Stack Abuse

Predicting Customer Ad Clicks via Machine Learning

Guest Contributor

Introduction

Internet marketing has taken over traditional marketing strategies in the recent past. Companies prefer to advertise their products on websites and social media platforms. However, targeting the right audience is still a challenge in online marketing. Spending millions to display the advertisement to the audience that is not likely to buy your products can be costly.

In this article, we will work with the advertising data of a marketing agency to develop a machine learning algorithm that predicts if a particular user will click on an advertisement. The data consists of 10 variables: 'Daily Time Spent on Site', 'Age', 'Area Income', 'Daily Internet Usage', 'Ad Topic Line', 'City', 'Male', 'Country', Timestamp' and 'Clicked on Ad'.

The main variable we are interested in is 'Clicked on Ad'. This variable can have two possible outcomes: 0 and 1 where 0 refers to the case where a user didn't click the advertisement, while 1 refers to the scenario where a user clicks the advertisement.

We will see if we can use the other 9 variables to accurately predict the value 'Clicked on Ad' variable. We will also perform some exploratory data analysis to see how 'Daily Time Spent on Site' in combination with 'Ad Topic Line' affects the user's decision to click on the add.

Importing Libraries

To develop our prediction model, we need to import the necessary Python libraries:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Importing the Dataset

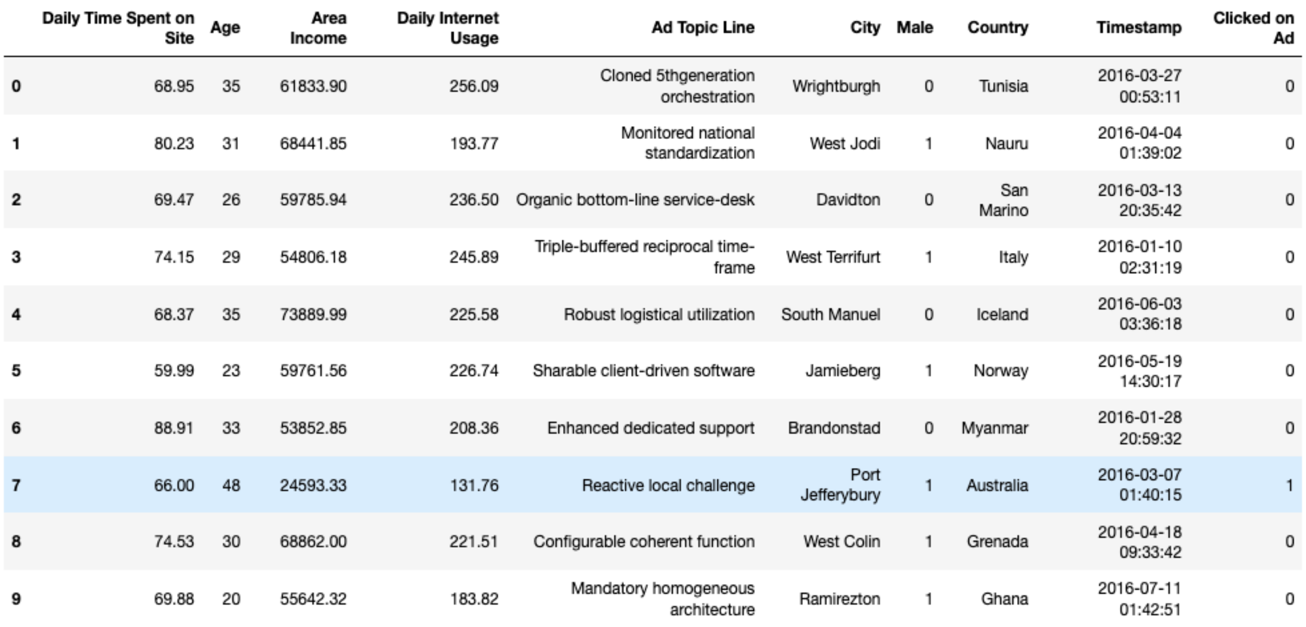
The dataset for this article can be downloaded from this Kaggle link. Unzip the downloaded zip file and place the "advertising.csv" file in your local drive. This is the file that we are going to use to train our machine learning model.

