

# Foundations for type-driven probabilistic modelling

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TutorialFest  
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## Partiality cf. [Vàkàr et al. '19]

A Borel embedding  $e: X \hookrightarrow Y$

- injective function  $e: [X] \rightarrow [Y]$
- its image is Borel:  $e[X] \in \mathcal{B}_Y$
- $e$  is **Strong**:  $\alpha \in R_X \iff e \circ \alpha \in R_Y$

## Examples

- $\mathbb{1} \hookrightarrow \mathbb{2}$
- $S$  is sbs  $\iff \exists S \hookrightarrow \mathbb{R}$

Def: A Partial map  $f: X \rightarrow Y$  is a morphism

$$f: X \rightarrow Y \sqcup \{\perp\}$$

Its domain of definition

$$f: (Y \sqcup \{\perp\})^X \vdash \text{Dom } f := \{x \in X \mid f x \neq \perp\} : \text{Type}$$

Depend-type  
interpretation

$$\begin{array}{ccc} \llbracket \text{Dom } f \rrbracket & \xrightarrow{\quad} & \{y \in Y \mid y \in E\} \\ \downarrow \text{dep} \quad \lceil & & \downarrow \text{dep} \\ \llbracket f : (Y \sqcup \{\perp\})^X \rrbracket & \xrightarrow{[E \mapsto \lambda x. f x \neq \perp]} & \llbracket E : \mathcal{B}_Y \rrbracket \end{array}$$

## Plan:

- 1) Type-driven probability: discrete case ✓
  - 2) Borel sets & measurable spaces ✓
  - 3) Quasi Borel spaces ✓
  - 4) Type structure & standard Borel spaces ✓
  - 5) Integration & random variables
- Lecture 1
- Lecture 2

please ask questions!

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## Full model

type : Qbs     $w := [0, \infty]$      $\mathcal{B}X := \mathbb{B}^X$

$\mathcal{D}X := \square$

$\mathcal{P}X := \{ \mu \in \mathcal{D}X \mid c_{\mu}[X] = 1 \}$

$c_{\mu}[E] := \square$

$\delta_n := \square$

$\phi_{\mu k} := \square$

Def: A **measure**  $\mu$  over  $R$  is a function

$$\mu : \mathcal{B}_R \rightarrow W := [0, \infty]$$

Satisfying the measure axioms:

$$E : \mathcal{B}^W \vdash$$

$$\mu \emptyset = 0, \quad \mu E = \mu(E \cap F) + \mu(E \cap F^c), \quad \mu(\bigcup_n E_n) = \sup_n \mu E_n$$

For **measurable spaces**, replace  $R$  with  $V$

We write  $\mathcal{G}V$  for the set of measures on  $V$

For qbs  $X$ , take  $\mathcal{G}^{\text{meas}} X$

Thm (Lebesgue measure):

There is a unique measure  $\lambda \in \text{GR}$ , s.t.:

$$\lambda(a, b) = b - a$$

# The unrestricted Giny spaces

Equip  $\mathcal{GV}$  with two qbs structures:

$$X \quad \mathcal{R}_{G'V} := \left\{ \alpha: \mathbb{R} \rightarrow \mathcal{GV} \mid \forall A \in \mathcal{B}_V, \lambda r. \alpha(r, A): \mathbb{R} \rightarrow \mathcal{W} \right\}$$

$$\checkmark \quad \mathcal{GV} \longleftrightarrow \mathcal{W}^{\mathcal{B}_X}$$

$\hookrightarrow \alpha$  is a kernel.

- Fewer random elements

$$\mathcal{R}_{GV} \subseteq \mathcal{R}_{G'V}$$

- Lebesgue integral

measurable in  
both arguments.

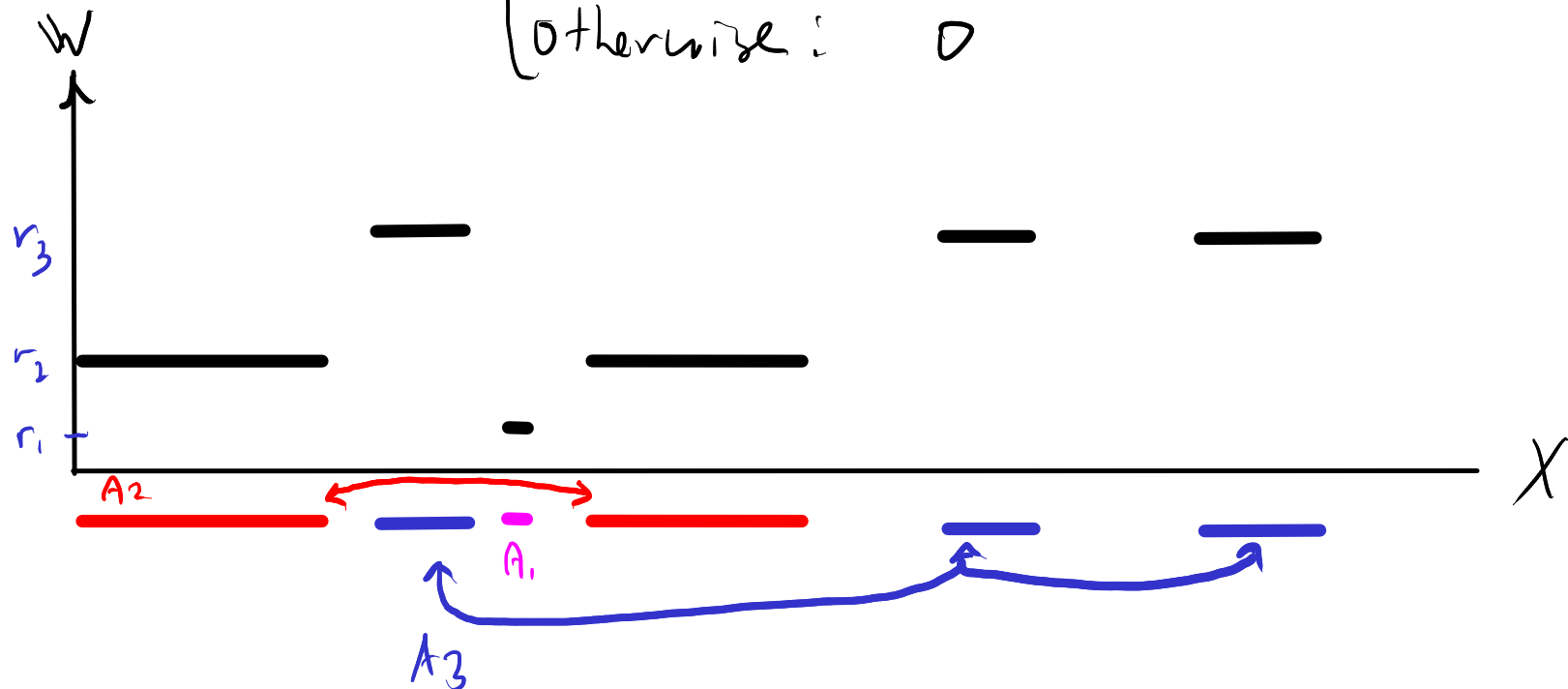
(upcoming)



Def: Simple function  $\varphi: X \rightarrow W$  when

$\exists n \in \mathbb{N}, \vec{A} \in \mathcal{B}_X^n, A_i \cap A_j = \emptyset, \vec{r} \in W$  s.t.  
 $(i \neq j)$

$$\varphi x = \begin{cases} r_i & x \in A_i \\ 0 & \text{otherwise} \end{cases}$$



Encode into a space:

$$\text{Simple Code} := \prod_{n \in \mathbb{N}} B_X^n \times W^n$$

$$\text{Simple} := \{ f \in W^X \mid f \text{ simple} \} \hookrightarrow W^X$$

and define an interpretation:

$$\llbracket - \rrbracket : \text{Simple Code} \longrightarrow \text{Simple}$$

$$\llbracket (n, \vec{A}, \vec{r}) \rrbracket := \sum_{i=1}^n r_i \cdot [- \in A_i]$$

↳ characteristic function  
for  $A_i$

Lemma:  $f: X \rightarrow W$  is measurable → remember!  
965  
morphisms!

iff  $f = \lim_{n \rightarrow \infty} f_n$  for some monotone sequence

$f_n \in \text{Simple}$ .

