# untitled2

## November 26, 2024

```
[1]:
     #1
     import pandas as pd
     df = pd.read_csv("Experiment7.csv")
[3]: df.head()
[3]:
        Survived
                   Pclass
                                                 Parch
                                                        Fare Embarked
                               Sex
                                    Age
                                          SibSp
     0
                0
                         3
                              male
                                     22
                                              1
                                                      0
                                                            7
                                                                      S
                1
                                                           71
                                                                      С
     1
                         1
                            female
                                              1
                                                      0
                                      38
     2
                1
                         3
                            female
                                              0
                                                      0
                                                            7
                                                                      S
                                      26
     3
                                                                      S
                                                      0
                                                           53
                         1
                            female
                                      35
                                              1
                0
                              male
                                      35
                                                            8
[4]: df.tail()
[4]:
          Survived
                     Pclass
                                            SibSp
                                                   Parch
                                                           Fare Embarked
                                 Sex
                                       Age
                  0
                                male
                                                              13
     886
                           2
                                        27
                                                0
                                                        0
                                                                        S
     887
                                                                        S
                  1
                           1
                              female
                                        19
                                                0
                                                        0
                                                             30
                              female
     888
                  0
                           3
                                        32
                                                 1
                                                        2
                                                             23
                                                                        S
     889
                           1
                                male
                                                0
                                                              30
                                                                        C
                                        26
                                                        0
     890
                           3
                                male
                                        32
                                                0
                                                        0
                                                              7
                                                                        Q
[5]: df.isna()
[5]:
          Survived Pclass
                                        Age SibSp Parch
                                Sex
                                                             Fare
                                                                    Embarked
                                            False
             False
                      False
                             False
                                     False
                                                    False
                                                            False
                                                                       False
     0
     1
             False
                      False False
                                     False False
                                                     False
                                                            False
                                                                       False
     2
             False
                      False
                              False
                                     False False
                                                     False
                                                            False
                                                                       False
     3
                      False
                              False
                                     False False
                                                            False
             False
                                                     False
                                                                       False
     4
             False
                      False
                              False
                                     False False
                                                     False
                                                            False
                                                                       False
                                       ...
     . .
     886
             False
                      False
                              False
                                     False False
                                                     False False
                                                                       False
     887
             False
                      False False
                                     False False
                                                     False
                                                            False
                                                                       False
     888
             False
                      False
                              False
                                     False
                                            False
                                                     False
                                                            False
                                                                       False
     889
             False
                      False
                              False
                                     False
                                             False
                                                     False
                                                            False
                                                                       False
     890
             False
                      False
                              False
                                     False
                                             False
                                                     False
                                                            False
                                                                       False
```

## [891 rows x 8 columns]

## [6]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):

| # | Column   | Non-Null Count | Dtype  |
|---|----------|----------------|--------|
|   |          |                |        |
| 0 | Survived | 891 non-null   | int64  |
| 1 | Pclass   | 891 non-null   | int64  |
| 2 | Sex      | 891 non-null   | object |
| 3 | Age      | 891 non-null   | int64  |
| 4 | SibSp    | 891 non-null   | int64  |
| 5 | Parch    | 891 non-null   | int64  |
| 6 | Fare     | 891 non-null   | int64  |
| 7 | Embarked | 891 non-null   | object |
| _ |          |                |        |

dtypes: int64(6), object(2)
memory usage: 55.8+ KB

- [7]: df.shape
- [7]: (891, 8)
- [8]: df.size
- [8]: 7128
- [9]: df.describe

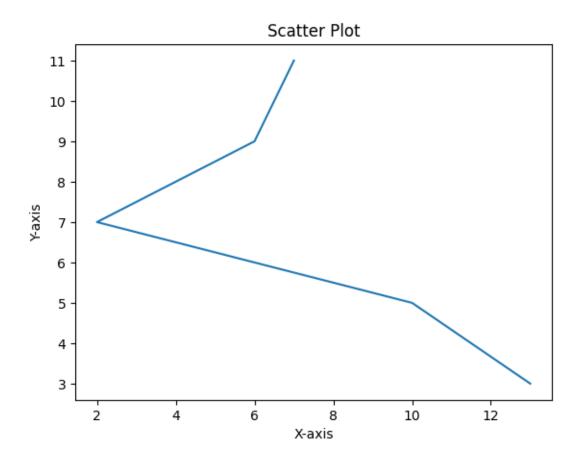
| [9]: | <box></box>         | method | NDFrame | .describ | e of | Su | rvived | Pclass | Sex | Age | SibSp |
|------|---------------------|--------|---------|----------|------|----|--------|--------|-----|-----|-------|
|      | Parch Fare Embarked |        |         |          |      |    |        |        |     |     |       |
|      | 0                   | 0      | 3       | male     | 22   | 1  | . 0    | 7      | S   |     |       |
|      | 1                   | 1      | 1       | female   | 38   | 1  | . 0    | 71     | C   |     |       |
|      | 2                   | 1      | 3       | female   | 26   | C  | 0      | 7      | S   |     |       |
|      | 3                   | 1      | 1       | female   | 35   | 1  | . 0    | 53     | S   |     |       |
|      | 4                   | 0      | 3       | male     | 35   | C  | 0      | 8      | S   |     |       |
|      |                     |        | •••     |          | •••  |    | •••    |        |     |     |       |
|      | 886                 | 0      | 2       | male     | 27   | C  | 0      | 13     | S   |     |       |
|      | 887                 | 1      | 1       | female   | 19   | C  | 0      | 30     | S   |     |       |
|      | 888                 | 0      | 3       | female   | 32   | 1  | . 2    | 23     | S   |     |       |
|      | 889                 | 1      | 1       | male     | 26   | C  | 0      | 30     | C   |     |       |
|      | 890                 | 0      | 3       | male     | 32   | C  | 0      | 7      | Q   |     |       |

