

# Laws of contraposition and law of importation for probabilistic implications and probabilistic S-implications

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# Content

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- Basic definitions.

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- Introduction of Probabilistic Implications and Probabilistic S-implications.

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- Introduction of Probabilistic Implications and Probabilistic S-implications.
- Laws of Contraposition.
- Law of Importation.
- What does still remain to do?

# Basic definitions

## Definition 1

A function  $I : [0, 1]^2 \rightarrow [0, 1]$  is called a **fuzzy implication** if it satisfies the following conditions

(I1) if  $I(\_, y)$  is decreasing;

(I2) if  $I(x, \_)$  is increasing;

(I3)  $I(0, 0) = 1$ ; (I4)  $I(1, 1) = 1$ ; (I5)  $I(1, 0) = 0$ .



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## Definition 2

An associative, commutative and non-decreasing operation

$T : [0, 1]^2 \rightarrow [0, 1]$  is called a **t-norm** if it has the neutral element 1.

## Definition 3

A non-increasing function  $N : [0, 1]^2 \rightarrow [0, 1]$  is called a **fuzzy negation** if  $N(0) = 1, N(1) = 0$ .

A fuzzy negation is called **strong** if it is an involution, i.e.  $N(N(x)) = x$  for all  $x \in [0, 1]$ .

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Cause of uncertainty of knowledge:

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- ⇒ random effects → probability theory
- ⇒ imprecision or fuzziness → fuzzy theory

# Derivation of Probabilistic Implications

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$$A \rightarrow B \equiv \neg A \vee B$$

$$\begin{aligned} P(A' \cup B) &= P(A') + P(B) - P(A' \cap B) \\ &= P(A') + P(A \cap B) \\ &= P(A \cap B) - P(A) + 1 \end{aligned}$$

# Copulas

## Definition 4

A **copula** (specifically a 2-copula) is a function  $C : [0, 1]^2 \rightarrow [0, 1]$  which satisfies the following conditions:

- (a)  $C(u, 0) = C(0, v) = 0$  for every  $u, v \in [0, 1]$
- (b)  $C(u, 1) = u$  for every  $u \in [0, 1]$
- (c)  $C(1, v) = v$  for every  $v \in [0, 1]$
- (d) for every  $u_1, u_2, v_1, v_2 \in [0, 1]$  such that  $u_1 \leq u_2$  and  $v_1 \leq v_2$

$$C(u_2, v_2) - C(u_2, v_1) - C(u_1, v_2) + C(u_1, v_1) \geq 0.$$

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## Theorem 1

Let  $X$  and  $Y$  be random variables with joint distribution function  $H$  and marginal distribution functions  $F$  and  $G$ , respectively. Then there exists a copula  $C$  such that

$$H(x, y) = C(F(x), G(y)) \tag{1}$$

for all  $x, y \in \mathbb{R}$ .

Conversely, if  $C$  is a copula and  $F$  and  $G$  are distribution functions, then the function  $H$  defined by (1) is a joint distribution function with margins  $F$  and  $G$ .

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$$P(Y \leq y | X \leq x) = \frac{P(X \leq x, Y \leq y)}{P(X \leq x)} = \frac{H(x,y)}{F(x)} = \frac{C(F(x), G(y))}{F(x)} = \frac{C(u, v)}{u},$$

where  $u = F(x)$  and  $v = G(y)$  ( $u, v \in [0, 1]$ ).

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**Grzegorzewski, EUSFLAT 2011:**

## Definition 5

A function  $I_C : [0, 1]^2 \rightarrow [0, 1]$  given by

$$I_C(u, v) = \begin{cases} 1 & \text{if } u = 0 \\ \frac{C(u, v)}{u} & \text{if } u > 0, \end{cases} \quad (2)$$

where  $C$  is a copula, is called a **probabilistic implication** (based on copula  $C$ ).

# Derivation of Probabilistic S-Implications

$$P(A' \cup B) =$$

$$P(A \cap B) - P(A) + 1$$

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$$\begin{aligned} P(X > x \text{ or } Y \leq y) &= P(X \leq x, Y \leq y) - P(X \leq x) + 1 \\ &= H(x, y) - F(x) + 1 \\ &= C(F(x), G(y)) - F(x) + 1 = C(u, v) - u + 1 \end{aligned}$$

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 P(X > x \text{ or } Y \leq y) &= P(X \leq x, Y \leq y) - P(X \leq x) + 1 \\
 &= H(x, y) - F(x) + 1 \\
 &= C(F(x), G(y)) - F(x) + 1 = C(u, v) - u + 1
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**Grzegorzewski, EUSFLAT 2011:**

## Definition 6

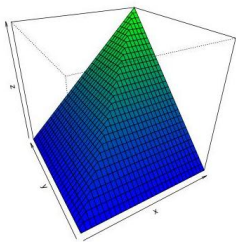
A function  $I_C : [0, 1]^2 \rightarrow [0, 1]$  given by

$$\tilde{I}_C(u, v) = C(u, v) - u + 1 \quad (3)$$

where  $C$  is a copula, is called a **probabilistic S-implication** (based on copula  $C$ ).

