A Breathless Introduction to Generalized Information Theory

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Modeling, Algorithms, and Informatics (CCS-3)



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ZOO OF AVAILABLE UQ FORMALISMS

Traditional:

- Set Theory
- Logic
- Probability Theory

More Novel:

- Interval Analysis
- Fuzzy Systems
- Fuzzy and Monotone Measures
- Dempster-Shafer Evidence Theory
- Random Sets and Intervals
- Possibility Theory
- Probability Bounds
- Rough Sets
- Imprecise Probabilities
- Probabilistic Robustness
- Info-Gap Theory



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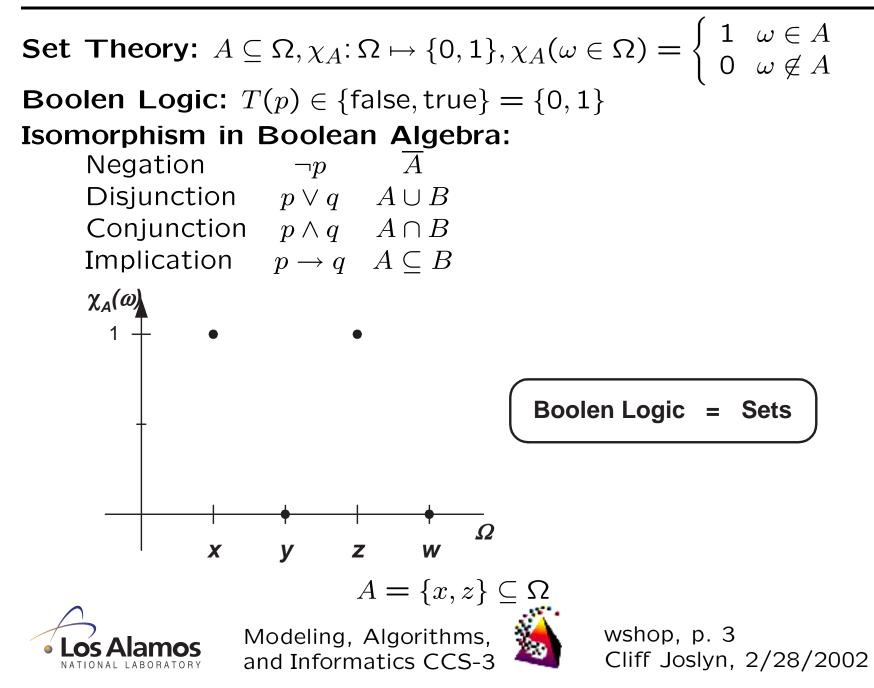
DEFER OBVIOUS CONTROVERSIES ...

- Why should I care, what's this good for, anyway?
- Isn't that just the same as probability?
- Why isn't probability good enough for you?
- Where do the numbers come from?
- Can you give me an example of where X does better than probability?
- Why do you use all those silly words like "fuzzy" and "belief"? Can you be serious?

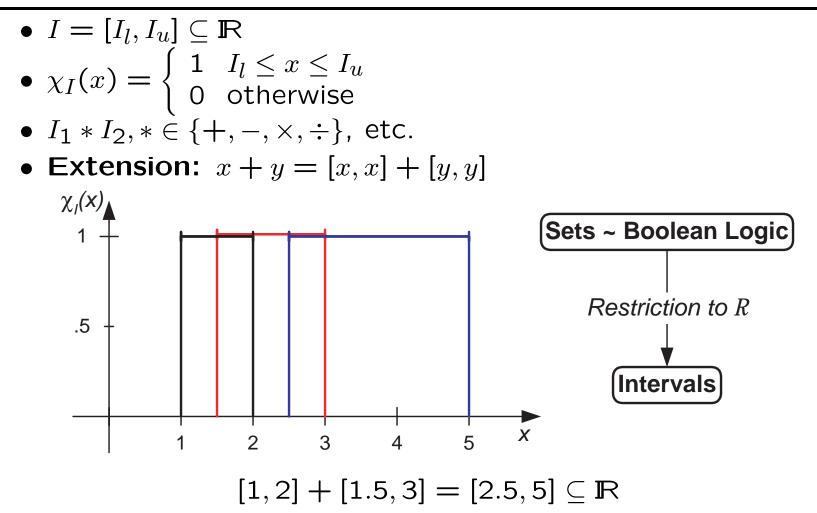




"CLASSICAL" POINT OF DEPARTURE: SETS AND LOGIC



INTERVALS





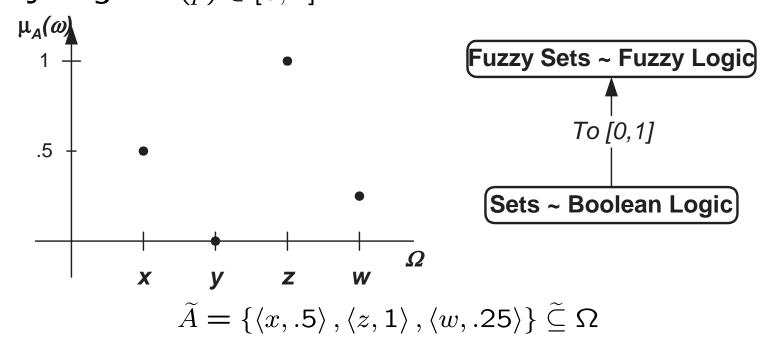
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FUZZINESS

Fuzzy Sets: $\widetilde{A} \subseteq \Omega, \mu_{\widetilde{A}} \colon \Omega \mapsto [0, 1], \mu_{\widetilde{A}}(\omega) = \widetilde{A}(\omega) \in [0, 1]$ is the "extent" or "degree" to which $\omega \in A$ **Fuzzy Logic:** $\widetilde{T}(p) \in [0, 1]$





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FUZZY OPERATIONS

(canonical example)

$$\begin{split} \widetilde{A} & \mu_{\widetilde{A}}(\omega) = c(\widetilde{A}(\omega)) & \mu_{\widetilde{A}}(\omega) = 1 - \widetilde{A}(\omega) \\ \widetilde{A} \cup \widetilde{B} & \mu_{\widetilde{A} \cup \widetilde{B}}(\omega) = \widetilde{A}(\omega) \sqcup \widetilde{B}(\omega) & \mu_{\widetilde{A} \cup \widetilde{B}}(\omega) = \widetilde{A}(\omega) \lor \widetilde{B}(\omega) \\ \widetilde{A} \cap \widetilde{B} & \mu_{\widetilde{A} \cap \widetilde{B}}(\omega) = \widetilde{A}(\omega) \sqcap \widetilde{B}(\omega) & \mu_{\widetilde{A} \cap \widetilde{B}}(\omega) = \widetilde{A}(\omega) \land \widetilde{B}(\omega) \\ \widetilde{A} \subseteq \widetilde{B} & \mu_{\widetilde{A} \subseteq \widetilde{B}}(\omega) = \widetilde{A}(\omega) \to \widetilde{B}(\omega) & \mu_{\widetilde{A} \subseteq \widetilde{B}}(\omega) = (1 - \widetilde{A}(\omega)) \lor \widetilde{B}(\omega) \\ \bullet \lor, \land \text{ are max and min} \\ \bullet c: [0, 1] \mapsto [0, 1] \text{ is a complement function} \\ c(0) = 1, c(1) = 0, x \leq y \to c(x) \geq c(y) \\ \bullet \sqcap (\sqcup) \text{ is a triangular norm (conorm) (associative copulas/co-copula):} \\ \sqcap, \sqcup: [0, 1]^2 \mapsto [0, 1], \text{ associative, monotonic,} \end{split}$$

 $\begin{array}{rcl} 0 \sqcup x = x \sqcup 0 = x, & 1 \sqcap x = x \sqcap 1 = x \\ x \sqcap y & x \land y & \geq & x \times y & \geq & 0 \lor (x + y - 1) & \geq & \lfloor x \rfloor \lfloor y \rfloor \\ x \sqcup y & x \lor y & \leq & x + y - xy & \leq & 1 \land (x + y) & \leq & \lceil x \rceil \lceil y \rceil \end{array}$

• **Extension:** When $\widetilde{A}, \widetilde{B}: \Omega \mapsto \{0, 1\}$, then "crisp" set operations recovered

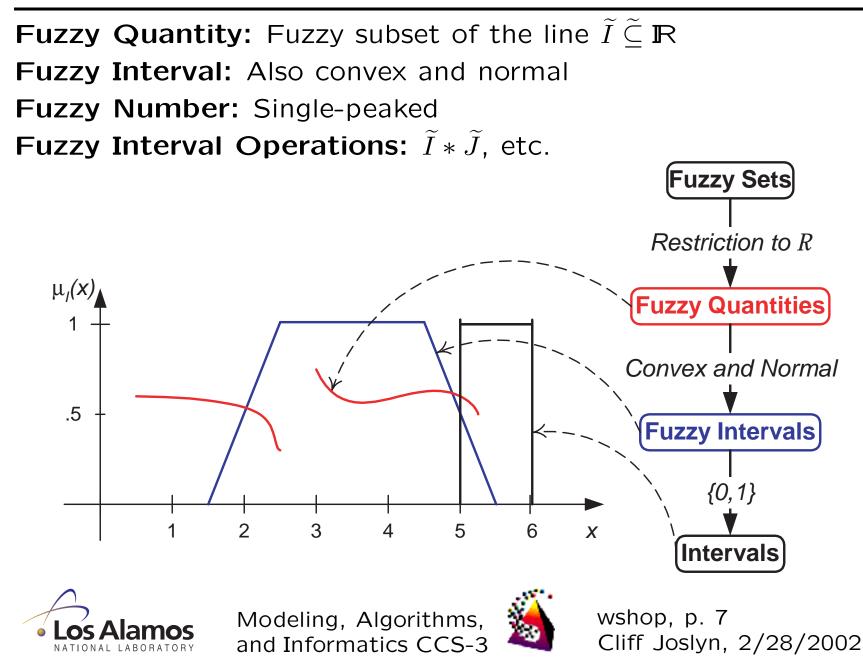


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FUZZY QUANTITIES, NUMBERS AND INTERVALS



FUZZY SETS AS GENERALIZED "DENSITIES" OR "DISTRIBUTIONS"

Fuzzy Quantity: $\widetilde{I} \subseteq \mathbb{R}$ Probability Distribution: Fuzzy quantity where $\int_{x\in {\rm I\!R}} \mu_{\widetilde{I}}(x) = 1$ **Fuzzy Interval = Possibility Distribution:** Fuzzy quantity where $\sup_{x\in {\rm I\!R}} \mu_{\widetilde{I}}(x) = 1$ $\mu_{l}(x)$ $\mu_{l}(x)$ $\mu_{l}(\mathbf{x})$ 2 3 Y **Fuzzy Quantity** .5 .5 2 3 4 x 2 3 **Fuzzy Interval Probability Distribution** Modeling, Algorithms, wshop, p. 8 and Informatics CCS-3 Cliff Joslyn, 2/28/2002

GENERALIZED MEASURES

- From point functions to set functions
- Generalizes relation between probability density and probability measure
- Fuzzy Measure: $\nu: 2^{\Omega} \mapsto [0, 1]$, where $\nu(\emptyset) = 0, \quad \nu(\Omega) = 1, \quad A \subseteq B \to \nu(A) \leq \nu(B).$
- **Trace** as concept of density $\rho_{\nu}: \Omega \mapsto [0, 1], \rho_{\nu}(\omega) := \nu(\{\omega\}).$
- Distributional or decomposable if $\exists \sqcup, \nu(A) = \bigsqcup_{\omega \in A} \rho_{\nu}(\omega)$.
- Normalization: $\bigsqcup_{\omega \in \Omega} \rho_{\nu}(\omega) = 1$.
- A probability measure is a fuzzy measure (A ⊆ B → Pr(A) ≤ Pr(B)) with an additional additive constraint:

 $\Pr(A \cup B) - \Pr(A \cap B) = \Pr(A) + \Pr(B)$ $\rho_{\Pr}(\omega) = p(\omega)$ Pr is distributional for $\sqcup = +_b$



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DEMPSTER-SHAFER EVIDENCE THEORY

• Belief and plausibility as dual fuzzy measures:

$$\begin{split} & \mathsf{Bel}(A \cup B) \ge \mathsf{Bel}(A) + \mathsf{Bel}(B) - \mathsf{Bel}(A \cap B) \\ & \mathsf{Pl}(A \cap B) \le \mathsf{Bel}(A) + \mathsf{Bel}(B) - \mathsf{Bel}(A \cup B) \\ & \mathsf{Bel}(A) + \mathsf{Bel}(\overline{A}) \le 1, \qquad \mathsf{Pl}(A) + \mathsf{Pl}(\overline{A}) \ge 1 \\ & \mathsf{Bel}(A) = 1 - \mathsf{Pl}(\overline{A}), \qquad \mathsf{Pl}(A) = 1 - \mathsf{Bel}(\overline{A}) \\ & \mathsf{Bel}(A) \le \mathsf{Pl}(A) \end{split}$$

• Codetermined by a basic probability assignment $m: 2^{\Omega} \mapsto$ [0,1] where $\sum_{A \subseteq \Omega} m(A) = 1:$ $\text{Bel}(A) = \sum_{B \subseteq A} m(B), \quad \text{Pl}(A) = \sum_{B \cap A \neq \emptyset} m(B)$ $m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} \text{Bel}(B) = \sum_{B \subseteq A} (-1)^{|A-B|} (1 - \text{Pl}(\overline{B}))$



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DEMPSTER-SHAFER EVIDENCE THEORY

Focal Set: $\mathcal{F} = \{A_j \subseteq \Omega : m(A_j) > 0\}$ Body of Evidence: $\langle \mathcal{F}, m \rangle = \langle \{A_j\}, \{m(A_j)\} \rangle$ Example:

$$\mathcal{F} = \{A_1, A_2, A_3, A_4\}$$

$$m(A_1) = .1, m(A_2) = .2$$

$$m(A_3) = .3, m(A_4) = .4$$

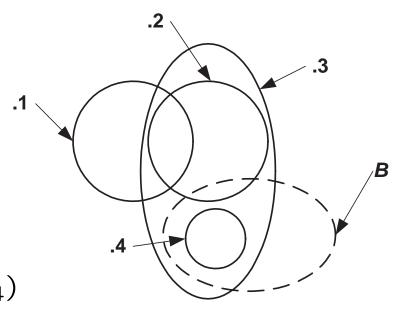
$$\mathsf{Bel}(B) = \sum_{A_j \subseteq B} m(A_j)$$

$$= m(A_4) = .4$$

$$\mathsf{Pl}(B) = \sum_{A_j \cap \subseteq B} m(A_j)$$

$$= m(A_2) + m(A_3) + m(A_4)$$

$$= .2 + .3 + .4 = .9$$





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RANDOM VARIABLES, RANDOM SETS, AND BODIES OF EVIDENCE

- Transform a body of evidence: $\langle \{A_j\}, \{m(A_j)\} \rangle = \{\langle A_j, m(A_j) \rangle \}$
- Recalling that $\sum_{A_j} m(A_j) = 1$, then $m(A_j)$ sure looks like a density $p(A_j)$
- Random Variable: Given a probability space $\langle X, \Sigma, \Pr \rangle$, then $S: X \mapsto \Omega$ is a random variable if S is Pr-measurable: $\forall \omega \in \Omega, S^{-1}(\omega) \in \Sigma$.
- General Random Set: S: X → 2^Ω {Ø} is a random subset of Ω if S is Pr-measurable: ∀Ø ≠ A ⊆ Ω, S⁻¹(A) ∈ Σ. m acts as density of S.
- Finite Random Set: $S = \{ \langle A_j, m(A_j) \rangle \}$. $\Pr(S = A) = m(A)$ $\Pr(S \subseteq A) = \operatorname{Bel}(A), \quad \Pr(S \cap A \neq \emptyset) = \operatorname{Pl}(A)$



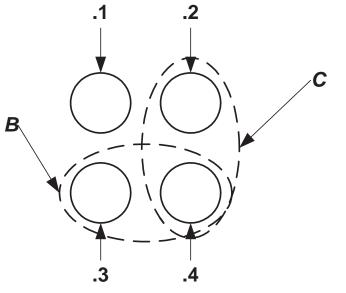
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DECOMPOSABLE CASE: PROBABILITY MEASURES

- Assume \mathcal{F} is a disjoint class: $\forall A_1, A_2 \in \mathcal{F}, A_1 \cap A_2 = \emptyset$.
- More particularly, $\mathcal{F} = \{\{\omega\}\}$.
- Bel(B) = Pl(B) = Pr(B)
- Probability distribution $p(\omega) = \Pr(\{\omega\}), \sqcup = +_b$:
 - $\Pr(A) = \sum_{\omega \in A} p(\omega), \qquad \Pr(\Omega) = \sum_{\omega \in \Omega} p(\omega) = 1$
 - Bel(B) = Pl(B) =Pr(B) = .3 + .4 = .7
 - $\Pr(B \cup C) = \Pr(B) + \Pr(C) \Pr(B \cap C) = .9$





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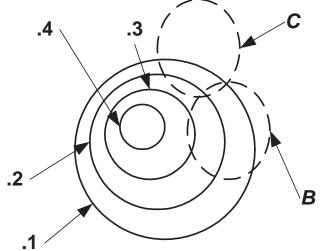
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DECOMPOSABLE CASE: POSSIBILITY MEASURES

- Assume \mathcal{F} is a nested class: $\forall A_1, A_2 \in \mathcal{F}, A_1 \subseteq A_2$ or $A_2 \subseteq A_1$
- PI becomes a **possibility measure** Π distributional for $\sqcup = \lor$: $\Pi(B \cup C) = \Pi(B) \lor \Pi(C)$
- Dual necessity measure $\mathrm{Bel}=\eta$
- Possibility distribution $\pi(\omega) = \Pi(\{\omega\}), \sqcup = \lor$:

 $\Pi(A) = \vee_{\omega \in A} \pi(\omega), \qquad \Pi(\Omega) = \vee_{\omega \in \Omega} \pi(\omega) = 1$

 $\Pi(B \cup C) = \Pr(B \cup C)$ = .1 + .2 + .3 = .6 = $\Pi(B) \lor \Pi(C) = .6 \lor .3$



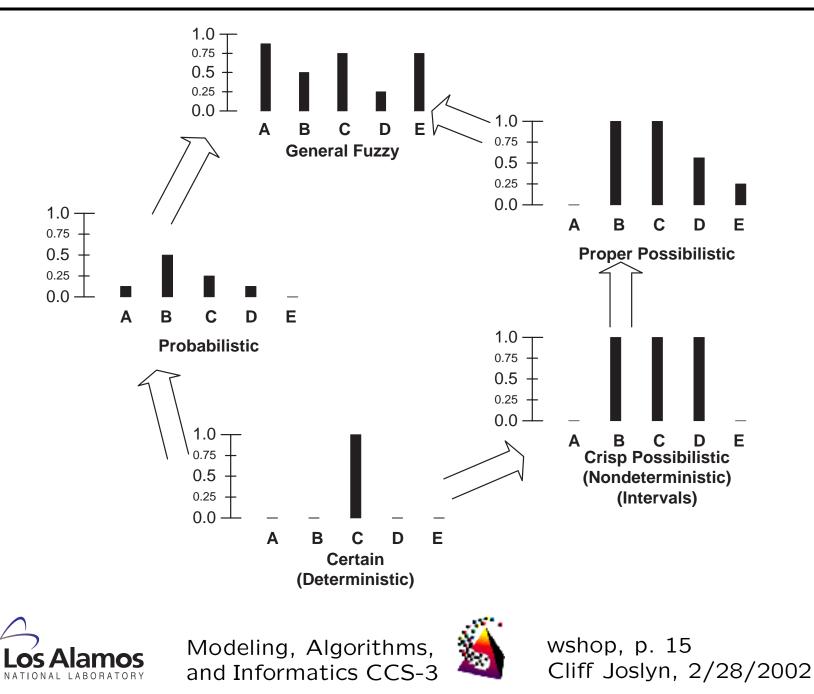


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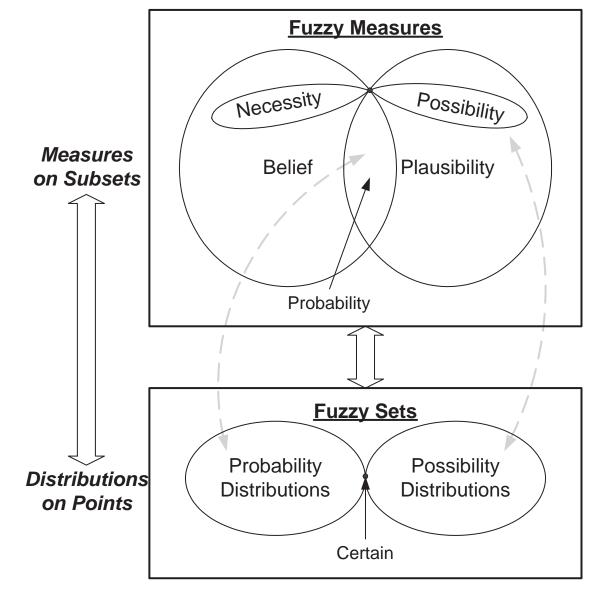


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CLASSES OF MEASURE TRACES



MEASURES AND DISTRIBUTIONS





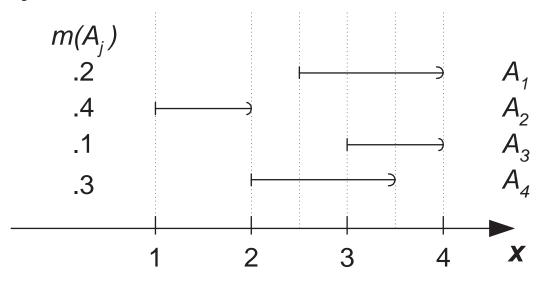
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RANDOM INTERVALS

- $\mathcal{D} := \{ [a, b) \subseteq \mathbb{R} : a, b \in \mathbb{R}, a < b \}.$
- Random Interval: \mathcal{A} , is a random set on $\Omega = \mathbb{R}$ for which $\mathcal{F}(\mathcal{A}) = \{I_j\} \subseteq \mathcal{D}$





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PROBABILITY BOUNDS

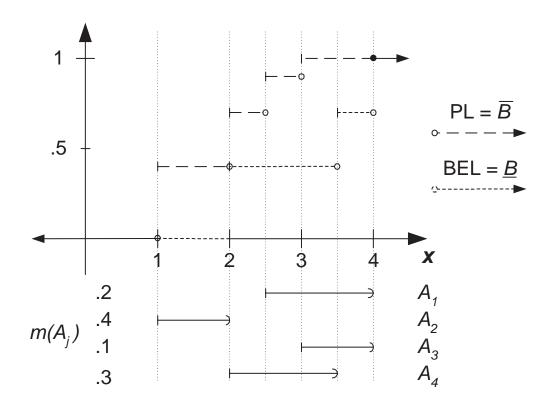
- Cumulative Belief and Plausibility: PL, BEL: $\mathbb{R} \mapsto [0, 1]$ BEL(x) := Bel $((-\infty, x))$, PL(x) := Pl $((-\infty, x))$.
- **Probability Bounds:** (Ferson) $\mathcal{B} := \langle \underline{B}, \overline{B} \rangle$, where $\underline{B}, \overline{B} : \mathbb{R} \mapsto [0, 1]$, $\lim_{x \to -\infty} B(x) \to 0$, $\lim_{x \to \infty} B(x) \to 1$, and $\underline{B}, \overline{B}$ are monotonic with $\underline{B} \leq \overline{B}$.





RANDOM INTERVALS TO PROBABILITY BOUNDS

- Given a random interval \mathcal{A} , then $\langle \mathsf{BEL},\mathsf{PL} \rangle$ is a PBound.
- Given a PBound \mathcal{B} , then $\overline{B} \underline{B} = \rho_{\text{Pl}}$
- If a random interval \mathcal{A} is consonant, then $\overline{B} \underline{B} = \pi$ is its possibility distribution





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CURRENT PROBLEM

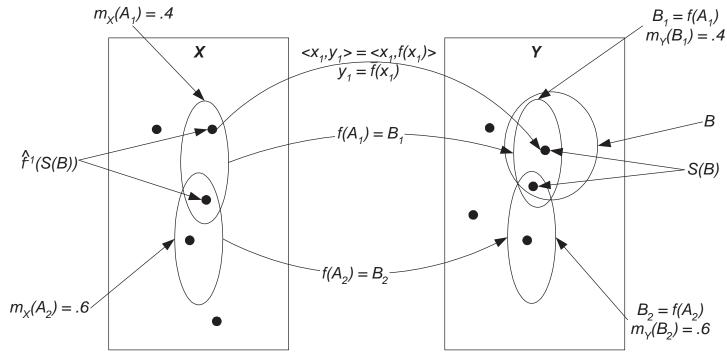
- Set of parameters $X = \{X_i\}$ with $\mathbf{X} := \underset{i}{\times} X_i$
- Unknown function $f: \mathbf{X} \mapsto \mathbf{Y}, f(\vec{x}) = \vec{y}$
- Knowledge on X characterized by a random interval structure: statistical collection of intervals A_i on each X_i
- \bullet Induces global $\mathit{n}\text{-dimensional}\ \mathcal{A}$ on \mathbf{X}
- f induces an output random interval $f(\mathcal{A})$ on \mathbf{Y}
- What knowledge of $f(\mathcal{A})$ can be gained by samples of $f(\vec{x})$?





SAMPLING ESTIMATION OF RANDOM SET PROPAGATION

- Initially simplify to finite random sets
- Estimate $\operatorname{Pl}_Y(B)$ by $\widehat{\operatorname{Pl}}_Y(B) := \operatorname{Pl}_X(\widehat{f}^{-1}(S(B)))$





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BREATHE!

Thank you!



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