

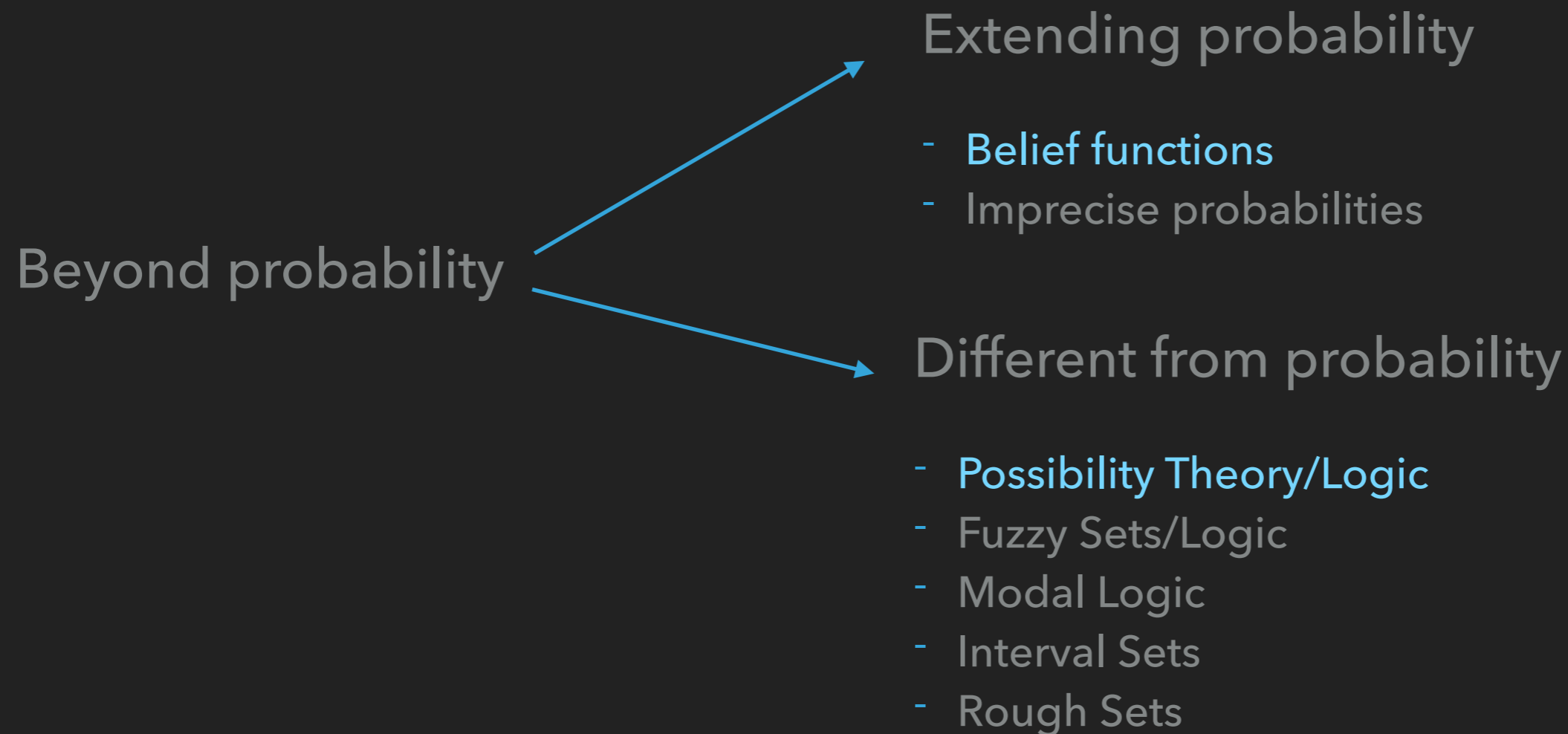
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# UNCERTAINTY THEORIES BEYOND PROBABILITY

# BEYOND PROBABILITY



## DIFFERENT TOOLS FOR DIFFERENT UNCERTAINTIES

- ▶ Possibility theory
- ▶ Belief function
- ▶ Rough Sets
  
- ▶ Starting from the notion of capacity

# CAPACITY: EXAMPLES

A capacity is a number associated to a set

- ▶ Example 1
  - ▶  $X$  = possible answers to a questions, only 1 answer is correct
  - ▶ The capacity of a set of answers  $A \subseteq X$  quantifies the uncertainty that  $A$  contains the correct answer
  - ▶ The bigger is  $A$ , the greater its capacity

# CAPACITY: EXAMPLES

Not necessarily related to uncertainty

- ▶ Example 2
  - ▶  $X$  = a set of goods
  - ▶ The capacity of a set of goods  $A \subseteq X$  is the total price
  - ▶ Usually, it is additive: the total price is the sum of the single prices
    - ▶ ...not always: the whole collection of Naruto volumes has much value than the sum of single volumes

## CAPACITY: FORMAL DEFINITION

A capacity on a universe  $X$  is a function  $\mu : 2^X \mapsto L$

- ▶  $L$  can be  $\mathfrak{R}, [0,1], \dots$
- ▶ grounded  $\mu(\emptyset) = 0$
- ▶ monotone  $A \subseteq B$  implies  $\mu(A) \leq \mu(B)$

A capacity is normalized if  $\mu(X) = 1$

## CAPACITY: COMMENTS

- ▶ Our interpretation will mostly be  $\mu(A)$  represents the confidence of an agent wrt A
- ▶ Monotony  $A \subseteq B$  implies  $\mu(A) \leq \mu(B)$ 
  - ▶ If A implies B then the agent has at least confidence in B as in A
  - ▶  $\mu(A \cup B) \geq \max\{\mu(A), \mu(B)\}$
  - ▶  $\mu(A \cap B) \leq \min\{\mu(A), \mu(B)\}$
- ▶ Capacities are sometimes called fuzzy measures or confidence measures

## CAPACITY AND PROBABILITY

More general than a probability measure

- ▶ An additive capacity is a probability measure
- ▶ Additivity:  $P(A \cup B) = P(A) + P(B)$



## CAPACITIES AND POSSIBILITY THEORY

More general than a possibility measure

- ▶ A **maxitive** capacity is a possibility measure
- ▶ Maxitivity:  $\Pi(A \cup B) = \max\{\Pi(A), \Pi(B)\}$
- ▶ What is a possibility measure? More generally, what is possibility theory?

# POSSIBILITY THEORY

- ▶ The term was coined in 1978 by L. Zadeh: imprecise linguistic statements modeled by **fuzzy sets interpreted as possibility distributions**
- ▶ The theory was formalized and developed by Dubois and Prade
- ▶ Spohn (1988): independently define similar ideas

## POSSIBILITY DISTRIBUTION

- ▶ A possibility distribution is a function  $\pi : X \mapsto [0,1]$
- ▶ it represents the state of knowledge of an agent
  - ▶ the state  $a$  is impossible  $\pi(a) = 0$
  - ▶ the state  $a$  is totally possible  $\pi(a) = 1$ 
    - ▶ more that one state can be totally possible  $\pi(a) = 1, \pi(b) = 1$
  - ▶ complete knowledge  $\exists a, \pi(a) = 1 \quad \forall b \neq a, \pi(b) = 0$
  - ▶ complete ignorance  $\forall a, \pi(a) = 1$
- ▶ Usually normalization is assumed:  $\exists a, \pi(a) = 1$

## POSSIBILITY & NECESSITY MEASURES

- ▶ Possibility measure  $\Pi(A) = \sup_{a \in A} \pi(a)$
- ▶ Necessity measure  $N(A) = 1 - \Pi(A^c) = \inf_{a \notin A} (1 - \pi(a))$
- ▶ Necessity implies possibility:  $N(A) \leq \Pi(A)$
- ▶ Necessity is a minitive capacity:

$$N(A \cap B) = \min\{N(A), N(B)\}$$

## EXAMPLES

- ▶ “I am highly confident that the thief’s car is blue or black”
  - ▶  $N(\{\text{blue, black}\}) = 0.8$
- ▶ “I exclude that she likes tomatoes, but she might like carrots and salad”  
 $\Pi(\{\text{tomatoes}\}) = 0, N(\{\text{carrots}\}) = N(\{\text{salad}\}) = 0.6$
- ▶ “I have no idea about A”, “I do not know A”  
 $\Pi(A) = 1, N(A) = 0$

# POSSIBILITY VS PROBABILITY

## Probability

## Possibility

$$P(A) = \sum_{a \in A} p(a)$$

$$\Pi(A) = \sup_{a \in A} \{\pi(a)\}$$

$$\sum_{a \in X} p(a) = 1$$

$$\exists a, \pi(a) = 1$$

$$P(A) = 1 - P(A^c)$$

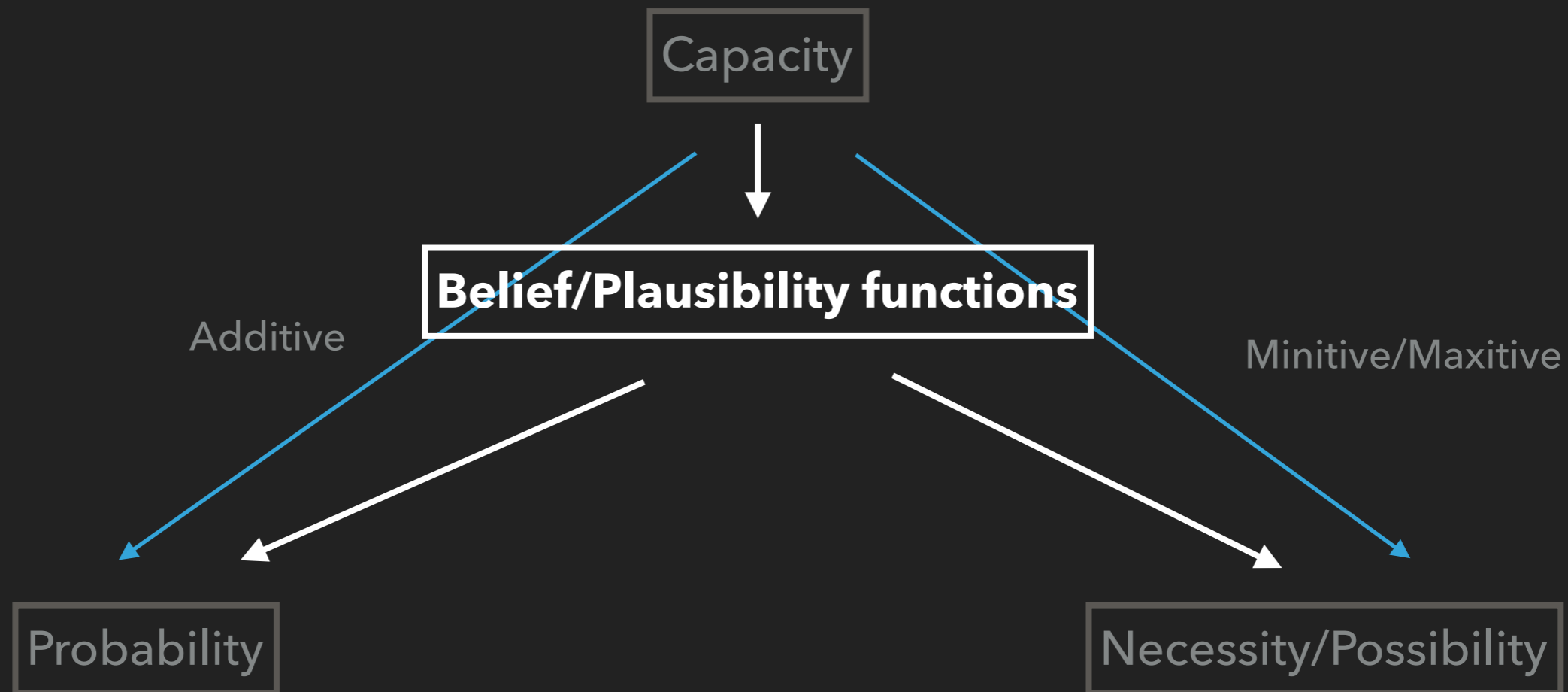
$$\Pi(A) = 1 - N(A^c)$$

$$\Pi(A) + \Pi(A^c) \geq 1$$

## BOOLEAN POSSIBILITY DISTRIBUTION

- ▶ A Boolean possibility distribution is a function  $\pi : X \mapsto \{0,1\}$
- ▶ If  $X$  is a set of propositional variables, then  $\pi$  is a **partial truth assignment**
- ▶  $X = \{v1, v2, v3, v4\}$
- ▶  $\pi(v1) = 1(\text{true}), \pi(v2) = 1(\text{true}), \pi(v3) = 0(\text{false})$
- ▶  $v4$  undefined

# BELIEF FUNCTIONS AND CAPACITIES





# BELIEF FUNCTION

- ▶ Evidence theory
  - ▶ “A mathematical theory of evidence”, Shafer, 1976
  - ▶ belief/plausibility functions: totally monotone/  
alternating normalized capacities
- ▶ Dempster-Shafer theory
  - ▶ Dempster (1967) used the names lower and upper probabilities

# THE IDEA

- ▶ To associate probabilities to incomplete and imprecise observations
  - ▶ A radar measuring the speed of vehicles is **imprecise**, it only returns an interval
  - ▶ I have a king of clubs in my hand and I reveal that it is a black card. Concerning the set {♠,♣,♥,♦} you have an **incomplete** information
- ▶ The true outcome lies in a set, but the exact value is unknown

## MASS FUNCTION

- ▶  $X$  a set of outcomes of an experiment
- ▶  $A \subseteq X$  an event
- ▶ We associate to an event a (belief) mass distribution  $m : 2^X \mapsto [0,1]$  such that
  - ▶  $m(\emptyset) = 0$  (normalization)
  - ▶  $\sum_{A \subseteq X} m(A) = 1$  ( $m$  is a probability distribution)

## MASS FUNCTION

- ▶ The card is black:  $m(\{\spadesuit, \clubsuit\}) = 1$ 
  - ▶ I am certain that the card is spade or club
- ▶  $m(A)$  represents the belief committed to  $A$ , not to its subsets
  - ▶ The fact that the card is black does not tell anything on the fact it is a club or a spade
- ▶ Focal sets:  $m(A) > 0$

## ON THE INTERPRETATION OF $m$

- ▶  $m(A)$  is the probability that the agent only knows that  $x$  is in  $A$   $\rightarrow$  Epistemic point of view
- ▶ It can be non-monotonic:  $A \subseteq B, m(B) \leq m(A)$  if the agent is sure enough that  $x$  in  $A$
- ▶  $m(X) = 1$  the agent knows nothing

# BELIEF AND PLAUSIBILITY FUNCTIONS

▶ Belief function  $Bel : 2^X \mapsto [0,1]$

▶  $Bel(A) = \sum_{B \subseteq A} m(B)$

▶ The total mass of belief **certainly** committed to A

▶ Plausibility function  $Pl : 2^X \mapsto [0,1]$

▶  $Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)$

▶ The total mass of belief **possibly** related to A

▶  $Bel(A) \leq Pl(A)$ ,  $Pl(A) = 1 - Bel(A^c)$  (as it was for possibility/necessity)

## EXAMPLE: CHINESE VASE

- ▶ In an antique shop you see a wonderful, expensive vase



[oroa.com](http://oroa.com), 1355€



[amazon.com](http://amazon.com), 9.39€

## EXAMPLE: CHINESE VASE

- ▶  $X = \{\text{genuine}, \text{counterfeit}\}$
- ▶ CASE 1: not an expert, total ignorance
  - ▶ total ignorance:  $m(\{\text{genuine}\}) = m(\{\text{counterfeit}\}) = 0$ ,  $m(X) = 1$
  - ▶  $\text{Bel}(\{\text{genuine}\}) = \text{Bel}(\{\text{counterfeit}\}) = 0$
  - ▶  $\text{Pl}(\{\text{genuine}\}) = \text{Pl}(\{\text{counterfeit}\}) = 1$



## EXAMPLE: CHINESE VASE

- ▶  $X = \{\text{genuine}, \text{counterfeit}\}$
- ▶ CASE 2: expert, there are as many clues in favor of genuine than of counterfeit
  - ▶  $m(\{\text{genuine}\}) = m(\{\text{counterfeit}\}) = 1/2, m(X) = 0$
  - ▶  $\text{Bel}(\{\text{genuine}\}) = \text{Bel}(\{\text{counterfeit}\}) = 1/2$
  - ▶  $\text{Pl}(\{\text{genuine}\}) = \text{Pl}(\{\text{counterfeit}\}) = 1/2$
- ▶ In probability theory the two cases (expert/non expert) are not distinguishable
  - ▶  $P(\text{genuine}) = P(\text{counterfeit}) = 1/2$

## COMBINING EVIDENCE: DEMPSTER'S RULE

▶  $m_1, m_2$  two mass distributions, both reliable

▶  $m_{1,2}(\emptyset) = 0$

▶  $m_{1,2}(A) = \frac{1}{1 - k} \sum_{B \cap C = A} m_1(B)m_2(C)$  where

$$K = \sum_{B \cap C = \emptyset} m_1(B)m_2(C)$$

▶  $K$  is a measure of conflict

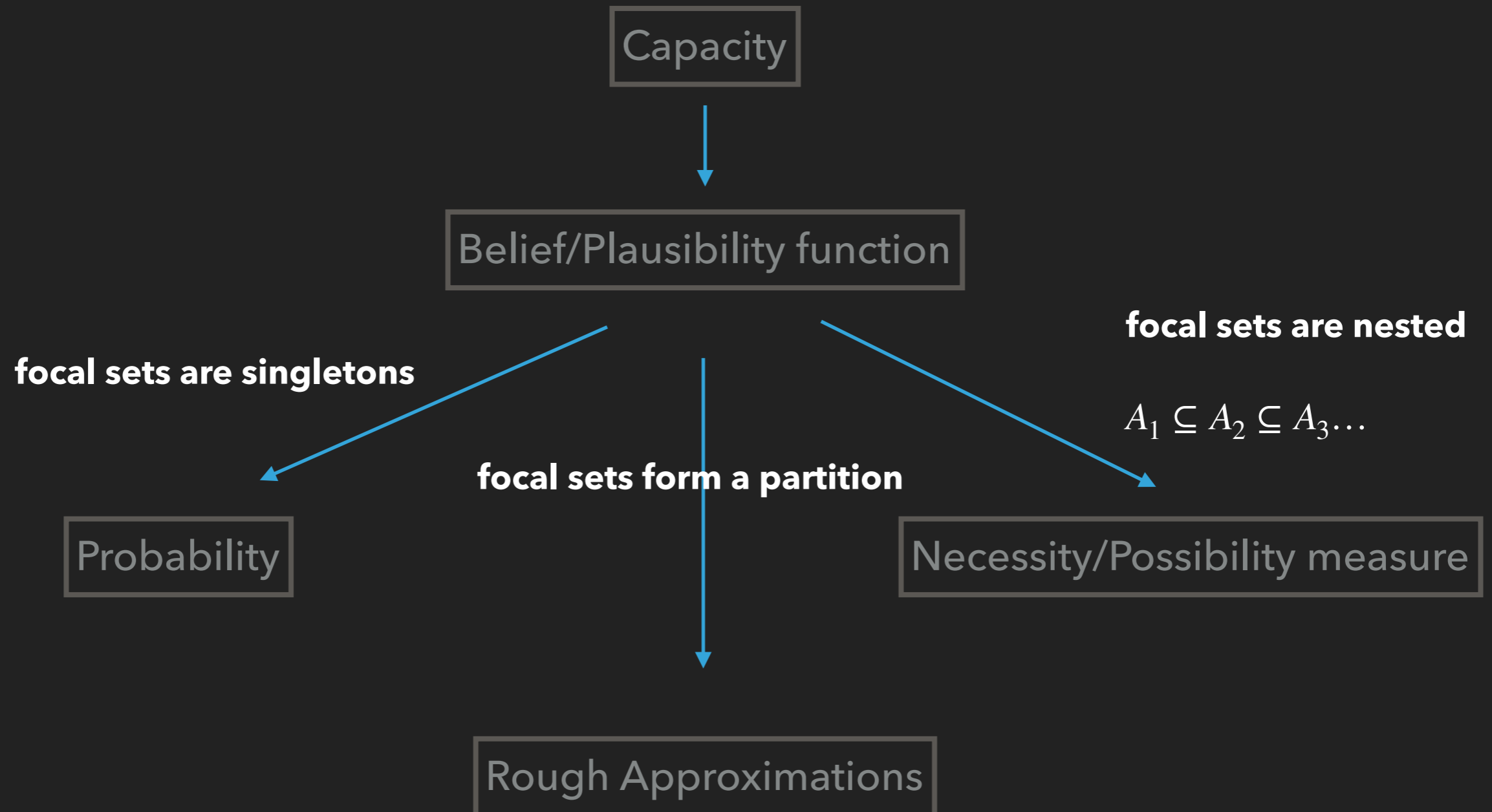
## DEMPSTER'S RULE: (COUNTERINTUITIVE) EXAMPLE

- ▶ Doctor A: illness a with 99%, illness b with 1% certainty
- ▶ Doctor B: illness c with 99%, illness b with 1% certainty
- ▶  $X = \{a, b, c\}$
- ▶  $m_1(\{a\}) = 0.99$   $m_1(\{b\}) = 0.01$
- ▶  $m_2(\{c\}) = 0.99$   $m_2(\{b\}) = 0.01$
- ▶  $K = 0.99 * 0.99 + 0.99 * 0.01 + 0.01 * 0.99 = 0.9999$
- ▶  $m_{1,2}(\{a\}) = m_{1,2}(\{c\}) = 0$ ,  $m_{1,2}(\{b\}) = 1$

## OTHER RULES

- ▶ Not normalized:  $m_{1,2}(A) = \sum_{B \cap C = A} m_1(B)m_2(C)$
- ▶  $m_{1,2}(\{a\}) = m_{1,2}(\{c\}) = 0, m_{1,2}(\{b\}) = 0.0001$
- ▶ Rule of thumb:
  - ▶ normalized in closed world hypothesis
  - ▶ Non-normalized in open world hypothesis
- ▶  $m_1, m_2$  two mass distributions, at least one reliable
- ▶  $(m_1 \cup m_2)(A) = \sum_{B \cup C = A} m_1(B)m_2(C)$
- ▶ Many others...

# BELIEF FUNCTIONS AND CAPACITIES



## QUALITATIVE CAPACITY

- ▶ A capacity on a universe  $X$  is a function  $\mu : 2^X \mapsto L$
- ▶  $L$  a non-numerical totally ordered set representing terms pertaining to belief
- ▶  $L = \{\text{zero, very low, low, medium, high, very high, top}\}$
- ▶ Similar theories to the quantitative case can be developed

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## TOTALLY MONOTONE CAPACITY

- ▶ A capacity  $\mu$  is totally monotone if

$\forall k \geq 2$  it is  $k$ -monotone

$$A_1, \dots, A_k \quad \mu(\cup A_i) \geq \sum_{I \subseteq \{1, \dots, k\}} (-1)^{|I|+1} (\mu(\cap_{i \in I} A_i))$$

- ▶ A generalized version of

$$|\cup A_i| = \sum_{I \subseteq \{1, \dots, k\}} (-1)^{|I|+1} (\cap_{i \in I} A_i)$$