Importing and Understanding Data

```
import pandas as pd
import numpy as np
```

```
# Importing Housing.csv
housing = pd.read_csv('newhousing.csv')
```

```
# Looking at the first five rows
housing.head()
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning
0	5250000	5500	3	2	1	1	0	1	0	0
1	4480000	4040	3	1	2	1	0	0	0	0
2	3570000	3640	2	1	1	1	0	0	0	0
3	2870000	3040	2	1	1	0	0	0	0	0
4	3570000	4500	2	1	1	0	0	0	0	0

```
housing.shape
```

```
(545, 16)
```

```
# What type of values are stored in the columns?
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 16 columns):
price               545 non-null int64
area                545 non-null int64
bedrooms            545 non-null int64
bathrooms           545 non-null int64
stories             545 non-null int64
mainroad            545 non-null int64
guestroom           545 non-null int64
basement            545 non-null int64
hotwaterheating     545 non-null int64
airconditioning     545 non-null int64
parking             545 non-null int64
prefarea            545 non-null int64
semi-furnished      545 non-null int64
unfurnished         545 non-null int64
areaperbedroom      545 non-null float64
```

```
bbratio            545 non-null float64
dtypes: float64(2), int64(14)
memory usage: 68.2 KB
```

Splitting Data into Training and Testing Sets

```
housing.columns
```

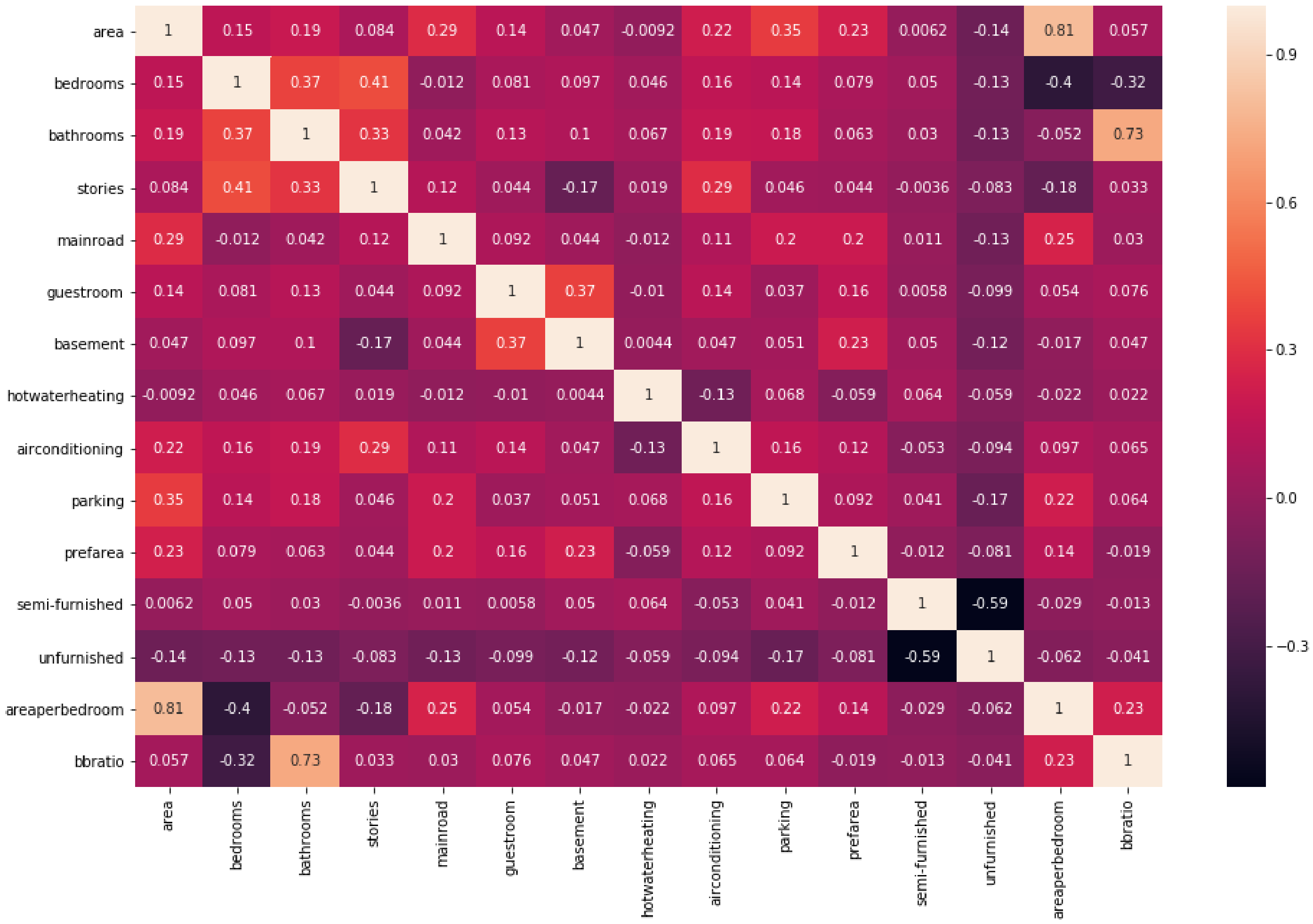
```
Index(['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
       'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
       'parking', 'prefarea', 'semi-furnished', 'unfurnished',
       'areaperbedroom', 'bbratio'],
      dtype='object')
```

