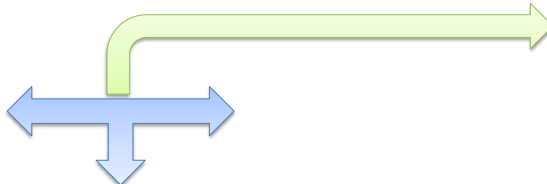


Complex **Directed** Networks: Dynamics & Communities



Hawoong Jeong (KAIST, Korea)

Y.D. Kim(KAIST, Korea→Samsung)

S.H. Lee(Umea Univ., Sweden→Oxford U., UK)
Y.H. Eom(ISI, Torino, Italy → U. Toulouse, France)
S.W. Son(U. Calgary, Canada→Hanyang U., Korea)
P.-J. Kim (UIUC→APCTP, Korea),
Y.Y. Ahn (NEU→Indiana U., USA)

Internet is fragile? (for our defense)

Error and attack tolerance of complex networks

Réka Albert, Hawoong Jeong & Albert-László Barabási

*Department of Physics, 225 Nieuwland Science Hall, University of Notre Dame,
Notre Dame, Indiana 46556, USA*

Many complex systems display a surprising degree of tolerance against errors. For example, relatively simple organisms grow, persist and reproduce despite drastic pharmaceutical or environmental interventions, an error tolerance attributed to the robustness of the underlying metabolic network¹. Complex communication networks² display a surprising degree of robustness: although key components regularly malfunction, local failures rarely lead to the loss of the global information-carrying ability of the network. The stability of these and other complex systems is often attributed to the redundant wiring of the functional web defined by the systems' components. Here we demonstrate that error tolerance is not shared by all redundant systems: it is displayed only by a class of inhomogeneously wired networks,

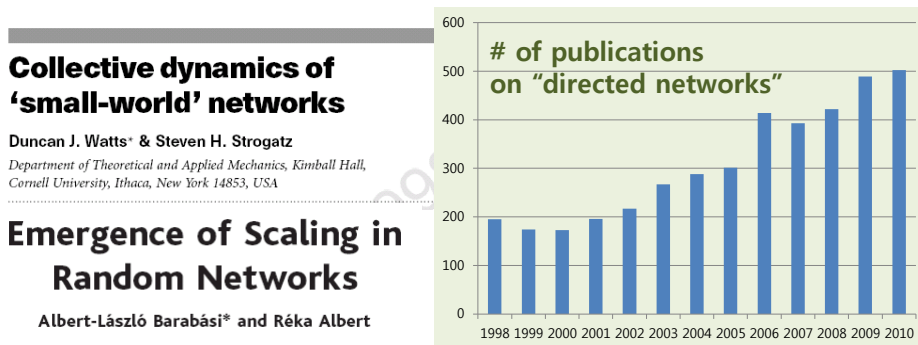
Please blame the Editor
of the Nature ;) not us!



Why directed network? Interestingly,

Network Science

- After 2 key papers, D. Watts, S. Strogatz (1998) and A.-L. Barabasi, R. Albert (1999)



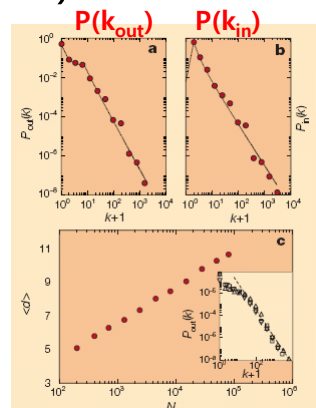
First empirical measurement
 on scale-free network
 was WWW, directed networks!
Nature (1999)

Internet

Diameter of the World-Wide Web

Réka Albert, Hawoong Jeong,
 Albert-László Barabási

*Department of Physics, University of Notre Dame,
 Notre Dame, Indiana 46556, USA
 e-mail: alb@nd.edu*

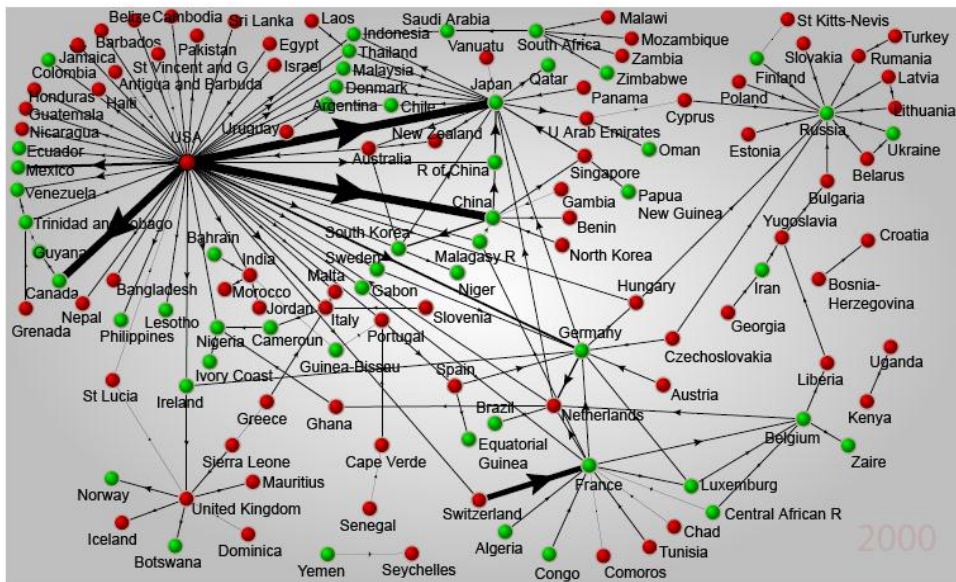


Many Directed Networks

- **Communication Networks:** World Wide Web
- **Economic Networks:** World trade web...

nodes: country

links: import/export



Backbone of the world trade system.

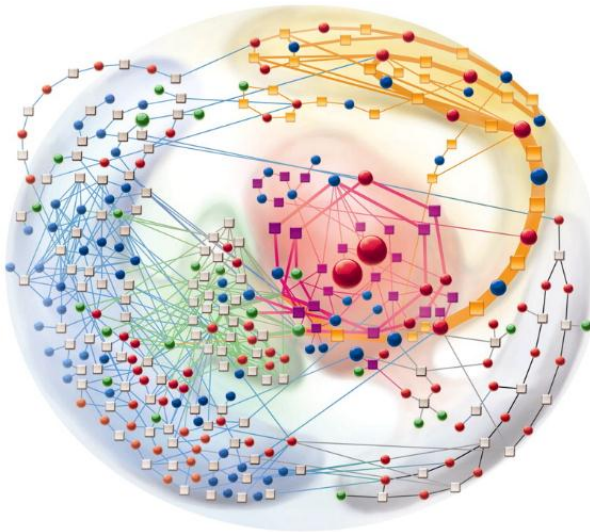
[Serrano et al \(2007\)](#)

Many Directed Networks

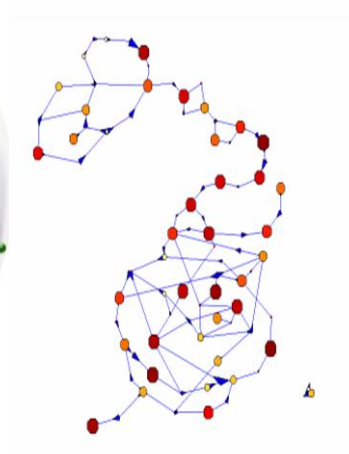
- **Communication Networks:** World Wide Web
- **Economic Networks:** World trade web...
- **Biological Networks:** **Metabolic network**, **neural network**, cortical network, gene regulatory network, food web ...

nodes: metabolites links: bio/chemical reactions

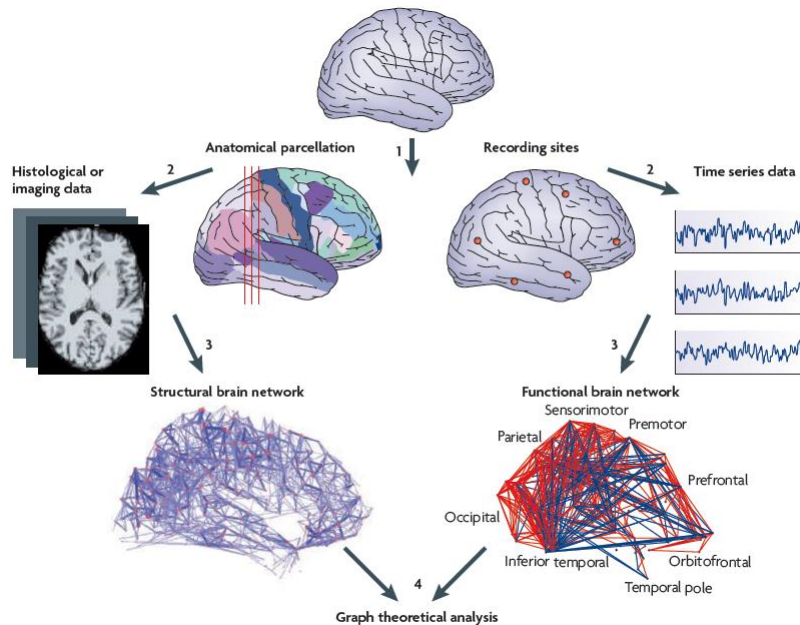
nodes: neurons links: synapses/correlation



E. coli metabolism



P.J. Kim et al (2007)



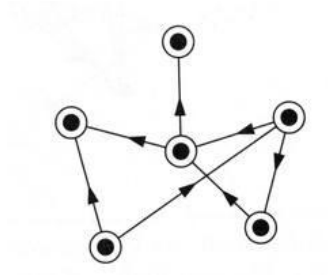
Structural and functional brain networks <http://www.nature.com/nrn/journal/v10/n3/pdf/nrn2575.pdf>

Many Directed Networks

- **Communication Networks:** World Wide Web
- **Economic Networks:** World trade web...
- **Biological Networks:** Metabolic network, neural network, cortical network, gene regulatory network, food web ...
- **Social Networks:** Friendship network, email network, phone call network etc

nodes: people links: social relationship

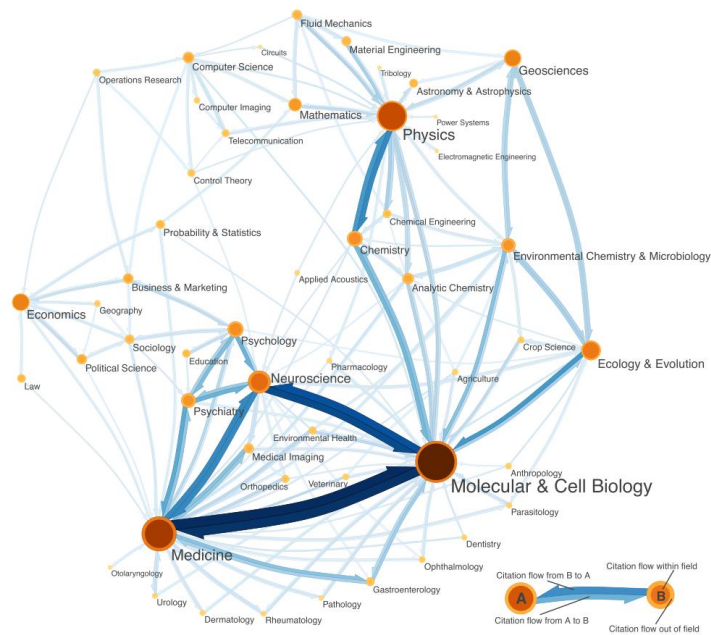
Facebook vs twitter



Many Directed Networks

- **Communication Networks:** World Wide Web
- **Economic Networks:** World trade web...
- **Biological Networks:** Neural network, cortical network, metabolic network, gene regulatory network, cell cycle network, food web ...
- **Social Networks:** Friendship network, email network, phone call network etc
- **Other networks:** Citation network, Word network etc

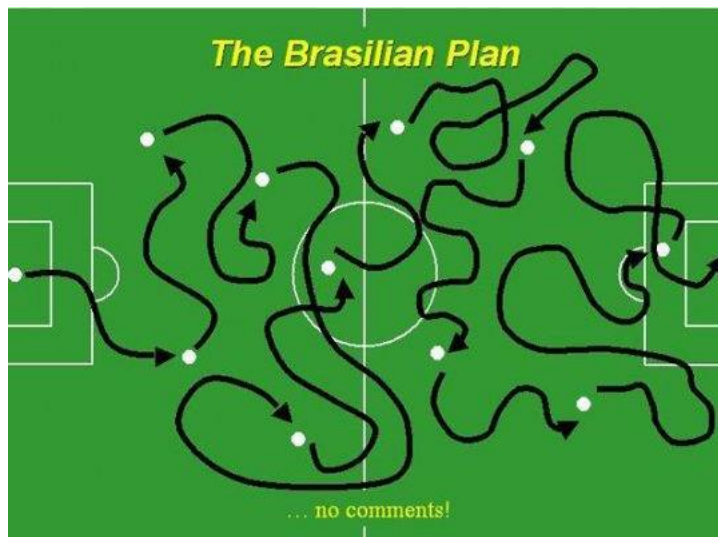
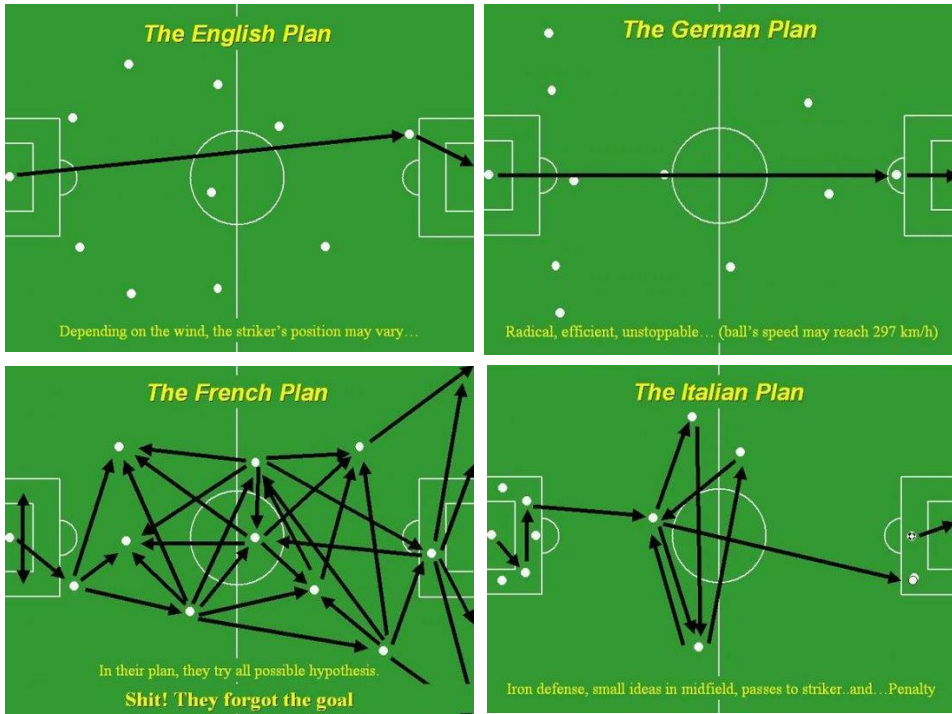
nodes: papers links: references/citations



A map of science based on citation patterns. Rosvall et al (2007)

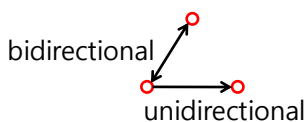


There are few funny cartoons I found from the Internet, which is directed networks... (Don't blame me, I didn't draw!)



