

Regularization

Ridge

$$R_w(w) = \sum_i w_i^2$$

Lasso

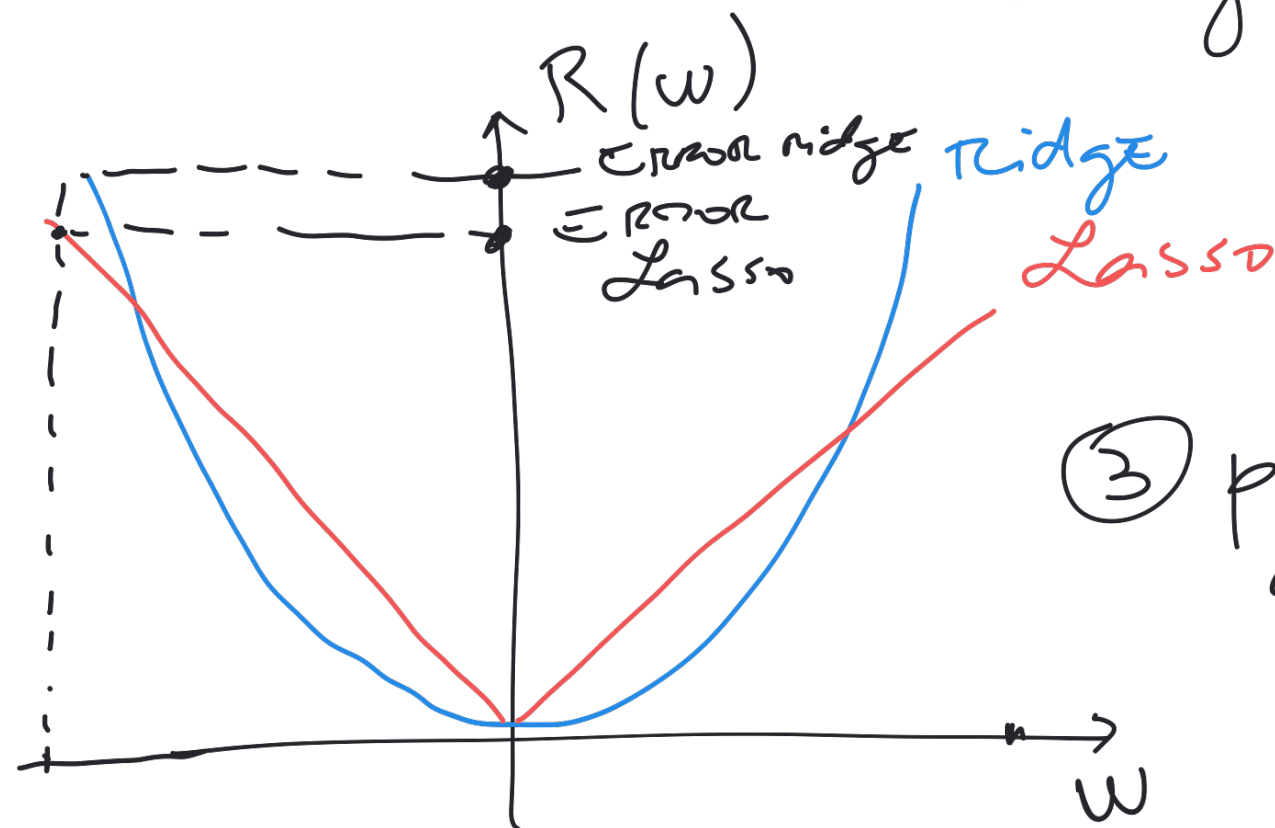
$$R_w(w) = \sum_i |w_i|$$

$$J(w) = \boxed{\frac{1}{2} \sum_n \ell_n^2} + \boxed{\frac{1}{2} \lambda \cdot R_w(w)}$$

$$\boxed{\arg \min_w J(w)}$$

Regularization
weight

Ridge: ① Will penalize large weight values more



Lasso

② Highly affected by outliers

③ prefers that coefficients are not zero but very small

Lasso: ① Less sensitive to outliers

② Makes weights go to zero much faster

③ prefers some coefficients exactly zero.