```
# Putting feature variable to X
X = housing[['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
       'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
       'parking', 'prefarea', 'semi-furnished', 'unfurnished',
       'areaperbedroom', 'bbratio']]

# Putting response variable to y
y = housing['price']
```

```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# Let's see the correlation matrix
plt.figure(figsize = (16,10))     # Size of the figure
sns.heatmap(X.corr(),annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f05462575c0>
```




```
#creating correlation matrix for the given data
corrmat = np.corrcoef(X.transpose())
```

```
#Make a diagonal matrix with diagonal entry of Matrix corrmat
p=np.diagflat(corrmat.diagonal())
```

```
# subtract diagonal entries making all diagonals 0
corrmat_diag_zero = corrmat - p
print("max corr:",corrmat_diag_zero.max(), ", min corr: ", corrmat_diag_zero.min(),)
```

```
max corr: 0.8056104195904636 , min corr:  -0.5884049771343842
```

```
# Retrieve the (i,j) index for which matrix has maximum value
ij_max = np.unravel_index(corrmat_diag_zero.argmax(), corrmat_diag_zero.shape)
print("ij_max",ij_max)
print("Maximum correlation :",corrmat_diag_zero[ij_max])
```

```
ij_max (0, 13)
Maximum correlation : 0.8056104195904636
```

```python
# Retrieve the (i,j) index for which matrix has absolute minimum value
ij_min = np.unravel_index(np.absolute(corrmat).argmin(), corrmat.shape)
print("ij_min",ij_min)
print("Minimum correlation :",corrmat_diag_zero[ij_min])
```

```
ij_min (3, 11)
Minimum correlation : -0.003648304604063477
```

```python
#random_state is the seed used by the random number generator, it can be any integer.
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 ,test_size = 0
```

Question No. 1 --

```python
X_train.shape
# We have 15 variables after splitting the data
```

```
(381, 15)
```

```python
from sklearn import preprocessing
X_scaler = preprocessing.StandardScaler().fit(X_train)
y_scaler = preprocessing.StandardScaler().fit(y_train.values.reshape(-1,1))
Xtrain=X_scaler.transform(X_train)
ytrain=y_scaler.transform(y_train.values.reshape(-1,1))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:475:
DataConversionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:475:
DataConversionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```python
Xtrain.shape
```

```
(381, 15)
```

```python
xtrain_df = pd.DataFrame(Xtrain,columns=X_train.columns)
Xtrain[:,0].max()
xtrain_df['area'].max()
```

```
4.98610656210858
```

```python
ytrain.shape
```

```
(381, 1)
```

```
Xtest=X_scaler.transform(X_test)
ytest=y_scaler.transform(y_test.values.reshape(-1,1))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:475:
DataConversionWarning: Data with input dtype int64 was converted to float64 by
StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
xtest_df = pd.DataFrame(Xtest,columns=X_train.columns)
xtest_df['guestroom'].min()
```

```
-0.4323377011671169
```

Question No. 2 --

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import  linear_model
from sklearn.metrics import mean_squared_error, r2_score
# Create linear regression object
regr = linear_model.LinearRegression()
# Train the model using the training sets
regr.fit(Xtrain, ytrain)
# Make predictions using the testing set
y_pred = regr.predict(Xtest)
```

```
print("Mean squared error: %.2f" % mean_squared_error(ytest, y_pred))
# Explained variance score: 1 is perfect prediction
print('R2 score: %.2f' % r2_score(ytest, y_pred))
```

```
Mean squared error: 0.35
R2 score: 0.65
```

```
from sklearn.metrics import explained_variance_score
explained_variance_score(ytest, y_pred)
```

```
0.650291403036704
```

