

## Last class - August 8

- 1) Quick recap
- 2) Overview of GD, SGD, MBGD
- 3) Polynomial Regression
- 4) Underfit vs Overfit
- 5) Bias Variance trade-off

## Today's class

- 1) Regularization
- 2) L1 and L2 Regularization
- 3) Parameters vs Hyper-parameters
- 4) Cross-validation
- 5) k-fold CV

$$m = 2^{10}$$
$$BS = 2^5$$

$$N.B = \frac{2^{10}}{2^5} = 2^5$$

$$\text{num\_iter} = \text{epochs} \times N.B$$
$$\downarrow$$
$$= 2 \times 2^5$$

Weight  
update is  
happening

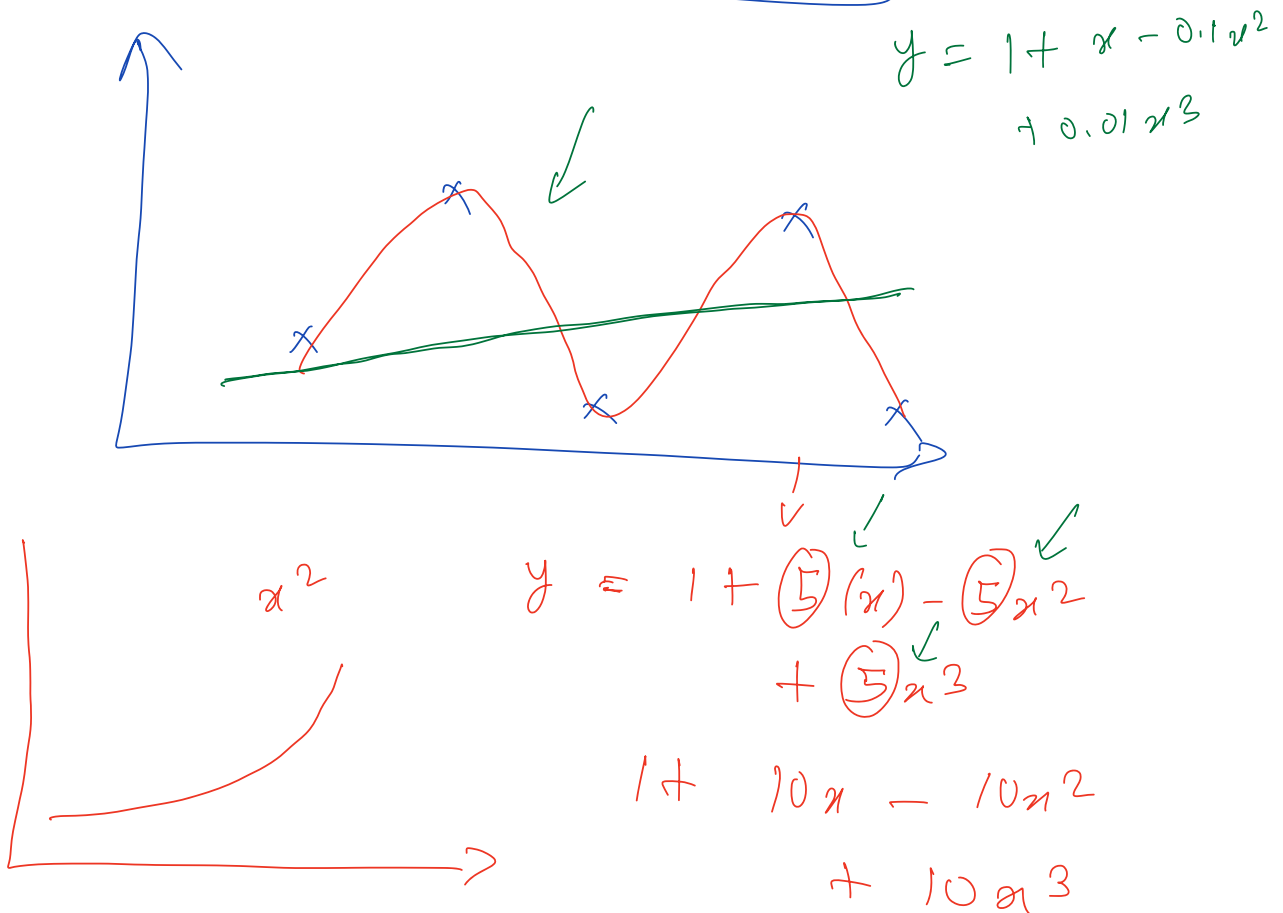
