

input:  $x_i \leftarrow \text{time}$

target:  $t_i \leftarrow \text{foam height}$

Polynomial Model  $M=3$

$$y = w_0 + w_1 x + w_2 x^2 + w_3 x^3$$

solution:  $w = (X^T X)^{-1} X^T t$

## Exponential Model

$$y(x) = e^{\omega_0 + \omega_1 \cdot x}, \quad x \equiv \text{time}$$

$$\Leftrightarrow \ln(y) = \omega_0 + \omega_1 \cdot x$$

$$\omega = (X^T X)^{-1} X^T \ln(t)$$

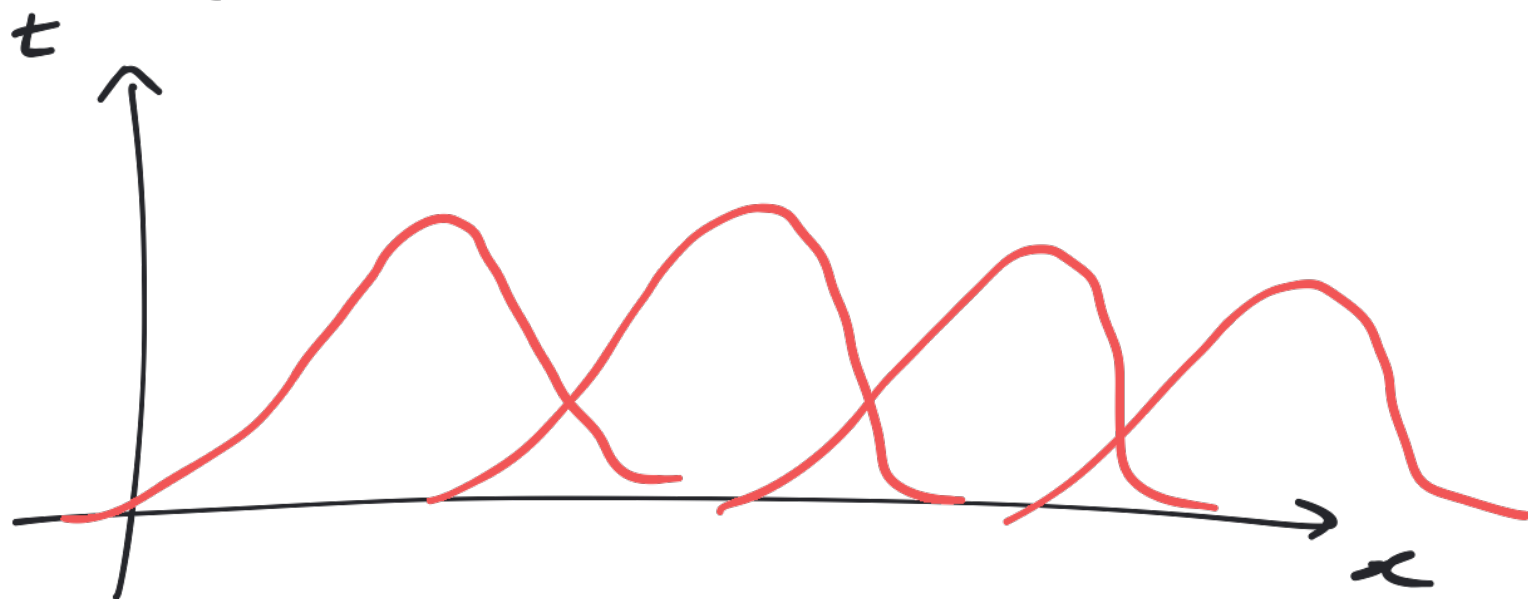
P2

$$y = \omega_0 + \omega_1 \phi_1(x) + \omega_2 \phi_2(x) + \omega_3 \phi_3(x) + \omega_4 \phi_4(x)$$

$$\phi_i(x) = e^{-\frac{(x-\mu_i)^2}{2\sigma^2}}, \quad \sigma = 0.01$$

$$X = \begin{bmatrix} 1 & e^{-\frac{(x_1-\mu_1)^2}{\sigma^2}} & \dots & e^{-\frac{(x_1-\mu_4)^2}{\sigma^2}} \\ 1 & e^{-\frac{(x_2-\mu_1)^2}{\sigma^2}} & \dots & e^{-\frac{(x_2-\mu_4)^2}{\sigma^2}} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & e^{-\frac{(x_N-\mu_1)^2}{\sigma^2}} & \dots & e^{-\frac{(x_N-\mu_4)^2}{\sigma^2}} \end{bmatrix}$$

$N \times 5$



## Ways to Avoid Overfitting

① Add more data!

