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Week 7

Course. Introduction to Machine Learning

Theory 7. Lazy learning

Dr. Maria Salamó Llorente
maria.salamo@ub.edu
Dept. Mathematics and Informatics,
Faculty of Mathematics and Informatics,
University of Barcelona (UB)

Introduction to Machine Learning

Unsupervised Learning			Supervised Learning					Decision Learning Theory
Cluster Analysis	Factor Analysis	Visualization	Non Linear Decision				Linear Decision	Basic concepts of Decision Learning Theory
K-Means, Fuzzy C-means, EM	PCA, ICA	Self Organized Maps (SOM) , Multi-Dimensional Scaling	Lazy Learning (K-NN, IBL, CBR)	Overfitting, model selection and feature selection	Kernel Learning	Ensemble Learning (Trees, Adaboost)	Perceptron, SVM	Bias/Variance, VC dimension, Practical advice of how to use learning algorithms

Contents

Introduction to Lazy Learning

Definition: lazy learning

- The computation undertaken by a learning system can be viewed as occurring at two distinct times:
  - **Training time**: Is the time prior to consultation during which the system makes inferences from training data in preparation for consultation time
  - **Consultation time**: Consultation time is the time between when an object is presented to a system for an inference to be made and the time when the inference is completed
- **LAZY LEARNING** refers to any machine learning process that defers the majority of computation to consultation time
  - Lazy learning stands in contrast to eager learning in which the majority of computation occurs at training time

Introduction to lazy learning

- **Lazy learning** delays **generalization** until a query is made to the system

- **Generalization Performance** of a learning algorithm refers to the performance on out-of-simple data of the models learned by the algorithm
  - Out-of-sample data are data that were not used to learn a model

Introduction to lazy learning

- **Advantages**:
  - The target function is approximated locally
  - It can simultaneously solve multiple problems
  - It deals successfully with changes in the problem domain
  - Suitable for complex and incomplete problem domains

- **Disadvantages**:
  - It requires a large space to store the entire training
  - It may be slow for solving a problem but it has a fast training

Lazy and Eager Learning

- Lazy: wait for query before generalizing
  - k-Nearest Neighbour, Case-Based Reasoning, …
- Eager: generalize before seeing query
  - Radial Basis Function Networks, ANN, ID3, …
- Does it matter?
  - Eager learner must create global approximation
  - Lazy learner can create many local approximations
  - Lazy learner can represent more complex functions

Lazy learning approaches

In this lesson we will learn about:

- Nearest Neighbour
- Instance-based learning
- Case-based reasoning

{case, exemplar, instance, memory}
-based-
{learning, reasoning}

Nearest Neighbor

(NN)

Nearest Neighbor

Definition

- In a data collection *M*, the *nearest neighbor* to a data object *q* is the data object M_i, which minimizes *dist(q,* M_i*)*,
  - where *dist* is a *distance measure* defined for the objects in question
  - note that the fact that the object M_i is the nearest neighbor to *q* does not imply that q is the nearest neighbor to M_i

Nearest Neighbour classifier

Basic idea:

1. Get some example set of cases with known outputs
   - E.g. Diagnoses of infectuous diseases by experts
2. When you see a new case, assign its output to be the same as the most similar known case
   - Your symptoms most resemble Mr. X
   - Mr. X had a flu
   - Ergo you have the flu

General learning task

- There is a set of possible examples, $X = \{x_i\}$
- Each example is an n-tuple of attribute values, $\vec{x}_1 = <a_1, ..., a_k>$
- There is a target function that maps X onto set Y, f: X➔Y
- The data is a set of duples <example, target function values>

$$D = \{< \vec{x}_1, f(\vec{x}_1) >, ... < \vec{x}_m, f(\vec{x}_m) >\}$$

- Find a hypothesis h such that

$$\forall \vec{x}, h(\vec{x}) \approx f(\vec{x})$$

Nearest neighbour

- Task: Given some set of training data

$$D = \{< \vec{x}_1, f(\vec{x}_1) >, \ldots < \vec{x}_m, f(\vec{x}_m) >\}$$

and a query point $\vec{x}_q$, predict $f(\vec{x}_q)$

distance function

1. Find the nearest member of the data set to the query

$$\vec{x}_{nn} = \arg\min_{x \in D}(d(\vec{x}, \vec{x}_q))$$

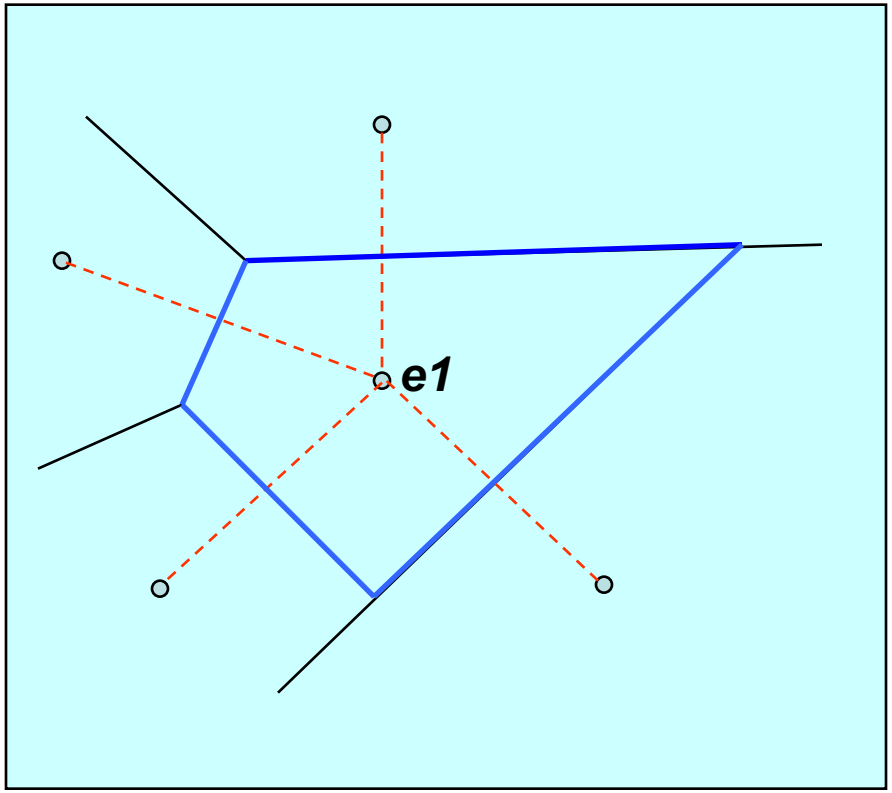
2. Assign the nearest neighbour output to the query

$$h(\vec{x}_q) = f(\vec{x}_{nn})$$

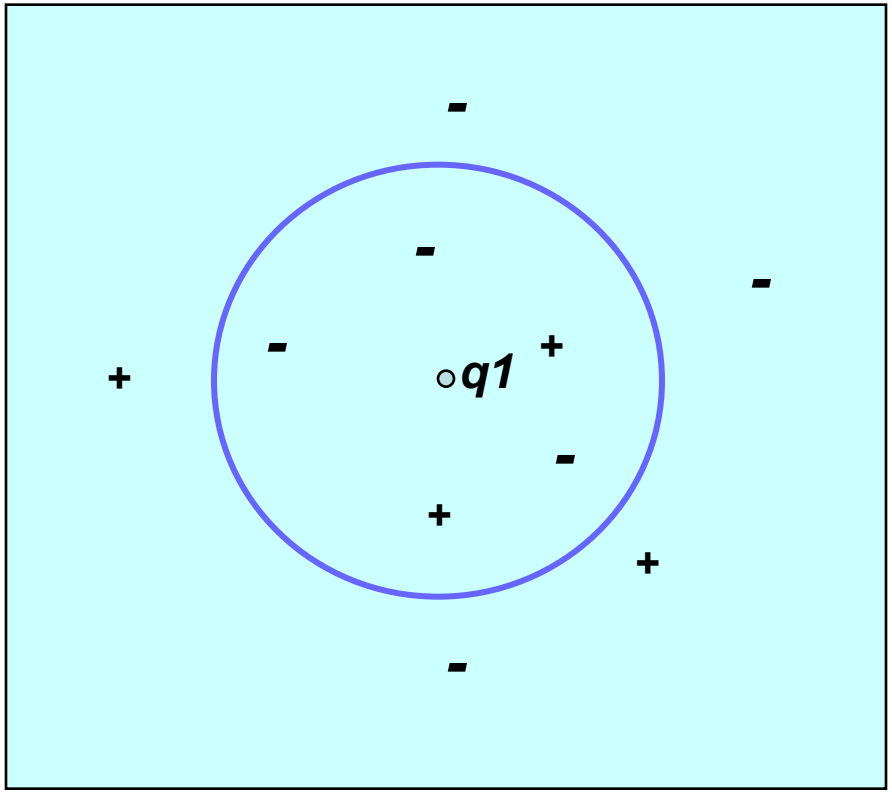
Our hypothesis

- In the nearest neighbor the problem is to find, among a set of points (or feature vectors), the one which is most similar or closest to a given *test point* according to some distance measure
- In mathematics, a **Voronoi diagram** is a way of dividing space into a number of regions
  - The regions are called Voronoi cells
  - A Voronoi diagram is the computational geometry concept that represents partition of the given space onto regions, with bounds determined by distances to a specified family of objects
  - The partitioning of a plane with n points into convex polygons such that each polygon contains exactly one generating point and every point in a given polygon is closer to its generating point than to any other

Voronoi diagram

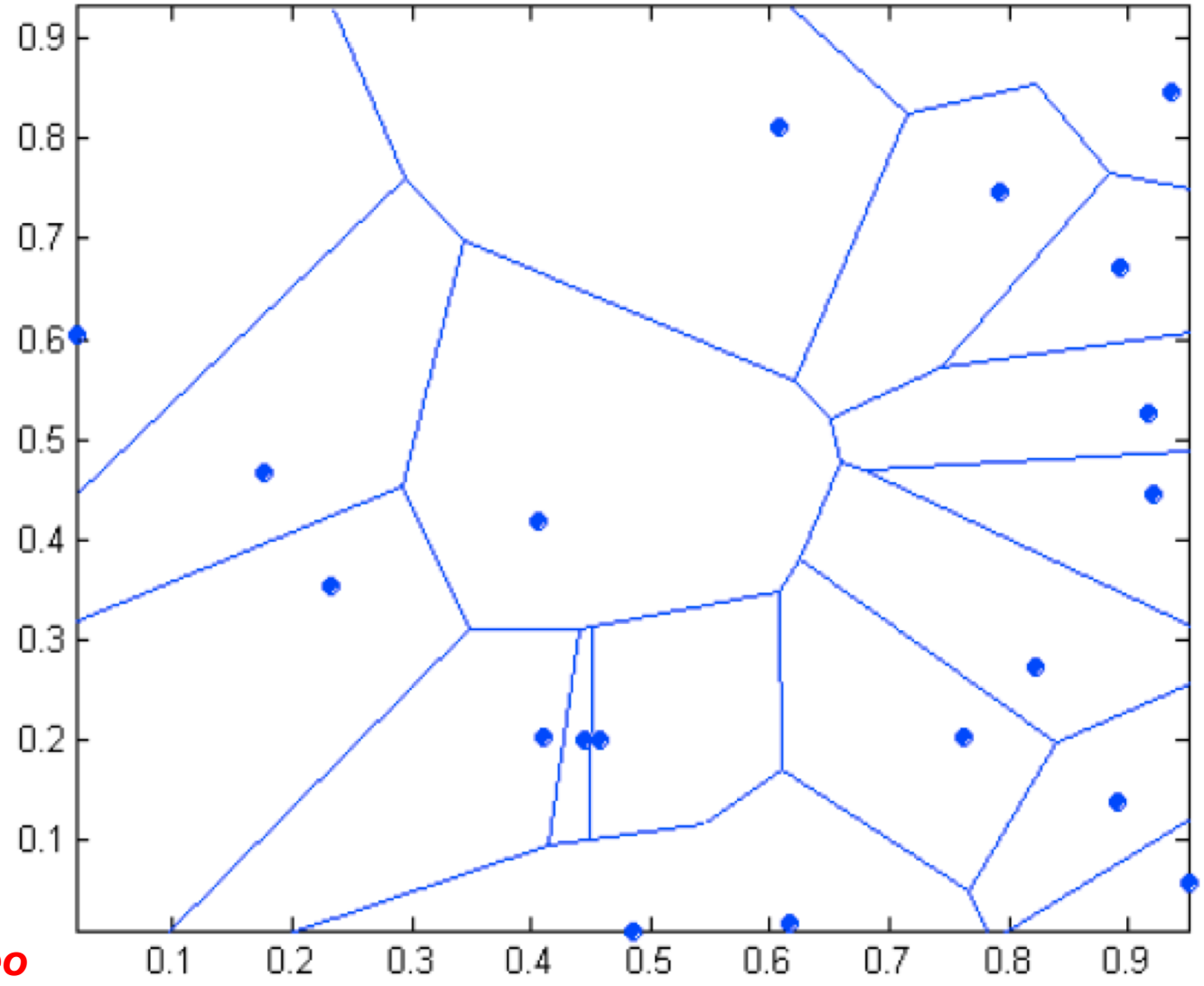


1-nearest neighbor:
the concept represented by e1



5-nearest neighbors:
q1 is classified as negative

Voronoi diagram

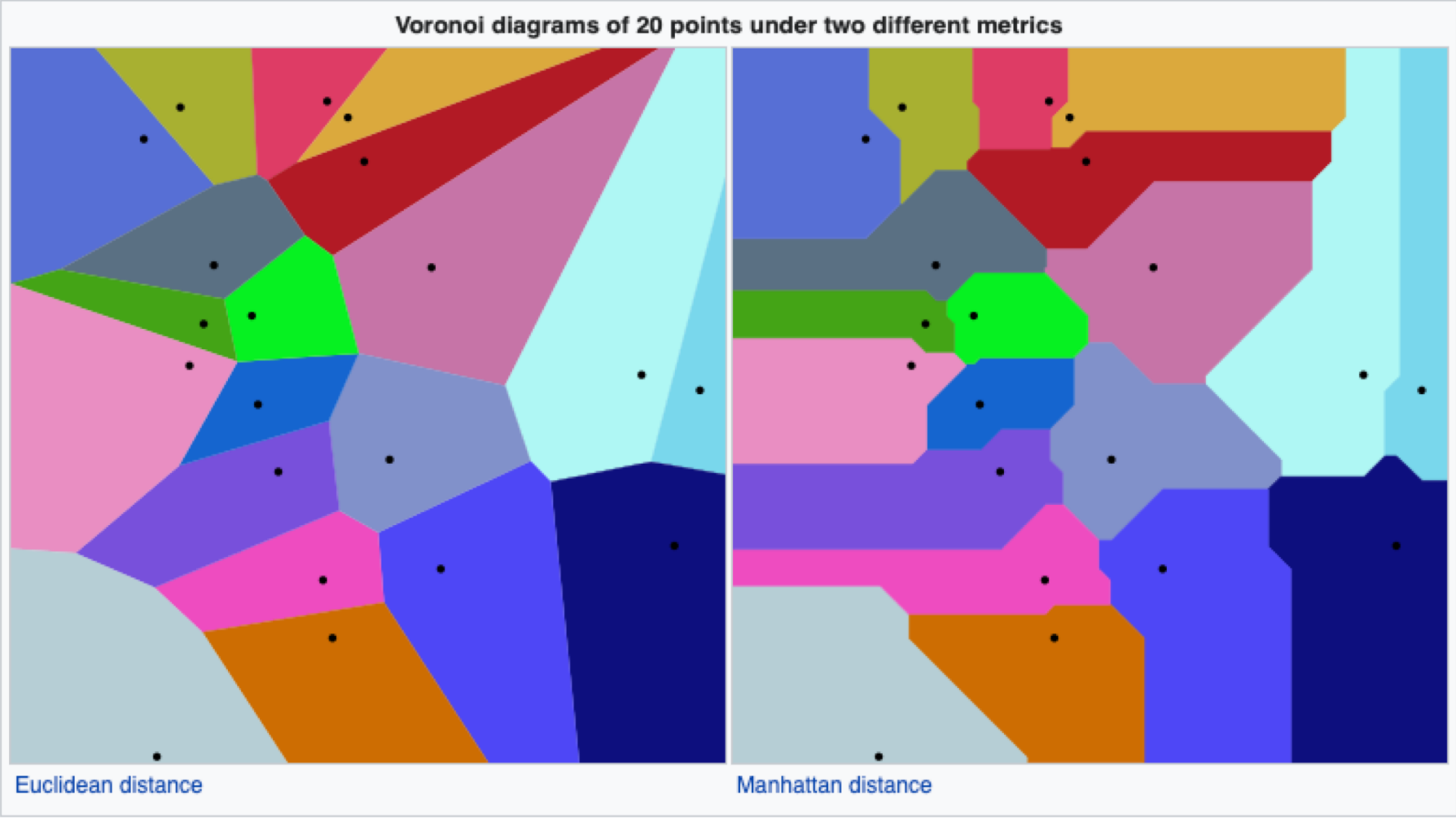


Look at the video

https://youtu.be/k_7gMp5wh5A

Voronoi diagram

Different metrices give rise to different Voronoi diagrams



Instance-based Learning

(IBL)

Instance-based learning

- A lazy learning algorithm
  - Similar to nearest neighbour algorithm
- Differences:
  - Normalizes all attributes in range [0..1]
  - Handles missing attributes
- One way of solving tasks of approximating **discrete or real valued** target functions
- It produces local approximations to the target function
- Key idea of instance based learning version 1 (IB1):
  - just store the training examples, D
  - when a test example is given then **find the closest** matches

What makes an instance-based learner?

- A distance measure
  - Nearest neighbour: typically Euclidean
- Number of neighbours to consider
  - Nearest neighbour: one
- A weighting function (optional)
  - Nearest neighbour: unused (equal weights)
- How to fit with neighbours
  - Nearest neighbour: same output as nearest neighbour

Instance-based learning

- IBL algorithms are derived from the nearest neighbor pattern classifier
- They only use selected instances to generate classification predictions
- IBL algorithms are incremental and their goals include:
  - maximizing classification accuracy on subsequently presented instances
- Instance-base learning is a carefully focused case-based learning approach that contributes evaluated algorithms for:
  - selecting good cases for classification,
  - reducing storage requirements,
  - tolerating noise, and
  - learning attribute relevance

Instance-based learning

- IBL algorithms assume that "***similar instances have similar classifications***"
- IB1 is identical to the nearest neighbor algorithm, except that
  - it normalizes its attributes' ranges,
  - processes instances incrementally, and
  - has a simple policy for tolerating missing values.

Table 1. The IB1 algorithm (CD = Concept Description).

$CD \leftarrow \emptyset$

for each $x \in$ Training Set **do**

1. **for each** $y \in CD$ **do**
   Sim[y] $\leftarrow$ Similarity(x, y)
2. $y_{max} \leftarrow$ some $y \in CD$ with maximal Sim[y]
3. **if** class(x) = class(y_{max})
   then classification $\leftarrow$ **correct**
   else classification $\leftarrow$ **incorrect**
4. $CD \leftarrow CD \cup \{x\}$

Instance-based learning

IBL algorithms

- Assume that "***similar instances have similar classifications***"

- **IB1** is identical to the nearest neighbor algorithm, except that
  - it normalizes its attributes' ranges,
  - processes instances incrementally, and
  - has a simple policy for tolerating missing values.
- **IB2** is identical to IB1, except that
  - it saves only misclassified instances
- **IB3** is an extension of IB2 that employs a "*wait and see*" evidence gathering method to determine which of the saved instances are expected to perform well during classification

What else?

TO READ:

Instance-based learning algorithms

D.W. Aha, D. Kibler, and M.K. Albert

Machine Learning , 6, 37- 66 (1991)

- Sections 1 and 2 (from page 37 to page 48)
- The remaining of the sections are optional

K-Nearest Neighbor

(KNN)

K-Nearest Neighbour

- A distance measure
  - typically Euclidean
- Number of neighbors to consider
  - k (it is a predefined positive integer, typically small and odd)
    - The optimal k can be calculated by special techniques (hyper parameter optimization techniques)
- A weighting function (optional)
  - Unused (equal weights)
- How to fit with neighbors
  - Vote using K nearest neighbors (or take average, for regression)

K-Nearest Neighbour

- Training method
  - Save the training examples
- At prediction time:
  - Find the k training examples that are closest to the test example *x*
  - **Classification**: The output is a class membership. Predict the most frequent class among those y_i's
  - **Regression**: The output is a value. Predict the average of among the y_i's
- Improvements:
  - Weighting examples from the neighborhood
  - Measuring "*closeness*"
  - Finding "*close*" examples in a large training set *quickly*

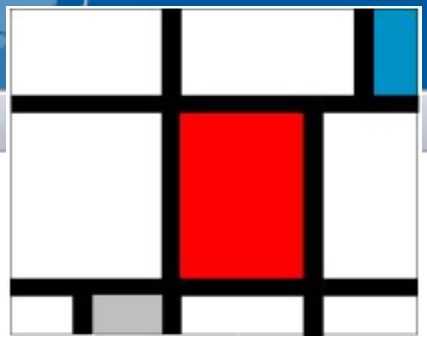
When to consider NN algorithms

- Instances map to points in $\Re^n$
- Not more then say 20 attributes per instance
- Lots of training data

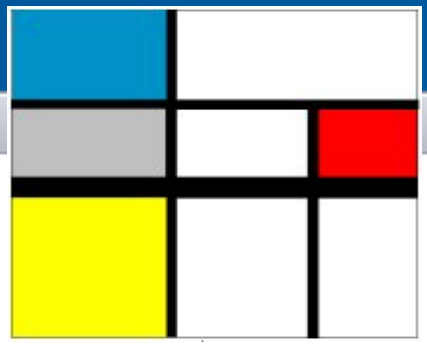
- Advantages:
  - Training is very fast
  - Can learn complex target functions
  - Don't lose information

- Disadvantages:
  - ??? (We will see them shortly…)

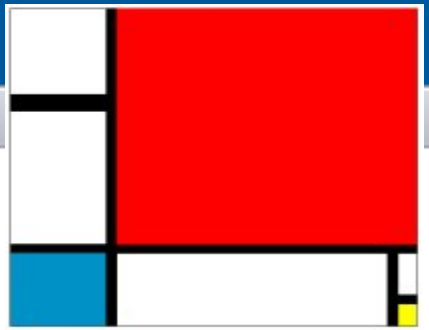
Mondrian Example



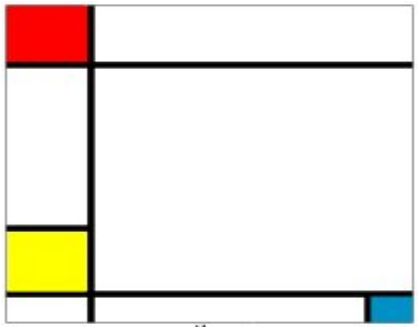
one



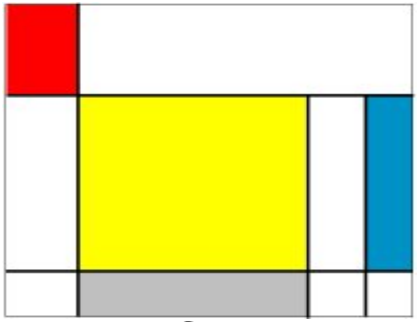
two



three

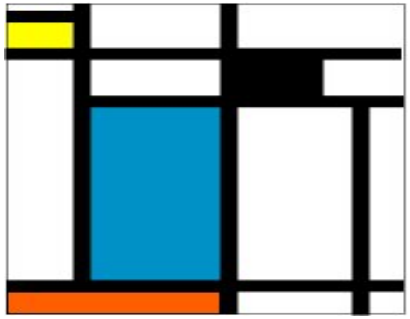


four

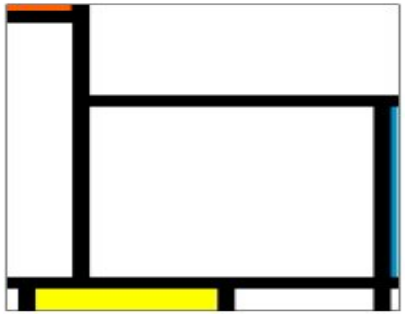


five

six



seven



Eight ?

Training data

Number	Lines	Line types	Rectangles	Colours	Mondrian?
1	6	1	10	4	*No*
2	4	2	8	5	*No*
3	5	2	7	4	Yes
4	5	1	8	4	Yes
5	5	1	10	5	*No*
6	6	1	8	6	Yes
7	7	1	14	5	*No*

Test instance x_q

Number	Lines	Line types	Rectangles	Colours	Mondrian?
8	7	2	9	4	

Keep data in normalised form

One way to normalise the data $a_r(x)$ *to a* $a'_r(x)$ *is*

$$x_t' \equiv \frac{x_t - \bar{x}_t}{\sigma_t}$$

$$\bar{x}_r \equiv mean\ \ of\ \ t^{th}\ attributes$$

$$\sigma_t \equiv sta\,ndard\ \ deviation\,of\ \ t^{th}\ attributes$$

Keep data in normalised form

Another way to normalise the data is rescaling the range of features to the range [0,1] or [-1 ,1]

$$x_t' \equiv \frac{x_t - \min}{\max - \min}$$

$$\min \equiv \min \; of \;\; t^{th} \; attributes$$

$$\max \equiv \max \; of \;\; t^{th} \; attributes$$

Normalised training data

Number	Lines	Line types	Rectangles	Colours	Mondrian?
1	0.632	-0.632	0.327	-1.021	*No*
2	-1.581	1.581	-0.588	0.408	*No*
3	-0.474	1.581	-1.046	-1.021	Yes
4	-0.474	-0.632	-0.588	-1.021	Yes
5	-0.474	-0.632	0.327	0.408	*No*
6	0.632	-0.632	-0.588	1.837	Yes
7	1.739	-0.632	2.157	0.408	*No*

Test instance (x_q)

Number	Lines	Line types	Rectangles	Colours	Mondrian?
8	1.739	1.581	-0.131	-1.021	

Computing distances

Example	Distance of test instance to the example	Mondrian?
1	2.517	*No*
2	3.644	*No*
3	2.395	Yes
4	3.164	Yes
5	3.472	*No*
6	3.808	Yes
7	3.490	*No*

Classification

1-NN	*Yes*
3-NN	*Yes*
5-NN	*No*
7-NN	*No*

Issues to consider in a k-NN

- About the k
  - In a binary classification, it is helpful to choose k to be an odd number to avoid tied votes
  - Small k captures fine structure of the problem better
  - Large k is less sensitive to noise (particularly class noise)
- The principle of “majority voting” for deciding the class labels can be problematic when the class distribution is skewed
  - Instances of a more frequent class tend to dominate the prediction of the new examples
- Irrelevant features within a large feature set, tend to degrade performance
- The simple model where all instances are treated fairly using the same distance metric may be inadequate

Distance-Weighted kNN

- We might want to weight nearer neighbours more heavily
  - A typical weight is the inverse of the square of the distance

$$f(\mathbf{x}_q) := \frac{\sum_{i=1}^{k} w_i f(\mathbf{x}_i)}{\sum_{i=1}^{k} w_i} \quad \text{where } w_i = \frac{1}{d(\mathbf{x}_q, \mathbf{x}_i)^2}$$

- The weighted k-NN algorithm can be used for classification or regression

- In the weighted approach one can extend the k-nearest neighbour method from k to all data items.
  - The alternative to keep to k elements is called a local weighted method
  - The extension to all data items is called global weighted method

Pros and Cons

- **Advantages**
  - Fast training (it's a lazy algorithm)
  - Learn complex functions easily
  - Do not lose information

- **Disadvantages**
  - Slow at query time
  - Needs lots of storage
  - Easily fooled by irrelevant attributes
    - Use statistical methods to remove irrelevant ones (e.g., PCA or cross-validation)

Irrelevant attributes

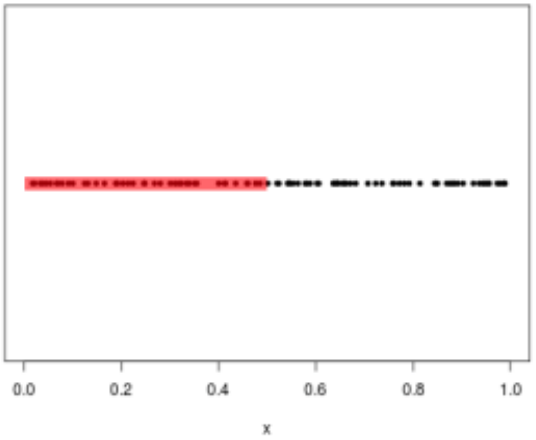
- Nearest neighbor easily misled when X has a high-dimension
- Low-dimensional intuitions do not extend to high dimensions

- **The curse of dimensionality**
  - When dimensionality increases, the volume of the space increases so fast that the available data becomes sparse.
  - The number of features is too large relative to the number of training samples

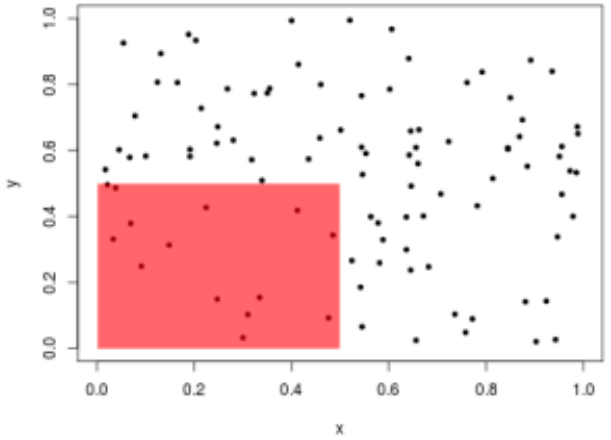
This makes a poor generalization ability of the classifier

Curse of dimensionality

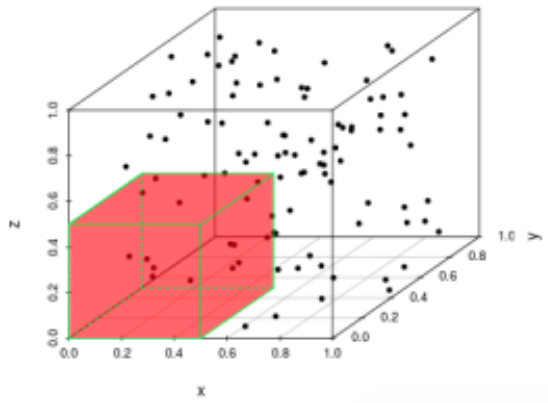
1-D: 42% of data captured.



2-D: 14% of data captured.

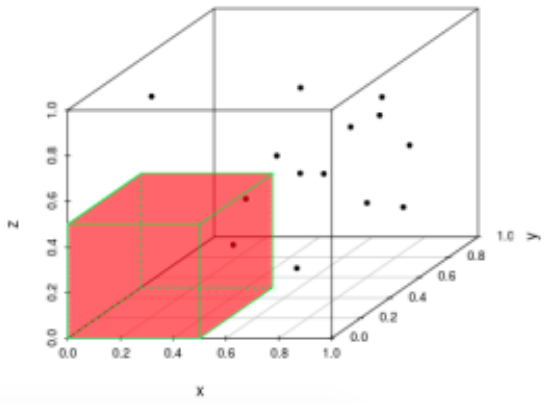


3-D: 7% of data captured.



4-D: 3% of data captured.

t = 0



Case-Based Reasoning

(CBR)

Introduction to CBR

- *In this course we focus on the basic principle rather than on specific applications or tools*

- Briefly
  - CBR is an advanced instance-based learning applied to more complex instance objects
  - Objects may include complex structural descriptions of cases and adaptation rules
  - The power comes from the organisation and content of the cases themselves

Faced this situation before?

- Oops the car stopped.
  - What could have gone wrong?
- Aah.. Last time it happened, there was no petrol.
  - Is there petrol?
    - Yes.
  - Oh but wait I remember the tyre was punctured (ban bocor)

This is the normal thought process of a human when faced with a problem which is similar to a problem he/she had faced before.

How do we solve problems?

- By knowing the steps to apply
  - from symptoms to a plausible diagnosis
- But not always applying causal knowledge
  - diseases cause symptoms
  - symptoms do not cause diseases!
- How does an expert solve problems?
  - uses same “book learning” as a novice
  - but quickly selects the right knowledge to apply
- Heuristic knowledge (“rules of thumb”)
  - “I don’t know why this works but it does and so I’ll use it again!”
  - difficult to elicit

Another way we solve problems?

- By remembering how we solved a similar problem in the past
- This is Case Based Reasoning (CBR)!
  - memory-based problem-solving
  - re-using past experiences
- Experts often find it easier to relate stories about past cases than to formulate rules

Problems we solve this way

- Medicine
  - doctor remembers previous patients especially for rare combinations of symptoms
- Law
  - English/US law depends on precedence
  - case histories are consulted
- Management
  - decisions are often based on past rulings
- Financial
  - performance is predicted by past results

What is Case-based Reasoning

- Case-based reasoning is […] reasoning by remembering – *[Leake, 1996]*
- A case-based reasoner solves new problems by adapting solutions that were used to solve old problems - *[Riesbeck & Schank, 1989]*
- Case-based reasoning is both […] the ways people use cases to solve problems and the ways we can make machines use them – *[Kolodner, 1993]*
- Case-based reasoning is a recent approach to problem solving and learning […] - *[Aamodt & Plaza, 1994]*

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Case-based reasoning is ...

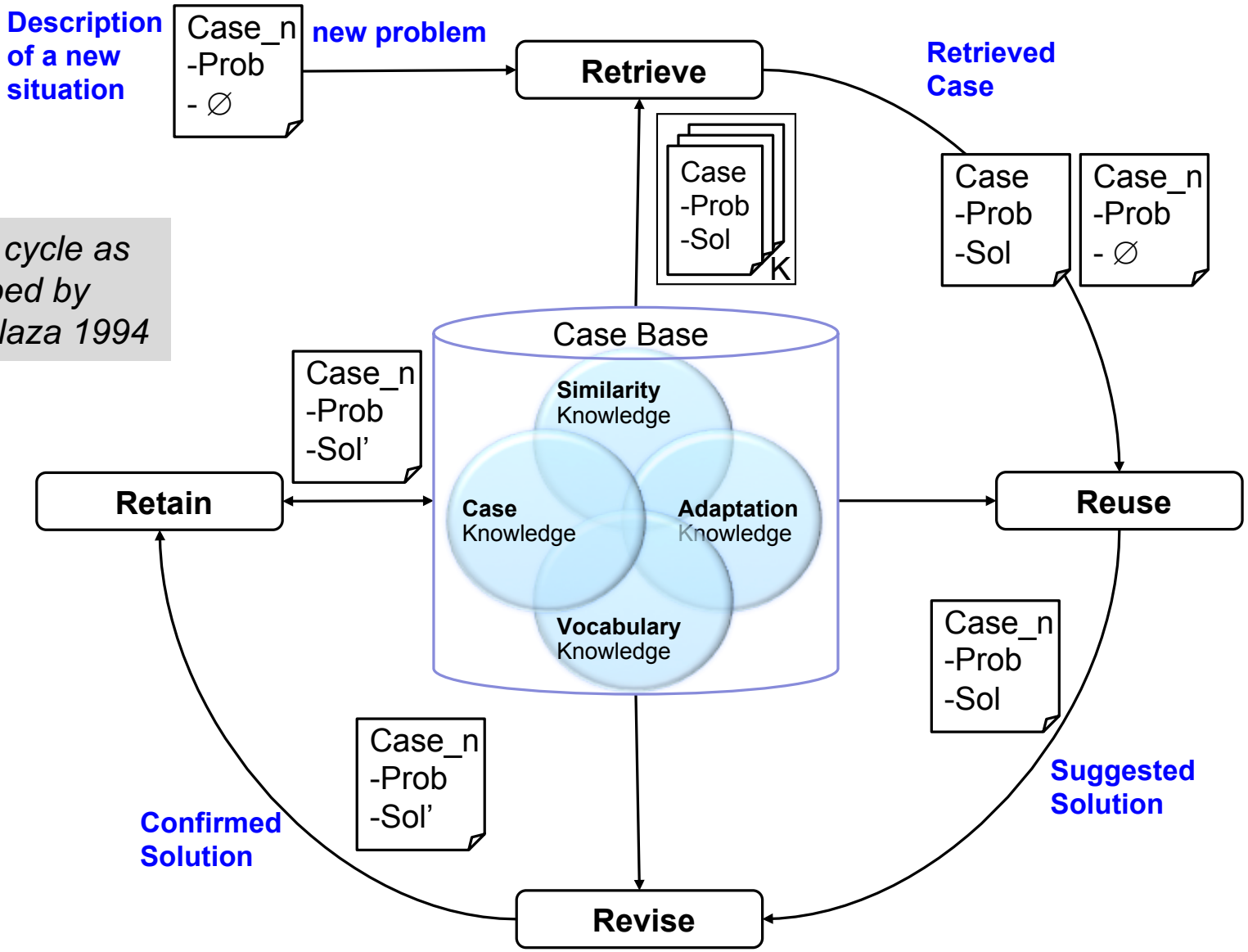
- A methodology to model human reasoning and thinking
- A methodology for building intelligent computer systems
- CBR in a nutshell:
  - Store previous experience (cases) in memory
  - To solve new problems:
    - Retrieve similar experience about similar situations from the memory
    - Reuse the experience in the context of the new situation : complete or partial reuse, or adapt according to differences
    - Store new experience in memory (**learning**)

A bit of history

- Roots of CBR is found in the works of Roger Shank on dynamic memory in 1983
- Other trails into the CBR field has come from
  - Analogical reasoning in 1990
  - Problem solving and experimental learning within philosophy and psychology
- The first CBR system, CYRUS developed by Janet Kolodner at Yale university (1983)

CBR cycle

The CBR cycle as described by Aamodt&Plaza 1994



Description of CBR Cycle

The CBR process is a cyclic procedure with 4 phases

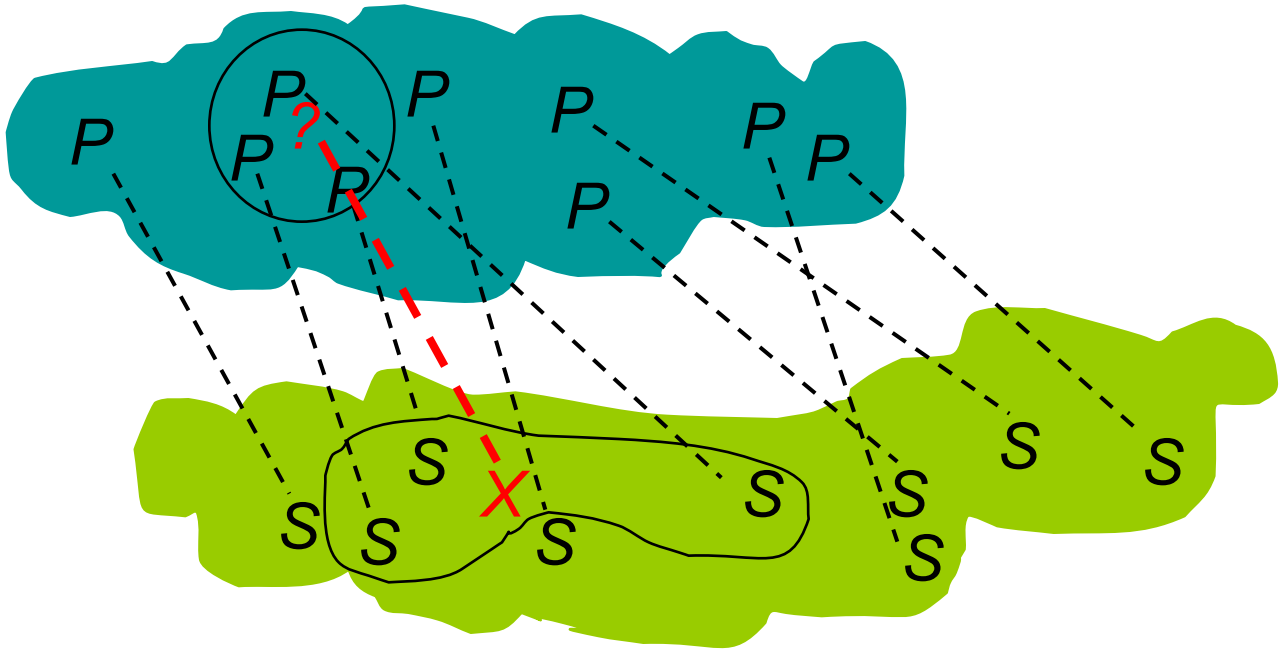
- A new problem to be solved is introduced in the problem space
- During **retrieval**, a new problem is matched against problems of the previous cases by computing a similarity function, and the most similar problem and its stored solution are found
- If the proposed solution does not meet the necessary requirements of a new problem situation, **adaptation** occurs (reuse phase) and a new solution is created
- **Revise** the proposed solution
- A received solution and a new problem together form a new case that is incorporated in the case base during the learning step (**retain** phase)
  - In this way CBR system evolves into a better reasoner as the capability of the system is improved by extending of stored experience

CBR System Components

- Case-base
  - database of previous cases (experience)
- Retrieval of relevant cases
  - index for cases in library
  - matching most similar case(s)
  - retrieving the solution(s) from these case(s)
- Adaptation of solution
  - alter the retrieved solution(s) to reflect differences between new case and retrieved case(s)

Main CBR Assumption

- New problem can be solved by
  - retrieving similar problems
  - adapting retrieved solutions
- Similar problems have similar solutions



CBR Assumption(s)

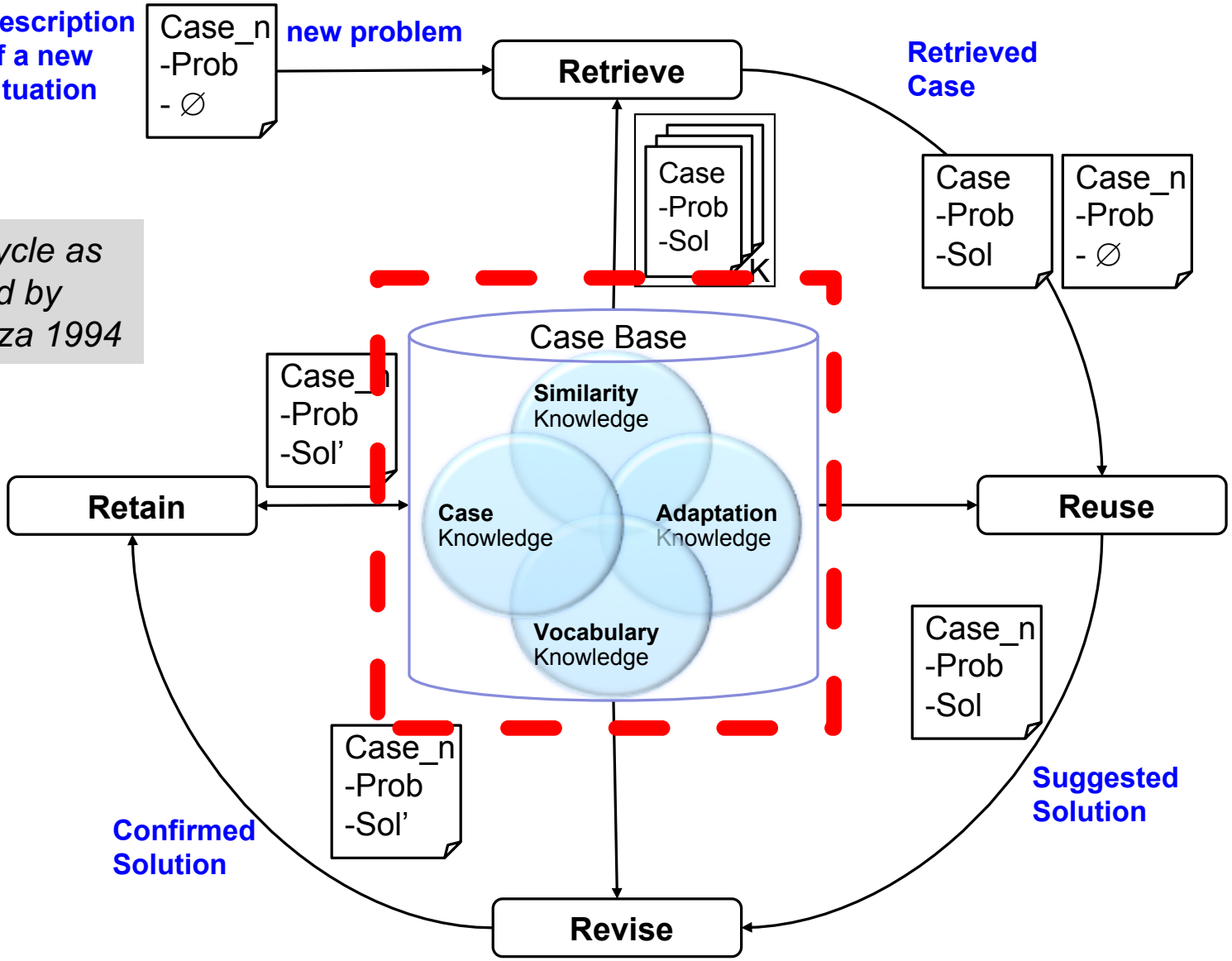
- The **main assumption** is that:
  - *Similar problems have similar solutions*:
    - e.g., an aspirin can be taken for any mild pain
- More assumptions:
  - The world is a regular place: what holds true today will probably hold true tomorrow
    - (e.g., if you have a headache, you take aspirin, because it has always helped)
  - Situations repeat: if they do not, there is no point in remembering them
    - (e.g., it helps to remember how you found a parking space near that restaurant)

Two big tasks of CBR

- Classification tasks (good for CBR)
  - Diagnosis - what type of fault is this?
  - Prediction / estimation - what happened when we saw this pattern before?
- Synthesis tasks (harder for CBR)
  - Engineering Design
  - Planning
  - Scheduling

CBR cycle

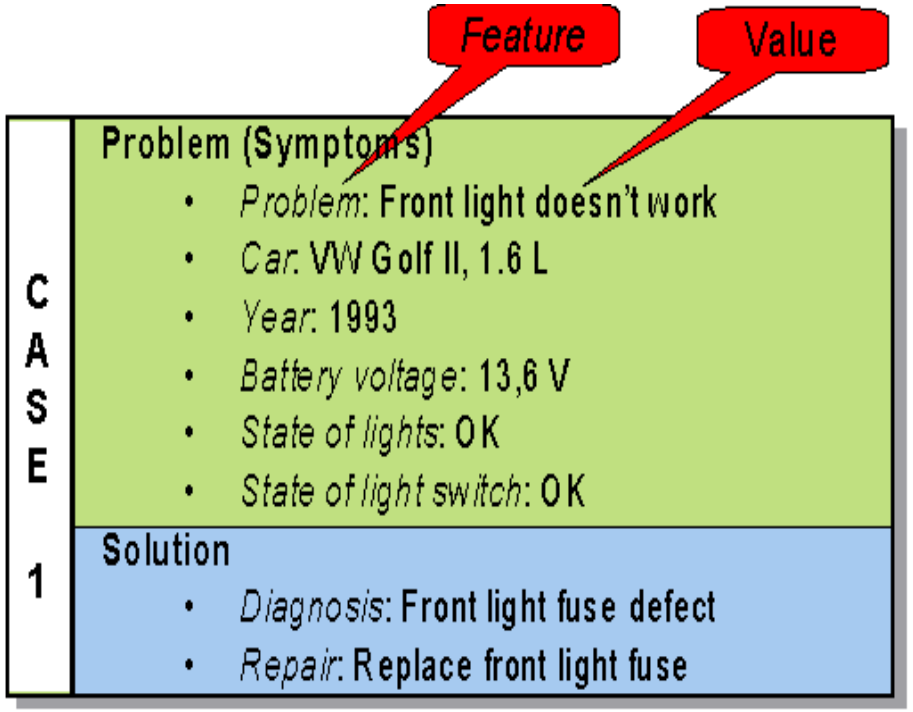
The CBR cycle as described by Aamodt&Plaza 1994



A simple example: What's a case?

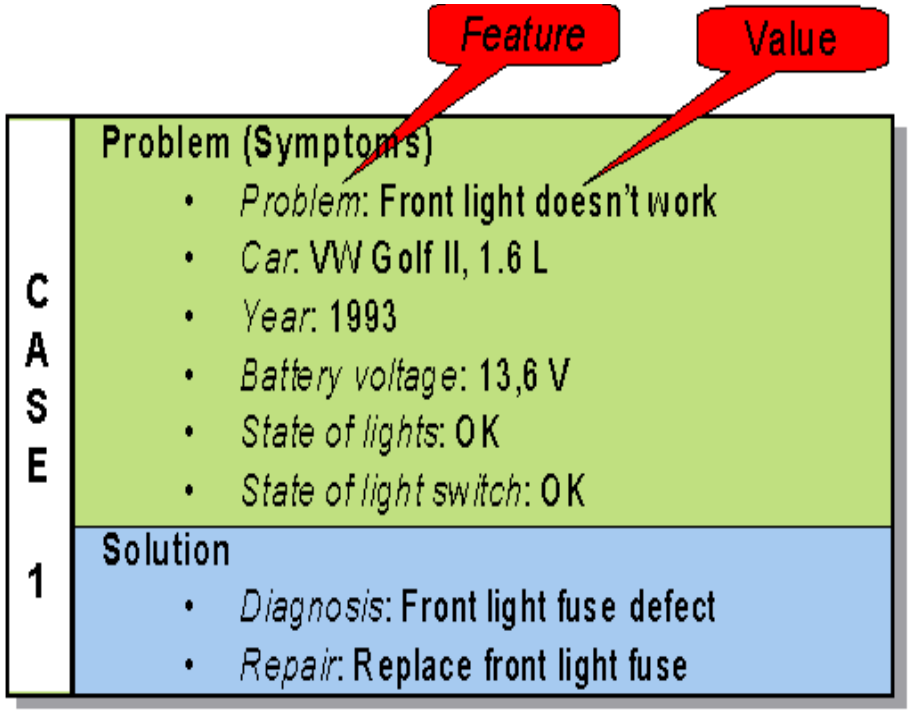
- A case describes one particular diagnostic situation
- A case records several features and their specific values occurred in that situation
- A case is not a rule !!!

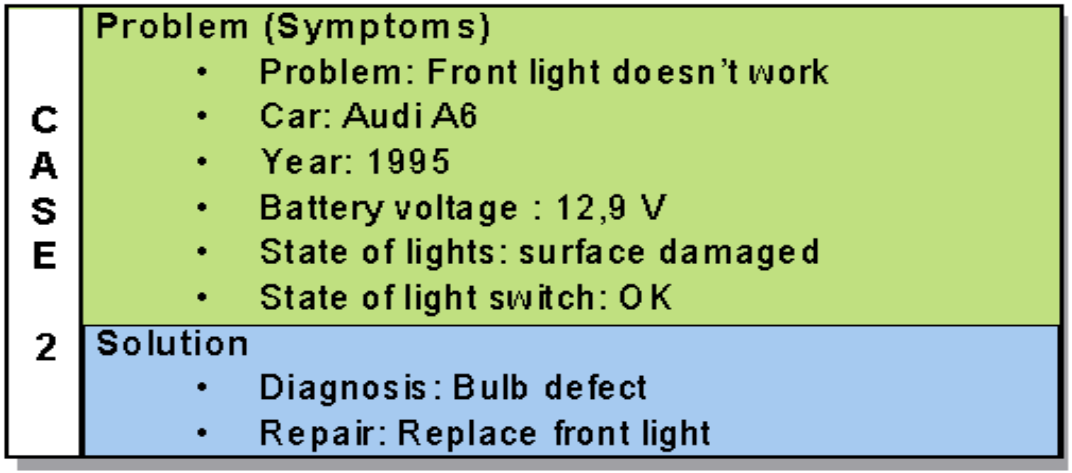
Technical Diagnosis of Car Faults



Figures of this example come from:

R. Bergmann, University of Kaiserslautern





A case base with two cases:

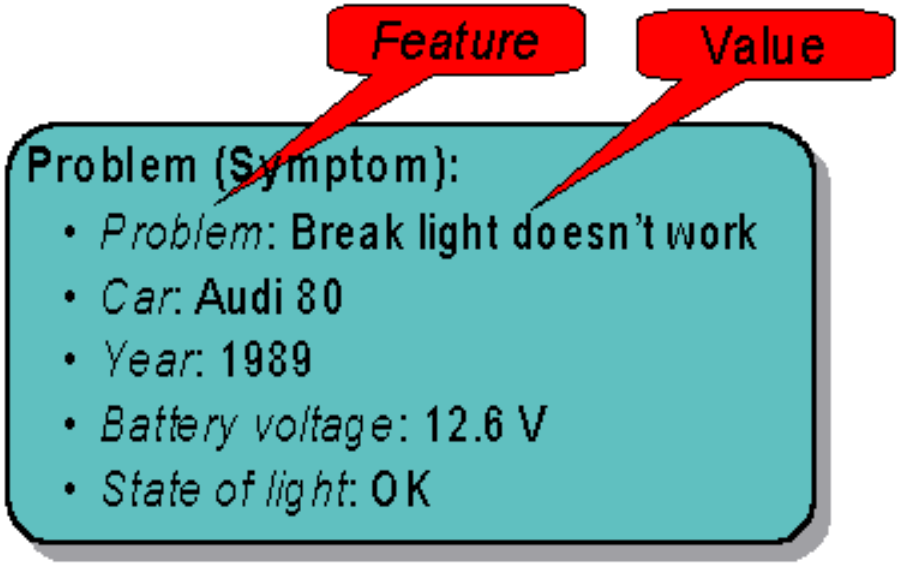
- Each case describes a particular situation
- All cases are independent from each other

Case Representation

- Flat feature-value list
  - Simple case structure is sometimes sufficient for problem solving
  - Easy to store and retrieve in a CBR system
- Object Oriented representation
  - Case: collection of objects (instances of classes) in the sense of OO
  - Required for complex and structured objects
- For special tasks:
  - Graph representations: case = set of nodes and arcs
  - Plans: case = (partially) ordered set of actions
  - Predicate logic: case = set of atomic formulas
- The choice of representation is
  - Dependent on requirements of domain and task
  - Structure of already available case data

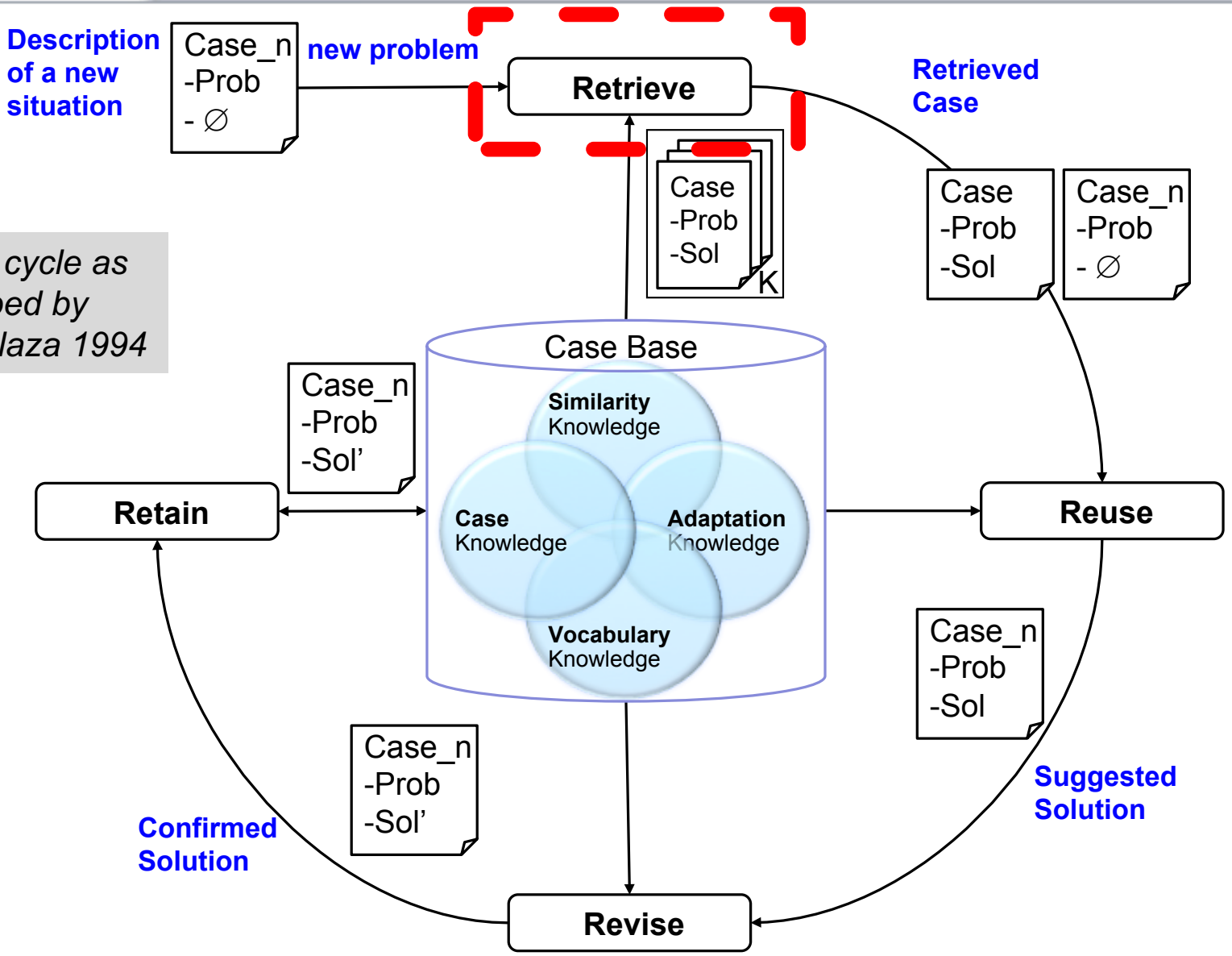
Solving a new diagnostic problem

- A new problem must be solved
- We make several observations in the current situation
- Observations define a new problem
- Not all feature values must be known
- Note: The new problem is a case without solution part



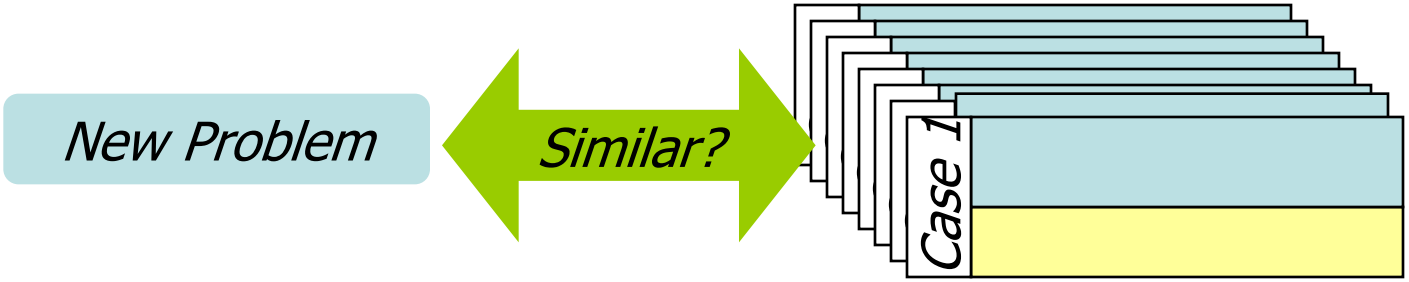
CBR cycle

The CBR cycle as described by Aamodt&Plaza 1994



Retrieving A Car Diagnosis Case

- Compare new problem to each case
- Select most similar



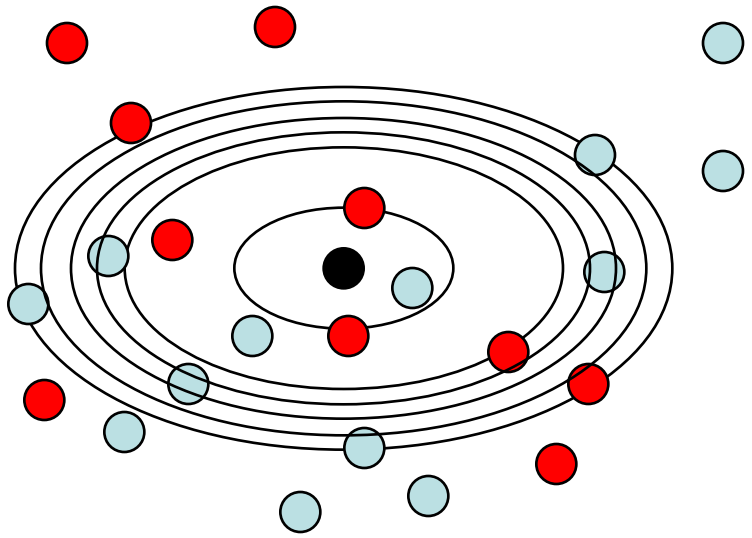
- Similarity is most important concept in CBR
  - When are two cases similar?
  - How are cases ranked according to similarity?
- Similarity of cases
  - Similarity for each feature
    - Depends on feature values
    - BUT: Importance of different feature values may be different

Retrieve: What is similarity?

- Purpose of similarity:
  - Select cases that can be adapted easily to the current problem
  - Select cases that have (nearly) the same solution than the current problem
- Basic assumption: similar problems have similar solutions
- Degree of similarity = utility /reusability solution
- Goal of similarity modeling: provide a good approximation
  - Close to real reusability
  - Easy to compute

Nearest Neighbour Retrieval

- Retrieve most similar
- k-nearest neighbour
  - k-NN
  - like scoring in bowls or curling
- Example
  - *1-NN*
  - *5-NN*

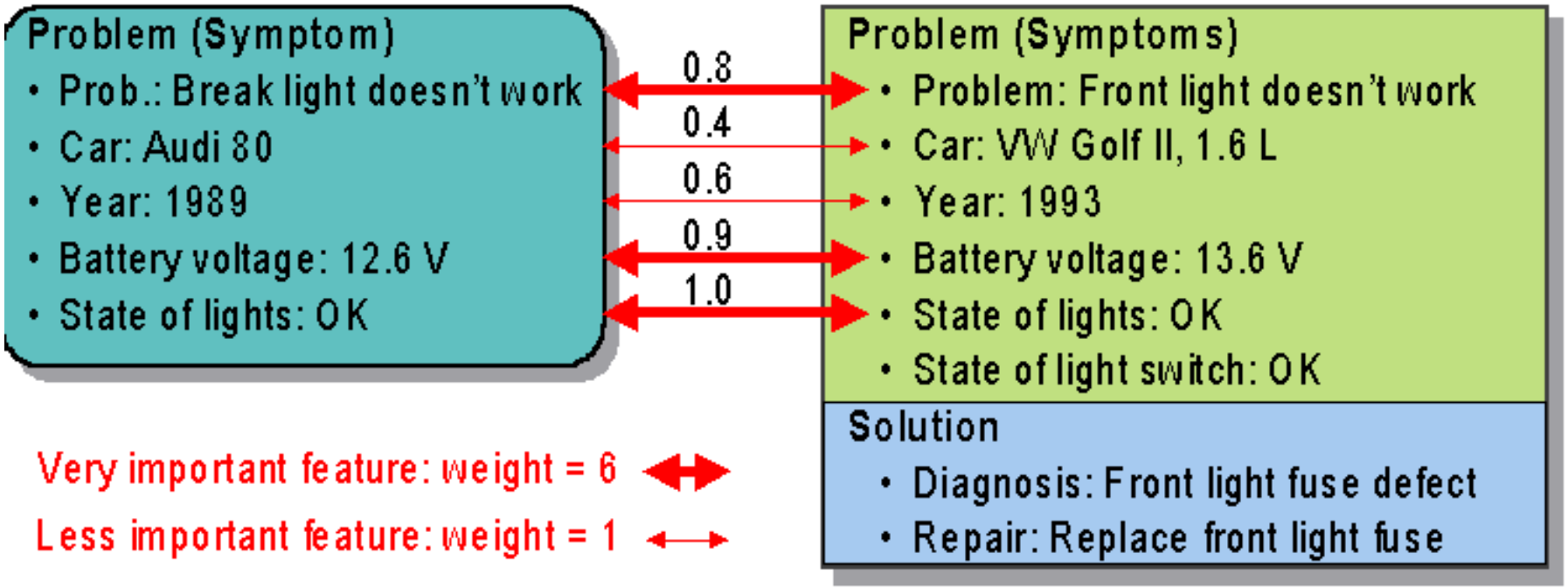


Retrieve: Modeling similarity

- Different approaches depending on case representation
- Similarity measures:
  - Function to compare two cases

    sim: Case x Case ➔[0..1]
  - Local similarity measure: similarity on feature level
  - Global similarity measure: similarity on case or object level
    - Combines local similarity measures
    - Takes care of different importance of attributes (weights)
  - (Sub-)Graph isomorphism for graph representations
  - Logical inferences

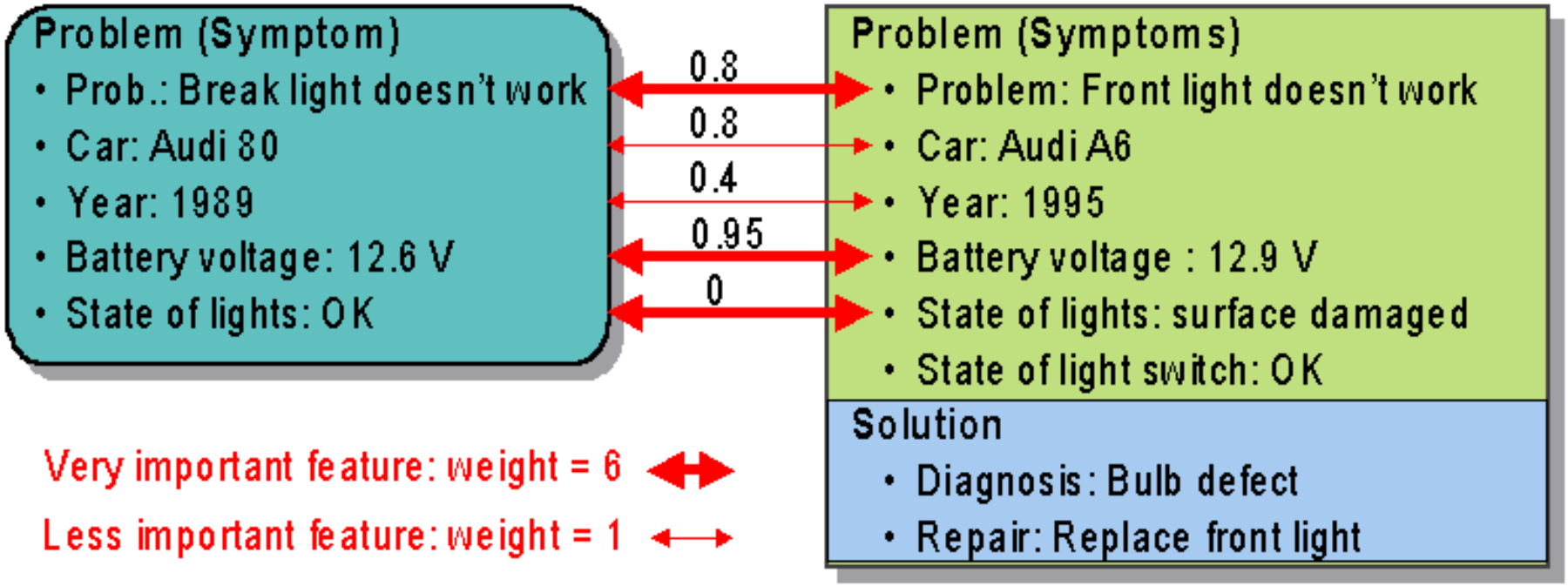
Similarity Computation for case



Similarity Computation by Weighted Average

similarity(new,case 1) = 1/20 * [6*0.8 + 1*0.4 + 1*0.6 + 6*0.9 + 6* 1.0] = **0.86**

Similarity Computation for case 2



Similarity Computation by Weighted Average

similarity(new,case 2) = 1/20 * [6*0.8 + 1*0.8 + 1*0.4 + 6*0.95 + 6*0] = **0.585**

Retrieve, but efficiently ...

- Efficient case retrieval is essential for large case bases
- Different approaches depending
  - On the case representation
  - Size of the case base
- Organisation of the case base:
  - Linear lists, only for small case bases
  - Index structures for large case bases
    - Kd-trees, Retrieval nets, discrimination nets, ...
- How to store cases:
  - Databases: for large case bases or if shared with other applications
  - Main memory: for small case bases, not shared

Reuse Solution from Case 1

New Problem

- Symptom: brakelight does not work
- Car: Ford Fiesta
- Year: 1997
- Battery: 9.2v
- Headlights: undamaged
- HeadlightSwitch: ?

Problem *Case 1*

- Symptom: headlight does not work
- …

Solution

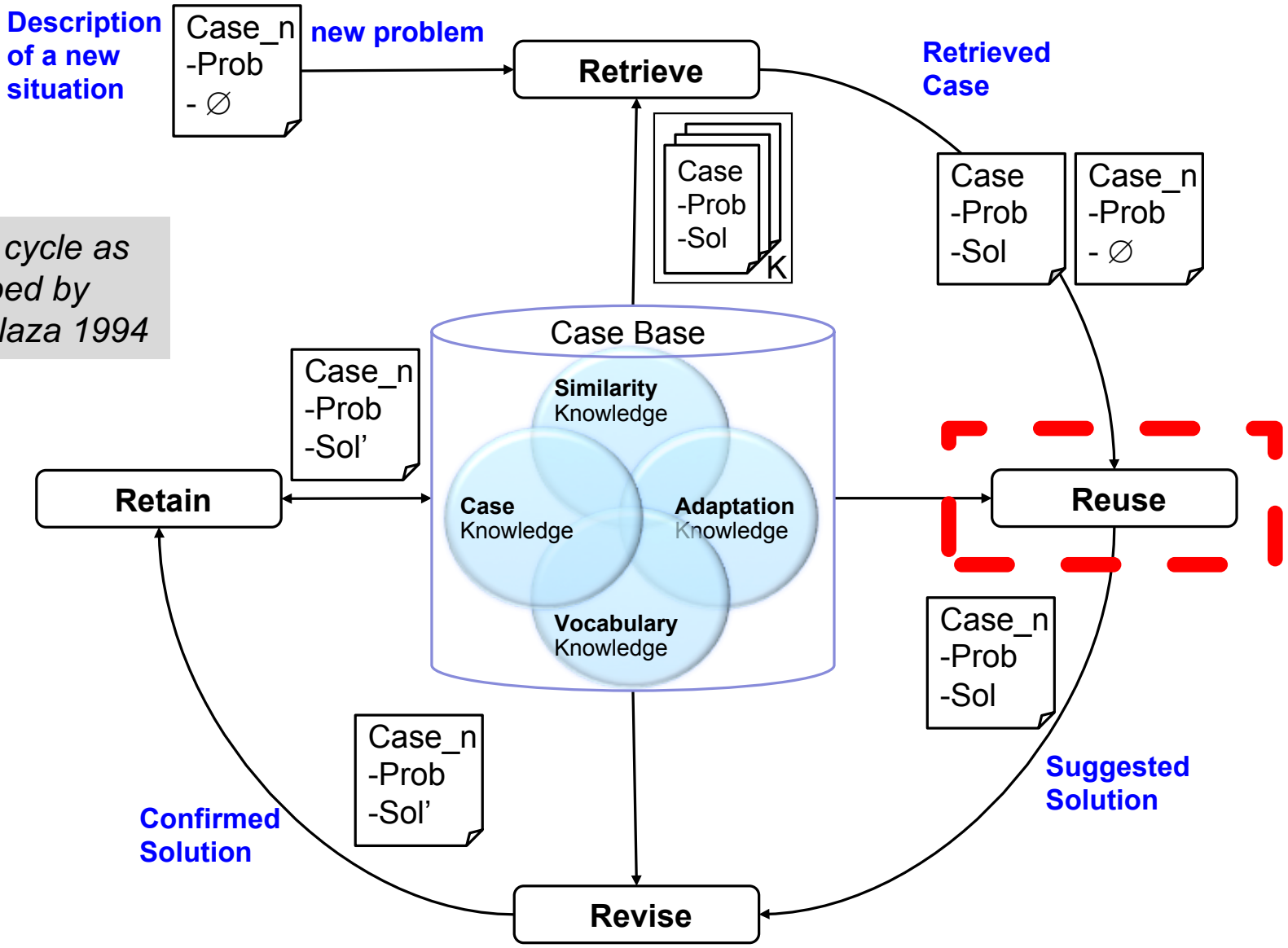
- Diagnosis: headlight fuse blown
- Repair: replace headlight fuse

– Solution to New Problem
  - Diagnosis: headlight fuse blown
  - Repair: replace headlight fuse

– After Adaptation
  - Diagnosis: brakelight fuse blown
  - Repair: replace brakelight fuse

CBR cycle

The CBR cycle as described by Aamodt&Plaza 1994



Re-Using Retrieved Solutions

- Single retrieved solution
  - Re-use this solution
- Multiple retrieved solutions
  - Vote/average of retrieved solutions
    - Weighted according to
      - Ranking
      - Similarity
- Iterative retrieval
  - Solve components of the solution one at a time

How to Adapt the Solution

- Adaptation alters proposed solution:
- Null adaptation - copy retrieved solution
  - Used by CBR-Lite systems
- Manual or interactive adaptation
  - User adapts the retrieved solution (Adapting is easier than solving?)
- Automated adaptation
  - CBR system is able to adapt the retrieved solution
  - Adaptation knowledge required

Automated Adaptation Methods

- *Substitution*
  - change some part(s) of the retrieved solution
  - simplest and most common form of adaptation
- *Transformation*
  - alters the structure of the solution
- *Generative*
  - replays the method of deriving the retrieved solution on the new problem
  - most complex form of adaptation

Examples of Adaptation

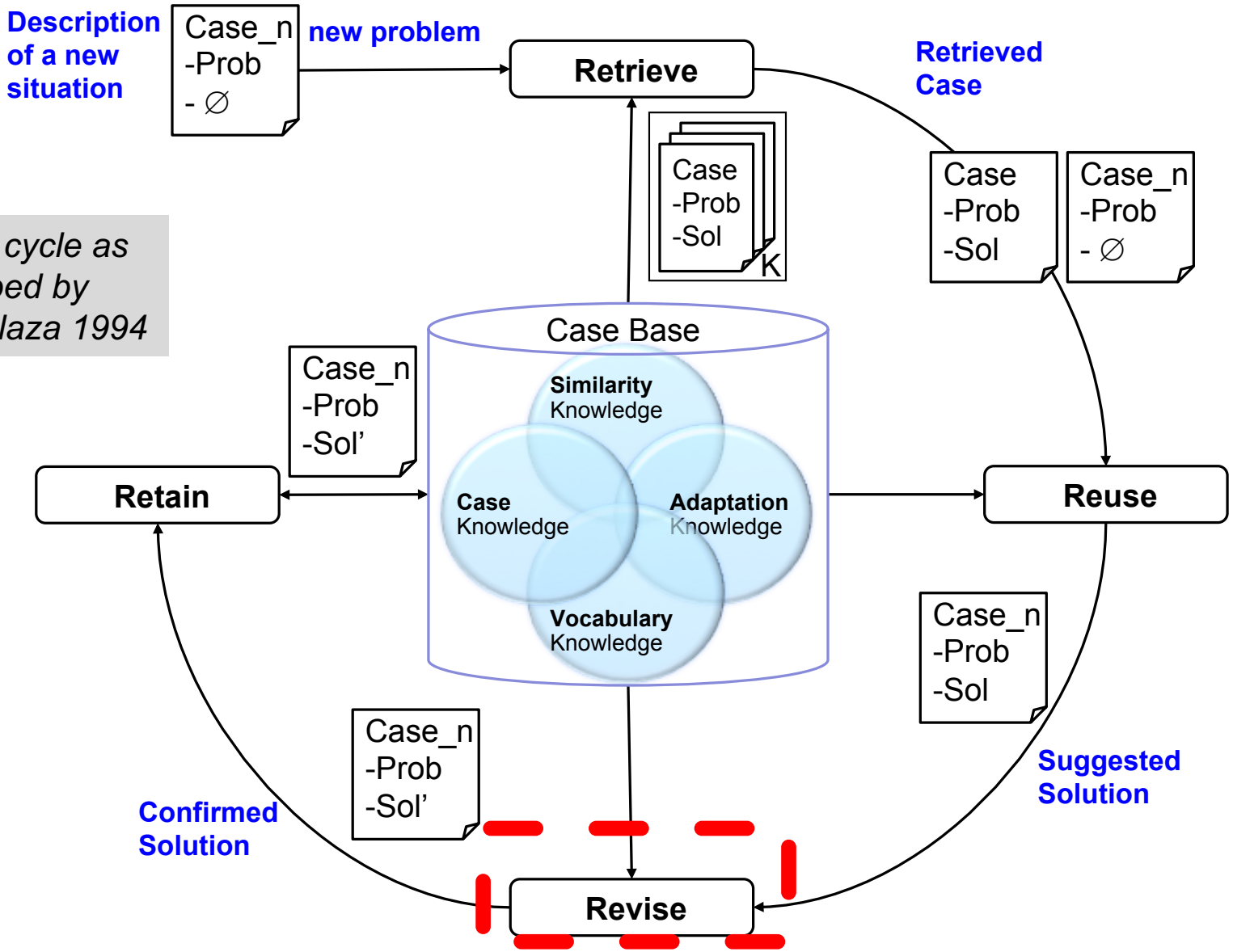
- CHEF
  - CBR system to plan Szechuan recipes
    - Hammond (1990)
- *Substitution* adaptation
  - substitute ingredients in the retrieved recipe to match the menu
    - Retrieved recipe contains beef and broccoli
    - New menu requires chicken and snowpeas
    - Replace chicken for beef, snowpeas for broccoli
- *Transformation* adaptation
  - Add, change or remove steps in the recipe
    - Skinning step added for chicken, not done for beef

Examples of Adaptation

- Car diagnosis example
  - Symptoms, faults and repairs for brake lights are analogous to those for headlight
  - *Substitution*: brake light fuse
- Planning example
  - Train journeys and flights are analogous
  - *Transformation*: flights need check-in step added

CBR cycle

The CBR cycle as described by Aamodt&Plaza 1994

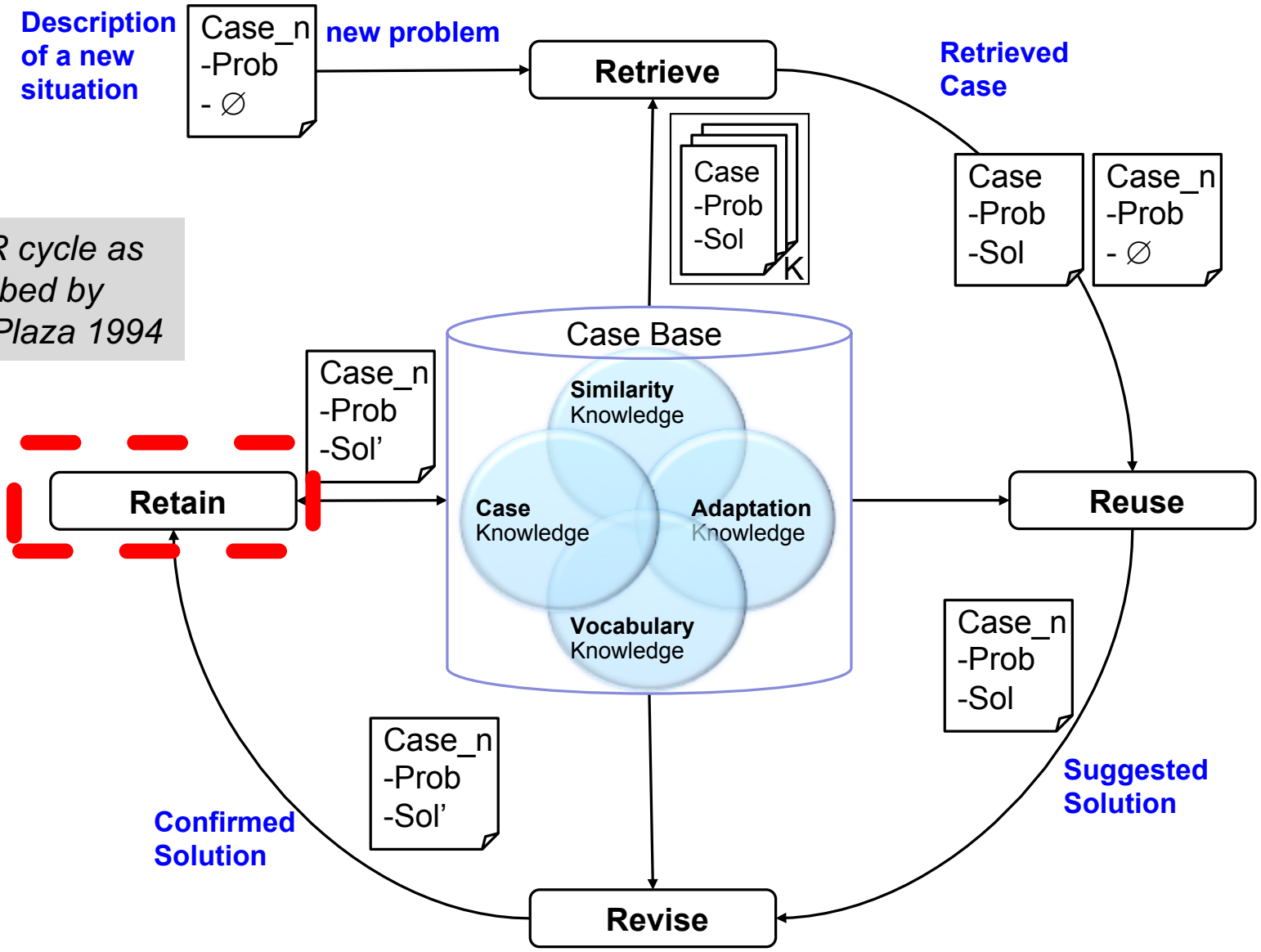


Revise: verify and correct solution

- Revise phase:
  - No revise phase
  - Verification of the solution by computer simulation
  - Verification / evaluation of the solution in the real world
- Criteria for revision
  - Correctness of the solution
  - Quality of the solution
  - Other, e.g., user preferences

CBR cycle

The CBR cycle as described by Aamodt&Plaza 1994



Retain: Learning from problem solving

- What can be learned:
  - New experience to be retained as new case
  - Improved similarity assessment, importance of features
  - Organization / Indexing of the case base to improve efficiency
  - Knowledge for solution adaptation
  - Forgetting cases (learn to forget)
    - For efficiency or because out of date
    - Deleting an old case
      - Old is not necessarily bad
      - Does it leave a gap?

Pros & Cons of CBR

- Advantages
  - solutions are quickly proposed
    - derivation from scratch is avoided
  - domains do not need to be completely understood
  - cases useful for open-ended/ill-defined concepts
  - highlights important features
- Disadvantages
  - old cases may be poor
  - library may be biased
  - most appropriate cases may not be retrieved
  - retrieval/adaptation knowledge still needed

Advantages of CBR over other techniques

- Reduces the knowledge acquisition effort
- Requires less maintenance effort
- Improves problem solving performance through reuse
- Makes use of existing data, e.g., in databases
- Improve over time and adapt to changes in the environment
- High user acceptance

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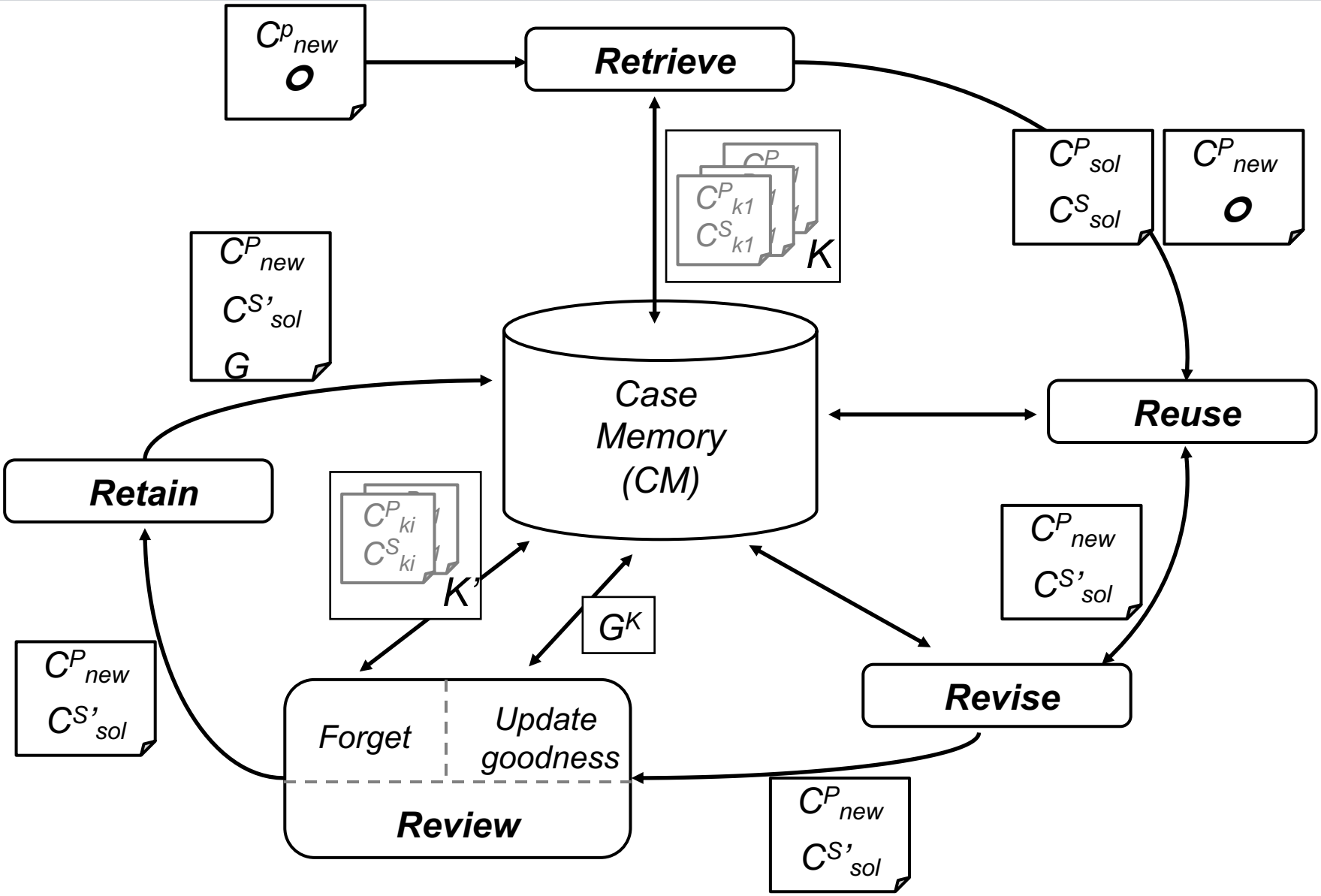
A CBR approach: ACBR Cycle



Summary of CBR

- CBR is a technique for solving problems based on experience
- CBR problem solving involves four phases
  - Retrieval, Reuse, Revise, and Retain
- Different techniques for:
  - Representing the knowledge, in particular, the cases
  - Realizing the four phases
- CBR has several advantages over tradition Knowledge-based Systems
- Several applications
  - Classification, diagnosis, decision support, planning, configuration, design, ...

What else?

TO READ:

Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches

Agnar Aamodt, Enric Plaza

AI Communications, Vol. 7 Nr. 1 (1994) pp. 35-59

- Sections 1, 2, and 3 (from page 1 to page 9)
- The remaining of the sections are optional

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Week 7

Course. Introduction to Machine Learning

Theory 7. Lazy learning

Dr. Maria Salamó Llorente
maria.salamo@ub.edu
Dept. Mathematics and Informatics,
Faculty of Mathematics and Informatics,
University of Barcelona (UB)