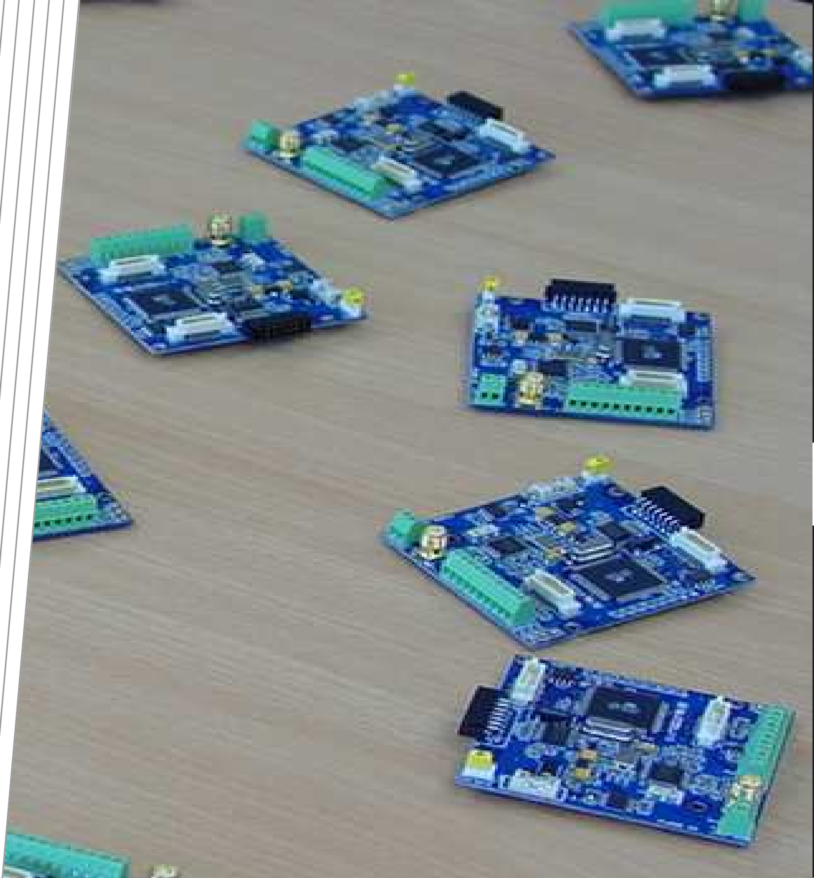

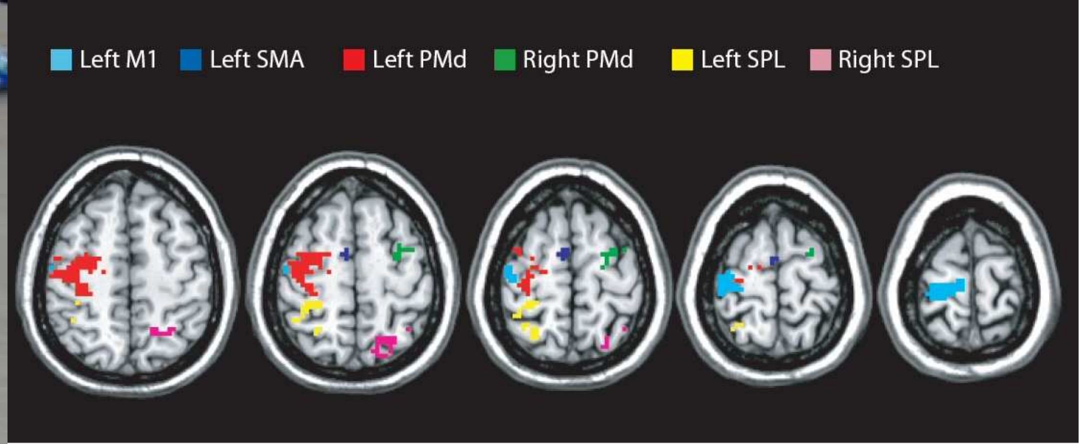

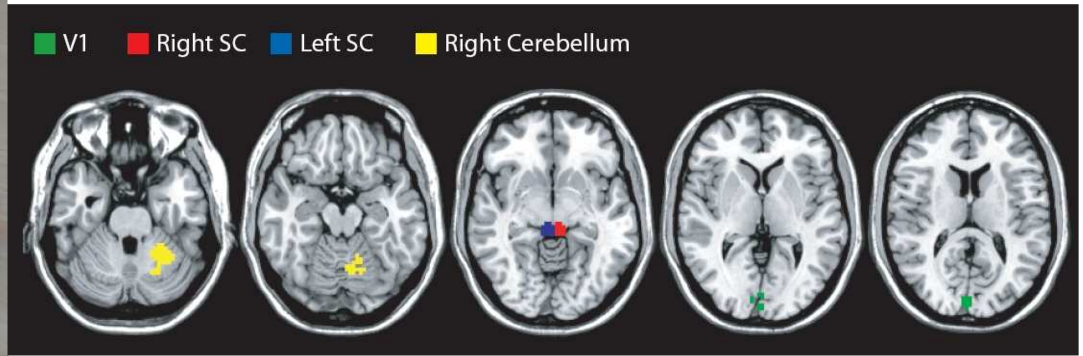

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Information transfer in networks

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Guided self-organisation workshop, MPI Leipzig, August 2009

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Overview

- Two studies regarding information transfer in networks, using this concept for two distinct purposes:

1. Using known dynamics to infer *logical structure* of nodes in a network
   - Aim: to study what sorts of functional and structural networks evolve in NNs in a computational ecology.

