

# Elicitation of Weighting Parameters in Rank-Dependent Preference Models

C. Gonzales, P. Perny, P. Viappiani

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## Preference Aggregation with Rank-Dependent Models

- Aggregation of preference information (for instance, from different conflicting criteria) is an essential component of a decision-support tool
- Growing interest in rank-dependent aggregation functions to represent the preferences of a decision maker (OWA, WOWA, Choquet integrals, etc)
- Such models are expressive as they are able to represent synergies between criteria, such as compensatory effects

**Key question:** how to assess the parameters required in order to use such models ?

→ We consider parameter assessment and adaptive elicitation with **minimax regret**

# Preference Parameters in Aggregation Functions

## Aggregation function:

$$\mathbf{x} = (x_1, \dots, x_n), \mathbf{y} = (y_1, \dots, y_n) \rightarrow \mathbf{x} \succsim \mathbf{y} \Leftrightarrow u(\mathbf{x}; \omega) \geq u(\mathbf{y}; \omega)$$

## Weighting parameters provide a control on:

- the type of compromise sought in MCDM
- the attitude towards equity in Social Choice

## Standard weighting parameters (weights attached to criteria)

- **Weighted sum** :  $u(\mathbf{x}; \omega) = \sum_{i=1}^n \omega_i x_i$
- **Weighted Tchebycheff** :  $u(\mathbf{x}; \omega) = \max_{i \in [1;n]} \left\{ \omega_i \frac{x_i^* - x_i}{x_i^* - x_{i^*}} \right\}$

## Rank-dependent weighting parameters (weights attached to ranks)

- **OWA** :  $u(\mathbf{x}; w) = \sum_{i=1}^n w_i x_{(i)}$
- **Choquet** :  $u(\mathbf{x}; v) = \sum_{i=1}^n [x_{(i)} - x_{(i-1)}] v(x_{(i)})$

## Utility-based Interactive Recommender System:

- *Bel*: belief about the user's utility function  $u$
- *Opt(Bel)*: optimal decision given incomplete beliefs about  $u$

## Algorithm: Adaptive Utility Elicitation

- 1 **Repeat** until *Bel* meets some termination condition
  - 1 Ask user some query
  - 2 Observe user response  $r$
  - 3 Update *Bel* given  $r$
- 2 Recommend *Opt(Bel)*

## Types of Beliefs

- *Probabilistic Uncertainty*: probability distribution of parameters, updated using Bayes
- *Strict Uncertainty*: feasible region of utility parameters (if linear constraints: a convex polytope)

# Minimax Regret

## Intuition

Adversarial game; the recommender selects the item reducing the “regret” wrt the “best” item when  $\omega$  is chosen by the adversary

- Robust criterion for decision making under uncertainty [Savage; Kouvelis]
- Showed to be effective when used for decision making under utility uncertainty [Boutilier et al., 2006] and as driver for elicitation

## Advantages

- No heavy Bayesian updates
- No prior assumption required
- MMR computation suggests queries to ask to the user

## Limitations

- No account for noisy responses
- Formulation of the optimization heavily depends on the assumption about the utility model

# Minimax Regret

**Assumption:** a set of feasible utility functions  $W$  is given

The *pairwise max regret*

$$PMR(\mathbf{x}, \mathbf{y}; W) = \max_{w \in W} u(\mathbf{y}; w) - u(\mathbf{x}; w)$$

