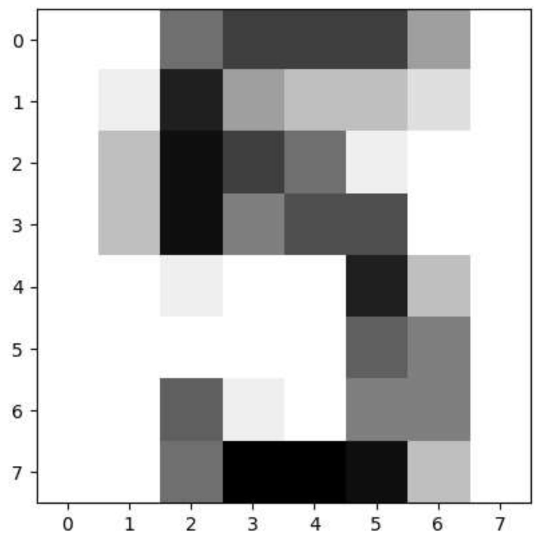
```
# Lab04 - Statistical Data Analytics
## Nguyen Quoc Tuan - 19522476
## Link github: https://github.com/tuNQws/data_mining.git
```

```
from  sklearn import datasets
import matplotlib.pyplot as plt

digits = datasets.load_digits()
```

```
plt.imshow(digits.images[1010],cmap=plt.cm.gray_r, interpolation='nearest')
plt.show()
```



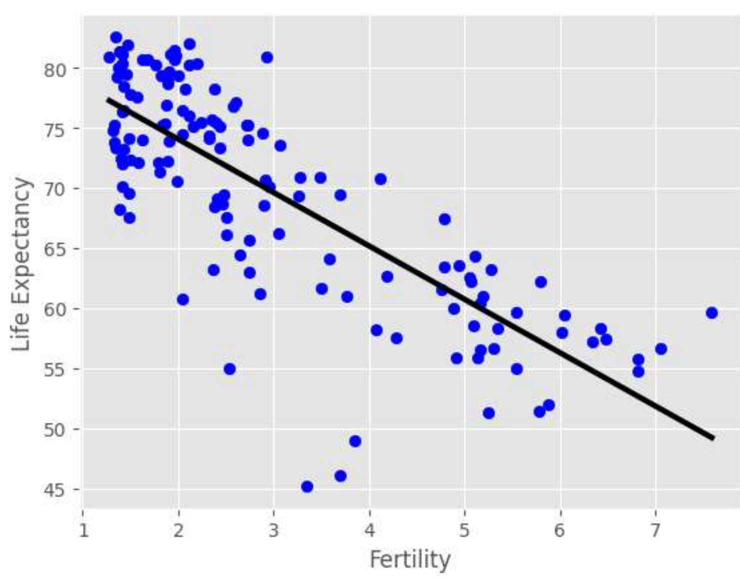

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from urllib.request import urlretrieve
```

```
df = pd.read_csv('gapminder.csv')
sns.heatmap(df.corr(), square=True, cmap='RdYlGn')
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.show()
```

```
<ipython-input-13-6be5d627e500>:2: FutureWarning: The default value of numeric_only in D
  sns.heatmap(df.corr(), square=True, cmap='RdYlGn')
```


```
# modified/added by Jinny
plt.style.use('ggplot')

y = df['life'].values
X = df.drop('life', axis=1)

# Reshape to 1-D
y = y.reshape(-1, 1)
X_fertility = X['fertility'].values.reshape(-1, 1)

_ = plt.scatter(X['fertility'], y, color='blue')
_ = plt.ylabel('Life Expectancy')
_ = plt.xlabel('Fertility')