[891 rows x 8 columns]>

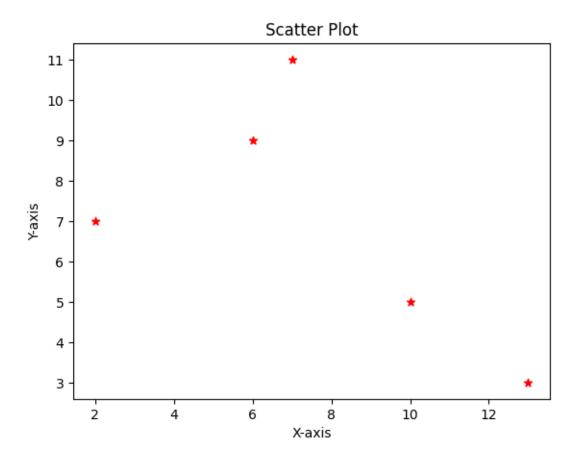
```
[10]: df.nunique()
[10]: Survived
                   2
     Pclass
                   3
      Sex
                   2
      Age
                  72
      SibSp
                   7
      Parch
                   7
      Fare
                  91
      Embarked
                   3
      dtype: int64
[11]: import numpy as np
[12]: mydata = {
          'EmpID' : [111,112,123,114,231],
          'EmpName':['Ashish','Vinod','Abhay','Munna','Deepak']
      }
[13]: employee = pd.DataFrame(mydata)
[14]: print(employee)
        EmpID EmpName
          111 Ashish
     0
     1
          112
                Vinod
     2
          123
                Abhay
     3
          114
                Munna
          231 Deepak
[15]: arr = np.array([11,12,13,14,15,16,17])
      print(arr)
     [11 12 13 14 15 16 17]
[16]: print(np.mean(arr))
     14.0
[17]: print(np.median(arr))
     14.0
[18]: print(np.max(arr))
     17
[19]: print(np.min(arr))
```

```
11
```

```
[20]: print(np.percentile(arr,7))
     11.42
[21]: print(np.stack(arr))
     [11 12 13 14 15 16 17]
[22]: print(np.vstack(arr))
     [[11]
      [12]
      [13]
      [14]
      [15]
      [16]
      [17]]
[23]: print(np.hstack(arr))
     [11 12 13 14 15 16 17]
[24]: import matplotlib.pyplot as plt
[25]: x = [13,10,2,6,7]
      y = [3,5,7,9,11]
      plt.plot(x,y)
      plt.xlabel('X-axis')
      plt.ylabel('Y-axis')
      plt.title('Scatter Plot')
[25]: Text(0.5, 1.0, 'Scatter Plot')
```

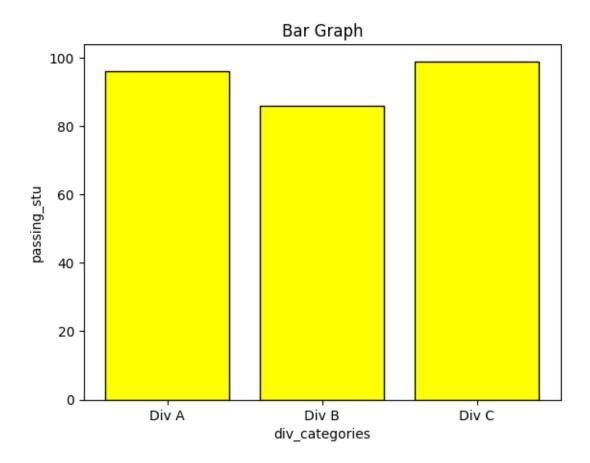


```
[26]: x = [13,10,2,6,7]
y = [3,5,7,9,11]
plt.scatter(x,y,color='red',marker='*')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.title('Scatter Plot')
plt.show()
```



```
[27]: div_categories = ['Div A' , 'Div B' , 'Div C']
  passing_stu = [96,86,99]

plt.bar(div_categories , passing_stu , color = 'yellow' , edgecolor='black')
  plt.xlabel('div_categories')
  plt.ylabel('passing_stu')
  plt.title('Bar Graph')
  plt.show()
```



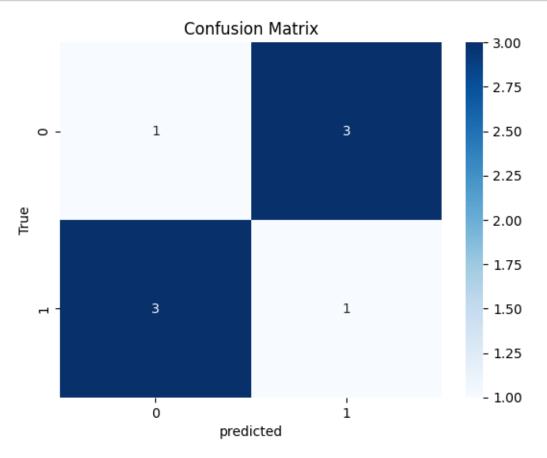
```
from sklearn.metrics import confusion_matrix
import numpy as np
true_values = np.array([0,1,1,0,1,0,0,1])
predicted_values = np.array([1,0,1,1,0,1,0,0])
cm = confusion_matrix(true_values,predicted_values)
print("Confusion Matrix")
print(cm)

Confusion Matrix
[[1 3]
    [3 1]]

[29]: import seaborn as sns
import matplotlib.pyplot as plt
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('predicted')
plt.ylabel('True')
```

[28]: #2

```
plt.title('Confusion Matrix')
plt.show()
```



```
[30]: from sklearn.metrics import confusion_matrix
  import numpy as np

  true_values = np.array([1,0,0,1,0,1])
  predicted_values = np.array([0,1,1,0,0,1])

  cm = confusion_matrix(true_values,predicted_values)

  TN,FP,FN,TP = cm.ravel()

  print("Confusion_matrix")
  print(cm)

  print(f"True Positive (TP): {TN}")
  print(f"False Positive (FP): {FP}")
  print(f"False Negative (FN): {FN}")
  print(f"True Negative (TN): {TN}")
```

```
Confusion_matrix
[[1 2]
[2 1]]
True Positive (TP): 1
False Positive (FP): 2
False Negative (FN): 2
True Negative (TN): 1

[31]: import matplotlib.pyplot as plt
import numpy as np
from sklearn import metrics

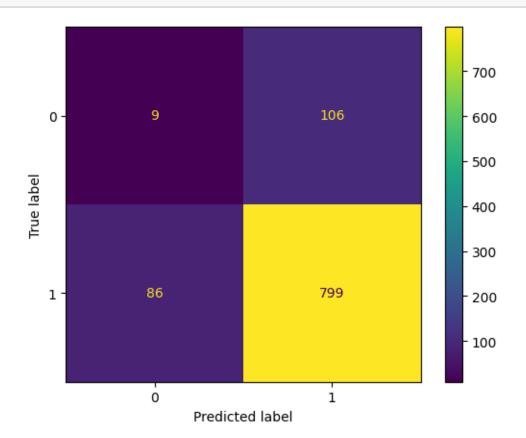
actual = np.random.binomial(1, 0.9, size=1000)
predicted = np.random.binomial(1, 0.9 , size=1000)

confusion_matrix = metrics.confusion_matrix(actual,predicted)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix)

cm_display.plot()
```

plt.show()



```
[32]: #3
      import pandas as pd
      import numpy as np
      from sklearn.model_selection import train_test_split
      X = X = np.array([[1, 2, 3],
                    [4, 5, 6],
                    [7, 8, 9],
                    [10, 11, 12],
                    [13, 14, 15],
                    [16, 17, 18],
                    [19, 20, 21],
                    [22, 23, 24],
                    [25, 26, 27],
                    [28, 29, 30]])
      y = np.array([1,2,3,4,5,6,7,8,9,10])
      df = pd.DataFrame(X, columns=['Feature1', 'Feature2', 'Feature3'])
      df['Target'] = y
      X = df.iloc[:, :-1]
      y = df.iloc[:, -1]
      X_train, X_test, y_train, y_test = train_test_split(
          X, y, test_size=0.3, random_state=0)
      print("X_train:")
      print(X_train)
      print("\nX_test:")
      print(X_test)
      print("\ny_train:")
      print(y_train)
      print("\ny_test:")
      print(y_test)
```

