

# Universal Representations for AI

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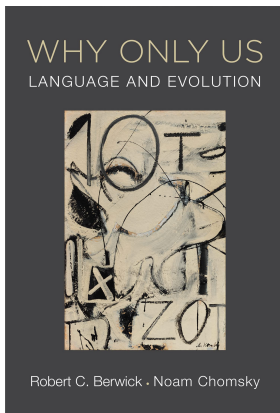
UMassAmherst  
College of Information  
& Computer Sciences

- 1 Motivation
- 2 (Higher-Order) Category Theory
- 3 Universal Decision Models
- 4 Structure Discovery as Horn Filling of Simplicial Objects

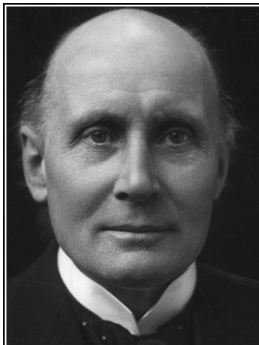
# Recent Papers on Universal AI

- Universal Decision Models
- On The Universality of Diagrams for Causal Inference and the Causal Reproducing Property
- Categoroids: Universal Conditional Independence
- **Unifying Causal Inference and Reinforcement Learning using Higher-Order Category Theory**
- On Arxiv or my UMass web page:  
[www.cics.umass.edu/~mahadeva](http://www.cics.umass.edu/~mahadeva)

# Language and Thought



# The Importance of Abstraction

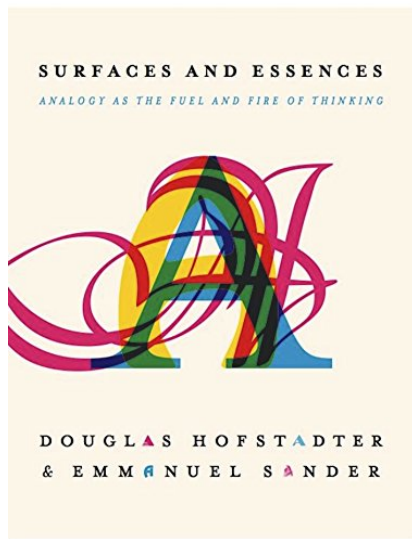


Civilization advances by extending the number of important operations which we can perform without thinking about them. Operations of thought are cavalry charges in a battle - they are limited in number, they require fresh horses, and must only be made at decisive moments.

— *Alfred North Whitehead* —

AZ QUOTES

# Analogy and Metaphor in Language



# Emerging Directions in Computing

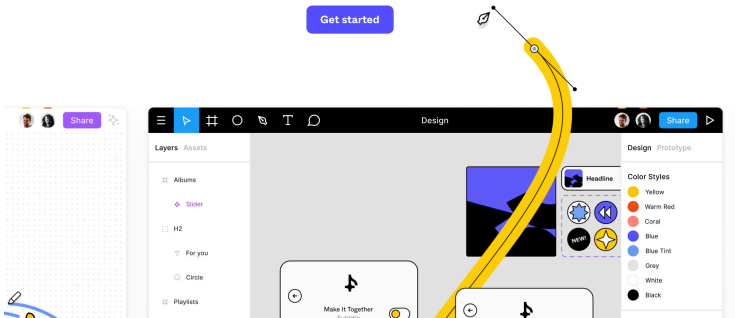
- Technological advances have greatly increased our ability our ability to perform tasks without “thinking” about them
- Computing in the cloud has decentralized collaborative activities and made remote work a reality
- Adobe just announced it will acquire Figma for \$20 billion! (<https://www.figma.com>)
- Blockchain, the “Internet of Money”, will redefine computing and economics in the 21st century

# Collaborative Design using Figma

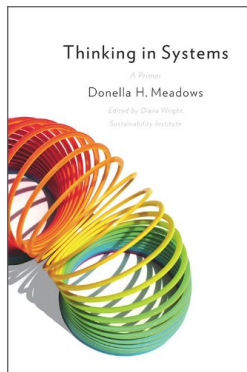
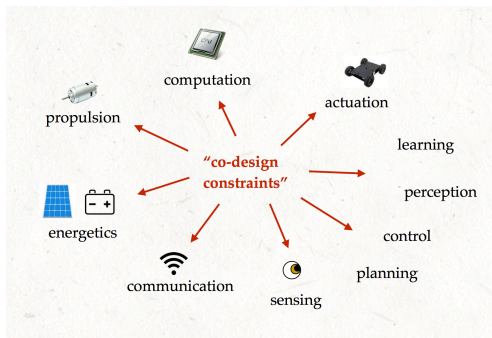
Nothing great is  
**brainstormed** alone.

Figma connects everyone in the design process  
so teams can deliver better products, faster.

Get started



# The Science of Collaborative Design



<https://co-design.science/papers/>

# Category Theory: The Power of Abstraction

- Objects are defined by their interactions
- Functors define analogies across categories
- Natural transformations between functors give rise to universal representations
- A huge library of design tools!
  - Pullbacks, pushforwards, (co)equalizers
  - Limits and colimits
  - Kan extensions
  - Braided monoidal categories
  - Cospans, operads, props, ...

# Category Theory in AI/CS/ML

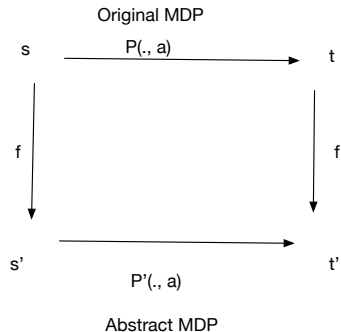
- Long been a foundation for programming languages (e.g., Haskell is widely used to implement blockchains such as Cardano)
- Uniform Manifold Approximation and Projection (<https://umap-learn.readthedocs.io/en/latest/>): widely used for visualizing high-dimensional data
- Clustering as a Functor (Gunnar Carlsson): overcomes Kleinberg's impossibility theorem.
- Seven Sketches in Compositionality (MIT Text on applied category theory): <https://arxiv.org/abs/1803.05316>
- **Offers unparalleled power to abstract complex objects and their interactions**

# Reinforcement Learning

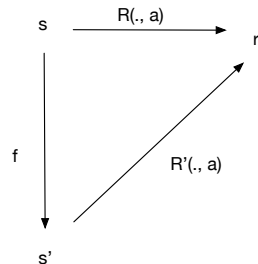
Markov Decision Processes:  $\langle S, A, \Psi, P, R \rangle$

- $S$  is a discrete set of states
- $A$  is the discrete set of actions
- $\Psi \subset S \times A$  is the set of admissible state-action pairs
- $P: \Psi \times S \rightarrow [0, 1]$  is the transition probability function specifying the one-step dynamics of the model
- $R: \Psi \rightarrow \mathbb{R}$  is the expected reward function

# RL as a Category: MDP Homomorphisms



Bisimulation  
Morphism



# MDP Homomorphism

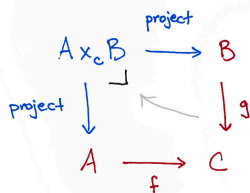
An MDP homomorphism from MDP  $M = \langle S, A, \Psi, P, R \rangle$  to  $M' = \langle S', A', \Psi', P', R' \rangle$ , denoted  $h: M \twoheadrightarrow M'$ , is defined by

- A tuple of surjections  $\langle f, \{g_s | s \in S\} \rangle$
- where  $f: S \twoheadrightarrow S', g_s: A_s \twoheadrightarrow A'_{f(s)}$
- $h((s, a)) = \langle f(s), g_s(a) \rangle$ , for  $s \in S$
- Stochastic substitution property and reward respecting properties below are respected:

$$P'(f(s), g_s(a), f(s')) = \sum_{s'' \in [s']_f} P(s, a, s'') \quad (1)$$

$$R'(f(s), g_s(a)) = R(s, a) \quad (2)$$


# Pullback: Reasoning with Diagrams




"a pullback diagram"

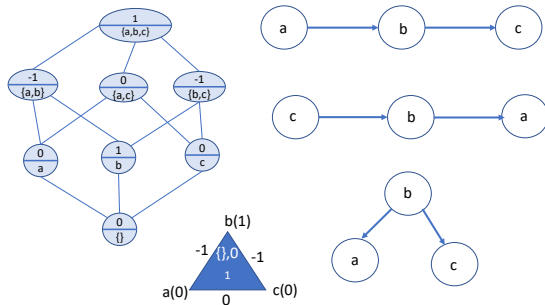
The **pullback** (limit) of the data in **red** is the data in **blue**.

People use this little symbol to say "Hey! Not only does  $A \times_c B$  fit into this diagram, it does so *universally*."

 = the diagram you start with

 = the limit of that diagram

# Category of Causal Models



- Pullback, pushforward: joins and meets
- Initial and terminal objects:  $\emptyset, V$

# Two Functors from MDPs to Graphs

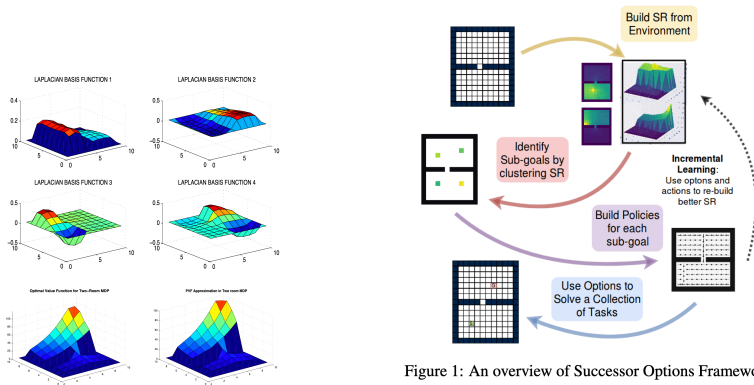


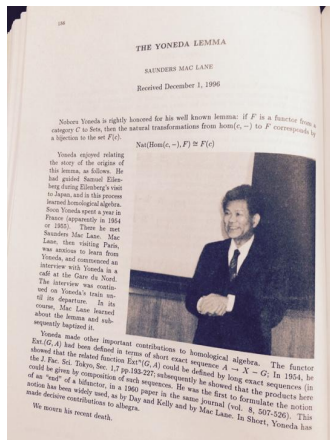
Figure 1: An overview of Successor Options Framework

## Natural Transformations between two Functors

$$\begin{array}{ccc} F(X) & \xrightarrow{F(f)} & F(Y) \\ \eta_X \downarrow & & \downarrow \eta_Y \\ G(X) & \xrightarrow{G(f)} & G(Y) \end{array}$$

# Le Lemme de la Gare du Nord: Yoneda Lemma

$$\mathbf{Hom}_C(X, Y) \simeq \mathbf{Nat}(\mathbf{Hom}_C(-, X), \mathbf{Hom}_C(-, Y))$$



# Adjunctions

$$F: \text{DirGraph} \rightleftarrows \text{Cat} : U$$

$$\text{DirGraph} \xrightarrow{F} \text{Cat}$$

$$G \longmapsto FG$$

a graph



"the free category on the graph G"



- includes identity morphisms at each vertex.
- morphisms are finite paths between vertices
- composition is path concatenation

$$\text{Cat} \xrightarrow{U} \text{DirGraph}$$

$$C \longmapsto UC$$

a category

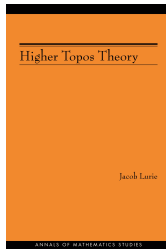


its underlying directed graph



forget all category data and structure except objects (vertices) and morphisms (edges)

# Higher-Order Category Theory

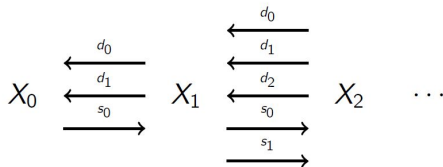
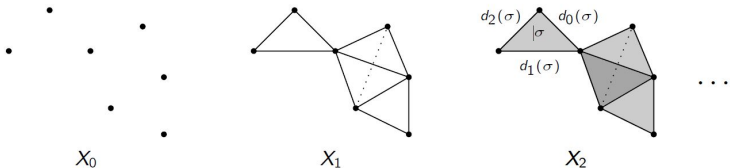


Kerodon

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# Simplicial Objects: Higher-Order Category Theory



# Constructing Simplicial Objects from a Category

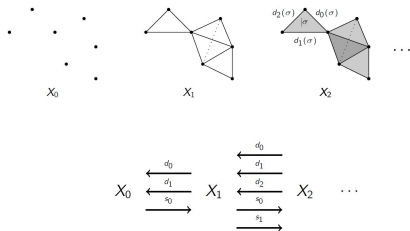
- The **nerve** of a category  $\mathcal{C}$  is the set of composable morphisms of length  $n$ , for  $n \geq 1$ . Let  $N_n(\mathcal{C})$  denote the set of sequences of composable morphisms of length  $n$ .

$$\{C_o \xrightarrow{f_1} C_1 \xrightarrow{f_2} \dots \xrightarrow{f_n} C_n \mid C_i \text{ is an object in } \mathcal{C}, f_i \text{ is a morphism in } \mathcal{C}\}$$

- **Theorem:** The **nerve functor**  $N_\bullet : \mathbf{Cat} \rightarrow \mathbf{Set}$  is fully faithful. More specifically, there is a bijection  $\theta$  defined as:

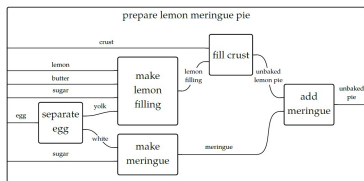
$$\theta : \mathbf{Cat}(\mathcal{C}, \mathcal{C}') \rightarrow \mathbf{Set}_\Delta(N_\bullet(\mathcal{C}), N_\bullet(\mathcal{C}'))$$

# Adjunctions between Categories and Simplicial Objects

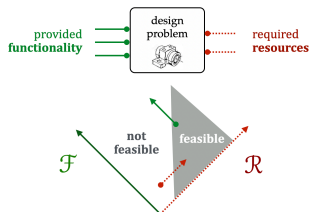


- Category to Simplicial Object: Nerve functor is a full and faithful embedding
- Simplicial object to Category: Lossy functor

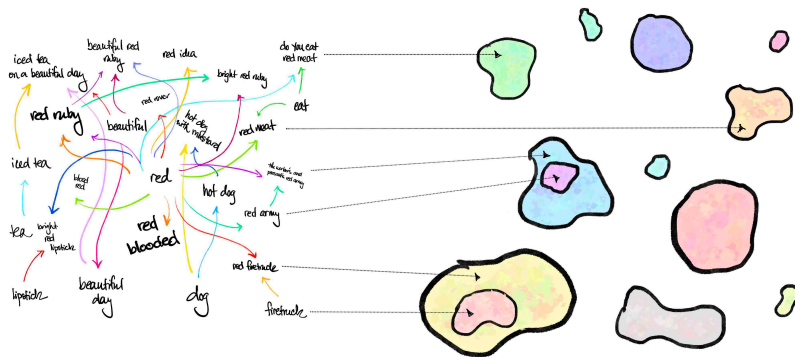
# Braided Monoidal Categories (Censi, Fong, Spivak)



$$dp: \mathcal{F}^{\text{op}} \times \mathcal{R} \rightarrow_{\text{Pos}} \text{Bool}$$



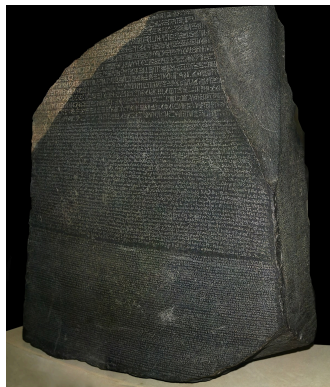
# Category Theory and Language: Words and Meaning



<https://www.math3ma.com/categories/category-theory>

<https://arxiv.org/abs/2106.07890>

# Deciphering Ancient Language: Indus Script



# Past vs. Future



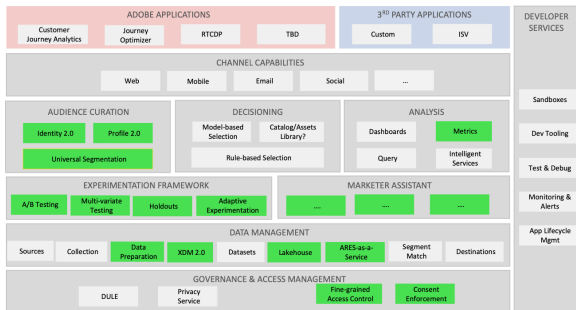
# Challenge: Universal Decision Making

- We reason causally to understand our world
- We compete to gain advantage in commerce, sports and war
- We often act without complete information, but try to make better decisions over time

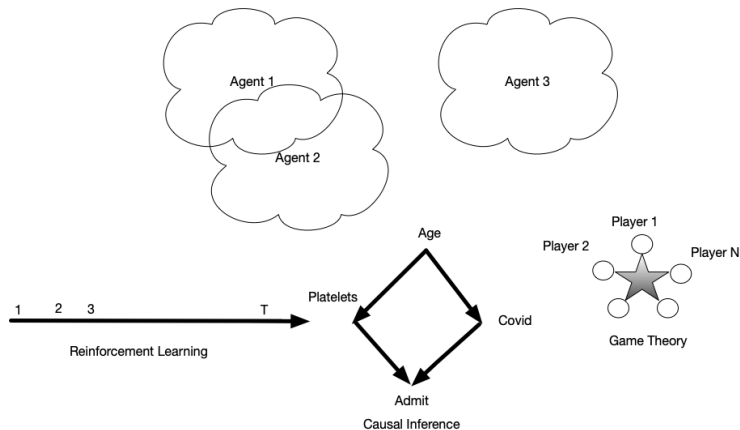
# Adobe Experience Platform: Datamining the Past

## AEP 2.0 Services

AEP 2.0 Strategic initiatives



# Universal Decision Models: Controlling the Future



# Category of Decision Problems

- Define categories of decision objects: causal models, RL models, Nash games, etc.
- Construct functors from one decision category to another
- Build universal representations for structure discovery

# Universal Decision Models

Decision Objects:  $\langle A, (\Omega, \mathcal{B}, P), (U_\alpha, \mathcal{F}_\alpha, \mathcal{I}_\alpha)_{\alpha \in A} \rangle$ :

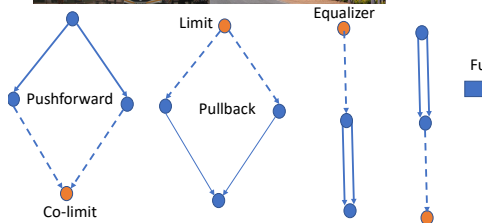
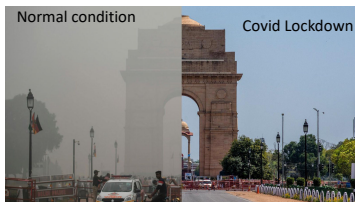
- $A$  describes a finite universe of decision points (e.g., in RL, causal inference, or Nash games)
- $(\Omega, \mathcal{B}, P)$  is a probability space
- $(U_\alpha, \mathcal{F}_\alpha)$  is a measurable decision space from which a decision  $u \in U_\alpha$  is chosen by  $\alpha$ .
- Policy of agent  $\alpha$ : any measurable function  $\pi_\alpha : \prod_\beta U_\beta \rightarrow U_\alpha$ .
- Each agent's policy is measurable from its **information field**  $\mathcal{I}_\alpha$ , a subfield of the overall product space  $(\prod_\beta U_\beta, \prod_\beta \mathcal{F}_\beta)$ , to the  $\sigma$ -algebra  $\mathcal{F}_\alpha$ .

# Scaling by Exploiting Conditional Independence

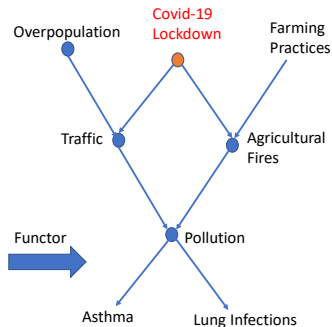
- Markov property: the past is conditionally independent of the future, given the current “state”
- Sufficient statistic:  $(\theta \perp\!\!\!\perp X \mid T(X))$
- Graphoids, Separoids, Imsets: See my Categoroids paper
  - **Separoid**  $(\mathcal{S}, \leq, \perp\!\!\!\perp)$  is a join semi-lattice.
  - **P1:**  $x \perp\!\!\!\perp y \mid x$
  - **P2:**  $x \perp\!\!\!\perp y \mid z \Rightarrow y \perp\!\!\!\perp x \mid z$
  - **P3:**  $x \perp\!\!\!\perp y \mid z$  and  $w \leq y \Rightarrow x \perp\!\!\!\perp w \mid z$
  - **P4:**  $x \perp\!\!\!\perp y \mid z$  and  $w \leq y \Rightarrow x \perp\!\!\!\perp y \mid (z \vee w)$
  - **P5:**  $x \perp\!\!\!\perp y \mid z$  and  $x \perp\!\!\!\perp w \mid (y \vee z) \Rightarrow x \perp\!\!\!\perp (y \vee w) \mid z$

# Universal Causality

Pollution in New Delhi, India



Indexing Category of Abstract Diagrams



Functor  
➡

Co-Equalizer

Actual Causal Model

# Yoneda Lemma Defines Universal Causality

**Causal Reproducing Property:** All causal influences between any two objects  $X$  and  $Y$  in a Universal Causal Model  $\mathcal{M} = \langle \mathcal{C}, \mathcal{X}, \mathcal{I}, \mathcal{O}, \mathcal{E} \rangle$  is reproducible from presheaf functor objects

$$\mathbf{Hom}_{\mathcal{C}}(X, Y) \simeq \mathbf{Nat}(\mathbf{Hom}_{\mathcal{C}}(-, X), \mathbf{Hom}_{\mathcal{C}}(-, Y))$$

# The Density Theorem in the Theory of Sheaves

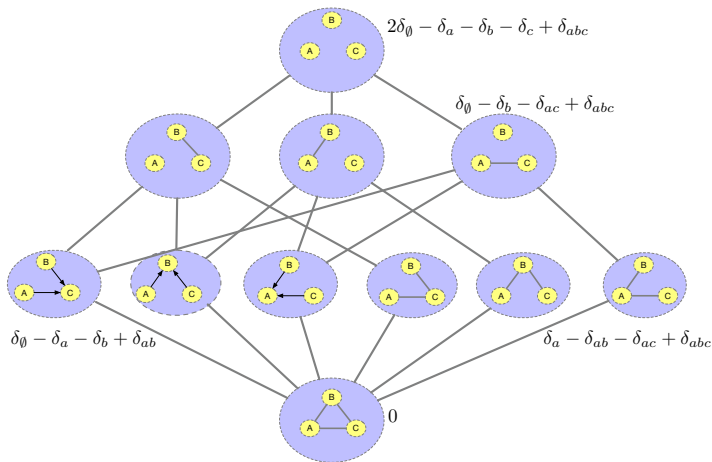
**Universal Causal Theorem:** Given any universal causal model defined as a tuple  $\mathcal{M} = \langle \mathcal{C}, \mathcal{X}, \mathcal{I}, \mathcal{O}, \mathcal{E} \rangle$ , any causal inference in  $\mathcal{M}$  can be represented as a co-limit of a diagram of representable objects in a unique way.

# Structure Discovery by solving Lifting Problems

$$\begin{array}{ccc} A & \xrightarrow{\mu} & X \\ \downarrow f & & \downarrow p \\ B & \xrightarrow{\nu} & Y \end{array}$$

$$\begin{array}{ccc} A & \xrightarrow{\mu} & X \\ \downarrow f & \nearrow h & \downarrow p \\ B & \xrightarrow{\nu} & Y \end{array}$$

# Lifting Problem in Causal Discovery



# Predictive State Representations



|           |              | Tests   |         |          |         |
|-----------|--------------|---|---------|----------|---------|
|           |              | $t_1$   | $\dots$ | $t_j$    | $\dots$ |
| Histories | $\phi = h_1$ | $p(t_1   h_1) \cdot \dots \cdot p(t_j   h_1)$ |         |          |         |
|           | $\vdots$     | $\vdots$                                      |         | $\vdots$ |         |
|           | $h_i$        | $p(t_1   h_i) \cdot \dots \cdot p(t_j   h_i)$ |         |          |         |
|           | $\vdots$     |   |         |          |         |

# Predictive State Representations

- Finite set of actions  $A$  and observations  $O$ .
- A *history*: sequence of actions and observations  
 $h = a_1 o_1 \dots a_k o_k$ .
- A *test*: possible sequence of future actions and observations  
 $t = a_1 o_1 \dots a_n o_n$ .
- $P(t|h)$  is a prediction test  $t$  will succeed from history  $h$ .
- State  $\psi$ : a vector of predictions of *core tests*  $\{q_1, \dots, q_k\}$ .
- The prediction vector  $\psi_h = \langle P(q_1|h) \dots P(q_k|h) \rangle$  is a sufficient statistic. The predictive state of a PSR is denoted  $\Psi$ .

# Category of PSRs

A **PSR homomorphism** from a PSR  $\Psi$  to another PSR  $\Psi'$  is defined as:

- A tuple of surjections  $\langle f, v_\psi(a) \rangle$
- where  $f: \Psi \rightarrow \Psi'$  and  $v_\psi: A \rightarrow A'$  for all prediction vectors  $\psi \in \Psi$
- such that

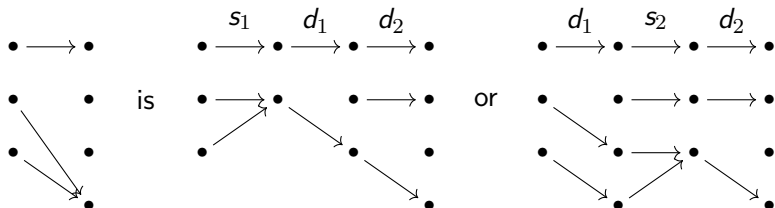
$$P(\psi' | f(\psi), v_\psi(a)) = P(f^{-1}(\psi') | \psi, a) \quad (3)$$

for all  $\psi' \in \Psi, \psi \in \Psi, a \in A$ .

# Category of Ordinal Numbers

- Category  $\Delta$ : objects are non-empty ordinals  $[n] = \{0, 1, \dots, n\}$
- Arrows: non-decreasing maps  $f: [m] \rightarrow [n]$ .
- Elementary injections  $d_i: [n] \rightarrow [n+1]$ , which omits  $i \in [n]$
- Elementary surjections  $s_i: [n] \rightarrow [n-1]$ , which repeats  $i \in [n]$ .
- Fundamental simplex  $\Delta([n])$ : Yoneda functor  $\Delta(-, [n])$ .

# Elementary Surjections and Injections



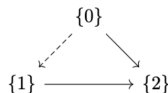
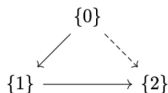
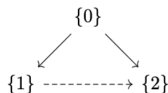
# Simplicial Objects are Functors!

- Simplicial objects over sets:  $X[n] = X_n : [n] \rightarrow X$
- $X_0$  is a set of objects:  $f : [0] = \{0\}$  to  $X$
- Arrows are in  $X_1$ : functors mapping  $[1] = \{0, 1\}$  and its non-identity morphism  $0 \rightarrow 1$  to  $X$ .
- 2-simplices  $X[2]$ : functor mapping  $[2] = \{0, 1, 2\}$ , with its non-identity morphisms  $0 \rightarrow 1, 1 \rightarrow 2, 0 \rightarrow 2$  into a category.
- Yoneda Lemma: An  $n$ -simplex  $x \in X_n$  is defined by the presheaf functor  $\Delta[n] \rightarrow X$ .

# Structure Discovery by Filling Horns of Simplicial Objects

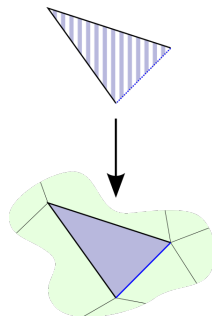
The **Horn**  $\Lambda_i^n : \Delta^{op} \rightarrow \mathbf{Set}$  is defined as

$$(\Lambda_i^n)([m]) = \{\alpha \in \mathbf{Hom}_{\Delta}([m], [n]) : [n] \not\subseteq \alpha([m]) \cup \{i\}\}$$



# Solving Lifting Problems with Kan Fibrations

$$\begin{array}{ccc}
 \Lambda_i^n & \xrightarrow{\sigma_0} & X \\
 \downarrow & \nearrow \sigma & \downarrow f \\
 \Delta^n & \xrightarrow{\bar{\sigma}} & S
 \end{array}$$



# Higher-Order Category Theory

- Weak Kan complexes
- Quasicategories
- $\infty$ -categories

# Universal PSR Theorems

**Theorem:** The **nerve functor** defined by a PSR  $N_{\bullet} : \mathbf{Cat}_{PSR} \rightarrow \mathbf{Set}$  is fully faithful. More specifically, there is a bijection  $\theta$  defined as:

$$\theta : \mathbf{Cat}(\mathcal{C}_{PSR}, \mathcal{C}'_{PSR}) \leftrightarrow \mathbf{Set}_{\Delta}(N_{\bullet}(\mathcal{C}_{PSR}), N_{\bullet}(\mathcal{C}'_{PSR}))$$

**Theorem:** The **nerve functor** defined by a PSR  $N_{\bullet} : \mathbf{Cat}_{PSR} \rightarrow \mathbf{Set}$  forms a quasicategory.

# Singular Homology Group Defined by a Topological Space

For any topological space  $X$ , the **singular homology groups**  $H_*(X; \mathbf{Z})$  are defined as the homology groups of a chain complex

$$\dots \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_2(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_1(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_0(X))$$

where  $\mathbf{Z}(\text{Sing}_n(X))$  denotes the free Abelian group generated by the set  $\text{Sing}_n(X)$  and the differential  $\partial$  is defined on the generators by the formula

$$\partial(\sigma) = \sum_{i=0}^n (-1)^i d_i \sigma$$

# Classifying Space of a PSR

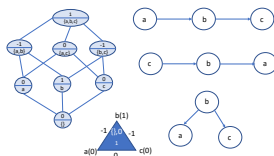
- The **classifying space** of a PSR  $\mathcal{C}$  is the topological space defined by its nerve functor  $|N_{\bullet}(\mathcal{C})|$ .
- For any topological space defined by a PSR  $|\mathcal{N}_{\bullet}(\mathcal{C})|$ , the **singular homology groups**  $H_*(|\mathcal{N}_{\bullet}(\mathcal{C})|; \mathbf{Z})$  are defined as the homology groups of a chain complex

$$\dots \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_2(|\mathcal{N}_{\bullet}(\mathcal{C})|)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_1(|\mathcal{N}_{\bullet}(\mathcal{C})|)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_0(|\mathcal{N}_{\bullet}(\mathcal{C})|))$$

where  $\mathbf{Z}(\text{Sing}_n(|\mathcal{N}_{\bullet}(\mathcal{C})|))$  denotes the free Abelian group generated by the set  $\text{Sing}_n(|\mathcal{N}_{\bullet}(\mathcal{C})|)$  and the differential  $\partial$  is defined on the generators by the formula

$$\partial(\sigma) = \sum_{i=0}^n (-1)^i d_i \sigma$$

# Singular Homology Defined by a Causal Model



$$\mathbf{Z}(\text{Sing}_3(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_2(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_2(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_1(X)) \xrightarrow{\partial} \mathbf{Z}(\text{Sing}_0(X))$$

$$\partial(\sigma) = \sum_{i=0}^3 (-1)^i d_i \sigma$$

$$\sigma_n : |\Delta^n| \rightarrow X \text{ where } |\Delta^n| = \{t_0, \dots, t_n\} \in [0, 1]^n : \sum_i t_i = 1\}$$

# Summary: Universal AI

- How to unify different models of decision making?
- How to build universal representations?
- How to solve the universal structure discovery problem?
- (Higher-order) category theory provides answers