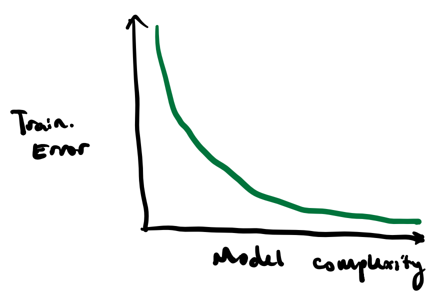
Assessing loss

Training error

$$E = \frac{1}{N} \sum_{i=1}^{N} \left(y^{(i)} - f_{\hat{w}}(x^{(i)})\right)^2$$

vs. model complexity!



Training data is not a good predictor of model performance

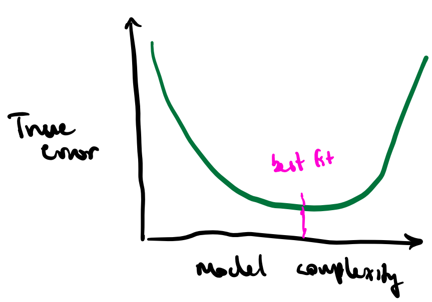
Generalization (true) error

Want estimate of loss over all possible feature vectors + labels

Formally!

$$\text{Generalization error} = E_{x,y}\left[L(y, f_{\hat{w}}(x))\right]$$

vs. model complexity:

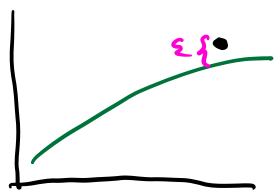


Sources of error

Noise

$$y^{(i)} = f_{w(true)}(x^{(i)}) + \varepsilon^{(i)}$$

Independent error



Bias

$$\text{Bias}(x) = f_{w(true)}(x) - f_{\hat{w}}(x)$$

Is approach flexible enough to capture $f_{w(true)}$?
If not, error

Low complexity – high bias

High complexity – low bias

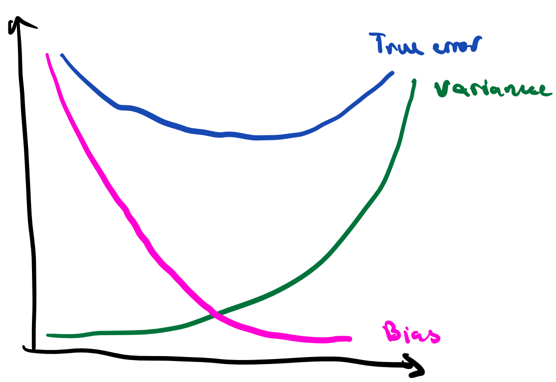
Variance

How much do specific fits vary from the expected fit?

Low complexity – low variance

High complexity – high variance

Bias-Variance Tradeoff



Error vs. amount of data