hw5-6

October 31, 2023

1 Lab: SVD and PCA Analysis – Layth Aljorani

[2]:
```
import numpy as np
```

1.1 1. SVD and PCA basics

1.1.1 setup

SVD factorization leads to A = U * sigma * V^T .

For i = 1, . . . , N , the i-th column of V is a unit vector that defines the i-th principle component.

[5]:
```
A = np.array([[17, 24, 1, 8, 15],
              [23, 5, 7, 14, 16],
              [4, 6, 13, 20, 22],
              [10, 12, 19, 21, 3],
              [11, 18, 25, 2, 9]])
A
```

[5]:
```
array([[17, 24,  1,  8, 15],
       [23,  5,  7, 14, 16],
       [ 4,  6, 13, 20, 22],
       [10, 12, 19, 21,  3],
       [11, 18, 25,  2,  9]])
```

1.1.2 Exercise 1:

Use numpy to perform singular value decomposition (SVD) and principal component analysis (PCA). (matrix is centered around zero)

1. Use X, s, Y = np.linalg.svd(A) to perform SVD analysis.

[8]:
```
X, s, Y = np.linalg.svd(A)
```

2. Calculate and print the variance explained by the i-th component, i.e.,

[10]:
```
var = (s ** 2) / np.sum(s ** 2)
var
```

[10]: array([0.76470588, 0.09201289, 0.08513021, 0.03251685, 0.02563417])

[11]:
```
# same things as above
summ = np.sum(s ** 2)
variance = []
for i in s:
    tmp = (i ** 2) / summ
    variance.append(tmp)
variance
```

[11]:
```
[0.764705882352941,
 0.09201288836360606,
 0.0851302114999976,
 0.03251684732353188,
 0.025634170459923528]
```

3. To verify the factorization is correct, use X, s, Y to recover matrix A (let's denote the recovered matrix as B). Is Y = V or Y = V T ?

Answer: Y is equal to V.T

[13]:
```
s
```

[13]: array([65.   , 22.54708869, 21.68742536, 13.403566 , 11.90078954])

[14]:
```
np.diag(s)
```

[14]:
```
array([[65.        ,  0.        ,  0.        ,  0.        ,  0.        ],
       [ 0.        , 22.54708869,  0.        ,  0.        ,  0.        ],
       [ 0.        ,  0.        , 21.68742536,  0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        , 13.403566  ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 11.90078954]])
```

[15]:
```
B = X @ np.diag(s) @ Y
B
```

[15]:
```
array([[17., 24.,  1.,  8., 15.],
       [23.,  5.,  7., 14., 16.],
       [ 4.,  6., 13., 20., 22.],
       [10., 12., 19., 21.,  3.],
       [11., 18., 25.,  2.,  9.]])
```

4. Use np.linalg.norm to calculate the difference of matrices A and B.

[17]:
```
A - B
```

[17]:
```
array([[-3.55271368e-15,  1.06581410e-14,  1.93178806e-14,
        -2.48689958e-14, -1.59872116e-14],
```

```
       [ 0.00000000e+00,  1.77635684e-14,  1.33226763e-14,
        -2.66453526e-14, -1.42108547e-14],
       [ 5.77315973e-15, -5.32907052e-15, -1.77635684e-14,
        -1.06581410e-14, -7.10542736e-15],
       [ 3.55271368e-15, -3.19744231e-14, -1.42108547e-14,
         1.77635684e-14,  6.66133815e-15],
       [-5.32907052e-15, -3.55271368e-14, -1.42108547e-14,
         2.17603713e-14,  1.95399252e-14]])
```

[18]:
```python
np.linalg.norm(A - B)
```

[18]:
```
8.523187293941492e-14
```

5. Define W as the matrix containing the first 2 columns of V , which defines a plane formed by the first 2 principal components.

Answer: Y = V.T ==> V = Y.T

[20]:
```python
V = Y.T
V
```

[20]:
```
array([[-4.47213595e-01, -4.04516436e-01,  2.46564896e-01,
        -6.62726001e-01,  3.69278287e-01],
       [-4.47213595e-01, -5.56615971e-03,  6.62726001e-01,
         2.46564896e-01, -5.47694274e-01],
       [-4.47213595e-01,  8.20165192e-01, -3.22455040e-14,
        -3.69575263e-17,  3.56831975e-01],
       [-4.47213595e-01, -5.56615971e-03, -6.62726001e-01,
        -2.46564896e-01, -5.47694274e-01],
       [-4.47213595e-01, -4.04516436e-01, -2.46564896e-01,
         6.62726001e-01,  3.69278287e-01]])
```

