

# **Quasi-Measurable Spaces**

# **A Convenient Foundation of Probability Theory**

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# The Category of Measurable Spaces

- Let  $\mathcal{X}$  be a set. A  $\sigma$ -algebra on  $\mathcal{X}$  is a set of subsets  $\mathcal{B} \subseteq 2^{\mathcal{X}}$  such that:
  - $\emptyset \in \mathcal{B}$ ,
  - $A_n \in \mathcal{B}, n \in \mathbb{N} \implies \bigcup_{n \in \mathbb{N}} A_n \in \mathcal{B}$
  - $A \in \mathcal{B} \implies \mathcal{X} \setminus A \in \mathcal{B}$
- A tuple  $(\mathcal{X}, \mathcal{B}_{\mathcal{X}})$  of a set  $\mathcal{X}$  and a  $\sigma$ -algebra  $\mathcal{B}_{\mathcal{X}}$  is called **measurable space**.
- A map  $f: \mathcal{X} \rightarrow \mathcal{Y}$  between measurable spaces  $(\mathcal{X}, \mathcal{B}_{\mathcal{X}})$  and  $(\mathcal{Y}, \mathcal{B}_{\mathcal{Y}})$  is called a **measurable map** if:
$$B \in \mathcal{B}_{\mathcal{Y}} \implies f^{-1}(B) \in \mathcal{B}_{\mathcal{X}}.$$
  - Note that the compositions of two measurable maps is a measurable map.
- Meas denotes the **category of measurable spaces and measurable maps**.

# Kolmogorov's approach to Probability Theory (1933)

- **Kolmogorov Axioms:**

- A probability distribution is just a normalized measure.

- Probability Theory can thus be viewed as a sub-field of Measure Theory.

- Andrei Kolmogoroff. *Grundbegriffe der Wahrscheinlichkeitsrechnung*. Ergebnisse der Mathematik und Ihrer Grenzgebiete. 1. Folge, Nr. 2, Springer (1933).

# How to formalize Random Variables?

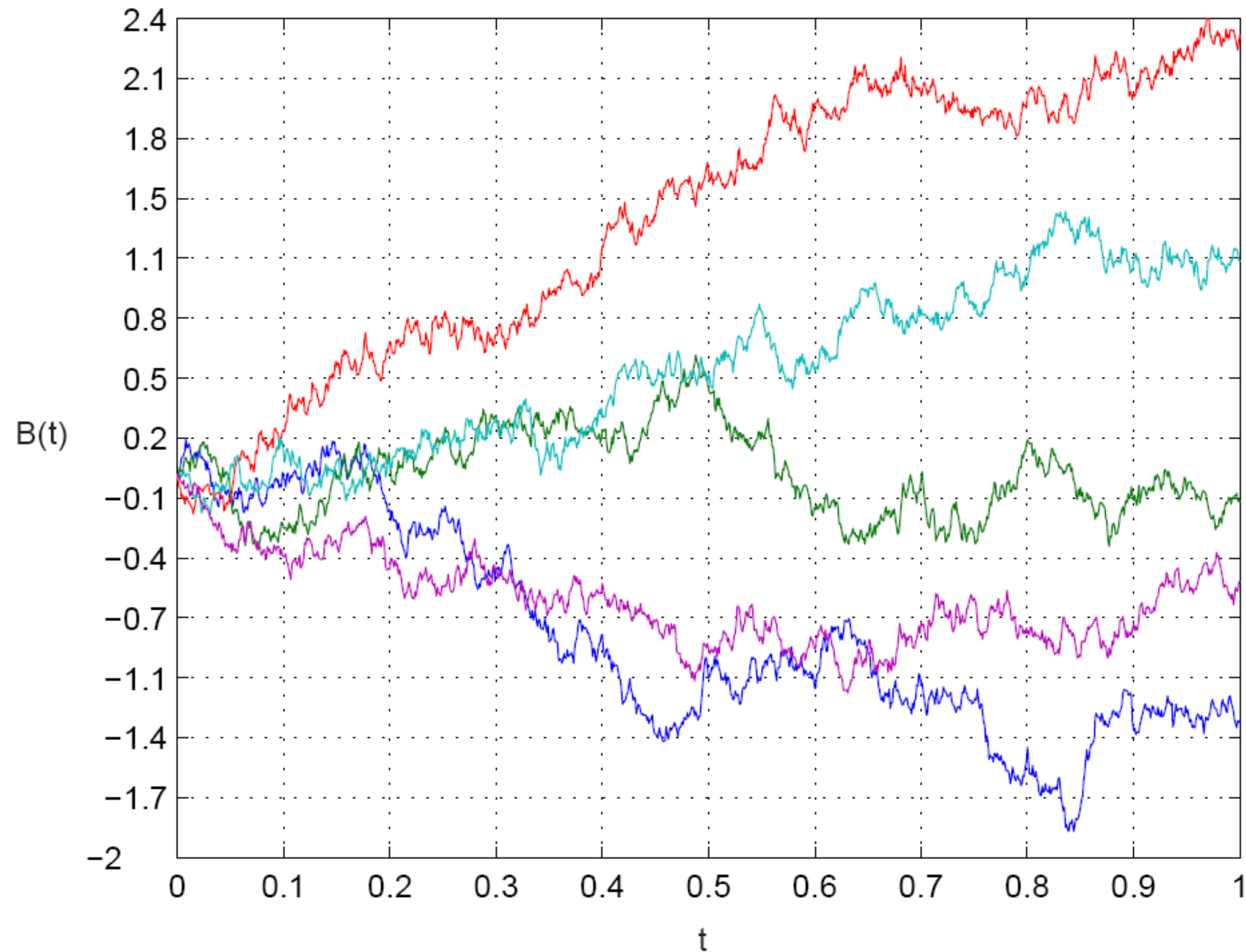
- **Sample space** is a measurable space:  $(\Omega, \mathcal{B}_\Omega)$ 
  - where  $\mathcal{B}_\Omega$  is the  $\sigma$ -algebra/set of admissible outcome events on  $\Omega$ .
- **State space** is a measurable space:  $(\mathcal{X}, \mathcal{B}_\mathcal{X})$ 
  - where  $\mathcal{B}_\mathcal{X}$  is another  $\sigma$ -algebra/set of admissible events on  $\mathcal{X}$ .
- Admissible **random variables** are all measurable maps:
  - $X \in \text{Meas}((\Omega, \mathcal{B}_\Omega), (\mathcal{X}, \mathcal{B}_\mathcal{X}))$
- For fixed **probability measure**  $P$  on  $(\Omega, \mathcal{B}_\Omega)$  the distribution of  $X$  is:
  - push-forward probability measure:  $X_*P$  on  $\mathcal{B}_\mathcal{X}$  (also written as:  $P(X)$ ).

**Motivation**

**- Problems with that Approach**

# Problem 1

## - Stochastic Processes



# Definitions - Stochastic Process

- Let  $(\Omega, \mathcal{B}_\Omega)$  be the sample space,  $(\mathcal{X}, \mathcal{B}_\mathcal{X})$  the state space,  $(\mathcal{T}, \mathcal{B}_\mathcal{T})$  the time space, e.g.  $\mathcal{T} = \mathbb{N}$  or  $\mathcal{T} = \mathbb{R}_{\geq 0}$ .