Using Lasso reg. we can
perform Feature Selection

$$J(w) = J_E(x, w) + \lambda \cdot R_w(w)$$

$\lambda = 0$: only minimizing $J_E(x, w)$

$\lambda \rightarrow \infty$: disregards $J_E(x, w)$ and
forces R_w to be small

For Regularized Polynomial
Regression:

we control:

- ① Model
- ② Cost function
- ③ Learning algorithm

Model order M and reg. weight λ

$$J(w) = \frac{1}{2} \sum_{i=1}^N \underbrace{(t_i - y_i)}_{=e_i}^2 + \frac{1}{2} \cdot \lambda \cdot \sum_{j=0}^M w_j^2$$

$$= \frac{1}{2} \|t - Xw\|_2^2 + \frac{1}{2} \cdot \lambda \cdot \|w\|_2^2$$

If we have $N \gg M$: likely will
 # samples \nearrow model order also be
 an overdetermined system of eqs

identity matrix

$$\lambda \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & 1 \end{bmatrix}_{(M+1) \times (M+1)}$$

$$w^* = (X^T X + \lambda \cdot \mathbf{I})^{-1} X^T t$$

regularized
polynomial
regression

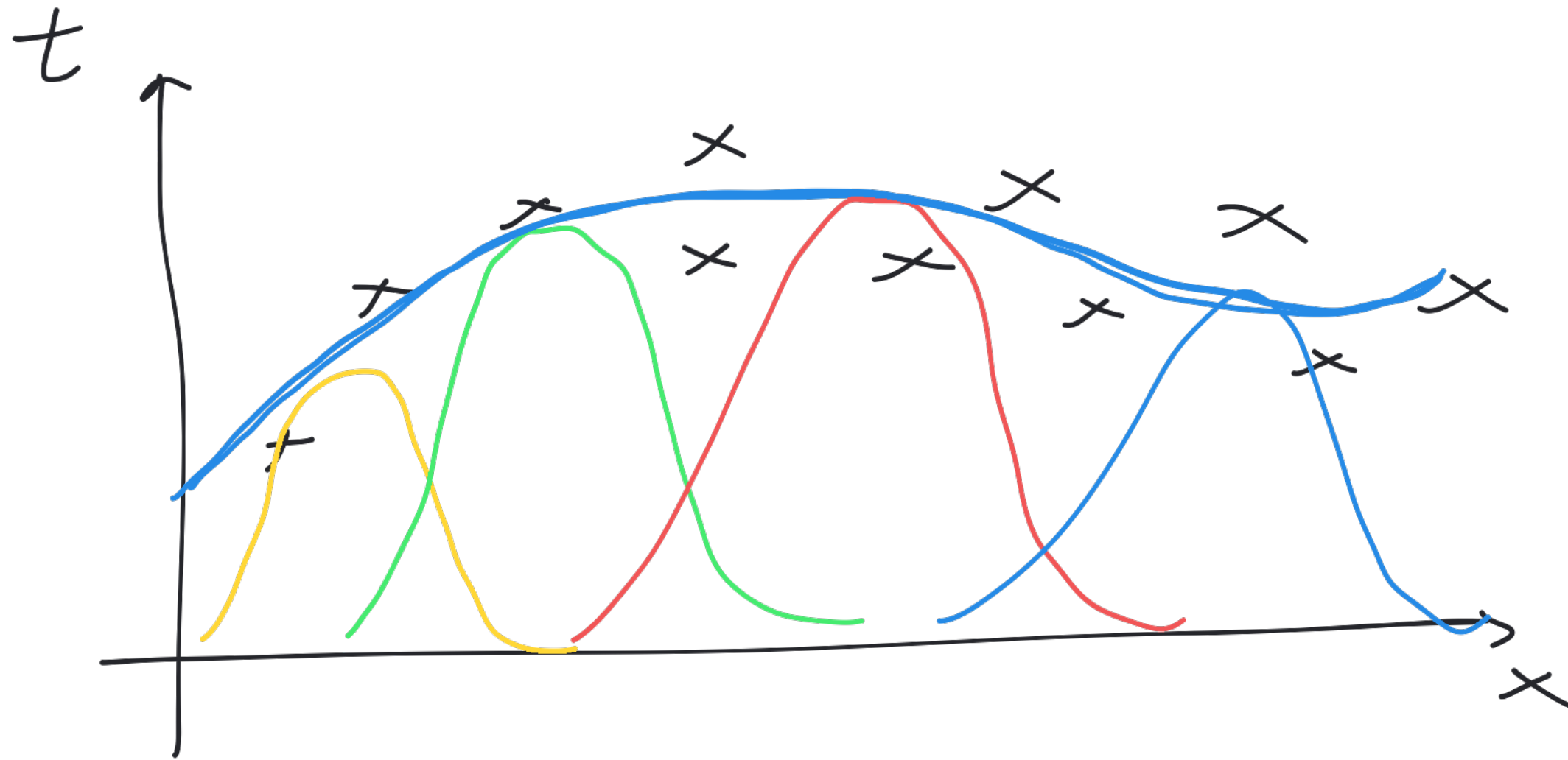
$$w^* = (X^T X)^{-1} X^T t$$

polynomial
reg. w/out reg.

