Belief functions over Belnap–Dunn logic

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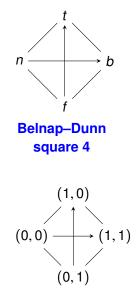
Representing incomplete/contradictory probabilistic information

- Belnap–Dunn Logic
- Non-standard probabilities
- 2 Dempster-Shafer theory
 - Mass functions, belief functions and plausibility functions
 - Representation of evidence
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Beinap–Dunn square $(4, \land, \lor, \neg)$ is a de Morgan algebra.

- (4, ∧, ∨) is a lattice
- each element represents the available positive and/or negative information
 - n: no information
 - f: false (is bottom)
 - t: true (is top)
 - b: contradictory information
- ¬ is an involutive de Morgan negation.



Belnap–Dunn Logic: models [Dunn 76]

Language. $L_{\mathsf{BD}} \ni \varphi := p \in \operatorname{Prop} | \varphi \land \varphi | \varphi \lor \varphi | \neg \varphi$

Models. $M = \langle W, v^+, v^- : W \times \text{Prop} \rightarrow 2 \rangle$ $v^+(p)$: states where one has information supporting the truth of p $v^-(p)$: states where one has information supporting the falsity of p

Semantics. Two satisfaction relations $\mathbb{H}^+, \mathbb{H}^-$

 $w \models^{+} p \text{ iff } w \in v^{+}(p) \qquad w \models^{-} p \text{ iff } w \in v^{-}(p) \\ w \models^{+} \neg \phi \text{ iff } w \models^{-} \phi \qquad w \models^{-} \neg \phi \text{ iff } w \models^{+} \phi \\ w \models^{+} \phi \land \phi' \text{ iff } w \models^{+} \phi \text{ and } w \models^{+} \phi' \qquad w \models^{-} \phi \land \phi' \text{ iff } w \models^{-} \phi \text{ or } w \models^{-} \phi' \\ w \models^{+} \phi \lor \phi' \text{ iff } w \models^{+} \phi \text{ or } w \models^{+} \phi' \qquad w \models^{-} \phi \lor \phi' \text{ iff } w \models^{-} \phi \text{ and } w \models^{-} \phi' \end{cases}$

Non-standard probabilities: frame semantics [Klein et al]

- Independence of the probability assigned to positive and negative information
- Extend BD model with a classical probability measure.

A probabilistic BD model is a tuple $M = \langle W, v^+, v^-, m \rangle$, s.t.

- $\langle W, v^+, v^- \rangle$ is a BD model and
- $m: W \to [0, 1]$ is a mass function on W i.e. $\sum_{s \in W} m(s) = 1$

Positive probability of φ : $p^+(\varphi) := \sum \{ m(s) \mid s \Vdash^+ \varphi \}$. Negative probability of φ : $p^-(\varphi) := \sum \{ m(s) \mid s \Vdash^- \varphi \}$.

Remark. $p^+(\varphi)$ and $p^-(\varphi)$ are independent.

[Klein et al] Lemma 1

Let $M = \langle W, v, m \rangle$ be a probabilistic BD frame. Then the non-standard probability function p^+ induced by *m* satisfies:

(A1) normalization(A2) monotonicity(A3) import-export

$$0 \le p^+(\varphi) \le 1$$

if $\varphi \vdash_{BD} \psi$ then $p^+(\varphi) \le p^+(\psi)$
 $p^+(\varphi \land \psi) + p^+(\varphi \lor \psi) = p^+(\varphi) + p^+(\psi).$

Remarks

•
$$p^-(\varphi) = p^+(\neg \varphi)$$

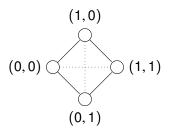
• Weaker than classical Kolmogorovian axioms. Additivity does not hold and is replaced by A3.

• In general
$$p^+(\neg \varphi) \neq 1 - p^+(\varphi)$$

• one can have 0 <
$$p^+(arphi \wedge
eg arphi)$$

Continuous extension of Belnap–Dunn square, which we can see as the product bilattice $L_{[0,1]} \odot L_{[0,1]}$ with $L_{[0,1]} = ([0, 1], \min, \max)$.