[ grad descent  
loop is running

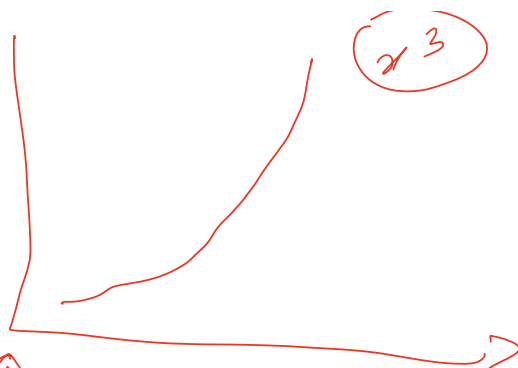
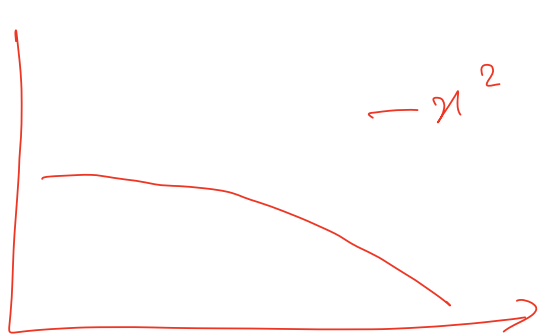
$$x_{ij} \rightarrow \begin{matrix} x_1 & x_1^2 & x_1^3 \\ \downarrow & \downarrow & \downarrow \\ w_1 & w_2 & w_3 \end{matrix}$$

$$|w_3| > |w_2| > |w_1|$$

$$SS(x) = x' = \frac{x - \mu}{\sigma}$$

Ridge Regularization





1 to 2 to 4, 8, 16, 32, ...

regression fit  
problem

overfitting

Arrows indicate that the regression fit problem leads to overfitting as the number of data points increases.

