Using Evolution Programs to Learn Local Similarity Measures

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Overview

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2. Learning Similarity Measures from Case Order Feedback
3. Evolution Programs to Learn Local Similarity Measures
   - Specialised Genetic Operators
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Motivation

- Similarity Measures: Heuristics to select ***useful*** cases

traditional approach alternative

- Knowledge-Poor Similarity Measures
  - e.g. Hamming Distance
  - mainly based on syntactical differences
  - consider no or only little domain knowledge
  - \+ easy to define
  - – lead often to poor retrieval results

- Knowledge-Intensive Similarity Measures
  - e.g. use of sophisticated ***local similarity measures***
  - based on knowledge about influences on the utility of cases
  - \+ better retrieval results
  - – require deeper analysis of the domain and more modelling effort

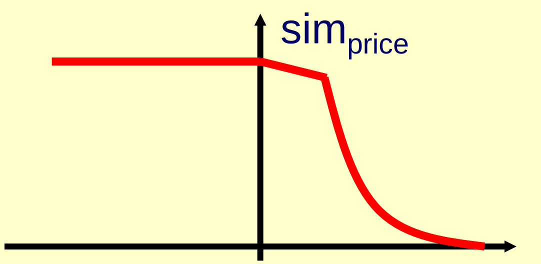
Local Similarity Measures

- compare query and case values of single attributes

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

- representation depends on attribute type

numeric: difference-based similarity function



price

„lower and slightly higher prices will be tolerated“

symbolic: similarity table

q \ c	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

encodes knowledge about the functionality of CD-Drives

Problems:

- modelling of local similarity measures is costly
- necessary domain knowledge is usually difficult to acquire

➡ **Idea:** Application of Machine Learning Techniques

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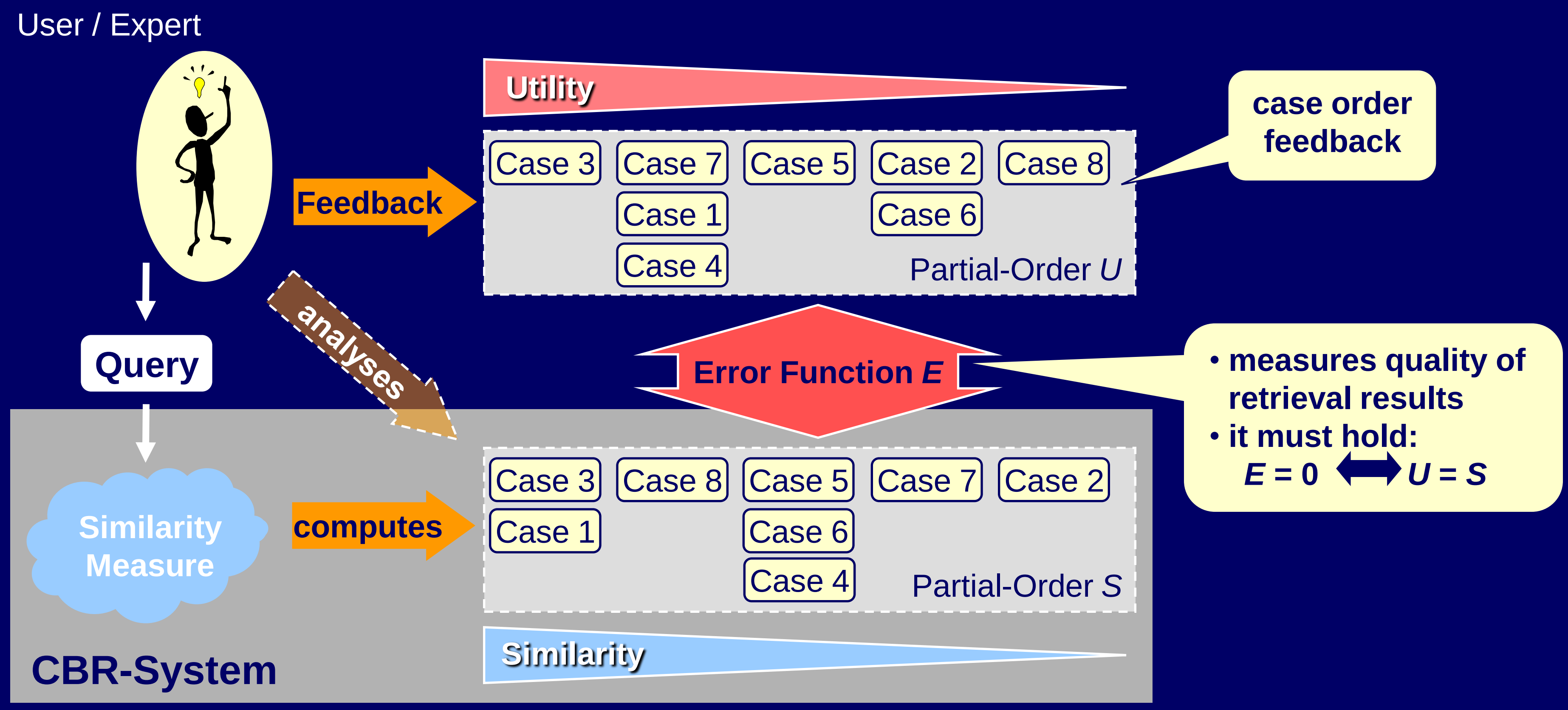
Learning Similarity Measures from Case Order Feedback



Learning Goal: Finding a similarity measure that minimises *E*

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Evolution Programs (EP)

- search algorithms based on the mechanics of natural genetics, selection, and the principle "survival of the fittest"
- reproduction via crossover and mutation of individuals
- differentiation from (standard) genetic algorithms
  1. representation of individuals (example)

GA	0	1	1	0	1	0	0	0	1	1	0	0	1	1	1	1	0 ...
EP	0.3	1.3	2.6	-0.1	1.4	0.7	4.1	7.6	-2.3	4.0	0.0	0.1	-0.7	8.3	2.4	6.2	0.1 ...

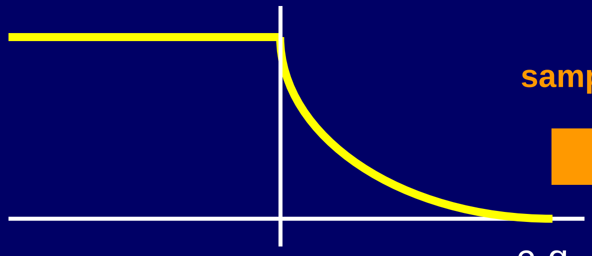
  2. specialised genetic operators

- Advantages
  - robust and powerful search strategy
  - ability to handle complex entities such as local similarity mesaures
  - adequate representation of local measures as individuals

Representing Individuals

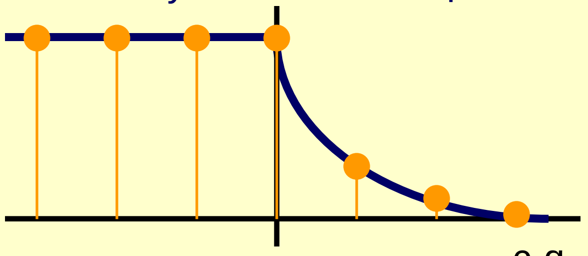
- Similarity Functions per Sampling

"Target" Similarity Measure



sampling (s=7)