Now we need to load the data:

```
data = pd.read_csv('E:/Datasets/advertising.csv')
```

Let's see the first ten lines of our DataFrame:

```
data.head(10)
```



	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
5	59.99	23	59761.56	226.74	Sharable client-driven software	Jamieberg	1	Norway	2016-05-19 14:30:17	0
6	88.91	33	53852.85	208.36	Enhanced dedicated support	Brandonstad	0	Myanmar	2016-01-28 20:59:32	0
7	66.00	48	24593.33	131.76	Reactive local challenge	Port Jefferybury	1	Australia	2016-03-07 01:40:15	1
8	74.53	30	68862.00	221.51	Configurable coherent function	West Colin	1	Grenada	2016-04-18 09:33:42	0
9	69.88	20	55642.32	183.82	Mandatory homogeneous architecture	Ramirezton	1	Ghana	2016-07-11 01:42:51	0

Based on the first lines in the table, we can get a basic insight into the data we are working with. We want to check how much data do we have within each variable.

```
data.info()
```

Output:

```
<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
```

Good news! All variables are complete and there are no missing values within them. Each of them contains 1000 elements and there will be no need for additional preprocessing of raw data.

We will also use the `describe` function to gain insight into the ranges in which variables change:

```
data.describe()
```

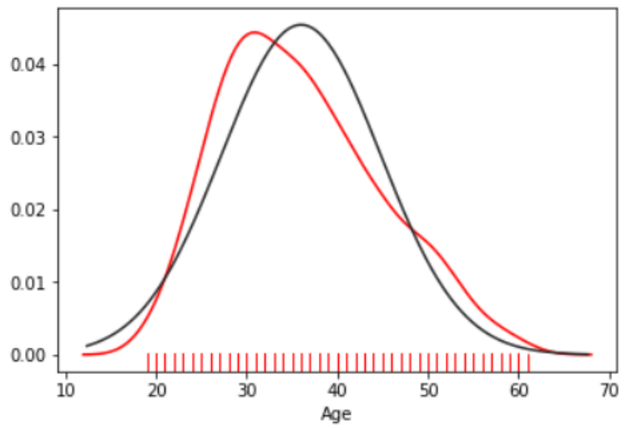
	Daily Time Spent on Site	Age	Area Income	Daily Internet Usage	Male	Clicked on Ad
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000
mean	65.000200	36.009000	55000.000080	180.000100	0.481000	0.50000
std	15.853615	8.785562	13414.634022	43.902339	0.499889	0.50025
min	32.600000	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

An interesting fact from the table is that the smallest area income is $13,996.50 and the highest is $79,484.80. This means that site visitors are people belonging to different social classes. It can also be concluded that we are analyzing a popular website since users spend between 32 and 91 minutes on the website in one session. These are really big numbers!

Furthermore, the average age of a visitor is 36 years. We see that the youngest user has 19 and the oldest is 61 years old. We can conclude that the site is targetting adult users. Finally, if we are wondering whether the site is visited more by men or women, we can see that the situation is almost equal (52% in favor of women).

To further analyze our data, let's first plot a histogram with Kernel density estimation for the 'Age' variable.