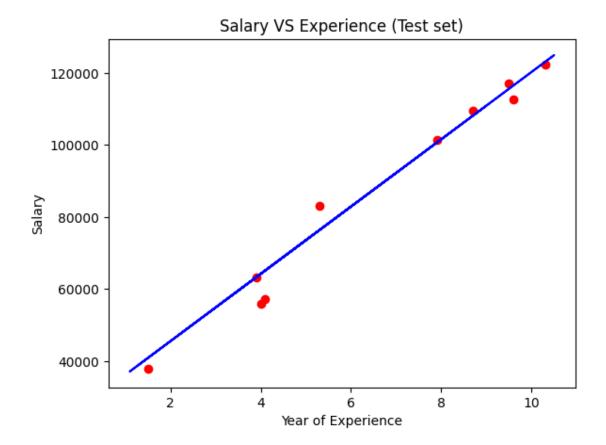
## X\_train:

Feature1 Feature2 Feature3 28 29 30 9 6 1 4 5

```
20
                                   21
     6
              19
     7
              22
                         23
                                   24
     3
              10
                         11
                                   12
     0
               1
                          2
                                    3
     5
              16
                         17
                                   18
     X test:
        Feature1 Feature2 Feature3
               7
                         8
                                   27
     8
              25
                         26
     4
              13
                        14
                                   15
     y_train:
          10
     9
     1
           2
     6
           7
     7
           8
     3
           4
     0
           1
     5
     Name: Target, dtype: int64
     y_test:
          3
     8
          9
     Name: Target, dtype: int64
[36]: #4
      import numpy as np
      import matplotlib.pyplot as plt
      import pandas as pd
      dataset = pd.read_csv('Salary_Data.csv')
      X = dataset.iloc[:, :-1].values
      y = dataset.iloc[:, 1].values
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1/3,__
       →random_state=0)
      from sklearn.linear_model import LinearRegression
```

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
viz_train = plt
viz_train.scatter(X_train, y_train, color='red')
viz_train.plot(X_train, regressor.predict(X_train), color='blue')
viz_train.title('Salary VS Experience (Training set)')
viz_train.xlabel('Year of Experience')
viz_train.ylabel('Salary')
viz_train.show()
viz_test = plt
viz_test.scatter(X_test, y_test, color='red')
viz_test.plot(X_train, regressor.predict(X_train), color='blue')
viz_test.title('Salary VS Experience (Test set)')
viz_test.xlabel('Year of Experience')
viz_test.ylabel('Salary')
viz_test.show()
y_pred = regressor.predict(X_test)
for pred in y_pred:
   print("Salary_Data:", pred)
```





