Watts' Network Cascades Model

A Simple Model of Global Cascades on Random Networks

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- Simulation
- Explanation
- Watts' Model
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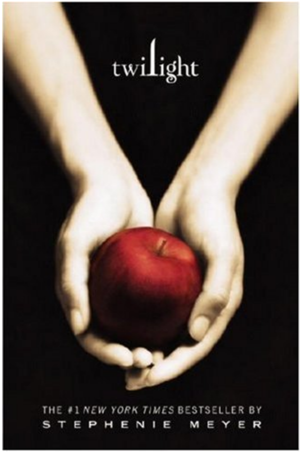
Motivation – Culture



Twilight

Source: `https://en.wikipedia.org/wiki/File:Twilightbook.jpg`

Motivation – Technology Adoption

WhatsApp

Source: `https://commons.wikimedia.org/wiki/File:WhatsApp.svg`

Motivation – Social Dynamics

Political Coups

Source: `http://tinyurl.com/jmv529r`

The Cause Revealed

Network Cascades

Network Cascades

(Maybe)

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(Maybe)

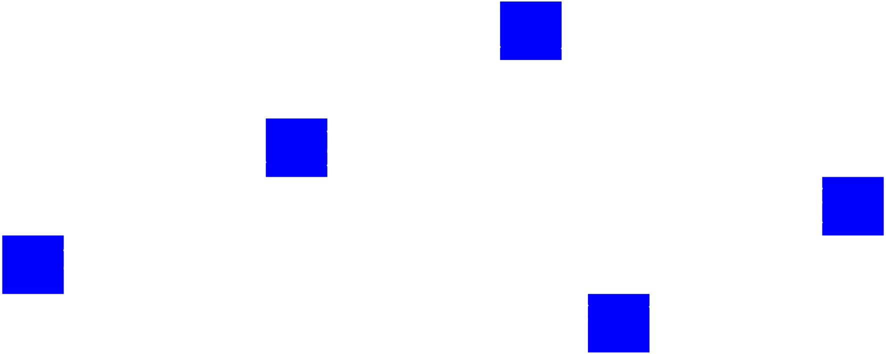
(It's a Nice Model Anyway)

Simulation

https://github.com/turbopope/nss/tree/master/simulator

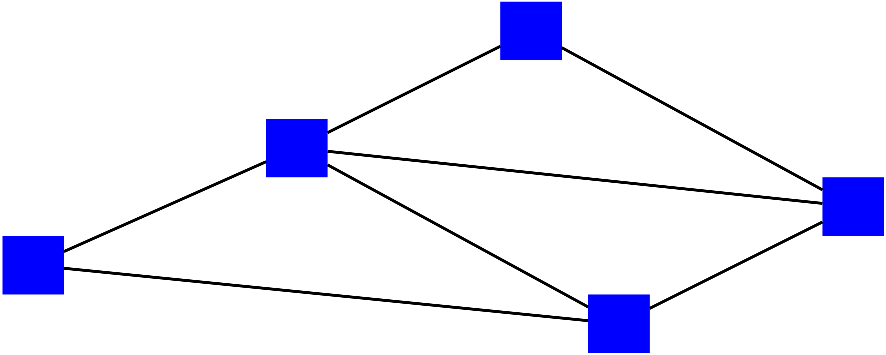
Explanation by Example

- Nodes



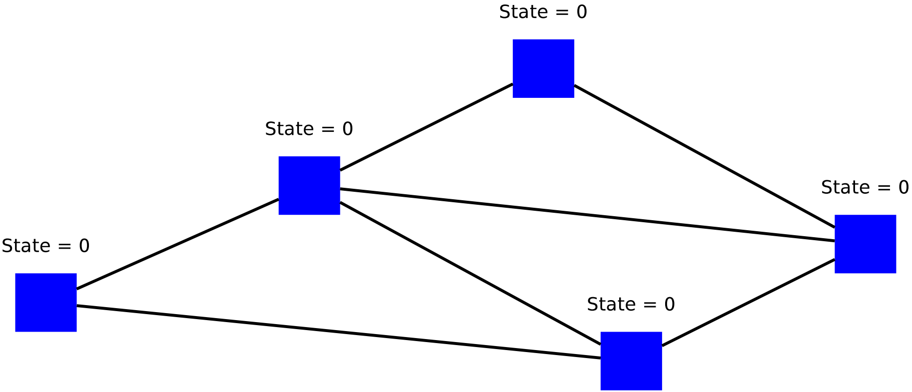
Explanation by Example

- Observe k Neighbors



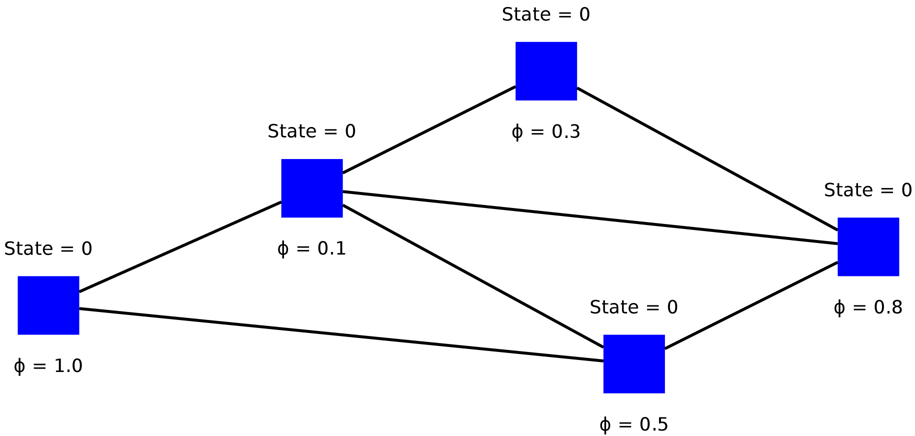
Explanation by Example

- State $\in \{0, 1\}$



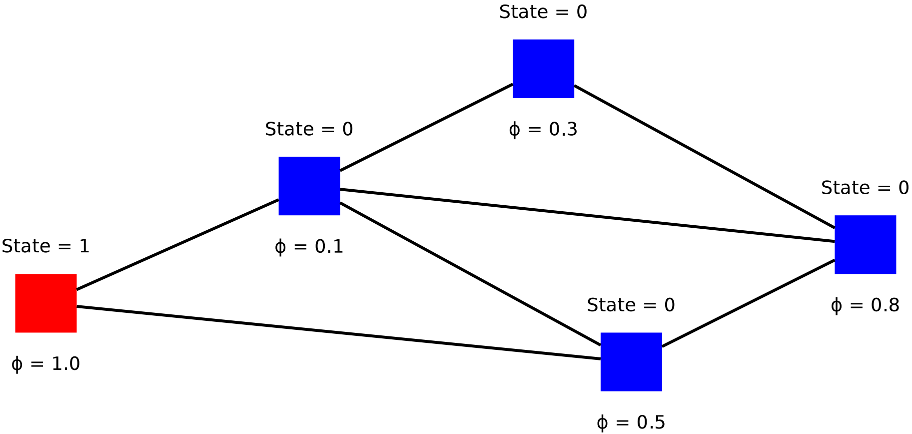
Explanation by Example

- Threshold $\Phi \in [0, 1]$



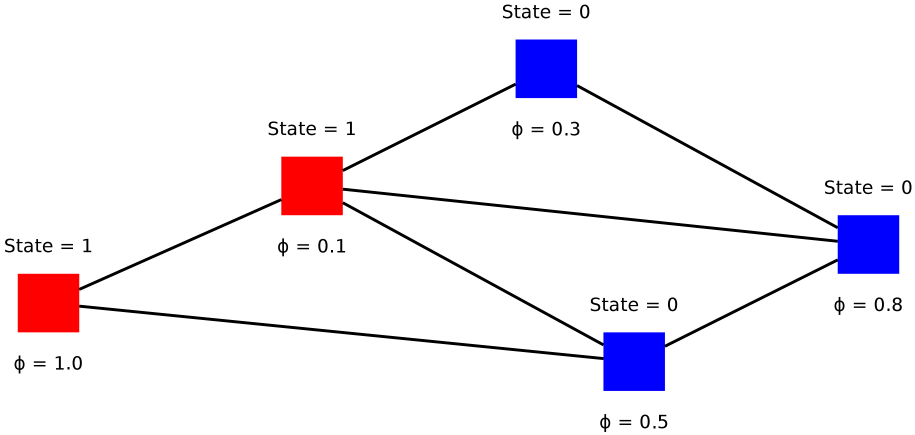
Explanation by Example

- Random Impulse Happens



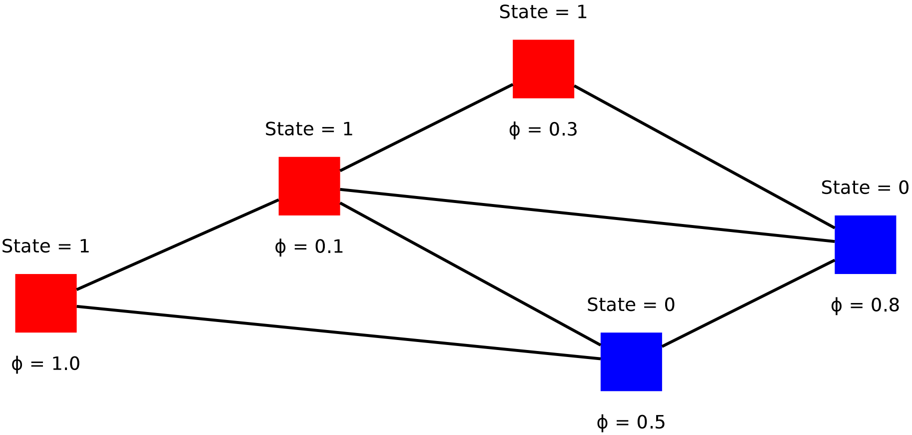
Explanation by Example

- Nodes Check in Random Intervals



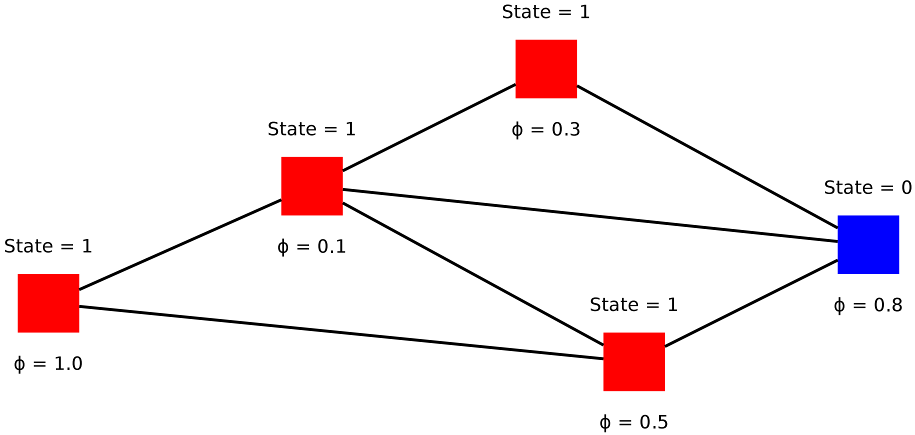
Explanation by Example

- Stuff Happens



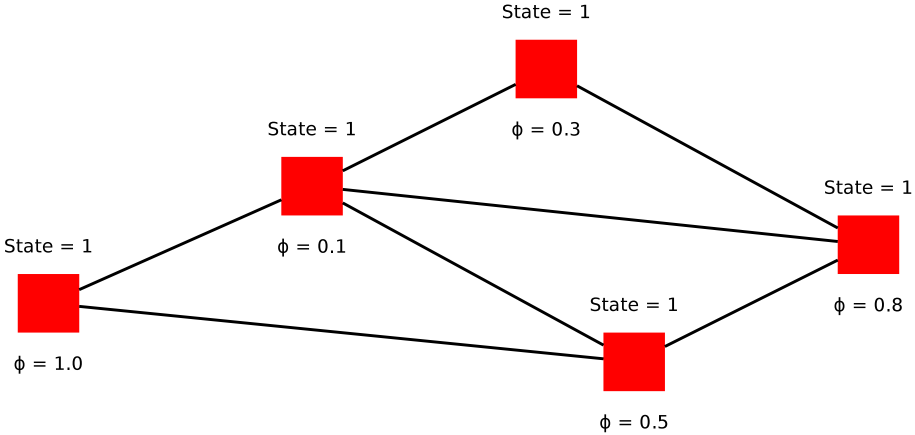
Explanation by Example

- Things Occur



Explanation by Example

- Coup Successful



Watts' Model

- Each person/agent is a node in a graph
- Agents have a state $\in \{0, 1\}$
- Agents observe their neighbors
- Agents change to a state if a fraction of their neighbors has that state

Watts' Model – Random Graph

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- n nodes

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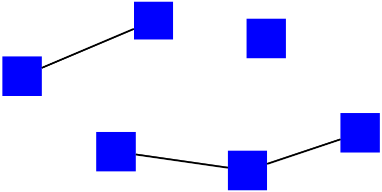
- n nodes
- p_k propability of n to have k neighbors
- $z = \langle k \rangle$ expectation value or average degree
- $p_k = \frac{e^{-z} z^k}{k!}$ Poisson-distributed (Erdős–Rényi-Model with $p = \frac{z}{n}$)

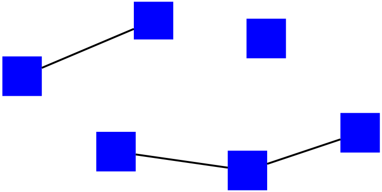
Findings

- Cascades in Sparse Networks



Findings

- Cascades in Sparse Networks
  - Limited by Connectivity



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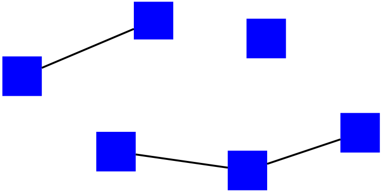
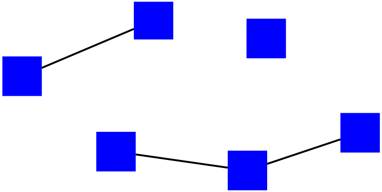


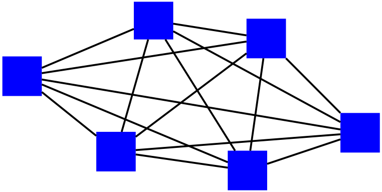
Findings

- Cascades in Sparse Networks
  - Limited by Connectivity
  - Cascade Size Exhibits Power-Law Distribution
  - Most Highly Connected Cluster is Critical Triggers



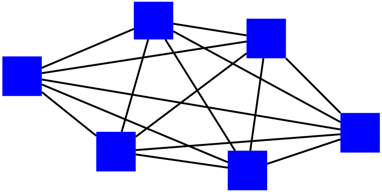
Findings

- Cascades in Dense Networks



Findings

- Cascades in Dense Networks
  - Limited by Threshold



Findings

- Cascades in Dense Networks
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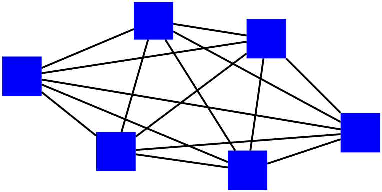
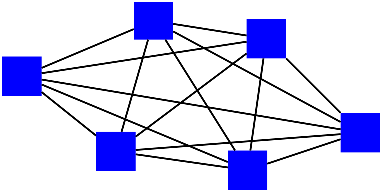
  - Cascade Size Bimodal (Most are Small, Some are Large)



Findings

- Cascades in Dense Networks
  - Limited by Threshold
  - Cascade Size Bimodal (Most are Small, Some are Large)
  - Cluster with Average Degrees are Triggers (Because They are Frequent)



Findings

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- Threshold Heterogenity Increases Cascade Likelihood

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- Threshold Heterogenity Increases Cascade Likelihood
- Degree Heterogenity Decreases Cascade Likelihood

Limitations

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- Sample Size for Bimodal Distribution Very Limited

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- No Personal Knowledge
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- No Relationship Strength
- One-Way Threshold
- Sample Size for Bimodal Distribution Very Limited
- No Threats to Validity Mentioned

Thank You All For Listening