### Project: Internet Worm Attacks and Stochastic Agent Models

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Produced with prosper and LATEX

JTB [08/2004] - p.1/21



# Passage or response times are useful in an agent modelling setting

- Internet worms at work!
- A formal agent description
- Our existing techniques
- Other solutions methods

Sequence of events:

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- 5. Repeat from (2) for each new infection

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In which time...

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- 3. server may be repaired and returned to the network unpatched
- 4. server may be repaired and patched
- 5. server may be rolled back, thus removing patch

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- Code Red, Nimbda, Code Red II (2001), SQL Slammer (January 2003), Nachi and MSBlast (August 2003), Sasser (1 May 2004)
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- Code Red, Nimbda, Code Red II (2001), SQL Slammer (January 2003), Nachi and MSBlast (August 2003), Sasser (1 May 2004)
- Usually malicious autonomous program that spreads without user intervention
- Emergent behaviour: causes huge network bottlenecks – brings internet to standstill for many hours, or even days

## Code Red II

- Example: Code Red II
  - **•** 19th July 2001
  - 350,000 hosts infected in 14 hours
  - c.f. Sasser: 1–1.5 million hosts in 2 days
  - utilised *buffer overflow* in Microsoft IIS web server
  - infected machines would probe for other victims on port 80
  - 20th July 2001: mode changes from one of propagation to DDOS attack on the www.whitehouse.gov

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  - ⇒ infected computers/computers susceptible to infection will mix homogeneously
    - potential to kill/disable a host, according to payload
    - Nicol et al use hybrid model of Internet worms: epidemiological/stochastic



Good news: We have an exact behavioural description of an individual worm in glorious detail

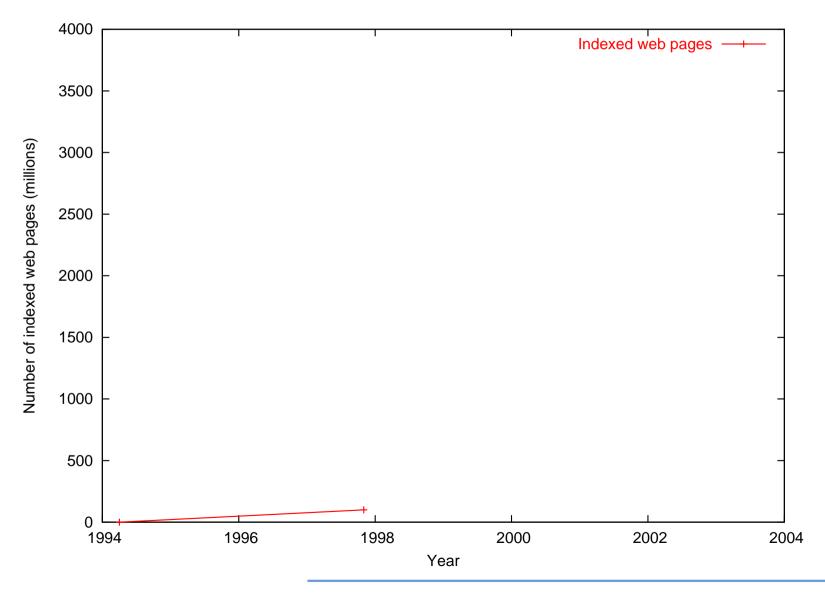


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# Not quite Biology!

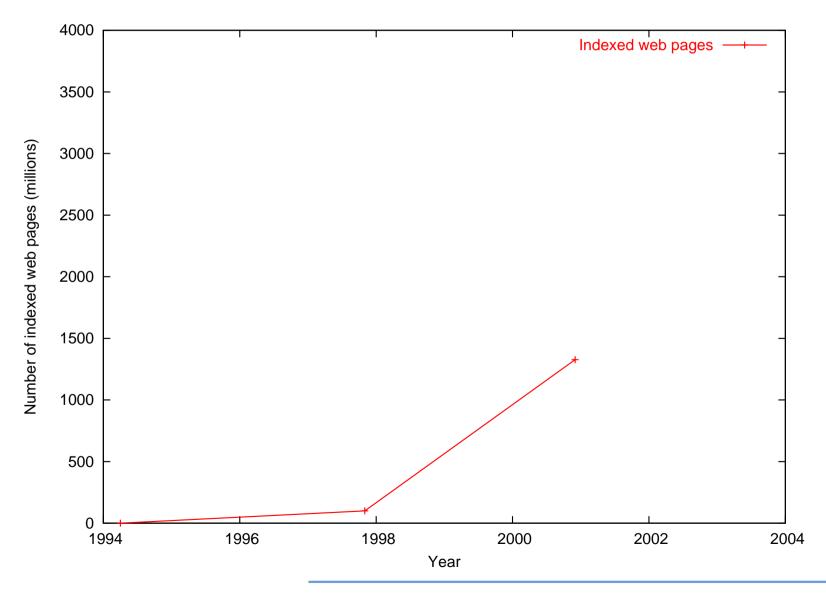
- Good news: We have an exact behavioural description of an individual worm in glorious detail
- Bad news: We have an exact behavioural description of an individual worm in glorious detail
- $\Rightarrow$  We have to learn to prune *unimportant* behaviour

### **Internet Growth**



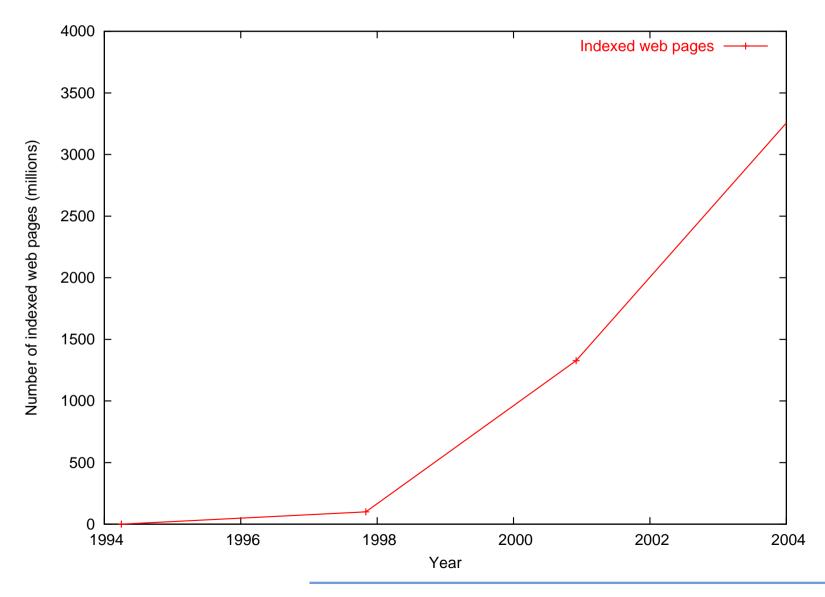
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P ::= 
$$(\mathbf{a}, \lambda)$$
.P | P + P | P  $\bowtie_L P$  | P/L | A

#### PEPA syntax:

$$\mathbf{P} ::= (\mathbf{a}, \lambda) \cdot \mathbf{P} \mid \mathbf{P} + \mathbf{P} \mid \mathbf{P} \bowtie_{L} \mathbf{P} \mid \mathbf{P} / \mathbf{L} \mid \mathbf{A}$$

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- Cooperation:  $P_1 \bowtie_L P_2$

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- Cooperation:  $P_1 \bowtie P_2$
- Action hiding: P/L
- Constant label: A

# **Biological PEPA Agent Modelling**

Require a pairwise cooperation paradigm:

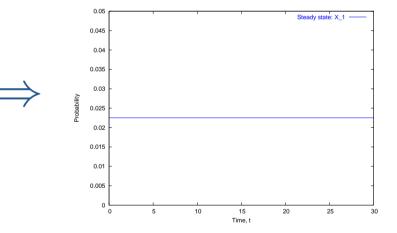
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- Action prefix:  $(a, \lambda)$ .P
- Competitive choice:  $P_1 + P_2$
- Pairwise agent cooperation:  $P_1 \oplus P_2$
- Action hiding: P/L
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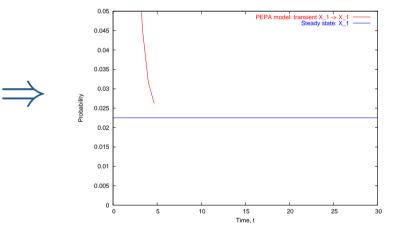
# **Types of Analysis**

#### Steady-state and transient analysis in PEPA:

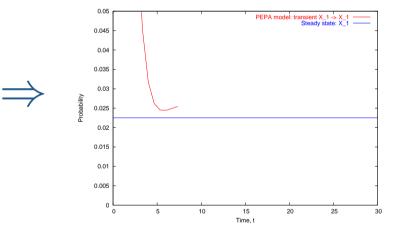
A1 
$$\stackrel{\text{def}}{=}$$
 (start,  $r_1$ ).A2 + (pause,  $r_2$ ).A3  
A2  $\stackrel{\text{def}}{=}$  (run,  $r_3$ ).A1 + (fail,  $r_4$ ).A3  
A3  $\stackrel{\text{def}}{=}$  (recover,  $r_1$ ).A1  
AA  $\stackrel{\text{def}}{=}$  (run,  $\top$ ).(alert,  $r_5$ ).AA  
Sys  $\stackrel{\text{def}}{=}$  AA  $\bigwedge_{\{run\}}$ A1



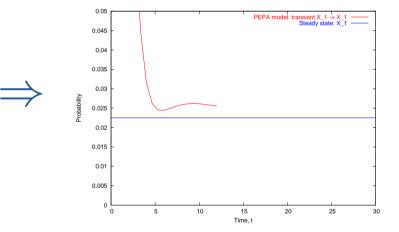
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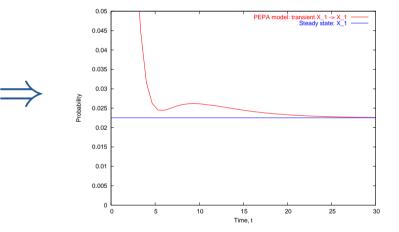
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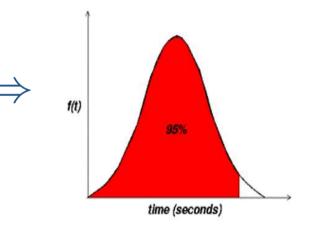
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### **Passage-time Quantiles**

### Extract a passage-time density from a PEPA model:

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### State of the Art

- Good news
  - PEPA model: passage time/transient analysis -O(10<sup>8</sup>) states
  - Semi-Markov PEPA: passage time/transient analysis  $O(10^7)$  states

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- Good news
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- Bad news
  - This only represents 8 agents with 10 states each!

# Ways forward for PEPA Agent modelling

- Either:
  - selective model aggregation
  - $\Rightarrow$  allows use of passage/transient
- or:
  - development of approximate techniques
  - ⇒ automated generation of MFA/ODE equations from PEPA model [c.f. Sumpter 2000, Hillston 2004]

# **SIR: Epidemiological model**

- Consider fixed population of N computers
- Partition population into, computers that are:
  - susceptible to infection, s(t)
  - infected, i(t)
  - removed, r(t)
- Deterministic system:

• 
$$\frac{\mathrm{d}s(t)}{\mathrm{d}t} = -\beta s(t)i(t)$$

• 
$$\frac{\mathrm{d}i(t)}{\mathrm{d}t} = \beta s(t)i(t) - \gamma i(t)$$

• 
$$\frac{\mathrm{d}r(t)}{\mathrm{d}t} = \gamma i(t)$$

### Susceptible = $(infect, \top)$ .Infected + $(patch, \lambda_p)$ .Removed

# Agent worm model

Susceptible =  $(infect, \top)$ .Infected +  $(patch, \lambda_p)$ .Removed Infected =  $(infect, \lambda_i)$ .Infected +  $(repair, \lambda_r)$ .Removed

# Agent worm model

Susceptible = (infect,  $\top$ ).Infected + (patch,  $\lambda_p$ ).Removed Infected = (infect,  $\lambda_i$ ).Infected + (repair,  $\lambda_r$ ).Removed Removed = (rollback,  $\lambda_s$ ).Susceptible System =  $\bigoplus_{i=1}^{N}$ Susceptible<sub>i</sub>

# Agent worm model

Susceptible = 
$$(infect, \top)$$
.Infected  
+  $(patch, \lambda_p)$ .Removed  
Infected =  $(infect, \lambda_i)$ .Infected  
+  $(repair, \lambda_r)$ .Removed  
Removed =  $(rollback, \lambda_s)$ .Susceptible

$$System(p,q) = \bigoplus_{i=1}^{p} Infected_{i} \bigoplus_{i=1}^{q} Susceptible_{i}$$
$$\bigcup_{i=1}^{N-p-q} Removed_{i}$$

# Sumpter Look to count numbers of agents, A(t), in a given state by solving a derived mean field equation (MFE)

$$f(t,i) = \mathbb{E}(A(t + \Delta t) \mid A(t) = i)$$

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Hillston Approximate number of components with a real numbered function
remodel using *bimodal assumption*

# **Agent Count-based Model**

#### Bimodal characterisation of variables:

 $S_{H} \stackrel{\text{def}}{=} (\text{infect}, \top).S_{L} + (\text{patch}, r_{2}).S_{L} + (\text{patch}, r_{2}).S_{L} \Rightarrow \frac{\frac{ds(t)}{dt}}{\frac{di(t)}{dt}} = -\beta s(t)i(t) - \gamma i(t) \frac{\frac{di(t)}{dt}}{\frac{dt}{dt}} = \beta s(t)i(t) - \gamma i(t) \frac{\frac{dr(t)}{dt}}{\frac{dt}{dt}} = \gamma i(t)$ 

## Conclusion

- Internet worms have a reasonable biological analogy
- State spaces too large for traditional temporal modelling
- The answer: Selective aggregation/agent counting
- Passage times in an agent setting
  - a useful cost function for a model
  - probability of extinction within a given time