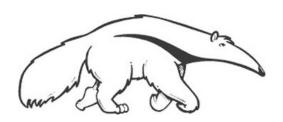
Machine Learning and Data Mining

Nearest neighbor methods

Prof. Alexander Ihler Fall 2012



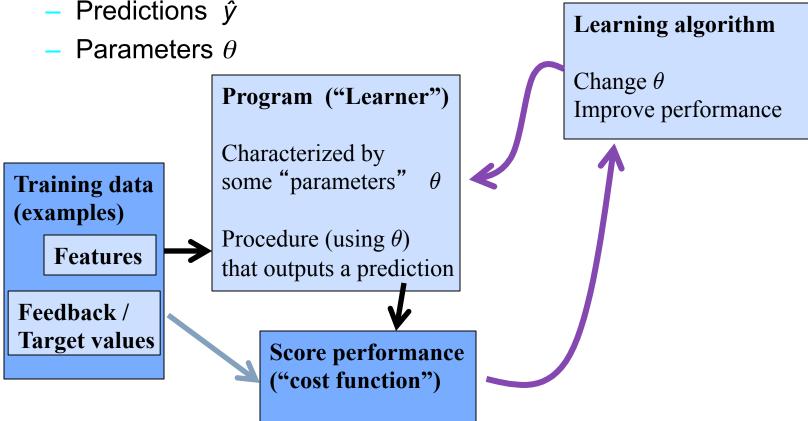




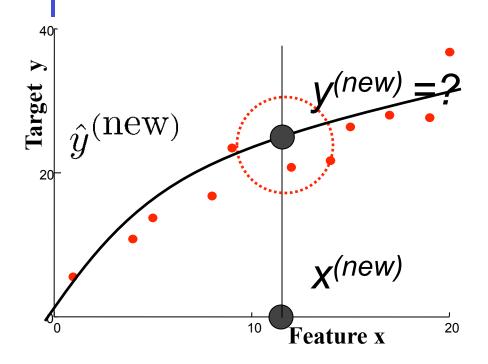
Supervised learning

Notation

- Features
- Targets
- Predictions ŷ

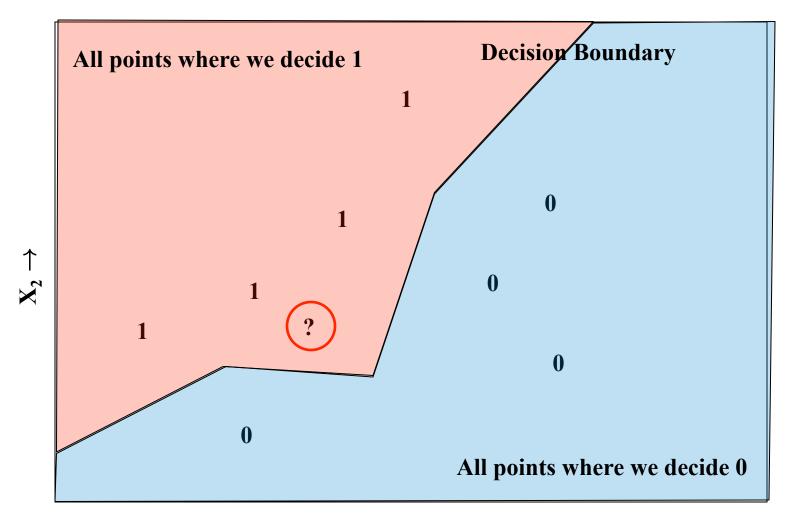


Regression; Scatter plots



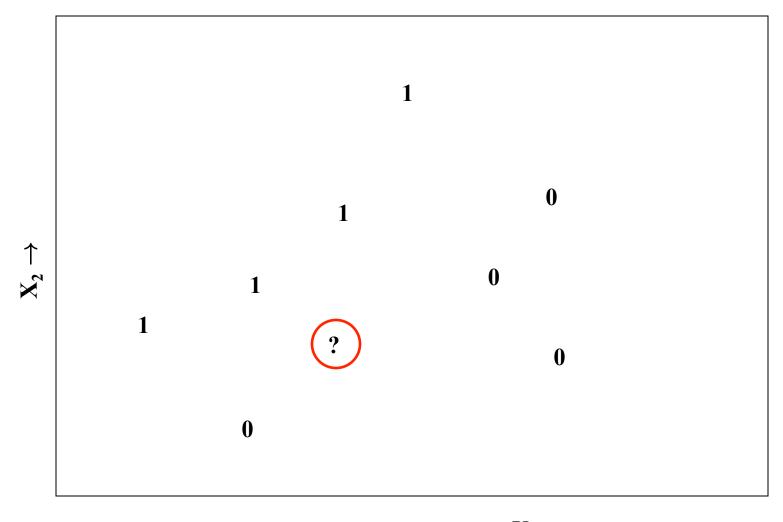
- Suggests a relationship between x and y
- Prediction: new x, what is y?

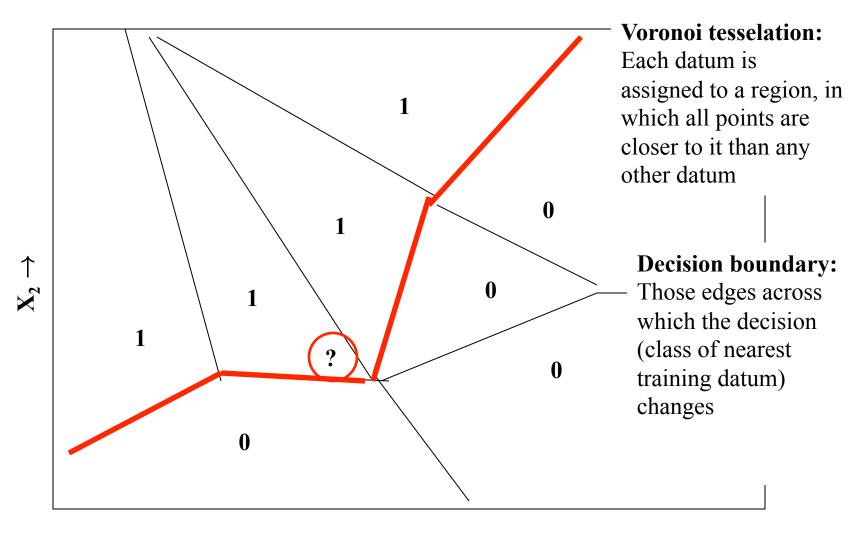
Classification

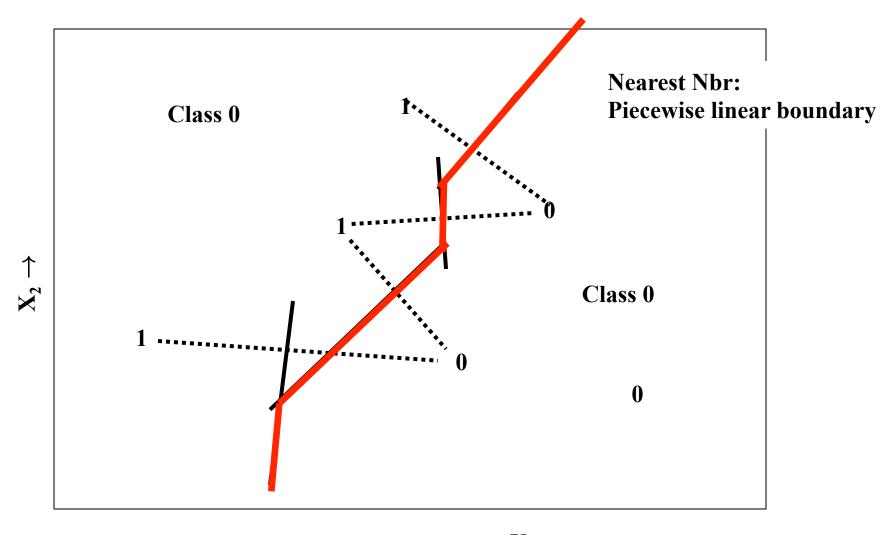


- <u>x</u> is a new feature vector whose class label is unknown
- Search training data for the closest feature vector to x
 - Suppose the closest one is $\underline{x}^{(j)}$
- Classify <u>x</u> with the same label as <u>x</u>^(j), i.e.
 - Assign <u>x</u> the predicted label <u>y</u>^(j)
- Interpretation as memorization
- How are "closest x" vectors determined?
 - typically use minimum Euclidean distance