Moreover, we have measurable such choice:

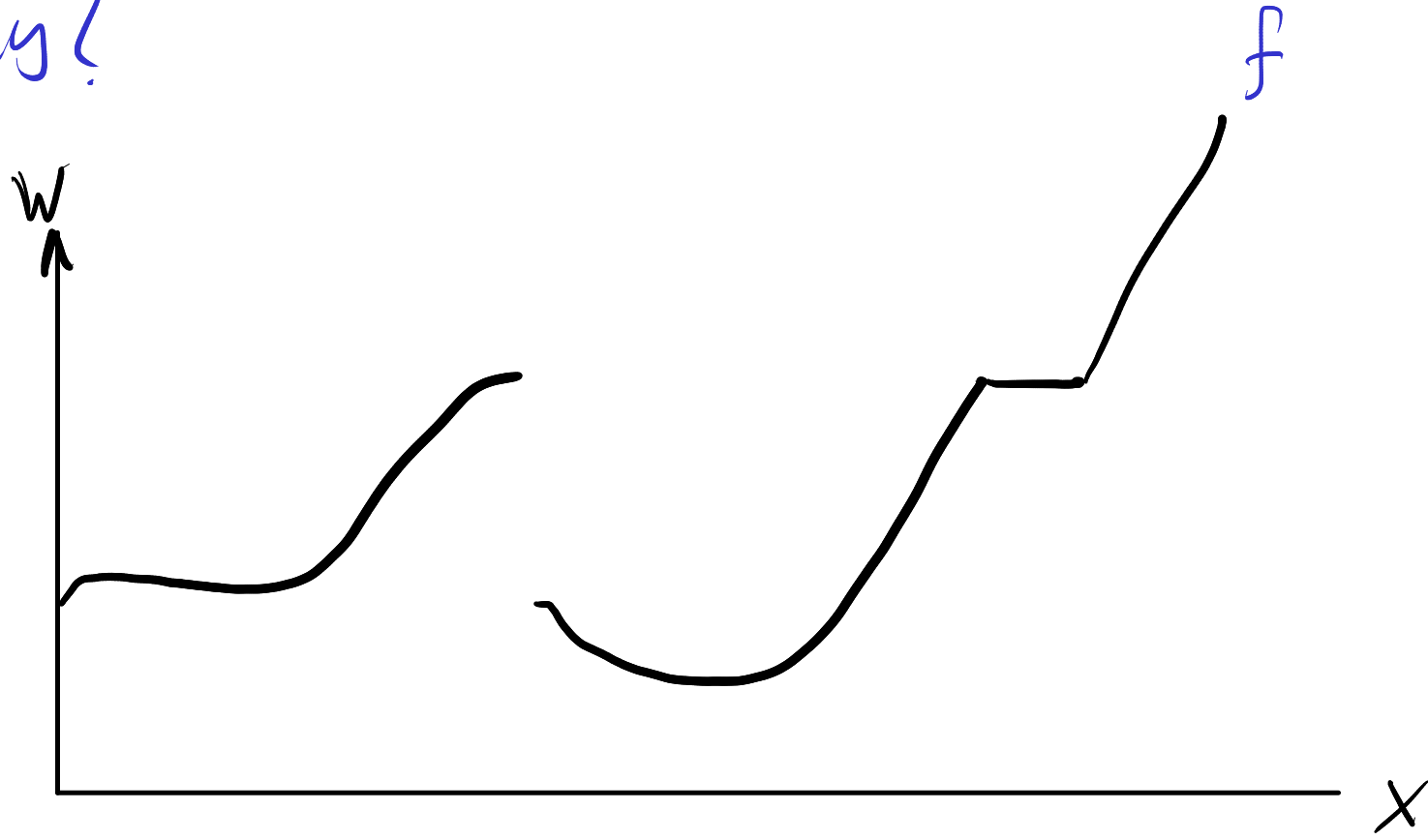
Simple Approx:

$$\left\{ \vec{\Delta} \in \mathbb{R}^+ \mid \Delta_n \rightarrow 0 \right\} \times \left\{ \vec{a} \in W^{\mathbb{N}} \mid \begin{array}{l} \vec{a} \text{ monotone} \\ a_n \rightarrow \infty \end{array} \right\} \times W^X \rightarrow \text{Simple Code}$$

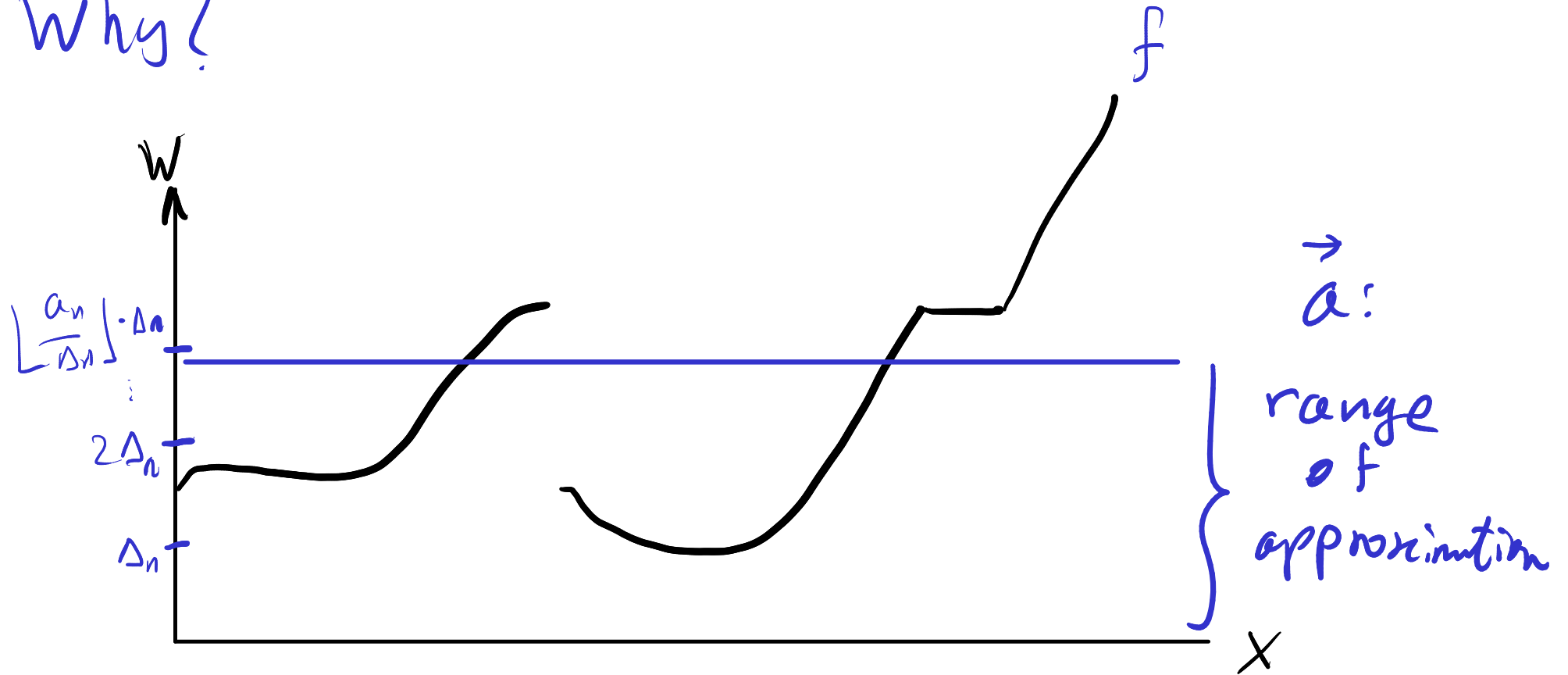
↑  
rate of  
convergence

↑  
range of  
approximation

Why?

