



University of Cyprus – MSc Artificial Intelligence

MAI644 – COMPUTER VISION Lecture 11: Visual Recognition – Image Classification

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This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423







Last time

- Visual Recognition Tasks
- Introduction to segmentation and clustering
- Agglomerative clustering
- K-means clustering
- Mean-shift clustering
- Efficient Graph-based image segmentation









Today's Agenda

- A simple Image Classification pipeline
 - Classification overview
- K-nearest neighbor algorithm
 - kNN: algorithm
 - kNN: analysis

[material based on Niebles-Krishna]







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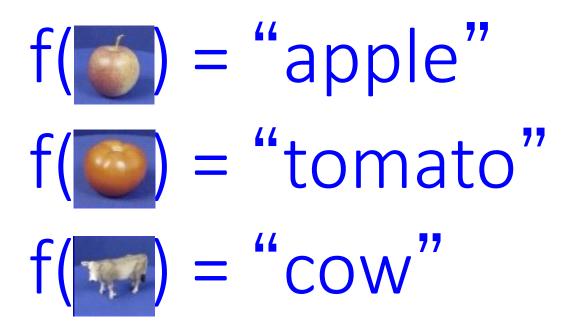






Visual recognition: a classification framework

• Apply a prediction function to a feature representation of the image to get the desired output:



Dataset: ETH-80, by B. Leibe Slide credit: L. Lazebnik

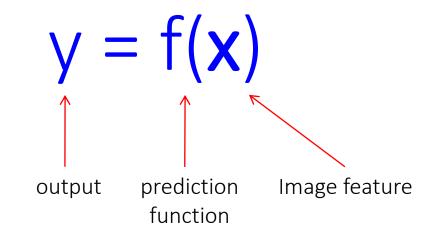








The machine learning framework



- **Training:** given a *training set* of labeled examples {(**x**₁,**y**₁), ..., (**x**_N,**y**_N)}, estimate the prediction function f by minimizing the prediction error on the training set
- Testing: apply f to a never-before-seen test example x and output the predicted value y = f(x)

Slide credit: L. Lazebnik

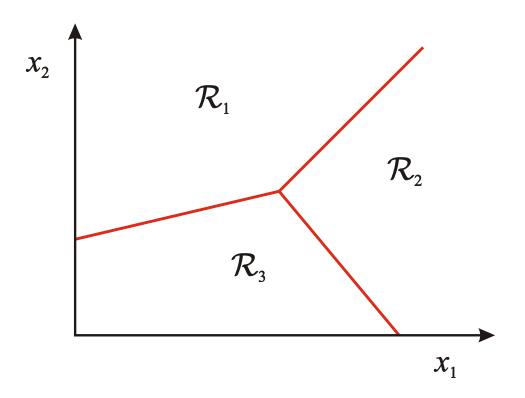






Classification

- Assign input feature vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Slide credit: L. Lazebnik

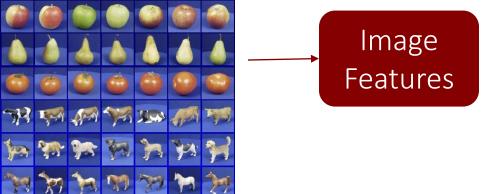






A simple pipeline - Training

Training Images

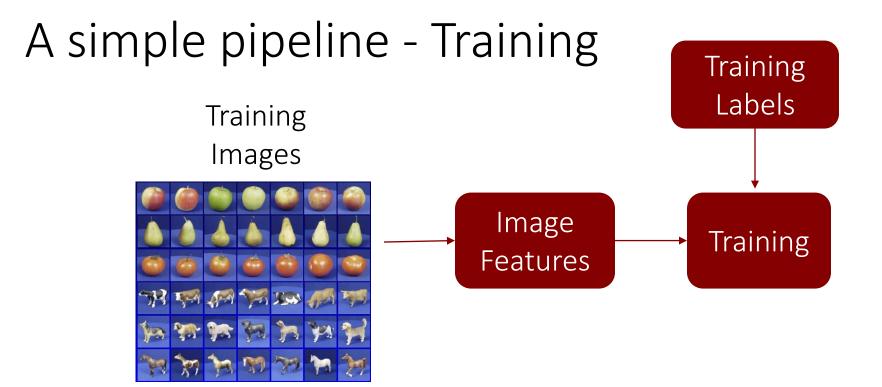








Visual Computing

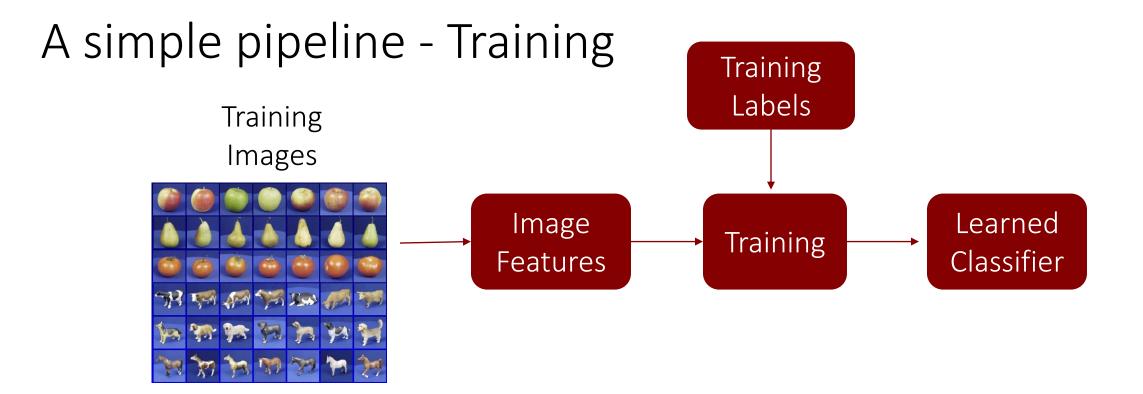




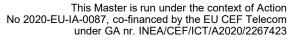








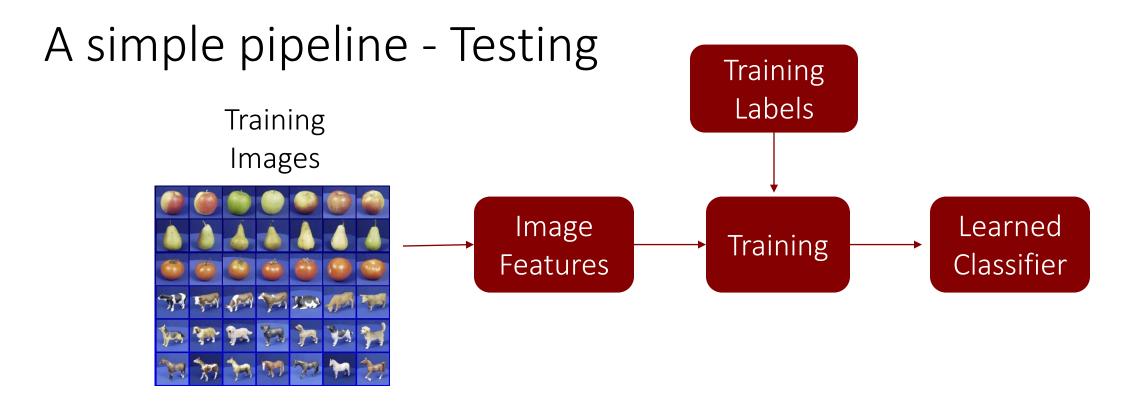


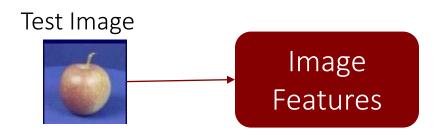










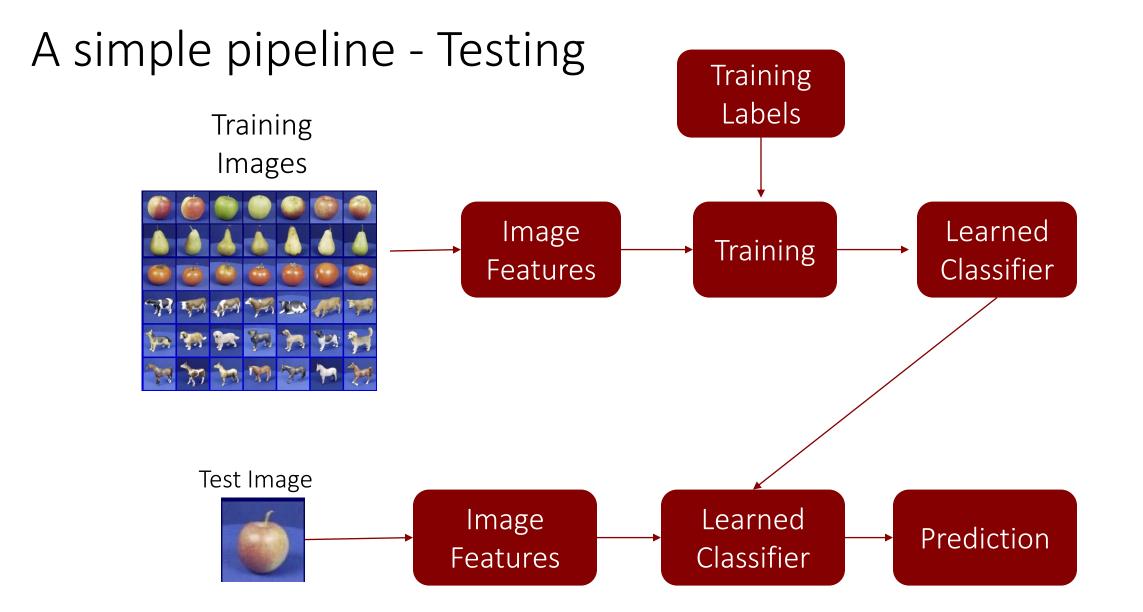




















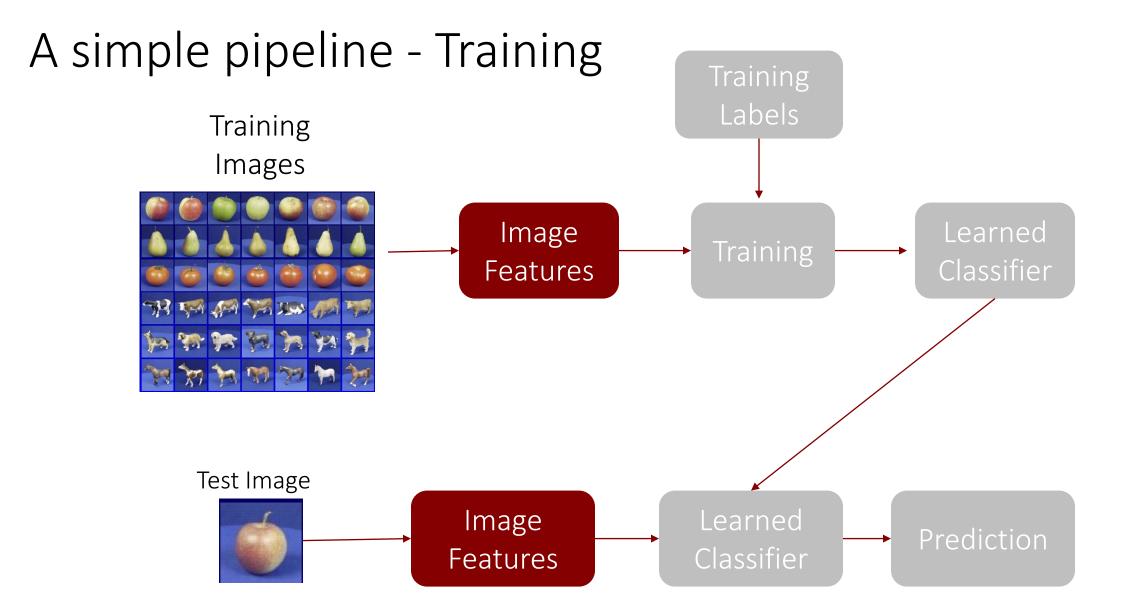










Image Features

Input image



Many features to choose from

- Histogram of Color
- Histogram of Gradients
- SIFT
- Bag of words
- etc...

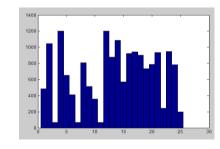


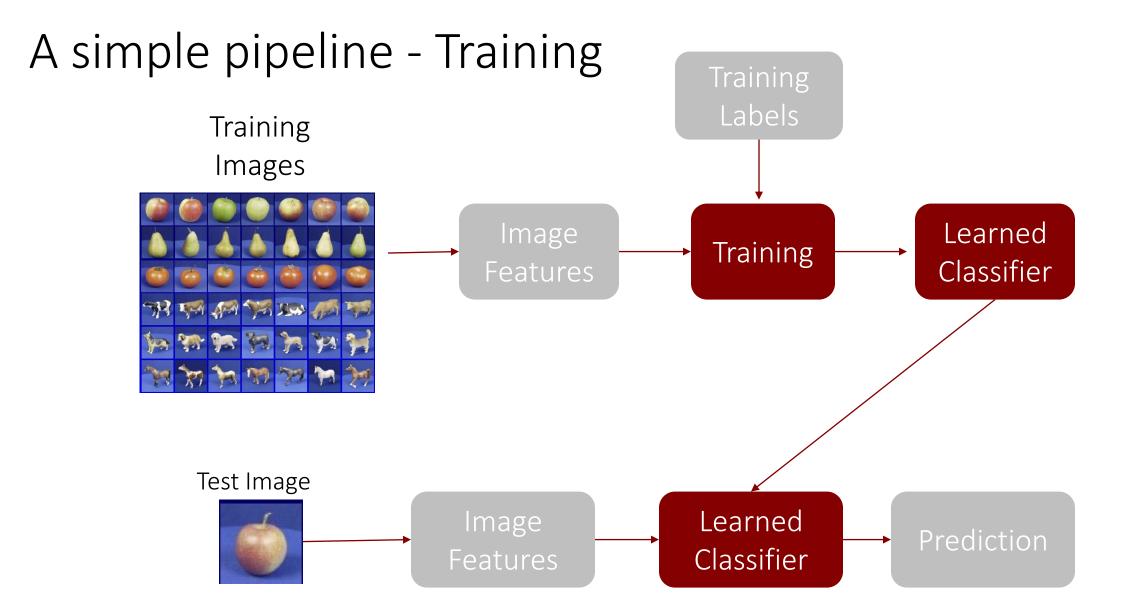
Image From ETH-80 dataset: Analyzing Appearance and Contour Based Methods for Object Categorization - by Leibe et al 2003



















Many classifiers to choose from

- K-nearest neighbor
- SVM
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- Restricted Boltzmann Machines
- Etc.

Which is the best one?

Slide credit: D. Hoiem

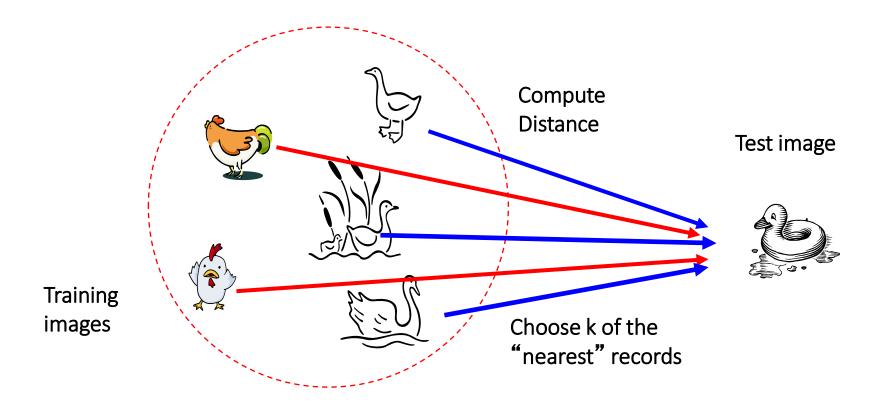






Classifiers: Nearest neighbor

Assign label of nearest training data point to each test data point

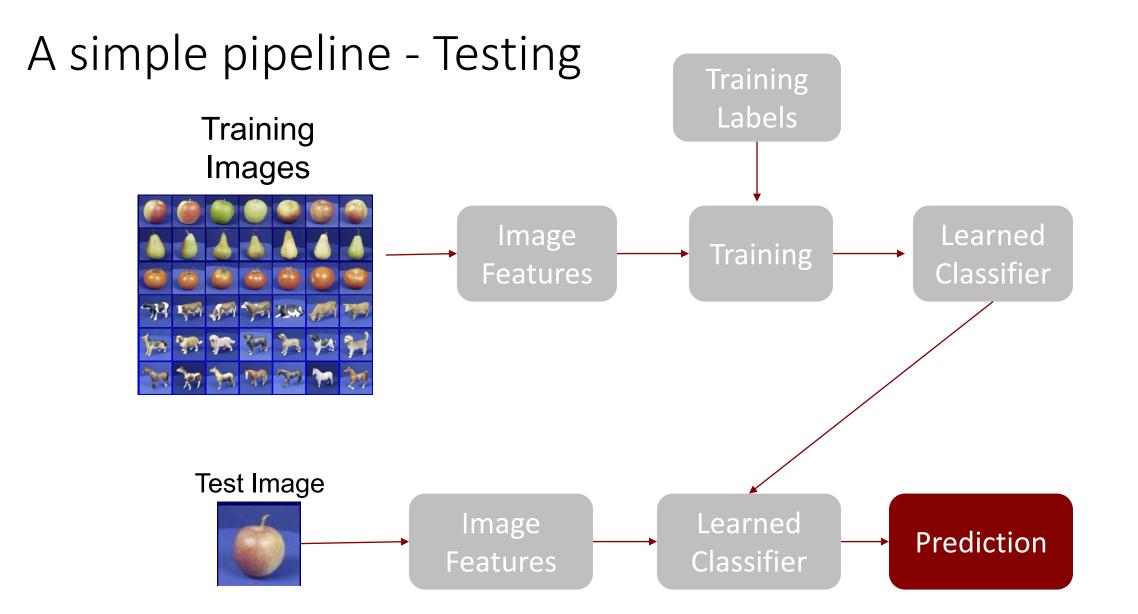


Source: N. Goyal









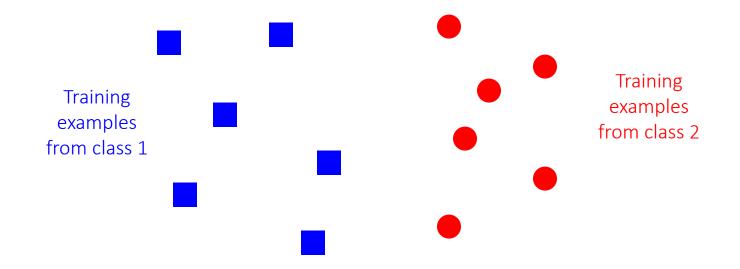








Classifiers: Nearest neighbor



Slide credit: L. Lazebnik

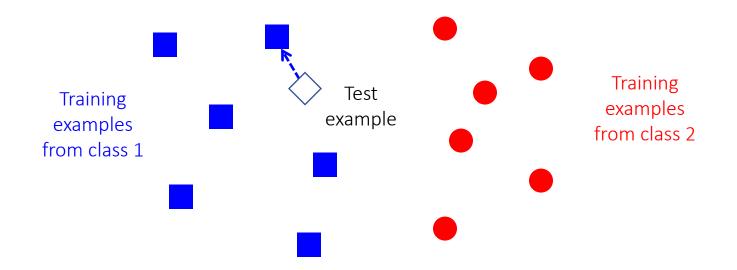








Classifiers: Nearest neighbor



Slide credit: L. Lazebnik









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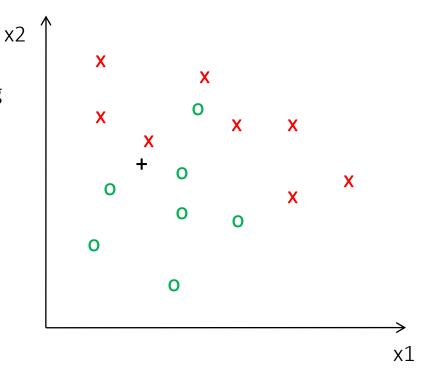






K-nearest neighbor

- Algorithm (training):
- 1. Store all training data points \boldsymbol{x}_i with their corresponding category labels \boldsymbol{y}_i
- Algorithm (testing):
- 1. We are given a new test point $oldsymbol{x}$
- 2. Compute distance to all training data points
- 3. Select k training points closest to \boldsymbol{x}
- 4. Assign \boldsymbol{x} to label \boldsymbol{y} that is most common among the \boldsymbol{k} nearest neighbors.



• Distance measurement: – Euclidean

$$Dist(X^{n}, X^{m}) = \sqrt{\sum_{i=1}^{D} (X_{i}^{n} - X_{i}^{m})^{2}}$$

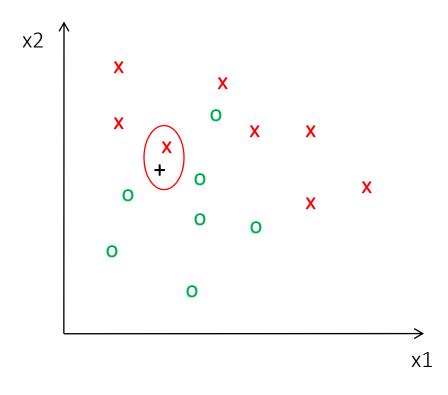
Where Xⁿ and X^m are the n-th and m-th data points







1-nearest neighbor



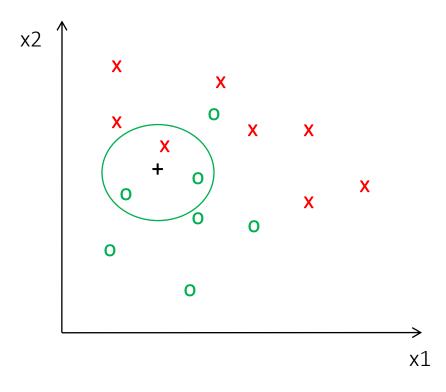








3-nearest neighbor





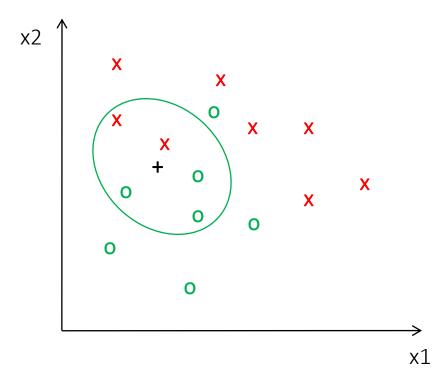








5-nearest neighbor













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K-NN: a very useful algorithm

- Simple, a good one to try first
- Very flexible decision boundaries



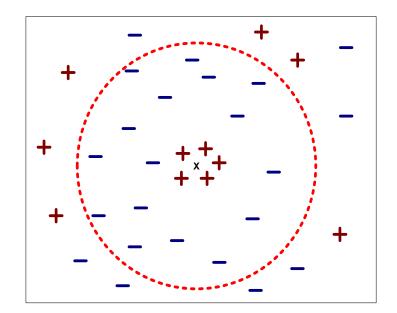






K-NN: issues to keep in mind

- Choosing the value of k:
 - If too small, sensitive to noise points
 - If too large, neighborhood may include points from other classes





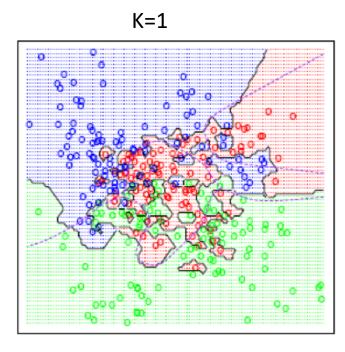


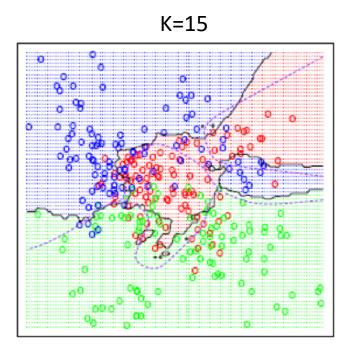




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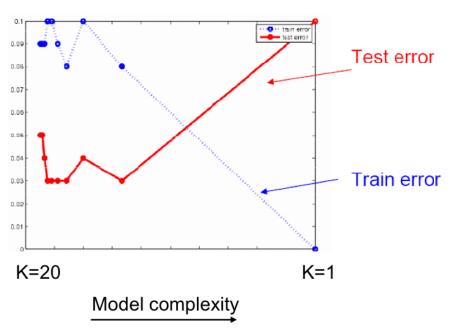






K-NN: issues to keep in mind

- Choosing the value of k:
 - If too small, sensitive to noise points
 - If too large, neighborhood may include points from other classes
 - Solution: cross validate!





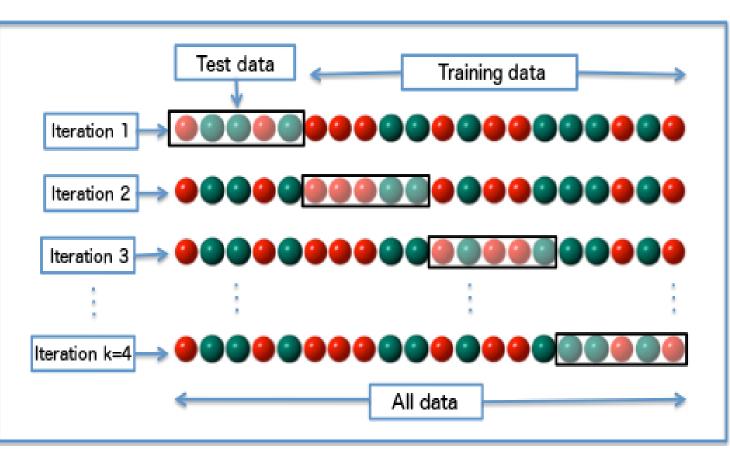






Cross validation

- For each value of *k* in the nearest neighbors algorithm:
- Create multiple train/test splits
 - For each split:
 - Measure performance
- Average performance over all splits
- Select *k* with best average performance









K-NN: issues to keep in mind

- Choosing the value of k:
 - If too small, sensitive to noise points
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 - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)

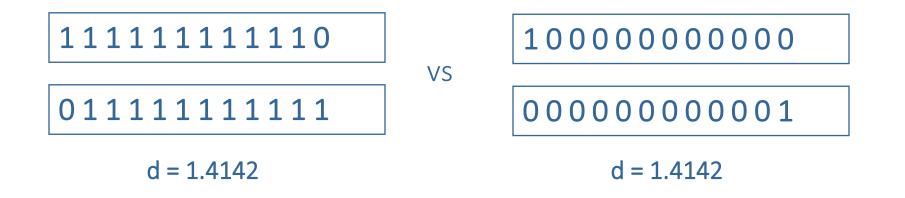








Euclidean measure











K-NN: issues to keep in mind

- Choosing the value of k:
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- Can produce counter-intuitive results (using Euclidean measure)
 - Solution: normalize the vectors to unit length









K-NN: issues to keep in mind

- Choosing the value of k:
 - If too small, sensitive to noise points
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 - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)
 - Solution: normalize the vectors to unit length
- Curse of Dimensionality



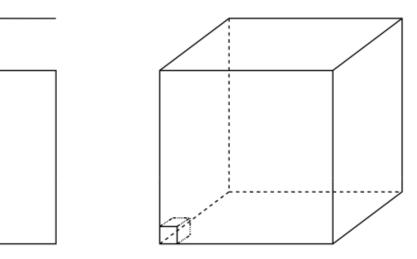






Curse of dimensionality

- Assume 5000 points uniformly distributed in the unit (hyper)cube and we want to apply 5-NN. Suppose our query point is at the origin.
 - In 1-dimension, we must go a distance of 5/5000=0.001 on average to capture 5 nearest neighbors.
 - In 2 dimensions, we must $go\sqrt{0.001}$ to get a square that contains 0.001 of the volume.
 - In d dimensions, we must $go(0.001)^{1/d}$





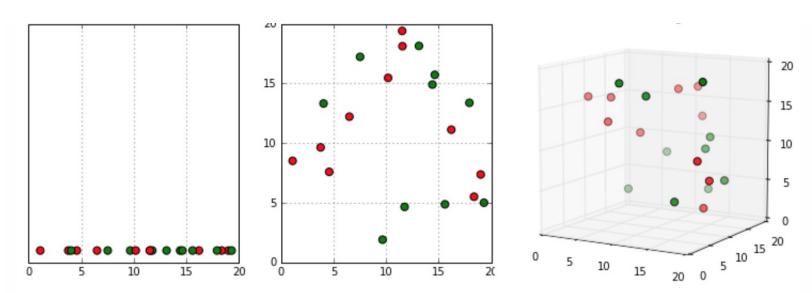






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K-NN: issues to keep in mind

- Choosing the value of k:
 - If too small, sensitive to noise points
 - If too large, neighborhood may include points from other classes
 - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)
 - Solution: normalize the vectors to unit length
- Curse of Dimensionality
 - Solution: no good one need to get more data









Thank you.



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