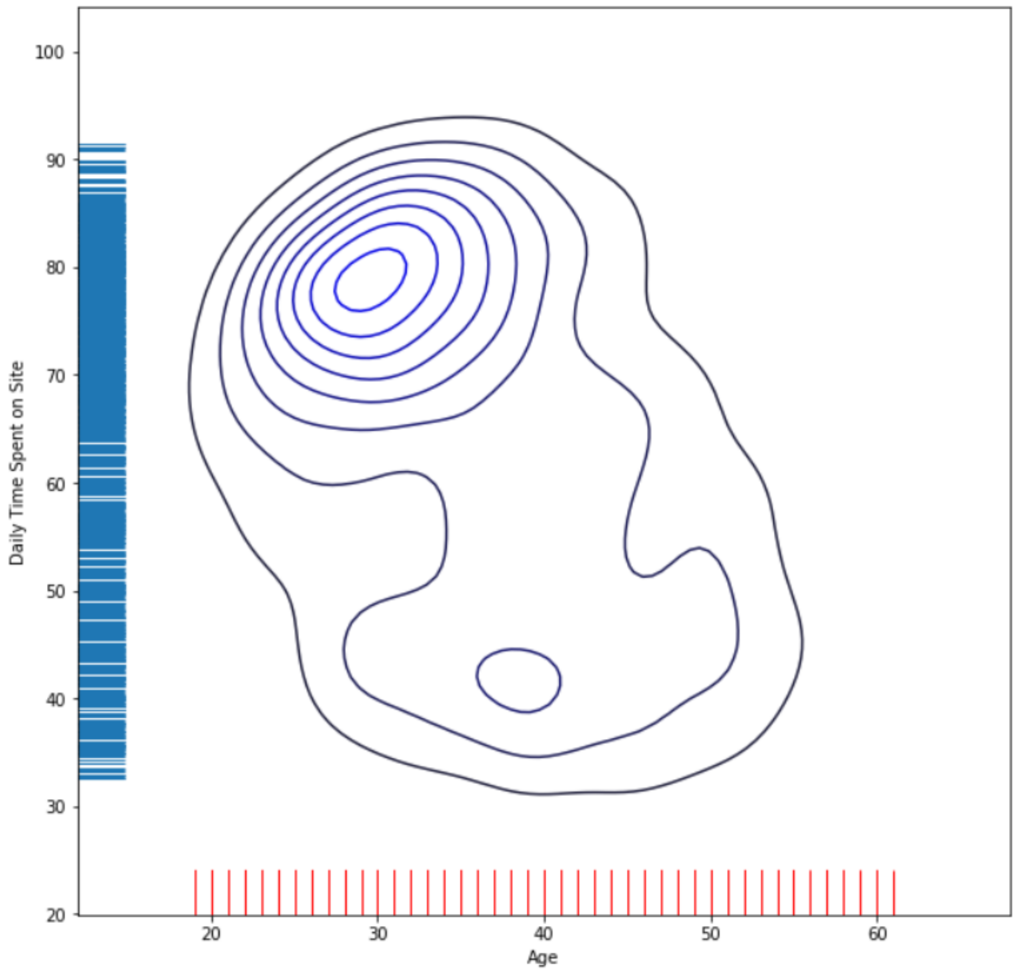
```
from scipy.stats import norm
sns.distplot(data['Age'], hist=False, color='r', rug=True, fit=norm);
```



It can be concluded that the variable 'Age' has a normal distribution of data. We will see in some of the following articles why this is good for effective data processing.

Let's plot a two-dimensional density plot to determine the interdependence of two variables. Let's see how the user's age and the time spent on the site are linked.

