Excercise_6_solutions_part_2

May 30, 2019

1 PART 2 - Logistic Regression Project

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

ad_data = pd.read_csv('advertising.csv')
```

In [2]:
```
ad_data.head()
```

Out[2]:

	Daily Time Spent on Site	Age	Area Income	Daily Internet Usage	Ad Topic Line	City	Male	Country	Timestamp	Clicked on Ad
0	68.95	35	61833.90	256.09	Cloned 5thgeneration orchestration	Wrightburgh	0	Tunisia	2016-03-27 00:53:11	0
1	80.23	31	68441.85	193.77	Monitored national standardization	West Jodi	1	Nauru	2016-04-04 01:39:02	0
2	69.47	26	59785.94	236.50	Organic bottom-line service-desk	Davidton	0	San Marino	2016-03-13 20:35:42	0
3	74.15	29	54806.18	245.89	Triple-buffered reciprocal time-frame	West Terrifurt	1	Italy	2016-01-10 02:31:19	0
4	68.37	35	73889.99	225.58	Robust logistical utilization	South Manuel	0	Iceland	2016-06-03 03:36:18	0

In [3]:
```
ad_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
```

```
Daily Time Spent on Site    1000 non-null float64
Age                         1000 non-null int64
Area Income                 1000 non-null float64
Daily Internet Usage        1000 non-null float64
Ad Topic Line               1000 non-null object
City                        1000 non-null object
Male                        1000 non-null int64
Country                     1000 non-null object
Timestamp                   1000 non-null object
Clicked on Ad               1000 non-null int64
dtypes: float64(3), int64(3), object(4)
memory usage: 78.2+ KB
```

```
In [4]: ad_data.describe()
```

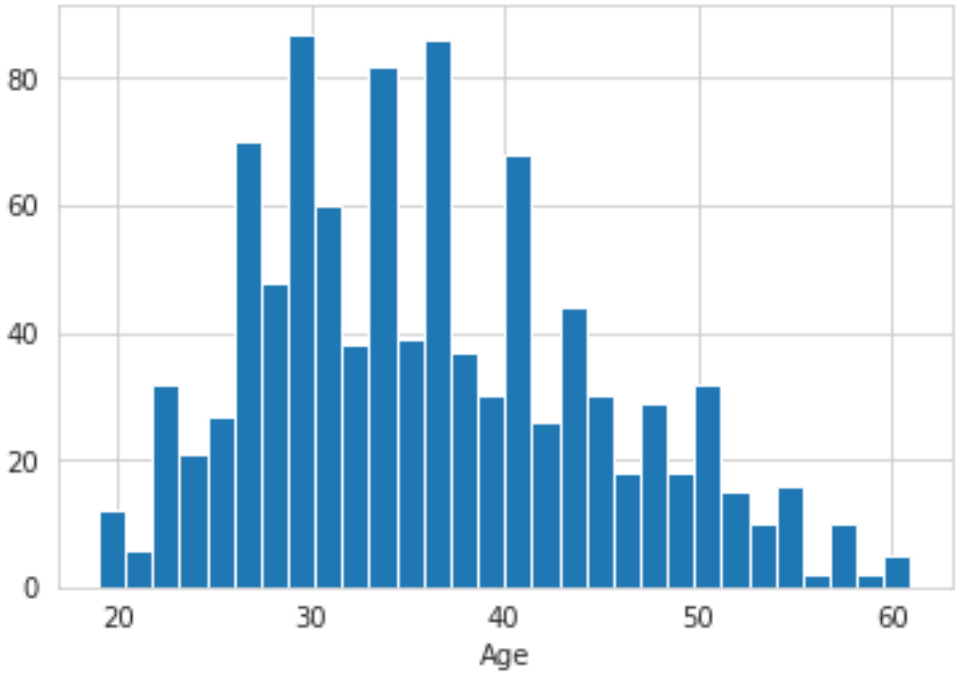
Out[4]:

	Daily Time Spent on Site	Age	Area Income	Daily Internet Usage	Male	Clicked on Ad
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000
mean	65.000200	36.009000	55000.000080	180.000100	0.481000	0.50000
std	15.853615	8.785562	13414.634022	43.902339	0.499889	0.50025
min	32.600000	19.000000	13996.500000	104.780000	0.000000	0.00000
25%	51.360000	29.000000	47031.802500	138.830000	0.000000	0.00000
50%	68.215000	35.000000	57012.300000	183.130000	0.000000	0.50000
75%	78.547500	42.000000	65470.635000	218.792500	1.000000	1.00000
max	91.430000	61.000000	79484.800000	269.960000	1.000000	1.00000

2 Exploratory Data Analysis