```
Salary_Data: 40835.105908714744
    Salary_Data: 123079.39940819162
    Salary_Data: 65134.556260832906
    Salary_Data: 63265.36777220843
    Salary_Data: 115602.64545369372
    Salary_Data: 108125.89149919583
    Salary_Data: 116537.23969800596
    Salary_Data: 64199.96201652067
    Salary_Data: 76349.68719257976
    Salary_Data: 100649.13754469794
[7]: #5
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import warnings
     warnings.filterwarnings("ignore")
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean squared error, mean_absolute_error
from sklearn.model_selection import train_test_split, cross_val_score
dp = pd.read_csv("Mobile_Price_Prediction_train.csv")
# Convert "Extracurricular Activities" to numerical (O for 'No', 1 for 'Yes')
dp['blue'] = dp['blue'].map({'No': 0, 'Yes': 1})
# Select numerical features, including 'Extracurricular Activities'
numerical_features = dp.select_dtypes(include=np.number).columns
# Calculate and print correlation matrix
print(dp[numerical_features].corr())
print(dp.describe())
                                    clock_speed dual_sim
                                                                         four_g \
               battery_power
                              blue
                                                                  fc
                    1.000000
                               NaN
                                        0.011482 -0.041847
                                                            0.033334 0.015665
battery_power
blue
                         {\tt NaN}
                               NaN
                                             NaN
                                                       NaN
                                                                 NaN
                                                                            NaN
clock_speed
                    0.011482
                               {\tt NaN}
                                        1.000000 -0.001315 -0.000434 -0.043073
dual_sim
                   -0.041847
                               NaN
                                       -0.001315 1.000000 -0.029123 0.003187
fc
                    0.033334
                               {\tt NaN}
                                       -0.000434 -0.029123 1.000000 -0.016560
                               NaN
                                       -0.043073 0.003187 -0.016560 1.000000
four_g
                    0.015665
int_memory
                   -0.004004
                               {\tt NaN}
                                       0.006545 -0.015679 -0.029133 0.008690
                                      -0.014364 -0.022142 -0.001791 -0.001823
                    0.034085
                               NaN
m dep
mobile_wt
                    0.001844
                               NaN
                                      0.012350 -0.008979 0.023618 -0.016537
n cores
                   -0.029727
                               NaN
                                       -0.005724 -0.024658 -0.013356 -0.029706
                               NaN
                                      -0.005245 -0.017143  0.644595 -0.005598
                    0.031441
рс
px_height
                    0.014901
                               NaN
                                       -0.014523 -0.020875 -0.009990 -0.019236
                   -0.008402
                               NaN
                                      -0.009476 0.014291 -0.005176 0.007448
px_width
ram
                   -0.000653
                               NaN
                                       0.003443 0.041072 0.015099 0.007313
sc_h
                   -0.029959
                               NaN
                                      -0.029078 -0.011949 -0.011014 0.027166
                   -0.021421
                               {\tt NaN}
                                      -0.007378 -0.016666 -0.012373 0.037005
sc_w
talk_time
                    0.052510
                               {\tt NaN}
                                       -0.011432 -0.039404 -0.006829 -0.046628
                               {\tt NaN}
                                      -0.046433 -0.014008 0.001793 0.584246
three_g
                    0.011522
touch_screen
                   -0.010516
                               {\tt NaN}
                                       0.019756 -0.017117 -0.014828 0.016758
                   -0.008343
                               {\tt NaN}
                                       -0.024471 0.022740 0.020085 -0.017620
wifi
                    0.200723
                                       -0.006606 0.017444 0.021998 0.014772
price_range
                               NaN
               int_memory
                              m_dep mobile_wt
                                                  n_cores ... px_height
                                       0.001844 -0.029727
                                                               0.014901
battery_power
                -0.004004 0.034085
blue
                      NaN
                                NaN
                                            NaN
                                                      NaN ...
                                                                    NaN
clock_speed
                 0.006545 -0.014364
                                       0.012350 -0.005724 ...
                                                             -0.014523
dual sim
                -0.015679 -0.022142 -0.008979 -0.024658 ... -0.020875
fc
                -0.029133 -0.001791
                                       0.023618 -0.013356
                                                              -0.009990
```

four\_g

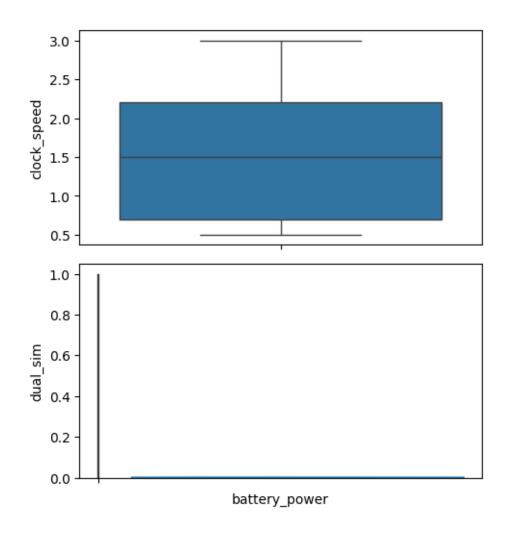
0.008690 -0.001823 -0.016537 -0.029706 ... -0.019236

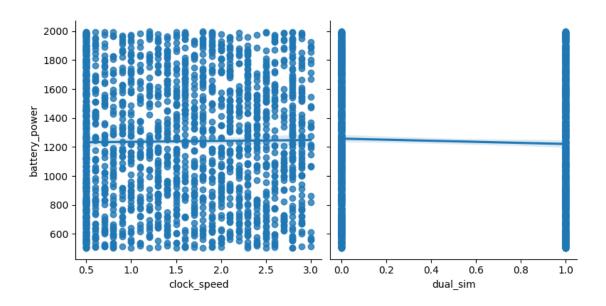
```
1.000000
                           0.006886
                                     -0.034214 -0.028310
                                                              0.010441
int_memory
m_dep
                 0.006886
                           1.000000
                                      0.021756 -0.003504
                                                              0.025263
mobile_wt
                -0.034214
                           0.021756
                                      1.000000 -0.018989
                                                              0.000939
                -0.028310 -0.003504 -0.018989
n_cores
                                               1.000000
                                                             -0.006872
                                      0.018844 -0.001193
рс
                -0.033273
                           0.026282
                                                             -0.018465
                           0.025263
                                      0.000939 -0.006872
px_height
                 0.010441
                                                              1.000000
px width
                -0.008335
                           0.023566
                                      0.000090 0.024480
                                                              0.510664
ram
                 0.032813 -0.009434
                                     -0.002581
                                                0.004868
                                                             -0.020352
                                     -0.033855 -0.000315
sc h
                 0.037771 -0.025348
                                                              0.059615
SC_W
                 0.011731 -0.018388
                                     -0.020761
                                               0.025826
                                                              0.043038
                -0.002790 0.017003
                                      0.006209
                                                0.013148
                                                             -0.010645
talk_time
                                      0.001551 -0.014733
three_g
                -0.009366 -0.012065
                                                             -0.031174
                -0.026999 -0.002638
                                     -0.014368
                                               0.023774
                                                              0.021891
touch_screen
wifi
                 0.006993 -0.028353
                                     -0.000409 -0.009964
                                                              0.051824
price_range
                 0.044435 0.000853
                                     -0.030302 0.004399
                                                              0.148858
                                                       talk_time
                                                                   three_g
               px_width
                              ram
                                       sc_h
                                                 SC_W
battery_power -0.008402 -0.000653 -0.029959 -0.021421
                                                        0.052510
                                                                  0.011522
blue
                                                  NaN
                    NaN
                              NaN
                                        NaN
                                                             NaN
                                                                       NaN
clock speed
              -0.009476
                         0.003443 -0.029078 -0.007378
                                                       -0.011432 -0.046433
dual sim
               0.014291
                         0.041072 -0.011949 -0.016666
                                                       -0.039404 -0.014008
fc
              -0.005176
                         0.015099 -0.011014 -0.012373
                                                       -0.006829 0.001793
four_g
               0.007448
                         0.007313
                                   0.027166 0.037005
                                                       -0.046628 0.584246
                         0.032813
                                   0.037771 0.011731
                                                       -0.002790 -0.009366
int_memory
              -0.008335
               0.023566 -0.009434 -0.025348 -0.018388
                                                        0.017003 -0.012065
m_dep
mobile_wt
               0.000090 -0.002581 -0.033855 -0.020761
                                                        0.006209 0.001551
               0.024480
                         0.004868 -0.000315
                                                        0.013148 -0.014733
n_cores
                                             0.025826
               0.004196
                         0.028984
                                   0.004938 -0.023819
                                                        0.014657 -0.001322
рс
px_height
               0.510664 -0.020352
                                   0.059615
                                             0.043038
                                                       -0.010645 -0.031174
px_width
               1.000000
                         0.004105
                                   0.021599
                                             0.034699
                                                        0.006720 0.000350
               0.004105
                         1.000000 0.015996
                                             0.035576
                                                        0.010820 0.015795
ram
sc_h
               0.021599 0.015996
                                   1.000000
                                             0.506144
                                                       -0.017335
                                                                  0.012033
               0.034699
                         0.035576
                                   0.506144
                                             1.000000
                                                       -0.022821
                                                                  0.030941
SC_W
               0.006720
                         0.010820 -0.017335 -0.022821
                                                        1.000000 -0.042688
talk_time
                                             0.030941
               0.000350
                         0.015795
                                   0.012033
                                                       -0.042688 1.000000
three g
touch screen
              -0.001628 -0.030455 -0.020023
                                             0.012720
                                                        0.017196 0.013917
wifi
               0.030319
                         0.022669
                                   0.025929
                                             0.035423
                                                       -0.029504
                                                                  0.004316
price_range
               0.165818 0.917046
                                   0.022986
                                             0.038711
                                                        0.021859
                                                                  0.023611
               touch_screen
                                 wifi
                                       price_range
                  -0.010516 -0.008343
                                          0.200723
battery_power
blue
                                  NaN
                                               NaN
                        NaN
clock_speed
                   0.019756 -0.024471
                                         -0.006606
dual_sim
                  -0.017117
                             0.022740
                                          0.017444
fc
                  -0.014828 0.020085
                                          0.021998
four_g
                   0.016758 -0.017620
                                          0.014772
int_memory
                  -0.026999 0.006993
                                          0.044435
                  -0.002638 -0.028353
                                          0.000853
m_{dep}
```

| mobile   | _wt -   | 0.014368 -0.0   | 000409 -0.0  | 30302   |   |              |
|--|---|---|--|---|---|--------------|
| n_core   | es 0.023774 -   |   | 0.0  | 04399   |   |              |
| рс   | _   | 0.008742 0.0  | 0.0  | 33599   |   |              |
| px_hei   | ght   | 0.021891 0.0  | 0.1  | 48858   |   |              |
| px_wid   | th -  | 0.001628 0.0  | 030319 0.1   | 65818   |   |              |
| ram  |   | 0.030455 0.0  | 0.9  | 17046   |   |              |
| sc_h   | _   |   |  | 22986   |   |              |
| sc_w   |   |   |  | 38711   |   |              |
| talk_t   |   | 0.017196 -0.0   |  | 21859   |   |              |
| three_   |   |   |  | 23611   |   |              |
|  | .0  |   |  | 30411   |   |              |
| wifi   |   |   |  | 18785   |   |              |
| price_   |   |   |  | 00000   |   |              |
| Price_   | i diige   | 0.000111 0.0  | 710700 1.0   | 00000   |   |              |
| [21 ro   | ws x 21 colum   | nel   |  |   |   |              |
| [21 10   |   |   | ck_speed d   | ual_sim   | fc \  |              |
| count  | 2000.00000  |   | - <b>-</b>   | <del>-</del>  | .000000   |              |
| count  |   |   |  |   |   |              |
| mean   | 1238.51850  |   |  |   | .309500   |              |
| std  | 439.41820   |   |  |   | .341444   |              |
| min  | 501.00000   |   |  |   | .000000   |              |
| 25%  | 851.75000   |   |  |   | .000000   |              |
| 50%  | 1226.00000  |   |  |   | .000000   |              |
| 75%  | 1615.25000  |   |  |   | .000000   |              |
| max  | 1998.00000  | 0 NaN 3   | 3.000000 1   | .000000 19  | .000000   |              |
|  |   |   |  |   |   |              |
|  | four_g  | <pre>int_memory</pre>   | m_dep  | mobile_wt   | n_cores   | \            |
| count  |   |   | _  |   |   |              |
| Count  | 2000.000000   | 2000.000000   | 2000.000000  | 2000.000000   | 2000.000000   |              |
| mean   | 2000.000000 0.521500  | 2000.000000<br>32.046500  | 2000.000000 0.501750   | 2000.000000<br>140.249000   | 2000.000000<br>4.520500   | •••          |
|  |   |   |  |   |   |              |
| mean   | 0.521500  | 32.046500   | 0.501750   | 140.249000  | 4.520500  | •••          |
| mean<br>std  | 0.521500<br>0.499662  | 32.046500<br>18.145715  | 0.501750<br>0.288416   | 140.249000<br>35.399655   | 4.520500<br>2.287837  | •••          |
| mean<br>std<br>min   | 0.521500<br>0.499662<br>0.000000  | 32.046500<br>18.145715<br>2.000000  | 0.501750<br>0.288416<br>0.100000   | 140.249000<br>35.399655<br>80.000000  | 4.520500<br>2.287837<br>1.000000  |              |
| mean<br>std<br>min<br>25%  | 0.521500<br>0.499662<br>0.000000<br>0.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000   | 0.501750<br>0.288416<br>0.100000<br>0.200000   | 140.249000<br>35.399655<br>80.000000<br>109.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000  |              |
| mean<br>std<br>min<br>25%<br>50%                                 | 0.521500<br>0.499662<br>0.000000<br>0.000000<br>1.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000  |              |
| mean<br>std<br>min<br>25%<br>50%<br>75%                          | 0.521500<br>0.499662<br>0.000000<br>0.000000<br>1.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000   | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>0.800000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>170.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000  |              |
| mean<br>std<br>min<br>25%<br>50%<br>75%                          | 0.521500<br>0.499662<br>0.000000<br>0.000000<br>1.000000<br>1.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>0.800000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>170.000000<br>200.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000  | <br><br><br> |
| mean<br>std<br>min<br>25%<br>50%<br>75%<br>max                   | 0.521500<br>0.499662<br>0.000000<br>0.000000<br>1.000000<br>1.000000<br>px_height   | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>0.800000<br>1.000000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>170.000000<br>200.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000  |              |
| mean<br>std<br>min<br>25%<br>50%<br>75%<br>max                   | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000   | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>ram<br>2000.0000000  | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000   | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000  | <br><br><br> |
| mean std min 25% 50% 75% max count mean                          | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>ram<br>2000.0000000<br>2124.213000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>sc_w<br>2000.0000000<br>5.767000  | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std                     | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>ram<br>2000.000000<br>2124.213000<br>1084.732044   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>sc_w<br>2000.000000<br>5.767000<br>4.356398                                       | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min                 | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.0000000   | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>ram<br>2000.000000<br>2124.213000<br>1084.732044<br>256.000000   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>\$c_w<br>2000.000000<br>5.767000<br>4.356398<br>0.000000                          | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25%             | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000  | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>ram<br>2000.0000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000                                   | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000  | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000                                      | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50%         | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000<br>1247.000000                               | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>1.000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000<br>2146.500000                               | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000                                     | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000                          | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50% 75%     | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000<br>947.250000                | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000<br>1247.000000<br>1633.000000                | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>1.000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000<br>2146.500000<br>3064.500000                | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000<br>16.000000                        | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000<br>9.000000              | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50%         | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000  | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000<br>1247.000000                               | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>1.000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000<br>2146.500000                               | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000                                     | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000                          | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50% 75%     | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000<br>947.250000<br>1960.000000 | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000<br>1247.000000<br>1633.000000<br>1998.000000 | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>1.000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000<br>2146.500000<br>3064.500000<br>3998.000000 | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>200.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000<br>16.000000<br>19.000000                    | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000<br>9.000000              | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50% 75% max | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000<br>947.250000<br>1960.000000 | 32.046500 18.145715 2.000000 16.000000 32.000000 48.000000 64.000000  px_width 2000.000000 1251.515500 432.199447 500.000000 874.750000 1247.000000 1633.000000 1998.0000000  | 0.501750 0.288416 0.100000 0.200000 0.500000 0.800000 1.0000000 2124.213000 1084.732044 256.000000 1207.500000 2146.500000 3064.500000 3998.0000000                                      | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>200.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000<br>16.000000<br>19.000000                    | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000<br>9.000000<br>18.000000 | <br><br><br> |
| mean std min 25% 50% 75% max  count mean std min 25% 50% 75%     | 0.521500<br>0.499662<br>0.000000<br>1.000000<br>1.000000<br>1.000000<br>1.000000<br>px_height<br>2000.000000<br>645.108000<br>443.780811<br>0.000000<br>282.750000<br>564.000000<br>947.250000<br>1960.000000 | 32.046500<br>18.145715<br>2.000000<br>16.000000<br>32.000000<br>48.000000<br>64.000000<br>px_width<br>2000.000000<br>1251.515500<br>432.199447<br>500.000000<br>874.750000<br>1247.000000<br>1633.000000<br>1998.000000 | 0.501750<br>0.288416<br>0.100000<br>0.200000<br>0.500000<br>1.000000<br>1.000000<br>2124.213000<br>1084.732044<br>256.000000<br>1207.500000<br>2146.500000<br>3064.500000<br>3998.000000 | 140.249000<br>35.399655<br>80.000000<br>109.000000<br>141.000000<br>200.000000<br>sc_h<br>2000.000000<br>12.306500<br>4.213245<br>5.000000<br>9.000000<br>12.000000<br>16.000000<br>wifi<br>2000.000000 | 4.520500<br>2.287837<br>1.000000<br>3.000000<br>4.000000<br>7.000000<br>8.000000<br>5.767000<br>4.356398<br>0.000000<br>2.000000<br>5.000000<br>9.000000              | <br><br><br> |

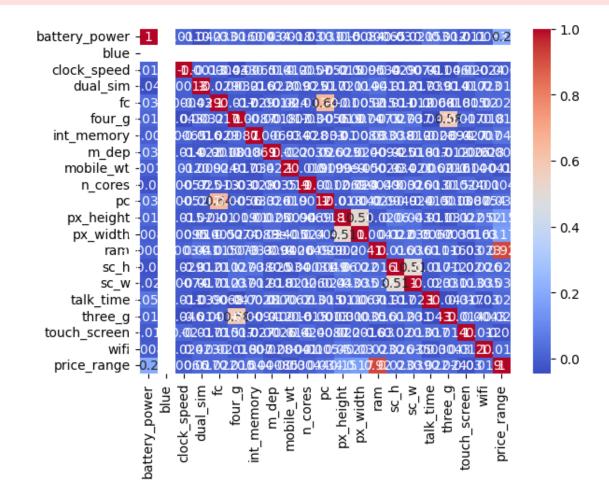
```
0.500116
                                                    0.500076
std
          5.463955
                        0.426273
                                                                 1.118314
min
          2.000000
                        0.000000
                                      0.000000
                                                    0.000000
                                                                 0.000000
25%
          6.000000
                        1.000000
                                      0.000000
                                                    0.000000
                                                                 0.750000
50%
         11.000000
                        1.000000
                                      1.000000
                                                    1.000000
                                                                 1.500000
         16.000000
                        1.000000
75%
                                      1.000000
                                                    1.000000
                                                                 2.250000
         20.000000
                        1.000000
                                      1.000000
                                                    1.000000
                                                                 3.000000
max
```

[8 rows x 21 columns]





[9]:

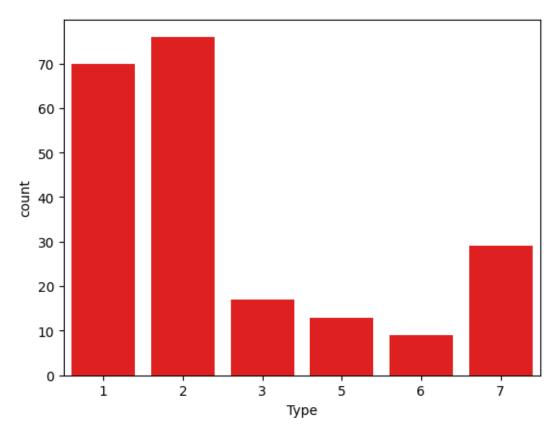