# Examples - $C = \min$

$$C(u, v) = M(u, v) = \min(u, v)$$

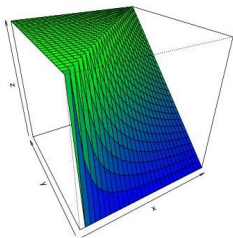
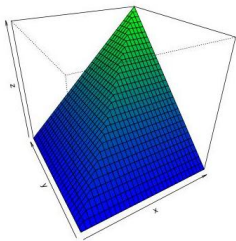




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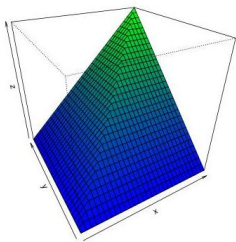
$$C(u, v) = M(u, v) = \min(u, v)$$

$$I_M(u, v) = I_{GG}(u, v) = \begin{cases} 1 & \text{if } u \leq v \\ \frac{v}{u} & \text{if } u > v \end{cases}$$

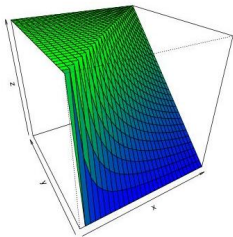


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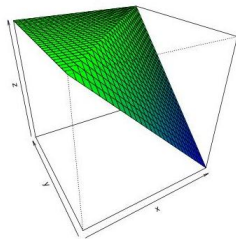
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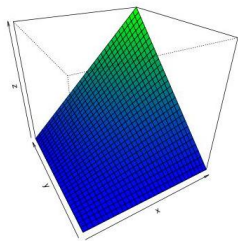


$$\tilde{I}_M(u, v) = I_{LK}(u, v) = \min(1, 1 - u + v)$$

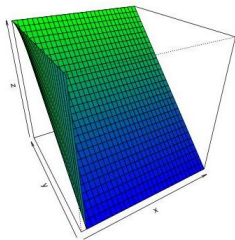


# Examples - $C = \Pi$

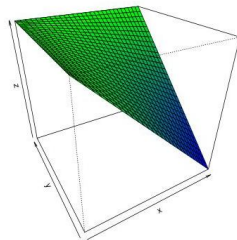
$$C(u, v) = \Pi(u, v) = uv$$



$$I_{\Pi}(u, v) = \begin{cases} 1 & \text{if } u = 0 \\ v & \text{if } u > 0 \end{cases}$$



$$\tilde{I}_{\Pi}(u, v) = I_{RC}(u, v) = uv - u + 1$$

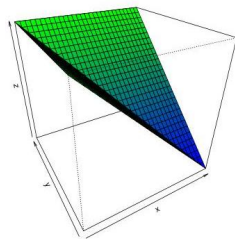
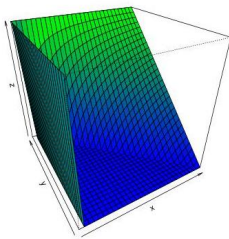
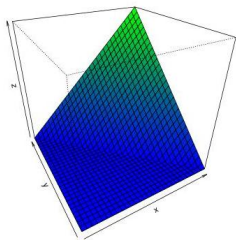


# Examples - $C = W$

$$C(u, v) = W(u, v) = \max(u + v - 1, 0)$$

$$I_W(u, v) = \begin{cases} 1 & \text{if } u = 0 \\ \frac{\max(u+v-1, 0)}{u} & \text{if } u > 0 \end{cases}$$

$$\tilde{I}_W(u, v) = I_{KD}(u, v) = \max(1 - u, v)$$

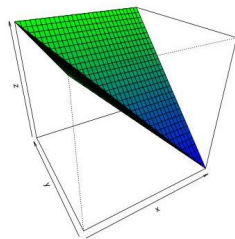
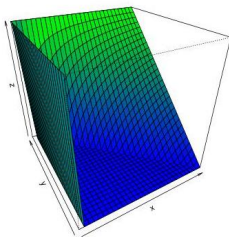
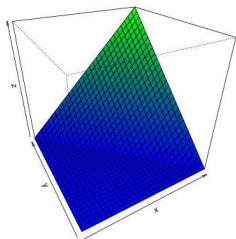


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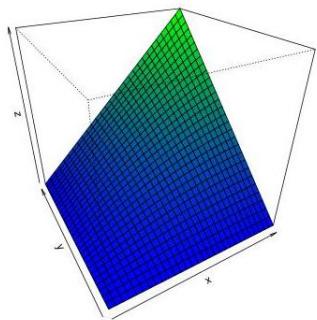


$I$  is a probabilistic S-implication  $\rightarrow I$  is a fuzzy implication

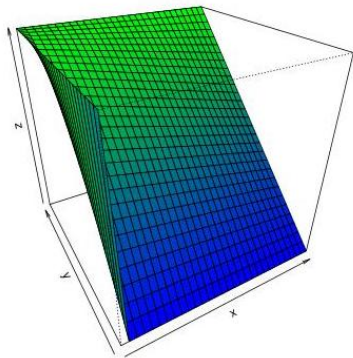
$I$  is a probabilistic implication + (I1)  $\rightarrow I$  is a fuzzy implication

# Examples - $C \in FGM(\Theta)$

$$C_{FGM(\Theta)}(u, v) = uv + \Theta uv(1-u)(1-v)$$

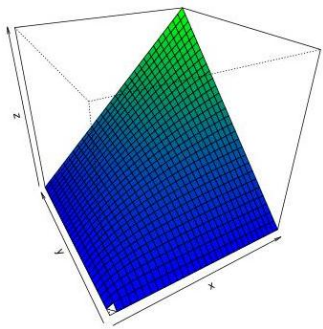


$$I_{C(FGM(\Theta))}(u, v) = \begin{cases} 1 & \text{if } u = 0 \\ v + \Theta v(1-u)(1-v) & \text{if } u > 0 \end{cases}$$

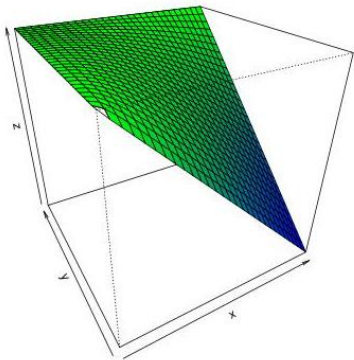


# Examples - $C \in AMH(\Theta)$

$$C_{AMH(\Theta)}(u, v) = \frac{uv}{1-\Theta(1-u)(1-v)}$$



$$\tilde{I}_{AMH(\Theta)}(u, v) = \frac{uv}{1-\Theta(1-u)(1-v)} - u + 1$$



# Main properties of Probabilistic Implications

	Probabilistic Implications	Probabilistic S-Implications
(NP)	✓	✓
(IP)	✓ ONLY FOR $I_{GG}$ (the Goguen implication - based on copula $M=\min$ )	✓ ONLY FOR $I_{LK}$ (the Łukasiewicz implication - based on copula $M=\min$ )
(OP)	✓ ONLY FOR $I_{GG}$	✓ ONLY FOR $I_{LK}$
(EP)	✓ FOR SOME (e.g. $I_{GG}$ , $I_{TT}$ ) ✗ FOR SOME (e.g. $I_{FGM(\theta)}$ , $\theta \neq 0$ )	✓ FOR SOME (e.g. $I_{LK}$ , $I_{RC}$ ) ✗ FOR SOME (e.g. some $I_{AMH(\theta)}$ )



# NEW RESULTS

# Laws of Contraposition - definition

$$p \rightarrow q \equiv \neg q \rightarrow \neg p$$

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$$p \rightarrow q \equiv \neg q \rightarrow \neg p$$

$$\longrightarrow \neg(\neg p) \equiv p$$

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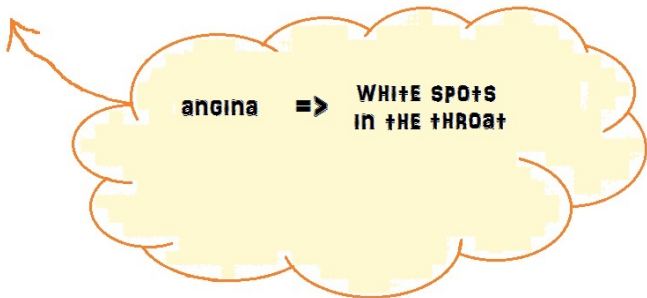
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## Definition 7

$I$  - fuzzy implication,  $N$  - fuzzy negation.  $I$  satisfies the

- 1 Law of Contraposition with respect to  $N$ , if**

$$I(x, y) = I(N(y), N(x)) \quad \forall_{x, y \in [0, 1]} \quad (\mathbf{CP}), (\mathbf{CP(N)}).$$

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- 2 **Law of Left Contraposition** with respect to  $N$ , if

$$I(N(x), y) = I(N(y), x) \quad \forall_{x, y \in [0, 1]} \quad (\mathbf{L-CP}), (\mathbf{L-CP(N)}).$$

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- 2 Law of Left Contraposition with respect to  $N$** , if

$$I(N(x), y) = I(N(y), x) \quad \forall_{x, y \in [0, 1]} \quad (\mathbf{L-CP}), (\mathbf{L-CP(N)}).$$

- 3 Law of Right Contraposition with respect to  $N$** , if

$$I(x, N(y)) = I(y, N(x)) \quad \forall_{x, y \in [0, 1]} \quad (\mathbf{R-CP}), (\mathbf{R-CP(N)}).$$



# Laws of Contraposition for Probabilistic Implications

## Lemma 1

*No probabilistic implication satisfies the Laws of Contraposition (CP) and (L-CP) with respect to any negation  $N$ .*

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## Lemma 2

*Every probabilistic implication satisfies (R-CP), but only with respect to the least negation  $N_{D1}(x) = \begin{cases} 1, & x = 0 \\ 0, & x > 0 \end{cases}$ .*

# Laws of Contraposition for Probabilistic S-Implications

# Laws of Contraposition for Probabilistic S-Implications

## Lemma 3

*Let  $\tilde{I}_C$  be any probabilistic S-implication. If  $\tilde{I}_C$  satisfies the (CP) with respect to a fuzzy negation  $N$ , then  $N$  is the strong negation  $N_C(x) = 1 - x$ .*

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## Corollary 1

Probabilistic S-implication  $\tilde{I}_C$  based on a copula  $C$  satisfies (CP) (with respect to  $N_C$ ) if and only if  $C$  satisfies the following equation

$$C(x, y) - x + 1 = C(1 - y, 1 - x) + y, \quad (4)$$

for all  $x, y \in (0, 1)$ .

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## Example 1

$C = \Pi$ ,  $C = M$ ,  $C = W$ ,  $C \in FGM(\Theta)$  OK

$C \in AMH(\Theta)$  X

# Law of Importation - definition

$$(p \wedge q) \rightarrow r \equiv p \rightarrow (q \rightarrow r)$$

# Law of Importation - definition

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## Definition 8

Let  $I$  be a fuzzy implication and  $T$  be a  $t$ -norm.  $I$  is said to satisfy the **Law of Importation** with  $t$ -norm  $T$ , if

$$I(T(x, y), z) = I(x, I(y, z)) \quad \forall_{x, y, z \in [0, 1]} \quad \textbf{(LI)}.$$



# Law of Importation for Probabilistic Implications

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## Lemma 4

*If a probabilistic implication  $I_C$  and a  $t$ -norm  $T$  satisfy the law of importation (LI), then  $T$  is positive, i.e.,  $\neg \exists_{x,y \neq 0} T(x,y) = 0$ .*

# Law of Importation for Probabilistic Implications

## Lemma 4

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## Example 2

- $I_{\Pi}$  - with any positive t-norm  $T$ .
- $I_M$  - only with  $T_P$ .
- $I_W$  - only with  $T_P$ .
- $FGM(\Theta)$  - with any t-norm  $T$ .
- $AMH(\Theta)$  - only for  $\Theta = 1$  and only with  $T_P$ .

# Law of Importation for Probabilistic S-Implications

# Law of Importation for Probabilistic S-Implications

## Lemma 5

*If a probabilistic S-implication  $\tilde{I}_C$  satisfies (LI) with any t-norm  $T$ , then  $T$  must be of the form  $T(x, y) = x - C(x, 1 - y)$ .*

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$C_{\Pi}$	$T_P(x, y) = xy$	OK
$C_M$	$T_{LK}(x, y) = \max(x + y - 1, 0)$	OK
$C_W$	$T_M(x, y) = \min(x, y)$	OK
$C \in FGM(\Theta)$	$T(x, y) = xy - \Theta xy(1 - x)(1 - y)$	X
$C \in AMH(\Theta)$	$T(x, y) = xy \frac{1 - \Theta(1 - x)}{1 - \Theta(1 - x)y}$	X

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- Questions:
  - Is there any particular family of copulas which satisfy the equation  $C(x, y) - x + 1 = C(1 - y, 1 - x) + y$ ?
  - If the formula  $T(x, y) = x - C(x, 1 - y)$  expresses any special kind of relation between functions  $T$  and  $C$  (some "duality")?



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- Questions:
  - Is there any particular family of copulas which satisfy the equation  $C(x, y) - x + 1 = C(1 - y, 1 - x) + y$ ?
  - If the formula  $T(x, y) = x - C(x, 1 - y)$  expresses any special kind of relation between functions  $T$  and  $C$  (some "duality")?
- Other properties of Probabilistic Implications and Probabilistic S-Implications may be checked still.



# THANK YOU !