2. Using known dynamics and structure to analyse *computation* in a network
   - Aim: to characterize the intrinsic computation in cascading failure events in power grids

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Contributors

- Functional and structural topologies in evolved neural networks
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  - Dany Pradhana (1)
  - Mikhail Prokopenko (1)
  - Larry Yaeger (3)
- Information dynamics of cascading failures in power grids
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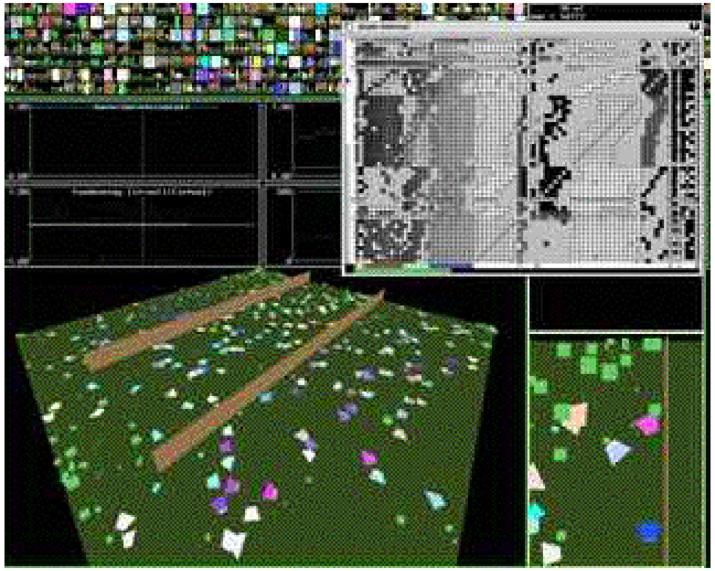
Functional and structural topologies in evolved neural networks

- What sorts of topologies evolve in neural networks in a computational ecology?
  - Studying agents in Polyworld.
  - Examining both known structural networks and inferred functional networks (using MI and TE).
  - Topological analysis of these networks.
  - Results: Trend of more integrated activity across the networks (more “small-world” character with evolutionary time.



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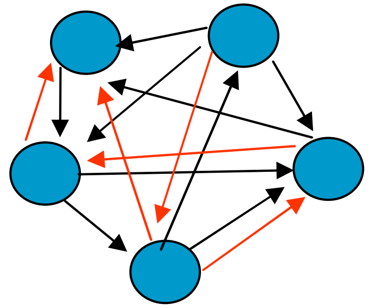
Functional networks

- *Functional connection* := a statistical dependence in time between two nodes
- *Functional network* := a set of functional connections.
- Two step process:
  1. Measuring statistical dependence / closeness
  2. Deciding whether the closeness should constitute a link
- Why use functional networks:
  - To infer structural network where it is unknown
  - Insight into the logical structure of the network and how this changes as a function of network activity.
- Our measures of closeness:
  - Mutual information $I_{X;Y} = \sum_{x,y} p(x,y) \log_2 \frac{p(x,y)}{p(x)p(y)}$
  - Transfer entropy $T_{Y \to X} = \sum_{w_n} p(w_n) \log_2 \frac{p(x_{n+1}|x_n^{(k)}, y_n^{(l)})}{p(x_{n+1}|x_n^{(k)})}$

$$w_n = x_{n+1}, x_n^{(k)}, y_n^{(l)}$$



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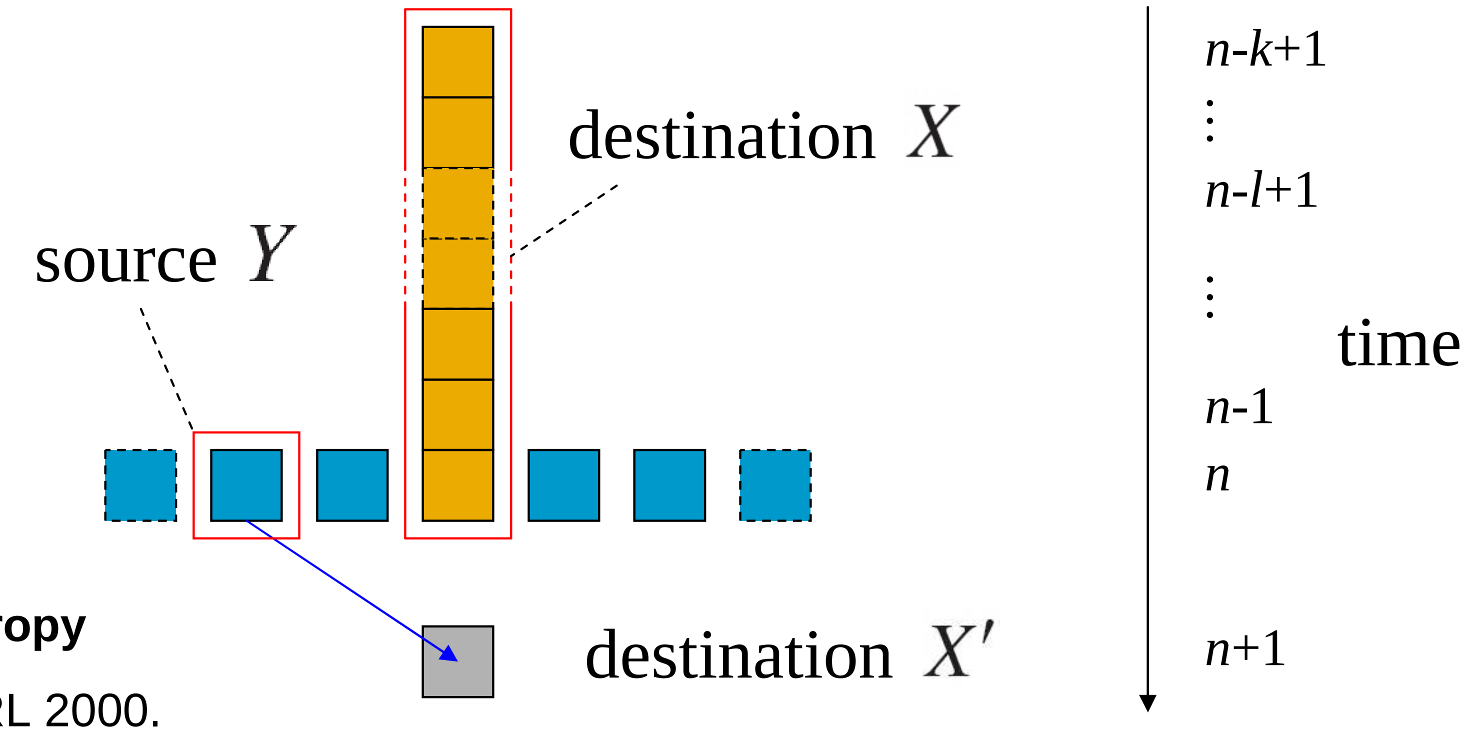
Transfer entropy

$$T_{Y\to X'} = I(Y;X'|X) = H(X'|X) - H(X'|X,Y)$$



Transfer entropy

Schreiber, PRL 2000.

$$T_{Y\to X} = \sum_{w_n} p(w_n) \log_2 \frac{p(x_{n+1}|x_n^{(k)}, y_n^{(l)})}{p(x_{n+1}|x_n^{(k)})}$$

$$w_n = x_{n+1}, x_n^{(k)}, y_n^{(l)}$$

Topological measures

- Assortativity
  - Assortativity is defined as a correlation function in terms of degrees
  - Defined in the prev. talk
- Modularity
  - Network modularity is the extent to which a network can be separated into independent sub-networks
  - Quantifies the fraction of links that are within the respective modules compared to all links in a network
  - Given an algorithm which can partison a network in to k modules, modularity is defined as

$$Q = \sum_{s=1}^{k} \left[\frac{l_s}{L} - \left(\frac{d_s}{2L} \right)^2 \right],$$

  - Here **k** is the number of modules, **L** is the number of links in the network, $\mathbf{l_s}$ the number of links between nodes in module **s**, and $\mathbf{d_s}$ is the sum of degrees of nodes in module s
- Closeness centrality
  - Closeness centrality of a node ***v*** is defined as the mean geodesic distance (shortest path length) between the node and all other nodes in the network
  - We use the non-inverted quantity
  - Formally defined as $C^C(v) = \sum d_G(v,t)$
  - Where $\mathbf{d_G(v,t)}$ is the shortest path distance between nodes v and t.
- Clustering coefficient
  - Clustering Coefficient of a node characterizes the density of links in the environment closest to a vertex
  - Formally, the clustering coefficient **C** of a node is the ratio between the total number y of links connecting its neighbours and the total number of all possible links between all these z nearest neighbours

$$C = 2y / (z(z-1))$$

  - The clustering coefficient $\mathbf{C_{net}}$ for a network is the average **C** over all nodes

➢ All calculated using the Brain Connectivity Toolbox.

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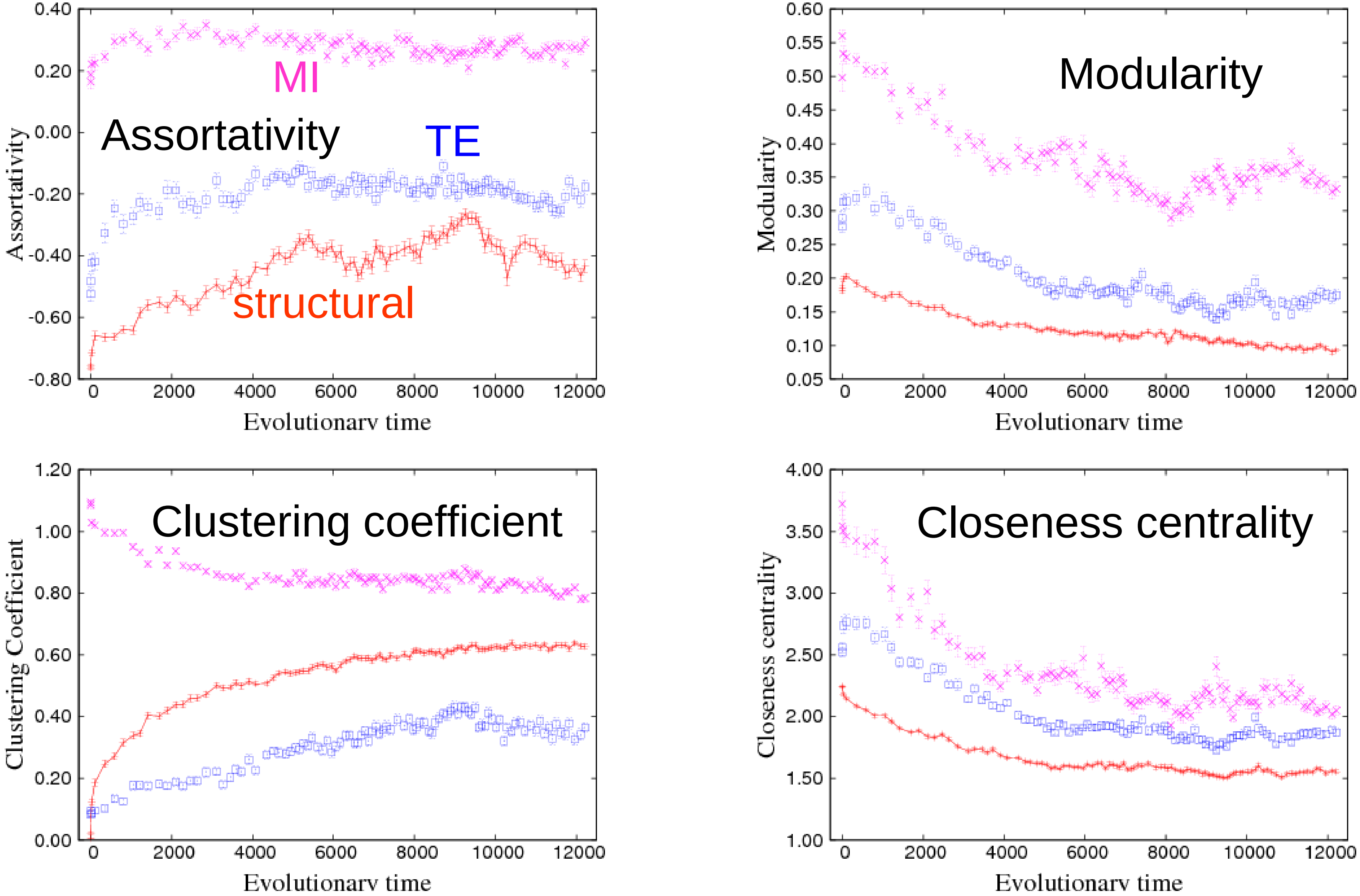
Results (1/4)

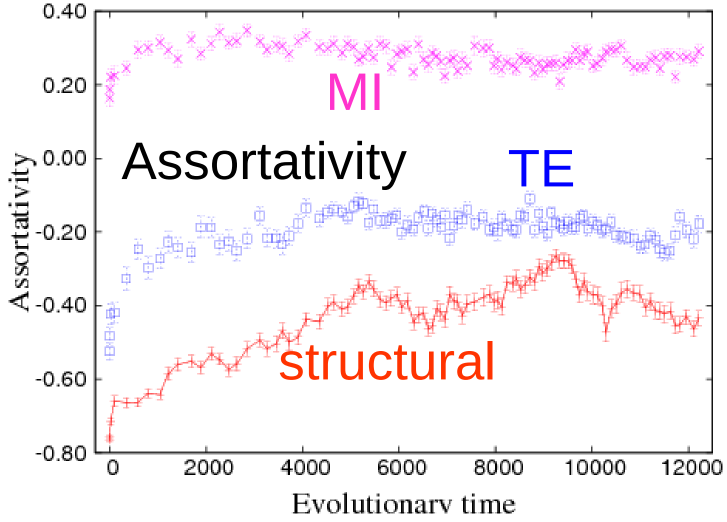


- Topological measures for structural, TE- and MI-inferred networks versus evolutionary time.

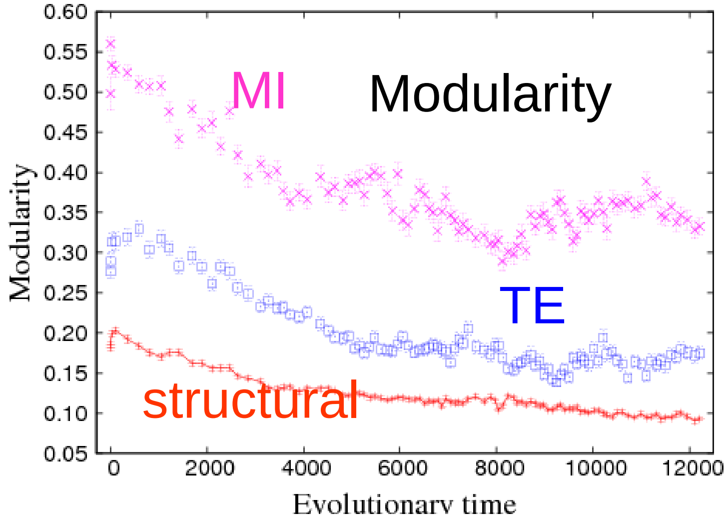
Results (2/4)

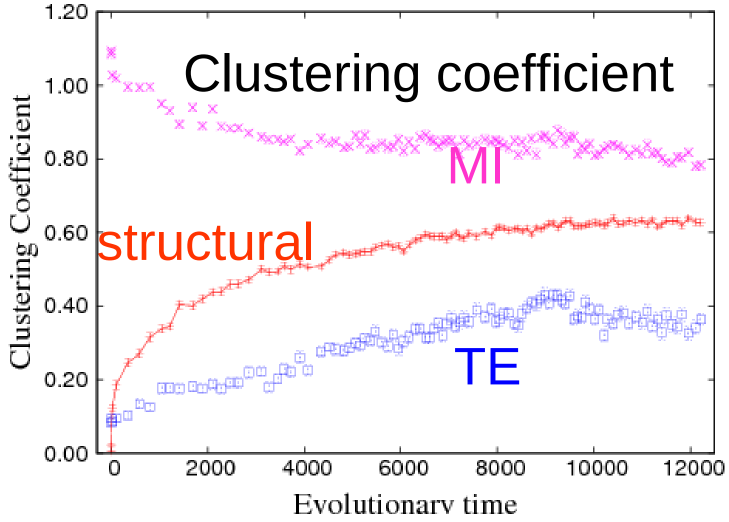
- General trends:
  - All measures reach a steady state once agents have found a good enough solution
  - Transfer entropy trends are more similar to those of the structural network than mutual information

- Assortativity:
  - Structural and TE networks are negatively assortative, while MI networks are assortative (all unsurprising).
  - Structural and TE networks become more neutrally assortative over time: possibly an artefact of increased global coupling or increased clustering.



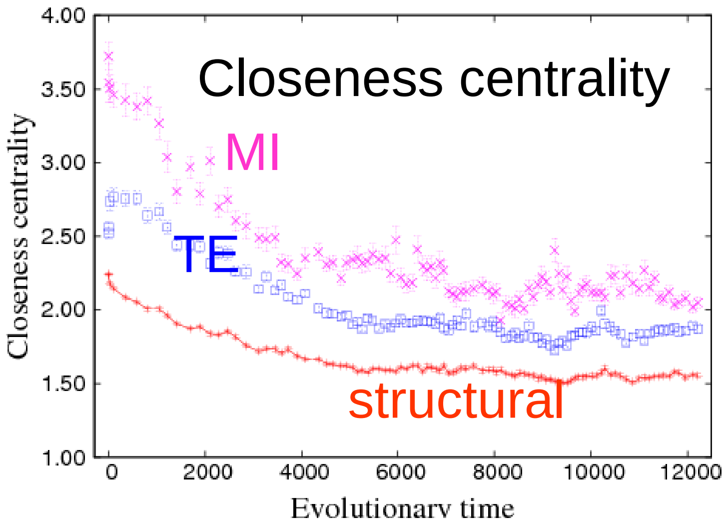
Results (3/4)





- Modularity and clustering
  - Structural and TE networks become more modular but less clustered: boundaries between modules are blurring, previously separated modules are becoming more strongly clustered both within themselves and across eachother.
  - MI networks exhibit decreased clustering (relic of the measure)

Results (4/4)



- Closeness centrality
  - Reduced for all networks with evo time: expected, as all other results have implied diversification of connectivity across network.

- Overall
  - Higher clustering + lower shortest path length → more small-world like with evo time

Conclusion

- Clear trends in structural and functional networks in ANNs of agents in Polyworld in evolutionary time
  - Higher clustering
  - Lower shortest path lengths

  } More small-world character

- Transfer-entropy inferred networks reflect trends in structural networks better than mutual information-inferred networks.

- Future work
  - Evaluate statistical significance of trends (multiple runs), and contrast with genetic drift.

Information dynamics of cascading failures in power grids

- Small failures in power grids can lead to large cascading failures that cause large and sustained power blackouts.
- There is an obvious need to understand and avoid these events

- Q: How is information intrinsically processed during these events?
  - Key question because network is technically *computing* it's new stable state (attractor) during these events.
  - Understanding the computation can help understand the dynamics
- We look at information storage and transfer as a function of network capacity.
  - Also examine relationship between local topological structure and information dynamics,
  - And relationships in time between information transfer and cascade spreading.

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Cascading failure events

- Energy, comms, transport, financial networks are all subject to cascading failure events:
  - local failures that trigger avalanche mechanisms with large effects over the whole network.
- Our focus is energy networks:
  - Usage has increased faster than investment
  - More frequent outages
- Cascading failures are akin to studies of damage spreading / perturbation avalanches
  - Unanswered questions over the relationship of these events to the concept of information transfer.
    - Is information transfer related to the size of avalanche (e.g. Langton, 1990) or the uncertainty in the size of the avalanche (e.g. Ramo et al, 2007) ?
    - How is information transfer affected by network structure?

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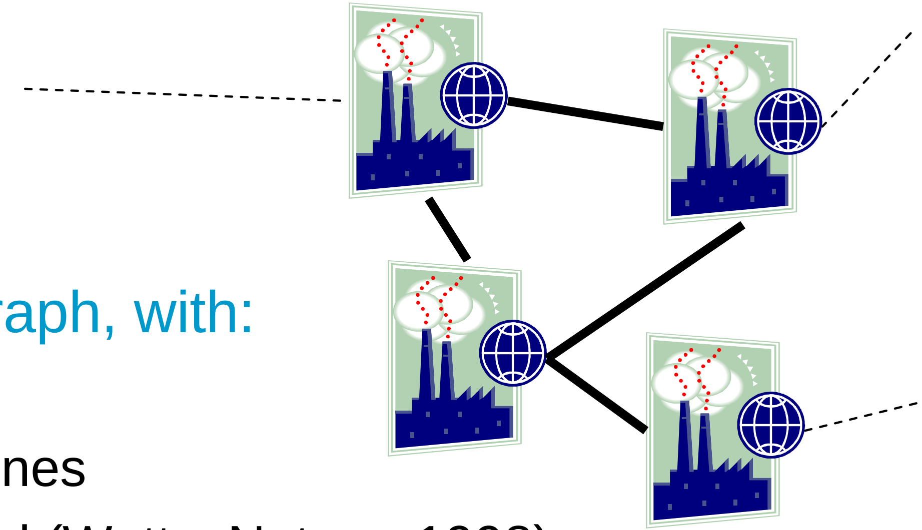
Cascading failures model



From Crucitti et al, PRE, 2004:

- Network is weighted undirected graph, with:
  - Nodes representing substations
  - Edges representing transmission lines
  - Topology of US Western power grid (Watts, Nature, 1998)
- Each edge *ij* has an efficiency $e_{ij}(n) \in (0,1]$, with $e_{ij}(0) = 1$
  - $e_{ij}(n)$ = inverse edge weight
  - Efficiency $\varepsilon_{ij}(n)$ of most efficient path from *i* to *j* is inverse of shortest path length.
- Each node *i* has a load $L_i(n)$ = betweeness centrality of node *i* at time *n*.
- Each node has a capacity $C_i = \alpha L_i(0)$, with $\alpha \geq 1$ the network tolerance.

Cascading failures model – dynamics

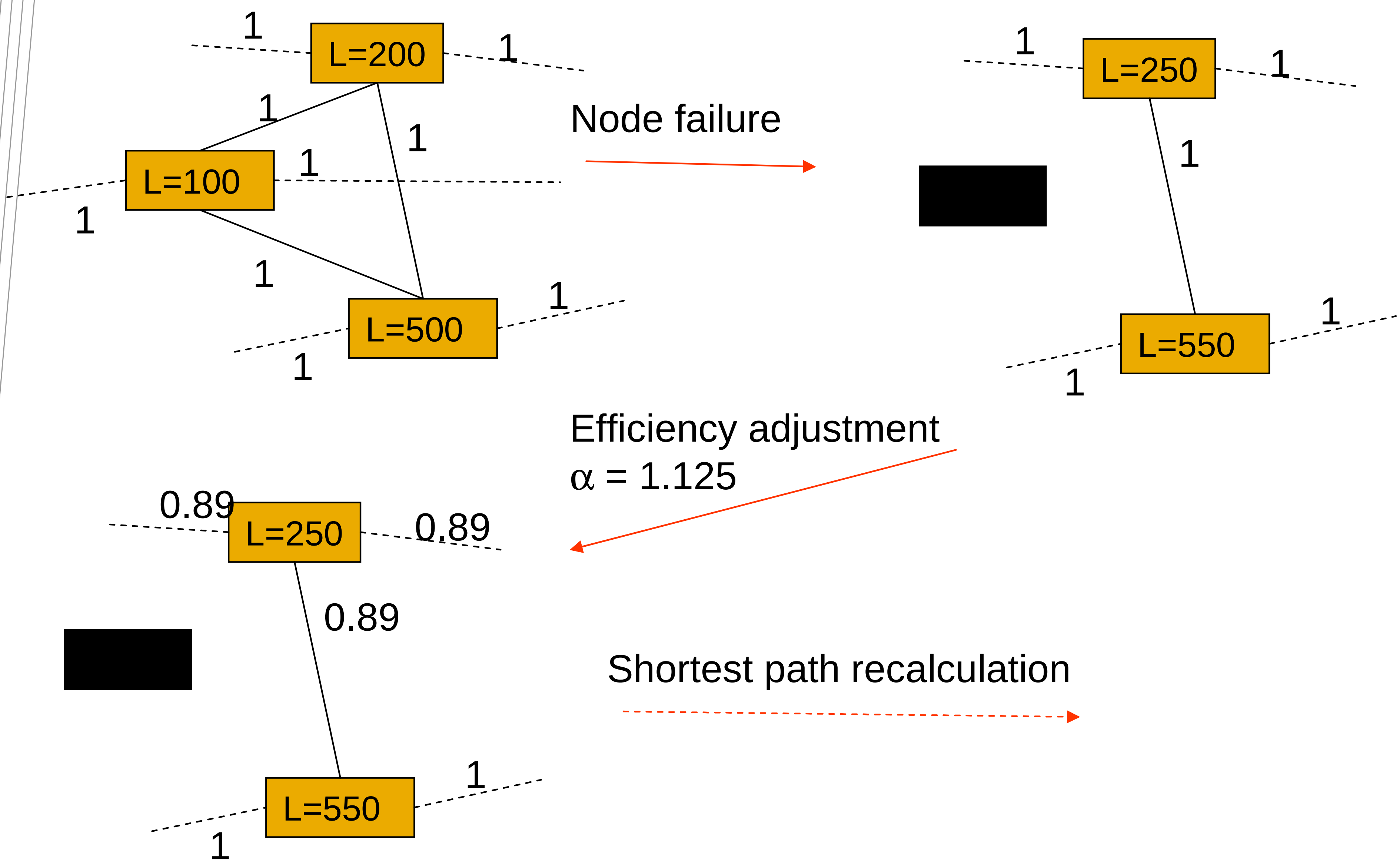
- Edge efficiencies become sub-optimal if (altering original model) either end-point is operating above capacity:

$$e_{ij}(n+1) = \begin{cases} e_{ij}(0) \ \min\left(\frac{C_i}{L_i(n)}, \frac{C_j}{L_j(n)}\right) & \text{if } L_i(n) > C_i \text{ or } L_j(n) > C_j, \\ e_{ij}(0) & \text{otherwise} . \end{cases}$$

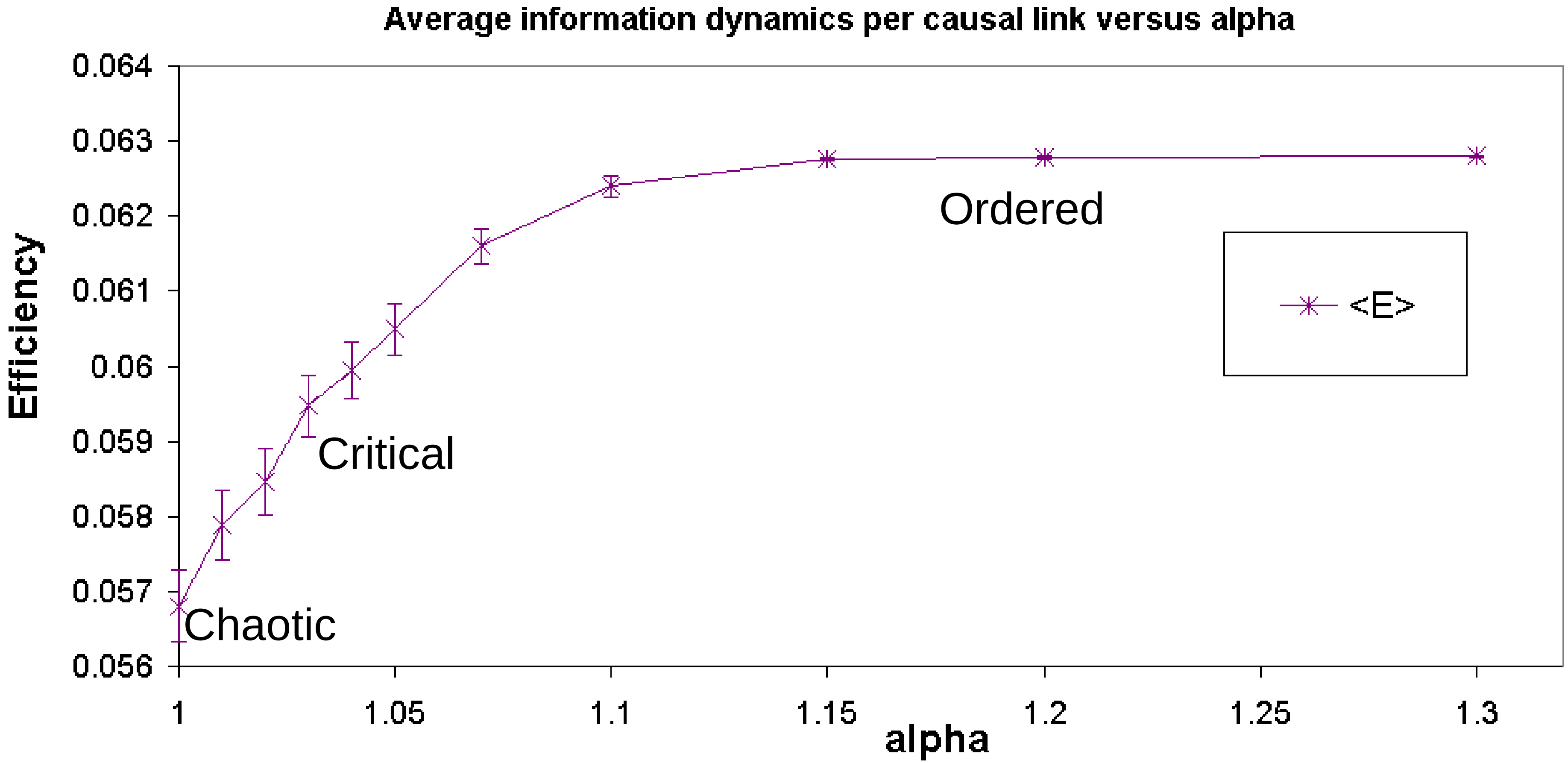
- Changes in edge efficiencies $\rightarrow$ changes in most efficient paths $\rightarrow$ changes in load distribution $\rightarrow$ changes in edge efficiencies …
- Initial network state is stable, but removal of a node (simulating initial substation failure) triggers a dynamical process where loads are redistributed.
  - Could cause other nodes to overload, etc, leading to a cascading failure.
  - Stable state may be oscillatory.
- Performance is tracked using average pairwise efficiency:

$$E(n) = \langle \epsilon_{ij}(n) \rangle$$

Cascading failures model – example

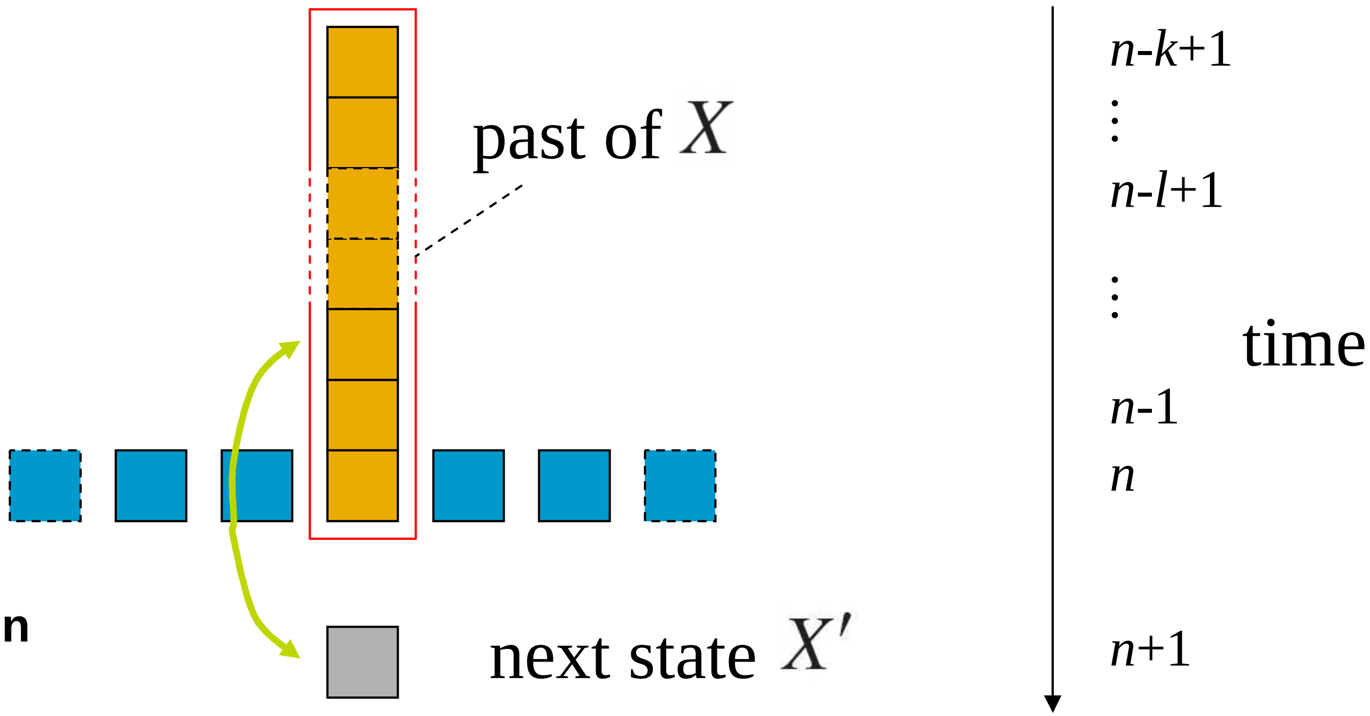


Phase transition with excess capacity alpha



Active information storage

$$A_X = I(X^{(k)}; X) =< i(x_n^{(k)}; x_{n+1}) >$$



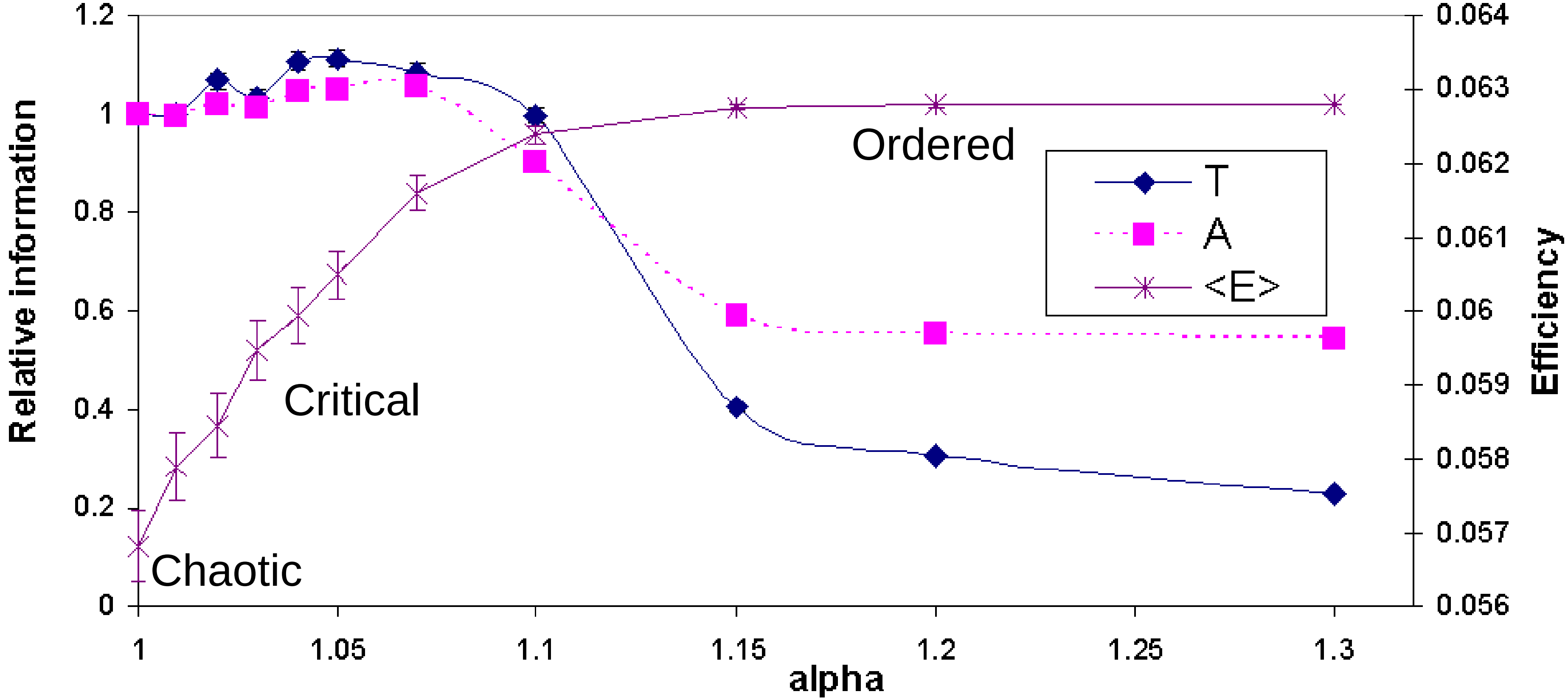
Active information storage

Lizier et al, 2007.

Active info storage = stored information that is currently in use

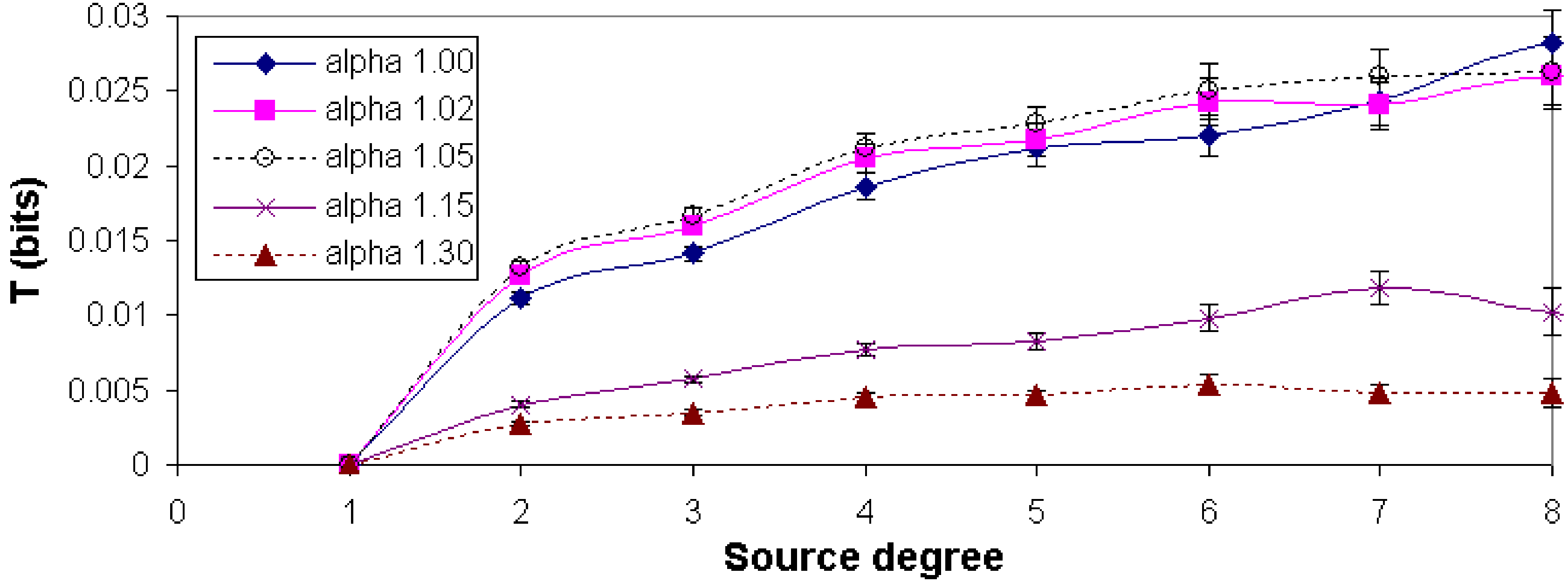
TE

Results: 1.Info dynamics through phase transition



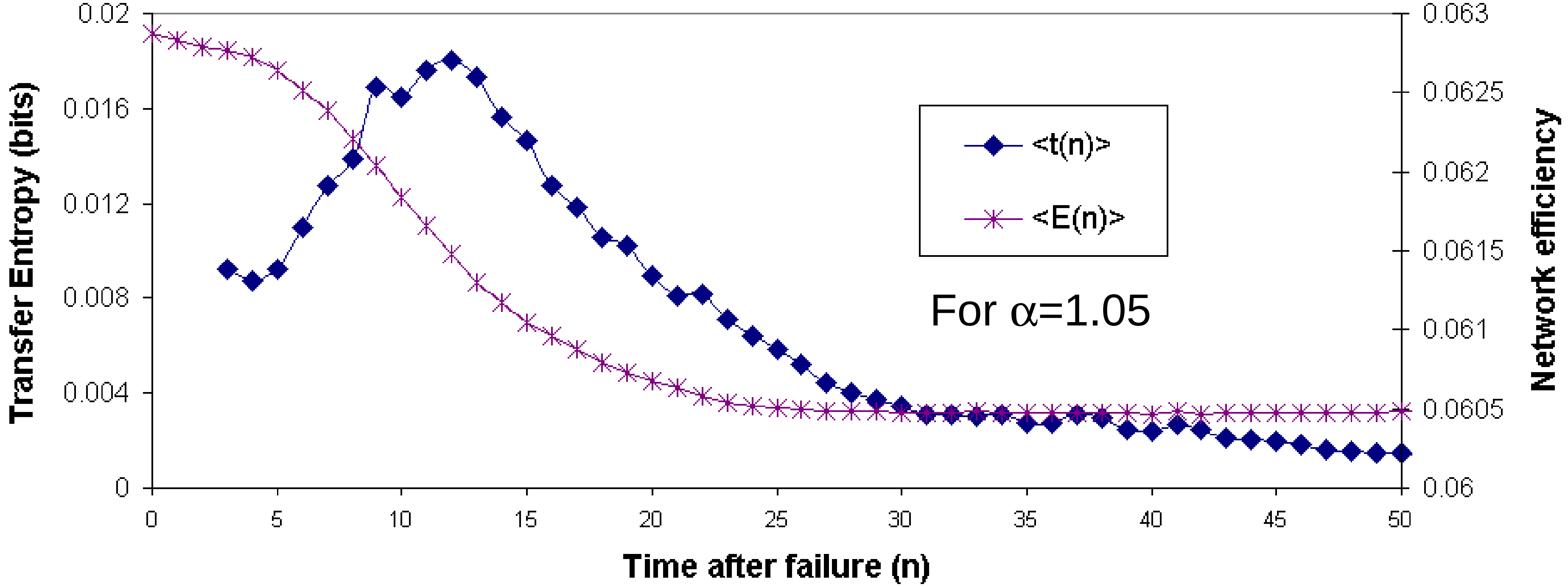
- Both info storage and transfer are maximised near the phase transition in efficiency.
- They change sharply well before efficiency – could be useful early indicators

Results: 2.Info transfer correlated with source degree



- In vicinity of phase transition, info transfer is correlated with degree of source node.
    - More neighbours = more diversity => more info to transfer
- Also a small correlation between info transfer and initial load (b/w centrality) of source node.

Results: 3. Info transfer evolution in time



- Peak in transfer lags the failure event, but coincides with steepest drop in efficiency.
- Large correlation b/w transfer and change in efficiency.
- No correlation to local loads – this seems to be an emergent effect.

Conclusion

- Characterised information dynamics of the intrinsic computation during cascading failures:
  - Maximising of computational capabilities near the phase transition.
  - Local info dynamics correlated with (source) degree.
  - Strong relationship between spread and application independent information transfer.

- Future work
  - Alter model to more realistically reflect power loads
  - Effect of altering topology of power grid, especially including mini-grids
  - Can our knowledge be used to control cascade events?

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Thank you