

Foundations of Preference Queries

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Plan of the course

- 1 Preference relations
- 2 Preference queries
- 3 Preference management
- 4 Advanced topics

Part I

Preference relations

- 1 Preference relations
 - Preference
 - Equivalence
 - Preference specification
 - Combining preferences
 - Skylines

Universe of objects

- constants: uninterpreted, numbers,...
- individuals (entities)
- tuples
- sets

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Preference relation \succ

- **binary** relation between objects
- $x \succ y \equiv x$ *is_better_than* $y \equiv x$ **dominates** y
- an abstract, uniform way of talking about desirability, worth, cost, timeliness,..., and their **combinations**
- preference relations used in **queries**

Buying a car

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Salesman: Which is more important for you: the age or the price?

Customer: The age, definitely.

Salesman: Those are the best cars, according to your preferences, that we have in stock.

Customer: Wait...it better be a BMW.

Applications of preferences and preference queries

- 1 decision making
- 2 e-commerce
- 3 digital libraries
- 4 personalization

Properties of preference relations

Properties of \succ

- **irreflexivity:** $\forall x. x \not\succeq x$
- **asymmetry:** $\forall x, y. x \succ y \Rightarrow y \not\succeq x$
- **transitivity:** $\forall x, y, z. (x \succ y \wedge y \succ z) \Rightarrow x \succ z$
- **negative transitivity:** $\forall x, y, z. (x \not\succeq y \wedge y \not\succeq z) \Rightarrow x \not\succeq z$
- **connectivity:** $\forall x, y. x \succ y \vee y \succ x \vee x = y$

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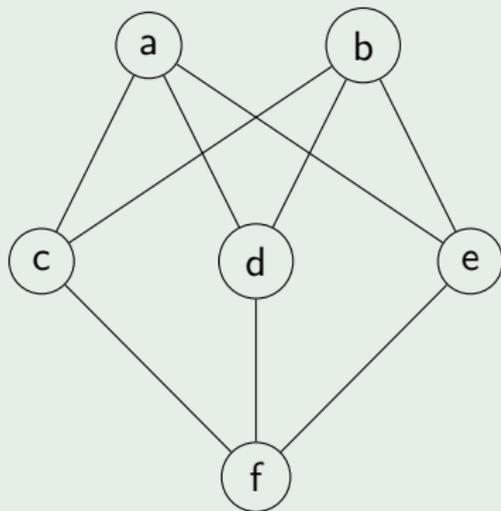
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Orders

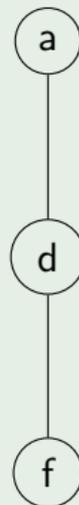
- **strict partial order (SPO)**: irreflexive and transitive
- **weak order (WO)**: negatively transitive SPO
- **total order**: connected SPO

Weak and total orders

Weak order



Total order



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We assume that preference relations are SPOs.

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Several notions of equivalence

- equality: $x \sim^{eq} y \equiv x = y$
- indifference: $x \sim^i y \equiv x \not\prec y \wedge y \not\prec x$
- restricted indifference:
 $x \sim^r y \equiv \forall z. (x \prec z \Leftrightarrow y \prec z) \wedge (z \prec y \Leftrightarrow z \prec x)$

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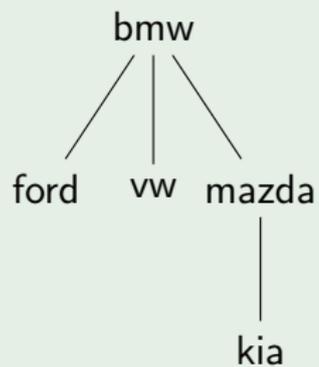
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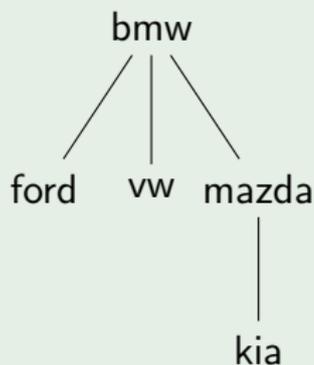
- **equivalence relation**: reflexive, symmetric, transitive
- **equality** and **restricted indifference** (if \succ is an SPO) are equivalence relations
- **indifference** is reflexive and symmetric; transitive for WO

Example

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Preference:

$bmw \succ ford$, $bmw \succ vw$
 $bmw \succ mazda$, $bmw \succ kia$
 $mazda \succ kia$

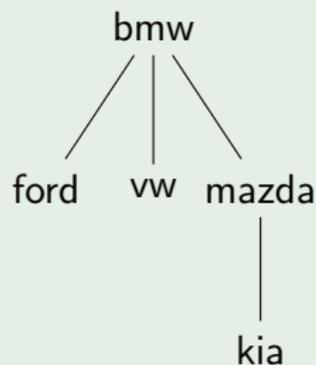
Indifference:

$ford \sim^i vw$, $vw \sim^i ford$,
 $ford \sim^i mazda$, $mazda \sim^i$
 $ford$,
 $vw \sim^i mazda$, $mazda \sim^i$
 vw ,
 $ford \sim^i kia$, $kia \sim^i ford$,
 $vw \sim^i kia$, $kia \sim^i vw$

Restricted indifference:

$ford \sim^r vw$, $vw \sim^r ford$

Example



This is a strict partial order which is not a weak order.