```
[10]: #7
      import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      import seaborn as sns
      dn = pd.read_csv("Experiment7.csv")
      from sklearn.preprocessing import LabelEncoder
      le = LabelEncoder()
      dn['Sex'] = le.fit transform(dn['Sex'])
      dn['Embarked'] = le.fit_transform(dn['Embarked'])
      print(dn)
      # Putting feature variable to X
      X = dn.drop('Survived', axis=1)
      # Putting response variable to y
      y = dn['Survived']
      # Splitting the data into train and test
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7,_
       →random_state=42)
      # Import Random Forest Model
      from sklearn.ensemble import RandomForestClassifier
      # Create a Gaussian Classifier
      clf = RandomForestClassifier(n_estimators=10)
      # Train the model using the training sets y_pred=clf.predict(X_test)
      clf.fit(X_train, y_train)
      Pred = clf.predict(X_test)
      print(Pred)
```

|     | Survived | Pclass | Sex | Age | SibSp | Parch | Fare | Embarked |
|-----|----------|--------|-----|-----|-------|-------|------|----------|
| 0   | 0        | 3      | 1   | 22  | 1     | 0     | 7    | 2        |
| 1   | 1        | 1      | 0   | 38  | 1     | 0     | 71   | 0        |
| 2   | 1        | 3      | 0   | 26  | 0     | 0     | 7    | 2        |
| 3   | 1        | 1      | 0   | 35  | 1     | 0     | 53   | 2        |
| 4   | 0        | 3      | 1   | 35  | 0     | 0     | 8    | 2        |
|     | •••      |        | ••  | ••• |       |       |      |          |
| 886 | 0        | 2      | 1   | 27  | 0     | 0     | 13   | 2        |
| 887 | 1        | 1      | 0   | 19  | 0     | 0     | 30   | 2        |
| 888 | 0        | 3      | 0   | 32  | 1     | 2     | 23   | 2        |

