CS306 Data Analysis and Visualization

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1 Importing required libraries and loading the dataset

[1]:
```
import numpy as np
import pandas as pd
import sklearn as sk
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
#reading the dataset
df = pd.read_csv('mnist_train.csv')
df_test = pd.read_csv('mnist_test.csv')
```

[3]:
```
df_vals = df.drop(['5'], axis =1)
```

[4]:
```
df = df.astype(float)
df.info()
from sklearn.preprocessing import StandardScaler
features = df.columns[1:]
# Separating out the features
train = df.loc[:, features].values
# Standardizing the features
train = StandardScaler().fit_transform(train)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59999 entries, 0 to 59998
Columns: 785 entries, 5 to 0.617
dtypes: float64(785)
memory usage: 359.3 MB
```

2 Performing PCA on the train dataset

[5]:
```python
# explained variance = 95%
pca95 = PCA(.95)
pca95.fit(train)
pc95_scores = pca95.transform(train)
pc95_weights = pca95.components_

# explained variance = 90%
pca90 = PCA(.90)
pca90.fit(train)
pc90_scores = pca90.transform(train)
pc90_weights = pca90.components_

# explained variance = 80%
pca80 = PCA(.80)
pca80.fit(train)
pc80_scores = pca80.transform(train)
pc80_weights = pca80.components_

# explained variance = 75%
pca75 = PCA(.75)
pca75.fit(train)
pc75_scores = pca75.transform(train)
pc75_weights = pca75.components_
```

[6]:
```python
print('Number of PCs for 95% variance: {}'.format(pca95.n_components_))
print('Number of PCs for 90% variance: {}'.format(pca90.n_components_))
print('Number of PCs for 80% variance: {}'.format(pca80.n_components_))
print('Number of PCs for 75% variance: {}'.format(pca75.n_components_))



weights_array = [pc95_weights.T, pc90_weights.T, pc80_weights.T , pc75_weights.
 ↪T]
scores_array = [pc95_scores, pc90_scores, pc80_scores , pc75_scores]
print(np.shape(scores_array[1][2:3] @ weights_array[1].T))
print('Shape of weights for 95% : {}'.format(np.shape(weights_array[0])))
print('Shape of scores for 95%: {}'.format(np.shape(scores_array[0])))
```

```
Number of PCs for 95% variance: 331
Number of PCs for 90% variance: 236
Number of PCs for 80% variance: 149
Number of PCs for 75% variance: 120
(1, 784)
Shape of weights for 95% : (784, 331)
Shape of scores for 95%: (59999, 331)
```

We know, $S = XW$, where S is the scores, X is the data and W are the weights. Hence, to reconstruct any data, we will use the following:

X = S.W^T

3 Reconstructing test images

[7]:
```
zeroes = np.array(df_test[df_test['7'] == 0].drop(['7'], axis=1))
ones = np.array(df_test[df_test['7'] == 1].drop(['7'], axis=1))
twos = np.array(df_test[df_test['7'] == 2].drop(['7'], axis=1))
threes = np.array(df_test[df_test['7'] == 3].drop(['7'], axis=1))
fours = np.array(df_test[df_test['7'] == 4].drop(['7'], axis=1))
fives = np.array(df_test[df_test['7'] == 5].drop(['7'], axis=1))
sixes = np.array(df_test[df_test['7'] == 6].drop(['7'], axis=1))
sevens = np.array(df_test[df_test['7'] == 7].drop(['7'], axis=1))
eights = np.array(df_test[df_test['7'] == 8].drop(['7'], axis=1))
nines = np.array(df_test[df_test['7'] == 9].drop(['7'], axis=1))
```

