CS9840
Learning and Computer Vision
Prof. Olga Veksler

Lecture 9

Validation

and

Cross-Validation

Outline

- Performance evaluation and model selection methods
  - validation
  - cross-validation
    - k-fold
    - Leave-one-out

Regression

- In this lecture, it is convenient to show examples in the context of regression

- In regression, labels y^i are continuous

- Classification/regression are solved very similarly

- Everything we have done so far transfers to regression with very minor changes

- Error: sum of distances from examples to the fitted model
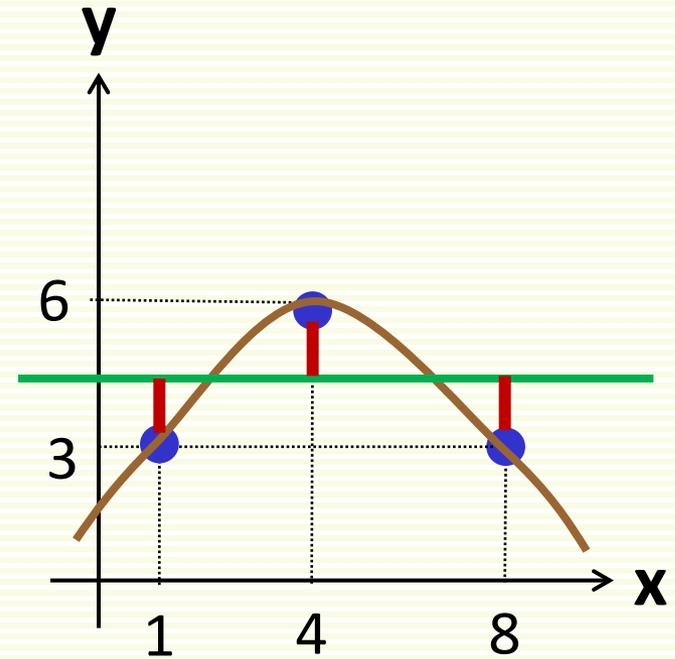
Training/Test Data Split

- Talked about splitting data in training/test sets
  - training data is used to fit parameters
  - test data is used to assess how classifier generalizes to new data
- What if classifier has "non-tunable" parameters?
  - a parameter is "non-tunable" if tuning (or training) it on the training data leads to overfitting
  - Examples:
    - **k** in kNN classifier
    - **T** (number of training epoch) in adaBoost
    - Kernel width in SVM
    - etc

Example of Overfitting

- Want to fit a polynomial machine $f(\mathbf{x},\mathbf{w})$

- Instead of fixing polynomial degree, make it parameter $\mathbf{d}$
  - learning machine $f(\mathbf{x},\mathbf{w},\mathbf{d})$

- Consider just three choices for $\mathbf{d}$
  - degree 1
  - degree 2
  - degree 3

- Training error is a bad measure to choose $\mathbf{d}$
  - degree 3 is the best according to the training error, but overfits the data
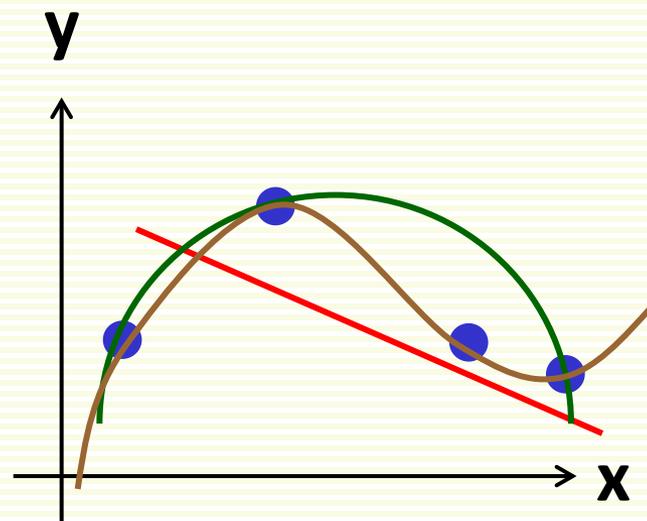
Training/Test Data Split
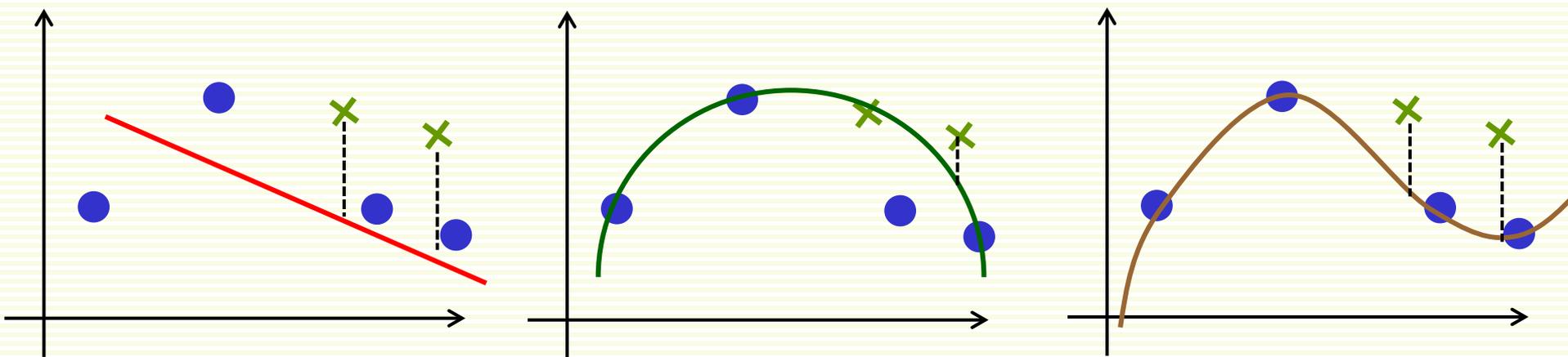
- What about test error? Seems appropriate
  - degree 2 is the best model according to the test error
- Except what do we report as the test error now?
- Test error should be computed on data that was **not used for training at all**
- Here used "test" data for training, i.e. choosing model

Validation data

- Same question when choosing among several classifiers
  - our polynomial degree example can be looked at as choosing among 3 classifiers (degree 1, 2, or 3)

- Solution: split the labeled data into three parts

labeled data
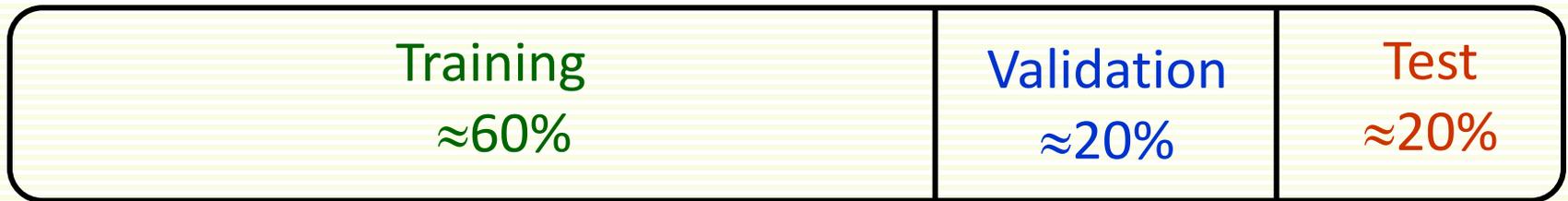
Training ≈60%	Validation ≈20%	Test ≈20%
train tunable parameters **w**	train other parameters, or to select classifier	use **only** to assess final performance

Training/Validation/Test Data

d = 1

validation error: 3.3

d = 2

validation error: 1.8

d = 3

validation error: 3.4
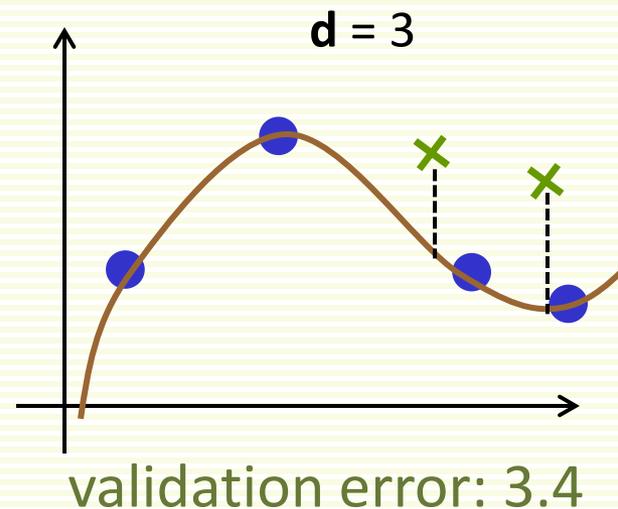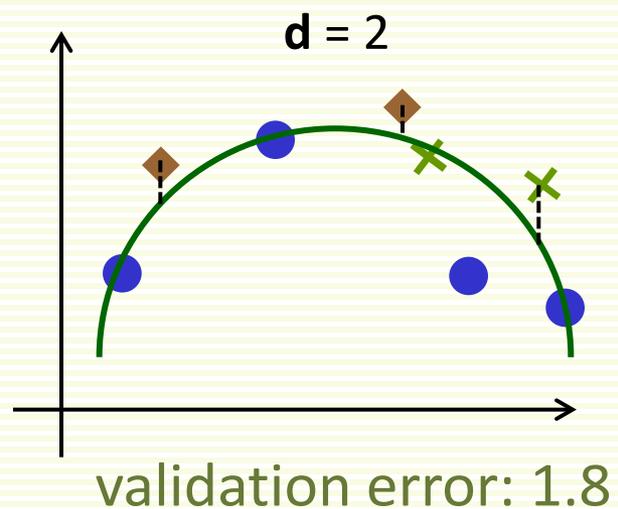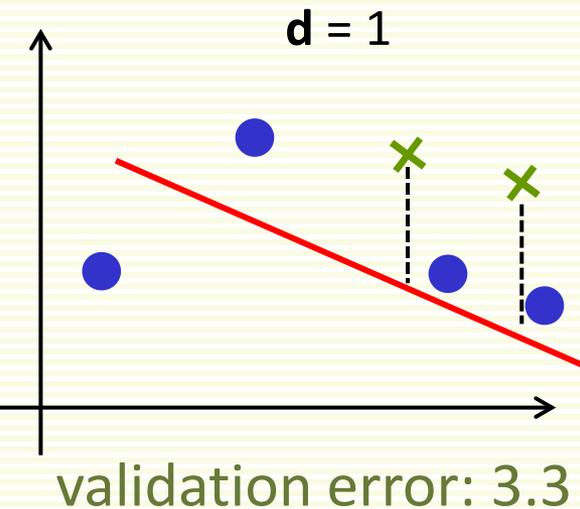
- Training Data

- Validation Data

  - **d** = 2 is chosen

- Test Data

  - 1.3 test error computed for **d** = 2

Training/Validation

labeled data

| Training ≈60%	Validation ≈20%	Test ≈20%
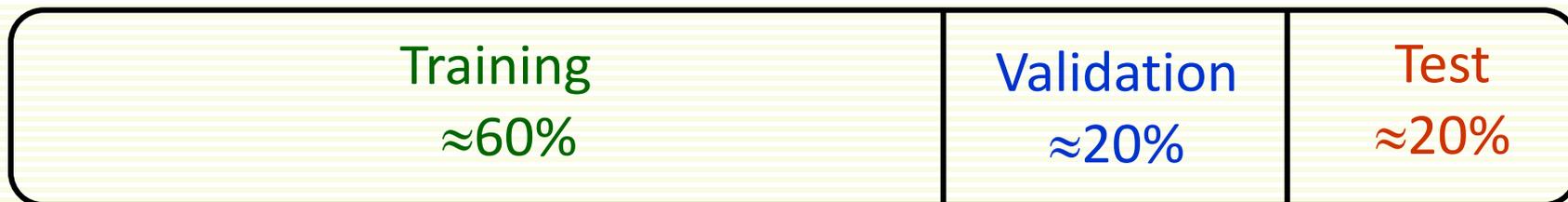
- After non-tunable parameters are chosen (using validation data), retrain on combined Training+Validation data before computing Test error

labeled data

| Training ≈60%	Validation ≈20%	Test ≈20%
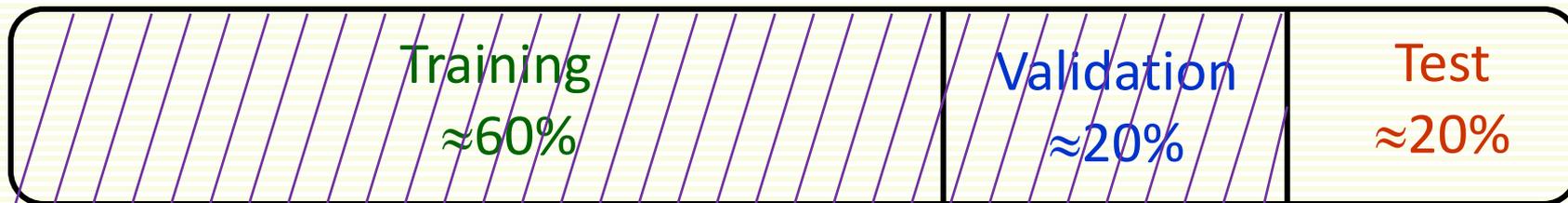
- The more data to train on, the better is the trained classifier (the more reliable test error)

Choosing Parameters: Example
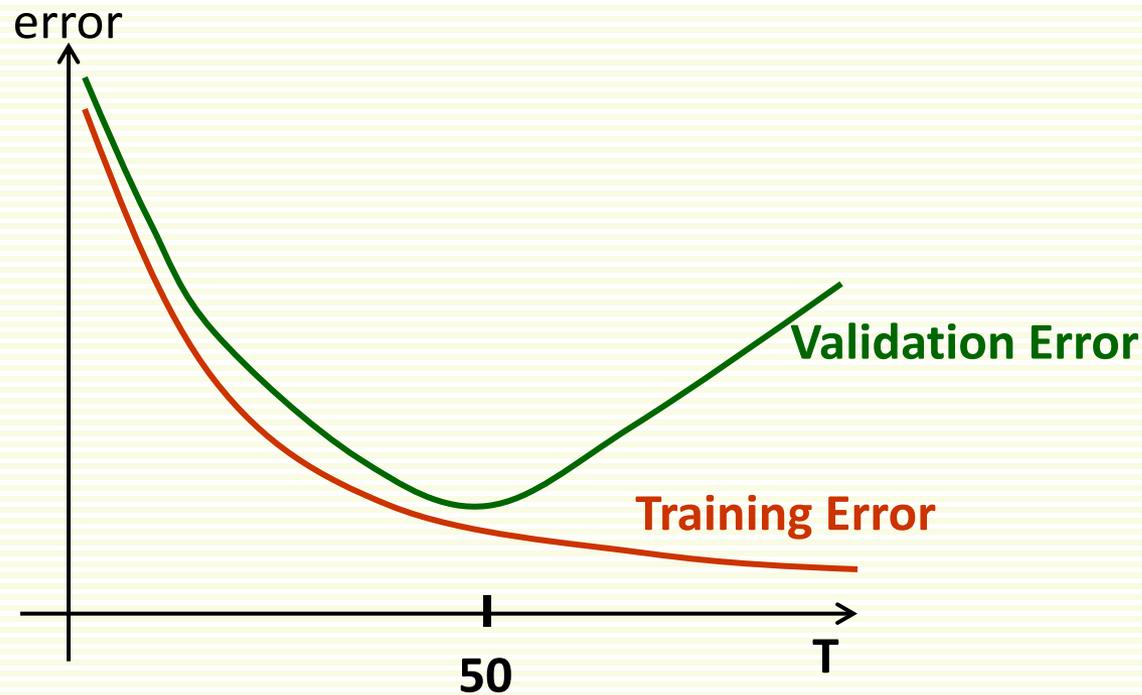
- Need to choose **T** for adaBoost
  - The more iterations, the better can fit training data
  - But at some point we overfit the data

Diagnosing Underfitting/Overfitting
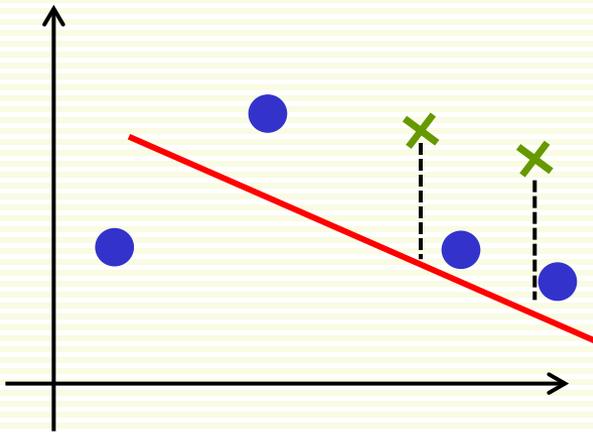
Underfitting
- large training error
- large validation error
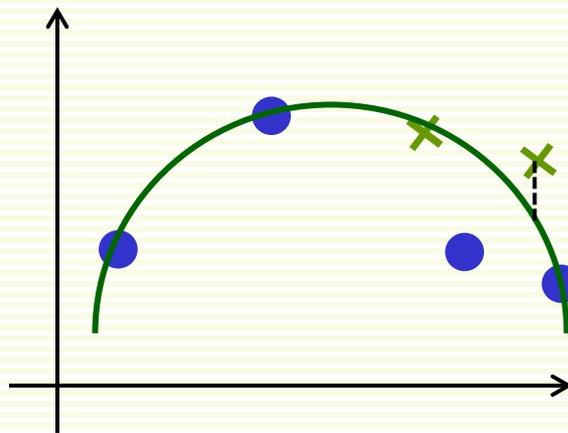
Just Right
- small training error
- small validation error
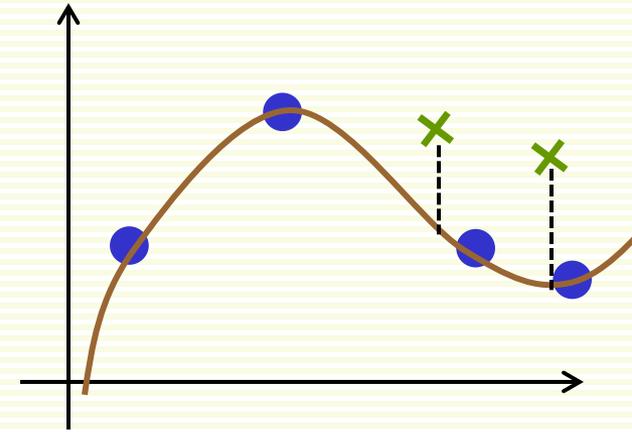
Overfitting
- small training error
- large validation error

Fixing Underfitting/Overfitting

- Fixing Underfitting
  - getting more training examples will not help
  - get more features
  - try more complex classifier
    - if using MNN, try more hidden units
- Fixing Overfitting
  - getting more training examples might help
  - try smaller set of features
  - Try less complex classifier
    - If using MNN, try less hidden units

Train/Test/Validation Method

- Good news
  - Very simple

- Bad news:
  - Wastes data
    - in general, the more data we have, the better are the estimated parameters
    - we estimate parameters on 40% less data, since 20% removed for test and 20% for validation data
  - If we have a small dataset our test (validation) set might just be lucky or unlucky

- Cross Validation is a method for performance evaluation that wastes less data

Small Dataset

Linear Model:
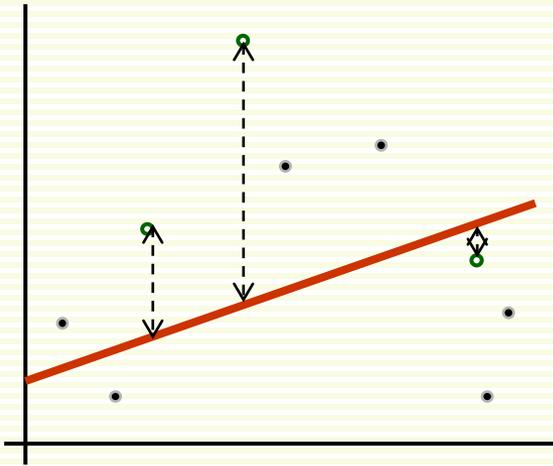
Quadratic Model:

Join the dots Model:

Mean Squared Error = 2.4

Mean Squared Error = 0.9
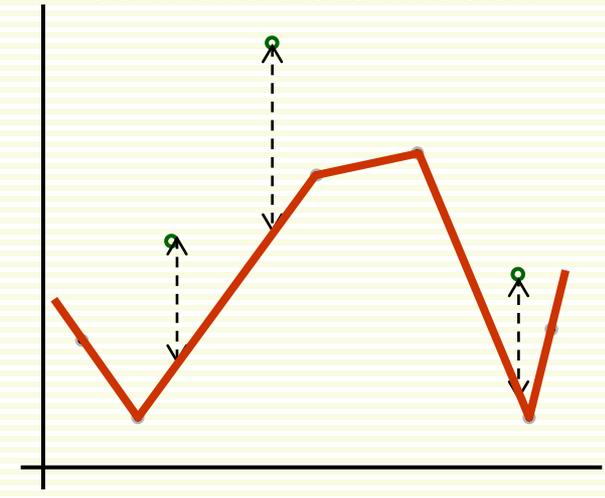
Mean Squared Error = 2.2

For k=1 to R

1. Let $(\mathbf{x}^k, \mathbf{y}^k)$ be the **k** example

y

x

LOOCV (Leave-one-out Cross Validation)

For $\mathbf{k}$=1 to $\mathbf{n}$

1. Let $(\mathbf{x}^k, \mathbf{y}^k)$ be the $\mathbf{k}$th example

2. Temporarily remove $(\mathbf{x}^k, \mathbf{y}^k)$ from the dataset

For **k**=1 to **n**

1. Let ($\mathbf{x}^k$,$\mathbf{y}^k$) be the **k**th example

2. Temporarily remove ($\mathbf{x}^k$,$\mathbf{y}^k$) from the dataset

3. Train on the remaining **n**-1 examples

y

x

LOOCV (Leave-one-out Cross Validation)

For **k**=1 to **n**

1. Let $(\mathbf{x}^k, \mathbf{y}^k)$ be the **k**th example

2. Temporarily remove $(\mathbf{x}^k, \mathbf{y}^k)$ from the dataset

3. Train on the remaining **n**-1 examples

4. Note your error on $(\mathbf{x}^k, \mathbf{y}^k)$

y

x
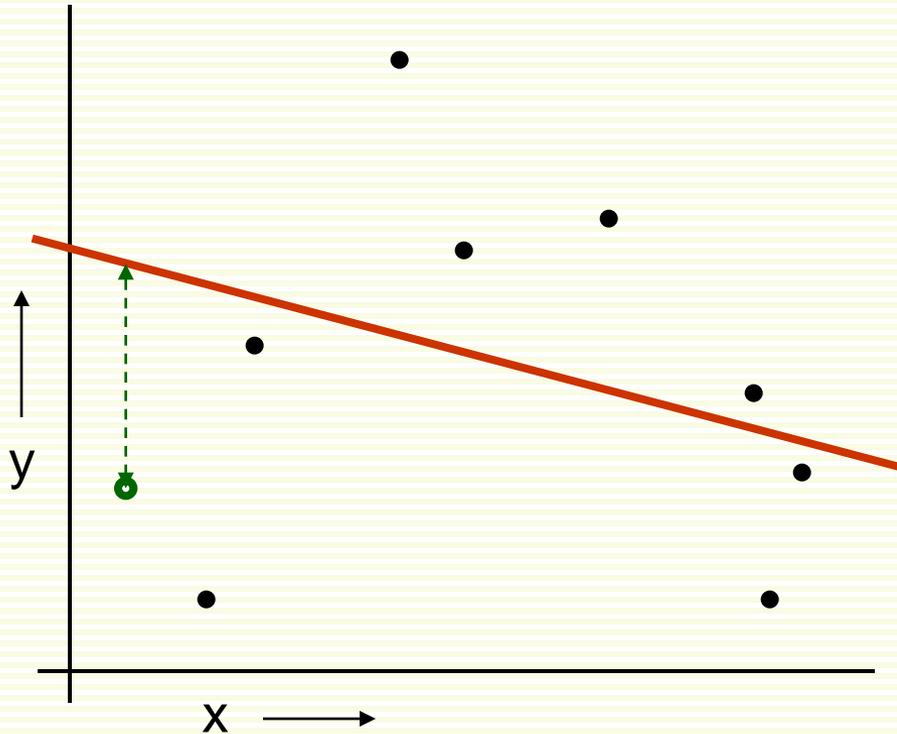
LOOCV (Leave-one-out Cross Validation)

For **k**=1 to **n**

1. Let (x^k,y^k) be the **k**th example

2. Temporarily remove (x^k,y^k) from the dataset

3. Train on the remaining **n**-1 examples

4. Note your error on (x^k,y^k)

When you've done all points, report the mean error
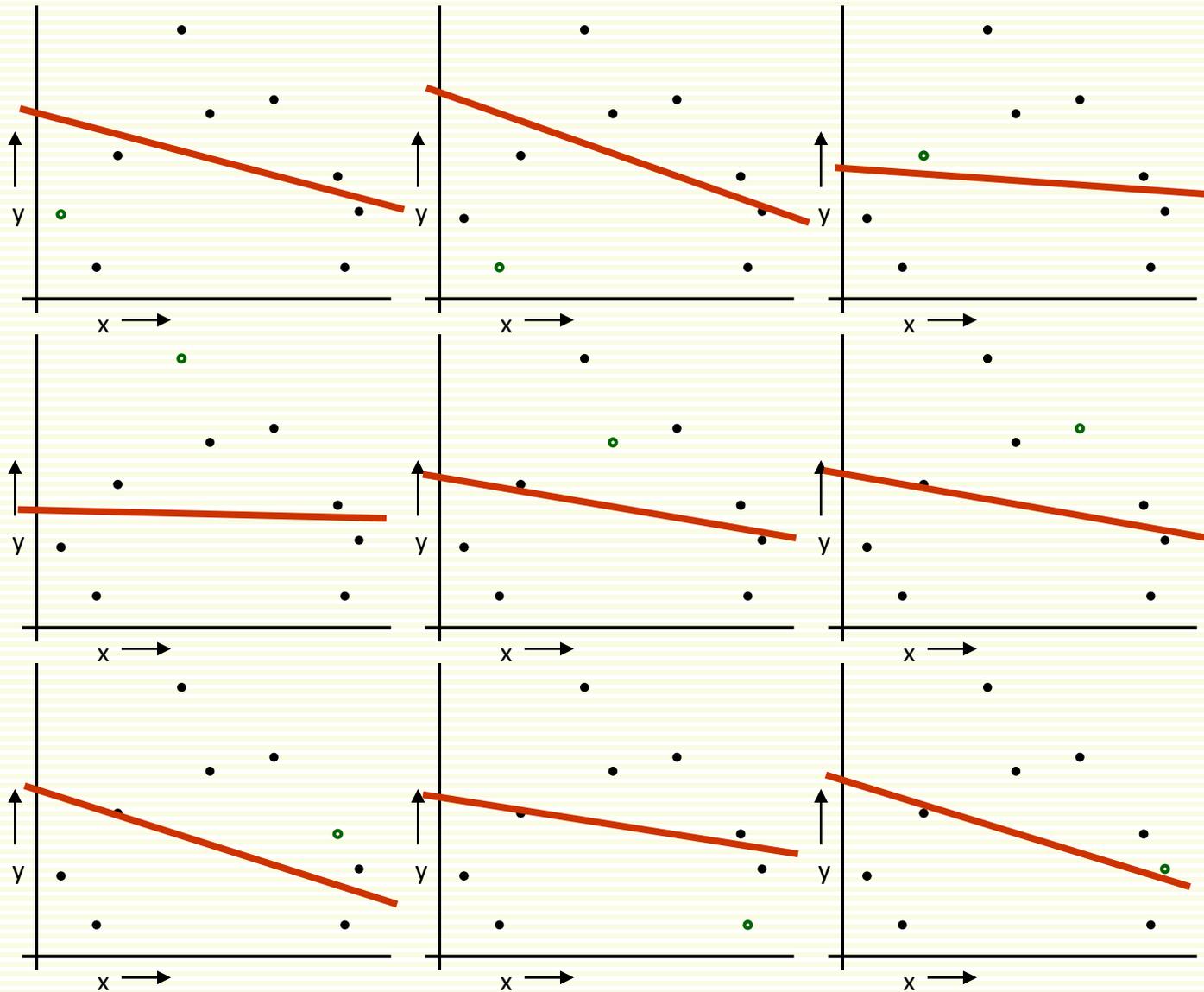
$MSE_{LOOCV} = 2.12$

LOOCV for Quadratic Regression
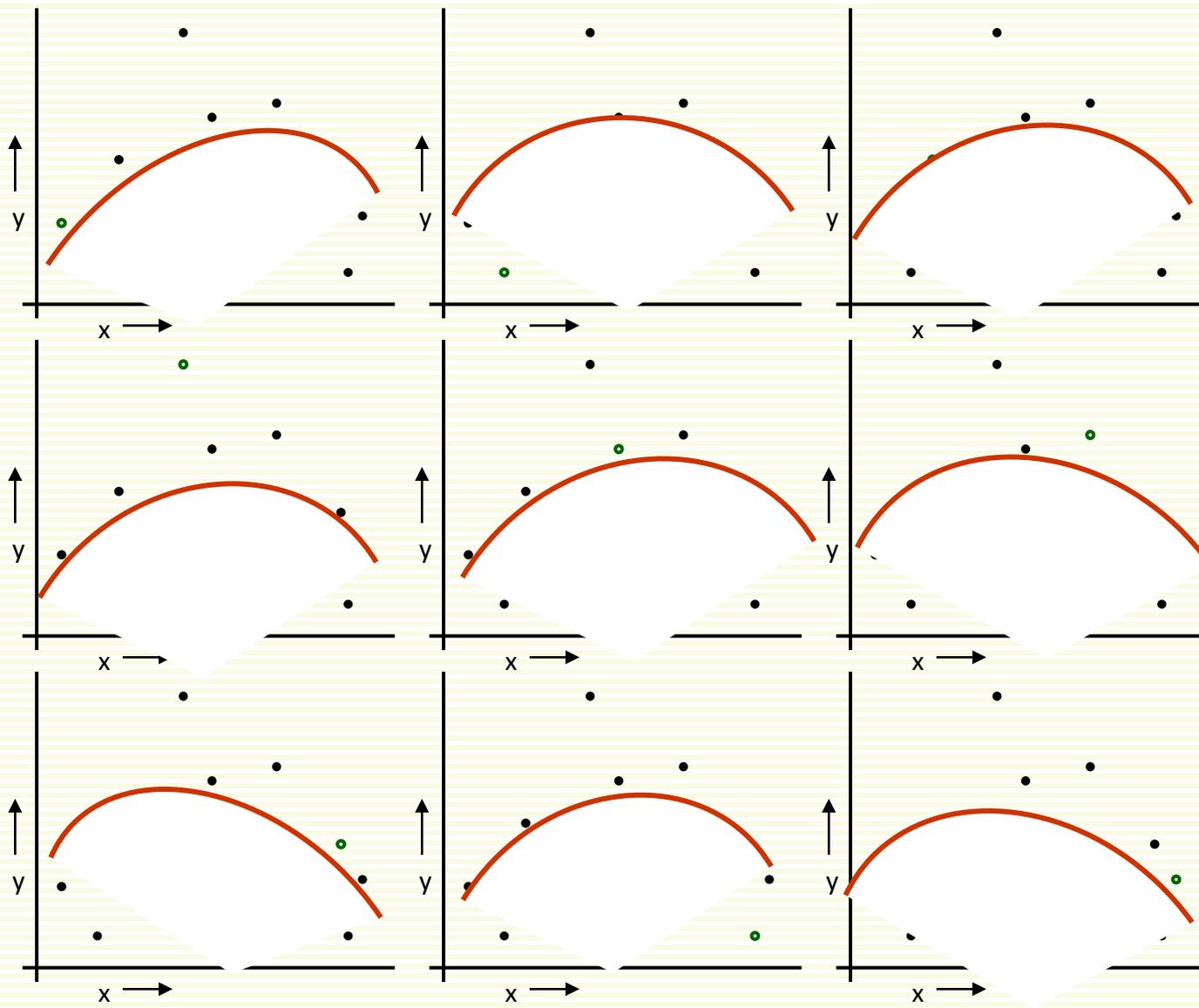
LOOCV for Join The Dots
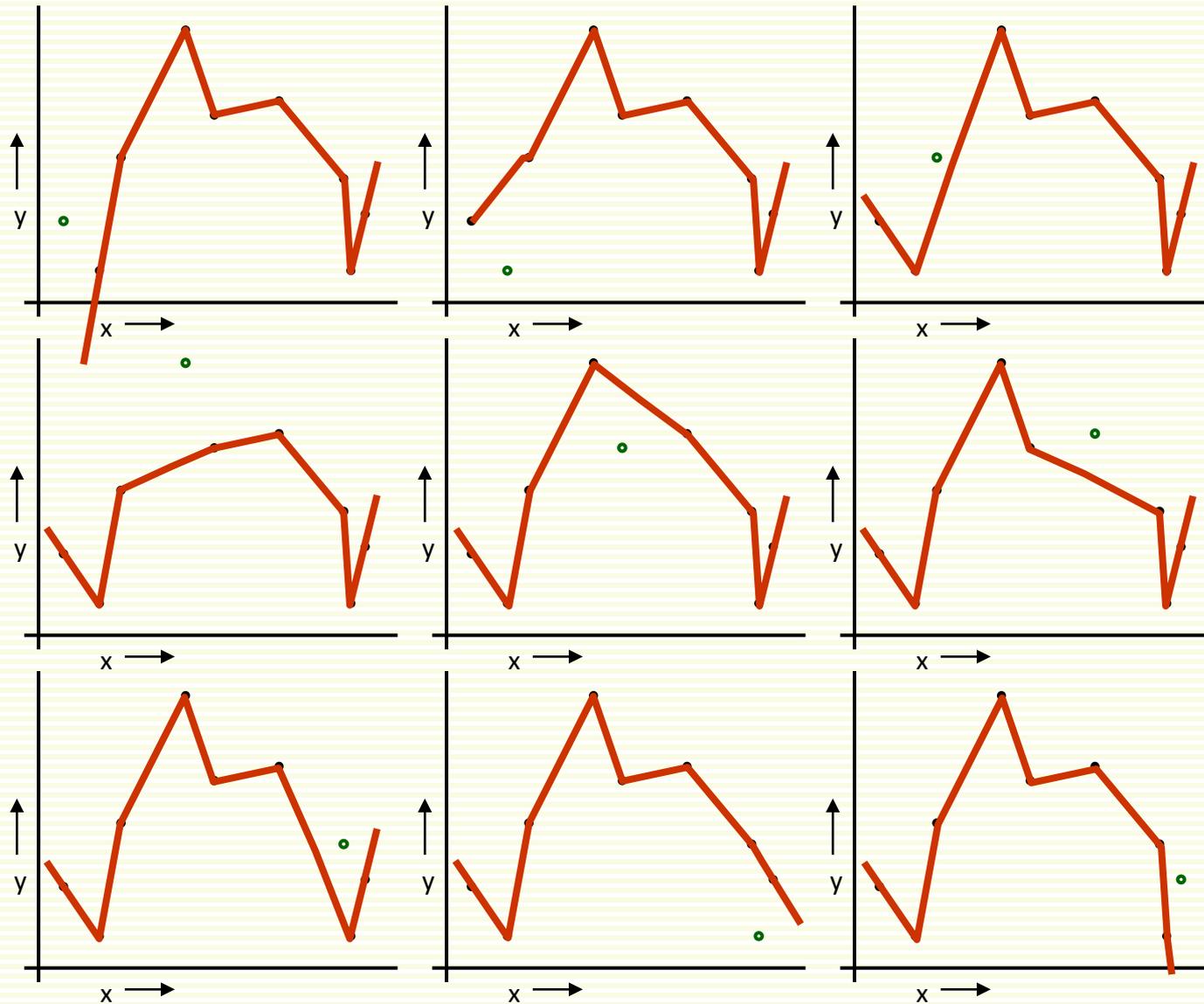
MSE_{LOOCV}
$=3.33$

Which kind of Cross Validation?

	Downside	Upside
Test-set	may give unreliable estimate of future performance	cheap
Leave-one-out	expensive	doesn't waste data

- Can we get the best of both worlds?

K-Fold Cross Validation
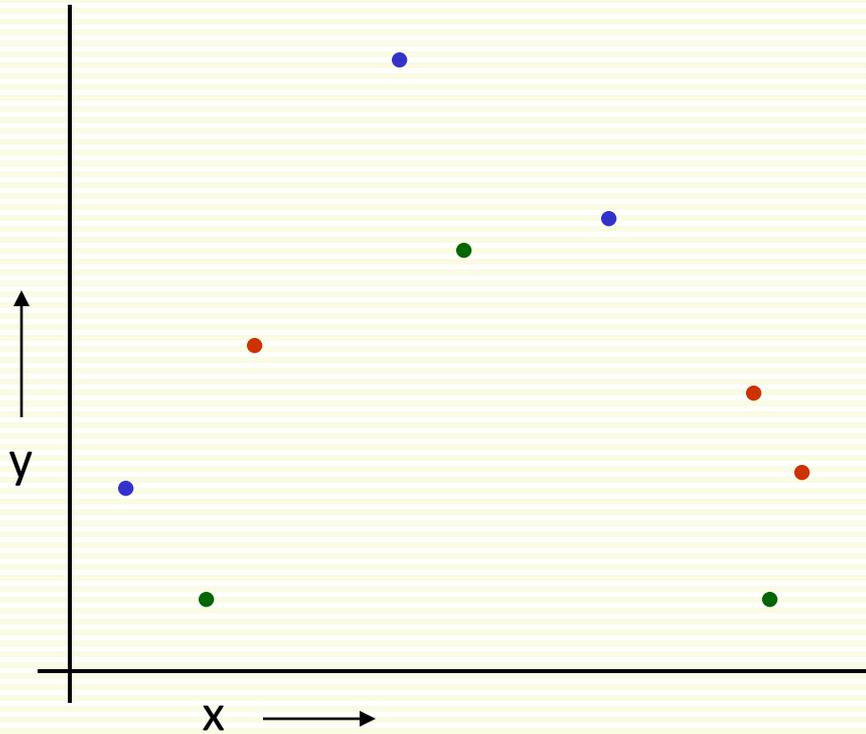
Randomly break the dataset into k partitions in this example we'll have k=3 partitions colored Red Green and Blue)
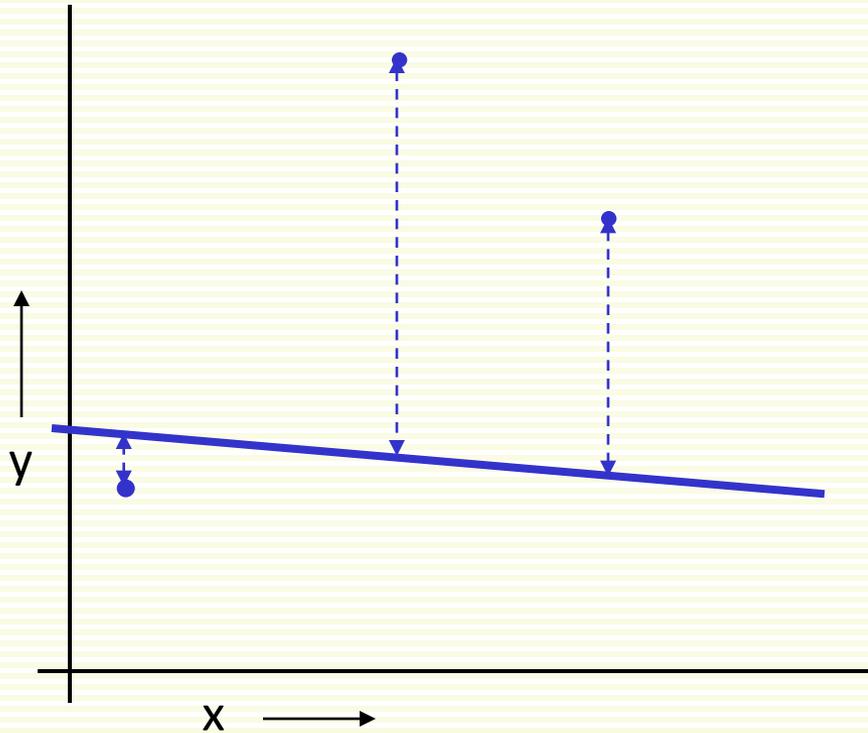
y

x

K-Fold Cross Validation

- Randomly break the dataset into k partitions
- in example have k=3 partitions colored red green and blue
- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points

K-Fold Cross Validation
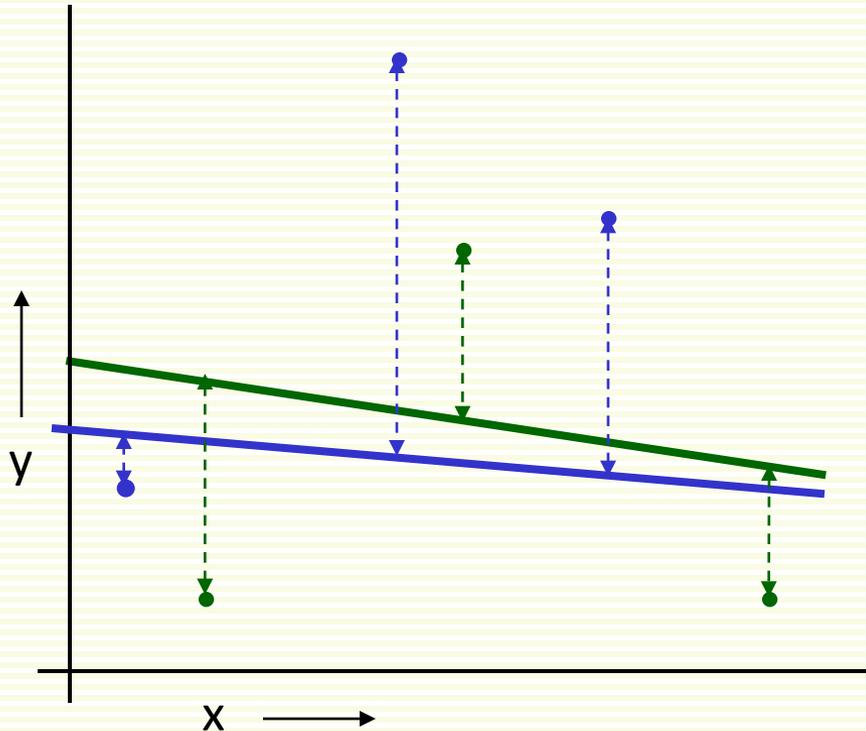
- Randomly break the dataset into k partitions
- in example have k=3 partitions colored red green and blue
- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points
- For the green partition: train on all points not in green partition. Find test-set sum of errors on green points

# K-Fold Cross Validation
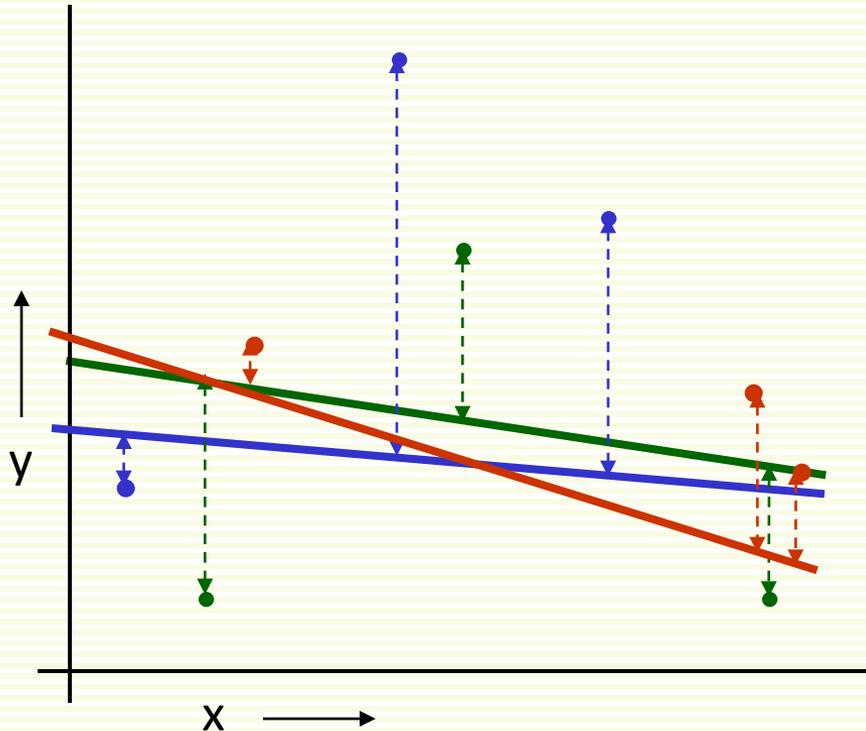
- Randomly break the dataset into k partitions

- in example have k=3 partitions colored red green and blue

- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points

- For the green partition: train on all points not in green partition. Find test-set sum of errors on green points

- For the red partition: train on all points not in red partition. Find the test-set sum of errors on red points

K-Fold Cross Validation
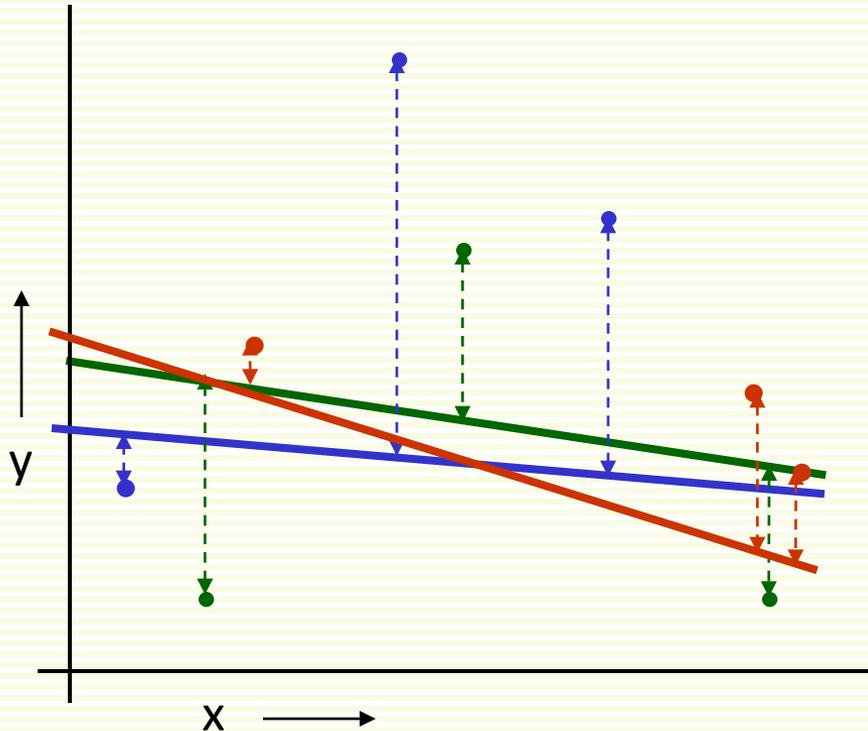
Linear Regression
$MSE_{3FOLD}=2.05$

- Randomly break the dataset into k partitions
- in example have k=3 partitions colored red green and blue
- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points
- For the green partition: train on all points not in green partition. Find test-set sum of errors on green points
- For the red partition: train on all points not in red partition. Find the test-set sum of errors on red points
- Report the mean error

# K-Fold Cross Validation
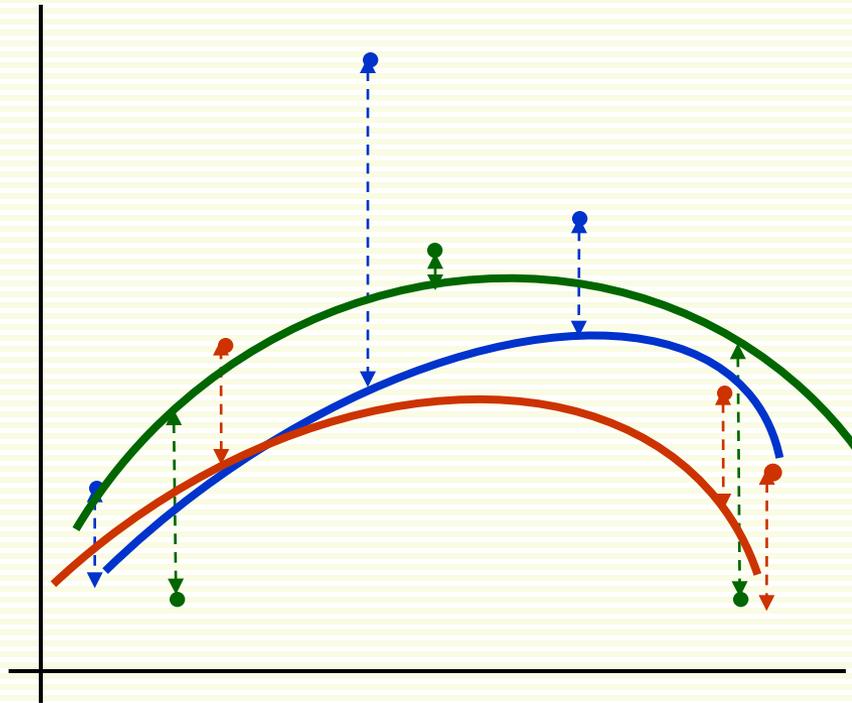
Quadratic Regression
$MSE_{3FOLD}=1.11$

- Randomly break the dataset into k partitions
- in example have k=3 partitions colored red green and blue
- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points
- For the green partition: train on all points not in green partition. Find test-set sum of errors on green points
- For the red partition: train on all points not in red partition. Find the test-set sum of errors on red points
- Report the mean error