# -----------------------
# Import LinearRegression
from sklearn.linear_model import LinearRegression

# Create the regressor: reg
reg = LinearRegression()

# Create the prediction space
prediction_space = np.linspace(min(X_fertility), max(X_fertility)).reshape(-1,1)

# Fit the model to the data
reg.fit(X_fertility, y)

# Compute predictions over the prediction space: y_pred
y_pred = reg.predict(prediction_space)

# Print R^2
print(reg.score(X_fertility, y))

# Plot regression line
plt.plot(prediction_space, y_pred, color='black', linewidth=3)
plt.show()
```

```
0.6192442167740035
```

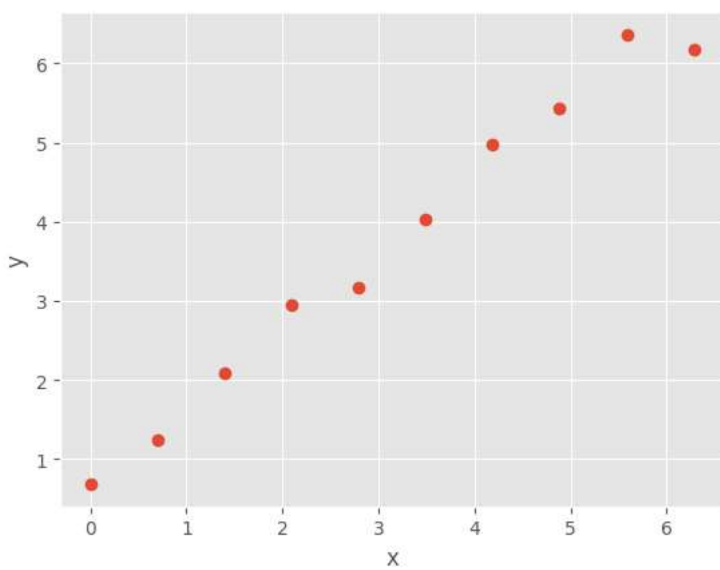



```
from sklearn.model_selection import train_test_split
features = pd.read_csv('gapminder.csv')
df = pd.read_csv('gapminder.csv')
del features['life']
del features['Region']

y_life = df['life'].values.reshape(-1,1)

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, y_life, test_size = 0.3, random_state=42)
```

```
# Create the regressor: reg_all
reg_all = LinearRegression()

# Fit the regressor to the training data
reg_all.fit(X_train, y_train)

# Predict on the test data: y_pred


# Compute and print R^2 and RMSE
print(reg_all.score(features, y_life))

     0.8914651485793176
```

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
N =10
m = .9
c = 1
x = np.linspace(0,2*np.pi,N)
y=m*x + c+ np.random.normal(0,.3,x.shape)
plt.figure()
plt.plot(x,y,'o')
plt.xlabel('x')
plt.ylabel('y')
plt.show()
```




```
import torch
```

```
from torch.utils.data import Dataset
class MyDataset(Dataset):
  def __init__(self, x, y):
    self.x=x
    self.y=y

  def __len__(self):
      return len(self.x)


  def __getitem__(self, idx):
    sample = {
      'feature': torch.tensor ([1, self.x[idx]]),
      'label': torch.tensor ([self.y[idx]])}
    return sample
```

```
dataset = MyDataset(x, y)
for i in range(len(dataset)):
  sample = dataset[i]
  print(i, sample['feature'], sample['label'])
```

```
0 tensor([1., 0.], dtype=torch.float64) tensor([1.3249], dtype=torch.float64)
1 tensor([1.0000, 0.6981], dtype=torch.float64) tensor([1.6252], dtype=torch.float64)
2 tensor([1.0000, 1.3963], dtype=torch.float64) tensor([2.5060], dtype=torch.float64)
3 tensor([1.0000, 2.0944], dtype=torch.float64) tensor([3.1148], dtype=torch.float64)
4 tensor([1.0000, 2.7925], dtype=torch.float64) tensor([3.4458], dtype=torch.float64)
5 tensor([1.0000, 3.4907], dtype=torch.float64) tensor([3.9926], dtype=torch.float64)
6 tensor([1.0000, 4.1888], dtype=torch.float64) tensor([4.6896], dtype=torch.float64)
7 tensor([1.0000, 4.8869], dtype=torch.float64) tensor([5.3221], dtype=torch.float64)
8 tensor([1.0000, 5.5851], dtype=torch.float64) tensor([6.2227], dtype=torch.float64)
9 tensor([1.0000, 6.2832], dtype=torch.float64) tensor([7.3215], dtype=torch.float64)
```

```
from torch.utils.data import DataLoader
dataset= MyDataset(x, y)
batch_size = 4
shuffle = True
num_workers = 4
dataloader = DataLoader( dataset, batch_size=batch_size, shuffle=shuffle, num_workers=num_workers )
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:561: UserWarning: This DataLoader will create 4 worker processes
  warnings.warn(_create_warning_msg(
```

```
import pprint as pp
for i_batch, samples in enumerate (dataloader):
  print('\nbatch# = %s' % i_batch)
  print('samples: ')
  pp.pprint(samples)
```

```
batch# = 0
samples:
{'feature': tensor([[1.0000, 1.3963],
        [1.0000, 2.7925],
        [1.0000, 4.1888],
        [1.0000, 6.2832]], dtype=torch.float64),
 'label': tensor([[2.5060],
        [3.4458],
        [4.6896],
        [7.3215]], dtype=torch.float64)}

batch# = 1
samples:
{'feature': tensor([[1.0000, 2.0944],
        [1.0000, 3.4907],
        [1.0000, 0.6981],
        [1.0000, 4.8869]], dtype=torch.float64),
 'label': tensor([[3.1148],
        [3.9926],
        [1.6252],
        [5.3221]], dtype=torch.float64)}

batch# = 2
samples:
{'feature': tensor([[1.0000, 5.5851],
        [1.0000, 0.0000]], dtype=torch.float64),
 'label': tensor([[6.2227],
        [1.3249]], dtype=torch.float64)}
```

```
import torch.nn as nn
import torch.nn. functional as F
class MyModel(nn.Module):
    def __init__(self, input_dim, output_dim):
      super (MyModel, self).__init__()
      self.linear = nn.Linear(input_dim, output_dim)
    def forward (self, x):
      out = self.linear(x)
      return out
```

```
input_dim = 2
output_dim = 1

model = MyModel(input_dim, output_dim)
```

```
cost = nn.MSELoss()


num_epochs = 10  # How many times the entire training data is seen?
l_rate = 0.01
optimiser = torch.optim.SGD(model.parameters(), lr = l_rate)

dataset = MyDataset(torch.Tensor(x), torch.Tensor(y)) # Convert x and y to tensors
batch_size = 4
shuffle = True
num_workers = 4
training_sample_generator = DataLoader(dataset, batch_size=batch_size, shuffle=shuffle, num_workers=num_workers)

for epoch in range(num_epochs):
    print('Epoch = %s' % epoch)
    for batch_i, samples in enumerate(training_sample_generator):
        features = samples['feature'].float() # Convert features to float
        labels = samples['label'].float() # Convert labels to float

        predictions = model(features)
        error = cost(predictions, labels)
        print('\tBatch = %s, Error = %s' % (batch_i, error.item()))

        optimiser.zero_grad()
        error.backward()
        optimiser.step()
```

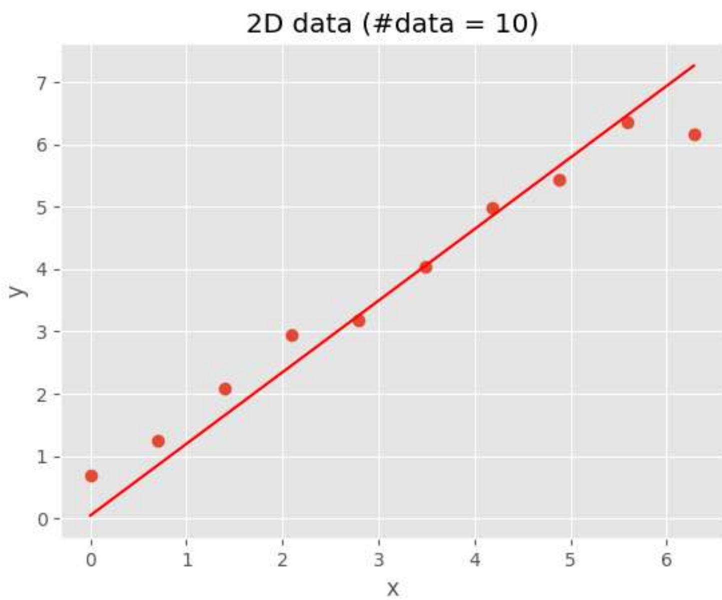
```
Epoch = 0
        Batch = 0, Error = 7.702254295349121
        Batch = 1, Error = 13.808805465698242
        Batch = 2, Error = 4.263489246368408
Epoch = 1
        Batch = 0, Error = 2.072721242904663
        Batch = 1, Error = 1.0039169788360596
        Batch = 2, Error = 0.7218696475028992
Epoch = 2
        Batch = 0, Error = 1.287321925163269
        Batch = 1, Error = 0.05091605335474014
        Batch = 2, Error = 0.5484017729759216
Epoch = 3
        Batch = 0, Error = 0.5535609722137451
        Batch = 1, Error = 0.19042828679084778
        Batch = 2, Error = 1.1805700063705444
Epoch = 4
        Batch = 0, Error = 0.018144484609365463
        Batch = 1, Error = 0.8546347618103027
        Batch = 2, Error = 0.7338478565216064
Epoch = 5
        Batch = 0, Error = 0.8474566340446472
        Batch = 1, Error = 0.2883010804653168
        Batch = 2, Error = 0.11646117269992828
Epoch = 6
        Batch = 0, Error = 0.22584526240825653
        Batch = 1, Error = 0.8822470903396606
        Batch = 2, Error = 0.058477893471717834
Epoch = 7
        Batch = 0, Error = 0.14788007736206055
        Batch = 1, Error = 0.8708349466323853
        Batch = 2, Error = 0.0920991450548172
Epoch = 8
        Batch = 0, Error = 0.32978326082229614
        Batch = 1, Error = 0.45812496542930603
        Batch = 2, Error = 0.424987256526947
Epoch = 9
        Batch = 0, Error = 0.7535368800163269
        Batch = 1, Error = 0.19133420288562775
        Batch = 2, Error = 0.0329524502158165
```

```
x_for_plotting = np.linspace(0, 2*np.pi, 1000)
design_matrix = torch.tensor(np.vstack([np.ones(x_for_plotting.shape), x_for_plotting]).T, dtype=torch.float32)
print('Design matrix shape:', design_matrix.shape)

y_for_plotting = model.forward(design_matrix)
print('y_for_plotting shape:', y_for_plotting.shape)
```

```
Design matrix shape: torch.Size([1000, 2])
y_for_plotting shape: torch.Size([1000, 1])
```

```
plt.figure()
plt.plot(x,y,'o')
```

```
plt.plot(x,y,'o')
plt.plot(x_for_plotting, y_for_plotting.data.numpy(), 'r-')
plt.xlabel('x')
plt.ylabel('y')
plt.title('2D data (#data = %d)' % N)
plt.show()
```




```
def user_cf(M, metric='cosine'):
  pred = np.copy (M)
  n_users, n_items= M. shape
  avg_ratings = np.nanmean (M, axis=1)
  sim_users = sim_matrix(M, 'user', metric)
  for i in range(n_users):
    for j in range(n_items):
      if np.isnan (M[i, j]):
        pred[i, j] = avg_ratings[i] + np.nansum(sim_users[i] * (M[:,j] - avg_ratings)) / sum(sim_users[i])
  return pred


def item_cf(M, metric='cosine'):
  pred = np.copy (M)
  n_users, n_items = M. shape
  avg_ratings = np.nanmean (M, axis=0)
  sim_items = sim_matrix (M, 'item', metric)
  for i in range(n_users):
    for j in range(n_items):
      if np.isnan (M[i, j]):
        pred[i, j] = avg_ratings[j] + np.nansum(sim_items[j] * (M[i,:] - avg_ratings)) / sum(sim_items[j])
  return pred
```

```
# Exercise
```

```
#1
```

```
from sklearn.datasets import load_iris
iris = load_iris()
```

```
type(iris)
```

```
    sklearn.utils._bunch.Bunch
```

```
iris.data
```

```
    array([[5.1, 3.5, 1.4, 0.2],
           [4.9, 3. , 1.4, 0.2],
           [4.7, 3.2, 1.3, 0.2],
           [4.6, 3.1, 1.5, 0.2],
           [5. , 3.6, 1.4, 0.2],
           [5.4, 3.9, 1.7, 0.4],
           [4.6, 3.4, 1.4, 0.3],
```

```
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.2],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.6, 1.4, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
       [4.5, 2.3, 1.3, 0.3],
       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.5, 1.6, 0.6],
       [5.1, 3.8, 1.9, 0.4],
       [4.8, 3. , 1.4, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [4.6, 3.2, 1.4, 0.2],
       [5.3, 3.7, 1.5, 0.2],
       [5. , 3.3, 1.4, 0.2],
       [7. , 3.2, 4.7, 1.4],
       [6.4, 3.2, 4.5, 1.5],
       [6.9, 3.1, 4.9, 1.5],
       [5.5, 2.3, 4. , 1.3],
       [6.5, 2.8, 4.6, 1.5],
       [5.7, 2.8, 4.5, 1.3],
       [6.3, 3.3, 4.7, 1.6],
       [4.9, 2.4, 3.3, 1. ],
```

```
iris.feature_names
```

```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

```
iris.target
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

Double-click (or enter) to edit

```
iris.target_names
```

```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

```
type(iris.data)
```

```
numpy.ndarray
```

```
type(iris.target)
```

```
numpy.ndarray
```

```
iris.data.shape
```

```
(150, 4)
```

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split

# Load the Iris dataset
iris = load_iris()

# Assign features to X and labels to y
X = iris.data
y = iris.target

# 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, random_state=4)
```

```
X_train.shape
```

```
(120, 4)
```

```
X_test.shape
```

```
(30, 4)
```

```
y_train.shape
```

```
(120,)
```

```
y_test.shape
```

```
(30,)
```

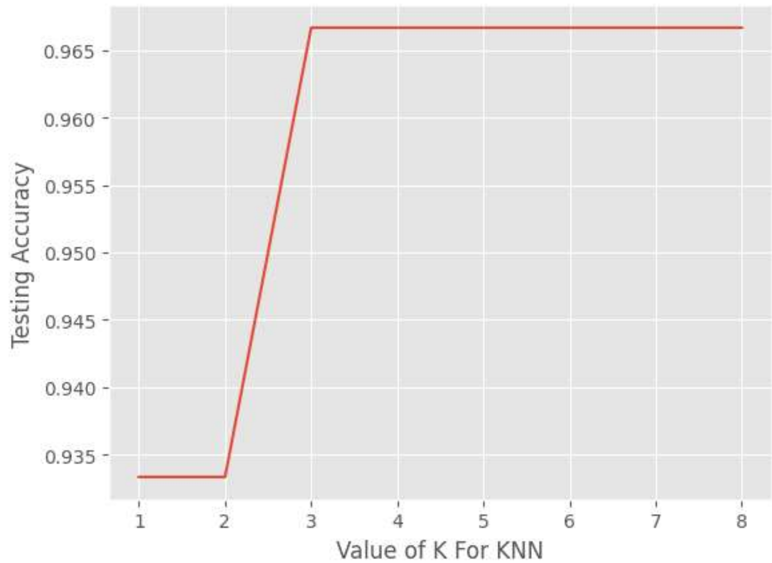
```
from sklearn.linear_model import LinearRegression
from sklearn import metrics

# Assuming you have your training and testing data stored in X_train, X_test, y_train, and y_test

regressor = LinearRegression()
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)

# Evaluate the regression model
mse = metrics.mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2_score = metrics.r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R^2 Score:", r2_score)
```

```
Mean Squared Error: 10.546912775288654
Root Mean Squared Error: 3.24760108007259
R^2 Score: 0.8380468731394584
```

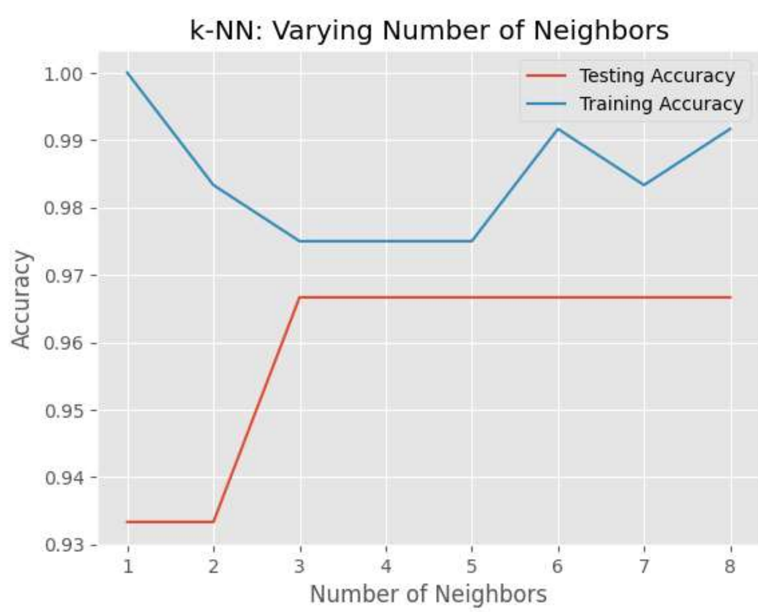
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
k_range = range(1,20)
scores = {}
scores_list = []
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train,y_train)
    y_pred=knn.predict(X_test)
    scores[k] = metrics.accuracy_score(y_test,y_pred)
    scores_list.append(metrics.accuracy_score(y_test,y_pred))
```

```
%matplotlib inline
import matplotlib.pyplot as plt

plt.plot(k_range,scores_list)
plt.xlabel('Value of K For KNN')
plt.ylabel('Testing Accuracy')
```

```
Text(0, 0.5, 'Testing Accuracy')
```




```
neighbors = np.arange(1,9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i, k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    train_accuracy[i] = knn.score(X_train, y_train)
    test_accuracy[i] = knn.score(X_test, y_test)

plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```



```
#2

#a

#Find list of used genres which is used to category the movies.

path1 = 'movies.csv'
path2 = 'ratings.csv'
path3 = 'users.csv'


movies = pd.read_csv(path1, encoding="ISO-8859-1")
ratings = pd.read_csv(path2)
users = pd.read_csv(path3)

from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.metrics.pairwise import cosine_similarity


genres_col = movies['genres']


genres_list = [genre.split('|') if type(genre) == str else [] for genre in genres_col]


unique_genres = set([genre for sublist in genres_list for genre in sublist])


genre_list = list(unique_genres)

genre_list
```

```
['Documentary',
 'Crime',
 'Musical',
 'Horror',
 'Sci-Fi',
 'Drama',
 'Animation',
 'Romance',
 'Comedy',
 'Adventure',
 'Fantasy',
 'Action',
 "Children's",
 'Thriller',
 'War']
```

```
#Vectorize the relationship between movies and genres and put them into Ij.

unique_genres = sorted(list(set([genre for sublist in genres_list for genre in sublist])))


Ij = np.zeros((len(movies), len(unique_genres)), dtype=int)
for i, genres in enumerate(genres_list):
    for genre in genres:
        j = unique_genres.index(genre)
        Ij[i, j] = 1


Ij[:4]
```

```
array([[0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]])
```

```
#Vectorize the relationship between users and genres and put them into Uj (if user rate for a movie, he/she has the related history with the

merged_df = pd.merge(ratings, movies, on='movie_id')
unique_user_ids = sorted(list(set(merged_df['user_id'])))


Uj = np.zeros((len(unique_user_ids), len(unique_genres)), dtype=int)
for i, user_id in enumerate(unique_user_ids):
    user_ratings = merged_df.loc[merged_df['user_id'] == user_id]
    user_genre_list = [genre.split('|') if type(genre) == str else [] for genre in user_ratings['genres']]
    user_genre_set = set([genre for sublist in user_genre_list for genre in sublist])
```

```
    for j, genre in enumerate(unique_genres):
        if genre in user_genre_set:
            Uj[i, j] = 1
```

```
Uj[:4]
```

```
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0]])
```