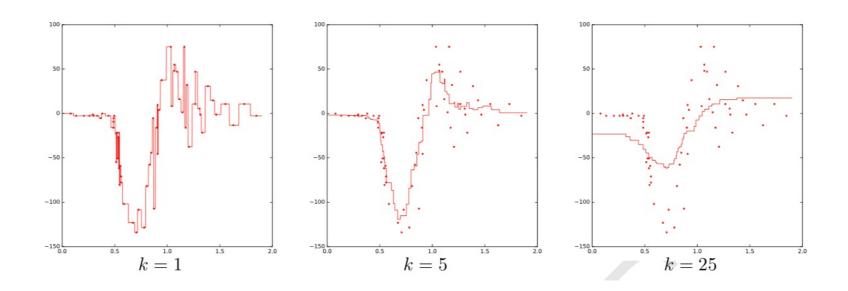
CS273A: Nearest Neighbor Methods



Prof. Alexander Ihler Fall 2024

Machine Learning

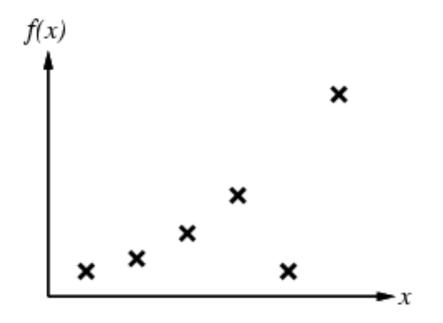
Complexity and Overfitting

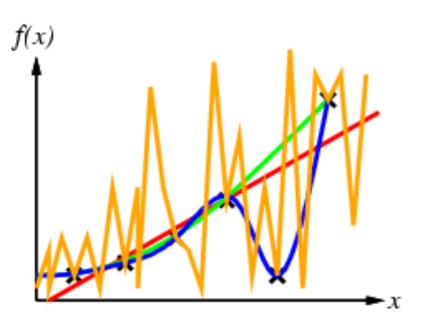
Nearest Neighbors

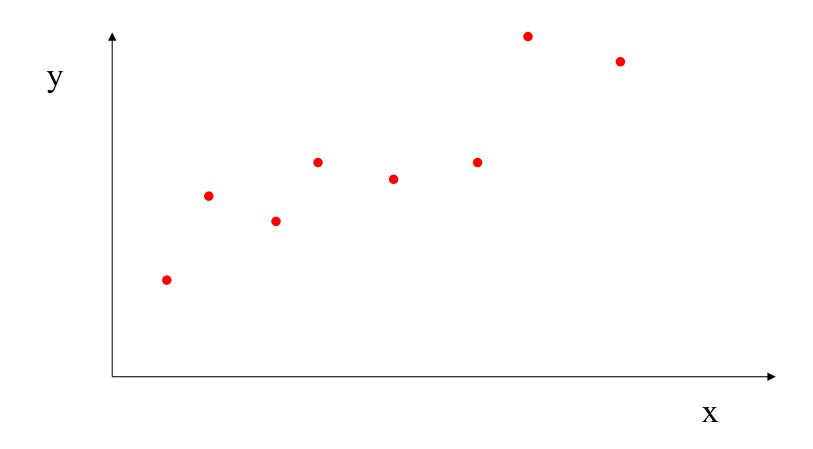
K-Nearest Neighbors

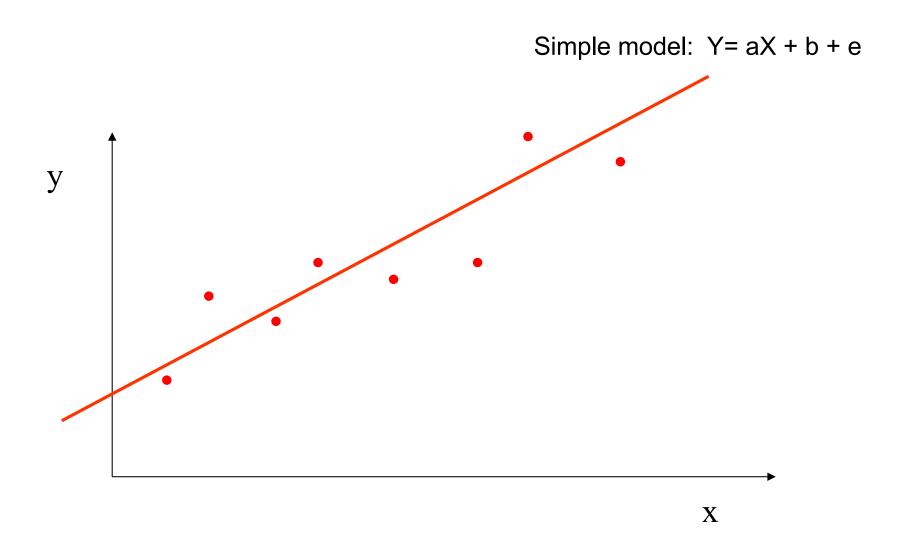
Inductive bias

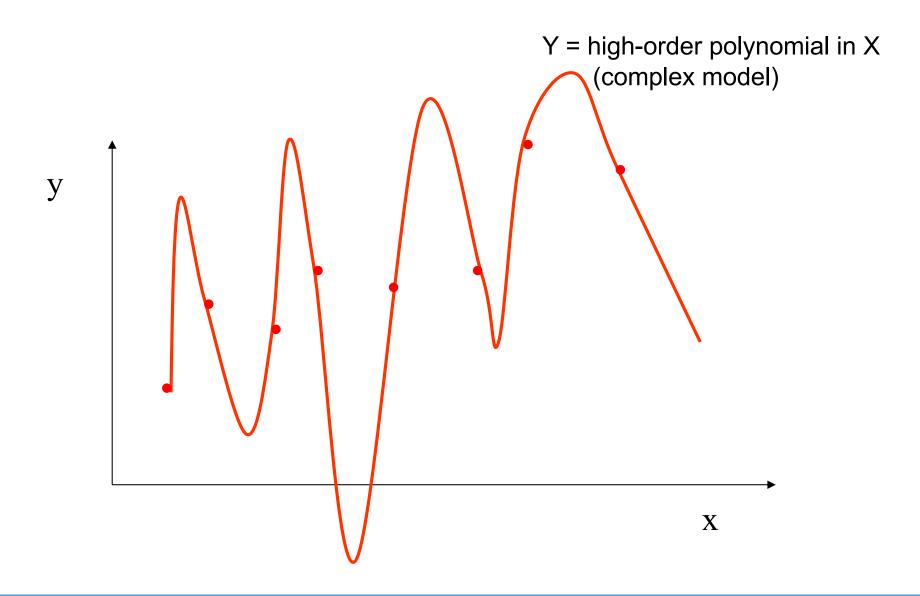
- "Extend" observed data to unobserved examples
 - "Interpolate" / "extrapolate"
- What kinds of functions to expect? Prefer these ("bias")
 - Usually, let data pull us away from assumptions only with evidence!

