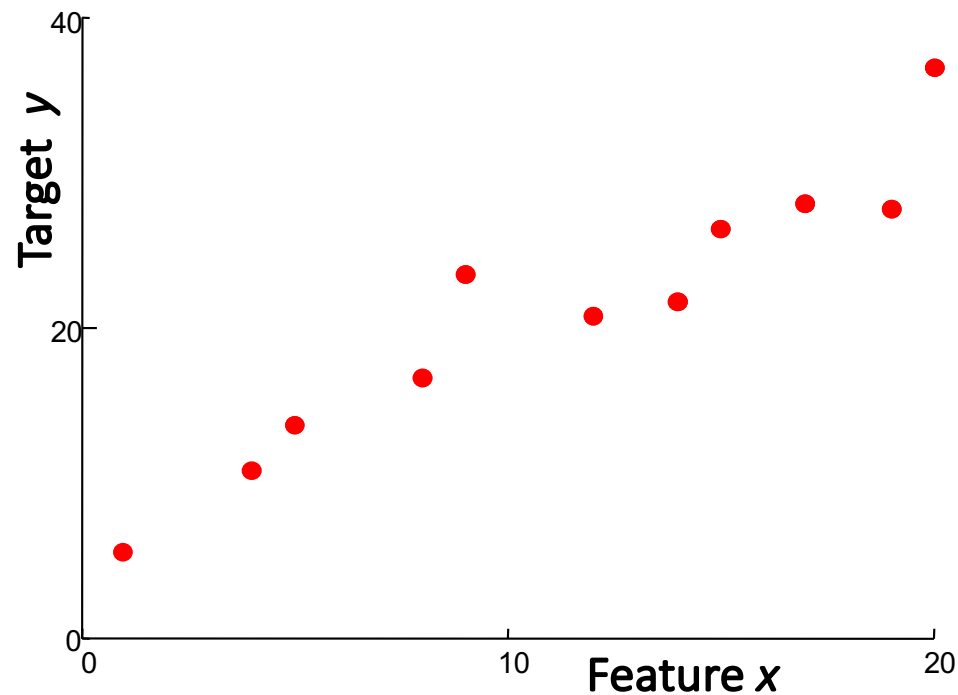
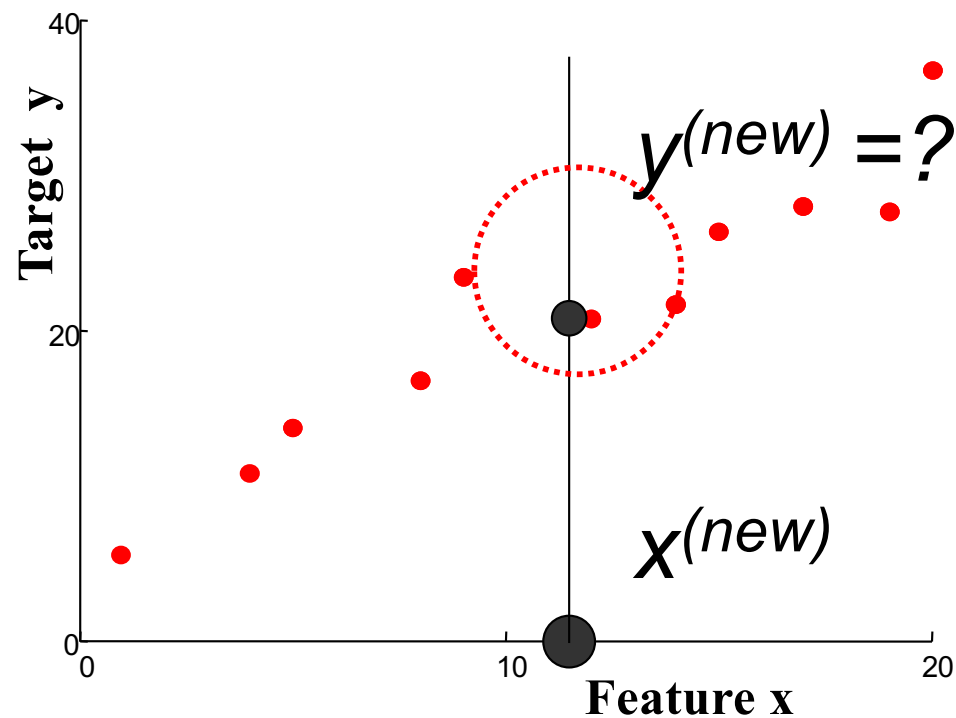


Nearest Neighbor Regression



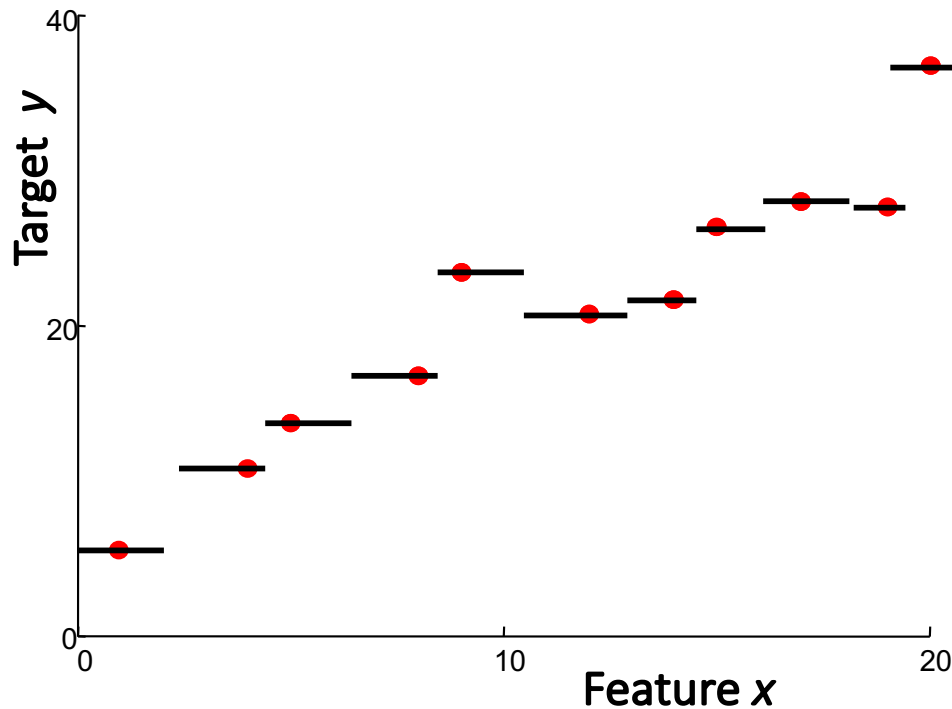
Find training datum $x(i)$ closest to $x(new)$ Predict $y(i)$

Nearest neighbor regression



Find training datum $x(i)$ closest to $x^{(new)}$ Predict $y(i)$

Nearest Neighbor Regression



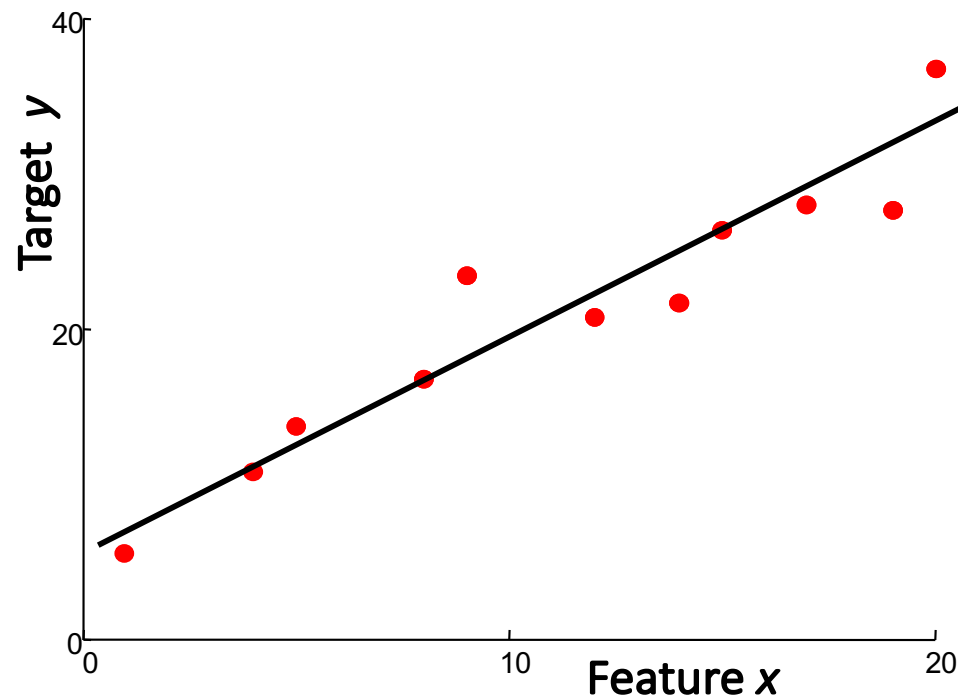
“Predictor”:

Given new features:
Find nearest example
Return its value

Defines a function $f(x)$ implicitly

“Form” is piecewise constant

Alternative: linear regression



“Predictor”:

Evaluate line:

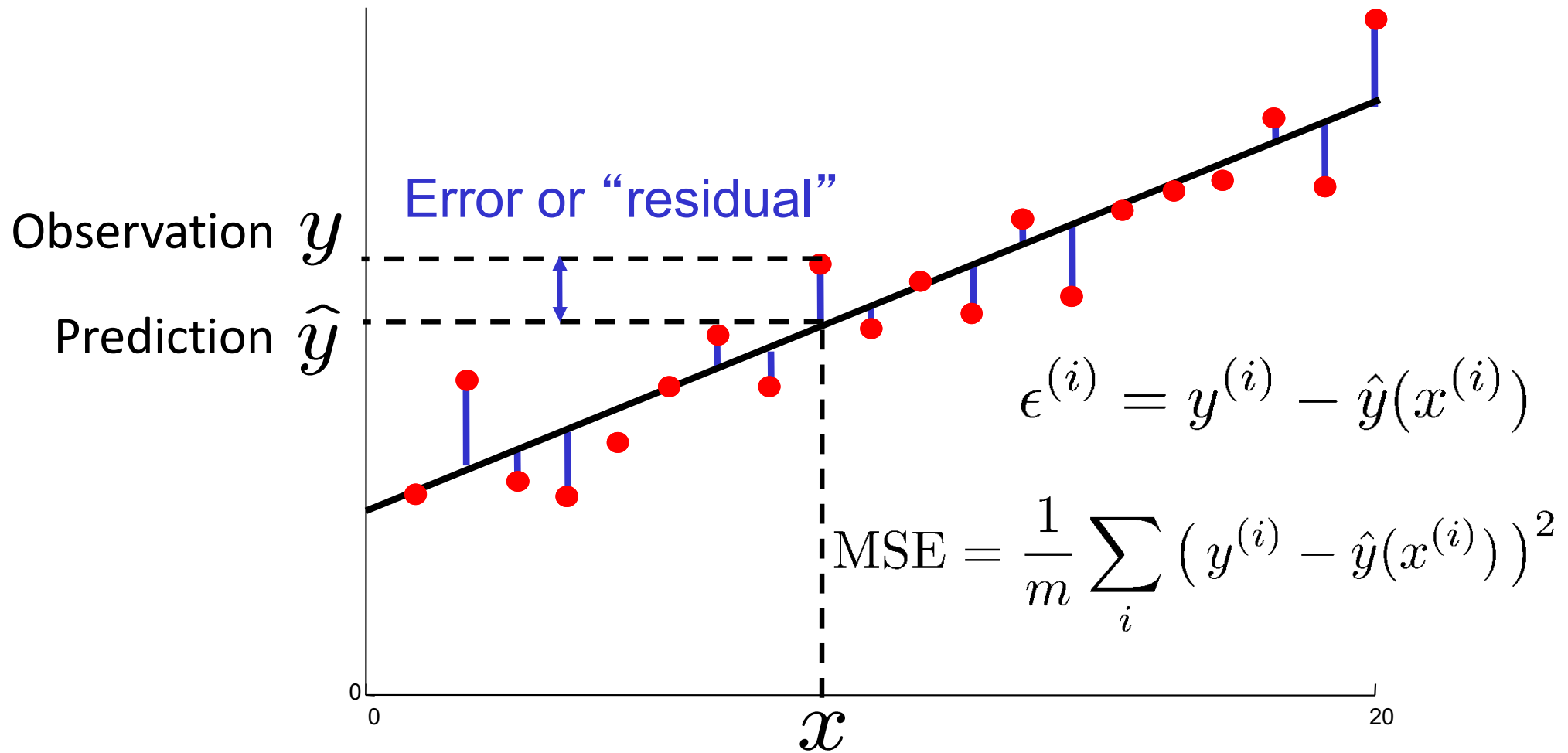
$$r = \theta_0 + \theta_1 x_1$$

return r

Define form of function $f(x)$ explicitly

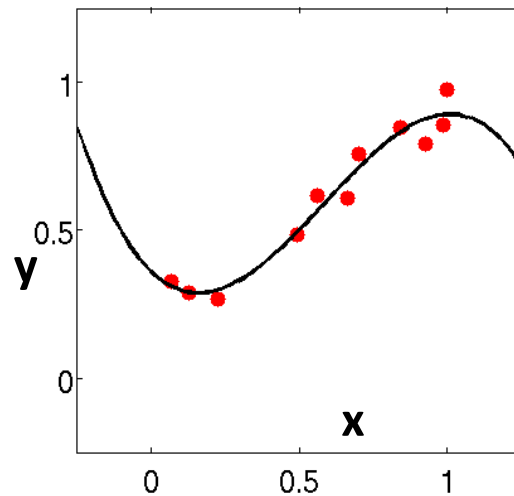
Find a good $f(x)$ within that family

Measuring error



Regression vs. Classification

Regression

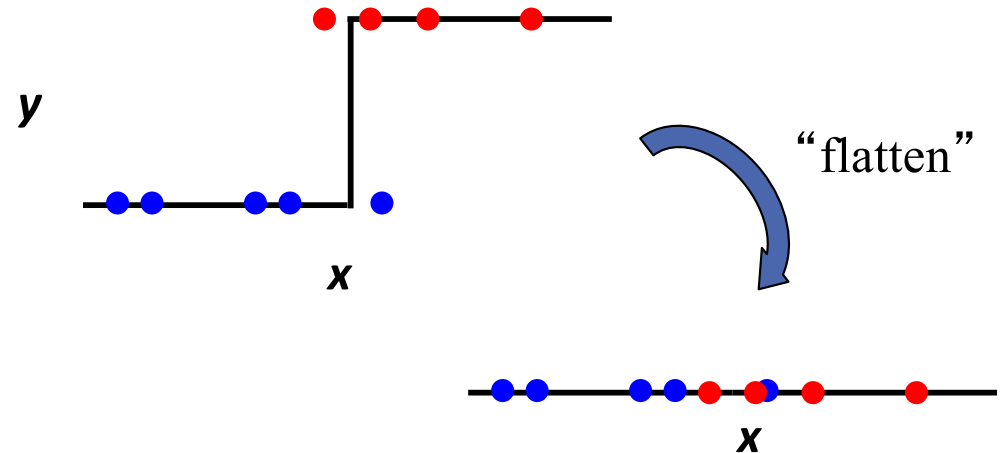


Features x

Real-valued target y

Predict continuous function $\hat{y}(x)$

Classification

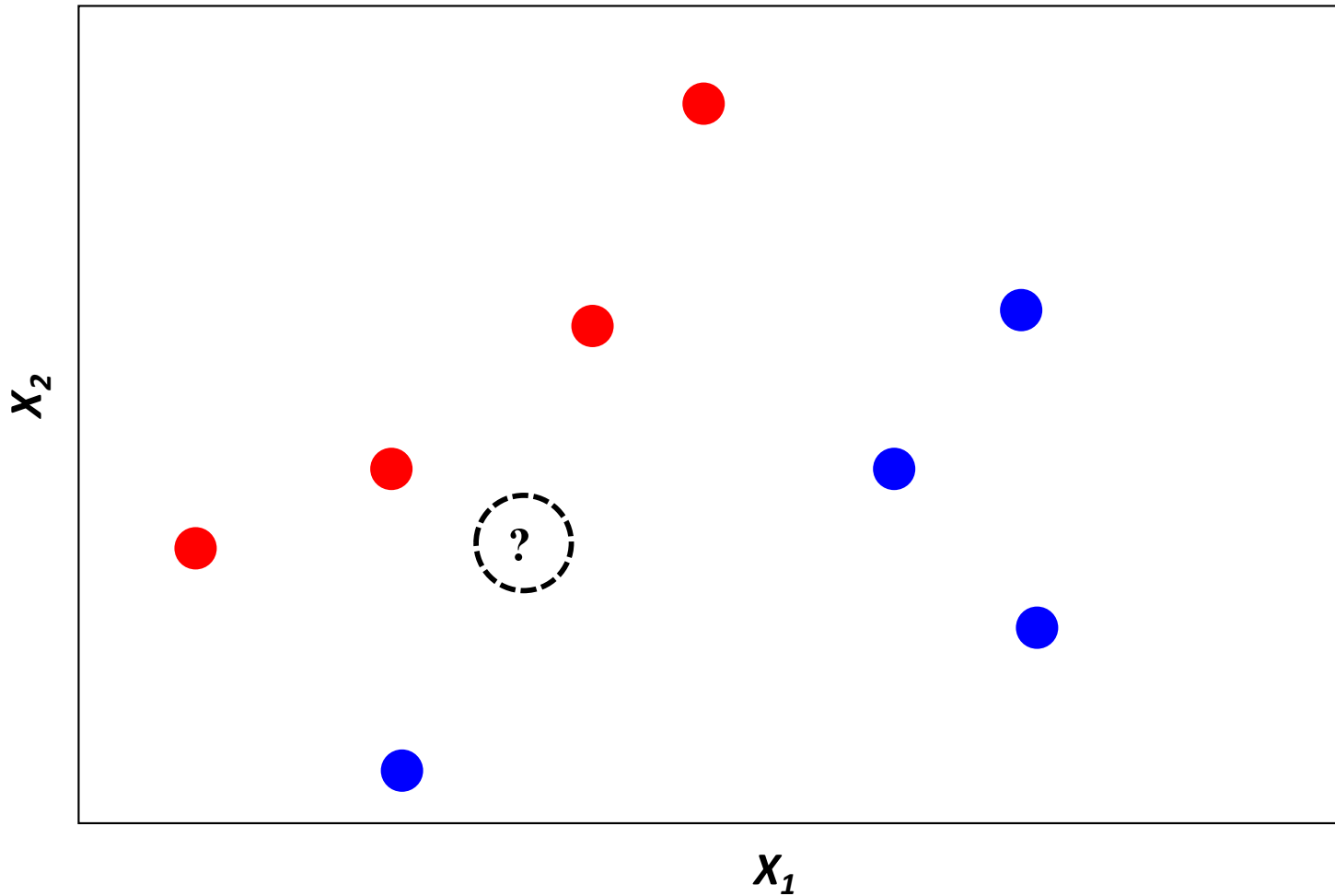


Features x

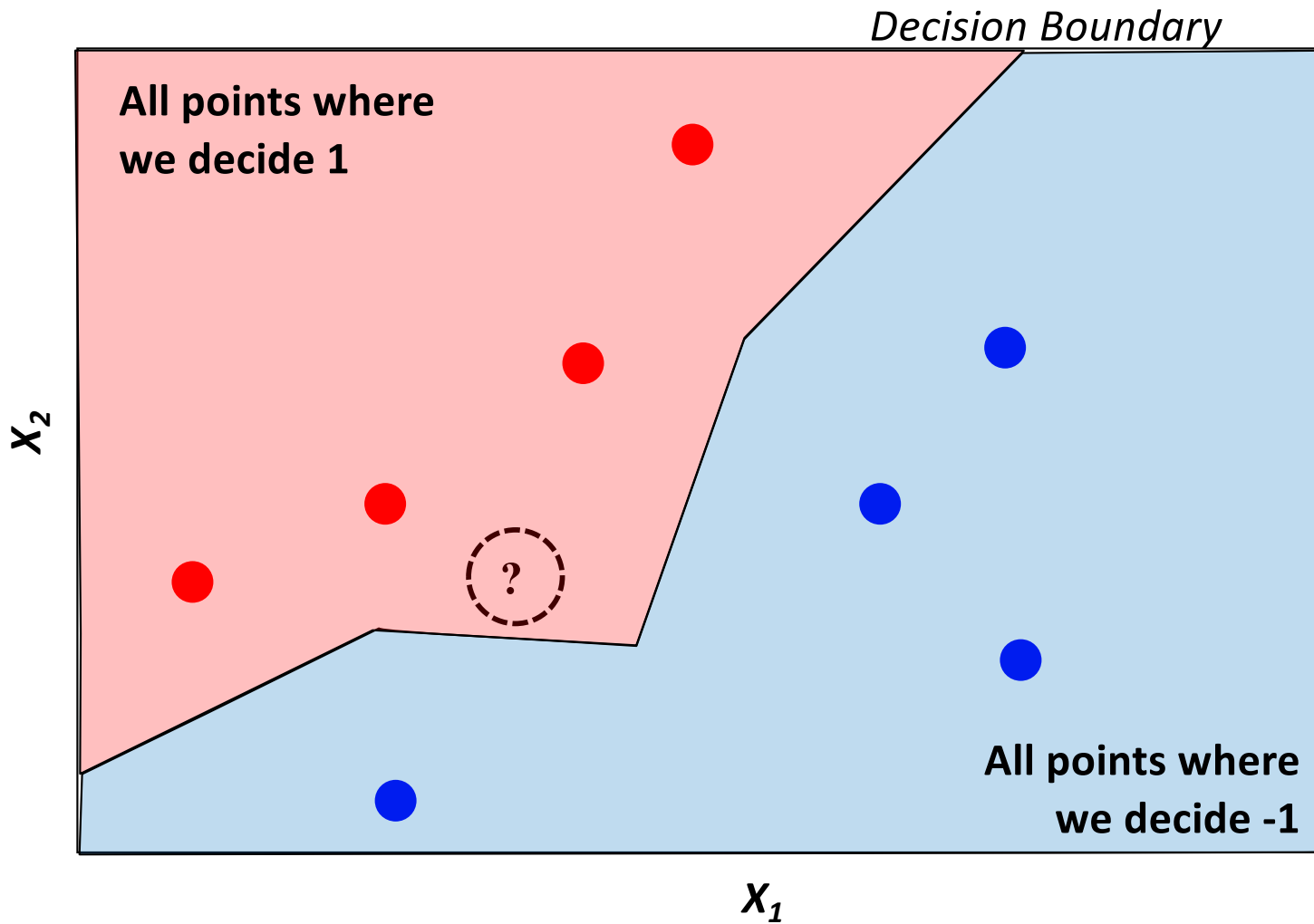
Discrete class c
(usually 0/1 or +1/-1)

Predict discrete function $\hat{y}(x)$

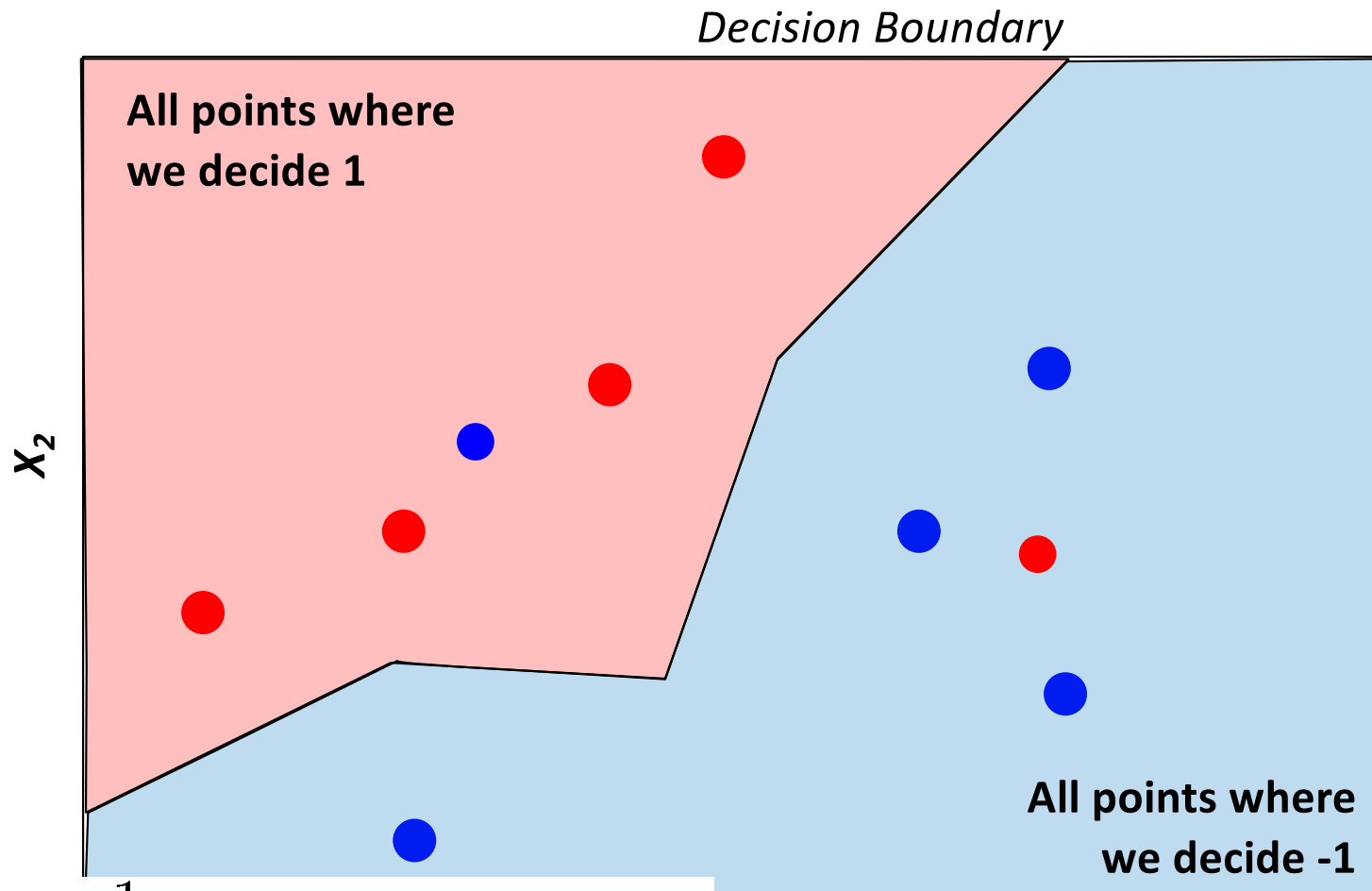
Classification



Classification



Measuring Error



$$\text{ERR} = \frac{1}{m} \sum_i [y^{(i)} \neq \hat{y}(x^{(i)})]$$

Summary


Supervised learning

- Training data: features x , targets y

Regression

- (x, y) scatterplots; predictor outputs $f(x)$
- Mean squared error

Classification

- (x, x) scatterplots
 - Decision boundaries, colors & symbols
 - Empirical error rate
- 

Machine Learning

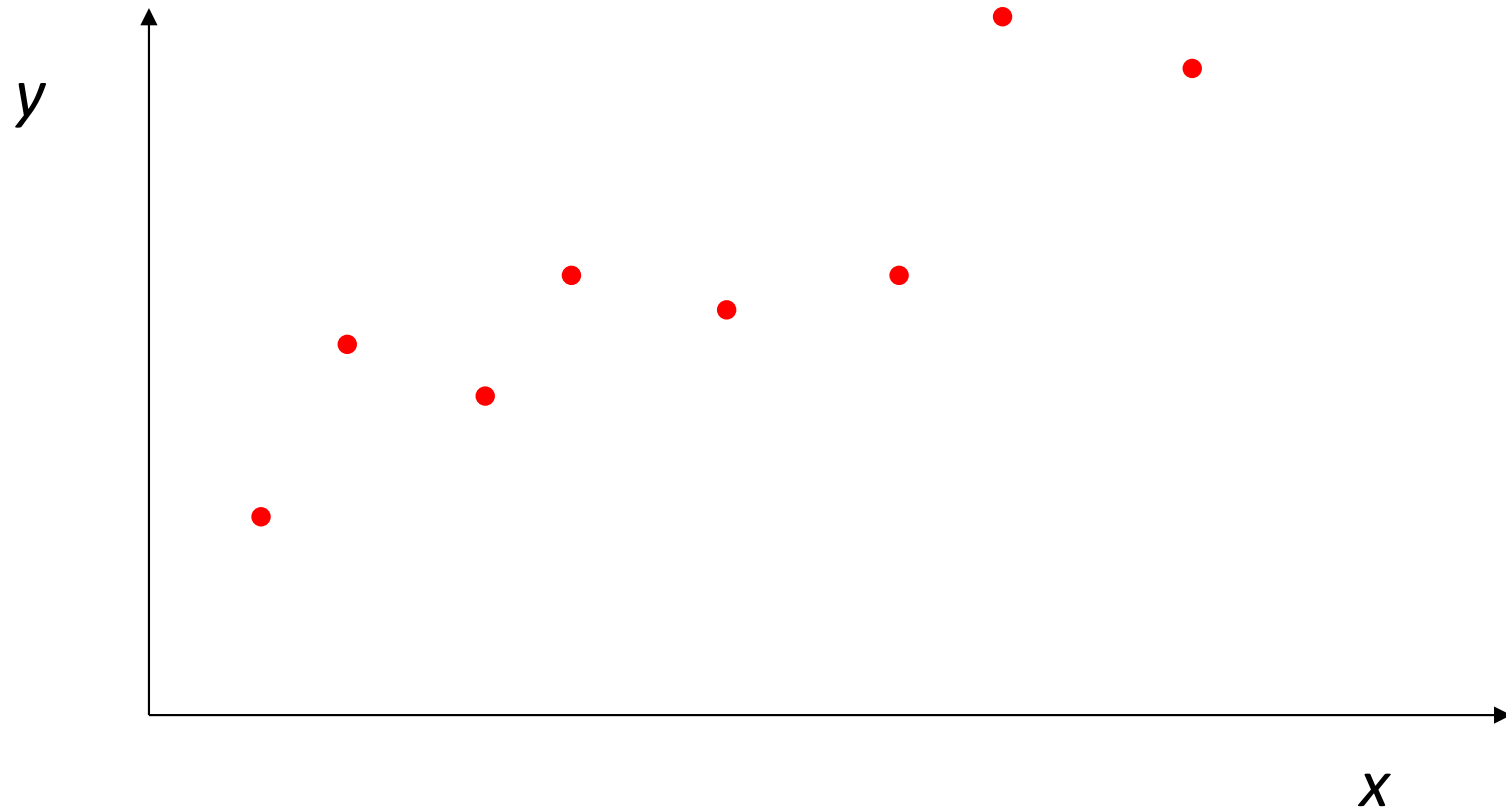
Complexity and Overfitting

Nearest Neighbors

K-Nearest Neighbors

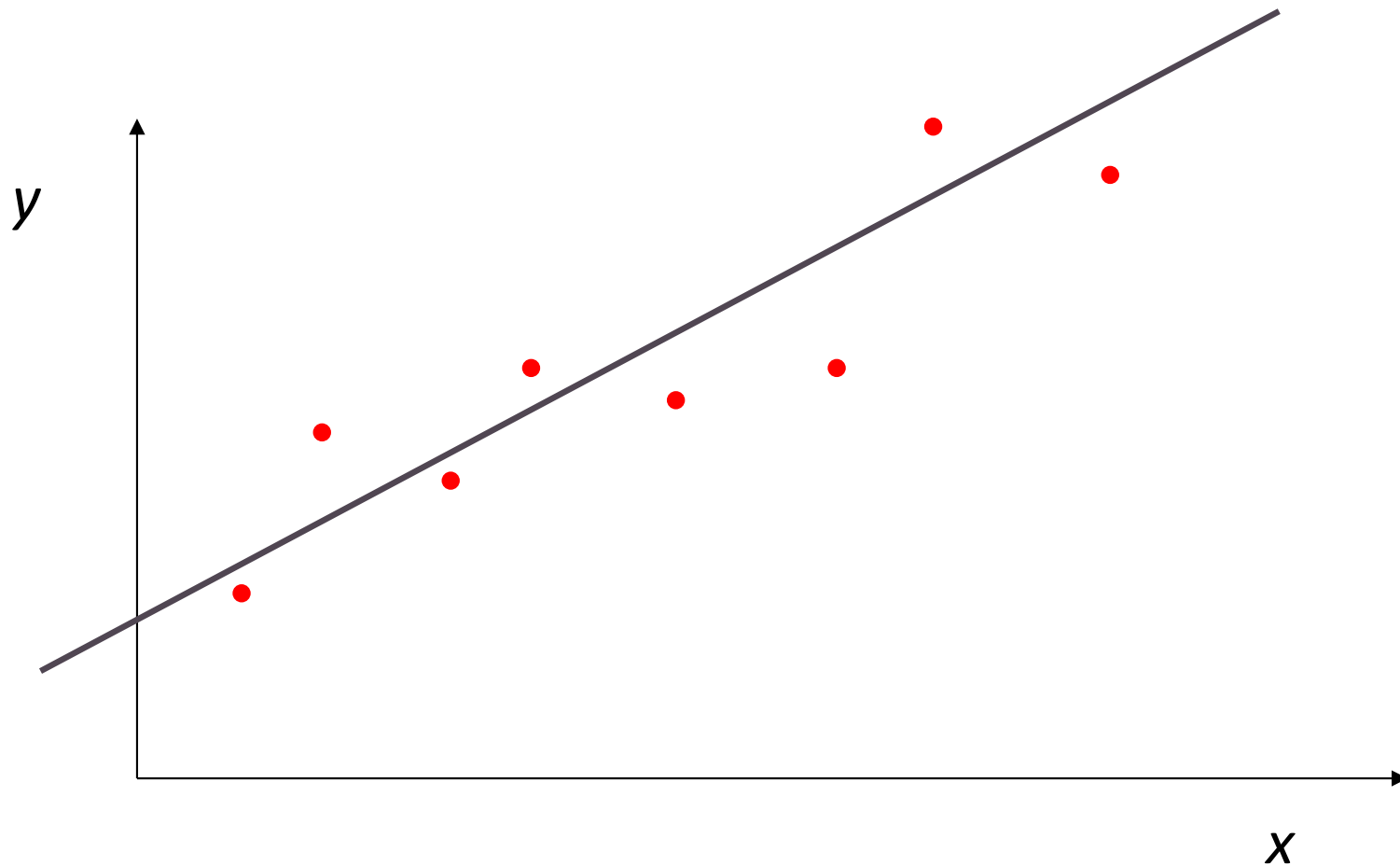
Bayes Classifiers

Overfitting and complexity

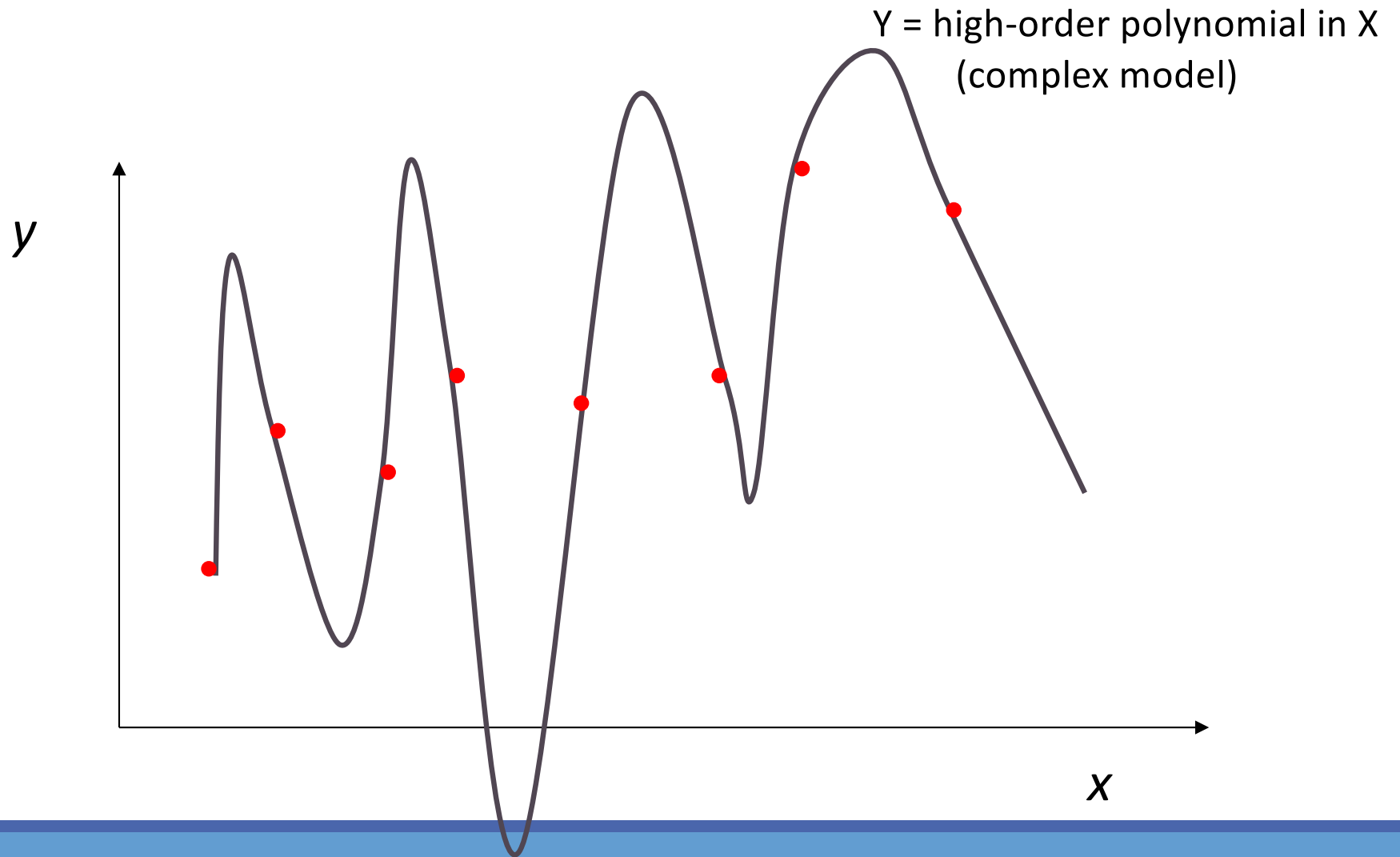


Overfitting and complexity

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

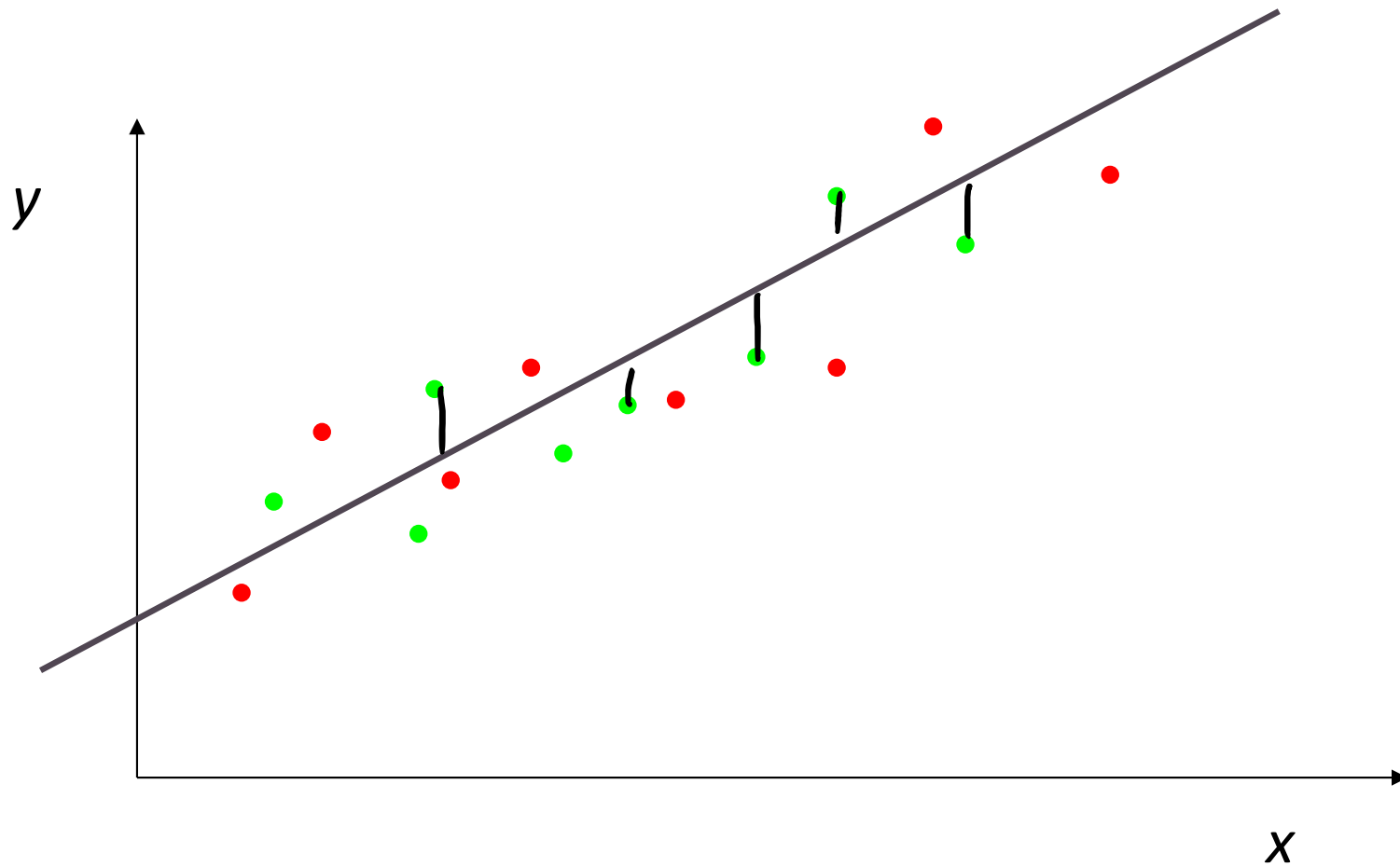


Overfitting and complexity

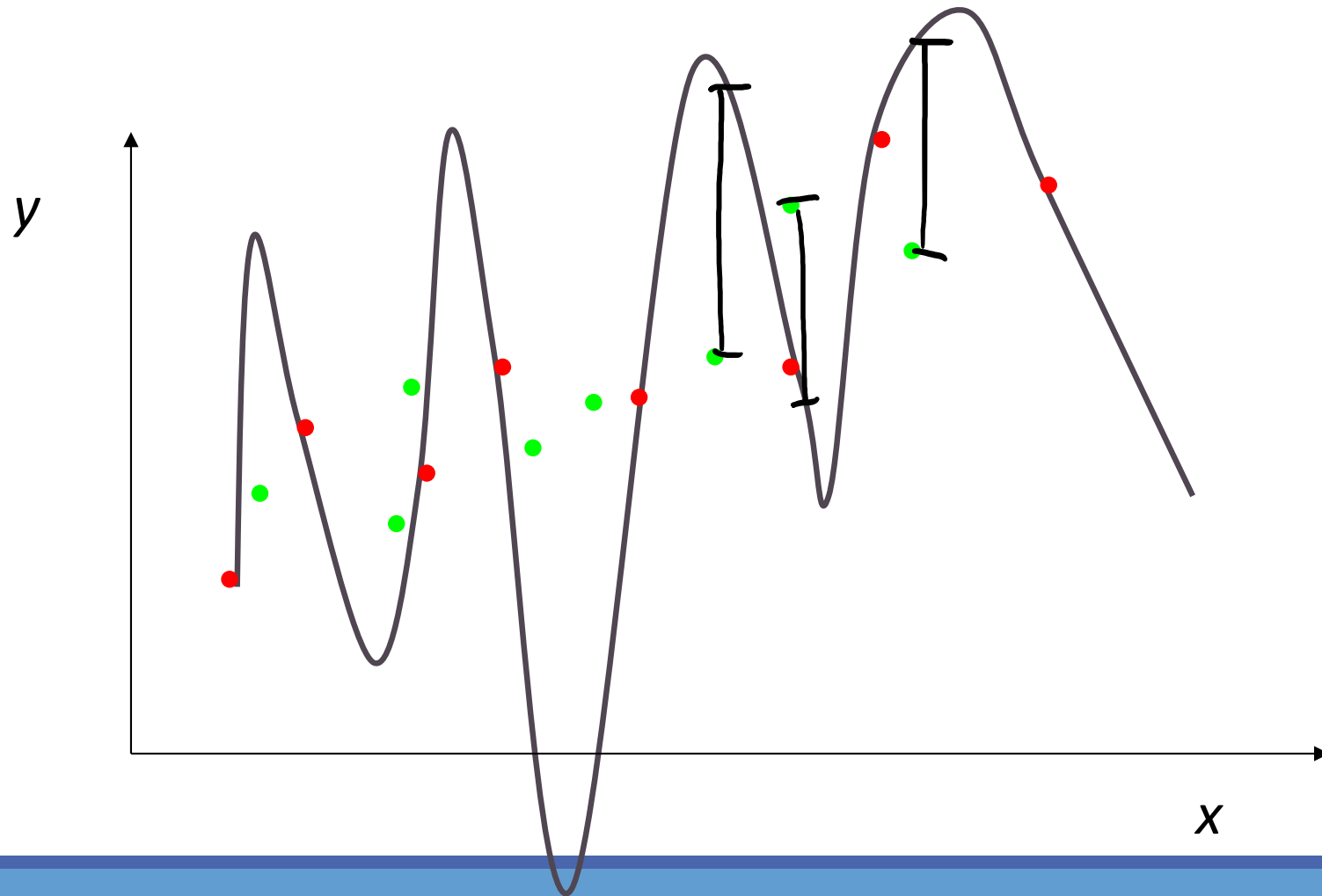


Overfitting and complexity

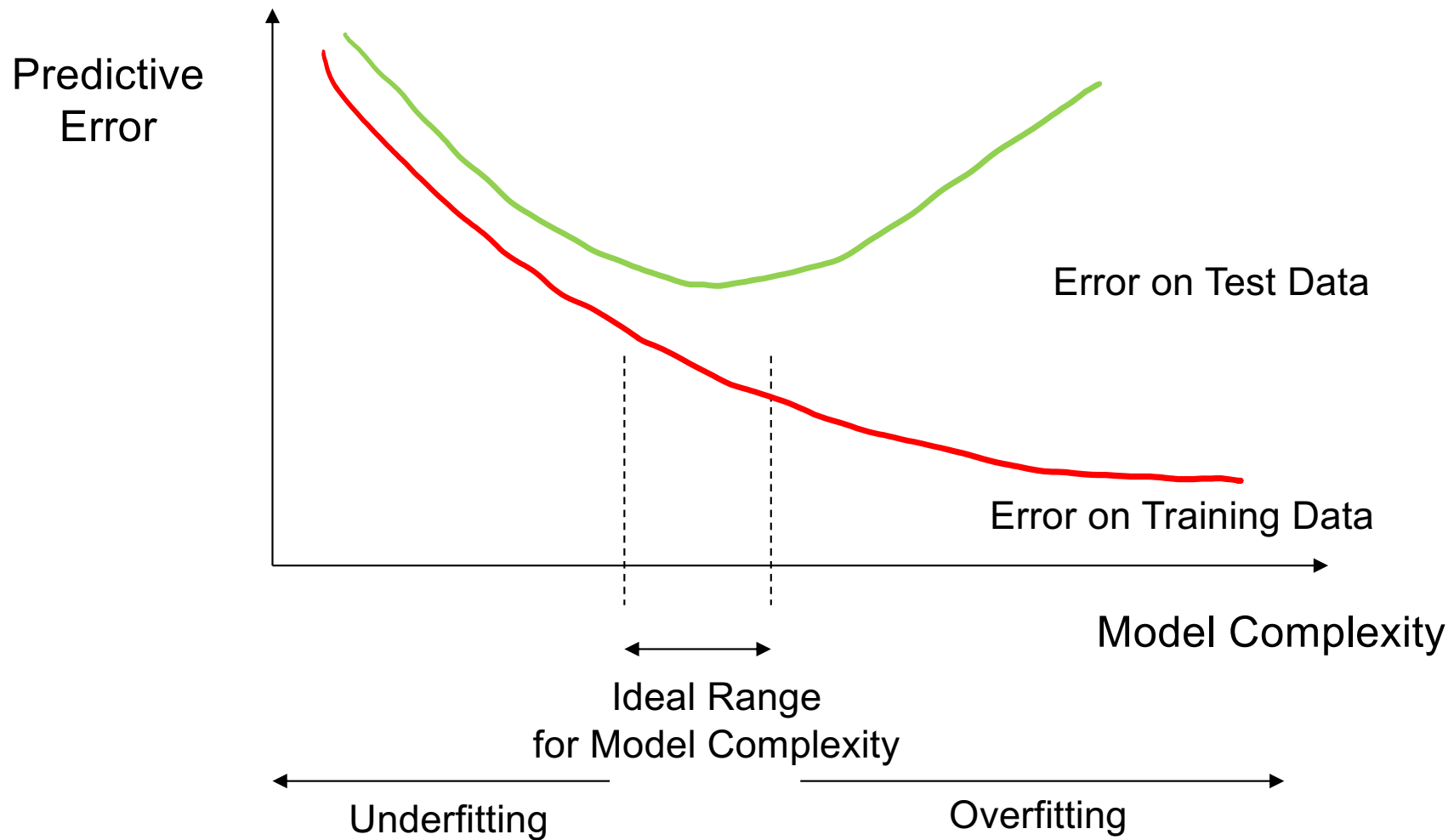
Simple model: $Y = aX + b + e$



Overfitting and complexity



How Overfitting affects Prediction



