



The Dark Side of Scale-Free Networks in Organizational Learning

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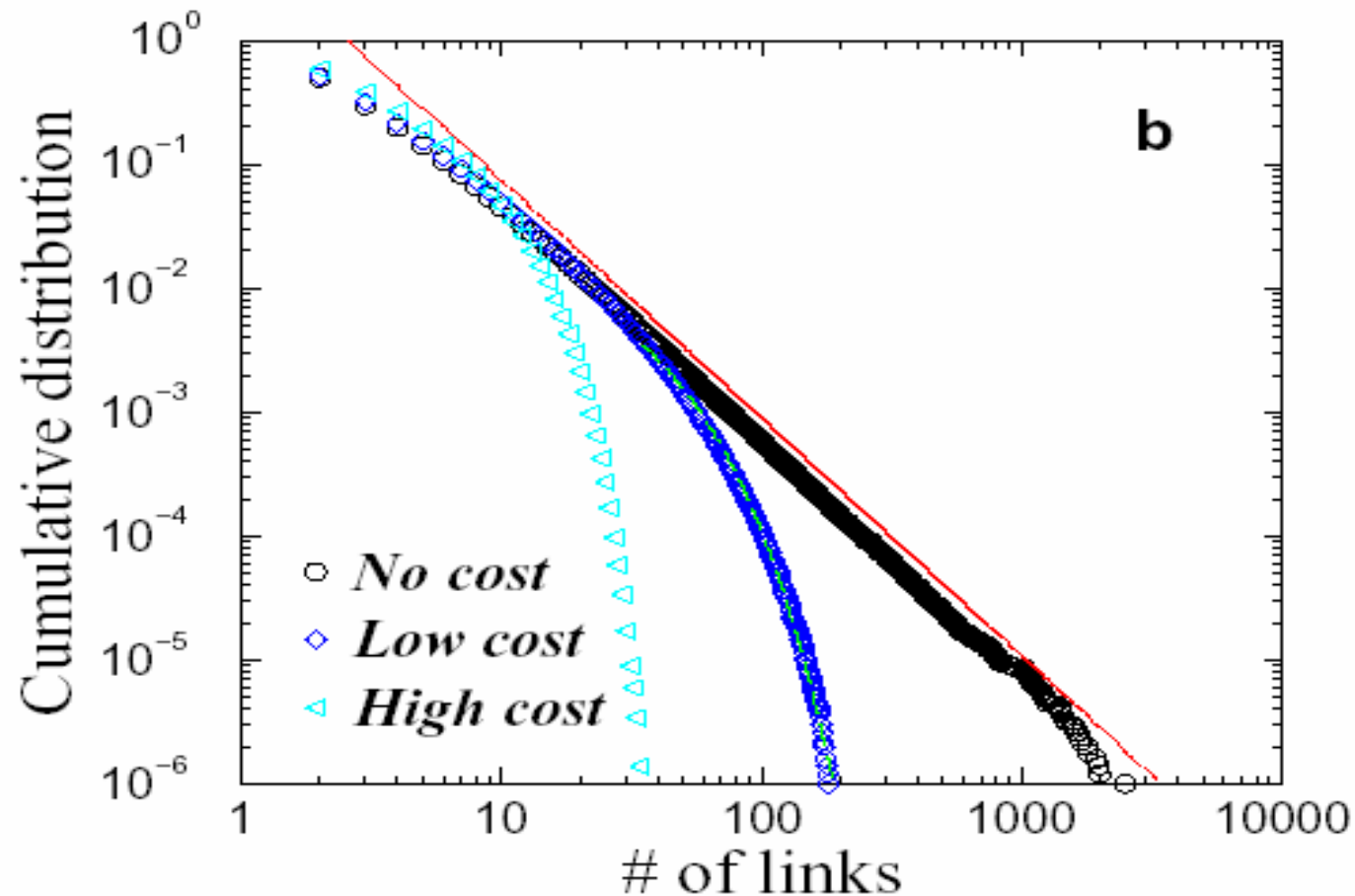
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Three Classes of Real-world Networks

- **Scale-free networks:**
 - It is characterized by a power-law tail with extreme outliers.
- **Broad-scale network:**
 - A connectivity distribution has a power-law regime followed by a sharp cut-off at the tail region.
- **Single-scale network:**
 - A connectivity distribution with a fast decaying tail

Truncation of Scale-Free Connectivity with **Constraint** ($p_{inactive}$)



* **Source:** Amaral, L.A.N., Scala, A., Barthelemy, M., & Stanley, H.E. 2000. Classes of small world networks. *Proceedings of the National Academy of Science of America*, 97(21): 11151



Conjecture:
Scale-free networks may have evolutionary advantage over other structural forms.

- Some favorable clues
 - They are far more common in reality.
 - Error tolerance (Albert, Jeong, and Barabási 2000)
 - Search efficiency (Adamic et al. 2001)
- But systematic research on the issue has been sparse.



Objective of Our Study

- We address the conjecture
 - by assuming the aforementioned networks as alternative structures for interpersonal learning.
 - by adding dynamics of organizational learning (March 1991, Fang, Lee, and Schilling 2007)
- Are scale-free networks more effective for improving organizational knowledge than single-scale networks?



Related Phenomenon

- Virtual Organizations
 - An emerging organizational form that departs radically from the traditional hierarchical structure (Ahuja and Carley 1999; Markus and Manville 2000).
 - Popular in developing and upgrading open source software products (e.g., the Linux community)
- Hubs tend to dominate innovation and knowledge creation processes (e.g., the Soar Group).
- Is it desirable for hubs to dominate?

Name	2007	2006	2005	2004	2003	2002	2001	2000	1999	1998	1997	1996
Cohen, M.A.	1	1										
Ritter, F.E.	1	1							1			
Haynes, S.R.	1	1										
Gorski, N.A.	2	1										
Laird, I.E.	9	4	3	8	5	2			1	7	1	3
Hogewoning, E.	1											
Broekens, J.	1											
Eggermont, J.	1											
Bovenkamp, E.G.P.	1			1								
Jones, R.M.	1	3	2	6	3	7	3	2	3	7	1	3
Lebiere, C.	1	2		1								
Crossman, J.A.	1	3		1								
Lathrop, S.D.	1	1										
Magerko, B.	1	1	2	2	1	1						
Marinier, R.P.	1			1								
Nuxoll, A.M.	1		1	2		1						
Pearson, D.	1		1	1	1							1
Lewis, R.L.	1	1										
Taylor, G.	1	1		1		3		1				
Stensrud, B.	1	2	1									
Eitelman, S.	1											
Dunham, C.	1											
Wang, Y.	1	1										
Wintermute, S.	3											
Xu, J.	1											
Irizarry, J.	1											
Yaldir, A.	1											
Kaminka, G.	1											
Wray, R.E.		1	5	7	5	3	1			1		2
Best, B.J.		2										
Kennedy, W.G.		1			1							
Trafton, J.G.		1										
Konik, T.		1		1								
Holt, L.		1	1									
Howes, A.		1										
John, B.		1										
Amant, R.		1										
McBride, S.P.		1										
Urbas, L.		1										
Leuchter, S.		1										
Vera, A.		1										
Rosenbloom, R.		1										
Chong, R.S.			2		2							
Nason, S.			1	1								
Wallace, S.A.			1		2	1						
Stokes, D.			1	1		1						
Kerfoot, A.			1	1		1						
Dijkstra, J.				1								
Bosch, J.G.				1								
Reiber, J.H.C.				1								
Wallace, A.J.				1								
Wessling, J.				1								
James, M.				1								
Lisse, S.				1								
Beard, J.				1								
Biddle, E.S.					1							
Henninger, A.					2	2	2					
Franceschini, R.					1							
Chown, E.					1	3	2					
De Jong, K.A.					1							
Assarie, M.						1						
Bachelor, B.						1						
Benninghoff, N.						1						
Enam, S.						1						
Jones, B.						1						
Lauver, C.						1						
Sheiman, J.						1						
Goldstein, M.						1						
Frederiksen, R.						1						
Beisaw, J.C.						1						
Koss, F.V.						1		1	1	1		
Nielsen, P.E.						1		1	1	4		1
Zachary, W.						1						
Kenny, P.G.								1	1	1		
Coulter, K.J.									1	1		
Baxter, G.D.									1			
Neville, K.										1		



Evolutionary Mechanisms in the Organizational Learning Model

- A miniature evolutionary system
- Selection:
 - Better performing bits of knowledge are more likely to be adopted than under-performing bits of knowledge.
- Recombination:
 - Individuals imitate some bits of knowledge from higher performers, while retaining the others.
- Mutation:
 - turnover and new hires



MODEL

- **Main Entities**
 1. **External Reality**
 2. **Individual**
 3. **Organization**



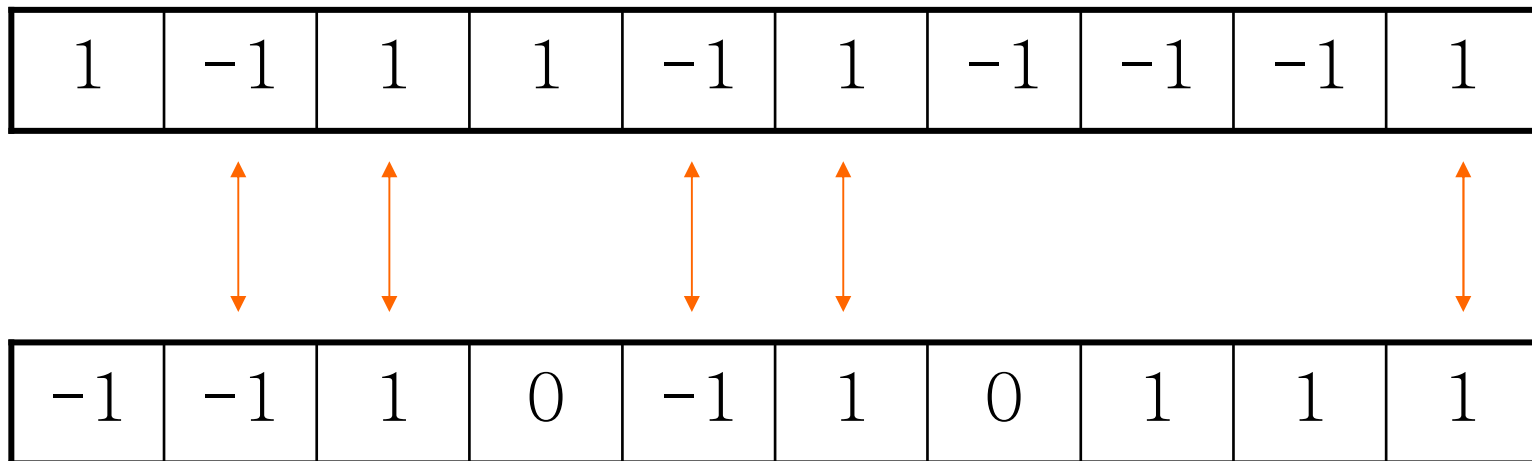
Representation of Reality and Individual

Reality:

Has m dimensions.

A value of 1 or -1.

Example) $m = 10$



Individual:

Holds m beliefs about reality.

A value of 1, 0, or -1.



Generalized Payoff Function

- Performance is a function of # of matches between reality and individual beliefs.

- The difficulty of a search problem: s

- s is an integer with $1 \leq s \leq m$.

- Payoff function

- $$\Phi(x) = \prod_{j=1}^s \delta_j + \prod_{j=s+1}^{2s} \delta_j + \dots + \prod_{j=m-s+1}^m \delta_j$$

where $\delta_j = 1$ if j th belief for an individual corresponds with reality on that dimension

$\delta_j = 0$ otherwise.



Learning

- Each individual is likely to change her beliefs when she interacts with “superior performers.”
 - She adapts to a dominant belief (or a majority view) within the superior performers on any particular dimension with probability p .

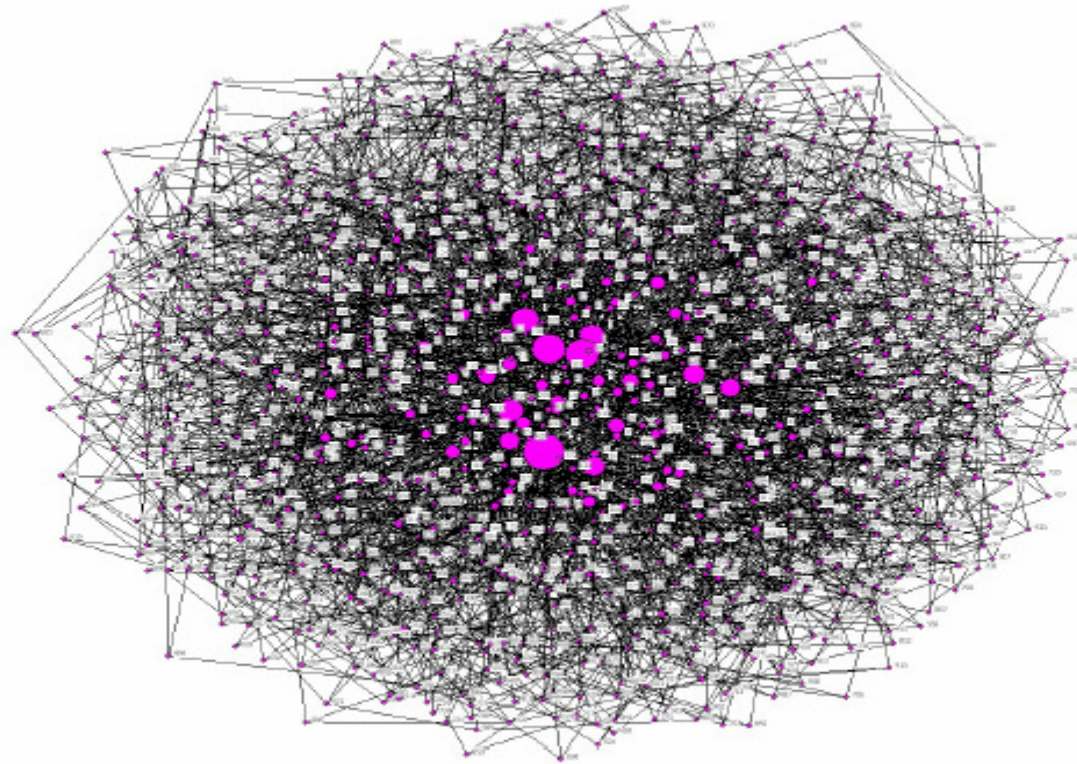


Representation of Organization

- Consists of n individuals.
- Structure for interactions among them.
- We used a scale-free network with a tunable parameter $p_{inactive}$ for connectivity constraint (Amaral et al. 2000)

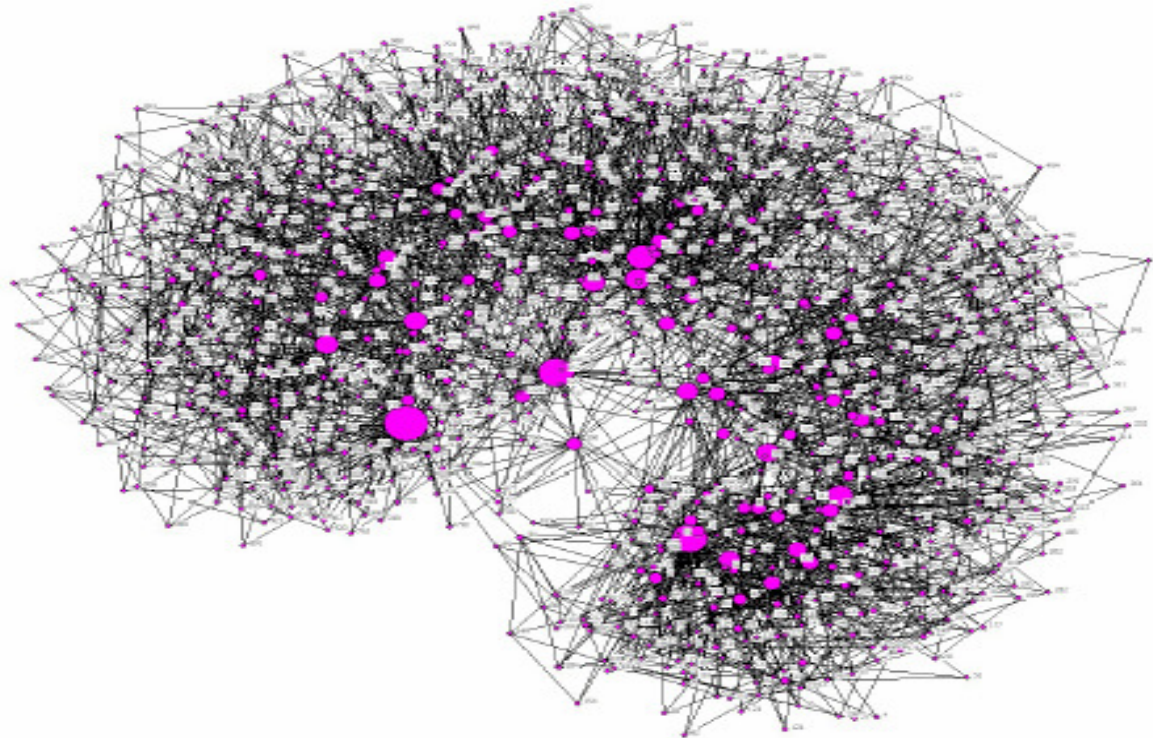
1) Scale-Free Network

$$P_{inactive} = 0$$



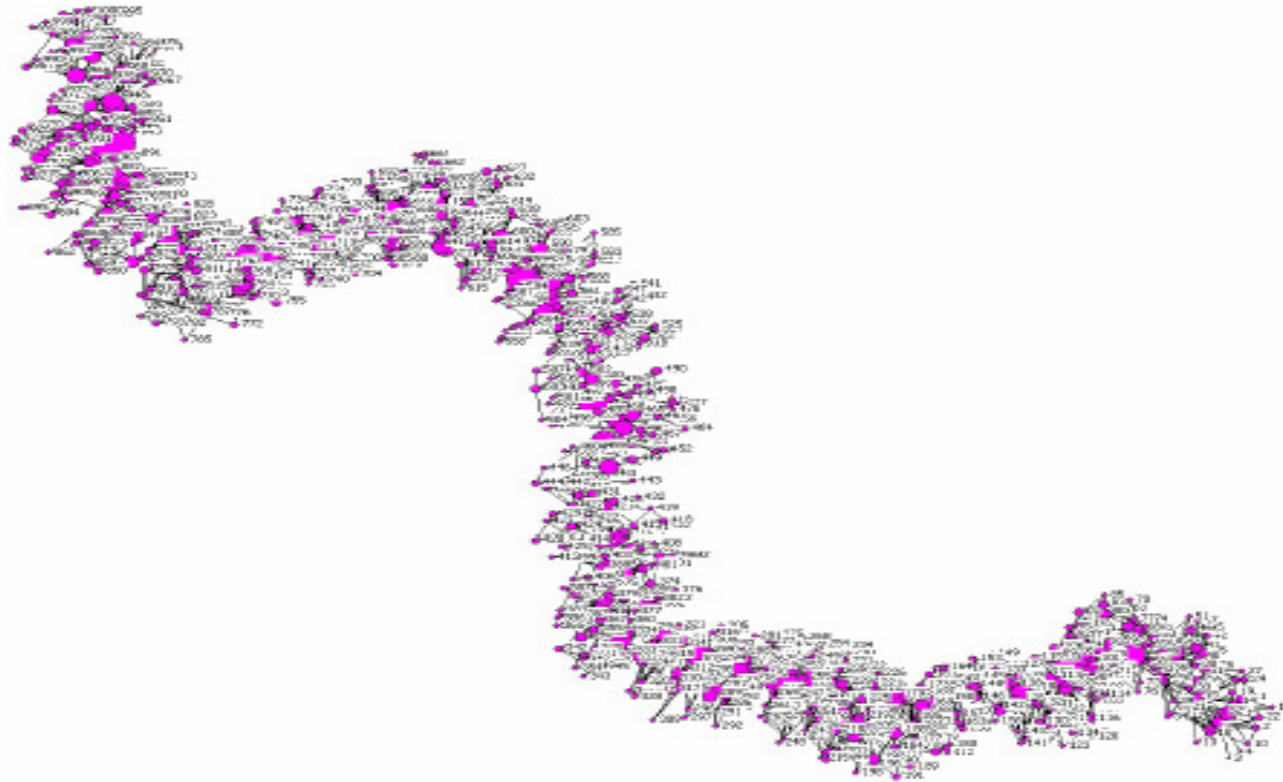
2) Broad-Scale Network

$$P_{inactive} = 0.01$$



3) Single-Scale Network

$$P_{inactive} = 0.1$$





Connectivity Constraint and Network Properties

Connectivity Constraint	Characteristic Path Length	Maximum Distance
0	2.58	4
0.01	2.67	5
0.10	13.98	43
0.20	45.02	133
0.30	75.10	225



RESULTS

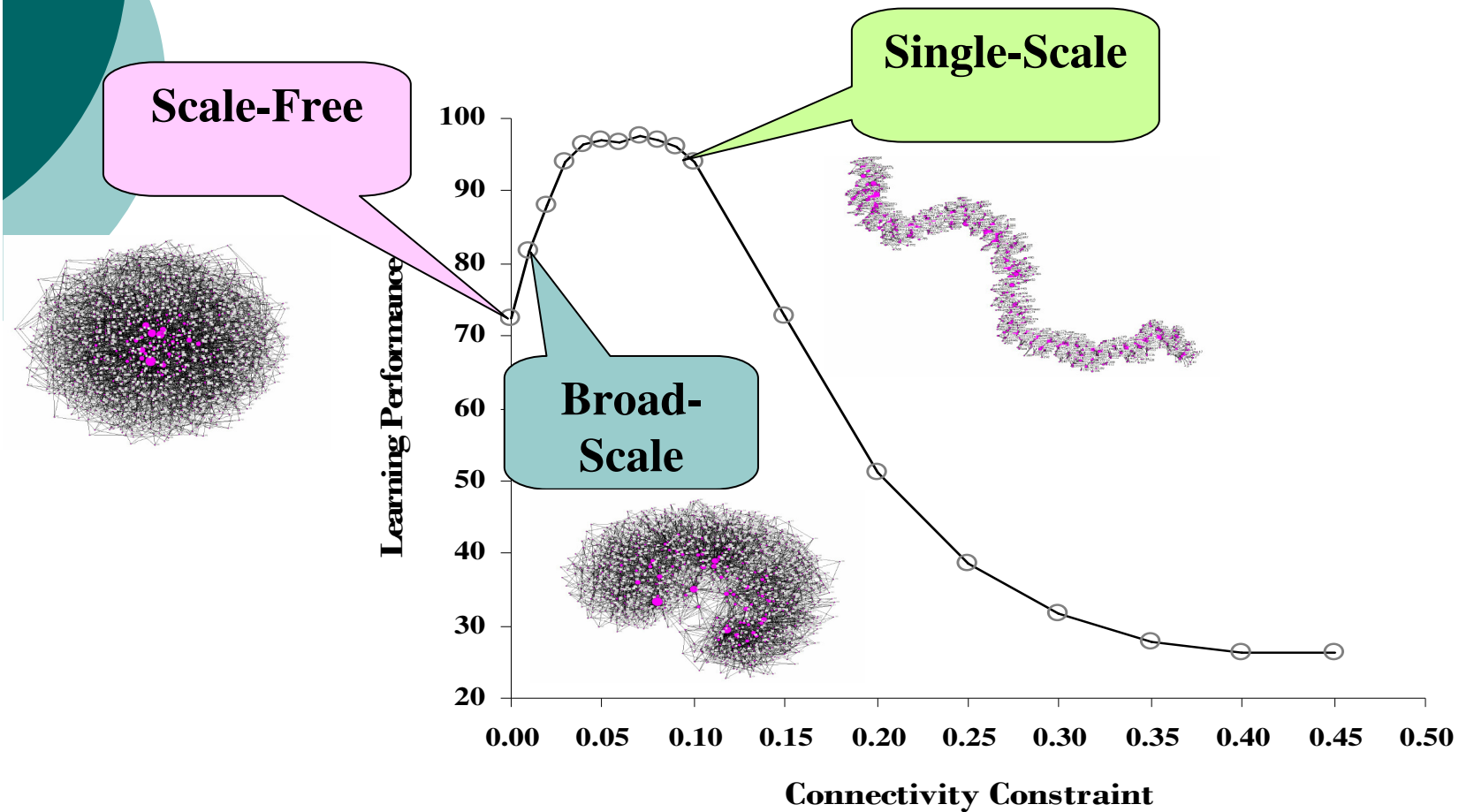


Learning performance in closed systems

Stable environment & no turnover

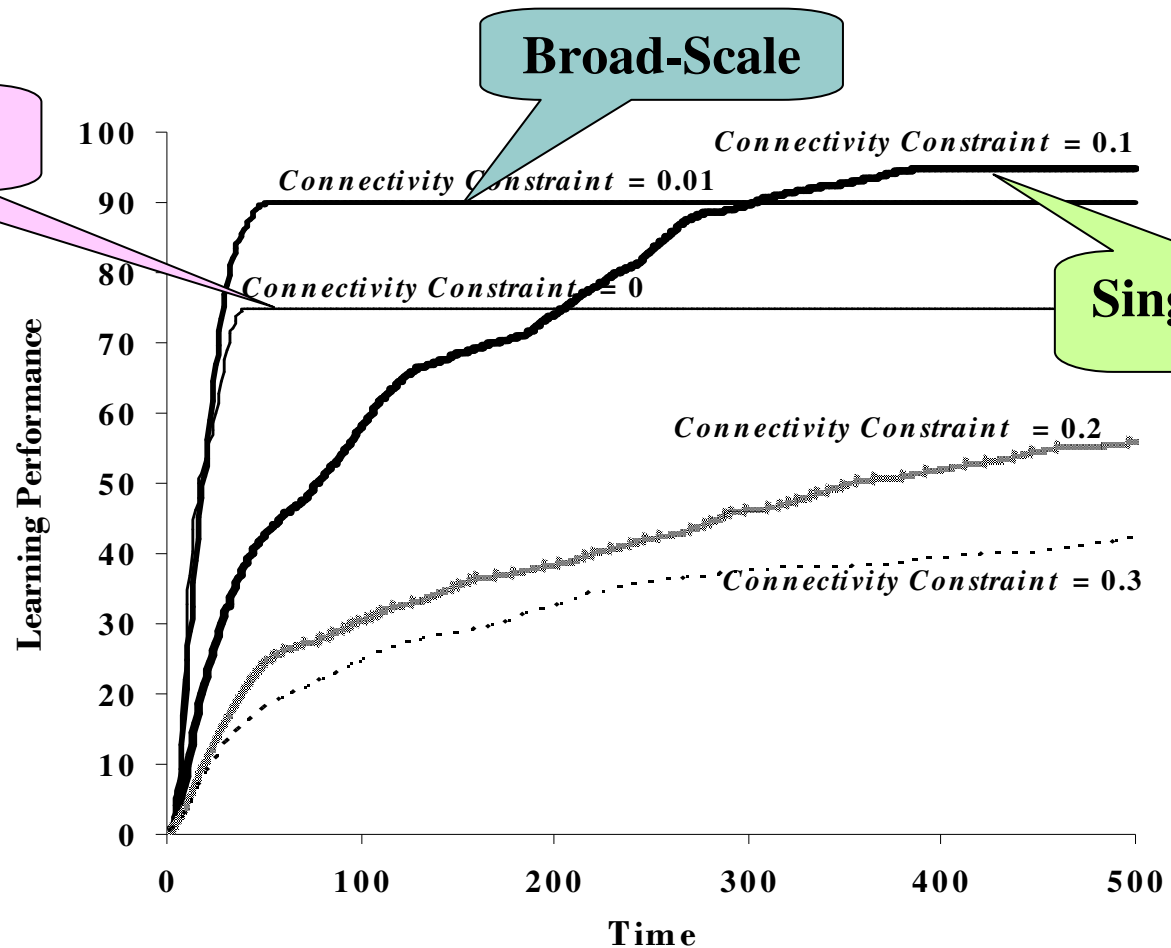
- Scale-free networks are suboptimal for organizational learning
- Learning outcome is highest when connectivity constraint is modest (e.g., $P_{inactive} = 0.1$).

Learning performance by constraint: Average over 100 simulations



Learning speed by network structure: Typical simulation run

Scale-Free





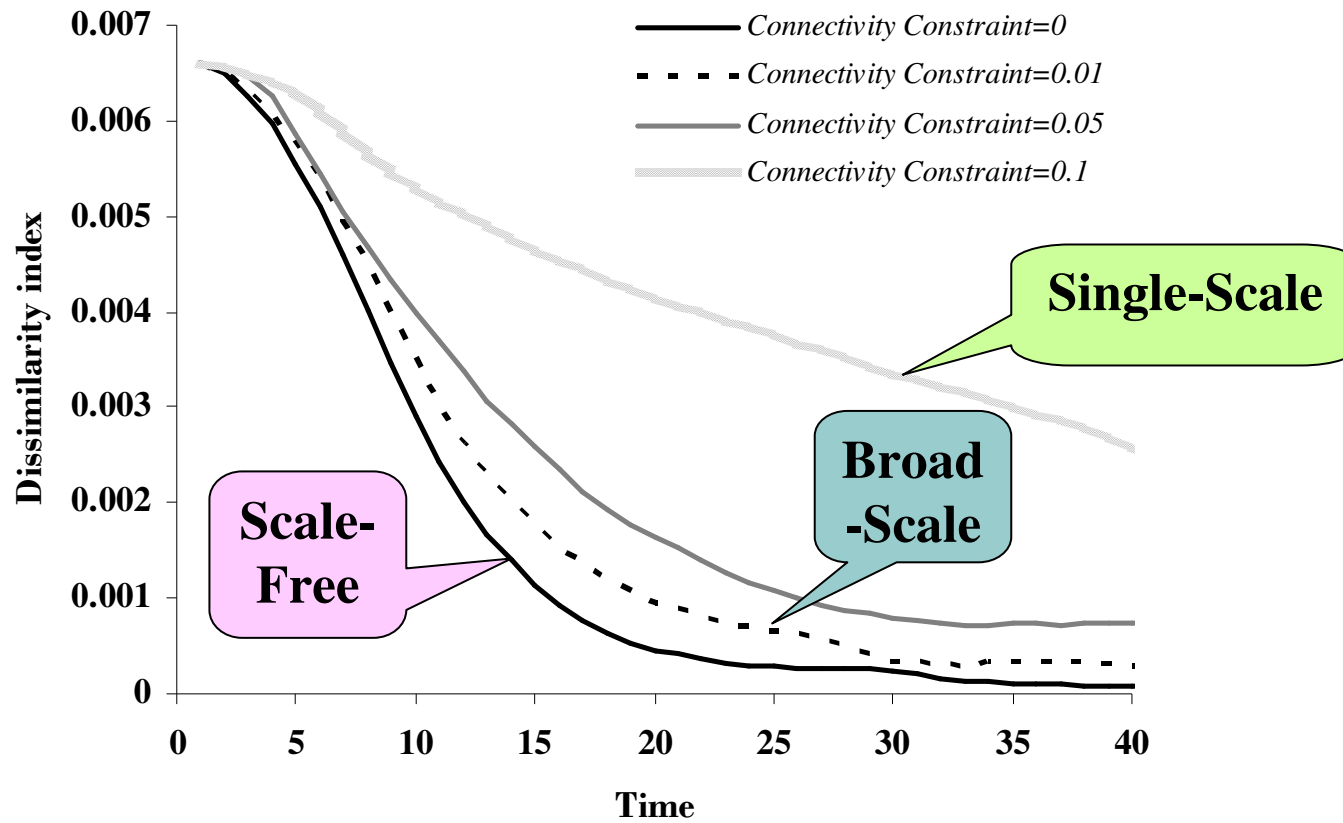
Dissimilarity Index (Fang, Lee and Schilling 2006)

- Make pairwise comparisons of all n individuals.
 - There are $n(n - 1)/2$ pairs.
 - For each pair of individuals, there are m beliefs to be compared.

- Dissimilarity =
$$\frac{2}{mn(n-1)} \sum_{i=1}^{\frac{1}{2}n(n-1)} \sum_{j=1}^m \omega_{ij}$$

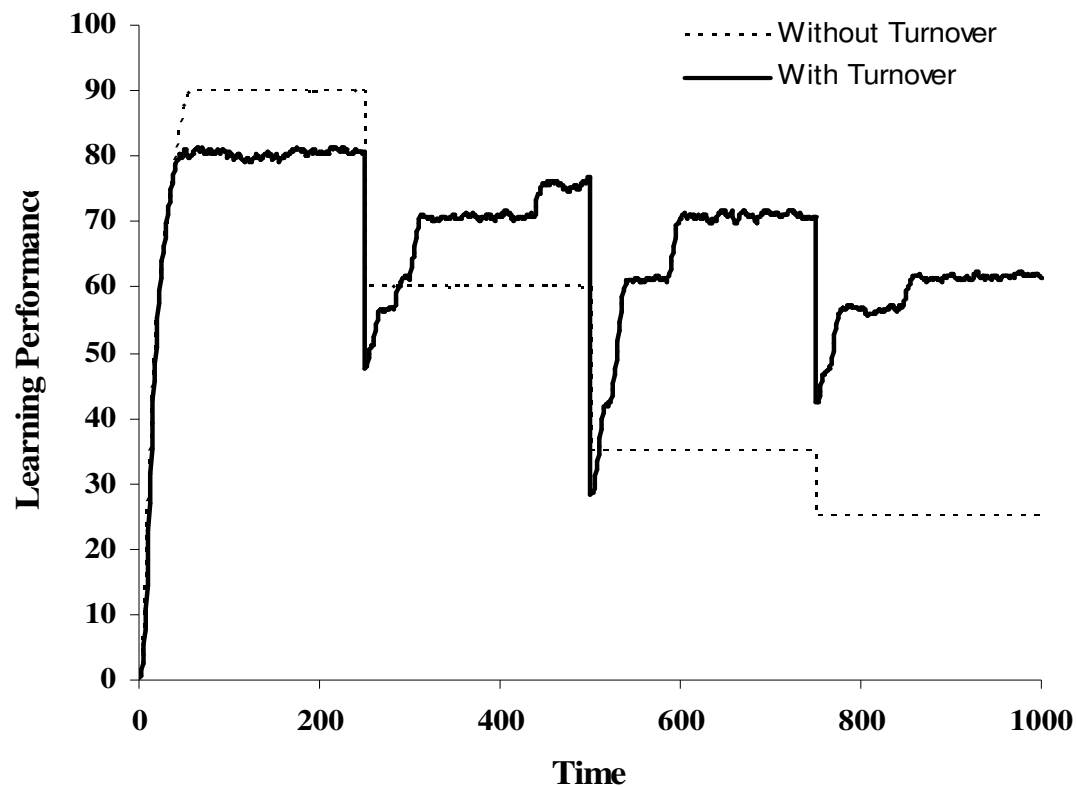
- $\omega_{ij} = 1$
 - if two chosen individuals for i th pair have different beliefs on j th dimension,
- $\omega_{ij} = 0$
 - otherwise.

Diversity over time by network structure



Effect of Turnover in Changing Environment: Open Systems

$$P_{inactive} = 0.01, P_{envir} = 0.1, P_{turnover} = 0.01$$





Variation in Environmental Change Rate

A network at the edge of single-scale and broad-scale regimes works best!

$$P_{\text{turnover}} = 0.01$$

	Low $P_{\text{turbulence}} = 0.1$	Medium $P_{\text{turbulence}} = 0.3$	High $P_{\text{turbulence}} = 0.7$
$P_{\text{inactive}} = 0$	59.71	34.61	29.16
$P_{\text{inactive}} = 0.01$	61.17	34.6	29.51
$P_{\text{inactive}} = 0.10$	69.68	44.27	37.1
$P_{\text{inactive}} = 0.20$	64.04	39.88	31.5
F statistics	16.47	18.26	17.99
P-value	0.0000	0.0000	0.0000



Variation in Turnover Rate

A network at the edge of single-scale and broad-scale regimes works best!

$$P_{\text{envir}} = 0.1$$

	Low $P_{\text{turnover}} = 0.001$	Medium $P_{\text{turnover}} = 0.01$	High $P_{\text{turnover}} = 0.1$
$P_{\text{inactive}} = 0$	43.74	59.71	42.78
$P_{\text{inactive}} = 0.01$	45.32	61.17	44.79
$P_{\text{inactive}} = 0.10$	49.85	69.68	48.36
$P_{\text{inactive}} = 0.20$	43.98	64.5	29.68
F statistics	4.14	9.17	162.61
P-value	0.0071	0.0000	0.0000



Key Findings

- **Trade-off between speed of diffusion and preservation of knowledge diversity**
 - Hubs facilitate rapid diffusion of superior knowledge, but they drive out knowledge diversity too quickly.
 - Constraints on connectivity preserve knowledge diversity, but slow down the diffusion of superior knowledge.
- The balance between the two is improved by modest amounts of constraint on connectivity.



Implications

- Differences between diffusion and evolution
- Linus Torvalds should not dominate innovation processes in the Linux community!



Diffusion vs. Evolution

○ No competition

- A single piece of information or one kind of disease

○ Competition

- Among alternatives
- Between current alternatives and future alternatives

○ No tradeoff

- The faster, the better

○ Tradeoff

- A fast spread may reduce adaptability