Basic Properties of Directed Networks

Reciprocity, r



Q: Do they know each other?
Or just one way connection?

$$r \equiv \frac{L^{\leftrightarrow}}{L} = \frac{\text{\# of links pointing in both directions}}{\text{total \# of links}}$$

- Tells how much information would be lost if the direction is ignored.
- Can be used as a criterion to verify a model.
- Related to propagation process on the network
- Influences degree dist. & degree correlation

Modified reciprocity

Limitations of original def.:

1. not compared with random network
2. link density affects reciprocity:
high link density -> high reciprocity

$$\rho \equiv \frac{\sum_{i \neq j} (a_{ij} - \bar{a})(a_{ji} - \bar{a})}{\sum_{i \neq j} (a_{ij} - \bar{a})^2}, \quad = \frac{L^{\leftrightarrow} / L - \bar{a}}{1 - \bar{a}} = \frac{r - \bar{a}}{1 - \bar{a}}$$

$$a \equiv \frac{L}{N(N-1)} \quad \text{the ratio of observed to possible directed links}$$

Garlaschelli (2004)

Network	ρ	σ_ρ	ρ_{\min}
Perfectly reciprocal	1	...	$-\frac{\bar{a}}{1-\bar{a}}$
World Trade Web (53 webs) [10]			
Most correlated (year 2000)	0.952	0.002	($\bar{a} > 0.5$)
Least correlated (year 1948)	0.68	0.01	-0.80
World Wide Web [7]	0.5165	0.0006	-0.0001
Neural networks [13,14]			
Neuron classes	0.44	0.03	-0.04
Neurons	0.41	0.02	-0.03
Email networks [5,6]			
Address books	0.231	0.003	-0.001
Actual messages	0.194	0.002	-0.001
Word networks [15]			
Dictionary terms	0.194	0.005	-0.002
Free associations	0.123	0.001	-0.001
Cellular networks (43 webs) [16]			
Most correlated (<i>H. influenzae</i>)	0.052	0.006	-0.001
Least correlated (<i>A. thaliana</i>)	0.006	0.004	-0.003
Areiprocal	0	...	$-\frac{\bar{a}}{1-\bar{a}}$
Shareholding networks [17]			
NYSE	-0.0012	0.0001	-0.0012
NASDAQ	-0.0034	0.0002	-0.0034
Food webs [11,12]			
Silwood Park	-0.0159	0.0008	-0.0159
Grassland	-0.018	0.002	-0.018
Ythan Estuary	-0.031	0.005	-0.034
Little Rock Lake	-0.044	0.007	-0.080
Adirondack lakes (22 webs)			
Most correlated (B. Hope)	-0.06	0.02	-0.10
Least correlated (L. Rainbow)	-0.102	0.007	-0.102
St. Marks Seagrass	-0.105	0.008	-0.105
St. Martin Island	-0.13	0.01	-0.13
Perfectly antireiprocal	-1	...	-1

Prey <-> Predator ??

Garlaschelli (2004)

Single node properties:

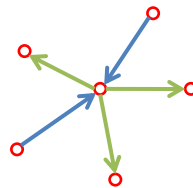
Centrality : which node is important?

"Directed" Degree

in-degree $k_i^{in} \equiv \sum_j A_{ji}$

out-degree $k_i^{out} \equiv \sum_j A_{ij}$

degree $k_i \equiv k_i^{in} + k_i^{out}$



degree distribution $P(k^{in})$ $P(k^{out})$ $P(k)$

In many real-world networks, in- & out-degree have different meaning and different generating mechanism

In World Wide Web,

In-degree & out-degree dist. show different behavior (different exponent)
High in-degree: authority; high out-degree: hub (portal)

Network	N	$\langle k \rangle$	γ_{in}	γ_{out}	L	Ref.
WWW (Web page)	325,729	4.51	2.1	2.45	11.2	Albert1999
WWW (Web page)	4×10^7	7	2.1	2.38		Kumar1999
WWW (Web page)	2×10^8	7.5	2.1	2.72	16	Broder2000

The webpage owner can only decide the out-degree, not in-degree(fame).

You can't increase in-degree by yourself... **BUT**

In Wikipedia

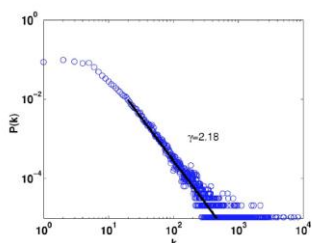


FIG. 3. (Color online) The probability distribution of the in-degree for the Japanese Wikipedia.

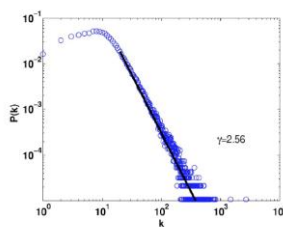
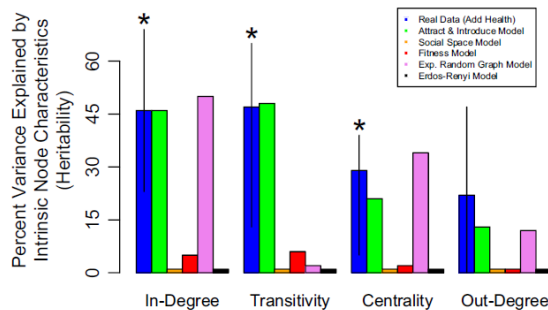


FIG. 4. (Color online) The probability distribution of the out-degree for the Japanese Wikipedia.

Zlatic2006

In human social network,

in-degree (how many times a person is named as a friend), ~ popularity
out-degree (how many friends a person names) ~ social activity



Fowler2009

A research based on twin study shows **in-degree**, transitivity(clustering coefficient), centrality are found to be **heritable**.

If your parents are famous, you have a chance to become famous too!

"Directed" Centrality (closeness, betweenness)

Straightforward in the SCC[giant cluster]

$$c_{Cl}(v) \equiv \frac{1}{\sum_{u \in V} dist(v, u)}$$

$$c_B(v) \equiv \sum_{s \neq t \neq v \in V} \frac{\sigma(s, t | v)}{\sigma(s, t)}$$

$\sigma(s, t | v)$ is the total number of shortest paths between s and t that pass through v

PageRank® is the probability that the random walker visiting node i at the stationary state.

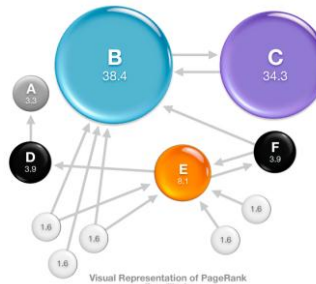
- A page with more recommendations (more incoming links) is considered to be more important.
- A webpage is considered important if it is pointed to by other important pages.

Undirected networks: PageRank $\sim k$, local information
Directed networks: PageRank is related to global structure.

- Rank web pages (Google)
- academic papers (eigenfactor.org), eigenfactor, to replace impact factor

Related quantities (spectrum based):
Eigenvector Centrality (Bonacich1972)
Influence
Katz status index (Katz1953)

Used for Directed network community



- **Google Matrix** $G_{ij} = \alpha H_{ij} + \frac{1}{n}(\alpha a_i + 1 - \alpha)$

Where $H_{ij} = A_{ij} / k_i^{out}$, and $a_i = 1$ if and only if i is a dangling node.

- G_{ij} is probability that the random walker moves from node i to j at next step when it is visiting node i .

- α and a_i is added to avoid random walker being trapped in dangling nodes and trap region.

- G is a completely dense, stochastic, and primitive matrix. There always exists the stationary vector π^T .

- **PageRank** $\pi^T G = \pi^T$

- π_i is the probability that the random walker visiting node i at the stationary state.

PageRank Distribution of *.brown.edu website

[Pandurangan2002](#)

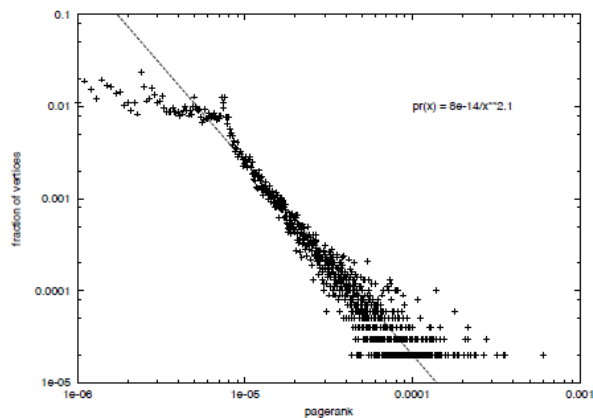


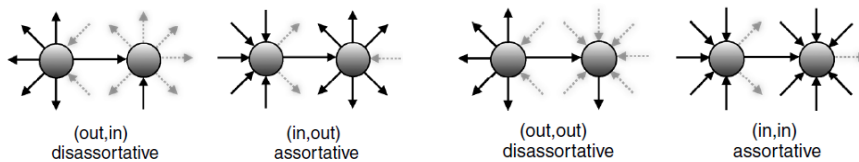
Figure 3. Log-log plot of the PageRank distribution of the Brown domain (*.brown.edu). A vast majority of the pages (except those with very low PageRank) follow a power law with exponent close to 2.1. The plot almost flattens out for pages with very low PageRank.

More than single node:

2-node correlations & more...

"directed" Assortativity

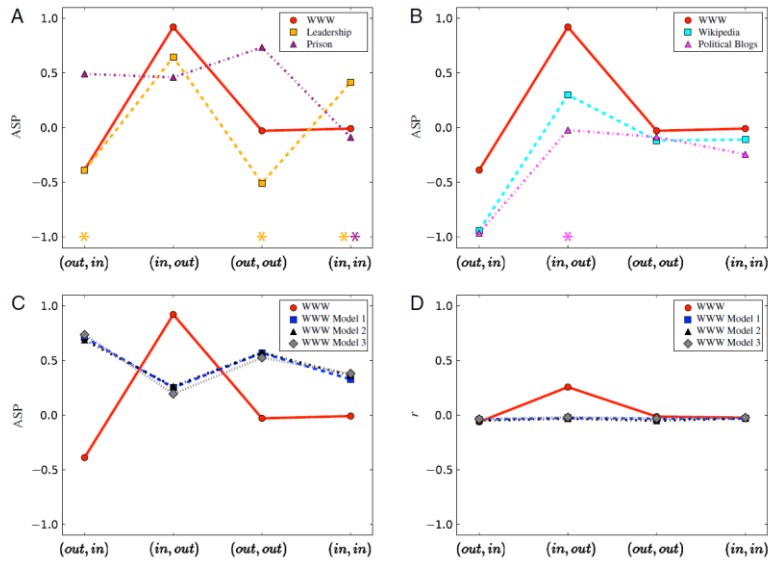
Foster (2009)



$$r(\alpha, \beta) = \frac{E^{-1} \sum_i [(j_i^\alpha - \bar{j}^\alpha)(k_i^\beta - \bar{k}^\beta)]}{\sigma^\alpha \sigma^\beta}$$

$$Z(\alpha, \beta) = \frac{r_{\text{rw}}(\alpha, \beta) - \langle r_{\text{rand}}(\alpha, \beta) \rangle}{\sigma[r_{\text{rand}}(\alpha, \beta)]}$$

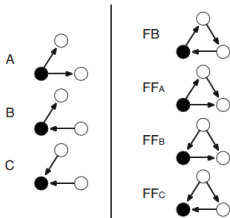
$$\text{ASP}(\alpha, \beta) = Z(\alpha, \beta) / (\sum_{\alpha, \beta} Z(\alpha, \beta)^2)^{1/2}$$



- WWW and social network show different profile.
- WWW, wikipedia and political blogs are also slightly different.
- Assortativity can be used to check the validity of models.

"directed" Clustering coefficient

[Fagiolo2006b](#)



$$C^{(i)} = \left(\frac{N_{FFB}^{(i)}}{M_B^{(i)}}, \frac{N_{FFA}^{(i)}}{M_A^{(i)}}, \frac{N_{FFB}^{(i)}}{M_B^{(i)}}, \frac{N_{FFC}^{(i)}}{M_C^{(i)}} \right),$$

where

$$M_A^{(i)} = \sum_{j,k} a_{ij}a_{ik}, \quad M_B^{(i)} = \sum_{j,k} a_{ij}a_{ki}, \quad M_C^{(i)} = \sum_{j,k} a_{ji}a_{ki},$$

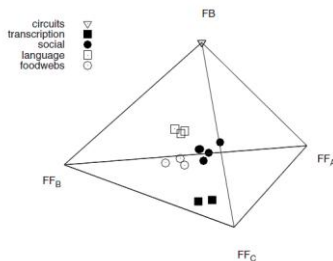
$$\tilde{C}^{(i)} = \frac{C^{(i)}}{T^{(i)}},$$

$$N_{FFB}^{(i)} = \sum_{j,k} a_{ij}a_{jk}a_{ki}, \quad N_{FFA}^{(i)} = \sum_{j,k} a_{ij}a_{kj}a_{ik},$$

$$N_{FFB}^{(i)} = \sum_{i,k} a_{ij}a_{kj}a_{ki}, \quad N_{FFC}^{(i)} = \sum_{i,k} a_{ij}a_{kj}a_{ki},$$

$$T^{(i)} = \frac{N_{FFB}^{(i)}}{M_B^{(i)}} + \frac{N_{FFA}^{(i)}}{M_A^{(i)}} + \frac{N_{FFB}^{(i)}}{M_B^{(i)}} + \frac{N_{FFC}^{(i)}}{M_C^{(i)}}$$

[Ahnert2008](#)



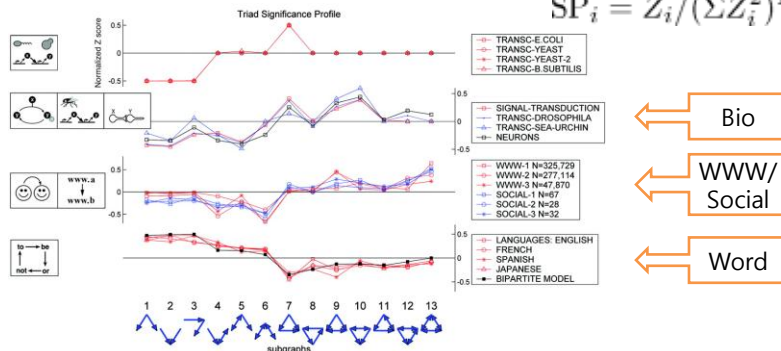
Networks of the same type are located in the same region of Clustering signature tetrahedron.

Motif : basic building block

13 possible triads.

$$Z_i = (N_{real_i} - \langle N_{rand_i} \rangle) / \text{std}(N_{rand_i})$$

$$SP_i = Z_i / (\sum Z_i^2)^{1/2}$$

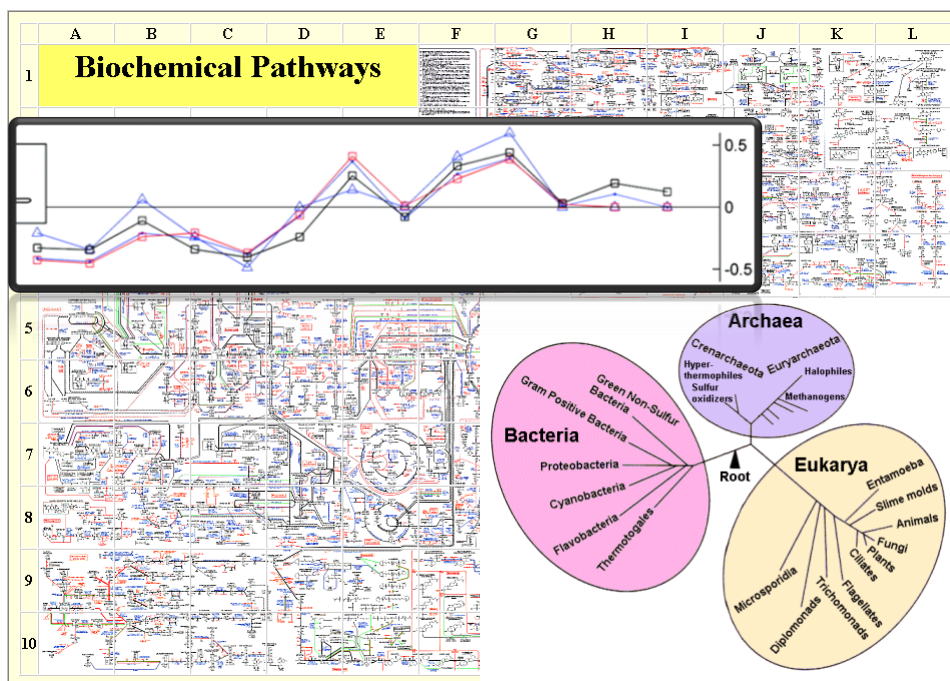


Motif profile **evolved** to perform similar tasks...

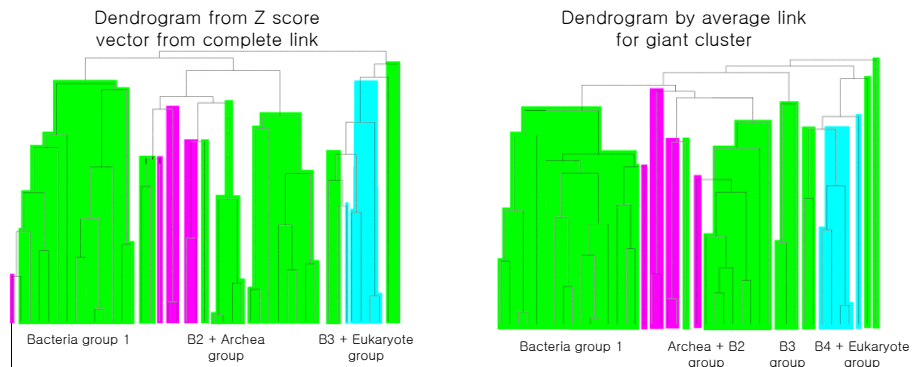
Applying to metabolic networks (Archea, Bacteria, Eukaryote) of organisms has **different kinds of "common motifs"** in details

→ Can be used for clustering (taxonomy !)

[Milo et al 2004](#)



Motif Clustering of 43 organisms



• Analysis

- In large scale, **we identified 3 domains of life**, Archae, Bateria, and Eukaryote of 43 organisms .

→ One exceptional species of Archea can be explained because it belongs to different phylum as compared to other 5 species.

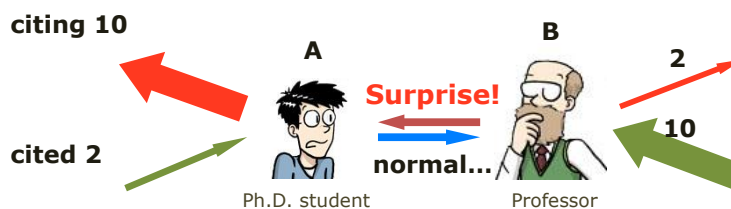
→ Aeropyrum pernix (name), Crenarchaeota (phylum : 동물 분류 상의 문(門)), thermophilic(열을 좋아하는 성질)

Y. Eom, S. Lee, H. Jeong (J. Theo. Bio. 2006)

What if we only have undirected network?

There is a simple way to construct directed network out of undirected (but **weighted**) network!

We start from the fact that all links between nodes are not equivalent!



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLOS ONE 2010)



Nature (2008/9): Google 10th anniversary

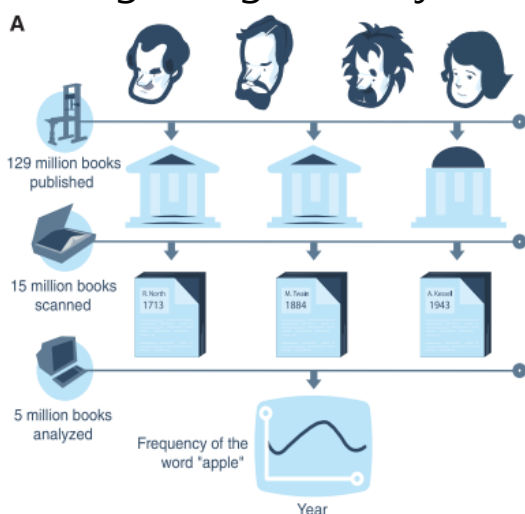
- **BIG DATA: PetaByte Era**
- Data wrangling
- Welcome to the petacentre

Let's see what google & we can do!

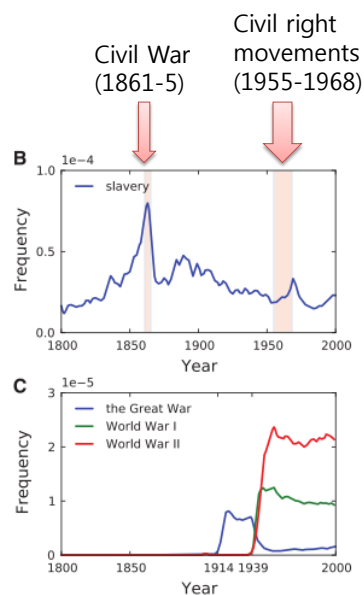
- Distilling meaning from data
- The Harvard computers
- The future of biocuration

Last year in Google...

- Google N-gram Project!

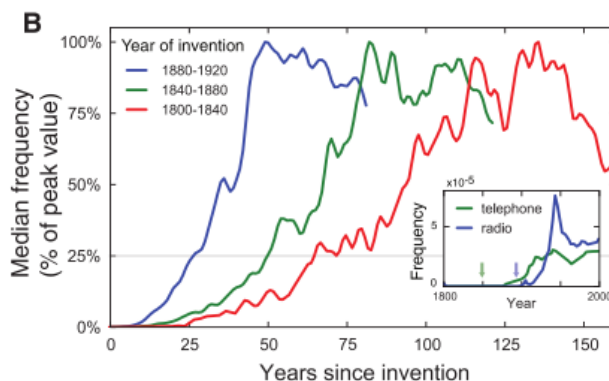


J.-B. Michael et al Science (2011)



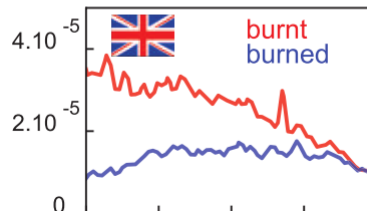
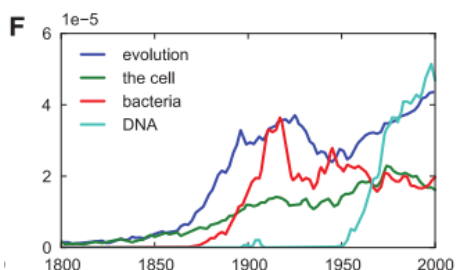
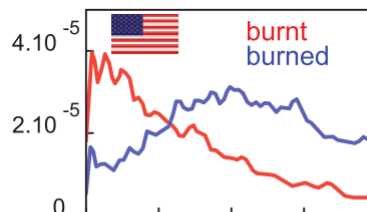
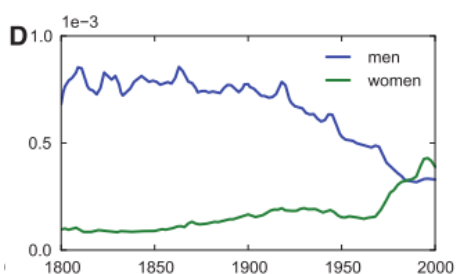
You can do many things with this N-gram data

- Culturomics : Finding culture trends!
E.g. cultural adoption is getting quicker!



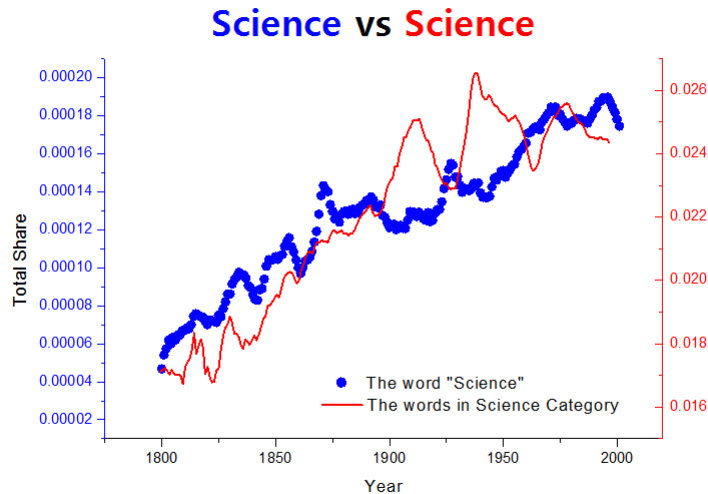
J.-B. Michael et al Science (2011)

Quantitative analysis possible in history/science ...



J.-B. Michael et al Science (2011)

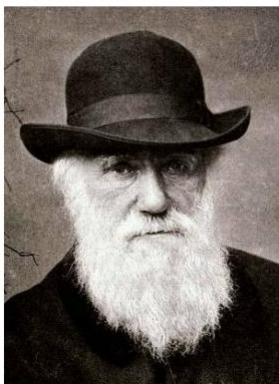
Which technology wins the race?



J. Yun, P.-J. Kim, H. Jeong (in preparation)

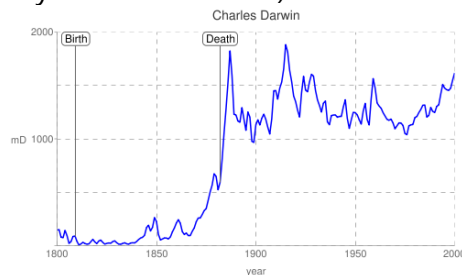
Science Hall of Fame

- Looking up the names of Scientists
(collected from Wikipedia ~ 7,500 → 4,169 after filtering)



Charles Darwin

Charles Darwin : 148,429 times appeared
(2% of English books) & increasing
(4% in year 2000 books)



UNIT: if average annual frequency=Darwin
→ 1 Darwin unit

1 Darwin = 1000 mili-Darwin (mD)

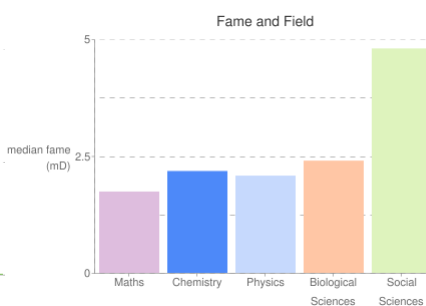
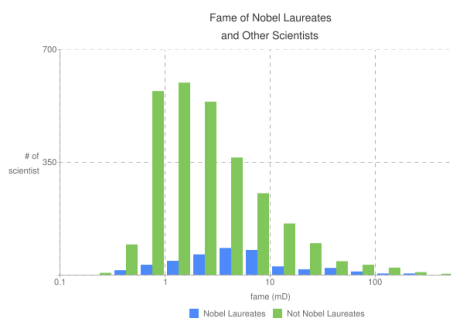
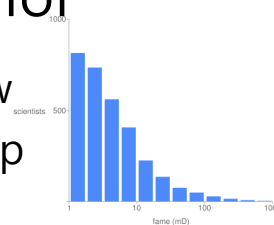
A. Veres et al Science (2011)

Science Hall of Fame (N-gram)

Full Name	Born	Died	milliDarwins	Nobel Prize Winner		
				Bio	Chem	Phy
Bertrand Russell	1872	1970	1500			
Charles Darwin	1809	1882	1000			
Albert Einstein	1879	1955	878			✓
Lewis Carroll	1832	1898	479			
Claude Bernard	1813	1878	429			
Oliver Lodge	1851	1940	394			
Julian Huxley	1887	1975	350			
Karl Pearson	1857	1936	346			
Niels Bohr	1885	1962	289			✓
Alexander Graham Bell	1847	1922	274			
Max Planck	1858	1947	256			✓
Francis Galton	1822	1911	255			
Robert Oppenheimer	1904	1967	252			
Louis Pasteur	1822	1895	237			
Chaim Weizmann	1874	1952	236			
Alfred North Whitehead	1861	1947	229			
Marie Curie	1867	1934	189		✓	✓
Robert Koch	1843	1910	185	✓		
Isaac Asimov	1920	1992	183			

Few things on SHoF

- Distribution of mD \sim power-law
- Not all Nobel winners are at top (80% are less than 10mD)



A. Veres et al Science (2011)

Any tips for immortal fame?

- Seek the social sciences: avoid mathematics
 - The most famous living scientist, Noam Chomsky 507mD
 - Other living scientist, Barry Commoner 109mD, @Queens College in NY, 93 years old, pioneer of ecology & the environmental movement
 - in Math, top = Bertrand Russel, 1500mD, author of Principia Mathematica) but "He's famous for not doing math!" by Michael Thaddeus @Columbia (0mD) & Mathematician doesn't care much...
- Do good work, but don't get caught up in the citation rat race
 - One of the most highly cited scientists, Edward Witten has only 8mD
 - Paul Erdos (wrote 1400 papers) has 3.5mD only
- Write a popular book
 - Isaac Asimov (183 mD), Carl Sagan (152 mD), Rachel Carson (12mD), Richard Dawkins (90mD)
- Embrace controversy
 - Timothy Leary (136mD) research on psychedelic drugs (not to mention his use and advocacy, Richard Nixon called him "the most dangerous man in USA")
 - Richard Feynman (47mD) gets more fame after TV appearance (hearing on 1986 Space shuttle Challenger disaster)
 - Charles Darwin (1000 mD) himself gets fame from world-shaking controversy...

Back to our topic, network!

ECT Workshop Spectral Properties of Complex Networks

Information retrieval becomes a formidable task. Various search engines have been developed by private companies which are actively used by Internet users. Due to the recent enormous development of World Wide Web, social and communication networks, new methods have been invented to characterize the properties of these networks on a more detailed and precise level. New characterization of complex networks will allow to manage in an efficient and rapid way information extraction for social networks, communication, bio-cell and other networks. Such type of problems of complex networks and Markov chains appear in various fields of science. The development of interdisciplinary approach to complex networks, which combines expertise from computer science, theoretical physics, mathematics, economy and biology, is the aim of this workshop.

[Workshop Poster](#)

Speakers (confirmed):
 A. Bencczur (MTA SZTAKI Budapest), G. Bianconi (Northeastern U), P. Blanchard (ZIF Bielefeld), A. Chepellanskii(Cambridge U), S. Dorogovtsev (U de Aveiro), Y.-H. Eom(ISI Torino), L. Ermann (CNEA BuenosAires), S. Fortunato (Aalto U), K. Frahm (U Toulouse III), A. Gabrielli (U Roma), J. Galtier (Orange Labs Nice), B. Geogot (CNRS Toulouse), C. Giardina(U Modena), K.-I. Goh(Korea U), T. Hasegawa(Tohoku U), E. Izhikevich (Brain Corporation CA), S. Jalan (IIT Indore), H. Jeong (KAIST), A. Kaltenbrunner(Barcelona Media), B. Li (NU Singapore), P. Van Mieghem (Delft UT), M. Olvera-Cravioto(Columbia U), A. Panconesi (Sapienza U)), F. Radicchi (U Rovira i Virgili), A. Scala (U Roma), F. Silvestri(ISTI CNR), L. Sirko (IPFAN Warsaw), S. Thurner(Med U Wien), S. Vigna (U Milano), Y. Volkovich(Barcelona Media), H.-J. Wang (Delft UT), V. Zlatić (Zagreb U)

Short communications: V.Kandiah (CNRS Toulouse), R.Palovics (MTA SZTAKI Budapest), G.M.Zhu (NU Singapore)

Program: [\(here\)](#)

Kick-off meeting of the [EC-FET Open project NADINE](#) is a part of the Workshop during dates 23 - 25 July

Information about ETC*
Travel and visitors information

Trento Workshop Key talks



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)

Basic idea: Using search engine for finding something...

Laszlo Barabasi's Google Hits (fame) = 175,000

S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)

To make a network, we need "link" information between 2 persons... HOW?

ASK Google!



Web [Images](#) [Groups](#) [News](#) [Froogle](#) [Local](#) [more >](#)

“Laszlo Barabasi” “Hawoong Jeong” [Advanced Search](#)

[Preferences](#) [Language Tools](#)

[Advertising Programs](#) - [Business Solutions](#) - [About Google](#) - [Go to Google Korea](#)

[Make Google Your Homepage!](#)

©2005 Google

S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)

Basic idea: Constructing weighted social networks by using web search engines

Results 1 - 10 of about 911 for "Laszlo Barabasi" "Hawoong Jeong". (0.13 seconds)

Alessandro Vespignani
 $w_{BV} = 963$

Byungnam Kahng
 $w_{BK} = 94$

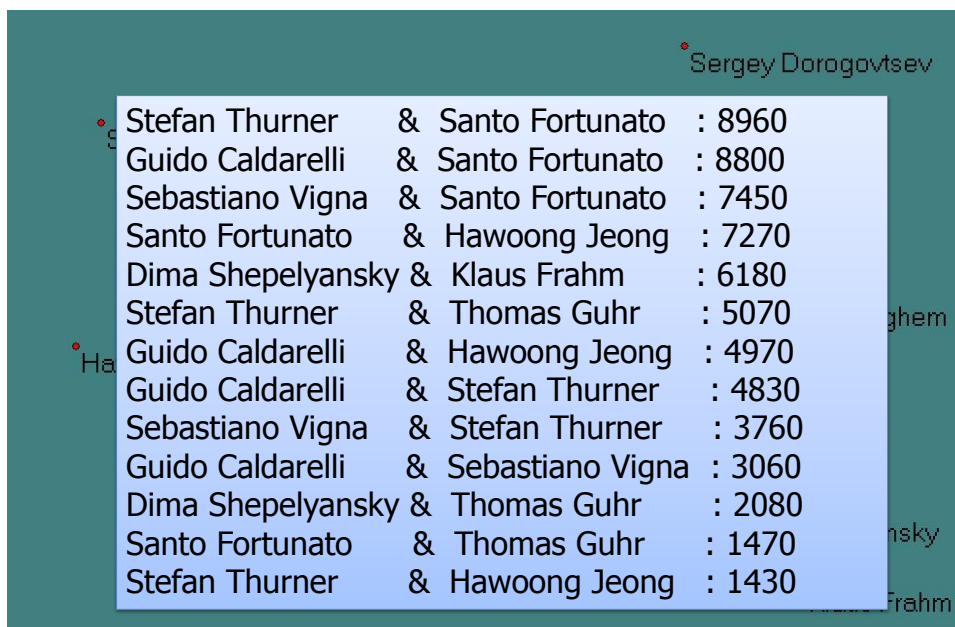
Laszlo Barabasi
 $w_{BJ} = 911$

Hawoong Jeong
 $w_{KJ} = 233$

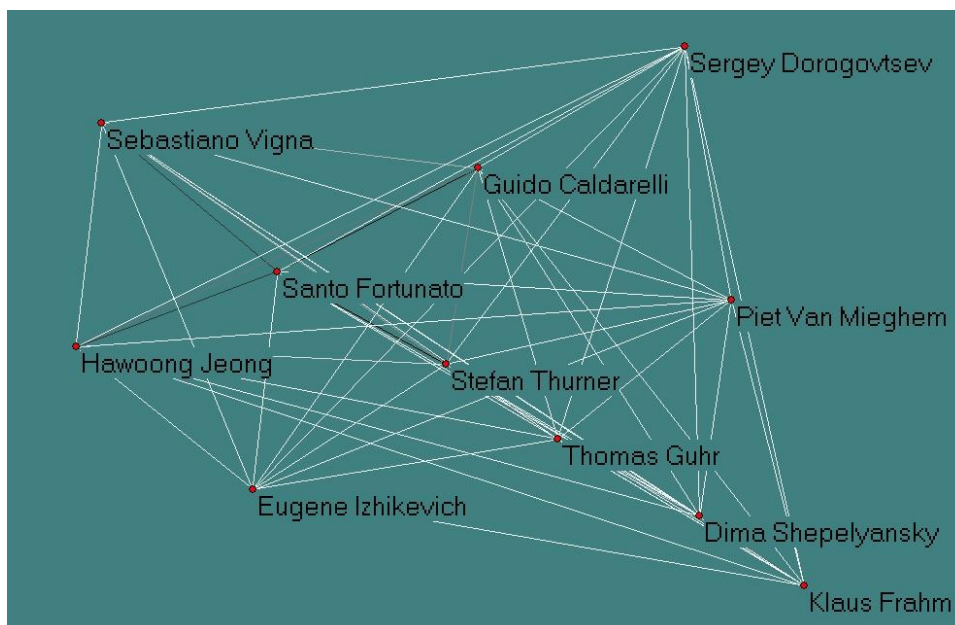
(Google correlation; relatedness)

and so on ...

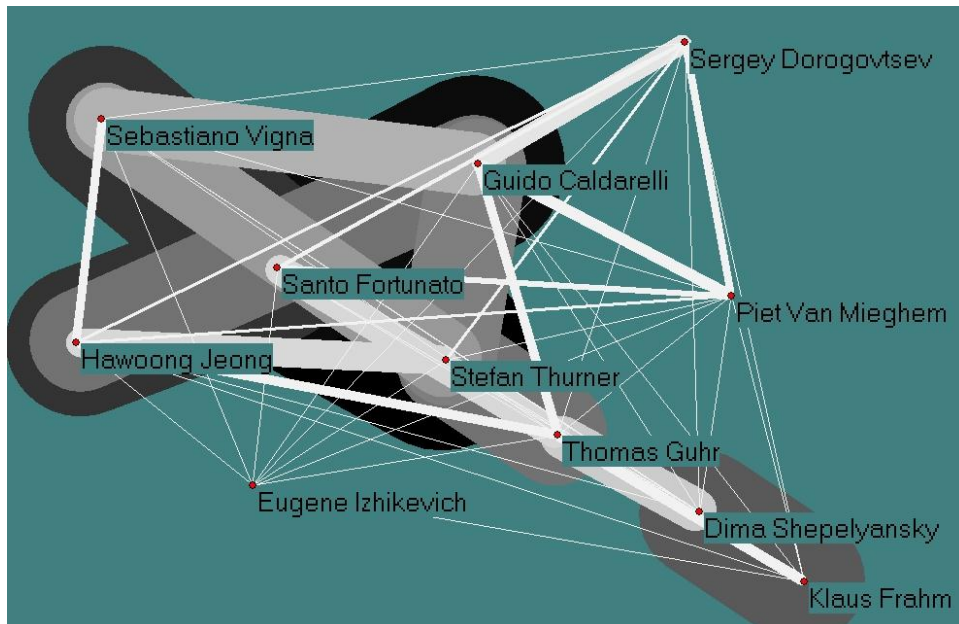
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



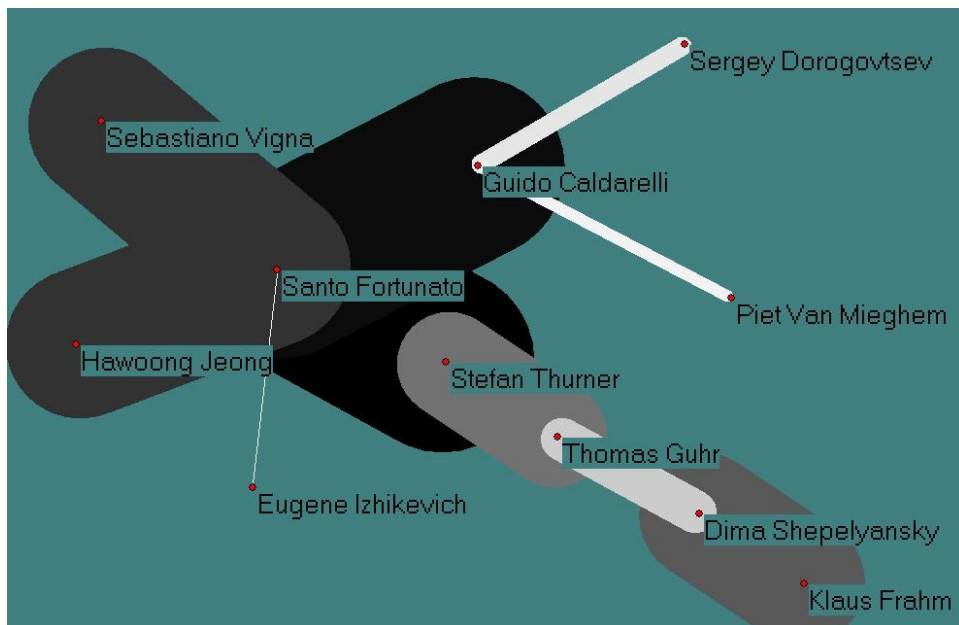
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



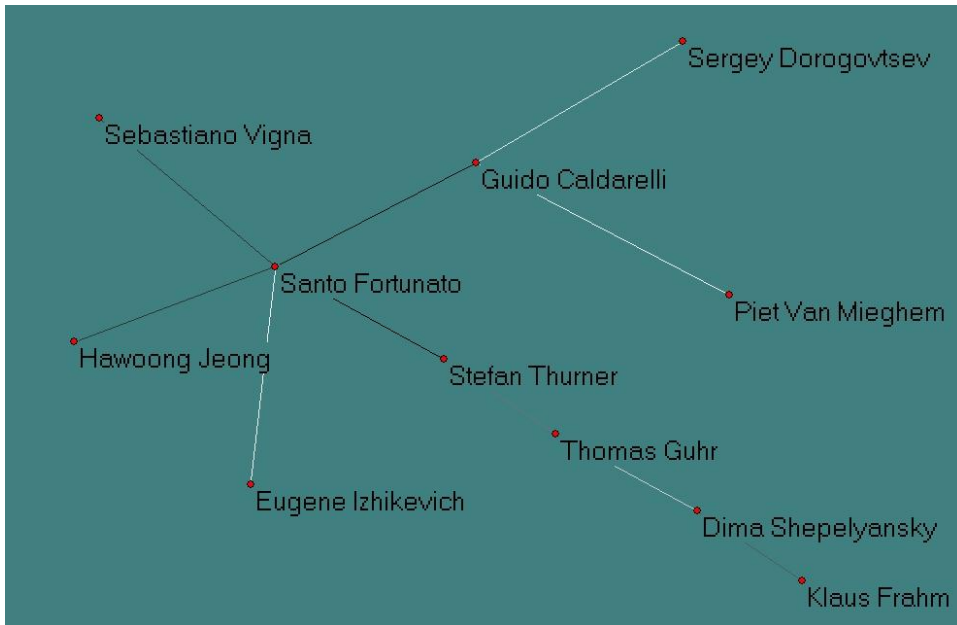
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



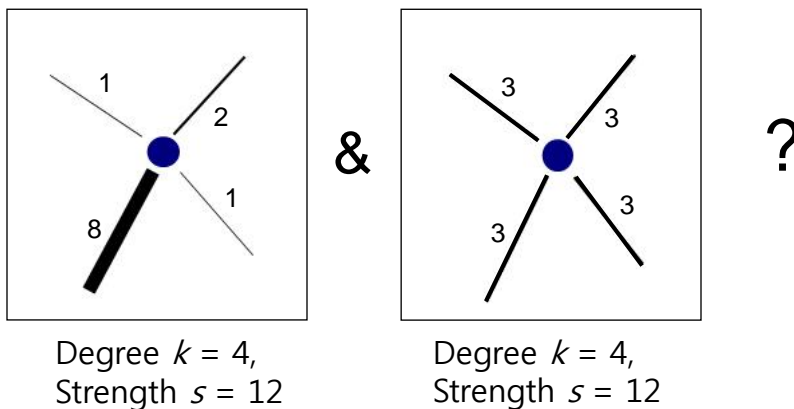
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)

Let's consider weighted "undirected" network.

How to quantify the difference between ...



(Strength $s = \text{Sum of its weights}$)

S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLOS ONE 2010)

"Quantifying broad distribution of weights"

$$D_\alpha(\{\tilde{w}\}) = \left(\sum_j \tilde{w}_{ij}^\alpha \right)^{\frac{1}{1-\alpha}} \quad \text{where} \quad \tilde{w}_{ij} = \frac{w_{ij}}{s_i} = \frac{w_{ij}}{\sum_k w_{ik}}$$

$$\longrightarrow D_{\alpha=0}(\{\tilde{w}\}) = \text{degree } k$$

$$\longrightarrow \lim_{\alpha \rightarrow 1} D_\alpha(\{\tilde{w}\}) = \exp\left(-\sum_j \tilde{w}_{ij} \log \tilde{w}_{ij}\right) = \prod_j \tilde{w}_{ij}^{-\tilde{w}_{ij}}$$

$$\longrightarrow D_{\alpha=2}(\{\tilde{w}\}) = \frac{1}{\sum_j \tilde{w}_{ij}^2}$$

$$\text{cf) } \log D_\alpha(\{\tilde{w}\}) = \frac{1}{1-\alpha} \log\left(\sum_i \tilde{w}_{ij}^\alpha\right) \equiv \text{Rényi entropy}$$

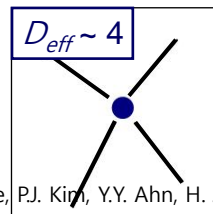
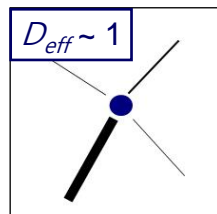
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLoS ONE 2010)

For $\alpha \rightarrow 1$, D_α is the "effective degree" D_{eff}

$$D_{eff}^{(i)} = \prod_j \tilde{w}_{ij}^{-\tilde{w}_{ij}} = \exp\left(-\sum_j \tilde{w}_{ij} \ln \tilde{w}_{ij}\right) = \exp(S) \leq N$$

where S is the Shannon entropy

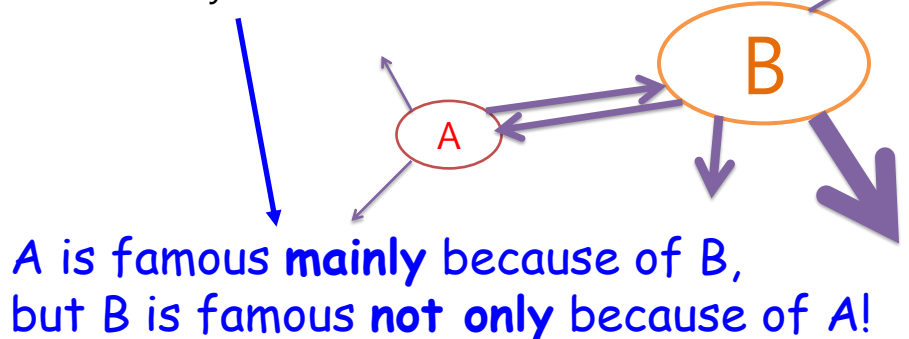
If weights are distributed **uniformly**, $D_{eff} \sim \text{degree } k$
 If weights are highly **heterogeneous**, $D_{eff} \sim 1$



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLoS ONE 2010)

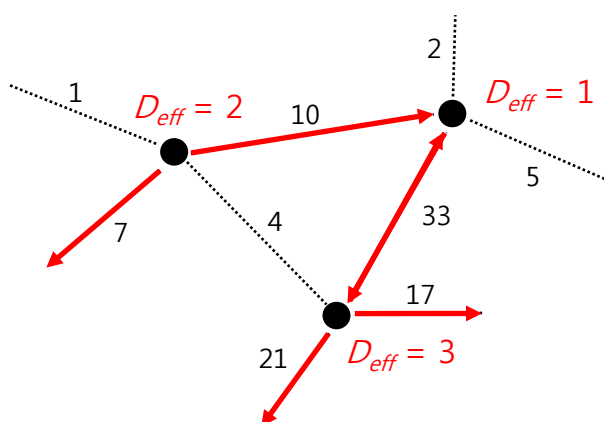
“hidden asymmetry” of relatedness

- Most social networks are undirected.
(believed to be “mutual” relationship)
- Relatedness, expressed by mutual correlation,
can be asymmetric!

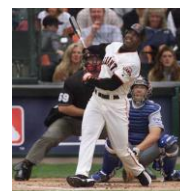


S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLoS ONE 2010)

weighted undirected network
→ directed network by D_{eff}



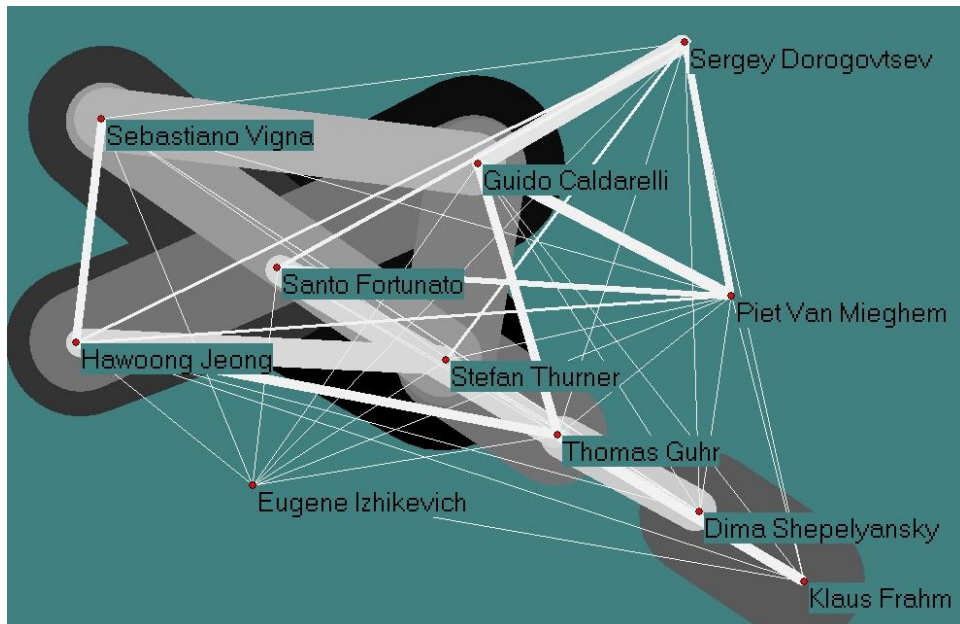
Maximum D_{in}
(US Senate)



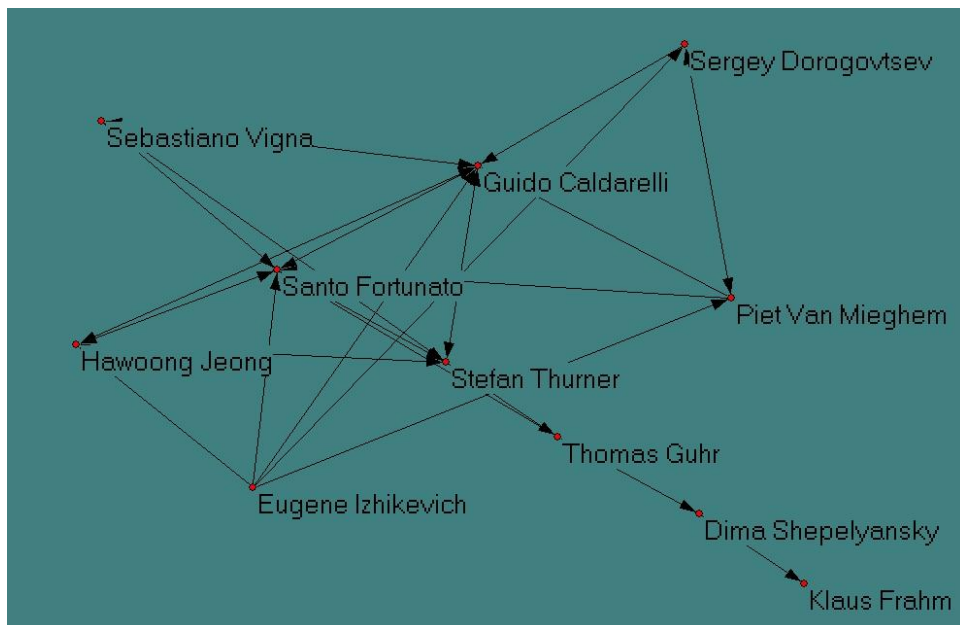
Maximum D_{in}
(MLB players)

The more incoming links (D_{in}) a node has, the more influential
the node is in the system!

S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (PLoS ONE 2010)



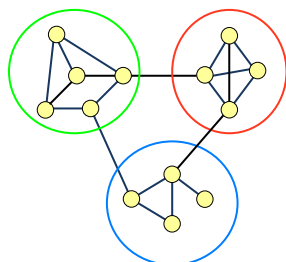
S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)



S.H. Lee, P.J. Kim, Y.Y. Ahn, H. Jeong (arXiv:0710.3268, PLoS ONE 2010)

More Specific Problems...

Community identification problem in directed networks:



General Definition:

More links are placed **within** communities and **less** links are placed **between** communities.

- Community structure is an **ubiquitous property** of many real-world networks, such as protein-protein interaction network, citation network, social relationship network, etc.
- Community structure is related to **the structural and dynamical** properties of many networks.

Y.D. Kim, S.W. Son, H. Jeong (PRE 2009)

Modularity

- Modularity Optimizing Methods

Find the **maximum of modularity Q** over possible community partitions of the network, and the partition of **maximum modularity** is taken as **the best estimate** of the communities in the network.

$$Q = \left(\begin{array}{l} \text{fraction of links within communities} \\ - \text{(expected value of that fraction)} \end{array} \right)$$

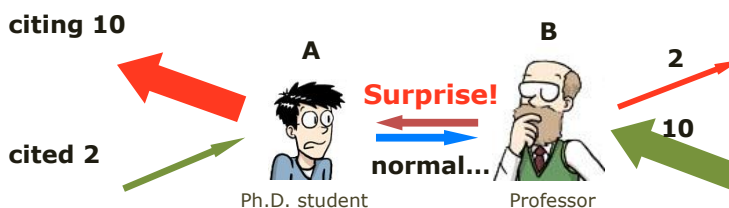
$$= \frac{1}{2M} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2M} \right] \delta_{c_i c_j}$$

where A_{ij} is the adjacency matrix, M is the total number of links, k_i is the degree of node i , and c_i is the community label of node i .

- However, modularity is only defined in **undirected networks**.

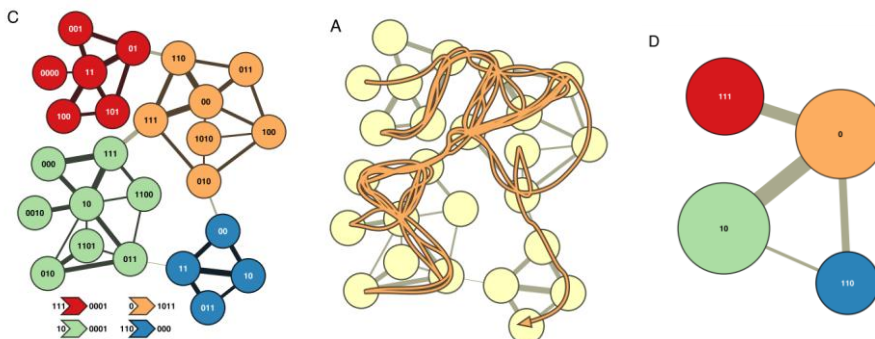
Newman and Girvan(2004) *Phys Rev E*, **69**, 026113

How to Consider Direction Information?



- a link from B to A implies **stronger relation** between A and B than a link from A to B.
 - A pairs of nodes should be more likely to be included in the same community when the link is directing **from more important node to less important node**.
- Remind me of "PageRank"!

Let Random Walkers walk on directed network, and watch how long they stay in each nodes...

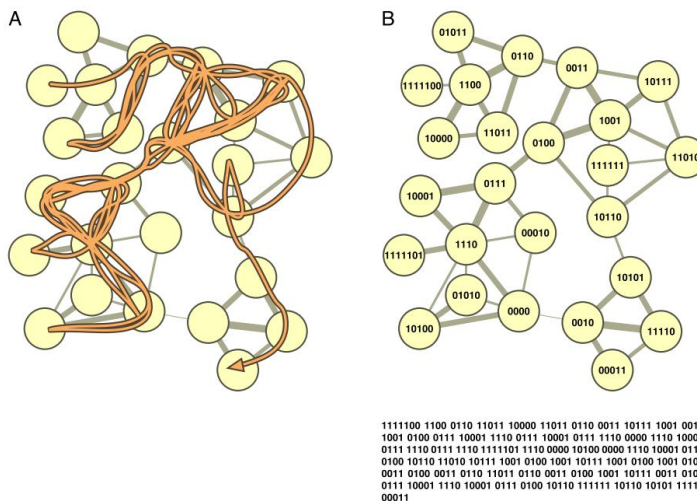


Picture from Rosvall2007

Rosvall2007

an information theoretic approach

Basic concept is the same. Detecting communities by compressing the description of information flows (random walk) on networks.



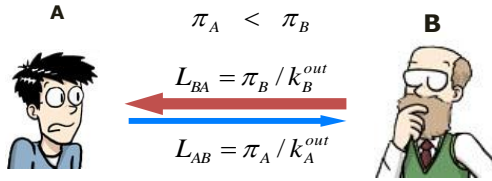
New Definitions:

Community A group of nodes within which a random walker is more likely to stay.

Modularity $Q^{lr} =$ (fraction of **time** spent moving within communities) - (expected value of that fraction).

- $L_{ij} \equiv \pi_i G_{ij}$ (**LinkRank**), the **probability** that a random walker found on the **link** $i \rightarrow j$.
- π_i (**PageRank**), the **probability** that the random walker visiting **node** i .
- $G_{ij} \equiv A_{ij} / k_i^{out}$ (**Google matrix**), the **probability** that the random walker moves to **node** j when it is on node i . (Random hopping needs to be added if the network is not a Strongly Connected Component.)
- $\pi^T G = \pi^T$

- The **direction** effect is **properly** considered!



In undirected networks,

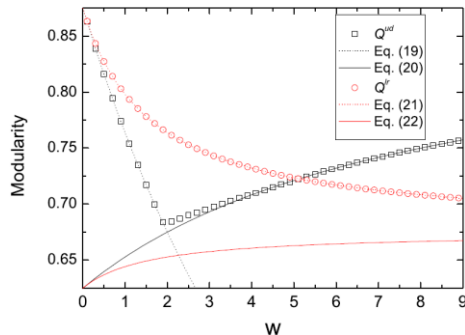
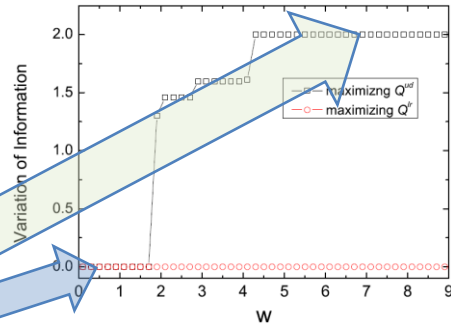
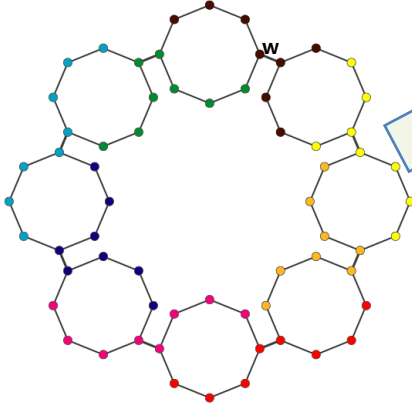
$$\pi_i = \frac{k_i}{2M}, \quad G_{ij} = \frac{A_{ij}}{k_i} \Rightarrow$$

$$Q^{lr} = \sum_{i,j} L_{ij} \delta_{c_i c_j} - \sum_{i,j} E(L_{ij}) \delta_{c_i c_j} = \sum_{i,j} \left[\frac{A_{ij}}{2M} - \frac{k_i}{2M} \frac{k_j}{2M} \right] \delta_{c_i c_j} = Q^{ud}.$$

- The new definitions **consist well** with the original ones.

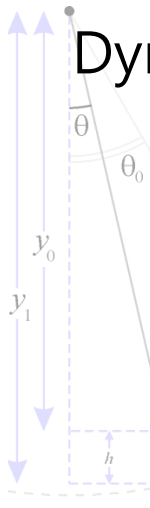
Results (m=n=8)

(...)



Dynamics on Directed Network

Synchronization



- Cristiaan Huygens, 1656
- **Syn** (the same) + **chro** (time) + **nize** : agreement in time.
- One of the most fascinating collective behaviors in nature.
- A unit interacts with other units, and tries to imitate other's behavior.
- Fireflies, cricket, neurons, and cardiac pacemaker cells.
- Coupled oscillators. [Kuramoto model \(1975\)](#)

$$\frac{d\phi_i}{dt} = \omega_i - \frac{K}{\langle k \rangle} \sum_{j=1}^N a_{ij} \sin(\phi_i - \phi_j)$$



S.W. Son, B.J. Kim, H.Hong, H. Jeong PRL (2009)

Motivation

Traffic

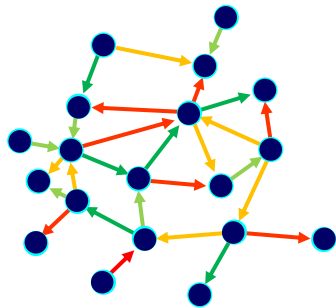


Parallel computing



Internet Power grid

Effect of link directions



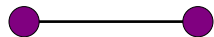
Randomly ?

Q. How can we enhance (or control) the synchronization on complex network?

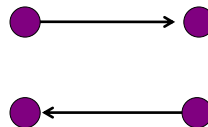
Directionality

Visiting every link...

Undirected Link

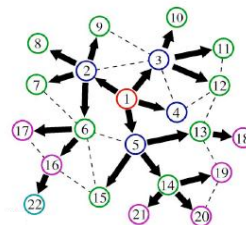


Directed Link



Maximum Synchronizability

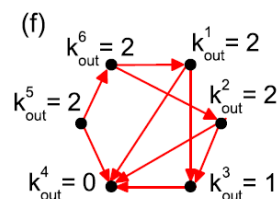
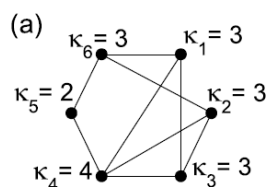
Nishikawa analytically shows that...



“ We first note that **maximum synchronizability** can always be achieved by imposing that the network (i) embeds an oriented spanning tree, (ii) has no directed loops, and (iii) has normalized input strengths in each node, i.e., the total input is the same for all nodes that have input. ”

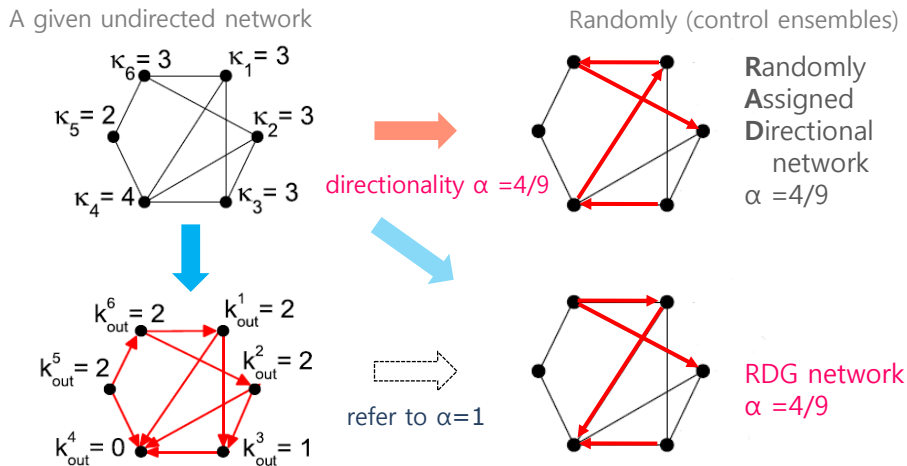
T. Nishikawa and A. E. Motter, Phys. Rev. E **73**, 065106(R) (2006).

Residual Degree Gradient (RDG) Network



κ_i : residual degree - Number of remaining links without assigning direction.

RDG vs. RAD with directionality α

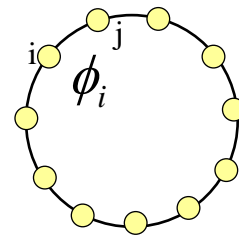


RDG with $\alpha = 1$. (Reference)

Kuramoto model

N coupled limit-cycle oscillators

$$\frac{d\phi_i}{dt} = \omega_i - \frac{K}{\langle k \rangle} \sum_{j=1}^N a_{ij} \sin(\phi_i - \phi_j) \quad \text{phase} \quad \{\phi_i(t) \mid i = 1, 2, \dots, N\}$$



1. Natural frequency

$$g(\omega) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\omega^2}{2}}$$

2. Adjacency matrix

$$a_{ij} \neq a_{ji}$$

3. Coupling strength

$$K > 0$$

4. Mean degree

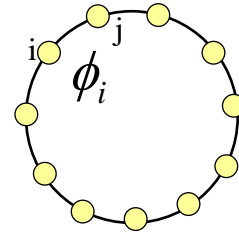
$$\langle k \rangle = \frac{\sum_{i=1}^N k_i}{N} = \frac{\sum_{i,j=1}^N a_{ij}}{N}$$

Y. Kuramoto, in *International Symposium on Mathematical Problems in Theoretical Physics*, edited by H. Araki, Lecture Notes in Physics Vol. 39 (Springer-Verlag, Berlin, 1975)

Kuramoto model

N coupled limit-cycle oscillators

$$\frac{d\phi_i}{dt} = \omega_i - \frac{K}{\langle k \rangle} \sum_{j=1}^N a_{ij} \sin(\phi_i - \phi_j) \quad \text{phase} \quad \{ \phi_i(t) \mid i = 1, 2, \dots, N \}$$



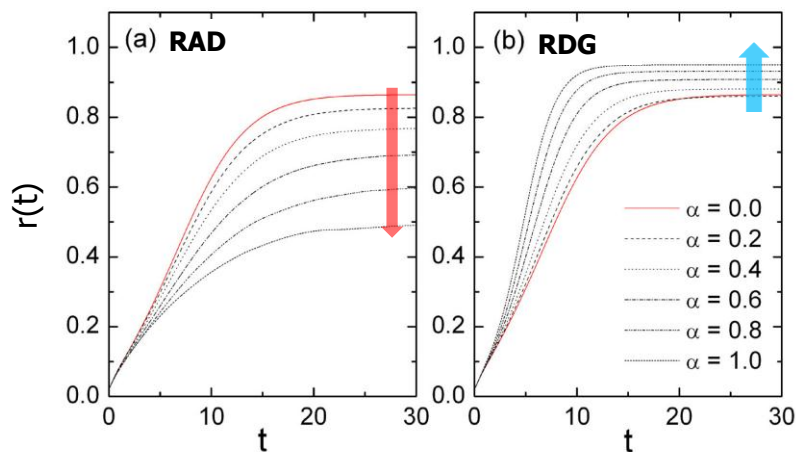
Order parameter

$$r(t) \equiv \left\langle \left| \frac{1}{N} \sum_{j=1}^N e^{i\phi_j(t)} \right| \right\rangle_{\text{ensemble}}$$

Y. Kuramoto, in *International Symposium on Mathematical Problems in Theoretical Physics*, edited by H. Araki, Lecture Notes in Physics Vol. 39 (Springer-Verlag, Berlin, 1975)

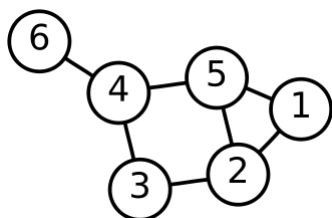
Kuramoto model

SW network, N=1600, P=0.2, <k>=6



α : directionality

Eigenvalues of Laplacian Matrix



Adjacency matrix

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

Laplacian matrix (positive semidefinite)

$$G = \begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$$

$$G_{ij} = -A_{ij} + \delta_{ij} \sum_{j=1}^N A_{ij}$$

Eigenvalues

$$0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N$$

Smallest nonzero eigenvalue Largest eigenvalue

Laplacian matrix is related with diffusion process and network community.

$$\dot{\mathbf{x}}_i = F(\mathbf{x}_i) + \sigma \sum_{j=1}^N A_{ij} [H(\mathbf{x}_j) - H(\mathbf{x}_i)]$$

$$= F(\mathbf{x}_i) - \sigma \sum_{j=1}^N G_{ij} H(\mathbf{x}_j)$$

$$G_{ij} = -A_{ij} + \delta_{ij} \sum_{j=1}^N A_{ij} = L_{ij}$$

$$0 = \lambda_1 \leq \text{Re } \lambda_2 \leq \dots \leq \text{Re } \lambda_N$$

Eigenratio

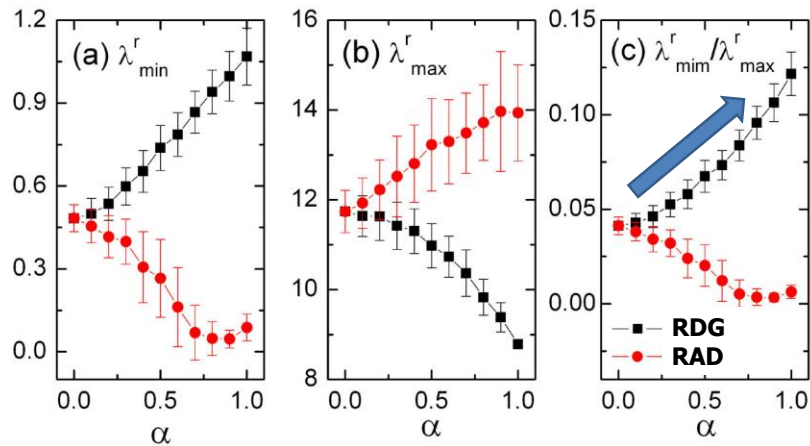
$$R = \frac{\lambda_{\min}^r}{\lambda_{\max}^r}$$

“The larger the eigenratio R,
the larger the synchronizability of the network
and vice versa.”

T.Nishikawa et. al., Phys. Rev. Lett. **91**, 014101 (2003).

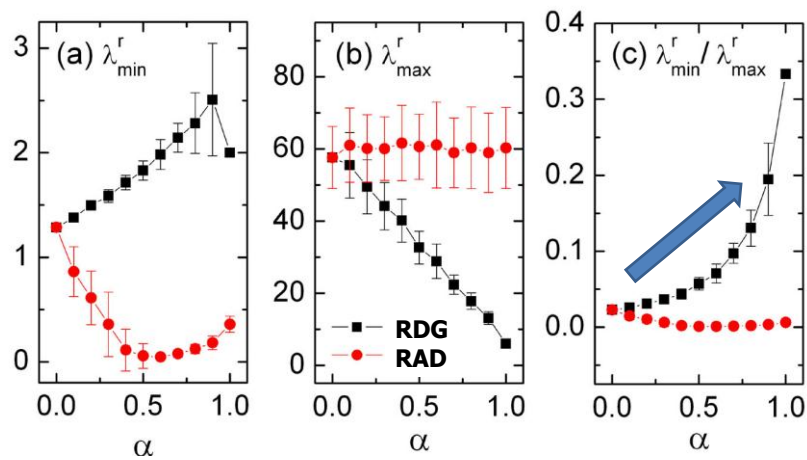
Eigenvalue Ratio

SW network, $N=400$, $P=0.2$, $\langle k \rangle = 6$

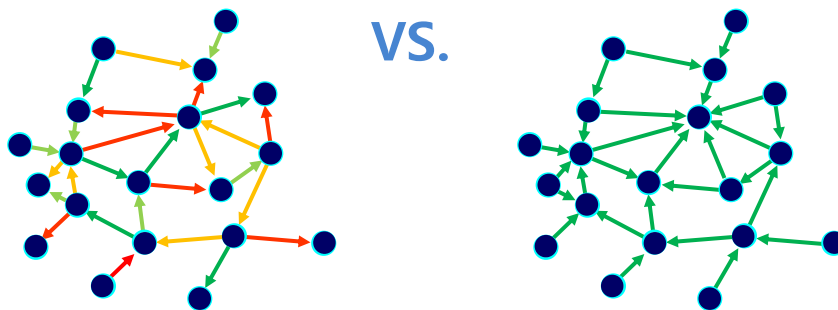


Eigenvalue Ratio

SF network, $N=400$, $\langle k \rangle = 6$



Smart link directions can enhance synchronization!

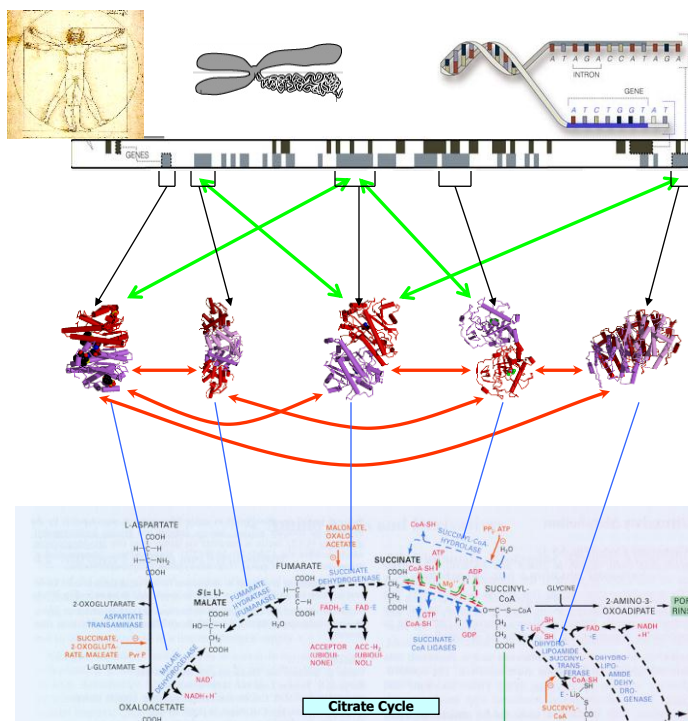


VS.

Randomly

Applying RDG

MORE DYNAMIC DIRECTED NETWORKS & APPLICATION



GENOME

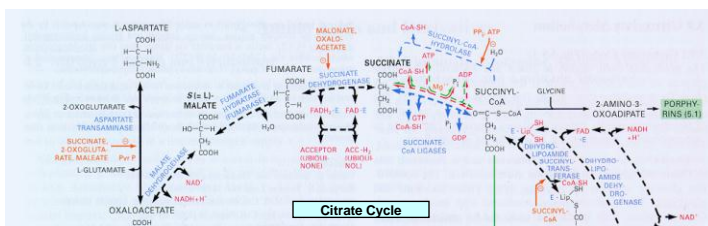
protein-gene interactions

PROTEOME

protein-protein interactions

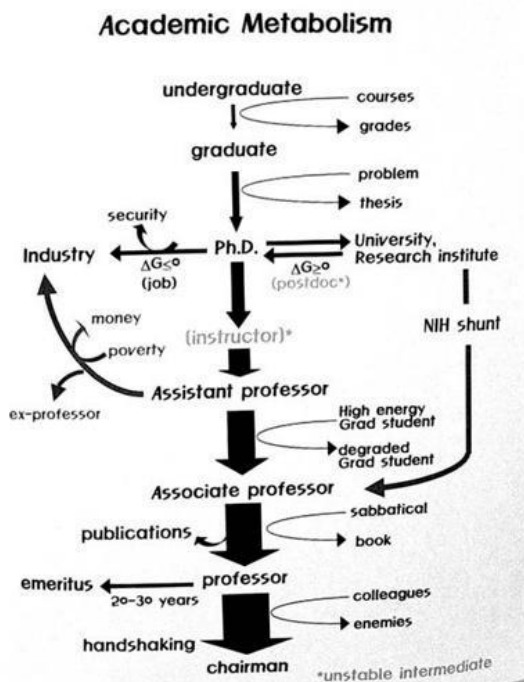
METABOLISM

Bio-chemical reactions

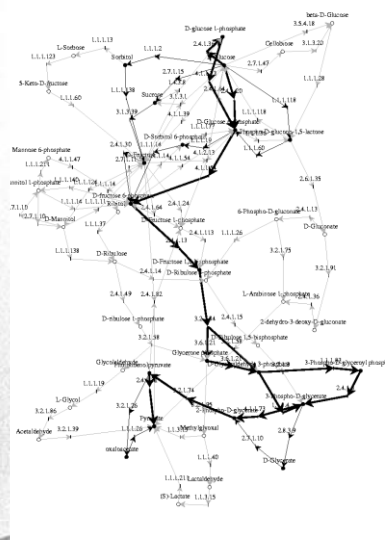


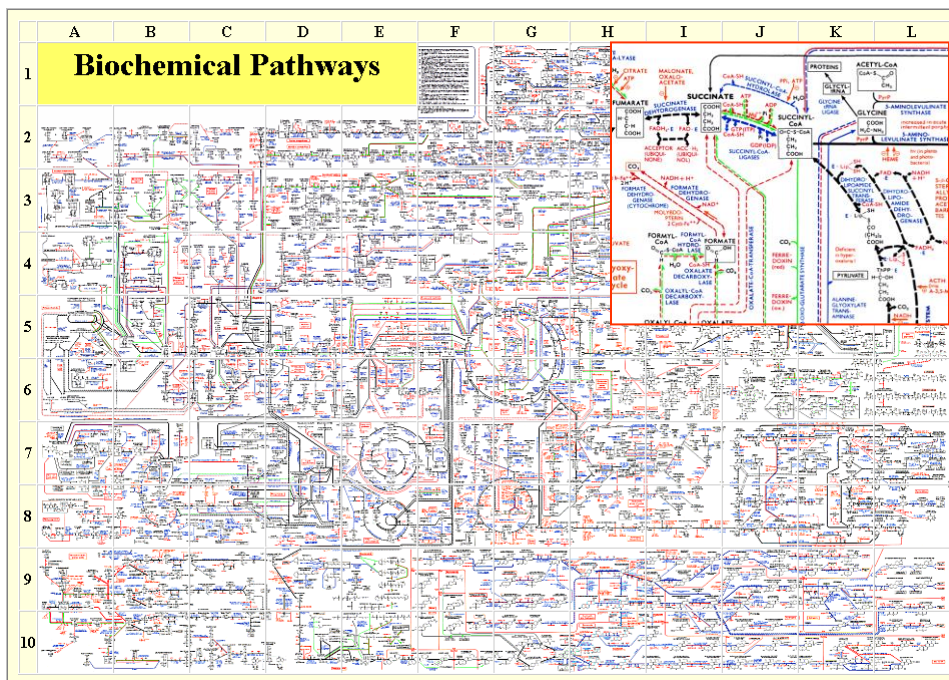
Metabolic Networks

Bio-chemical reactions

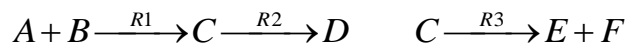


- **Nodes:** chemicals (proteins, substrates)
- **Links:** bio-chem. reaction



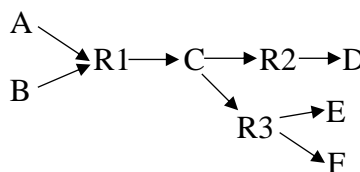


Construction of metabolic pathway as a graph



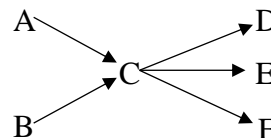
1. Bipartite network

- Two kinds of nodes: substrates and reactions



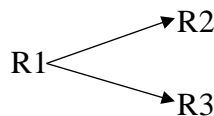
2. Substrate to substrate network

- Node: substrate. Link: chemical reaction

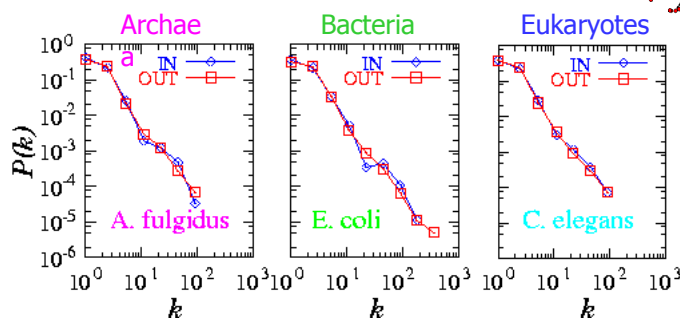
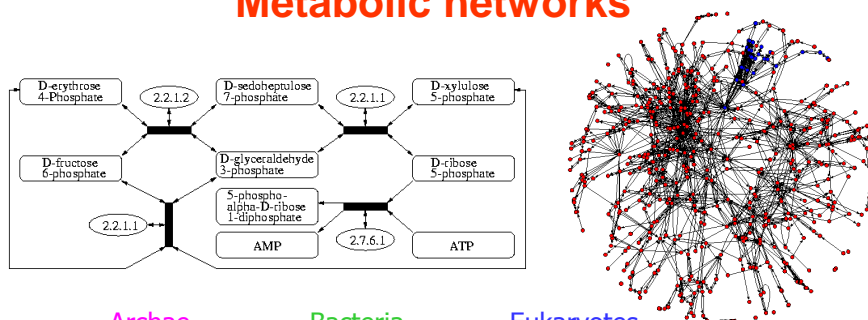


3. Reaction to reaction network

- Node: reaction. Link: substrate



Metabolic networks



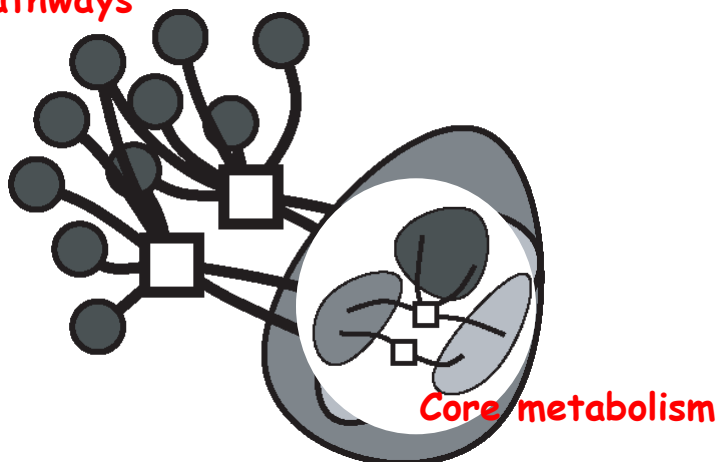
Organisms from all three domains of life are **scale-free** networks!

$$P(k) \sim k^{-\gamma}$$

H. Jeong, B. Tombor, R. Albert, Z.N. Oltvai, and A.L. Barabasi, Nature, **407** 651 (2000)

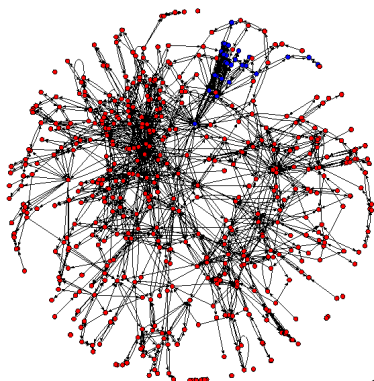
Schematic picture of metabolic networks

Linear pathways

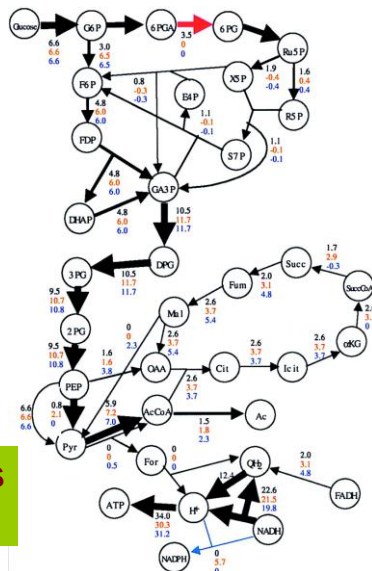


P. Holme, M. Huss, H. Jeong, Bioinformatics (2003)

All these works were about STATIC topological properties of metabolic networks

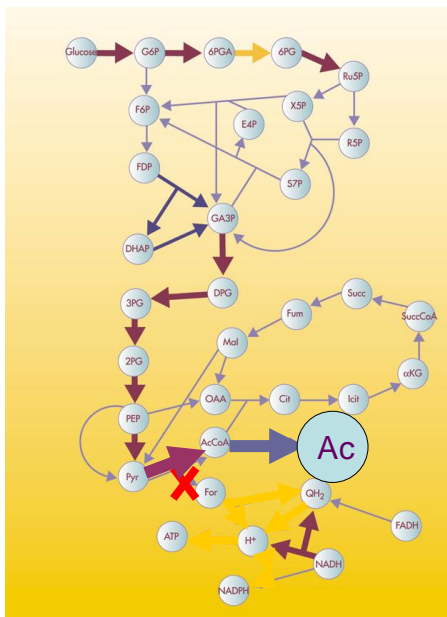


But real metabolic networks are DYNAMIC!!

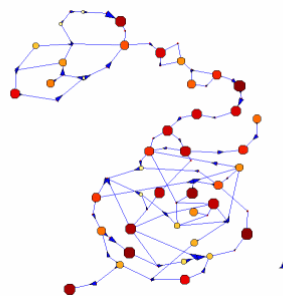


Metabolic Engineering

Complex network research center



Metabolic networks are not static! They are dynamical systems!



Q: How to control the metabolic networks?
e.g. How to increase product Ac?

To fully understand the dynamics of metabolism inside a cell

Requirements

- Complete knowledge of all the biochemical pathways in a cell, i.e. complete knowledge of all the possible stoichiometric reactions in a cell
- Enzyme kinetics
- Regulation of all enzymes in a cell

Problems

- Complete kinetic and regulatory control parameters are not available for all the enzymes in a cell.
- The kinetic constants are based on *in vitro* conditions which are almost completely different from the *in vivo* conditions

To fully understand the dynamics of metabolism inside a cell

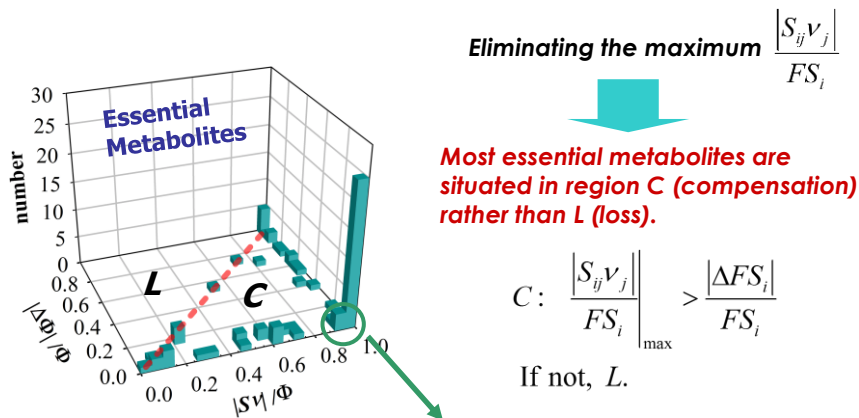
Approaches

- Complete knowledge of all the biochemical pathways in a cell, i.e. complete knowledge of all the possible stoichiometric reactions in a cell
- ~~• Enzyme kinetics~~
- ~~• Regulation of all enzymes in a cell~~

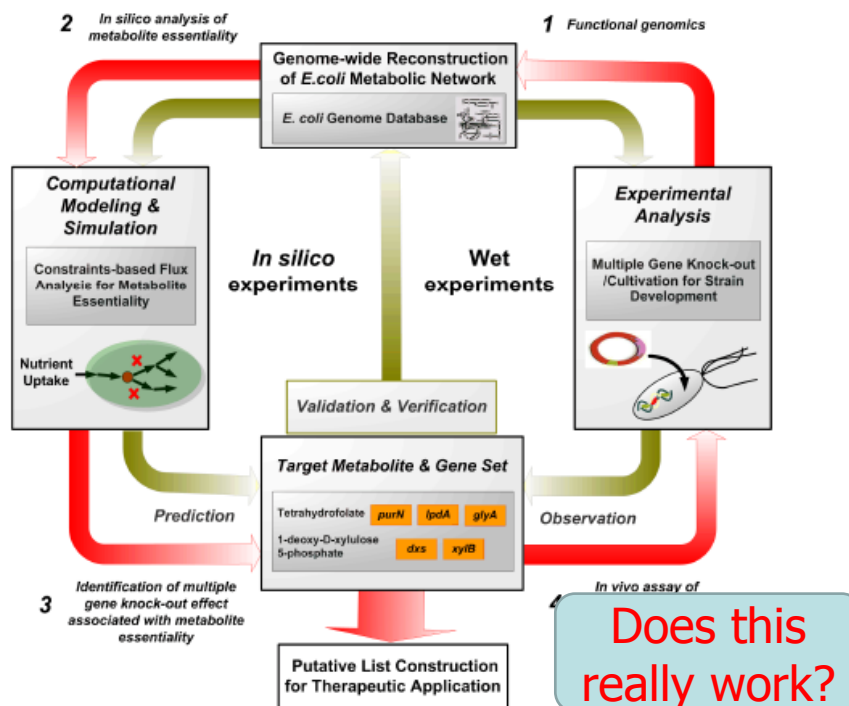
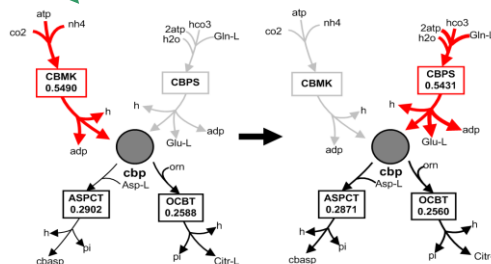


Flux Balance Analysis

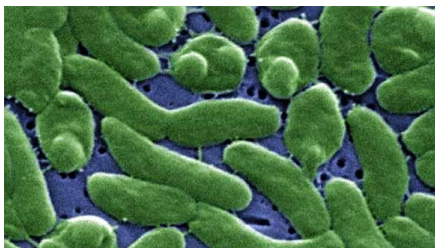
- Linear metabolic model based on stoichiometric balance equations in a cell. (mass conservation)
- Steady state solution. (no net accumulation of metabolites)
- Uses linear optimization techniques to study the flux distribution in a cell. (with appropriate objective function)



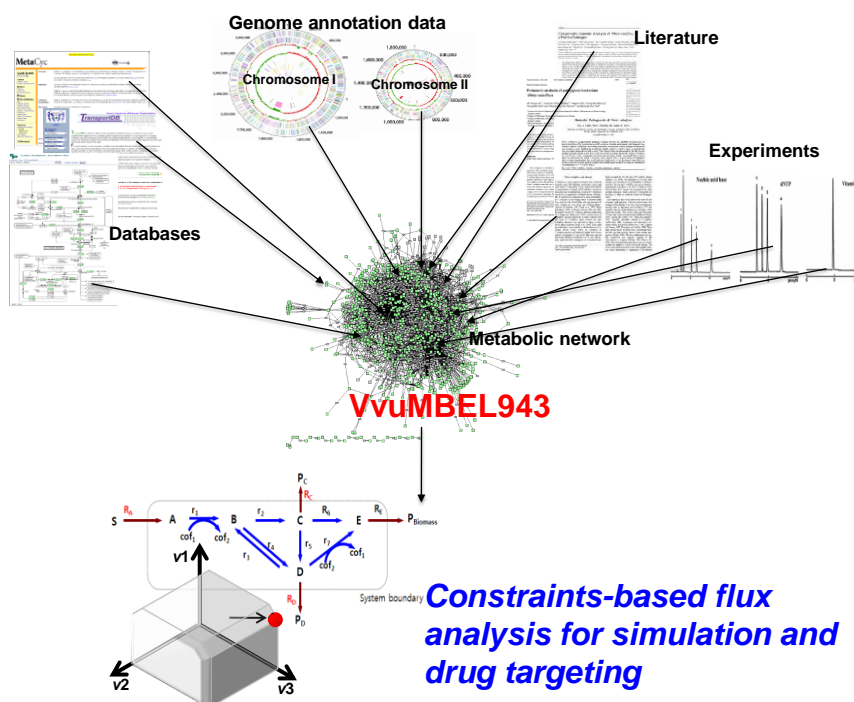
Carbamoyl phosphate (cbp):
 98.9% of the flux-sum is recovered when the highest flux of carbamate kinase is eliminated.

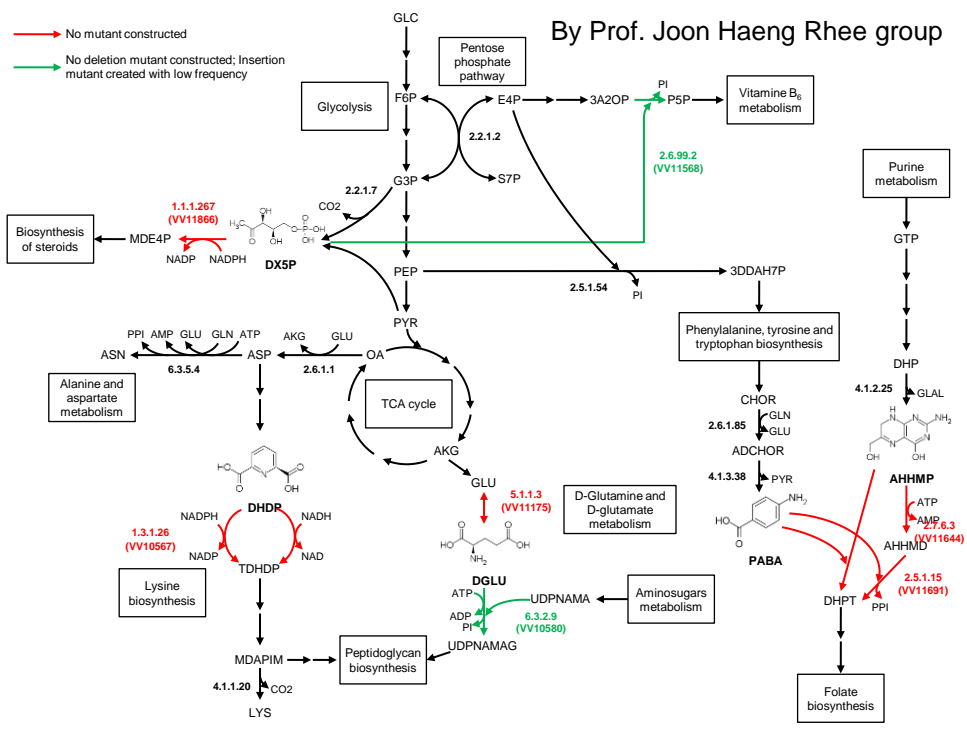
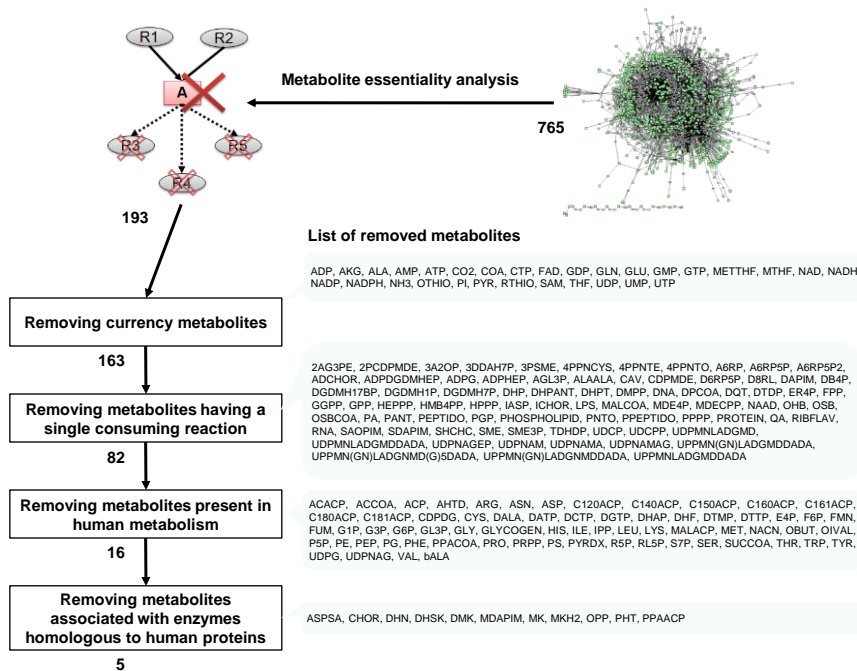


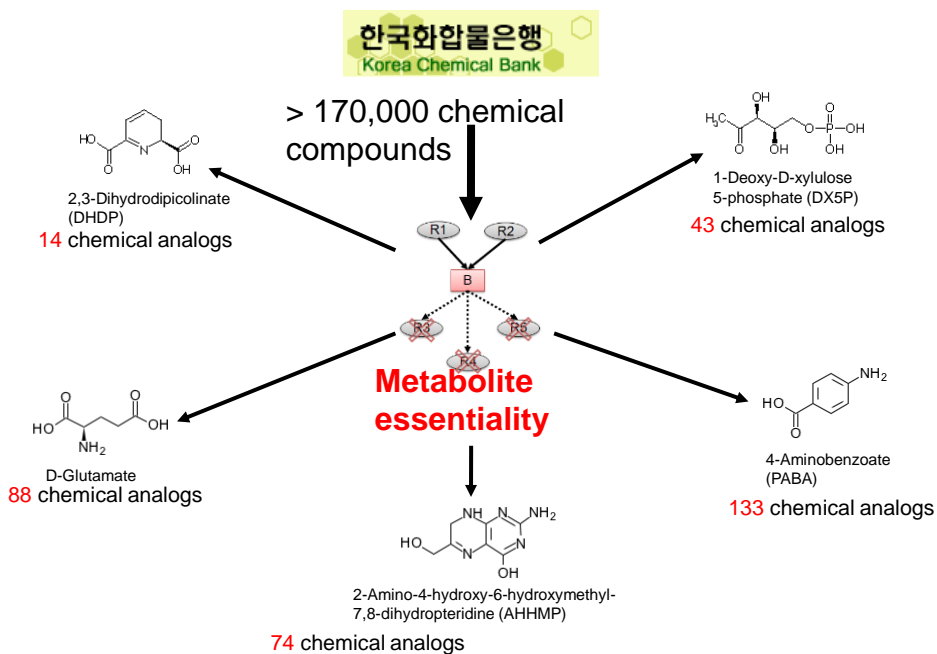
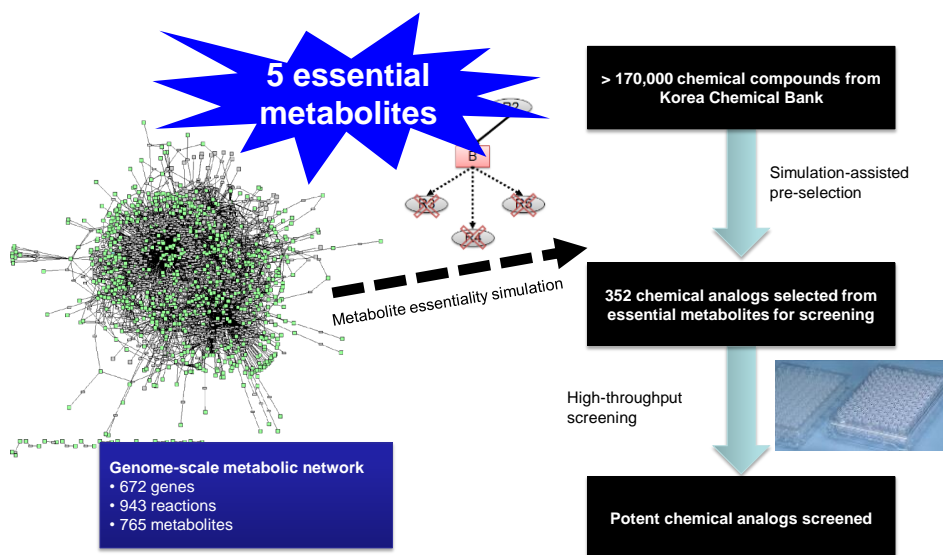
Characteristics of *Vibrio vulnificus* CMCP6



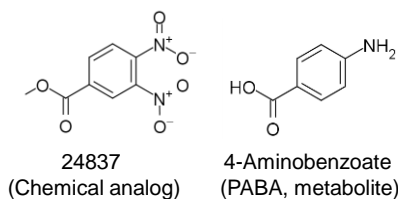
- ✓ Gram-negative bacterium
- ✓ Biotype 1: predominant human pathogens
- ✓ Typically found in estuarine waters
- ✓ Currently two strains' genomes sequenced: YJ016 (Chen *et al.* *Genome Res.* **13**, 2577-2587, 2003) and CMCP6 (not reported)
- ✓ Genome size: 5.12 Mb
- ✓ Causing agent of septicemia, necrotizing wound infection, and gastroenteritis





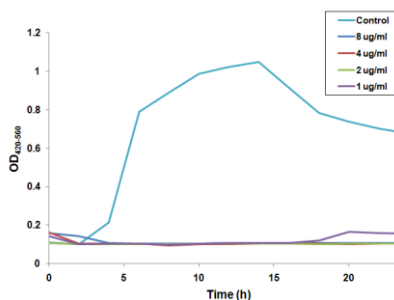


Final 'hit', the most potent analog



Compound ID	MIC (µg/ml)	MBC (µg/ml)
24837	2	4

Growth Inhibition



- MIC: minimal inhibitory concentration
- MBC: minimal bactericidal concentration

Final essential metabolites of *A. baumannii* AYE

Essential metabolites	ORFs	Metabolism	E.C. Number	Enzyme
AHHMP	ABAYE1418 OR ABAYE3176	Folate biosynthesis	2.7.6.3	2-amino-4-hydroxy-6-hydroxymethyl-dihydropteridine pyrophosphokinase
	ABAYE0807 OR ABAYE3568 OR ABAYE3612 OR ABAYE3616	Folate biosynthesis	2.5.1.15	dihydropteroate synthase
DGLU	ABAYE0082 OR ABAYE3395	D-Glutamine and D-glutamate metabolism	5.1.1.3	glutamate racemase
	ABAYE3524	Peptidoglycan biosynthesis	6.3.2.9	UDP-N-acetylmuramoylalanine-D-glutamate ligase
DHDP	ABAYE0036	Lysine biosynthesis	1.3.1.26	dihydrodipicolinate reductase
DHP	ABAYE1417	Folate biosynthesis	4.1.2.25	dihydrooneopterin aldolase
	ABAYE0811	Folate biosynthesis	3.1.3.1	alkaline phosphatase D precursor
DHSK	ABAYE1539 OR ABAYE1682	Phenylalanine, tyrosine and tryptophan biosynthesis	4.2.1.10	3-dehydroquininate dehydratase II; catabolic 3-dehydroquininate dehydratase (3-dehydroquinase)
	ABAYE0377	Phenylalanine, tyrosine and tryptophan biosynthesis	1.1.1.25	shikimate 5-dehydrogenase
	ABAYE1685	Phenylalanine, tyrosine and tryptophan biosynthesis	1.1.99.25	quininate/shikimate dehydrogenase
	ABAYE1683	Phenylalanine, tyrosine and tryptophan biosynthesis	4.2.1.-	3-dehydroshikimate dehydratase
DXSP	ABAYE1581	Biosynthesis of steroids	1.1.1.267	1-deoxy-D-xylulose-5-phosphate reductoisomerase
	ABAYE0945	Vitamin B6 metabolism	2.6.99.2	pyridoxine 5-phosphate synthase
DQT	ABAYE1539 OR ABAYE1682	Phenylalanine, tyrosine and tryptophan biosynthesis	4.2.1.10	3-dehydroquininate dehydratase II; catabolic 3-dehydroquininate dehydratase (3-dehydroquinase)
	ABAYE1685	Phenylalanine, tyrosine and tryptophan biosynthesis	1.1.99.25	quininate/shikimate dehydrogenase
KDO	ABAYE2076	Lipopolysaccharide biosynthesis	2.7.7.38	3-deoxy-manno-octulosonate cytidyltransferase
	-	Lipopolysaccharide biosynthesis	-	Hypothetical reaction that consumes KDO to generate lipopolysaccharide
PABA	ABAYE0807 OR ABAYE3568 OR ABAYE3612 OR ABAYE3616	Folate biosynthesis	2.5.1.15	dihydropteroate synthase

AHHMP, 2-Amino-4-hydroxy-6-hydroxymethyl-7,8-dihydropteridine; DGLU, D-Glutamate; DHDP, 2,3-Dihydrodipicolinate; DHP, 2-Amino-4-hydroxy-6-(D-erythro-1,2,3-trihydroxypropyl)-7,8-dihydropteridine; DHSK, 3-Dehydroshikimate; DXSP, 1-Deoxy-D-xylulose 5-phosphate; DQT, 3-Dehydroquininate; KDO, 2-Dehydro-3-deoxy-D-octonate; PABA, 4-Aminobenzoate.

Kim et al. *Mol. BioSyst.*, 6, 339-348 (2010)

Summary

- There are many "directed" networks & interesting properties!
- Undirected (weighted) network can be mapped into directed network using "effective degree".
(arXiv:0710.3268, PLoS ONE 2010)
- LinkRank: one way of detecting communities on directed networks
(PRE 2009)
- Increasing the directionality may enhance the network synchronization if follow the **residual degree gradient** method contrary to the result of *randomly assigned direction*
(PRL 2009)
- Biological application to find drug target via network dynamics(FBA)
(PNAS 2007)

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