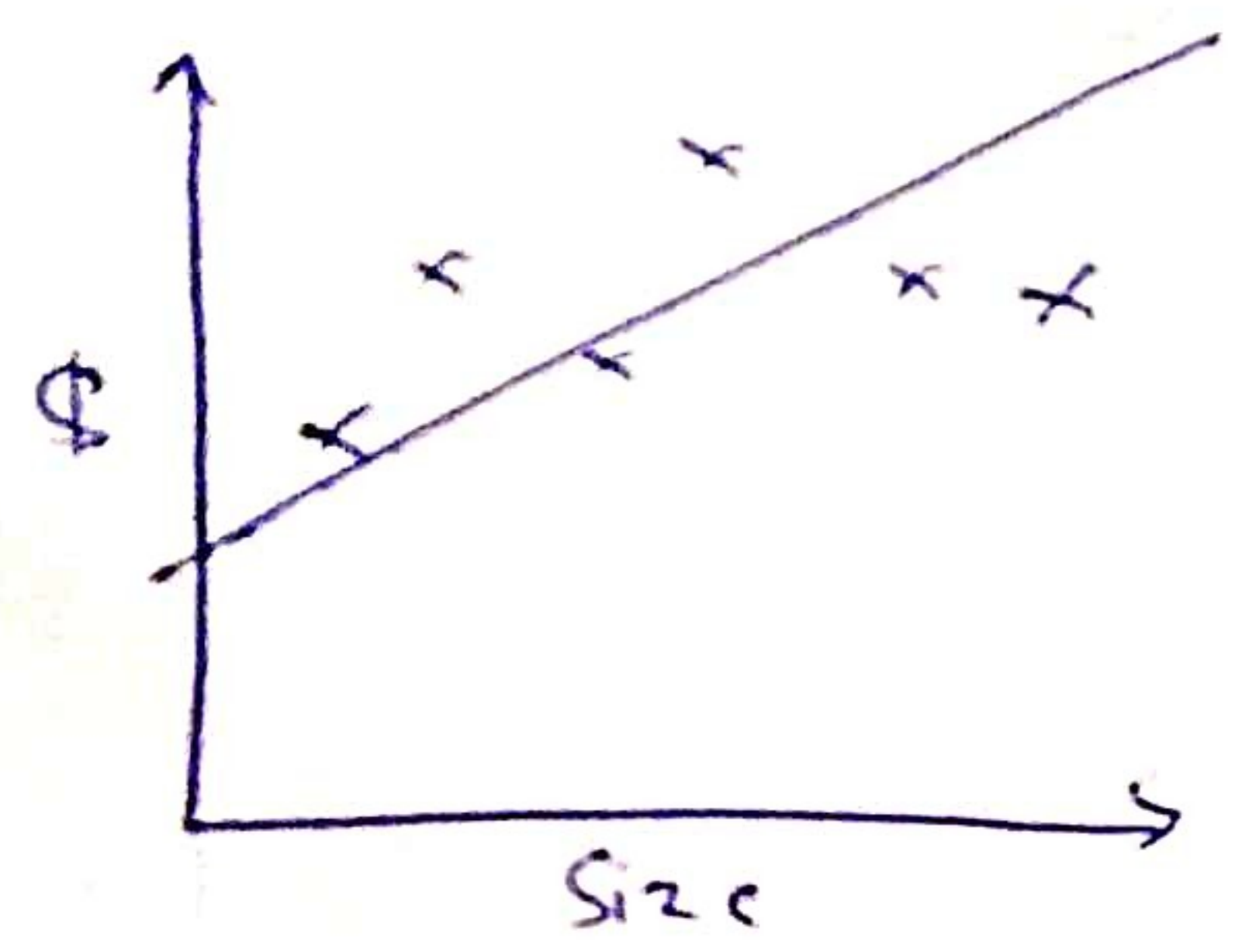


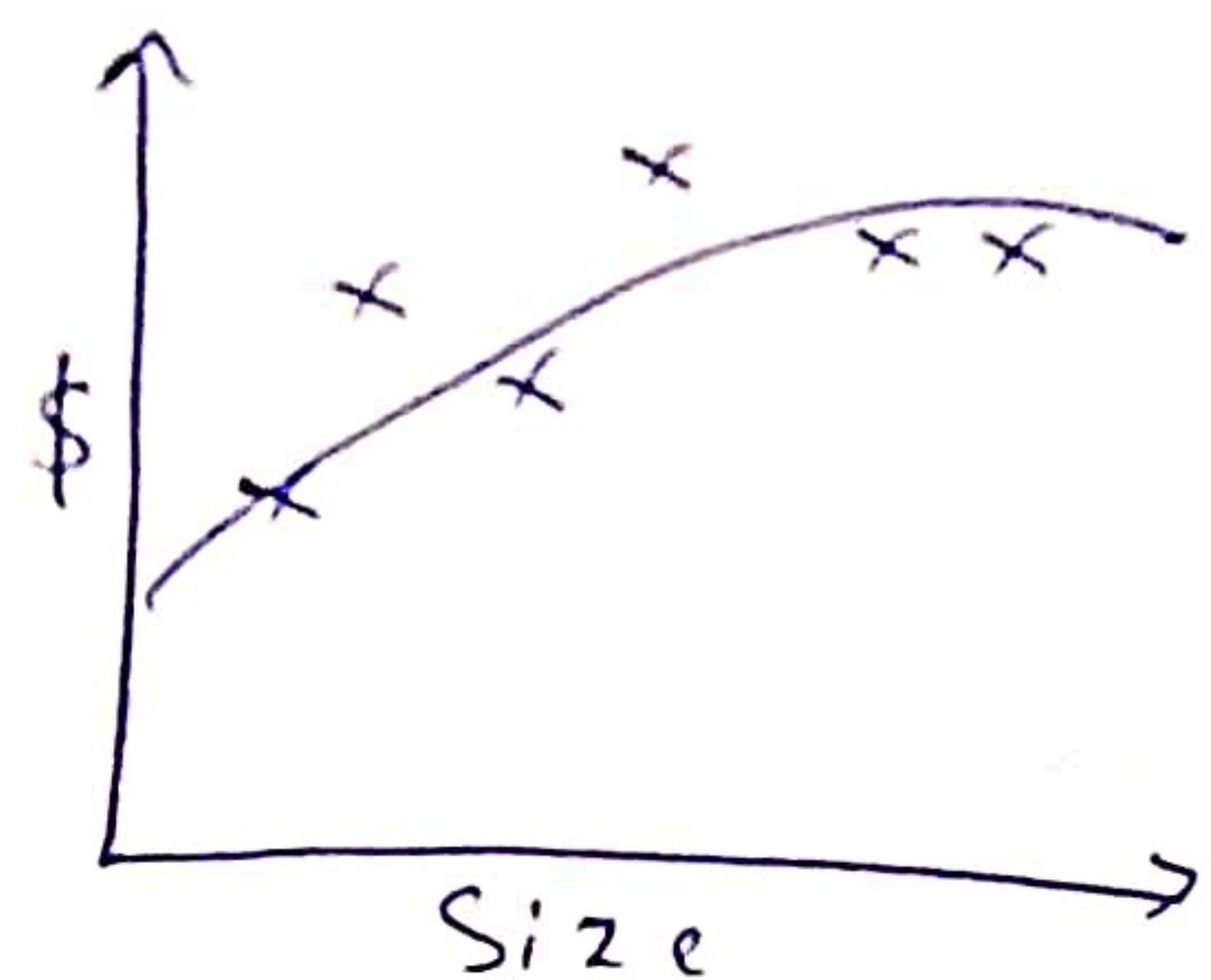
# Data Split, Models & Cross-Validation



$$\theta_0 + \theta_1 x$$

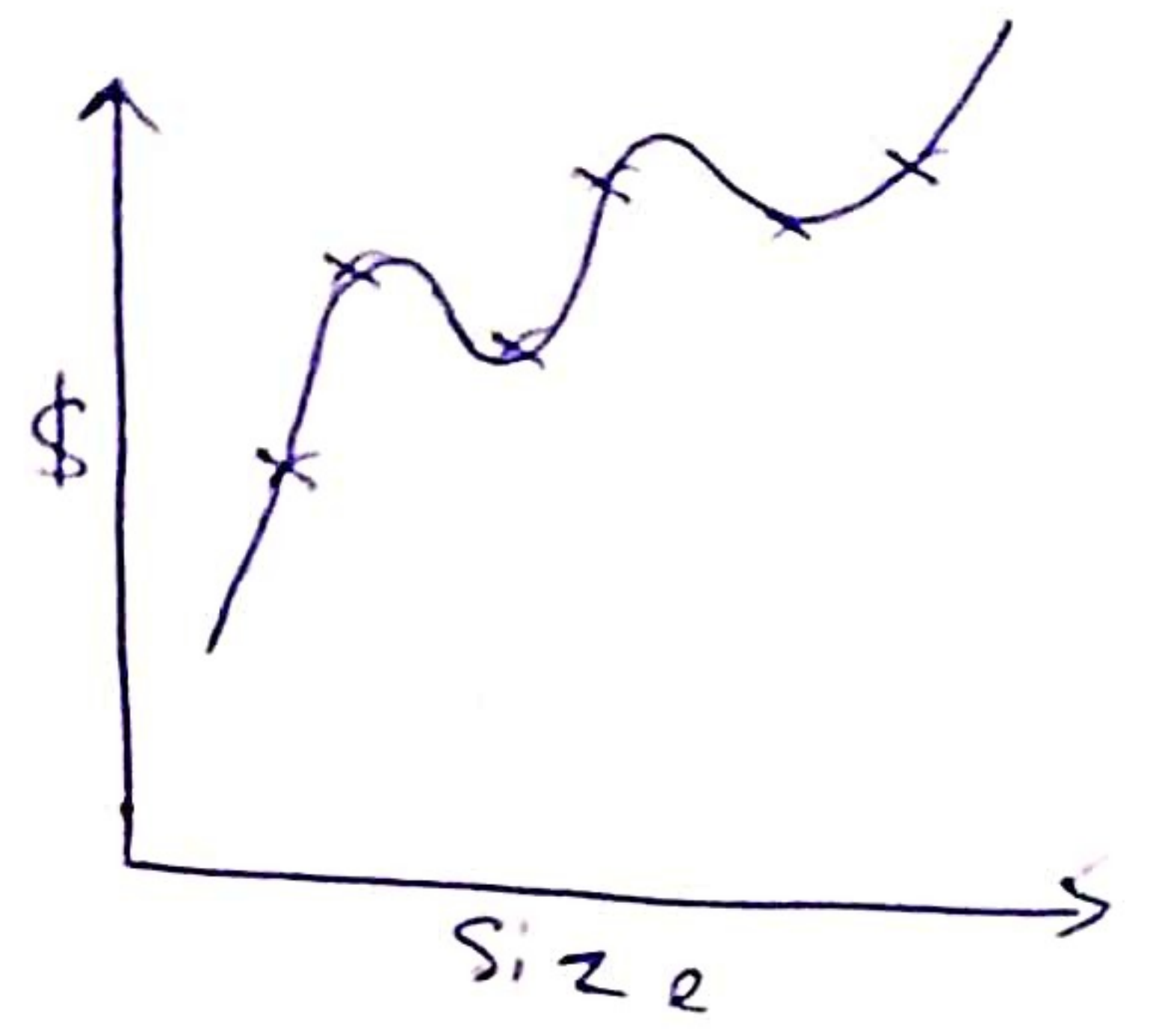
Underfit

high bias



$$\theta_0 + \theta_1 x + \theta_2 x^2$$

Just right



$$\theta_0 + \theta_1 x + \dots + \theta_5 x^5$$

Overfit

high variance

{ Very Strong preconception }

{ Changing training data a little bit will drastically change the fitted curve }

⇒ One of the most effective ways to prevent overfitting is regularization.