K-Fold Cross Validation
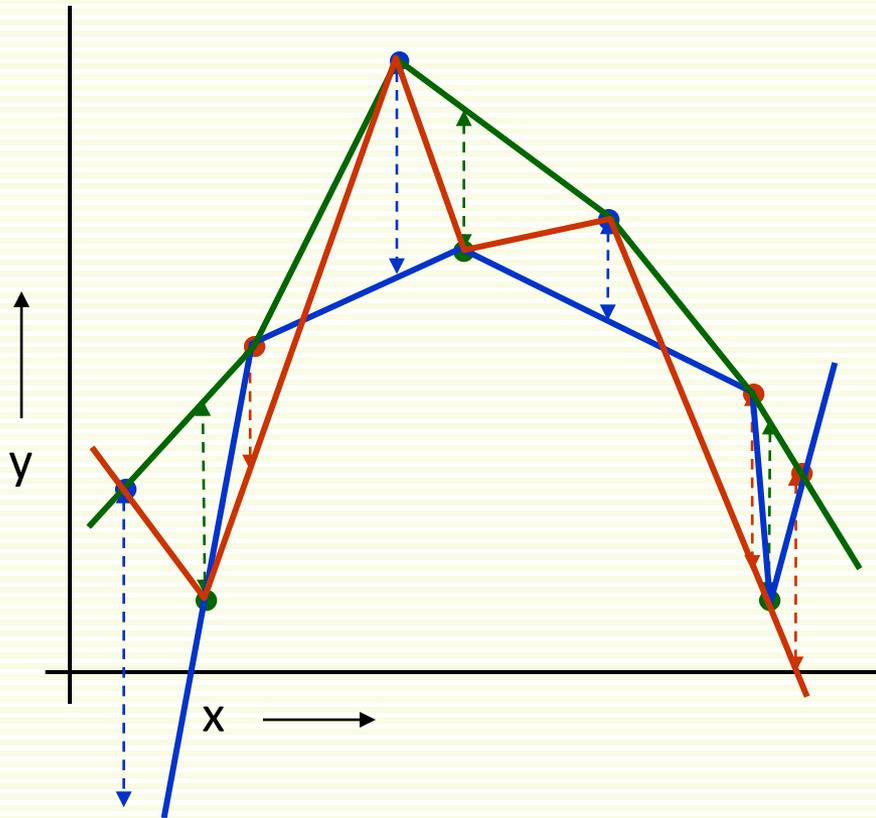
Joint-the-dots

$MSE_{3FOLD} = 2.93$

- Randomly break the dataset into k partitions

- in example have k=3 partitions colored red green and blue

- For the blue partition: train on all points not in the blue partition. Find test-set sum of errors on blue points

- For the green partition: train on all points not in green partition. Find test-set sum of errors on green points

- For the red partition: train on all points not in red partition. Find the test-set sum of errors on red points

- Report the mean error

Which kind of Cross Validation?

	Downside	Upside
Test-set	may give unreliable estimate of future performance	cheap
Leave-one-out	expensive	doesn't waste data
10-fold	wastes 10% of the data,10 times more expensive than test set	only wastes 10%, only 10 times more expensive instead of **n** times
3-fold	wastes more data than 10-fold, more expensive than test set	slightly better than test-set
N-fold	Identical to Leave-one-out	

Cross-validation for classification

- Instead of computing the sum squared errors on a test set, you should compute…

Cross-validation for classification

- Instead of computing the sum squared errors on a test set, you should compute…

  The total number of misclassifications on a testset

Cross-validation for classification

- Instead of computing the sum squared errors on a test set, you should compute...

The total number of misclassifications on a testset
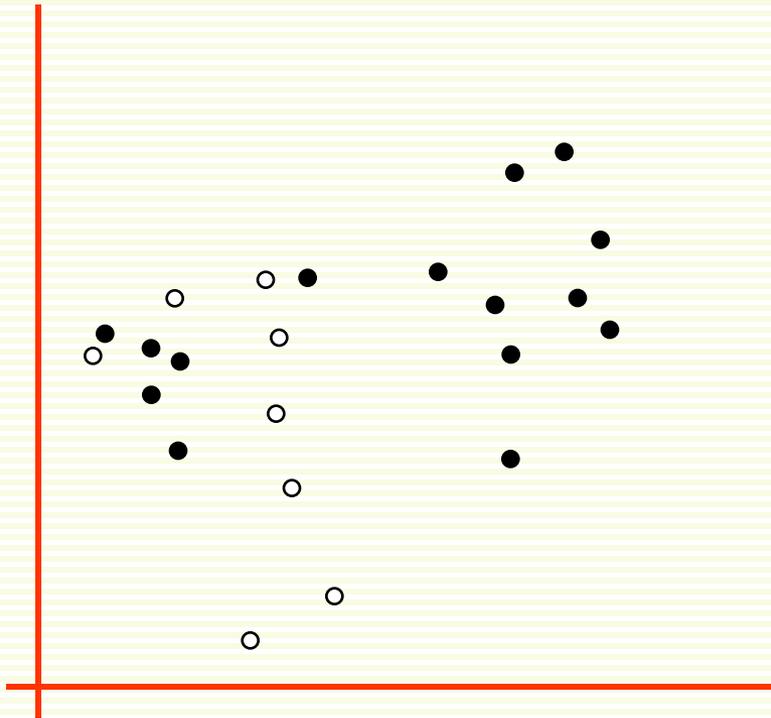
- What's LOOCV of 1-NN?

- What's LOOCV of 3-NN?

- What's LOOCV of 22-NN?

Cross-Validation for classification

- Choosing k for k-nearest neighbors
- Choosing Kernel parameters for SVM
- Any other "free" parameter of a classifier
- Choosing Features to use
- Choosing which classifier to use

CV-based Model Selection

- We're trying to decide which algorithm to use.
- We train each machine and make a table…

f_i	Training Error	10-FOLD-CV Error	Choice
f_1			
f_2			
f_3			⊠
f_4			
f_5			
f_6			

CV-based Model Selection

- Example: Choosing "k" for a k-nearest-neighbor regression.
- Step 1: Compute LOOCV error for six different model classes:

Algorithm	Training Error	10-fold-CV Error	Choice
k=1			
k=2			
k=3			
k=4			⊠
k=5			
k=6			

- Step 2: Choose model that gave best CV score
- Train it with all the data, and that's the final model you'll use

CV-based Model Selection

- Why stop at **k**=6?

  - No good reason, except it looked like things were getting worse as K was increasing

- Are we guaranteed that a local optimum of K vs LOOCV will be the global optimum?

  - No, in fact the relationship can be very bumpy

- What should we do if we are depressed at the expense of doing LOOCV for **k** = 1 through 1000?

  - Try: **k**=1, 2, 4, 8, 16, 32, 64, … ,1024
  - Then do hillclimbing from an initial guess at **k**