

# Diversity vs Uniformity: Understanding the Evolution of Large Networks

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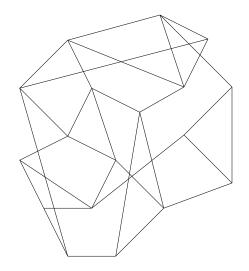
#### **ROBUST**

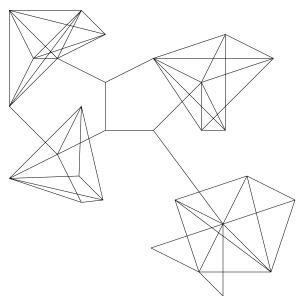
# **Diversity**

- Many, equally-sized subcommunities
- High entropy
- 'Flat' structure

# Regularity

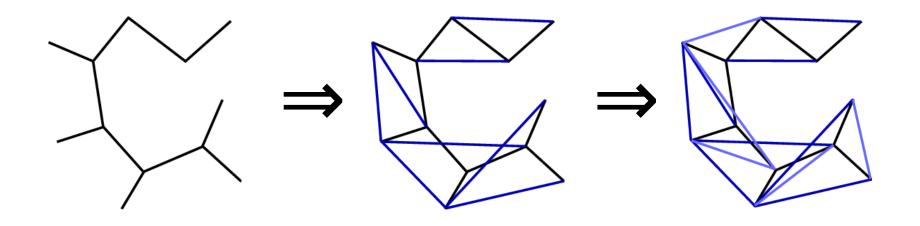
- Few large subcommunities
- Low entropy
- Many 'hubs'











- How did a network look at time t?
- Idea: Observe the change of diversity/regularity over time



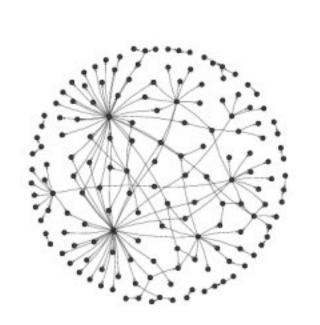


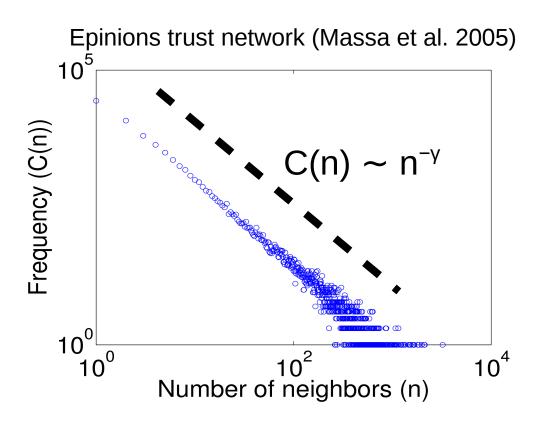
- 1. Power-law exponent
- 2. Weighted spectral distribution
- 3. Network entropy
- 4. Network rank





#### Number of neighbors is unevenly distributed:



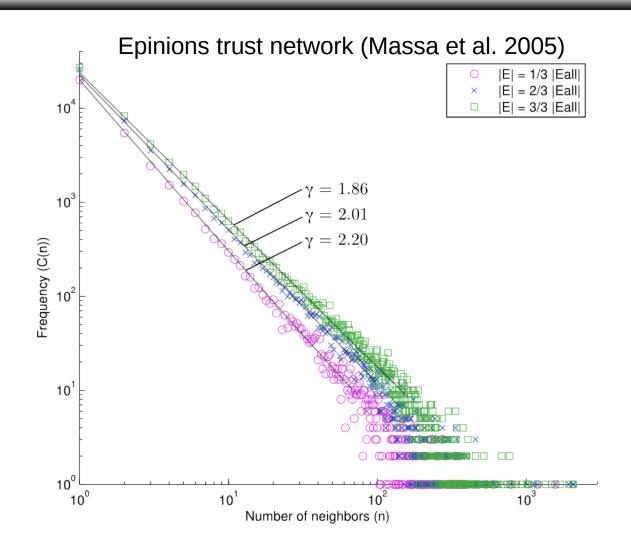


Results in a power-law (Newman 2006) Exponent γ denotes regularity



### 1. Power-law Exponent over Time





γ shrinks ⇒ Network becomes more regular





• Consider the  $n \times n$  matrix N defined by

$$\mathbf{N}_{ij} = 1 \ / \ \mathrm{sqrt}(d(i)d(j))$$
 when  $(i,j)$  is an edge  $\mathbf{N}_{ij} = 0$  otherwise

Then the distribution of the eigenvalues of  ${\bf N}$  is called the weighted spectral distribution (WSD) (Fay et al. 2010)