```
In [5]: sns.set_style('whitegrid')
        ad_data['Age'].hist(bins=30)
        plt.xlabel('Age')
```

```
Out[5]: Text(0.5, 0, 'Age')
```

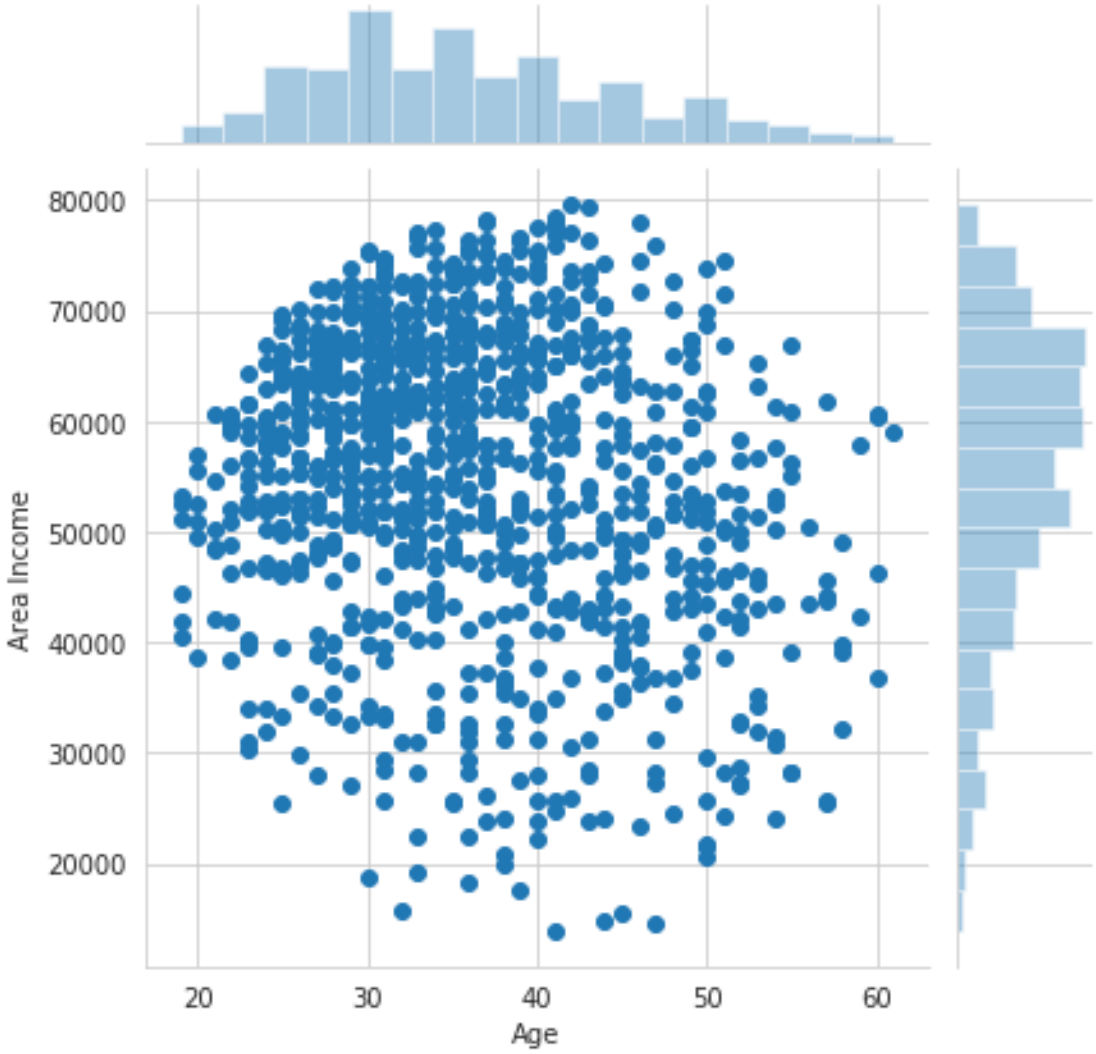


Create a jointplot showing Area Income versus Age.

```
In [6]: sns.jointplot(x='Age',y='Area Income',data=ad_data)
```

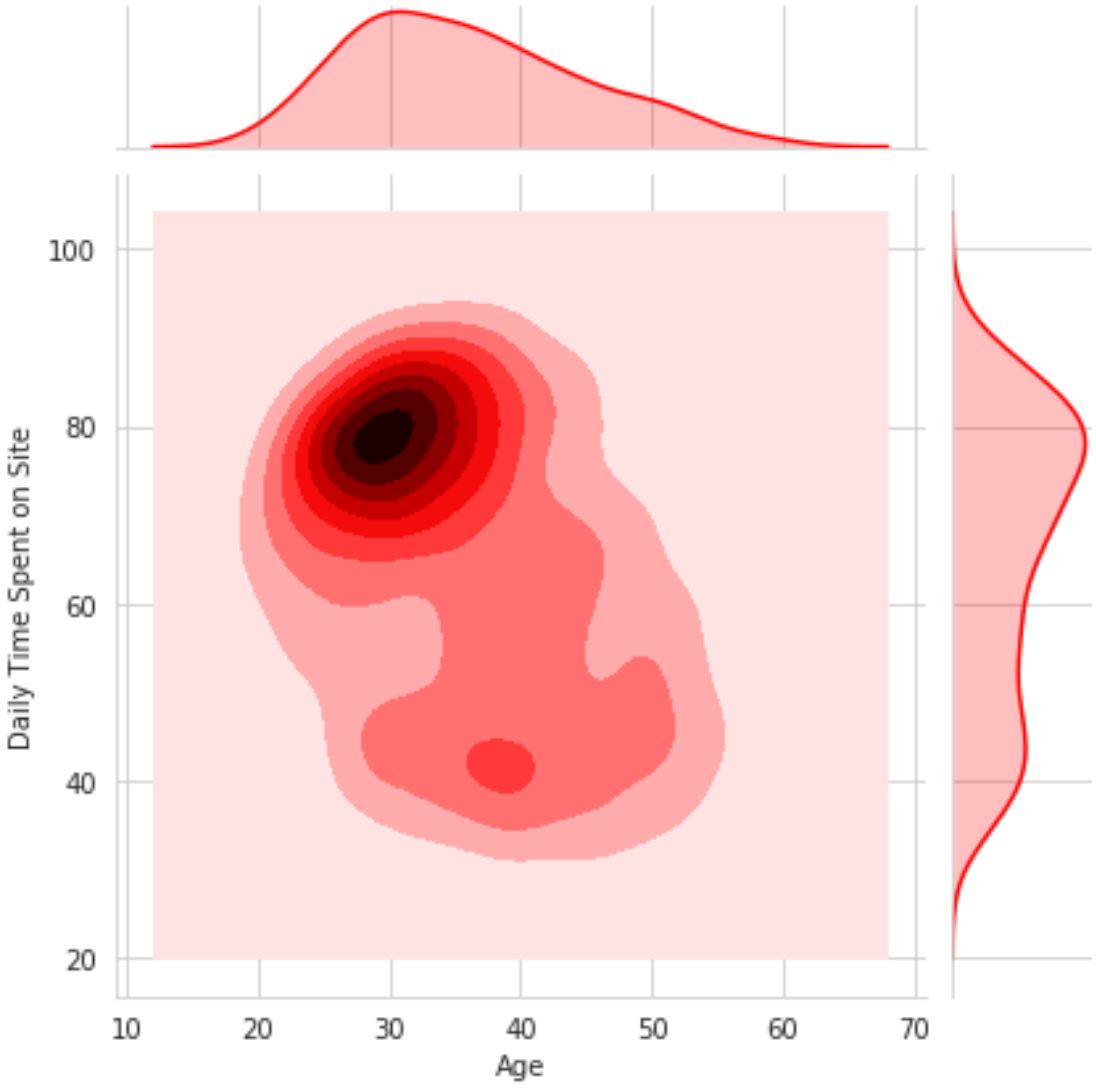
```
/home/kamil/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Usi
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[6]: <seaborn.axisgrid.JointGrid at 0x7ff04c566f28>
```



Create a jointplot showing the kde distributions of Daily Time spent on site vs. Age.

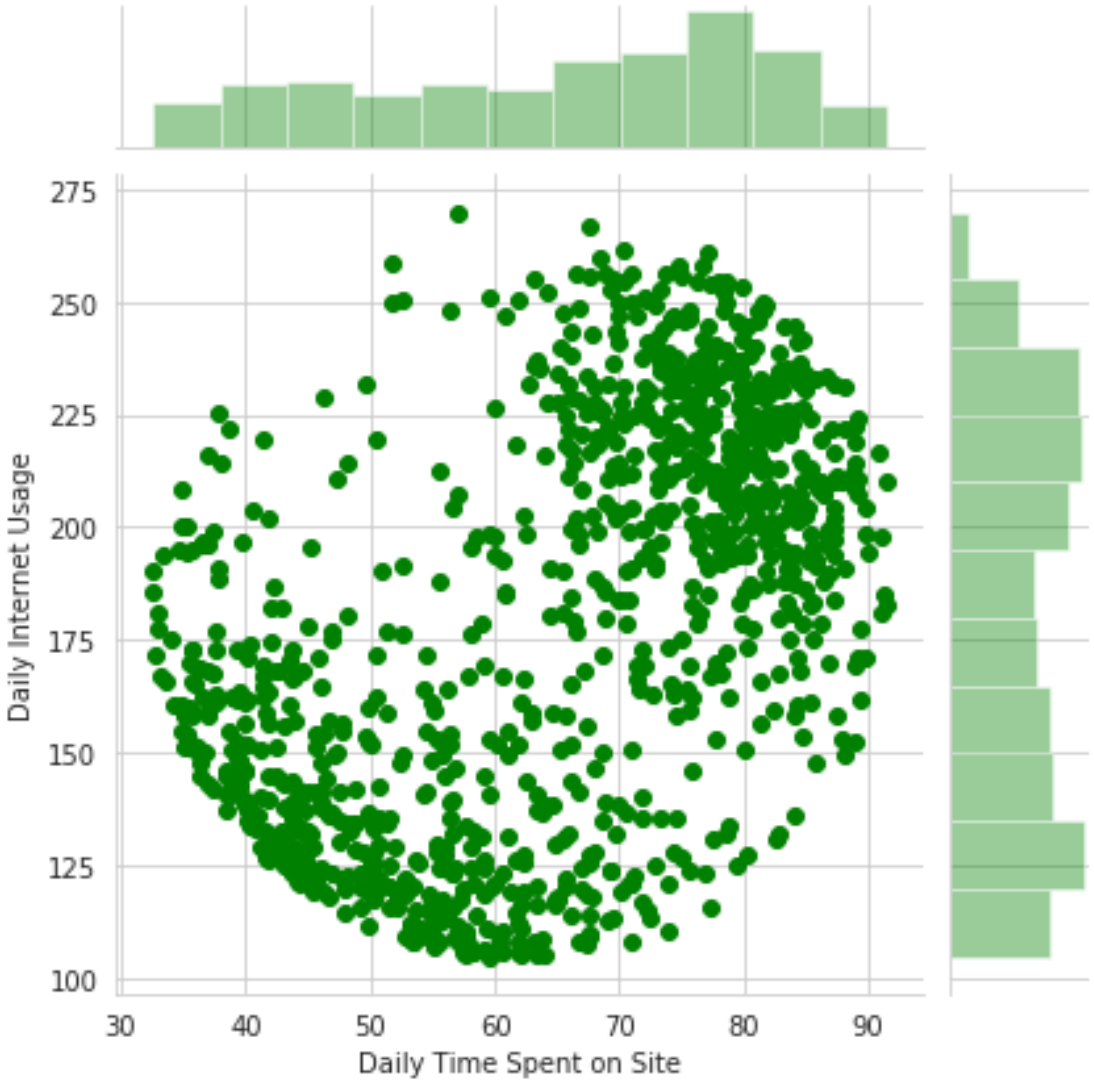
```
In [7]: sns.jointplot(x='Age',y='Daily Time Spent on Site',data=ad_data,color='red',kind='kde'
```



Create a jointplot of 'Daily Time Spent on Site' vs. 'Daily Internet Usage'

```
In [8]: sns.jointplot(x='Daily Time Spent on Site',y='Daily Internet Usage',data=ad_data,color=
```

```
Out[8]: <seaborn.axisgrid.JointGrid at 0x7ff01b3bb198>
```

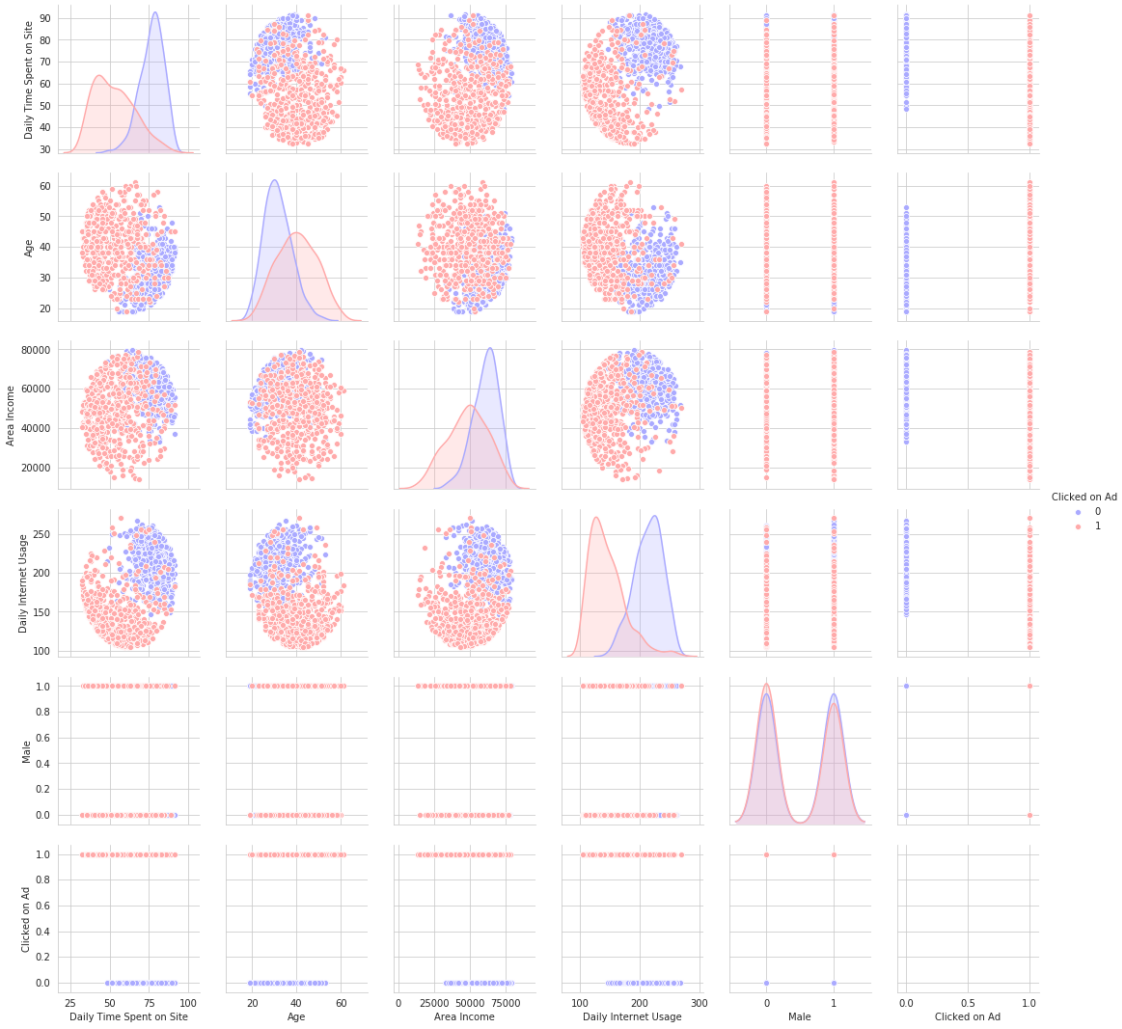


Finally, create a pairplot with the hue defined by the 'Clicked on Ad' column feature.

