

# PRINCIPAL COMPONENT ANALYSIS

ACTIVITY 03  
PHYSICS 301

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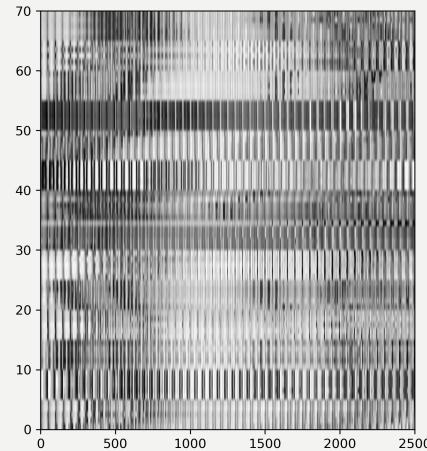
# THE DATASET

5 grayscale faces x 14 people = 70 images



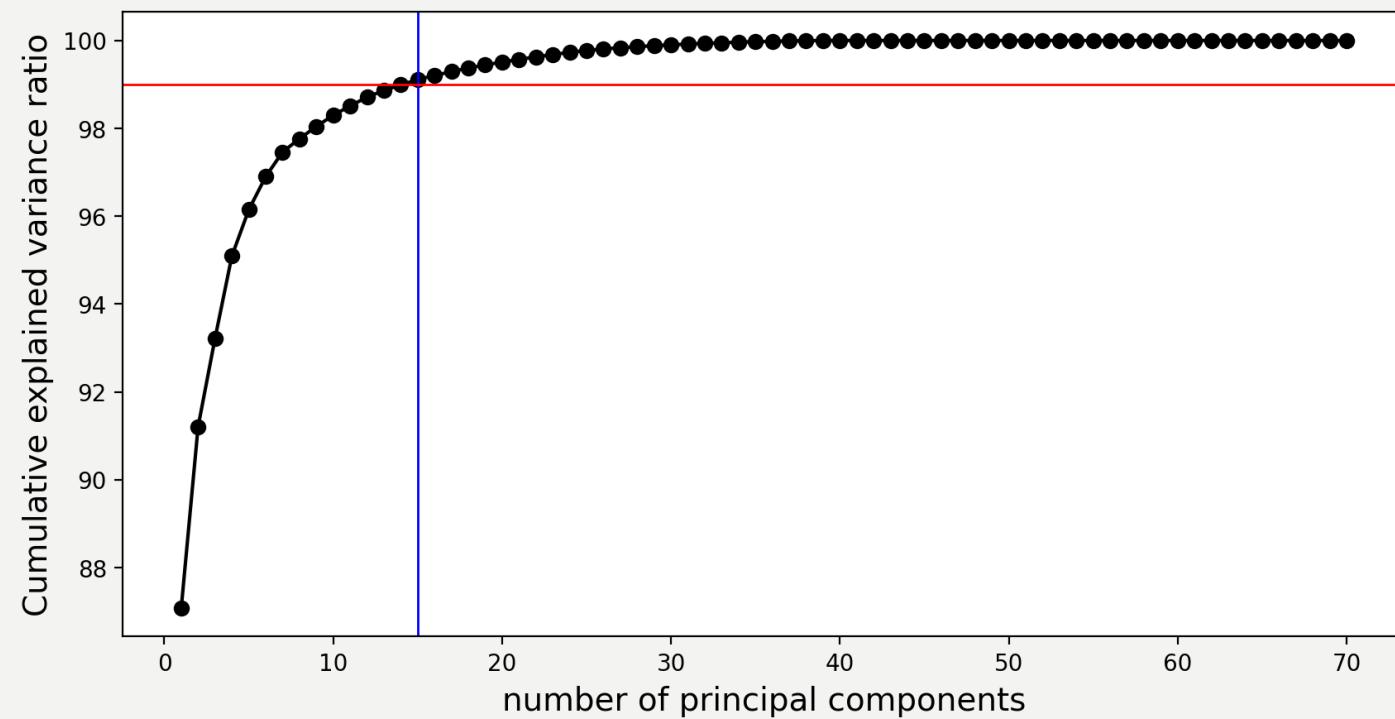
The size of each image is set at  $50 \times 50$  pixels. Though some appear gray, when read in Python, they still have RGB channels so to convert those images to grayscale, we use the function `rgb2gray()`.

We converted these images first into 1D arrays and then stacked them together to create a single matrix whose size is given by  $70 \times 2500$ . Then, to perform Principal Component Analysis (PCA), we use sklearn's built-in PCA function.



