Logistic Regression Project

In this project we will be working with a fake advertising data set, indicating whether or not a particular internet user clicked on an Advertisement. We will try to create a model that will predict whether or not they will click on an ad based off the features of that user.

This data set contains the following features:

- 'Daily Time Spent on Site': consumer time on site in minutes
- · 'Age': cutomer age in years
- 'Area Income': Avg. Income of geographical area of consumer
- 'Daily Internet Usage': Avg. minutes a day consumer is on the internet
- · 'Ad Topic Line': Headline of the advertisement
- 'City': City of consumer
- · 'Male': Whether or not consumer was male
- 'Country': Country of consumer
- · 'Timestamp': Time at which consumer clicked on Ad or closed window
- 'Clicked on Ad': 0 or 1 indicated clicking on Ad

Import Libraries

Import a few libraries you think you'll need (Or just import them as you go along!)

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

Get the Data

Read in the advertising.csv file and set it to a data frame called ad_data.

```
In [2]: |ad_data = pd.read_csv('advertising.csv')
```

Check the head of ad_data

In [3]: ad_data.head()

Out[3]:

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 [10]: ad_data.info()

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

#	Column	Non-Null Count	Dtype
0	Daily Time Spent on Site	1000 non-null	float64
1	Age	1000 non-null	int64
2	Area Income	1000 non-null	float64
3	Daily Internet Usage	1000 non-null	float64
4	Ad Topic Line	1000 non-null	object
5	City	1000 non-null	object
6	Male	1000 non-null	int64
7	Country	1000 non-null	object
8	Timestamp	1000 non-null	object
9	Clicked on Ad	1000 non-null	int64

dtypes: float64(3), int64(3), object(4)

memory usage: 78.2+ KB

^{**} Use info and describe() on ad_data**

In [12]: ad_data.describe()

Out[12]:

	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

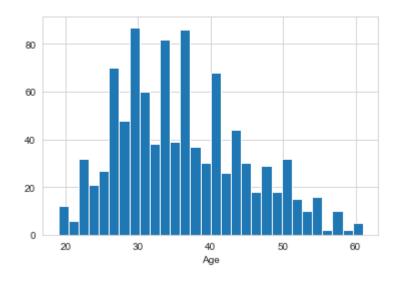
Exploratory Data Analysis

Let's use seaborn to explore the data!

Try recreating the plots shown below!

```
In [27]:
         sns.set_style('whitegrid')
         ad_data['Age'].hist(bins=30)
         plt.xlabel('Age')
```

Out[27]: Text(0.5, 0, 'Age')

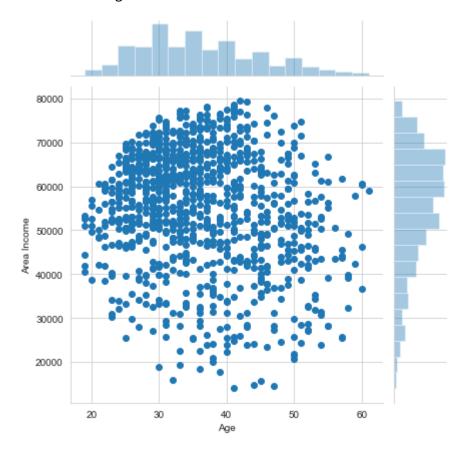


Create a jointplot showing Area Income versus Age.

^{**} Create a histogram of the Age**

In [29]: sns.jointplot(x='Age',y='Area Income',data=ad_data)

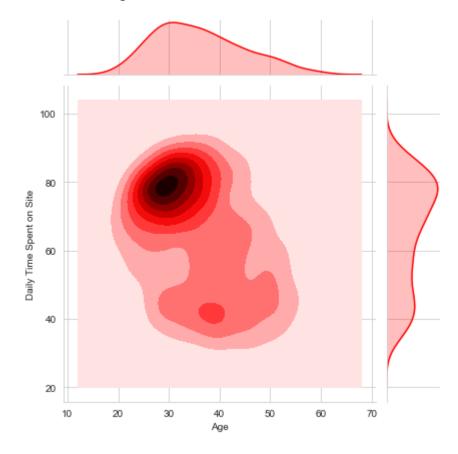
Out[29]: <seaborn.axisgrid.JointGrid at 0x1b2a54ef288>



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

In [33]: sns.jointplot(x='Age',y='Daily Time Spent on Site',data=ad_data,kind='kde',color=

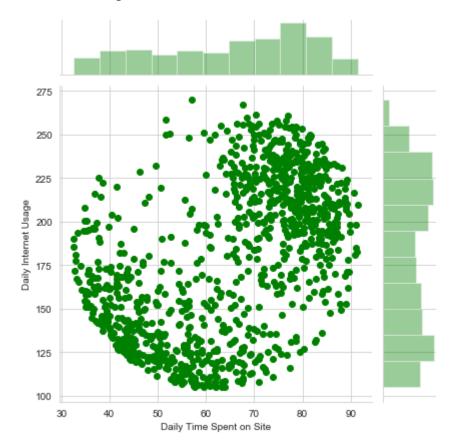
Out[33]: <seaborn.axisgrid.JointGrid at 0x1b2a54a4548>



^{**} Create a jointplot of 'Daily Time Spent on Site' vs. 'Daily Internet Usage'**

In [35]: sns.jointplot(x='Daily Time Spent on Site',y='Daily Internet Usage',data=ad_data,

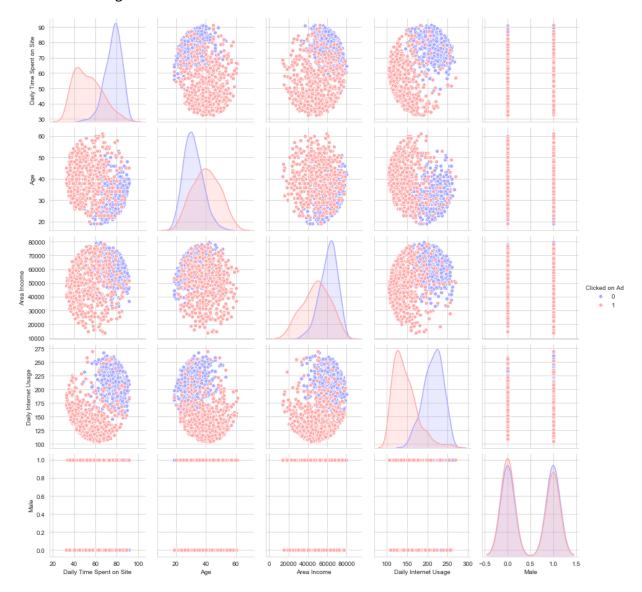
Out[35]: <seaborn.axisgrid.JointGrid at 0x1b2a4f8aac8>



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

In [39]: sns.pairplot(ad_data,hue='Clicked on Ad',palette='bwr')

Out[39]: <seaborn.axisgrid.PairGrid at 0x1b2a8fd2348>



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 [42]: from sklearn.model selection import train test split
In [44]: | ad data.columns
Out[44]: Index(['Daily Time Spent on Site', 'Age', 'Area Income',
                 'Daily Internet Usage', 'Ad Topic Line', 'City', 'Male', 'Country',
                 'Timestamp', 'Clicked on Ad'],
               dtype='object')
In [54]: X=ad_data[['Daily Time Spent on Site', 'Age', 'Area Income', 'Daily Internet Usage
         y=ad data['Clicked on Ad']
In [55]: X train, X test, y train, y test = train test split(X, y, test size=0.33, random
         ** Train and fit a logistic regression model on the training set.**
 In [ ]: from sklearn.linear model import LogisticRegression
In [58]: lr=LogisticRegression()
         lr.fit(X_train,y_train)
Out[58]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                             intercept scaling=1, l1 ratio=None, max iter=100,
                             multi_class='auto', n_jobs=None, penalty='12',
                             random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                             warm_start=False)
```

Predictions and Evaluations

** Now predict values for the testing data.**

```
In [62]: | predictions = lr.predict(X_test)
```

^{**} Create a classification report for the model.**

```
In [63]: from sklearn.metrics import classification_report
```

In [66]: print(classification_report(y_test,predictions))

support	f1-score	recall	precision	
162	0.91	0.96	0.86	0
168	0.90	0.85	0.96	1
330	0.91			accuracy
330	0.91	0.91	0.91	macro avg
330	0.91	0.91	0.91	weighted avg