.shape)
```

```
print(X_test.shape)
print(y_test.shape)
```

```
Model Evaluation Using a Validation Set
(4456, 17)
(4456,)
(1910, 17)
(1910,)
```

```
#We will use the statsmodels Logit function for logistic regression
logit = sm.Logit(y_train, X_train)
# fit the model
result = logit.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.538031
         Iterations 6
```

```
result.summary()
```

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	4456
Model:	Logit	**Df Residuals:**	4439
Method:	MLE	**Df Model:**	16
Date:	Tue, 19 Sep 2023	**Pseudo R-squ.:**	0.1443
Time:	17:49:25	**Log-Likelihood:**	-2397.5
converged:	True	**LL-Null:**	-2801.6
Covariance Type:	nonrobust	**LLR p-value:**	1.071e-161

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	3.3423	0.650	5.144	0.000	2.069	4.616
occ_2	0.3924	0.496	0.791	0.429	-0.579	1.364
occ_3	0.7035	0.488	1.442	0.149	-0.253	1.660
occ_4	0.3934	0.490	0.802	0.422	-0.567	1.354
occ_5	0.9981	0.495	2.014	0.044	0.027	1.969
occ_6	0.9368	0.566	1.654	0.098	-0.173	2.047
occ_husb_2	-0.0348	0.212	-0.164	0.869	-0.450	0.380
occ_husb_3	0.0430	0.233	0.184	0.854	-0.414	0.500
occ_husb_4	-0.0382	0.205	-0.186	0.852	-0.441	0.364
occ_husb_5	-0.0814	0.208	-0.392	0.695	-0.489	0.326
occ_husb_6	-0.1385	0.237	-0.584	0.559	-0.603	0.326
rate_marriage	-0.7472	0.038	-19.504	0.000	-0.822	-0.672
age	-0.0605	0.012	-4.873	0.000	-0.085	-0.036
yrs_married	0.1084	0.013	8.202	0.000	0.083	0.134
children	0.0195	0.039	0.503	0.615	-0.056	0.096
religious	-0.3701	0.042	-8.775	0.000	-0.453	-0.287
educ	-0.0027	0.021	-0.129	0.897	-0.044	0.038

```
predictions = result.predict(X_test)
predictions
```

```
2700    0.098601
442     0.233797
2261    0.136980
2686    0.336494
4901    0.062733
          ...
1332    0.489072
1878    0.413433
2020    0.664015
2431    0.178414
5608    0.890911
Length: 1910, dtype: float64
```

```
dta.groupby('affair').mean()
# Women who has affairs have rated their marriage less compare to not having affair.
```

	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

```
dta.groupby('rate_marriage').mean()
```

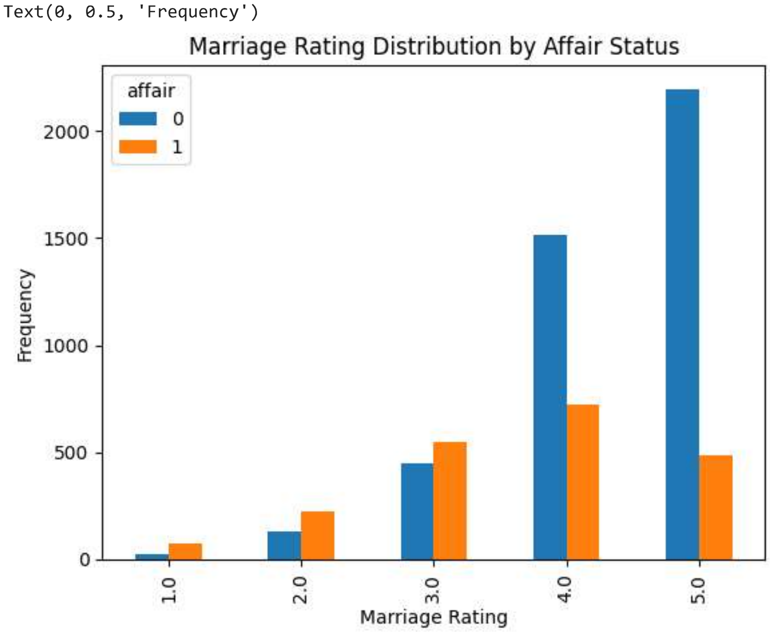
	age	yrs_married	children	religious	educ	occupation	occupation_husb	affairs	affair
rate_marriage									
1.0	33.823232	13.914141	2.308081	2.343434	13.848485	3.232323	3.838384	1.201671	0.747475
2.0	30.471264	10.727011	1.735632	2.330460	13.864943	3.327586	3.764368	1.615745	0.635057
3.0	30.008056	10.239174	1.638469	2.308157	14.001007	3.402820	3.798590	1.371281	0.550856
4.0	28.856601	8.816905	1.369536	2.400981	14.144514	3.420161	3.835861	0.674837	0.322926
5.0	28.574702	8.311662	1.252794	2.506334	14.399776	3.454918	3.892697	0.348174	0.181446