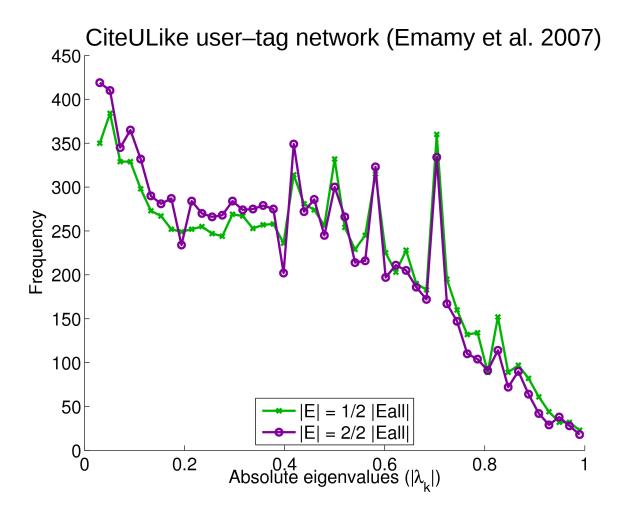
Eigenvalues nearer to  $\pm 1$ : diversity

Eigenvalues nearer to 0: regularity



#### 2. Weighted Spectral Distribution over Time





The WSD shifts towards zero ⇒ The network becomes regular





• Write the graph G as a sum of subgraphs  $G_k$ 

$$G = G_1 \cup G_2 \cup \ldots \cup G_r$$

Each  $G_k$  has weighted edges, with total weight  $\lambda_k$ 

• When picking an edge from G at random, the probability of it being in community  $G_k$  is

$$\lambda_k / (\lambda_1 + \lambda_2 + \ldots + \lambda_r) = \lambda_k / L$$

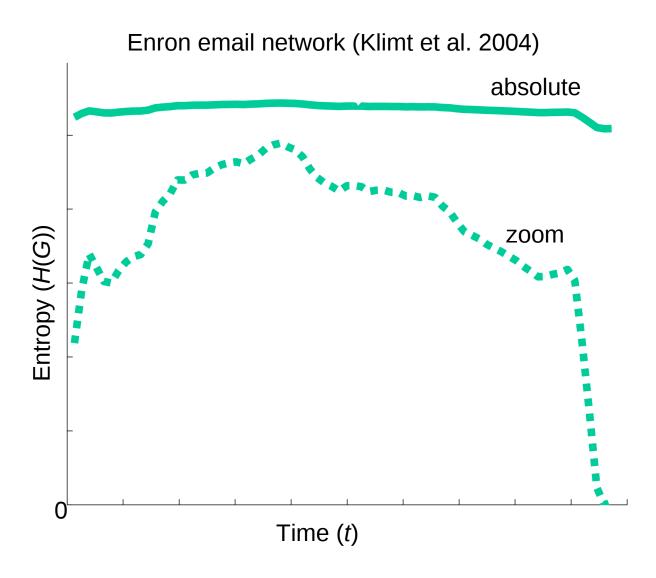
The entropy of this distribution is (Kunegis et al. 2011)

$$H(G) = -\sum_{k} (\lambda_{k} / L) \log (\lambda_{k} / L)$$

Entropy: Effective number of subcommunities









#### 4. Network Rank



Decompose network into subcommunities:

$$G = G_1 \cup G_2 \cup \ldots \cup G_r$$

The rank r is a measure of diversity:

$$rank(G) = r$$

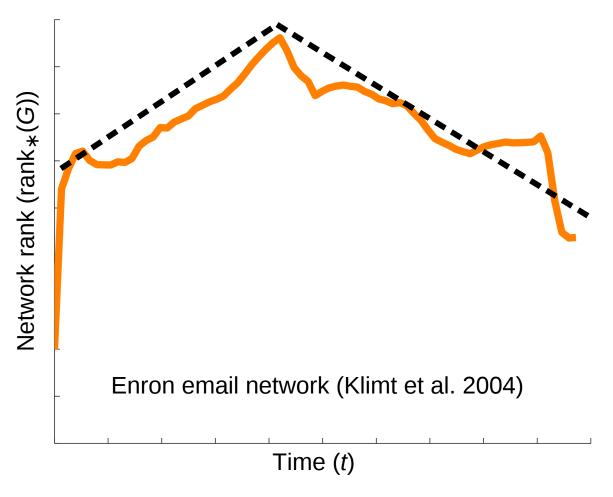
Weighted rank:

$$\operatorname{rank}_*(G) = \sum_k |G_k| / |G_1|$$

Robust measure of diversity (Kunegis et al. 2011)