```
889
                         26
                                        30
            1
                  1
                      1
    890
                         32
                                         7
    [891 rows x 8 columns]
    [0\ 0\ 0\ 1\ 0\ 1\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0
    1 1 1 1 0 0 0 0 0]
[11]: #8
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.naive_bayes import GaussianNB
    from sklearn.metrics import accuracy_score
    from sklearn.model_selection import train_test_split
    import warnings
    warnings.filterwarnings('ignore')
    glass = pd.read_csv("Experiment8.csv")
    print(glass.head())
    print(glass.tail())
    print(glass.shape)
    print(glass.isnull().sum())
    sns.countplot(x='Type', data=glass, color='red')
    plt.show()
    nb = GaussianNB()
    x = glass.drop(columns=['Type'])
    y = glass['Type']
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,_
     →random_state=4)
    nb.fit(x_train, y_train)
    y_pred = nb.predict(x_test)
    print("Predictions:", y_pred)
    print("Accuracy Score:", accuracy_score(y_test,y_pred))
          RΙ
               Na
                   Mg
                        Al
                             Si
                                  K
                                      Ca
                                          Ba
                                             Fe Type
     1.52101 13.64
                  4.49
                      1.10 71.78 0.06 8.75
                                         0.0
                                             0.0
    1 1.51761
            13.89
                  3.60
                      1.36 72.73 0.48 7.83
                                         0.0
                                             0.0
    2 1.51618 13.53
                  3.55
                      1.54 72.99 0.39 7.78
                                         0.0
                                             0.0
    3 1.51766 13.21 3.69
                     1.29 72.61 0.57 8.22 0.0
                                             0.0
                                                   1
                  3.62 1.24 73.08 0.55
                                    8.07
    4 1.51742 13.27
                                         0.0
                                             0.0
                                                   1
           RΙ
                              Si
                                   K
                         Al
                                       Ca
                                           Ba
                                               Fe
                                                  Type
                Na
                    Mg
    209 1.51623 14.14 0.0 2.88 72.61 0.08 9.18 1.06 0.0
```

