# Advertisement Click - Logistic Regression

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Advertisement Click - Logistic Regression

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Will be working with an advertising data set, indicating whether or not a particular internet user clicked on an Advertisement.

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

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

#### 0.1 Get the Data

Read in the advertising.csv file and set it to a data frame called ad\_data.

```
[2]: ad_data = pd.read_csv('advertising.csv')
[3]: ad_data.head()
[3]:
        Daily Time Spent on Site
                                        Area Income
                                                     Daily Internet Usage \
                                  Age
                            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 68.37	29 35	5480 7388				15.89 25.58	
	0 1 2 3 4	Ad Cloned 5thgeneration or Monitored national stand Organic bottom-line s Triple-buffered reciprocal Robust logistical	chesti dardi: ervico time	zation e-desk -frame	West	City Wrightburgh West Jodi Davidton Terrifurt	Male 0 1 0 1	Country Tunisia Nauru San Marino Italy Iceland	\
		· ·							
		Timestamp Click	ed 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 4	2016-01-10 02:31:19 2016-06-03 03:36:18		0 0					
	4	2010-00-03 03.30.10		U					
[4]:	ad	_data.info()							
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		geIndex: 1000 entries, 0 to							
	Dat	a columns (total 10 columns	):						
	#	Column	Non-	Null Co	unt	Dtype			
				. <b></b>					
	0	Daily Time Spent on Site		) non-nu		float64			
	1	Age		) non-nu		int64			
	2	Area Income		) non-nu		float64			
	3	Daily Internet Usage		) non-nu		float64			
	4	Ad Topic Line		) non-nu		object			
	5	City		) non-nu		object			
	6 7	Male		non-nu		int64			
	8	Country Timestamp		) non-nu ) non-nu		object object			
	9	Clicked on Ad		) non-nu		int64			
		pes: float64(3), int64(3),			.1.1	111004			
	-	ory usage: 78.2+ KB	objec	, ( ( + )					
		abago. 10.21 ND							
[5]:	ad	_data.describe()							
[5]:		Daily Time Spent on Si	te		Age	Area Income	\		
[0].	COI	unt 1000.0000		000.000	-	1000.000000	`		
	mea			36.009		55000.000080			
	sto			8.785		13414.634022			
	200			5.,50					

29.000000

35.000000

19.000000 13996.500000

42.000000 65470.635000

47031.802500

57012.300000

32.600000

51.360000

68.215000

78.547500

 $\min$ 

25%

50%

75%

91.430000	61.000000	79484.800000

	Daily Internet Usage	Male	Clicked on Ad
count	1000.000000	1000.000000	1000.00000
mean	180.000100	0.481000	0.50000
std	43.902339	0.499889	0.50025
min	104.780000	0.000000	0.00000
25%	138.830000	0.000000	0.00000
50%	183.130000	0.000000	0.50000
75%	218.792500	1.000000	1.00000
max	269.960000	1.000000	1.00000

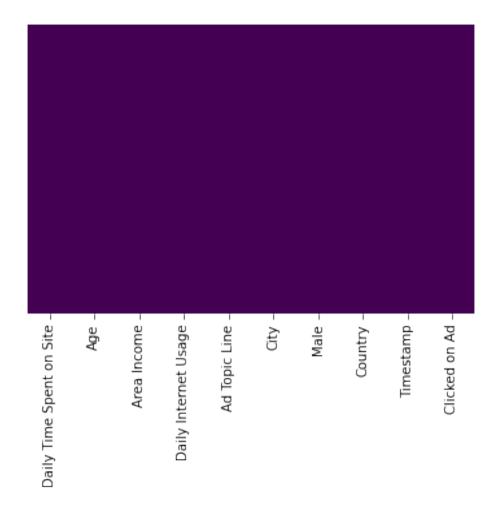
### 0.2 Exploratory Data Analysis

## 0.3 Missing Data

```
[6]: sns.heatmap(ad_data.isnull(),yticklabels=False,cbar=False,cmap='viridis')
# the heatmap below does not show any nulls
```

### [6]: <AxesSubplot:>

max



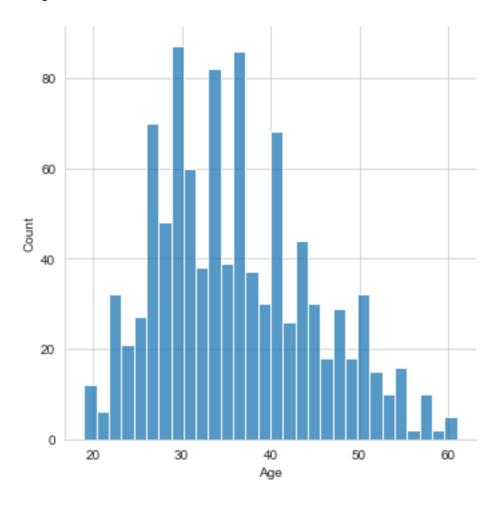
#### 0.4 Some Plots

```
[7]: sns.set_style('whitegrid')
```

Age Histogram - using seaborn

```
[41]: sns.displot(ad_data['Age'],bins=30)
```

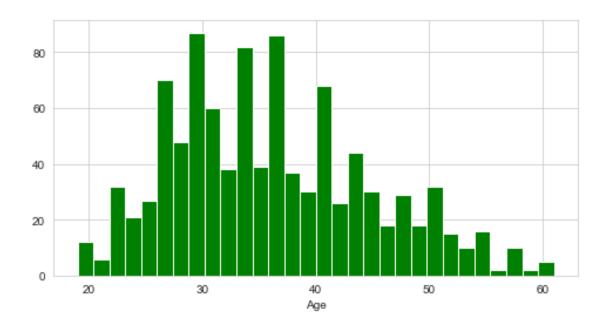
[41]: <seaborn.axisgrid.FacetGrid at 0x20e40861cd0>



### Age Histogram - using built-in

```
[37]: ad_data['Age'].hist(color='green',bins=30,figsize=(8,4))
plt.xlabel('Age')
```

[37]: Text(0.5, 0, 'Age')



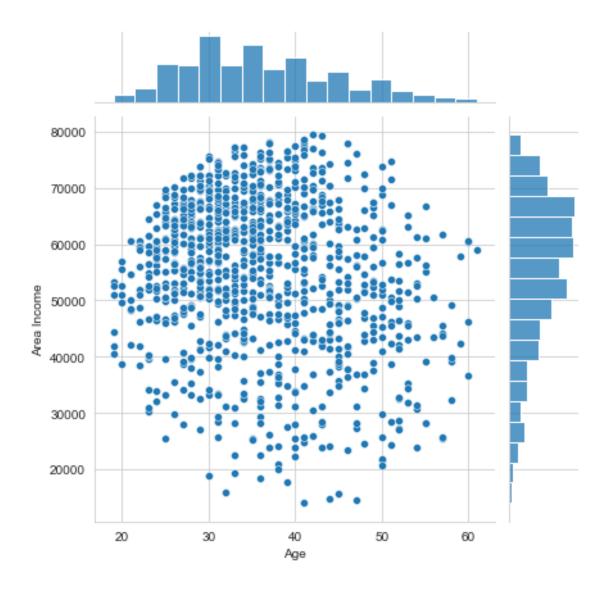
#### ${\bf Age\ Histogram\ -\ interactive,\ using\ cufflinks}$

```
[86]: import cufflinks as cf cf.go_offline()
```

#### jointplot showing Area Income versus Age

```
[23]: sns.jointplot(x='Age',y='Area Income',data=ad_data,kind='scatter')
```

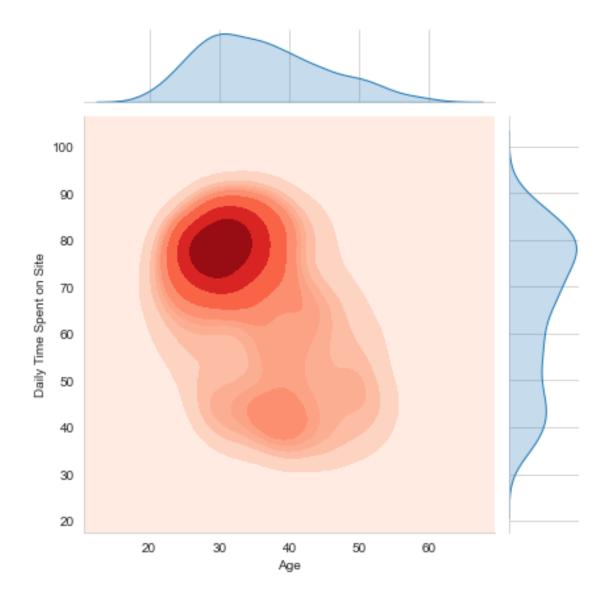
[23]: <seaborn.axisgrid.JointGrid at 0x20e3eff7d90>



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

```
[50]: sns.jointplot(x='Age',y='Daily Time Spent on Site',data=ad_data,\
fill=True, thresh=0,cmap='Reds',kind='kde')
```

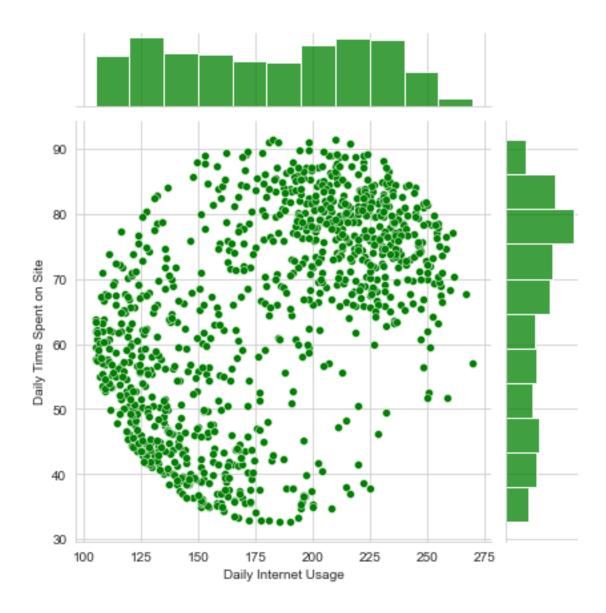
[50]: <seaborn.axisgrid.JointGrid at 0x20e41daa9a0>



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

```
[55]: sns.jointplot(x='Daily Internet Usage',y='Daily Time Spent on Site',\
data=ad_data,color="Green")
```

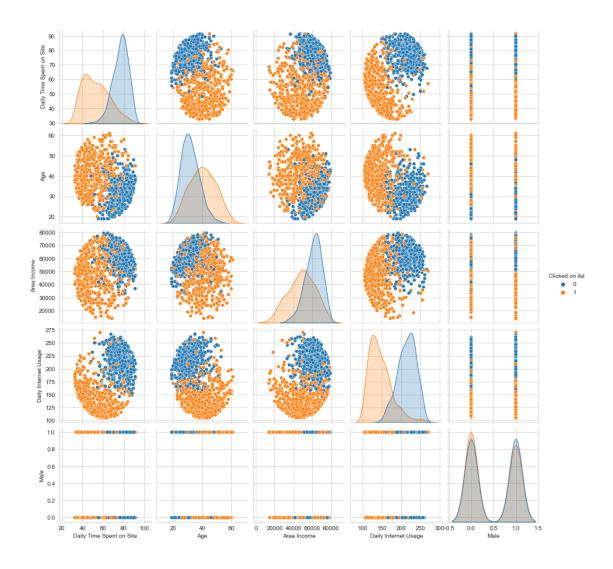
[55]: <seaborn.axisgrid.JointGrid at 0x20e43344d30>



pairplot with the hue defined by the 'Clicked on Ad' column feature.

[58]: sns.pairplot(ad\_data,hue='Clicked on Ad')

[58]: <seaborn.axisgrid.PairGrid at 0x20e447fe640>



# 1 Build a Logistic Regression model

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

#### 1.1 Train Test Split

```
ad_data.head(2)
[64]:
[64]:
         Daily Time Spent on Site
                                                       Daily Internet Usage
                                    Age
                                         Area Income
      0
                             68.95
                                     35
                                             61833.90
                                                                      256.09
                             80.23
                                     31
      1
                                             68441.85
                                                                      193.77
                                                                   Country \
                               Ad Topic Line
                                                      City
                                                            Male
                                                                   Tunisia
         Cloned 5thgeneration orchestration
                                              Wrightburgh
                                                               0
         Monitored national standardization
                                                 West Jodi
                                                                     Nauru
```

```
Timestamp Clicked on Ad
      0 2016-03-27 00:53:11
                                          0
      1 2016-04-04 01:39:02
                                          0
[65]: ad_data.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 1000 entries, 0 to 999
     Data columns (total 10 columns):
      #
          Column
                                     Non-Null Count
                                                     Dtype
          Daily Time Spent on Site 1000 non-null
      0
                                                     float64
                                     1000 non-null
      1
          Age
                                                     int64
                                     1000 non-null
      2
          Area Income
                                                     float64
          Daily Internet Usage
                                     1000 non-null
                                                     float64
          Ad Topic Line
                                     1000 non-null
      4
                                                     object
      5
          City
                                     1000 non-null
                                                     object
      6
          Male
                                     1000 non-null
                                                     int64
      7
                                     1000 non-null
          Country
                                                     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
[68]: ad_data.columns
[68]: Index(['Daily Time Spent on Site', 'Age', 'Area Income',
             'Daily Internet Usage', 'Ad Topic Line', 'City', 'Male', 'Country',
             'Timestamp', 'Clicked on Ad'],
            dtype='object')
[69]: from sklearn.model_selection import train_test_split
[76]: y = ad_data['Clicked on Ad']
      X = ad_data[['Daily Time Spent on Site', 'Age', 'Area Income',\
                   'Daily Internet Usage', 'Male']]
[77]: X_train, X_test, y_train, y_test = train_test_split(X, y,\
                      test_size=0.30, random_state=101)
     Train and fit a logistic regression model on the training set.
[78]: from sklearn.linear_model import LogisticRegression
[79]: logmodel = LogisticRegression()
```

```
[80]: logmodel.fit(X_train,y_train)
```

[80]: LogisticRegression()

#### 1.2 Predictions and Evaluations

predict values for the testing data

```
[94]: predictions = logmodel.predict(X_test)
```

Create a classification report for the model.

```
[83]: from sklearn.metrics import classification_report
```

[85]: print(classification\_report(y\_test,predictions))

support	f1-score	recall	precision	
157	0.93	0.95	0.91	0
157	0.95	0.95	0.91	O
143	0.92	0.90	0.94	1
300	0.93			accuracy
300	0.93	0.93	0.93	macro avg
300	0.93	0.93	0.93	weighted avg