TDT4171 Artificial Intelligence Methods

Case-Based Reasoning
(Lecture 8)

Kerstin Bach

Department of Computer Science

Data and Artificial Intelligence Group

NTNU

About me

Professor in Computer Science

- Data and Artificial Intelligence Group

DART
DATA and AI Research Unit

Member of the Norwegian Open AI Lab

- NTNU Lab for AI research across faculties
- Research projects, seminars

norwegian open ai lab

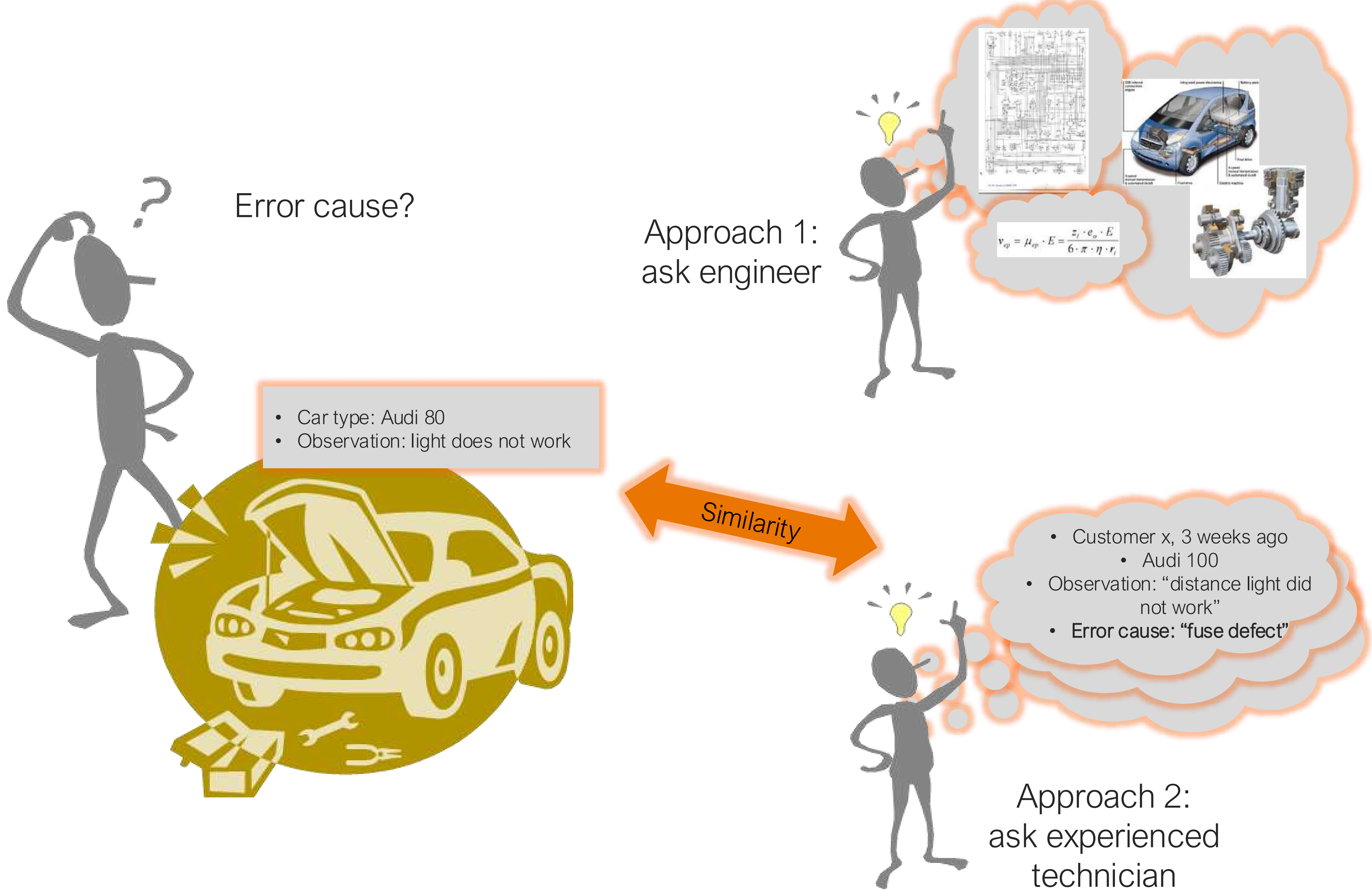
Research Director of NorwAI

- Research center for AI-based innovation

NorwAI
Norwegian Research Center for AI Innovation

What is Case-Based Reasoning?

Experience-based problem solving



Case-Based Reasoning

Case-Based Reasoning is …

- … a **cognitive apporach** for modeling human problem solving behaviour
  - Cognitive science point of view
  - Goal: Understanding of cognitive procedures
- ... an **engineering approach** for developing and implementing intelligent systems for problem solving
  - Technical and computer science point of view
  - Goal: Development of practical systems

Basic assumption:

- “Similar problems have similar solutions”

Statements about Case-Based Reasoning

"A case-based reasoner solves new problems by adapting solutions that were used to solve old problems" (Riebeck & Schank, 1989)

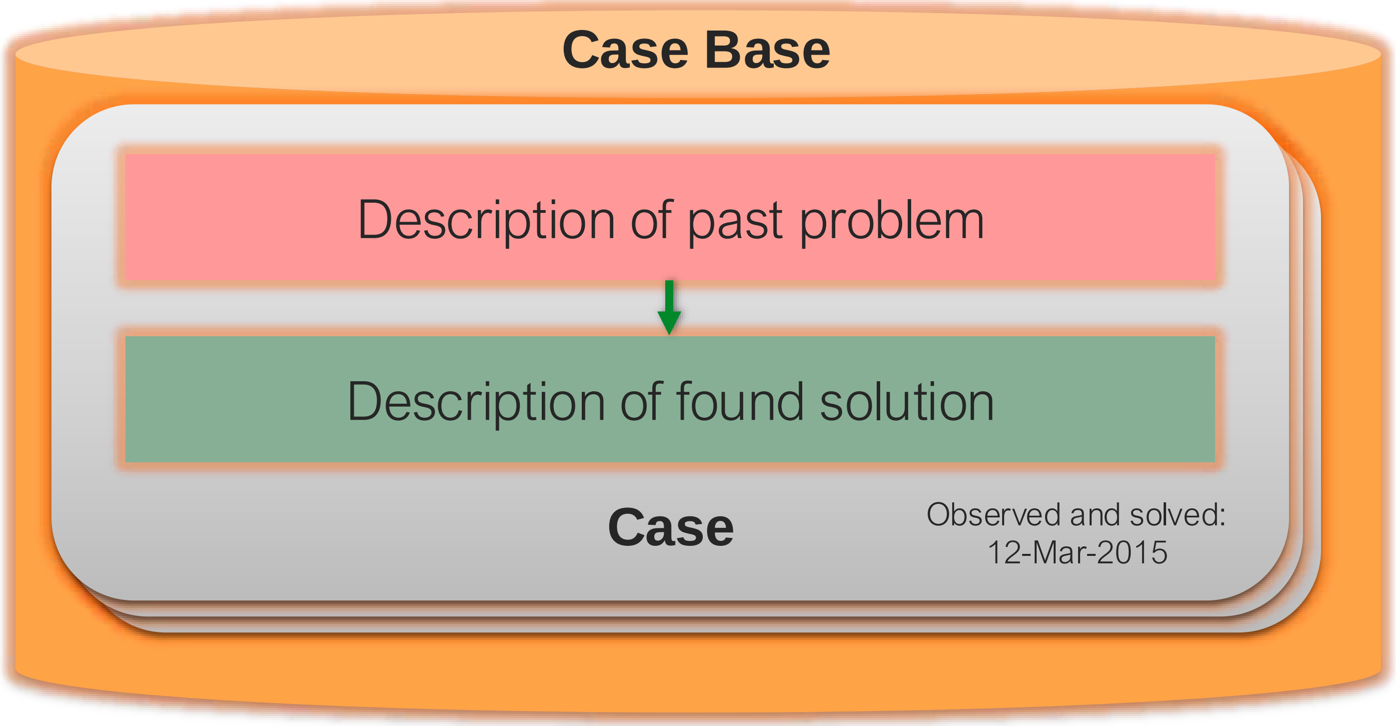
"Case-based reasoning is both […], the ways people use cases to solve problems and the ways we can make machines use them."
(Kolodner, 1993)

"Case-based reasoning is a recent approach to problem solving and learning […]" (Aamodt & Plaza, 1994)

"Case-based Reasoning is [..] reasoning by remembering."
(Leake, 1996)

Formalization of Experience Knowledge

- Idea: Drawing conclusions directly from stored **situation-specific experience knowledge**
- Situation-specific experience knowledge stored as tuples of past problem and corresponding solution descriptions – called **cases**

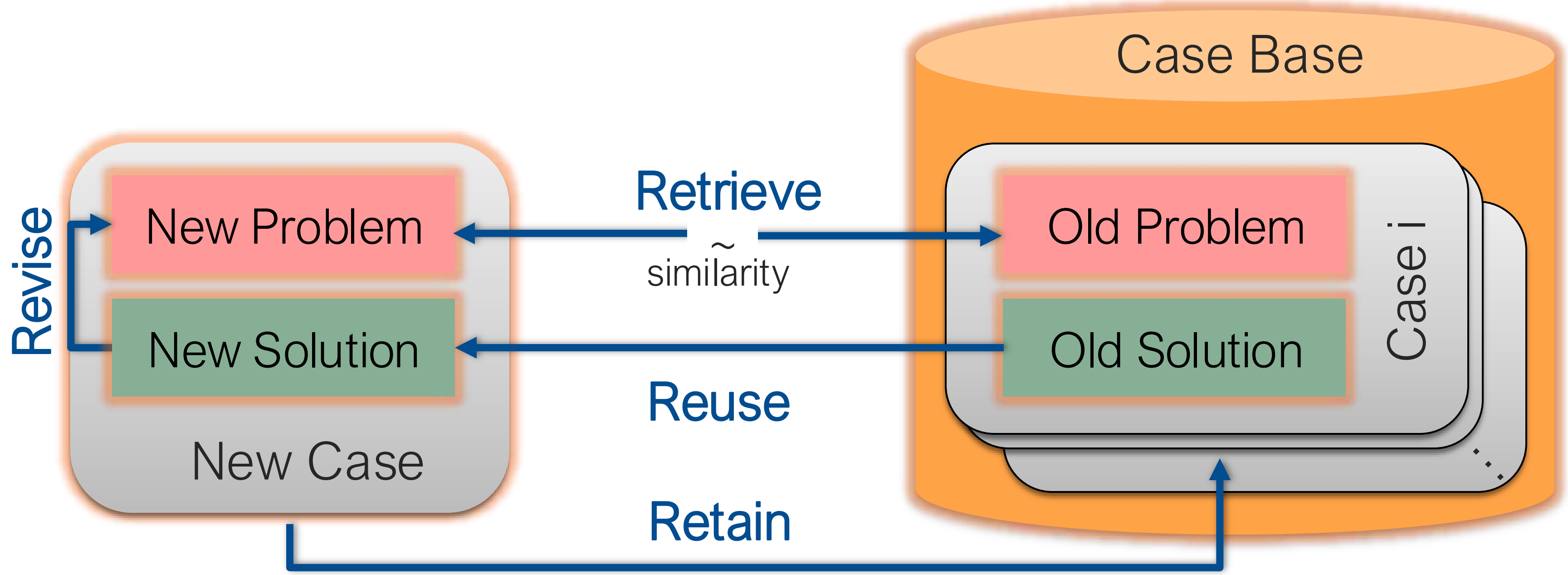


- Solving of new problems by reusing solutions of similar, already solved problems stored in a **case base**

Basic Idea of Case-Based Reasoning

Case-Based Problem Solving

1. **Retrieving** relevant experiences from the case base
2. **Reusing** of retrieved experiences in the context of the current problem (may require ***adaptation*** of the retrieved solution)
3. **Revising** the solution
4. **Retaining** the new experience in the case base



Case-Based Reasoning Cycle

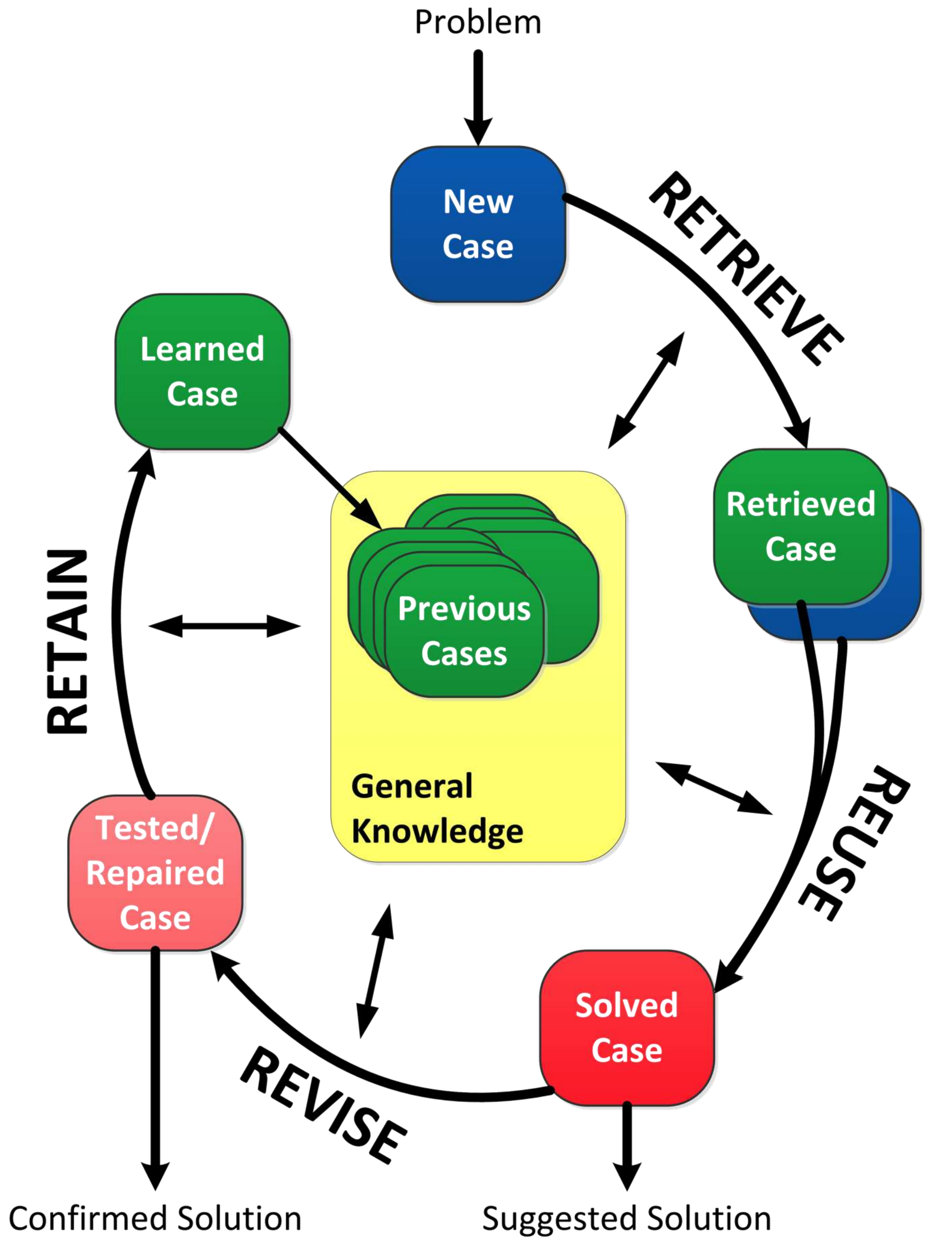
Overall process model

CBR is neither …

- a single algorithm
- nor a collection of similar algorithms

CBR is more …

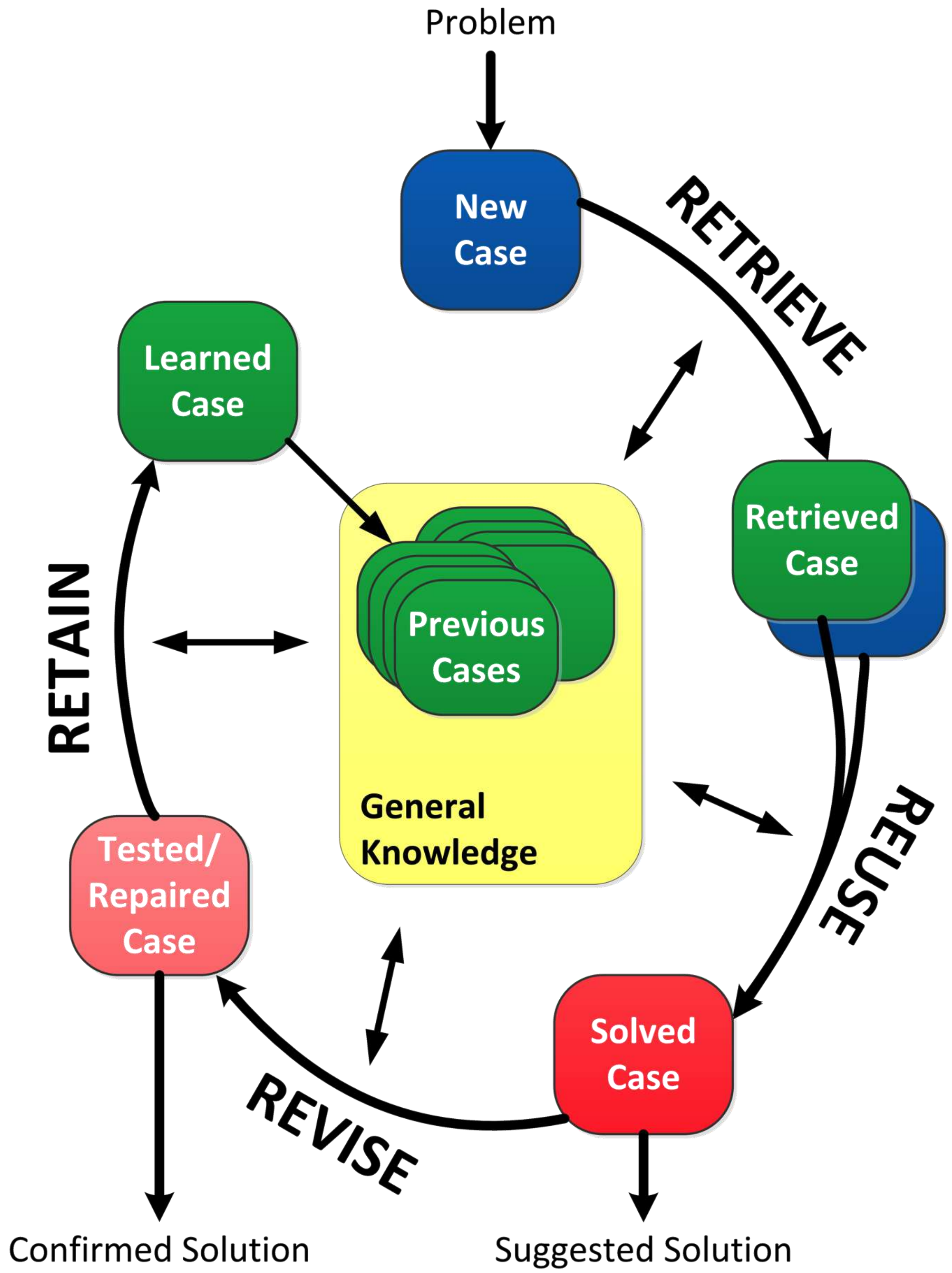
- a paradigm
- a methodology
- a general procedure for problem solving



(Aamodt & Plaza, 1994)

Case-Based Reasoning Cycle

- Retrieve: the most similar case or cases: The case(s) with the most similar problem description (s)
- Reuse: the information/experience stored in the solution descriptions of the retrieved case(s) to solve the presented problem
- Revise: the retrieved solution if it is necessary to solve the presented problem in a satisfying way
- Retain: the tested adapted new solution/experience as a new case, consisting of the presented problem description and the adapted solution description as a new experience in the case base



(Aamodt & Plaza, 1994)

What are the main processes of a CBR system?

NTNU

CBR process model: Retrieve

Case Representation

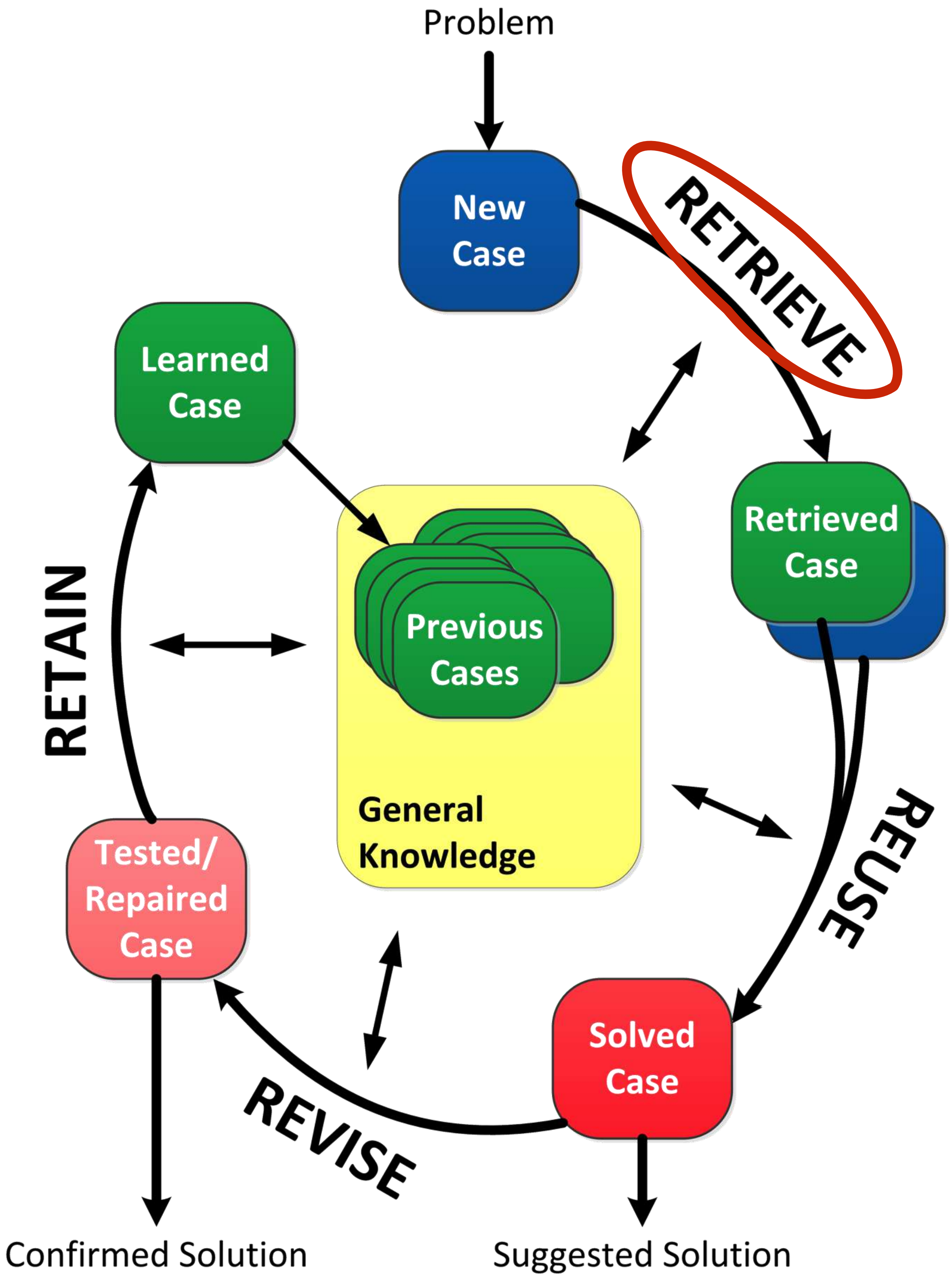
- Attribute-value based representation
- Object-oriented representation
- Specific representations

Similarity

- Conceptual meaning and formalization of similarity
- Traditional similarity measures
- Knowledge-intensive similarity measures

Retrieval

- Index structures
- Use of data bases
- Retrieval algorithms



Example (I): Technical Diagnosis of Car Faults

Case describing a particular diagnostic situation

Attribute

Value

CASE 1

Problem (Symptoms)

- *Problem*: Front light does not work
- *Car*: VW Golf IV, 1.6 l
- *Year*: 1998
- *Battery voltage*: 13,6 V
- *State of lights*: OK
- *State of light switch*: OK

Solution

- *Diagnosis*: Front light fuse defect
- *Repair*: Replace front light fuse

CASE 2

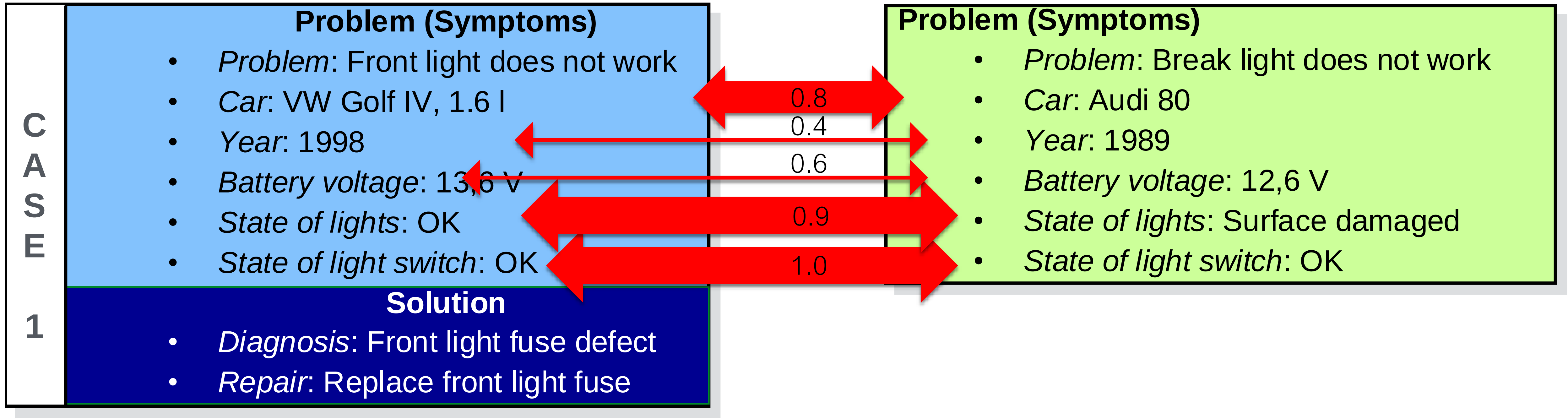
Problem (Symptoms)

- *Problem*: Front light does not work
- *Car*: Audi A4
- *Year*: 1997
- *Battery voltage*: 12,9 V
- *State of lights*: surface damaged
- *State of light switch*: OK

Solution

- Diagnosis: Bulb defect
- Repair: Replace front light

Example (II): Similarity Comparison



Very important feature → weight = 6

Less important feature → weight = 1

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

Traditional assumption of CBR:

„**similar** problems have **similar** solutions"

Similarity is a central concept in CBR

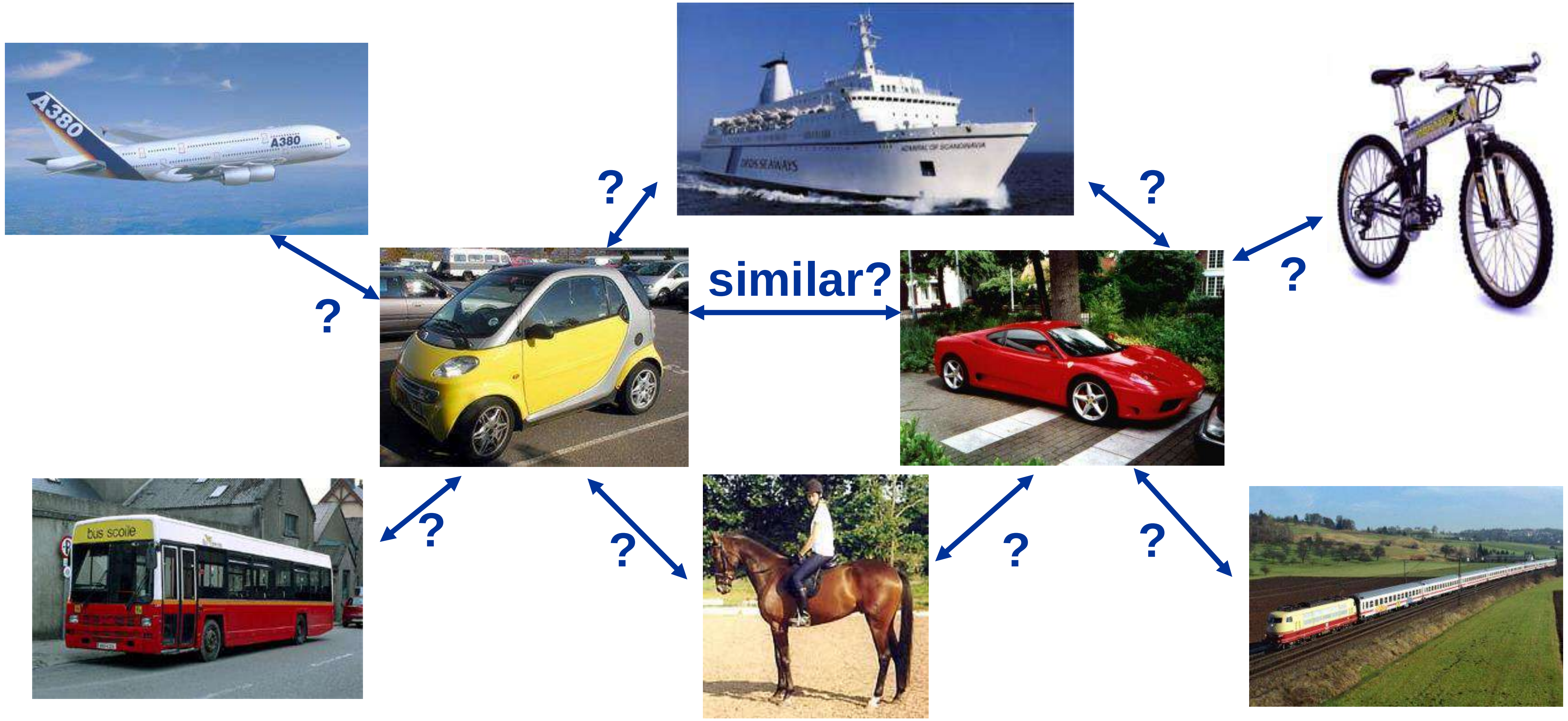
Selection of cases in the retrieval step based on

- Similarity between problem descriptions (traditional view)
- Similarity between queries and cases (generalized view)

First it has to be distinguished between …

- … the conceptional meaning of the term „similarity“
- … the mathematical formalization of this meaning
- … the modeling of similarity in practical CBR systems

Characteristics of Similarity: Relativly



Observation 1: Similarity is always a ***relative*** phenomenon

- Similarity depends strongly on the domain of the objects / values to be compared

Characteristics of Similarity: Aspect/Purpose Dependency

similar color

similar sporty

similar expensive

Observation 2: Similarity is always related to a certain ***aspect*** or ***purpose***

- Similarity is related to *abstraction*
  - abstraction selects a certain aspect which is of interest (e.g. color, price, speed)
- *Conclusion*: there is no absolute meaning of similarity
  - The definition of the relevant domain and the appropriate degree of abstraction is important

Characteristics of Similarity: Transitivity

Example 1

Example 2

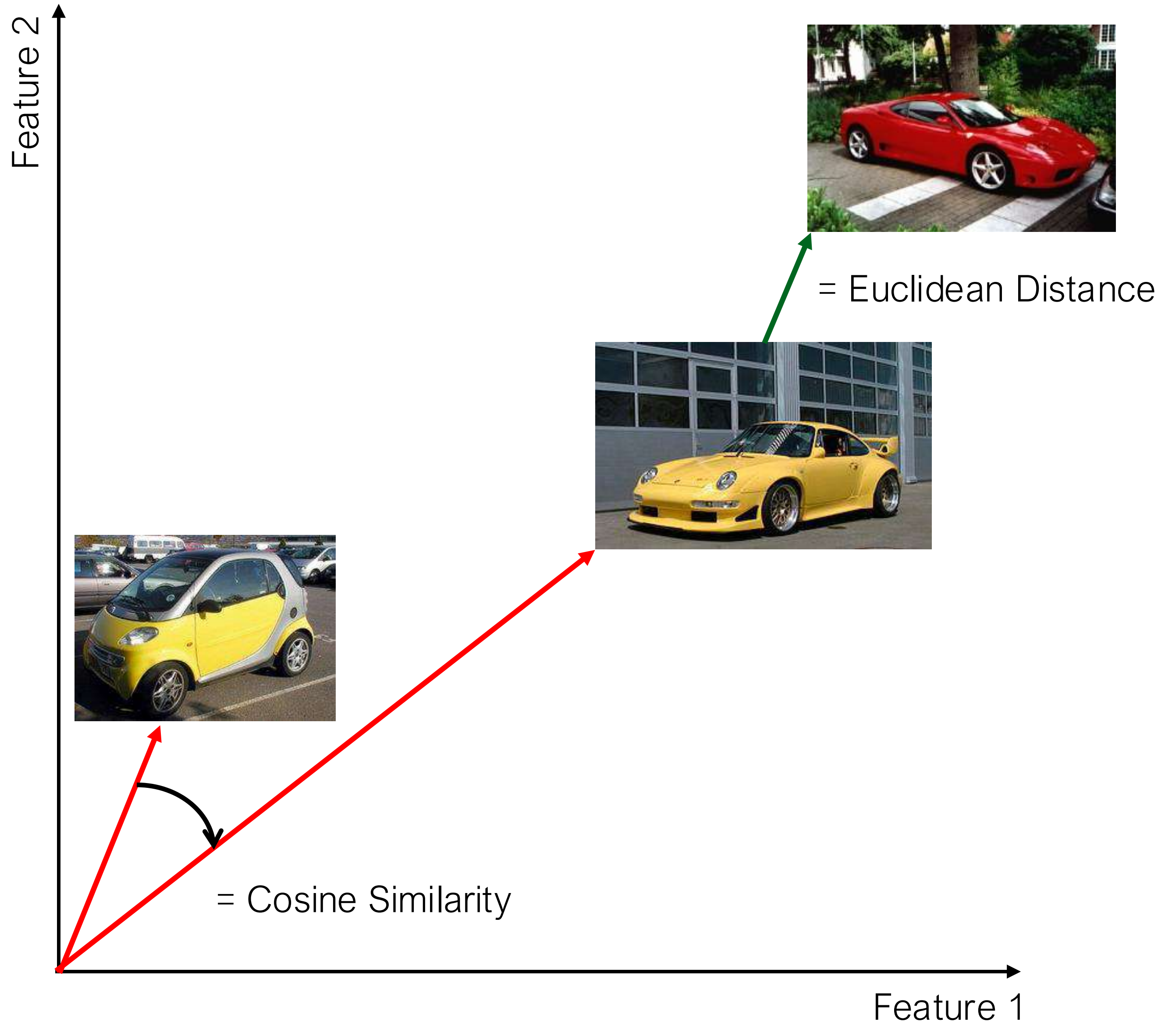
10€ $\xleftrightarrow{\text{similar}}$ 11€ $\xleftrightarrow{\text{similar}}$ 12€ … 999€ $\xleftrightarrow{\text{similar}}$ 1000€

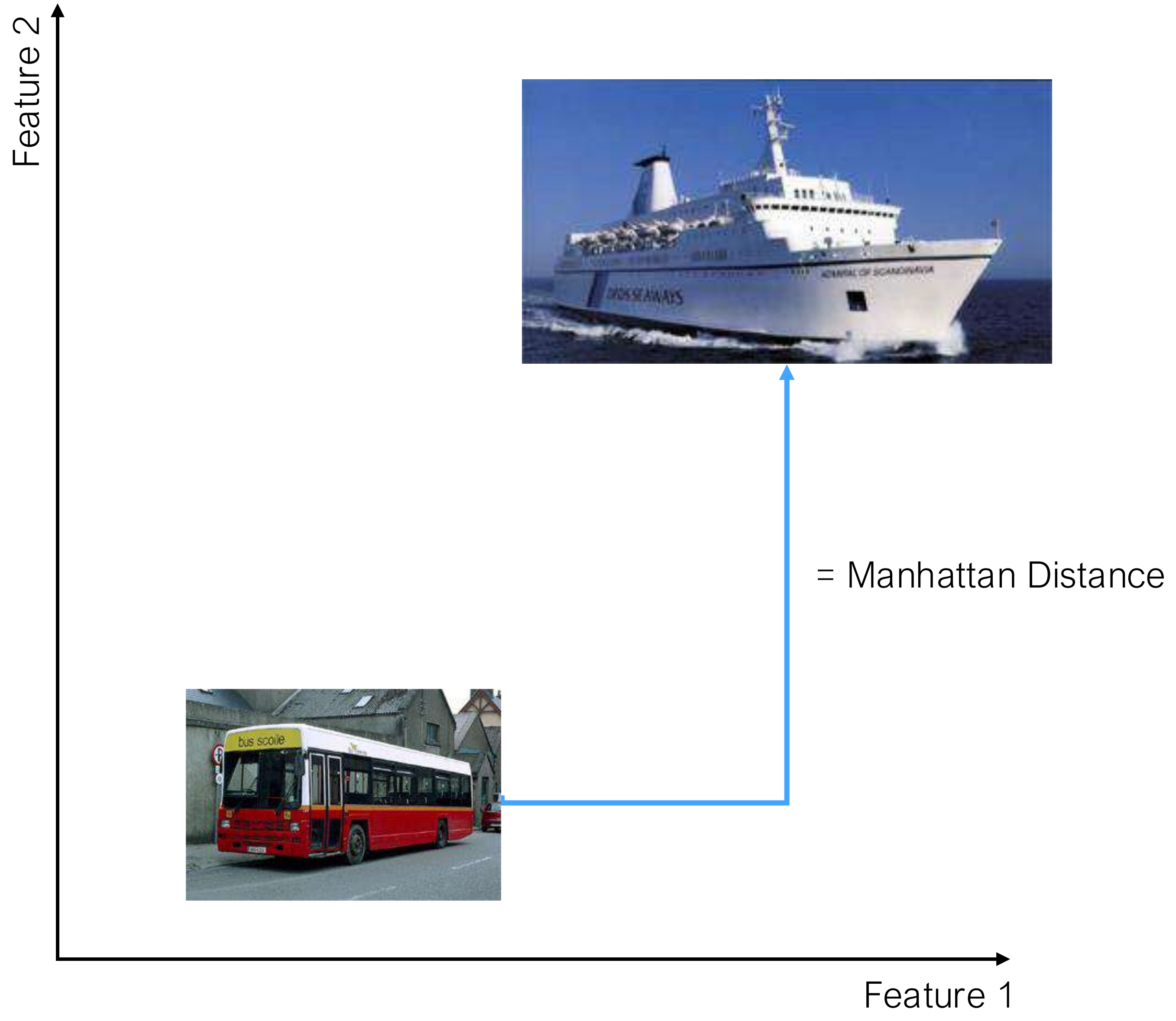
dissimilar

Observation 3: Similarity is mostly ***not transitive***

- Reason example 1: similarity between different aspects
- Reason example 2: the property “low difference” is not transitive

Popular distance similarity measures





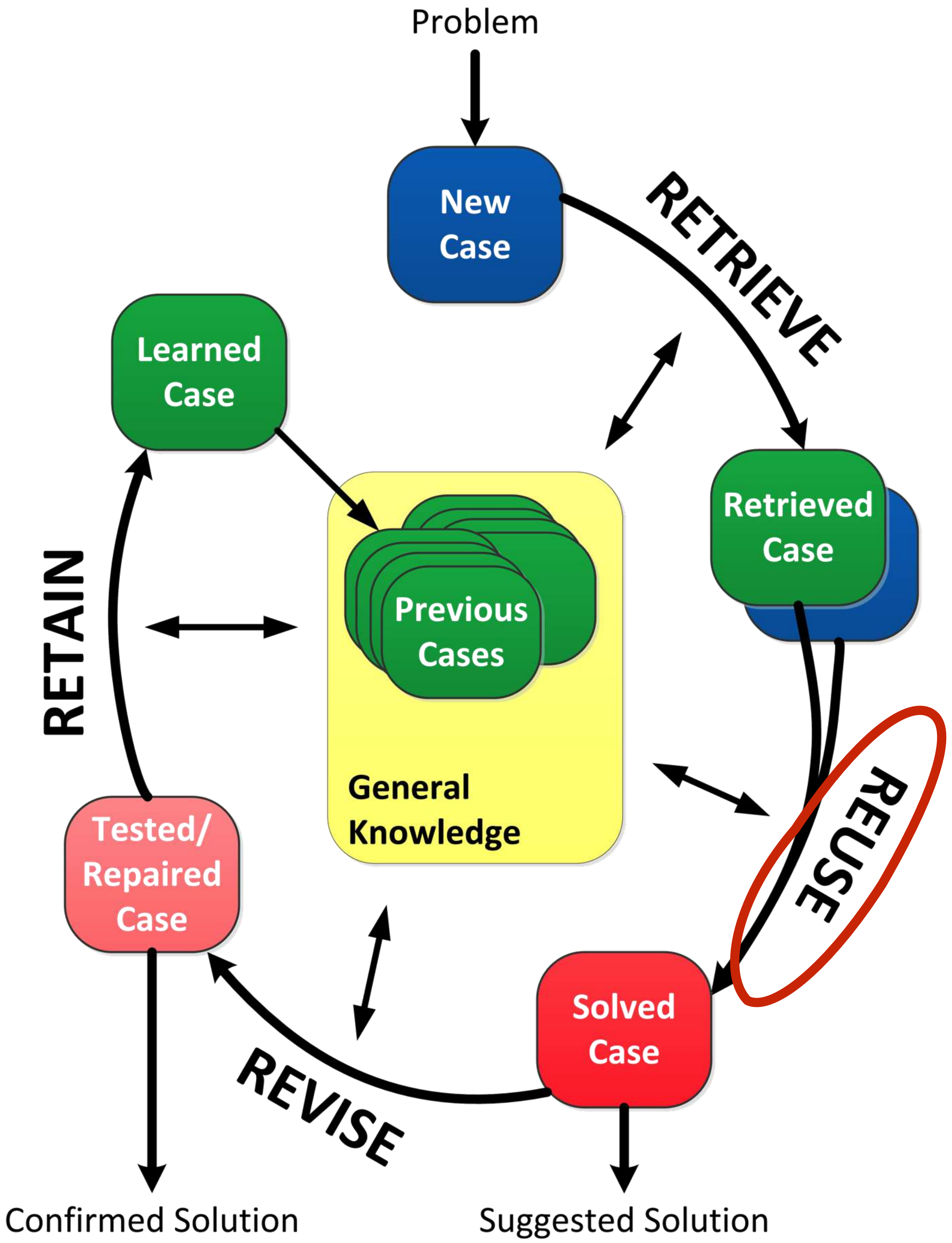
CBR process model: Reuse

Statistical reuse approaches

- Voting

Adaptation approaches

- Derivational analogy: reuse of solution procedures
- Transformational analogy: reuse of final solutions
  - Adaptation rules
  - Adaptation operators
  - Compositional adaptation
- Generalized cases



Example (III): Case Adaptation

CASE 1

Problem (Symptoms)

- *Problem*: **Front light** does not work
- ...

Solution

- *Diagnosis*: Front light fuse defect
- *Repair*: Replace front light fuse

Problem (Symptoms)

- *Problem*: **Break light** does not work
- *Car*: Audi 80
- *Year*: 1989
- *Battery voltage*: 12,6 V
- *State of lights*: Surface damaged
- *State of light switch*: OK

Adaptation

New Solution:

- Diagnosis: **Break light** fuse defect
- Repair: Replace **break light** fuse

CBR process model: Revise

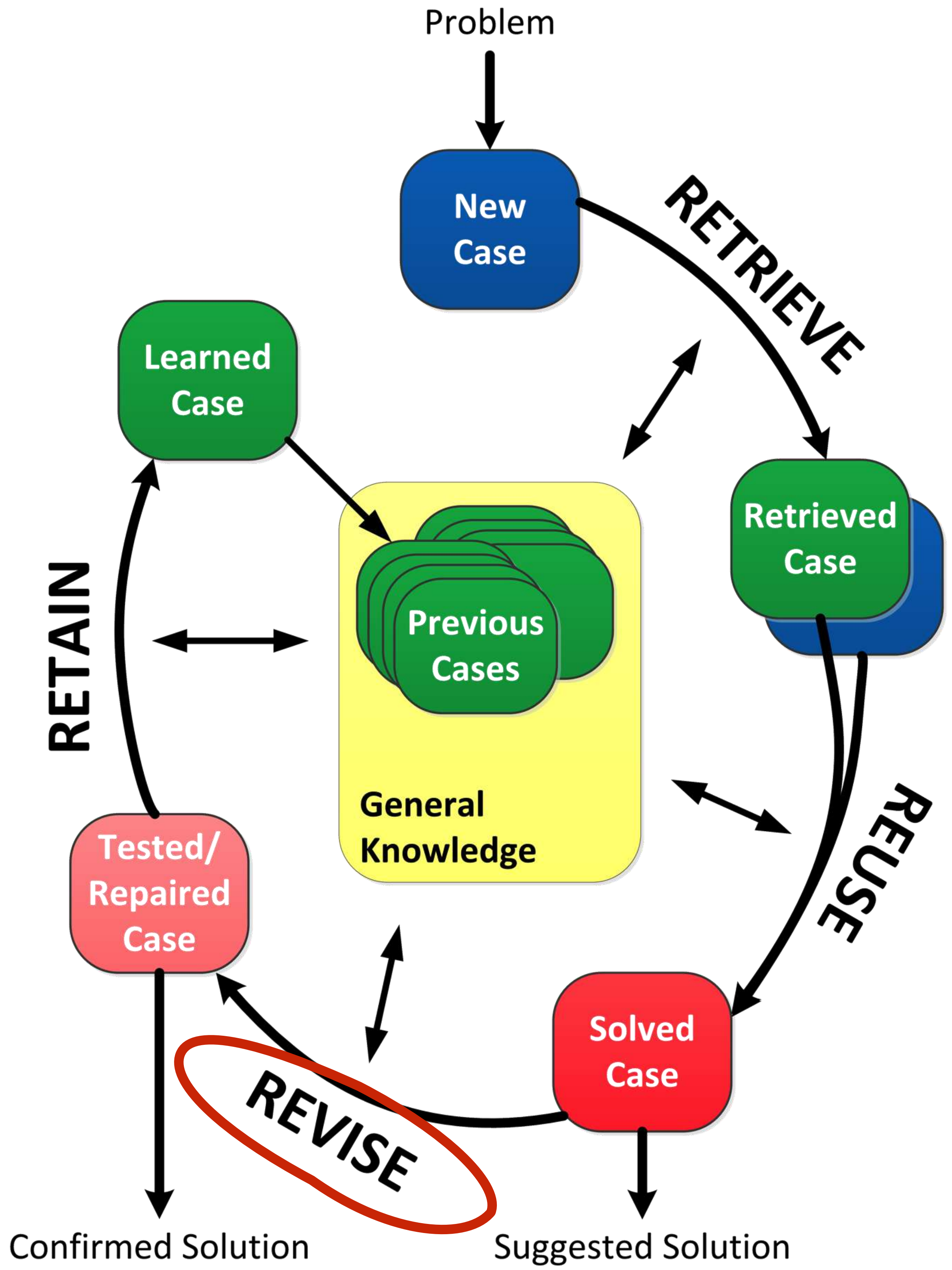
Limited support by current CBR systems

Mostly done manually

- Revision by domain experts
- Application in the real world
- Simulation approaches

Revision criteria

- Correctness of the solution
- Quality of the solution
- Other application / user specific criteria



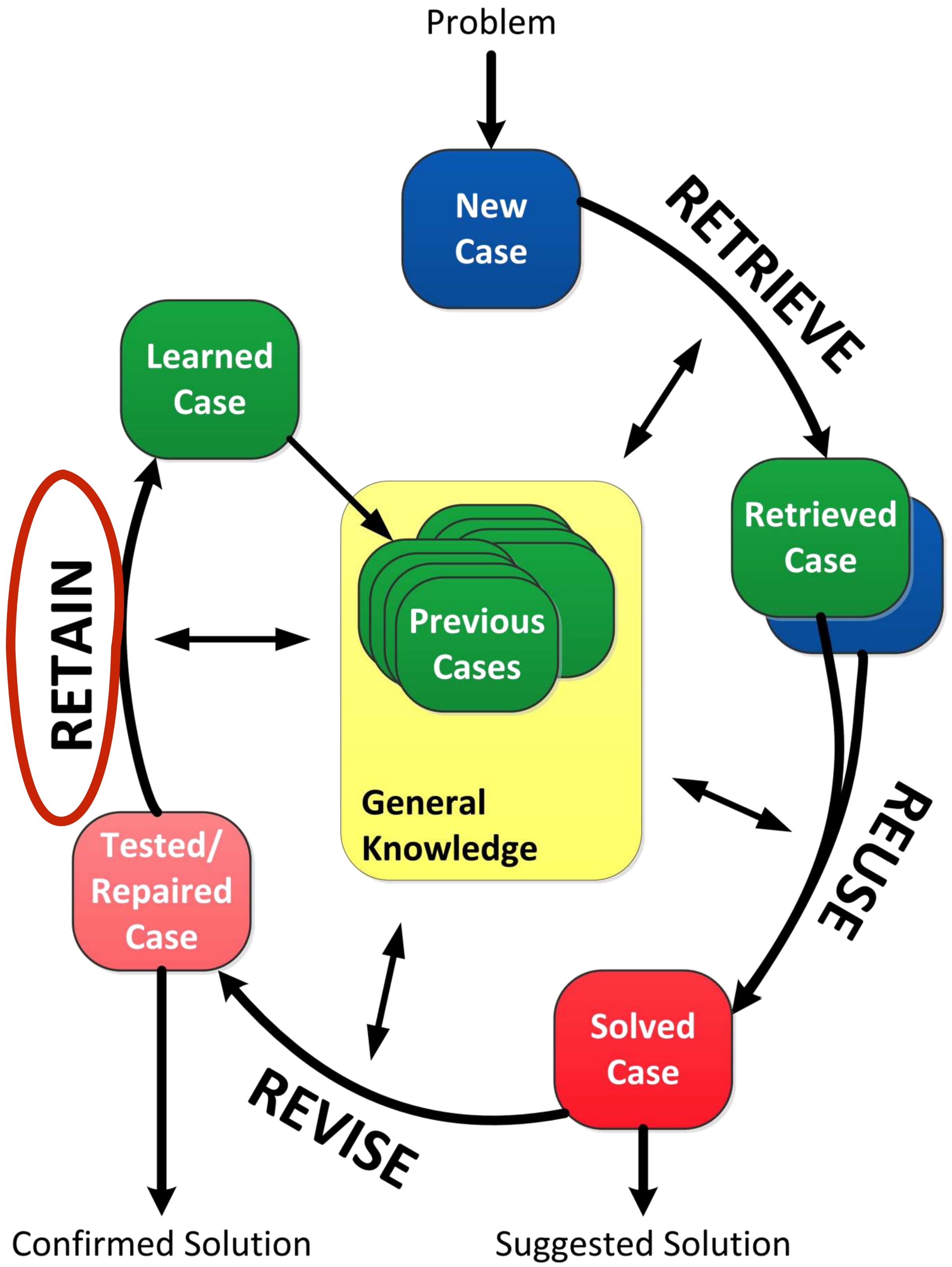
CBR process model: Retain

Learning of

- New experiences (cases)
- Organization of the case base
- Similarity measures & attribute weights
- Adaptation knowledge

Methods

- Storing and deleting cases
- Optimization and Machine Learning algorithms
  - Hill climbing approaches
  - Genetic algorithms
- Symbolic inductive learning algorithms



Example (IV): Retention

If the diagnosis is correct: Store the new case in the case base

CASE 3	**Problem (Symptoms)** • *Problem*: Break light does not work • *Car*: Audi 80 • *Year*: 1989 • *Battery voltage*: 12,6 V • *State of lights*: Surface damaged • *State of light switch*: OK
	New Solution: • Diagnosis: **Break light** fuse defect • Repair: Replace **break light** fuse

Case Information

Typically specific knowledge about a *past situation*

Application domain and task of a CBR system determine…

- … the **kind of knowledge** described in cases
    - Description of the past situation (typically a problem description)
    - „Lesson learned“ during this situation (typically a solution description)
    - Quality information (optional)
- … the **amount of knowledge** stored in the cases
    - Complete or partial situation descriptions
    - Detailed or abstract descriptions
- … the **used knowledge representation formalism**
    - Attribute-value-based, object-oriented, graphs or trees, first order logic, plans, etc.

Solution Description

In the traditional view, the solution description contains all relevant information for reproducing the stored solution.

Possible components of the solution description:

- Solution itself (e. g. a class label, a repair description, a plan, ...)
- Solution procedure, i.e. a sequence of action used for solving the problem
- Information, which helps to adapt the solution
- Justifications for decisions made during problem solving (e. g. selection of an action)
- Alternative solution steps, which would also be successful
- Failed solution steps

How can knowledge be represented in a CBR system?

Knowledge Containers

Similarity Measures

The retrieval of similar cases is based upon the use of similarity functions (or measures) to compute the distance or similarity of two cases.

Case base

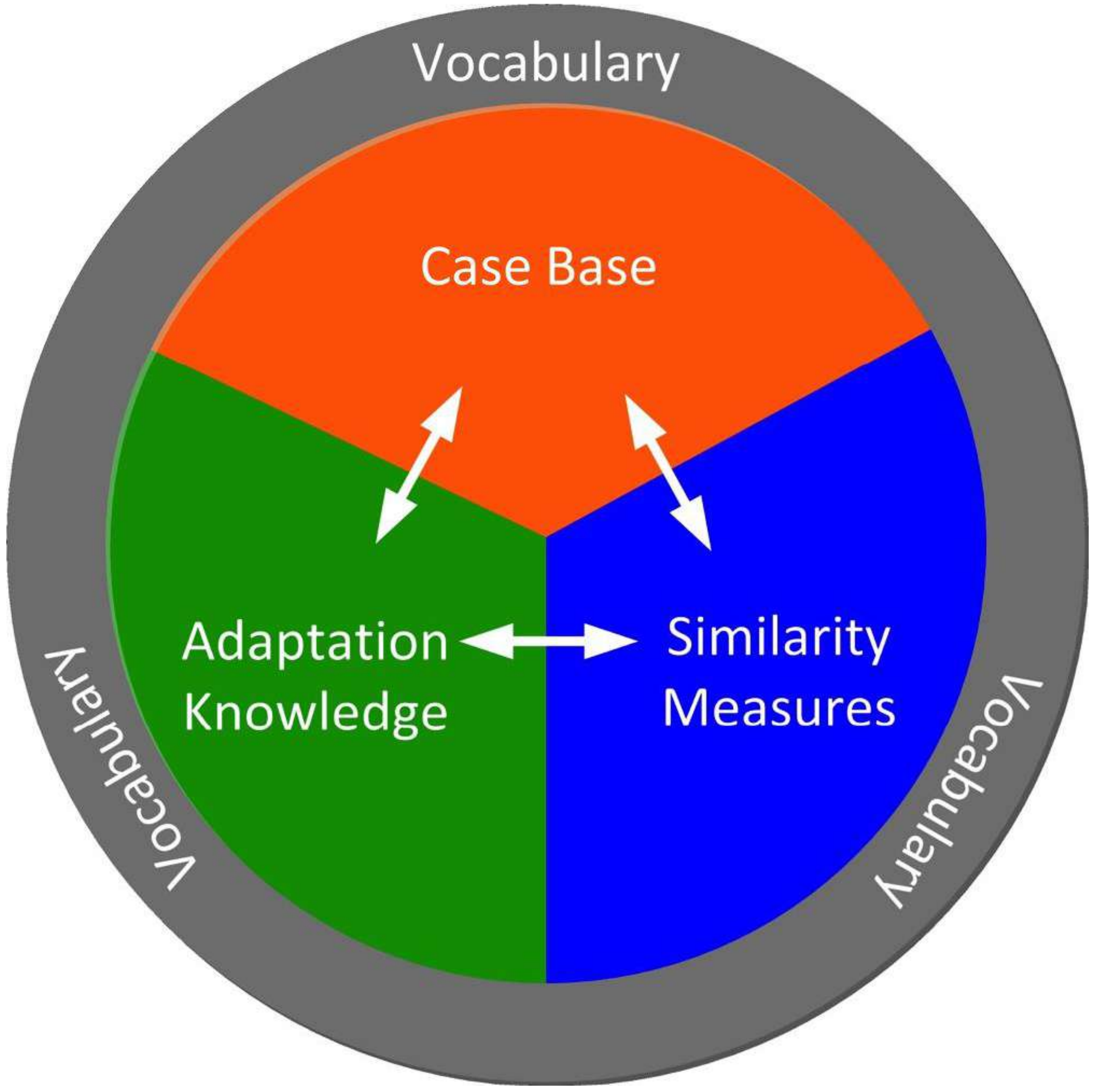
The systems experience is stored as cases within the case base which can be seen as a special form of a data base.

Vocabulary

The cases themselves, the similarity measures and the adaptation knowledge are composed upon a vocabulary that contains the objects of interests (terms, attributes, concepts).

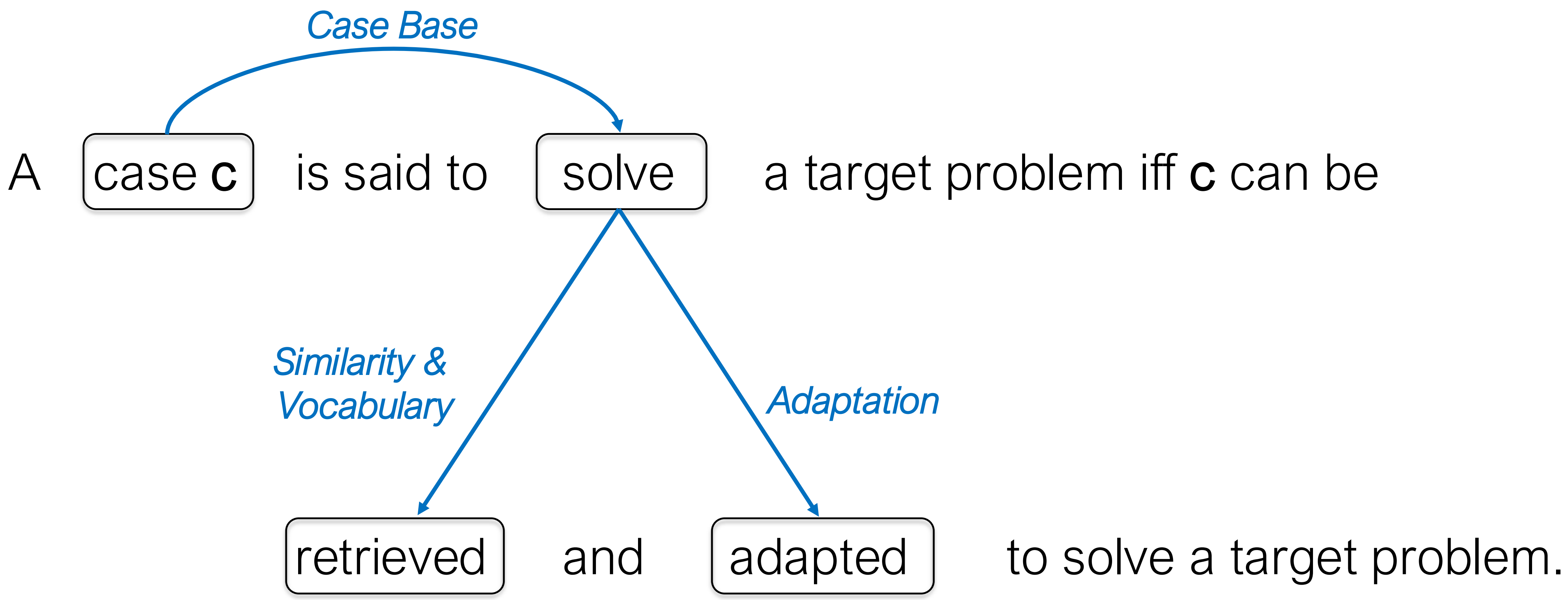
Adaptation knowledge

Adaptation knowledge is used whenever a retrieved case’s solution has to be adapted to be suitable to solve the presented problem. An example for this kind of knowledge is given by adaptation rules like
“If X is not available use Y instead.”



Competence of a CBR System

- Competence = range of target problems a CBR system can solve



More: https://www.ijcai.org/proceedings/2018/0251.pdf

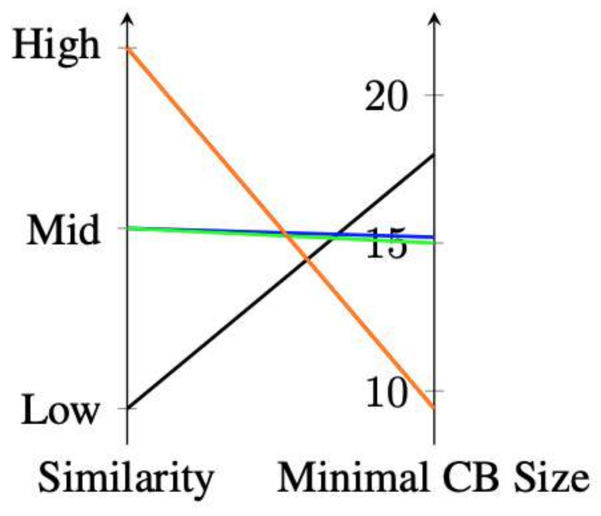
Footprint of a CBR System

- Minimal set of cases – consistent competence

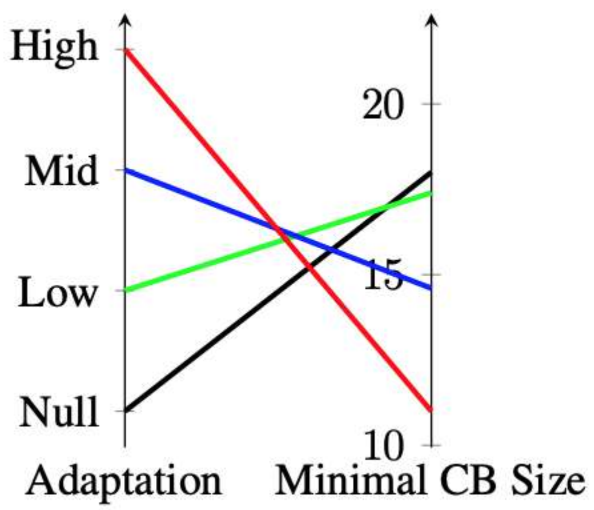
More: https://www.youtube.com/watch?v=23UhRkCBgSU&index=2&list=PLAzG2mxsMxthbl2QBspYGannN0bmffodP

Knowledge Container Trade-offs

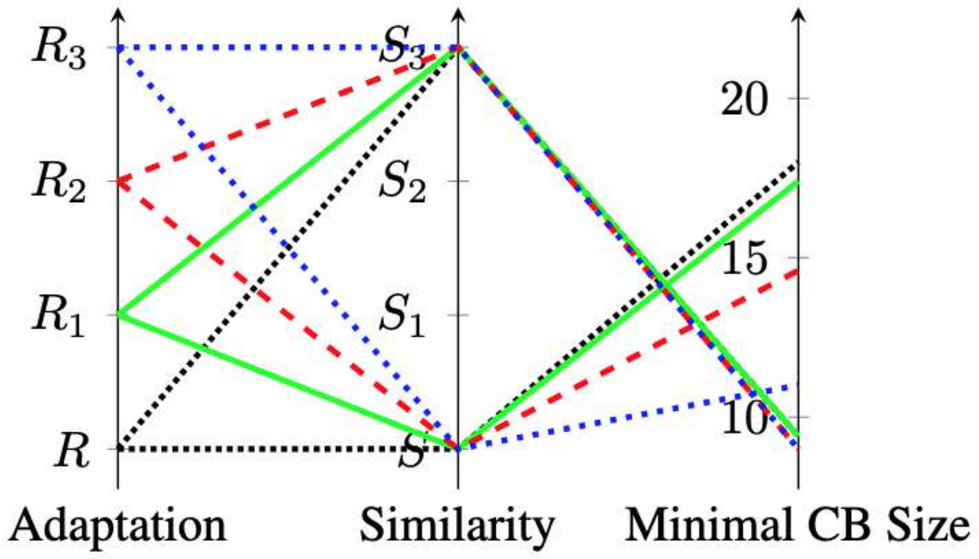
- Challenge: Move knowledge from one container
  - Case base and vocabulary trade-off
  - Case base and similarity trade-off
  - Case base and adaptation trade-off
  - Similarity and adaptation trade-off



(b) Similarity versus CB



(c) Adaptation versus CB

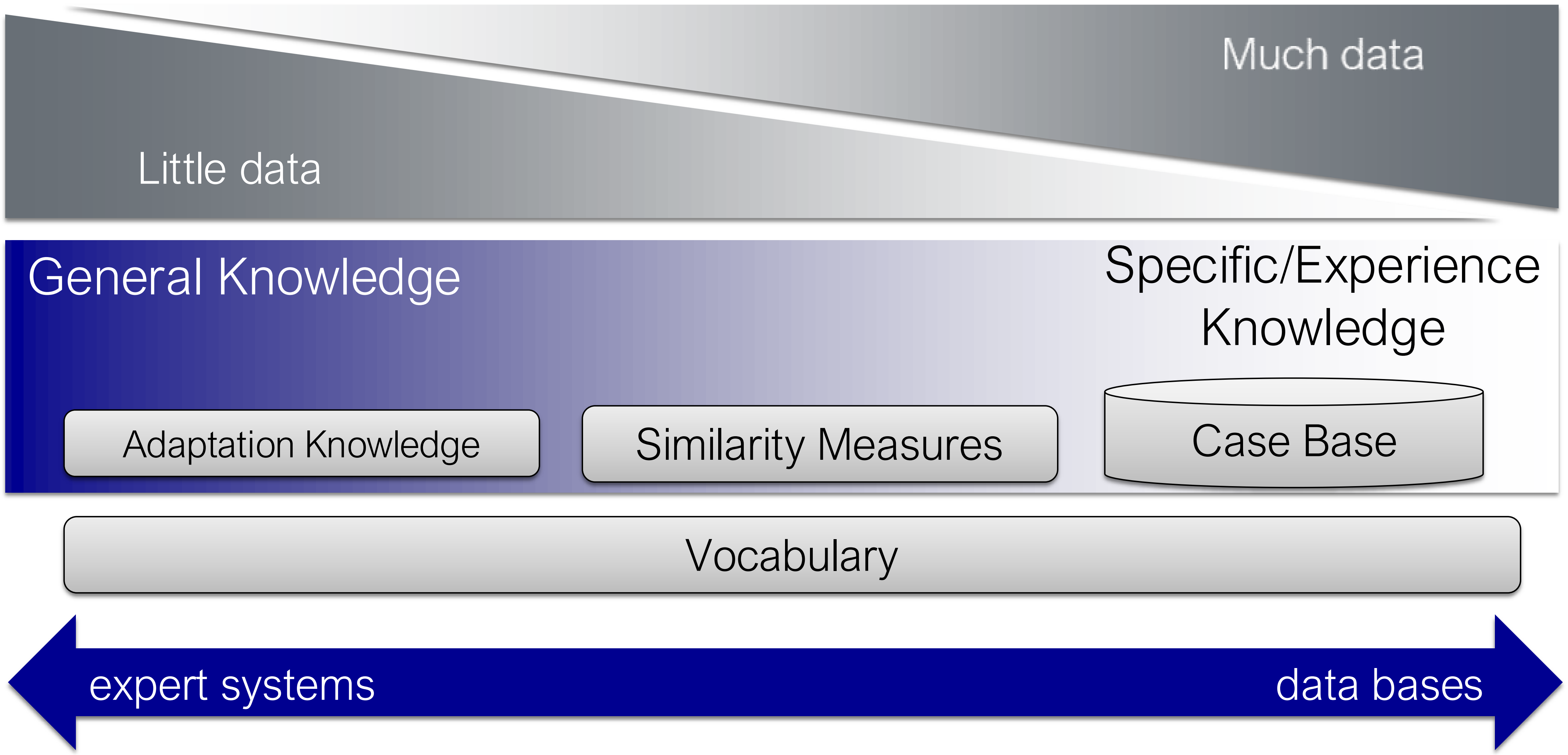


(d) Similarity versus Adaptation

Distribution of Knowledge

Knowledge can be distributed flexibly between containers

- Actual distribution of knowledge depends on preconditions of the application domain



What are applications of CBR?

NTNU

Examples of CBR in human reasoning

- A medical doctor remembers the case history of another Patient
- A lawyer argues with similar original precedence
- An architect studies the construction of existing building to base his new designs on it
- A work scheduler remembers the construction steps of a similar work piece
- A mathematician tries to transfers a known proof to a new problem
- A service technician remembers a similar defect at another device
- A salesperson recommends similar products to similar customers

Example Application: Running with Cases

Research presented at ICCBR’17 and ICCBR’18

Novel application of case-based reasoning to address the dual task of

1. Predicting a challenging, but achievable, personal best race-time for a marathon runner
2. Recommending a race-plan to achieve this time

Reference:

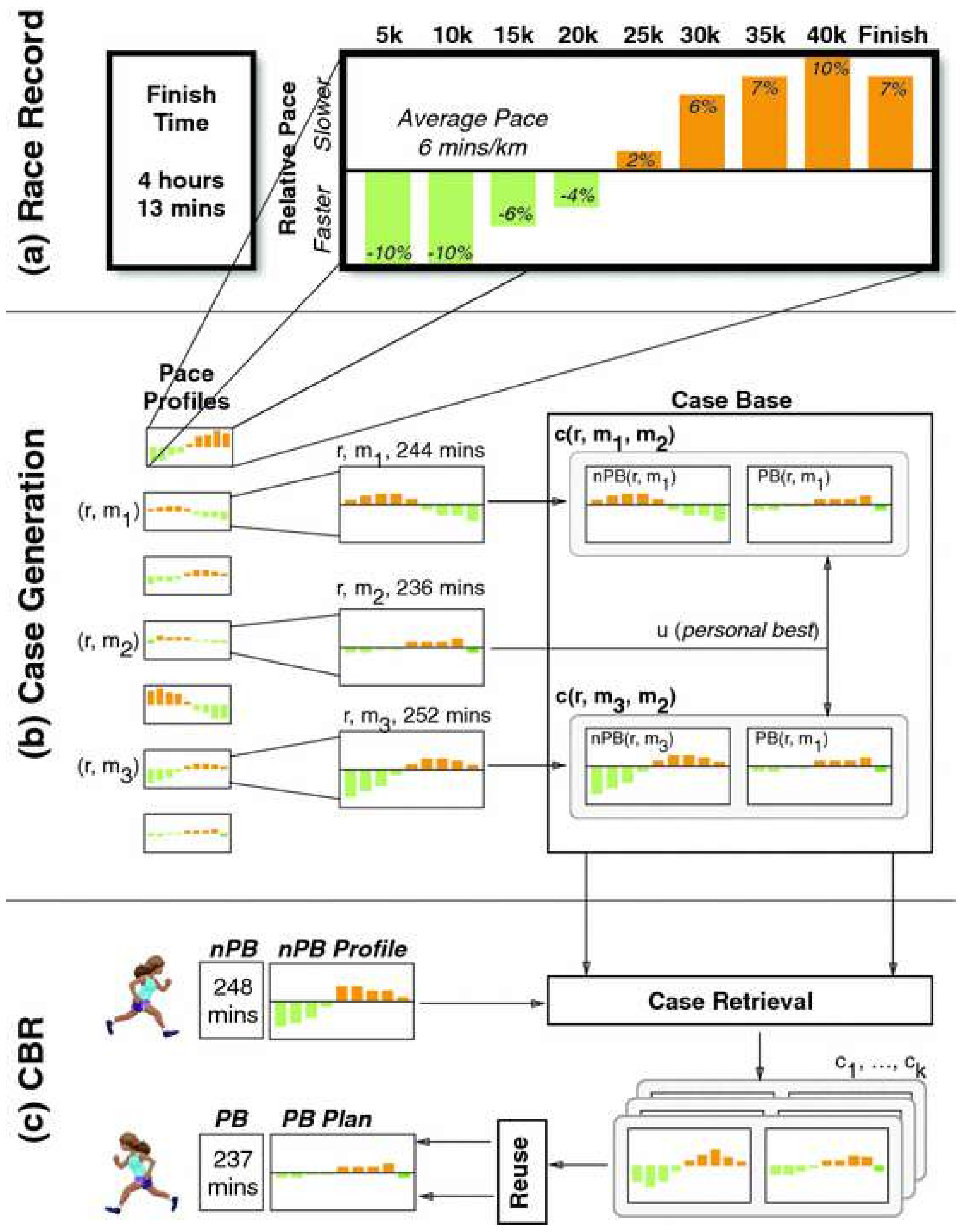
- Smyth B., Cunningham P. (2017) **Running with Cases: A CBR Approach to Running Your Best Marathon**. In: Aha D., Lieber J. (eds) Case-Based Reasoning Research and Development. ICCBR 2017. LNCS 10339. Springer, Cham
- https://link.springer.com/chapter10.1007/978-3-319-61030-6_25

Example Application: Running with Cases

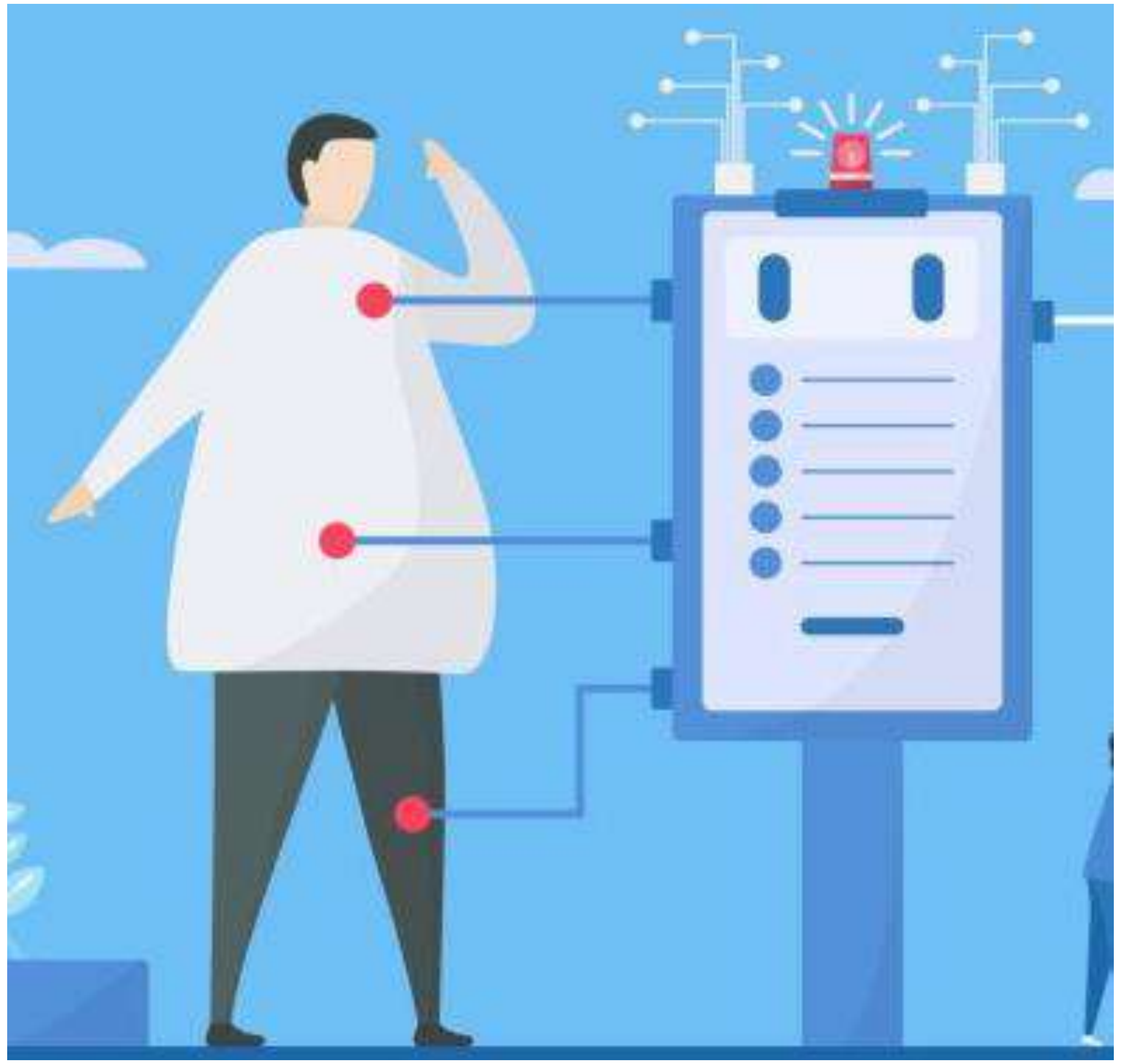
(a) An example race record for a runner, showing a finish-time and a pacing profile containing pacing data for each of the 5 km race segments;

(b) Converting race records into cases;

(c) An overview of the CBR process: given an nPB race record as a query, the system retrieves a set of k cases with similar nPB parts, and combines these to generate a personal best finish-time prediction and a pacing plan to achieve this finish-time.



AI in e-Health Interventions



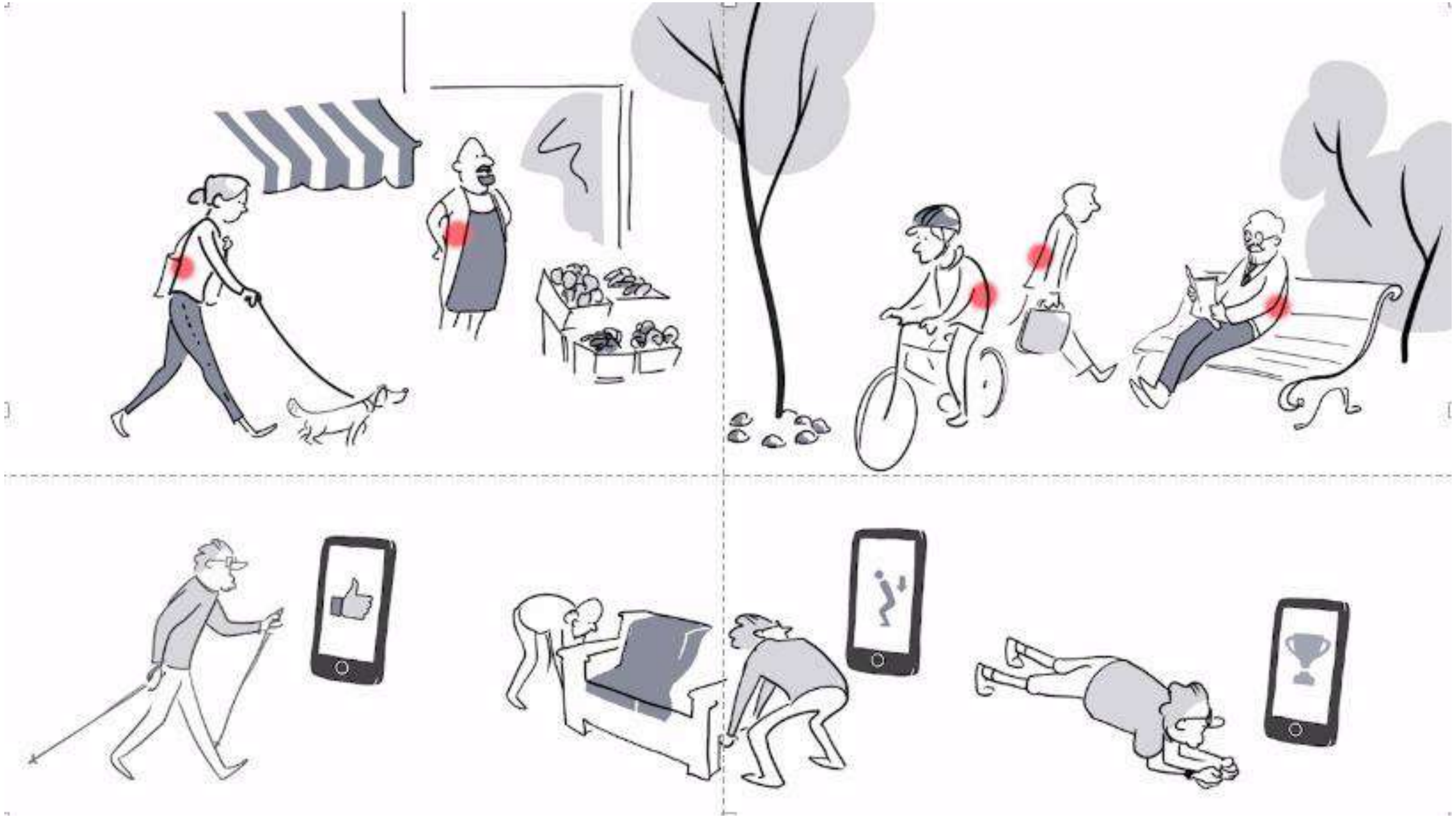
- Diagnosis and treatment planning
- Personalized medicine
- Predictive analytics
- Clinical decision support

Example Application: SELFBACK

EU Project (2016-2021)

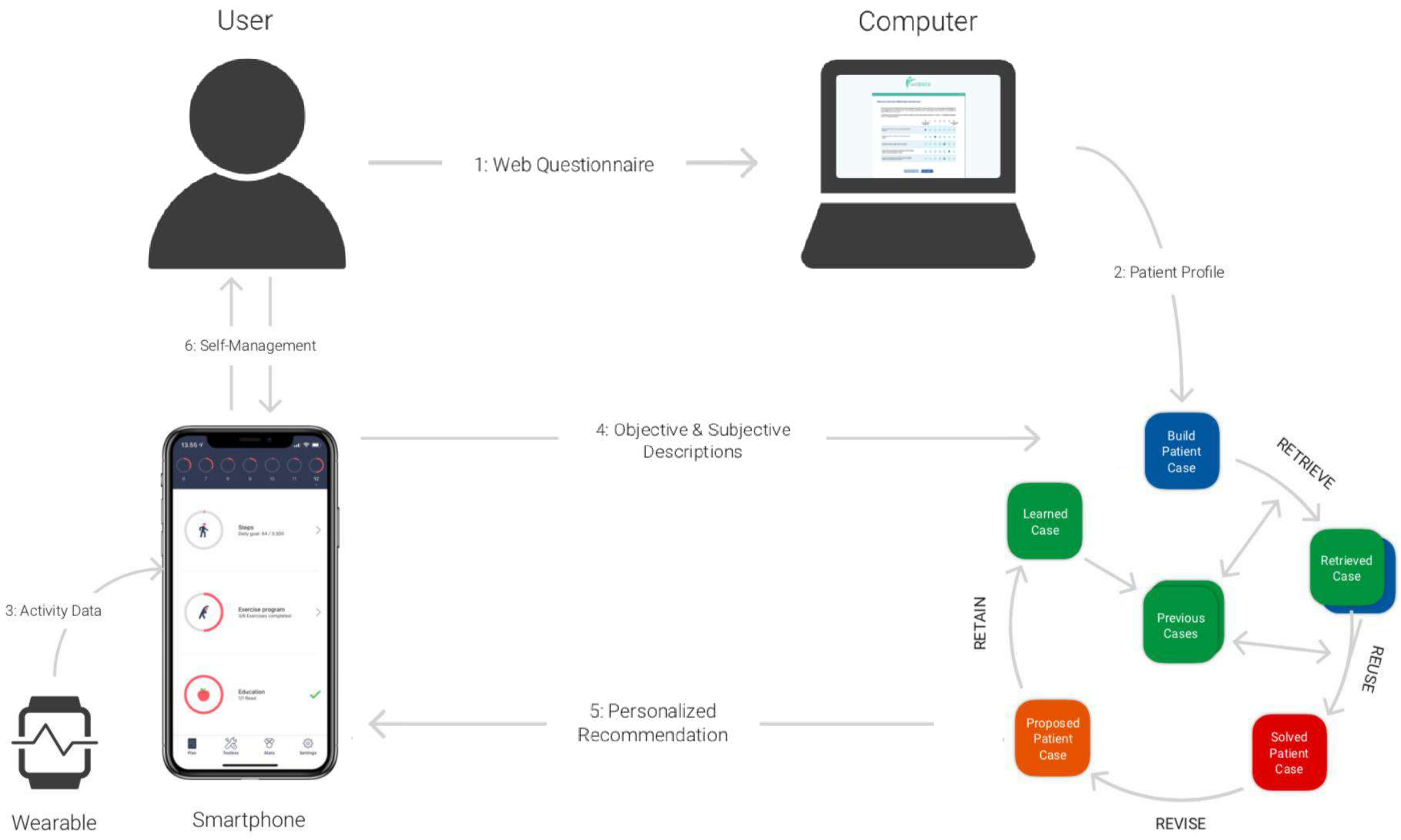
- Coordinated by NTNU
- A decision support system for self-management of low back pain

Example Application: SELFBACK



Video: https://youtu.be/j8_1pcBLbko?si=6JFDN1G1L2NX_SAf

Example Application: SELFBACK



Example Application: SELFBACK

Case Representation

- Goal: translation of an experts view on how to compare patients to each other in order to find the most similar one

	Case Part	Content	Updates
Problem Description	Subjective Description	- Demographics	Initially
		- Quality of Life - Pain Intensity - Functionality	Weekly/biweekly
	Objective Description	- Activity Stream	Continuously
Solution	Advice	- Activity Plan - Exercise Plan	Weekly
		- Educational Session	
Outcome		- Pain Intensity - Functionality	Weekly

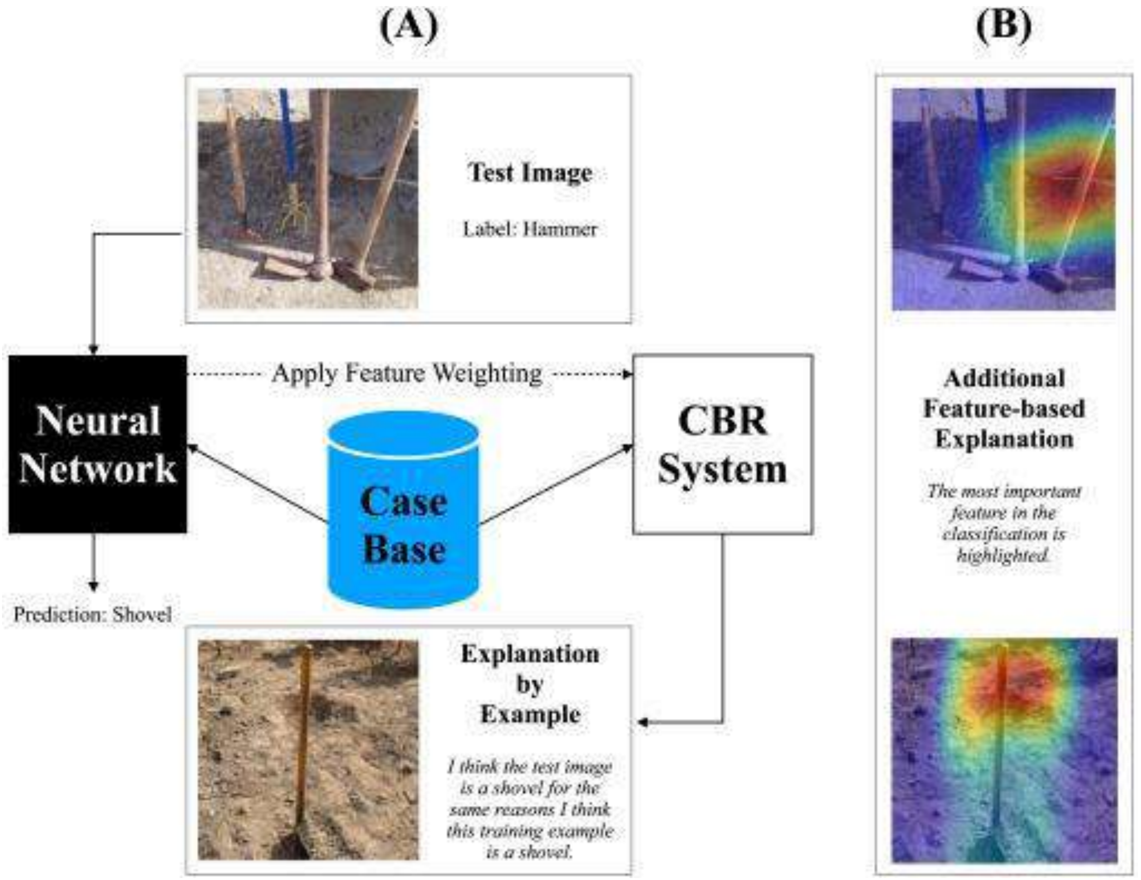
Research Trends in CBR

CBR as an eXplainable AI (XAI) Methodology

- Knowledge is accessible and can be presented as justification

Twin Systems to explain Black Box Models

- NN and CBR system trained on the same data
  - NN does the prediction
  - CBR generates a post-hoc explanation by example



Full paper: https://doi.org/10.1016/j.knosys.2021.107530

More on CBR

AAAI – AI Topics:	https://aitopics.org/search?q=case-based+reasoning
ICCBR conference:	http://www.iccbr.org

IDI Courses:	TDT4173	Machine learning (Fall semester, Master's level)
	TDT55	Knowledge-intensive CBR (Specialization course, Master's level)
	IT8000	Advanced topics in CBR (Ph.D. level)
	Project & Master's thesis	