

Logic for probability, belief, and change.

Joshua Sack

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Monty Hall Puzzle (Probability Dynamics)

A game show host presents to you three closed doors and says that behind one of them is a prize, and behind the other two there is nothing. He then does the following:

- 1 He lets you pick a door.
- 2 He then opens a door to an empty room that you did not select.
- 3 He then asks if you would like to switch.

Question: Should you switch?

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What is Probability Exactly?

Definition

A *probability space* is a tuple $(\Omega, \mathcal{A}, \mu)$, where

- 1 Ω is a **set** called the sample space.
- 2 $\mathcal{A} \subseteq \mathcal{P}(\Omega)$ is a **σ -algebra**: a set of subsets of Ω containing \emptyset , which is closed under complements and countable unions and intersections.
- 3 $\mu : \mathcal{A} \rightarrow [0, 1]$ is a **probability measure**, that is
 - $\mu(\Omega) = 1$ and $\mu(\emptyset) = 0$
 - If $\{A_1, A_2, \dots\}$ is a countable set of pairwise disjoint elements of \mathcal{A} , then $\mu(\bigcup_{j=1}^{\infty} A_j) = \sum_{j=1}^{\infty} \mu(A_j)$. (Countable additivity)

(Ω, \mathcal{A}) is called a *measurable space*. Sets in the σ -algebra \mathcal{A} are called *measurable*.

Probability Model

Definition (Probability Model)

A probability model is a tuple $(\mathbf{P}, \|\cdot\|)$, where

- $\mathbf{P} = (\Omega, \mathcal{A}, \mu)$ is a probability space.
- $\|\cdot\|$ is a function from Φ to the set \mathcal{A} .

Probability logic is generated by the rule:

$$\varphi ::= p \mid \neg\varphi_1 \mid \varphi_1 \wedge \varphi_2 \mid [\geq a]\varphi \mid [> a]\varphi \mid [= a]\varphi$$

where $a \in \mathbb{Q}$.

Semantics (selected components)

$$\begin{aligned} \llbracket p \rrbracket &= \llbracket p \rrbracket \\ \llbracket [\geq a]\varphi \rrbracket &= \begin{cases} \Omega & \mu(\llbracket \varphi \rrbracket) \geq a \\ \emptyset & \text{otherwise} \end{cases} \end{aligned}$$

Suppose you select door A...

Let

$$\begin{aligned}\Phi &= \{(x, y) \mid x \in \{A, B, C\}, y \in \{B, C\}, x \neq y\} \\ &= \{(A, B), (A, C), (B, C), (C, B)\}\end{aligned}$$

where

- x represents the door that opens to a prize, and
- y represents the door the host will open.

Define

- $isA \equiv \bigvee \{(x, y) \in \Phi \mid x = A\}$, and similarly for isB and isC .
- $openB \equiv \bigvee \{(x, y) \in \Phi \mid y = B\}$, and similarly for $openC$.

Then

- $\llbracket [= \frac{1}{3}] isA \rrbracket = \llbracket [= \frac{1}{3}] isB \rrbracket = \llbracket [= \frac{1}{3}] isC \rrbracket = \Omega$ that is
 $\mu(\llbracket (A, B) \vee (A, C) \rrbracket) = \mu(\llbracket (B, C) \rrbracket) = \mu(\llbracket (C, B) \rrbracket) = \frac{1}{3}$.
- $\llbracket [= \frac{1}{2}] openB \rrbracket = \llbracket [= \frac{1}{2}] openC \rrbracket = \Omega$.

probability distribution

We end up with the following probabilities:

	$x = A$	$x = B$	$x = C$
$y = B$	$\mu(\llbracket(A, B)\rrbracket) = 1/6$		$\mu(\llbracket(C, B)\rrbracket) = 2/6$
$y = C$	$\mu(\llbracket(A, C)\rrbracket) = 1/6$	$\mu(\llbracket(B, C)\rrbracket) = 2/6$	

Probability Dynamics

Start with a probability model $M = ((\Omega, \mathcal{A}, \mu), \|\cdot\|)$ where $\mu(A) \neq 0$ for every $A \in \mathcal{A}$.

- Input: A subset $Y \subseteq \Omega$
- Update: $M[Y] = ((Y, \mathcal{A}^{M[Y]}, \mu^{M[Y]}, \|\cdot\|^{M[Y]})$, where
 - $\mathcal{A}^{M[Y]} = \{A \cap Y \mid A \in \mathcal{A}\}$
 - $\mu^{M[Y]} = \mu(\cdot \mid Y)$ maps $B \in \mathcal{A} \cap Y$ to $\mu(B)/\mu(Y)$.
 - $\|p\|^{M[Y]} = \|p\| \cap Y$.

Add formulas of the form $[!\varphi]\psi$ to the language:

$$\llbracket [!\varphi]\psi \rrbracket = \llbracket \neg\varphi \rrbracket \cup \llbracket \psi \rrbracket_{M[\llbracket \varphi \rrbracket]}$$

Using dynamics

Recall

	$x = A$	$x = B$	$x = C$
$y = B$	$\mu(\llbracket(A, B)\rrbracket) = 1/6$		$\mu(\llbracket(C, B)\rrbracket) = 2/6$
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Note that

$$\mu^{M(\llbracket\text{open}B\rrbracket)}(\llbracket\text{is}C\rrbracket) = \frac{\mu(\llbracket\text{is}C\rrbracket)}{\mu(\llbracket\text{open}B\rrbracket)} = \frac{\mu(\llbracket(C, B)\rrbracket)}{\mu(\llbracket(A, B)\rrbracket \cup \llbracket(C, B)\rrbracket)} = \frac{\frac{2}{6}}{\frac{3}{6}} = \frac{2}{3}$$

Hence

$$\begin{aligned}\llbracket\text{!open}B\rrbracket[\llbracket= 2/3\rrbracket\text{is}C] &= \llbracket\neg\text{open}B\rrbracket \cup \llbracket[\llbracket= 2/3\rrbracket\text{is}C]\rrbracket_{M(\llbracket\text{open}B\rrbracket)} \\ &= \llbracket\neg\text{open}B\rrbracket \cup \llbracket\text{open}B\rrbracket = \Omega.\end{aligned}$$

Probability vs Epistemics

Probabilities may offer more detail than qualitative epistemics, but numerical details might not be appropriate. Should we:

- assign a probability to a **computer outputing a bit 1**?
- assign a probability to a **coin flip resulting in heads**?

We may wish to involve *both* qualitative and quantitative uncertainty.

One of many options

One may define

$$\llbracket \text{Knows } \varphi \rrbracket = \llbracket [= 1] \varphi \rrbracket$$

$$\llbracket \text{Poss } \varphi \rrbracket = \llbracket [> 0] \varphi \rrbracket$$

The next example shows the utility of more flexibility in the relationship between epistemics and probability.

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Coin and bit example (Probability and Epistemics)

Suppose there are two agents i and k .

- 1 k is first given a bit 0 or 1. k learns he has this bit, i is aware that k received a bit, but i does not know what bit k received.
- 2 k flips a fair coin and looks at the result. i sees k look at the result, but does not what the result is.
- 3 k performs action s if the coin agrees with the bit (given that heads agrees with 1 and tails agrees with 0), and performs action d otherwise.

This example is from

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Probabilistic Epistemic Model

Definition

Let Φ be a set of proposition letters, and \mathbf{I} be a set of agents.

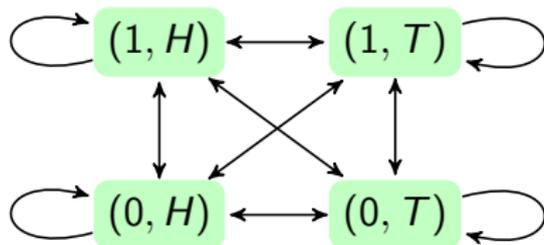
A probabilistic epistemic model is a tuple

$\mathcal{M} = (X, \{\overset{i}{\rightarrow}\}_{i \in \mathbf{I}}, \|\cdot\|, \{\mathbf{P}_{i,x}\}_{i \in \mathbf{I}, x \in X})$, where

- X is a finite set
- $\overset{i}{\rightarrow}$ (a subset of X^2) is an epistemic relation for each agent $i \in \mathbf{I}$, that is $x \overset{i}{\rightarrow} y$ if i considers y possible from x
- $\|\cdot\|$ is a function assigning to each proposition letter p the set of states where it is true.
- for each agent i and state x , the probability space $\mathbf{P}_{i,x}$ is defined as the tuple $(\Omega_{i,x}, \mathcal{A}_{i,x}, \mu_{i,x})$, where
 - $\Omega_{i,x} \subseteq X$ is the sample space (finite because X is finite)
 - $\mathcal{A}_{i,x}$ is a σ -algebra
 - $\mu_{i,x} : \mathcal{A}_{i,x} \rightarrow [0, 1]$ is a probability measure over $\Omega_{i,x}$

Discussion

There are four possible sequences of events:
 $(1, H), (1, T), (0, H), (0, T)$ (note that the action s or d is determined from the first two events). Until k performs the action s or d , agent i considers any of these four states possible.



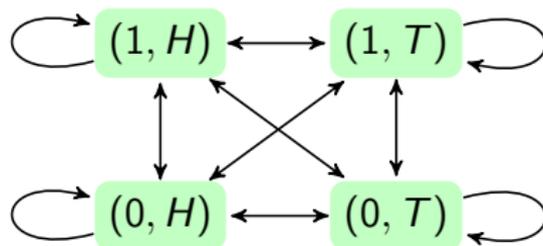
We indicate i 's uncertainty between two states using a bidirectional arrow between the two states. In particular, an arrow from state x to state y indicates that i considers y possible if x is the actual state.

Note

It is reasonable that i can calculate the probability of d and s

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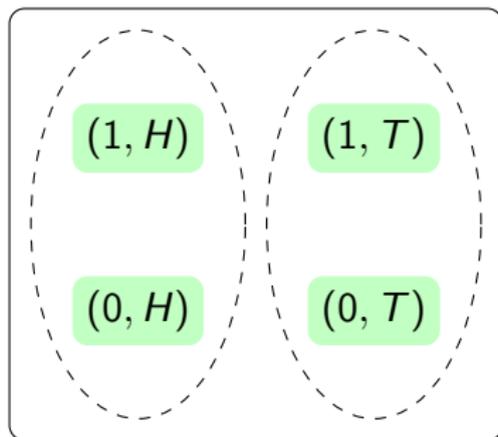
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Here is a possibility for i 's probability spaces.

- **sample space** is enclosed in a box,
- **σ -algebra equivalence classes** are enclosed in the dotted ovals.



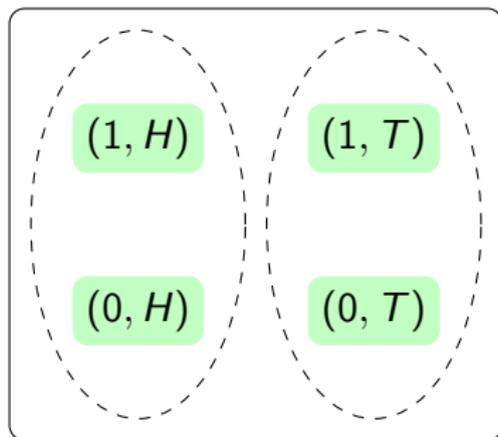
M_1

- **sample space** is the same as **set of states i considers possible**.
- Individual states cannot be measurable (otherwise 0 or 1 must be assigned a probability).

Consequence: s and d are not measurable.

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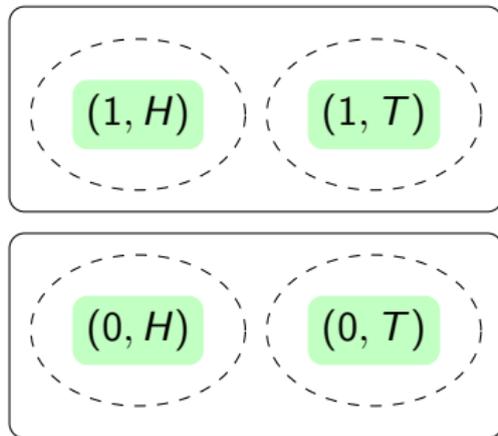


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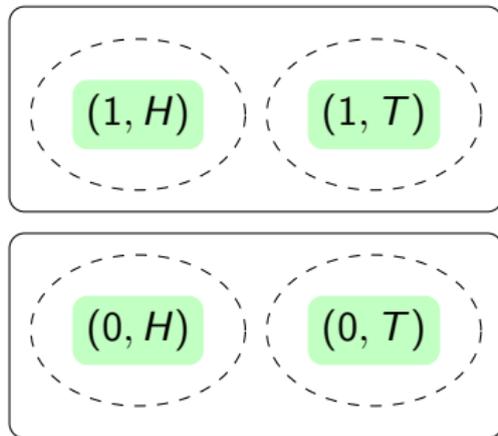
Another possibility has a sample space containing only the states with the correct bit (but recall that i considers all states possible and both sample spaces possible).



M_2

Without assigning probability to the bit, i can now assign a probability to the actions s and d .

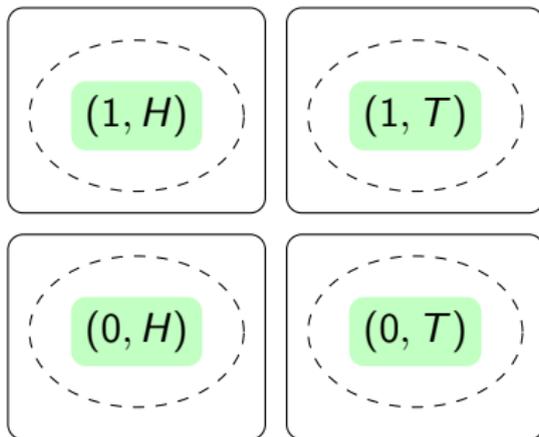
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Here i is uncertain among 4 probability spaces.



M_3

Main point of example

The action s has probability $1/2$ (as does d). The only model to let us reason about the probability of s as having probability $1/2$ is M_2 .

Observations about M_2 :

- Epistemics is not defined in terms of probability
- In fact epistemics reflects uncertainty about what probability distribution there actually is:

the set of (epistemic) possibilities is larger than the (probabilistic) sample spaces.

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Related Papers

- 1 D. Gerbrandy. (1998) *Bisimulations on Planet Kripke*.
Dissertation, ILLC.
(Discusses Muddy Children Puzzle and Surprise Exam Puzzle)
- 2 B. Kooi: Probabilistic Dynamic Epistemic Logic. (2003)
Journal of Logic Language and Information, 12(4): 381–408.
(Adds probability to Public Announcement Logic)
- 3 J. Sack. (2008) Temporal Languages for Epistemic Programs.
Journal of Logic Language and Information. 17(2): 183–216.
(Adds temporal operators to Dynamic Epistemic Logic)
- 4 J. Sack. (2009) Extending Probabilistic Dynamic Epistemic
Logic. *Synthese*, 169:2, pp. 241–257.
(Adds previous-time operator and σ -algebras to Probabilistic Dynamic
Epistemic Logic)

Books and Textbooks Relating to Topic

- 1 H. van Ditmarsch, W. van Der Hoek, B. Kooi (2008) *Dynamic Epistemic Logic*. Springer Synthese Library 337.
- 2 D. Harel, D. Kozen, J. Tiuryn (2000) *Dynamic Logic*. Foundations of Computing.
- 3 J.-J. Ch. Meyer and W. van Der Hoek (1995) *Epistemic Logic for AI and Computer Science*. Cambridge Tracts in Theoretical Computer Science 41.

Thank you!