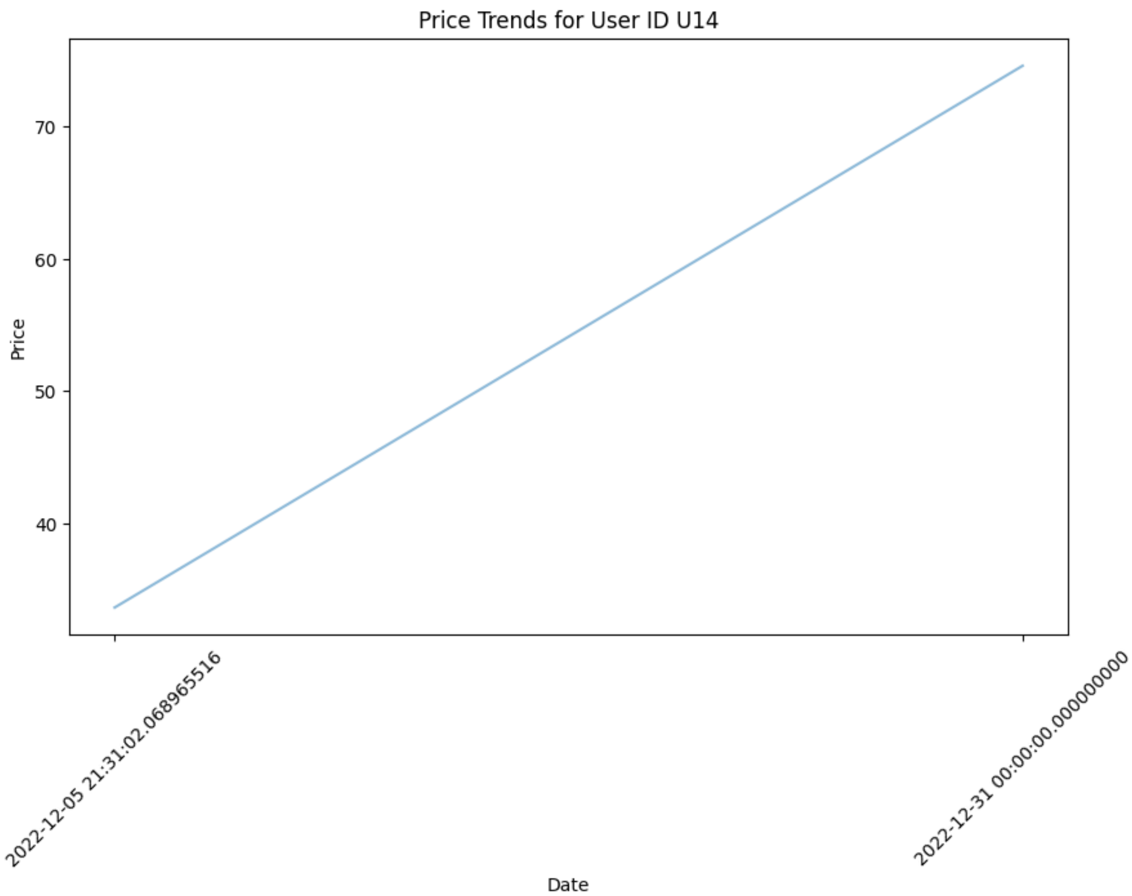
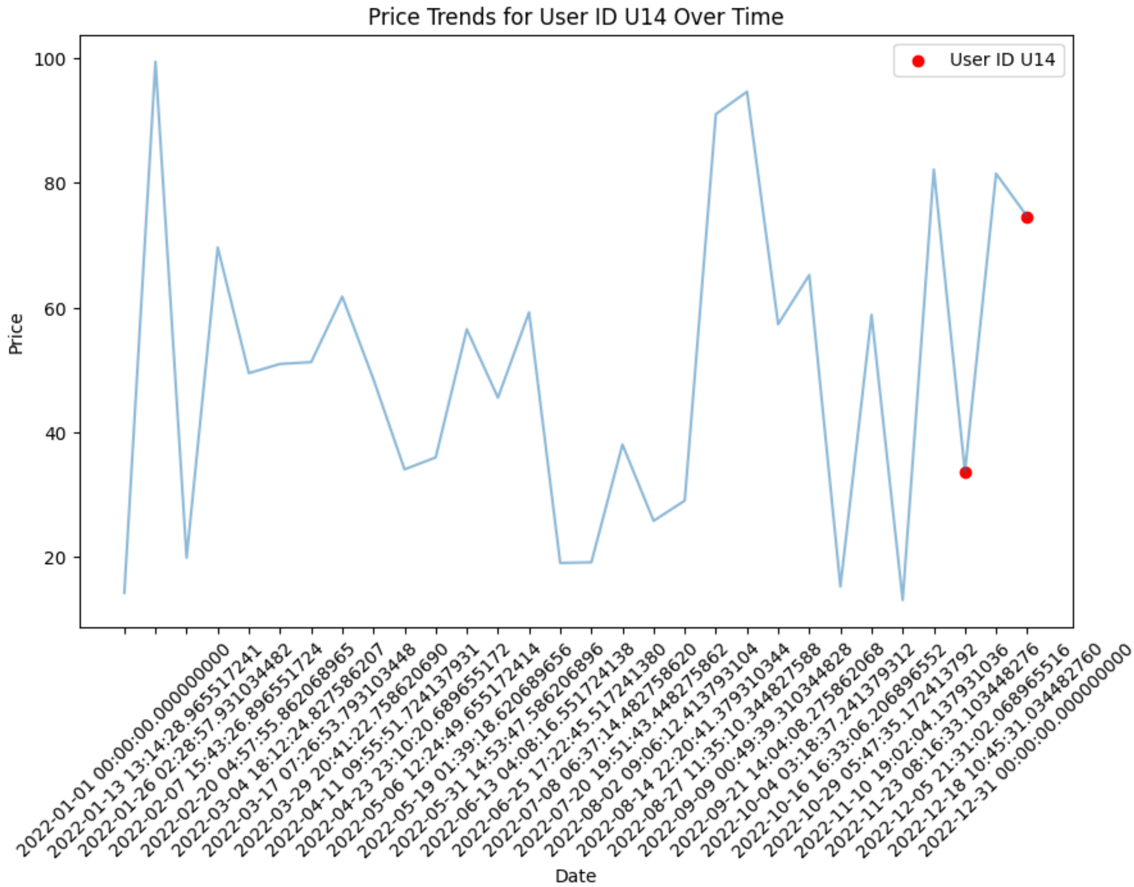
In [1]:
```
# Prepare a dataset of customer having the features date, price, product_
import pandas as pd
import random
import datetime

# Define the number of records in the dataset
num_records = 30

# Generate random data for each feature
dates = pd.date_range(start='2022-01-01', end='2022-12-31', periods=num_r
prices = [round(random.uniform(10, 100), 2) for _ in range(num_records)]
product_ids = [random.randint(1, 100) for _ in range(num_records)]
quantities = [random.randint(1, 10) for _ in range(num_records)]
serial_nos = [f'SN-{random.randint(1000, 9999)}' for _ in range(num_recor
user_ids = ['U' + str(random.randint(10, 20)) for _ in range(num_records)
user_types = ['Retail', 'Wholesale']
user_classes = ['Class A', 'Class B', 'Class C']
purchase_weeks = [date.isocalendar()[1] for date in dates]

# Create a dictionary with the data
data = {
    'Date': dates,
    'Price': prices,
    'Product_ID': product_ids,
    'Quantity_Purchased': quantities,
    'Serial_No': serial_nos,
    'User_ID': user_ids,
    'User_Type': random.choices(user_types, k=num_records),
    'User_Class': random.choices(user_classes, k=num_records),
    'Purchase_Week': purchase_weeks
}

# Create a DataFrame from the dictionary
df = pd.DataFrame(data)

# Print the first few rows of the dataset
print(df.head())

# Save the dataset to a CSV file
df.to_csv('customer_dataset.csv', index=False)
```

```
                           Date  Price  Product_ID  Quantity_Purchased  \
0 2022-01-01 00:00:00.000000000  14.21          74                  10
1 2022-01-13 13:14:28.965517241  99.46          16                   9
2 2022-01-26 02:28:57.931034482  19.86          44                   6
3 2022-02-07 15:43:26.896551724  69.66          12                   2
4 2022-02-20 04:57:55.862068965  49.47          39                   8

  Serial_No User_ID  User_Type User_Class  Purchase_Week
0   SN-5443     U13  Wholesale    Class C             52
1   SN-8106     U15  Wholesale    Class C              2
2   SN-4667     U12     Retail    Class C              4
3   SN-6509     U16  Wholesale    Class C              6
4   SN-5567     U12  Wholesale    Class B              7
```

a) Plot diagram for Price Trends for Particular User, Price Trends for Particular User Over Time using above dataset

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Read the dataset from the CSV file
df = pd.read_csv('customer_dataset.csv')

# Define the user ID for analysis
user_id = 'U14'

# Filter the dataset for the particular user
user_data = df[df['User_ID'] == user_id]

# Plot the price trends for the particular user
plt.figure(figsize=(10, 6))
plt.plot(user_data['Date'], user_data['Price'], alpha=0.5)
plt.xlabel('Date')
plt.ylabel('Price')
plt.title(f'Price Trends for User ID {user_id}')
plt.xticks(rotation=45)
plt.show()

# Plot the price trends for the particular user over time
plt.figure(figsize=(10, 6))
plt.plot(df['Date'], df['Price'], alpha=0.5)
plt.scatter(user_data['Date'], user_data['Price'], color='red', label=f'U
plt.xlabel('Date')
plt.ylabel('Price')
plt.title(f'Price Trends for User ID {user_id} Over Time')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```

