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Statistical Models for Partial Orders
based on
Data Depth and Formal Concept Analysis

IPMU 2022

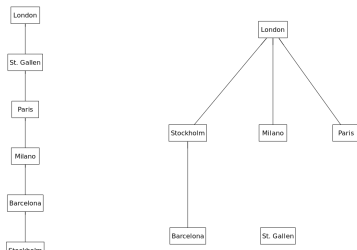
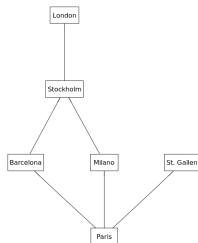
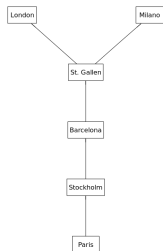
Motivation

In the most approaches

- **incompleteness** of a partial order stems from **missing knowledge/data**, e.g. an unresolved conflict in values or goals (e.g. Stewart 2020).
→ an explicit missing mechanism is assumed and included in the model (e.g. by the distance measure used)

In what follows

- an observed **incomparability** is understood as a **precise observation** and we consider a depth function instead of a distance measure.



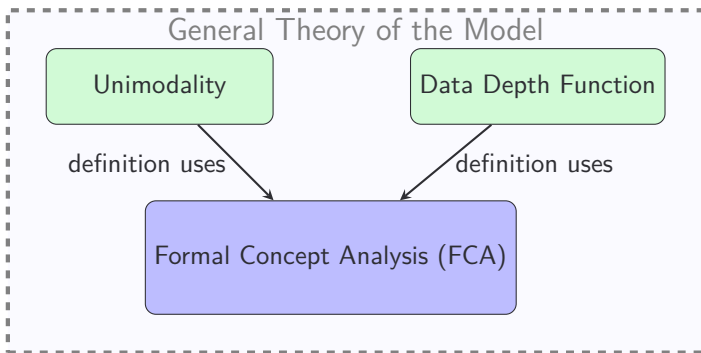
This distinction is to be represented in the construction of the stochastic model via the set of partial order.

Thus, we consider the statistical model

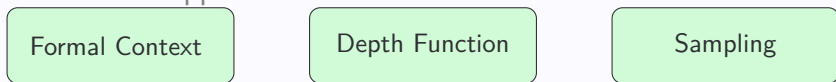
$$P(X = x) = C_\lambda \cdot \Gamma(\lambda \cdot (1 - D^\mu(x)))$$

with

- 1 C_λ normalizing constant,
- 2 $\Gamma : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ (weakly decreasing) decay function,
- 3 $\mu \in \mathcal{P}$ location parameter and $\lambda \in \mathbb{R}_{> 0}$ a scale parameter and
- 4 D^μ a depth function that is maximal at partial order μ .



Application on the Set of Partial Orders



- 1 Formal Concept Analysis
 - (i) Introduction to Formal Concept Analysis
 - (ii) Introduction to Depth Functions
 - (iii) Definition of Unimodality

- 2 Application on the Set of Partial Orders
 - (i) Formal Context
 - (ii) Depth Function
 - (iii) Sampling

Representation of a data set as cross table

		a	b	c	d	e	f	g	h	i
1	Leech	x	x					x		
2	Bream	x	x					x	x	
3	Frog	x	x	x				x	x	
4	Dog	x		x				x	x	x
5	Spike – weed	x	x		x		x			
6	Reed	x	x	x	x		x			
7	Bean	x		x	x	x				
8	Maize	x		x	x		x			

Figure 1.1 Context of an educational film “Living Beings and Water”. The attributes are: a: needs water to live, b: lives in water, c: lives on land, d: needs chlorophyll to produce food, e: two seed leaves, f: one seed leaf, g: can move around, h: has limbs, i: suckles its offspring.

Formal Concept Analysis: Scaling Method

Convert a non-binary attribute into a set of binary attributes by using

$$t : V \rightarrow 2^{M_{new}}$$

where V is the set of non-binary values and M_{new} is the set of binary attributes. Note that the binary relation \tilde{I} (given by the crosses) must also be adjusted accordingly.

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For example:

Let $g_1, \dots, g_n \in \mathbb{R}^d$, $d \in \mathbb{N}$ be observations. Then a possible scaling method is

$$t : \mathbb{R}^d \rightarrow 2^{\{\text{set of all half-spaces}\}}, x \mapsto \{H \mid H \text{ half-space in } \mathbb{R}^d\}$$

and we say $(g_j, H) \in \tilde{I}$ iff g_j lies in half-space H .

Formal Concept Analysis: Formal Context and Deviation Operators

Definition

A **formal context** is given by a triple $\mathbb{K} = (G, M, I)$. G is the set of **objects**, M is the set of **attributes** and I defines a binary relation between G and M .

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The **derivation operators**

$$\psi: 2^G \rightarrow 2^M, A \mapsto A' := \{m \in M \mid \forall g \in A: glm\},$$

$$\varphi: 2^M \rightarrow 2^G, B \mapsto B' := \{g \in G \mid \forall m \in B: glm\}$$

give us the **closure operator**

$$\psi \circ \varphi: 2^G \rightarrow 2^G, A \mapsto A''.$$

Formal Concept Analysis: Closure System and Implications

This gives us

- 1 the **closure system** $\{A'' \mid A \subseteq G\}$ on G which describes the formal context and
- 2 a **family of implications** which describes the closure system completely. Let $A, B \subseteq G$. We say premise A implies conclusion B iff

$$\psi \circ \varphi(A) \supseteq \psi \circ \varphi(B).$$

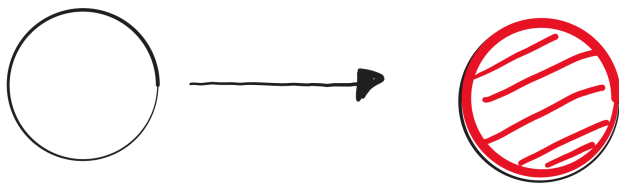


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Summary:

Data Set $\xrightarrow{\text{scaling method}}$ Formal Context $\xleftrightarrow{\varphi, \psi}$ Closure System $\xleftrightarrow{\varphi, \psi}$ Family of Implications

For further readings we refer to Ganter and Wille 2012

General Theory of the Model

Unimodality

Data Depth Function

Formal Concept Analysis (FCA)

Data Set $\xrightarrow{\text{scaling method}}$ Formal Context $\xleftrightarrow{\varphi, \psi}$ Closure System $\xleftrightarrow{\varphi, \psi}$ Family of Implications

Application on the Set of Partial Orders

Formal Context

Depth Function


Sampling

Depth Functions

Measures **centrality** and **outlyingness** of a data point with respect to a data cloud or an underlying distribution

¹<https://de.wikipedia.org/wiki/Box-Plot> (visited: 20.10.21)

²<https://link.springer.com/article/10.1007/s10994-015-5524-x> (visited: 20.10.21)

³https://en.wikipedia.org/wiki/Simplicial_depth (visited: 20.10.21) 

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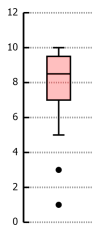


Figure: Quantiles¹

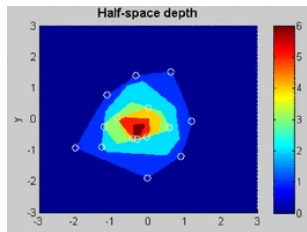


Figure: Halfspace Depth²

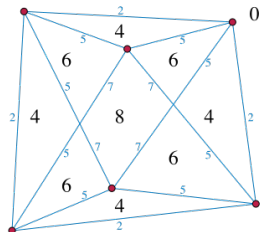


Figure: Simplicial Depth³

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Depth Functions: Selection of Properties in \mathbb{R}^d

- Affine Invariance
- Monotonicity Relative to the Deepest Point, Quasi-Concavity, ...
(Unimodality)
- Vanishing at Infinity
- Computability

³For further readings, we refer to Zou and Serfling 2000 and Chen et al. 2015 

Combining Formal Concept Analysis and Depth Function

- The depth function based on a formal context has as input the set of objects and is defined as $f : G \rightarrow \mathbb{R}_{\geq 0}$.
- Approach to obtain a depth function: Use the different representations of a data set given by FCA and define the statistical depth function based on this representation.
- Transfer the properties of \mathbb{R}^d for statistical depth functions to general depth functions defined by a formal context. Here, we restrict to **unimodality** property.

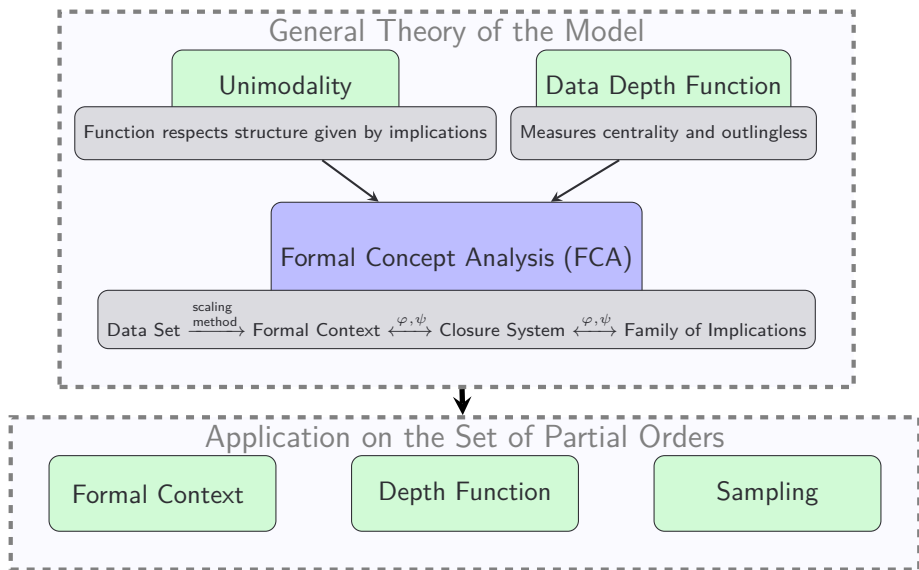
A function respects the structure of the family of implications given by a formal context.

Definition

Let $\mathbb{K} = (G, M, I)$ be a formal context and let $f : H \rightarrow \mathbb{R}_{\geq 0}$ with $H \subseteq G$ be a (depth, probability) function.

Then f is called **unimodal** if for every finite set of objects $\{g_1, \dots, g_n\} \subseteq H$ with $\{g_1, \dots, g_{n-1}\}$ implying g_n we have

$$f(g_n) \geq \min\{f(g_1), \dots, f(g_{n-1})\}$$



Application on the Set of Partial Orders

For now on, let \mathcal{P} be the set of all partial orders on $\mathcal{X} = \{x_1, \dots, x_n\}$ with $n \in \mathbb{N}$.

The formal context \mathbb{K} is given by

1 $G = \mathcal{P}$

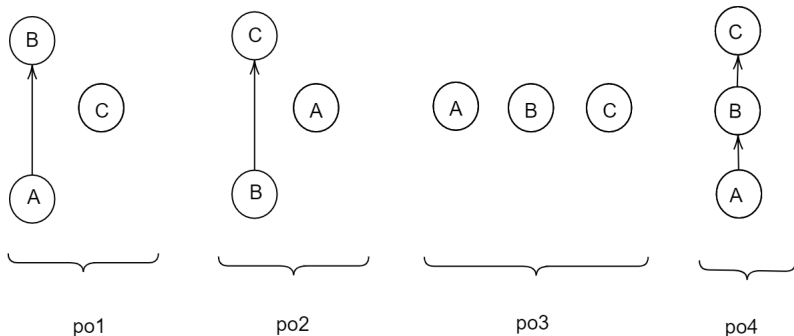
2 $M = \underbrace{\{“x_i \leq x_j” \mid i, j = 1, \dots, n, i \neq j\}}_{:=M_{\leq}} \cup \underbrace{\{“x_i \not\leq x_j” \mid i, j = 1, \dots, n, i \neq j\}}_{:=M_{\not\leq}}$

This corresponds to the closure operator which maps each subset $\{g_1, \dots, g_m\} \subseteq \mathcal{P} = G$, $m \in \mathbb{N}$ to

$$\{g \in \mathcal{P} \mid \bigcap_{i=1}^m g_i \subseteq g \subseteq \bigcup_{i=1}^m g_i\}.$$

Application on the Set of Partial Orders: Formal Context

Let $\mathcal{X} = \{A, B, C\}$. Consider the set $\{\text{po1}, \text{po2}\}$ and its implications.



We obtain

- 1 $\{\text{po1}, \text{po2}\}$ implies $\{\text{po1}, \text{po2}, \text{po3}\}$, but
- 2 $\{\text{po1}, \text{po2}\}$ does not imply $\{\text{po4}\}$.

Application on the Set of Partial Orders: Generalized Localized Tukeys Depth Function

Definition

Let $\mathbb{K} = (G, M, I)$ be a formal context, then the **generalized localized Tukey's depth** function (see Schollmeyer 2017) is given by

$$\mathcal{J}^\mu(g) := 1 - \frac{\max_{m \in M \setminus \Psi(\{g\})} |\Phi(\{m\})|}{\mu |G|}.$$

	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}
$\mu = g_1$	X		X	X	X		X	X		X	
g_2		X		X		X					
g_3	X	X		X	X						
g_4	X			X			X				
g_5	X						X		X		X

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	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}
$\mu = \mathfrak{g}_1$	X		X	X	X		X	X		X	
\mathfrak{g}_2		X		X		X		X			X
\mathfrak{g}_3	X	X		X	X						
\mathfrak{g}_4	X			X			X				
\mathfrak{g}_5	X						X		X		X

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For the formal context with $G = \mathcal{P}$ and $M = M_{\leq} \cup M_{\not\leq}$ we get

$$\mathcal{T}^\mu(g) = 1 - \max \left\{ \max_{(p,q) \in \mu \setminus g} \alpha_{p,q}, \max_{(p,q) \in g \setminus \mu} \beta_{p,q} \right\} \text{ with } \alpha_{p,q}, \beta_{p,q} \in [0, 1],$$

→ Note that $\alpha_{p,q}$ and $\beta_{p,q}$ are constant and not dependent of p or q .

Application on the Set of Partial Orders: Generalized Localized Tukeys Depth Function

Regarding reweighted version of $\alpha_{p,q}$ and $\beta_{p,q}$:

- $\alpha_{p,q} \propto |\{r \in \mathcal{X} \mid p \leq_{\mu} r \leq_{\mu} q\}|$
- $\beta_{p,q} \propto |\{r \in \mathcal{X} \mid p \wedge_{\mu} q \leq_{\mu} r \leq_{\mu} p \vee_{\mu} q\}| - 1$

General Theory of the Model

Unimodality

Function respects structure given by implications

Data Depth Function

Measures centrality and outlingness

Formal Concept Analysis (FCA)

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Application on the Set of Partial Orders

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$$G = \mathcal{P} \\ M = M_{\leq} \cup M_{\not\leq}$$

Depth Function

generalized Tukey's depth

Sampling

the statistical model

$$P(X = x) = C_\lambda \cdot \Gamma(\lambda \cdot (1 - D^\mu(x)))$$

with

- 1 C_λ normalizing constant,
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Acceptance-Rejection Method:

- **Step 1:** Draw systematically a partial order

$$P_{\text{algo_select}}(g) = |\text{ext}(g)| \cdot 2^{|\text{g}| - |\text{reduc}(g)|} \cdot \left(n! 2^{n(n-1)/2} \right)^{-1}$$

- **Step 2:** Compute the acceptance probability

$$\text{acc}(g) = f(g) \cdot \left(P_{\text{algo_select}}(g) \cdot n! 2^{n(n-1)/2} \right)^{-1}.$$

- **Step 3:** Sample uniformly a value between $[0, 1]$ and if its lower than $\text{acc}(g)$ accept the partial order given in Step 1.

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Depth Function

generalized Tukey's depth

Sampling

Acceptance Rejection Methode

- How to estimate a statistical model from a sample?
- Inference?
- How to deal with non-transitive or/and cyclic observations? How to deal with NA's?

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