

SYCO 13

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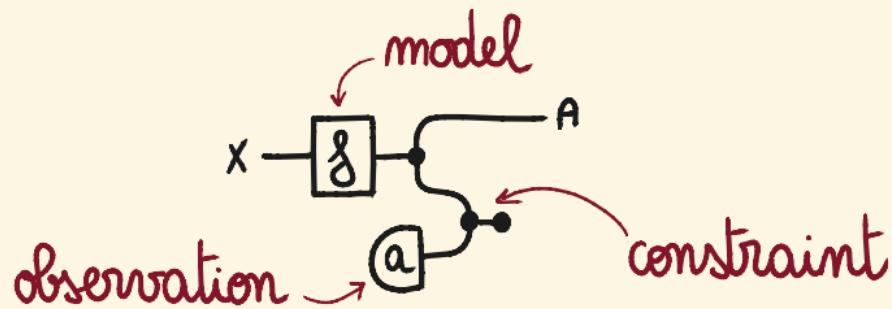
PARTIAL MARKOV CATEGORIES

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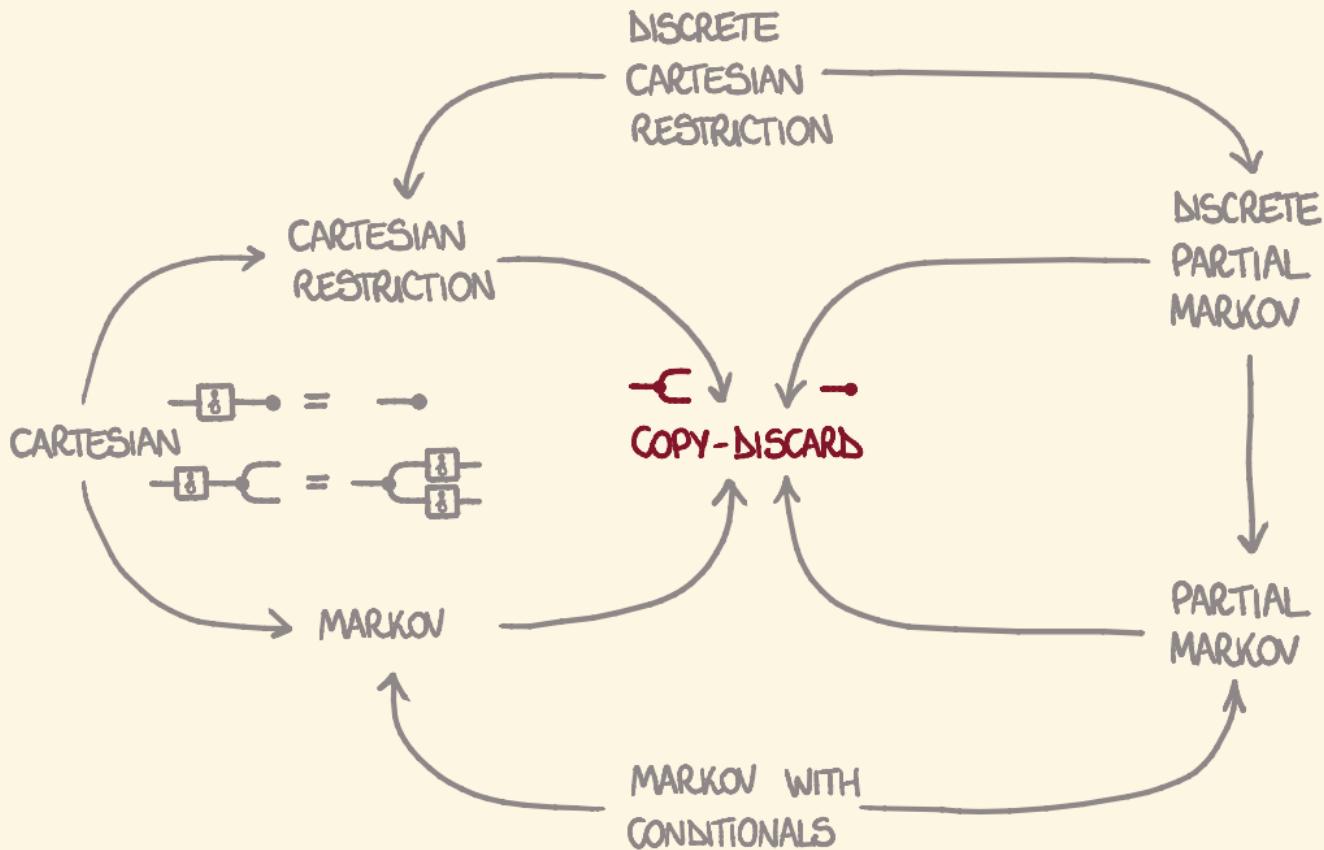
MOTIVATION

- Find the algebraic structure to express belief updates.
- Markov categories express probabilistic processes.



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

OUTLINE



STRING DIAGRAMS FOR COPY-DISCARD CATEGORIES

composition



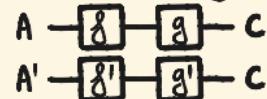
$$f;g: A \rightarrow C$$

monoidal product



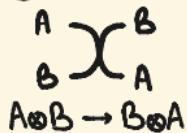
$$f \otimes f': A \otimes A' \rightarrow B \otimes B'$$

interchange



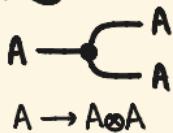
$$(f \otimes f'); (g \otimes g') = (f; g) \otimes (f'; g')$$

symmetries



$$A \otimes B \rightarrow B \otimes A$$

copy



$$A \rightarrow A \otimes A$$

discard



$$A \rightarrow I$$

counitality

$$\text{---} \bullet = \text{---}$$

coassociativity

$$\text{---} \bullet \text{---} = \text{---} \bullet \text{---}$$

cocommutativity

$$\text{---} \bullet \text{---} = \text{---} \bullet \text{---}$$

EXAMPLES

- Kleisli of monoidal monads on cartesian categories

cartesian categories = $\text{Kl}(\text{id})$ $\text{Kl}\mathcal{D}$ $\text{Kl}\mathcal{C}_Y$

$\text{Rel} = \text{Kl}\mathcal{P}$ $\text{Par} = \text{Kl}(\cdot + 1)$ $\text{Kl}\mathcal{D}_\leq$ $\text{Kl}\mathcal{C}_Y^\leq$

- not only Kleisli categories

Gauss hypergraph categories Mat_R

DETERMINISTIC & TOTAL MAPS

Deterministic maps can be copied.

$$A \xrightarrow{\delta} B = A \xrightarrow{\delta} \begin{array}{c} B \\ B \end{array}$$

Total maps can be discarded.

$$A \xrightarrow{\delta} \bullet = A \xrightarrow{\quad}$$

EXAMPLES

$$A \xrightarrow{\delta} B = A \xrightarrow{\delta} \begin{array}{c} B \\ B \end{array}$$

$$A \xrightarrow{\delta} \bullet = A \xrightarrow{\quad}$$

Set

✓

✓

Par

✓

✗

$\rightarrow \bullet \neq \bullet$

Kl(\mathcal{D})

✗ $\text{G}\text{C} \neq \text{G}\text{C}$

✓

Rel

✗

✗

Kl($\mathcal{D}_{\leq 1}$)

✗

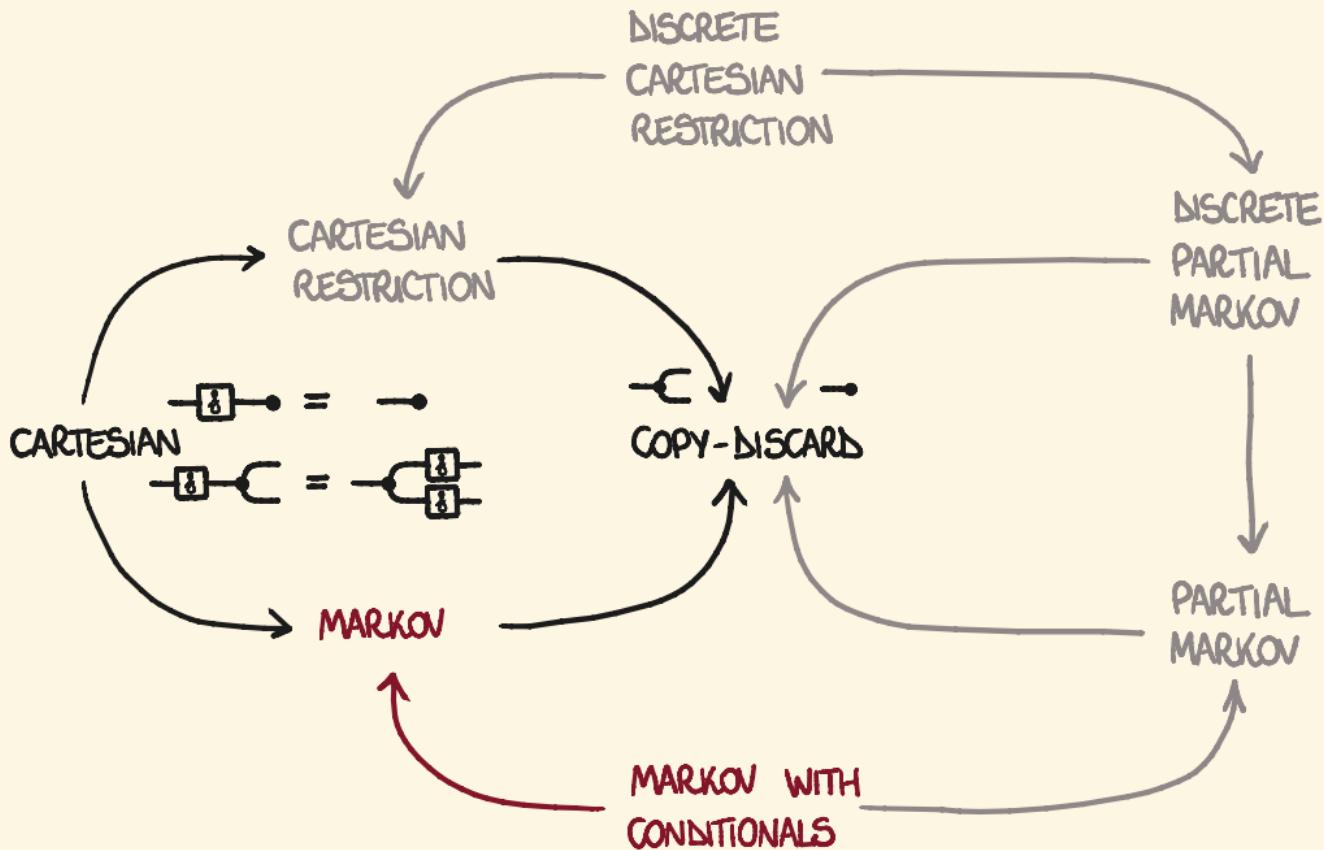
✗

FOX'S THEOREM

A copy-discard category is cartesian if and only if all morphisms are deterministic and total,

$$\text{---} \square \text{---} \curvearrowleft = \text{---} \bullet \text{---} \square \text{---} \quad \text{and} \quad \text{---} \square \text{---} \bullet = \text{---} \bullet \quad \text{for all } g.$$

OUTLINE



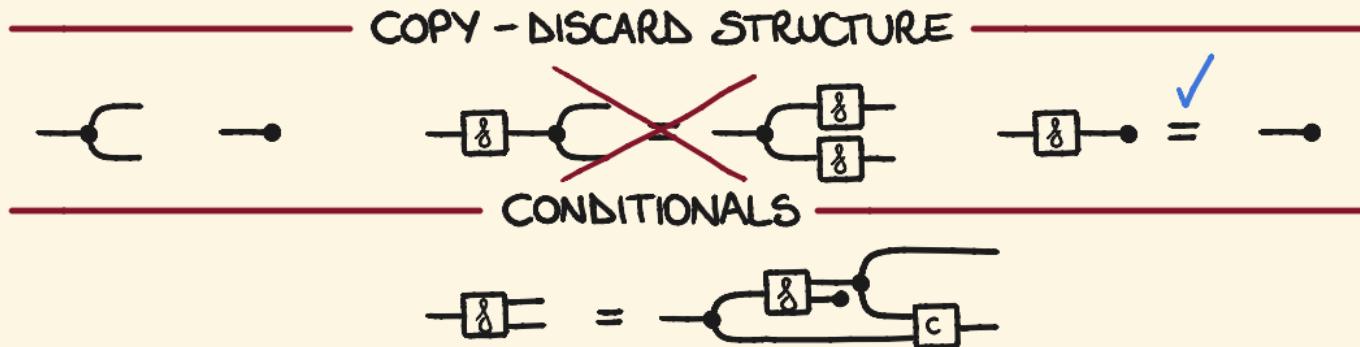
PROBABILISTIC PROCESSES

Markov categories express probabilistic processes,
for example

- throwing a coin  2
- tomorrow's weather given today's clouds c —  w
- developing cancer given smoking habits s —  c — 2

MARKOV CATEGORIES & CONDITIONALS

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



[Fritz (2020); Cho, Jacobs (2019)]

FINITARY DISTRIBUTIONS

A finitary distribution $\sigma \in \mathcal{D}(A)$ 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 1, $\sum_{a \in A} \sigma(a) = 1$.

$\rightsquigarrow \mathcal{D}: \text{Set} \rightarrow \text{Set}$ is a monad

A morphism $x - \boxed{\delta} - A$ in $\text{Kl}\mathcal{D}$ is a function $X \rightarrow \mathcal{D}(A)$
 $\delta(a|x) = \text{"probability of a given } x\text{"}$

composition is

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

CONDITIONALS

KlD has conditionals.



$$x - \text{---} \begin{matrix} g \\ \square \end{matrix} \bullet^A (a|x) = \sum_{b \in B} g(a, b|x)$$

$$c(b|a,x) := \begin{cases} \frac{g(a,b|x)}{\sum_{b'} g(a,b'|x)} & \text{if } \sum_{b'} g(a,b'|x) \neq 0 \\ \sigma(b) & \text{if } \sum_{b'} g(a,b'|x) = 0 \end{cases}$$

any distribution on B

NON-DISCRETE EXAMPLES

- Giry monad. $\text{cl}_g : \text{Meas} \rightarrow \text{Meas}$. $\text{Kl } \text{cl}_g$ is Markov

$\text{cl}_g : \text{Borel} \rightarrow \text{Borel}$ $\text{Kl } \text{cl}_g$ is Markov with conditionals

$f : (X, \sigma) \rightarrow (A, \tau)$ is $f : \tau \times X \rightarrow [0, 1]$

$f(S|x)$ = "probability of event S given input x "

- Radon monad. $R : \text{CHaus} \rightarrow \text{CHaus}$. $\text{Kl } R$ is Markov

• $\text{cl}_R : \text{QBS} \rightarrow \text{QBS}$ $\text{Kl } \text{cl}_R$ is Markov

• Gauss is Markov with conditionals

$f : n \rightarrow m$ is $(M_g \in \mathbb{R}^{m \times n}, C_g \in \mathbb{R}^{m \times m}, s_g \in \mathbb{R}^m)$, C_g positive semidefinite

$$Y = M_g \cdot X + z \quad z \sim N(s_g, C_g)$$

NON-UNIQUENESS OF CONDITIONALS

ex KLD. $c(b|a,x) := \begin{cases} \frac{g(a,b|x)}{\sum_b g(a,b|x)} & \text{if } \sum_b g(a,b|x) \neq 0 \\ \sigma(b) & \text{if } \sum_b g(a,b|x) = 0 \end{cases}$

PROPOSITION [Brito (2020)]

In a Markov category \mathcal{C} with conditionals,
if conditionals are unique then \mathcal{C} is a preorder.

→ conditionals of g are  - almost surely unique

$$\text{---} \square \text{---} \bullet \text{---} c = \text{---} \square \text{---} \bullet \text{---} d$$

BAYES INVERSION

The Bayes inversion of a channel $g: B \rightarrow A$ with respect to a distribution $\sigma: I \rightarrow B$ is classically defined as

$$g_\sigma^+(b|a) := \frac{g(a|b)\sigma(b)}{\sum_{b' \in B} g(a|b')\sigma(b')}$$

In a Markov category, it is a $g_\sigma^+: A \rightarrow B$ such that

$$\textcircled{\sigma} \xrightarrow{\quad g \quad} A = \textcircled{\sigma} \xrightarrow{\quad g \quad} \textcircled{A} \xrightarrow{\quad g_\sigma^+ \quad} B$$

↑ marginal
↑ conditional

Bayes inversions are instances of conditionals.

[Cho, Jacobs (2019)]

MARKOV CATEGORIES : A VERY ACTIVE FIELD

- Markov categories and conditionals

[cCho, Jacobs (2019); Brito (2020)]

- Theorems from probability theory

[Brito, clyonida, Perrone (2021); Brito, Rischel (2020); Perrone, Van Belle (2024)]

- Probabilistic programming constructions

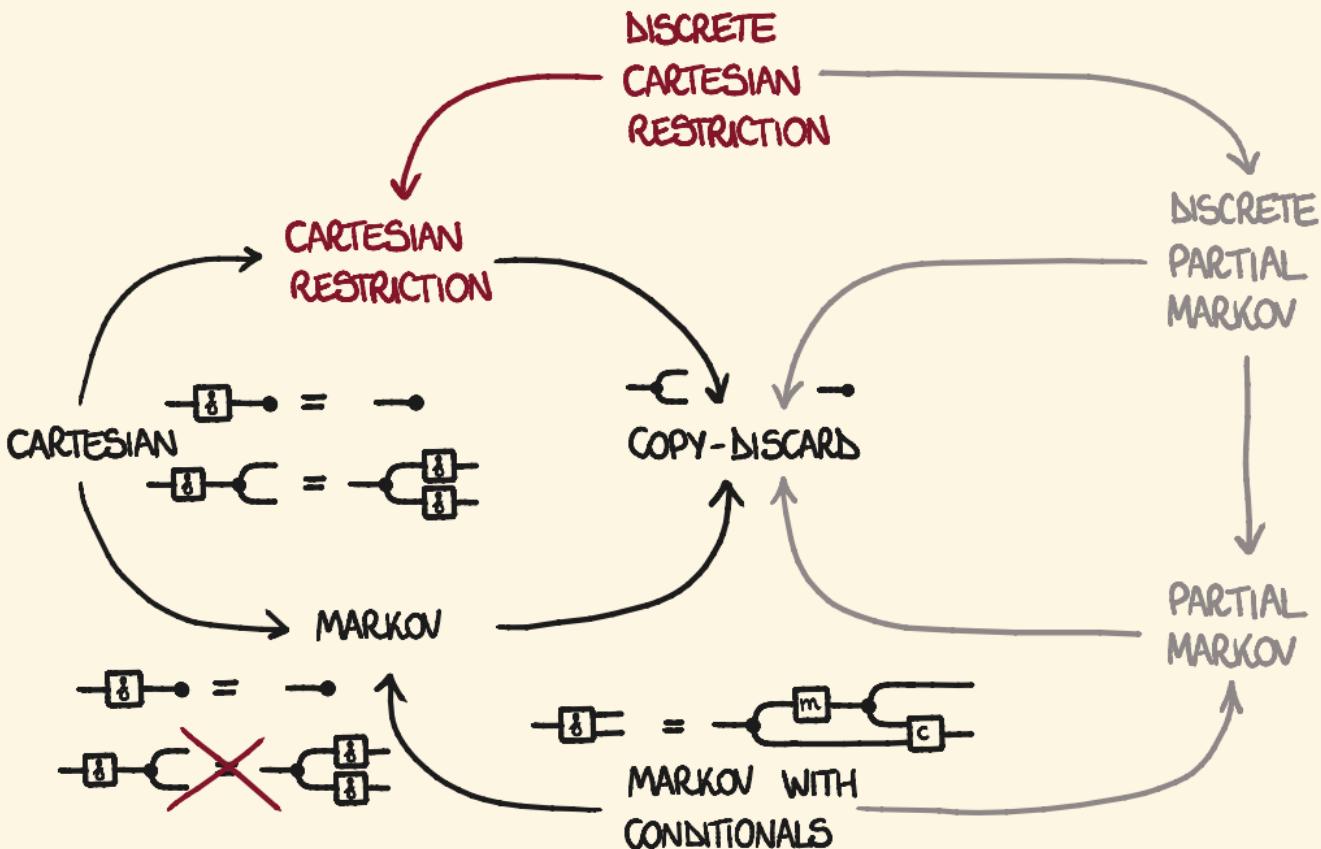
[Stein, cStaton (2023); Moss, Perrone (2022); Fleuriot, Kammar, Staton, Yang (2017)]

- Inference methods

[Jacobs, Stein (2023); Jacobs, Zanasi, Kissinger (2021)]

⋮

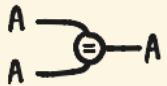
OUTLINE



PARTIAL PROCESSES

Cartesian restriction categories express partial computations,
for example

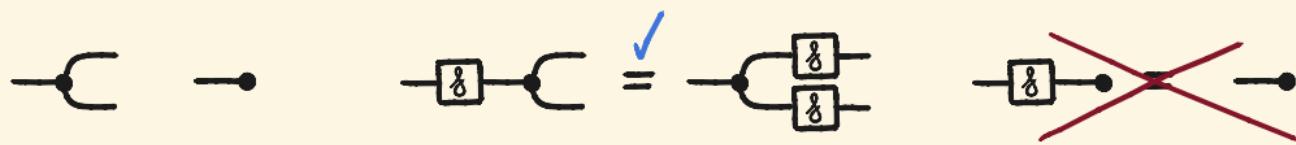
- computing $\frac{1}{x}$
- checking equality
- non-terminating computations



CARTESIAN RESTRICTION CATEGORIES

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

COPY - DISCARD STRUCTURE



[Cockett, Slack (2003, 2007), Mester (2024)]

PARTIAL FUNCTIONS

$(\text{Par}, \times, \{\ast\})$ is a cartesian restriction category

- objects are sets A, B, C, \dots
- morphisms are partial functions $f: A \rightarrow B, g: B \rightarrow C, \dots$
i.e. functions $f: A \rightarrow B+1, g: B \rightarrow C+1, \dots$
- composition is

$$f;g(a) := \begin{cases} g(f(a)) & \text{if } f(a) \neq \perp \\ \perp & \text{if } f(a) = \perp \end{cases}$$

- monoidal product is

$$f \times f'(a, a') := \begin{cases} (f(a), f'(a')) & \text{if } f(a) \neq \perp \text{ and } f'(a') \neq \perp \\ \perp & \text{if } f(a) = \perp \text{ or } f'(a') = \perp \end{cases}$$

PREDICATES, DOMAINS, RESTRICTIONS

Morphisms $q: A \rightarrow 1$ in Par are predicates.

$$A \xrightarrow{q} (a) = \begin{cases} * & \text{if } a \text{ satisfies } q \\ \perp & \text{if } a \text{ does not satisfy } q \end{cases}$$

The domain of $A \xrightarrow{g} B$ is the predicate $A \xrightarrow{g} \bullet$.

$$A \xrightarrow{g} B = A \xrightarrow{g} \left\{ \begin{array}{c} B \\ \bullet \end{array} \right\} = A \xrightarrow{\left[\begin{array}{c|c} g & B \\ g & \bullet \end{array} \right]} \bullet$$

The restriction preorder on morphisms is

$$f \leq g \quad \text{iff} \quad A \xrightarrow{g} B = A \xrightarrow{\left[\begin{array}{c|c} g & B \\ f & \bullet \end{array} \right]} \bullet$$

g restricted to the domain of f

EQUALITY CHECK

Par has equality checks.

$$\begin{array}{c} {}^A \\[-1ex] \text{A} \end{array} \multimap A \quad (a, a') := \begin{cases} a & \text{if } a = a' \\ \perp & \text{if } a \neq a' \end{cases}$$

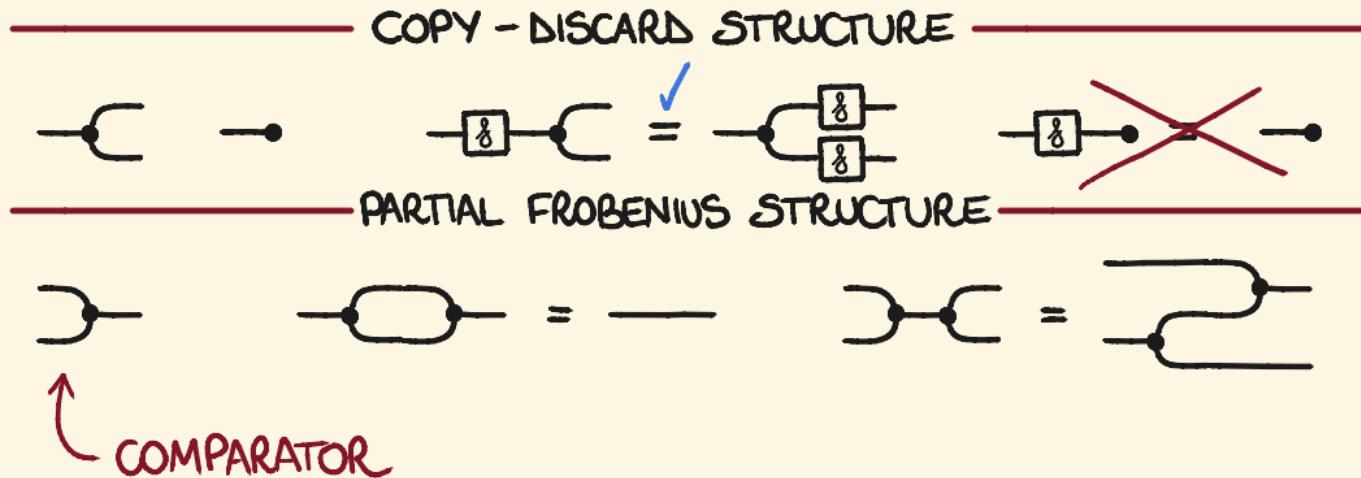
Equality checks interact with the comonoid structure.

$$A - \text{---} \bullet \text{---} A = A - \text{---} \quad \text{and}$$

$$A \begin{array}{c} \nearrow \\[-1ex] \text{A} \end{array} \multimap A \quad \text{---} \begin{array}{c} \searrow \\[-1ex] \text{A} \end{array} = \begin{array}{c} A \\[-1ex] \text{---} \end{array} \begin{array}{c} \nearrow \\[-1ex] \text{A} \end{array} \multimap A \quad \text{---} \begin{array}{c} \searrow \\[-1ex] \text{A} \end{array} \begin{array}{c} A \\[-1ex] \text{---} \end{array}$$

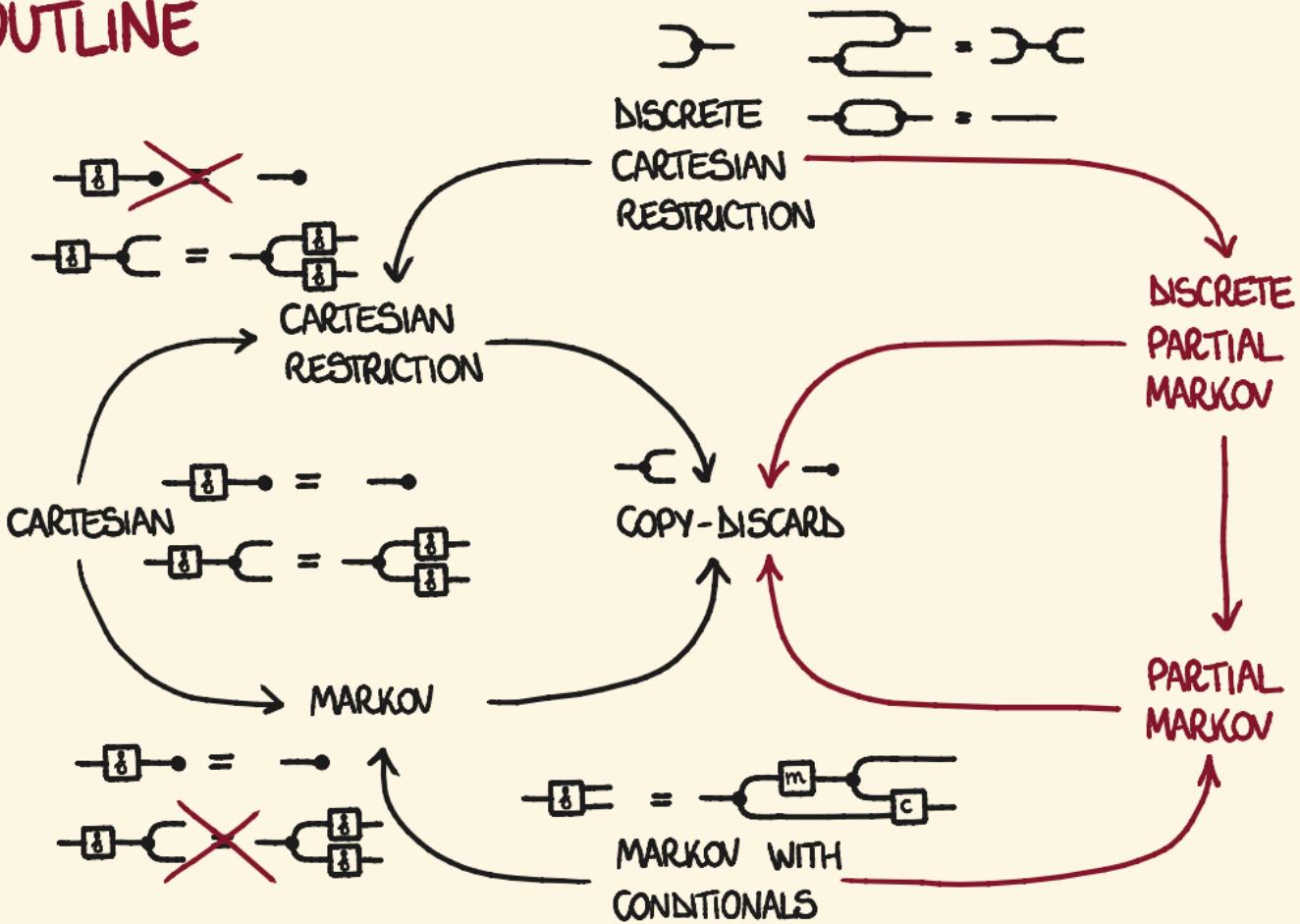
CONSTRAINTS VIA PARTIAL FROBENIUS

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



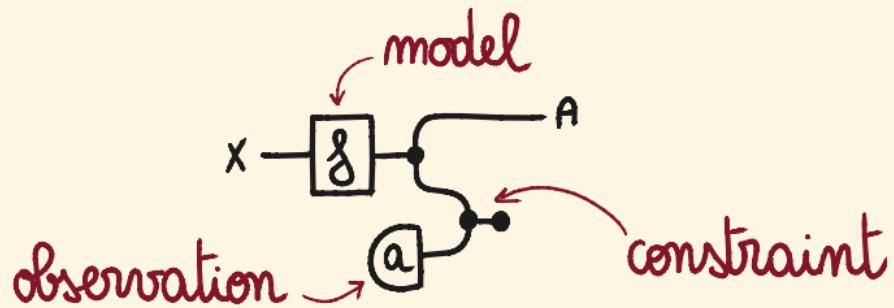
[Cockett, Guo & Hofstra 2012, Di Liberti, Słonecki, Nester & Sobociński 2020]

OUTLINE



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.

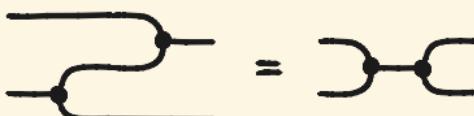
cartesian
restriction

Markov
with conditionals



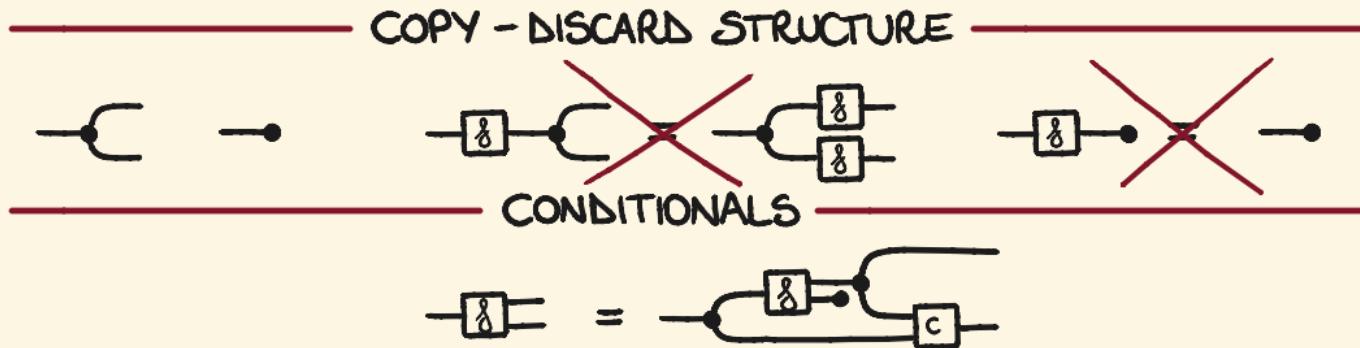
Add the discrete structure to express equality checking.

discrete cartesian
restriction



PARTIAL MARKOV CATEGORIES

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



[EDL, Román (2023); EDL, Román, Sobociński (2025)]

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, $\sum_{a \in A} \sigma(a) \leq 1$.

A morphism $x - \boxed{\delta} - A$ in $\text{Kl}\mathcal{D}_{\leq 1}$ is a function $x \rightarrow \mathcal{D}_{\leq 1}(A)$

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

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

composition is

$$x - \boxed{\delta} - \boxed{g} - B \quad (\delta|_B) := \sum_{a \in A} \delta(a|x) \cdot g(\delta|_a)$$

$$x - \boxed{\delta} - \boxed{g} - B \quad (\perp|_B) := \sum_{a \in A} \delta(a|x) \cdot g(\perp|_a) + \delta(\perp|x)$$

EXAMPLES : PARTIAL STOCHASTIC PROCESSES

A partial stochastic process is a stochastic process

that may fail.

↳ Maybe monad

a Markov category with conditionals

Partial stochastic processes form a partial Markov category.

PROPOSITION

The Kleisli category of the Maybe monad on a distributive Markov category with conditionals is partial Markov.

EXAMPLES

- $\text{Kl}\mathcal{D}_\leq = \text{Kl}(\cdot +_1)$ on $\text{Kl}\mathcal{D}$
- $\text{Kl}\mathcal{C}\mathcal{G}_{\leq}$ = $\text{Kl}(\cdot +_1)$ on $\text{Kl}\mathcal{C}\mathcal{G}$

- $\text{Par} = \text{Kl}(\cdot +_1)$ on Set
- (non-example) Rel

CONDITIONALS IN SUBDISTRIBUTIONS

The marginal of $f: X \rightarrow A \otimes B$ is

$$x \dashv_m^A (a|x) = x \dashv_{\delta}^A (a|x) = \sum_{b \in B} f(a, b|x)$$

$$x \dashv_m^A (\perp|x) = x \dashv_{\delta}^A (\perp|x) = f(\perp|x)$$

A conditional of f is:

$$x \dashv_c^B (b|a,x) = \begin{cases} \frac{f(a,b|x)}{m(a|x)} & m(a|x) \neq 0 \\ 0 & m(a|x) = 0 \end{cases}$$

$$x \dashv_c^B (\perp|a,x) = \begin{cases} 0 & m(a|x) \neq 0 \\ 1 & m(a|x) = 0 \end{cases}$$

BAYES INVERSION

The Bayes inversion of a channel $g: B \rightarrow A$ with respect to a distribution $\sigma: I \rightarrow B$ is classically defined as

$$g_\sigma^+(b|a) := \frac{g(a|b)\sigma(b)}{\sum_{b' \in B} g(a|b')\sigma(b')}$$

In a partial Markov category, it is a $g_\sigma^+: A \rightarrow B$ such that

$$\textcircled{a} \xrightarrow{g} A = \textcircled{a} \xrightarrow{\sigma} \textcircled{g} \xrightarrow{g_\sigma^+} B$$

↑ marginal
↑ conditional

Bayes inversions are instances of conditionals.

NORMALISATION

The normalisation of a partial channel $\tilde{f}: X \rightarrow A$ is classically defined as

$$\tilde{f}(a|x) := \frac{f(x|a)}{1 - f(\perp|a)}$$

In a partial Markov category, it is a $\bar{f}: X \rightarrow A$ such that

The diagram shows a partial channel f represented by a box with two inputs and one output. A red oval encloses the top input and the output, with an arrow pointing from it to the word "marginal". Another red oval encloses the bottom input and the output, with an arrow pointing from it to the word "conditional". To the right of the boxes is an equals sign followed by a box with a single input and output, representing the normalization of the channel.

$$f = \bar{f}$$

Normalisations are instances of conditionals.

PREDICATES & DOMAINS

Morphisms $q: A \rightarrow 1$ in $\text{Kl}(\mathcal{D}_\epsilon)$ are 'fuzzy' predicates.

$A \xrightarrow{q} 1$ (*1a) \rightsquigarrow probability of a being true

Deterministic predicates are classical predicates.

$A \xrightarrow{q} 1 = A \xrightarrow{\begin{array}{c} q \\ q \end{array}}$ $\Rightarrow q$ is a classical predicate

Self-normalising morphisms have a domain.

$$x \xrightarrow{\delta} y = x \xrightarrow{\begin{array}{c} \delta \\ \delta \end{array}} y \Leftrightarrow x \xrightarrow{\delta} \bullet = x \xrightarrow{\begin{array}{c} \delta \\ \delta \end{array}} \bullet$$

probability of success of $\delta \Rightarrow$ domain of δ

EQUALITY CHECK

Kl \mathbb{D}_\leq has equality checks.

$$\begin{array}{c} \text{A} \\ \text{A} \end{array} \rightrightarrows \text{A} \quad (a, a') := \begin{cases} \delta_a & \text{if } a = a' \\ \delta_\perp & \text{if } a \neq a' \end{cases}$$

Equality checks interact with the comonoid structure.

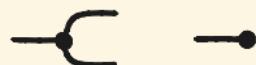
$$\text{A} \xrightarrow{\quad} \text{A} = \text{A} \xrightarrow{\quad} \text{and}$$

$$\begin{array}{c} \text{A} \\ \text{A} \end{array} \rightrightarrows \text{A} \times \text{A} = \begin{array}{c} \text{A} \\ \text{A} \end{array} \times \text{A}$$

DISCRETE PARTIAL MARKOV CATEGORIES

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

COPY - DISCARD STRUCTURE



CONDITIONALS

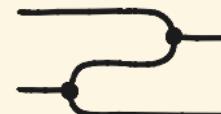
$$\boxed{\delta} = \text{---} \quad \text{---} \quad \text{---}$$


PARTIAL FROBENIUS STRUCTURE



$$\text{---} = \text{---}$$



$$= \text{---}$$


COMPARATOR

[EDL, Román (2023); EDL, Román, Sobociński (2025)]

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 .

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

classical formula
for Bayes theorem

SYNTHETIC BAYES THEOREM

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 .

$$\begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad = \quad \begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad \begin{array}{c} \text{a} \\ \text{---} \\ c_\sigma^+ \\ \text{---} \\ x \end{array}$$

PROOF

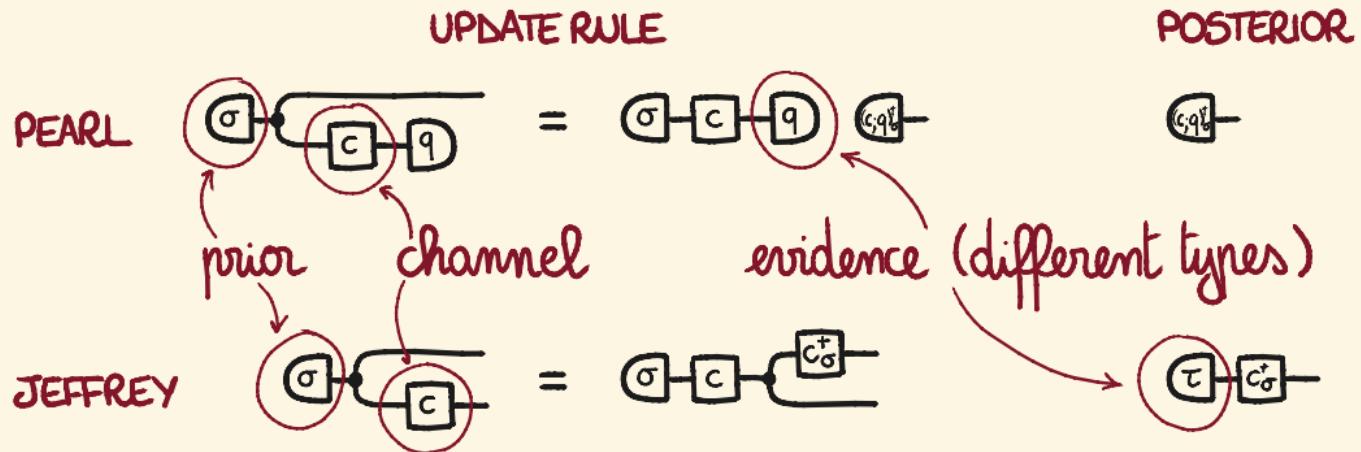
$$\begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad = \quad \begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad \begin{array}{c} c_\sigma^+ \\ \text{---} \\ x \end{array} \quad = \quad \begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad \begin{array}{c} \text{c} \\ \text{---} \\ \text{a} \\ \text{---} \\ c_\sigma^+ \\ \text{---} \\ x \end{array} \quad = \quad \begin{array}{c} \text{σ} \\ \text{---} \\ \text{c} \\ \text{---} \\ \text{a} \end{array} \quad \begin{array}{c} \text{a} \\ \text{---} \\ c_\sigma^+ \\ \text{---} \\ x \end{array}$$

↑ ↑ ↑

conditionals Frobenius determinism

□

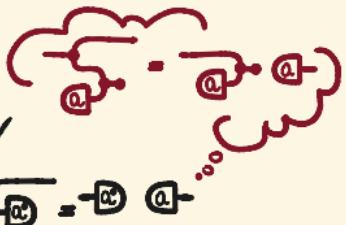
PEARL'S VS JEFFREY'S UPDATES



Pearl's update on \overrightarrow{a} coincides with Jeffrey's update on \overleftarrow{a} , whenever \overleftarrow{a} is deterministic.

PROCESSES WITH EXACT OBSERVATIONS

We can add exact observations to any Markov category:

$$\text{exOb}(\mathcal{C}) = (\mathcal{C} + \{\text{A} - \boxed{a} \mid \boxed{a} - \text{A deterministic}\}) / \begin{array}{l} \text{embeds into } (\mathcal{C} + \mathcal{D}) / \text{partial} \\ \text{Frobenius} \end{array}$$


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

$$-\boxed{\delta} = -\begin{array}{c} \boxed{\delta} \\ \hbox{\scriptsize } \\ \boxed{h} \end{array} - \boxed{a}$$

$$-\boxed{\delta} = -\begin{array}{c} \boxed{\delta} \\ \hbox{\scriptsize } \\ \bullet \end{array} - \boxed{c}$$

$\Rightarrow \text{exOb}(\mathcal{C})$ is a partial Markov category.

MINIMAL CONDITIONALS IN SUBDISTRIBUTIONS



The conditionals of \mathfrak{f} are:

$$\overset{A}{x} \rightarrow \underset{C}{\square} \rightarrow \underset{B}{\mathfrak{f}}(b|a,x) = \begin{cases} \frac{\mathfrak{f}(a,b|x)}{m(a|x)} & m(a|x) \neq 0 \\ \sigma(b) & m(a|x) = 0 \end{cases}$$

$$\overset{A}{x} \rightarrow \underset{C}{\square} \rightarrow \underset{B}{\mathfrak{f}}(\perp|a,x) = \begin{cases} 0 & m(a|x) \neq 0 \\ \sigma(\perp) & m(a|x) = 0 \end{cases}$$

for some $\sigma \in \mathcal{D}(B+1)$.

⇒ The 'minimal' choice for σ is $\begin{cases} \sigma(b) = 0 & \text{for } b \in B \\ \sigma(\perp) = 1 \end{cases}$ for $b \in B$.

⇒ fail on unexpected observations

PARTIAL MARKOV CATEGORIES ARE PREORDERED

$f, g : X \rightarrow A$ in a partial Markov category

CONDITIONAL INEQUALITY

$$f \leq g \text{ if } \exists r : A \otimes X \rightarrow I \quad -\boxed{f}- = -\bullet \xrightarrow{g} \circ \xrightarrow{r} -$$

THEOREM

Any partial Markov category is preorder-enriched.

EXAMPLES

- In KlD_\leq , $f \leq g$ is pointwise order: $\forall y, x \quad f(y|x) \leq g(y|x)$.
- In KlAlg_\leq , $f \leq g$ is pointwise order: $\forall T, x \quad f(T|x) \leq g(T|x)$.

SUBUNITAL PREORDERS

The conditional preorder is the minimal subunital preorder.

PROPOSITION

cl preorder-enriched partial Markov category s.t. $\forall p \ -\Box_p \subseteq \top$.

If $f \leq g$, then $f \sqsubseteq g$.

truth \nwarrow is top

EXAMPLES

- In Par (any cartesian restriction), $f \sqsubseteq g$ iff $\begin{array}{c} f \\ \sqsubseteq \\ g \end{array} = \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array}$

Then, $f \sqsubseteq g \Leftrightarrow f \leq g$.

- In Rel (any cartesian bicategory), $f \sqsubseteq g$ iff $\begin{array}{c} f \\ \sqsubseteq \\ g \end{array} = \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array}$

Then, $f \sqsubseteq g \Leftrightarrow f \leq g$.

LEAST CONDITIONALS

A partial Markov category has least conditionals if, for every $f: X \rightarrow A \otimes B$, the preorder of its conditionals has a least element.

EXAMPLES

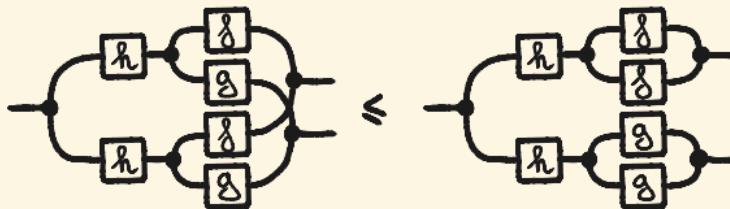
- KlD_\leq , $\begin{array}{c} A \\ x = \square \\ C \\ \longrightarrow \\ B \end{array} (b|a, x) = \begin{cases} \frac{f(a, b|x)}{m(a|x)} & m(a|x) \neq 0 \\ 0 & m(a|x) = 0 \end{cases}$.
- Par (any discrete cartesian restriction), $\begin{array}{c} A \\ x = \square \\ C \\ \longrightarrow \\ B \end{array} = \begin{array}{c} A \\ \xrightarrow{x} \square \\ \xrightarrow{\delta} B \end{array}$.
- Rel (any cartesian bicategory), $\begin{array}{c} A \\ x = \square \\ C \\ \longrightarrow \\ B \end{array} = \begin{array}{c} A \\ \xrightarrow{x} \square \\ \xrightarrow{\delta} B \end{array}$.

UPDATING INCREASES VALIDITY

CAUCHY-SCHWARZ INEQUALITY

- classical : $(\sum_i u_i \cdot v_i)^2 \leq (\sum_i u_i^2) \cdot (\sum_j v_j^2)$
- parametric : $(\sum_i h_i(x) \cdot f_i(y) \cdot g_i(z))^2 \leq (\sum_i h_i(x)^2) \cdot (\sum_j f_j(y)^2) \cdot (\sum_k g_k(z)^2)$

- synthetic :



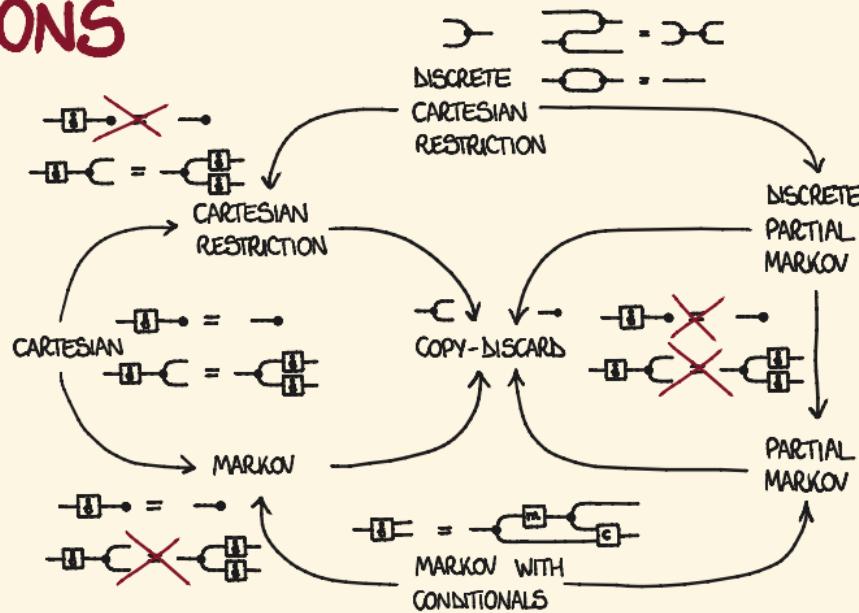
THEOREM

In a partial Markov category that satisfies the Cauchy-Schwarz inequality and has non-zero cancellative scalars, updating a prior $\sigma: I \rightarrow X$ with a predicate $p: X \rightarrow I$ increases the validity of p :

$$\textcircled{S} \textcircled{P} \leq \textcircled{S} \textcircled{P}$$

[EDL, Román, Sobociński, Szeler (2025); cf. Jacobs (2019)]

CONCLUSIONS



- Partial Markov categories support updating on observations.

$$\sigma \cdot \text{c} \cdot \text{a} = \sigma \cdot \text{c} \cdot \text{a} \cdot \text{c}^{\dagger} \sigma \cdot x$$

Synthetic Bayes theorem