



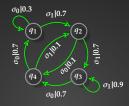
State Set	Q	$q_1, \cdots, q_4$
Alphabet	Σ	$\sigma_0, \sigma_1$
Morph probabilities	$\widetilde{\pi}: Q \times \Sigma^{\star} \to [0,1]$	0.4 0.6 0.3 0.7 0.1 0.9 0.7 0.3
Stationary distribution	ø*	$\wp^{\star}P=\wp^{\star}$





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Stationary distribution	ø*	$\wp^{\star}P = \wp^{\star}$	



Algorithm GenESeSS



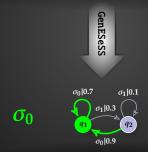


Algorithm GenESeSS



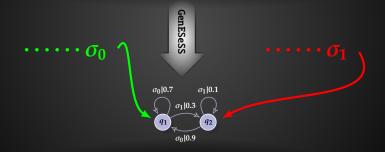


Algorithm GenESeSS



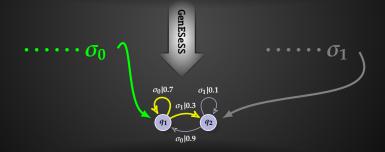


#### Algorithm GenESeSS



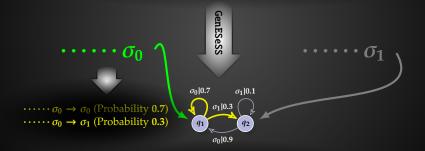


#### Algorithm GenESeSS



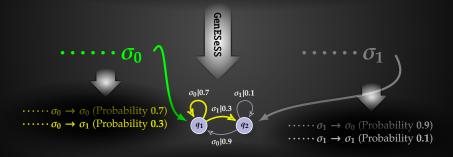


#### Algorithm GenESeSS



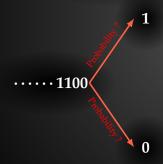


#### Algorithm GenESeSS





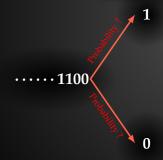
Estimating Average Immediate Future



$$\phi_{\omega}^{s} = \begin{pmatrix} Pr(\sigma_{0}) \\ Pr(\sigma_{1}) \end{pmatrix}$$
where  $\omega = \sigma_{1}\sigma_{1}\sigma_{0}\sigma_{0}$ 



	11000	11001		
00101001000 <b>1100011001</b>		11001	11001	
010001000000000011 <b>11000</b> 0000100				
001000000010000 <b>11000</b> 100000001				



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λ	0.750285	0.249715
0	0.700112	0.299888
1	0.901009	0.098990
00	0.699844	0.300156
01	0.899111	0.100889
10	0.700711	0.299289
11	0.918285	0.081715
000	0.699004	0.300996
001	0.898769	0.10123
010	0.701038	0.298962
011	0.917181	0.082819
100	0.701763	0.298237
101	0.899911	0.100089
110	0.697797	0.302203
111	0.930693	0.069306
0000	0.699284	0.300716
0001	0.902025	0.097975



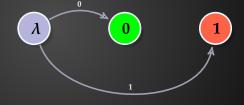


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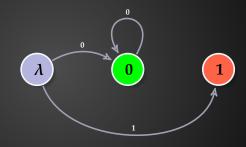


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0001	0.902025	0.0979754



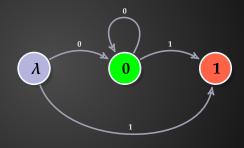


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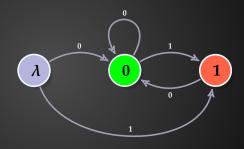


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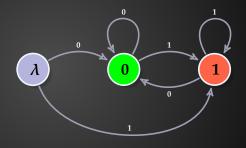


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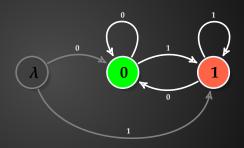


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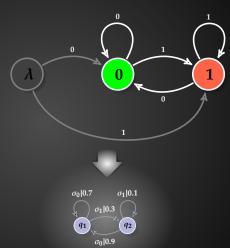
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Estimating Average Immediate Future

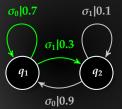
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#### Estimating Average Immediate Future

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#### Combining GenESeSS with data smashing



**PFSA** 





Combining GenESeSS with data smashing



**PFSA** 

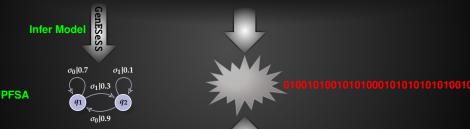


#### Generate data





Combining GenESeSS with data smashing



Generate data



Invert



Combining GenESeSS with data smashing





# **Probably Approximately Correct**

How Hard Is It To Learn PFSAs

### Time Complexity

Assuming  $|s| > |\Sigma|$ , the asymptotic time complexity of **GenESeSS** is:

$$\mathcal{T} = O\left(\frac{|s||\Sigma|}{\epsilon}\right)$$

### **PAC-Learnability**

Ergodic, stationary quantized stochastic processes with finite number of causal states has the following property:

For  $\epsilon, \eta > 0$ , and for every sufficiently long sequence s generated by QSP  $\mathcal{H}$ , GenESeSS computes  $\mathcal{P}'_{\mathcal{H}}$  as an estimate for  $\mathcal{P}_{\mathcal{H}}$  with:

$$Pr(\Theta(\mathcal{P}_{\mathcal{H}}, \mathcal{P}'_{\mathcal{H}}) \leq \epsilon) \geq 1 - \eta$$

Asymptotic runtime is polynomial in  $1/\epsilon$ ,  $1/\eta$ , |s|, and sample complexity is:

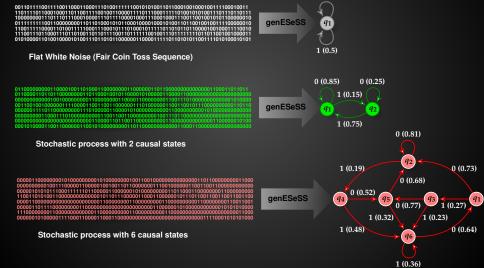
$$|s| = O(C_0^{|Q|} \frac{1}{\epsilon} \log \frac{1}{\eta})$$



## Learning Quantized Stochastic Processes

#### Algorithm GenESeSS

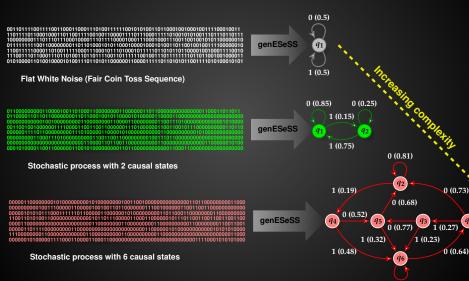
0(0.5)





# Learning Quantized Stochastic Processes

Algorithm GenESeSS

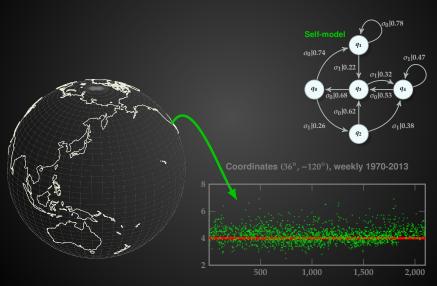


1 (0.36)



# **Predicting Seismic Events**

With Both Space & Time Quantization



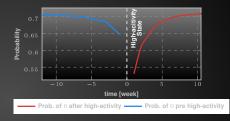


# Validating The Omori-Utsu Law

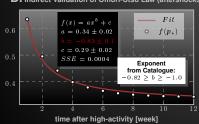
# A. Inferred Self-Model for California (400 mile radius around lat. 36° and long. -120°)



### B Increasing probability of no-EQ before & after high-activity state



### D. Indirect Validation of Omori-Utsu Law (aftershocks)



### D. Indirect Validation of Omori-Utsu Law (foreshocks)

