

Ranking with Multiple reference Points

Efficient Elicitation and Learning Procedure

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- 2** Ranking with Multiple reference Points (RMP)
- 3** Inferring the parameters of an RMP model
- 4** MAX-SAT formulation for inferring an RMP Model
- 5** Experimental results
- 6** Conclusion and further research

1 Introduction

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6 Conclusion and further research

Ranking alternatives/objects

Problem

- ▶ Ranking alternative/object by preference
- ▶ e.g. ranking of cars



MCDA ranking methods/models

- ▶ UTilités Additives (UTA)
- ▶ ELimination and Choice Expressing REality (ELECTRE II)
- ▶ Ranking with Multiple reference Points (RMP)

1 Introduction

2 Ranking with Multiple reference Points (RMP)

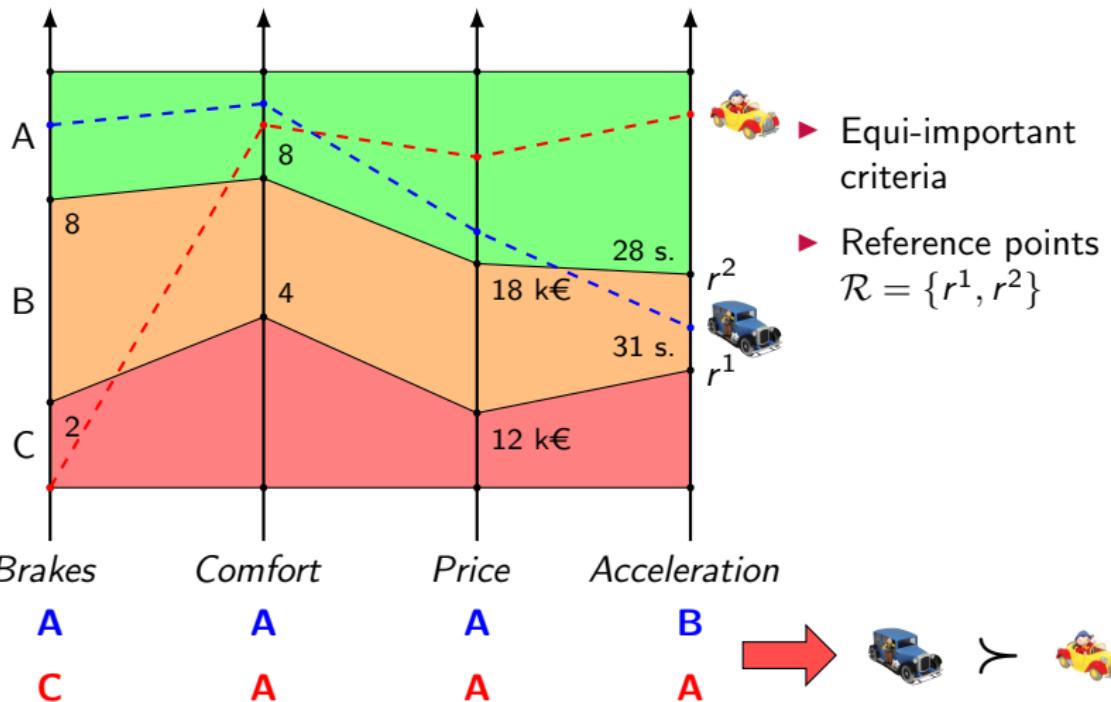
3 Inferring the parameters of an RMP model

4 MAX-SAT formulation for inferring an RMP Model

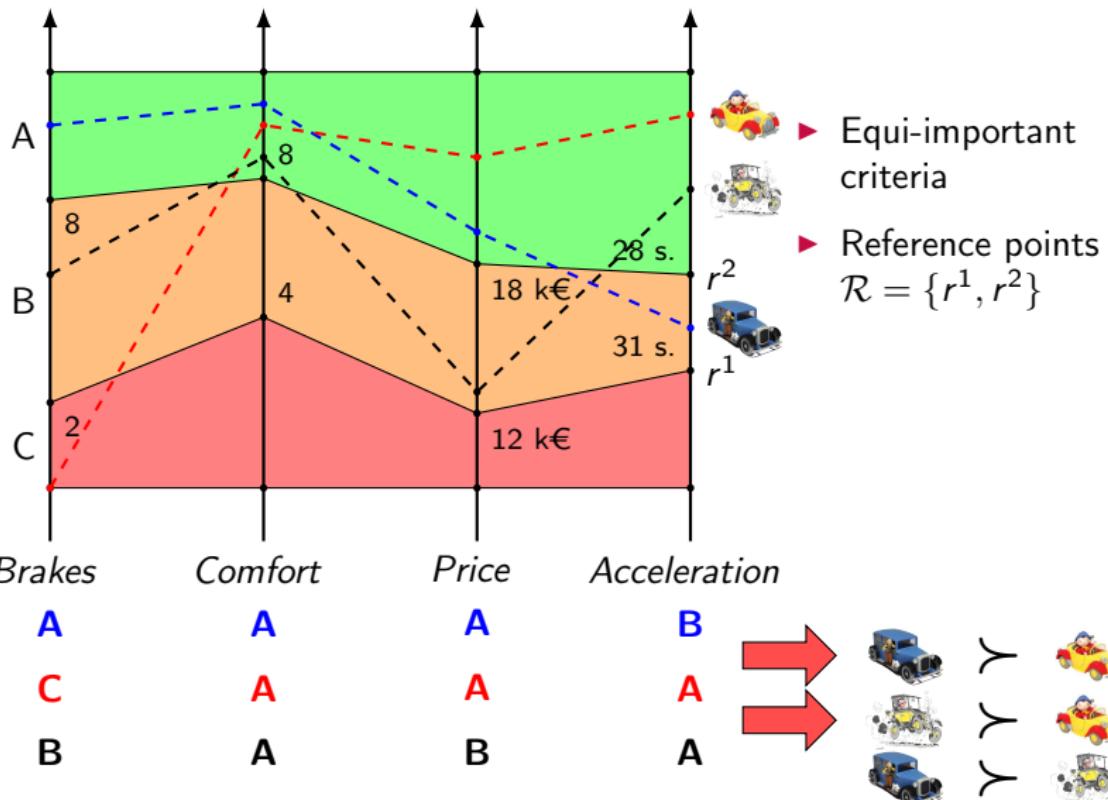
5 Experimental results

6 Conclusion and further research

Ranking with Multiple reference Points (RMP) I



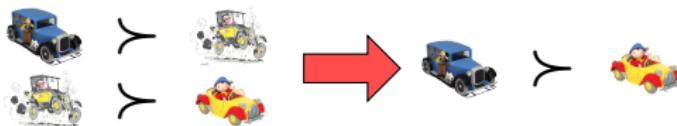
Ranking with Multiple reference Points (RMP) II



Ranking with Multiple reference Points (RMP) III

Some characteristics of RMP

- ▶ Model introduced by Antoine Rolland (Rolland, 2013)
- ▶ Transitivity ensured



- ▶ Safe regarding rank-reversal



- ▶ No need for commensurate scales

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3 Inferring the parameters of an RMP model

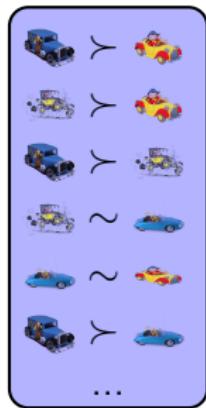
4 MAX-SAT formulation for inferring an RMP Model

5 Experimental results

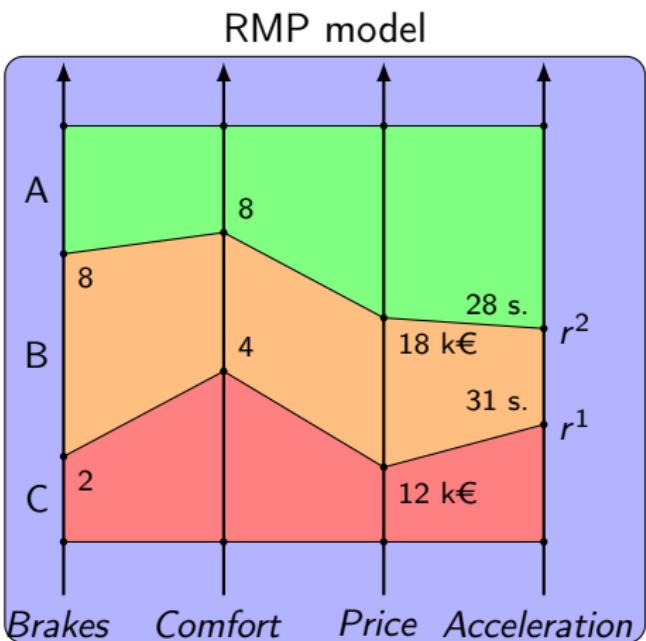
6 Conclusion and further research

Inferring the parameters of an RMP model I

Learning set



Algorithm



Inferring the parameters of an RMP model II

Existing algorithms

- ▶ MIP-based algorithms (Zheng et al., 2012; Liu, 2016)
 - ▶ S-RMP model (RMP with additive weights)
 - ▶ Mixed Integer Program
 - ▶ Minimization of Kemeny distance (Kemeny, 1959)
- ▶ Metaheuristic algorithm (Liu et al., 2014; Liu, 2016)
 - ▶ S-RMP model (RMP with additive weights)
 - ▶ Evolutionnary algorithm
 - ▶ Reasonable computing time

Limitations of the existing algorithms

- ▶ Additive representation of criteria importance relation
- ▶ MIP only able to handle very limited datasets
- ▶ Metaheuristic cannot always restore a S-RMP model

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SAT formulation for inferring an RMP Model I

Boolean Satisfiability problem

- ▶ Boolean variables V ;
- ▶ Logical proposition about these variables $f : \{0, 1\}^V \rightarrow \{0, 1\}$;
- ▶ SATisfiable if v^* exists such that $f(v^*) = 1$
- ▶ f can be expressed as conjunction of clauses \mathcal{C} :
$$f = \bigwedge_{c \in \mathcal{C}} c;$$
- ▶ Each clause $c \in \mathcal{C}$ is a disjunction of their variables or their negation :
$$\forall c \in \mathcal{C}, \exists c^+, c^- \in \mathcal{P}(V) : c = \bigvee_{v \in c^+} v \vee \bigvee_{v \in c^-} \neg v;$$
- ▶ NP-complete problem BUT efficient SAT algorithms exist

SAT for learning an RMP model

- ▶ Expression of constraints as a SAT problem
- ▶ Limited to strict preferences ($a \succ b$)

SAT formulation for inferring an RMP Model II

$$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$$

1. φ_{scales} : Monotonicity of criteria scales

$$\varphi_{\text{scales}} := \bigwedge_{i \in N} \bigwedge_{k' < k \in \mathbb{X}_i} (x_{i,h,k} \vee \neg x_{i,h,k'})$$

- ▶ $x_{i,h,k}$: equal to 1 if value k above reference point r^h on criterion i
- ▶ N : set of criteria indices
- ▶ \mathbb{X}_i : set of values on criterion i

SAT formulation for inferring an RMP Model II

$$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$$

2. $\varphi_{\text{profiles}}$: Dominance of the profiles

$$\varphi_{\text{profiles}} := \varphi_{\text{profiles}_1} \wedge \varphi_{\text{profiles}_2}$$

$$\varphi_{\text{profiles}_1} := \bigwedge_{h \neq h' \in H} \bigwedge_{i \in N} \bigwedge_{k \in \mathbb{X}_i} (x_{i,h',k} \vee \neg x_{i,h,k} \vee \neg d_{h,h'})$$

$$\varphi_{\text{profiles}_2} := \bigwedge_{h < h' \in H} (d_{h,h'} \vee d_{h',h})$$

- ▶ N : set of criteria indices
- ▶ \mathbb{X}_i : set of values on criterion i
- ▶ H : set of reference points indices
- ▶ $d_{h,h'}$: equal to 1 if value if r^h dominates $r^{h'}$
- ▶ $x_{i,h,k}$: equal to 1 if value k above reference point r^h on criterion i

SAT formulation for inferring an RMP Model II

$$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$$

3. φ_{order} : Order among criteria sets

$$\varphi_{\text{order}} := \varphi_{\text{Pareto}} \wedge \varphi_{\text{completeness}} \wedge \varphi_{\text{transitivity}}$$

$$\varphi_{\text{Pareto}} := \bigwedge_{A \subseteq B \in \mathcal{P}(N)} (y_{B,A})$$

$$\varphi_{\text{completeness}} := \bigwedge_{A,B \in \mathcal{P}(N)} (y_{A,B} \vee y_{B,A})$$

$$\varphi_{\text{transitivity}} := \bigwedge_{A,B,C \in \mathcal{P}(N)} (\neg y_{A,B} \vee \neg y_{B,C} \vee y_{A,C})$$

- ▶ $\mathcal{P}(N)$: set of possible criteria coalitions
- ▶ $y_{A,B}$: equal to 1 if criteria coalition A is more important than criteria coalition B

SAT formulation for inferring an RMP Model II

$$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$$

4. $\varphi_{\text{outranking}}$: Outranking relation between pairs

$$\varphi_{\text{outranking}} := \varphi_{\text{outranking}_1} \wedge \varphi_{\text{outranking}_2} \wedge \varphi_{\text{outranking}_3}$$

$$\varphi_{\text{outranking}_1} := \bigwedge_{A,B \in \mathcal{P}(N)} \bigwedge_{j \in J} \bigwedge_{h \in H} \left(\bigvee_{i \notin A} x_{i,h,p_j^i} \vee \bigvee_{i \in B} \neg x_{i,h,n_j^i} \vee y_{A,B} \vee \neg z_{j,h} \right)$$

- ▶ $p_j \succ n_j$: pairwise comparison j
- ▶ J : set of pairwise comparisons indices
- ▶ $\mathcal{P}(N)$: set of possible criteria coalitions
- ▶ H : set of reference points indices
- ▶ $x_{i,h,k}$: equal to 1 if value k above reference point r^h on criterion i
- ▶ $y_{A,B}$: equal to 1 if criteria coalition A is more important than criteria coalition B
- ▶ z_j : equals to 1 if criteria set on which p_j above r^h is more important than the criteria set on which n_j is above r^h

SAT formulation for inferring an RMP Model II

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4. $\varphi_{\text{outranking}}$: Outranking relation between pairs

$$\varphi_{\text{outranking}} := \varphi_{\text{outranking}_1} \wedge \varphi_{\text{outranking}_2} \wedge \varphi_{\text{outranking}_3}$$

$$\varphi_{\text{outranking}_2} := \bigwedge_{A,B \in \mathcal{P}(N)} \bigwedge_{j \in J} \bigwedge_{h \in H} \left(\bigvee_{i \notin A} x_{i,h,n_j^i} \vee \bigvee_{i \in B} \neg x_{i,h,p_j^i} \vee y_{A,B} \vee \neg z'_{j,h} \right)$$

- ▶ $p_j \succ n_j$: pairwise comparison j
- ▶ J : set of pairwise comparisons indices
- ▶ $\mathcal{P}(N)$: set of possible criteria coalitions
- ▶ H : set of reference points indices
- ▶ $x_{i,h,k}$: equal to 1 if value k above reference point r^h on criterion i
- ▶ $y_{A,B}$: equal to 1 if criteria coalition A is more important than criteria coalition B
- ▶ z'_j : equals to 1 if criteria set on which n_j above r^h is more important than the criteria set on which p_j is above r^h

SAT formulation for inferring an RMP Model II

$$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$$

4. $\varphi_{\text{outranking}}$: Outranking relation between pairs

$$\varphi_{\text{outranking}} := \varphi_{\text{outranking}_1} \wedge \varphi_{\text{outranking}_2} \wedge \varphi_{\text{outranking}_3}$$

$$\begin{aligned} \varphi_{\text{outranking}_3} := & \bigwedge_{A,B \in \mathcal{P}(N)} \bigwedge_{j \in J} \bigwedge_{h \in H} \left(\bigvee_{i \in A} \neg x_{i,h,p_i^j} \vee \bigvee_{i \notin A} x_{i,h,p_i^j} \vee \bigvee_{i \in B} \neg x_{i,h,n_i^j} \vee \bigvee_{i \notin B} x_{i,h,n_i^j} \right. \\ & \left. \vee \neg y_{B,A} \vee z'_{j,h} \right) \end{aligned}$$

- ▶ $p_j \succ n_j$: pairwise comparison j
- ▶ J : set of pairwise comparisons indices
- ▶ $\mathcal{P}(N)$: set of possible criteria coalitions
- ▶ H : set of reference points indices
- ▶ $x_{i,h,k}$: equal to 1 if value k above reference point r^h on criterion i
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SAT formulation for inferring an RMP Model II