[21]:
```python
W = V[:,:2]
W
```

[21]:
```
array([[-0.4472136 , -0.40451644],
       [-0.4472136 , -0.00556616],
       [-0.4472136 ,  0.82016519],
       [-0.4472136 , -0.00556616],
       [-0.4472136 , -0.40451644]])
```

6. Project the matrix A to the new plane by perform the dot product of A and W , denoted the reduced matrix as Ar

[23]:
```python
Ar = np.dot(A, W)
Ar
```

[23]: array([[-2.90688837e+01, -1.23024779e+01],
        [-2.90688837e+01, -1.01407417e+01],
        [-2.90688837e+01, -5.29465360e-13],
        [-2.90688837e+01, 1.01407417e+01],
        [-2.90688837e+01, 1.23024779e+01]])

1.1.3 Exercise 2: Use Scikit-Learn to perform PCA analysis in Exercise 1.

(this matrix will be centered around the mean)

1. Load library: from sklearn.decomposition import PCA.

[26]:
```
from sklearn.decomposition import PCA
```

2. Initialize a PCA model with 2 components.

[28]:
```
model = PCA(n_components=2)
```

3. Use Model.fit(A) to fit the model.

[30]:
```
model.fit(A)
```

[30]: PCA(n_components=2)

[31]:
```
print(f"components: {model.components_}")
print(f"explained variance: {model.explained_variance_}")
print(f"explained variance ratio: {model.explained_variance_ratio_}")
print(f"n components: {model.n_components_}")
print(f"n samples: {model.n_samples_}")
print(f"n features in: {model.n_features_in_}")
```

```
components: [[ 4.04516436e-01  5.56615971e-03 -8.20165192e-01  5.56615971e-03
   4.04516436e-01]
 [-2.46564896e-01 -6.62726001e-01 -3.54216581e-15  6.62726001e-01
   2.46564896e-01]]
explained variance: [127.09280205 117.58610463]
explained variance ratio: [0.39105478 0.3618034 ]
n components: 2
n samples: 5
n features in: 5
```

4. Use Model.transform(A) to transform reduce the dimension of matrix A.

[33]:
```
model.transform(A)
```

[33]: array([[1.23024779e+01, -1.10967458e+01],
        [1.01407417e+01, 4.23857973e+00],
        [-6.25055563e-14, 1.37163321e+01],
        [-1.01407417e+01, 4.23857973e+00],

```
       [-1.23024779e+01, -1.10967458e+01]])
```

5. Print the percentage of variance explained by each of the selected components.

```
[35]: print(f"explained variance ratio: {model.explained_variance_ratio_} per␣
       ↪component")
      print(f"total variance explained by all components {sum(model.
       ↪explained_variance_ratio_)}")
```

```
explained variance ratio: [0.39105478 0.3618034 ] per component
total variance explained by all components 0.7528581744203147
```

6. Compare the reduced matrix here with that obtained in Exercise 1. What is your observation?

Answer: they are not the same

7. If 80% of information, how many components should we use?

```
[38]: model2 = PCA(n_components=3)
      model2.fit(A)
      print(f"explained variance ratio: {model2.explained_variance_ratio_} per␣
       ↪component")
      print(f"total variance explained by all components {sum(model2.
       ↪explained_variance_ratio_)}")
```

```
explained variance ratio: [0.39105478 0.3618034  0.1381966 ] per component
total variance explained by all components 0.8910547755453252
```

1.1.4 Exercise 3: Revisit Exercise 1

1. Center the data by performing A_centered = A_i - mean(A)

```
[41]: A_centered_around_mean = A - np.mean(A)
      A_centered_around_mean
```

```
[41]: array([[  4.,  11., -12.,  -5.,   2.],
             [ 10.,  -8.,  -6.,   1.,   3.],
             [ -9.,  -7.,   0.,   7.,   9.],
             [ -3.,  -1.,   6.,   8., -10.],
             [ -2.,   5.,  12., -11.,  -4.]])
```

2. Repeat the tasks in Exercise 1 for A center , and compare the reduced matrix here with that obtained in Exercise 2

```
[43]: Xc, sc, Yc = np.linalg.svd(A_centered_around_mean) # c = centered
      var = (sc ** 2) / np.sum(sc ** 2)
      var
```

```
[43]: array([3.91054776e-01, 3.61803399e-01, 1.38196601e-01, 1.08945224e-01,
             4.85090051e-34])
```

[44]:
```
Bc = Xc @ np.diag(sc) @ Yc
Bc
```

[44]:
```
array([[ 4.00000000e+00,  1.10000000e+01, -1.20000000e+01,
        -5.00000000e+00,  2.00000000e+00],
       [ 1.00000000e+01, -8.00000000e+00, -6.00000000e+00,
         1.00000000e+00,  3.00000000e+00],
       [-9.00000000e+00, -7.00000000e+00,  4.46161833e-15,
         7.00000000e+00,  9.00000000e+00],
       [-3.00000000e+00, -1.00000000e+00,  6.00000000e+00,
         8.00000000e+00, -1.00000000e+01],
       [-2.00000000e+00,  5.00000000e+00,  1.20000000e+01,
        -1.10000000e+01, -4.00000000e+00]])
```

[45]:
```
Vc = Yc.T
Wc = Vc[:,:2]
A_centered_around_mean_reduced = np.dot(A_centered_around_mean, Wc)
A_centered_around_mean_reduced
```

[45]:
```
array([[-1.23024779e+01,  1.10967458e+01],
       [-1.01407417e+01, -4.23857973e+00],
       [ 6.25055563e-14, -1.37163321e+01],
       [ 1.01407417e+01, -4.23857973e+00],
       [ 1.23024779e+01,  1.10967458e+01]])
```

The matrix is the same as the one obtained in exercise 2 value-wise but complementary sign-wise which is fine. it is due to picking different pos and negative axes

1.2 2. SVD and PCA for image compression

1.2.1 setup

Load the picture "swim.jpg" from Homework 4, and define the data as "image". It is a RGB color image. Split the three colors, e.g.

red = image[:, :, 0] green = image[:, :, 1] blue = image[:, :, 2]

[50]:
```
import imageio
import matplotlib.pyplot as plt
```

[51]:
```
image = imageio.imread("./swim.jpg") # W x H x D (where D is 3)
print(f"{np.shape(image)}")
plt.imshow(image)
plt.show()
```

```
(1200, 1600, 3)
```

[52]:
```
red = image[:,:,0]
green = image[:,:,1]
blue = image[:,:,2]

red
```

[52]:
```
Array([[ 90, 106, 116, …,  89,  94,  99],
       [ 93, 107, 117, …,  84,  86,  86],
       [ 95, 107, 117, …,  77,  76,  76],
       …,
       [ 57,  61,  63, …,  88,  94,  87],
       [ 60,  61,  62, …,  72, 101,  87],
       [ 58,  57,  58, …,  58,  83,  94]], dtype=uint8)
```

1.2.2 Exercise 4: Use SVD to perform image compression.

1. For each color,

- (a) Perform SVD, e.g., Ur, sr, VrT = np.linalg.svd(red).
- (b) Compute the k-rank approximation, e.g.,

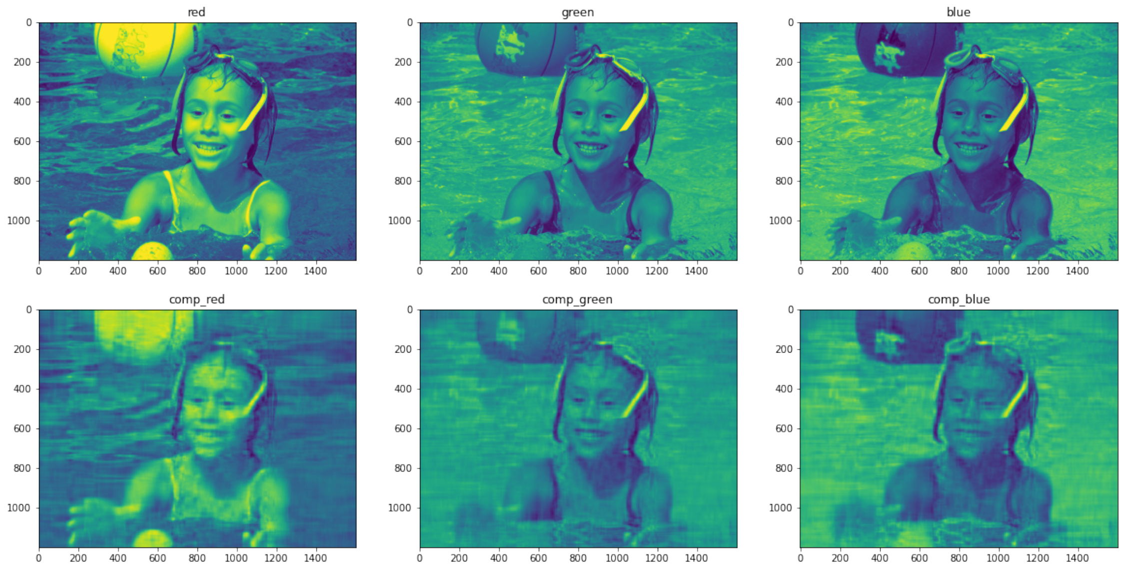
[55]:
```
# Compressed color matrices
k = 20

Ur, sr, VTr = np.linalg.svd(red) # r = red, T = Transpose
Ug, sg, VTg = np.linalg.svd(green) # r = green, T = Transpose
```

```python
Ub, sb, VTb = np.linalg.svd(blue) # b = blue, T = Transpose

comp_red = 0
comp_green = 0
comp_blue = 0
for j in range(k): # k-rank approximation
    comp_red += sr[j] * np.outer(Ur[:,j], VTr.T[:,j])
    comp_green += sg[j] * np.outer(Ug[:,j], VTg.T[:,j])
    comp_blue += sb[j] * np.outer(Ub[:,j], VTb.T[:,j])

print(f"shape: {np.shape(comp_red)}")
print(f"shape: {np.shape(comp_green)}")
print(f"shape: {np.shape(comp_blue)}")
```

```
shape: (1200, 1600)
shape: (1200, 1600)
shape: (1200, 1600)
```