$w_1$	$w_2$	$w_3$	$w_4$	$\sum w_j$	$x$
100	-50	-25	-25	$\rightarrow 0$	

$$\sum w_j^4$$

$$\sum w_j^2$$

Occam's razor

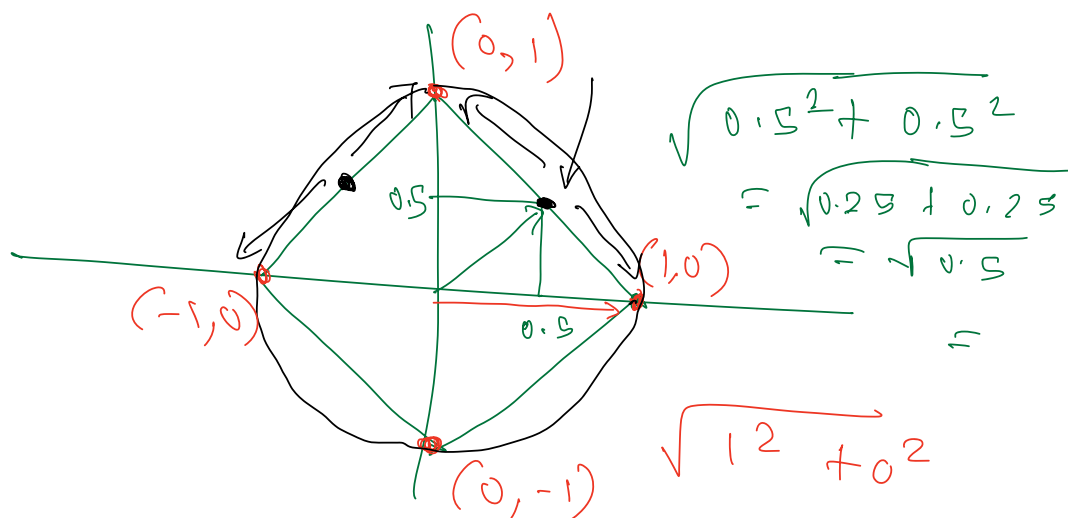
$$\sum w_j^3$$

$x$

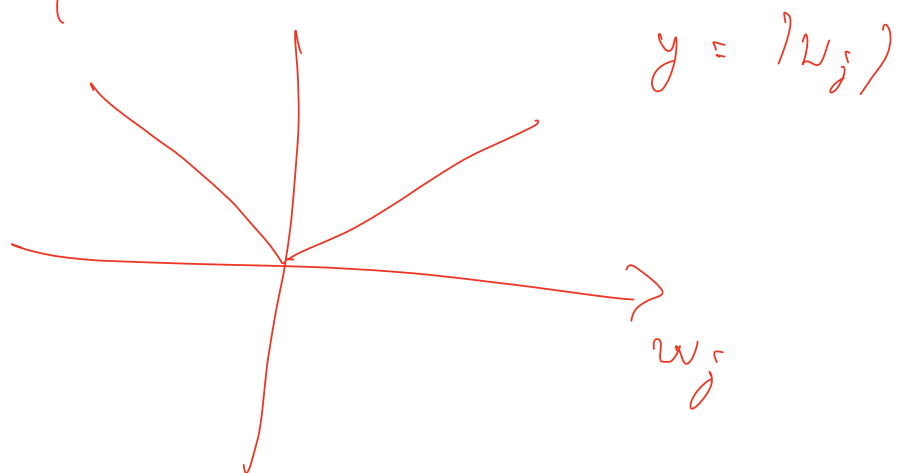
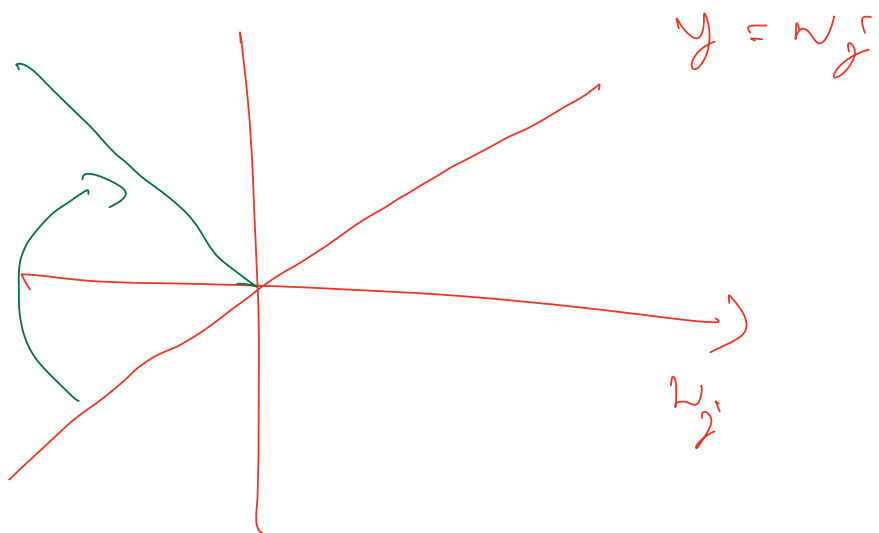
$$w = \begin{matrix} 1.5 & 2.0 & 3.5 & 4 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ 0.1 & 0.2 & 0.3 & 0.4 \end{matrix} \quad \left. \vphantom{\begin{matrix} 1.5 & 2.0 & 3.5 & 4 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ 0.1 & 0.2 & 0.3 & 0.4 \end{matrix}} \right\} \angle 2$$

$$w = \begin{matrix} 1.5 & 2.0 & 3.5 & 4 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ 0 & 2.0 & 0 & 4.0 \end{matrix} \quad \left. \vphantom{\begin{matrix} 1.5 & 2.0 & 3.5 & 4 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ 0 & 2.0 & 0 & 4.0 \end{matrix}} \right\} \begin{matrix} 1.5 + 2.7 \\ 3.5 + 4 \\ = 11 \end{matrix}$$