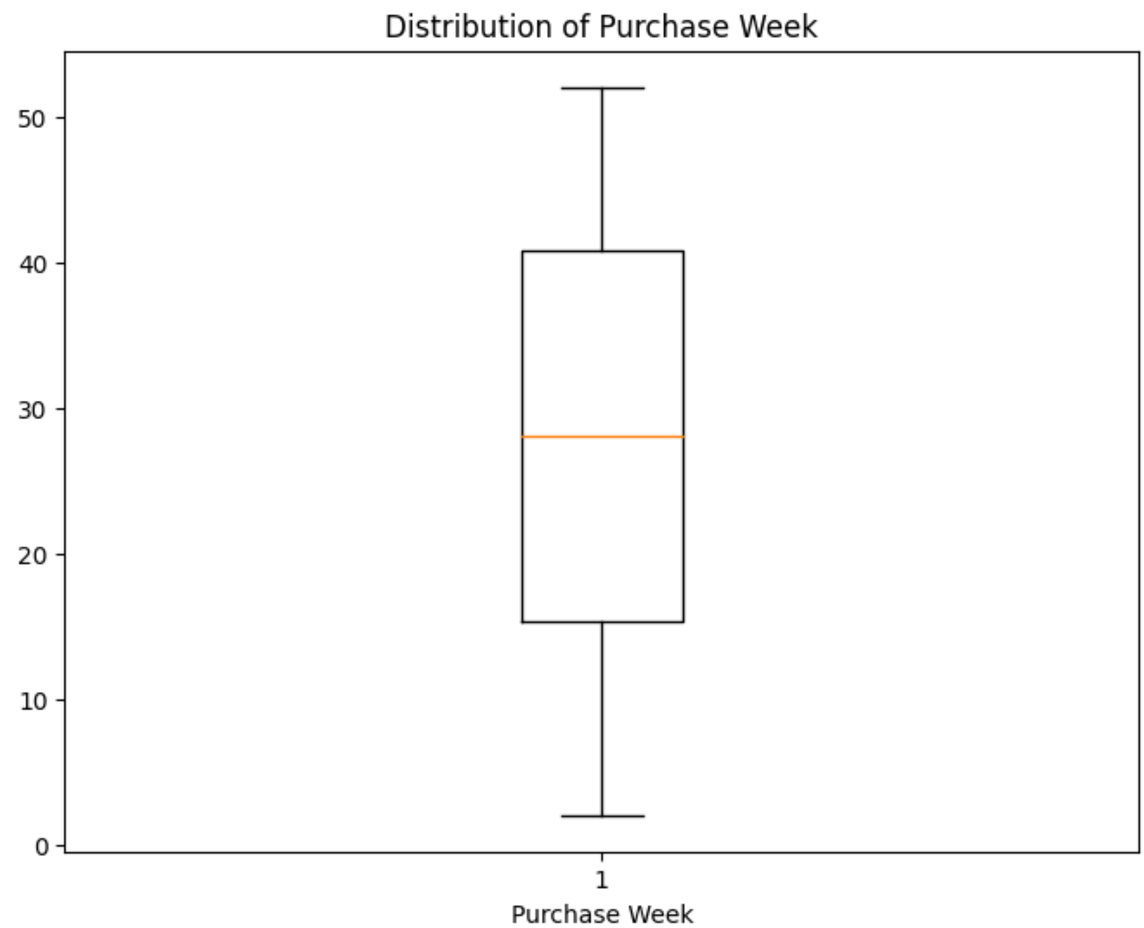




b) Create box plot Quantity and Week value distribution having parameters of quantity_purchased','purchase_week'

In [3]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset from the CSV file
df = pd.read_csv('customer_dataset.csv')
# Create a box plot for Quantity_Purchased
plt.figure(figsize=(8, 6))
plt.boxplot(df['Quantity_Purchased'])
plt.xlabel('Quantity Purchased')
plt.title('Distribution of Quantity Purchased')
plt.show()

# Create a box plot for Purchase_Week
plt.figure(figsize=(8, 6))
plt.boxplot(df['Purchase_Week'])
plt.xlabel('Purchase Week')
plt.title('Distribution of Purchase Week')
plt.show()
```


Distribution of Quantity Purchased
10
8
6
4
2
1
Quantity Purchased


Distribution of Purchase Week
50
40
30
20
10
0
1
Purchase Week

2. Write a program to Transforming Nominal Features, Transforming Ordinal Features and Encoding Categorical Features using one-hot Encoding Scheme

In [4]:
```
import pandas as pd

# Load the dataset from the CSV file
df = pd.read_csv('/home/shyma/Desktop/Machinelearning/pokemon.csv', encod

# Transforming nominal features
nominal_features = ['Generation']
df_nominal = pd.get_dummies(df[nominal_features])

# Transforming ordinal features
gen_ord_map = {'Gen1': 1, 'Gen2': 2, 'Gen3': 3,
               'Gen4': 4, 'Gen5': 5, 'Gen6': 6}

df['GenerationLabel'] = df['Generation'].map(gen_ord_map)

# Encoding categorical features using one-hot encoding scheme
categorical_features = ['Generation', 'Legendary']
df_encoded = pd.get_dummies(df[categorical_features])

# Combine the transformed and encoded features with the original dataset
df_transformed = pd.concat([df, df_nominal, df_encoded], axis=1)

# Print the transformed dataset
print(df_transformed.head())
```

```
   #                   Name Type 1  Type 2  Total  HP  Attack  Defense  \
0  1              Bulbasaur  Grass  Poison    318  45      49       49
1  2                Ivysaur  Grass  Poison    405  60      62       63
2  3               Venusaur  Grass  Poison    525  80      82       83
3  3  VenusaurMega Venusaur  Grass  Poison    625  80     100      123
4  4             Charmander   Fire     NaN    309  39      52       43

   Sp. Atk  Sp. Def  Speed  Generation  Legendary  GenerationLabel  \
0       65       65     45           1      False              NaN
1       80       80     60           1      False              NaN
2      100      100     80           1      False              NaN
3      122      120     80           1      False              NaN
4       60       50     65           1      False              NaN

   Generation  Generation  Legendary
0           1           1      False
1           1           1      False
2           1           1      False
3           1           1      False
4           1           1      False
```

3. Write a program to implement Raw Measures such as Values, count, Binarization, Rounding, Interactions, Binning, Fixed-width binning,Quantile based binning and Mathematical Transformations such as Log transform, Box–Cox transform.

In [5]:
```
import pandas as pd
import numpy as np
from scipy import stats

# Load the dataset from the CSV file

df = pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/bank-data.c

# Raw Measures - Values and Count
print("Raw Measures - Values and Count:")
print(df['married'].values)
print(df['married'].count())
print()

# Binarization
threshold = 5
df['married'] = np.where(df['married'] > threshold, 1, 0)
print("Binarization:")
print(df['married'].values)
print()

# Rounding
df['income_Rounded'] = df['income'].round(decimals=2)
print("Rounding:")
print(df['income_Rounded'].values)
print()

# Interactions
df['Interaction'] = df['save_act'] * df['income']
print("Interactions:")
print(df['Interaction'].values)
print()

# Binning - Fixed-width binning
bin_width = 10
df['Income_Bin'] = pd.cut(df['income'], bins=np.arange(0, df['income'].ma
print("Binning - Fixed-width binning:")
print(df['Income_Bin'].values)
print()

# Binning - Quantile based binning
num_bins = 3
df['Income_Quantile_Bin'] = pd.qcut(df['income'], q=num_bins, labels=Fals
print("Binning - Quantile based binning:")
print(df['Income_Quantile_Bin'].values)
print()

# Mathematical Transformations - Log transform
df['Income_Log_Transformed'] = np.log(df['income'])
print("Mathematical Transformations - Log transform:")
print(df['Income_Log_Transformed'].values)
print()

# Mathematical Transformations - Box-Cox transform
df['Income_BoxCox_Transformed'], _ = stats.boxcox(df['income'])
print("Mathematical Transformations - Box-Cox transform:")
print(df['Income_BoxCox_Transformed'].values)
print()
```

```
Raw Measures - Values and Count:
[0 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 0 0 1
1
 0 1 0 1 1 0 1 0 1 0 0 0 1 0 1 1 0 1 0 0 1 1 0 1 0 1 1 0 1 0 0 0 1 1 0 1
1
 0 0 0 1 1 1 0 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 0 1
0
 1 1 0 1 1 1 1 0 1 0 1 1 0 0 1 1 1 1 0 0 1 0 1 1 1 1 0 1 0 1 1 1 1 1 1 1
0
 1 1 1 0 1 1 0 1 1 1 1 1 1 1 0 0 1 1 0 0 0 1 1 1 1 1 1 0 1 1 1 1 1 0 0 1
0
 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 0 1 0 0 1 1 0 0 1 1 0 1 1 1 1 0 1 0
1
 1 1 1 0 1 0 0 0 1 0 1 1 0 0 0 1 1 1 1 0 1 1 1 0 0 1 1 1 0 1 1 1 0 0 0 1
0
 0 1 1 1 1 0 1 0 0 1 0 0 0 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1
1
 0 1 0 1 1 1 1 1 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 1 1 0 1 0 1 1 0 1 1 1
1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 1 0 0 1 1 1 0 0 1 0 1 1 1 1 1 0 1 1
1
 1 0 0 1 1 1 0 0 1 1 0 1 1 1 1 0 0 0 0 1 1 0 1 1 0 1 1 1 0 1 0 0 1 0 1 1
0
 0 1 1 0 0 0 1 1 1 0 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 0 1 1 0 1 0 1 1 1 1 1
0
 1 1 1 1 1 0 1 0 0 0 0 1 1 1 0 1 1 1 1 1 0 1 1 0 1 0 1 1 1 0 0 1 0 1 1 0
1
 0 0 1 1 1 1 1 1 1 1 0 1 0 1 1 0 0 0 1 1 0 1 0 1 1 1 0 0 1 1 1 1 0 0 1 0
1
 0 1 1 1 0 1 1 1 0 0 1 1 1 0 0 1 0 1 0 0 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1
1
 1 1 1 1 1 0 0 1 0 1 1 1 1 1 0 0 1 0 1 1 1 1 1 0 1 1 1 0 0 1 0 1 0 1 1 1
0
 1 1 1 0 1 1 1 0]
600

