Naive Bayes Import libraries and load dataset In [1]: **import** pandas **as** pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns In [2]: df = pd.read_csv('Social_Network_Ads.csv') df.head() Age EstimatedSalary Purchased **0** 19 19000 0 0 **1** 35 20000 **2** 26 43000 0 **3** 27 57000 **4** 19 76000 0 In [3]: df.isnull().sum() Out[3]: EstimatedSalary 0 Purchased 0 dtype: int64 observations: * There are no missing values. Separating independent and dependent data In [4]: # independent features x = df.drop(columns = ['Purchased'], axis = 1) # dependent features y = df['Purchased'] Train Test Split In [5]: from sklearn.model_selection import train_test_split x_{train} , x_{test} , y_{train} , y_{test} = $train_{test}$, y_{test} , y_{test} = 0.3, $train_{test}$, y_{test} **Standard Scaling** In [6]: **from** sklearn.preprocessing **import** StandardScaler scaler = StandardScaler() x_train = scaler.fit_transform(x_train) x_test = scaler.transform(x_test) **Model Training** In [7]: from sklearn.naive_bayes import GaussianNB classifier = GaussianNB() classifier.fit(x_train, y_train) Out[7]: GaussianNB() Prediction In [8]: y_pred = classifier.predict(x_test) Evaluation In [9]: from sklearn.metrics import confusion_matrix, accuracy_score print(confusion_matrix(y_test, y_pred), '\n') print(accuracy_score(y_test, y_pred)) [[72 1] [8 39]] 0.925

2.5

-1.5

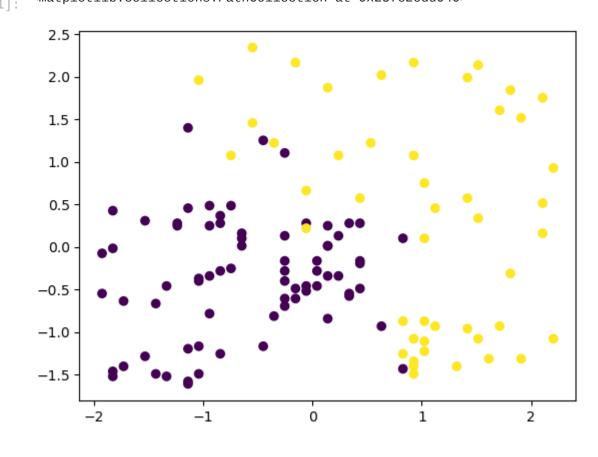
1. Visualising training result

In [10]: $plt.scatter(x = x_train[:, 0], y = x_train[:, 1], c = y_train)$ <matplotlib.collections.PathCollection at 0x287e2b768e0> Out[10]:

2.0 1.5 1.0 0.5 0.0 -0.5 · -1.0

2. Visualising test result

In [11]: $plt.scatter(x = x_test[:, 0], y = x_test[:, 1], c = y_test)$ Out[11]: <matplotlib.collections.PathCollection at 0x287e2cdd940>



