# Complements on belief functions 

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## Outline

(1) Belief functions on product spaces
2) Belief functions on infinite spaces

- Definition
- Practical models
- Combination and propagation


## Belief functions on product spaces

## Motivation



- In many applications, we need to express uncertain information about several variables taking values in different domains
- Example: fault tree (logical relations between Boolean variables and probabilistic or evidential information about elementary events)


## Fault tree example

(Dempster \& Kong, 1988)


## Multidimensional belief functions

Marginalization, vacuous extension

- Let $X$ and $Y$ be two variables defined on frames $\Omega_{X}$ and $\Omega_{Y}$
- Let $\Omega_{X Y}=\Omega_{X} \times \Omega_{Y}$ be the product frame
- A mass function $m_{X Y}$ on $\Omega_{X Y}$ can be seen as an uncertain relation between variables $X$ and $Y$
- Two basic operations on product frames
(1) Express a joint mass function $m_{X Y}$ in the coarser frame $\Omega_{X}$ or $\Omega_{Y}$ (marginalization)
(2) Express a marginal mass function $m_{X}$ on $\Omega_{X}$ in the finer frame $\Omega_{X Y}$ (vacuous extension)


## Marginalization



- Problem: express $m_{X Y}$ in $\Omega_{X}$
- Solution: transfer each mass $m_{X Y}(A)$ to the projection of $A$ on $\Omega_{X}$
- Marginal mass function

$$
m_{X Y \downarrow X}(B)=\sum_{\left\{A \subseteq \Omega_{X Y}, A \downarrow \Omega_{X}=B\right\}} m_{X Y}(A) \quad \forall B \subseteq \Omega_{X}
$$

- Generalizes both set projection and probabilistic marginalization


## Vacuous extension



- Problem: express $m_{X}$ in $\Omega_{X Y}$
- Solution: transfer each mass $m_{X}(B)$ to the cylindrical extension of $B$ : $B \times \Omega_{Y}$
- Vacuous extension:

$$
m_{X \uparrow X Y}(A)= \begin{cases}m_{X}(B) & \text { if } A=B \times \Omega_{Y} \\ 0 & \text { otherwise }\end{cases}
$$

## Operations in product frames

Application to approximate reasoning

- Assume that we have:
- Partial knowledge of $X$ formalized as a mass function $m_{X}$
- A joint mass function $m_{X Y}$ representing an uncertain relation between $X$ and Y
- What can we say about $Y$ ?
- Solution:

$$
m_{Y}=\left(m_{X \uparrow X Y} \oplus m_{X Y}\right)_{\downarrow Y}
$$

- Infeasible with many variables and large frames of discernment, but efficient algorithms exist to carry out the operations in frames of minimal dimensions


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## Belief function: general definition

- Let $\Omega$ be a set (finite or not) and $\mathcal{B}$ be an algebra of subsets of $\Omega$
- A belief function (BF) on $\mathcal{B}$ is a mapping Bel: $\mathcal{B} \rightarrow[0,1]$ verifying $\operatorname{Bel}(\emptyset)=0, \operatorname{Bel}(\Omega)=1$ and the complete monotonicity property: for any $k \geq 2$ and any collection $B_{1}, \ldots, B_{k}$ of elements of $\mathcal{B}$,

$$
\operatorname{Bel}\left(\bigcup_{i=1}^{k} B_{i}\right) \geq \sum_{\emptyset \neq I \subseteq\{1, \ldots, k\}}(-1)^{|/|+1} B e l\left(\bigcap_{i \in I} B_{i}\right)
$$

- A function $P I: \mathcal{B} \rightarrow[0,1]$ is a plausibility function iff $B e l: B \rightarrow 1-P I(\bar{B})$ is a belief function


## Source



- Let $S$ be a state space, $\mathcal{A}$ an algebra of subsets of $S, \mathbb{P}$ a finitely additive probability on $(S, \mathcal{A})$
- Let $\Omega$ be a set and $\mathcal{B}$ an algebra of subsets of $\Omega$
- 「 a multivalued mapping from $S$ to $2^{\Omega}$
- The four-tuple $(S, \mathcal{A}, \mathbb{P}, \Gamma)$ is called a source
- Under some conditions, it induces a belief function on $(\Omega, \mathcal{B})$


## Strong measurability



- Lower and upper inverses: for all $B \in \mathcal{B}$,

$$
\begin{gathered}
\Gamma_{*}(B)=B_{*}=\{s \in S \mid \Gamma(s) \neq \emptyset, \Gamma(s) \subseteq B\} \\
\Gamma^{*}(B)=B^{*}=\{s \in S \mid \Gamma(s) \cap B \neq \emptyset\}
\end{gathered}
$$

- 「 is strongly measurable wrt $\mathcal{A}$ and $\mathcal{B}$ if, for all $B \in \mathcal{B}, B^{*} \in \mathcal{A}$
- $\left(\forall B \in \mathcal{B}, B^{*} \in \mathcal{A}\right) \Leftrightarrow\left(\forall B \in \mathcal{B}, B_{*} \in \mathcal{A}\right)$
- A strongly measurable multi-valued mapping $\Gamma$ is called a random set


## Belief function induced by a source

Lower and upper probabilities


- Lower and upper probabilities:

$$
\forall B \in \mathcal{B}, \quad \mathbb{P}_{*}(B)=\frac{\mathbb{P}\left(B_{*}\right)}{\mathbb{P}\left(\Omega^{*}\right)}, \quad \mathbb{P}^{*}(B)=\frac{\mathbb{P}\left(B^{*}\right)}{\mathbb{P}\left(\Omega^{*}\right)}=1-\operatorname{Bel}(\bar{B})
$$

- $\mathbb{P}_{*}$ is a BF, and $\mathbb{P}^{*}$ is the dual plausibility function
- Conversely, for any belief function, there is a source that induces it (Shafer's thesis, 1973)


## Interpretation



- Typically, $\Omega$ is the domain of an unknown quantity $\omega$, and $S$ is a set of interpretations of a given piece of evidence about $\omega$
- If $s \in S$ holds, then the evidence tells us that $\omega \in \Gamma(s)$, and nothing more
- Then
- $\operatorname{Bel}(B)$ is the probability that the evidence supports $B$
- $P I(B)$ is the probability that the evidence is consistent with $B$


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## Consonant belief function

## Source



- Let $\pi$ be a mapping from $\Omega=\mathbb{R}^{p}$ to $S=[0,1]$ s.t. $\sup \pi=1$
- Let $\Gamma$ be the multi-valued mapping from $S$ to $2^{\Omega}$ defined by

$$
\forall s \in[0,1], \quad \Gamma(s)=\{\omega \in \Omega \mid \pi(\omega) \geq s\}
$$

- Let $\mathcal{B}([0,1])$ be the Borel $\sigma$-field on $[0,1]$, and $P$ the uniform probability measure on $[0,1]$
- We consider the source $([0,1], \mathcal{B}([0,1]), P, \Gamma)$


## Consonant belief function

## Properties

- Let Bel and $P /$ be the belief and plausibility functions induced by $([0,1], \mathcal{B}([0,1]), P, \Gamma)$
- The focal sets $\Gamma(s)$ are nested, i.e., for any $s$ and $s^{\prime}$,

$$
s \geq s^{\prime} \Rightarrow \Gamma(s) \subseteq \Gamma\left(s^{\prime}\right)
$$

The belief function is said to be consonant.

- The corresponding contour function $p /$ is equal to $\pi$
- The corresponding plausibility function is a possibility measure: for any $B \subseteq \Omega$,

$$
\begin{gathered}
P l(B)=\sup _{\omega \in B} p l(\omega) \\
\operatorname{Bel}(B)=\inf _{\omega \notin B}(1-p l(\omega))
\end{gathered}
$$

## Random closed interval



- Let $(U, V)$ be a bi-dimensional random vector from a probability space $(S, \mathcal{A}, \mathbb{P})$ to $\mathbb{R}^{2}$ such that $U \leq V$ a.s.
- Multi-valued mapping:

$$
\Gamma: s \rightarrow \Gamma(s)=[U(s), V(s)]
$$

- The source $(S, \mathcal{A}, \mathbb{P}, \Gamma)$ is a random closed interval. It defines a BF on ( $\mathbb{R}, \mathcal{B}(\mathbb{R})$ )


## Random closed interval

## Properties

- Lower/upper cdfs:

$$
\begin{aligned}
\operatorname{Bel}((-\infty, x]) & =\mathbb{P}([U, V] \subseteq(-\infty, x])=\mathbb{P}(V \leq x)=F_{V}(x) \\
P l((-\infty, x]) & =\mathbb{P}([U, V] \cap(-\infty, x] \neq \emptyset)=\mathbb{P}(U \leq x)=F_{U}(x)
\end{aligned}
$$

- Lower/upper expectation:

$$
\begin{aligned}
\mathbb{E}_{*}(\Gamma) & =\mathbb{E}(U) \\
\mathbb{E}^{*}(\Gamma) & =\mathbb{E}(V)
\end{aligned}
$$

- Lower/upper quantiles

$$
\begin{aligned}
q_{*}(\alpha) & =F_{U}^{-1}(\alpha), \\
q^{*}(\alpha) & =F_{V}^{-1}(\alpha) .
\end{aligned}
$$

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## Dempster's rule

## Definition



- Let $\left(S_{i}, \mathcal{A}_{i}, \mathbb{P}_{i}, \Gamma_{i}\right), i=1,2$ be two sources representing independent items of evidence, inducing BF $\mathrm{Bel}_{1}$ and $\mathrm{Bel}_{2}$
- The combined BF Bel $=B e l_{1} \oplus B e l_{2}$ is induced by the source $\left(S_{1} \times S_{2}, \mathcal{A}_{1} \otimes \mathcal{A}_{2}, \mathbb{P}_{1} \otimes \mathbb{P}_{2}, \Gamma_{\cap}\right)$ with

$$
\Gamma_{\cap}\left(s_{1}, s_{2}\right)=\Gamma_{1}\left(s_{1}\right) \cap \Gamma_{2}\left(s_{2}\right)
$$

## Dempster's rule

Definition

- For each $B \in \mathcal{B}, \operatorname{Bel}(B)$ is the conditional probability that $\Gamma_{\cap}(s) \subseteq B$, given that $\Gamma_{\cap}(s) \neq \emptyset$ :

$$
B e l(B)=\frac{\mathbb{P}\left(\left\{\left(s_{1}, s_{2}\right) \in S_{1} \times S_{2} \mid \Gamma_{\cap}\left(s_{1}, s_{2}\right) \neq \emptyset, \Gamma_{\cap}\left(s_{1}, s_{2}\right) \subseteq B\right\}\right)}{\mathbb{P}\left(\left\{\left(s_{1}, s_{2}\right) \in S_{1} \times S_{2} \mid \Gamma_{\cap}\left(s_{1}, s_{2}\right) \neq \emptyset\right\}\right)}
$$

- It is well defined iff the denominator is non null
- As in the finite case, the degree of conflict between the belief functions can be defined as one minus the denominator in the above equation.


## Approximate computation

Monte Carlo simulation

Require: Desired number of focal sets $N$
$i \leftarrow 0$
while $i<N$ do
Draw $s_{1}$ in $S_{1}$ from $\mathbb{P}_{1}$
Draw $s_{2}$ in $S_{2}$ from $\mathbb{P}_{2}$
$\Gamma_{\cap}\left(s_{1}, s_{2}\right) \leftarrow \Gamma_{1}\left(s_{1}\right) \cap \Gamma_{2}\left(s_{2}\right)$
if $\Gamma_{\cap}\left(s_{1}, s_{2}\right) \neq \emptyset$ then
$i \leftarrow i+1$
$B_{i} \leftarrow \Gamma_{\cap}\left(s_{1}, s_{2}\right)$
end if
end while
$\widehat{B e l}(B) \leftarrow \frac{1}{N} \#\left\{i \in\{1, \ldots, N\} \mid B_{i} \subseteq B\right\}$
$\hat{P} l(B) \leftarrow \frac{1}{N} \#\left\{i \in\{1, \ldots, N\} \mid B_{i} \cap B \neq \emptyset\right\}$

## Combination of dependent evidence



- The case of complete dependence between two pieces of evidence can be modeled by two sources formed by different multivalued mappings $\Gamma_{1}$ and $\Gamma_{2}$ from the same probability space.
- The combined BF is induced by the source $\left(S, \mathcal{A}, \mathbb{P}, \Gamma_{\cap}\right)$
- This combination rule preserves consonance: the combination of two consonant BFs is still consonant.
- This is the rule used in Possibility Theory.


## Propagation of belief functions

- Assume that a quantity $Z$ is defined as function of two other quantities $X$ and $Y$

$$
Z=\varphi(X, Y)
$$



- Solution:

$$
B e I_{Z}=\left(B e l_{X \uparrow X Y z} \oplus B e l_{Y \uparrow X Y Z} \oplus B e l_{\varphi}\right)_{\downarrow Z}
$$

- For any $A \subseteq \Omega_{X}$ and $B \subseteq \Omega_{Y}$,

$$
\left(A \uparrow \Omega_{X Y Z}\right) \cap\left(B \uparrow \Omega_{X Y Z}\right) \cap R_{\varphi}=\varphi(A, B)
$$

- Consequently, if $\mathrm{Be}_{X}$ and $\mathrm{Be}_{Y}$ are induced by random sets $\Gamma(U)$ and $\Lambda(V)$, where $U$ and $V$ are independent rvs, then $B e I_{z}$ is induced by the RS

$$
\varphi(\Gamma(U), \wedge(V))
$$

## Exercise

- In R, we can represent (an approximation of) a random interval (RI) by a matrix $B$ of size $N \times 2$, where $B[i$,$] is a realization of the random interval.$
- Write a function in R that generates a RI representation for the consonant belief function with contour function $\pi: \mathbb{R} \rightarrow[0,1]$ (assumed to be continuous and unimodal)
- Write a function that computes the RI representation of $Z=\varphi(X, Y)$, as a function of $\varphi$, and the RI representations of $X$ and $Y$.
- Run some examples. Draw the lower and upper cdfs of the RIs obtained, and compute their lower and upper expectations.

