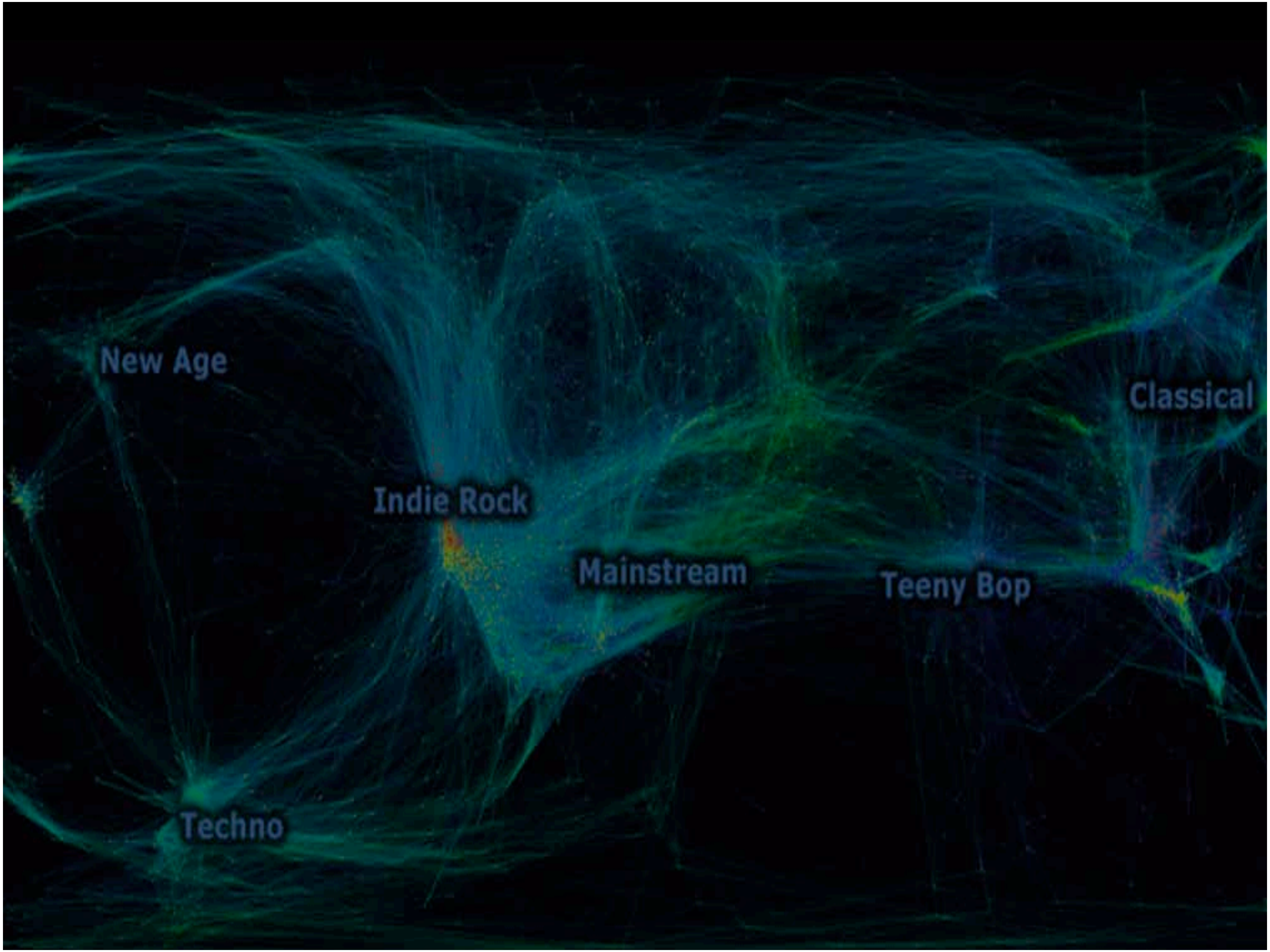
bmat
music innovation

Music recommendation systems: A complex networks perspective

Pedro Cano

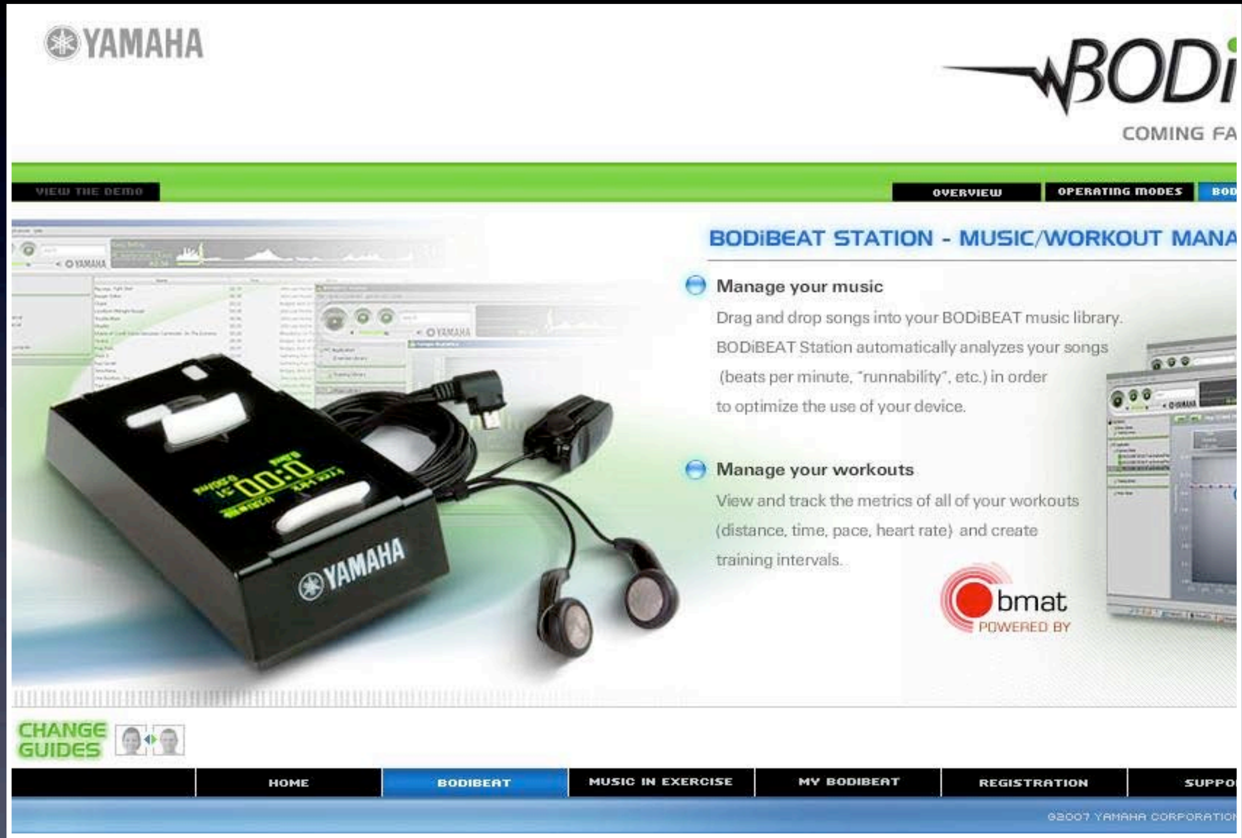

New Age
Indie Rock
Mainstream
Teeny Bop
Classical
Techno

bmat
music innovation

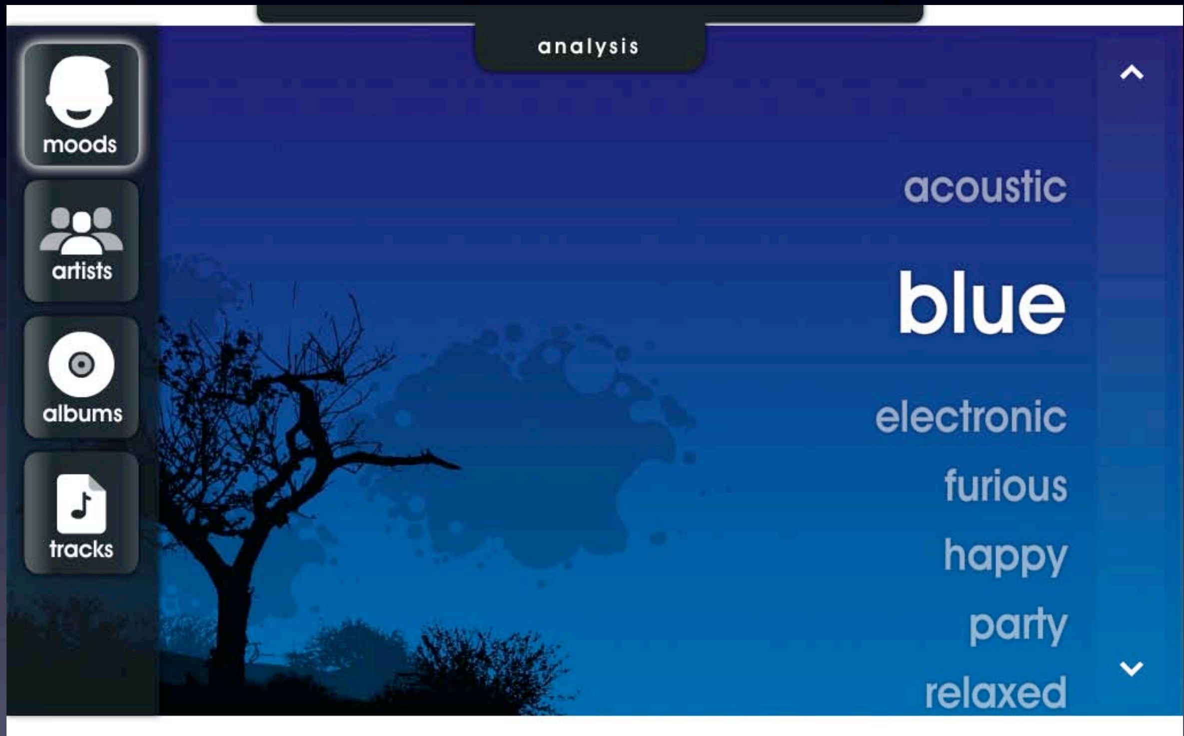
bmat
music innovation

Never has so much music been heard…never has been so much music available

bmat
music innovation



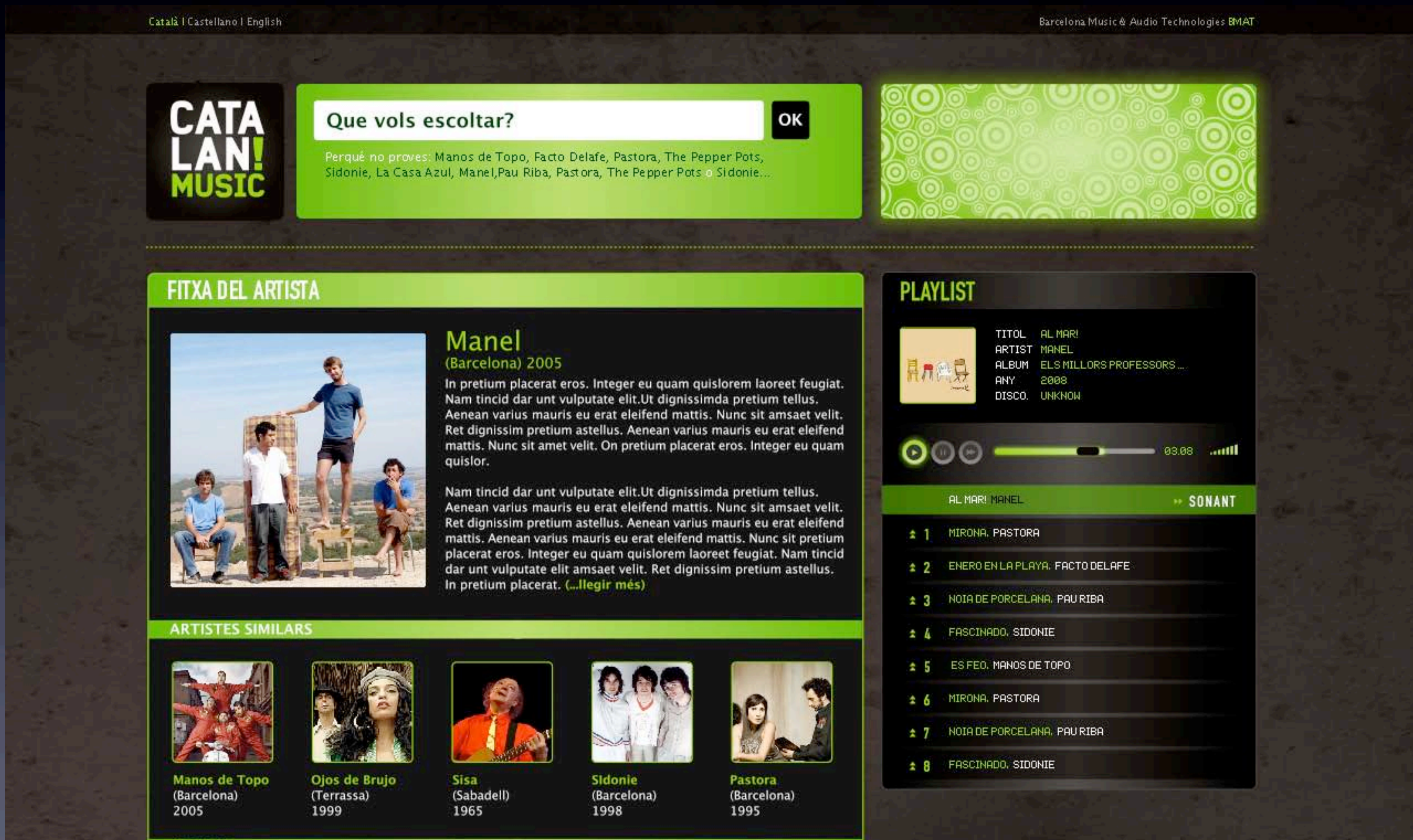
bmat
music innovation



Ella
Music search & recommendation.

bmat
music innovation

BMAT services the ICIC to promote catalan music internationally



Why Music Recommenders?

iTunes: 6M tracks

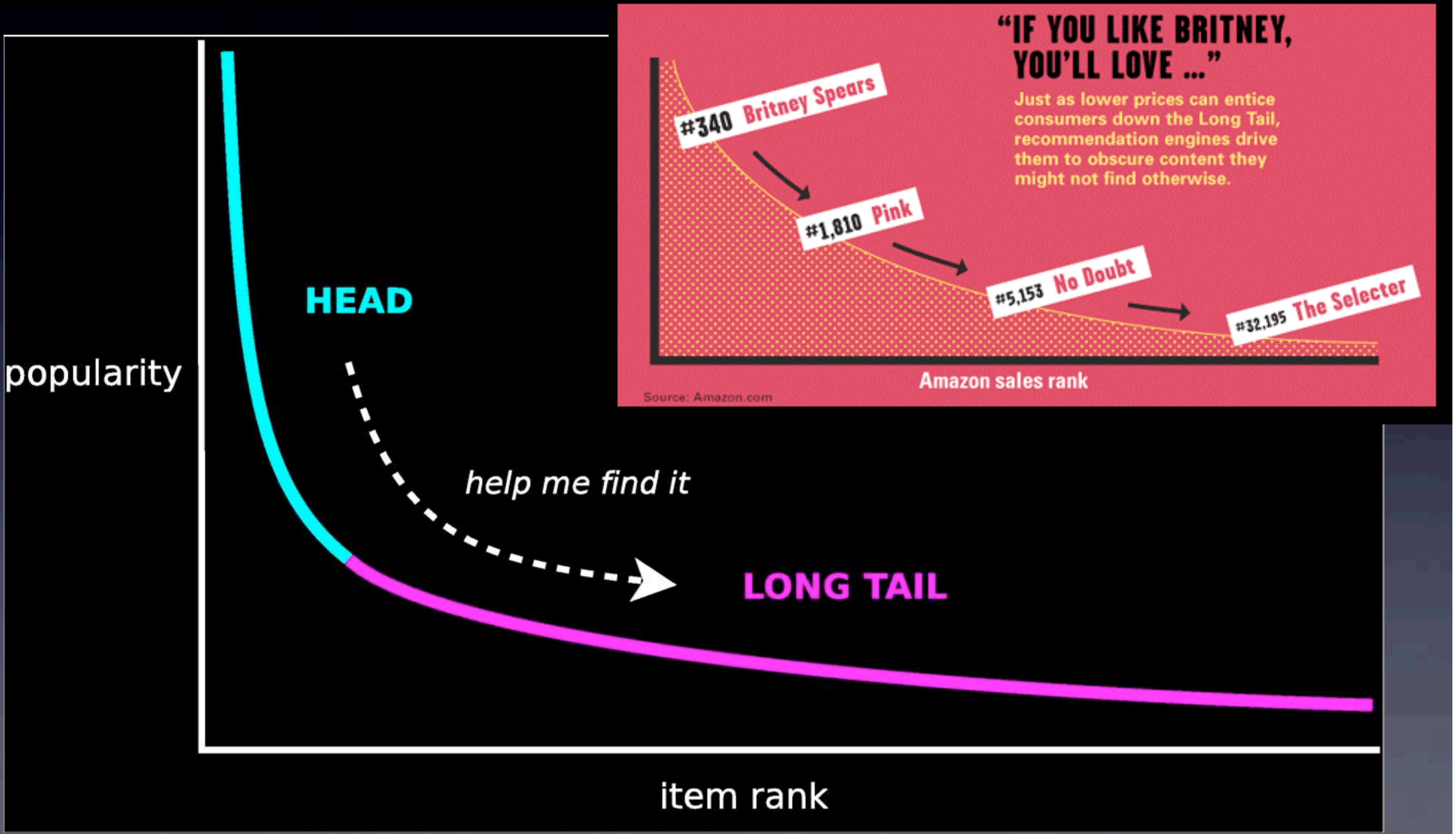
P2P: 15B tracks

1% of tracks account for 80% of sales

3.6 million tracks sold less than 100 copies

Data from Nielsen Soundscan 'State of the (US) industry' 2007 report

- Help me find it! [Anderson, 2006]



Types of Recommenders


last.fm
Music Videos Listen Events Charts
Music
Search
The Beatles
Similar Artists
Based on overall listening habits
John Lennon
The Animals
Led Zeppelin
Blue Öyster Cul
amazon.com
Hello, Oscar Celma. We have recommendations for you. (Not Oscar?)
Oscar's Amazon.com
Today's Deals
Gifts & Wish Lists
Gift Cards
Shop All Departments
Search
Music
Music
Advanced Search
Browse Genres
New Releases
Top Sellers
Music Deals
Music You Should Hear
Prime
Get Free Shipping for a full month with a Free Trial of Amazon Prime learn more
FREE Upgrade to Two-Day Shipping on this item with Amazon Prime
The Beatles (The White Album)
The Beatles
(994 customer reviews) | More about this product
List Price: $34.98
Price: $24.97 & eligible for FREE Super Saver Shipping on orders over $25. Details
You Save: $10.01 (29%)
Special Offers Available
In Stock.
Ships from and sold by Amazon.com. Gift-wrap available.
48 new from $15.25
27 used from $14.49
13 collectible from $34.98
Customer image from R. T. Stark
Customers Who Bought This Item Also Bought
Sgt. Pepper's Lonely Hearts Club Band ~ The Beatles (1,168) $9.99
Revolver [UK] ~ The Beatles (824) $12.99
Rubber Soul ~ The Beatles (633) $12.99
Let It Be ~ The Beatles (372) $13.97
Magical Mystery Tour ~ The Beatles (467) $12.99

music recommendation approaches

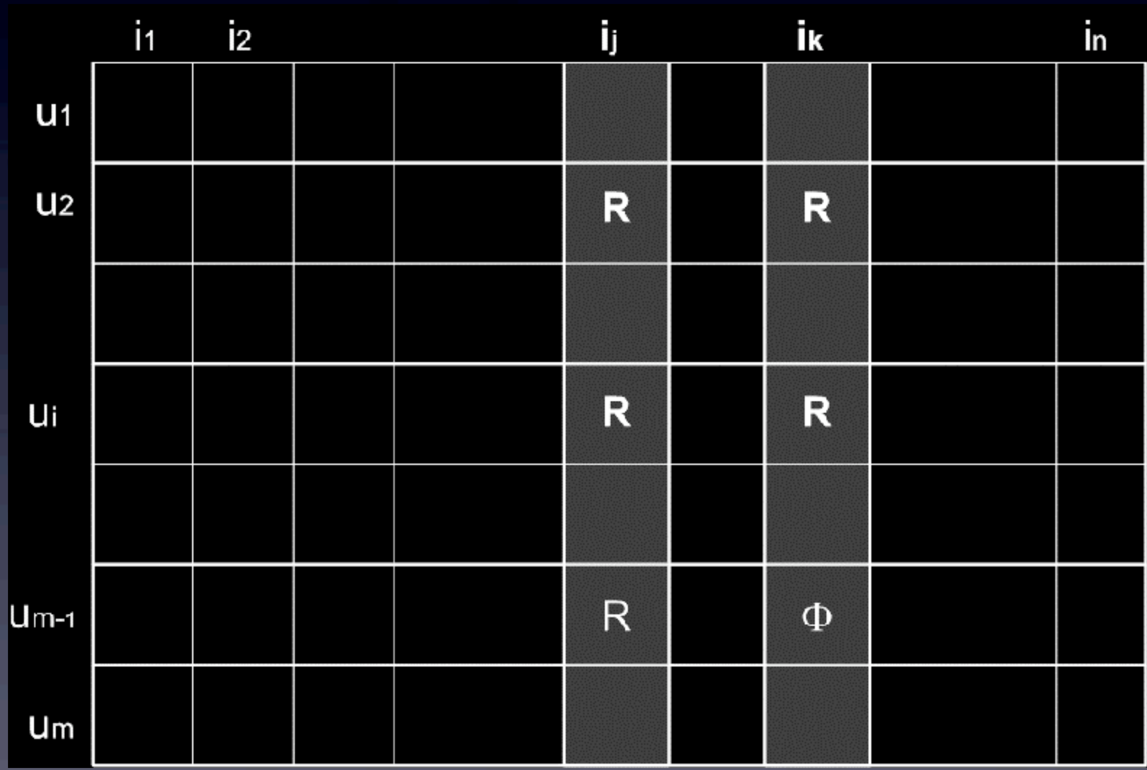
- Expert-based
- Collaborative filtering
- Context-based
- Content-based
- Hybrid (combination)

music recommendation approaches

- Expert-based
- Colla
- Conte
- Conte
- Hybri

music recommendation approaches

- Expert-based
- Collaborative filtering
- Context-based
- Content-based
- Hybrid (combination)



[Resnick, 1994], [Shardanand, 1995], [Sarwar, 2001]

- Expert-based
- Collaborative filtering
  - User-Item matrix [Resnick, 1994], [Shardanand, 1995], [Sarwar, 2001]
  - Similarity
    - Cosine

$$sim(i,j) = cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{\|i\| * \|j\|} = \frac{\sum_{u\in U} R_{u,i}R_{u,j}}{\sqrt{\sum_{u\in U} R_{u,i}^2}\sqrt{\sum_{u\in U} R_{u,j}^2}}$$

    - Adj. cosine

$$sim(i,j) = \frac{\sum_{u\in U}(R_{u,i}-\bar{R}_u)(R_{u,j}-\bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_u)^2}}$$

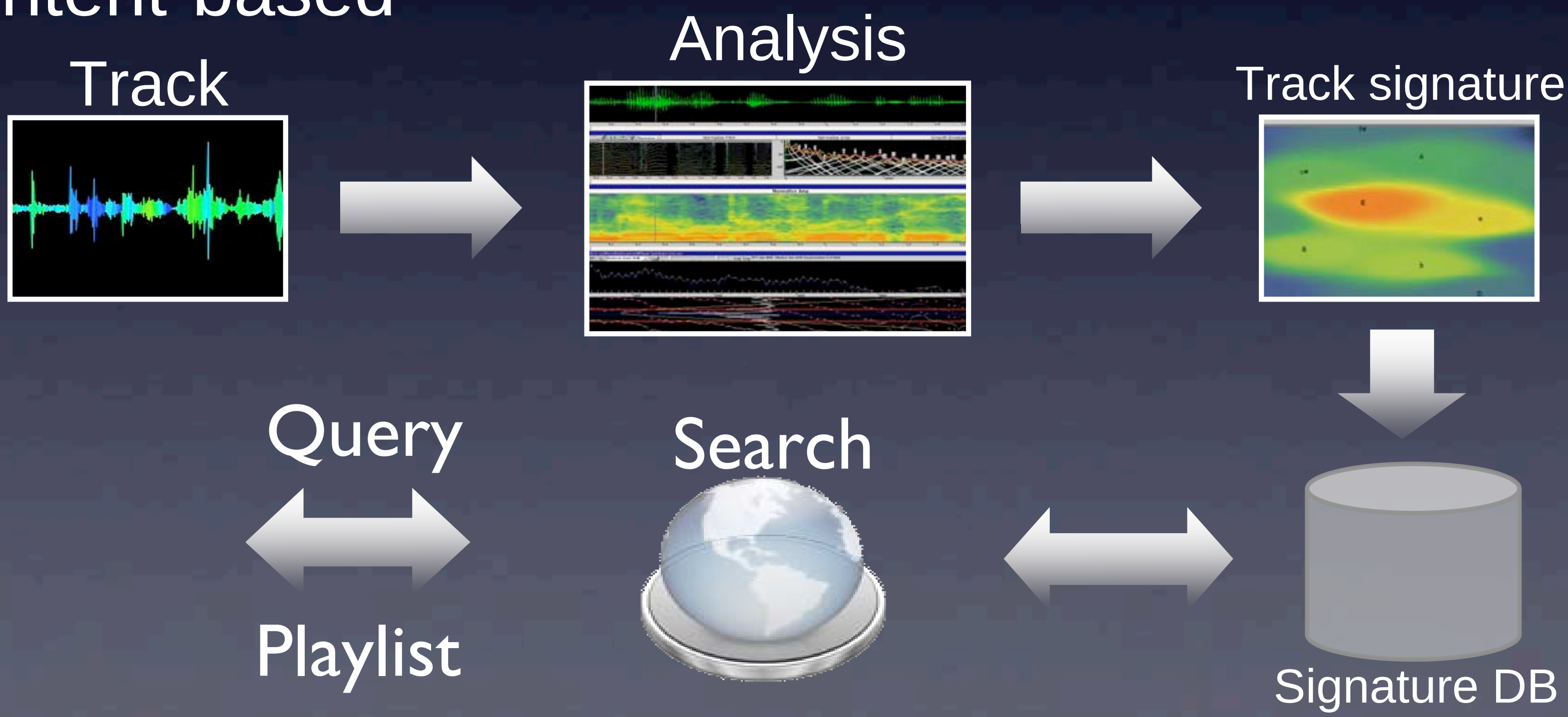
    - Pearson

$$sim(i,j) = \frac{Cov(i,j)}{\sigma_i\sigma_j} = \frac{\sum_{u\in U}(R_{u,i}-\bar{R}_i)(R_{u,j}-\bar{R}_j)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_i)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_j)^2}}$$

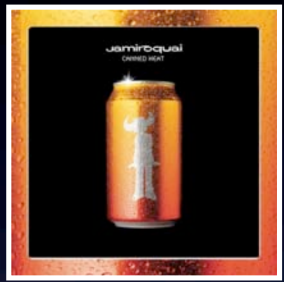
    - SVD / NMF: matrix factorization
- Context-based
- Content-based

- Expert-based
- Collaborative filtering
- Context-based

- Expert-based
- Collaborative filtering
- Context-based
- Content-based



Analyzing…



Jamiroquai - Canned Heat

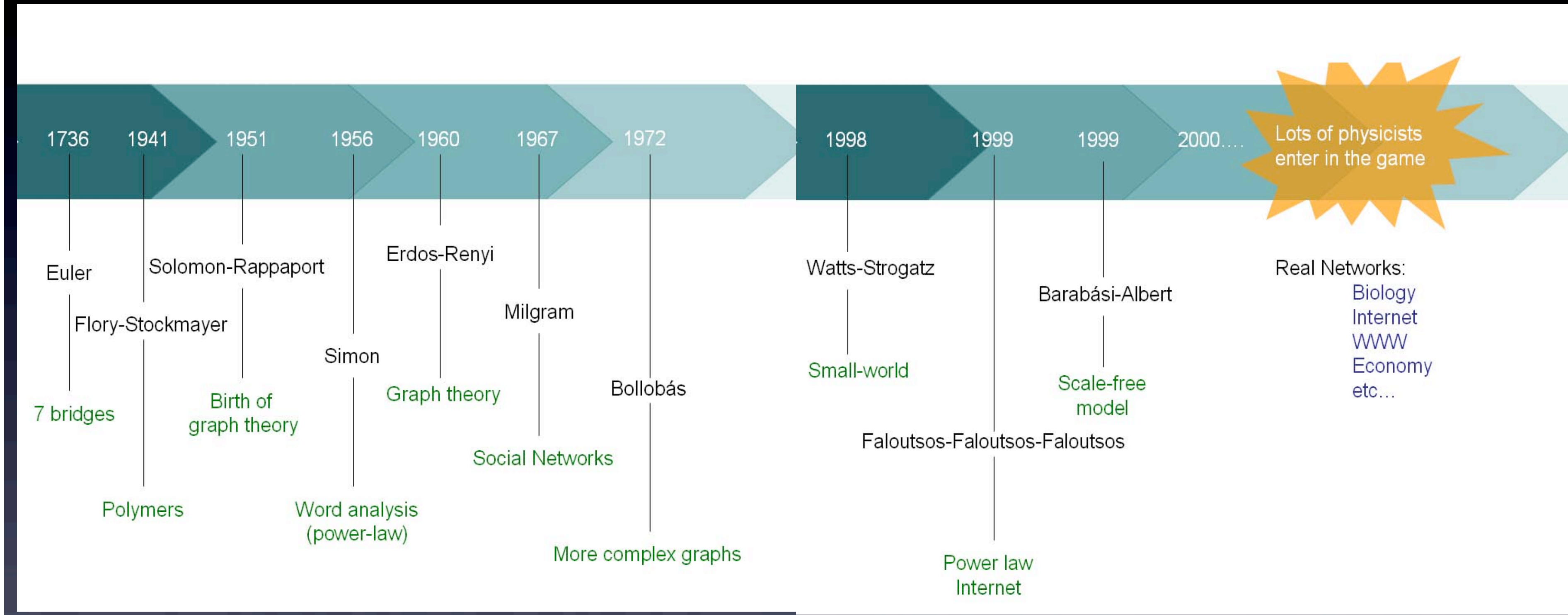
Mood: upbeat, energetic.
Rhythm: 120bpm, no rubato, high percusiveness.
Harmony: Dm.
Instrumentation: no electronic, singing voice

Similar to: Sereia Mundo Azul.

- Expert-based
- Collaborative filtering
- Context-based
- Content-based
- Hybrid (combination)
  - Weighted
  - Cascade
  - Switching

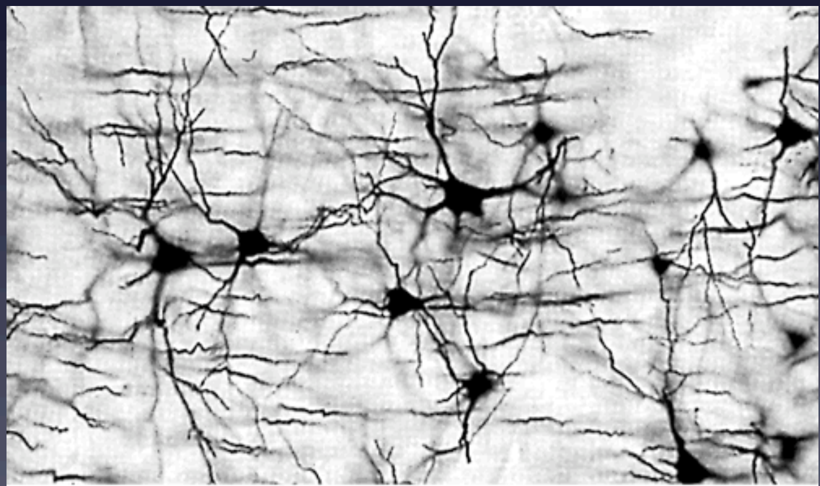
Complex Networks

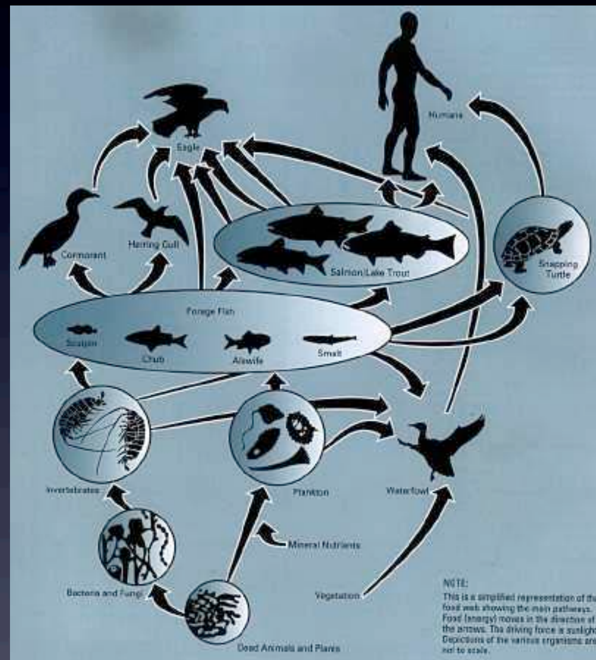
The problem of Konigsberg's bridges



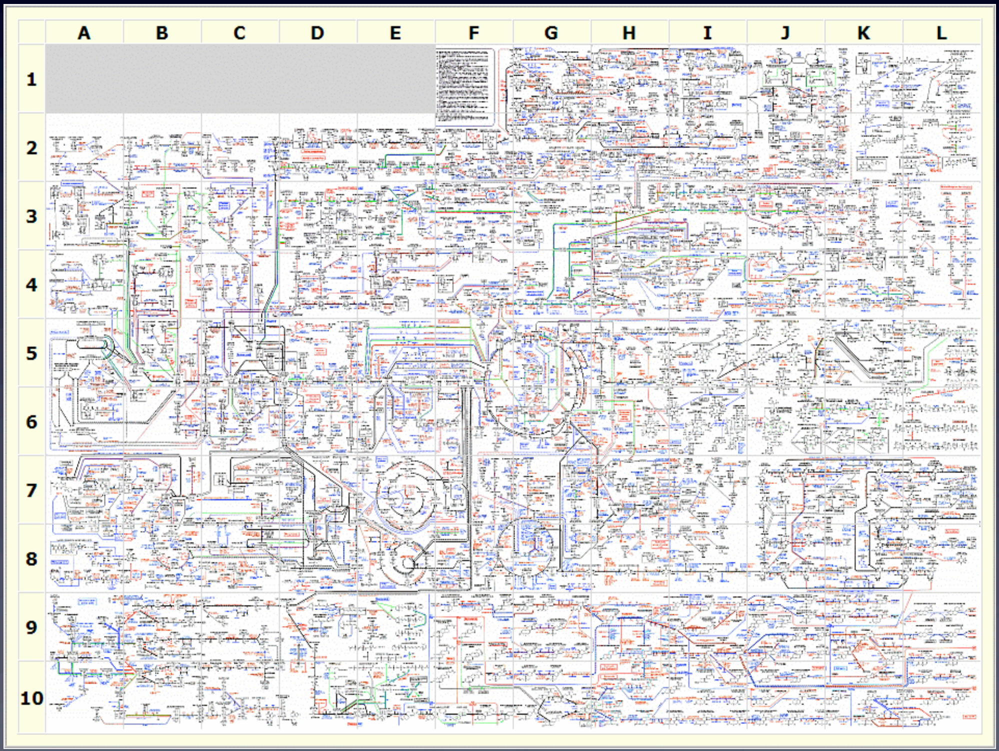
(figure by J.F.F. Mendes)

Neural Networks



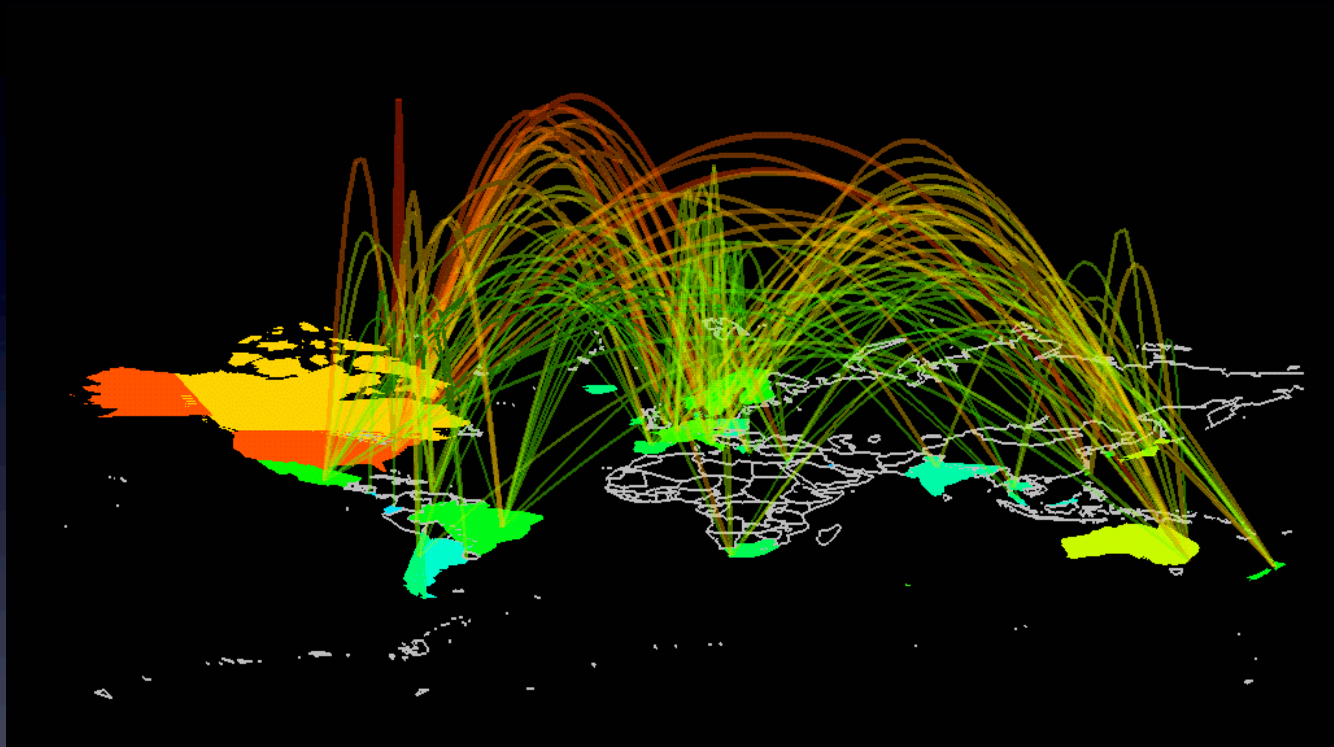


Food chain



Metabolic pathways

bmat
music innovation



Internet A/S

Social Networks

bmat
music innovation

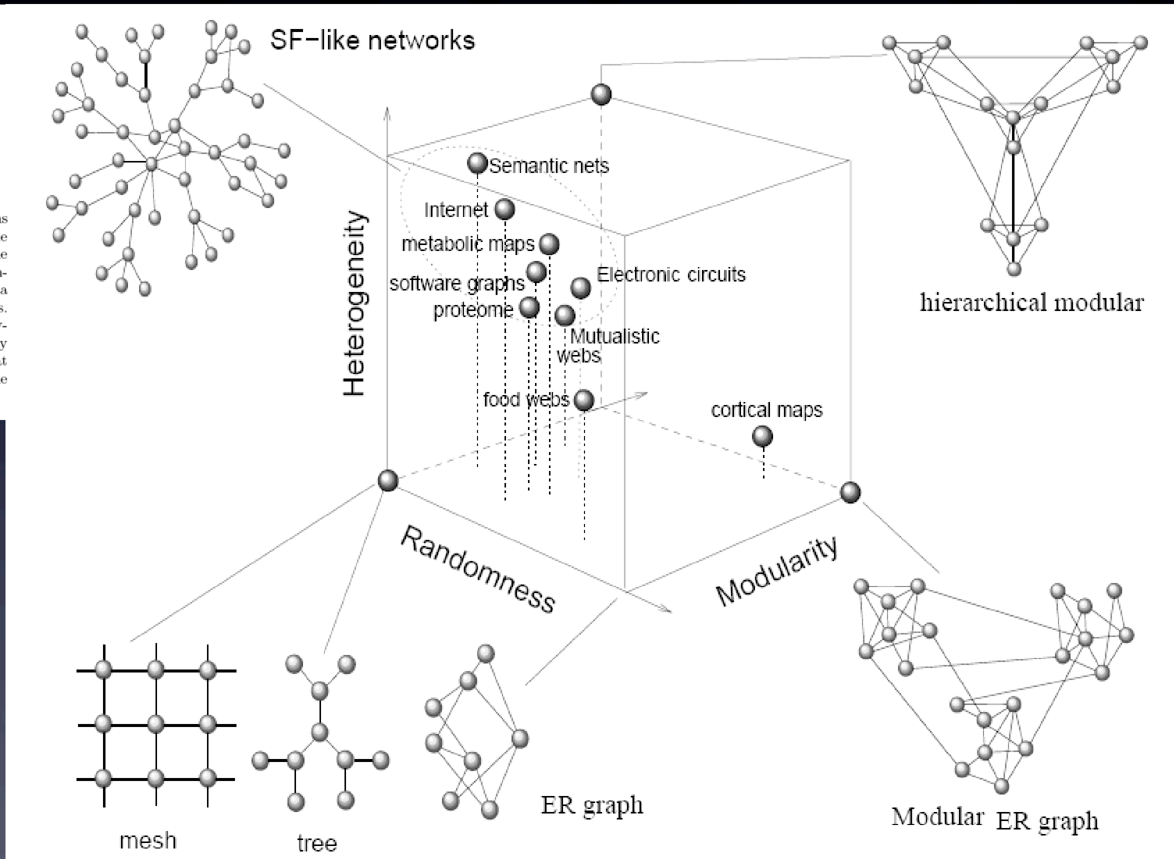
From: R.V. Solé and S. Valverde, Lecture Notes in Physics, 650, 189, 2004

Information Theory of Complex Networks: On Evolution and Architectural Constraints

Ricard V. Solé and Sergi Valverde

[1] Complex Systems Lab-ICREA, Universitat Pompeu Fabra (GRIB), Dr Aiguader 80, 08003 Barcelona, Spain
[2] Santa Fe Institute, 1399 Hyde Park Road, Santa Fe NM 87501, USA

Abstract. Complex networks are characterized by highly heterogeneous distributions of links, often pervading the presence of key properties such as robustness under node removal. Several correlation measures have been defined in order to characterize the structure of these nets. Here we show that mutual information, noise and joint entropies can be properly defined on a static graph. These measures are computed for a number of real networks and analytically estimated for some simple standard models. It is shown that real networks are clustered in a well-defined domain of the entropy-noise space. By using simulated annealing optimization, it is shown that optimally heterogeneous nets actually cluster around the same narrow domain, suggesting that strong constraints actually operate on the possible universe of complex networks. The evolutionary implications are discussed.



Do recommenders differ? How?

bmat
music innovation

msn Entertainment

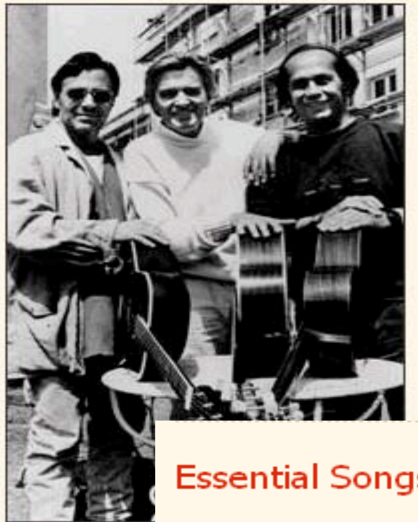
Settings

Movies | Music | TV | News | Celebs | Games | Tickets | Local Entertainment

Radio Stations | Downloads | Music Videos | Music News | Music Charts | My Favorites | Shopping

Artist Information

Search by: artist Go!



Paco de Lucía

Play Paco de Lucía SoundsLike Station (Radio Plus required)

Essential Songs

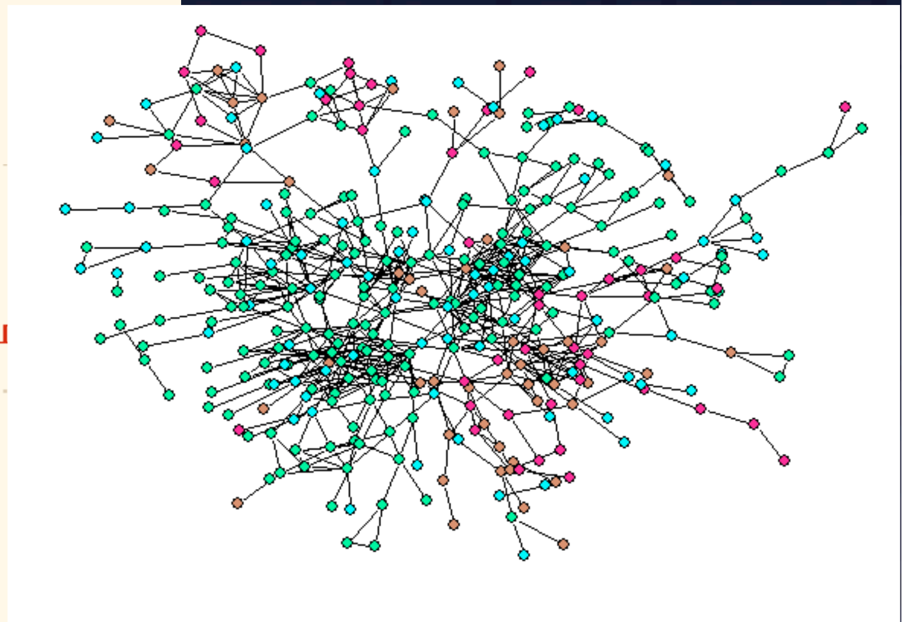
MSN Music Most Popular Songs

- Chanela
- Orient Blue
- Rio de la Miel
- Zyryab
- Playa del Carmen
- La Villa Vieja

SoundsLike Artists

These artists sound like Paco de Lucía

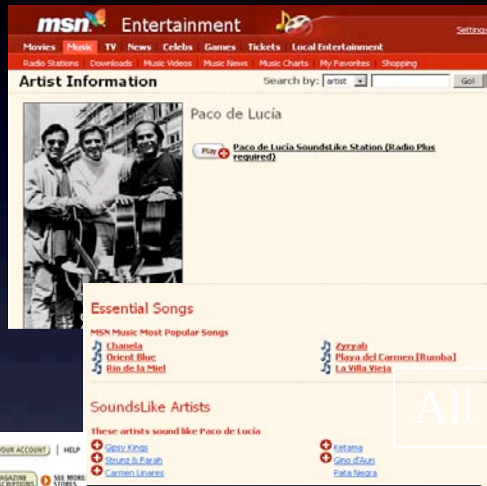
- Gipsy Kings
- Strunz & Farah
- Carmen Linares
- Ketama
- Gino d'Auri
- Pata Negra



bmat
music innovation

Launch Yahoo

Amazon



MSN

All Music Guide (AMG)

	n	<k>	C	d	d_r	r	γ_{in}	γ_{out}
MSN	51,616	5.5	0.54	7.7	6.4	-0.07	2.4±.01	
Amazon	23,566	13.4	0.14	4.2	3.9	-0.06	2.3±.02	2.4±.04
Yahoo!	16,302	62.8	0.38	2.7	2.3	-0.21		
AMG	29,206	8.15	0.20	6.2	4.9	0.18		

	n	<k>	C	d	d_r	r	γ_{in}	γ_{out}
MSN	51,616	5.5	0.54	7.7	6.4	-0.07	2.4±.01	
Amazon	23,566	13.4	0.14	4.2	3.9	-0.06	2.3±.02	2.4±.04
Yahoo!	16,302	62.8	0.38	2.7	2.3	-0.21		
AMG	29,206	8.15	0.20	6.2	4.9	0.18		

Small-world: sparse, short distances and high Clustering coefficient.

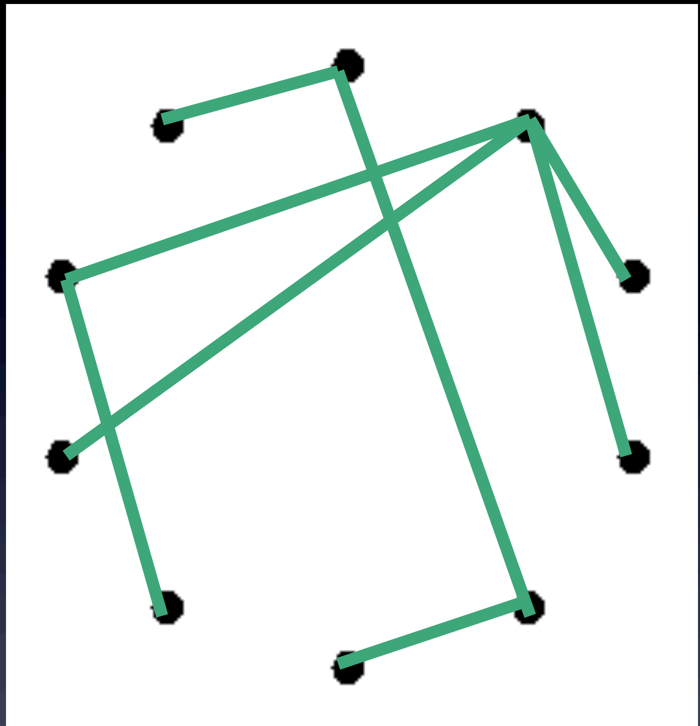
Watts& Strogatz, Nature 393, 440 (1998)

bmat
music innovation

	n	<k>	C	d	d_r	r	γ_{in}	γ_{out}
MSN	51,616	5.5	0.54	7.7	6.4	-0.07	2.4±.01	
Amazon	23,566	13.4	0.14	4.2	3.9	-0.06	2.3±.02	2.4±.04
Yahoo!	16,302	62.8	0.38	2.7	2.3	-0.21		
AMG	29,206	8.15	0.20	6.2	4.9	0.18		

Small-world:
Good navigation properties
Kleinberg, Nature 406:845 (2000)
de Moura..., PRE 68, 036106 (2003)

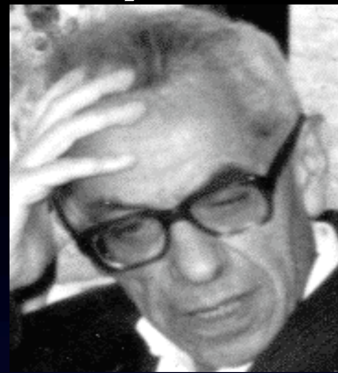
Erdös-Rényi model (1960)



Connect with probability p

p=1/6

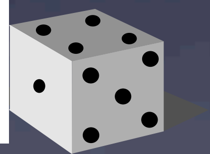
N=10 $\langle k \rangle \sim 1.5$

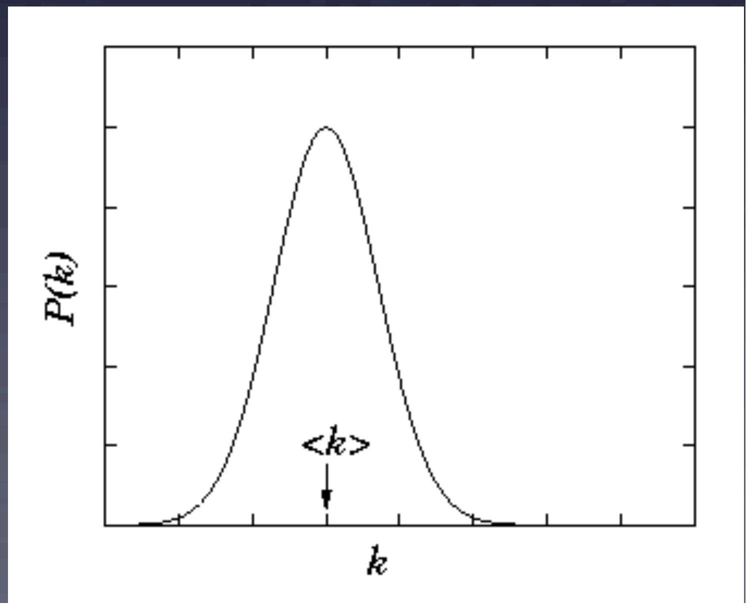


Pál Erdös

(1913-1996)

Poisson distribution



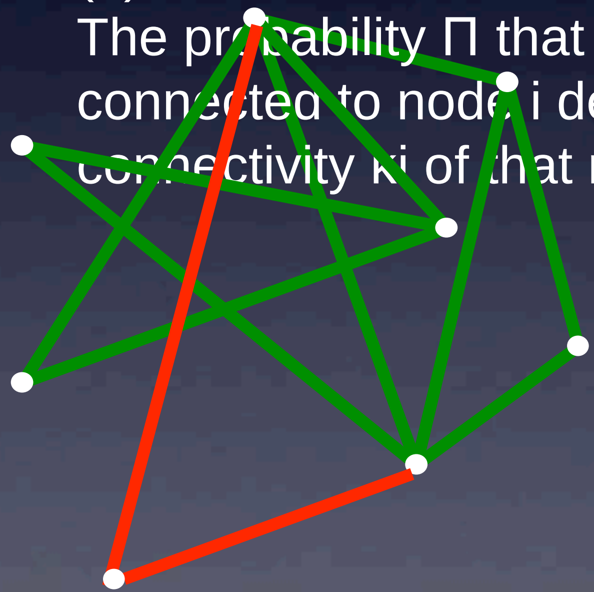


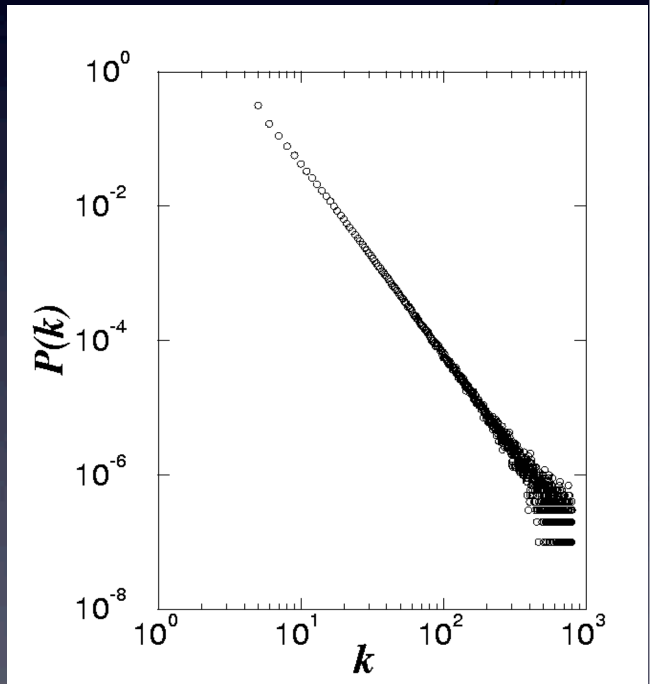
- Democratic
- Random

B.A. Scale Free Model

- (1) GROWTH :
  At every timestep we add a new node with m edges (connected to the nodes already present in the system).
- (2) PREFERENTIAL ATTACHMENT :
  The probability Π that a new node will be connected to node i depends on the connectivity ki of that node

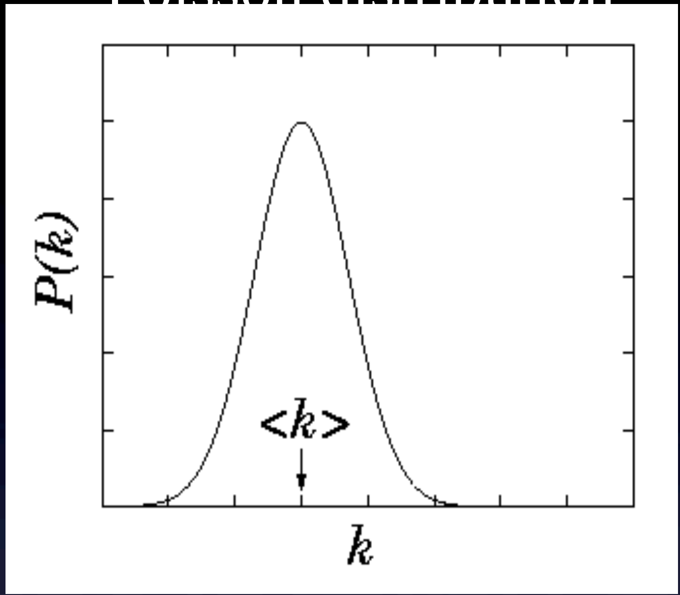
$$\Pi(k_i) = \frac{k_i}{\Sigma_j k_j}$$



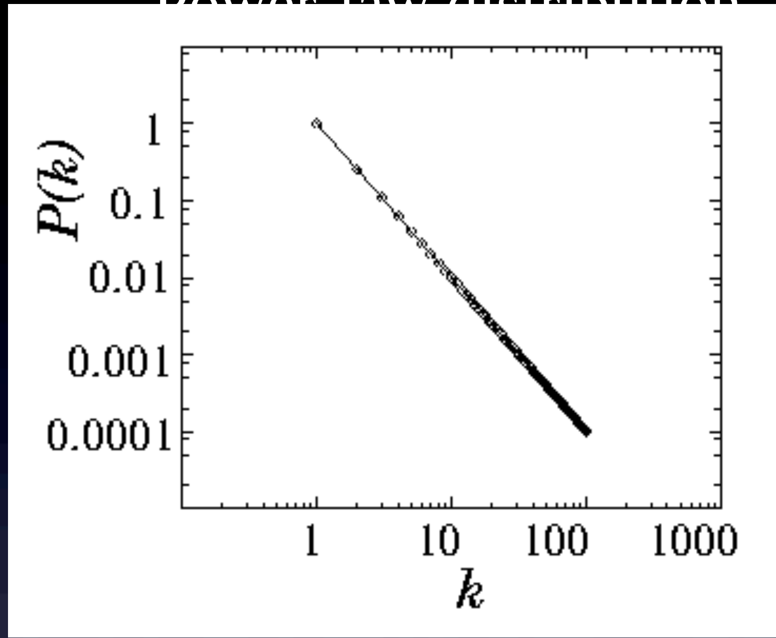


A.-L.Barabási, R. Albert, Science **286,** 509 (1999)

Poisson distribution



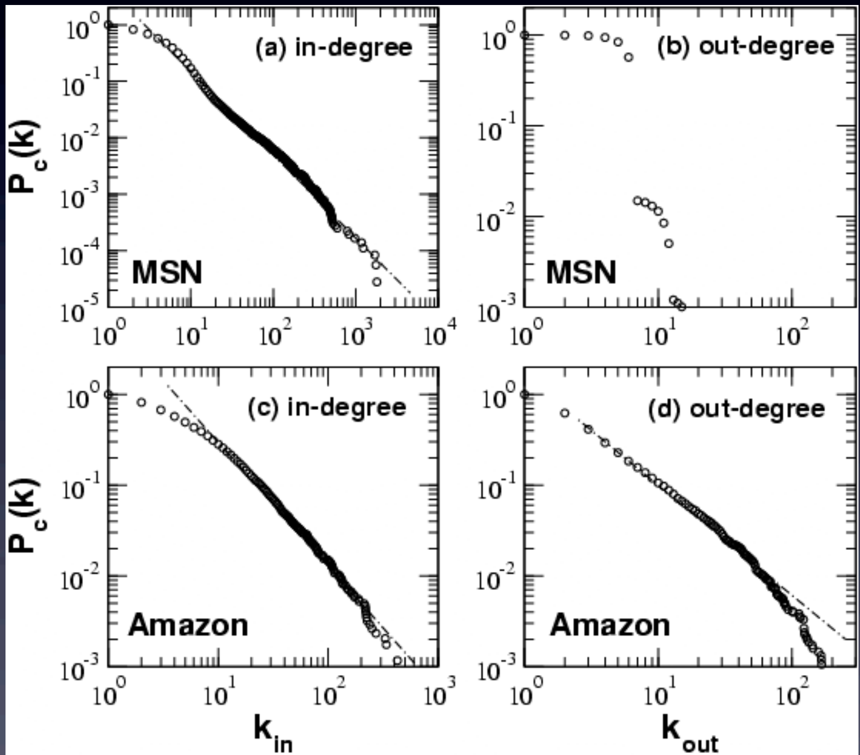
Power law distribution

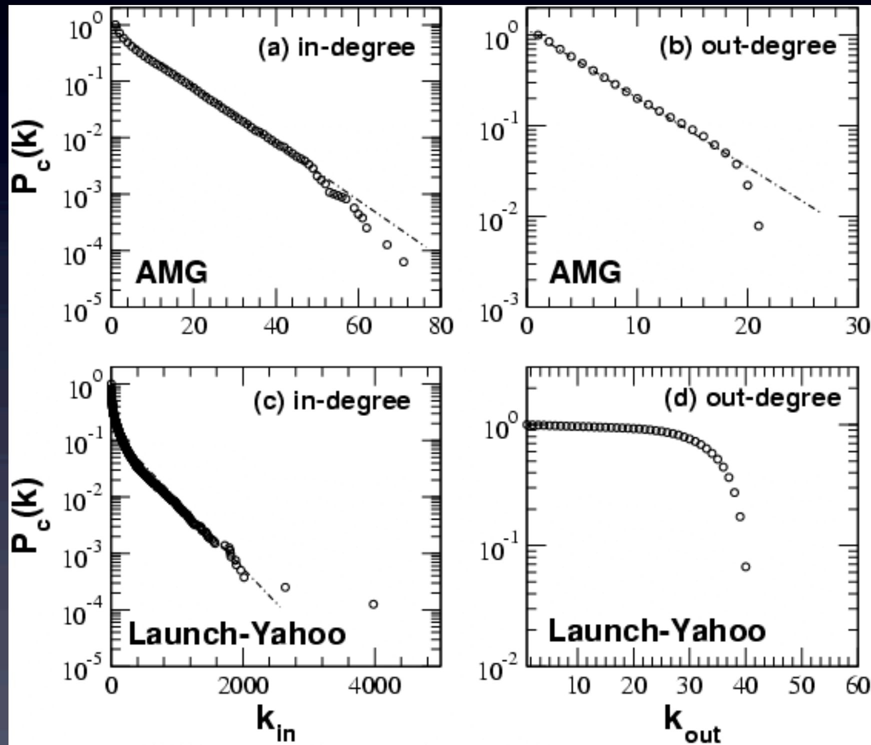


Exponential Network

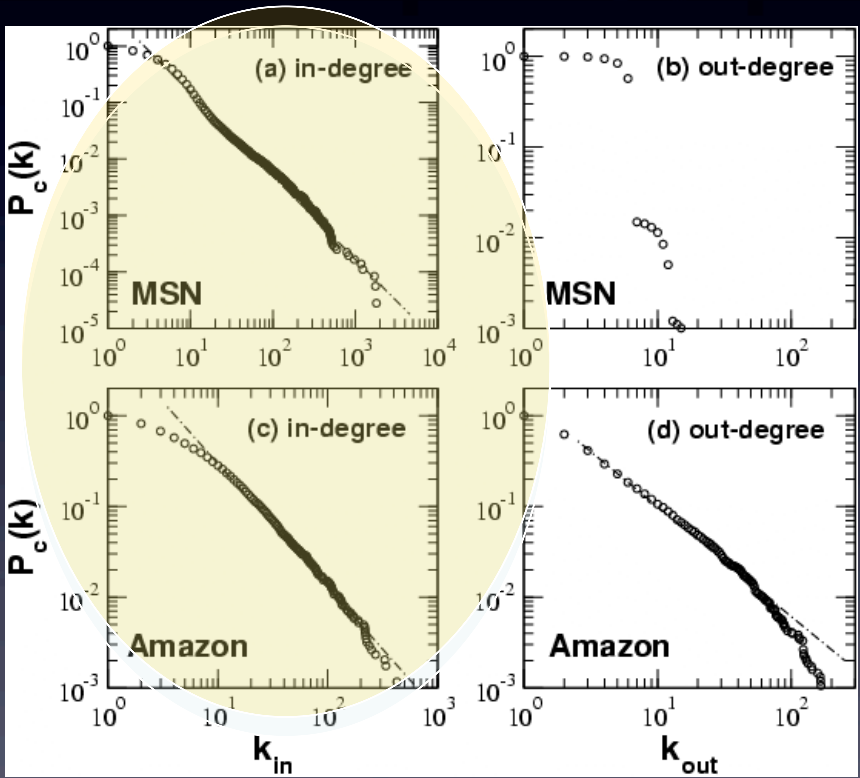
Scale-free Network

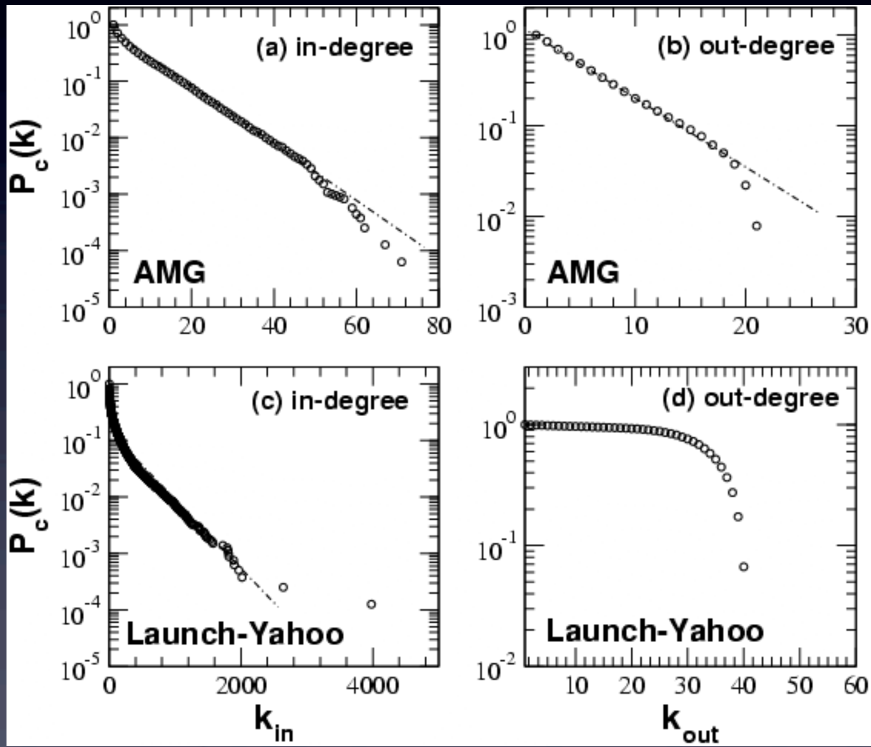
Network properties: $P_c(k)$





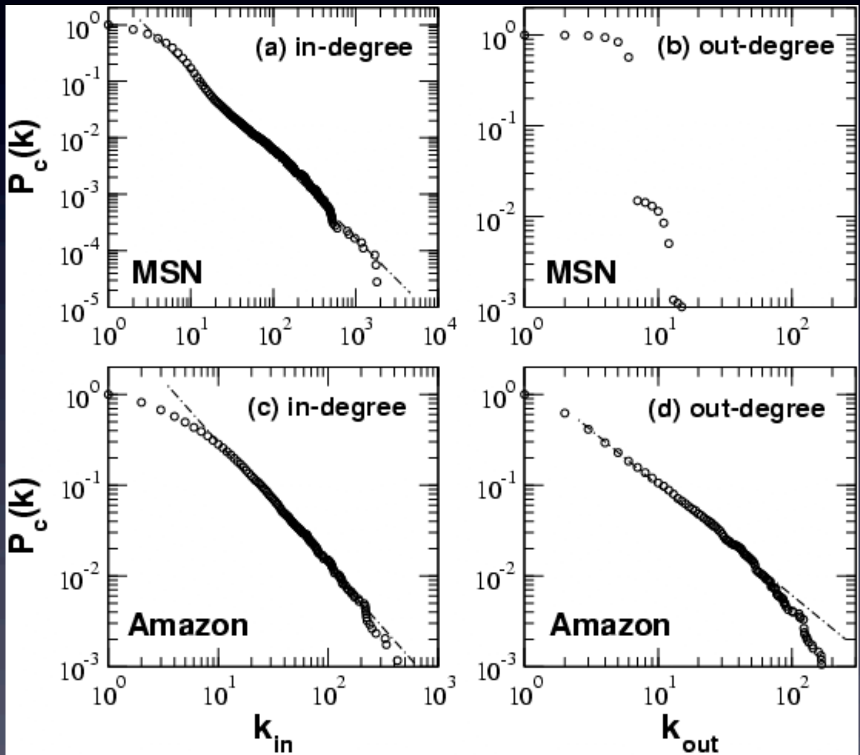
Network properties: $P_c(k)$

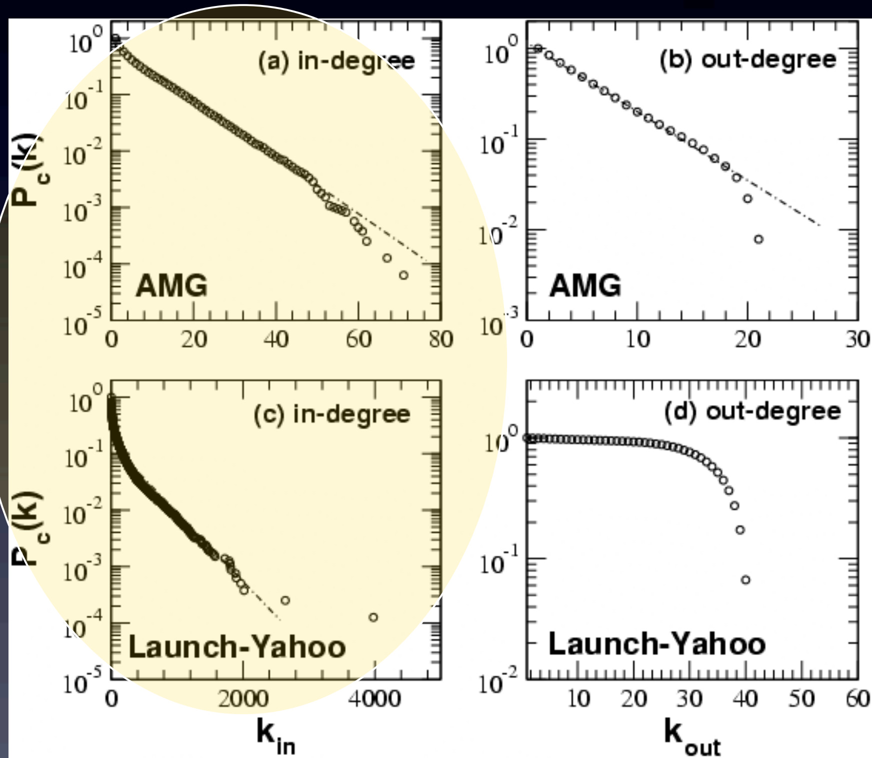




Power-law with γ_{msn}=2.4 and γ_{am}=2.3

Network properties: $P_c(k)$





Exponential

MSN and Amazon are “scale-free” suggesting preferential attachment growth mechanism.

AMG and Yahoo are exponential or “single-scale”,

Barabasi & Albert, Science 286, 509 (1999)
Amaral & al., Proc Nat Acad Sci USA 97, 11149 (2000)

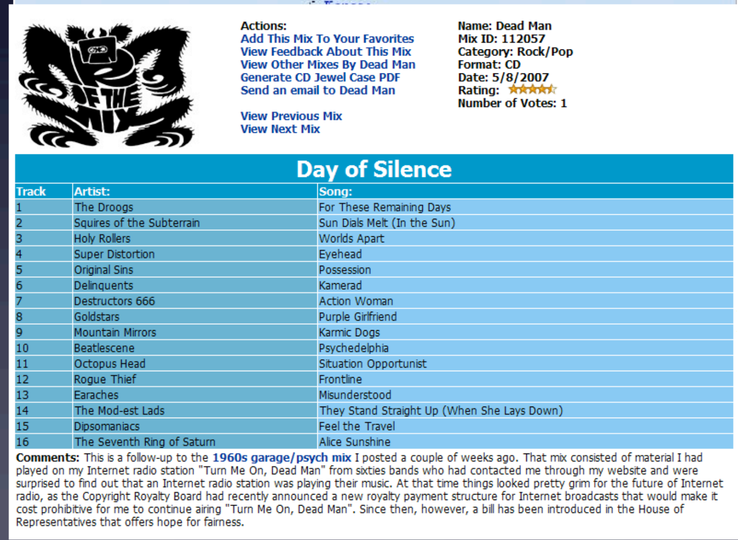
“Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market” shows that social influence increases both inequality and unpredictability of music success.

Salganik, Dodds and Watts, Science 311, 5762 (2006)

bmat
music innovation

Music Seer:

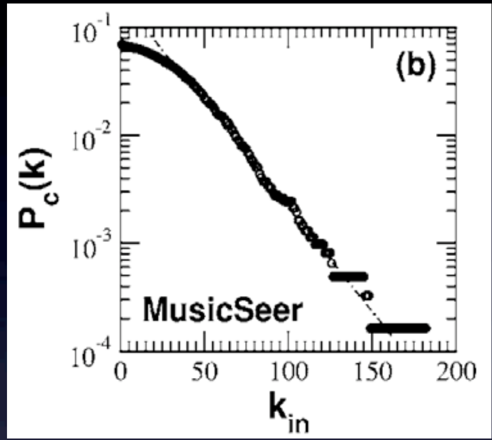
Art of the Mix:

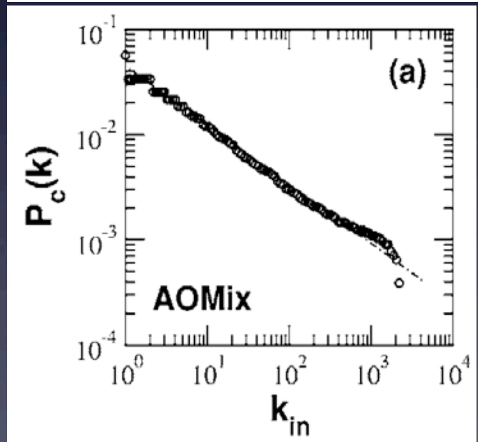


Music Seer:

Art of the Mix:

	type	n	m	$\langle k \rangle$	C	C_r
ArtOfTheMix	undirected	48,170	300,708	12.5	0.1	0.003
MusicSeer	directed	6,144	10,219	2.9	0.02	$4.7 . 10^{-4}$

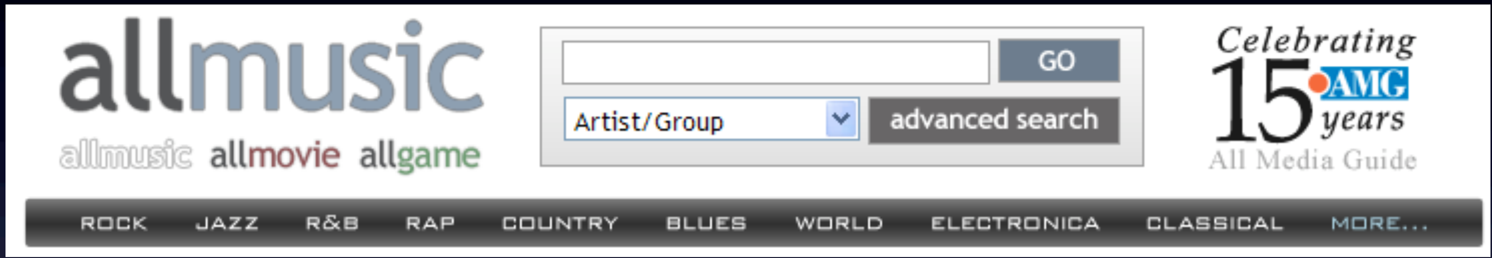


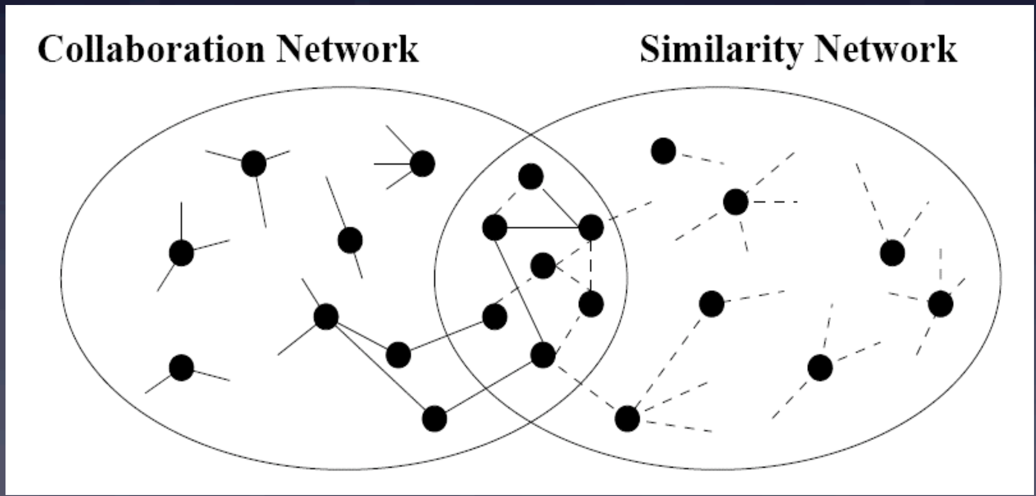


Major recommendation networks are small world.
Collaborative-filtering networks, biased by popularity, are scale-free
Human supervised networks, with stress on musically similarity are exponential.

Recommendation and Musicians networks

- Similarity and collaboration networks



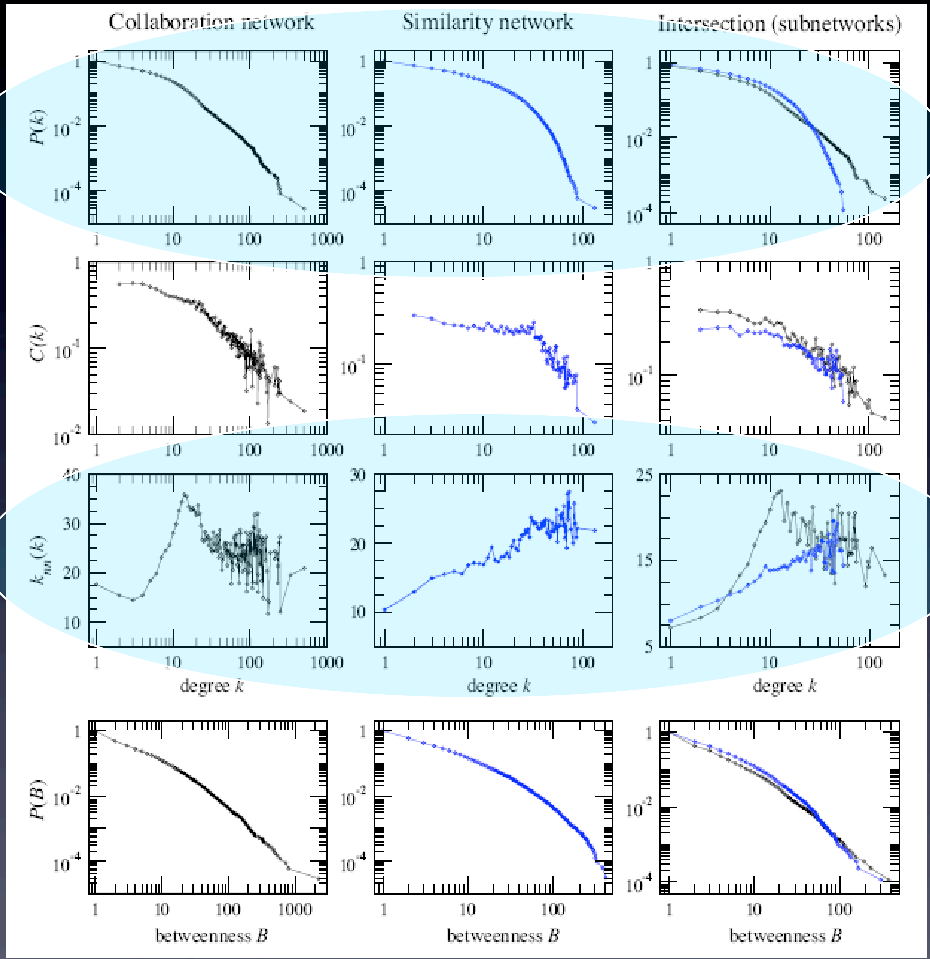


	Similarity network		Collaboration network	
	entire	intersection	entire	intersection
n	32 377	8 509	34 724	8 509
m	117 621	24 950	123 122	20 232
size of S_0	30 384 (94%)	7 219 (85%)	30 945 (89%)	6 054 (71%)
$\bar{d}$ ($d_{\max}$)	6.5 (22)	6.0 (20)	6.4 (23)	6.3 (19)
C	0.185 (18.5%)	0.178 (17.8%)	0.182 (18.2%)	0.171 (17.1%)
$k_{\max}$	131 R.E.M.	55 Eric Clapton	508 P. Da Costa	143 P. Da Costa R. Van Gelder
highest-betweenness artist	Sting	Sting	P. Da Costa	P. Da Costa

	SIMILARITY	
	Mean d	Clustering
Real network	6.0	0.178
Random Network	8.4	0.0003

	COLLABORATION	
	Mean d	Clustering
Real Network	6.3	0.171
Random Network	10.45	0.00028

Small World Networks



Collaboration: Scale-Free
Similarity: Exponential

(Social networks use to be scale-free)

Collaboration: Not assortative
Similarity: Assortative

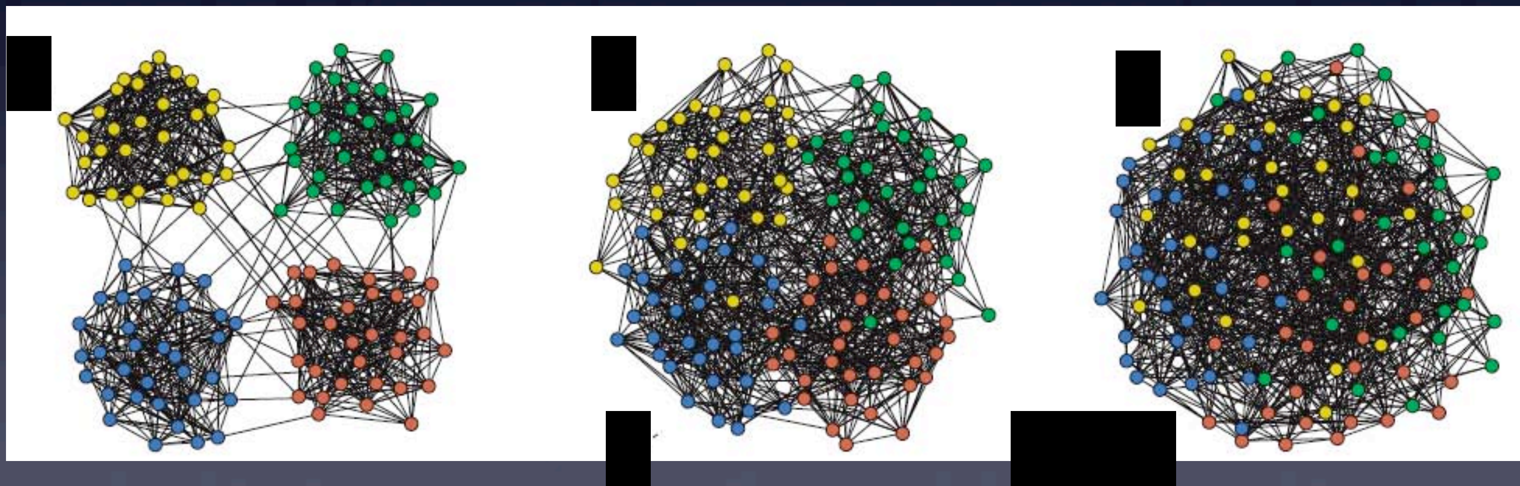
(Social networks use to be assortative)

Community structure in social and biological networks

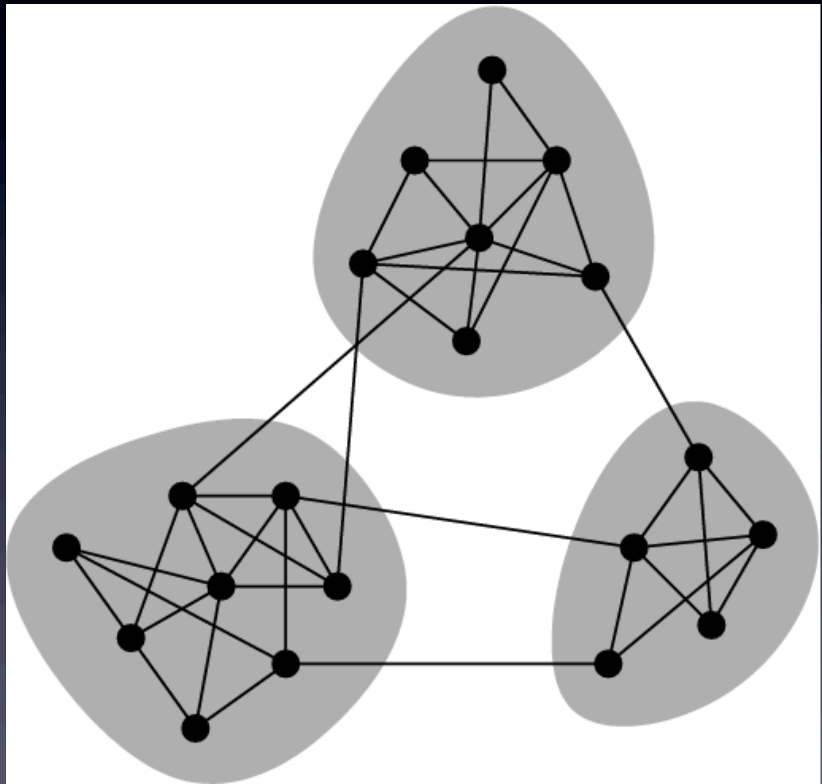
M. Girvan*[†‡] and M. E. J. Newman*[§]

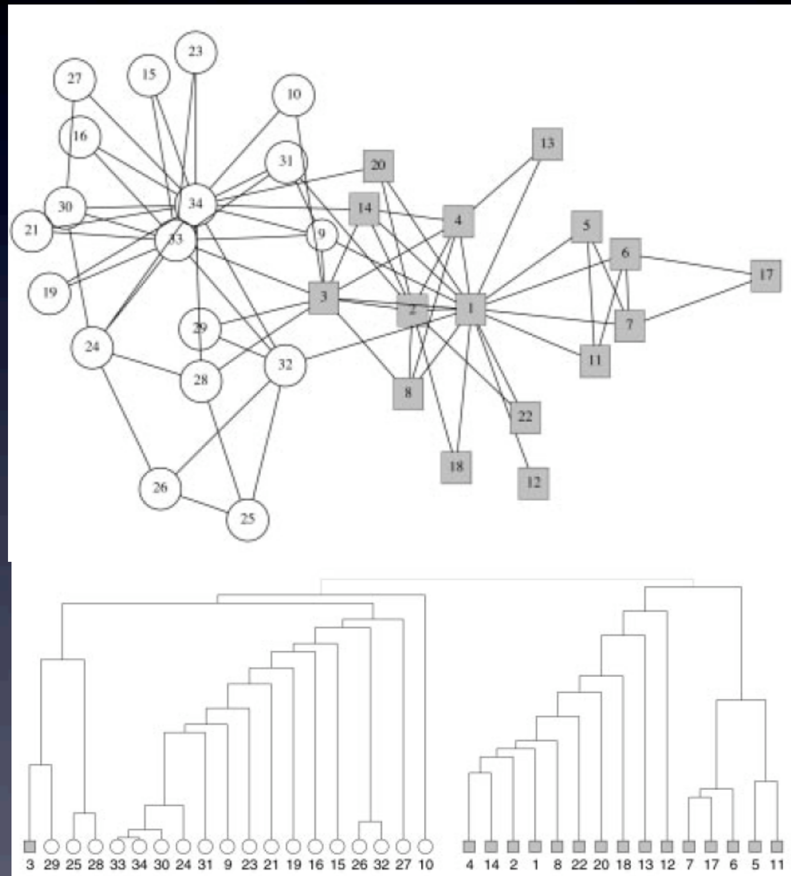
*Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501; [†]Department of Physics, Cornell University, Clark Hall, Ithaca, NY 14853-2501; and [§]Department of Physics, University of Michigan, Ann Arbor, MI 48109-1120

PNAS | June 11, 2002 | vol. 99 | no. 12 | 7821–7826

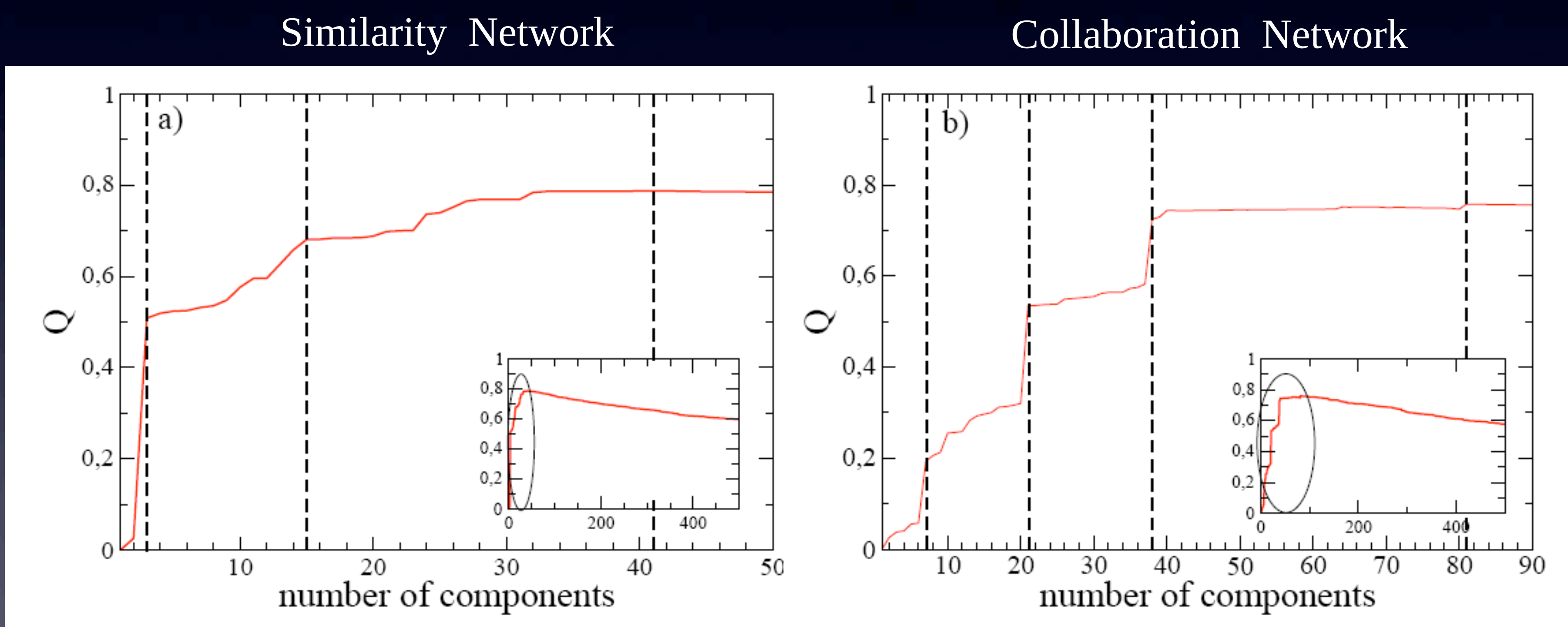


- The Girvan-Newman algorithm

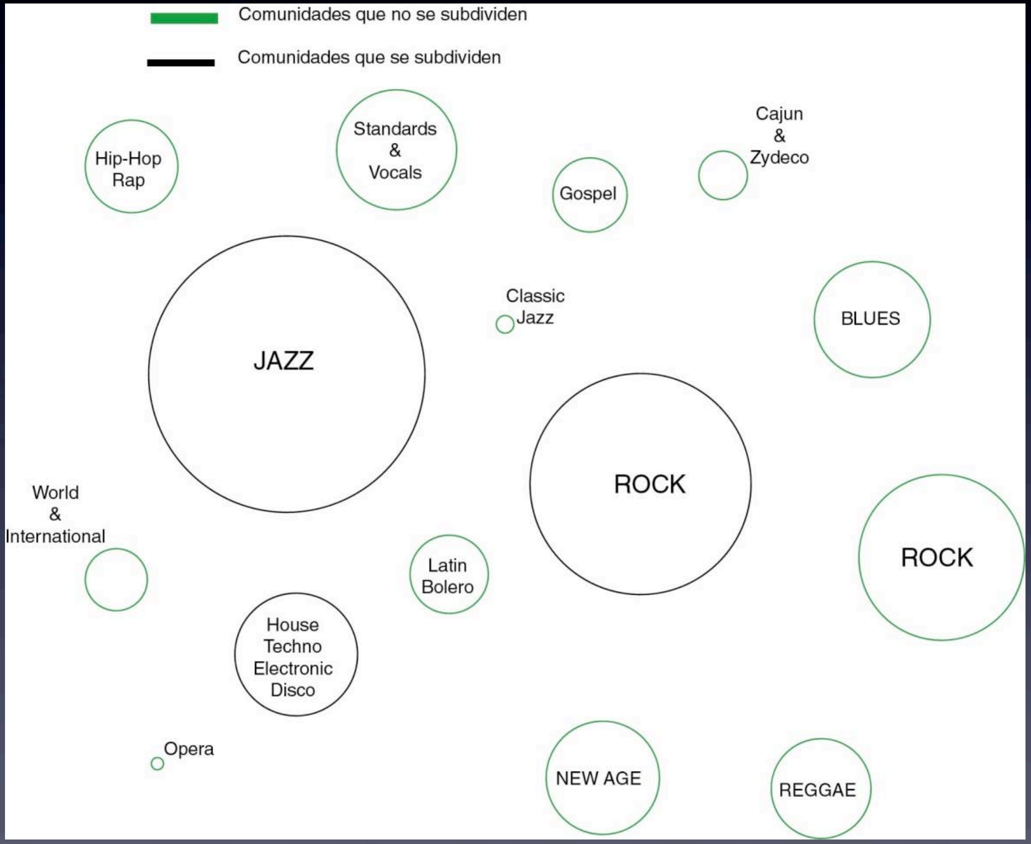




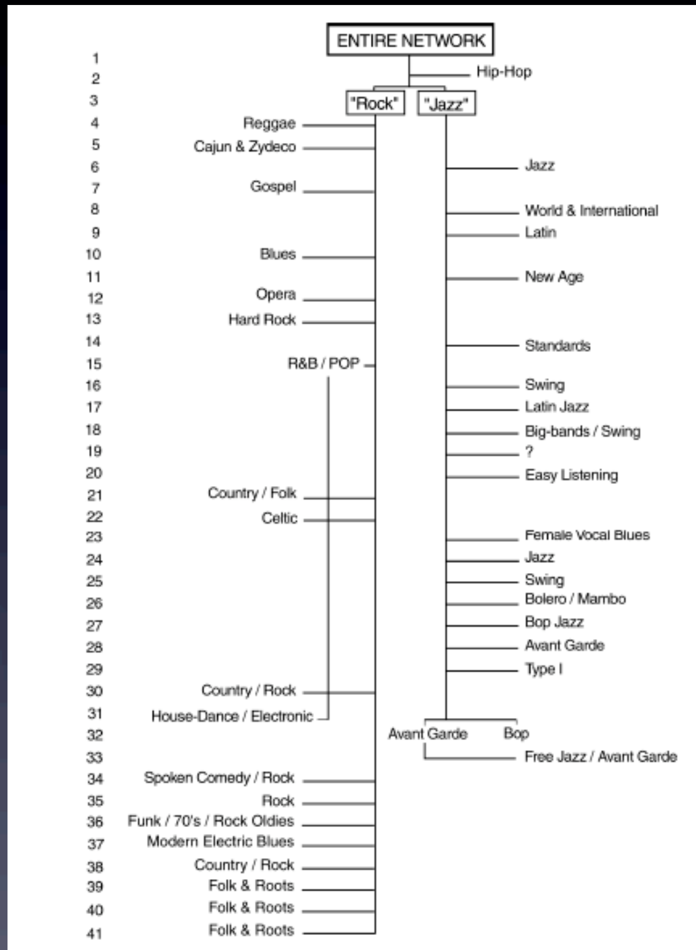
- Community structure in similarity/collaboration networks



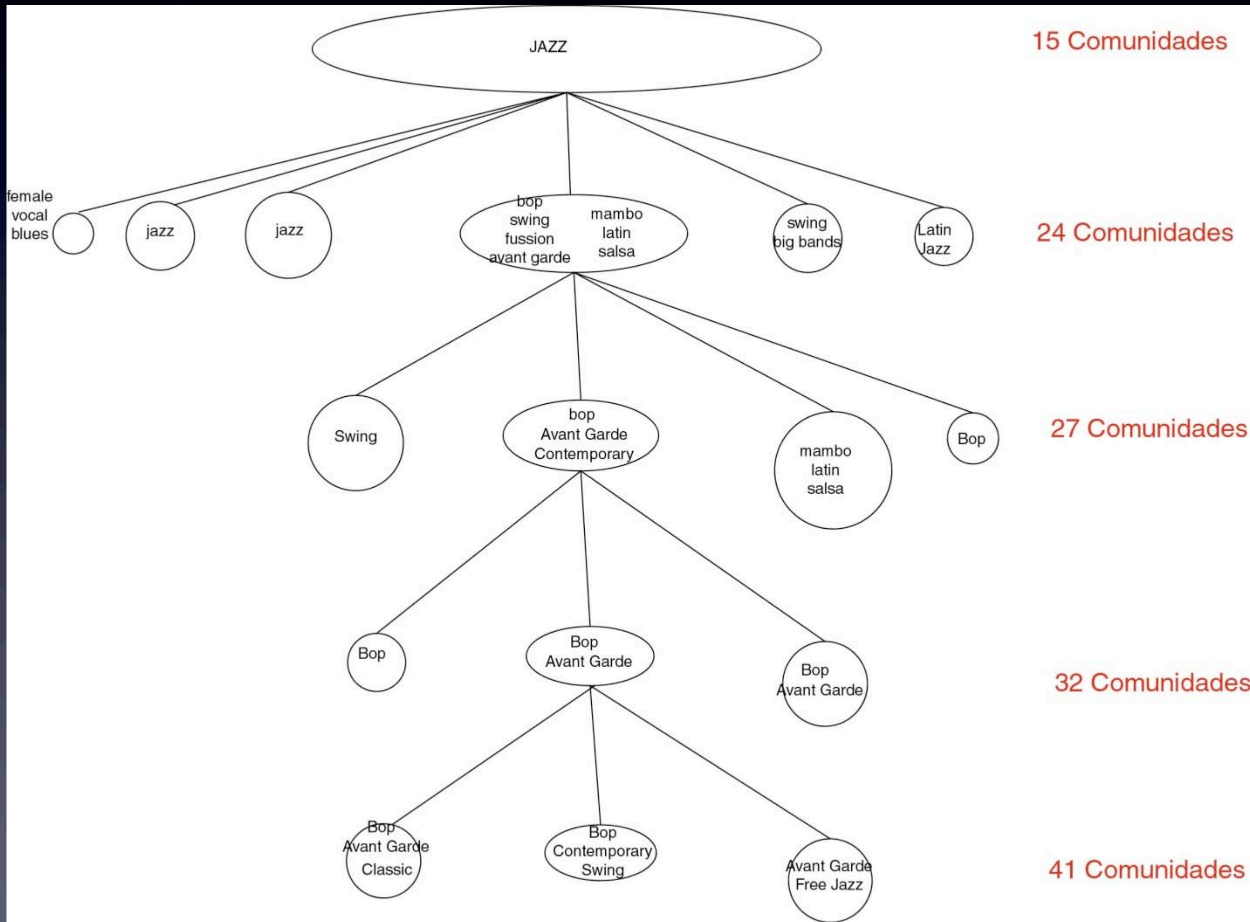
- Community structure in similarity networks



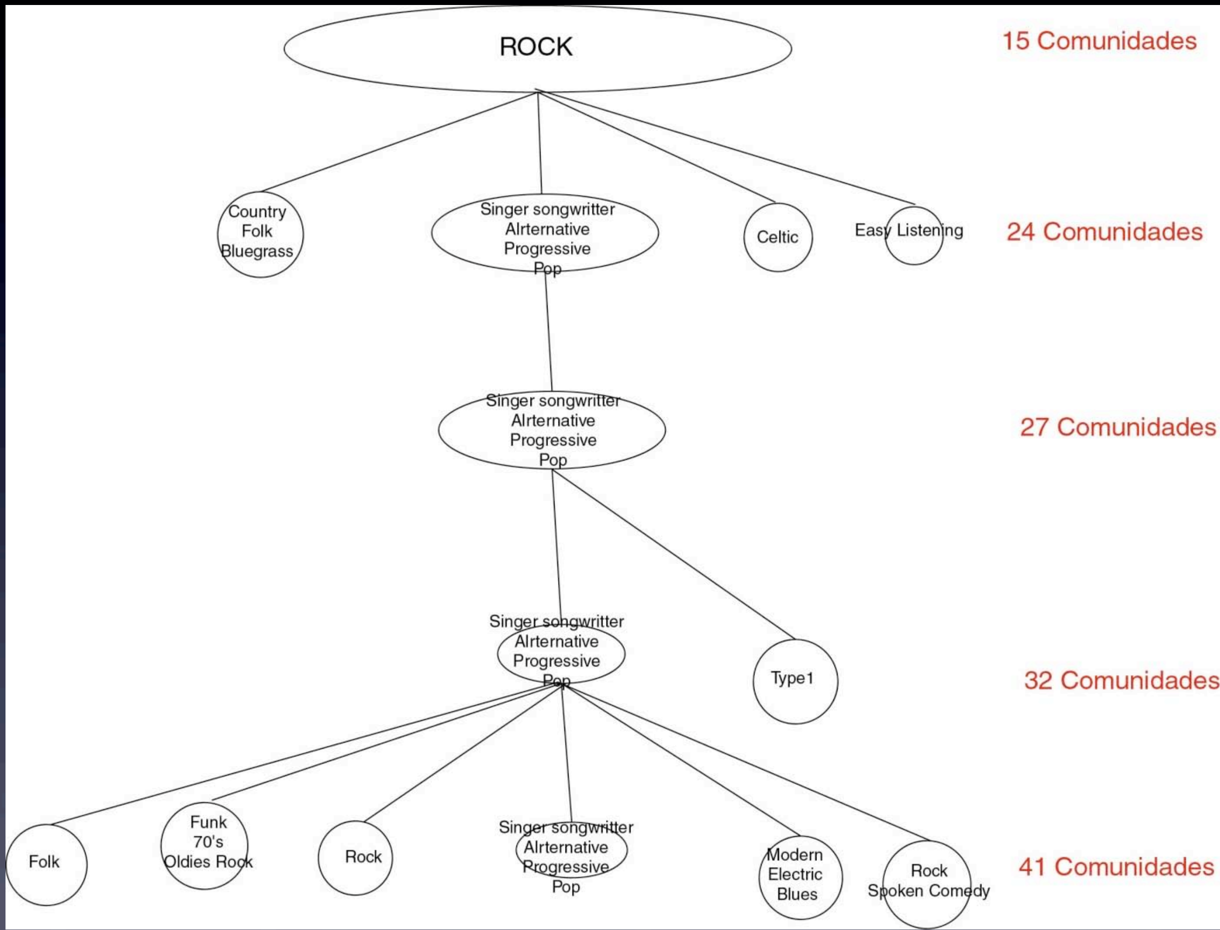
- Splitting the network



- Jazz community

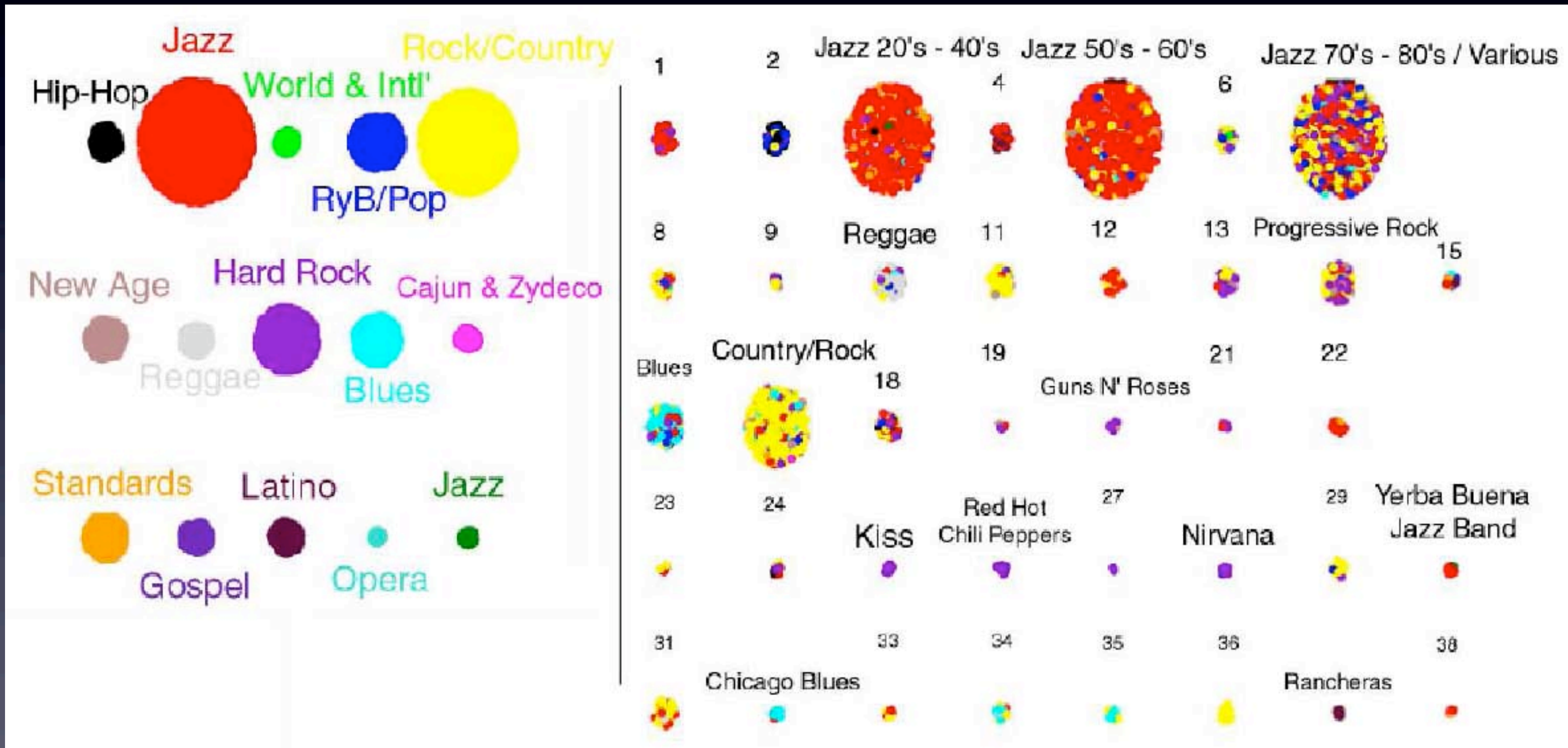


- Rock community



- Similarity

Collaboration



Identifying roles from community structures

Functional cartography of complex metabolic networks

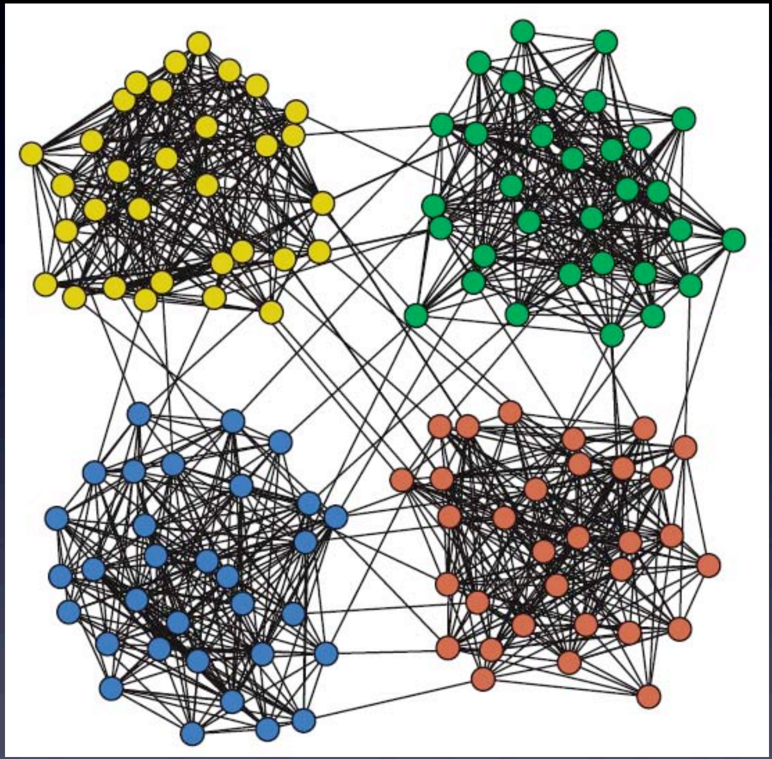
Roger Guimerà & Luís A. Nunes Amaral

NICO and Department of Chemical and Biological Engineering, Northwestern University, Evanston, Illinois 60208, USA

High-throughput techniques are leading to an explosive growth in the size of biological databases and creating the opportunity to revolutionize our understanding of life and disease. Interpretation of these data remains, however, a major scientific challenge. Here, we propose a methodology that enables us to extract

895

NATURE | VOL 433 | 24 FEBRUARY 2005 | www.nature.com/nature



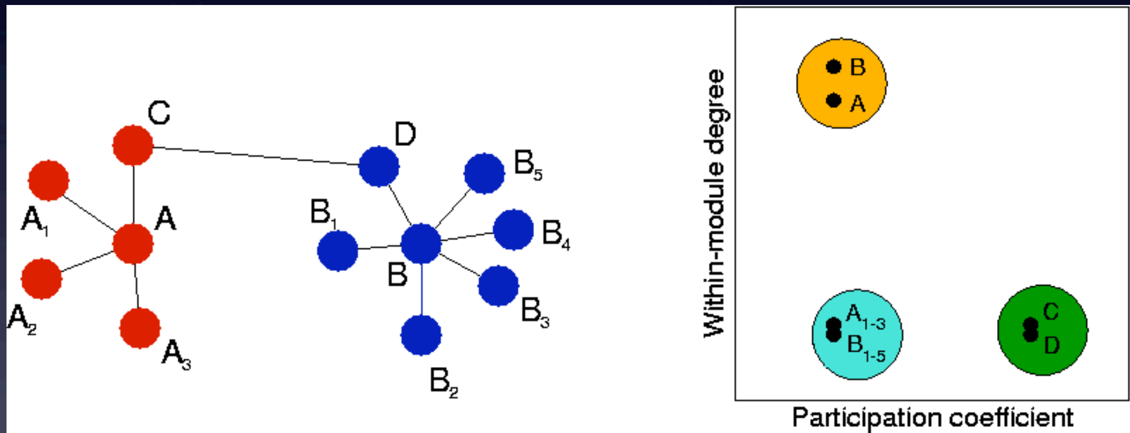
- ¿Is it possible to evaluate functionality from topologial properties?

Within-module connectivity:

$$z_i = \frac{\kappa_i - \bar{\kappa}_{s_i}}{\sigma_{\kappa_{s_i}}}$$

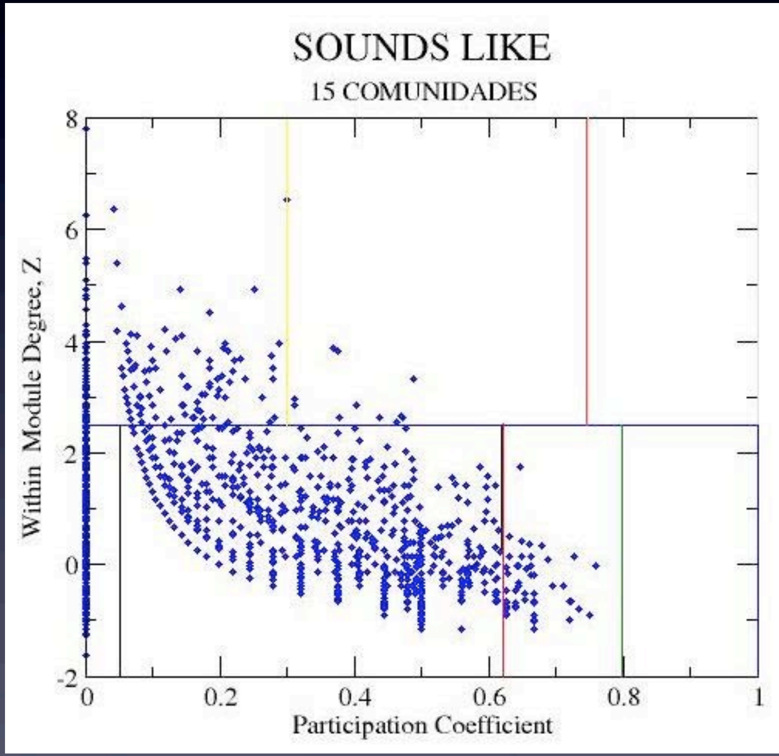
Participation coeficient:

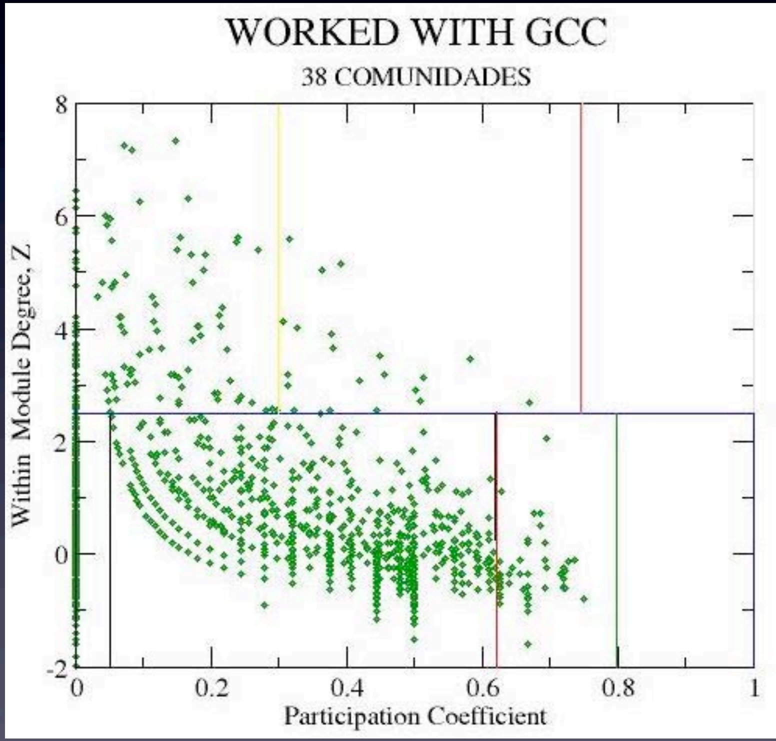
$$P_i = 1 - \sum_{s=1}^{N_M} \left(\frac{\kappa_{is}}{k_i} \right)^2$$



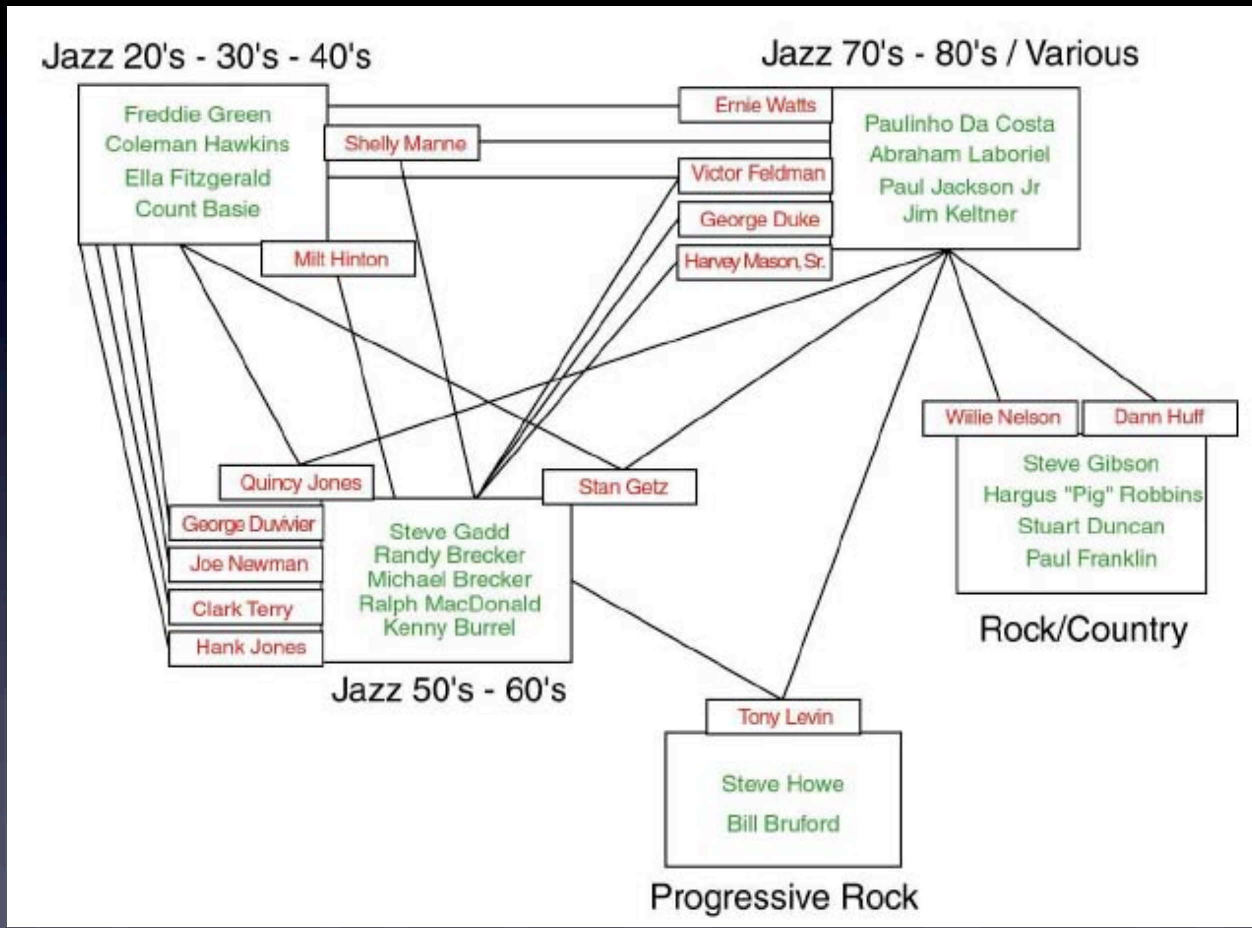
(Figures from R. Guimerà et al., Nature 433, 895 2005)

- Identifying roles in music networks

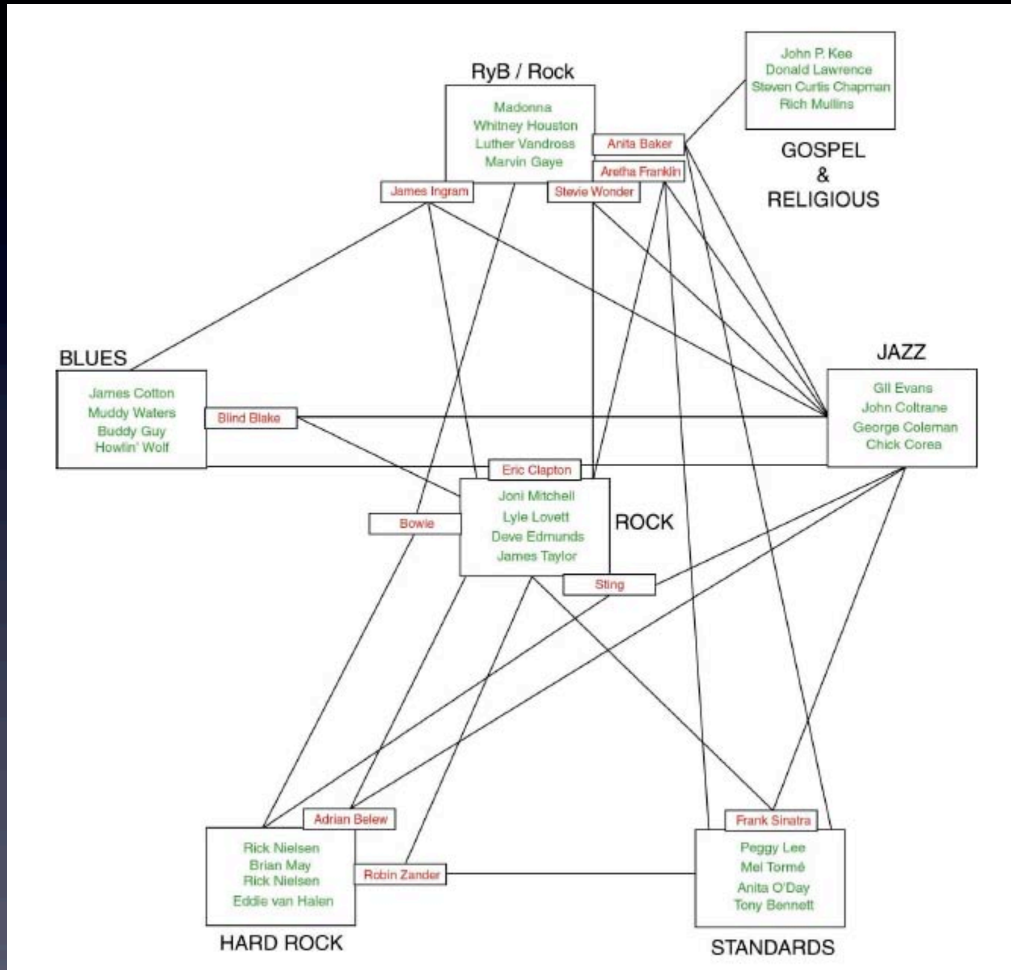




Collaboration cartography



Music similarity cartography

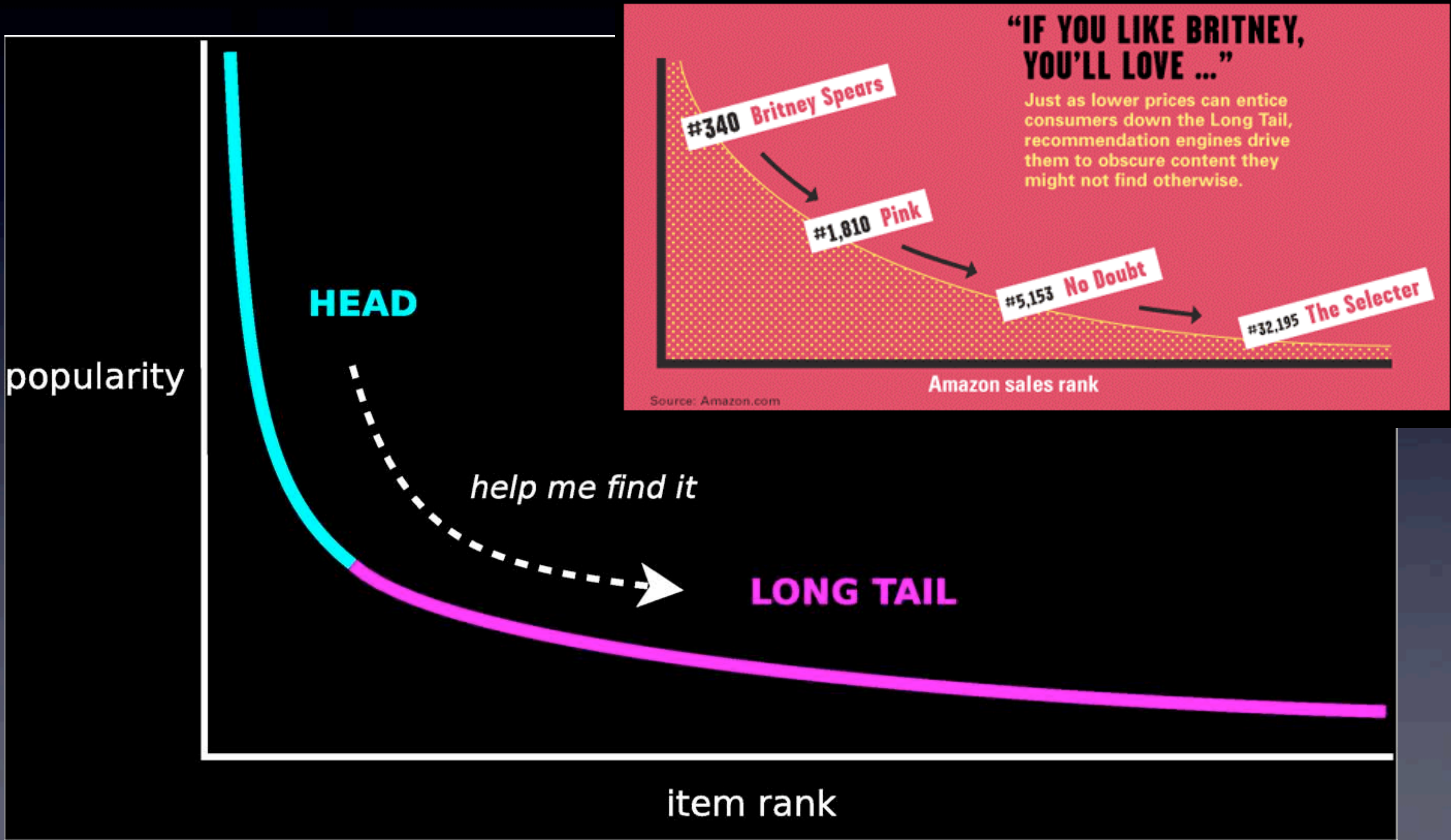


Some conclusions

- The analysis of community structures gives additional information about the understanding of music networks.
- We can identify/assign the role of leader artists just by looking at the topological properties of the network.
- Results can be a source of information for designing optimal recommendation algorithms.

How far into the Long Tail?

- Help me find it! [Anderson, 2006]



- 3 Artist similarity (directed) networks
  - CF*: Social-based, incl. item-based CF (**Last.fm**)
    - "people who listen to *X* also listen to *Y*"
  - CB: Content-based Audio similarity
    - "*X* and *Y* sound similar"
  - EX: Human expert-based (**AllMusicGuide**)
    - "*X* similar to (or influenced by) *Y*"

Property	**CF (*Last.fm*)**	**CB**	**Expert–based (*AMG*)**
N	122,801	59,583	74,494
$\langle k \rangle$	14.13	19.80	5.47
$\langle d_d \rangle$ ($\langle d_r \rangle$)	5.64 (4.42)	4.48 (4.30)	5.92 (6.60)
D	10	7	9
SGC	99.53%	99.97%	95.80%
γ_{in}	2.31($\pm$0.22)	1.61($\pm$0.07)	NA (exp. decay)
r	0.92	0.14	0.17
C (C_r)	0.230 (0.0001)	0.025 (0.0002)	0.027 (0.00007)

- **Small-world** networks [Watts & Strogatz, 1998]

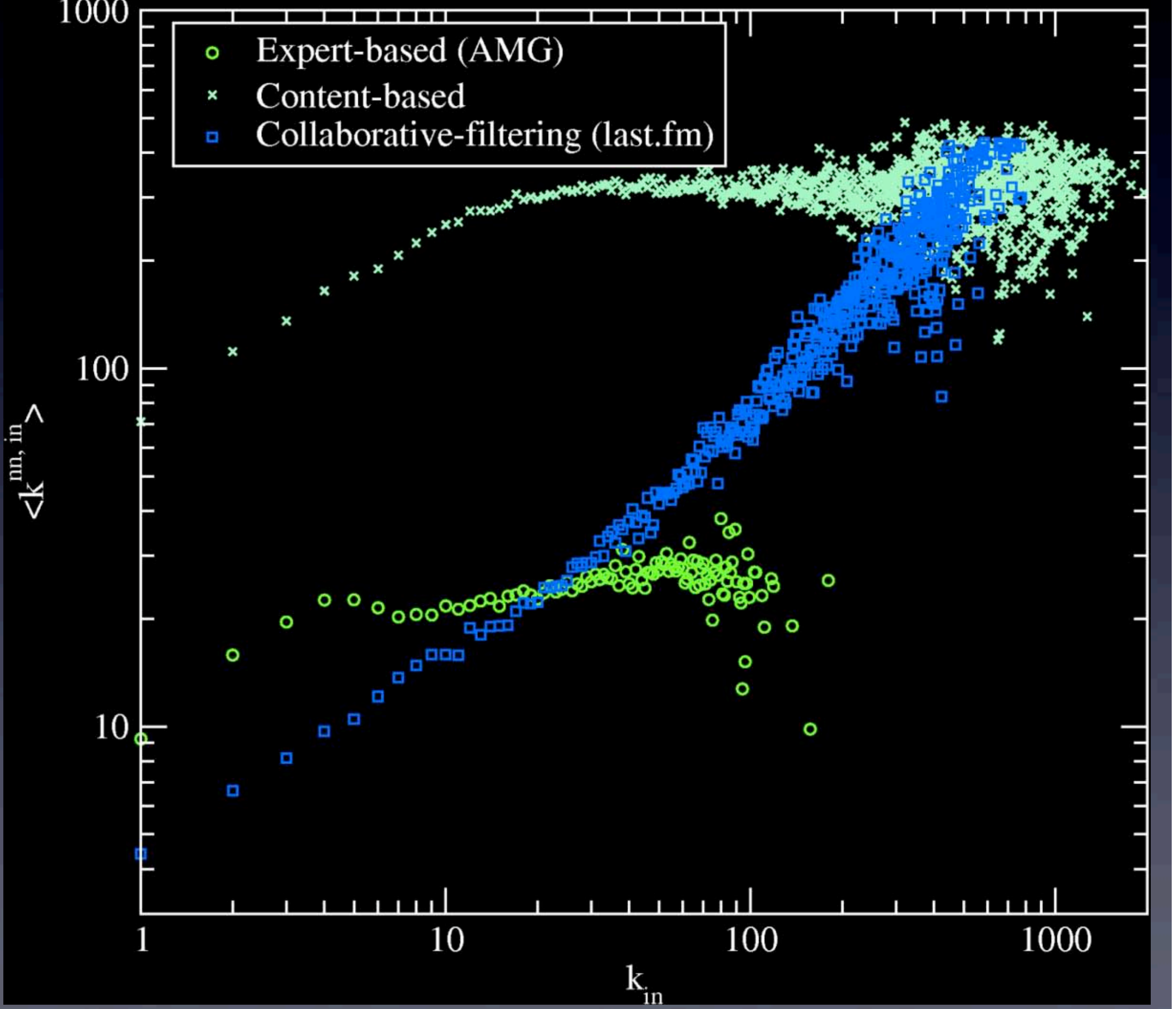
Property	CF (*Last.fm*)	CB	Expert–based (*AMG*)
N	122,801	59,583	74,494
$\langle k \rangle$	14.13	19.80	5.47
$\langle d_d \rangle$ ($\langle d_r \rangle$)	5.64 (4.42)	4.48 (4.30)	5.92 (6.60)
D	10	7	9
SGC	99.53%	99.97%	95.80%
γ_{in}	2.31($\pm$0.22)	1.61($\pm$0.07)	NA (exp. decay)
r	0.92	0.14	0.17
C (C_r)	0.230 (0.0001)	0.025 (0.0002)	0.027 (0.00007)

- Network traverse in a few clicks

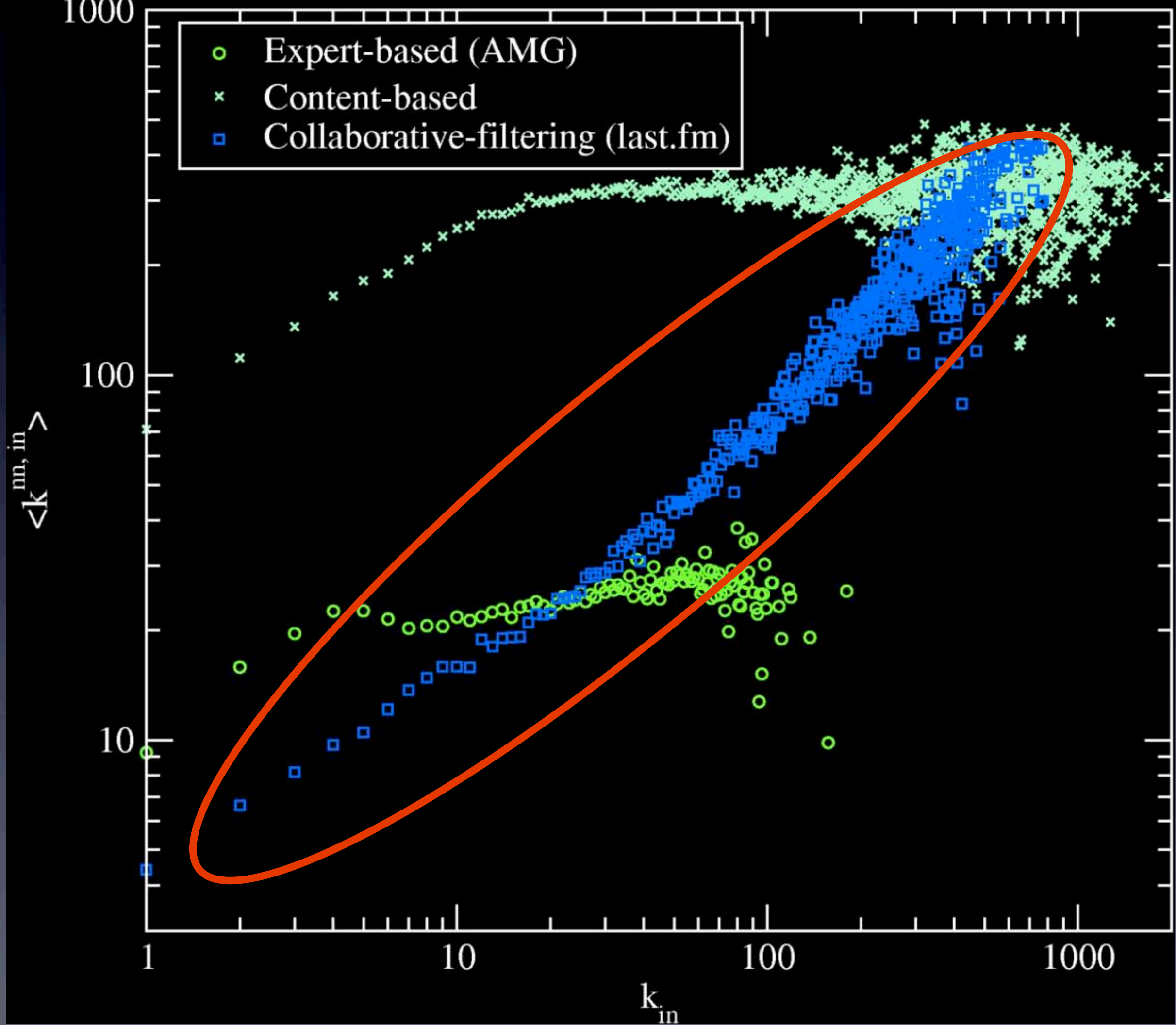
- Indegree – avg. neighbor indegree correlation
  - r = Pearson correlation [Newman, 2002]

Property	CF ($Last.fm$)	CB	Expert–based (AMG)
N	122,801	59,583	74,494
$\langle k \rangle$	14.13	19.80	5.47
$\langle d_d \rangle$ ($\langle d_r \rangle$)	5.64 (4.42)	4.48 (4.30)	5.92 (6.60)
D	10	7	9
SGC	99.53%	99.97%	95.80%
γ_{in}	2.31($\pm$0.22)	1.61($\pm$0.07)	NA (exp. decay)
r	0.92	0.14	0.17
C (C_r)	0.230 (0.0001)	0.025 (0.0002)	0.027 (0.00007)

- Indegree – avg. neighbor indegree correlation

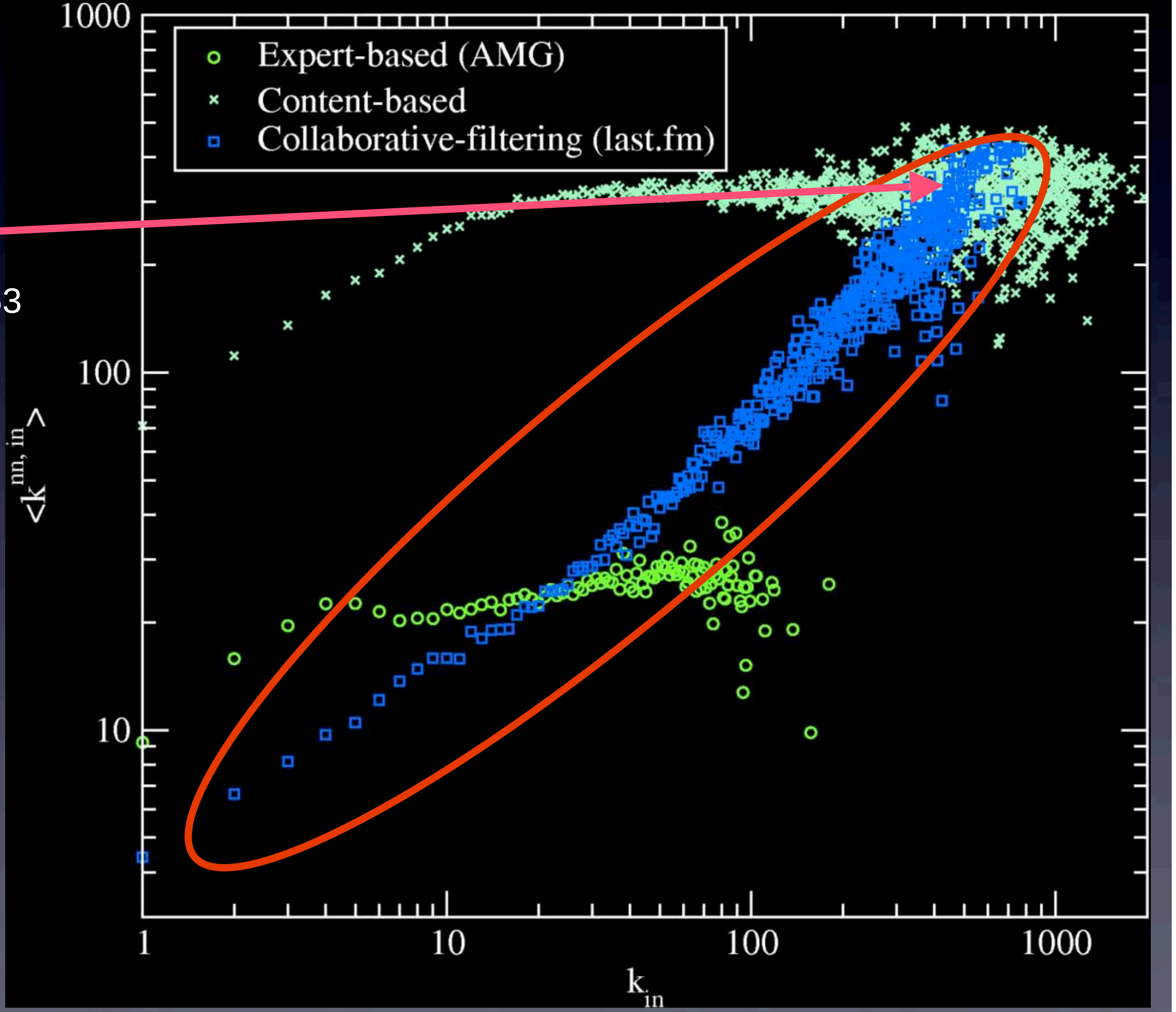


- Indegree – avg. neighbor indegree correlation



- Indegree – avg. neighbor indegree correlation

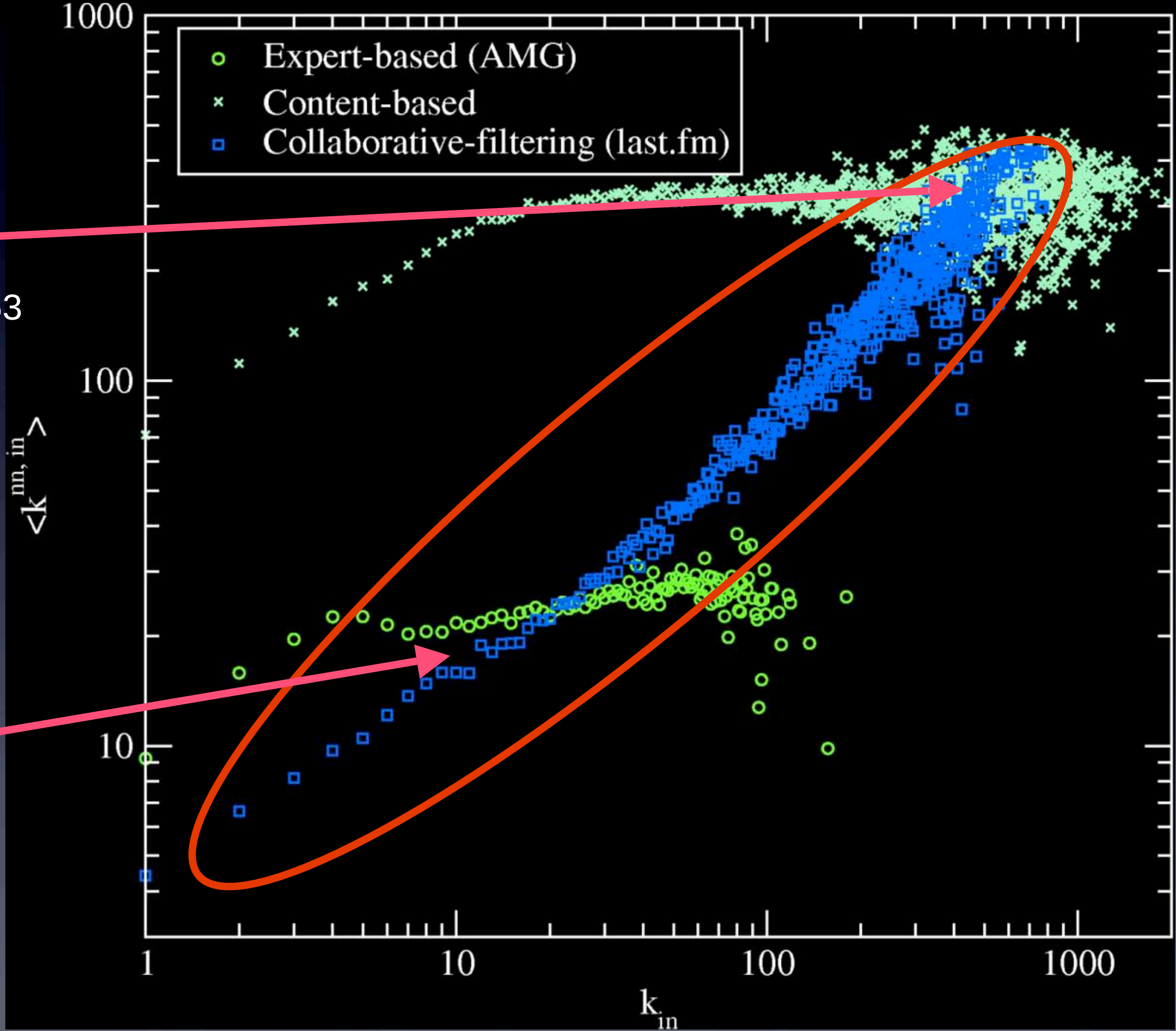
Kin(Bruce Springsteen)=534
=>
avg(Kin(sim(Bruce Springsteen)))=463



- Indegree – avg. neighbor indegree correlation

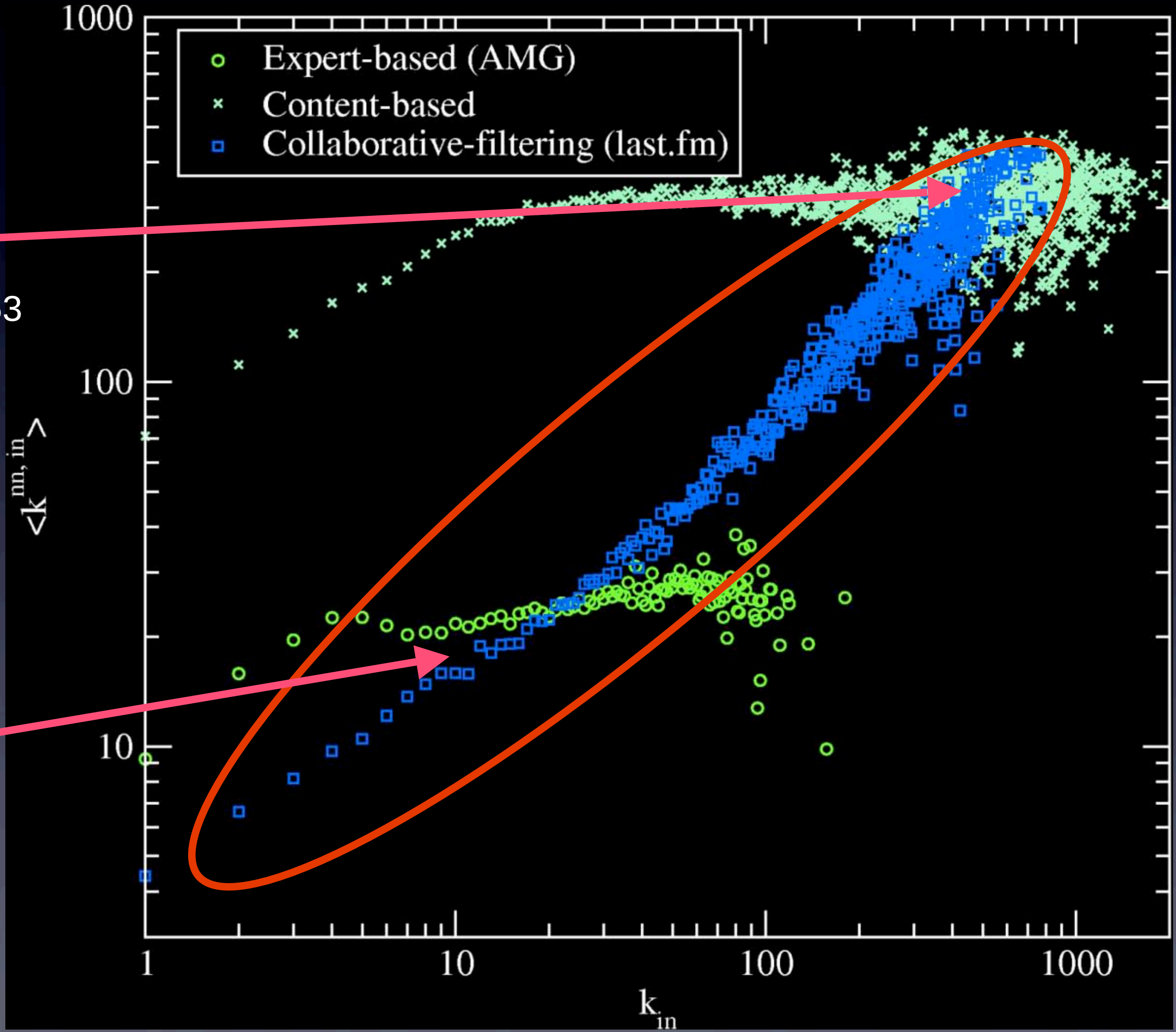
Kin(Bruce Springsteen)=534
=>
avg(Kin(sim(Bruce Springsteen)))=463

Kin(Mike Shupp)=14
=>
avg(Kin(sim(Mike Shupp)))=15



- Indegree – avg. neighbor indegree correlation

Kin(Bruce Springsteen)=534
=>
avg(Kin(sim(Bruce Springsteen)))=463



Kin(Mike Shupp)=14
=>
avg(Kin(sim(Mike Shupp)))=15

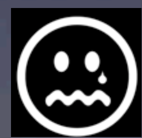
Homophily effect!

- Indegree – avg. neighbor indegree correlation
  - Last.fm presents **assortative mixing** (homophily)

Property	CF (*Last.fm*)	CB	Expert–based (*AMG*)
N	122,801	59,583	74,494
$\langle k \rangle$	14.13	19.80	5.47
$\langle d_d \rangle$ ($\langle d_r \rangle$)	5.64 (4.42)	4.48 (4.30)	5.92 (6.60)
D	10	7	9
SGC	99.53%	99.97%	95.80%
γ_{in}	2.31(±0.22)	1.61(±0.07)	NA (exp. decay)
r	0.92	0.14	0.17
C (C_r)	0.230 (0.0001)	0.025 (0.0002)	0.027 (0.00007)

- Last.fm is a **scale-free** network [Barabasi, 2000]
  - power law exponent for the cumulative indegree distribution [Clauset, 2007]

Property	**CF (*Last.fm*)**	**CB**	**Expert–based (*AMG*)**
N	122,801	59,583	74,494
$\langle k \rangle$	14.13	19.80	5.47
$\langle d_d \rangle$ ($\langle d_r \rangle$)	5.64 (4.42)	4.48 (4.30)	5.92 (6.60)
D	10	7	9
SGC	99.53%	99.97%	95.80%
γ_{in}	2.31($\pm$0.22)	1.61($\pm$0.07)	NA (exp. decay)
r	0.92	0.14	0.17
C (C_r)	0.230 (0.0001)	0.025 (0.0002)	0.027 (0.00007)

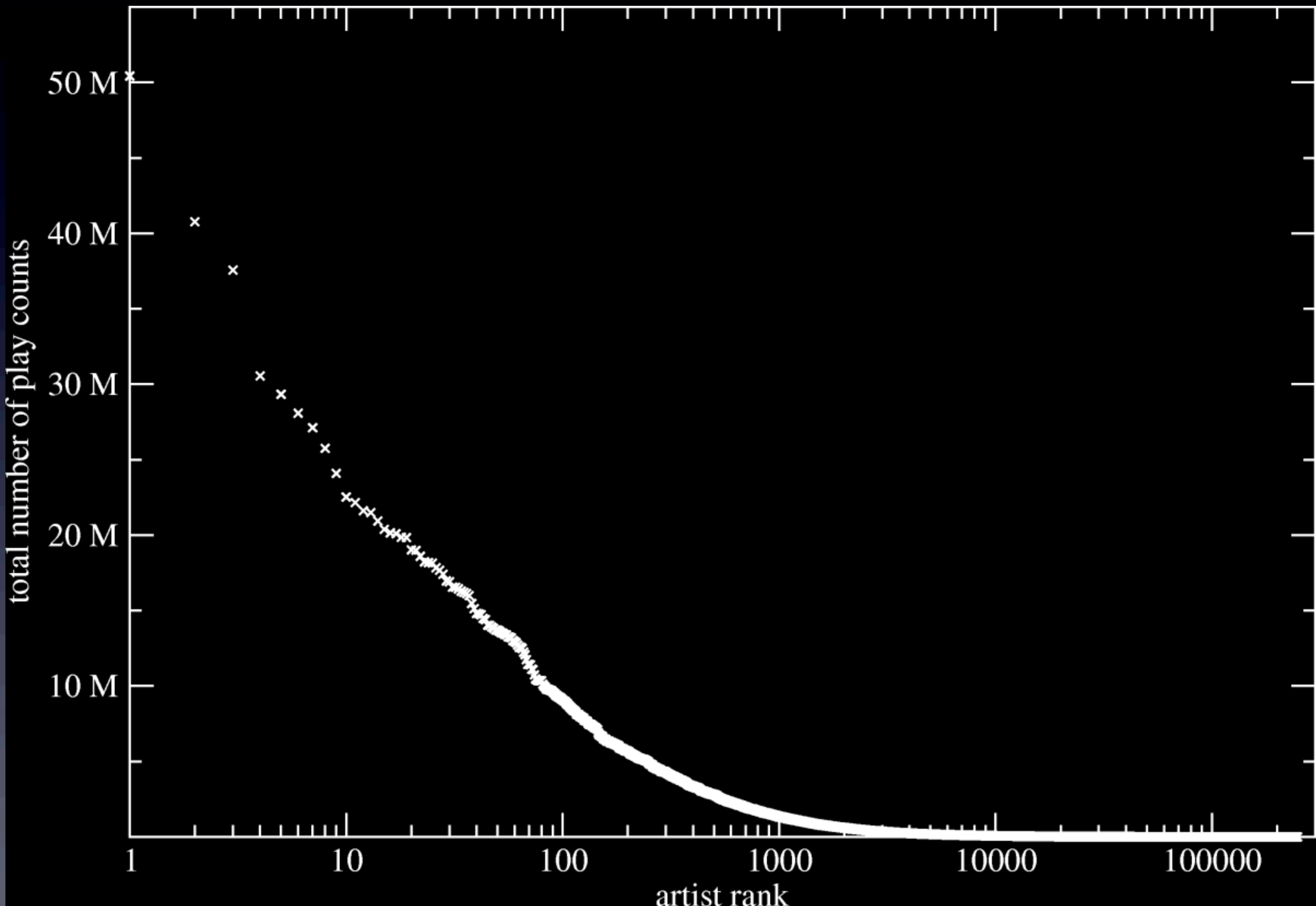


But, still some remaining questions...

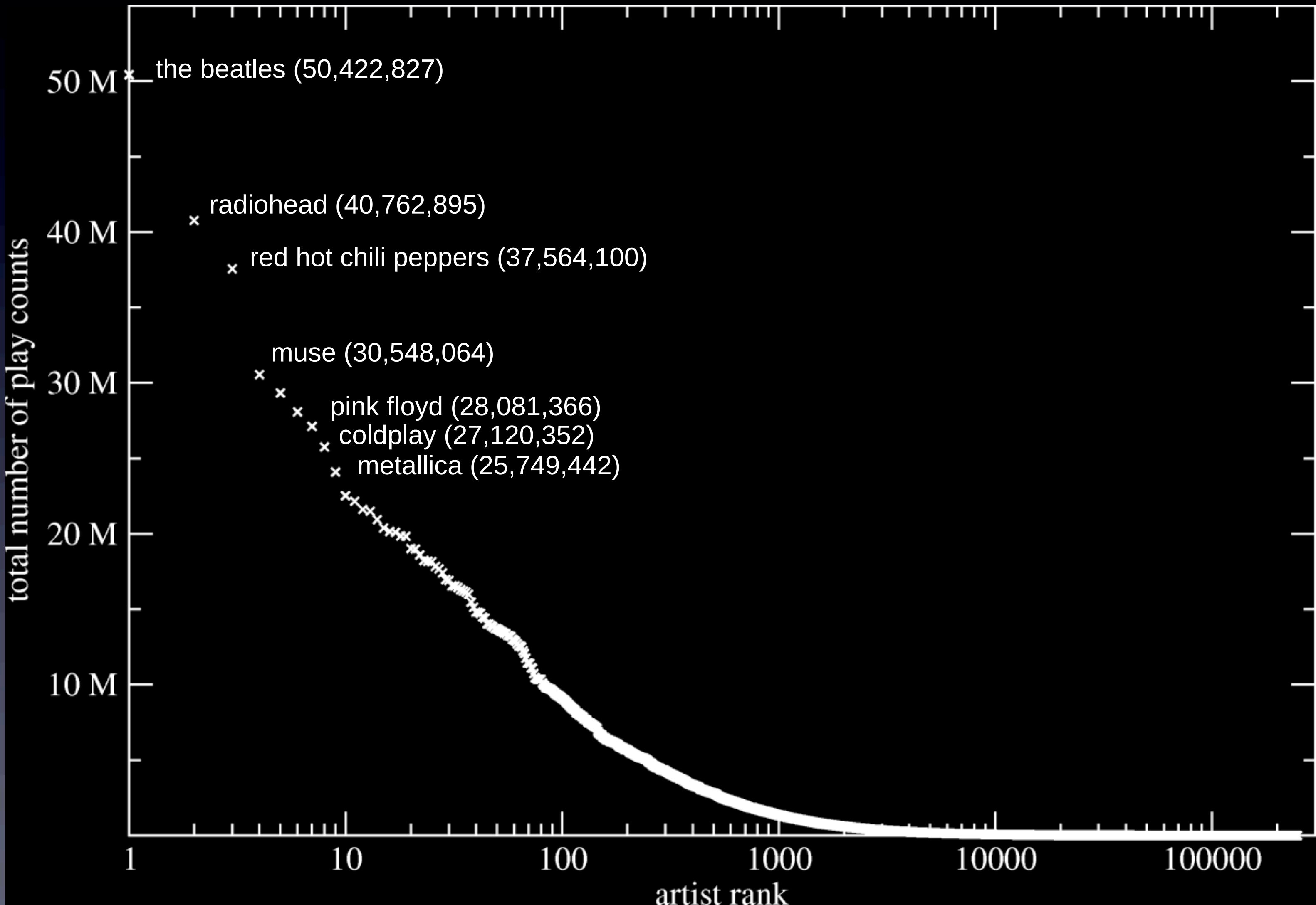
Are the hubs the most popular artists?

How can we navigate along the Long Tail, using the artist similarity network?

- last.fm dataset (~260K artists)



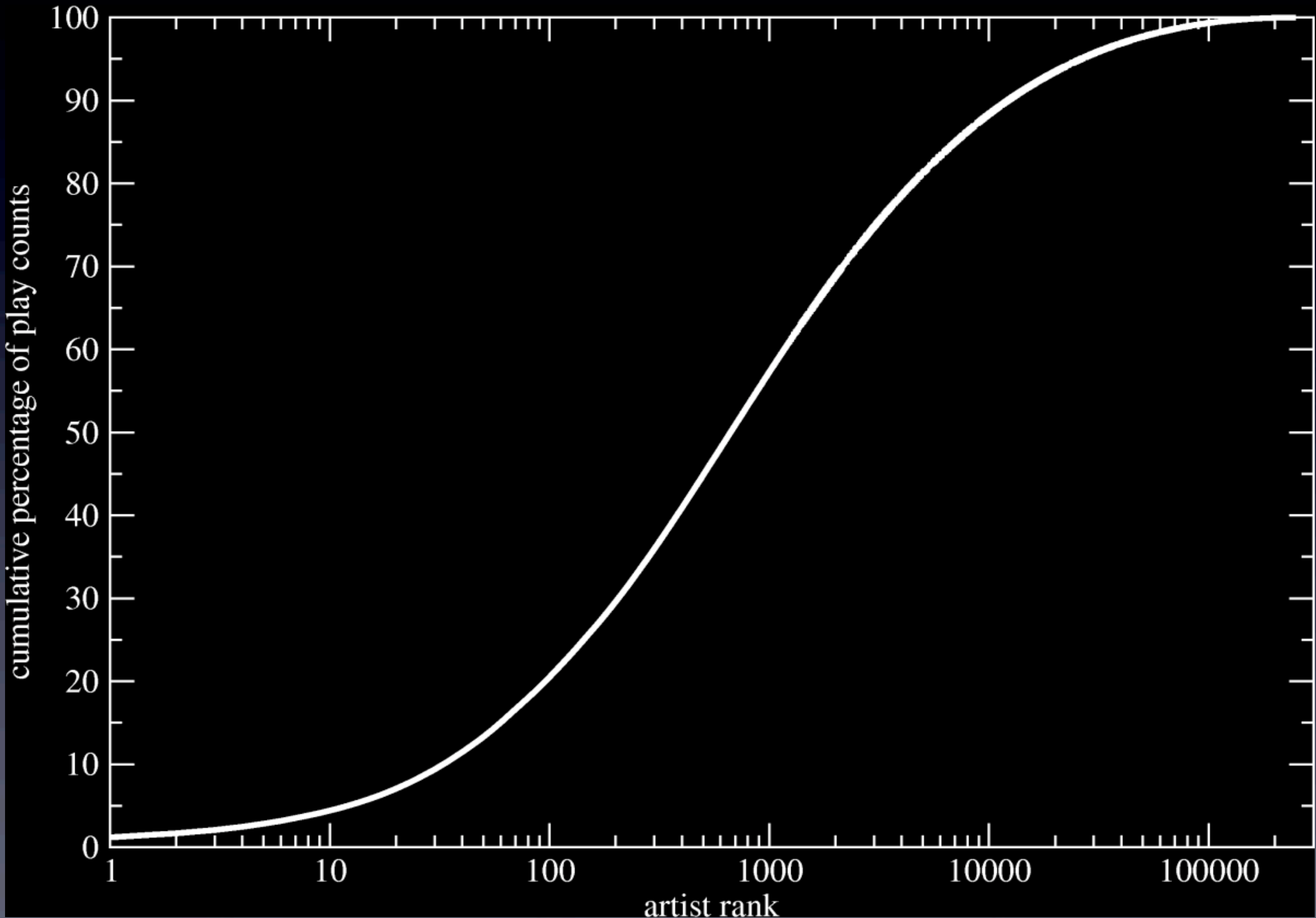
- last.fm dataset (~260K artists)



The Long Tail model [Kilkki, 2007]

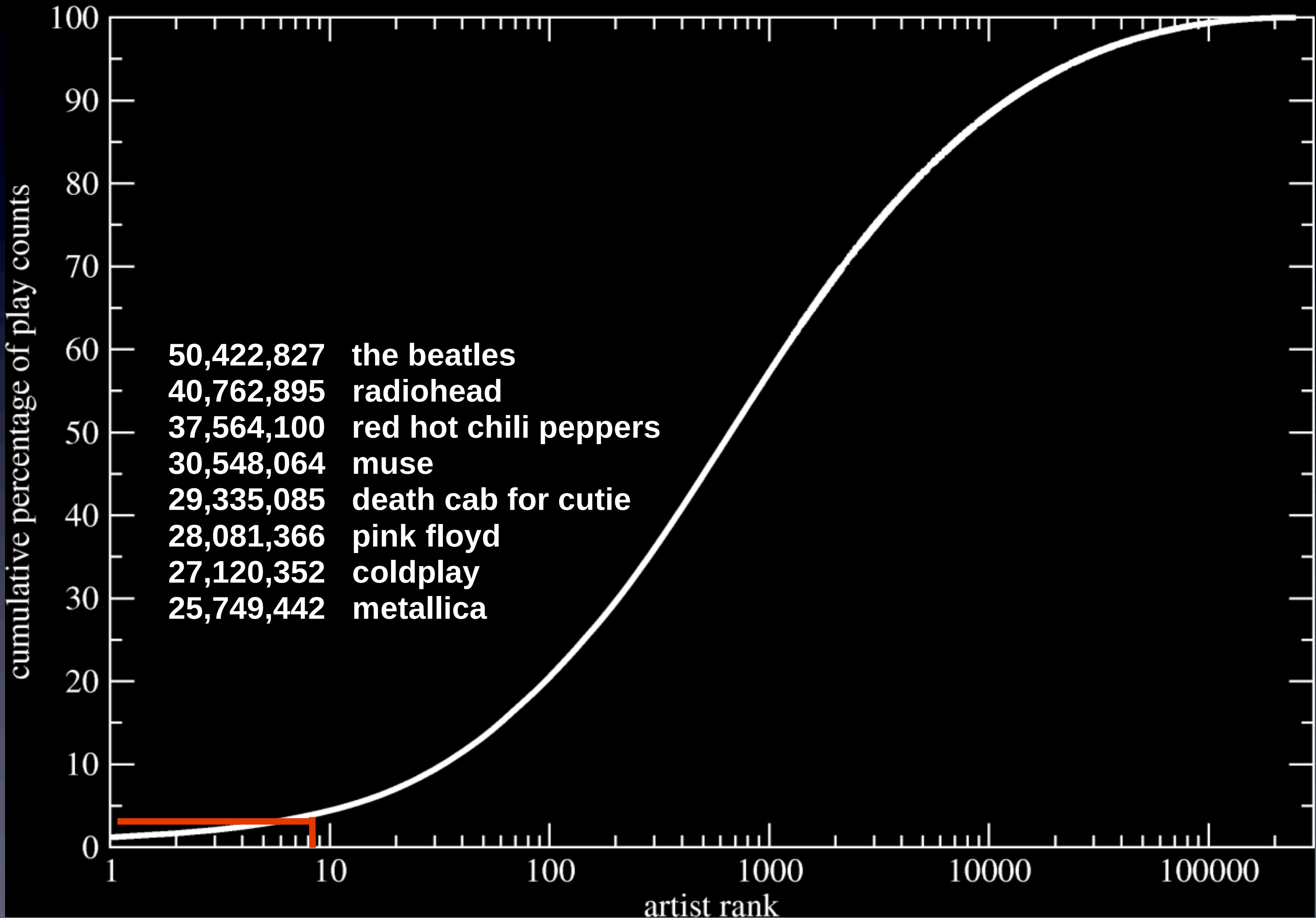
$$F(x) = \frac{\beta}{\left(\frac{N_{50}}{x}\right)^{\alpha} + 1}$$

- *F(x)* = Cumulative distribution up to *x*



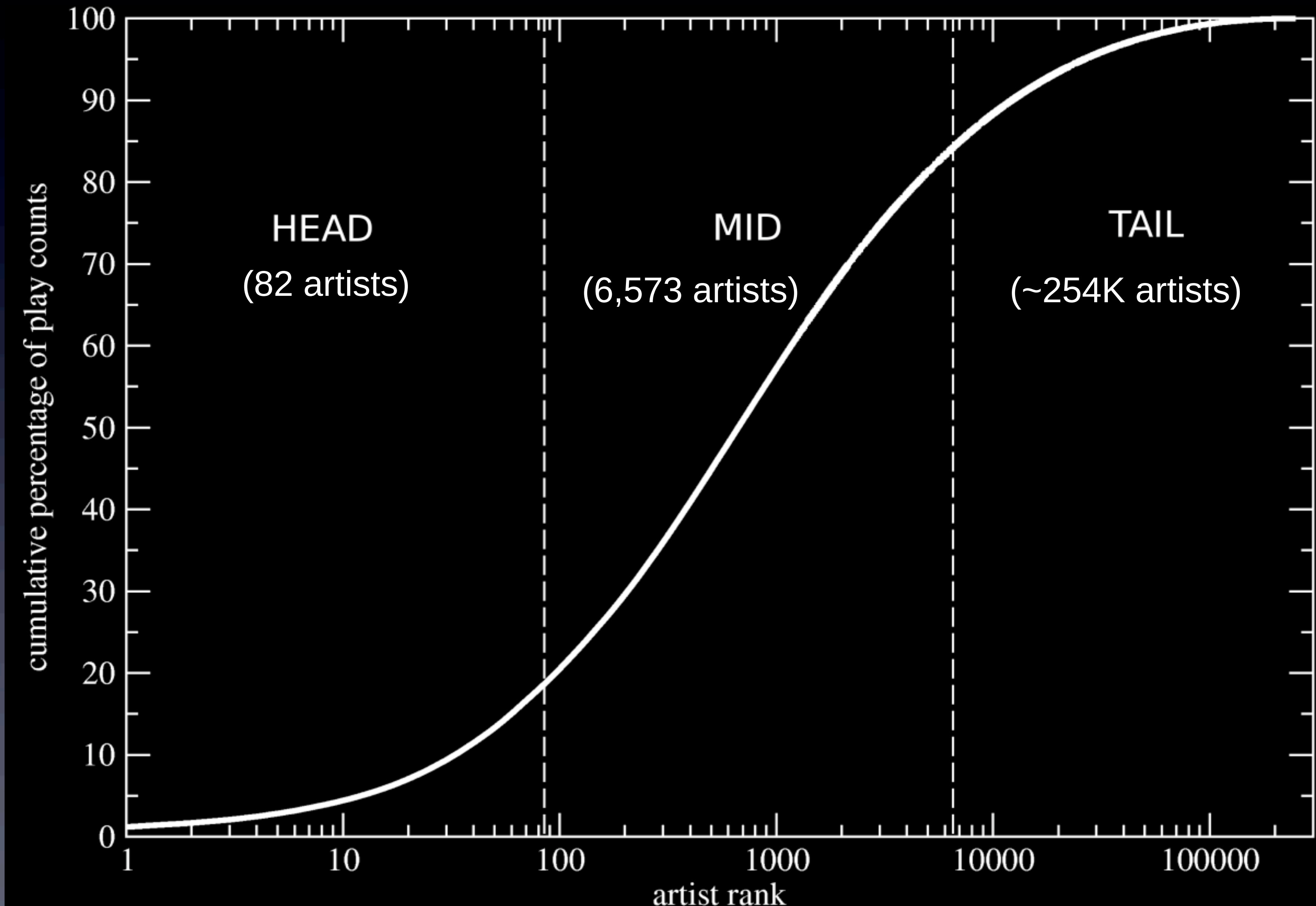
$$F(x) = \frac{\beta}{\left(\frac{N_{50}}{x}\right)^{\alpha} + 1}$$

- Top-8 artists: F(8)~ **3.5%** of total plays



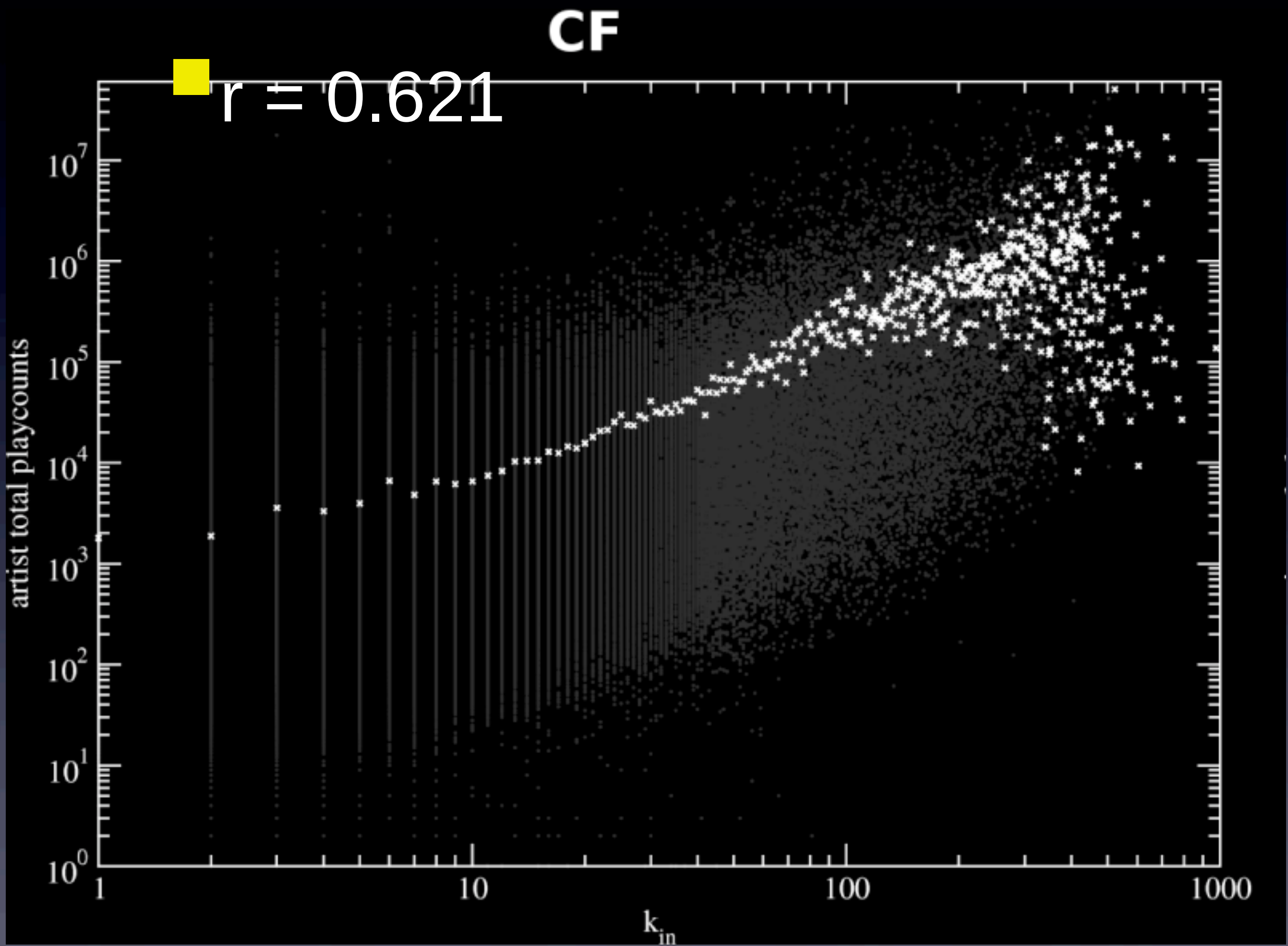
$$F(x) = \frac{\beta}{\left(\frac{N_{50}}{x}\right)^{\alpha} + 1}$$

- Split the curve in three parts

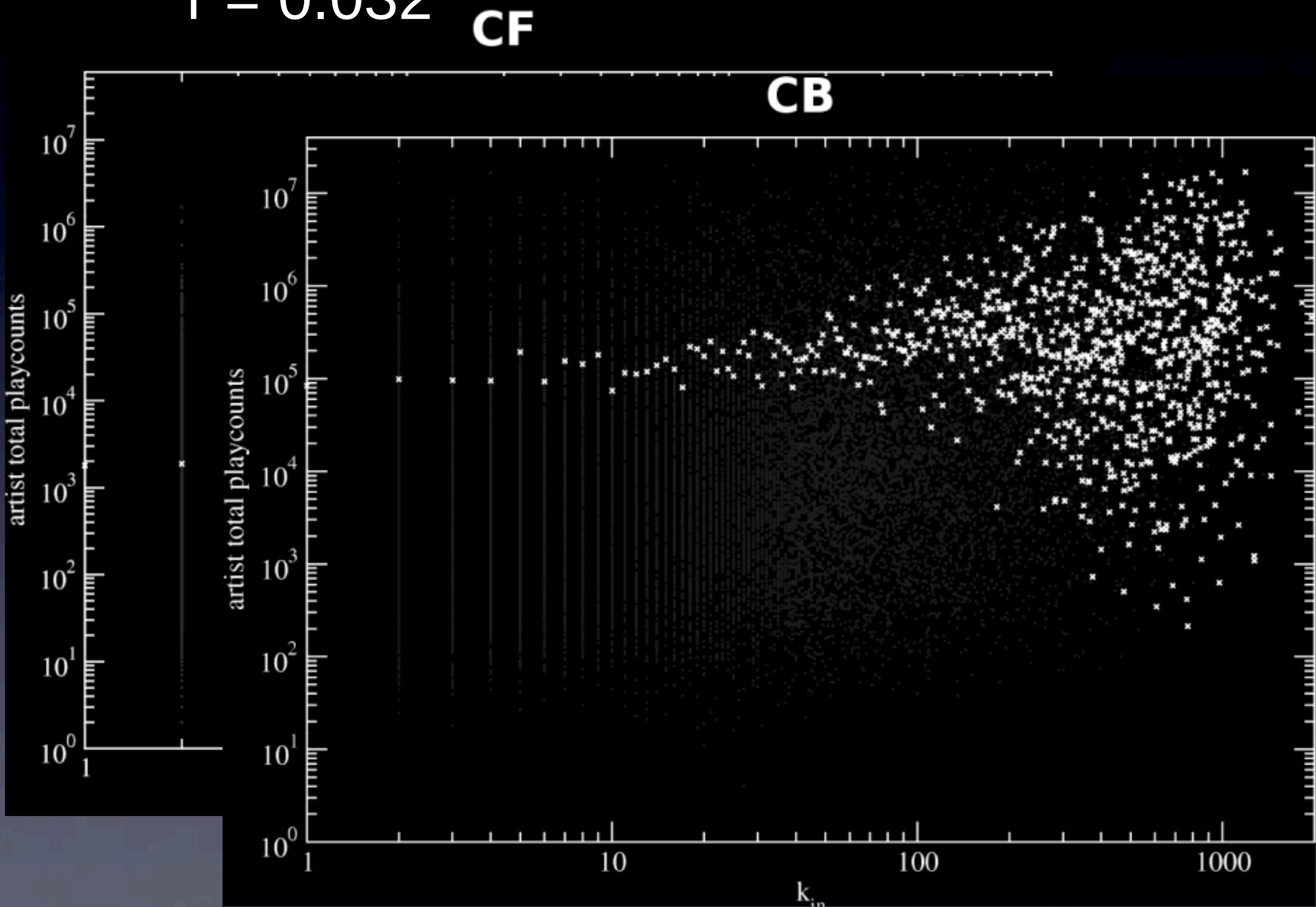


artist indegree vs. artist popularity

- **Last.fm**: correlation between *Kin* and playcounts
  - r = 0.621

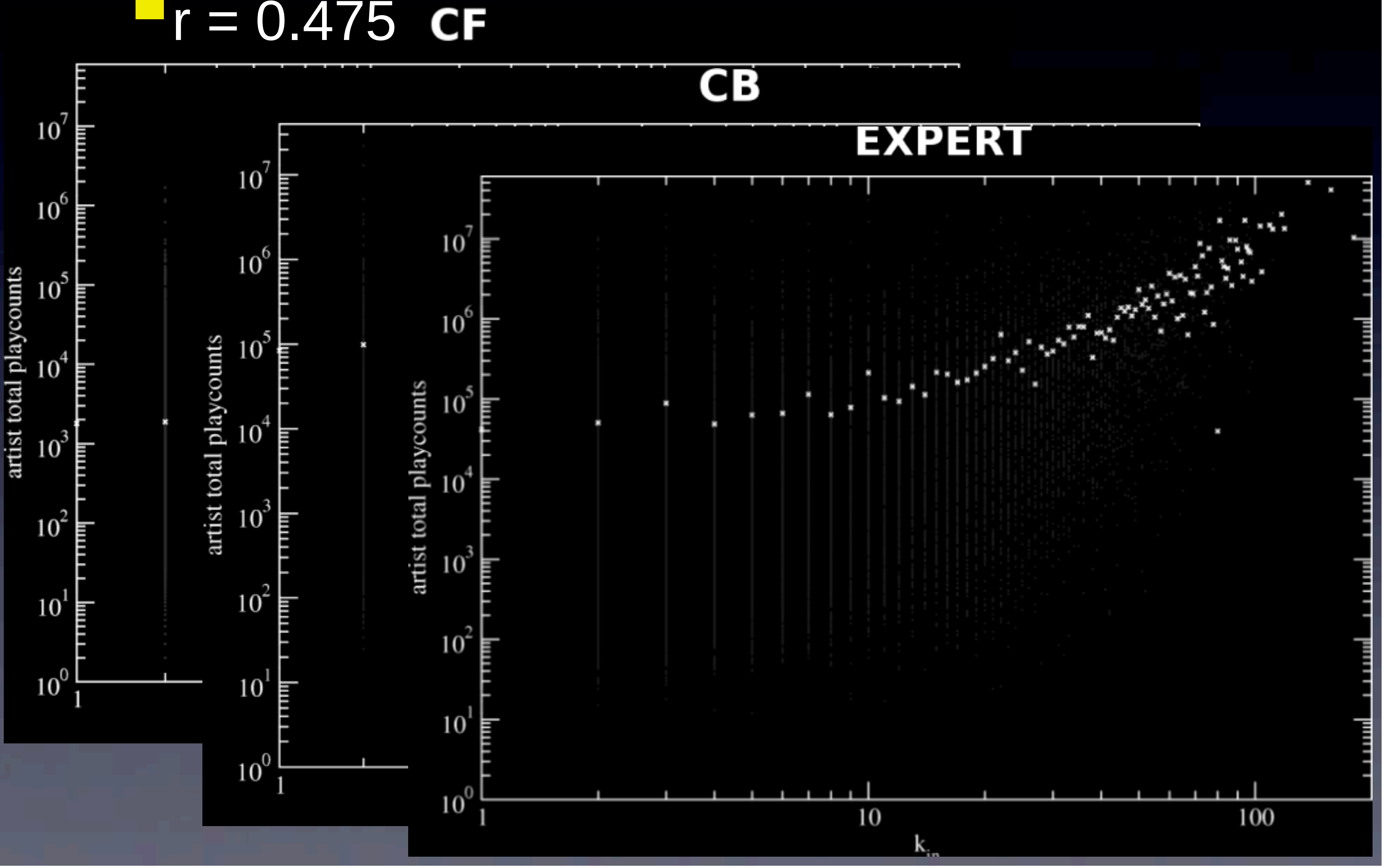


- **Audio CB similarity**: no correlation
  - r = 0.032



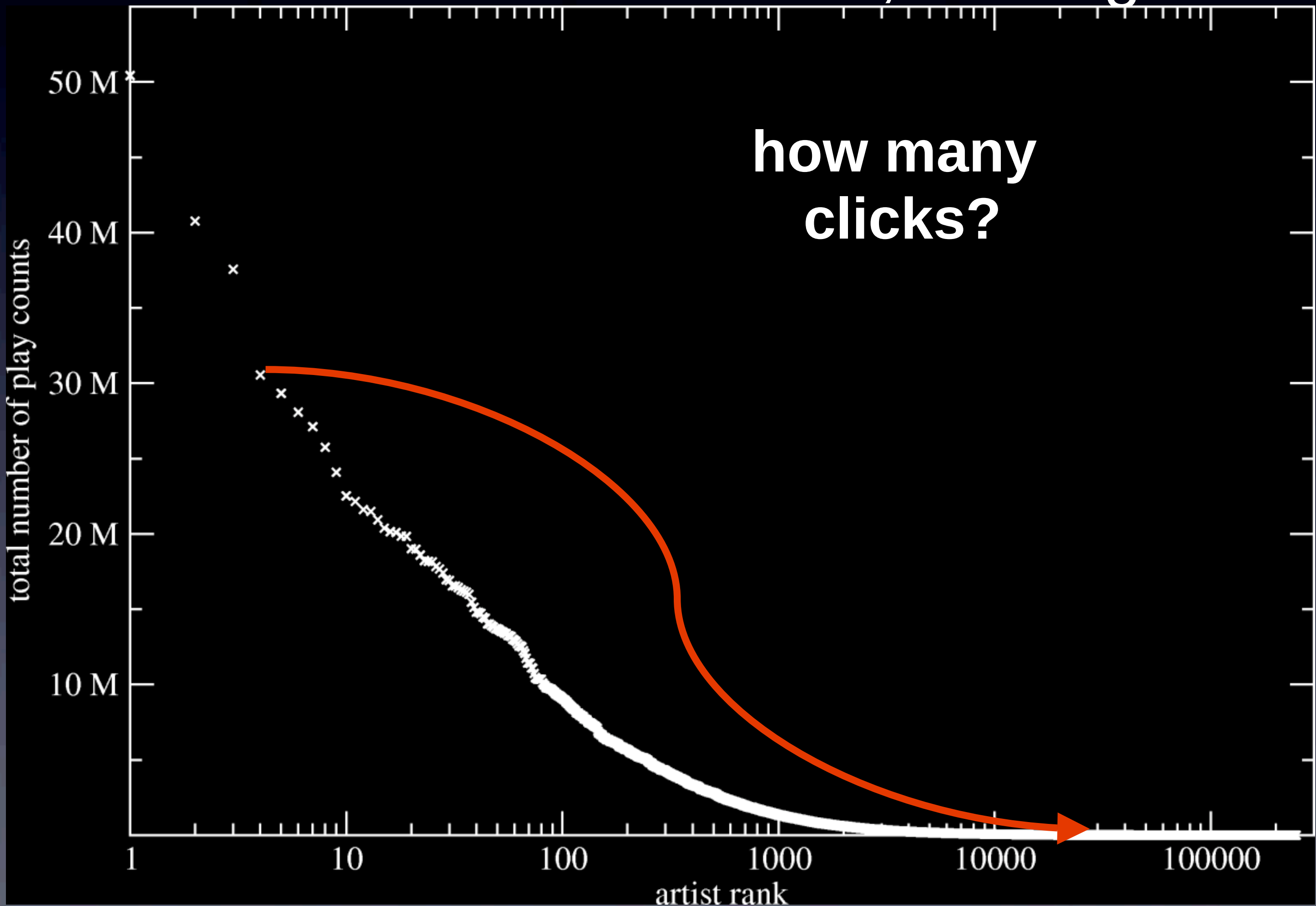
❖ **Expert**: correlation between *Kin* and playcounts

- r = 0.475

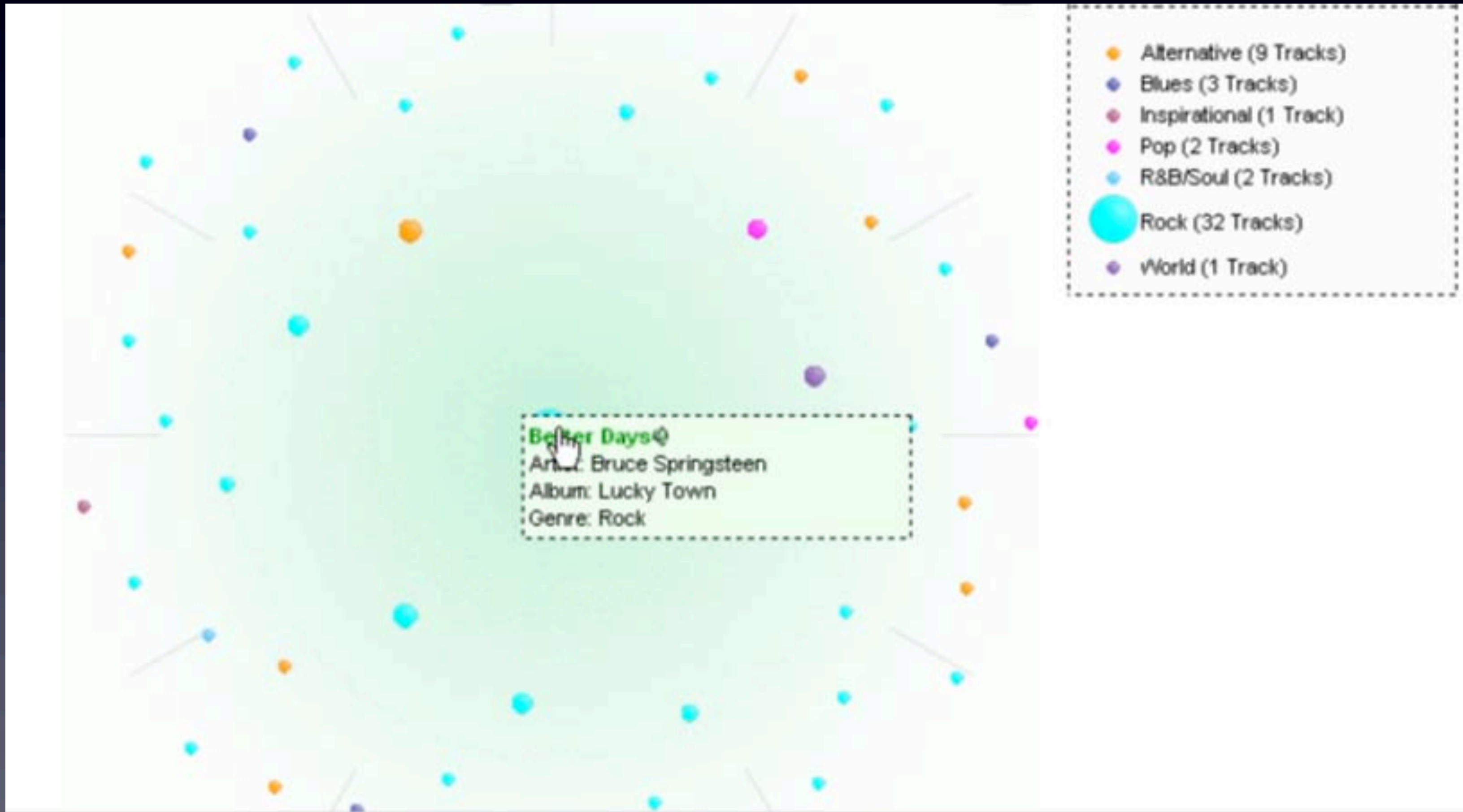


navigation along the Long Tail

- "From Hits to Niches"
  - # clicks to reach a **Tail** artist, starting in the **Head**



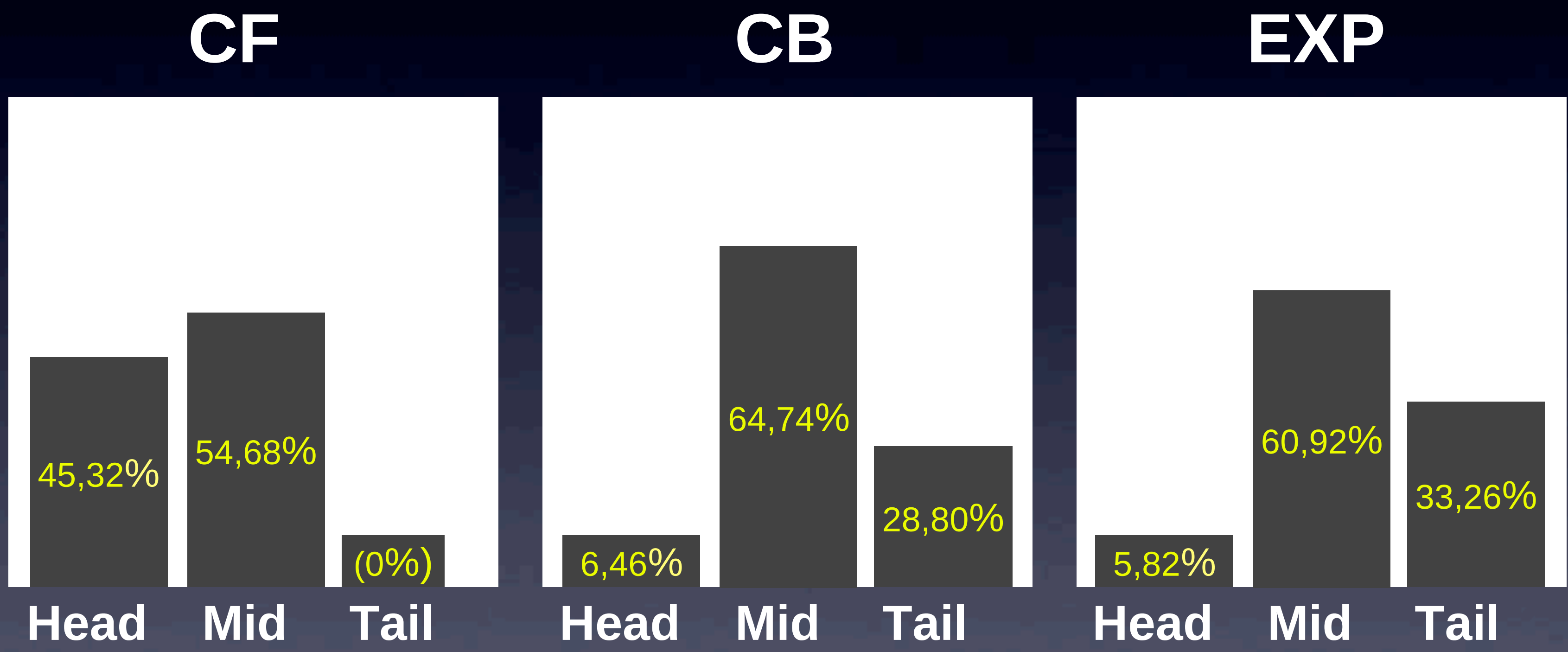
- “From Hits to Niches”
  - Audio CB similarity example (VIDEO)



- “From Hits to Niches”
  - Audio CB similarity example
    - Bruce Springsteen (14,433,411 plays)
    - The Rolling Stones (27,720,169 plays)
    - Mike Shupp (**577 plays**)

- “From Hits to Niches”
  - Audio CB similarity example
    - Bruce Springsteen (14,422,411 plays)

- navigation in the Long Tail
  - Similar artists, given an artist in the **HEAD** part:



Method	$a_i \rightarrow a_j$	Head	Mid	Tail
CF top–20	**Head**	45.32%	54.68%	0%
	Mid	5.43%	71.75%	22.82%
	Tail	0.24%	17.16%	82.60%
CB top–20	**Head**	6.46%	64.74%	28.80%
	Mid	4.16%	59.60%	36.24%
	Tail	2.83%	47.80%	49.37%
Expert	**Head**	5.82%	60.92%	33.26%
	Mid	3.45%	61.63%	34.92%
	Tail	1.62%	44.83%	53.55%

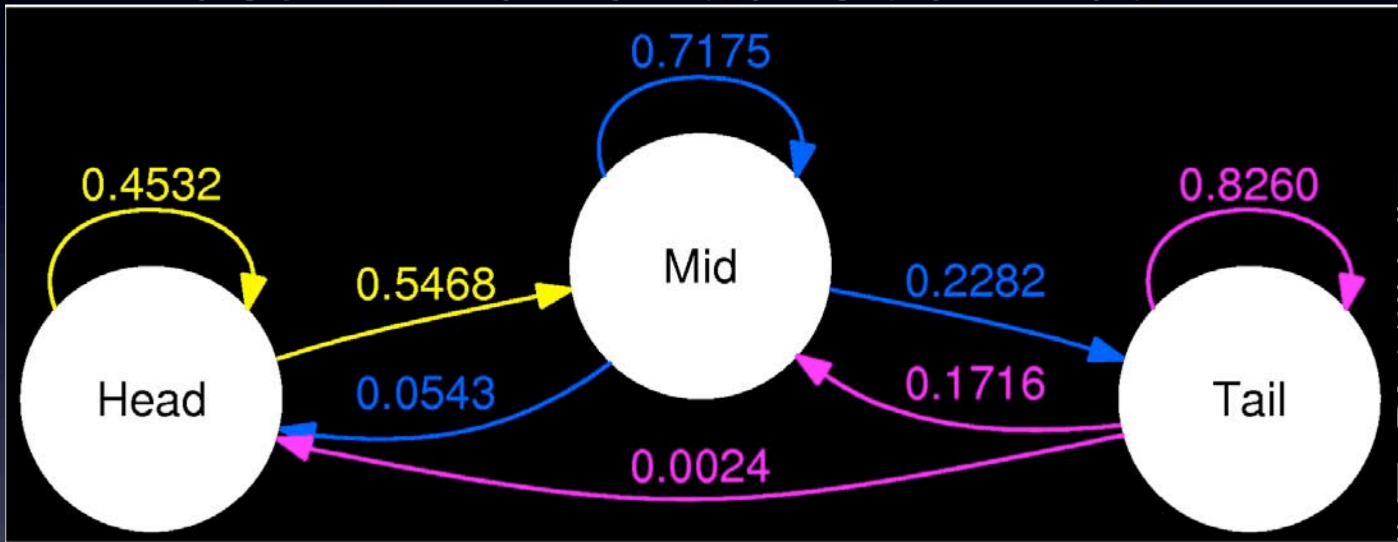
- navigation in the Long Tail

Method	$a_i \rightarrow a_j$	Head	Mid	Tail
CF top–20	Head	45.32%	54.68%	0%
	Mid	5.43%	71.75%	22.82%
	Tail	0.24%	17.16%	82.60%
CB top–20	Head	6.46%	64.74%	28.80%
	Mid	4.16%	59.60%	36.24%
	Tail	2.83%	47.80%	49.37%
Expert	Head	5.82%	60.92%	33.26%
	Mid	3.45%	61.63%	34.92%
	Tail	1.62%	44.83%	53.55%

- navigation in the Long Tail
  - **Last.fm** Markov transition matrix

Method	$a_i \rightarrow a_j$	Head	Mid	Tail
CF top–20	**Head**	45.32%	54.68%	0%
	Mid	5.43%	71.75%	22.82%
	Tail	0.24%	17.16%	82.60%
CB top–20	**Head**	6.46%	64.74%	28.80%
	Mid	4.16%	59.60%	36.24%
	Tail	2.83%	47.80%	49.37%
Expert	**Head**	5.82%	60.92%	33.26%
	Mid	3.45%	61.63%	34.92%
	Tail	1.62%	44.83%	53.55%

- navigation in the Long Tail
  - **Last.fm** Markov transition matrix

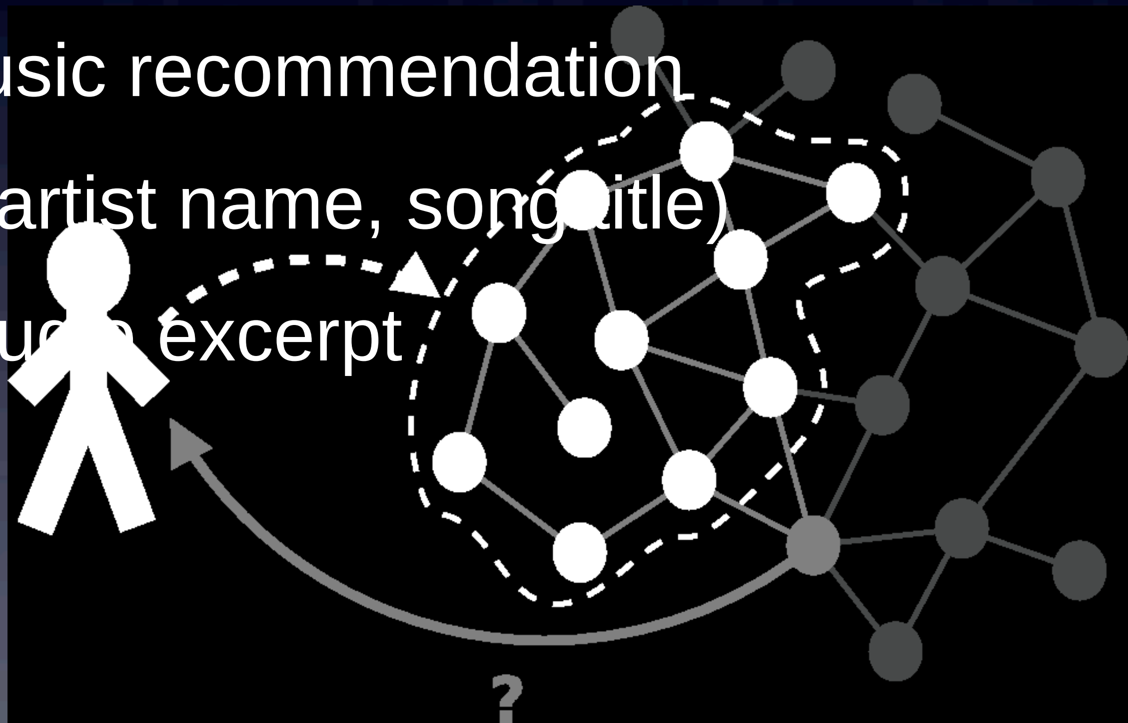


			id	Tail
			68%	0%
			75%	22.82%
			16%	82.60%
CB top–20	**Head**	6.46%	64.74%	28.80%
	Mid	4.16%	59.60%	36.24%
	Tail	2.83%	47.80%	49.37%
Expert	**Head**	5.82%	60.92%	33.26%
	Mid	3.45%	61.63%	34.92%
	Tail	1.62%	44.83%	53.55%

- navigation in the Long Tail
  - From **Head** to **Tail**, with P(T|H)>0.4
  - Number of clicks needed
    - CF : **5**
    - CB : **2**
    - EXP: **2**

How do users perceive novel, non-obvious recommendations?

- Survey
  - 288 participants
- Method: blind music recommendation
  - no metadata (artist name, song title)
  - only 30 sec. audio excerpt



3 approaches:

- **CF**
- **CB**
- **HY**brid

User profile:

- last.fm, top-10 artists

Procedure

- Do you recognize the song?
- Rating: [1..5]

- Overall results

Method	Case	%	Avg.Rating (Stdev)
CF	*Recall A&S*	15.50	4.64(±0.67)
	Recall only A	12.81	3.88(±0.99)
	Unknown	71.69	3.03(±1.19)
HY	*Recall A&S*	10.71	4.55(±0.81)
	Recall only A	10.95	3.67(±1.18)
	Unknown	78.34	2.77(±1.20)
CB	*Recall A&S*	10.50	4.56(±1.21)
	Recall only A	8.53	3.61(±1.10)
	Unknown	80.97	2.57(±1.19)

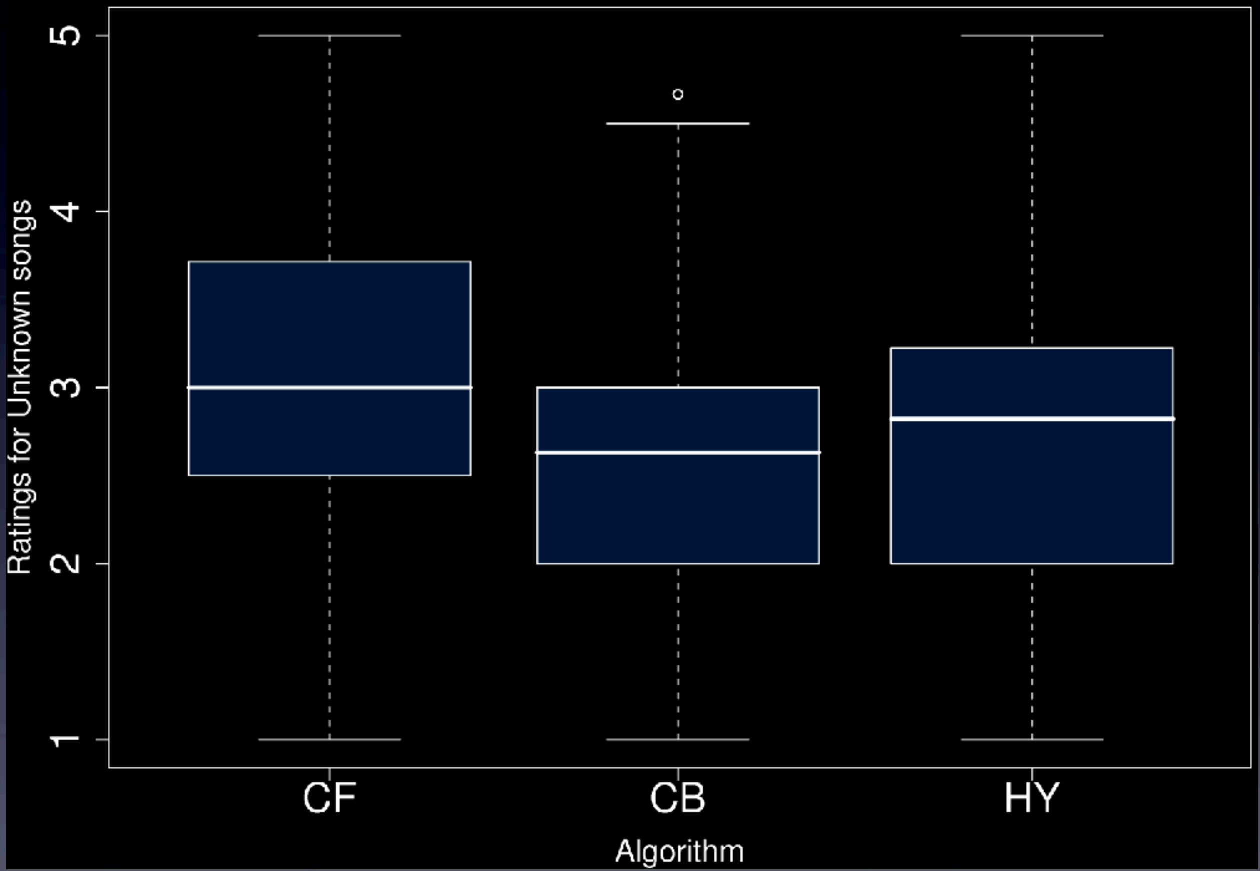
- Familiar recommendations (Artist & Song)

Method	Case	%	Avg.Rating (Stdev)
CF	*Recall A&S*	15.50	4.64($\pm$0.67)
	Recall only A	12.81	3.88($\pm$0.99)
	Unknown	71.69	3.03($\pm$1.19)
HY	*Recall A&S*	10.71	4.55($\pm$0.81)
	Recall only A	10.95	3.67($\pm$1.18)
	Unknown	78.34	2.77($\pm$1.20)
CB	*Recall A&S*	10.50	4.56($\pm$1.21)
	Recall only A	8.53	3.61($\pm$1.10)
	Unknown	80.97	2.57($\pm$1.19)

- Ratings for **novel** recommendations

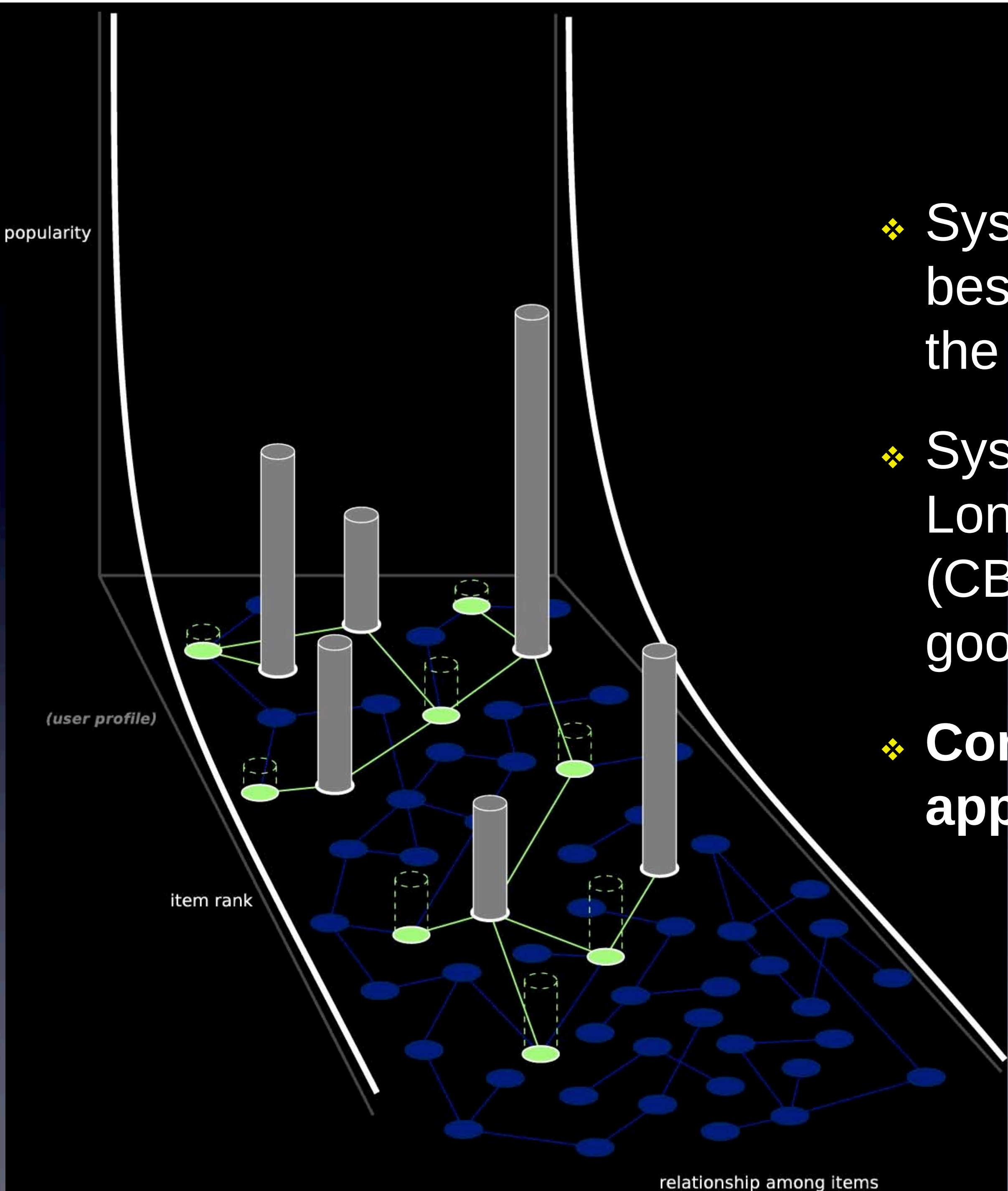
Method	Case	%	Avg.Rating (Stdev)
CF	*Recall A&S*	15.50	$4.64(\pm 0.67)$
	Recall only A	12.81	$3.88(\pm 0.99)$
	Unknown	71.69	$\boxed{3.03(\pm 1.19)}$
HY	*Recall A&S*	10.71	$4.55(\pm 0.81)$
	Recall only A	10.95	$3.67(\pm 1.18)$
	Unknown	78.34	$\boxed{2.77(\pm 1.20)}$
CB	*Recall A&S*	10.50	$4.56(\pm 1.21)$
	Recall only A	8.53	$3.61(\pm 1.10)$
	Unknown	80.97	$\boxed{2.57(\pm 1.19)}$

- Ratings for **novel** recommendations

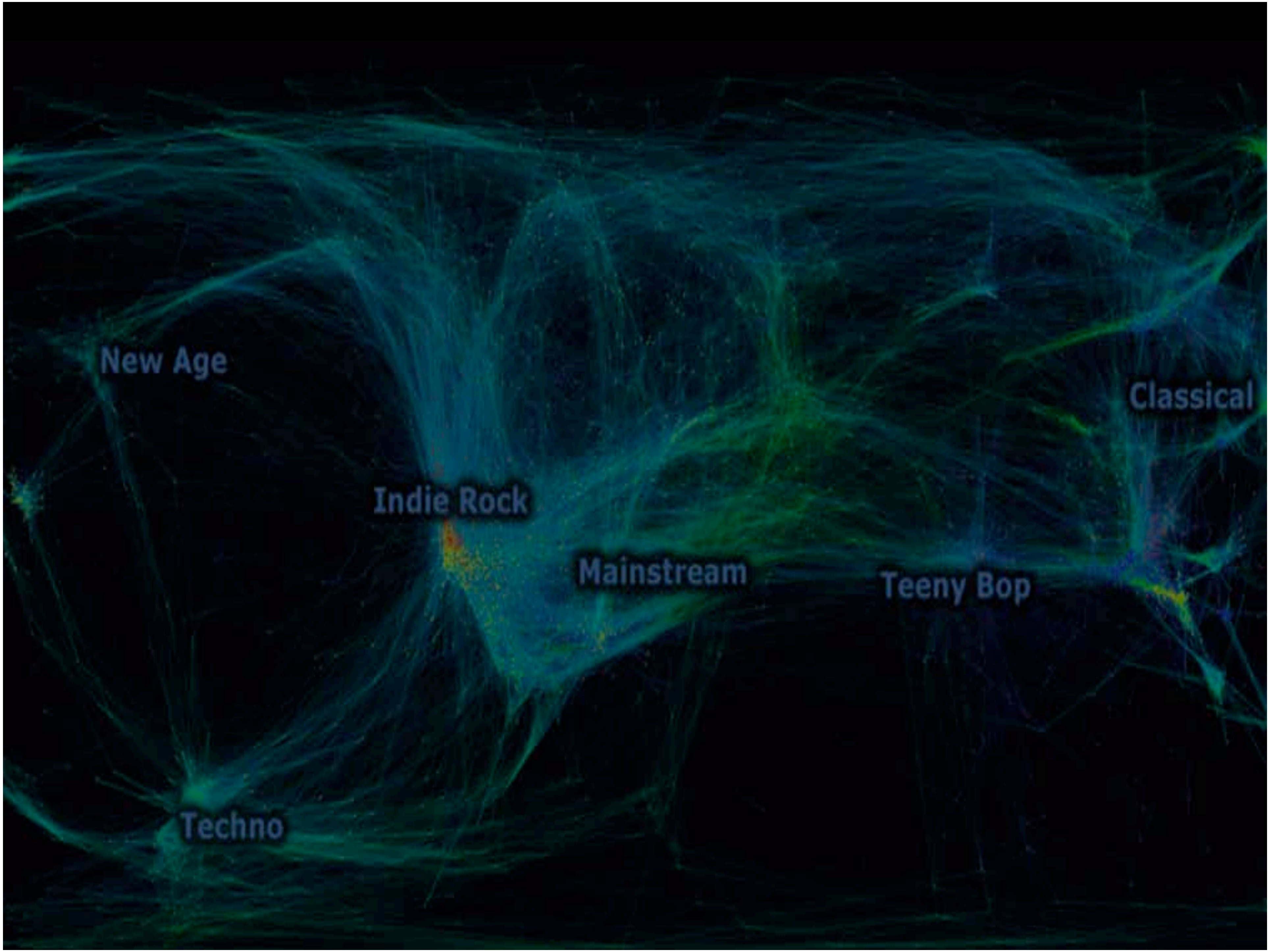


- % of **novel** recommendations

Method	Case	%	Avg.Rating (Stdev)
CF	*Recall A&S*	15.50	4.64(±0.67)
	Recall only A	12.81	3.88(±0.99)
	Unknown	71.69	3.03(±1.19)
HY	*Recall A&S*	10.71	4.55(±0.81)
	Recall only A	10.95	3.67(±1.18)
	Unknown	78.34	2.77(±1.20)
CB	*Recall A&S*	10.50	4.56(±1.21)
	Recall only A	8.53	3.61(±1.10)
	Unknown	80.97	2.57(±1.19)



- Systems that perform best (CF) do not exploit the Long Tail, and
- Systems that can ease Long Tail navigation (CB) do not perform good enough
- **Combine different approaches!**


New Age
Classical
Indie Rock
Mainstream
Teeny Bop
Techno

Topology of music recommendation networks.
Chaos. 16, 013107, (2006)

The complex network of musical tastes.
New Journal of Physics. 9, 172 (2007)

Preferential Attachment, Aging and Weights in Recommendation Systems.
International Journal of Bifurcation and Chaos. 19(2), 755-763. (2009)

The social network of contemporary popular musicians.
International *Journal of Bifurcation and Chaos (IJBC).*
17, 2281 - 2288. (2007)

Community structures and role detection in music networks,
Chaos, 18, 043105 (2008).

From hits to niches? or how popular artists can bias music recommendation
Proc of the *ACM KDD*. (2008)

COLLABORATORS

Óscar Celma, Markus Koppenberger
Music Technology Group, UPF, Barcelona
Javier M. Buldú
URJC, Madrid, Spain
Stefano Boccaletti
CNR- Istituto dei Sistemi Complessi, Florence, Italy
and The Italian Embassy in Tel Aviv, Israel
Juyong Park
Department of Physics, University of Michigan
Massimiliano Zanin
Universidad Autónoma de Madrid
Adilson Motter
Northwestern University
Pablo Balenzuela, Tomás Teitelbaum,
Universidad Buenos Aires

bmat
music innovation

pedro@bmat.com

bmat

music innovation