

Principal Component Analysis

Exploring the Concepts and Applications

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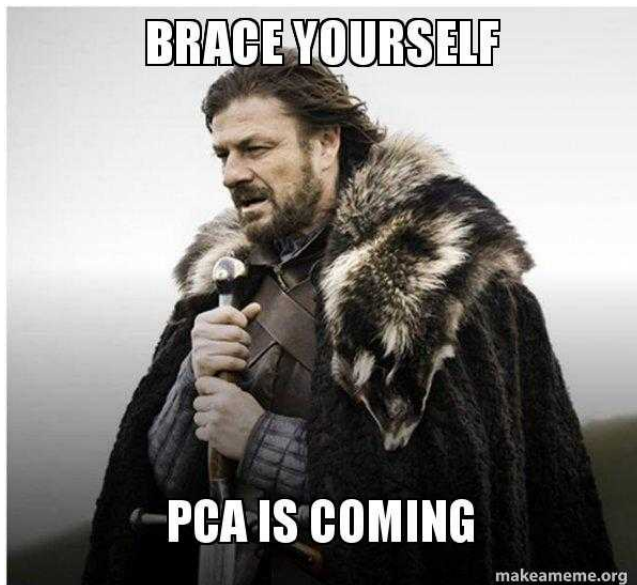
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Outline

- 1 Introduction to PCA
 - A Terrible Curse: Dimensionality
- 2 Applications of PCA
- 3 PCA in Machine Learning
- 4 Conclusion and Disadvantages

Introduction to PCA



A Terrible Curse



The Curse of Dimensionality

Need for Data Points with Increase in Dimensions

1 Binary feature	→	2^1 unique values	→	$2^1 \times 10 = 20$ data points
2 Binary features	→	2^2 unique values	→	$2^2 \times 10 = 40$ data points
3 Binary features	→	2^3 unique values	→	$2^3 \times 10 = 80$ data points
⋮		⋮		⋮
⋮		⋮		⋮
⋮		⋮		⋮
k Binary features	→	2^k unique values	→	$2^k \times 10$ data points

Figure: Scaling of datapoints with dimensions¹

- Higher dimensional data needs more computational effort
- As the dimensionality increases, number of minimum data points for nominal analysis increases.

¹<https://towardsdatascience.com/>

Curse of Dimensionality

- Are dimensions to be discarded then?

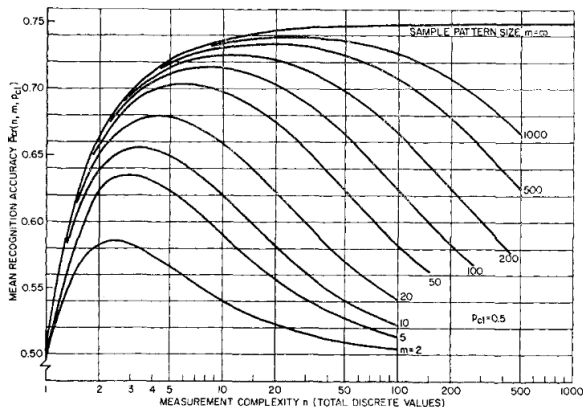
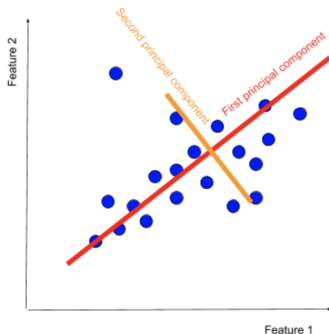
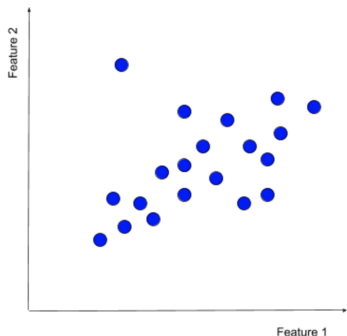


Figure: The tradeoff between dimensionality and number of datapoints (Hughes 1968).

Principal Component Analysis

Principal Component Analysis (PCA) is an algorithm to find best set of basis.

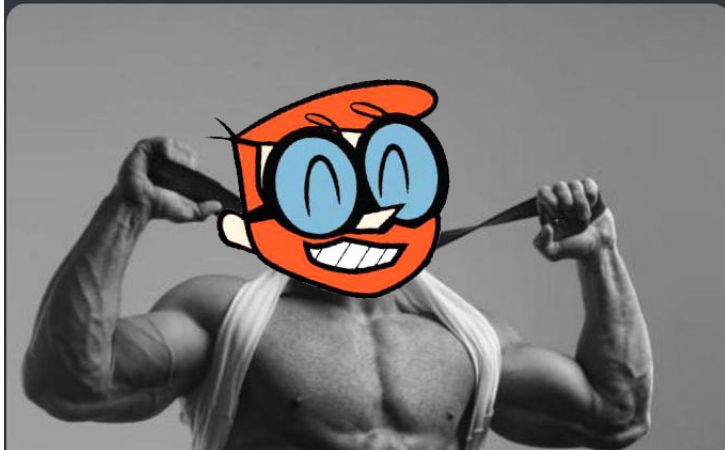


Principal Components are new variables that are constructed from linear combinations of the old feature dimensions.

PCA tries to assign maximum information in the first Principal Component, and gradually decreases over the later ones.

Geometrically, it represents directions which explain maximal amount of variance.

- >Barges into any discussion or argument
- >PCA is just the eigenvectors of the covariance matrix
- >Refuses to elaborate further
- >Leaves



Principal Component Analysis

- **Standardization:** This basically sets the scales in the data, so that each data contributes equally to it.

$$z = \frac{\text{value} - \text{mean}}{\text{standard deviation}} \quad (1)$$

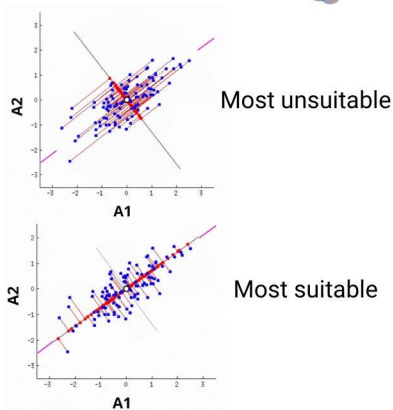
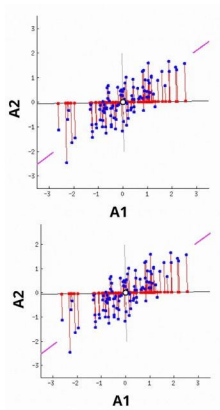
- **Covariance Matrix Computation:** Calculate the covariance matrix over all the feature dimensions.

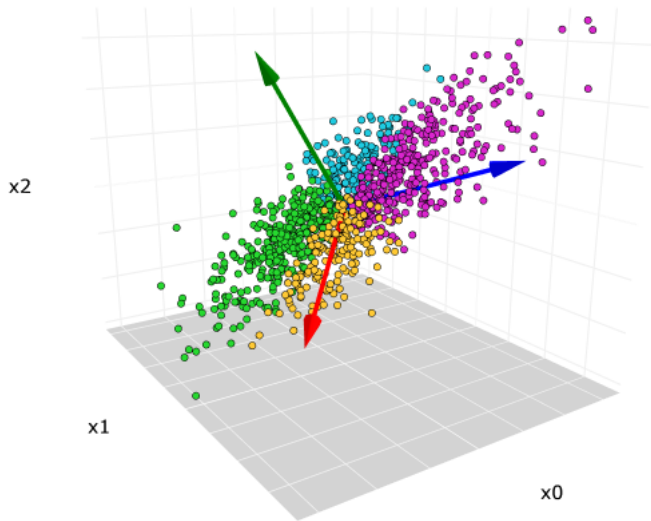
$$\text{covar}(x, y) = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{n} \quad (2)$$

- **Compute the eigenvectors and eigenvalues of Covariance Matrix:** Then pick dominant eigenvectors, as per requirement.

Principal Component Analysis

Does not look very promising, for a two dimensional case, but this is extremely useful in higher dimensions.





Seems all Statistics!!



Applications of PCA

- Image compression: Calculate the PCA of the image, and remove components with less information.
- Feature reduction in machine learning.
- Anomaly detection.

- PCA can be used to reduce the dimensions, and re-cast the data to newer dimensions. If the data size is lesser than dimensionality, we can try to do some trade-off.

Disadvantages

- Interpretability
- Information Loss
- Outliers affect PCA strongly
- Computationally expensive for big datasets.



Thank You



References I



Hughes, G. (Jan. 1968). “On the mean accuracy of statistical pattern recognizers”. In: *IEEE Transactions on Information Theory* 14.1. Conference Name: IEEE Transactions on Information Theory, pp. 55–63. ISSN: 1557-9654. DOI: 10.1109/TIT.1968.1054102. URL: <https://ieeexplore.ieee.org/document/1054102/citations#citations> (visited on 02/03/2024).