Assignment 21

Problem Statement

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.

Use Logistic Regression to predict the classification for each women

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 [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sqlite3
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import r2_score
from math import sqrt
import statsmodels.formula.api as smf
import statsmodels.api as sm
```

In [2]:
```
# load dataset

df = sm.datasets.fair.load_pandas().data
```

In [3]:
```
df.head()
```

Out[3]:

	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
4	5.0	27.0	9.0	1.0	1.0	14.0	3.0	4.0	4.666666

In [4]:
```
# Add an "affair" column: 1 represents having affairs, 0 represents not

df['affair'] = (df.affairs > 0).astype(int)
```

In [5]:
```
df.head()
```

Out[5]:

	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
4	5.0	27.0	9.0	1.0	1.0	14.0	3.0	4.0	4.666666	1

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6366 entries, 0 to 6365
Data columns (total 10 columns):
rate_marriage      6366 non-null float64
age                6366 non-null float64
yrs_married        6366 non-null float64
children           6366 non-null float64
religious          6366 non-null float64
educ               6366 non-null float64
occupation         6366 non-null float64
occupation_husb    6366 non-null float64
affairs            6366 non-null float64
affair             6366 non-null int32
dtypes: float64(9), int32(1)
memory usage: 472.6 KB
```

Exploratory Data Analysis

Data Cleaning

In [7]:
```
# Since I created the Affair column based on the data in the Affairs column
# (if affairs > 0 then the woman had an affair else no) I am going to drop the affairs column

df.drop('affairs', axis=1, inplace=True)
```

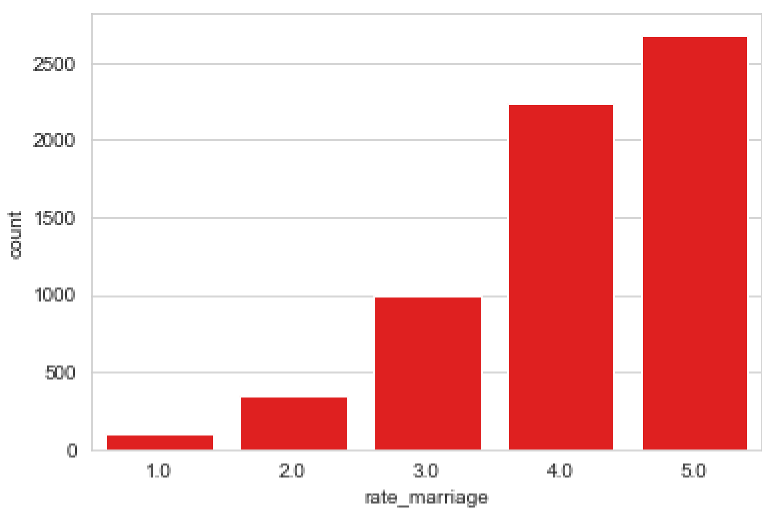
In [8]:
```
# Count the number of null values in the columns
df.isnull().sum(axis=0)
```

Out[8]:
```
rate_marriage      0
age                0
yrs_married        0
children           0
religious          0
educ               0
occupation         0
occupation_husb    0
affair             0
dtype: int64
```

In [9]:
```
# See the distribution of Marriage Rate

sns.set_style('whitegrid')
sns.countplot(x='rate_marriage', data=df, color='red')
```

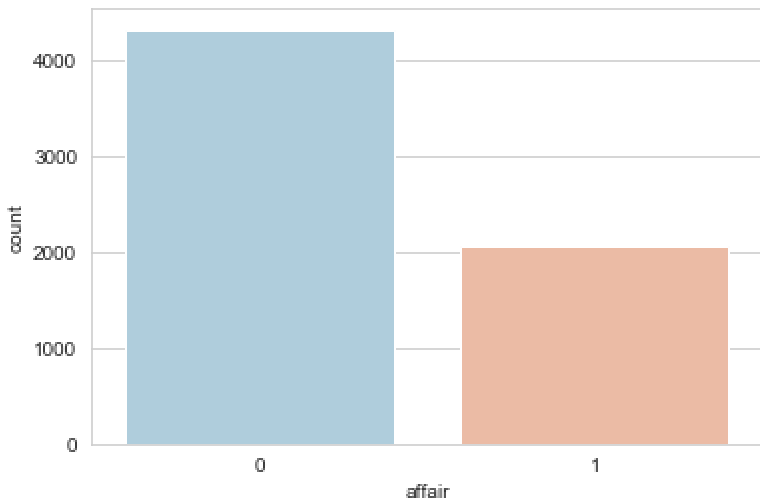
Out[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x213810f0b70>
```



In [10]:
```
# Visualize the number of women who had affairs

sns.set_style('whitegrid')
sns.countplot(x='affair', data=df, palette='RdBu_r')
```

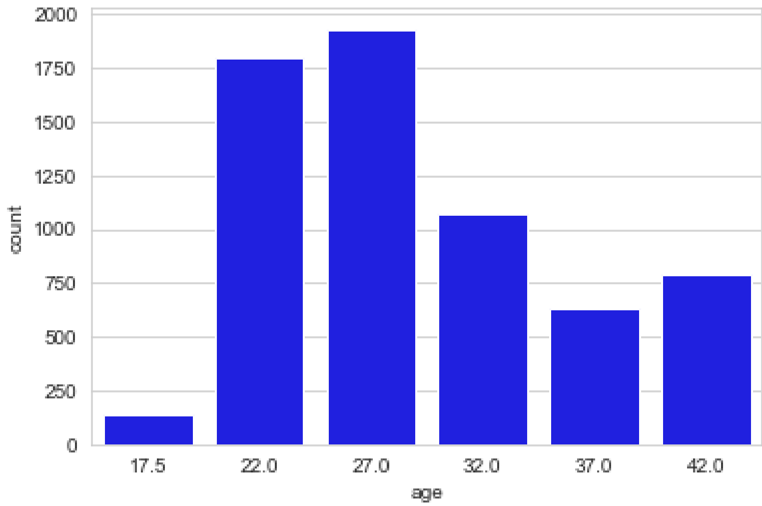
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2138116e940>



In [11]:
```
# See the distribution of Age for the dataset

sns.set_style('whitegrid')
sns.countplot(x='age', data=df, color='blue')
```

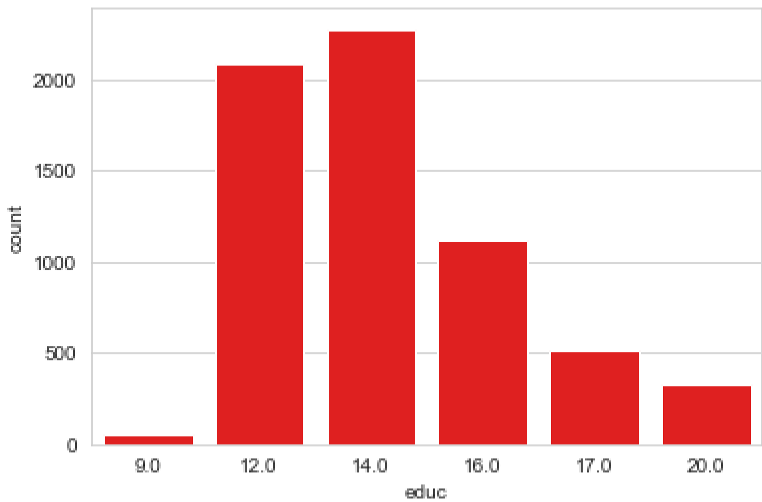
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x213811f15f8>



In [12]:
```
# See the distribution of education

sns.set_style('whitegrid')
sns.countplot(x='educ', data=df, color='red')
```

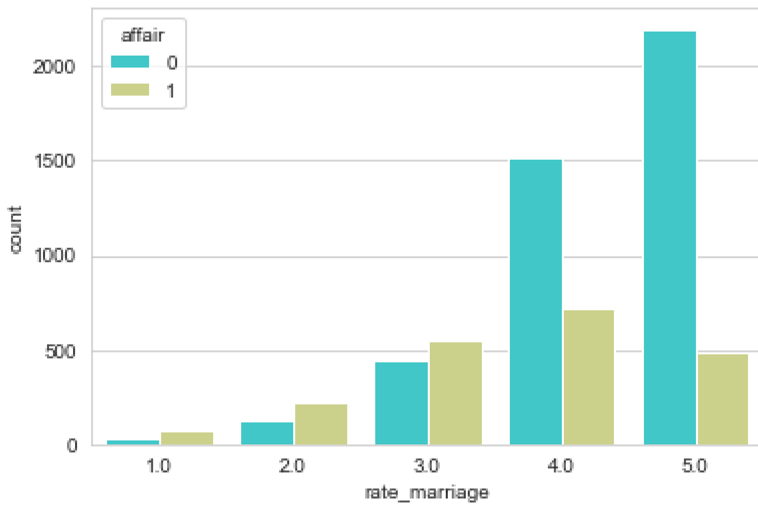
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x213812a75c0>



In [13]:
```
# Visualize how many had affairs based on marriage rate

sns.set_style('whitegrid')
sns.countplot(x='rate_marriage', hue='affair', data=df, palette='rainbow')
```

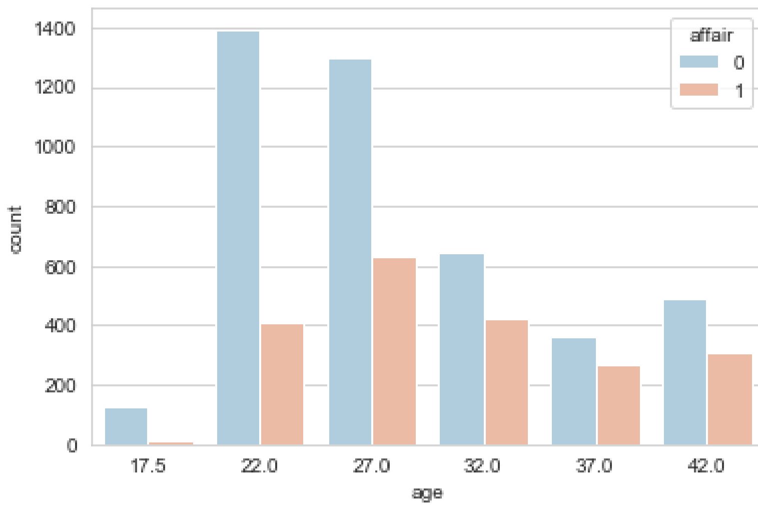
Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x213811e3d30>
```



In [14]:
```
# Visualize how many had affairs based on age

sns.set_style('whitegrid')
sns.countplot(x='age', hue='affair', data=df, palette='RdBu_r')
```

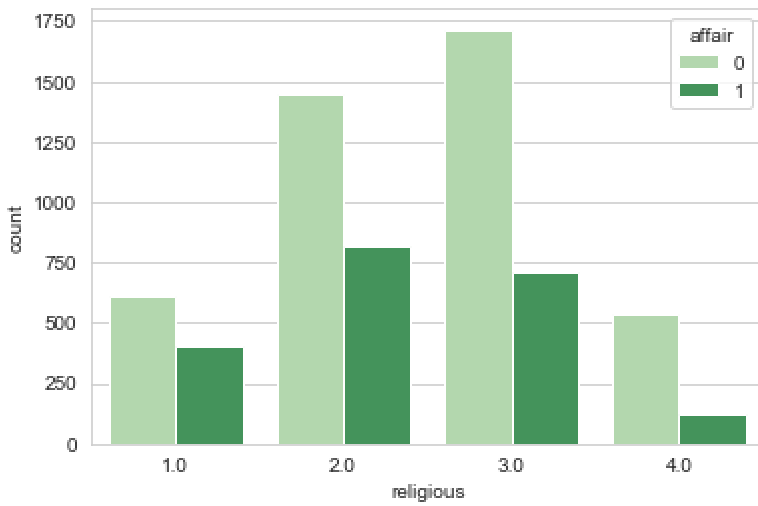
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x213fb572898>



In [15]:
```
# Visualize how many had affairs based on religious preference

sns.set_style('whitegrid')
sns.countplot(x='religious', hue='affair', data=df, palette='Greens')
```

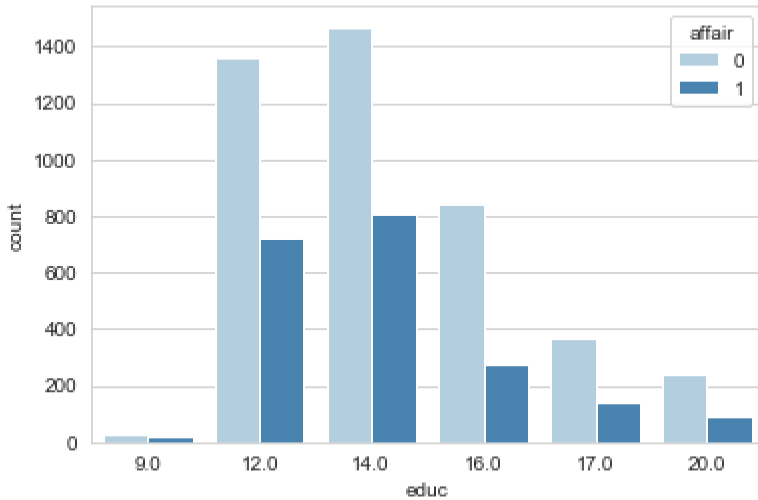
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x21381054080>



In [16]:
```
# Visualize how many had affairs based on level of education

sns.set_style('whitegrid')
sns.countplot(x='educ', hue='affair', data=df, palette='Blues')
```

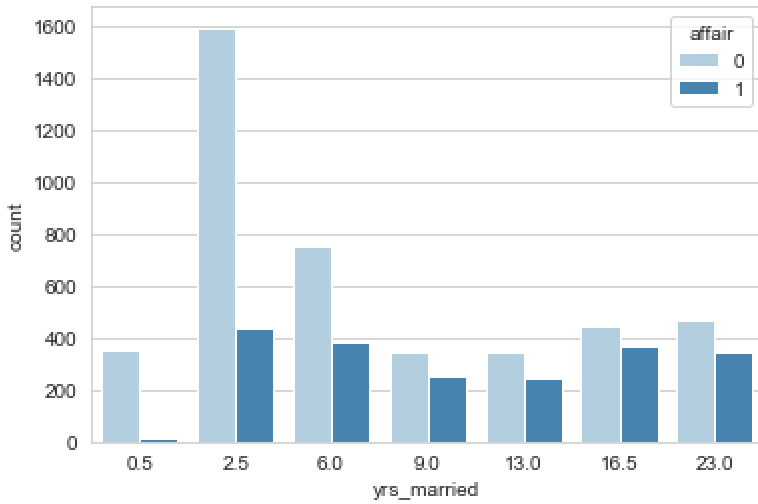
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x2138130fb00>



In [17]:
```
# Visualize how many had affairs based on number of years they were married

sns.set_style('whitegrid')
sns.countplot(x='yrs_married', hue='affair', data=df, palette='Blues')
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2138130f1d0>



Building Logistic Regression Model

Prepare the dataset

In [18]:
```
# We will convert wife's and husbands occupation to
# to dummy variable (LabelEncoding) and drop one column (OneHotEncoding)
# This will create a new dataframe for each feature

wife_occup = pd.get_dummies(df['occupation'],prefix='wife_occup_', drop_first=True)
husb_occup = pd.get_dummies(df['occupation_husb'], prefix='husb_occup_', drop_first=True)
```

In [19]:
```
wife_occup.head()
```

Out[19]:

	wife_occup__2.0	wife_occup__3.0	wife_occup__4.0	wife_occup__5.0	wife_occup__6.0
0	1	0	0	0	0
1	0	1	0	0	0
2	0	1	0	0	0
3	0	0	0	1	0
4	0	1	0	0	0

In [20]:
```
# I will drop the wife and husbands occupation columns from the dataset since I created the dummy variables

df.drop(['occupation', 'occupation_husb'], axis=1, inplace=True)
```

In [21]:
```
# I will concatenate the dummy variables to my dataset.

df = pd.concat([df,wife_occup,husb_occup], axis=1)
```

Split the dataset into Training and Test set

In [58]:
```
X_train, X_test, y_train, y_test = train_test_split(df.drop('affair', axis=1), df['affair'],
                                                    test_size = 0.30, random_state = 101)
```

In [59]:
```
# Print the shape of train and test data

print('X_train: ', X_train.shape)
print('X_test: ', X_test.shape)
print('y_train: ', y_train.shape)
print('y_test: ', y_test.shape)
```

```
X_train:  (4456, 26)
X_test:  (1910, 26)
y_train:  (4456,)
y_test:  (1910,)
```

Create and Train the Logistic Regression Model

In [65]:
```
lrm = LogisticRegression()
lrm.fit(X_train, y_train)
```

```
C:\Users\KSamrari\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarning: Default so
lver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[65]:
```
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)
```

Make the predictions

In [66]:
```
y_pred = lrm.predict(X_test)
```

In [77]:
```
# Compare the Actual Overall Rating to the Predicted Overall Rating

ActualvsPred = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
```

In [78]:
```
print(ActualvsPred.head(20))
```

```
       Actual  Predicted
2432        0          0
603         1          0
659         1          0
3632        0          0
582         1          1
2383        0          0
4883        0          0
6213        0          0
4711        0          0
5247        0          0
4974        0          0
1388        1          0
589         1          1
5279        0          0
2523        0          0
5071        0          0
2816        0          0
2486        0          0
4251        0          0
5201        0          0
```

In [71]:
```
# Look at the confusion matrix to see how our test data compares to the predicted data
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test,y_pred)
```

In [76]:
```
print(cm)
```

```
[[1159  118]
 [ 433  200]]
```

In [74]:
```
# Calculate the accuracy of our model.

from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_test,y_pred)
```

In [75]:
```
print(accuracy)
```

```
0.7115183246073299
```

In [79]:
```
## Based on the accuracy of 0.7115, our model is 71% accurate at predicting if the women had affairs based on
the given dataset
```

In [ ]: