Dimensionality Reduction

Dimensionality Reduction

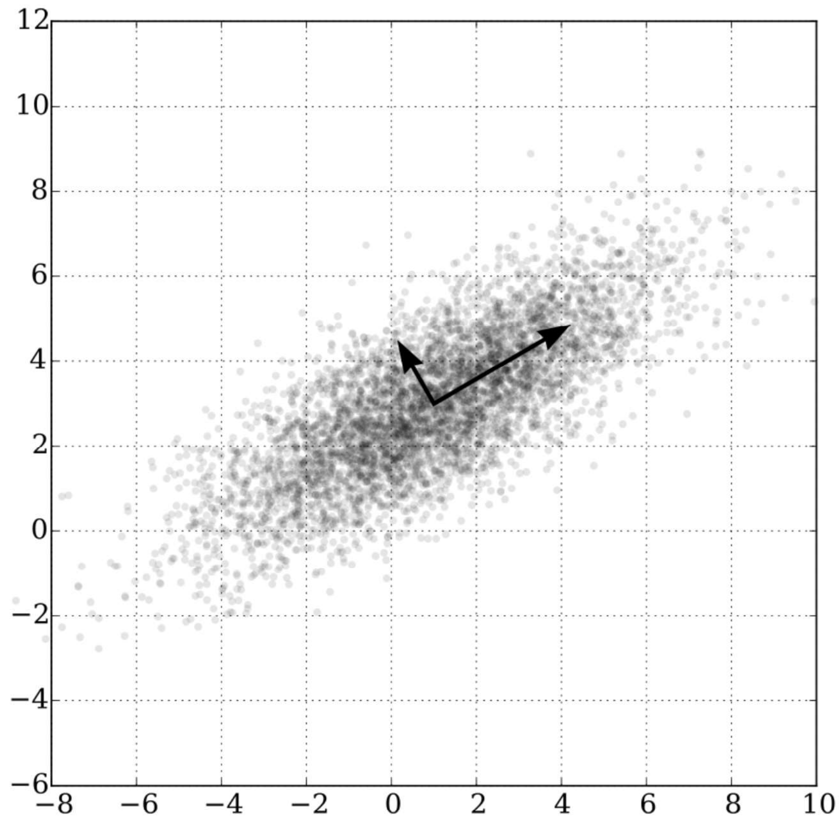
- The process of reducing the number of independent variables
- Reducing dimensionality of independent variables helps in many ways
  - removes multi-collinearity to improve ML model performance
  - helps reduce over fitting
  - decreases computational times for fitting models
  - makes visualization easier
  - decreases storage requirements
  - avoids curse of dimensionality
- Hence dimensionality reduction plays a significant role in analyzing data

Dim. Reduction Techniques

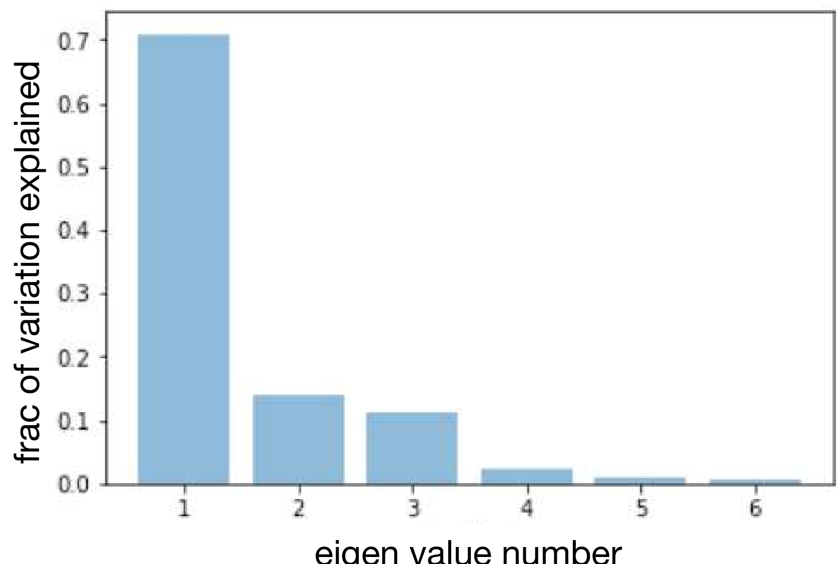
- Feature elimination
  - Simply identify and remove variables (columns) that are not important
  - The disadvantage is that we would gain no insight from those dropped variables and loose any information they contain
- Feature extraction
  - Create a few new variables from the old variables
  - <u>**PCA**</u> Principal Component Analysis: is the most popular feature extraction technique (linear)
  - t-SNE (non-linear)

