Network analysis of innovation ecosystems

Vito Latora

School of Mathematical Sciences,
Queen Mary University of London
and
Departimento di Fisica and INFN, Catania

(1) The advantages of **interdisciplinarity** in modern **science**

arXiv:1712.07910

(2) How **funding** shapes collaboration networks in **science**

PNAS 112 ,14760 (2015)

arXiV: 1904.08171

(3) Predicting the **success** of **startups**

Common denominators:

- ``Big”-data analysis

- The role of the network

- Policy implications?

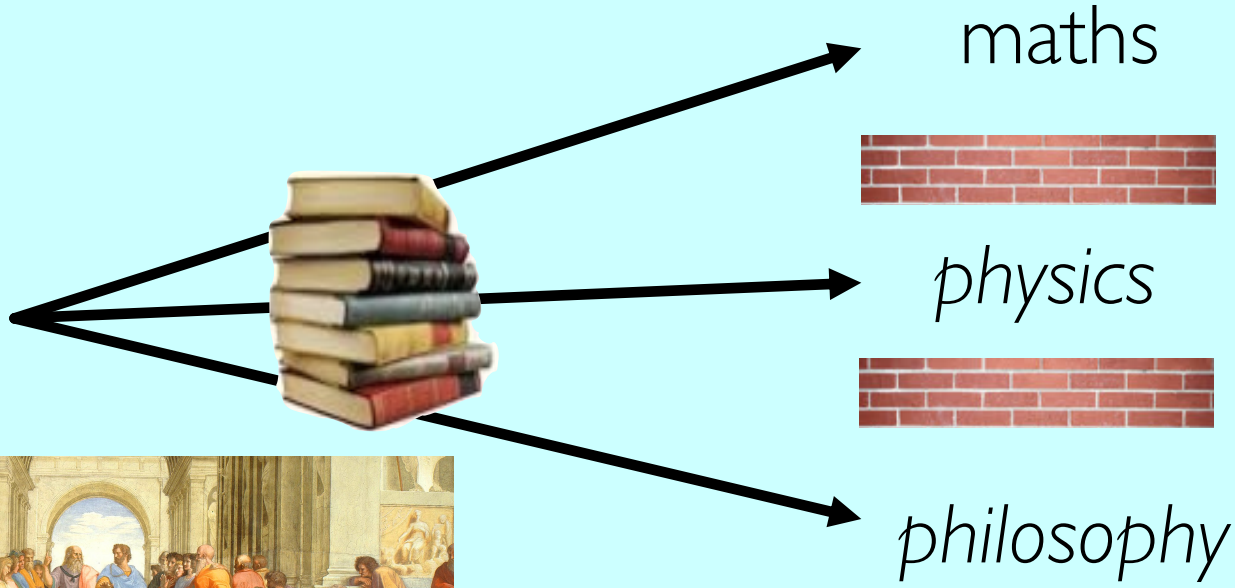
(1) The advantages of **interdisciplinarity** in modern **science**

arXiv:1712.07910

From polymaths to specialisation

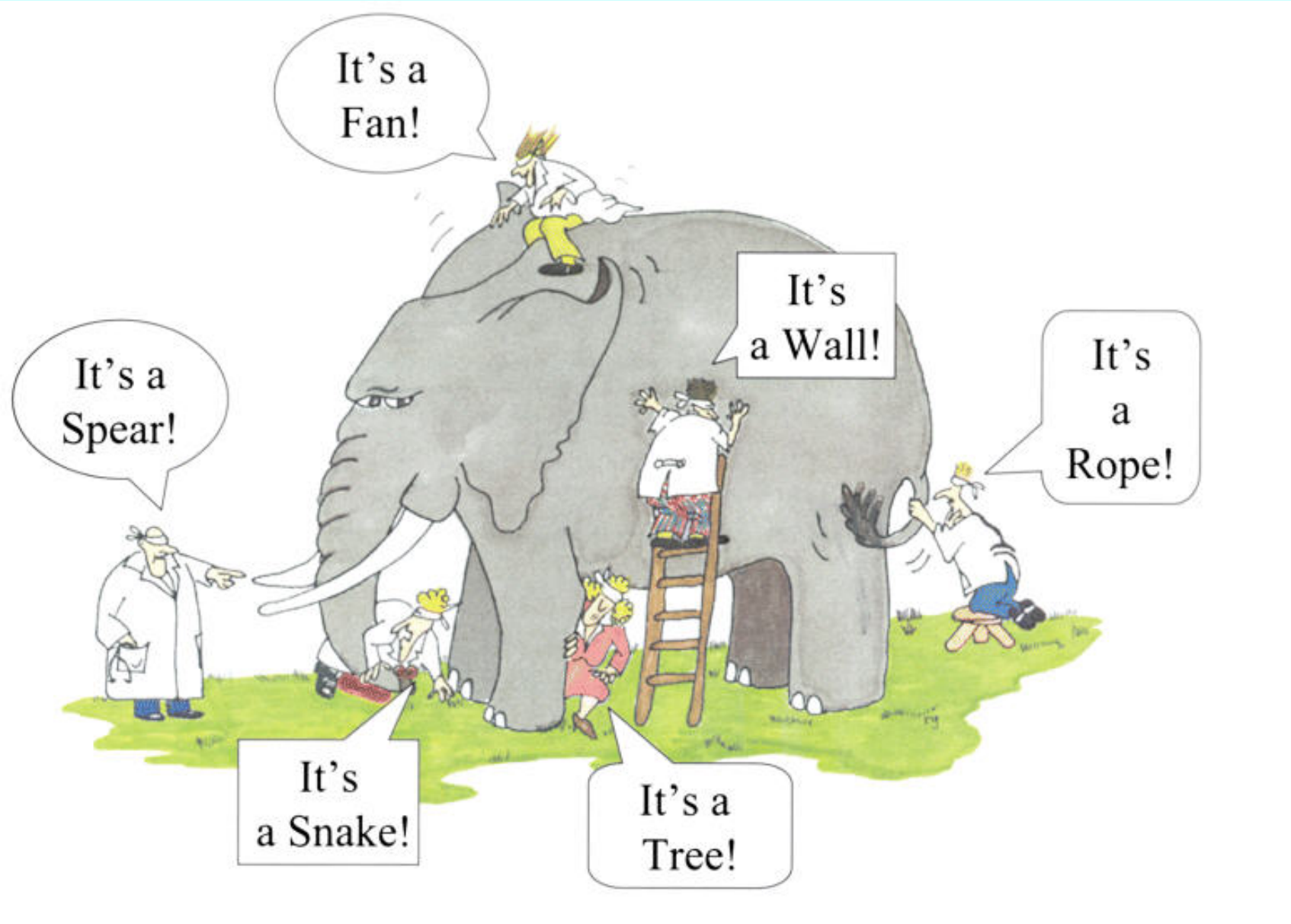
Homo Universalis

Greek philosophers, Leonardo,
Pico della Mirandola,
the Renaissance man



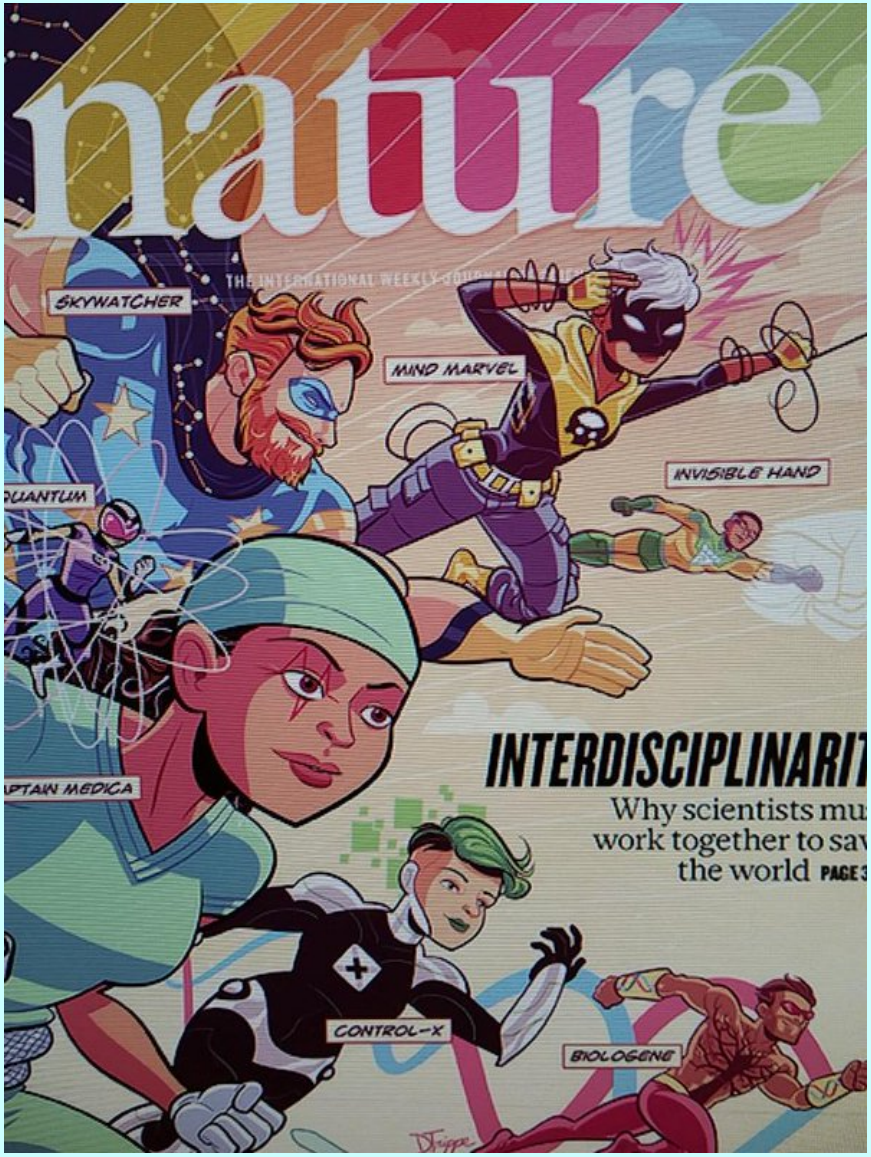
Specialisation of disciplines in modern age

