# Instance Based Learning

[Read Ch. 8]

- $k$-Nearest Neighbor
- Locally weighted regression
- Radial basis functions
- Case-based reasoning
- Lazy and eager learning

# Instance-Based Learning

Key idea: just store all training examples $\langle x_i, f(x_i) \rangle$

Nearest neighbor:

- Given query instance $x_q$, first locate nearest training example $x_n$, then estimate $\hat{f}(x_q) \leftarrow f(x_n)$

$k$-Nearest neighbor:

- Given $x_q$, take vote among its $k$ nearest nbrs (if discrete-valued target function)
- take mean of $f$ values of $k$ nearest nbrs (if real-valued)

$$\hat{f}(x_q) \leftarrow \frac{\sum_{i=1}^{k} f(x_i)}{k}$$

# When To Consider Nearest Neighbor

- Instances map to points in $\Re^n$
- Less than 20 attributes per instance
- Lots of training data

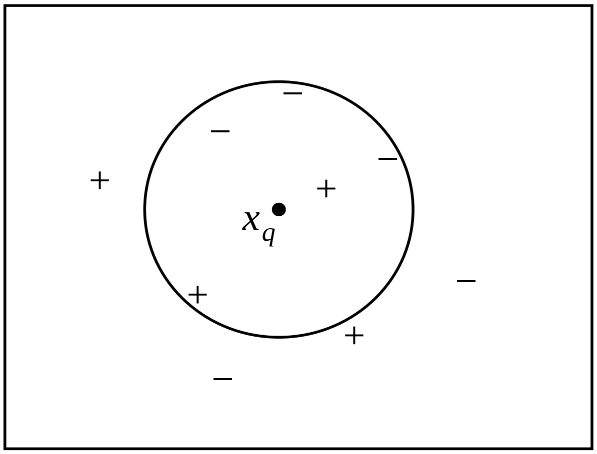
Advantages:

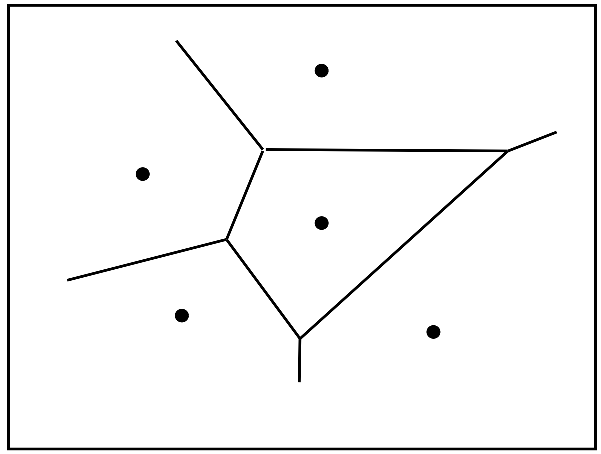
- Training is very fast
- Learn complex target functions
- Don't lose information

Disadvantages:

- Slow at query time
- Easily fooled by irrelevant attributes

# Voronoi Diagram



# Behavior in the Limit

Consider $p(x)$ defines probability that instance $x$ will be labeled 1 (positive) versus 0 (negative).

Nearest neighbor:

- As number of training examples $\rightarrow \infty$, approaches Gibbs Algorithm

  Gibbs: with probability $p(x)$ predict 1, else 0

$k$-Nearest neighbor:

- As number of training examples $\rightarrow \infty$ and $k$ gets large, approaches Bayes optimal

  Bayes optimal: if $p(x) > .5$ then predict 1, else 0

Note Gibbs has at most twice the expected error of Bayes optimal

# Distance-Weighted $k$NN

Might want weight nearer neighbors more heavily...

$$\hat{f}(x_q) \leftarrow \frac{\Sigma_{i=1}^{k} w_i f(x_i)}{\Sigma_{i=1}^{k} w_i}$$

where

$$w_i \equiv \frac{1}{d(x_q, x_i)^2}$$

and $d(x_q, x_i)$ is distance between $x_q$ and $x_i$

Note now it makes sense to use *all* training examples instead of just $k$

$\rightarrow$ Shepard's method

# Curse of Dimensionality

Imagine instances described by 20 attributes, but only 2 are relevant to target function

*Curse of dimensionality*: nearest nbr is easily mislead when high-dimensional $X$

One approach:

- Stretch $j$th axis by weight $z_j$, where $z_1, \ldots, z_n$ chosen to minimize prediction error
- Use cross-validation to automatically choose weights $z_1, \ldots, z_n$
- Note setting $z_j$ to zero eliminates this dimension altogether

see [Moore and Lee, 1994]

# Locally Weighted Regression

Note $k$NN forms local approximation to $f$ for each query point $x_q$

Why not form an explicit approximation $\hat{f}(x)$ for region surrounding $x_q$

- Fit linear function to $k$ nearest neighbors
- Fit quadratic, ...
- Produces "piecewise approximation" to $f$

Several choices of error to minimize:

- Squared error over $k$ nearest neighbors

$$E_1(x_q) \equiv \frac{1}{2} \sum_{x \in \ k \ nearest \ nbrs \ of \ x_q} (f(x) - \hat{f}(x))^2$$

- Distance-weighted squared error over all nbrs

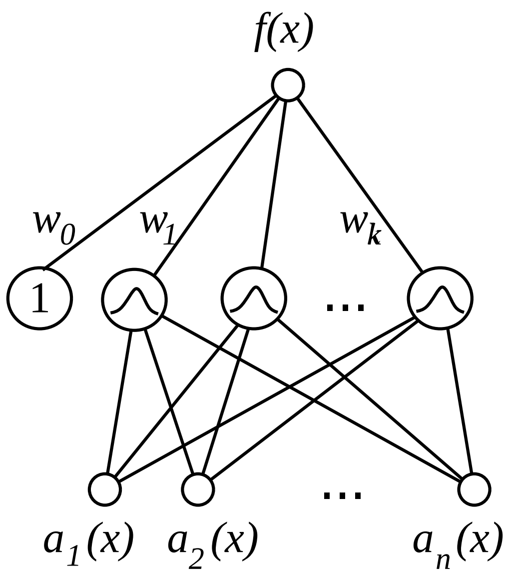
$$E_2(x_q) \equiv \frac{1}{2} \sum_{x \in D} (f(x) - \hat{f}(x))^2 \ K(d(x_q, x))$$

- ...

# Radial Basis Function Networks

- Global approximation to target function, in terms of linear combination of local approximations
- Used, e.g., for image classification
- A different kind of neural network
- Closely related to distance-weighted regression, but "eager" instead of "lazy"

# Radial Basis Function Networks




where $a_i(x)$ are the attributes describing instance $x$, and

$$f(x) = w_0 + \sum_{u=1}^{k} w_u K_u(d(x_u, x))$$

One common choice for $K_u(d(x_u, x))$ is

$$K_u(d(x_u, x)) = e^{-\frac{1}{2\sigma_u^2} d^2(x_u, x)}$$

# Training Radial Basis Function Networks

Q1: What $x_u$ to use for each kernel function $K_u(d(x_u, x))$

- Scatter uniformly throughout instance space
- Or use training instances (reflects instance distribution)

Q2: How to train weights (assume here Gaussian $K_u$)

- First choose variance (and perhaps mean) for each $K_u$
  - e.g., use EM
- Then hold $K_u$ fixed, and train linear output layer
  - efficient methods to fit linear function

# Case-Based Reasoning

Can apply instance-based learning even when $X \neq \Re^n$

$\rightarrow$ need different "distance" metric

Case-Based Reasoning is instance-based learning applied to instances with symbolic logic descriptions

```
((user-complaint error53-on-shutdown)
 (cpu-model PowerPC)
 (operating-system Windows)
 (network-connection PCIA)
 (memory 48meg)
 (installed-applications Excel Netscape VirusScan)
 (disk 1gig)
 (likely-cause ???))
```

# Case-Based Reasoning in CADET

CADET: 75 stored examples of mechanical devices

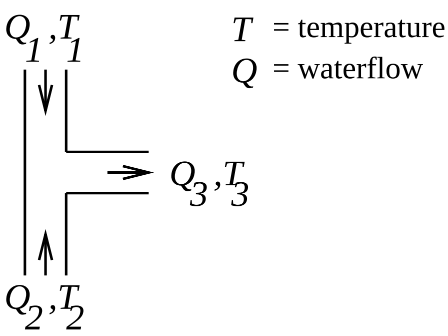
- each training example: $\langle$ qualitative function, mechanical structure$\rangle$
- new query: desired function,
- target value: mechanical structure for this function

Distance metric: match qualitative function descriptions

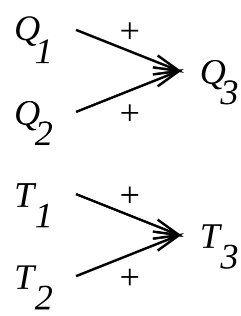
# Case-Based Reasoning in CADET

**A stored case:** T−junction pipe

Structure:




Function:

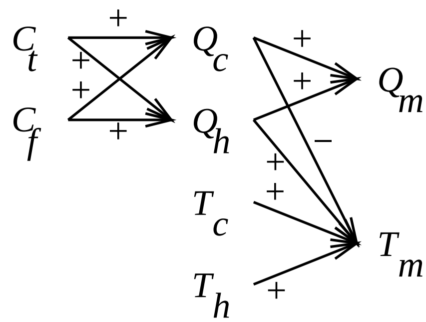



**A problem specification:** Water faucet

Structure:

?

Function:



# Case-Based Reasoning in CADET

- Instances represented by rich structural descriptions
- Multiple cases retrieved (and combined) to form solution to new problem
- Tight coupling between case retrieval and problem solving

Bottom line:

- Simple matching of cases useful for tasks such as answering help-desk queries
- Area of ongoing research

# Lazy and Eager Learning

Lazy: wait for query before generalizing

- $k$-Nearest Neighbor, Case based reasoning

Eager: generalize before seeing query

- Radial basis function networks, ID3, Backpropagation, NaiveBayes, ...

Does it matter?

- Eager learner must create global approximation
- Lazy learner can create many local approximations
- if they use same $H$, lazy can represent more complex fns (e.g., consider $H =$ linear functions)