```
In [9]: sns.pairplot(ad_data,hue='Clicked on Ad',palette='bwr')
```

```
/home/kamil/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:488: Runtime
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
/home/kamil/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kdetools.py:34: Ru
  FAC1 = 2*(np.pi*bw/RANGE)**2
/home/kamil/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:83: RuntimeWarning
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```

```
Out[9]: <seaborn.axisgrid.PairGrid at 0x7ff01b2d1c88>
```



3 Logistic Regression

Now it's time to do a train test split, and train our model!

You'll have the freedom here to choose columns that you want to train on!

- Split the data into training set and testing set using train_test_split

```
In [10]: from sklearn.model_selection import train_test_split
```

```
In [11]: ad_data.head()
```

```
Out[11]:    Daily Time Spent on Site  Age  Area Income  Daily Internet Usage  \
         0                     68.95   35     61833.90                256.09
         1                     80.23   31     68441.85                193.77
         2                     69.47   26     59785.94                236.50
```

```
3                     74.15   29     54806.18                245.89
4                     68.37   35     73889.99                225.58

                           Ad Topic Line            City  Male     Country  \
0     Cloned 5thgeneration orchestration     Wrightburgh     0     Tunisia
1     Monitored national standardization       West Jodi     1       Nauru
2       Organic bottom-line service-desk        Davidton     0  San Marino
3  Triple-buffered reciprocal time-frame  West Terrifurt     1       Italy
4           Robust logistical utilization    South Manuel     0     Iceland

              Timestamp  Clicked on Ad
0  2016-03-27 00:53:11              0
1  2016-04-04 01:39:02              0
2  2016-03-13 20:35:42              0
3  2016-01-10 02:31:19              0
4  2016-06-03 03:36:18              0
```

```
In [12]: X = ad_data[['Daily Time Spent on Site', 'Age', 'Area Income','Daily Internet Usage',
         y = ad_data['Clicked on Ad']
```

```
In [13]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state
```

Train and fit a logistic regression model on the training set.

```
In [14]: from sklearn.linear_model import LogisticRegression
```

```
In [15]: lm = LogisticRegression()
         lm.fit(X_train,y_train)
```

```
/home/kamil/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433: FutureW
  FutureWarning)


Out[15]: 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)
```

4 Predictions and Evaluations

Now predict values for the testing data.

```
In [23]: y_pred = lm.predict(X_test)
```

Create a classification report for the model.

```
In [24]: from sklearn.metrics import classification_report
```

```
In [25]: print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.97      0.90       146
           1       0.96      0.82      0.89       154

   micro avg       0.89      0.89      0.89       300
   macro avg       0.90      0.90      0.89       300
weighted avg       0.90      0.89      0.89       300
```

In [ ]: