

# From Determinism to Stochasticity

## Measurement Theory I

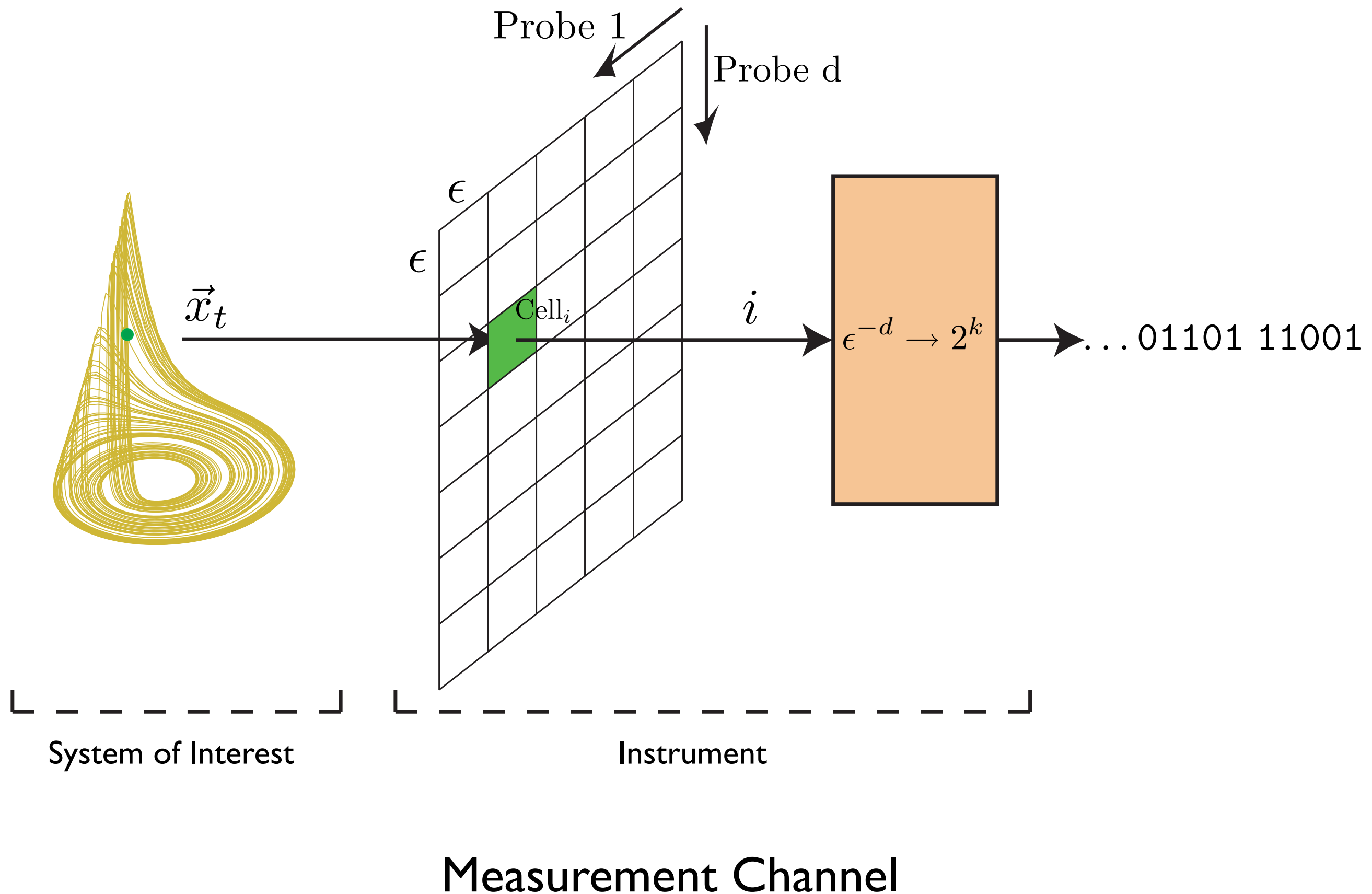
Reading for this lecture:

(These) *Lecture Notes*.

CMPy Interactive Labs:

Symbolic Dynamics and Partitions

# From Determinism to Stochasticity ...



# From Determinism to Stochasticity ...

## Measurement Theory: Making the connection

### Hidden Dynamical System:

What can we learn from discrete time series?

Know how to evolve:

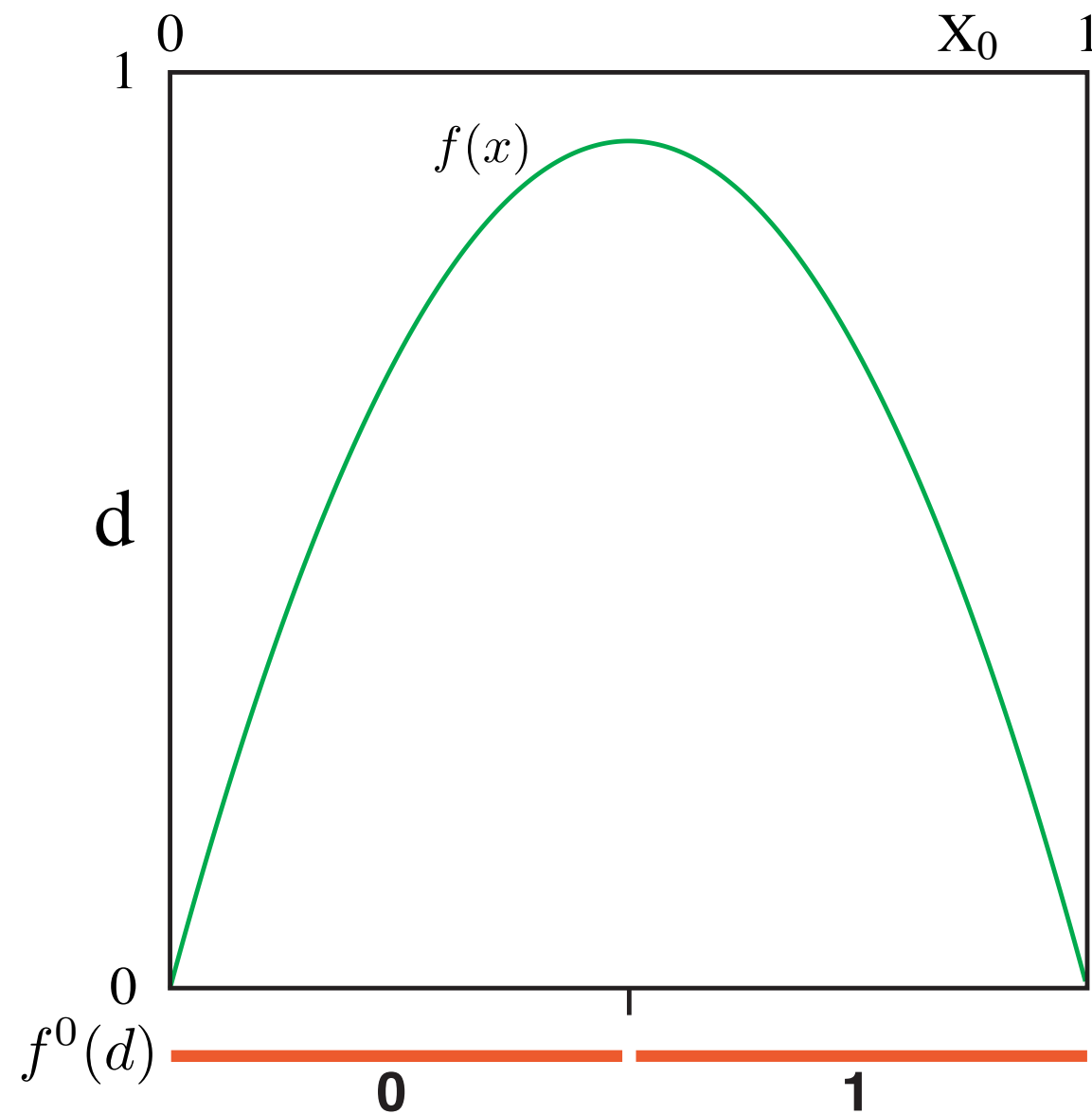
$$\mathcal{T} : \vec{x}_0 \longrightarrow \vec{x}_1$$

$$\mathcal{T} : p_0(x) \longrightarrow p_1(x)$$

How to evolve boundaries?

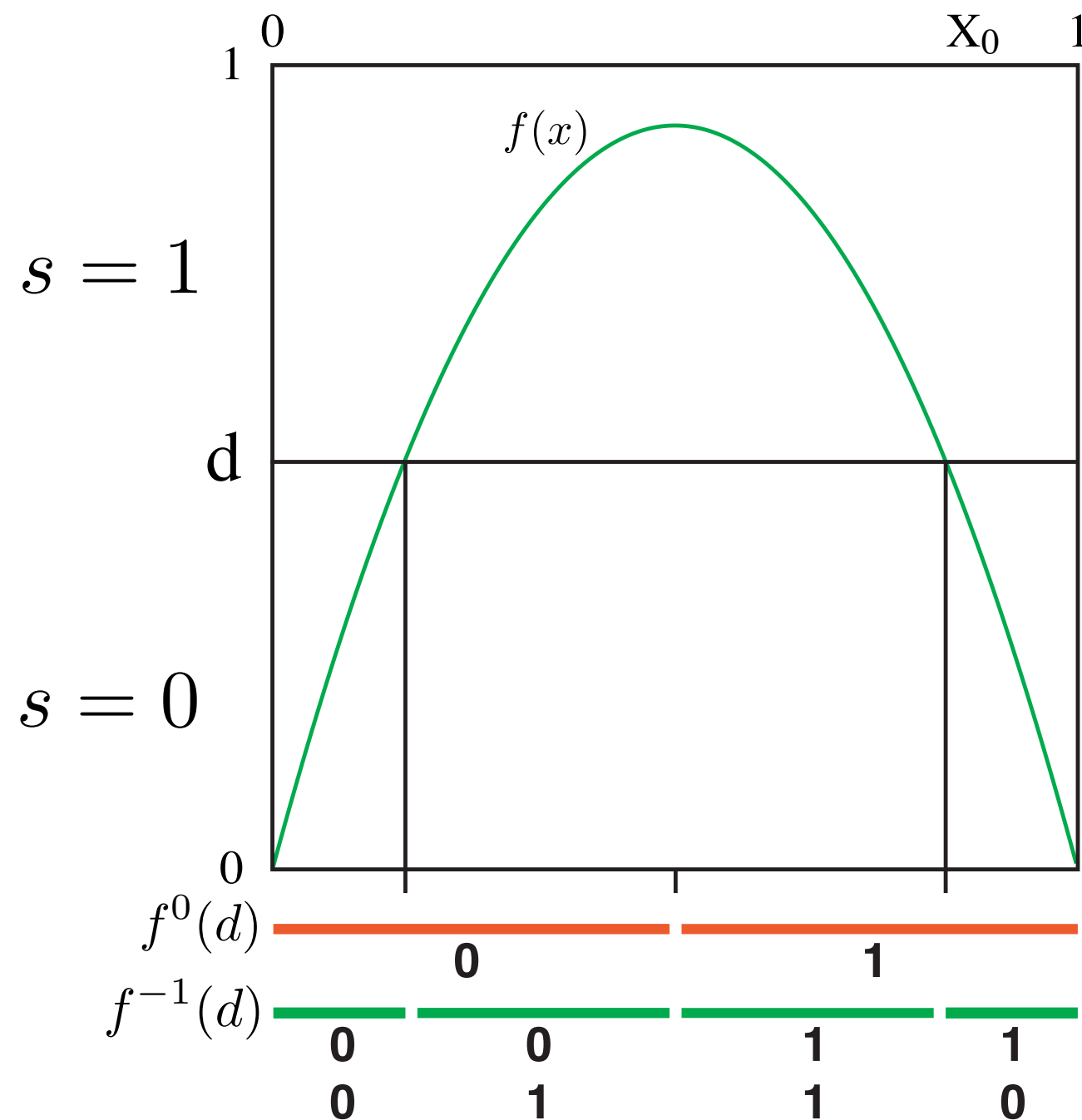
# From Determinism to Stochasticity ...

## Measurement Theory of ID Maps ...



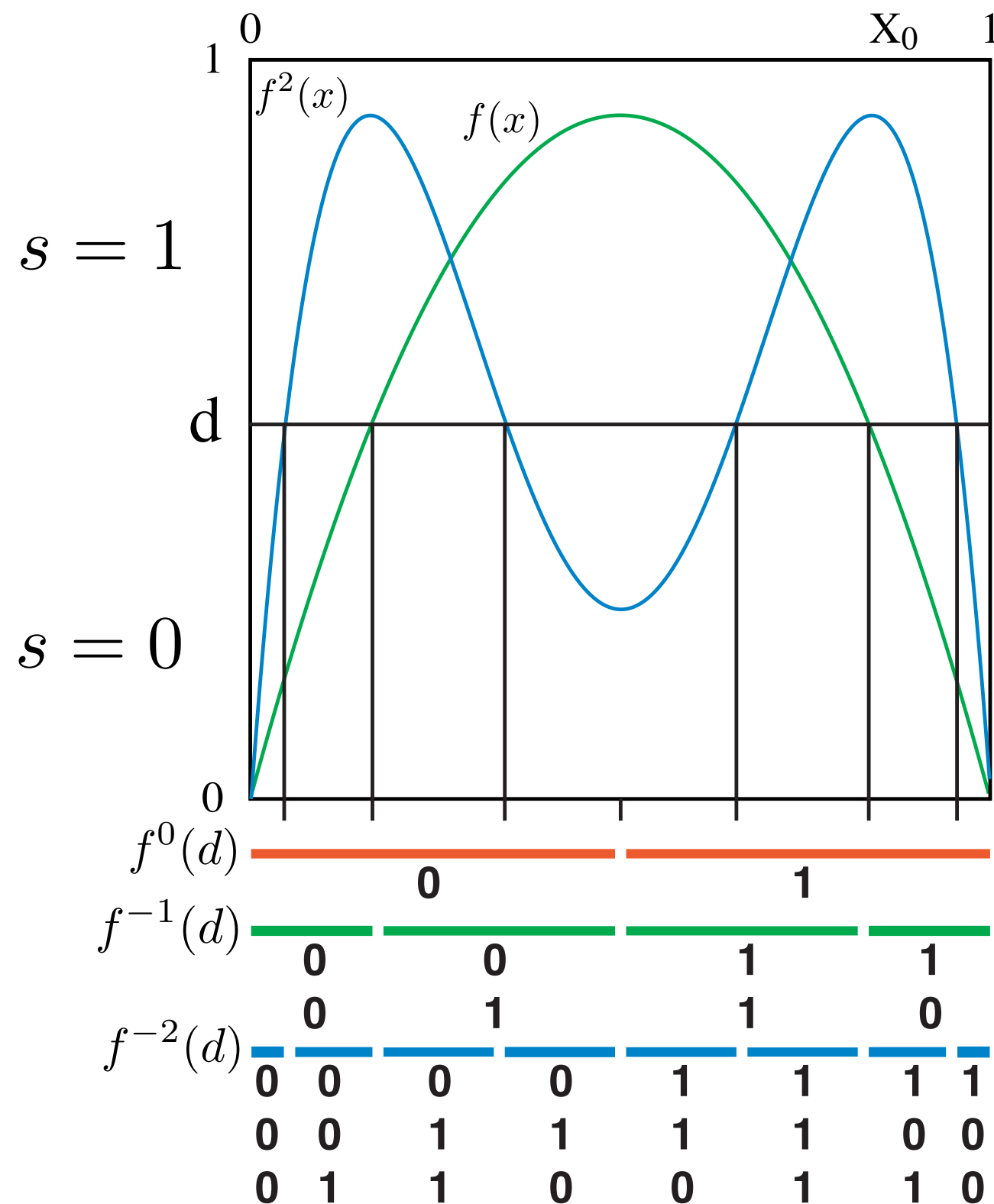
# From Determinism to Stochasticity ...

## Measurement Theory of ID Maps ...



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# From Determinism to Stochasticity ...

## Measurement Theory ...

Dynamical System:  $\{f, M\}$

$$f : M \rightarrow M$$

### Partition:

$$\mathcal{P} = \{P_i \subset M : i = 1, \dots, p\}$$

$$M = \bigcup_{i=1}^p P_i$$

$$P_i \cap P_j = \emptyset, \quad i \neq j$$

### Two Partitions: $\mathcal{P}$ & $\mathcal{Q}$

**Refinement:**  $\mathcal{P} \vee \mathcal{Q} = \{P_i \cap Q_j : P_i \in \mathcal{P} \text{ \& } Q_j \in \mathcal{Q}\}$

This is a partition, too.

# From Determinism to Stochasticity ...

## Measurement Theory ...

Partition:  $\mathcal{P}$

**Measurement symbols:**  $\text{Label}(P_i) = s \in \mathcal{A}$

**Measurement operator:**  $\pi(x) = s, \ x \in P_s$

**Orbit:**  $\mathbf{x} = \{x_0, x_1, x_2, \dots\}$

**Measurement sequence:**

$$\begin{aligned} \mathbf{s} &= \pi(\mathbf{x}) \\ &= \{s_0, s_1, s_2, \dots : s_i = \pi(x_i)\} \end{aligned}$$



# From Determinism to Stochasticity ...

## Measurement Theory ...

**Orbit Space:**  $\cdots \times M \times M \times M \times \cdots$

**Sequence Space:**  $\Sigma = \cdots \times \mathcal{A} \times \mathcal{A} \times \mathcal{A} \times \cdots$   
 $= \{\mathbf{s} = (\cdots s_{-1} s_0 s_1 s_2 \cdots), s_i \in \mathcal{A}\}$

Dynamic over state space:  $f : M \rightarrow M$

Dynamic over sequence space: **Shift operator**

$$\sigma(\mathbf{s}) = \mathbf{s}'$$

$$s'_i = (\sigma(\mathbf{s}))_i = s_{i-1}$$

**Trivial dynamics: All structure now in sequences!**

# From Determinism to Stochasticity ...

## Measurement Theory ...

**Admissible sequences**  $\Sigma_f : f^i(x_0) \in P_{s_i}$

$$\Sigma_f \subseteq \Sigma$$

$x_0 \in \Lambda$  **f**-invariant set, then  $\Sigma_f$  is a closed, shift-invariant set:

$$\Sigma_f = \sigma(\Sigma_f)$$

**Symbolic Dynamical System** under partition  $\mathcal{P}$ :

**Subshift:**  $\{\Sigma_f, \sigma_f\}$

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## Measurement Theory ...

**Projection Operator:**  $\Delta(\mathbf{s}) \subset M$

$$\Delta(\mathbf{s}) = \bigcap_{i=0}^{\infty} f^{-i}(P_{s_i})$$

**Admissible:**  $s^L = s_0 \dots s_{L-1}$

Sequences that are close to  $s^L$  : **L-cylinder**

$$s^L = \{\mathbf{s} : s_i = (s^L)_i, i = 0, 1, \dots, L-1\}$$

**Initial conditions whose orbit stays close to  $x_0, x_1, x_2, \dots, x_{L-1}$**

$$\Delta(\mathbf{s}^L)$$

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## Measurement Theory ...

**L-cylinder-induced partition of M:**

$$\Delta(\mathbf{s}^L) = \left\{ \bigcap_{i=0}^L f^{-i}(P_{s_i}) : s^L = s_0 \dots s_{L-1} \in \Sigma_f \right\}$$

**L-refinement of partition:**

$$\mathcal{P}^L = \mathcal{P} \vee f^{-1}\mathcal{P} \vee \dots \vee f^{L-1}\mathcal{P}$$

$$\Delta(\mathbf{s}^L) \in \mathcal{P}^L$$

# From Determinism to Stochasticity ...

## Measurement Theory ...

### Symbolic dynamics:

1. Replace complicated dynamic ( $f$ ) with trivial dynamic ( $\sigma$ )
2. Replace infinitely precise point  $x \in M$   
with discrete infinite sequence  $s \in \Sigma_f$
3. If the partition is “good” then
  - a. Study discrete sequences to learn about continuous system
  - b. Can often calculate quantities directly

# From Determinism to Stochasticity ...

## Measurement Theory of 1D Maps:

$$x_{n+1} = f(x_n) \quad x \in [0, 1]$$

$f(x)$  with two monotone pieces

Binary partition:  $\mathcal{P} = \{0 \sim x \in [0, d], 1 \sim x \in (d, 1]\}$

**Decision point:**  $d \in [0, 1]$

L-cylinder induced partition dividers:

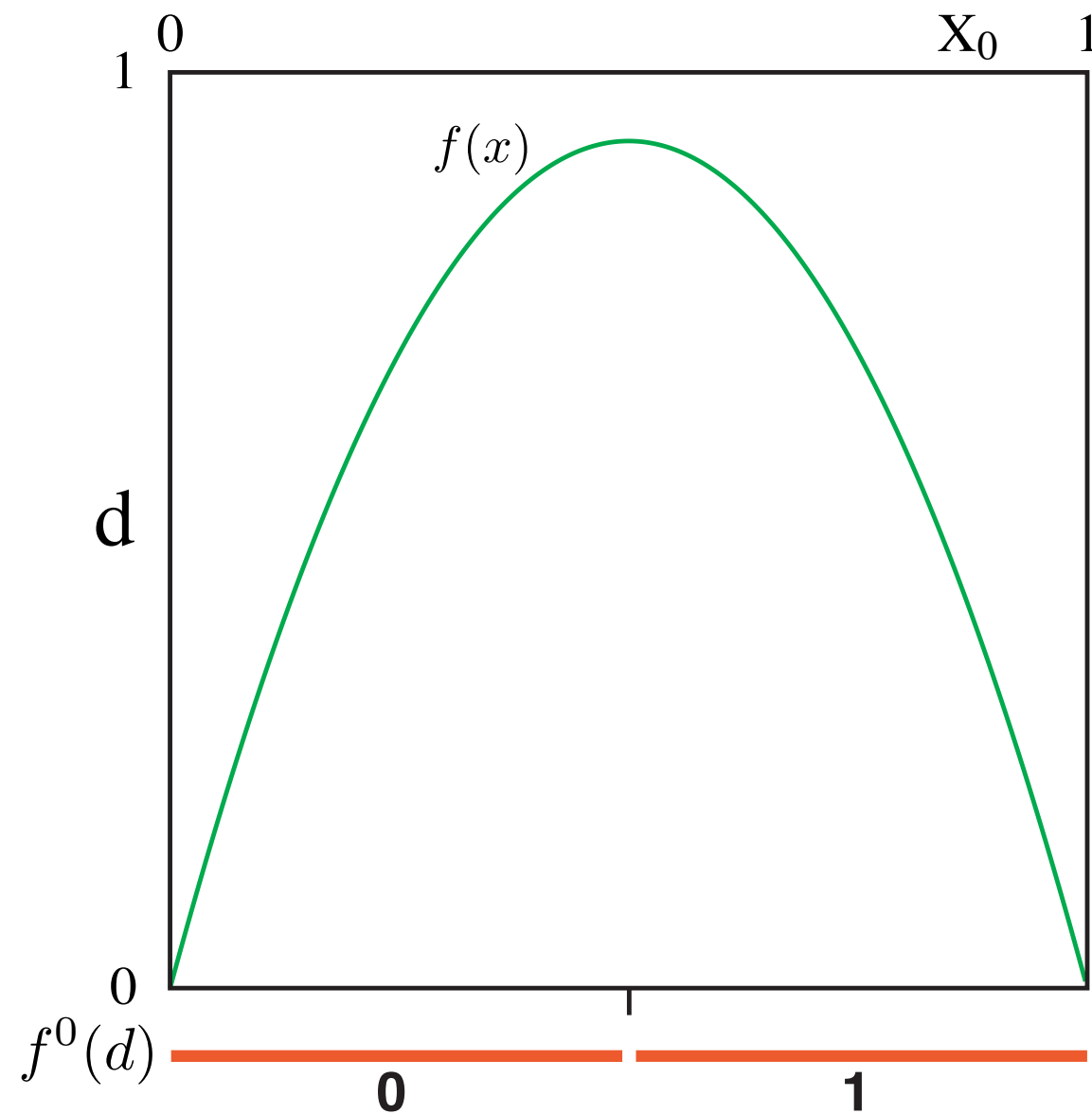
$$\mathcal{P}^L = \{d, f^{-1}(d), f^{-2}(d), \dots, f^{-(L-1)}(d)\}$$

Metrize states:

$$\phi(x) = \sum_{i=0}^{\infty} \frac{\pi(f^i(x))}{2^i}$$

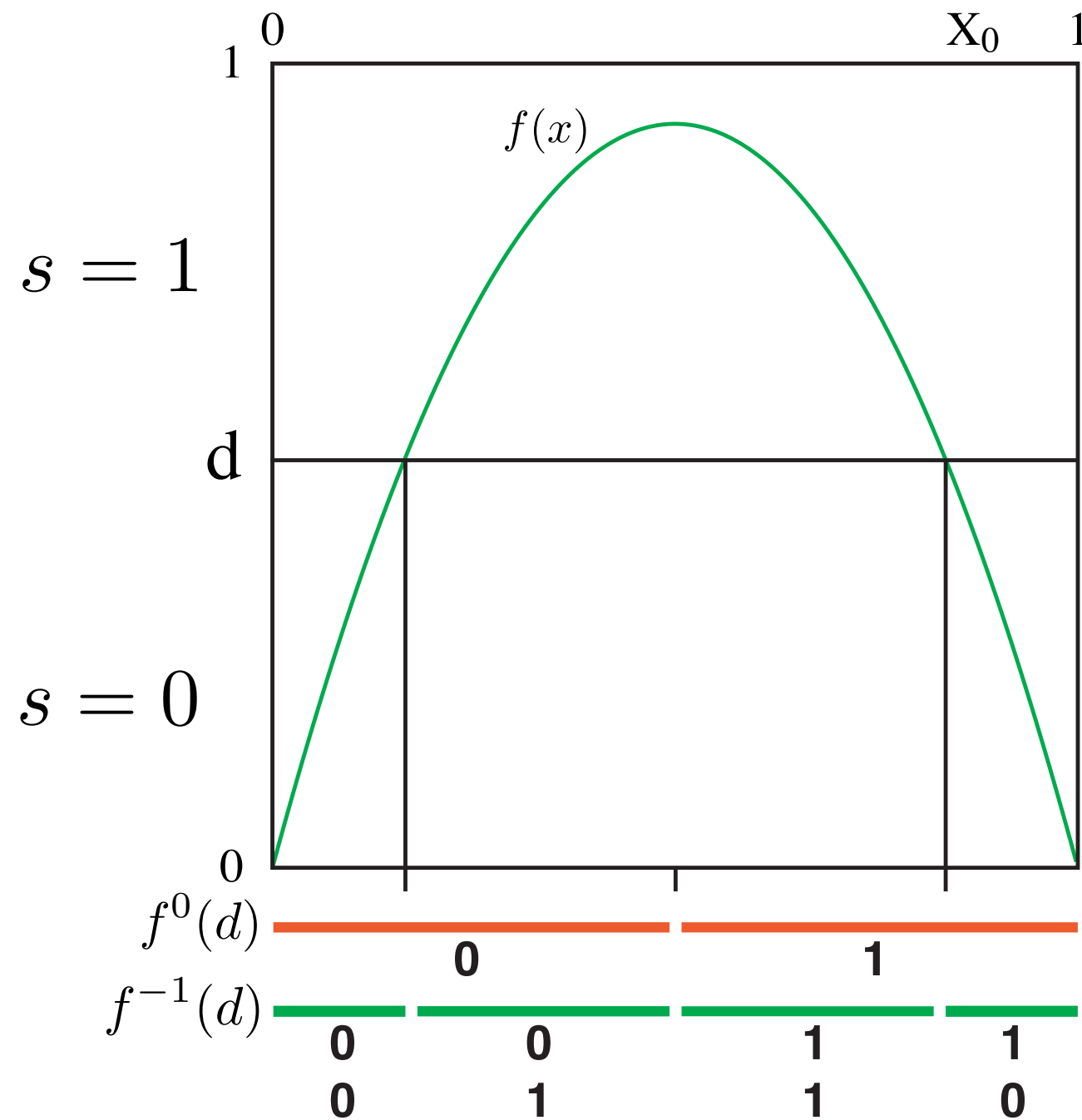
# From Determinism to Stochasticity ...