```
dta.groupby('occupation_husb').mean()
```

	rate_marriage	age	yrs_married	children	religious	educ	occupation	affairs	affair
occupation_husb									
1.0	4.318777	23.862445	3.449782	0.353712	2.327511	14.991266	3.445415	0.657557	0.209607
2.0	4.035933	28.310398	8.530581	1.400229	2.443425	13.521407	3.130734	0.763874	0.325688
3.0	4.034694	29.358163	9.212245	1.369388	2.451020	13.812245	3.244898	0.809943	0.353061
4.0	4.114286	28.592611	8.678325	1.380049	2.415271	14.109852	3.393596	0.717594	0.314778
5.0	4.114671	30.243114	10.090219	1.521079	2.426082	14.358628	3.577853	0.615542	0.338392
6.0	4.235849	30.973585	10.046226	1.512264	2.445283	15.822642	3.905660	0.739709	0.311321

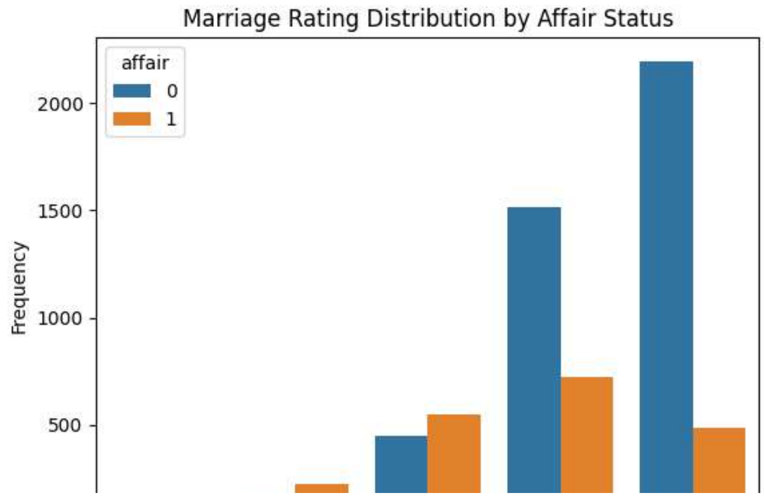
```
# barplot of marriage rating grouped by affair (True or False)
pd.crosstab(dta.rate_marriage, dta.affair).plot(kind='bar')
plt.title('Marriage Rating Distribution by Affair Status')
plt.xlabel('Marriage Rating')
plt.ylabel('Frequency')
```

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



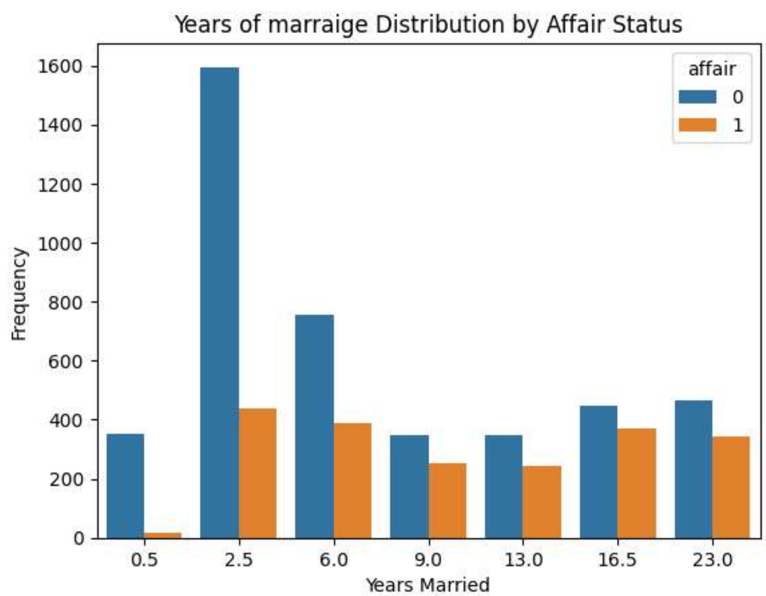

