



CS 329P : Practical Machine Learning (2021 Fall)

# 5. Model Combination

Qingqing Huang, Mu Li, Alex Smola

<https://c.d2l.ai/stanford-cs329p>

# So far...



- Data
- ML Models for different types of data
- Good models perform well on unseen data
  - Model specific metrics VS business metrics
  - Generalization error depends on model / data complexity
  - TODAY: Methods for reducing generalization error



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# 5.1 Bias & Variance

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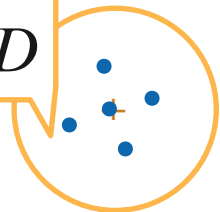


# Bias & Variance

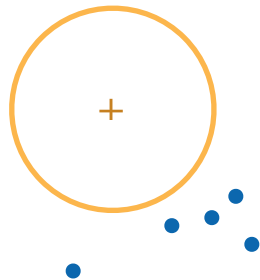
- Sample data  $D = \{(x_1, y_1), \dots, (x_n, y_n)\}$  from  $y = f(x) + \varepsilon$
- Learn  $\hat{f}_D$  from data  $D$  by minimizing MSE:  $\min_{\hat{f}_D} \sum_{(x_i, y_i) \in D} (y_i - \hat{f}_D(x_i))^2$
- We want  $\hat{f}_D$  generalizes well to an unseen data point  $(x, y)$ .

Distribution of  $\hat{f}_D(x)$  for different experiment  $D$

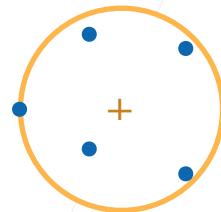
low bias  
low variance



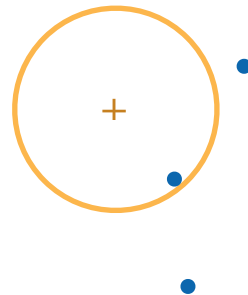
high bias  
low variance



low bias  
high variance



high bias  
high variance



# Bias-Variance Decomposition



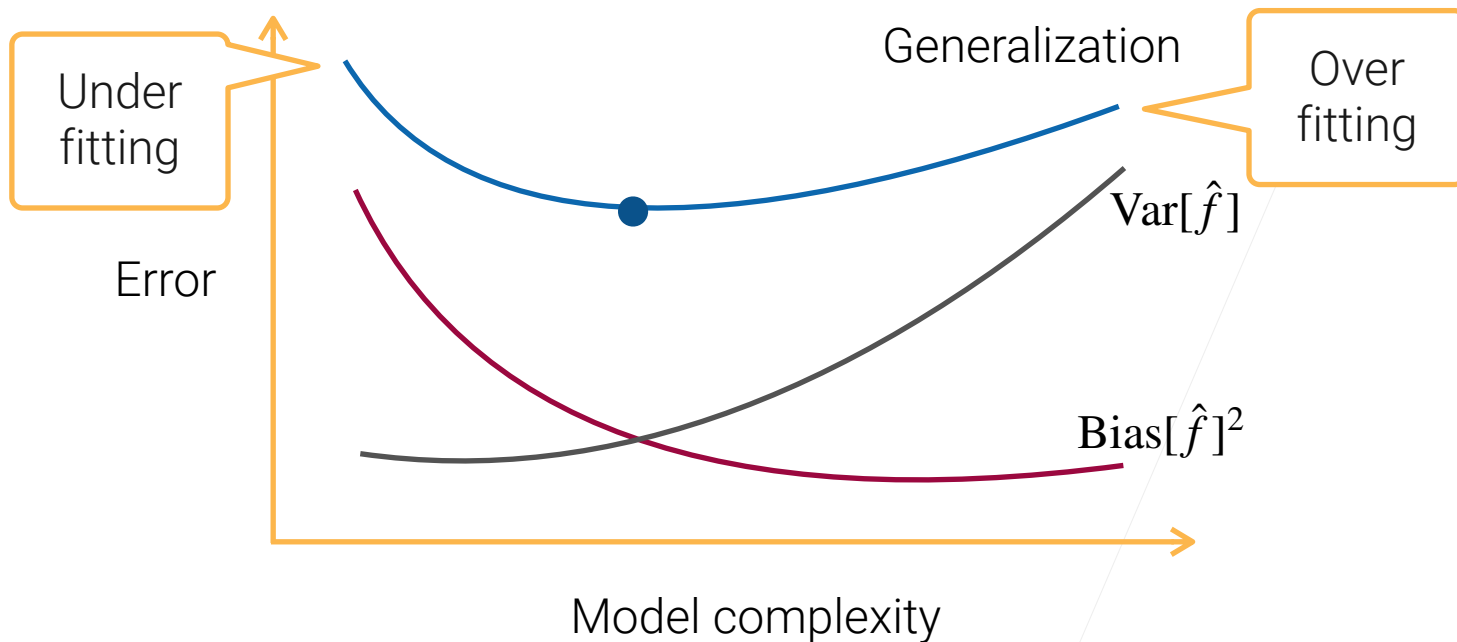
- Learn  $\hat{f}_D$  from dataset  $D$  sampled from  $y = f(x) + \varepsilon$
- Evaluate generalization error  $(y - \hat{f}_D(x))^2$  on a new data point  $(x, y)$

$$\begin{aligned} \mathbb{E}_D \left[ (y - \hat{f}_D(x))^2 \right] &= \mathbb{E}_D \left[ \left( (f - \mathbb{E}_D[\hat{f}_D]) - (\hat{f}_D - \mathbb{E}_D[\hat{f}_D]) + \varepsilon \right)^2 \right] \\ &= (f - \mathbb{E}_D[\hat{f}_D])^2 + \mathbb{E}_D \left[ (\hat{f}_D - \mathbb{E}_D[\hat{f}_D])^2 \right] + \varepsilon^2 \\ &= \text{Bias}[\hat{f}_D]^2 + \text{Var}[\hat{f}_D] + \varepsilon^2 \end{aligned}$$

# Bias-Variance Tradeoff



$$E_D \left[ (y - \hat{f}_D(x))^2 \right] = \text{Bias}[\hat{f}_D]^2 + \text{Var}[\hat{f}_D] + \epsilon^2$$



# Reduce Bias & Variance



$$E_D \left[ (y - \hat{f}_D(x))^2 \right] = \text{Bias}[\hat{f}_D]^2 + \text{Var}[\hat{f}_D] + \epsilon^2$$

- Reduce bias
  - A more complex model
    - e.g. increase #layers, #hidden units of MLP
- Reduce variance
  - A simpler model
    - e.g. regularization
- Reduce  $\sigma^2$ 
  - Improve data

- Boosting
- Stacking

- Bagging
- Stacking

**Ensemble learning:** train and combine multiple models to improve predictive performance