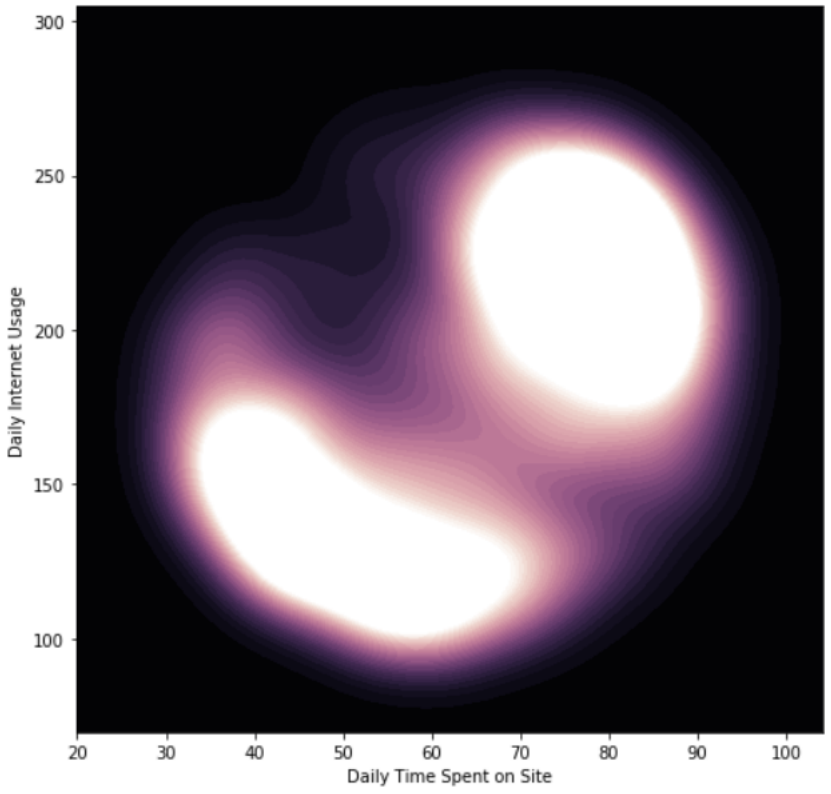
```
f, ax = plt.subplots(figsize=(10, 10))
sns.kdeplot(data.Age, data['Daily Time Spent on Site'], color="b", ax=ax)
sns.rugplot(data.Age, color="r", ax=ax)
sns.rugplot(data['Daily Time Spent on Site'], vertical=True, ax=ax)
```



From the picture, we can conclude that younger users spend more time on the site. This implies that users of the age between 20 and 40 years can be the main target group for the marketing campaign. Hypothetically, if we have a product intended for middle-aged people, this is the right site for advertising. Conversely, if we have a product intended for people over the age of 60, it would be a mistake to advertise on this site.

We will present another density graphic and determine the interdependency of 'Daily Time Spent on Site' and 'Daily Internet Usage'.

