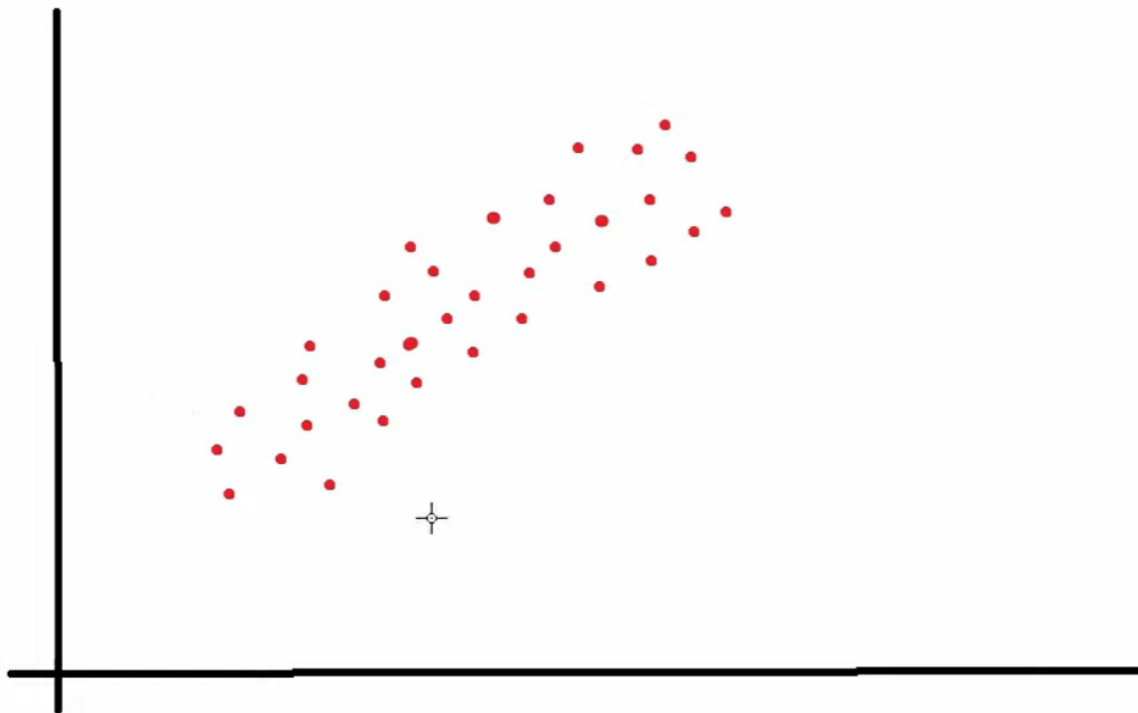


# Principle Component Analysis

Ahman Smith

Main principle: Dimensionality reduction

Unsupervised learning algorithm



If we wanted to reduce the dimensionality, we'd project all of these points onto a line.

However, **we want a good line. Not a shitty one.** We find the best line by testing which line can preserve most of the data that we care about.

Takes n-dimensional dataset and finds the best axis that preserves the most variance

## An application of PCA: Image Compression

I will apply PCA to this image of a robot in order to compress it:



I begin by importing the necessary libraries and loading the image with the RGB color set:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
```

✓ 6.9s Python

```
img = cv2.cvtColor(cv2.imread('C:\\Users\\defra\\Downloads\\download.jpg'), cv2.COLOR_BGR2RGB)
```

✓ 0.0s Python

I then print out the shape of the image just to take a peek:

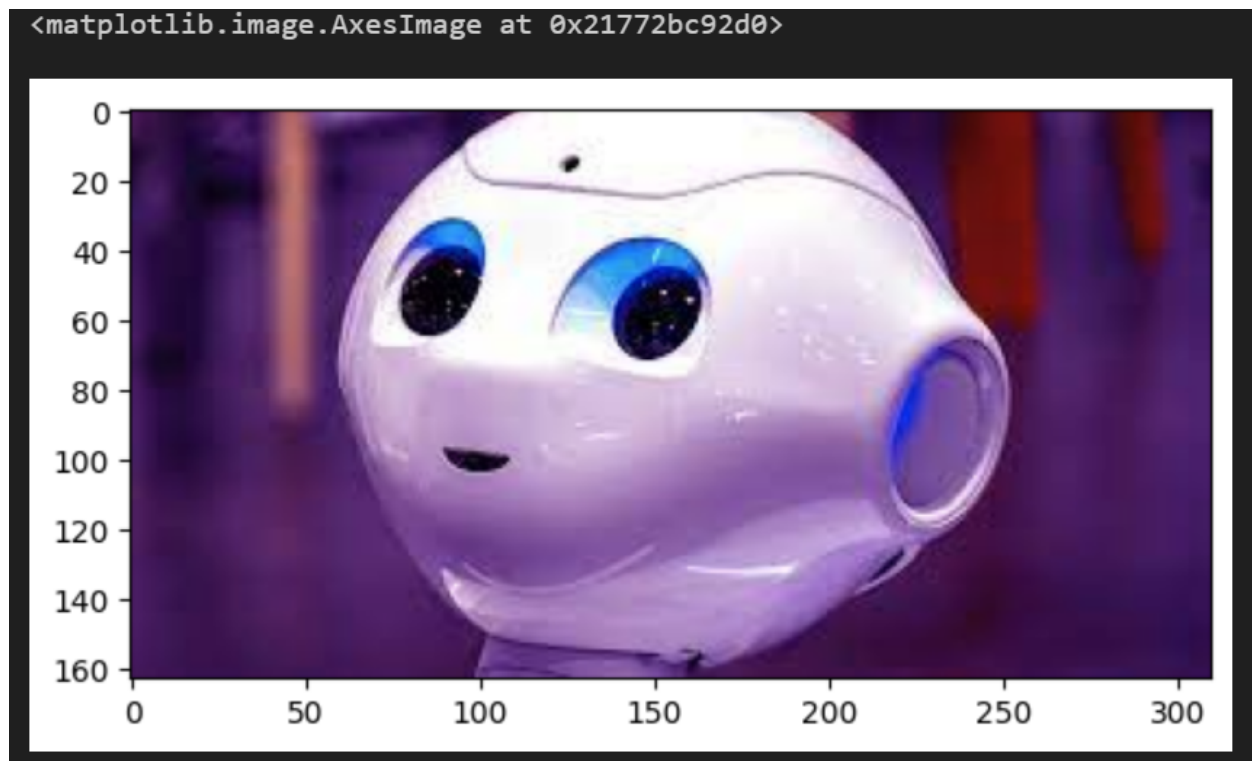
```
img.shape
```

[6] ✓ 0.0s Python

... (163, 310, 3)

163 rows, 310 columns

We can also show the image on a graph by using `plt.imshow()`:



## Reduction

Our image has three channels. We want to split it up.