- (p⁺(φ), p⁻(φ)): positive and negative probabilistic support of φ.
- (0, 0): no information concerning φ is available
- (1, 1): maximally conflicting information
- vertical dashed line: "classical" case





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Belief functions and plausiblity functions

Let $f : \mathcal{P}(S) \to [0, 1]$ be a monotone function such that $f(\emptyset) = 0$ and f(S) = 1.

• *f* is a belief function if, for every $k \ge 1$, and for every $A_1, \ldots, A_k \in \mathcal{P}(S)$, it holds that

$$f\left(\bigvee_{1\leq i\leq k}A_{i}\right)\geq\sum_{\substack{J\subseteq\{1,\ldots,k\}\\J\neq\varnothing}}(-1)^{|J|+1}\cdot f\left(\bigwedge_{j\in J}A_{j}\right).$$
 (1)

• *f* is a plausibility function if, for every $k \ge 1$, and for every $A_1, \ldots, A_k \in \mathcal{P}(S)$, it holds that

$$f\left(\bigwedge_{\substack{1\leq i\leq k}} A_i\right) \leq \sum_{\substack{J\subseteq\{1,\ldots,k\}\\J\neq\emptyset}} (-1)^{|J|+1} \cdot f\left(\bigvee_{j\in J} A_j\right).$$
(2)

Mass function

Let bel, pl : $\mathcal{P}(S) \rightarrow [0, 1]$ be a monotone function such that $f(\emptyset) = 0$ and f(S) = 1, and m : $\mathcal{P}(S) \rightarrow [0, 1]$.

Definition

m is a mass function if
$$\sum_{A \in \mathcal{P}(S)} m(A) = 1$$
.

Theorem

- bel is a belief function iff there is a mass function $m_{bel} : \mathcal{P}(S) \to [0, 1]$ such that, for every $A \in \mathcal{P}(S)$,

$$\mathsf{bel}(A) = \sum_{B \leq A} \mathsf{m}_{\mathsf{bel}}(B)$$

- if bel is a belief function, then $pl(A) = 1 - bel(\neg A)$ is a plausibility function.

- if pl is a plausibility function, then $bel(A) = 1 - pl(\neg A)$ is a belief function.

Representation of evidence. Example

- $m: \mathcal{P}(S) \rightarrow [0, 1]$ is computed based on the evidence
- $bel(A) = \sum_{B \le A} m(B)$: the evidence supporting *a*
- pl(A) = 1 bel(¬A) = ∑_{B∩A≠∅} m(B) : the evidence not contradicting A

•
$$bel(A) \leq pl(A)$$
.

Example

Scenario. A patient has disease *a*, *b* or *c*.

A doctor says "the patient has disease a or b with certainty 0.7." The doctor gives no information about disease c.

Representation of evidence. An example

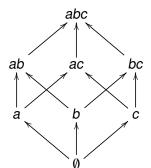
Scenario. A patient has disease *a*, *b* or *c*.

A doctor says "the patient has disease a or b with certainty 0.7." It is assumed it is impossible for the patient to have two of these diseases.

Representation

•
$$S = \{a, b, c\}$$
 and m, bel, pl : $\mathcal{P}(S) \rightarrow [0, 1]$

•
$$m(\{a, b\}) = 0.7$$
 and $m(S) = 0.3$.



An example

Scenario. A patient has disease *a*, *b* or *c*.

A doctor says "the patient has disease a or b with certainty 0.7." The doctor gives no information about disease c.

Representation

- $S = \{a, b, c\}$ and m, bel, pl : $\mathcal{P}(S) \rightarrow [0, 1]$
- $m(\{a, b\}) = 0.7$ and m(S) = 0.3.

We get: $bel(\{a\}) = bel(\{b\}) = bel(\{c\}) = 0$ $bel(\{a,b\}) = \sum_{X \subseteq \{a,b\}} m(X) = 0.7$ $pl(\{a,b\}) = 1 - bel(\{c\}) = 1$ $pl(\{a\}) = pl(\{b\}) = 1$ $pl(\{c\}) = 1 - bel(\{a,b\}) = 0.3$

- m({a, b}): the 'probability' that the disease is in the set {a, b} without being able to say to which subset it belongs.
- if m is non-zero only on singletons, then bel and pl are probability functions.

Dempster-Shafer combination rule

Let m_1 and m_2 be two mass functions on a powerset algebra $\mathcal{P}(S)$. Dempster-Shafer combination rule computes their aggregation $m_{1\oplus 2}$ as follows.

$$\begin{split} m_{1\oplus 2} \ : \ \mathcal{P}(\mathcal{S}) &\to [0,1] \\ X &\mapsto \begin{cases} 0 & \text{if } X = \varnothing \\ \frac{\sum\{m_1(X_1) \cdot m_2(X_2) \mid X_1 \cap X_2 = X\}}{\sum\{m_1(X_1) \cdot m_2(X_2) \mid X_1 \cap X_2 \neq \varnothing\}} & \text{otherwise.} \end{cases}$$

Normalization factor:

$$\sum \{ \mathsf{m}_1(X_1) \cdot \mathsf{m}_2(X_2) \mid X_1 \cap X_2 \neq \emptyset \}$$

= 1 - \sum \{\mathbf{m}_1(X_1) \cdot \mathbf{m}_2(X_2) \cdot X_1 \cdot X_2 = \varnot \}

What happens with contradictory evidence?

Scenario

A patient has disease *a*, *b* or *c*.

Doctor 1: "the patient has disease *a* with certainty 0.9 and disease *b* with certainty 0.1."

Doctor 2: "the patient has disease *c* with certainty 0.9 and disease *b* with certainty 0.1."

Representation

$$\begin{split} S &= \{a, b, c\} \\ m_1(\{a\}) &= 0.9 \text{ and } m_1(\{b\}) = 0.1. \\ m_2(\{c\}) &= 0.9 \text{ and } m_2(\{b\}) = 0.1. \end{split}$$

Dempster-Shafer combination rule gives

$$\mathsf{m}_{1\oplus 2}(\{b\}) = 1$$

because $\{a\} \cap \{b\} = \{a\} \cap \{c\} = \emptyset$.



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Our proposal over BD

Define belief and plausibility on BD-models

Let Prop be a finite set of variables. $M = \langle W, v^+, v^-, bel \rangle$ with $bel : \mathcal{P}(W) \rightarrow [0, 1]$.

 $\mathsf{bel}^+(\phi) := \mathsf{bel}(|\phi|^+) \quad \mathsf{and} \quad \mathsf{bel}^-(\phi) := \mathsf{bel}(|\phi|^-)$

bel⁺: belief function on the associated Lindenbaum algebra \mathcal{L}_{BD} . bel⁻: belief function on \mathcal{L}_{BD}^{op} .

Remark. if \perp and \top are not in the language bel⁺ (resp. pl⁺) are general belief (resp. plausibility) functions. **Consequence.** $0 \leq \sum_{a \in \mathcal{L}_{BD}} m_{bel^+}(a) \leq 1$

Combination of evidence

Let \mathcal{L} be a finite distributive lattice.

Without \perp and \top

$$\begin{array}{rcl} \mathfrak{m}_{1\oplus 2} & : & \mathcal{L} \to [0,1] \\ & & x \mapsto \sum \{\mathfrak{m}_1(x_1) \cdot \mathfrak{m}_2(x_2) \mid x_1 \wedge x_2 = x\}. \end{array}$$

With \perp and \top

$$\begin{split} \mathbf{m}_{1\oplus 2} &: \ \mathcal{L} \to [0,1] \\ & x \mapsto \begin{cases} 0 & \text{if } x = \bot \\ \frac{\sum\{\mathbf{m}_1(x_1) \cdot \mathbf{m}_2(x_2) \mid x_1 \land x_2 = x\}}{\sum\{\mathbf{m}_1(x_1) \cdot \mathbf{m}_2(x_2) \mid x_1 \land x_2 \neq \bot\}} & \text{otherwise.} \end{cases}$$

Examples. The two doctors

Scenario. A patient has disease *a*, *b* or *c*. Doctor 1: *a* with certainty 0.9 and *b* with certainty 0.1. Doctor 2: *c* with certainty 0.9 and *b* with certainty 0.1. **Representation.** $m_1, m_2 : \mathcal{DM}_3 \rightarrow [0, 1]$

$$m_1(x) = \begin{cases} 0.9 & \text{if } x = a \\ 0.1 & \text{if } x = b \\ 0 & \text{otherwise.} \end{cases} m_2(x) = \begin{cases} 0.9 & \text{if } x = c \\ 0.1 & \text{if } x = b \\ 0 & \text{otherwise.} \end{cases}$$

Dempster-Shafer combination rule gives

$$\mathsf{m}_{1\oplus 2}(x) = \begin{cases} 0.81 & \text{if } x = a \land c \\ 0.09 & \text{if } x = a \land b \text{ or } x = b \land c \\ 0.01 & \text{if } x = b \\ 0 & \text{otherwise.} \end{cases}$$

 $bel_{1\oplus 2}(a) = bel_{1\oplus 2}(c) = 0.9$ and $bel_{1\oplus 2}(b) = 0.19$

Representation. $m_1, m_2 \ : \ \mathcal{DM}_3 \rightarrow [0, 1]$

$$m_1(x) = \begin{cases} 0.9 & \text{if } x = a \land \neg b \\ 0.1 & \text{if } x = \neg a \land b \\ 0 & \text{otherwise.} \end{cases} m_2(x) = \begin{cases} 0.9 & \text{if } x = \neg b \land c \\ 0.1 & \text{if } x = b \land \neg c \\ 0 & \text{otherwise.} \end{cases}$$

Dempster-Shafer combination rule gives

$$\mathsf{m}_{1\oplus 2}(x) = \begin{cases} 0.81 & \text{if } x = a \land \neg b \land c \\ 0.09 & \text{if } x = a \land b \land \neg b \land \neg c \text{ or } x = \neg a \land b \land \neg b \land c \\ 0.01 & \text{if } x = \neg a \land b \land \neg c \\ 0 & \text{otherwise.} \end{cases}$$

$$bel_{1\oplus 2}(a) = bel_{1\oplus 2}(c) = 0.9$$
 and $bel_{1\oplus 2}(b) = 0.19$

Examples. The two doctors

Representation. $m_1, m_2 : \mathcal{DM}_3 \rightarrow [0, 1]$

$$m_1(x) = \begin{cases} 0.9 & \text{if } x = a \land \neg b \land \neg c \\ 0.1 & \text{if } x = \neg a \land b \land \neg c \\ 0 & \text{otherwise.} \end{cases}$$
$$m_2(x) = \begin{cases} 0.9 & \text{if } x = \neg a \land \neg b \land c \\ 0.1 & \text{if } x = \neg a \land b \land \neg c \\ 0 & \text{otherwise.} \end{cases}$$

Dempster-Shafer combination rule gives

$$m_{1\oplus 2}(x) = \begin{cases} 0.81 & \text{if } x = a \land \neg a \land \neg b \land c \land \neg c \\ 0.09 & \text{if } x = a \land \neg a \land b \land \neg b \land \neg c \\ & \text{or } x = \neg a \land b \land \neg b \land c \land \neg c \\ 0.01 & \text{if } x = \neg a \land b \land \neg c \\ 0 & \text{otherwise.} \end{cases}$$

 $\mathsf{bel}_{1\oplus 2}(a) = \mathsf{bel}_{1\oplus 2}(c) = 0.9$ and $\mathsf{bel}_{1\oplus 2}(b) = 0.19$

What about plausibility?

- $1 bel^+(\neg \phi)$ defines a plausibility function
- 1 bel⁺(¬φ) is the sum of the masses of the set of states that do not support the negation of φ.
 Problem: a set of states can support both φ and ¬φ and a set of states can support neither.
- In general, we can have $1 bel^+(\neg \phi) \le bel^+(\phi)$
- We can define plausibility independently of belief and impose $\mathrm{bel}^+(\phi) \leq \mathrm{pl}^+(\phi)$

$$M = \langle W, v^+, v^-, \text{bel}, \text{pl} \rangle$$
 with $\text{bel}, \text{pl} : \mathcal{P}(W) \rightarrow [0, 1]$.

$bel^+(\phi) := bel(\phi ^+)$	and	$bel^-(\phi) := bel(\phi ^-)$
$pl^+(\phi) := pl(\phi ^+)$	and	$pl^-(\phi):=pl(\phi ^-)$

- What kind of two-dimensional reading of belief/plausibility can we propose?
- How can we interpret it?

Non-standard probabilities

Models: $(W, v^+, v^-, m : W \rightarrow [0, 1])$ $p^+(\phi) = \sum_{s \in |\phi|^+} m(s) \text{ and } p^-(\phi) = \sum_{s \in |\phi|^-} m(s)$

Immediate generalisation for belief.

Non-standard probabilities

Models:
$$(W, v^+, v^-, \text{bel} : \mathcal{P}(W) \to [0, 1])$$

bel⁺ $(\phi) = \sum_{X \subseteq |\phi|^+} m(X)$ and bel⁻ $(\phi) = \sum_{X \subseteq |\phi|^-} m(X)$

- $p^+(\phi)$, bel⁺(ϕ): the probability/belief that ϕ is true
- $p^{-}(\phi)$, bel⁻(ϕ): the probability/belief that ϕ is false
- bel⁺ is monotone and in [0, 1], it satisfies the axioms of belief functions instead of import-export: p⁺(φ ∧ ψ) + p⁺(φ ∨ ψ) = p⁺(φ) + p⁺(ψ).

Two-dimensional interpretation (2/2)

Models: $(W, v^+, v^-, \text{bel}, \text{pl} : \mathcal{P}(W) \rightarrow [0, 1])$

- Notice that in BD logic |φ| = (1, 1) reads as: there is evidence that φ is true and evidence that φ is false.
- In the classical case, bel(φ) = 1 pl(¬φ).
 → interpretation: pl(¬φ) is the degree of evidence against bel(φ) → (bel⁺(φ), pl⁻(φ))
 - $\rightarrow \text{pl}^-(\phi)$ maximum evidence against ϕ we can consider
- Consider both belief (bel⁺(φ), bel⁻(φ)) and plausibility (pl⁺(φ), pl⁻(φ)) independently
- If we ask bel(X) ≤ pl(X), for X ∈ P(W), then bel and pl come from different mass functions.

 \rightarrow one piece of evidence does not support belief and plausibility in the same manner.

 \rightarrow the same piece of evidence gives rise to two mass functions

e.g., circumstantial evidence vs. direct evidence

$$s_0$$
: s_1 : p s_2 : $\neg p$ s_3 : $p, \neg p$

Assume that $bel(X) \le pl(X)$ and $bel(|p \land \neg p|^+) = 1$.

Therfore, we have

$$\sum_{X \subseteq |p \wedge \neg p|^+} m_{bel}(X) = \sum_{X \subseteq \{s_3\}} m_{bel}(X) = m_{bel}(\emptyset) + m_{bel}(\{s_3\}) = 1.$$

$$m_{bel}(\emptyset) = 0, \text{ hence } m_{bel}(\{s_3\}) = 1.$$

We get

$$1 \le pl(|p \wedge \neg p|^+) = \sum_{X \not\subseteq |p \wedge \neg p|^-} m_{pl}(X) = \sum_{X \not\subseteq |p|^- \cup |p|^+} m_{pl}(X)$$

$$=\sum_{X \not\subseteq \{s_1, s_2, s_3\}} \mathsf{m}_{\mathsf{pl}}(X) = \mathsf{m}_{\mathsf{pl}}(S)$$

Therefore, evidence that is strongly persuasive considering $p \land \neg p$ is inconclusive regarding the plausibility of either *p* or $\neg p$.

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