The *max regret*

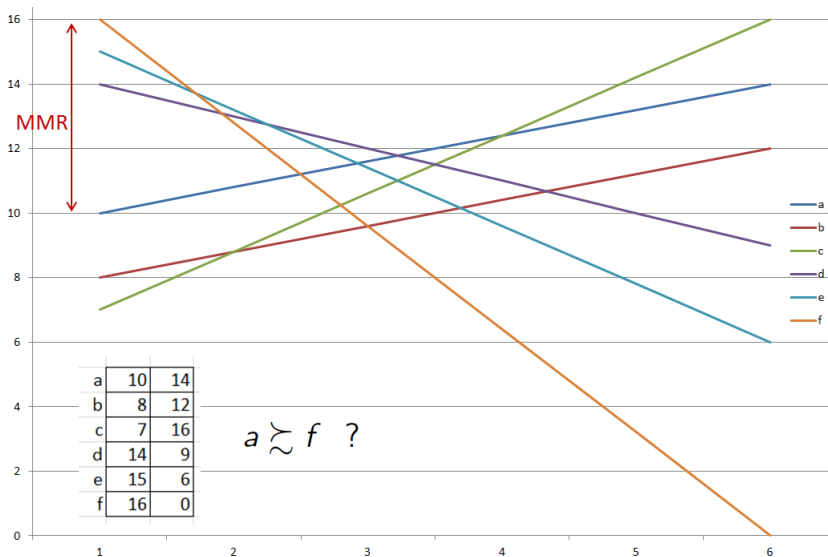
$$MR(\mathbf{x}; W) = \max_{\mathbf{y} \in \mathbf{X}} PMR(\mathbf{x}, \mathbf{y}; W)$$

The *minimax regret*

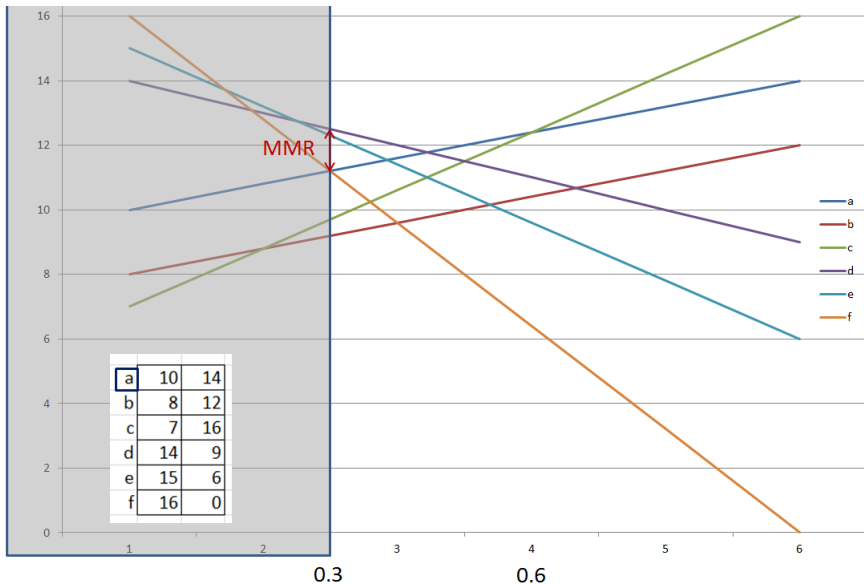
$MMR(W)$  of  $W$  and the *minimax optimal item*  $\mathbf{x}_W^*$ :

$$\begin{aligned} MMR(W) &= \min_{\mathbf{x} \in \mathbf{X}} MR(\mathbf{x}, W) \\ \mathbf{x}_W^* &= \arg \min_{\mathbf{x} \in \mathbf{X}} MR(\mathbf{x}, W) \end{aligned}$$