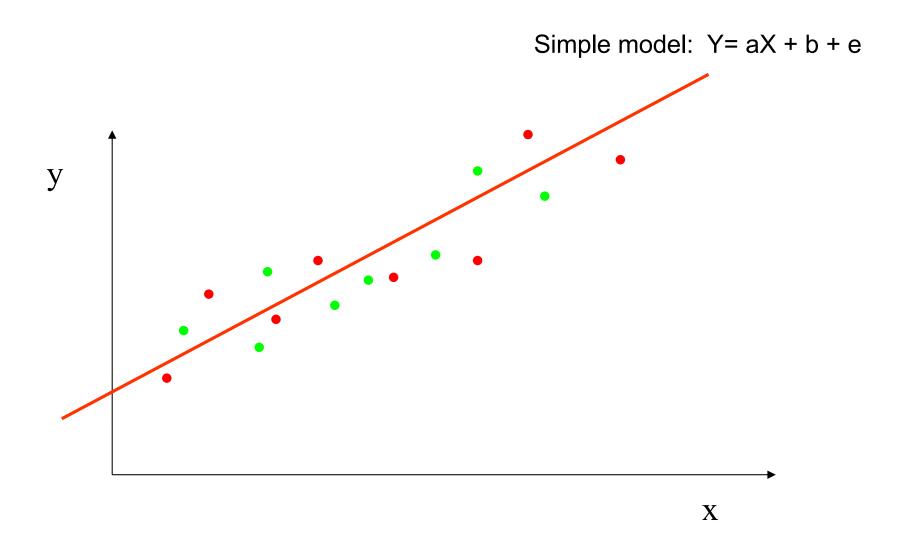


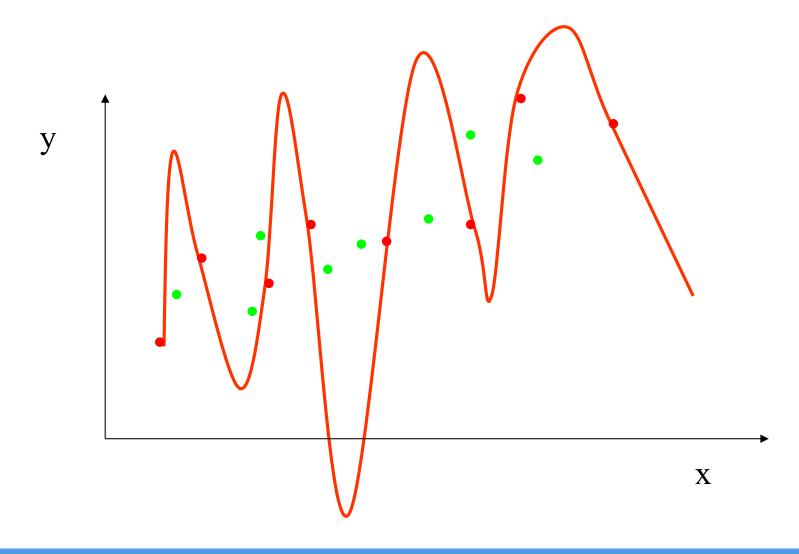




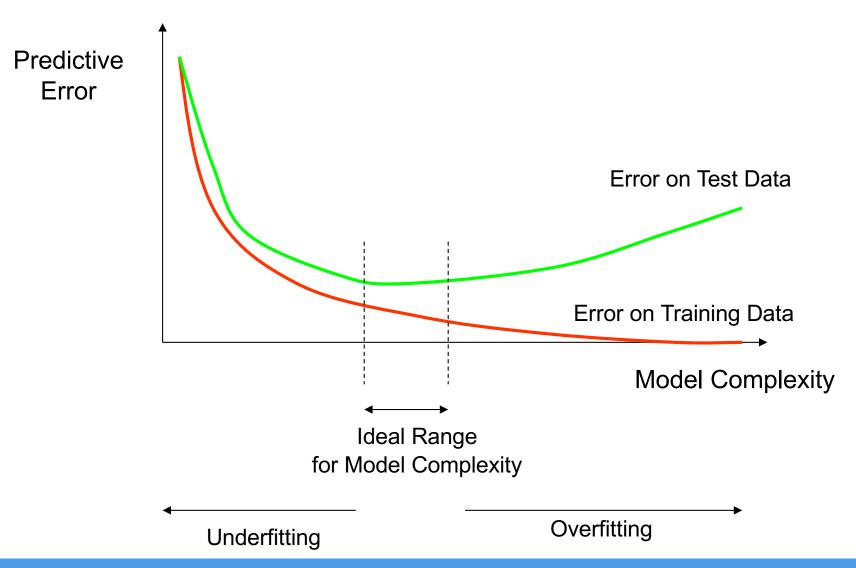








How Overfitting affects Prediction



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

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 ②	Entries	Last Submission U1
1	-	BrickMover 4 *	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