Question No. 3 --

```
#Importing the PCA module
from sklearn.decomposition import PCA
pca = PCA( random_state=100)
```

```
#Doing the PCA on the train data
pca.fit(Xtrain)
```

```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=100,
  svd_solver='auto', tol=0.0, whiten=False)
```

```
components = pd.DataFrame({'PC1':pca.components_[0],'PC2':pca.components_[1],'Feature':
components
```

	Feature	PC1	PC2
0	area	0.466911	0.253614
1	bedrooms	0.131123	-0.501994
2	bathrooms	0.320620	-0.322073
3	stories	0.181371	-0.391036
4	mainroad	0.298975	0.132957
5	guestroom	0.202099	-0.060133
6	basement	0.149324	-0.043661
7	hotwaterheating	0.004933	-0.122714
8	airconditioning	0.257295	-0.113094
9	parking	0.332199	0.046879
10	prefarea	0.236127	0.040036
11	semi-furnished	0.114761	-0.224264
12	unfurnished	-0.247093	0.228075
13	areaperbedroom	0.349103	0.518731
14	bbratio	0.219420	0.028230

```
colnames = list(X_train.columns)
pcs_df = pd.DataFrame({'PC1':pca.components_[0],'PC2':pca.components_[1],'PC3':pca.comp
                       'PC4':pca.components_[3],'PC5':pca.components_[4],
                       'PC6':pca.components_[5],'PC7':pca.components_[6],'PC8':pca.comp
                       'PC9':pca.components_[8],'PC10':pca.components_[9],'PC11':pca.cc
                       'PC12':pca.components_[11],'PC13':pca.components_[12],
                       'PC14':pca.components_[13],'PC15':pca.components_[14],'Feature':
```

```
pcs_df
```

	Feature	PC1	PC10	PC11	PC12	PC13	PC14	PC15	PC2	
0	area	0.466911	0.026806	-0.140376	-0.012615	-0.022318	-0.481254	0.431188	0.253614	-0.08
1	bedrooms	0.131123	-0.085303	-0.178241	-0.260943	-0.022348	0.522411	0.148812	-0.501994	-0.16
2	bathrooms	0.320620	-0.017169	-0.105249	-0.190787	-0.064773	-0.334211	-0.554016	-0.322073	0.49
3	stories	0.181371	-0.066632	0.172781	0.679243	0.073244	0.008986	-0.012729	-0.391036	0.10

	Feature	PC1	PC10	PC11	PC12	PC13	PC14	PC15	PC2	
4	mainroad	0.298975	-0.552863	-0.299977	-0.160644	-0.090223	-0.002066	-0.000785	0.132957	-0.07
5	guestroom	0.202099	-0.373524	0.444739	-0.193923	-0.055659	0.013803	-0.003411	-0.060133	-0.09
6	basement	0.149324	0.011200	-0.456305	0.497569	-0.021707	-0.011530	-0.010790	-0.043661	-0.25
7	hotwaterheating	0.004933	0.352480	-0.118630	-0.010145	-0.016878	0.008806	0.004608	-0.122714	0.07
8	airconditioning	0.257295	0.500269	-0.246527	-0.241065	-0.046889	0.006514	0.005219	-0.113094	-0.06
9	parking	0.332199	0.064100	0.434333	0.161911	-0.048221	0.009496	-0.009763	0.046879	0.02
10	prefarea	0.236127	0.393982	0.375213	-0.111942	-0.064743	0.021767	-0.004757	0.040036	-0.28
11	semi-furnished	0.114761	-0.035805	0.039720	0.040304	-0.674623	0.018057	-0.004841	-0.224264	-0.28
12	unfurnished	-0.247093	0.049768	-0.031590	0.098685	-0.714919	0.022679	-0.011190	0.228075	0.26
13	areaperbedroom	0.349103	0.060210	-0.068353	0.119992	0.038672	0.522083	-0.444329	0.518731	0.00
14	bbratio	0.219420	0.027235	0.008636	0.016367	-0.031805	0.330576	0.535690	0.028230	0.62