Sampled Similarity Measure

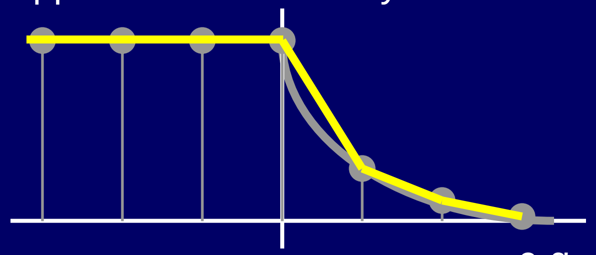


Representation as Individual

index	sim value
1	1.0
2	1.0
3	1.0
4	1.0
5	0.2
6	0.05
7	0.0

usage

Approximated Similarity Measure



- Similarity Tables as Matrices

q \ c	SD	DDR	RD
SD	1.0	0.9	0.75
DDR	0.5	1.0	0.75
RD	0.25	0.5	1.0

RAM-Type

similarity table individual represented as matrix

1.0	0.9	0.75
0.5	1.0	0.75
0.25	0.5	1.0

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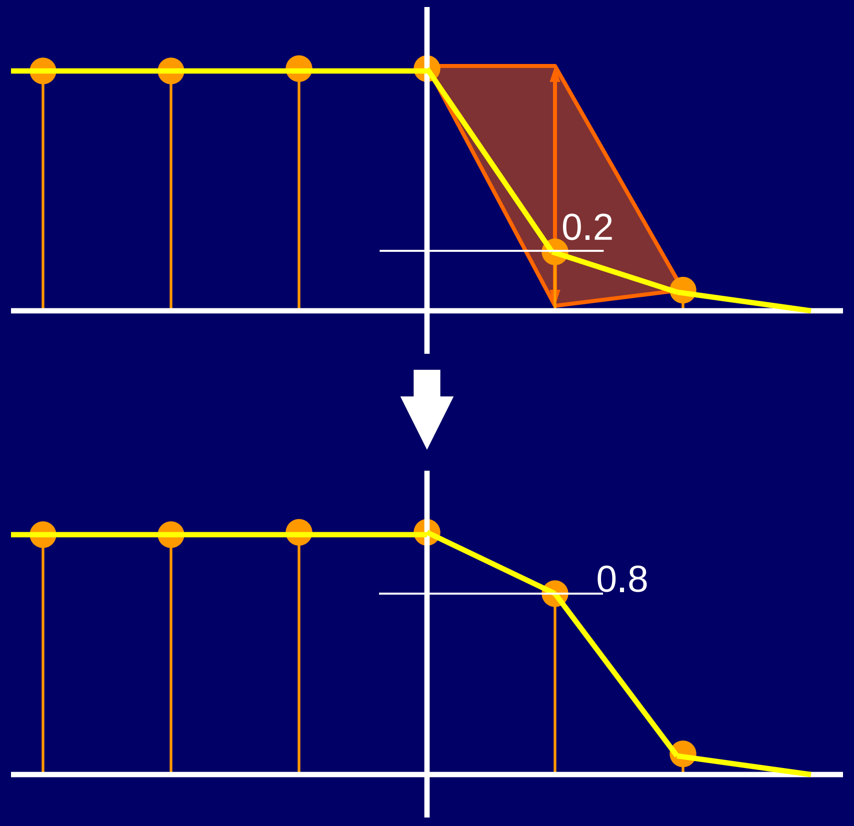
Specialised Genetic Operators

Exemplary Operators:

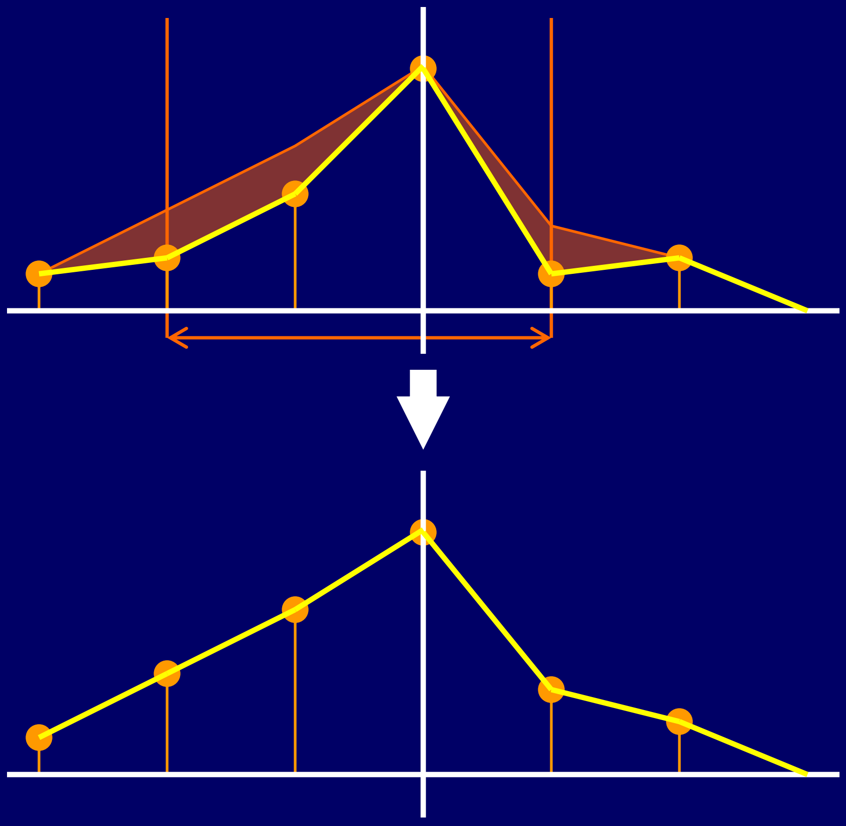
- simple mutation



Specialised Genetic Operators

Exemplary Operators:

- simple mutation
- in-/decreasing mutation



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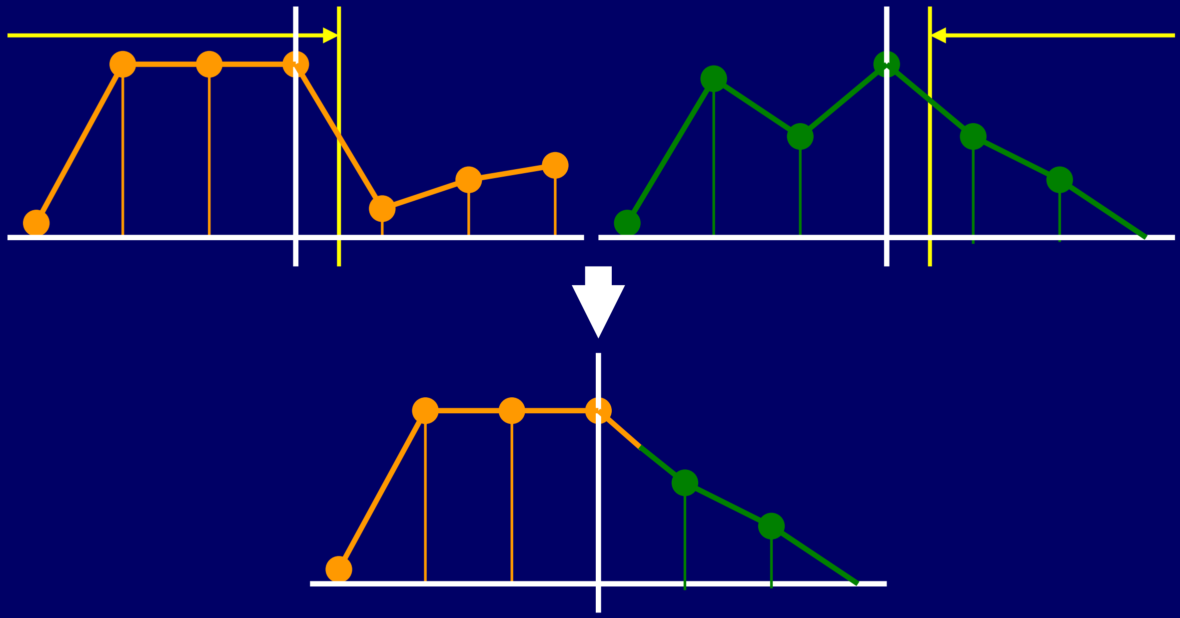
Specialised Genetic Operators

<u>Exemplary Operators:</u>

- simple mutation
- in-/decreasing mutation

- simple crossover



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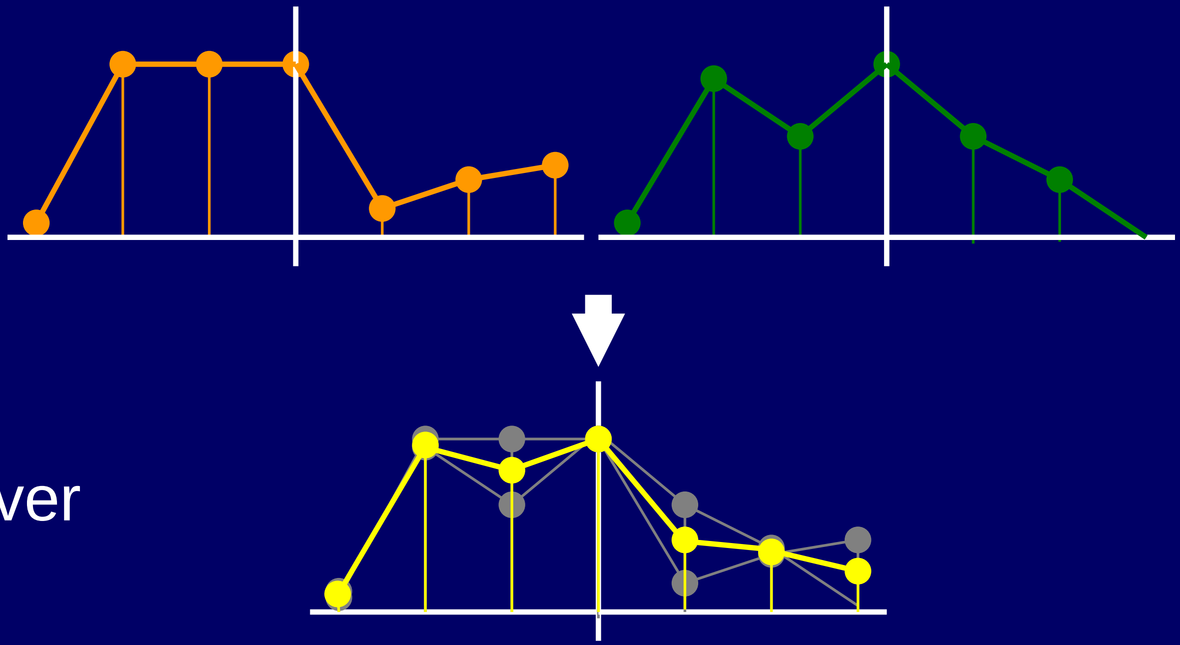
Specialised Genetic Operators

Exemplary Operators:

- simple mutation
- in-/decreasing mutation

- simple crossover
- arithmetical crossover



Specialised Genetic Operators

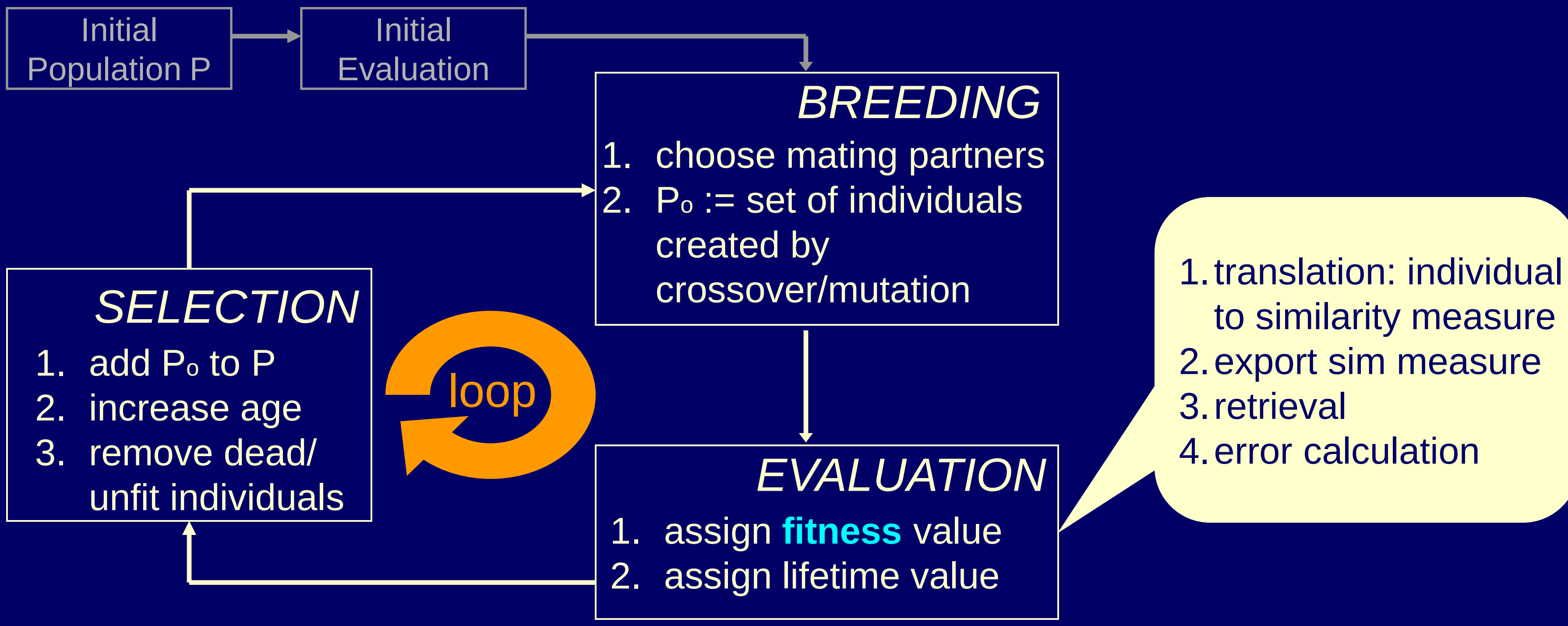
Exemplary Operators:

- simple mutation
- in-/decreasing mutation

- simple crossover
- arithmetical crossover

- line/row crossover

Control Algorithm



- simultaneous learning of several local similarity measures: round robin optimisation

Experimental Evaluation (I)

- Idea: learn a similarity measure that considers provided case adaptation possibilities during case retrieval
- Scenario: product recommendation system for PCs with adaptation rules for customisation
- Example:

Semantic 1:

Utility with respect to performance

q \ c	SD	DDR	RD
SD	1.0	0.9	0.75
DDR	0.5	1.0	0.75
RD	0.25	0.5	1.0

RAM-Type

Semantic 2:

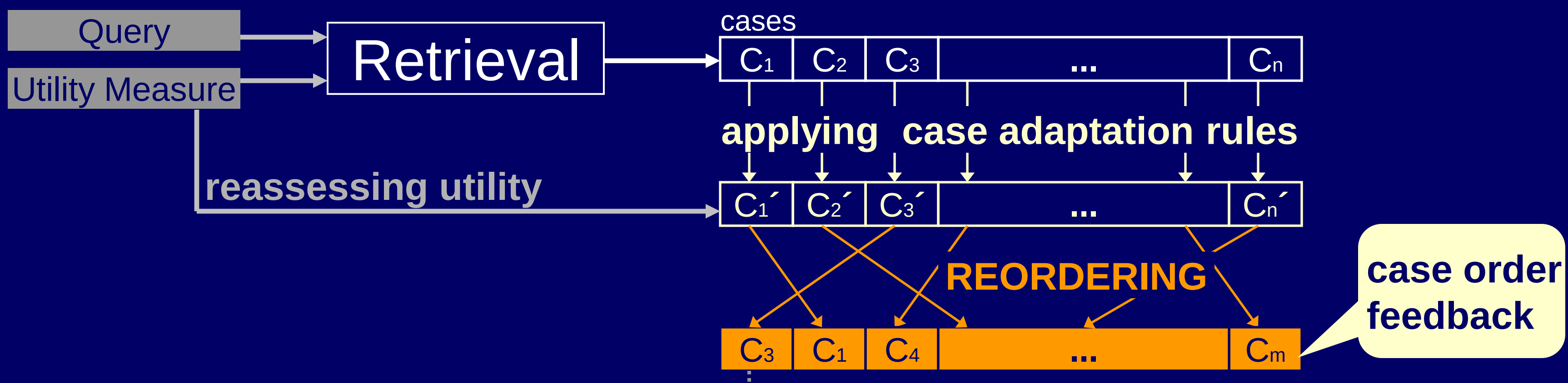
Utility with respect to performance but under consideration of possibilities to **adapt cases**

q \ c	SD	DDR	RD
SD	1.0	**1.0**	0.75
DDR	**1.0**	1.0	0.75
RD	0.25	0.5	1.0

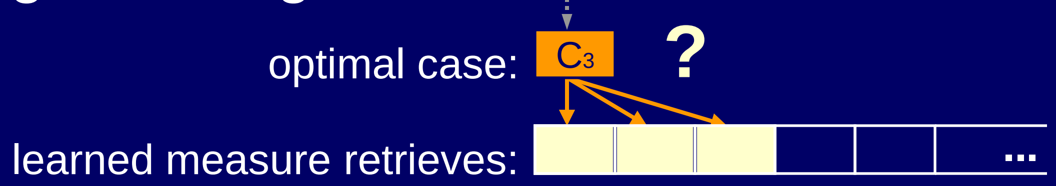
RAM-Type

Experimental Evaluation (II)

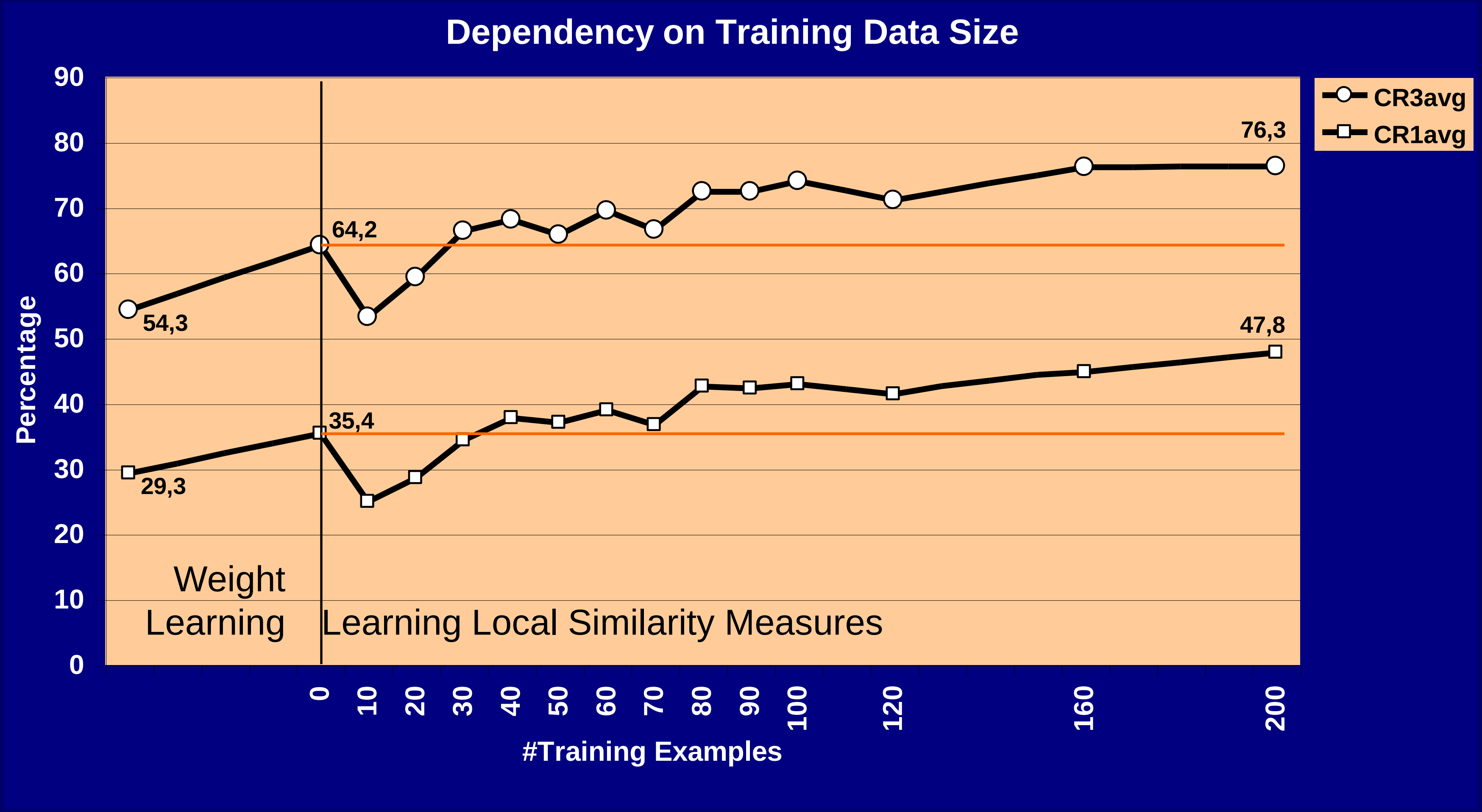
- Automated Creation of Training Examples



- Measuring Learning Results
  - CR1
  - CR3



Experimental Evaluation (III)



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Summary

- Learning Knowledge-Intensive Local Similarity Measures
  - simplified definition of accurate similarity measures
  - overcome the problems of knowledge acquisition
  - better approximation of the underlying utility function
- Necessary Precondition
  - sufficient amount of easily acquirable training data
- Future Work:
  - applying the approach to other, real-world domains
  - analysing the relations between weight learning and learning local similarity measures more thoroughly
  - incorporating background knowledge to improve the learn process

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