```
210 1.51685 14.92 0.0 1.99 73.06 0.00 8.40 1.59
                                                     0.0
                                                             7
211 1.52065 14.36 0.0 2.02 73.42 0.00 8.44
                                               1.64 0.0
                                                             7
212 1.51651 14.38 0.0 1.94 73.61
                                    0.00 8.48
                                               1.57
                                                     0.0
                                                             7
213 1.51711 14.23 0.0 2.08 73.36 0.00 8.62 1.67 0.0
                                                             7
(214, 10)
       0
RΙ
       0
{\tt Na}
Mg
       0
Al
       0
Si
       0
K
       0
Ca
       0
Вa
       0
Fe
       0
Туре
       0
dtype: int64
```



Predictions: [1 7 5 3 3 1 2 1 1 1 5 1 1 7 1 1 1 7 7 1 1 1 7 1 6 7 3 3 7 2 1 7 1

1 1 1 1

2 1 1 5 7 2]

Accuracy Score: 0.4883720930232558

```
[12]: #9
      import pandas as pd
      # Importing the dataset
      dataset = pd.read_csv("Experiment9.csv")
      X = dataset.iloc[:, [2, 3]].values
      y = dataset.iloc[:, -1].values
      # Splitting the dataset into the Training set and Test set
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, __
       →random_state = 0)
      # Feature Scaling
      from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      X_train = sc.fit_transform(X_train)
      X_test = sc.transform(X_test)
      from sklearn.neighbors import KNeighborsClassifier
      classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
      classifier.fit(X_train, y_train)
      y_pred = classifier.predict(X_test)
      from sklearn.metrics import confusion_matrix, accuracy_score
      cm = confusion_matrix(y_test, y_pred)
      print(cm)
      accuracy_score(y_test, y_pred)
      from sklearn.neighbors import KNeighborsClassifier
      classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
      classifier.fit(X_train, y_train)
      y_pred = classifier.predict(X_test)
      from sklearn.metrics import confusion_matrix, accuracy_score
      cm = confusion_matrix(y_test, y_pred)
      ac = accuracy_score(y_test, y_pred)
      print(ac)
      print(cm)
```

```
print(y_pred)
    [[55 3]
     [ 1 21]]
    0.95
    [[55 3]
     [ 1 21]]
    0 0 0 0 1 1]
[13]: #10
     import pandas as pd
     from sklearn.model_selection import train_test_split
     from sklearn.svm import SVC
     fish = pd.read_csv("Experiment10.csv")
     X = fish.drop('Species', axis=1)
     y = fish['Species']
     # Split data into training and testing sets (80% training, 20% testing)
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,__
     →random state=42)
     model = SVC(kernel='linear', C=1)
     model.fit(X_train, y_train)
     svm_pred = model.predict(X_test)
     accuracy = model.score(X test, y test)
     print(f"Accuracy: {accuracy:.4f}")
     print(svm_pred)
    Accuracy: 0.9375
    ['Perch' 'Smelt' 'Pike' 'Roach' 'Perch' 'Bream' 'Smelt' 'Roach' 'Perch'
     'Pike' 'Bream' 'Whitefish' 'Bream' 'Parkki' 'Bream' 'Bream' 'Perch'
     'Perch' 'Perch' 'Bream' 'Smelt' 'Bream' 'Bream' 'Bream' 'Perch'
     'Perch' 'Roach' 'Smelt' 'Smelt' 'Pike' 'Perch']
```

```
[14]: #CP1exp
      def sum_of_array(arr):
          return sum(arr)
      # Example usage
      arr = [1, 2, 3, 4, 5]
      print("Sum =", sum_of_array(arr))
     Sum = 15
[15]: #1.2
      def sort array(arr):
          return sorted(arr)
      # Example usage
      arr = [5, 2, 8, 1, 3]
      print("Sorted Array =", sort_array(arr))
     Sorted Array = [1, 2, 3, 5, 8]
[16]: # To implement Bubble Sort and Insertion Sort
      def bubble_sort(arr):
          n = len(arr)
          for i in range(n):
              for j in range(0, n-i-1):
                  if arr[j] > arr[j+1]:
                      arr[j], arr[j+1] = arr[j+1], arr[j]
          return arr
      # Example usage
      arr = [64, 34, 25, 12, 22, 11, 90]
      print("Sorted Array (Bubble Sort):", bubble_sort(arr))
     Sorted Array (Bubble Sort): [11, 12, 22, 25, 34, 64, 90]
[17]: def insertion_sort(arr):
          for i in range(1, len(arr)):
              key = arr[i]
              j = i - 1
              while j \ge 0 and key < arr[j]:
                  arr[j + 1] = arr[j]
                  j -= 1
              arr[j + 1] = key
          return arr
      # Example usage
      arr = [64, 34, 25, 12, 22, 11, 90]
      print("Sorted Array (Insertion Sort):", insertion_sort(arr))
```

```
Sorted Array (Insertion Sort): [11, 12, 22, 25, 34, 64, 90]
```

```
[18]: def linear_search(arr, target):
    for i in range(len(arr)):
        if arr[i] == target:
            return i
    return -1

# Example usage
arr = [10, 20, 30, 40, 50]
target = 30
index = linear_search(arr, target)
print(f"Element found at index {index}" if index != -1 else "Element not found")
```

#### Element found at index 2

```
[19]: def binary_search(arr, target):
          low, high = 0, len(arr) - 1
          while low <= high:</pre>
              mid = (low + high) // 2
              if arr[mid] == target:
                   return mid
              elif arr[mid] < target:</pre>
                   low = mid + 1
              else:
                  high = mid - 1
          return -1
      # Example usage
      arr = [10, 20, 30, 40, 50]
      target = 30
      index = binary_search(arr, target)
      print(f"Element found at index {index}" if index != -1 else "Element not found")
```

#### Element found at index 2

```
[21]: #3
   text = "Ht India"
   print(text.upper())
   print(text.lower())
   print(text.capitalize())
   print(text.swapcase())
   print(text.title())
```

