

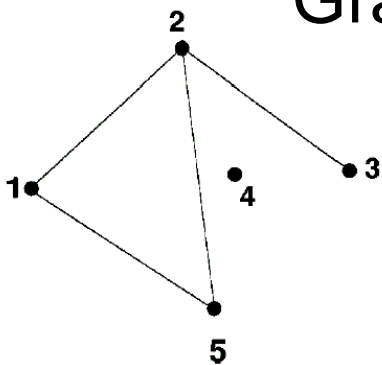
# Very short introduction into the Bielefeld view on NEMO

[www.AndreasKrueger.de/networks](http://www.AndreasKrueger.de/networks)

IRU day  
Dublin 1.7.2009

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## Graph $G=(V,E)$



- KNOTEN, node, vertex, actor, point, individual ...
- KANTE, edge, line, bond, tie, connection...

$V \subseteq \mathbb{Z}^+$  elements represented by dots

e.g.  $V=\{1,2,3,4,5\}$

$E \subseteq \binom{V}{2}$ , elements represented by lines

e.g.  $E=\{ (1,2) , (1,5) , (2,3) , (2,5) \}$

Neighbours:

$x \sim y := \{ \exists e \in E \text{ with } e=(x,y) \text{ or } e=(y,x) \}$

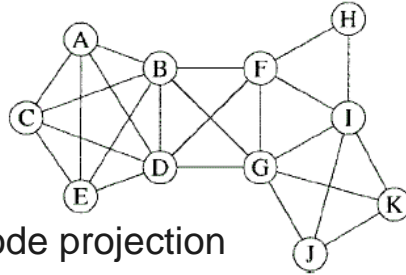
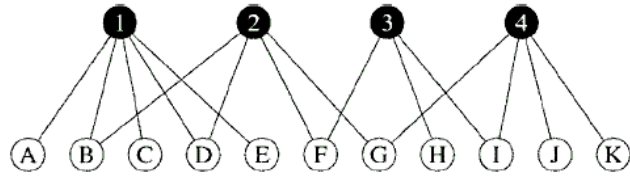
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# Bipartite Graphs

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).

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

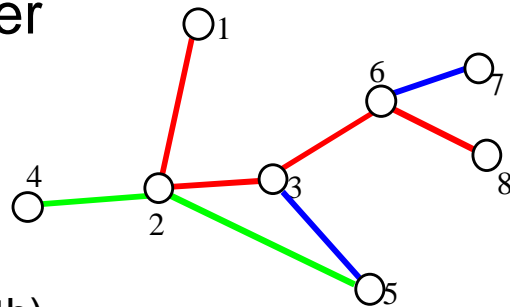


1-mode projection

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).

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# Pfade, Durchmesser



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

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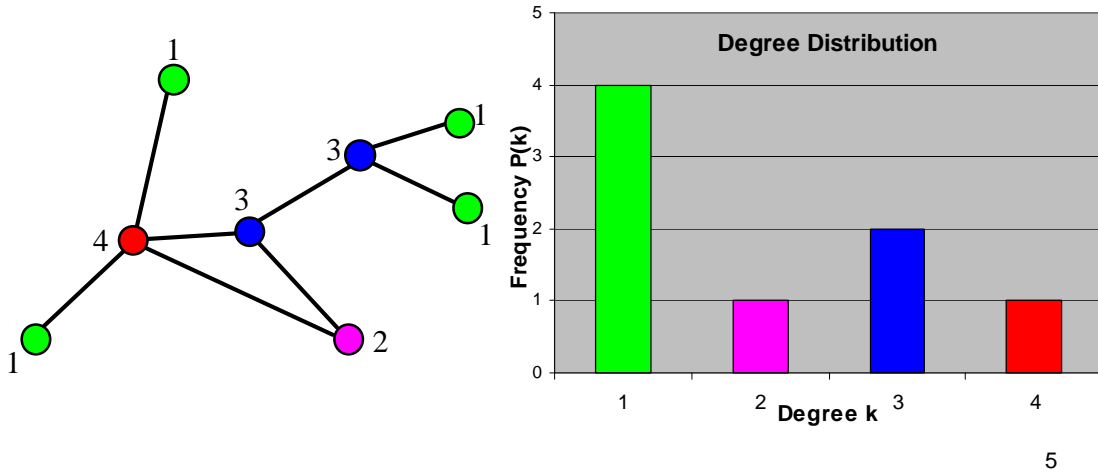
## degree of a node

$$k_x = \text{deg}(x) = |N_1(x)|$$

= number of  $N_1$ -Neighbours of node  $x$

$$P(k) = \text{Degree-Distribution (frequency)}$$

= number of nodes with  $\text{deg}=k$



## Degree Distribution of ER $G(N,p)$ is $\sim$ Poisson

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

$$\begin{aligned} \langle k \rangle &= (N-1)p \\ &= (N-1) \frac{M}{N(N-1)/2} = \frac{2M}{N} \\ &= \mu \end{aligned}$$

The degree has a binomial distribution. For  $N \gg 1$  it becomes Poissonian:

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

with an exponential tail for large  $k$

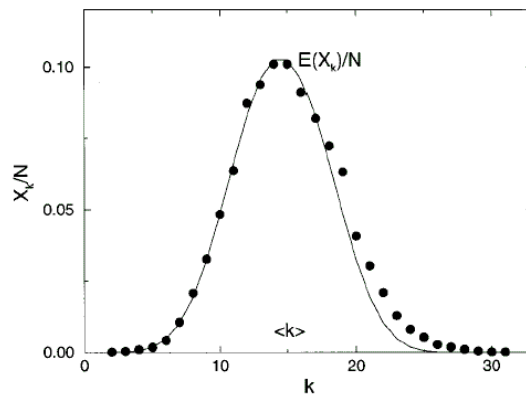
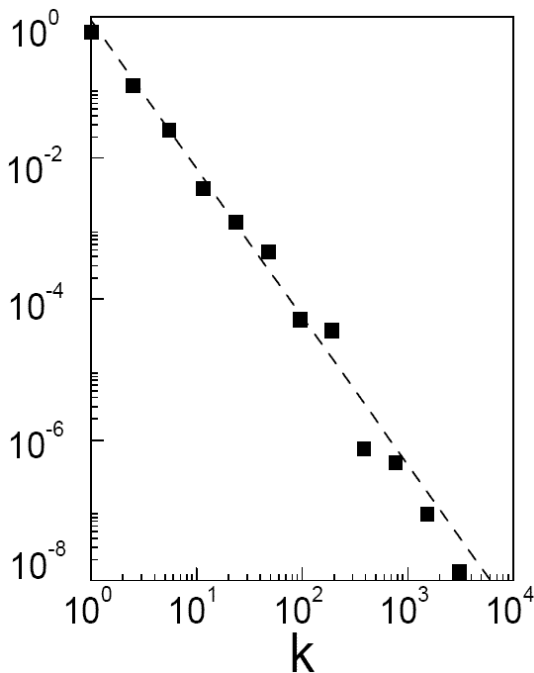


FIG. 7. The degree distribution that results from the numerical simulation of a random graph. We generated a single random graph with  $N=10\,000$  nodes and connection probability  $p=0.0015$ , and calculated the number of nodes with degree  $k, X_k$ . The plot compares  $X_k/N$  with the expectation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

## Empirical Property 1: scale free



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

but "fat tail"  
→ falling power-law

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

$$\gamma \sim 2.5$$

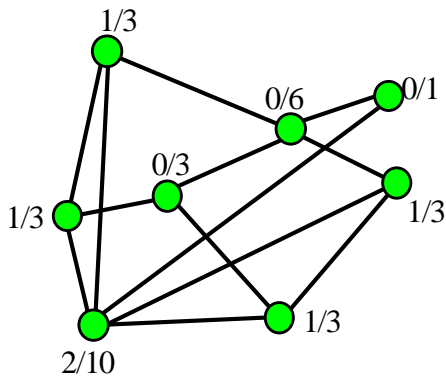
An average  $\langle k \rangle$  doesn't really make sense here  
= no *built-in scale*

→ „scale-free“

WWW-Ausschnitt N=325729  
kmean=5.46 gamma=2.1 (condmat9910332)

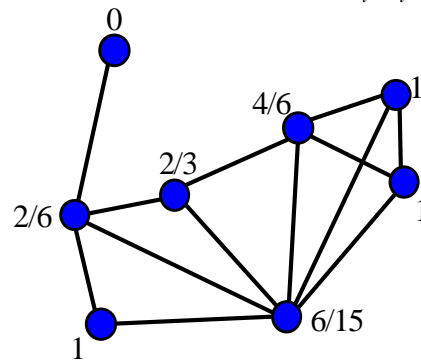
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## high clustering



$$C=0.1917$$

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



$$C=0.6333$$

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 !

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graph characteristic	FP1	FP2	FP3	FP4
# vertices: $N$	2500	6135	9615	20873
( $N$ for larg. comp.)	(2038)	(5875)	(8920)	(20130)
$N$ outside larg.comp.	462	260	695	743
# edges: $M$	9557	64300	113693	199965
(# edges $M$ larg.comp.)	(9410)	(64162)	(113219)	(199182)
mean degree: $\bar{d}$	7.65	20.96	23.65	19.16
( $\bar{d}$ larg.comp.)	(9.23)	(21.84)	(25.39)	(19.79)
maximal degree: $d_{\max}$	140	386	648	649
mean triangles per vertex: $\Delta$	22.90	169.70	244.91	146.04
( $\Delta$ larg.comp.)	(27.97)	177.16	263.84	151.26
maximal triangle-number	966	5295	15128	10730
cluster coefficient: $\bar{C}$	0.57	0.72	0.72	0.79
( $\bar{C}$ larg. comp.)	(0.67)	(0.74)	(0.75)	(0.81)
number of components	369	183	455	467
diameter of largest component	9	7	9	10
mean path length: $\lambda$ of l.c.	3.70	3.27	3.32	3.59
exponent of degree distribution	-2.1	-2.0	-2.0	-2.1
variance of degree exponent	0.4	0.3	0.3	0.3
exponent of org-size distr.	-2.1	-1.9	-1.7	-1.8
variance of size exponent	0.5	0.3	0.5	0.3
mean # projects per org: $\mathbb{E}( O )$	2.40	4.87	5.6	6.24
maximal size (max $ O $ )	130	82	138	172

## O-graph Organisations Projection

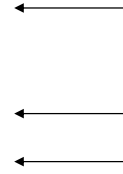


TABLE II: Basic network properties of FP1–4 organizations projection.

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graph characteristic	FP1	FP2	FP3	FP4
# vertices: $N$	3283	3884	5528	9087
( $N$ for larg. comp.)	(2764)	(3662)	(5027)	(8566)
$N$ outside larg.comp.	519	222	501	521
# edges: $M$	51217	94527	202358	348542
(# edges $M$ larg.comp.)	(50940)	(94471)	(202306)	(348474)
mean degree: $\bar{d}$	31.20	48.68	73.20	76.71
( $\bar{d}$ larg. comp.)	(36.86)	(51.60)	(80.49)	(81.36)
maximal degree: $d_{\max}$	282	387	917	771
mean triangles per vertex: $\Delta$	774.41	871.19	1970.30	2034.31
( $\Delta$ larg.comp.)	919.53	923.98	2167.05	2158.03
maximal triangle-number	12903	11125	37247	41141
cluster coefficient: $\bar{C}$	0.67	0.54	0.44	0.47
( $\bar{C}$ larg.comp.)	(0.75)	(0.57)	(0.48)	(0.50)
number of components	369	183	455	467
diameter of largest component	9	7	10	9
mean path length: $\lambda$ of l.c.	3.24	2.80	2.72	2.80
exponent of degree distribution	(-0.8, -3.4)	(-0.7, -3.3)	(-0.6, -3.7)	(-0.3, -2.2)
variance of degree exponent	(0.4, 3.6)	(0.3, 1.7)	(0.3, 1.4)	(0.2, 0.6)
exponent of proj-size distr.	-3.59	-2.9	-3.2	-4.1
variance of size exponent	0.6	0.4	0.2	0.3
mean # orgs per project: $\mathbb{E}( P )$	3.15	3.08	3.22	2.71
maximal size (max $ P $ )	20	44	73	54

## P-graph Projects Projection

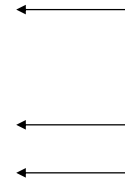


TABLE III: Basic network properties of FP1–4 projects projection.

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Um **empirische** und **generierte** Graphen zu **vergleichen** ...

... sehen wir immer *3 Diagramme zusammen*

**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

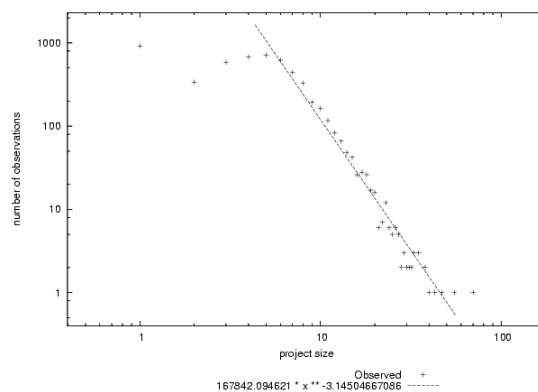
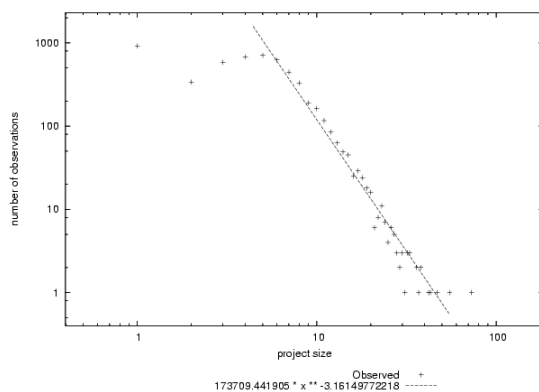
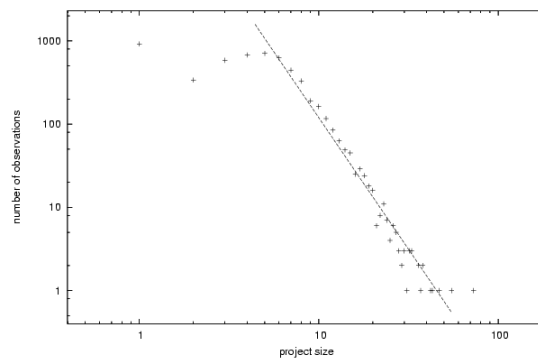
**bipMolloyReed Network**

- ~ 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**

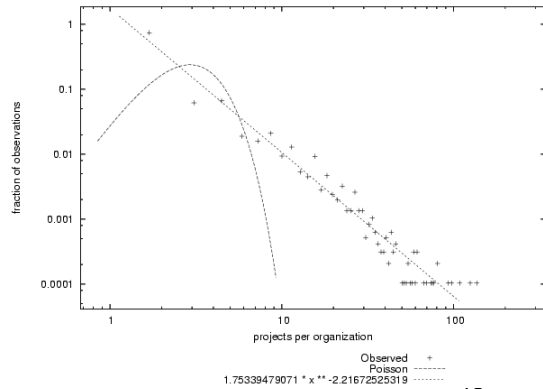
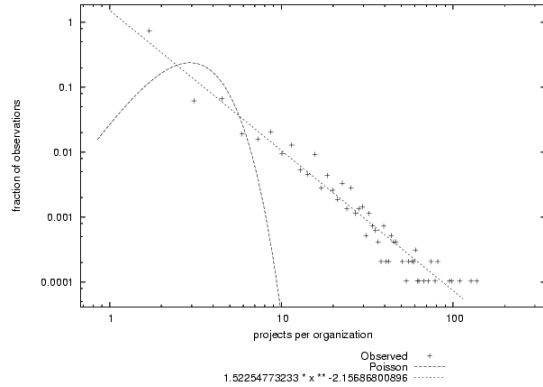
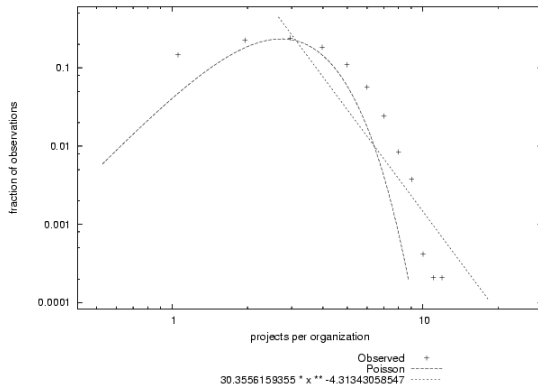


## Organization Sizes:

RandomSetModel:

Exponential Decay ~ Poisson Distrib.  
predicted by theory!

FP3 <-> MolloyReed  
identical because input



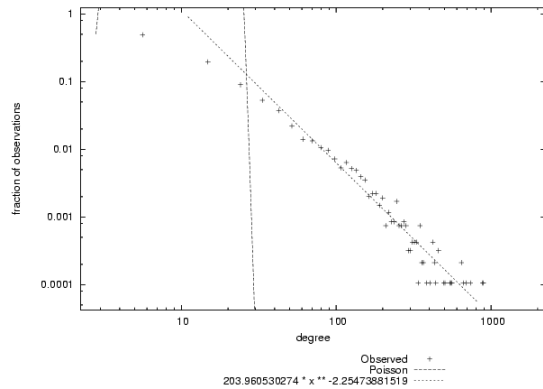
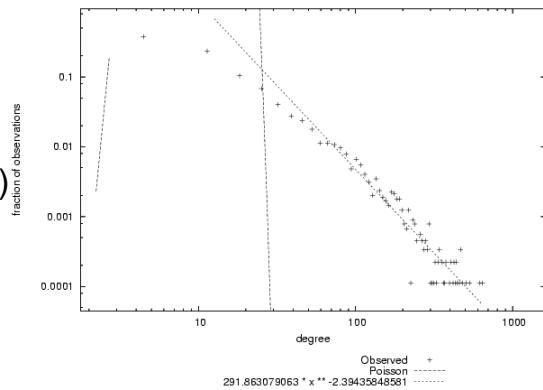
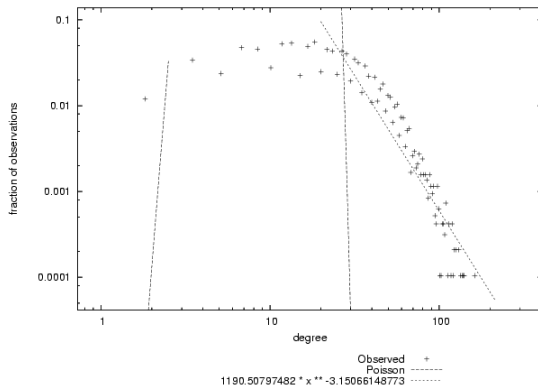
## Organization Graph: Projection onto organisations

RandomSet:

fat tail *but* much steeper (exponent >3.2)

MolloyReed:

similar to empirical FP3;  
both are ~ on a straight power law  
with exponent 2.3 - 2.4

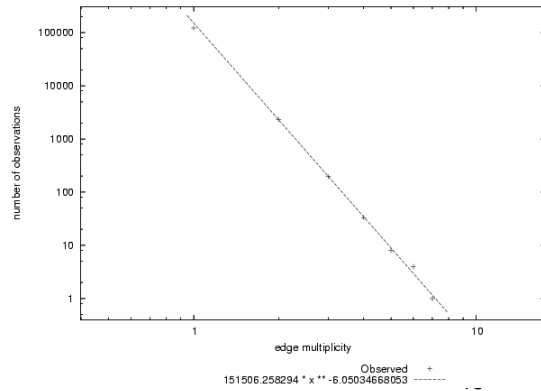
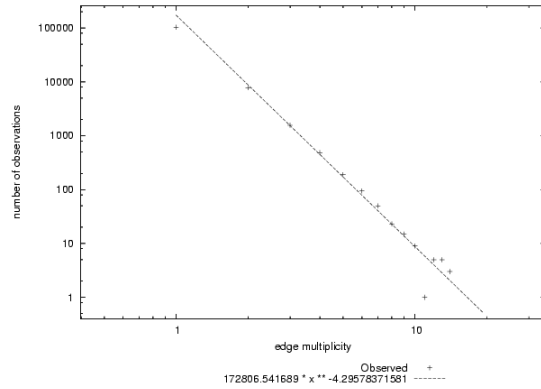
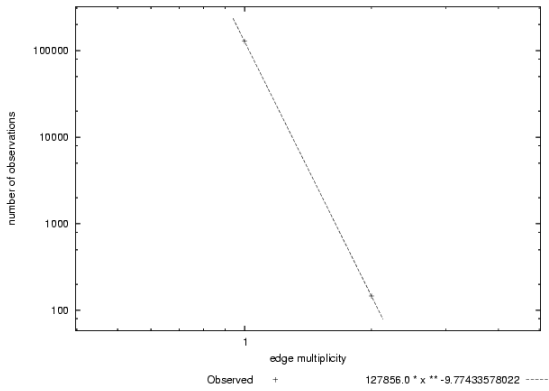


# Organization Graph: Edge Multiplicities

Empirical FP3:  
highest multiplicity 14

RandomSet:  
only 1 and 2

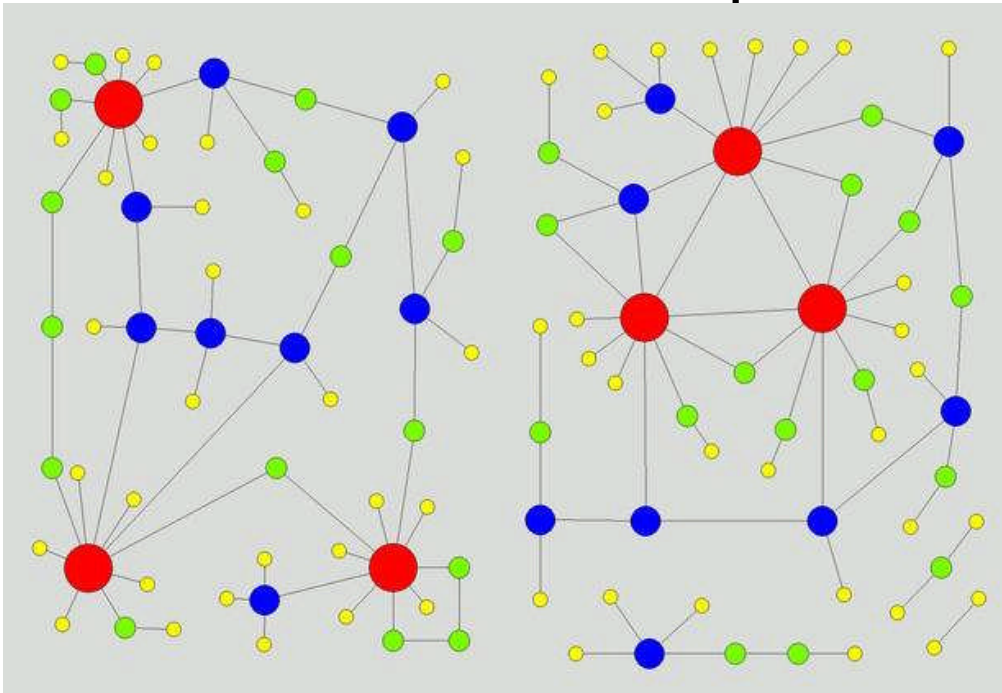
MolloyReed:  
highest multiplicity only 7





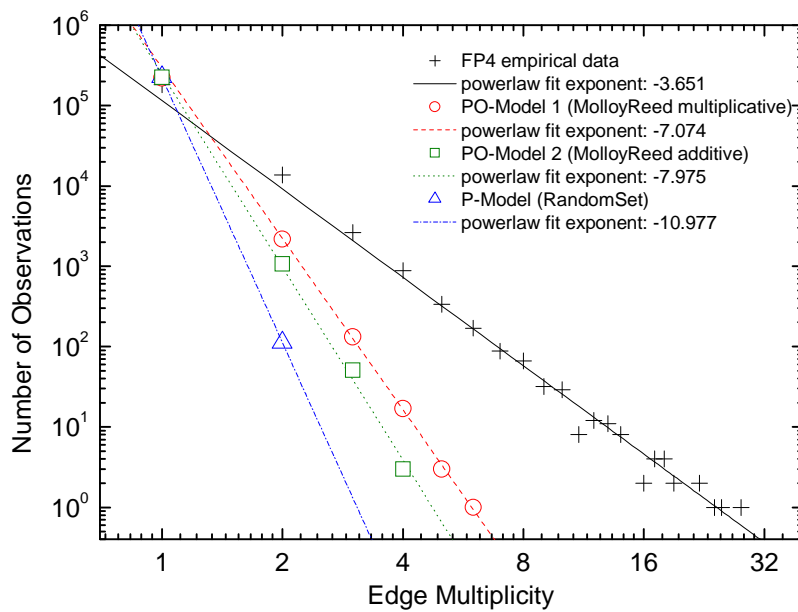
additive

multiplicative



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## Multiplicative vs. Additive: OrganisationsGraph Edge Multiplicity



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