① Lin. Regr

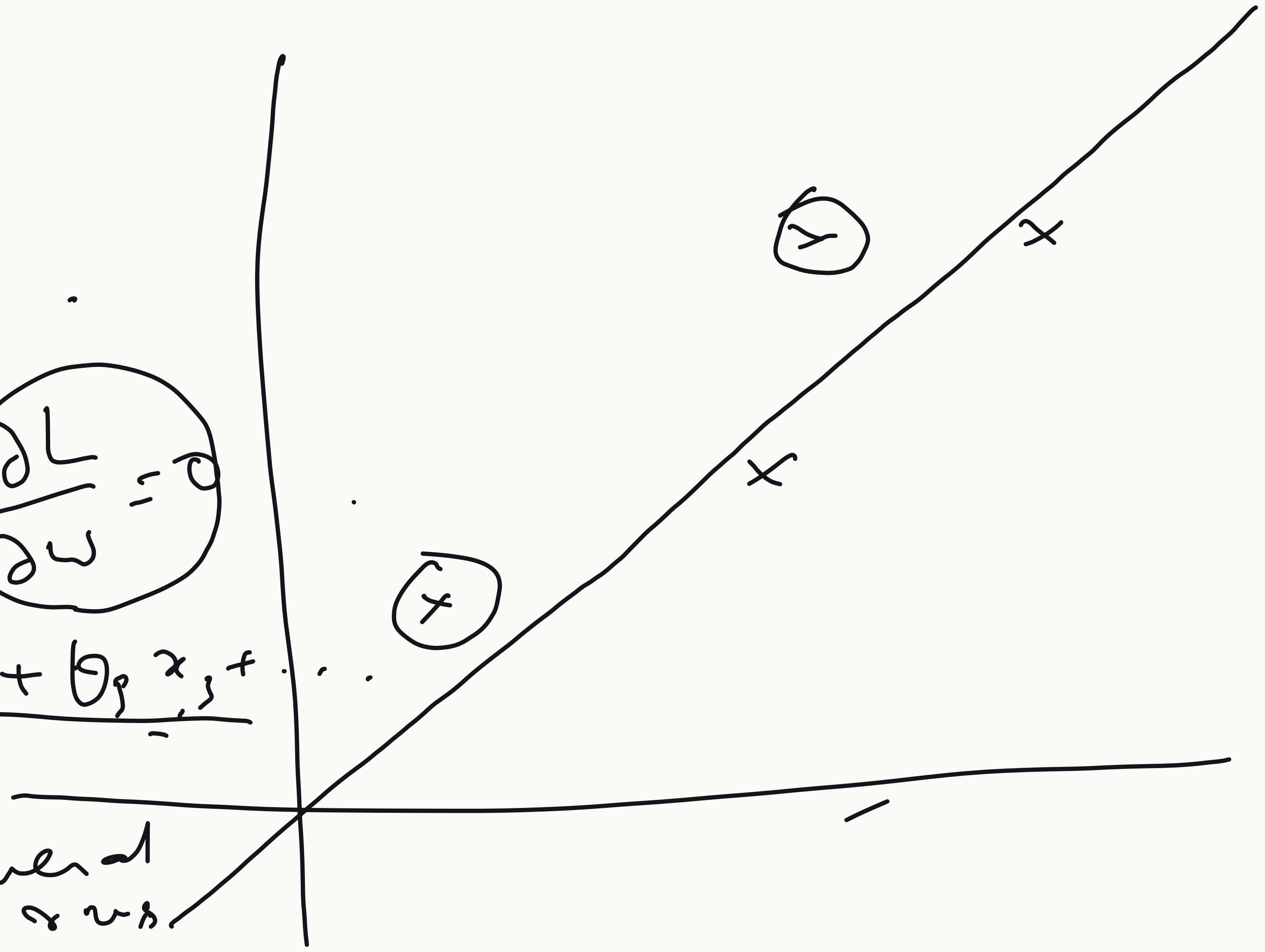
→ Loss = MSE

- OLS → $\frac{\partial L}{\partial w} = 0$

$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots$

(n+1)

