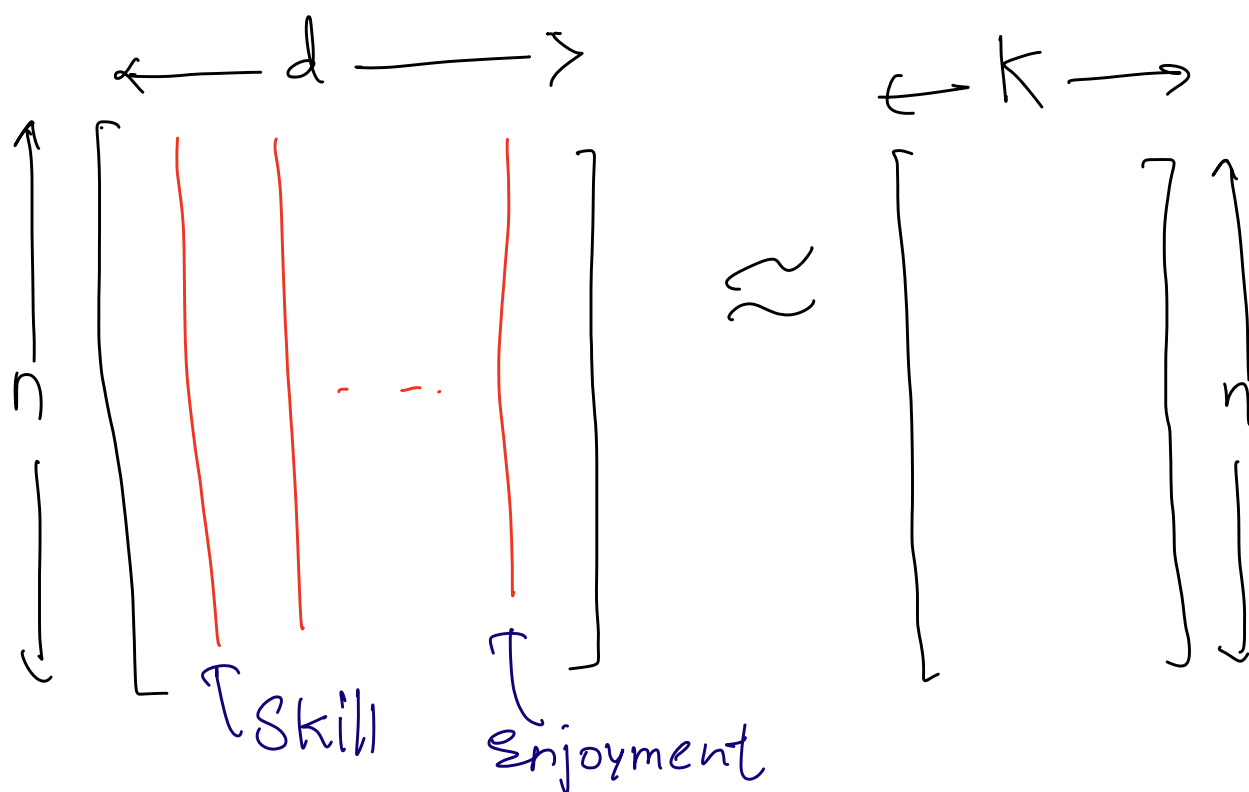
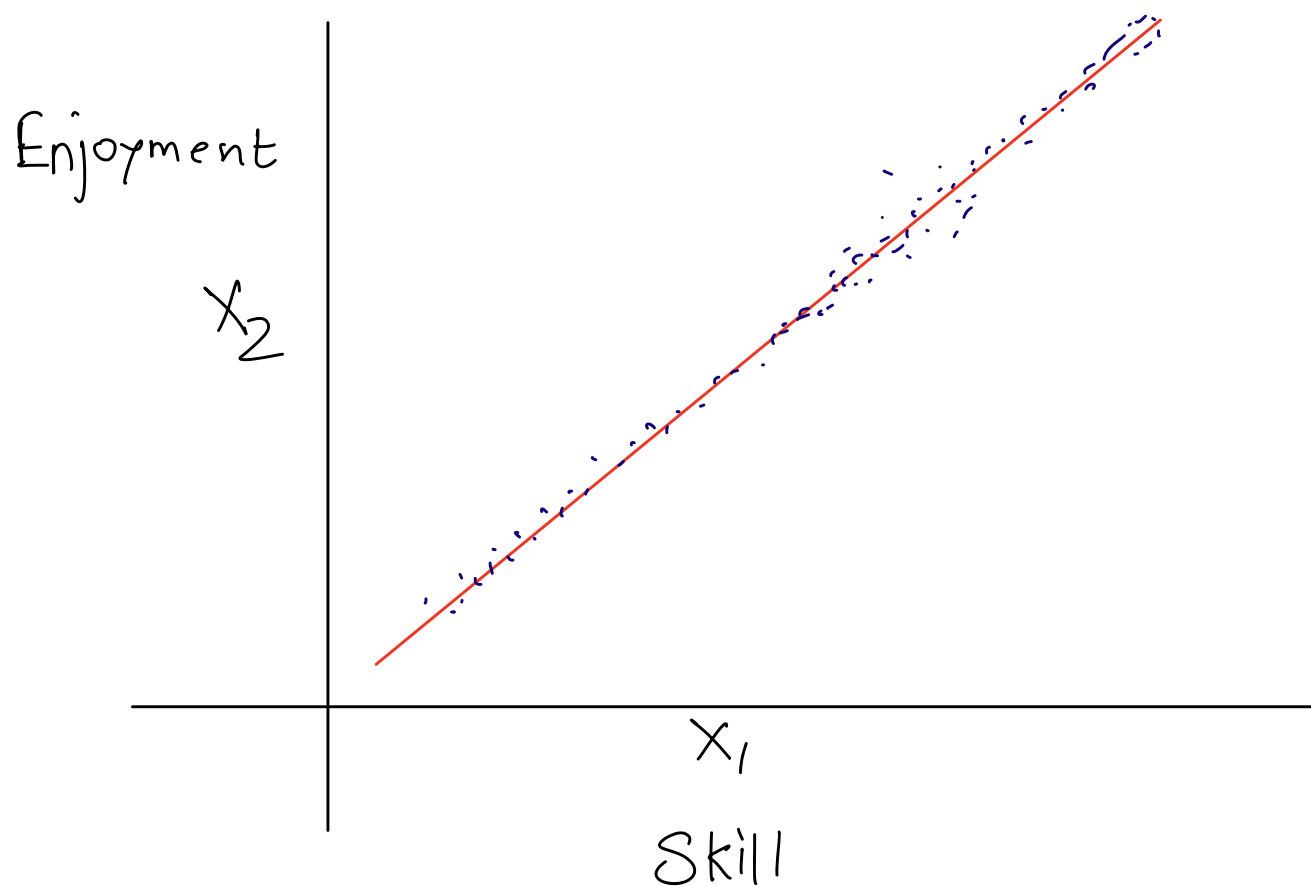


$$\{x^{(i)}\}_{i=1}^n \quad x^{(i)} \in \mathbb{R}^d$$

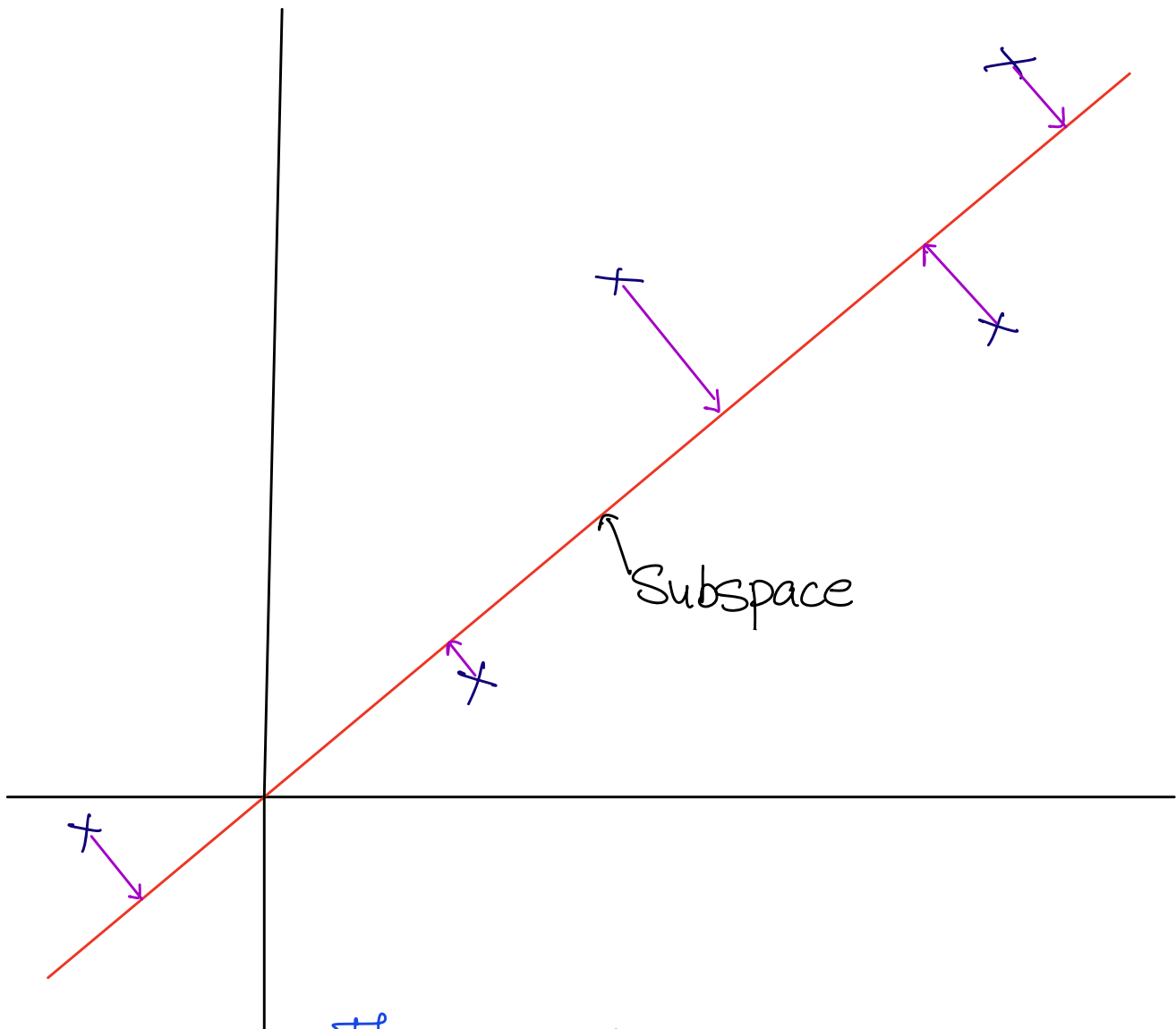


$$x_j^{(i)} := \frac{x_j^{(i)} - \mu_j}{\sigma_j}$$

$$\mu_j = \frac{1}{n} \sum_{i=1}^n x_j^{(i)}$$

$$\sigma_j^2 = \frac{1}{n} \sum_{i=1}^n (x_j^{(i)} - \mu_j)^2$$

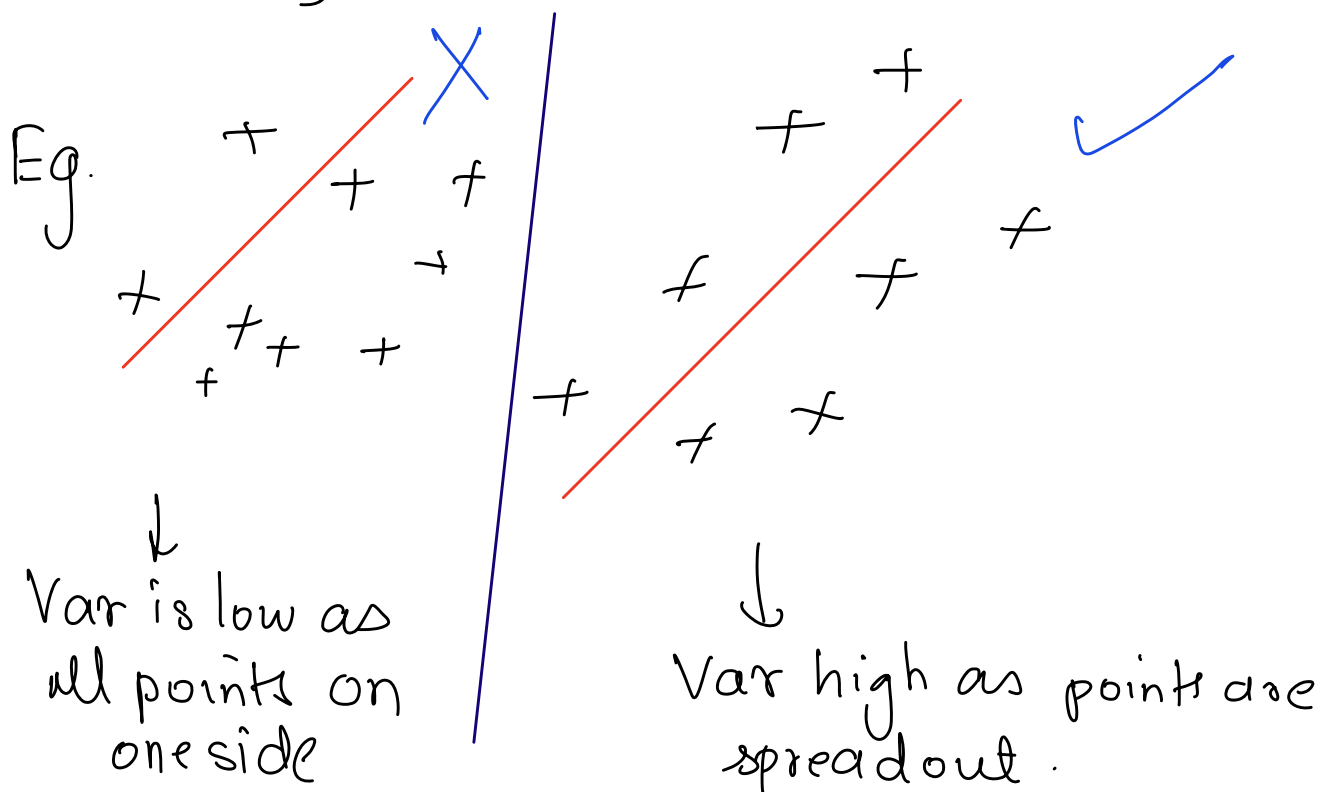
Standardizing
the dataset
(Standardize
each column
independently)



There can be ∞ subspaces

We find subspace which has maximum variance.

We want to lose no. of dimensions but not variance



$u \in \mathbb{R}^d$ unit length (subspace)

$\text{Proj}(u) \vec{x}$

$$\frac{u u^T \vec{x}}{u^T u} = \frac{(x^T u) u}{1} = (x^T u) u$$

What we want to do is max the norm.
i.e. we want to max dist from origin to
the projected point for all points

$$\begin{aligned} u &= \arg \max_u \frac{1}{n} \sum_{i=1}^n \|\text{Proj}(u) x_i\|_2^2 \\ &= \frac{1}{n} \sum_{i=1}^n \|(x_i^T u) u\|_2^2 \quad \|u\| = 1 \\ &= \frac{1}{n} \sum_{i=1}^n (x_i^T u)^2 \end{aligned}$$

$$\frac{1}{n} \sum_{i=1}^n (u^T x_i x_i^T u)$$

$$u^T \left(\frac{1}{n} \sum_{i=1}^n x_i x_i^T \right) u$$

$$\arg \max_u u^T (\text{Samp Cov Matrix}) u$$

$u \rightarrow$ Eigen vector corr. max
eigen value of
Sample Covar. Matrix

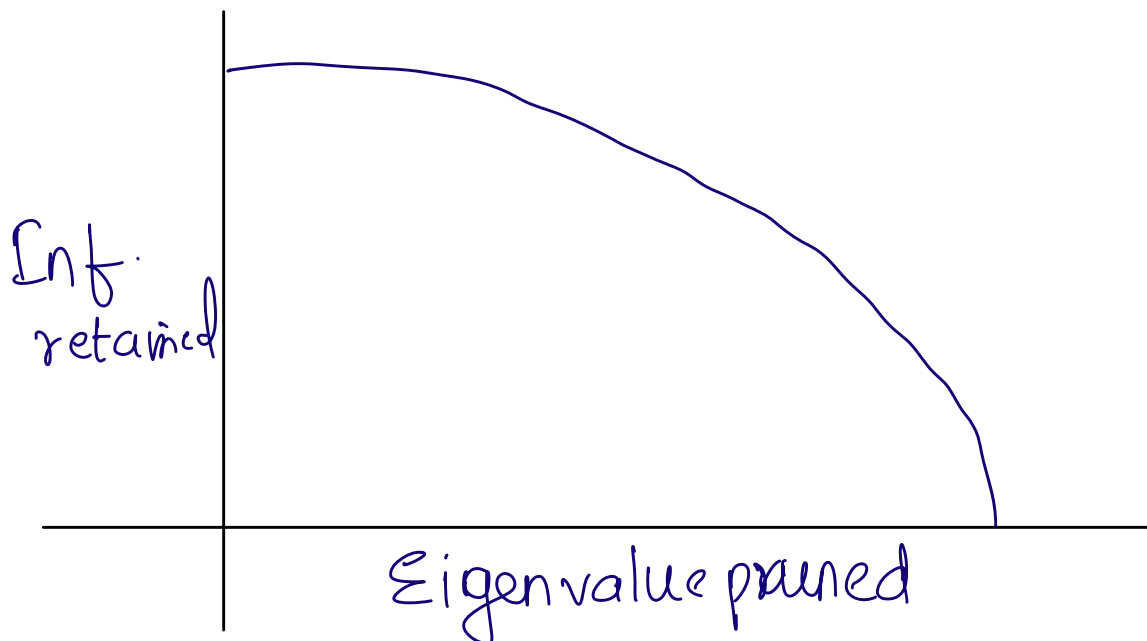
$X \rightarrow$ matrix of data

$X^T X \rightarrow$ find eigenvalue & eigen vectors

Depending on number of subspace
you want to retain choose eigen
vectors

Find k such that

$$\frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^d \lambda_i} = \underline{\underline{95\%}}$$



$X^T X$ is square, sym, PSD

Eigen decomp = SVD decomp.

Maximizing variance = Minimizing residuals

Probabilistic

Non Probabilistic

Clustering
(Classification)

GMM

K-Means

Subspace
(Regression)

Factor Analysis

\downarrow
 $d \gg n$

$L \rightarrow Z \rightarrow X$

PCA

\downarrow
 $n > d$
(not necessary)

$U \rightarrow X \rightarrow Z$

Power Iteration

$$\begin{aligned}
 u^{(0)} &\rightarrow (X^T X) u^{(0)} \\
 u^{(1)} &\rightarrow (X^T X) u^{(0)} \\
 \hline
 &\quad \quad \quad \|(X^T X) u^{(0)}\|
 \end{aligned}$$

$$(X^T X) u^{(1)} \rightarrow \frac{u^{(2)}}{\|u^{(2)}\|}$$

ICA

$d \rightarrow$ speakers

$d \rightarrow$ microphones

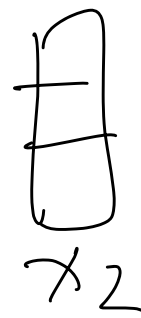
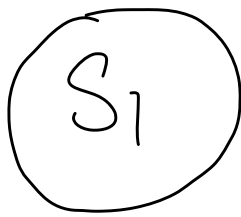
$S \in \mathbb{R}^d \rightarrow$ collection of speeches

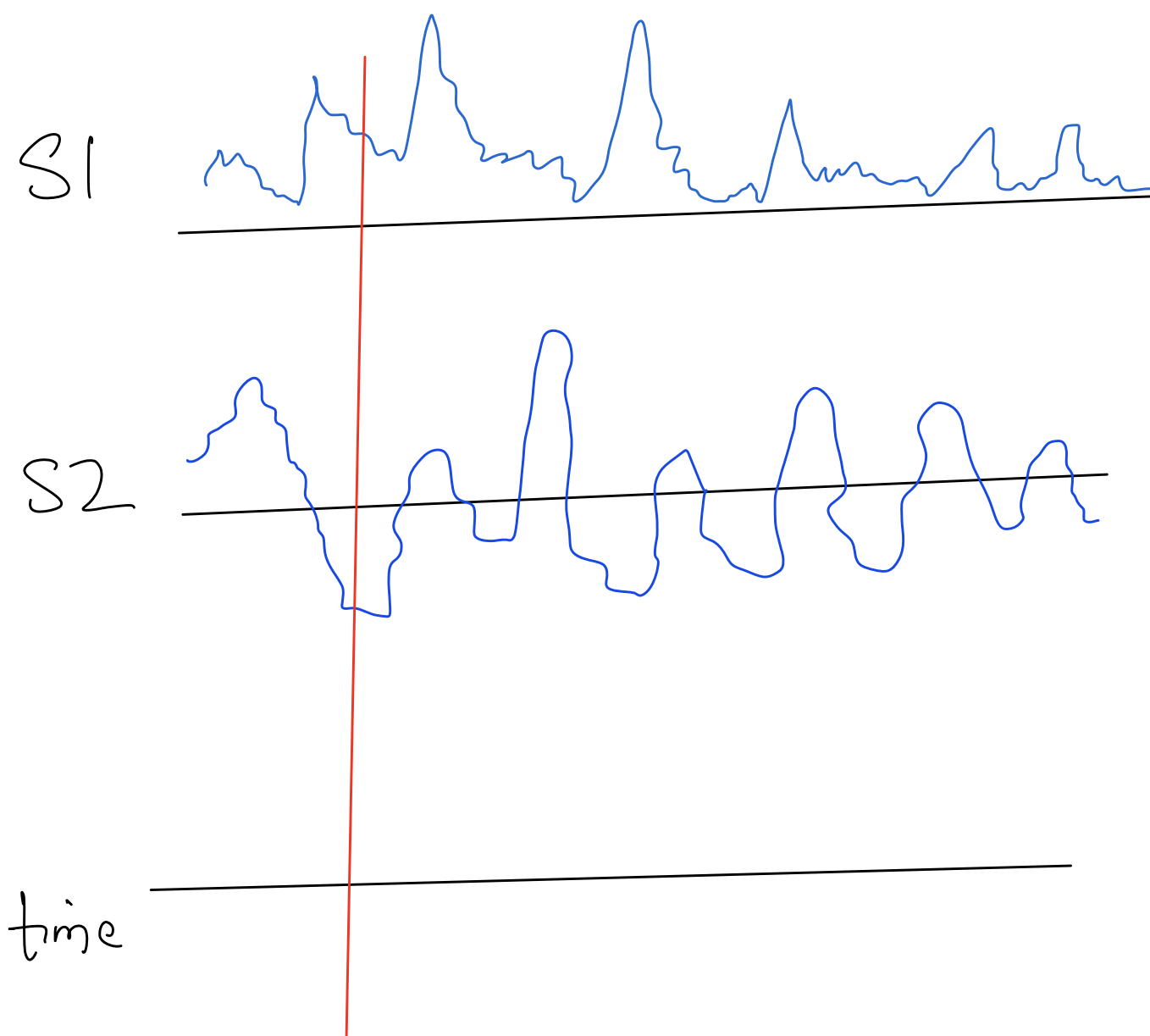
$x \in \mathbb{R}^d \rightarrow$ recording

$$x = \underset{\substack{\downarrow \\ \text{mixing matrix}}}{A} S$$

$S_j^{(i)} \rightarrow j^{\text{th}}$ speaker at i^{th} time

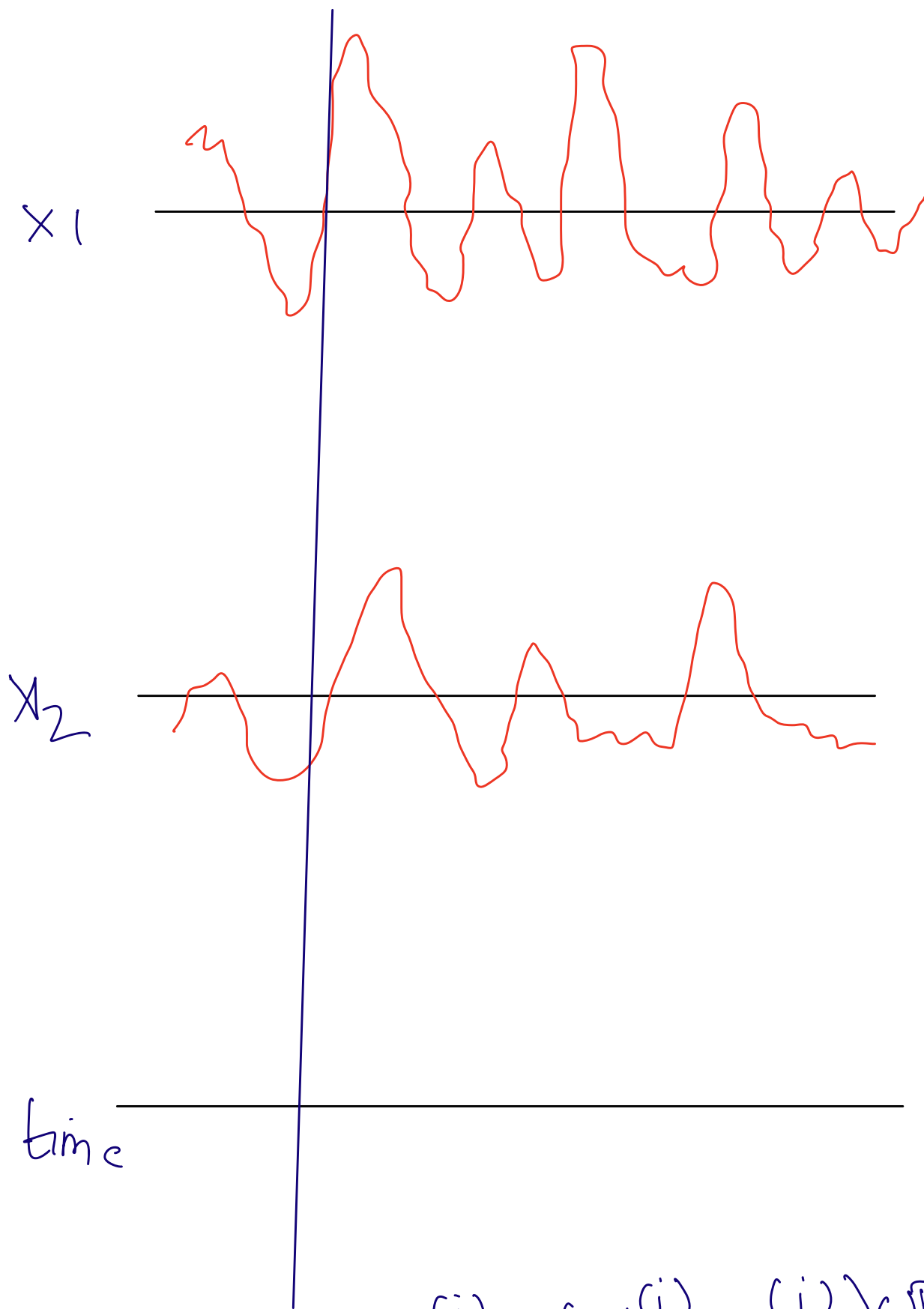
$x_j^{(i)} \rightarrow$ time
 \nwarrow microphone





$$S^{(i)} = (S_1^{(i)}, S_2^{(i)}) \in \mathbb{R}^d$$

$S_1^{(i)}$ → amplitude for wave 1
at time i



$$x^{(i)} = (x_1^{(i)}, x_2^{(i)}) \in \mathbb{R}^d$$

$d=2$

$$X^{(i)} = A S^{(i)}$$

$W = A^{-1}$ which is unmixing matrix

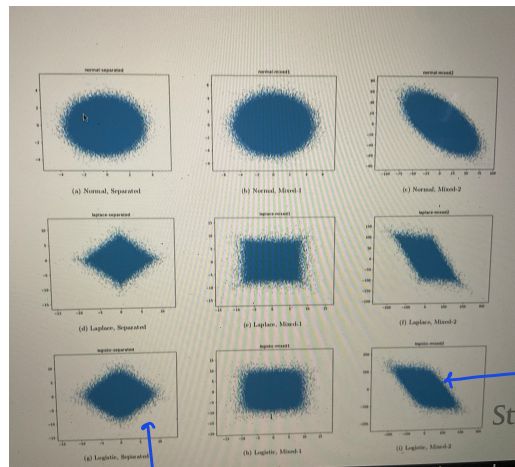
$$S^{(i)} \leftarrow W X^{(i)}$$

Assumption:

- ① $\#S = \#X$
- ② $S = WX$
- ③ $S_j \perp S_k \quad j \neq k$
- ④ S_j is NOT Gaussian

1st & 2nd
are same.

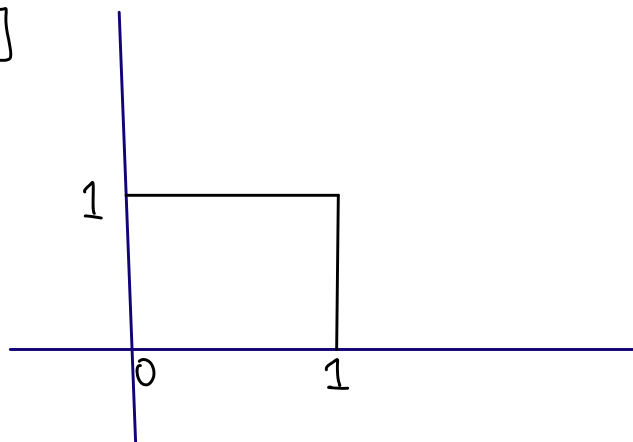
1, 2, 3 all
are different.
We want to
recover 1st
from 3rd



In 2nd & 3rd Case, we can map corners from one space to another

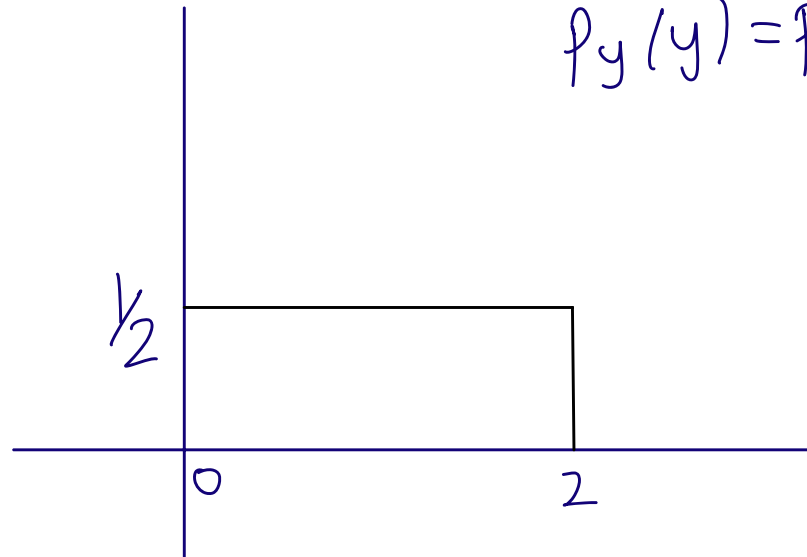
When we separate using ICA, we may swap out the source even though we separate.

$X \sim \text{Unif}[0, 1]$



$$y = 2x$$

$$p_y(y) = p_x\left(\frac{y}{2}\right) \cdot \frac{1}{2}$$



$$p_y(y) = p_x(w_x) \cdot \frac{1}{w}$$

$$p(x) = \prod_{j=1}^d p_s(w_j^T x) \cdot |w|$$

$$w = \begin{bmatrix} -w_j \end{bmatrix} \begin{bmatrix} x \end{bmatrix} \text{ unmixing matrix}$$

$p_s \sim$ logistic distribution

$$\text{pdf of } f(x) = \sigma(x) \cdot (1 - \sigma(x))$$

$$l(w) = \sum_{i=1}^n \left[\left(\sum_{j=1}^d \log [\sigma^{(i)}(x)(1-\sigma^{(i)}(x))] \right) + \log |w| \right]$$

↓

Jacobiar