2. Make a plot with 2 3 subplots. The first row shows the original image of each color, while the second row shows the corresponding compressed image with k = 20.

[57]:
```python
fix, axes = plt.subplots(2, 3, figsize=(20,10))

axes[0,0].set_title("red")
axes[0,0].imshow(red)
axes[0,1].set_title("green")
axes[0,1].imshow(green)
axes[0,2].set_title("blue")
axes[0,2].imshow(blue)

axes[1,0].set_title("comp_red")
axes[1,0].imshow(comp_red)
axes[1,1].set_title("comp_green")
axes[1,1].imshow(comp_green)
axes[1,2].set_title("comp_blue")
axes[1,2].imshow(comp_blue)

plt.show()
```



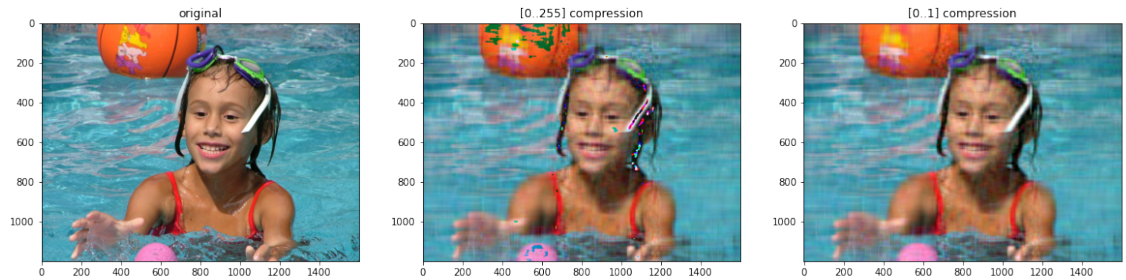
3. Combine three compressed image into a RGB image. Make a plot with 2 1 subplots to compare the compressed image with the original one.

[59]:
```
# keeping both versions as a constructive example
new_comp_image1 = np.zeros((1200,1600,3), np.uint8) # uses 0..255
new_comp_image2 = np.zeros((1200,1600,3)) # gets divided bt 255, thus uses 0...
↪1 float values (similar to using np.float64)

new_comp_image1[:,:,0] = comp_red
new_comp_image1[:,:,1] = comp_green
new_comp_image1[:,:,2] = comp_blue

new_comp_image2[:,:,0] = comp_red
new_comp_image2[:,:,1] = comp_green
new_comp_image2[:,:,2] = comp_blue

# np.stack((comp_red, comp_green, comp_blue), axis=-1) # axis = -1 because we␣
↪are inputting back into the 3rd dim
```