$L = \sum(\hat{y} - y)^2$ overall rows



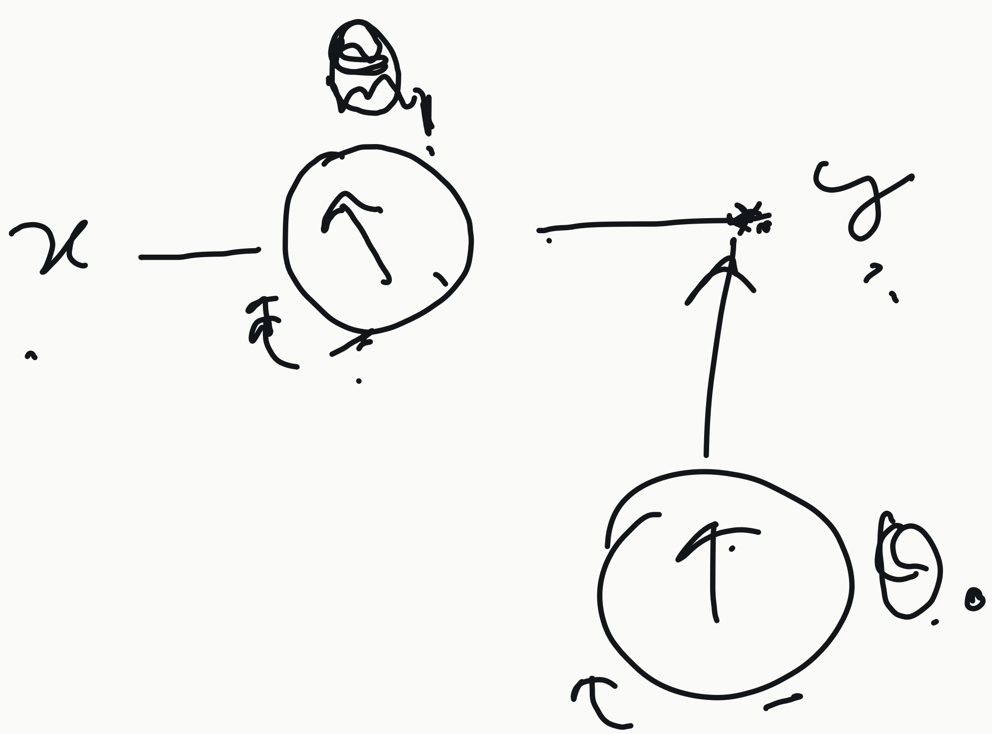
$\frac{\partial L}{\partial \theta_0} = 0, \quad \frac{\partial L}{\partial \theta_1} = 0, \quad \frac{\partial L}{\partial \theta_2} = 0, \quad \dots \dots$ (n+1)

$\boxed{O(n^3)}$

Linear Regression (GD)