Binarization:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

```
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0]

Rounding:
[17546.   30085.1  16575.4  20375.4  50576.3  37869.6   8877.07 24946.6
 25304.3  24212.1  59803.9  26658.8  15735.8  55204.7  19474.6  22342.1
 17729.8  41016.   26909.2  22522.8  57880.7  16497.3  38446.6  15538.8
 12640.3  41034.   20809.7  20114.   29359.1  24270.1  22942.9  16325.8
 23443.2  29921.3  37521.9  19868.   10953.   13381.   18504.3  25391.5
 26774.2  26952.6  55716.5  27571.5  13740.   52670.6  13283.9  13106.6
 39547.8  17867.3  14309.7  23894.8  16259.7  29794.1  56842.5  47835.8
 24977.5  23124.9  15143.8  25334.3  24763.3  36589.   27022.6  11700.4
  5014.21 17390.1  10861.   34892.9  19403.1  10441.9  14064.9   8062.73
 31982.   23197.5  52674.   35610.5  26948.   49456.7  14724.5  34524.9
 22052.1  27808.1  12591.4  16394.4  24026.1  31683.1  15525.   22562.2
 15848.7  31095.6  24814.5  25429.3  34866.5  42579.1  41127.4   9990.11
  7948.62 30870.8  12125.8  15348.9  26707.9  11604.4  15499.9  33088.5
 34513.6  32395.5  46633.   13039.9  12681.9  24031.5  37330.5  25333.2
 37094.2  33630.6  43228.2  47796.8  21730.3  10044.1  17270.1  45765.
 29525.5  54863.8  20799.   33028.3  45031.9  39010.8  25257.7  42603.9
 14092.7  21350.3  23246.4  41609.5  16716.1  36436.4  59503.8  31334.8
 14048.9  39205.3  42173.9  55263.   37095.2  22791.4  17240.6  48974.8
 18923.   51204.2  20236.2  18860.3  25732.5  28240.4  28193.6  36432.8
 54618.8  24760.8  23356.1   8143.75 26462.5  20467.3  21506.2  15315.3
 18875.7  12977.2  20708.5   7549.38 24904.   24071.8   9589.91  8562.86
 26707.5  34020.5  49175.7  19726.3  24346.6  26999.4  41558.1  56340.3
 37558.5  30099.3  15254.8  36086.1  17655.   56658.9  37706.5  18516.
 29622.   32669.9  18275.5  34410.   34866.9  21796.6  63130.1  14996.4
 49024.9  16249.8  36192.1  17839.9  18802.4  48720.3  14585.9  20819.
 26077.8  41627.1  16977.3  19012.8  12764.8  14388.6  59409.1  14960.2
 39666.6  20771.9  24474.1  33123.7  14433.4  13175.5   9824.37 17610.3
 15156.2  31774.1  31693.5  28598.7  26261.7  42124.1  39308.7  43530.
 49874.4  27434.8  50474.6  24888.2  28021.6  12279.5  30189.4  28969.4
 14058.5  30404.3  41438.2  16711.3  52255.9  17866.9  18067.5  12823.7
 11299.3  56031.1  35263.5  19968.1  27825.5  37773.9   7606.25 21384.4
 20347.   21332.3  57671.7  36057.8  14290.5  17882.9  10629.1  24262.8
 26097.9  23371.   21495.6  12166.9  17180.2  28882.3  21612.2  46358.4
 19166.   17921.8  33229.   30396.1  34625.2  16672.8  60747.5  56394.3
 13236.4  28409.4  27056.5   9362.58 28702.7  22366.1  24477.5  36972.4
 22327.8  15610.2  54314.5  39175.8  13739.    9485.84 24675.7  28253.6
 14136.5  37162.1  13519.2  39253.6  46323.8  20950.7  22495.7  32548.9
 24583.4   8639.24 17139.5  13667.7   8162.42 15349.6  29231.4  41462.3
 57398.1  11520.8  52117.3  26281.4  25683.4  11920.7  30658.7  36646.4
 30760.4  16109.9  18036.7  42628.3  22110.1  37689.1  23171.8  21951.3
 38103.4  22882.9  11043.7  24027.6  28495.1   9465.21 34852.3  21268.4
 50849.2  18555.9  52769.9  11601.4  29541.7  17861.   21042.   26688.1
 26900.6  38080.9  37554.1  18184.6  28864.9  48346.1  53104.3  19416.8
 23638.1  42378.2  39745.3  45189.8  37930.9  24042.   31207.1  24424.3
 24607.8  43057.   30198.5  50186.1  22916.1   9592.73 34253.6  22792.3
 51620.8  19918.9  29625.1  12549.   51299.3  17364.8  29866.9  47750.2
 11281.5  34073.8  46870.4  38453.7   7756.36 28413.8  47198.6  20866.3
 33204.3  24823.5  17986.8   9909.82 26542.8  32583.5  14606.6  34836.8
```

```
 26920.8  38248.3  15689.1  30157.7  14642.2  15933.3  44288.3  22197.1
 38248.3  22053.2  25468.5  23485.9  25768.6  34182.2  57444.5  38059.8
 19481.3  19563.8  38598.4  20754.3  13864.6  36599.   45856.1  22362.3
 21984.   11073.   18158.5   7304.2  58092.   16518.6  46461.5  20058.7
 12533.2  22848.5  25699.4  21612.6  48950.9  41438.   11411.   43940.6
 17239.5  30488.7  29866.3  32184.4  17308.7  27863.9  28920.6  58367.3
 16849.3  28138.5  23038.2  11736.9  16479.5  31415.7  12117.3  15417.1
 29414.6  44682.1  36281.   33302.8  15797.1  31864.8  43719.5  30799.5
 48971.6  34061.4  28938.6  38540.   27045.1  51284.3  16352.2  11866.4
 13267.6  61554.6  13700.2  46963.9  23475.6  24554.1  18050.   15237.6
 20555.   28421.7  21876.5  12810.2  15109.4  37414.7  41521.6  25372.8
 21139.8  27757.6  22678.1  12178.5  26106.7  27417.6  23337.2  43395.5
 11536.2  44658.6  32762.5  16403.8  21184.7  49917.3  21623.8  16625.9
 14014.5  20409.3  31671.3  17149.2  27756.3  40949.9  43743.2  38459.9
 40972.9  46587.9  43799.6  18912.2  27765.8  33007.3  26325.3  15308.2
 59805.6  28658.3  23175.   11595.4  50409.9  11215.3  13327.8  16088.8
 43943.   14505.3  33886.4  16662.5  20262.6  33615.4  22007.1  28981.1
 12163.9  17247.7  12683.6  16291.   18707.3  19326.9  14511.8  10672.
 25830.5  43499.5  59175.1  27642.9  30067.5  29714.4  13950.4  10072.6
 37850.6  57176.4  38784.   10191.8  21821.4  37389.   14627.9  48770.5
 21096.2  36256.9  15281.8   9316.98 20736.2  52662.5   8020.19 32245.4
 41107.2  39358.3  36095.9   7723.93 18565.8  25132.9  31290.6  24858.4
 16398.8  23287.9  50897.6  22446.5  23092.1  24867.6  22234.7  17371.1
 29574.   17944.2  33665.5  36166.2  27712.9  22400.7  28469.9  30488.
 19160.3  45342.5   6294.21 25127.7  51879.3  12644.9  21984.4  29093.1
 23528.4   9516.91 18364.9  31273.8  49673.6  12623.4  23818.6  31473.9
 20268.   51417.   30971.8  47025.    9672.25 15976.3  14711.8  26671.6 ]

Interactions:
[    0.       0.   16575.4      0.   50576.3  37869.6      0.   24946.6
     0.   24212.1  59803.9  26658.8  15735.8  55204.7  19474.6  22342.1
     0.   41016.   26909.2  22522.8  57880.7  16497.3  38446.6  15538.8
 12640.3  41034.   20809.7      0.       0.       0.   22942.9  16325.8
 23443.2  29921.3  37521.9  19868.   10953.       0.   18504.3      0.
     0.       0.   55716.5      0.   13740.   52670.6  13283.9  13106.6
     0.   17867.3  14309.7      0.   16259.7  29794.1  56842.5  47835.8
     0.   23124.9      0.   25334.3  24763.3      0.   27022.6  11700.4
  5014.21 17390.1  10861.   34892.9  19403.1      0.   14064.9      0.
 31982.   23197.5  52674.       0.   26948.   49456.7      0.   34524.9
 22052.1      0.   12591.4  16394.4      0.   31683.1  15525.   22562.2
 15848.7      0.       0.   25429.3      0.   42579.1  41127.4   9990.11
     0.   30870.8  12125.8      0.   26707.9  11604.4      0.   33088.5
 34513.6  32395.5  46633.       0.   12681.9  24031.5  37330.5      0.
     0.   33630.6  43228.2  47796.8  21730.3  10044.1      0.   45765.
 29525.5  54863.8  20799.   33028.3  45031.9      0.   25257.7  42603.9
 14092.7  21350.3      0.   41609.5  16716.1      0.   59503.8  31334.8
     0.   39205.3  42173.9  55263.   37095.2      0.       0.   48974.8
 18923.   51204.2      0.   18860.3  25732.5  28240.4  28193.6      0.
 54618.8  24760.8      0.    8143.75 26462.5  20467.3      0.   15315.3
 18875.7      0.       0.       0.       0.       0.    9589.91     0.
 26707.5      0.   49175.7      0.   24346.6  26999.4  41558.1  56340.3
 37558.5  30099.3      0.       0.   17655.   56658.9  37706.5  18516.
 29622.   32669.9      0.       0.       0.       0.   63130.1  14996.4
 49024.9      0.       0.   17839.9      0.   48720.3      0.   20819.
 26077.8  41627.1      0.       0.   12764.8      0.   59409.1  14960.2
 39666.6  20771.9      0.   33123.7  14433.4      0.    9824.37 17610.3
     0.   31774.1  31693.5  28598.7      0.   42124.1  39308.7  43530.
 49874.4  27434.8  50474.6  24888.2      0.       0.       0.       0.
     0.   30404.3  41438.2  16711.3  52255.9  17866.9  18067.5  12823.7
     0.   56031.1  35263.5  19968.1  27825.5  37773.9      0.       0.
```

```
 20347.       0.     57671.7  36057.8      0.         0.     10629.1      0.
 26097.9      0.         0.       0.     17180.2  28882.3      0.     46358.4
 19166.       0.     33229.   30396.1      0.         0.     60747.5  56394.3
 13236.4      0.     27056.5      0.     28702.7  22366.1  24477.5      0.
     0.   15610.2  54314.5  39175.8  13739.       0.     24675.7      0.
 14136.5  37162.1  13519.2  39253.6  46323.8  20950.7  22495.7  32548.9
 24583.4      0.         0.   13667.7   8162.42 15349.6  29231.4  41462.3
 57398.1      0.     52117.3  26281.4  25683.4  11920.7  30658.7  36646.4
     0.   16109.9  18036.7  42628.3  22110.1  37689.1  23171.8  21951.3
 38103.4      0.     11043.7  24027.6  28495.1      0.     34852.3      0.
 50849.2      0.     52769.9  11601.4  29541.7  17861.       0.     26688.1
     0.   38080.9  37554.1      0.     28864.9  48346.1  53104.3  19416.8
 23638.1  42378.2  39745.3  45189.8  37930.9      0.         0.     24424.3
 24607.8  43057.       0.   50186.1      0.      9592.73     0.     22792.3
 51620.8  19918.9      0.   12549.   51299.3  17364.8      0.     47750.2
 11281.5  34073.8  46870.4  38453.7      0.         0.     47198.6  20866.3
     0.       0.         0.       0.     26542.8  32583.5      0.     34836.8
     0.       0.         0.       0.         0.   15933.3  44288.3      0.