Regularization:

→ diagonally loading $X^T X$

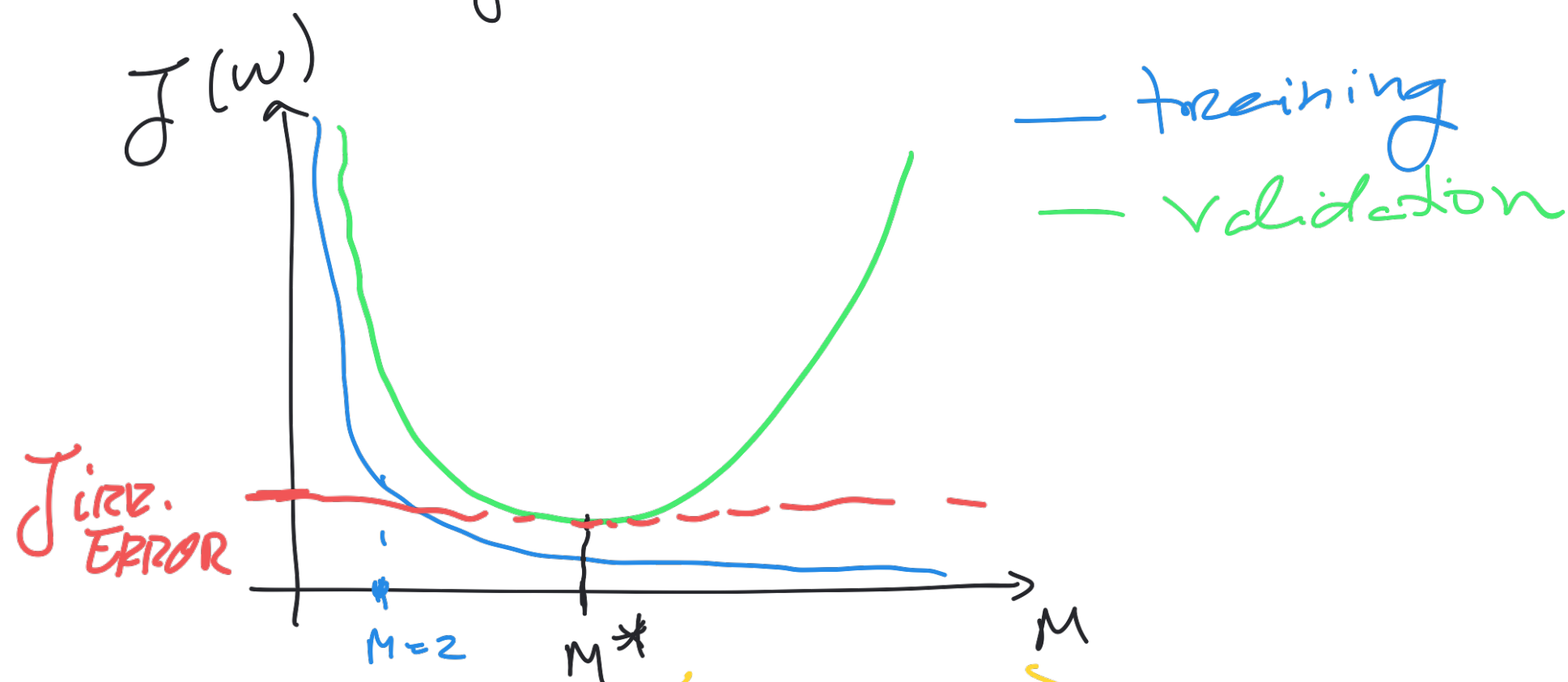
→ make such $X^T X$ is full rank



$$w_0 \cdot G + w_1 \cdot G + w_2 \cdot G + w_3 \cdot G$$

$$y = \sum_{j=0}^M w_j \cdot \phi_j(x)$$

- we are looking for the best combination of controllable parameters (M, λ) :



underfitting
 J_{train} will be high
 J_{val} will be high

high bias
 low variance

overfitting

J_{train} will be small
 $J_{\text{val}} \gg J_{\text{train}}$

low bias &
 high variance