

# PCA

Thursday, April 25, 2024

8:13 PM

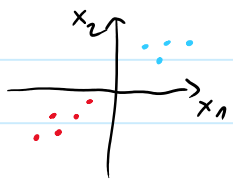
## PCA - Principal Component Analysis

If input has too many dimensions:

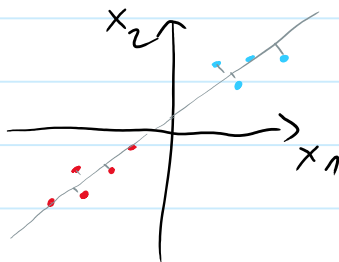
- need more data to train
- more computationally difficult
- some ML Algos don't work well in high dimensions

Intuitive solution:

Assume we have data for a classification problem



We can project on a line



Now our new data is only



We got rid of 1 dimension.

Formally:

Instead of inputs  $(x_1, \dots, x_D)$ , use  $(y_1, \dots, y_n)$ , where  $y_i = \sum_j a_{ij} x_j + b_i$

(new input feature is just a linear combination of the original ones. (linear with bias).

(linear with bias).

$y_i$ 's are called principal components

$y_1$  such that projecting on  $y_1$  gives maximal variance.

To get  $y_2$ , project onto  $\langle y_1 \rangle^\perp$  and again, take  $y_2$  in  $\langle y_1 \rangle^\perp$  that maximizes Variance.

### Algorithm

#### Step 1 Standardizing

transform each input  $x \in \mathbb{R}^D$   
 $x \mapsto \frac{x - \mu}{\sigma}$ , where  $\mu$  is the mean,  
 $\sigma$  the standard deviation  
(componentwise)

#### Step 2 Let $A = (\text{Cov}(x_i, x_j))_{i,j \in [1, D]^2}$

Where  $\text{Cov}(x_i, x_j) = \frac{1}{N-1} \sum_{i=1}^N (x_i^i - \bar{x}_i)(x_j^i - \bar{x}_j)$ .

One can show, that the first  $k$  principal components are the  $k$  eigenvectors corresponding to the  $k$  largest eigenvalues of  $A$  (without abs. val.).