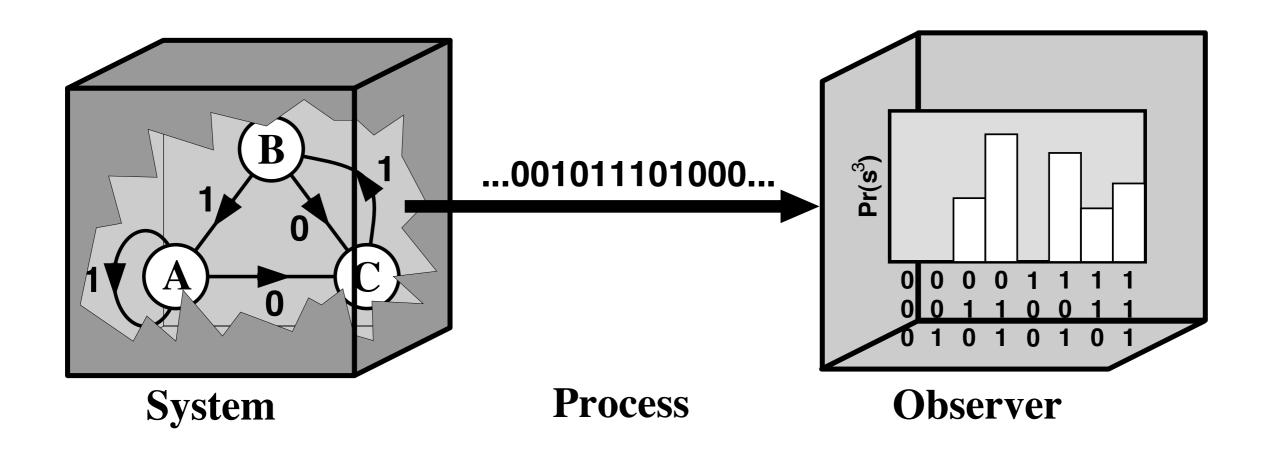
## From Determinism to Stochasticity Stochastic Processes

Reading for this lecture:

(These) Lecture Notes.

Note: We will skip the z-Transform and so the last slides here and also Computational Mechanics Reader (CMR) articles ZT and RI.

The Measurement Channel:



Stochastic Processes:

Chain of random variables:

$$\stackrel{\leftrightarrow}{S} \equiv \dots S_{-2}S_{-1}S_0S_1S_2\dots$$

Random variable:  $S_t$ 

Alphabet: 
$$\mathcal{A} = \{1, 2, \dots, k\}$$

Realization:

 $\cdots s_{-2}s_{-1}s_0s_1s_2\cdots;\ s_t\in\mathcal{A}$ 

Stochastic Processes:

Chain of random variables:  $\overleftrightarrow{S} = \overleftarrow{S}_t \overrightarrow{S}_t$ 

Past:  $\overleftarrow{S}_t = \dots S_{t-3} S_{t-2} S_{t-1}$ Future:  $\overrightarrow{S}_t = S_t S_{t+1} S_{t+2} \dots$ 

L-Block: 
$$S_t^L \equiv S_t S_{t+1} \dots S_{t+L-1}$$
  
Word:  $s_t^L \equiv s_t s_{t+1} \dots s_{t+L-1} \in \mathcal{A}^L$ 

Stochastic Processes ...

Process:  

$$\Pr(\overset{\leftrightarrow}{S}) = \Pr(\dots S_{-2}S_{-1}S_0S_1S_2\dots)$$

Sequence (or word) distributions:

$$\{\Pr(S_t^L) = \Pr(S_t S_{t+1} \dots S_{t+L-1}) : S_t \in \mathcal{A}\}$$

Process:  $\{\Pr(S_t^L): \forall t, L\}$ 

Stochastic Processes ...

Word: 
$$s_t^L = s_t s_{t+1} \dots s_{t+L-1}$$

Allowed (admissable) word:  $Pr(s_t^L) > 0$ 

Word distribution consistency conditions:

$$\Pr(s_t^{L-1}) \ge \Pr(s_t^L)$$
$$\Pr(s_t^{L-1}) = \sum_{\{s_{t+L-1}\}} \Pr(s_t^L)$$
$$\Pr(s_t^{L-1}) = \sum_{\{s_t\}} \Pr(s_t^L)$$

Subword closed: All subwords in  $s_t^L$  are admissable.

#### Processes are subword closed.

Types of Stochastic Process:

Stationary process:

$$\Pr(S_t S_{t+1} \dots S_{t+L-1}) = \Pr(S_0 S_1 \dots S_{L-1})$$

Ignore process's starting condition. Or, over many realizations.  $Pr(\cdot)$  is independent of time.

Assume stationarity, unless otherwise stated.

Drop time indices:

$$S_t^L \to S^L$$
$$s_t^L \to s^L$$

Types of Stochastic Process ...

**Uniform Process:** 

Equal-length sequences occur with same probability

$$U^L: \operatorname{Pr}(s^L) = 1/|\mathcal{A}|^L$$

Example: Fair coin

$$\mathcal{A} = \{H, T\}$$
$$\Pr(H) = \Pr(T) = 1/2$$
$$\Pr(s^L) = 2^{-L}$$

Types of Stochastic Process ...

Independent, Identically Distributed (IID) Process:

$$\Pr(\overset{\leftrightarrow}{S}) = \dots \Pr(S_t) \Pr(S_{t+1}) \Pr(S_{t+2}) \dots$$

$$\Pr(S_t) = \Pr(S_\tau), \ \forall \ t, \tau$$

**Example: Biased coin** 

$$Pr(H) = p$$

$$Pr(T) = 1 - p = q$$

$$Pr(s^{L}) = p^{n}q^{L-n}$$
Number of bods in sec.

Number of heads in sequence: n

Types of Stochastic Process ...

**R-Block Process:** 

$$\Pr(\overset{\leftrightarrow}{S}) = \cdots \Pr(S_1 \dots S_R) \Pr(S_{R+1} \dots S_{2R}) \cdots$$

Example: A 2-block process with no consecutive 0s

$$\mathcal{A} = \{0, 1\}$$
  

$$\Pr(00) = 0$$
  

$$\Pr(01) = 0$$
  

$$\Pr(10) = \frac{1}{2}$$
  

$$\Pr(11) = \frac{1}{2}$$
  

$$\Pr(111010) = \Pr(11)\Pr(10)\Pr(10)$$

Types of Stochastic Process ...

Markov Process:

$$\Pr(\overset{\leftrightarrow}{S}) = \dots \Pr(S_{t+1}|S_t)\Pr(S_{t+2}|S_{t+1})\Pr(S_{t+3}|S_{t+2})\dots$$

Example: No Consecutive 0s (Golden Mean Process)

 $\mathcal{A} = \{0, 1\}$   $\Pr(0|0) = 0$   $\Pr(1|0) = 1$   $\Pr(0|1) = 1/2$  $\Pr(1|1) = 1/2$ 

#### Not Noisy Period-2 Process: GMP @ L = 4 has 0110.

Types of Stochastic Process ...

**Order-R Markov Process:** 

$$\Pr(S_i|\ldots, S_{i-2}, S_{i-1}) = \Pr(S_i|S_{i-R}, \ldots, S_{i-1})$$

Order-R processes are more general than R-block processes:

$$Pr(S_1 S_2 S_3 S_4) = Pr(S_1) Pr(S_2 | S_1) Pr(S_3 | S_2) Pr(S_4 | S_3)$$
  
=  $Pr(S_1 S_2) \frac{Pr(S_2 S_3)}{Pr(S_2)} \frac{Pr(S_3 S_4)}{Pr(S_3)}$   
=  $Pr(S_1 S_2) Pr(S_3 S_4)$ 

Only when blocks are independent:

$$\frac{\Pr(S_2 S_3)}{\Pr(S_2) \Pr(S_3)} = 1$$

Types of Stochastic Process ...

Hidden Markov Process:

Internal Order-R Markov Process:  $\Pr(\overset{\leftrightarrow}{S})$ 

$$\Pr(S_t | \dots S_{t-2} S_{t-1}) = \Pr(S_t | S_{t-R} \dots S_{t-1})$$
$$s_t \in \mathcal{A}$$

Observed via a function of the internal sequences  $\stackrel{\leftrightarrow}{Y} = f(\stackrel{\leftrightarrow}{S})$ 

Measurement alphabet:  $y_t \in \mathcal{B}$ 

Measurement random variables:  $\stackrel{\leftrightarrow}{Y} = \dots Y_{-2}Y_{-1}Y_0Y_1\dots$ Observation process:  $\Pr(\stackrel{\leftrightarrow}{Y} | \stackrel{\leftrightarrow}{S})$ Observed process:  $\Pr(\stackrel{\leftrightarrow}{Y})$ Block Distribution:  $\Pr(Y^L)$  From Determinism to Stochasticity ... Types of Stochastic Process ... Hidden Markov Process ... Example: The Even Process Internal Process: Golden Mean  $s_t \in \{0, 1\}$ **Observation Process:**  $y_t \in \{a, b\}$  $Y_t = f(S_{t-1}S_t)$  $y_t = \begin{cases} a, & s_{t-1}s_t = 11 \\ b, & s_{t-1}s_t = 01 \text{ or } 10 \end{cases}$  $\overset{\leftrightarrow}{s} = 1101110111101011111011\ldots$  $\stackrel{\leftrightarrow}{\mathcal{Y}}$  = . abbaabbaaabbbaaaabba . . .

Models of Stochastic Processes:

Markov chain model of a Markov process:

States: 
$$v \in \mathcal{A} = \{1, \dots, k\}$$
  
 $\stackrel{\leftrightarrow}{V} = \dots V_{-2}V_{-1}V_0V_1\dots$   
Transition matrix:  $T_{ij} = \Pr(v_{t+1}|v_t) \equiv p_{vv'}$   
 $T = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix}$   
Stochastic matrix:  $\sum_{i=1}^{k} T_{ij} = 1$ 

Exercise:

An R-block Markov process is a Markov chain with  $k = |\mathcal{A}|^R$ 

Models of Stochastic Processes ...

Markov chain ...

State distribution:

$$\vec{p}_V = (\Pr(v = 1), \Pr(v = 2), \dots, \Pr(v = k))$$
  
 $\vec{p}_V = (p_1, p_2, \dots, p_k)$ 

Evolve probability distribution:

$$\vec{p_n} = \vec{p_{n-1}}T$$

Initial distribution:  $\vec{p_0}$ 

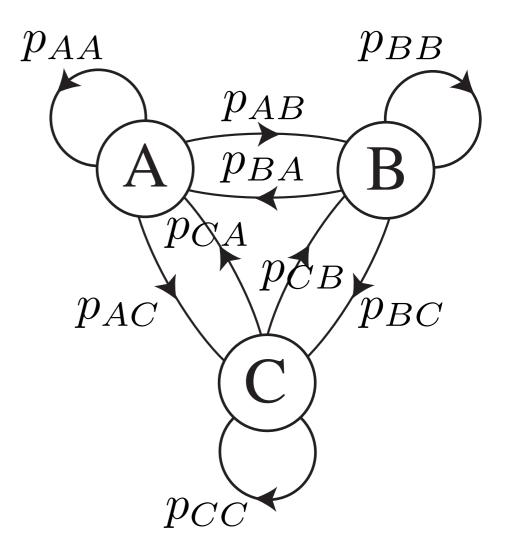
$$\vec{p}_n = \vec{p}_0 T^n$$

### State sequence distribution: Path: $v^L = v_0 v_1 v_2 \dots v_{L-1}$ $\Pr(v^L) = p(v_0)p(v_1|v_0)p(v_2|v_1)\dots p(v_{L-1}|v_{L-2})$

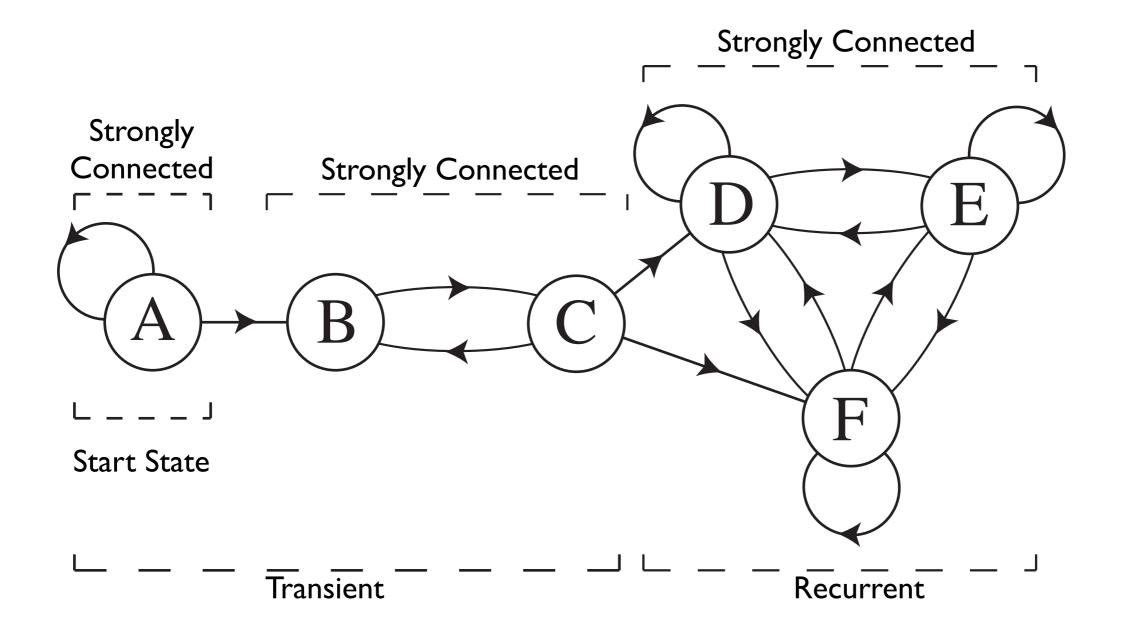
Models of Stochastic Processes ...

Markov chain ...

Example: 
$$\mathcal{A} = \{A, B, C\}$$
  
 $T = \begin{pmatrix} p_{AA} & p_{AB} & p_{AC} \\ p_{BA} & p_{BB} & p_{BC} \\ p_{CA} & p_{CB} & p_{CC} \end{pmatrix}$   
 $p_{AA} + p_{AB} + p_{AC} = 1$   
 $p_{BA} + p_{BB} + p_{BC} = 1$   
 $p_{CA} + p_{CB} + p_{CC} = 1$ 



#### Models of Stochastic Processes ... Kinds of state:



Models of Stochastic Processes ...

Statistical equilibrium: 
$$\pi = \lim_{n \to \infty} \vec{p_n}$$
  
=  $\vec{p_0} \lim_{n \to \infty} T^n$ 

**Principal (left) eigenvector:**  $\pi = \pi T$  (Eigenvalue = I)

Normalized in probability:

$$\sum_{i=1}^{k} \pi = 1$$

Asymptotic state sequence distribution:

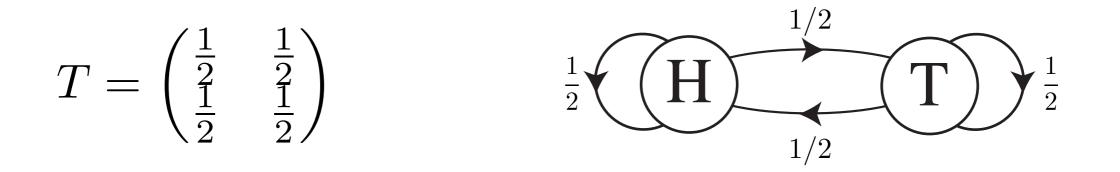
$$v^{L} = v_{0}v_{1}v_{2}\dots v_{L-1}$$
  

$$\Pr(v^{L}) = \pi(v_{0})p(v_{1}|v_{0})p(v_{2}|v_{1})\cdots p(v_{L-1}|v_{L-2})$$

Models of Stochastic Processes ...

**Example:** 

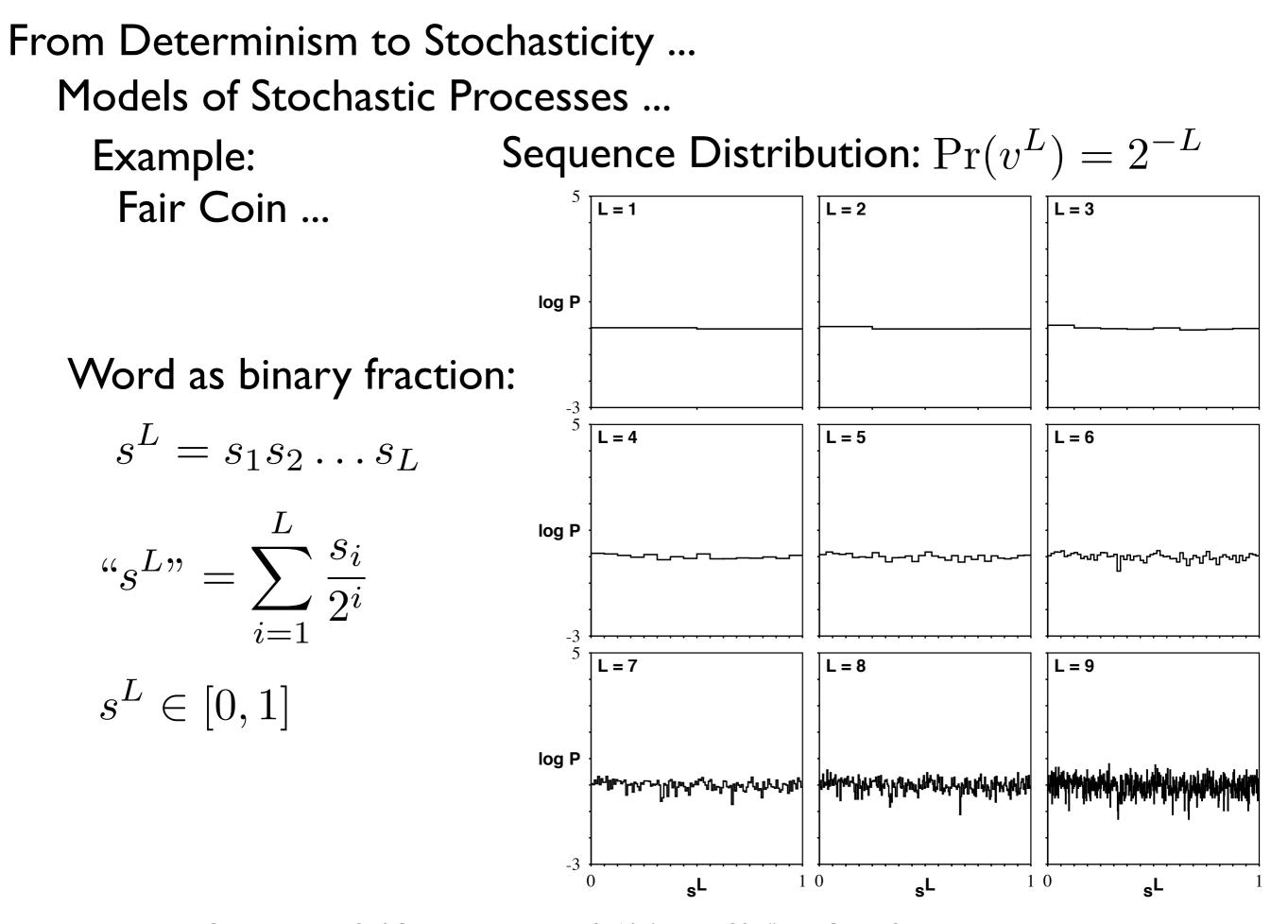
Fair Coin:  $\mathcal{A} = \{H, T\}$ 



$$\pi = (1/2, 1/2)$$

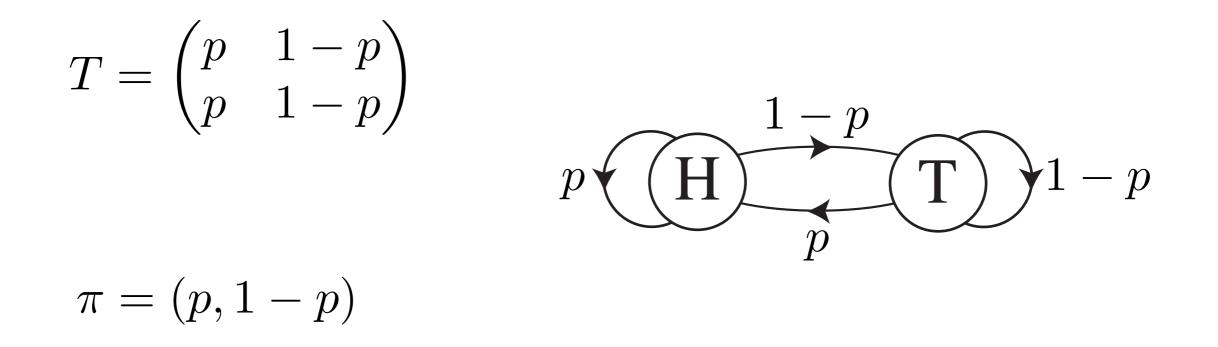
 $\Pr(H) = \Pr(T) = 1/2$ 

General uniform process: Markov chain has as many states as symbols, with uniform transition probabilities leaving them going to all states.

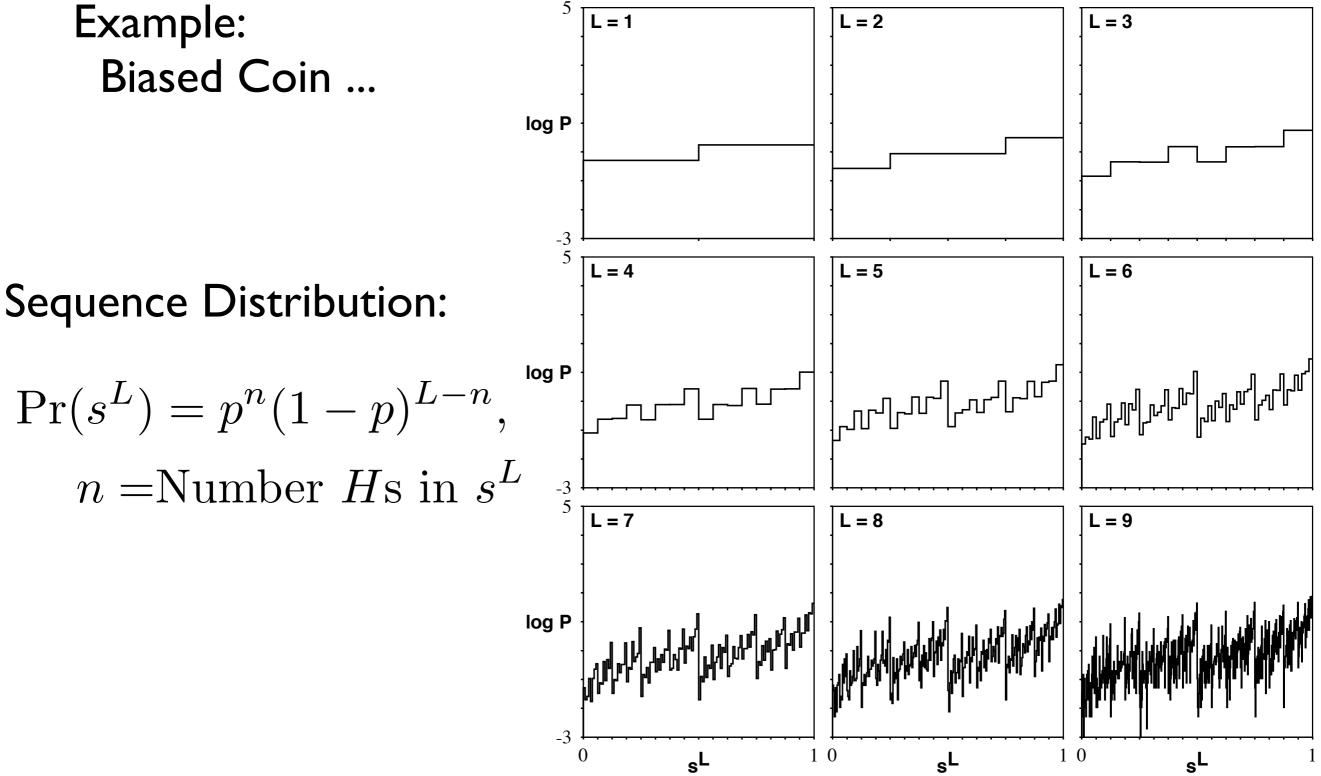


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Models of Stochastic Processes ... Example: Biased Coin:  $\mathcal{A} = \{H, T\}$ 



IID processes: Markov chain has as many states as symbols. Transitions leave each state and go to all states. Transitions entering state i have the same probability, which is  $\pi_i$ .



Models of Stochastic Processes ...

Example:

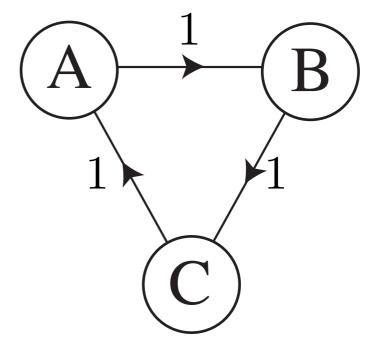
Periodic:  $\mathcal{A} = \{A, B, C\}$ 

$$T = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix}$$

$$\pi = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$$
 Careful!

Sequence distribution:

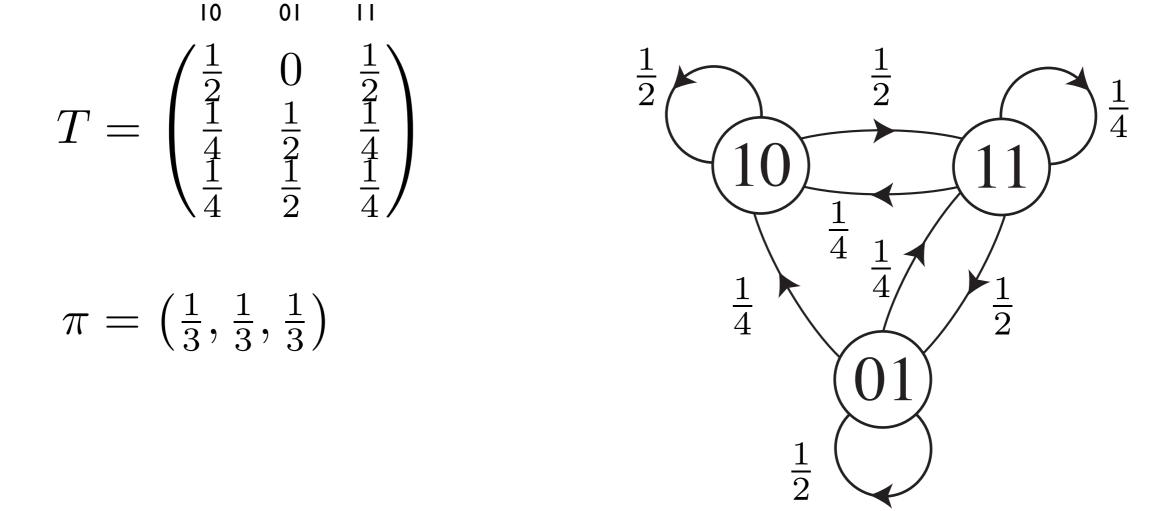
$$\begin{aligned} \Pr(A) &= \Pr(B) = \Pr(C) = \frac{1}{3} \\ \Pr(AB) &= \Pr(BC) = \Pr(CA) = \frac{1}{3} \\ \Pr(ABC) &= \Pr(BCA) = \Pr(CAB) = \frac{1}{3} \\ \Pr(s^3) &= 0 \text{ otherwise} \end{aligned}$$



Models of Stochastic Processes ...

Example:

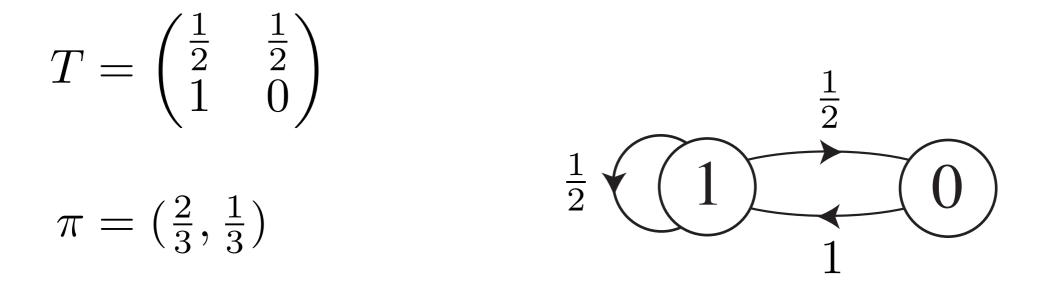
Golden Mean over 2-Blocks:  $\mathcal{A} = \{10, 01, 11\}$ 



Models of Stochastic Processes ...

Example ...

Golden Mean over I-Blocks:  $\mathcal{A} = \{0, 1\}$ 

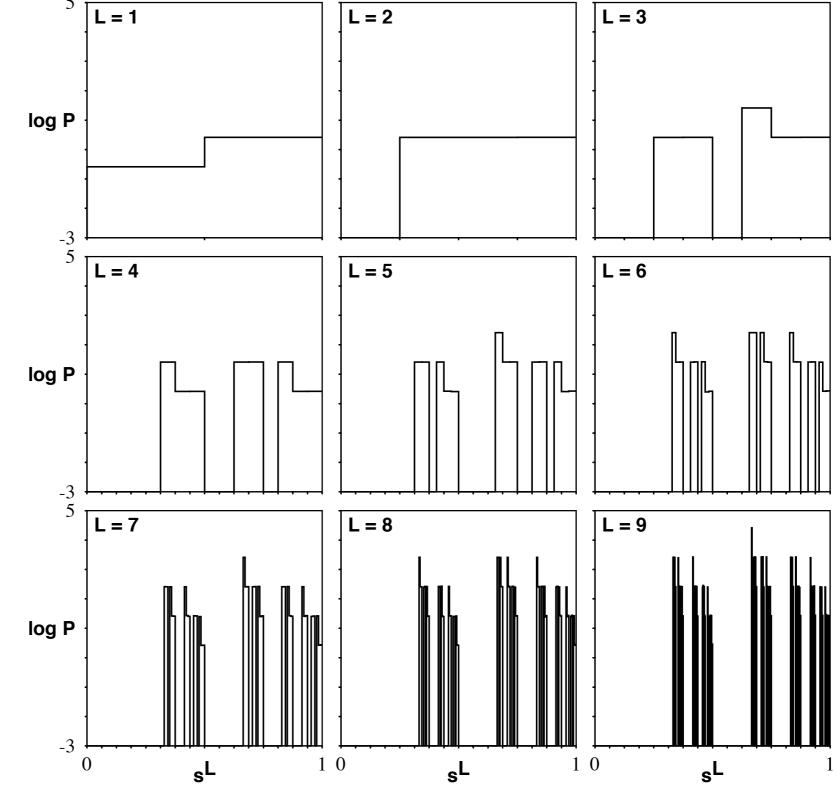


Also an order-I Markov chain. Minimal order.

#### Previous model and this: Different presentations of the Golden Mean Process

Models of Stochastic Processes ...

Example: <sup>5</sup> L=1 Golden mean: <sup>1</sup> log P



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Models of Stochastic Processes ...

Two Lessons:

Structure in the behavior: supp  $Pr(s^L)$ 

Structure in the distribution of behaviors:  $Pr(s^L)$ 

Models of Stochastic Processes ...

Hidden Markov Models of Processes:

Internal states:  $v \in \mathcal{A}$ 

Transition matrix:  $T = \Pr(v'|v), v, v' \in \mathcal{A}$ 

**Observation: Symbol-labeled transition matrices** 

$$T^{(s)} = \Pr(v', s | v), \ s \in \mathcal{B}$$

$$T = \sum_{s \in \mathcal{B}} T^{(s)}$$

Stochastic matrices:

$$\sum_{j} T_{ij} = \sum_{j} \sum_{s} T_{ij}^{(s)} = 1$$

From Determinism to Stochasticity ... Models of Stochastic Processes ... Hidden Markov Models ... Internal state distribution:  $\vec{p}_V = (p_1, p_2, \dots, p_k)$ Evolve internal distribution:  $\vec{p}_n = \vec{p}_0 T^n$ State sequence distribution:  $v^L = v_0 v_1 v_2 \dots v_{L-1}$  $\Pr(v^L) = \pi(v_0)p(v_1|v_0)p(v_2|v_1)\cdots p(v_{L-1}|v_{L-2})$ 

Observed sequence distribution:  $s^L = s_0 s_1 s_2 \dots s_{L-1}$ 

$$\Pr(s^L) = \sum_{v^L \in \mathcal{A}^L} \pi(v_0) p(v_1, s_1 | v_0) p(v_2, s_2 | v_1) \cdots p(v_{L-1}, s_{L-1} | v_{L-2})$$

No longer I-I map between internal & observed sequences: Multiple state sequences can produce same observed sequence.

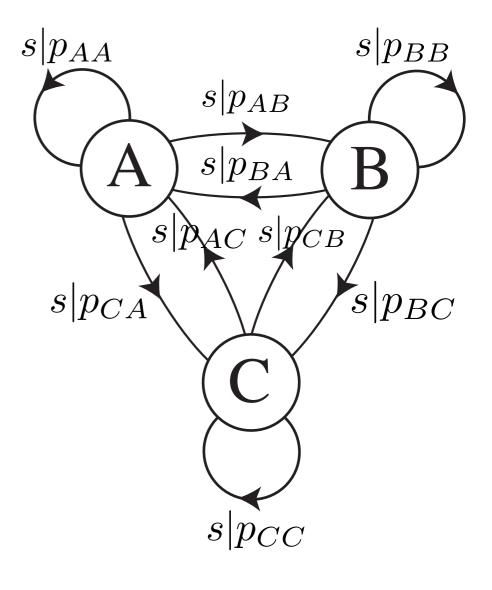
Hidden Markov Models ...

Internal:  $\mathcal{A} = \{A, B, C\}$ 

$$T = \begin{pmatrix} p_{AA} & p_{AB} & p_{AC} \\ p_{BA} & p_{BB} & p_{BC} \\ p_{CA} & p_{CB} & p_{CC} \end{pmatrix}$$

**Observed:**  $B = \{0, 1\}$ 

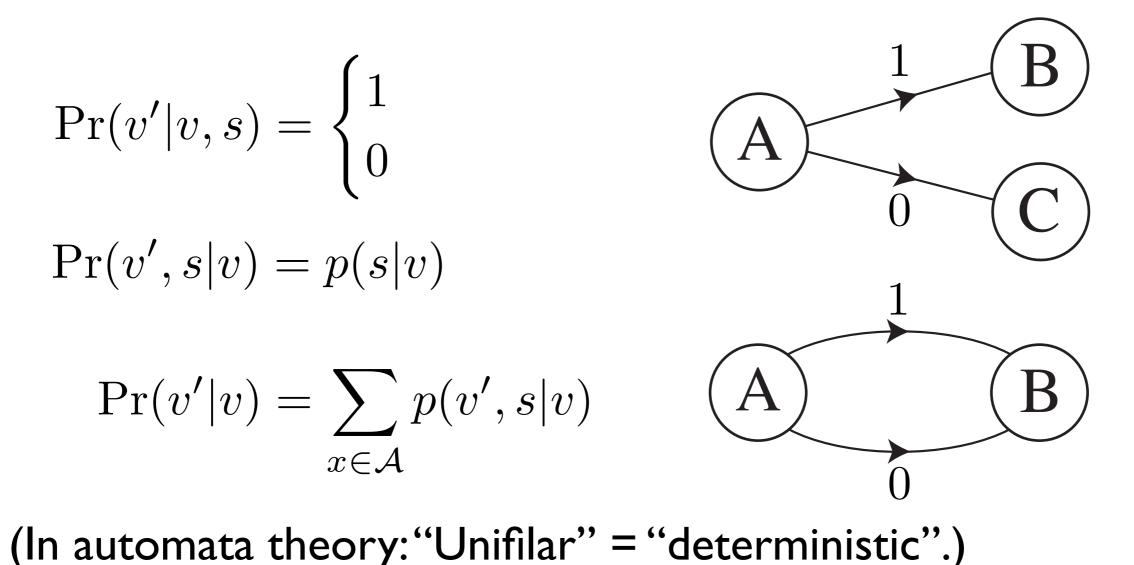
$$T^{(s)} = \begin{pmatrix} p_{AA;s} & p_{AB;s} & p_{AC;s} \\ p_{BA;s} & p_{BB;s} & p_{BC;s} \\ p_{CA;s} & p_{CB;s} & p_{CC;s} \end{pmatrix}$$
$$p_{AA} = \sum_{s \in \mathcal{B}} p_{AA;s}$$



symbol | transition probability

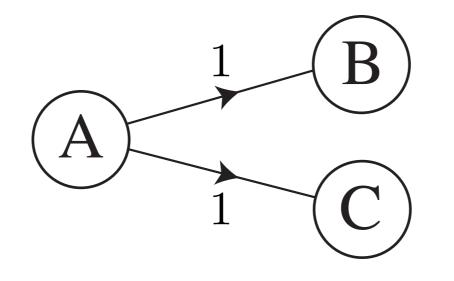
> Types of Hidden Markov Model: Edge(v, s, v'), its probability: Pr(v, s, v').

Unifilar HMM: State + symbol "determine" next state



Types of Hidden Markov Model:

Nonunifilar HMM: At least one violation of unifilarity



Consequence:

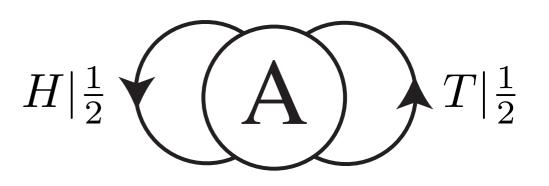
# Multiple internal edge paths can generate same observed sequence.

#### Example:

Fair Coin as a unifilar HMM:

Internal: 
$$\mathcal{A} = \{A\}$$

$$T = (1) \qquad \pi_V = (1)$$



**Observed:**  $\mathcal{B} = \{H, T\}$ 

$$T^{(0)} = \left(\frac{1}{2}\right) \qquad T^{(1)} = \left(\frac{1}{2}\right)$$

One one state!

HMM for general uniform process has more transitions with equal transition probabilities, but still needs only one state.

> Example: Biased Coin as a unifilar HMM:

Internal: 
$$\mathcal{A} = \{A\}$$

$$T = (1) \qquad \pi_V = (1)$$

$$H|p$$
 (A)  $T|1-p$ 

**Observed:**  $\mathcal{B} = \{H, T\}$ 

$$T^{(0)} = \left(\frac{1}{2}\right) \qquad T^{(1)} = \left(\frac{1}{2}\right)$$

Also, one one state!

#### HMMs for IID processes need have only one state!

Example:

Golden Mean Process as a unifilar HMM:

nternal: 
$$\mathcal{A} = \{A, B\}$$
  
 $T = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ 1 & 0 \end{pmatrix}$ 
 $\pi_V = (2/3, 1/3)$ 
 $\pi_V = \begin{pmatrix} 0 & 1 \end{pmatrix}$ 

**Observed:**  $B = \{0, 1\}$ 

$$T^{(0)} = \begin{pmatrix} 0 & \frac{1}{2} \\ 0 & 0 \end{pmatrix} \quad T^{(1)} = \begin{pmatrix} \frac{1}{2} & 0 \\ 1 & 0 \end{pmatrix}$$

Initial ambiguity only: At most 2-to-1 mapping

$$\begin{array}{ll} BA^{n-1} = 1^n & \mbox{Sync'd: } s = 0 \Rightarrow v = B \\ AA^{n-1} = 1^n & s = 1 \Rightarrow v = A \\ \mbox{Irreducible forbidden words: } \mathcal{F} = \{00\} \end{array}$$

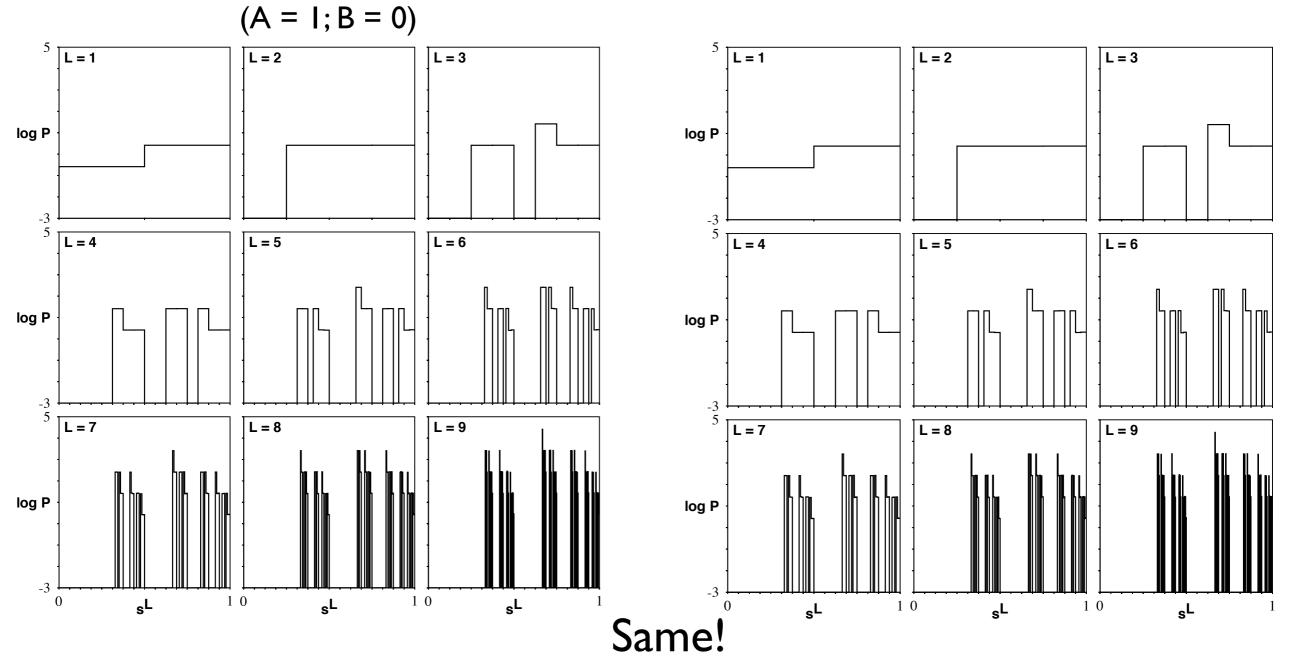
Models of Stochastic Processes ...

Example:

Golden Mean Process ... Sequence distributions:

Internal state sequences

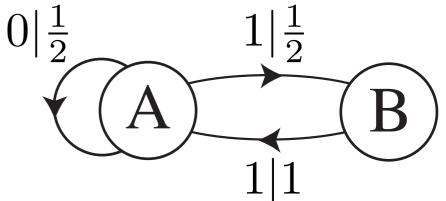
**Observed sequences** 



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Example:

Even Process as a unifilar HMM: Internal (= GMP):  $\mathcal{A} = \{A, B\}$ 



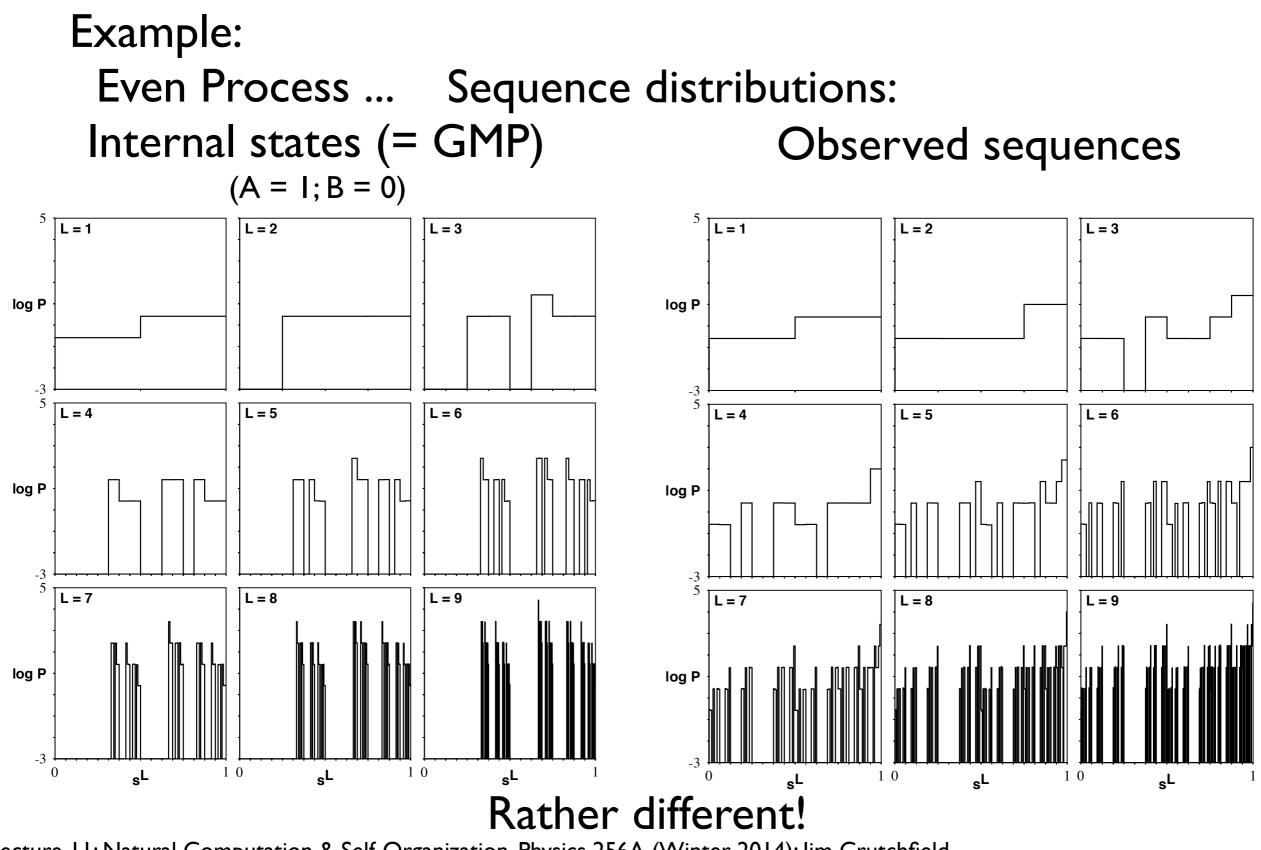
$$T = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ 1 & 0 \end{pmatrix} \quad \pi_V = (2/3, 1/3)$$

**Deserved:** 
$$\mathcal{B} = \{0, 1\}$$
  
 $T^{(0)} = \begin{pmatrix} \frac{1}{2} & 0\\ 0 & 0 \end{pmatrix} \quad T^{(1)} = \begin{pmatrix} 0 & \frac{1}{2}\\ 1 & 0 \end{pmatrix}$ 

 $v^L = \dots AABAABABAA\dots$ 

 $s^L = \dots 0 \ 1 \ 1 \ 0 \ 1 \ 1 \ 1 \ 1 \ 0 \dots s^L = \{\dots 01^{2n} \ 0 \dots \}$ Irreducible forbidden words:  $\mathcal{F} = \{010, 01110, 0111110, \dots\}$ No finite-order Markov process can model the Even process! Lesson: Finite Markov Chains are a subset of HMMs.

Models of Stochastic Processes ...

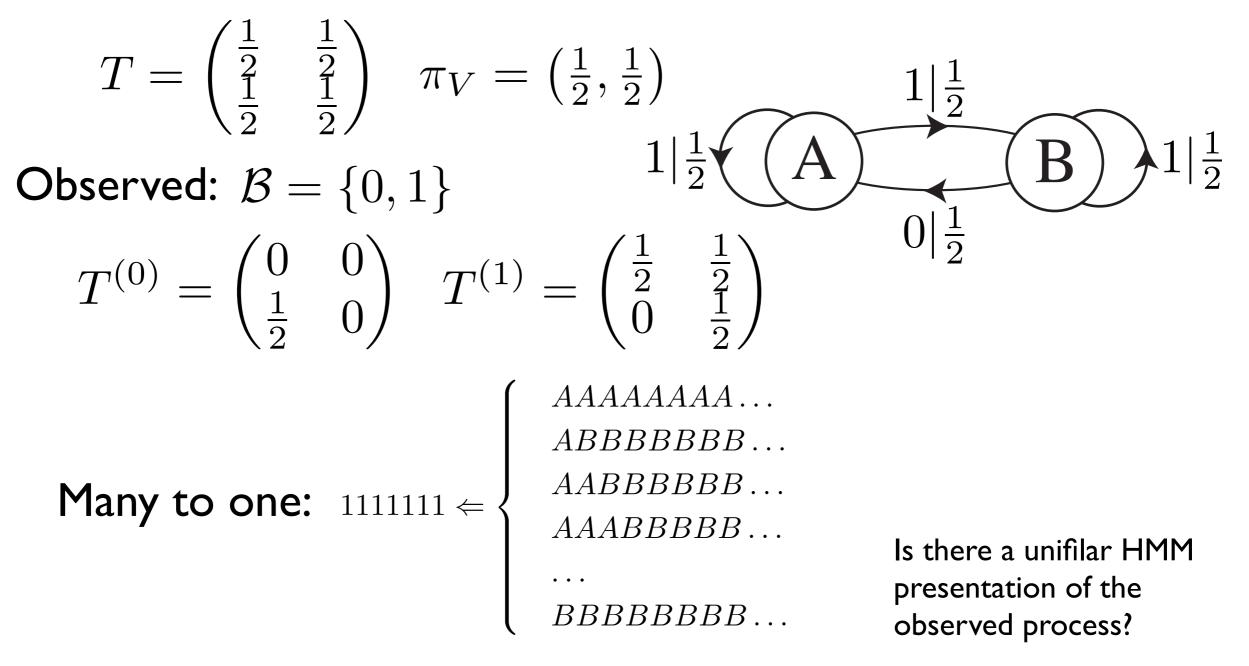


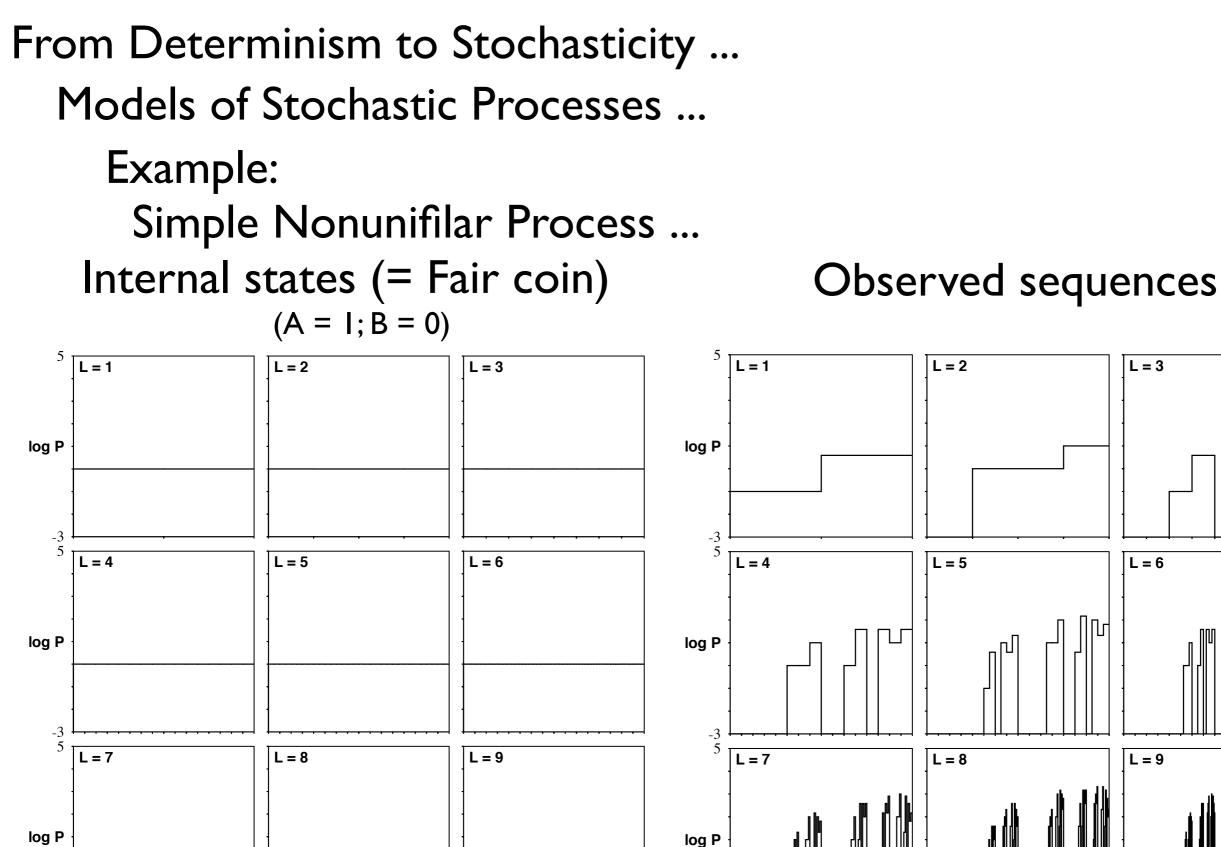
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Example:

Simple Nonunifilar Source:

Internal (= Fair Coin):  $\mathcal{A} = \{A, B\}$ 





L = 3

L = 6

L = 9

10

sL

sL

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sL

1 0

sL

-3

0

sL

1 0

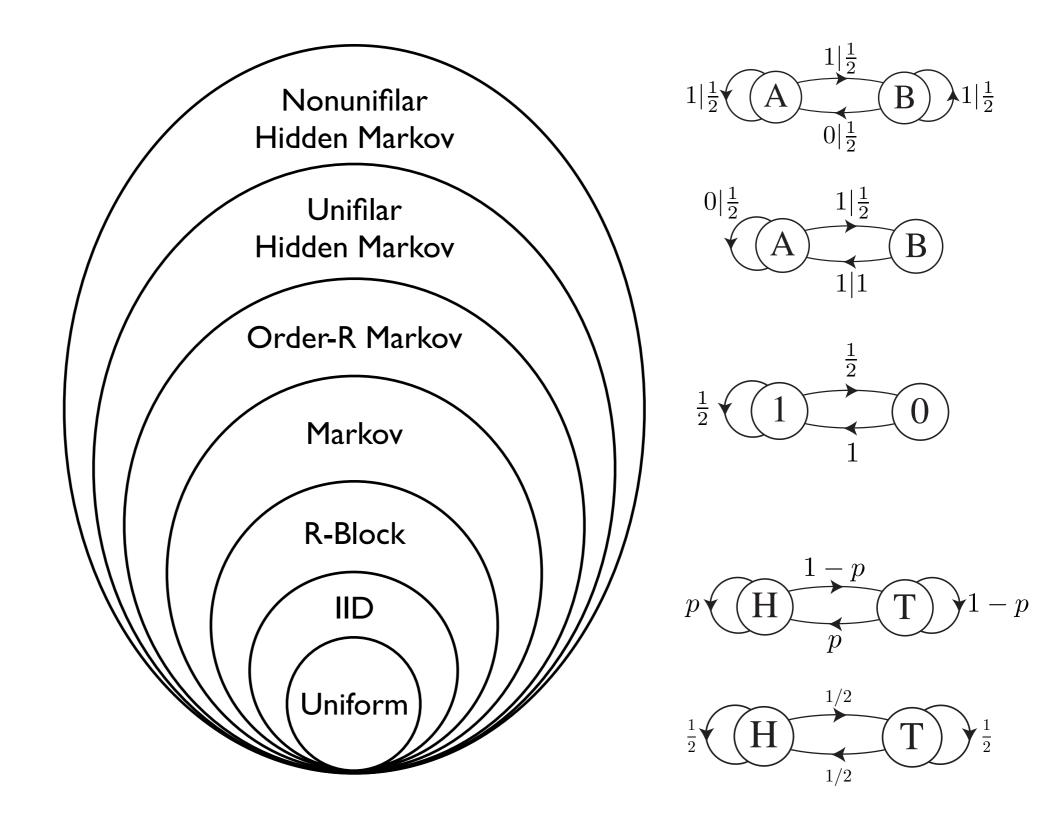
-3

0

sL

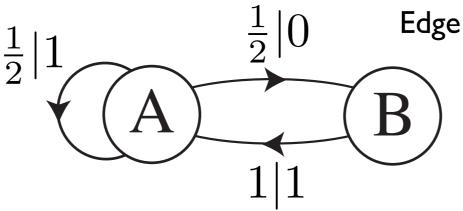
1 0

Classification of Discrete Stochastic Processes via Their Models:



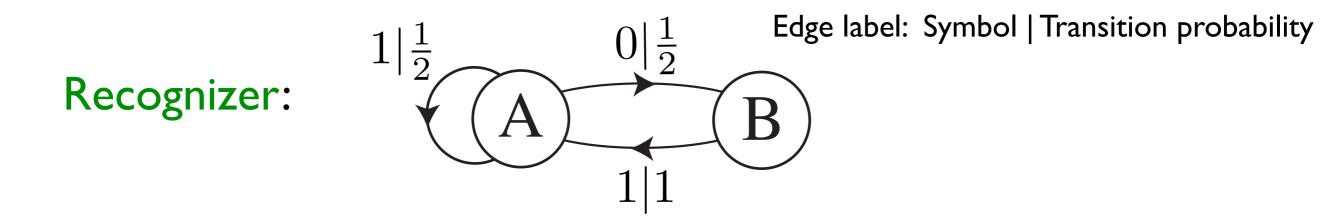
Two uses of HMMs:

Generator:



Edge label: Transition probability | Symbol

Produces sequences, word distributions, ....



Scan sequence, compare word distribution to a given distribution. A sequence is probabilistically recognized when model assigns correct probability.

From Determinism to Stochasticity ... Stochastic Processes ... To calculate state distribution evolution

$$\vec{p}_V = (p_1, p_2, \dots, p_k)$$

 $p_V(t+1) = p_V(t) T$ 

## z-Transform:

$$q_V(z) = \mathcal{Z}(p_V(t))$$
$$\mathcal{Z}(p_V(t)) = \sum_{t=0}^{\infty} p_v(t) z^{-t}$$

## Inverse z-Transform:

$$p_V(t) = \mathcal{Z}^{-1}(q_V(z))$$
$$\mathcal{Z}^{-1}(q_V(z)) = \frac{1}{2\pi i} \int_{-\infty}^{\infty} dz q_V(z) z^{t-1}$$

Stochastic Processes ...

z-Transform ... 
$$p_V(t+1) = p_V(t) T$$
  

$$\sum_{t=0}^{\infty} p_V(t+1) z^{-t} = \sum_{t=0}^{\infty} p_V(t) T z^{-t}$$

$$\sum_{t=1}^{\infty} p_V(t) z^{-(t-1)} = q_V(z) T$$

$$z \left( \sum_{t=0}^{\infty} p_V(t) z^{-t} - p_V(0) \right) = q_V(z) T$$
$$z \left( q_V(z) - p_V(0) \right) = q_V(z) T$$
$$q_V(z) = \frac{p_V(0)}{(I - z^{-1}T)}$$

Stochastic Processes ...

z-Transform Response Matrix:

$$R(t) = \mathcal{Z}^{-1}(\mathcal{T}(z)), \ \mathcal{T}(z) = (I - z^{-1}T)^{-1}$$

$$p_V(t) = \mathcal{Z}^{-1}(q_V(z)) = p_V(0)R(t)$$

$$p_V(t) = p_V(0) T^t$$
$$R(t) = T^t$$
$$(R(t))_{vv'} = \Pr(v', t | v, 0)$$

Stochastic Processes ...

z-Transform Response Matrix ... R(t) = A + B(t)  $p_V(t) = p_V(0)A + p_V(0)B(t)$ 

Asymptotic response matrix (time independent):

Recurrent or strongly connected states:  $A_i = p_V(\infty), \forall i$ 

Multiply recurrent:  $A_i \neq A_j$   $p_V(0) = (0, \dots, p_v = 1, \dots, 0)$  $A_v = p_V(\infty)$ 

Transient response matrix (time dependent):

$$B(t) \to 0, \ t \to \infty$$
$$\sum_{j} B_{ij}(t) = 0$$

Stochastic Processes ...

z-Transform Properties:

Fourier transform:  $F(\omega) = \mathcal{F}(p_V(t)) = q_V(z = e^{2\pi i\omega})$ 

Linearity: 
$$\mathcal{Z}(ap_V(t) + bp'_V(t)) = aq_V(z) + bq'_V(z)$$

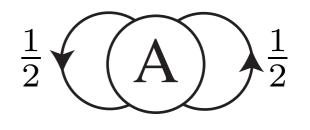
Time shift: 
$$\mathcal{Z}(p_V(t-\tau)) = z^{-\tau}q_V(z)$$

Scaling: 
$$a^{-t}p_V(t) = q_V(az), a > 0$$

Time reversal:  $p_V(-t) = q_V(1/z)$ 

**Convolution:** 
$$p_V(t) \star g(t) = q_V(z) \cdot G(z)$$

z-Transform Examples:  $V = \{A\}$ T = (1) $p_V = (1)$ 



$$q_V(z) = \mathcal{Z}(1) = \sum_{t=0}^{\infty} z^{-t} = \frac{1}{1 - z^{-1}}$$

$$p_V(t) = \mathcal{Z}^{-1} \left( \frac{1}{1 - z^{-1}} \right)$$
  
=  $(2\pi i)^{-1} \int_{-\infty}^{\infty} dz \frac{z^{t-1}}{1 - z^{-1}}$   
=  $(2\pi i)^{-1} (2\pi i \cdot 1) = 1$ 

**Residue Theorem** 

z-Transform Examples:  $V = \{A, \ldots\}$  $p_A(t) = 2^{-t}$ 

$$p_A(t) = 2^{-t}$$

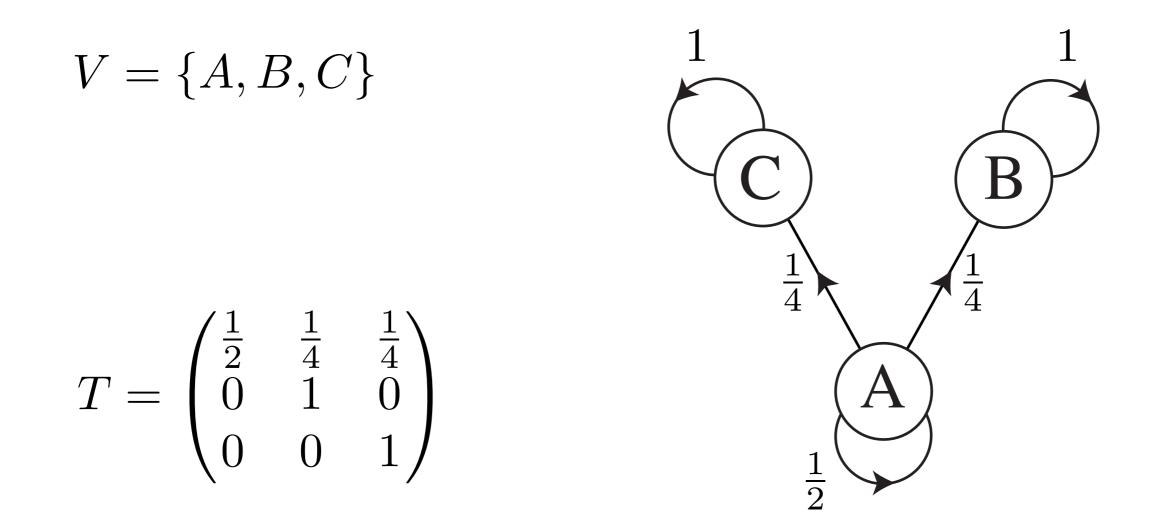
$$p_A(t) = 2^{-t}$$

$$T = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & \dots \\ 0 & \ddots & 0 & \dots \\ 0 & \cdots & 0 & \dots \\ 0 & \dots & 0$$

 $\frac{1}{2}$ 

 $\overline{2}$ 

z-Transform Example:



z-Transform Example ...

$$\begin{split} I - z^{-1}T &= \begin{pmatrix} 1 - \frac{1}{2}z^{-1} & -\frac{1}{4}z^{-1} & 0\\ 0 & 1 - z^{-1} & 0\\ 0 & 0 & 1 - z^{-1} \end{pmatrix}\\ \mathcal{T}(z) &= (I - z^{-1}T)^{-1} &= \begin{pmatrix} \frac{2}{2-z^{-1}} & \frac{z^{-1}}{2(1-z^{-1})(2-z^{-1})} & \frac{z^{-1}}{2(1-z^{-1})(2-z^{-1})}\\ 0 & \frac{1}{1-z^{-1}} & 0\\ 0 & 0 & \frac{1}{1-z^{-1}} \end{pmatrix}\\ \mathcal{T}(z) &= \frac{1}{1-z^{-1}} \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2}\\ 0 & 1 & 0\\ 0 & 0 & 1 \end{pmatrix} + \frac{2}{2-z^{-1}} \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2}\\ 0 & 0 & 0\\ 0 & 0 & 0 \end{pmatrix}\\ R(t) &= \mathcal{Z}^{-1}(\mathcal{T}(z)) &= \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2}\\ 0 & 1 & 0\\ 0 & 0 & 1 \end{pmatrix} + 2^{-t} \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2}\\ 0 & 0 & 0\\ 0 & 0 & 0 \end{pmatrix} \end{split}$$

z-Transform Example ...

$$R(t) = \mathcal{Z}^{-1}(\mathcal{T}(z)) = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} + 2^{-t} \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$p_V(0) = (1, 0, 0)$$

$$p_V(t) = \left(2^{-t}, \frac{1}{2}(1 - 2^{-t}), \frac{1}{2}(1 - 2^{-t})\right)$$

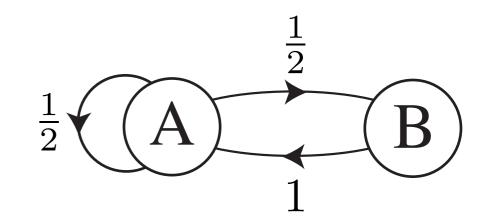
$$p_V(\infty) = \left(0, \frac{1}{2}, \frac{1}{2}\right)$$

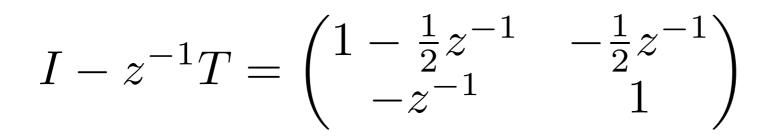
$$p_V(0) = (0, 1, 0)$$

$$p_V(\infty) = (0, 1, 0)$$

z-Transform of Golden Mean Process:

$$V = \{A, B\} \quad T = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ 1 & 0 \end{pmatrix}$$





$$\mathcal{T}(z) = (I - z^{-1}T)^{-1} = \begin{pmatrix} \frac{2z^2}{(2z+1)(z-1)} & \frac{z}{(2z+1)(z-1)} \\ \frac{2z}{(2z+1)(z-1)} & \frac{2z^2-z}{(2z+1)(z-1)} \end{pmatrix}$$

z-Transform of Golden Mean Process ...

$$R(t) = \begin{pmatrix} \mathcal{Z}^{-1}(\mathcal{T}_{00}) & \mathcal{Z}^{-1}(\mathcal{T}_{01}) \\ \mathcal{Z}^{-1}(\mathcal{T}_{10}) & \mathcal{Z}^{-1}(\mathcal{T}_{11}) \end{pmatrix}$$

$$R(t) = \begin{pmatrix} \frac{2}{3} & \frac{1}{3} \\ \frac{2}{3} & \frac{1}{3} \end{pmatrix} + \frac{1}{3} (\frac{-1}{2})^t \begin{pmatrix} 1 & -1 \\ -2 & 2 \end{pmatrix}$$

$$p_V(0) = (1,0) \Rightarrow p_V(t) = \left(\frac{2}{3} + \frac{1}{3}\left(-\frac{1}{2}\right)^t, \frac{1}{3} - \frac{1}{3}\left(-\frac{1}{2}\right)^t\right)$$
$$p_V(\infty) = \left(\frac{2}{3}, \frac{1}{3}\right)$$

Reading for next lecture:

Lecture Notes.