- A *stochastic process* is a measurable map:

$$\bullet X = (X_t)_{t \in \mathcal{T}} : \Omega \rightarrow \prod_{t \in \mathcal{T}} \mathcal{X}, \quad \omega \mapsto (X_t(\omega))_{t \in \mathcal{T}},$$

- i.e. a random tuple indexed by time

- A *random time* is a measurable map:

$$\bullet T : \Omega \rightarrow \mathcal{T}, \quad \omega \mapsto T(\omega).$$

# Problem

- The *stopped process*:

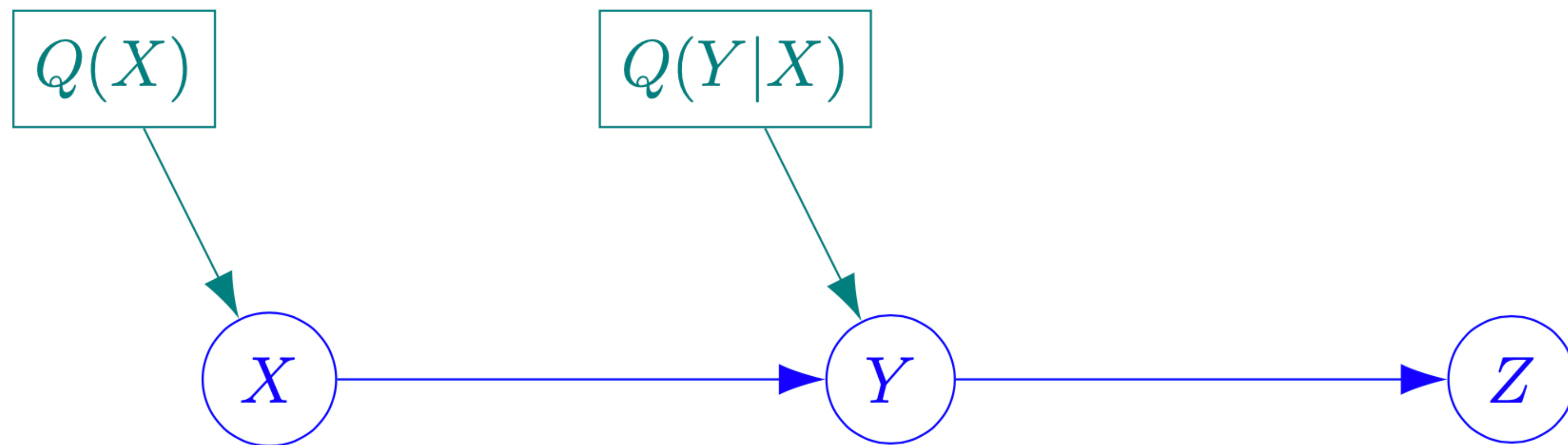
- $X_T : \Omega \rightarrow \mathcal{X}, \quad \omega \mapsto X_{T(\omega)}(\omega)$

- is **not** measurable anymore in general (or only guaranteed under additional, typically topological, assumptions).



# Problem 2

## - Probabilistic Graphical Models



# Conditional Independence in Probabilistic Graphical Models

- Consider a **Markov chain**:



- We have:

- factorization:  $P(X, Y, Z) = P(Z|Y) \otimes P(Y|X) \otimes P(X)$

- tells us that  $Z$  is only dependent on  $Y$ , and, independent of  $X$  when conditioned on  $Y$ , but then also of the choice of  $P(Y|X)$  and  $P(X)$ .

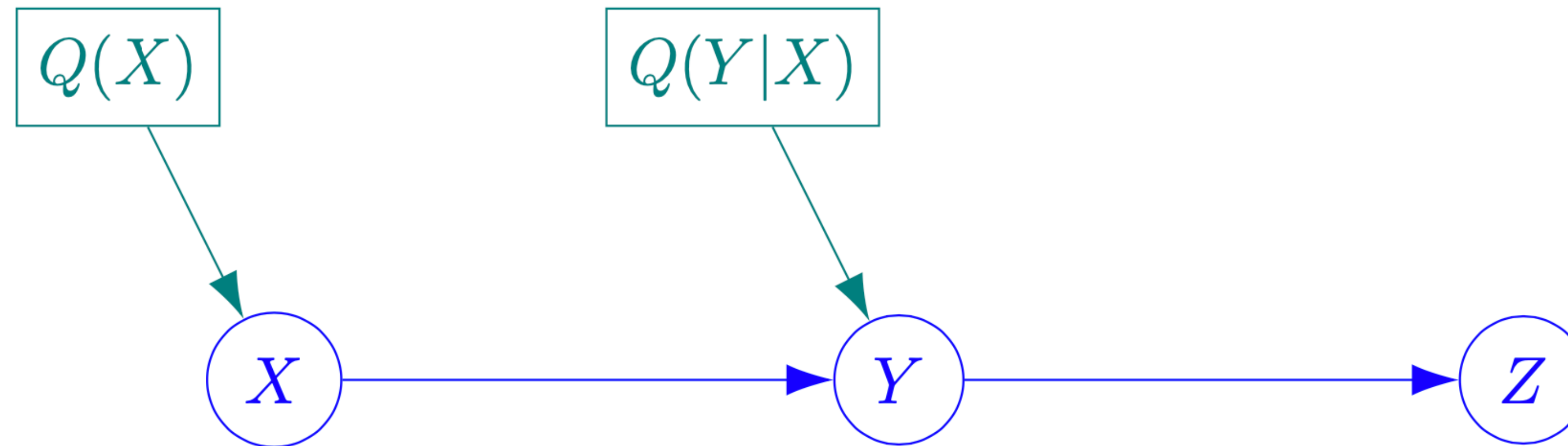
- We want to be able to:

- formalize conditional independence:  $Z \perp\!\!\!\perp X, Q(Y|X), Q(X) \mid Y$

- including non-random variables  $Q(X)$  and  $Q(Y|X)$

- read this off a graph via d-separation (or similar).

# Including Non-Random Variables



- $Q(Y|X)$  is non-random and takes values in  $\mathcal{L} := \text{Meas}(\mathcal{X}, \mathcal{P}(\mathcal{Y}))$
- Then  $Y$  is determined by the new mechanism:
  - $\mathcal{L} \times \mathcal{X} \rightarrow \mathcal{P}(\mathcal{Y}), \quad (Q(Y|X), x) \mapsto Q(Y|X = x).$
- similarly for  $X$ .

# Problem

- For the map:
  - $\mathcal{L} \times \mathcal{X} \rightarrow \mathcal{P}(\mathcal{Y}), \quad (Q(Y|X), x) \mapsto Q(Y|X = x).$
  - to become measurable we need a well-behaved  $\sigma$ -algebra on:
    - $\mathcal{L} := \text{Meas}(\mathcal{X}, \mathcal{P}(\mathcal{Y})).$
- This is generally impossible!

# Random Functions do not exist in Meas

- Theorem (Aumann, 1961):
  - There is **no**  $\sigma$ -algebra  $\mathcal{B}_{\mathcal{L}}$  on  $\mathcal{L} := \text{Meas}(\mathbb{R}, \mathbb{R})$  such that the evaluation map is measurable:
    - $ev : \mathcal{L} \times \mathbb{R} \rightarrow \mathbb{R}, (f, x) \mapsto f(x),$
    - where  $\mathbb{R}$  carries the Borel- $\sigma$ -algebra and  $\mathcal{L}$  is the space of all measurable maps from  $\mathbb{R}$  to  $\mathbb{R}$ , and the product carries the product- $\sigma$ -algebra.
  - So there is no well-behaved way to define a probability distribution over all measurable functions in a fully non-parametric way.
- Robert J. Aumann. *Borel structures for function spaces*. Illinois Journal of Mathematics 5.4 (1961): 614-630.

# Problem 3

## - Probabilistic Programs

```
def prog_prob_prog(a):  
    return lambda m,s: [Z:=np.random.uniform(), a*m+s*Z][-1]
```

```
for n in range(5):  
    print(prog_prob_prog(a=n)(m=5, s=2))
```

```
1.8106662116099772  
6.762509413168864  
10.365457994333775  
15.884402920590935  
21.48676872656254
```

# Definition - Probabilistic Programs

- A *probabilistic program* with inputs  $x \in \mathcal{X}$  and outputs  $z \in \mathcal{Z}$  is a measurable map:

- measurable map:  $K : \mathcal{X} \rightarrow \mathcal{P}(\mathcal{Z})$

- i.e. a Markov kernel.

- The set of probabilistic programs:  $\text{Meas}(\mathcal{X}, \mathcal{P}(\mathcal{Z}))$ .

# Problem

- *Curry / Uncurry* probabilistic programs would translate to isomorphism:
  - $\text{Meas} \left( \mathcal{X} \times \mathcal{Y}, \mathcal{P}(\mathcal{L}) \right) \cong \text{Meas} \left( \mathcal{X}, \text{Meas} \left( \mathcal{Y}, \mathcal{P}(\mathcal{L}) \right) \right)$ 
    - $K \mapsto \tilde{K}$  with  $\tilde{K}(x)(y) = K(x, y)$
- There does **not exists** any  $\sigma$ -algebra on  $\text{Meas} \left( \mathcal{Y}, \mathcal{P}(\mathcal{L}) \right)$  that would make that work (similar argument as before).



# **Problem 4**

## **- Causal Assumptions**

# Causal Inference - Estimating Treatment Effects

- For estimating treatment effect, in the typical case, we have the variables:
  - $X$  = observed treatment variable,
  - $Y$  = observed outcome,
  - $Y_x$  = potential outcome variable under (forced) treatment  $X = x$ ,
  - $Z$  = all other relevant features of the patient.
- Estimation is not possible without further assumptions.
- Typical assumptions made are:
  - **Strong Ignorability:**  $X \perp\!\!\!\perp (Y_x)_{x \in \mathcal{X}} \mid Z$ ,
  - **Consistency:**  $Y = Y_X$  a.s.

# Problem

- Here,  $(Y_x)_{x \in \mathcal{X}}$  is used as a vector of random variables from which we can pick components:  $(\tilde{x}, (Y_x)_{x \in \mathcal{X}}) \mapsto Y_{\tilde{x}}$ .

- However, the following map is, in general, not measurable:

$$\bullet \mathcal{X} \times \prod_{x \in \mathcal{X}} \mathcal{Y} \rightarrow \mathcal{Y}, \quad (\tilde{x}, (y_x)_{x \in \mathcal{X}}) \mapsto y_{\tilde{x}}.$$

- So *Strong Ignorability* does formally not go well with *Consistency*.

# **Problem 5**

## **- Counterfactual Probabilities**

# Counterfactual Probabilities

- For reasoning about treatment effect we consider the variables:
  - $X$  = observed treatment variable,
  - $Y$  = observed outcome,
  - $Y_x$  = potential outcome variable under (forced) treatment  $X = x$ .
- **Conditional counterfactual probabilities:**
  - $C(A | x, x') := P(Y_x \in A | X = x')$
  - “What would have happened (with which probability) under treatment  $X = x$  given that the patient was actually treated with  $X = x'$ ?”

# Problems

- Not clear if conditional counterfactual probabilities are probability measures in  $A$  and/or measurable in  $x, x'$  or jointly.
  - $C(A | x, x') := P(Y_x \in A | X = x')$
- Not clear if conditioning is well-defined here, dependent on how to view  $x \mapsto Y_x$ .

# Quasi-Measurable Spaces

# References

- The talk is based on the following papers:
  - Chris Heunen, Ohad Kammar, Sam Staton, Hongseok Yang. ***A convenient category for higher-order probability theory.*** 32nd Annual ACM/IEEE Symposium on Logic in Computer Science (LICS), 2017.
  - Patrick Forré, ***Quasi-Measurable Spaces***, 2021, <https://arxiv.org/abs/2109.11631>.



# Main Idea behind Quasi-Measurable Spaces

- Main idea: *Exchange the role of  $\sigma$ -algebras and random variables!!!*
- **Sample space** is a measurable space:  $(\Omega, \mathcal{B}_\Omega)$ 
  - where  $\mathcal{B}_\Omega$  is the  $\sigma$ -algebra/set of admissible outcome events on  $\Omega$ .
- **State space** is a “*quasi-measurable space*”:  $(\mathcal{X}, \mathcal{X}^\Omega)$ 
  - where  $\mathcal{X}^\Omega$  is a set of admissible **random variables**.
- **$\sigma$ -algebra** of admissible events is:
  - $\mathcal{B}_\mathcal{X} := \mathcal{B}(\mathcal{X}^\Omega) := \{A \subseteq \mathcal{X} \mid \forall X \in \mathcal{X}^\Omega . X^{-1}(A) \in \mathcal{B}_\Omega\}$
- For fixed **probability measure**  $P$  on  $(\Omega, \mathcal{B}_\Omega)$  the distribution of  $X$  is:
  - push-forward probability measure:  $X_*P$  on  $\mathcal{B}_\mathcal{X}$  (also written as:  $P(X)$  ).

# The Sample Space - Act 1 - Random Variables

- The **Sample Space**  $(\Omega, \Omega^\Omega)$  consists of:
  - a set:  $\Omega$
  - a set of maps:  $\Omega^\Omega \subseteq \{\Phi : \Omega \rightarrow \Omega\}$ 
    - such that:
      - $\text{id}_\Omega \in \Omega^\Omega$ ,
      - $\Omega^\Omega$  contains all constant maps,
      - $\Omega^\Omega$  is closed under composition:
        - $\Phi_1, \Phi_2 \in \Omega^\Omega \implies \Phi_2 \circ \Phi_1 \in \Omega^\Omega$ .
- Standard example:
  - $\Omega^\Omega := \text{Meas} \left( (\Omega, \mathcal{B}_\Omega), (\Omega, \mathcal{B}_\Omega) \right)$  for some carefully chosen  $\sigma$ -algebra:  $\mathcal{B}_\Omega$ .

# Quasi-Measurable Spaces

- A **Quasi-Measurable Space**  $(\mathcal{X}, \mathcal{X}^\Omega)$  w.r.t. sample space  $(\Omega, \Omega^\Omega)$  - per definition - consists of:
  - a set:  $\mathcal{X}$
  - a set of **admissible random variables**:  $\mathcal{X}^\Omega$ ,
  - i.e. a set of maps:  $X : \Omega \rightarrow \mathcal{X}$ , such that:
    - all *constant maps*  $\Omega \rightarrow \mathcal{X}$  are in  $\mathcal{X}^\Omega$ ,
    - $\mathcal{X}^\Omega$  is *closed under pre-composition* with  $\Omega^\Omega$ :
      - $X \in \mathcal{X}^\Omega, \Phi \in \Omega^\Omega \implies X \circ \Phi \in \mathcal{X}^\Omega$ .

# Quasi-Measurable Maps

- Let  $(\mathcal{F}, \mathcal{F}^\Omega)$  and  $(\mathcal{X}, \mathcal{X}^\Omega)$  two quasi-measurable spaces.
- A map  $g : \mathcal{F} \rightarrow \mathcal{X}$  is called **quasi-measurable** if
  - $Z \in \mathcal{F}^\Omega \implies g(Z) := g \circ Z \in \mathcal{X}^\Omega$
- The set of all quasi-measurable maps is abbreviated:
  - $\text{QMS} \left( (\mathcal{F}, \mathcal{F}^\Omega), (\mathcal{X}, \mathcal{X}^\Omega) \right)$  or  $\text{QMS} (\mathcal{F}, \mathcal{X})$  for short.
- Note that the *composition* of two quasi-measurable maps is again *quasi-measurable*.
- The class of all quasi-measurable spaces (w.r.t. a fixed sample space) together with all **quasi-measurable maps** builds a **category**: QMS.

# The Product Space

- Let  $(\mathcal{X}_i, \mathcal{X}_i^\Omega)$  be a family of quasi-measurable spaces,  $i \in I$ .

- Then we turn the product space:  $\prod_{i \in I} \mathcal{X}_i$

- into a quasi-measurable space by putting:  $\left( \prod_{i \in I} \mathcal{X}_i \right)^\Omega := \prod_{i \in I} \mathcal{X}_i^\Omega$

- product random variables on the product are of the form:

- $X(\omega) = (X_i(\omega))_{i \in I}$  with  $X_i \in \mathcal{X}_i^\Omega$  for all  $i \in I$ .

# The Function Space

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  and  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  two quasi-measurable spaces. We put:
  - $\mathcal{X}^{\mathcal{Z}} := \text{QMS} \left( (\mathcal{Z}, \mathcal{Z}^\Omega), (\mathcal{X}, \mathcal{X}^\Omega) \right)$
  - $(\mathcal{X}^{\mathcal{Z}})^\Omega := \left\{ X : \Omega \rightarrow \mathcal{X}^{\mathcal{Z}} \mid ((\omega, z) \mapsto X(\omega)(z)) \in \text{QMS}(\Omega \times \mathcal{Z}, \mathcal{X}) \right\}$ 
    - function-valued random variables are defined via the product structure
- Then  $(\mathcal{X}^{\mathcal{Z}}, (\mathcal{X}^{\mathcal{Z}})^\Omega)$  is a quasi-measurable space.
- Note that such a construction was not possible for measurable spaces!!!

# Currying, Uncurrying and the Evaluation Map

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$ ,  $(\mathcal{Y}, \mathcal{Y}^\Omega)$  and  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  be quasi-measurable spaces.
- We can then **curry** and **uncurry**:
  - $\text{QMS}(\mathcal{Z} \times \mathcal{Y}, \mathcal{X}) \cong \text{QMS}(\mathcal{Y}, \mathcal{X}^{\mathcal{Z}}) = \text{QMS}\left(\mathcal{Y}, \text{QMS}(\mathcal{Z}, \mathcal{X})\right)$
- In particular, the **evaluation map** is quasi-measurable:
  - $\text{ev} : \mathcal{X}^{\mathcal{Z}} \times \mathcal{Z} \rightarrow \mathcal{X}, \quad \text{ev}(g, z) := g(z).$
- Note that this was not possible in Meas for measurable spaces!

# Theorem - QMS cartesian closed

- Theorem: The category of quasi-measurable spaces QMS is **cartesian closed**.
- Remark: We can also construct the following in QMS:
  - **coproducts, equalizers, coequalizers**, thus:
  - all small **limits** and all small **colimits**
- Remark: This means that QMS allows for **simply typed  $\lambda$ -calculus**.
- Remark: Note that most of this is not true for the category of measurable spaces Meas!



# The Slice Categories

- Let  $(\mathcal{T}, \mathcal{T}^\Omega)$  be a quasi-measurable space.
- The slice category  $\text{QMS}_{\mathcal{T}}$  of all *quasi-measurable spaces over  $\mathcal{T}$*  is given by:
  - objects: quasi-measurable maps:  $T_{\mathcal{X}} : \mathcal{X} \rightarrow \mathcal{T}$
  - morphisms: quasi-measurable maps:  $f : \mathcal{X} \rightarrow \mathcal{Y}$ 
    - s.t.:  $T_{\mathcal{Y}} \circ f = T_{\mathcal{X}}$ .
- By abuse of notation we will just write  $\mathcal{X}$  instead of  $(\mathcal{X}, \mathcal{X}^\Omega, T_{\mathcal{X}})$

# The Fibre Product

- Let  $\mathcal{T} \in \text{QMS}$  and  $\mathcal{X}, \mathcal{Y} \in \text{QMS}_{\mathcal{T}}$ .
- The *fibre product* of  $\mathcal{X}$  and  $\mathcal{Y}$  over  $\mathcal{T}$  is given as follows:
  - $\mathcal{X} \times_{\mathcal{T}} \mathcal{Y} := \left\{ (x, y) \in \mathcal{X} \times \mathcal{Y} \mid T_{\mathcal{X}}(x) = T_{\mathcal{Y}}(y) \right\}$
  - $(\mathcal{X} \times_{\mathcal{T}} \mathcal{Y})^{\Omega} := \left\{ (X, Y) \in \mathcal{X}^{\Omega} \times \mathcal{Y}^{\Omega} \mid T_{\mathcal{X}} \circ X = T_{\mathcal{Y}} \circ Y \right\}$
  - $T : \mathcal{X} \times_{\mathcal{T}} \mathcal{Y} \rightarrow \mathcal{T}, \quad T(x, y) := T_{\mathcal{X}}(x) = T_{\mathcal{Y}}(y)$
- This makes  $\mathcal{X} \times_{\mathcal{T}} \mathcal{Y}$  a quasi-measurable space over  $\mathcal{T}$ .
- In fact, the fibre product is the categorical product of  $\text{QMS}_{\mathcal{T}}$ .

# The Internal Hom

- Let  $\mathcal{T} \in \text{QMS}$  and  $\mathcal{X}, \mathcal{Y}, \mathcal{Z} \in \text{QMS}_{\mathcal{T}}$ .
- The *internal hom* from  $\mathcal{Y}$  to  $\mathcal{Z}$  over  $\mathcal{T}$  is given as follows:
  - $\mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z}) := \coprod_{t \in \mathcal{T}} \text{QMS}(\mathcal{Y}_t, \mathcal{Z}_t)$  (coproduct taken in Sets)
  - $T_{\mathcal{Q}} : \mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z}) \rightarrow \mathcal{T}, \quad T_{\mathcal{Q}}(t, g) := t.$
  - $\mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z})^{\Omega} := \left\{ (T, G) : \Omega \rightarrow \mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z}) \mid T \in \mathcal{T}^{\Omega} \text{ and } \right.$   
 $\left. \forall \Phi \in \Omega^{\Omega}, \forall Y \in \mathcal{Y}^{\Omega} \text{ s.t. } T \circ \Phi = T_{\mathcal{Y}} \circ Y. \right.$   
 $\left. G(\Phi)(Y) \in \mathcal{Z}^{\Omega} \right\}$
  - with  $G(\Phi)(Y) : \Omega \rightarrow \mathcal{Z}, \quad \omega \mapsto G(\Phi(\omega))(Y(\omega))$

# The Internal Hom - Theorem

- Let  $\mathcal{T} \in \text{QMS}$  and  $\mathcal{X}, \mathcal{Y}, \mathcal{Z} \in \text{QMS}_{\mathcal{T}}$ .
- The *internal hom*  $\mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z})$  is a quasi-measurable space over  $\mathcal{T}$ .
- The internal hom defines an exponential object in the slice category  $\text{QMS}_{\mathcal{T}}$ :
  - The curry map is well-defined and a canonical bijection:
    - $\text{QMS}_{\mathcal{T}}(\mathcal{X} \times_{\mathcal{T}} \mathcal{Y}, \mathcal{Z}) \cong \text{QMS}_{\mathcal{T}}(\mathcal{X}, \mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z}))$
    - $g \mapsto \tilde{g}$  with  $\tilde{g}(x) = (T_{\mathcal{X}}(x), g_x)$  with  $g_x(y) := g(x, y)$ .
- Furthermore, it induces an isomorphism in  $\text{QMS}_{\mathcal{T}}$ :
  - $\mathcal{Q}_{\mathcal{T}}(\mathcal{X} \times_{\mathcal{T}} \mathcal{Y}, \mathcal{Z}) \cong \mathcal{Q}_{\mathcal{T}}(\mathcal{X}, \mathcal{Q}_{\mathcal{T}}(\mathcal{Y}, \mathcal{Z}))$ .

# Strong Monomorphism = Embeddings

- A quasi-measurable map  $i : \mathcal{X} \rightarrow \mathcal{Y}$  is called an *embedding* iff
  - $i$  is injective, and:
  - $\mathcal{X}^\Omega = \{X : \Omega \rightarrow \mathcal{X} \mid i \circ X \in \mathcal{Y}^\Omega\}$
- Lemma: Embeddings are exactly the *strong monomorphisms* in QMS.

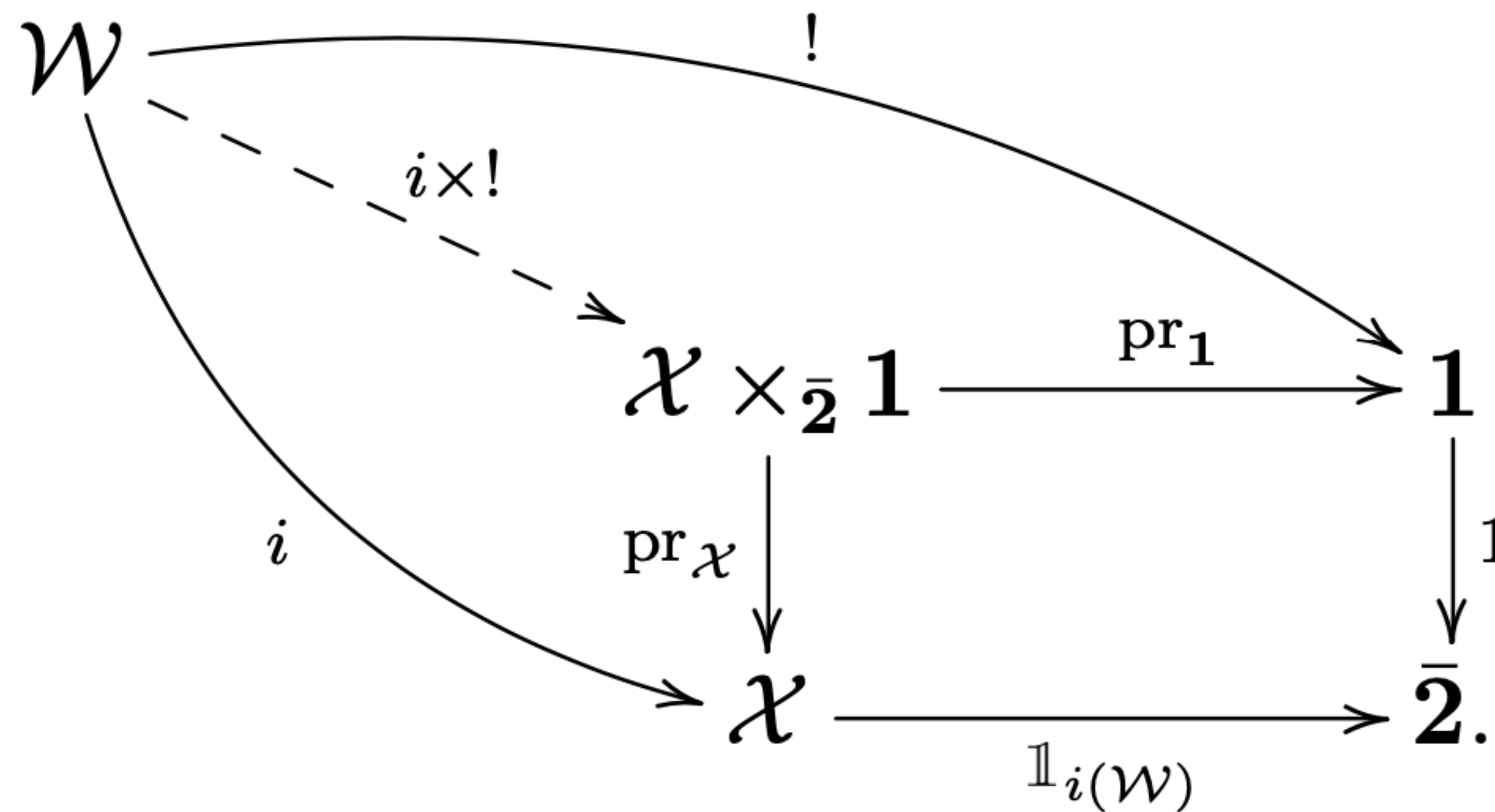
$$\begin{array}{ccc}
 \mathcal{Z} & \xrightarrow{f} & \mathcal{X} \\
 t \downarrow & & \downarrow i \\
 \mathcal{W} & \xrightarrow{g} & \mathcal{Y}
 \end{array}$$

(for  $t$  epimorphisms)

$$\begin{array}{ccc}
 \mathcal{Z} & \xrightarrow{f} & \mathcal{X} \\
 t \downarrow & \nearrow h & \downarrow i \\
 \mathcal{W} & \xrightarrow{g} & \mathcal{Y}
 \end{array}$$

# Subobject Classifier for Strong Monomorphisms

- Let  $\mathbf{2} = \{0,1\}$  be the quasi-measurable space with  $\mathbf{2}^\Omega := \text{Sets}(\Omega, \mathbf{2})$ .
- Lemma: Then  $\mathbf{2}$  together with the constant-1-map  $1 : \mathbf{1} \rightarrow \mathbf{2}$  is a subobject classifier for strong monomorphisms in QMS.



# Definition - Quasitopos

- A **quasitopos** is a category that:
  - has all finite limits,
  - has all finite colimits,
  - is locally cartesian closed,
  - has a subobject classifier for strong monomorphisms.

# Main Theorems

- Theorem: The category of quasi-measurable spaces QMS forms a **quasitopos**, and, is in particular, **locally cartesian closed**.
- Remark: This means that, besides **simply typed  $\lambda$ -calculus**, we get a **dependent type theory** for QMS.
  - Roughly speaking, this means that we can model programs that can vary the output type/space dependent on the input.
- Remark: Note that most of this is not true for the category of measurable spaces Meas!



# The Sample Space - Act 2 - The $\sigma$ -Algebra

- We now endow the Sample Space  $(\Omega, \Omega^\Omega)$  with an additional  $\sigma$ -algebra  $\mathcal{B}_\Omega$  such that:
  - $\Omega^\Omega \subseteq \text{Meas}((\Omega, \mathcal{B}_\Omega), (\Omega, \mathcal{B}_\Omega))$ .
- The **Sample Space** is now the triple:  $(\Omega, \Omega^\Omega, \mathcal{B}_\Omega)$ .
- Standard example:
  - $\Omega^\Omega = \text{Meas}((\Omega, \mathcal{B}_\Omega), (\Omega, \mathcal{B}_\Omega))$

# Topological and Measurable Spaces as Quasi-Measurable Spaces

- If  $(\mathcal{X}, \mathcal{E}_{\mathcal{X}})$  is a measurable space or a topological space, etc., then we can turn this into a quasi-measurable space via allowing for the following random variables:
  - $\mathcal{X}^{\Omega} := \mathcal{F}(\mathcal{E}_{\mathcal{X}}) := \{X : \Omega \rightarrow \mathcal{X} \mid \forall A \in \mathcal{E}_{\mathcal{X}}. X^{-1}(A) \in \mathcal{B}_{\Omega}\}$
- Note that the later introduced  $\sigma$ -algebra  $\mathcal{B}_{\mathcal{X}}$  might be strictly bigger than the one we started with to turn  $(\mathcal{X}, \mathcal{E}_{\mathcal{X}})$  into quasi-measurable space  $(\mathcal{X}, \mathcal{X}^{\Omega})$ :
  - $\mathcal{E}_{\mathcal{X}} \subsetneq \mathcal{B}_{\mathcal{X}} := \mathcal{B}(\mathcal{X}^{\Omega})$

# The $\sigma$ -Algebra

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  be a quasi-measurable space.
- Then the **induced  $\sigma$ -algebra** is:
  - $\mathcal{B}_\mathcal{X} := \{A \subseteq \mathcal{X} \mid \forall X \in \mathcal{X}^\Omega . X^{-1}(A) \in \mathcal{B}_\Omega\}$
- We can then define the set of admissible random variables with values in  $\mathcal{B}_\mathcal{X}$  via:
  - $(\mathcal{B}_\mathcal{X})^\Omega := \{\Psi : \Omega \rightarrow \mathcal{B}_\mathcal{X} \mid \exists D \in \mathcal{B}_{\Omega \times \mathcal{X}} \forall \omega \in \Omega . \Psi(\omega) = D_\omega\} \cong \mathcal{B}_{\Omega \times \mathcal{X}}$ 
    - where  $D_\omega := \{x \in \mathcal{X} \mid (\omega, x) \in D\}$
- Then  $(\mathcal{B}_\mathcal{X}, (\mathcal{B}_\mathcal{X})^\Omega)$  is a quasi-measurable space.
- Note that this was not possible in the category of measurable spaces!!!

# Theorem - The Adjunction

- A **map**  $g : \mathcal{X} \rightarrow \mathcal{Y}$  from a quasi-measurable space  $(\mathcal{X}, \mathcal{X}^\Omega)$  to a measurable space  $(\mathcal{Y}, \mathcal{B}_\mathcal{Y})$  is
  - **measurable if and only if it is quasi-measurable,**
  - *provided* we use the corresponding choices:
    - $\mathcal{B}_\mathcal{X} := \mathcal{B}(\mathcal{X}^\Omega) := \{A \subseteq \mathcal{X} \mid \forall X \in \mathcal{X}^\Omega . X^{-1}(A) \in \mathcal{B}_\Omega\},$
    - $\mathcal{Y}^\Omega := \mathcal{F}(\mathcal{B}_\mathcal{Y}) := \{Y : \Omega \rightarrow \mathcal{Y} \mid \forall B \in \mathcal{B}_\mathcal{Y} . Y^{-1}(B) \in \mathcal{B}_\Omega\}.$
- In other words, we have the natural identification of sets of maps:
  - $\text{Meas} \left( (\mathcal{X}, \mathcal{B}(\mathcal{X}^\Omega)), (\mathcal{Y}, \mathcal{B}_\mathcal{Y}) \right) = \text{QMS} \left( (\mathcal{X}, \mathcal{X}^\Omega), (\mathcal{Y}, \mathcal{F}(\mathcal{B}_\mathcal{Y})) \right).$

# The Sample Space - Act 3 - Probability Measures

- We now endow the Sample Space  $(\Omega, \Omega^\Omega, \mathcal{B}_\Omega)$  with some additional set of **product compatible probability measures**  $\mathcal{P}$  on  $\mathcal{B}_\Omega$ , i.e. such that:
  - for all  $P \in \mathcal{P}$  and  $D \in \mathcal{B}_{\Omega \times \Omega}$  the map:
    - $\Omega \rightarrow [0,1], \quad \omega \mapsto P(D^\omega),$  is (quasi-)measurable,
      - where  $D^\omega := \{\tilde{\omega} \in \Omega \mid (\tilde{\omega}, \omega) \in D\},$
  - for all  $P_1, P_2 \in \mathcal{P}$  there exist  $\Phi_1, \Phi_2 \in \Omega^\Omega$  and  $P \in \mathcal{P}$  such that:
    - $P_1 \otimes P_2 = P(\Phi_1, \Phi_2)$  on  $\mathcal{B}_{\Omega \times \Omega},$  i.e. for all  $D \in \mathcal{B}_{\Omega \times \Omega}$  we have:
      - $(P_1 \otimes P_2)(D) := \int P_1(D^\omega) P_2(d\omega) = P(\{\omega \in \Omega \mid (\Phi_1(\omega), \Phi_2(\omega)) \in D\}).$
- The **Sample Space** is now the quadruple:  $(\Omega, \Omega^\Omega, \mathcal{B}_\Omega, \mathcal{P}).$

# The Space of Push-forward Probability Measures

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  be a quasi-measurable space. Define:
  - $\mathcal{P}(\mathcal{X}) := \mathcal{P}(\mathcal{X}, \mathcal{X}^\Omega) := \{P(X) : \mathcal{B}_{\mathcal{X}} \rightarrow [0,1] \mid X \in \mathcal{X}^\Omega, P \in \mathcal{P}\}$
  - $\mathcal{P}(\mathcal{X})^\Omega := \mathcal{P}(\mathcal{X}, \mathcal{X}^\Omega)^\Omega := \{P(X|I) \mid X \in (\mathcal{X}^\Omega)^\Omega, P \in \mathcal{P}\}$
  - $P(X \in A \mid I = \omega) := P\left(\{\tilde{\omega} \in \Omega \mid X(\omega)(\tilde{\omega}) \in A\}\right)$  for  $A \in \mathcal{B}_{\mathcal{X}}$
- Lemma:  $(\mathcal{P}(\mathcal{X}), \mathcal{P}(\mathcal{X})^\Omega)$  is also a quasi-measurable space.

# The Spaces of Markov Kernels and Random Functions

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  and  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  be quasi-measurable spaces.
- Then the **space of Markov kernels** from  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  to  $(\mathcal{X}, \mathcal{X}^\Omega)$ :
  - $\mathcal{P}(\mathcal{X})^{\mathcal{Z}} = \text{QMS} \left( (\mathcal{Z}, \mathcal{Z}^\Omega), (\mathcal{P}(\mathcal{X}), \mathcal{P}(\mathcal{X})^\Omega) \right)$
  - is again a quasi-measurable space.
- Also the space of probability distribution over functions:
  - $\mathcal{P}(\mathcal{X}^{\mathcal{Z}})$  is again a quasi-measurable space.
- Note that these construction were not possible in the category of measurable spaces!!!

# Some surprising Lemmata

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  and  $(\mathcal{Y}, \mathcal{Y}^\Omega)$  be quasi-measurable spaces.
- Then the following maps are all quasi-measurable:
  - $\mathcal{Y}^{\mathcal{X}} \times \mathcal{B}_{\mathcal{Y}} \rightarrow \mathcal{B}_{\mathcal{X}}, \quad (f, B) \mapsto f^{-1}(B).$
  - $\mathcal{P}(\mathcal{X}) \times \mathcal{B}_{\mathcal{X}} \rightarrow [0,1], \quad (P, A) \mapsto P(A).$
  - $\mathcal{Y}^{\mathcal{X}} \times \mathcal{P}(\mathcal{X}) \rightarrow \mathcal{P}(\mathcal{Y}), \quad (f, P) \mapsto f_*P.$
  - $[0,\infty]^{\mathcal{X}} \times \mathcal{P}(\mathcal{X}) \rightarrow [0,\infty], \quad (h, P) \mapsto \int h(x) P(dx).$
- Note that such statements were not known or even possible in the category of measurable spaces!!!



# Theorem: The Product of Markov Kernels

- Assume that there exists an isomorphism of quasi-measurable spaces:
  - $\Omega \times \Omega \cong \Omega$ .
- Then for all quasi-measurable spaces  $(\mathcal{X}, \mathcal{X}^\Omega)$ ,  $(\mathcal{Y}, \mathcal{Y}^\Omega)$ ,  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  the **product of Markov kernels**:

$$\bullet \otimes : \mathcal{P}(\mathcal{X})^{\mathcal{Y} \times \mathcal{Z}} \times \mathcal{P}(\mathcal{Y})^{\mathcal{Z}} \rightarrow \mathcal{P}(\mathcal{X} \times \mathcal{Y})^{\mathcal{Z}}$$

$$(P(X|Y, Z) \otimes Q(Y|Z))(D|z) := \int P(X \in D^y | Y = y, Z = z) Q(Y \in dy | Z = z)$$

- is a well-defined quasi-measurable map.

# Theorem: Strong Probability Monad

- If  $\Omega \times \Omega \cong \Omega$  then the triple  $(\mathcal{P}, \delta, \mathbb{M})$  is a **strong probability monad** on the cartesian closed category QMS, where:

- $\delta : \mathcal{X} \rightarrow \mathcal{P}(\mathcal{X}),$   $\delta_x(A) := \mathbb{1}_A(x),$

- $\mathbb{M} : \mathcal{P}(\mathcal{P}(\mathcal{X})) \rightarrow \mathcal{P}(\mathcal{X}),$   $\mathbb{M}(\Pi)(A) := \int P(A) d\Pi(P).$

- This thus allows for a notion of computation of monadic type and simply typed  $\lambda$ -calculus.
- We thus get semantics for higher-order probability theory for probabilistic programming language.

# Construction of well-behaved Sample Spaces

- Theorem: Let  $\Omega_0$  be a set, and:
  - $\mathcal{E}_0$  a countable set of subsets of  $\Omega_0$  that separates the points of  $\Omega_0$ .
  - $\Omega := \prod_{n \in \mathbb{N}} \Omega_0$ , and  $\mathcal{E} := \{\text{pr}_n^{-1}(A) \mid A \in \mathcal{E}_0, n \in \mathbb{N}\}$ ,
  - $\tilde{\mathcal{P}} := \{P \text{ complete perfect probability measure on } \Omega, \mathcal{E} \subseteq \mathcal{B}_P\}$ ,
  - $\mathcal{B}_\Omega := \bigcap_{P \in \tilde{\mathcal{P}}} \mathcal{B}_P$ , the perfect-universal completion of  $\mathcal{E}$ ,
  - $\Omega^\Omega := \text{Meas}((\Omega, \mathcal{B}_\Omega), (\Omega, \mathcal{B}_\Omega))$ ,  $\mathcal{P} := \tilde{\mathcal{P}}|_{\mathcal{B}_\Omega}$
- Then  $(\Omega, \Omega^\Omega, \mathcal{B}_\Omega, \mathcal{P})$  satisfies all points of act 1-3 and  $\Omega \times \Omega \cong \Omega$ .

# Fubini Theorem

- Let  $(\Omega, \Omega^\Omega, \mathcal{B}_\Omega, \mathcal{P})$  be the sample space from the last slide.
- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  and  $(\mathcal{Y}, \mathcal{Y}^\Omega)$  be quasi-measurable spaces and:
  - $f \in [0, \infty]^{\mathcal{X} \times \mathcal{Y}}$ ,  $P \in \mathcal{P}(\mathcal{X})$  and  $Q \in \mathcal{P}(\mathcal{Y})$ .
- Then we have the equality:

$$\bullet \int \int f(x, y) P(dx) Q(dy) = \int \int f(x, y) Q(dy) P(dx).$$

# The Sample Space - Act 4 - The Universal Hilbert Cube

- $\Omega = [0,1]^{\mathbb{N}} = \prod_{n \in \mathbb{N}} [0,1]$ , the **Hilbert Cube**,
- $\mathcal{B}_{\Omega}$  = set of all *universally measurable* subsets of  $\Omega$ .
  - Note that this is bigger than the Borel  $\sigma$ -algebra on  $\Omega$ .
- $\mathcal{P}$  = all probability measures on  $\mathcal{B}_{\Omega}$ ,  $\Omega^{\Omega} = \text{Meas} \left( (\Omega, \mathcal{B}_{\Omega}), (\Omega, \mathcal{B}_{\Omega}) \right)$ .
- We call this Sample Space  $(\Omega, \Omega^{\Omega}, \mathcal{B}_{\Omega}, \mathcal{P})$  the **Universal Hilbert Cube**.
- Interpretation: Countably infinite sequence of uniformly distributed samples (e.g. from a (pseudo-)random number generator).
- Note that it satisfies act 1-3 and the iso:  $\Omega \times \Omega \cong \Omega$  (via “Hilbert’s Hotel”).

# The Category of Quasi-Universal Spaces

- Definition: A **quasi-universal space**  $(\mathcal{X}, \mathcal{X}^\Omega)$  is - per definition - just a quasi-measurable space where the sample space  $\Omega$  is the **universal Hilbert cube**.
- We abbreviate the category of quasi-universal spaces as QUS.

# Countably Separated and Standard Quasi-Measurable Spaces

- Definition: A quasi-measurable space  $(\mathcal{X}, \mathcal{X}^\Omega)$  is called:
  - **countably separated** if there exists a countable subset  $\mathcal{E} \subseteq \mathcal{B}_\mathcal{X}$  that separates the points of  $\mathcal{X}$ .
  - **standard quasi-measurable space** if there are quasi-measurable maps:
    - $\iota : (\mathcal{X}, \mathcal{X}^\Omega) \rightarrow (\Omega, \Omega^\Omega)$  and  $r : (\Omega, \Omega^\Omega) \rightarrow (\mathcal{X}, \mathcal{X}^\Omega)$  s.t.:
    - $r \circ \iota = \text{id}_\mathcal{X}$ .

# Theorem: Disintegration of Markov Kernels

- Let  $(\mathcal{X}, \mathcal{X}^\Omega)$  and  $(\mathcal{Y}, \mathcal{Y}^\Omega)$  and  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  be quasi-universal spaces.
  - Let  $(\mathcal{Y}, \mathcal{Y}^\Omega)$  be *countably separated*. and:
  - either  $(\mathcal{X}, \mathcal{X}^\Omega)$  or  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  be a *standard* quasi-universal space.
- Then the product of Markov kernels:
  - $\otimes : \mathcal{P}(\mathcal{X})^{\mathcal{Y} \times \mathcal{Z}} \times \mathcal{P}(\mathcal{Y})^{\mathcal{Z}} \rightarrow \mathcal{P}(\mathcal{X} \times \mathcal{Y})^{\mathcal{Z}}$
  - is a (surjective) quotient map of quasi-universal spaces.
- More concretely, for every  $P(X, Y | Z) \in \mathcal{P}(\mathcal{X} \times \mathcal{Y})^{\mathcal{Z}}$  there exists  $P(X | Y, Z) \in \mathcal{P}(\mathcal{X})^{\mathcal{Y} \times \mathcal{Z}}$  such that:  $P(X, Y | Z) = P(X | Y, Z) \otimes P(Y | Z)$ .



# Conditional Kolmogorov Extension Theorem

- Let  $(\mathcal{X}_n, \mathcal{X}_n^\Omega)$ ,  $n \in \mathbb{N}$ , a sequence of *standard* quasi-universal spaces and  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  be any quasi-universal space.
- Assume we have  $Q_n(X_{0:n} | Z) \in \mathcal{P}(\mathcal{X}_{0:n})^{\mathcal{Z}}$  such that for every  $n \in \mathbb{N}$ :
  - $\text{pr}_{0:n,*} Q_{n+1}(X_{0:n+1} | Z) = Q_n(X_{0:n} | Z)$ .
- Then there exists a unique  $Q(X_{\mathbb{N}} | Z) \in \mathcal{P}(\mathcal{X}_{\mathbb{N}})^{\mathcal{Z}}$  such that:
  - $\text{pr}_{0:n,*} Q(X_{0:n+1} | Z) = Q_n(X_{0:n} | Z)$  for all  $n \in \mathbb{N}$ ,
- where  $\mathcal{X}_{\mathbb{N}} := \prod_{n \in \mathbb{N}} \mathcal{X}_n$ .

# Conditional De Finetti Theorem

- $(\mathcal{X}, \mathcal{X}^\Omega)$  standard quasi-universal spaces,  $(\mathcal{Z}, \mathcal{Z}^\Omega)$  any quasi-universal space.
- For a Markov kernel  $Q(X_{\mathbb{N}} | Z) \in \mathcal{P}(\mathcal{X}^{\mathbb{N}})^{\mathcal{Z}}$  the following is equivalent:
  - $Q(X_{\mathbb{N}} | Z)$  is **exchangable**, i.e. invariant under all finite permutations:  $\rho : \mathbb{N} \cong \mathbb{N}$ .
  - There exists a quasi-universal space  $\mathcal{Y}$  and  $K(X | Y) \in \mathcal{P}(\mathcal{X})^{\mathcal{Y}}$  and  $P(Y | Z) \in \mathcal{P}(\mathcal{Y})^{\mathcal{Z}}$  such that :

$$\bullet Q(X_{\mathbb{N}} | Z) = \left( \bigotimes_{n \in \mathbb{N}} K(X_n | Y) \right) \circ P(Y | Z).$$

- In this case we can w.l.o.g. take:  $\mathcal{Y} = \mathcal{P}(\mathcal{X})$  and  $K(X \in A | Y = P) := P(A)$ .

# Transitional Conditional Independence

- Consider a Markov kernel:  $P(X, Y, Z | T) \in \mathcal{P}(\mathcal{X} \times \mathcal{Y} \times \mathcal{Z})^{\mathcal{T}}$ .
- We say that  $X$  is **conditional independent** of  $Y$  given  $Z$  w.r.t.  $P(X, Y, Z | T)$ ,
  - in symbols:  $X \perp\!\!\!\perp Y | Z$  if:
  - there *exists* a Markov kernel  $Q(X | Z) \in \mathcal{P}(\mathcal{X})^{\mathcal{Z}}$  such that:
    - $P(X, Y, Z | T) = Q(X | Z) \otimes P(Y, Z | T)$ .

# Partially Generic Causal Bayesian Networks

- A **partially generic causal Bayesian network** - per definition - consists of:
  - a **conditional directed acyclic graph (CDAG)**:  $G = (J, V, E)$ ,
  - an input variable  $X_j$  on a quasi-universal space  $\mathcal{X}_j$  for each  $j \in J$ ,
  - an output variable  $X_v$  on a *standard* quasi-universal space  $\mathcal{X}_v$  for each  $v \in V$ ,
  - an **exceptional set**:  $W \subseteq V$ ,
  - a Markov kernel:  $P_v(X_v | X_{\text{Pa}^G(v)}) \in \mathcal{P}(\mathcal{X}_v)^{\mathcal{X}_{\text{Pa}^G(v)}}$  for  $v \in V \setminus W$ .

# Partially Generic Causal Bayesian Networks

- For a partially generic causal Bayesian network with exceptional set  $W$  we introduce for  $w \in W$ :
  - an **indicator variable**:  $I_w \rightarrow w$ ,
  - a quasi-universal space:  $\mathcal{X}_{I_w} := \mathcal{P}(\mathcal{X}_w)^{\mathcal{X}_{\text{Pa}G(w)}}$ ,
  - a “**generic**” Markov kernel:
    - $P_w \left( X_w \in A \mid X_{\text{Pa}G(w)} = x, X_{I_w} = Q \right) := Q \left( X_w \in A \mid X_{\text{Pa}G(w)} = x \right)$ .
- So we get a joint Markov kernel:  $P(X_V, X_J, X_{I_W} \mid X_J, X_{I_W})$ .

# Theorem: Global Markov Property

- For every partially generic causal Bayesian network with exceptional set  $W$  and any subsets:  $A, B, C \subseteq V \cup I_W \cup J$  we have the implication:

- $A \perp B | C \implies X_A \perp\!\!\!\perp X_B | X_C.$

**(Proposed)  
Answers**

# Answers - Stochastic Process

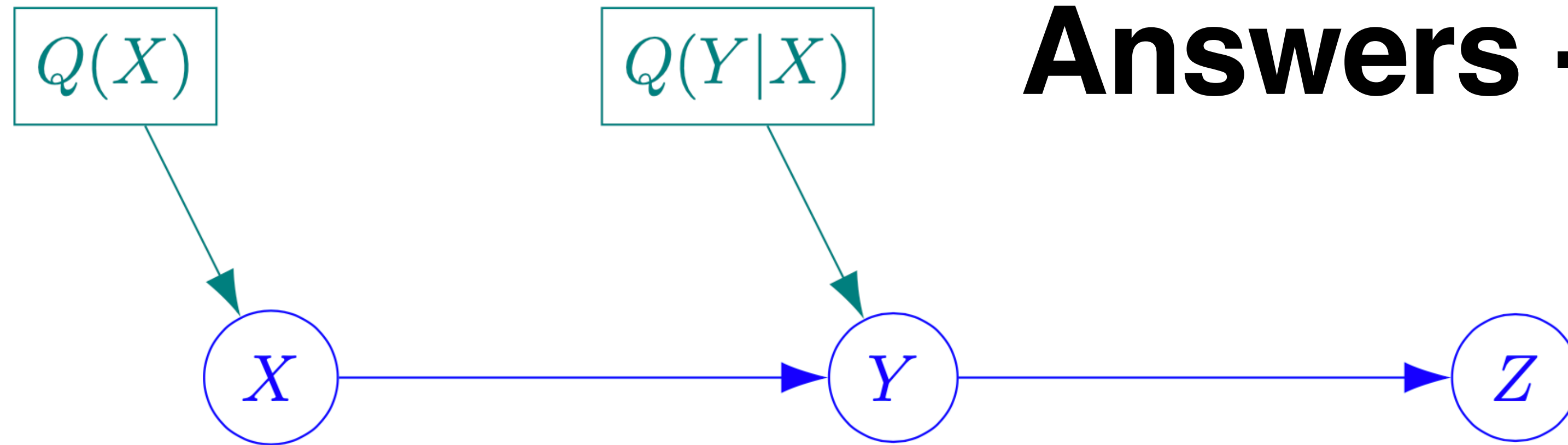
- Definition: A **stochastic process** is a quasi-measurable map:
  - $X : \Omega \rightarrow \mathcal{X}^{\mathcal{T}}, \quad \omega \mapsto (t \mapsto X(\omega)(t)).$
- Lemma: This is *equivalent* to a quasi-measurable map:  $X : \Omega \times \mathcal{T} \rightarrow \mathcal{X}, \quad (\omega, t) \mapsto X(\omega, t).$
- Lemma: The map:  $\mathcal{X}^{\mathcal{T}} \rightarrow \prod_{t \in \mathcal{T}} \mathcal{X}, \quad X \mapsto (X(t))_{t \in \mathcal{T}},$  is quasi-measurable.
- Lemma: If  $T : \Omega \rightarrow \mathcal{T}$  is quasi-measurable (random time) then the map:
  - $\Omega \rightarrow \mathcal{X}, \quad \omega \mapsto X(\omega)(T(\omega))$  is again quasi-measurable.



# Answers - Probabilistic Programs

- Definition: A **probabilistic program** with input  $x \in \mathcal{X}$  and output  $z \in \mathcal{Z}$  is quasi-measurable map:  $\mathcal{X} \rightarrow \mathcal{P}(\mathcal{Z})$ .
- Theorem: We have the natural **curry / uncurry isomorphism**:
  - $\text{QMS}(\mathcal{X} \times \mathcal{Y}, \mathcal{P}(\mathcal{Z})) \cong \text{QMS}(\mathcal{X}, \text{QMS}(\mathcal{Y}, \mathcal{P}(\mathcal{Z})))$
- Theorem: QMS is a **quasitopos**, thus allows for **dependent type theory**.
- Theorem: The triple  $(\mathcal{P}, \delta, \mathbb{M})$  forms a **strong probability monad** on the category of quasi-measurable spaces QMS (for certain sample spaces, e.g. the universal Hilbert cube). Thus allows for **higher-order probabilistic programs**.

# Answers - Graphical Models



- **Partially generic causal Bayesian networks** can model graphical models with non-random input variables.
- **Transitional conditional independence** also works with non-random input variables.
- Theorem: **Global Markov Property**: For  $A, B, C \subseteq V \cup I_W \cup J$  we have:
  - $A \perp B | C \implies X_A \perp\!\!\!\perp X_B | X_C$ .
- Example: Here  $Q(Y|X)$  is a non-random input variable with values in  $\mathcal{L} := \text{QUS}(\mathcal{X}, \mathcal{P}(\mathcal{Y}))$ 
  - Then  $Y$  is determined by the new quasi-measurable mechanism:
    - $\mathcal{L} \times \mathcal{X} \rightarrow \mathcal{P}(\mathcal{Y}), \quad (Q(Y|X), x) \mapsto Q(Y|X = x)$ .
  - We can now read off the graph:  $Z \perp\!\!\!\perp X, Q(Y|X), Q(X) | Y$ .

# Answers - Causal Assumptions

- Model **potential outcome** as quasi-measurable map / random function:
  - $G : \Omega \rightarrow \mathcal{Y}^{\mathcal{X}}$
- Potential outcome under treatment  $X = x$  then:  $Y_x := G(x)$ .
- Rephrase causal assumptions:
  - Strong Ignorability:  $X \perp\!\!\!\perp G \mid Z$ ,
  - Consistency:  $Y = G(X)$ .
- Everything is well-defined and quasi-measurable.

# Answers - Counterfactual Probabilities

- Theorem: Disintegration of Markov kernels.
- Model potential outcome as:  $G \in (\mathcal{Y}^{\mathcal{X}})^{\Omega}$
- Assume that  $\mathcal{X}$  to countably separated quasi-universal space.
- Then via the disintegration theorem there exists conditional:
  - $P(G | X) \in \mathcal{P}(\mathcal{G})^{\mathcal{X}}$  such that  $P(G, X) = P(G | X) \otimes P(X)$ .
- Evaluation maps and push-forwards are quasi-measurable, which implies:
  - $C(A | x, x') := P(G(x) \in A | X = x')$  defines:
  - well-defined and quasi-measurable  $C \in \mathcal{P}(\mathcal{Y})^{\mathcal{X} \times \mathcal{X}}$
- So, conditional counterfactual probabilities are well-defined and quasi-measurable.

# Answers - Statistics and Probability Theory

- For (standard) quasi-universal spaces we at least can do the following:
  - Theorem: Disintegration of Markov kernels.
    - Remark: This allows for Bayes' Rule and thus Bayesian Statistics.
  - Theorem: Fubini Theorem.
  - Theorem: Conditional de Finetti Theorem.
  - Theorem: Kolmogorov Extension Theorem.
  - Theorem: Global Markov Property for graphical models like partially generic causal Bayesian networks.

# Recommendation

- For probabilistic programming, graphical models, causality, statistics, etc.
  - use for:
    - sample space  $\rightarrow$  the universal Hilbert cube
  - replace:
    - measurable spaces  $\rightarrow$  quasi-measurable spaces
    - measurable maps  $\rightarrow$  quasi-measurable maps
    - categorical construction in  $\mathbf{Meas}$   $\rightarrow$  categorical construction in  $\mathbf{QMS}$
- study more of the (classical) theory in this framework (e.g. martingales).

• Patrick Forré, *Quasi-Measurable Spaces*, 2021, <https://arxiv.org/abs/2109.11631>.

# More about Convenient Categories

- Probability Theory

- **Quasi-Borel Spaces** - by Chris Heunen, Ohad Kammar, Sam Staton, Hongseok Yang
- **Quasi-Measurable Spaces** - by Patrick Forré, <https://arxiv.org/abs/2109.11631>

- Topology

- **Compactly Generated Weakly Hausdorff Spaces (CGWH)** - by Witold Hurewicz, David Gale, Norman Steenrod, John C. Moore, Michael C. McCord, Neil Strickland, et al ([script](#))
- **Condensed Sets** - by Peter Scholz, Dustin Clausen ([script](#))

- Differential Geometry

- **Diffeological Spaces** - by Kuo Tsai Chen, Jean-Marie Souriau, Patrick Iglesias-Zemmour, John Baez, Alexander Hoffnung, Andrew Stacey, et al.

**Thank you for your attention!**