Naive Baye's Algorithm Load dataset
<pre>from sklearn.datasets import load_iris from sklearn.model_selection import train_test_split x, y = load_iris(return_X_y = True) print(x)</pre>
<pre>print() print(y) [[5.1 3.5 1.4 0.2] [4.9 3. 1.4 0.2] [4.7 3.2 1.3 0.2] [4.6 3.1 1.5 0.2] [5. 3.6 1.4 0.2]</pre>
[5.4 3.9 1.7 0.4] [4.6 3.4 1.4 0.3] [5. 3.4 1.5 0.2] [4.4 2.9 1.4 0.2] [4.9 3.1 1.5 0.1] [5.4 3.7 1.5 0.2] [4.8 3.4 1.6 0.2] [4.8 3. 1.4 0.1] [4.8 3. 1.4 0.1]
[4.3 3.
[5.1 3.7 1.5 0.4] [4.6 3.6 1. 0.2] [5.1 3.3 1.7 0.5] [4.8 3.4 1.9 0.2] [5. 3. 1.6 0.2] [5. 3.4 1.6 0.4] [5.2 3.5 1.5 0.2] [5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2] [4.8 3.1 1.6 0.2] [5.4 3.4 1.5 0.4] [5.2 4.1 1.5 0.1] [5.5 4.2 1.4 0.2] [4.9 3.1 1.5 0.2] [5. 3.2 1.2 0.2] [5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1] [4.4 3.
[4.8 3.
[5.5 2.3 4. 1.3] [6.5 2.8 4.6 1.5] [5.7 2.8 4.5 1.3] [6.3 3.3 4.7 1.6] [4.9 2.4 3.3 1.] [6.6 2.9 4.6 1.3] [5.2 2.7 3.9 1.4] [5. 2. 3.5 1.]
[5. 9 3. 4.2 1.5] [6. 2.2 4. 1.] [6.1 2.9 4.7 1.4] [5.6 2.9 3.6 1.3] [6.7 3.1 4.4 1.4] [5.6 3. 4.5 1.5] [5.8 2.7 4.1 1.] [6.2 2.2 4.5 1.5]
[5.6 2.5 3.9 1.1] [5.9 3.2 4.8 1.8] [6.1 2.8 4. 1.3] [6.3 2.5 4.9 1.5] [6.1 2.8 4.7 1.2] [6.4 2.9 4.3 1.3] [6.6 3. 4.4 1.4]
[6.8 2.8 4.8 1.4] [6.7 3. 5. 1.7] [6. 2.9 4.5 1.5] [5.7 2.6 3.5 1.] [5.5 2.4 3.8 1.1] [5.5 2.4 3.7 1.] [5.8 2.7 3.9 1.2] [6. 2.7 5.1 1.6]
[5.4 3. 4.5 1.5] [6. 3.4 4.5 1.6] [6.7 3.1 4.7 1.5] [6.3 2.3 4.4 1.3] [5.6 3. 4.1 1.3] [5.5 2.5 4. 1.3] [5.5 2.6 4.4 1.2] [6.1 3. 4.6 1.4]
[5. 2.6 4. 1.2] [5. 2.3 3.3 1.] [5.6 2.7 4.2 1.3] [5.7 3. 4.2 1.2] [5.7 2.9 4.2 1.3] [6.2 2.9 4.3 1.3] [5.1 2.5 3. 1.1] [5.7 2.8 4.1 1.3]
[6.3 3.3 6. 2.5] [5.8 2.7 5.1 1.9] [7.1 3. 5.9 2.1] [6.3 2.9 5.6 1.8] [6.5 3. 5.8 2.2] [7.6 3. 6.6 2.1] [4.9 2.5 4.5 1.7] [7.3 2.9 6.3 1.8]
[6.7 2.5 5.8 1.8] [7.2 3.6 6.1 2.5] [6.5 3.2 5.1 2.] [6.4 2.7 5.3 1.9] [6.8 3. 5.5 2.1] [5.7 2.5 5. 2.] [5.8 2.8 5.1 2.4] [6.4 3.2 5.3 2.3]
[6.5 3. 5.5 1.8] [7.7 3.8 6.7 2.2] [7.7 2.6 6.9 2.3] [6. 2.2 5. 1.5] [6.9 3.2 5.7 2.3] [5.6 2.8 4.9 2.] [7.7 2.8 6.7 2.] [6.3 2.7 4.9 1.8]
[6.7 3.3 5.7 2.1] [7.2 3.2 6. 1.8] [6.2 2.8 4.8 1.8] [6.1 3. 4.9 1.8] [6.4 2.8 5.6 2.1] [7.2 3. 5.8 1.6] [7.4 2.8 6.1 1.9]
[7.9 3.8 6.4 2.] [6.4 2.8 5.6 2.2] [6.3 2.8 5.1 1.5] [6.1 2.6 5.6 1.4] [7.7 3. 6.1 2.3] [6.3 3.4 5.6 2.4] [6.4 3.1 5.5 1.8] [6. 3. 4.8 1.8]
[6.9 3.1 5.4 2.1] [6.7 3.1 5.6 2.4] [6.9 3.1 5.1 2.3] [5.8 2.7 5.1 1.9] [6.8 3.2 5.9 2.3] [6.7 3.3 5.7 2.5] [6.7 3. 5.2 2.3] [6.3 2.5 5. 1.9]
[6.5 3. 5.2 2.] [6.2 3.4 5.4 2.3] [5.9 3. 5.1 1.8]] [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Observation: Multiclass Classification problem as there are 3 categories in output feature. As input feature are continuous data we have to use gaussian naive bayes.
<pre>1. Train Test Split x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.3, random_state = 0)</pre>
2. Model Building from sklearn.naive_bayes import GaussianNB
<pre>gnb = GaussianNB() gnb.fit(x_train, y_train) GaussianNB()</pre>