[60]:
```
fix, axes = plt.subplots(1, 3, figsize=(20,10))

axes[0].set_title("original")
axes[0].imshow(image)

axes[1].set_title("[0..255] compression")
axes[1].imshow(new_comp_image1)

axes[2].set_title("[0..1] compression")
```

```
axes[2].imshow(new_comp_image2/255)

plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```



[0..255] creats more jumps in RGB data while [0..1] is more continuous

[62]:
```
new_comp_image1[:,:,0]
```

[62]:
```
array([[90, 90, 89, …, 76, 76, 76],
       [91, 91, 90, …, 76, 77, 77],
       [91, 91, 91, …, 77, 78, 78],
       …,
       [63, 65, 65, …, 62, 61, 59],
       [64, 65, 65, …, 59, 59, 57],
       [64, 65, 65, …, 57, 57, 55]], dtype=uint8)
```

[63]:
```
new_comp_image2[:,:,0]/255
```

[63]:
```
array([[0.35465665, 0.35431185, 0.35246822, …, 0.29921647, 0.3005075 ,
        0.30114719],
       [0.35736373, 0.35716577, 0.35548999, …, 0.30110658, 0.30255269,
        0.30311513],
       [0.35934212, 0.35934207, 0.35779764, …, 0.30583563, 0.30729739,
        0.30760134],
       …,
       [0.25056304, 0.25558621, 0.25638659, …, 0.24450831, 0.24251457,
        0.23424918],
       [0.25132471, 0.25639013, 0.25750143, …, 0.23527269, 0.23352885,
        0.22547061],
       [0.25250537, 0.25767154, 0.25879431, …, 0.22708176, 0.22543199,
        0.21730521]])
```

1.2.3 Exercise 5: Use PCA to perform image compression.

1. For each color,

(a) Perform PCA, e.g.,

- pcar = PCA(n components = 10)
- reduced red = pcar.fit transform(red)

It reduces the original dimension to, e.g. 10, dimensions.

(b) Use pcar.inverse transform(reduced red) to decompress it back to original dimensions.

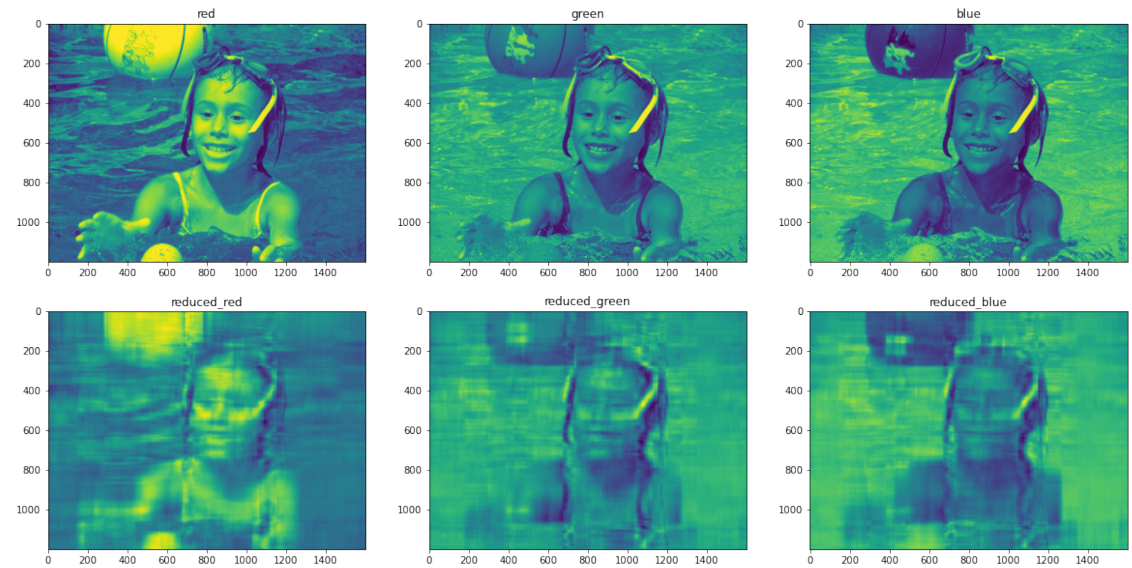
[66]:
```
from sklearn.decomposition import PCA
```

[67]:
```
k = 10

# Red
PCAr = PCA(n_components = k)
reduced_red = PCAr.fit_transform(red)
reduced_red = PCAr.inverse_transform(reduced_red)

# Green
PCAg = PCA(n_components = k)
reduced_green = PCAg.fit_transform(green)
reduced_green = PCAg.inverse_transform(reduced_green)

# Blue
PCAb = PCA(n_components = k)
reduced_blue = PCAb.fit_transform(blue)
reduced_blue = PCAb.inverse_transform(reduced_blue)
```

2. Make a plot with 2 3 subplots. The first row shows the original image of each color, while the second row shows the corresponding reduced(i.e., compressed) image with 20 components.

[69]:
```
fix, axes = plt.subplots(2, 3, figsize=(20,10))

axes[0,0].set_title("red")
axes[0,0].imshow(red)
axes[0,1].set_title("green")
axes[0,1].imshow(green)
axes[0,2].set_title("blue")
axes[0,2].imshow(blue)

axes[1,0].set_title("reduced_red")
axes[1,0].imshow(reduced_red)
axes[1,1].set_title("reduced_green")
axes[1,1].imshow(reduced_green)
axes[1,2].set_title("reduced_blue")
axes[1,2].imshow(reduced_blue)
```

```
plt.show()
```

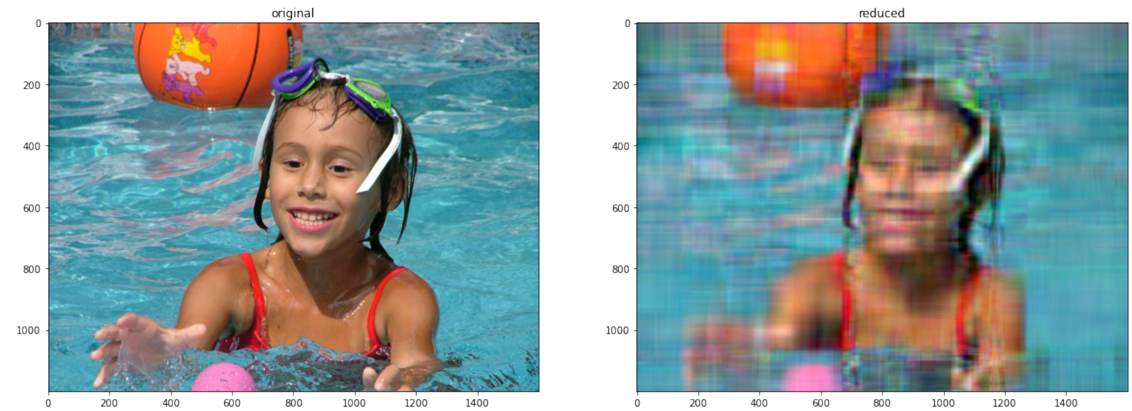


3. Combine three compressed image into a RGB image. Make a plot with 2 1 subplots to compare the compressed image with the original one.

[71]:
```
# keeping both versions as a constructive example
new_reduced_image = np.zeros((1200,1600,3))

new_reduced_image[:,:,0] = reduced_red
new_reduced_image[:,:,1] = reduced_green
new_reduced_image[:,:,2] = reduced_blue

# np.stack((reduced_red, reduced_green, reduced_blue), axis=-1) # axis = -1 because we are inputting back into the 3rd dim
```

[72]:
```
fix, axes = plt.subplots(1, 2, figsize=(20,10))

axes[0].set_title("original")
axes[0].imshow(image)

axes[1].set_title("reduced")

#normalize_reduced_image = new_reduced_image / np.max(new_reduced_image)
#clipped_reduced_image = np.clip(new_reduced_image/255, 0., 1.)
axes[1].imshow(new_reduced_image/255)

plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```



1.3 3. PCA for dimensionality reduction

1.3.1 Exercise 6: Consider the data diagnosis.csv for cancer diagnosis.

1. Use Scikit-Learn to perform PCA analysis for the features of data, and reduce the data to two dimensions.

[76]:
```python
import pandas as pd
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
```

[77]:
```python
cancer_data = pd.read_csv("diagnosis.csv", delimiter=",", header=0).
 ↪drop('Unnamed: 32',axis=1)
cancer_data
```

[77]:
```
           id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0      842302         M        17.99         10.38          122.80     1001.0
1      842517         M        20.57         17.77          132.90     1326.0
2    84300903         M        19.69         21.25          130.00     1203.0
3    84348301         M        11.42         20.38           77.58      386.1
4    84358402         M        20.29         14.34          135.10     1297.0
..        …       …          …           …             …          …
564    926424         M        21.56         22.39          142.00     1479.0
565    926682         M        20.13         28.25          131.20     1261.0
566    926954         M        16.60         28.08          108.30      858.1
567    927241         M        20.60         29.33          140.10     1265.0
568     92751         B         7.76         24.54           47.92      181.0

     smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0            0.11840           0.27760         0.30010              0.14710
1            0.08474           0.07864         0.08690              0.07017
2            0.10960           0.15990         0.19740              0.12790
```

```
3           0.14250          0.28390         0.24140                0.10520
4           0.10030          0.13280         0.19800                0.10430
..              …                …               …                    …
564         0.11100          0.11590         0.24390                0.13890
565         0.09780          0.10340         0.14400                0.09791
566         0.08455          0.10230         0.09251                0.05302
567         0.11780          0.27700         0.35140                0.15200
568         0.05263          0.04362         0.00000                0.00000

     …  radius_worst  texture_worst  perimeter_worst  area_worst  \
0    …        25.380          17.33           184.60      2019.0
1    …        24.990          23.41           158.80      1956.0
2    …        23.570          25.53           152.50      1709.0
3    …        14.910          26.50            98.87       567.7
4    …        22.540          16.67           152.20      1575.0
..   …            …              …                …          …
564  …        25.450          26.40           166.10      2027.0
565  …        23.690          38.25           155.00      1731.0
566  …        18.980          34.12           126.70      1124.0
567  …        25.740          39.42           184.60      1821.0
568  …         9.456          30.37            59.16       268.6

     smoothness_worst  compactness_worst  concavity_worst  \
0             0.16220            0.66560           0.7119
1             0.12380            0.18660           0.2416
2             0.14440            0.42450           0.4504
3             0.20980            0.86630           0.6869
4             0.13740            0.20500           0.4000
..                …                  …               …
564           0.14100            0.21130           0.4107
565           0.11660            0.19220           0.3215
566           0.11390            0.30940           0.3403
567           0.16500            0.86810           0.9387
568           0.08996            0.06444           0.0000

     concave points_worst  symmetry_worst  fractal_dimension_worst
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
4                  0.1625          0.2364                  0.07678
..                    …               …                      …
564                0.2216          0.2060                  0.07115
565                0.1628          0.2572                  0.06637
566                0.1418          0.2218                  0.07820
567                0.2650          0.4087                  0.12400
568                0.0000          0.2871                  0.07039
```

```
[569 rows x 32 columns]
```