# EXPLAINED VARIANCE RATIO

| Number of components | Cumulative variance |
|----------------------|---------------------|
| 1                    | 87.07642052 %       |
| 2                    | 91.21159146 %       |
| 3                    | 93.21508751 %       |
| 4                    | 95.09459801 %       |
| 5                    | 96.14693623 %       |
| 6                    | 96.89970176 %       |
| 7                    | 97.46013982 %       |
| 8                    | 97.76318455 %       |
| 9                    | 98.04219112 %       |
| 10                   | 98.29744237 %       |
| 11                   | 98.51020153 %       |
| 12                   | 98.71002222 %       |
| 13                   | 98.86092503 %       |
| 14                   | 98.99008769 %       |
| 15                   | 99.10895945 %       |



The minimum number of principal components is 15 in order to have a face reconstruction that is 99% accurate.

# PRINCIPAL COMPONENTS

Principal Component: 1



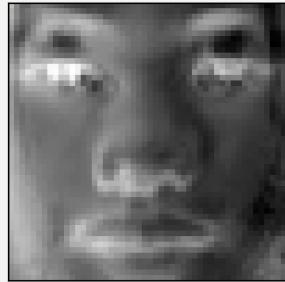
Principal Component: 2



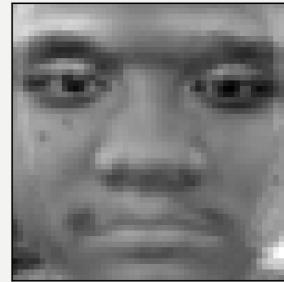
Principal Component: 3



Principal Component: 4



Principal Component: 5



Principal Component: 6



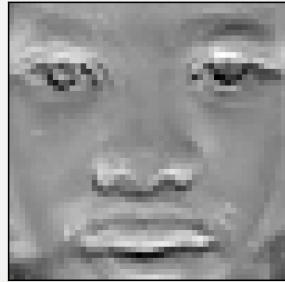
Principal Component: 7



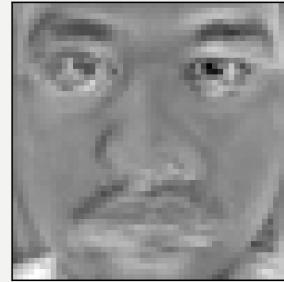
Principal Component: 8



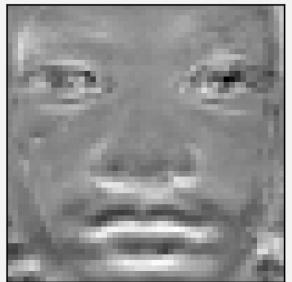
Principal Component: 9



Principal Component: 10



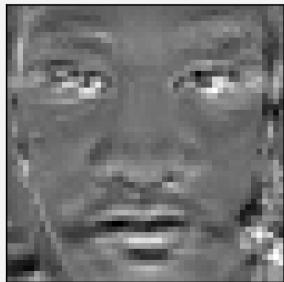
Principal Component: 11



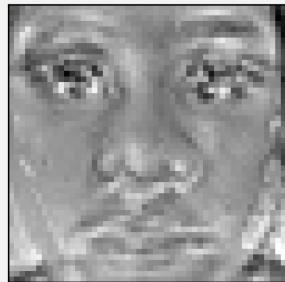
Principal Component: 12



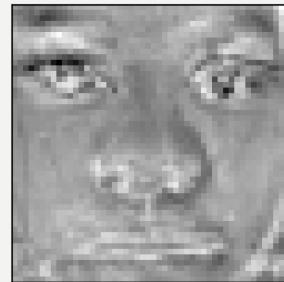
Principal Component: 13



Principal Component: 14



Principal Component: 15



Looking at the top 15 principal components (PCs) , we see that the first PC is basically a combination of all the images while the others are just superposition of other faces with different weights.