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Indifference:

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 $ford \sim^i mazda$, $mazda \sim^i ford$,
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 $ford \sim^i kia$, $kia \sim^i ford$,
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Restricted indifference:

$ford \sim^r vw$, $vw \sim^r ford$

Not every SPO is a WO

Canonical example

$mazda \succ kia$, $mazda \sim^i vw$, $kia \sim^i vw$

Violation of negative transitivity

$mazda \not\succeq vw$, $vw \not\succeq kia$, $mazda \succ kia$

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for relation $\text{Car}(\text{Make}, \text{Year}, \text{Price})$.

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- defined using **preference constructors** (Preference SQL)
- defined using real-valued **scoring functions**: $F(m, y, p) = \alpha \cdot y + \beta \cdot p$
 $(m_1, y_1, p_1) \succ_2 (m_2, y_2, p_2) \equiv F(m_1, y_1, p_1) > F(m_2, y_2, p_2)$

Logic formulas

The language of logic formulas

- constants
- object (tuple) attributes
- comparison operators: $=, \neq, <, >, \dots$
- arithmetic operators: $+, \cdot, \dots$
- Boolean connectives: \neg, \wedge, \vee
- quantifiers:
 - \forall, \exists
 - usually can be eliminated (**quantifier elimination**)

Definition

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Sufficient condition for representability

- \succ is a weak order
- the domain is **countable** or some **continuity** conditions are satisfied (studied in decision theory)

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Lexicographic order in $R \times R$

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- 7 Each such interval contains a rational number: contradiction with the countability of the set of rational numbers.

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Prefer values closer to v_0 .

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AROUND(Price, 12K)

Combining preferences

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Preference accumulation

- defining preferences over objects in terms of preferences over **simpler objects**
- **dimensionality** is increased (preferences over Cartesian product).

Combining preferences: composition

Boolean composition

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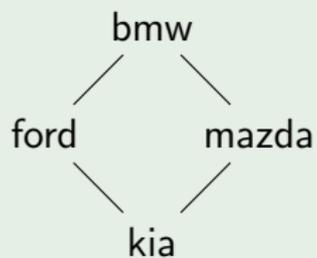
Pareto composition

$$x \succ^{Par} y \equiv (x \succ_1 y \wedge y \not\succeq_2 x) \vee (x \succ_2 y \wedge y \not\succeq_1 x).$$

Preference composition

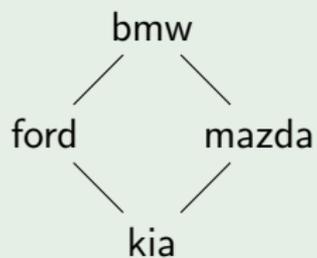
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Preference relation \succ_1

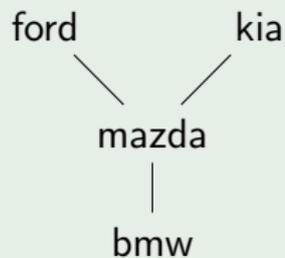


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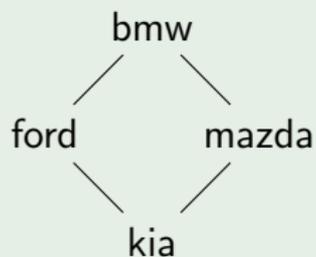


Preference relation \succ_2

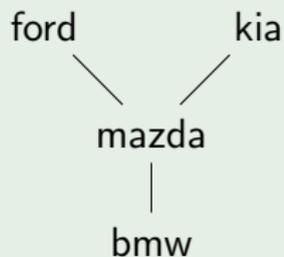


Preference composition

Preference relation \succ_1



Preference relation \succ_2

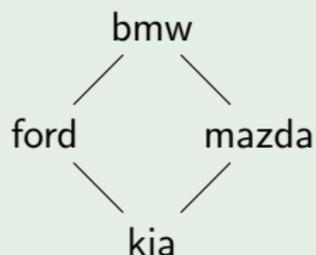


Prioritized composition

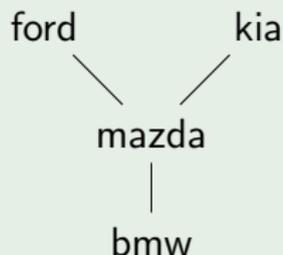


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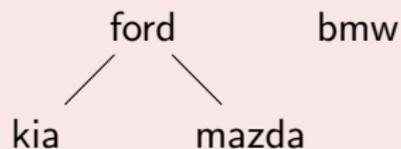
Preference relation \succ_2



Prioritized composition



Pareto composition



Combining preferences: accumulation [Kie02]

Prioritized accumulation: $\succ^{pr} = (\succ_1 \& \succ_2)$

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Prioritized accumulation: $\succ^{pr} = (\succ_1 \& \succ_2)$

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Pareto accumulation: $\succ^{pa} = (\succ_1 \otimes \succ_2)$

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Combining preferences: accumulation [Kie02]

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Properties

- closure
- associativity
- commutativity of Pareto accumulation

Skyline

Given single-attribute total preference relations $\succ_{A_1}, \dots, \succ_{A_n}$ for a relational schema $R(A_1, \dots, A_n)$, the **skyline** preference relation \succ^{sky} is defined as

$$\succ^{sky} \equiv \succ_{A_1} \otimes \succ_{A_2} \otimes \dots \otimes \succ_{A_n}.$$

Unfolding the definition

$$(x_1, \dots, x_n) \succ^{sky} (y_1, \dots, y_n) \equiv \bigwedge_i x_i \succeq_{A_i} y_i \wedge \bigvee_i x_i \succ_{A_i} y_i.$$

Skyline in Euclidean space

Skyline in Euclidean space

Two-dimensional Euclidean space

$$(x_1, x_2) \succ^{sky} (y_1, y_2) \equiv x_1 \geq y_1 \wedge x_2 > y_2 \vee x_1 > y_1 \wedge x_2 \geq y_2$$

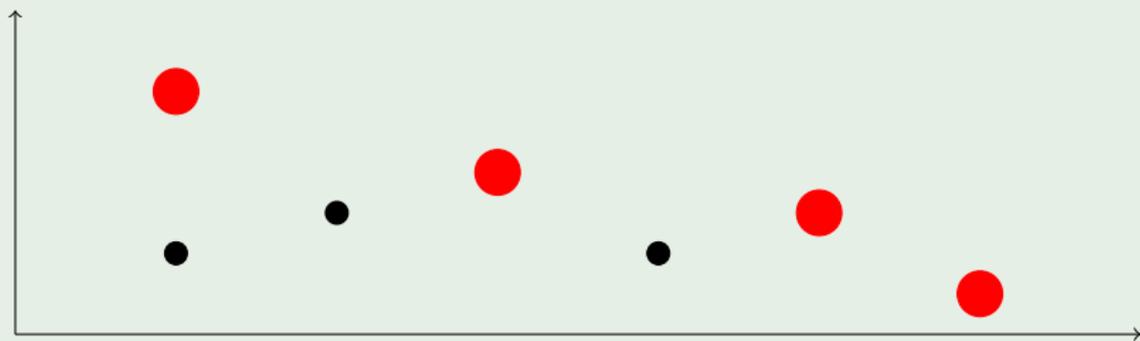
Skyline consists of \succ_{sky} -maximal vectors

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Skyline properties

Invariance

A skyline preference relation is unaffected by **scaling** or **shifting** in any dimension.

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Maxima

A skyline consists of the maxima of **monotonic** scoring functions.

Skyline is not a weak order

$$(2, 0) \not\succ_{sky} (0, 2), (0, 2) \not\succ_{sky} (1, 0), (2, 0) \succ_{sky} (1, 0)$$

Skyline in SQL

Grouping

Designating attributes **not used** in comparisons (DIFF).

Example

```
SELECT * FROM Car
SKYLINE Price MIN,
        Year MAX,
        Make DIFF
```

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Dynamic skylines

- dimensions defined using **dimension functions** g_1, \dots, g_n
- variable **query point**.

Dynamic skylines

Relation $Hotel(XCoord, YCoord, Price)$

- tuple $p = (p_x, p_y, p_z)$, query point (u_x, u_y)
- dimension functions based on 2D Euclidean distance:

$$g_1(p_x, p_y) = \sqrt{(p_x - u_x)^2 + (p_y - u_y)^2}$$

$$g_2(p_z) = p_z$$

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XCoord	YCoord	Price
0	5	80
2	6	100
5	3	120

Query point: (3,4).

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- scoring functions f_1, \dots, f_n
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Numerical vs. logical combination

- logical combination cannot be defined numerically
- numerical combination cannot be defined logically (unless arithmetic operators are available)

Part II

Preference Queries

- 2 Preference queries
 - Retrieving non-dominated elements
 - Rewriting queries with winnow
 - Retrieving Top- K elements
 - Optimizing Top- K queries

Winnow

- new relational algebra operator ω (other names: Best, BMO [Kie02])
- retrieves the non-dominated (**best**) elements in a database relation
- can be expressed in terms of other operators

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Given a preference relation \succ and a database relation r :

$$\omega_{\succ}(r) = \{t \in r \mid \neg \exists t' \in r. t' \succ t\}.$$

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Skyline query

$\omega_{\succ_{sky}}(r)$ computes the set of maximal vectors in r (the **skyline set**).

Example of winnow

Example of winnow

Relation *Car*(*Make*, *Year*, *Price*)

Preference relation:

$$(m, y, p) \succ_1 (m', y', p') \equiv y > y' \vee (y = y' \wedge p < p').$$

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Make	Year	Price
mazda	2009	20K
ford	2009	15K
ford	2007	12K

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Make	Year	Price
mazda	2009	20K
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Computing winnow using BNL [BKS01]

Require: SPO \succ , database relation r

```
1: initialize window  $W$  and temporary file  $F$  to empty
2: repeat
3:   for every tuple  $t$  in the input do
4:     if  $t$  is dominated by a tuple in  $W$  then
5:       ignore  $t$ 
6:     else if  $t$  dominates some tuples in  $W$  then
7:       eliminate them and insert  $t$  into  $W$ 
8:     else if there is room in  $W$  then
9:       insert  $t$  into  $W$ 
10:    else
11:      add  $t$  to  $F$ 
12:    end if
13:  end for
14:  output tuples from  $W$  that were added when  $F$  was empty
15:  make  $F$  the input, clear  $F$ 
16: until empty input
```

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

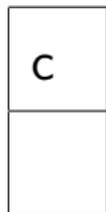
c,e,d,a,b

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

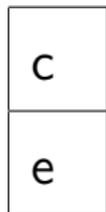
e,d,a,b

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

d,a,b

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file

d

Window

c
e

Input

a,b

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file

d

Window

a
e

Input

b

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file

d

Window

a
b

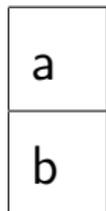
Input

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

d

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window

a
b

Input

Computing winnow with presorting

SFS: adding presorting step to BNL [CGGL03]

- **topologically sort** the input:
 - if x **dominates** y , then x **precedes** y in the sorted input
 - window contains only winnow points and can be output after every pass
- for skylines: sort the input using a monotonic **scoring** function, for example $\prod_{i=1}^k x_i$.

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LESS: integrating different techniques [GSG07]

- adding an **elimination filter** to the first external sort pass
- combining the last external sort pass with the first SFS pass
- average running time: $O(kn)$

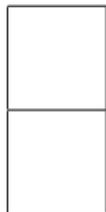
Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

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Temporary file



Window



Input

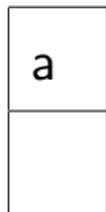
a,b,c,d,e

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

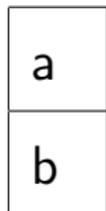
b,c,d,e

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

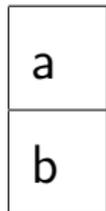
c,d,e

Preference relation: $a \succ c$, $a \succ d$, $b \succ e$.

Temporary file



Window



Input

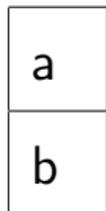
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Window



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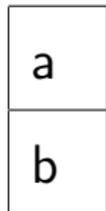
e

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Temporary file



Window



Input

Generalizations of winnow

Iterating winnow

$$\omega_{\gamma}^0(r) = \omega_{\gamma}(r)$$

$$\omega_{\gamma}^{n+1}(r) = \omega_{\gamma}(r - \bigcup_{1 \leq i \leq n} \omega_{\gamma}^i(r))$$

Iterating winnow

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Ranking

Rank tuples by their minimum distance from a winnow tuple:

$$\eta_{\succ}(r) = \{(t, i) \mid t \in \omega_{\succ}^i(r)\}.$$

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k -band

Return the tuples dominated by at most k tuples:

$$\omega_{\succ}(r) = \{t \in r \mid \#\{t' \in r \mid t' \succ t\} \leq k\}.$$

Preference SQL

The language

- basic preference constructors
- Pareto/prioritized accumulation
- new SQL clause `PREFERRING`
- groupwise preferences
- implementation: translation to SQL

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- basic preference constructors
- Pareto/prioritized accumulation
- new SQL clause PREFERRING
- groupwise preferences
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Winnow in Preference SQL

```
SELECT * FROM Car
PREFERRING HIGHEST(Year)
          CASCADE LOWEST(Price)
```

Algebraic laws [Cho03]

Commutativity of winnow with selection

If the formula

$$\forall t_1, t_2. [\alpha(t_2) \wedge \gamma(t_1, t_2)] \Rightarrow \alpha(t_1)$$

is valid, then for every r

$$\sigma_\alpha(\omega_\gamma(r)) = \omega_\gamma(\sigma_\alpha(r)).$$

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Under the preference relation

$$(m, y, p) \succ_{C_1} (m', y', p') \equiv y > y' \wedge p \leq p' \vee y \geq y' \wedge p < p'$$

the selection $\sigma_{Price < 20K}$ commutes with ω_{C_1} but $\sigma_{Price > 20K}$ does not.

Other algebraic laws

Distributivity of winnow over Cartesian product

For every r_1 and r_2

$$\omega_C(r_1 \times r_2) = \omega_C(r_1) \times r_2$$

if C refers only to the attributes of r_1 .

