

Instance-Based Learning

(a.k.a. memory-based learning)

Part I: Nearest Neighbor Classification

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Containing selected slides adapted
from the Andrew Moore tutorial
with the same main title

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1-Nearest-Neighbor Classification

Given: datapoints $(\mathbf{x}_1, y_1) (\mathbf{x}_2, y_2) \dots (\mathbf{x}_N, y_N)$, where each \mathbf{x}_i is an attribute vector and y_i is the corresponding class label, determined according to $y_i = f(\mathbf{x}_i)$ for some unknown function f (possibly corrupted by noise). Given query point \mathbf{x}_q , your job is to predict

$$\hat{y} = \hat{f}(\mathbf{x}_q)$$

Nearest Neighbor Classifier:

Find the closest \mathbf{x}_i in the set of datapoints

$$i(nn) = \arg \min_i d(\mathbf{x}_i, \mathbf{x}_q)$$

where d is some distance metric. Then classify \mathbf{x}_q using

$$\hat{y} = y_{i(nn)}$$

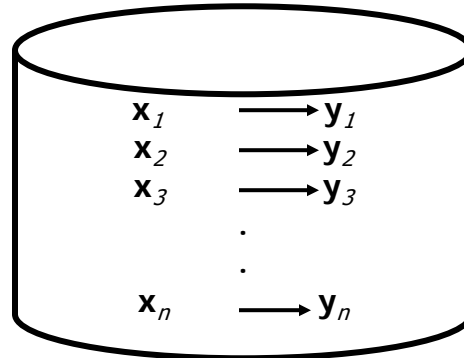
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Instance-based learning I: Slide 2

1-Nearest-Neighbor is an example of... **Instance-based learning**

A classifier and function approximator that has been around since about 1910.

To make a prediction, search database for similar datapoints, and predict based on these nearby points.



Four things make a memory-based learner:

- A distance metric
- How many nearby neighbors to look at?
- A weighting function (optional)
- How to fit with the local points?

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Instance-based learning I: Slide 3

Nearest Neighbor

Four things make a memory based learner:

- 1. A distance metric*
Euclidian or related generalizations
- 2. How many nearby neighbors to look at?*
One
- 3. A weighting function (optional)*
N/A
- 4. How to fit with the local points?*
Just predict the same output as the nearest neighbor

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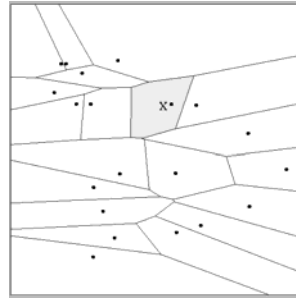
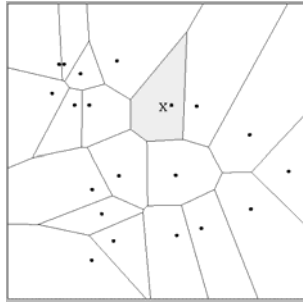
Instance-based learning I: Slide 4

Multivariate Distance Metrics

Suppose the input vectors $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ are two dimensional:

$\mathbf{x}_1 = (x_{11}, x_{12}), \mathbf{x}_2 = (x_{21}, x_{22}), \dots, \mathbf{x}_N = (x_{N1}, x_{N2})$.

One can draw the nearest-neighbor regions in input space.



$$d^2(\mathbf{x}_i, \mathbf{x}_j) = (x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2$$

$$d^2(\mathbf{x}_i, \mathbf{x}_j) = (x_{i1} - x_{j1})^2 + (3x_{i2} - 3x_{j2})^2$$

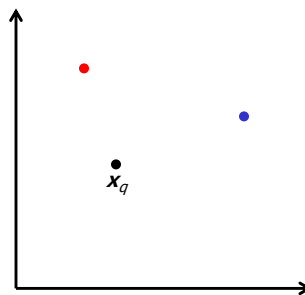
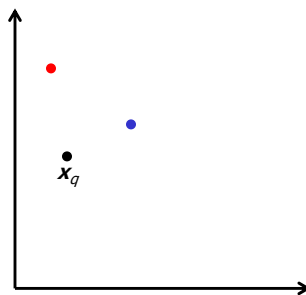
The relative scalings in the distance metric affect region shapes.

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Effect of Axis Scaling

Which data point is closer to the query point?



Horizontal axis rescaled by a factor of 2

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Euclidean Distance Metric

Or equivalently,

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

where

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_N^2 \end{bmatrix}$$

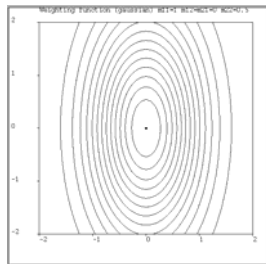
Other Metrics...

- Mahalanobis, Rank-based, Correlation-based
(Stanfill+Waltz, Maes' Ringo system...)

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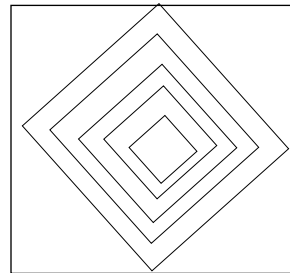
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Notable Distance Metrics

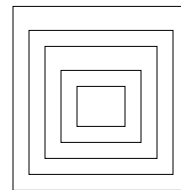


Scaled Euclidean (L_2)

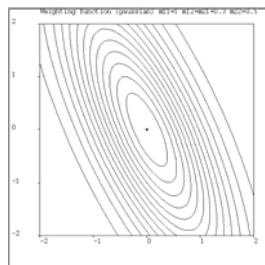
L_1 norm (absolute)



L_{∞} (max) norm



Mahalanobis
(here, Σ on the previous
slide is not necessarily
diagonal, but is symmetric)



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Distance Metric: Things to Worry about

- In practice, should at least rescale every axis to have approximately the same range
 - Gives every feature more nearly equal weight
 - Can use cross-validation to fine-tune axis weightings or other metric parameters
- But try to eliminate irrelevant features
 - Many irrelevant features could dominate the distance measure and create a bad classifier
 - Cross-validation can be very helpful with this

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What about noise?

- If each data point has a noisy class label, what would be better than using only the single nearest neighbor? ...

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k-Nearest Neighbor

Four things make a memory based learner:

1. *A distance metric*
Euclidian or related generalizations
2. *How many nearby neighbors to look at?*
k
3. *A weighting function (optional)*
N/A
4. *How to fit with the local points?*
Just take the majority vote among the k nearest neighbors

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Weighted Nearest Neighbor Classifier

Four things make a memory based learner:

1. *A distance metric*
Euclidian
2. *How many nearby neighbors to look at?*
Potentially all of them
3. *A weighting function (optional)*
Nearby points to the query are weighted strongly, far points weakly.
4. *How to fit with the local points?*
Give each point a vote based on this weighting function. Classify according to this vote.

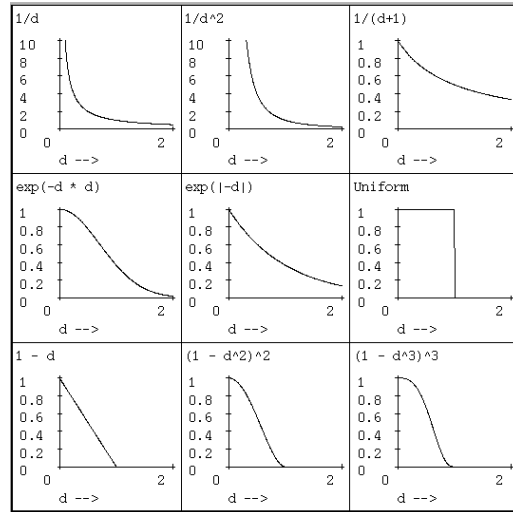
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Weighting functions

Let $d = d(x_i, x_{query})$

Then here are some commonly used weighting functions...



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Categorical Attributes

- If attribute $x[j]$ can take on one of several discrete values v_1, v_2, \dots, v_k (and there is no reason to consider some pairs of these values as being "closer" than some other pairs), then a sensible interpretation of

$$x_i[j] - x_q[j]$$

in the distance computation is

$$0 \text{ if } x_i[j] = x_q[j] \text{ or}$$

$$1 \text{ if } x_i[j] \neq x_q[j]$$

- This has a similar effect as when a 1-out-of-k encoding is used for input to a neural network

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