

B4M36SAN

# Dimensionality reduction

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# Outline

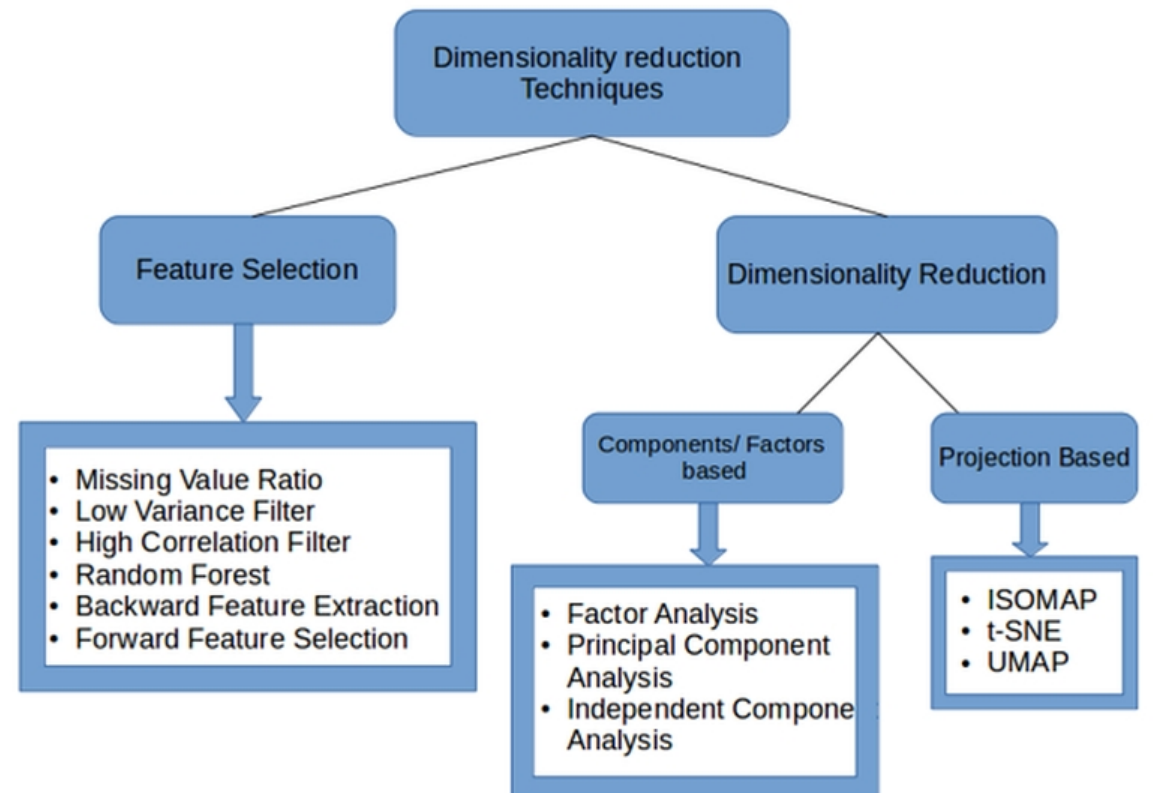
- PCA
  - motivational example (*BreastCancer* dataset)
  - PCA principles with an artificial dataset
  - *BreastCancer* dataset revisited
- PCA vs LDA
- tSNE
  - gentle introduction

# Dimensionality reduction principles

- Benefits of reducing dimensionality
  - faster and often more accurate learning of classifiers
  - removing redundancy
  - visualization