 38248.3  22053.2      0.       0.     25768.6  34182.2  57444.5  38059.8
     0.       0.         0.       0.     13864.6  36599.   45856.1  22362.3
     0.   11073.       0.    7304.2  58092.       0.     46461.5  20058.7
 12533.2      0.     25699.4  21612.6  48950.9  41438.       0.     43940.6
     0.   30488.7  29866.3      0.         0.   27863.9  28920.6  58367.3
 16849.3      0.     23038.2  11736.9      0.   31415.7      0.         0.
 29414.6  44682.1  36281.       0.     15797.1  31864.8  43719.5      0.
 48971.6  34061.4      0.   38540.       0.   51284.3  16352.2  11866.4
 13267.6  61554.6  13700.2  46963.9      0.   24554.1      0.         0.
 20555.   28421.7      0.   12810.2      0.   37414.7  41521.6  25372.8
 21139.8  27757.6  22678.1  12178.5      0.   27417.6  23337.2  43395.5
     0.   44658.6  32762.5  16403.8  21184.7  49917.3  21623.8      0.
 14014.5  20409.3  31671.3  17149.2  27756.3  40949.9  43743.2      0.
 40972.9  46587.9  43799.6      0.   27765.8      0.         0.   15308.2
 59805.6  28658.3      0.   11595.4  50409.9  11215.3  13327.8  16088.8
 43943.   14505.3  33886.4  16662.5  20262.6  33615.4      0.   28981.1
     0.   17247.7  12683.6  16291.   18707.3      0.   14511.8  10672.
     0.   43499.5  59175.1      0.   30067.5      0.   13950.4      0.
 37850.6  57176.4  38784.   10191.8  21821.4  37389.   14627.9  48770.5
 21096.2      0.         0.    9316.98 20736.2  52662.5      0.         0.
 41107.2      0.     36095.9   7723.93 18565.8      0.   31290.6      0.
 16398.8      0.     50897.6      0.         0.   24867.6      0.   17371.1
 29574.   17944.2      0.       0.     27712.9  22400.7  28469.9  30488.
 19160.3  45342.5   6294.21      0.   51879.3      0.   21984.4  29093.1
 23528.4   9516.91     0.   31273.8  49673.6  12623.4      0.   31473.9
 20268.   51417.   30971.8  47025.    9672.25 15976.3  14711.8      0.  ]

Binning - Fixed-width binning:
[[17540.0, 17550.0), [30080.0, 30090.0), [16570.0, 16580.0), [20370.0, 20
380.0), [50570.0, 50580.0), ..., [47020.0, 47030.0), [9670.0, 9680.0), [1
5970.0, 15980.0), [14710.0, 14720.0), [26670.0, 26680.0)]
Length: 600
Categories (6314, interval[float64, left]): [[0.0, 10.0) < [10.0, 20.0) <
[20.0, 30.0) < [30.0, 40.0) ... [63100.0, 63110.0) < [63110.0, 63120.0) <
[63120.0, 63130.0) < [63130.0, 63140.0)]

Binning - Quantile based binning:
[0 1 0 1 2 2 0 1 1 1 1 2 1 0 2 0 1 0 2 1 1 2 0 2 0 0 2 1 0 1 1 1 0 1 1 2 0
0
 0 0 1 1 1 2 1 0 2 0 0 2 0 0 1 0 1 2 2 1 1 0 1 1 2 1 0 0 0 0 2 0 0 0 0 2
1
 2 2 1 2 0 2 1 1 0 0 1 2 0 1 0 1 1 1 2 2 2 0 0 1 0 0 1 0 0 2 2 2 2 0 0 1
```

```
2
 1 2 2 2 2 1 0 0 2 1 2 1 2 2 2 1 2 0 1 1 2 0 2 2 2 0 2 2 2 2 1 0 2 0 2 0
0
 1 1 1 2 2 1 1 0 1 1 1 0 0 0 1 0 1 1 0 0 1 2 2 0 1 1 2 2 2 1 0 2 0 2 2 0
1
 2 0 2 2 1 2 0 2 0 2 0 0 2 0 1 1 2 0 0 0 0 2 0 2 1 1 2 0 0 0 0 0 2 2 1 1
2
 2 2 2 1 2 1 1 0 1 1 0 1 2 0 2 0 0 0 0 2 2 0 1 2 0 1 1 1 2 2 0 0 0 1 1 1
1
 0 0 1 1 2 0 0 2 1 2 0 2 2 0 1 1 0 1 1 1 2 1 0 2 2 0 0 1 1 0 2 0 2 2 1 1
2
 1 0 0 0 0 0 1 2 2 0 2 1 1 0 1 2 1 0 0 2 1 2 1 1 2 1 0 1 1 0 2 1 2 0 2 0
1
 0 1 1 1 2 2 0 1 2 2 0 1 2 2 2 2 1 2 1 1 2 1 2 1 0 2 1 2 0 1 0 2 0 1 2 0
2
 2 2 0 1 2 1 2 1 0 0 1 2 0 2 1 2 0 1 0 0 2 1 2 1 1 1 1 2 2 2 0 0 2 1 0 2
2
 1 1 0 0 0 2 0 2 0 0 1 1 1 2 2 0 2 0 1 1 2 0 1 1 2 0 1 1 0 0 2 0 0 1 2 2
2
 0 2 2 1 2 2 1 2 1 2 0 0 0 2 0 2 1 1 0 0 1 1 1 0 0 2 2 1 1 1 1 0 1 1 1 2
0
 2 2 0 1 2 1 0 0 1 2 0 1 2 2 2 2 2 2 0 1 2 1 0 2 1 1 0 2 0 0 0 2 0 2 0 1
2
 1 1 0 0 0 0 0 0 0 0 1 2 2 1 1 1 0 0 2 2 2 0 1 2 0 2 1 2 0 0 1 2 0 2 2 2
2
 0 0 1 2 1 0 1 2 1 1 1 1 0 1 0 2 2 1 1 1 1 0 2 0 1 2 0 1 1 1 0 0 2 2 0 1
2
 1 2 1 2 0 0 0 1]

Mathematical Transformations - Log transform:
[ 9.77258128 10.31178531  9.71567495  9.92208357 10.83123837 10.54190396
  9.09122683 10.12449282 10.13872962 10.09460779 10.99882616 10.19087458
  9.66369365 10.91880337  9.87686633 10.01422807  9.78300212 10.62171751
 10.20022351 10.02228341 10.96613927  9.71095201 10.55702554  9.6510954
  9.4446454  10.62215627  9.9431745   9.90917137 10.28735783 10.09700042
 10.0407638   9.70050196 10.06233575 10.30632588 10.53268004  9.89686568
  9.30136867  9.50159107  9.82575842 10.14216975 10.19519402 10.20183505
 10.92803161 10.22453791  9.52806657 10.8718127   9.49430805  9.4808712
 10.58526535  9.79072751  9.56869291 10.08141614  9.69644493 10.30206567
 10.94803956 10.77552959 10.1257307  10.04866524  9.62534649 10.13991449
 10.117118   10.50750293 10.20442883  9.36737831  8.52003116  9.76365636
  9.29293367 10.46003865  9.87318813  9.25358184  9.55143761  8.99500749
 10.37292852 10.05179979 10.87187725 10.48039582 10.20166436 10.80885282
  9.59726805 10.44943608 10.00116311 10.23308262  9.44076932  9.70469509
 10.08689602 10.36353869  9.65020691 10.02403122  9.67084276 10.34482161
 10.11918344 10.14365733 10.45928176 10.6591188  10.62442985  9.20935088
  8.98075361 10.33756603  9.40309069  9.63879909 10.19271468  9.35913962
  9.64858885 10.40694107 10.44910873 10.3857748  10.75006372  9.47576917
  9.44793106 10.08712075 10.52756597 10.13987107 10.5212159  10.42319165
 10.67424834 10.77471397  9.98646288  9.21474068  9.75673196 10.73127489
 10.29300958 10.91260903  9.94266019 10.40512005 10.71512641 10.57159381
 10.13688634 10.65970108  9.55341221  9.96882107 10.05390556 10.63608379
  9.72412761 10.50332355 10.99379546 10.35248458  9.55029938 10.57656722
 10.64955683 10.91985889 10.52124286 10.03413855  9.75502235 10.79906116
  9.84813339 10.84357684  9.91522836  9.84481446 10.15551006 10.24850886
 10.24685028 10.50322475 10.90813342 10.11701704 10.05861347  9.00500604
 10.18348392  9.92658377  9.97609654  9.63660761  9.84563066  9.47094925
  9.93829952  8.92922072 10.12278371 10.08879631  9.16846678  9.05518953
 10.1926997  10.43471856 10.80315488  9.88970805 10.10014749 10.20356992
 10.63484773 10.93916537 10.533655   10.31225719  9.63264949 10.49366303
```

```
  9.77877431 10.94480436 10.53758777  9.8263905  10.29627261 10.39420944
  9.81331664 10.4461025  10.45929323  9.98950927 11.05295296  9.61556545
 10.80008361  9.69583588 10.49659614  9.7891928   9.8417398  10.79385106
  9.58781059  9.94362131 10.16883966 10.63650668  9.73963244  9.85286772
  9.45444666  9.57419151 10.99220269  9.61314862 10.5882648   9.94135639
 10.10537069 10.40800432  9.57730024  9.48611432  9.19262131  9.77623924
  9.62616497 10.36640677 10.36386689 10.26111654 10.17586688 10.6483753
 10.57920115 10.68120563 10.81726312 10.21956756 10.82922552 10.12214907
 10.24073092  9.41568648 10.31524615 10.27399538  9.55098247 10.32233932
 10.63195844  9.72384042 10.86390808  9.79070512  9.80187002  9.4590503
  9.33249606 10.93366217 10.47060371  9.90189128 10.23370815 10.53937367
  8.93672556  9.97041696  9.92068876  9.96797764 10.96252186 10.49287849
  9.56735026  9.79160023  9.2713508  10.09669959 10.16961013 10.05925122
  9.97560354  9.40647443  9.75151284 10.27098423  9.98101325 10.74415778
  9.86089315  9.79377313 10.41117827 10.32206959 10.45233702  9.72153393
 11.01448121 10.94012337  9.49072589 10.25447536 10.20568255  9.14447617
 10.26474647 10.0153017  10.10550961 10.51792697 10.01358782  9.65567983
 10.90254651 10.57581449  9.52799378  9.15755544 10.11357423 10.24897616
  9.55651538 10.5230447   9.51186618 10.57779844 10.74341115  9.94992734
 10.02107946 10.39049885 10.1098267   9.06406989  9.74914102  9.52279066
  9.00729597  9.63884469 10.28299875 10.63253986 10.95776648  9.35190938
 10.86125223 10.17661674 10.15360015  9.38603166 10.33067175 10.50907048
 10.33398343  9.68718927  9.80016385 10.66027363 10.0037898  10.53712621
 10.0506913   9.99658164 10.5480588  10.03814519  9.30961541 10.08695845
 10.25748742  9.15537825 10.45887441  9.96497768 10.83661967  9.82854308
 10.87369623  9.35888106 10.2935581   9.79037484  9.95427572 10.19197305
 10.19990387 10.54746812 10.53353784  9.80833036 10.2703816  10.78614084
 10.88001318  9.87389395 10.0706151  10.65438936 10.59024687 10.71862668
 10.54352136 10.08755758 10.34840091 10.10333382 10.11081874 10.6702801
 10.31554753 10.82349337 10.039595    9.1687608  10.44154695 10.03417804
 10.85167997  9.89942431 10.29637725  9.43739626 10.84543239  9.76220045
 10.30450612 10.77373853  9.33091949 10.43628404 10.75514163 10.5572102
  8.95626843 10.25463022 10.76211951  9.9458907  10.41043466 10.11954606
  9.79739343  9.20128146 10.1865138  10.3915613   9.58922876 10.45842958
 10.2006545  10.55185439  9.66072148 10.31419556  9.59166305  9.67616654
 10.69847581 10.00771693 10.55185439 10.001213   10.14519767 10.06415552
 10.15691198 10.43946032 10.95857454 10.54691389  9.87721031  9.8814362
 10.5609661   9.94050873  9.53709411 10.5077762  10.73326351 10.01513178
  9.9980702   9.31226499  9.80689405  8.8962048  10.96978324  9.7122423
 10.74637929  9.90641825  9.4361364  10.03664075 10.15422292  9.98103176
 10.79857303 10.63195361  9.34233308 10.690594    9.75495854 10.3251114
 10.30448603 10.37923714  9.75896454 10.23508722 10.27230942 10.97451108
  9.73206439 10.24489402 10.04490899  9.370493    9.70987246 10.35506305
  9.40238946  9.64323256 10.28924643 10.70732825 10.49904947 10.41339676
  9.66758166 10.36925723 10.68554951 10.33525374 10.79899582 10.43592006
