

# MARKOV CATEGORIES

## A TUTORIAL

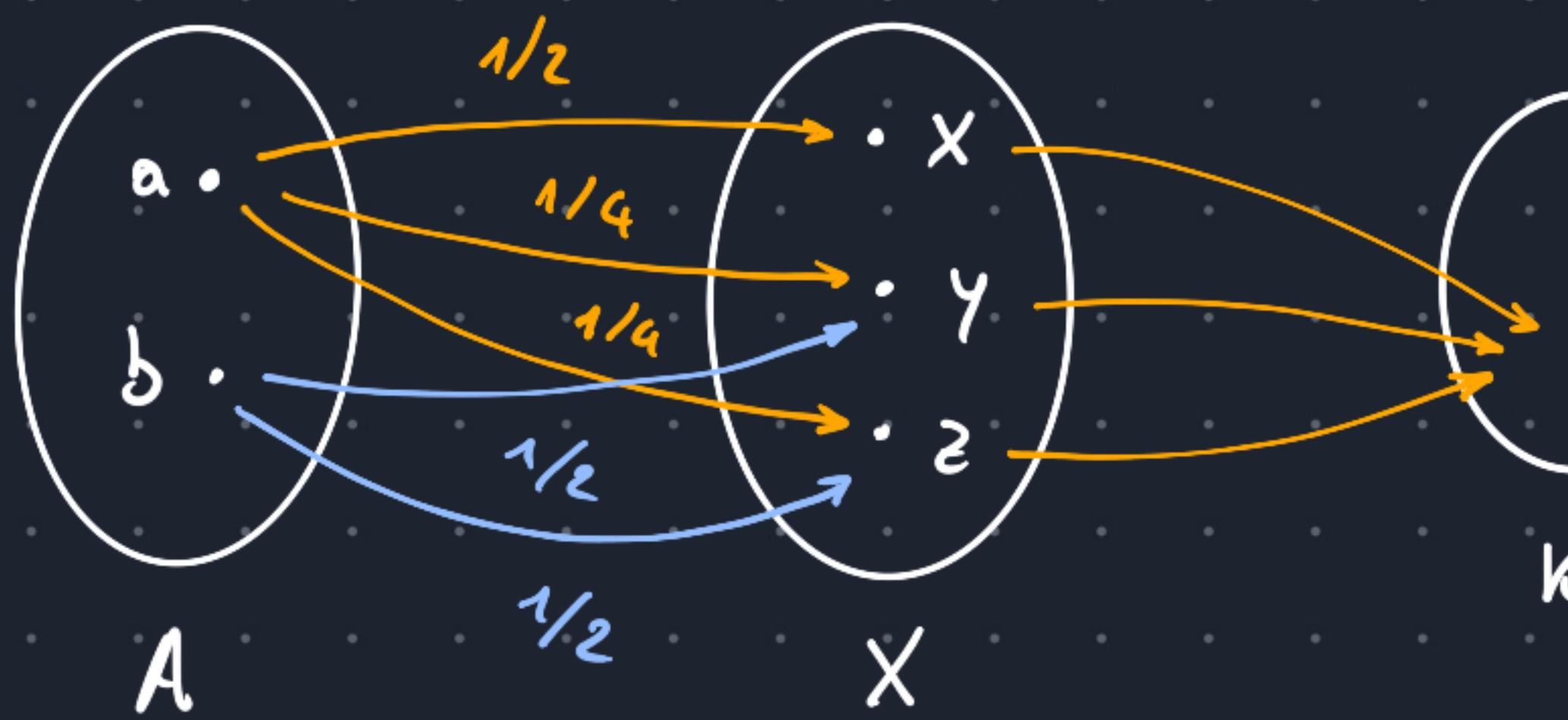
Applied Category Theory 2023

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## Basic idea

Morphisms with "randomness"!

Example. The category  $\text{Fin Stoch}$  whose morphisms are stochastic matrices.



	a	b
x	1/2	0
y	1/4	1/2
z	1/4	1/2

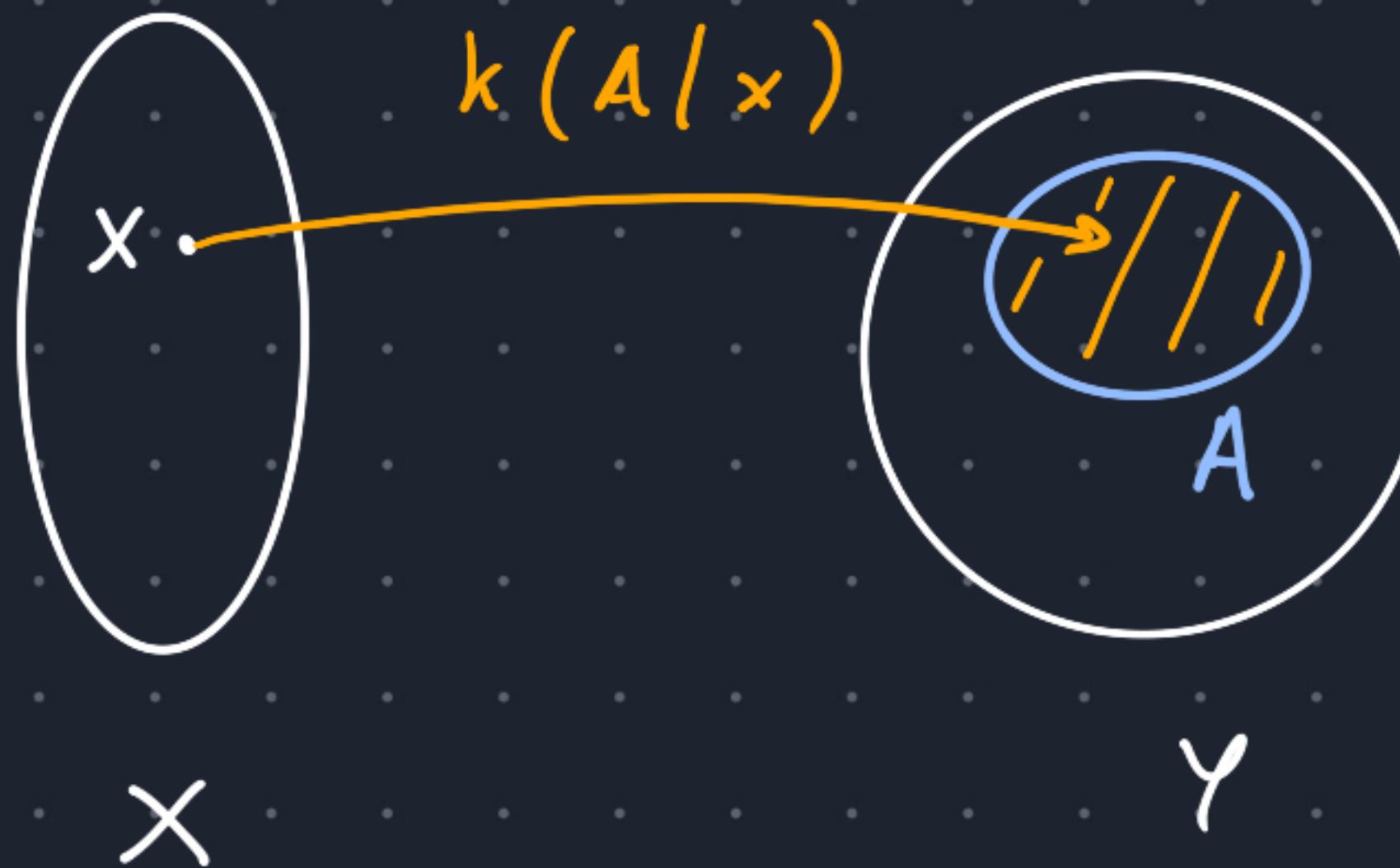
$f(z|b)$

$$g \cdot f(k|a) = \sum_{x \in X} g(k|x) f(x|a) \quad (\text{Chapman-Kolmogorov})$$

$$1 \xrightarrow{P} X$$

"states" = prob. measures (of finite support)

Example. The category  $\text{Stoch}$  whose morphisms are Markov kernels.



$$X \times \sum_Y \longrightarrow [0,1]$$

$$(x, A) \longmapsto k(A|x)$$

prob. measure  
measurable

$$h \circ k(B|x) = \int_Y h(B|y) k(dy|x)$$

$$X \xrightarrow{f} Y \quad K_f(A|x) := \begin{cases} 1 & f(x) \in A \\ 0 & f(x) \notin A \end{cases} \quad \text{Meas} \xrightarrow{K} \text{Stoch}$$

Main definition A Markov category is a symmetric monoidal category

$(\mathcal{C}, \otimes, I)$ , where each object  $X$  is equipped with maps

$$X \xrightarrow{\text{copy}} X \otimes X \quad X \xrightarrow{\text{del}} I$$

$$\begin{array}{c} X \quad X \\ \diagdown \quad \diagup \\ \text{---} \\ \text{---} \\ X \end{array}$$

such that

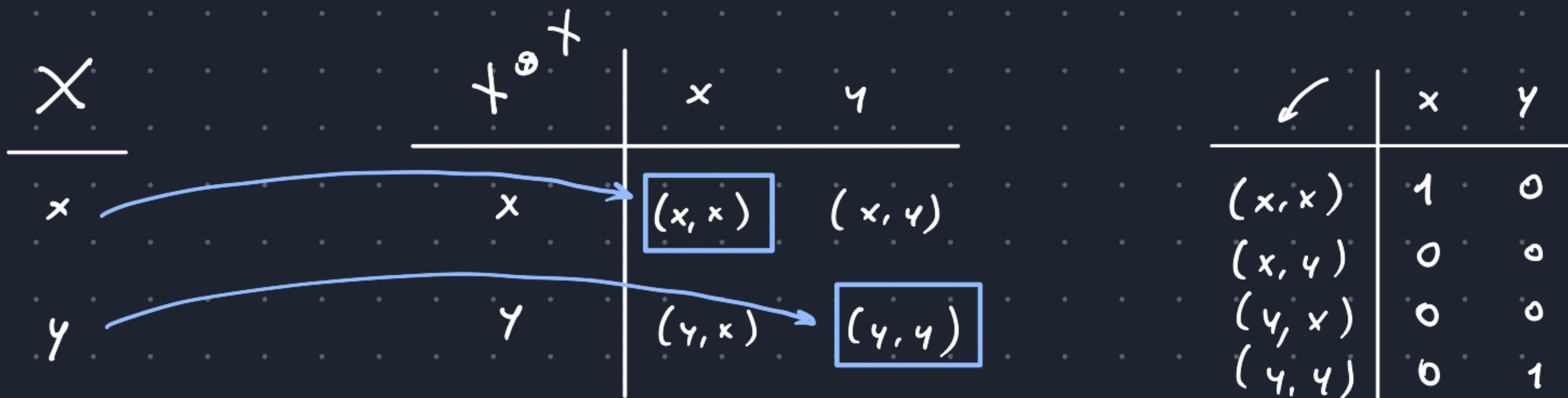
$$\begin{array}{c} X \quad X \quad X \\ \diagdown \quad \diagup \\ \text{---} \\ \text{---} \\ X \end{array} = \begin{array}{c} X \quad X \quad X \\ \diagup \quad \diagdown \\ \text{---} \\ \text{---} \\ X \end{array}$$

$$\begin{array}{c} X \otimes Y \quad X \otimes Y \\ \diagdown \quad \diagup \\ \text{---} \\ \text{---} \\ X \otimes Y \end{array} = \begin{array}{c} X \quad Y \quad X \quad Y \\ \diagup \quad \diagdown \quad \diagup \quad \diagdown \\ \text{---} \\ \text{---} \\ X \quad Y \end{array}$$

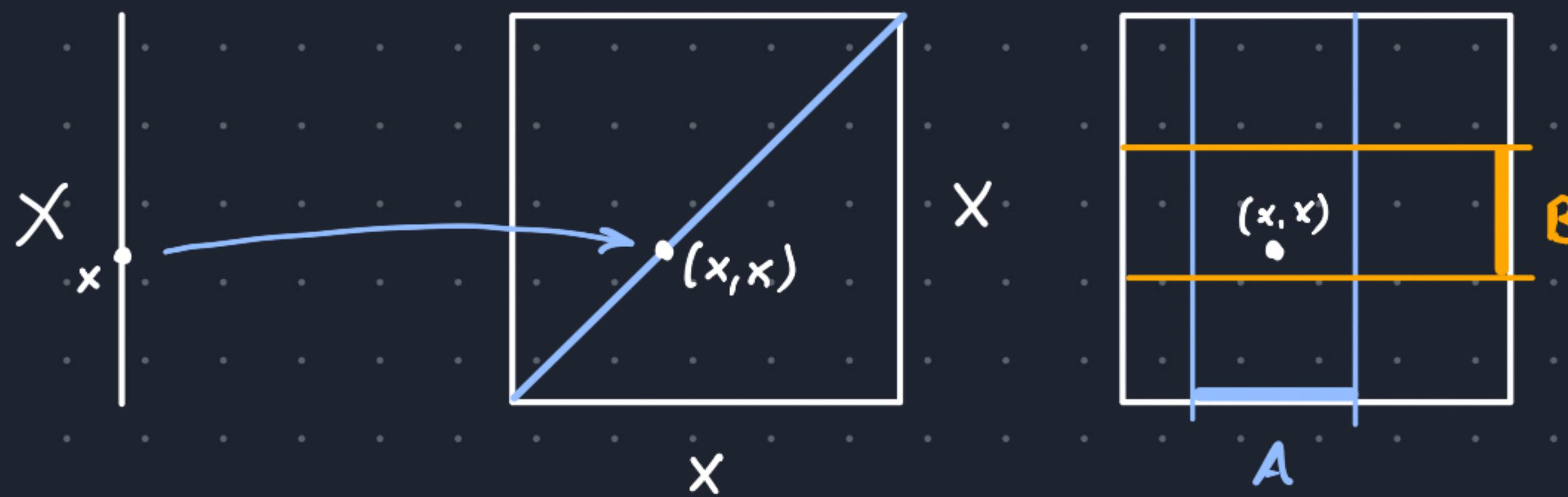
$$\begin{array}{c} X \\ \diagdown \quad \diagup \\ \text{---} \\ \text{---} \\ X \end{array} = \begin{array}{c} X \\ | \\ X \quad X \end{array} = \begin{array}{c} X \quad X \\ \diagup \quad \diagdown \\ \text{---} \\ \text{---} \\ X \end{array} = \begin{array}{c} X \quad X \\ \diagup \quad \diagdown \\ \text{---} \\ \text{---} \\ X \end{array}$$

$$\boxed{f} = \begin{array}{c} \text{---} \\ \text{---} \\ X \end{array} \quad \leftarrow \text{Without this: "GS" or "CD" category}$$

Example. In FinStock,  $X \xrightarrow{\text{copy}} X \otimes X$  for  $X = \{x, y\}$  is:



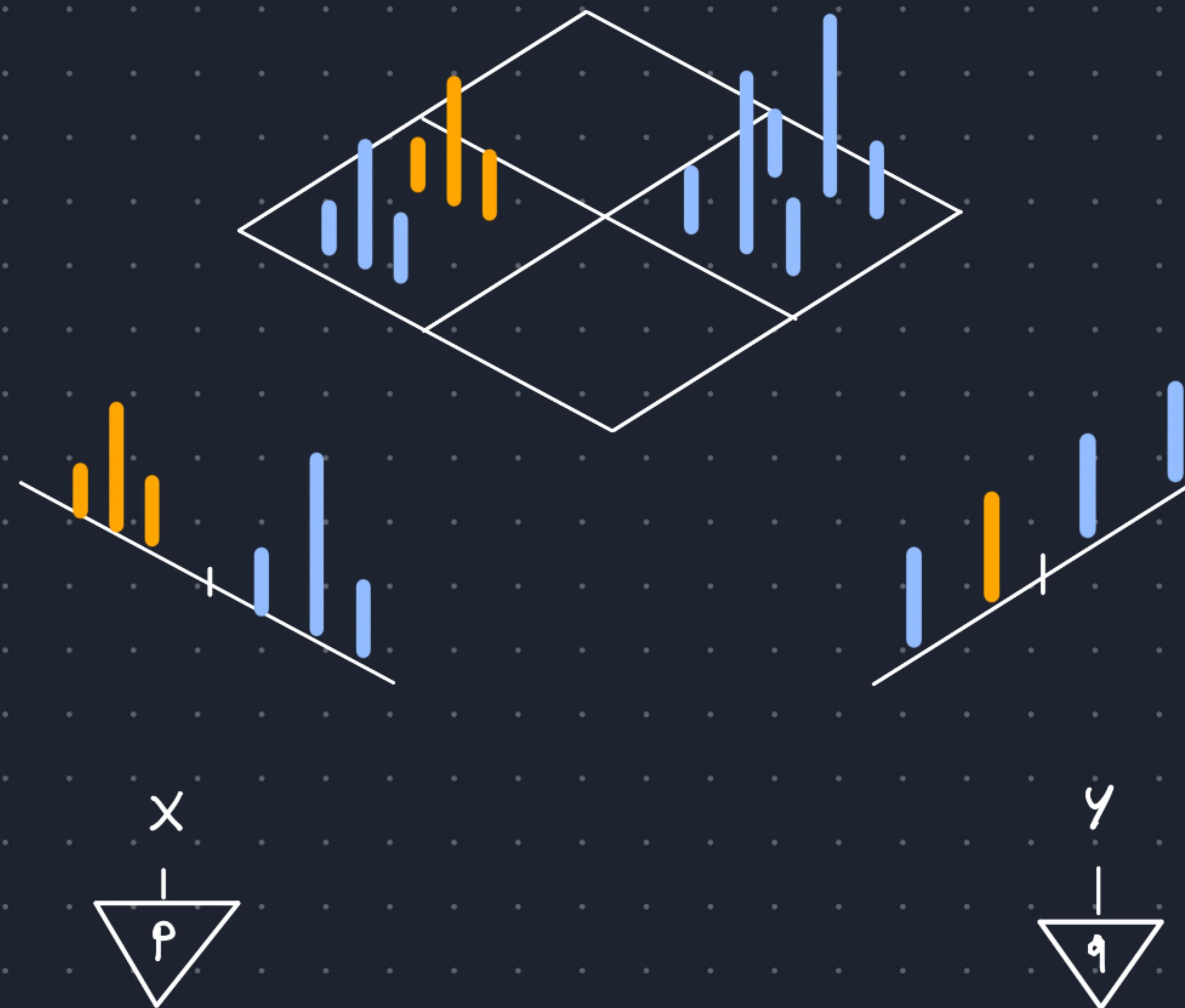
Example. In Stock, more generally,



$$(x, x) \in A \times B \Leftrightarrow x \in A \cap B$$

$$\text{copy}(A \times B | x) = \begin{cases} 1 & x \in A \cap B \\ 0 & x \notin A \cap B \end{cases}$$

## Joints & Marginals



$$\sum_y r(x, y) = p(x)$$

(Same for  $y$ )

## Stochastic independence



p exhibits independence of X, Y

$$p(x, y) = p(x)p(y)$$



h exhibits conditional independence  
of X, Y given A.

$$p(x, y | a) = p(x | a)p(y | a)$$

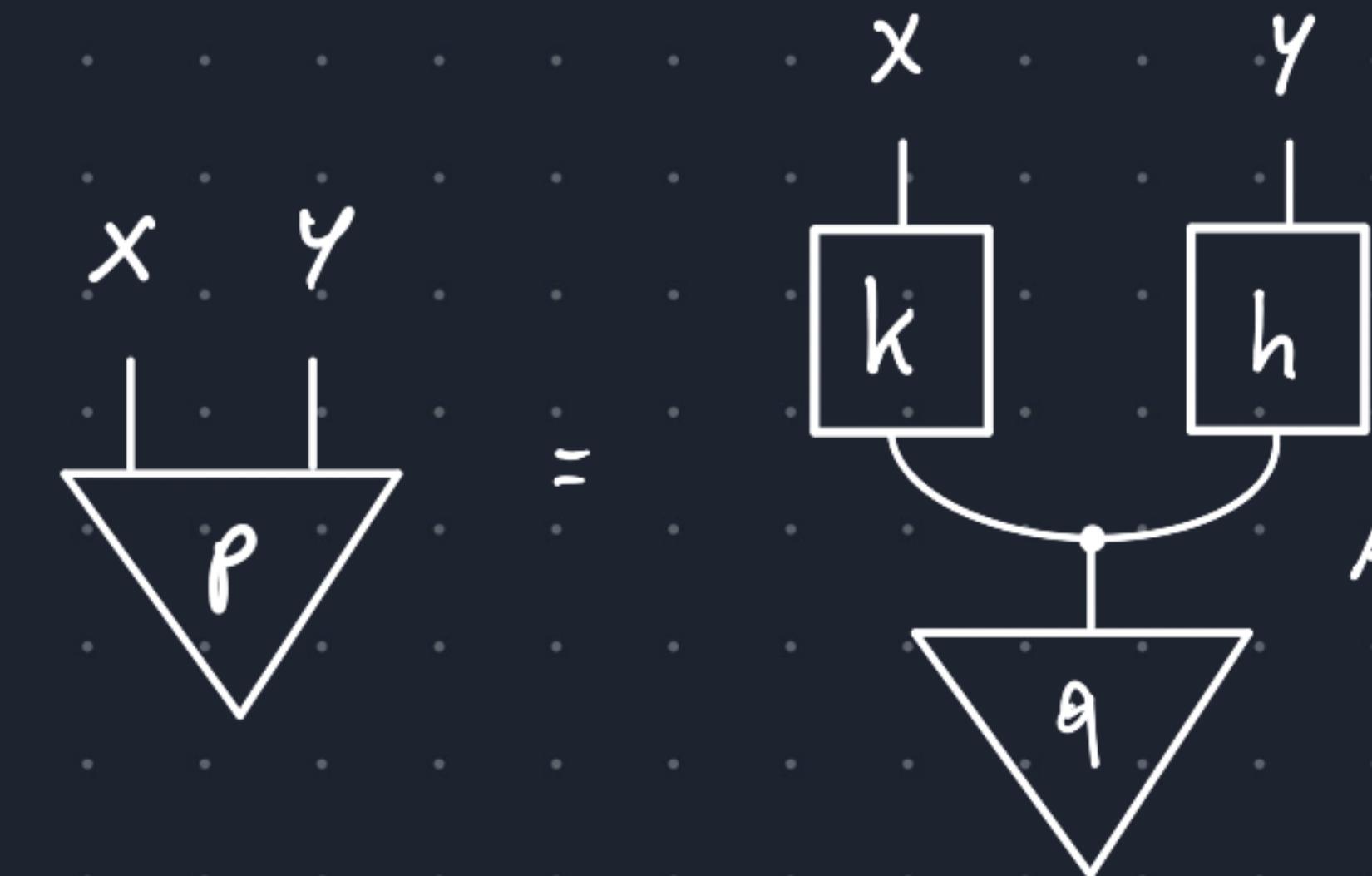
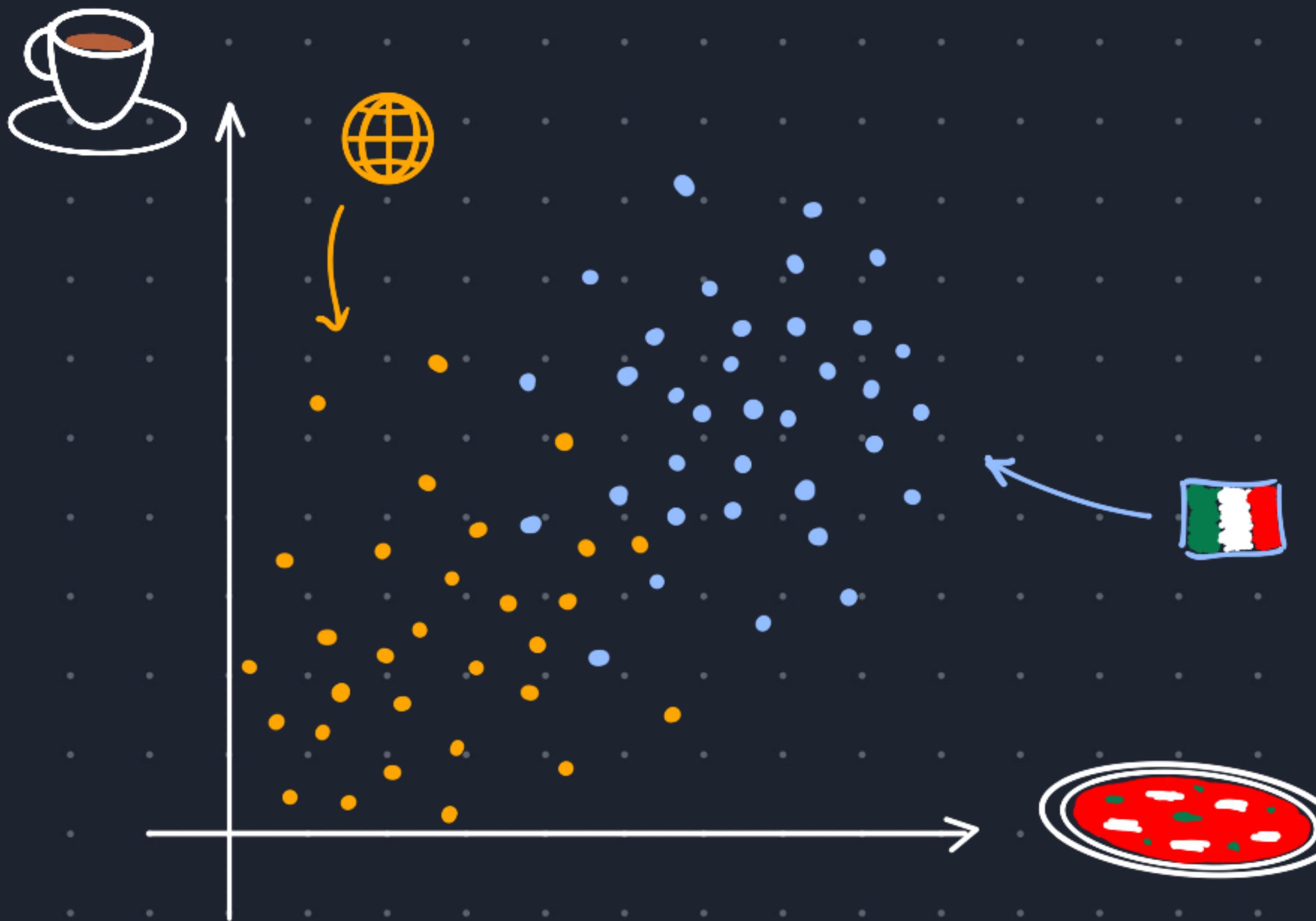
(See Exercise 1.1 later for more.)

## Stochastic independence



$\rho$  exhibits independence of  $X, Y$

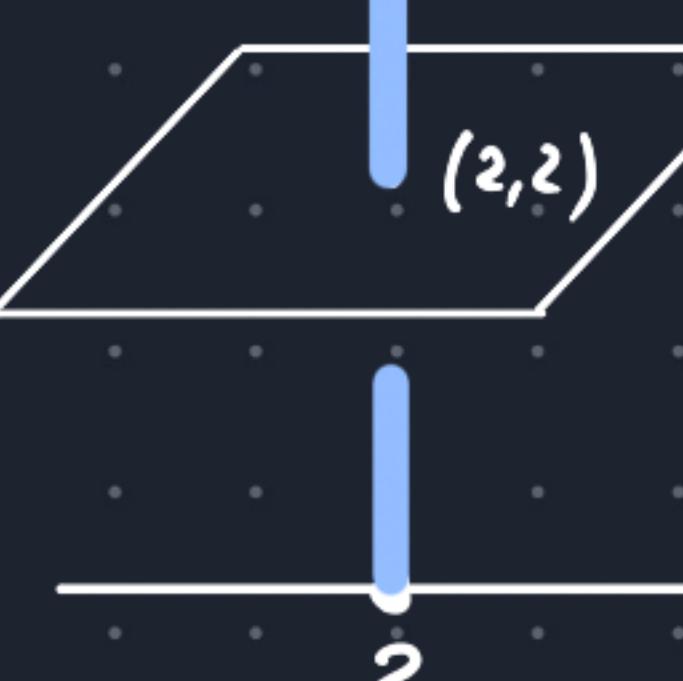
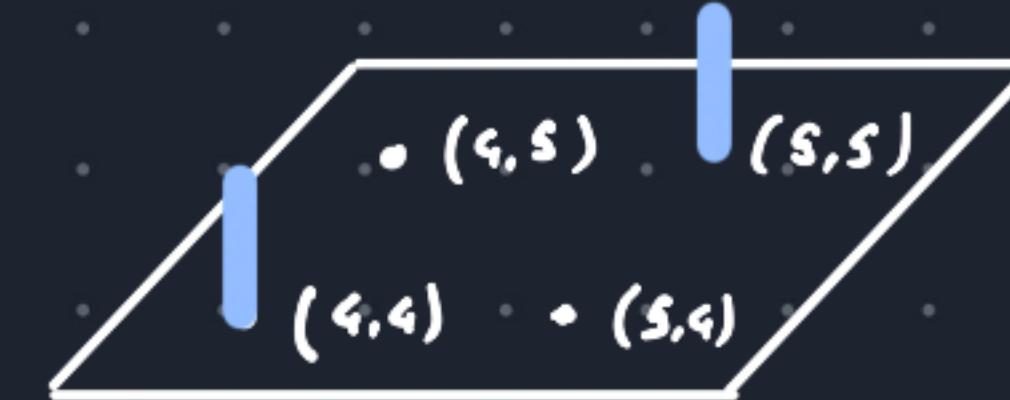
$$\rho(x, y) = \rho(x) \rho(y)$$



# Determinism (a.k.a. copyability)



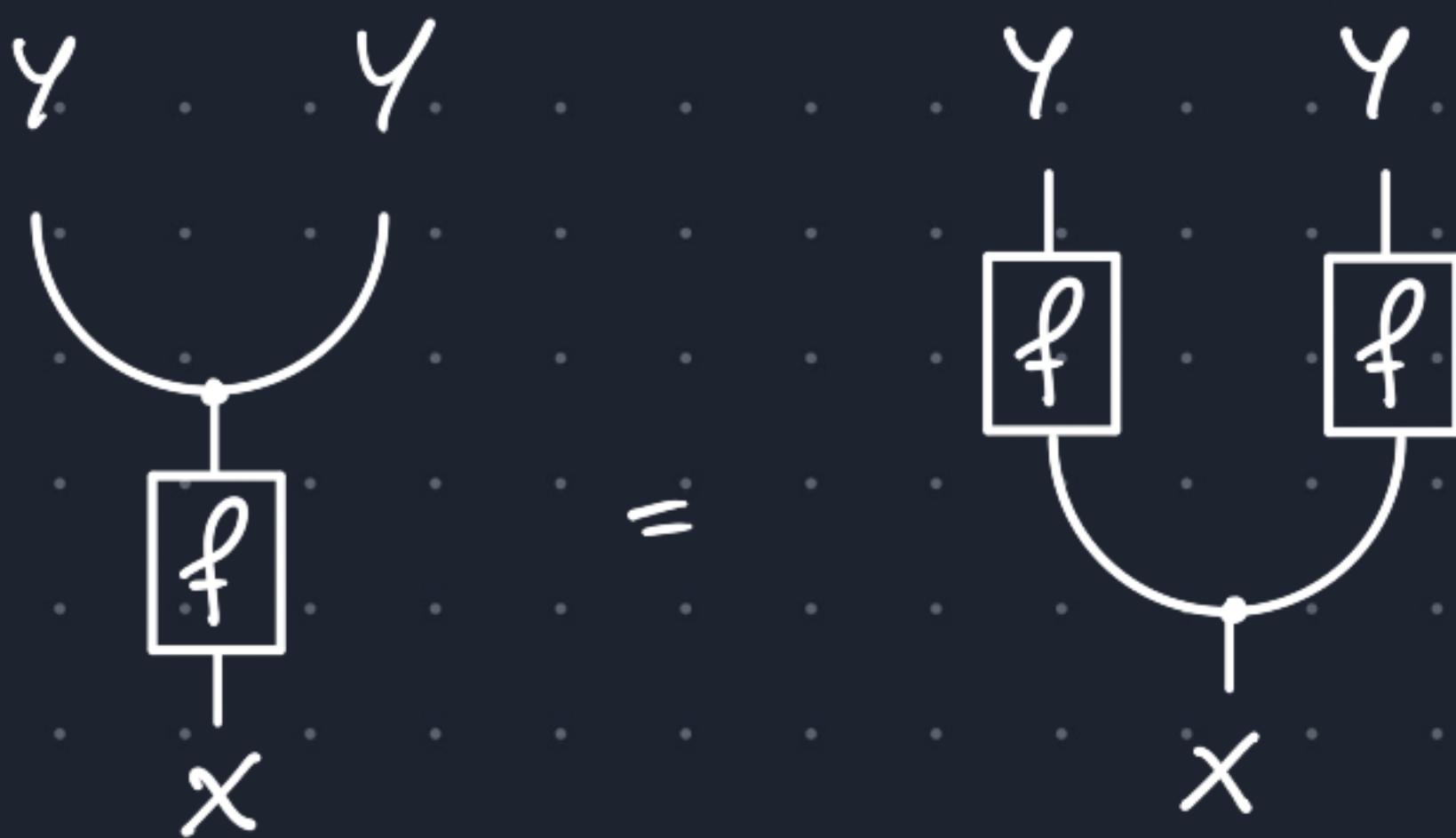
is called deterministic if



## Determinism (a.k.a. copyability)



is called deterministic if



Example.

In FinStock, a matrix is deterministic

iff all its entries are  $f(y|x) = 0$  or  $1$ .

In Stock, similarly,  $f(A|x) = 0$  or  $1$ .

(See Exercise 1.2 later.)



## Determinism (a.k.a. copyability)



is called deterministic if



- The category  $\text{Borel Stock}$  is the subcategory of standard Borel spaces.  
(e.g. finite & countable sets,  $\mathbb{R} \cong [0,1] \cong \mathbb{R}^n$ , etc.)

In this category, deterministic morphisms  
are just the measurable functions.

$$K_f(A|x) := \begin{cases} 1 & f(x) \in A \\ 0 & f(x) \notin A \end{cases}$$

## Determinism (a.k.a. copyability)

Proposition. For a Markov category  $\mathcal{C}$ , TFAE:

- 1) Every morphism is deterministic;
- 2) The copy maps are a natural transformation;
- 3)  $\mathcal{C}$  is cartesian monoidal ( $\otimes = \times$ )

Markov = cartesian + randomness!

cartesian = Markov + determinism



Stochastic interaction is  
a feature of randomness.

## Exercises :

1.1. Show that if a joint morphism decomposes

as a product, i.e.

$$\begin{array}{c} X \quad Y \\ | \quad | \\ \boxed{h} \\ A \end{array} = \begin{array}{c} X \quad Y \\ | \quad | \\ \boxed{f} \quad \boxed{g} \\ A \end{array}$$

then it is the product of its marginals, i.e.

$$\begin{array}{c} X \quad Y \\ | \quad | \\ \boxed{h} \\ A \end{array} = \begin{array}{c} X \quad Y \\ | \quad | \\ \boxed{h} \quad \boxed{h} \\ A \end{array}$$

1.2. Show that the deterministic morphisms of

FiniStoch are exactly the matrices of entries  $\{0, 1\}$ .

What's the analogous statement in Stock?

1.3. Prove

Proposition. For a Markov category  $\mathcal{C}$ , TFAE:

- 1) Every morphism is deterministic;
- 2) The copy maps are a natural transformation;
- 3)  $\mathcal{C}$  is cartesian monoidal ( $\otimes = \times$ )

Hint: show that if a morphism

$$\begin{array}{c} X \quad Y \\ | \quad | \\ \boxed{h} \\ A \end{array}$$

is deterministic, then it is always

making  $X$  and  $Y$  conditionally independent

given  $A$ .

## Almost-sure equality

Given

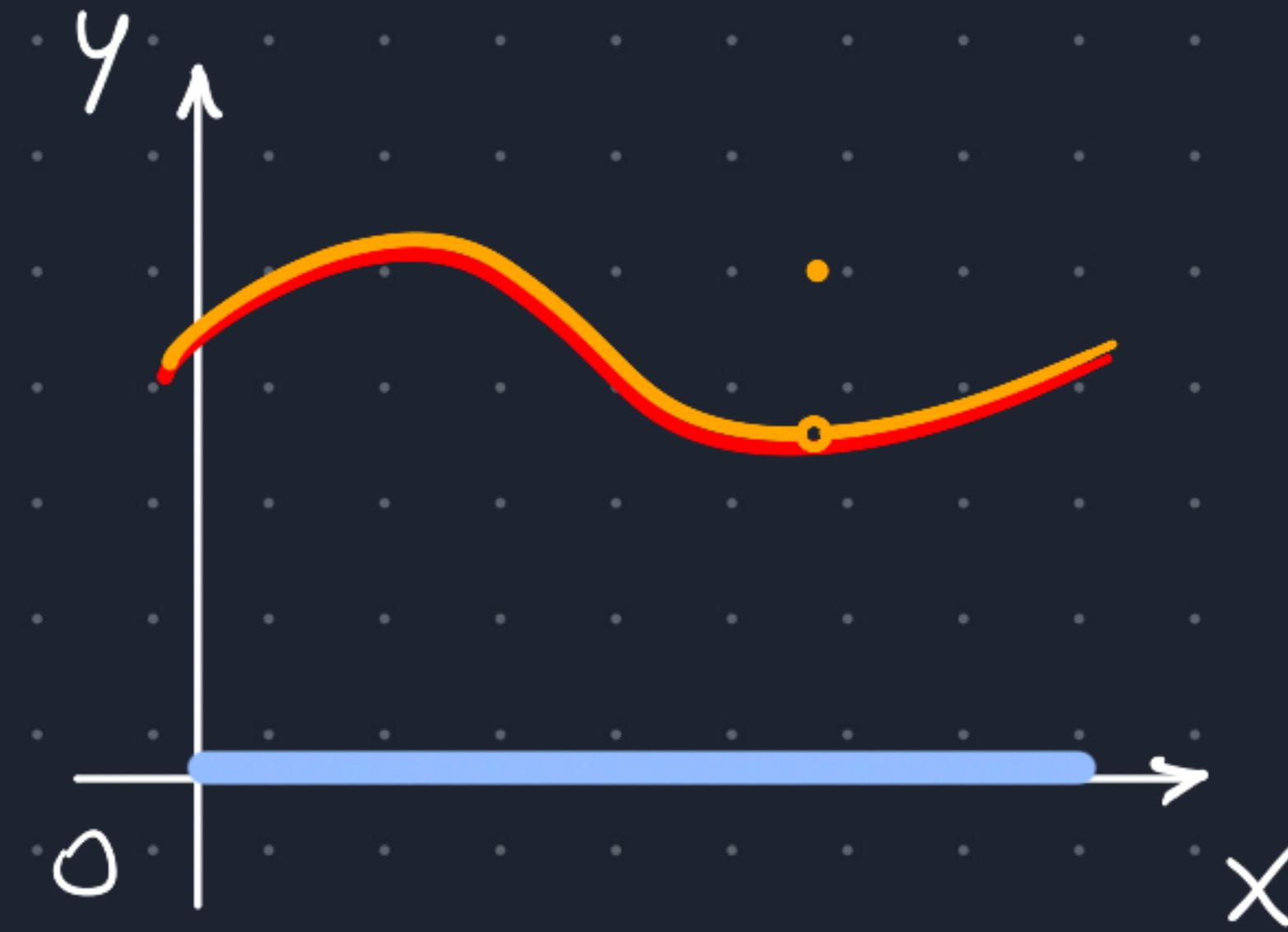


and



, we say that  $f = g$   $p$ -almost surely

if



Example. In FinStock,  $f(x) = g(x)$  at each  $x$  s.t.  $\rho(x) \neq 0$ .

In Borel Stock, the set  $\{x \in X; f(x) \neq g(x)\}$  has  $p$ -measure zero.

(See Exercise 2.1 later.)

## Conditioning & Bayesian inverses

Given



, a conditional distribution of  $p$  given  $X$

is a morphism \*



such that

$$\begin{array}{ccc} \begin{array}{c} X \\ \downarrow \\ Y \\ \downarrow \\ p \end{array} & = & \begin{array}{c} X \\ \downarrow \\ Y \\ \downarrow \\ p \\ \downarrow \\ p|_x \\ \downarrow \\ p \end{array} \end{array}$$

(\* see Exercise 2.2 later)

$$p(x, y) = p(x) p(y|x)$$

Theorem. FinStock has all conditional distributions.

Borel Stock too.



Traditionally the chosen category  
for "classical" prob. theory -

Stock, in general, does not.

## Conditioning & Bayesian inverses

Given



, a conditional distribution of  $p$  given  $X$

is a morphism



such that

$$\begin{array}{ccc} \begin{array}{c} X \\ \downarrow \\ Y \end{array} & \xrightarrow{\quad p \quad} & \begin{array}{c} X \\ \downarrow \\ Y \end{array} \\ \begin{array}{c} X \\ \downarrow \\ Y \end{array} & = & \begin{array}{c} X \\ \downarrow \\ Y \end{array} \end{array}$$

Given



and



, a Bayesian inverse of  $f$  relative to  $q$ , is a conditional dist.

for the joint



, ie. a morphism



such that

$$\begin{array}{ccc} \begin{array}{c} X \\ \downarrow \\ Y \end{array} & \xrightarrow{\quad f \quad} & \begin{array}{c} X \\ \downarrow \\ Y \end{array} \\ \begin{array}{c} X \\ \downarrow \\ Y \end{array} & = & \begin{array}{c} X \\ \downarrow \\ Y \end{array} \end{array}$$

$$p(x) p(y|x) = p(y) p(x|y)$$

## The ProbStoch construction

"Cat. of probability spaces & transport plans"

Definition. Let  $\mathcal{C}$  be a Markov category with all conditional distributions.

The category  $\text{ProbStoch}(\mathcal{C})$  has:

- As objects, pairs  $(X, \begin{smallmatrix} X \\ \downarrow p \end{smallmatrix})$  where  $X \in \mathcal{C}$ ,  $p: I \rightarrow X$   
(e.g. prob. spaces)

- As morphisms  $(X, \begin{smallmatrix} X \\ \downarrow p \end{smallmatrix}) \rightarrow (Y, \begin{smallmatrix} Y \\ \downarrow q \end{smallmatrix})$ , equivalence classes

under  $p$ -a.s. equality of morphisms  $\begin{smallmatrix} f \\ \downarrow \end{smallmatrix}$  such that  $\begin{smallmatrix} Y \\ \downarrow f \\ X \end{smallmatrix} = \begin{smallmatrix} Y \\ \downarrow q \end{smallmatrix}$ .

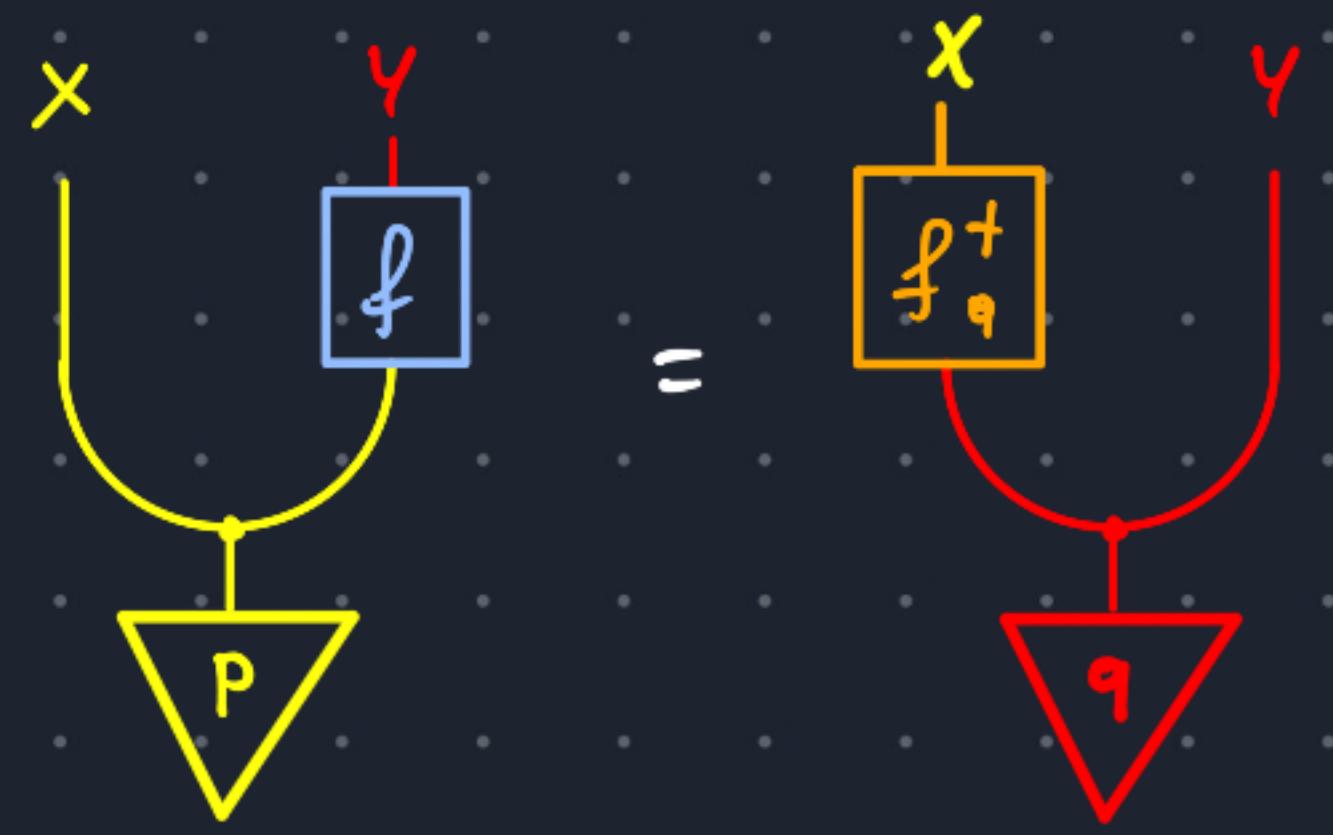
(See Exercise 2.4 later.)

(measure-preserving)

## The Prob Stock construction

"Cat. of probability spaces & transport plans"

Theorem.  $\text{ProbStock}(\mathcal{C})$  is a dagger category, where  $\dagger = \text{Bayesian inversion}$ .



$$(X, p) \xrightarrow{f} (Y, q)$$

Definition. A dagger structure on a category  $\mathcal{C}$  is a "self-duality" functor  $\mathcal{C} \xrightarrow{\cong} \mathcal{C}^{\text{op}}$  which is

- Identity on objects:  $X^\dagger = X$
- Involutive:  $f^{\dagger\dagger} = f$ .

Equivalently, morphisms of  $\text{ProbStock}(\mathcal{C})$  are couplings: joint distributions

with

$$\begin{array}{ccc} X & & Y \\ \downarrow & = & \downarrow \\ \text{---} & & \text{---} \\ & p & \end{array}, \quad \begin{array}{ccc} & Y & \\ \downarrow & & \downarrow \\ \text{---} & = & \text{---} \\ & q & \end{array}.$$



## Exercises:

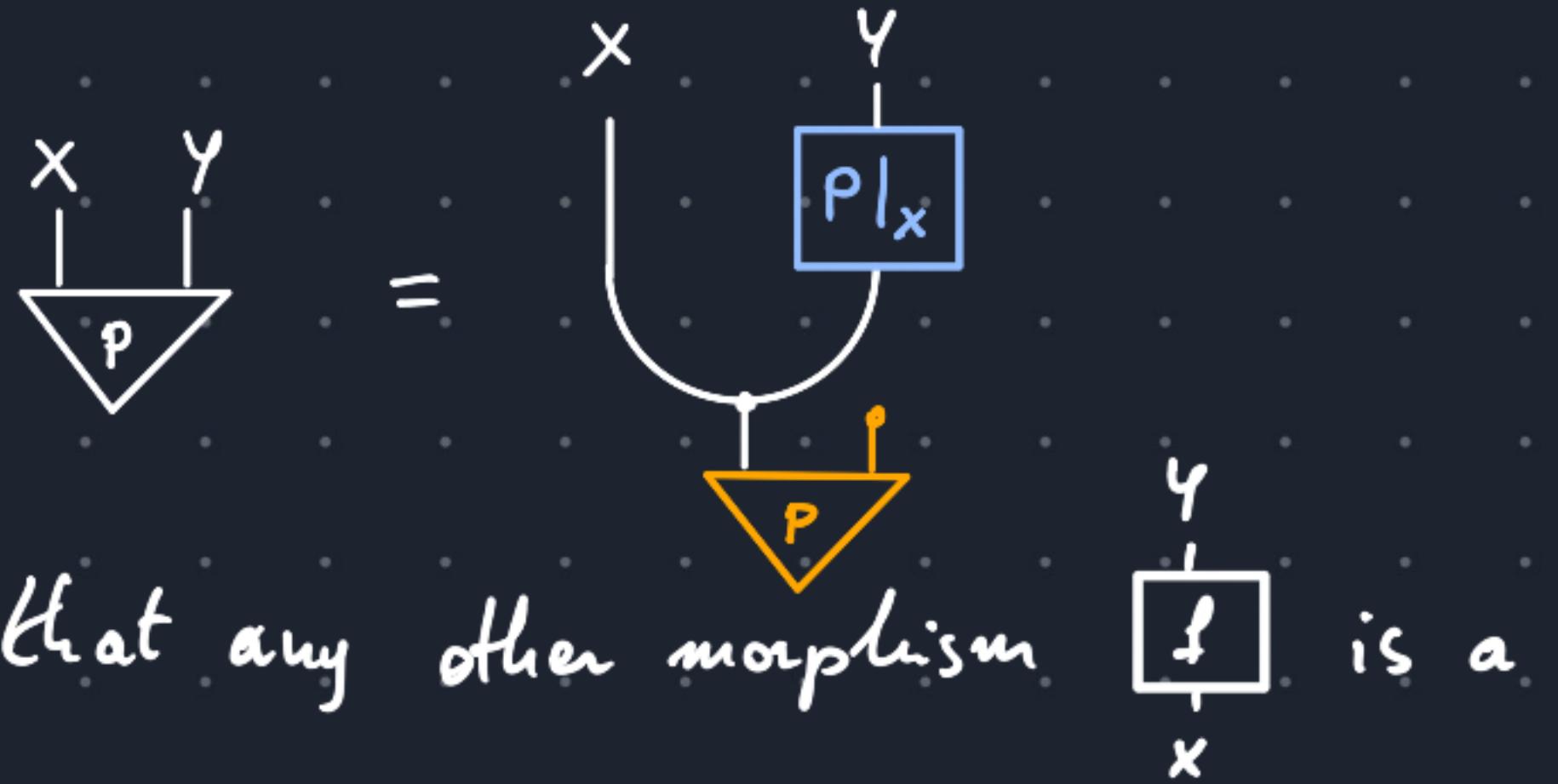
2.1. Show that, in FinStock, BorelStock,

given  $p : I \rightarrow X$  and  $f, g : X \rightarrow Y$ ,

we have that  $f = g$   $p$ -almost surely

iff  $p(\{x \in X ; f(x) \neq g(x)\}) = 0$ .

2.2. Suppose the following cond. dist. exists:



Show that any other morphism  $\boxed{f}$  is a conditional iff it is  $p$ -a.s. equal to  $\boxed{P|_X}$ .

2.3. Suppose  $\mathcal{C}$  has conditional distributions.

Prove the equality strengthening property:

$$\text{If } \begin{array}{c} X \\ \downarrow \\ \boxed{f} \\ \downarrow \\ P \end{array} = \begin{array}{c} X \\ \downarrow \\ \boxed{g} \\ \downarrow \\ P \end{array}$$

then also

$$\begin{array}{c} X \\ \downarrow \\ \boxed{f} \\ \downarrow \\ P \end{array} = \begin{array}{c} X \\ \downarrow \\ \boxed{g} \\ \downarrow \\ P \end{array}$$

2.4. Use Ex. 2.3 to show that composition in Prob Stock( $\mathcal{C}$ ) is well defined.

## Markov categories and monads

Proposition. Let  $\mathcal{D}$  be cartesian monoidal.

Let  $(P, \mu, \eta)$  be a monad on  $\mathcal{D}$  which is

- Affine :  $P1 \cong 1$
- Monoidal (= commutative) :  $PA \times PB \xrightarrow{\nabla} P(A \times B)$

Then Kleisli( $P$ ) is a Markov category.

Example. Stock is the Kleisli category of the Giry monad on Meas. (Exercise 3.2)

FinStock is almost the Kleisli cat. of the distribution monad on Set.

## Markov categories and monads

$$\mathcal{D}(A, PB) \cong \mathcal{D}_p(A, B)$$

$$\mathcal{D}(PB, PB) \cong \mathcal{D}_p(PB, B)$$

$\text{id} \xrightarrow{\quad} \text{Samp}$



In basic probability theory:

$$\text{Bernoulli}(p) = \begin{cases} 1 & \text{with prob. } p \\ 0 & \text{with prob. } 1-p \end{cases}$$

$$\begin{array}{ccc} [0,1] & \xrightarrow{\text{Bernoulli}} & \{0,1\} \\ \pi_2 & & \\ P(\{0,1\}) & & \end{array}$$

The unit of the adjunction is

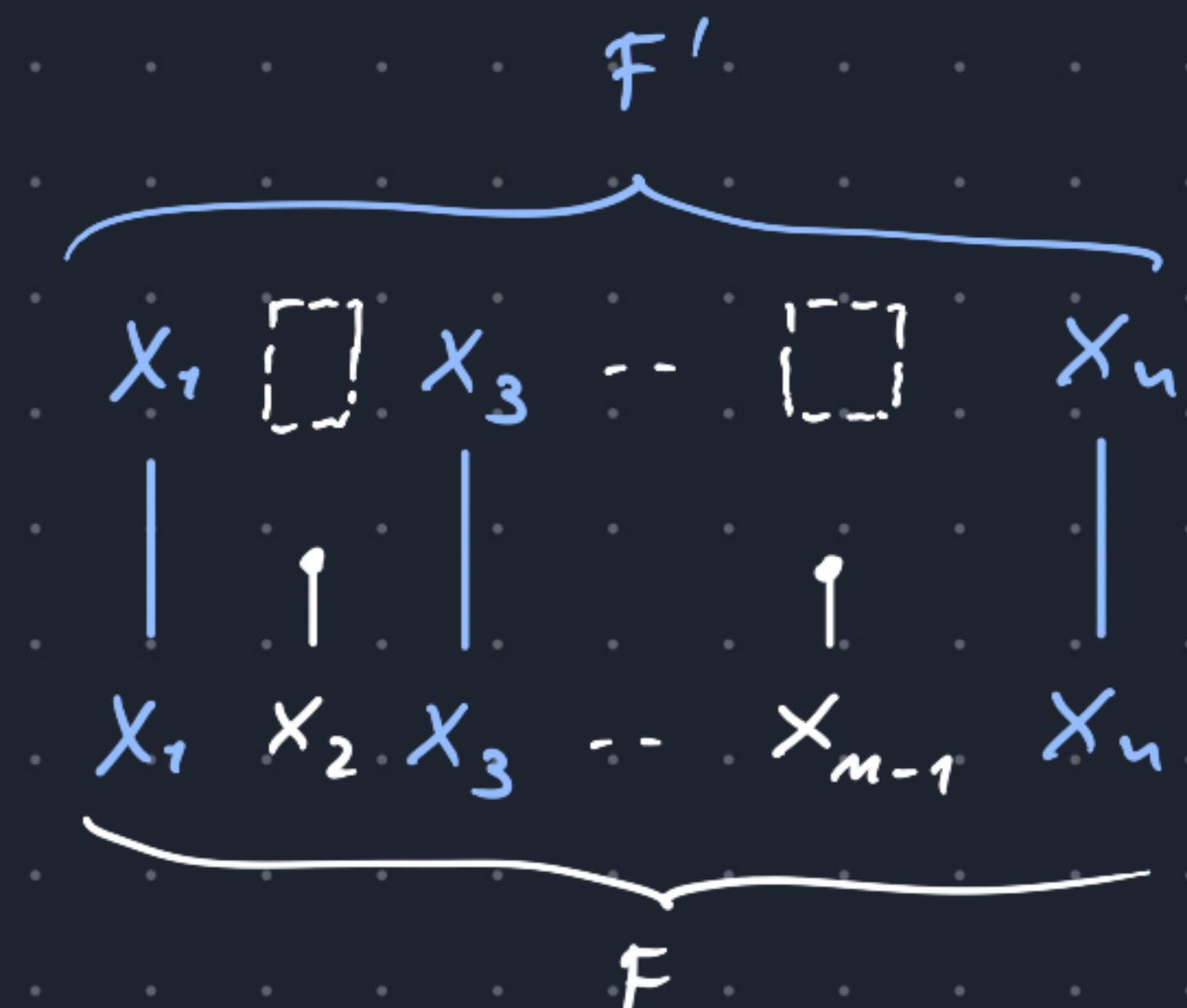
$$\mathcal{D}(A, PA) \cong \mathcal{D}_p(A, A)$$

$\delta \xleftarrow{\quad} \text{id}$

$$X \xrightarrow{\delta} PX$$

## Kolmogorov products

- Probability theory is all about stochastic processes in infinite time, which need objects in the form  $X^N$  (at least!)
- While cartesian products can be infinite, we need infinite monoidal products.
- For finite sets  $F$ , we have  $\bigotimes_{i \in F} X_i$ .
- Given subsets  $F' \subseteq F$ , we can marginalize  $\bigotimes_{i \in F} X_i \rightarrow \bigotimes_{i \in F'} X_i$  by discarding:



## Kolmogorov products

Definition. Let  $\mathcal{C}$  be a Markov category. Let  $I$  be an infinite set,  $\{X_i\}_{i \in I}$ :

A Kolmogorov product is a cofiltered limit

$$X^I := \lim_{F \subseteq I} \left( \bigotimes_{i \in F} X_i \right) \rightarrow \dots$$

```
graph TD; F1["F ⊆ I"] --> S1["..."]; S1 --> X1["X_i"]; S1 --> X2["X_j"]; S1 --> X3["X_k"]; F2["F ⊆ I"] --> X1; F2 --> X2; F2 --> X3; F3["F ⊆ I"] --> X1; F3 --> X2; F3 --> X3;
```

- such that
- It is preserved by  $Y \otimes -$
  - The arrows  $X^I \longrightarrow X^F$  are deterministic.

Theorem (Kolmogorov extension). Borel Stock has countable Kolmogorov products.

## Kolmogorov products

When  $\mathcal{C}$  is the Kleisli category of a probability monad,

a Kolmogorov product encodes the absence of infinitary stochastic interactions:

"No products":  $P$  does not preserve finite products

$$P(X \times Y) \xrightarrow{\text{not }} P X \times P Y$$



Kolmogorov ext. thm:

$$P(X^N) = P\left(\lim_{F \subseteq N} X^F\right) \xrightarrow{\cong} \lim_{F \subseteq N} P(X^F) \xrightarrow{\text{not }} \lim_{F \subseteq N} (P X)^F = (P X)^N$$

## Exercises

3.1. Prove

**Proposition.** Let  $\mathcal{D}$  be cartesian monoidal.

Let  $(P, \mu, \eta)$  be a monad on  $\mathcal{D}$  which is

- Affine :  $P1 \cong 1$
- Monoidal :  $PA \times PB \xrightarrow{\nabla} P(A \times B)$

Then Kleisli ( $P$ ) is a Markov category.

3.2. (For people who know some measure theory.)

Prove that Stock  $\simeq$  Kleisli (Giry monad)

Hint: why is a kernel a Kleisli morphism?

3.3. Prove that sampling from a product distribution is the same as sampling the factors independently :

$$\begin{array}{ccc} P(X \otimes Y) & \xrightarrow{\nabla} & P(X \otimes Y) \\ & \searrow \text{samp} \otimes \text{samp} & \downarrow \text{samp} \\ & & X \otimes Y \end{array}$$

3.4. Prove that the Kolmogorov product

$$\bigotimes_{i \in I} X_i$$

is the cartesian product  $\prod_{i \in I} X_i$  in the subcategory  $\mathcal{C}_{\text{det}}$ .

## The de Finetti theorem

A morphism  $\boxed{P}$  in  $A$  is called exchangeable if it commutes with finite permutations (in the result).

$$\begin{array}{c} X^N \\ \boxed{P} \\ A \end{array} = \begin{array}{c} X \dots X \\ \boxed{P} \\ A \end{array}$$

$$\begin{array}{ccc} & X^N & \\ P & \nearrow & \downarrow \sigma \\ A & & X^N \\ & P & \searrow \end{array}$$

**Theorem.** In Borel Stock, for every  $A$  and  $X$ , there is a natural bijection

$$\begin{array}{ccc} & X^N & \\ P & \nearrow & \downarrow \sigma \\ A & \dashrightarrow & PX \\ & P & \searrow \end{array}$$



taking i.i.d. samples!  
(limiting cone)

## The de Finetti theorem



The  $X$  are conditionally independent given  $\mu$  (the distribution from which they are sampled - independently).

Example. Let  $X = \{\text{Heads, Tails}\}$ . Flip a coin repeatedly (exchangeable).

Suppose you see Heads, Heads, Heads, Heads.

What do you expect to see next?

What if you know that the coin is fair?

"Some coin!"

## Results so far

Classical probability :

- De Finetti theorem (Fritz-Gonda-Penone '21)
- d-separation criterion (Fritz-Klingler '22)
- Kolmogorov extension theorem (Fritz-Rischel '19)
- Kolmogorov, H-S 0-1 laws (Fritz-Rischel '19)
- Multinomial, hypergeometric distributions (Jacobs '21)

Statistics :

- Theorems on sufficient statistics (Fritz '19)
- Comparison of experiments (Fritz-Gonda-Penone-Rischel '20)

Ergodic theory, information theory:

- Ergodic decomposition theorem (Moss-Penone '22)
- Entropy, data processing inequalities (Penone '22)

Theoretical computer science :

- Privacy eqn (Sabok et.al '20, Fritz et.al. '22)
- Observational monads (Moss-Penone '22)

Quantum probability :

- Quantum Markov categories (Pawlynuk '20, '21)
- + more in progress!

## Some references:

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  - T. Fritz, T. Gonda, P. Perone, E.F. Rischel, Representable Markov categories and comparison of statistical experiments in categorical probability. arXiv: 2010.07416
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  - T. Fritz, T. Gonda, N. Gauguin Houghton-Larsen, P. Perone, D. Stein, Dilations and information flow axioms in categorical probability. arXiv: 2211.02507
  - P. Perone, Markov Categories and Entropy. arXiv: 2212.11719
- ... & more