[8]:
```
zeroes_scores = []
for i in range(4):
    zeroes_scores.append(StandardScaler().fit_transform(zeroes) @␣
 ↪weights_array[i])

ones_scores = []
for i in range(4):
    ones_scores.append(StandardScaler().fit_transform(ones) @ weights_array[i])

twos_scores = []
for i in range(4):
    twos_scores.append(StandardScaler().fit_transform(twos) @ weights_array[i])

threes_scores = []
for i in range(4):
    threes_scores.append(StandardScaler().fit_transform(threes) @␣
 ↪weights_array[i])

fours_scores = []
for i in range(4):
    fours_scores.append(StandardScaler().fit_transform(fours) @␣
 ↪weights_array[i])

fives_scores = []
for i in range(4):
    fives_scores.append(StandardScaler().fit_transform(fives) @␣
 ↪weights_array[i])

sixes_scores = []
for i in range(4):
```

```
    sixes_scores.append(StandardScaler().fit_transform(sixes) @␣
 ↪weights_array[i])

sevens_scores = []
for i in range(4):
    sevens_scores.append(StandardScaler().fit_transform(sevens) @␣
 ↪weights_array[i])

eights_scores = []
for i in range(4):
    eights_scores.append(StandardScaler().fit_transform(eights) @␣
 ↪weights_array[i])

nines_scores = []
for i in range(4):
    nines_scores.append(StandardScaler().fit_transform(nines) @␣
 ↪weights_array[i])
```

```
/Users/riddhi/anaconda3/lib/python3.6/site-
packages/sklearn/utils/validation.py:475: DataConversionWarning: Data with input
dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

[9]:

```
zer = pca95.inverse_transform(zeroes_scores[0])

zeroes_r = []

zeroes_r.append(pca95.inverse_transform(zeroes_scores[0]))
zeroes_r.append(pca90.inverse_transform(zeroes_scores[1]))
zeroes_r.append(pca80.inverse_transform(zeroes_scores[2]))
zeroes_r.append(pca75.inverse_transform(zeroes_scores[3]))



ones_r = []

ones_r.append(pca95.inverse_transform(ones_scores[0]))
ones_r.append(pca90.inverse_transform(ones_scores[1]))
ones_r.append(pca80.inverse_transform(ones_scores[2]))
ones_r.append(pca75.inverse_transform(ones_scores[3]))

twos_r = []
twos_r.append(pca95.inverse_transform(twos_scores[0]))
twos_r.append(pca90.inverse_transform(twos_scores[1]))
twos_r.append(pca80.inverse_transform(twos_scores[2]))
twos_r.append(pca75.inverse_transform(twos_scores[3]))

threes_r = []
```

```
threes_r.append(pca95.inverse_transform(threes_scores[0]))
threes_r.append(pca90.inverse_transform(threes_scores[1]))
threes_r.append(pca80.inverse_transform(threes_scores[2]))
threes_r.append(pca75.inverse_transform(threes_scores[3]))

fours_r = []
fours_r.append(pca95.inverse_transform(fours_scores[0]))
fours_r.append(pca90.inverse_transform(fours_scores[1]))
fours_r.append(pca80.inverse_transform(fours_scores[2]))
fours_r.append(pca75.inverse_transform(fours_scores[3]))

fives_r = []
fives_r.append(pca95.inverse_transform(fives_scores[0]))
fives_r.append(pca90.inverse_transform(fives_scores[1]))
fives_r.append(pca80.inverse_transform(fives_scores[2]))
fives_r.append(pca75.inverse_transform(fives_scores[3]))

sixes_r = []
sixes_r.append(pca95.inverse_transform(sixes_scores[0]))
sixes_r.append(pca90.inverse_transform(sixes_scores[1]))
sixes_r.append(pca80.inverse_transform(sixes_scores[2]))
sixes_r.append(pca75.inverse_transform(sixes_scores[3]))

sevens_r = []
sevens_r.append(pca95.inverse_transform(sevens_scores[0]))
sevens_r.append(pca90.inverse_transform(sevens_scores[1]))
sevens_r.append(pca80.inverse_transform(sevens_scores[2]))
sevens_r.append(pca75.inverse_transform(sevens_scores[3]))

eights_r = []
eights_r.append(pca95.inverse_transform(eights_scores[0]))
eights_r.append(pca90.inverse_transform(eights_scores[1]))
eights_r.append(pca80.inverse_transform(eights_scores[2]))
eights_r.append(pca75.inverse_transform(eights_scores[3]))