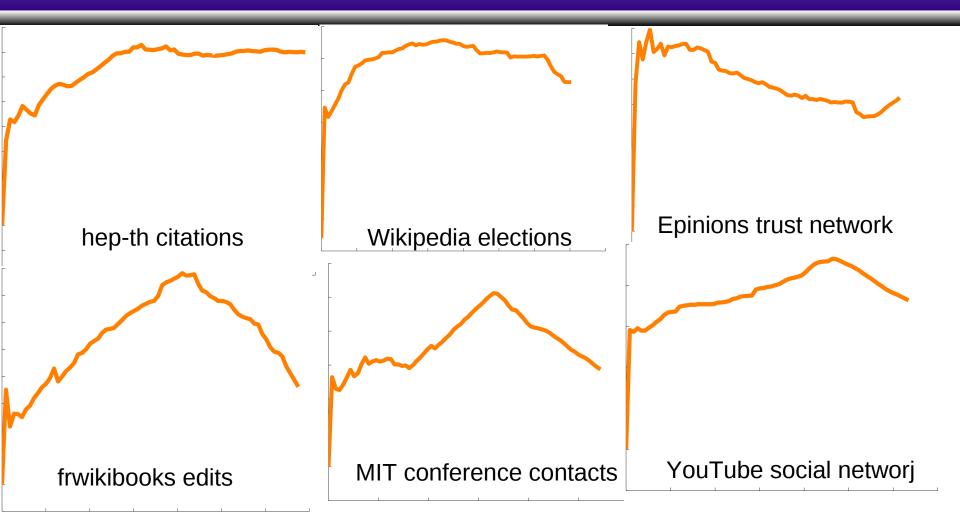


- Increasing network rank: increasing diversity
- Shrinking network rank: shrinking diversity



#### More Network Rank Plots





(biased towards good examples of convex evolution)



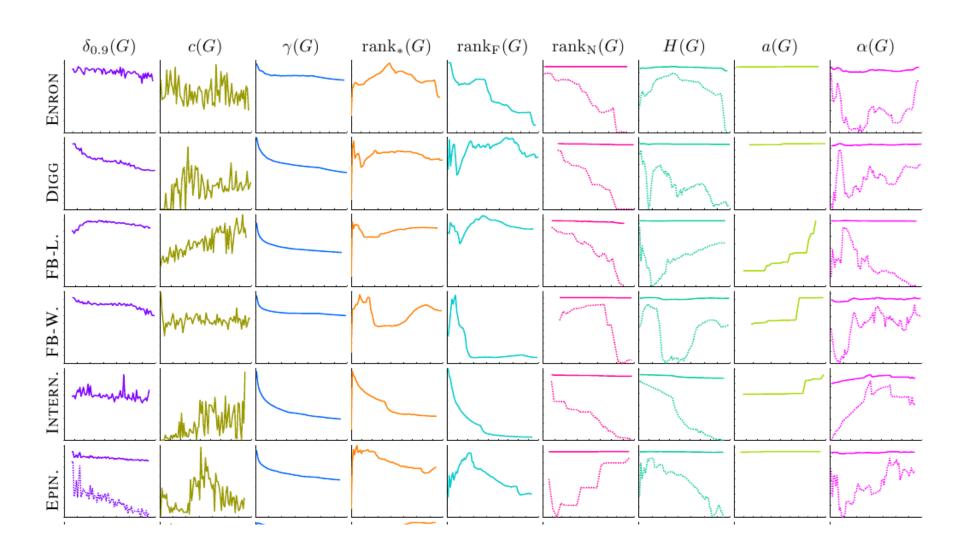


- Power-law exponent shrinks
  - Connection diversity shrinking
- Weighted spectral distribution shifts to zero
  - Emerging main components
- Entropy is constant
  - Effective number of communities is constant
- Network rank increases, then shrinks
  - Two-phase- model of expansion

Dissemination: submitted to ICDM 2011







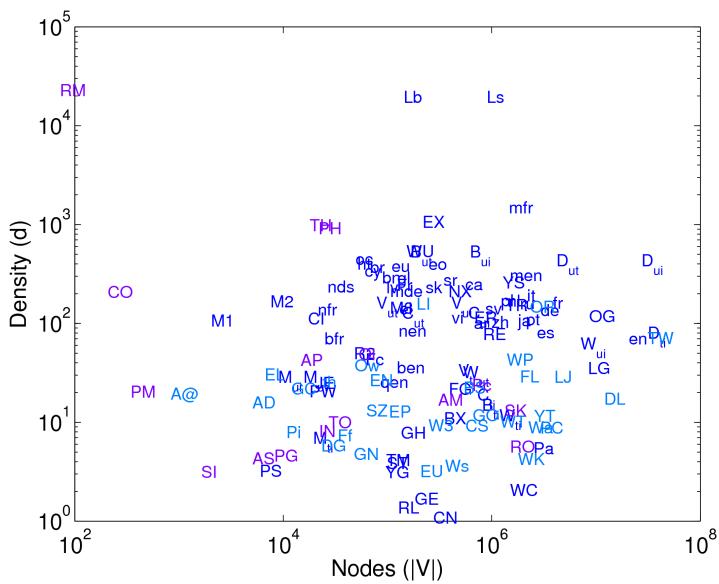




- 121 network datasets
- Categories: authorship, communication, cooccurrence, features, folksonomy, interaction, physical, ratings, reference, social, trust
- All code free/open

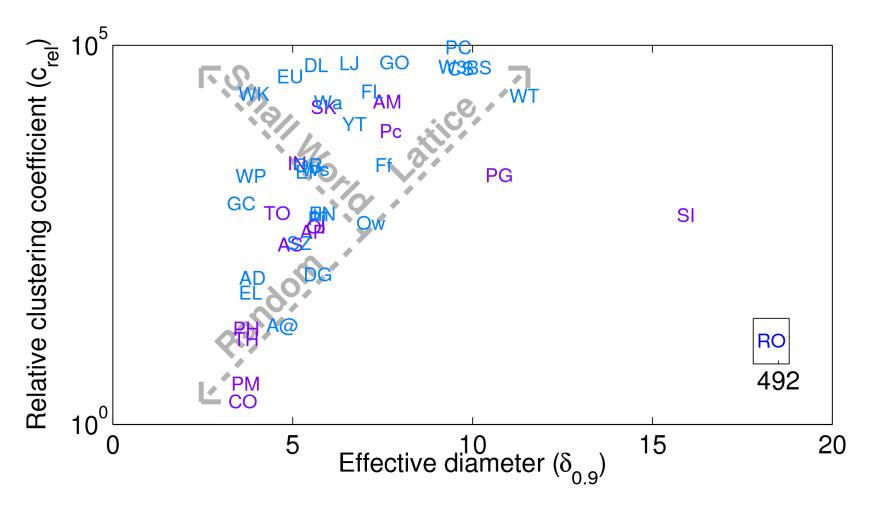






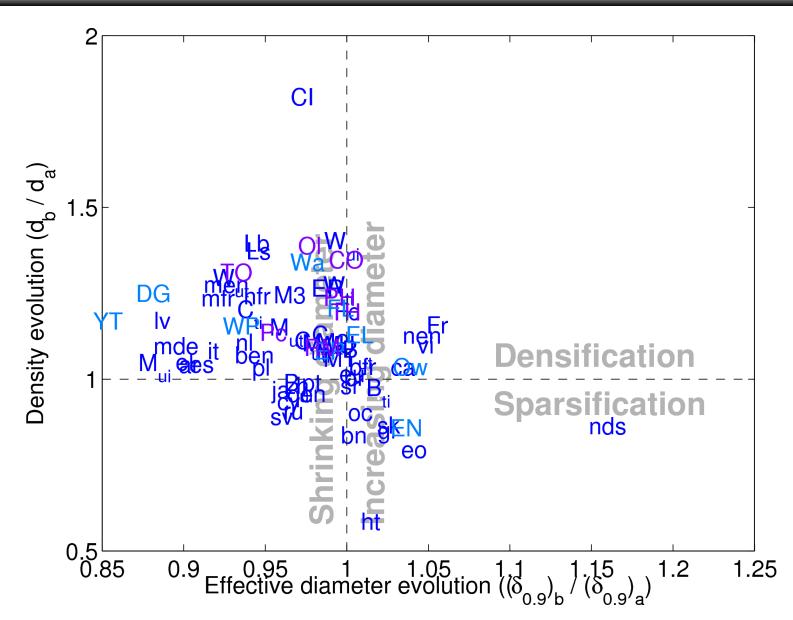














# KONECT – Roadmap



- Release extraction code
- Website (including statistics, plots)
- Datasets (where legally possible)
- Analysis code (Matlab/Octave)

- Which datasets would you like to have?
- What datasets can you contribute?



- **Emamy K., Cameron R., 2007**; CiteULike: A researcher's social bookmarking service; Ariadne, no. 51
- Fay D., Haddadi H., Thomason A., Moore A. W., Mortier R., Jamakovic A., Uhlig S., Rio M., 2010; Weighted spectral distribution for Internet topology analysis: Theory and applications; IEEE Trans. Networking, vol. 18, no. 1, pp. 164–176
- **Klimt B., Yang Y., 2004**; The Enron corpus: A new dataset for email classification research; Proc. European Conf. on Machine Learning, pp. 217–226
- **Kunegis J., Sizov S., 2011**; Diversity vs uniformity: understanding the evolution of large networks; unpublished
- Massa P., Avesani P., 2005; Controversial users demand local trust metrics: an experimental study on epinions.com community; Proc. American Association for Artificial Intelligence Conf., pp. 121–126
- **Newman M. E. J., 2006**; Power laws, Pareto distributions and Zipf's law; Contemporary Phys., vol. 46, no. 5, pp. 323–351





