# Approximation of coherent lower probabilities by 2-monotone measures

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# 1. Personal Background: Andrey Bronevich

Associate Professor at the Technological Institute, Taganrog, Russia

- imprecise probabilities
- non-additive measure theory
- possibility theory
- multi-criteria decision-making under risk and uncertainty
- pattern recognition and image processing.



# **Personal Background: Thomas Augustin**

- Department of Statistics, University of Munich, Germany
- Kurt Weichselberger
- Marco Cattaneo, Gero Walter; Andrea Wiencierz, Carolin Strobl; Robert Hable, Martin Gümbel
- IP in statistics and decision making; foundations of statistics (poster on handling unobserved data heterogeneity by credal maximum likelihood)
- Statistics in the social sciences; handling of deficient data (measurement error, misclassification) --?--> partial identification (poster)
- Nonparametric predictive inference
- Classification trees

2. Background of the paper

# Why can approximation of coherent lower probabilities by 2-monotone measures be reasonable?

I do not "...know any 'rationality' argument for two-monotonicity, beyond its computational convenience."

Walley (1981, p. 51)

# On the computational convenience of two-monotonicity:

"Lower and upper distribution functions fit":

For any underlying order of the elements of the sample space corresponding lower and upper distribution function are attained *simultaneously* by a certain element of the structure (core, creedal set)

- Closed form expressions for natural extension/expectation: Choquet integral
- Closed from expressions for conditional probabilities (c.p.)
- Closeness of GBR (intuitive concept of c.p.) and Dempster's rule of conditioning (maximum likelihood updating)
- Statistical hypotheses testing (Huber-Strassen theory)

# **Statistical hypotheses testing (Huber-Strassen theory)**

- Which distribution governs the data?
- (Level-alpha-)Maximin testing to decide between two hypotheses
- Two-monotonicity of the underlying hypotheses is sufficient to guaranty the existence of a globally least favorable pair
  - à big sample sizes are no computational problem
  - à just use the product measure of the globally least favorable pair of sample size 1
  - à k-dimensional problem, instead of a  $k^n$ -dimensional problem

# 3. Find optimal outer approximation by two-monotone measure!

Not unique

uniformly

criterion-based

linear imprecision index or metric

set of Pareto optimal solutions

improve given approximation

optimal solution via linear programming

\*

• characterization

• approximate calculation via linear programming \*

measures

\* methods also applicable for approximation by completely-monotone

# **Notation and Definitions**

X is a measurable space with a  $\sigma$ -algebra A.

D1.  $\mu$ : A  $\rightarrow$  [0,1] is a monotone measure if

1)  $\mu(\emptyset) = 0, \ \mu(X) = 1;$ 

2)  $\mu(A) \le \mu(B)$  if  $A \subseteq B$  for  $A, B \in A$ .

# Notation.

 $M_{mon}$  is the set of all monotone measures on A.

$$\mu_1 \leq \mu_2$$
 for  $\mu_1, \mu_2 \in M_{mon}$  if  $\mu_1(A) \leq \mu_2(A)$  for all  $A \in A$ .

 $M_{pr}$  is the set of all probability measures on A.

 $M_{low} = \left\{ \mu \in M_{mon} \mid \exists P \in M_{pr} : \mu \leq P \right\} \text{ is the set of all$ *lower probabilities* $on A.}$ 

 $M_{coh} = \left\{ \mu \in M_{mon} \mid \forall B \in A, \exists P \in M_{pr} : \mu \le P, \mu(B) = P(B) \right\} \text{ is the set of all } coherent lower probabilities on A.$ 

 $\mu \in M_{mon}$  is 2-monotone if  $\mu(A) + \mu(B) \le \mu(A \cup B) + \mu(A \cap B)$  for all  $A, B \in A$ .

 $M_{2-mon}$  is the set of all 2-monotone measures on A.

## Description of Pareto optimal 2-monotone measures (finite case)

*X* is a finite set;  $A = 2^{X}$ . D2.  $v \in M_{mon}$  is a *Pareto optimal approximation* of  $\mu \in M_{low}$  if a)  $v \leq \mu$ ; b)  $v' \in M_{mon}$ ,  $v \leq v' \leq \mu \Rightarrow v' = v$ .  $v \leq v' \leq \mu \ v' \in M_{mon}$  implies that v' = v. For any  $\mu \in M_{low}$ , we denote  $M_{2-mon \leq \mu} = \{v \in M_{2-mon} | v \leq \mu\}$ . **Notation.**  $M_{2-mon \leq \mu} = \{v \in M_{2-mon} | v \leq \mu\}$  for  $\mu \in M_{mon}$ .

**Lemma 1.** Any Pareto optimal 2-monotone measure for a  $\mu \in M_{coh}$  can be represented as a convex linear combination of Pareto optimal extreme points of  $M_{2-mon \le \mu}$ .

**D3.**  $\Lambda \subseteq A$  is a *lattice* if  $A, B \in \Lambda \Rightarrow A \cap B, A \cup B \in \Lambda$ . **D4.**  $\mu \in M_{2-mon}$  is *additive* on L if  $\mu(A) + \mu(B) = \mu(A \cup B) + \mu(A \cap B)$  for any  $A, B \in \Lambda$ .

*core*(
$$\mu$$
) = { $P \in M_{pr} | P \ge \mu$ }, where  $\mu \in M_{low}$ .  
S <sub>$\mu$</sub>  is the covering of A:  $\Lambda \in S_{\mu}$  if  $\Lambda$  is a maximal lattice, on which  $\mu \in M_{2-mon}$  is additive.

**Proposition 1.** There is the one-to-one correspondence between maximal lattices in  $S_{\mu}$  and extreme points of  $core(\mu)$  for every extreme point P defined by  $\Lambda = \{A \in A \mid P(A) = \mu(A)\}.$ 

Proposition 1 is the generalization of the following result:

Let  $X = \{x_1, x_2, ..., x_n\}$  and  $\mu \in M_{2-mon}$ , then every extreme point  $P_{\gamma}$  of  $core(\mu)$  correspond to a maximal chain  $\gamma = \{B_0, B_1, ..., B_n\}$  of  $A = 2^X$ , where  $\gamma = \{B_0, B_1, ..., B_n\}$ ,  $\emptyset = B_0 \subset B_1 \subset ... \subset B_n = X$ , and  $|B_k \setminus B_{k-1}| = 1$ , k = 1, ..., n, by the rule  $P_{\gamma}(B_k) = \mu(B_k)$ , k = 1, ..., n.

**Proposition 2.** Let  $\mu \in M_{coh}, \nu \in M_{2-mon \le \mu}, S_{\nu=0} = \{A \in A | \nu(A) = 0\},\$  $S_{\nu=\mu} = \{A \in A | \nu(A) = \mu(A)\}$ . Then  $\nu$  is an extreme point of  $M_{2-mon \le \mu}$  iff its values are defined by the sets  $S_{\nu=\mu}, S_{\nu=0}, S_{\nu}$  uniquely.

#### Necessary and sufficient condition of 2-monotonicity

$$\mu: 2^{X} \to [0,1] \text{ is in } M_{2-mon} \text{ iff}$$

$$1) \ \mu(\emptyset) = 0, \ \mu(X) = 1;$$

$$2) \ \mu(A) \le \mu(A \cup \{x_i\}) \text{ for all possible } A \in 2^{X} \text{ and } x_i \notin A;$$

$$3) \ \mu(A \cup \{x_i\}) + \mu(A \cup \{x_j\}) \le \mu(A) + \mu(A \cup \{x_i\} \cup \{x_j\}) \text{ for all possible } A \in 2^{X} \text{ and } x_i, x_j \notin A.$$

This result can be reformulated trough elementary lattices:

*Type 1 elementary lattices:*  $\{A, A \cup \{x_i\}\}$ , where  $A \in 2^X$  and  $x_i \notin A$ ,

Type 2 elementary lattices:  $\{A, A \cup \{x_i\}, A \cup \{x_j\}, A \cup \{x_i\} \cup \{x_j\}\}$ , where  $A \in 2^X$ ,  $x_i, x_j \notin A$ . **Proposition 3.**  $\mu: 2^X \to [0,1]$  is in  $M_{2-mon}$  iff 1)  $\mu(\emptyset) = 0, \ \mu(X) = 1;$ 

2)  $\mu$  is monotone on all lattices in  $2^{x}$  of the first type;

3)  $\mu$  is 2-monotone on all lattices in  $2^{x}$  of the second type.

**Proposition 4.** Let  $v \in M_{2-mon \le \mu}$ ,  $L_1$  be the set of all elementary lattices of the first type on which v is constant, and  $L_2$  be the set of all elementary lattices of the second type, on which v is additive. Then v is not Pareto optimal iff there is a non-identical zero, non-negative set function  $\Delta v : 2^X \rightarrow j_{+}$  such that

1)  $\Delta v(A) = 0$  if  $A \in S_{v=\mu}$ ;

2)  $\Delta v$  is monotone on all lattices in L<sub>1</sub>;

3)  $\Delta v$  is 2-monotone on all lattices in L<sub>2</sub>.

# **Algorithms for finding Pareto optimal 2-monotone measures**

# Algorithm I.

**Input data:** coherent lower probability  $\mu$  on  $2^{x}$ .

**First step.** Searching a 2-monotone measure  $v_0$  with  $v_0 \le \mu$ .

- 1) Compute 2-monotone set function g on  $2^{x}$ :
- a)  $g(A) = \mu(A)$  for all  $A \in 2^X$  with  $|A| \le 1$ ;
- b) for sets A with cardinality |A| = k, k = 1, 2, ...:

$$g(A) = \max\left\{\mu(A), \max_{x_i, x_j \in A} g\left(A \setminus \{x_i\}\right) + g\left(A \setminus \{x_j\}\right) - g\left(A \setminus \{x_i, x_j\}\right)\right\}.$$

2)  $v_0 = \varphi \circ g$ , where  $\varphi : [0, g(X)] \rightarrow [0, 1]$  is a convex distortion function such that:

(i)  $\varphi(0) = 0, \ \varphi(g(X)) = 1;$ (ii)  $\varphi(g(A)) \le \mu(A)$  for all  $A \in 2^X$ . Second step. Finding a Pareto optimal 2-monotone measure v with  $v_0 \le v \le \mu$ . Let  $v_k \in M_{2-mon \le \mu}$ . Let exist  $A \in 2^X$  such that  $\Delta_1 = \mu(A) - v_k(A) > 0$ ,  $\Delta_2 = \min_{x_i \in X \setminus A} \left( v_k \left( A \cup \{x_i\} \right) - v_k(A) \right) > 0$ ,  $\Delta_3 = \min_{x_i \in X \setminus A, x_j \in A} \left( v_k \left( A \cup \{x_i\} \right) - v_k(A) - v_k \left( \left( A \setminus \{x_j\} \right) \cup \{x_i\} \right) + v_k \left( A \setminus \{x_j\} \right) \right) > 0$ .

Then

$$v_{k+1}(B) = \begin{cases} v_k(B) + d, & B = A, \\ v_k(B), & otherwise. \end{cases}$$

where  $d = \min\{\Delta_1, \Delta_2, \Delta_3\}.$ 

# **Algorithm II.**

Based on a linear imprecision index. D1.  $f: M_{low} \rightarrow [0,1]$  is a linear imprecision index if 1) f(P) = 0 for any  $P \in M_{pr}$ ; 2)  $f(\eta_{\langle X \rangle}) = 1$ , where  $\eta_{\langle X \rangle}(A) = 1$  if A = X,  $\eta_{\langle X \rangle}(A) = 0$  otherwise; 3)  $f(v_1) \leq f(v_2)$  for any  $v_1, v_2 \in M_{low}$  such that  $v_1 \geq v_2$ ; 4)  $f(av_1 + (1-a)v_2) = af(v_1) + (1-a)f(v_2)$  for arbitrary  $a \in [0,1]$  and  $v_1, v_2 \in M_{low}$ .

A Pareto optimal  $v \in M_{2-mon \le \mu}$ ,  $\mu \in M_{coh}$ , is the solution of the linear programming problem:

find  $v \in M_{2-mon \le \mu}$  such that  $f(v) \to \min$ .

#### **Examples of imprecision indices**

a) the generalized Hartley measure:  $GH(v) = \frac{1}{\ln|X|} \sum_{A \in 2^X} m(A) \ln|A|$ , where *m* is the Möbius transform of  $v \in M_{low}$ ;

b) the imprecision index based on  $L_1$  distance:

 $f_{L_1}(v) = \frac{1}{2^{|X|} - 2} \sum_{A \in 2^X} \left| \overline{v}(A) - v(A) \right|$ 

#### Approximate the set of Pareto-optimal approximations by linear programming

A two-monotone set-function  $\nu(\cdot)$  is <u>not</u> a Pareto-optimal approximation of  $\mu(.)$  iff  $\exists \nu'(\cdot)$  two-monotone,  $\varepsilon > 0$ :

$$L(\cdot) \leq L'(\cdot) \leq \mu(.)$$
 and  $\sum_{A \subseteq \omega} L'(A) - L(A) \geq \varepsilon$ 

Therefore, for arbitrary small  $\varepsilon > 0$ , consider the following optimization problem:

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 $\tilde{\varepsilon} \longrightarrow \min$ 

subject to the constraints

$$\begin{array}{llll} \nu'(A) - \nu(A) & \geq & 0 & \forall A \\ \mu(A) - \nu'(A) & \geq & 0 & \forall A \\ \sum_{A} \nu'(A) - \nu(A) & \geq & \tilde{\varepsilon} \geq \varepsilon \\ \nu(.) \mbox{ two-monotone } & \nu'(.) \mbox{ two-monotone } \end{array}$$

Then the set of optimal solutions has the form  $\begin{pmatrix} L^*(.) \\ L'^*(.) \end{pmatrix}$ , projection on the first part approximates the set of not-Pareto optimal approximations, subtracting it from the set of all 2-monotone measures dominated by  $\mu(\cdot)$  gives an approximation of the set of all Pareto-optimal approximations.

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