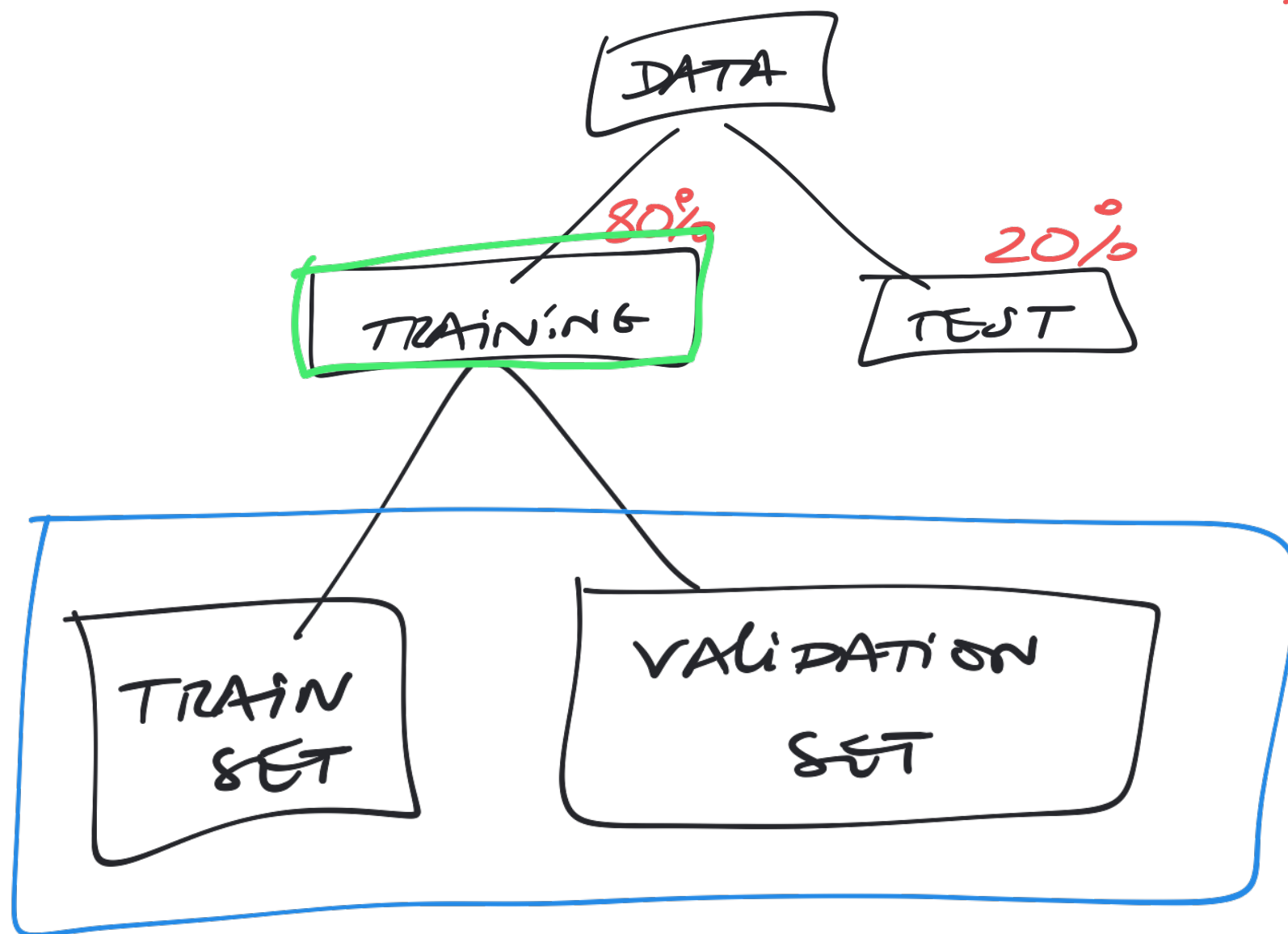
② Cross-validation

③ Regularization

④ Low complexity — Apply  
Occam's Razor principle

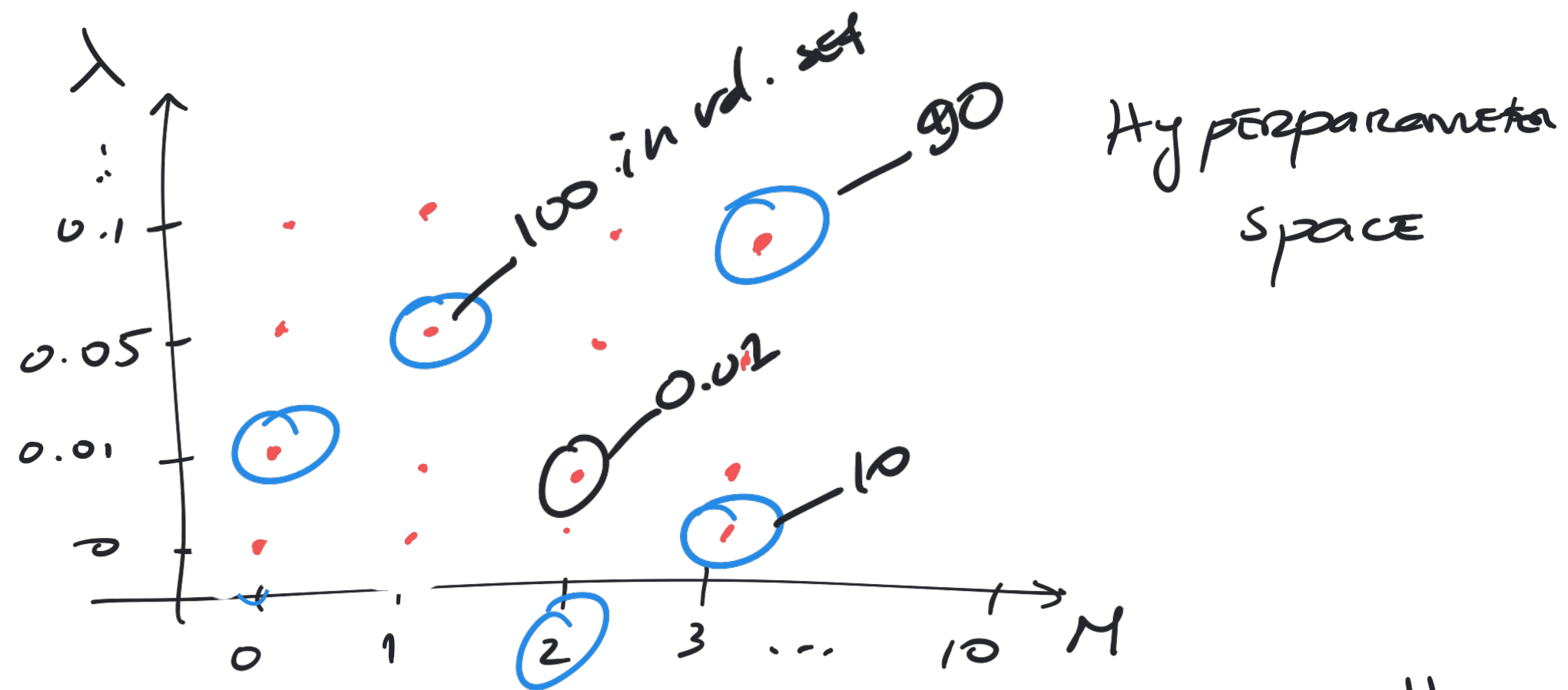
## Cross-validation

Helps us determine the best values for the hyperparameters using the training data.



Regularized  
Polynomial  
Regression  
 $\{M, \lambda\} = \theta$

EXPERIMENTAL  
DESIGN  
via  
Cross-Validation



① Factorial DESIGN. Experiment all possibilities.

② One parameter at a time.  
Requires more knowledge about problem/  
engineer regarding the model.

③ RANDOM SEARCH.

## K-Fold CV

- ① Define performance measure. E.g. MSE, coefficient of determination ( $R^2$ ), ...
- ② PARTITION DATA 

TRAIN SET (80%)			
$S_1$	$S_2$	$S_3$	$S_4$

 4-fold CV  
(it usually a good idea to shuffle the data before partitioning it into folds)
- ③ Iterate through several possible values for the hyperparameters ( $\mu$  and  $\lambda$ ):

(\*)

⑧

for model order  $M$  in some range:

$$M = \{2, 3, \dots, 10\}$$

