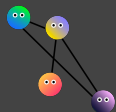


Bipartite Growth Models

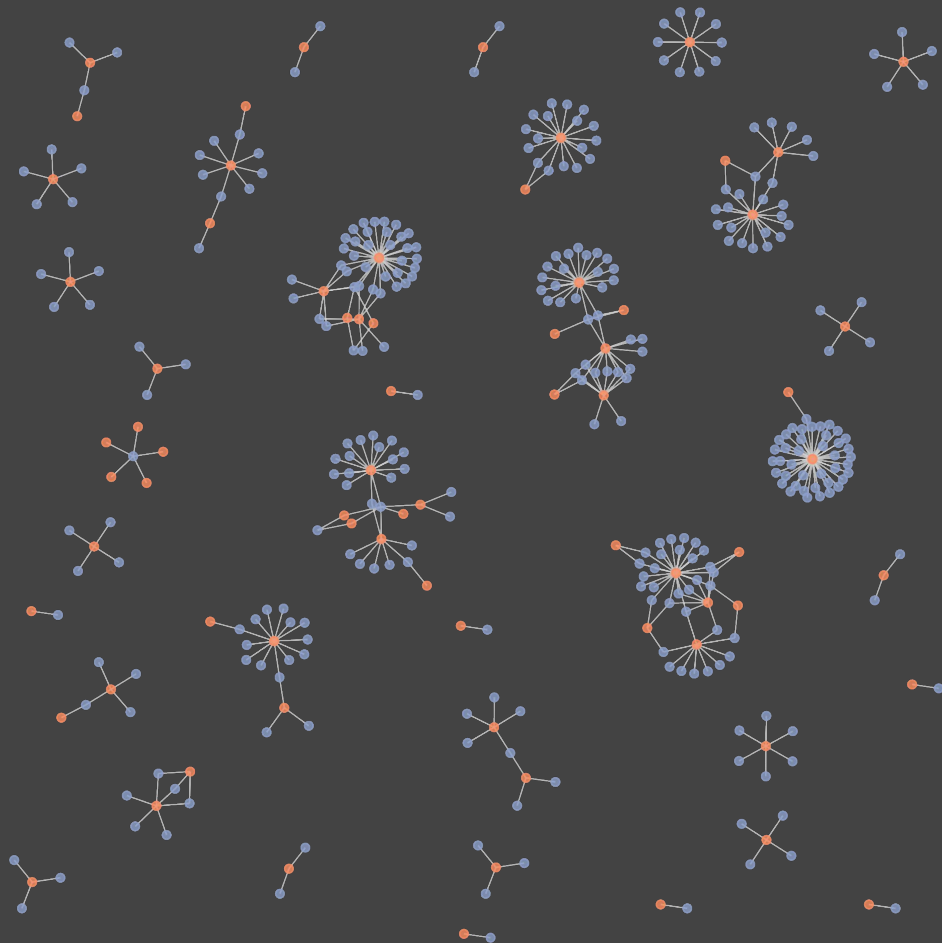
Chakresh Kr. Singh
Interaction Data Lab



@chakresh_iitgn

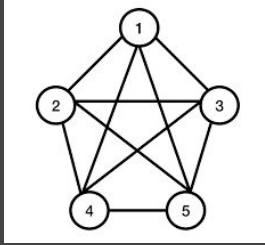


<https://chakreshiitgn.github.io/>

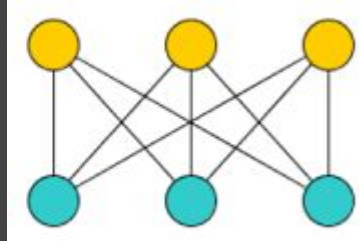


Different Network Types

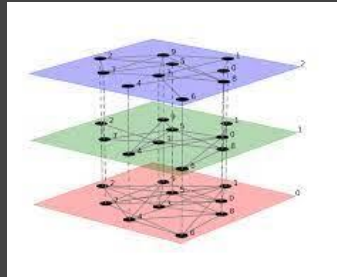
- Unipartite



- Bipartite

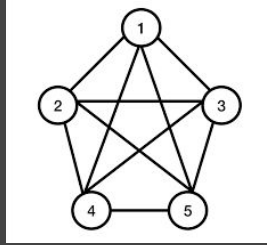


- Multilayer

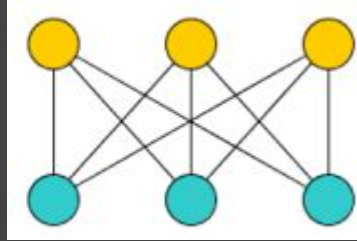


Different Network Types

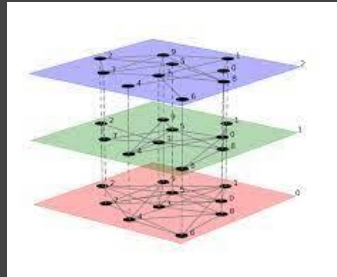
- Unipartite



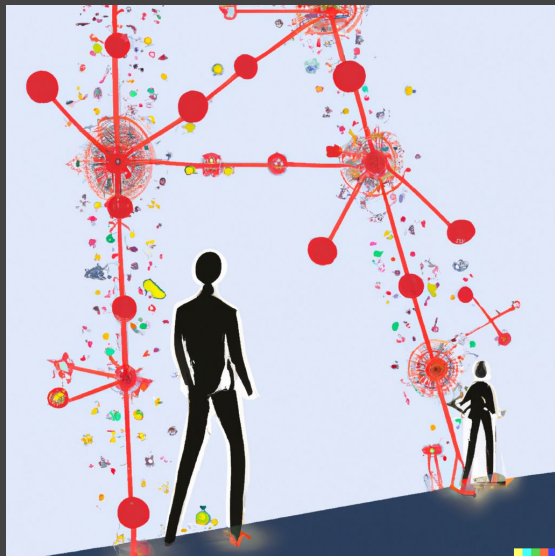
- Bipartite



- Multilayer



On the shoulder of Giants



Mathew Effect

Simon's Model
Scalefree

Preferential
Polya's Urn Model

Power Law *Barabasi-Albert*

Yule-process 1924

Zipfs Law

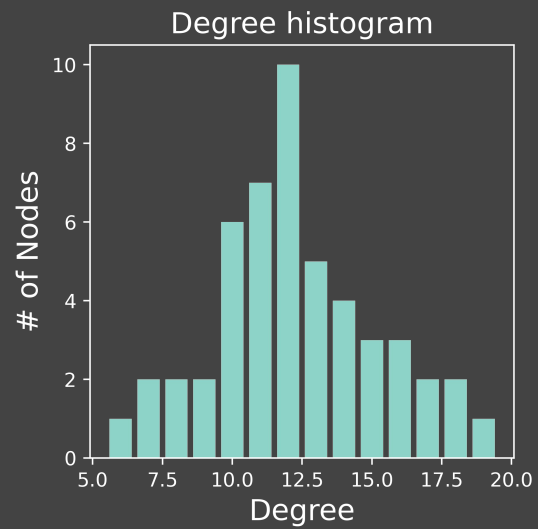
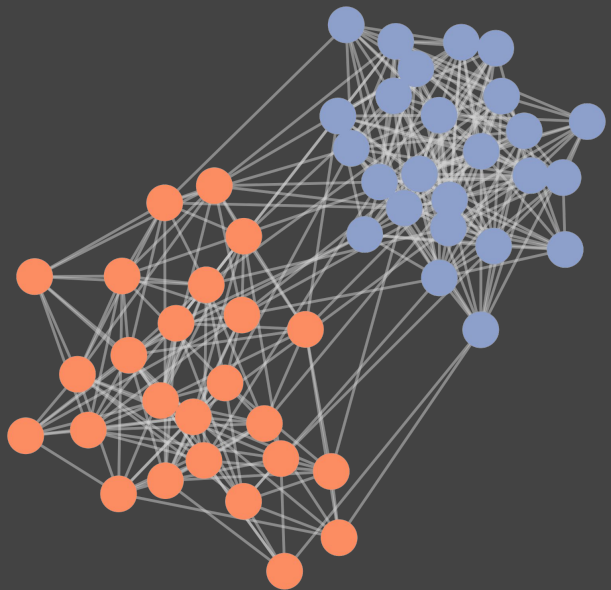
Evolution