# A graphical illustration for the weighted sum (1/3)

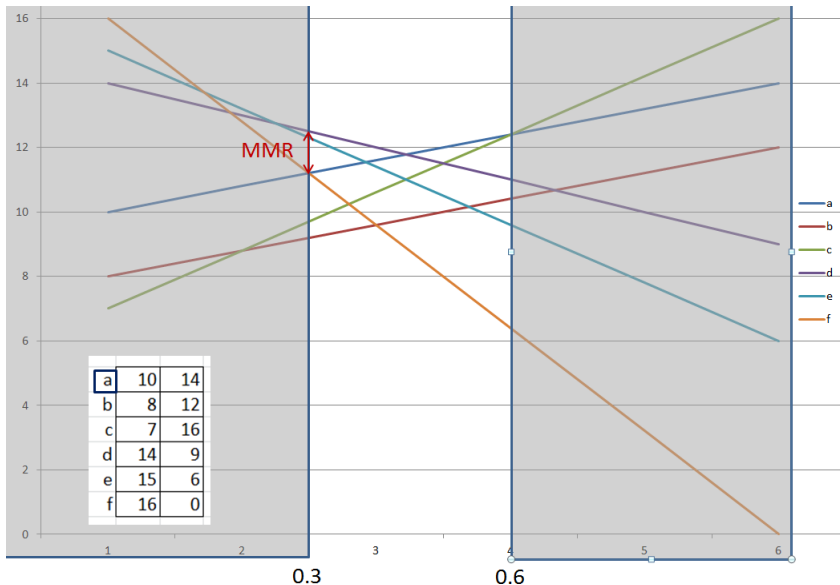


# A graphical illustration for the weighted sum (2/3)





# A graphical illustration for the weighted sum (3/3)



# Minimax Regret Computation

## Computation of Pairwise Max Regret as Linear Program

- Objective function:  $\max_{w \in W} w \cdot (\mathbf{y} - \mathbf{x})$
- Usually  $W$  expressed by linear constraints such as  $w \cdot \mathbf{z}^+ \geq w \cdot \mathbf{z}^-$  for  $(\mathbf{z}^+, \mathbf{z}^-) \in \mathcal{D}_{pref}$  (a set of comparisons)

## Computation of Minimax Regret

- Naive approach: test all  $n^2 - n$  combinations of choices
- Better idea: implement a *search* problem [Braziunas, 2012]
  - $i$ =choice of recommender,  $j$ =choice of adversary
  - $UB$ : upper bound on minimax regret (max regret of best solution found)
  - $LB_i$ : lower bound on the max regret of option  $i$
  - After testing  $i$  against  $j$ :  $LB_i \leftarrow \max(LB_i, PMR(i, j))$
  - Whenever  $LB_i \geq UB$ : prune option  $i$
- Empirically, a small number of *PMR* checks is needed

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (0  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	?	?	?	0
$i=2$	?	0	?	?	0
$i=3$	?	?	0	?	0
$i=4$	?	?	?	0	0

UB

+Inf

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (1  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	1	?	?	1
$i=2$	?	0	?	?	0
$i=3$	?	?	0	?	0
$i=4$	?	?	?	0	0

UB

+Inf

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (3  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	1	2	3	3
$i=2$	?	0	?	?	0
$i=3$	?	?	0	?	0
$i=4$	?	?	?	0	0

UB

3

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (6  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	?	?	0	?	0
$i=4$	?	?	?	0	0

UB

2

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (7  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	?	0	?	4
$i=4$	?	?	?	0	0

UB

2

# Example of Minimax Regret Computation

## Example

Complete “pairwise max regret” table

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$MR(i)$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	1	0	1	4
$i=4$	3	2	3	0	3

Evaluation (8  $PMR$  checks)

$PMR(i, j)$	$j=1$	$j=2$	$j=3$	$j=4$	$LB_i$
$i=1$	0	1	2	3	3
$i=2$	2	0	2	2	2
$i=3$	4	?	0	?	4
$i=4$	3	?	?	0	3

UB
2



## Positive normalized weights (general case)

$$u(\mathbf{x}; \mathbf{w}) = \sum_{i=1}^n w_i x_{(i)} \text{ non-linear in } x \text{ but linear in } w !$$

$$u(x, w) \geq u(y, w) \iff w \cdot x^\uparrow \geq w \cdot y^\uparrow$$

where  $x^\uparrow$  is the vector  $x$  sorted by increasing order

→ preference of type  $x \succsim y$  is equivalent to a linear inequality

## Positive normalized decreasing weights (fair optimization)

OWA with decreasing weights:  $w_i > w_j$  whenever  $i < j$   
ensures the compatibility with *Pigou-Dalton transfers*, i.e:

$$\forall i, j : x_j > x_i, \forall \varepsilon \in (0, x_j - x_i),$$

$$(x_1, x_i + \varepsilon, \dots, x_j - \varepsilon, x_n) \succ (x_1, \dots, x_n)$$

→ add inequalities of type  $w_i - w_{i+1} \geq \delta$  with  $\delta > 0$

## Dataset Manipulation

$\mathbf{x}^\uparrow = (x_{(1)}, \dots, x_{(n)})$  permutation of features from worst to best

