

# Ch 5.1.4-5: More Cross-Validation

## Lecture 14 - CMSE 381

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# Announcements

## Last time:

- k-fold CV

## This lecture:

- More  $k$ -fold CV
- Bias-Variance Tradeoff
- CV for classification

## Announcements:

- Exam 1 grades.... hopefully soon
- HW #4 will be posted soon.
  - ▶ Due Sunday 3/2.

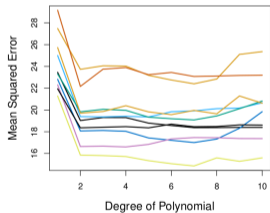
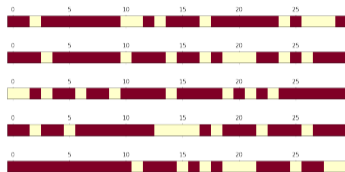
12	F	2/14	Leave one out CV	5.1.1, 5.1.2		
13	M	2/17	k-fold CV	5.1.3		
14	W	2/19	More k-fold CV	5.1.4-5		Q5
15	F	2/21	k-fold CV for classification	5.1.5		
16	M	2/24	Subset selection	6.1		
17	W	2/26	Shrinkage: Ridge	6.2.1		
18	F	2/28	Shrinkage: Lasso	6.2.2	HW #4 Due Sun 3/2	
	M	3/3	Spring Break			
	W	3/5	Spring Break			
	F	3/7	Spring Break			
19	M	3/10	PCA	6.3		
20	W	3/12	PCR	6.3		Q6
	F	3/14	<b>Review</b>		HW #5 Due Sun 3/16	
	M	3/17	<b>Midterm #2</b>			

# Section 1

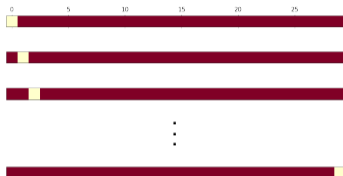
## *k*-fold CV

# Approximations of Test Error

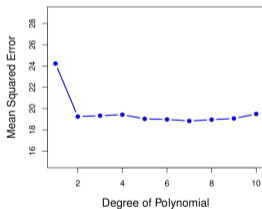
## Validation Set



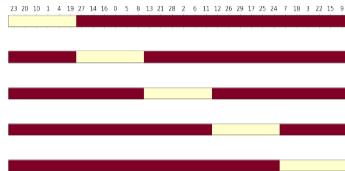
## LOOCV



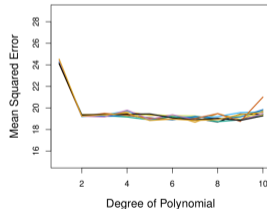
LOOCV



## K-fold CV

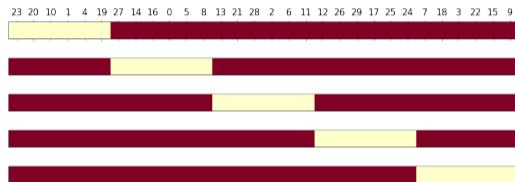


10-fold CV



# Definition of $k$ -fold CV

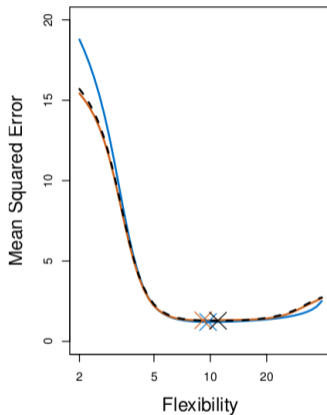
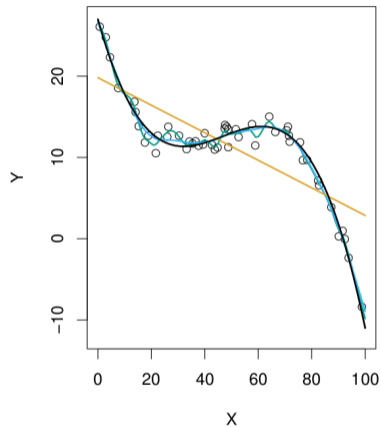
- Randomly split data into  $k$ -groups (folds)
- Approximately equal sized. For the sake of notation, say each set has  $\ell$  points
- Remove  $i$ th fold  $U_i$  and reserve for testing.
- Train the model on remaining points
- Calculate 
$$\text{MSE}_i = \frac{1}{\ell} \sum_{(x_j, y_j) \in U_i} (y_j - \hat{y}_j)^2$$
- Rinse and repeat



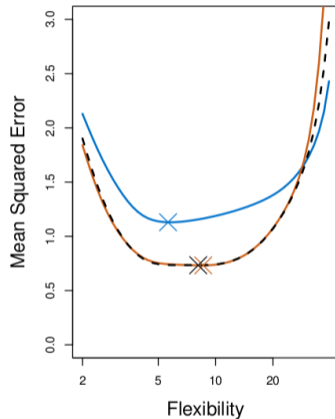
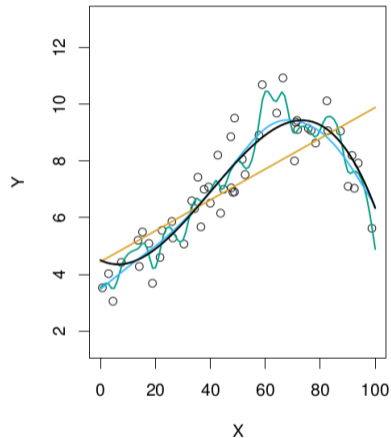
Return

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^k \text{MSE}_i$$

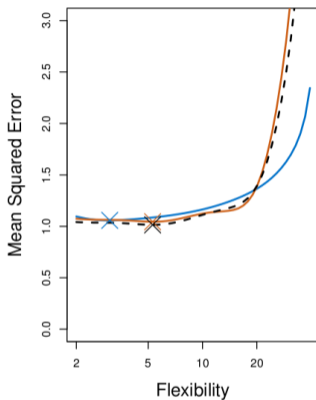
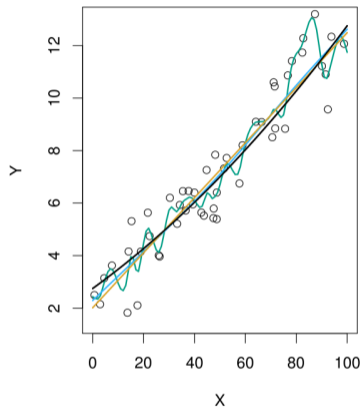
## Comparison with simulated data: Ex 3



# Comparison with simulated data: Ex 1



## Comparison with simulated data: Ex 2





# Takeaways from the examples

## Bias-Variance Tradeoff: Bias

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

## Bias-Variance Tradeoff: Variance

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

## Section 2

# Using K-Fold CV on Polynomial Linear Regression

# Polynomial regression

Replace linear model

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i$$

with

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \cdots + \beta_d x_1^d + \varepsilon_i$$

# Faking linear regression into doing our work for us

## Coding - Build a plot for train/test scores vs flexibility

# Next time

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