A Generalization of Credal Networks

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hierarchical model:

description with two levels:

probabilistic level: set \mathcal{P} of probability measures P on (Ω, \mathcal{A})

possibilistic level: likelihood function $lik : \mathcal{P} \to (0, \infty)$

• description as **set of measures**:

set \mathcal{M} of measures μ on (Ω, \mathcal{A}) with $\mu(\Omega) \in (0, \infty)$

connection between the two descriptions:

• two levels \rightsquigarrow set of measures:

$$\mathcal{M} = \{ lik(P) P : P \in \mathcal{P} \}$$

set of measures → two levels:

probabilistic level:
$$\mathcal{P} = \left\{ \frac{\mu}{\mu(\Omega)} : \mu \in \mathcal{M} \right\}$$

possibilistic level:
$$lik: \mathcal{P} \rightarrow (0, \infty)$$
 with

$$lik(P) \propto \sup_{\mu \in \mathcal{M}: \frac{\mu}{\mu(\Omega)} = P} \mu(\Omega)$$

updating of hierarchical model (event $A \in \mathcal{A}$ observed):

description with two levels:

probabilistic level:
$$\mathcal{P} \leadsto \mathcal{P}' = \{P(\cdot \mid A) : P \in \mathcal{P}, \ P(A) > 0\}$$
 possibilistic level: $lik \leadsto lik' : \mathcal{P}' \to (0, \infty)$ with
$$lik'(P') \propto \sup_{P \in \mathcal{P} : P(\cdot \mid A) = P'} lik(P) \ P(A)$$

• description as set of measures:

$$\mathcal{M} \rightsquigarrow \mathcal{M}' = \{\mu(\cdot \cap A) : \mu \in \mathcal{M}, \ \mu(A) > 0\}$$
 in particular (**Theorem 2**): if $\mathcal{M} = \operatorname{ch}(\{\mu_i : i \in \{1, \dots, m\}\})$, then $\mathcal{M}' = \operatorname{ch}(\{\mu_i(\cdot \cap A) : i \in \{1, \dots, m\}, \ \mu_i(A) > 0\})$

hierarchical network:

directed acyclic graph with nodes $X_1 \in \mathcal{X}_1, \ldots, X_k \in \mathcal{X}_k$, such that to each node X_i are associated a set \mathcal{P}_i of stochastic kernels P_i from $\mathcal{P}\mathcal{A}_i$ (the set of all possible values of the parents of X_i) to \mathcal{X}_i , and a likelihood function $lik_i : \mathcal{P}_i \to (0, \infty)$

• description with two levels:

prob. level:
$$\mathcal{P} = \left\{ P_{P_1,\ldots,P_k} : P_1 \in \mathcal{P}_1,\ldots,P_k \in \mathcal{P}_k \right\} \text{ with }$$

$$P_{P_1,\ldots,P_k}(x_1,\ldots,x_k) = \prod_{i=1}^k P_i \left(x_i \, | \, pa_i(x_1,\ldots,x_k) \right)$$
 poss. level:
$$lik : \mathcal{P} \to (0\,,\infty) \text{ with }$$

$$lik(P) \propto \sup_{\substack{P_1 \in \mathcal{P}_1,\ldots,P_k \in \mathcal{P}_k : \\ P_{P_1,\ldots,P_k} = P}} \prod_{i=1}^k lik_i(P_i)$$

description as set of measures:

$$\mathcal{M} = \left\{ \mu_{P_1,\dots,P_k} : P_1 \in \mathcal{P}_1,\dots,P_k \in \mathcal{P}_k \right\} \text{ with}$$

$$\mu_{P_1,\dots,P_k}(x_1,\dots,x_k) = \prod_{i=1}^k \left[lik_i(P_i) \, P_i\left(x_i \,|\, pa_i(x_1,\dots,x_k)\right) \right]$$

inference about the value g(P) of $g: \mathcal{P} \to \mathcal{G}$ (extension principle):

profile likelihood function $lik_g: \mathcal{G} \to (0, \infty)$ with

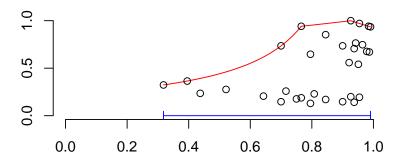
$$lik_g(\gamma) \propto \sup_{P \in \mathcal{P}: g(P) = \gamma} lik(P) \propto \sup_{\mu \in \mathcal{M}: g\left(\frac{\mu}{\mu(\Omega)}\right) = \gamma} \mu(\Omega)$$

in particular (**Theorem 3**): if $\mathcal{M} = \operatorname{ch}(\{lik(P_i) \ P_i : i \in \{1, \dots, m\}\})$, then the profile likelihood function of the expected value $E_P(X)$ of a random variable X is **piecewise hyperbolic** and determined by the pairs $(E_{P_i}(X), lik(P_i))$ with $i \in \{1, \dots, m\}$

example of piecewise hyperbolic profile likelihood function:

 $X, Y, Z \in \{0, 1\}$ 1.0 0.5 0.0 0.2 0.4 P(X=1) 1.0 1.0 0.5 0.5 0.0 0.0 0.2 0.4 0.6 0.8 0.2 0.4 0.8 1.0 P(Y=1 | X=1) P(Z=1 | X=1) 1.0 1.0 0.5 0.5 0.0 0.2 0.4 0.6 0.8 1.0 0.0 0.2 0.4 0.6 0.8 1.0 P(Y=1 | X=0) P(Z=1 | X=0)

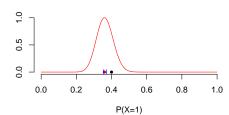


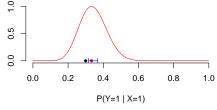


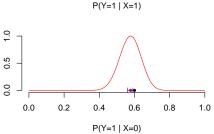
profile likelihood functionprobability intervalextreme points

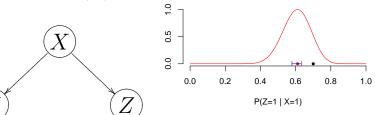
example with training data:

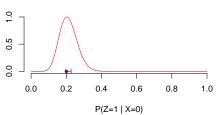




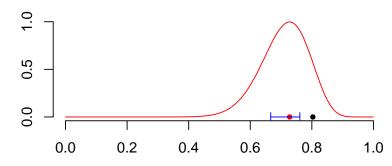








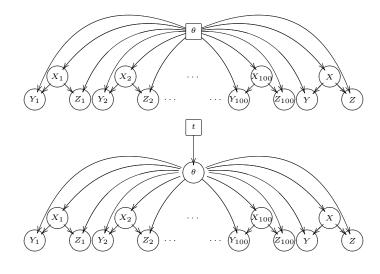
$$\Rightarrow P(X = 1 | Y = 0, Z = 1) :$$



profile likelihood functionIDM probability interval (s=2)

- MLE probability
- true probability

global models (without and with IDMs):



$$\theta, t \in [0, 1]^5$$

prior ignorance about the root, and precise (conditional) probabilities about the other nodes