for regularizer term  $\lambda$  in some range:

$$\lambda = \{0, 0.01, 0.05, 0.1\}$$

① TRAINING SET:  $\{S_1, S_2, S_3\} \leftarrow \text{MSE}_{\text{train}} = 50$

VAL. SET:  $\{S_4\} \leftarrow \text{MSE}_{\text{val}} = 100$

$W_1$

② TRAIN SET:  $\{S_1, S_2, S_4\} \leftarrow \text{MSE}_{\text{train}} = 0.5$

VAL. SET:  $\{S_3\} \leftarrow \text{MSE}_{\text{val}} = 1$

$W_2$

③ TRAIN SET:  $\{S_1, S_3, S_4\} \leftarrow 2$

VAL. SET:  $\{S_2\} \leftarrow 3$

④ TRAIN SET:  $\{S_2, S_3, S_4\} \leftarrow 10$

VAL. SET:  $\{S_1\} \leftarrow 20$

$$\left\{ \begin{array}{l} \text{A) MSE AVERAGE in val. SET} = \frac{100 + 1 + 3 + 20}{4} \\ \text{train. SET} = \frac{50 + 0.5 + 2 + 10}{4} \end{array} \right.$$

$$\left\{ \begin{array}{l} \text{B) MSE MAXIMUM in val. SET} = 100 \\ \text{train SET} = 20 \end{array} \right.$$

④ Pick set of hyperparameters that optimizes performance in validation set.



## STRATIFIED CV

Partition the data such  
that prior probabilities for  
each class representation is  
preserved in all subsets.