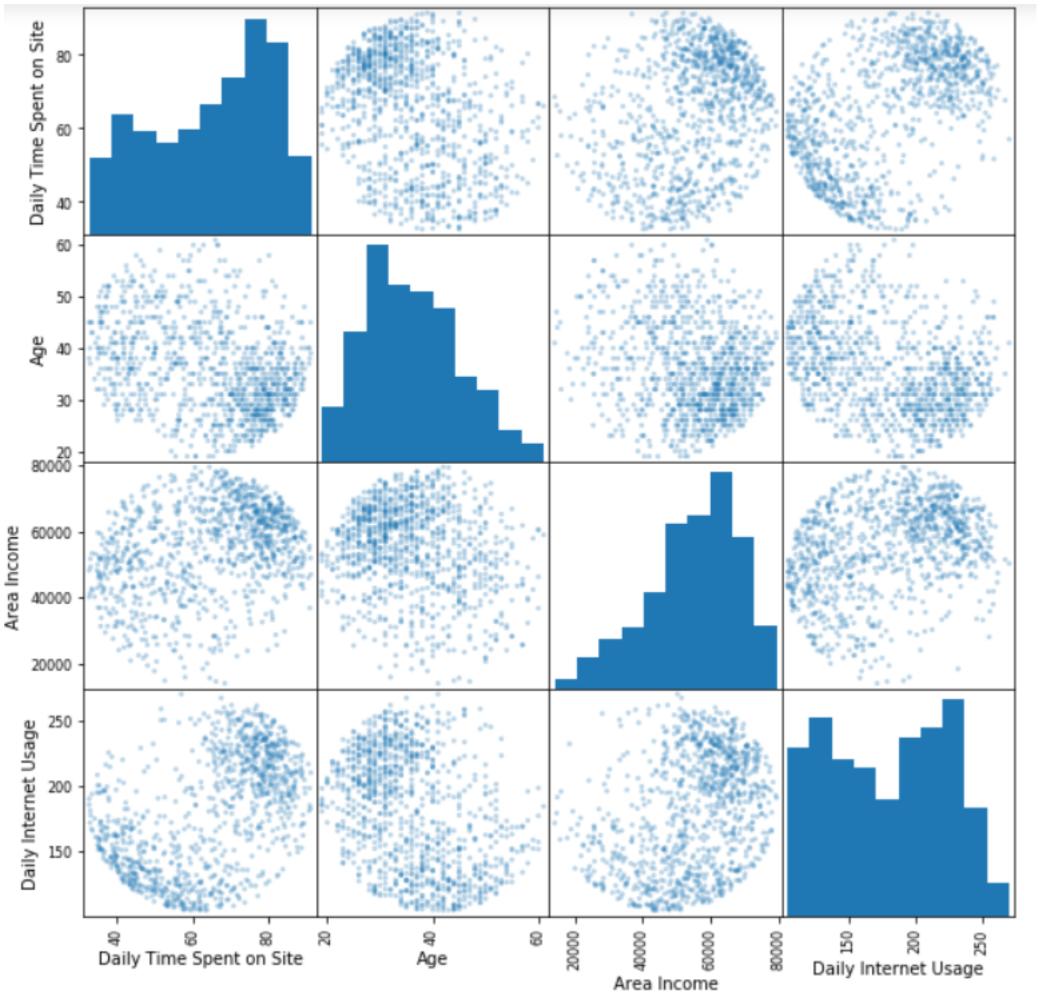
```
f, ax = plt.subplots(figsize=(8, 8))
cmap = sns.cubehelix_palette(as_cmap=True, start=0, dark=0, light=3, reverse=True)
sns.kdeplot(data["Daily Time Spent on Site"], data['Daily Internet Usage'],
    cmap=cmap, n_levels=100, shade=True);
```



From the figure above, it is clear that users who spend more time on the internet also spend more time on the site.

Now we will show how to visualize trends in the data using the `scatter_matrix` function. We will include only numerical variables for performing analysis.

```
from pandas.plotting import scatter_matrix
scatter_matrix(data[['Daily Time Spent on Site', 'Age','Area Income', 'Daily Internet Usage']],
    alpha=0.3, figsize=(10,10))
```

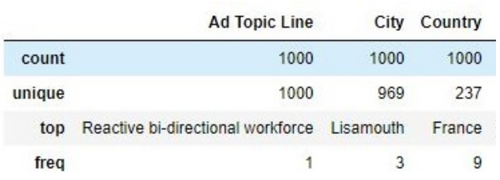


The big picture gives a good insight into the properties of the users who click on the advertisements. On this basis, a large number of further analyzes can be made. We leave them to you, try to find other interesting facts from the data and share it with us in the comments.

Data Preprocessing

You may have noticed that "Ad Topic Line", "City", and "Country" are categorical columns. Let's plot all the unique values for these columns.

```
object_variables = ['Ad Topic Line', 'City', 'Country']
data[object_variables].describe(include=['O'])
```



	Ad Topic Line	City	Country
count	1000	1000	1000
unique	1000	969	237
top	Reactive bi-directional workforce	Lisamouth	France
freq	1	3	9

As we can see from the table above that all the values in column "Ad Topic Line" is unique, while the "City" column contains 969 unique values out of 1000. There are too many unique elements within these two categorical columns and it is generally difficult to perform a prediction without the existence of a data pattern. Because of that, they will be omitted from further analysis. The third categorical variable, i.e "Country", has a unique element (France) that repeats 9 times. Additionally, we can determine countries with the highest number of visitors:

```
pd.crosstab(index=data['Country'], columns='count').sort_values(['count'], ascending=False).head(20)
```

The table below shows the 20 most represented countries in our DataFrame.

Country	
France	9
Czech Republic	9
Afghanistan	8
Australia	8
Turkey	8
South Africa	8
Senegal	8
Peru	8
Micronesia	8
Greece	8
Cyprus	8
Liberia	8
Albania	7
Bosnia and Herzegovina	7
Taiwan	7
Bahamas	7
Burundi	7
Cambodia	7
Venezuela	7
Fiji	7

We have already seen, there are 237 different unique countries in our dataset and no single country is too dominant. A large number of unique elements will not allow a machine learning model to establish easily valuable relationships. For that reason, this variable will be excluded too.

```
data = data.drop(['Ad Topic Line', 'City', 'Country'], axis=1)
```

Next, we will analyze the 'Timestamp' category. It represents the exact time when a user clicked on the advertisement. We will expand this category to 4 new categories: month, day of the month, day of the week, and hour. In this way, we will get new variables that an ML model will be able to process and find possible dependencies and correlations. Since we have created new variables, we will exclude the original variable "Timestamp" from the table. The "Day of the week" variable contains values from 0 to 6, where each number represents a specific day of the week (from Monday to Sunday).

```
data['Timestamp'] = pd.to_datetime(data['Timestamp'])

data['Month'] = data['Timestamp'].dt.month
data['Day of the month'] = data['Timestamp'].dt.day
data["Day of the week"] = data['Timestamp'].dt.dayofweek
data['Hour'] = data['Timestamp'].dt.hour
data = data.drop(['Timestamp'], axis=1)

data.head()
```

	Daily Time Spent on Site	Age	Area Income	Daily Internet Usage	Male	Clicked on Ad	Month	Day of the month	Day of the week	Hour
0	68.95	35	61833.90	256.09	0	0	3	27	6	0
1	80.23	31	68441.85	193.77	1	0	4	4	0	1
2	69.47	26	59785.94	236.50	0	0	3	13	6	20
3	74.15	29	54806.18	245.89	1	0	1	10	6	2
4	68.37	35	73889.99	225.58	0	0	6	3	4	3

Train and Test Data Sets

Once the dataset is processed, we need to divide it into two parts: training and test set. We will import and use the `train_test_split` function for that. All variables except 'Clicked on Ad' will be the input values `X` for the ML models. The variable 'Clicked on Ad' will be stored in `y`, and will represent the prediction variable. We arbitrarily chose to allocate 33% of the total data for the training set.

```
from sklearn.model_selection import train_test_split

X = data[['Daily Time Spent on Site', 'Age', 'Area Income', 'Daily Internet Usage',
    'Male', 'Month', 'Day of the month' ,'Day of the week']]
y = data['Clicked on Ad']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

Model Development and Fitting Procedures

In this article, two different ML models will be developed: a Logistic Regression model and a Decision Tree model.

The Logistic Regression model is an algorithm that uses a logistic function to model binary dependent variables. It is a tool for predictive analysis and it is used to explain the relationships between multiple variables. You can find out more about this technique at the following link: Logistic Regression.

The Decision Tree is one of the most commonly used data mining techniques for analysis and modeling. It is used for classification, prediction, estimation, clustering, data description, and visualization. The advantages of Decision Trees, compared to other data mining techniques are simplicity and computation efficiency. Some background on decision trees and how to use them with Scikit-Learn can be found here: Decision Trees in Python with Scikit-Learn

The first model we will import will be a Logistic Regression model. First, it is necessary to load the `LogisticRegression` function from the `sklearn.linear_model` library. Also, we will load the `accuracy_score` to evaluate the classification performances of the model.

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
```

The next steps are the initialization of the model, it's training, and finally, making predictions.

```
model_1 = LogisticRegression(solver='lbfgs')
model_1.fit(X_train, y_train)
predictions_LR = model_1.predict(X_test)

print('Logistic regression accuracy:', accuracy_score(predictions_LR, y_test))
print('')
print('Confusion matrix:')
print(confusion_matrix(y_test,predictions_LR))
```