nines_r = []
nines_r.append(pca95.inverse_transform(nines_scores[0]))
nines_r.append(pca90.inverse_transform(nines_scores[1]))
nines_r.append(pca80.inverse_transform(nines_scores[2]))
nines_r.append(pca75.inverse_transform(nines_scores[3]))
```

4 Plotting the reconstructed images along with the original image

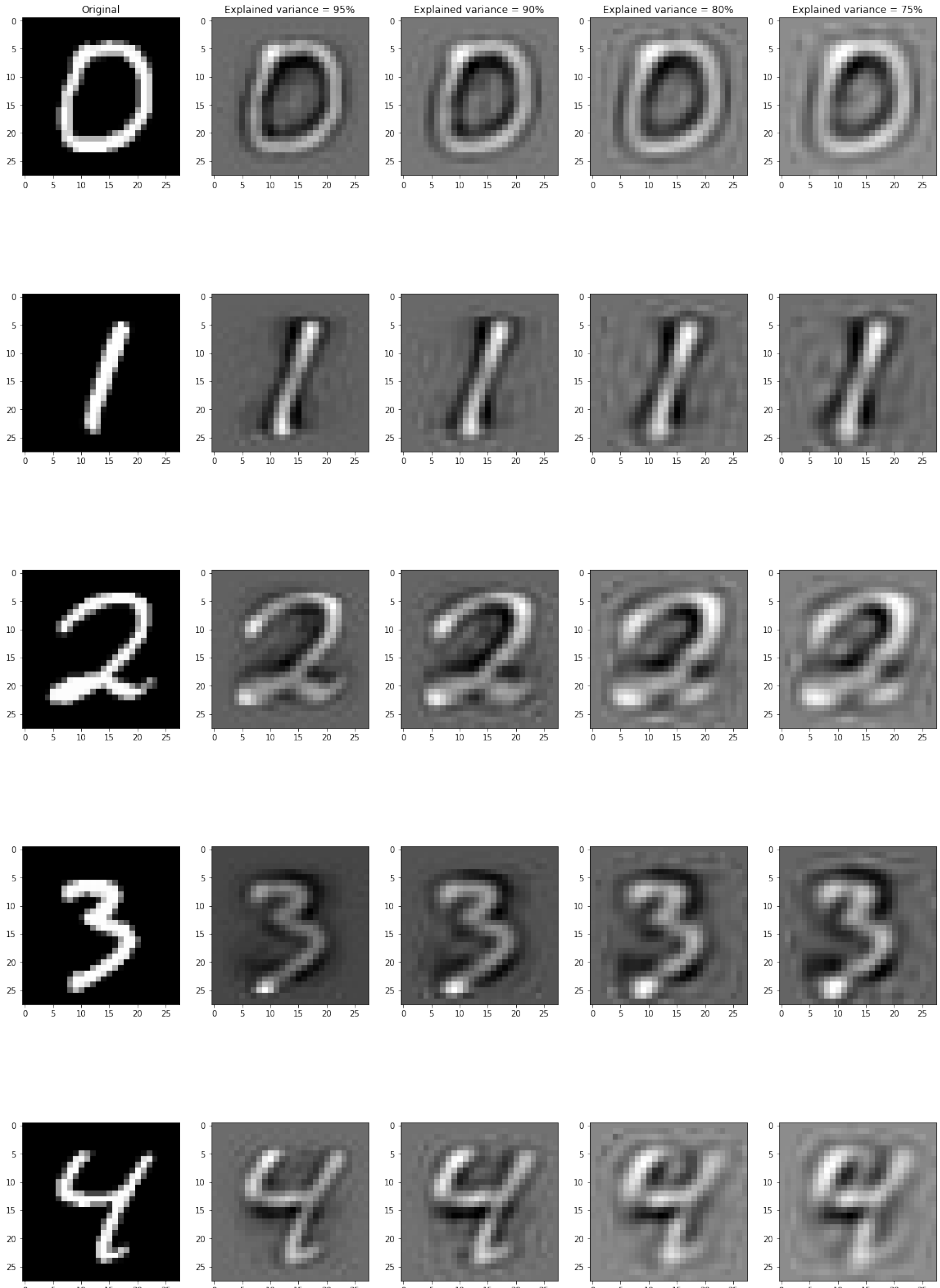
[10]:

```python
variance = [95,90,80,75]

#ZERO
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.title('Original')
plt.imshow(np.array(zeroes[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.title('Explained variance = {}%'.format(variance[i]))
    plt.imshow((zeroes_r[i][1:2]).reshape(28,28), interpolation = "none", cmap␣
↪= "gray")
plt.show()

