

UTA–NM: Explaining Stated Preferences with Additive Minimum Non–Monotonic Utility Functions

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Outline

- ▶ Introduction to the UTA method
 - Not well known in Preference Learning community (according to one reviewer)
- ▶ Motivation for the non-monotonic extension
- ▶ Illustrative Example
- ▶ Limitations and further work

Example

- ▶ g_1 looks, g_2 wittiness, g_3 sport attitude
- ▶ Alternatives $a_1 \dots a_5$
- ▶ The DM preferences:

Stated Preference	Name	Look	Wittiness	Sport
1.	John	4	2	1
2.	Ashley	2	1	2
3.	Peter	3	3	3
4.	Martin	2	4	4
5.	Stan	2	4	5

Legend: 1(Low) ... 5 (High)

UTA Method

- UTA Method is a **linear-programming method** for disaggregation-aggregation analysis of preferences.
- Input for the method are implicit preferences in the form of the order of alternatives. E.g. $a_1 > a_2 \sim a_3 > a_4 > a_5$
- Alternatives are described by a set of criteria g_1, \dots, g_n
- The utility from an alternative is given by the sum of utilities from the criteria:

$$u(a) = \sum_{i=1}^n u_i(g_i(a))$$

Name	Look	Wittiness	Sport
John	4	2	1

$$u(\text{John}) = u_{\text{looks}}(4) + u_{\text{wittiness}}(2) + u_{\text{sport}}(1)$$

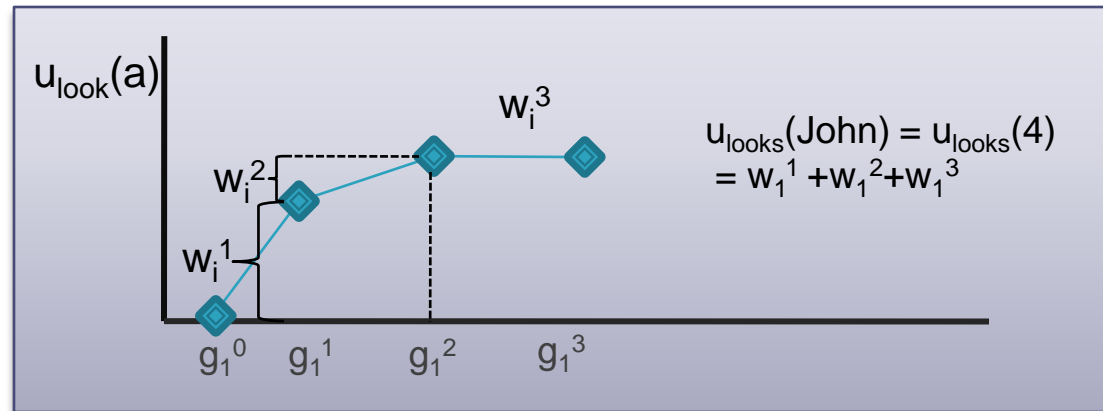
Partial Utility Function

- The value at breakpoints of partial utility function u_i is given by the sum of marginal utilities w_i^j

$$u_i(g_i^0) = 0$$

$$j = 1 \dots \varphi_i$$

$$u_i(g_i^j) = \sum_{t=1}^j w_{it}$$



- Partial utility functions in traditional UTA methods are monotonic
- UTA finds values of marginal utility variables w_i^j that generate the most similar ranking to the reference ranking

Infering marginal utilities from the ranking

- ▶ Introduce two errors σ^+ and σ^- for each alternative
- ▶ Subtract utilities of consecutive alternatives:

$$\Delta(a_k, a_{k+1}) = u[\mathbf{g}(a_k)] - \sigma^+(a_k) + \sigma^-(a_k) - u[\mathbf{g}(a_{k+1})] + \sigma^+(a_{k+1}) - \sigma^-(a_{k+1})$$

$$k = 1, 2, \dots, K - 1 \begin{cases} \Delta(a_k, a_{k+1}) > \delta & \text{if } a_k > a_{k+1} \\ \Delta(a_k, a_{k+1}) = 0 & \text{if } a_k \sim a_{k+1} \\ \sigma^+(a_k), \sigma^-(a_k) \geq 0 \end{cases}$$