# Dimensionality reduction principles

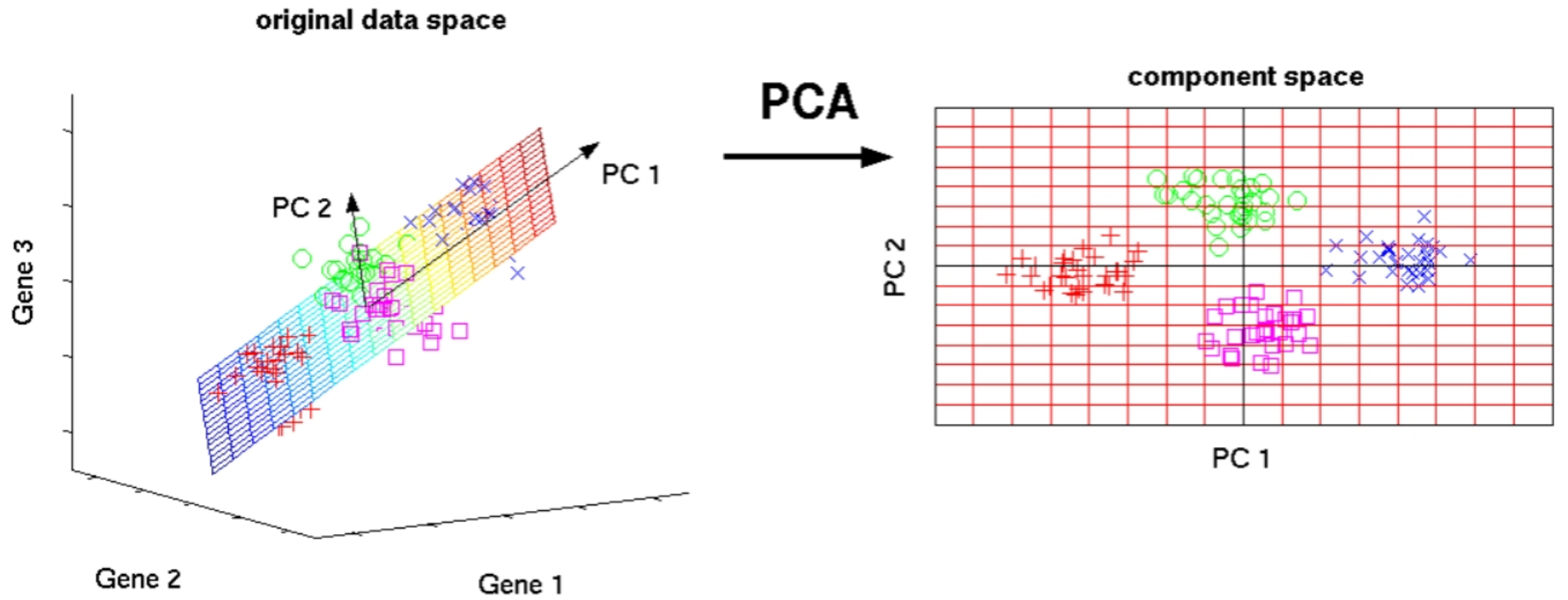
- Benefits of reducing dimensionality
  - faster and often more accurate learning of classifiers
  - removing redundancy
  - visualization