Commutativity of winnow

If $\forall t_1, t_2. [C_1(t_1, t_2) \Rightarrow C_2(t_1, t_2)]$ is valid and \succ_{C_1} and \succ_{C_2} are SPOs, then for all finite instances r :

$$\omega_{C_1}(\omega_{C_2}(r)) = \omega_{C_2}(\omega_{C_1}(r)) = \omega_{C_2}(r).$$

Semantic query optimization [Cho07b]

Using information about **integrity constraints** to:

- eliminate redundant occurrences of winnow.
- make more efficient computation of winnow possible.

Eliminating redundancy

Given a set of integrity constraints F , ω_C is **redundant w.r.t.** F iff F implies the formula

$$\forall t_1, t_2. R(t_1) \wedge R(t_2) \Rightarrow t_1 \sim_C t_2.$$

Integrity constraints

Constraint-generating dependencies (CGD) [BCW99, ZO97]

$$\forall t_1 \dots \forall t_n. [R(t_1) \wedge \dots \wedge R(t_n) \wedge \gamma(t_1, \dots, t_n)] \Rightarrow \gamma'(t_1, \dots, t_n).$$

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CGD entailment

Decidable by reduction to the validity of \forall -formulas in the constraint theory (assuming the theory is decidable).

Top- K queries

Scoring functions

- each tuple t in a relation has numeric **scores** $f_1(t), \dots, f_m(t)$ assigned by numeric **component** scoring functions f_1, \dots, f_m
- the **aggregate** score of t is $F(t) = E(f_1(t), \dots, f_m(t))$ where E is a numeric-valued expression
- F is **monotone** if $E(x_1, \dots, x_m) \leq E(y_1, \dots, y_m)$ whenever $x_i \leq y_i$ for all i

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Top- K queries

- return K elements having top F -values in a database relation R
- query expressed in an extension of SQL:

```
SELECT *  
FROM R  
ORDER BY  $F$  DESC  
LIMIT K
```

Top- K sets

Definition

Given a scoring function F and a database relation r , s is a Top- K set if:

- $s \subseteq r$
- $|s| = \min(K, |r|)$
- $\forall t \in s. \forall t' \in r - s. F(t) \geq F(t')$

There may be more than one Top- K set: one is selected **non-deterministically**.

Example of Top-2

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Relation $Car(Make, Year, Price)$

- component scoring functions:

$$f_1(m, y, p) = (y - 2005)$$

$$f_2(m, y, p) = (20000 - p)$$

- aggregate scoring function:

$$F(m, y, p) = 1000 \cdot f_1(m, y, p) + f_2(m, y, p)$$

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Make	Year	Price	Aggregate score
mazda	2009	20000	4000
ford	2009	15000	9000
ford	2007	12000	10000

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Computing Top- K

Naive approaches

- sort, output the first K -tuples
- scan the input maintaining a priority queue of size K
- ...

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Better approaches

- the entire input does not need to be scanned...
- ... provided additional data structures are available
- variants of the **threshold algorithm**

Threshold algorithm (TA)[FLN03]

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Inputs

- a monotone scoring function $F(t) = E(f_1(t), \dots, f_m(t))$
 - lists S_i , $i = 1, \dots, m$, each sorted on f_i (descending) and representing a different ranking of the same set of objects
- 1 For each list S_i in parallel, retrieve the current object w in sorted order:
 - (random access) for every $j \neq i$, retrieve $v_j = f_j(w)$ from the list S_j
 - if $d = E(v_1, \dots, v_m)$ is among the highest K scores seen so far, remember w and d (ties broken arbitrarily)
 - 2 Thresholding:
 - for each i , w_i is the last object seen under sorted access in S_i
 - if there are already K top- K objects with score at least equal to the threshold $T = E(f_1(w_1), \dots, f_m(w_m))$, return collected objects sorted by F and terminate
 - otherwise, go to step 1.

Aggregate score

$$F(t) = P_1(t) + P_2(t)$$

Priority queue

OID	P_1
5	50
1	35
3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10



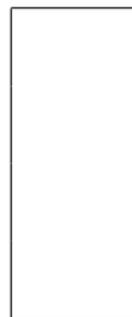
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2	40
1	30
4	20
5	10



T=100

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3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10

5:60

T=100

Aggregate score

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Priority queue

OID	P_1
5	50
1	35
3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10

3:80
5:60

T=100

Aggregate score

$$F(t) = P_1(t) + P_2(t)$$

Priority queue

OID	P_1
5	50
1	35
3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10

3:80
5:60

T=75

Aggregate score

$$F(t) = P_1(t) + P_2(t)$$

Priority queue

OID	P_1
5	50
1	35
3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10

3:80
1:65
5:60

T=75

Aggregate score

$$F(t) = P_1(t) + P_2(t)$$

Priority queue

OID	P_1
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1	35
3	30
2	20
4	10

OID	P_2
3	50
2	40
1	30
4	20
5	10

3:80
1:65
5:60
2:60

T=75

- objects: **tuples** of a single relation r
- **single-attribute** component scoring functions
- **sorted** list access implemented through **indexes**
- **random** access to all lists implemented by **primary index** access to r that retrieves entire tuples

Optimizing Top- K queries [LCIS05]

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Goals

- **integrating** Top- K with relational query evaluation and optimization
- replacing blocking by **pipelining**

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Example

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SELECT *  
FROM Hotel  $h$ , Restaurant  $r$ , Museum  $m$   
WHERE  $c_1$  AND  $c_2$  AND  $c_3$   
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Is there a better evaluation plan than **materialize-then-sort**?

Partial ranking of tuples

Partial ranking of tuples

Model

- set of component scoring functions $P = \{f_1, \dots, f_m\}$ such that $f_i(t) \leq 1$ for all t
- aggregate scoring function $F(t) = E(f_1(t), \dots, f_m(t))$
- how to rank **intermediate** tuples?

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- how to rank **intermediate** tuples?

Ranking principle

Given $P_0 \subseteq P$,

$$\bar{F}_{P_0}(t) = E(g_1(t), \dots, g_m(t))$$

where

$$g_i(t) = \begin{cases} f_i(t) & \text{if } f_i \in P_0 \\ 1 & \text{otherwise} \end{cases}$$

Relations with rank

Rank-relation R_{P_0}

- relation R
- monotone aggregate scoring function F (the same for all relations)
- set of component scoring functions $P_0 \subseteq P$
- order:

$$t_1 >_{R_{P_0}} t_2 \equiv \bar{F}_{P_0}(t_1) > \bar{F}_{P_0}(t_2)$$

Ranking intermediate results

Operators

- **rank operator** μ_f : ranks tuples according to an additional component scoring function f
- standard relational algebra operators suitably extended to work on rank-relations

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Operator	Order
$\mu_f(R_{P_0})$	$t_1 >_{\mu_f(R_{P_0})} t_2 \equiv \bar{F}_{P_0 \cup \{f\}}(t_1) > \bar{F}_{P_0 \cup \{f\}}(t_2)$
$R_{P_1} \cap S_{P_2}$	$t_1 >_{R_{P_1} \cap S_{P_2}} t_2 \equiv \bar{F}_{P_1 \cup P_2}(t_1) > \bar{F}_{P_1 \cup P_2}(t_2)$

Example

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Query

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SELECT *  
FROM S  
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Unranked relation S

A	f_1	f_2	f_3
1	0.7	0.8	0.9
2	0.9	0.85	0.8
3	0.5	0.45	0.75

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Rank-relation $S_{\{f_1\}}$

A	$\bar{F}_{\{f_1\}}$
2	2.9
1	2.7
3	2.5

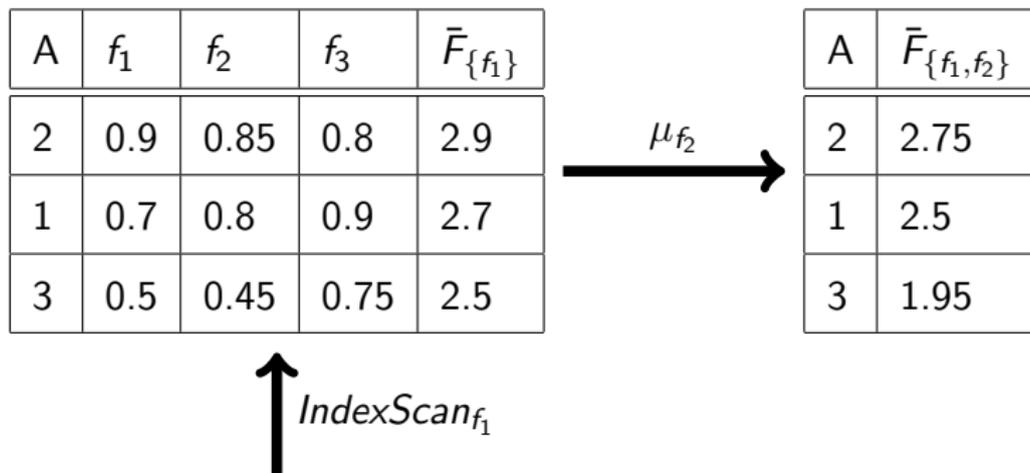
Pipelined execution

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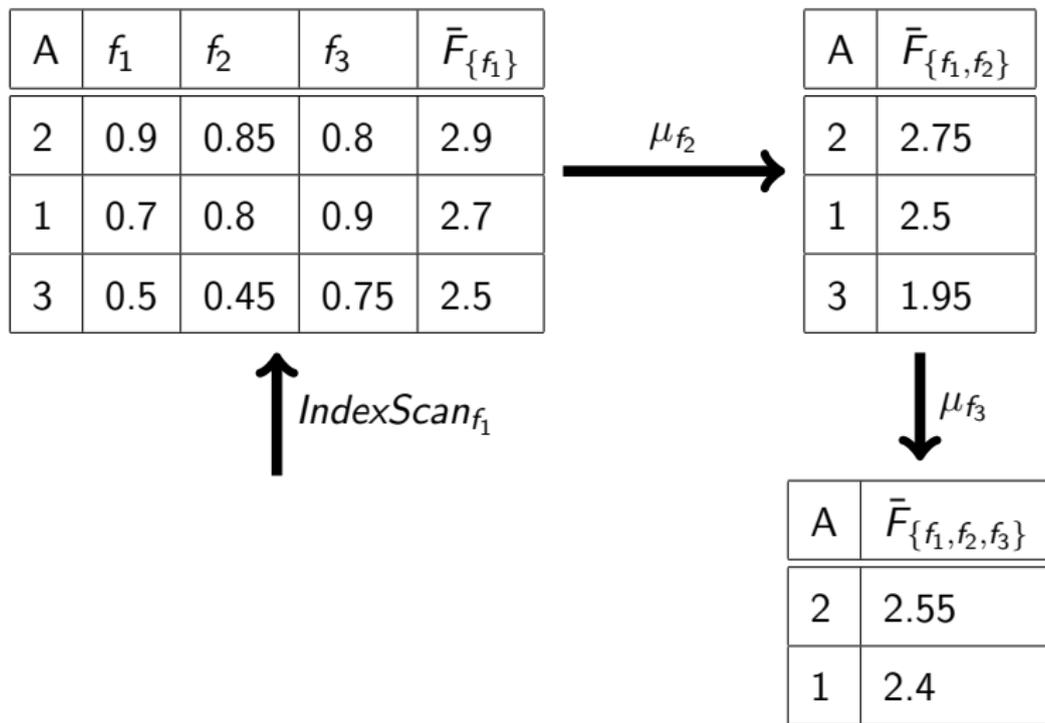
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↑ $IndexScan_{f_1}$

Pipelined execution



Pipelined execution



Algebraic laws for rank-relation operators

Splitting for μ

$$R_{\{f_1, f_2, \dots, f_m\}} \equiv \mu_{f_1}(\mu_{f_2}(\dots(\mu_{f_m}(R))\dots))$$

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Distributivity of μ over Cartesian product

$\mu_f(R_{P_1} \times S_{P_2}) \equiv \mu_f(R_{P_1}) \times S_{P_2}$ if f refers only to the attributes of R .

Part III

Preference management

- 3 Preference management
 - Preference modification

Preference modification

Goal

Given a preference relation \succ and additional preference or indifference information \mathcal{I} , construct a new preference relation \succ' whose contents depend on \succ and \mathcal{I} .

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General postulates

- **fulfillment**: the new information \mathcal{I} should be completely incorporated into \succ'
- **minimal change**: \succ should be changed as little as possible
- **closure**:
 - order-theoretic properties of \succ should be preserved in \succ' (SPO, WO)
 - finiteness or finite representability of \succ should also be preserved in \succ'

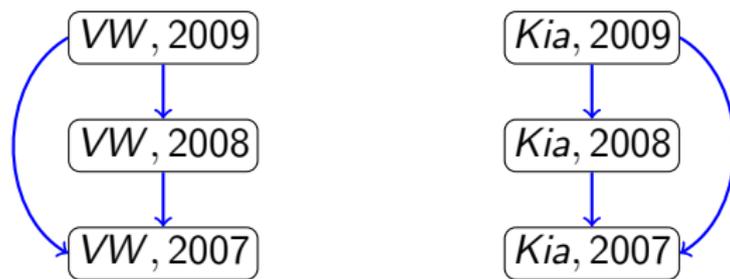
Preference revision [Cho07a]

Setting

- new information: **revising** preference relation \succ_0
- composition operator θ : union, prioritized or Pareto composition
- composition eliminates (some) preference conflicts
- additional assumptions: interval orders
- $\succ' = TC(\succ_0 \theta \succ)$ to guarantee SPO

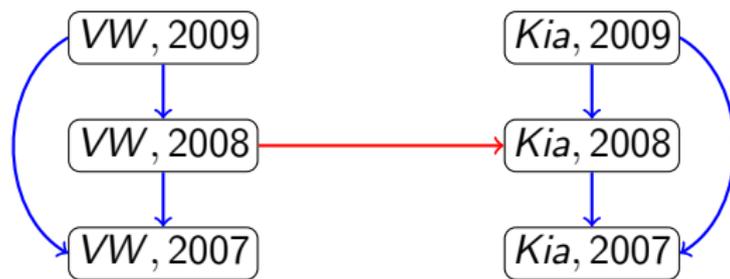
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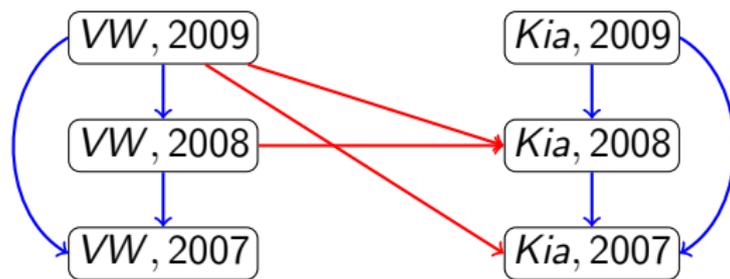
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Preference contraction [MC08]

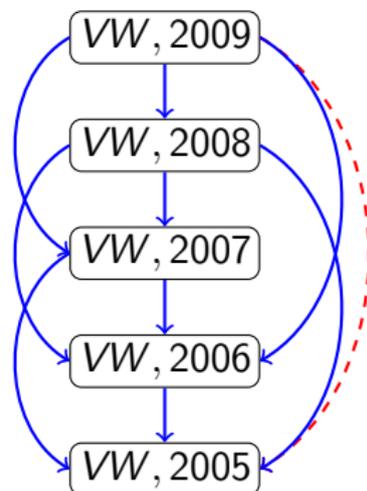
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- new information: **contractor** relation CON
- \succ' : maximal subset of \succ disjoint with CON

Preference contraction [MC08]

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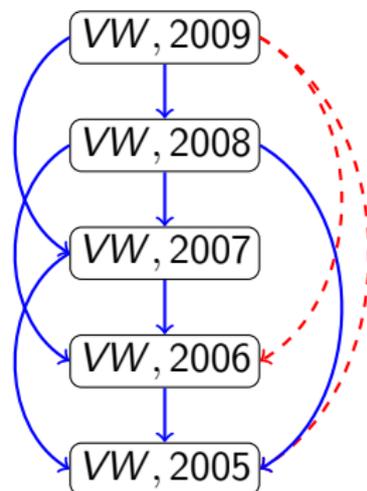
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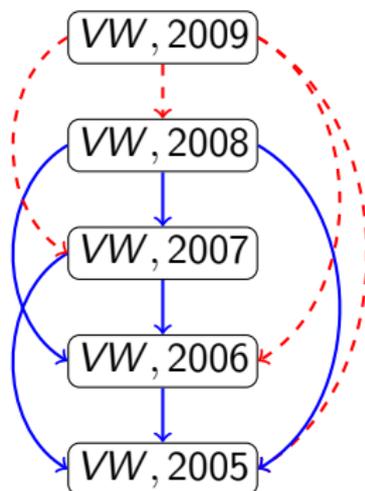
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Preference contraction [MC08]

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Substitutability [BGS06]

Setting

- new information: set of **indifference** pairs
- additional preferences are added to convert indifference to restricted indifference
- achieving **object substitutability**

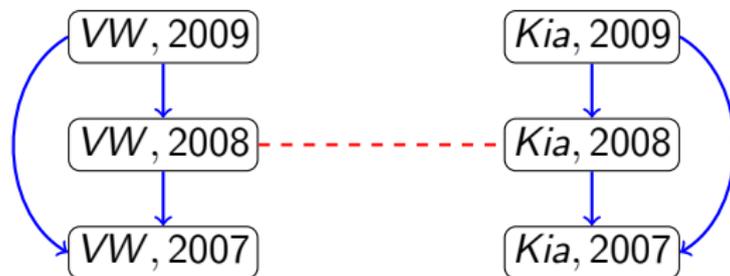
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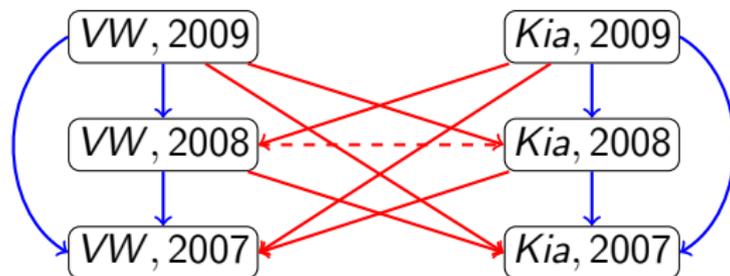
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Part IV

Advanced topics

Outline of Part IV

Prospective research topics

Definability

Given a preference relation \succ_C , how to construct a **definition** of a scoring function F representing \succ_C , if such a function exists?

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Extrinsic preference relations

Preference relations that are not fully defined by tuple contents:

$$x \succ y \equiv \exists n_1, n_2. \text{Dissatisfied}(x, n_1) \wedge \text{Dissatisfied}(y, n_2) \wedge n_1 < n_2.$$

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Incomplete preferences

- tuple scores and **probabilities** [SIC08, ZC08]
- **uncertain** tuple scores
- **disjunctive** preferences: $a \succ b \vee a \succ c$

Preference modification

- beyond revision and contraction: merging, arbitration,...
- general parametric framework?
- **conflict resolution**

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Variations

- preference and **similarity**: *“find the objects similar to one of the best objects”*

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Variations

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Applications

- preference queries as **decision components**: workflows, event systems
- **personalization** of query results
- preference **negotiation**: applying contraction

Acknowledgments

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