$\sum_{j=1}^d |w_j^i| \quad \angle > 2 + 4 = 6$



$$1 > \sqrt{0.5} \quad \checkmark \quad = \sqrt{1} = 1$$



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$$w_j = 0.5$$

$$\eta = 0.1$$

$w_j^1:$

$$0.5 - 0.1 \times 1 = 0.4$$

$$\frac{\partial |w_j^1|}{\partial w_j^1}$$

$$0.4 - 0.1 \times 1 = 0.3$$

$$0.3 - 0.1 \times 1 = 0.2$$

$$0.2 - 0.1 \times 1 = 0.1$$

$$0.1 - 0.1 \times 1 = 0$$

L2:

$$w_j = 0.5 - 0.1 \times \left( \frac{\partial w_j^2}{\partial w_j} = 2w_j \right) \downarrow$$

$$= 0.5 - 0.1$$

$$= 0.4$$

$$0.4 - 0.1 \times (2 \times 0.4) \downarrow$$

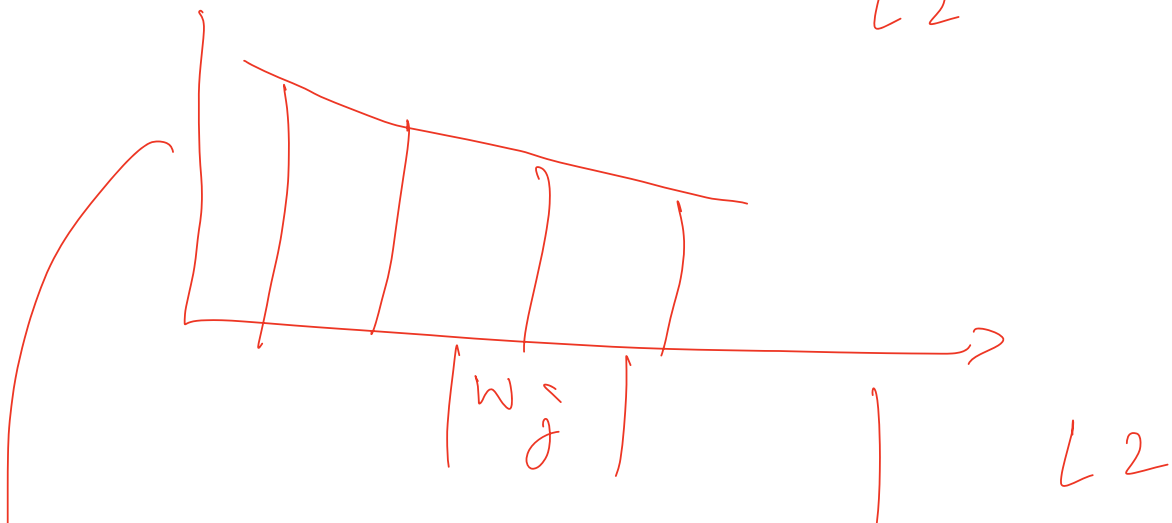
$$0.4 - 0.08 = 0.32$$

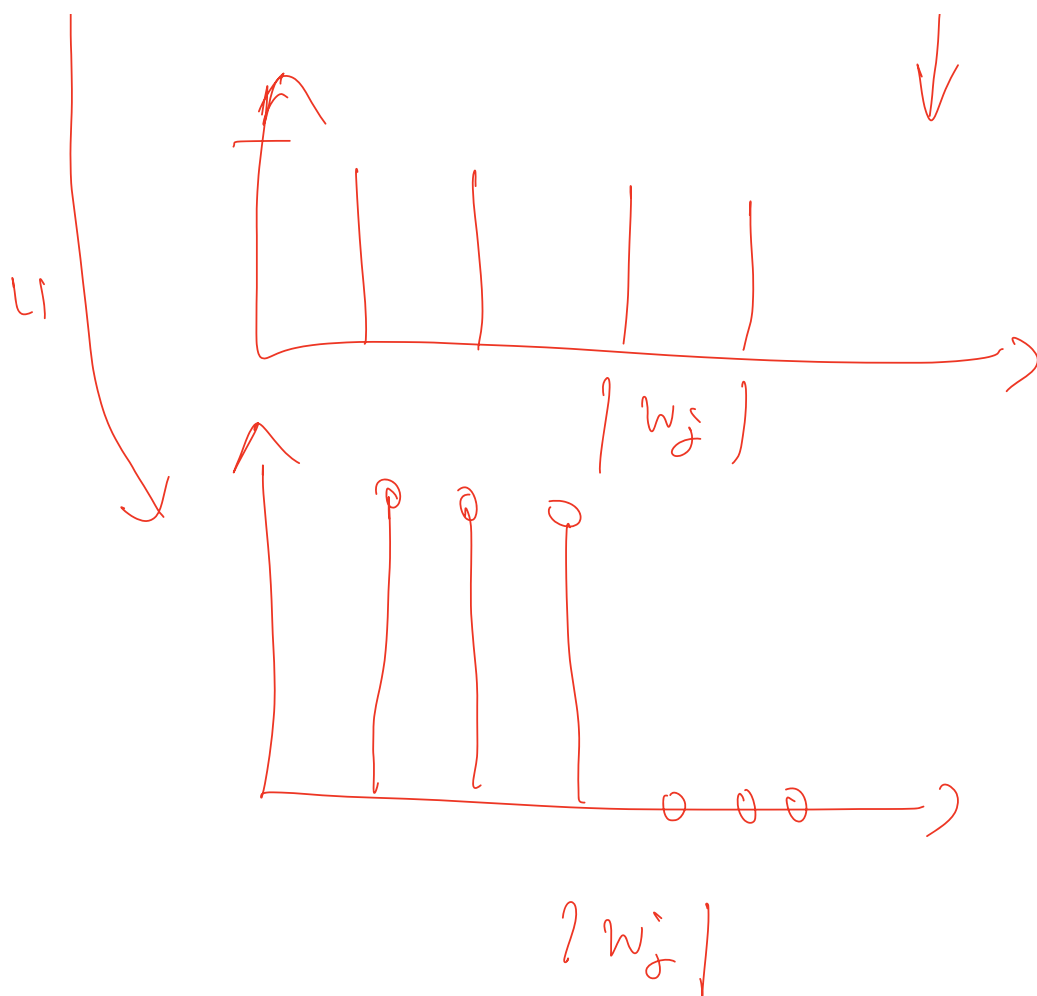
$$0.32 - 0.1 \times (2 \times 0.32) \downarrow$$

