

LiCS 2023

27th June 2023

EVIDENTIAL DECISION THEORY VIA PARTIAL MARKOV CATEGORIES

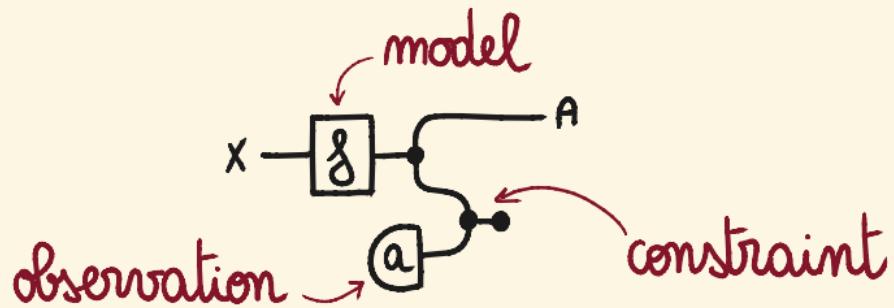
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PARTIALITY FOR OBSERVATIONS

Updating a model on an observation means restricting the model to scenarios that are compatible with this observation.



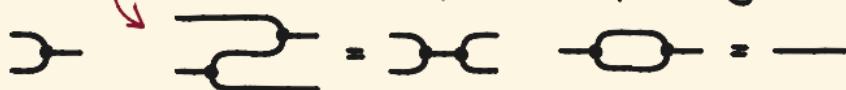
constraints \rightarrow cannot be total computations
because $\neq \equiv$.

OVERVIEW

Combine Markov and cartesian restriction categories to express partial stochastic processes.



Add the discrete structure to express equality checking.



Morphisms $x - \delta - A$ are partial stochastic channels

$\delta(a|x)$ = "probability of a given x "

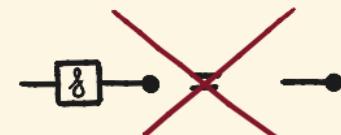
$\delta(\perp|x)$ = "probability of failure"

[Trifunovic 2020, Cockett & Lack 2007, Cockett, Guo & Hofstra 2012, Cho & Jacobs 2019]

PARTIAL MARKOV CATEGORIES

A partial Markov category is a copy-discard category with quasi-total conditionals.

COPY - DISCARD STRUCTURE



CONDITIONALS

$$\boxed{\delta} = \text{---} \circlearrowleft \text{---} \circlearrowright \text{---}$$

$$\text{---} \circlearrowleft \text{---} \circlearrowright \text{---} = \text{---} \circlearrowleft \text{---} \circlearrowright \text{---}$$

quasi-totality

domain of definition

EXAMPLES : PARTIAL STOCHASTIC PROCESSES

Partial stochastic processes form a partial Markov category.
↓
maybe monad on a Mäkrov category

THEOREM

{ cf Markov category with conditionals and coproducts
{ some ugly technical conditions
⇒ $\text{Kl}(\cdot + 1)$ is a partial Markov category.

EXAMPLES

- $\text{Kl}(\mathcal{D}(\cdot + 1))$ → finitary subdistributions
- $\text{Kl}(\text{dgiry}_{\mathbb{B}}(\cdot + 1))$ → subdistributions on standard Borel spaces

BAYES INVERSION & NORMALISATION

BAYES INVERSION

$$\text{Diagram: } \sigma \rightarrow g \rightarrow A = \text{marginal} \quad \text{Diagram: } \sigma \rightarrow g \rightarrow A \rightarrow B = \text{marginal} \quad \rightsquigarrow g_\sigma^\dagger(b|a) := \frac{g(a|b)\sigma(b)}{\sum_{b' \in B} g(a|b')\sigma(b')}$$

g_σ^\dagger is a Bayes inversion of g w.r.t. σ

NORMALISATION

$$\text{Diagram: } x \rightarrow g \rightarrow A = \text{marginal} \quad \text{Diagram: } x \rightarrow g \rightarrow A \rightarrow \bar{g} \quad \rightsquigarrow \bar{g}(a|x) := \frac{g(x|a)}{1 - g(\perp|a)}$$

\bar{g} is a normalisation of g

→ Both are particular cases of quasi-total conditionals.

DISCRETE PARTIAL MARKOV CATEGORIES

A discrete partial Markov category is a copy-discard category with quasi-total conditionals and comparators.

COPY - DISCARD STRUCTURE



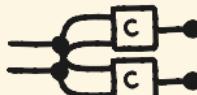
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CONDITIONALS



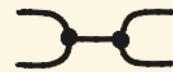
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PARTIAL FROBENIUS STRUCTURE



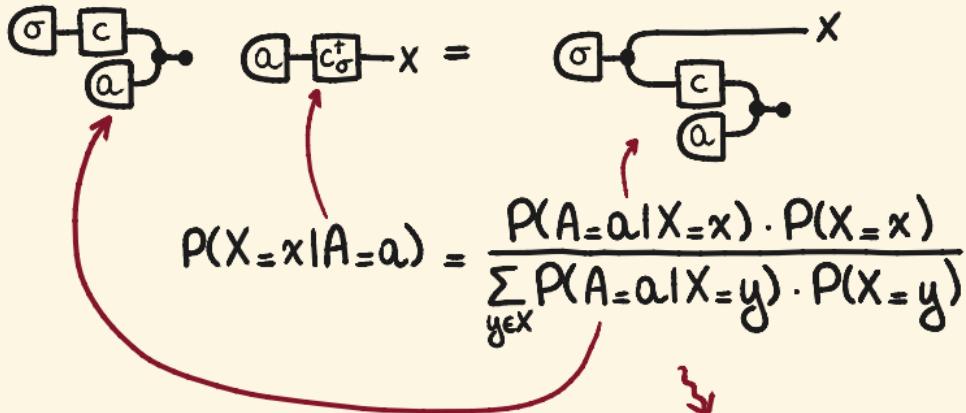
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COMPARATOR

SYNTHETIC BAYES THEOREM

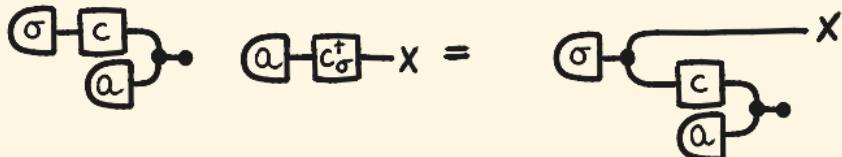
A deterministic observation $a: I \rightarrow A$ from a prior $\sigma: I \rightarrow X$ through a channel $c: X \rightarrow A$ determines an update proportional to the Bayes inversion c_σ^+ evaluated on a .



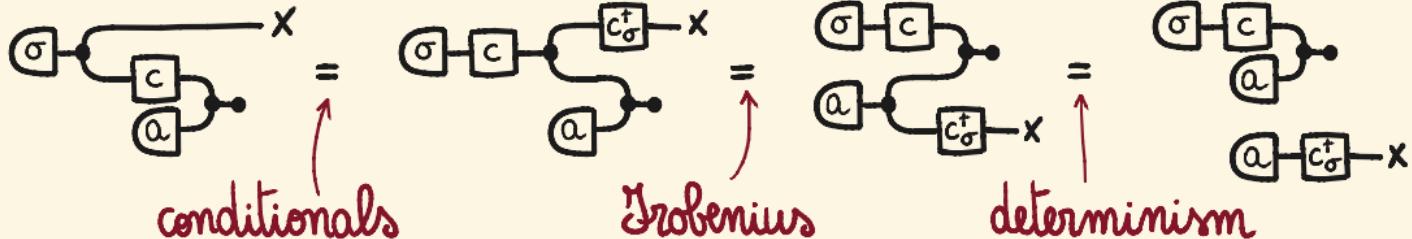
classical formula
for Bayes theorem

SYNTHETIC BAYES THEOREM

A deterministic observation $a: I \rightarrow A$ from a prior $\sigma: I \rightarrow X$ through a channel $c: X \rightarrow A$ determines an update proportional to the Bayes inversion c_σ^+ evaluated on a .



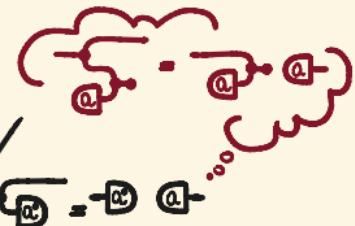
PROOF



□

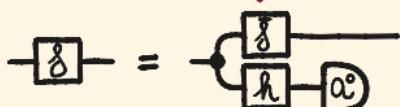
PROCESSES WITH EXACT OBSERVATIONS

For a Markov category \mathcal{C} with conditionals, we construct a partial Markov category $\text{exOb}(\mathcal{C})$:



$$\text{exOb}(\mathcal{C}) = (\mathcal{C} + \{\mathbf{A} - \square\mid \square \rightarrow \mathbf{A} \text{ deterministic}\}) /$$

conditionals and normalisations are computed in \mathcal{C}
normalisation of \mathbf{g} conditional of $\bar{\mathbf{g}}$



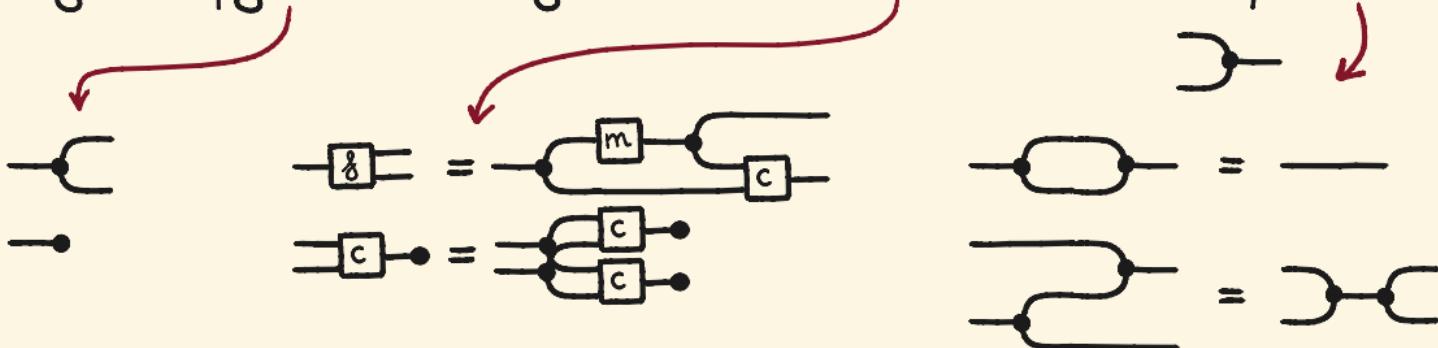
SUMMARY

Discrete partial Markov categories express stochastic processes with observations and updates.

$$\begin{array}{c} \text{Diagram 1: } (\sigma \square c) \square a \\ \text{Diagram 2: } a \square c^\dagger \square \sigma \\ \text{Diagram 3: } \sigma \square c \square a \end{array} = x$$

Synthetic Bayes theorem

They are copy-discard categories with conditionals and comparators.



NEWCOMB'S PROBLEM

I PREDICT THAT
THE AGENT WILL ...

"ONE-BOX" $\Rightarrow X = 10\ 000$
"TWO-BOX" $\Rightarrow X = 0$



PREDICTOR

very accurate:
it is right 90%
of the times



OPAQUE
BOX WITH $X \in$



TRANSPARENT
BOX WITH 1€

SHOULD I
"ONE-BOX" OR
"TWO-BOX" ?



AGENT

EVIDENTIAL DECISION THEORY

Evidential decision theory answers :

“Which action would be evidence for the best-case scenario ? ”

My action is evidence for the prediction:

if I one-box I expect 10 000 €,

if I two-box I expect 1€ .

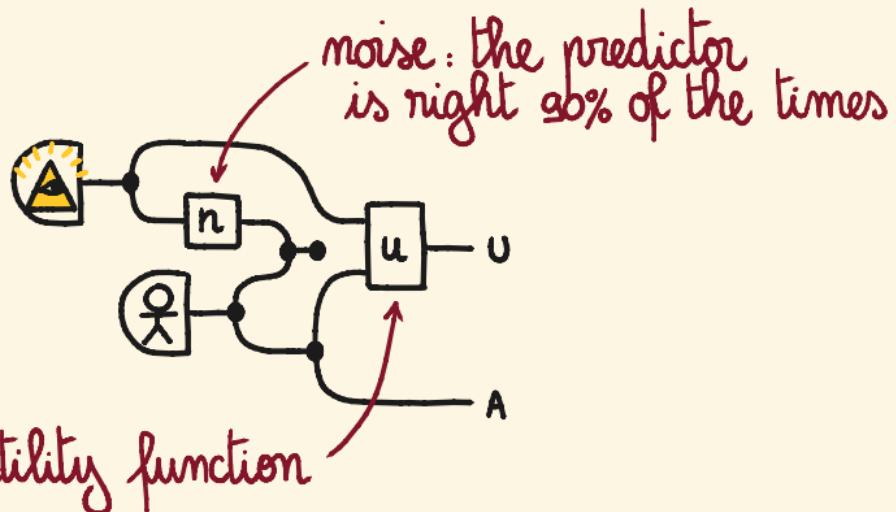
⇒ I will one-box



AGENT PREDICTOR	ONE-BOX	TWO-BOX
ONE-BOX	10 000 €	10 001 €
TWO-BOX	0 €	1 €

MOST LIKELY

NEWCOMB'S PROBLEM CATEGORICALLY



AGENT PREDICTOR	ONE-BOX	TWO-BOX
ONE-BOX	10 000 €	10 001 €
TWO-BOX	0 €	1 €

SOLVING NEWCOMB'S PROBLEM

Evidential decision theory asks:

"Which action would be evidence for the best-case scenario?"
i.e. "Which action maximises the average of the state below?"

