

# PCA for Color image compression

September 20, 2022

[ ]: Normally images have a lot of pixels to retain their clarity, but that ↴ significantly increases its size and slows down the performance of the system when it has to process multiple images. To ↴ overcome this situation we can use the dimensionality reduction technique which comes under Unsupervised Machine ↴ Learning. We will use one picture and reduce its dimensions or in other words compress the image using PCA in python.

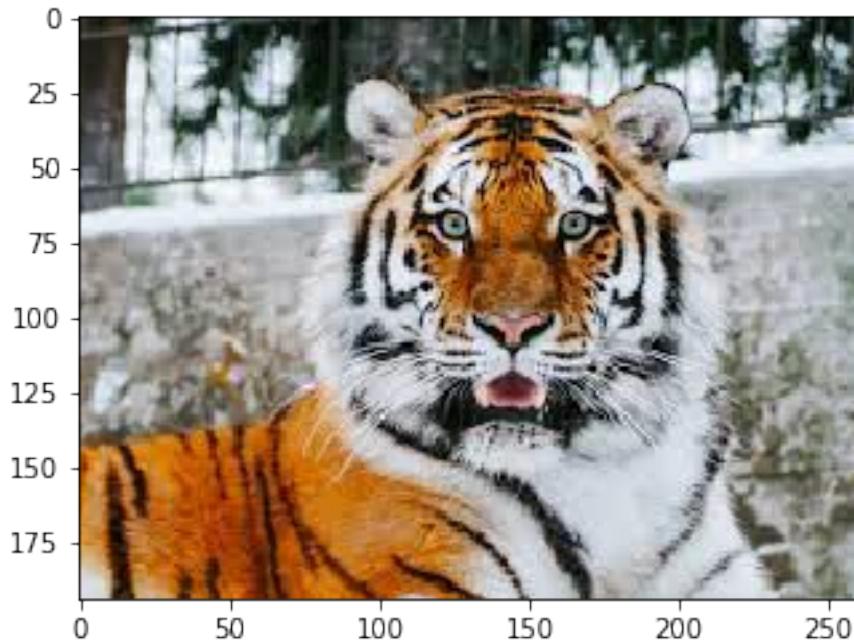
Algorithm:

- i) Split the image into the three channels (Blue, Green, and Red) first
- ii) Perform PCA separately on each dataset representing each channel
- iii) Merge them to reconstruct the compressed image.

[41]: #Load and pre-process the image

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import cv2
from scipy.stats import stats
import matplotlib.image as mpimg
```

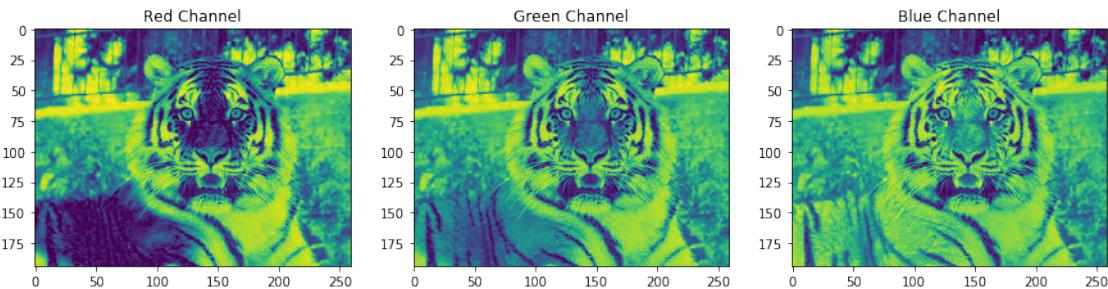
[42]: img = cv2.cvtColor(cv2.imread('tiger.jfif'), cv2.COLOR\_BGR2RGB)
plt.imshow(img)
plt.show()



```
[44]: img.shape
```

```
[44]: (194, 259, 3)
```

```
[45]: #Splitting into channels
blue,green,red = cv2.split(img)
# Plotting the images
fig = plt.figure(figsize = (15, 7.2))
fig.add_subplot(131)
plt.title("Red Channel")
plt.imshow(red)
fig.add_subplot(132)
plt.title("Green Channel")
plt.imshow(green)
fig.add_subplot(133)
plt.title("Blue Channel")
plt.imshow(blue)
plt.show()
```



```
[46]: blue_temp_df = pd.DataFrame(data = blue)
blue_temp_df
```

```
[46]:      0    1    2    3    4    5    6    7    8    9    ...   249   250   251   \
0     40   52   55   45   36   36   34   28   27   33   ...    13     8     2
1     48   60   61   49   38   37   33   26   27   33   ...    16    12     3
2     44   55   55   42   29   27   22   15   31   35   ...    18    12     5
3     43   54   56   45   33   33   29   22   29   33   ...    12     0     6
4     40   53   57   49   41   44   42   37   43   47   ...    4     0     8
...
189   230  228  225  220  217  216  217  221  228  207  ...  133  123  108
190   233  230  226  221  214  213  214  217  221  204  ...  113  103  92
191   232  229  225  221  215  211  212  214  224  212  ...  95   87   83
192   224  222  221  219  216  214  215  216  215  215  ...  99   90   84
193   222  221  220  219  218  216  216  217  215  214  ...  119  108  101

      252  253  254  255  256  257  258
0     12    3   22   14   13   32   48
1     11    9   24    8   11   30   46
2     15   20   28    8    7   29   46
3     16   25   30   15    5   27   44
4     11   16   19   16    5   27   45
...
189   105  115  122  119  150  155  163
190    96  111  117  111  153  158  165
191    94  115  124  120  154  158  164
192   101  127  121   98  115  115  161
193   119  144  139  116  115  114  160
```

[194 rows x 259 columns]

```
[47]: df_blue = blue/255
df_green = green/255
df_red = red/255
```

```
[48]: pca_b = PCA(n_components=50)
pca_b.fit(df_blue)
trans_pca_b = pca_b.transform(df_blue)
pca_g = PCA(n_components=50)
pca_g.fit(df_green)
trans_pca_g = pca_g.transform(df_green)
pca_r = PCA(n_components=50)
pca_r.fit(df_red)
trans_pca_r = pca_r.transform(df_red)
```

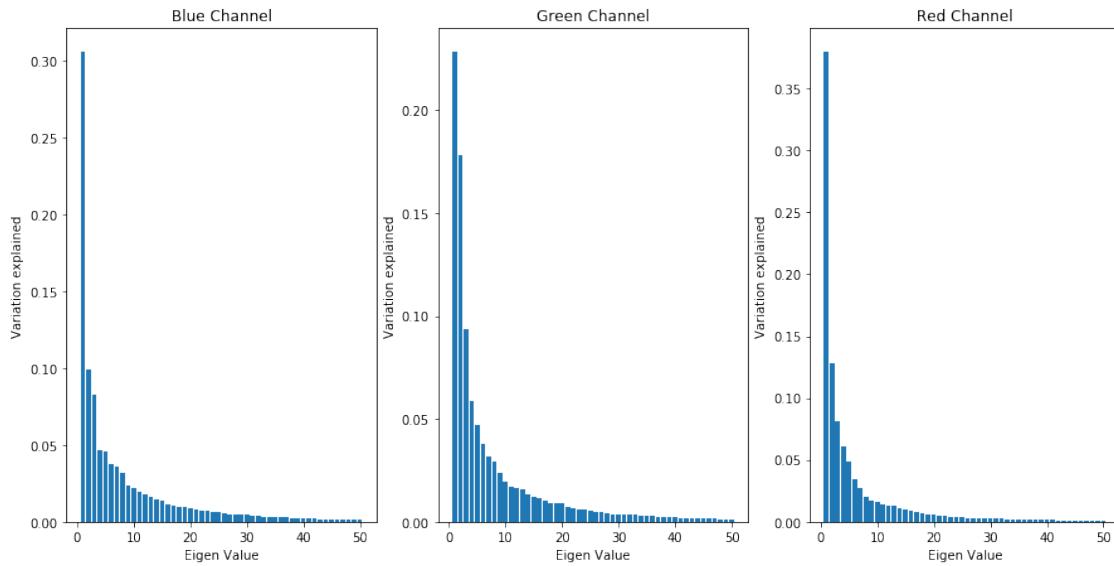
```
[50]: print(trans_pca_b.shape)
print(trans_pca_r.shape)
print(trans_pca_g.shape)
```