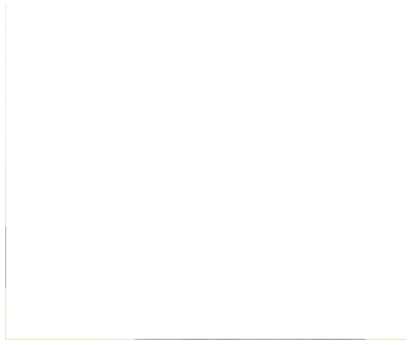
Output:

```
Logistic regression accuracy: 0.906060606060606

Confusion matrix:
[[158   4]
 [ 27 141]]
```

The accuracy of the logistic regression model is 0.906 or 90.6%. As can be observed, the performance of the model is also determined by the confusion matrix. The condition for using this matrix is to be exploited on a data set with known true and false values. You can find additional information on the confusion matrix here: Confusion Matrix.

Our confusion matrix tells us that the total number of accurate predictions is `158 + 141 = 299`. On the other hand, the number of incorrect predictions is `27 + 4 = 31`. We can be satisfied with the prediction accuracy of our model.



Now we will import `DecisionTreeClassifier` from `sklearn.tree` library. `model_2` will be based on the decision tree technique, it will be trained as in the previous case, and desired predictions will be made.

```
from sklearn.tree import DecisionTreeClassifier

model_2 = DecisionTreeClassifier()
model_2.fit(X_train, y_train)
predictions_DT = model_2.predict(X_test)

print('Decision tree accuracy:', accuracy_score(predictions_DT, y_test))
print('')
print('Confusion matrix:')
print(confusion_matrix(y_test,predictions_DT))
```

Output:

```
Decision tree accuracy: 0.9333333333333333

Confusion matrix:
[[151  11]
 [ 11 157]]
```

It can be concluded that the Decision Tree model showed better performances in comparison to the Logistic Regression model. The confusion matrix shows us that the 308 predictions have been done correctly and that there are only 22 incorrect predictions. Additionally, Decision Tree accuracy is better by about 3% in comparison to the first regression model.

Conclusion

The obtained results showed the use value of both machine learning models. The Decision Tree model showed slightly better performance than the Logistic Regression model, but definitely, both models have shown that they can be very successful in solving classification problems.

The prediction results can certainly be changed by a different approach to data analysis. We encourage you to do your analysis from the beginning, to find new dependencies between variables and graphically display them. After that, create a new training set and a new test set. Let the training set contain a larger amount of data than in the article. Fit and evaluate your model. In the end, praise yourself in a comment if you get improved performances.

We wish you successful and magical work!

#python #machine learning #scikit-learn

Last Updated: June 6th, 2019

Sign Up

No spam ever. Unsubscribe at any time. Read our Privacy Policy.

Guest Contributor *Author*

ALSO ON STACKABUSE

Integrating MongoDB with Flask Using …	**Get HTTP POST Body in Spring Boot with …**	**Python: How to Remove a Key from …**	**Padding Strings in Python**	**Kernel Density Estimation in …**
4 months ago • 1 comment	8 months ago • 4 comments	4 months ago • 1 comment	8 months ago • 1 comment	8 months ago • 3 comments
In this tutorial, we'll go over everything you need to know to Integrate …	In this article, we'll see how to get the HTTP POST body in Spring using the …	Let's learn three ways in Python to remove key-value pairs from a dictionary - …	In this article, we take a look at what types of padding exist, and examples of …	Introduction to kernel density estimation using scikit-learn. Examples of …

1 Comment StackAbuse Login

Recommend Tweet Share Sort by Best

Join the discussion…

LOG IN WITH

OR SIGN UP WITH DISQUS ?

Name

Computer Scholar • 5 months ago

dataset not found 404 error

• Reply • Share ›

Subscribe Add Disqus to your siteAdd DisqusAdd

Want a remote job?