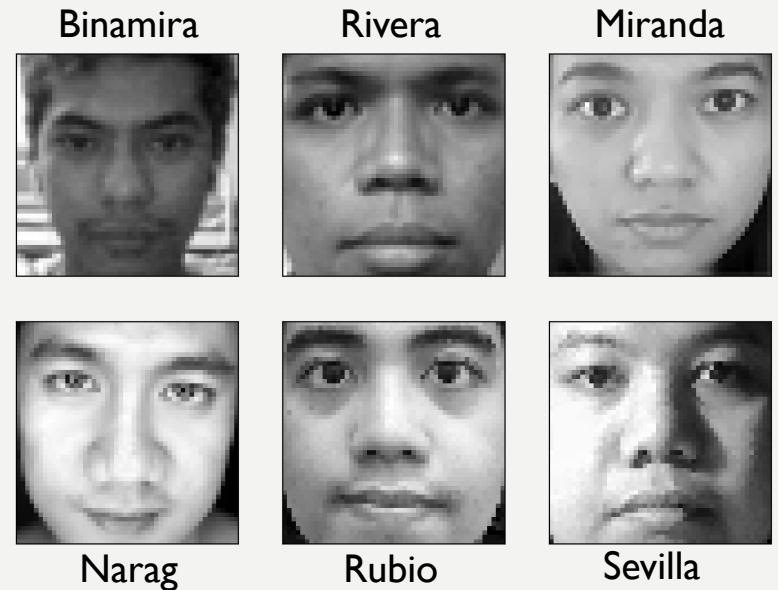
What's interesting here, and a possible limitation of PCA, is that we see that the principal component 2 has a very distinct image and is almost like one of the faces used. This is what happens when you add data that are way too different compared to the others in our dataset.

# RECONSTRUCTED IMAGES

Image Reconstruction using the top 15 principal components



Images not reconstructed properly

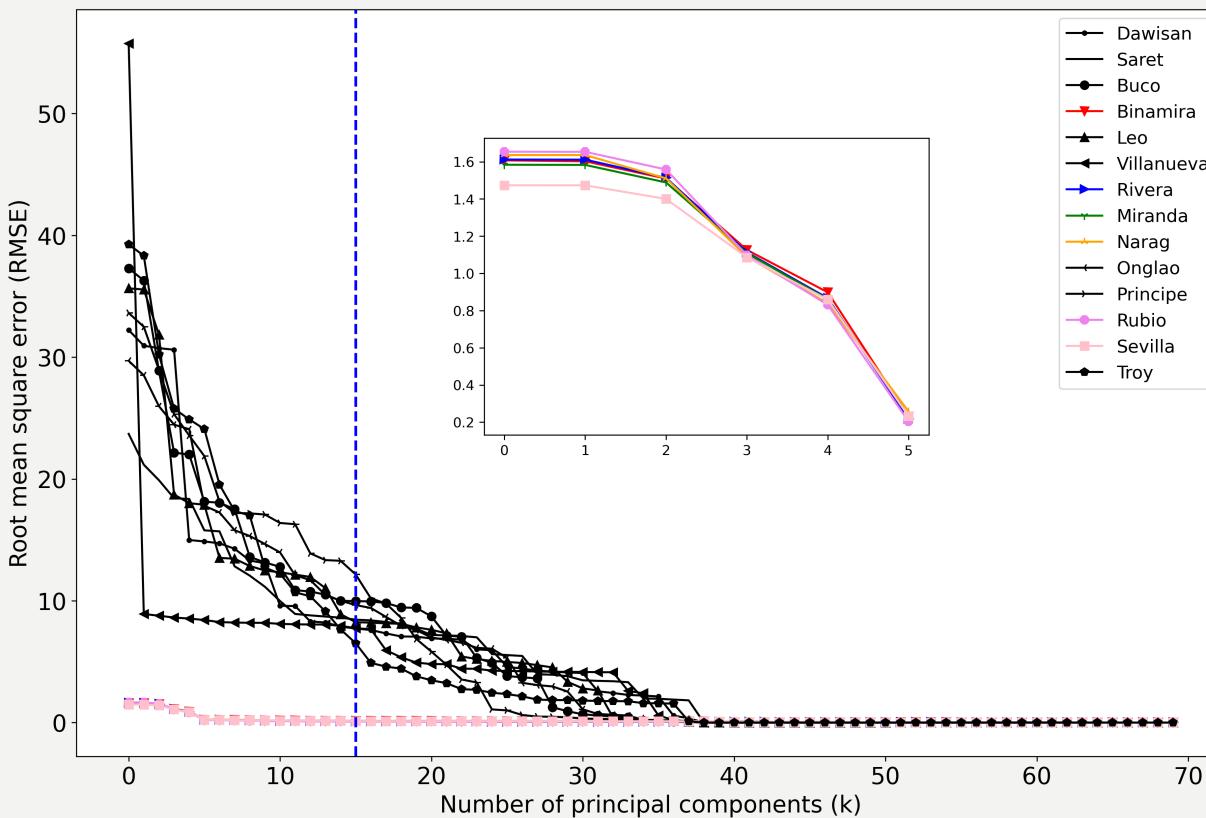


The 6 faces above were not reconstructed properly using the top 15 principal components. The reason behind this is that these photos have darker lighting and did not follow the prescribed cropping which made them very different from the others. To confirm this, let us look at the average RMSE and SSIM of each person.