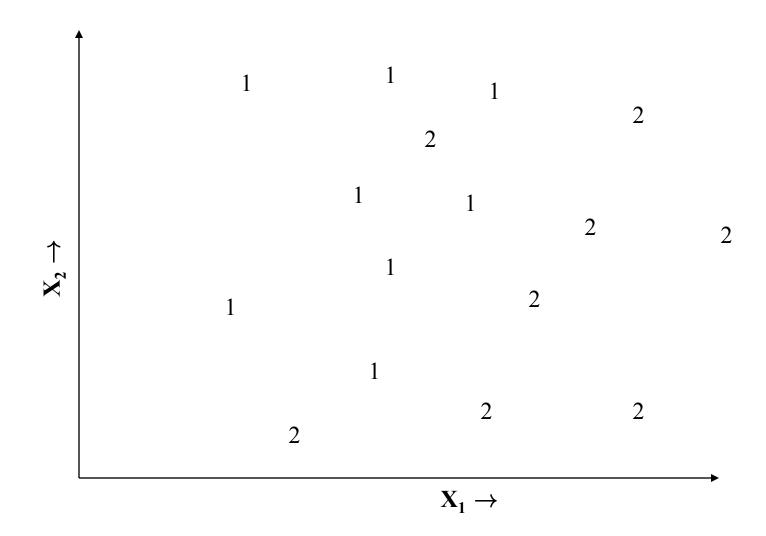
$$d(x, x') = \sqrt{\sum_{i} (x_i - x'_i)^2}$$



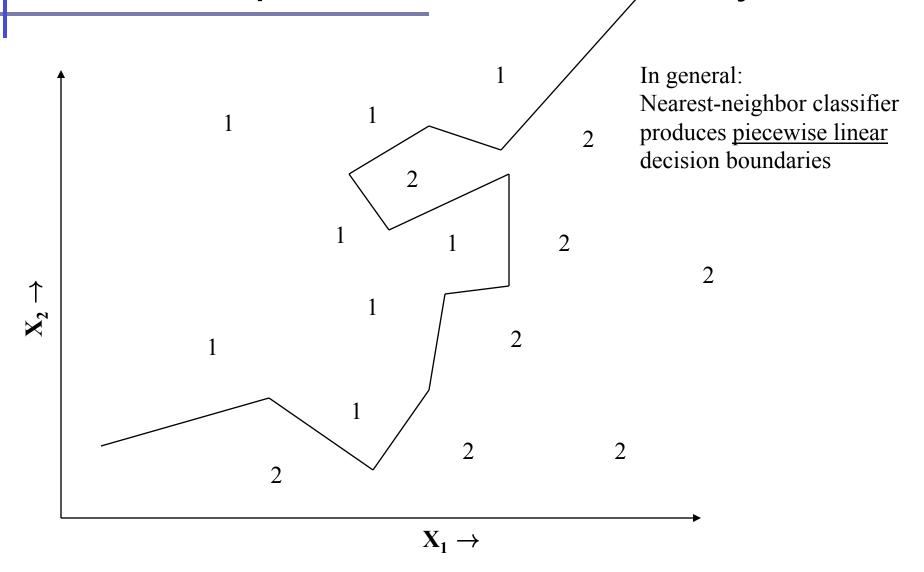




More Data Points



More Complex Decision Boundary



K-Nearest Neighbor (kNN) Classifier

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

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 <u>x</u> as belonging to this class

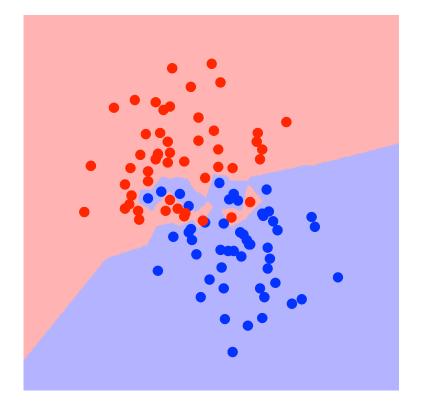
Notes:

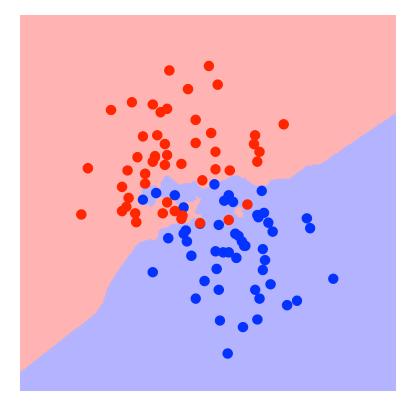
- Nearest k feature vectors from training "vote" on a class label for x
- the single-nearest neighbor classifier is the special case of k=1
- for two-class problems, if we choose k to be odd (i.e., k=1, 3, 5,...) then there will never be any "ties"
- "training" is trivial for the kNN classifier, i.e., we just use 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

$$K = 1$$
 $K = 3$

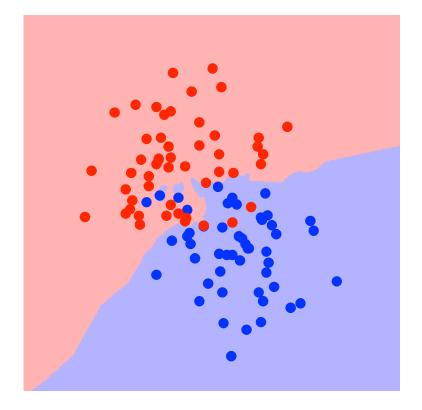


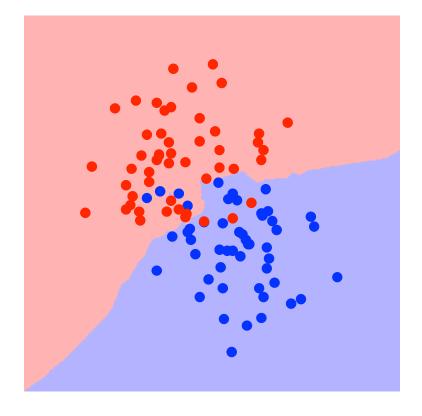


kNN Decision Boundary

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

$$K = 5$$
 $K = 7$

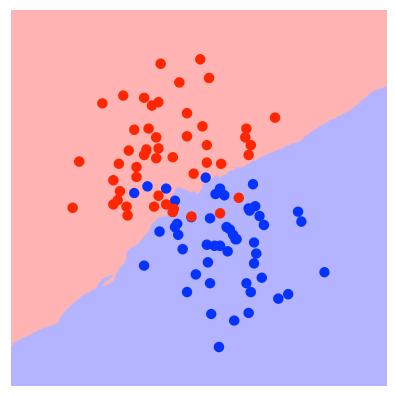




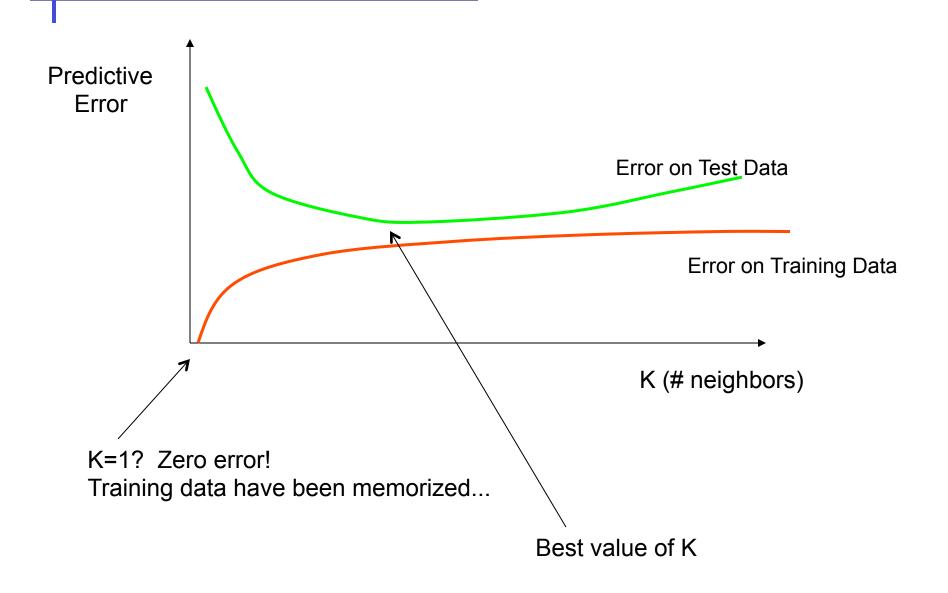
kNN Decision Boundary

- Recall: piecewise linear decision boundary
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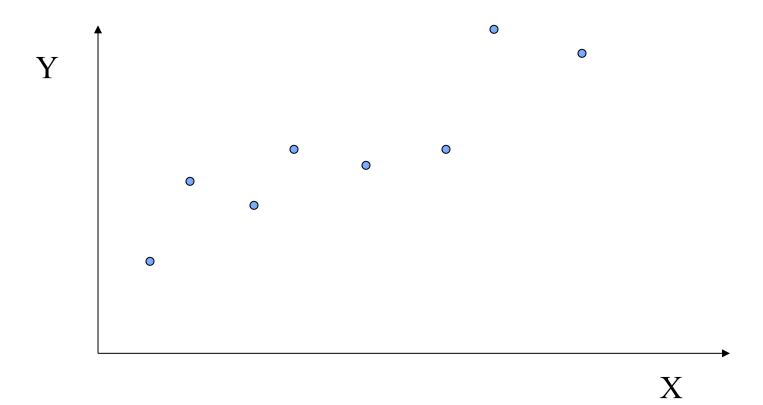
$$K = 25$$



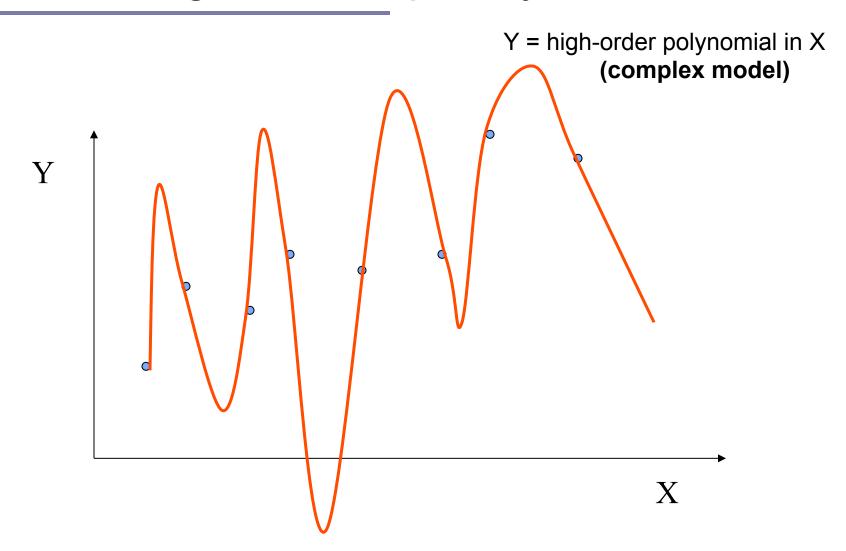
Error rates and K



Overfitting and complexity

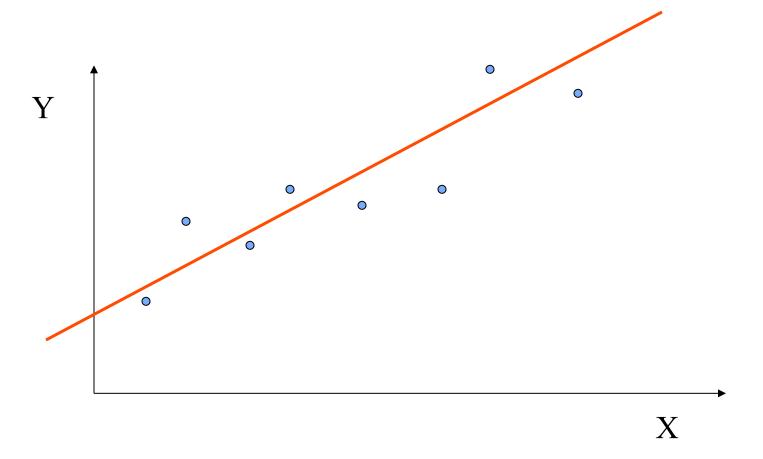


Overfitting and complexity



Overfitting and complexity

Simple model: Y= aX + b + e



Detecting overfitting

- Overfitting effect
 - Do better on training data than on future data
 - Need to choose the "right" complexity
- One solution: "Hold-out" or "validation" data
- Separate our data into two sets
 - Training
 - Test
- Learn only on training data
- Use test data to estimate generalization quality
 - Model selection
- All good competitions use this formulation
 - Often multiple splits: one by judges, then another by you

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
 - k=1, m increasing to infinity : error < 2x optimal</p>
- Extensions of the Nearest Neighbor classifier
 - weighted distances
 - e.g., if some of the features are more important
 - · e.g., if features are irrelevant

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

fast search techniques (indexing) to find k-nearest neighbors in d-space

Summary

- K-nearest neighbor models
 - Classification (vote)
 - Regression (average or weighted avg)
- Piecewise linear decision boundary
 - How to calculate
- Test data and overfitting
 - Model "complexity" for knn
 - Validation data for test error rates