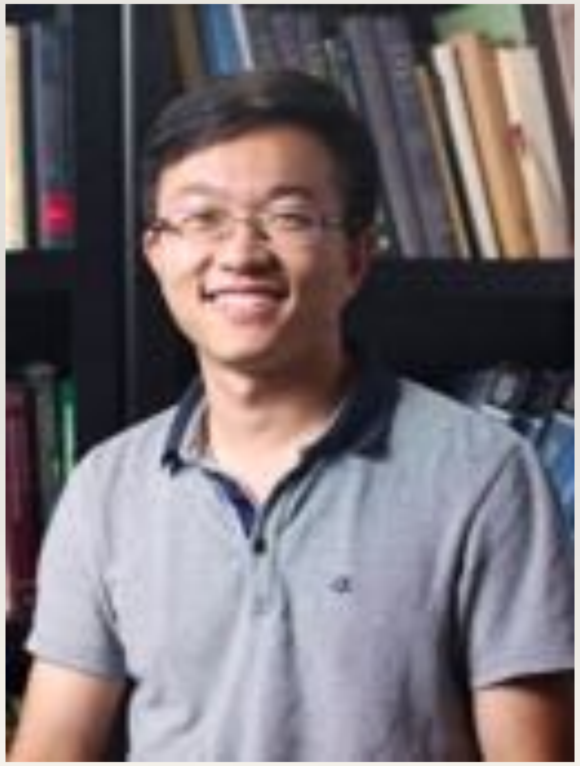
Practical Statistical Learning (F18)

Feng Liang



Changbo Zhu

Yinyin (Elaine) Chen

Joshua Daniel Loyal

Overview

- Types of statistical learning problems
- Why learning is difficult?
- Bias variance tradeoff
- An example: kNN *vs* Linear Regression (in a separate pdf file)
- Not all about prediction

Problems (I)

- Project 1 (Ames Housing Data): Predict the sale price of a house given its features.
- Project 2 (Sales Forecasting): Provide sales forecasting for Walmart for each department in each store based on historical data.

Y: Target
X: Feature/Covariates

Problems (II)

- Project 3 (Lending Club): Determine the chance that a borrower will miss a payment next month given various characteristics of the borrower and the loan.
- Project 4 (Sentiment Analysis): Determine whether a movie review is positive or negative.

Y: Target
X: Feature / Covariates

Problems (III)

- Based on the recent real estate transactions at Ames, Iowa, can we identify any home buying/selling trends? Further, can we identify distinctive groups of buyers?
- Based on the transaction data at Walmart, can we recommend any marketing strategies to Walmart?

Association Rule (chap 14.2 of ESL)
Market Segmentation (cluster customers)

Problems (III)

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~~Y: Target~~
X: Feature/Covariates

Types of Statistical Learning Problems

- Supervised Learning
  - Regression: response is a number
  - Classification: response is a label (binary or multi-class)

Semi-supervised Learning *Recommender System*

- Unsupervised Learning: identify latent structures in the data, e.g., clustering, association rule, HMM, etc.

How does Supervised Learning Work?

Data: {x_i, y_i}
i=1, 2, …, n

Goal: learn w
y <—–- $f(x; w)$

Minimize an objective function

$$F(w) = \sum_{i=1}^{n} \text{loss}(y_i, f(x_i; w))$$

$$\text{loss} = \Big[y_i - f(x_i; w)\Big]^2$$

$$\text{loss} = \mathbf{1}\Big\{y_i \neq f(x_i; w)\Big\}$$

$$\text{loss} = \begin{cases} -\log f(x_i; w) & \text{if } y_i = 1 \\ -\log(1 - f(x_i; w)) & \text{if } y_i = 0 \end{cases}$$

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1. The minimizer w^* may be in closed form.
2. Try optimization algorithms that can guarantee to converge to the global minimizer.
3. In the worst case, try *gradient descent*.

