Modeling User Networks in Recommender Systems

3RD INTERNATIONAL WORKSHOP ON SEMANTIC MEDIA ADAPTATION AND PERSONALIZATION

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Presentation Summary

- Aim and rational
- Power-law & Previous work in the field
- Recommender systems
- User’s (social) network
- Question to explore
- Experimental Setting
- Results
- Conclusions
- Future work
- PServer

Aim and rational

- Discover the nature of social networks formed by recommender systems
  - Discover any laws connecting the ranking of user (based on the number of similarities with other users) with the number of similarities with other users
  - Hypothesis: Power-law holds

- Rational
  - Synthetic data generation for fast proof of concept
  - Identification of influential users or experts in a field

Literature on Power laws: $P(X=x) = k\,x^{-a}$

- Internet topology (1997-1998)
  - Power-law: Outdegree of nodes & their rank (Faloutsos et al. 1999)
- Recommender systems
  - Power-law: Influential users & their ranking (Rachid et al. 2005)
  - Power-law: Network value of individual users & their ranking
    - network value of customers=marketing value of a customer in terms of other customers that maybe influenced by him (P. Domingos et al. 2001)
- Observed Elsewhere
  - Power-laws in: Physics, biology, geology

Recommender systems

- User modeling
- Computation of common user preferences
- *Link* people that have something in common
- In Collaborative Filtering
  - Active user receives recommendation about product
  - Recommendation based on similarity of user to other users (community)
  - Similarity is high if two users have evaluated similarly a number of items in the past
  - Item unknown to the user that belongs to a community will receive recommendation based on the community's evaluation

Network of users

- Nodes represent users
- If two users are similar→ edge connects them
- similarity –s definition for users: a and b

$$s ::= 1 - \frac{H(a,b)}{n}$$

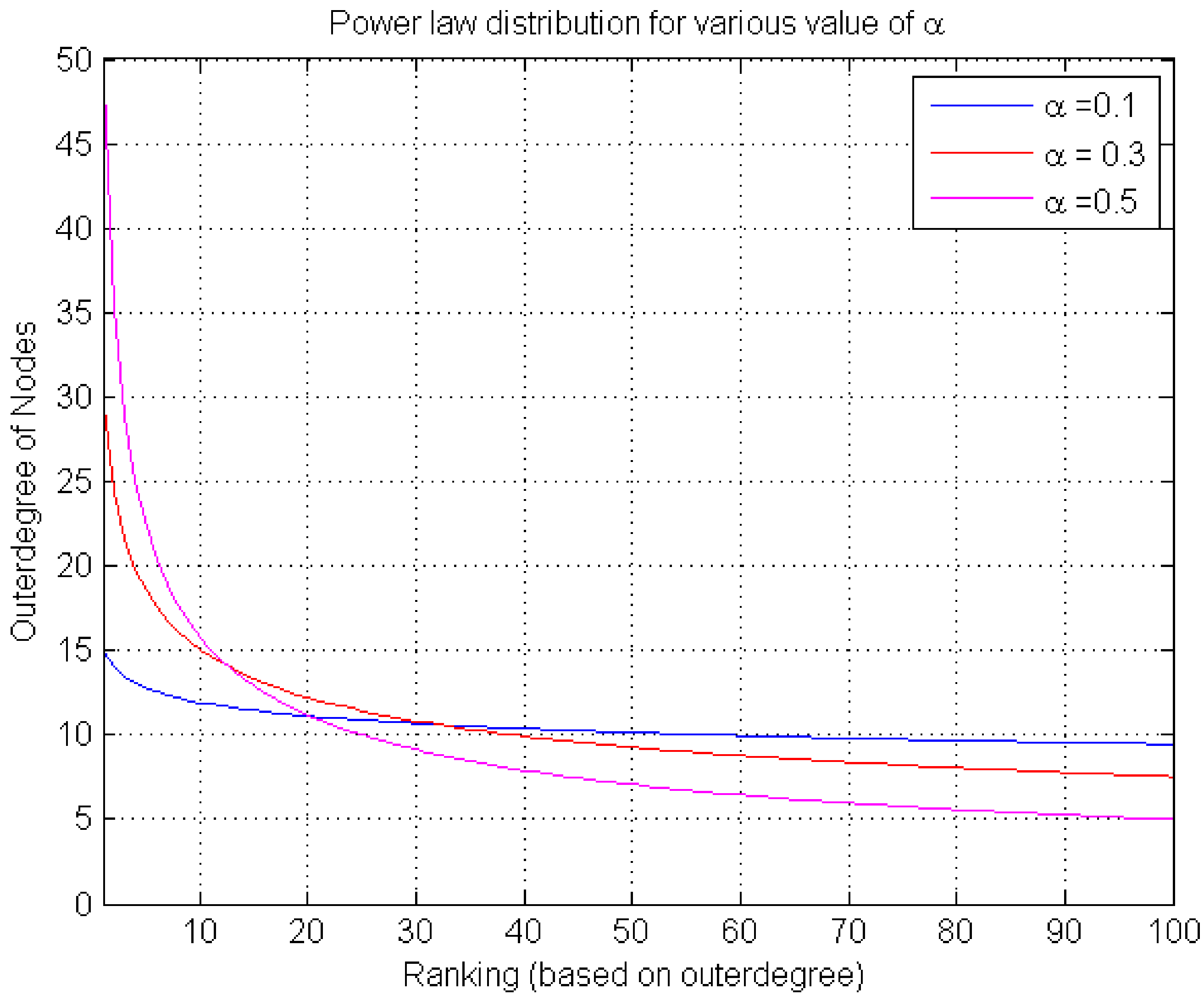
- a=(1,0,0,1….), movie ratings for user a, e.g. 1: positive 0: negative
- b=(1,0,1,0,…), movie ratings for user b
- n = number of commonly evaluated items
- H = hamming distance
- s in [0,1], higher values → closer similarity