3. Prediction y_pred = gnb.predict(x_test)
y_pred array([2, 1, 0, 2, 0, 2, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 2, 1, 0, 0, 2, 0, 0, 1, 1, 0, 2, 1, 0, 2, 1, 0, 1, 1, 0, 2, 1, 0, 1, 1, 1, 2, 0, 2, 0, 0]) 4. Performance Metrics
<pre>from sklearn.metrics import accuracy_score, classification_report, confusion_matrix print(accuracy_score(y_test, y_pred)) print() print(confusion_matrix(y_test, y_pred)) print()</pre>
<pre>print(classification_report(y_test, y_pred)) 1.0 [[16 0 0] [0 18 0] [0 0 11]]</pre>
precision recall f1-score support 0
weighted avg 1.00 1.00 1.00 45 Internal assignment
<pre>import seaborn as sns df = sns.load_dataset('tips') df total_bill tip sex smoker day time size</pre>
0 16.99 1.01 Female No Sun Dinner 2 1 10.34 1.66 Male No Sun Dinner 3 2 21.01 3.50 Male No Sun Dinner 3 3 23.68 3.31 Male No Sun Dinner 2 4 24.59 3.61 Female No Sun Dinner 4
239 29.03 5.92 Male No Sat Dinner 3 240 27.18 2.00 Female Yes Sat Dinner 2 241 22.67 2.00 Male Yes Sat Dinner 2
242 17.82 1.75 Male No Sat Dinner 2 243 18.78 3.00 Female No Thur Dinner 2 244 rows × 7 columns from sklearn.preprocessing import OneHotEncoder
<pre>encoder = OneHotEncoder() encoded = encoder.fit_transform(df[['sex','day','time']]).toarray() encoded array([[1., 0., 0.,, 0., 1., 0.],</pre>
<pre>[0., 1., 0.,, 0., 1., 0.],, [0., 1., 0.,, 0., 1., 0.], [0., 1., 0.,, 0., 1., 0.], [1., 0., 0.,, 1., 1., 0.]]) import pandas as pd df_encoded = pd.DataFrame(encoded, columns = encoder.get_feature_names_out())</pre>
<pre>final_df = pd.concat([df[['total_bill','tip','size']],df_encoded,df[['smoker']]],axis=1) con = {'Yes' : 1 , 'No' :0} final_df['smoker'] = final_df['smoker'].map(con) final_df</pre>
total_bill tip size sex_Female sex_Male day_Sat day_Sat day_Thur time_Lunch smoker 0 16.99 1.01 2 1.0 0.0 0.0 1.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0
4 24.59 3.61 4 1.0 0.0 0.0 0.0 1.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 1.0 0.0 1.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0
242 17.82 1.75 2 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0 0.0
<pre>y = final_df.iloc[:,-1] x , y (total_bill tip size sex_Female sex_Male day_Fri day_Sat day_Sun \ 0 16.99 1.01</pre>
$egin{array}{cccccccccccccccccccccccccccccccccccc$
243 18.78 3.00 2 1.0 0.0 0.0 0.0 0.0 day_Thur time_Dinner time_Lunch 0 0.0 1.0 0.0 1 0.0 0.0 2 0.0 1.0 0.0 2 0.0 1.0 0.0 3 0.0 1.0 0.0 4 0.0 1.0 0.0
239 0.0 1.0 0.0 240 0.0 1.0 0.0 241 0.0 1.0 0.0 242 0.0 1.0 0.0 243 1.0 1.0 0.0 [244 rows x 11 columns],
0 0 1 0 2 0 3 0 4 0 239 0 240 1
240 1 241 1 242 0 243 0 Name: smoker, Length: 244, dtype: category Categories (2, int64): [1, 0]) x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3,random_state = 0)
<pre>gnb = GaussianNB() gnb.fit(x_train, y_train) y_pred = gnb.predict(x_test) print(accuracy_score(y_test, y_pred)) print()</pre>
<pre>print(confusion_matrix(y_test, y_pred)) print() print(classification_report(y_test, y_pred))</pre>
0.6351351351351351 [[30 9]