Expert Judgment Workshop

Glasgow, August 28, 2015

Modelling consumer preferences with an additive value function: an experimental study

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Motivation: application

- Transports sector: concerns about energy dependency and environmental impacts
- Electric Vehicles (EV) as an alternative to traditional vehicles
- Need to estimate EV adoption and its drivers
- Consumer preferences are the main factor

Motivation: MCDA methodology

- To investigate the potential of UTA-based approaches (additive value model inference) for modelling individual preferences
- To confront two methods to elicit holistic preferences (the inputs for UTA)
  - Five best-worst questions in sets of three alternatives
  - A ranking of a set of seven alternatives

Summary

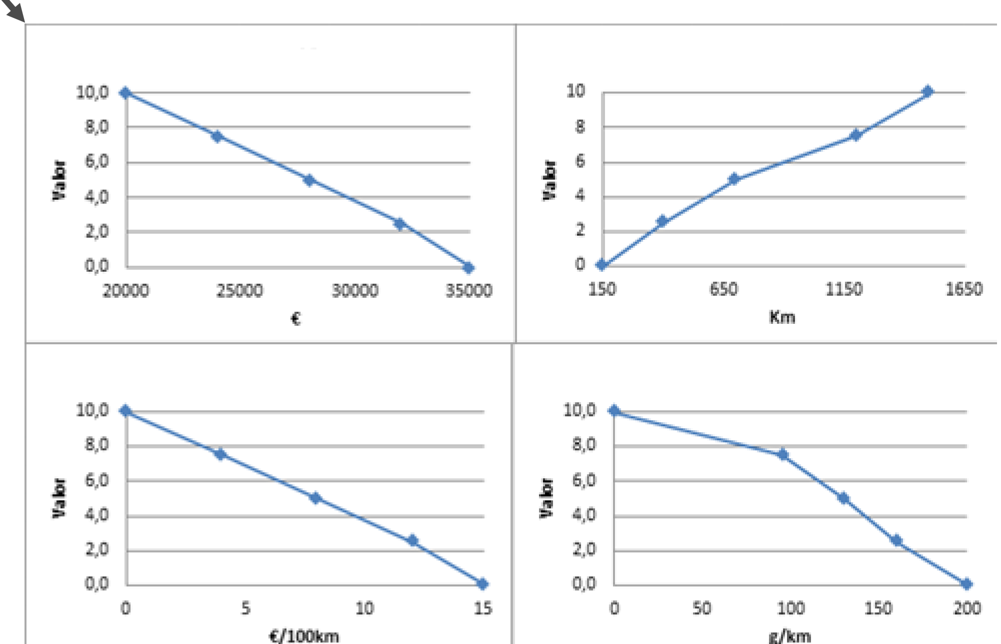
- Motivation
- Background
- Research questions (outline)
- Preliminary survey and lessons learnt
- Second survey
- Results
- Conclusions and work in progress

Background: Additive value model

$$V(a_i) = \sum_{k=1}^{n} w_j v_j(a_i) = \sum_{k=1}^{n} v_{ki}$$

$$\sum_{j=1}^{n} k_j = 1$$

$$k_1, \ldots, k_n \geq 0$$



Background: UTA
(Utilités Additives, Jacquet-Lagrèze and Siskos 1981)

- Input: a set of statements concerning preferences

  $(a_i, a_j) \in S \Leftrightarrow$

  the consumer has made a holistic comparison of alternatives a_i and a_j and has stated that $a_i \succ a_j$

- Output: additive model characterization by solving

  Max ε, Subject to: $V(a_i) \geq V(a_j) + \varepsilon$, $\forall (a_i, a_j) \in S$

  (ε^*, the optimal value of this mathematical program, is a strictly positive number iff there exists an additive model compatible able to reproduce the statements S)

Background: UTA
(Utilités Additives, Jacquet-Lagrèze and Siskos 1981)