- degree of a node= #edges connecting node to other *sufficiently* similar nodes

Questions to explore

- Is there a power law distribution observed?
  - $P(X=x) = k\,x^{-a}$
  - $\text{Log}(p(X=x)) = (-a) \log(x) + \log(k)$
  - x: ranking of node's outdegree
  - P(X=x): node's outdegree
- Does the rule hold over time?
  - As more users are added, or more rankings are added?

Power Law



Power law distribution for various value of α
Outerdegree of Nodes
Ranking (based on outerdegree)
α =0.1
α = 0.3
α =0.5
0
5
10
15
20
25
30
35
40
45
50
10
20
30
40
50
60
70
80
90
100

Experimental Setting: Movie Lens Data

Data sets	users	movies	evaluations	Time period
Small *movie Lens**	943	1,682	100,000 scale 1-5	9/1997-4/1998
Big *movie Lens**	6,040	3,952	1,000,000 scale 1-5	4/2000-2/2003

What do we study

•Degree of node vs ranking of node
•Nodes denote users
•Degree of node = #neighbours
•Evolution of the above over time

Data set

•Group Lens Lab, Dept. of CS, Univ. of Minnesota
•Each user has evaluated ≥ 20 movies
•Eval. grade 1,2 → 0, 3,4,5→1
•Split each data set into four time periods (data sorted according to timeStamp)

- T1 start: 1/4 data
- T2 start: 2/4 data
- T3 start: 3/4 data
- T4 start: end of data

Movie Lens data form →

UserID	MovieID	Rating	TimeStamp
User-1	Movie-1	3/5	1233545
User-1	Movie-2	4/5	45545666

Results summarised

$Z=\log_{10}(y) = a*x + b$

- Relation holds for both *small & big*
- Relation holds true over time
- y: node degree
- x: ranking of node
- a,b: parameters
  - Depend on data set
  - Change over time altering slope of line (z)

A **power law** was **not found**! If it were found it would like: $\log_{10}(y) = a*\log_{10}(x) + b$

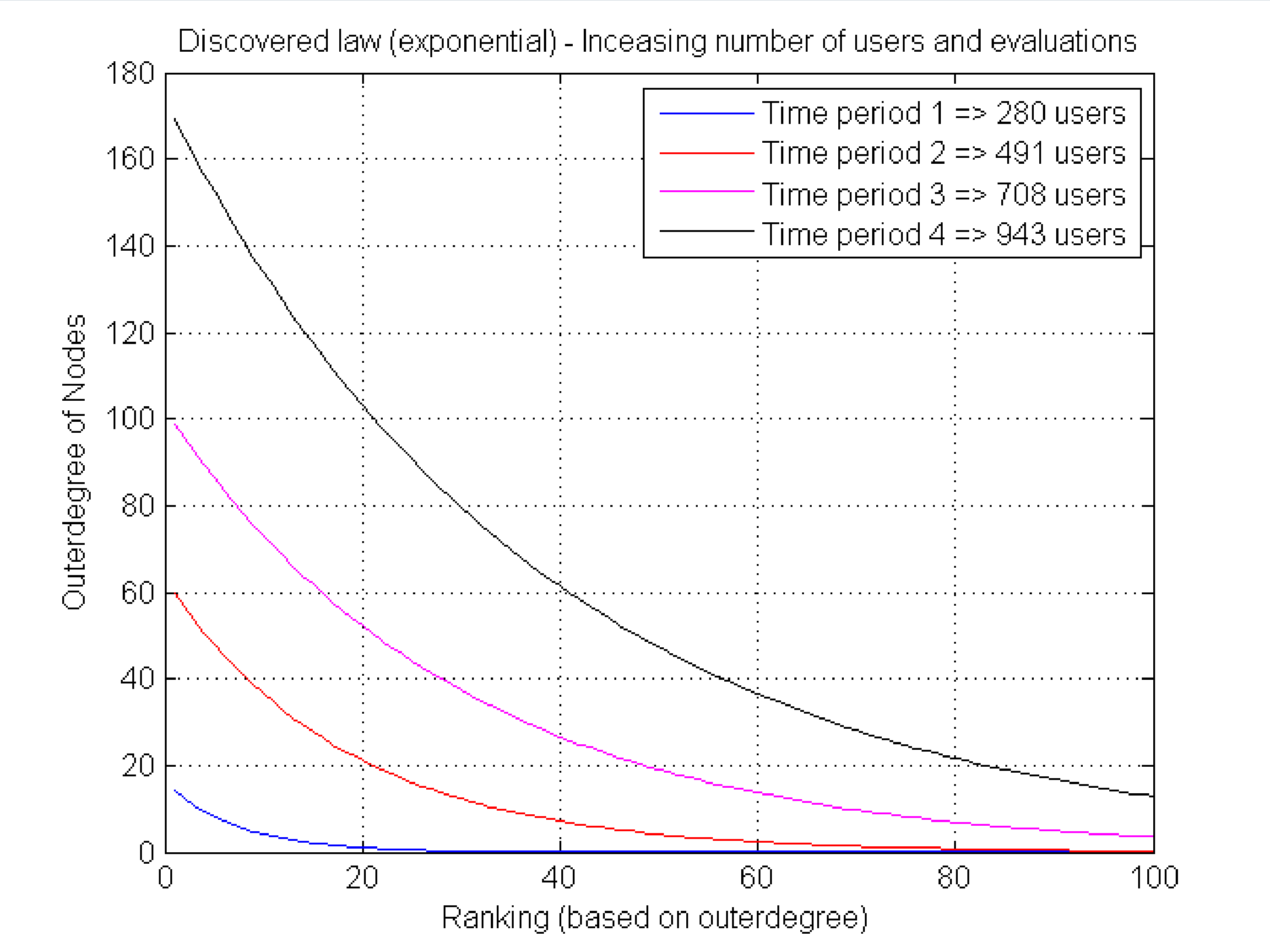
Results summarised (cont.)