```
(194, 50)
(194, 50)
(194, 50)
```

```
[51]: print(f"Blue Channel : {sum(pca_b.explained_variance_ratio_)}")
print(f"Green Channel: {sum(pca_g.explained_variance_ratio_)}")
print(f"Red Channel   : {sum(pca_r.explained_variance_ratio_)}")
```

```
Blue Channel : 0.967393998073789
Green Channel: 0.9685616475342463
Red Channel   : 0.9786243808465617
```

```
[52]: fig = plt.figure(figsize = (15, 7.2))
fig.add_subplot(131)
plt.title("Blue Channel")
plt.ylabel('Variation explained')
plt.xlabel('Eigen Value')
plt.bar(list(range(1,51)),pca_b.explained_variance_ratio_)
fig.add_subplot(132)
plt.title("Green Channel")
plt.ylabel('Variation explained')
plt.xlabel('Eigen Value')
plt.bar(list(range(1,51)),pca_g.explained_variance_ratio_)
fig.add_subplot(133)
plt.title("Red Channel")
plt.ylabel('Variation explained')
plt.xlabel('Eigen Value')
plt.bar(list(range(1,51)),pca_r.explained_variance_ratio_)
plt.show()
```



```
[54]: b_arr = pca_b.inverse_transform(trans_pca_b)
g_arr = pca_g.inverse_transform(trans_pca_g)
r_arr = pca_r.inverse_transform(trans_pca_r)
print(b_arr.shape, g_arr.shape, r_arr.shape)
```

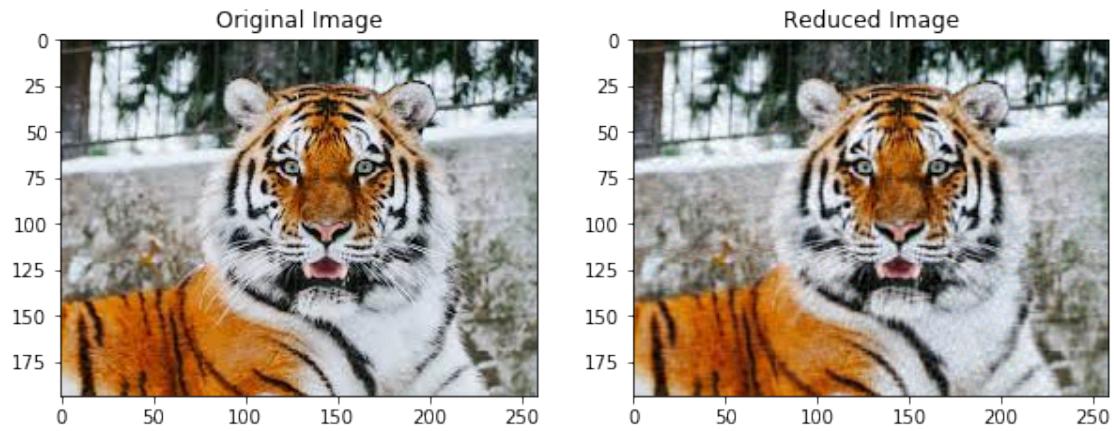
(194, 259) (194, 259) (194, 259)

```
[55]: img_reduced= (cv2.merge((b_arr, g_arr, r_arr)))
print(img_reduced.shape)
```

(194, 259, 3)

```
[56]: fig = plt.figure(figsize = (10, 7.2))
fig.add_subplot(121)
plt.title("Original Image")
plt.imshow(img)
fig.add_subplot(122)
plt.title("Reduced Image")
plt.imshow(img_reduced)
plt.show()
```

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



[ ]: