

From Classical Channels Towards Abstract Models of Computation

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ISR

Oxford 2011

Work partially supported by ONR

Overview

- Early work: Woodcock & Roscoe (94?),
Lowe (95), Ryan & Schneider...
- Quantitative Information Flow
 - Looping constructs (Malacaria)
 - Min-entropy, Min-capacity (Smith)
- *Goal*: Understand capacity from domain-theoretic, abstract perspective
- Peter Shor: *“Capacity is the most important statistic about a channel”*

Plan of the Talk

Classical channels

- Capacity from binary to n-ary channels
- Domain theory and generalization of Jensen's Inequality
- Categorical properties of inputs, outputs and channels
- Lifting results to abstract models of computation

Channels

- Classical Discrete, Memoryless Channel (DMC)
 - Noisy, lossless
 - Each input produces a probability distribution on the outputs.
 - Capacity gives maximum rate of reliable transmission

Channel Capacity

$C : X \longrightarrow \text{PROB}(Y)$ noisy, lossless channel

$$(\forall y \in Y) \sum_{x \in X} p(y|x) = 1$$

$C = (p(y|x))$ — $|X| \times |Y|$ -stochastic matrix

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$\text{ST}(n)$ — Monoid of $n \times n$ -stochastic matrices

The Binary Case

Martin, Allwein & Moskowitz:

- Binary channels: $M = \begin{bmatrix} a & 1 - a \\ b & 1 - b \end{bmatrix}$
- $M \longleftrightarrow (a, b) \in [0, 1] \times [0, 1]$
- $\text{ST}(2)$ – 2×2 stochastic matrices
- $\mathcal{N} = \{(a, b) \mid a \geq b\}$ – lower triangle in square
– submonoid of $\text{ST}(2)$

Binary Channels

- Capacity of a binary channel

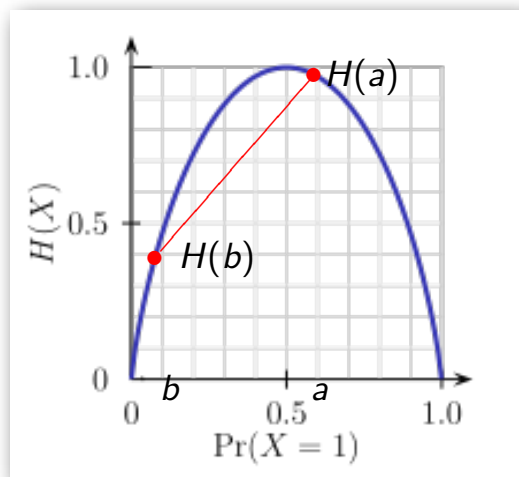
$$M = \begin{bmatrix} a & 1 - a \\ b & 1 - b \end{bmatrix}$$

Binary Channels

- Capacity of a binary channel

$$M = \begin{bmatrix} a & 1 - a \\ b & 1 - b \end{bmatrix}$$

$$\text{Cap}(M) = \sup_{x \in [0,1]} H(xa + (1-x)b) - xH(a) - (1-x)H(b)$$



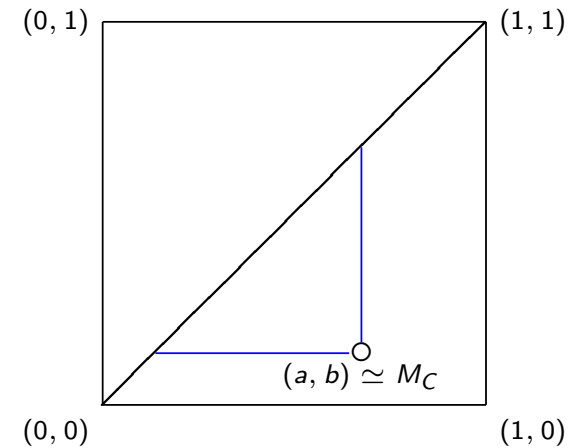
where $H(r) = r \log r - (1 - r) \log(1 - r)$

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- Capacity of a binary channel

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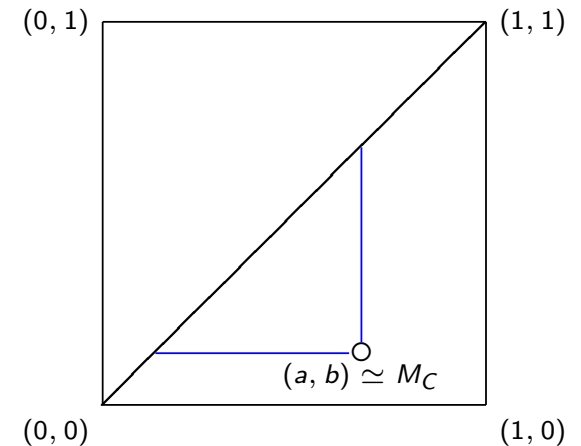
$(a, b) \mapsto [b, a]: \mathcal{N} \rightarrow (\mathbf{I}([0, 1]), \supseteq)$ order isomorphism

$$(a, b) \leq (a', b') \iff (a, b) \supseteq (a', b')$$

– defines domain structure on \mathcal{N}

Cap: $\mathcal{N} \rightarrow [0, 1]^{op}$ measures \mathcal{N}

Note: $ST(2)/H(1) \simeq \mathcal{N}$



Topology

$f: \mathbb{R} \rightarrow \mathbb{R}$ convex if $f(r \cdot x + (1 - r)y) \leq r \cdot f(x) + (1 - r) \cdot f(y)$.

Jensen's Inequality: If X is a random variable and f is convex, then $E(f(X)) \geq f(E(X))$, & $E(f(X)) = f(E(X)) \Rightarrow f$ constant.

Topology

K – compact, convex subset of a locally convex TVS

$f: K \rightarrow \mathbb{R}$ strictly concave if

$$f(r \cdot x + (1 - r)y) > r \cdot f(x) + (1 - r) \cdot f(y).$$

Proposition: For $f: K \rightarrow \mathbb{R}$ TAE:

- f is strictly concave.
- $\forall (r_1, \dots, r_n) \in [0, 1]^n, \forall (k_1, \dots, k_n) \in K^n$
 $\sum_i r_i = 1 \Rightarrow f(\sum_i r_i k_i) > \sum_i r_i f(k_i).$

Corollary: $M \in \text{ST}(n)$, $(r_1, \dots, r_n) \in (0, 1)^n$, $\sum_i r_i = 1$
implies $I(pM; p) = H(pM) - \sum_{i \leq n} p(i)H(M(i)) > 0.$

Domain Theory

P — partially ordered set

$D \subseteq P$ *directed* if $\forall F \subseteq D$ finite, $\exists d \in D . F \subseteq \downarrow d$

P *directed complete* if every directed subset has a supremum *in* P

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P directed complete if every directed subset has a supremum in P

$x, y \in P$, x approximates y ($x \ll y$) iff $\forall D \subseteq P$ directed,

$y \leq \sqcup D \Rightarrow (\exists d \in D) x \leq d$. $\Downarrow y = \{x \mid x \ll y\}$

P continuous if $(\forall y \in P) \Downarrow y$ is directed and $y = \sqcup \Downarrow y$

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Examples: 1. $(\mathcal{P}(X), \subseteq)$; $A \ll B$ iff A is finite

2. X compact, T_2 . $(\Gamma(X), \supseteq)$; $C \ll C'$ iff $C' \subseteq C^\circ$.

3. $K \subseteq \mathbb{R}^n$ compact, convex. $(\text{Con}(K), \supseteq)$; $C \ll C'$ iff $C' \subseteq C^\circ$.

Domains and Topology

P a dcpo. $U \subseteq P$ Scott open if

1. $U = \uparrow U$, and
2. $(\forall D \subseteq P \text{ directed}) \sqcup D \in U \Rightarrow D \cap U \neq \emptyset$.

Basic Results: 1. $\uparrow x = \{y \mid x \ll y\}$ is basis for Scott topology on a domain.

2. P a domain implies P is sober in the Scott topology.

3. $f: P \rightarrow Q$ is Scott continuous iff f is monotone and preserves sups of directed sets.

Domains and Topology

Lawson topology: common refinement of Scott topology with weak lower topology – $\{P \setminus \uparrow F \mid F \subseteq P \text{ finite}\}$.

Lawson topology on a domain is T_2 ; P *coherent* if it is compact.

Examples: 1. $(\mathcal{P}(X), \subseteq)$.

2. $(\Gamma(X), \supseteq)$ — Lawson is Vietoris topology.

3. $K \subseteq \mathbb{R}^n$ compact, convex. $(\text{Con}(K), \supseteq)$ coherent.

$$\text{Con}_n(K) = \{\overline{\text{conv}}(F) \mid \emptyset \neq F \subseteq K, \& \ |F| \leq n\}.$$

Domains and Convexity

$$\Delta^k = \{(r_1, \dots, r_k) \in [0, 1]^k \mid \sum_{i \leq k} r_i = 1\} \simeq \text{Prob}(\underline{k})$$

$K \subseteq \mathbb{R}^m$ compact convex, $f: K \rightarrow \mathbb{R}$ concave

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$$(\forall \vec{r} \in \Delta^k, \forall \vec{x} \in K^k) \phi_{\vec{r}}(\vec{x}) = \sum_{i \leq n} r_i x_i$$

$$\begin{array}{ccc}
 K^k & \xrightarrow{f^n} & \mathbb{R}^k \\
 \phi_{\vec{r}} \downarrow & \geq & \downarrow \phi_{\vec{r}} \\
 K & \xrightarrow{f} & \mathbb{R}
 \end{array}$$

Domains and Convexity

Proposition: Let $K \subseteq \mathbb{R}^m$ compact, convex, and $f: K \rightarrow \mathbb{R}_+$ continuous and concave. Then $\hat{f}: (Con_n(K), \supseteq) \rightarrow \mathbb{R}_+$ by

$$\hat{f}(\overline{\text{conv}}(\{x_1, \dots, x_k\})) = \sup_{(r_1, \dots, r_k) \in \Delta^k} f\left(\sum_{i \leq k} r_i x_i\right) - \sum_{i \leq k} r_i f(x_i)$$

is (Lawson) continuous and monotone.

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is (Lawson) continuous and monotone.

Corollary: For each $n \geq 1$, $\text{cap}: (Con_n(\text{Prob}(n)), \supseteq) \rightarrow \mathbb{R}_+^{op}$ by

$$\text{cap}(\overline{\text{conv}}(\{x_1, \dots, x_k\})) = \sup_{(r_1, \dots, r_k) \in \Delta^k} H\left(\sum_{i \leq k} r_i x_i\right) - \sum_{i \leq k} r_i H(x_i)$$

is (Lawson) continuous and strictly monotone.

On Measurements

$m: P \rightarrow [0, \infty)^{op}$ measures the content at $x \in P$ if $\forall U \subseteq P$ Scott open

$$x \in U \Rightarrow (\exists \epsilon > 0) m_\epsilon(x) \subseteq U$$

where $m_\epsilon(x) = \{y \leq x \mid m(y) < m(x) + \epsilon\}$. m measures P if m measures P at each $x \in P$.

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Example: $\mathbb{I}([0, 1]) = (\{[a, b] \mid a \leq b \in [0, 1]\}, \supseteq)$,

$$m([a, b]) = b - a.$$

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Fact: $f: P \rightarrow Q$ Scott continuous, P, Q domains \Rightarrow

f is proper iff $f^{-1}(\uparrow y) \subseteq P$ is compact $\forall y \in Q$.

Proposition: $m: P \rightarrow [0, \infty)^{op}$ Scott continuous, P domain, m proper at $x \in P$. TAE:

1. m measures the content at x .
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In particular, if m is Scott continuous and proper, then m measures P iff m is strictly monotone.

On Measurements

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For each $n \geq 1$, $\text{cap}: (Con_n(\text{Prob}(\underline{n})), \supseteq) \rightarrow \mathbb{R}_+^{op}$

measures $(Con_n(\text{Prob}(\underline{n})), \supseteq)$ at $\{\{x\} \mid x \in \text{Prob}(\underline{n})\}$.

Relating *cap* to *Cap*

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$$\begin{aligned} C \in \text{ST}(n) \Rightarrow \text{Cap}(C) &= \sup_{p \in \text{PROB}(\underline{n})} H(pC) - H(pC | p) \\ &= \sup_{p \in \text{PROB}(\underline{n})} H(pC) - \sum_{i \leq n} p(i) H(C(i)) \end{aligned}$$

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$$C \leq C' \Leftrightarrow C(\text{PROB}(\underline{n})) \supseteq C'(\text{PROB}(\underline{n})) \implies \text{Cap}(C) \geq \text{Cap}(C')$$

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$$\begin{aligned} C \equiv C' &\Leftrightarrow C(\text{PROB}(\underline{n})) = C'(\text{PROB}(\underline{n})) \\ &\Leftrightarrow S(n) \circ C = S(n) \circ C' \end{aligned}$$