$$\theta' = \theta - \eta \frac{\partial L}{\partial \theta}$$

repeat this for every θ until each θ stabilising



$$\hat{y} = \theta_1 x + \theta_0$$

$$L = \sum(\hat{y} - y)$$

It can go batchwise

M1

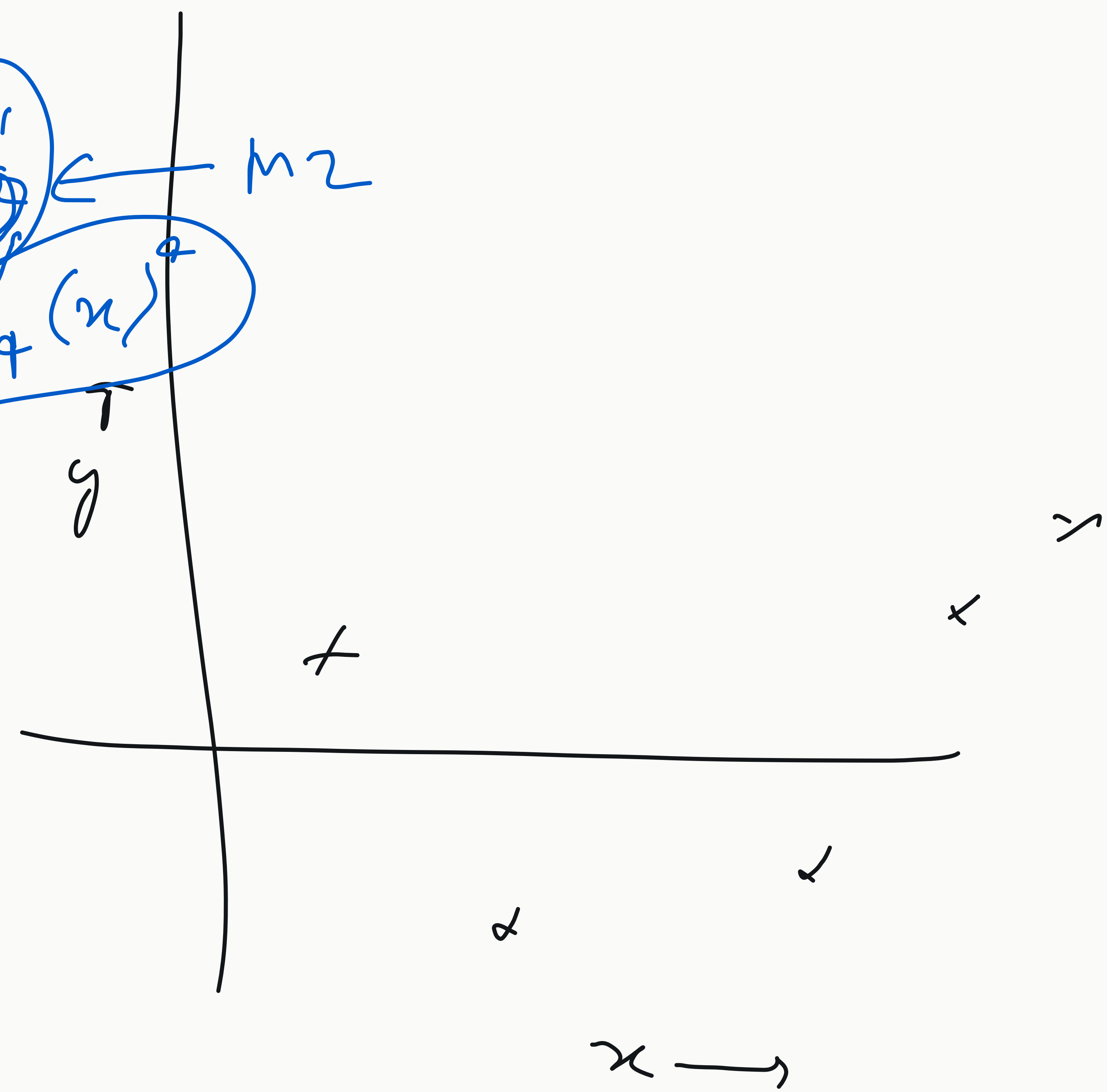
$$y = \theta_0 + \theta_1 x$$

M2

$$y = \theta_0 + \cancel{\theta_1} x + \theta_2 x^2 + \cancel{\theta_3} (x^3) + \cancel{\theta_4} (x)^4$$

x_1

0 0



Logistic Reg

* Lin R for classification.

$$\hat{y} = \sigma(\theta_0 + \theta_1 x_1 + \theta_2 x_2 \ldots\ldots)$$

$$L = -\left[y \log \hat{y} + (1-y) \log(1-\hat{y})\right]$$

Min. L , $\theta = ?$

Using OLS ✗ | GD ✓

p	A
0	0
1	2
2	3
3	4
0.9	0
0.9	0

→ MSE ✓ $= \sum (p - A)^2$

→ $\underline{\text{multiply}}$ ✓ $= \sum (p A)$

→ $\underline{\underline{\sum A (\log p)}}$

$A * p + (1 - A) * \underline{\underline{(1 - p)}}$

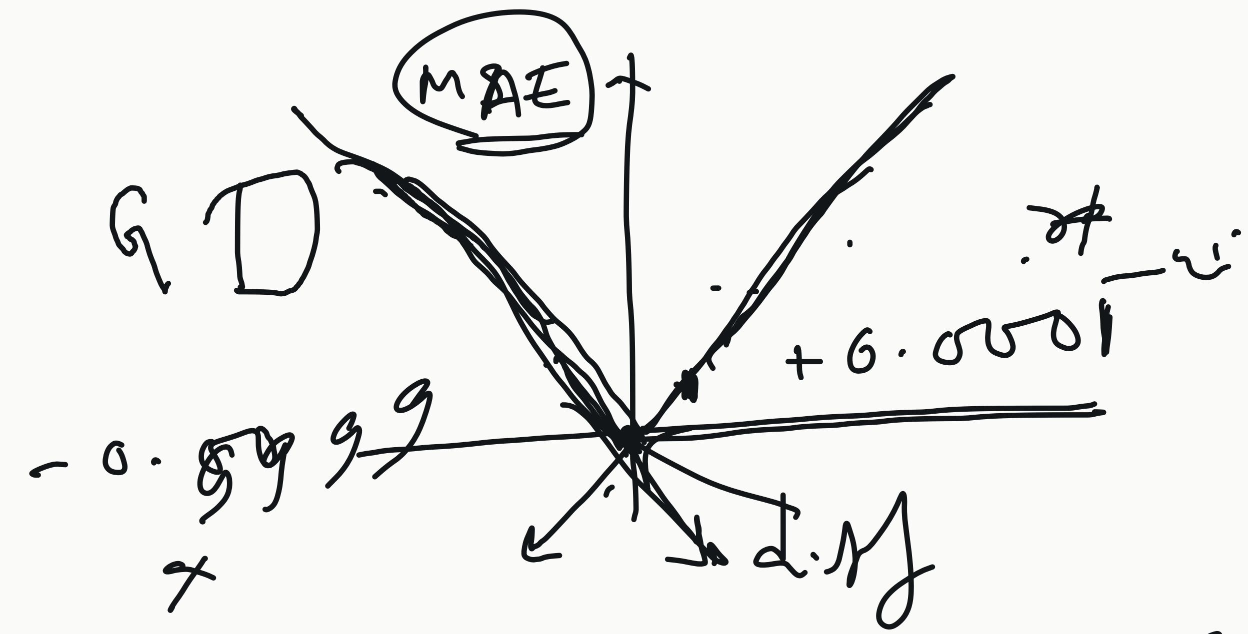
$\boxed{A * \log p + (1 - A) \log (1 - p)}$