# METRICS

## Root Mean Square Error (RMSE)

- Measures the amount of change per pixel due to image processing
- An RMSE value closer to zero means that the error signal of the test image is almost non-existent.



### Discussion:

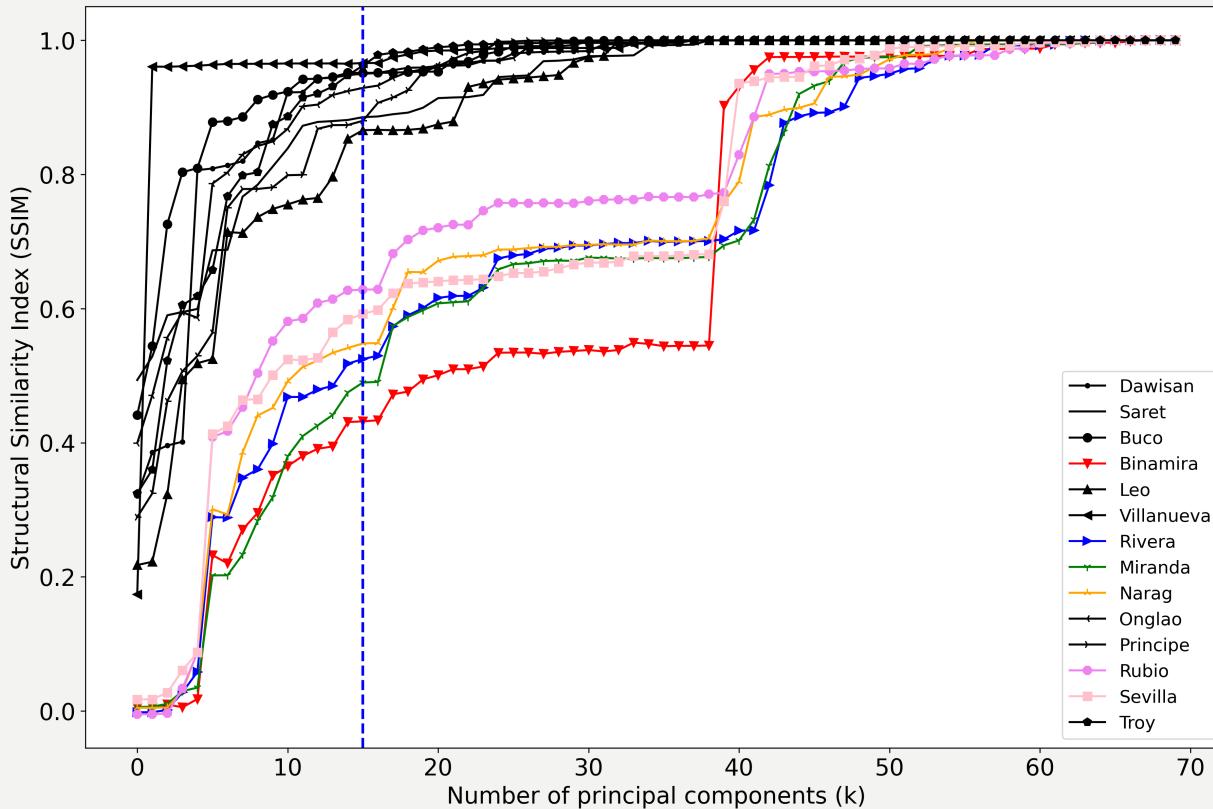
We can see from the RMSE plot of each person's face (each plot was average since each person submitted 5 faces) that the 6 persons whose faces were not reconstructed properly have the same trend.

Now, we can see that though the RMSE value is very low for these faces, we were still not able to reconstruct the original images. This is because one disadvantage of using MSE and RMSE is that it has poor correlation with human perception of visual system. With RMSE, there is a possibility of mismatch between error visibility and loss of quality. Therefore, we use another metric, called **Structural Similarity Index (SSIM)**.

# METRICS

## Structural Similarity Index (SSIM)

- Measures the perceptual difference between two similar images
- SSIM values close to 1 means that two images are almost identical



### Discussion:

We now see here that the 6 people with poorly reconstructed images have low SSIM values ( $SSIM \in [0.4, 0.65]$ ) at  $k = 15$  while the other images have SSIM values greater than 0.80.

We also see that for the 6 images, we can get a proper reconstructed of the images if we use at least 40 principal components.