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- Theorem:**
- $(\text{Con}_n(\text{Prob}(m)), \supseteq)$ is a domain.
 - $\text{cap}: (\text{Con}_n(\text{Prob}(m)), \supseteq) \rightarrow \mathbb{R}_+^{op}$ is a measurement
 - $(\text{ST}(m)/\equiv, \leq) \simeq (\text{Con}_n(\text{Prob}(m)), \supseteq)$ *qua* domain.
 - $C \equiv C' \implies \text{Cap}(C) = \text{Cap}(C')$

Where Channels Come From

Monad I : $\text{Prob} : \text{Comp} \rightarrow \text{CompConv}_{LC}$

Comp – Compact, T_2 spaces, continuous maps

CompConv_{LC} – compact, convex $\subseteq TVS_{LC}$, affine maps

Barycentric spaces : $\epsilon_Y : \text{Prob}(Y) \rightarrow Y$

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$$\text{Prob}(X)_s = \left\{ \sum_{i \leq n} r_i \delta_{x_i} \mid x_i \in X, \sum_i r_i = 1 \right\}$$

$\text{Prob}(X) = \langle \text{Prob}(X)_s \rangle$ where $\text{PROB}(X) \subseteq \mathcal{M}(X) = C(X, \mathbb{R})^*$

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In the Kleisli category :

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$$\text{ST}(m, n) = \text{Aff}(\text{PROB}(\underline{m}), \text{PROB}(\underline{n})) \simeq \{ \hat{C} \mid C : \underline{m} \rightarrow \text{PROB}(\underline{n}) \}$$

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$$\underline{m} \rightarrow \text{Prob}(\underline{n}) \simeq \text{Aff}(\text{Prob}(\underline{m}), \text{Prob}(\underline{n})) \Leftrightarrow \text{ST}(m, n)$$

Monad II : $\text{Prob} : \text{CMon} \rightarrow \text{CAM}_{LC}$

CMon – Compact, T_2 monoids, continuous monoid maps

CAM_{LC} – compact, convex, monoids $\subseteq \text{TVS}_{LC}$,
affine, monoid homomorphisms

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$$\phi : S \rightarrow \text{PROB}(S) \Leftrightarrow \hat{\phi} : \text{PROB}(S) \rightarrow \text{PROB}(S)$$

$$\text{CMon}(S, \text{PROB}(S)) \Leftrightarrow \text{CAM}_{LC}(\text{PROB}(S), \text{PROB}(S))$$

Where Channels Come From

Monad I : $\text{Prob} : \text{Comp} \rightarrow \text{CompConv}_{LC}$

$$\underline{m} \rightarrow \text{Prob}(\underline{n}) \simeq \text{Aff}(\text{Prob}(\underline{m}), \text{Prob}(\underline{n})) \Leftrightarrow \text{ST}(m, n)$$

Monad II : $\text{Prob} : \text{CMon} \rightarrow \text{CAM}_{LC}$

CMon – Compact, T_2 monoids, continuous monoid maps

CAM_{LC} – compact, convex, monoids $\subseteq \text{TVS}_{LC}$,

affine, monoid homomorphisms

$$\phi : S \rightarrow \text{PROB}(S) \Leftrightarrow \hat{\phi} : \text{PROB}(S) \rightarrow \text{PROB}(S)$$

$$\text{CMon}(S, \text{PROB}(S)) \Leftrightarrow \text{CAM}_{LC}(\text{PROB}(S), \text{PROB}(S))$$

In particular : $\text{ST}(m) = \text{Prob}([\underline{m} \rightarrow \underline{m}])$

$$= \left\{ \sum_{i \leq m} r_i \delta_{f(x_i)} \mid \sum_i r_i = 1 \wedge f : \underline{m} \rightarrow \underline{m} \right\}$$

Where Channels Come From

Monad I : $\text{Prob} : \text{Comp} \rightarrow \text{CompConv}_{LC}$

$$\underline{m} \rightarrow \text{Prob}(\underline{n}) \Leftrightarrow \text{ST}(m, n)$$

Monad II : $\text{Prob} : \text{CMon} \rightarrow \text{CAM}_{LC}$

$$\text{ST}(m) \simeq \text{Prob}([\underline{m} \rightarrow \underline{m}])$$

Adjunction III : $\text{Prob} : \text{CGrp} \rightarrow \text{CAM}_{LC} : H$

$$H(S) = H(1_S) \quad H(\phi) = \phi|_{H(1_S)} : S \rightarrow T$$

CMGrp – Compact groups, continuous group homomorphisms

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Where Channels Come From

Monad I : $\text{Prob} : \text{Comp} \rightarrow \text{CompConv}_{LC}$

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CMGrp – Compact groups, continuous group homomorphisms

CAM_{LC} – compact, convex, monoids $\subseteq \text{TVS}_{LC}$,
affine, monoid homomorphisms

In particular : $\text{DST}(m) = \text{Prob}(S(m))$

More Generally

Monad I : $\text{Prob} : \text{LocComp} \rightarrow \text{CompConv}_{LC}$

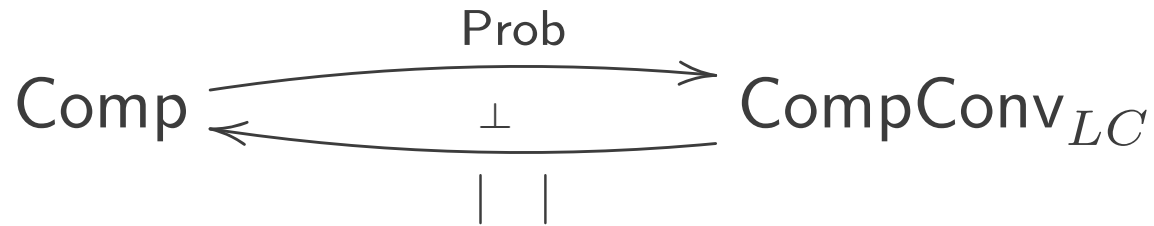
$$X \mapsto \text{Prob}(X)$$

Monad II : $\text{Prob} : \text{LCMon} \rightarrow \text{CAM}_{LC}$

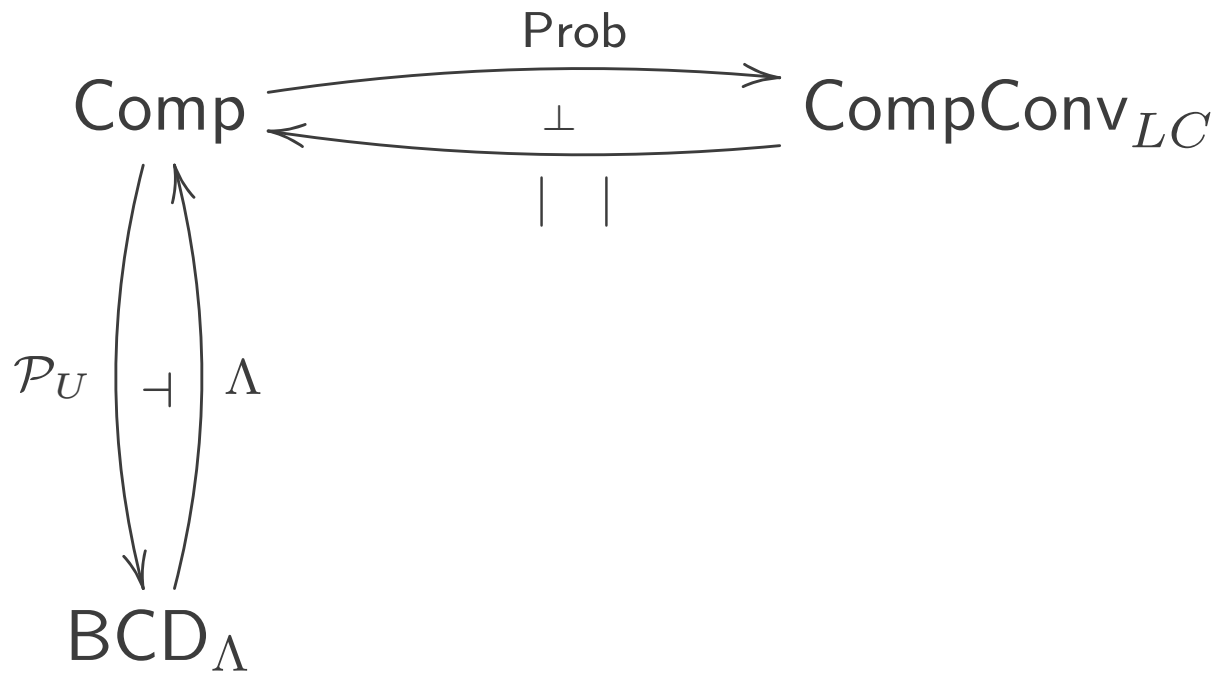
$$S \mapsto \text{Prob}(S)$$

In particular: This works for discrete spaces

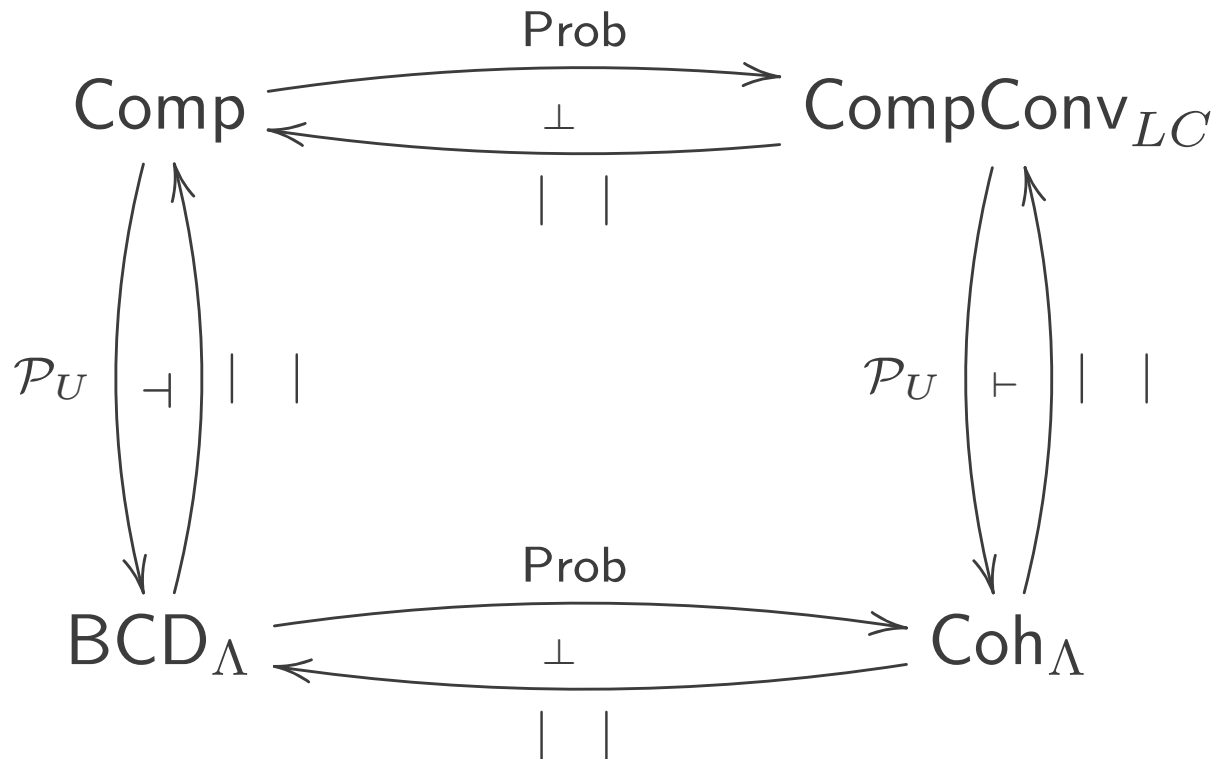
Toward Abstract Models



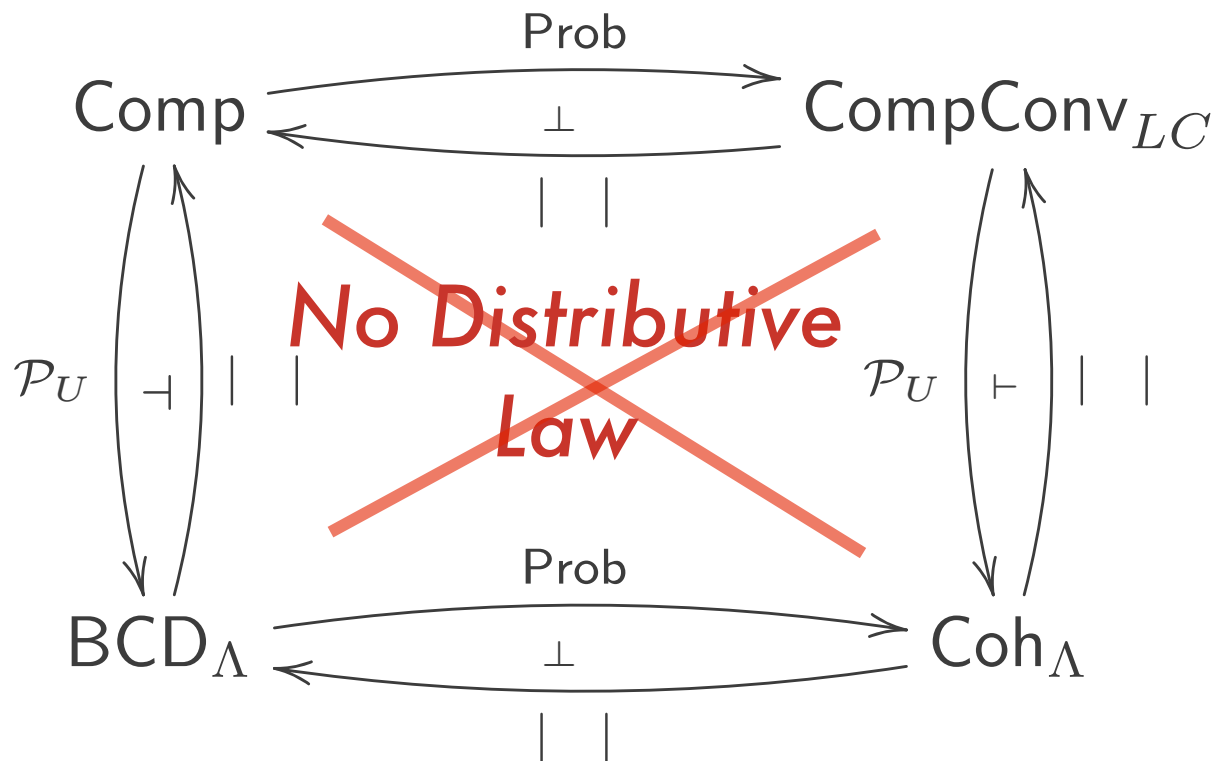
Toward Abstract Models



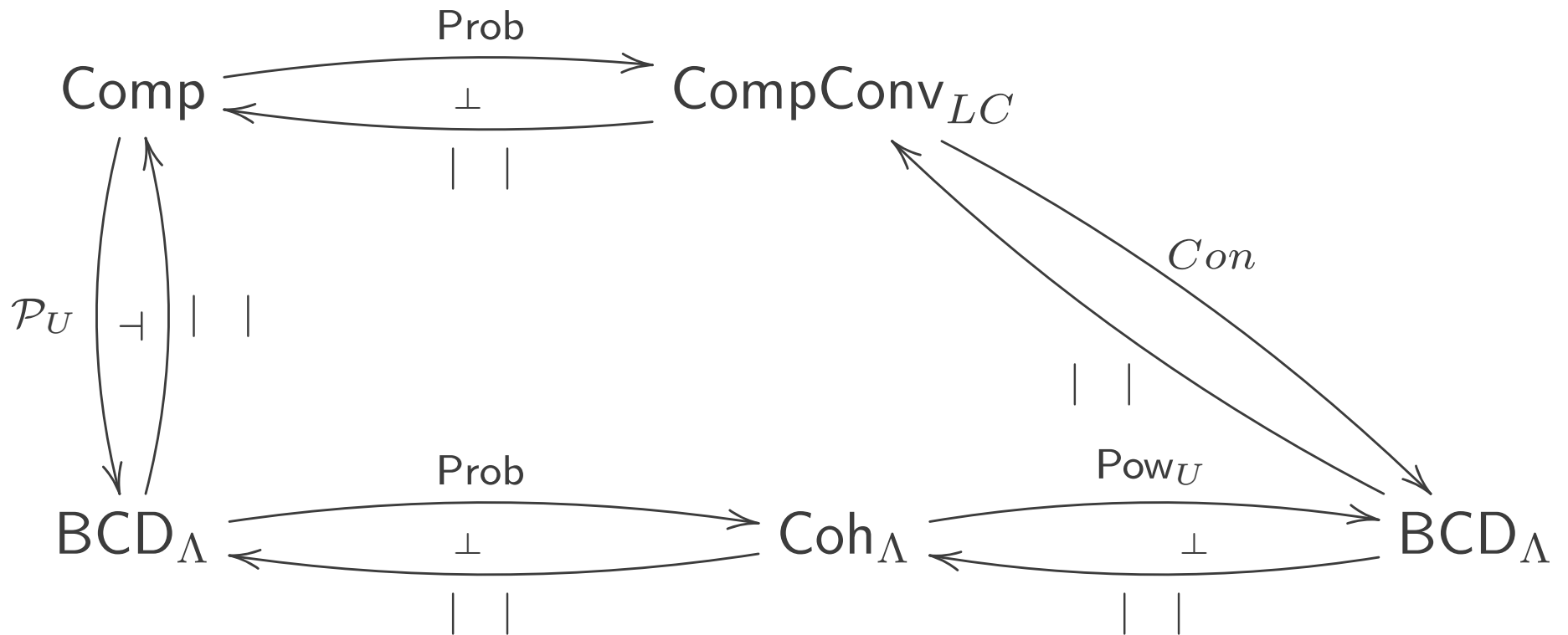
Toward Abstract Models



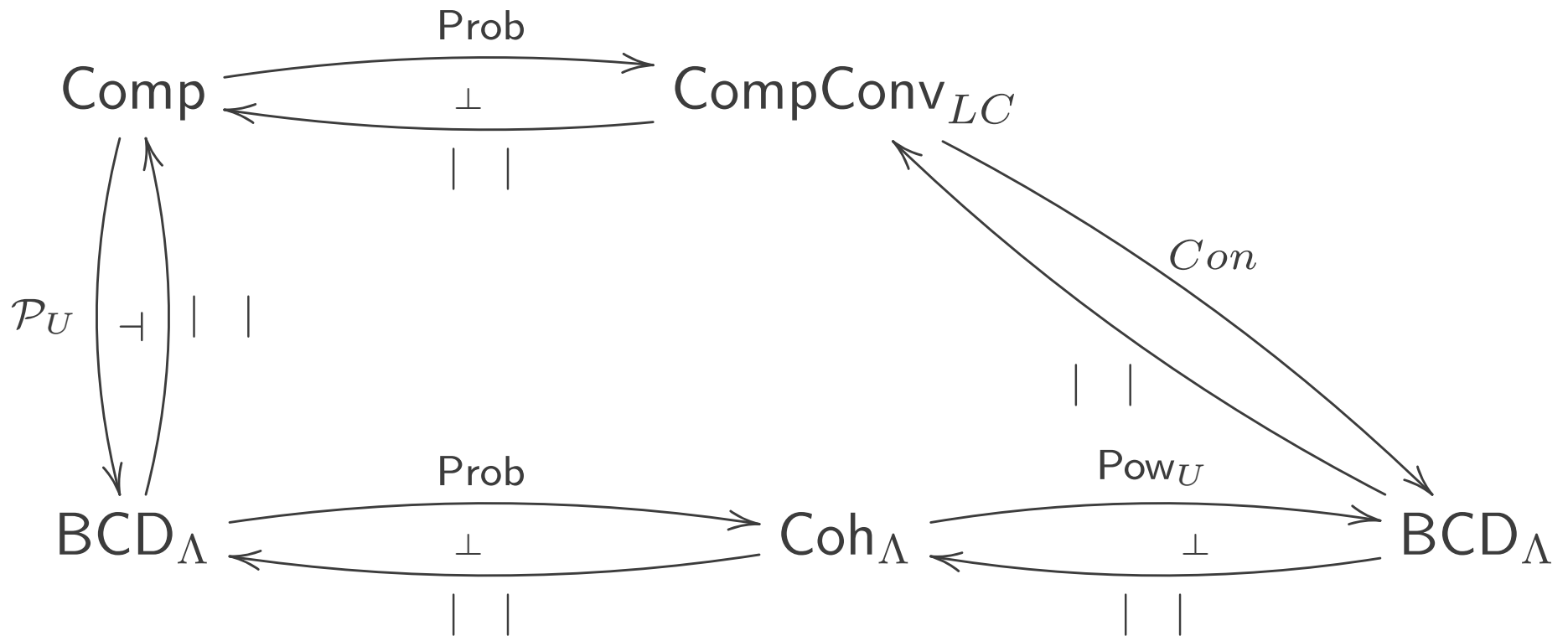
Toward Abstract Models



Toward Abstract Models



Toward Abstract Models



Thank You!!

Questions?