LogisticRegression_Affairs

December 18, 2020

[1]:
```
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.model_selection import train_test_split,cross_val_score
from sklearn import metrics
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
dta=sm.datasets.fair.load_pandas().data
```

[3]:
```
dta
```

[3]:
```
      rate_marriage   age  yrs_married  children  religious  educ  occupation  \
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
…             …   …          …       …        …   …         …
6361            5.0  32.0         13.0       2.0        3.0  17.0         4.0
6362            4.0  32.0         13.0       1.0        1.0  16.0         5.0
6363            5.0  22.0          2.5       0.0        2.0  14.0         3.0
6364            5.0  32.0          6.0       1.0        3.0  14.0         3.0
6365            4.0  22.0          2.5       0.0        2.0  16.0         2.0

      occupation_husb   affairs
0                 5.0  0.111111
1                 4.0  3.230769
2                 5.0  1.400000
3                 5.0  0.727273
4                 4.0  4.666666
…               …       …
6361              3.0  0.000000
```

```
6362                5.0  0.000000
6363                1.0  0.000000
6364                4.0  0.000000
6365                4.0  0.000000

[6366 rows x 9 columns]
```

[4]:
```python
dta['affair'] = (dta.affairs >0).astype(int)
```

[5]:
```python
#Checking the distribution of dependent feature
dta.affair.value_counts()
```

[5]:
```
0    4313
1    2053
Name: affair, dtype: int64
```

Seems to be an imbalanced dataset as one category has double the records of other

[6]:
```python
#Checking for NULL Values
dta.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6366 entries, 0 to 6365
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   rate_marriage    6366 non-null   float64
 1   age              6366 non-null   float64
 2   yrs_married      6366 non-null   float64
 3   children         6366 non-null   float64
 4   religious        6366 non-null   float64
 5   educ             6366 non-null   float64
 6   occupation       6366 non-null   float64
 7   occupation_husb  6366 non-null   float64
 8   affairs          6366 non-null   float64
 9   affair           6366 non-null   int32
dtypes: float64(9), int32(1)
memory usage: 472.5 KB
```

NULL values are not present in above dataset

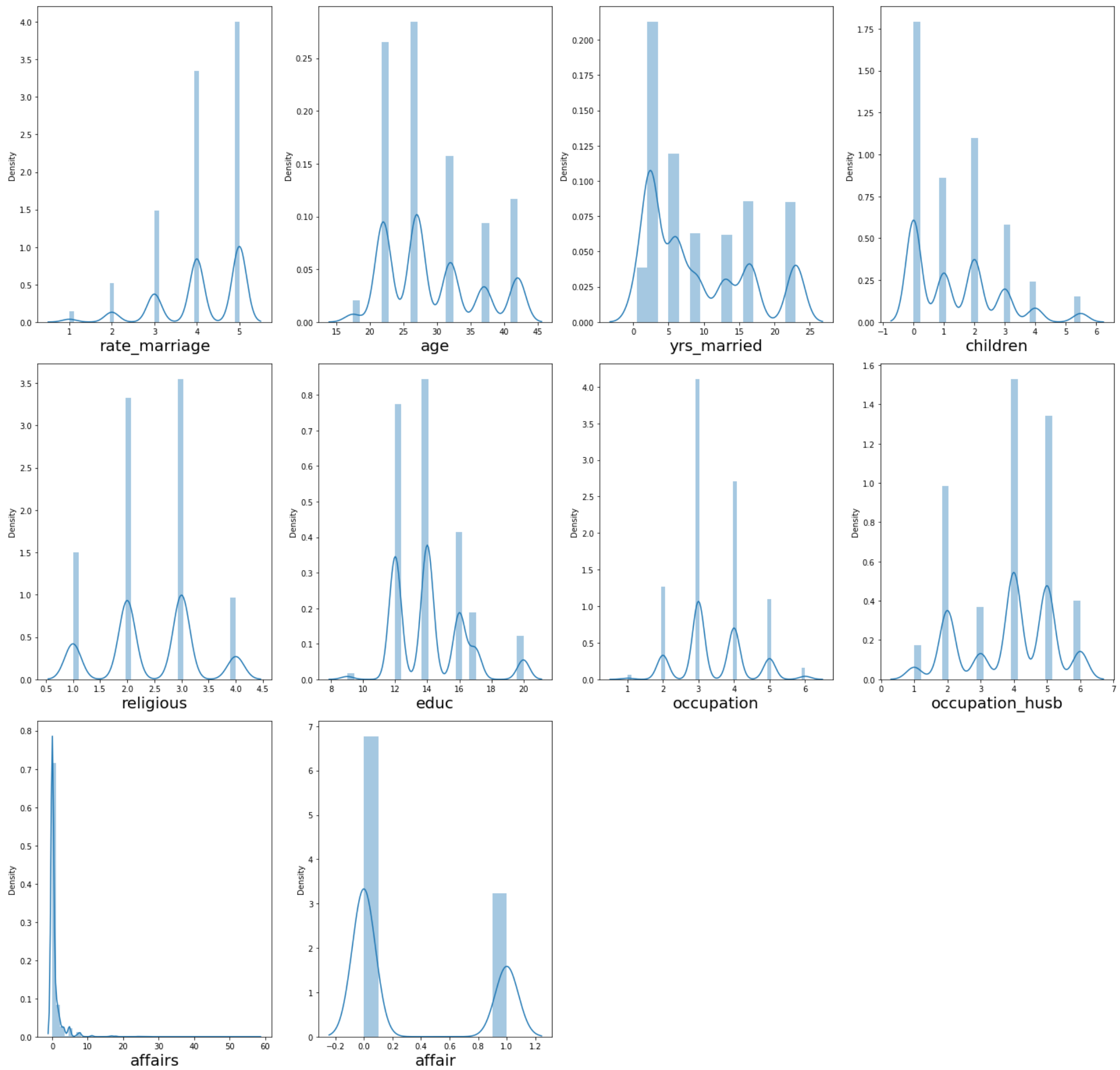
[7]:
```python
#Getting a summary of data
dta.describe()
```