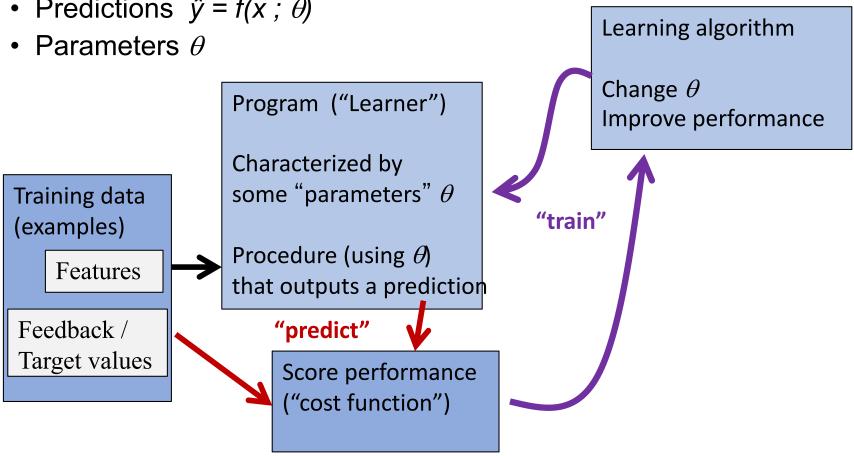
Nearest Neighbors

K-Nearest Neighbors

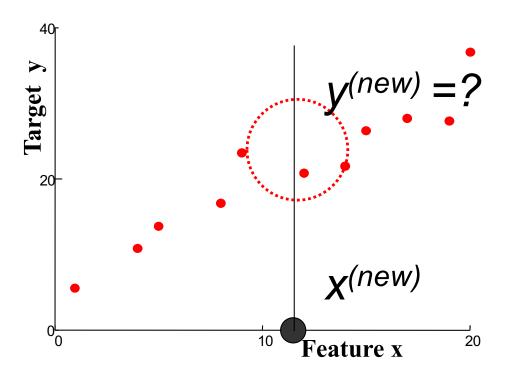
Supervised learning

Notation

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

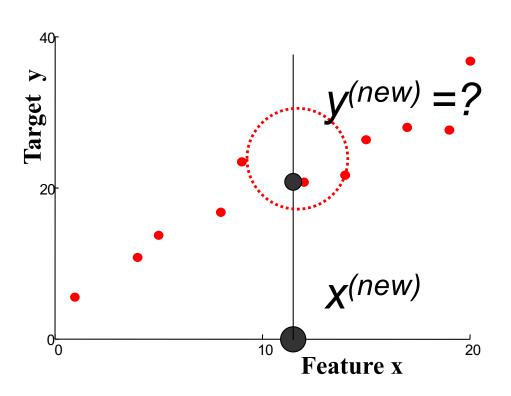


Regression; Scatter plots



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

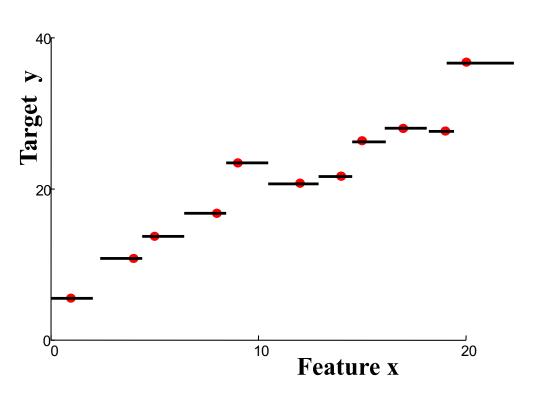
Nearest neighbor regression