#ONE
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(ones[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)

    plt.imshow((ones_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
↪"gray")
plt.show()

plt.show()

#TWO
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(twos[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((twos_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
↪"gray")
plt.show()
```

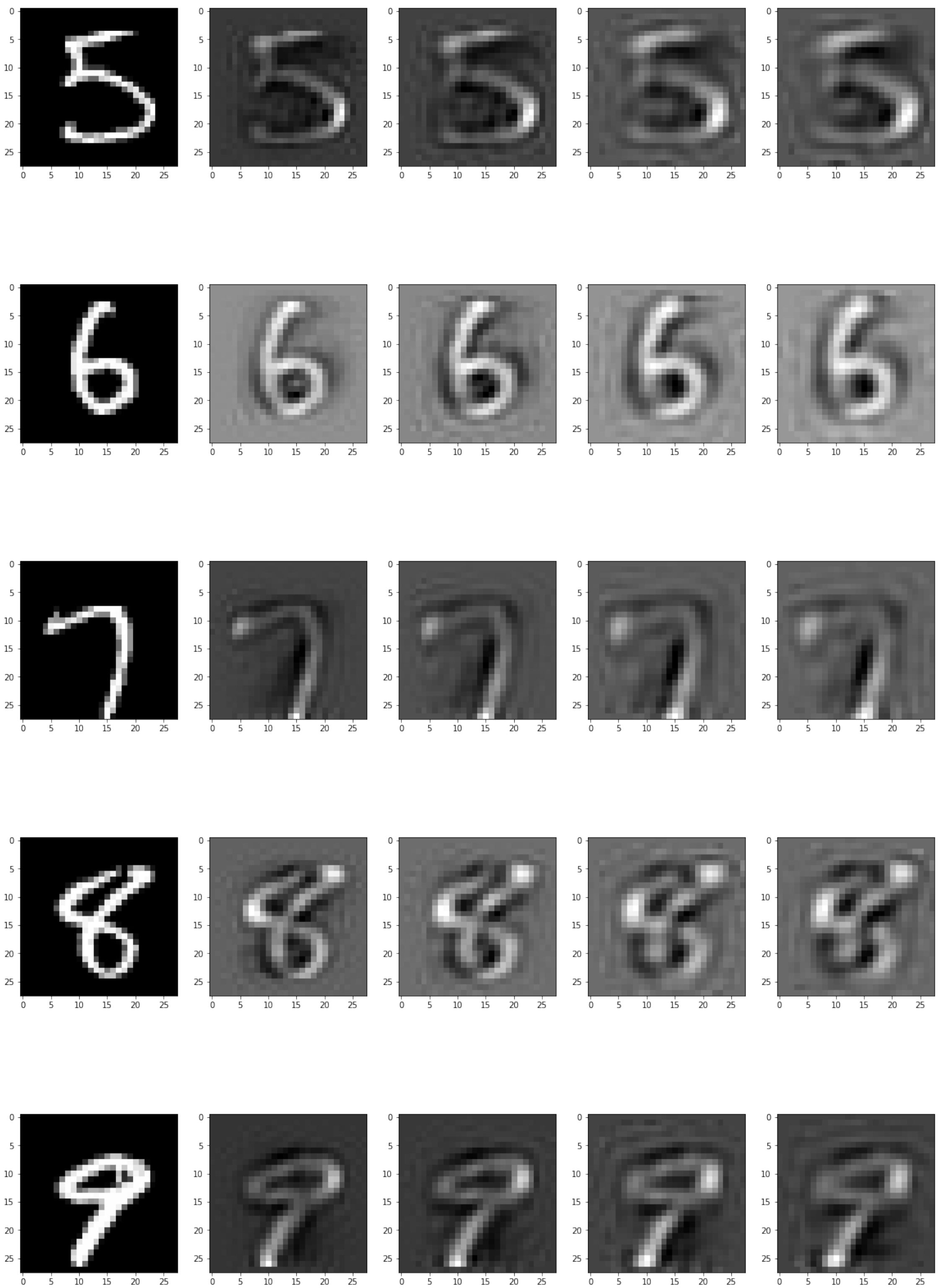
```
#THREE
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(threes[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((threes_r[i][1:2]).reshape(28,28), interpolation = "none", cmap␣
 ↪= "gray")
plt.show()