Question No. 4 --

```
pca.explained_variance_
```

```
array([2.65559436, 2.03987639, 1.67075622, 1.47650977, 1.38551446,
       1.05847568, 0.93569155, 0.85802694, 0.78835172, 0.70619007,
       0.58761968, 0.45176984, 0.37115289, 0.03589467, 0.01804947])
```

```
print("pca.explained_variance_ratio_: ",pca.explained_variance_ratio_.round(3)*100)
```

```
pca.explained_variance_ratio_:  [17.7 13.6 11.1  9.8  9.2  7.   6.2  5.7  5.2  4.7  3.9
3.   2.5  0.2
  0.1]
```

```

```

```
print (pca.explained_variance_ratio_.cumsum())
```

```
[0.17657495 0.31220978 0.42330118 0.52147681 0.613602   0.68398184
 0.74619755 0.80324921 0.85566805 0.90262382 0.94169564 0.97173458
 0.99641316 0.99879986 1.        ]
```

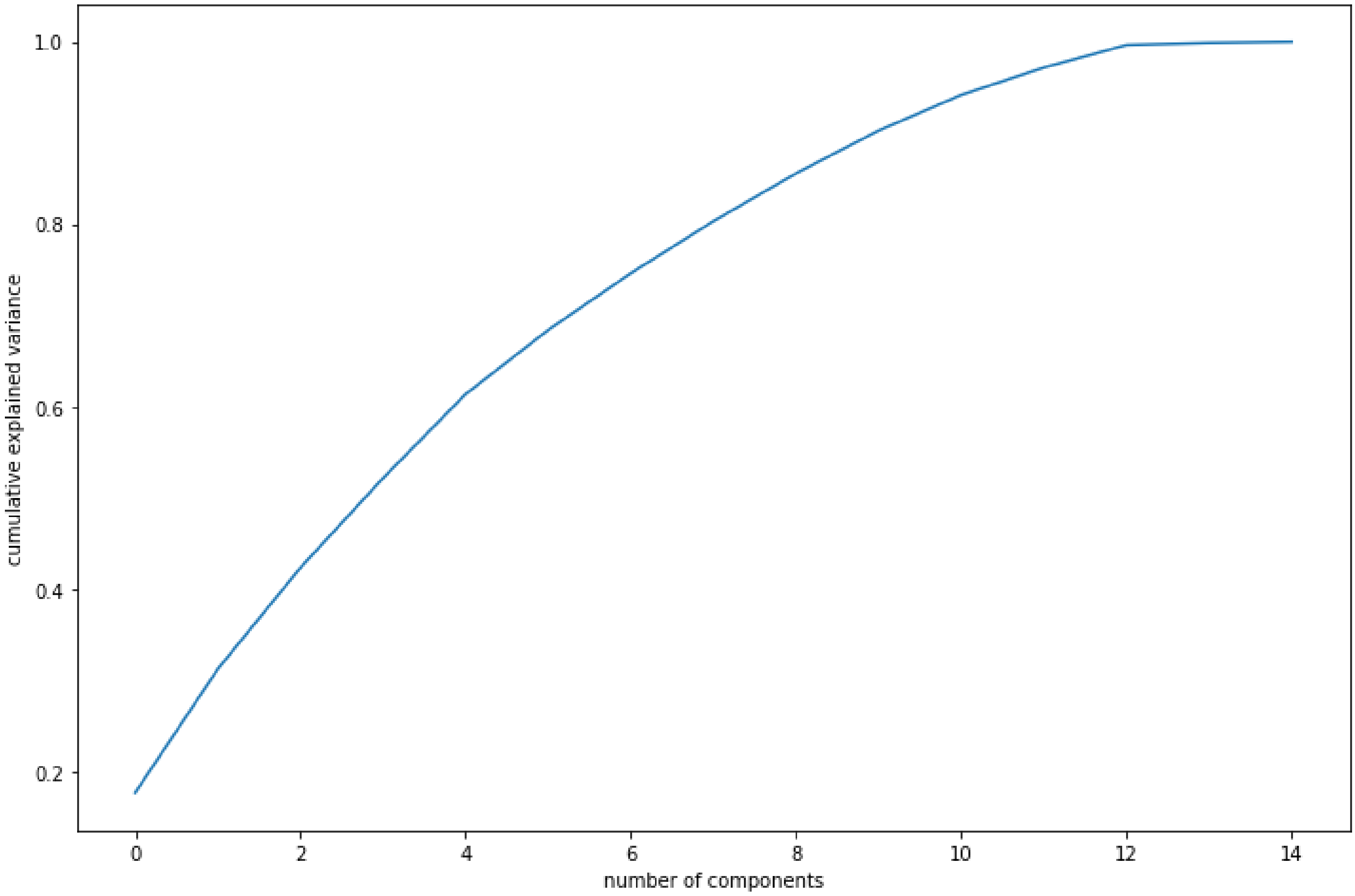
Question No. 5 --

```
np.cumsum(np.round(pca.explained_variance_ratio_, decimals=4)*100)
```

```
array([ 17.66,  31.22,  42.33,  52.15,  61.36,  68.4 ,  74.62,  80.33,
        85.57,  90.27,  94.18,  97.18,  99.65,  99.89, 100.01])
```

