

EVIDENTIAL DECISION THEORY VIA PARTIAL MARKOV CATEGORIES

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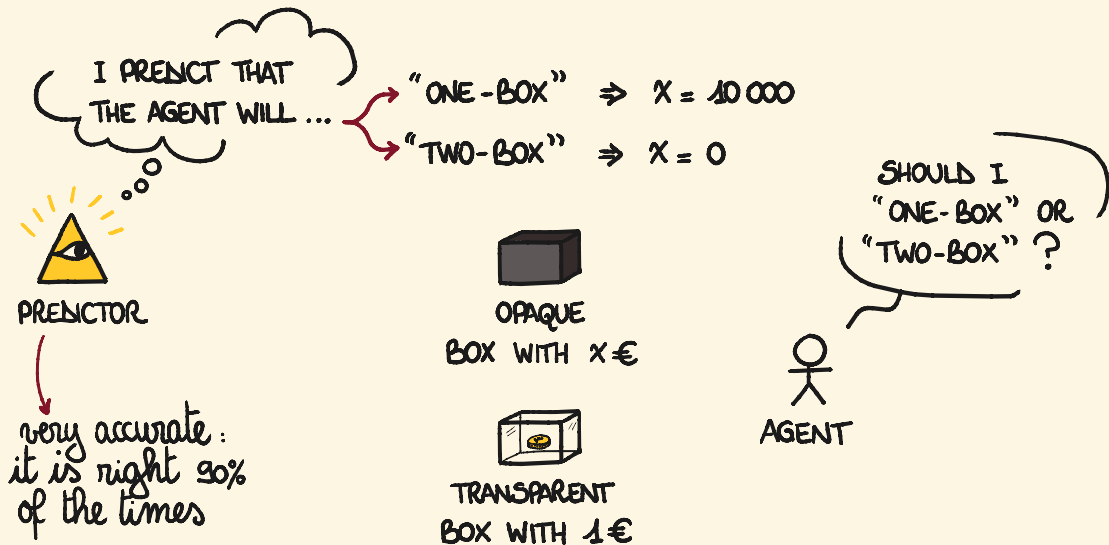
Tallinn University of Technology



OUTLINE

- [• motivation: Evidential Decision Theory]
- (discrete) partial Markov categories
- Bayes, observations & updates

NEWCOMB'S PROBLEM



(drawing inspired by Mario's slides for NWPT '22)

CAUSAL DECISION THEORY

Causal decision theory answers:

“Which action would cause the best-case scenario?”

Whatever the predictor did,
I get 1€ extra if I two-box
⇒ I will two-box



BEST!

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

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 €.

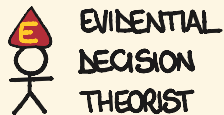
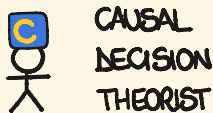
⇒ I will one-box

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

MOST LIKELY



EVIDENTIAL VS CAUSAL DECISION THEORY

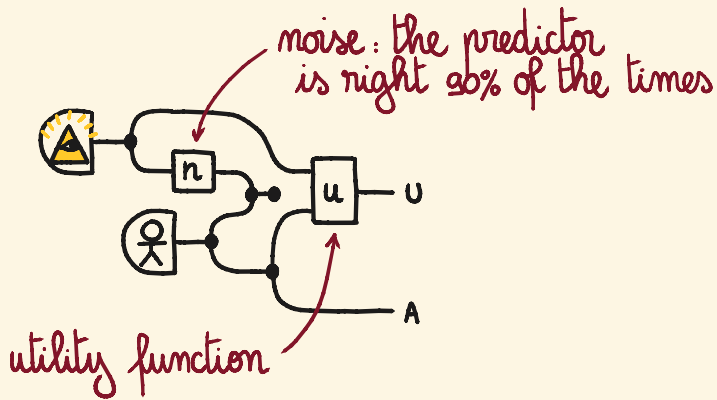


EXPECTED
UTILITY

$$\begin{aligned} & 0.9 \times 1 \text{ €} \\ & + 0.1 \times 10\,001 \text{ €} \\ & = 1\,001 \text{ €} \end{aligned}$$

$$\begin{aligned} & 0.9 \times 10\,000 \text{ €} \\ & + 0.1 \times 0 \text{ €} \\ & = 9\,000 \text{ €} \end{aligned}$$

A DIAGRAM FOR NEWCOMB



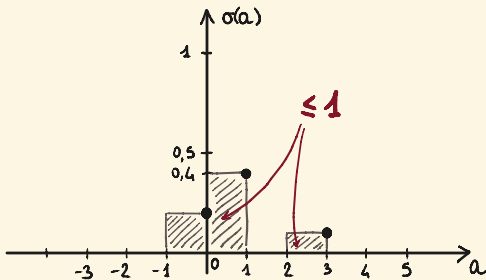
AGENT PREDICTOR	ONE-BOX	TWO-BOX
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SUBDISTRIBUTIONS

A subdistribution σ on A is a distribution on $A+1$:

- $\sigma \in \mathcal{D}_{\leq 1}(A)$ is a function $\sigma: A \rightarrow [0, 1]$ such that
- its support, $\text{supp}(\sigma) := \{a \in A \mid \sigma(a) > 0\}$, is finite, and
 - its total probability mass is at most 1, $\sum_{a \in A} \sigma(a) \leq 1$.

ex $A = \mathbb{N}$, $\sigma =$



Subdistributions give a monad $\mathcal{D}_{\leq 1}: \text{Set} \rightarrow \text{Set}$
(there's a distributive law $\mathcal{D}(-)+1 \rightarrow \mathcal{D}(-+1)$)

SUBDISTRIBUTIONS

A morphism $X \xrightarrow{\delta} A$ in $\text{KlD}_{\leq 1}$ is a function $X \rightarrow \mathcal{D}_{\leq 1}(A)$

$f(a|x) =$ "probability of a given x "

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

Composition is:

$$X \xrightarrow{\delta} A \xrightarrow{g} B \quad (b|x) := \sum_{a \in A} f(a|x) \cdot g(b|a)$$

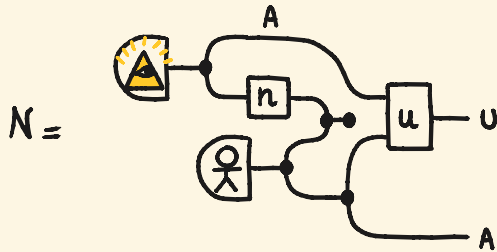
$$X \xrightarrow{\delta} A \xrightarrow{g} B \quad (\perp|x) := f(\perp|x) + \sum_{a \in A} f(a|x) \cdot g(\perp|a)$$

Equality checks are lifted from partial functions:

$$\begin{array}{c} A \\ A \end{array} \xrightarrow{\delta} A \quad (a|a_1, a_2) := \begin{cases} 1 & a_1 = a_2 = a \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{array}{c} A \\ A \end{array} \xrightarrow{\delta} A \quad (\perp|a_1, a_2) := \begin{cases} 0 & a_1 = a_2 \\ 1 & a_1 \neq a_2 \end{cases}$$

READING NEWCOMB'S DIAGRAM



$$N(\sigma, a | *) = \sum_{p \in A} \text{Hazard}(\Delta)(p | *) \cdot n(a | p) \cdot \text{Hazard}(\Delta)(a | *) \cdot u(\sigma | p, a)$$

$$N(\perp | *) = \sum_{a \neq a' \in A} \sum_{p \in A} \text{Hazard}(\Delta)(p | *) \cdot n(a' | p) \cdot \text{Hazard}(\Delta)(a | *)$$

WANTED: a calculus to reason with diagrams of this kind:

1. stochastic processes
2. partiality & constraints

OUTLINE

- motivation: Evidential Decision Theory
- [• (discrete) partial Markov categories]
- Bayes, observations & updates

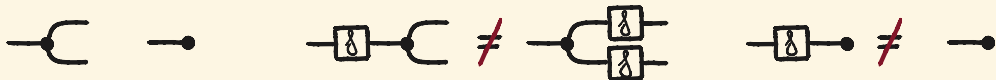
(DISCRETE) PARTIAL MARKOV CATEGORIES

• add partiality to Markov categories

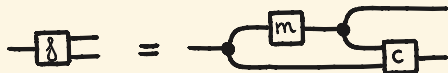
OR

• add probability to (discrete) cartesian restriction categories

COPY - DISCARD STRUCTURE



CONDITIONALS



PARTIAL FROBENIUS STRUCTURE



(DISCRETE) PARTIAL MARKOV CATEGORIES

REMOVE TOTALITY FROM

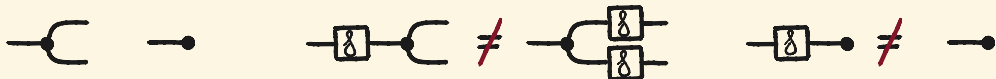
- ~~add partiality to~~ Markov categories

REMOVE DETERMINISM FROM

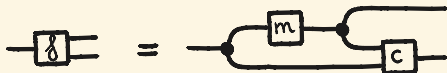
OR

- ~~add probability to~~ (discrete) cartesian restriction categories

COPY - DISCARD STRUCTURE



CONDITIONALS



PARTIAL FROBENIUS STRUCTURE

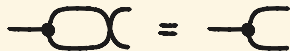
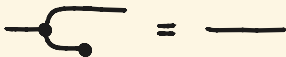
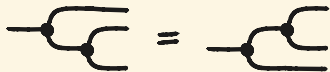


COPY-DISCARD CATEGORIES

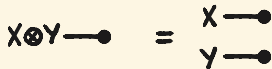
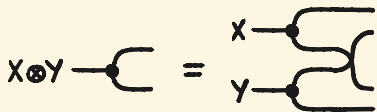
A copy-discard category is a symmetric monoidal category where every object is a uniform cocommutative comonoid.



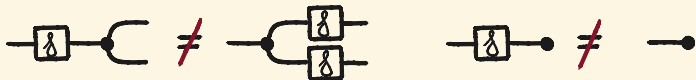
COCOMMUTATIVE COMONOID



UNIFORMITY



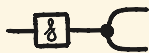
NO NATURALITY REQUIRED



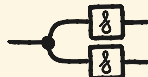
MARKOV CATEGORIES & CONDITIONALS

A Markov category with conditionals is a copy-discard category with conditionals where all morphisms are total.

COPY - DISCARD STRUCTURE



\neq



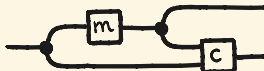
$=$



CONDITIONALS



$=$

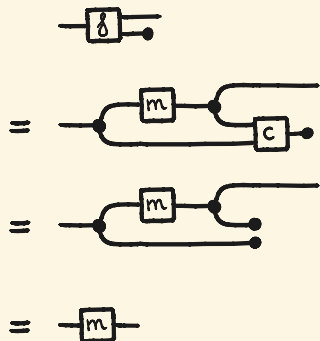


MARGINALS IN MARKOV CATEGORIES

Marginals in Markov categories are as expected :

$$X \text{---} [m] \text{---} A = X \text{---} [\delta] \text{---} \begin{matrix} A \\ B \end{matrix}$$

PROOF



conditionals :



\rightsquigarrow totality

□

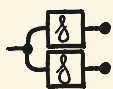
DROPPING TOTALITY

We want to keep the nice marginals of Markov categories.

Should we ask conditionals to be total? ~~X~~ NO
→ too strong: total conditionals fail to exist in $\text{KL}(\mathcal{D}_{\leq 1})$.

Can we ask conditionals to be quasi-total? \checkmark YES
→ sweet spot: quasi-total conditionals usually exist
and give nice marginals.

QUASI-TOTAL MORPHISM (in a copy-discard category)



=



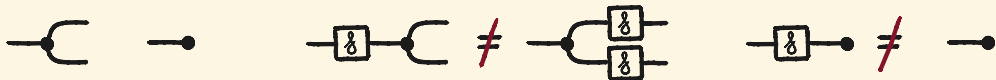
→ failure is deterministic

domain of definition

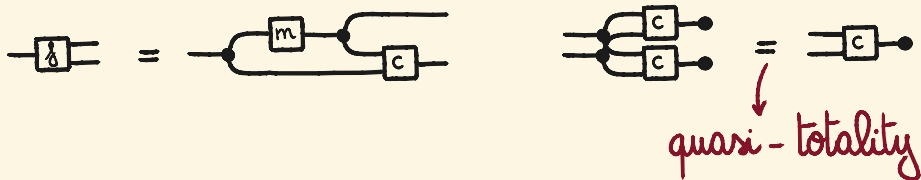
PARTIAL MARKOV CATEGORIES

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

COPY - DISCARD STRUCTURE



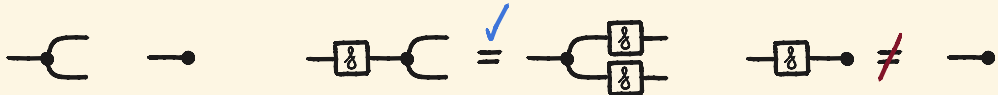
CONDITIONALS



CONSTRAINTS VIA PARTIAL FROBENIUS

A discrete cartesian restriction category is a copy-discard category with comparators where all morphisms are deterministic.

COPY - DISCARD STRUCTURE



PARTIAL FROBENIUS STRUCTURE



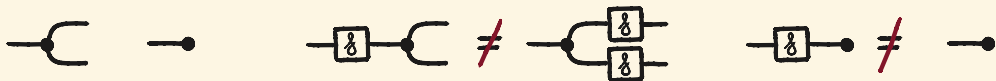
↑
COMPARATOR

[Lockett & Slack 2003, Lockett, Guo & Hofstra 2012]

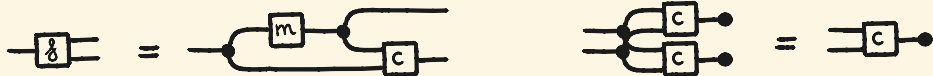
DISCRETE PARTIAL MARKOV CATEGORIES

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

COPY - DISCARD STRUCTURE



CONDITIONALS



PARTIAL FROBENIUS STRUCTURE



COMPARATOR

EXAMPLES : PARTIAL STOCHASTIC PROCESSES

A partial stochastic process is a stochastic process that may fail.

↳ Maybe monad

↳ your favourite Markov category with conditionals

PROPOSITION

Partial stochastic processes form a partial Markov category.

{ \mathcal{C} Markov category with conditionals and coproducts
+ some ugly technical conditions

$\Rightarrow \text{Kl}(\cdot + 1)$ is a partial Markov category.

EXAMPLES

• $\text{Kl}(\mathcal{D}(\cdot + 1))$

\rightsquigarrow finitary subdistributions

• $\text{Kl}(\text{Giry}_{\mathcal{B}}(\cdot + 1))$

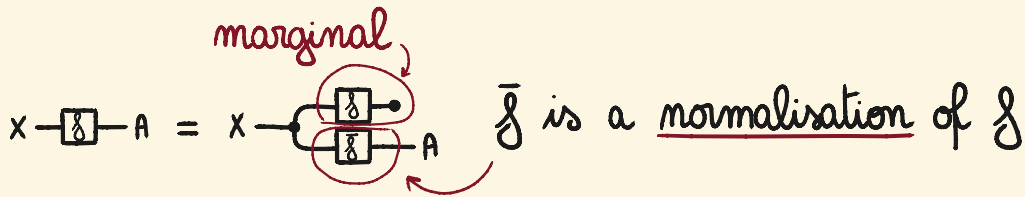
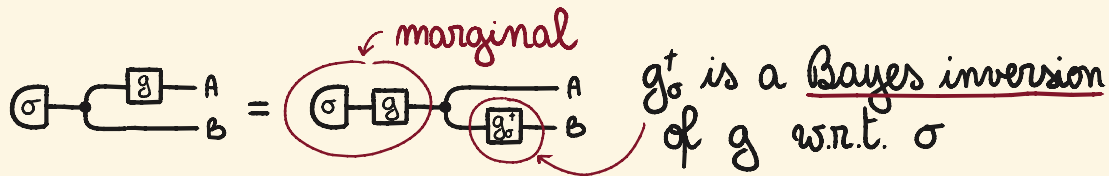
\rightsquigarrow subdistributions on standard Borel spaces

OUTLINE

- motivation: Evidential Decision Theory
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- [• Bayes, observations & updates]

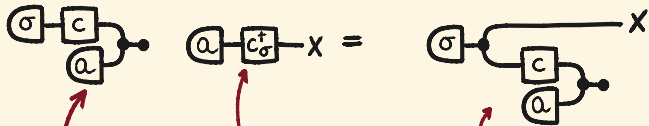
BAYES INVERSION & NORMALISATION

Bayes inversions and normalisations are particular cases of quasi-total conditionals:



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^\dagger evaluated on a .

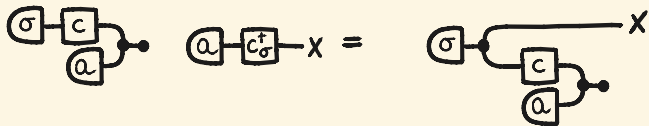


$$P(X=x|A=a) = \frac{P(A=a|X=x) \cdot P(X=x)}{\sum_{y \in X} P(A=a|X=y) \cdot P(X=y)}$$

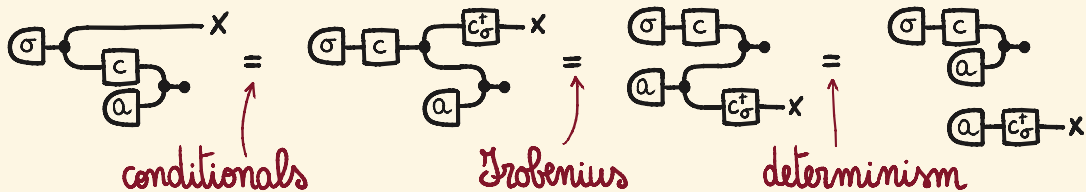
classical formula
for Bayes theorem

SYNTHETIC BAYES THEOREM

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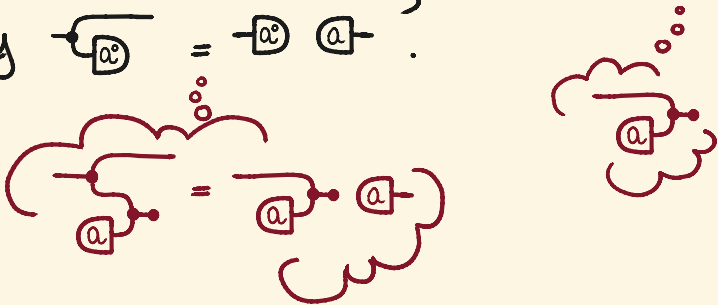
PROOF



□

PROCESSES WITH EXACT OBSERVATIONS

We construct a partial Markov category $\text{exOb}(\mathcal{C})$ on top of a Markov category \mathcal{C} with conditionals by freely adding, for every deterministic state $\mathbb{Q} \vdash A$ in \mathcal{C} , a costate $A \vdash \mathbb{Q}^\circ$ and quotienting by $\overline{\mathbb{Q}^\circ} = \mathbb{Q}^\circ \mathbb{Q}$.

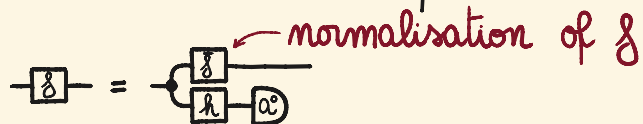


$$\text{exOb}(\mathcal{C}) = (\mathcal{C} + \{A \vdash \mathbb{Q}^\circ \mid \mathbb{Q} \vdash A \text{ deterministic}\}) / \overline{\mathbb{Q}^\circ} = \mathbb{Q}^\circ \mathbb{Q}$$

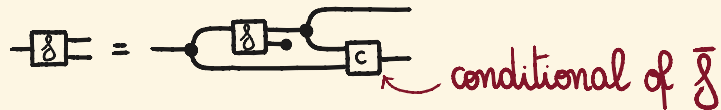
↑ embeds faithfully into $(\mathcal{C} + \overline{\mathbb{Q}^\circ}) / \text{partial Frobenius}$

COMPUTING PROCESSES WITH EXACT OBSERVATIONS

Morphisms in $\text{exOb}(\mathcal{C})$ have a normal form



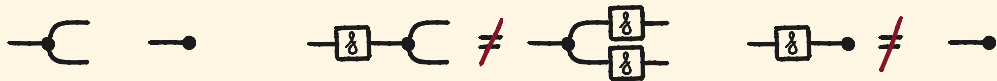
that can be computed by conditioning in \mathcal{C} ,
and they have conditionals



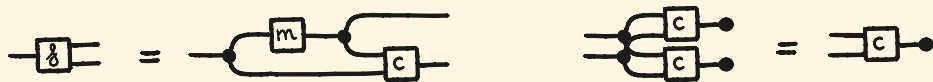
that can be computed by conditioning in \mathcal{C} .

SUMMARY : DISCRETE PARTIAL MARKOV CATS

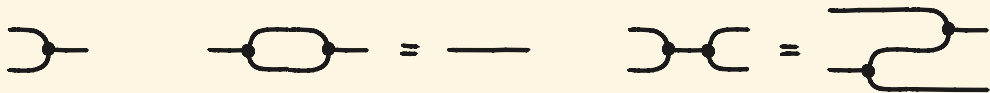
COPY - DISCARD STRUCTURE



CONDITIONALS



PARTIAL FROBENIUS STRUCTURE



THANKS FOR LISTENING!