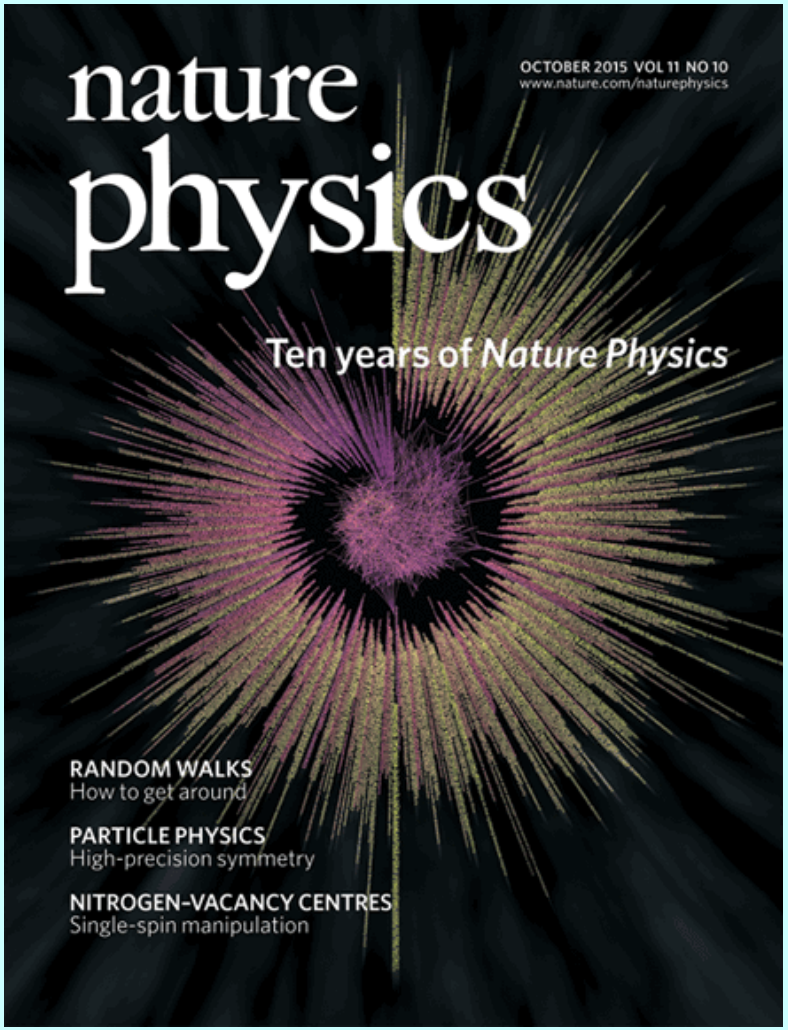
Why interdisciplinary research matters?



Mind meld

Special issue Sept 2015

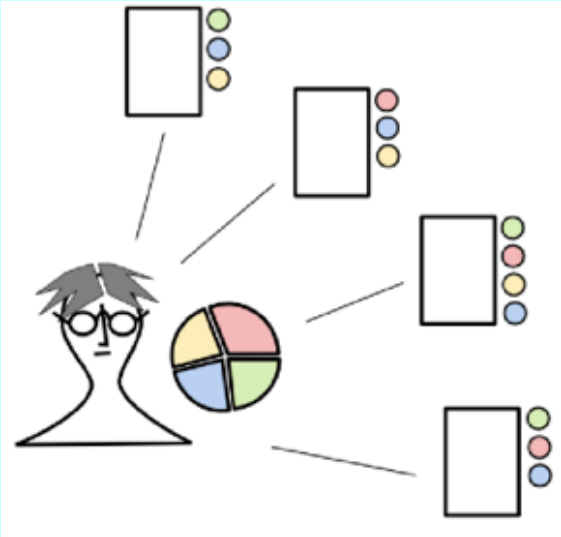




A century of physics

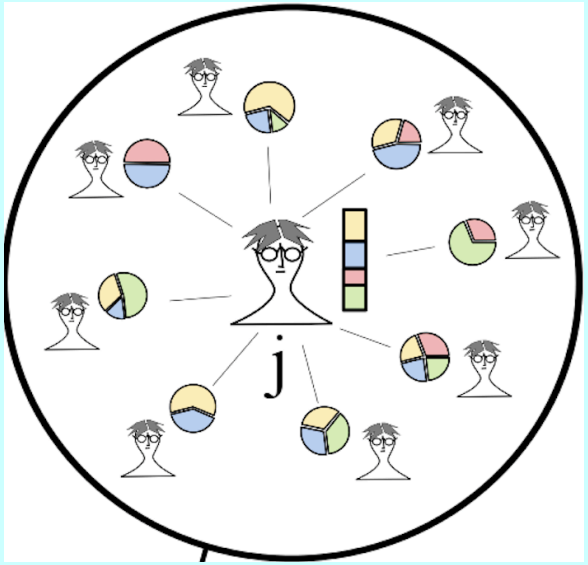
Sinatra et al. Oct 2015

How interdisciplinary are you?



- Astrophysics
- Biology
- Complex Nets
- … … … … … …

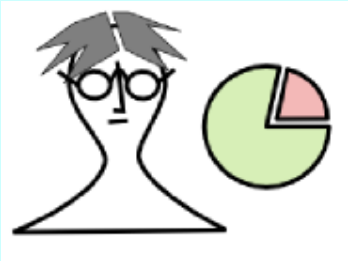
And your social environment?



Collaboration network

Success in science?

Specialised scientists



Interdisciplinary scientists

Citation network

Success in science?

Interdisciplinary scientists

Specialised scientists

Citations

Success in science?

Specialised scientists

Interdisciplinary scientists

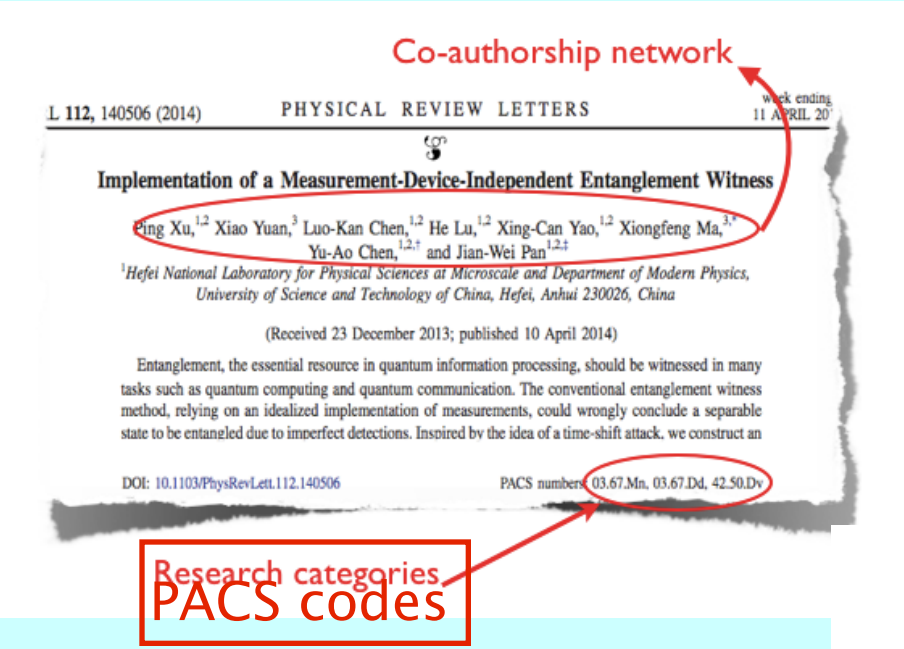
Citations

Data sets

APS 1980-2014

American Physical Society

