BOSTON UNIVERSITY

Dependency network and node influence: Overview and Applications

Dror Y. Kenett
Department of Physics, Boston University, USA

Outline

(1) Introduction to network science

- Terminology
- Network properties
- Matrix representation

(2) Correlation based networks

- Estimating correlations from time series
- Partial correlations
- Dependency network
- Node influence
- Applications in financial markets
- Applications in other systems

(3) Node influence

I. Cascading failures in industry networks
II. Overlapping communities in networks
III. Failure and recovery in networks
IV. Evolution of networks
V. Cascading failures in the financial system
VI. Interdependent networks

(4) Discussion

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(4) Discussion

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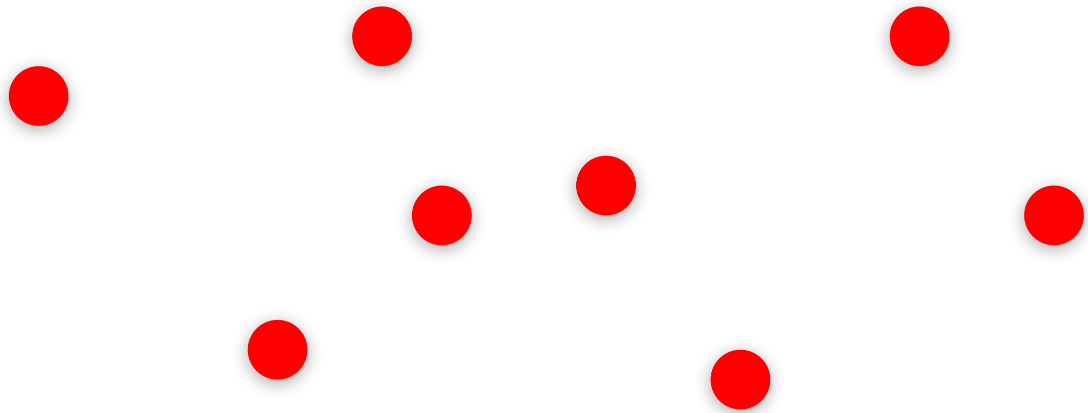

- **components**: nodes, vertices N

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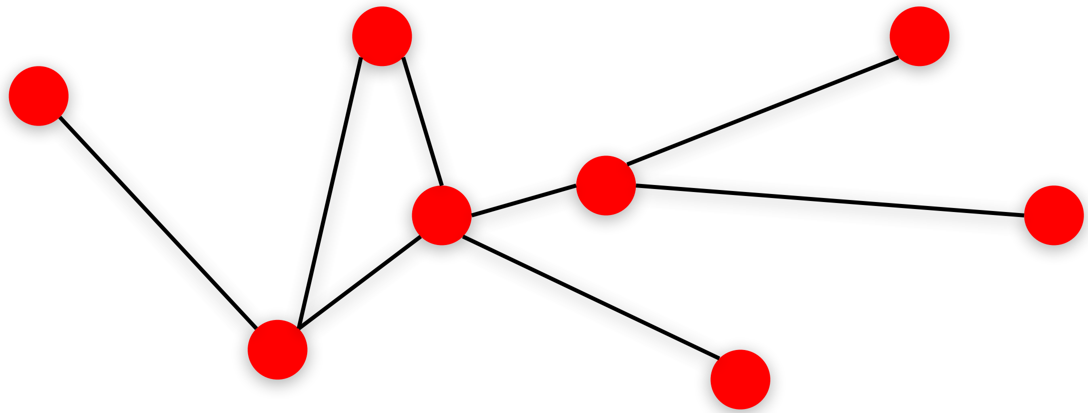

- **components**: nodes, vertices N
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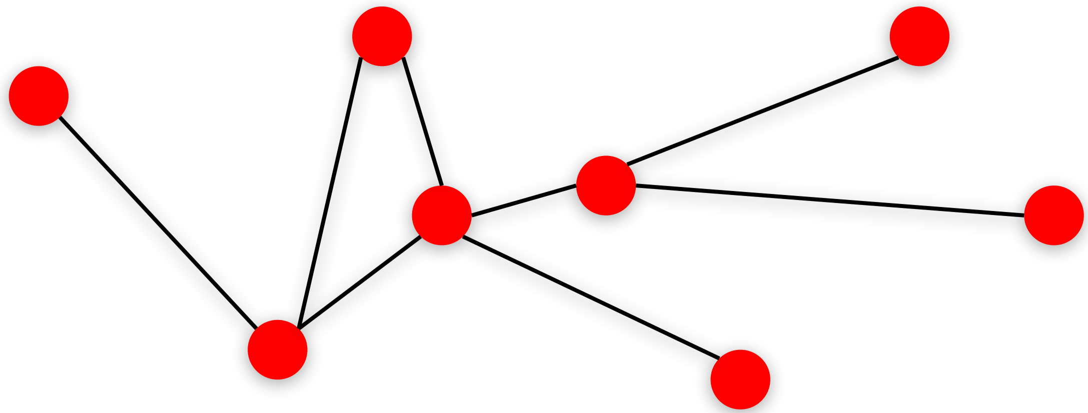
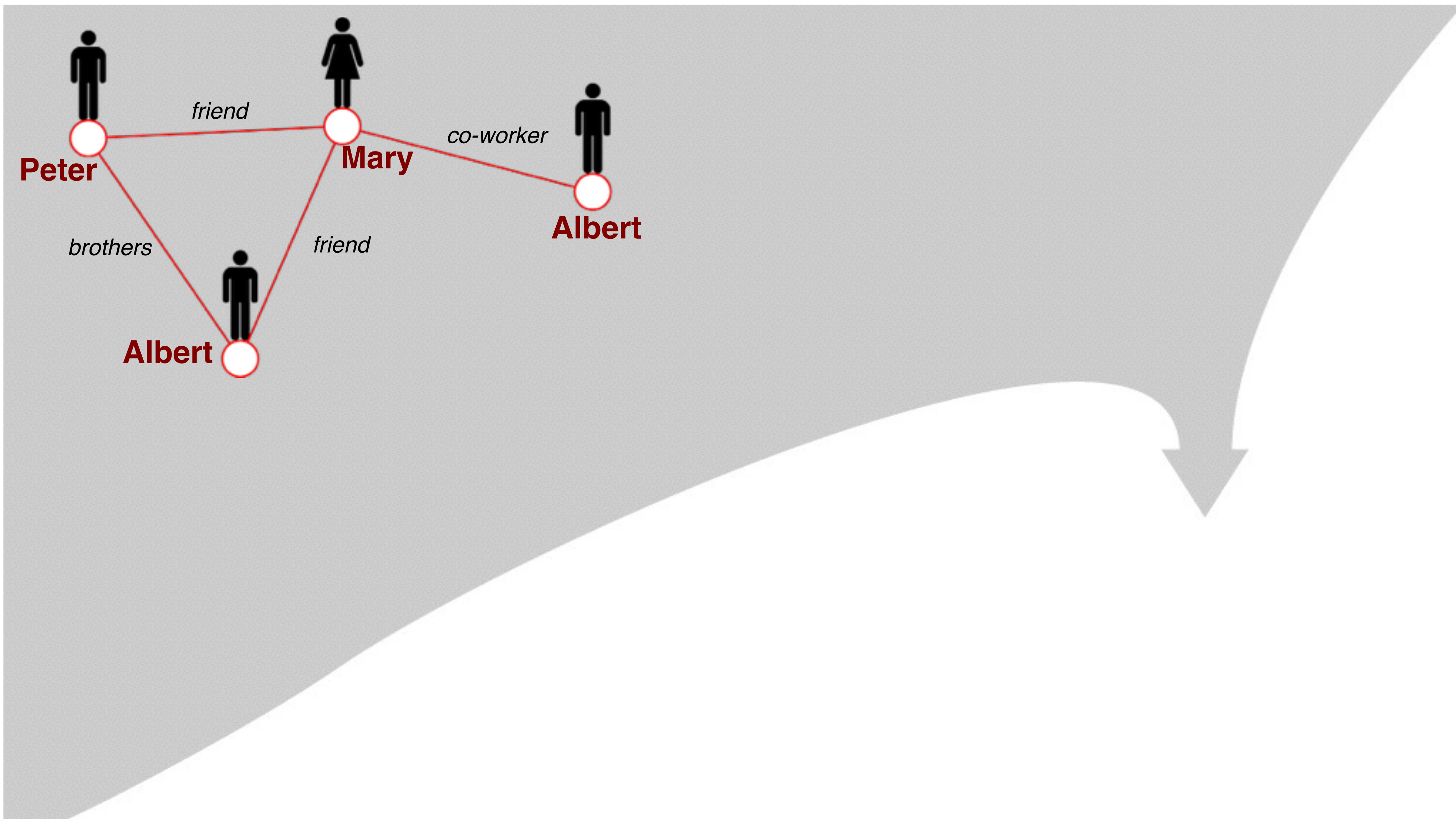
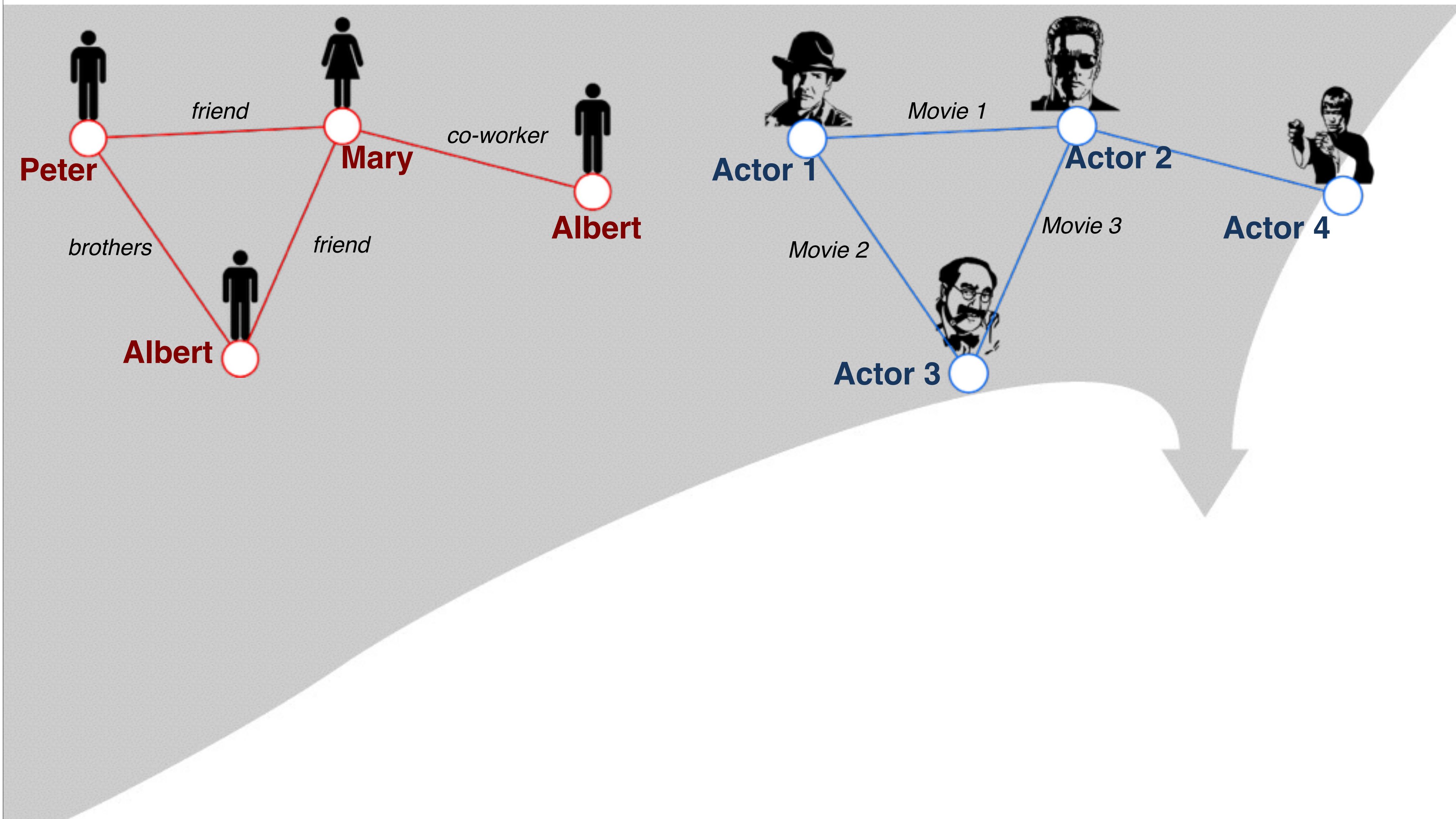


- **components**: nodes, vertices N
- **interactions**: links, edges L
- **system**: network, graph (N,L)


friend
co-worker
Peter
Mary
Albert
brothers
friend
Albert


friend
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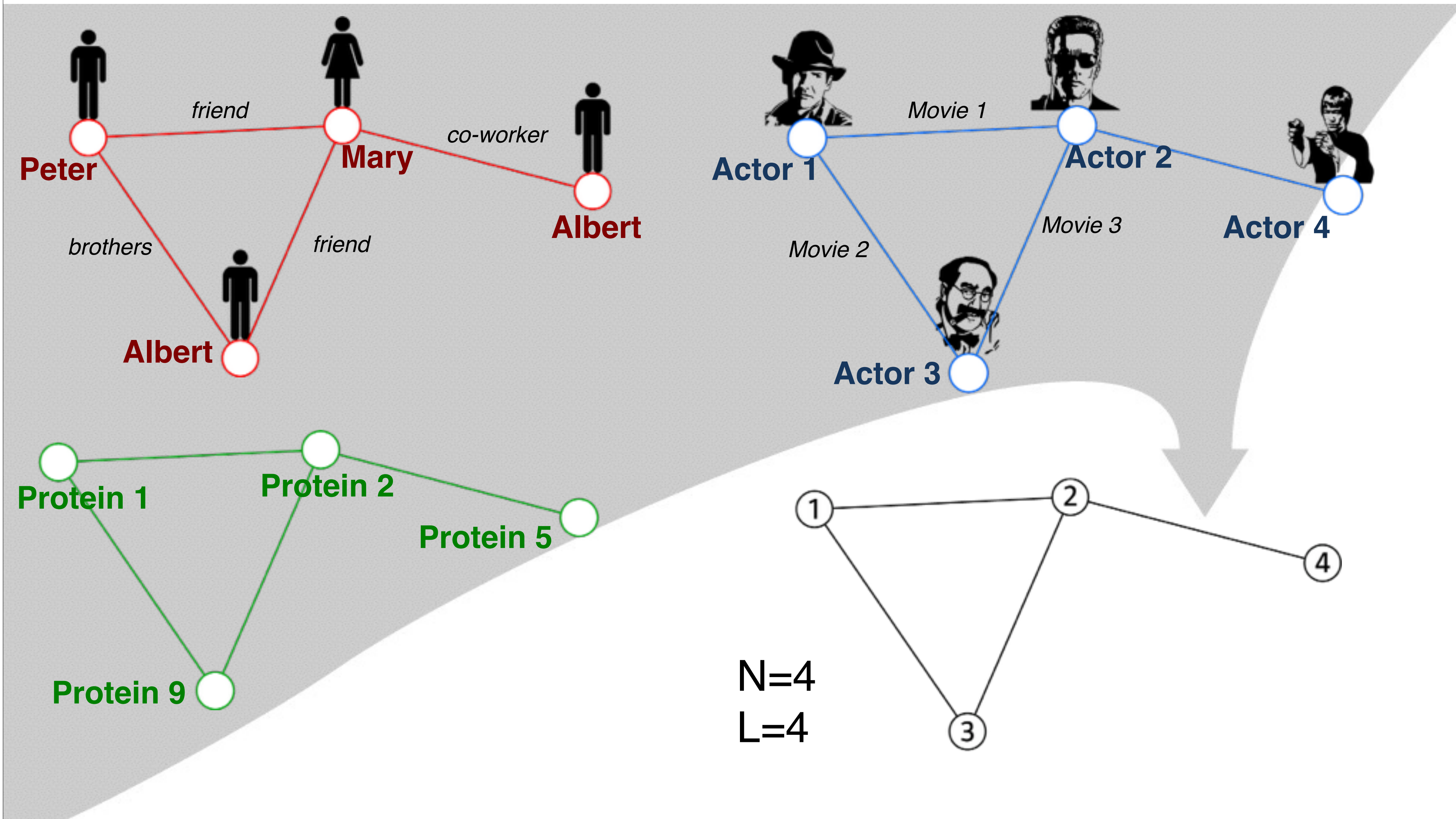
Movie 1
Actor 1
Actor 2
Movie 3
Movie 2
Actor 4
Actor 3



friend
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Movie 1
Actor 1
Actor 2
Movie 3
Actor 4
Movie 2
Actor 3
Protein 1
Protein 2
Protein 5
Protein 9
1
2
3
4
N=4
L=4

Network representation?

The choice of the proper network representation determines our ability to use network theory successfully.

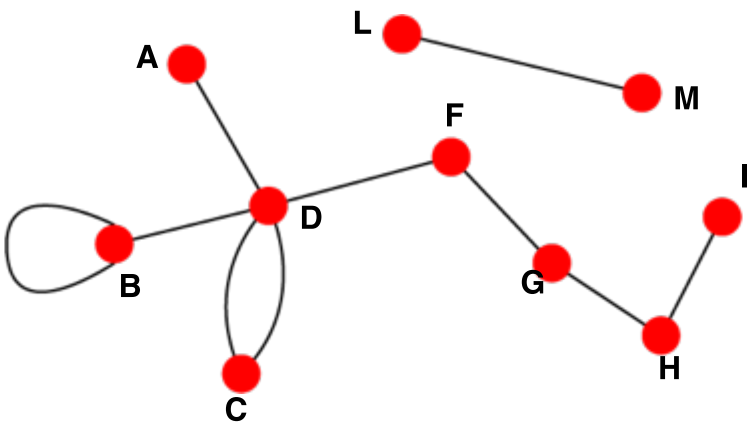
In some cases there is a unique, unambiguous representation. In other cases, the representation is by no means unique.

For example,, the way we assign the links between a group of individuals will determine the nature of the question we can study.

Undirected

Links: undirected (*symmetrical*)

Graph:

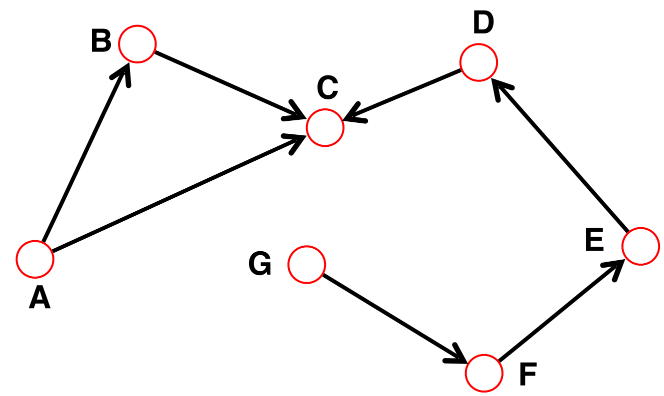


Undirected links :
coauthorship links
Actor network
protein interactions

Directed

Links: directed (*arcs*)

Digraph = directed graph:

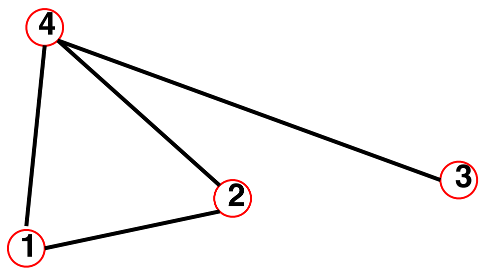


An undirected link is the superposition of two opposite directed links.

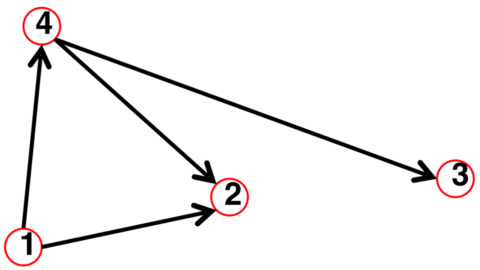
Directed links :
URLs on the www
phone calls
metabolic reactions

The Adjacency Matrix

Undirected



Directed



A_{ij}=1 if there is a link between node *i* and *j*

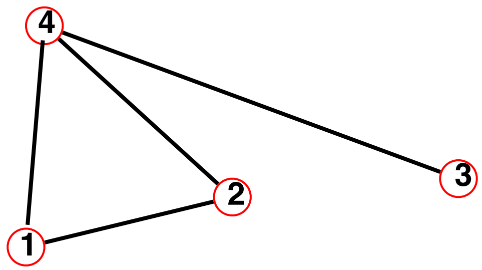
A_{ij}=0 if nodes *i* and *j* are not connected to each other.

$$A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \qquad A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Note that for a directed graph (right) the matrix is not symmetric.

Example of topological properties of a network: Node Degree

Undirected



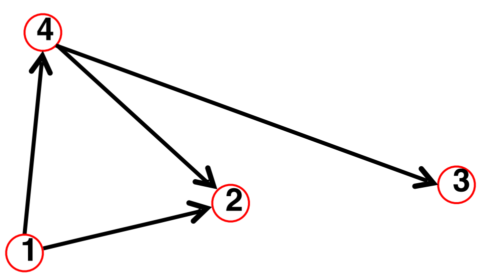
$$A_{ij} = A_{ji}$$
$$A_{ii} = 0$$

$$k_i = \sum_{j=1}^{N} A_{ij}$$

$$k_j = \sum_{i=1}^{N} A_{ij}$$

$$L = \frac{1}{2}\sum_{i=1}^{N} k_i = \frac{1}{2}\sum_{ij}^{N} A_{ij}$$

Directed



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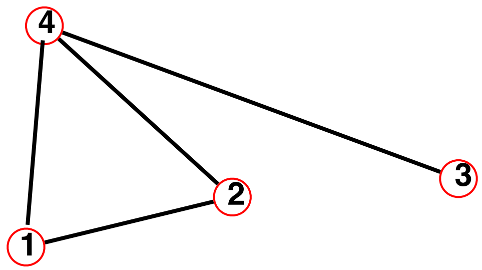

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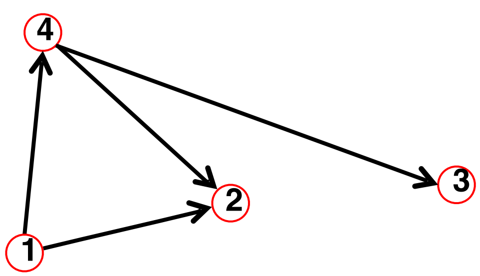

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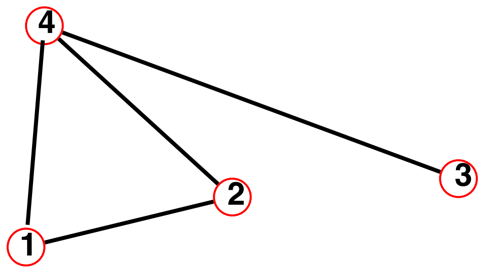

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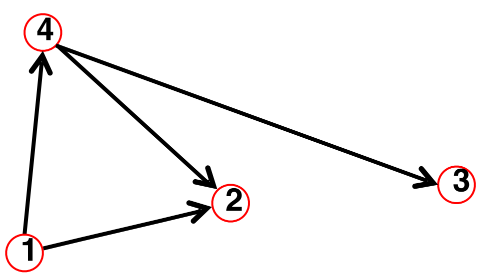

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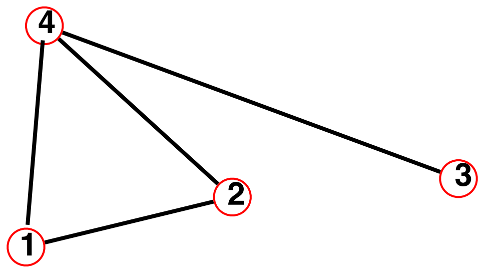

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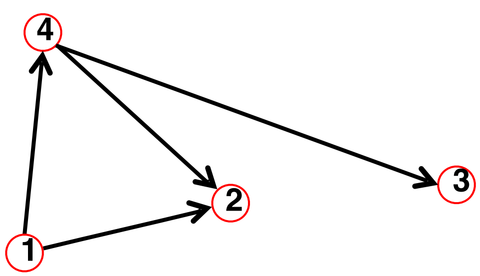

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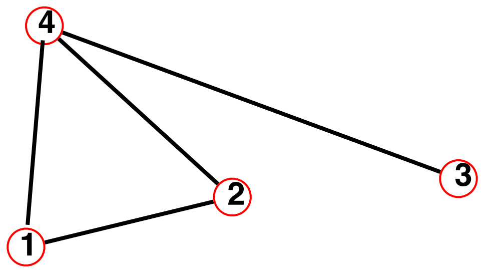

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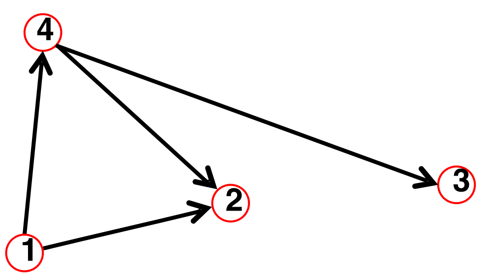

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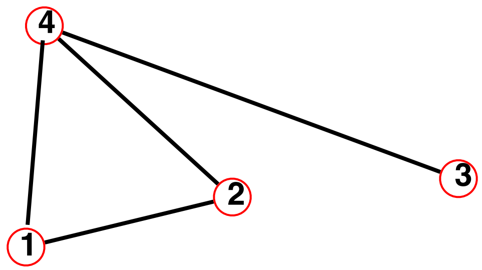

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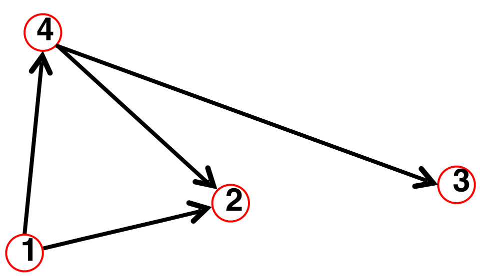

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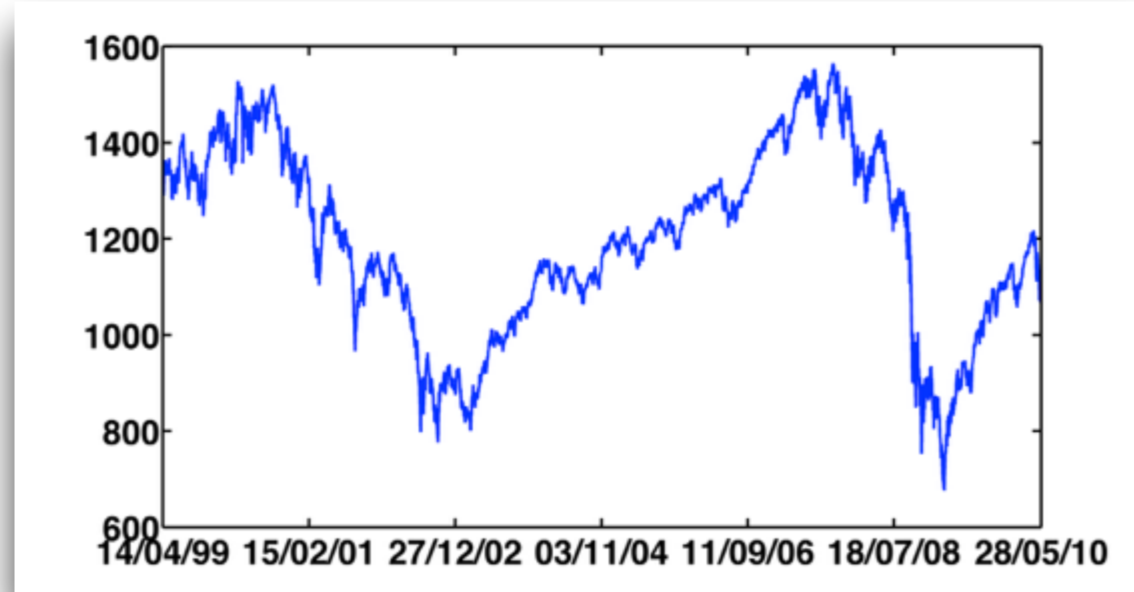
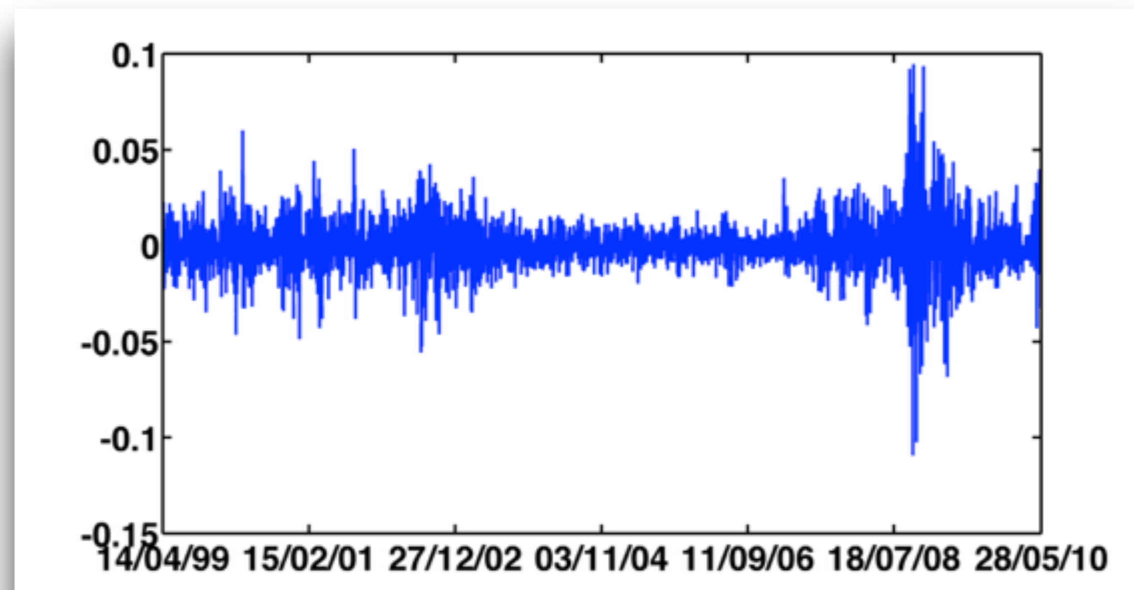
S&P500 Price



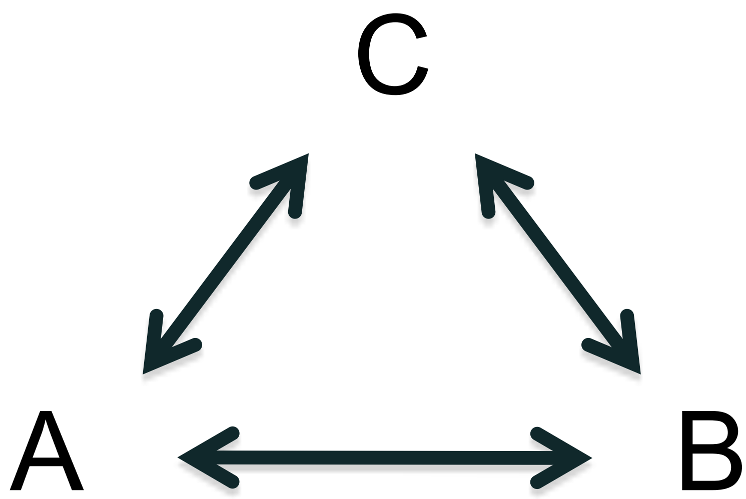
$$r_i(t) = \log\left[P_i(t)\right] - \log\left[P_i(t-1)\right]$$

S&P500 Return



Quantifying functional relationships

Correlation



$$C\left(i,j\right)=\frac{\left\langle\left(r_i-\left\langle r_i\right\rangle\right)\cdot\left(r_j-\left\langle r_j\right\rangle\right)\right\rangle}{\sigma_i\cdot\sigma_j}$$

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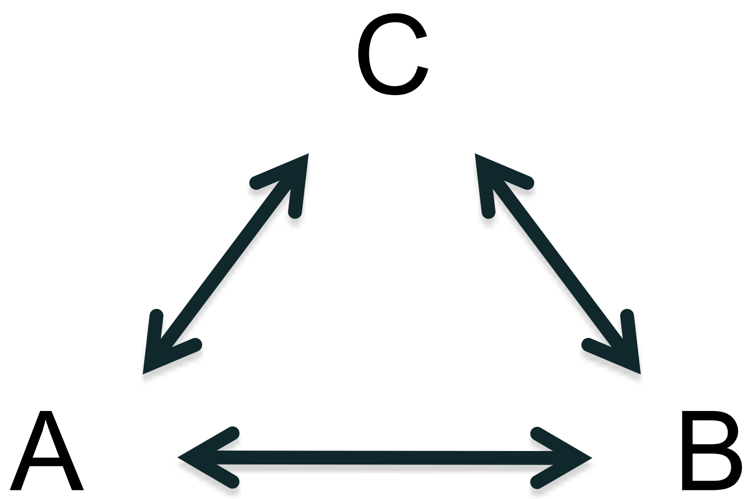

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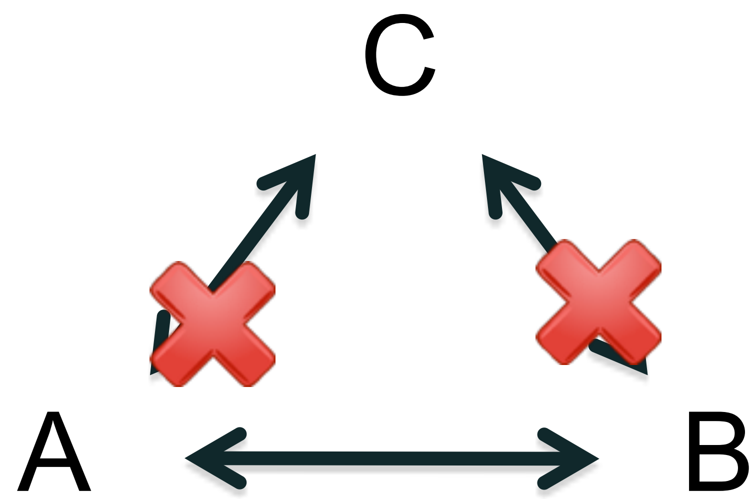
Partial Correlation



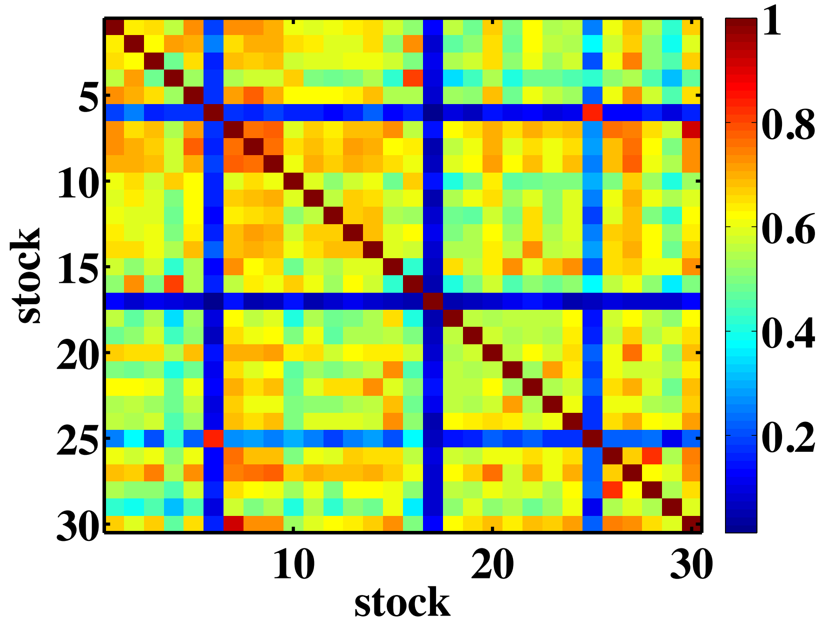
$$PC(i,j\mid m)=\frac{C(i,j)-C(i,m)\cdot C(j,m)}{\sqrt{\left(1-C^2(i,m)\right)\cdot\left(1-C^2(j,m)\right)}}$$

PARTIAL CORRELATION:

The partial correlation (residual correlation) between *i* and *j* given *m*, is the correlation between *i* and *j* after removing their dependency on *m*; thus, it is a measure of the correlation between *i* and *j* after removing the affect of *m* on their correlation

Quantifying functional relationships

Correlation



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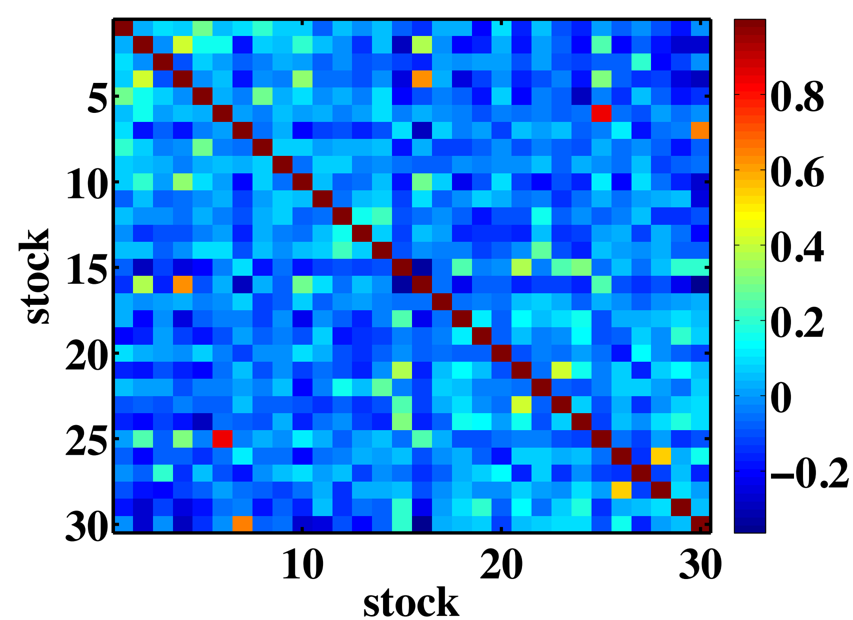

$$C(i,j) = \frac{\left\langle \left(r_i - \langle r_i \rangle\right) \cdot \left(r_j - \langle r_j \rangle\right) \right\rangle}{\sigma_i \cdot \sigma_j}$$

$$PC(i,j \mid m) = \frac{C(i,j) - C(i,m) \cdot C(j,m)}{\sqrt{\left(1 - C^2(i,m)\right) \cdot \left(1 - C^2(j,m)\right)}}$$

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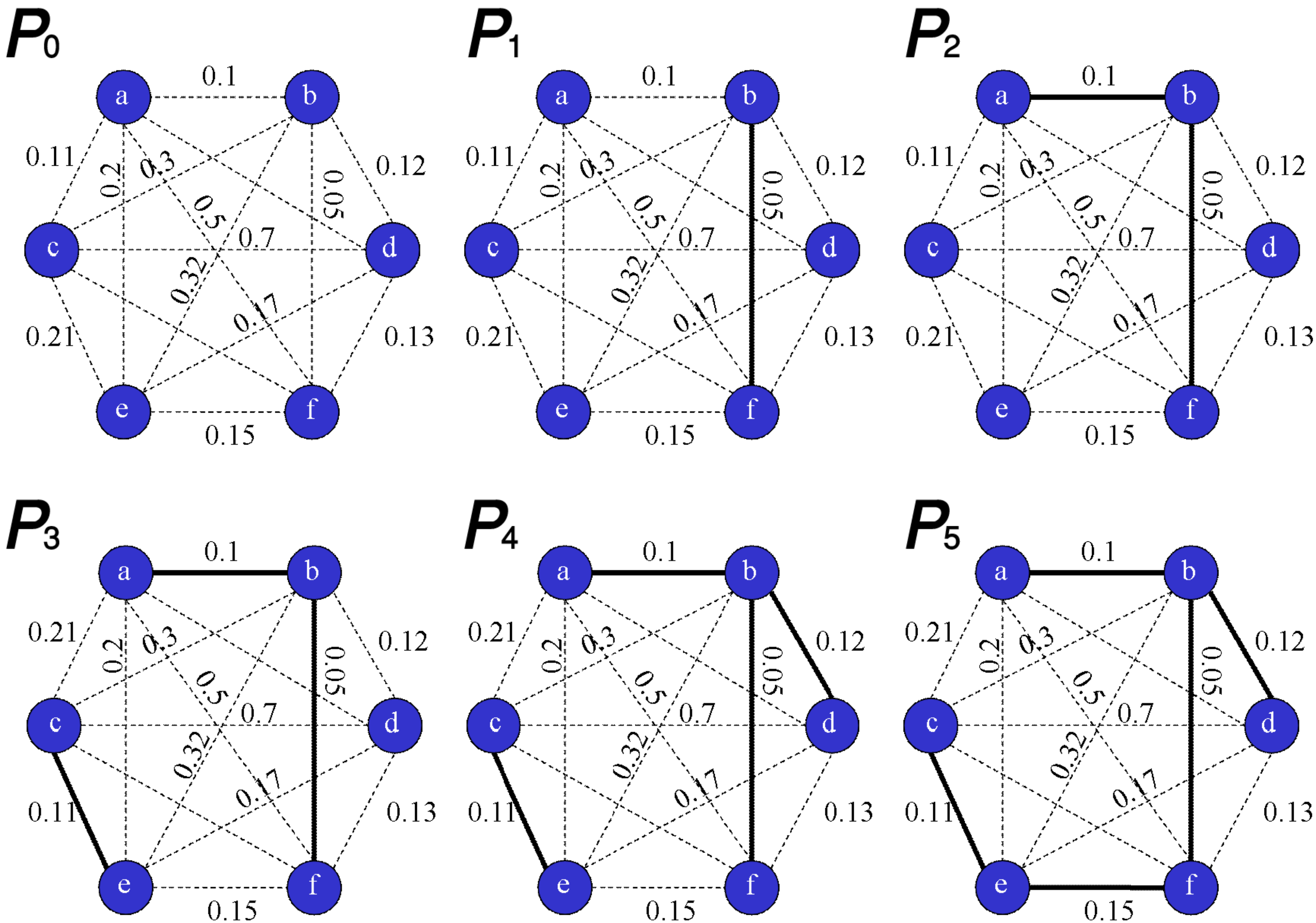
	a	b	c	d	e	f
a	0	0.1	0.11	0.4	0.2	0.5
b	0.1	0	0.3	0.12	0.32	0.05
c	0.11	0.3	0	0.7	0.21	0.5
d	0.4	0.12	0.7	0	0.17	0.13
e	0.2	0.32	0.21	0.17	0	0.15
f	0.5	0.05	0.5	0.13	0.15	0



P0
a
b
c
d
e
f
0.1
0.11
0.12
0.2
0.3
0.05
0.5
0.7
0.32
0.17
0.21
0.13
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P1
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0.7
0.32
0.17
0.11
0.13
0.15
P4
a
b
c
d
e
f
0.1
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0.12
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a
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0.32
0.17
0.11
0.13
0.15

Stock Dependency Networks

1. Calculate partial correlation $PC(i,k \mid j) \quad j = 1,2,\ldots,N$

2. Correlation Influence

$$D(i,k \mid j) \equiv C(i,k) - PC(i,k \mid j)$$

3. Dependency Matrix $d(i \mid j) = \frac{1}{N-1} \sum_{k \neq j,i}^{N-1} D(i,k \mid j)$

4. Construct Planar Graph (PMFG, Tumminello *et al., PNAS 2005)*

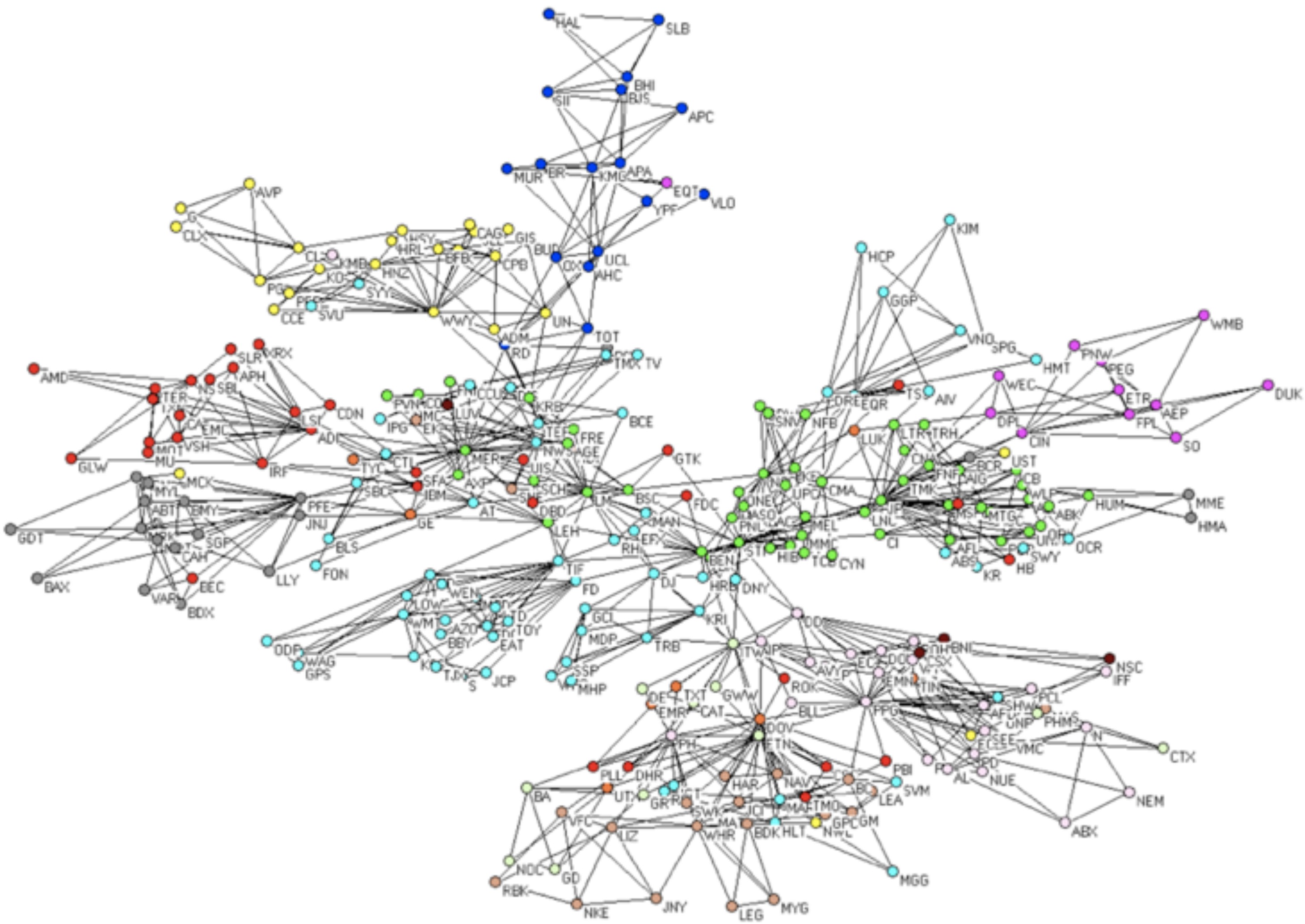
5.Influence and Relative Influence $R_u(s) = \frac{o(s) - i(s)}{o(s) + i(s)}$

Data

N = 300 T = 748

Index	Sector	# stocks
1	Basic Materials	24
2	Consumer Cyclical	22
3	Consumer Non Cyclical	25
4	Capital Goods	12
5	Conglomerates	8
6	Energy	17
7	Financial	53
8	Healthcare	19
9	Services	69
10	Technology	34
11	Transportation	5
12	Utilities	12

Stock Dependency Network: S&P Stocks



D.Y. Kenett, M. Tumminello, A. Madi, G. Gur-Gershgoren, R.N. Mantegna and E. Ben Jacob (2010), Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market, PLoS ONE 5(12) e15032, doi:10.1371/journal.pone.0015032

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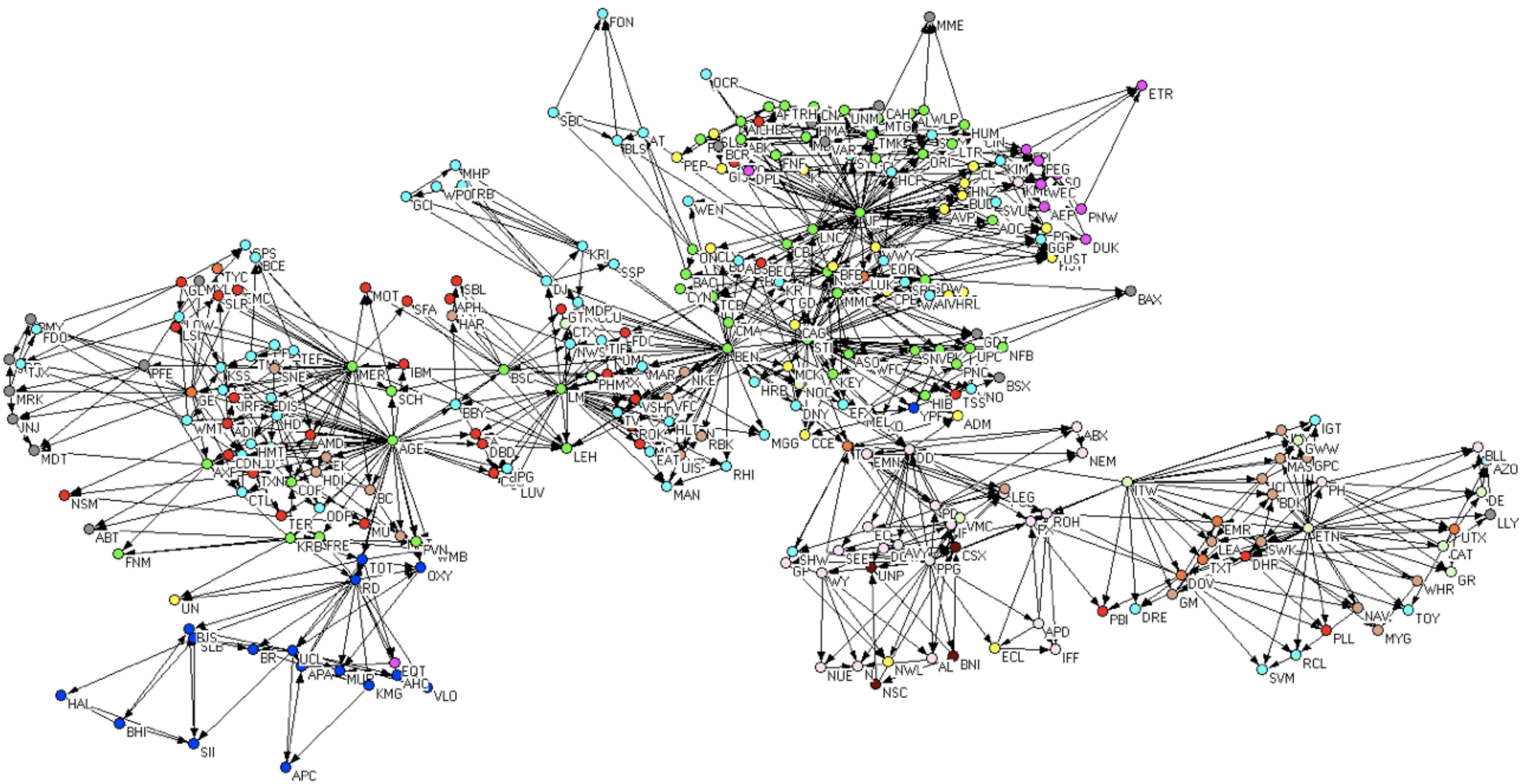

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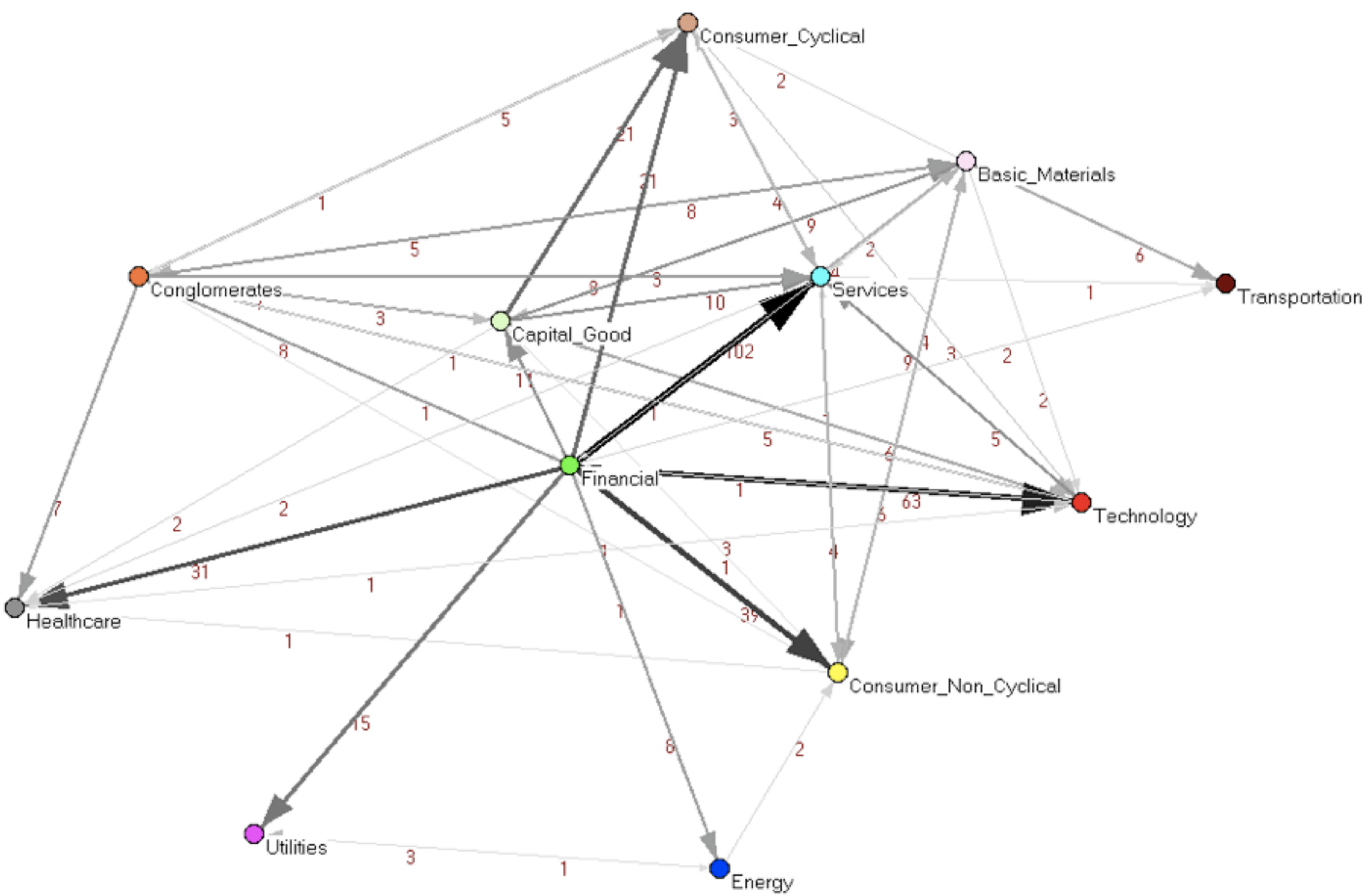
Sector Dependency Network



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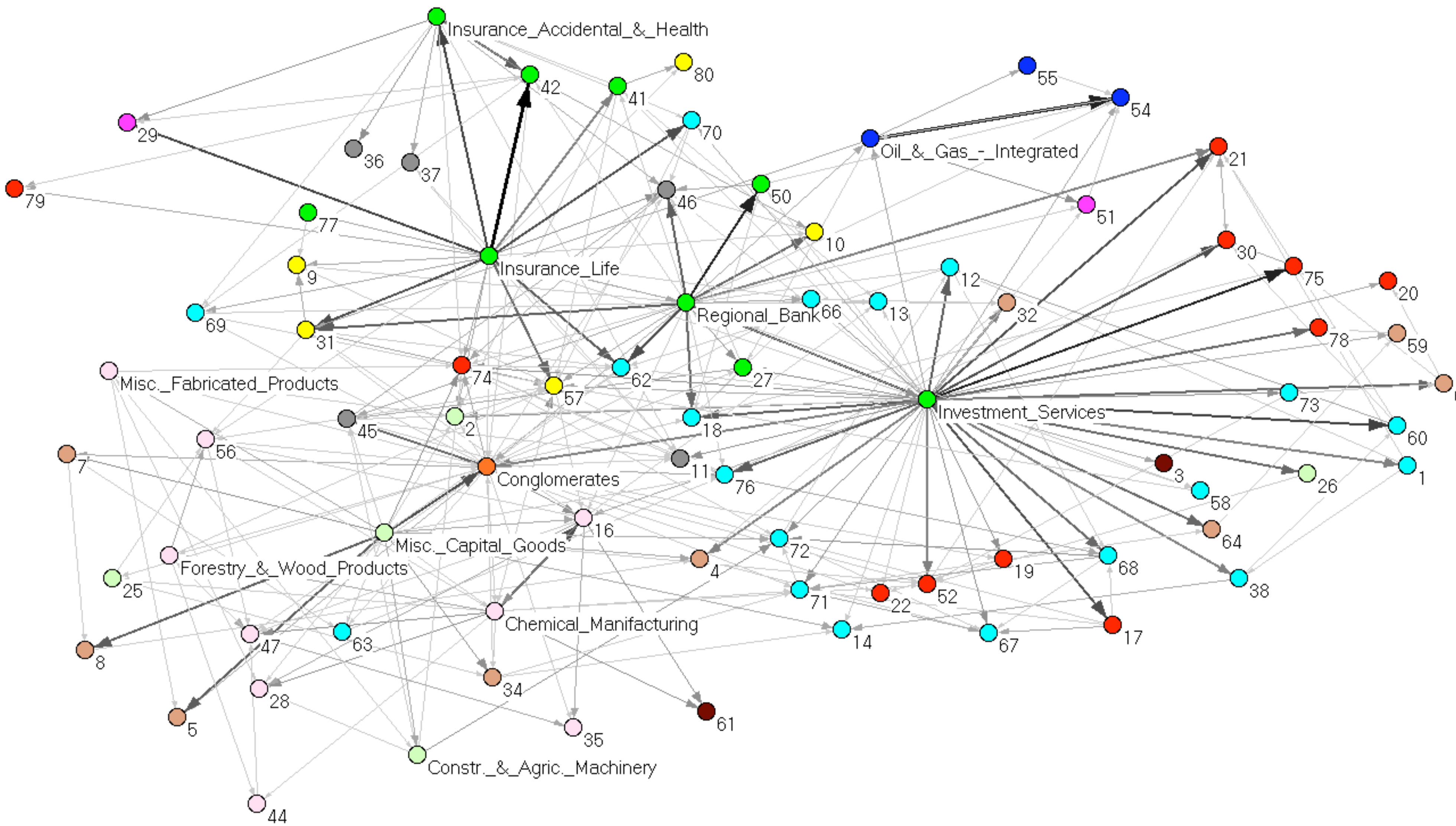


Factor models

Factor models are simple and widespread model of multivariate time series

A general multifactor model for N variables $x_i(t)$ is

$$x_i(t) = \sum_{j=1}^{K} \gamma_i^{(j)} f_j(t) + \gamma_i^{(0)} \epsilon_i(t)$$

$\gamma_i^{(j)}$ is a constant describing the weight of factor j in explaining the dynamics of the variable $x_i(t)$.

The number of factors is K and they are described by the time series $f_j(t)$.

$\epsilon_i(t)$ is a (Gaussian) zero mean noise with unit variance

Factor models: examples

<u>Multifactor models</u> have been introduced to model a set of asset prices, generalizing CAPM

$$\mathbf{R}(t) = \mathbf{a} + \mathbf{B}\mathbf{f}(t) + \epsilon(t)$$

where now **B** is a (NxK) matrix and **f**(t) is a (Kx1) vector of factors.

The factors can be selected either on a theoretical ground (e.g. interest rates for bonds, inflation, industrial production growth, oil price, etc.) or on a statistical ground (i.e. by applying factor analysis methods, etc.)

Examples of multifactor models are Arbitrage Pricing Theory (Ross 1976) and the Intertemporal CAPM (Merton 1973).

Factor models and Principal Component Analysis (PCA)

A factor is associated to each relevant eigenvalue-eigenvector

Number of relevant eigenvalues

i-th component of the h-th eigenvector of *C*

$$x_i(t) = \sum_{h=1}^{K} \gamma_i^{(h)} \sqrt{\lambda_h}\, f^{(h)}(t) + \sqrt{1 - \sum_{h=1}^{K} {\gamma_i^{(h)}}^2 \lambda_h}\; \varepsilon_i(t)$$

h-th eigenvalue **h-th factor** **Idiosyncratic term**

$f^{(h)}(t)$ for $h = 1,\ldots,K$ and $\varepsilon_i(t)$ for $i = 1,\ldots,n$

are i.i.d. random variables with mean 0 and variance 1

How many eigenvalues should be included ?

Random Matrix Theory

The idea is to **compare** the properties of an **empirical correlation matrix C with the** null hypothesis of a **random matrix.**

$$Q = T/N \geq 1 \ \text{fixed}; \quad T \to \infty; \quad N \to \infty$$

Density of eigenvalues of a Random Matrix

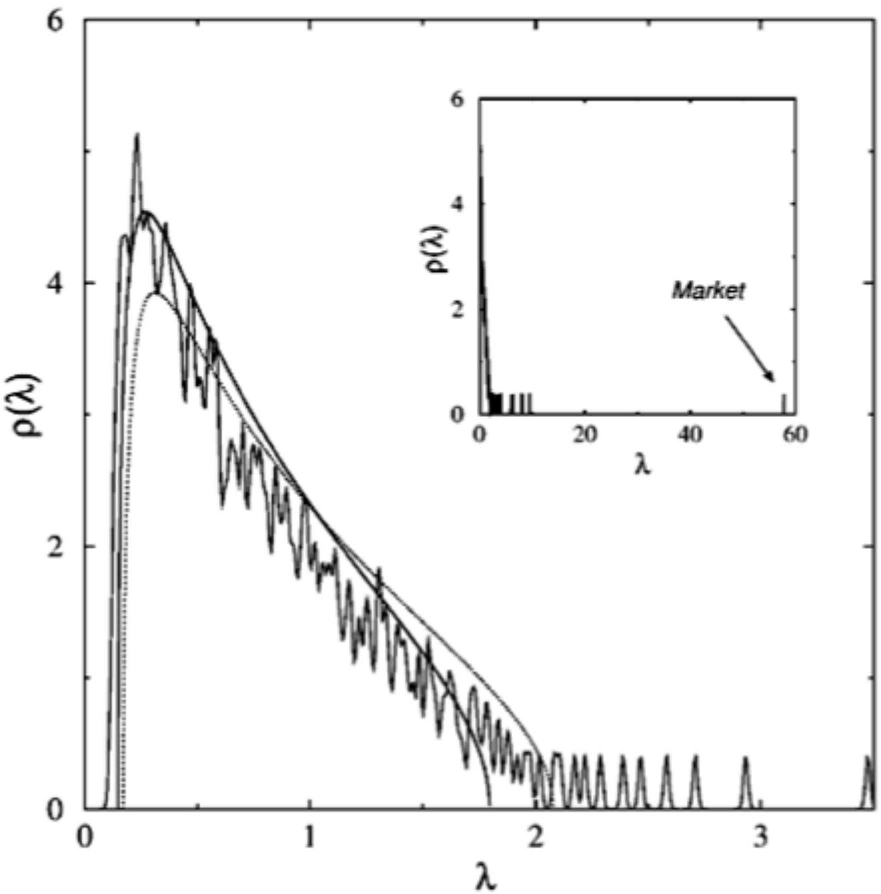
$$\rho(\lambda) = \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_{MAX} - \lambda)(\lambda - \lambda_{MIN})}}{\lambda}$$

$$\lambda_{MIN}^{MAX} = \sigma^2\left(1 + 1/Q \pm 2\sqrt{1/Q}\right)$$

For correlation matrices $\sigma^2 = 1$

Random Matrix Theory

Random Matrix Theory helps to select the relevant eigenvalues



$N = 406$ assets of the

S & P 500 (1991-1996)

Q = 3.22

$$\sigma^2 = 1 - \frac{1}{\lambda_1} \cong 0.85 \text{ (dotted line)}$$

$$\text{best fit: } \sigma^2 = 0.74 \text{ (solid line)}$$

V. Plerou et al.
PRL 83, 1471 (1999)
L.Laloux et al,
PRL 83, 1468 (1999)

Theoretical Models

Simple Index

$$r_i = \gamma_i f + \sqrt{1-\gamma_i^2 f}\,\varepsilon_i, \qquad i = 1,\dots,N,$$

$$\langle r_i f \rangle = \gamma_i \langle f^2 \rangle = \gamma_i,$$

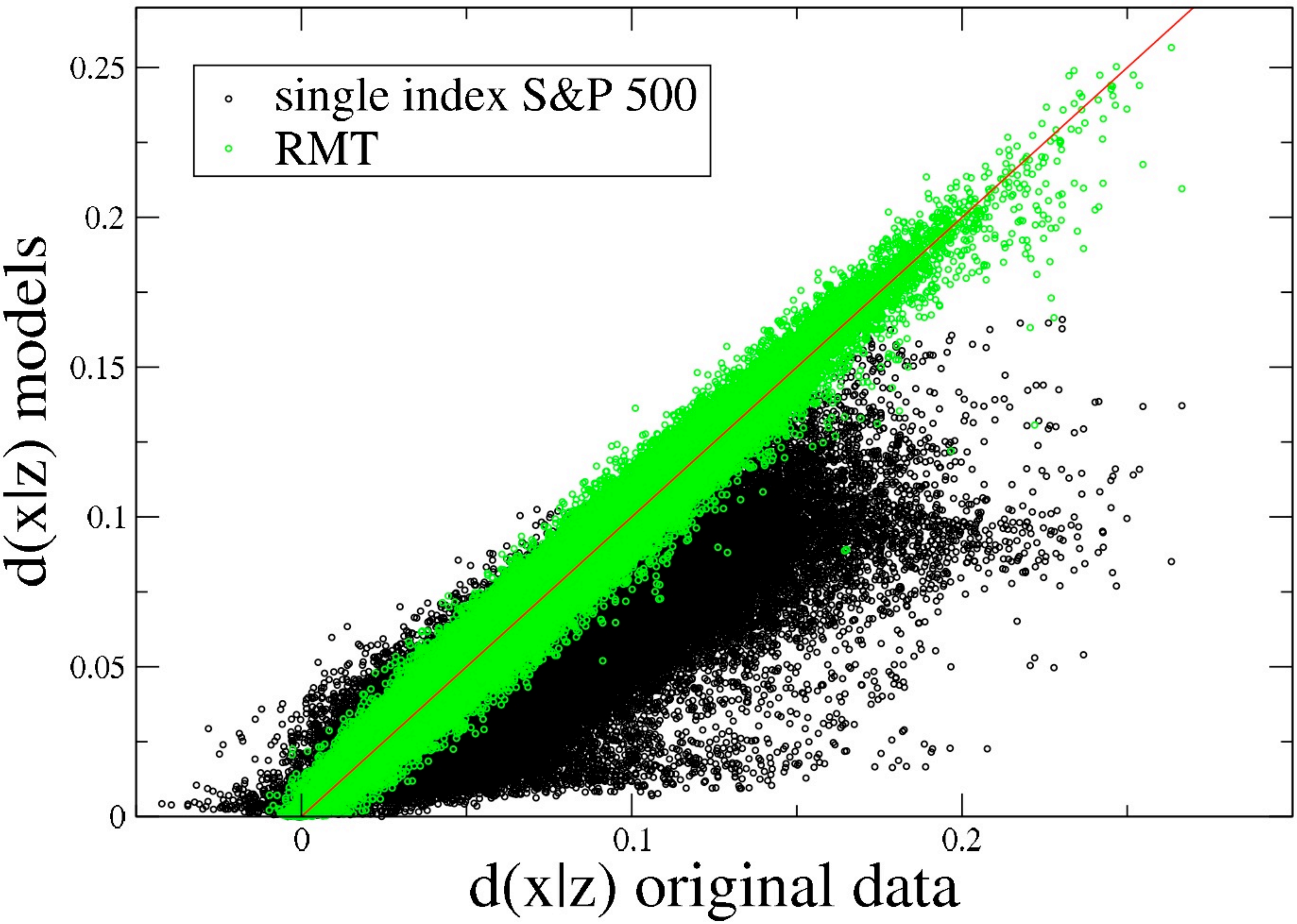
$$\rho_{i,j}(SI) = \langle r_i\, r_j \rangle = \gamma_i\, \gamma_j$$

RMT

$$r_i = \sum_{h=1}^{K} \gamma_{i,h} \sqrt{\lambda_h} f_h + \sqrt{1 - \sum_{h=1}^{k} \gamma_{i,h}^2 \lambda_h \varepsilon_i} \qquad i = 1,\dots,N,$$

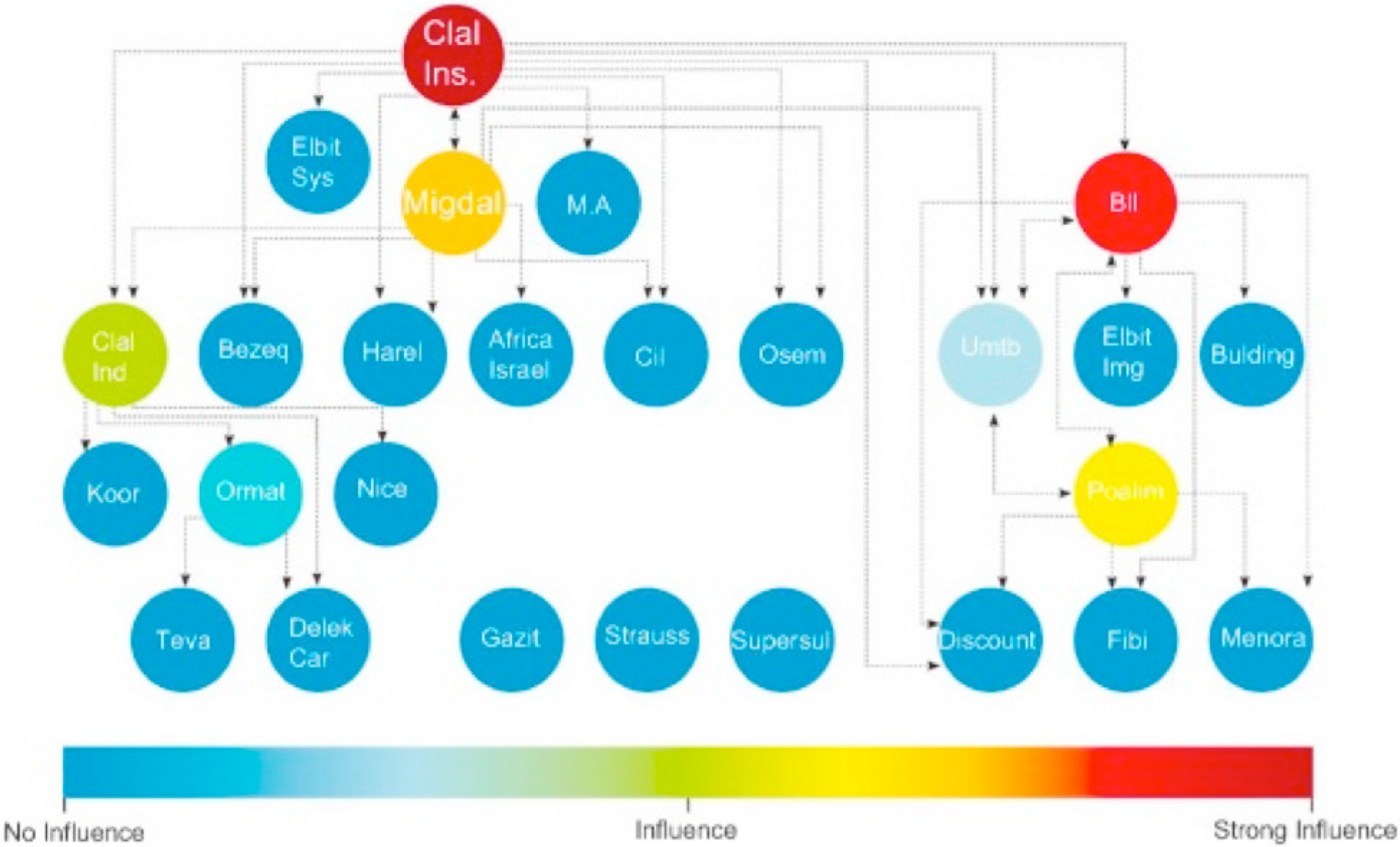
$$\lambda_{\max} = \left(1 - \frac{\lambda_1}{N}\right)\left(1 + \frac{N}{T} + 2\sqrt{\frac{N}{T}}\right)$$

$$\rho_{i,j}(RMT) = \langle r_i\, r_j \rangle = \sum_{h=1}^{K} \gamma_{i,h} \gamma_{j,h} \lambda_h$$

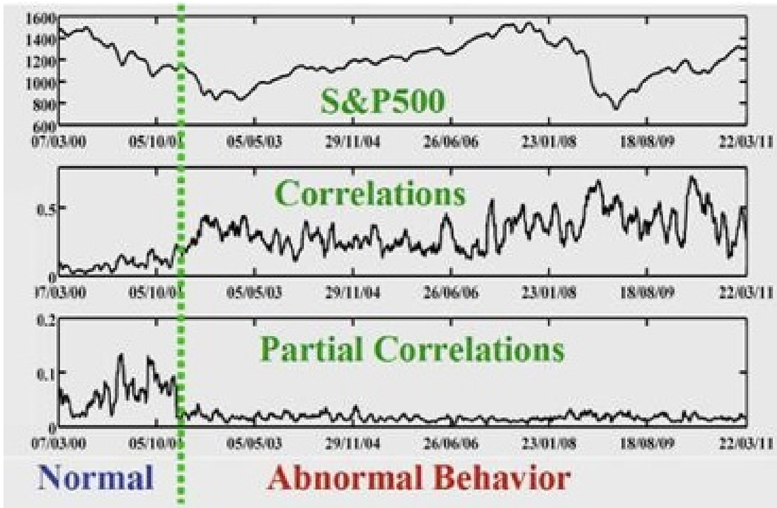


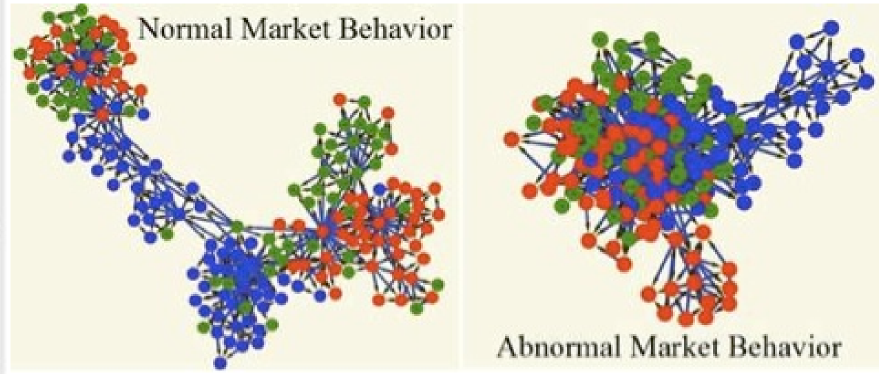
single index S&P 500
RMT
d(x|z) models
d(x|z) original data
0
0.05
0.1
0.15
0.2
0.25
0
0.1
0.2

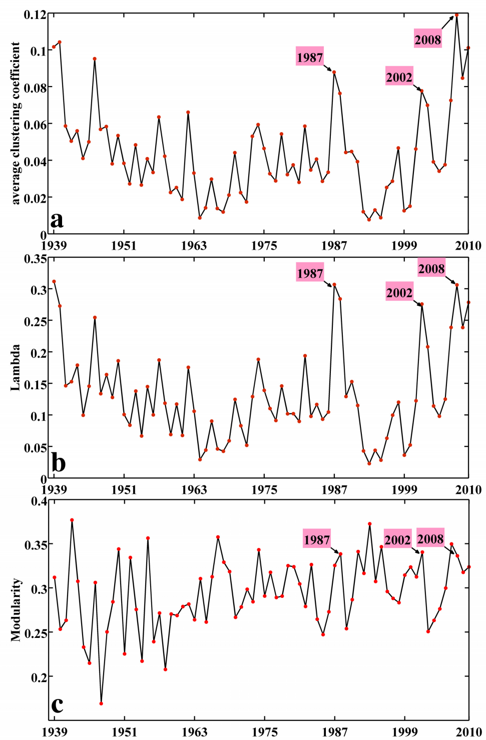
Case study - Tel-Aviv market

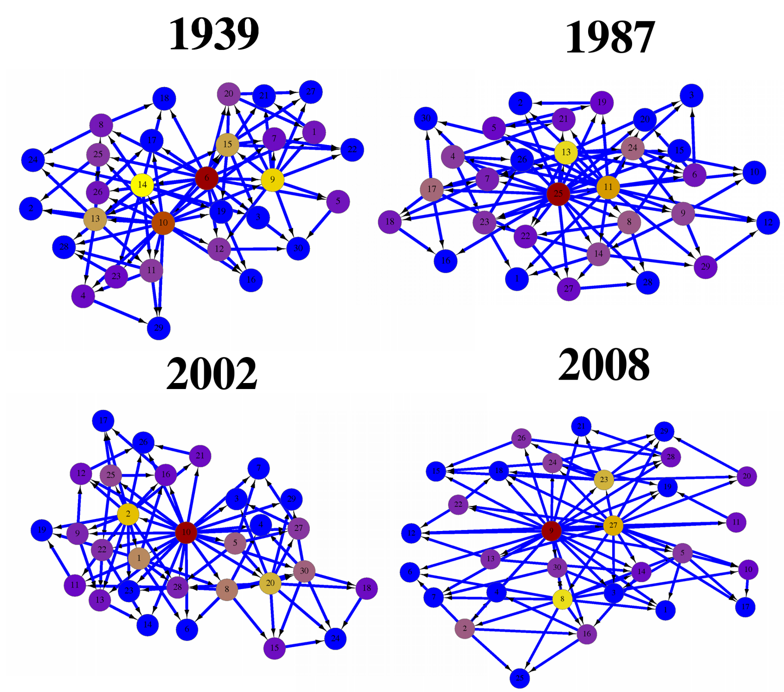


Market states







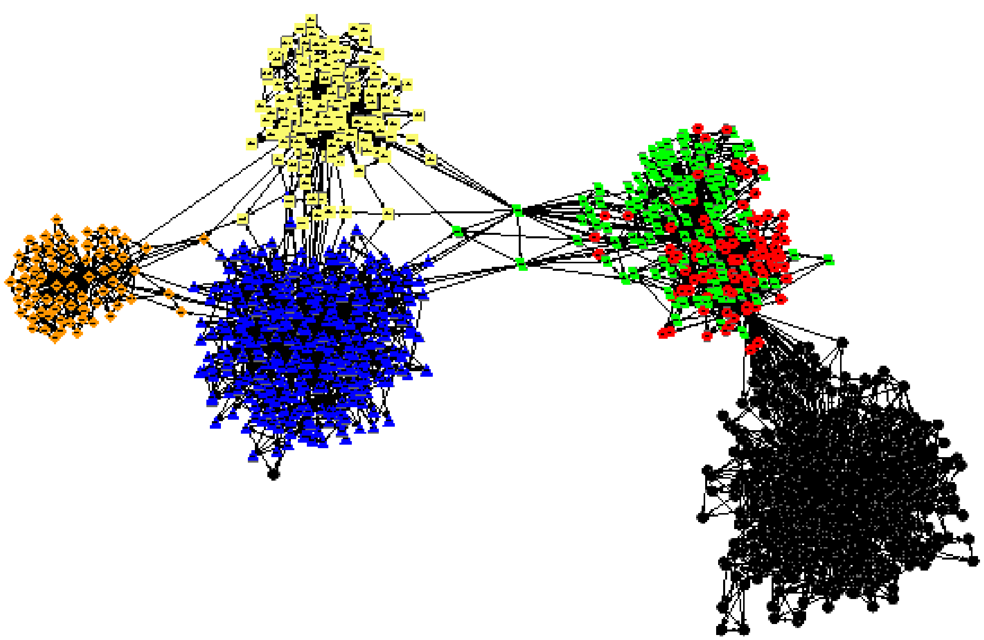


Dynamics analysis of Dependency networks

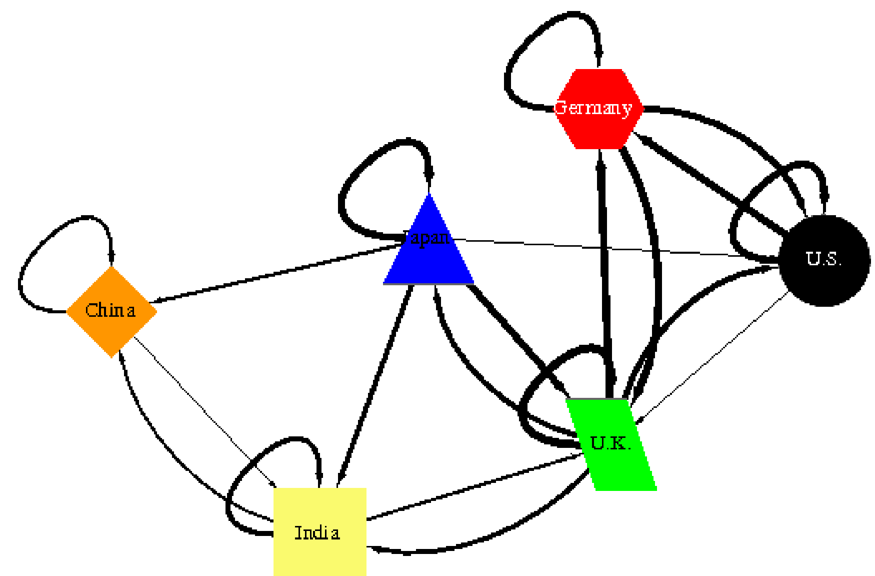
Interdependencies in the global financial village

Network analysis of influence and dependencies between Companies/Countries

Stock dependency network



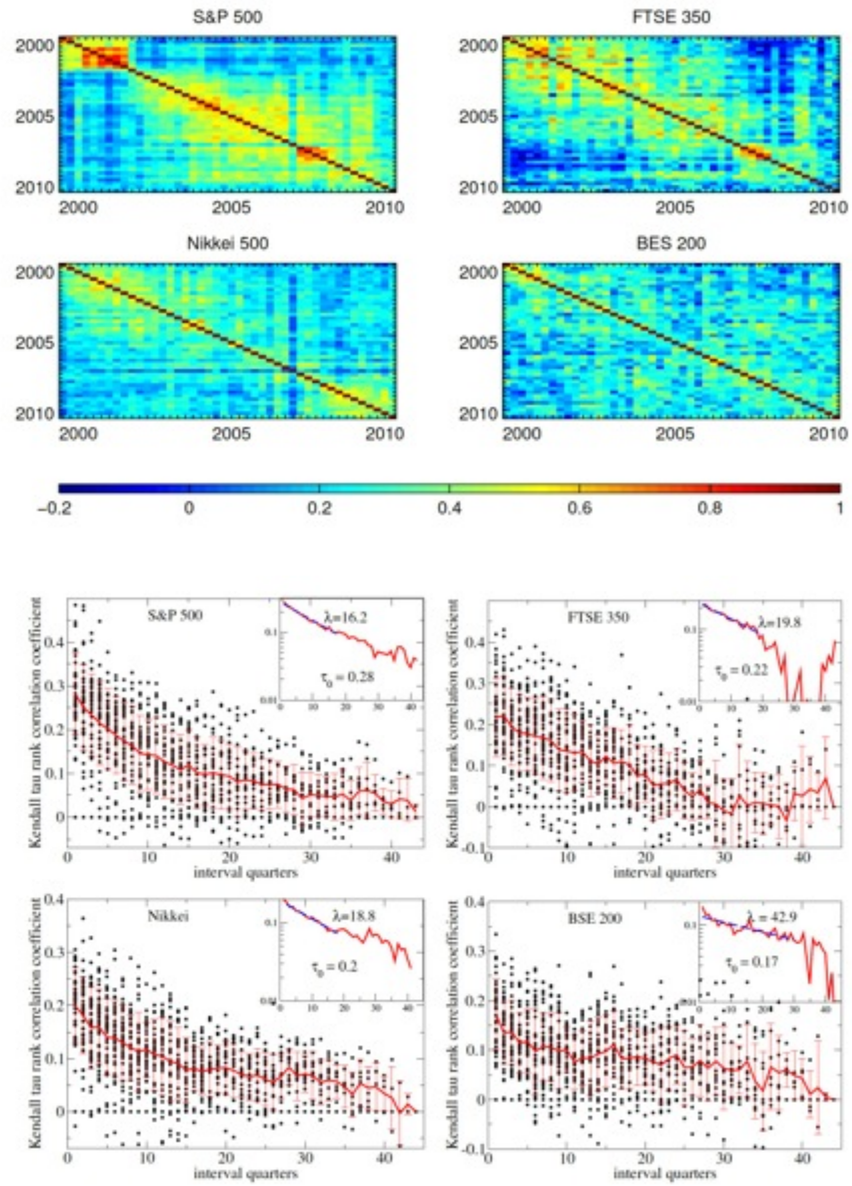
Country dependency network



Dror Y. Kenett, Matthias Raddant, Lior Zatlavi, Thomas Lux and Eshel Ben-Jacob (2012), Correlations in the global financial village, International Journal of Modern Physics Conference Series 16(1) 13-28.

Investigating market structure

2)



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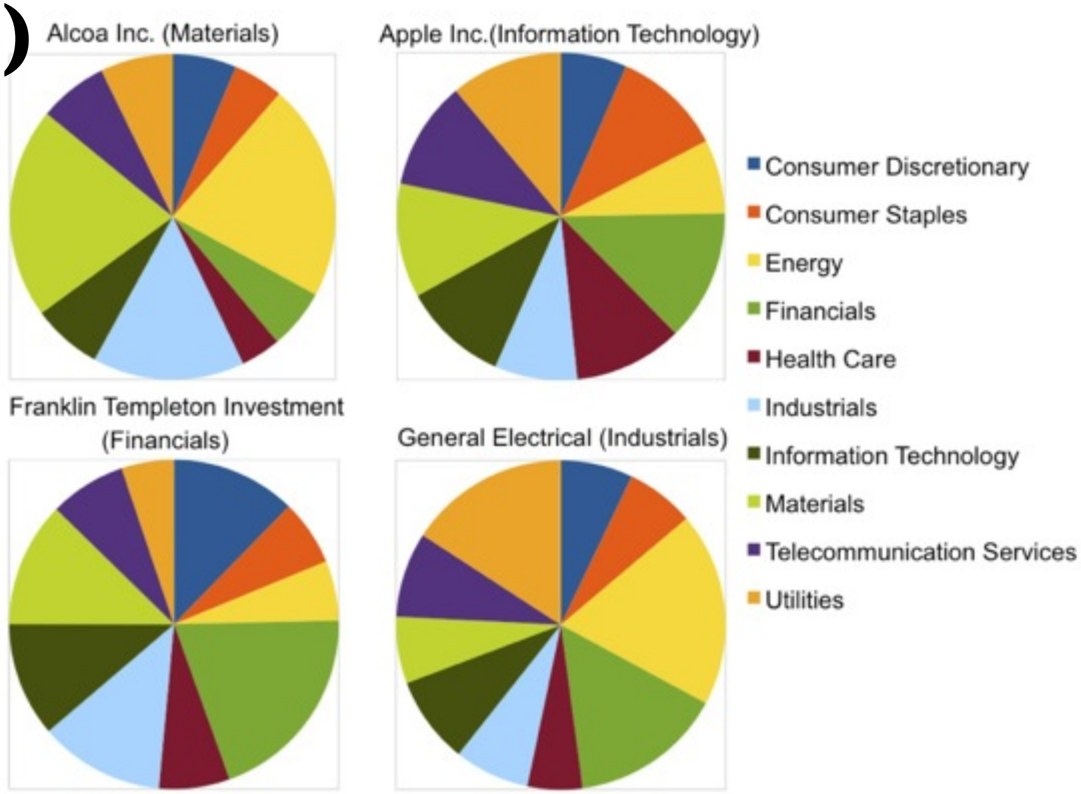
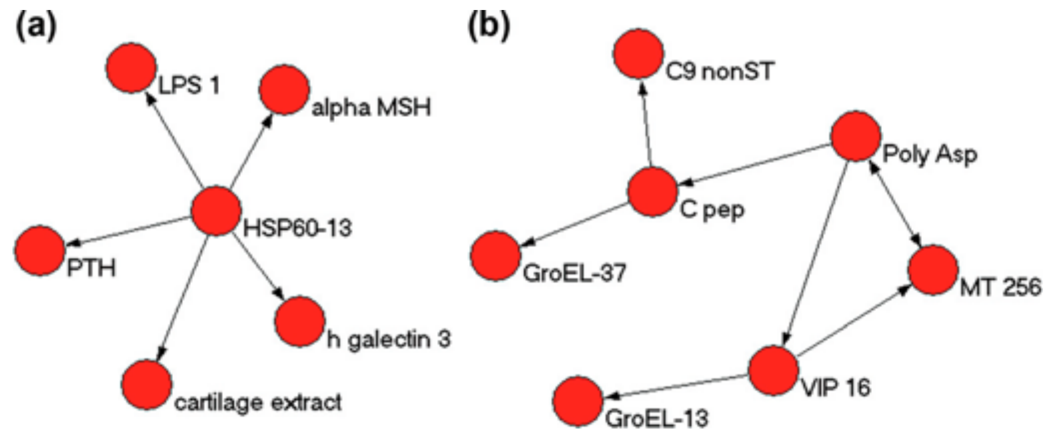
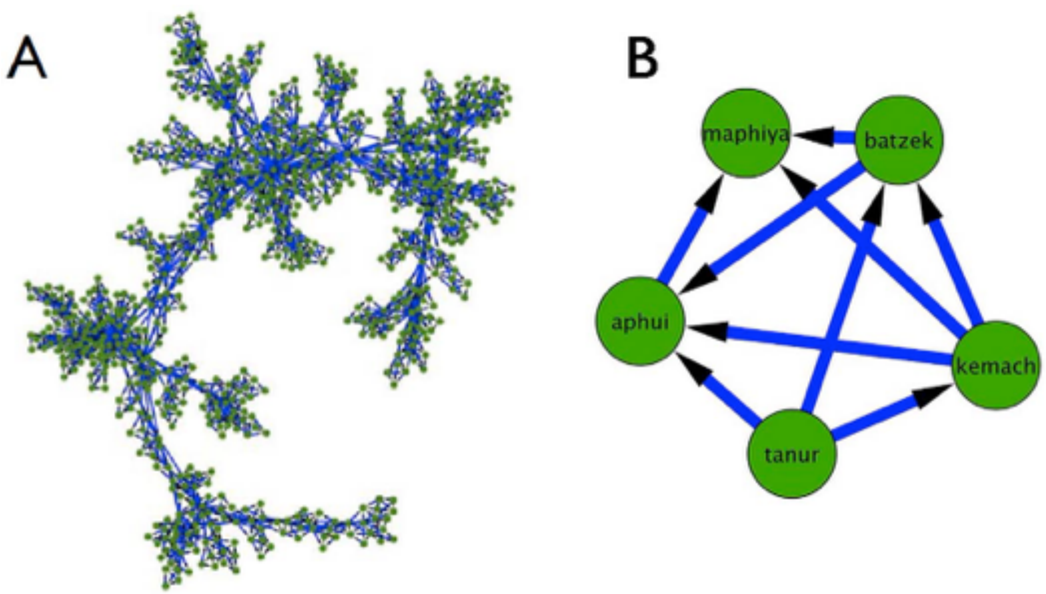


Dror Y. Kenett, Xuqing Huang, Irena Vodenska, Shlomo Havlin, and H. Eugene Stanley (2014
Applications for financial markets, arXiv:1402.1405

Application to other systems

Immune system
Dependency network





Semantic Dependency network

Outline

(1) Introduction to network science

- Terminology
- Network properties
- Matrix representation

(2) Correlation based networks

- Estimating correlations from
- Partial correlations
- Dependency network
- Node influence
- Applications in financial markets
- Applications in other systems

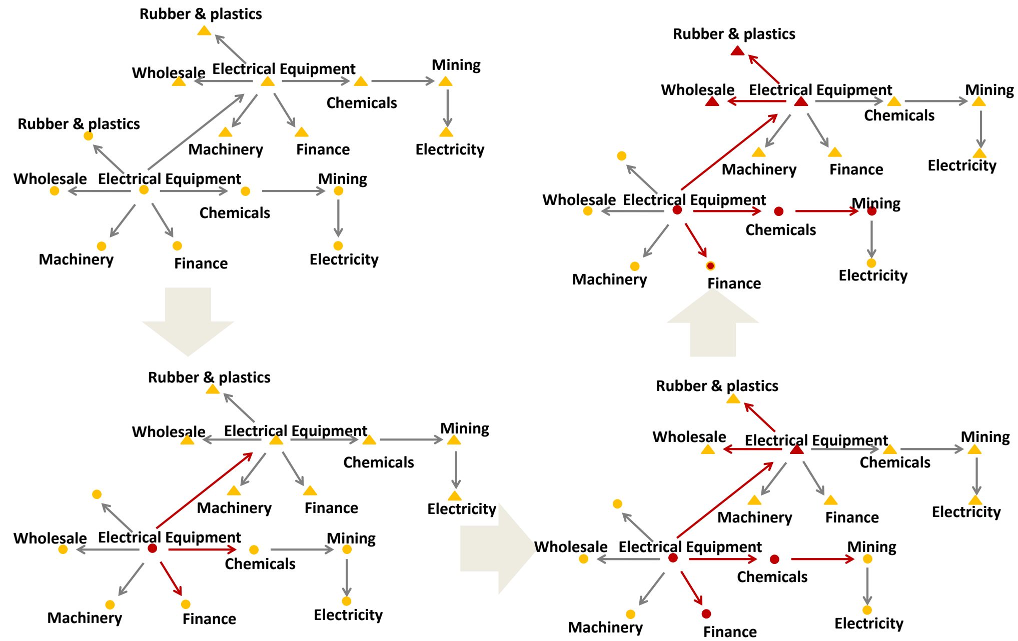
(3) Node influence

I. Cascading failures in industry networks
II. Overlapping communities in networks
III. Failure and recovery in networks
IV. Evolution of networks
V. Cascading failures in the financial system
VI. Interdependent networks

(4) Discussion

I. Cascading failures in industry networks

1)



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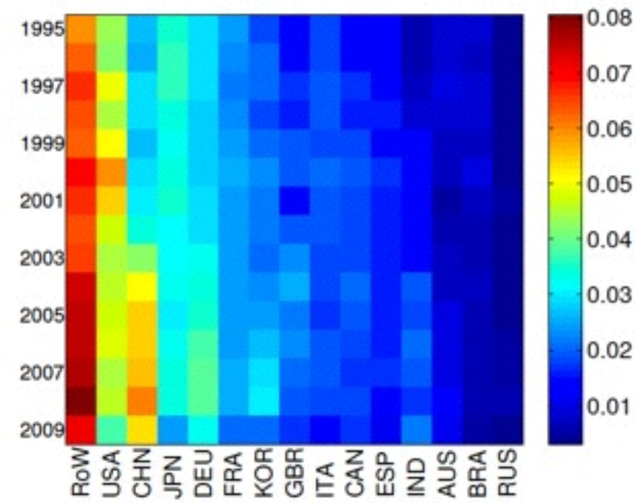

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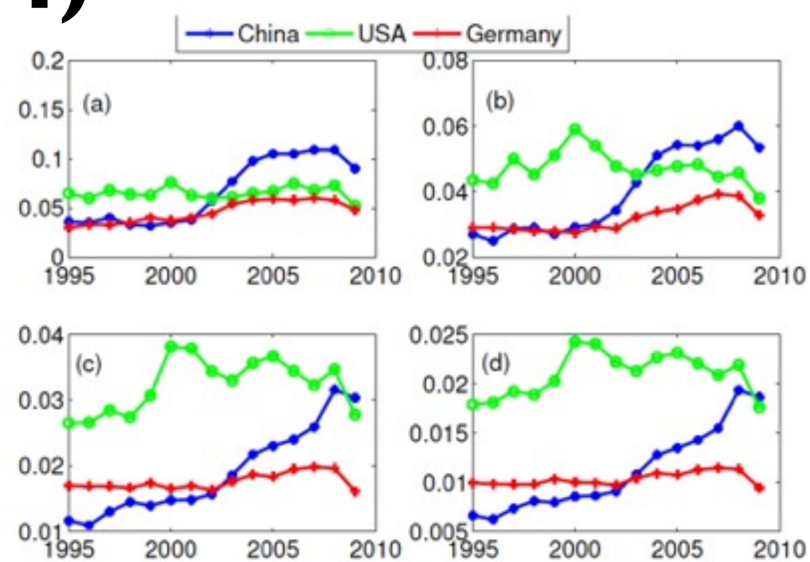

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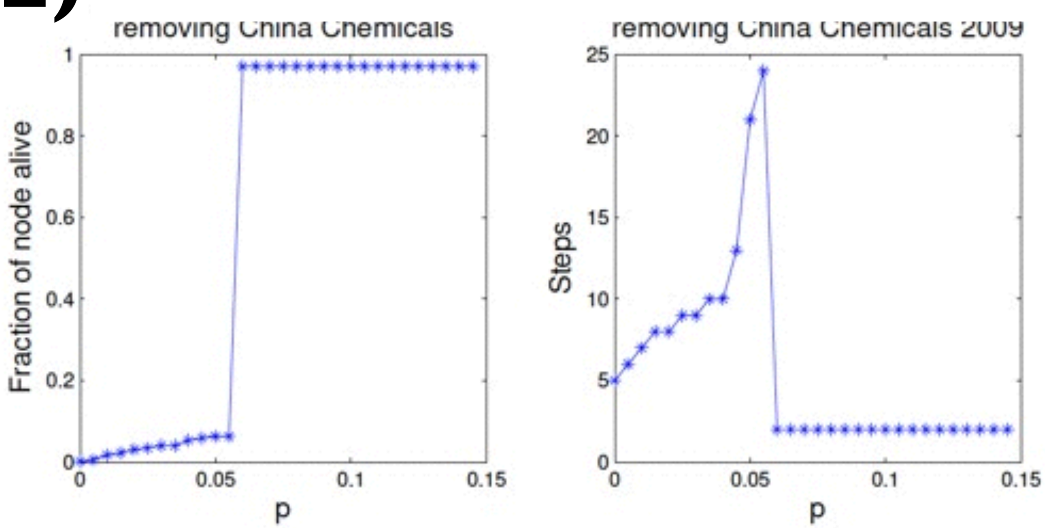
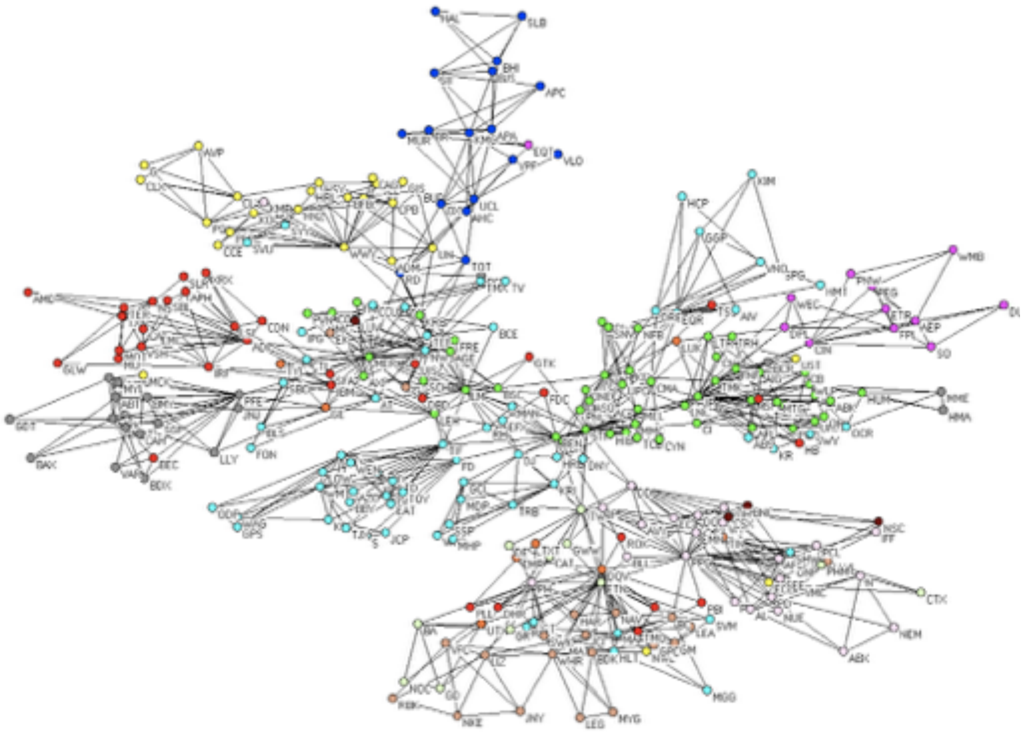
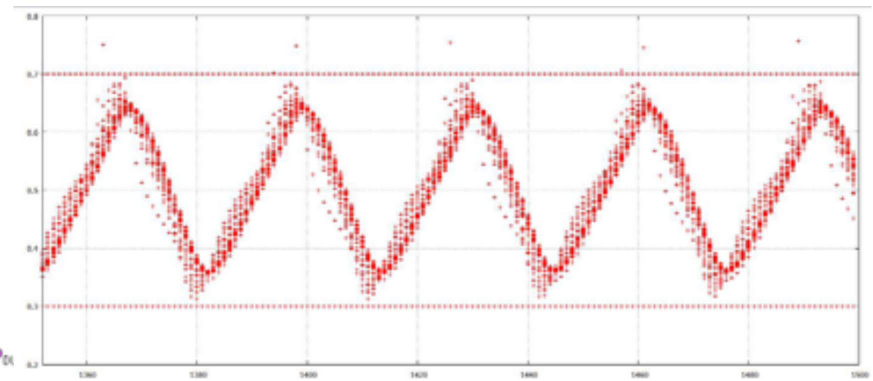
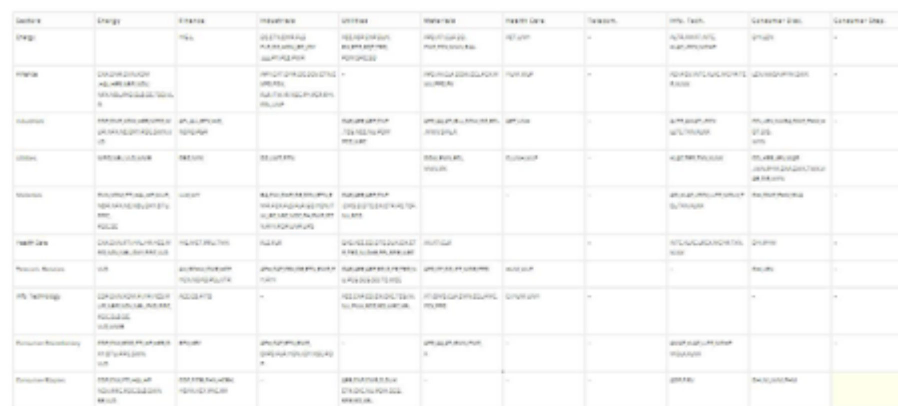


Wei Li, Dror Y. Kenett, Kazuko Yamasaki, H. Eugene Stanley, Shlomo Havlin (preprint), Ranking the economic importance of countries and industries

II. Overlapping communities



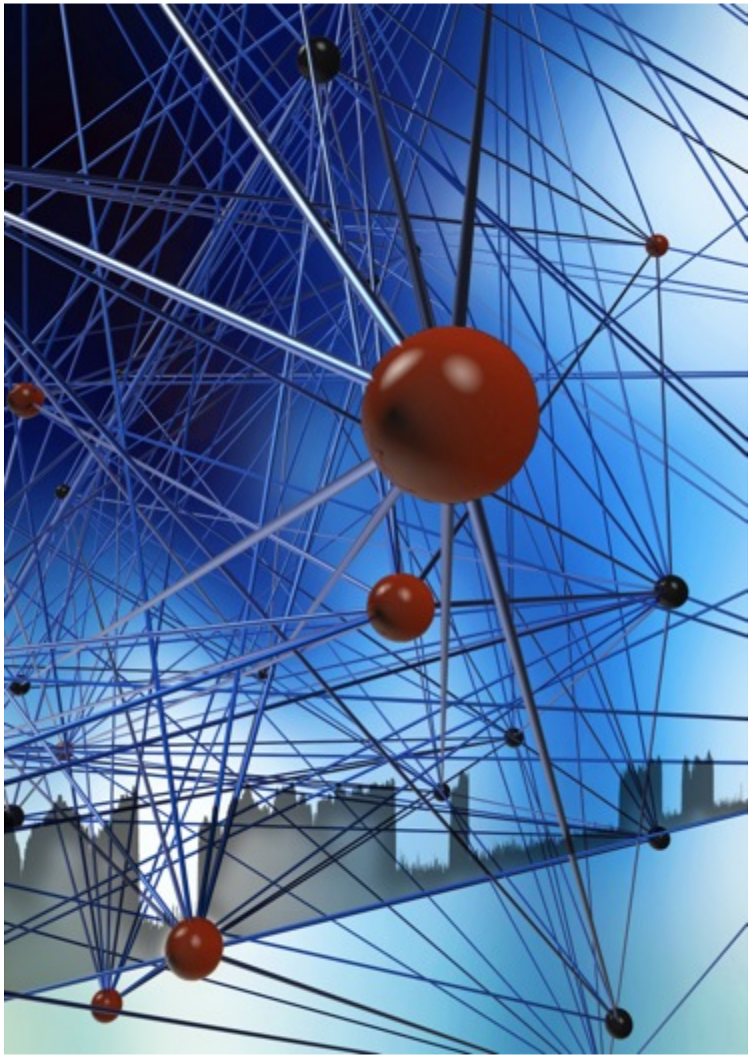


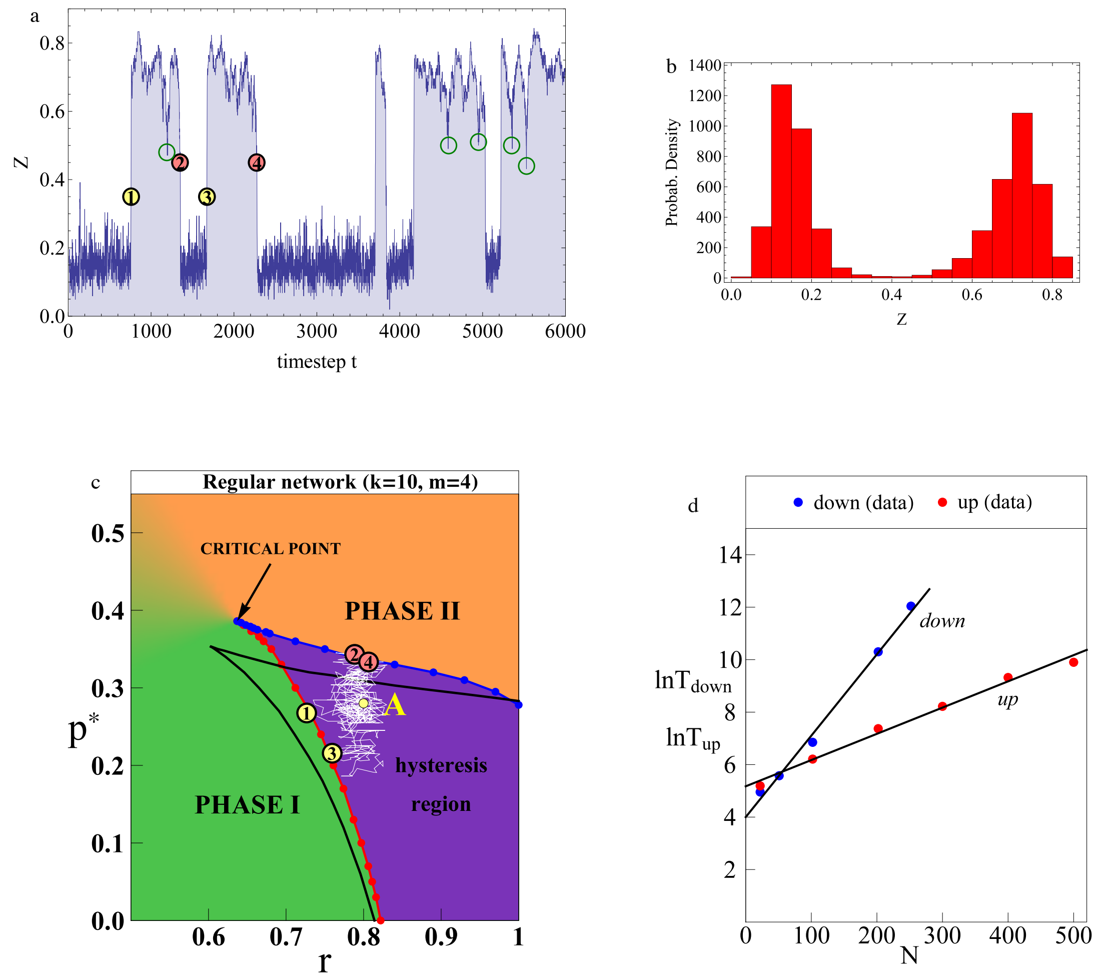


$$\dot{\phi}_i = \omega_i + \frac{d}{k_i + k_{p_i}} \sum_{i=1}^{N} \sin\left(\phi_j - \phi_i\right) + \frac{d_p k_{p,i}}{k_i + k_{p_i}} \sin\left(\phi_{p_i} + \phi_i\right) \qquad i = 1, \ldots, N$$

Ammar Tareen, Dror Y. Kenett, H. Eugene Stanley, Shlomo Havlin (preprint), Overlapping behavior of financial assets

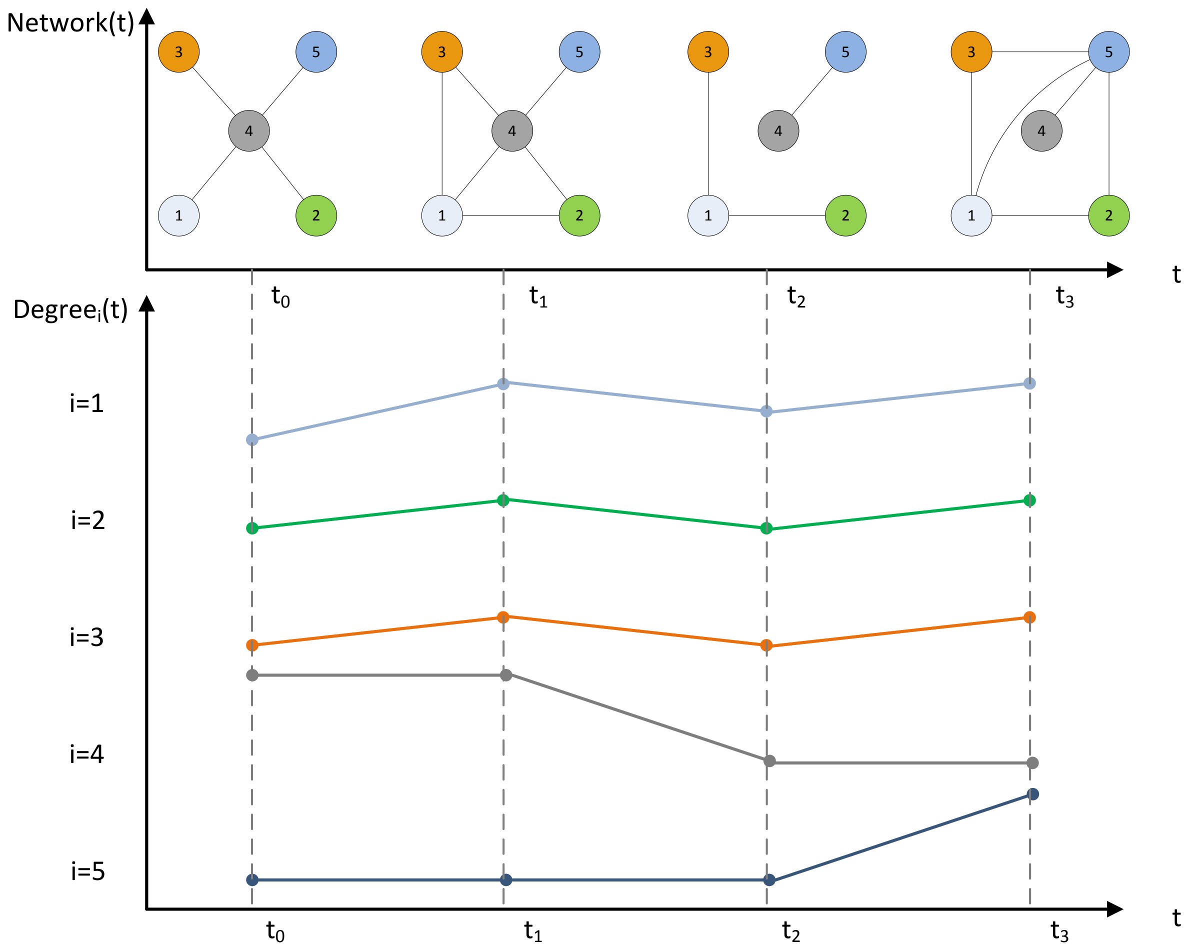
III. Failure and recovery in networks





Antonio Majdandzic, Boris Podobnik, Sergey Buldyrev, Dror Y. Kenett, Shlomo Havlin, and H. Eugene Stanley (2014), Spontaneous recovery in dynamical networks, Nature Physics 10, 34-38.

IV. Evolution of networks



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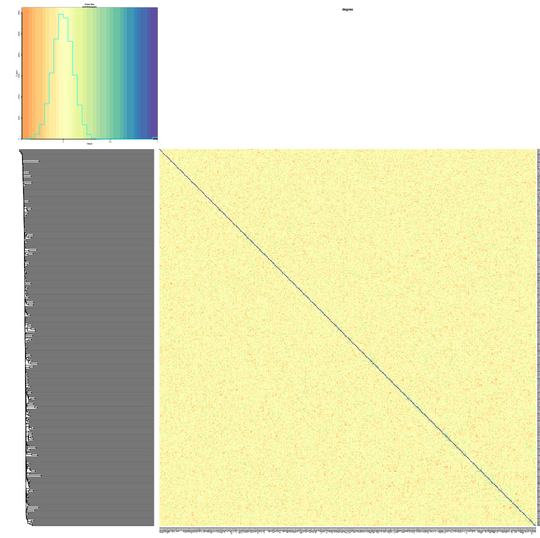

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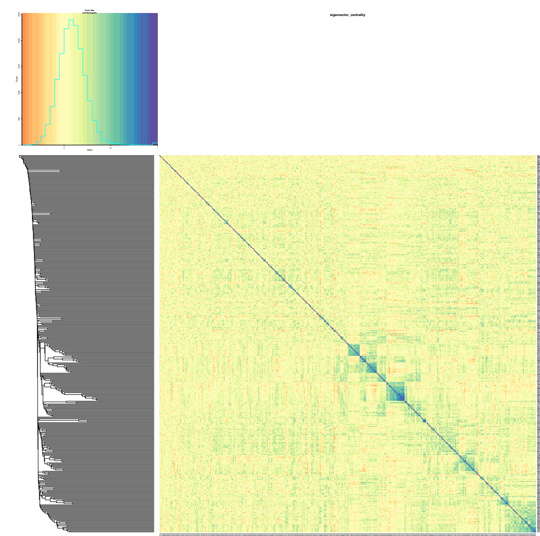
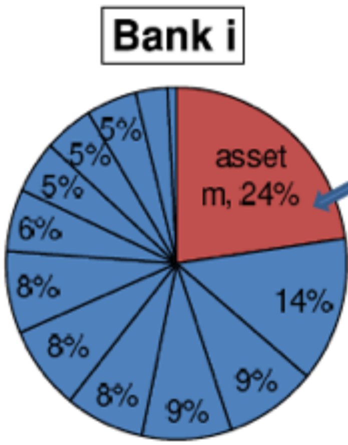
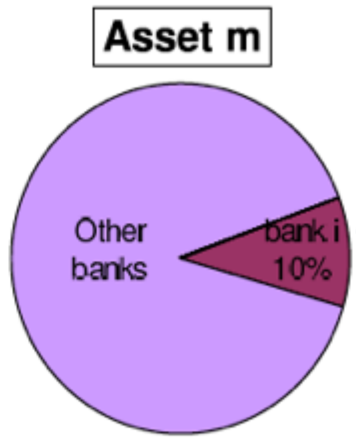


V. Cascading failures in the financial system

Bipartite Model

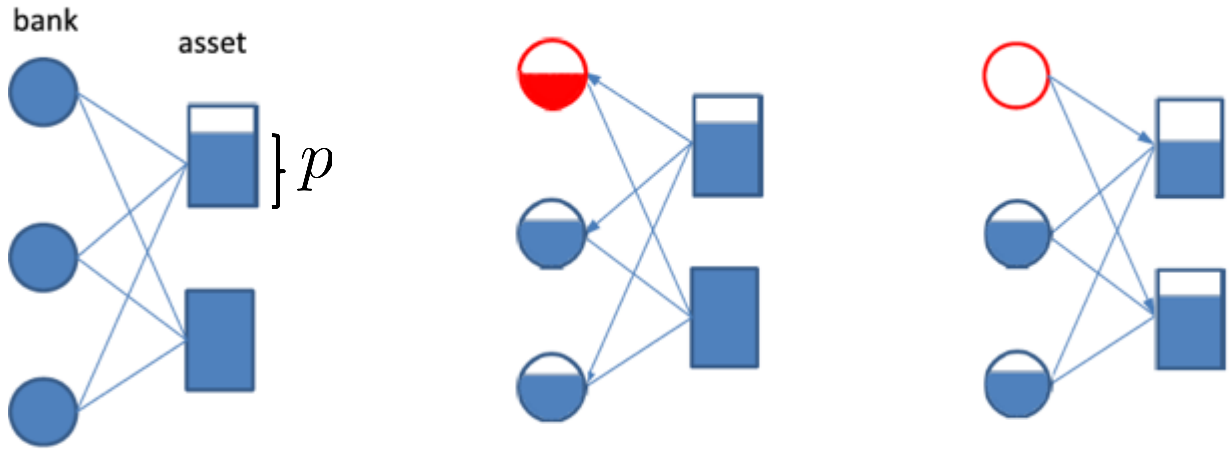


$$w_{i,m} = \frac{B_{i,m}}{B_i}$$



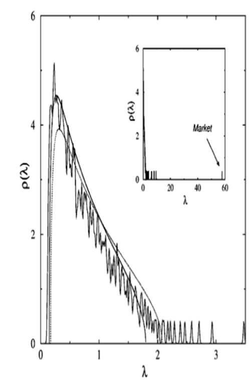
$$s_{i,m} = \frac{B_{i,m}}{A_m}$$

B_i: Total asset of bank i.
$B_{i,m}$: The amount of asset m that bank i owns.
A_m: Total market value of asset m.



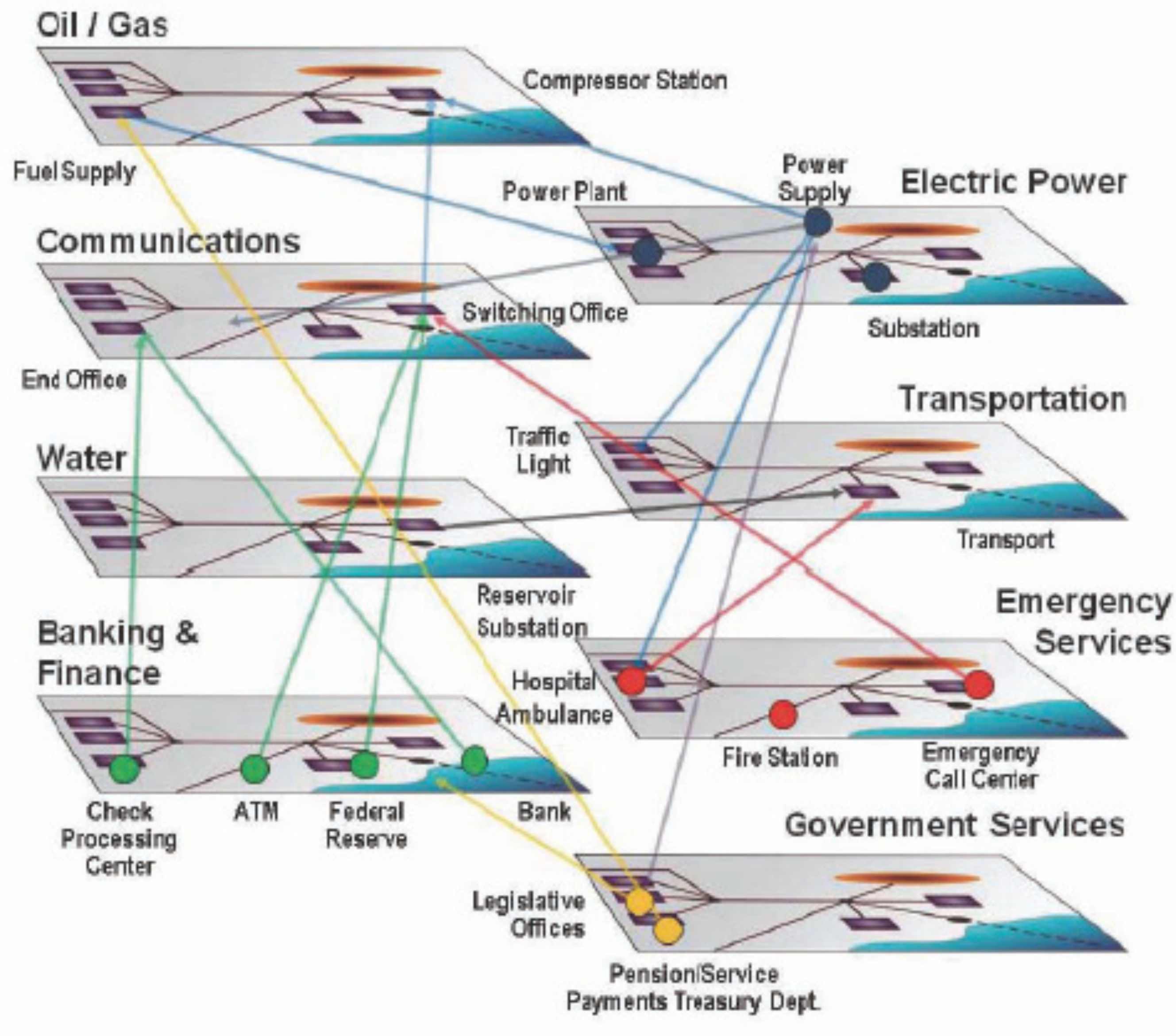
fail when asset < liability

assets depreciate $\alpha B_{i,m}$



1-p: initial shock to an asset
α : liquidity parameter
describes market's reaction to bank failure

VI. Interdependent networks



Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., & Havlin, S. (2010). Catastrophic cascade of failures in interdependent networks. Nature, 464(7291), 1025-1028.

Summary

- Dependency Networks
- Node influence
- Network in finance and economics
- Topology of networks
- Dynamics in networks and of networks
- Interdependent networks
- Cascading failures and targeted attacks
- Recovery in networks

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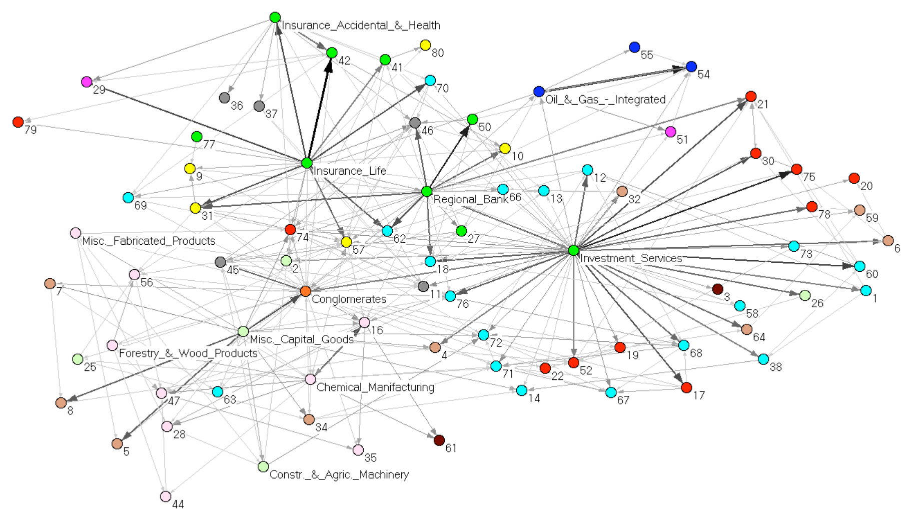
Thank You



Questions?

Email: drorkenett@gmail.com