#FOUR
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(fours[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((fours_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
 ↪"gray")
plt.show()

#FIVE
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(fives[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((fives_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
 ↪"gray")
plt.show()

#SIX
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
```

```
plt.imshow(np.array(sixes[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((sixes_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
 ↪"gray")
plt.show()

#SEVEN
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(sevens[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((sevens_r[i][1:2]).reshape(28,28), interpolation = "none", cmap␣
 ↪= "gray")
plt.show()

#EIGHT
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(eights[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((eights_r[i][1:2]).reshape(28,28), interpolation = "none", cmap␣
 ↪= "gray")
plt.show()

#NINE
fig , ax = plt.subplots(figsize=[20,10])

plt.subplot(1, 5, 1)
plt.imshow(np.array(nines[1:2]).reshape(28,28), interpolation = 'none', cmap =␣
 ↪'gray')

for i in range(4):
    plt.subplot(1, 5, i+2)
    plt.imshow((nines_r[i][1:2]).reshape(28,28), interpolation = "none", cmap =␣
 ↪"gray")
```

```
plt.show()
```



Original
Explained variance = 95%
Explained variance = 90%
Explained variance = 80%
Explained variance = 75%



[11]:

```python
# calculating rmse
from math import sqrt
from sklearn.metrics import mean_squared_error
rmse_0 = []
rmse_1 = []
rmse_2 = []
rmse_3 = []
rmse_4 = []
rmse_5 = []
rmse_6 = []
rmse_7 = []
rmse_8 = []
rmse_9 = []


for i in range(4):
    s0 = ((np.array(zeroes[1:2]) - zeroes_r[i][1:2])**2).mean()
    s0 = sqrt(s0)
    rmse_0.append(s0)

    s1 = ((np.array(ones[1:2]) - ones_r[i][1:2])**2).mean()
    s1 = sqrt(s1)
    rmse_1.append(s1)

    s2 = ((np.array(twos[1:2]) - twos_r[i][1:2])**2).mean()
    s2 = sqrt(s2)
    rmse_2.append(s2)

    s3 = ((np.array(threes[1:2]) - threes_r[i][1:2])**2).mean()
    s3 = sqrt(s3)
    rmse_3.append(s3)

    s4 = ((np.array(fours[1:2]) - fours_r[i][1:2])**2).mean()
    s4 = sqrt(s4)
    rmse_4.append(s4)

    s5 = ((np.array(fives[1:2]) - fives_r[i][1:2])**2).mean()
    s5 = sqrt(s5)
    rmse_5.append(s5)

    s6 = ((np.array(sixes[1:2]) - sixes_r[i][1:2])**2).mean()
    s6 = sqrt(s6)
    rmse_6.append(s6)

    s7 = ((np.array(sevens[1:2]) - sevens_r[i][1:2])**2).mean()
    s7 = sqrt(s7)
    rmse_7.append(s7)
```

```
    s8 = ((np.array(eights[1:2]) - eights_r[i][1:2])**2).mean()
    s8 = sqrt(s8)
    rmse_8.append(s8)

    s9 = ((np.array(nines[1:2]) - nines_r[i][1:2])**2).mean()
    s9 = sqrt(s9)
    rmse_9.append(s9)
```

[12]:
```
df_rmse = pd.DataFrame([rmse_0, rmse_1, rmse_2, rmse_3, rmse_4, rmse_5, rmse_6,␣
↪rmse_7, rmse_8, rmse_9], columns=['95%','90%','80%','75%'])
```

[13]:
```
df_rmse
```

[13]:

	95%	90%	80%	75%
0	89.733254	89.754097	89.774559	89.785759
1	61.895642	61.905274	61.922819	61.929079
2	88.717891	88.748300	88.807625	88.820994
3	83.320120	83.332281	83.359066	83.371391
4	74.444416	74.471198	74.526635	74.548468
5	74.385725	74.443611	74.516997	74.547605
6	77.511429	77.538638	77.572832	77.585161
7	62.509477	62.544135	62.597488	62.616687
8	86.454097	86.489826	86.544806	86.568192
9	93.305434	93.319364	93.346286	93.366121

We can see that as we take higher number of components for PCA, the explained variance increases and hence, the error in reconstruction is lower.