$4 \cdot 10^5$ articles $1.4 \cdot 10^5$ authors, 1154 PACS

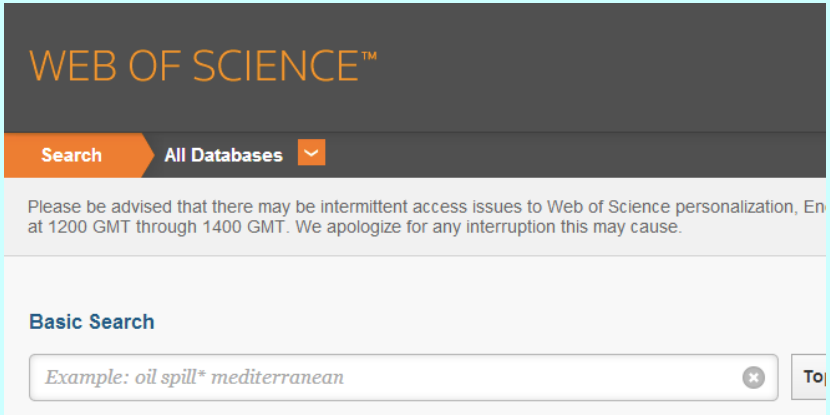


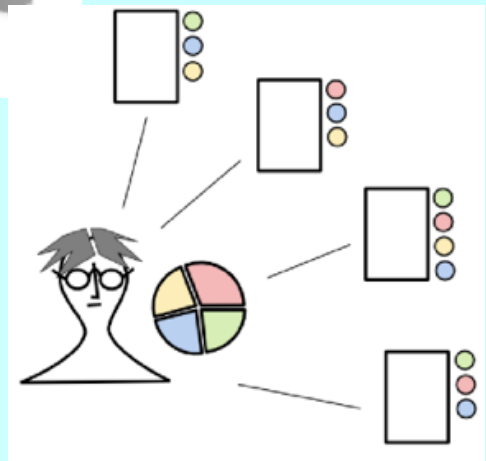
Example: **87.14.ep**

WOS 1946-2014

Web of Science

$1.1 \cdot 10^6$ articles $1.5 \cdot 10^6$ authors 50 categories





biology

chemistry

computer science

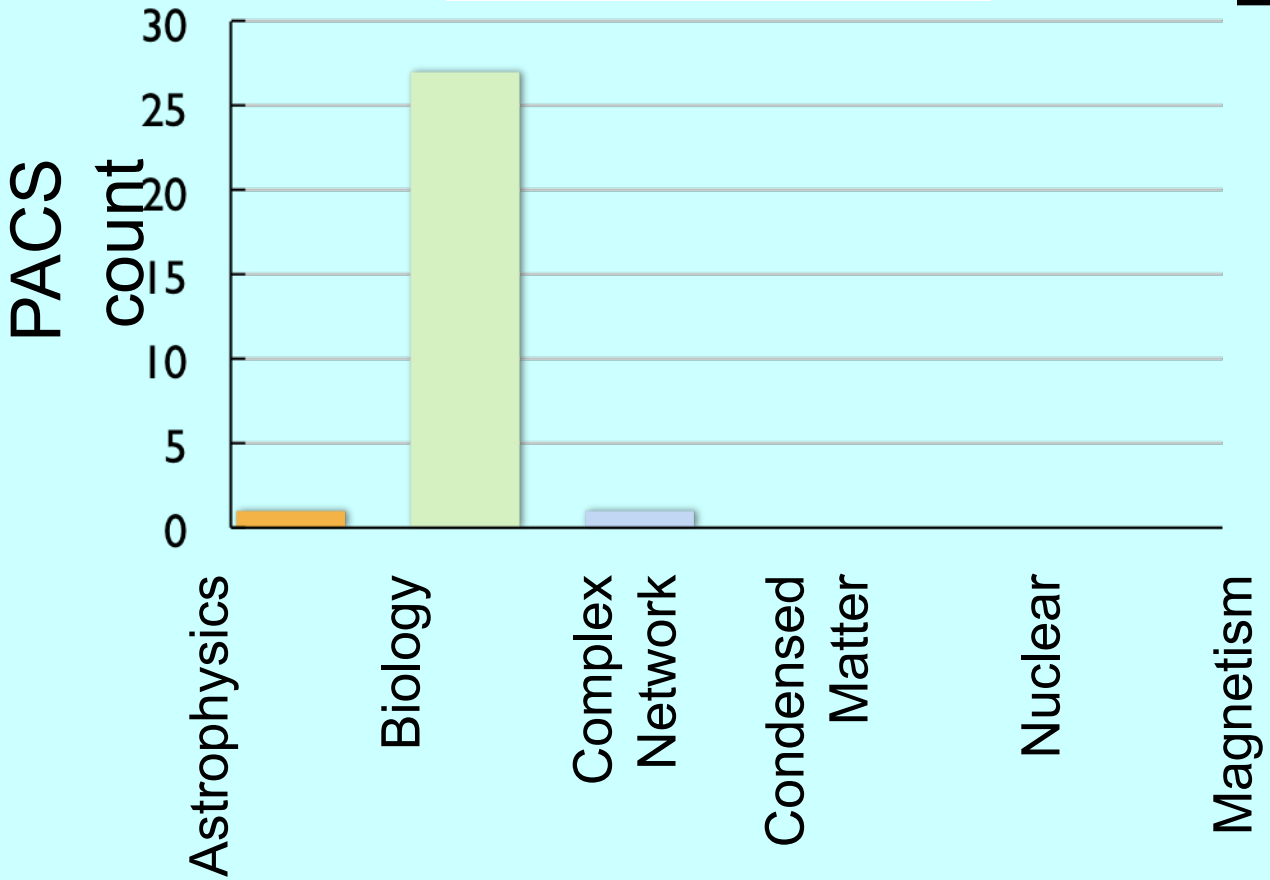
mathematics

nanoscience

zoology

Measures of interdisciplinarity

$$B = 0.13$$

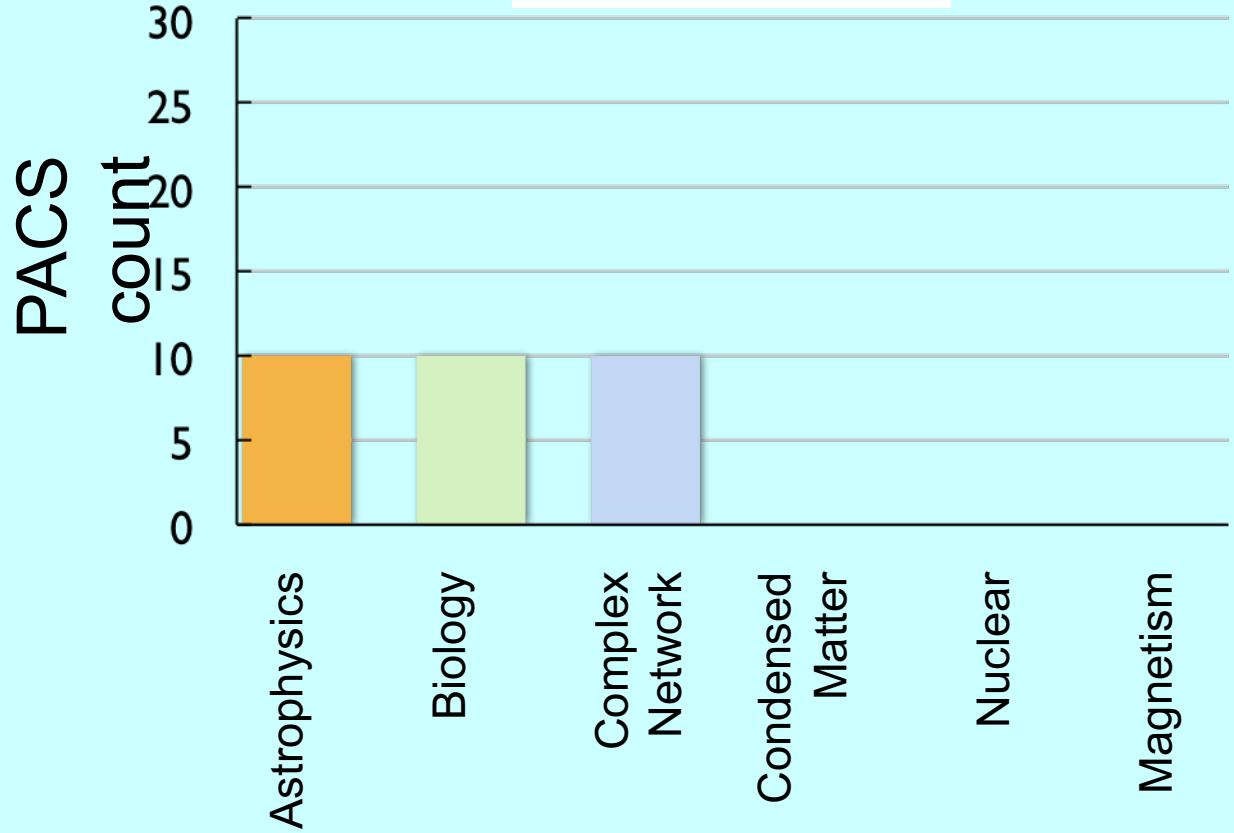


Background Entropy

$$B_i = -\sum_c p_i^c \log(p_i^c)$$

Measures of interdisciplinarity

$$B = 0.48$$

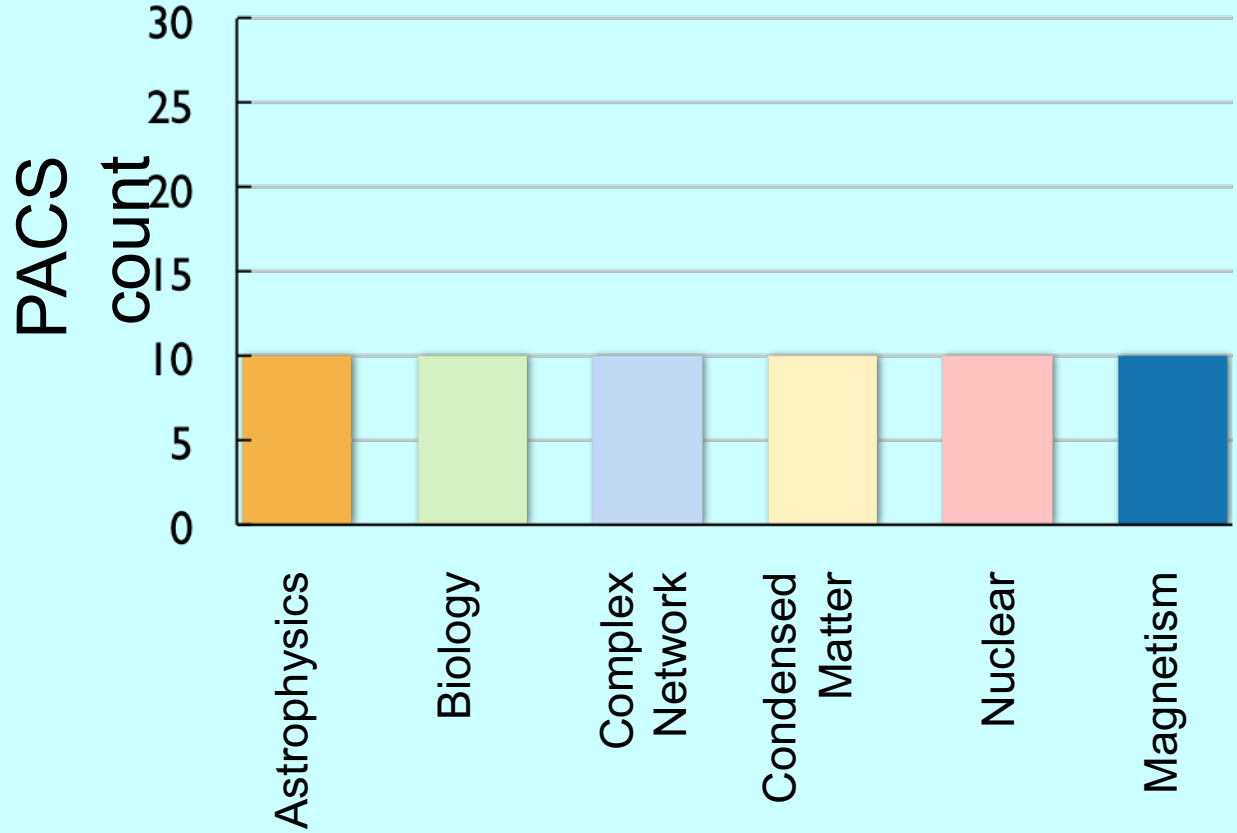


Background Entropy

$$B_i = -\sum_c p_i^c \log(p_i^c)$$

Measures of interdisciplinarity

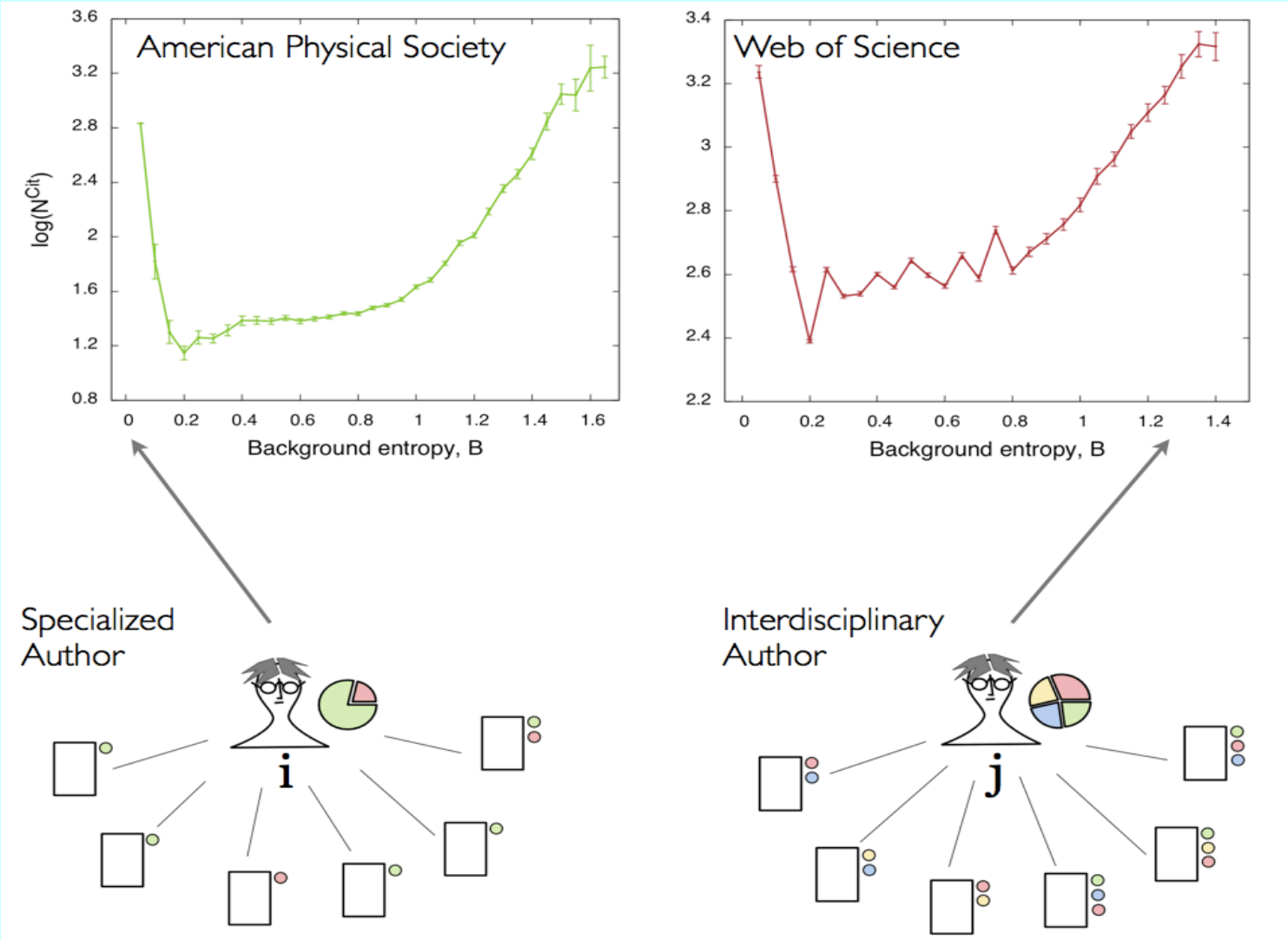
$$B = 0.78$$



Background Entropy

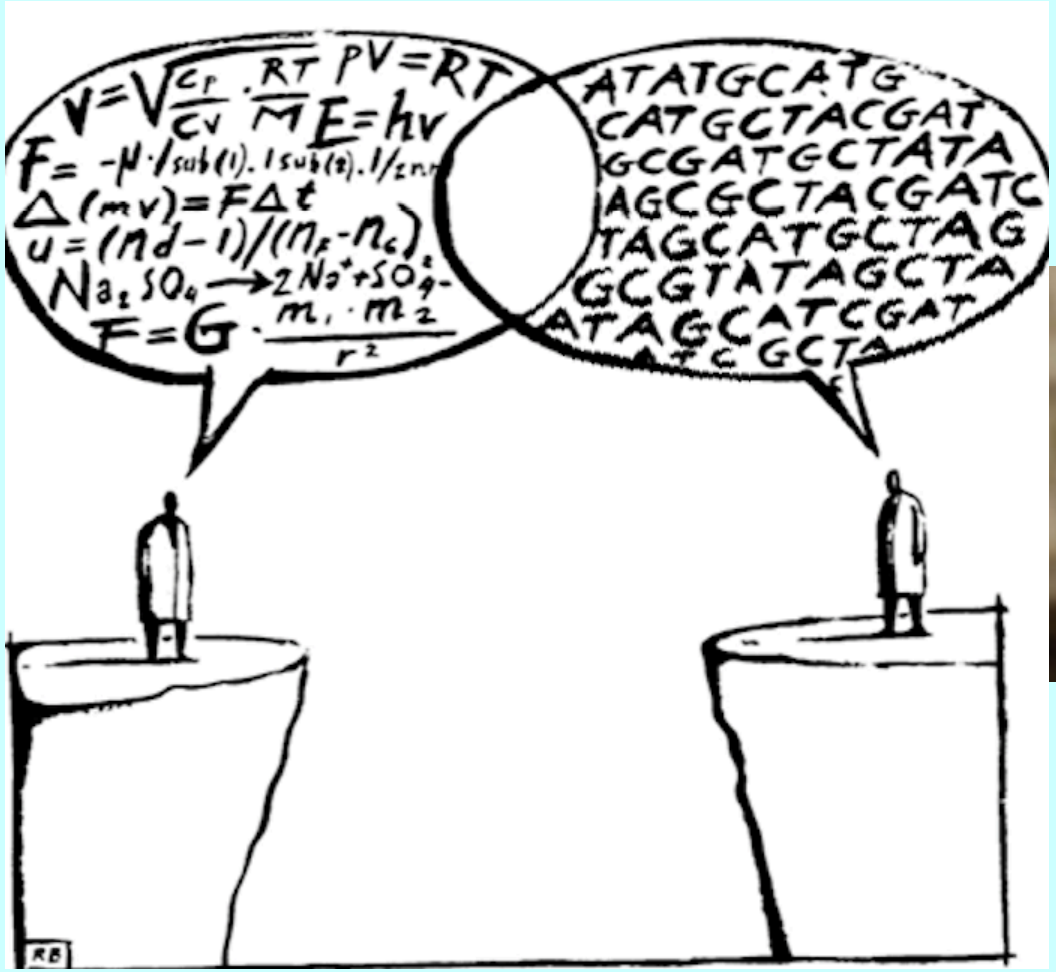
$$B_i = -\sum_c p_i^c \log(p_i^c)$$

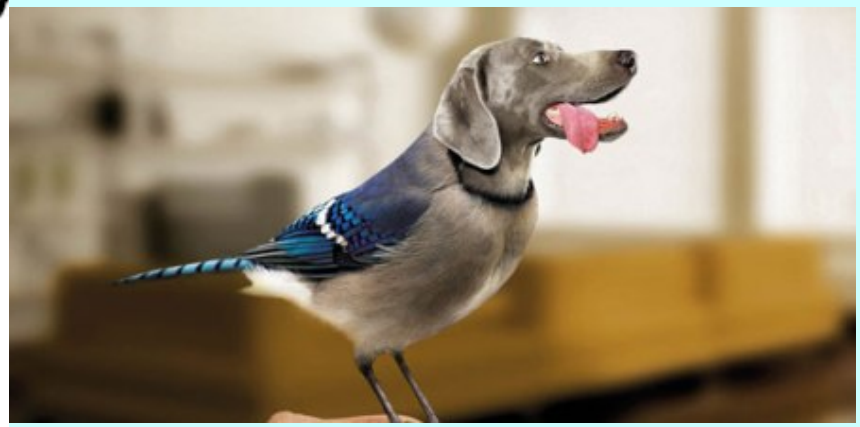
The advantages of interdisciplinarity



Bonaventura, Latora, Nicosia, Panzarasa 2015
arXiv:1712.07910

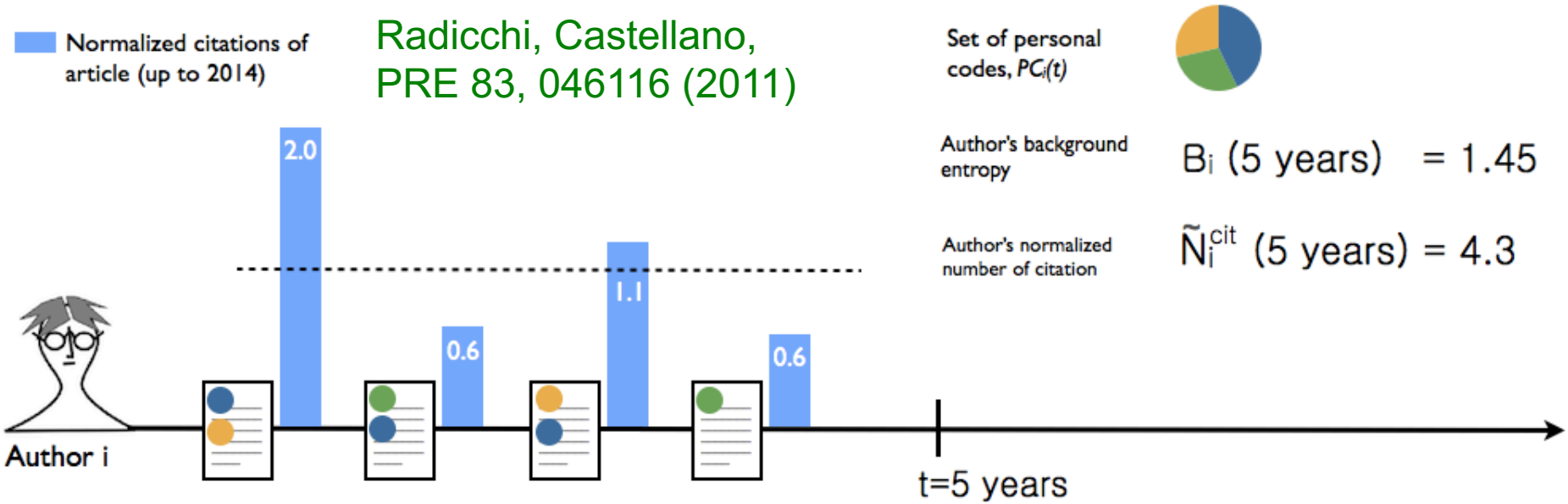