Question No. 6 --

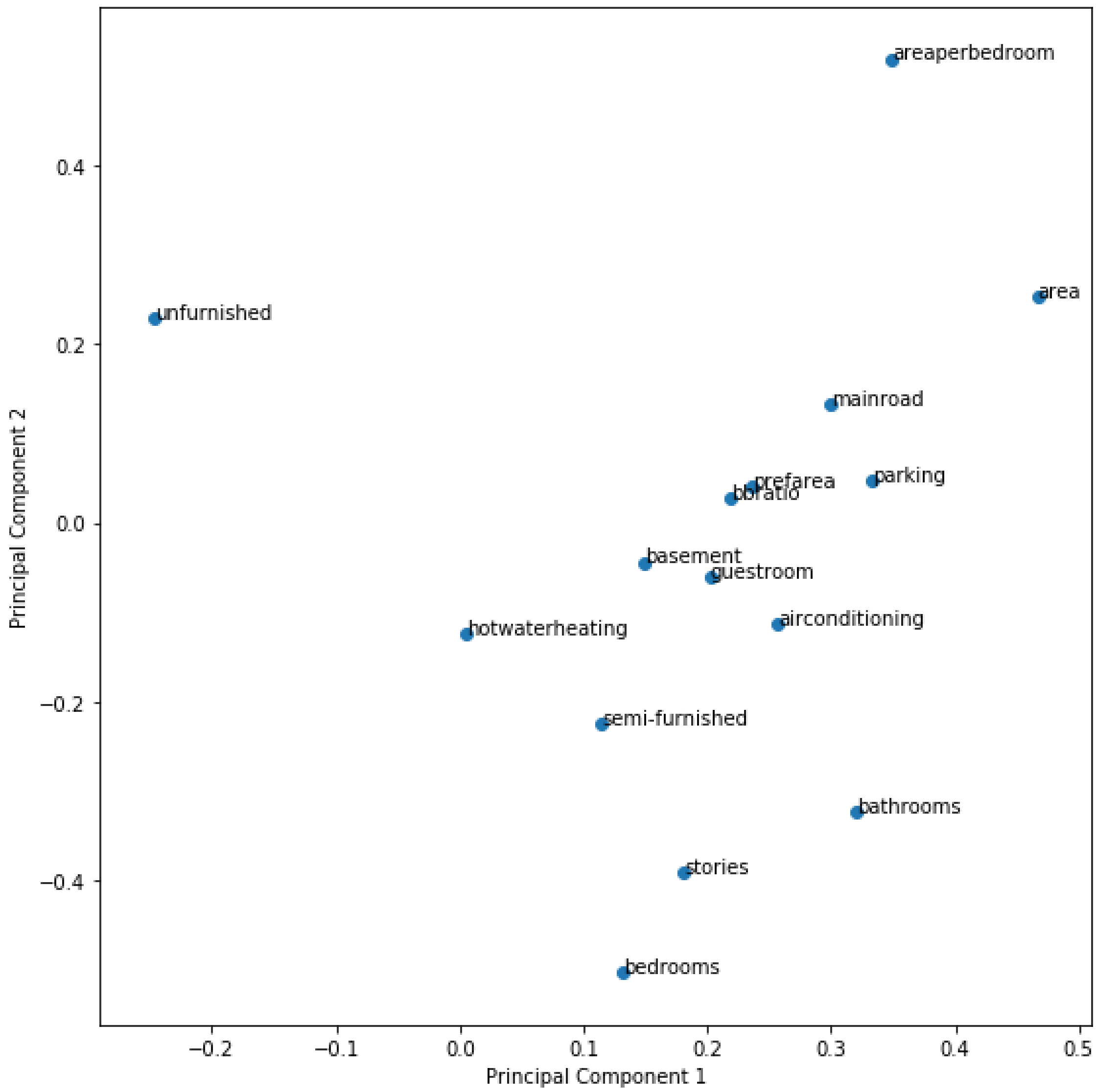
```
#Making the screeplot - plotting the cumulative variance against the number of componer
%matplotlib inline
fig = plt.figure(figsize = (12,8))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```




