L2 Regularization

overfitting and underfitting

$$w^* = \arg\min \sum_{i=1}^{d} \log\left(1 + \exp\left(-y_i w^T x_i\right)\right)$$

$\exp(-x)$

plot e^{-x}

↑

always +ve

but $z = y_i w^T x_i$

$$\arg\min \sum_{i=1}^{d} \log\left(1 + \exp(-z_i)\right)$$

↑

$\exp(-z_i) \geq 0$

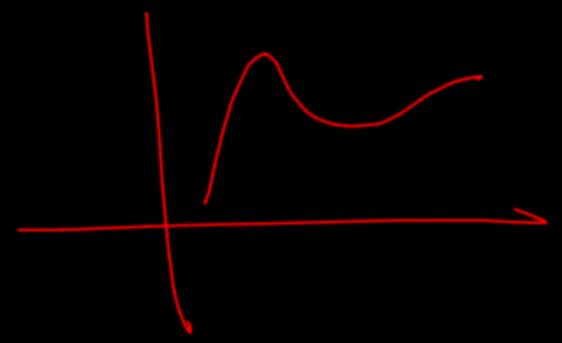
=

↑

ie $\log(1 + \exp(-z_i)) \geq 0$

ie. $\sum_{i=1}^{n} \log(1 + \exp(-z_i)) \geq 0$

$$w^* = \underset{w}{\operatorname{argmin}} \sum_{i=1}^{n} \log\left(1+\exp(-z_i)\right) \geq 0$$



Minimal → '0' ← Best

But when '0' → occurs

$z_i = y_i \, w^T \, x_i \rightarrow \uparrow \rightarrow \infty$

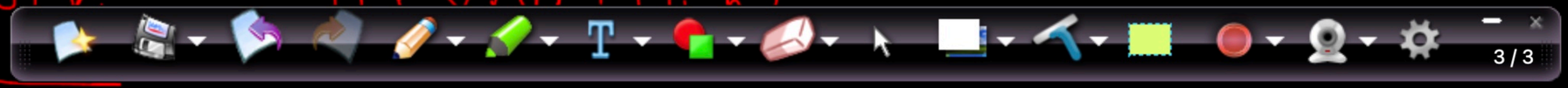
w^T

$w \rightarrow \infty$ big val

$e(\infty) \rightarrow 0$

$z_i \rightarrow \infty$

$z_i = y_i w^T x_i$



$z_i \to \infty$

↳ modify my (w) such way that $z_i \to \infty$

If $z_i = +ve$ → correct classification

2) $z_i \to +\infty$ (minimum value)

Regularization

↑

"overfitting"

→ If I pick my (w) s.t.

a) all the training pts are correctly classified

b) $z_i \to \infty$

$$w^* = \underset{w}{\operatorname{argmin}} \sum_{i=1}^{n} \log(1+\exp(-z_i)) + \lambda\, w^T \cdot w$$

loss - term

x

G

$L1$ $L2$

$\lambda = 0$ ↑

$\|w\|$

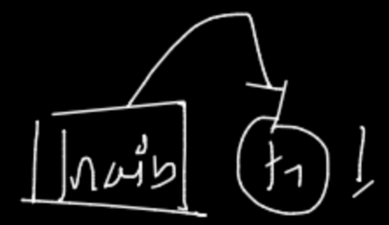
$\lambda \uparrow$

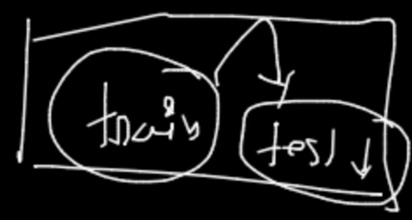
$\lambda \cdot \|w\| \cdot \|w\|$

$\lambda = 0$

overfitting ↑

$w \to \infty$





Hyper-parameter tuning : Search / optimisation

if $\begin{cases} \lambda = 0 \longrightarrow \text{overfitting} \\ \lambda = \infty \longrightarrow \text{underfitting} \end{cases}$

→ (i) GridSearchCV
(ii) RandomSearchCV
} → Sklearn

(iii) Bayesian optimisation → "Hyperopt"

$\lambda = 0.001$

loss

one p

$M(x)$

$\lambda = [0.1, 0.01, 0.001, 0.0001]$

→ M (~~0.01~~ 0.1)

$M(D_x)$

Note → 85% ~~86%~~

↓↓

$M(\lambda_1, \lambda_2)$

$\lambda_1 = [0.1, 0.01, 0.001, 0.0001]$

$\lambda_2 = [0.1, 0.01, 0.001, 0.0001]$

$\lambda_3 = [$ $\lambda_1 = 0.001$ → Min, $\lambda_2 = 0.01$] → 100 → 200 Min → get pm

$M1(0.1, 0.1)$ → loss/error → 0.54

↳ loss/error → 0.55

↳ error/loss → 0.54

↳ loss/ —

0.001, 0.001 → Min

$kNN(k = ?, \text{metrics} = ?)$

λ_1 λ_2

Gridsearch

λ_1 and λ_2

$\lambda_1 \longrightarrow m^1$

$\lambda_1 \lambda_2 \longrightarrow m_1 \times m_2 \longrightarrow m^2$

K ↑ → m^K

↑

K → m^K

K	m^K

101 Hi → ?

↓

(Big data) → RandomSearch CV

↑