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

• Find training datum $x^{(i)}$ closest to $x^{(new)}$; predict $y^{(i)}$

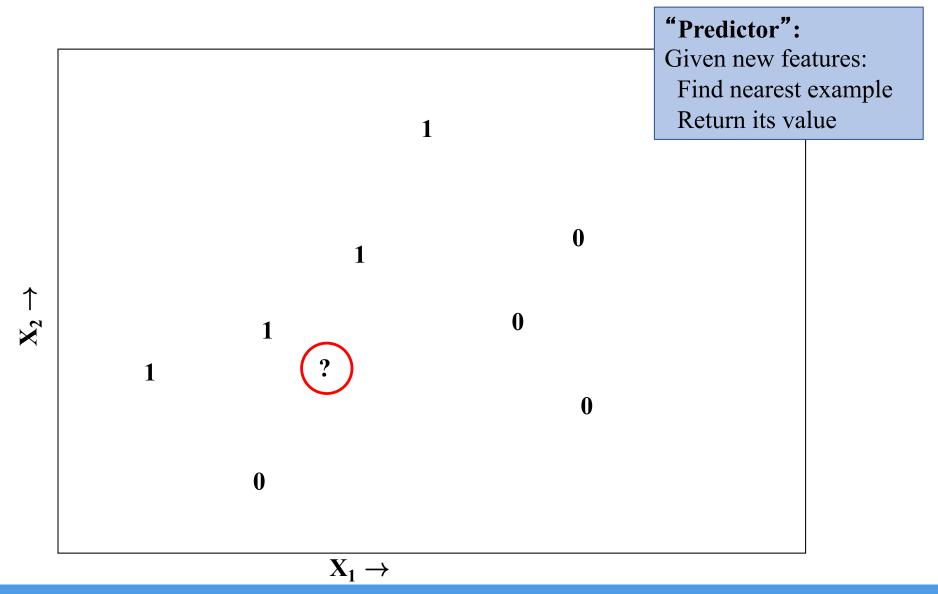
Nearest neighbor regression

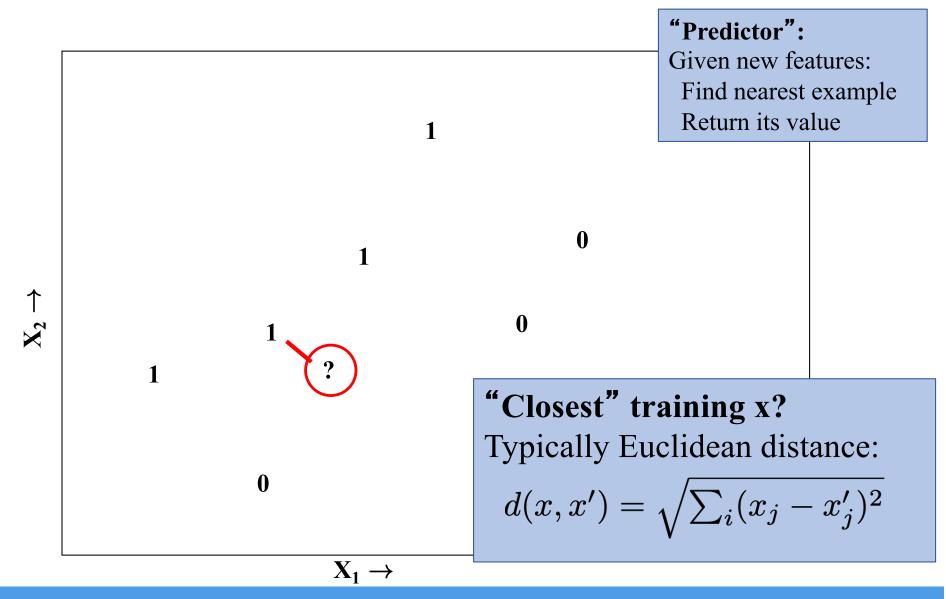


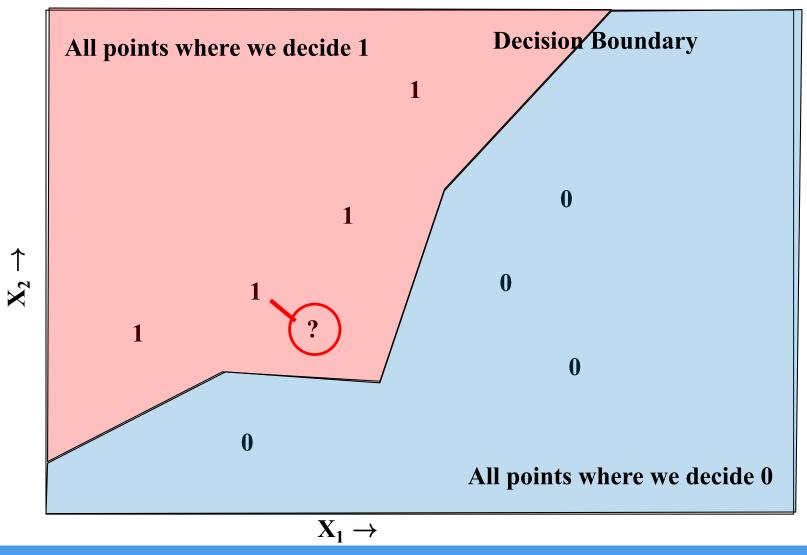
"Predictor":

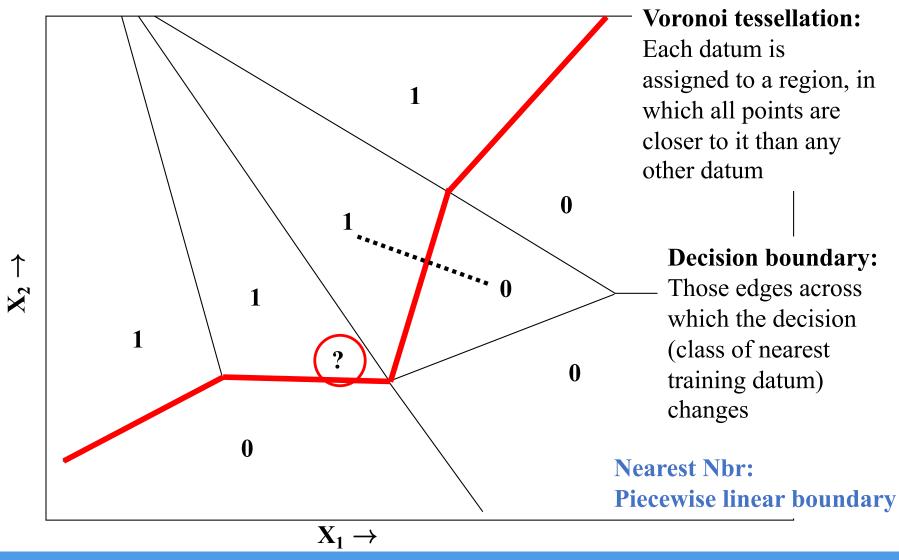
Given new features:
Find nearest example
Return its value

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

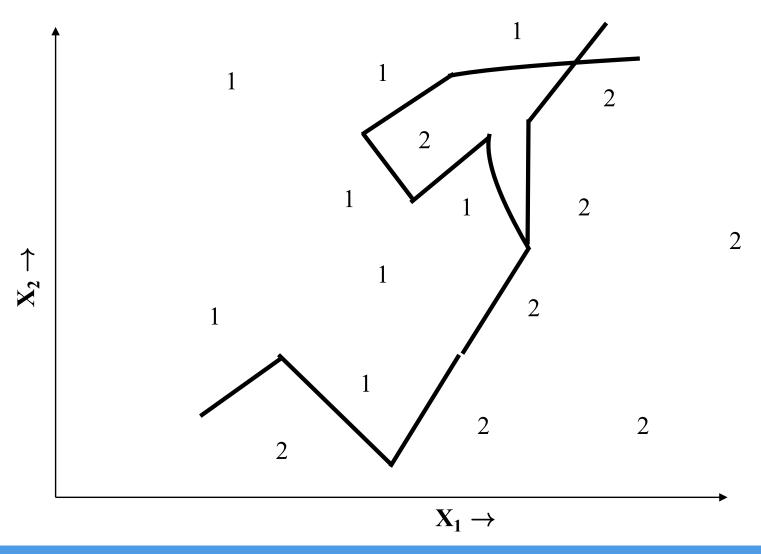




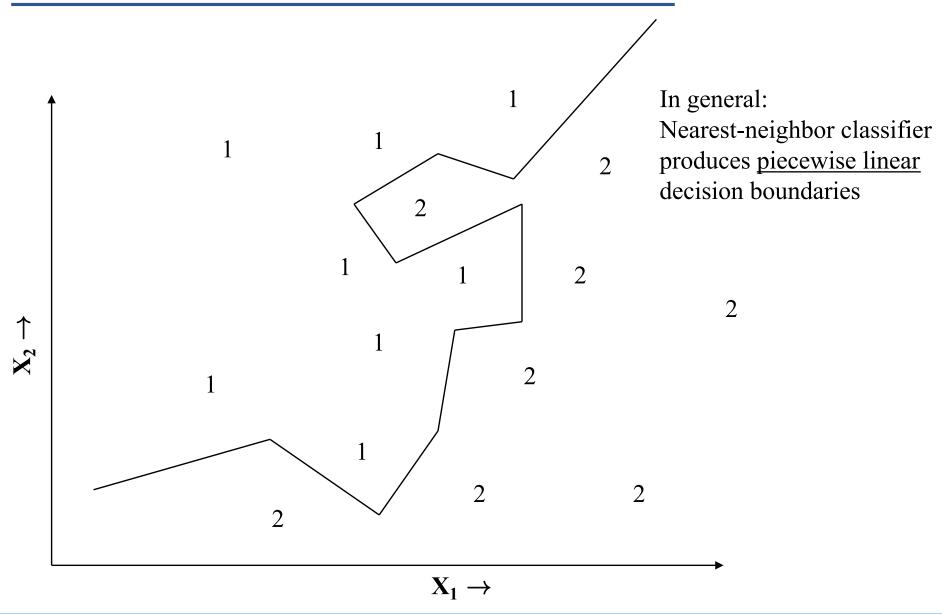




More Data Points

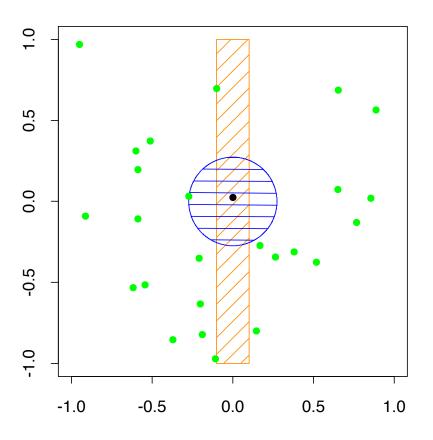


More Complex Decision Boundary

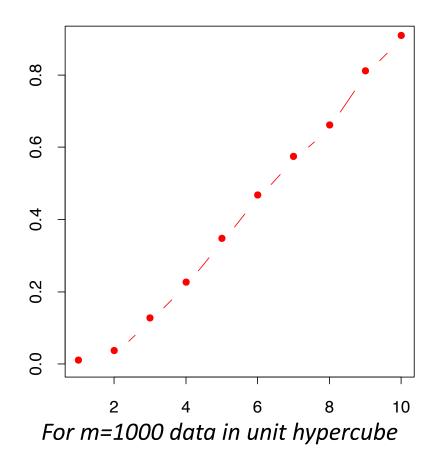


Issue: Neighbor Distance & Dimension

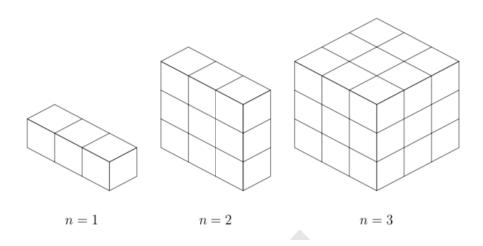
1-NN in One vs. Two Dimensions



Distance to 1-NN vs. Dimension

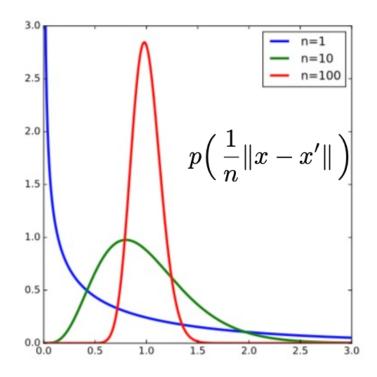


The "Curse of Dimensionality"



- Function is "smooth"?
 - Want a training example that is close by (epsilon)
 - How many data do we need?

- How far away are the other data points?
 - In higher dimension, "almost all" data are equally far away!



Machine Learning

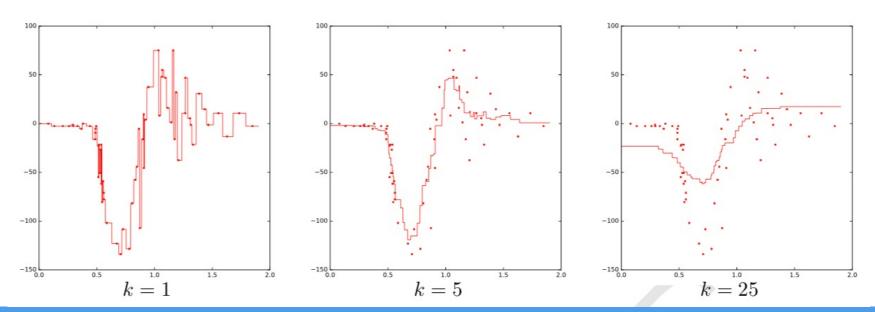
Complexity and Overfitting

Nearest Neighbors

K-Nearest Neighbors

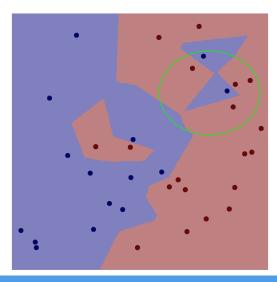
K-Nearest Neighbor (kNN) Predictor

- Find the k-nearest neighbors to \underline{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
 - Ranking gives k closest examples and their target values "y"
 - Usually just average the y-values of the k closest training examples
 - Larger k = average over a larger area for prediction



K-Nearest Neighbor (kNN) Predictor

- Find the k-nearest neighbors to \underline{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
- 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")
 - 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

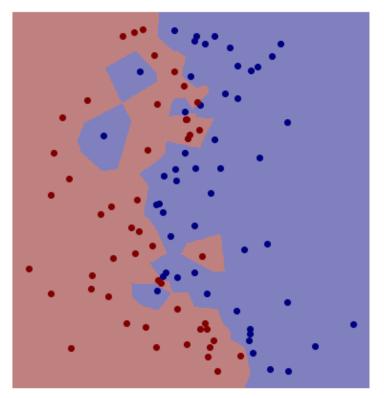


Predict blue?
Or just noise?

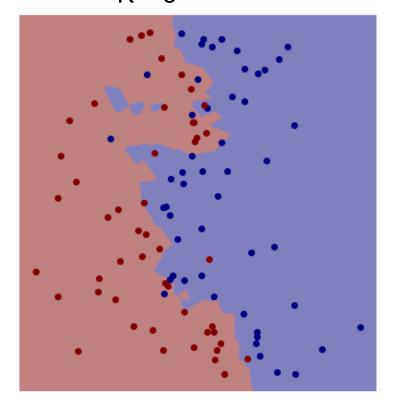
kNN Decision Boundary

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

$$K = 1$$



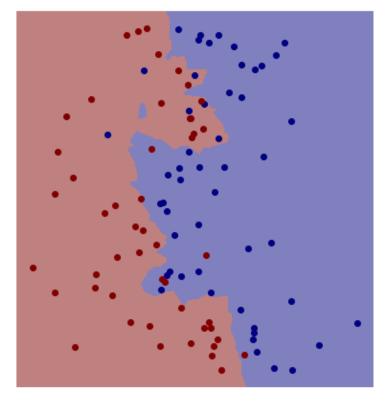
$$K = 3$$



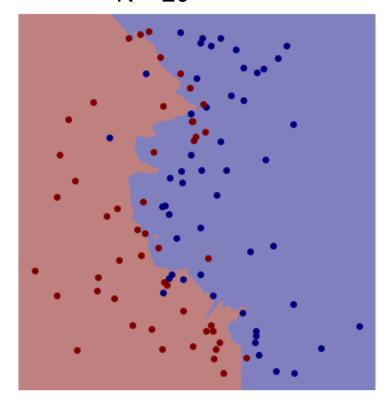
kNN Decision Boundary

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

$$K = 5$$



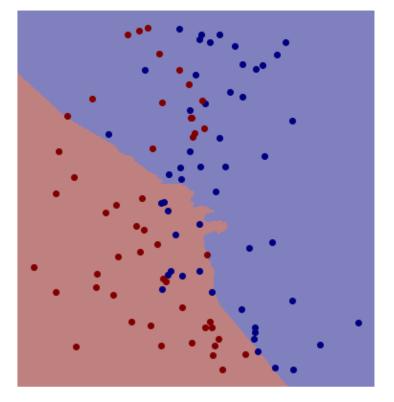
$$K = 20$$



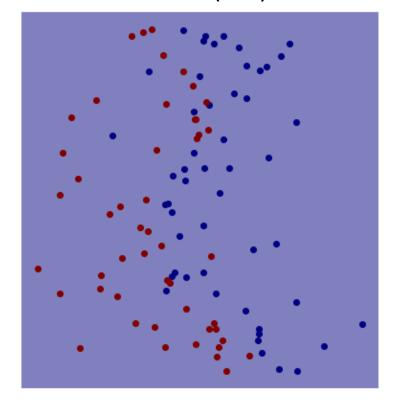
kNN Decision Boundary

- Piecewise linear decision boundary
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 - Majority voting means less emphasis on individual points

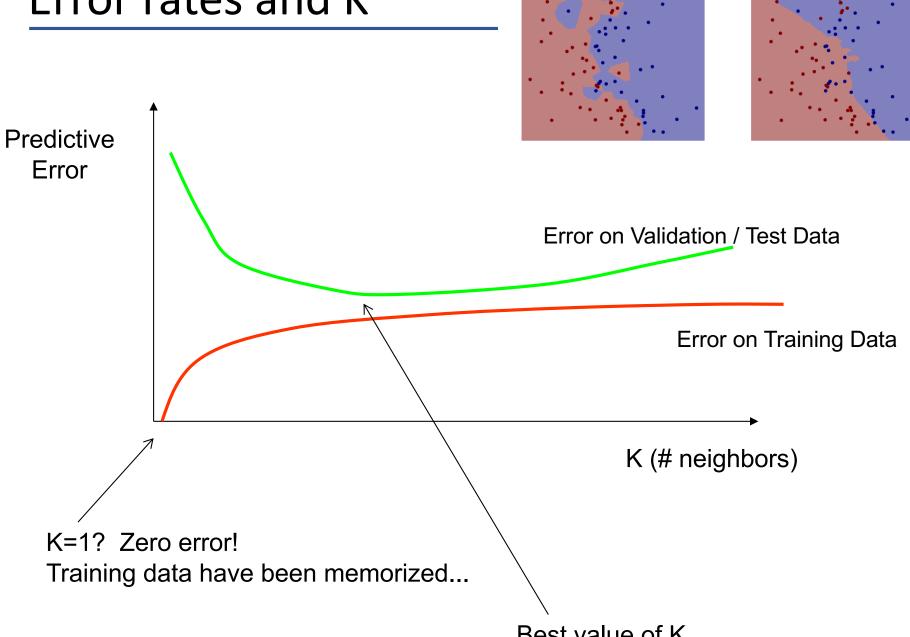
$$K = 70$$



$$K = 100 (=m)$$

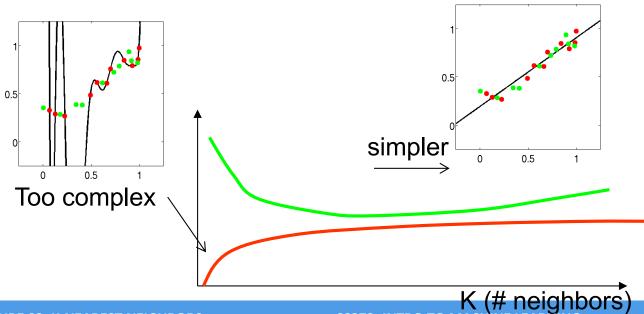






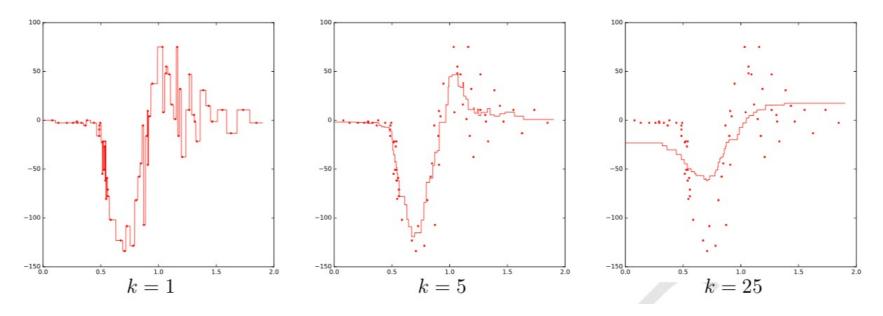
Complexity & Overfitting

- 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.



Regression example

Similar behavior for regression predictions:



- K (& data density) defines a local area to average over
- K too small: follow "noise" in the data
- K too big: smooth over too large an area

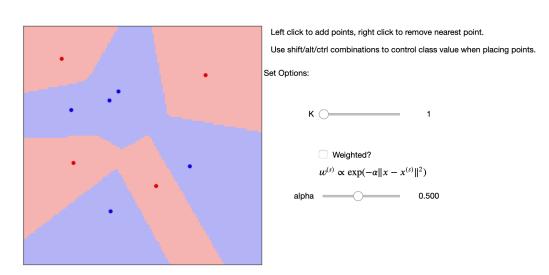
Live Demo

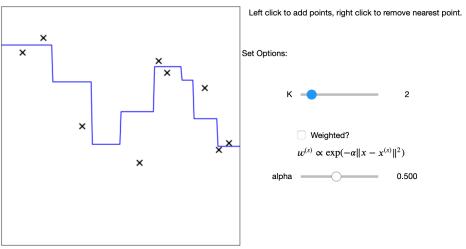
• Via Binder:

https://mybinder.org/v2/gh/ihler/ml-demos/HEAD?filepath=notebooks%2FDemo-Live-KNN.ipynb

(can be slow to start...)

• Ex:

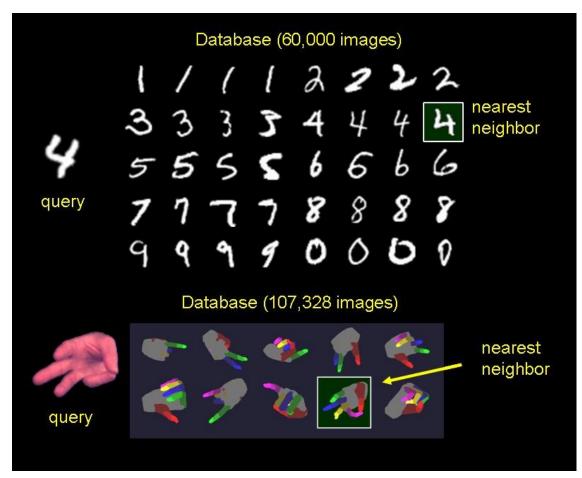




K-Nearest Neighbor (kNN) Classifier

- 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