 10.27293162 10.55945194 10.20526112 10.84513994  9.70211772  9.38146616
  9.49308025 11.02767986  9.52516571 10.7571345  10.06371686 10.10863413
  9.80090096  9.63152134  9.9308595  10.25490822  9.99316828  9.45799701
  9.62307235 10.52981895 10.63396905 10.14143301  9.9589128  10.23126496
 10.02915498  9.40742738 10.16994727 10.21894042 10.05780393 10.67811103
  9.3532452  10.70680218 10.39703985  9.70526829  9.9610345  10.81812292
  9.98154984  9.718717    9.54784779  9.92374596 10.36316619  9.7497068
 10.23121812 10.62010465 10.68609145 10.55737142 10.62066615 10.74909613
 10.68737996  9.8475625  10.23156033 10.40448403 10.17828573  9.63614391
 10.99885458 10.26319838 10.05082939  9.35836375 10.82794286  9.3250342
  9.49760736  9.68587866 10.69064862  9.58226938 10.43076903  9.72091596
  9.9165321  10.42273957  9.99912041 10.27439917  9.40622783  9.75543408
  9.4480651   9.69836809  9.8366691   9.86925319  9.58271739  9.27537877
 10.15931124 10.68050472 10.98825612 10.22712419 10.31120013 10.29938706
  9.54326346  9.21757415 10.54140211 10.9538965  10.56576307  9.22933875
```

```
  9.99064642 10.52913182  9.59068594 10.7948809   9.95684821 10.49838499
  9.63441786  9.13959382  9.93963624 10.87165891  8.98971739 10.38113068
 10.62393857 10.58046216 10.49393456  8.95207858  9.82907646 10.13193302
 10.35107301 10.120951    9.70496344 10.05568919 10.83757105 10.01888998
 10.04724585 10.12132103 10.00940941  9.76256318 10.29465088  9.79502222
 10.42422885 10.49588026 10.22965329 10.01684749 10.25660267 10.32508844
  9.86059571 10.72200006  8.74738544 10.1317261  10.85667515  9.44500925
  9.99808839 10.27825631 10.06596348  9.1608255   9.81819651 10.35053597
 10.81322888  9.44330751 10.07822207 10.35691391  9.91679857 10.84772414
 10.34083239 10.75843465  9.17701624  9.67886165  9.59640517 10.19135461]

Mathematical Transformations - Box-Cox transform:
[37.9708847  43.66863677 37.41055727 39.47911757 49.88352826 46.32860271
 31.72941358 41.60728463 41.76081319 41.28667072 52.05575806 42.32754155
 36.9052238  51.00786144 39.01735411 40.43541376 38.07430654 47.28524839
 42.4298841  40.5200011  51.62534487 37.36438841 46.50847674 36.783676
 34.8422105  47.29055702 39.69618233 39.34675644 43.39462004 41.31225672
 40.71466504 37.26241612 40.94296474 43.60725888 46.21919561 39.22098533
 33.54907644 35.36836862 38.50130059 41.79798831 42.37479839 42.44754821
 51.12770344 42.69710716 35.61539822 50.40162977 35.30068325 35.17610985
 46.84610856 38.15114077 35.99745999 41.14586141 37.22289476 43.55941785
 51.38842882 49.18016269 41.62061347 40.7981532  36.53636589 41.77361384
 41.52795661 45.92176664 42.47599289 34.13944193 27.21375341 37.88250995
 33.47429391 45.36580679 38.98000697 33.1273607  35.83474105 30.92571843
 44.36144192 40.83131644 50.40245796 45.60349655 42.44567701 49.59978794
 36.26837966 45.24246055 40.29856112 42.79137906 34.80665184 37.30330296
 41.20430139 44.25439981 36.77511737 40.5383756  36.97435834 44.04173143
 41.5501599  41.81407287 45.35699127 47.73974461 47.31807432 32.74121822
 30.80819555 43.95954265 34.46267364 36.66538738 42.34766733 34.06525761
 36.75953567 44.75115889 45.23865713 44.50826954 48.86168704 35.1289116
 34.87237802 41.20669962 46.15863832 41.77314469 46.08354642 44.9384598
 47.92473347 49.16993301 40.14508018 32.78805767 37.81407189 48.62793156
 43.45787922 50.92756441 39.69087628 44.73021465 48.42784739 46.68237377
 41.74090645 47.74685195 35.85332833 39.96158488 40.85360893 47.45935392
 37.49331372 45.87256363 51.98929979 44.12868715 35.82403058 46.74187617
 47.62316865 51.02155565 46.08386498 40.6447806  37.79719182 49.47614503
 38.72646648 50.04055883 39.40879583 38.69299238 41.94243212 42.9620527
 42.9436728  45.87140098 50.86961994 41.52687156 40.90348862 31.00839121
 42.24679489 39.52534282 40.03716622 36.64434149 38.70122197 35.08437506
 39.64591423 30.38657356 41.58888822 41.22458454 32.38784203 31.42627538
 42.34750348 45.07175052 49.52780337 39.14799727 41.34593231 42.46657177
 47.44435098 51.27263725 46.2307486  43.67394563 36.6063571  45.75901657
 38.03231704 51.34618755 46.2773779  38.50764523 43.49444009 44.60491501
 38.37660606 45.2037423  45.35712488 40.17684323 52.77578879 36.44281319
 49.48904263 37.21696495 45.79346434 38.13586599 38.66200518 49.41047092
 36.17851261 39.70079244 42.08721232 47.46448786 37.6455425  38.77426111
 34.93227041 36.04945086 51.96827488 36.41973    46.88210137 39.67742824
 41.40187878 44.76339185 36.07887462 35.22467224 32.59620842 38.00715935
 36.54420417 44.28707027 44.25813721 43.10200201 42.16372151 47.60878213
 46.77341689 48.01002108 49.70621508 42.64235732 49.85795406 41.58205901
 42.87592148 34.57732564 43.70758613 43.24538943 35.83045798 43.78751394
 47.40929856 37.49049927 50.30030677 38.15091791 38.26220637 34.97464299
 33.82632864 51.20095201 45.48902244 39.27230594 42.79828772 46.29856674
 30.4476584  39.97815278 39.46480024 39.9528312  51.57791429 45.74980657
 35.98477505 38.15982935 33.28361852 41.30903899 42.09559472 40.91024969
 40.03204058 34.49344049 37.76256154 43.21182576 40.08831658 48.78809901
 38.85540213 38.18146987 44.79992716 43.78447206 45.27617846 37.46790264
 52.26307258 51.28512577 35.2674345  43.02823112 42.48974799 32.18205571
 43.14237225 40.44667846 41.40336763 46.0446975  40.42869747 36.8278649
 50.79737294 46.73286594 35.61471701 32.29410318 41.48988656 42.96723257
```

```
35.88255647 46.10516122 35.46405827 46.75661732 48.77880316 39.76590891
40.50734853 44.56237489 41.44966187 31.50073728 37.73917365 35.56604887
31.02735277 36.66582546 43.34588684 47.41635035 51.51562412 34.00027188
50.26630565 42.1718931  41.92172453 34.30793486 43.88157608 45.94023356
43.91901167 37.1328718  38.24518086 47.75384156 40.32604137 46.27190308
40.81958593 40.25067047 46.40173859 40.68703039 33.62233316 41.2049676
43.06167517 32.27542777 45.35224748 39.92170988 49.95195967 38.52925905
50.42580094 34.0629318  43.46402328 38.14763027 39.81086678 42.33955484
42.42638125 46.39471524 46.22936017 38.32673442 43.20511145 49.31342958
50.50694399 38.98717115 41.03089387 47.68205234 46.90589969 48.47115236
46.34781155 41.21136167 44.08232818 41.38005335 41.46030671 47.87615022
43.71097951 49.78519057 40.70232841 32.39037123 45.15088034 40.64519681
50.1439343  39.24710609 43.49561307 34.77573416 50.06421356 37.86811106
43.58681765 49.15770147 33.81223743 45.08988063 48.92503932 46.51067719
30.60723143 43.02995008 49.0122192  39.72421517 44.79136511 41.55405919
38.21755003 32.67120242 42.27988096 44.5745516  36.19197571 45.34706771
42.43460752 46.44689311 36.87651595 43.69575912 36.21509553 37.02591671
48.22233447 40.36715848 46.44689311 40.29908281 41.83073383 40.96227657
41.95763777 45.12668627 51.52620393 46.38812601 39.0208484  39.0637998
46.55545537 39.66868726 35.69998126 45.92498547 48.65262367 40.4448955
40.26622483 33.64589983 38.3123796  30.11911823 51.67316437 37.37699648
48.81576703 39.3185865  34.76419249 40.67116151 41.92847575 40.08850923
49.46998873 47.40924002 33.91436927 48.12533153 37.79656197 43.81878663
43.58659204 44.43349148 37.83612573 42.81352274 43.22659405 51.73526848
37.57116908 42.92200326 40.7584446  34.16752522 37.35384253 44.15798155
34.45630071 36.70799735 43.41574954 48.33149729 45.82229548 44.82548034
36.9428079  44.31956185 48.06334209 43.9333791  49.47532089 45.08566468
43.2335296  46.53739867 42.48512385 50.06048476 37.27816653 34.26662712
35.28928395 52.43845071 35.58825684 48.94992322 40.95762067 41.43686866
38.25253551 36.59553719 39.56930762 43.03303588 40.21502367 34.96494429
36.51459524 46.18530767 47.43368851 41.79002436 39.85886007 42.7713093
40.59228448 34.50210968 42.09926307 42.63545376 40.89490775 47.97206794
34.01226999 48.3250037  44.63738914 37.30889532 39.88083691 49.71710704
40.0939025  37.44032182 35.80097143 39.49618764 44.25015816 37.74475152
42.77079228 47.26573862 48.06999829 46.51259845 47.27252993 48.84962382
48.08582725 38.72070666 42.77457005 44.72290165 42.19008604 36.63988977
52.05613381 43.12515098 40.82104708 34.05827878 49.84166361 33.75968101
35.3313313  37.12014025 48.1260031  36.12595135 45.02603978 37.46185053
39.4221611  44.93323965 40.27720211 43.2498921  34.49119742 37.8012565
34.87360922 37.24162441 38.61095026 38.94008873 36.13019844 33.3191306
41.98367271 48.00142248 51.91621295 42.72562108 43.66205412 43.52936227
35.75788784 32.81270542 46.32264408 51.46498309 46.61270259 32.91521878
40.18870542 46.17717237 36.20581381 49.42344586 39.83748533 45.81448496
36.62332303 32.14031766 39.65969204 50.39965656 30.88205583 44.455138
47.3121271  46.78852414 45.76220461 30.57295846 38.53461637 41.68745522
44.1126576  41.56916958 37.30592096 40.87249978 49.96406692 40.48434795
40.78314422 41.57315013 40.38489047 37.87169805 43.47626579 38.19391494
44.95043872 45.78505452 42.75352125 40.46290214 43.05184898 43.81852753
38.85239208 48.5129212  28.93895911 41.68522368 50.20775812 34.84555006
40.26641499 43.29292432 40.98147128 32.32217089 38.42546992 44.10656038
49.65513808 34.82993323 41.11183297 44.17902044 39.42489326 50.09344329
43.99652557 48.96616378 32.46145795 37.05204223 36.2601721  42.33279092]
```