```
[8] r, g, b = cv2.split(img)
    ✓ 0.0s

[9] r, g, b = r / 255, g / 255, b / 255
    ✓ 0.1s

[10] plt.imshow(r)
    ✓ 0.5s

... <matplotlib.image.AxesImage at 0x217726bf2d0>

</> 
```

Split it up into R, G, B channels. Divided it all by 255 since that is the maximum value it can have. I printed out the red channel. There isn't much red.

## Components

We're going to reduce the components to 25, declared by `pca_components = 25`

```
[11] ✓ 0.1s

pca_components = 25
pca_r = PCA(n_components=pca_components)
reduced_r = pca_r.fit_transform(r)

[12] ✓ 0.0s

print(reduced_r.shape)

... (163, 25)
```

As we can see, the columns are reduced.

I did this to every channel.

```
pca_components = 50
pca_r = PCA(n_components=pca_components)
reduced_r = pca_r.fit_transform(r)

pca_g = PCA(n_components=pca_components)
reduced_g = pca_g.fit_transform(g)

pca_b = PCA(n_components=pca_components)
reduced_b = pca_b.fit_transform(b)
```

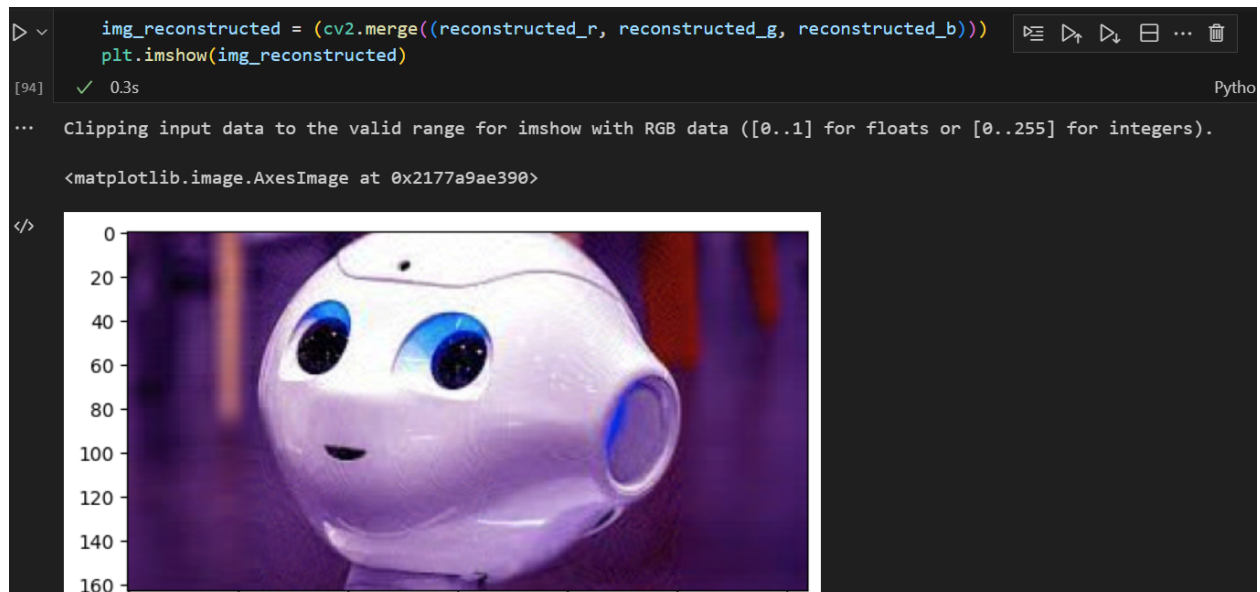
98] ✓ 0.1s Python

Then, we reconstruct each channel that's reduced:

```
reconstructed_r = pca_r.inverse_transform(reduced_r)
reconstructed_g = pca_g.inverse_transform(reduced_g)
reconstructed_b = pca_b.inverse_transform(reduced_b)
```

99] ✓ 0.0s Python

Finally, we can see the output as:



Compared to before, there is not much of a difference. This is with 50 principle components.