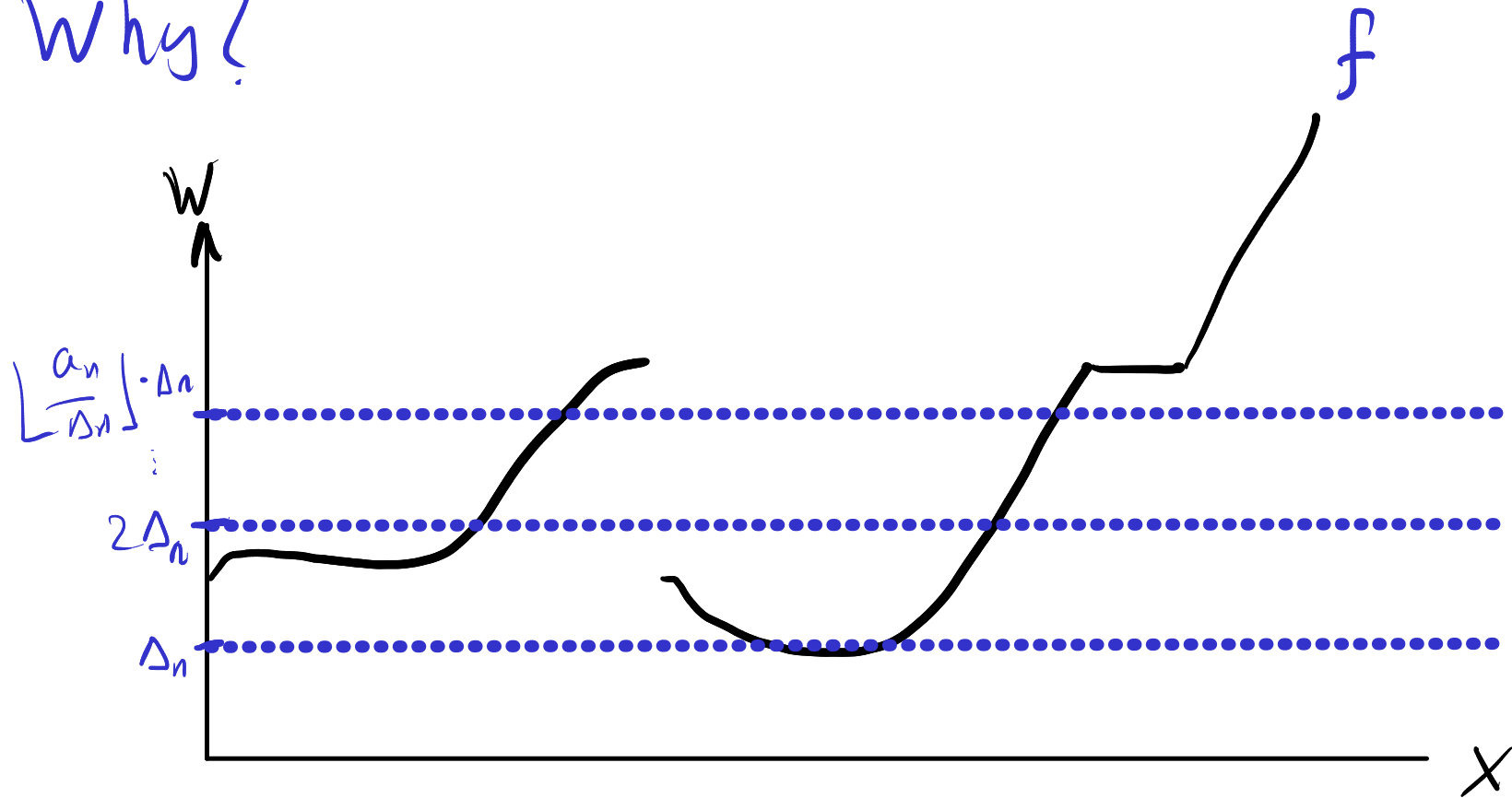


Why?

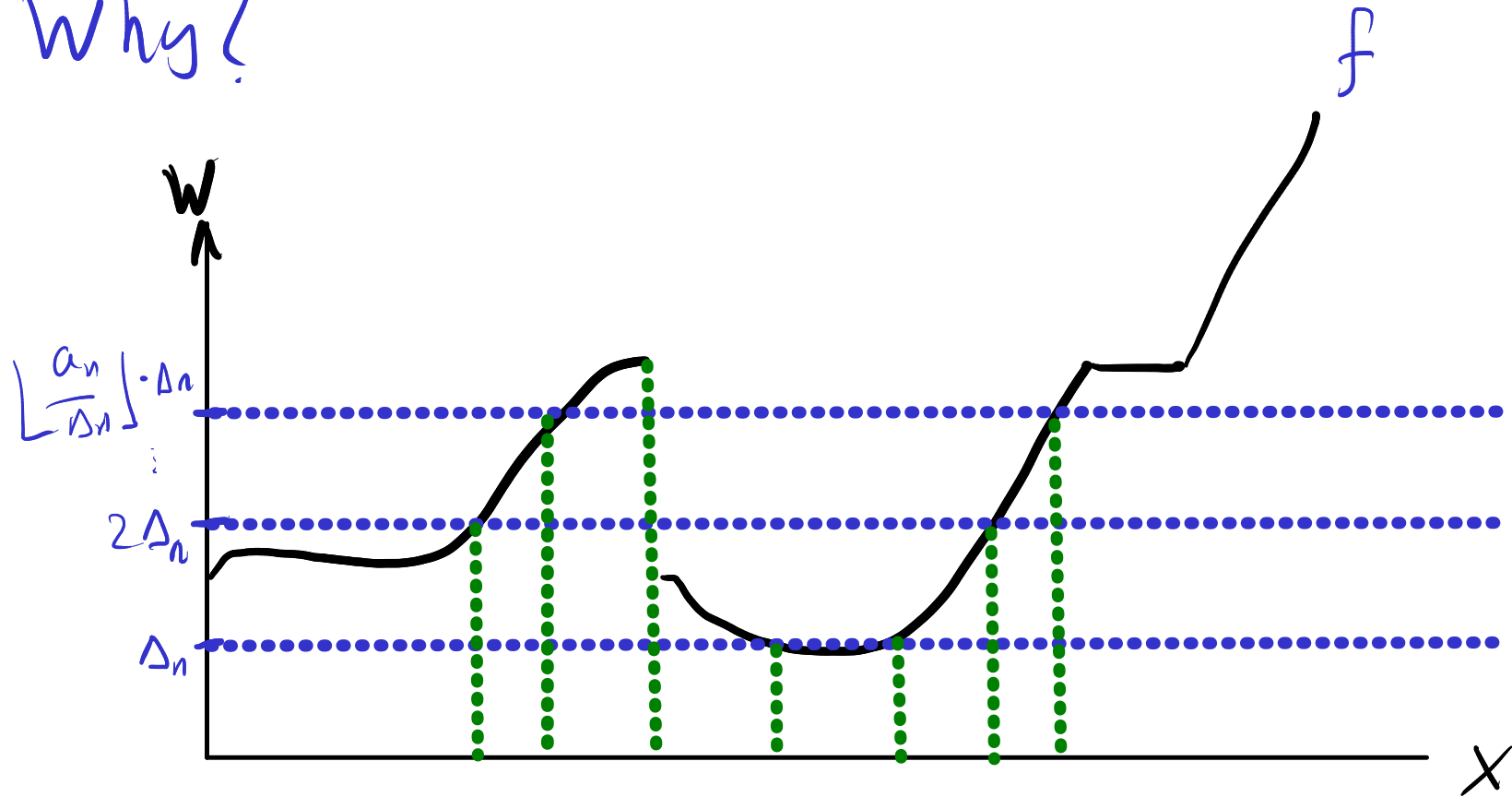


resolution of approximation

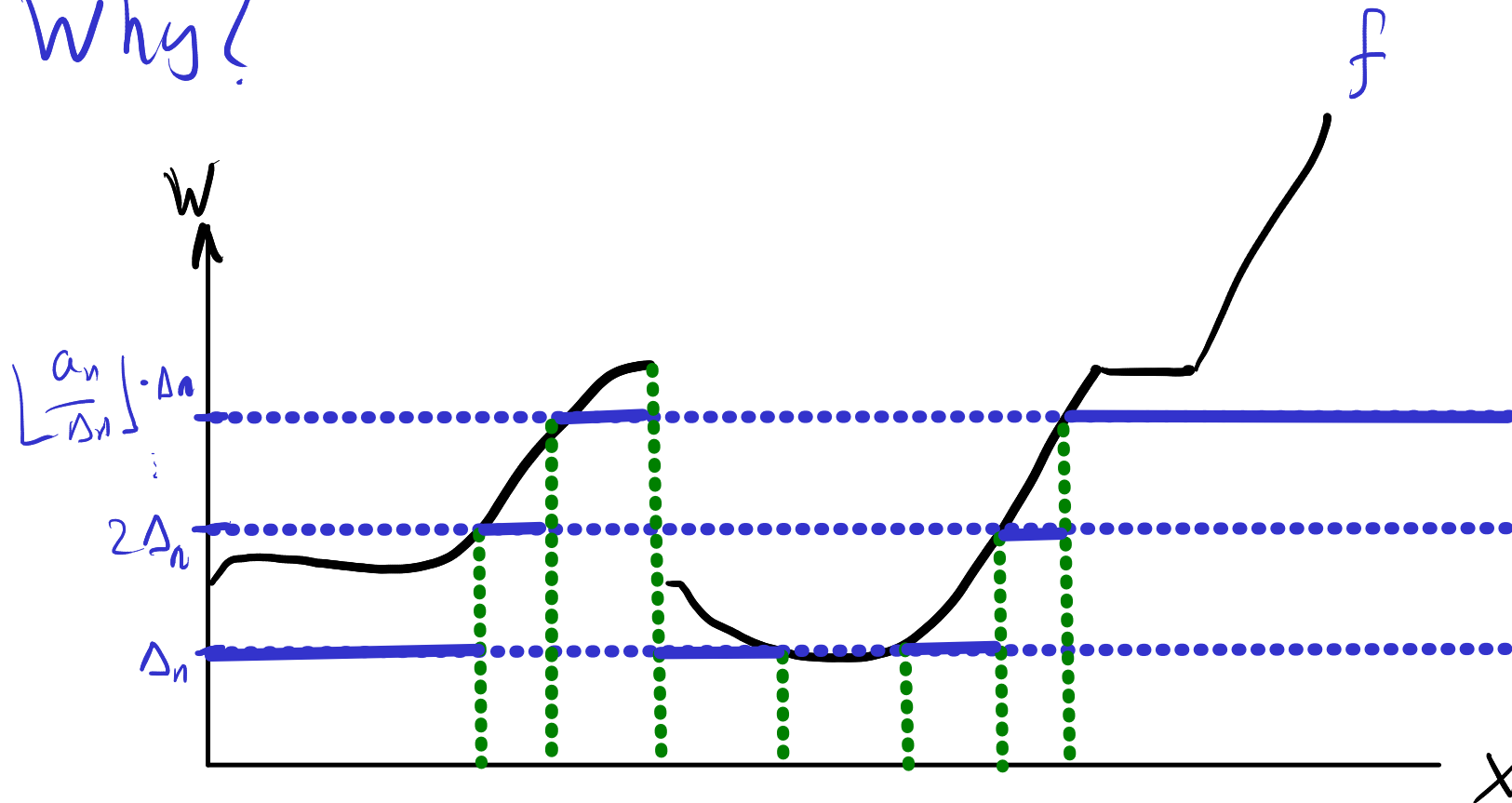
Why?



Why?

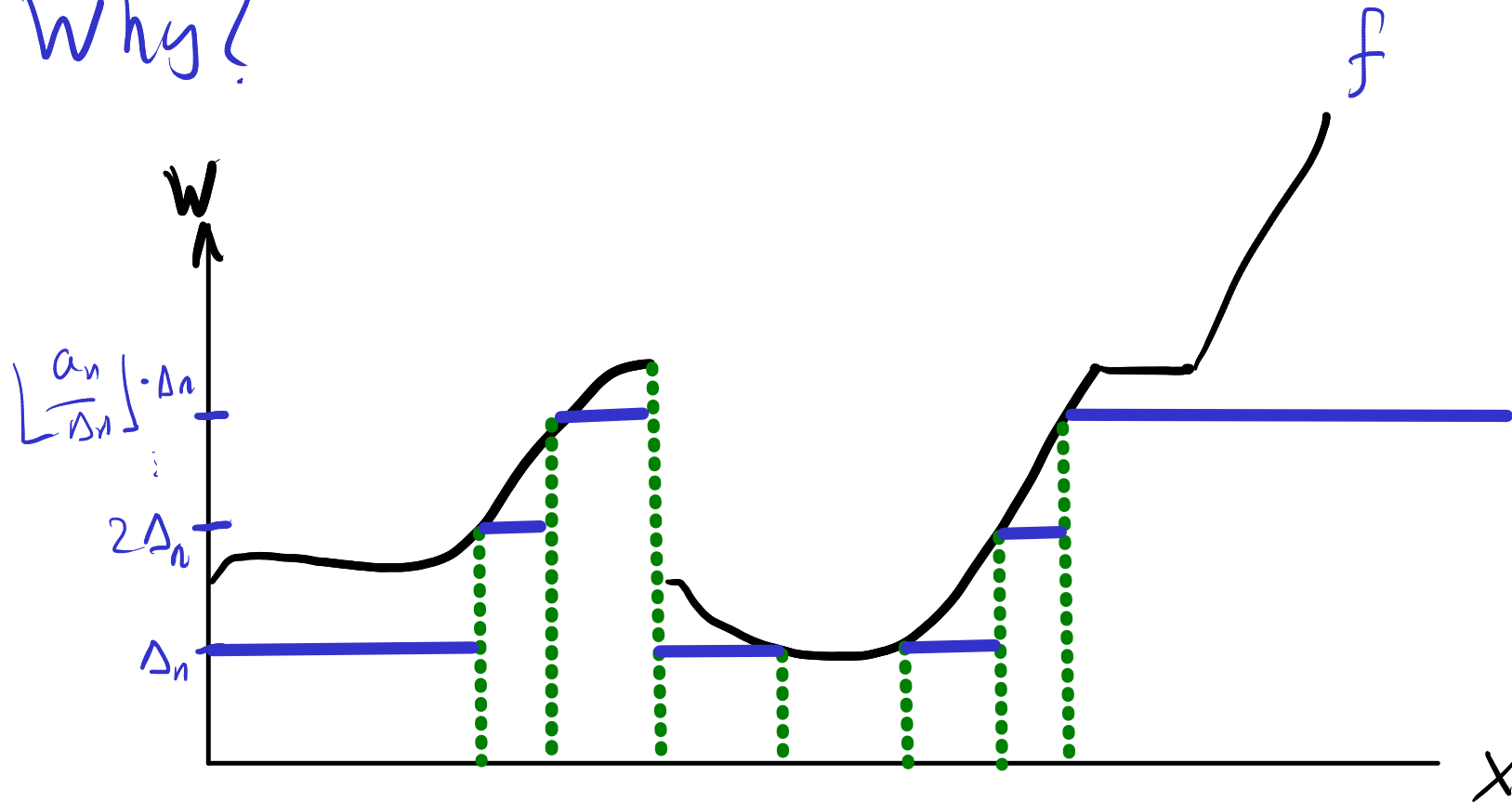


Why?

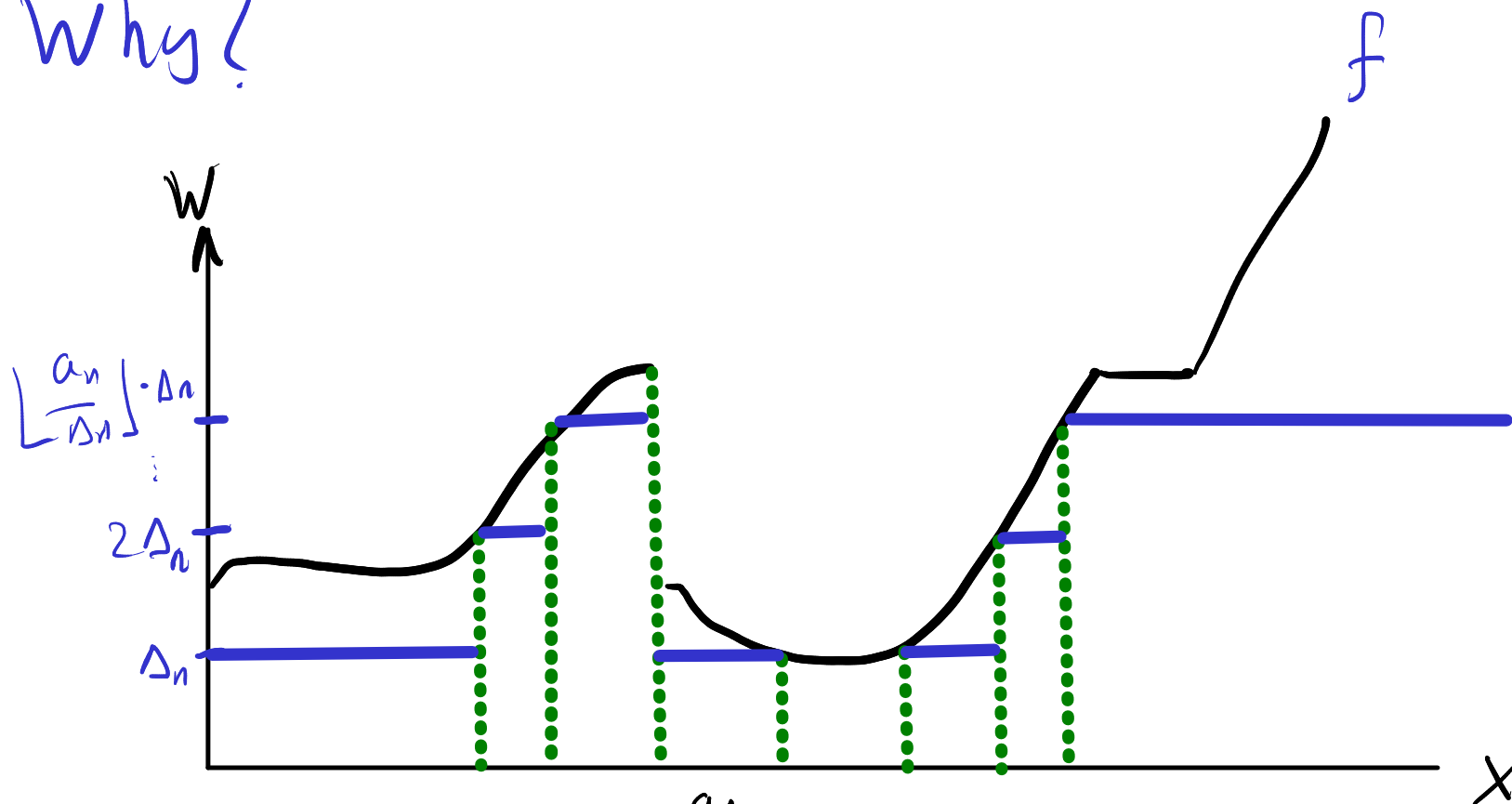




Why?

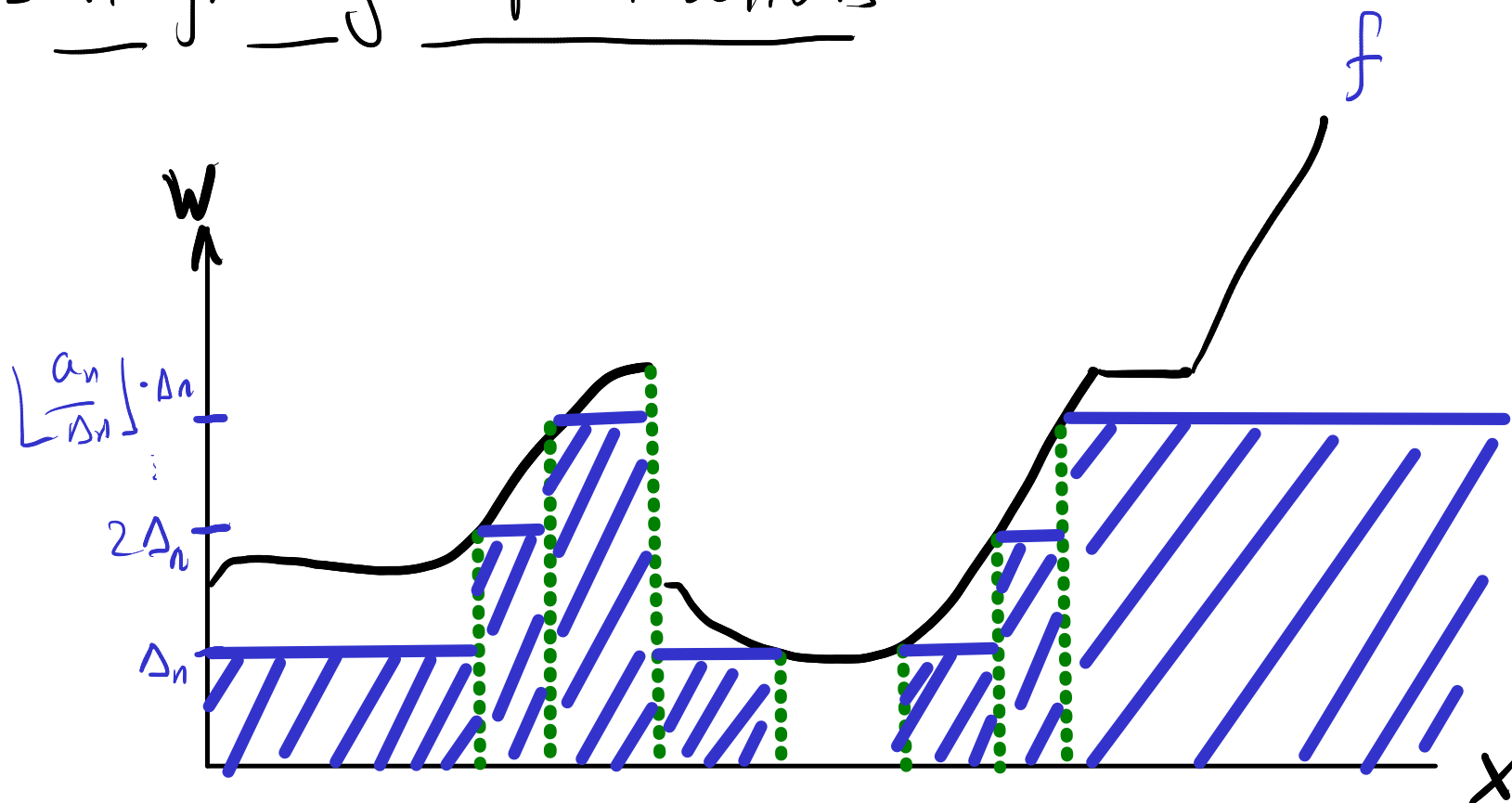


Why?



$$\| \text{Simple Approx}_{\vec{\Delta}, \vec{a}} f \|_0 = \sum_{i=1}^{\lfloor \frac{a_n}{\Delta_n} \rfloor} i \cdot \Delta_n [i \cdot \Delta_n \leq f < (i+1) \Delta_n] + \lfloor \frac{a_n}{\Delta_n} \rfloor \Delta_n [f \geq \lfloor \frac{a_n}{\Delta_n} \rfloor \cdot \Delta_n] \in \text{Simple}$$

# Integrating Simple Functions



$$\int : GX \times \text{Simple Code} \rightarrow W$$

$$\int \mu(n, \vec{A}, \vec{r}) := \sum_{I \subseteq \{1, \dots, n\}} \left( \sum_{i \in I} r_i \right) \cdot \mu \left( \bigcap_{i \in I} A_i \setminus \bigcup_{i \notin I} A_i \right)$$

# Integration

$$\int : G^X \times W^X \longrightarrow W$$

Proper higher-order  
operation

$$\int \mu f := \sup \{ \int \mu \varphi \mid \varphi \in \text{Simple}, \varphi \leq f \}$$

$$= \lim_{n \rightarrow \infty} \int \mu (\text{Simple Approx}_{\vec{\Delta}_n, \vec{a}_n} f)_n$$

we also  
write

$\int \mu(dx) t$   
for  $\int \mu(x, t)$

measurable  
by  
type

for  $\frac{a_n}{\Delta_n} \rightarrow 0$ , e.g.  $\Delta_n = \frac{1}{2^n}$   $a_n = n$ .

resolution

# The unrestricted Giry Strong Monad

Dirac:

$$\delta: X \rightarrow GX$$

$$x \mapsto \lambda A. \begin{cases} x \in A: 1 \\ x \notin A: 0 \end{cases}$$

Unlike the unrestricted Giry on Meas.

but: non-commutative

Kleisli extension / Kock integral:

$$\oint: GX \times GX^X \rightarrow GP$$

$$\oint \mu f := \lambda A. \int \mu(d\mu) f(\mu; A)$$

(Fubini **fails**,  
just line in  
Meas)

# Fubini-Tonelli fails

$$\# \in G\mathbb{R} \quad \# E := \begin{cases} E \text{ finite:} & |E| \\ \text{o.w.} & ; \quad \infty \end{cases}$$

$$\lambda \in G\mathbb{R}$$

Lebesgue

$$k: \mathbb{R} \times \mathbb{R} \rightarrow W \cong G\mathbb{1}$$

$$k(x, y) := [x = y]$$

$$\int \#(dr) \int \lambda(dx) k(x, y) = \int \# \underline{0} = \underline{0} \approx 0$$

$$y: \mathbb{R} + \{\infty\} \mapsto \lambda\{y\} \cdot 1 + \lambda\{y\}^c \cdot 0 = 0 \quad \#$$

$$\int \lambda(dx) \int \#(dr) k(x, y) = \int \lambda(dx) \delta_{\infty} \approx \infty$$

$$x: \mathbb{R} + \{\infty\} \mapsto \mathbb{1}\{x\} \cdot 1 + 0 = 1$$

# Randomisable measures monad

$$D \rightsquigarrow G$$

$$LDX := \left\{ \lambda \alpha \mid \alpha: \mathbb{R} \rightarrow X \right\}$$

$\lambda A. \int_{\text{Dom } \alpha} \lambda(\text{Dom } \alpha)$   
 Lebesgue measure

$$R_{DX} := \left\{ \lambda x. \lambda_{\alpha x} \mid \alpha: \mathbb{R} \times \mathbb{R} \rightarrow X \right\}$$

$$\delta: X \rightarrow DX \quad \oint: D\Gamma \times (DX)^{\Gamma} \rightarrow DX \quad \text{lift along } D \rightsquigarrow G.$$

$D$  validates our measure axioms including Fubini-Tonelli  
 $\mu \in DX, \nu \in DY \vdash$

$$\oint \mu(\lambda x) \oint \nu(\lambda y) \delta_{(x,y)} = \oint \nu(\lambda y) \oint \mu(\lambda x) \delta_{(x,y)} =: \mu \otimes \nu$$

Thm: For sbs  $S$ ,  $PS$ ,  $D_{\leq 1}S$ ,  $D_{<\infty}S \in Sbs$

and agree with their counterparts on Meas.

$$\mathcal{D}S = \{ \mu \mid \mu \text{ s-finite} \}$$

see [Staton'16]

$$R_{\mathcal{D}S} = \{ k: \mathbb{R} \rightarrow \mathbb{G}D \mid k \text{ s-finite kernel} \}$$

Open: Is there a counterpart to  $D$  in Meas?

More modestly, is  $\mathcal{D}S \in Sbs$ ?

(Hypothesis: **no**)



# Distribution Submonoids

A measure space

$$\Omega = (\Omega, \mu)$$

is a qbs  $\Omega$  with  
 $\mu \in DX$ .

Similarly: finite measure space  
- (sub) probability space.

$$PX := \{ \mu \in DX \mid \mu X = 1 \}$$



$$P_{\leq 1} X := \{ \mu \in DX \mid \mu X \leq 1 \}$$



$$P_{< \infty} X := \{ \mu \in DX \mid \mu X < \infty \}$$



$DX$

# Full model

$$\text{type : Obs} \quad W := [0, \infty] \quad B_X \cong B^X$$

$$DX := \left( \{ \lambda_\alpha \mid \alpha : R \rightarrow X \}, \{ \lambda_{r, \lambda_\alpha} \mid \alpha : R \times R \rightarrow X \} \right)$$

$$P_X := \{ \mu \in DX \mid C_\mu[X] = 1 \}$$

$$C_\mu[E] := \mu E \quad \delta_x := E \mapsto \begin{cases} x \in E : 1 \\ x \notin E : 0 \end{cases}$$

$$\oint \mu k := \lambda E. \int \mu(x) k(x; E)$$

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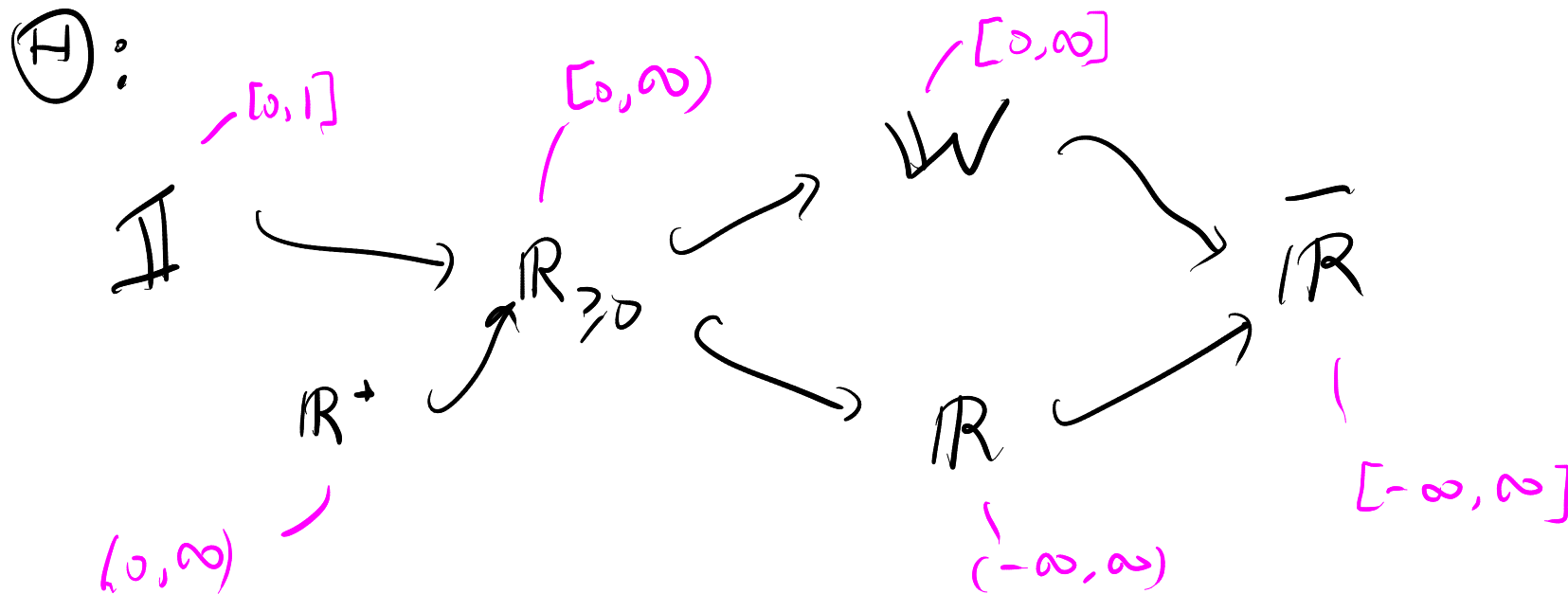
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snibble

Random variable:  $\xi: \Omega \rightarrow \mathbb{H} \hookrightarrow \overline{\mathbb{R}}$



- $\mathbb{H}^\Omega$  is a space
- $W^\Omega$  measurable  $\sigma$ -Semi-module for  $W$ :  $\sum_{n=0}^{\infty} \alpha_n \xi_n := \lambda W. \sum_{n=0}^{\infty} \alpha_n \cdot \xi_n$
- $\mathbb{R}^\Omega$  measurable vector space:  
 $\alpha \xi + \zeta := \lambda W. \alpha \cdot \xi W + \zeta W$

$$Pr: \mathcal{P}\Omega \times \mathcal{B}_\Omega \rightarrow \mathbb{W}$$

$$Pr_\lambda A := \text{eval}(\lambda, A) = \lambda A$$

Probability Space  $\Omega = (\Omega, \lambda_\Omega)$

$P: \mathcal{P}\Omega \vdash$  "  $Px$  holds  $\lambda(x)$ -almost surely "

for some  $Q \hookrightarrow \Omega$ ,  $P \sqsupseteq Q$ ,  $[- \in Q] \cdot \lambda = \lambda$

Example  $(\xi, \zeta \in \oplus^\Omega)$

$\xi = \zeta$  a.s., when  $Pr_{W \sim \lambda} [\xi W \neq \zeta W] = 0$

Integrating Random Variables (as discretely)

$$(-)_+, (-)_- : \mathbb{R}^n \longrightarrow \mathbb{W}^n$$

in Obs!

$$\xi_+ := \max(\xi, 0) \quad \xi_- := \max(-\xi, 0)$$

So:  $\xi = \xi_+ - \xi_-$

$$\int : \mathcal{P}\Omega \times \mathbb{W}^n \longrightarrow \mathbb{W}$$

$\int$  respects  
a.s. equality:

$$\int \lambda \xi := \int \lambda \xi_+ - \int \lambda \xi_-$$

$$\xi = \zeta \text{ (a.s.)}$$

$$\Rightarrow \int \lambda \xi = \int \lambda \zeta$$

## Example

$$\lambda: P\Omega \vdash \text{ASConverge}(\overline{\mathbb{R}})^{\Omega} : \mathcal{B}(\overline{\mathbb{R}}^{N \times \Omega})$$
$$:= \left\{ \vec{z} \in \overline{\mathbb{R}}^{N \times \Omega} \mid \Pr_{\omega \sim \lambda} [\lim z_n \omega \neq \perp] \right\}$$

So:

$$l_{\text{lim}}^{\text{as}}: \overline{\mathbb{R}}^{N \times \Omega} \longrightarrow \overline{\mathbb{R}}^{\Omega} \quad \text{Dom } l_{\text{lim}}^{\text{as}} := \text{ASConverge}(\overline{\mathbb{R}})^{\Omega}$$

$$l_{\text{lim}}^{\text{as}} \vec{z} := \lambda \omega. \limsup_{n \rightarrow \infty} f_n \omega$$

↳  $l_{\text{lim}}^{\text{as}}$  respects a.s. equality.

Thm (monotone convergence):

let  $\vec{\Sigma} \in W^{N \times \Omega}$   $\lambda$ -a.s. monotone.

$$\vec{\Sigma} = \lim_{n \rightarrow \infty} \vec{\Sigma}_n \quad (\text{a.s.})$$



$$\int \lambda \vec{\Sigma} = \lim_{n \rightarrow \infty} \int \lambda \vec{\Sigma}_n$$



# Lebesgue Space

$$\left( \Omega \text{ prob. space, } p \in [1, \infty) \right)$$

$$p: [1, \infty), \lambda: P\Omega \vdash L_{(\Omega, \lambda)}^p: B(\mathbb{R}^\Omega)$$

$$:= \left\{ \Sigma \in \mathbb{R}^\Omega \mid \int |\Sigma|^p < \infty \right\} \hookrightarrow \mathbb{R}^\Omega$$

$$\text{Ensemble } L_\Omega := \prod_{\substack{\lambda \in P\Omega \\ p \in [1, \infty)}} L_{(\Omega, \lambda)}^p$$

$$L \quad p \leq q \Rightarrow L_\Omega^p \supseteq L_\Omega^q$$

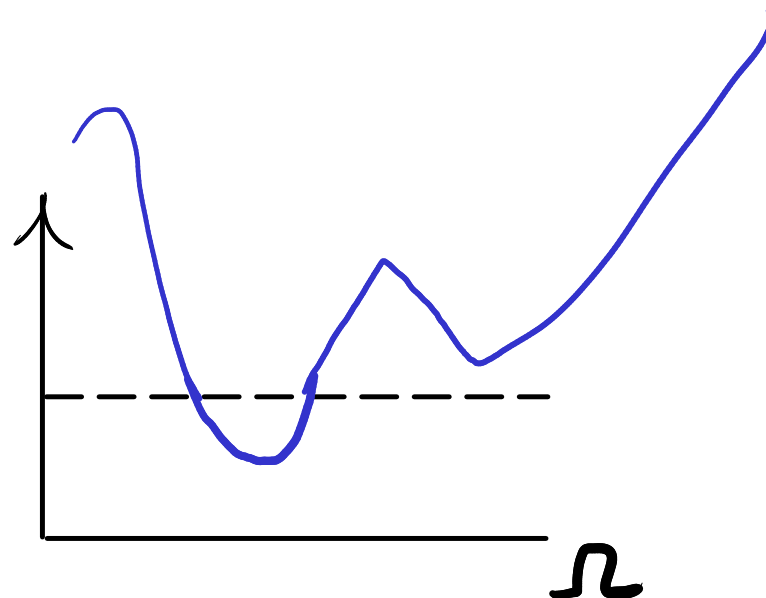
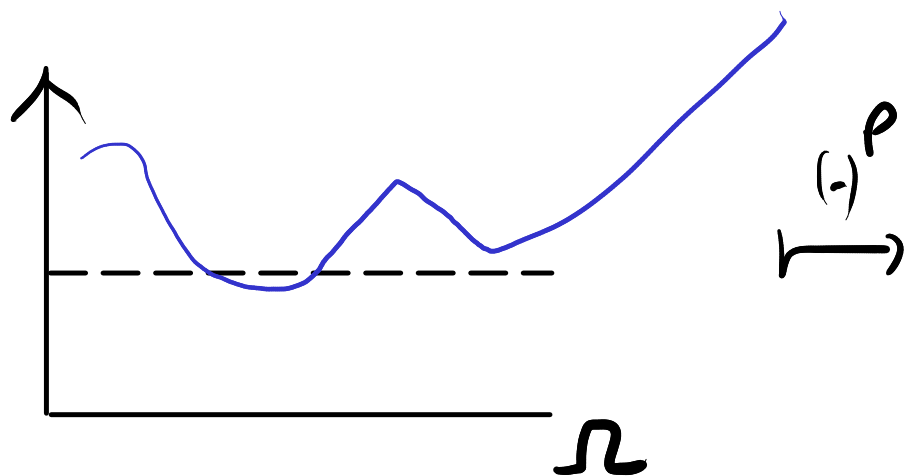
$L^p$  semi norms

$$\| - \| : \prod_{P, \lambda} L^p_{(\Omega, \lambda)} \rightarrow \mathbb{R}_{\geq 0} \quad \| \xi \|_p := \sqrt[p]{\int \lambda |\xi|^p}$$

$L^2$  inner product

$$\langle - , - \rangle : \prod_{P, \lambda} L^p_{(\Omega, \lambda)} \times L^p_{(\Omega, \lambda)} \rightarrow \mathbb{R}$$

$$\langle \xi , \eta \rangle_{P, \lambda} := \int \lambda \xi \eta$$



## Statistics

### Expectation

$$\mathbb{E} : \prod_{\lambda} L' \rightarrow \mathbb{R}$$

$$\mathbb{E}_{\lambda} \xi := \int \lambda \xi$$

### Covariance and Correlation

$$\text{Cov}, \text{Corr} : \prod_{\lambda} L^2 \rightarrow \mathbb{R}$$

$$\text{Cov}(\xi, \zeta) := \langle \xi - \mathbb{E} \xi, \zeta - \mathbb{E} \zeta \rangle$$

$$\text{Corr}(\xi, \zeta) := \frac{\langle \xi, \zeta \rangle}{\|\xi\|_2 \cdot \|\zeta\|_2} = \cos(\text{angle}(\xi, \zeta))$$

# Sequential limits

$p: [1, \infty)$ ,  $\lambda: \mathcal{P}(X)$  **Cauchy**  $L^p_{(\Omega, \lambda)} \subset B(L^p_{(\Omega, \lambda)})^{\mathbb{N}}$

$$= \left\{ \vec{z} \mid \forall \varepsilon \in \mathbb{Q}^+ \exists k \in \mathbb{N} \forall m, n \geq k. \right. \\ \left. \| z_{k+n} - z_{k+m} \|_p < \varepsilon \right\}$$

Thm:  $L^p_{\Omega}$  is **Cauchy-complete**

**lim**:  $\text{Cauchy } L^p \rightarrow L^p$  (convergence in mean)

Why?

1. Every Cauchy sequence has an a.s. converging subseq.
2. We can find it measurably

## Example

Then (dominated convergence)

For  $\vec{Z}_n, Z \in L^1$  s.t.  $Z_n \leq Z$  a.s.:

1.  $\lim_{n \rightarrow \infty} \vec{Z}_n \in L^1$

2.  $\lim_{n \rightarrow \infty} \vec{Z}_n = \lim_{n \rightarrow \infty} \vec{Z}_n$

3.  $\lim_{n \rightarrow \infty} \int \vec{Z}_n = \int \lim_{n \rightarrow \infty} \vec{Z}_n$

# Separability

Def:  $L^p$  separable: has countable dense subset

Fact: Separability is property of  $\ell_2$ :

TFAE:

- $\exists p \geq 1. L^p$  separable
- $\forall p \geq 1. L^p$  separable

Measurable separability in  $I \hookrightarrow P\Omega \times [1, \infty)$

$$\vec{\beta} : \prod_{(\lambda, p) \in I} L_{(\Omega, \lambda)}^p \quad \text{s.t.}$$

$$\{\vec{\beta}_n^{\lambda, p} \mid n \in \mathbb{N}\} \text{ dense in } L_{(\Omega, \lambda)}^p$$

Prop. - Every sbs  $S$  measurably separable in  $P\Omega \times [1, \infty)$

-  $I \hookrightarrow P\Omega \times \{2\}$  measurably separable

$$\Rightarrow \exists \vec{\beta} \in \prod_{\lambda \in I} L_{(\Omega, \lambda)}^2 \text{ orthonormal system}$$

$$\langle \beta_n, \beta_m \rangle = 0$$

$$\|\beta_n\|_2 = 1$$

$(\beta_n)$  dense

## Example

Let  $S \hookrightarrow L^2$  closed vector subspace.

Orthogonal decomposition / linear in fact.

$$\langle P, P^\perp \rangle : L^2 \rightarrow S \times S^\perp$$

When  $S$  is separable with orthonormal system  $\beta$

We have a measurable version of

$$\langle P, P^\perp \rangle : L^2 \rightarrow S \times S^\perp$$

$$P\xi := \sum_{n=0}^{\infty} \langle \xi, \beta_n \rangle \beta_n$$

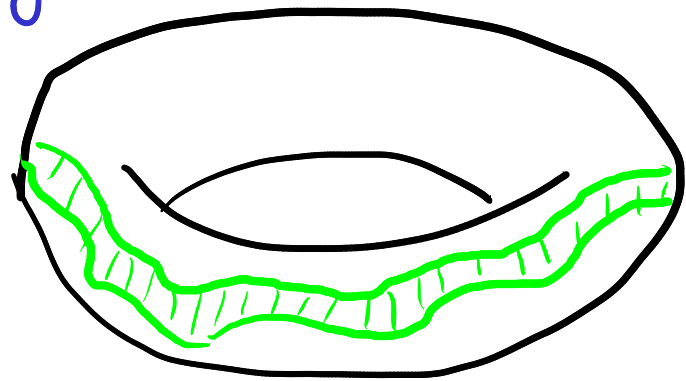
$$P^\perp := \text{Id} - P.$$



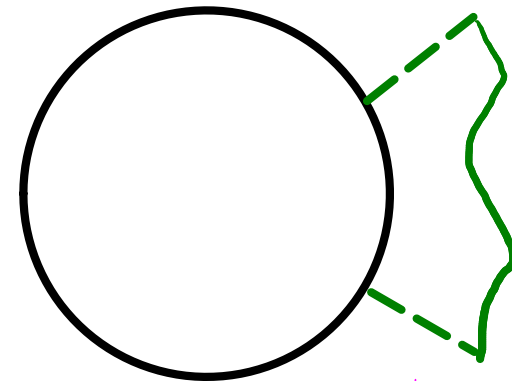
# Kolmogorov's Conditional Expectation

$\Omega$  ground truth space

$\mathcal{H}$  Sample space



$H$   
observation



$\Sigma$   
Statistic  
of interest

Conditional  
expectation  
 $E[\Sigma | H = -]$   
Observed  
statistic

$R$

# Kolmogorov's Conditional Expectation

A conditional expectation

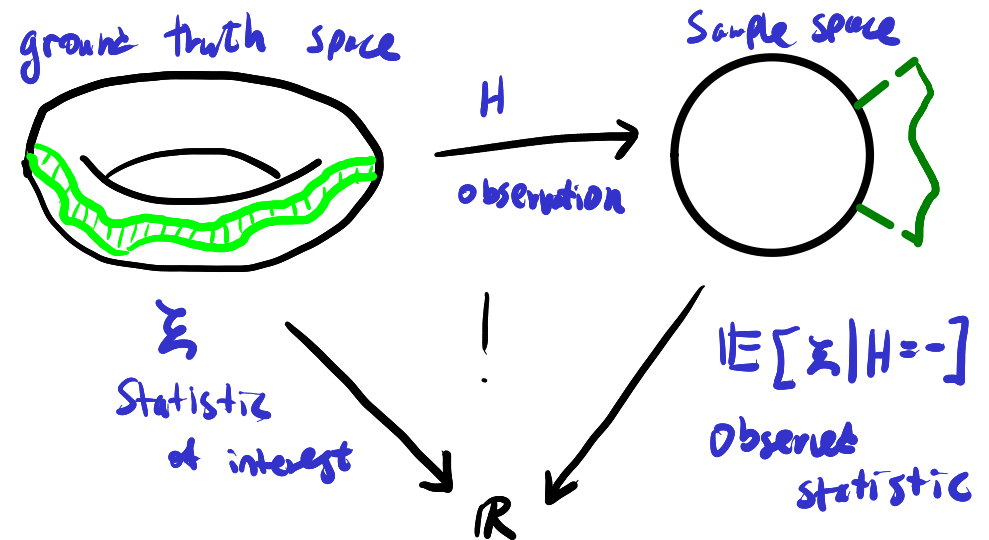
of  $Z \in \mathcal{L}'_\Omega$  wrt

$H: \Omega \rightarrow \mathbb{H}$  is

$Z \in \mathcal{L}'_{\mathbb{H}}$  s.t. for all  $A \in \mathcal{B}_{\mathbb{H}}$ :

$$\int_A \mu Z = \int_{H^{-1}[A]} \lambda Z$$

where  $\mu := \lambda_H$

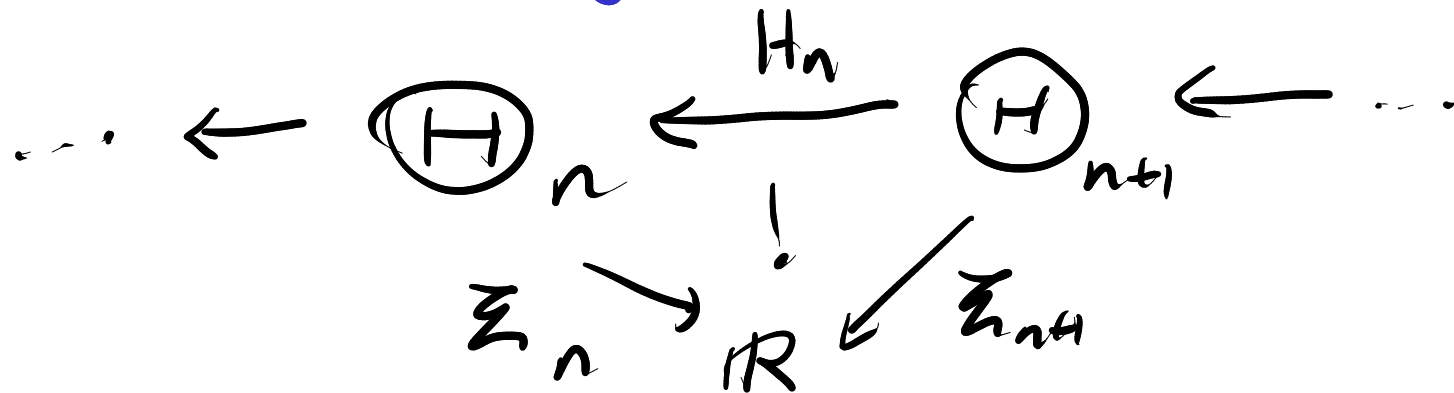


# Conditional expectations

1. *unique a.s.*

2. fundamental to modern Probability, eg:

*a martingale*



s.t.  $\Sigma_n = \mathbb{E}[\Sigma_{n+1} | H_n = -]$

Thm (Existence)

- $\exists \mathbb{E}[-|\mathcal{H}=-]: \mathcal{L}'_{(\Omega, \lambda)} \rightarrow \mathcal{L}'_{(\mathcal{H}, \mu)}$

- When  $(\Omega, \lambda)$  is separable

$$\mathbb{E}[-|\mathcal{H}=-]: \mathcal{L}'_{(\Omega, \lambda)} \rightarrow \mathcal{L}'_{(\mathcal{H}, \mu)}$$

- When  $\mathcal{H}$  is  $\mathcal{I}'$ -measurably separable

$$\mathbb{E}[-|\mathcal{H}=-]: \prod_{\substack{\mathcal{H} \in \mathcal{H} \\ \lambda \in \mathcal{H}'_*[I]}} \mathcal{L}'_{(\Omega, \lambda)} \rightarrow \mathcal{L}'_{(\mathcal{H}, \mu)}$$

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## Discrete model

$\text{type} : \text{set} \quad \mathbb{W} := [0, \infty] \quad \mathcal{B}X := \mathcal{P}X$

$\mathcal{D}X := \{ \mu : X \rightarrow \mathbb{W} \mid \text{supp } \mu \text{ countable} \}$

$\mathcal{P}X := \{ \mu \in \mathcal{D}X \mid \sum_{\mu} \mathbb{C}_e[X] = 1 \}$

$\mathbb{C}_e[E] := \sum_{x \in E} \mu_x \quad \delta_x := \lambda x'. \begin{cases} x = x' : 0 \\ x \neq x' : 1 \end{cases}$

$\oint \mu k := \lambda x. \sum_{r \in \Gamma} \mu r \cdot k(r; x)$

# Full model

$$\text{type : Obs} \quad w := [0, \infty] \quad \mathcal{B}X \cong \mathcal{B}^{X^X}$$

$$\mathcal{D}X := \left( \{ \lambda_\alpha \mid \alpha : \mathbb{R} \rightarrow X \}, \{ \lambda_{r,1} \mid \alpha : \mathbb{R} \times \mathbb{R} \rightarrow X \} \right)$$

$$\mathcal{P}X := \{ \mu \in \mathcal{D}X \mid C_\mu[X] = 1 \}$$

$$C_\mu[E] := \mu E$$

$$\delta_x := E \mapsto \begin{cases} x \in E : 1 \\ x \notin E : 0 \end{cases}$$

$$\oint \mu k := \lambda E. \int \mu(x) k(x; E)$$

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Enough!

Lunch.