$$= 0.32 - 0.064$$

$$= 0.256$$

Elutic ref: combination of L1 & L2





Loss = MSE

①

②

$$\sum (\hat{y} - y)^2 + \lambda_2 \left( \sum_{j=1}^d w_j^2 \right)$$

$$\sum (\hat{y} - y)^2 + \lambda_1 \sum_{j=1}^d |w_j|$$

$$= 0.1$$

$$\lambda_2 = 10^3$$

$$\lambda_2 = 10^6$$

$\lambda$  high  $\rightarrow$  Underfitting  
very less learning

$\lambda$  low  
Overfitting  
too much learning

$$\lambda_1 / \lambda_2 = [0.01, 0.05, 0.1, 0.5, 1.0]$$

$\lambda_1 \rightarrow$  min ~~RSE~~ error on test data

parameters  $\rightarrow$

$$b, \underbrace{w_0, w_1, w_2, \dots, w_d}_w$$



hyper-params  $\rightarrow \eta$ , no. of epochs  
for gradient descent,

$\lambda_1, \lambda_2$  degree of  
of model  
regularization

Big data

$\rightarrow$  1 M data-points

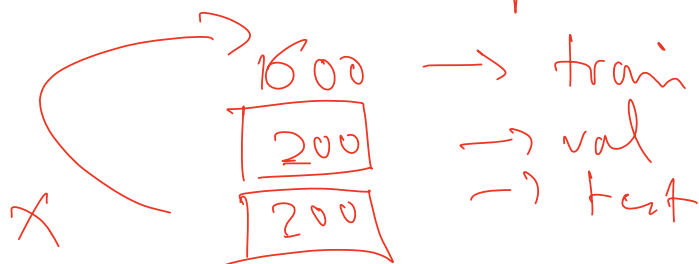
60%  $\rightarrow$  train

20%  $\rightarrow$  val

20%  $\rightarrow$  test

} randomly

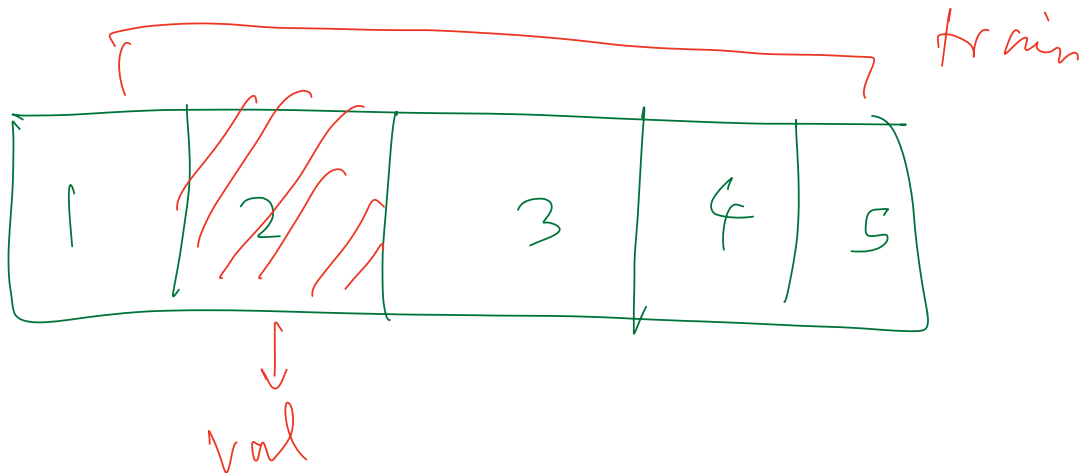
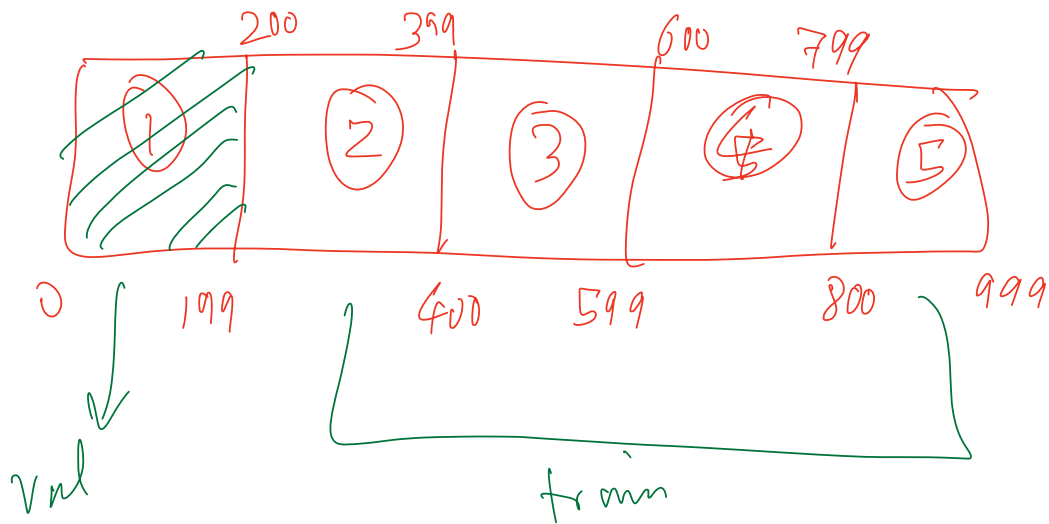
1000 data-points



1000 data points 0 to 999

↓ 5 folds

5-fold  
CV



$\lambda_1', \lambda_2', \eta', d', \text{epoch}'$

↓  
hyper-param set

for every

avg of  $\frac{5}{k}$  val fold errors  
X

1) Train on entire 1000  
train data with optimal  
hyper-param ✓

2) Train on 4 folds individually  
[4 out of 5 folds]

X with optimal hyper-param,  
2 then finally avg out  
the lin reg coefficients.