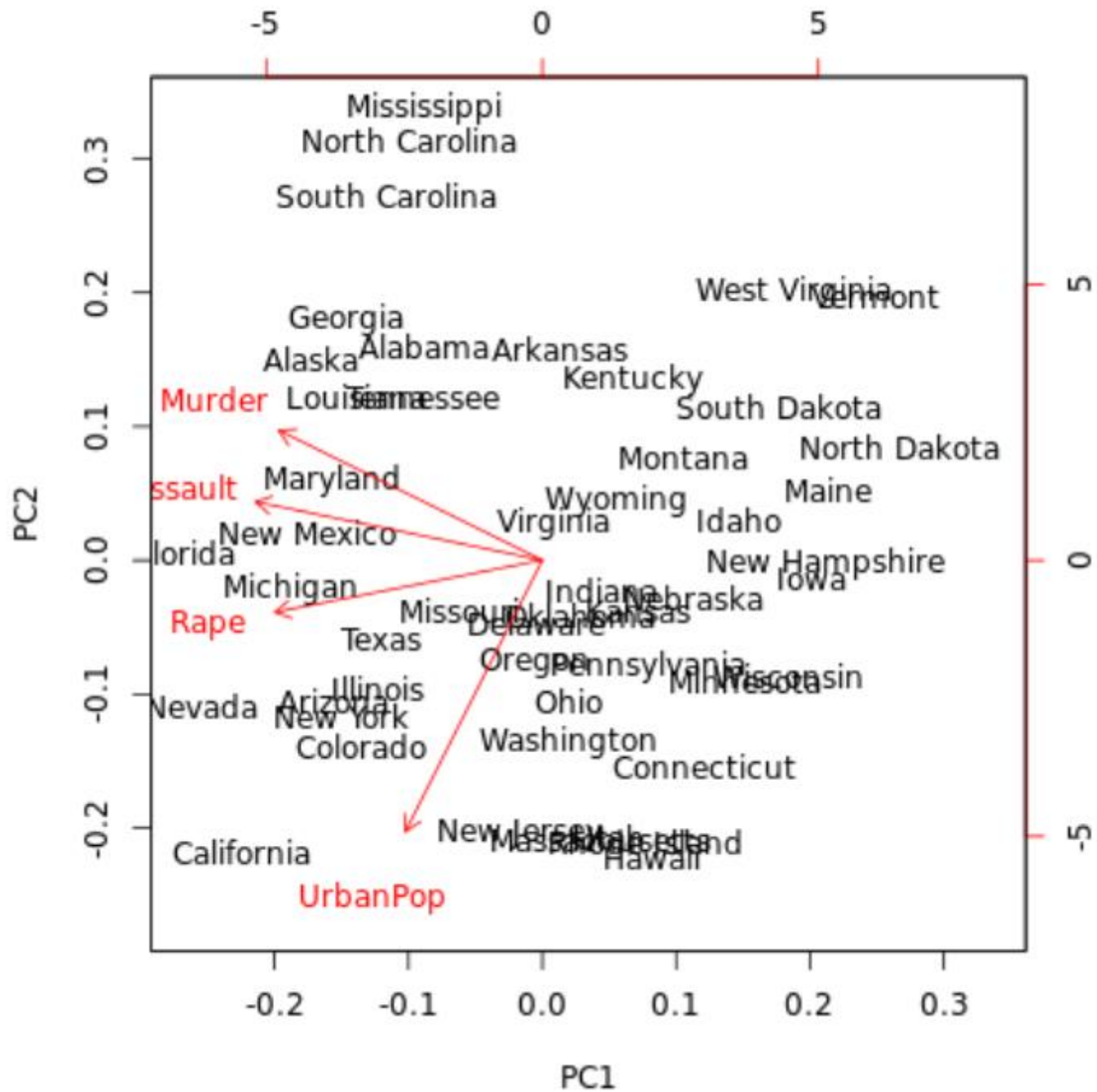


# Dimensionality reduction principles

- Benefits of reducing dimensionality
  - faster and often more accurate learning of classifiers
  - removing redundancy
  - visualization
- Cost of reducing dimensionality
  - information loss
  - new axes may be difficult to interpret

Math score	English score	Age
3.5	3.7	17
4.0	3.2	18
2.3	2.1	18
2.0	3.9	17
1.0	2.9	18

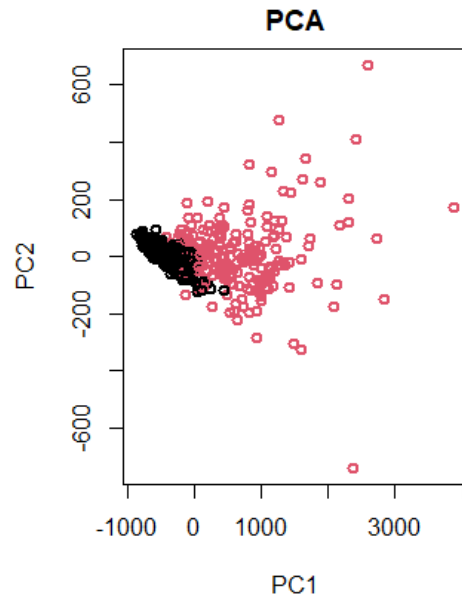




# PCA

max scatter  
of the **entire data set**

$Cov(X)$



Finds axes/directions  
of:

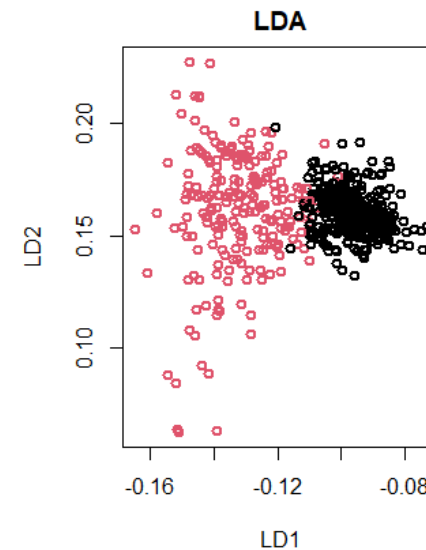
Eigenproblem  
leading to the new  
axes

Projection  
(*BreastCancer*)

# LDA

max scatter **between**  
AND  
min scatter **within** classes

$S_W^{-1}S_B$





# t-SNE

- PCA focuses on data as whole
  - “Makro” method
  - cannot capture finer details of the topology of the data
- Project into a lower dimension while preserving neighborhood relationships
  - t-SNE, ISOMAP

