Learning

Schedule

- Search
- Machine learning
- Knowledge based systems
- Discovery

From last lecture

Function Approximation

- Problem:
  - Storing Q or U,T,R for each state in a table is too expensive, if number of states is large
  - Does not exploit "similarity" of states (i.e. agent has to learn separate behavior for each state, even if states are similar)
- Solution:
  - Approximate function using parametric representation $U(s) = \vec{w} \cdot \Phi(s)$
  - For example:
    - Φ(s) is feature vector describing the state
      - "Material values" of board
      - Is the queen threatened?
      - …

Bonus: Can predict utilities in areas it has never been to…

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 (memorization, like RL)
- learning from instruction (being told)
- learning by analogy (from known to new, adaptation)
- learning from examples (inductive)
- learning from observation and discovery (unsupervised)

— 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.

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

Will the following situation yield a big tip?

Food=great chat=no fast=yes price=high bar=no

A=Yes B=No

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

Challenge

- Design a Fashion advisor: Looks at your online store options and helps you decide

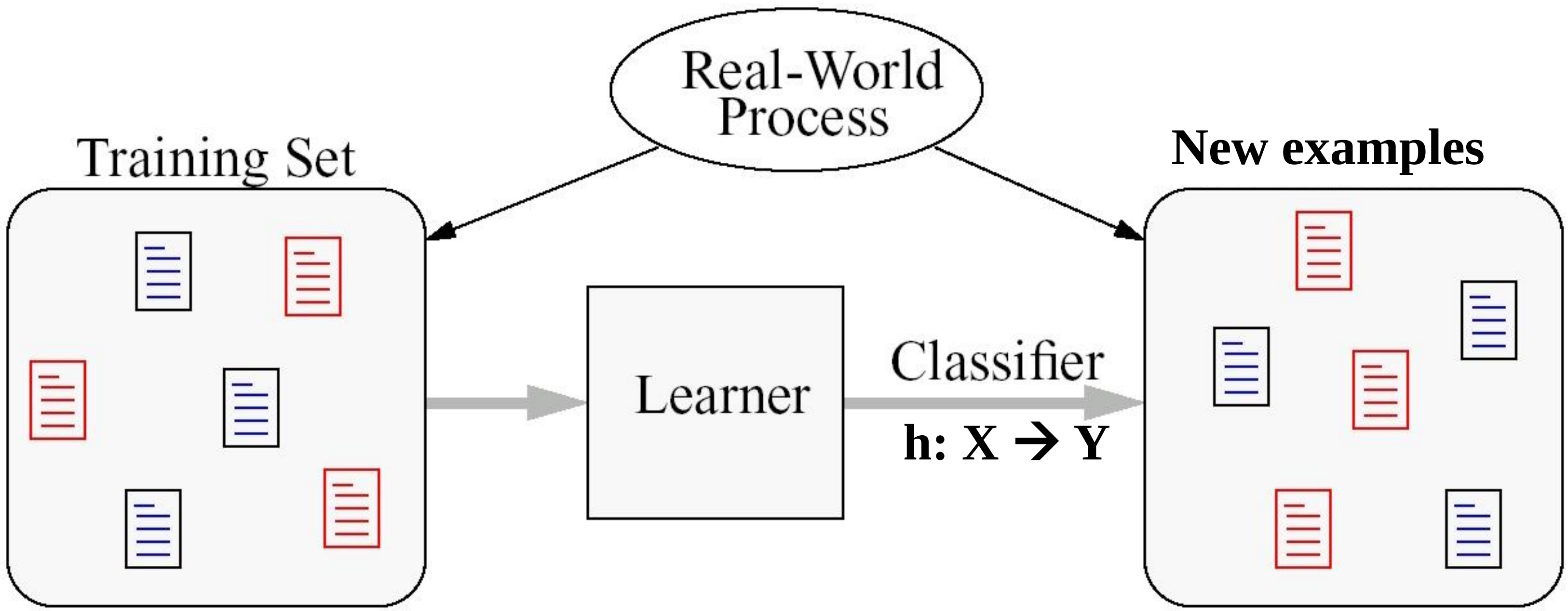
Challenge 2

- Backseat driver: Watches your driving and "helps"

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 largest $K(\vec{x}_i, \vec{x}')$

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

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) 21
  - (mediocre, yes, no, normal, no) 31

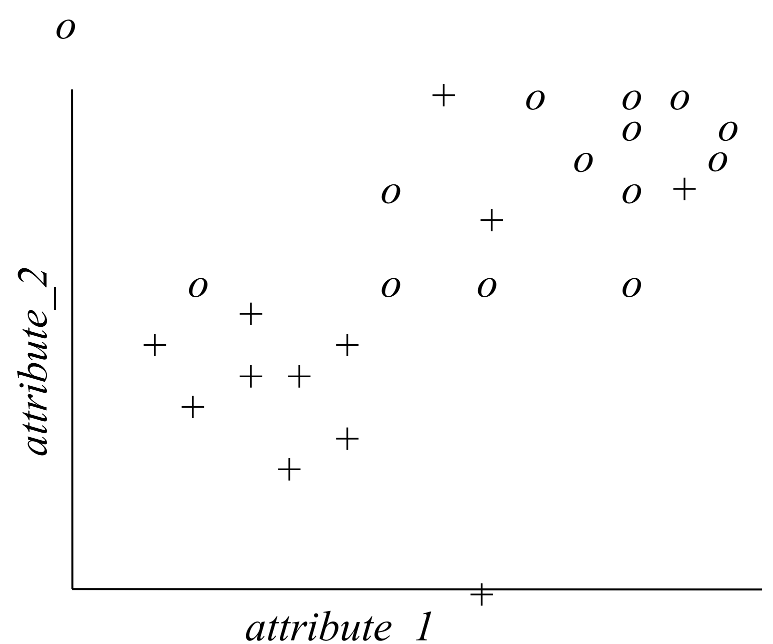
A = YES B = NO

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
    - Edit distance

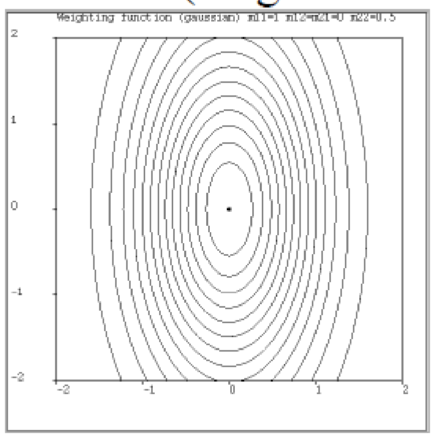
KNN for Real-Valued Attributes

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

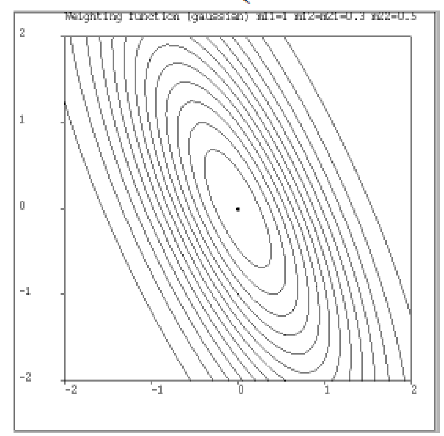


Other distance metrics

Scaled Euclidean (diagonal covariance)

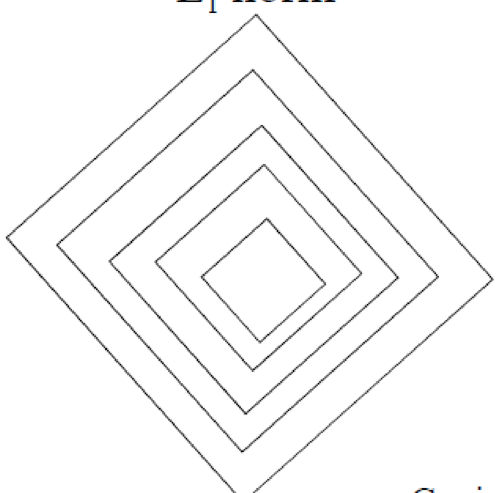


Mahalanobis (full covariance)

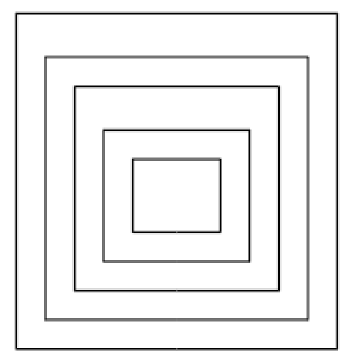


PCA

L_1 norm



L_∞(max) norm



Copied from Andrew Moore

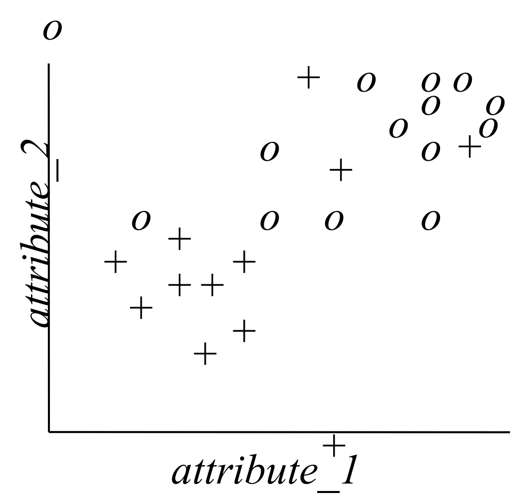
Computing answers from samples

- Classification
  - Majority vote
- Regression
  - Weighted sum
  - Local hyper-plane fit

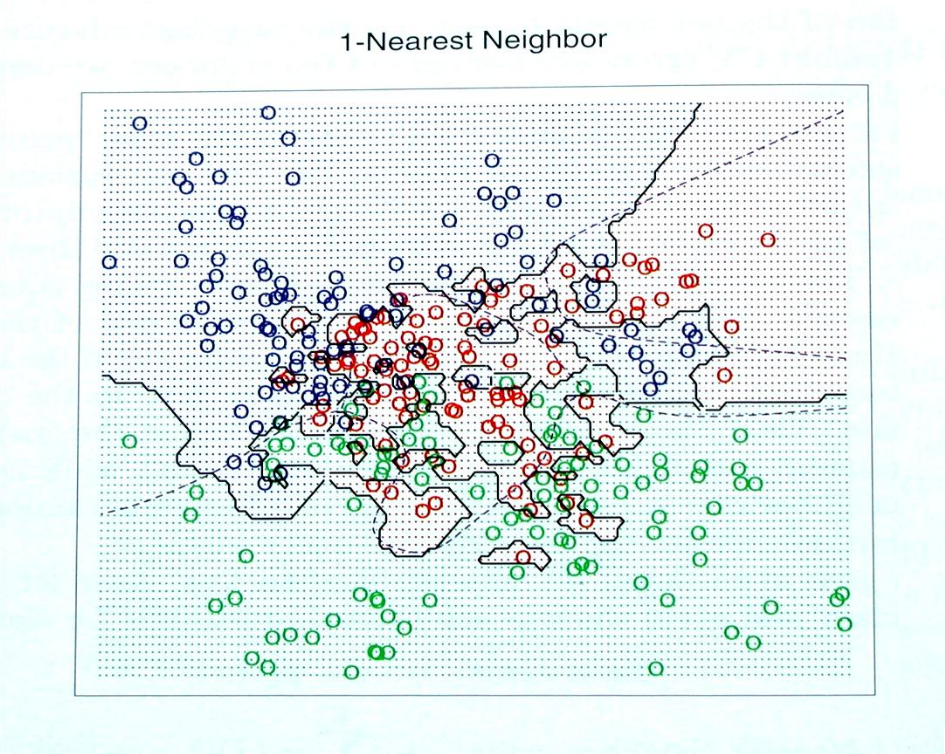
Selecting the Number of Neighbors

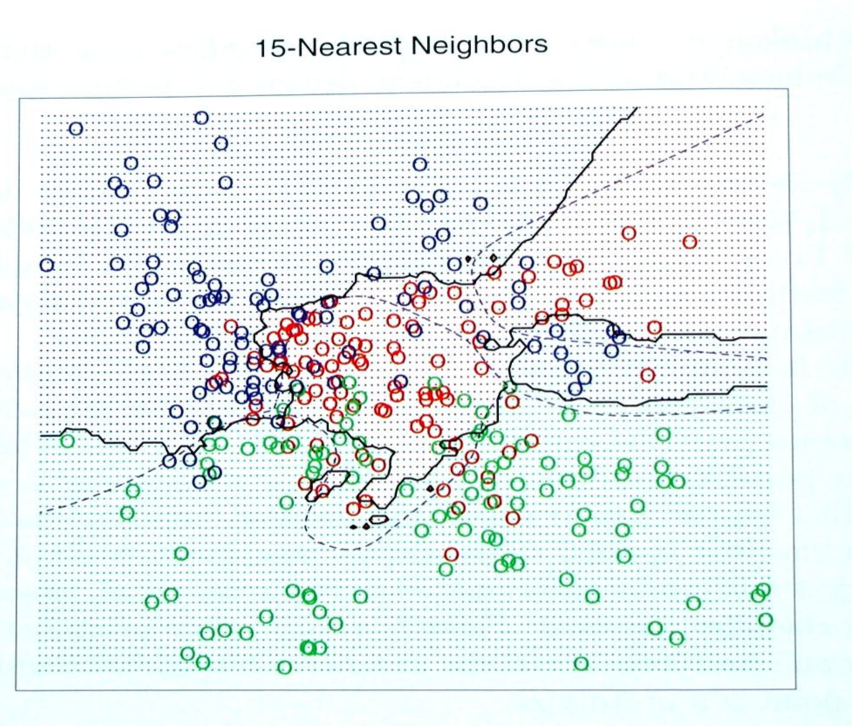
- Increase k:
  - Makes KNN less sensitive to noise
- Decrease k:
  - Allows capturing finer structure of space

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

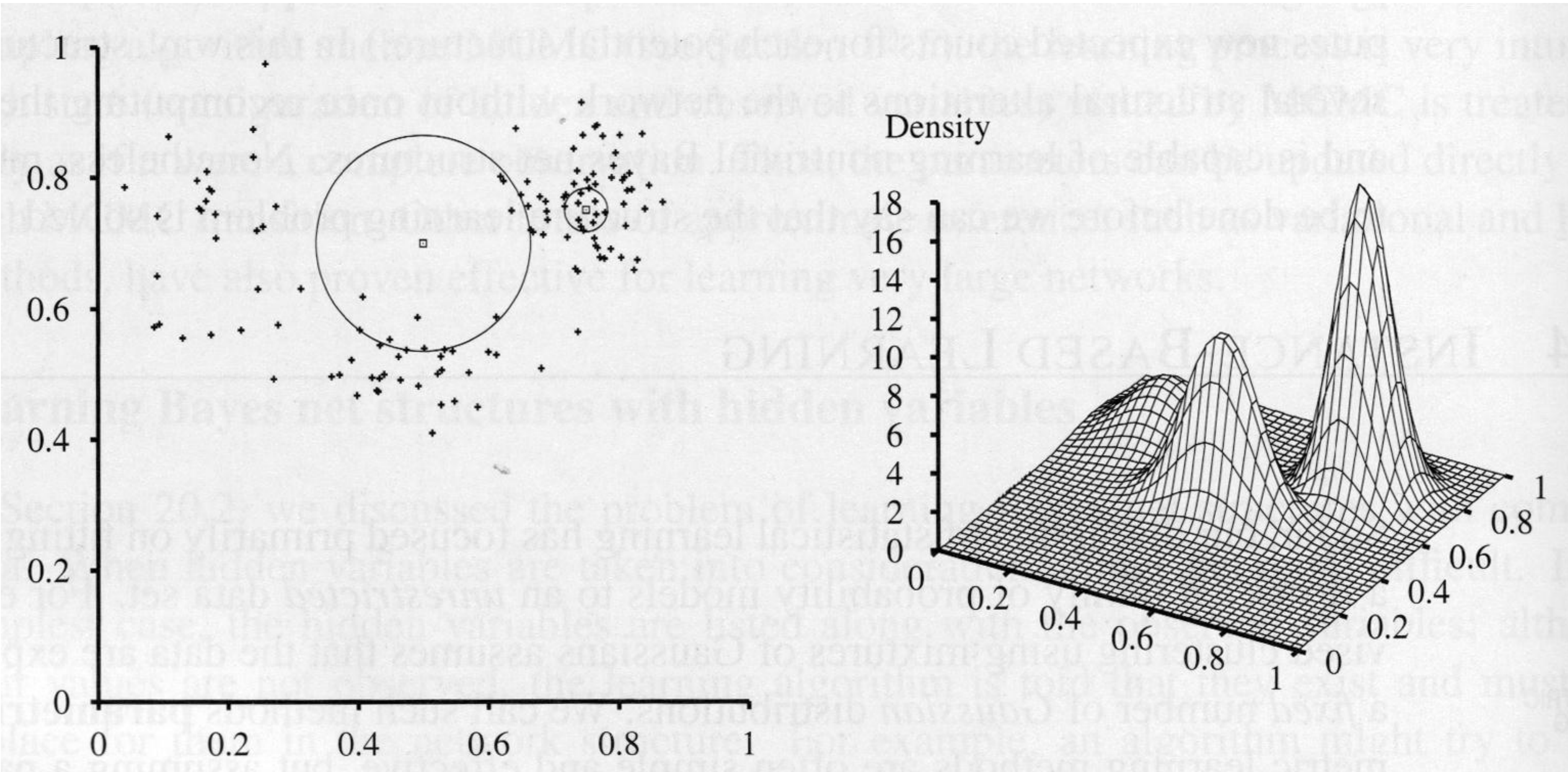


Example: Effect of k

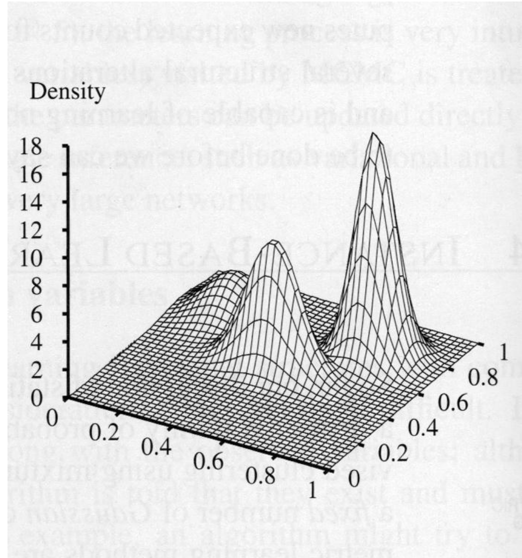


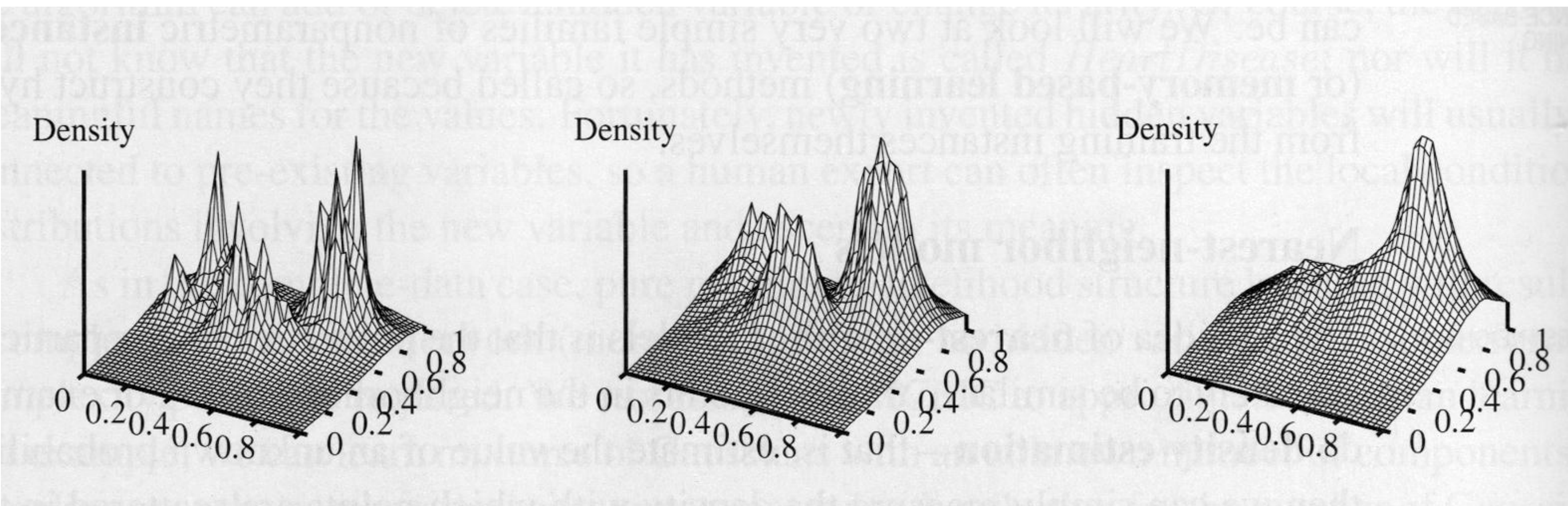


Hastie, Tibshirani, Friedman 2001



128 samples with 10-neighborhoods on two query points,
and the Gaussian distribution that generated the samples





Estimation of density using k = 3, 10 40

Cross Validation

- Train with 80% of data, test on remaining 20%
  - Repeat 5 times with other subsets
  - Can be different ratios
- Try for different k's, choose best

Curse-of-Dimensionality

- Dataset size N in d-dimensional space (d attributes) in unit cube
- Looking for hypercubic neighborhood of size b^d to contain k neighbors
  - $B^d = k/N \rightarrow b = (k/N)^{1/d}$
  - d=100, k=10, N=1,000,000 → b=0.89
  - d=2, k=10, N=1,000,000 → b=0.003

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

Curse-of-Dimensionality

- Remedy
  - Try to remove irrelevant attributes in pre-processing step
  - Weight attributes differently
- **How can we use Cross-validation to do this?**

Performance

- Need to search through all points
  - *O(n)* per query
- How can we improve?
  - Hierarchical access
  - Random subsampling
  - Thin data: Remove duplicate points

What about Uncertainty?

- Confidence is an important factor in learning
  - How can we estimate uncertainty in our answer?
- Classification
  - Voting balance levels
- Regression
  - Linear fit error
- General
  - Compare results from subsets of data

Advantages and Disadvantages of KNN

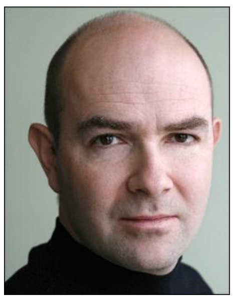
- Simple algorithm
- Need similarity measure and attributes that "match" target function.
- For large training sets, requires large memory
- Is slow when making a prediction.
- Prediction accuracy can quickly degrade when number of attributes grows.

Remarks on KNN

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

“The End of Science”

Wired July 16, 2008



Chris Anderson

WIRED

“Correlation is enough. Faced with massive data, [the Scientific Method] is becoming obsolete. We can stop looking for models.”