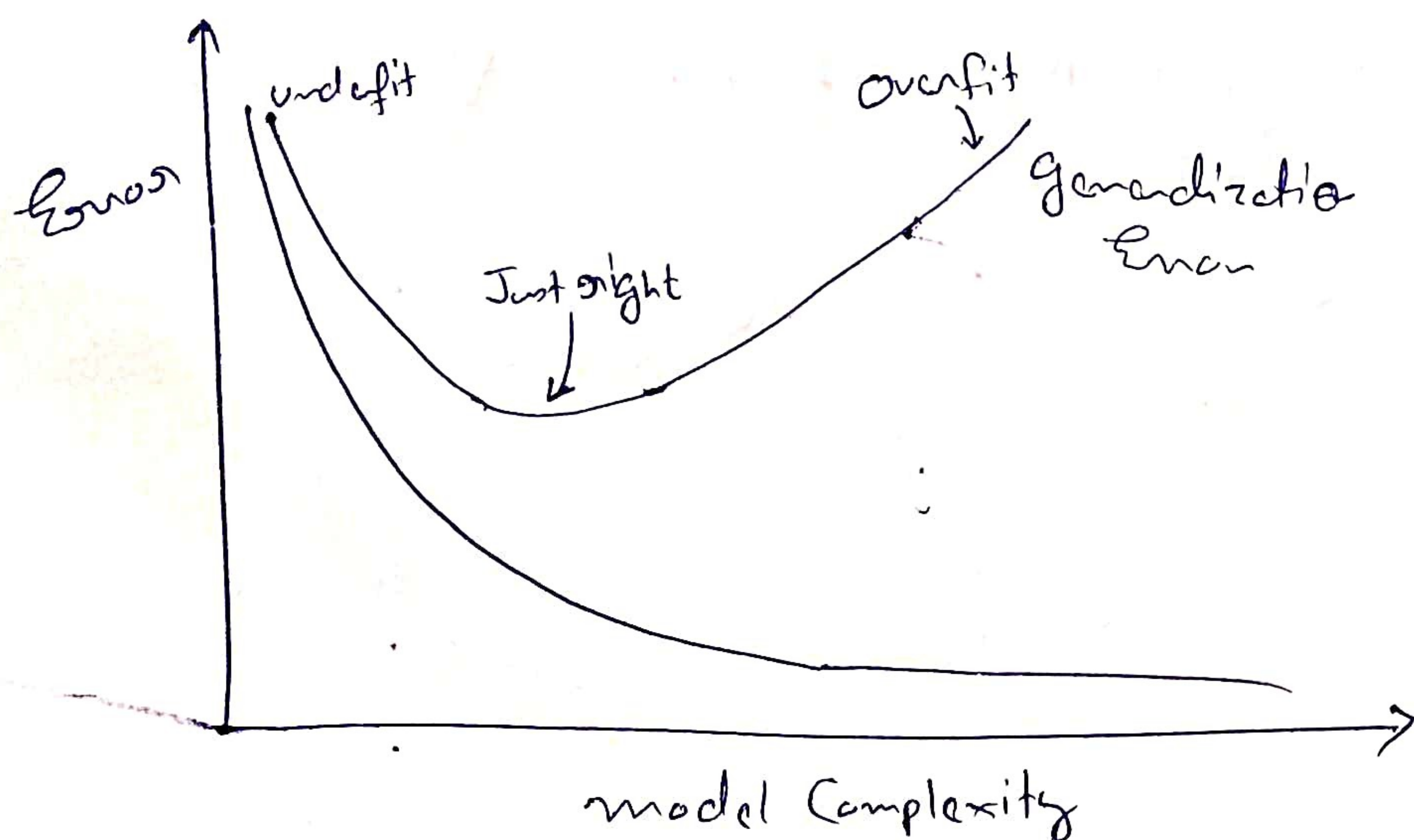
## \* Regularization

$$\min_{\theta} \frac{1}{2} \sum_{i=1}^m \|y^{(i)} - \theta^T x^{(i)}\|^2 \quad \left\{ \text{Cost function for Linear regression} \right\}$$

↓ After regularization

$$\min_{\theta} \frac{1}{2} \sum_{i=1}^m \|y^{(i)} - \theta^T x^{(i)}\|^2 + \frac{\lambda}{2} \|\theta\|^2$$





### ★ Simple Holdout Cross validation

$$\left( \frac{\text{Train Set}}{S_{\text{train}}} \right) + \left( \frac{\text{Dev Set}}{S_{\text{dev}}} \right) + \left( \frac{\text{Test Set}}{S_{\text{test}}} \right) = \left( \frac{\text{Data Set}}{S} \right)$$

$S_{\text{train}}$   
60%

$S_{\text{dev}}$   
20%

$S_{\text{test}}$   
20%

⇒ Train each model on  $S_{\text{train}}$

↳ Get some hypothesis  $h_i$

Also called Cross-validation Set

⇒ Measure the error on  $S_{\text{dev}}$ . Pick the one with lowest error on  $S_{\text{dev}}$ .

⇒ Evaluate the algorithm on separate  $S_{\text{test}}$  and report that error.



★ K-fold CV {Use this only for small dataset}

$$\begin{bmatrix} x^{(1)} & y^{(1)} \\ \vdots & \vdots \\ x^{(100)} & y^{(100)} \end{bmatrix}$$

⇒ Divide dataset into ~~randomly~~  $K$  subsets.  
(let  $K=5$ )

→ For  $i=1 \dots K$

→ Train on  $K-1$  pieces

→ Test on the remaining 1 piece

→ Take Average

→ Refit the best model found  
on 100% of the data

★ Feature Selection

Start with  $F = \emptyset$

Repeat

1) Try adding each feature to  $F$ , and  
See which feature addition, most  
improves the dev set performance.

2) Add that feature to  $F$ .

↙ Forward Search