

Hierarchical organization versus self-organization

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UGent

10 juni 2011

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Hierarchy

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- Structure so that for some it is easy to oppress/force their views for their own profit, while for most, it is the easiest to follow

Hierarchy

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- Structure so that for some it is easy to oppress/force their views for their own profit, while for most, it is the easiest to follow
- Unequality

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- Structure so that for some it is easy to oppress/force their views for their own profit, while for most, it is the easiest to follow
- Unequality
- Order: some are "higher" then others

Hierarchy

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- Structure so that for some it is easy to oppress/force their views for their own profit, while for most, it is the easiest to follow
- Unequality
- Order: some are "higher" than others
- Unequal relations: one has power over the other (local)

Hierarchy vs self-organization

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- Organization = structure with function

Hierarchy vs self-organization

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- Organization = structure with function
- Hierarchical organization vs self-organization

Hierarchy vs self-organization

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- Organization = structure with function
- Hierarchical organization vs self-organization
- Two ways to approach it:
 - difference on structure
 - different way in achieving goal

Hierarchy vs self-organization

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- Organization = structure with function
- Hierarchical organization vs self-organization
- Two ways to approach it:
 - difference on structure
 - different way in achieving goal
- see how the two agree

Network

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- Structure → by network/graph

Network

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- Structure → by network/graph
- Graph = 'nodes' connected by 'edges'

Network

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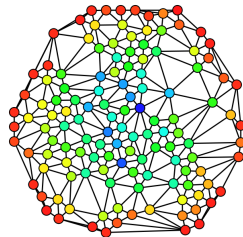
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- Structure \rightarrow by network/graph
- Graph = 'nodes' connected by 'edges'
- $G(V, E)$:
 - V = set of vertices/nodes
 - E set of edges (pair of nodes)



Degree

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- Degree of node = number of neighbours

Degree

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- Degree of node = number of neighbours
- Hierarchical = a lot of difference in degree?

Degree

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- Degree of node = number of neighbours
- Hierarchical = a lot of difference in degree?
- $P(k)$ = probability of degree k

Random network vs scale-free network

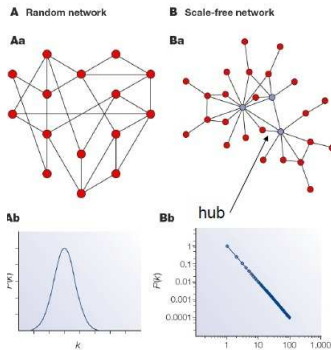
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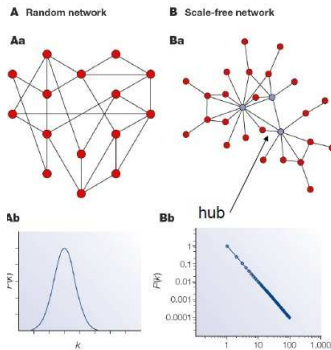
Function

Conclusion



- random: $P(k)$ normally distributed

Random network vs scale-free network



- random: $P(k)$ normally distributed
- scale free: $P(k) \sim k^{-\lambda}$: power-law

Clustering coefficient

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- But: having lots of neighbours \neq having influence, being leader

Clustering coefficient

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- But: having lots of neighbours \neq having influence, being leader
- Looking at clustering coefficient $C(v)$ of node v : how good neighbours are connected

Clustering coefficient

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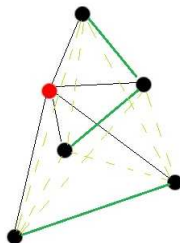
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$$\begin{aligned} C(v) &= \frac{|\text{edges between neighbours}|}{|\text{total possible edges between neighbours}|} \\ &= \frac{n_v}{\frac{k(k-1)}{2}} \end{aligned}$$

with $n_v = |\text{edges between neighbours}|$; $k = \text{number of neighbours}$.



Hierarchical vs scale-free

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- low clustering coefficient: neighbours depend on node, "leader"

Hierarchical vs scale-free

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- low clustering coefficient: neighbours depend on node, "leader"
- high clustering coefficient: node is interchangeable with neighbours, "follower"

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- low clustering coefficient: neighbours depend on node, "leader"
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- hierarchical network: higher degree, lower clustering coefficient

Hierarchical vs scale-free

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- low clustering coefficient: neighbours depend on node, "leader"
- high clustering coefficient: node is interchangeable with neighbours, "follower"
- hierarchical network: higher degree, lower clustering coefficient
- scale-free network: clustering coefficient the same for every degree

Summary

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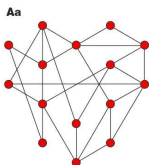
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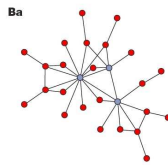
Function

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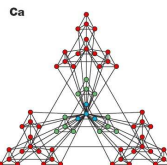
A Random network



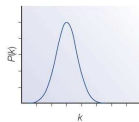
B Scale-free network



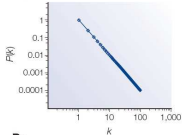
C Hierarchical network



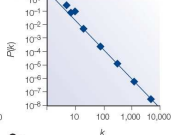
Ab



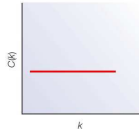
Bb



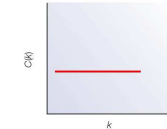
Cb



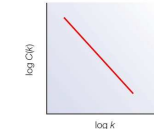
Ac



Bc



Cc



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- Diameter of network = biggest distance between two nodes; distance = length of smallest path

Failure and attack

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- Diameter of network = biggest distance between two nodes; distance = length of smallest path
- Failure: nodes deleted randomly

Failure and attack

- Diameter of network = biggest distance between two nodes; distance = length of smallest path
- Failure: nodes deleted randomly
- Attack: delete most connected nodes

Failure and attack

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- Diameter of network = biggest distance between two nodes; distance= length of smallest path
- Failure: nodes deleted randomly
- Attack: delete most connected nodes
- random: diameter increases, same for failure and attack

Failure and attack

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- Diameter of network = biggest distance between two nodes; distance= length of smallest path
- Failure: nodes deleted randomly
- Attack: delete most connected nodes
- random: diameter increases, same for failure and attack
- scale-free: diameter unchanged for failure; for attack it increases with bigger scope than random

Failure and attack

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- Diameter of network = biggest distance between two nodes; distance = length of smallest path
- Failure: nodes deleted randomly
- Attack: delete most connected nodes
- random: diameter increases, same for failure and attack
- scale-free: diameter unchanged for failure; for attack it increases with bigger scope than random
- Civil war: attack in hierarchical network → fall apart → new highest fight for leadership. Not because hierarchy is necessary, but because hierarchical structure is still present

Changing network

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Find easiest way from hierarchical to scale-free network

- two networks with same number of nodes (and edges)

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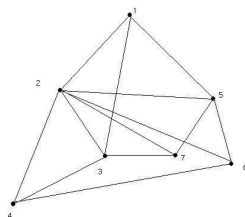
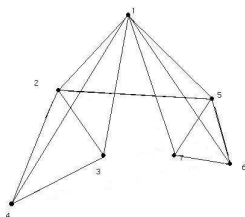
Find easiest way from hierarchical to scale-free network

- two networks with same number of nodes (and edges)
- Find best mapping from nodes of one network to the other

Changing network

Find easiest way from hierarchical to scale-free network

- two networks with same number of nodes (and edges)
- Find best mapping from nodes of one network to the other
- best= least edges to add/remove



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Find easiest way from hierarchical to scale-free network

- Algorithm to equalize clustercoefficients:

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Find easiest way from hierarchical to scale-free network

- Algorithm to equalize clustercoefficients:
- Look at node v , do for all neighbours b :

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Find easiest way from hierarchical to scale-free network

- Algorithm to equalize clustercoefficients:
- Look at node v , do for all neighbours b :
 - $C(v) < C(b)$: destroy edge $\{v, b\}$, unless $\text{degree}(v) < k$ (k some threshold): then connect neighbour of b that isn't connected yet to v (if possible)

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Find easiest way from hierarchical to scale-free network

- Algorithm to equalize clustercoefficients:
- Look at node v , do for all neighbours b :
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 - $C(v) > C(b)$: create edge between v and neighbour of b not yet connected with v

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Find easiest way from hierarchical to scale-free network

- Algorithm to equalize clustercoefficients:
- Look at node v , do for all neighbours b :
 - $C(v) < C(b)$: destroy edge $\{v, b\}$, unless $\text{degree}(v) < k$ (k some threshold): then connect neighbour of b that isn't connected yet to v (if possible)
 - $C(v) > C(b)$: create edge between v and neighbour of b not yet connected with v
- algorithm still needs to be optimized and implemented/tested

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Build scale-free network

- Start from small graph

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Build scale-free network

- Start from small graph
- Add nodes, with m edges (m mostly between 1 and 5)

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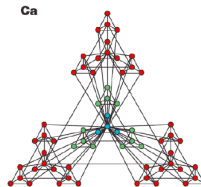
Conclusion

Build scale-free network

- Start from small graph
- Add nodes, with m edges (m mostly between 1 and 5)
- Preferable attachment: more chance to connect with nodes with higher degree

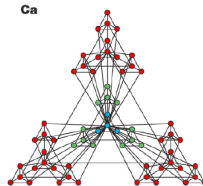
Changing network

- Build hierarchical network: Leader of cluster connected with everything in cluster and leader of other clusters, rest not connected with other clusters



Changing network

- Build hierarchical network: Leader of cluster connected with everything in cluster and leader of other clusters, rest not connected with other clusters



- Build random network: randomly choose two nodes and connect it, repeat for the number of edges you want

Networks

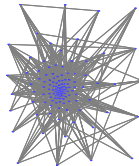
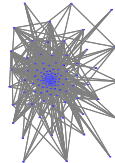
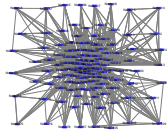
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PLplot

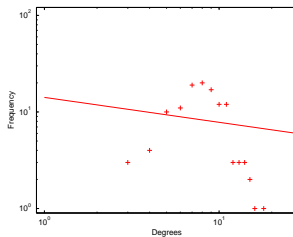
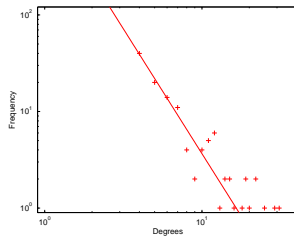
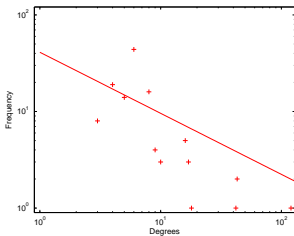
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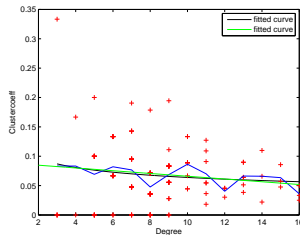
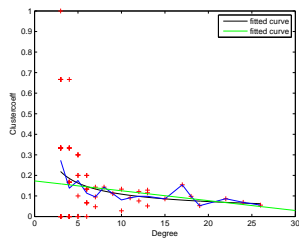
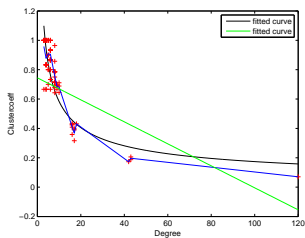
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Degree-Clustercoefficient

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Organization

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- Organization = structure with function
→ reach a global goal, global pattern

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- Organization = structure with function
→ reach a global goal, global pattern
- Self-organization: function, global activity arise spontaneously: by local interactions, common goal put by collective

Organization

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- Organization = structure with function
→ reach a global goal, global pattern
- Self-organization: function, global activity arise spontaneously: by local interactions, common goal put by collective
- Hierarchical: structure and function (organization) decided from above, 1 agent put the common goal

Coordination

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- Coordination: structuring of actions to
 - minimize friction
 - maximize synergy

Coordination

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- Coordination: structuring of actions to
 - minimize friction
 - maximize synergy
- → 4 processes:
 - alignment
 - division of labor
 - workflow
 - aggregation

Alignment

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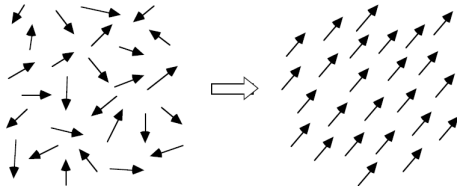
Function

Conclusion

- Alignment= Aim at same target to avoid friction

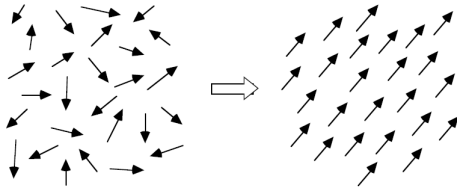
Alignment

- Alignment= Aim at same target to avoid friction
 - Self-organization: agents adapt towards neighbours by variation+selection



Alignment

- Alignment= Aim at same target to avoid friction
 - Self-organization: agents adapt towards neighbours by variation+selection



- Hierarchical: agents adapt towards one leader

Model

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- represented by graph

Model

- represented by graph
- each node i get number n_i between 0 and 1, represented by color on greyscale (0=black;1=white)

Model

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- represented by graph
- each node i get number n_i between 0 and 1, represented by color on greyscale (0=black;1=white)
- color of each node moves toward neighbour colors

$$n_i = n_i + \frac{\sum_{j \in N_i} (n_j - n_i)}{2 \cdot |N_i|}$$

Model

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- represented by graph
- each node i get number n_i between 0 and 1, represented by color on greyscale (0=black;1=white)
- color of each node moves toward neighbour colors

$$n_i = n_i + \frac{\sum_{j \in N_i} (n_j - n_i)}{2 \cdot |N_i|}$$

- higher fitness if less variation with neighbours (less friction)

$$f(n_i) = \sqrt{\frac{|N_i|}{\sum_{j \in N_i} (n_i - n_j)^2}}$$

Expectations

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- We expect/hope:

Expectations

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 - hierarchical network: all colors move towards "leading" color, who gets the fittest

Expectations

- We expect/hope:
 - hierarchical network: all colors move towards "leading" color, who gets the fittest
 - non-hierarchical network: all colors change the same amount, and all nodes have same fitness

Expectations

- We expect/hope:
 - hierarchical network: all colors move towards "leading" color, who gets the fittest
 - non-hierarchical network: all colors change the same amount, and all nodes have same fitness
- create plots with degree/clustercoeff against fitness/difference in color between node and rest

Degree-hierarchical network

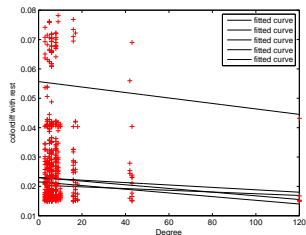
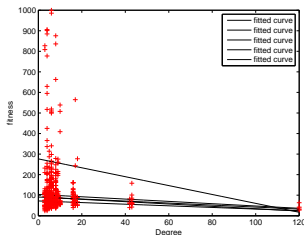
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- Higher degree, lower fitness and colordifference

Degree-scale-free network

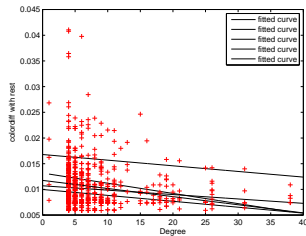
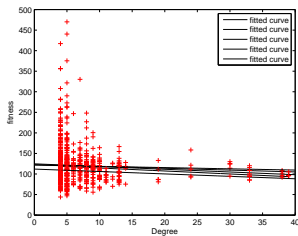
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- Fitness independent of degree

Degree-scale-free network

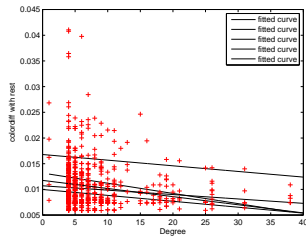
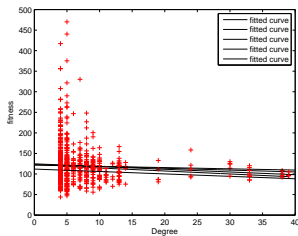
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- Fitness independent of degree
- higher degree, lower colordiff

Degree-random network

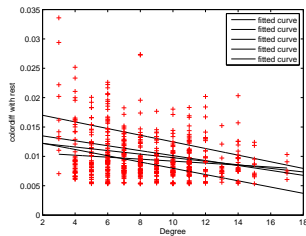
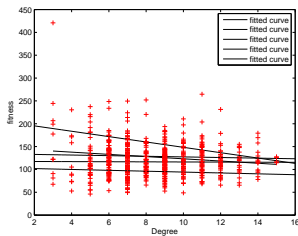
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- Fitness independent of degree

Degree-random network

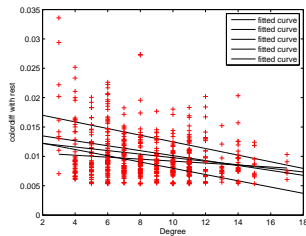
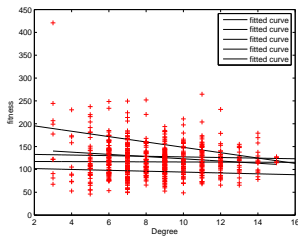
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- Fitness independent of degree
- Higher degree, lower colordiff

Clustercoeff-hierarchical network

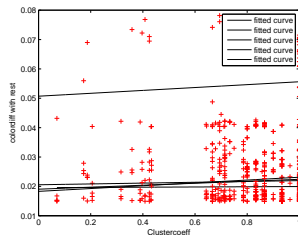
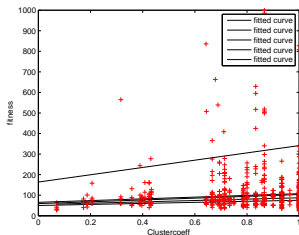
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- Higher clustercoefficient, higher fitness and colordiff

Clustercoeff-scale-free network

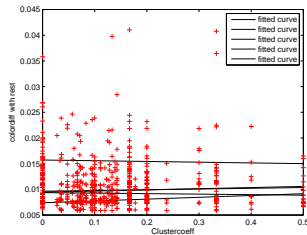
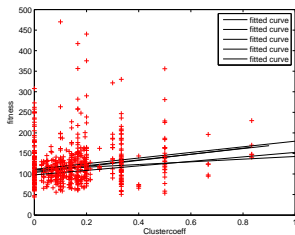
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- Higher clustercoefficient, higher fitness

Clustercoeff-scale-free network

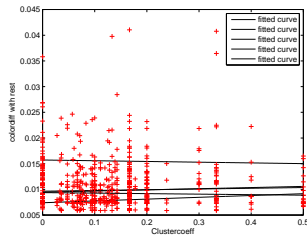
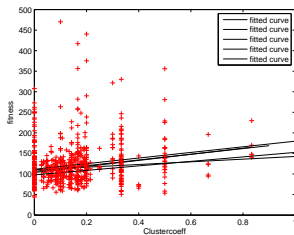
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- Higher clustercoefficient, higher fitness
- Colordiff independent of clustercoeff

Clustercoeff-random network

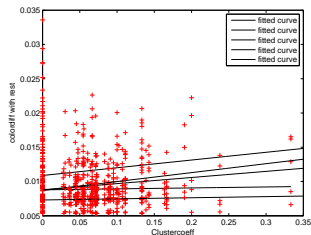
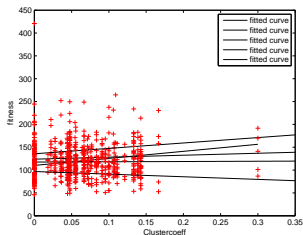
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- Fitness and colordiff independent of clustercoefficient

Some numbers

- mean fitness: 131.7; 124.4; 92.0 for resp hierarchical, scale-free and random network → much lower for random network

Some numbers

- mean fitness: 131.7; 124.4; 92.0 for resp hierarchical, scale-free and random network → much lower for random network
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- standard deviation difference in color: 0.0090; 0.0048; 0.0039 for resp hierarchical, scale-free and random network → more variation in colordiff for hierarchical network

Summary

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- Hierarchical: higher degree, lower fitness. Rest: independent

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- Hierarchical: higher degree, lower fitness. Rest: independent
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- Hierarchical: higher degree, lower fitness. Rest: independent
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- Higher clustercoeff, higher fitness, except random

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- Hierarchical: higher degree, lower fitness. Rest: independent
- Higher degree, lower colordifference
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- Hierarchical: higher clustercoefficient, higher colordifference. Rest:independent

Maximize synergy

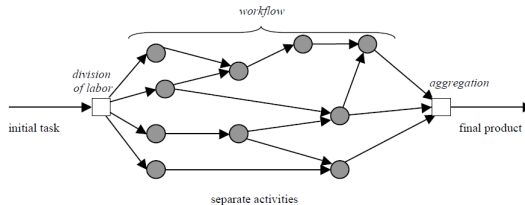
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- Division of labor

Maximize synergy

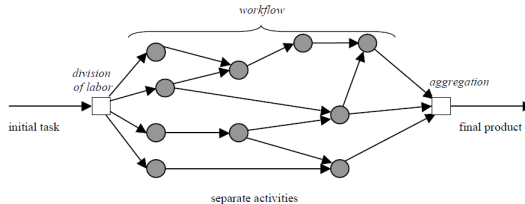
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- Division of labor
- Workflow

Maximize synergy

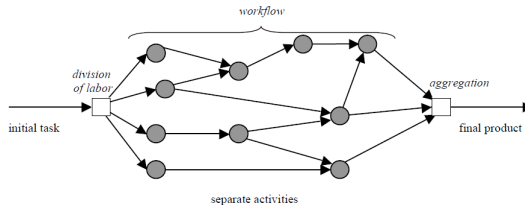
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- Division of labor
- Workflow
- Aggregation

Selforganization in

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- Division of labor + workflow : pick task most skilled at.
Example: evolution of different species

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- Division of labor + workflow : pick task most skilled at.
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 - shared medium. Example: ant pheromones

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- Again by variation-selection:
 - division of labor: variation → some more skilled → select task → get better at it
 - aggregation: random interaction, best are selected

Model

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- inspired by ecosystem, with agents who need products and produce products others can use

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- inspired by ecosystem, with agents who need products and produce products others can use
- graph, each node (agent) has a vector of length n

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- inspired by ecosystem, with agents who need products and produce products others can use
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- is foodvector, with m ones on it, the foodproducts the node need (rest is zero)

Model

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Function

- inspired by ecosystem, with agents who need products and produce products others can use
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Model

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- inspired by ecosystem, with agents who need products and produce products others can use
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- the products get "garbageproducts", by a random permutation of the foods (so each product become another product); same for all nodes
- with these two vectors, we can generate a garbagevector for each node

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- fitness of node = number of garbageproducts of neighbours that are foodproducts of node

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- fitness of node = number of garbageproducts of neighbours that are foodproducts of node
- simple evolution: for each node we generate 10 random fluctuations of foodvector (variation), and choose the best (selection)

Model

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Function

- fitness of node = number of garbageproducts of neighbours that are foodproducts of node
- simple evolution: for each node we generate 10 random fluctuations of foodvector (variation), and choose the best (selection)
- Colordiff \rightarrow Difference in food of node with rest
Bad variable: you can't influence food by food \rightarrow don't use it

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Model

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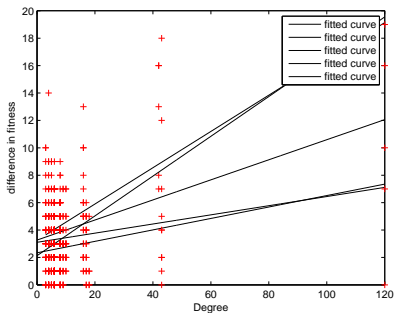
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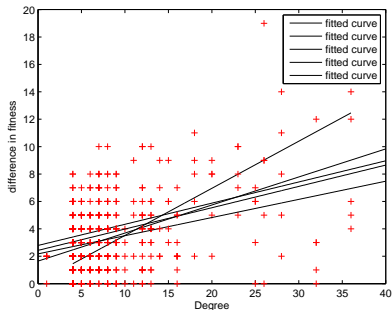
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Bad variable: you can't influence food by food \rightarrow don't use it
- for each sort of network (random, scale-free, hierarchical), we plot clustercoefficient and degree against difference in fitness
- the bigger your fitnessdifference, the more you got stronger

Degree-hierarchical network



- Higher degree, higher difference in fitness

Degree-scale-free network



- Higher degree, higher difference in fitness, but less then hierarchical

Degree-random network

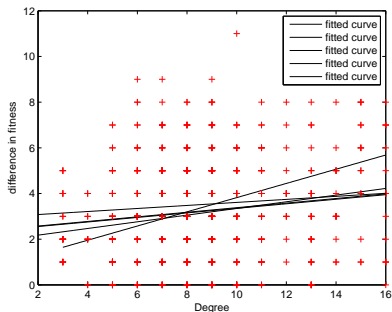
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- Higher degree, a little bit higher difference in fitness

Clustercoeff-hierarchical network

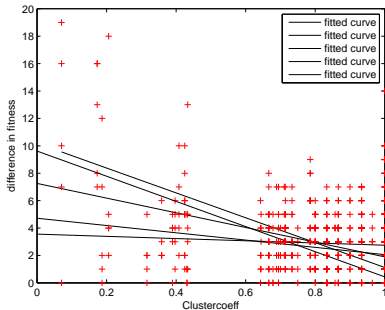
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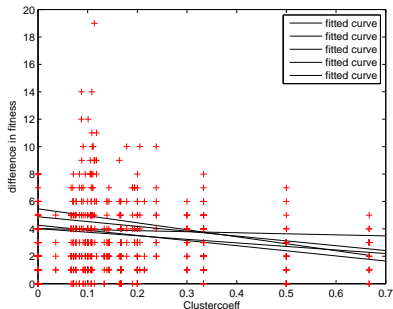
Function

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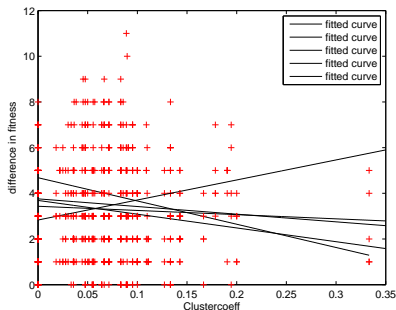
- Higher clustercoefficient, lower difference in fitness

Clustercoeff-scale-free network



- Higher clustercoefficient, a little bit lower difference in fitness

Clustercoeff-random network



- Higher clustercoefficient, a little bit lower difference in fitness

Some numbers

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- mean difference in fitness: 3.21; 3.17; 3.07 for resp hierarchical, scale-free and random network → a bit lower for random network

Some numbers

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- mean difference in fitness: 3.21; 3.17; 3.07 for resp hierarchical, scale-free and random network → a bit lower for random network
- standard deviation difference in fitness: 3.15; 2.58; 2.24 for resp hierarchical, scale-free and random network → a bit higher for hierarchical network

Summary

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- Higher degree, higher difference in fitness; more if hierarchical network, and only a little bit for random network

Summary

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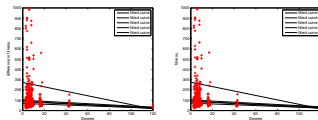
Function

Conclusion

- Higher degree, higher difference in fitness; more if hierarchical network, and only a little bit for random network
- Higher clustercoefficient, lower difference in fitness; only a little bit for scale-free and random

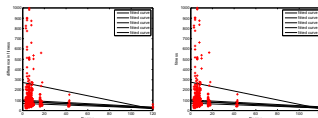
Why not look at...

- Difference in fitness (fitness in beginning different?)?
Equivalent to fitness:

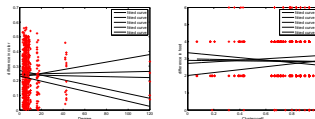


Why not look at...

- Difference in fitness (fitness in beginning different?)?
Equivalent to fitness:



- Difference in color/food between end and beginning?
Independent of degree/clustercoeff:



Fitness

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- The overall fitness of the network is:
a little bit higher for hierarchical network, particularly lower for random network.

Fitness

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- The overall fitness of the network is:
a little bit higher for hierarchical network, particularly lower for random network.
- The unequality of fitness of the network is:
higher for hierarchical network, a bit lower for random network

Fitness

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Conclusion

- The overall fitness of the network is:
a little bit higher for hierarchical network, particularly lower for random network.
- The inequality of fitness of the network is:
higher for hierarchical network, a bit lower for random network
- So intuition that hierarchical network = more inequality, holds.

Influence

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- In the first model, the overall difference in color with the rest of the network is:
a little bit higher for hierarchical network, particularly lower for random network

Influence

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- In the first model, the overall difference in color with the rest of the network is:
a little bit higher for hierarchical network, particularly lower for random network
- Unequality of influence: higher in hierarchical network

Influence

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- In the first model, the overall difference in color with the rest of the network is:
a little bit higher for hierarchical network, particularly lower for random network
- Unequality of influence: higher in hierarchical network
- So while nodes in a hierarchical network agree more with their neighbours, they do less with the whole network

Strange things

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- Higher degree/lower clustercoeff \rightarrow lower fitness in hierarchical network of 1st model: clusters evolve independent, leading node is 'in between' (only local problem)

Strange things

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- Higher degree/lower clustercoeff \rightarrow lower fitness in hierarchical network of 1st model: clusters evolve independent, leading node is 'in between' (only local problem)
- Hierarchical properties of scale-free network: the network used isn't completely scale-free

Normal things

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- Higher degree \rightarrow lower colordifference in first model:
Leaders differ less with rest

Normal things

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Conclusion

- Higher degree \rightarrow lower colordifference in first model:
Leaders differ less with rest
- Higher degree/Lower clustercoeff \rightarrow higher fitness in
second model: Leaders become fitter, particularly in
hierarchical network

Further research

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- Work with directed graph;
 - Hierarchy= graph represents order
 - Look at what it does in the models

Further research

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On second model:

- Use something else then fooddiff (garbage in it)

Further research

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On second model:

- Use something else then fooddiff (garbage in it)
- Complex evolution: choose partner by fitness, in the group of neighbours with enough in common, cross-over and mutate (based on genetic algorithm)

Further research

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On second model:

- Use something else then fooddiff (garbage in it)
- Complex evolution: choose partner by fitness, in the group of neighbours with enough in common, cross-over and mutate (based on genetic algorithm)
- Avoide friction: fitness lower if garbage is used by more nodes, higher if more neighbours with garbage

Further research

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- Changing network:
 - Get children by GA, connected to parents and same fitness as parent (mothermilk/feeding by parent)

Further research

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Further research

- Changing network:
 - Get children by GA, connected to parents and same fitness as parent (mothermilk/feeding by parent)
 - Connect to neighbours of neighbours, more chance if more increase of fitness
 - Dying:
 - Some garbage is "vital", neighbour can eat you, depending on your and his fitness
 - The lower fitness, the more chance to die

The end

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Thank you!