SMALL	Mean degree	# users	MSE
T-1	5.14	280	8e-3
T-2	13.72	491	3.7e-3
T-3	20.81	708	6.1e-3
T-4	31.86	943	1.4e-2

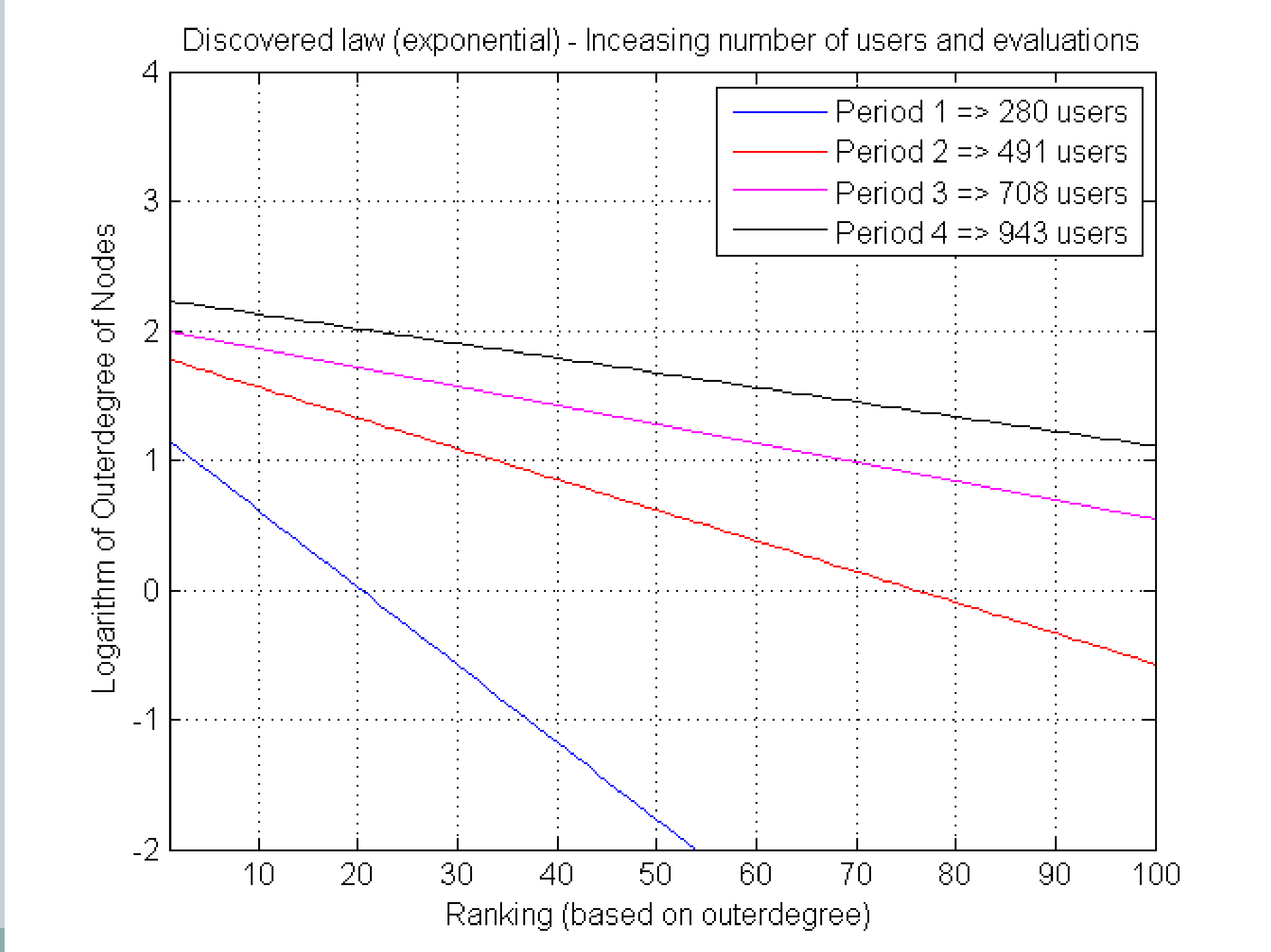
BIG	Mean degree	# users	MSE
T-1	15.93	1772	4.1e-3
T-2	36.12	3255	9.1e-3
T-3	38.58	5140	3.6e-3
T-4	64.26	6040	2.8e-3