$\log$:

OLS vs GD

OLS

- No hyperpa
- No iteration
- Not good for Large n feat / log m var
- Not suitable for complex fn.

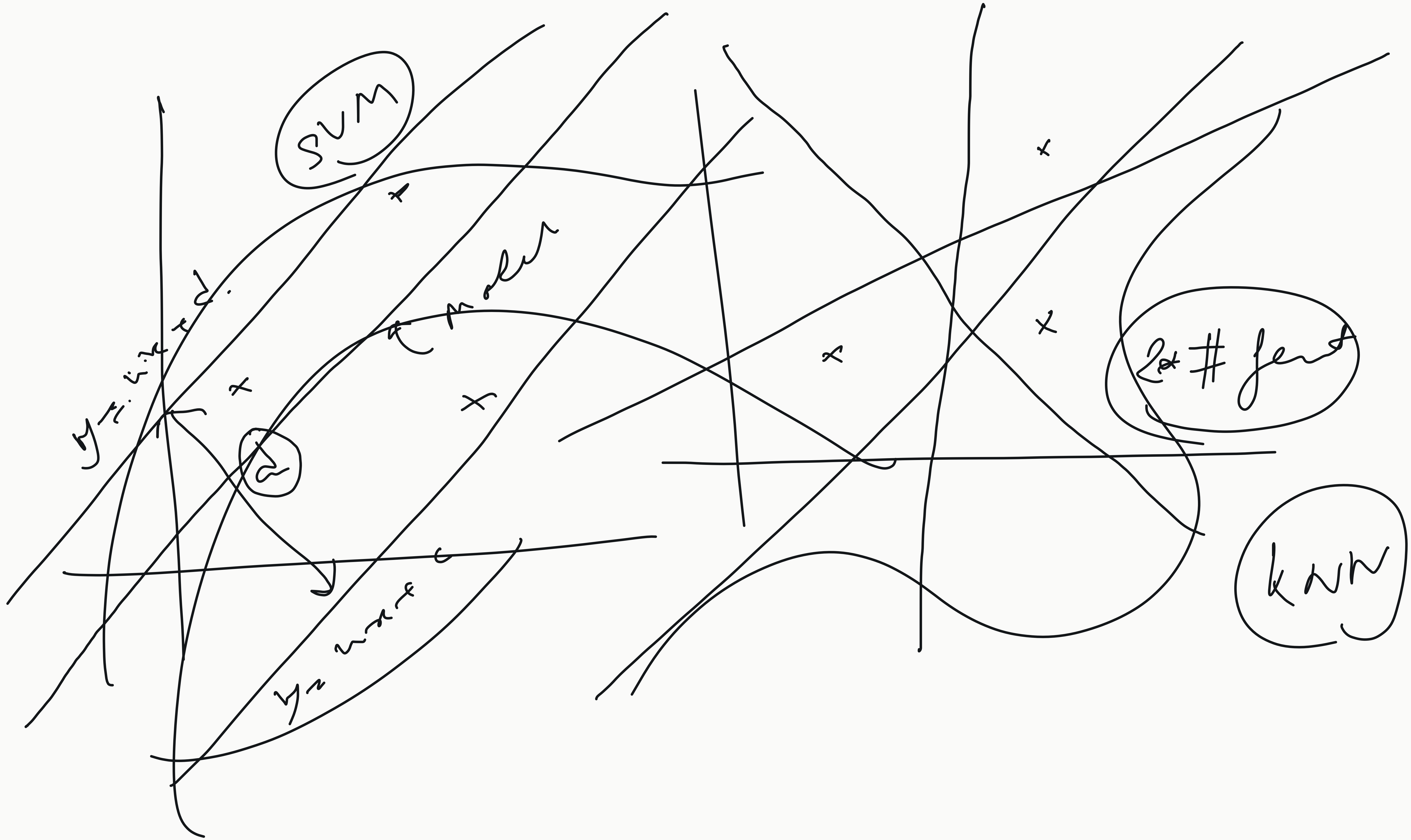


Batchwise

MSE = $(y-\hat{y})^2$

MAE = $|y-\hat{y}|$

Can Any loss funct as long it is cont.


SVM
KNN