## PMR for OWA

$$\max_w \quad w \cdot (\mathbf{y}^\uparrow - \mathbf{x}^\uparrow) \quad (1)$$

$$s.t. \quad 0 \leq w_i \leq 1 \quad \forall i \quad (2)$$

$$\sum_i w_i = 1 \quad (3)$$

$$w_i - w_{i+1} \geq \delta \quad (4)$$

$$w \cdot \mathbf{z}_+^\uparrow \geq w \cdot \mathbf{z}_-^\uparrow \quad \text{for } (\mathbf{z}_+, \mathbf{z}_-) \in \mathcal{D}_{pref} \quad (5)$$

# Application to Choquet integrals

$$C_v(x) = x_{(1)}v(X_{(1)}) + \sum_{i=2}^n [x_{(i)} - x_{(i-1)}] v(X_{(i)})$$

$x_{(i)} \leq x_{(i+1)}$  for all  $i = 1, \dots, n-1$  and  $X_{(i)} = \{j \in N, x_j \geq x_{(i)}\}$ ,

## Example

	$\emptyset$	$\{1\}$	$\{2\}$	$\{3\}$	$\{1, 2\}$	$\{1, 3\}$	$\{2, 3\}$	$\{1, 2, 3\}$
$v$	0	0.1	0.2	0.3	0.5	0.6	0.7	1

$x = (10, 6, 14)$  and  $y = (10, 12, 8)$

$$C_v(x) = 6 + (10 - 6)v(\{1, 3\}) + (14 - 10)v(\{3\}) = 9.6$$

$$C_v(y) = 8 + (10 - 8)v(\{1, 2\}) + (12 - 10)v(\{2\}) = 9.4$$

With  $C_v$  we observe that  $x$  is preferred to  $y$ .

# Fairness and convex capacities in the Choquet integral

$v$  is said to be *convex* or *supermodular* when  
 $v(A \cup B) + v(A \cap B) \geq v(A) + v(B)$  for all  $A, B \subseteq N$ ,

## Proposition (Chateauneuf and Tallon, 1999)

When preferences are represented by a Choquet integral, then choosing  $v$  convex is equivalent to the following property:

$\forall x^1, x^2, \dots, x^p \in \mathbb{R}^n, \forall k \in \{1, 2, \dots, p\}$  and

$\forall i \in \{1, 2, \dots, p\}, \lambda_i \geq 0$  such that  $\sum_{i=1}^p \lambda_i = 1$  we have:

$$C_v(x^1) = C_v(x^2) = \dots = C_v(x^p) \Rightarrow C_v\left(\sum_{i=1}^p \lambda_i x^i\right) \geq C_v(x^k)$$

## Example (convex $v$ and fairness)

$$x = (18, 18, 0), y = (0, 18, 18), z = (18, 0, 18)$$

$$t = (12, 12, 12) = (x + y + z)/3$$

$$v \text{ convex} \Rightarrow [C_v(x) = C_v(y) = C_v(z) \Rightarrow t \succsim x, t \succsim y, t \succsim z]$$

# Choquet integral and Möbius masses

an alternative representation in terms of the Möbius inverse:

## Möbius inverse and Möbius masses

To any set-function  $\nu : 2^N \rightarrow \mathbb{R}$  is associated  $m : 2^N \rightarrow \mathbb{R}$  a mapping called *Möbius inverse*, defined by:

$$\forall A \in N, \quad m(A) = \sum_{B \subseteq A} (-1)^{|A \setminus B|} \nu(B), \quad \nu(A) = \sum_{B \subseteq A} m(B)$$

Coefficients  $m(B)$  for  $B \subseteq A$  are called Möbius masses.

**Remark:**  $\nu$  convex if Möbius masses are positive (*belief function*, Shafer, 1976)

## Choquet integral as a function of Möbius masses

$$C_\nu(x) = \sum_{B \subseteq A} m(B) \bigwedge_{i \in B} x_i$$

2-additive capacity ( $m(B) = 0$  iff  $|B| > 2$ )  $\rightarrow$  capacity completely characterized by  $(n^2 + n)/2$  coefficients.

Good compromise between **compactness** of the model and **expressivity**.

# PMR for Choquet (1/2)

$m$  vector of variables:

$$m = (m_1, \dots, m_n, m_{11}, m_{12}, \dots, m_{1n}, m_{23}, \dots, m_{2n}, \dots, m_{n-1n})$$

$$\bar{x} = (x_1, \dots, x_n, x_{11}, x_{12}, \dots, x_{1n}, x_{23}, \dots, x_{2n}, \dots, x_{n-1n}), x_{ij} = x_i \wedge x_j$$

## The case of a 2-additive capacity

$$\max_m m \cdot (\bar{x} - \bar{y}) \quad (6)$$

$$\text{s.t. } \sum_{j \in J} m_{ij} \geq 0, \quad i = 1, \dots, n, \{i\} \subseteq J \subseteq N \quad (7)$$

$$\sum_{i=1}^n m_i + \sum_i \sum_{j=i+1}^n m_{ij} = 1 \quad (8)$$

$$m \cdot \bar{z}_+ \geq m \cdot \bar{z}_-, \quad (\mathbf{z}_+, \mathbf{z}_-) \in \mathcal{D}_{pref} \quad (9)$$

Remark: monotonicity (7) requires an exponential number of constraints

$m$  vector of variables:

$$m = (m_1, \dots, m_n, m_{11}, m_{12}, \dots, m_{1n}, m_{23}, \dots, m_{2n} \dots, m_{n-1n})$$

$$\bar{x} = (x_1, \dots, x_n, x_{11}, x_{12}, \dots, x_{1n}, x_{23}, \dots, x_{2n} \dots, x_{n-1n}), x_{ij} = x_i \wedge x_j$$

The case of (2-additive) belief functions

$$\max_m m.(\bar{x} - \bar{y}) \quad (10)$$

$$s.t. \sum_{i=1}^n m_i + \sum_i \sum_{j=i+1}^n m_{ij} = 1 \quad (11)$$

$$m.\bar{z}_+ \geq m.\bar{z}_-, (\mathbf{z}_+, \mathbf{z}_-) \in \mathcal{D}_{pref} \quad (12)$$

$$m_i \geq 0, i=1, \dots, n, \quad (13)$$

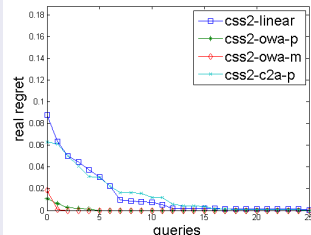
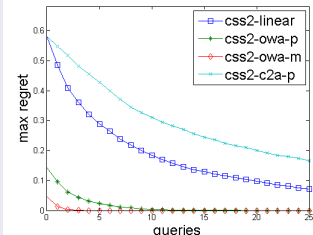
$$m_{ij} \geq 0, i=1, \dots, n, j=i+1, \dots, n, \quad (14)$$

# Interactive Elicitation

## Strategies for Choosing the Next Query

- Different types of Queries: comparisons, bound queries (local/global),...
- **Choice of Query:** *Current Solution Strategy (CSS)* asking to compare  $\mathbf{x}^*$  and  $\mathbf{x}^a$  (the adversary's choice):  $\mathbf{x}^a = \arg \max_{\mathbf{y}} PMR(\mathbf{x}, \mathbf{y})$
- It is possible to optimize queries wrt analogous of value of information [Viappiani and Boutilier, 2009]

## Simulations



Random dataset: 100 data points, 10 features. Sampled random utility weights between 0 and 1; then normalized  
The simulated user answers a comparison query at each step according to utility weights; 30 runs



## Observation

- Empirically, a user whose utility function is based on OWA requires less queries to identifying the true best item
- When assuming monotonicity for the weights (favouring well-balanced solutions) this is even more striking
- MMR seems to be lower when assuming OWA than linear aggregation

## Conclusions

- The assessment of the parameters of models such as OWA and Choquet is usually problematic
- Minimax regret can be used to assess the parameters of non-linear utility models such as OWA and Choquet
- Regret can be used to select the next query to ask in Interactive elicitation
- Preliminary simulation results