Discovering relative importance of skyline attributes

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August 26, 2009

Main contributions

- 1. generalizing skylines to p-skylines to capture relative attribute importance
- 2. discovering p-skylines on the basis of user feedback: algorithms and complexity

Skylines

Skyline preferences

- Atomic preferences (\mathcal{H}) : total orders over (single) attributes
- ▶ Skyline preference relation (sky_H) : t_1 preferred to t_2 if
 - t₁ equal or better than t₂ in every attribute, and
 - ▶ *t*₁ strictly better than *t*₂ in at least one attribute
- ► Skyline: the set w_{sky_H}(O) of best tuples (according to sky_H) in a set of tuples O

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- ▶ Skyline: the set $w_{sky_{\mathcal{H}}}(\mathcal{O})$ of best tuples (according to $sky_{\mathcal{H}}$) in a set of tuples \mathcal{O}



Skyline properties

- Simple, unique way of composing atomic preferences
- Equal attribute importance
- Skyline of exponential size

p-skylines



p-skylines



Each atomic preference must be used exactly once in \succ

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- ► Many different ways of composing atomic preferences (different combinations of ⊗ and &)
- Differences in attribute importance
- Reduction in query result size

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p-graphs

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- Γ_\succ represents attribute importance induced by a p-skyline relation \succ
 - Nodes: attributes
 - Edges: from more important to less important attributes

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$$\succ' = \succ_A \otimes \succ_B \otimes \succ_C \qquad \qquad \succ'' = \succ_A \& (\succ_B \otimes \succ_C)$$

$$(A \quad B \quad C)$$

Containment of p-skyline relations

Containment

 $\succ \subset \succ' \Leftrightarrow E(\Gamma_{\succ}) \subset E(\Gamma_{\succ'})$

Containment hierarchy



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Minimal extensions of ≻

- Correspond to immediate children of Γ_> in the hierarchy
- Obtained in PTIME using rewriting rules applied to syntax trees of p-skyline formulas

Containment hierarchy



Discovery of p-skyline relations from user feedback

Problem

Given a set \mathcal{A} of relevant attributes and a set \mathcal{H} of atomic preferences over \mathcal{A} , discover the relative importance of attributes [in the form of a p-skyline relation \succ], based on user feedback.

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\succ favors *G*/disfavors *W* in *O*

- 1. G are among the best tuples in \mathcal{O} according to \succ
- 2. W are not among the best tuples in \mathcal{O} according to \succ

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Complexity of p-skyline relation discovery

	Arbitrary W	$W = \emptyset$
Checking existence of \succ favoring <i>G</i> and disfavoring <i>W</i> in <i>O</i>	NP-complete	PTIME
Computing maximal \succ favoring <i>G</i> and disfavoring <i>W</i> in <i>O</i>	FNP-complete	PTIME

Computing maximal \succ favoring G in \mathcal{O}

Approach

- 1. Construct a system ${\mathcal N}$ of negative constraints from ${\textit{G}}$ and ${\mathcal O}$
- 2. Apply minimal extension rules to find maximal \succ satisfying ${\cal N}$
- 3. Various optimizations possible

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Negative constraint

represents $t_1 \not\succ t_2$

- Syntax: $\tau = < \mathcal{L}_{\tau}, \mathcal{R}_{\tau} >$
- Semantics:
 - some attr in R_τ is not a child (in Γ_≻) of any attr in L_τ
 - ► L_τ = attrs in which t₁ is better
 - ▶ R_τ = attrs in which t₂ is better

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Example

id	make	price	year
t_1	bmw	20 <i>k</i>	2006
<i>t</i> ₂	kia	10 <i>k</i>	2007

 $t_1 \not\succ t_2$ represented by $< \{make\}, \{price, year\} >$

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Algorithm complexity

 $\mathcal{O}(|\mathcal{O}| \cdot |\mathcal{G}| \cdot |\mathcal{A}|^3)$

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Experiments: Accuracy

Setup

- \mathcal{O} : NHL player stats of $\sim 10k$ tuples
- $\blacktriangleright |\mathcal{A}| \in \{9, 12\}$
- \succ_{fav} generated randomly
- G drawn from $w_{\succ_{fav}}(\mathcal{O})$

Accuracy measures

• Precision =
$$\frac{|w_{\succ}(\mathcal{O}) \cap w_{\succ_{fav}}(\mathcal{O})|}{|w_{\succ}(\mathcal{O})|}$$

•
$$Recall = \frac{|w_{\succ}(\mathcal{O}) \cap w_{\succ_{fav}}(\mathcal{O})|}{|w_{\succ_{fav}}(\mathcal{O})|}$$

Conclusions

Due to the maximality of \succ :

- Precision is consistently high
- Recall is low for small G but grows fast

Results





Experiments: Performance

Setup

- Three datasets (anticorrelated, uniform, correlated) of 50k tuples
- ▶ $|\mathcal{A}| \in \{10, 15, 20\}$

Conclusions

Algorithm is scalable w.r.t. the number of superior examples and |A|



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Related work

- 1. [Holland et al, PKDD'2003]
 - Mining p-skyline-like preferences (atomic preferences, operators)
 - Web server logs used as input
 - Heuristics used
- 2. [Jiang et al, KDD'2008]
 - Mining atomic preference relations using superior/inferior examples [skyline semantics]
 - Intractable problems, heuristics used
- 3. [Lee et al, DEXA'2008]
 - Mining of [Skyline+equivalence] preference relations
 - Answers to simple comparison questions used as feedback

Future work

- Attribute importance relationships between sets of attributes
- Selecting "good " superior examples
- Other scenarios of discovery (various forms of feedback, various result criteria)
- p-skylines: expressiveness, algorithms