# RECONSTRUCTED FACES (AGAIN)

If we compare the reconstructed image of these 6 faces using 15 PCs vs 45 PCs, we see that the actual face becomes more distinguishable.



Components: 15



Components: 45



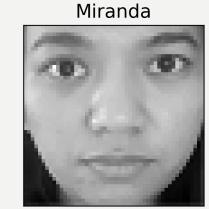
Rivera



Components: 15



Components: 45



Components: 15



Components: 45



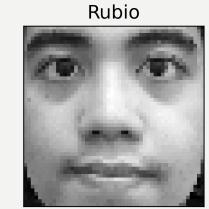
Narag



Components: 15



Components: 45



Components: 15



Components: 45



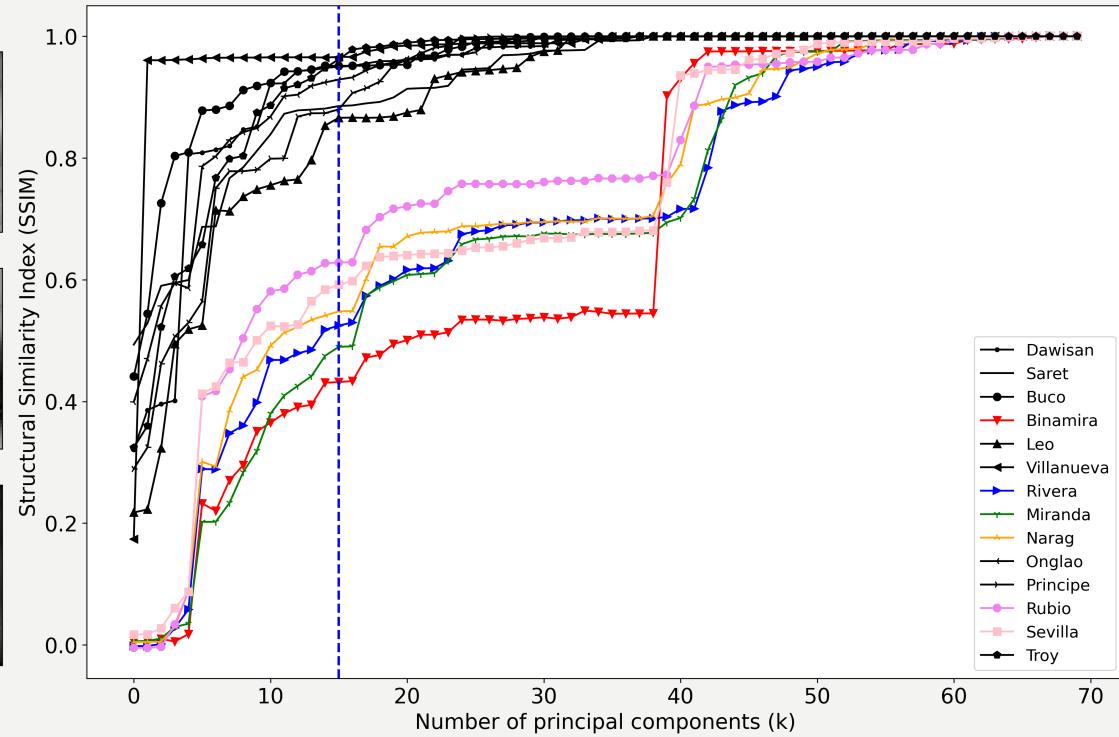
Sevilla



Components: 15



Components: 45



# SUMMARY AND REFERENCES

## Summary

For this experiment, I was able to successfully perform PCA using the dataset compiled by the class. But other than that, I was also successful in mastering or familiarizing myself with some of the built-in matrix multiplication functions in python such as '@' and '\*'. I was also able to use two different metrics to quantitatively describe the reconstructed images and we can see that using just one type of metric (RMSE) is not enough, so we need to use another metric (SSIM) to make sure that our findings are indeed possible and not just some error.

## References

- [1] Gandhi, S.A., & Kulkarni, C.V. (2013). MSE Vs SSIM. *International Journal of Scientific & Engineering Research*, 4(7), 930–934.
- [2] Niku Ekhtiari, P. D. (n.d.). *Comparing ground truth with predictions using image similarity measures*. UP42 Official Website. Retrieved June 7, 2022, from <https://up42.com/blog/tech/image-similarity-measures>

### Score:

Technical Correctness – 30  
Quality of Presentation – 30  
Reflection – 30  
Ownership – 10

Total – 100/100