Mean degree: mean number of edges of node (user) stemming out to reach other users
Next Slide plots

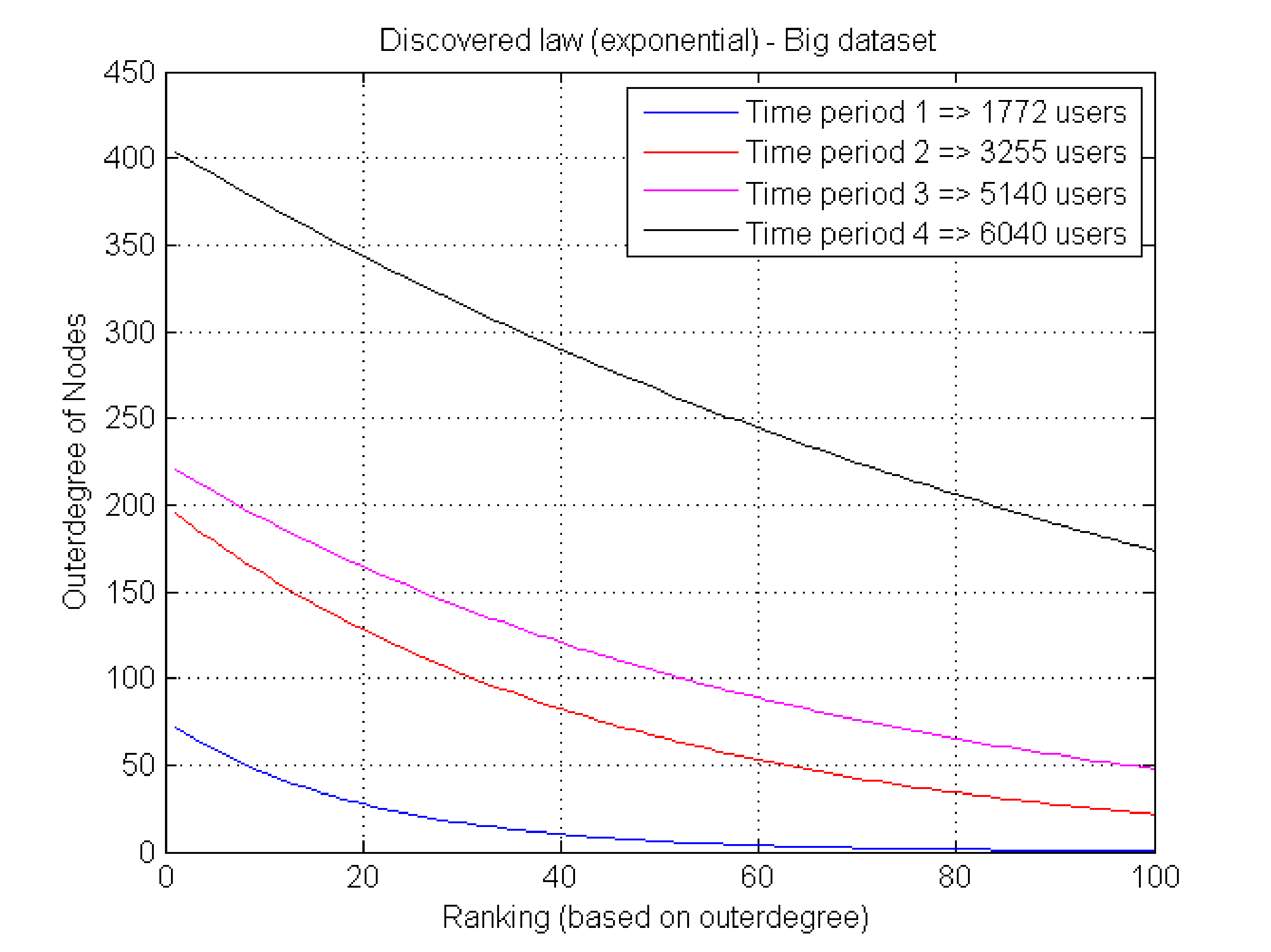
Discovered Law (small data set)