```
HT INDIA
ht india
Ht india
hT iNDIA
```

```
[22]: #4
      def matrix_multiplication(A, B):
          # Get dimensions of matrices
          rows_A, cols_A = len(A), len(A[0])
          rows_B, cols_B = len(B), len(B[0])
          # Ensure matrices can be multiplied
          if cols_A != rows_B:
              return "Matrix multiplication not possible"
          # Initialize result matrix with zeros
          result = [[0 for _ in range(cols_B)] for _ in range(rows_A)]
          # Perform multiplication
          for i in range(rows_A):
              for j in range(cols_B):
                  for k in range(cols_A): # or rows_B
                      result[i][j] += A[i][k] * B[k][j]
          return result
      # Example usage
      A = [[1, 2], [3, 4]]
      B = [[5, 6], [7, 8]]
      result = matrix_multiplication(A, B)
      print("Matrix Multiplication Result:")
      for row in result:
          print(row)
     Matrix Multiplication Result:
     [19, 22]
     [43, 50]
[23]: def transpose_matrix(matrix):
          # Number of rows and columns in the matrix
          rows, cols = len(matrix), len(matrix[0])
          # Initialize transposed matrix
          transposed = [[0 for _ in range(rows)] for _ in range(cols)]
          # Perform transpose
          for i in range(rows):
              for j in range(cols):
                  transposed[j][i] = matrix[i][j]
          return transposed
```

```
# Example usage
      matrix = [[1, 2, 3], [4, 5, 6]]
      transposed = transpose_matrix(matrix)
      print("Transpose of Matrix:")
      for row in transposed:
          print(row)
     Transpose of Matrix:
     [1, 4]
     [2, 5]
     [3, 6]
[26]: class Node:
          def __init__(self, data):
              self.data = data
              self.next = None
      class LinkedList:
          def __init__(self):
              self.head = None
          # Display the linked list
          def display(self):
              temp = self.head
              while temp:
                  print(temp.data, end=" -> ")
                  temp = temp.next
              print("None")
          # Create a linked list from a list of values
          def create_linked_list(self, values):
              for value in values:
                  new_node = Node(value)
                  if self.head is None:
                      self.head = new_node
                  else:
                      temp = self.head
                      while temp.next:
                          temp = temp.next
                      temp.next = new_node
          # Add a node at the beginning
          def add_at_beginning(self, data):
              new_node = Node(data)
              new_node.next = self.head
              self.head = new_node
```

```
# Add a node at a specific index
def add_at_index(self, index, data):
    if index == 0: # Add at the beginning
        self.add_at_beginning(data)
        return
    new node = Node(data)
    temp = self.head
    for _ in range(index - 1):
        if temp is None:
            print("Index out of bounds")
            return
        temp = temp.next
    if temp is None:
        print("Index out of bounds")
        return
    new_node.next = temp.next
    temp.next = new_node
# Remove a node from the beginning
def remove_from_beginning(self):
    if self.head is None:
        print("List is empty")
        return
    self.head = self.head.next
# Remove a node from the end
def remove_from_end(self):
    if self.head is None:
        print("List is empty")
        return
    if self.head.next is None:
        self.head = None
        return
    temp = self.head
    while temp.next.next:
        temp = temp.next
    temp.next = None
# Remove a node at a specific index
def remove_at_index(self, index):
    if index == 0: # Remove from beginning
        self.remove_from_beginning()
        return
```

```
temp = self.head
        for _ in range(index - 1):
            if temp is None:
                print("Index out of bounds")
                return
            temp = temp.next
        if temp is None or temp.next is None:
            print("Index out of bounds")
            return
        temp.next = temp.next.next
# Example usage
if __name__ == "__main__":
   linked_list = LinkedList()
    # Create a linked list
    print("Creating linked list...")
    linked_list.create_linked_list([10, 20, 30])
    linked_list.display()
    # Add at the beginning
    print("\nAdding 5 at the beginning...")
    linked_list.add_at_beginning(5)
    linked_list.display()
    # Add at a specific index
    print("\nAdding 25 at index 2...")
    linked_list.add_at_index(2, 25)
    linked_list.display()
    # Remove from the beginning
    print("\nRemoving from the beginning...")
    linked_list.remove_from_beginning()
    linked_list.display()
    # Remove from the end
    print("\nRemoving from the end...")
    linked_list.remove_from_end()
    linked_list.display()
    # Remove at a specific index
    print("\nRemoving at index 1...")
    linked_list.remove_at_index(1)
    linked_list.display()
```

```
Creating linked list...
     10 -> 20 -> 30 -> None
     Adding 5 at the beginning...
     5 -> 10 -> 20 -> 30 -> None
     Adding 25 at index 2...
     5 -> 10 -> 25 -> 20 -> 30 -> None
     Removing from the beginning...
     10 -> 25 -> 20 -> 30 -> None
     Removing from the end...
     10 -> 25 -> 20 -> None
     Removing at index 1...
     10 -> 20 -> None
[27]: #6
      class Node:
          def __init__(self, data):
              self.data = data
              self.left = None
              self.right = None
      def is_complete_binary_tree(root):
          if not root:
              return True # An empty tree is complete
          queue = []
          queue.append(root)
          encountered_none = False # Flag to indicate if a null node has been_
       \rightarrow encountered
          while queue:
               current = queue.pop(0)
               if current:
                   # If we've previously encountered a None node, then the tree is not_{\sqcup}
       \hookrightarrow complete
                   if encountered none:
                       return False
                   # Add left and right children to the queue
                   queue.append(current.left)
                   queue.append(current.right)
               else:
```

```
# Mark the flag when encountering the first None
            encountered_none = True
    return True
# Example Usage
if __name__ == "__main__":
    # Create a binary tree
    root = Node(1)
    root.left = Node(2)
    root.right = Node(3)
   root.left.left = Node(4)
    root.left.right = Node(5)
    root.right.left = Node(6)
    # Uncomment below to make the tree incomplete
    # root.right.right = Node(7)
    if is_complete_binary_tree(root):
        print("The binary tree is complete.")
    else:
        print("The binary tree is not complete.")
```

The binary tree is complete.

```
[28]: class Node:
          def __init__(self, data):
             self.data = data
              self.left = None
              self.right = None
      # Function to check if the tree is a BST
      def is_bst(node, min_val=float('-inf'), max_val=float('inf')):
          # Base case: An empty tree is a BST
          if node is None:
              return True
          # Check if the current node violates the min/max constraints
          if node.data <= min_val or node.data >= max_val:
              return False
          # Recursively check the left and right subtrees
          # For left subtree, the max value is the current node's value
          # For right subtree, the min value is the current node's value
          return is_bst(node.left, min_val, node.data) and is_bst(node.right, node.

data, max_val)

      # Example Usage
```

```
if __name__ == "__main__":
    # Create a binary tree
    root = Node(10)
    root.left = Node(5)
    root.right = Node(15)
    root.left.left = Node(2)
    root.left.right = Node(7)
    root.right.left = Node(12)
    root.right.right = Node(20)

if is_bst(root):
    print("The binary tree is a Binary Search Tree (BST).")
    else:
        print("The binary tree is NOT a Binary Search Tree (BST).")
```

The binary tree is a Binary Search Tree (BST).

[]: