PCA

ML ⇒ ✓

Machine Learning

⇓

⇒ NLTK
Open CV

→ Diwali holidays

⇒ Anova ⇐ ✓

5-10 min

Variants of GD

$$\theta^{t+1} = \theta^{t} - \eta \frac{\partial t}{\partial \theta}$$

$$\theta^{t+1} = \theta^{t} - \eta \sum_{i=1}^{n} \frac{\partial f(x_i)}{\partial \theta}$$

$\Rightarrow$ highly computation

Case $\Rightarrow$ $\forall$ Data Points (millions of dat

20 iterations $\Rightarrow$

for(i=0

$\Downarrow$

2 min $\Rightarrow$ 20*2 = 40 min

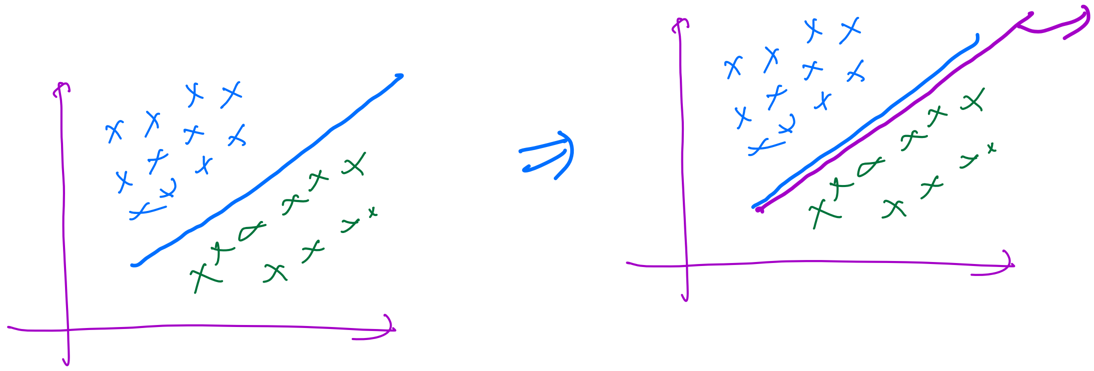
Case $\Rightarrow$ Batch 200 data points

40 iteration

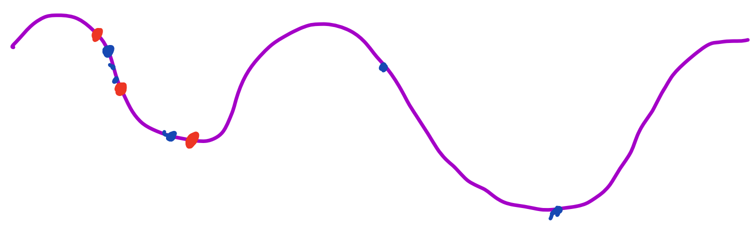
$\Downarrow$

10 sec

Batch Gradient Descent



$\forall$ data



Batch GD

$$\theta^{t+1} = \theta^{t} - \eta \sum_{i \in B} \frac{\partial f(x_i)}{\partial \theta}$$

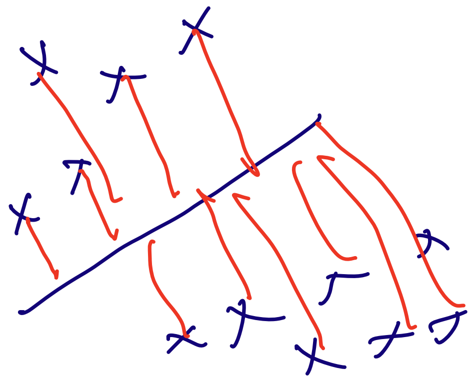
B is a random sample of N

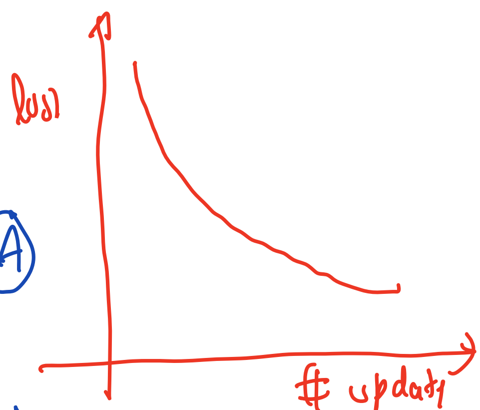
Batch $\Rightarrow$ 1 data point

$$\boxed{\theta^{t+1} = \theta^{t} - \eta \frac{\partial f(x_k)}{\partial \theta},}$$

Stochastic GD

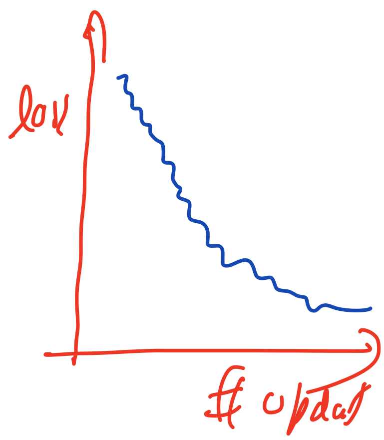
K is any random data point 1-n





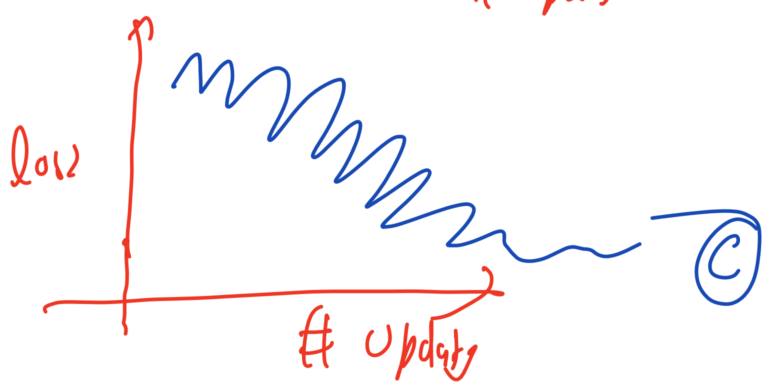
A

GD



B

Batch GD

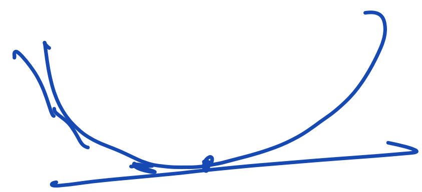


C

Stocastic GD

PCA (Principal Component Analysis)

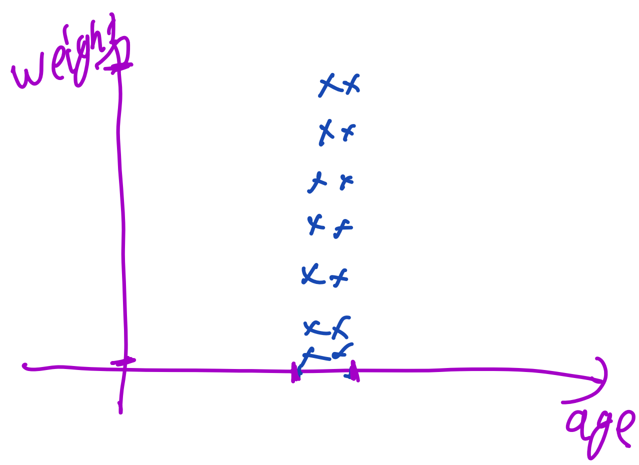
low $\gamma = 0$ good



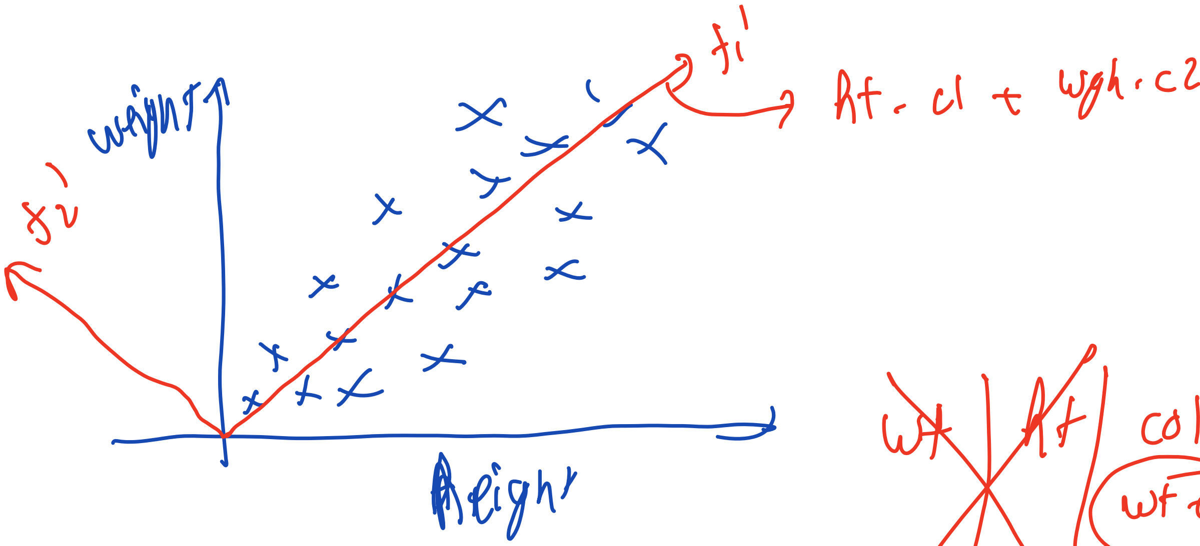
5000	70.9865
5001	70.9864
5002	70.9864
5003	70.9863

Diabetes

Weight	Age	Diabetic
10	30	
20	31	
30	30	
35	31	
	30	
40	30	
50	31	



w_1 weight + w_2 age



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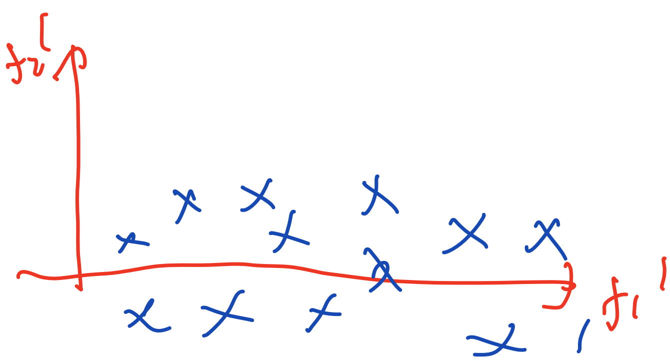
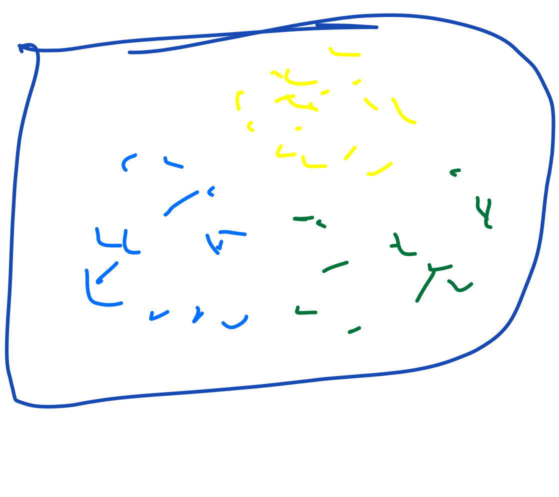
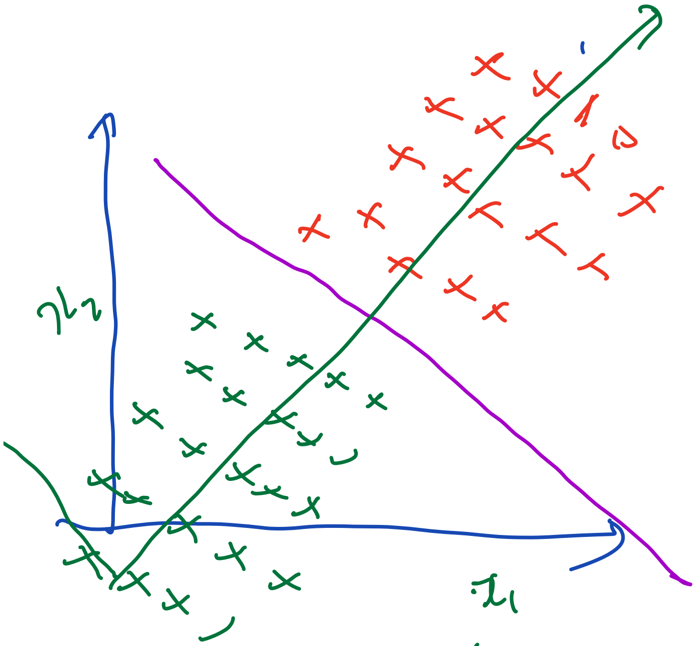






100%

80%

C_1 C_2 C_3 C_4

Principal

x_1 x_2 $w_1 x_1 + w_2 x_2$

C_1 C_2 C_3 C_4 C_5 C_6

$$w_1 c_1 + w_2 c_2 + w_3 c_3 \;|\; w_5 c_5 + w_6 c_6 + w_7$$

PCA $\rightarrow$ 10% ✓ 40%

100 col $\Rightarrow$ 8 col

$\searrow$ 2 col

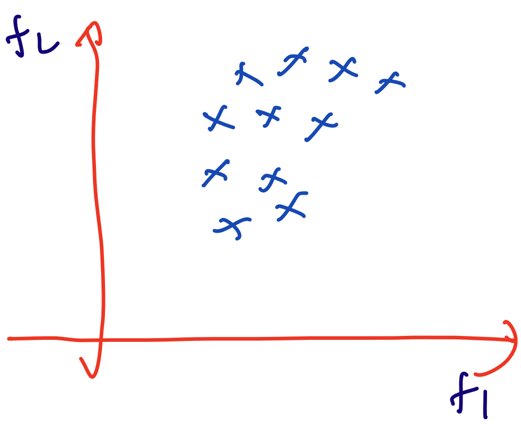
$\Rightarrow$

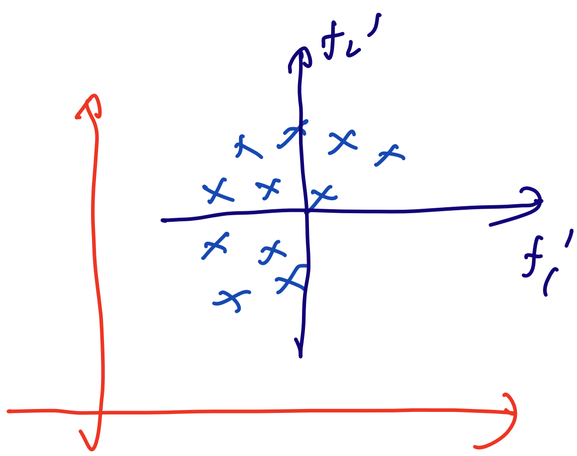
Standardisation

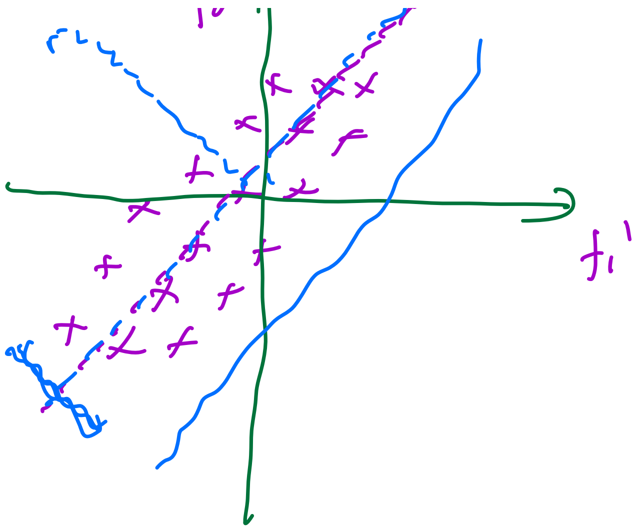
$$x' = \frac{x - x_{mean}}{x.std()}$$

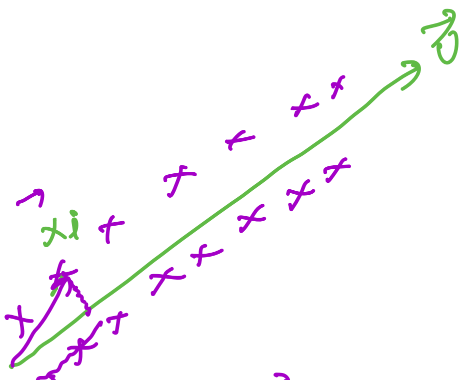
mean = 0

std = 1



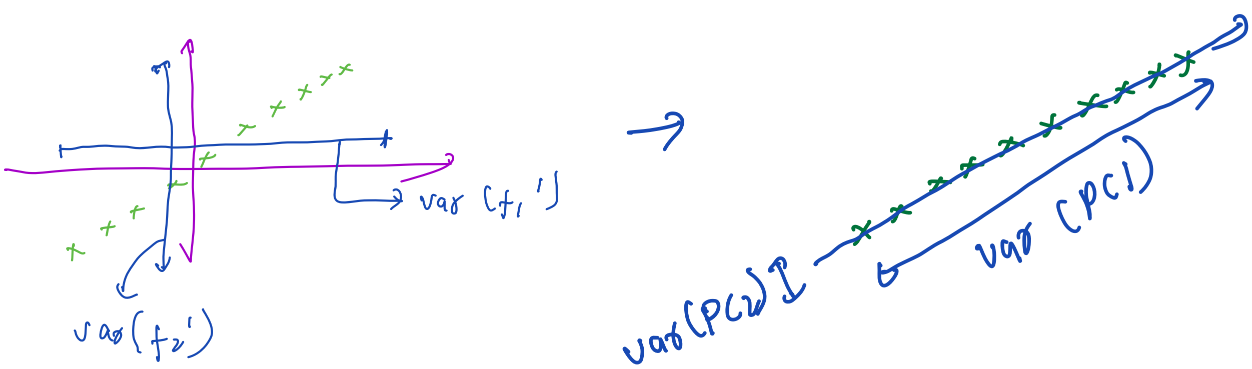






$$\frac{\vec{x} \cdot \vec{v}}{\|\vec{v}\|}$$

$$\max_{\vec{v}} \sum_{i=1}^{n} \frac{\vec{v} \cdot \vec{x}}{\|v\|} \cdot \frac{1}{n}$$



$$\max_{\vec{v}} \quad \frac{1}{n} \sum \frac{(\vec{v} \cdot \vec{x_i})^2}{\|\vec{v}\|} \Rightarrow \begin{matrix}\text{constraint} \\ \|\vec{v}\| = 1\end{matrix}$$

$$\max_{\vec{v}, \lambda} \quad \frac{1}{n} \sum (\vec{v} \cdot x_i)^2 + \lambda (\|\vec{v}\| - 1)$$