## Measurement Theory of ID Maps ...



# From Determinism to Stochasticity ...

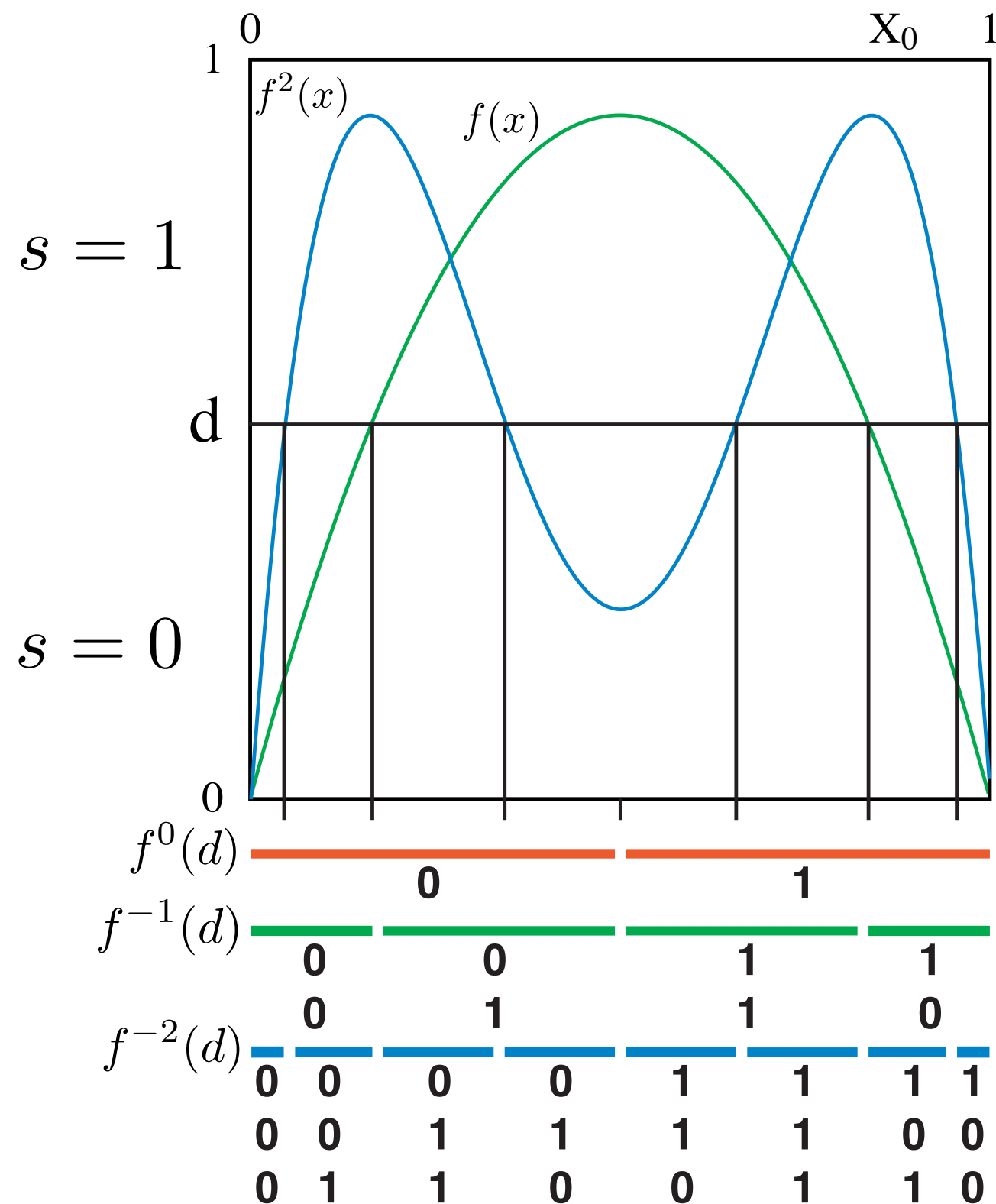
## Measurement Theory of ID Maps ...





# From Determinism to Stochasticity ...

## Measurement Theory of ID Maps ...



# From Determinism to Stochasticity ...

Kinds of Instruments:

When are partitions good?

When symbol sequences **encode** orbits

Diagram **commutes**:

$$\mathcal{T}(x) = \Delta \circ \sigma \circ \Delta^{-1}(x)$$

$$\begin{array}{ccc} M & \xrightarrow{\mathcal{T}} & M \\ \Delta \uparrow & & \Delta \uparrow \\ \mathcal{A}^{\mathbb{Z}} & \xrightarrow{\sigma} & \mathcal{A}^{\mathbb{Z}} \end{array}$$

Good kinds of instruments:

**Markov partitions**

**Generating partitions**

# From Determinism to Stochasticity ...

## Measurement Theory ...

### Markov Partitions for 1D Maps:

Discrete symbol sequences:  $\overleftrightarrow{s} = \overleftarrow{s} \overrightarrow{s}$ ,  $s \in \mathcal{A}$

Markov = Given symbol, ignore history

$$\Pr(\overrightarrow{s} \mid \overleftarrow{s}) = \Pr(\overrightarrow{s} \mid s_1)$$

### Maps of the interval?

$$f : I \rightarrow I, \quad I = [0, 1]$$

Partition:  $\mathcal{P} = \{P_1, \dots, P_p\}$

Open sets:  $P_i = (d_{i-1}, d_i)$ ,  $0 = d_0 < d_1 < \dots < d_p = 1$

$$I = \bigcup_{i=1}^p \bar{P}_i$$

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## Measurement Theory ...

### Markov Partitions for 1D Maps ...

$\mathcal{P}$  is a **Markov partition** for  $f$  :

$$f(P_i) = \bigcup_j P_j, \forall i$$

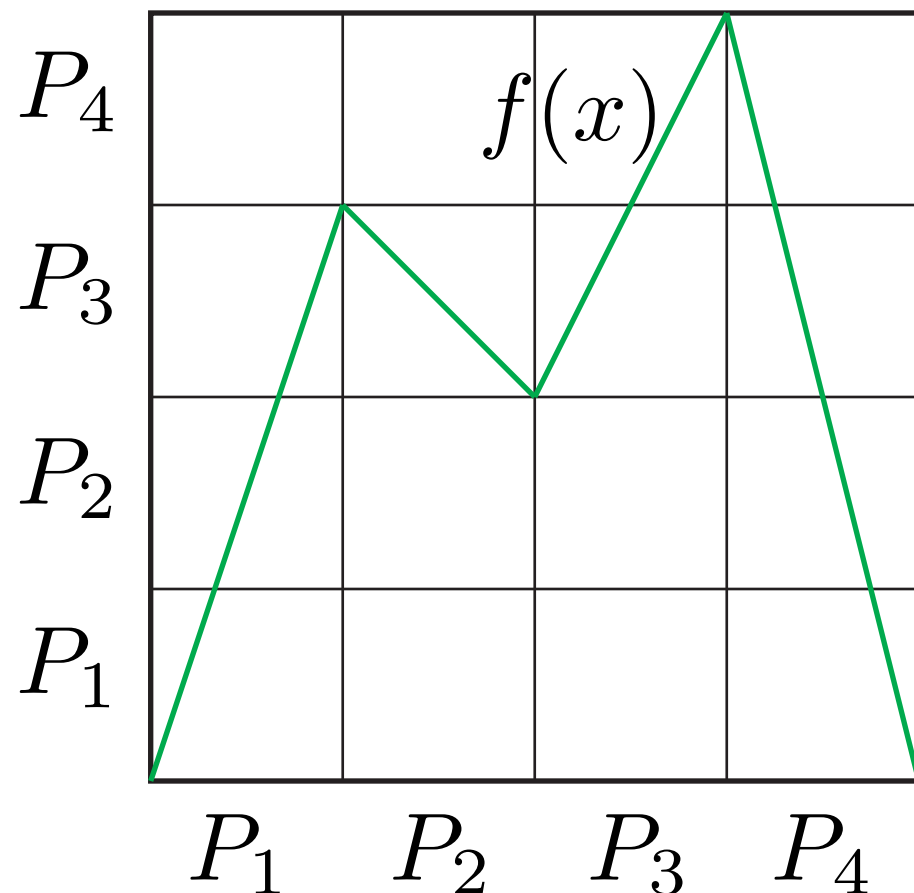
$f(P_i)$  is 1-to-1 and onto (homeomorphism)

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## Measurement Theory ...

### Markov Partitions for ID Maps ...

$$s \in \mathcal{A} = \{1, 2, 3, 4\}$$



$$f(P_1) = P_1 \cup P_2 \cup P_3$$

$$f(P_2) = P_3$$

$$f(P_3) = P_3 \cup P_4$$

$$f(P_4) = P_1 \cup P_2 \cup P_3 \cup P_4$$

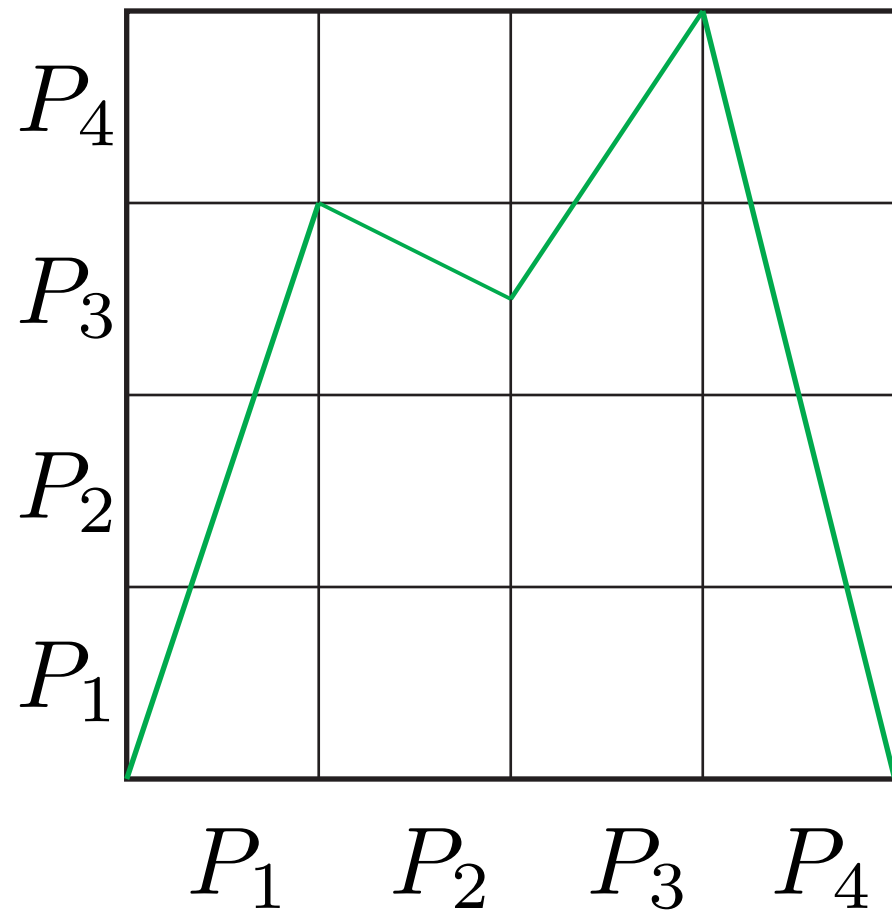
**Markov!**

$\Rightarrow \vec{s}, s \in \mathcal{A}$       **Good coding**

# From Determinism to Stochasticity ...

## Measurement Theory ...

### Markov Partitions for ID Maps ...



$$f(P_2) \subset P_3$$

$$f(P_2) \neq \bigcup_i P_i$$

$$f(P_3) \subset P_3 \cup P_4$$

$$f(P_3) \neq \bigcup_i P_i$$

**Not Markov!**

$$\Rightarrow \vec{s}, s \in \mathcal{A}$$

**Bad coding**

# From Determinism to Stochasticity ...

## Measurement Theory ...

### Why Markov Partition?

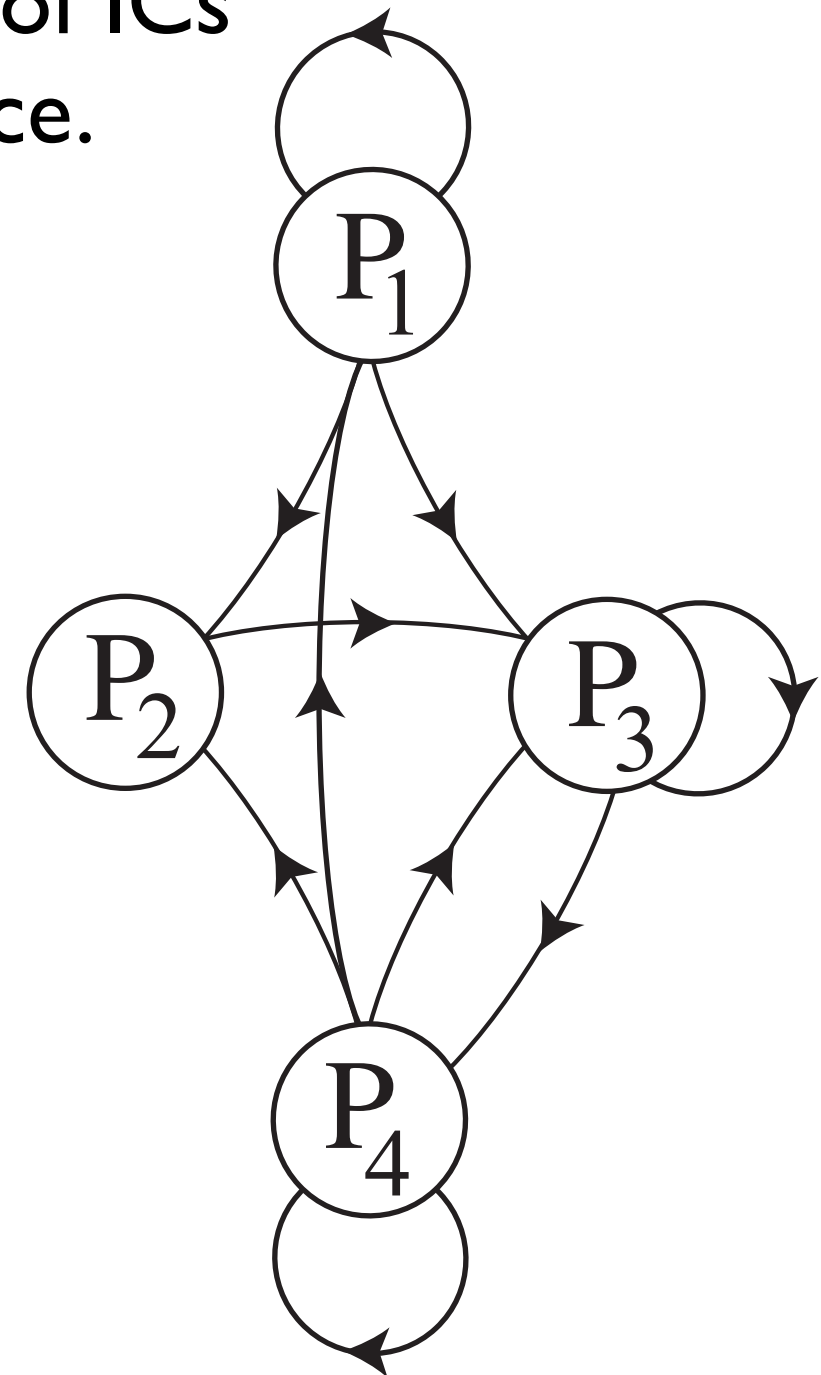
Symbol sequences track orbits:

Longer the sequence, the smaller the set of ICs that could have generated that sequence.

$$\lim_{L \rightarrow \infty} ||\Delta(s^L)|| \rightarrow 0$$

Markov Partition is stronger:

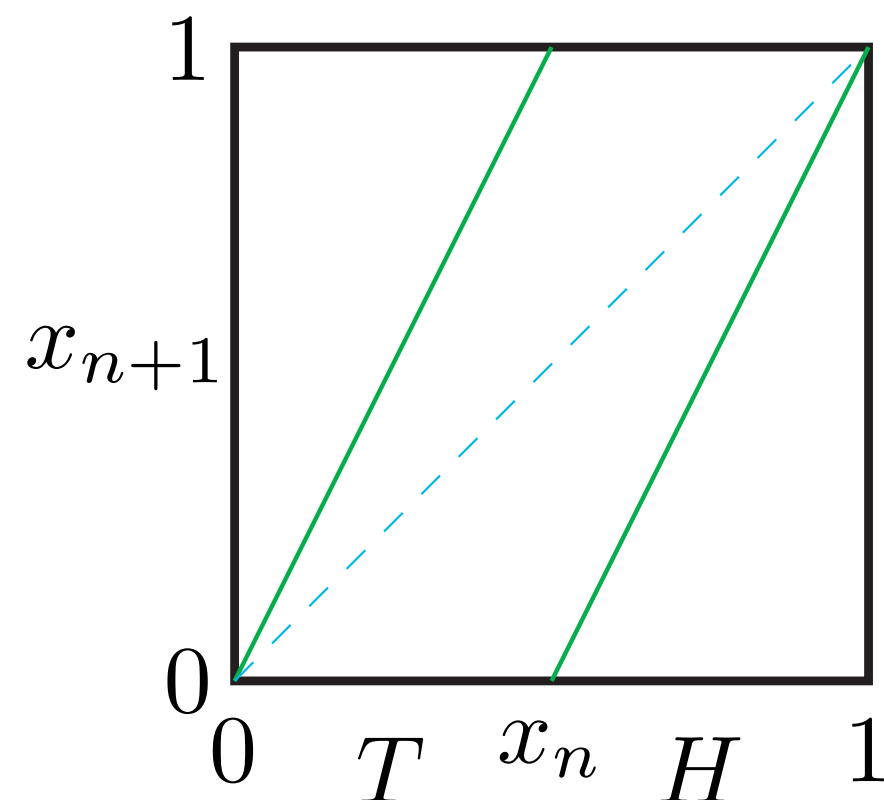
Summarize map with a Markov chain over the partition elements.



# From Determinism to Stochasticity ... Measurement Theory ...

Markov partition for Shift map:

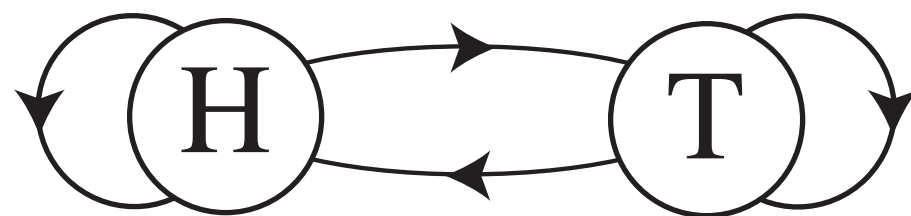
$$\mathcal{P} = \{T \sim (0, \frac{1}{2}), H \sim (\frac{1}{2}, 1)\}$$



$$f(P_T) = P_T \cup P_H \text{ \& } f|_{P_T} \text{ is monotone}$$

$$f(P_H) = P_T \cup P_H \text{ \& } f|_{P_H} \text{ is monotone}$$

Associated (topological) Markov chain:



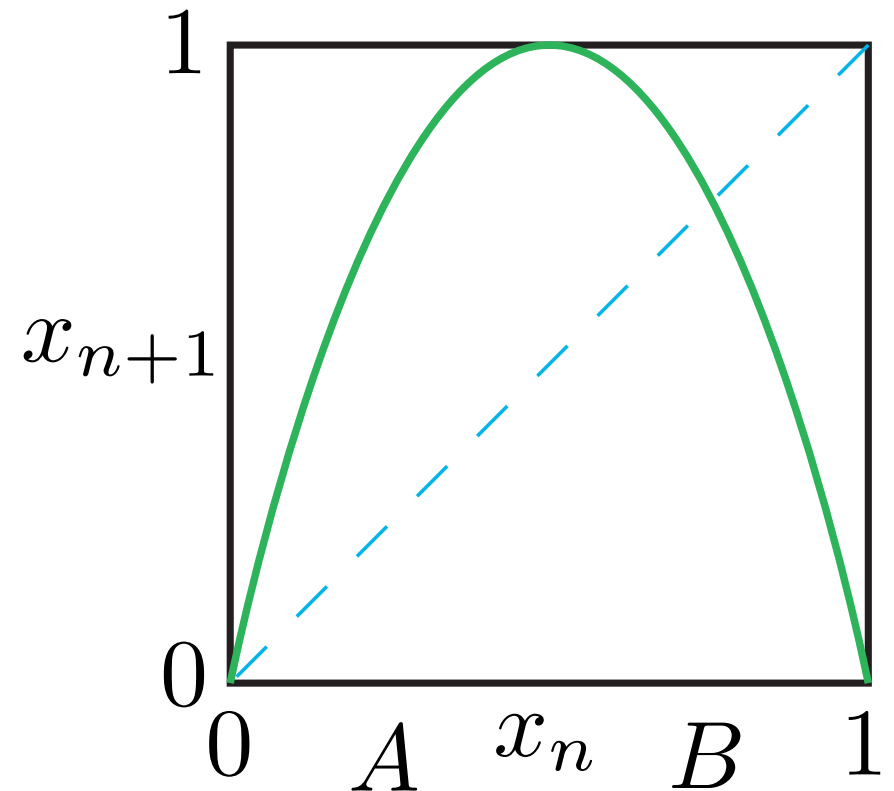
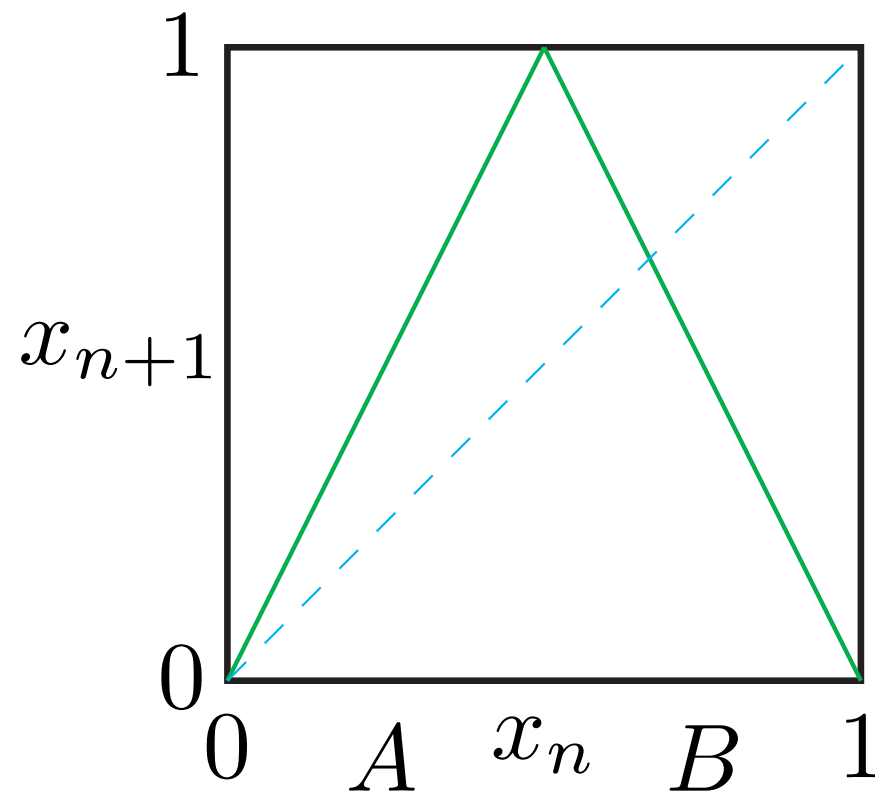


# From Determinism to Stochasticity ...

## Measurement Theory ...

Markov partition for Tent and Logistic maps (Two-onto-One):

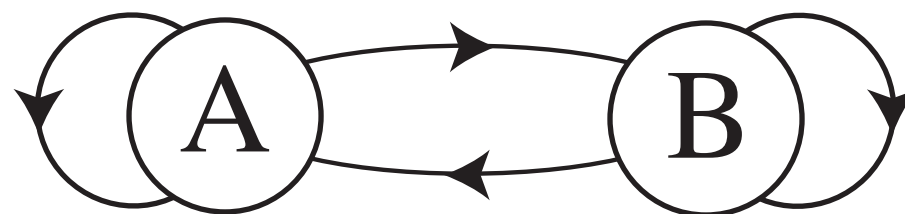
$$\mathcal{P} = \{A \sim (0, \frac{1}{2}), B \sim (\frac{1}{2}, 1)\}$$



$$f(P_A) = P_A \cup P_B \text{ \& } f|_{P_A} \text{ is monotone}$$

$$f(P_B) = P_A \cup P_B \text{ \& } f|_{P_B} \text{ is monotone}$$

Associated Markov chain:



Notice what is  
thrown away

# From Determinism to Stochasticity ...

## Measurement Theory ...

Markov partition for Golden Mean map:

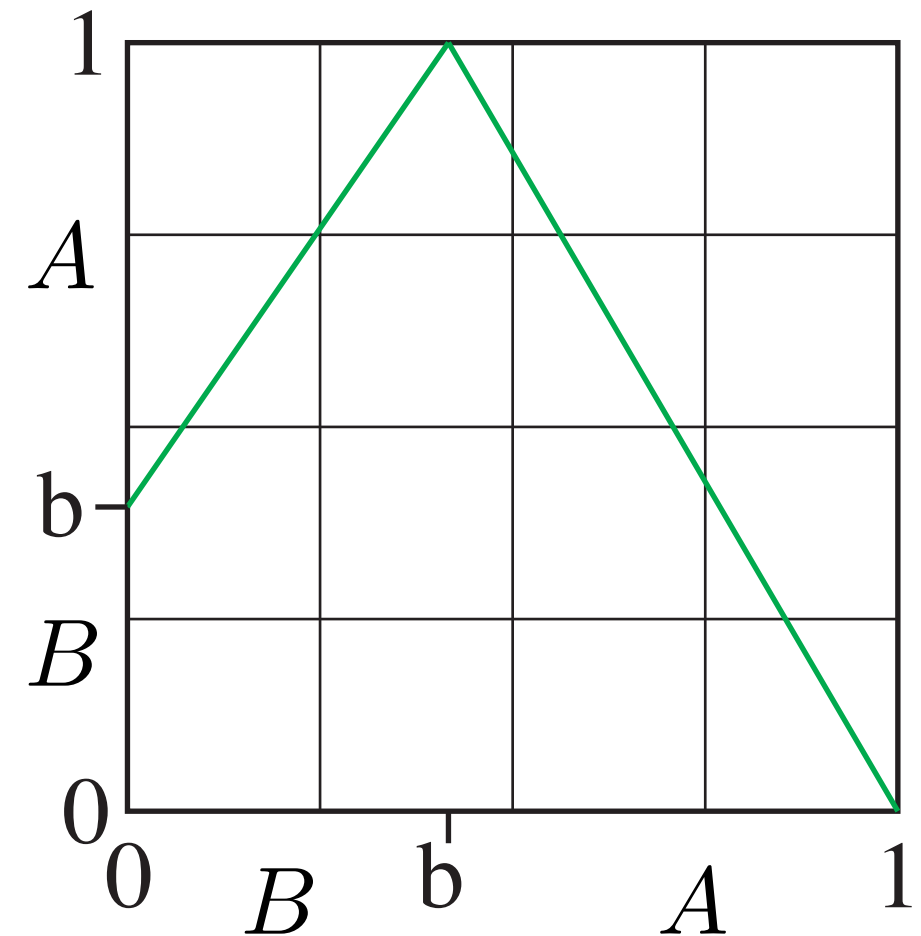
$$x_{n+1} = \begin{cases} \phi x_n + b & 0 \leq x_n \leq b \\ (x_n - 1)/(b - 1) & b < x_n \leq 1 \end{cases}$$

$$\phi = \frac{1 + \sqrt{5}}{2} \quad b = \frac{1}{1 + \phi}$$

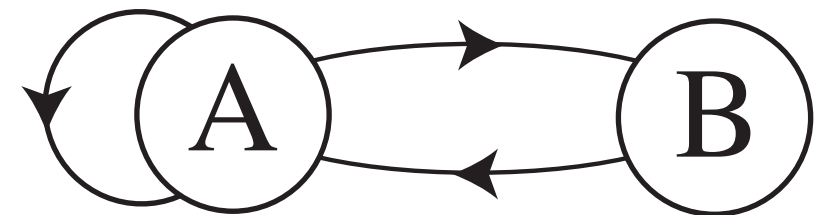
$$\mathcal{P} = \{B \sim (0, b), A \sim (b, 1)\}$$

$$f(P_B) = P_A \text{ \& } f|_{P_B} \text{ is monotone}$$

$$f(P_A) = P_B \cup P_A \text{ \& } f|_{P_A} \text{ is monotone}$$



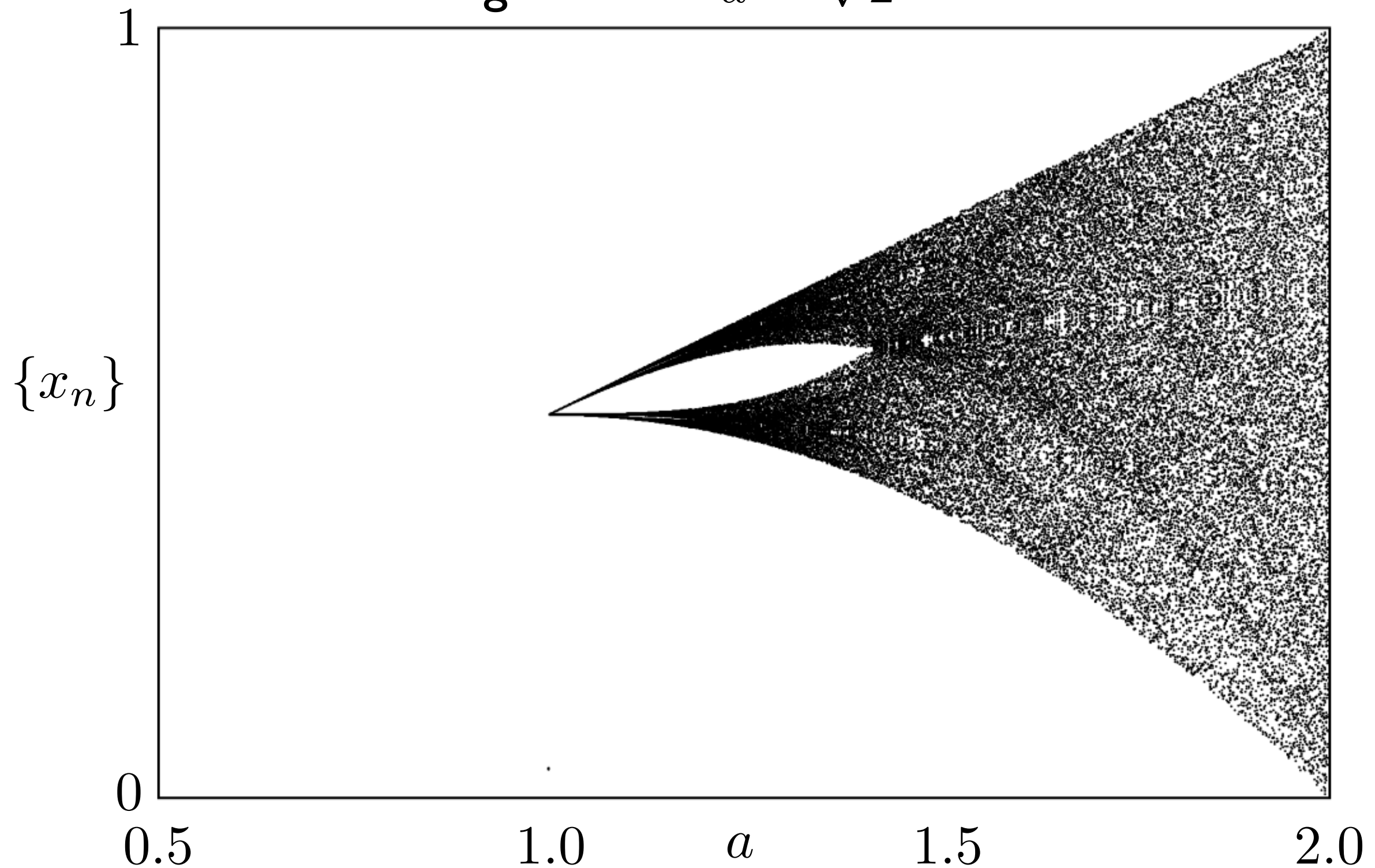
Markov chain is Golden Mean Process:



# From Determinism to Stochasticity ... Measurement Theory ...

Markov partition for Tent map:

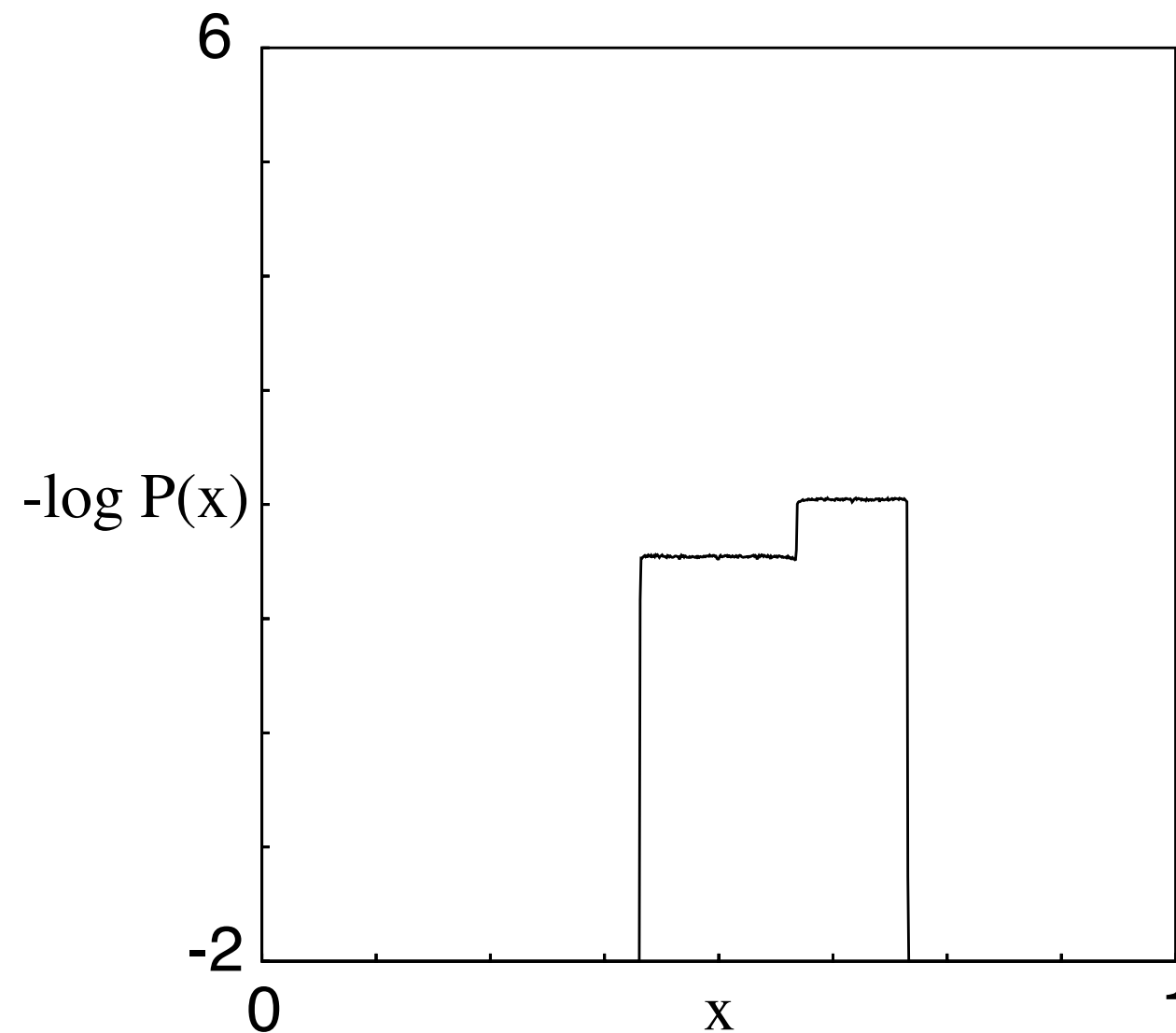
2 bands merge to 1 at  $a = \sqrt{2}$ .



# From Determinism to Stochasticity ... Measurement Theory ...

Markov partition for Tent map:

2 bands merge to 1 at  $a = \sqrt{2}$ .



# From Determinism to Stochasticity ...

## Measurement Theory ...

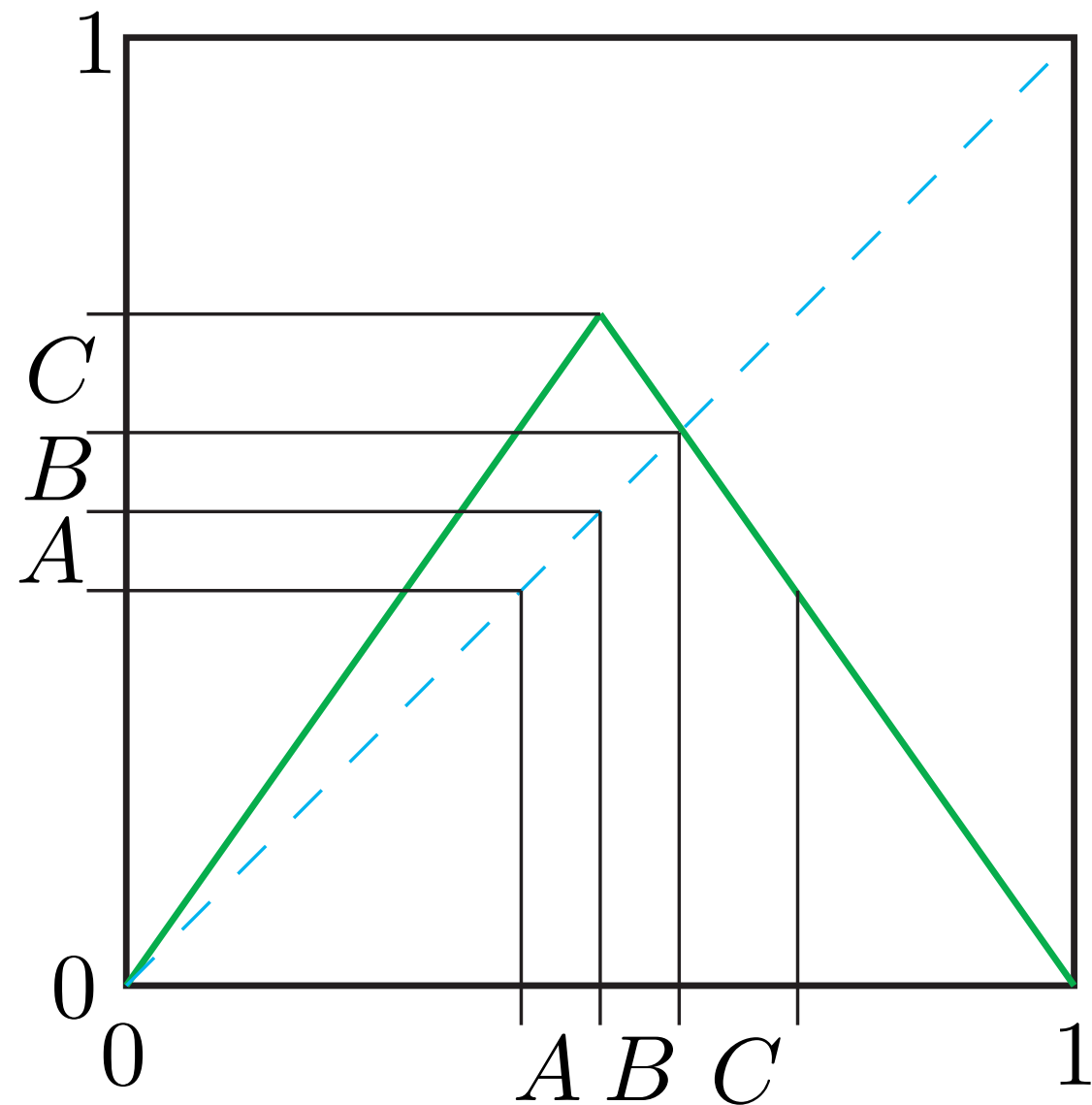
Markov partition for Tent map 2 bands merge to 1:  $a = \sqrt{2}$

Attractor:

$$\Lambda = (f^2(\frac{1}{2}), f(\frac{1}{2}))$$

Partition:

$$\mathcal{P} = \{A \sim (f^2(\frac{1}{2}), \frac{1}{2}), \\ B \sim (\frac{1}{2}, f^3(\frac{1}{2})), \\ C \sim (f^3(\frac{1}{2}), f(\frac{1}{2}))\}$$



# From Determinism to Stochasticity ...

## Measurement Theory ...

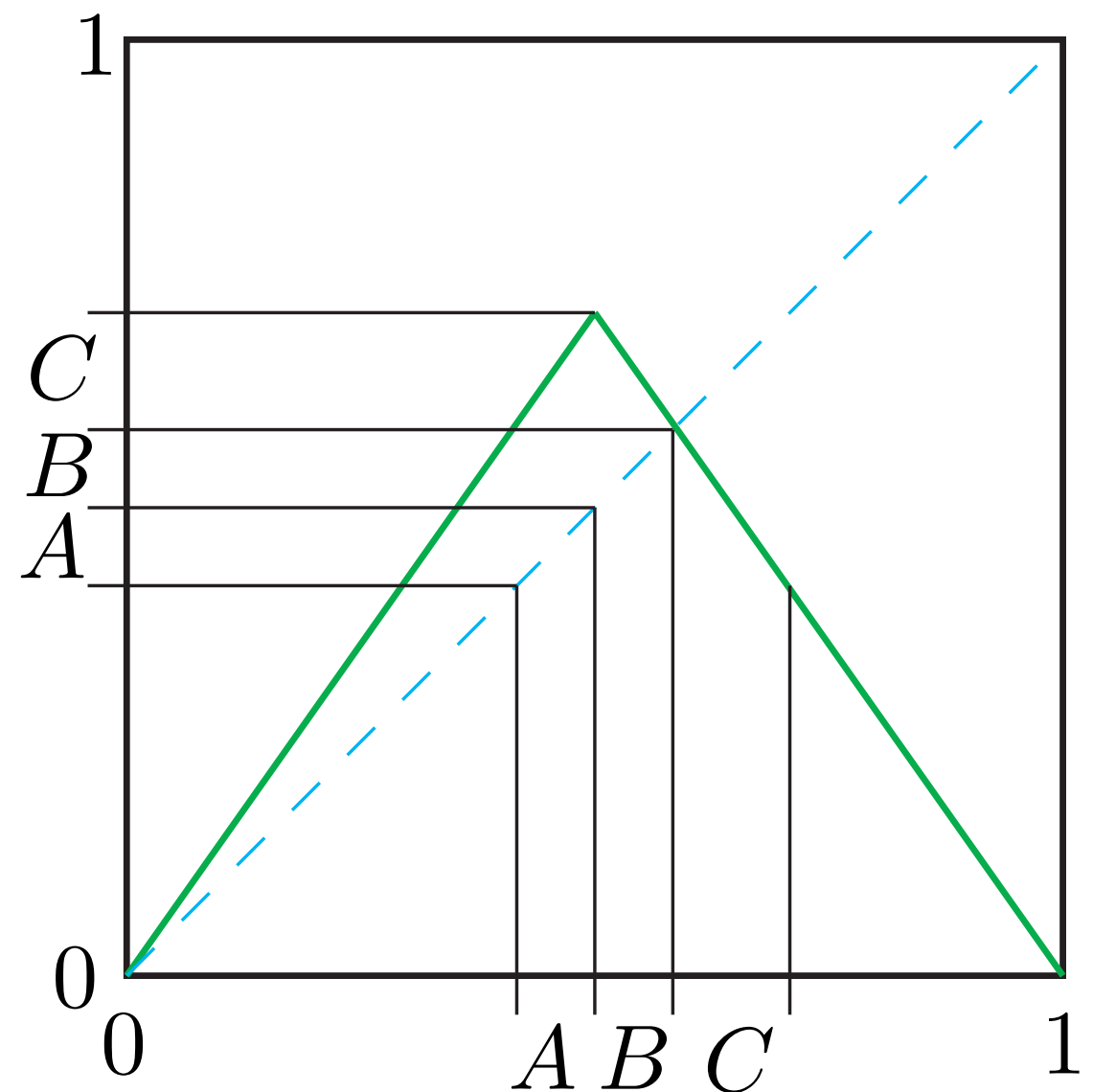
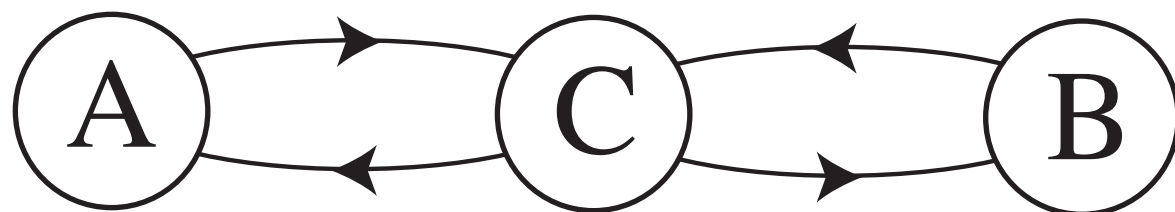
Markov partition for Tent map 2 bands merge to 1:  $a = \sqrt{2}$

$f(P_C) = P_A \cup P_B$  &  $f|_{P_C}$  is monotone

$f(P_B) = P_C$  &  $f|_{P_B}$  is monotone

$f(P_A) = P_C$  &  $f|_{P_A}$  is monotone

Markov chain:



# From Determinism to Stochasticity ...

Reading for next lecture:

*Lecture Notes.*