4. Write a classification program for implementing logistic regression using wine dataset

In [6]:
```
import pandas as mypd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
#download the dataset
from sklearn.datasets import load_wine

wine_data=mypd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/Wine

for col in wine_data.columns:
    if wine_data[col].isnull().sum() > 0:
        wine_data[col] = wine_data[col].fillna(wine_data[col].mean())

wine_data.isnull().sum().sum()

wine_data.replace({'white': 1, 'red': 0}, inplace=True)

# Split the dataset into features (X) and target (y)
X = wine_data.drop('quality', axis=1)
y = wine_data['quality']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Create a logistic regression model
logreg = LogisticRegression()

# Train the model on the training data
logreg.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = logreg.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Display the classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:")
print(class_report)
```

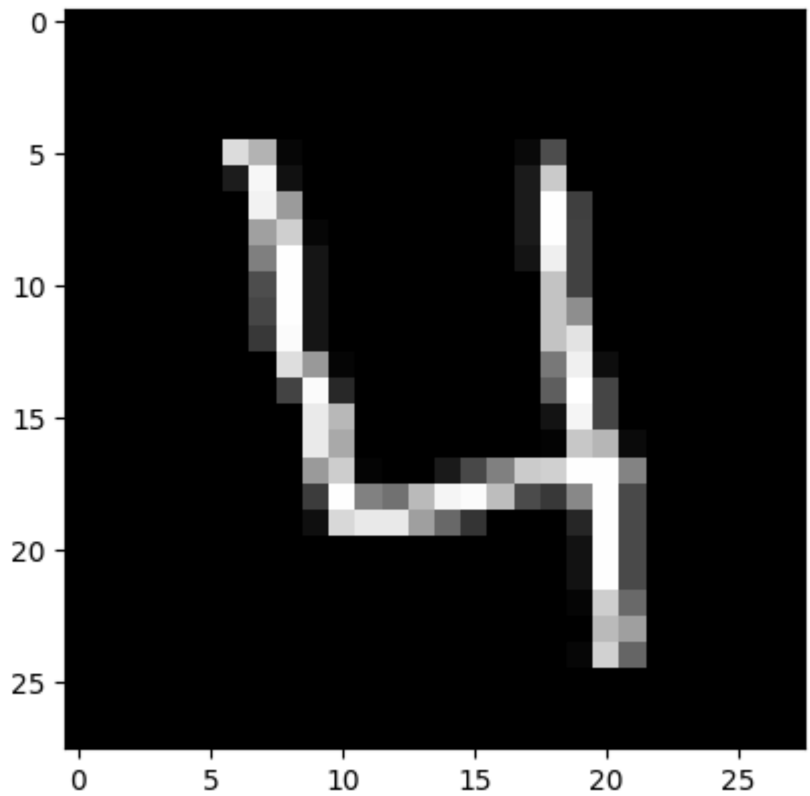
```
/home/shyma/.local/lib/python3.10/site-packages/sklearn/linear_model/_log
istic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression
  n_iter_i = _check_optimize_result(
/home/shyma/.local/lib/python3.10/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-def
ined and being set to 0.0 in labels with no predicted samples. Use `zero_
division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
Accuracy: 0.47615384615384615
Classification Report:
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00        46
           5       0.50      0.41      0.45       420
           6       0.47      0.77      0.58       579
           7       0.33      0.00      0.01       221
           8       0.00      0.00      0.00        32

    accuracy                           0.48      1300
   macro avg       0.22      0.20      0.17      1300
weighted avg       0.43      0.48      0.41      1300

/home/shyma/.local/lib/python3.10/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-def
ined and being set to 0.0 in labels with no predicted samples. Use `zero_
division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/shyma/.local/lib/python3.10/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-def
ined and being set to 0.0 in labels with no predicted samples. Use `zero_
division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

5. Write a classification program for implementingSVM using MNIST dataset

In [7]:
```
import numpy as np
import pandas as pd
from sklearn import svm
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import scale
import gc
import cv2
digits = pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/train.c
four = digits.iloc[3, 1:]
four = four.values.reshape(28, 28)
plt.imshow(four, cmap='gray')
X = digits.iloc[:, 1:]
Y = digits.iloc[:, 0]

X = scale(X)

# train test split with train_size=10% and test size=90%
x_train, x_test, y_train, y_test = train_test_split(X, Y, train_size=0.10
# an initial SVM model with linear kernel
svm_linear = svm.SVC(kernel='linear')

# fit
svm_linear.fit(x_train, y_train)
predictions = svm_linear.predict(x_test)
accuracy=metrics.accuracy_score(y_true=y_test, y_pred=predictions)
print(f"Accuracy: {accuracy}")
class_report=metrics.classification_report(y_true=y_test, y_pred=predicti
print("Classification Report:")
print(class_report)
```

```
Accuracy: 0.9042592592592592
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.95      3715
           1       0.94      0.98      0.96      4185
           2       0.89      0.89      0.89      3790
           3       0.88      0.87      0.87      3900
           4       0.88      0.92      0.90      3702
           5       0.87      0.85      0.86      3418
           6       0.94      0.94      0.94      3693
           7       0.90      0.92      0.91      3954
           8       0.91      0.84      0.88      3665
           9       0.88      0.85      0.87      3778

    accuracy                           0.90     37800
   macro avg       0.90      0.90      0.90     37800
weighted avg       0.90      0.90      0.90     37800
```



6. Write a classification program for implementing Naïve Bayes algorithm using iris dataset

In [8]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import pandas as mypd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
mydata = mypd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/Iris_
X = mydata.iloc[:,:4].values
y = mydata['Species'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
classifier = GaussianNB()
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
print ("Accuracy : ", accuracy_score(y_test, y_pred))
class_report=metrics.classification_report(y_test, y_pred )
print("Classification Report:")
print(class_report)
```

```
Accuracy :  0.9523809523809523
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         5
           1       0.91      1.00      0.95        10
           2       1.00      0.83      0.91         6

    accuracy                           0.95        21
   macro avg       0.97      0.94      0.95        21
weighted avg       0.96      0.95      0.95        21
```

7. Write a classification program for implementing decision tree using pima-indians-diabetes

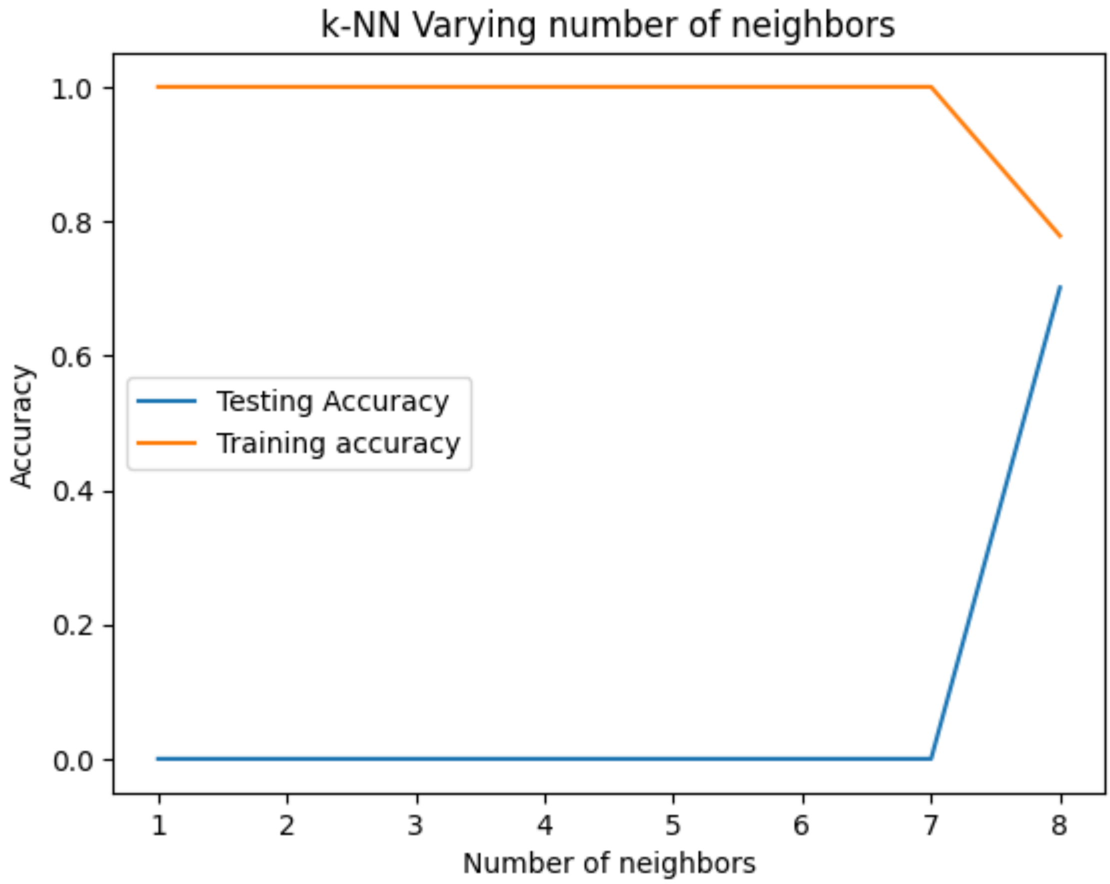
dataset.

In [9]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import pandas as mypd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
import numpy as np
from sklearn.tree import DecisionTreeClassifier
pima =  pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/diabetes
feature_cols = ['Pregnancies', 'Insulin', 'BMI', 'Age', 'Glucose', 'Blood
x = pima[feature_cols]
y = pima.Outcome
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size = 0.3
classifier = DecisionTreeClassifier()
classifier = classifier.fit(X_train, Y_train)
y_pred = classifier.predict(X_test)
print("Accuracy:", metrics.accuracy_score(Y_test,y_pred))
class_report=metrics.classification_report(Y_test, y_pred )
print("Classification Report:")
print(class_report)
```

```
Accuracy: 0.645021645021645
Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.74      0.72       146
           1       0.52      0.48      0.50        85

    accuracy                           0.65       231
   macro avg       0.61      0.61      0.61       231
weighted avg       0.64      0.65      0.64       231
```

8. Write a classification program for implementing kNN.

In [10]:
```
import numpy as np
import matplotlib.pyplot as myplot
import matplotlib.image as mpimg
import pandas as mypd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
pima =  pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/diabetes
X = pima.drop('Outcome',axis=1).values
y = pima['Outcome'].values
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.4,random
#Setup arrays to store training and test accuracies
neighbors = np.arange(1,9)
train_accuracy =np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    #Setup a knn classifier with k neighbors
    knn = KNeighborsClassifier(n_neighbors=k)

    #Fit the model
    knn.fit(X_train, y_train)
train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the test set
test_accuracy[i] = knn.score(X_test, y_test)
myplot.title('k-NN Varying number of neighbors')
myplot.plot(neighbors, test_accuracy, label='Testing Accuracy')
myplot.plot(neighbors, train_accuracy, label='Training accuracy')
myplot.legend()
myplot.xlabel('Number of neighbors')
myplot.ylabel('Accuracy')
myplot.show()
y_pred = knn.predict(X_test)
print("Accuracy:", metrics.accuracy_score(y_test,y_pred))
class_report=metrics.classification_report(y_test, y_pred )
print("Classification Report:")
print(class_report)
```