- Inference of weights, with fixed single-attribute values

$$\max_{(w_1,\ldots,w_n)} \varepsilon$$

Subject to:

$$\sum_{k=1}^{n} w_k v_k(a_i) - \sum_{k=1}^{n} w_k v_k(a_j) - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

$$\sum_{k=1}^{n} w_k = 1, \quad (w_1, \ldots, w_n) \geq 0$$

Background: UTA
(Utilités Additives, Jacquet-Lagrèze and Siskos 1981)

- Inference of single-attribute values, with fixed weights

$$\max_{(v_{11},\dots,v_{1m},\dots,v_{n1},\dots,v_{nm})} \varepsilon$$

Subject to:

$$\sum_{k=1}^{n} w_k v_{ki} - \sum_{k=1}^{n} w_k v_{kj} - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

$$v_{ki} - v_{kj} - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S, k \in \{1, \dots, n\}\colon\ a_i \succ_k a_j$$

$$v_{ki} - v_{kj} = 0, \quad \forall (a_i, a_j) \in S, k \in \{1, \dots, n\}\colon\ a_i \sim_k a_j$$

$$v_{ki} \in [0,1], \quad \forall (a_i, a_j) \in S, k \in \{1, \dots, n\}$$

Background: UTA
(Utilités Additives, Jacquet-Lagrèze and Siskos 1981)

- Inference of single-attribute value and weights

$$\max_{(V_{11},\ldots,V_{1m},\ldots,V_{n1},\ldots,V_{nm})} \varepsilon$$

Subject to:

$$\sum_{k=1}^{n} V_{ki} - \sum_{k=1}^{n} V_{kj} - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

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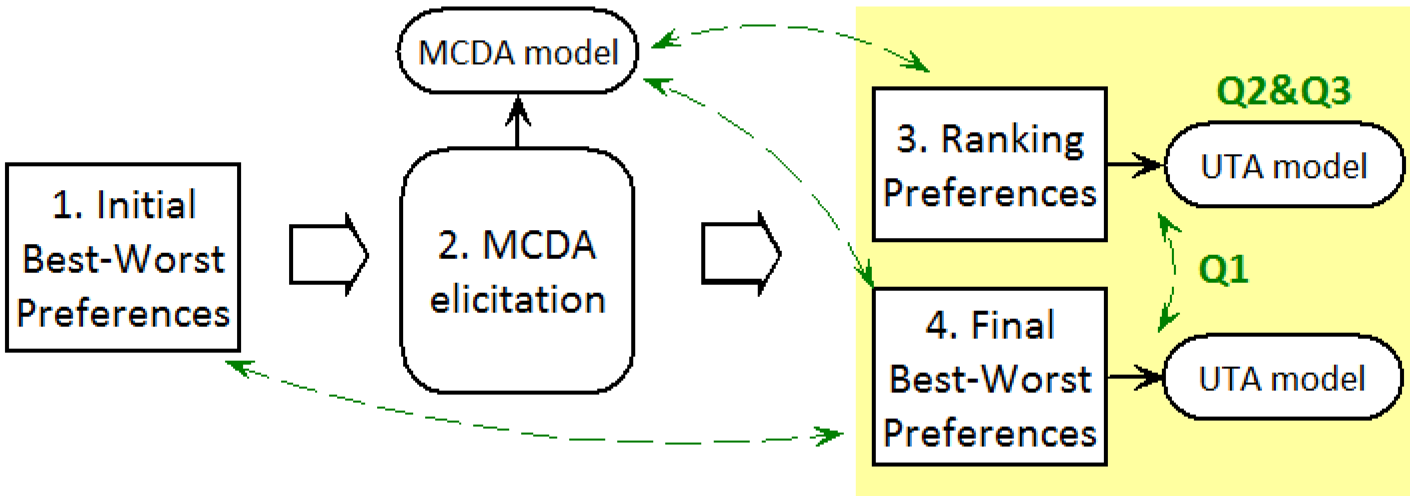
$$V_{ki} \in [0,1], \quad \forall (a_i, a_j) \in S, k \in \{1, \ldots, n\}$$

$$\sum_{k=1}^{n} V_{k[Best(k)]} = 1,$$

$$\left(V_{1[Worst(1)]}, \ldots, V_{n[Worst(n)]}\right) = 0$$

Research questions (outline)