```
import seaborn as sns
sns.countplot(x='rate_marriage',data=dta,hue='affair')
plt.title('Marriage Rating Distribution by Affair Status')
plt.xlabel('Marriage Rating')
plt.ylabel('Frequency')
```

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



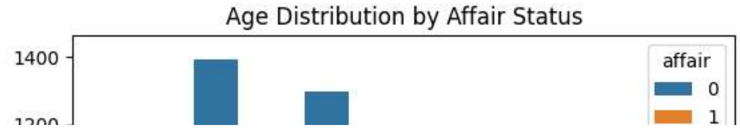

```
sns.countplot(x='yrs_married',data=dta,hue='affair')
plt.title('Years of marraige Distribution by Affair Status')
plt.xlabel('Years Married')
plt.ylabel('Frequency')
```

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




```
sns.countplot(x='age',data=dta,hue='affair')
plt.title('Age Distribution by Affair Status')
plt.xlabel('Age')
plt.ylabel('Frequency')
```

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




```
#Logistic Regression
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
print(model.score(X_train,y_train))
print("Training set has 73% accuracy")
```

```
0.7302513464991023
Training set has 73% accuracy
```

```
print("Use the test data set to predict the class / labels")
# predict class labels for the test set
predicted = model.predict(X_test)
predicted
```

```
Use the test data set to predict the class / labels
array([0., 0., 0., ..., 1., 0., 1.])
```

```
# generate class probabilities
probs = model.predict_proba(X_test)
probs
```

```
array([[0.90502047, 0.09497953],
       [0.76498723, 0.23501277],
       [0.86199942, 0.13800058],
       ...,
       [0.32044926, 0.67955074],
       [0.82578373, 0.17421627],
       [0.10389084, 0.89610916]])
```

```
print('Evaluating the model')
# generate evaluation metrics
print(metrics.accuracy_score(y_test,predicted))
print(metrics.roc_auc_score(y_test, probs[:, 1]))
print("The accuracy of the model is 71% nearer to the training data.")
```

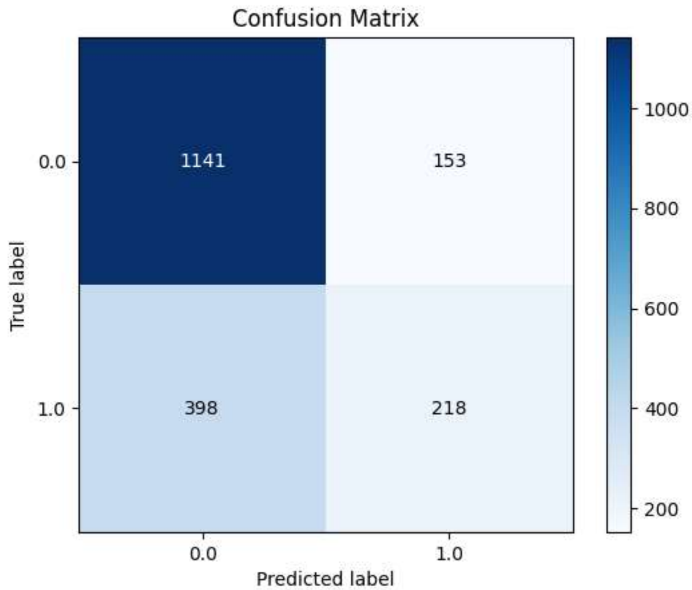
```
Evaluating the model
0.7115183246073299
0.7327061462494229
The accuracy of the model is 71% nearer to the training data.
```

