The physics of networks. Analyzing structural properties of the EU-funded R&D projects network by computer simulations

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www.AndreasKrueger.de/networks
networks@AndreasKrueger.de

V1.04

Übersicht über den "roten Faden"

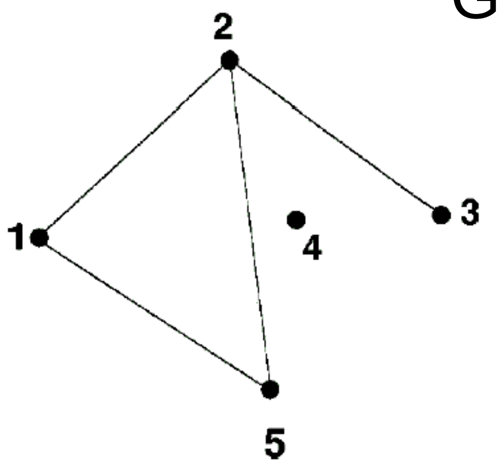
Derzeitiger Netzwerk-"Hype" der Physik:

- Graphen in Statistische-Mechanik Modellen
- Begriffsklärung, 3 wichtigste Graph-Maße
- "altes" Erdös-Renyi Zufallsgraphen Modell
- 1998: Paradigmenwechsel bei Zufallsgraphen
  → neue empirische Ergebnisse
  → neue Modelle für Zufallsgraphen
  → neue Community von Physikern

ProjektNetzwerke für Analyse von EU-finanziertem R&D:

- Organisationen und Projekte bilden bipartite Graphen
- Projektionen auf unimodale Graphen
- Struktur unserer Zusammenarbeit aus 4 Fakultäten
- Modelle, Algorithmen
- *Allererste* Simulations-Ergebnisse, Vergleich mit Empirie

Graph G=(V,E)



- node, vertex, actor, point, individual ...

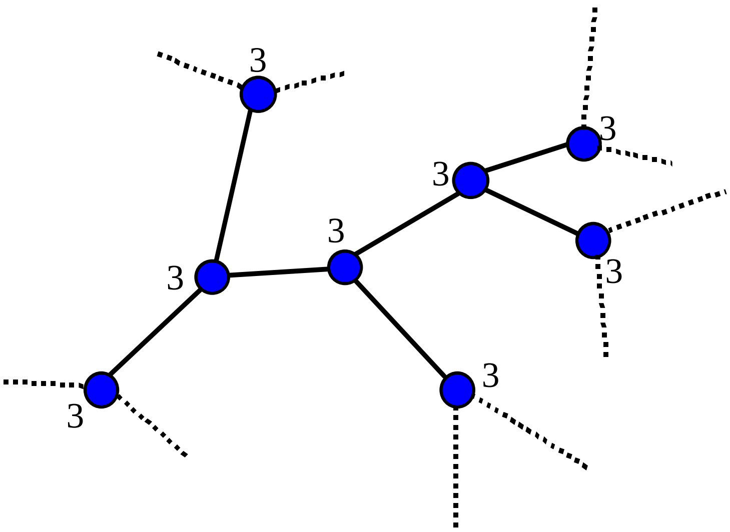
- edge, line, bond, tie, connection ...

V $\subseteq Z^+$ elements represented by dots
e.g. **V**={1,2,3,4,5}

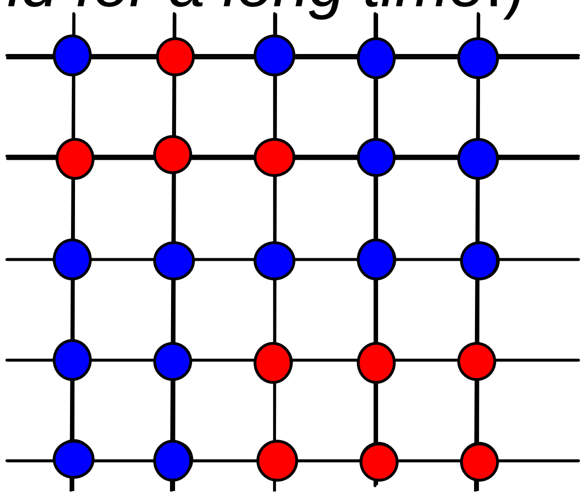
E $\subseteq$ VxV, elements represented by lines
e.g. **E**={ (1,2) , (1,5) , (2,3) , (2,5) }

Neighbours:
x~y := {$\exists$ **e**$\in$**E** with e=(x,y) or e=(y,x)}

Special cases of <u>graphs</u>: Trees, Lattices are *regular* graphs (*around for a long time*!)



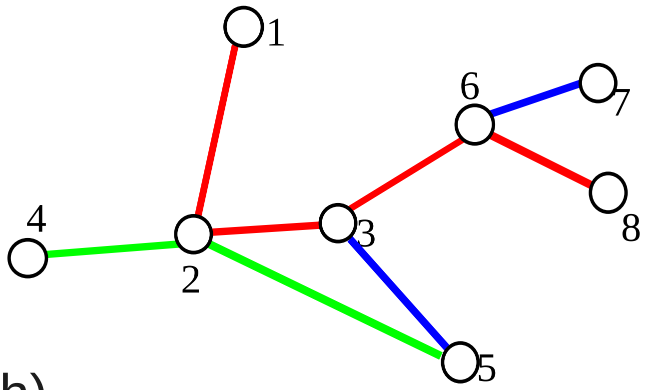
Caley-Tree with coordination number (degree) z=3
... *branching process* ...



<u>Lattice Z^2 - some processes:</u>

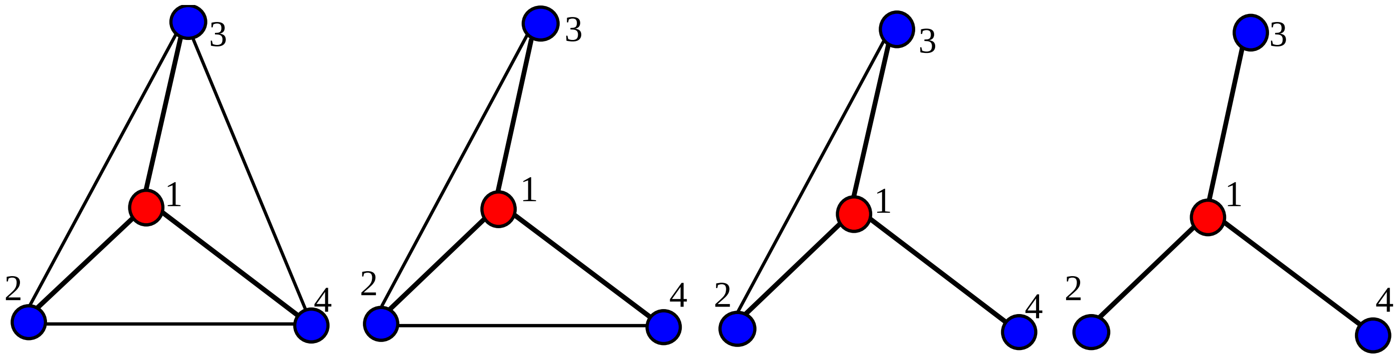
- condensed matter - crystals
- elementary particle theory
- self organized criticality (SOC)
- Ising (model magnet with *spins*)
- ...

graph measures 1: diameter, paths



- pathlength (geodesic path)
  - **Shortest** connection between 2 nodes
  - Example pathlength(1,8) = 4
- global graph-properties
  - *Diameter* = **longest** geodesic path (here 4)
  - *characteristic pathlength* = **average** of all paths (i,j)

graph measures 2: Cluster-Coefficient, Triangle Number



$C_1=1$ $C_1=2/3$ $C_1=1/3$ $C_1=0$

$$C_i = \frac{\#T_i}{k_i(k_i-1)/2}$$

$$C = \frac{1}{N}\sum_i C_i$$

(global)

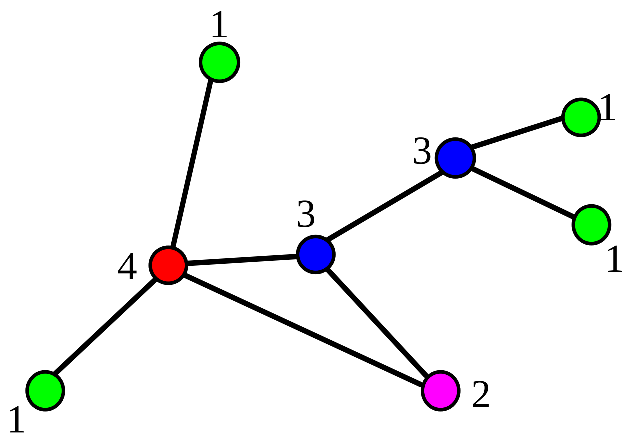
$\#T_i$ = Number of Triangles around vertex i

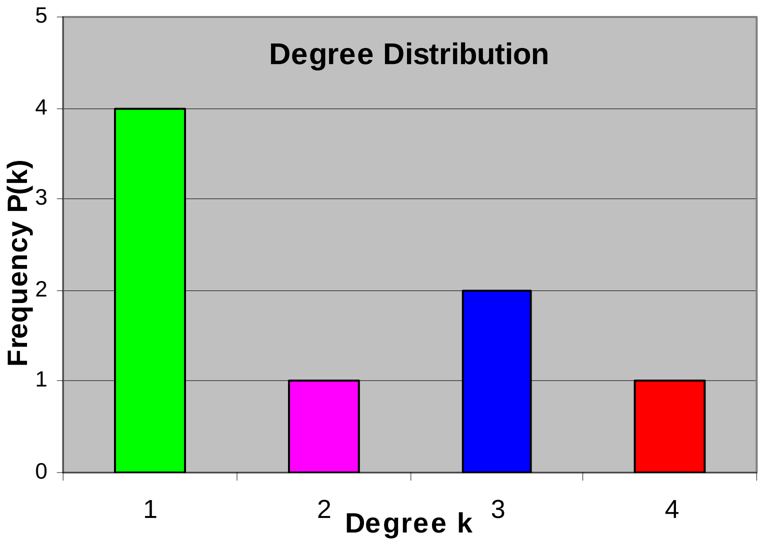
C_i: Estimator for **local density of connections**, "*how many of my friends are friends to each other?*"

graph measure 3: **degree** of a node

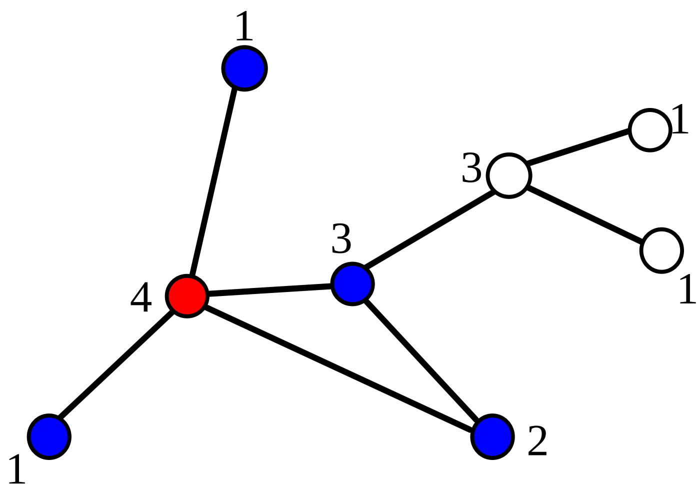
$k_x = \deg(x) = |N_1(x)|$
$= \text{number of } N_1\text{-Neighbours of node } x$

$P(k)$ = *Degree-Distribution (frequency)*
= **number of nodes** with deg=k

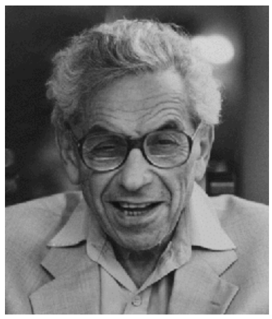




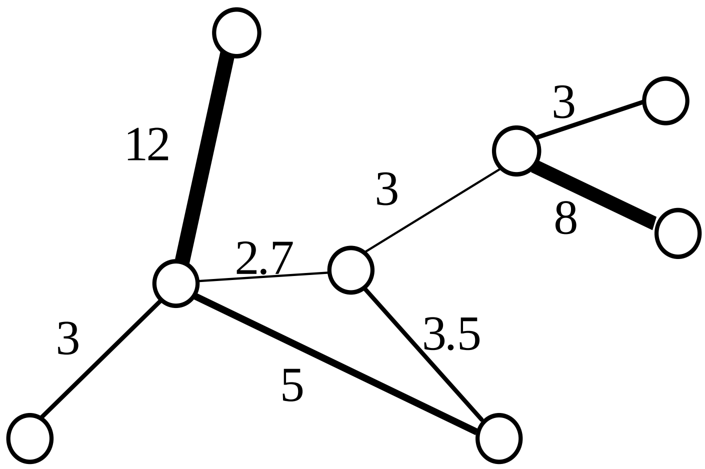
Hubs and *Authorities*



- *Hub* ~ high degree
  - e.g. plane traffic: Chicago, Frankfurt Main
  - e.g. mathematics: Erdös
- *Authority* ~ linked by a Hub



Gewichtete Kanten, gewichteter Graph



Funktion g(e) mit $g: E \rightarrow \mathbb{R}$

Gibt jeder Kante eine Stärke, Intensität, etc.

(*ungewichtet*: g(e)=1 für alle e)

Bipartite Graphs

Up to now we have only seen so called *1-mode graphs*, i.e. there is **one** type of vertices

Now imagine for example 4 **films** (black) and 11 playing **Actors** (white).

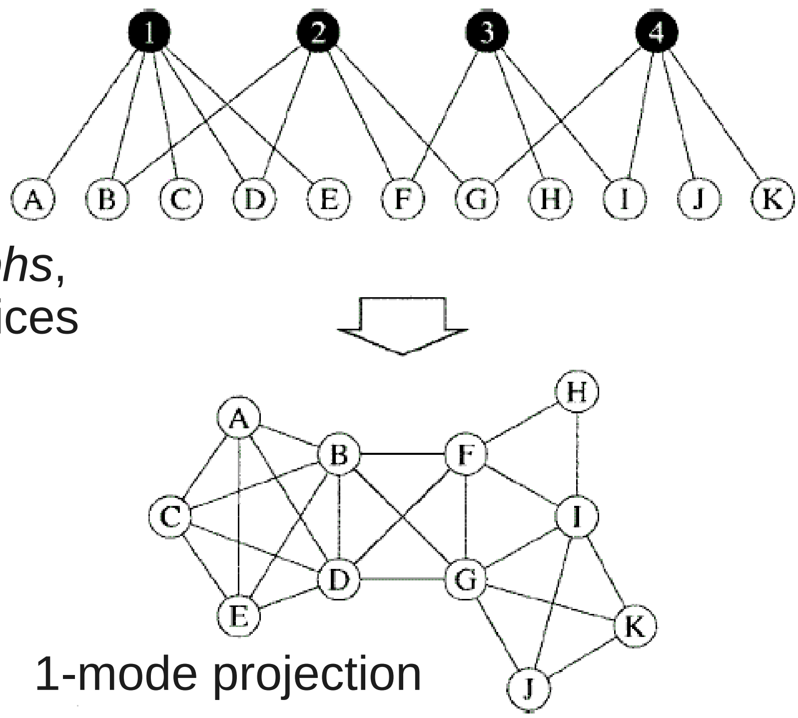


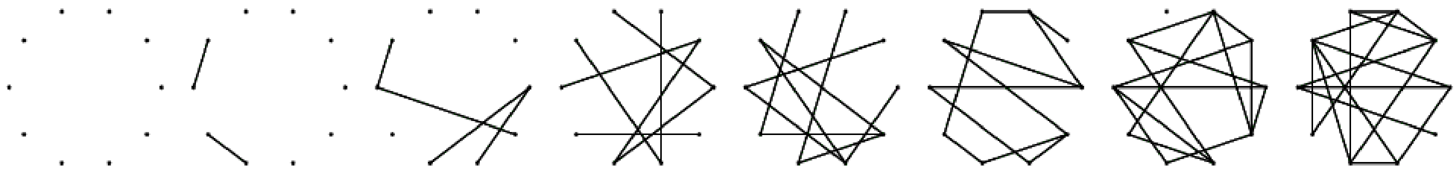
FIG. 14. A schematic representation of a bipartite graph, such as the graph of movies and the actors who have appeared in them. In this small graph we have four movies, labeled 1 to 4, and eleven actors, labeled A to K, with edges joining each movie to the actors in its cast. The bottom figure shows the one-mode projection of the graph for the eleven actors. After Newman, Strogatz, and Watts (2001).

From the 2-mode graph we can generate a 1-mode graph by projection (under information loss)

THE *random* graph model: Erdös Renyi RandomGraph (~19**60**)

http://www.nd.edu/~networks/linked/newfile6.htm

- G(N,p) random graph
- N vertices → # possible edges: $$M_{max} = \frac{N(N-1)}{2}$$
- p independent probability for each edge (Bernoulli-process) $$p \in [0,1]$$



p=0	p=0.05	p=0.1	p=0.15	p=0.2	p=0.25	p=0.3	p=0.35
B=0	B=2	B=4	B=7	B=9	B=11	B=14	B=16
NOC=10	NOC=8	NOC=6	NOC=3	NOC=1	NOC=1	NOC=2	NOC=1

Degree Distribution with ER G(N,p) is ~ Poisson

The average is good estimator for the whole distribution (bellshaped)

$$\langle k \rangle = (N-1)p$$

$$= (N-1)\frac{M}{N(N-1)/2} = \frac{2M}{N}$$

$$= \mu$$

The degree has a binomial distribution. For N>>1 it becomes Poissonian:

$$P(k) = e^{-\mu}\frac{\mu^k}{k!}$$

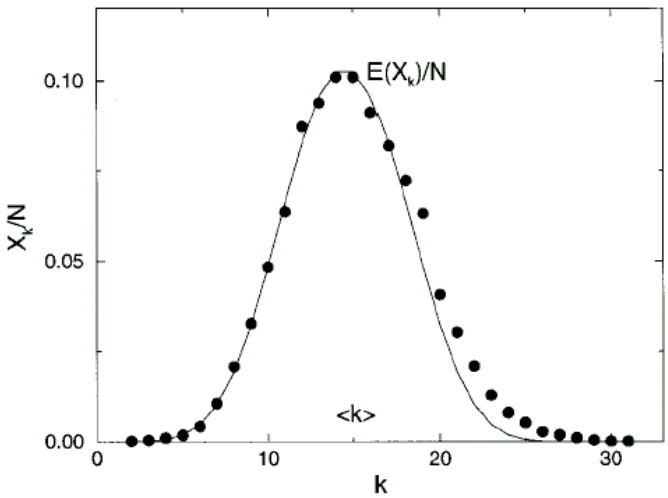


FIG. 7. The degree distribution that results from the numerical simulation of a random graph. We generated a single random graph with $N = 10\,000$ nodes and connection probability $p = 0.0015$, and calculated the number of nodes with degree k, X_k. The plot compares X_k/N with the expectation value of the Poisson distribution (13), $E(X_k)/N = P(k_i = k)$, and we can see that the deviation is small.

with an exponential tail for large k

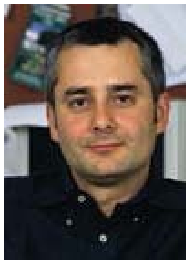
paradigm shift 1998/99
static random → grown networks

Starting Papers

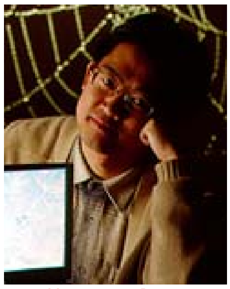
- **Watts**, D. J. and **Strogatz** S. H., *Collective dynamics of small-world networks*, **1998**.06.04 Nature, 393, 440.
- **Barabasi**, A.-L. and **Albert**, R., *Emergence of scaling in random networks*, **1999**, Science 286, 509–512 .
- Albert, R., **Jeong**, H. and Barabasi, A.-L., *The diameter of the world-wide web*, 1999, Nature (London) 401, 130-131; cond-mat/9907038.
- Barabasi, A.-L., Albert, R., and Jeong, H., *Mean-field theory for scale-free random networks*, 1999, Physica A 272, 173–187.
- Barabasi, A.-L., ***Linked: The New Science of Networks***, Perseus, Cambridge, MA (2002).

Watts and Strogatz

Reka Albert



Albert-László Barabási



Hawoong Jeong

Property 1: small world

http://www.nd.edu/~networks/linked/newfile8.htm

1998: Watts-Strogatz random rewiring

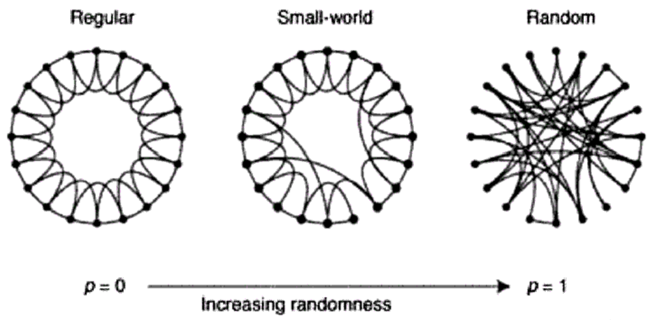


FIG. 15. The random rewiring procedure of the Watts-Strogatz model, which interpolates between a regular ring lattice and a random network without altering the number of nodes or edges) nodes, each connected to its four neare) the original ring is unchanged; as p incr comes increasingly disordered until for p ed randomly. After Watts and Strogatz,

1967: Milgram
"6 degrees of separation"

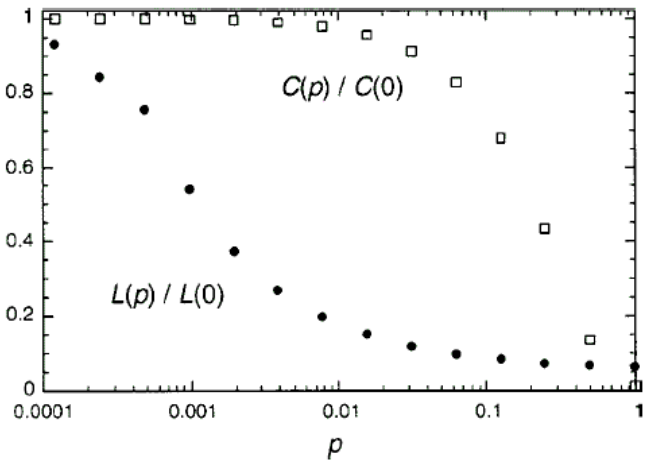
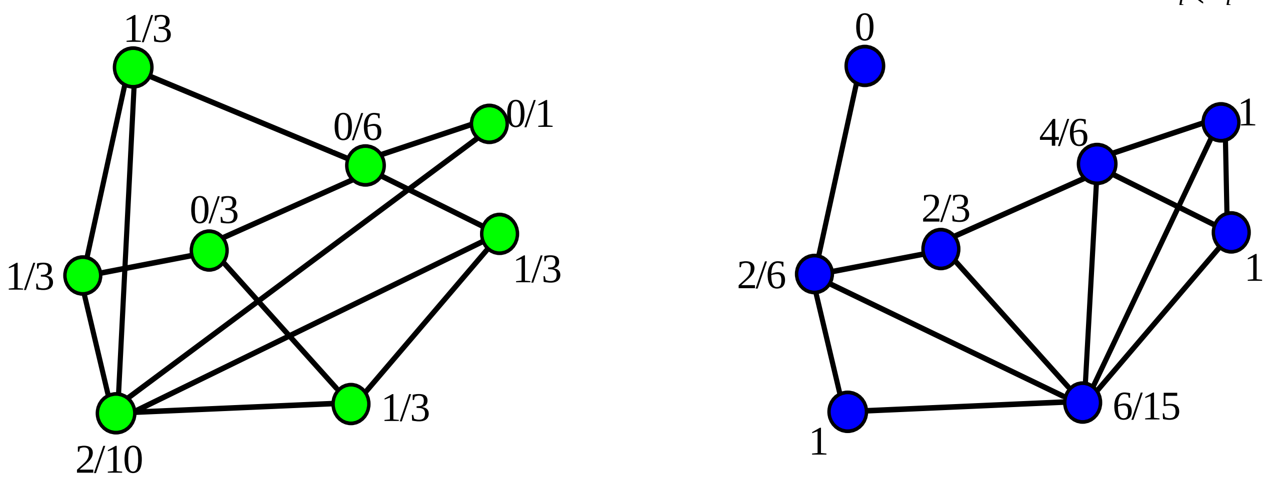


FIG. 16. Characteristic path length $\ell(p)$ and clustering coefficient $C(p)$ for the Watts-Strogatz model. The data are normalized by the values $\ell(0)$ and $C(0)$ for a regular lattice. A logarithmic horizontal scale resolves the rapid drop in $\ell(p)$, corresponding to the onset of the small-world phenomenon. During this drop $C(p)$ remains almost constant, indicating that the transition to a small world is almost undetectable at the local level. After Watts and Strogatz, 1998.

$L \sim \log N$

Property 2: high clustering

$$C_i = \frac{\#T_i}{k_i(k_i-1)/2}$$



C=0.1917 C=0.6333

In both cases M=13 and N=8, but in the *right* picture
many more friends are themselves direct friends to each other

! “Empirical Networks” have a significantly **higher clustering-coefficient** than ErdosRenyi-RandomGraphs !

Property 3: scale free

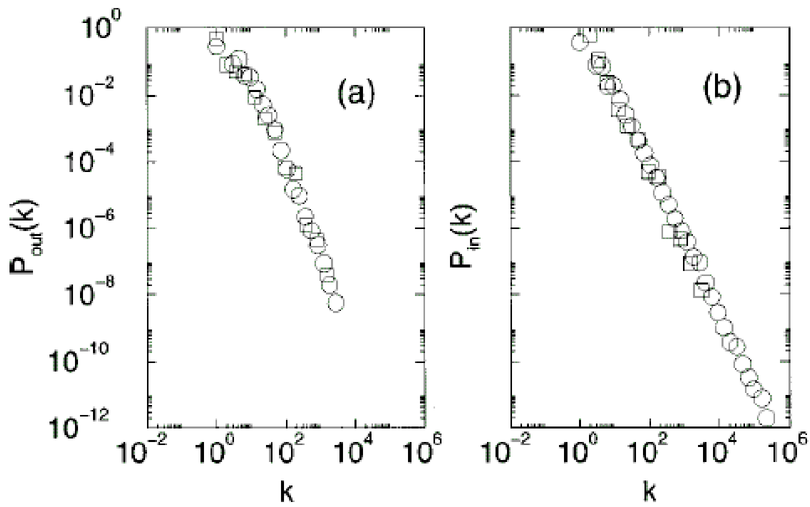


FIG. 2. Degree distribution of the World Wide Web from two different measurements: □, the 325 729-node sample of Albert *et al.* (1999); ○, the measurements of over 200 million pages by Broder *et al.* (2000); (a) degree distribution of the outgoing edges; (b) degree distribution of the incoming edges. The data have been binned logarithmically to reduce noise. Courtesy of Altavista and Andrew Tomkins. The authors wish to thank Luis Amaral for correcting a mistake in a previous version of this figure (see Mossa *et al.*, 2001).

In MEASURED networks, the degree distribution is **not** Poissonian (with exponential tail) for large k

but "fat tail"
→ falling **power-law**

$$P(k) = \frac{1}{k^{\gamma}}$$

$$\gamma \sim 2.5$$

An average <k> doesn‘t really make sense here
= no *built-in scale*

→ „scale-free“

property 3: scale free

- Now an incredible run on real life data started...
- Almost identical scale-free distributions were measured in totally different objects, here e.g.
  - a) Internet Router
  - b) Actor-Movie-network
  - c) coauthors high energy physics
  - d) coauthors neuro sciences
- ! The <u>measurements(!)</u> almost perfectly lie on a straight line!
- ! And the power-law exponents differ only a little!

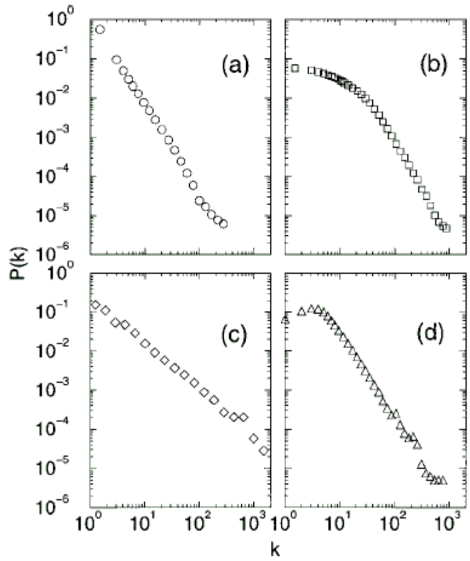


FIG. 3. The degree distribution of several real networks: (a) Internet at the router level. Data courtesy of Ramesh Govindan; (b) movie actor collaboration network. After Barabási and Albert 1999. Note that if TV series are included as well, which aggregate a large number of actors, an exponential cut-off emerges for large k (Amaral *et al.*, 2000); (c) co-authorship network of high-energy physicists. After Newman (2001a, 2001b); (d) co-authorship network of neuroscientists. After Barabási *et al.* (2001).

Property 3: scale free – Some objects that seem to have a scale-free degree

- WWW
- Internet-Routing
- Protein-Protein-docking
- citations
- collaborations
  - publications
  - Movie-Actor-Network
- Human Sexuality Networks
- Telefone calls
- brains
  - Caenorhabditis elegans
  - Humans
- computer code
- The Word Web of language

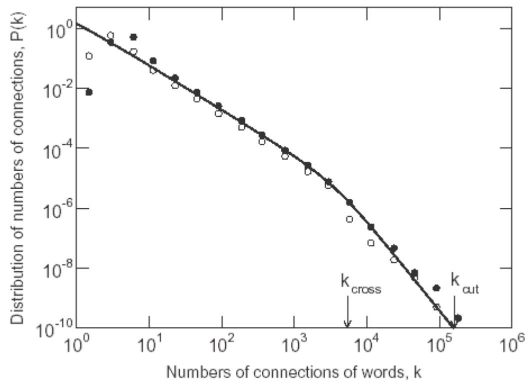


FIG. 9. The distribution of the numbers of connections (degrees) of words in the word web in a log-log scale [126]. Empty and filled circles show the distributions of the number of connections obtained in Ref. [126] for two different methods of the construction of the Word Web. The solid line is the result of theory of Ref. [127] (see Sec. IX J where the parameters of the Word Web, namely, the size $t \approx 470\,000$ and the average number of connections of a node, $\overline{k}(t) \approx 72$, were used. The arrows indicate the theoretically obtained point of crossover, k_{cross} between the regions with different power laws, and the cutoff k_{cut} due to the size effect. For a better comparison, the theoretical curve is displaced upward to exclude two experimental points with the smallest k (note that the comparison is impossible in the region of the smallest k where the empirical distribution essentially depends on the definition of the Word Web).

citations of the Phys. Rev. D **11-50** (1975-1994)	$24,296$	$351,872$	$\gamma_i = 3.0$	[27]
"————" (another fitting of the same data)			$\gamma_i = 2.6$	[99]
"————" (another estimate from the same data)			$\gamma_i = 2.3$	[94,95]
citations of the Phys. Rev. D (1982-June 1997)	—	—	$\gamma_i = 1.9$	[100]
collaboration network of movie actors	$212,250$	$61,085,555$	2.3	[55]
"————" (another fitting of the same data)			3.1	[102]
collaboration network of MEDLINE	$1,388,989$	$1.028\ 10^7$	2.5	[13]
collaboration net collected from mathematical journals	$70,975$	0.132×10^6	2.1	[15]
collaboration net collected from neuro-science journals	$209,293$	1.214×10^6	2.4	[15]
networks of metabolic reactions	$\sim 500 - 800$	$\sim 1500 - 3000$	$\gamma_i = 2.2$ $\gamma_o = 2.2$	[41]
net of protein-protein interactions (yeast proteome) [3]	1870	2240	~ 2.5	[44,45]
word web [4]	$470,000$	$17,000,000$	1.5	[126]
digital electronic circuits	2×10^4	4×10^4	3.0	[128]
telephone call graph [5]	47×10^6	8×10^7	$\gamma_i = 2.1$	[32]
web of human sexual contacts [6]	2810	—	3.4	[132]
food webs [7]	$93 - 154$	$405 - 366$	~ 1	[48,49]

TABLE I. Sizes and values of the γ exponent of the networks or subgraphs reported as having power-law (in-, out-) degree distributions. For each network (or class of networks) data are presented in more or less historical order, so that the recent exciting progress is visible. Errors are not shown (see the caption of Fig. 24). They depend on the size of a network and on the value of γ. We recommend our readers to look at the remark at the end of Sec. V C 2 before using these values. [1]The data for the network of operating AS was obtained for one of days in December 1999. [2]The value of the γ exponent was estimated from the degree distribution plot in Ref. [104]. [3]The network of protein-protein interaction is treated as undirected. [4]The value of the γ exponent for the word web is given for the range of degrees below the crossover point (see Fig. 9). [5]The out-degree distribution of the telephone call graph cannot be fitted by a power-law dependence (notice the remark in Sec. V F). [6]In fact, the data was collected from a small set of vertices of the web of human sexual contacts. These vertices almost surely have no connections between them. [7]These food webs are truly small. In Refs. [50,51] degree distributions of such food webs were interpreted as exponential-like.

First Model
Albert Barabasi: ***Preferential-Attachment***

1. Growth ! Not in static systems...
   - Per time step **1 new node** and **m new edges**
2. Preferential Attachment
   - **y~x**: new node y, an old node x, but which one?
   - Probability to choose x linearly proportional to current degree of x:

$$\mathbf{P(\ deg(x)=k_i\ )\ =\ k_i\ /\ sum(k_i);}$$

„the rich get richer “

YES → scale-free, exponent gamma=3

YES → small world property

NO → high clustering

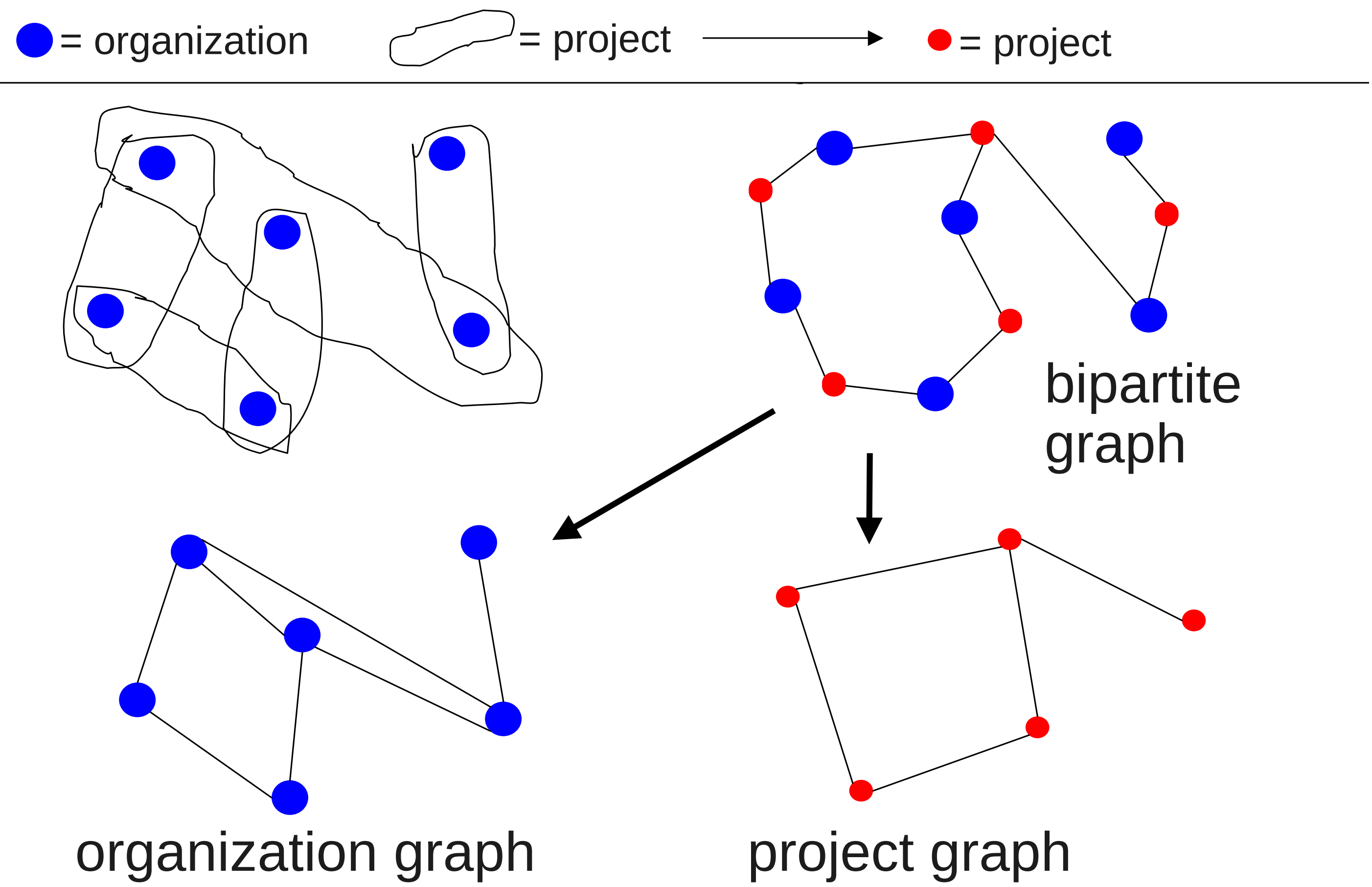
This can only be a *very short* glance

- The whole subject was born out of the Internet, which is not a small but at least a *medium sized* system (e.g. ~ 10^{10} webpages) and can be measured much easier than nature or society
- Our (physics) explanatory approach usually goes for the „thermodynamical limit“ of N→infinity; very different from the sociological viewpoint
- Within 6 years, some 3000(?) papers have been published about networks in the physics community
  `pre-prints on www.arxiv.org → cond-mat`
- Many scientists leave their (neighbouring) fields and do research on networks now
- It resembles a little bit the hype of the 80ies „Fractals/Nonlinearity/Chaos„ – everything was a fractal back then, now everything is networks
- Suggestions for further reading at the end of the talk ...

Teil 2: Projekt-Netzwerke

- Datensatz beim ARC systems research GmbH, Seibersdorf bei Wien
  - ca. 40,000 EU-geförderte Forschungsprojekte 1984-2004
  - Rahmenprogramm der EU dauern 4 Jahre; mittlerweile 2stellige Milliardenbeträge für Forschungs- und Entwicklungsförderung, Aber “nur” ca. 6% aller Forschungsprojekte (Rest zB nationale Förderung)
  - Quelle: CORDIS-Datenbank der EU, Download, Standardisierung
- Was wissen wir über ein Projekt
  - Beteiligte Institutionen
  - Titel, Themen
  - Beginn, Dauer
  - Verantwortliche, Anschrift, Department/Faculty, …
- **Grundidee:** DB → Netzwerk Es ist ein bipartiter Graph: Projekte ←→ Organisationen
  Dann unimodale Projektion: Projekte werden im Graph verbunden, wenn nicht-leere Schnittmenge von Organisationen
  - Projektion auf Projektgraph
  - Projektion auf Organisations-Graph
  - Frühes Ergebnis: ***skalenfreie*** *Degree-Verteilung* auf Organisationsgraph !!!

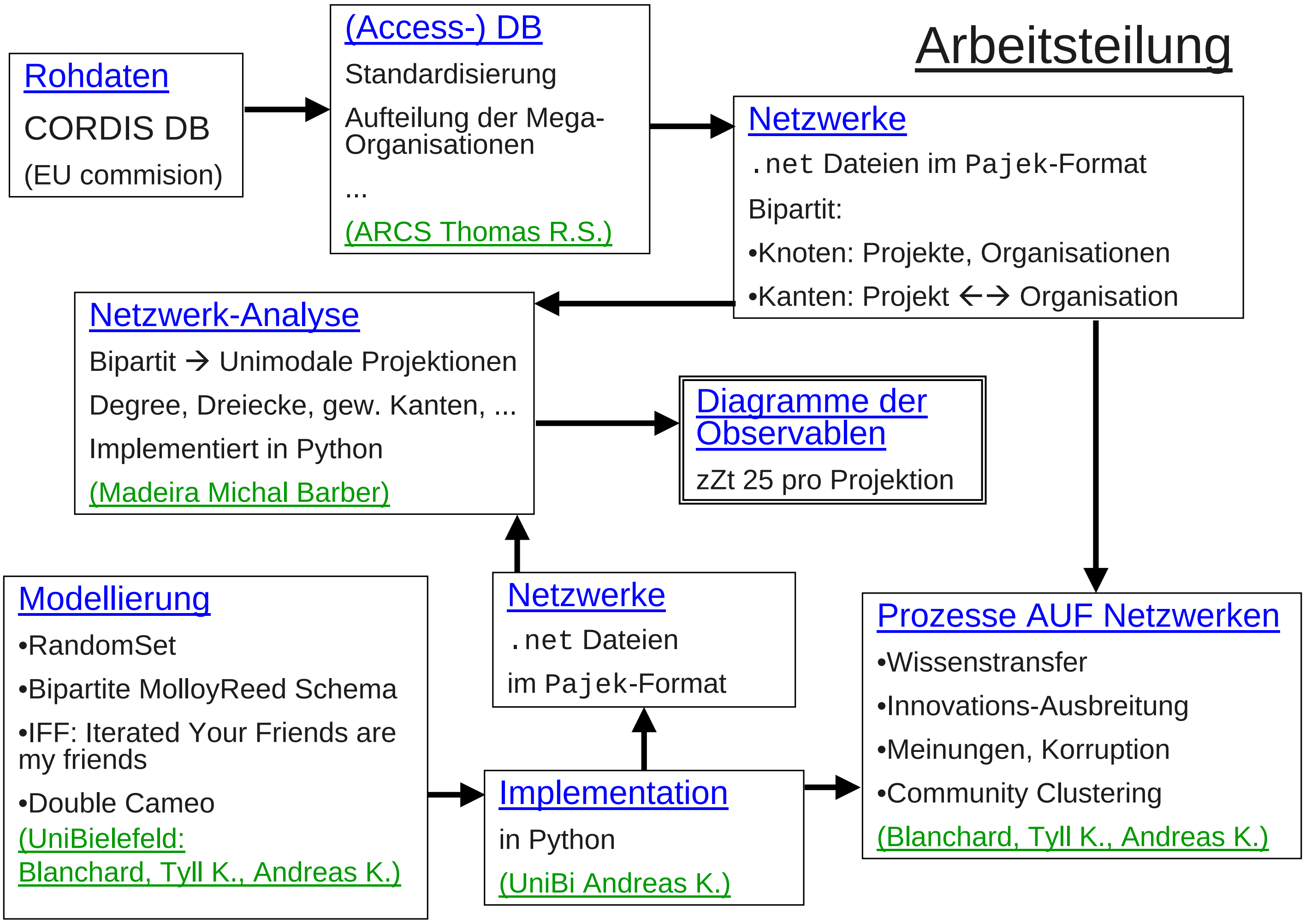
Set Graphs



Projekt-Netzwerke

- unsere ersten Hypothesen zur Struktur-Enstehung:
  - Basismodell: *RandomSets* von rein zufällig zusammengewürfelten Mengen von Organisationen sind Projekte
  - Erweitertes IFF (Iteriertes your Friends are my Friends) – Prinzip: Projekt aus bisherigen Projekt-Bekanntschaften und N_2-Umgebung
- Nur einige Fragen, die uns leiten:
  - Rekonstruierbarkeit durch Simulation?
  - Wesentliche Eigenschaften des empirischen Netzwerkes
  - Nützliche neue Netzwerk-Observablen entwickeln
    - meso-Skala zwischen lokal und global
    - Dreieckszahl/Clusterkoeffizienten auf gewichteten Graphen
  - nach unterschiedlichen Rollen im Netzwerk untersuchen
    - Hubs, zentralste Knoten... (topologische Rollen)
    - stabile Akteurs-Konfigurationen
    - Knoten/Kanten mit Eigenschaften (Industrie vs. Wissenschaft, Agrar vs. Telekommunikation, Kontraktformen, etc.)
  - welche Partitionierung in Communities ergibt instruktive Einsichten?
  - Übersetzung der Netzwerk-Sichtweise in die Wirtschaftswissenschaften

Arbeitsteilung



Programmierung

- **Python**: freie Script-Sprache mit vielen fertigen Libraries und abstrakten leistungsfähigen Datentypen; 1991 in Holland gestartet, seitdem im Netz weiterentwickelt
- Da sowohl Michael Barber wie ich nun in Python programmieren, können wir zum Teil den fertigen Code gegenseitig verwenden!
- **Einige Teilaufgaben**: Histogramme generieren, laden, speichern, auf-addieren und entpacken; Verteilungen aufeinander tunen, Netzwerke aufbauen, ablegen, einlesen, abspeichern; Knoten entfernen, Re-Index-ing; Rankings sortieren; Graph-Traversals; Zufalls-Verteilungen, Random-Pairing von Knotenmengen, u.v.m.
- Schon ersten *Prozess* auf unseren Netzwerken implementiert: **Korruptions-Ausbreitung** Ph.Blanchard, T.Krüger, A.Krueger, P.Martin (FU Berlin)

Algorithmus 1: RandomSetModel

1. Zielgröße: P Projekte, O Organisationen
2. Wähle eine Projektgrösse $|P_i|$ aus
   - zB random-Variable mit power law Verteilung, mit zB exponent –3, und cut-off für Maximalgröße ~ Sqrt(O)
   - zB tatsächliche Projekt-Größenverteilung aus empirischer Untersuchung
3. Für das Projekt P_i wähle $|P_i|$ zufällige Organisationen aus dem Organisations-Pool
4. Wiederhole 2. und 3. bis P Projekte kreiert wurden
5. Identifiziere eventuell unbenutzte Organisationen und lösche sie (d.h. Pool muss vorher etwas größer sein)
6. Speichere Netzwerk als bipartiten Graph zur Weiterverarbeitung

Algorithmus 2: bipartite MolloyReed Schema

1. Zielgröße P Projekte, O Organisationen
2. Wähle alle Projekt-Größen $|P_i|$ und alle Organisations-Größen (Projekte pro Organisation) $|O_j|$ aus → Degree jedes Knotens
   - zB power-law Verteilungen mit Exponenten λ_O und λ_P und Minimal- und Maximalgrößen
   - zB gemessene Projekt- und Organisations-Größenverteilungen aus empirischer Untersuchung
3. Tune die beiden Verteilungen auf P und aufeinander, so daß die selbe Anzahl M von Kanten herauskommt
4. Erstelle für beide Knotentypen „virtuelle“ Knoten, d.h. vervielfältige einen Knoten so oft wie sein Degree angibt
5. Random Pairing: Bilde aus den „virtuellen“ Knoten M Zufalls-Paare (Organisation, Projekt)
6. Entferne im entstandenen Netzwerk eventuelle Doppelpaare
7. Speichere Netzwerk als bipartiten Graph zur Weiterverarbeitung

The very first results:

We will always see
3 diagrams at a time

to compare empirical
and generated graphs

Empirical Network: „FP3“

3rd framework programme

O=9615 P=5529 M=31380

Project-Sizes: min=1 max=73 mean=5.6
Orgas-Sizes: min=1 max=138 mean=3.2

RandomSet Network

~ same #orgs, #projs as FP3

~ same project sizes as FP3

bipMolloyReed Network

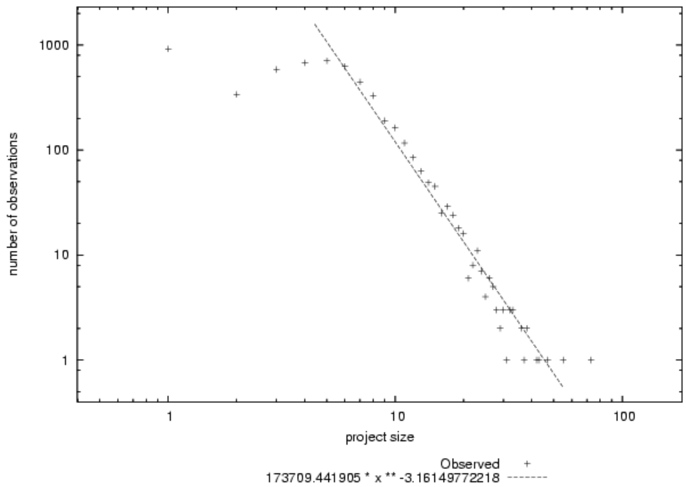
~ same #orgs, #projs as FP3

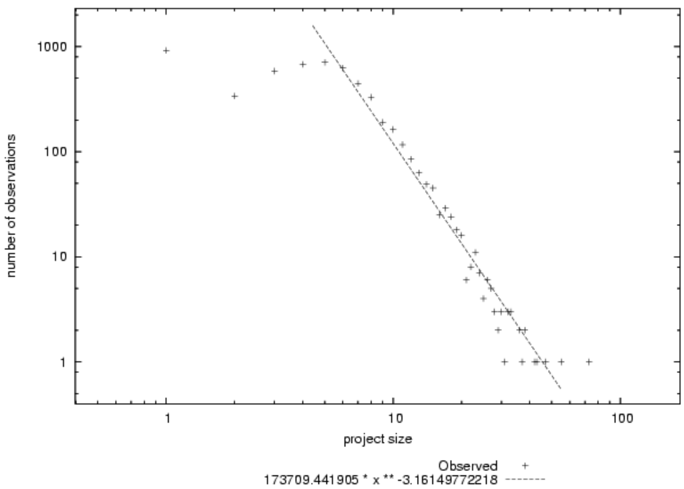
~ same project sizes as FP3
~ same organization sizes as FP3

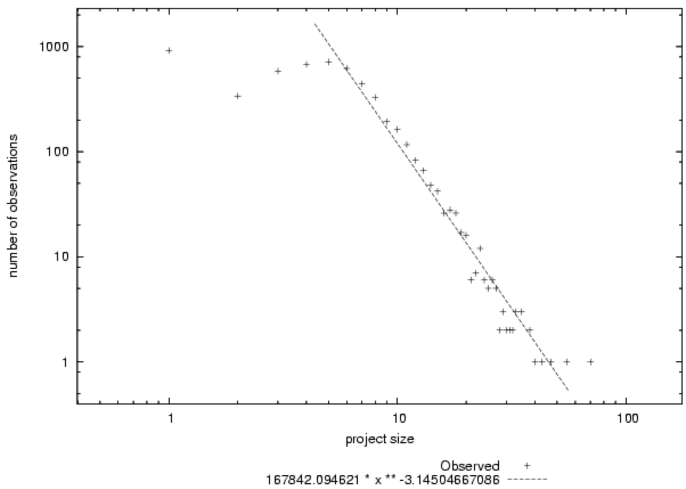
Project Sizes:

identical

Because the empirical
project sizes are the inputs
for both simulations



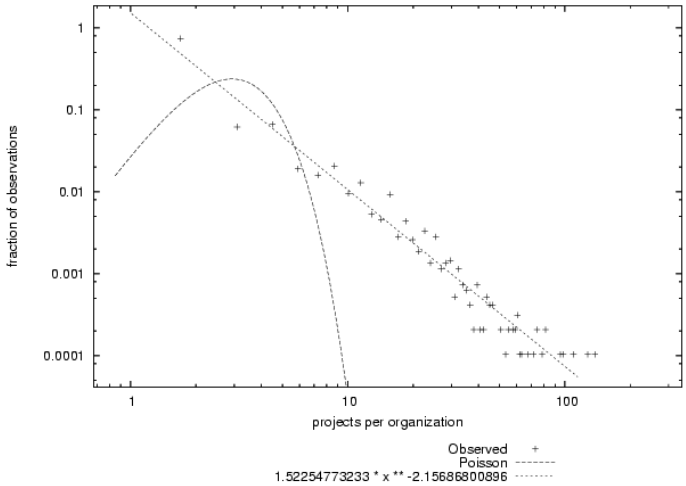


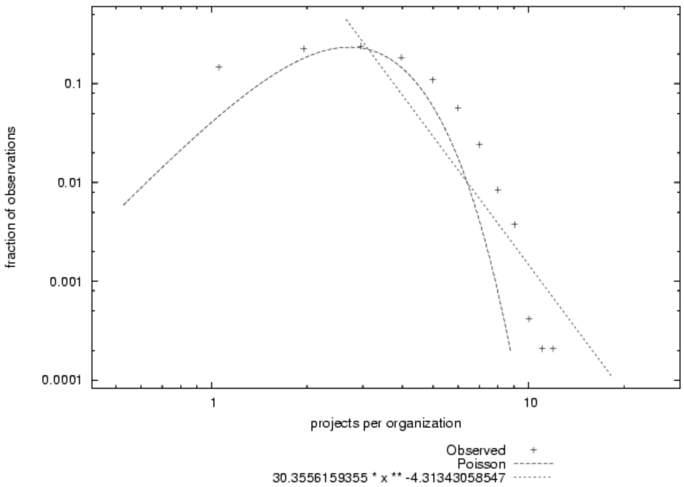


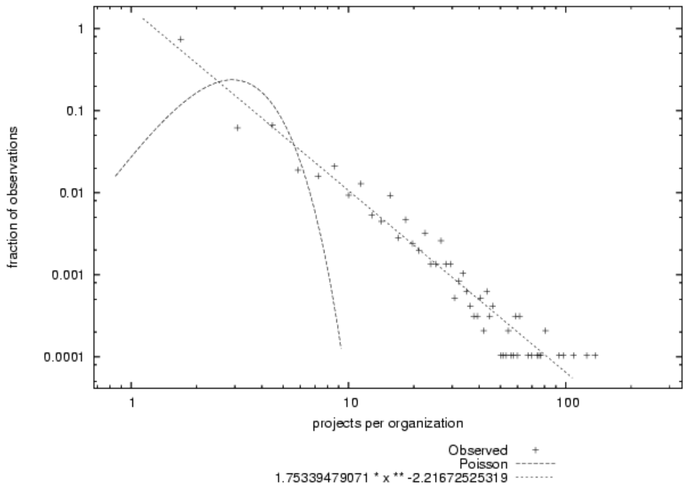
Organization Sizes:

RandomSetModel:
Exponential Decay ~ Poisson Distrib.
predicted by theory!

FP3 <-> MolloyReed
identical because input





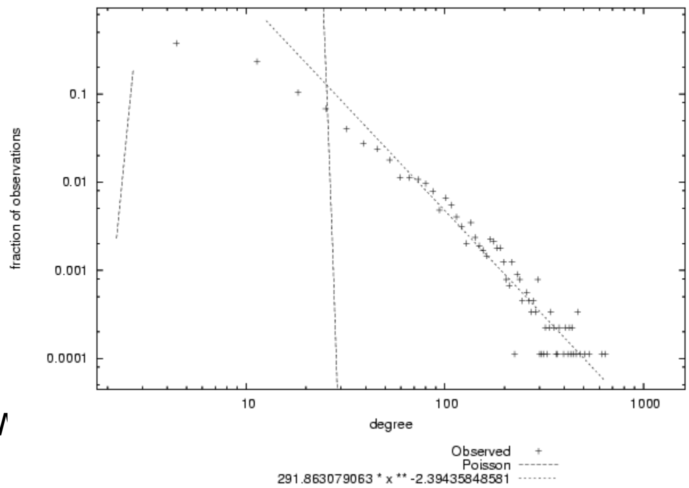


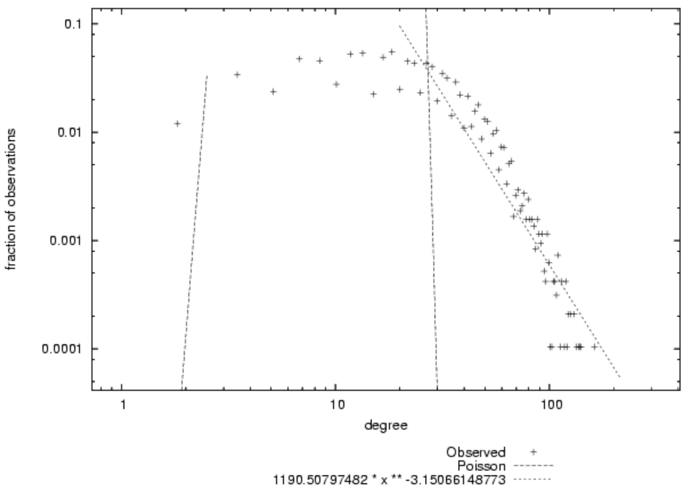
Organization Graph:

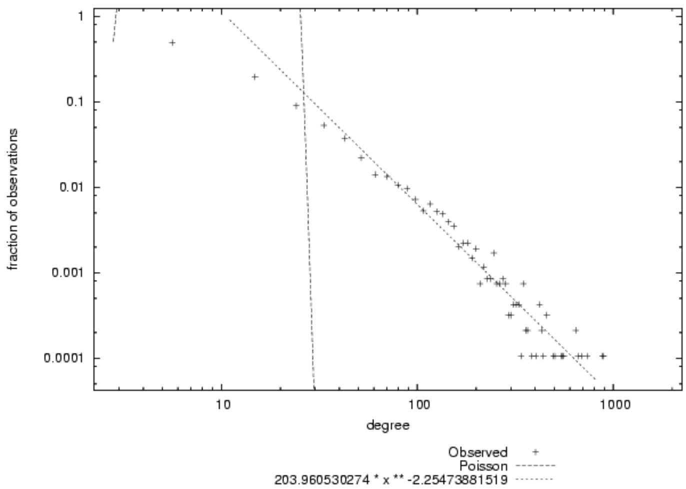
Here the **degree** distribution partly correlates with the organization sizes

RandomSet:
fat tail but much steeper

MolloyReed:
similiar to empirical FP3;
both are almost on a straight power lav
with exponent 2.3 - 2.4



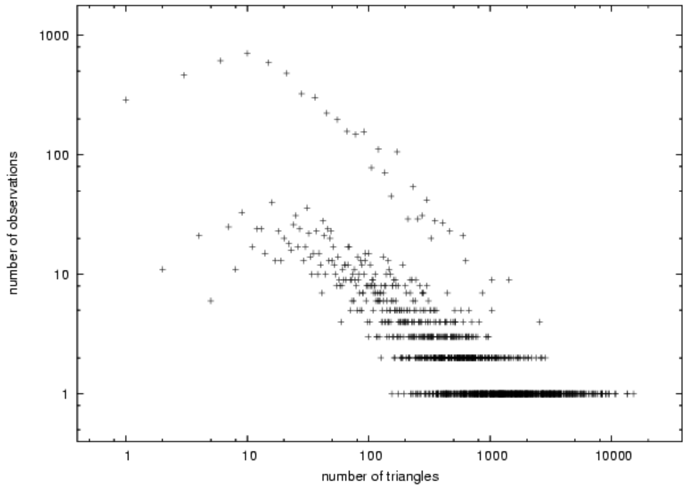


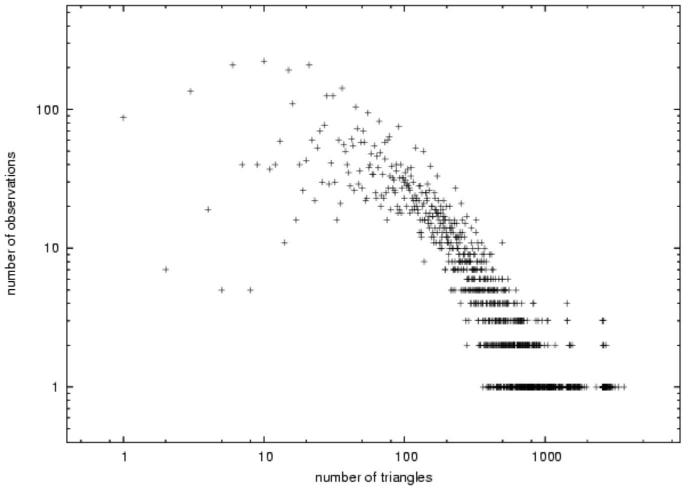


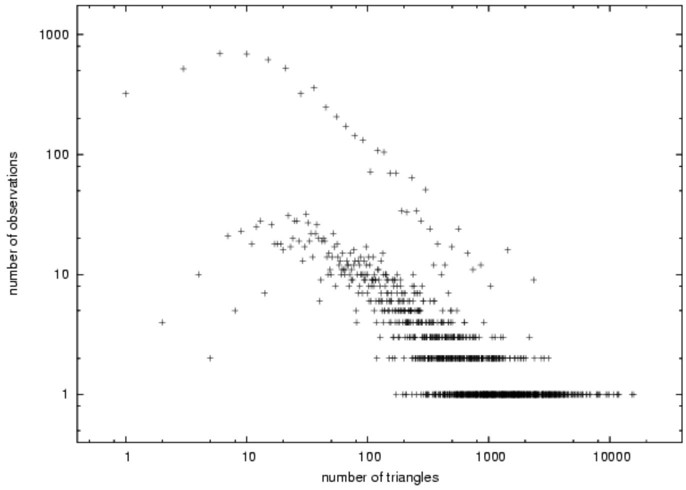
Organization Graph:

The triangle count looks similiar qualitatively in all three, but

RandomSet:
lower highest-number-of-triangles
lower highest-number-of-observations



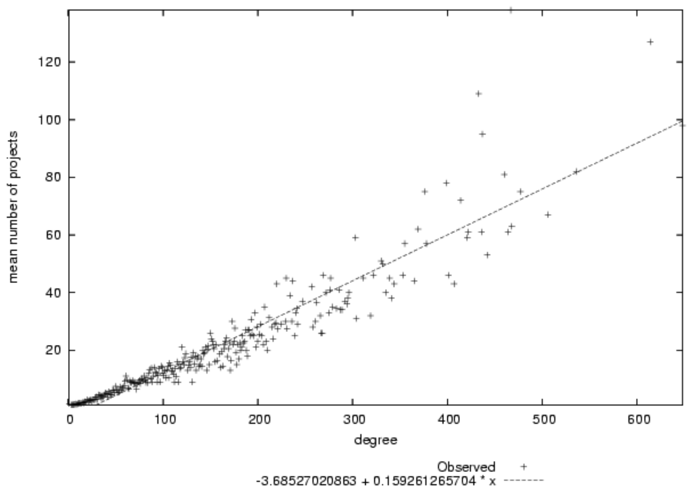


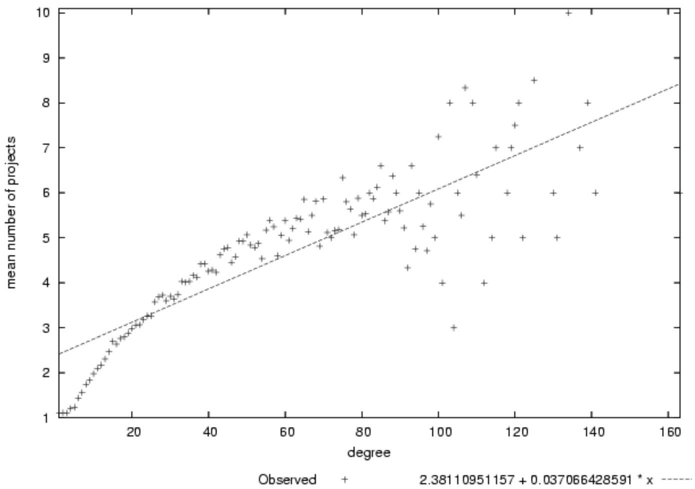


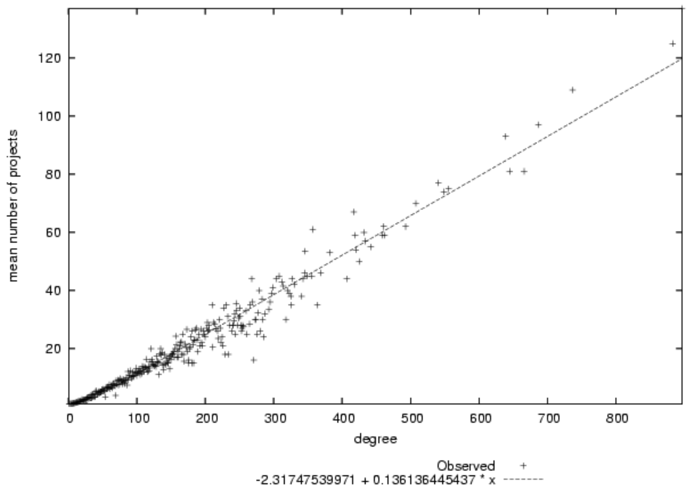
Organization Graph:

multivariat:
mean #projects vs. degree

RandomSet:
totally different picture due to much smaller occuring degrees and mean number of projects per node







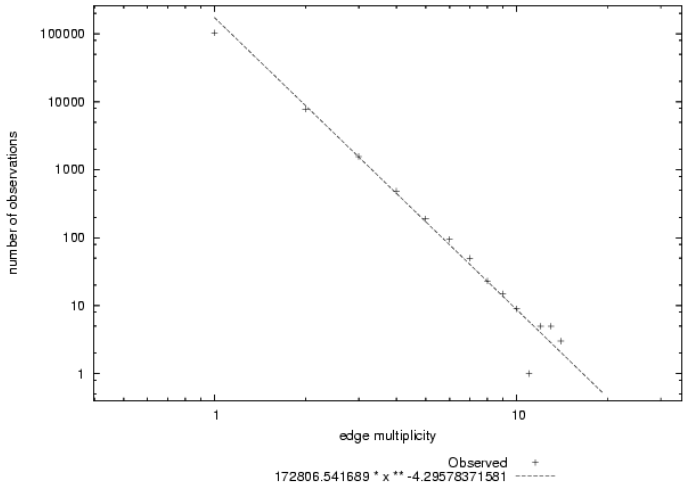
Organization Graph:

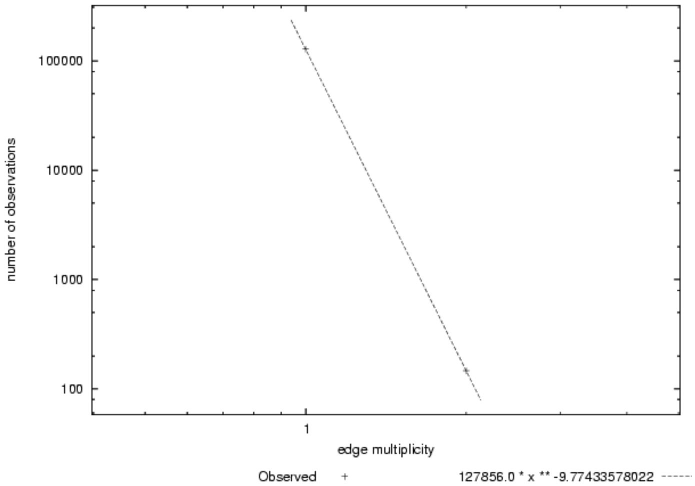
Edge Multiplicities

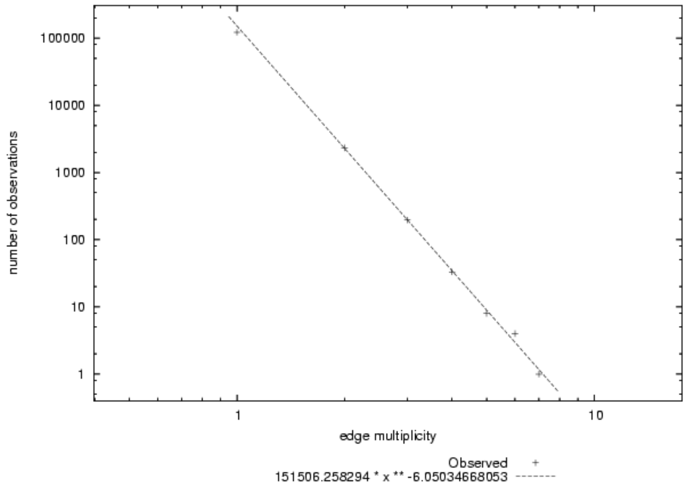
Empirical FP3:
highest multiplicity 14

RandomSet:
only 1 and 2

MolloyReed:
highest multiplicity only 7





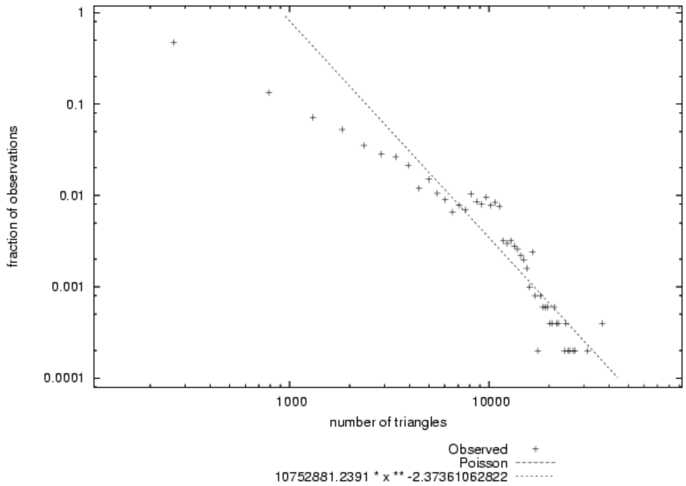


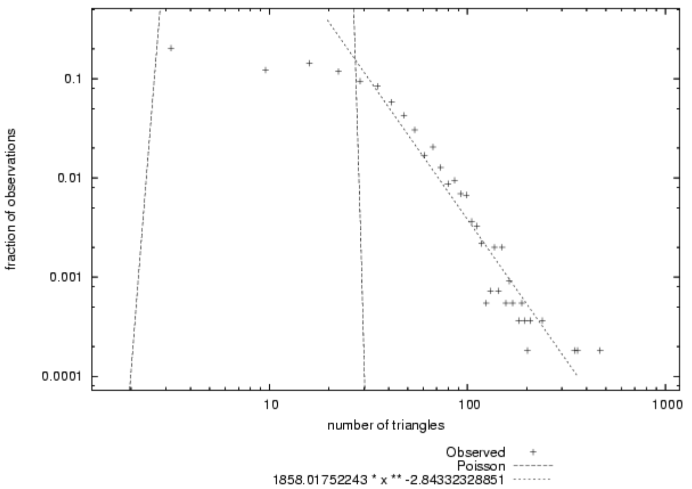
Project Graph:

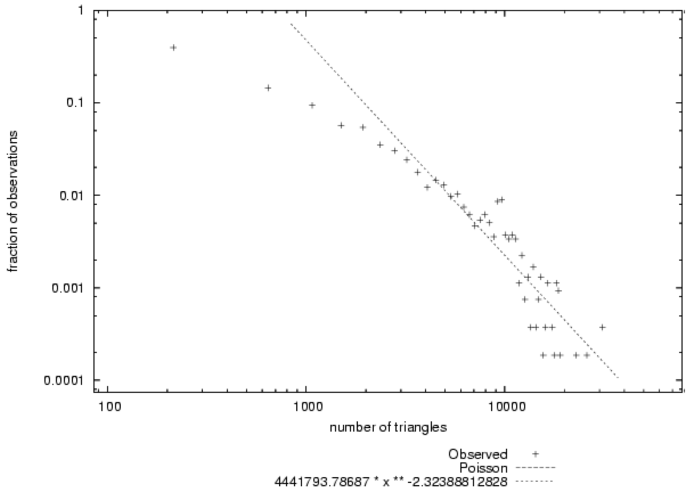
Number of Triangles

RandomSet:
lower highest-number-of-triangles,
a little lower
highest-number-of-observations

→ much less triangles





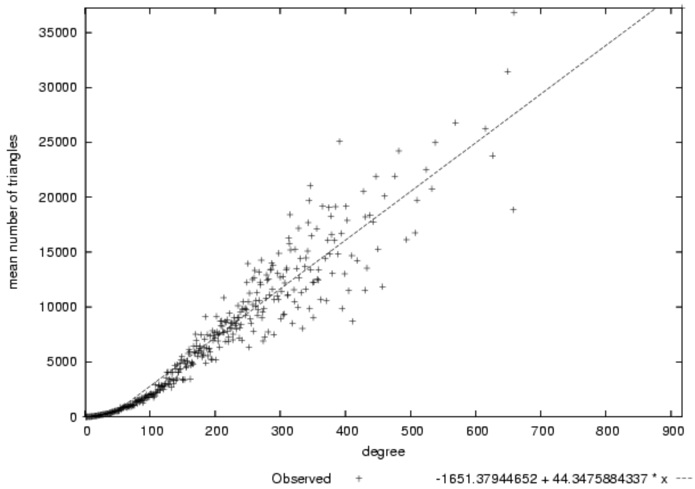


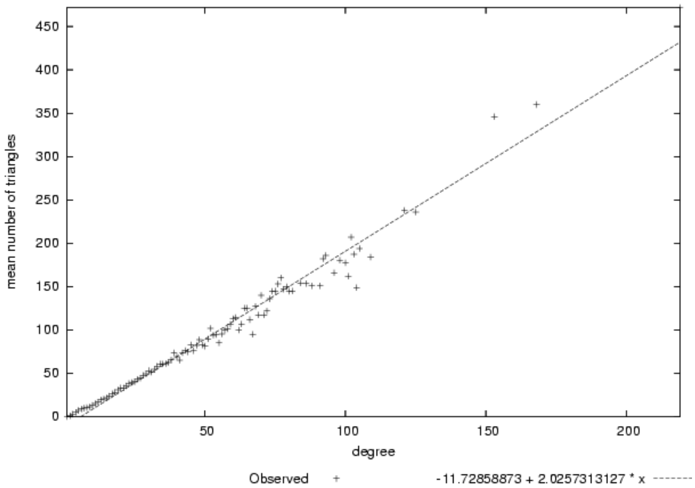
Project Graph:

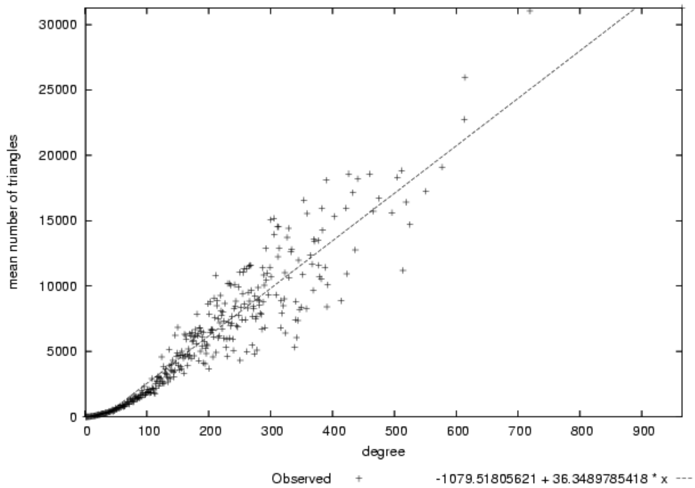
Mean triangle count

vs. degree

RandomSet:
much lower degree
and lower triangle counts





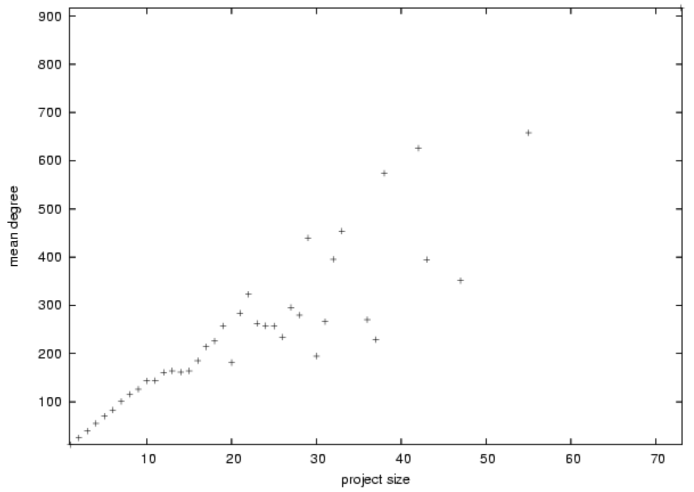


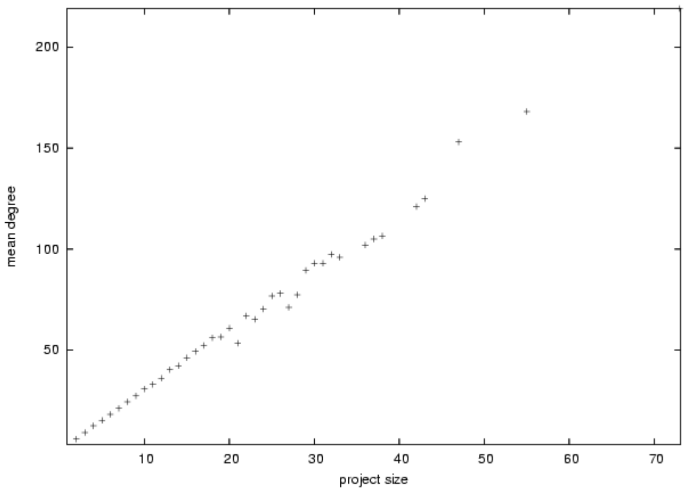
Project Graph:

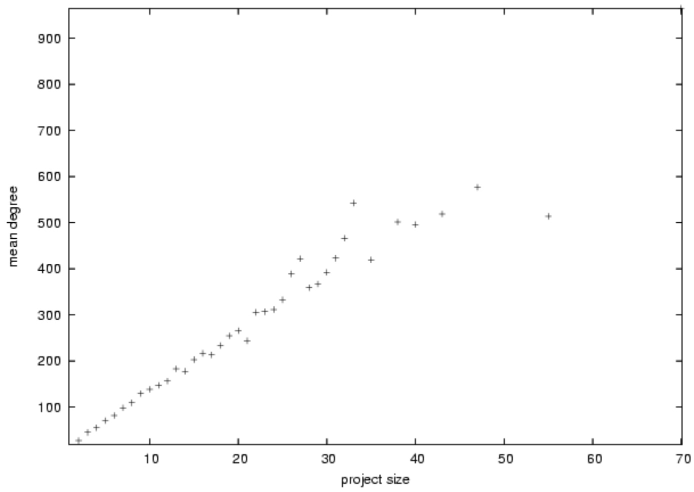
mean degree vs. project size

RandomSet:
Much lower degree, so
only the lower part of the diagram

MolloyReed: on straighter line than
in more complex empirical result







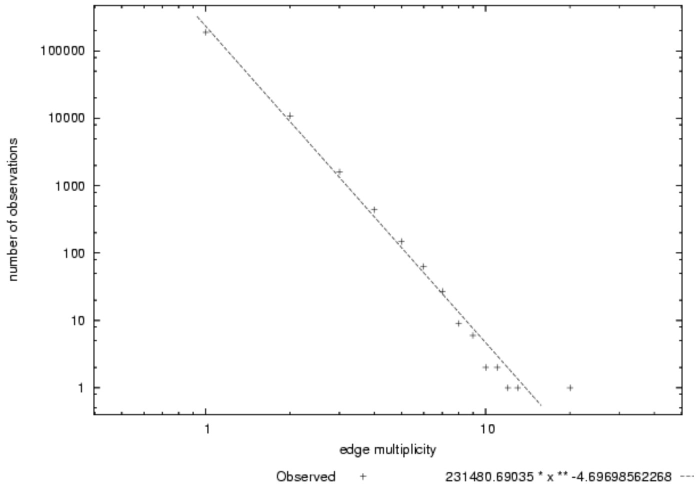
Project Graph:

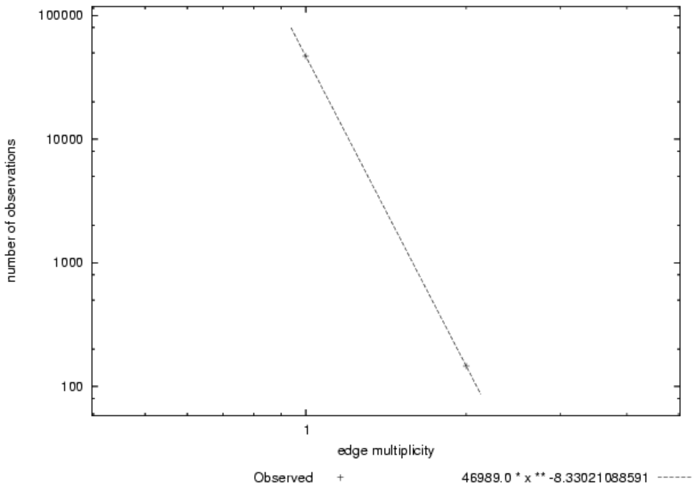
Edge Multiplicities

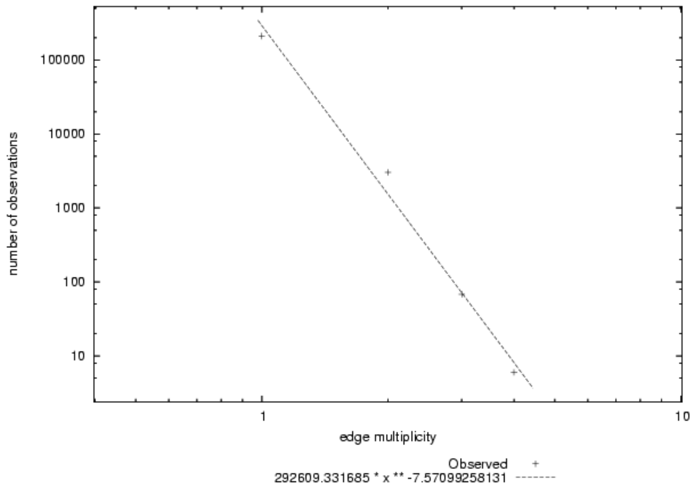
Empirical FP3:
highest multiplicity 20

RandomSet: only 1 and 2

MolloyReed: highest multiplicity 4





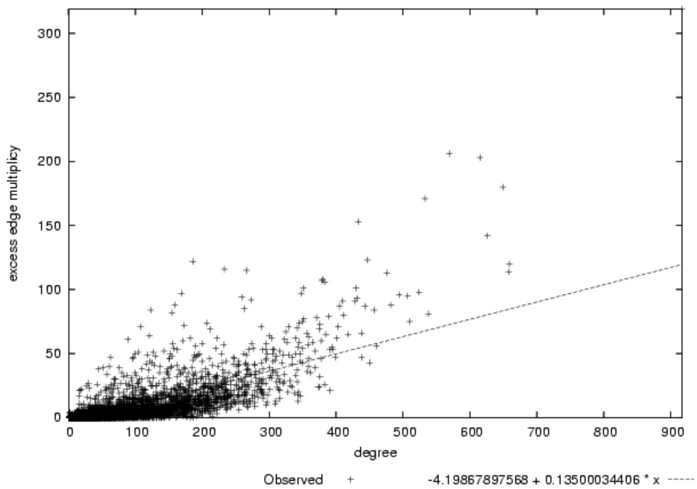


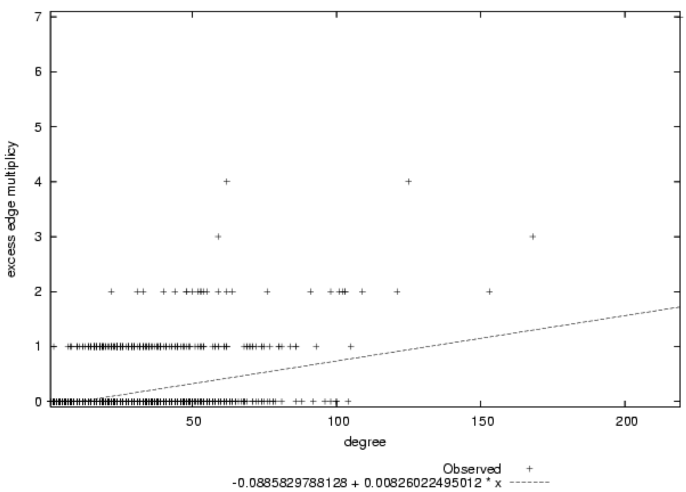
Project Graph:

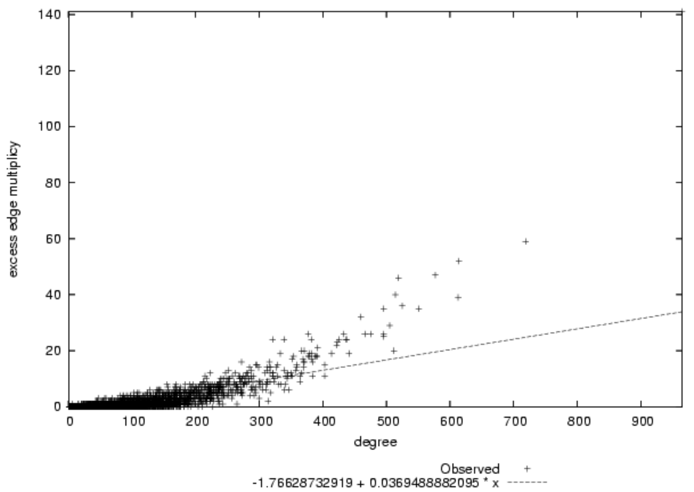
sum of excess edge multiplicities
at vertices

RandomSet:
only *very small* excess edge multiplicities

MolloyReed:
Much smaller excess edge multiplicities
than in empirical FP3,
much more focussed on a line







nächste Modelle:

IFF = Iterated-Your-Friends-are-my-Friends Prinzip:

- Starte mit zusammenhängender Anfangsstruktur von Organisationen
- Würfle neues Projekt nur aus der N_1- und N_2-Nachbarschaft, d.h. früheren Projektpartnern und deren früheren Projektpartnern
- Iteriere solange, bis ?
- Erste Untersuchungen auf unimodalen Graphen haben gezeigt, daß eine skalenfreie Degree-Verteilung entsteht !
  (2003 Ph. Blanchard, T.Krueger, A.Ruschhaupt cond-mat/0304563)
- und sowieso: lokale Vorschrift → hohes Clustering

Double Cameo:

Jede Organisation und jedes Projekt hat individuelle Parameter:

- Attraktivität ω, Affinität α für den Attraktivitätsparameter der anderen
- Attraktivität muss eine Seltenheitsverteilung Φ(ω) haben (zB falling power-law)
- Das Zusammenwürfeln geschieht umgekehrt proportional zur Häufigkeit $\Phi(\omega_i)$ der einzelnen Attraktivität ω_i hoch α:

$$P_{AB} \sim \frac{1}{[\Phi(\omega_B)]^{\alpha_A}}$$

Erste Untersuchungen zeigen, daß eine skalenfreie Degree-Verteilung entsteht und nur die „Extremisten" in der Affinität den Exponenten bestimmen
(2003/4 Ph. Blanchard, T.Krueger cond-mat/0302611 und mit S.Fortunato cond-mat/0407434)

Projekt-Netzwerke

Zusammenfassend einige Ziele unserer Forschungskollaboration

- Publizieren ☺
- Theorien / Modelle / Methoden ←→ Empirie
- Interdisziplinäre Synergie-Effekte nutzen:
  Physik Mathematik Informatik Wirtschaft Systemwissenschaften
- neue Methoden nahe an der Anwendung entwickeln
- Unsere neue „Netzwerk-Physik" *anwenden* und in die Wirtschaftswissenschaft / Systemanalyse *transferieren:*
  Was bedeuten diese mathematische Kenngrößen praktisch?

- Forschungsförderung in Europa:
  - Was ist eigentlich in diesen 20 Jahren passiert?
  - Fernziel: Maßnahmen-Katalog zur Auswahl von förderungswerten Projekten mit dem Blick auf das Gesamtsystem
  - Zum Beispiel:
    Förderung von Strukturen, die Innovations-Ausbreitung erleichtern!

THE END

Vielen Dank
für Ihre Aufmerksamkeit!

networks@AndreasKrueger.de
www.AndreasKrueger.de/networks

Lese-Empfehlungen:

Linked: The New Science of Networks,
Barabasi, A.-L.; Perseus Cambridge MA (**2002**).
Englisches Buch, sehr flockig geschrieben & leicht lesbar, “Prosa”

Statistical Mechanics of Complex Networks
Reka Albert and Albert-Laszlo Barabasi, **2001**
arXiv:**cond-mat/0106096** **(** **www.arxiv.org** **)**
54 Seiten Review-Artikel, nicht mehr ganz neu, aber guter Einstieg