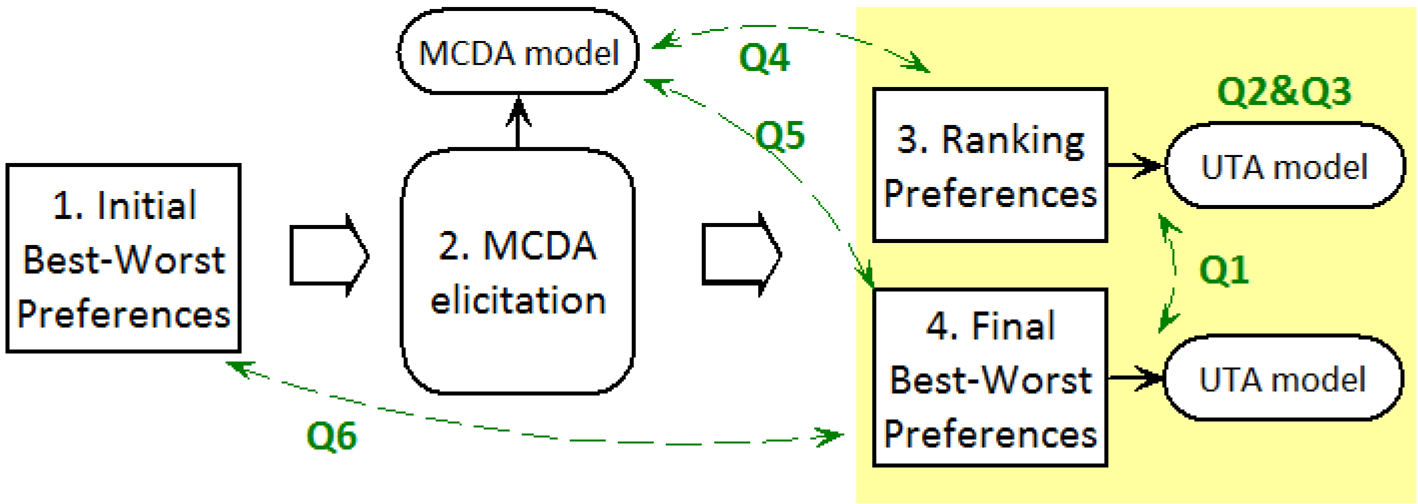


Q1: can single-attribute value functions and weights be inferred using a multi-attribute additive model?

Q2: can weights be inferred using a multi-attribute additive model, after eliciting single-attribute value functions?

Q3: can single-attribute value functions be inferred using a multi-attribute additive model, after eliciting their weights?

Research questions (outline)



Q4: Do the holistic rankings agree with the elicited MCDA model?

Q5: Do the best-worst answers agree with the answers that would correspond to the elicited MCDA model?

Q6: Are the best-worst answers, before and after MCDA analysis, the same?

Preliminary survey
- Data collection

- MCDA conducted by trained analysts (MSc & PhD students)
- Each analyst interacted with several subjects (the potential decision makers), one at a time (convenience sample, n=376)
- Excel template to collect data about the decision maker, his/her vehicle, and preferences (criteria, piece-wise linear value functions, scaling weights, final ranking)
- The Excel template also performs the additive model computations

Preliminary survey
- Mandatory and elicited values

- Predefined set of alternatives

  (Nissan Leaf, Opel Ampera, Renault Fluence 1.5 dci and ZE, Toyota Auris 1.4 D-4D, 1.6 valvematic and 1.8 hybrid, Toyota Prius)

- Free set of criteria (to be elicited and structured)

- Performance table to be built from scratch (data available)

- Value functions to be elicited by direct rating (with instructions)

- Scaling weights to be elicited (with instructions)

Preliminary survey
- Lessons learnt

- A few criteria are used more often: initial cost, running costs, design, performance, comfort, brand),

but…

- Affect can be an overwhelming factor (“I would never buy this ugly car”, “All my life I had Opel cars”, “I would never buy a Toyota”, etc.)
- Direct rating for the value function tends to elicit round ordinal scores (e.g. best=10, 2^{nd} best=9, etc.)
- Scaling weights are confused with intuitive importance

$\rightarrow$ DMs rarely agree with the ranking provided by MCDA

Second survey
- Data collection

- MCDA conducted by trained analysts (MSc & PhD students)
- Each analyst interacted with several subjects, one at a time (convenience sample, n=256)
- Excel template to collect data about the decision maker, his/her vehicle, and preferences
- Anonymous vehicles
- Template invites the elicitation of single-attribute value by the bisection technique and elicitation of scaling weights using the swings technique
- The Excel template also performs the additive model computations

Second survey
- Mandatory and elicited values

- Mandatory and fixed set of 7 general alternatives (same unnamed brand and model assumed)
- Five mandatory criteria (other may be added)

	Price (€)	Range (Km)	Fuel consumption (€/100km)	CO_2 Emissions (g/km)	Privileges
BEV 1	30.000	175	2,4	50	Yes
BEV 2	29.000	175	2,4	50	No
HEV	25.500	2+1200	6,5	110	No
Gasoline	25.700	833	11,2	170	No
Diesel	24.900	1300	6,3	130	No
PHEV 1	28.500	20+1180	4,7	100	Yes
PHEV 2	28.000	20+1180	4,7	100	No

First meeting between analyst and DM

- Stated preferences (best-worst): the DM ranks 3 alternatives in each of 5 questions, e.g.:

	Price	Range	Fuel consumption	CO_2 Emissions	Privileges	Indicate best and worst
Vehicle A	34000€	800 km	2 €/100km	50 g/km	Yes	
Vehicle B	21000€	800 km	15 €/100km	200 g/km	No	
Vehicle C	26000€	500 km	2 €/100km	50 g/km	Yes	

The alternatives are a fractional factorial design for the following levels:

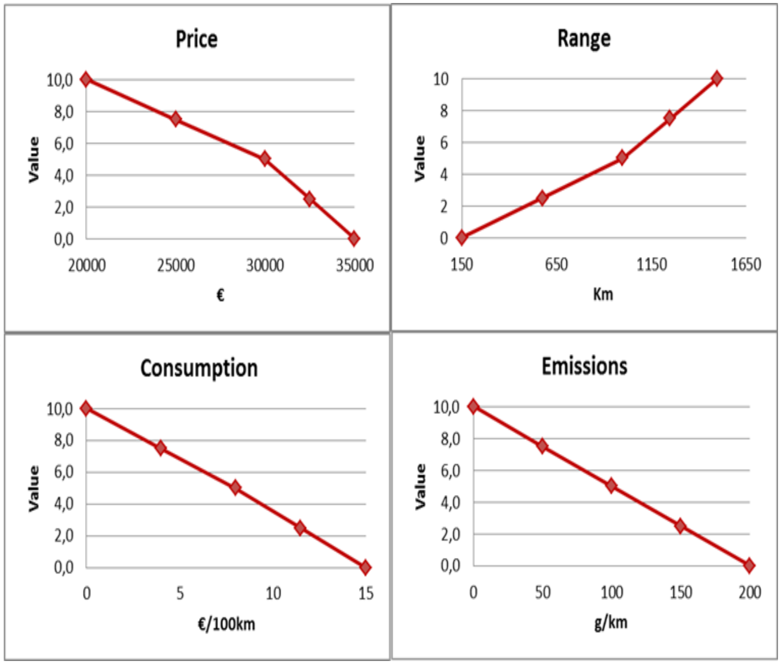
Criteria	*Levels*
Price	21,000€ / 26,000€ / 30,000€ / 34,000€
Range	200 km / 500 km / 800 km / 1300 km
Fuel consumption (per 100 km)	2€ / 7€ / 15€
CO_2 emissions (per km)	50 g / 100 g / 200 g
Privileges	Yes / No

Second meeting between analyst and DM

- Elicitation of value functions (bisection method suggested)

Evaluating value (0-10 scale)

	Price	Range	Consumption	Emissions	Privileges
Level 10 (best)	20000	1500	0	0	10
Level 7,5	25000	1250	4	50	- - -
Level 5	30000	1000	8	100	- - -
Level 2.5	32500	575	11,5	150	- - -
Level 0 (worst)	35000	150	15	200	0



Second meeting between analyst and DM

- Global value as a function of the scaling weights (swing weights recommended but template does not explicitly support this)

Value	Preço	Autonomia	Consumos	Emissões/l	Privilégios	crit6	crit7		*Vglobal*	*Ordem/Rank*
BEV 1	3,750	0,250	8,500	8,684	10				5,2146053	5
BEV 2	4,375	0,250	8,500	8,684	0				4,9208553	6
HEV	6,563	7,517	5,938	6,429	0				6,2532202	3
Gasolina	6,438	5,665	3,000	1,875	0				4,435675	7
Diesel	6,938	8,333	6,063	5,000	0				6,4202083	2
PHEV 1	4,688	7,500	7,063	7,143	10				6,5315179	1
PHEV 2	5,000	7,500	7,063	7,143	0				6,1346429	4

Atribuição de coeficientes de escala / Scaling coefficients:

Preço	Autonomia	Consumos	Emissões/l	Privilégios	crit6	crit7		Soma dos coeficientes
0,33	0,22	0,28	0,12	0,05				1

$$V(a_i) = w_1 v_1(a_i) + w_2 v_2(a_i) + \ldots + w_n v_n(a_i)$$

Second meeting between analyst and DM

- Opportunity to revise (stated ranking):

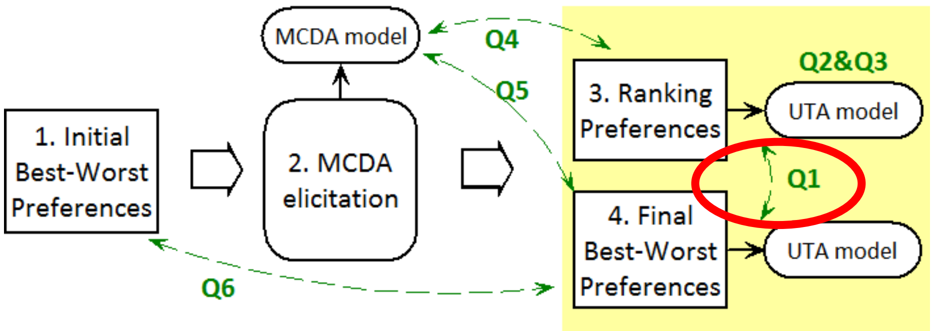
	Ordenação final (do melhor para o pior) / Final ranking (best to worst)
1	Diesel
2	PHEV 1
3	HEV
4	PHEV 2
5	Gasolina
6	BEV 1
7	BEV 2

Alterar/change

- Best-worst stated preference questions are repeated:

	Price	Range	Fuel consumption	CO_2 Emissions	Privileges	Indicate best and worst
Vehicle A	34000€	800 km	2 €/100km	50 g/km	Yes	
Vehicle B	21000€	800 km	15 €/100km	200 g/km	No	
Vehicle C	26000€	500 km	2 €/100km	50 g/km	Yes	

Results



Q1: To which extent can single-attribute value functions and weights be inferred using a multi-attribute additive model?

$$\max_{(V_{11},\dots,V_{1m},\dots,V_{n1},\dots,V_{nm})} \varepsilon$$

Subject to:

$$\textstyle\sum_{k=1}^{n} V_{ki} - \sum_{k=1}^{n} V_{kj} - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

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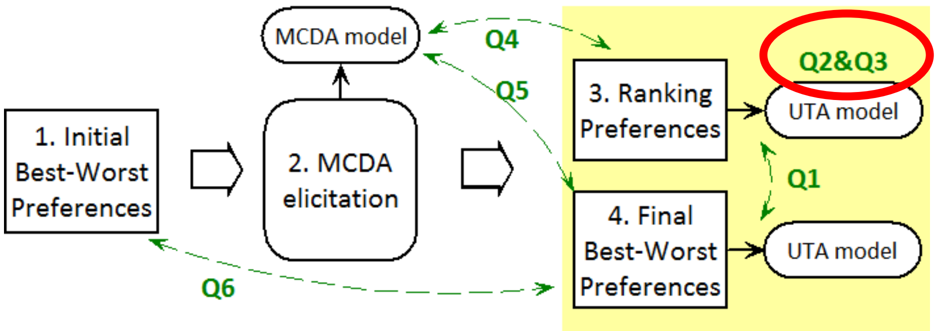
$$\left(V_{1[Worst(1)]}, \dots, V_{n[Worst(n)]}\right) = 0$$

S from stated rankings: 86% successful inferences
S from 5 best-worst questions: 75% successful inferences

Results



Q2: To which extent can weights be inferred using a multi-attribute additive model, after eliciting single-attribute value functions?

$$\max_{(w_1,\dots,w_n)} \varepsilon$$

Subject to:

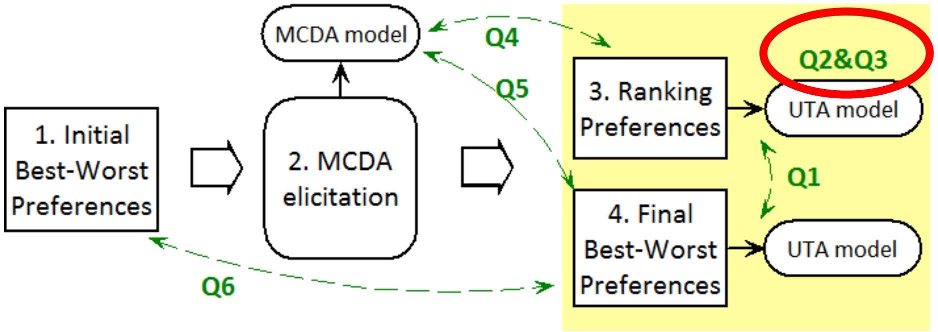
$$\sum_{k=1}^{n} w_k v_k(a_i) - \sum_{k=1}^{n} w_k v_k(a_j) - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

$$\sum_{k=1}^{n} w_k = 1, \qquad (w_1, \dots, w_n) \geq 0$$

S from stated rankings: 77% successful inferences

(vs. 86% if single-attribute values are also not fixed).

Results



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Subject to:

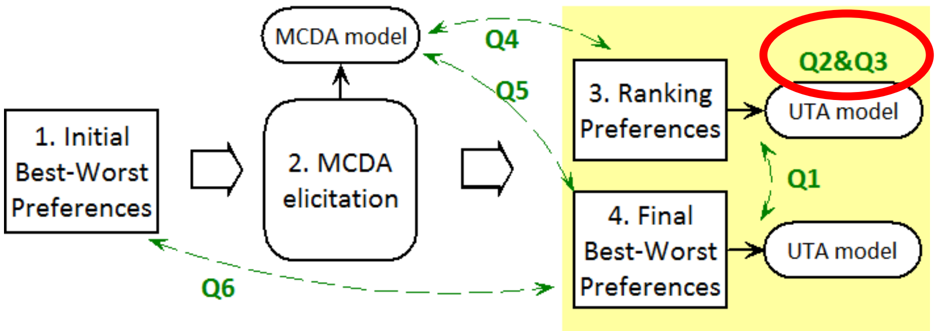
$$\sum_{k=1}^{n} w_k v_k(a_i) - \sum_{k=1}^{n} w_k v_k(a_j) - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

$$\sum_{k=1}^{n} w_k = 1, \qquad (w_1, \dots, w_n) \geq 0$$

If a rank order constraint is also imposed (derived from swing weights)

S from stated rankings: only 11% successful inferences

Results



Q3: To which extent can single-attribute value functions be inferred using a multi-attribute additive model, after eliciting their weights?

$$\max_{(v_{11},\dots,v_{1m},\dots,v_{n1},\dots,v_{nm})} \varepsilon$$

Subject to:

$$\sum_{k=1}^{n} w_k v_{ki} - \sum_{k=1}^{n} w_k v_{kj} - \varepsilon \geq 0, \quad \forall (a_i, a_j) \in S$$

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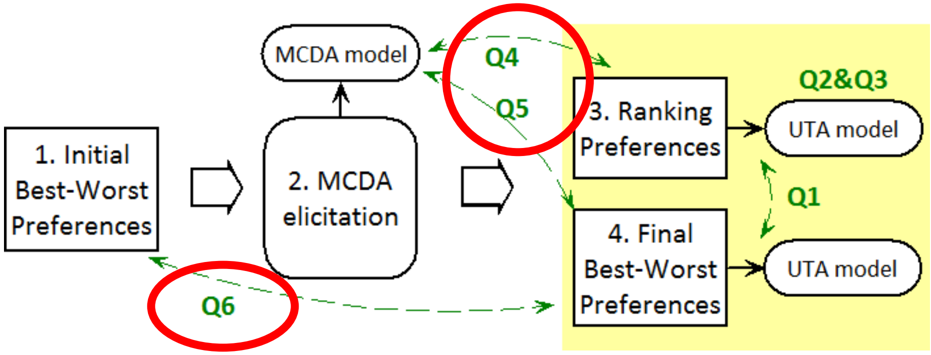
$$v_{ki} \in [0,1], \quad \forall (a_i, a_j) \in S, k \in \{1, \dots, n\}$$

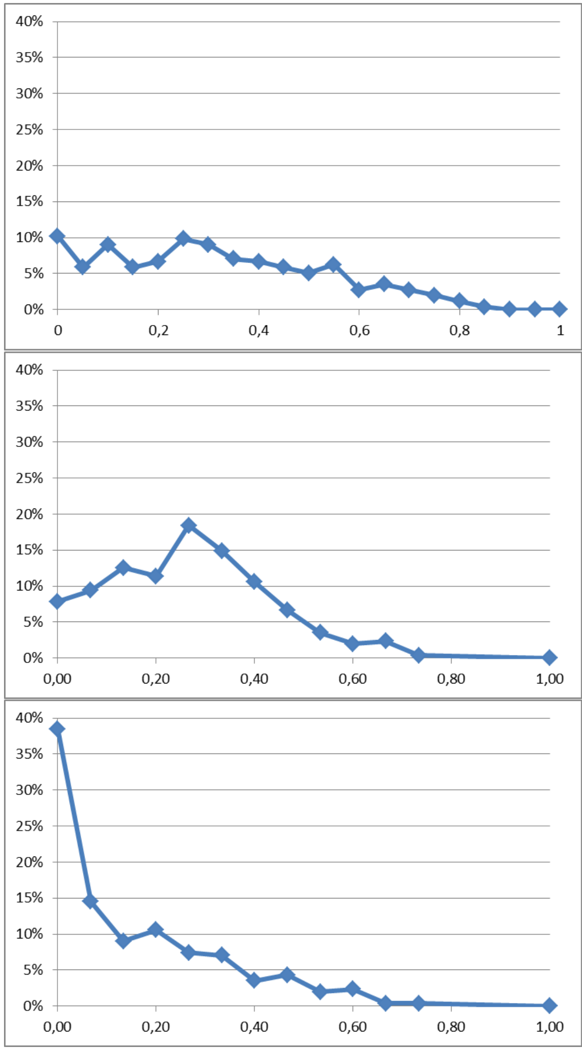
S from stated rankings: 68% successful inferences

(vs. 86% if single-attribute values are also not fixed).

Results



Kendall distances



Q4: Do the holistic rankings agree with the elicited MCDA model?

Q5: Do the best-worst SP answers agree with the answers that would correspond to the elicited MCDA model?

Q6: Are the best-worst SP answers, before and after MCDA analysis, the same?

Conclusions and work in progress

- The additive value function model is in general an adequate approximation for most of the cases
  - Ranking less inconsistent than multiple choices
- MCDA model elicited in a fairly standard way does not match the holistic preferences
  - Time to revise the model is essential
- The MCDA analysis seems to have influenced the (second set of) multiple choices (learning?)

Conclusions and work in progress

- Three possibilities

To infer all parameters

To infer some parameters and elicit other parameters

To elicit all parameters

- Inferring value functions after eliciting weights did not work well

- Need to support weight elicitation: trade-offs method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Thank you!