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Machine Learning and Data Mining

Nearest neighbor methods

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BREN:ICS
INFORMATION AND COMPUTER SCIENCES

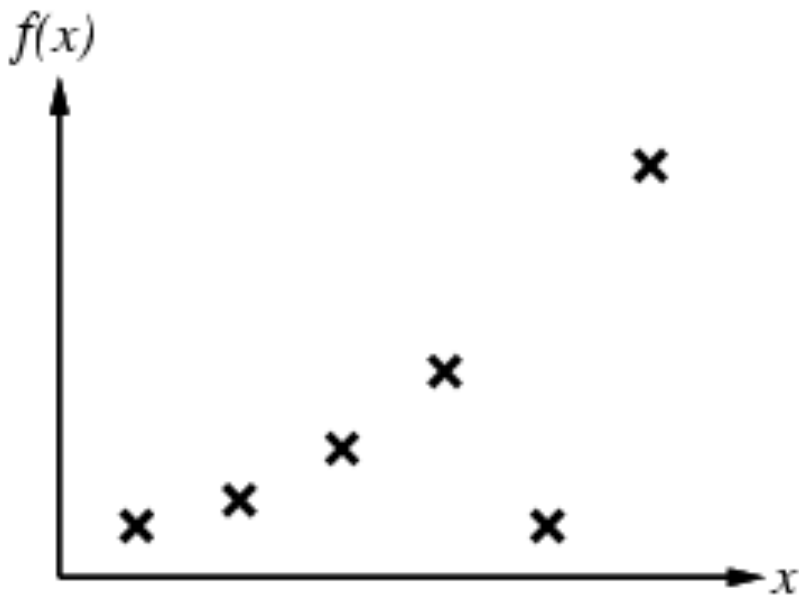UNIVERSITY *of* CALIFORNIA IRVINE
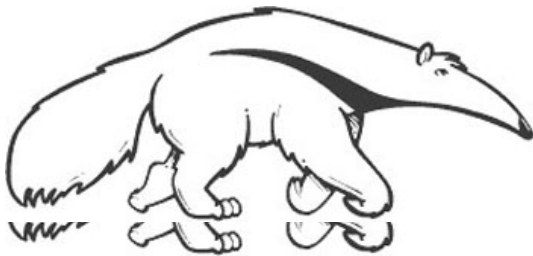
Machine Learning

Complexity and Overfitting
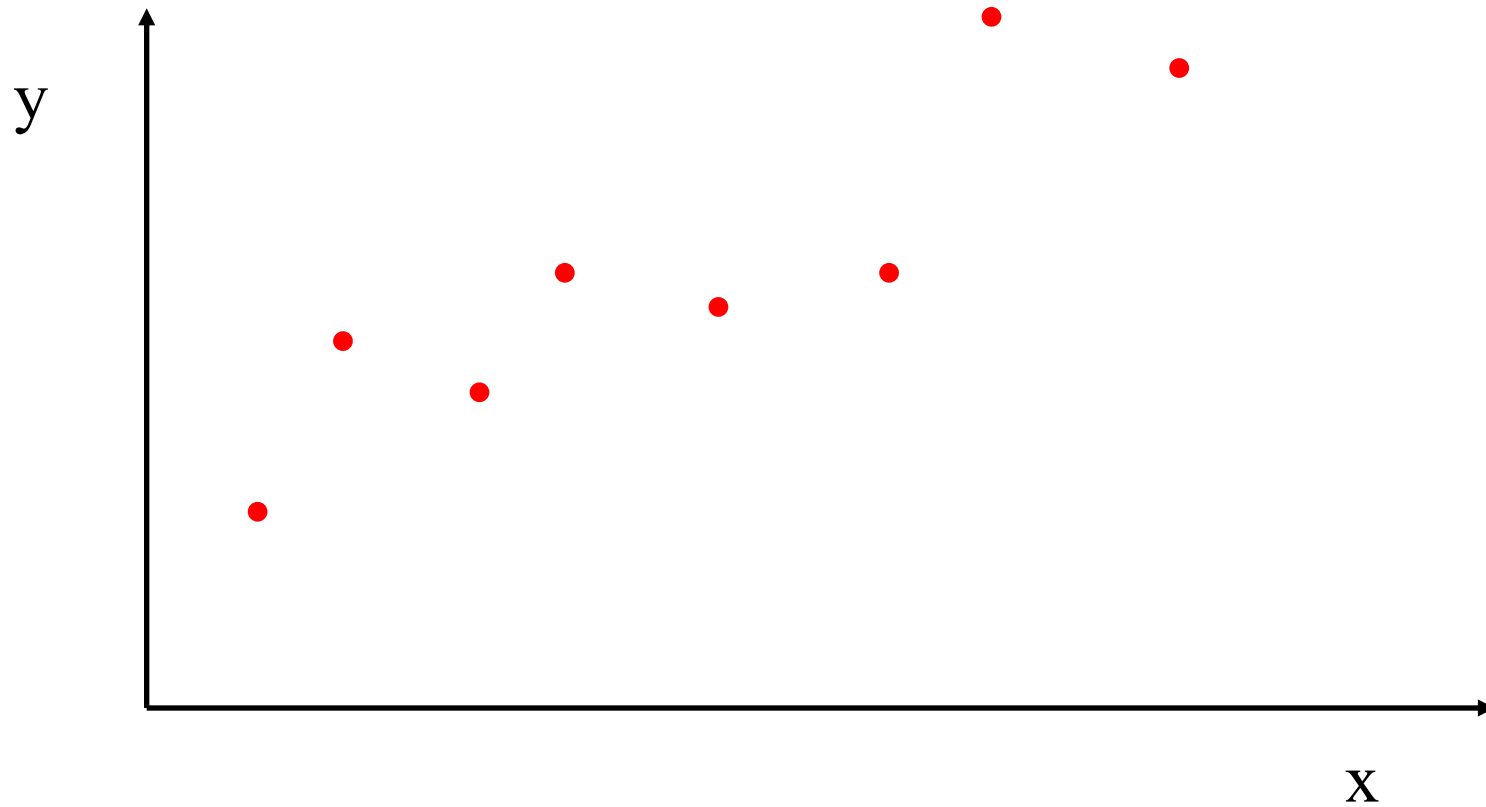
Nearest Neighbors

K-Nearest Neighbors
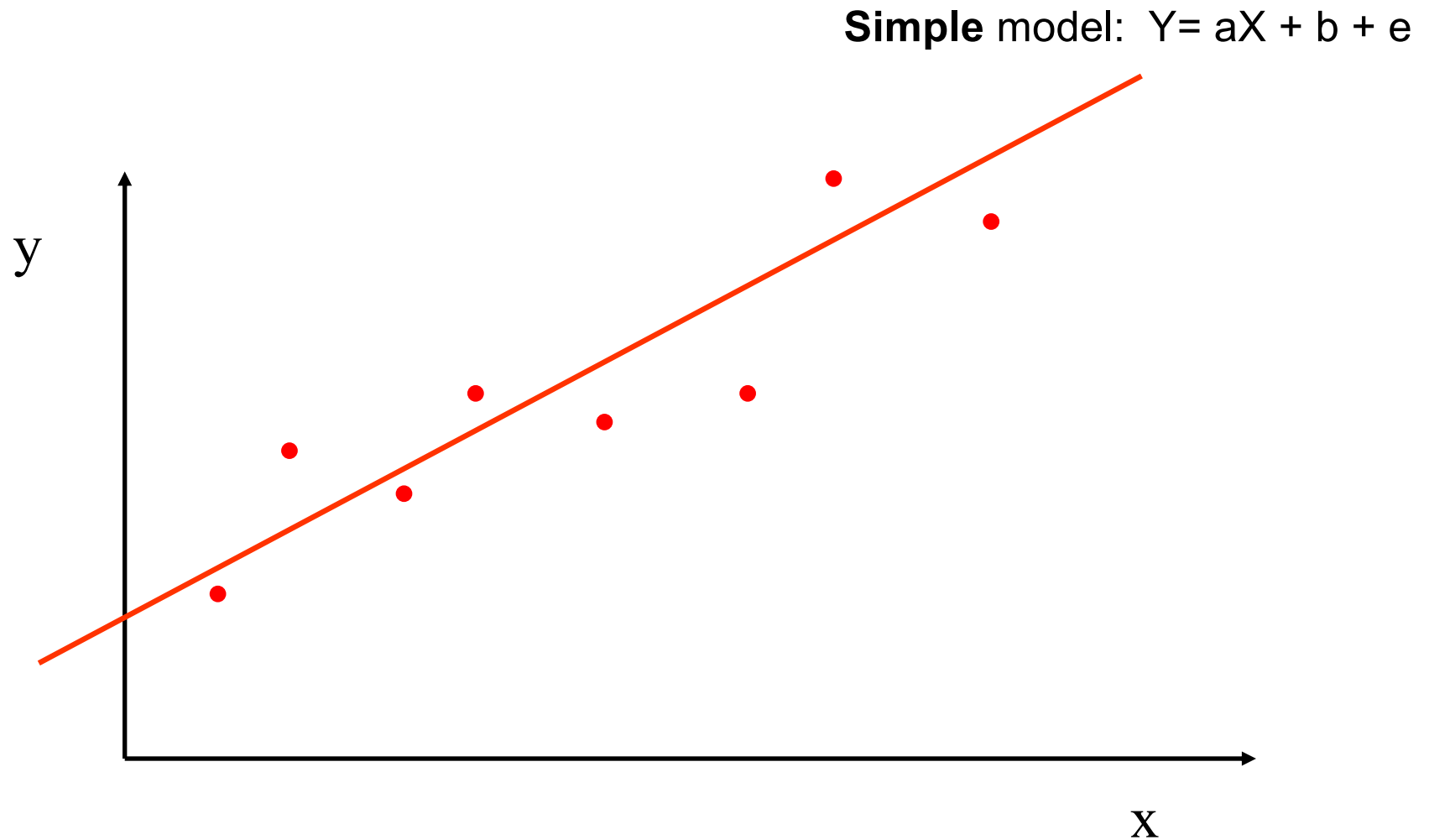
Inductive bias

- "Extend" observed data to unobserved examples
  - "Interpolate" / "extrapolate"
- What kinds of functions to expect? Prefer these ("bias")
  - Usually, let data pull us away from assumptions only with evidence!
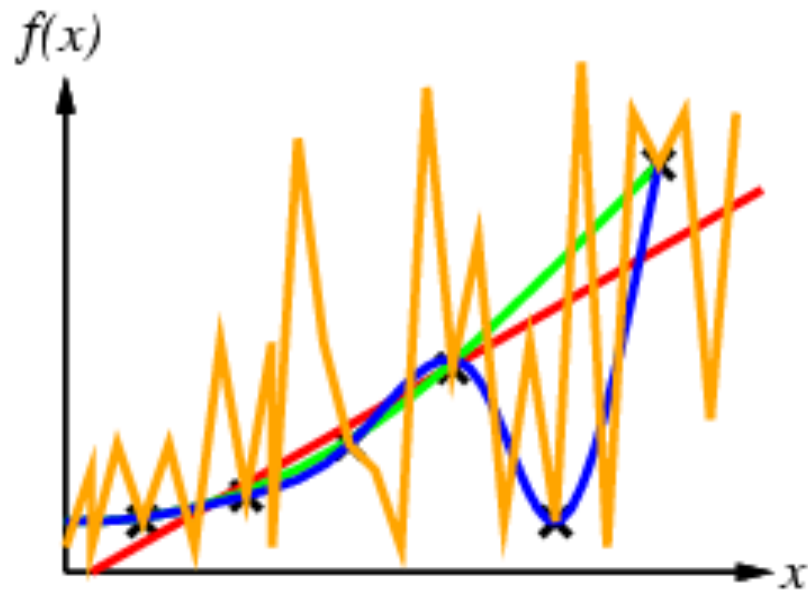
Overfitting and complexity

Overfitting and complexity

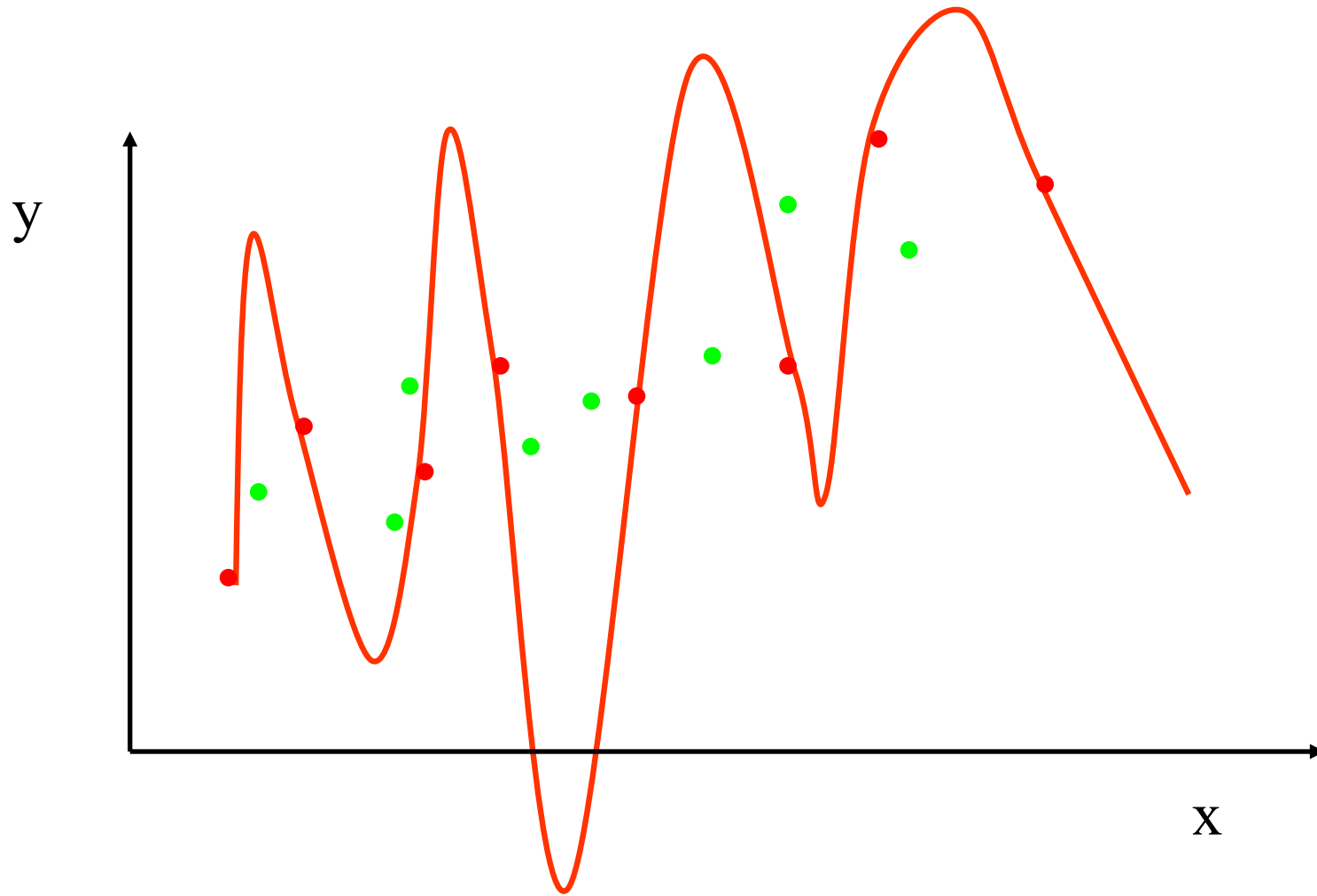**Simple** model: $Y = aX + b + e$

Overfitting and complexity

Y = high-order polynomial in X
(complex model)

y

x

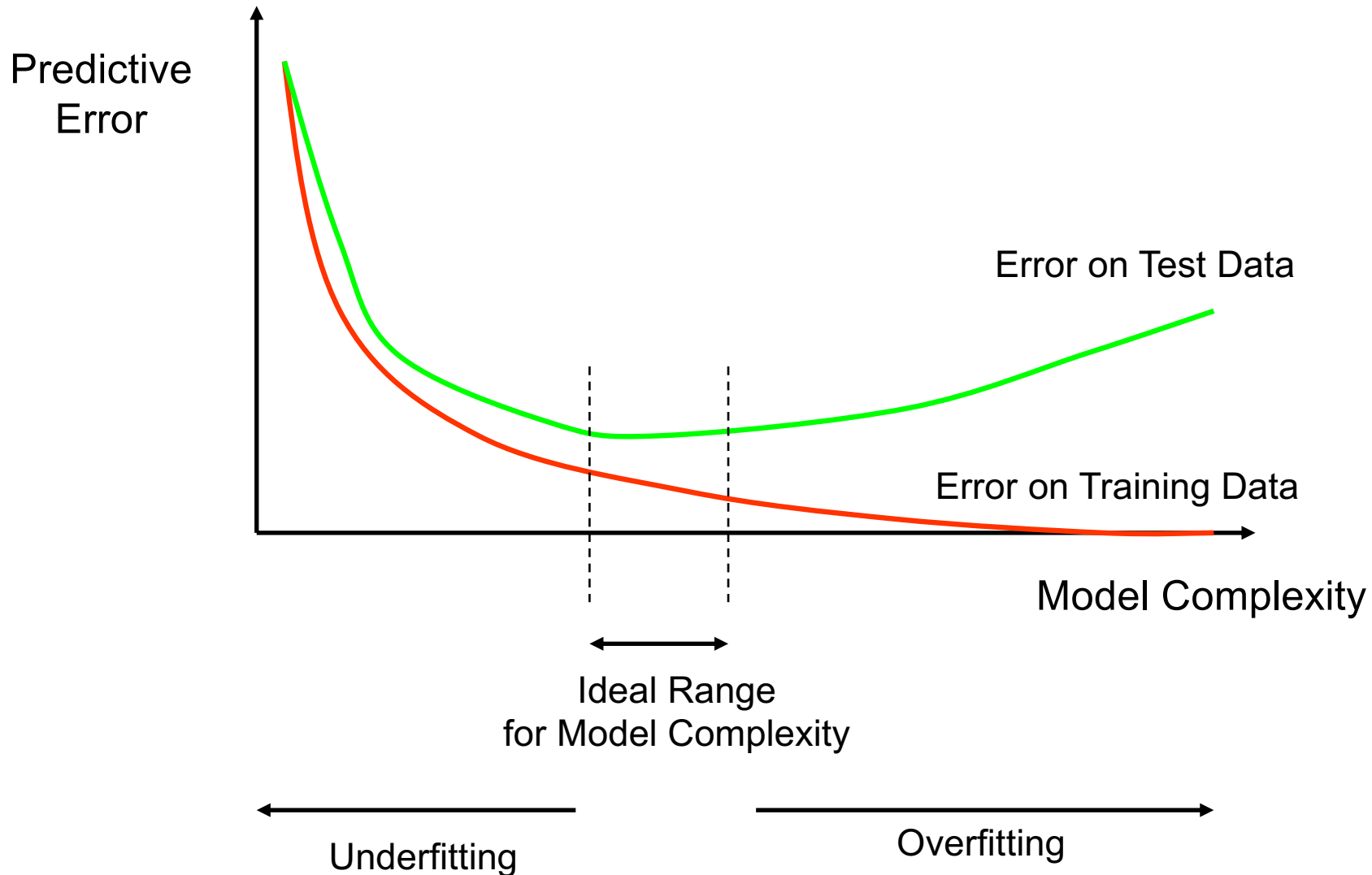# Overfitting and complexity

Simple model: Y= aX + b + e
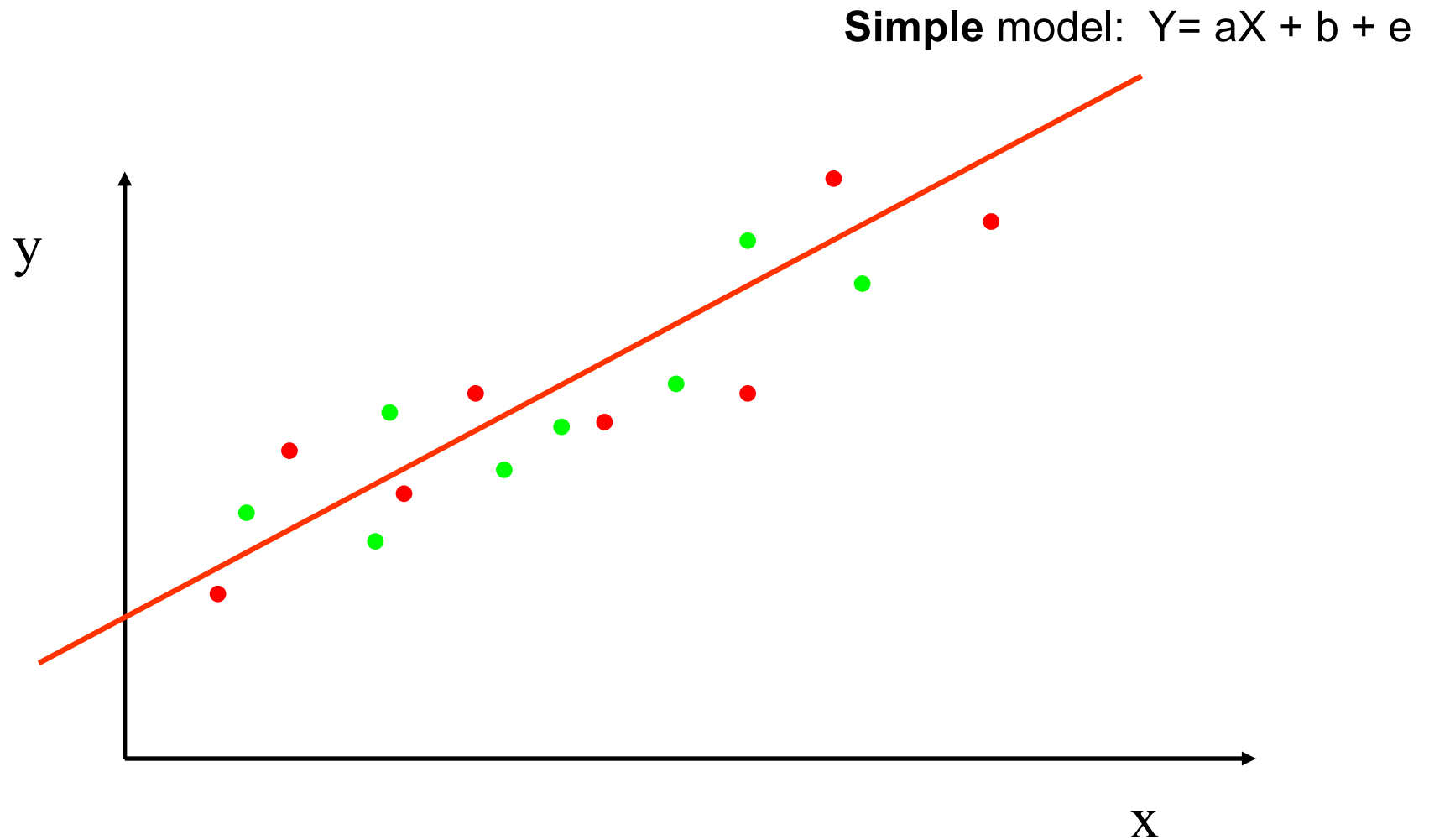
Overfitting and complexity

How Overfitting affects Prediction

Training and Test Data

Data

- Several candidate learning algorithms or models, each of which can be fit to data and used for prediction
- How can we decide which is best?

Approach 1: Split into train and test data

Training Data	Test Data

- Learn parameters of each model from training data
- Evaluate all models on test data, and pick best performer

Problem:

- Over-estimates test performance ("lucky" model)
- Learning algorithms should *never* have access to test data

Training, Validation, and Test Data

Data

- Several candidate learning algorithms or models, each of which can be fit to data and used for prediction
- How can we decide which is best?

Approach 2: Reserve some data for validation

| Training Data	Validation	Test Data

- Learn parameters of each model from training data
- Evaluate models on validation data, pick best performer
- Reserve test data to benchmark chosen model

Problem:

- Wasteful of training data (learning can't use validation)
- May bias selection towards overly simple models

Cross-Validation

- Divide training data into K equal-sized *folds*
- Train on K-1 folds, evaluate on remainder
- Pick model with best average performance across K trials

Fold 1	Fold 2	Fold 3	Fold 4
			Validation
		Validation	
	Validation		
Validation			
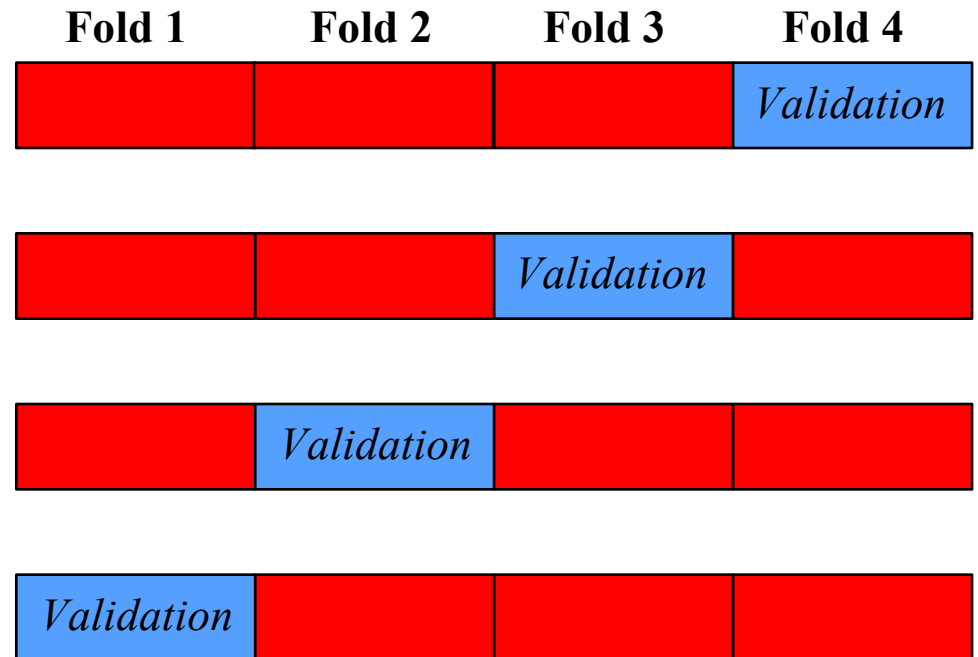
Test

How many folds?

- *Bias:* Too few, and effective training dataset much smaller
- *Variance:* Too many, and test performance estimates noisy
- *Cost:* Must run training algorithm once per fold (parallelizable)
- *Practical rule of thumb:* 5-fold or 10-fold cross-validation
- *Theoretically troubled:* Leave-one-out cross-validation, K=N

Competitions

- Training data
  - Used to build your model(s)
- Validation data
  - Used to assess, select among, or combine models
  - Personal validation; leaderboard; …
- Test data
  - Used to estimate "real world" performance

#	Δ1w	Team Name * in the money	Score	Entries	Last Submission UT
1	-	BrickMover 👥 *	1.21251	40	Sat, 31 Aug 2013 23:
2	new	vsu *	1.21552	13	Sat, 31 Aug 2013 20:
3	↑2	Merlion	1.22724	29	Sat, 31 Aug 2013 23:
4	↓2	Sergey	1.22856	15	Sat, 31 Aug 2013 23:
5	new	liuyongqi	1.22980	13	Sat, 31 Aug 2013 13:

Machine Learning
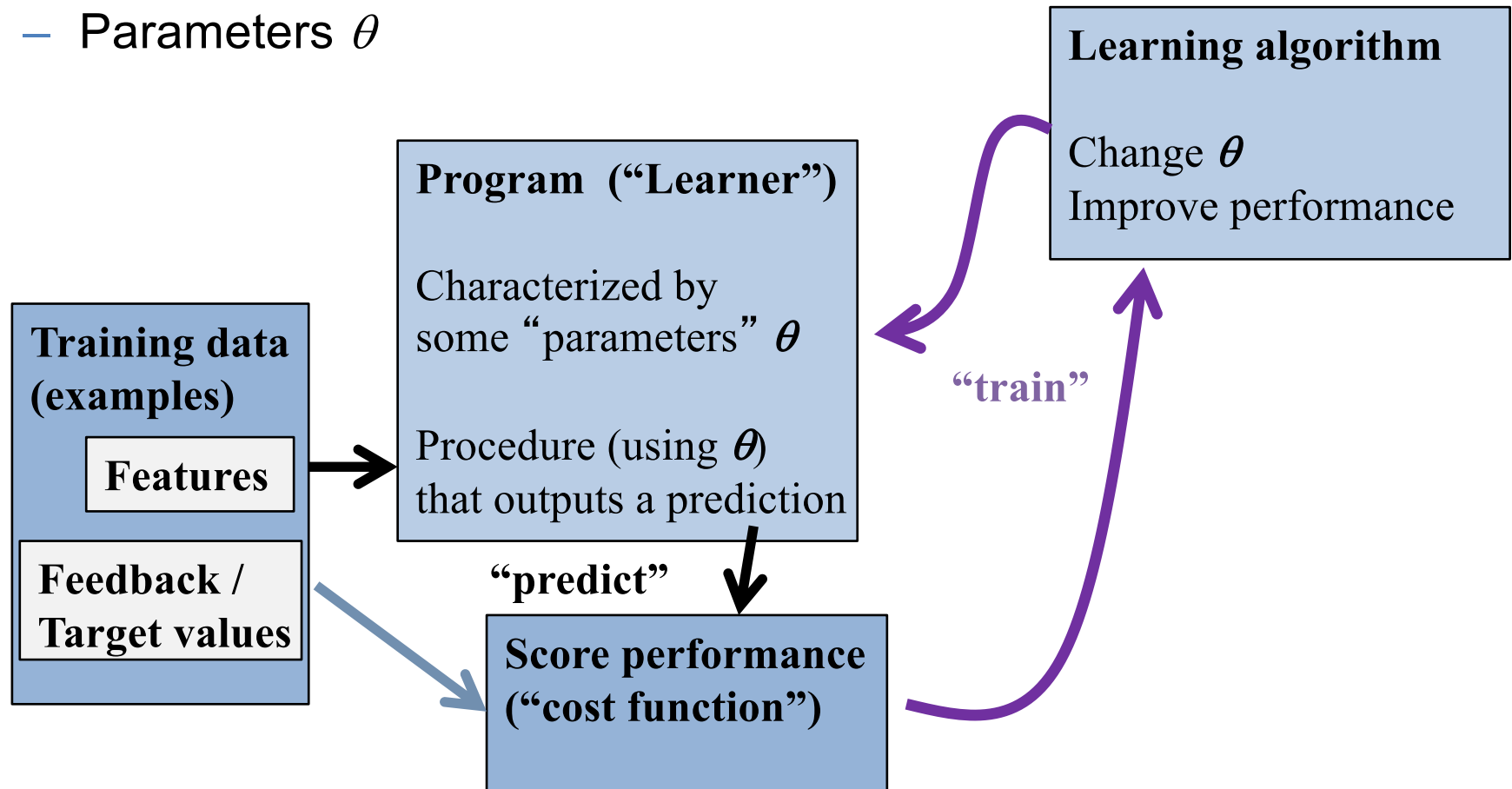
Complexity and Overfitting

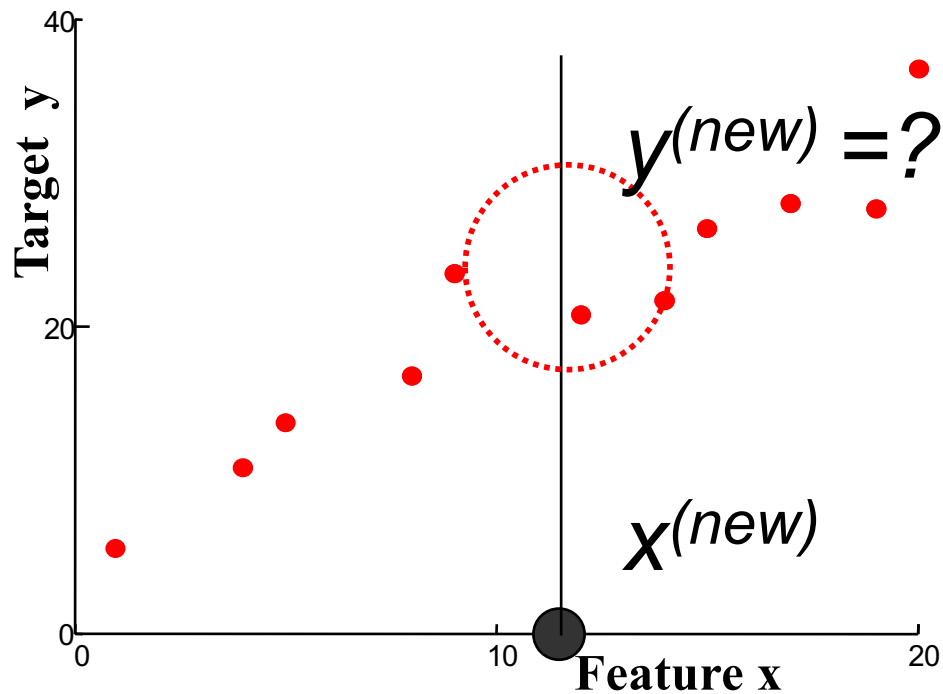**Nearest Neighbors**

K-Nearest Neighbors

Supervised learning

- Notation
  - Features x
  - Targets y
  - Predictions $\hat{y} = f(x ; \theta)$
  - Parameters θ

Learning algorithm

Change $\boldsymbol{\theta}$
Improve performance

Program ("Learner")

Characterized by some "parameters" $\boldsymbol{\theta}$

Procedure (using $\boldsymbol{\theta}$) that outputs a prediction

Training data (examples)

Features

Feedback / Target values

"predict"

"train"
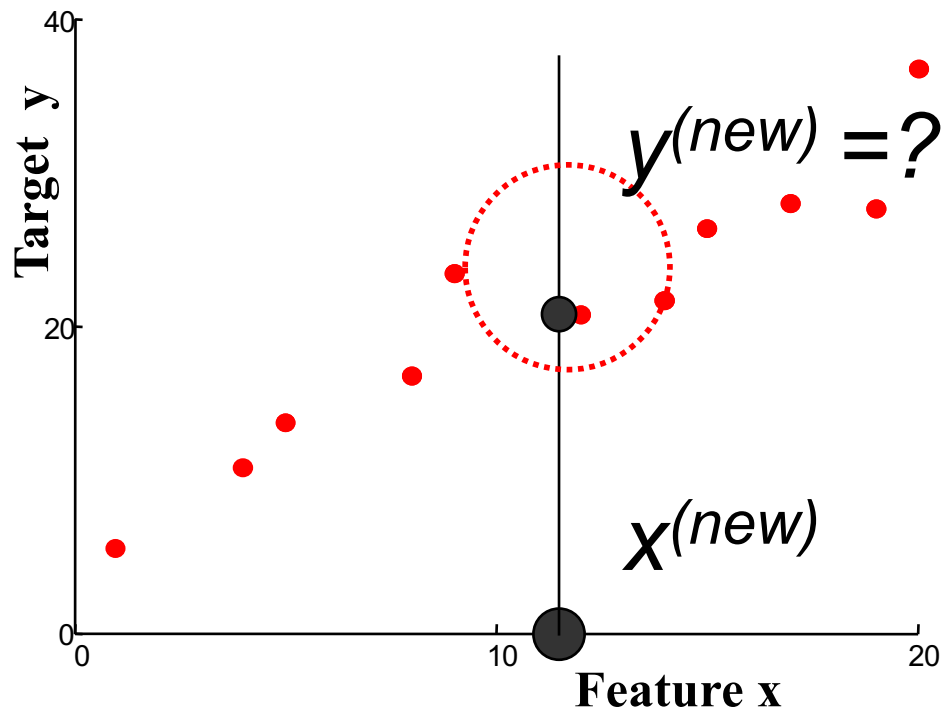
Score performance ("cost function")

Regression; Scatter plots

- Suggests a relationship between x and y
- Regression: given new observed $x^{(new)}$, estimate $y^{(new)}$
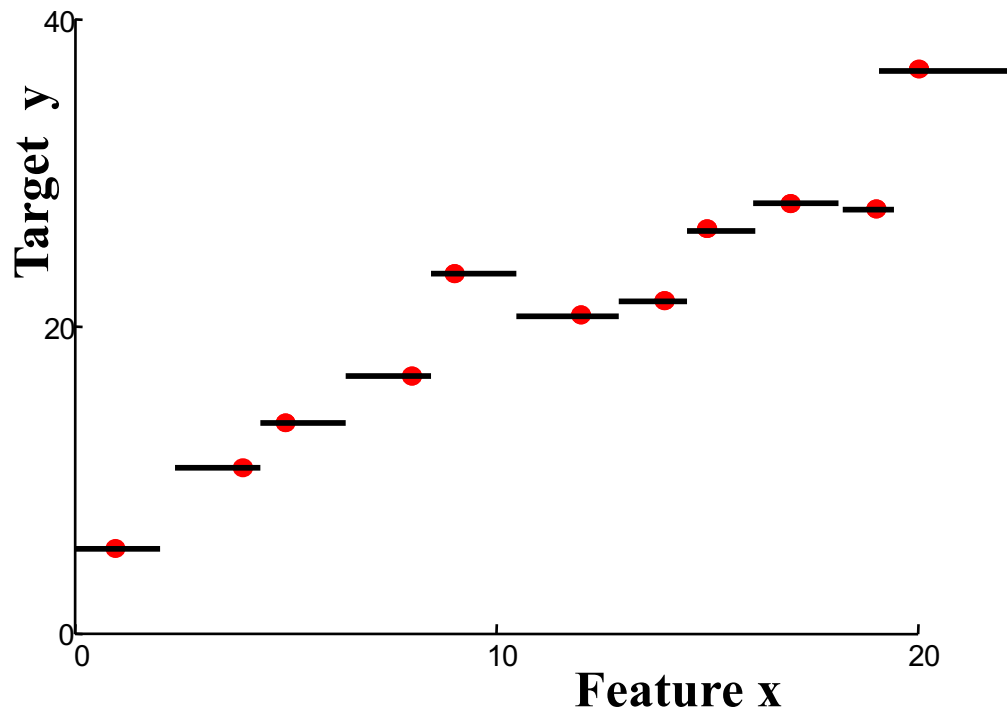
Nearest neighbor regression

"**Predictor**":
Given new features:
  Find nearest example
  Return its value

- Find training datum $x^{(i)}$ closest to $x^{(new)}$; predict $y^{(i)}$
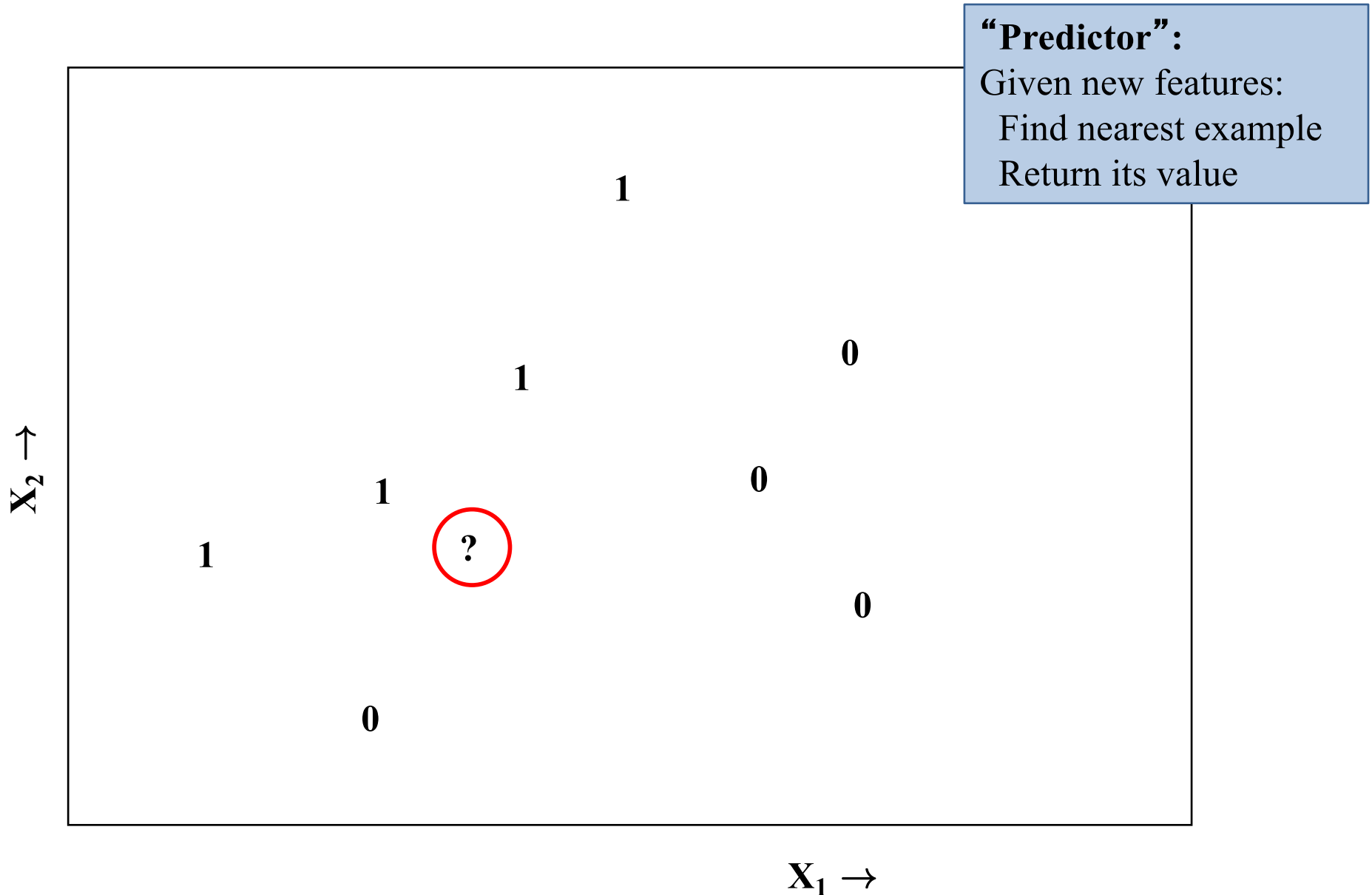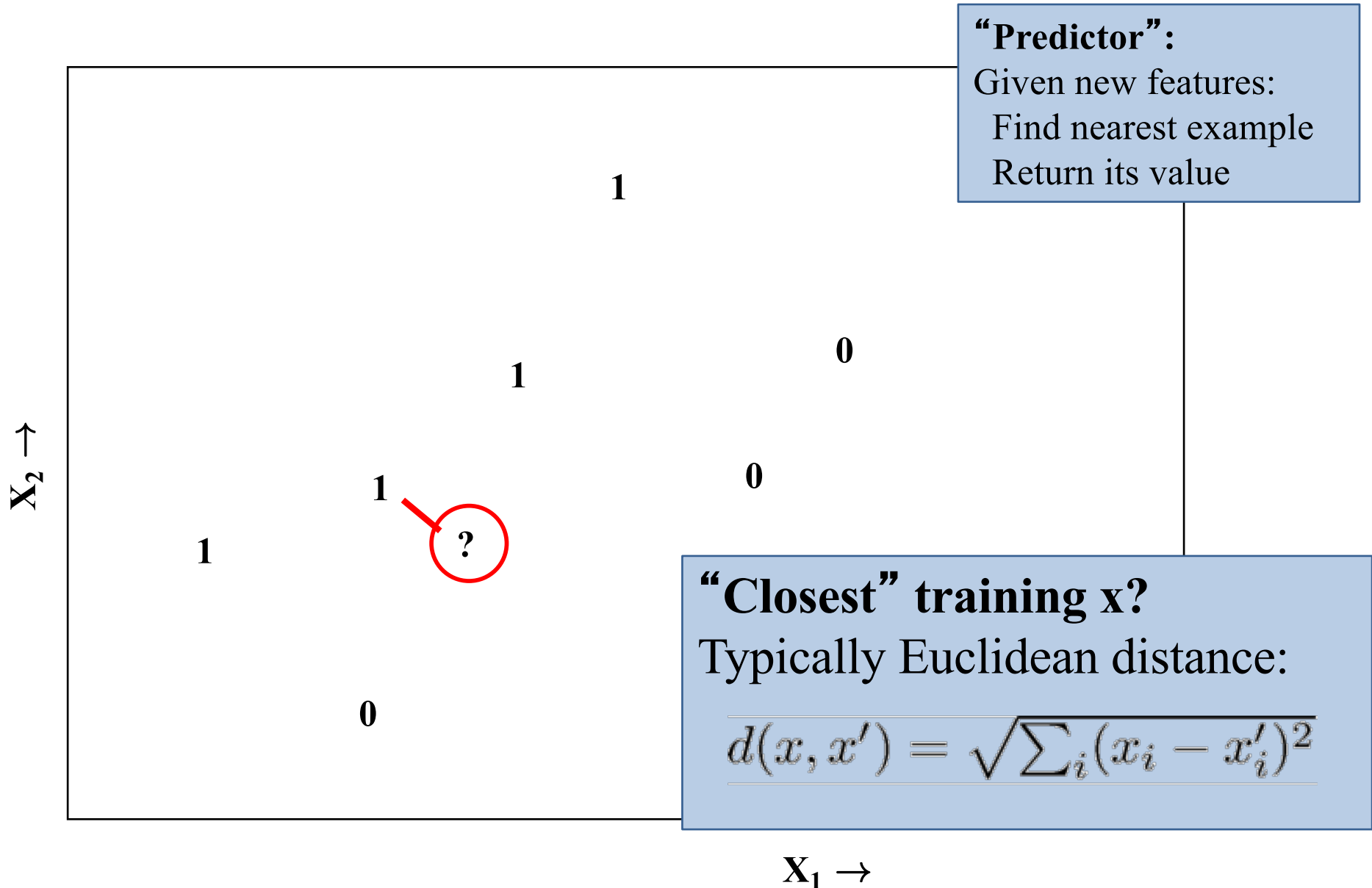
Nearest neighbor regression

- Find training datum $x^{(i)}$ closest to $x^{(new)}$; predict $y^{(i)}$
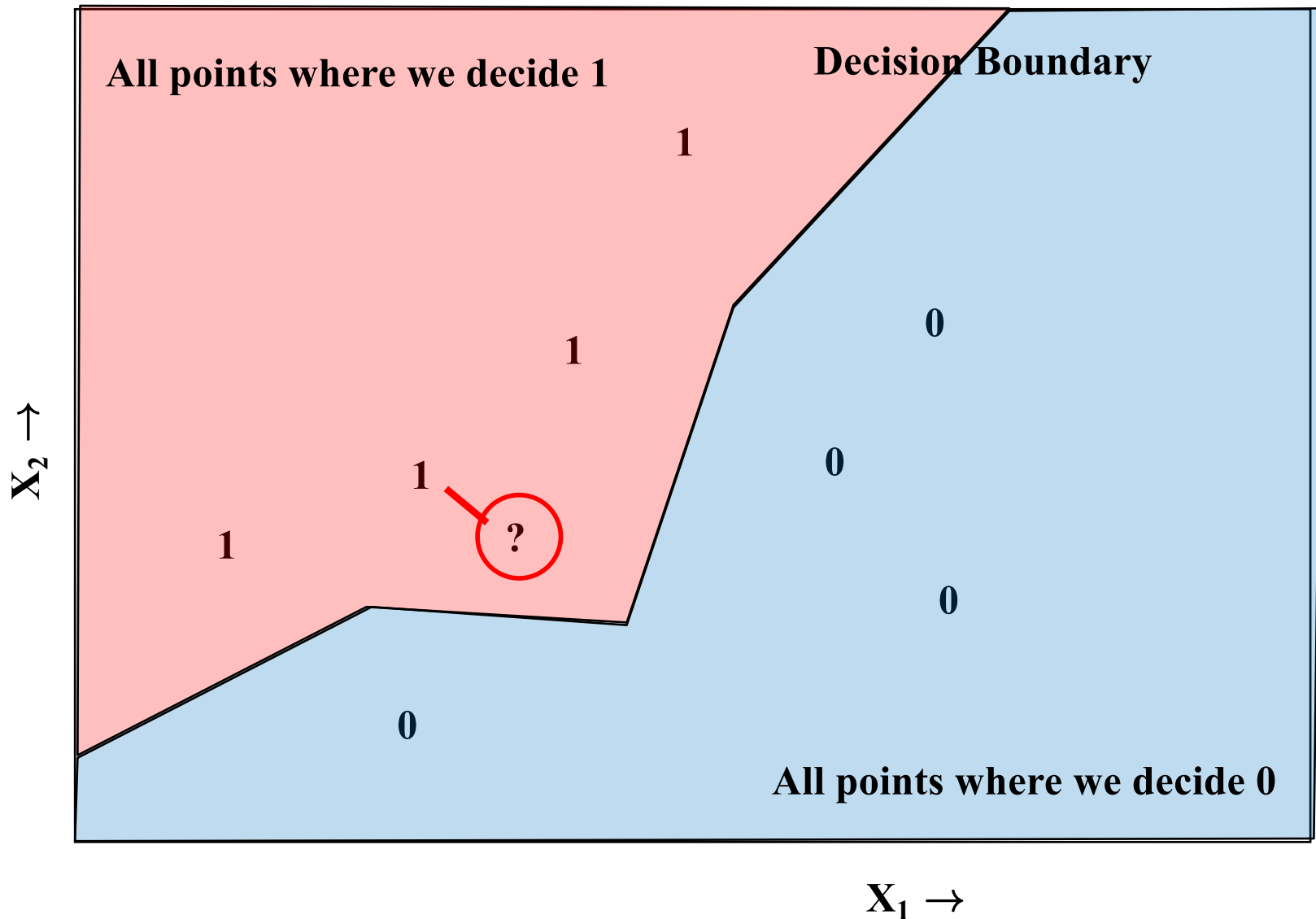- Defines an (implict) function f(x)
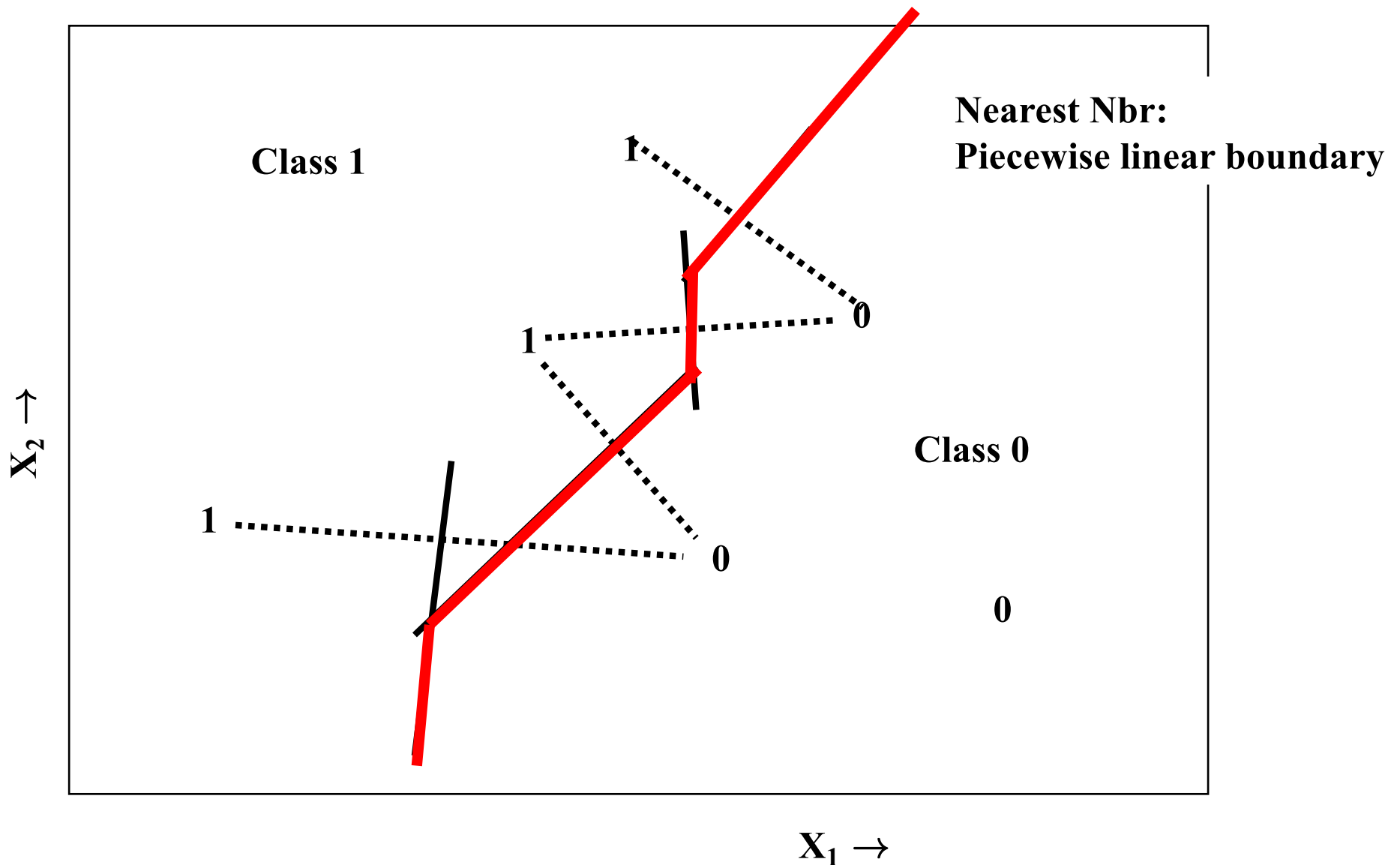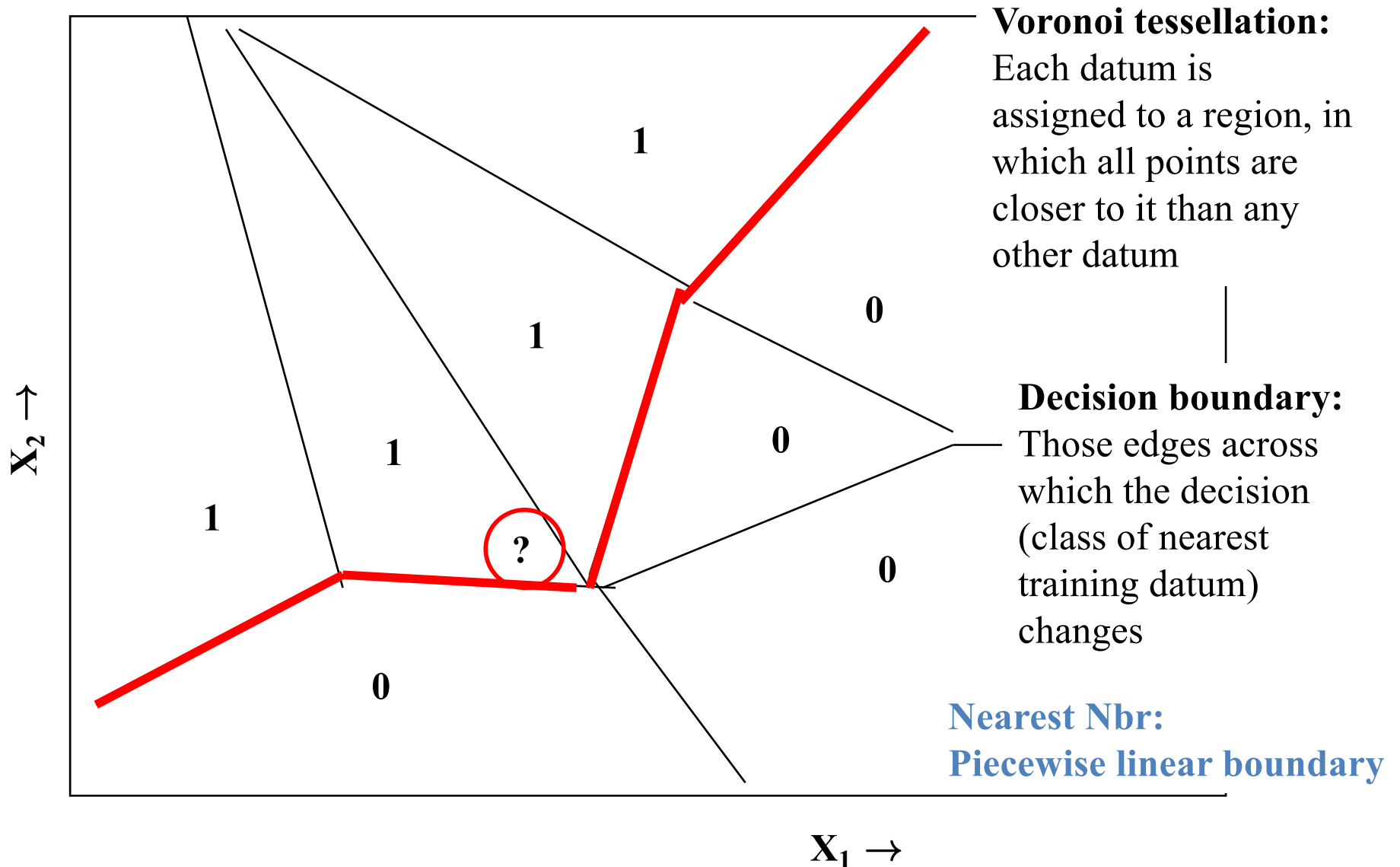- "Form" is piecewise constant

Nearest neighbor classifier

"**Predictor**":
Given new features:
Find nearest example
Return its value

Nearest neighbor classifier

X₂ →

$X_2 \rightarrow$

1

0

1

0

1

0

1

?

1

0

$X_1 \rightarrow$

"Predictor":
Given new features:
  Find nearest example
  Return its value

"Closest" training x?
Typically Euclidean distance:

$$d(x, x') = \sqrt{\sum_i (x_i - x_i')^2}$$

Nearest neighbor classifier

Nearest neighbor classifier

Class 1

Nearest Nbr:
Piecewise linear boundary

1

0

1

Class 0

1

0

0

$X_2 \rightarrow$

$X_1 \rightarrow$

Nearest neighbor classifier

Voronoi tessellation: Each datum is assigned to a region, in which all points are closer to it than any other datum

Decision boundary: Those edges across which the decision (class of nearest training datum) changes

Nearest Nbr: Piecewise linear boundary
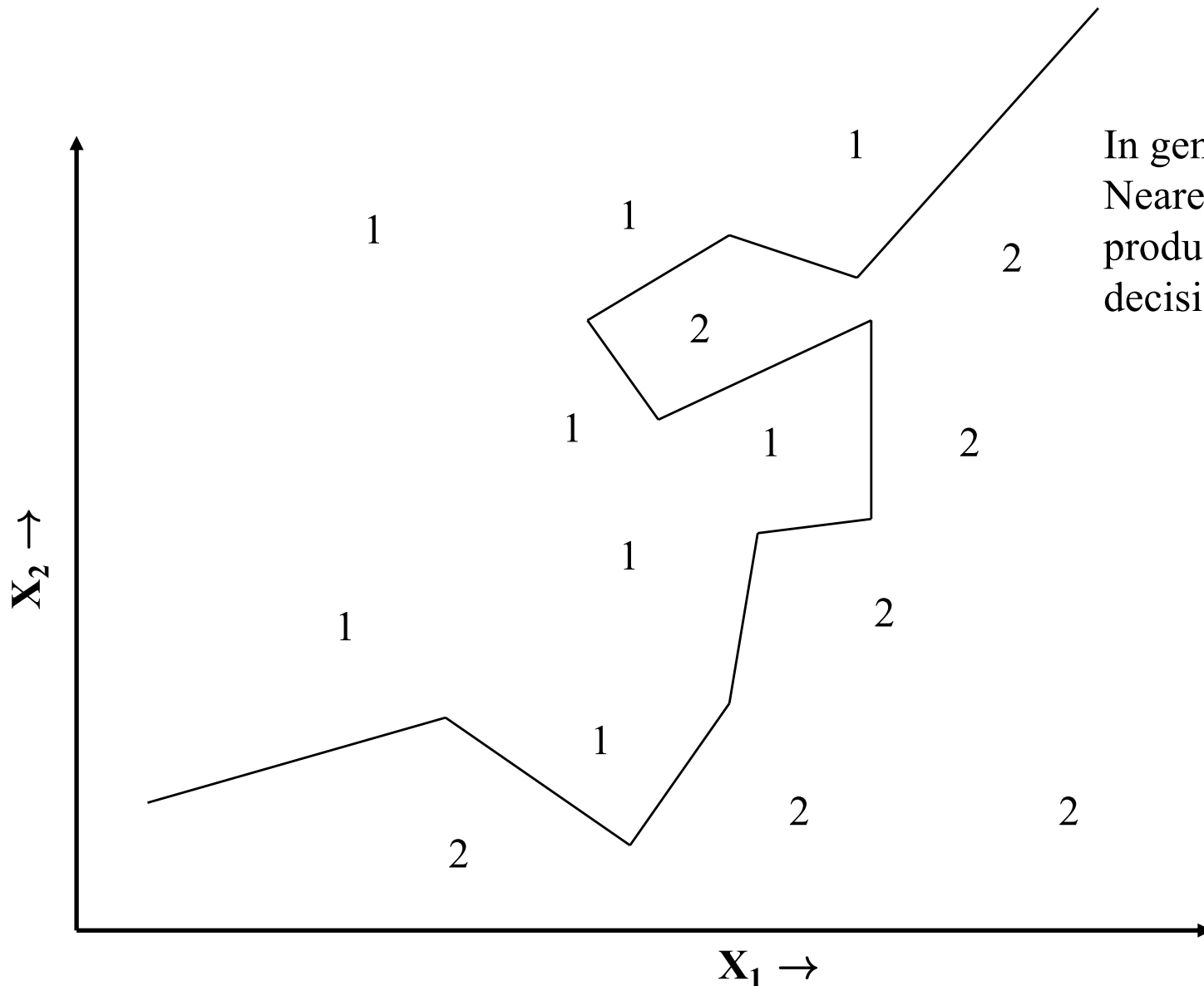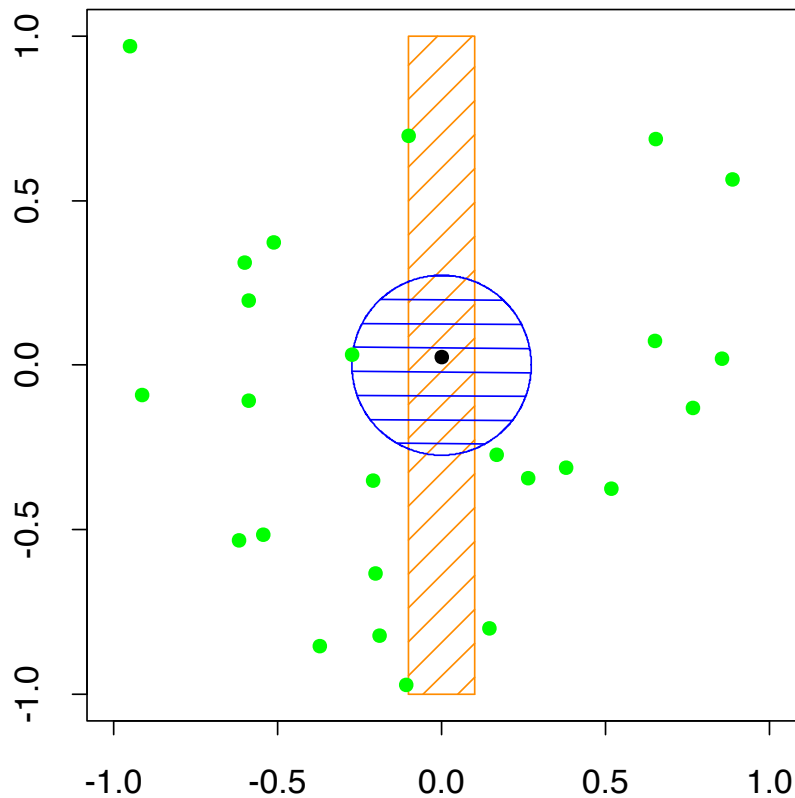
More Data Points
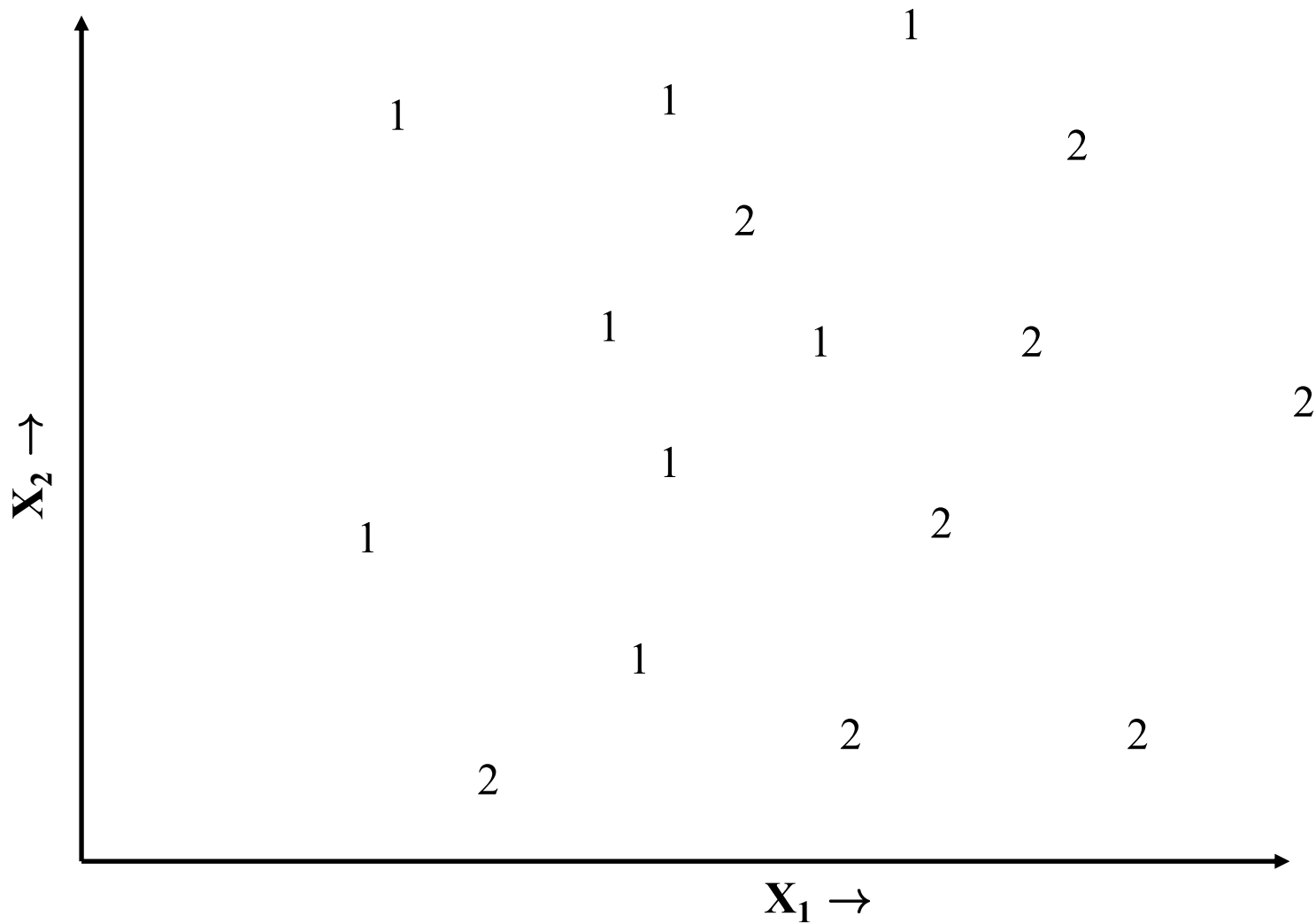
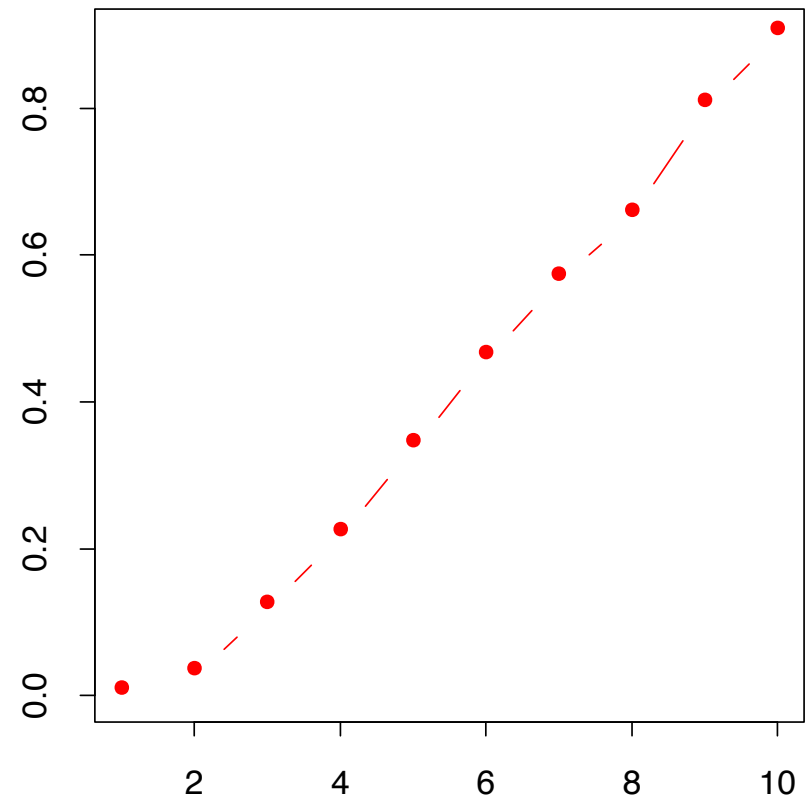# More Complex Decision Boundary

In general:
Nearest-neighbor classifier produces piecewise linear decision boundaries

Issue: Neighbor Distance & Dimension

1-NN in One vs. Two Dimensions

Distance to 1-NN vs. Dimension

For m=1000 data in unit hypercube

Machine Learning

Complexity and Overfitting

Nearest Neighbors

K-Nearest Neighbors

K-Nearest Neighbor (kNN) Classifier

- Find the k-nearest neighbors to x in the data
  - i.e., rank the feature vectors according to Euclidean distance
  - select the k vectors which are have smallest distance to x

- Regression
  - Usually just average the y-values of the k closest training examples

- Classification
  - ranking yields k feature vectors and a set of k class labels
  - pick the class label which is most common in this set ("vote")
  - classify x as belonging to this class
  - Note: for two-class problems, if k is odd (k=1, 3, 5, …) there will never be any "ties"; otherwise, just use (any) tie-breaking rule

- "Training" is trivial: just use training data as a lookup table, and search to classify a new datum
- "Testing" can be computationally expensive: must find nearest neighbors within a potentially large training set
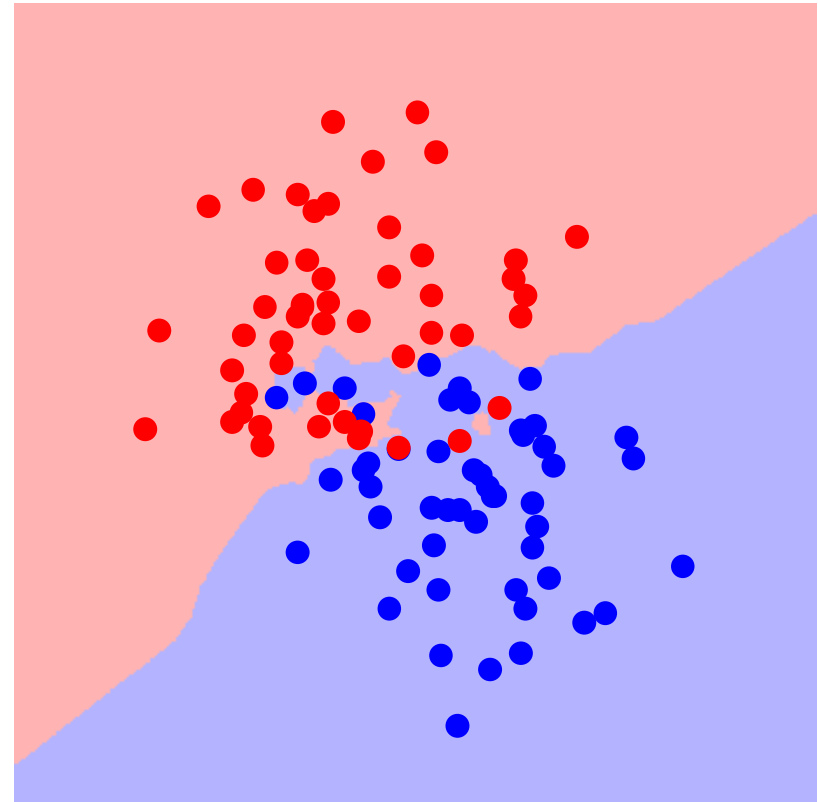
kNN Decision Boundary

- Piecewise linear decision boundary
- Increasing k "simplifies" decision boundary
  - Majority voting means less emphasis on individual points
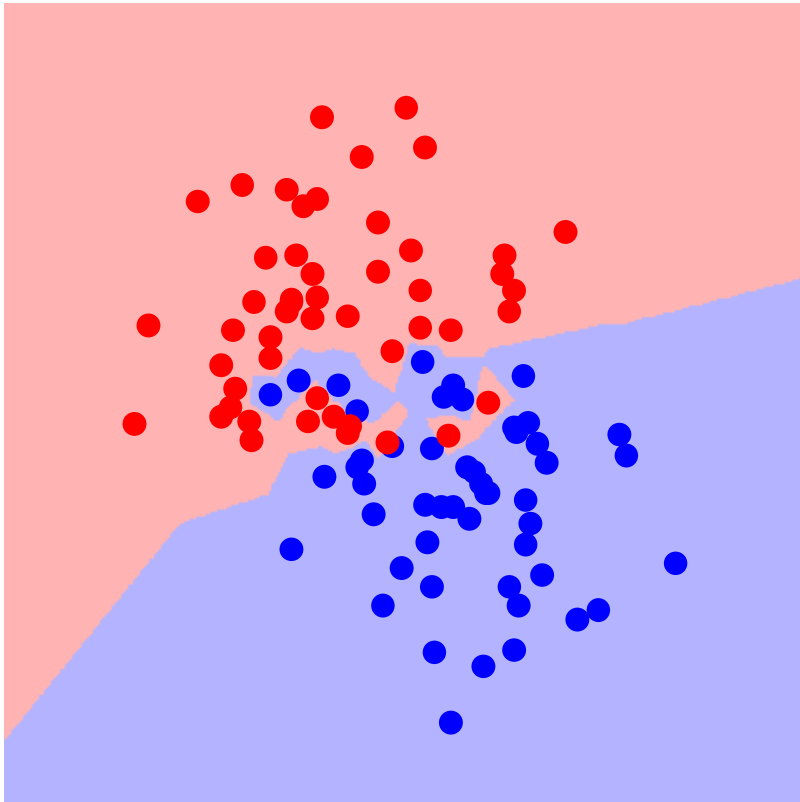
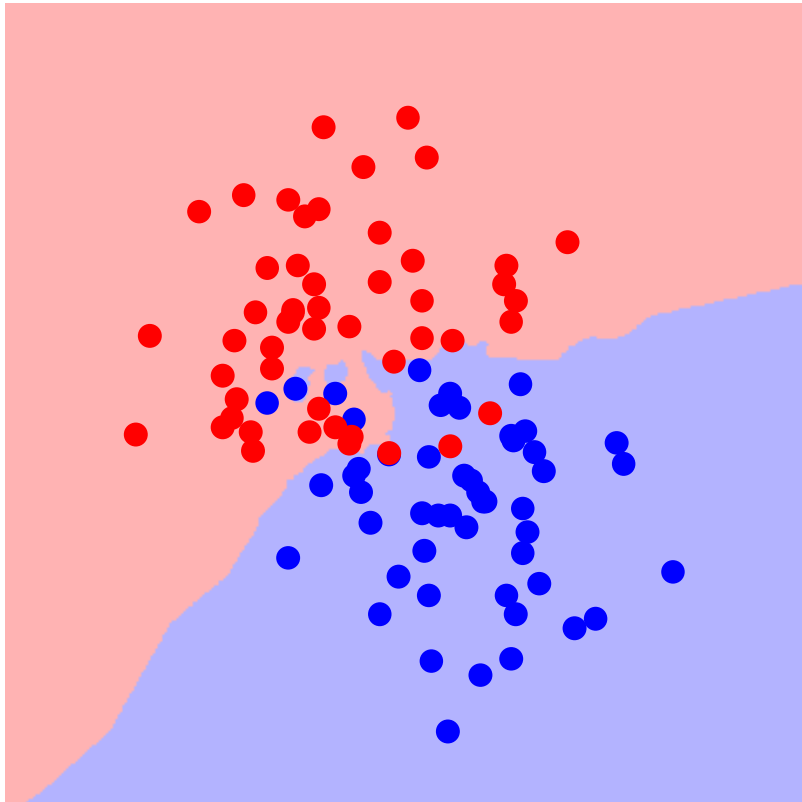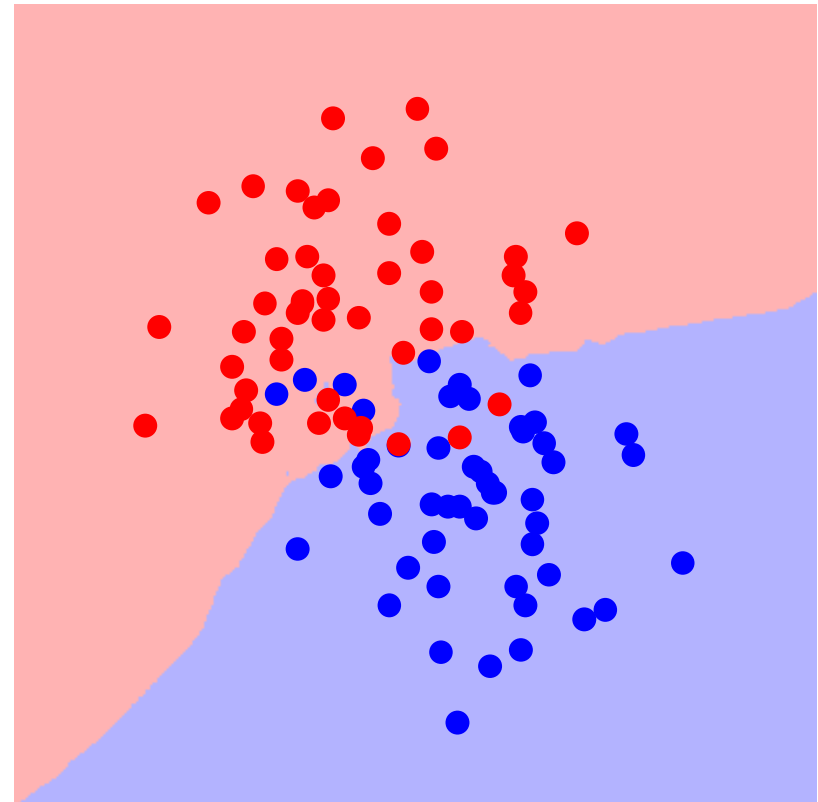K = 1   K = 3

kNN Decision Boundary

- Piecewise linear decision boundary
- Increasing k "simplifies" decision boundary
  - Majority voting means less emphasis on individual points

