Instance-Based Learning

CS472/CS473 – Fall 2005

What is Learning?

- **Examples**
  - Riding a bike (motor skills)
  - Telephone number (memorizing)
  - Read textbook (memorizing and operationalizing rules)
  - Playing backgammon (strategy)
  - Develop scientific theory (abstraction)
  - Language
  - Recognize fraudulent credit card transactions
  - Etc.

(One) Definition of Learning

Definition [Mitchell]:

A computer program is said to learn from

- experience E with respect to some class of
- tasks T and
- performance measure P,

if its performance at tasks in T, as measured by P, improves with experience E.

Examples

- **Spam Filtering**
  - T: Classify emails HAM / SPAM
  - E: Examples (e_1,HAM),(e_2,SPAM),(e_3,HAM),(e_4,SPAM), ...
  - P: Prob. of error on new emails
- **Personalized Retrieval**
  - T: find documents the user wants for query
  - E: watch person use Google (queries / clicks)
  - P: # relevant docs in top 10
- **Play Checkers**
  - T: Play checkers
  - E: games against self
  - P: percentage wins

How can an Agent Learn?

Learning strategies and settings

- rote learning
- learning from instruction
- learning by analogy
- learning from observation and discovery
- learning from examples

–Carbonell, Michalski & Mitchell.

Inductive Learning / Concept Learning

- **Task:**
  - Learn (to imitate) a function f: X → Y
- **Training Examples:**
  - Learning algorithm is given the correct value of the function for particular inputs → **training examples**
  - An **example** is a pair (x, $f(x)$), where x is the input and $f(x)$ is the output of the function applied to x.
- **Goal:**
  - Learn a function h: X → Y that approximates f: X → Y as well as possible.

Concept Learning Example

Food (3)	Chat (2)	Fast (2)	Price (3)	Bar (2)	BigTip
great	yes	yes	normal	no	yes
great	no	yes	normal	no	yes
mediocre	yes	no	high	no	no
great	yes	yes	normal	yes	yes

Instance Space X: Set of all possible objects described by attributes (often called features).

Target Function f: Mapping from Attributes to Target Feature (often called label) (f is unknown)

Hypothesis Space H: Set of all classification rules h_i we allow.

Training Data D: Set of instances labeled with Target Feature

Classification and Regression Tasks

Naming:

If Y is a the real numbers, then called "regression".
If Y is a discrete set, then called "classification".

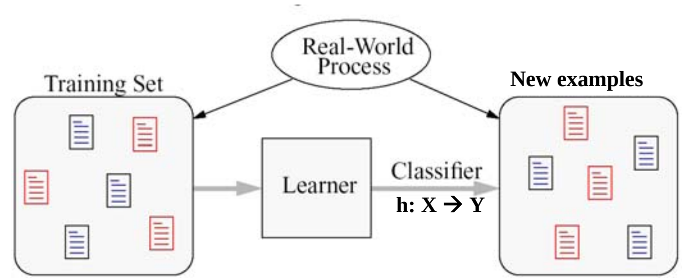
Examples:

- **Steering a vehicle:** image in windshield → direction to turn the wheel (how far)
- **Medical diagnosis:** patient symptoms → has disease / does not have disease
- **Forensic hair comparison:** image of two hairs → match or not
- **Stock market prediction:** closing price of last few days → market will go up or down tomorrow (how much)
- **Noun phrase coreference:** description of two noun phrases in a document → do they refer to the same real world entity

Inductive Learning Algorithm

- **Task:**
  - Given: collection of examples
  - Return: a function *h* (*hypothesis*) that approximates *f*
- **Inductive Learning Hypothesis:**
  Any hypothesis found to approximate the target function well over a sufficiently large set of training examples will also approximate the target function well over any other unobserved examples.
- **Assumptions of Inductive Learning:**
  - The training sample represents the population
  - The input features permit discrimination

Inductive Learning Setting



Task:

- Learner induces a general rule h from a set of observed examples that classifies new examples accurately.

Instance-Based Learning

- **Idea:**
  - Similar examples have similar label.
  - Classify new examples like similar training examples.
- **Algorithm:**
  - Given some new example x for which we need to predict its class y
  - Find most similar training examples
  - Classify *x* "like" these most similar examples
- **Questions:**
  - How to determine similarity?
  - How many similar training examples to consider?
  - How to resolve inconsistencies among the training examples?

K-Nearest Neighbor (KNN)

- **Given: Training data $(\vec{x}_1, y_1), \ldots, (\vec{x}_n, y_n)$**
  - Attribute vectors: $\vec{x}_i \in X$
  - Target attribute: $y_i \in \{-1, +1\}$
- **Parameter:**
  - Similarity function: $K : X \times X \longrightarrow \Re$
  - Number of nearest neighbors to consider: *k*
- **Prediction rule**
  - New example *x'*
  - K-nearest neighbors: *k* training examples with smallest $K(\vec{x}_i, \vec{x}')$

$$h(\vec{x}') = \arg\max_{y \in Y} \left\{ \sum_{i \in knn(\vec{x}')} 1_{[y_i = y]} \right\}$$

KNN Example

	Food (3)	Chat (2)	Fast (2)	Price (3)	Bar (2)	BigTip
1	great	yes	yes	normal	no	yes
2	great	no	yes	normal	no	yes
3	mediocre	yes	no	high	no	no
4	great	yes	yes	normal	yes	yes

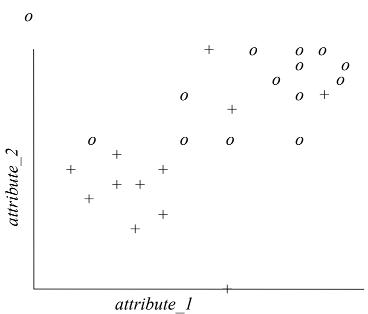
- **New examples:**
  - (great, no, no, normal, no)
  - (mediocre, yes, no, normal, no)

Types of Attributes

- **Symbolic (nominal)**
  - *EyeColor {brown, blue, green}*
- **Boolean**
  - *anemic {TRUE,FALSE}*
- **Numeric**
  - Integer: *age* [0, 105]
  - Real: *length*
- **Structural**
  - Natural language sentence: parse tree
  - Protein: sequence of amino acids

KNN for Real-Valued Attributes

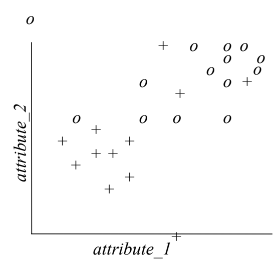
- **Similarity Functions:**
  - Gaussian: $K(\vec{x}_i,\vec{x}') \sim e^{-(\vec{x}_i-\vec{x}')^2}$
  - Cosine: $K(\vec{x}_i,\vec{x}') = cos(\vec{x}_i,\vec{x}')$



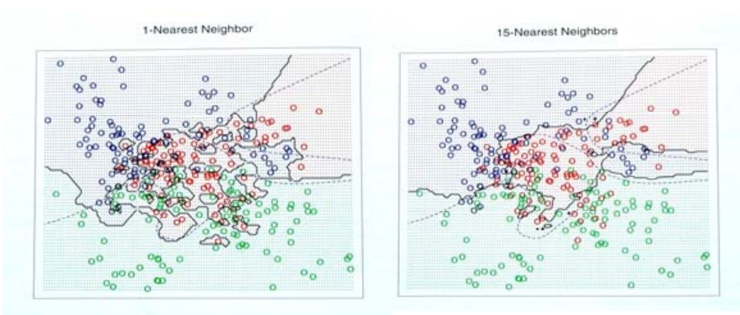
Selecting the Number of Neighbors

- **Increase k:**
  - Makes KNN less sensitive to noise
- **Decrease k:**
  - Allows capturing finer structure of space

➔**Pick k not too large, but not too small (depends on data)**



Example: Effect of k



Hastie, Tibshirani, Friedman 2001

Advantages and Disadvantages of KNN

- **Simple algorithm**
- **Need similarity measure and attributes that “match” target function.**
- **For large training sets, requires large memory is slow when making a prediction.**
- **Prediction accuracy can quickly degrade when number of attributes grows.**

Curse-of-Dimensionality

- **Prediction accuracy can quickly degrade when number of attributes grows.**
  - Irrelevant attributes easily “swamp” information from relevant attributes

$$K(\vec{x}_i, \vec{x}') \sim e^{-\left(\sum_{j \in A_{rel}} (\vec{x}_i[j] - \vec{x}'[j])^2 + \sum_{j \in A_{irrel}} (\vec{x}_i[j] - \vec{x}'[j])^2\right)}$$

  ➔ When many irrelevant attributes, similarity measure becomes less reliable
- **Remedy**
  - Try to remove irrelevant attributes in pre-processing step
  - Weight attributes differently
  - Increase k (but not too much)

Remarks on KNN

- **Memorizes all observed instances and their class**
- **Is this rote learning?**
- **Is this really learning?**
- **When does the induction take place?**