2000

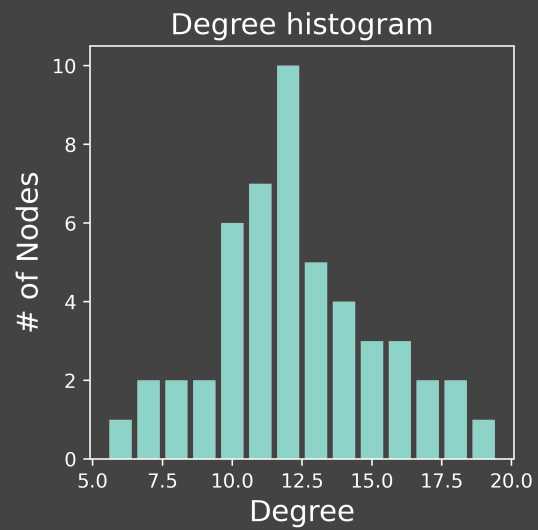
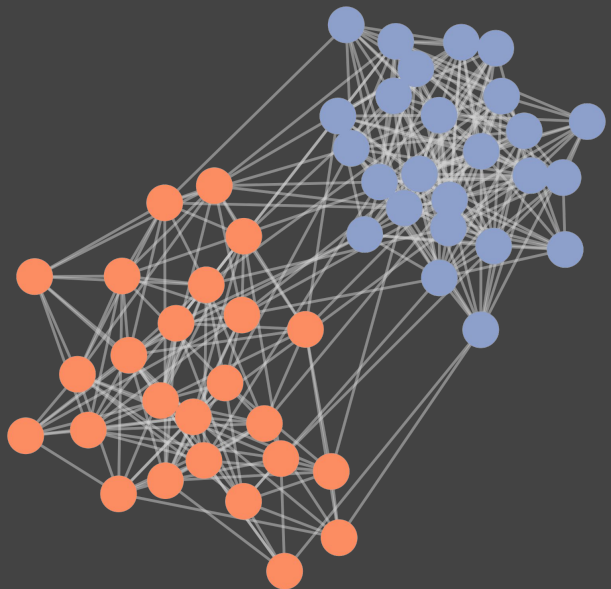
1955



What do we want to model ?

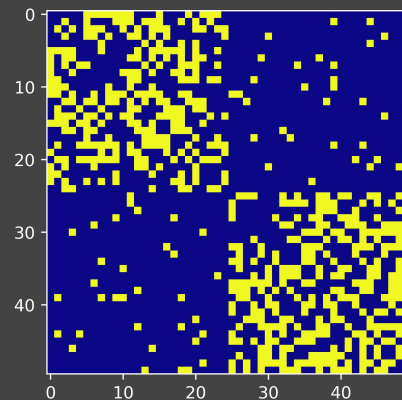


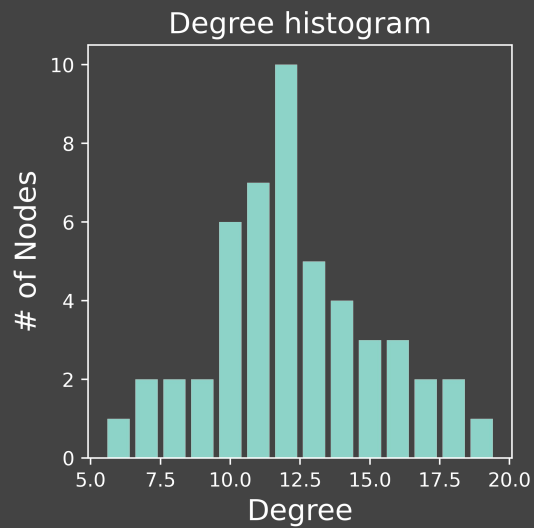
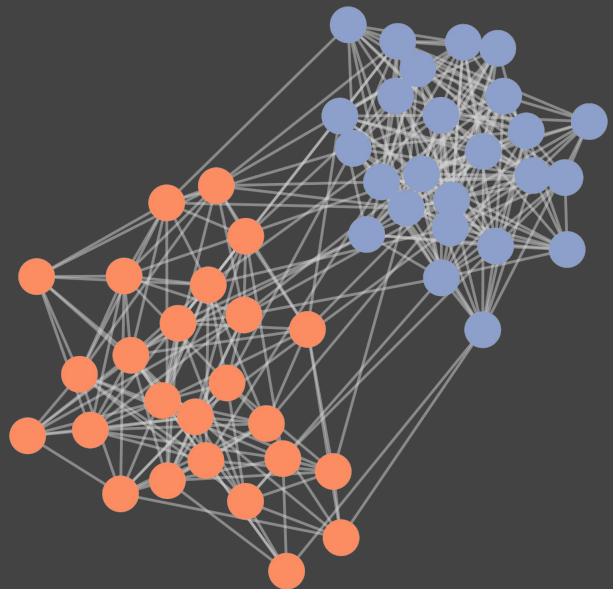
Degree



Degree

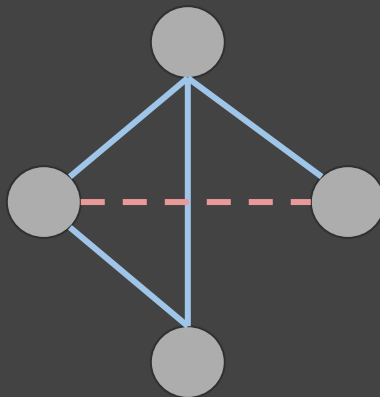
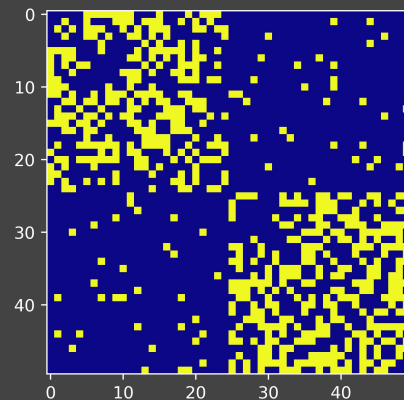
Assortativity





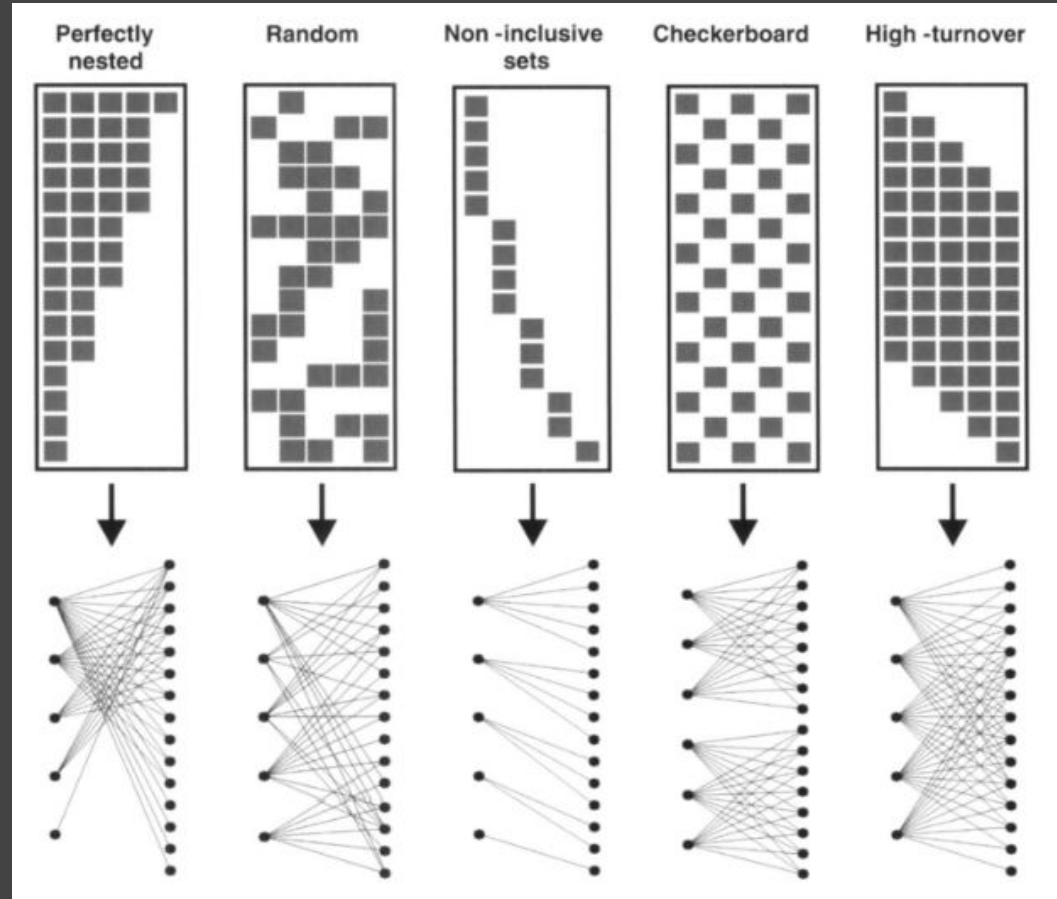
Degree

Assortativity



Clustering

Nestedness



Almeida-Neto, M., R. Guimarães Jr, P., & M. Lewinsohn, T. (2007). On nestedness analyses: Rethinking matrix temperature and anti-nestedness. *Oikos*, 116(4), 716-722.

Self-organization of collaboration networks

José J. Ramasco,^{1,*} S. N. Dorogovtsev,^{2,3,4} and Romualdo Pastor-Satorras⁵

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²*Departamento de Física, Universidade de Aveiro, Campus Universitario de Santiago, 3810-193 Aveiro, Portugal*

³*Laboratory of Physics, Helsinki University of Technology, FIN-02015 HUT, Finland*

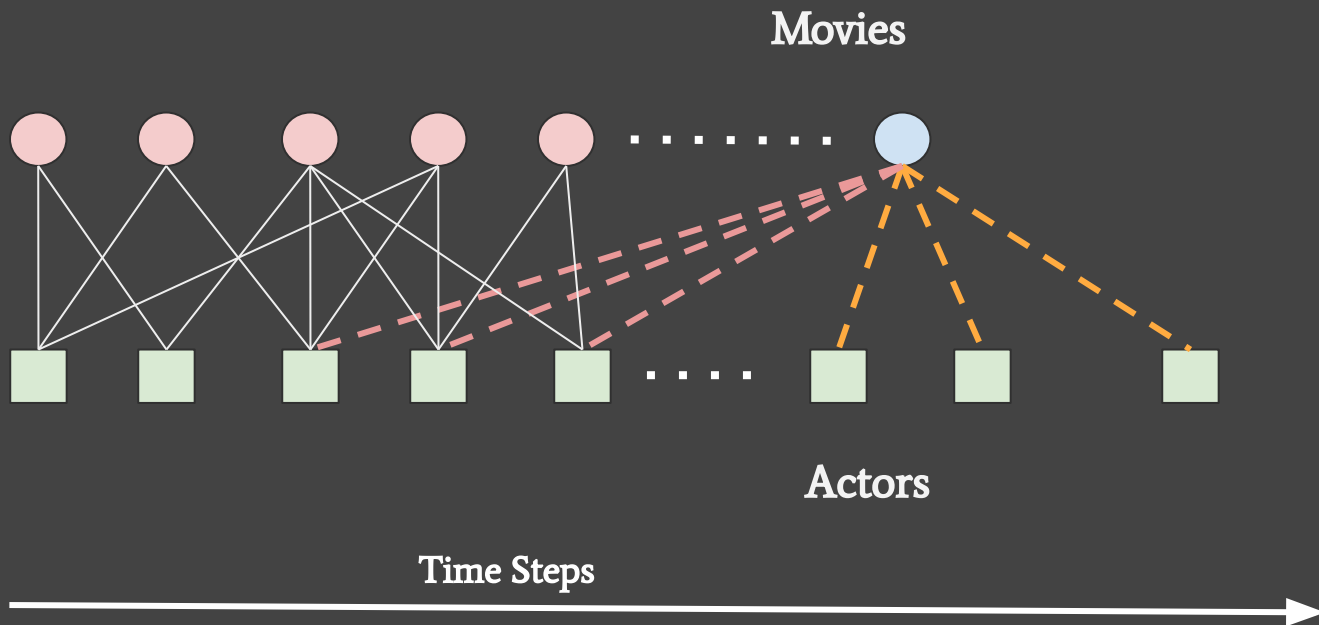
⁴*A. F. Ioffe Physico-Technical Institute, 194021 St. Petersburg, Russia*

⁵*Departament de Física i Enginyeria Nuclear, Universitat Politècnica de Catalunya, Campus Nord, 08034 Barcelona, Spain*

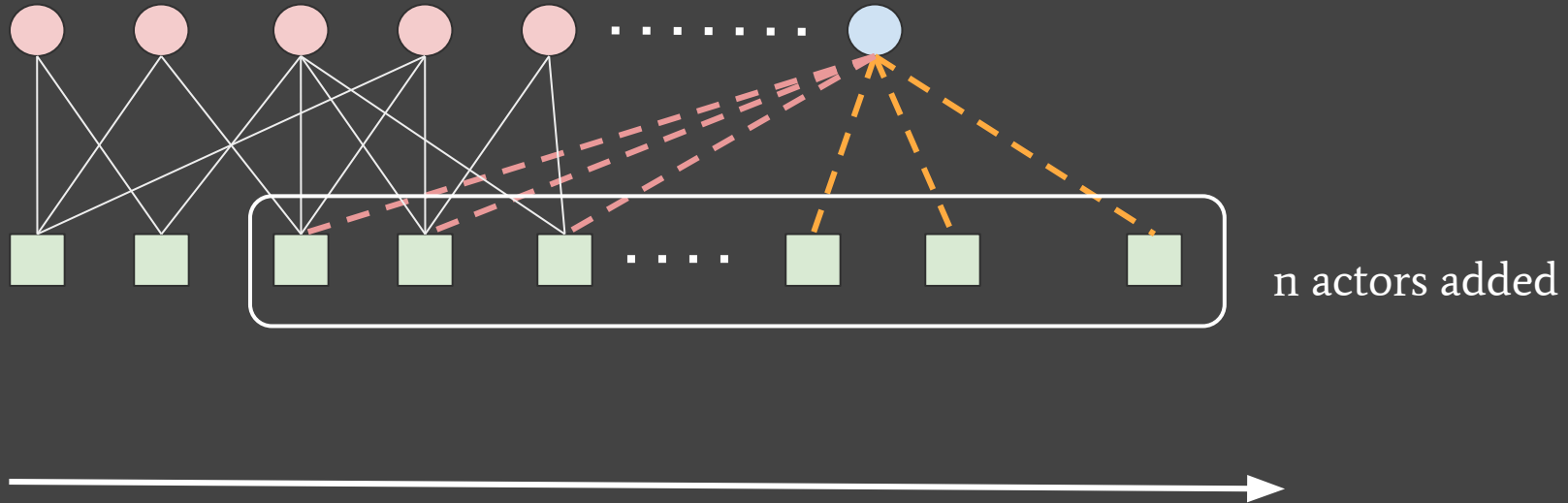
(Received 29 March 2004; published 14 September 2004)

We study collaboration networks in terms of evolving, self-organizing bipartite graph models. We propose a model of a growing network, which combines preferential edge attachment with the bipartite structure, generic for collaboration networks. The model depends exclusively on basic properties of the network, such as the total number of collaborators and acts of collaboration, the mean size of collaborations, etc. The simplest model defined within this framework already allows us to describe many of the main topological characteristics (degree distribution, clustering coefficient, etc.) of one-mode projections of several real collaboration networks, without parameter fitting. We explain the observed dependence of the local clustering on degree and the degree-degree correlations in terms of the “aging” of collaborators and their physical impossibility to participate in an unlimited number of collaborations.

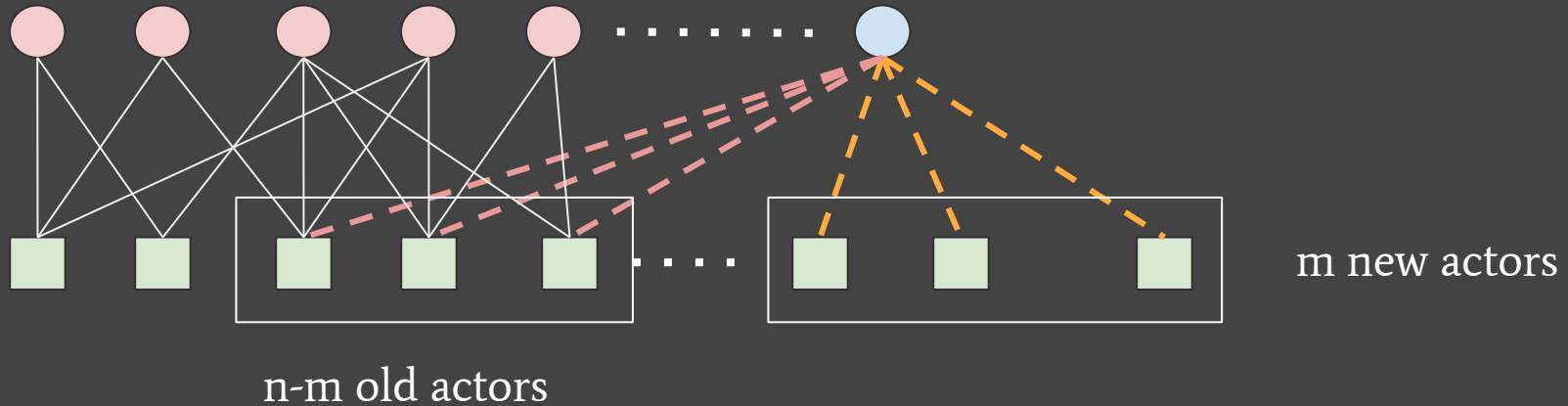
Ramasco's Model (Self organization in Collaboration Networks)



Ramasco's Model (Self organization in Collaboration Networks)



Ramasco's Model (Self organization in Collaboration Networks)

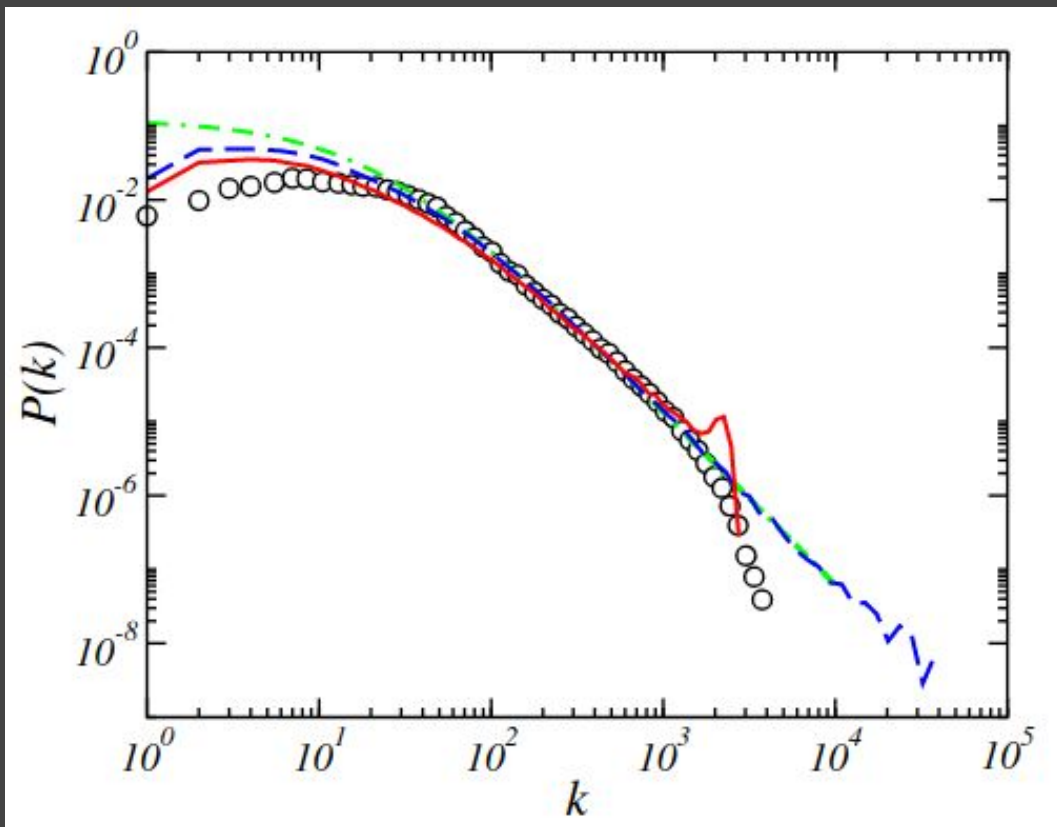
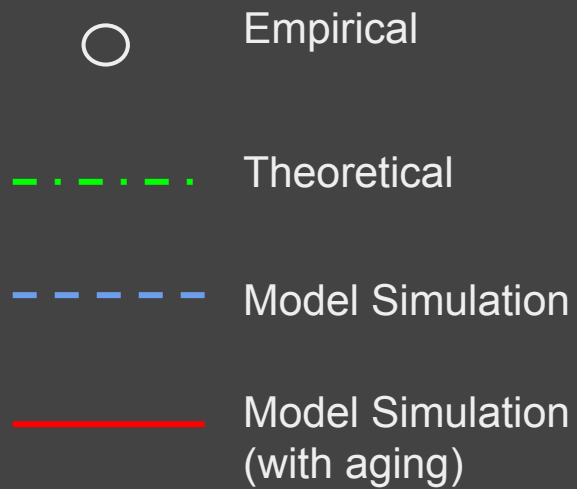


What can be further improved ?

What can be further improved ?

Aging effect !!

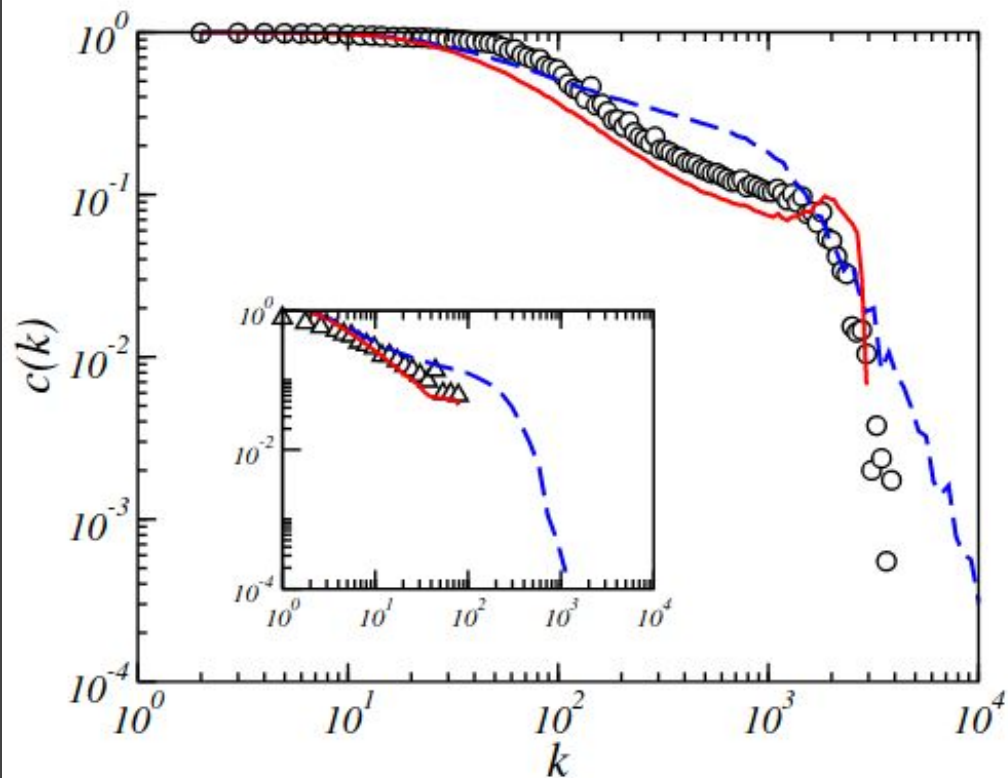
Introduce inactivity using a survival function (Exponential)



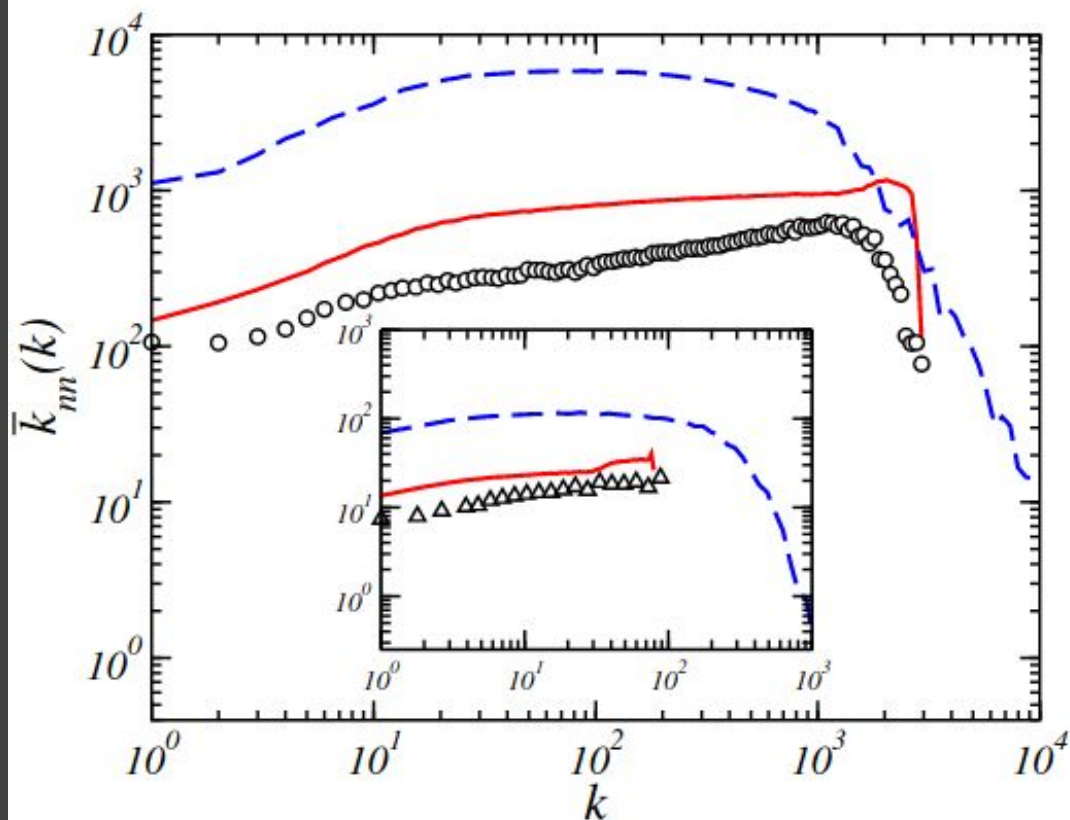
○ △ Empirical

--- Model Simulation

— Model Simulation
(with aging)



- △ Empirical
- Model Simulation
- Model Simulation (with aging)

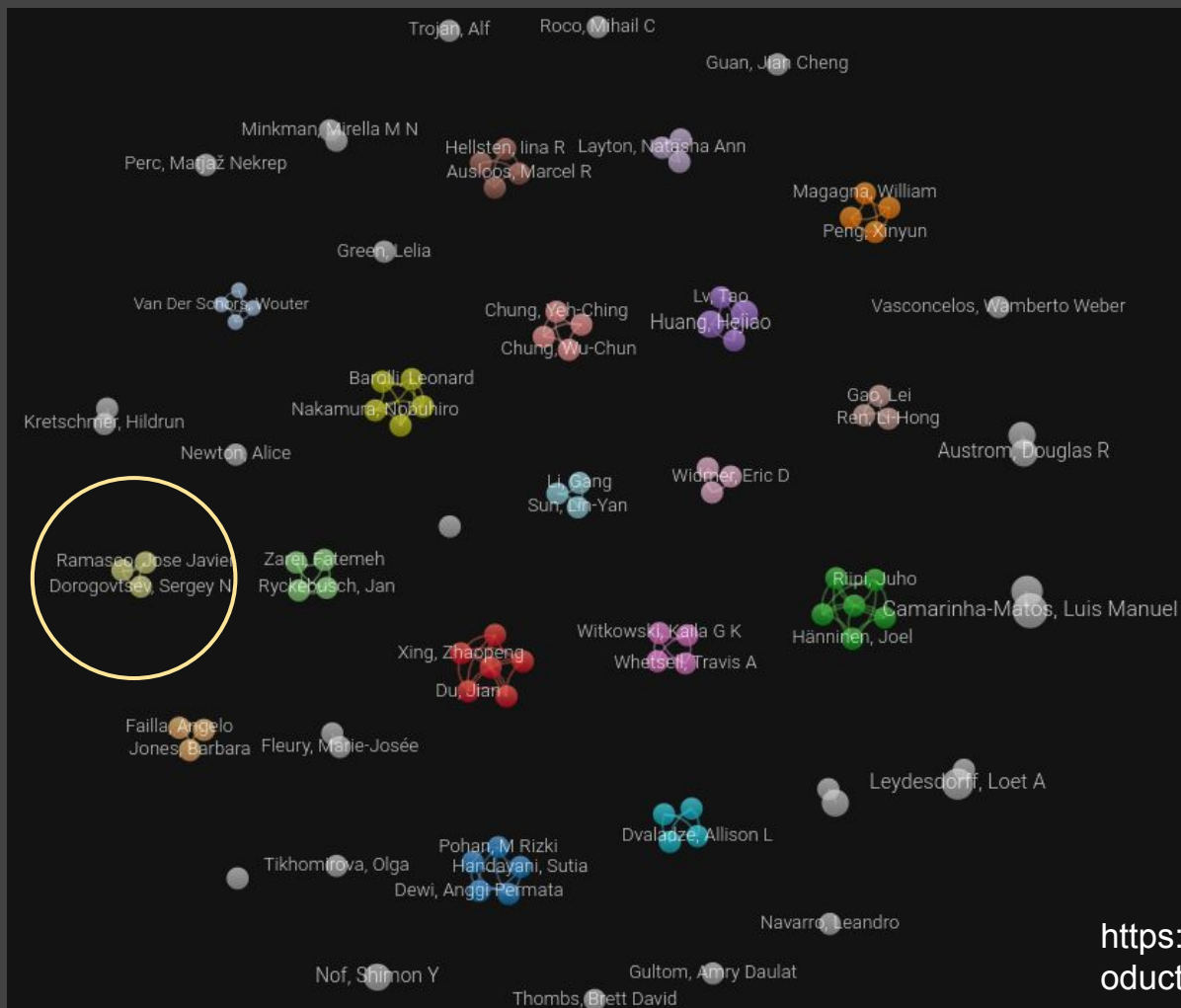


Take Away

- A simplistic model to explain the growth of a bipartite network structure
- Assortativity and Clustering are better predicted when 'aging' is incorporated in the model

To Consider

- More complicated rules of selection
- How does this affect the nestedness



<https://www.dimensions.ai/products/free/>

A different model with an even sophisticated mechanism



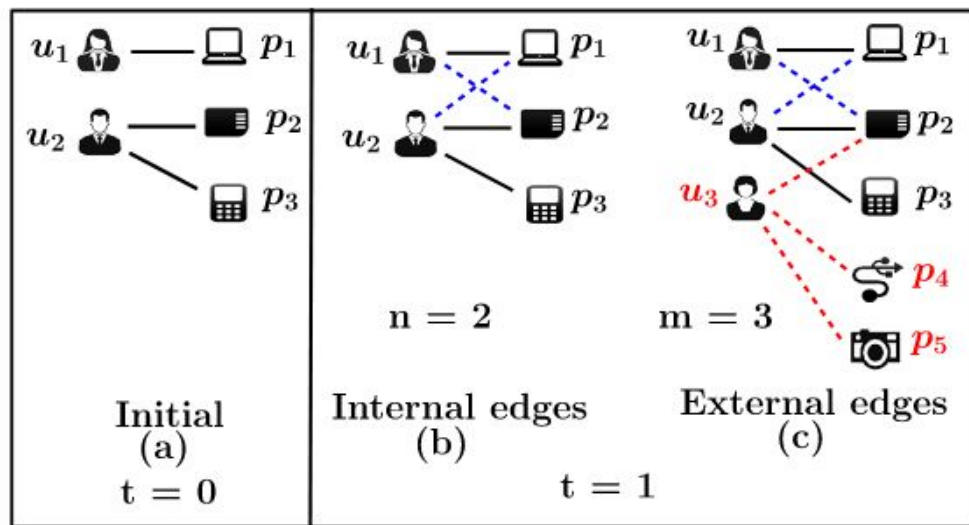
Physica A: Statistical Mechanics and its Applications

Volume 517, 1 March 2019, Pages 370-384



A general growth model for online emerging user–object bipartite networks ☆

Anita Chandra, Himanshu Garg, Abyayananda Maiti  



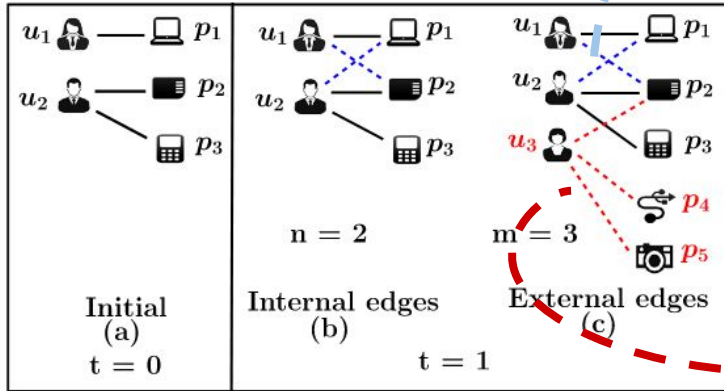
$$\tilde{A}(k_{v,t}) = \frac{k_{v,t} + \gamma}{\sum_{v=1}^N (k_{v,t} + \gamma)}$$

Attachment Kernel

Growth of the model

Probability of connection for internal edges

$$\frac{k_v + \gamma_i}{\sum_{v=1}^{o_0+wt} (k_v + \gamma_i)}$$



Probability of connection for external edges

$$\frac{k_v + \gamma_e}{\sum_{v=1}^{o_0+wt} (k_v + \gamma_e)}$$

This is a little different from
Ramasco's Model (movie-actor)

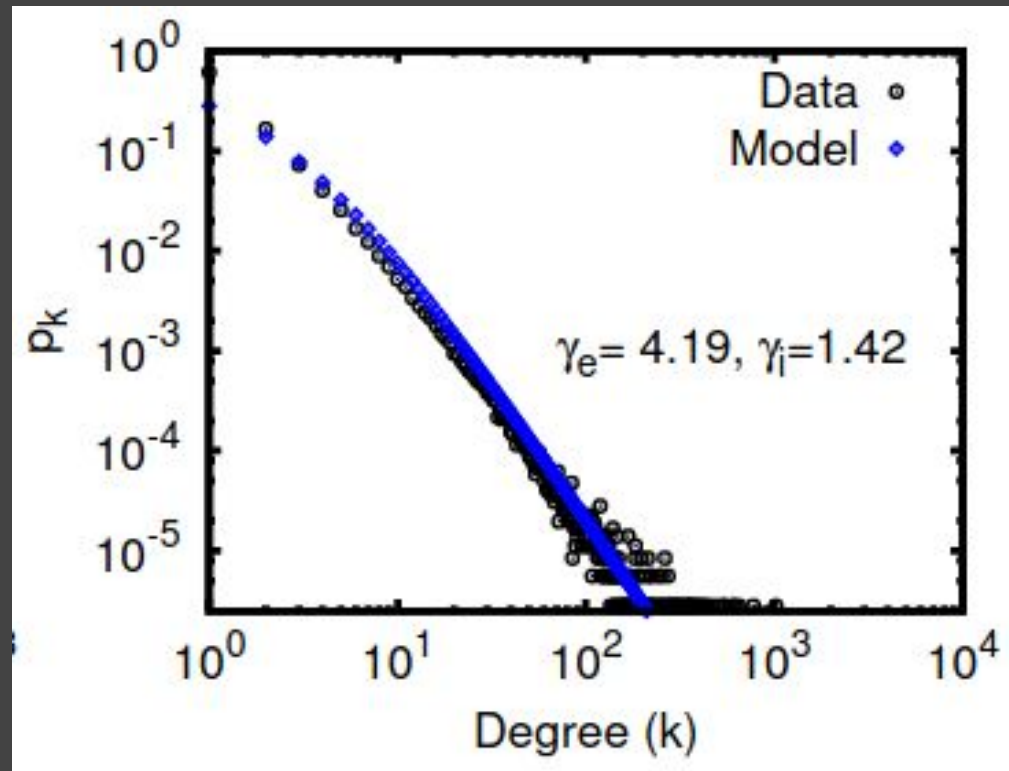
$$\frac{\partial k_v}{\partial t} = m \frac{k_v + \gamma_e}{\sum_{v=1}^{o_0+wt} k_v + \gamma_e} + n \frac{k_v + \gamma_i}{\sum_{v=1}^{o_0+wt} k_v + \gamma_i}.$$

$$\frac{\partial k_v}{\partial t} = m \frac{k_v + \gamma_e}{(c + w\gamma_e)t} + n \frac{k_v + \gamma_i}{(c + w\gamma_i)t}.$$

$$c = m+n$$

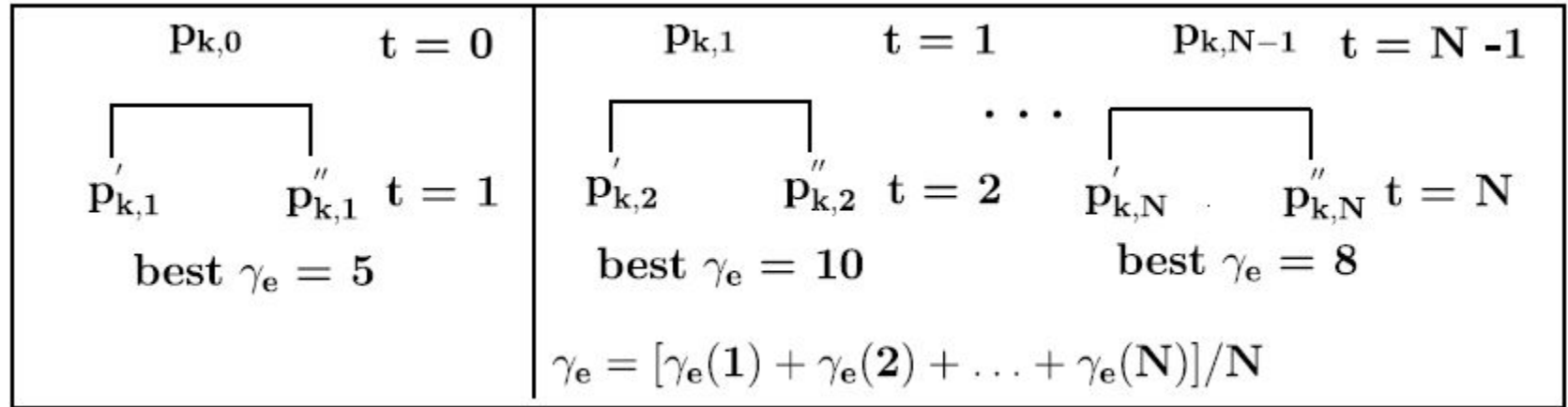
$$p(k) = \frac{\partial P(k_v(t) < k)}{\partial k} = \frac{r}{s} (k_0)^{\frac{r}{s}} (k + k_0)^{-(1+\frac{r}{s})}.$$

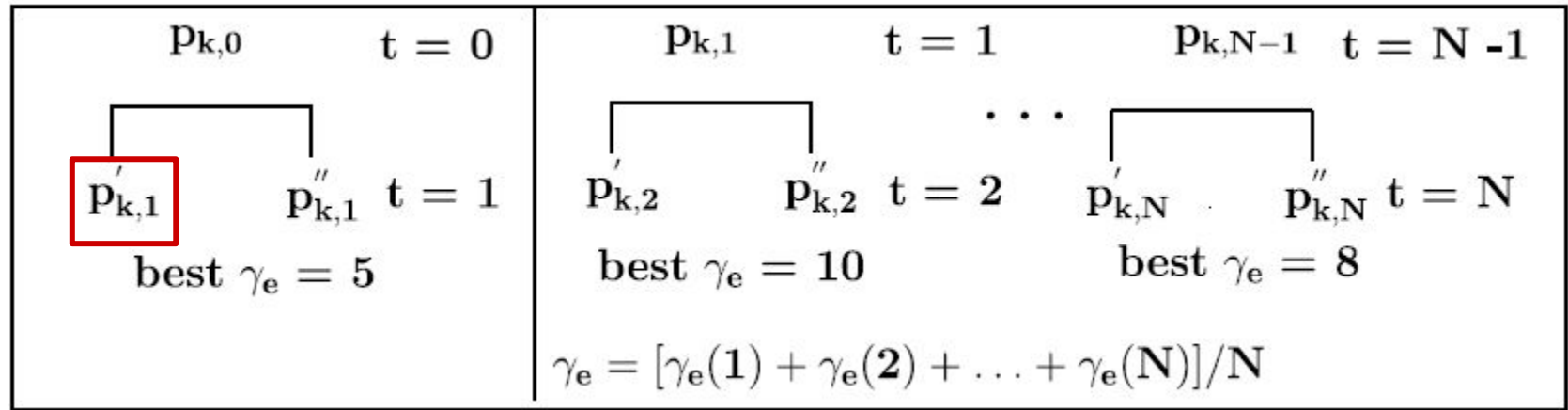
Shifted power law



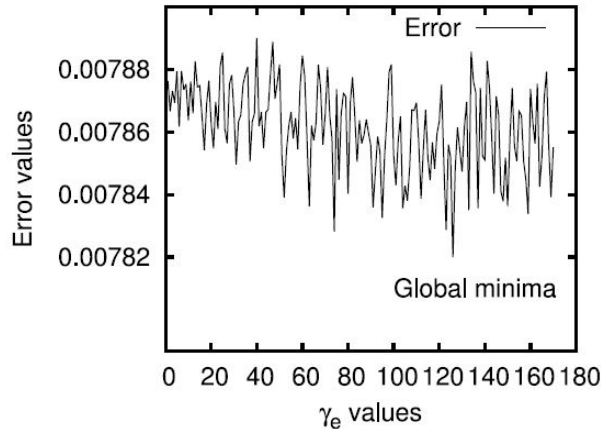
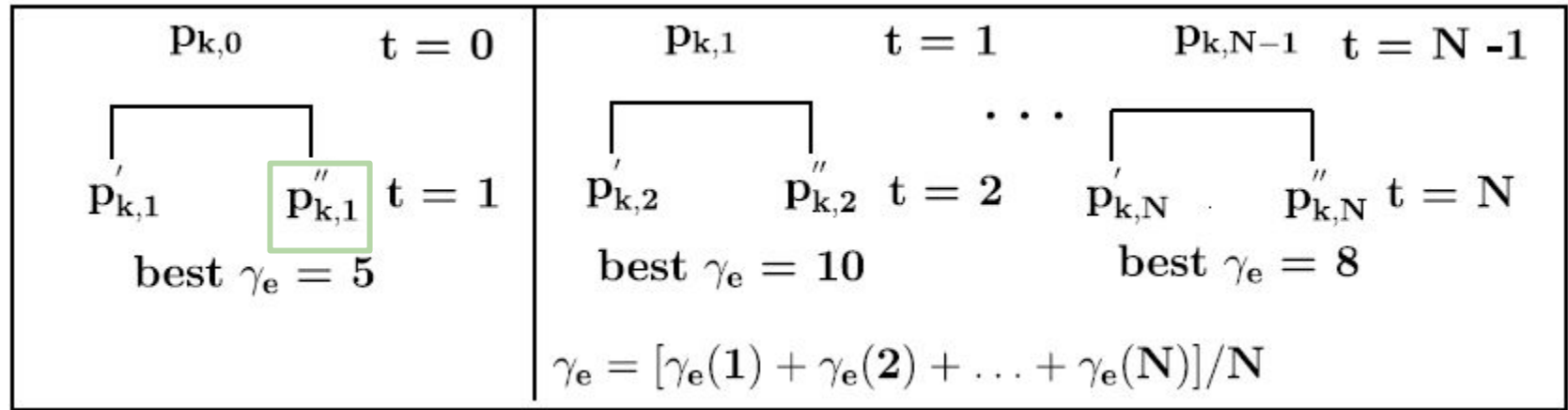
Amazon product rating

Estimating the randomness for every user





$p'(k,t+1)$ - derived from original $p(k,t)$ after excluding n internal edges arriving at $t+1$



- $p''(k,t+1)$ - derived from original $p(k,t)$ by simulating only considering the m edges.
 - Then the difference b/w $p'(k,t+1)$ and $p''(k,t+t)$ is minimized to estimate γ_e
- Similarly considering only n internal edges they estimate γ_i

Take Away

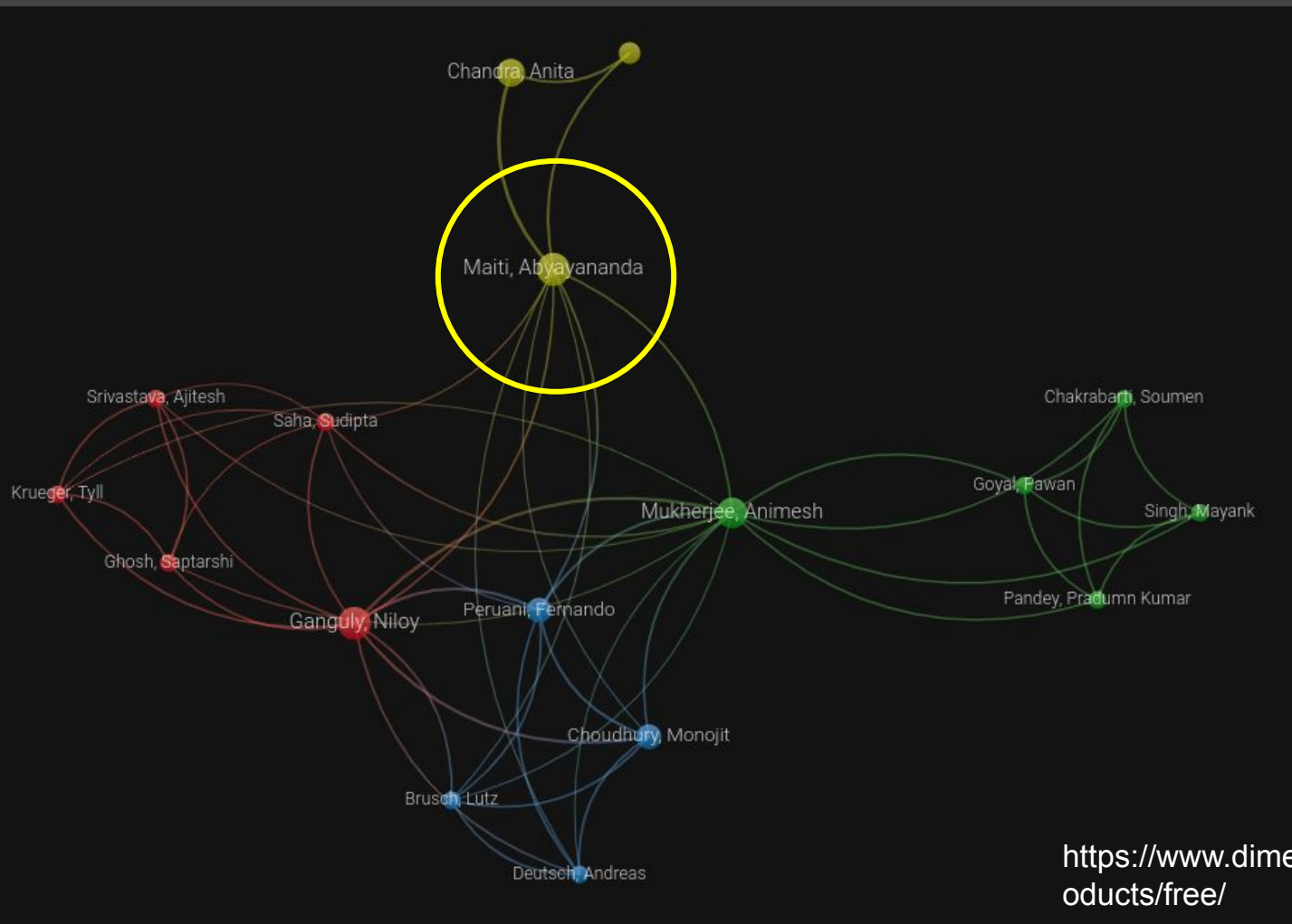
- The model is flexible to different attachment kernels
- The estimation of randomness parameter y_e and y_i differentiate between user choice of preferential vs random behavior... also telling which user is what.

To Consider

- The appearance of n edges is not clearly defined. Maybe because they focus on only one set of nodes.
- It would have been better to use KL-div test statistic to compare distributions

Perspectives

- These models focus on one mode projections
- We also want to predict the nestedness
- Is there a more generic way to define the growth?
- Data-sets
 - Publications (arXiv)
 - Github repos
 - Editors on wiki etc.



<https://www.dimensions.ai/products/free/>

THANK YOU