

What is a pattern? An introduction to a theory of grounded computation

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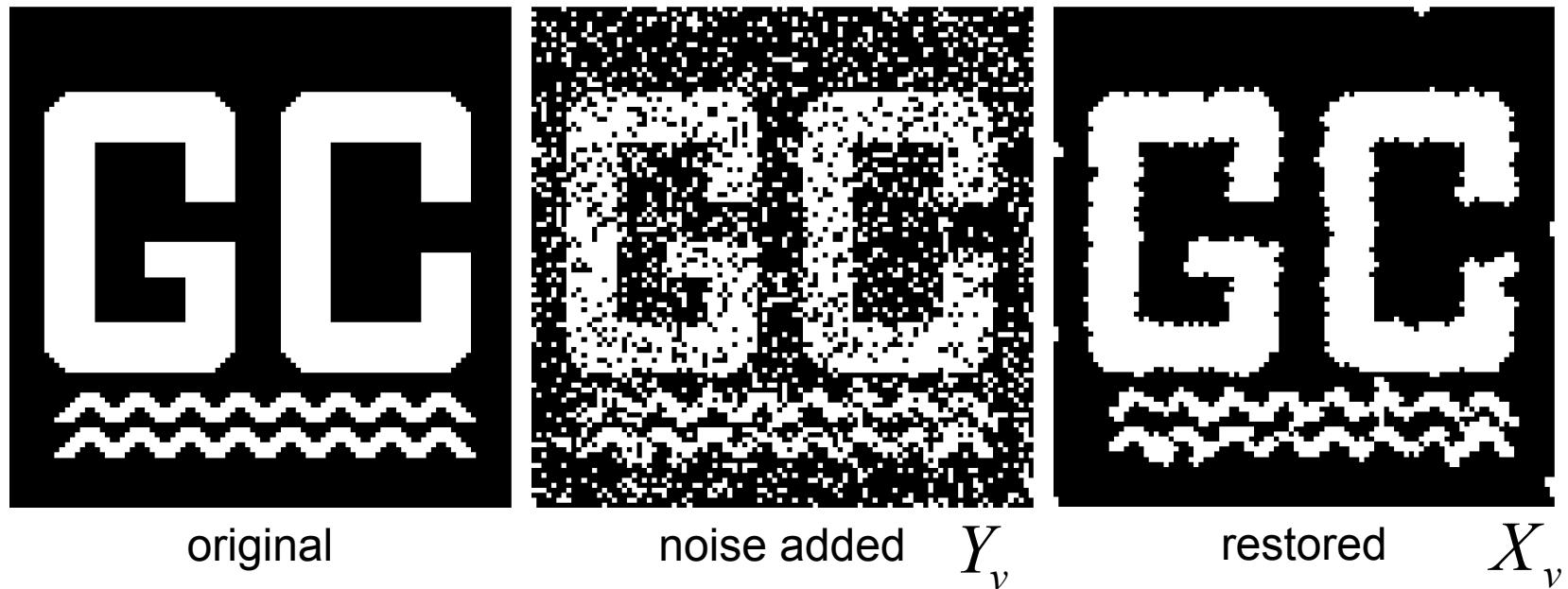


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Motivation

Example: Binary Restoration



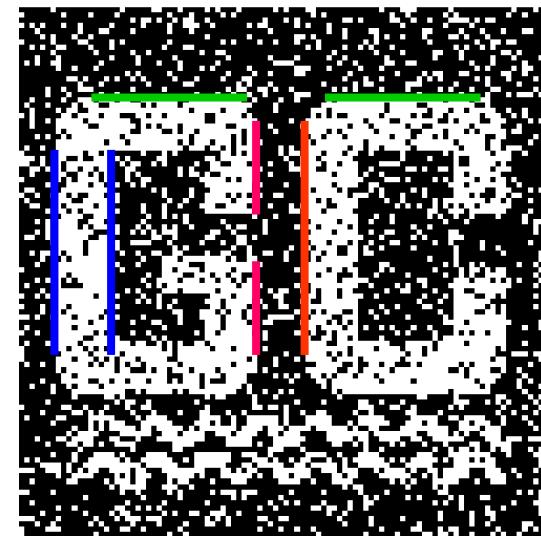
Greig, Porteous, and Seheult '89

$$E(X) = \sum_{v \in V} \lambda |Y_v - X_v| + \sum_{(u,v) \in E} |X_u - X_v|$$

- This is the optimal solution, given the smoothing prior.
- But it does not look perfect.

Higher-order Relationships

- Boundary smoothness
- Linearity
- Collinearity
- Parallelism



Higher-order Relationships

- Boundary smoothness
- Linearity
- Collinearity
- Parallelism
- Larger structure
- Regular structure
- Higher-level knowledge



Can we state the problem?

- We see “patterns” in these.
- How can we state the problem precisely?
- What space do these things live in?

What is a pattern?

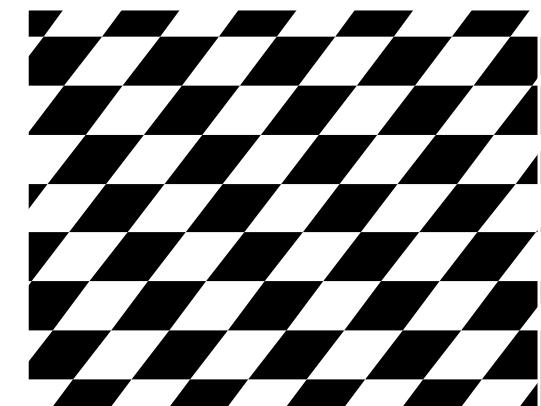
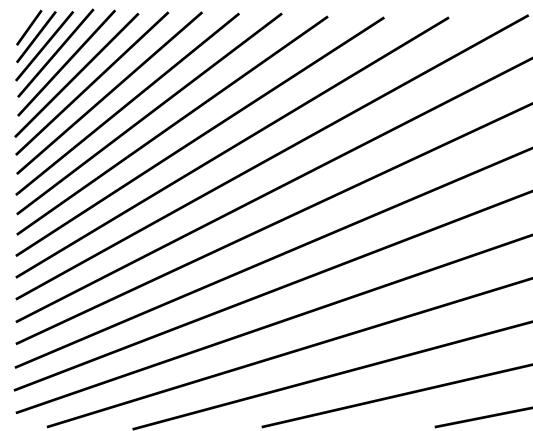
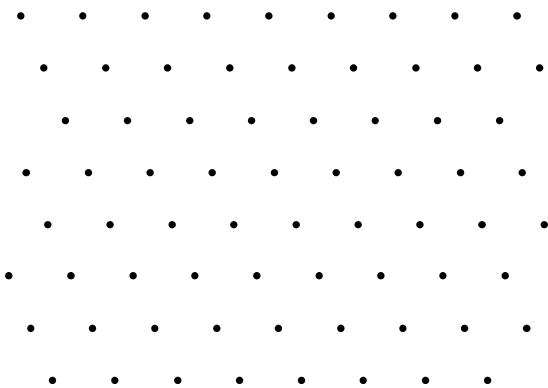


From "Fluid Concepts and Creative Analogies: Computer Models of the Fundamental Mechanisms of Thought" by Douglas R. Hofstadter and the Fluid Analogies Research Group, Basic Books, 1995. ISBN: 0465051545.

The Problem

What is a pattern?

- Define patterns in these



From dictionaries:

pattern

- a combination of qualities, acts, tendencies, etc., forming a **consistent or characteristic arrangement**: “the behavior patterns of teenagers.”
- a model or original used as an **archetype**.
- a perceptual **structure**; “a visual pattern must include not only objects but the spaces between them”

[There are many more (less abstract) meanings.

Only pertinent ones are shown here.]

In the case of strings

These strings “have patterns”

01...

0101101110111101111101111110111111...

110010010000111110110101010001000...

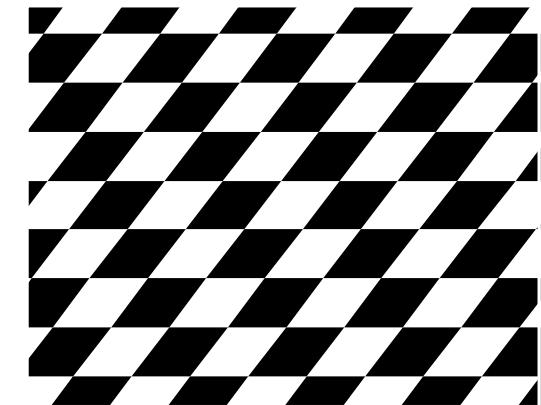
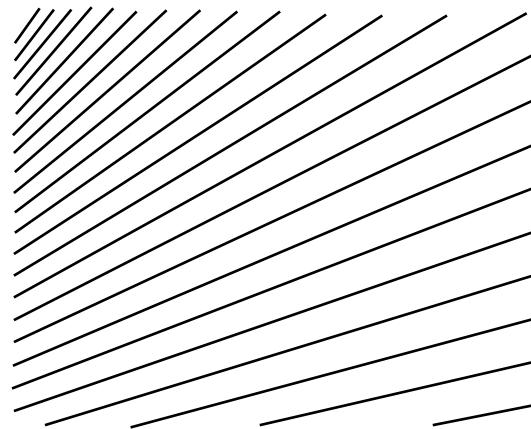
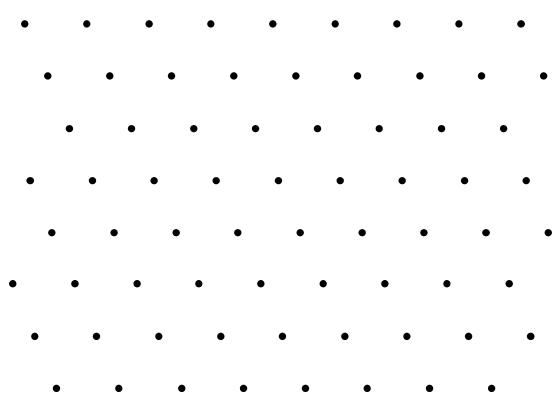
- We can say a string with much less information than its length have pattern
- That is, if there is a much shorter program to print out the string

Two descriptions

- To describe a string by another string, there are two ways:
 - Describe the string by itself (*dense*)
 - By a program that prints out the string (*sparse*)
- The latter can exploit any **pattern** in the string
- If the string has a pattern, the latter description can be much shorter.
- The length of the shortest such description is called its Kolmogorov Complexity
- **Pattern is computation**

What about objects other than strings?

Infinite set but finite information

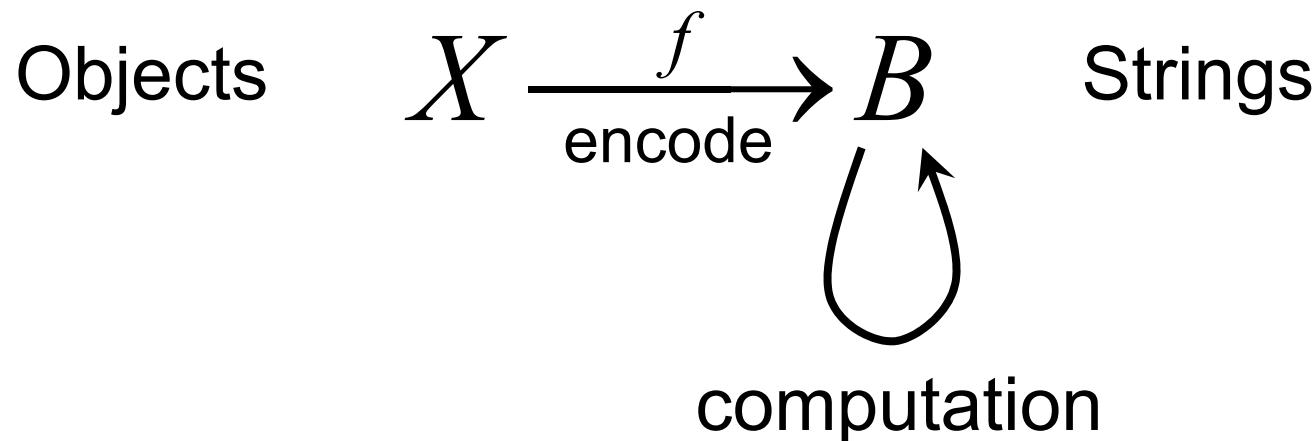


- Can we define a measure of information in these?

The Thesis of Computer Science

“Information can be encoded”

- Computation is only defined in the world of symbols and strings
- Everything else can be encoded into strings
 - Ex. Real numbers → binary expansion



Encoding the Universe

To define an information measure in general objects:

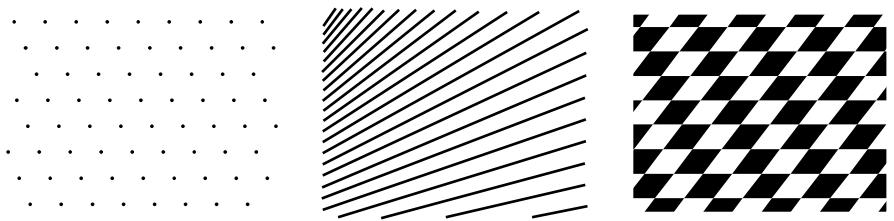
- Fix an encoding (an enumeration) of the objects
- Define the information in an object x by the Kolmogorov Complexity $K(f(x))$ of its code string

$$\begin{array}{ccccc} X & \xrightarrow[f]{\text{encode}} & B & \xrightarrow{K} & \mathbb{N} \\ \Downarrow & & \Downarrow & & \Downarrow \\ x & & f(x) & & K(f(x)) \end{array}$$

Example: Shapes on Euclidean Plane

Encode:

- Real number: binary expansion
- Point: a pair of reals
- Line: two points
- Circle: a point and a real
-



$$\begin{array}{ccc} X & \xrightarrow[\text{encode}]{f} & B \xrightarrow{K} \mathbb{N} \\ \Downarrow & & \Downarrow \\ x & & f(x) & & K(f(x)) \end{array}$$

Example: Shapes on Euclidean Plane

But then:

- How far must we go?
 - We can never exhaust all possible shapes
 - This is only one example
- We are presupposing what the patterns are
- The encoding f is doing the actual computation

$$\begin{array}{ccccc} X & \xrightarrow[f]{\text{encode}} & B & \xrightarrow{K} & \mathbb{N} \\ \Downarrow & & \Downarrow & & \Downarrow \\ x & & f(x) & & K(f(x)) \end{array}$$

Example: Shapes on Euclidean Plane

So let's encode only the points

- Point \rightarrow 2 reals \rightarrow alternate binary expansion
 $(0.x_0x_1x_2x_3..., 0.y_0y_1y_2y_3...) \rightarrow x_0y_0x_1y_1x_2y_2x_3y_3\dots$
- Finite number of points \rightarrow rotate among points
 $a \rightarrow a_0a_1a_2a_3\dots, b \rightarrow b_0b_1b_2b_3\dots, c \rightarrow c_0c_1c_2c_3\dots,$
 $\{a,b,c\} \rightarrow a_0b_0c_0a_1b_1c_1a_2b_2c_2a_3b_3c_3\dots$
- Countable number of points \rightarrow rotate among increasingly many points
 $\{a,b,c,d,\dots\} \rightarrow a_0a_1b_0a_2b_1c_0a_3b_2c_1d_0\dots$
- We can only encode a countable subset

Example: Shapes on Euclidean Plane

So let's only consider countable sets.

1. Require the coordinates of the points to be rational
 - Then any set of such points are countable
 - But many sets don't have many rational points
example: the line $y = \sqrt{2}x$
2. Only consider any countable sets
 - Even a single point can have an infinite information

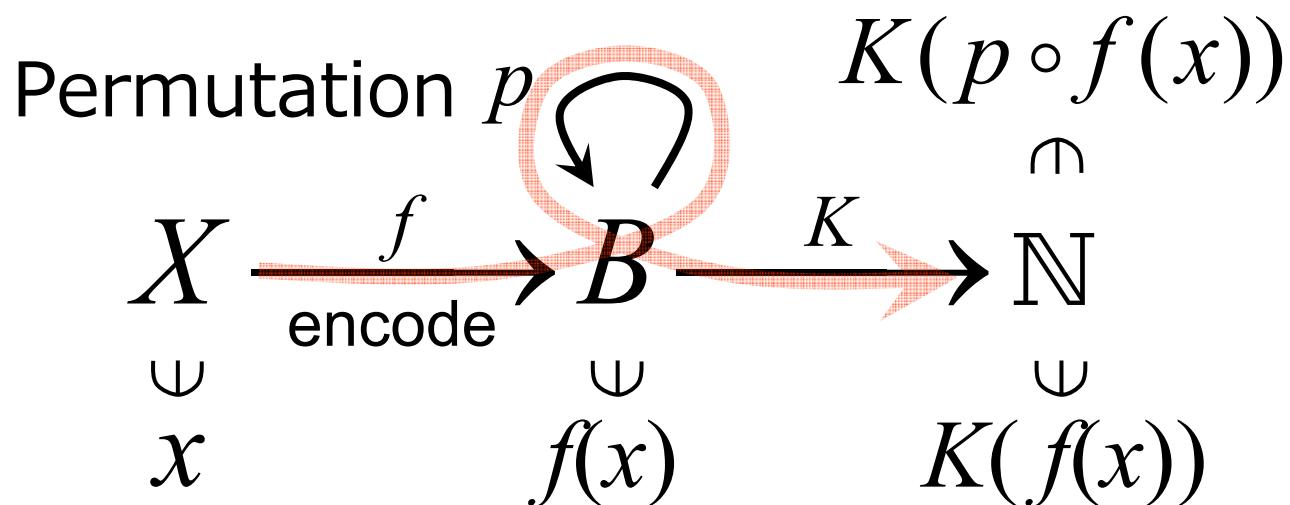
Fundamental Problems

- Hard to define general enough encoding f
- We need to be able to define the information amount in specific parts *a priori*
 - Ex: Points to have the same amount of information

$$\begin{array}{ccc} X & \xrightarrow[\text{encode}]{f} & B \xrightarrow{K} \mathbb{N} \\ \Downarrow & & \Downarrow \\ x & & f(x) & & K(f(x)) \end{array}$$

The Arbitrariness Trap

- In CS, the encoding f is just said to “exist”.
- The arbitrariness of f makes the information measure arbitrary, too
- So Computer Science does have to think about encoding seriously



A Solution

Remember the two descriptions

- To describe a string by another string, there are two ways:
 - Describe the string by itself (dense)
 - By a program that prints out the string (sparse)
- Similarly, we will represent an object in two ways:
 - Represent it by a subset (dense representation)

Ground representation

- By a new representation (sparse representation) that produces the dense representation

*Representation by **diagrams** and **cross sections***

Ground Representation

- Something like bitmap, representing raw data
- Abstract a bit → subsets
 - Subsets of Euclidean plane
 - Image: a subset of $\mathbb{R}^2 \times Color$
 - i.e., image function $I(p)$ on $D \subset \mathbb{R}^2$
 $\Leftrightarrow \{(p, I(p)) \mid p \in D\} \subset \mathbb{R}^2 \times Color$
 - Objects in 3D space (at a level of abstraction) :
 $Car \subset \mathbb{R}^3 \times Material$
 $Material = \{\text{iron, rubber, glass, plastic, ...}\}$

Ground Representation

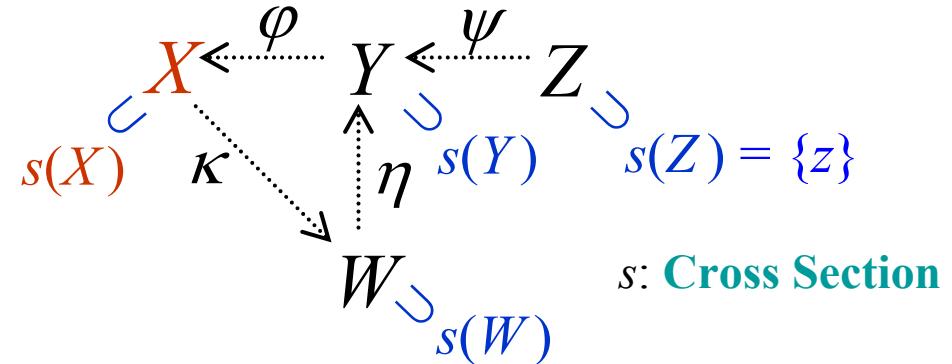
- Raw signal
- *A priori*
- Almost everything can be easily represented
- Does not reflect the structure in the object, even if there is any
- Most that can be represented is random noise

Representation

- Specify sets and *power maps* between them (*diagram*)

Ex.

$$\begin{aligned}\varphi : \mathcal{P}(Y) &\rightarrow \mathcal{P}(X) \\ \psi : \mathcal{P}(Z) &\rightarrow \mathcal{P}(Y) \\ \eta : \mathcal{P}(W) &\rightarrow \mathcal{P}(Y) \\ \kappa : \mathcal{P}(X) &\rightarrow \mathcal{P}(W)\end{aligned}$$



- Consider an assignment s to each set of its subset that satisfies

$$s(S) = \bigcap_{\mu \in \text{in}(S)} \mu(s(\text{dm}(\mu)))$$

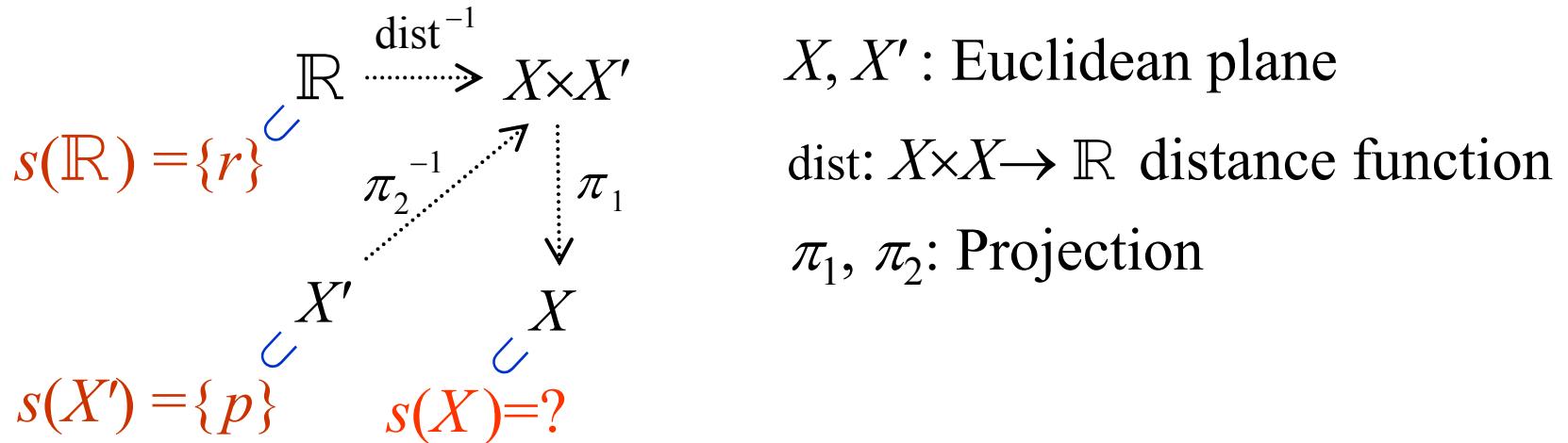
$$s(X) = \varphi(s(Y))$$

$$s(Y) = \psi(s(Z)) \cap \eta(s(W))$$

$$s(W) = \kappa(s(X))$$

- Specify some of the $s(.)$
- Designate one set (say X) whose assigned subset ($s(X)$) is the dense representation of what is represented.

The Simplest Examples



$$s(S) = \bigcap_{\mu \in \text{in}(S)} \mu(s(\text{dm}(\mu)))$$

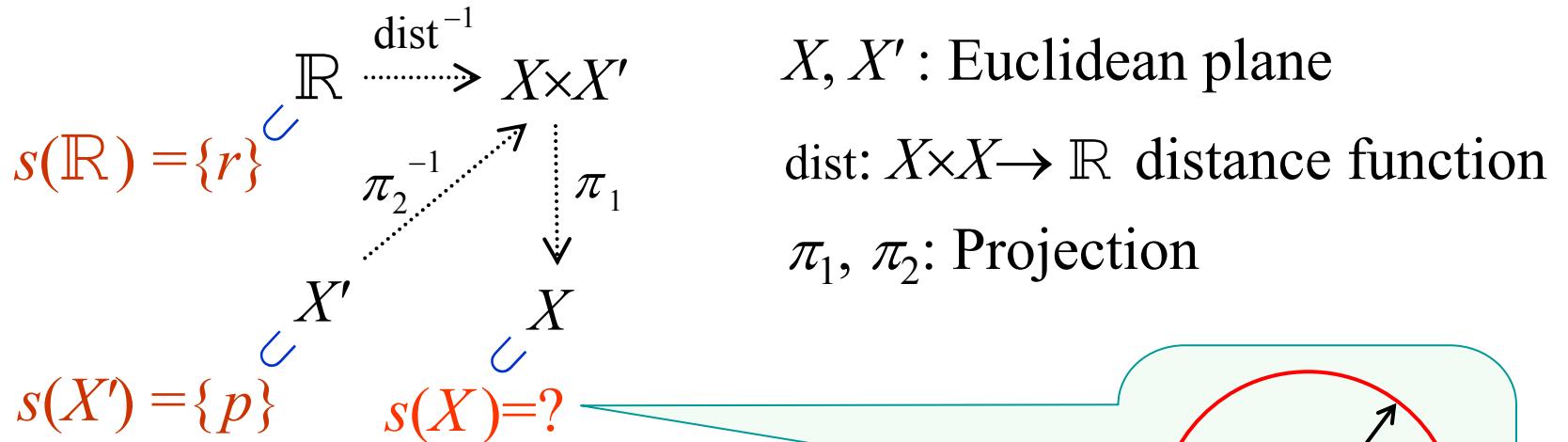
$$f: A \rightarrow B$$

\rightarrow

$$f: \mathcal{P}(A) \rightarrow \mathcal{P}(B) \quad A \supset S \mapsto \{f(x) \mid x \in S\} \subset B$$

$$f^{-1}: \mathcal{P}(B) \rightarrow \mathcal{P}(A) \quad B \supset S \mapsto \{x \in A \mid f(x) \in S\} \subset A$$

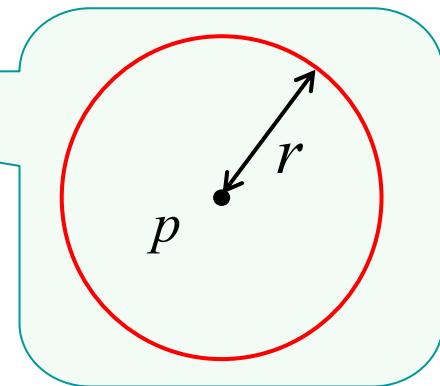
The Simplest Examples



$$s(S) = \bigcap_{\mu \in \text{in}(S)} \mu(s(\text{dm}(\mu)))$$

$$\begin{aligned}
 s(X \times X') &= \text{dist}^{-1}(s(\mathbb{R})) \cap \pi_2^{-1}(s(X')) \\
 &= \{(x, y) \mid \text{dist}(x, y) \in s(\mathbb{R}), \pi_2(x, y) = p\} \\
 &= \{(x, p) \mid \text{dist}(x, p) = r\}
 \end{aligned}$$

$$\begin{aligned}
 s(X) &= \pi_1(s(X \times X')) \\
 &= \{x \mid \text{dist}(x, p) = r\}
 \end{aligned}$$



The Simplest Examples

$$\begin{array}{ccccc}
 & V & \xrightarrow{\pi_1^{-1}} & V \times \mathbb{R} & \xrightarrow{\text{mult}} V' \\
 s(V) = \{v\} & \swarrow & & \downarrow \text{sub}^{-1} & \leftarrow \pi_2^{-1} \\
 & X' & \xrightarrow{\pi_2^{-1}} & X \times X' & \xrightarrow{\pi_1} X \\
 s(X') = \{p\} & \swarrow & & \downarrow & \leftarrow s(X) = ?
 \end{array}$$

X, X' : Euclidean plane

V, V' : 2D vector space

mult: $V \times \mathbb{R} \rightarrow V$ $(v, c) \mapsto cv$

sub: $X \times X \rightarrow V$ $(x, y) \mapsto x - y$

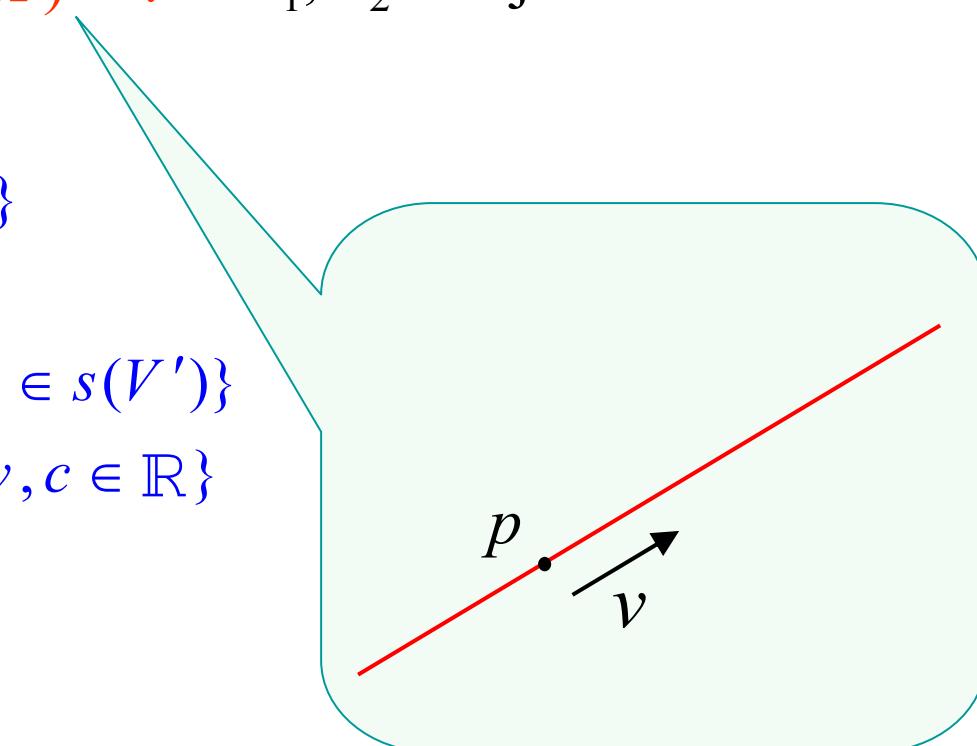
π_1, π_2 : Projection

$$s(V \times \mathbb{R}) = \{(v, c) \mid c \in \mathbb{R}\}$$

$$s(V') = \{cv \mid c \in \mathbb{R}\}$$

$$s(X \times X') = \{(x, p) \mid x - p \in s(V')\}$$

$$s(X) = \{x \mid x = p + cv, c \in \mathbb{R}\}$$



A little extension

- Choose some of the sets

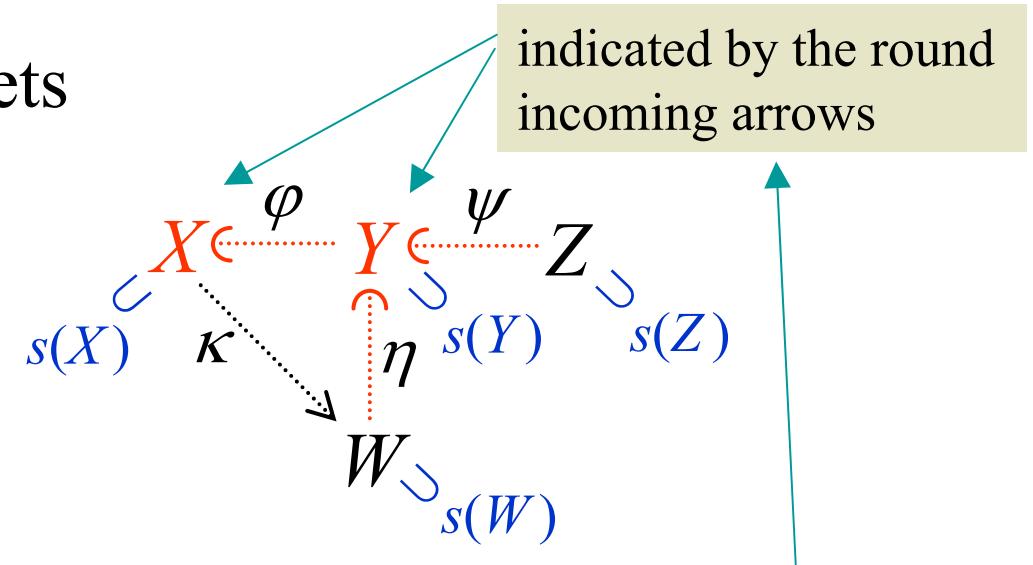
Ex.

$$\varphi: \mathcal{P}(Y) \rightarrow \mathcal{P}(X)$$

$$\psi: \mathcal{P}(Z) \rightarrow \mathcal{P}(Y)$$

$$\eta: \mathcal{P}(W) \rightarrow \mathcal{P}(Y)$$

$$\kappa: \mathcal{P}(X) \rightarrow \mathcal{P}(W)$$



- Assume the assignment s satisfies **for the chosen sets**

$$s(S) = \bigcup_{\mu \in \text{in}(S)} \mu(s(\text{dm}(\mu)))$$

instead of

$$s(S) = \bigcap_{\mu \in \text{in}(S)} \mu(s(\text{dm}(\mu)))$$

$$s(X) = \varphi(s(Y))$$

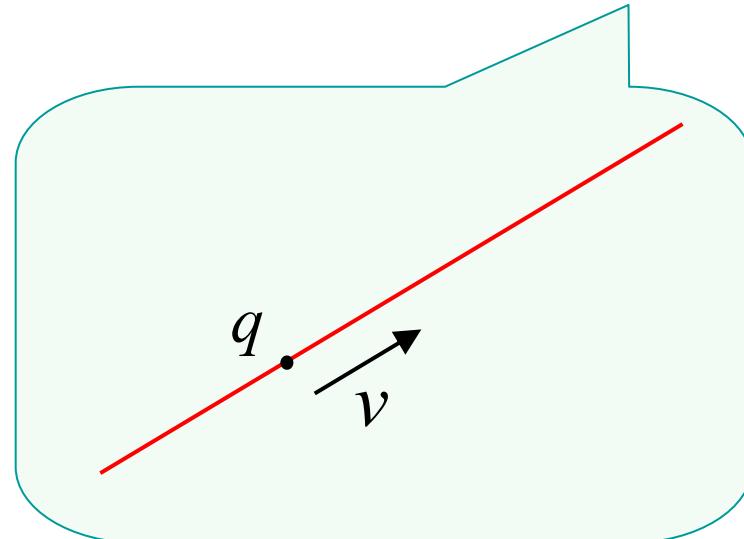
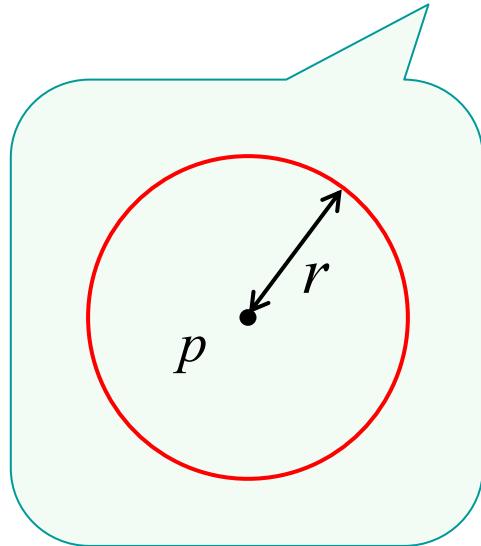
$$s(Y) = \psi(s(Z)) \cup \eta(s(W))$$

$$s(W) = \kappa(s(X))$$

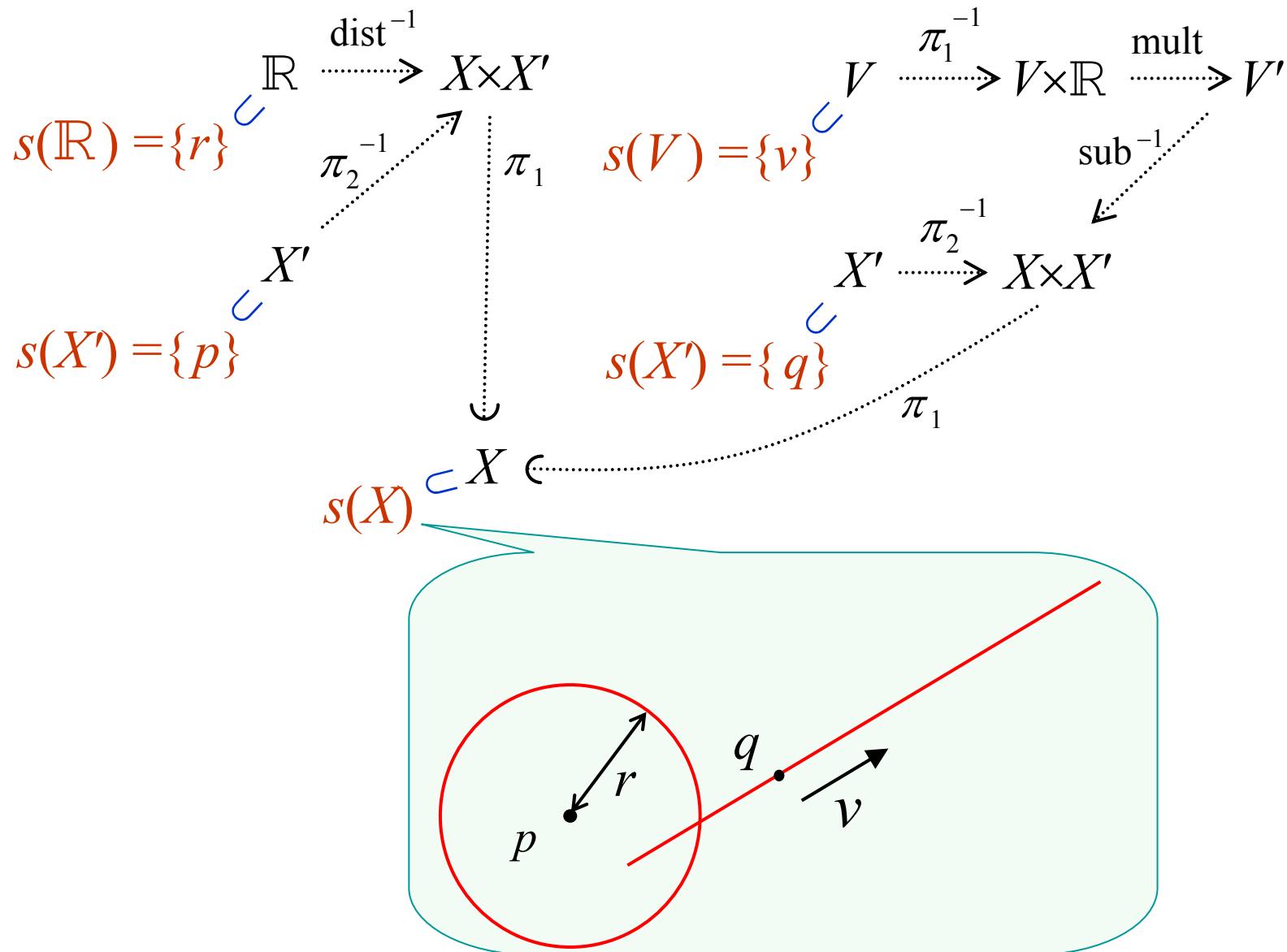
Combination

$$\begin{array}{ccc} & \mathbb{R} \xrightarrow{\text{dist}^{-1}} X \times X' & \\ s(\mathbb{R}) = \{r\} & \swarrow \pi_2^{-1} \quad \downarrow \pi_1 & s(V) = \{v\} \\ X' & & X \\ s(X') = \{p\} & \curvearrowleft s(X) & s(X') = \{q\} \\ & & \curvearrowleft s(X) \end{array}$$

The diagram illustrates the construction of a product space. On the left, a point r in \mathbb{R} is mapped via dist^{-1} to the product space $X \times X'$. This mapping is decomposed into projections π_1 onto X and π_2^{-1} onto X' . Below this, a point v in V is mapped via π_1^{-1} to $X \times X'$, which is then mapped via mult to V' . This decomposition uses projections π_2^{-1} onto X' and π_1 onto X .



Combination



Recursive definition

$$\begin{array}{ccc}
 & V & \xrightarrow{\pi_2^{-1}} X \times V \\
 s(V) = \{v\} & \swarrow & \uparrow \pi_1^{-1} \quad \text{add} \\
 & X' & \xrightarrow{\text{id.}} X \\
 & \cup & \cup \\
 s(X') = \{p\} & & s(X) = ?
 \end{array}$$

X, X' : Euclidean plane

V : 2D vector space

add: $X \times V \rightarrow X$ $(x, v) \mapsto x + v$

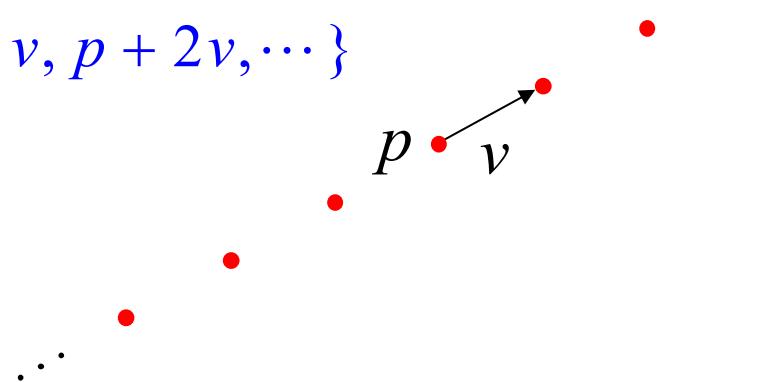
π_1, π_2 : Projection

$$s(X \times V) = \{(x, v) \mid x \in s(X)\}$$

$$s(X) = s(X') \cup \text{add}(s(X \times V))$$

$$= \{p\} \cup \{x + v \mid x \in s(X)\}$$

$$\supset \{\dots, p - 2v, p - v, p, p + v, p + 2v, \dots\}$$



Recursive definition

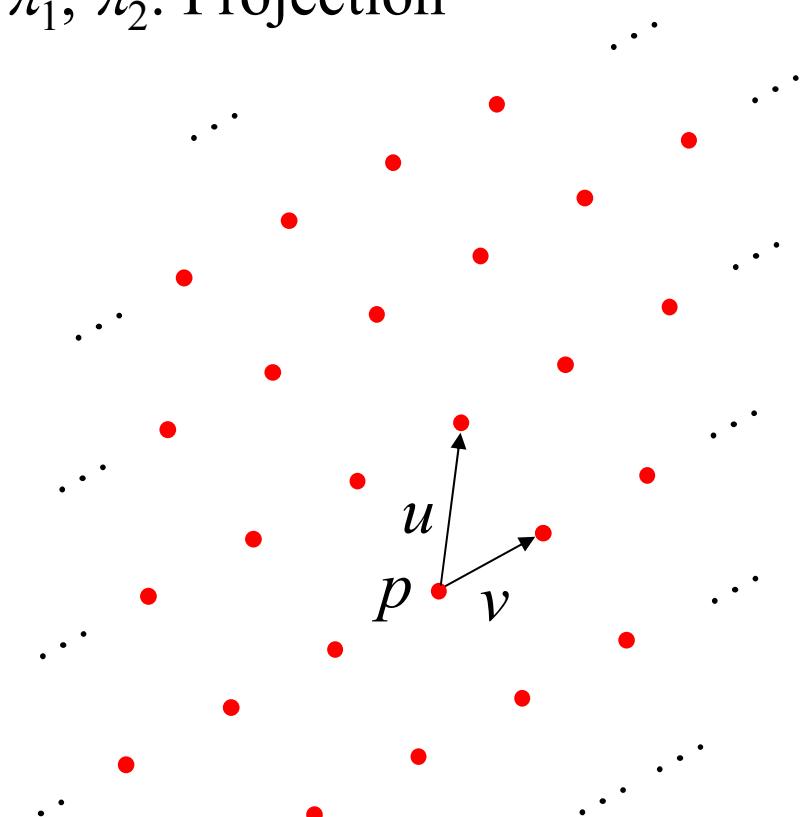
$$\begin{array}{ccc} s(V) = \{u, v\} & \begin{matrix} V & \xrightarrow{\pi_2^{-1}} & X \times V \\ & \uparrow \pi_1^{-1} & \downarrow \text{add} \\ X' & \xrightarrow{\text{id.}} & X \end{matrix} & s(X) = ? \end{array}$$

X, X' : Euclidean plane

V : 2D vector space

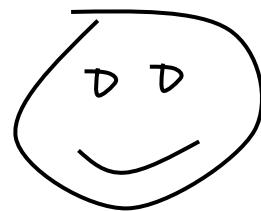
add: $X \times V \rightarrow X$ $(x, v) \mapsto x + v$

π_1, π_2 : Projection



Hierarchical definition

$$\begin{array}{ccc}
 & V & \xrightarrow{\pi_2^{-1}} X \times V \\
 s(V) = \{u, v\} & \uparrow \pi_1^{-1} & \uparrow \text{add} \\
 & X' & \xrightarrow{\text{id.}} X \\
 & s(X') = A & s(X) = ?
 \end{array}$$



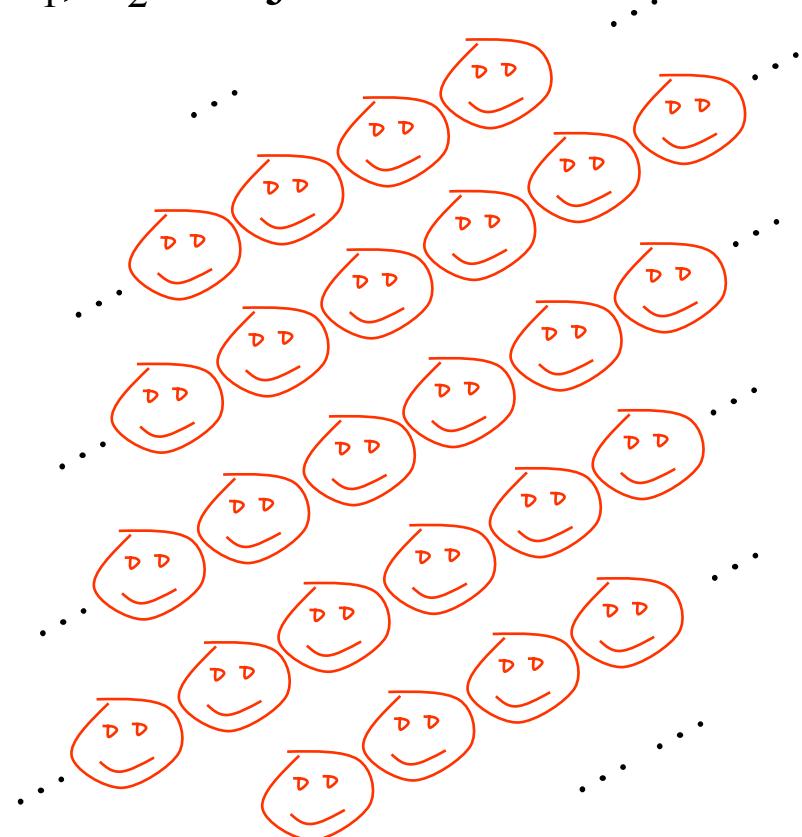
$$A \subset X$$

X, X' : Euclidean plane

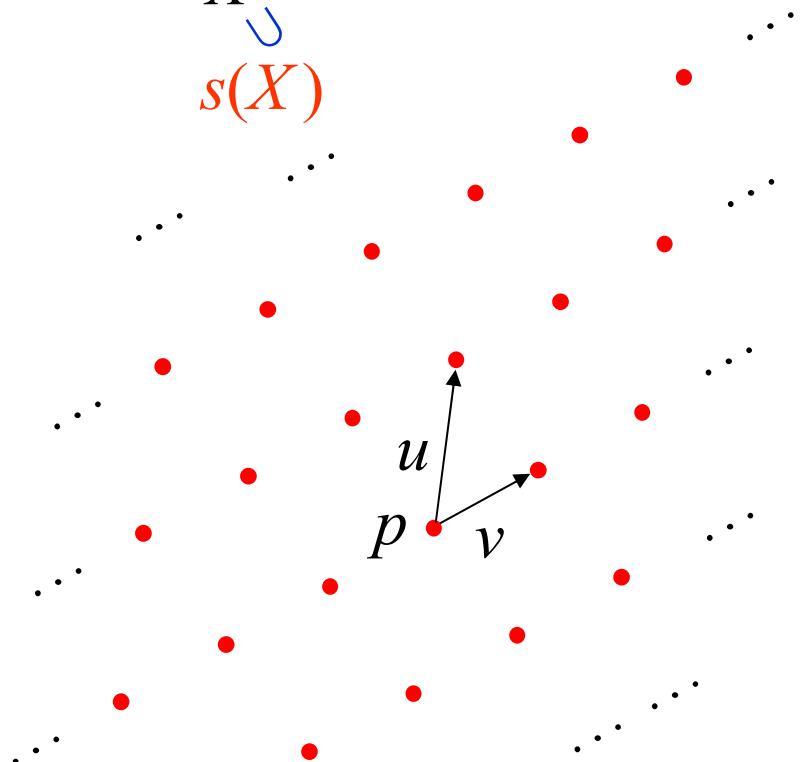
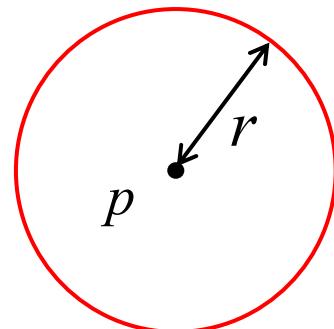
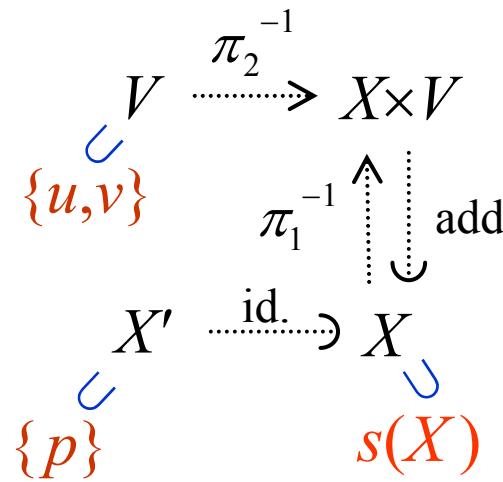
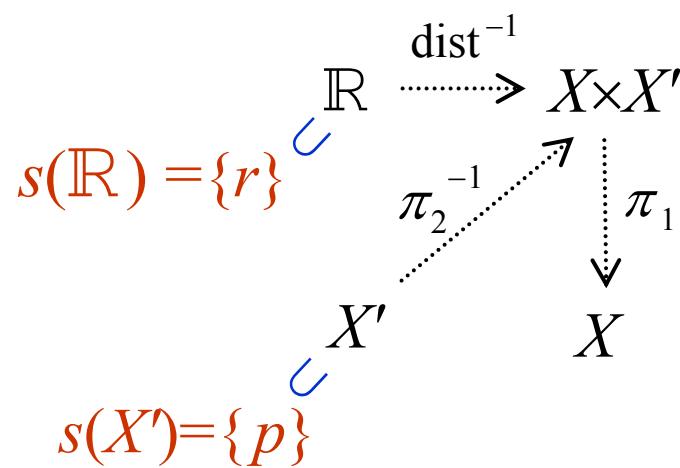
V : 2D vector space

add: $X \times V \rightarrow X$ $(x, v) \mapsto x + v$

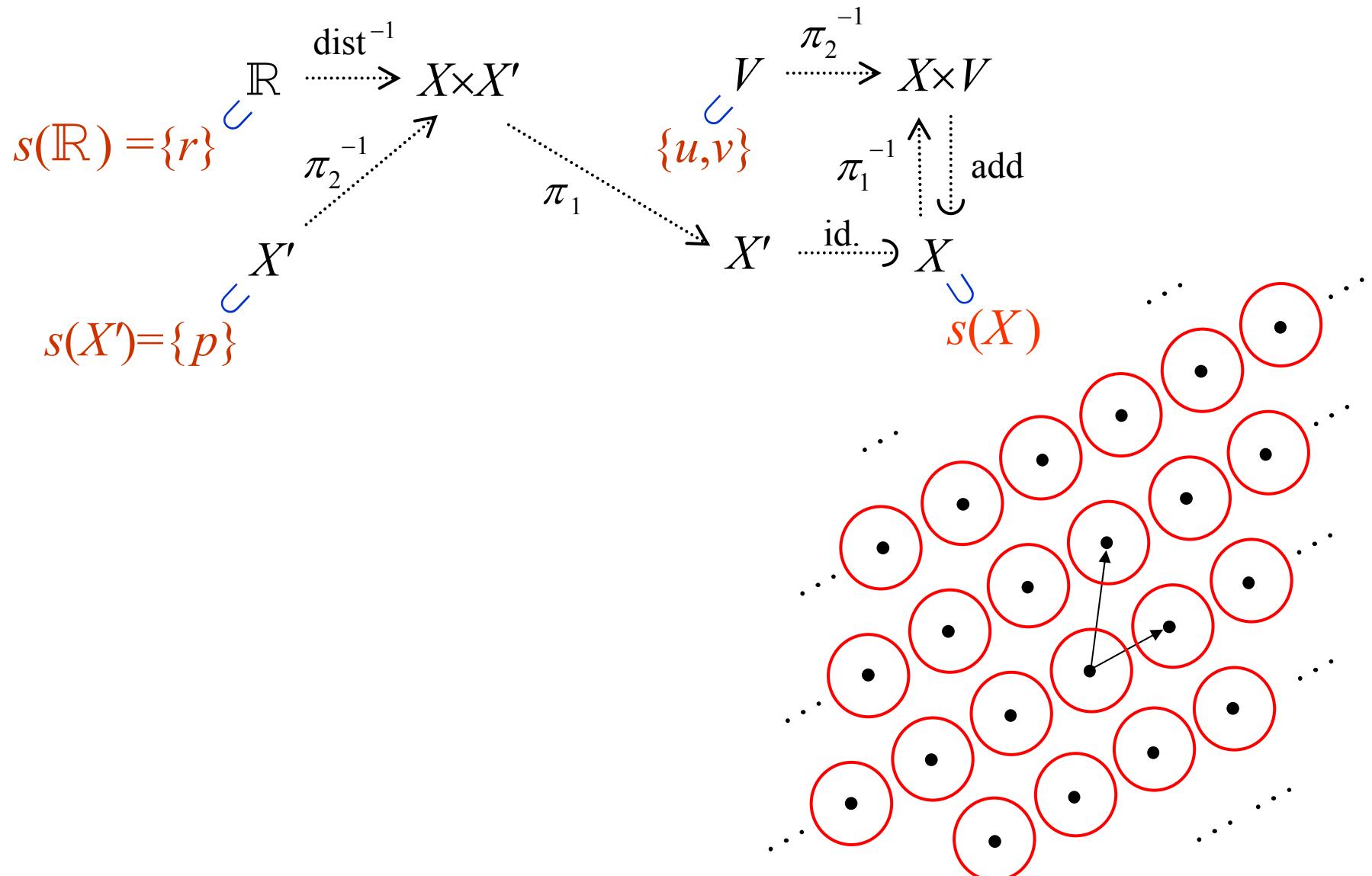
π_1, π_2 : Projection



Hierarchical definition



Hierarchical definition



Computation

- Ex: Factorials

$$\begin{array}{ccc} \mathbb{N} \times \mathbb{N} & \xrightarrow{\quad \text{id} \quad} & \mathbb{N} \times \mathbb{N} \\ s(\mathbb{N} \times \mathbb{N}) = \{(0,1)\} & \swarrow & \downarrow \\ & & \{(0,1), (1,1), (2,2), (3,6), \dots, (n, n!), \dots\} \end{array}$$

- Ex: Fibonacci numbers

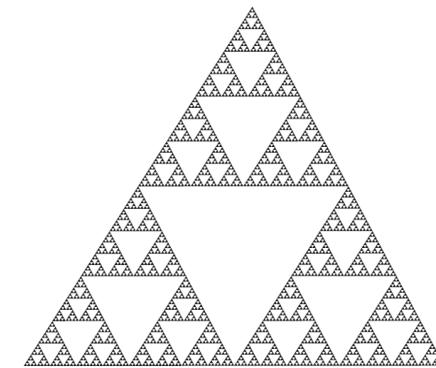
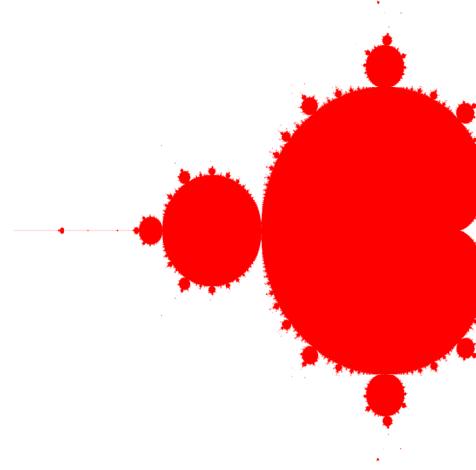
$$\begin{array}{ccc} \mathbb{N}^+ \times \mathbb{N}^+ & \xrightarrow{\quad \text{id} \quad} & \mathbb{N}^+ \times \mathbb{N}^+ \\ s(\mathbb{N}^+ \times \mathbb{N}^+) = \{(1,1)\} & \swarrow & \circlearrowleft \\ & & (n, m) \mapsto (m, n+m) \end{array}$$

$$\mathbb{N}^+ \cup \{1, 1, 2, 3, 5, 8, \dots\}$$

- Can emulate any Turing machine

Computation

- Can embed computation in any space



$$\begin{array}{ccccc} & \pi_1 \times \pi_2 & & \text{cmpl} \circ \pi_1 & \\ \text{---} \curvearrowleft & \mathbb{C} \times \mathbb{C} \times \mathbb{N} & \xrightarrow{\quad \text{id} \quad} & \mathbb{C} \times \mathbb{C} & \xrightarrow{\quad \text{---} \quad} \mathbb{C} \\ (c, z, k) \mapsto & & \uparrow & & \uparrow \\ (c, c + z^2, k) & & & \pi_2^{-1} & \\ & \mathbb{C} \times \mathbb{C} \times \mathbb{N} & & \mathbb{C} & \\ & \cup & & \cup & \\ \mathbb{C} \times \{0\} \times \{0\} & & \{z \in \mathbb{C} \mid |z| > 2\} & & \end{array}$$

Information Measure

- **Define** the complexity of any subset **by** the size of the **minimum diagram** that represents it
- The size of a diagram is measured by the total size of maps **generated** from a fixed set of **structure maps**
 - $\text{id}: X \rightarrow X, \quad \pi_i: X_1 \times \dots \times X_n \rightarrow X_i, \quad \omega: X \rightarrow \{0\}$
 - $f: X \rightarrow Y, g: Y \rightarrow Z \Rightarrow g \circ f: X \rightarrow Z$
 - $f_i: X \rightarrow Y_i \Rightarrow f_1 \times \dots \times f_n: X \rightarrow Y_1 \times \dots \times Y_n$

Information Measure

- The information measure of a subset $A \subset X$ relative to the set of maps \mathcal{M} is denoted by

$$I(A|\mathcal{M})$$

- But any subset can be represented by the **trivial representation**

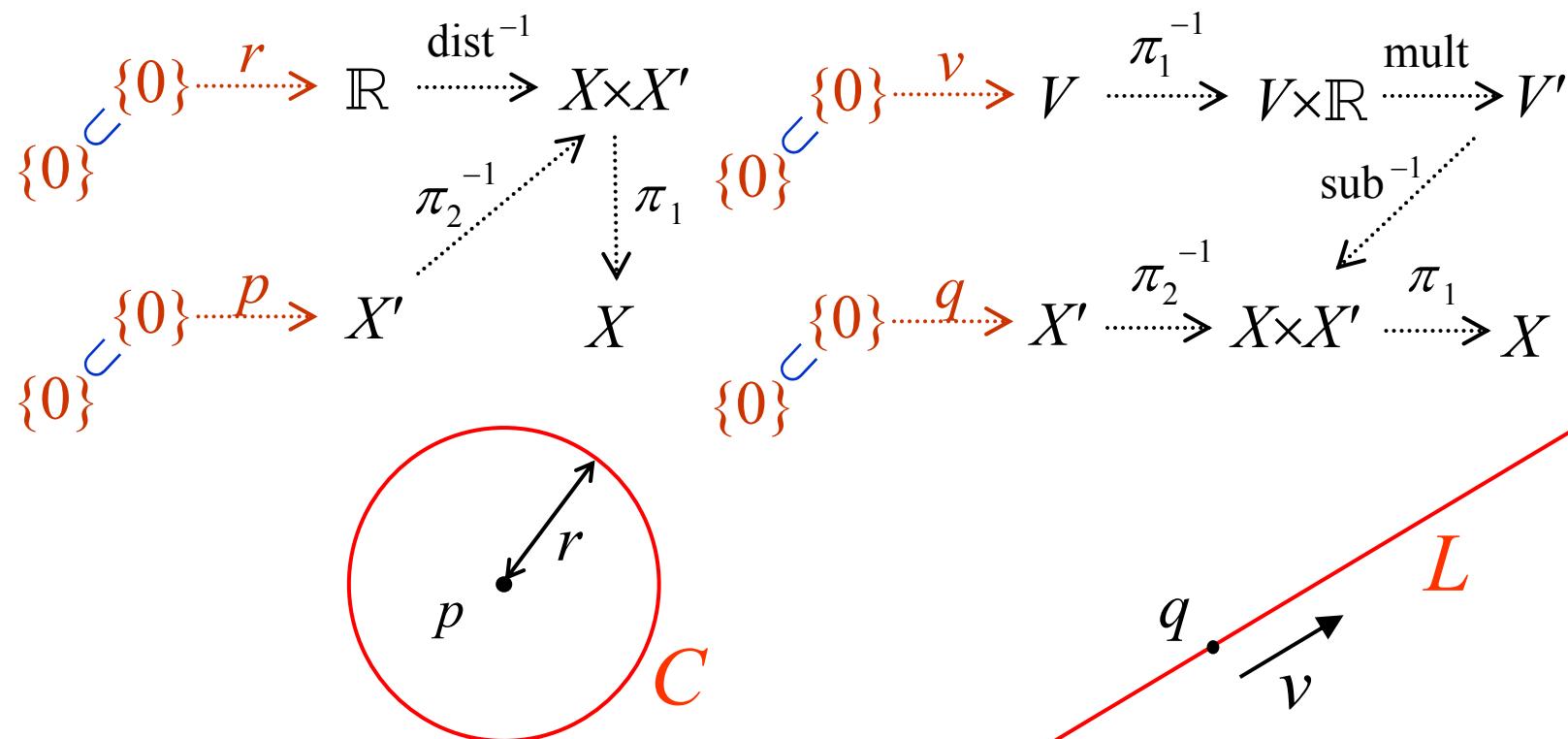
$$s(X)=A \cup^X$$

by defining the given set as the **fixed partial cross section** part of the representation.

- No map is needed, so the size is 0.

Information Measure

Consider constant $x \in X$ as a map $x : \{0\} \rightarrow X$, only allow the fixed partial cross section $s(\{0\}) = \{0\}$



$$I(C | \{r, p, \text{dist}\}) \leq 5$$

$$I(L | \{v, q, \text{mult}, \text{sub}\}) \leq 7$$

Information Measure

We choose the maps and constants that characterize the structure of the space in question.

For instance, for a Euclidean space X , it might be

$$\mathcal{M}_E = \{\text{dist}, \text{add}, \text{sub}, \text{mult}\} \cup X \cup V \cup \mathbb{R}$$
$$\{x: \{0\} \rightarrow X \mid x \in X\}$$

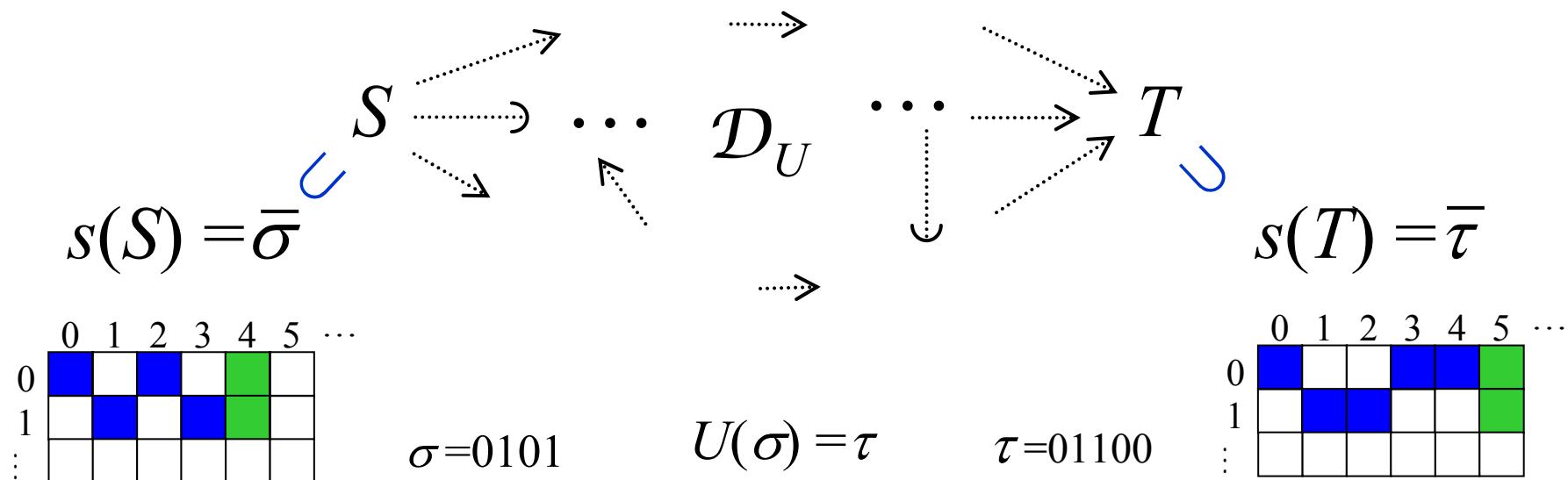
Then,

- $I(C \mid \mathcal{M}_E) \leq 5, I(L \mid \mathcal{M}_E) \leq 7$
- For any finite set $A \subset X, I(A \mid \mathcal{M}_E) \leq |A|$

Relation with Kolmogorov Complexity

Theorem For any Turing machine U , there exists a diagram \mathcal{D}_U generated by $\mathcal{M}_{\mathbb{N}}$ including the sets

$S = \mathbb{N} \times \mathbb{N}$ and $T = \mathbb{N} \times \mathbb{N}$ such that, for any $\sigma \in b^*$ and any cross section s with $s(S) = \bar{\sigma}$, $s(T) = \emptyset$ if $U(\sigma) = \uparrow$ and $s(T) = \bar{\tau}$ if $U(\sigma) = \tau \in b^*$.



Relation with Kolmogorov Complexity

For $b = \{0,1\}$, $\sigma \in b^*$, define $\bar{\sigma} \subset \mathbb{N} \times \mathbb{N}$ as

$$\bar{\sigma} = \{(i, \sigma[i]) \mid i = 0, 1, \dots, |\sigma|-1\} \cup \{(|\sigma|, 0), (|\sigma|, 1)\}$$

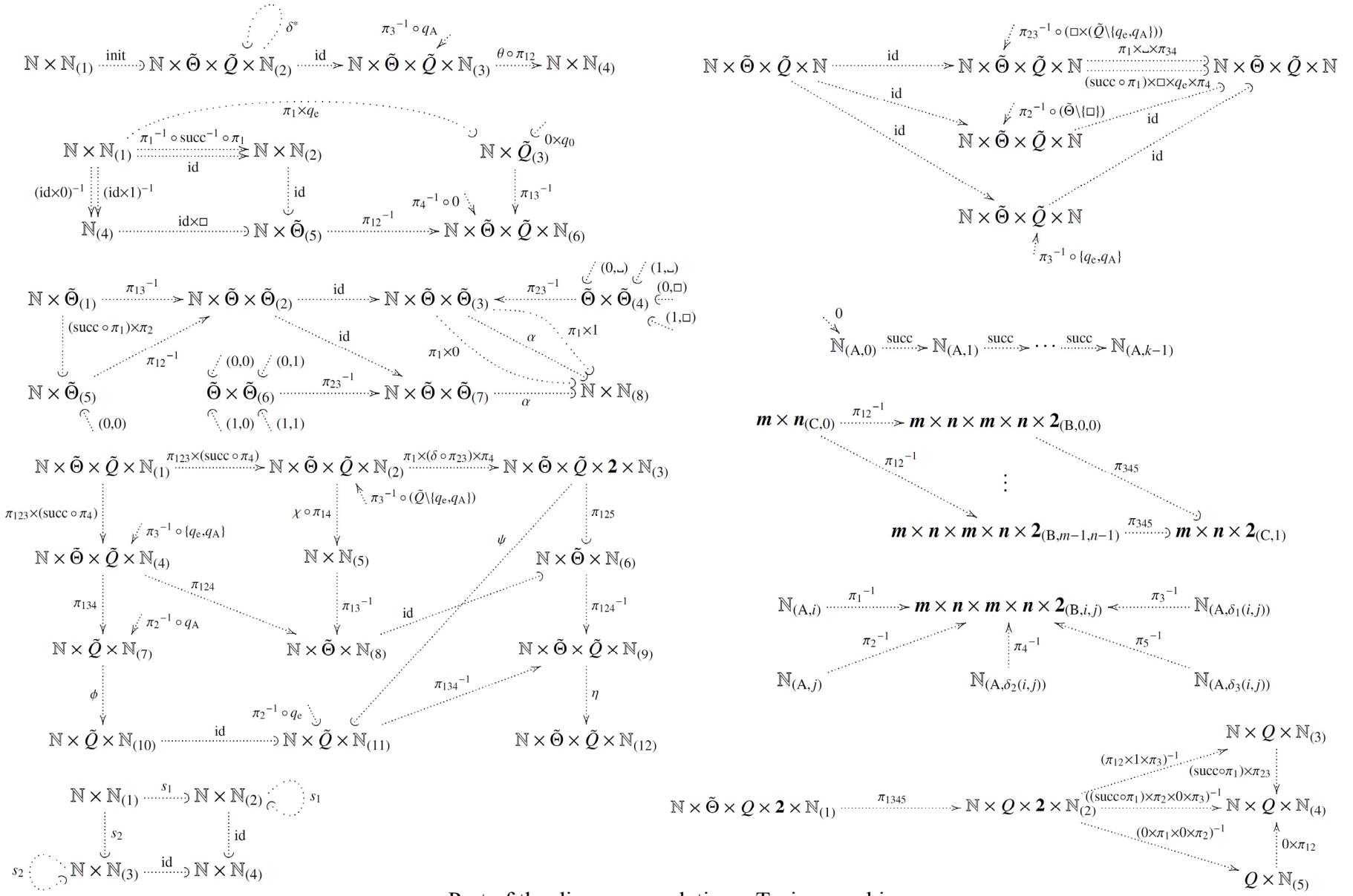
Ex: If $\sigma = 0110$, $\bar{\sigma} = \{(0, 0), (1, 1), (2, 1), (3, 0), (4, 0), (4, 1)\}$

	0	1	2	3	4	5	\dots
0	Blue	White	White	Blue	Green	White	
1	White	Blue	Blue	White	Green	White	
\vdots							

$$\mathcal{M}_{\mathbb{N}} = \{0, \text{succ}\}$$

- $0: \{0\} \rightarrow \mathbb{N}$, $0(0) = 0$
- $\text{succ}: \mathbb{N} \rightarrow \mathbb{N}$ [$\text{succ}(n) = n+1$]

Relation with Kolmogorov Complexity



Relation with Kolmogorov Complexity

Theorem There exists a Turing machine that, given an encoded diagram \mathcal{D}_σ representing $\bar{\sigma}$ for $\sigma \in b^*$, outputs σ and terminates.

Since \mathcal{D}_σ can be encoded with size $\sim I(\bar{\sigma} \mid \mathcal{M}_{\mathbb{N}})$, $K(\sigma)$ is dominated by a constant multiple of $I(\bar{\sigma} \mid \mathcal{M}_{\mathbb{N}})$

Automatic handling of structures

- Implement basic components approximately:
spaces and maps
 - real numbers, spaces, ...
- Structural varieties are generated combinatorially
- The structure does not depend on the approximation.
 - Data exchange between systems does not change the structure itself

Pattern Discovery as Optimization

- Given a signal-level data, find ever smaller diagrams representing it.
- The upper bound is the trivial representation
- Regular parts can be represented more compactly

Concluding Remarks

- Patterns and computations are defined directly
- Can mix sparse and dense representation
- Hierarchical and recursive representation possible
- Connects the representation to the represented.
No arbitrariness in encoding across structures.
- The representation is a formalization of definition;
i.e., a meta-definition.
- We can treat consistently and automatically what
we usually define in natural languages