## Ch 5.1.5: *k*-fold Cross-Validation for Classification Lecture 15 - CMSE 381

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#### Last time:

k-fold CV

#### This lecture:

• CV for classification

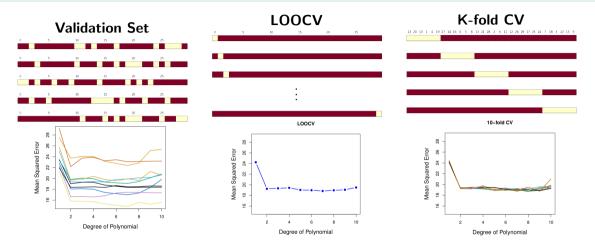
#### **Announcements:**

• Homework #4 is posted, Due Sunday (3/2)

# Section 1

# Last time

## Approximations of Test Error



# Definition of k-fold CV

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

23 20	10	1	4	19	27	14	16	0	5	8	13	21	28	2	6	11	12	26	29	17	25	24	7	18	3	22	15	9
			.,																				_					
						_				_																		
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Return

$$CV_{(k)} = rac{1}{k} \sum_{i=1}^k \mathrm{MSE}_i$$

# Section 2

## CV for Classification

# Setup: LOOCV

- Remove *i*th point (*x<sub>i</sub>*, *y<sub>i</sub>*) and reserve for testing.
- Train the model on remaining points
- Calculate  $\operatorname{Err}_i = \operatorname{I}(y_j \neq \hat{y}_j)$
- Rinse and repeat

0	5	10	15	20	25	
			:			
		F	Return			
		-	$1 \frac{n}{n}$	<b>`</b>		

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^{n} \operatorname{Err}_i$$

# Setup: *k*-fold

- Randomly split data into k-groups (folds)
- Approximately equal sized. For the sake of notation, say each set has *l* points
- Remove *i*th fold *U<sub>i</sub>* and reserve for testing.
- Train the model on remaining points
- Calculate  $\operatorname{Err}_{i} = \frac{1}{\ell} \sum_{(x_{j}, y_{j}) \in U_{i}} \operatorname{I}(y_{j} \neq \hat{y}_{j})$
- Rinse and repeat

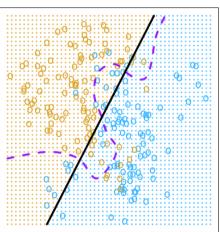
23 20	0	10	1	4	19	27	14	16	0	5	8	13	21	28	2	6	11	12	26	29	17	25	24	7	18	3	22	15	9
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Return

$$CV_{(k)} = rac{1}{k}\sum_{i=1}^k \mathrm{Err}_i$$

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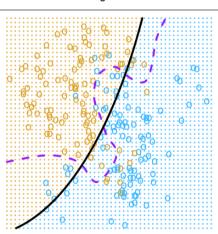
#### Example on simulated data: Linear



#### Degree=1

- Purple: Bayes decision boundary.
  - Error rate: 0.133
- Black: Logistic regression
  - $\log(p/(1-p)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$
  - Error rate: 0.201

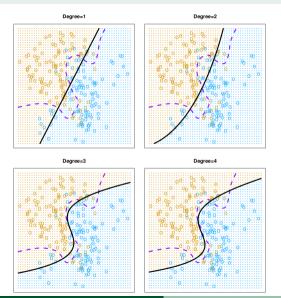
### Example on simulated data: Quadratic logistic regression



#### Degree=2

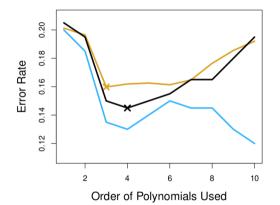
- Purple: Bayes decision boundary.
  - Error rate: 0.133
- Black: Logistic regression
  - ►  $\log(p/(1-p)) = \beta_0 + \beta_1 X_1 + \beta_2 X_1^2 + \beta_3 X_2 + \beta_4 X_2^2$
  - Error rate: 0.197

## Example on simulated data: all the polynomials!



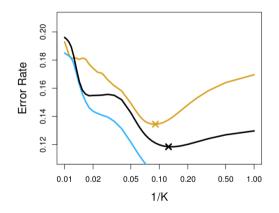
- Purple: Bayes decision boundary.
  - Error rate: 0.133
- Black: Logistic regression
  - Deg 1 Error rate: 0.201
  - Deg 2 Error rate: 0.197
  - Deg 3 Error rate: 0.160
  - ▶ Deg 4 Error rate: 0.162

### Decide degree based on CV



- Test error (brown)
- Training error (blue)
- 10-fold CV error (black)

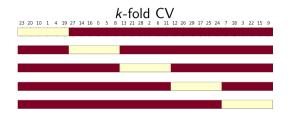
## Similar game for KNN



- Test error (brown)
- Training error (blue)
- 10-fold CV error (black)

## Coding - k-fold for penguin classification section

TL;DR



#### k-fold CV for classification

$$\operatorname{Err}_i = \operatorname{I}(y_j \neq \hat{y}_j)$$

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^{k} \operatorname{Err}_{i}$$

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

Use k = 5 or 10 usually

# Next time

	W	2/12	Midterm #1		
12	F	2/14	Leave one out CV	5.1.1, 5.1.2	
13	М	2/17	k-fold CV	5.1.3	
14	W	2/19	More k-fold CV	5.1.4-5	
15	F	2/21	k-fold CV for classification	5.1.5	
16	М	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
	М	3/3	Spring Break		Sun 3/2
	W	3/5	Spring Break		
	F	3/7	Spring Break		
19	М	3/10	PCA	6.3	
20	W	3/12	PCR	6.3	
	F	3/14	Review		HW #5 Due
	М	3/17	Midterm #2		Sun 3/16