```
Accuracy: 0.7012987012987013
Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.84      0.79       201
           1       0.59      0.45      0.51       107

    accuracy                           0.70       308
   macro avg       0.67      0.64      0.65       308
weighted avg       0.69      0.70      0.69       308
```

9. Write a clustering program for implementing k Means , k-medoids and Hierarchical Clustering

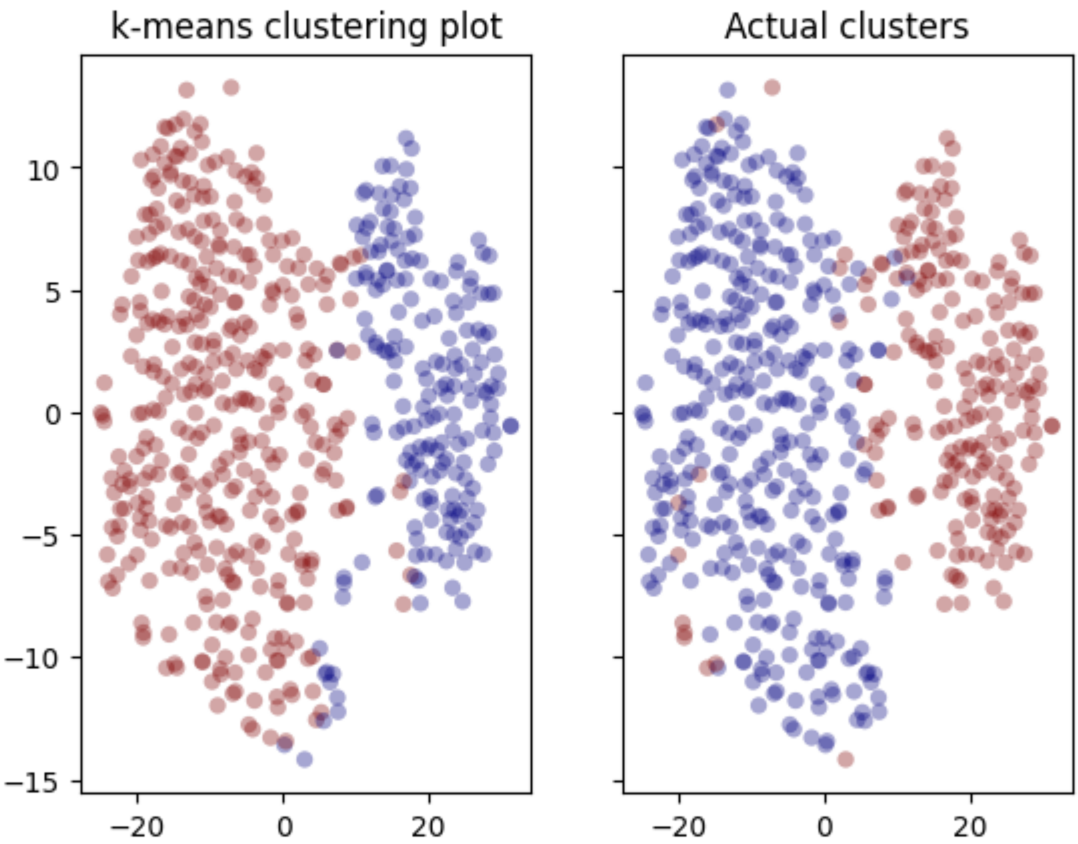
using Wisconsin Breast Cancer Dataset

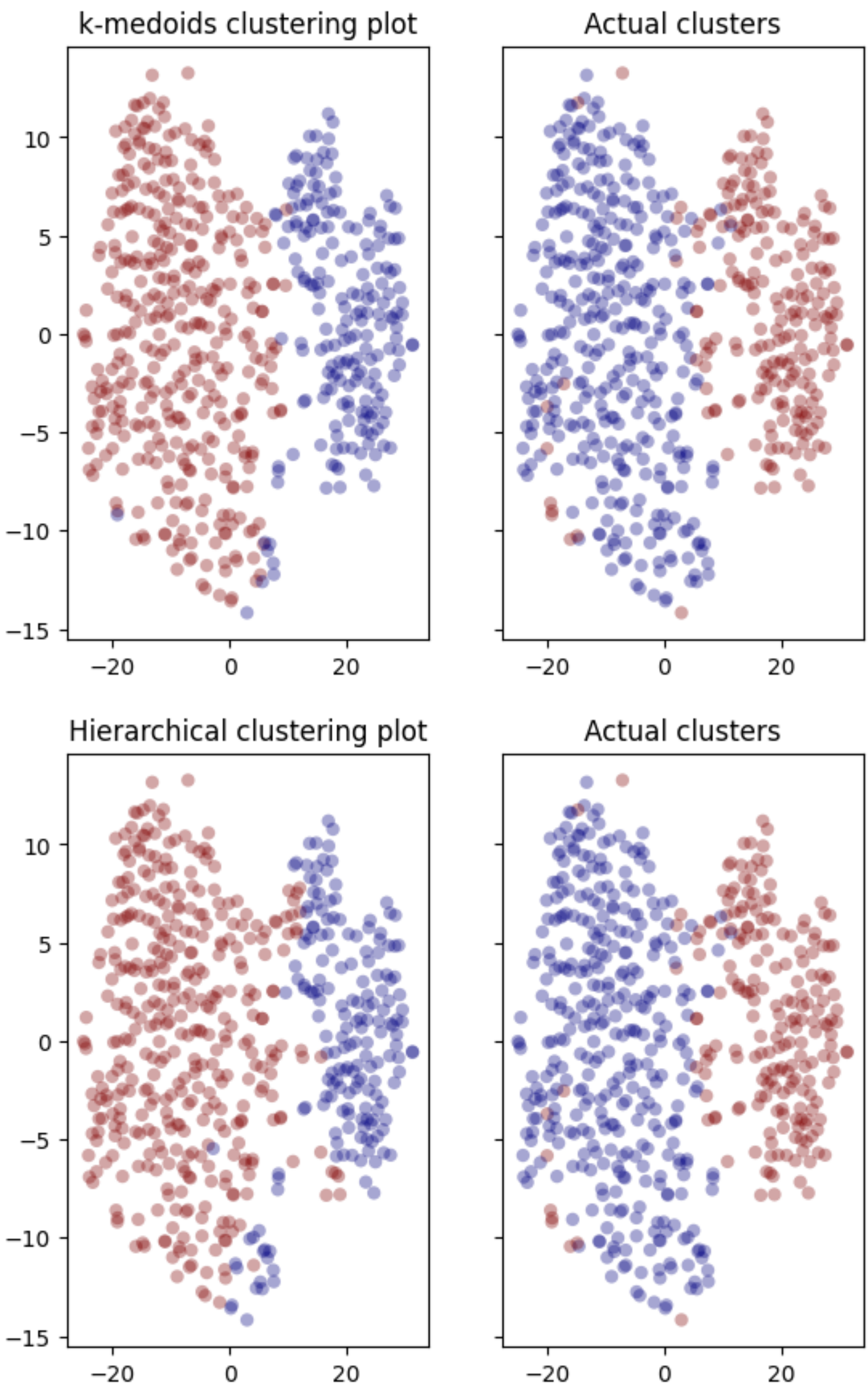
In [11]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt2
import matplotlib.cm as cm
from sklearn import preprocessing
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans
from sklearn_extra.cluster import KMedoids
from sklearn.cluster import AgglomerativeClustering
df= pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/data.csv")
df = df.drop('id',axis=1)
df = df.drop('Unnamed: 32',axis=1)
# Mapping Benign to 0 and Malignant to 1
df['diagnosis'] = df['diagnosis'].map({'M':1,'B':0})
# Scaling the dataset
datas = pd.DataFrame(preprocessing.scale(df.iloc[:,1:32]))
datas.columns = list(df.iloc[:,1:32].columns)
datas['diagnosis'] = df['diagnosis']
# Creating the high dimensional feature space X
data_drop = datas.drop('diagnosis',axis=1)
X = data_drop.values

#Creating a 2D visualization to visualize the clusters

tsne = TSNE(verbose=1, perplexity=40, n_iter= 4000)
Y = tsne.fit_transform(X)

kmns = KMeans(n_clusters=2, init='k-means++', n_init=50, max_iter=300, to
kY = kmns.fit_predict(X)

f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)

ax1.scatter(Y[:,0],Y[:,1],  c=kY, cmap = "jet", edgecolor = "None", alpha
ax1.set_title('k-means clustering plot')

ax2.scatter(Y[:,0],Y[:,1],  c = datas['diagnosis'], cmap = "jet", edgecol
ax2.set_title('Actual clusters')
kmedoids = KMedoids(n_clusters=2, random_state=0)
kY = kmedoids.fit_predict(X)
f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)

ax1.scatter(Y[:,0],Y[:,1],  c=kY, cmap = "jet", edgecolor = "None", alpha
ax1.set_title('k-medoids clustering plot')

ax2.scatter(Y[:,0],Y[:,1],  c = datas['diagnosis'], cmap = "jet", edgecol
ax2.set_title('Actual clusters')

aggC = AgglomerativeClustering(n_clusters=2, linkage='ward')
kY = aggC.fit_predict(X)


f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)


ax1.scatter(Y[:,0],Y[:,1],  c=kY, cmap = "jet", edgecolor = "None", alpha
ax1.set_title('Hierarchical clustering plot')

ax2.scatter(Y[:,0],Y[:,1],  c = datas['diagnosis'], cmap = "jet", edgecol
```

```
ax2.set_title('Actual clusters')
```

```
[t-SNE] Computing 121 nearest neighbors...
[t-SNE] Indexed 569 samples in 0.001s...
[t-SNE] Computed neighbors for 569 samples in 5.207s...
[t-SNE] Computed conditional probabilities for sample 569 / 569
[t-SNE] Mean sigma: 1.522404
[t-SNE] KL divergence after 250 iterations with early exaggeration: 57.17
4534
[t-SNE] KL divergence after 2350 iterations: 0.868606
```

Out[11]: `Text(0.5, 1.0, 'Actual clusters')`



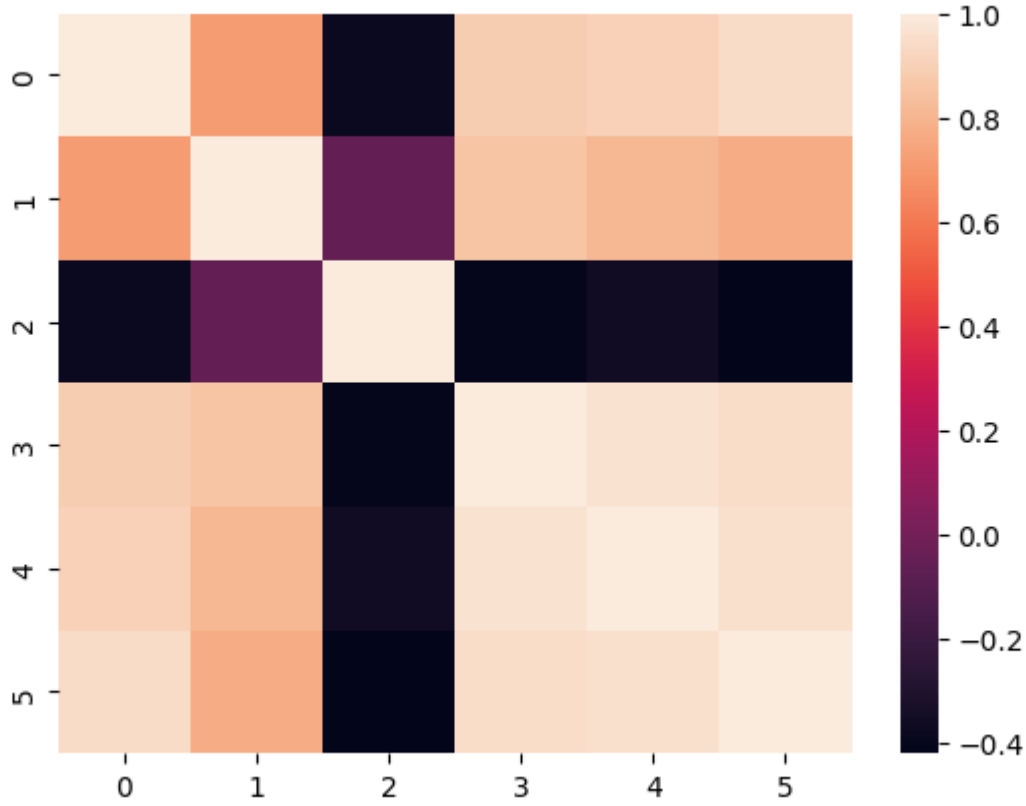


10. Write a program to implement PCA

In [12]:

```
import numpy as np
import matplotlib.pyplot as myplot
import matplotlib.image as mpimg
import pandas as mypd
import seaborn as mysb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
from sklearn.decomposition import PCA
import numpy as np
mydata = mypd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/Iris_
scalar = StandardScaler()
scaled_data = mypd.DataFrame(scalar.fit_transform(mydata))
print(scaled_data)
mysb.heatmap(scaled_data.corr())
pca = PCA(n_components = 2)
pca.fit(mydata)
data_pca = pca.transform(mydata)
data_pca = mypd.DataFrame(data_pca,columns=['PC1','PC2'])
print(data_pca)
```

