1. Download the mammography dataset given. Implement PCA. Find the first two principal components of the dataset and plot it using scatter plot with different colors for each target. Dataset is obtained from https://www.openml.org/d/310 What are your interpretations?

```
%matplotlib inline

import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

```
from google.colab import files
uploaded = files.upload()
```

Choose Files phpn1jVwe.csv

- **phpn1jVwe.csv**(application/vnd.ms-excel) - 827961 bytes, last modified: 5/8/2021 - 100% done

```
Saving phpn1jVwe.csv to phpn1jVwe.csv
```

```
# Load the Dataset
df_data = pd.read_csv("phpn1jVwe.csv")
```

```
df_data.head(5)
```

	attr1	attr2	attr3	attr4	attr5	attr6	class
0	0.230020	5.072578	-0.276061	0.832444	-0.377866	0.480322	'-1'
1	0.155491	-0.169390	0.670652	-0.859553	-0.377866	-0.945723	'-1'
2	-0.784415	-0.443654	5.674705	-0.859553	-0.377866	-0.945723	'-1'
3	0.546088	0.131415	-0.456387	-0.859553	-0.377866	-0.945723	'-1'
4	-0.102987	-0.394994	-0.140816	0.979703	-0.377866	1.013566	'-1'

```
# Seperating the features and target columns
df_features = df_data[df_data.columns[:5]]
df_target = df_data[df_data.columns[6]]
```

```
df_features.head(5)
```

	attr1	attr2	attr3	attr4	attr5
0	0.230020	5.072578	-0.276061	0.832444	-0.377866
1	0.155491	-0.169390	0.670652	-0.859553	-0.377866
2	-0.784415	-0.443654	5.674705	-0.859553	-0.377866
3	0.546088	0.131415	-0.456387	-0.859553	-0.377866

```
df_target.head(2)
```

```
0    '-1'
1    '-1'
Name: class, dtype: object
```

```
df_features.describe()
# data is standadized
```

	attr1	attr2	attr3	attr4	attr5
count	1.118300e+04	1.118300e+04	1.118300e+04	1.118300e+04	1.118300e+04
mean	1.096535e-10	1.297595e-09	5.698113e-10	-2.435705e-09	-1.120680e-09
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
min	-7.844148e-01	-4.701953e-01	-5.916315e-01	-8.595525e-01	-3.778657e-01
25%	-7.844148e-01	-4.701953e-01	-5.916315e-01	-8.595525e-01	-3.778657e-01
50%	-1.085769e-01	-3.949941e-01	-2.309790e-01	-8.595525e-01	-3.778657e-01
75%	3.139489e-01	-7.649473e-02	2.198366e-01	8.202077e-01	-3.778657e-01
max	3.150844e+01	5.085849e+00	2.947777e+01	9.591164e+00	2.361712e+01

```
# Make an instance of PCA
pca = PCA(n_components=2)
print(pca)
```

```
PCA(copy=True, iterated_power='auto', n_components=2, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

```
principalComponents = pca.fit_transform(df_features)
```

```
principalDf = pd.DataFrame(data = principalComponents, columns = ['pc_1', 'pc_2'])
```

```
principalDf.head(5)
```

	pc_1	pc_2
0	2.736372	2.874728
1	-0.524351	0.146989
2	-0.201428	-2.521152

```
print((pca.explained_variance_ratio_))
#[0.36013997 0.22577113 0.19901983 0.11863644 0.09643263]
#0.585911094389204
```

```
[0.36013997 0.22577113]
```

```
finalDf = pd.concat([principalDf, df_target], axis = 1)
```

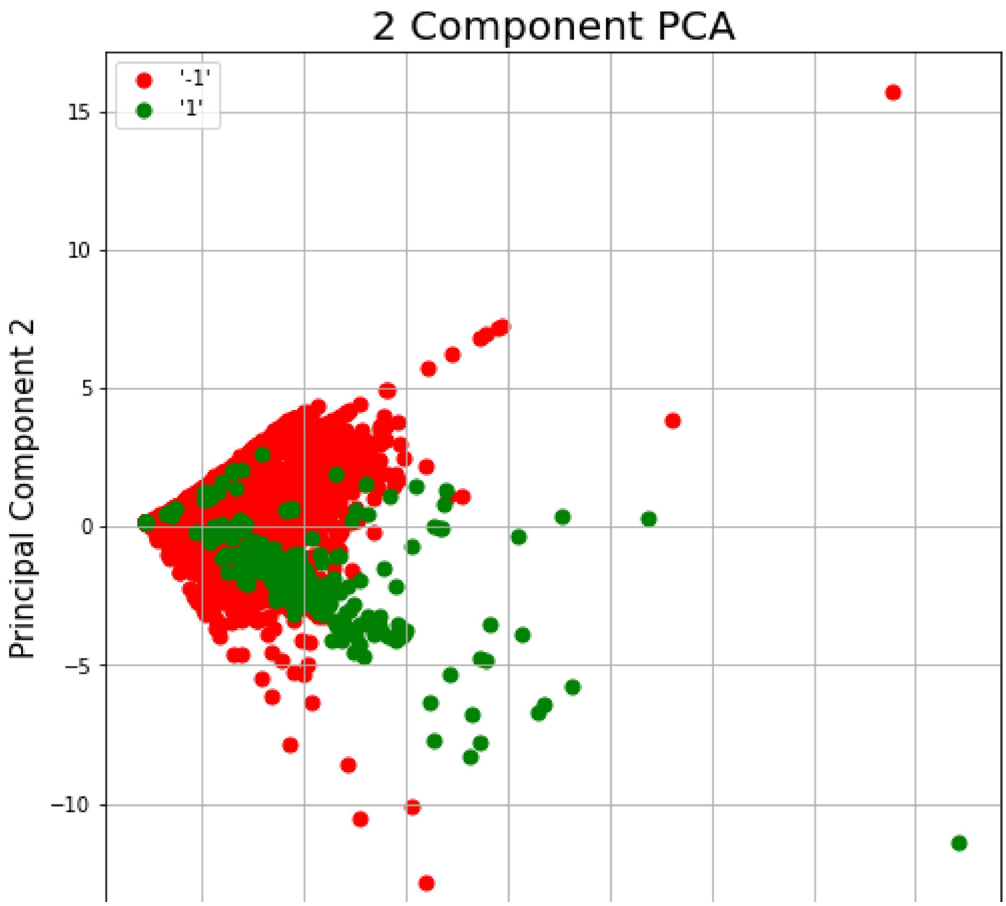
```
finalDf.head(5)
```

	pc_1	pc_2	class
0	2.736372	2.874728	'-1'
1	-0.524351	0.146989	'-1'
2	-0.201428	-2.521152	'-1'
3	-0.396001	0.950692	'-1'
4	0.167044	-0.304127	'-1'

```
df_target.unique()
```

```
array(["'-1'", "'1'"], dtype=object)
```

```
fig, ax = plt.subplots(nrows = 1, ncols = 1, figsize = (8,8));
targets = df_target.unique()
colors = ['r', 'g']

for target, color in zip(targets,colors):
    indicesToKeep = finalDf['class'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'pc_1'], finalDf.loc[indicesToKeep, 'pc_2'], c = co

ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 Component PCA', fontsize = 20)
ax.legend(targets)
ax.grid()
```



OBSERVATION: 1) 59 % of information is compressed into the principal components 1 and 2 2) With only the 1st two principal components we are able to distingush the data.

2. Download the image “bird.png”. Apply PCA and find the optimal number of components required to compress it to reconstruct the original image with less errors. Plot following graphs.

a. Graph with ‘x’ axis to be number of PCs and ‘y’ axis to be the reconstruction error.

b. Graph with ‘x’ axis to be number of PCs and ‘y’ axis to be the sum of eigen values.What are your conclusions?

```
from sklearn.datasets import load_digits
digits = load_digits()
print(digits.keys())
```

```
dict_keys(['data', 'target', 'target_names', 'images', 'DESCR'])
```

```
import pandas as pd
pd.options.mode.chained_assignment = None # Supress warning
```

```
print(digits.data.shape)
```

```
(1797, 64)
```

```
from pylab import imread,subplot,imshow,title,gray,figure,show,NullLocator
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
```

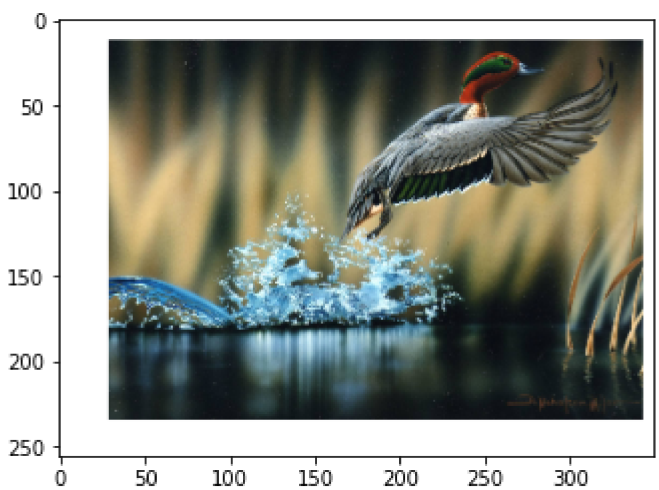
```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mou
```

```
input_file = open("/content/gdrive/MyDrive/Project/bird.png","r")
```

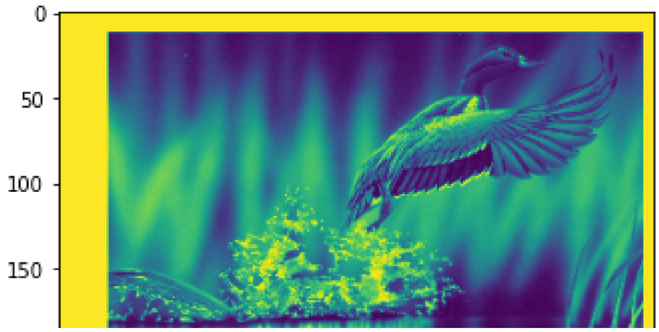
```
from sklearn.decomposition import PCA
from numpy import size,mean
A = plt.imread("/content/gdrive/MyDrive/Project/bird.png")
print(A.shape)
plt.imshow(A)
```

```
(256, 349, 4)
<matplotlib.image.AxesImage at 0x7f7d76aa7250>
```



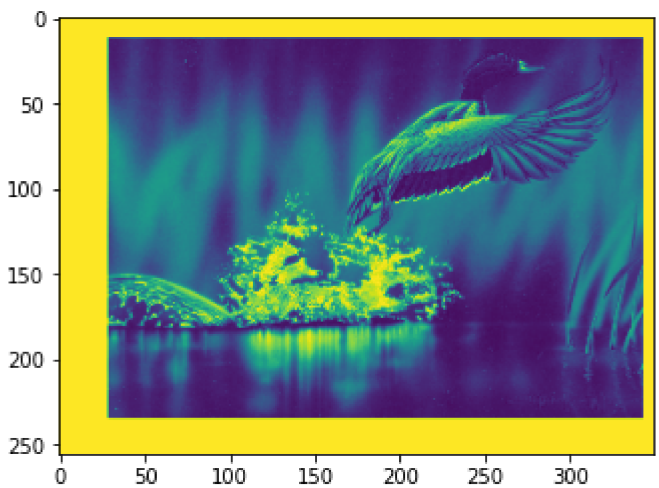

```
A_1 = A[:, :, 1]
print(A_1.shape)
plt.imshow(A_1)
```

```
(256, 349)
<matplotlib.image.AxesImage at 0x7f7d76b5b210>
```




```
A_2 = A[:, :, 2]
print(A_2.shape)
plt.imshow(A_2)
```

```
(256, 349)
<matplotlib.image.AxesImage at 0x7f7d76ac93d0>
```



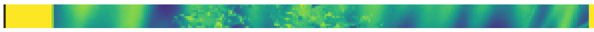

```
A_0 = A[:, :, 0]
print(A_0.shape)
plt.imshow(A_0)
```

```
(256, 349)
```

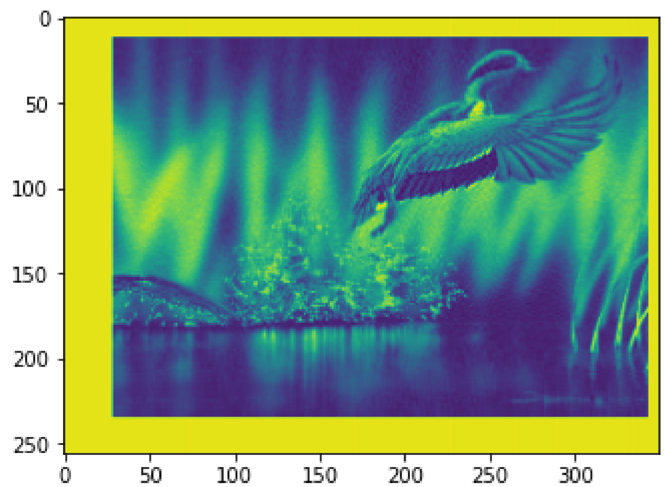
```
pca = PCA(70)
```

```
principalComponents = pca.fit_transform(A_0)
```

```
#print(pca.explained_variance_ratio_)
```



```
pca_image  = pca.inverse_transform(principalComponents)
plt.imshow(pca_image)
plt.show()
```




```
pca_loss = ((A_0 - pca_image) ** 2).mean()
pca_loss
```

```
0.00055416266
```

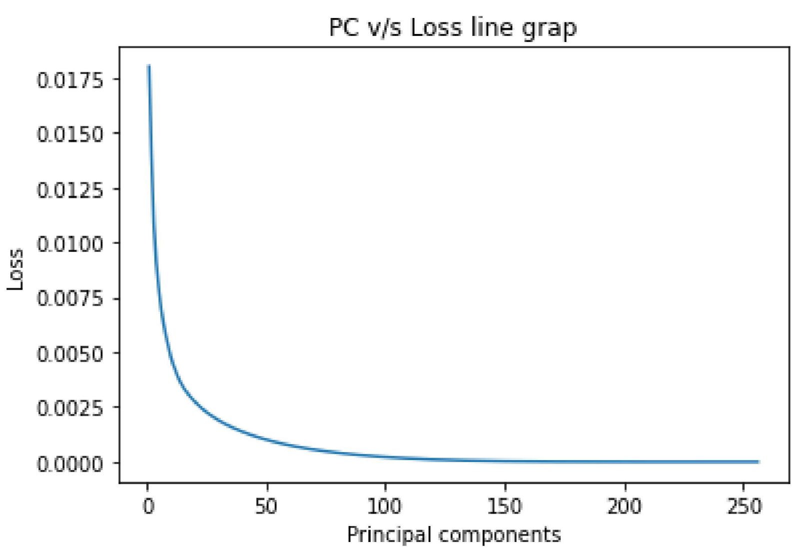
```
df = pd.DataFrame(columns = ['Loss', 'Sum_Eigen_Values'])
df.insert(loc=0, column='PC_Number', value=np.arange(1,257))


for i in range(1,257,1):
  pca = PCA(i)
  principalComponents = pca.fit_transform(A_0)
  pca_image  = pca.inverse_transform(principalComponents)
  pca_loss = ((A_0 - pca_image) ** 2).mean()
  df["Loss"][i-1] = pca_loss
  df["Sum_Eigen_Values"][i-1] = sum(pca.explained_variance_)
```

```
df.head()
```

	PC_Number	Loss	Sum_Eigen_Values
0	1	0.0180043	24.3891
1	2	0.0139901	25.7956
2	3	0.010812	26.9091
3	4	0.00909526	27.5106
4	5	0.00795072	27.9116

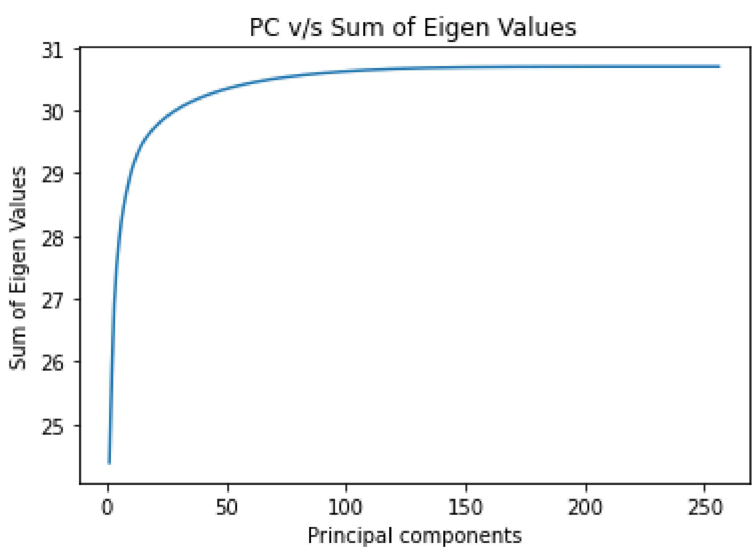
a. Graph with ‘x’ axis to be number of PCs and ‘y’ axis to be the reconstruction error.

```
# x axis values
x = df['PC_Number']
# corresponding y axis values
y = df['Loss']

# plotting the points
plt.plot(x, y)

# naming the x axis
plt.xlabel('Principal components')
# naming the y axis
plt.ylabel('Loss')

# giving a title to my graph
plt.title('PC v/s Loss line grap')

# function to show the plot
plt.show()
```



b. Graph with ‘x’ axis to be number of PCs and ‘y’ axis to be the sum of eigen values.What are your conclusions?

```
# x axis values
x = df['PC_Number']
# corresponding y axis values
y = df['Sum_Eigen_Values']

# plotting the points
plt.plot(x, y)

# naming the x axis
plt.xlabel('Principal components')
# naming the y axis
plt.ylabel('Sum of Eigen Values')

# giving a title to my graph
plt.title('PC v/s Sum of Eigen Values')

# function to show the plot
plt.show()
```



OBSERVATION : 1) Image recunstruction error decreses as the number of principle components increases. 2) The loss fattens around, when the number of principle component is 100 in this scenario. 3) The first 100 eigen values contribute maximum to the to total sum of all the eigen values in our example

3. Perform Latent Semantic Indexing (LSI) on the following set of Documents.

d1: Shipment of gold damaged in a fire. d2: Delivery of silver arrived in a silver truck. d3: Shipment of gold arrived in a truck.

Use Latent Semantic Indexing (LSI) to rank these documents for the query “gold silver truck.” State your observations.

```
import sklearn
# Import all of the scikit learn stuff
from __future__ import print_function
from sklearn.decomposition import TruncatedSVD
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import Normalizer
from sklearn import metrics
from sklearn.cluster import KMeans, MiniBatchKMeans
from sklearn.metrics.pairwise import cosine_similarity
import pandas as pd
import warnings
# Suppress warnings from pandas library
warnings.filterwarnings("ignore", category=DeprecationWarning,
module="pandas", lineno=570)
import numpy
```

```
example = ['Shipment of gold damaged in a fire' , 'Delivery of silver arrived in a silver tru
```

```
vectorizer = CountVectorizer(min_df = 1, stop_words = 'english')
dtm = vectorizer.fit_transform(example)
pd.DataFrame(dtm.toarray(),index=example,columns=vectorizer.get_feature_names
()).head(10)
```

	arrived	damaged	delivery	gold	shipment	silver	tı
Shipment of gold damaged in a fire	0	1	0	1	1	0	
Delivery of silver arrived in a silver truck	1	0	1	0	0	2	
Shipment of gold arrived in a truck	1	0	0	1	1	0	

```
# Get words that correspond to each column
vectorizer.get_feature_names()
```

```
['arrived', 'damaged', 'delivery', 'gold', 'shipment', 'silver', 'truck']
```

```
# Fit LSA.
lsa = TruncatedSVD(2, algorithm = 'arpack')
dtm = dtm.astype(float)
dtm_lsa = lsa.fit_transform(dtm)
dtm_lsa = Normalizer(copy=False).fit_transform(dtm_lsa)
```

```
df_term = pd.DataFrame(lsa.components_,index = ["component_1","component_2"],columns = vector
df_term
```

```
df_term
```

	arrived	damaged	delivery	gold	shipment	silver	truck
component_1	0.469809	0.067207	0.295892	0.241124	0.241124	0.591784	0.469809
component_2	0.036554	0.310765	-0.223350	0.570669	0.570669	-0.446700	0.036554

```
df_doc = pd.DataFrame(dtm_lsa, index = example, columns = ["component_1","component_2"])
df_doc
```

	component_1	component_2
Shipment of gold damaged in a fire	0.353898	0.935284
Delivery of silver arrived in a silver truck	0.918195	-0.396129
Shipment of gold arrived in a truck	0.760391	0.649466

```
xs = [w[0] for w in dtm_lsa]
ys = [w[1] for w in dtm_lsa]
xs, ys
```

```
([0.35389846513661666, 0.9181950424290773, 0.7603906169668817],
 [0.9352838480236612, -0.3961285953559332, 0.649466018840651])
```

```
# Plot scatter plot of points
%pylab inline
import matplotlib.pyplot as plt
figure()
plt.scatter(xs,ys)
xlabel('First principal component')
ylabel('Second principal component')
title('Plot of points against LSA principal components')
```

```
    Populating the interactive namespace from numpy and matplotlib
```

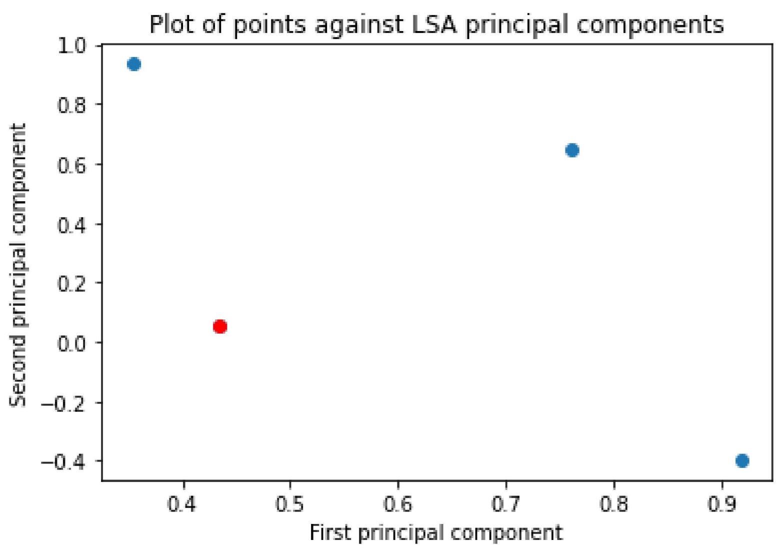
```
def Query_Ranking(query = q1, doc_df = df_doc , term_df = df_term):
  """
  This function ranks the passed documents as per the cosine similarity with the query provid
  """
  concept_term = []
  query_word = query.split()
  #print(query_word)
  # Get the query word in the conceputal space
  for i in range(0,len(query_word)):
    concept_term.append(term_df[query_word[i]])

  query_doc_con = 0
  for i in range(0,len(concept_term)):
    query_doc_con =  query_doc_con +  concept_term[i]
    #print(concept_term[i] )

  query_doc_con = query_doc_con / len(query_word)
  #print(query_doc_con)
  xs.append(query_doc_con[0])
  ys.append(query_doc_con[1])
  query_doc_array = np.array([query_doc_con[0],query_doc_con[1]])
  query_doc_array = query_doc_array.reshape(1,-1)

  sim ={}
  # Calculate cosine similarity of docs
  for i in range(0, len(doc_df)):
    b = doc_df.iloc[i]
    doc_array = np.array([b[0],b[1]])
    doc_array = doc_array.reshape(1,-1)
    csim = cosine_similarity(query_doc_array,doc_array)
    sim[doc_df.index[i]] = csim
    sim_rank_df = pd.DataFrame(list(sim_dic.items()),columns = ['Documents', 'Similarity'] )
    sim_rank_df = sim_rank_df.sort_values("Similarity", ascending=False)

  return (sim_rank_df)



q1 = "gold silver truck"


result = Query_Ranking(q1) # Call the function to find the similarity between the query and t
print("The document ranked as per the query: "+q1+"\n")
result.head()
```

```
The document ranked as per the query: gold silver truck
```

Documents	Similarity

```
# Plot scatter plot of points
%pylab inline
import matplotlib.pyplot as plt
figure()
plt.scatter(xs,ys)
plt.plot(xs[3],ys[3],'ro')
xlabel('First principal component')
ylabel('Second principal component')
title('Plot of points against LSA principal components')
```

```
Populating the interactive namespace from numpy and matplotlib
Text(0.5, 1.0, 'Plot of points against LSA principal components')
```



OBSERVATIONS : 1) Query is most similar to document "Delivery of silver arrived in a silver truck"