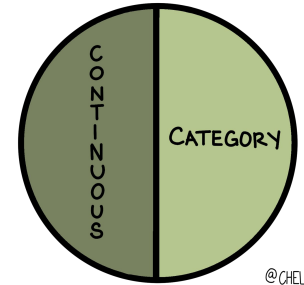


PREDICT



@CHELSEA PARLETT

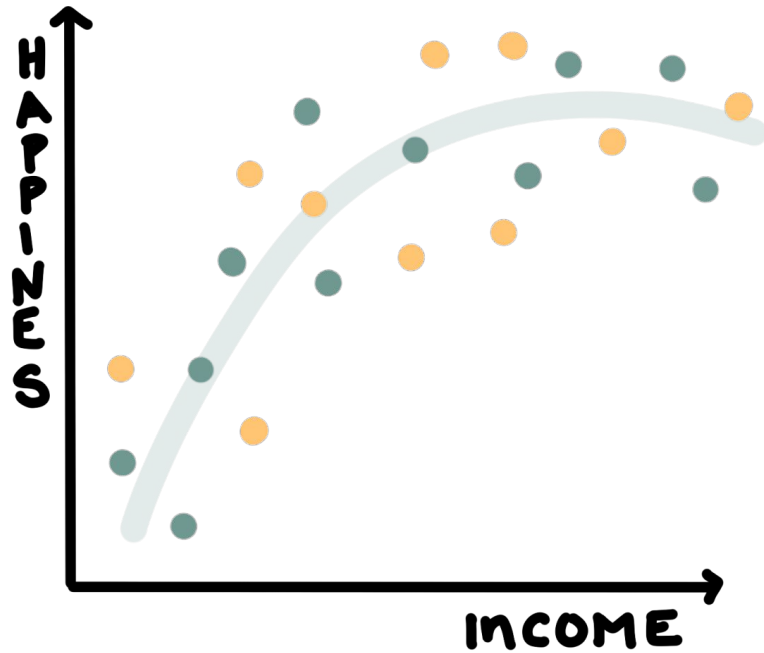
Linear Regression II

Dr. Chelsea Parlett-Pelleriti

Linear Regression

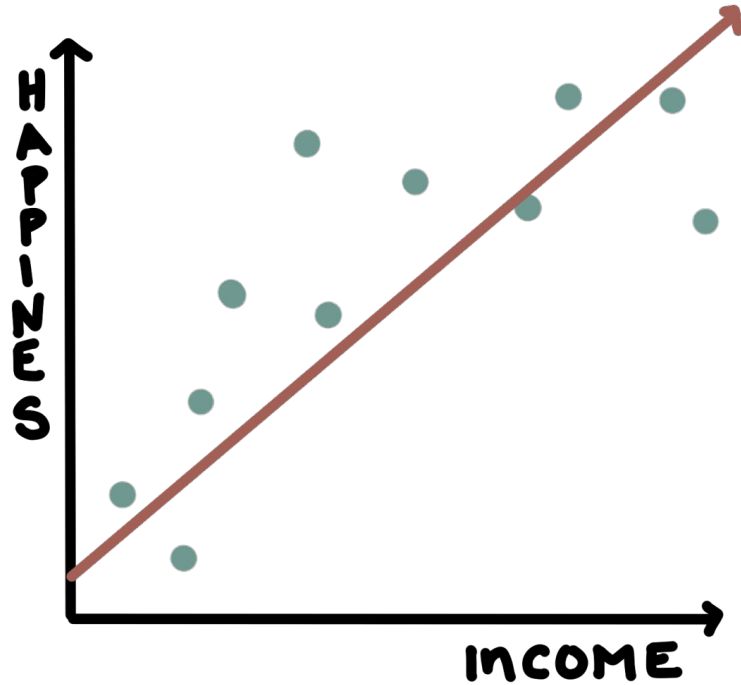
- Bias and Variance Definition
- Bias Variance Tradeoff
- Model Validation
- Double Descent

Bias and Variance



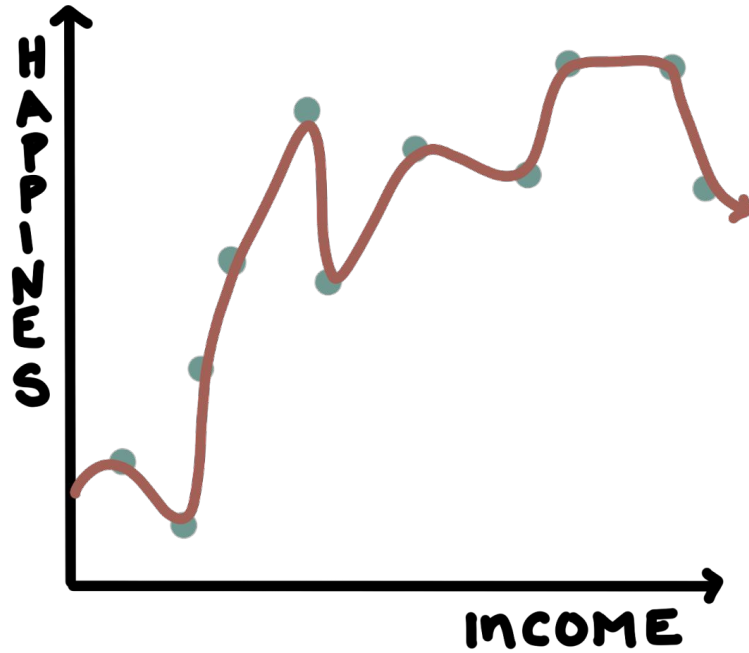
■ data we have now
■ future data

Bias and Variance



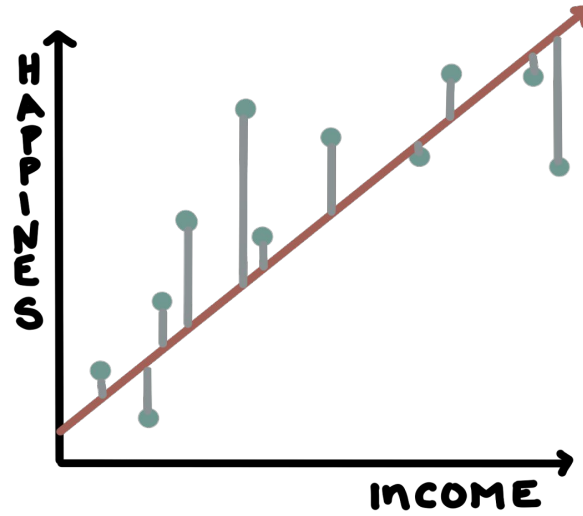
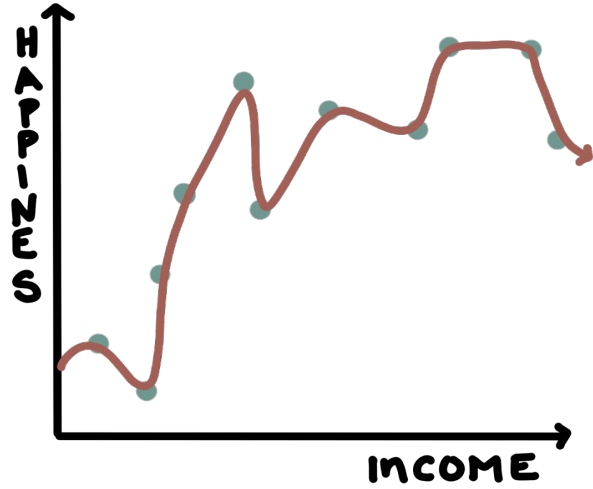
- data we have now
- future data

Bias and Variance



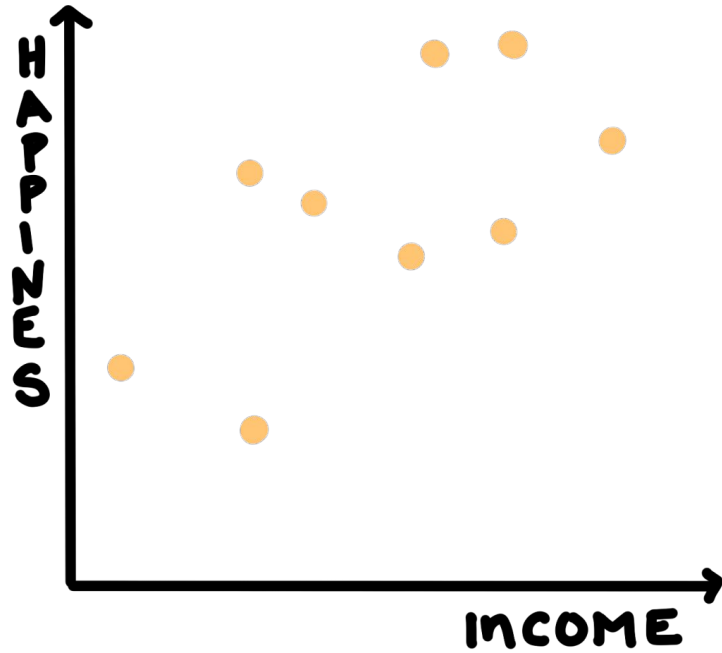
■ data we have now
■ future data

Bias and Variance



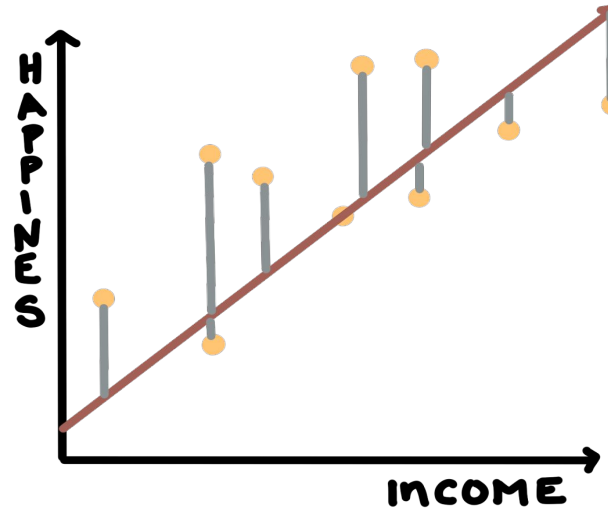
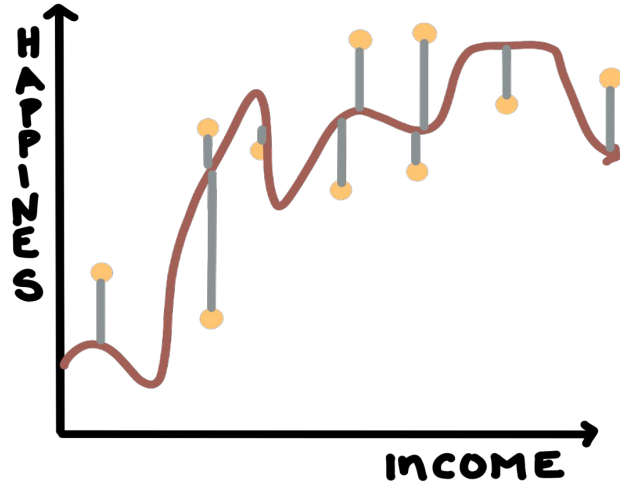
- data we have now
- future data

Bias and Variance



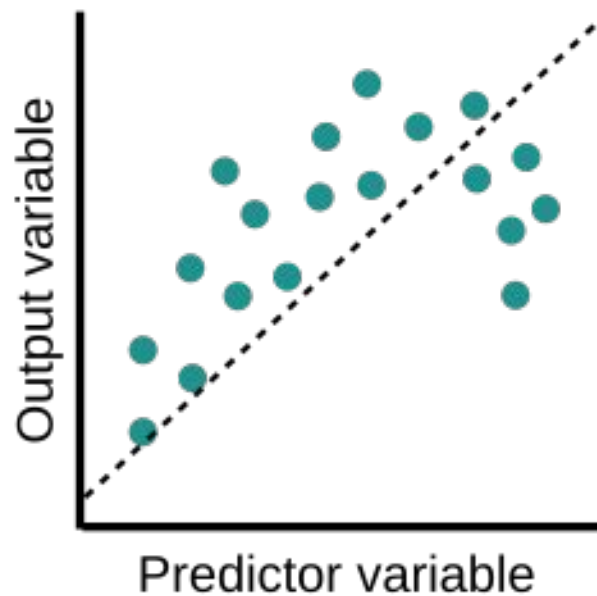
■ data we have now
■ future data

Bias and Variance

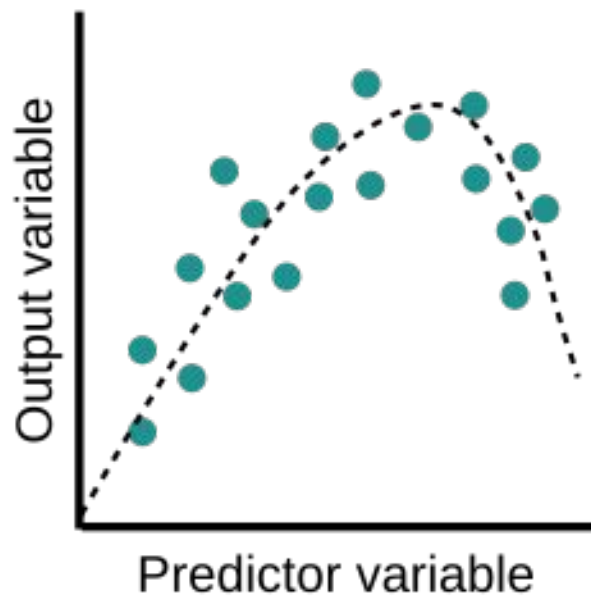


■ data we have now
■ future data

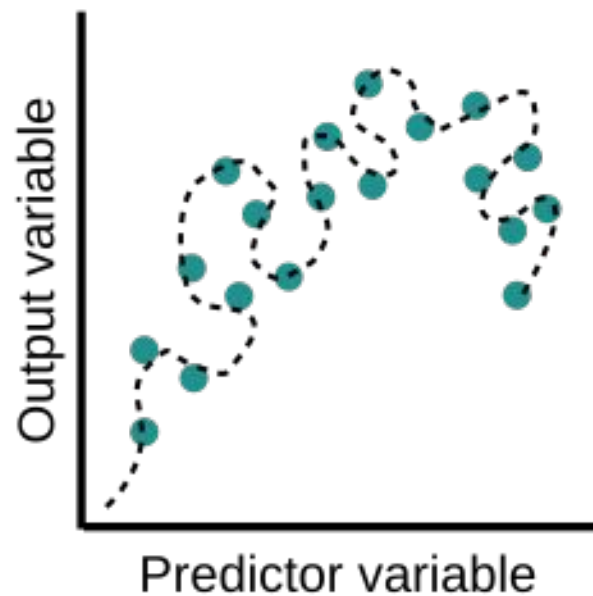
Underfit



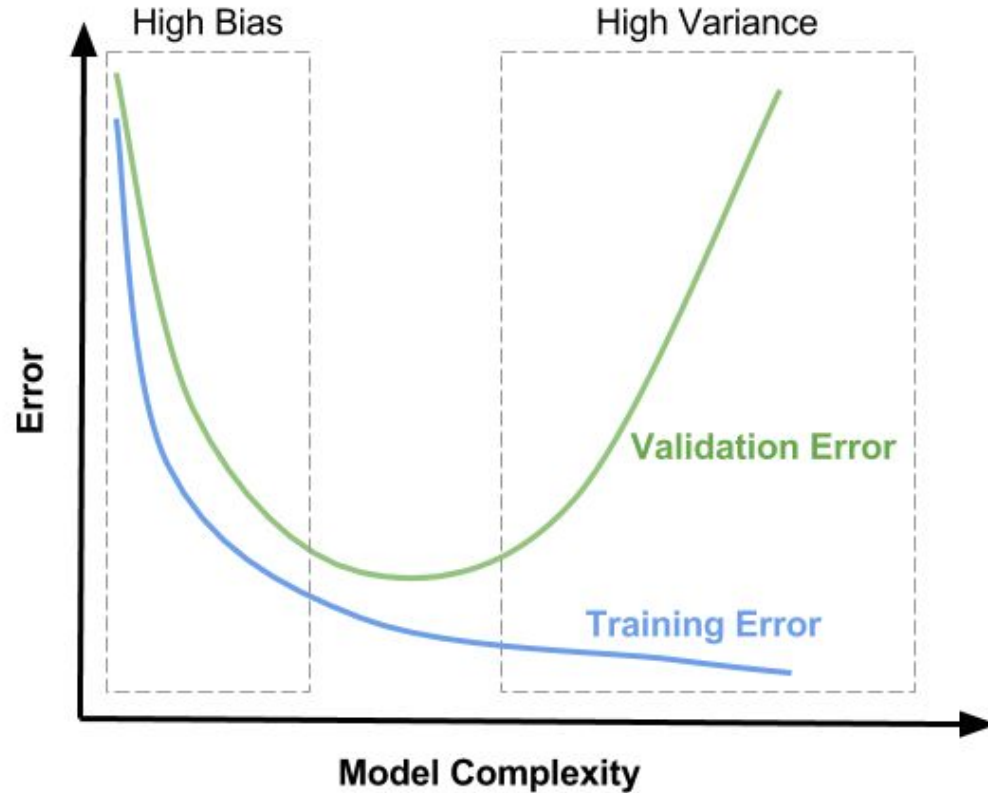
Optimal



Overfit

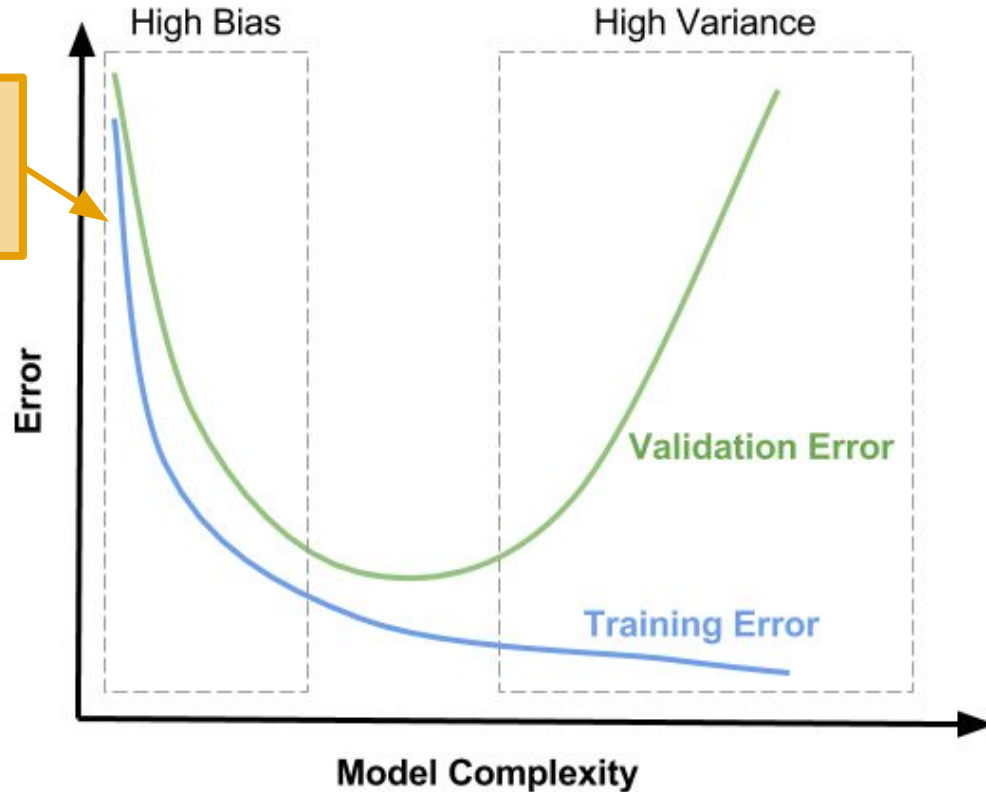


Bias and Variance

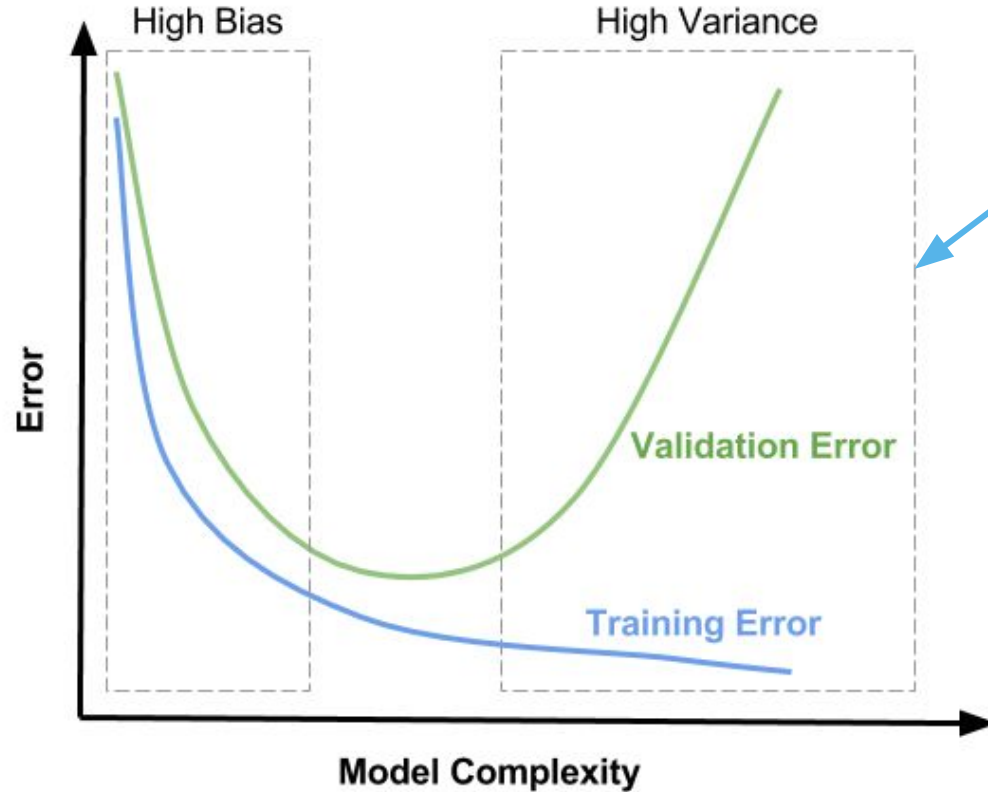


Bias and Variance

underfitting

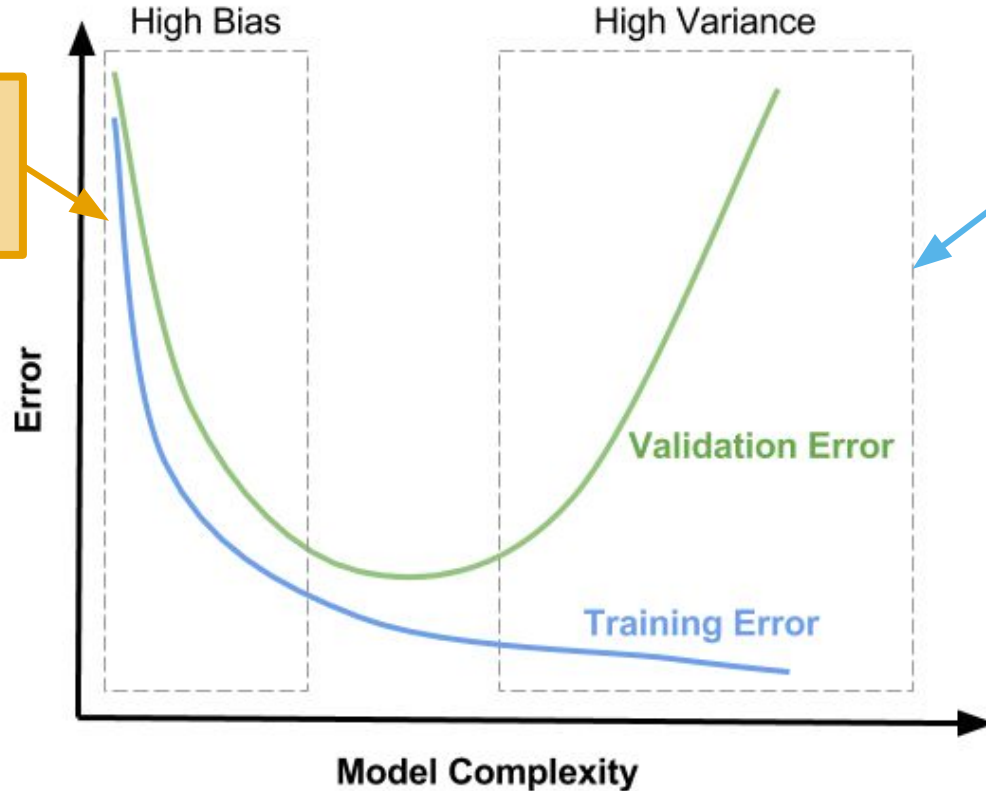


Bias and Variance



Bias and Variance

underfitting



overfitting

Math

Our Goal

$$Y = f(X) + \epsilon$$

Our Goal

$$Y = f(X) + \epsilon$$

$$\hat{f}(X)$$

Sources of Error

$$Y = f(X) + \epsilon$$

1. Irreducible: ϵ
2. Reducible: $\hat{f}(X)$ is not similar to $f(X)$

Bias Variance Tradeoff

Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

Bias Variance Tradeoff


$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$



Expected MSE at x_0
if we repeatedly
estimated $f(x)$ with
different training
sets

Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$



Irreducible
Error

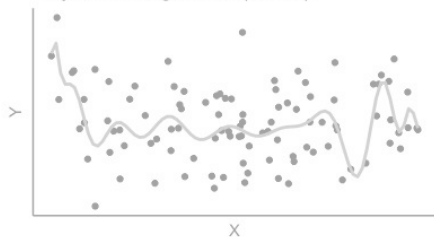
Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

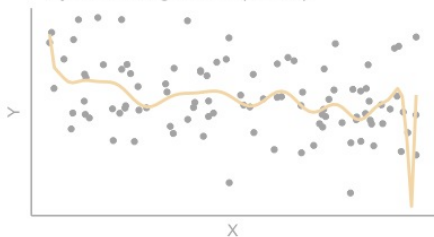
Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \boxed{\text{Var}(\hat{f}(x_0))} + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

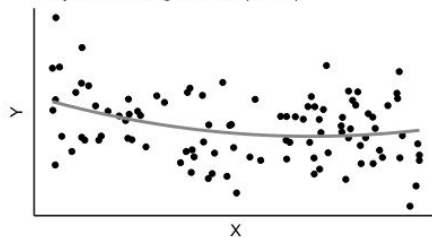
Polynomial Regression (d = 20)



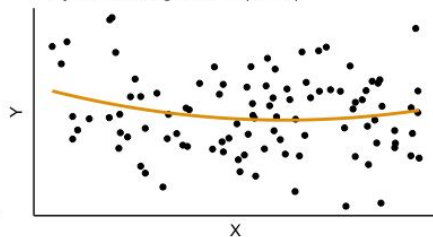
Polynomial Regression (d = 20)



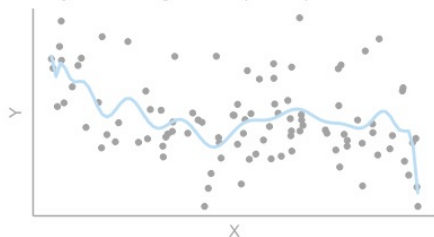
Polynomial Regression (d = 2)



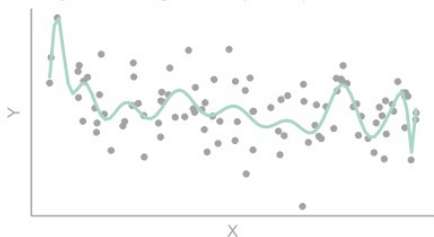
Polynomial Regression (d = 2)



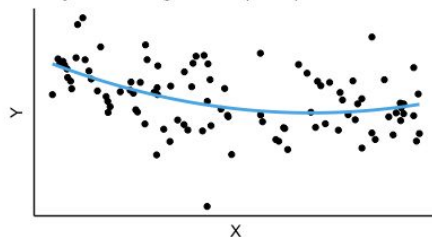
Polynomial Regression (d = 20)



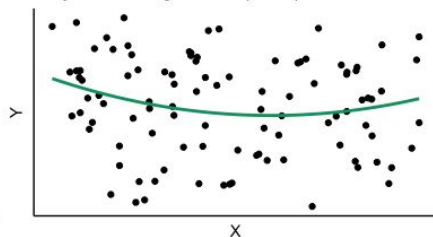
Polynomial Regression (d = 20)



Polynomial Regression (d = 2)



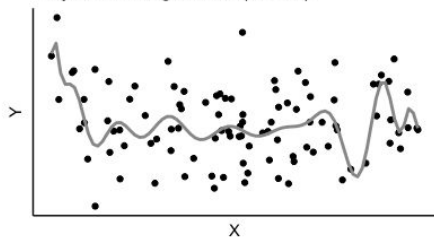
Polynomial Regression (d = 2)



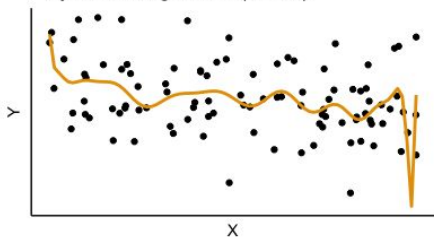
Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \boxed{\text{Var}(\hat{f}(x_0))} + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

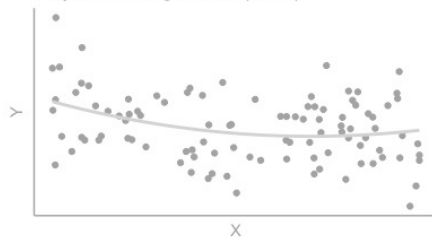
Polynomial Regression (d = 20)



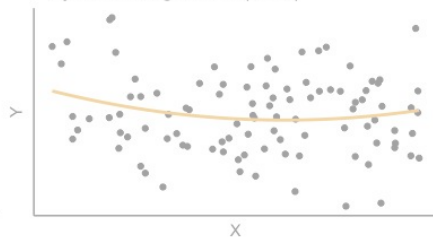
Polynomial Regression (d = 20)



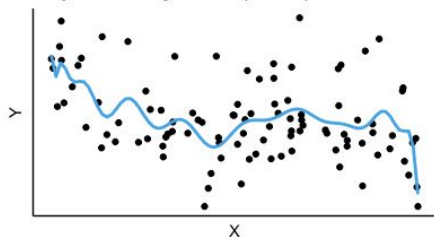
Polynomial Regression (d = 2)



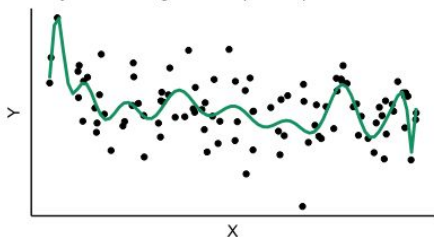
Polynomial Regression (d = 2)



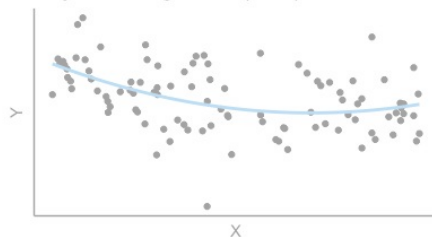
Polynomial Regression (d = 20)



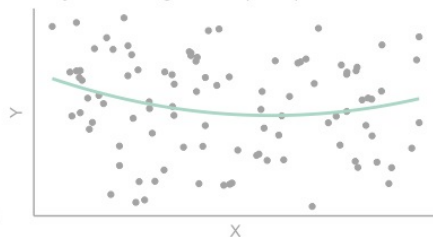
Polynomial Regression (d = 20)



Polynomial Regression (d = 2)

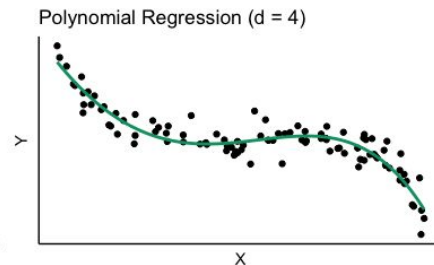
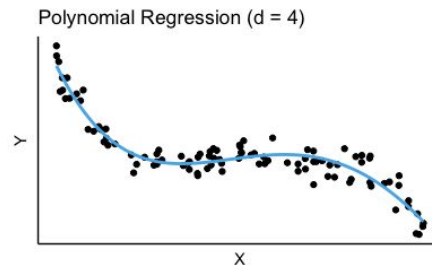
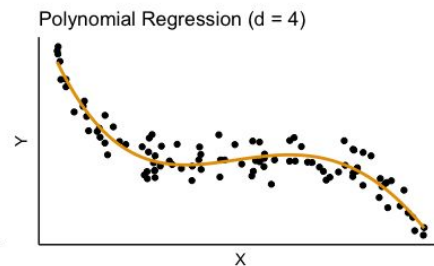
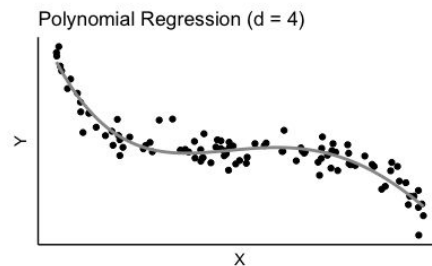
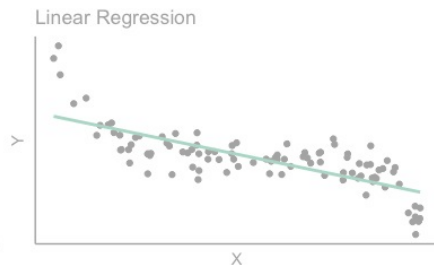
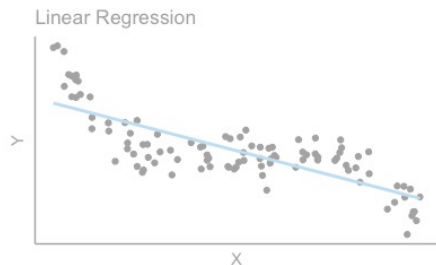
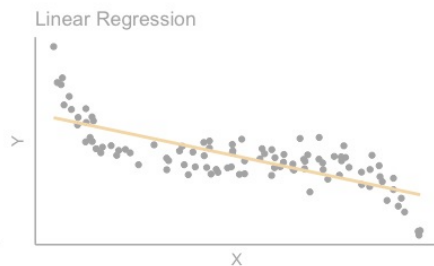
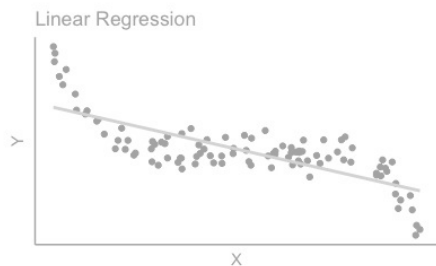


Polynomial Regression (d = 2)



Bias Variance Tradeoff

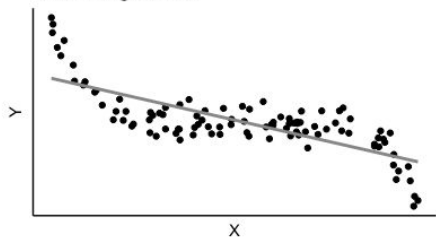
$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$



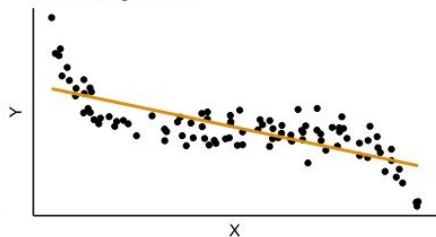
Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

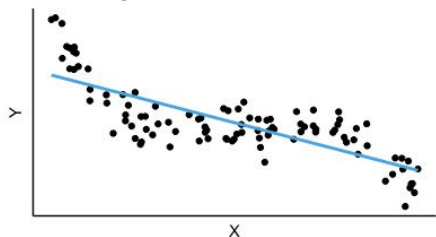
Linear Regression



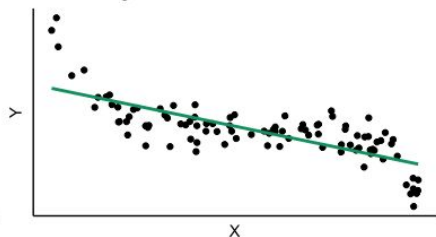
Linear Regression



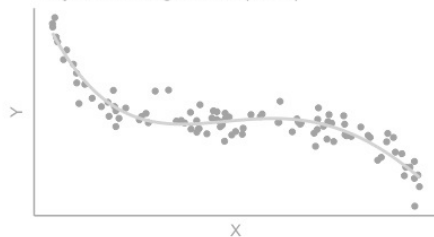
Linear Regression



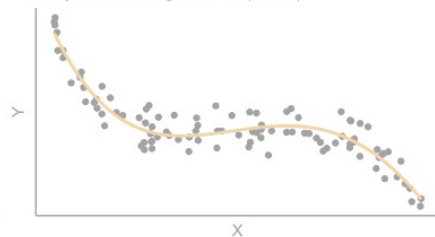
Linear Regression



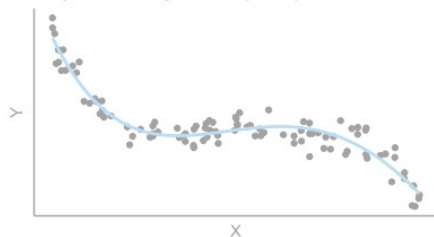
Polynomial Regression (d = 4)



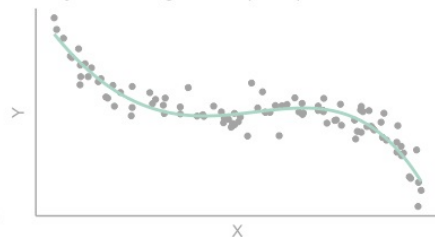
Polynomial Regression (d = 4)



Polynomial Regression (d = 4)



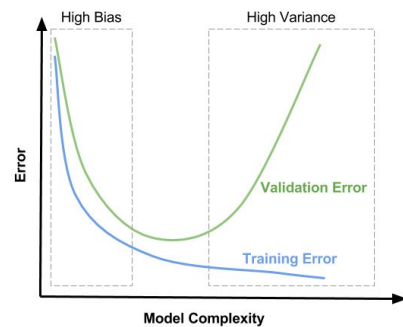
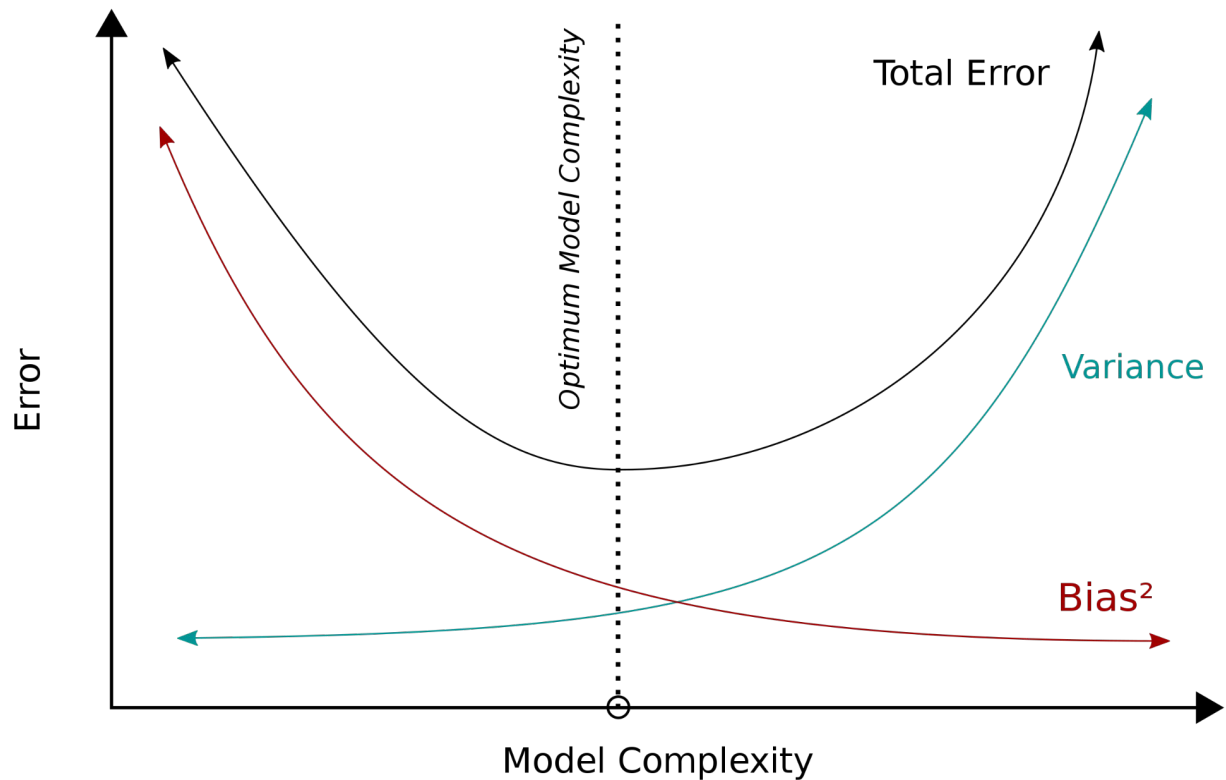
Polynomial Regression (d = 4)



Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

Bias Variance Tradeoff



Model Validation

Validation

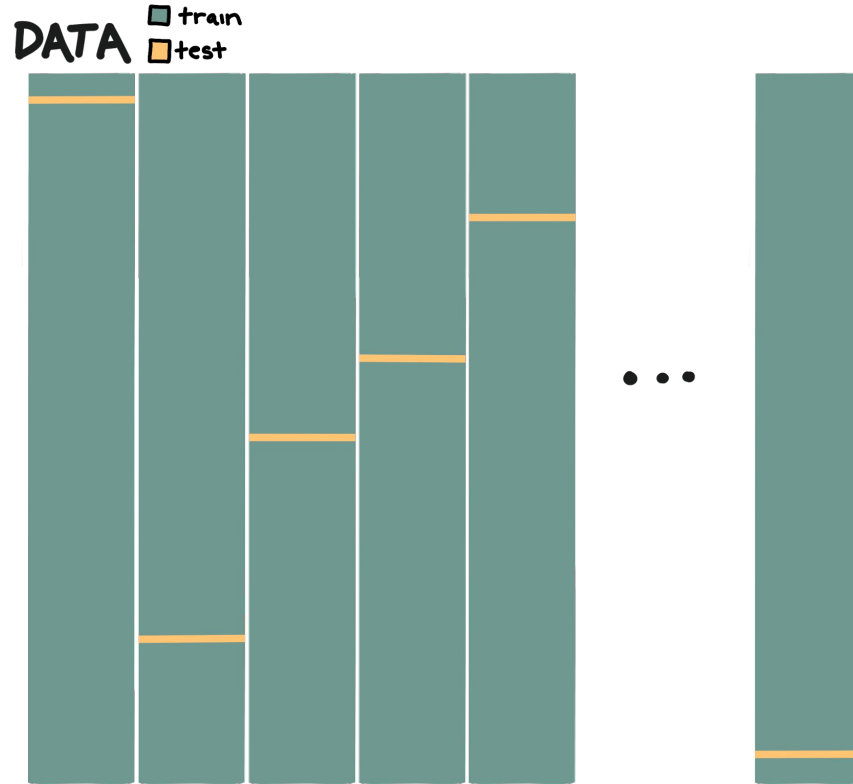
1. **Split** Data
2. Train Model on **Training Set**
3. Evaluate **Train and Test Set**

Validation (Train Test Split)

DATA  train  test



Cross Validation (Leave One Out)



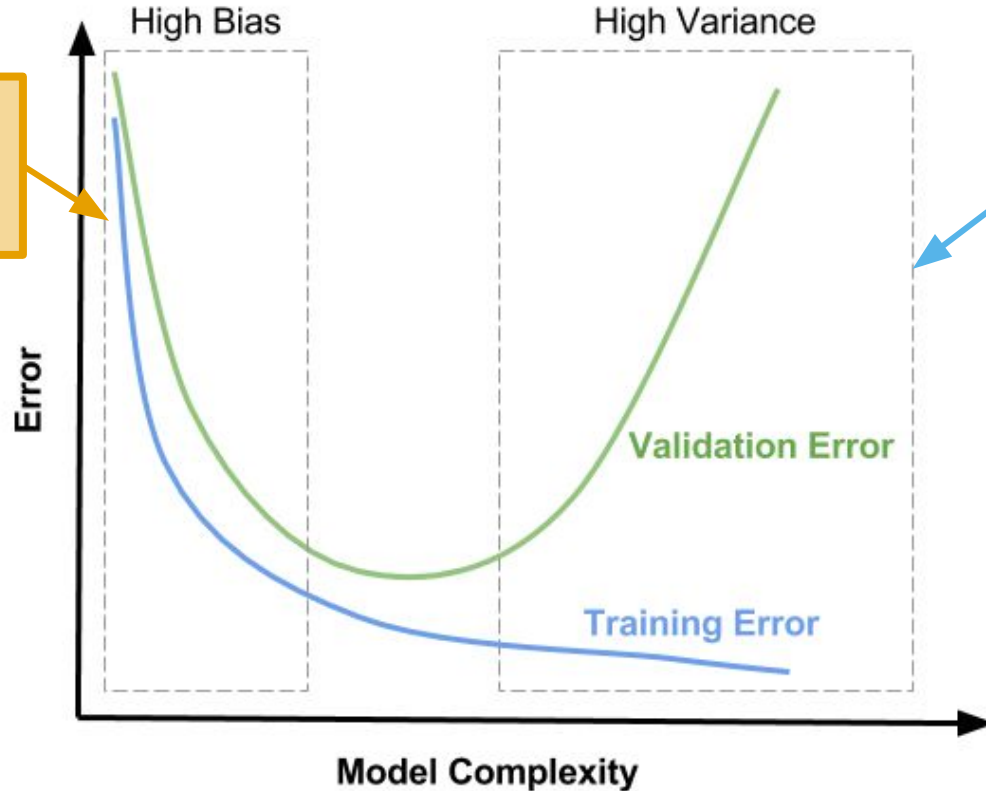
Validation

How to decide

- Size of your Dataset (rows AND columns)
- Computational Expense

Bias and Variance

underfitting



overfitting

Regularization

Review: Loss Functions

MINIMIZE:

$$\sum (x_i - \hat{x}_i)^2$$

how off
we were

true
value

model's
guess

Ridge

MINIMIZE:

$$\sum (x_i - \hat{x}_i)^2 + \lambda \sum \beta_j^2$$

Annotations:

- x_i : true value
- \hat{x}_i : model's guess
- λ : how HARSHLY we penalize
- β_j^2 : how big the coefs are
- Red bracket over $(x_i - \hat{x}_i)^2$: how off we were

LASSO

MINIMIZE:

$$\sum (x_i - \hat{x}_i)^2 + \lambda \sum |B_j|$$

how off we were

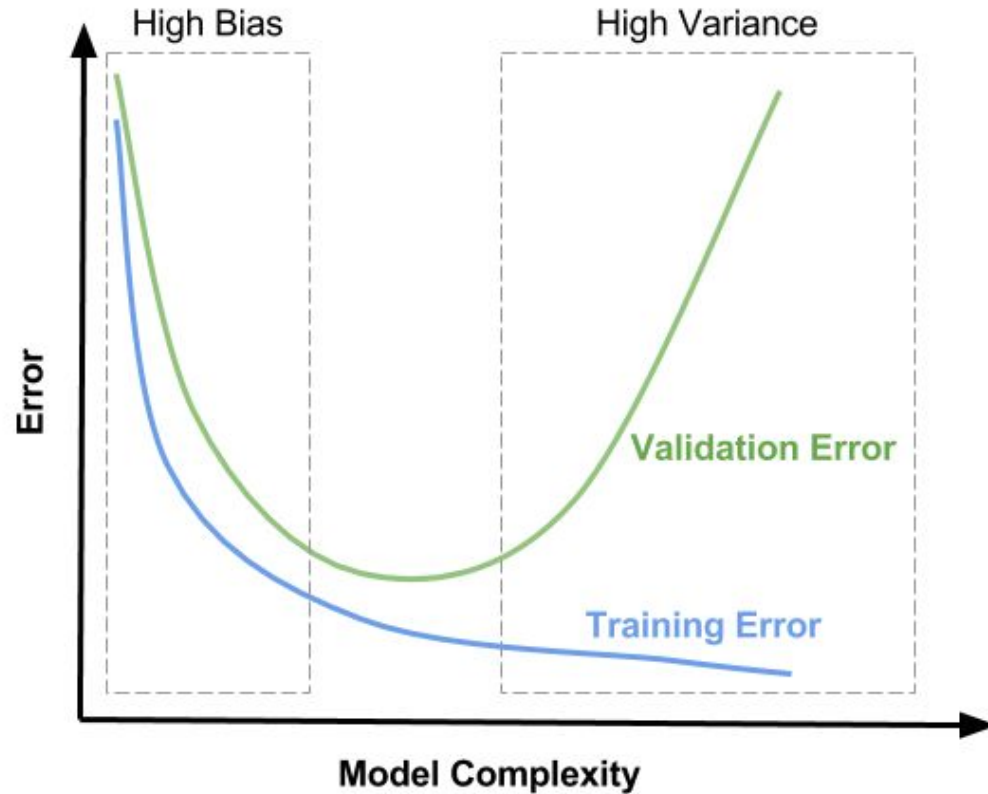
true value

model's guess

how HARSHLY we penalize

how big the coefs are

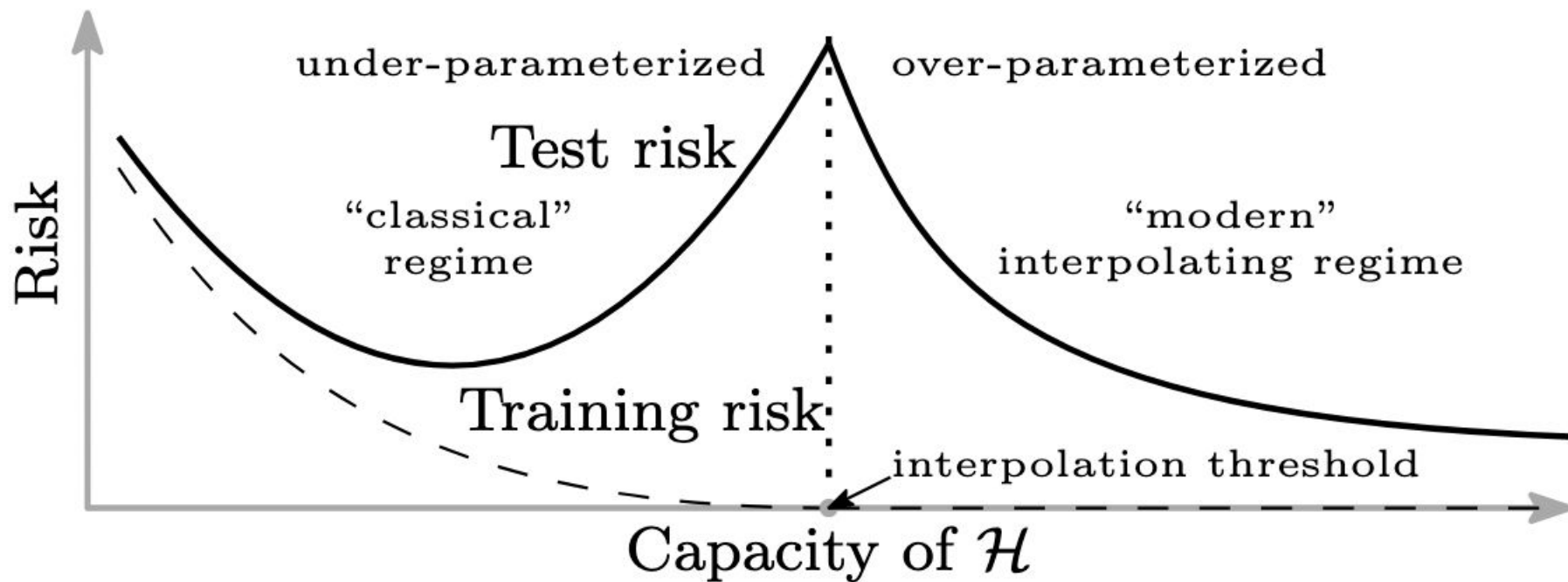
Bias and Variance



Double Descent

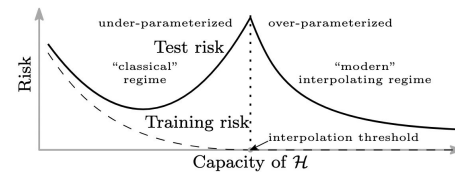
Everything I've Just
Taught You is
Wrong

Double Descent

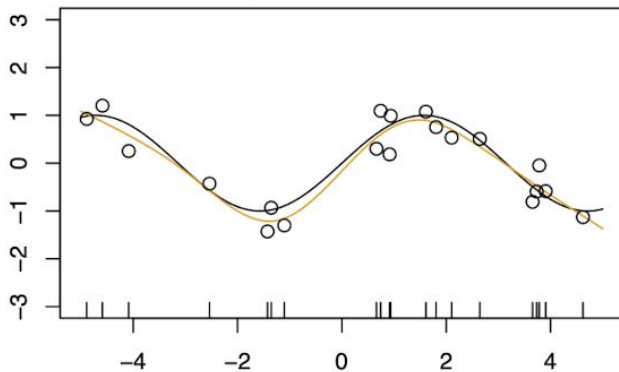


Or is it?

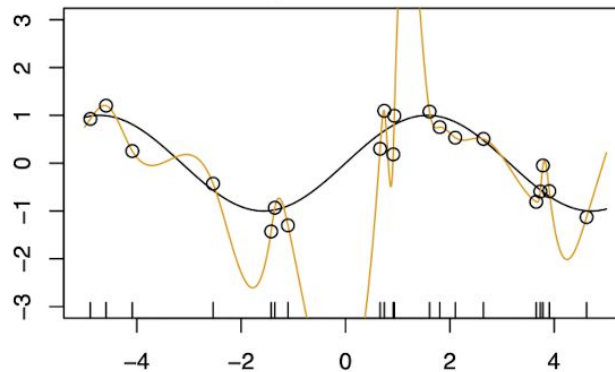
Double Descent



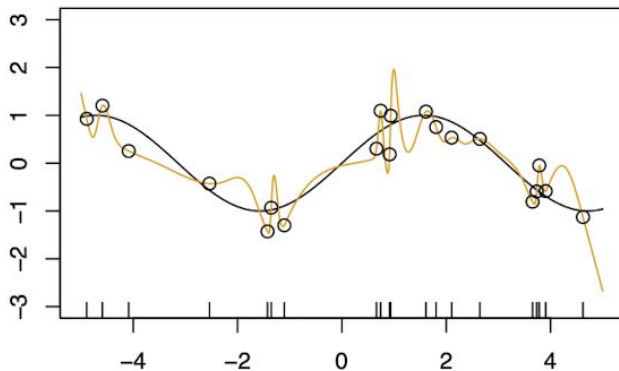
8 Degrees of Freedom



20 Degrees of Freedom



42 Degrees of Freedom



80 Degrees of Freedom