[7]:
```
       rate_marriage          age  yrs_married     children    religious  \
count    6366.000000  6366.000000  6366.000000  6366.000000  6366.000000
mean        4.109645    29.082862     9.009425     1.396874     2.426170
std         0.961430     6.847882     7.280120     1.433471     0.878369
```

```
min        1.000000    17.500000     0.500000     0.000000     1.000000
25%        4.000000    22.000000     2.500000     0.000000     2.000000
50%        4.000000    27.000000     6.000000     1.000000     2.000000
75%        5.000000    32.000000    16.500000     2.000000     3.000000
max        5.000000    42.000000    23.000000     5.500000     4.000000

              educ   occupation  occupation_husb      affairs       affair
count  6366.000000  6366.000000      6366.000000  6366.000000  6366.000000
mean     14.209865     3.424128         3.850141     0.705374     0.322495
std       2.178003     0.942399         1.346435     2.203374     0.467468
min       9.000000     1.000000         1.000000     0.000000     0.000000
25%      12.000000     3.000000         3.000000     0.000000     0.000000
50%      14.000000     3.000000         4.000000     0.000000     0.000000
75%      16.000000     4.000000         5.000000     0.484848     1.000000
max      20.000000     6.000000         6.000000    57.599991     1.000000
```

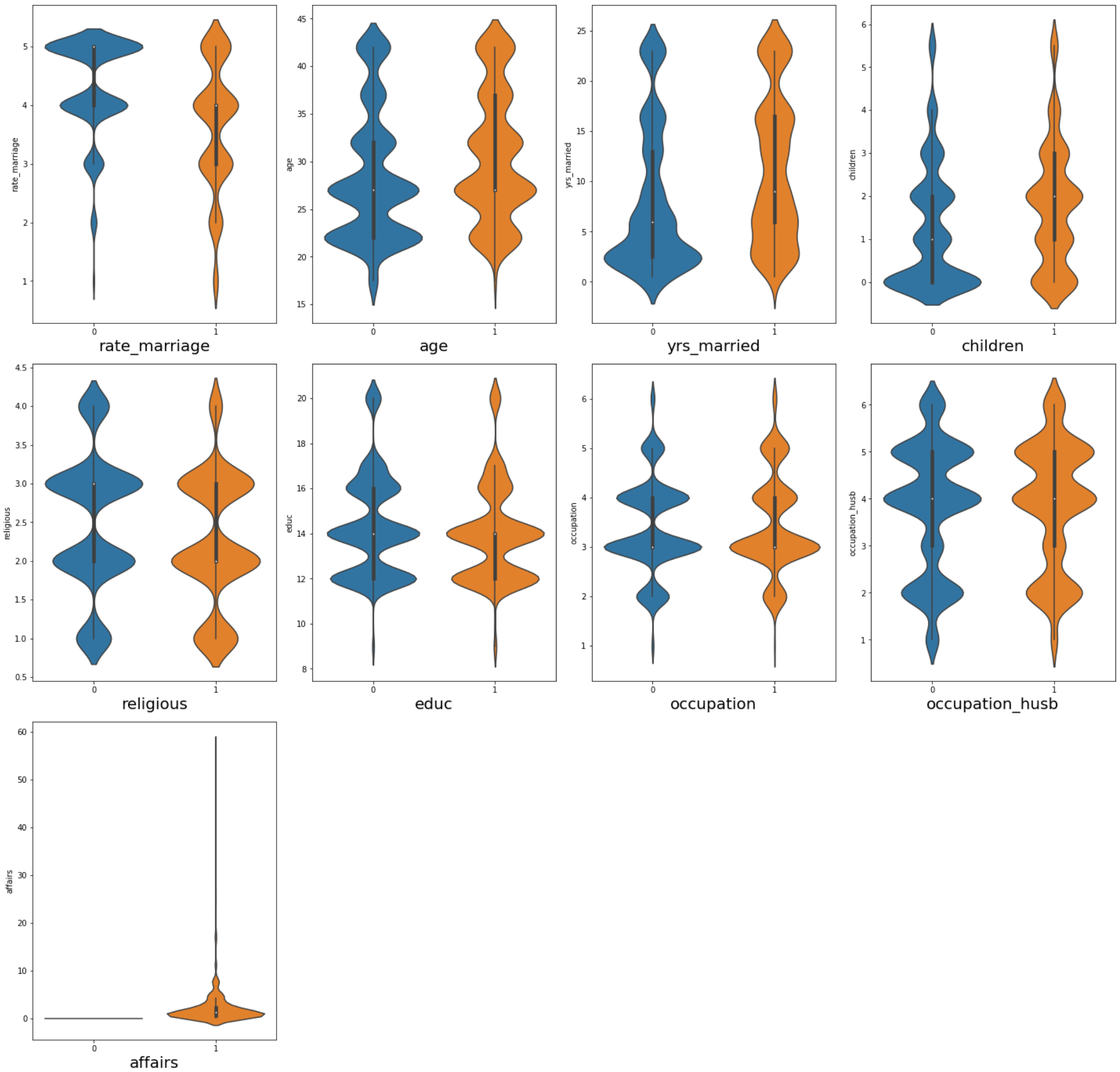
[8]:

```python
# let's see how data is distributed for every column
plt.figure(figsize=(20,25), facecolor='white')
plotnumber = 1

for column in dta:
    if plotnumber<=16 :
        ax = plt.subplot(4,4,plotnumber)
        sns.distplot(dta[column])
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.tight_layout()
```



[9]:

```
# let's see how data is distributed for every column and each category.
plt.figure(figsize=(20,25), facecolor='white')
plotnumber = 1

for column in dta.drop(columns=['affair']):
    if plotnumber<=16:
        ax = plt.subplot(4,4,plotnumber)
        sns.violinplot(y=column,x='affair',data=dta)
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.tight_layout()
```



Some of the attributes(rate__marriage,age,yrs__married,children,education) give us an idea how we can distribute the data

[10]:
```
y, X = dmatrices('affair ~ rate_marriage + age + yrs_married + children + religious + educ + C(occupation) + C(occupation_husb)',dta, return_type="dataframe")
```

[11]:
```
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'})
```

[12]:
```
#Flattening the array
y=np.ravel(y)
```

[13]:
```
y
```

[13]:
```
array([1., 1., 1., …, 0., 0., 0.])
```

[14]:
```
X.head()
```

[14]:
```
   Intercept  occ_2  occ_3  occ_4  occ_5  occ_6  occ_husb_2  occ_husb_3  \
0        1.0    1.0    0.0    0.0    0.0    0.0         0.0         0.0
1        1.0    0.0    1.0    0.0    0.0    0.0         0.0         0.0
2        1.0    0.0    1.0    0.0    0.0    0.0         0.0         0.0
3        1.0    0.0    0.0    0.0    1.0    0.0         0.0         0.0
4        1.0    0.0    1.0    0.0    0.0    0.0         0.0         0.0

   occ_husb_4  occ_husb_5  occ_husb_6  rate_marriage   age  yrs_married  \
0         0.0         1.0         0.0            3.0  32.0          9.0
1         1.0         0.0         0.0            3.0  27.0         13.0
2         0.0         1.0         0.0            4.0  22.0          2.5
3         0.0         1.0         0.0            4.0  37.0         16.5
4         1.0         0.0         0.0            5.0  27.0          9.0

   children  religious  educ
0       3.0        3.0  17.0
1       3.0        1.0  14.0
2       0.0        1.0  16.0
3       4.0        3.0  16.0
4       1.0        1.0  14.0
```

[15]:
```
from sklearn.preprocessing import StandardScaler
```

[16]:
```
scalar = StandardScaler()
X_scaled = scalar.fit_transform(X)
```

[17]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif["vif"] = [variance_inflation_factor(X_scaled,i) for i in range(X_scaled.
 ↪shape[1])]
vif["Features"] = X.columns

#let's check the values
vif
```

[17]:
```
          vif       Features
0         NaN      Intercept
1   19.340780          occ_2
2   39.335618          occ_3
3   32.931910          occ_4
4   17.057165          occ_5
5    3.697959          occ_6
6    5.566292     occ_husb_2
7    2.991070     occ_husb_3
8    6.930281     occ_husb_4
9    6.577077     occ_husb_5
10   3.185266     occ_husb_6
11   1.038746  rate_marriage
12   5.477890            age
13   7.169611    yrs_married
14   2.585691       children
15   1.037556      religious
16   1.635790           educ
```

[18]:
```
from sklearn.decomposition import PCA
```

[19]:
```
pca=PCA(n_components=16)
pca.fit(X_scaled)
X_scaled=pca.transform(X_scaled)
```

[20]:
```
'''vif = pd.DataFrame()
vif["vif"] = [variance_inflation_factor(X_scaled,i) for i in range(X_scaled.
 ↪shape[1])]
vif["Features"] = X.columns

#let's check the values
vif'''
```

[20]:
```
'vif = pd.DataFrame()\nvif["vif"] = [variance_inflation_factor(X_scaled,i) for i
in range(X_scaled.shape[1])]\nvif["Features"] = X.columns\n\n#let\'s check the
values\nvif'
```

[21]:
```
from sklearn.model_selection import GridSearchCV
```

[22]:
```
tuned_parameters = [{'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}]
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, train_size=0.
 ↪80, random_state=355)
```

[23]:
```
#Creating a logistic regression model
model=LogisticRegression()
model
```

[23]: LogisticRegression()

[24]:
```
model.fit(X_train,y_train)
```

[24]: LogisticRegression()

[25]:
```
print(model.intercept_)
print(model.coef_)
```

```
[-0.86820103]
[[ 0.28642491 -0.17805779 -0.09754933  0.01492019  0.04037216  0.16600263
   0.02201041  0.67325349  0.22110419  0.19475182 -0.07096377  0.03170189
   0.01096669 -0.80204922 -0.1783994  -0.4970327 ]]
```

[26]:
```
pd.DataFrame(list(zip(X.columns,np.transpose(model.coef_))))
```

[26]:

	0	1
0	Intercept	[0.28642491290349936]
1	occ_2	[-0.1780577903713062]
2	occ_3	[-0.09754933236456209]
3	occ_4	[0.014920192101074918]
4	occ_5	[0.04037215803868455]
5	occ_6	[0.166002627277531]
6	occ_husb_2	[0.022010408780076218]
7	occ_husb_3	[0.6732534932736467]
8	occ_husb_4	[0.2211041855874721]
9	occ_husb_5	[0.19475181622036805]
10	occ_husb_6	[-0.07096376688454989]
11	rate_marriage	[0.031701888926905564]
12	age	[0.010966693279125533]
13	yrs_married	[-0.8020492195767321]
14	children	[-0.17839939712683522]
15	religious	[-0.4970327021039477]

[27]:
```
y_pred=model.predict(X_test)
```

[28]:
```
print(model)
```

```
LogisticRegression()
```

[29]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve,␣
↪roc_auc_score
```

[30]:
```
accuracy = accuracy_score(y_test,y_pred)
accuracy
```

[30]: 0.7189952904238619

[31]:
```
# Confusion Matrix
conf_mat = confusion_matrix(y_test,y_pred)
conf_mat
```

[31]:
```
array([[773,  90],
       [268, 143]], dtype=int64)
```

[32]:
```
true_positive = conf_mat[0][0]
false_positive = conf_mat[0][1]
false_negative = conf_mat[1][0]
true_negative = conf_mat[1][1]
```

[33]:
```
# Breaking down the formula for Accuracy
Accuracy = (true_positive + true_negative) / (true_positive +false_positive +␣
↪false_negative + true_negative)
Accuracy
```

[33]:
```
0.7189952904238619
```

[34]:
```
# Precison
Precision = true_positive/(true_positive+false_positive)
Precision
```

[34]:
```
0.895712630359212
```

[35]:
```
# Recall
Recall = true_positive/(true_positive+false_negative)
Recall
```

[35]:
```
0.7425552353506244
```

[36]:
```
# F1 Score
F1_Score = 2*(Recall * Precision) / (Recall + Precision)
F1_Score
```

[36]:
```
0.8119747899159663
```

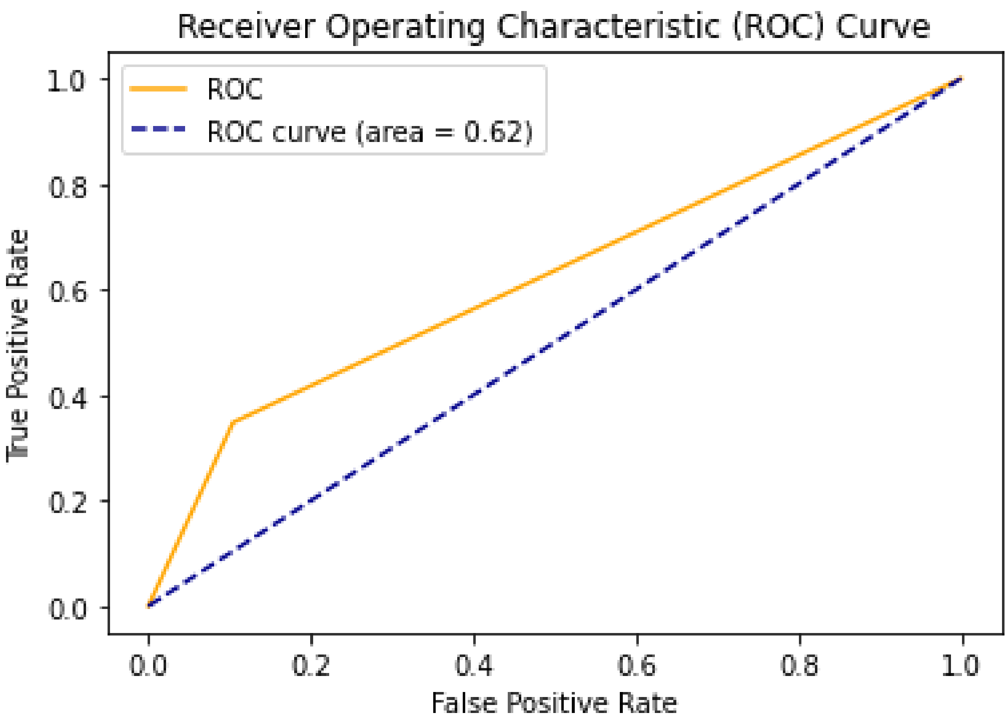
[37]:
```
# Area Under Curve
auc = roc_auc_score(y_test, y_pred)
auc
```

[37]:
```
0.6218222519192653
```

[38]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
```

[39]:
```
plt.plot(fpr, tpr, color='orange', label='ROC')
```

```
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--',label='ROC curve␣
↪(area = %0.2f)' % auc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



[40]:
```
# evaluate the model using 10-fold cross-validation
scores = cross_val_score(LogisticRegression(), X, y, scoring='accuracy', cv=10)
scores, scores.mean()
```

[40]:
```
(array([0.72213501, 0.69701727, 0.73469388, 0.70800628, 0.71585557,
        0.72841444, 0.72798742, 0.70440252, 0.75      , 0.75628931]),
 0.724480169426261)
```

[ ]: