AAAI-06 Nectar Track

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Optimizing Similarity Assessment in Case-Based Reasoning

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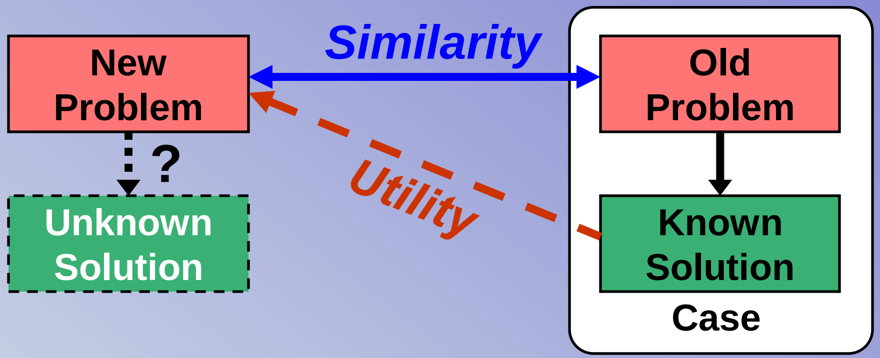
Similarity Measures in CBR

- Semantics: Heuristic for selecting *useful* Cases



- Traditional Approaches
  - similarity is based on geometric distance
  - mainly estimate syntactical differences only
    - e.g. Hamming Distance, Euclidean Distance, ...

- Utility is influenced by
  - characteristics of the domain, preferences of users, functionality of the CBR system, ...

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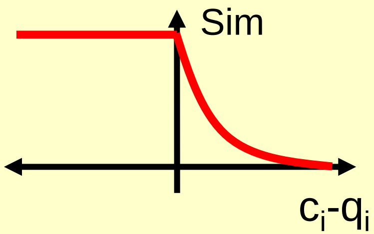
Knowledge-Intensive Similarity Measures

- kiSM encode specific knowledge about the application domain
- kiSM allow a much more accurate estimation of the cases' utility
- typical structure:

$$Sim(Q,C) = \sum_{i=1}^{n} \boxed{w_i} \cdot \boxed{sim_i(q_i, c_i)}$$

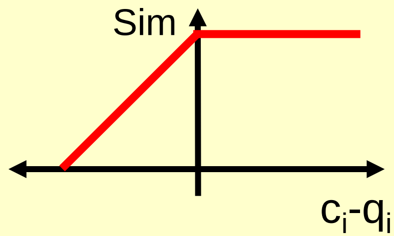
- examples (product recommendation system):

$w_{price} = 0.5$ $w_{CPU\text{-}clock} = 0.4$ $w_{CD\text{-}Drive} = 0.1$



price

„A lower price does not decrease the utility“



CPU-clock

„A higher clock rate does not decrease the utility“

q_i \ c_i	ROM	RW	DVD
ROM	1.0	1.0	0.9
RW	0.0	1.0	0.3
DVD	0.0	0.3	1.0

CD-Drive

The measure encodes knowledge about functionality of CD-Drives

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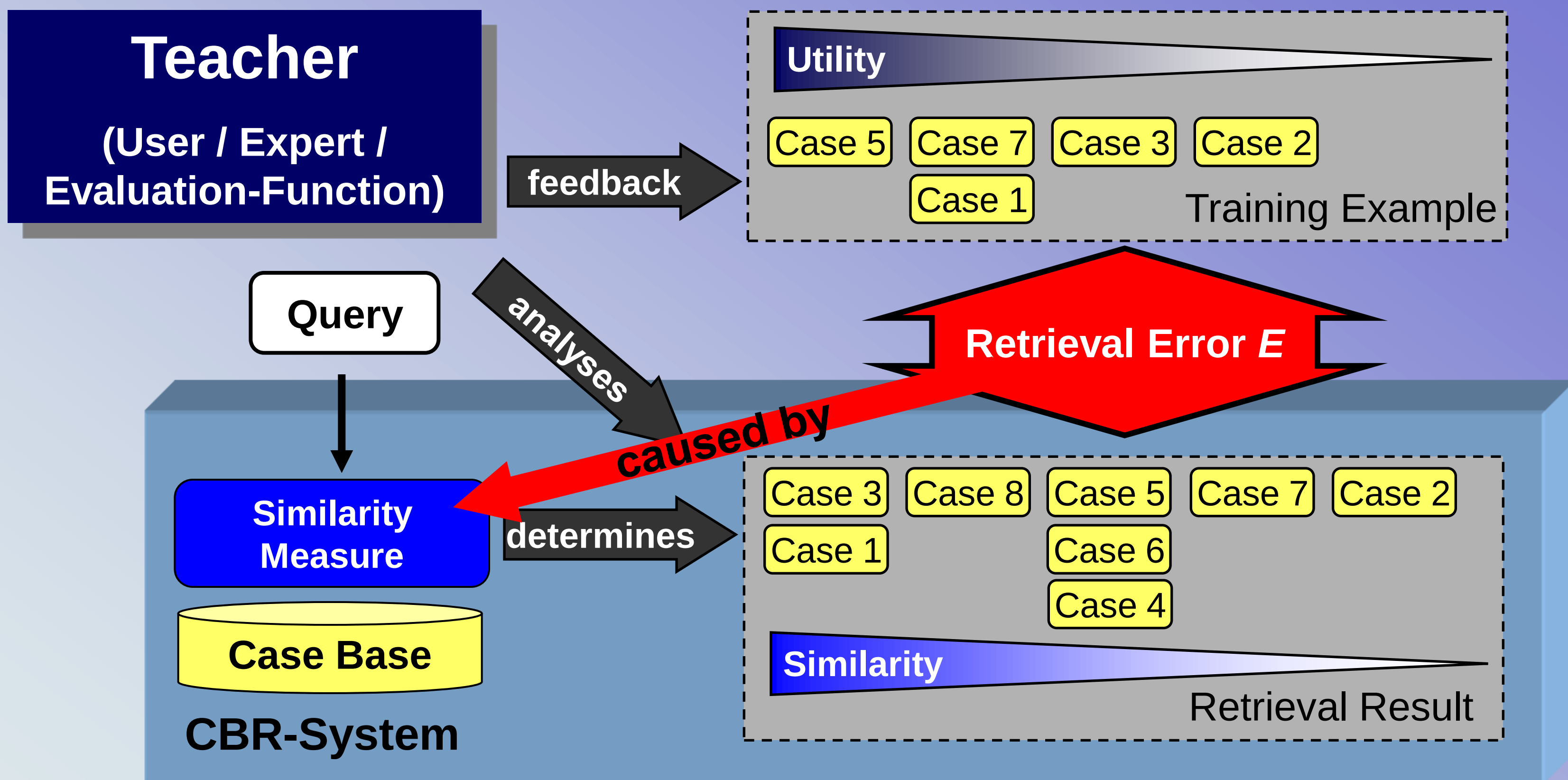
Knowledge Acquisition

- Problems of kiSM
  - modelling kiSM manually is costly
  - required domain knowledge is often only partially available
  - contradicts with the original idea of CBR
- Alternative: Applying Machine Learning Approaches
  - statistical analysis of case base
  - optimization by performing Leave-One-Out test
- Existing Approaches e.g. [Hastie & Tibshirani, 1996; Wettschereck & Aha, 1995]
  - rely on labeled data which provides absolute utility information
  - only applicable for classification tasks
  - allow optimization of attribute weights only

→ *not suited for many CBR applications (e.g. recommender systems)*

Learning from Relative Case Utility Feedback

[Stahl, ICCBR 2001]



Goal: Finding a similarity measure that minimises *E*

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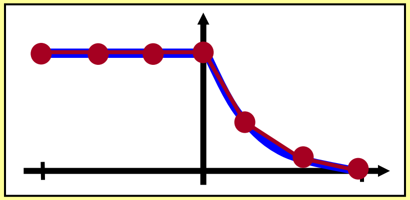
Applying Evolutionary Algorithms
[Stahl & Gabel, ICCBR 2003]

- Idea:
  - encode attribute weights and local similarity measures as individuals to be optimised be a GA
  - define corresponding mutation/crossover operators

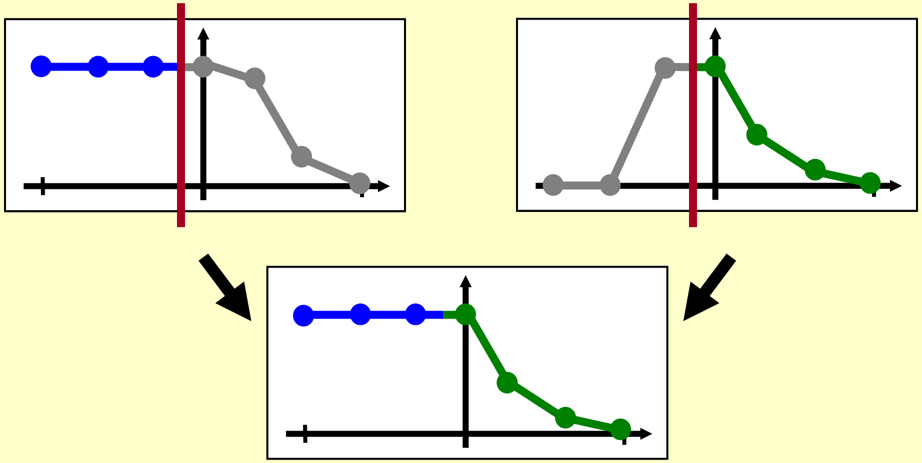
Representation



1.0	1.0	1.0	1.0	0.4	0.1	0.0

similarity function as **vector** of sampling points

Crossover and Mutation-Operators



Example: Similarity Functions

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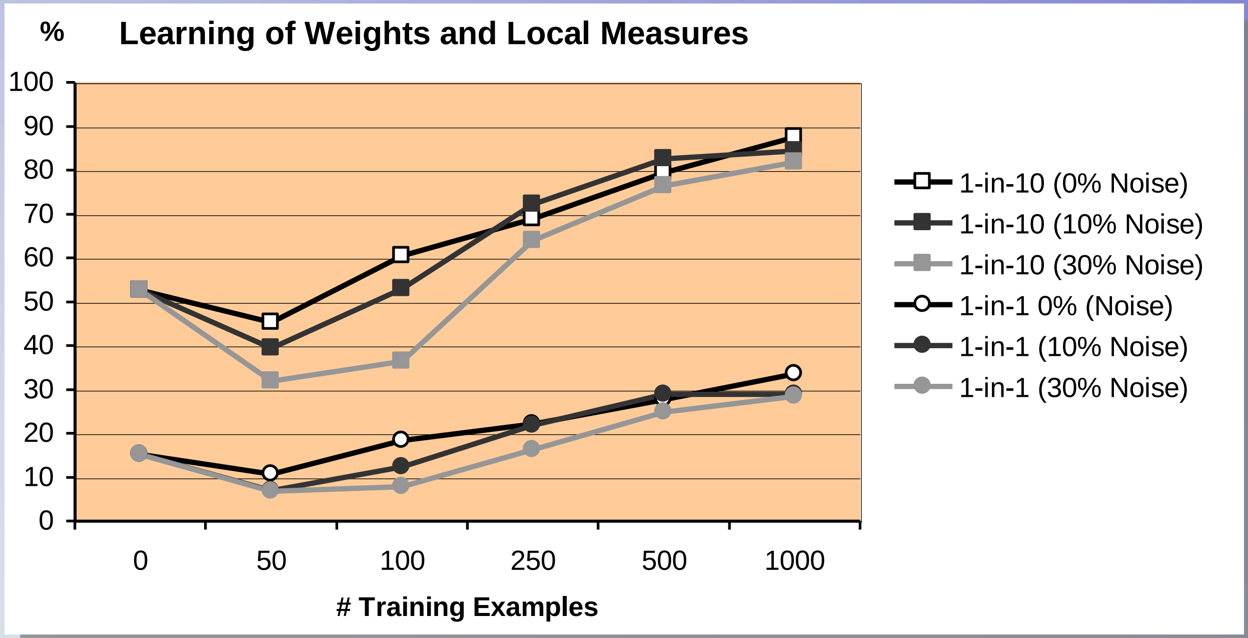
Experimental Evaluation
[Stahl, Ph.D. Thesis 2004]

- Product Recommendation Scenario
  - generation of RCUF by simulating user preferences (with noise)
  - quality measures on test set: percentage of retrievals where
    - 1-in-1: the optimal product is the most similar product
    - 1-in-10: the optimal product is in the retrieval set (10 most similar)



Drawbacks of Brute-Force Learning

[Stahl, ECCBR 2002]

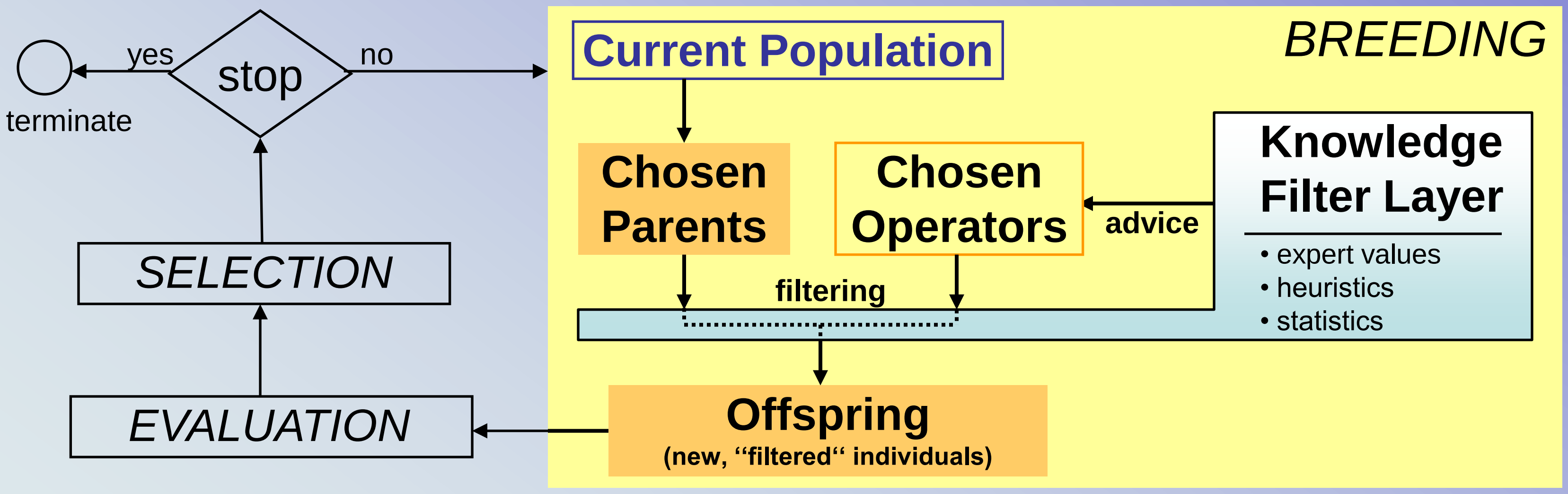
- Learning kiSM from Utility Feedback only may be critical:
  - underlying hypothesis space is huge
    - given only few training data, learning tends to overfitting
  - some certain low-level knowledge is often easily available
    - trying to learn this knowledge is needless and counterproductive
  - similarity measures have typical properties, e.g. monotony
    - learning algorithms should ensure compliance with these properties
- Idea:
  - model partially known knowledge manually
  - learn remaining knowledge from relative case utility feedback

Goal: Restricting the Search Space and biasing the Learner by exploiting available Background Knowledge

Incorporating Background Knowledge

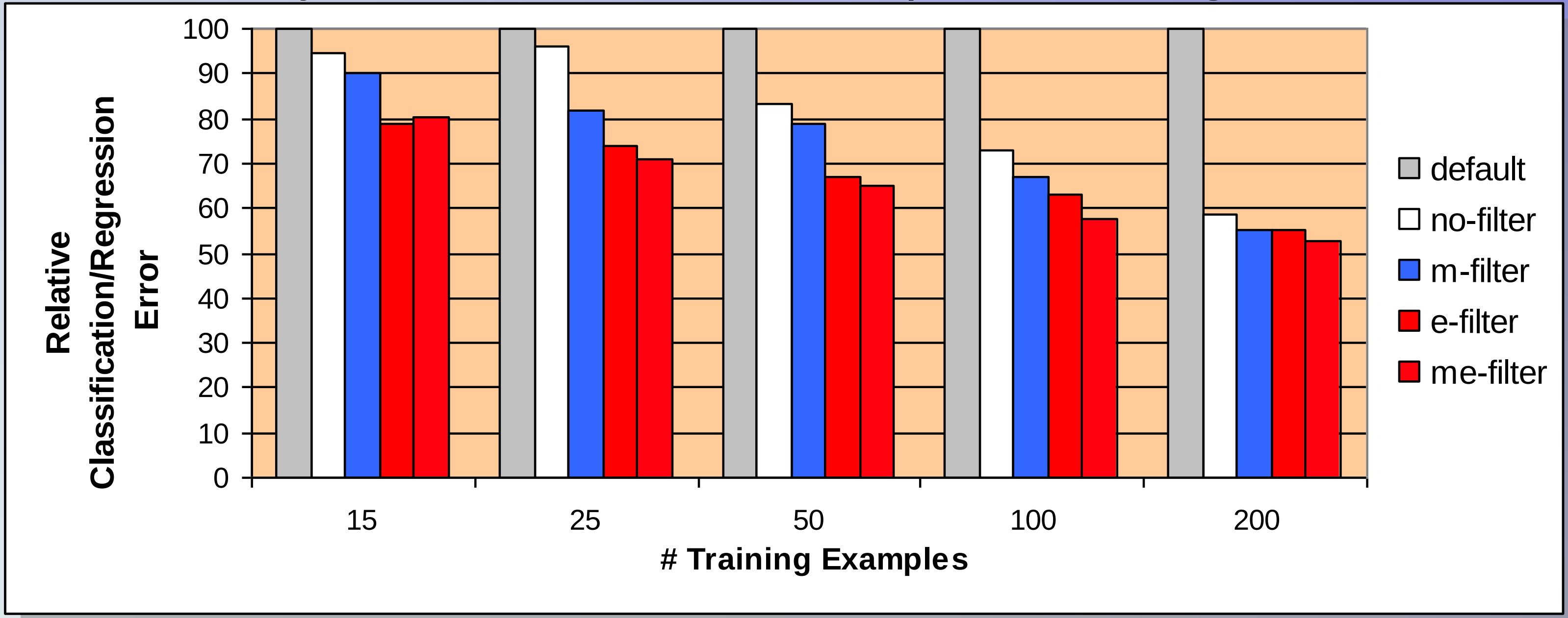
[Gabel & Stahl, ECCBR 2004; Gabel, GWCBR 2005]

- Definition of *Knowledge-Based Optimization Filters*
  - *m-Filters*: Similarity-Meta Knowledge
    - e.g. monotony property
  - *e-Filters*: Expert Knowledge
    - e.g. predefined similarity values, constraints
- Modification of Offspring Generation during GA



Experimental Evaluation

- 6 Domains of the UCI Repository
- Comparison: Average Accuracies achieved with
  - default similarity measures (knowledge-poor, Euclidean Distance)
  - learnt similarity measures (without using background knowledge)
  - similarity measures learnt with help of knowledge filters



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Conclusions

- Knowledge-Intensive Similarity Measures in CBR
  - manual definition is difficult and costly
  - existing learning approaches are not suited for many CBR applications
- Novel Approach:
  - acquisition of relative case utility feedback [Stahl, ICCBR 2001]
    - allows learning in non-classification domains
  - optimization with Genetic Algorithms [Stahl & Gabel, ICCBR 2003]
    - allows optimization of weights and local similarity measures
  - incorporation of background knowledge [Stahl, ECCBR 2002; Gabel & Stahl, ECCBR 2004; Gabel, GWCBR 2005]
    - avoids overfitting for small training data sets
- Current Work
  - combination with case-based learning [Stahl, ECCBR 2006]

Questions?

Thank You!

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