```
!pip install scikit-plot
```

```
Collecting scikit-plot
  Downloading scikit_plot-0.3.7-py3-none-any.whl (33 kB)
Requirement already satisfied: matplotlib>=1.4.0 in /usr/local/lib/python3.10/dist-packages (from scikit-plot) (3.7.1)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.10/dist-packages (from scikit-plot) (1.2.2)
Requirement already satisfied: scipy>=0.9 in /usr/local/lib/python3.10/dist-packages (from scikit-plot) (1.11.2)
Requirement already satisfied: joblib>=0.10 in /usr/local/lib/python3.10/dist-packages (from scikit-plot) (1.3.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (4.42.
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.4.5
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.23.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (23.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=1.4.0->scikit-plot) (2.
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.18->scikit-plot) (3
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=1.4.0->scikit
Installing collected packages: scikit-plot
Successfully installed scikit-plot-0.3.7
```

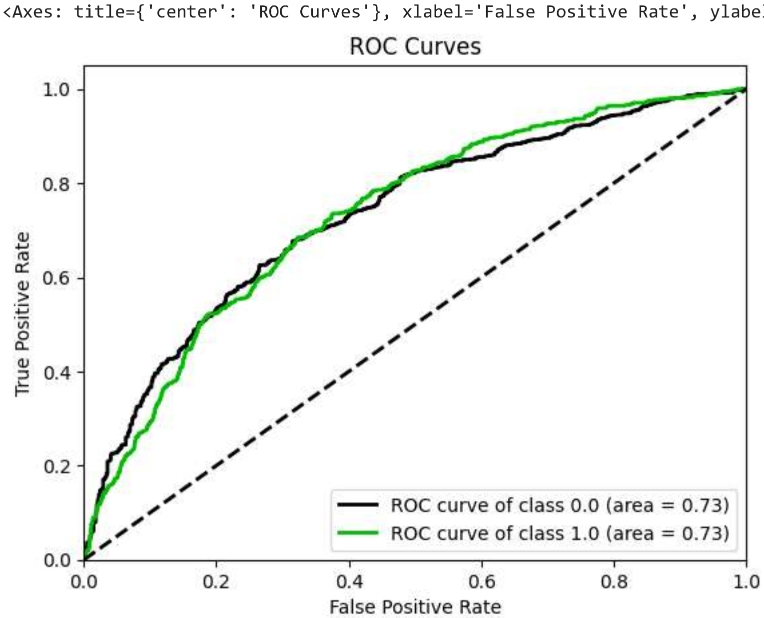
```
#Using confusion matrix to describe the performance of the classification mo
import scikitplot
scikitplot.metrics.plot_confusion_matrix(y_test,predicted)
```

```
<Axes: title={'center': 'Confusion Matrix'}, xlabel='Predicted label', ylabel='True label'>
```




```
# Plotting the true positive rate (TPR) against the false positive rate (FPR)
scikitplot.metrics.plot_roc_curve(y_test, probs,curves=['each_class'])
```

```
<Axes: title={'center': 'ROC Curves'}, xlabel='False Positive Rate', ylabel='True Positive Rate'>
```




```
#accuracy report
print(metrics.classification_report(y_test, predicted))
```

	precision	recall	f1-score	support
0.0	0.74	0.88	0.81	1294
1.0	0.59	0.35	0.44	616
accuracy			0.71	1910
macro avg	0.66	0.62	0.62	1910
weighted avg	0.69	0.71	0.69	1910

```
from sklearn.metrics import confusion_matrix
cf = confusion_matrix(y_test,predicted)
type(cf)
```

```
numpy.ndarray
```

```
cf.shape
```

```
(2, 2)
```

```
#Calculation of Precision Recall and F1 score
TN = cf[0,0] #True Negative
FP = cf[0,1] #False Positive
FN = cf[1,0] #False Negative
TP = cf[1,1] #True Positive
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1 = (2 *(Precision * Recall)) / (Precision + Recall)
print("Precision : {} , Recall : {}, F1 : {}".format(Precision,Recall,F1))
```

```
Precision : 0.5876010781671159 , Recall : 0.3538961038961039, F1 : 0.4417426545086119
```

```
#Calculation of True Positive Rate and False Positive Rate
TPR = (TP) / (TP + FN ) #equal to Recall
FPR = FP / (FP + TN )
print("True Positive Rate : {}, False Positive Rate : {}".format(TPR,FPR))
```

```
True Positive Rate : 0.3538961038961039, False Positive Rate : 0.11823802163833076
```

```
# evaluate the model using 10-fold cross-validation
scores = cross_val_score(LogisticRegression(), X, y, scoring='accuracy', cv=10)
scores, scores.mean()
```

```
(array([0.71899529, 0.69858713, 0.73783359, 0.70800628, 0.71428571,
        0.72841444, 0.72955975, 0.70440252, 0.74685535, 0.75      ]),
 0.7236940059042485)
```

```
print('Predicting the Probability of an Affair')
print(model.predict_proba(np.array([[1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 3, 25, 3, 1, 4,16]])))
print('The predicted probability of an affair is 23%')
```

```
Predicting the Probability of an Affair
[[0.76335699 0.23664301]]
The predicted probability of an affair is 23%
```

```
print(model.predict_proba(np.array([[1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 3, 30, 3, 1, 4,16]])))
print('The predicted probability of an affair is 18%')
```

```
[[0.81124059 0.18875941]]
The predicted probability of an affair is 18%
```