K = 5
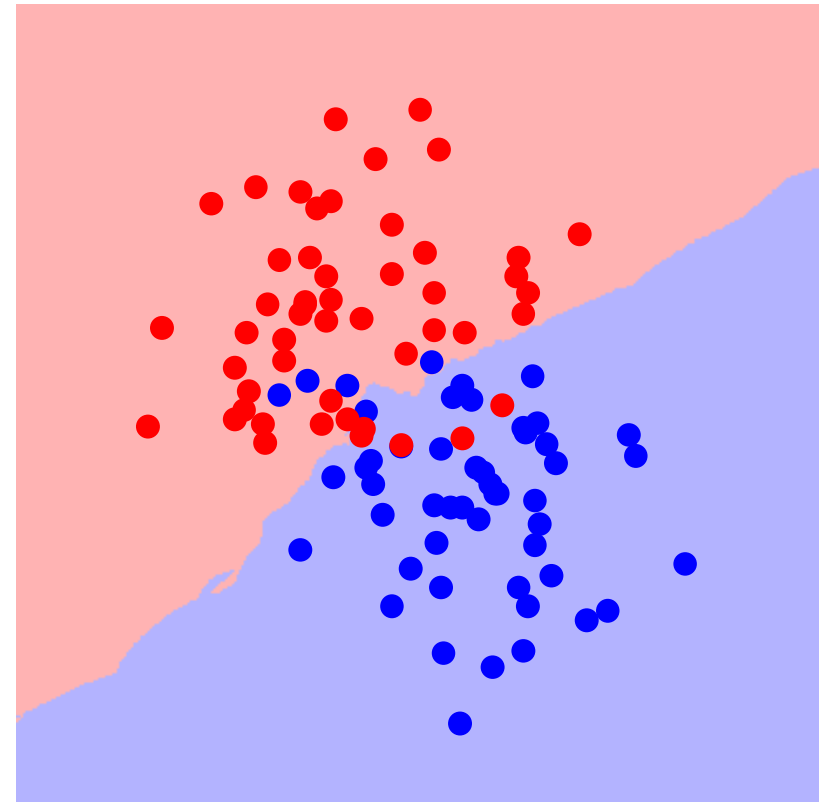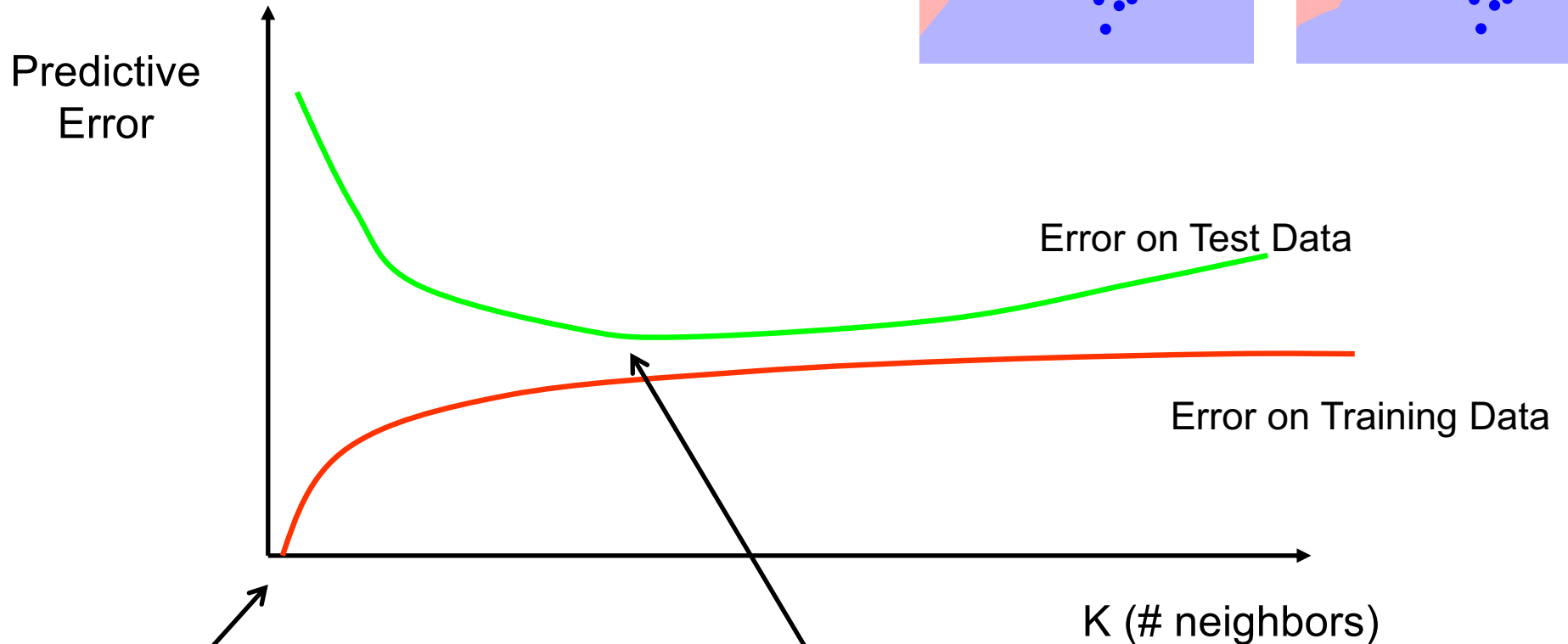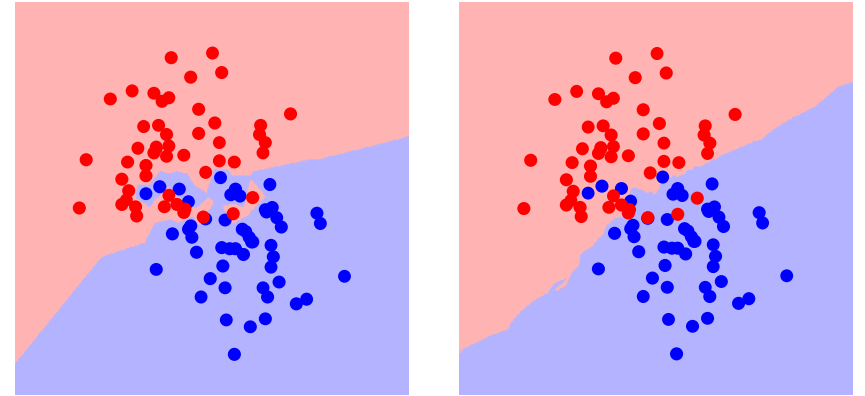
K = 7

kNN Decision Boundary

- Piecewise linear decision boundary

- Increasing k "simplifies" decision boundary
  - Majority voting means less emphasis on individual points

K = 25

Error rates and K

Predictive Error

Error on Test Data

Error on Training Data
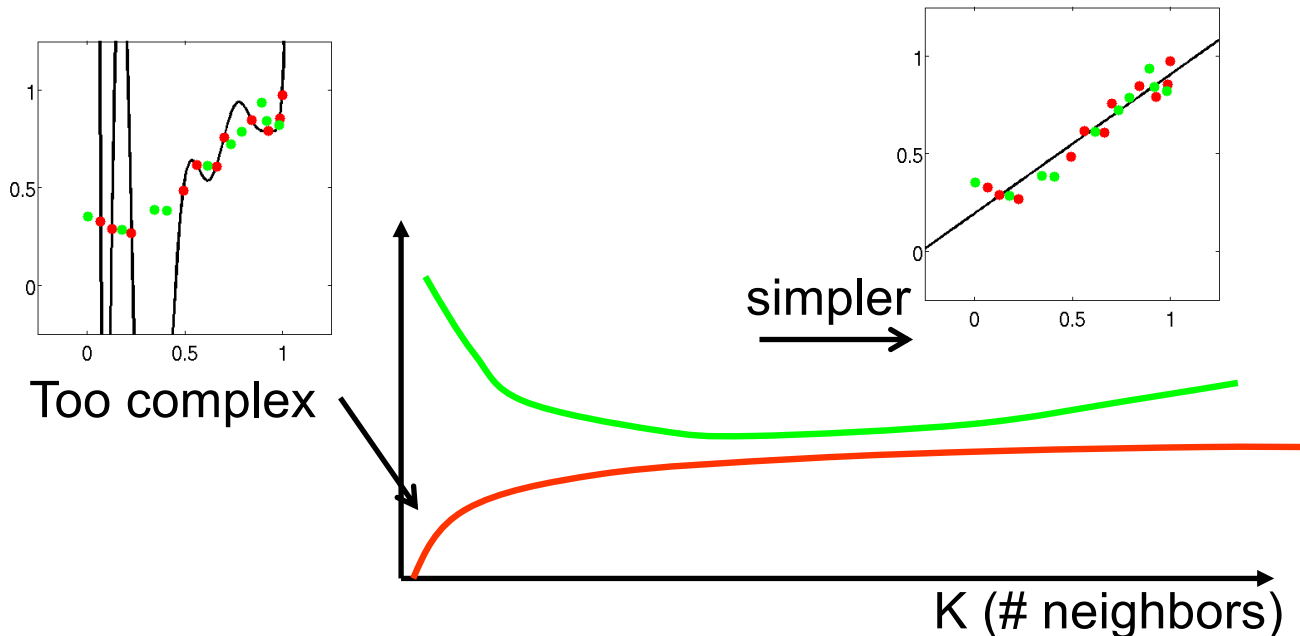
K (# neighbors)

K=1? Zero error!
Training data have been memorized...

Best value of K

Complexity & Overfitting

- Complex model predicts all training points well
- Doesn't generalize to new data points
- k = 1 : perfect memorization of examples (complex)
- k = m : always predict majority class in dataset (simple)
- Can select k using validation data, etc.

Too complex

simpler

K (# neighbors)

K-Nearest Neighbor (kNN) Classifier

- Theoretical Considerations
  - as k increases
    - we are averaging over more neighbors
    - the effective decision boundary is more "smooth"
  - as m increases, the optimal k value tends to increase
  - k=1, m increasing to infinity : error < 2x optimal

- Extensions of the Nearest Neighbor classifier
  - Weighted distances $d(x, x') = \sqrt{\sum_i w_i (x_i - x'_i)^2}$
    - e.g., some features may be more important; others may be irrelevant
  - Fast search techniques (indexing) to find k-nearest points in d-space
  - Weighted average / voting based on distance

Digit & Hand Gesture Recognition
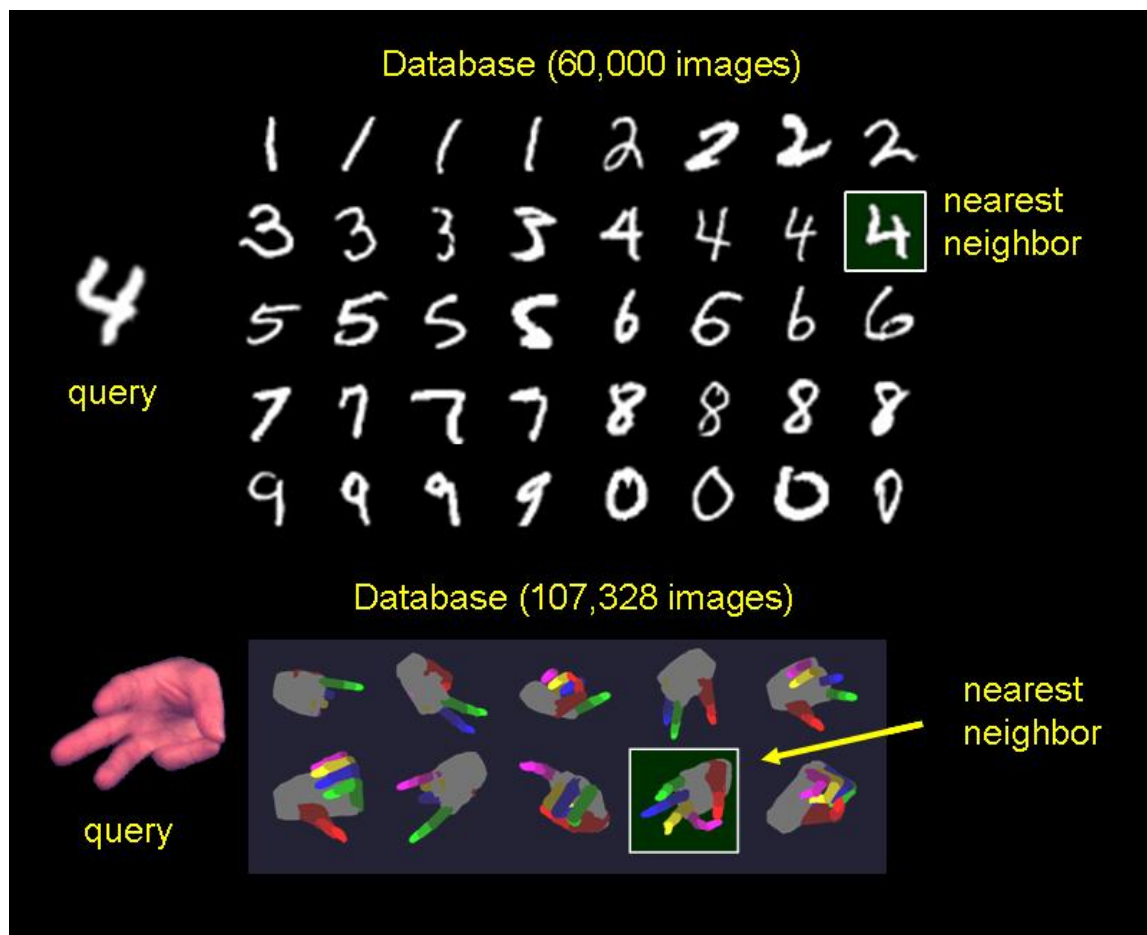
Athitsos et al., CVPR 2004 & PAMI 2008

Tricks to build efficient & accurate nearest-neighbor classifiers:

➢ Gather large training sets (possibly by generating synthetic data)

➢ Engineer clever distance functions that are invariant to aspects of the data unrelated to the class label

➢ Use algorithms to find (approximate) nearest neighbors in sub-linear time (locality sensitive hashing, class-sensitive embeddings, KD-trees, etc.)

Summary

- K-nearest neighbor models
  - Classification   (vote)
  - Regression   (average or weighted average)

- Piecewise linear decision boundary
  - How to calculate

- Test data and overfitting
  - Model "complexity" for knn
  - Use validation data to estimate test error rates & select k