$$\max_{\vec{v}, \lambda} \quad \frac{1}{n} \sum_{i=1}^{n} (\vec{x} \cdot \vec{v})^2 + \lambda (\|v\|^2 - 1)$$

$$A^2 = A^T \cdot A = \|A\|^2$$

$$\Rightarrow \max_{\vec{v}, \lambda} \quad \frac{1}{n} \sum_{i=1}^{n} (x_i v)^T \cdot (x_i \cdot v) + \lambda (\|v\|^2 - 1)$$

$$(AB)^T = \underline{B^T A^T}$$

$$\Rightarrow \max_{\vec{v}, \lambda} \quad \frac{1}{n} \sum v^T \underbrace{x^T x}_{V} \cdot v + \lambda (v^T \cdot v - 1)$$

$$\Rightarrow \quad L = v^T V v + \lambda (v^T v) - \lambda$$

$$\frac{\partial L}{\partial v} = 2Vv + 2\lambda v$$

$$\frac{\partial L}{\partial \lambda} = v^T v - 1$$

$$\frac{\partial A^T A}{\partial A} = 2A$$

$$v^T v - 1 = 0$$

$$\boxed{v^T v = 1}$$

$$\frac{\partial\, x \cdot x}{\partial x} = 2x$$

$$Vv = \underbrace{-\lambda}_{x'} v$$

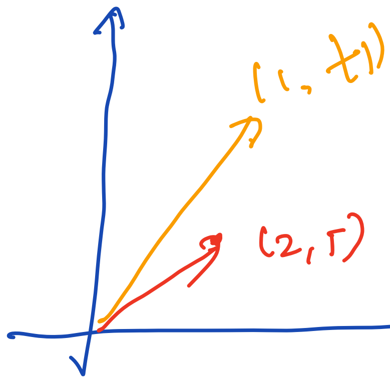
$$\boxed{V\vec{v} = x'\vec{v}}$$

$$A\vec{x} = \lambda\vec{x}$$

Ex: $\vec{x} = \begin{bmatrix} 2 \\ 5 \end{bmatrix}$, $A = \begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix}$

$$A \cdot \vec{x} = \vec{y}$$

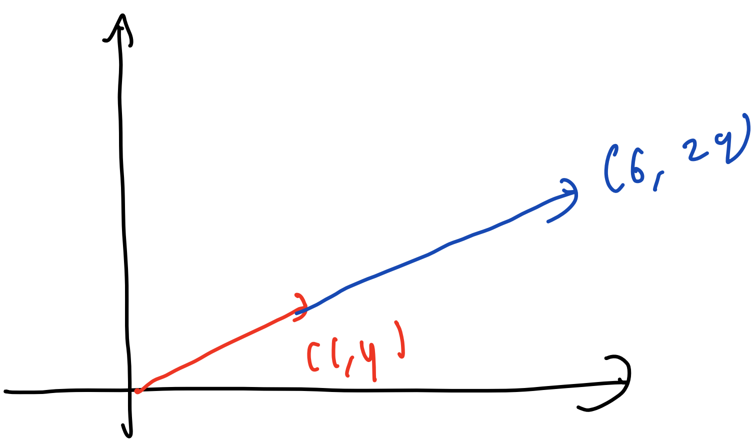
$$\begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 \\ 33 \end{bmatrix} \Rightarrow 3 \begin{bmatrix} 1 \\ 11 \end{bmatrix}$$



$$\begin{bmatrix} -6 & 3 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \end{bmatrix} = \begin{bmatrix} 6 \\ 24 \end{bmatrix} = 6 \begin{bmatrix} 1 \\ 4 \end{bmatrix}$$

scaler → eigen value

eigen vector



Eigen Value / Vector

For any matrix A, there exist one or more vectors, s.t.

$$A\vec{x} = \lambda \vec{x}$$

eigen
value

eigen
vector