[78]:
```
# Encoding categorical column
label_encoder = LabelEncoder()
label_encoder.fit(cancer_data["diagnosis"])
cancer_data['diagnosis'] = label_encoder.transform(cancer_data['diagnosis'])

X = cancer_data.iloc[:,2:] # features, avoiding the id and diagnosis columns
y = cancer_data["diagnosis"] # labels
```

[79]:
```
k = 2

PCA_cancer = PCA(n_components = k)
reduced_cancer_data = PCA_cancer.fit_transform(X)
reduced_cancer_data
```

[79]:
```
array([[1160.1425737 , -293.91754364],
       [1269.12244319,   15.63018184],
       [ 995.79388896,   39.15674324],
       …,
       [ 314.50175618,   47.55352518],
       [1124.85811531,   34.12922497],
       [-771.52762188,  -88.64310636]])
```

[80]:
```
print("shape of reduced data: ", np.shape(reduced_cancer_data))
```

```
shape of reduced data:  (569, 2)
```

2. What is the total percentage of variance explained by this reduced data?

[82]:
```
print(f"explained variance ratio: {PCA_cancer.explained_variance_ratio_} per␣
↪component")
print(f"total variance explained by the components above: {sum(PCA_cancer.
↪explained_variance_ratio_)}")
```

```
explained variance ratio: [0.98204467 0.01617649] per component
total variance explained by the components above: 0.9982211613741724
```

3. Use the reduced data to perform the logistic regression (split 25% data as test data with random state=20).

[84]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

[85]:
```
x_train, x_test, y_train, y_test = train_test_split(reduced_cancer_data, y,␣
↪test_size=0.25, shuffle=True, random_state=20)
model = LogisticRegression()
```

```
model.fit(x_train, y_train)

print("trained model parameters are:")
print(model.coef_, model.intercept_)
```

```
trained model parameters are:
[[ 0.01286424 -0.03663826]] [1.22540627]
```

4. Print out the in-sample and out-sample confusing matrix and accuracy.

[87]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
```

[88]:
```
ypred_train        = model.predict(x_train)
accuracy_train     = accuracy_score(y_train, ypred_train)
conf_matrix_train  = confusion_matrix(y_train, ypred_train)
print('Accuracy for training data (R^2): ', accuracy_train, '\n')
print('Confusion matrix for training data:\n', conf_matrix_train, '\n')

ypred_test         = model.predict(x_test)
accuracy_test      = accuracy_score(y_test,ypred_test)
conf_matrix_test   = confusion_matrix(y_test, ypred_test)
print('Accuracy for test data (R^2): ', accuracy_test, '\n')
print('Confusion matrix for test data:\n', conf_matrix_test, '\n')
```

```
Accuracy for training data (R^2):  0.9295774647887324

Confusion matrix for training data:
 [[261  10]
 [ 20 135]]

Accuracy for test data (R^2):  0.9370629370629371

Confusion matrix for test data:
 [[84  2]
 [ 7 50]]
```

1.3.2 Exercise 7: Revisit Exercise 6. Normalize the reduced data before performing the logistic regression.

[90]:
```
from sklearn.preprocessing import MinMaxScaler
```

[91]:
```
scaler = MinMaxScaler().fit(reduced_cancer_data)
reduced_normalized_data = scaler.transform(reduced_cancer_data)
print(np.shape(reduced_normalized_data))
reduced_normalized_data
```

```
(569, 2)
```

[91]:
```
array([[0.42772682, 0.267593  ],
       [0.4507654 , 0.48695099],
       [0.39298315, 0.50362286],
       …,
       [0.24895651, 0.50957316],
       [0.42026761, 0.50006016],
       [0.01936754, 0.41305874]])
```

[92]:
```
x_train, x_test, y_train, y_test = train_test_split(reduced_normalized_data, y,␣
 ↪test_size=0.25, shuffle=True, random_state=20)
norm_model = LogisticRegression()
norm_model.fit(x_train, y_train)

print("trained model parameters are:")
print(norm_model.coef_, norm_model.intercept_)
```