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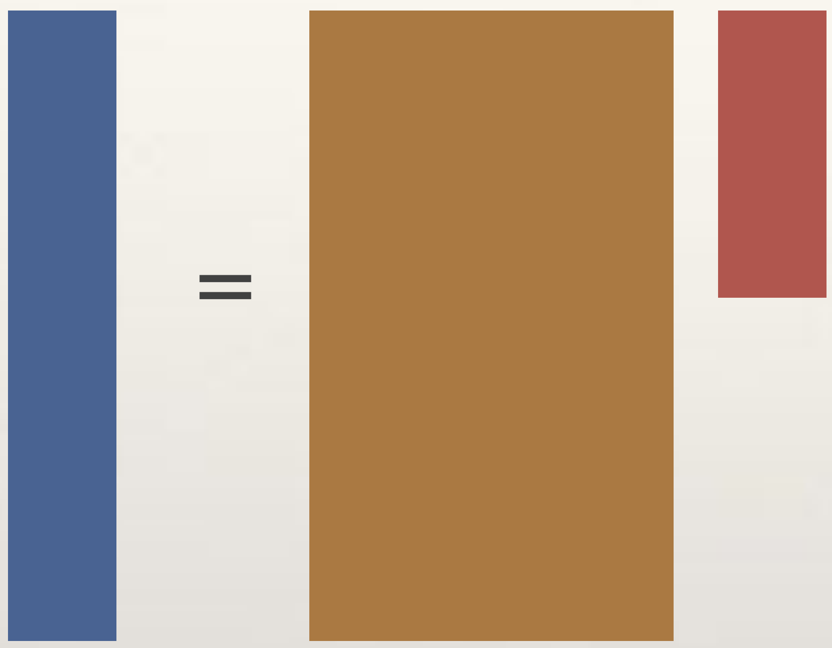
Challenges

- Training error underestimates test/generalization error.
- Overfitting: perform well on the training data but not on the future (unseen) data.
- p denotes the number of parameters the regression/classification function f has, i.e., the number of parameters we need to learn from the data.
- The gap between the two errors (training *vs.* test) gets large when p is large.

Curse of Dimensionality

- Curse of Dimensionality in Classification:
  - 1NN (one-nearest-neighbor) predicts perfectly on the training data
  - Illustration on how dimensionality changes the performance of linear classifiers: http://www.visiondummy.com/2014/04/curse-dimensionality-affect-classification/

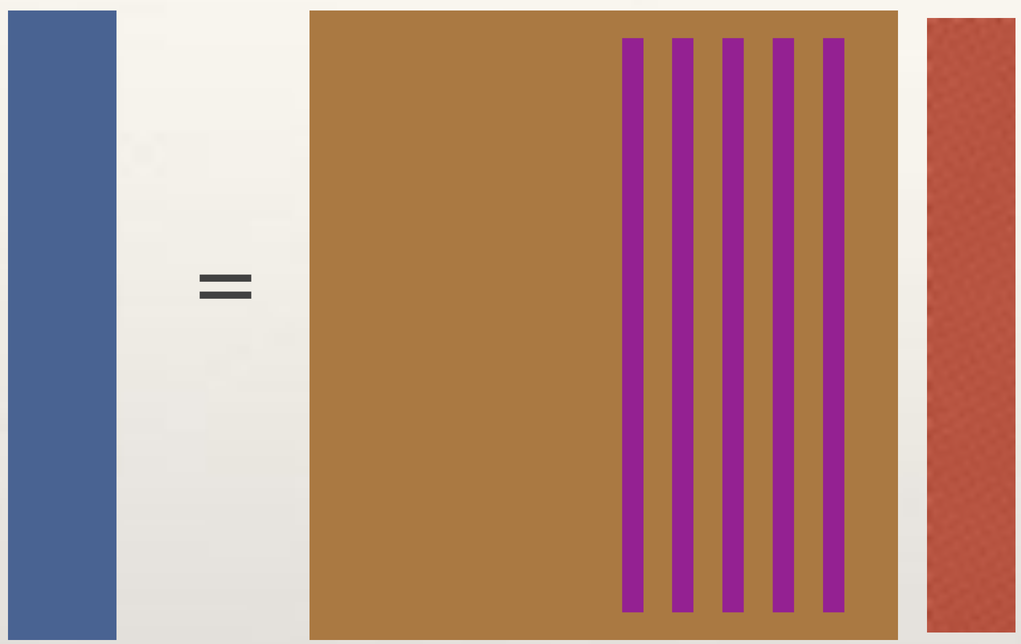
Curse of Dimensionality



$$y_{n\times 1} = X_{n\times p} w_{p\times 1}$$

Curse of Dimensionality in Regression

Curse of Dimensionality



$$y_{n\times 1} = X_{n\times n} w_{n\times 1}$$

n equations and n parameters

Perfect fit on the training data!

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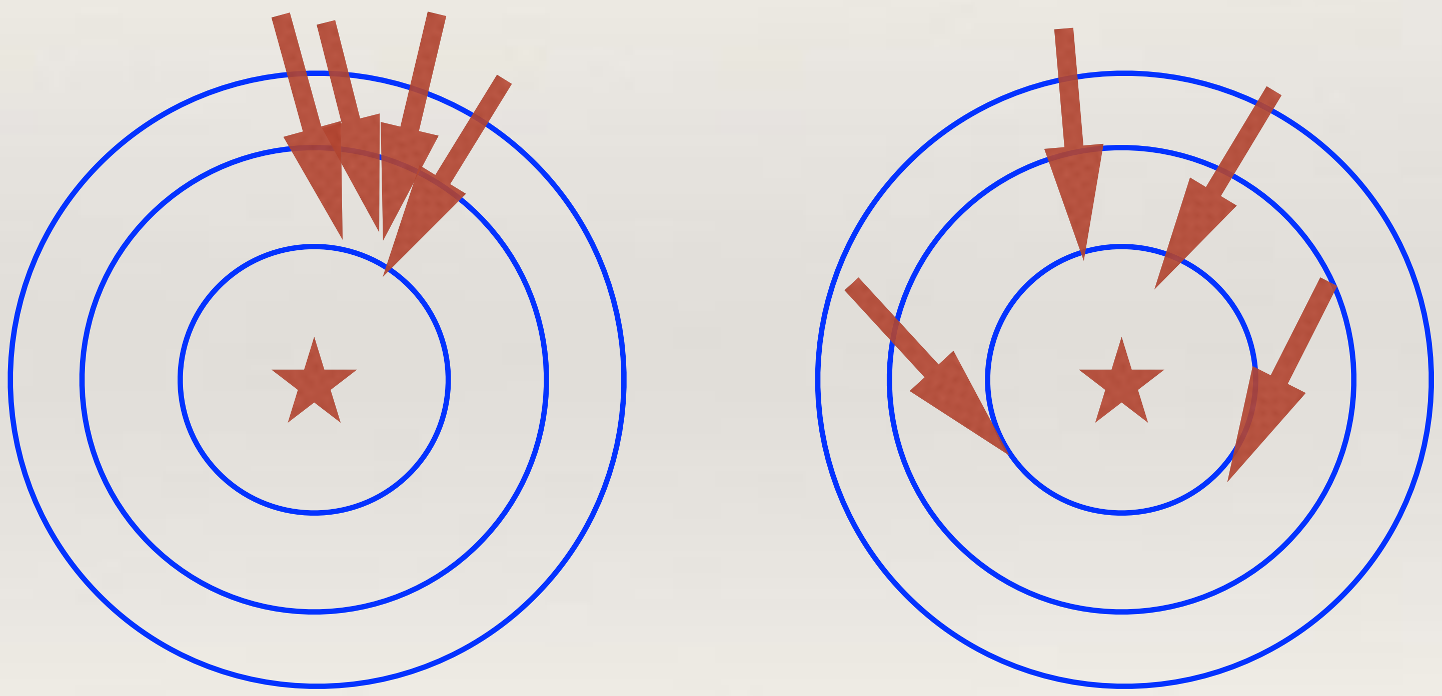
Bias Variance Tradeoff

Goal of ML: Minimize *generalization error* (i.e., error on unseen future datasets), not training error.

Source of errors:

- Bias
- Variance



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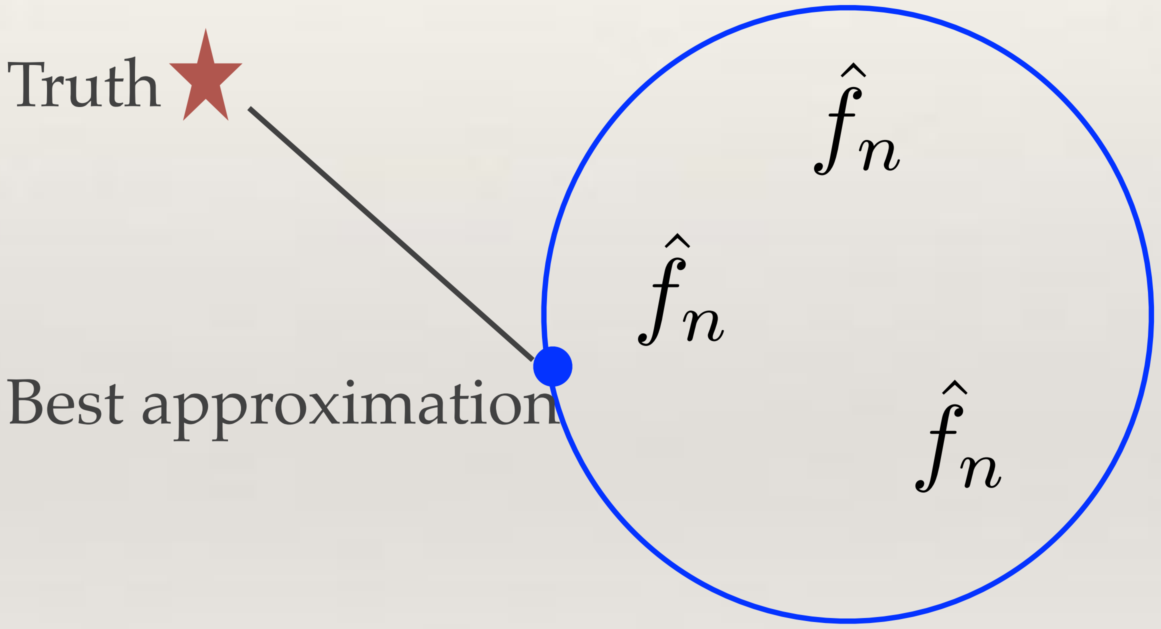

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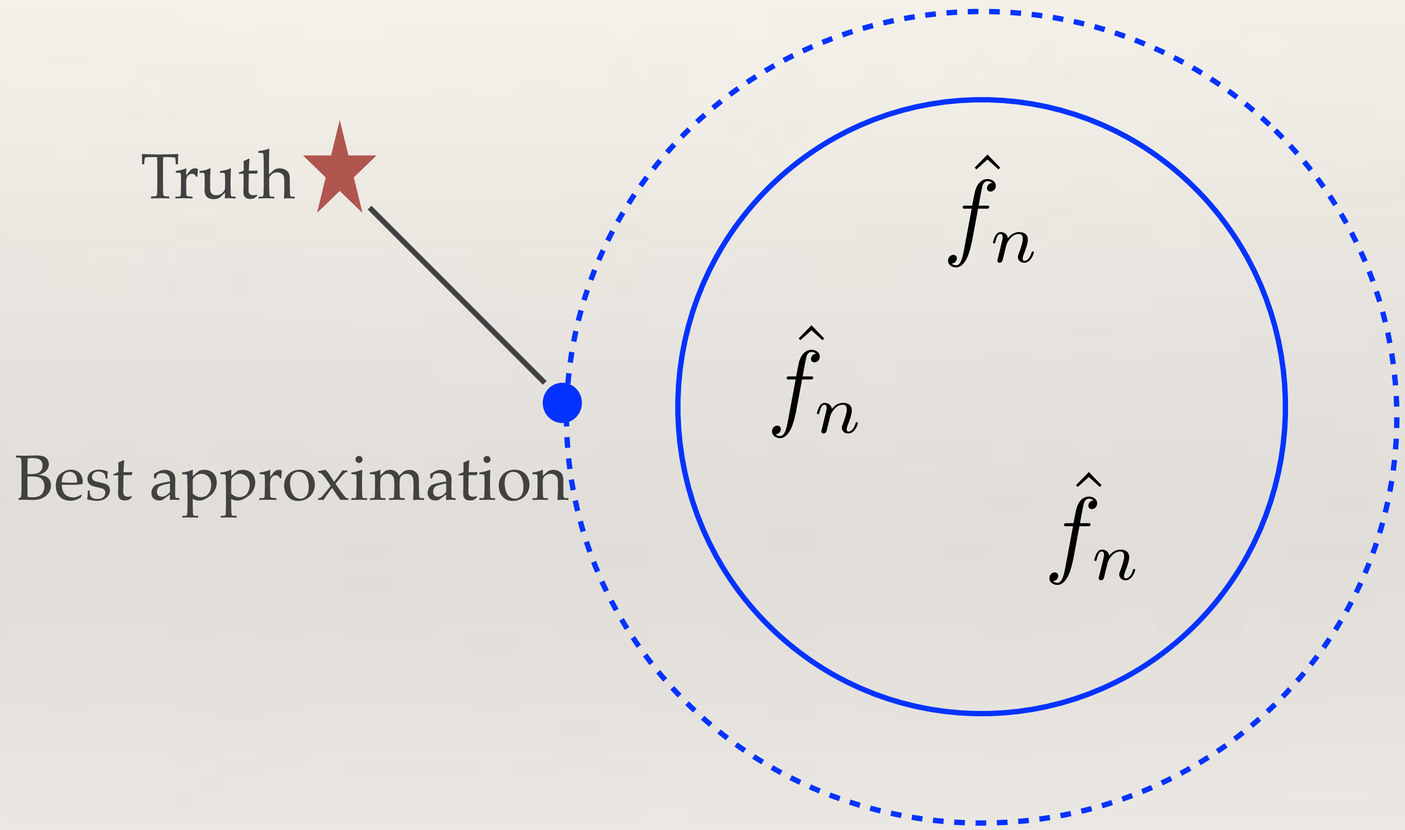

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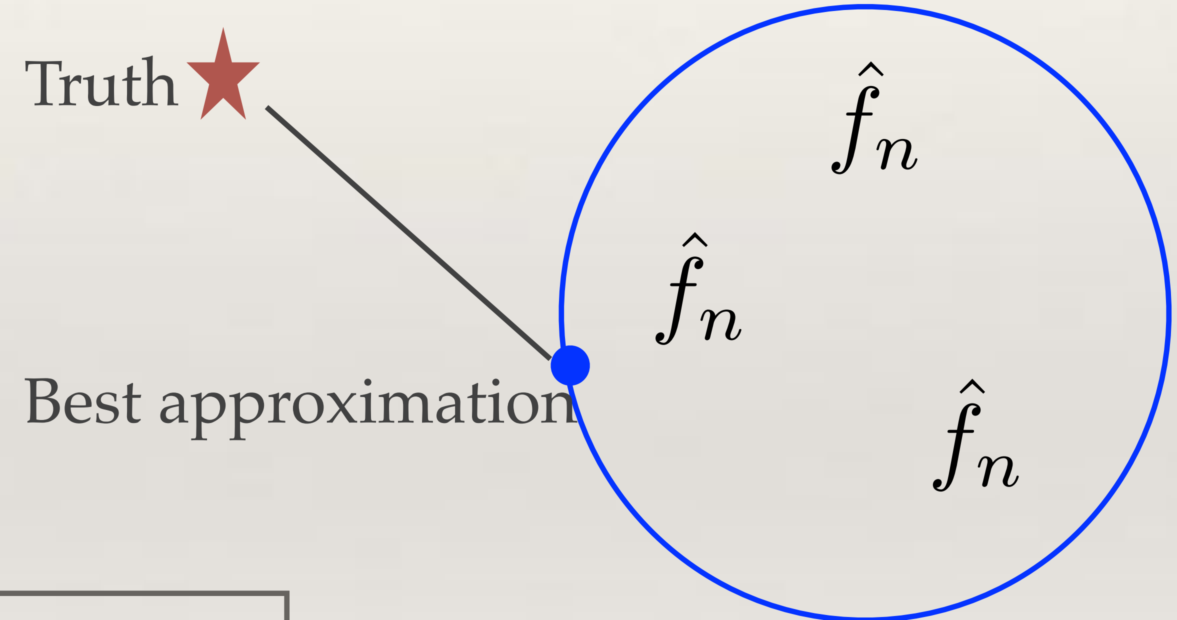

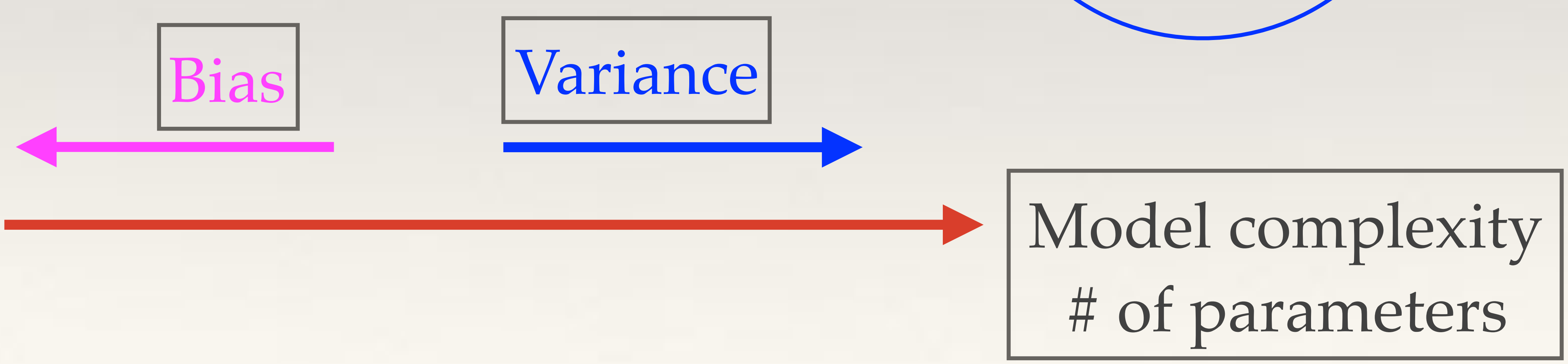

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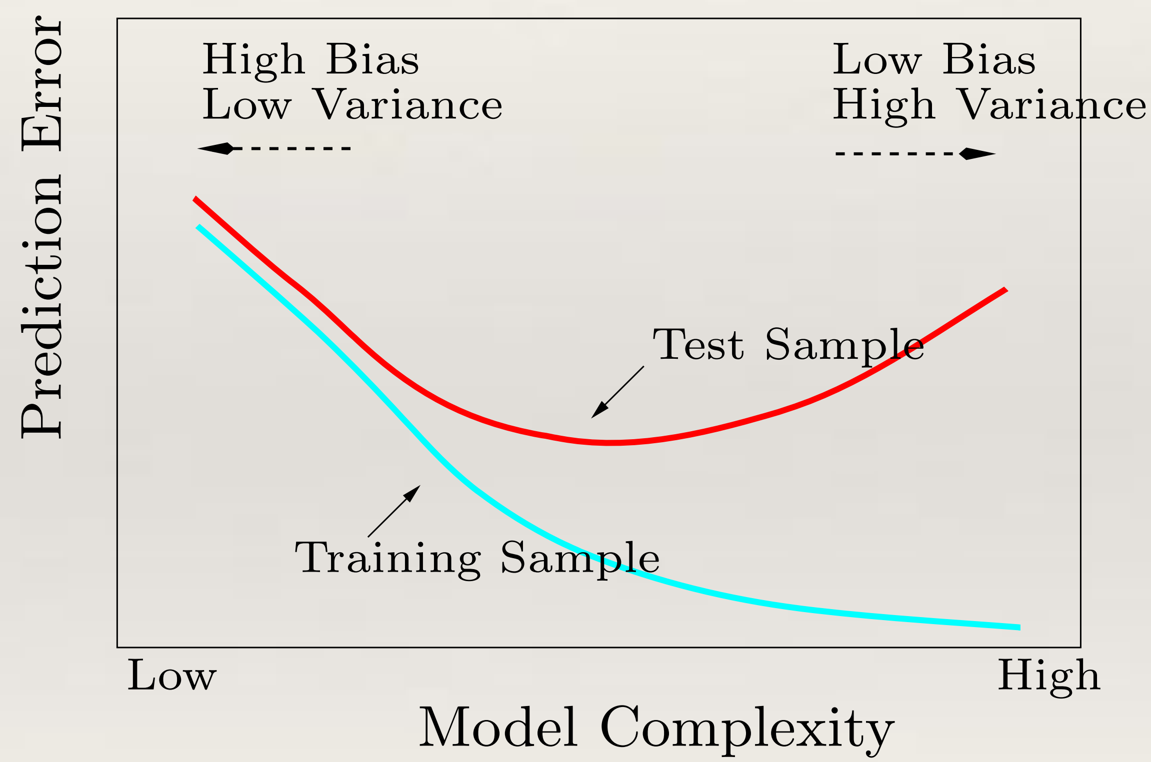


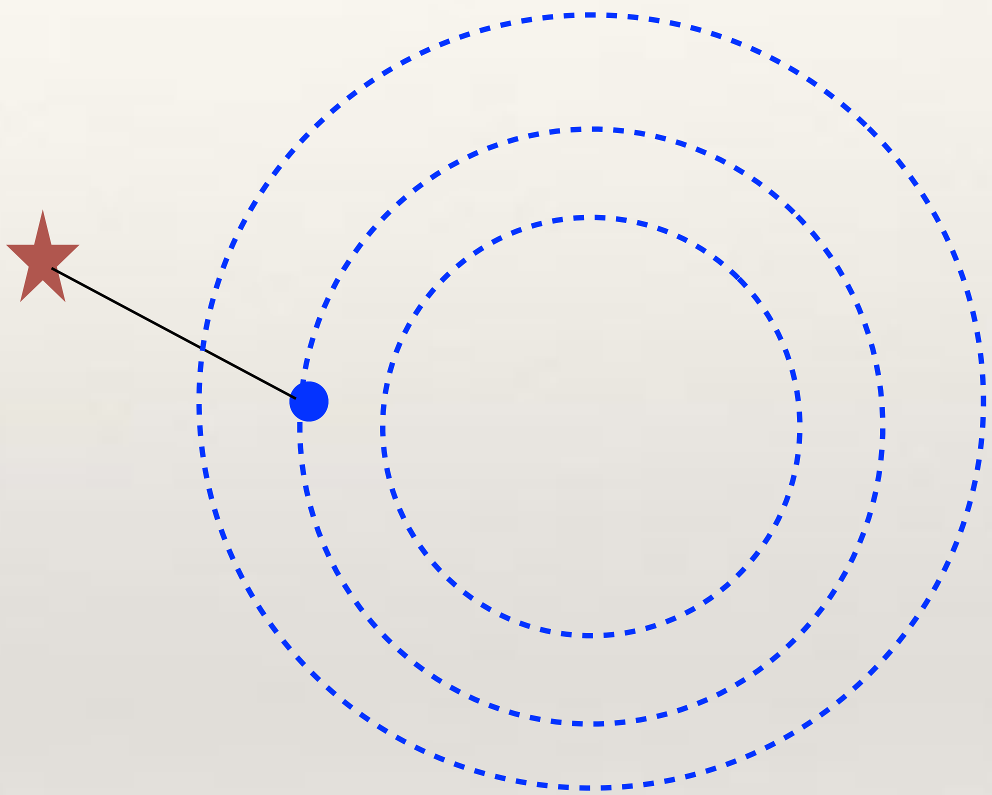
FIGURE 2.11. *Test and training error as a function of model complexity.*

What'll be Covered in Stat542

- Flexible modeling techniques to reduce bias
- Useful strategies to achieve the tradeoff between bias and variance

Two Successful Strategies

- Regularization: Restrict the parameters to a low-dimensional space, which is *adaptively* determined by the data.



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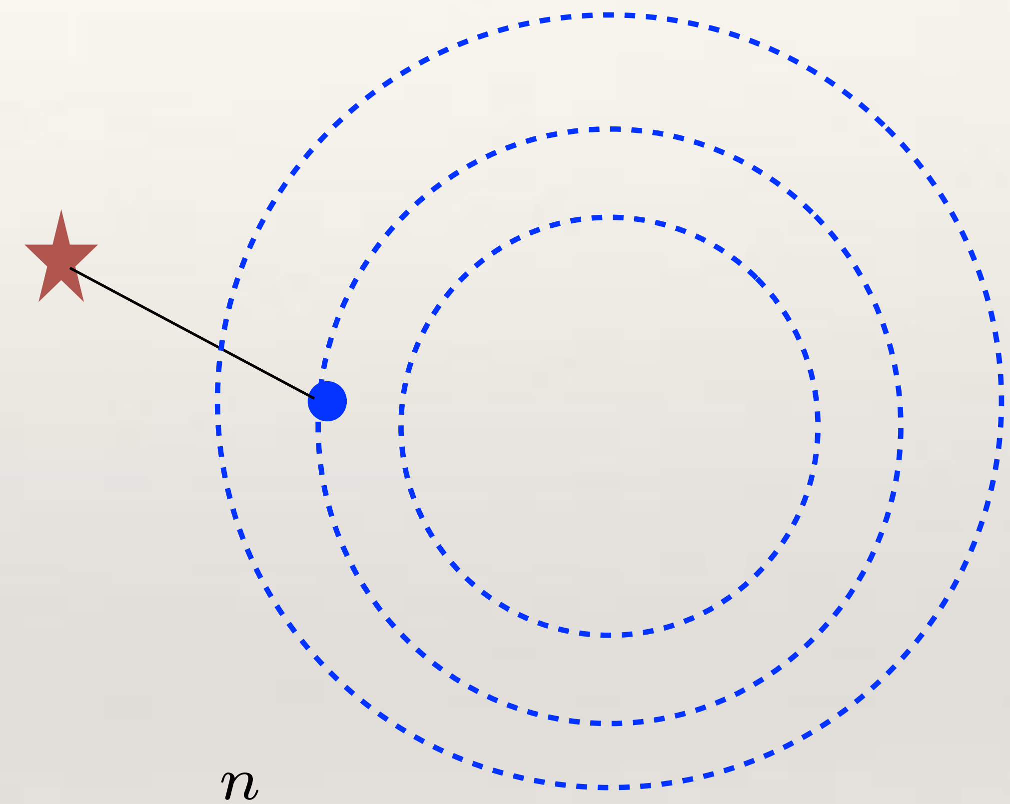

$$\min_w \left[\sum_{i=1}^{n} \text{loss}(y_i, f(x_i; w) + \lambda |w| \right]$$

LASSO

Two Successful Strategies

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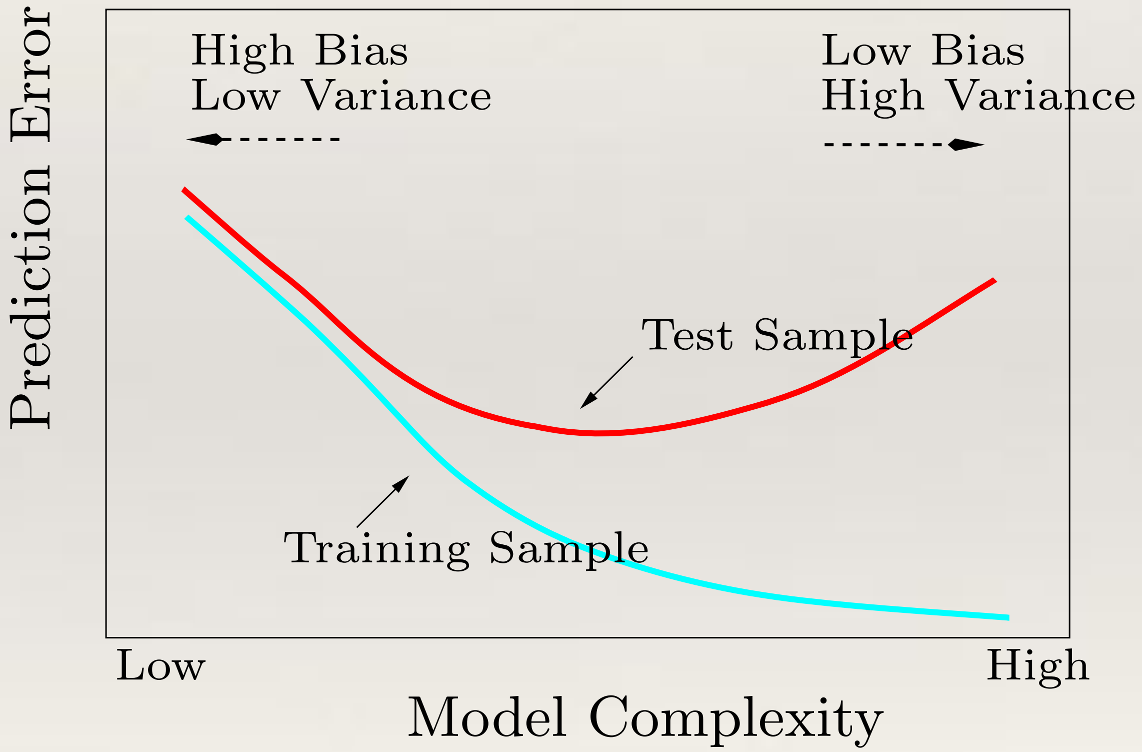
- Ensemble: Average many low-bias high-variance models; averaging reduces variance.



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Not All About Prediction

- Although the focus of this course is prediction, statistical learning $\neq$ prediction
- Exploration *vs.* Prediction
- Data product *vs.* decision making
- Make your model to generate actionable insights