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# Uniqueness of Reconstruction for Yager's t-Norm Combination of Probabilistic and Possibilistic Knowledge

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## Abstract

Often, about the same real-life system, we have both measurement-related probabilistic information expressed by a probability measure  $P(S)$  and expert-related possibilistic information expressed by a possibility measure  $M(S)$ . To get the most adequate idea about the system, we must combine these two pieces of information. For this combination, R. Yager – borrowing an idea from fuzzy logic – proposed to use a t-norm  $f_{\&}(a, b)$  such as the product  $f_{\&}(a, b) = a \cdot b$ , i.e., to consider a set function  $f(S) = f_{\&}(P(S), M(S))$ . A natural question is: can we uniquely reconstruct the two parts of knowledge from this function  $f(S)$ ? In our previous paper, we showed that such a unique reconstruction is possible for the product t-norm; in this paper, we extend this result to a general class of t-norms.

## 1 Formulation of the Problem

**Need to combine probabilistic and possibilistic knowledge.** In many practical situations, we have both *probabilistic* information about some objects – e.g., information coming from measurements with known probability of measurement errors – and *possibilistic* information – describing expert knowledge. In the probabilistic case, for every set  $S$ , we have a probability  $P(S) \in [0, 1]$  that the actual (unknown) state  $s$  of the object belongs to the set  $S$ . In the possibilistic case, for each set  $S$ , we know the possibility  $M(S) \in [0, 1]$  that  $s$  belongs to  $S$ .

It is often desirable to combine these two numbers  $P(S)$  and  $M(S)$  into a single value  $f(S)$ .

**Yager's approach: the use of t-norms.** [5, 6] We need to combine two degrees from the interval  $[0, 1]$ . The desired combination must satisfy some reasonable properties; for example:

- if it is not possible for the state  $s$  to be in the set  $S$ , i.e., if  $M(S) = 0$ , then the resulting degree  $f(S)$  must also reflect this impossibility, i.e., we should have  $f(S) = 0$ ;
- if the probability  $P(S)$  of  $s$  being in the set  $S$  is equal to 0, i.e., if  $P(S) = 0$ , then we should also have  $f(S) = 0$ ,
- etc.

Different procedures of combining such degrees have been actively analyzed in fuzzy logic; see, e.g., [2, 3]. In particular, procedures that satisfy the above properties (and several other similar properties) are known as *t-norms* (or *and-operations*)  $f_{\&}(a, b)$ . It is therefore reasonable to combine  $P(S)$  and  $M(S)$  by using a t-norm, i.e., to consider the set function  $f(S) = f_{\&}(P(S), M(S))$ .

One of the simplest (and most widely used) t-norms is the algebraic product  $f_{\&}(a, b) = a \cdot b$ . In this case, we get a combination with a set function  $f(S) = P(S) \cdot M(S)$ .

**Uniqueness: a natural question.** A natural question is: once we have the combined measure  $f(S) = f_{\&}(P(S), M(S))$ , can we reconstruct both  $P(S)$  and  $M(S)$ ?

**Continuous case.** We will consider a continuous case, in which the set  $X$  of all possible states is either an  $n$ -dimensional space  $\mathbb{R}^n$  or its open subset, and we restrict ourselves to open subsets  $S \subseteq X$ . We assume that a probability measure  $P(S)$  is described by a continuous probability density function  $\rho(x) \geq 0$  for which  $P(S) = \int_S \rho(x) dx$  and  $\int_X \rho(x) dx = 1$ . Similarly, we assume that a possibility measure is described by a continuous possibility function  $\mu(x) \geq 0$  for which  $M(S) = \sup_{x \in S} \mu(x)$  and  $\sup_{x \in X} \mu(x) = 1$ . We will also assume that a t-norm  $f_{\&}(a, b)$  is continuous.

**What is known and what we do in this paper.** In [1], we showed that reconstruction is unique for the case when the t-norm is the algebraic product. In this paper, we extend this result to a general class of t-norms.

## 2 First Result: Reconstructing $P(S)$ from $f(S) = f_{\&}(P(S), M(S))$

**Reminder.** In this paper, we consider situations in which the universal set  $X$  is an open subset of an  $n$ -dimensional space  $\mathbb{R}^n$ , a probability measure is defined by a continuous probability density function, and a possibility measure is defined by a continuous possibility function.

**Theorem 1.** *Let  $f_{\&}(a, b)$  be a continuous t-norm, let  $P(S)$  and  $P'(S)$  be probability measures on the same set  $X$ , and let  $M(S)$  and  $M'(S)$  be possibility measures on  $X$ . If for every open set  $S \subseteq X$ , we have  $f_{\&}(P(S), M(S)) = f_{\&}(P'(S), M'(S))$ , then  $P(S) = P'(S)$  for all sets  $S$ .*

*Comment.* In other words, if we know the combined measure

$$f(S) = f_{\&}(P(S), M(S)),$$

then we can uniquely reconstruct the probability measure.

**Proof.**

1°. For every point  $x_0 \in X$  and for every positive real number  $\delta$ , let  $B_\delta(x_0) \stackrel{\text{def}}{=} \{x : d(x, x_0) < \delta\}$  denote an open ball with a center in  $x$  and radius  $\delta$ . In this proof, we will consider sets of the type  $S \cup B_\delta(x_0)$  in the limit  $\delta \rightarrow 0$ .

We want to know the limit of

$$f(S \cup B_\delta(x_0)) = f_{\&}(P(S \cup B_\delta(x_0)), M(S \cup B_\delta(x_0)))$$

when  $\delta \rightarrow 0$ . Since the t-norm  $f_{\&}(a, b)$  is continuous, it is sufficient to find the limits of  $P(S \cup B_\delta(x_0))$  and  $M(S \cup B_\delta(x_0))$ ; then, the limit of  $f(S \cup B_\delta(x_0))$  is simply equal to the result of applying the t-norm  $f_{\&}(a, b)$  to the limits of  $P(S \cup B_\delta(x_0))$  and  $M(S \cup B_\delta(x_0))$ .

2°. Let us start with computing the limit of  $P(S \cup B_\delta(x_0))$ . A probability measure is monotonic and additive, so we have

$$P(S) \leq P(S \cup B_\delta(x_0)) \leq P(S) + P(B_\delta(x_0)).$$

Let us show that  $P(B_\delta(x_0)) \rightarrow 0$  as  $\delta \rightarrow 0$ ; this will imply that

$$P(S \cup B_\delta(x_0)) \rightarrow P(S).$$

Indeed, since the probability density function  $\rho(x)$  is continuous, for every  $\varepsilon > 0$ , there exists a  $\delta > 0$  such that  $d(x, x_0) \leq \delta$  implies that  $|\rho(x) - \rho(x_0)| \leq \varepsilon$ . Let us pick any  $\varepsilon_0 > 0$  (e.g.,  $\varepsilon_0 = 1$ ). Then, there exists a  $\delta_0 > 0$  for which  $d(x, x_0) \leq \delta_0$  implies that  $|\rho(x) - \rho(x_0)| \leq \varepsilon_0$ .

In this case, for every  $\delta \leq \delta_0$ , if  $x \in B_\delta(x_0)$ , then  $d(x, x_0) < \delta \leq \delta_0$  hence  $\rho(x) \leq \rho(x_0) + \varepsilon_0$ . Thus,

$$0 \leq P(B_\delta(x_0)) = \int_{B_\delta(x_0)} \rho(x) dx \leq (\rho(x_0) + \varepsilon_0) \cdot V(B_\delta(x_0)).$$

When  $\delta \rightarrow 0$ , the sum  $\rho(x_0) + \varepsilon_0$  is a constant and the volume  $V(B_\delta(x_0)) \sim \delta^n$  tends to 0, so indeed  $P(B_\delta(x_0)) \rightarrow 0$  and  $P(S \cup B_\delta(x_0)) \rightarrow P(S)$ .

3°. Let us now compute the limit of  $M(S \cup B_\delta(x_0))$  when  $\delta \rightarrow 0$ . From the definition of a possibility measure, it follows that  $M(A \cup B) = \max(M(A), M(B))$

for all  $A$  and  $B$ ; in particular,  $M(S \cup B_\delta(x_0)) = \max(M(S), M(B_\delta(x_0)))$ . Since  $\max(a, b)$  is a continuous function, it is sufficient to find the limit of  $M(B_\delta(x_0))$ .

The possibility function  $\mu(x)$  is also assumed to be continuous, so for every  $\varepsilon > 0$ , there exists a  $\delta > 0$  such that  $d(x, x_0) \leq \delta$  implies that  $|\mu(x) - \mu(x_0)| \leq \varepsilon$ , i.e., for all  $x \in B_\delta(x_0)$ , we have

$$\mu(x_0) - \varepsilon \leq \mu(x) \leq \mu(x_0) + \varepsilon.$$

Since all the values  $\mu(x)$  are between  $\mu(x_0) - \varepsilon$  and  $\mu(x_0) + \varepsilon$ , the largest of these values  $M(B_\delta(x_0)) = \sup_{B_\delta(x_0)} \mu(x)$  also lies within the same interval:

$$\mu(x_0) - \varepsilon \leq M(B_\delta(x_0)) \leq \mu(x_0) + \varepsilon.$$

Thus, for every  $\varepsilon > 0$  there exists a  $\delta$  for which  $|M(B_\delta(x_0)) - \mu(x_0)| \leq \varepsilon$ . By definition of the limit, this means that  $M(B_\delta(x_0)) \rightarrow \mu(x_0)$ . So, due to the continuity of the maximum function,

$$M(S \cup B_\delta(x_0)) = \max(M(S), M(B_\delta(x_0))) \rightarrow \max(M(S), \mu(x_0)).$$

4°. Since the t-norm  $f_\&(a, b)$  is continuous and we know the limits for

$$P(S \cup B_\delta(x_0)) \text{ and } M(S \cup B_\delta(x_0)),$$

we conclude that

$$\begin{aligned} f(S \cup B_\delta(x_0)) &= f_\&(P(S \cup B_\delta(x_0)), M(S \cup B_\delta(x_0))) \rightarrow \\ &f_\&(P(S), \max(M(S), \mu(x_0))), \end{aligned}$$

i.e., that

$$\lim_{\delta \rightarrow 0} f(S \cup B_\delta(x_0)) = f_\&(P(S), \max(M(S), \mu(x_0))).$$

5°. We now want to find the largest value of  $f_\&(P(S), \max(M(S), \mu(x)))$ , i.e.,

$$\sup_{x_0 \in X} f_\&(P(S), \max(M(S), \mu(x_0))).$$

Since the t-norm is monotonic, it is sufficient to find the largest possible value of  $\max(M(S), \mu(x_0))$ :

$$\sup_{x_0 \in X} f_\&(P(S), \max(M(S), \mu(x_0))) = f_\&\left(P(S), \sup_{x_0 \in X} \max(M(S), \mu(x_0))\right).$$

By definition of a possibility measure,

$$M(X) = \sup_{x_0 \in X} \mu(x_0) = 1.$$

Since  $\mu(x_0) \leq \max(S, \mu(x_0)) \leq 1$ , we can thus conclude that  $\sup_{x_0 \in X} \max(S, \mu(x_0)) = 1$  and thus,  $\sup_{x_0 \in X} f_{\&}(P(S), \max(M(S), \mu(x_0))) = f_{\&}(P(S), 1)$ . By definition of a t-norm,  $f_{\&}(a, 1) = a$ , hence  $f_{\&}(P(S), 1) = P(S)$  and thus, for every set  $S$ ,

$$\sup_{x_0 \in X} f_{\&}(P(S), \max(M(S), \mu(x_0))) = P(S).$$

We already know how to describe  $f_{\&}(P(S), \max(M(S), \mu(x_0)))$  in terms of the combined function  $f(S)$ :  $f_{\&}(P(S), \max(M(S), \mu(x_0))) = \lim_{\delta \rightarrow 0} f(S \cup B_{\delta}(x_0))$ ; thus,

$$P(S) = \sup_{x_0 \in X} \lim_{\delta \rightarrow 0} f(S \cup B_{\delta}(x_0)).$$

This formula describes the probability measure in terms of the combined measure. So, the probability measure can indeed be uniquely reconstructed from the combined measure. The theorem is proven.

### 3 Second Result: For Strictly Archimedean t-Norms, We Can Also Reconstruct $M(S)$ from $f(S) = f_{\&}(P(S), M(S))$

**Discussion.** In the previous section, we showed that we can uniquely reconstruct the probability measure  $P(S)$  from the combined measure  $f(S) = f_{\&}(P(S), M(S))$ . Let us show that for strictly Archimedean t-norms, we can also reconstruct the possibility measure  $M(S)$ .

When  $\rho(x) = 0$  for all points  $x$  from some region  $S$ , this means that the probability  $P(S) = 0$  of this region is 0, so points  $x$  from this region are not possible. We can therefore exclude these points from our universal set  $X$ , and assume that  $\rho(x) > 0$  for all  $x \in X$ . Such probability measures will be called *strictly positive*.

**Theorem 2.** *Let  $f_{\&}(a, b)$  be a strictly Archimedean continuous t-norm, let  $P(S)$  and  $P'(S)$  be strictly positive probability measures on the same set  $X$ , and let  $M(S)$  and  $M'(S)$  be possibility measures on  $X$ . If for every open set  $S \subseteq X$ , we have  $f_{\&}(P(S), M(S)) = f_{\&}(P'(S), M'(S))$ , then  $P(S) = P'(S)$  and  $M(S) = M'(S)$  for all sets  $S$ .*

*Reminder.* A strictly Archimedean t-norm (see, e.g., [2, 3]) can be described, e.g., by the property that when  $a > 0$  and  $b > 0$ , the function  $f_{\&}(a, b)$  is strictly increasing, i.e., if  $0 < a < a'$  and  $0 < b < b'$ , then  $f_{\&}(a, b) < f_{\&}(a', b)$  and  $f_{\&}(a, b) < f_{\&}(a, b')$ . The algebraic product t-norm  $f_{\&}(a, b) = a \cdot b$  is a classical example of a strictly Archimedean t-norm.

*Comment.* The restriction to strictly Archimedean t-norms is not very restrictive, since, as shown in [4], an arbitrary t-norm with an arbitrary accuracy can be approximated by a strictly Archimedean one. Thus, for any given accuracy, strict Archimedean t-norms are sufficient for representing experts' "and" operations.

**Proof.** According to Theorem 1, the fact that

$$f_{\&}(P(S), M(S)) = f_{\&}(P'(S), M'(S))$$

for all open sets  $S$  implies that  $P(S) = P'(S)$  for all such sets. Thus, for every open set  $S$ , we have  $f_{\&}(P(S), M(S)) = f_{\&}(P(S), M'(S))$ . For strictly positive probability measures, with continuous positive density function  $\rho(x) > 0$ , the probability  $P(S) = \int_S \rho(x) dx$  is always positive  $P(S) > 0$ .

Thus, we cannot have  $M(S) < M'(S)$ , because then, due to the above strict monotonicity property of strictly Archimedean t-norms, we would have  $f_{\&}(P(S), M(S)) < f_{\&}(P(S), M'(S))$ . Similarly, we cannot have  $M'(S) < M(S)$ , because then, due to the above property of strictly Archimedean t-norms, we would have  $f_{\&}(P(S), M'(S)) < f_{\&}(P(S), M(S))$ . Since we cannot have  $M(S) < M'(S)$  and we cannot have  $M'(S) < M(S)$ , the only remaining possibility is  $M(S) = M'(S)$ . The theorem is proven.

#### 4 Auxiliary Result: For t-Norms Which Are Not Strictly Archimedean, We Cannot Always Reconstruct $M(S)$ from $f(S) = f_{\&}(P(S), M(S))$

Let us show that the requirement that the t-norm be strictly Archimedean is necessary. Specifically, we will show that even for the simplest possible non-strictly-Archimedean t-norm  $f_{\&}(a, b) = \min(a, b)$ , we sometimes cannot uniquely reconstruct  $M(S)$  from  $f(S) = f_{\&}(P(S), M(S))$ . Specifically, we will show an example of a strictly positive probability measure  $P(S)$  and two different possibility measures  $M(S) \neq M'(S)$  for which  $\min(P(S), M(S)) = \min(P(S), M'(S))$  for all open sets  $S$ .

As a universal set  $X$ , let us take the interval  $[0, 1]$ . As  $P(S)$ , we take the uniform probability measure, with  $\rho(x) = 1$  for all  $x \in X$ . The possibility functions  $\mu(x)$  and  $\mu'(x)$  defining the possibility measures  $M(S)$  and  $M'(S)$  are as follows:  $\mu(x) = 1$  and  $\mu'(x) = \min(0.5 + x, 1)$  for all  $x$ .

In this case, for every set  $S$ , we have  $M(S) = \sup_{x \in S} \mu(x) = 1$ . In particular, this means that  $M(S) \geq 0.5$  for every set  $S$ . Since  $\mu'(x) \geq 0.5$  for all  $x$ , for every set  $S$ , we have  $M'(S) = \sup_{x \in S} \mu'(x) \geq 0.5$ .

We will prove that  $\min(P(S), M(S)) = \min(P(S), M'(S))$  for all open sets  $S$  by considering two possible cases:  $P(S) \leq 0.5$  and  $P(S) > 0.5$

If  $P(S) \leq 0.5$ , then  $P(S) \leq M(S)$  and  $P(S) \leq M'(S)$ , hence

$$\min(P(S), M(S)) = P(S), \quad \min(P(S), M'(S)) = P(S),$$

and therefore,  $\min(P(S), M(S)) = \min(P(S), M'(S))$ .

If  $P(S) > 0.5$ , this means that the set  $S$  must contain some points  $x_0$  from the second half  $[0.5, 1]$  of the interval  $X = [0, 1]$ : indeed, otherwise, if  $S \subseteq [0, 0.5]$ , we would then have  $P(S) \leq P([0, 0.5]) = 0.5$  but we have  $P(S) > 0.5$ . For all points  $x_0 \in [0.5, 1]$ , we have  $\mu'(x_0) = 1$ . Thus, in this case, we have  $M'(S) = \sup_{x \in S} \mu(x) \geq \mu(x_0) = 1$  hence  $M'(S) = 1$ . We already know that  $M(S) = 1$ . Thus,  $\min(P(S), M(S)) = \min(P(S), 1) = P(S)$ ,  $\min(P(S), M'(S)) = \min(P(S), 1) = P(S)$ , and therefore,  $\min(P(S), M(S)) = \min(P(S), M'(S))$ .

The desired equality have thus been proven for both possible cases. The example has been proven.

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