- ▶ Objective function minimizes the sum of errors σ^+ and σ^-

$$A1: u(\text{John}) = w_1^1 + w_1^2 + w_1^3 + w_2^1 \quad A2: u(\text{Ashley}) = w_1^1 + w_3^1$$

Since Rank(John) = 1 and Rank(Ashley) = 2 then

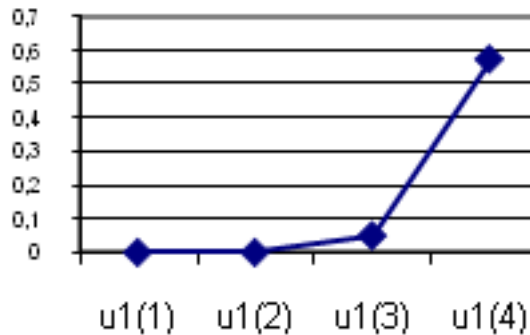
$$d(A1, A2) = w_1^2 + w_1^3 + w_2^1 - w_3^1 - \sigma_1^+ + \sigma_1^- + \sigma_2^+ - \sigma_2^- > \delta, \delta = 0.05$$

Example

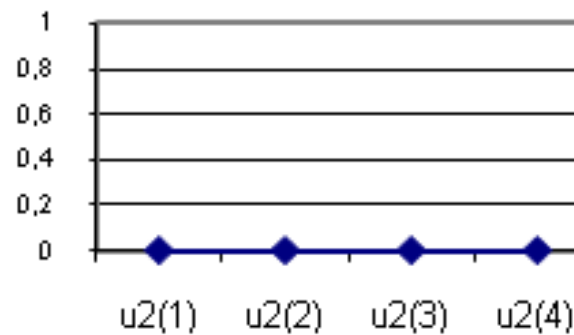
Pref	Name	Look	Wittiness	Sport
1	John	4	2	1
2	Ashley	2	1	2
3	Peter	3	3	3
4	Martin	2	4	4
5	Stan	2	4	5

▶ Explanation for stated order

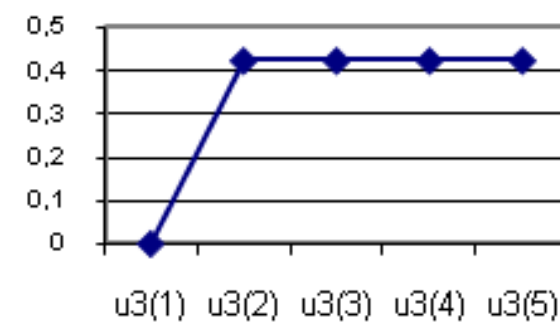
- $a_1 > a_2 > a_3 > a_4 > a_5$



Looks



Wittiness



Attitude to sport

By applying the model back to data we get:

$$a_1 > a_2 = a_3 = a_4 = a_5$$

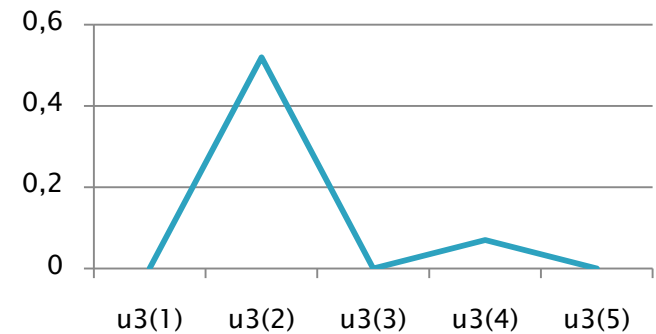
The discovered solution does not fully comply with the stated order of the alternatives

Motivation for non-monotonic UTA

- ▶ In the example, a fully fitting model was not found because the preferences of the DM were actually non-monotonic in criterion „g3: Sport“
- ▶ UTA assumes monotonic preferences
- ▶ The only non monotonic UTA algorithm (Despotis, Zopounidis 93) has following limitations
 - The exact utility function shape need to be known beforehand
 - There is maximum one change of shape per utility function
 - Proposed fully non-monotonic version: UTA-NM

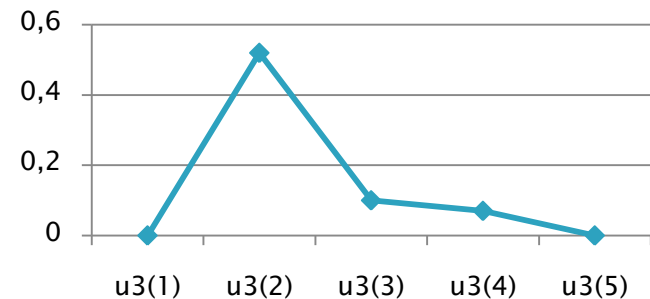
UTA – NM

- ▶ Inspired by UTA
- ▶ Relaxes the monotonicity assumption (by allowing negative marginal utility)
- ▶ Problem: solutions have many changes of shape in partial utility functions
 - ▶ overfitting
 - ▶ not interpretable



UTA – NM

- ▶ Inspired by UTA
- ▶ Relaxes the monotonicity assumption (by allowing negative marginal utility)
- ▶ Problem: solutions have many changes of shape in partial utility functions
 - ▶ overfitting
 - ▶ not interpretable
- ▶ UTA – NM **simultaneously** minimizes the **sum of errors** σ^+ and σ^- and the complexity of the model expressed by the **number of changes** in shape of partial utility functions.
- ▶ Challenge: **Keep the problem linear**



First approach: non-linear model, non-linear methods

- ▶ It is simple to count the number of changes in the shape if we can use nonlinear functions such as *if* or *abs*.
- ▶ The work on linearized UTA-NM was preceded by experiments with non-linear methods Branch&Bound/GRG Solver
- ▶ Interval Global Solver – found optimal solution in (4h)
- ▶ Genetic algorithms
- ▶ These experiments were not successful. Best result Branch&Bound/GRG Solver initialized with UTA Star

LP program outline

$$[\min] z = \sum_{a \in A_R} \sigma^+(a) - \sigma^-(a) + E$$

s.t.

$$k = 1, 2, \dots, K - 1 \begin{cases} \Delta(a_k, a_{k+1}) > \delta & \text{if } a_k > a_{k+1} \\ \Delta(a_k, a_{k+1}) = 0 & \text{if } a_k \sim a_{k+1} \\ \sigma^+(a_k), \sigma^-(a_k) \geq 0 \end{cases}$$

$$\forall i: \min(u_i(g_i^0), u_i(g_i^1), \dots, u_i(g_i^j), \dots, u_i(g_i^{y_i})) = 0$$

$$\sum_{i=1}^n \max(u_i(g_i^0), u_i(g_i^1), \dots, u_i(g_i^j), \dots, u_i(g_i^{y_i})) = 1$$

Utility calculation

$$g_i: A \rightarrow [g_i^*, g_i^*], g_i(a)$$

$$u(a) = \sum_{i=1}^n u_i(g_i(a)).$$

$$[g_i^0, g_i^1], \dots, [g_i^{\gamma_i-1}, g_i^{\gamma_i}], g_i^* = g_i^{\gamma_i}$$

$$w_i^k = u_i(g_i^k) - u_i(g_i^{k-1})$$

$$u_i(g_i^j) = \sum_{k=0}^j w_i^k \quad w_i^j, j = 0, \dots, \gamma_i$$

$$u'(a) = \sum_{i=1}^n u_i(g_i(a)) + \sigma^+(a) - \sigma^-(a)$$

Normalization

▶ UTA

$$u_i(g_i^0) = u_i(g_i^*) = w_i^0 = 0,$$

$$\sum_{i=1}^n u_i(g_i^{\gamma_i}) = \sum_{i=1}^n u_i(g_i^*) = 1$$

▶ UTA NM

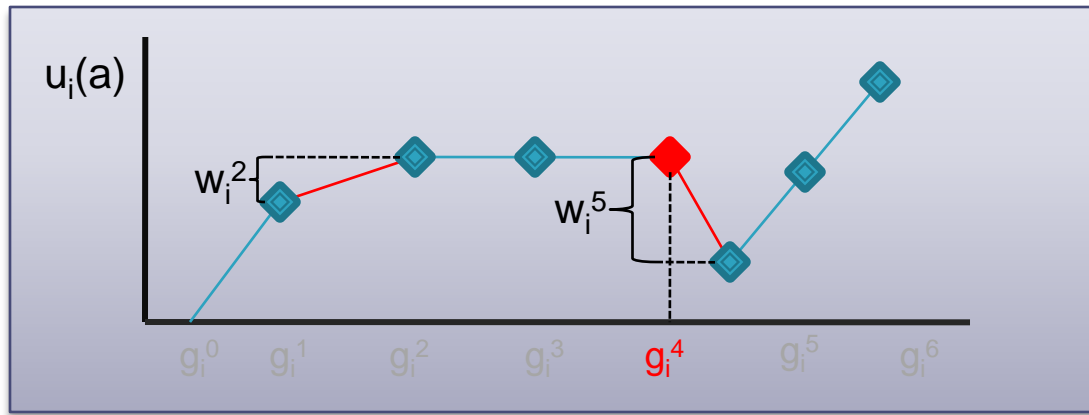
$$\min(u_i(g_i^0), u_i(g_i^1), \dots, u_i(g_i^j), \dots, u_i(g_i^{\gamma_i})) = 0$$

$$\sum_{i=1}^n \max(u_i(g_i^0), u_i(g_i^1), \dots, u_i(g_i^j), \dots, u_i(g_i^{\gamma_i})) = 1$$

More details in the paper

Penalization

- ▶ The value of the objective function is increased for each point in which the partial utility function u_i changes its shape
- ▶ The change of shape is detected from signs of marginal utilities w_i^l and w_i^{j+1} and is saved to binary variable e_i^j
 - w_i^l is nearest previous non-zero marginal utility



- ▶ Penalization element:

$$E = \sum_{i=1}^n \gamma_i^{-1} \sum_{j=1}^m \mu_i^j \delta e_i^j$$

sign (w_i^l)	sign (w_i^{l+1})	e_{ij}
-1	-1	0
-1	0	0
-1	+1	1
0	-1	0
0	0	0
0	+1	0
1	-1	1
+1	0	0
+1	+1	0

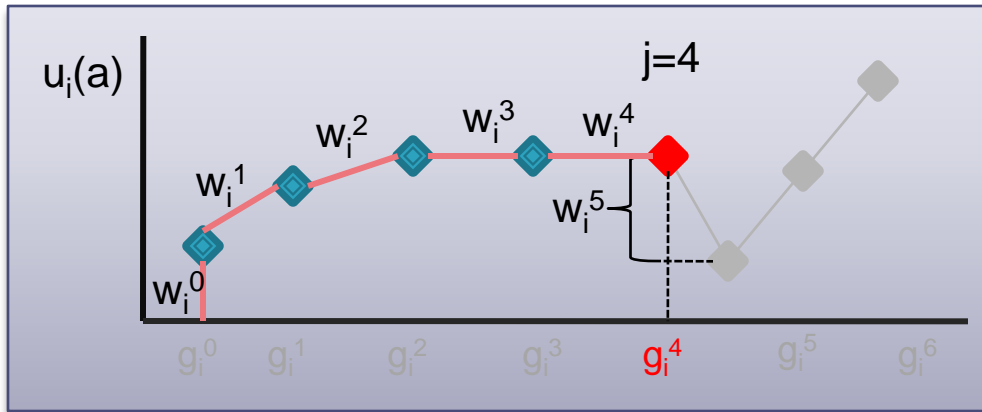
Locating the nearest previous nonzero w_i^j

For g_i^4 ($j=4$) we search the nearest previous **nonzero** marginal utility w_i^j .

$$q = j, j-1, \dots, 0 \left\{ \begin{array}{l} \sum_{r=q}^j p_i^r + \sum_{r=q}^j n_i^r - \sum_{r=q}^j r k_i^j \geq 0 \\ p_i^q + n_i^q - \sum_{r=q}^j r k_i^j \leq 0 \\ \sum_{r=0}^j r k_i^j \leq 1 \end{array} \right.$$

sign(w_i)	p_i^r	y_i^r
+	1	0
-	0	1
0	0	0

Sign of marginal utility variable is expressed by the binary variables p_i^r, y_i^r .



q	4	3	2	1	0
p_i^q	0	0	1	1	1
y_i^q	0	0	0	0	0
k_i^q	0	0	1	0	0
$\sum_{r=q}^{j=4} r k_i^j$	0	0	1	1	1

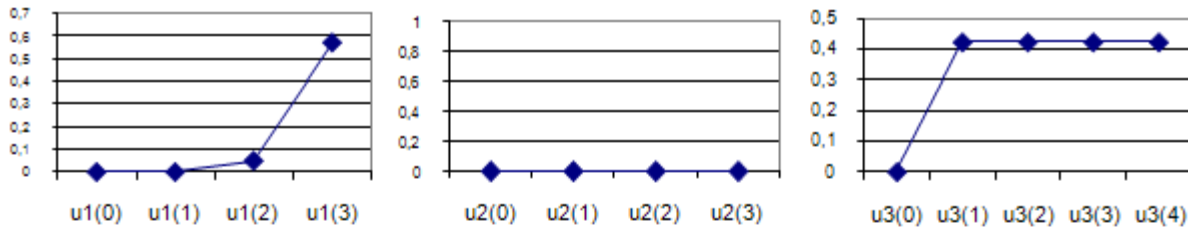
Variable $r k_i^q$ is set to 1 only iff w_i^q is the nearest previous nonzero utility to g_i^j

Example

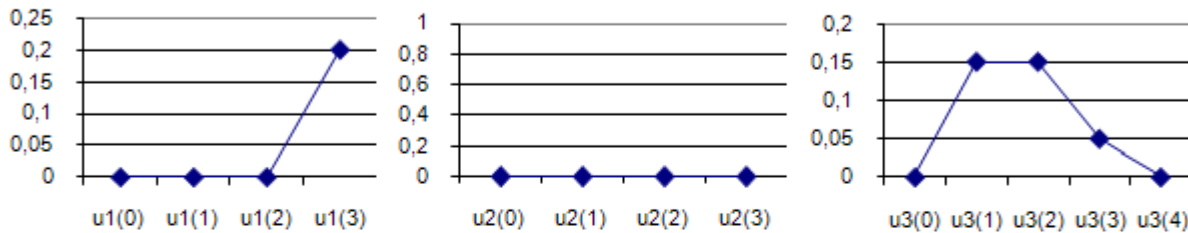
- ▶ Partner selection
- ▶ Explicit preferences :
 - the DM prefers middle value of sport endorsement
- ▶ Software used:
 - Frontline Premium Solver (commercial solver)
 - LP Solve (Open source solver)
 - Visual UTA 1.0 (Academic UTA Star implementation)

Information supplied

Higher values are better
In all criteria

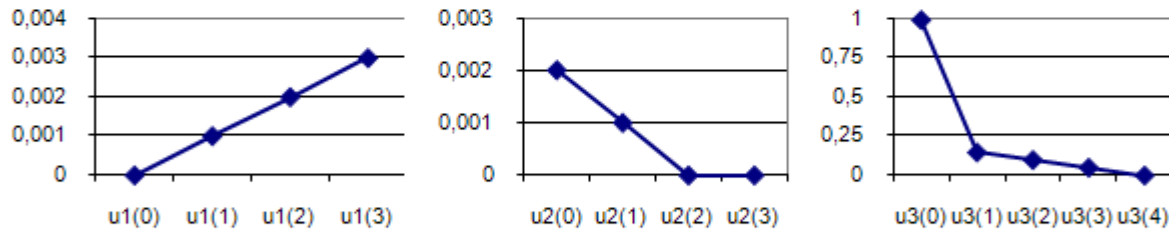


Utility functions found by **UTA Star**



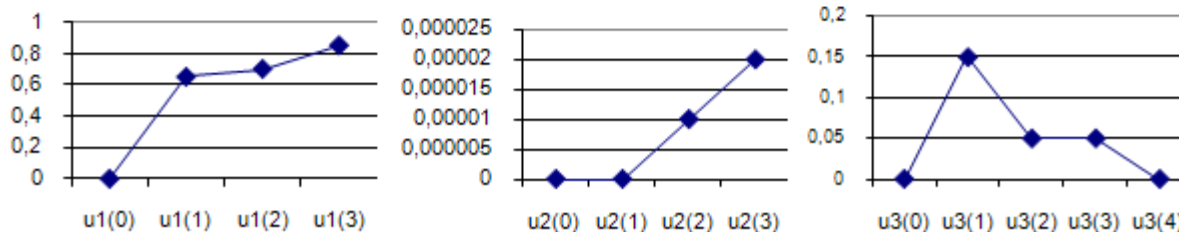
Higher values are better
in u_1 and u_2 , maximum of
 u_3 is in $u_3(3)$

Utility functions found by **Despotis Method**



None

Utility functions found by **UTA-NM**



The worst value
(nonexclusive) is at the
first breakpoint

Utility functions found by **UTA-NM with $w_i^0 = 0$**

Experimental results

- Model found with UTA–NM was the only one to fully match the stated order (Pearson coefficient equal to 1)
- The deviation from the explicitly expressed preferences is also small
- Performance-wise, UTA–NM was slowest with 40/20 seconds (LPSolve on T1 / RiskSolver on T2) compared to less than 1 sec for other methods.

Method	Final rank	Error sum	Pearson Coefficient	Local Extremes	Explicit preferences
DM	a1>a2>a3>a4>a5	NA	NA	NA	NA
UTA Star	a1>a2=a3=a4=a5	0,15	0,73	0	no
Despotis	a1>a2=a3=a4>a5	0,1	0,96	1	yes/NA
NM T1	a1>a2>a3>a4>a5	0	1	0	No
NM T2	a1>a2>a3>a4>a5	0	1	1	Partially

Conclusion

- ▶ UTA Star was generalized to work with non-monotonic preferences
- ▶ If there is a monotonic solution fully compliant with stated preferences exists, UTA-NM outputs it
- ▶ UTA-NM has means to prevent overfitting
- ▶ Expert can input prior knowledge about the shape of the utility functions, these are used to weight contribution of changes in shape to the objective f .
- ▶ Resulting problem is linear and convex and hence processable with standard LP solvers

- ▶ Further work needs to focus on performance optimisations

Direction of further research

- The method is general but suffers from severe performance issues
 - Even for very small toy problems tens of binary variables
 - Real-world problems computationally infeasible
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- ▶ Linearization with less binary variables
 - ▶ Simplification (1 change of shape within criterion)
 - ▶ Run as many Despotis UTA as there are positions in which the change of shape may occur