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 <small>* in the money</small>	Score <small>?</small>	Entries	Last Submission UT
1	-	BrickMover <small>👤 *</small>	1.21251	40	Sat, 31 Aug 2013 23:
2	new	vsu <small>*</small>	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:

Summary

Complexity

- Training versus Test errors
- Under- and Over-fitting

Machine Learning

Complexity and Overfitting

Nearest Neighbors

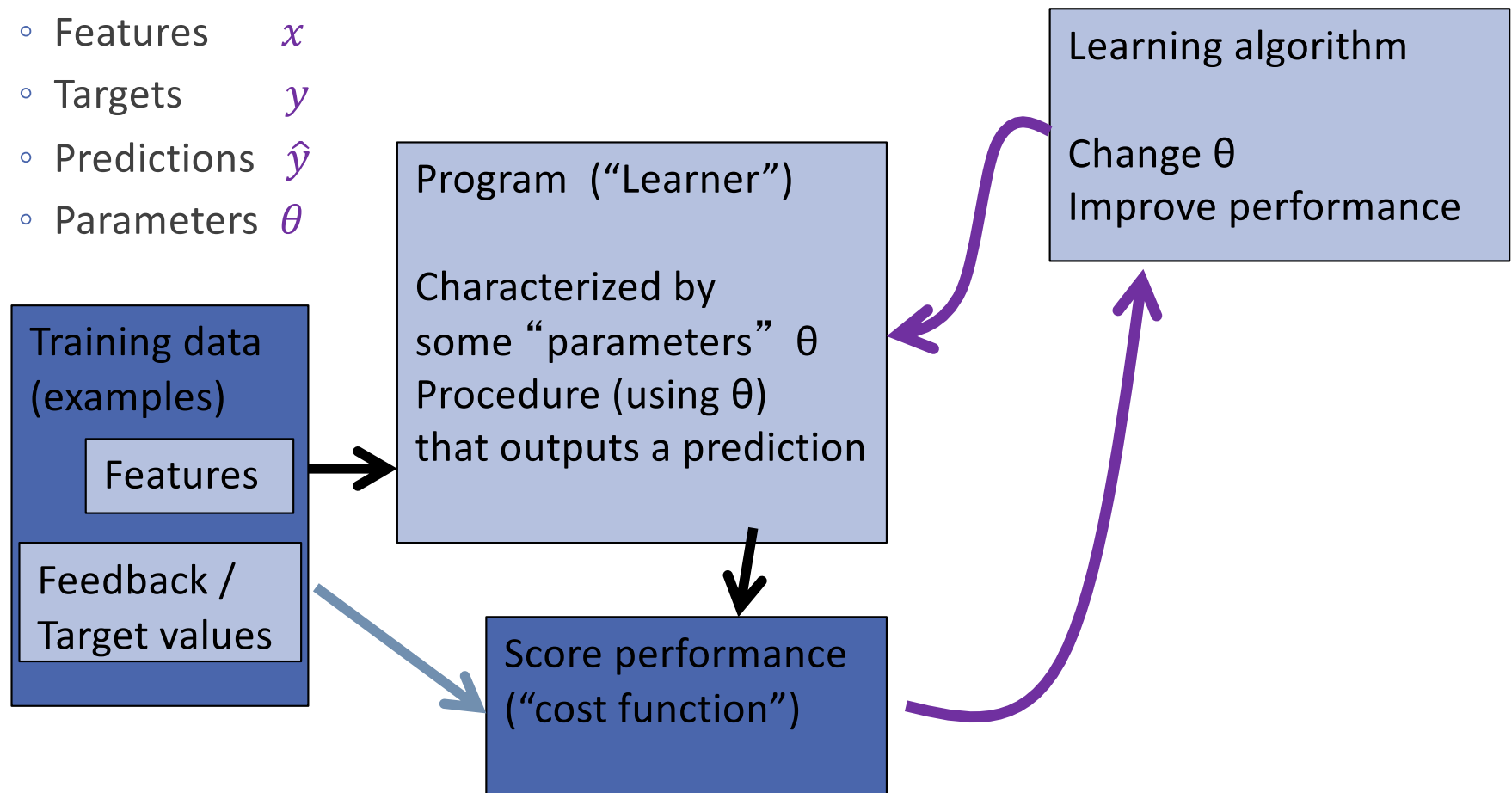
K-Nearest Neighbors

Bayes Classifiers

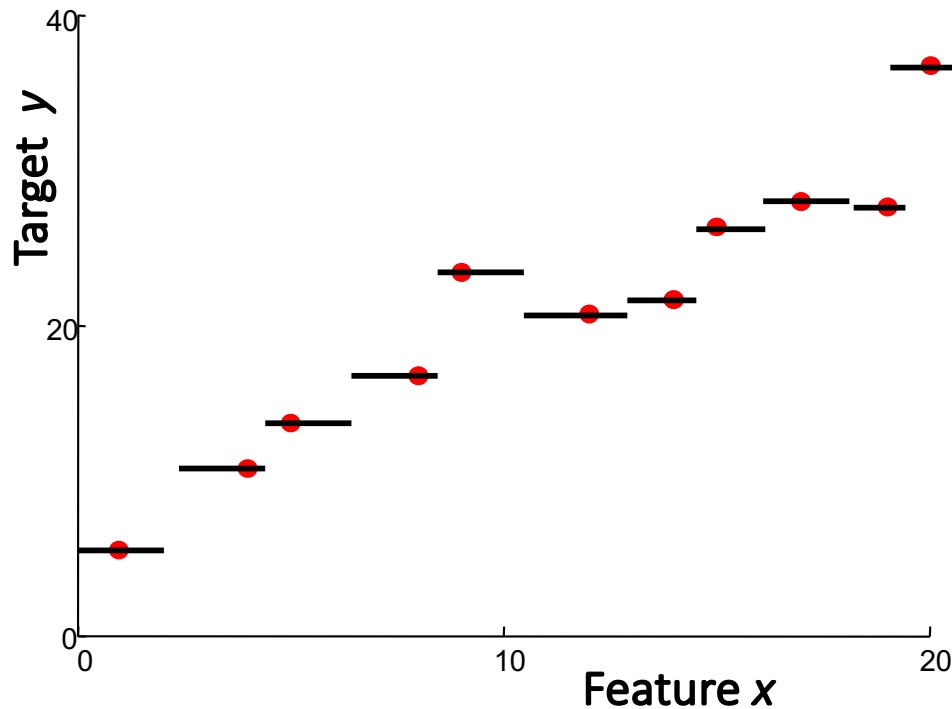
Supervised learning

Notation

- Features x
- Targets y
- Predictions \hat{y}
- Parameters θ



Nearest Neighbor Regression



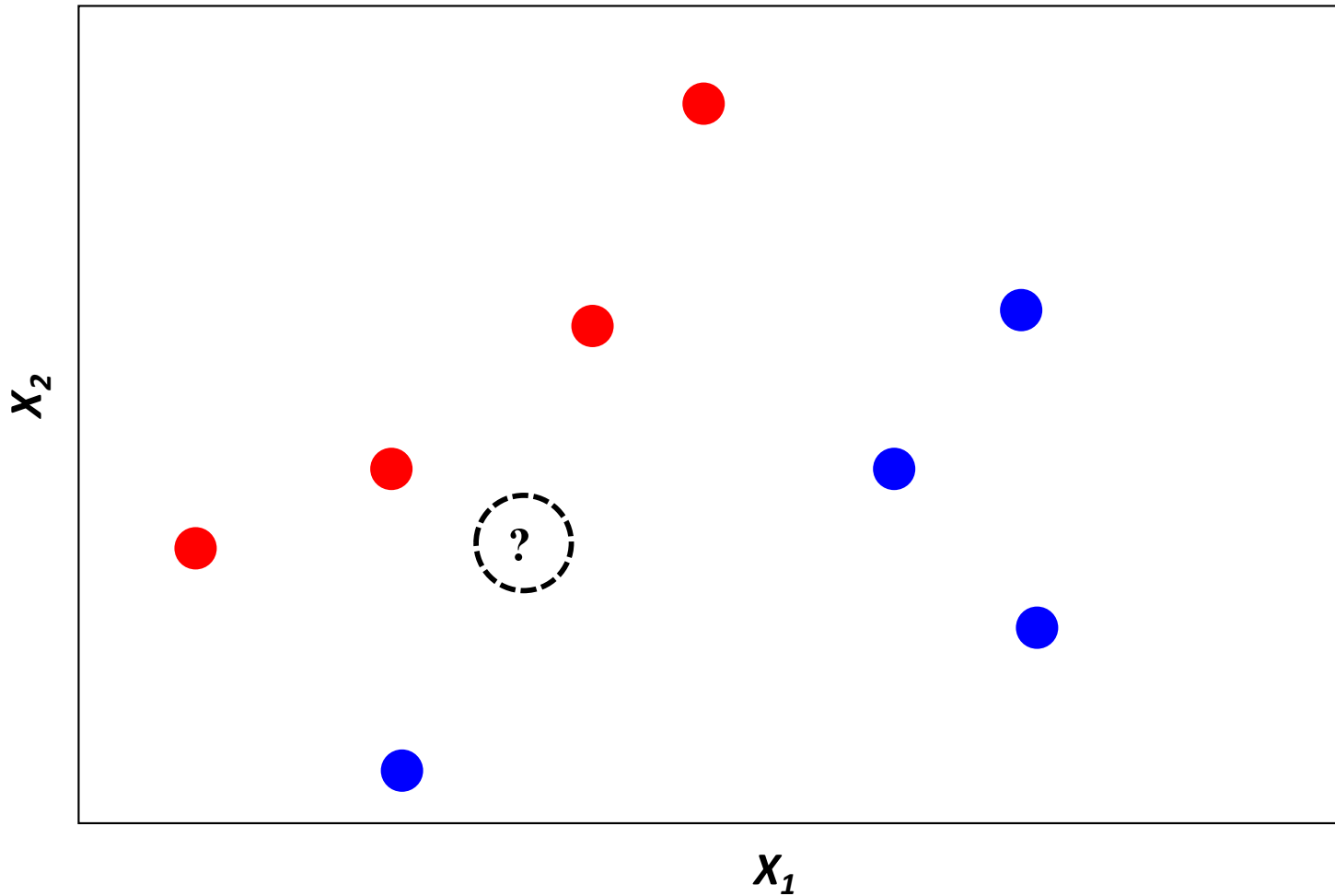
“Predictor”:

Given new features:
Find nearest example
Return its value

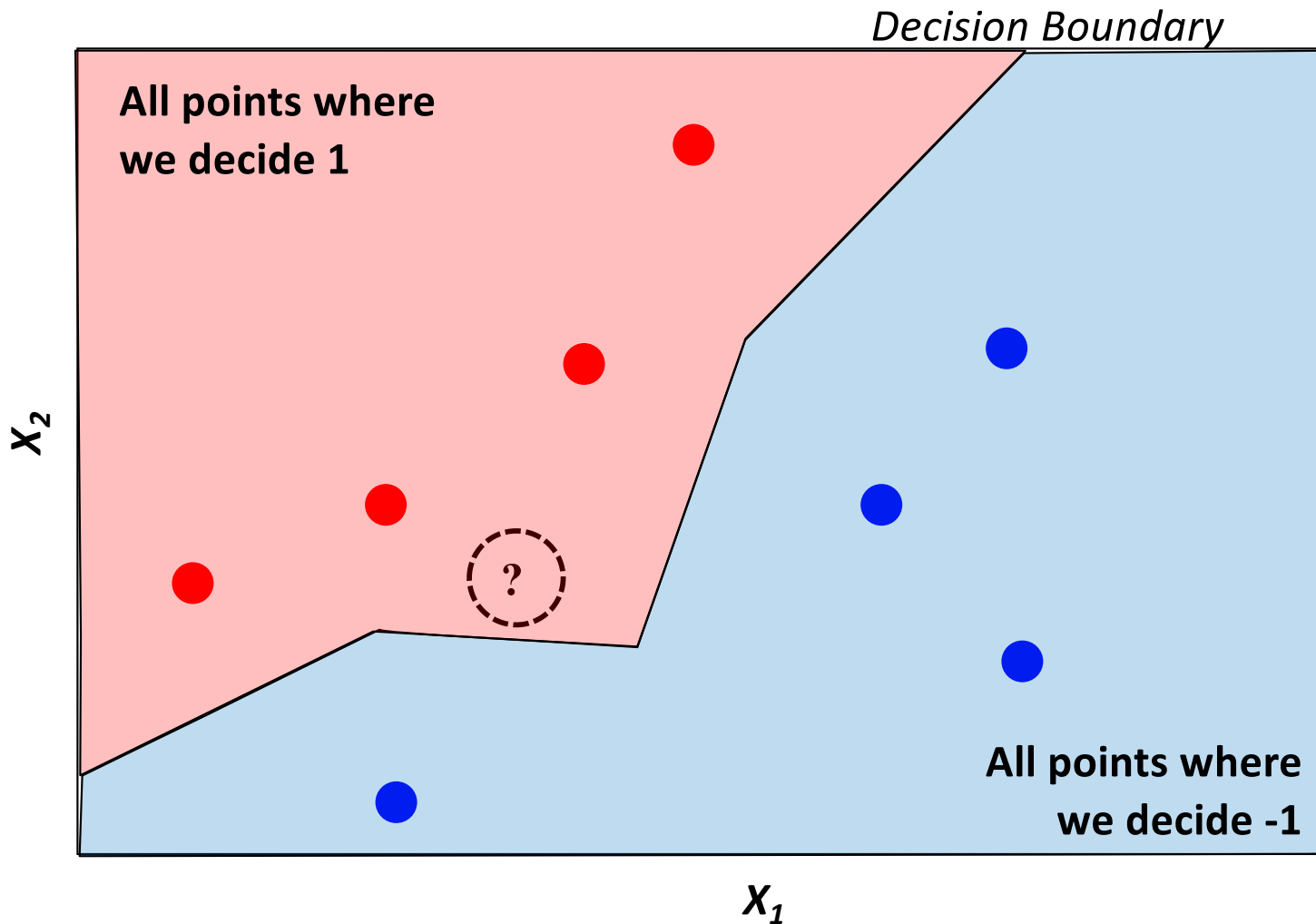
Defines a function $f(x)$ implicitly

“Form” is piecewise constant

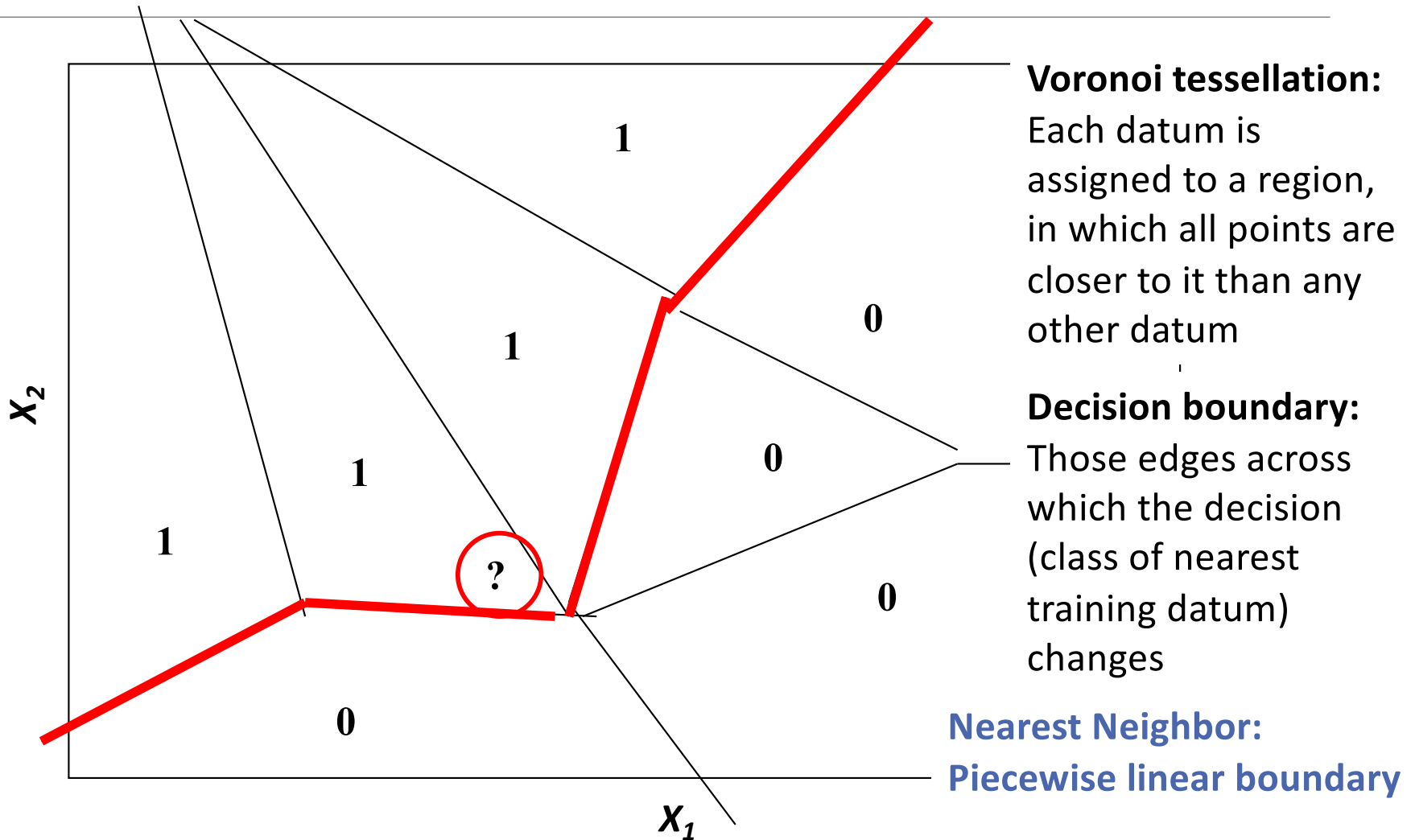
Classification



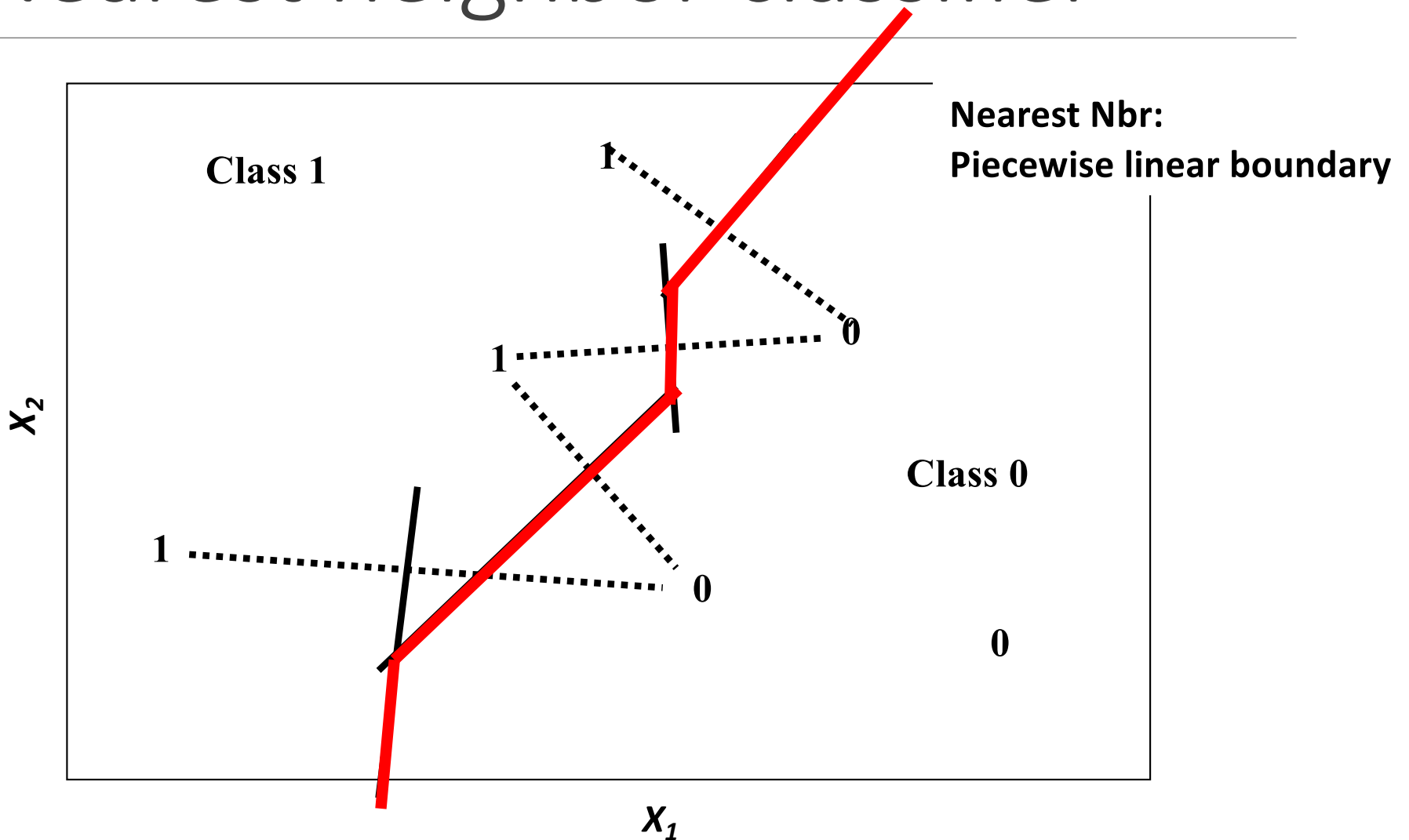
Nearest Neighbor Classification



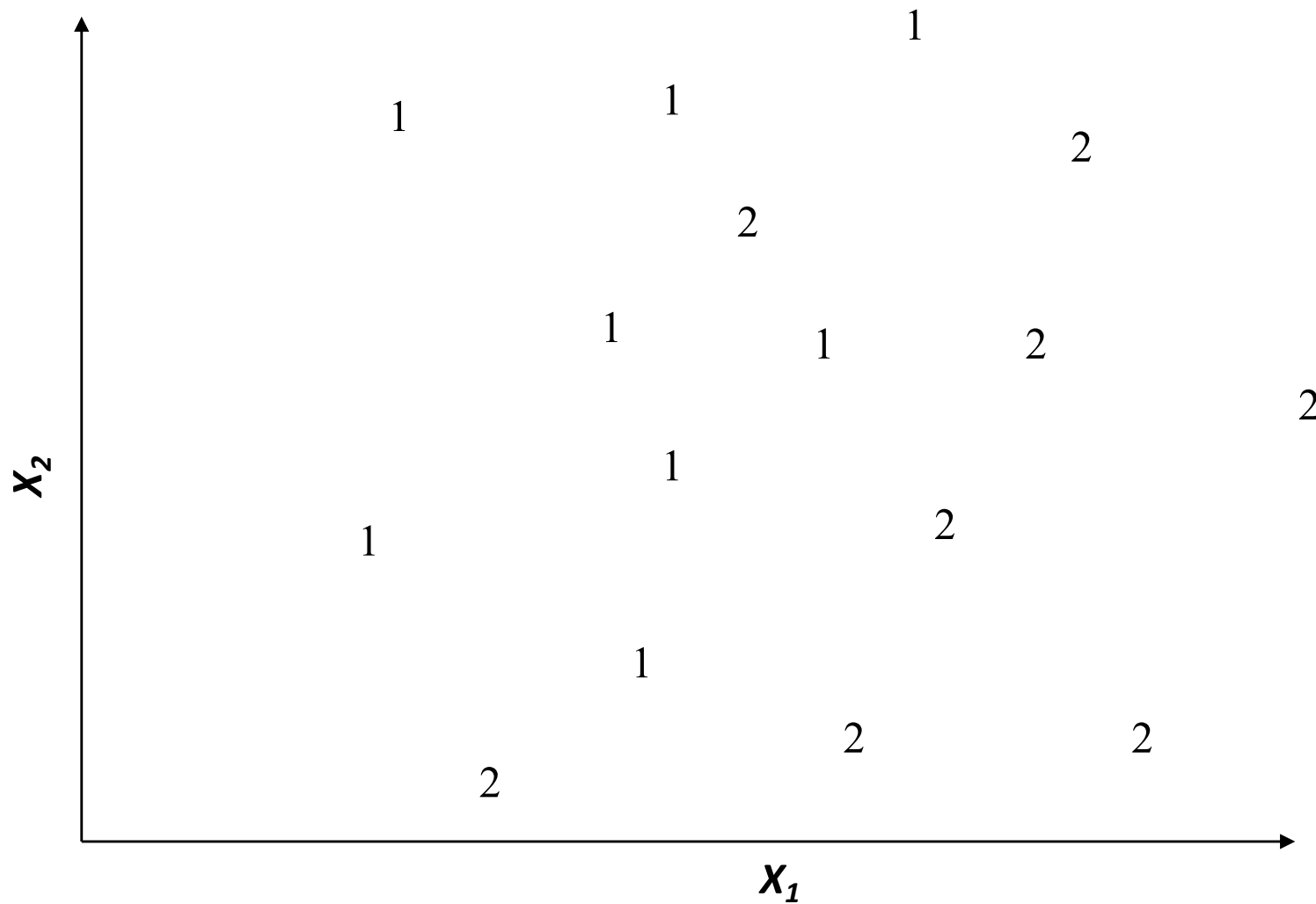
Nearest neighbor classifier



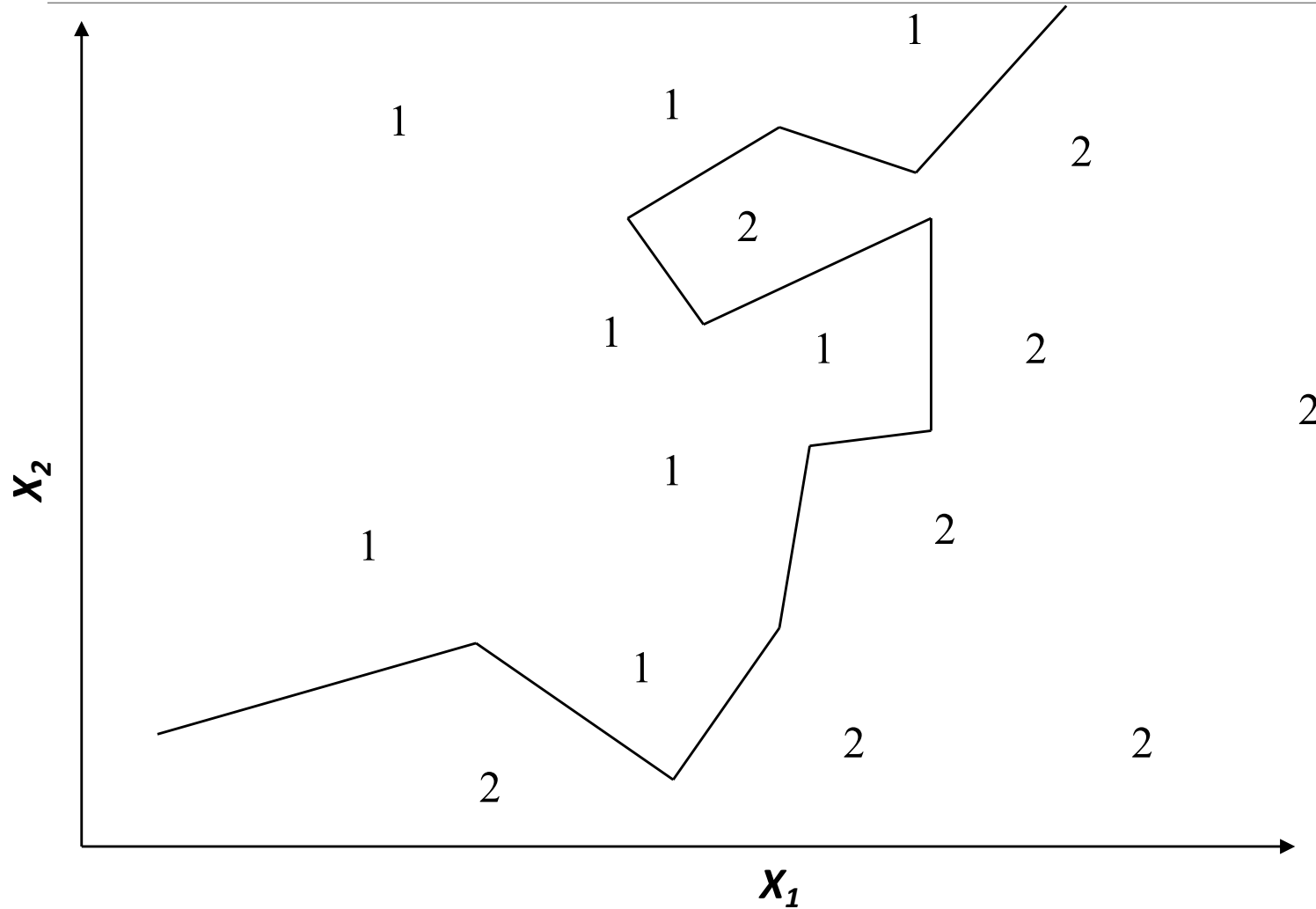
Nearest neighbor classifier



More Data Points



More Complex Decision Boundary



Machine Learning

Complexity and Overfitting

Nearest Neighbors

K-Nearest Neighbors

Bayes Classifiers

K-Nearest Neighbor (kNN)

Find the k-nearest neighbors to x in the data

- i.e., rank the feature vectors according to Euclidean distance, $d(x, x^{(j)})^2 = \frac{1}{n} \sum_i (x_i - x_i^{(j)})^2$
- select the k vectors which 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 **majority** 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 ($k=1, 3, 5, \dots$) there will never be any “ties”; otherwise, just use (any) tie-breaking rule

“Training” is trivial

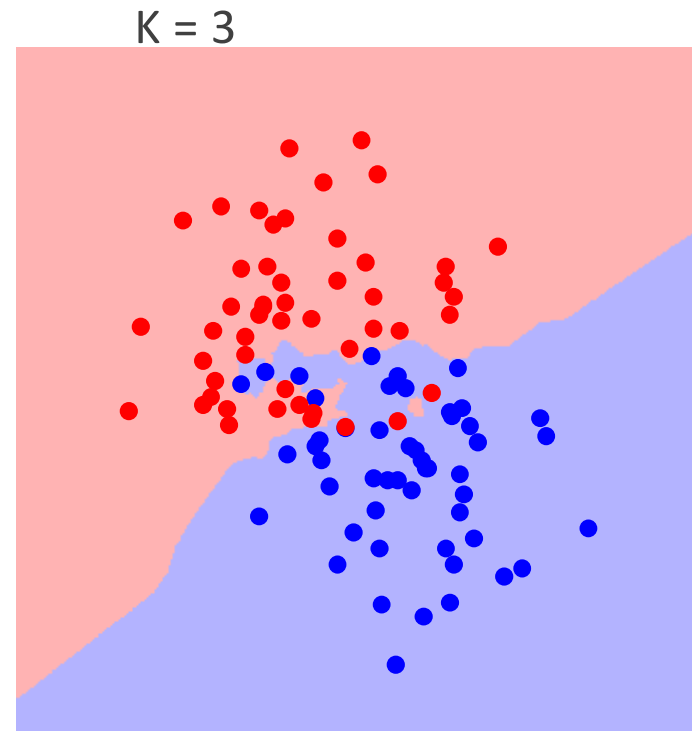
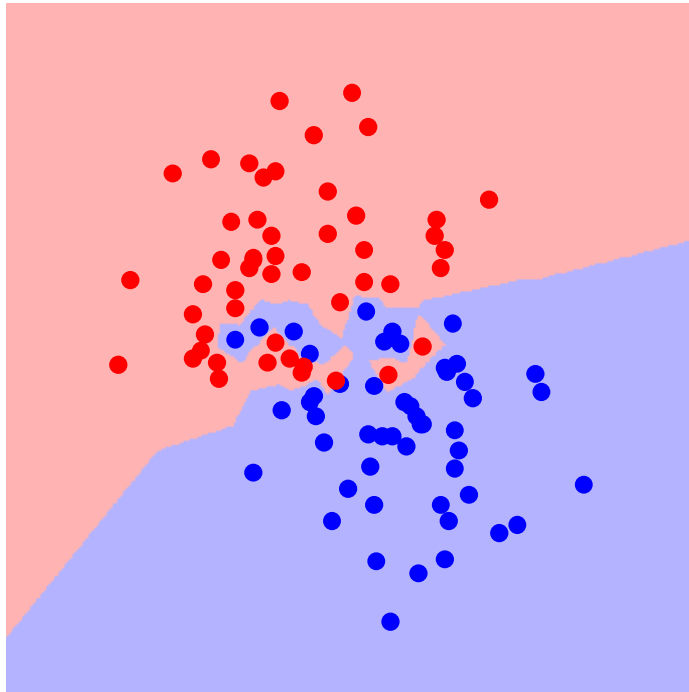
- store training data as a lookup table, and search to classify a new datum

kNN Decision Boundary

Piecewise linear decision boundary

Increasing k “simplifies” decision boundary

- Majority voting means less emphasis on individual points
- $K = 1$

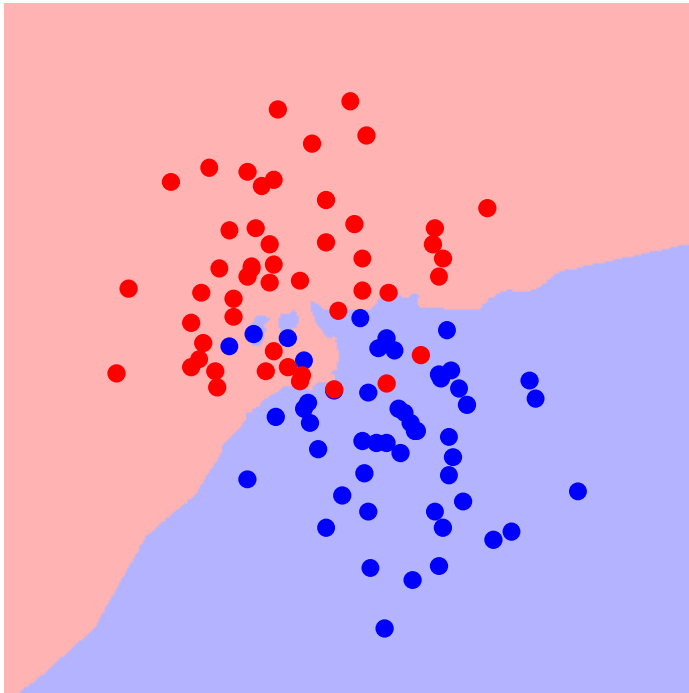


kNN Decision Boundary

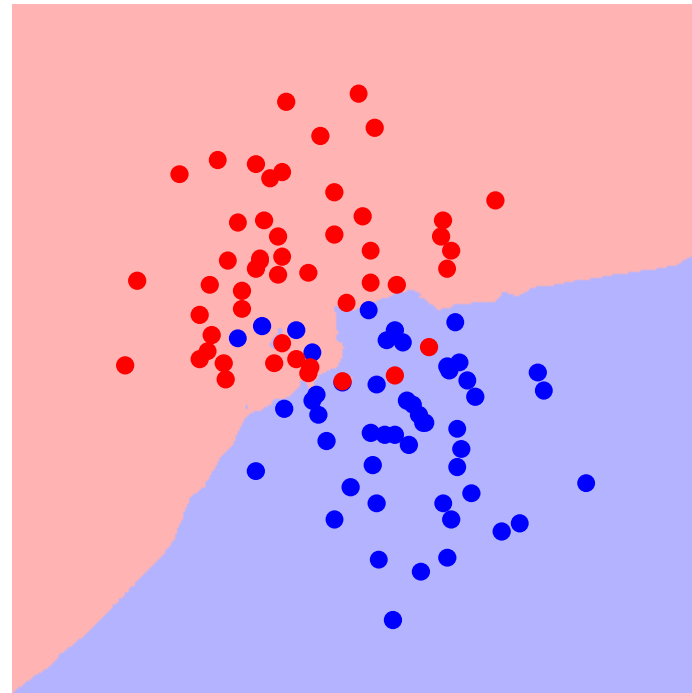
Piecewise linear decision boundary

Increasing k “simplifies” decision boundary

- Majority voting means less emphasis on individual points
- $K = 5$



$K = 7$

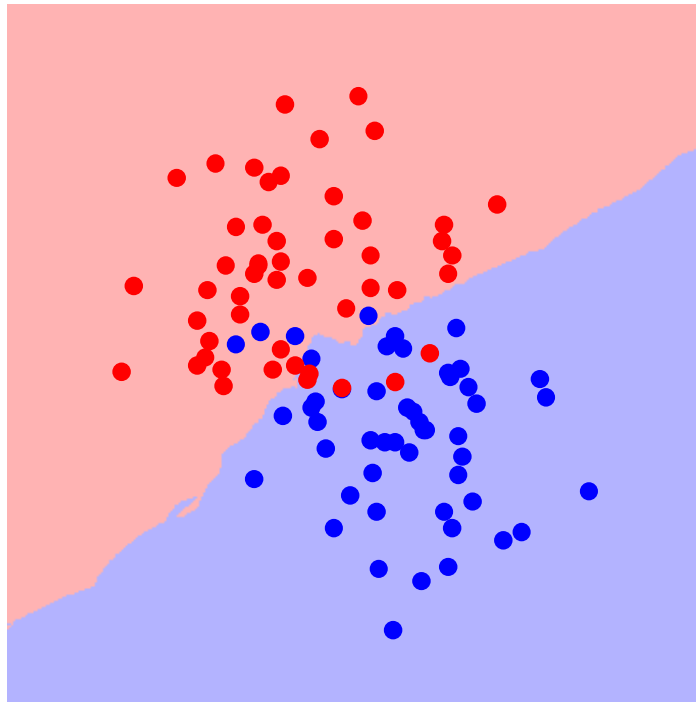


kNN Decision Boundary

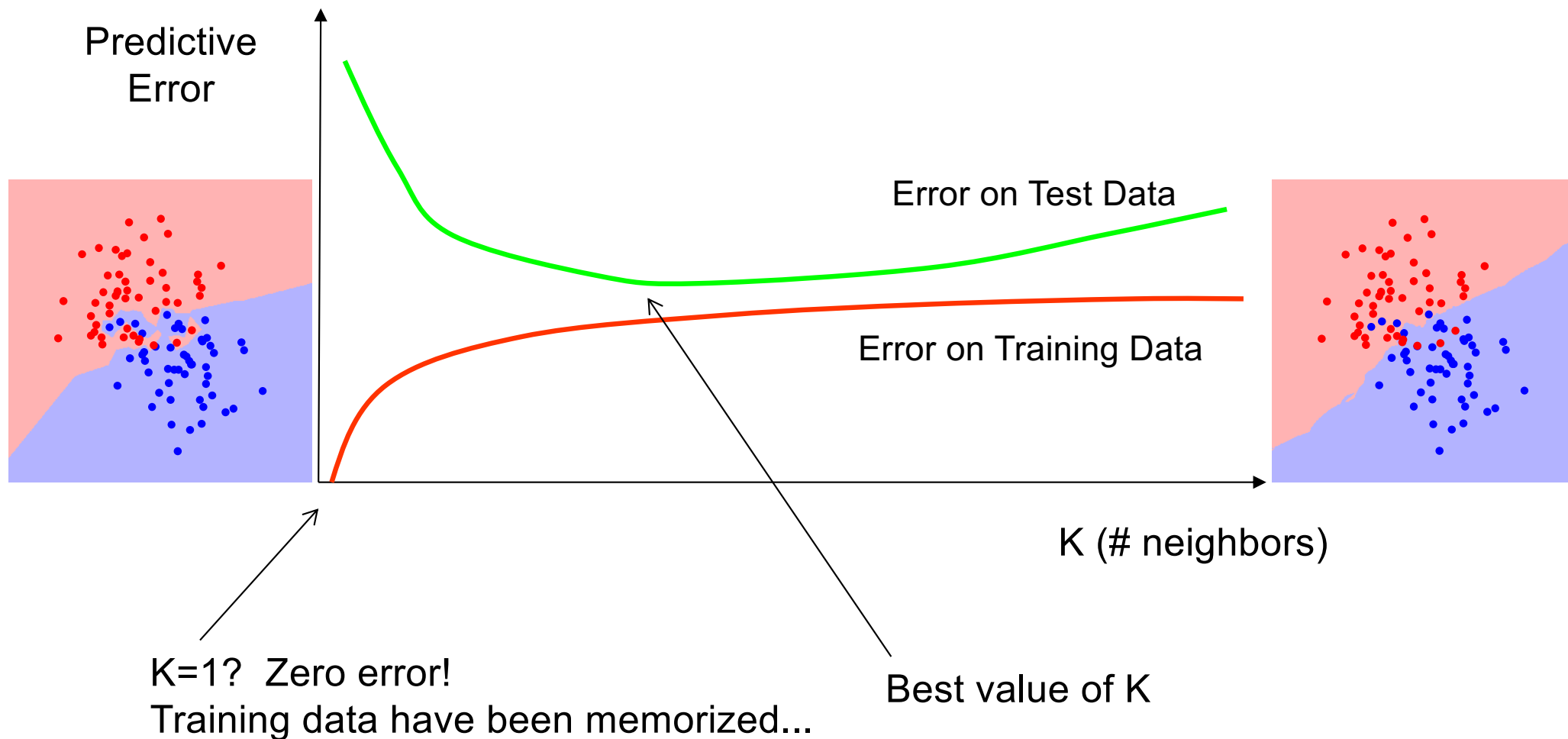
Piecewise linear decision boundary

Increasing k “simplifies” decision boundary

- Majority voting means less emphasis on individual points
- $K = 25$



Error rates and K



Complexity & Overfitting

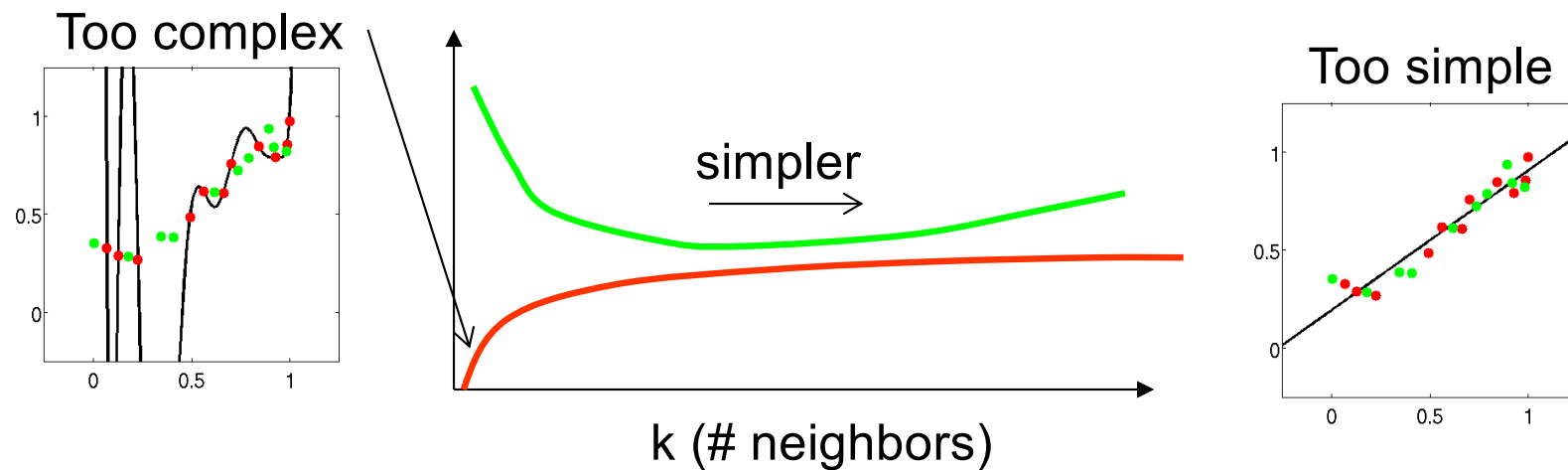
Complex model predicts all training points well

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.



K-Nearest Neighbor (kNN) Classifier

Theoretical Considerations

- as k increases
 - we are averaging over more neighbors
 - the effective decision boundary is more “smooth”
- as n increases, the optimal k value tends to increase

Extensions of the Nearest Neighbor classifier

- Weighted distances
 - 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

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

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