From set relations to belief function relations

Sébastien Destercke, Frédéric Pichon, and John Klein

Sorbonne Universités, Université Technologique de Compiègne, CNRS, UMR 7253 - Heudiasyc, 57 Avenue de Landshut, Compiègne, France
Univ. Artois, EA 3926, Laboratoire de Génie Informatique et d'Automatique de l'Artois (LGI2A), Béthune, F-62400, France.
Univ. Lille, CNRS, Centrale Lille, UMR 9189 - CRIStAL - Centre de Recherche en Informatique Signal et Automatique de Lille, F-59000 Lille, France
sebastien.destercke@hds.utc.fr
frederic.pichon@univ-artois.fr
john.klein@univ-lille.fr

Abstract. In uncertainty theories, a common problem is to define how we can extend relations between sets (e.g., inclusion, ranking, consistency, . . .) to corresponding notions between uncertainty representations. Such definitions can then be used to perform the same operations as those that are done for sets: comparing information content, ordering alternatives or checking consistency, to name a few. In this paper, we propose a general way to extend set relations to belief functions, using constrained stochastic matrices to identify those belief functions in relation. We then study some properties of our proposal, as well as its connections with existing works focusing on specific relations.

Keywords: set relations, belief functions, specificity, ranking, consistency.

1 Introduction

One can define many relations between two (or more) subsets A, B of some finite set X, i.e. between elements of some boolean algebra $\left(2^X, \cap, \cup, .^C\right)$. Such relations can check whether the sets are consistent ($A \cap B \neq \emptyset$); whether one set is more informative than another, or implies it ($A \subseteq B$); when the space on which they are defined is ordered, whether one set is "higher" than another ($A \prec B$); etc. These relations can then be related to practical problems such as restoring consistency or ranking alternatives.

To address the same questions in those uncertainty theories that formally generalise set theory (based, e.g., on possibility distributions, belief functions or sets of probabilities [12]), it is desirable to carry over relations between sets to uncertainty representations. Given the higher expressiveness of such theories, the problem is ill-posed in the sense that there is not a unique way to do so. We can cite as a typical example the notion of inclusion between belief functions, that has many definitions [15]. Yet, the works that deal with such issues usually focus on extending one particular relation (e.g., inclusion, non-empty intersection) in meaningful ways.

In this paper, we propose a simple way to extend any set relation to an equivalent relation between belief functions, in the sense that the relation is exactly recovered when considering categorical belief functions (i.e., belief functions having a single focal element), that are equivalent to sets. Basically, for a pair of belief functions to be in relation, we require that there must exist at least one (left) stochastic matrix such that one of these belief functions is obtained as the dot product of the matrix with the other belief function. Additionally, the matrix is constrained to have null entries on pairs of focal sets not satisfying the relation to extend.

To our knowledge, no systematic ways of extending set relations has been proposed in the literature before, and while there may be other ways to perform such an extension, the presented solution has the advantage to be a formal extension (as the relation is exactly recovered for the case of sets), and to connect with other more specific proposals of the literature. The proposal is presented in Section 2, along with the necessary reminders. To which extent it can preserve properties of the initial relation, including its compatibility with (multivariate) functions, is studied in Sections 3 (properties on initial spaces) and 5 (compatibility property). To make the approach more concrete, Section 4 relates it to existing works on specific relations, while Section 6 illustrates the results by applying them to simple examples, sometimes inspired from applications (system reliability and multi-criteria decision making). Finally, Section 7 discusses a mean to make the relation no longer binary but gradual, building first connections to fuzzy relations.

2 Main proposal

This section recalls the basic tools that are necessary to understand this paper, and present our main proposal. The next sections will then focus on studying its properties and connection with other works.

2.1 Relations and their properties

Given some (here finite) space X, a relation $\mathbf{R}$ between subsets of X (i.e., on the power set 2^X) is just a subset $\mathbf{R} \subseteq 2^X \times 2^X$ that specifies which pair of subsets are related to each others. For convenience, we will write $A\mathbf{R}B$ whenever $(A, B) \in \mathbf{R}$, and $\neg A\mathbf{R}B$ whenever $(A, B) \notin \mathbf{R}$.

Example 1. As an illustration, let us consider the binary space $X = \{a, b\}$, and the strict inclusion relation $\mathbf{R} = \subset$. Then we have

$$\mathbf{R} = \{(\emptyset, \{a\}), (\emptyset, \{b\}), (\emptyset, \{a, b\}), (\{a\}, \{a, b\}), (\{b\}, \{a, b\})\}$$

and the fact that $(\{a\}, \{a, b\}) \in \mathbf{R}$ can be denoted $\{a\}\mathbf{R}\{a, b\}$. The fact that $(\{a\}, \{b\}) \notin \mathbf{R}$ is denoted $\neg\{a\}\mathbf{R}\{b\}$.

Such relations can have many different properties, the main ones that can be found in the literature being the following:

1. Symmetry: $\mathbf{R}$ is symmetric iff $A\mathbf{R}B \implies B\mathbf{R}A$ for all $A, B \subseteq X$
2. Antisymmetry: $\mathbf{R}$ is antisymmetric iff $A\mathbf{R}B \wedge B\mathbf{R}A \implies A = B$ for all $A, B \subseteq X$
3. Asymmetry: $\mathbf{R}$ is asymmetric iff $A\mathbf{R}B \implies \neg(B\mathbf{R}A)$ for all $A, B \subseteq X$
4. Reflexivity: $\mathbf{R}$ is reflexive iff $A\mathbf{R}A$ for all $A \subseteq X$
5. Irreflexivity: $\mathbf{R}$ is irreflexive iff $\neg(A\mathbf{R}A)$ for all $A \subseteq X$
6. Transitivity: $\mathbf{R}$ is transitive iff $A\mathbf{R}B \wedge B\mathbf{R}C \implies A\mathbf{R}C$ for all $A, B, C \subseteq X$
7. Completeness: $\mathbf{R}$ is complete, or total, iff $A\mathbf{R}B \vee B\mathbf{R}A$ for all $A, B \subseteq X$

In addition to those properties, more complex relations have been defined as combination of those properties, that play an important role in many problems. These are, for instance, equivalence relations as well as order relations of different types. They are summarised in Table 1, together with the properties they satisfy.

Name	1	2	3	4	5	6	7
Tolerance	✓			✓			
Partial equivalence	✓					✓	
Equivalence	✓			✓		✓	
Preorder				✓		✓	
Total Preorder				✓		✓	✓
Partial order		✓		✓		✓	
Total order		✓		✓		✓	✓

Table 1. Complex relations

2.2 Belief functions

Belief functions or their equivalent representations as mathematical tools can be traced back at least to Choquet [4], but their use as uncertainty representation was popularised first by Dempster [6] and Shafer [27], before being used by Smets [29] in his Transferable Belief Model.

Their mathematical properties makes them interesting uncertainty models, as they generalise a number of uncertainty representations [9] (possibility measures, sets of cumulative distributions, probabilities), while remaining of limited complexity when compared to more complex models such as lower previsions or desirable gambles [7].

Formally, a belief function on a finite space $X = \{x_1, \ldots, x_K\}$ is in one-to-one correspondence with a mass function $m : 2^X \to [0, 1]$ that satisfies $\sum_{A \subseteq X} m(A) = 1$. From such a mass function, the belief and plausibility of an event $A \subseteq X$ respectively read

$$Bel(A) = \sum_{\emptyset \neq E \subseteq A} m(E) \text{ and } Pl(A) = \sum_{E \cap A \neq \emptyset} m(E). \tag{1}$$

If $m(\emptyset) = 0$, they can be interpreted as bounds of the probability $P(A)$ of A, inducing the probability set

$$\mathcal{P} = \{P : Bel(A) \leq P(A) \leq Pl(A), \forall A \subseteq X\}. \tag{2}$$

Within this latter interpretation and in contrast with the works set within the so-called Dempster-Shafer theory, the mass function is not a central tool, but merely a possible transformation of the lower envelope of $\mathcal{P}$ given by the belief function. As the mass function m plays a fundamental role in our proposal, the current work is more in-line with the Dempster-Shafer interpretation of belief functions, however it does not prevent it to have links with an imprecise probabilistic interpretation.

We denote by $\mathcal{B}^X$ the set of all belief functions on X. A particularly interesting subclass of belief functions for this study are categorical ones. A categorical mass function, denoted m_B, is such that $m_B(B) = 1$.

2.3 Extending set relations to belief functions

Let $\mathbf{R}$ be a relation on 2^X (equivalently a subset of $2^X \times 2^X$). We then propose the following simple definition to extend this relation to belief functions, i.e. into a relation on $\mathcal{B}^X$:

Definition 1. *Given two mass functions m_1, m_2 and a subset relation $\mathbf{R}$, we say that $m_1 \tilde{\mathbf{R}} m_2$ iff there is a (left)*[1] *stochastic matrix S such that $\forall A, B \subseteq X$*

$$m_1(A) = \sum_{B \subseteq X} S(A, B) m_2(B) \tag{3}$$

$$\textit{with } S(A, B) > 0 \ \wedge \ m_2(B) > 0 \implies A\mathbf{R}B. \tag{4}$$

Definition 1 states that $m_1 \tilde{\mathbf{R}} m_2$ iff m_1 can be obtained from m_2 by transferring each mass $m_2(B)$ to a subset A such that $A\mathbf{R}B$. It is easily checked that $\tilde{\mathbf{R}}$ is a generalisation of $\mathbf{R}$ in the sense that

$$m_A \tilde{\mathbf{R}} m_B \Leftrightarrow A\mathbf{R}B, \ \forall A, B \subseteq X. \tag{5}$$

Indeed, if $A\mathbf{R}B$, we can choose $S(E, F) = m_A(E)$ for all $F \subseteq X$, and this matrix matches the conditions of Definition 1, hence $m_A \tilde{\mathbf{R}} m_B$. Conversely, if $m_A \tilde{\mathbf{R}} m_B$, then (3) implies $S(A, B) = 1$ and (4) then gives $A\mathbf{R}B$.

Also, there is only one relation $\tilde{\mathbf{R}}$ on belief functions spanned by Definition 1 from a given set relation $\mathbf{R}$. To see this, suppose two such belief function relations exist. If a matrix matching the conditions of Definition 1 was found for the first one then the same matrix also works for the other and the relations are equivalent. Likewise, two relations $\mathbf{R}$ and $\mathbf{R}'$ defined on sets cannot lead, through Definition 1, to the same relation $\tilde{\mathbf{R}}$ on belief functions. This is an immediate consequence of (5). Consequently and by a small abuse of notation, we will use

[1] We use left-stochasticity only throughout the paper.

the same notation for a relation $\mathbf{R}$ on the subset or belief function side in the remainder of the paper, as it introduces no ambiguity. However, in general, the stochastic matrix S involved in Definition 1 is not unique when $m_1\tilde{\mathbf{R}}m_2$ holds.

Definition 1 is inspired from previous works on specificity of belief functions [15, 16, 30], as well as on recent proposals dealing with set ordering [24]. In particular, Definition 1 can be endowed with an interpretation similar to the one given in [15], as $S(A, B)$ can be seen as the ratio of $m(B)$ that flows from B to A, with the flow being possibly non-null only when $A\mathbf{R}B$.

Remark 1. Readers that are familiar with the belief function literature may wonder why the condition $m_2(B) > 0$ is necessary in (4), as this condition does not appear in related works. This condition is necessary to generalise any relation on sets that is not inverse serial, i.e. a relation such that there is a B_* with $\neg(A\mathbf{R}B_*), \forall A \subseteq X$. For such sets B_*, left stochasticity is incompatible with the implication $S(A, B_*) > 0 \implies A\mathbf{R}B_*$, and without checking $m_2(B) > 0$ in Definition 1 the relation on belief functions of a not inverse serial $\mathbf{R}$ would always be empty. By checking $m_2(B) > 0$ in Definition 1, we can induce a non empty relation on belief functions. When B_* is a focal element of m_2, we have $\neg(m_1\mathbf{R}m_2)$, which makes perfect sense. When $m(B_*) = 0$, then a null mass can be distributed to any set A without harm.

As the above mentioned related works dealt with directional, or rather asymmetric relations, Definition 1 is naturally asymmetric. However, Proposition 1 shows that it has a somehow symmetric counterpart.

Proposition 1. *Consider two mass functions m_1, m_2 and a belief function relation $\mathbf{R}$. Then the two following conditions are equivalent:*

1. *there is a stochastic matrix $S(A, B)$ such that*

$$m_1(A) = \sum_{B \subseteq X} S(A, B) m_2(B),$$
$$\text{with } S(A, B) > 0 \wedge m_2(B) > 0 \implies A\mathbf{R}B.$$

2. *there is a joint mass function $m_{12}(A, B)$ on $2^X \times 2^X$ such that*

$$m_{12}(A, B) > 0 \implies A\mathbf{R}B, \tag{6}$$
$$m_1(A) = \sum_B m_{12}(A, B), \tag{7}$$
$$m_2(B) = \sum_A m_{12}(A, B). \tag{8}$$

Proof. 1. $\implies$ 2. First, consider the matrix $S(A, B)$, that we know exists if $m_1\mathbf{R}m_2$. Let us now simply define the joint m_{12} as

$$m_{12}(A, B) = m_2(B)S(A, B) \text{ for any } A, B.$$

We clearly have $m_{12}(A,B) > 0$ only if $A\mathbf{R}B$, since $S(A,B) > 0$ means that either $A\mathbf{R}B$ or $m_2(B) = 0$ (in the other cases it is null), and moreover

$$\sum_B m_{12}(A,B) = \sum_B m_2(B)S(A,B) = m_1(A),$$

$$\sum_A m_{12}(A,B) = \sum_A m_2(B)S(A,B) = m_2(B)\sum_A S(A,B) = m_2(B)$$

with the last equality following from S being stochastic.

2. $\implies$ 1. Again, consider the joint $m_{12}(A,B)$ satisfying constraints (6)-(8), that we know exists by assumption. If we assume that this implies the existence of matrix S, we get

$$m_1(A) = \sum_B m_{12}(A,B) = \sum_B m_2(B)S(A,B).$$

For any B s.t. $m_2(B) > 0$, we thus define

$$S(A,B) = \frac{m_{12}(A,B)}{m_2(B)}. \tag{9}$$

The other entries of S are set to arbitrary values provided that these latter are compliant with left stochasticity. For those entries which are set according to (9), i.e. when $m_2(B) > 0$, we can now check that $S(A,B)$ satisfies the required properties, as

$$\sum_A S(A,B) = \frac{\sum_A m_{12}(A,B)}{m_2(B)} = \frac{m_2(B)}{m_2(B)} = 1,$$

$$S(A,B) > 0 \Leftrightarrow \frac{m_{12}(A,B)}{m_2(B)} > 0 \Rightarrow A\mathbf{R}B$$

□

This proposition shows, in particular, that any stochastic matrix S can be associated to a unique joint mass function m_{12}, and vice-versa. Also note that, using a transformation similar to the one of the second part of the proof, we can alternatively build a stochastic matrix S' such that

$$S'(B,A) = \begin{cases} \frac{m_{12}(A,B)}{m_1(A)} & \text{if } m_1(A) > 0 \\ \lambda_B^{(A)} & \text{if } m_1(A) = 0 \end{cases},$$

with $\sum_B \lambda_B^{(A)} = 1$. S' is such that

$$m_2(B) = \sum_{A \subseteq X} S'(B,A)m_1(A).$$

Moreover, $S'(A,B) > 0$ and $m_1(A) > 0$ imply $B\mathbf{R}A$ but gives no guarantee on $A\mathbf{R}B$.

Remark 2. Proposition 1 shows that we can view our definition of relations in two different ways: as a "transfer" matrix S allowing to go from m_2 to m_1 without violating the relation on sets, or as the existence of a joint structure consistent with m_1, m_2 and the relation $\mathbf{R}$. Although we consider that the joint structure is more intuitive and easier to explain, both views have been adopted in the past and are in our opinion useful, as:

- there are settings where one mathematical tool is more natural then the other. For instance, Smets' matrix computations [28] make a heavy use of the first view, while recent works about consistency adopt the second view [11];
- mathematically, it may also be more convenient to use one or the other, for instance in proofs. For example, most of our negative proofs and examples use joint matrices and the second view, but Propositions 7 and 10 are simpler to prove using the first view.

Finally, let us note that the relation $\mathbf{R}$ on belief functions can be interpreted in exactly the same way as the relation on sets it extends, this interpretation varying according to the application and pursued goal. For instance, the relation $A\mathbf{R}B$ iff $A \cap B \neq \emptyset$ will often be used when A, B concern the same object of interests but are issued from different sources, and when one wants to check whether they are consistent. In contrast, ranking relations between A, B will often be used when A, B concern different objects or alternatives evaluated on the same scale (e.g., movies given a finite number of stars). Generally speaking, mass functions are random set distributions [26] and relation $\mathbf{R}$ is one way to propagate a relation (and its interpretation) on sets to their random counterparts.

3 Property preservation

3.1 Preservation of simple properties

We may now wonder how many of the initial relation $\mathbf{R}$ properties between sets are preserved when extended to belief functions according to Definition 1. We will now provide a series of results for common properties, either by providing proofs or counter-examples. We will keep the proposition/proof format, to provide a uniform presentation.

Proposition 2 (Preserved symmetry). *If* $\mathbf{R}$ *is symmetric on sets, it is so on belief functions:*

$$m_1 \mathbf{R} m_2 \implies m_2 \mathbf{R} m_1, \forall m_1, m_2.$$

Proof. Let us assume that $S(A, B)$ is a stochastic matrix satisfying Definition 1 for $m_1 \mathbf{R} m_2$, and m_{12} is its associated joint mass. Then we can see that

$$S'(A, B) > 0 \text{ and } m_1(A) > 0 \implies B\mathbf{R}A \Leftrightarrow A\mathbf{R}B,$$

since $\mathbf{R}$ is symmetric. Matrix S' satisfies the conditions of Definition 1, hence $m_2 \mathbf{R} m_1$. □

Proposition 3 (Unpreserved antisymmetry). *If* $\mathbf{R}$ *is antisymmetric on sets, it is not necessarily so on belief functions, as*

$$m_1\mathbf{R}m_2 \wedge m_2\mathbf{R}m_1 \not\Rightarrow m_2 = m_1$$

Proof. Consider two mass functions that are positive only on subsets A, B, C and such that

$$m_1(A) = 0.3,\ m_1(B) = 0.5,\ m_1(C) = 0.2,$$
$$m_2(A) = 0.4,\ m_2(B) = 0.3,\ m_2(C) = 0.3,$$

as well as the antisymmetric relation $\mathbf{R}$ on those subsets summarised by the matrix

$$\begin{array}{c} \\ A \\ B \\ C \end{array} \begin{array}{c} \begin{array}{ccc} A & B & C \end{array} \\ \begin{bmatrix} A\mathbf{R}A & A\mathbf{R}B & \\ & B\mathbf{R}B & B\mathbf{R}C \\ C\mathbf{R}A & & C\mathbf{R}C \end{bmatrix} \end{array}.$$

We can then consider the joint mass function

$$m_{12}(A, A) = 0.3,\ m_{12}(B, B) = 0.3,$$
$$m_{12}(B, C) = 0.2, m_{12}(C, A) = 0.1,\ m_{12}(C, C) = 0.1,$$

that shows that we have $m_1\mathbf{R}m_2$, while the joint mass function

$$m_{12}(A, A) = 0.2,\ m_{12}(B, B) = 0.3,$$
$$m_{12}(A, C) = 0.1, m_{12}(B, A) = 0.2,\ m_{12}(C, C) = 0.2,$$

shows that $m_2\mathbf{R}m_1$, hence we can have both without $m_1 = m_2$. □

Proposition 4 (Unpreserved asymmetry). *If* $\mathbf{R}$ *is asymmetric on sets, it is not necessarily so on belief functions, as*

$$m_1\mathbf{R}m_2 \not\Rightarrow \neg(m_2\mathbf{R}m_1)$$

Proof. Simply consider two mass functions m_1, m_2 that are positive only on subsets A, B, C, D, E and such that

$$m_1(A) = 0.2,\ m_1(B) = 0.3,\ m_1(C) = 0.2,\ m_1(D) = 0.1,\ m_1(E) = 0.2,$$

$$m_2(A) = 0.2,\ m_2(B) = 0.1,\ m_2(C) = 0.3,\ m_2(D) = 0.3,\ m_2(E) = 0.1$$

as well as the asymmetric relation $\mathbf{R}$ on those subsets summarised by the matrix

$$\begin{array}{c} \\ A \\ B \\ C \\ D \\ E \end{array} \begin{array}{c} \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{bmatrix} & & A\mathbf{R}C & A\mathbf{R}D & \\ B\mathbf{R}A & & & & B\mathbf{R}E \\ & C\mathbf{R}B & & C\mathbf{R}D & \\ & D\mathbf{R}B & & & D\mathbf{R}E \\ E\mathbf{R}A & & E\mathbf{R}C & & \end{bmatrix} \end{array}$$

We can then consider the joint mass function

$$m_{12}(A,C) = 0.1,\ m_{12}(A,D) = 0.1,\ m_{12}(B,A) = 0.2$$
$$m_{12}(B,E) = 0.1, m_{12}(C,D) = 0.2,\ m_{12}(D,B) = 0.1,\ m_{12}(E,C) = 0.2$$

that shows that we have $m_1\mathbf{R}m_2$, while the joint mass function

$$m_{12}(A,B) = 0.1,\ m_{12}(A,E) = 0.1,\ m_{12}(B,C) = 0.2$$
$$m_{12}(B,D) = 0.1, m_{12}(C,A) = 0.2,\ m_{12}(D,C) = 0.1,\ m_{12}(E,D) = 0.2$$

shows that $m_2\mathbf{R}m_1$, hence we can have both. □

Proposition 5 (Preserved reflexivity). *If* $\mathbf{R}$ *is reflexive on sets, it is so on belief functions:*

$$\forall m, \text{ we have } m\mathbf{R}m$$

Proof. Simply observe that, if $\mathbf{R}$ is reflexive ($A\mathbf{R}A$ for any subset) and if $m_1 = m_2 = m$, we can always define the joint mass function such that for any A we have $m_{12}(A,A) = m(A)$, that satisfies Equations (6)-(8). □

Proposition 6 (Unpreserved irreflexivity). *If* $\mathbf{R}$ *is irreflexive on sets, it is not necessarily so on belief functions, as we may have* $m\mathbf{R}m$ *for some* $m \in \mathcal{B}^X$.

Proof. Consider the following mass function

$$m(A) = 0.5, m(B) = 0.5$$

and the relation $\mathbf{R}$ summarised in the following matrix

$$\begin{array}{c} \\ A \\ B \end{array} \begin{array}{c} \begin{array}{cc} A & B \end{array} \\ \begin{bmatrix} & A\mathbf{R}B \\ B\mathbf{R}A & \end{bmatrix} \end{array}$$

which is irreflexive. However, the joint $m(A,B) = m(B,A) = 0.5$ shows that we have $m\mathbf{R}m$, hence $\mathbf{R}$ may not be irreflexive for belief functions. □

Proposition 7 (Preserved transitivity). *If* $\mathbf{R}$ *is transitive on sets, it is so on belief functions:*

$$m_1\mathbf{R}m_2 \wedge m_2\mathbf{R}m_3 \implies m_1\mathbf{R}m_3$$

Proof. If we have $m_1\mathbf{R}m_2 \wedge m_2\mathbf{R}m_3$, this means that there are two matrices S_{12} and S_{23} satisfying Definition 1 and such that

$$m_1(A) = \sum_B S_{12}(A,B)m_2(B),$$

$$m_2(B) = \sum_C S_{23}(B,C)m_3(C).$$

We therefore have

$$\begin{aligned} m_1(A) &= \sum_B S_{12}(A,B) \sum_C S_{23}(B,C) m_3(C) \\ &= \sum_B \sum_C S_{12}(A,B) S_{23}(B,C) m_3(C) \\ &= \sum_C m_3(C) \sum_B S_{12}(A,B) S_{23}(B,C) \end{aligned}$$

Now, let us define the matrix S_{13} elements as

$$S_{13}(A,C) = \sum_B S_{12}(A,B) S_{23}(B,C),$$

meaning that $S_{13} = S_{12} \cdot S_{23}$ is the result of a matrix product. One can then show that S_{13} satisfies Definition 1 and that $m_1 \mathbf{R} m_3$ as

- S_{13} is stochastic, being the product of stochastic matrices ;
- we have that

$$\begin{aligned} S_{13}(A,C) > 0 &\Leftrightarrow \exists (A,B) \text{ and } (B,C) \text{ s.t. } S_{12}(A,B) S_{23}(B,C) > 0 \\ &\Rightarrow A\mathbf{R}B \wedge B\mathbf{R}C \\ &\Rightarrow A\mathbf{R}C. \end{aligned}$$

□

Proposition 8 (Unpreserved completeness). *If $\mathbf{R}$ is complete (or total) on sets, it is not necessarily so on belief functions: for any two m_1, m_2 we may have neither $m_1 \mathbf{R} m_2$ nor $m_2 \mathbf{R} m_1$.*

Proof. Consider the relation $\mathbf{R}$ =“having a lower cardinality than” on the space $X = \{a,b,c\}$, meaning that $A\mathbf{R}B \Leftrightarrow |A| \leq |B|$, which is a complete relation on sets. Consider now the two mass functions

$$m_1(\{a\}) = 0.6, \quad m_1(\{a,b\}) = 0.4,$$

$$m_2(\{a\}) = 0.8, \quad m_2(X) = 0.2.$$

Then, we have neither $m_1 \mathbf{R} m_2$, nor $m_2 \mathbf{R} m_1$, as indeed all stochastic matrices such that $m_1 = S \cdot m_2$ or $m_2 = S \cdot m_1$ must contain non-null value on pairs of subsets A, B with $\neg(A\mathbf{R}B)$. Consider for instance the case

$$m_1 : \begin{matrix} \{a\} \\ \{a,b\} \\ X \end{matrix} \begin{pmatrix} 0.6 \\ 0.4 \\ 0 \end{pmatrix} = \begin{pmatrix} 3/4 & 0 & 0 \\ \mathbf{1/4} & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} 0.8 \\ 0 \\ 0.2 \end{pmatrix} : m_2.$$

We only display the submatrix of S corresponding to focal elements of the mass functions. Entries in green can be set to either 0 or some positive number. Entries in red cannot be assigned a positive number. It is clear that at least some non-null value must be given to $S(\{a,b\},\{a\})$, hence $\neg m_1 \mathbf{R} m_2$. A similar observation can be made for the reverse case.

□

The expected cardinality [17] of a belief function, defined as

$$C(m) = \sum_{A \subseteq X} m(A)|A|,$$

yields a complete relation between belief functions that is a generalisation of the relation **R** defined in the above proof. This is therefore also an illustration that not all binary relations on belief functions can be retrieved via the mechanism under study.

Table 2 summarises our obtained results so far, and in particular which properties existing on subsets is guaranteed to be preserved when considering them on the richer language of belief functions. It should be noted that even if a property is not guaranteed to be preserved in general, it may be preserved in specific cases: for instance, the inclusion relation is antisymmetric, and its generalisation to belief functions, called specialisation [15], is too. The same remark is true for strict inclusion, that is asymmetric. We will see later on that all partial orders (among which inclusion) are in fact preserved by Definition 1.

$\mathbf{R}$ on 2^X is	$\Longrightarrow$ $\mathbf{R}$ on $\mathcal{B}^X$ is
Symmetric	Yes
Antisymmetric	No
Asymmetric	No
Reflexive	Yes
Irreflexive	No
Transitive	Yes
Complete	No

Table 2. Summary of properties preservation

Finally, we can also consider two different binary relations $\mathbf{R}$ and $\mathbf{R}'$ and check whether a property for this pair of relations is preserved. There is mainly one such property which is implication.

Proposition 9 (Preserved implication). *If* $\mathbf{R}$ *and* $\mathbf{R}'$ *are such that* $A\mathbf{R}B \Rightarrow A\mathbf{R}'B$ *for any subsets* A *and* B*, it is so on belief functions.*

Proof. Let m_1 and m_2 denote two mass functions and S is a stochastic matrix compliant with definition 1 for relation $\mathbf{R}$. Obviously, S is also compliant with definition 1 for relation $\mathbf{R}'$ because when $m_2(B) > 0$, then $S(A, B) > 0 \Rightarrow A\mathbf{R}B \Rightarrow A\mathbf{R}'B$.

3.2 Preservation of classical relations

In this section, we study whether some classical relations composed of multiple properties are preserved by our definition. We will limit ourselves to the relations recalled in Table 1, as those are the most common, but clearly others could be studied, such as specific order relations (semi-orders, interval orders, tournaments, ...) [19].

A very first remark is that, if the relation is defined by a set of properties that are all preserved by our definition, then it is immediate that it is preserved when considering it on belief functions. Among other things, this means that

- Tolerance relations
- (Partial) Equivalence relations
- Preorder relations

are preserved when extended to belief functions. However, total preorders are usually not preserved when extended to belief functions. A simple example is given in the proof of Proposition 8. In this proof we examine the relation "having a lower cardinality than" which is a total preorder on sets while the induced relation on belief functions fails to be complete.

Moreover, it is easy to see that total orders are not preserved either, as any refinement of the relation "having a lower cardinality than" into a total order would constrain even more the element on which the stochastic matrix has to be positive. Another very common class of binary relations on sets are partial orders, for which we can show that they are preserved:

Proposition 10 (Preserved partial order). *If* $\mathbf{R}$ *is a partial order on sets, it is so on belief functions.*

See Appendix A for a proof of the above proposition.

4 Related works

4.1 Inclusion and consistency

In the case where the relations are either inclusion or consistency, then we retrieve well-known results of the literature:

- in the case of inclusion we have $A\mathbf{R}B$ iff $A \subseteq B$, and Definition 1 is then essentially equivalent to that of specialisation [15]. The only difference amounts to checking if $m_2(B) > 0$ in condition (4), that we need to handle generic relations, but that is not needed in the specific case of specialisation (as in this case, for any B there is always a subset A such that $A\mathbf{R}B$). Beyond this difference, the notion of specialisation and the extension of inclusion to belief functions proposed in this paper are actually formally equivalent in the sense that for any mass functions m_1 and m_2, m_1 is a specialisation of m_2 if and only if $m_1\mathbf{R}m_2$.
- in the case of consistency, we have $A\mathbf{R}B$ iff $A \cap B \neq \emptyset$, and one can see that $m_1\mathbf{R}m_2$ iff there is a joint mass assigning positive mass to pairs of sets having a non-empty intersection. This is equivalent to require $\mathcal{P}_1 \cap \mathcal{P}_2 \neq \emptyset$, with $\mathcal{P}_i$ the probability set induced by m_i [3].

4.2 Rankings

When the space $X = \{x_1, \dots, x_n\}$ is ordered (with $x_i \leq x_{i+1}$) and possibly infinite, it makes sense to consider relations of the kind "higher than" in order to compare sets. There are many ways to rank two sets A, B, such as:

- Single-bound dominance, that can be declined itself into four notions:
  - loose dominance: $A\mathbf{R}_{\leq_{LD}}B$ if $\min A \leq \max B$
  - lower bound: $A\mathbf{R}_{\leq_{LB}}B$ if $\min A \leq \min B$
  - upper bound: $A\mathbf{R}_{\leq_{UP}}B$ if $\max A \leq \max B$
  - strict dominance: $A\mathbf{R}_{\leq_{SD}}B$ if $\max A \leq \min B$
- Pairwise-bound or lattice dominance: $A\mathbf{R}_{\leq_{PD}}B$ if $\min A \leq \min B$ and $\max A \leq \max B$, whose extension to belief functions studied in [24] correspond to our proposal.

Extensions of this kind of relations to belief functions have already been investigated in [24], and are connected to the extensions of stochastic dominance explored in [8] for belief functions, and in [25] for the general case of sets of cumulative distributions. In fact, let us first define the following stochastic dominance notions:

- stochastic loose dominance:

$$m_1 \prec_{LD}^{St} m_2 \text{ iff } Pl_1([x_1, \dots, x_i]) \geq Bel_2([x_1, \dots, x_i]), \forall x_i \in X$$

- stochastic lower bound:

$$m_1 \prec_{LB}^{St} m_2 \text{ iff } Pl_1([x_1, \dots, x_i]) \geq Pl_2([x_1, \dots, x_i]), \forall x_i \in X$$

- stochastic upper bound:

$$m_1 \prec_{UB}^{St} m_2 \text{ iff } Bel_1([x_1, \dots, x_i]) \geq Bel_2([x_1, \dots, x_i]), \forall x_i \in X$$

- stochastic strict dominance:

$$m_1 \prec_{SD}^{St} m_2 \text{ iff } Bel_1([x_1, \dots, x_i]) \geq Pl_2([x_1, \dots, x_i]), \forall x_i \in X$$

- stochastic lattice dominance:

$$m_1 \prec_{PD}^{St} m_2 \text{ iff } (m_1 \prec_{LB}^{St} m_2) \wedge (m_1 \prec_{UB}^{St} m_2)$$

We then have the following strong relationships between the extensions of ranking to belief functions and the stochastic dominance relations:

Proposition 11. *For $y \in \{LD, LB, UB, SD\}$, we have that*

$$m_1\mathbf{R}_{\leq_y}m_2 \Leftrightarrow m_1 \preceq_y^{St} m_2$$

Proof. We will only demonstrate the relation for one of the y, that is SD (the strongest relation), as proofs for the other cases are analogous.

$\Leftarrow$ First, let us remind that if $m_1 \prec_{SD}^{St} m_2$, it means that the cumulative distribution induced by the minimal values of the focal elements of m_2 stochastically dominates the one induced by the maximal values of m_1. Let us denote $A_1, \ldots, A_n$ and $B_1, \ldots, B_m$ the focal sets of m_1, m_2, and assume without loss of generality that they are ordered according to their maximal values for m_1, and their minimal values for m_2, that is $\max A_i \leq \max A_{i+1}$ for any $i = 1, \ldots, n-1$ and $\min B_i \leq \min B_{i+1}$ for any $i = 1, \ldots, m-1$.

Let us denote by $\alpha_i = \sum_{j=1}^{i} m_1(A_j)$ and $\beta_i = \sum_{j=1}^{i} m_2(B_j)$ the cumulated weights of the first i elements of m_1 and m_2, assuming all α_i, β_i are all distinct for easiness. We denote by

$$\gamma_1, \ldots, \gamma_{n+m-1} = \{\alpha_1, \ldots, \alpha_n\} \cup \{\beta_1, \ldots, \beta_m\}$$

the union of all distinct possible cumulative values of masses, assuming that they are also ordered, i.e., $\gamma_i \leq \gamma_{i+1}$ (we have $m + n - 1$ distinct values because $\alpha_n = \beta_m = 1$). Let us now define the following joint mass function m_{12} such that, for any $i = 1, \ldots, m + n - 1$,

$$m_{12}(A_{\gamma_i}, B_{\gamma_i}) = \gamma_i - \gamma_{i-1}$$

with $\gamma_0 = 0$, and the following definitions for the focal sets:

$$A_{\gamma_i} = \{A_i : (\sum_{j=1}^{i} m_1(A_j) \geq \gamma_i) \wedge (\sum_{j=1}^{i-1} m_1(A_j) < \gamma_i)\},$$

$$B_{\gamma_i} = \{B_i : (\sum_{j=1}^{i} m_2(B_j) \geq \gamma_i) \wedge (\sum_{j=1}^{i-1} m_2(B_j) < \gamma_i)\},$$

that by construction satisfy Equations (7)-(8). The construction is illustrated in Figure 1 for the case of $n = 3$ and $m = 2$. This comes down to construct the joint mass in a level-wise manner, and since we also have that $m_1 \prec_{SD}^{St} m_2$, we have that for any i, $\max A_{\gamma_i} \leq \min B_{\gamma_i}$, hence $A_{\gamma_i} \mathbf{R}_{\leq_{SD}} B_{\gamma_i}$

$\Rightarrow$ if $m_1 \mathbf{R}_{\leq_{SD}} m_2$, this means that there is a joint $m_{12}(A, B)$ that is positive only if $\max A \leq \min B$. Let us now show that this implies, for any $x_i \in X$,

$$Bel_1([x_1, \ldots, x_i]) \geq Pl_2([x_1, \ldots, x_i]),$$

which is equivalent to

$$\sum_{A: \max A \leq x_i} m_1(A) \geq \sum_{B: \min B \leq x_i} m_2(B).$$

Using the relation between m_{12}, m_1 and m_2, we get

$$\sum_{A: \max A \leq x_i} \sum_{B} m_{12}(A, B) \geq \sum_{B: \min B \leq x_i} \sum_{A} m_{12}(A, B)$$

but since $m_{12}(A,B) > 0$ only if $\max A \leq \min B$, we can write

$$\sum_{A:\max A \leq x_i} \sum_{B} m_{12}(A,B) \geq \sum_{B:\min B \leq x_i} \sum_{A:\max A \leq x_i} m_{12}(A,B)$$

as all the elements on the right-hand side summation are also in the left-hand side, this latter can only be bigger. □

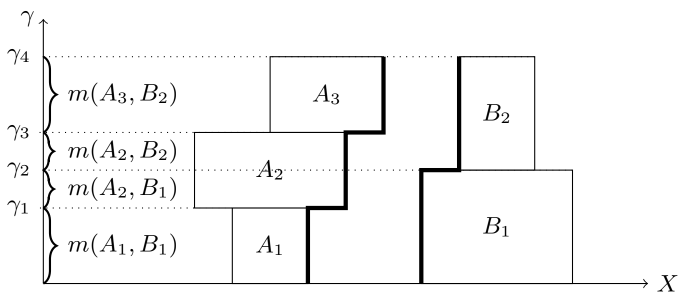

Fig. 1. Illustration of proof of Proposition 11 (construction of joint mass).

The above proposition shows a clear relation between ranking relations (when extended according to Definition 1) and the corresponding stochastic dominance relation. While this confirms the interest of our proposal and its links with existing, more specific works, this also provides an efficient computational way to check whether m_1, m_2 are in a ranking relation, as checking stochastic dominance is easier than checking whether a relation holds (which can be done by solving a linear programming problem, as suggested in Section 7).

The next example however shows that the property is not true for pairwise bounds, essentially because focal elements are usually not totally ordered with respect to pairwise bounds.

Example 2. Let us consider the space $X = \{x_1, \ldots, x_{12}\}$ and the two following mass functions

$$m_1(\{x_1,.,x_7\} = A_1) = 1/3, \quad m_2(\{x_2,.,x_{12}\} = B_1) = 1/3,$$

$$m_1(\{x_3,.,x_9\} = A_2) = 1/3, \quad m_2(\{x_4,.,x_8\} = B_2) = 1/3,$$

$$m_1(\{x_5,.,x_{11}\} = A_3) = 1/3, \quad m_2(\{x_6,.,x_{10}\} = B_3) = 1/3.$$

The pairs of sets satisfying the relation $\mathbf{R}_{\leq_{PD}}$ is summarised in the matrix

$$\begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \end{array} \begin{array}{c} \begin{array}{ccc} B_1 & B_2 & B_3 \end{array} \\ \begin{bmatrix} \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} \\ & & \mathbf{R}_{\leq_{PD}} \\ & & \end{bmatrix} \end{array}$$

which shows that there are no m_{12} for which $m_1\mathbf{R}_{\leq_{PD}}m_2$, since at least a positive number must be put on the third row. However, we do have $m_1 \prec_{PD}^{St} m_2$, as the bounds of each focal elements, once increasingly re-ordered separately, satisfy the pairwise dominance notion.

However, that the converse holds (if $m_1\mathbf{R}_{\leq_{PD}}m_2$, then $m_1 \prec_{PD}^{St} m_2$) has been shown in [24]. Finally, from Proposition 9 and the existing implications between the different rankings, we can easily conclude that:

$$m_1\mathbf{R}_{\leq_{SD}}m_2 \Rightarrow m_1\mathbf{R}_{\leq_{PD}}m_2 \Rightarrow \left\{ \begin{matrix} m_1\mathbf{R}_{\leq_{UB}}m_2 \\ m_1\mathbf{R}_{\leq_{LB}}m_2 \end{matrix} \right\} \Rightarrow m_1\mathbf{R}_{\leq_{LD}}m_2 \tag{10}$$

5 Preservation through functional mapping

5.1 Univariate functions

This section investigates whether a function that is compatible (in the sense of Definition 2 below) with set relations given respectively on its domain and codomain, is also compatible with the extensions of these relations to belief functions. We consider first the case of univariate functions; multivariate functions are handled in Section 5.2.

Let f be some function with domain X and codomain Y, i.e., $f : X \to Y$. We recall that the image $f(A)$ of some subset $A \subseteq X$ under f is the subset $f(A) = \{f(x) : x \in A\} \subseteq Y$. More generally, the image $f(m)$ of some mass function $m \in \mathcal{B}^X$ under f is the mass function $f(m) \in \mathcal{B}^Y$ defined, for all $B \subseteq Y$, as

$$f(m)(B) = \sum_{f(A)=B} m(A). \tag{11}$$

Definition 2. *Let $f : X \to Y$. Let $\mathbf{R}^X$ and $\mathbf{R}^Y$ be relations on 2^X and 2^Y, respectively. The function f is said to be $(\mathbf{R}^X; \mathbf{R}^Y)$-compatible if*

$$A\mathbf{R}^X B \Rightarrow f(A)\mathbf{R}^Y f(B), \forall A, B \subseteq X.$$

Example 3. Let $\mathbf{R}_{\subseteq}^X$ be the relation corresponding to inclusion on X, i.e., $A\mathbf{R}_{\subseteq}^X B$ iff $A \subseteq B$, $A, B \subseteq X$. Similarly, let $\mathbf{R}_{\subset}^X$ and $\mathbf{R}_{\cap}^X$ denote the relations corresponding, respectively, to strict inclusion and consistency on X, and let $\mathbf{R}_{\subseteq}^Y$ denote inclusion on Y.

Since for any function f and any $A, B \subseteq X$ such that $A \subseteq B$ it holds that $f(A) \subseteq f(B)$, any function f is $(\mathbf{R}^X_\subseteq; \mathbf{R}^Y_\subseteq)$-compatible. Similarly, any function f is $(\mathbf{R}^X_\subset; \mathbf{R}^Y_\subseteq)$-compatible.

However, not all functions f are $(\mathbf{R}^X_\cap; \mathbf{R}^Y_\subseteq)$-compatible. For instance, if f is a constant function, i.e. $f(x) = y$ for some $y \in Y$ and all $x \in X$, then f is $(\mathbf{R}^X_\cap; \mathbf{R}^Y_\subseteq)$-compatible (in this case we have $f(A) \subseteq f(B)$ for all $A, B \subseteq X$ such that $A \cap B \neq \emptyset$ since $f(A) = f(B) = \{y\}$). However, if f is the identity function, i.e. $X = Y$ and $f(x) = x$ for all $x \in X$, then f is not $(\mathbf{R}^X_\cap; \mathbf{R}^Y_\subseteq)$-compatible (in this case $f(A) = A$ for all $A \subseteq X$ and in general $A \cap B \neq \emptyset \not\Rightarrow A \subseteq B$, $A, B \subseteq X$).

Similarly, let X and Y be two ordered spaces and let $\mathbf{R}^X_{\leq_{PD}}$ and $\mathbf{R}^Y_{\leq_{PD}}$ be the relations corresponding to pairwise-bound dominance on X and on Y, respectively. Then, not all functions f are $(\mathbf{R}^X_{\leq_{PD}}; \mathbf{R}^Y_{\leq_{PD}})$-compatible. For instance, if f is decreasing, i.e. $f(x) \leq f(x')$ for all $x \in X$ and $x' \in X$ such that $x \geq x'$, then we have $f(A) \geq_{PD} f(B)$ for all $A, B \subseteq X$ such that $A \leq_{PD} B$, and thus f is not $(\mathbf{R}^X_{\leq_{PD}}; \mathbf{R}^Y_{\leq_{PD}})$-compatible since in general we have in this case $A \leq_{PD} B \not\Rightarrow f(A) \leq_{PD} f(B)$. However, if f is monotonically non-decreasing, then it is $(\mathbf{R}^X_{\leq_{PD}}; \mathbf{R}^Y_{\leq_{PD}})$-compatible since if $f(x) \leq f(x')$ for all $x \in X$ and $x' \in X$ such that $x \leq x'$ then we have $A \leq_{PD} B \Rightarrow f(A) \leq_{PD} f(B)$.

Proposition 12 (Preserved compatibility). *If f is $(\mathbf{R}^X; \mathbf{R}^Y)$-compatible, it is so on belief functions:*

$$m_1 \mathbf{R}^X m_2 \Rightarrow f(m_1) \mathbf{R}^Y f(m_2). \tag{12}$$

Proof. Since $m_1 \mathbf{R}^X m_2$, there exists a joint mass function m_{12} on X^2 satisfying (6)-(8) for $\mathbf{R}^X$. Consider the joint mass function m on Y^2 defined as

$$m(A', B') = \sum_{f(A)=A', f(B)=B'} m_{12}(A, B),\ \forall A', B' \subseteq Y. \tag{13}$$

Since $m_{12}(A, B) > 0 \Rightarrow A \mathbf{R}^X B$ and $A \mathbf{R}^X B \Rightarrow f(A) \mathbf{R}^Y f(B)$, then $m(A', B') > 0 \Rightarrow A' \mathbf{R}^Y B'$. Besides,

$$\begin{aligned}
\sum_{B'} m(A', B') &= \sum_{B'} \sum \{m_{12}(A, B) | f(A) = A', f(B) = B'\} \\
&= \sum_{f(A)=A'} \sum_{B'} \sum_{f(B)=B'} m_{12}(A, B) \\
&= \sum_{f(A)=A'} \sum_{B} m_{12}(A, B) \\
&= \sum_{f(A)=A'} m_1(A) \\
&= (f(m_1))(A')
\end{aligned}$$

Similarly, $\sum_{A'} m(A', B') = (f(m_2))(B')$.

In sum, when $m_1\mathbf{R}^X m_2$ and f is $(\mathbf{R}^X;\mathbf{R}^Y)$-compatible, there exists a joint mass function m on Y^2 such that $m(A',B')>0 \Rightarrow A'\mathbf{R}^Y B'$, for all $A',B'\subseteq Y$, and whose marginals are $f(m_1)$ and $f(m_2)$, hence $f(m_1)\mathbf{R}^Y f(m_2)$. □

Corollary 1. *For any function f, $m_1\mathbf{R}^X_\subseteq m_2 \Rightarrow f(m_1)\mathbf{R}^Y_\subseteq f(m_2)$, which follows from the $(\mathbf{R}^X_\subseteq;\mathbf{R}^Y_\subseteq)$-compatibility of any f.*

Corollary 1 was already known [16, Proposition 2]. Proposition 12 is a generalisation of this latter result.

5.2 Multivariate functions

These results can be extended to functions having more than one argument:

Definition 3. *Let $f: X_1\times X_2 \to Y$. Let $\mathbf{R}^{X_1}$, $\mathbf{R}^{X_2}$ and $\mathbf{R}^Y$ be relations on 2^{X_1}, 2^{X_2} and 2^Y, respectively. The function f is said to be $(\mathbf{R}^{X_1},\mathbf{R}^{X_2};\mathbf{R}^Y)$-compatible if, for all $A_1,B_1\subseteq X_1$ and all $A_2,B_2\subseteq X_2$*

$$A_1\mathbf{R}^{X_1}B_1 \wedge A_2\mathbf{R}^{X_2}B_2 \Rightarrow f(A_1,A_2)\mathbf{R}^Y f(B_1,B_2). \tag{14}$$

Example 4. Since for any function f and any $A_1,B_1\subseteq X_1$ and $A_2,B_2\subseteq X_2$, such that $A_1\subseteq B_1$ and $A_2\subseteq B_2$ it holds that $f(A_1,A_2)\subseteq f(B_1,B_2)$, any function is $(\mathbf{R}^{X_1}_\subseteq,\mathbf{R}^{X_2}_\subseteq;\mathbf{R}^Y_\subseteq)$-compatible.

Let X_1, X_2 and Y be ordered spaces. If f is non-decreasing in both its arguments (for short, *non-decreasing*), i.e., for all $(x_1,x_2),(x_1',x_2')\in X_1\times X_2$,

$$x_1\le x_1' \wedge x_2\le x_2' \Rightarrow f(x_1,x_2)\le f(x_1',x_2'),$$

then for $y\in\{LD,LB,UB,SD,PD\}$ we have $f(A_1,A_2)\le_y f(B_1,B_2)$ for all $A_1,B_1\subseteq X_1$ and $A_2,B_2\subseteq X_2$ such that $A_1\le_y B_1$ and $A_2\le_y B_2$, i.e. f is $(\mathbf{R}^{X_1}_{\le_y},\mathbf{R}^{X_2}_{\le_y};\mathbf{R}^Y_{\le_y})$-compatible. This can easily be shown as follows (we provide only the proof for the case $y=LD$, the other cases being similar). Since f is non-decreasing, we have $\min f(A_1,A_2)=f(\min A_1,\min A_2)$ and $\max f(B_1,B_2)=f(\max B_1,\max B_2)$. Besides, since $\min A_1\le\max B_1$ and $\min A_2\le\max B_2$ and f is non-decreasing, we obtain $\min f(A_1,A_2)\le\max f(B_1,B_2)$.

We remind that the image $f(m_{12})$ of some joint mass function $m_{12}\in\mathcal{B}^{X_1\times X_2}$ under f is the mass function $f(m_{12})\in\mathcal{B}^Y$ defined, for all $B\subseteq Y$, as [16]:

$$(f(m_{12}))(B)=\sum_{f(A_1,A_2)=B} m_{12}(A_1,A_2).$$

Let us also recall that if m_{12} satisfies $m_{12}(A_1,A_2)=m_1(A_1)m_2(A_2)$ with m_i the marginal of m_{12} on X_i, $i=1,2$, then m_1 and m_2 are said to be independent. This independence notion is the main one used in evidence theory, but can also be interpreted and used as an outer approximation within imprecise probability [18, 5].

Proposition 13 (Preserved compatibility, several arguments). *Let m_{12} (resp. m'_{12}) denote the joint mass function on $X_1 \times X_2$ obtained from independent mass functions m_1 and m_2 (resp. m'_1 and m'_2) defined on X_1 and X_2, respectively.*

If f is $(\mathbf{R}^{X_1}, \mathbf{R}^{X_2}; \mathbf{R}^Y)$-compatible, it is so on belief functions:

$$m_1 \mathbf{R}^{X_1} m'_1 \wedge m_2 \mathbf{R}^{X_2} m'_2 \Rightarrow f(m_{12}) \mathbf{R}^Y f(m'_{12}).$$

Proof. Since $m_i \mathbf{R}_i^X m'_i$, $i = 1, 2$, there exist joint mass functions $m_{11'}$ and $m_{22'}$ satisfying

$$\begin{aligned} m_{11'}(A_1, B_1) > 0 &\implies A_1 \mathbf{R}_1^X B_1, \\ m_{22'}(A_2, B_2) > 0 &\implies A_2 \mathbf{R}_2^X B_2. \end{aligned}$$

Furthermore, let $m_{11'22'}$ denote the joint mass function on $X_1 \times X_1 \times X_2 \times X_2$ obtained from independent marginals $m_{11'}$ and $m_{22'}$. Mass function $m_{11'22'}$ satisfies

$$m_{11'22'}(A_1, B_1, A_2, B_2) > 0 \Rightarrow A_1 \mathbf{R}_1^X B_1 \wedge A_2 \mathbf{R}_2^X B_2. \tag{15}$$

Moreover, we have

$$\begin{aligned} \sum_{B_1, B_2} m_{11'22'}(A_1, B_1, A_2, B_2) &= \sum_{B_1, B_2} m_{11'}(A_1, B_1) m_{22'}(A_2, B_2) \\ &= \sum_{B_1} m_{11'}(A_1, B_1) \cdot \sum_{B_2} m_{22'}(A_2, B_2) \\ &= \sum_{B_1} m_{11'}(A_1, B_1) \cdot m_2(A_2) \\ &= m_1(A_1) \cdot m_2(A_2) \\ &= m_{12}(A_1, A_2) \end{aligned}$$

and similarly

$$\sum_{A_1, A_2} m_{11'22'}(A_1, B_1, A_2, B_2) = m'_{12}(B_1, B_2).$$

In other words, $m_{11'22'}$ has m_{12} and m'_{12} as marginals.

Consider the joint mass function m on Y^2 defined as, for any $A', B' \subseteq Y$,

$$m(A', B') = \sum_{f(A_1, A_2) = A', f(B_1, B_2) = B'} m_{11'22'}(A_1, B_1, A_2, B_2).$$

Since Eqs. (15) and (14) hold, then $m(A', B') > 0 \Rightarrow A'\mathbf{R}^Y B'$. Besides,

$$\begin{aligned}
\sum_{B'} m(A', B') &= \sum_{B'} \sum \{m_{11'22'}(A_1, B_1, A_2, B_2) | f(A_1, A_2) = A', f(B_1, B_2) = B'\} \\
&= \sum_{f(A_1,A_2)=A'} \sum_{B'} \sum_{f(B_1,B_2)=B'} m_{11'22'}(A_1, B_1, A_2, B_2) \\
&= \sum_{f(A_1,A_2)=A'} \sum_{B_1,B_2} m_{11'22'}(A_1, B_1, A_2, B_2) \\
&= \sum_{f(A_1,A_2)=A'} m_{12}(A_1, A_2) \\
&= (f(m_{12}))(A')
\end{aligned}$$

Similarly, $\sum_{A'} m(A', B') = (f(m'_{12}))(B')$. □

Corollary 2. *For any function f, $m_1\mathbf{R}_{\subseteq}^{X_1} m'_1 \wedge m_2\mathbf{R}_{\subseteq}^{X_2} m'_2 \Rightarrow f(m_{12})\mathbf{R}_{\subseteq}^{Y} f(m'_{12})$, which follows from any f being $(\mathbf{R}_{\subseteq}^{X_1}, \mathbf{R}_{\subseteq}^{X_2}; \mathbf{R}_{\subseteq}^{Y})$-compatible.*

Corollary 3. *For X_1, X_2 and Y ordered spaces and f any monotonically non decreasing function, $m_1\mathbf{R}_{\leq_y}^{X_1} m'_1 \wedge m_2\mathbf{R}_{\leq_y}^{X_2} m'_2 \Rightarrow f(m_{12})\mathbf{R}_{\leq_y}^{Y} f(m'_{12})$, for $y \in \{LD, LB, UB, SD, PD\}$, which follows from the $(\mathbf{R}_{\leq_y}^{X_1}, \mathbf{R}_{\leq_y}^{X_2}; \mathbf{R}_{\leq_y}^{Y})$-compatibility of any such functions for $y \in \{LD, LB, UB, SD, PD\}$.*

Corollary 2 was already known [16, Proposition 3], and Corollary 3 generalises a result in [24, proof of Proposition 5], where f is the addition of integers and $y = PD$. Proposition 13, which can be readily extended to the case of functions having more than two arguments, is thus a generalisation of these results of [16, 24].

We note that the setting of Corollary 3, *i.e.*, monotonic non-decreasing functions on ordered spaces, is commonly encountered in multi-criteria decision making [23, 10], reliability analysis [13], and optimisation problems [21] hence this corollary may be useful for such problems when function arguments are tainted with uncertainty. Next section provides such examples.

6 Illustrative applications

6.1 System reliability

In multi-state system reliability assessment, one main issue is to assess the availability, or the performance of a whole system, given the performances of its components. Usually, the system is assumed to have n components x_i that take values on a finite, ordered scale X_i, that we will denote here by natural numbers. The performance of the system then depends on the state of each of its component, and is usually modelled by structure function $f(x_1, \ldots, x_n)$ that is non-decreasing, as the system performance can only increase or stay the same if a component performance increases.

Let us consider a simple communication system made of one source and one receiver, with a channel in between made of n repeaters x_i, where each of them can be in different states $X_i = \{1, 2, \ldots, K\}$ which is the maximal number of messages this repeater can store and send. Given this, we may be interested in the global capacity of a channel, which is

$$f(x_1, \ldots, x_n) = \min(x_1, \ldots, x_n),$$

as this is a series system. Now, assume we want to compare the capacity of two different channels in order to choose the best one, with repeaters whose state is uncertain due to the fact that they have degraded over time. If this uncertainty is modelled by belief functions and that m_i^j models the state of the i^{th} repeater of the j^{th} channel, then if we have $m_i^1 \mathbf{R}_{\leq_y} m_i^2$ for any $y \in \{LD, LB, UB, SD, PD\}$, then we know from Corollary 3 that channel 1 achieves at most the same level of performance than channel 2, without even computing the propagated mass function through f. Note that this would be true, whatever the function f is (as long as it is non-decreasing).

Example 5. Assume we have four identical repeaters x_1, x_2, x_3 and x_4 working independently with $X_i = \{1, 2, 3\}$, and are considering two different, partially known technologies at our disposal to build the system. Then, if our knowledge of these two technologies is such that, $\forall i$

$$m_i^1(\{2\}) = 0.5 \qquad m_i^2(\{3\}) = 0.5$$

$$m_i^1(\{1, 2\}) = 0.3 \qquad m_i^2(\{2, 3\}) = 0.3$$

$$m_i^1(\{1, 2, 3\}) = 0.2 \qquad m_i^2(\{1, 2, 3\}) = 0.2$$

we can easily conclude that $f^1 \mathbf{R}_{\leq_{PD}} f^2$ and this without performing any computation, as $m_i^1 \mathbf{R}_{\leq_{PD}} m_i^2$.

6.2 Multi-criteria decision making

In multi-criteria decision making, it is quite common to consider as variables x_i the utilities of the criteria. For instance, these could be scores obtained by students over different courses, or the evaluation of students regarding the quality of courses (e.g., with respect to interest, teaching quality and study time required). It could be that, for some reasons, those assessments are uncertain (e.g., because students are allowed to provide imprecise assessments in case of hesitation).

One common function to aggregate utilities is the weighted average, that is to have

$$f(x_1, \ldots, x_n) = \sum_{i=1}^{n} w_i x_i \tag{16}$$

or one of its extension such as the Choquet integral. Again, if we want to compare two courses, and we have $m_i^1 \mathbf{R}_{\leq_{PD}} m_i^2$ for all x_i, then we know from Corollary 3, without any computation, that the second course is considered better by the students. Besides, if there is a third course such that $m_i^2 \mathbf{R}_{\leq_{PD}} m_i^3$ for all x_i, then, without any computation, we know from Corollary 3 that this course is preferred over the second one but also over the first one as the set relation $\mathbf{R}_{\leq_{PD}}$ is transitive, a property that we know is preserved thanks to Proposition 7.

Example 6. Assume three courses evaluated by students against two criteria x_1 and x_2 with $X_i = \{0, \ldots, 10\}$. Let m_i^j be the mass function representing the uncertain evaluation of course j according to criterion i. Suppose we have for criterion x_1

$$m_1^1(\{2,3,4\}) = 1, \qquad m_1^2(\{2,3,4\}) = 0.6, \qquad m_1^3(\{6,7,8\}) = 1,$$
$$m_1^2(\{3,4\}) = 0.4,$$

and for criterion x_2

$$m_2^1(\{4\}) = 0.13, \qquad m_2^2(\{5,6\}) = 0.65, \qquad m_2^3(\{5,6,7\}) = 0.3,$$
$$m_2^1(\{7\}) = 0.07, \qquad m_2^2(\{7\}) = 0.35, \qquad m_2^3(\{7,8\}) = 0.2,$$
$$m_2^1(\{5,6\}) = 0.8, \qquad m_2^3(\{8\}) = 0.5.$$

If the weighted average (16) is used to aggregate these evaluations, then whatever the weights w_i, we can easily conclude that the overall uncertain score f^1 of the first course will be such that $f^1 \mathbf{R}_{\leq_{PD}} f^2$, with f^2 the uncertain score of the second course, since $m_i^1 \mathbf{R}_{\leq_{PD}} m_i^2$ for all x_i. Indeed, for the first criterion the only joint mass function obtainable from m_1^1 and m_1^2 is

$$m_1^{12}(\{2,3,4\},\{2,3,4\}) = 0.6, \quad m_1^{12}(\{2,3,4\},\{3,4\}) = 0.4$$

and we can easily see that $\{2,3,4\}\mathbf{R}_{\leq_{PD}}\{2,3,4\}$ and $\{2,3,4\}\mathbf{R}_{\leq_{PD}}\{3,4\}$. For the second criterion, we can consider the joint mass function

$$m_2^{12}(\{5,6\},\{5,6\}) = 0.65, \quad m_2^{12}(\{5,6\},\{7\}) = 0.15,$$
$$m_2^{12}(\{7\},\{7\}) = 0.07, \quad m_2^{12}(\{4\},\{7\}) = 0.13.$$

where every pair of sets satisfy the relation $\mathbf{R}_{\leq_{PD}}$. From those two facts and Corollary 3, we can conclude that $f^1 \mathbf{R}_{\leq_{PD}} f^2$ for any increasing function of the two criteria. Similarly, we obtain $f^2 \mathbf{R}_{\leq_{PD}} f^3$ and $f^1 \mathbf{R}_{\leq_{PD}} f^3$. Since $\mathbf{R}_{\leq_{PD}}$ is transitive, the latter comparison could have been deduced from $f^1 \mathbf{R}_{\leq_{PD}} f^2$ and $f^2 \mathbf{R}_{\leq_{PD}} f^3$.

As an illustration, let us confirm that for the first two courses and the simple weighted average with $w_1 = 0.5$ and $w_2 = 0.5$, we do have $f^1 \mathbf{R}_{\leq_{PD}} f^2$: denoting by m_f^j the propagated evaluation of course j, we get

$$m_f^1(\{3,3.5,4\} = A_1) = 0.13, \qquad m_f^2(\{3.5,4,4.5,5\} = B_1) = 0.39$$
$$m_f^1(\{4.5,5,5.5\} = A_2) = 0.07, \qquad m_f^2(\{4.5,5,5.5\} = B_2) = 0.21$$
$$m_f^1(\{3.5,4,4.5,5\} = A_3) = 0.8, \qquad m_f^2(\{4,4.5,5\} = B_3) = 0.26$$
$$m_f^2(\{5,5.5\} = B_4) = 0.14$$

With the following matrix summarising the pairs of sets where the relation $\mathbf{R}_{\leq_{PD}}$ holds

$$\begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \end{array} \begin{array}{c} \begin{array}{cccc} B_1 & B_2 & B_3 & B_4 \end{array} \\ \begin{bmatrix} \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} \\ & \mathbf{R}_{\leq_{PD}} & & \mathbf{R}_{\leq_{PD}} \\ \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} & \mathbf{R}_{\leq_{PD}} \end{bmatrix} \end{array}.$$

This means that any joint mass function where $m(A_2, B_1)$ and $m(A_2, B_3)$ are null satisfy our definition, and it is easy to see that such a mass function exists, for example by taking $m(A_2, B_2) = 0.07$.

6.3 Equivalence relations in taxonomies

Let us now assume that the elements of space X are concepts linked together by a taxonomy, modelled as a rooted tree. Then, one possible question about two uncertain observations of such a taxonomy is whether they belong to the same general sub-concept of interest, or in other words whether they belong to the same branch of the tree. In practice, this comes down to define a corresponding partition $C_1, \ldots, C_K$ of X, and to say that $A\mathbf{R}B$ iff $A \cup B \subseteq C_i$ for some i.

Example 7. Assume we have the space $X = \{(M)otorcycle, (T)ruck, (C)at, (D)og\}$ together with the taxonomy provided by Figure 2. The partition defined by the concepts of the first level (Vehicle and Animal) is $C_1 = \{M, T\}$ and $C_2 = \{C, D\}$. We could then wonder whether two uncertain objects belong to the same category, given this granularity. For instance, consider the three mass functions

$$m_1(\{C\}) = 0.6, \qquad m_2(\{T, C\}) = 0.2, \qquad m_3(\{D\}) = 0.4,$$

$$m_1(\{D, C\}) = 0.4, \qquad m_2(X) = 0.8, \qquad m_3(\{D, C\}) = 0.6.$$

We do have $m_1\mathbf{R}m_3$, as $\{C\}\mathbf{R}\{D\}\mathbf{R}\{D, C\}$, but not $m_1\mathbf{R}m_2$ nor $m_3\mathbf{R}m_2$, concluding that while the first and third objects belong to the same category, m_2 does not. To see that $m_1\mathbf{R}m_3$, one can consider the joint mass function

$$m_{13}(\{D, C\}, \{D\}) = 0.4, \quad m_{13}(\{C\}, \{D, C\}) = 0.6,$$

and to see that $\neg m_1\mathbf{R}m_2$ and $\neg m_3\mathbf{R}m_2$, it is sufficient to observe that $\neg X\mathbf{R}A$ for any A, and that the mass $m_2(X)$ is strictly positive, hence that some joint mass must be given to it. Since we know that $\mathbf{R}$ is an equivalence relation, that is preserved when considering belief functions, we could have deduced from $\neg m_1\mathbf{R}m_2$ that $\neg m_3\mathbf{R}m_2$.

Such notions could be used for example in formal concept analysis [22], where we may want to know the most specific common concept to which two uncertain objects belong. Another possibility includes for instance hierarchical classification [1], in which a usually very large number of classes are structured according to a taxonomy that is used to find the right class (leaf) of an object. Being able to tell whether two classifiers agree that a particular instance belong to a common sub-tree may then be a helpful item of information.

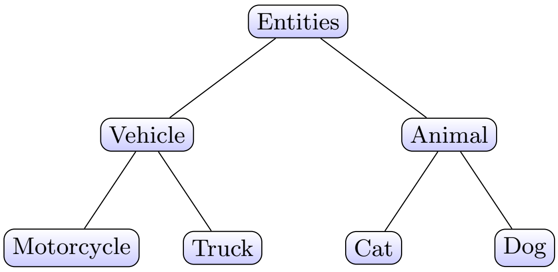

Fig. 2. Taxonomy of Example 7

7 From binary to gradual relations

So far, we have been concerned with the problem of assessing whether or not two mass functions m_1, m_2 were in relation, viewing this as a binary value that could only takes values 0 ($\neg m_1 \mathbf{R} m_2$) or 1 ($m_1 \mathbf{R} m_2$). It can be interesting to relax this assumption by allowing the relation to be gradual, that is to take any value between 0 and 1.

An easy way to do that is to follow an optimistic principle and to say that for any two mass functions m_1, m_2, the degree $\alpha_{\mathbf{R}}$ to which m_1 is in relation $\mathbf{R}$ with m_2 is the solution of the optimisation problem

$$1 - \alpha_{\mathbf{R}} = \min \sum_{A,B:\neg(A\mathbf{R}B)} m_{12}(A,B)$$

$$m_1(A) = \sum_B m_{12}(A,B),$$

$$m_2(B) = \sum_A m_{12}(A,B).$$

This generalises the approach taken so far, as we will have $m_1 \mathbf{R} m_2$ iff $\alpha_{\mathbf{R}} = 1$, that is if the degree to which they are in relation is maximal. Conversely, $\alpha_{\mathbf{R}} = 0$ iff there is no pair of subsets A, B having positive mass such that $A\mathbf{R}B$.

For instance, if we consider again the "having a lower cardinality than" example from the proof of Proposition 8, we would have that $m_1 \alpha_{\mathbf{R}} m_2$ with $\alpha_{\mathbf{R}} = 1 - 0.2 = 0.8$, a quite high value. Such gradual relations have been proposed in the past, for example the conflict measure κ_m^2 proposed in [11] is nothing else but the solution of the optimisation problem applied to the relation $A\mathbf{R}B$ iff $A \cap B \neq \emptyset$.

Studying the properties and implications of using such gradual relations in detail goes out of the scope of the current paper, yet a clear first step would be to relate such a gradual view to the large literature concerning fuzzy relations. Indeed, fuzzy relations are also $[0,1]$-valued, and researchers of this field have come with various proposals of how classical properties can be extended to this case, e.g., to deal with fuzzy preferences [20, 14] or fuzzy equivalence relations [2].

8 Conclusions

In this paper, a universal way to generalise a binary relation from sets to belief functions is introduced. Several results are provided showing which properties of the relation are preserved through this mechanism, including its compatibility with functions. Our proposal is also connected to more specific generalisation of binary relations such as the notion of specialisation. Consequently, our results are also a generalisation of pre-existing ones for specific relations.

There are however several questions that remain to address. A first one is to consider not relations on the same space, but more general relations on different spaces, including compositions of such relations.

Finally, we have also proposed a way to transform the initial binary relation on sets into a gradual relation on belief functions. This also opens up a whole avenue of research, as this directly connect our proposal to the various notions of fuzzy relations, that consist in providing a number in the unit interval reflecting how much a relation holds. Performing such a study goes beyond the actual scope of the present paper.

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A Proof of Proposition 10

In this appendix, we give a proof that if $\mathbf{R}$ is a partial order on sets then the mechanism described in Definition 1 yields a partial order on belief functions. We already know that the induced relation on belief functions inherits the reflexivity and transitivity properties (c.f. Propositions 5 and 7). So we only need to prove that antisymmetry holds.

Suppose there exist two mass functions m_1 and m_2 such that $m_1\mathbf{R}m_2$ and $m_2\mathbf{R}m_1$. This means that there are two matrices S_1 and S_2 compliant with Definition 1 and such that $m_1 = S_1 \cdot m_2$ and $m_2 = S_2 \cdot m_1$ (mass functions are seen as vectors here). By plugging these two equations together, we obtain

$$m_2 = S_2 \cdot S_1 \cdot m_2.$$

To complete the proof, we will be needing the following intermediate result:

Lemma 1. *If $\mathbf{R}$ is a partial order on sets, then there is an indexation of subsets of X such that for any pair of mass functions $(m_1; m_2)$ with $m_1\mathbf{R}m_2$, the stochastic matrix S satisfying Definition 1 is upper triangular.*

Proof. Define a refinement $\mathbf{R}_*$ of $\mathbf{R}$ such that $\mathbf{R}_*$ is a total order (subsets that cannot be ordered using $\mathbf{R}$ can be ordered in an arbitrary way). Let N denote the cardinality of 2^X. Let $(A_i)_{i=1}^N$ denote all subsets of X indexed using $\mathbf{R}_*$ so that

$$A_i \mathbf{R}_* A_j \Leftrightarrow i \leq j.$$

Now suppose S_* is a stochastic matrix compliant with Definition 1 for relation $\mathbf{R}_*$ for some pair of mass functions m_1 and m_2. If $m_2(A_j) > 0$, we need to have $S_*(A_i, A_j) = 0$ whenever $\neg(A_i \mathbf{R}_* A_j) \Leftrightarrow i > j$.

Suppose S is a stochastic matrix compliant with Definition 1 for relation $\mathbf{R}$ for the same pair of mass functions m_1 and m_2. If $m_2(A_j) = 0$, we can reassign entries of the j^{th} column of S as we want while remaining compliant with Definition 1. For instance, we can set

$$S(A_i, A_j) = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{otherwise.} \end{cases}$$

Provided that the above reassignment is completed, the matrix S is upper triangular because when $m_2(A_j) > 0$,

$$i > j \Leftrightarrow \neg(A_i \mathbf{R}_* A_j) \Rightarrow \neg(A_i \mathbf{R} A_j) \Rightarrow S(A_i, A_j) = 0.$$

□

Based on the above lemma, we can require that S_1 and S_2 are upper triangular and consequently $S_{21} = S_2 \cdot S_1$ as well. Since left stochasticity is preserved by matrix product, we know that S_{21} is also left stochastic. Consequently, we have that S_{21} coincides with the identity matrix I on every column corresponding to a focal element of m_2. In other words, if $m_2(A_j) > 0$, then

$$S_{21}(A_i, A_j) = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}, \tag{17}$$

where $(A_i)_{i=1}^N$ are all subsets of X ordered in the way arising from the definitions of matrices S_1 and S_2 and their upper triangularities. To prove this, observe that

$$m_2(A_i) = \sum_{j=1}^{N} S_{21}(A_i, A_j)\, m_2(A_j), \tag{18}$$

$$= \sum_{j=i}^{N} S_{21}(A_i, A_j)\, m_2(A_j) \tag{19}$$

Let A_{k_1} denote the focal element of m_2 with maximal index, i.e. A_i is not a focal element of m_2 if $i > k_1$. We necessarily have that

$$m_2(A_{k_1}) = S_{21}(A_{k_1}, A_{k_1})\, m_2(A_{k_1}).$$

This obviously implies that $S_{21}(A_{k_1}, A_{k_1}) = 1$ and that all other entries of the column corresponding to A_{k_1} are null because S_{21} is left stochastic. Now, let A_{k_2} to be the focal element of m_2 with the second maximal index, i.e. if $i > k_2$, then A_i is either A_{k_1} or not a focal element of m_2. We have now

$$m_2(A_{k_2}) = S_{21}(A_{k_2}, A_{k_2})\, m_2(A_{k_2}) + S_{21}(A_{k_2}, A_{k_1})\, m_2(A_{k_1}).$$

$S_{21}(A_{k_2}, A_{k_1})$ is in the k_1^{th} column of S_{21} therefore we deduce that $S_{21}(A_{k_2}, A_{k_2}) = 1$ and that all other entries of the corresponding column are null. We can continue to iterate on the focal elements of m_2 to obtain (17).

Furthermore, the upper triangularities of S_1 and S_2 give that $S_{21}(A_i, A_i) = S_2(A_i, A_i) \times S_1(A_i, A_i), \forall i$. When $m_2(A_i) > 0$, we know that $S_{21}(A_i, A_i) = 1$ and we deduce that $S_1(A_i, A_i) > 0$ and $S_2(A_i, A_i) > 0$. From the upper triangularity of the matrices, we also have

$$S_{21}(A_{i-1}, A_i) = S_2(A_{i-1}, A_{i-1})\, S_1(A_{i-1}, A_i) + S_2(A_{i-1}, A_i)\, S_1(A_i, A_i).$$

When $m_2(A_i) > 0$, we know that $S_{21}(A_{i-1}, A_i) = 0$ and we deduce that $S_1(A_{i-1}, A_i) = 0$. We can iterate and show that $S_1(A_{i-k}, A_i) = 0$ for any $k \in \{1; \ldots; i-1\}$ which in turn implies that $S_1(A_i, A_i) = 1$ because S_1 is stochastic. Since $m_1 = S_1 \cdot m_2$, we see that, for any focal element A of m_2, we have $m_1(A) \geq m_2(A)$. Finally, we necessarily have that $m_1 = m_2$ because the masses of m_1 need to sum to one.

References

1. Bengio, S., Weston, J., Grangier, D.: Label embedding trees for large multi-class tasks. In: Advances in Neural Information Processing Systems. pp. 163–171 (2010)
2. Boixader, D., Jacas, J., Recasens, J.: Fuzzy equivalence relations: advanced material. In: Fundamentals of Fuzzy Sets, pp. 261–290. Springer (2000)
3. Chateauneuf, A.: Combination of compatible belief functions and relation of specificity. In: Advances in the Dempster-Shafer theory of evidence. pp. 97–114. John Wiley & Sons, Inc. (1994)
4. Choquet, G.: Theory of capacities. In: Annales de l'institut Fourier. vol. 5, pp. 131–295 (1954)
5. Couso, I., Moral, S., Walley, P.: A survey of concepts of independence for imprecise probabilities. Risk, Decision and Policy 5(2), 165–181 (2000)
6. Dempster, A.: Upper and lower probabilities induced by a multiple valued mapping. Annals of Mathematical Statistics 38, 325 – 339 (1967)
7. Denoeux, T., Dubois, D., Prade, H.: Representations of uncertainty in artificial intelligence: Beyond probability and possibility. In: Marquis, P., Papini, O., Prade, H. (eds.) A Guided Tour of Artificial Intelligence Research. Springer Verlag, to appear (2018)
8. Denœux, T.: Extending stochastic ordering to belief functions on the real line. Information Sciences 179(9), 1362–1376 (2009)
9. Destercke, S., Dubois, D., Chojnacki, E.: Unifying practical uncertainty representations: I. generalized p-boxes. International Journal of Approximate Reasoning 49, 649–663 (2008)

10. Destercke, S.: A generic framework to include belief functions in preference handling and multi-criteria decision. International Journal of Approximate Reasoning 98, 62–77 (2018)
11. Destercke, S., Burger, T.: Toward an axiomatic definition of conflict between belief functions. IEEE transactions on cybernetics 43(2), 585–596 (2013)
12. Destercke, S., Dubois, D.: Other uncertainty theories based on capacities. In: Augustin, T., Coolen, F., Cooman, G.D., Troffaes, M. (eds.) Introduction to Imprecise Probabilities, pp. 93–112. Wiley series in probability and statistics, Wiley (May 2014), https://hal.archives-ouvertes.fr/hal-00999503
13. Destercke, S., Sallak, M.: An extension of universal generating function in multi-state systems considering epistemic uncertainties. IEEE Transactions on reliability 62(2), 504–514 (2013)
14. Díaz, S., De Baets, B., Montes, S.: General results on the decomposition of transitive fuzzy relations. Fuzzy Optimization and Decision Making 9(1), 1–29 (2010)
15. Dubois, D., Prade., H.: A set-theoretic view of belief functions: logical operations and approximations by fuzzy sets. International Journal of General Systems 12(3), 193–226 (1986)
16. Dubois, D., Prade, H.: Random sets and fuzzy interval analysis. Fuzzy Sets and Systems 42, 87–101 (1991)
17. Dubois, D., Prade, H.: Consonant approximations of belief functions. International Journal of Approximate Reasoning 4, 419 – 449 (1990)
18. Fetz, T., Oberguggenberger, M.: Propagation of uncertainty through multivariate functions in the framework of sets of probability measures. Reliability Engineering & System Safety 85(1-3), 73–87 (2004)
19. Fishburn, P.C.: Interval graphs and interval orders. Discrete mathematics 55(2), 135–149 (1985)
20. Fodor, J., De Baets, B.: Fuzzy preference modelling: fundamentals and recent advances. In: Fuzzy Sets and Their Extensions: Representation, Aggregation and Models, pp. 207–217. Springer (2008)
21. Fortin, J., Zieliński, P., Dubois, D., Fargier, H.: Criticality analysis of activity networks under interval uncertainty. Journal of Scheduling 13(6), 609–627 (2010)
22. Ganter, B., Wille, R.: Formal concept analysis: mathematical foundations. Springer Science & Business Media (2012)
23. Grabisch, M., Labreuche, C.: A decade of application of the choquet and sugeno integrals in multi-criteria decision aid. Annals of Operations Research 175(1), 247–286 (2010)
24. Helal, N., Pichon, F., Porumbel, D., Mercier, D., Lefèvre., E.: The capacitated vehicle routing problem with evidential demands. International Journal of Approximate Reasoning 95, 124–151 (2018)
25. Montes, I., Miranda, E., Montes, S.: Stochastic dominance with imprecise information. Computational Statistics & Data Analysis 71, 868–886 (2014)
26. Nguyen, H.T.: On random sets and belief functions. Journal of Mathematical Analysis and Applications 65(3), 531 – 542 (1978)
27. Shafer, G.: A mathematical theory of evidence. Princeton University Press (1976)
28. Smets, P.: The application of the matrix calculus to belief functions. International Journal of Approximate Reasoning 31, 1–30 (2002)
29. Smets, P., Kennes, R.: The transferable belief model. Artificial Intelligence 66(2), 191 – 234 (1994)
30. Yager, R.R.: The entailment principle for Dempster-Shafer granules. International Journal of Intelligent Systems 1(4), 247–262 (1986)