```
product = np.dot(pca.components_[0],pca.components_[1])
product.round(5)
```

```
-0.0
```

```
%matplotlib inline
fig = plt.figure(figsize = (8,8))
plt.scatter(components.PC1, components.PC2)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
for i, txt in enumerate(components.Feature):
    plt.annotate(txt, (components.PC1[i],components.PC2[i]))
plt.tight_layout()
plt.show()
```




```
pca_train = pca.transform(Xtrain)
pca_train.shape
```

```
(381, 15)
```

```
pca_train
```

```
array([[-1.89382742,  1.04859781,  1.12366889, ..., -0.29454944,
        -0.04714831,  0.04708571],
       [ 2.41706253,  0.75177319,  1.560377  , ..., -0.94956138,
        -0.02958512,  0.02039269],
       [ 1.61007146,  0.66810948, -1.0816004 , ...,  0.89630176,
        -0.05850229,  0.02082749],
       ...,
       [ 0.70040283,  1.37263147, -0.36736473, ...,  1.01379374,
        -0.12498705,  0.02645665],
       [ 0.8871212 , -1.01626729,  1.66713038, ..., -0.6926666 ,
         0.04631442, -0.11892837],
       [ 2.20141726, -2.46443025,  1.02634462, ...,  0.89723256,
         0.01122933, -0.0874458 ]])
```

Question No. 7 --

```
#creating correlation matrix for the principal components
corrmat = np.corrcoef(pca_train.transpose())
```

```
#plotting the correlation matrix
%matplotlib inline
plt.figure(figsize = (20,10))
sns.heatmap(corrmat,annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f053901e5c0>
```


```
# 1s -> 0s in diagonals
corrmat_nodiag = corrmat - np.diagflat(corrmat.diagonal())
print("max corr:",corrmat_nodiag.max(), ", min corr: ", corrmat_nodiag.min(),)
# we see that correlations are indeed very close to 0
```

```
max corr: 1.1151493214234663e-15 , min corr:  -2.733842144727878e-15
```

```
#Applying selected components to the test data - 13 components
pca_test = pca.transform(Xtest)
pca_test.shape
```

```
(164, 15)
```

Question No. 8 --

```python
import matplotlib.pyplot as plt
import numpy as np
from sklearn import  linear_model
from sklearn.metrics import mean_squared_error, r2_score
# Create linear regression object
regrpca = linear_model.LinearRegression()
# Train the model using the principal components of the transformed training sets
regrpca.fit(pca_train, ytrain)
# Make predictions using the principal components of the transformed testing set
y_pca_pred = regrpca.predict(pca_test)
print("Mean squared error: %.2f" % mean_squared_error(ytest, y_pca_pred))
# Explained variance score: 1 is perfect prediction
print('R2 score: %.2f' % r2_score(ytest, y_pca_pred))
```

```
Mean squared error: 0.35
R2 score: 0.65
```

```python
pca = PCA(n_components=6,random_state=100)
#Scale and transform data to get Principal Components

Xtrain_reduced = pca.fit_transform(Xtrain)
Xtest_reduced = pca.transform(Xtest)
regrpca6 = linear_model.LinearRegression()
# Train the model using the principal components of the transformed training sets
regrpca6.fit(Xtrain_reduced, ytrain)
# Make predictions using the principal components of the transformed testing set
y_pred = regrpca6.predict(Xtest_reduced)
print("Mean squared error: %.2f" % mean_squared_error(ytest, y_pred))
# Explained variance score: 1 is perfect prediction
print('R2 score: %.2f' % r2_score(ytest, y_pred))
```

```
Mean squared error: 0.33
R2 score: 0.66
```