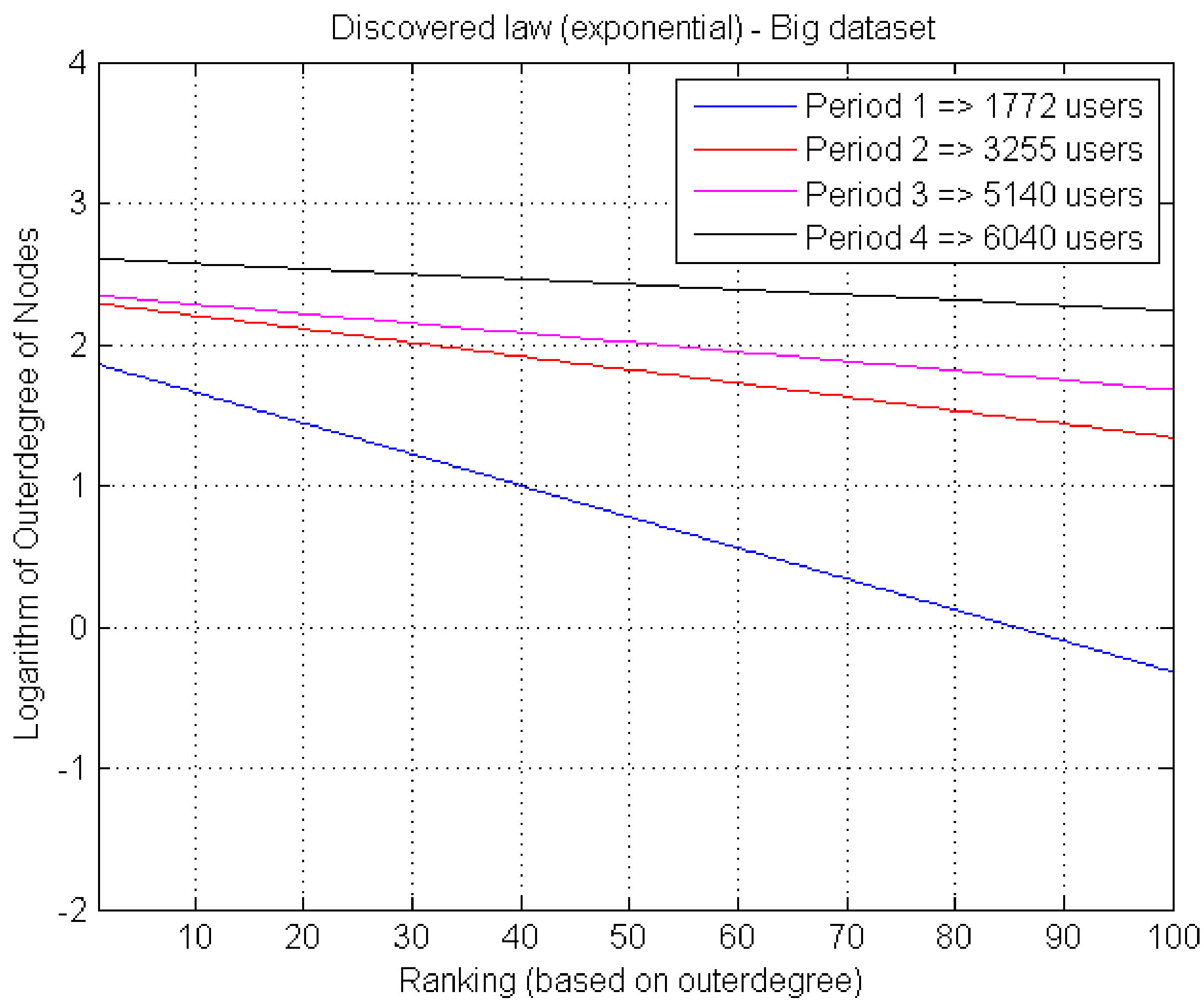
Discovered Law (small data set)



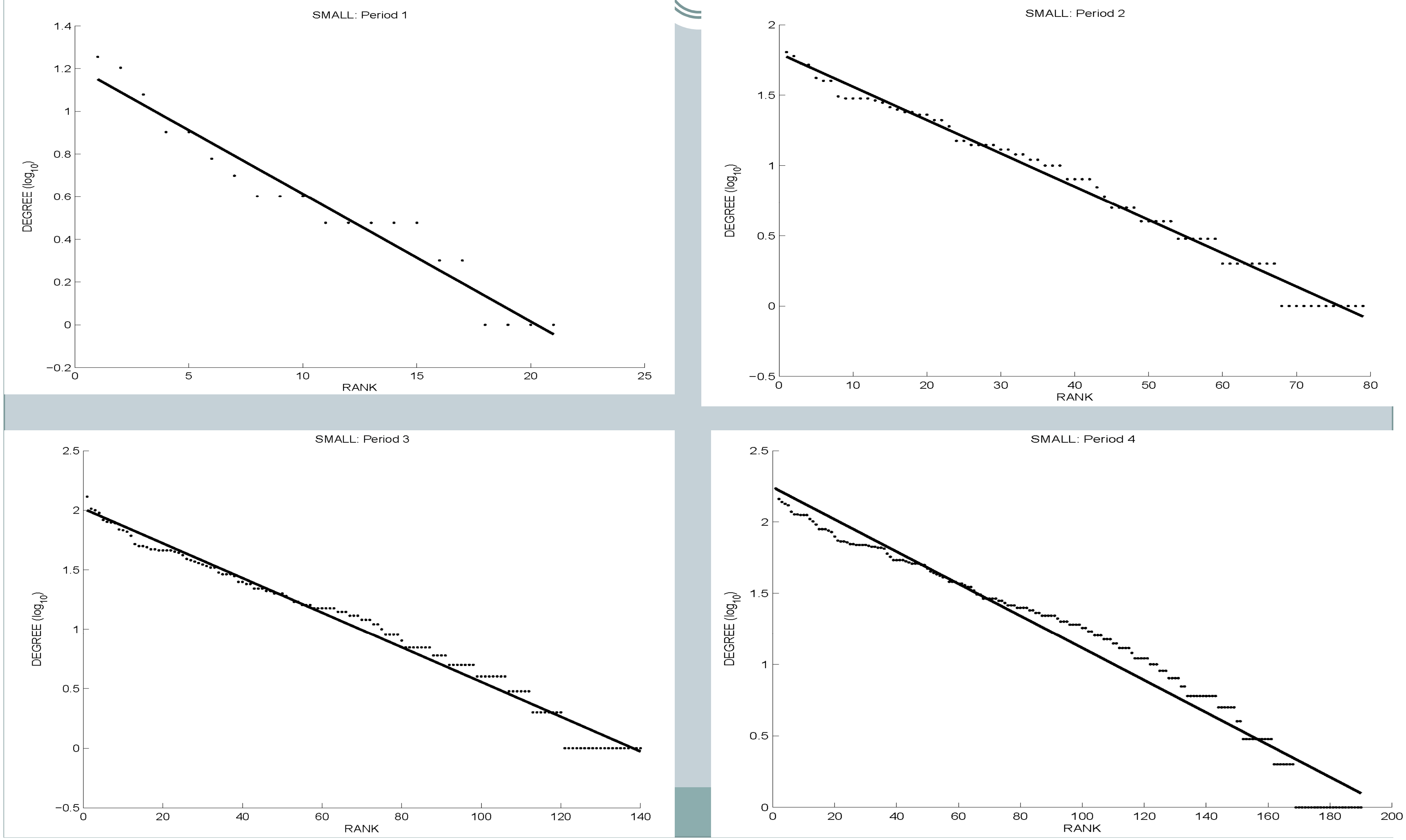
Discovered Law (big data set)



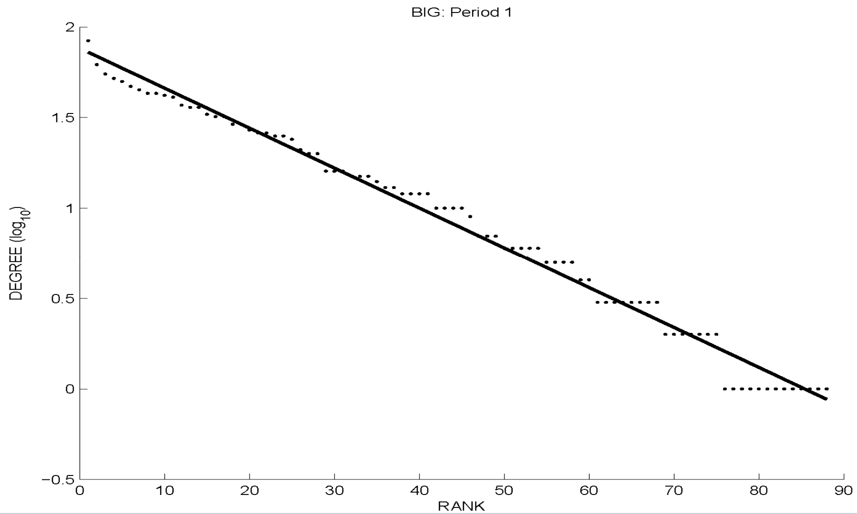
Discovered Law (big data set)

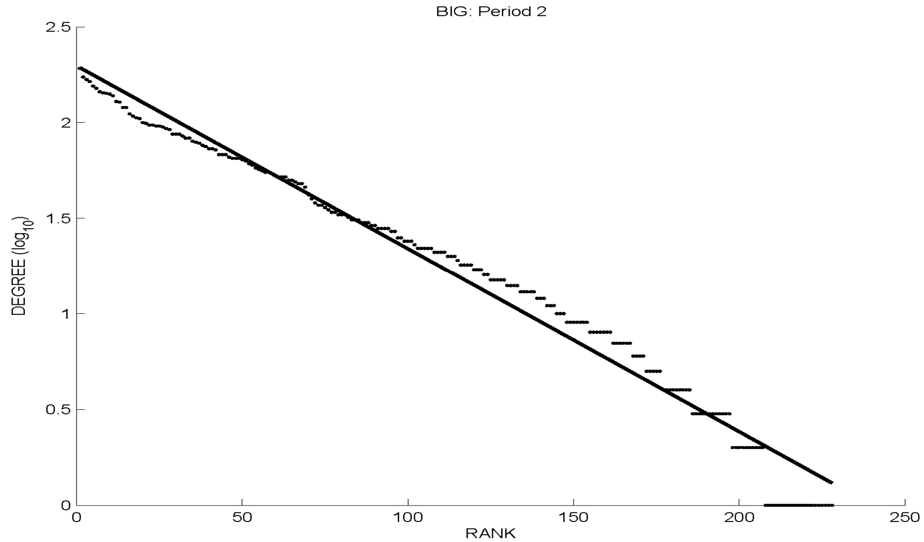


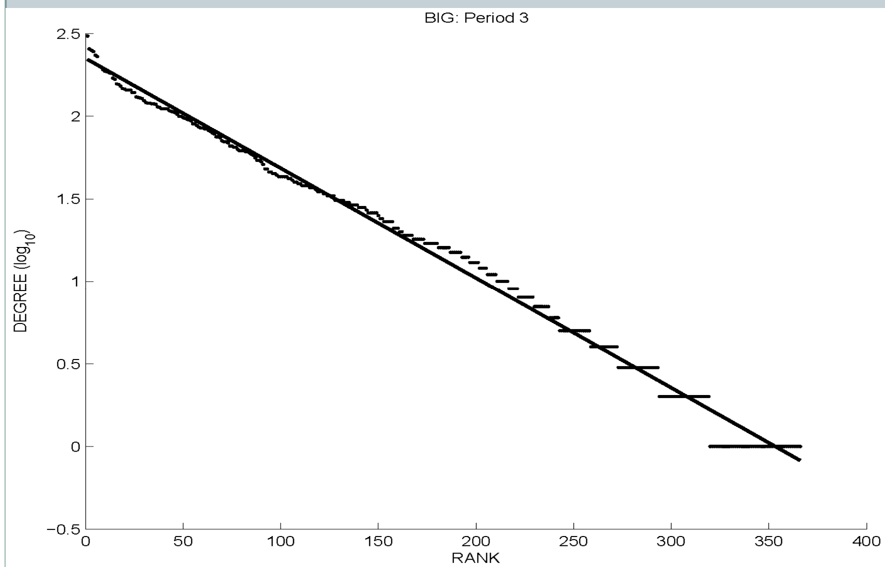
Results: Small Data Set

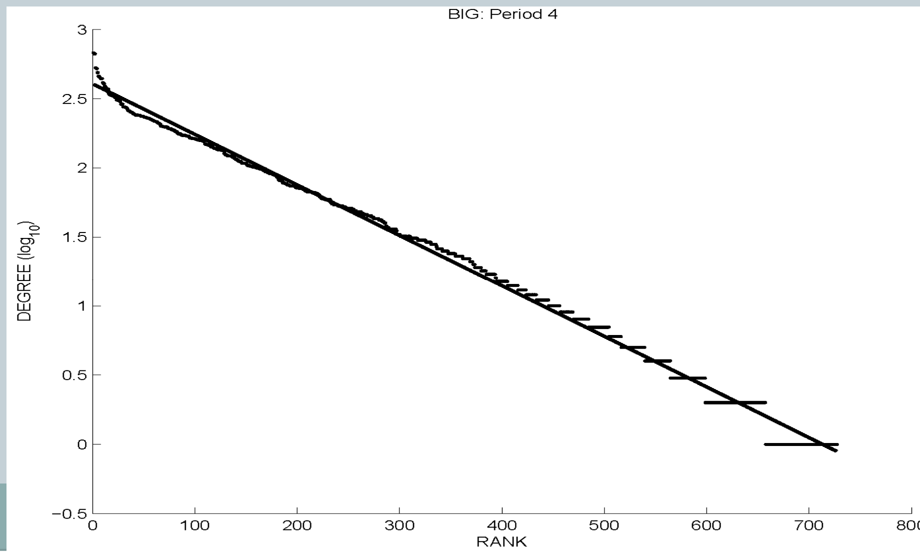


Results: Big Data Set









Conclusions

- Recommender System Network:
  - Social networks created by recommender systems do not follow a power law. It seems that an exponential law is more accurate
  - As the network size increases (as a result of new users and new evaluations) the slope of the exponential function decreases. This means that the biggest the network the more difficult to identify influential users or experts
  - Modeling of networks feasible
- Issues:
  - Similarity measure
  - Product type

Future work

- Expand work on other data sets
  - We possess a large collection of apparels orders by online customers
  - Customers: gender, age
  - Apparels: size, material, pattern, style, etc…
- Integrate information about demographics of user, to see if we observe the same behaviour
  - Use user stereotypes
  - for that use PServer (see next slide)

PServer

- general-purpose personalization server developed @NCSR "Demokritos" (Skel lab, www.iit.demokritos.gr)
- PServer will be released as open source
- Separates user modeling modules from rest of application at both *logical & physical levels*
- 2 important concepts in PServer
  - **Attributes**: refer to application independent data, such as user demographics (e.g. age, sex, occupation)
  - **Features:** which are application characteristics that may or may not attract user preference (e.g. Film genres…)

PServer: Logical Level

- PServer purpose: **user modeling**
- **Individual User models:** user specific & made of features & attributes.
  - *Attributes* have constant values (e.g. age, sex),
  - *features* are application specific and they assume values depending on user interest (e.g. comedy, thriller, etc.)
- **Stereotypes:** predefined user groups with certain common attributes & features. Stereotypes have features & attributes like user models, but it is not necessary for all stereotypes to have the same number of features and attributes. In the future stereotypes will be automatically derived
- **User & features communities** can be created with machine learning algorithms based on user interaction data (feature values), thus they are data driven
  - For users we would like to discover the ones which are similar with respect to their interest expressed in feature values
  - For features we would like to discover which have the similar values for various users. (i.e. if a feature is equally important as another one, then it can be suggested to a new user

Pserver: user models & stereotypes

Example of user model: many user model fall in a stereotype, with a certain degree

ID	ag e	sex	occupati on	Zip-code	Rommanc e	..	Comedy
123 4	25	Femal e	Engineer	55	4/4	…	3/4

Example of stereotype, contains ranges of values for some features

Attributes		Features' rating	
age	gender	Romance	Comedy
young (20-30)	Female	4-5	4-5

Future work: automatic derivation of stereotypes

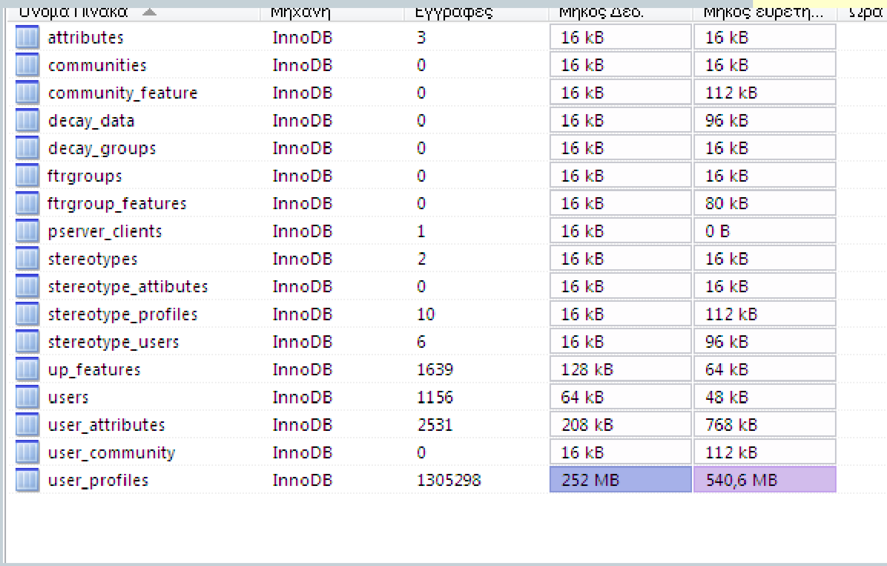
PServer: Physical Level

- PServer may reside at a different machine from the recommender application
- PServer: implemented as a Web server that listens to a dedicated port, all requests have the form of HTTP messages
- Web browsers can be used as a PServer clients
- Responses :encoded in XML, & especially made XSL stylesheets allow them to be displayed on web browsers
- To facilitate applications
  - Available client-side library of classes is available
  - Classes can incorporated into the application to handle all low-level communication details

PServer

- PServer has already been used successfully in a number of european and national projects
  - Xenios/Xenios (Personalised Information presentation in web museums, national)
  - Crossmark (Personalised information extraction from the Web)
  - Servive (SERvice Oriented Intelligent Value Adding Network, FP7)

PServer screen shots



Ονομα Πινακα	Μηχανη	Εγγραφες	Μηκος Δεδ.	Μηκος ευρετη...	Σφα
attributes	InnoDB	3	16 kB	16 kB	
communities	InnoDB	0	16 kB	16 kB	
community_feature	InnoDB	0	16 kB	112 kB	
decay_data	InnoDB	0	16 kB	96 kB	
decay_groups	InnoDB	0	16 kB	16 kB	
ftrgroups	InnoDB	0	16 kB	16 kB	
ftrgroup_features	InnoDB	0	16 kB	80 kB	
pserver_clients	InnoDB	1	16 kB	0 B	
stereotypes	InnoDB	2	16 kB	16 kB	
stereotype_attibutes	InnoDB	0	16 kB	16 kB	
stereotype_profiles	InnoDB	10	16 kB	112 kB	
stereotype_users	InnoDB	6	16 kB	96 kB	
up_features	InnoDB	1639	128 kB	64 kB	
users	InnoDB	1156	64 kB	48 kB	
user_attributes	InnoDB	2531	208 kB	768 kB	
user_community	InnoDB	0	16 kB	112 kB	
user_profiles	InnoDB	1305298	252 MB	540,6 MB	

Thank you

Questions?