

# “Hit and Run” for the efficient generation of weights

**Gert van Valkenhoef**, Tommi Tervonen,  
Nalan Baştürk, Douwe Postmus

EURO 2012, Vilnius, Lithuania, July 2012



umcg



university of  
groningen



# Background

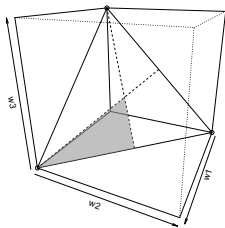
- Many MCDA models consist of per-criterion attractiveness measurement followed by their additive aggregation to an overall measurement of performance, value, or utility.

$$f(f_1(x_1^i), \dots, f_n(x_n^i)) = \sum_{j=1}^n w_j f_j(x_j^i)$$

$$g(g_1(x_1^i, x_1^k), \dots, g_n(x_n^i, x_n^k)) = \sum_{j=1}^n w_j g_j(x_j^i, x_j^k)$$

# Simulation-based MCDA

- Weights sum to unity and are non-negative:  
 $(n - 1)$ -simplex  $W_n$
- In simulation-based MCDA the weights can be imprecise
- Expressed as linear constraints
- Uniform distribution within the feasible weight space  $W' \subset W_n$



$$w_1 > w_2 > w_3$$

# Weight constraints

- Ordinal: poor information, but compatible with all models
- Upper- and lower bounds ( $0.4 \leq w_1 \leq 0.6$ ): correspond to meaning of weights in outranking methods
- Intervals for weight ratios ( $0.6 \leq (w_2/w_4) \leq 0.7$ ): correspond to meaning of weights in MAVT/MAUT
  
- Efficient algorithms exist only for unrestricted, ordinal and lower-bounded weight generation (see Tervonen & Lahdelma, EJOR, 2007)
- But not for arbitrary (combinations of) constraints!

# Hit-and-Run

Purpose:

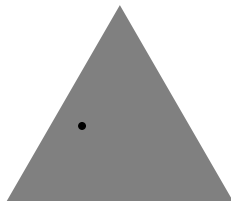
- Uniformly sample over convex volume  $X$

Need:

- Starting point  $x_0$  within  $X$
- Intersect line with boundary of  $X$

Procedure:

- Sample random direction, obtain a line segment through  $x_i$
- Uniformly sample a point within the segment  $\rightarrow x_{i+1}$



# Hit-and-Run

Purpose:

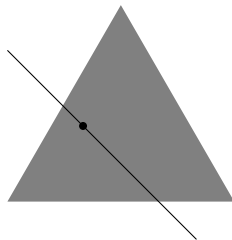
- Uniformly sample over convex volume  $X$

Need:

- Starting point  $x_0$  within  $X$
- Intersect line with boundary of  $X$

Procedure:

- Sample random direction, obtain a line segment through  $x_i$
- Uniformly sample a point within the segment  $\rightarrow x_{i+1}$



# Hit-and-Run

Purpose:

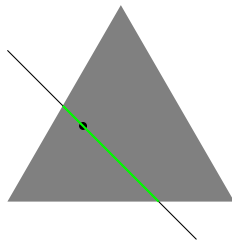
- Uniformly sample over convex volume  $X$

Need:

- Starting point  $x_0$  within  $X$
- Intersect line with boundary of  $X$

Procedure:

- Sample random direction, obtain a line segment through  $x_i$
- Uniformly sample a point within the segment  $\rightarrow x_{i+1}$



# Hit-and-Run

Purpose:

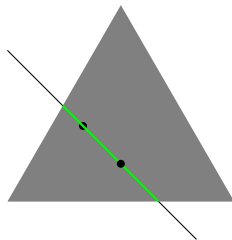
- Uniformly sample over convex volume  $X$

Need:

- Starting point  $x_0$  within  $X$
- Intersect line with boundary of  $X$

Procedure:

- Sample random direction, obtain a line segment through  $x_i$
- Uniformly sample a point within the segment  $\rightarrow x_{i+1}$





# Hit-and-Run

Purpose:

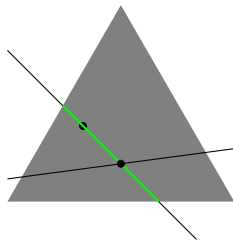
- Uniformly sample over convex volume  $X$

Need:

- Starting point  $x_0$  within  $X$
- Intersect line with boundary of  $X$

Procedure:

- Sample random direction, obtain a line segment through  $x_i$
- Uniformly sample a point within the segment  $\rightarrow x_{i+1}$

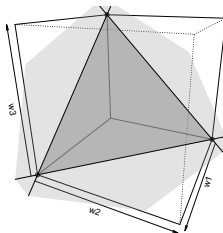


# Problems and our solution

- 1  $Vol(W') = 0 \Rightarrow$  probability of hitting  $W'$  also 0
  - Transform the weight space
- 2 MCMC samplers might get “stuck” in some areas, causing slower convergence to uniformity
  - Assess required thinning

# Transformation: idea

- The  $(n - 1)$ -simplex  $W_n$  is coincident with the hyperplane  $W_n^* = \left\{ w \in R^n : \sum_{j=1}^n w_j = 1 \right\}$
- We transform the simplex for sampling in  $n - 1$  dimensions



# Transformation

- The centroid of  $W_n$  is at  $(1/n, \dots, 1/n)^T$ , so if we translate the plane  $W_n^*$  by  $(-1/n, \dots, -1/n)^T$ , it forms an  $n - 1$  dimensional subspace  $V \subset R^n$ .
- We obtain an orthonormal basis  $\{v^1, \dots, v^{n-1}\}$  of  $V$  by first defining a basis of  $V$  and then performing orthogonalization and normalization.

# Transformation

- To map an arbitrary point  $x \in R^{n-1}$  to the target space  $w \in W_n^*$ , apply an affine transformation: a change of basis followed by a translation.
- Use homogeneous coordinate representation  $x = (x_1, x_2, \dots, x_{n-1}, 1)^T$ :

$$w = TBx$$

where

- $B$ : change-of-basis matrix
- $T$ : translation matrix
- Both transformations are isometric (preserve uniformity)

# Constraints

- Linear constraints defining  $W' \subseteq W_n$  need to be defined in  $n - 1$  dimensions
- Constraint set defining  $W'$  is:

$$Cw \leq b ; \sum_{i=1}^n w_i = 1$$

- Since we sample directly from the plane  $W_n^*$ , the equality constraint can be dropped.
- Then the constraints can be expressed in  $n - 1$  dimensions as:

$$Ax \leq b ; A = CTB$$

since  $Ax = C(TBx) = Cw$ .

# Transformation: visualized

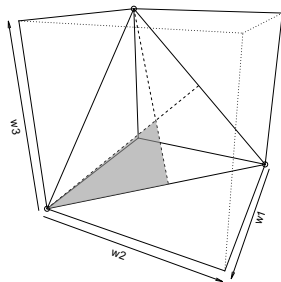


Figure: Constraints in 3D:  $Cw \leq b$

# Transformation: visualized

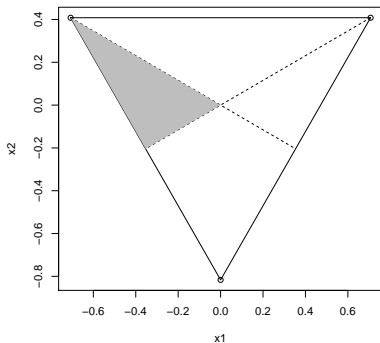


Figure: Constraints in 2D:  $Ax = CTBx \leq b$



# Transformation: visualized

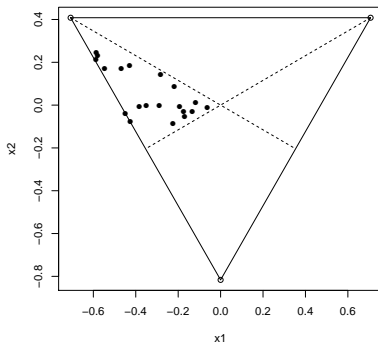


Figure: Hit-and-Run obtains samples  $x$  in 2D

# Transformation: visualized

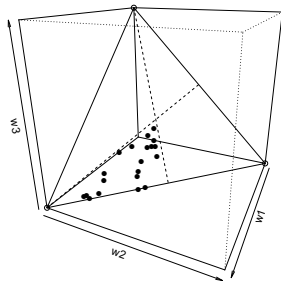


Figure: Transform samples to 3D:  $w = TBx$

# Line intersection, starting point

- The polytope is defined as  $Ax \leq b$ , so line intersection is some simple linear algebra
- A starting point can be found with convex combination of points of the polytope (obtainable with LPs or Fukuda-Avis vertex enumeration)

# Thinning: computational tests

- HAR mixes with  $O^*(n^3)$  iterations,  $n = 2 \Rightarrow$  thinning = 1

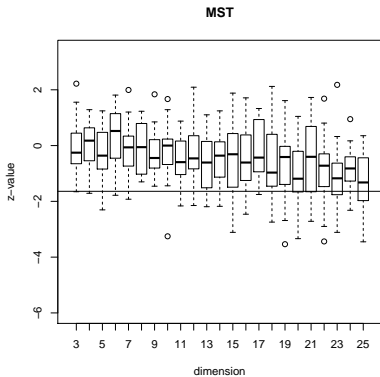
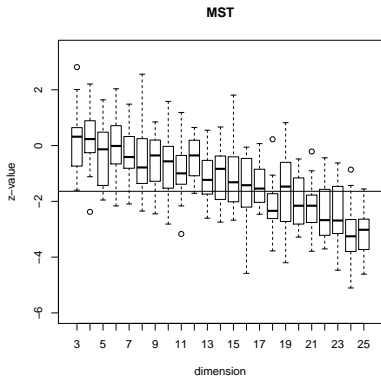
$$f_a(n) = a(n - 1)^3 + (1 - a)$$

- How much thinning is required?
- How to assess sample uniformity?
  - Minimum Spanning Tree (MST) test (Friedman-Rafsky two-sample test)
  - Coefficient of Variation (COV) of the nearest neighbour-distances
  - Standardized Component-wise Error (SCE)
  - Autocorrelation at lag 25 (decided after visual inspection on exploratory tests)

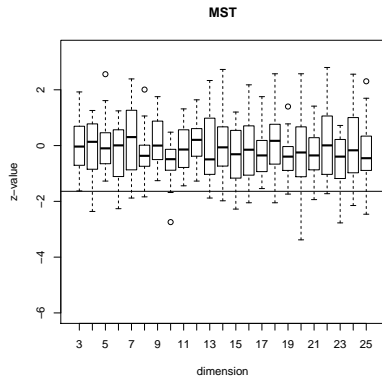
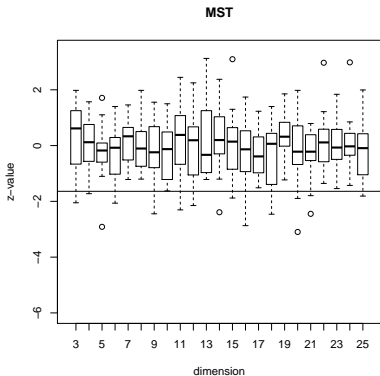
# Test setup

- Use ordinal weight information ( $w_1 > w_2 \cdots > w_n$ )
- Sample  $Y = 10k$  weight vectors with HAR
- Sample  $X = 10k$  weight vectors with an efficient procedure
- $n \in \{3, \dots, 25\}$
- $f_a(n)$ ,  $a \in \{0.125, 0.25, 0.5, 0.75, 1.0\}$
- For each test instance, 20 runs

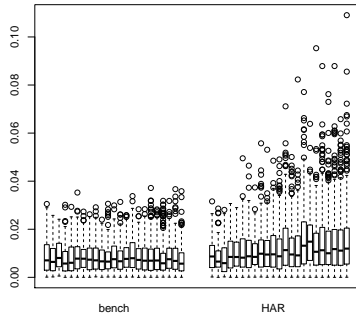
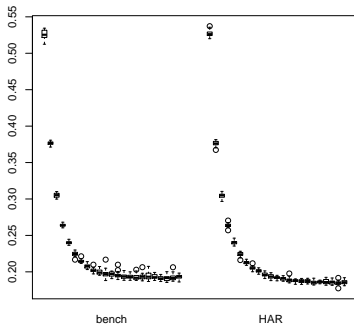
# MST metric, HAR, $a = 0.25$ and $a = 0.5$



# MST metric, benchmark and HAR with $a = 1.0$



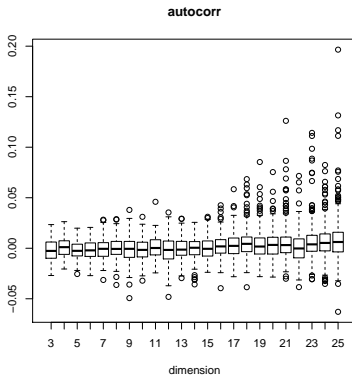
# COV and SCE metrics, benchmark and HAR with $f_{1.0}$



- COV reaches acceptable levels too early (before MST), and depends on dimension  $\Rightarrow$  not suitable
- SCE more suitable, but requires enumerating the vertices

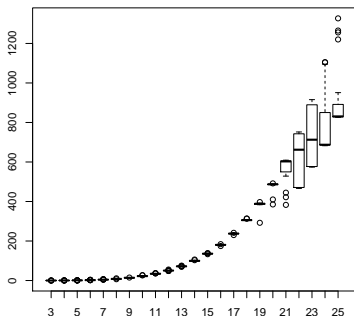


# Autocorrelation (lag 25) metric, HAR with $f_{1.0}$



- Quite suitable, fast to compute

# Results: execution times (s) with thinning $f_{1.0}$



- Up to  $n = 15$  within  $\approx 3$  minutes ( $O^*(n^3)$ )
- Rejection sampling takes hours for  $n > 10$  (exponential)

# Conclusions

- Transformation: enables efficient uniform sampling of linearly constrained weight space
- Evaluated four convergence metrics
  - 'Gold standard' MST only usable when HAR not needed
  - Autocorrelation at lag 25 is a good proxy
- The technique is sufficiently fast to be applied in interactive decision analysis with problems of modest sizes
- Sampling code available as the R package 'hitandrun'

Thank you!

Questions?



umcg



university of  
groningen