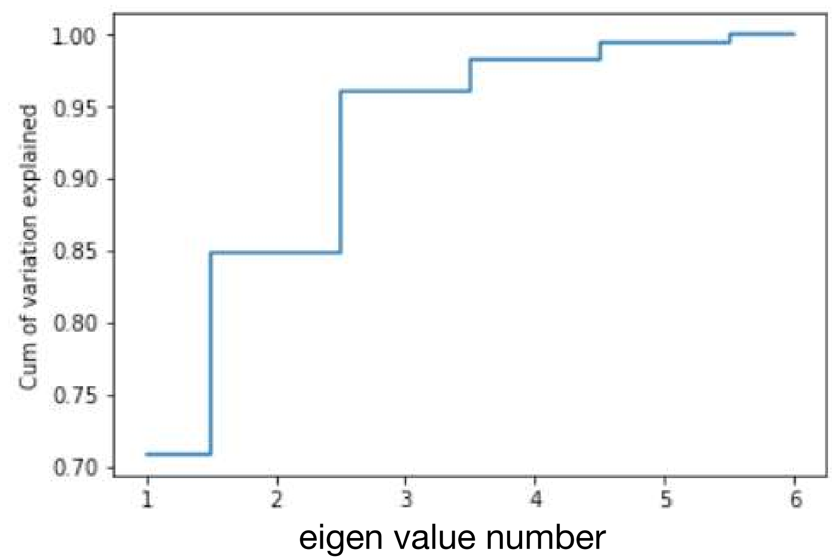
PCA

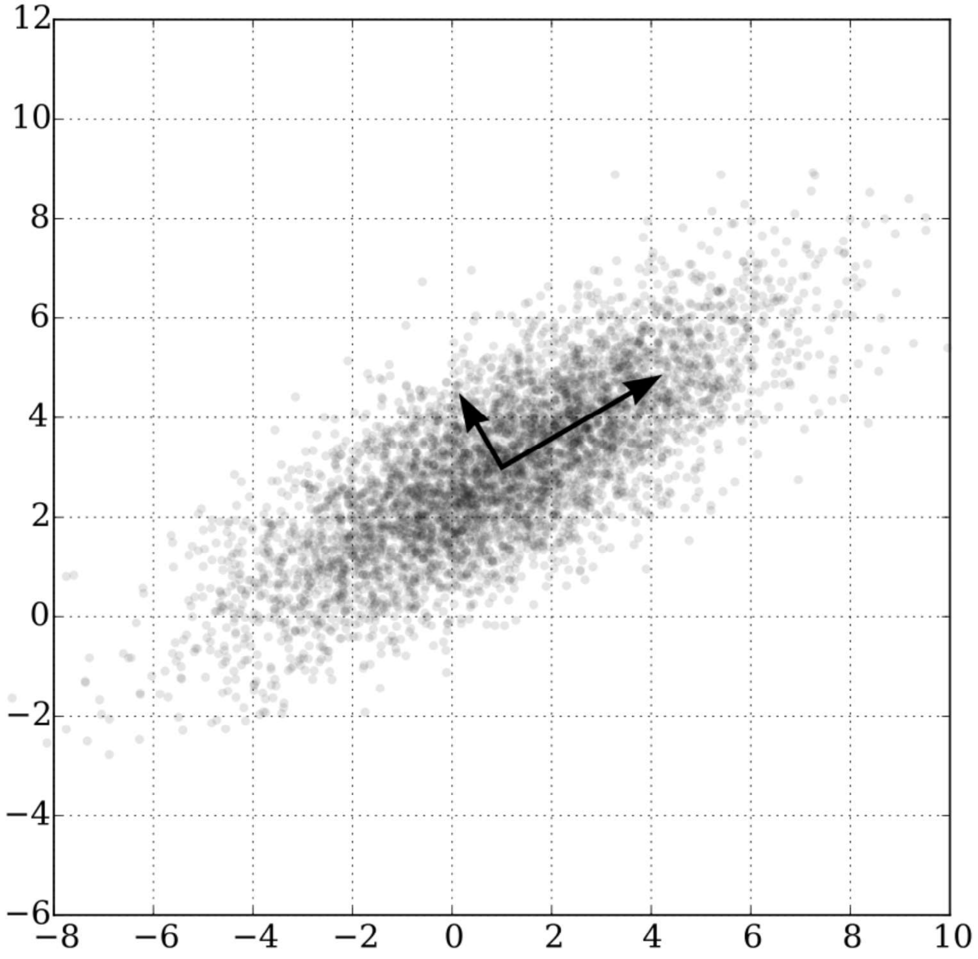
- creates new variables using linear combinations of old variables
- is designed to create variables that are independent of one another
- also manages to tell us how important each of these new variables are
- this “importance”, helps us to choose how many variables we will use



- Scale the data and compute the covariance matrix
- Break the covariance matrix into magnitude and direction. Eigen Vectors and the Eigen Values of the covariance matrix can be thought of as the natural axis/directions and magnitudes along those axis, of the data
    - The eigen values also can be used to calculate the percentage of variation explained by each component
- Sort in the eigen values in desending order and calculate the cumulative percentage of variation explained
- Pick the number of principal components you will use
- Transform to new variables



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