```
trained model parameters are:
[[ 8.1668785 -0.526361 ]] [-1.79846019]
```

[93]:
```
ypred_train        = norm_model.predict(x_train)
accuracy_train     = accuracy_score(y_train, ypred_train)
conf_matrix_train  = confusion_matrix(y_train, ypred_train)
print('Accuracy for training data (R^2): ', accuracy_train, '\n')
print('Confusion matrix for training data:\n', conf_matrix_train, '\n')

ypred_test         = norm_model.predict(x_test)
accuracy_test      = accuracy_score(y_test,ypred_test)
conf_matrix_test   = confusion_matrix(y_test, ypred_test)
print('Accuracy for test data (R^2): ', accuracy_test, '\n')
print('Confusion matrix for test data:\n', conf_matrix_test, '\n')
```

```
Accuracy for training data (R^2):  0.8568075117370892

Confusion matrix for training data:
 [[270   1]
 [ 60  95]]

Accuracy for test data (R^2):  0.8601398601398601

Confusion matrix for test data:
 [[86  0]
 [20 37]]
```

[ ]:
```
We can see that the results are around
```

[94]:
```
!pip install nbconvert
```

```
Defaulting to user installation because normal site-packages is not writeable
Looking in links: /usr/share/pip-wheels
Requirement already satisfied: nbconvert in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (6.4.4)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.5.13)
Requirement already satisfied: jupyter-core in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (4.9.2)
Requirement already satisfied: pandocfilters>=1.4.1 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (1.5.0)
Requirement already satisfied: jupyterlab-pygments in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.1.2)
Requirement already satisfied: nbformat>=4.4 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (5.3.0)
Requirement already satisfied: traitlets>=5.0 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (5.1.1)
Requirement already satisfied: defusedxml in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.7.1)
Requirement already satisfied: mistune<2,>=0.8.1 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.8.4)
Requirement already satisfied: testpath in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.5.0)
Requirement already satisfied: beautifulsoup4 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (4.11.1)
Requirement already satisfied: bleach in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (4.1.0)
Requirement already satisfied: pygments>=2.4.1 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (2.11.2)
Requirement already satisfied: jinja2>=2.4 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (2.11.3)
Requirement already satisfied: entrypoints>=0.2.2 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbconvert) (0.4)
Requirement already satisfied: MarkupSafe>=0.23 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
```

```
jinja2>=2.4->nbconvert) (2.0.1)
Requirement already satisfied: nest-asyncio in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbclient<0.6.0,>=0.5.0->nbconvert) (1.5.5)
Requirement already satisfied: jupyter-client>=6.1.5 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbclient<0.6.0,>=0.5.0->nbconvert) (6.1.12)
Requirement already satisfied: tornado>=4.1 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from jupyter-
client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (6.1)
Requirement already satisfied: pyzmq>=13 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from jupyter-
client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (22.3.0)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from jupyter-
client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (2.8.2)
Requirement already satisfied: fastjsonschema in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbformat>=4.4->nbconvert) (2.15.1)
Requirement already satisfied: jsonschema>=2.6 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
nbformat>=4.4->nbconvert) (4.4.0)
Requirement already satisfied: attrs>=17.4.0 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
jsonschema>=2.6->nbformat>=4.4->nbconvert) (21.4.0)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
jsonschema>=2.6->nbformat>=4.4->nbconvert) (0.18.0)
Requirement already satisfied: six>=1.5 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from python-
dateutil>=2.1->jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert)
(1.16.0)
Requirement already satisfied: soupsieve>1.2 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
beautifulsoup4->nbconvert) (2.3.1)
Requirement already satisfied: webencodings in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
bleach->nbconvert) (0.5.1)
Requirement already satisfied: packaging in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
bleach->nbconvert) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/opt/conda/envs/anaconda-2022.05-py39/lib/python3.9/site-packages (from
packaging->bleach->nbconvert) (3.0.4)
```

[4]:

```
!jupyter nbconvert --to pdf "hw5-6.ipynb"
```

```
[NbConvertApp] Converting notebook hw5-6.ipynb to pdf
```

```
[NbConvertApp] Support files will be in hw5-6_files/
[NbConvertApp] Making directory ./hw5-6_files
[NbConvertApp] Making directory ./hw5-6_files
[NbConvertApp] Making directory ./hw5-6_files
[NbConvertApp] Making directory ./hw5-6_files
[NbConvertApp] Making directory ./hw5-6_files
[NbConvertApp] Writing 94324 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 2654145 bytes to hw5-6.pdf
```

[ ]:

```

```