$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$

5. $\varphi_{\text{lexicography}}$: Lexicography of reference points

$$\varphi_{\text{lexicography}} := \varphi_{\text{lexicography}_1} \wedge \varphi_{\text{lexicography}_2} \wedge \varphi_{\text{lexicography}_3}$$

$$\varphi_{\text{lexicography}_1} := \bigwedge_{j \in J} \bigwedge_{h \leq h' \in H} (z_{j,h} \vee \neg s_{j,h'})$$

$$\varphi_{\text{lexicography}_2} := \bigwedge_{j \in J} \bigwedge_{h < h' \in H} (z'_{j,h} \vee \neg s_{j,h'})$$

$$\varphi_{\text{lexicography}_3} := \bigwedge_{h \in H} (\neg z'_{j,h} \vee \neg s_{j,h})$$

- ▶ J : set of pairwise comparisons indices
- ▶ H : set of reference points indices
- ▶ z_j : equals to 1 if criteria set on which p_j above r^h is more important than the criteria set on which n_j is above r^h
- ▶ z'_j : equals to 1 if criteria set on which n_j above r^h is more important than the criteria set on which p_j is above r^h
- ▶ $s_{j,h}$: equals to 1 if p^j indifferent to n^j for all reference points $r^{h'}$ such that $h' < h$ and strictly outranks n^j at reference point r^h

SAT formulation for inferring an RMP Model II

$\varphi := \varphi_{\text{scales}} \wedge \varphi_{\text{profiles}} \wedge \varphi_{\text{order}} \wedge \varphi_{\text{outranking}} \wedge \varphi_{\text{lexicography}} \wedge \varphi_{\text{preference}}$

6. $\varphi_{\text{preference}}$: Strict preference

$$\varphi_{\text{preference}} := \bigwedge_{j \in J} \left(\bigvee_{h \in H} s_{j,h} \right)$$

- ▶ J : set of pairwise comparisons indices
- ▶ H : set of reference points indices
- ▶ $s_{j,h}$: equals to 1 if p^j indifferent to n^j for all reference points $r^{h'}$ such that $h' < h$ and strictly outranks n^j at reference point r^h

MAX-SAT formulation

Goal

- ▶ Handle incompatibilities in the learning set
(e.g. $a \succ b$ and $b \succ a$)

How ?

- ▶ By allowing the violation of some clauses
- ▶ Weighting the clauses :
 - ▶ Some cannot be violated (e.g. monotonicity of the scales)
⇒ Huge weights for these clauses
 - ▶ Others can be violated (e.g. pairwise comparison)
⇒ Small weights for these clauses

MAX-SAT solvers

- ▶ Lot of different ones (MAX-SAT competition every year)
- ▶ Chosen solvers : MaxHS (Davies, 2013), maxino (Alviano et al., 2015).

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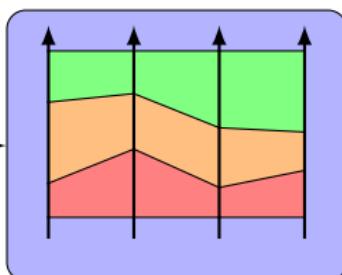
5 Experimental results

6 Conclusion and further research

Experimental results I

Pairs of alternatives

- (3, 5, 2, 7) ? (2, 7, 3, 9)
- (1, 2, 3, 4) ? (4, 1, 2, 1)
- (4, 3, 6, 5) ? (2, 7, 5, 9)
- (5, 9, 7, 6) ? (2, 8, 3, 1)
- (2, 6, 4, 7) ? (2, 7, 1, 4)
- ...

 \mathcal{M}^0


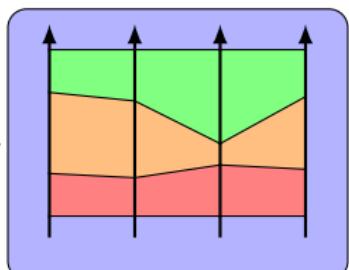
Learning set

- $(3, 5, 2, 7) \succ (2, 7, 3, 9)$
- $(1, 2, 3, 4) \prec (4, 1, 2, 1)$
- $(4, 3, 6, 5) \succ (2, 7, 5, 9)$
- $(5, 9, 7, 6) \prec (2, 8, 3, 1)$
- $(2, 6, 4, 7) \succ (2, 7, 1, 4)$
- ...

Learning set

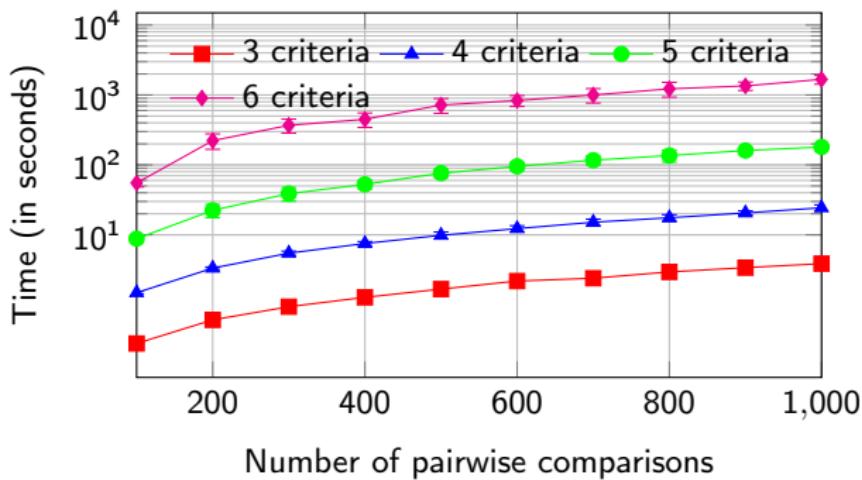
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- $(2, 6, 4, 7) \succ (2, 7, 1, 4)$
- ...

SAT-RMP

 $\mathcal{M}^{\text{learned}}$


Experimental results II

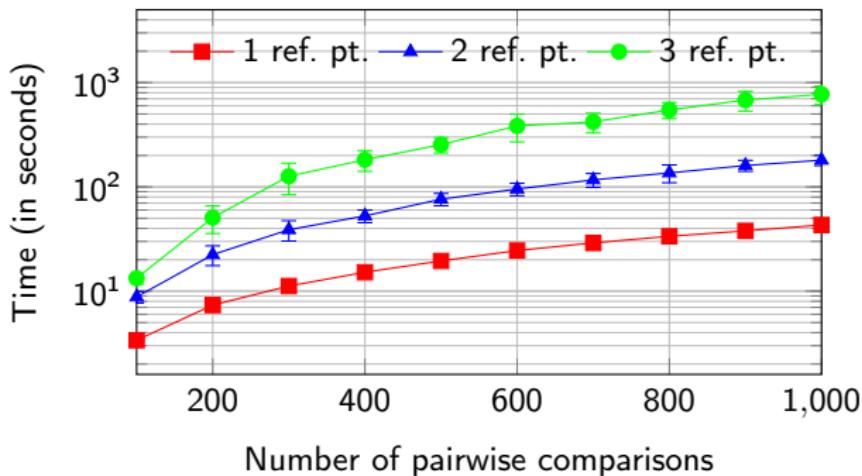
Computing time



- ▶ 2 reference points
- ▶ Computing time grows fast when the number of criteria increases
- ▶ More efficient than MIP based algorithms

Experimental results III

Computing time

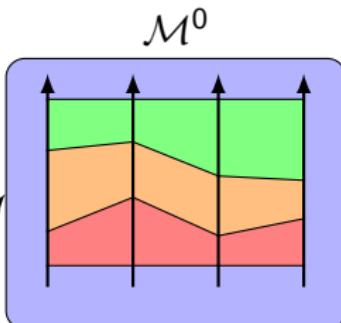


- ▶ 5 criteria
- ▶ Computing time also significantly impacted by the number of reference points

Experimental results IV

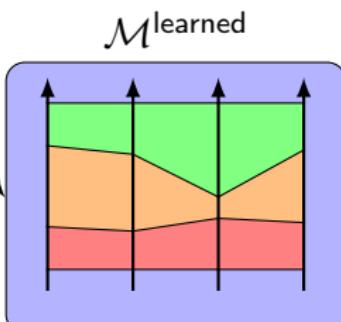
Test set

- (3, 5, 2, 7) ? (2, 7, 3, 9)
- (1, 2, 3, 4) ? (4, 1, 2, 1)
- (4, 3, 6, 5) ? (2, 7, 5, 9)
- (5, 9, 7, 6) ? (2, 8, 3, 1)
- (2, 6, 4, 7) ? (2, 7, 1, 4)
- ...



Comparisons

- (3, 5, 2, 7) \succ (2, 7, 3, 9)
- (1, 2, 3, 4) \prec (4, 1, 2, 1)
- (4, 3, 6, 5) \succ (2, 7, 5, 9)
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- ...

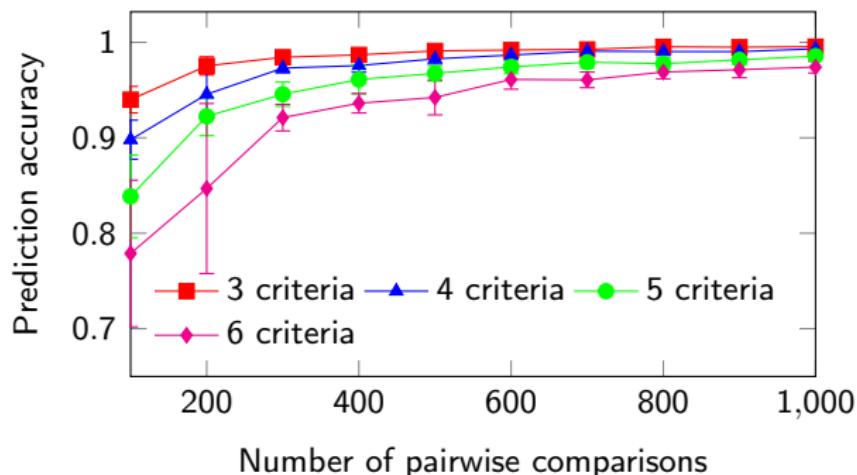


Comparisons

- (3, 5, 2, 7) \succ (2, 7, 3, 9)
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- ...

Experimental results V

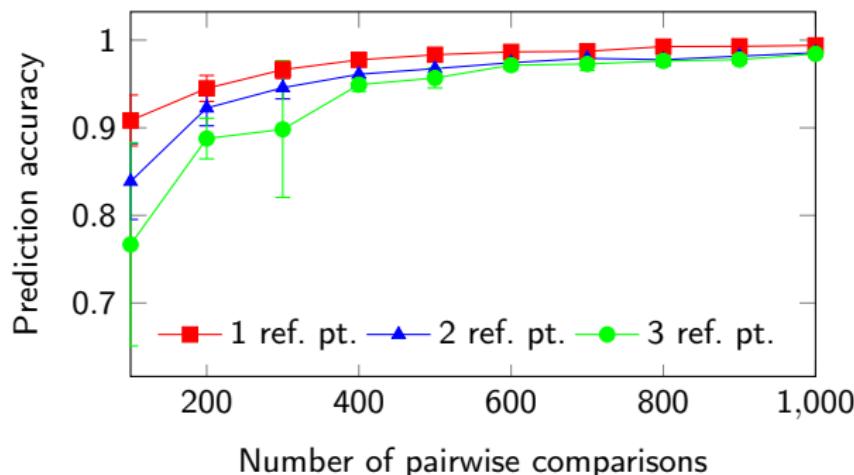
Model retrieval



- ▶ 2 reference points
- ▶ Accuracy above 90% with barely 300 pairwise comparisons

Experimental results VI

Model retrieval

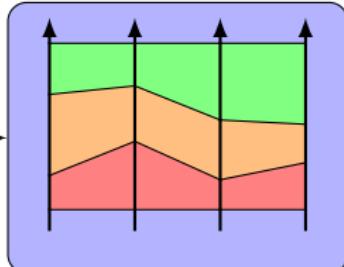


- ▶ 5 criteria
- ▶ Number of reference points hasn't lot of impact on the accuracy when the number of pairwise comparisons is greater than 300

Experimental results VII

Pairs of alternatives

- (3, 5, 2, 7) ? (2, 7, 3, 9)
- (1, 2, 3, 4) ? (4, 1, 2, 1)
- (4, 3, 6, 5) ? (2, 7, 5, 9)
- (5, 9, 7, 6) ? (2, 8, 3, 1)
- (2, 6, 4, 7) ? (2, 7, 1, 4)
- ...

 \mathcal{M}^0


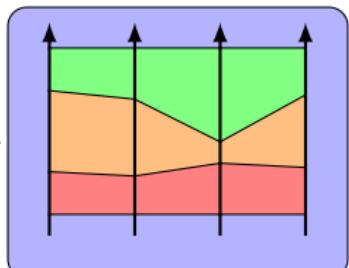
Learning set

- $(3, 5, 2, 7) \succ (2, 7, 3, 9)$
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- $(4, 3, 6, 5) \succ (2, 7, 5, 9)$
- $(5, 9, 7, 6) \prec (2, 8, 3, 1)$
- $(2, 6, 4, 7) \succ (2, 7, 1, 4)$
- ...

Learning set*

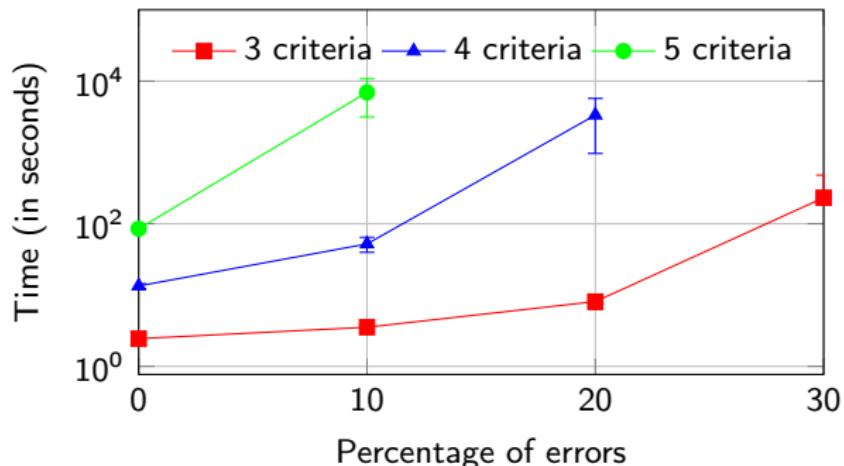
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- ...

MAXSAT-RMP

 $\mathcal{M}^{\text{learned}}$


Experimental results VIII

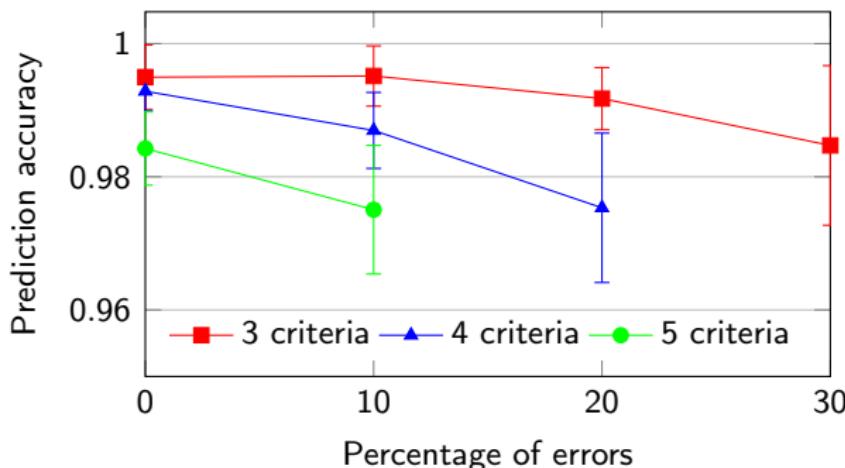
Tolerance for errors



- ▶ 1 profile
- ▶ 500 pairwise comparisons
- ▶ Computing time increases quickly when the number of inversion increases

Experimental results IX

Tolerance for errors



- ▶ 1 profiles
- ▶ 500 pairwise comparisons
- ▶ MAX-SAT formulation identifies errors

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Conclusion and further research

Conclusion

- ▶ Efficient formulation for problems involving less than 7 criteria (1000 pairwise comparisons)
- ▶ Computing time increases when there are errors in the learning set

Further research

- ▶ Support for indifference
- ▶ Formalization of SAT clauses (demonstration)

That's all Folks!

İlginiz için teşekkürler !
(Thank you for your attention !)

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