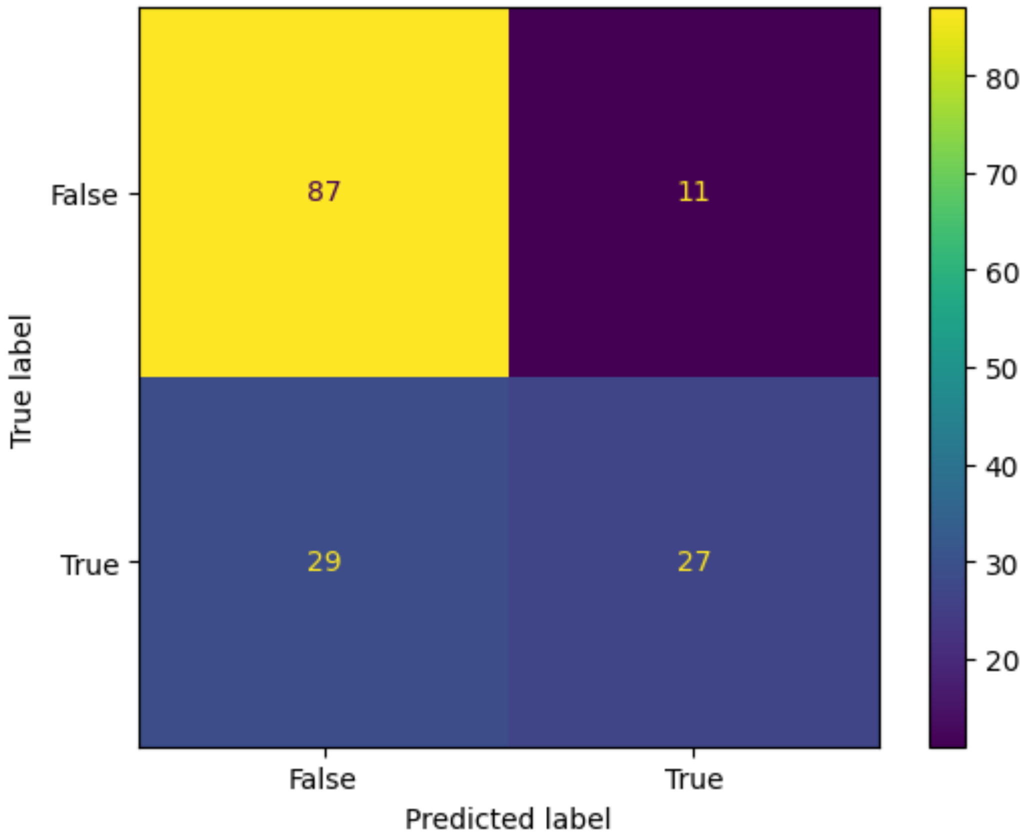
```
            0         1         2         3         4         5
0   -1.690187 -0.820478  0.975487 -1.301159 -1.299067 -1.210338
1   -1.667444 -1.073126 -0.136524 -1.301159 -1.299067 -1.210338
2   -1.644701 -1.325773  0.308280 -1.358874 -1.299067 -1.210338
3   -1.621958 -1.452097  0.085878 -1.243444 -1.299067 -1.210338
4   -1.599215 -0.946802  1.197889 -1.301159 -1.299067 -1.210338
..        ...       ...       ...       ...       ...       ...
96   1.584803  1.200700  0.530683  1.180586  1.789707  1.284440
97   1.607546  1.200700 -0.136524  0.892011  1.521118  1.284440
98   1.630289  0.695405 -1.248535  0.776581  0.983940  1.284440
99   1.675775  0.569082  0.753085  1.007441  1.521118  1.284440
100  1.698518  0.190111 -0.136524  0.834296  0.849645  1.284440

[101 rows x 6 columns]
           PC1       PC2
0   -74.365395  0.527860
1   -73.366955  0.401515
2   -72.374772  0.182620
3   -71.369647  0.259184
4   -70.370931  0.311149
..         ...       ...
96   69.736694 -0.260211
97   70.716416 -0.761859
98   71.699201 -1.255177
99   73.712492 -0.961413
100  74.691154 -1.519958

[101 rows x 2 columns]
```



11. Write a program to evaluate Classification Model using different Evaluation Metrics

In [17]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt2
import matplotlib.cm as cm
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.model_selection import train_test_split
pima =  pd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/diabetes
feature_cols = ['Pregnancies', 'Insulin', 'BMI', 'Age', 'Glucose', 'Blood
x = pima[feature_cols]
y = pima.Outcome

# Splitting the data into training and testing set
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
print(f"Train Data: {X_train.shape}, {y_train.shape}")
print(f"Train Data: {X_test.shape}, {y_test.shape}")

# Training a binary classifier using Random Forest Algorithm with default
classifier = RandomForestClassifier(random_state=18)
classifier.fit(X_train, y_train)

# Here X_test, y_test are the test data points
predictions = classifier.predict(X_test)
print(f"Accuracy of the classifier is: {metrics.accuracy_score(y_test, pr
# confusion_matrix funnction a matrix containing the summary of predictio
print(metrics.confusion_matrix(y_test, predictions))

# plot_confusion_matrix function is used to visualize the confusion matri
#plot_confusion_matrix(classifier, X_test, y_test)
#plt.show()
print(f"Precision Score of the classifier is: {metrics.precision_score(y_
print(f"F1 Score of the classifier is: {metrics.f1_score(y_test, predicti
confusion_matrix = metrics.confusion_matrix(y_test, predictions)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_

cm_display.plot()
plt.show()
class_report=metrics.classification_report(y_test, predictions )
print("Classification Report:")
print(class_report)
```

```
Train Data: (614, 7), (614,)
Train Data: (154, 7), (154,)
Accuracy of the classifier is: 0.7402597402597403
[[87 11]
 [29 27]]
Precision Score of the classifier is: 0.7105263157894737
F1 Score of the classifier is: 0.5744680851063829
```



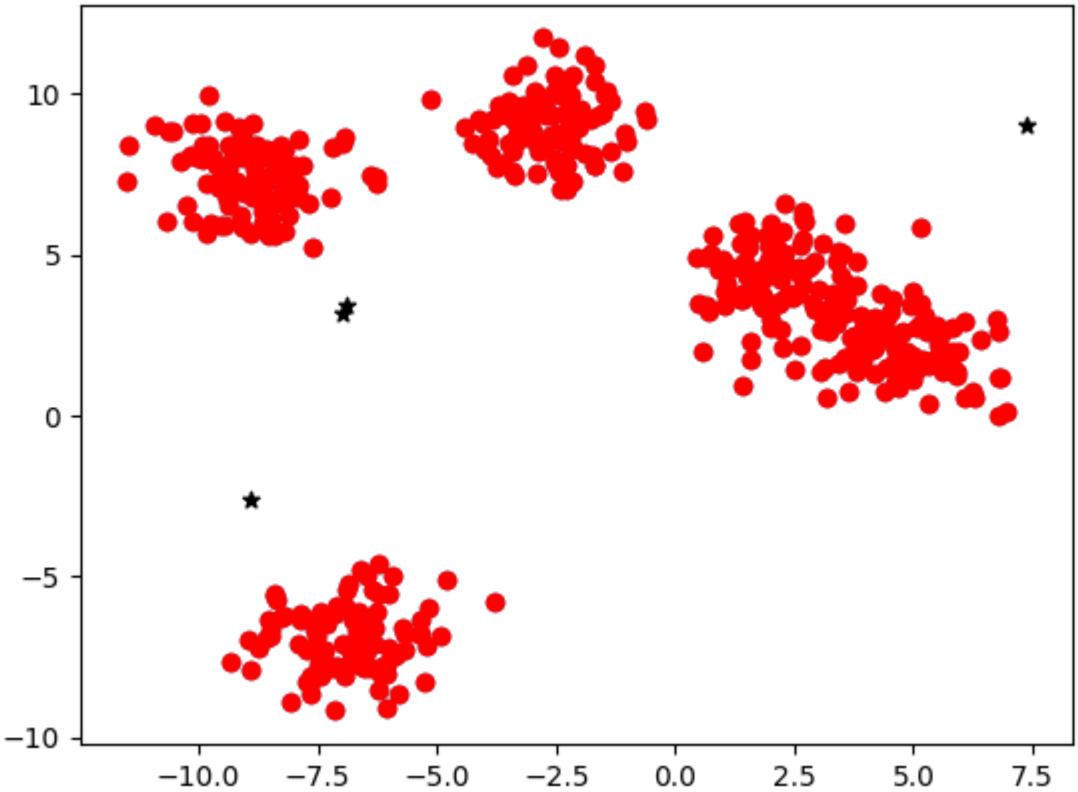

```
Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.89      0.81        98
           1       0.71      0.48      0.57        56

    accuracy                           0.74       154
   macro avg       0.73      0.68      0.69       154
weighted avg       0.74      0.74      0.73       154
```

11. Write a program to evaluate Classification Model using different Evaluation Metrics

In [16]:

```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt2
import matplotlib.cm as cm
from sklearn import preprocessing
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.metrics import rand_score, adjusted_rand_score,silhouette_sc
mydata = mypd.read_csv("/home/shyma/Desktop/Machinelearning/ML Data/Iris_
feature, target = make_blobs(n_samples=500,
                             centers=5,
                             random_state=42,
                             shuffle=False)
plt.scatter(feature[:, 0], feature[:, 1])
model = KMeans(n_clusters=4)
model.fit(feature)
plt.scatter(feature[:, 0], feature[:, 1], color="r")
plt.scatter(model.cluster_centers_[1],
            model.cluster_centers_[3],
            color="k", marker="*")
plt.scatter(model.cluster_centers_[2],
            model.cluster_centers_[0],
            color="k", marker="*")
RI = rand_score(target, model.labels_)
ARI = adjusted_rand_score(target, model.labels_)
print(ARI)
ris = rand_score(target, model.labels_)
print(ris)
print(silhouette_score(feature, model.labels_))
```

```
/home/shyma/.local/lib/python3.10/site-packages/sklearn/cluster/_kmeans.p
y:870: FutureWarning: The default value of `n_init` will change from 10 t
o 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the war
ning
  warnings.warn(
0.7812362998684788
0.9198396793587175
0.7328381899726921
```



In [ ]: