

Foundations for type-driven probabilistic modelling

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Partiality cf. [Vakar et al. '19]

A Borel embedding $e: X \hookrightarrow Y$

- injective function $e: \llbracket X \rrbracket \rightarrow \llbracket Y \rrbracket$

- its image is Borel: $e[\llbracket X \rrbracket] \in \mathcal{B}_Y$

- 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

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

Its domain of definition

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

Depend-type
interpretation

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

Plan:

- 1) Type-driven probability: discrete case (Mon + Tue)
- 2) Borel sets & measurable spaces (Wed)
- 3) Quasi Borel spaces (Web) Simple type structure (Thu)
- 4) Dependent type structure & standard Borel spaces (Thu)
- 5) Integration & random variables (Fri)

please ask questions!



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smile

Full model

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

$\mathcal{D}X := (\text{Fri})$

$\mathcal{P}_X := \left\{ \mu \in \mathcal{D}X \mid \mathcal{C}_\mu[X] = 1 \right\}$

$\mathcal{C}_\mu[E] := (\text{Fri})$ $\delta_x := (\text{Fri})$

$\oint \mu_k := (\text{Fri})$

Def: A measure μ over \mathbb{R} is a function

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

Satisfying the measure axioms:

$$E: \mathcal{B}^{\omega}$$

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

For measurable spaces, replace \mathbb{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 $\lambda \in \mathcal{LGR}$ s.t.:

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

Thm (Lebesgue measure):

There is a unique measure $\lambda \in \mathcal{L}(\mathbb{R})$ s.t.:

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

Proof sketch (standard analysis textbook):

1) restrict attention to $(0, 1]$ & extend via σ -additivity

2) Take $\Sigma_0 \subseteq \mathcal{B}_{(0, 1]}$ $E \in \Sigma_0 \Leftrightarrow E = \bigcup_{i=1}^n (a_i, b_i]$ ←

3) Defining $\lambda: \Sigma_0 \rightarrow \mathbb{W}$, $\lambda \left(\bigcup_{i=1}^n (a_i, b_i] \right) := \sum_{i=1}^n (b_i - a_i)$ independent of

4) $\lambda \emptyset = 0$, $\lambda E = \lambda(E \cap F) + \lambda(E \cap F^c)$ (straightforward)

↳

5) **Technical gadget**: $\forall (E_n \supseteq E_{n+1})$ in Σ_0 ,

$$\inf \lambda E_n > 0 \Rightarrow \bigcap E_n \neq \emptyset.$$

6) λ is continuous on Σ_0 : If $(E_n \subseteq E_{n+1})_n$ in Σ_0

$$\text{and } \bigcup_n E_n \in \Sigma_0 \text{ then } \lambda \bigcup E_n = \sup_n \lambda E_n$$

7) Noting that: Σ_0 is a Boolean algebra

$$\& \sigma(\Sigma_0) = \mathcal{B}_{(0,1]}$$

we use Carathéodory's extension theorem:

$$\lambda \text{ extends uniquely to } \lambda: \mathcal{B}_{(0,1]} \rightarrow \mathbb{W}.$$

The unrestricted Giry spaces

Equip $\mathcal{G}V$ with two qbs structures:

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

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

$\hookrightarrow \alpha$ is a kernel.

- Fewer random elements
 $\mathcal{R}_{\mathcal{G}V} \subseteq \mathcal{R}_{\mathcal{G}'V}$
- Lebesgue integral
measurable in
both arguments.

Farewell Meas

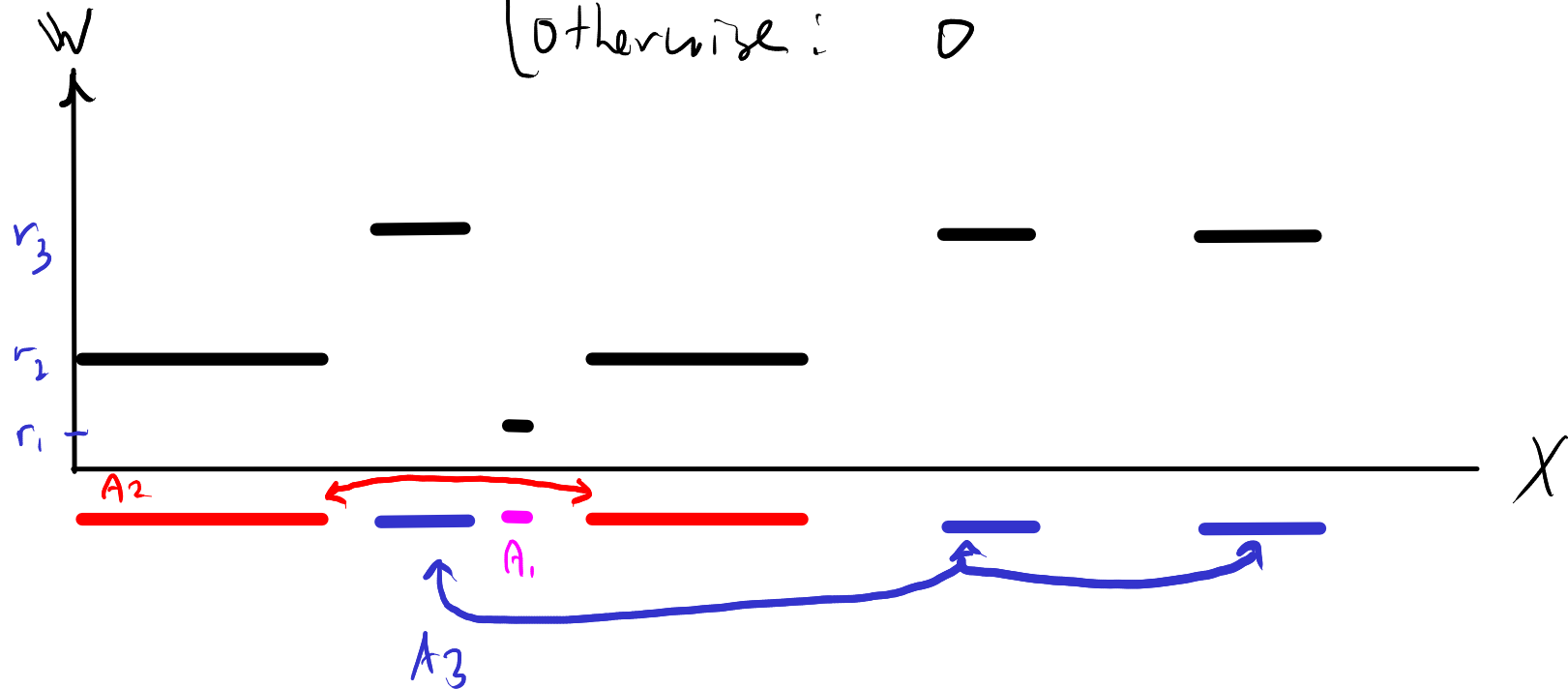
Now on:

1. All spaces are quasi-Borel (upcoming)
2. "measurable function" means qbs morphism!

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:

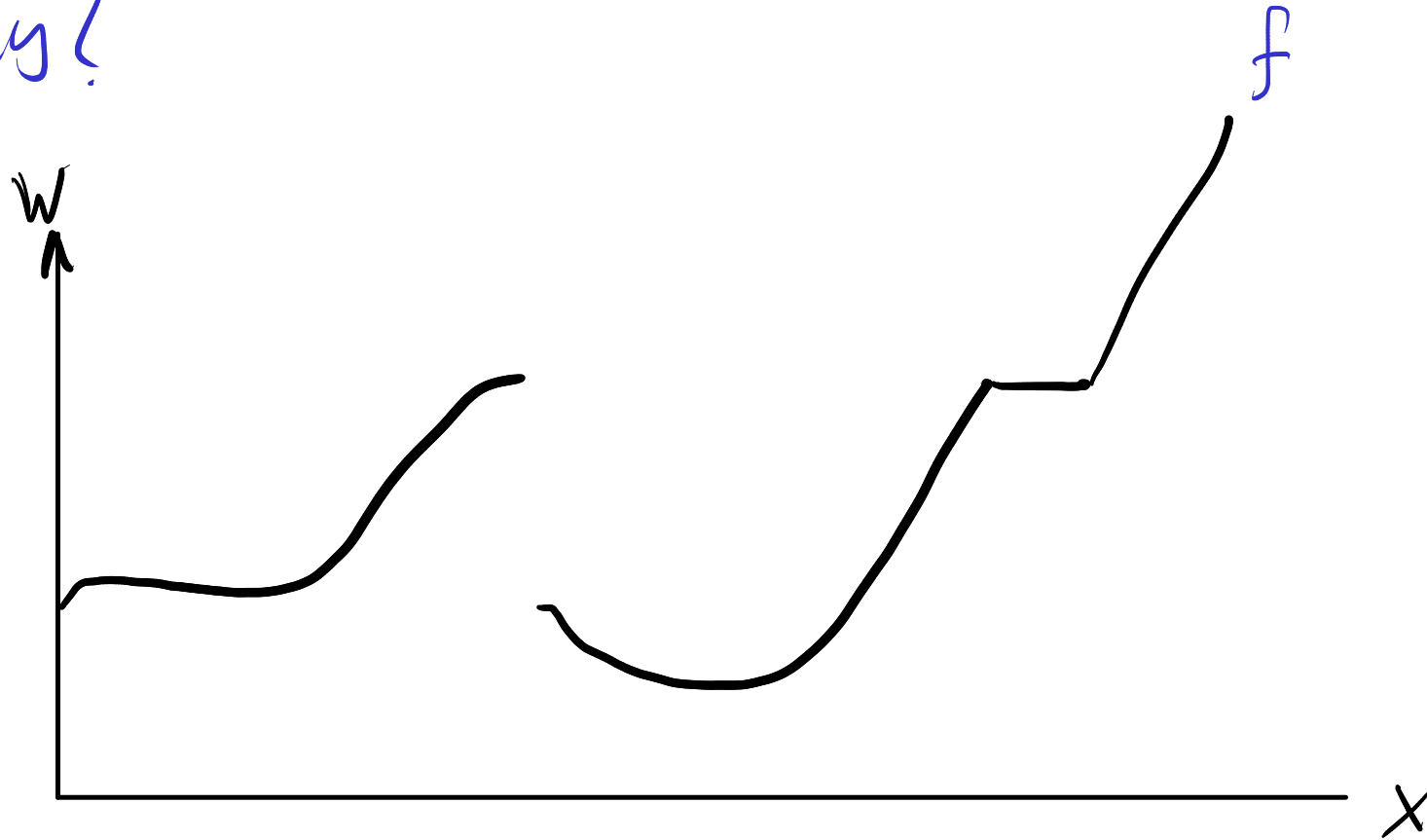
Simple Approx:

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

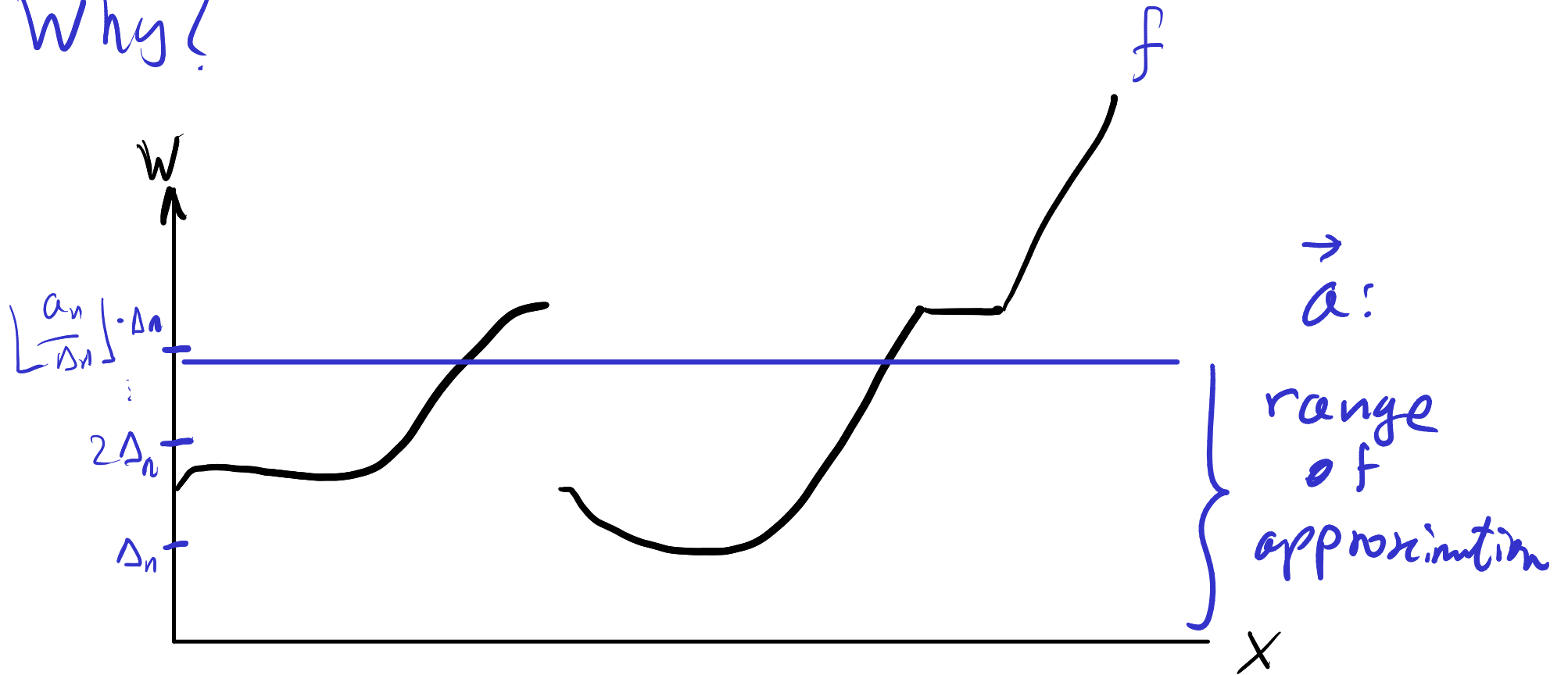
↑
rate of
convergence

↑
range of
approximation

Why?

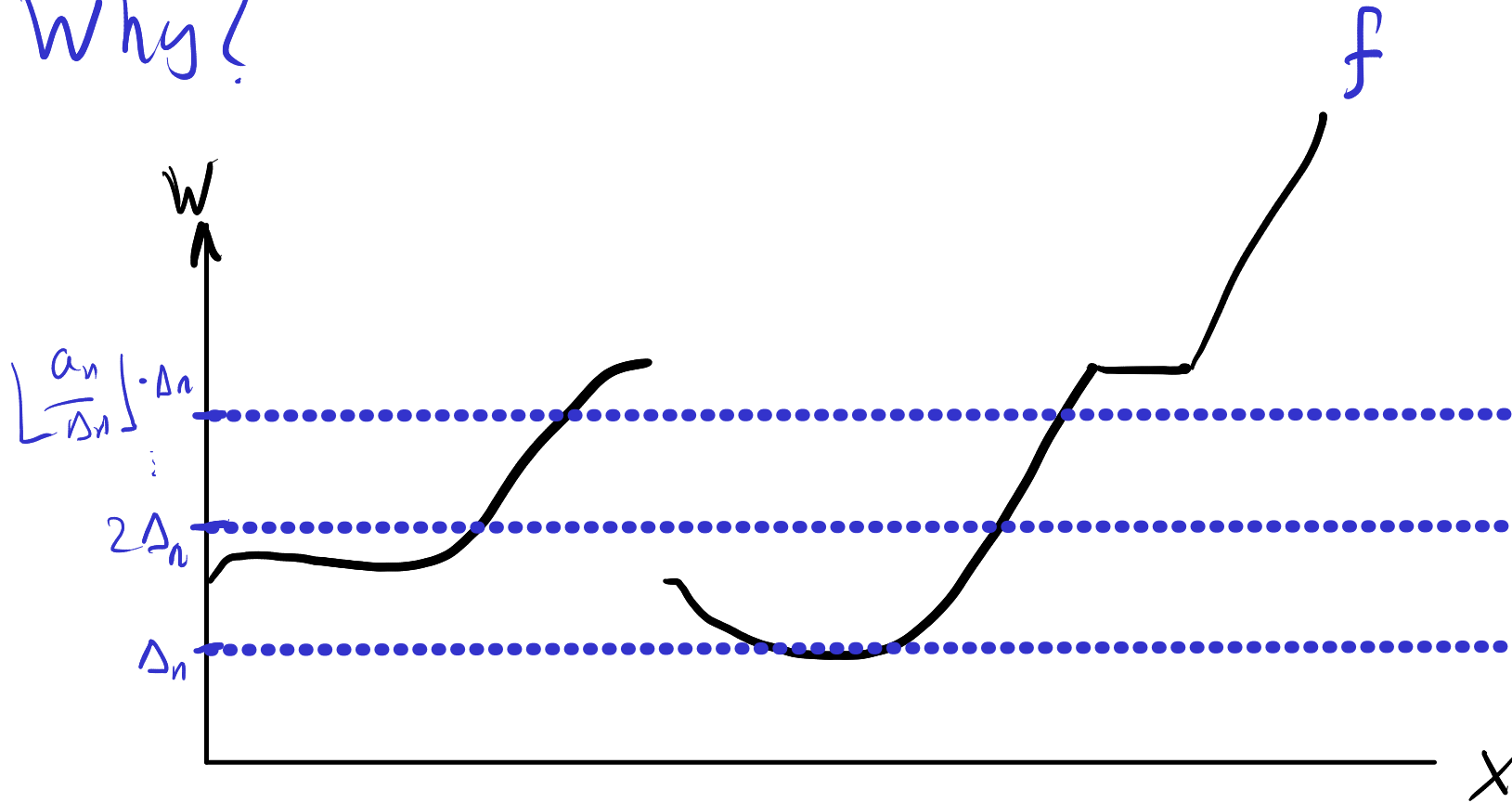


Why?

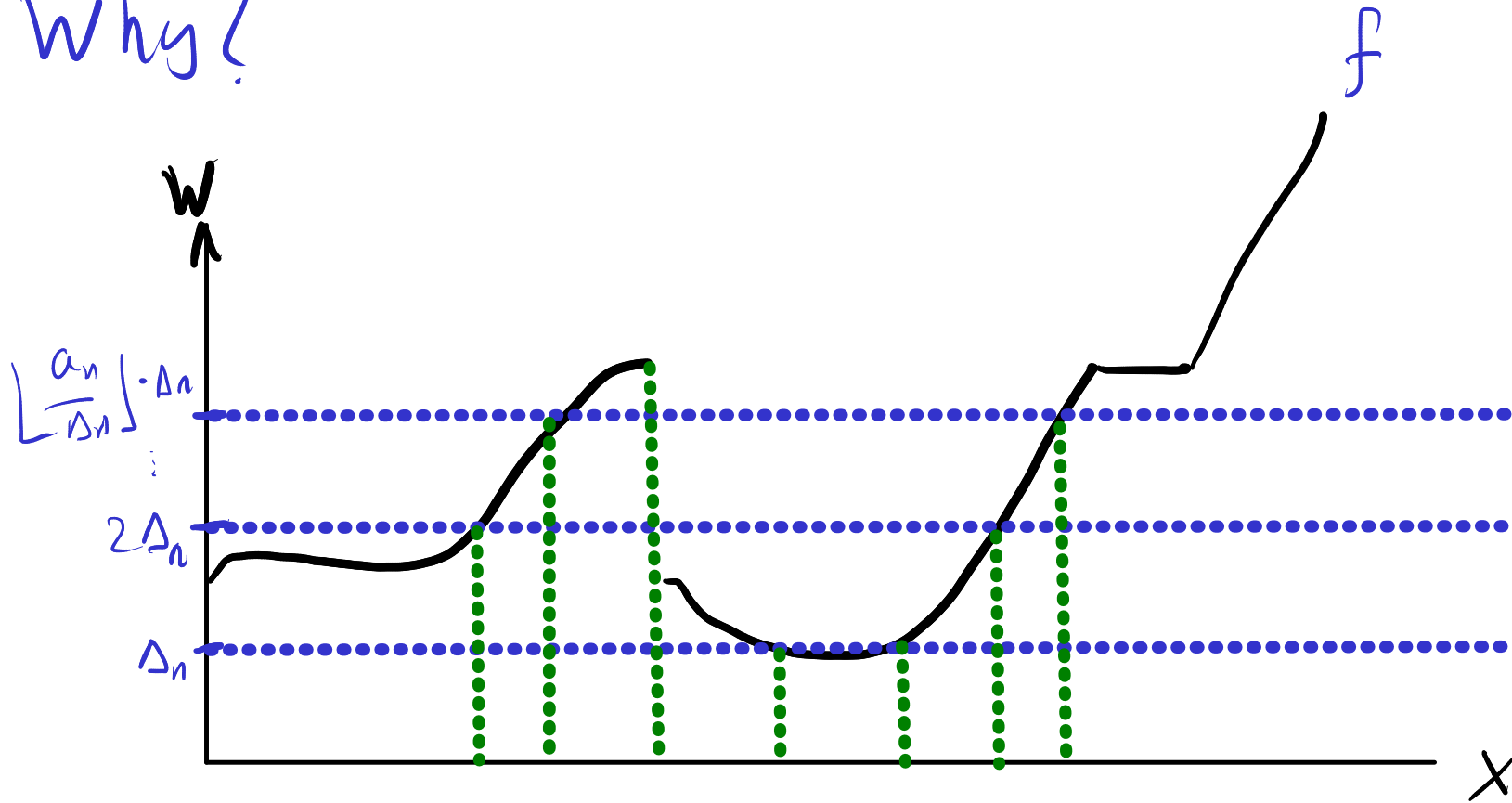


\uparrow resolution of approximation

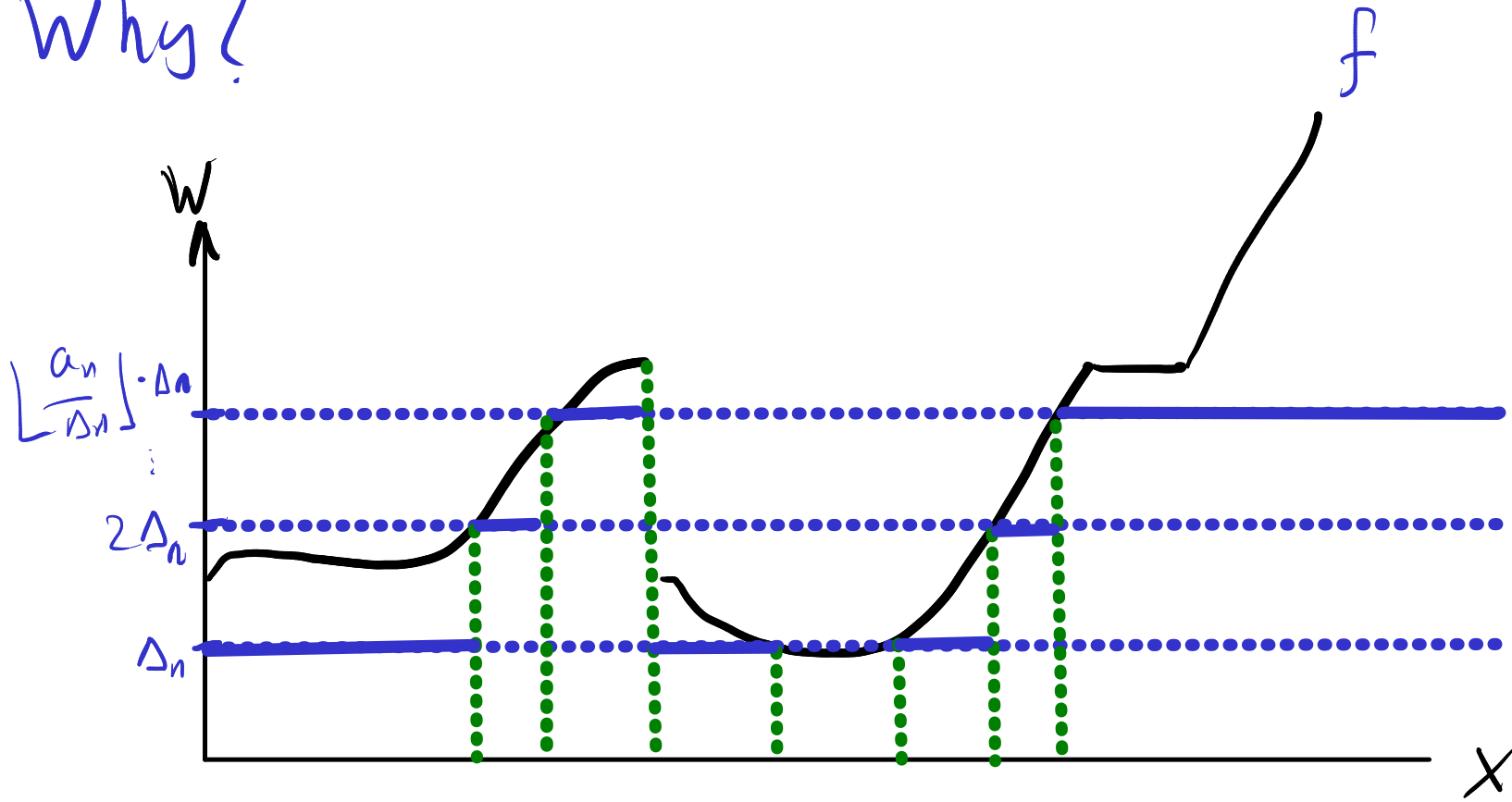
Why?



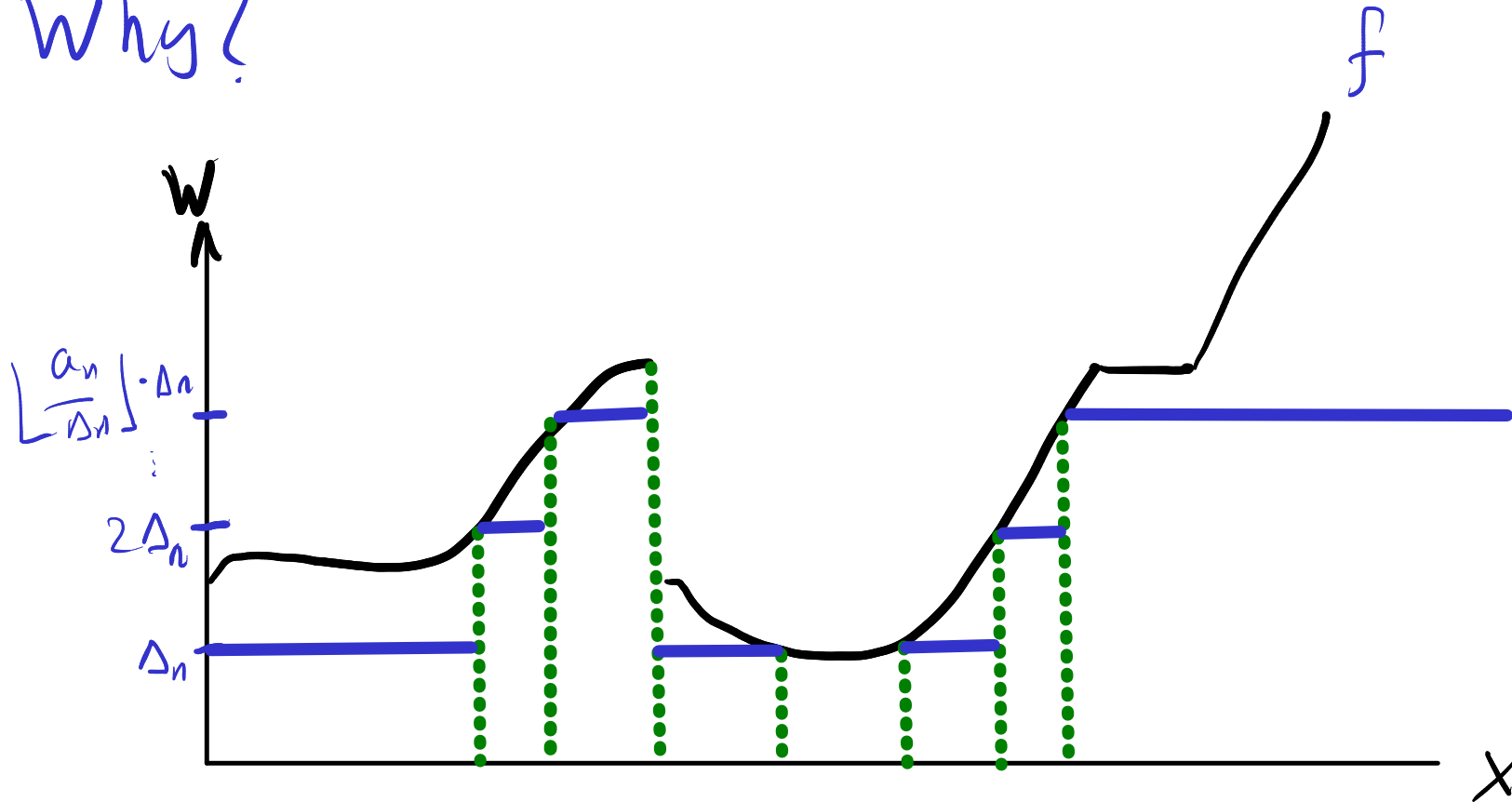
Why?



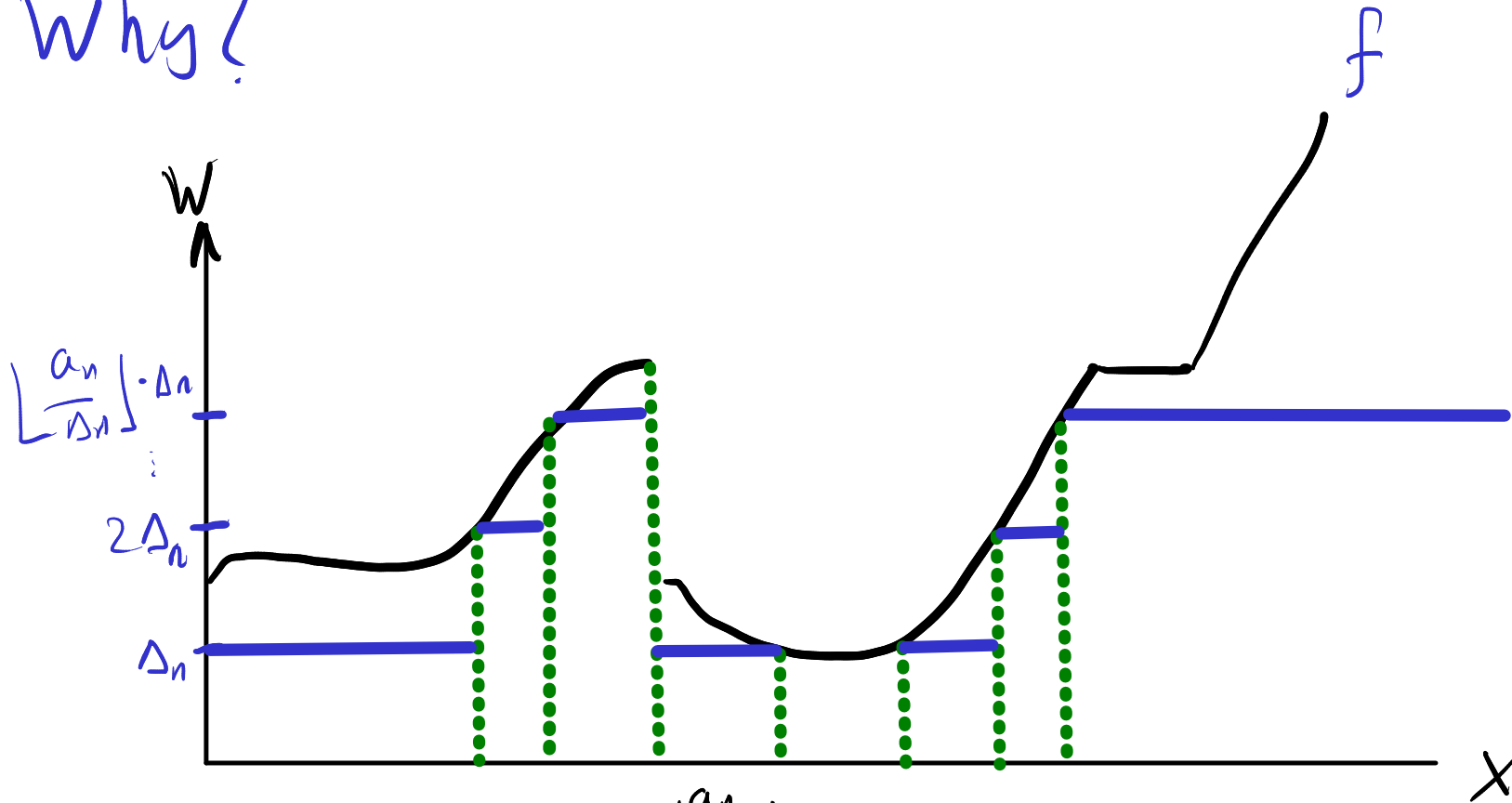
Why?



Why?

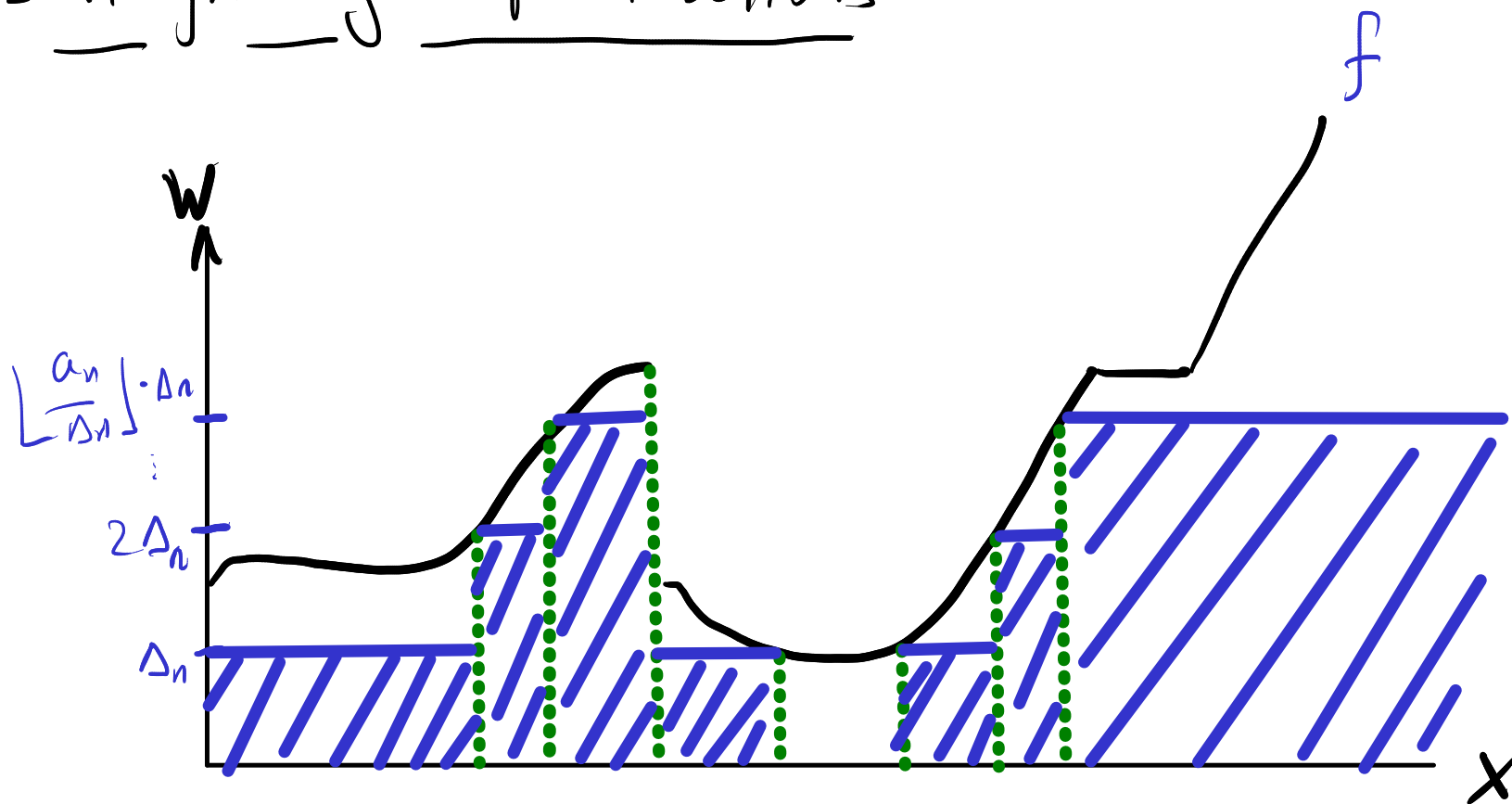


Why?



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

Integrating Simple Functions



$$\int : \mathcal{G}X \times \text{Simple Code} \rightarrow W$$

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

Integration

Proper higher-order operation

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

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

we also write

$$\int \mu(dx) t$$

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

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

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:

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

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

(Fubini fails,
just line in
Meas)

Fubini-Tonelli fails

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

$$\lambda \in \mathbb{GIR}$$

Lebesgue

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

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

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

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

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

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

Randomisable measures monad

$$D \rightsquigarrow G$$

$$L_{DX} := \left\{ \lambda_\alpha \mid \alpha: \mathbb{R} \rightarrow X \right\}$$

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

$$R_{DX} := \left\{ \lambda_\pi \cdot \lambda_{d\pi} \mid \alpha: \mathbb{R} \times \mathbb{R} \rightarrow X \right\}$$

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

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

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

Thm: For sbs S , PS , $D_{\leq 1}S$, $D_{< \infty}S \in Sbs$
and agree with their counterparts on Meas.

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

See [Staton'16]

$$\mathcal{R}_{DS} = \{ k: \mathbb{R} \rightarrow GD \mid k \text{ s-finite kernel} \}$$

Open: Is there a counterpart to D in Meas?

More modestly, is $DS \in Sbs$?

(Hypothesis: **no**)

Distribution Submonoids

A measure space

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

is a qbs Ω with
 $\mu \in \mathcal{D}X$.

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

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



$$\mathcal{P}_{\leq 1} X := \{ \mu \in \mathcal{D}X \mid \mu X \leq 1 \}$$



$$\mathcal{P}_{< \infty} X := \{ \mu \in \mathcal{D}X \mid \mu X < \infty \}$$



$\mathcal{D}X$

Full model

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

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

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

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

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

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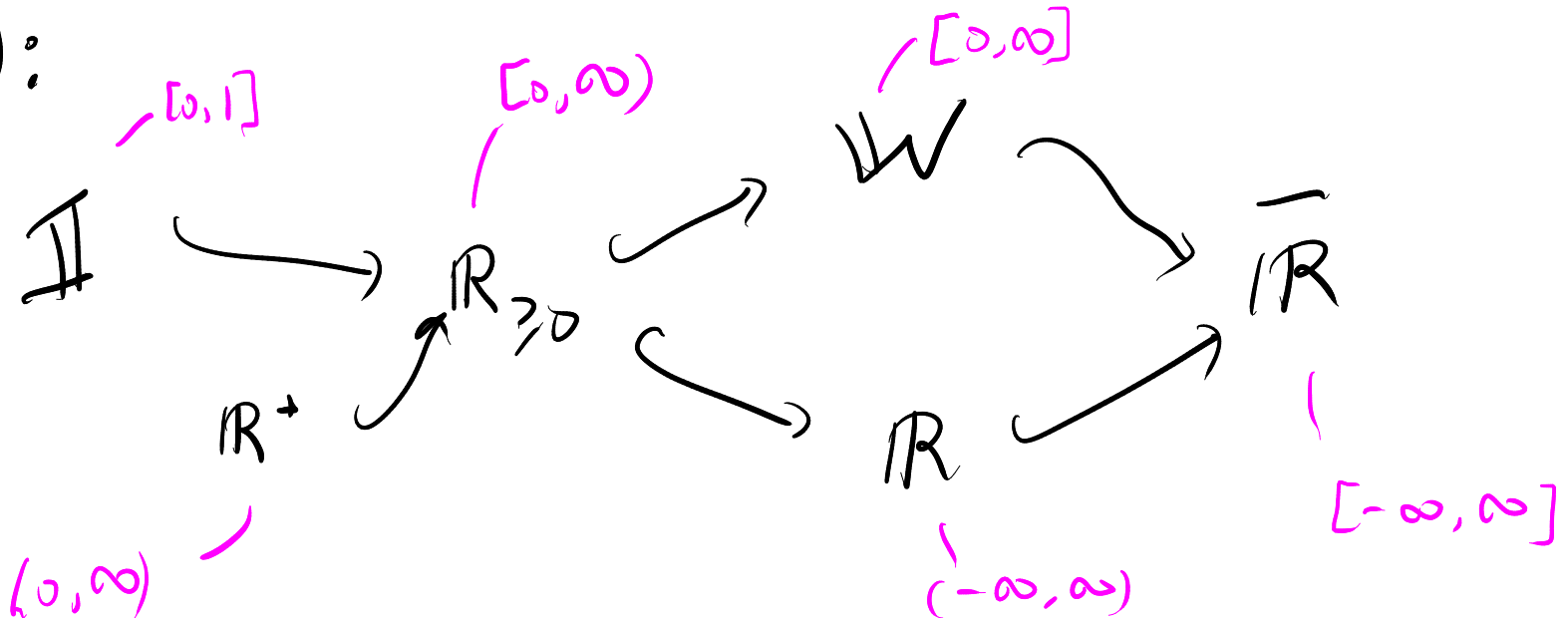
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Random variable $\xi: \Omega \rightarrow \mathbb{H} \cong \overline{\mathbb{R}}$

\mathbb{H} :



- \mathbb{H}^Ω is a space
- W^Ω measurable σ -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}^Ω 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 $Q \hookrightarrow \Omega$, $P \supseteq Q$, $[- \in Q] \cdot \lambda = \lambda$

Example $(\xi, \zeta \in \mathbb{H}^\Omega)$

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

Integrating Random Variables (as discretely)

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

in Obs!

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

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

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

\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

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

So:

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

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

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

Thm (monotone convergence):

let $\vec{\xi} \in W^{\mathbb{N} \times \Omega}$ λ -a.s. monotone.

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



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

Lebesgue space

(Ω prob. space,
 $P \in [1, \infty)$)

$$P: [1, \infty), \lambda: P_{\Omega} \quad L_{(\Omega, \lambda)}^P: \mathcal{B}(\mathbb{R}^{\Omega})$$

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

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

$$L \quad P \leq q \Rightarrow L_{\Omega}^P \supseteq L_{\Omega}^q$$

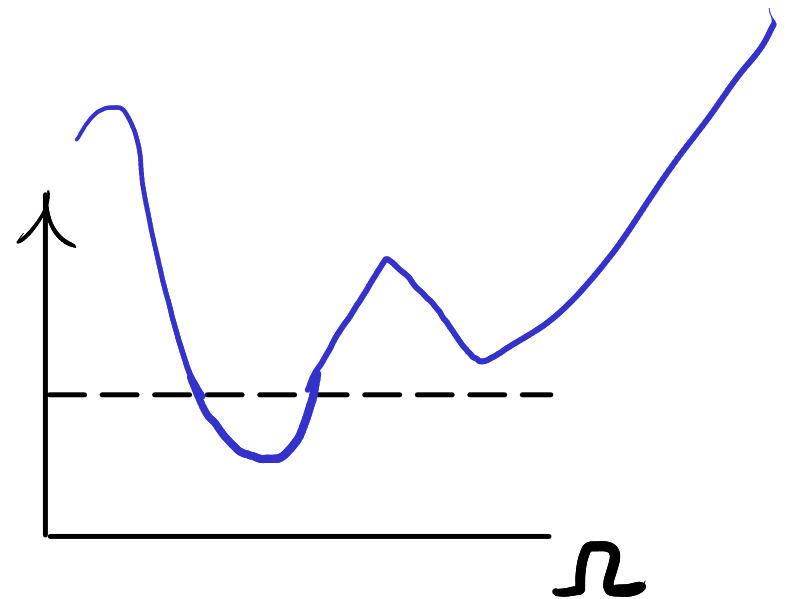
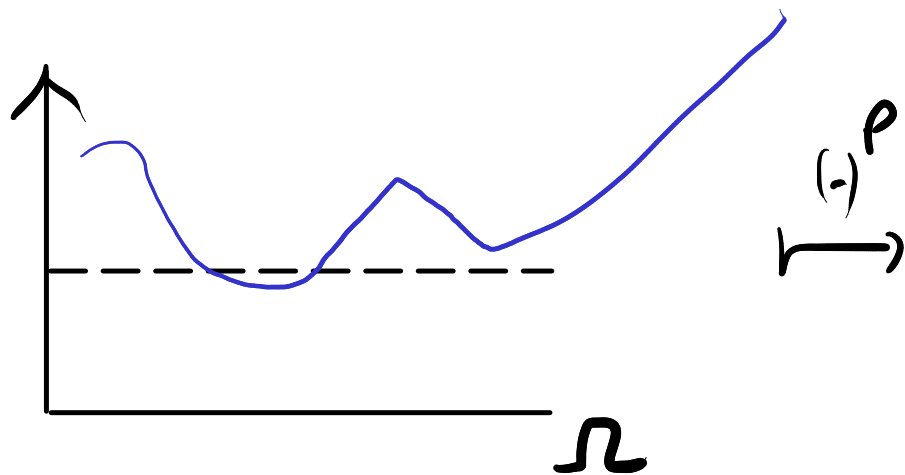
L^p semi norms

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

L^2 inner product

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

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



Statistics

Expectation

$$\mathbb{E} : \prod_{\lambda} L^1 \rightarrow \mathbb{R}$$

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

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

$p \in [1, \infty)$, $X: \Omega \rightarrow \mathbb{R}^d$ Cauchy $L^p_{(\Omega, \mathcal{F}, \mathbb{P})}$

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

Thm: L^p_{Ω} is Cauchy-complete

lim: 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 $\vec{\Sigma}_n, \vec{\Sigma} \in L^1$ s.t. $\vec{\Sigma}_n \leq \vec{\Sigma}$ a.s.:

1. $\lim^{as} \vec{\Sigma} \in L^1$

2. $\lim^1 \vec{\Sigma} = \lim^{as} \vec{\Sigma}$

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

Separability

Def: L^p separable: has countable dense subset

Fact: Separability is property of \mathbb{R}^2 :

TFAE:

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

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

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

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

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

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

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

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

$$\begin{aligned} \langle \beta_n, \beta_m \rangle &= 0 \\ \|\beta_n\|_2 &= 1 \\ (\beta_n) &\text{ dense} \end{aligned}$$

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 β

We have a measurable version of

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

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

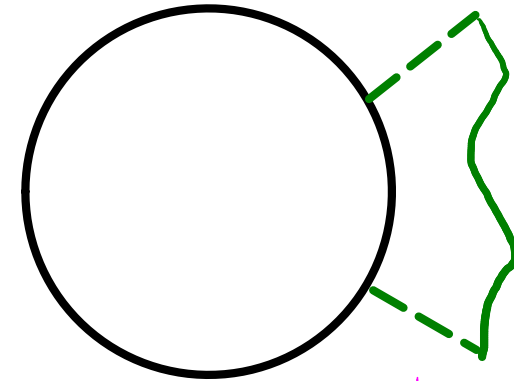
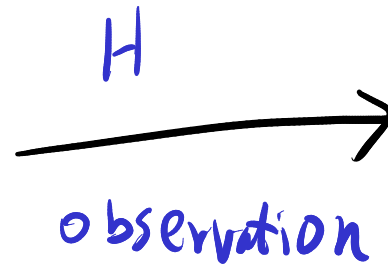
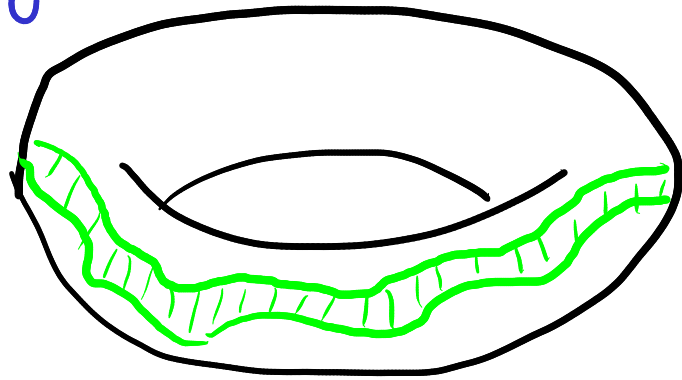
$$P^\perp := \text{Id} - P.$$

Kolmogorov's Conditional Expectation

ground truth space

\mathcal{H}

Sample space



Σ
Statistic
of interest

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

\mathbb{R}

Kolmogorov's Conditional Expectation

A conditional expectation

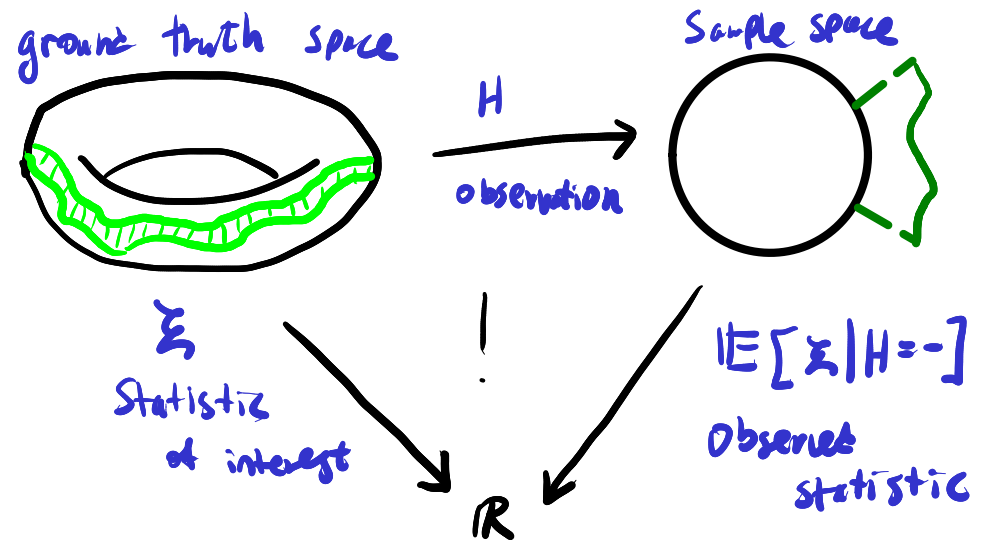
of $Z \in \mathcal{L}'_\Omega$ wrt

$H: \Omega \rightarrow \mathbb{H}$ 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 $\mu := \lambda_H$

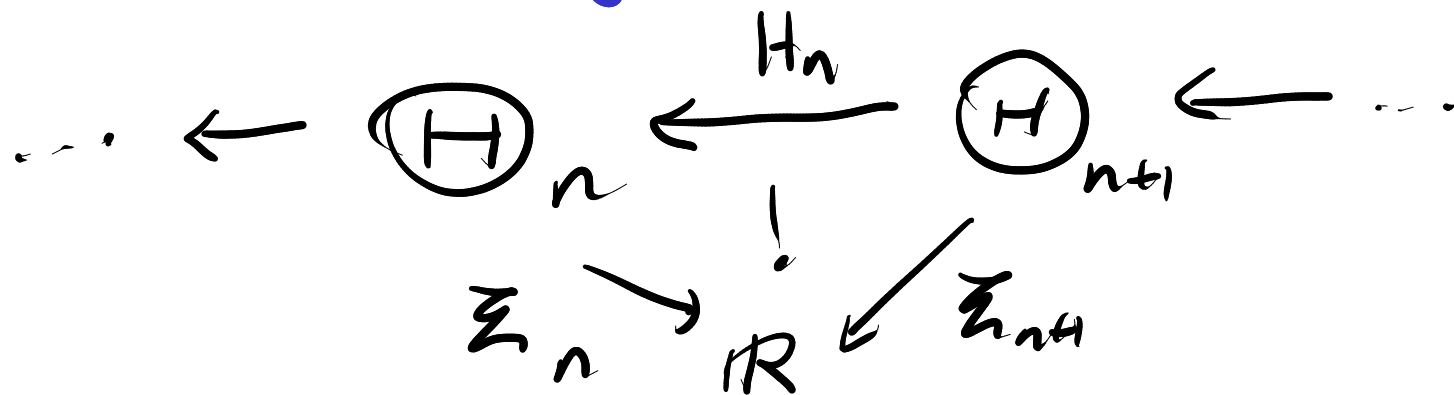


Conditional expectations

1. unique a.s.

2. fundamental to modern Probability, eg.:

a martingale



s.t. $\xi_n = \mathbb{E}[\xi_{n+1} | H_n = \cdot]$

Thm (Existence)

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

- When (Ω, λ) is separable

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

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

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

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Discrete model

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

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

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

$C_{\mu}[E] := \sum_{x \in E} \mu x$ $\delta_x := \lambda x'. \begin{cases} x = x' : 0 \\ x \neq x' : 1 \end{cases}$

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

Full model

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

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

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

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

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

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