The price of interdisciplinarity



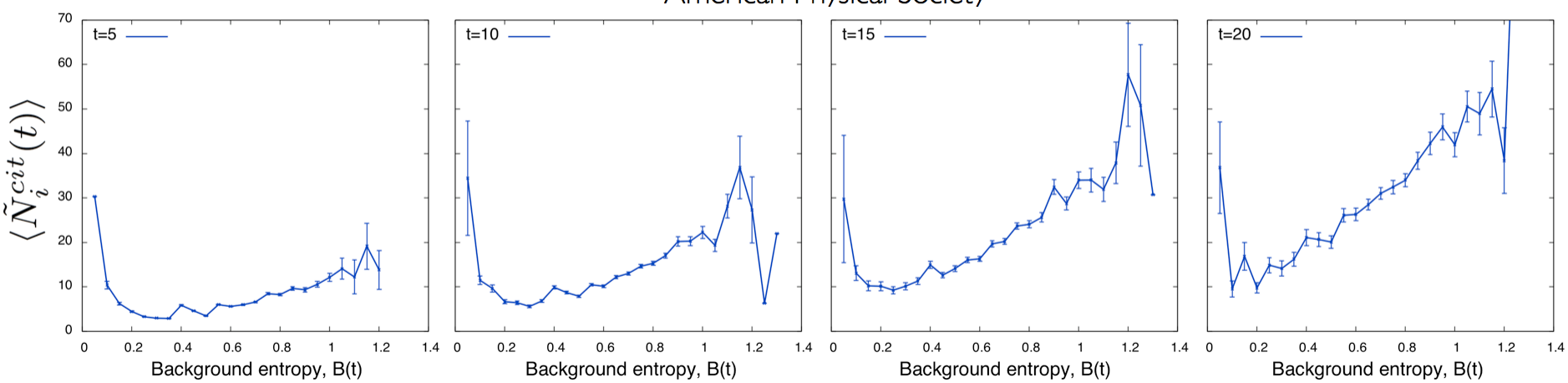


Different career lengths, and fields

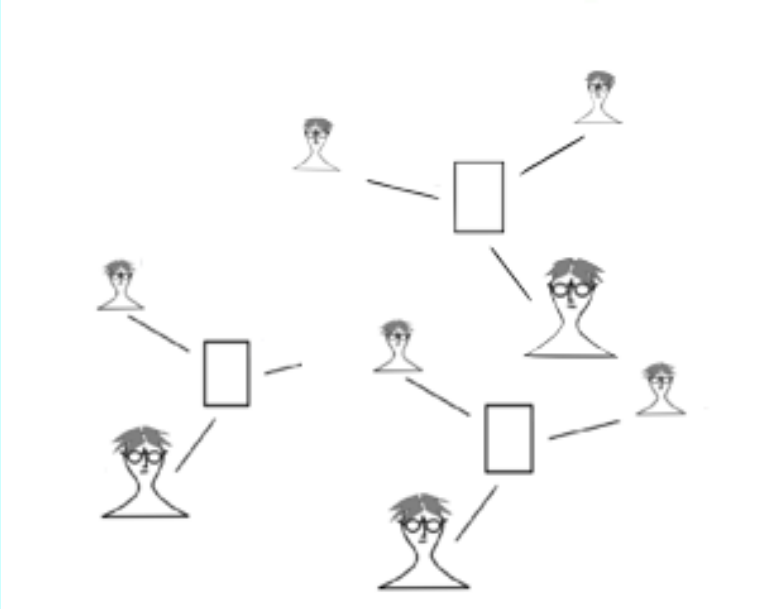
Radicchi, Castellano, PRE 83, 046116 (2011)



American Physical Society



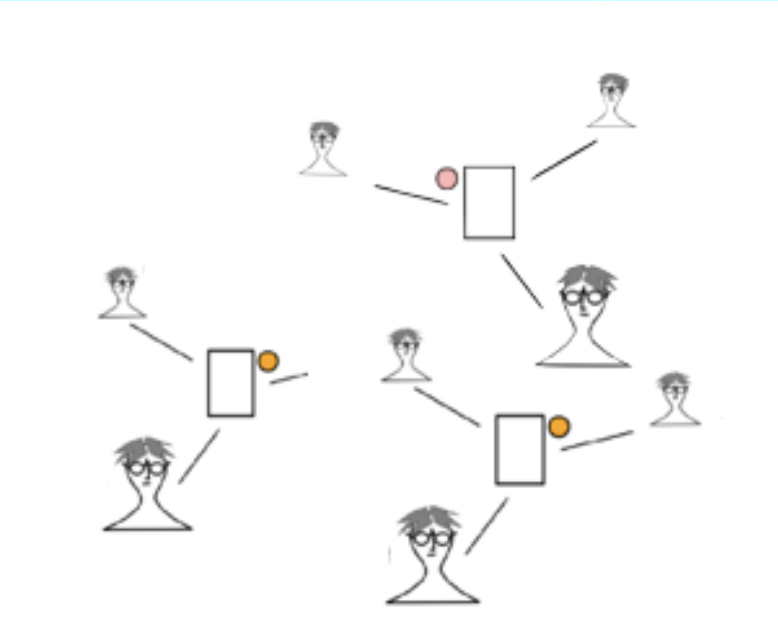
Social exposure to interdisciplinarity



Coauthorship networks

Newman, The structure of scientific collaborations, PNAS 2001

Social exposure to interdisciplinarity



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- Complex Nets
- ... ...

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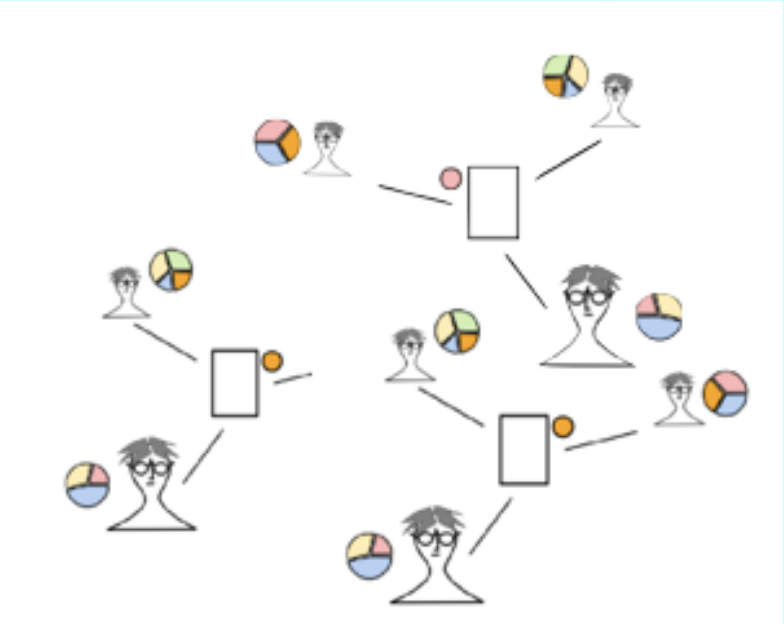
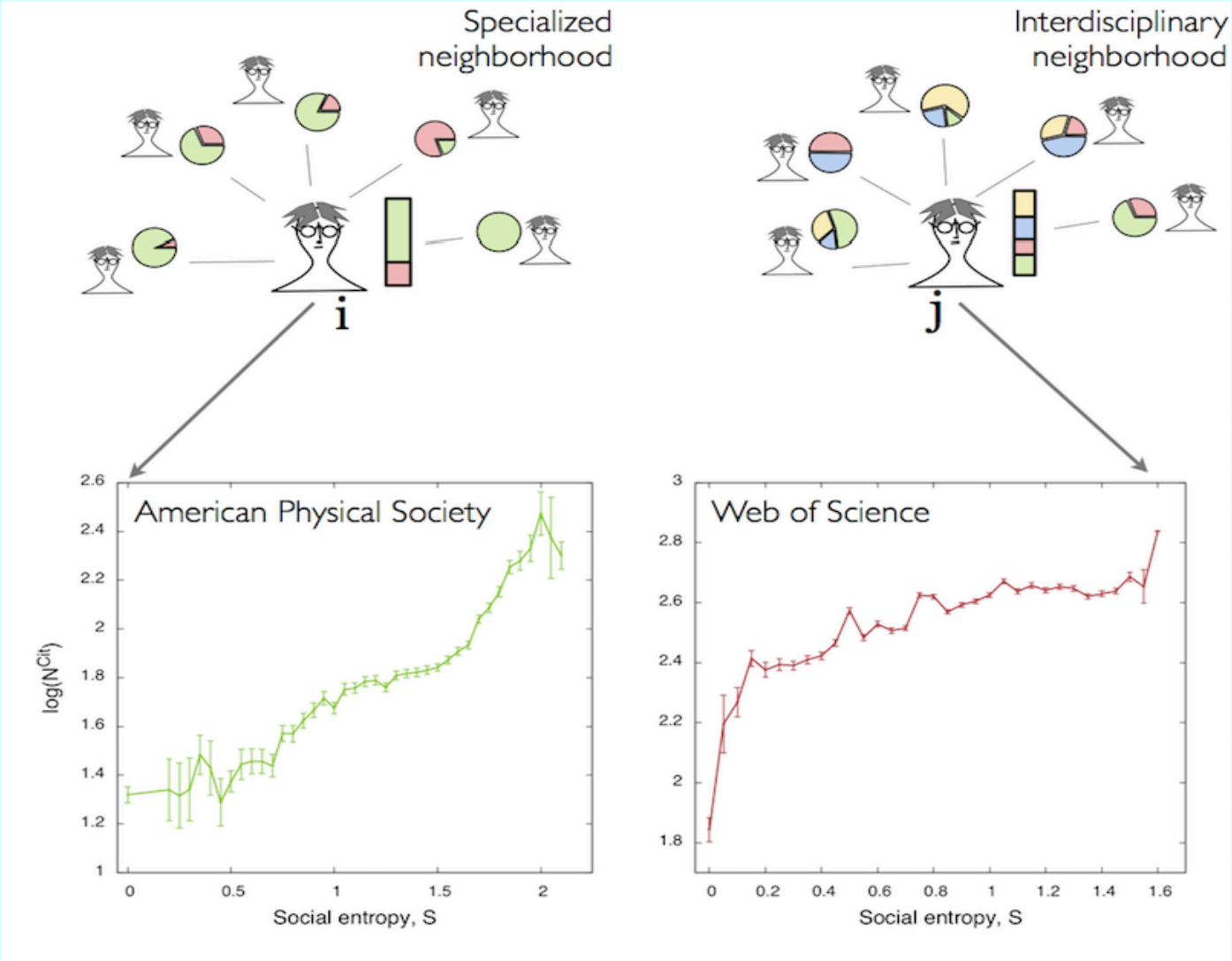


- Astrophysics
- Biology
- Complex Nets
- ... ...

Coauthorship networks

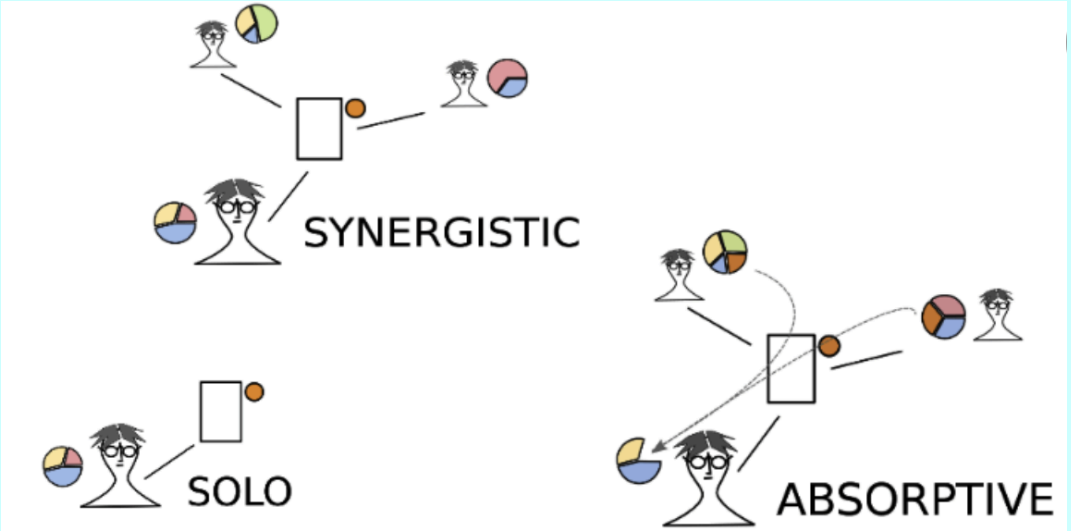
Newman, The structure of scientific collaborations, PNAS 2001

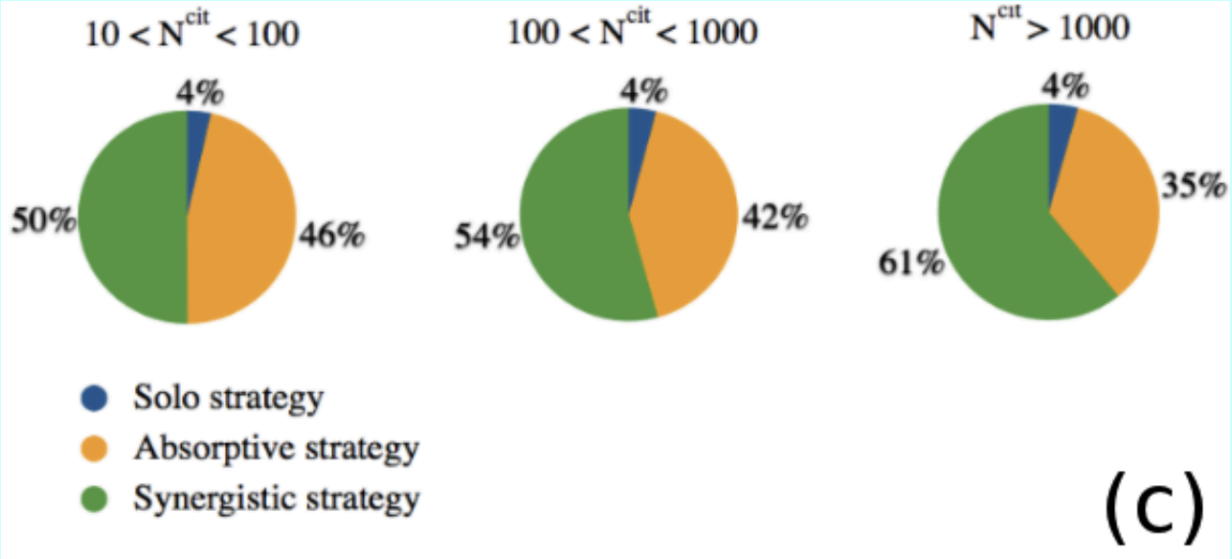
Exposure to interdisciplinarity



Bonaventura, Latora, Nicosia, Panzarasa 2015 arXiv:1712.07910

Strategies to interdisciplinarity



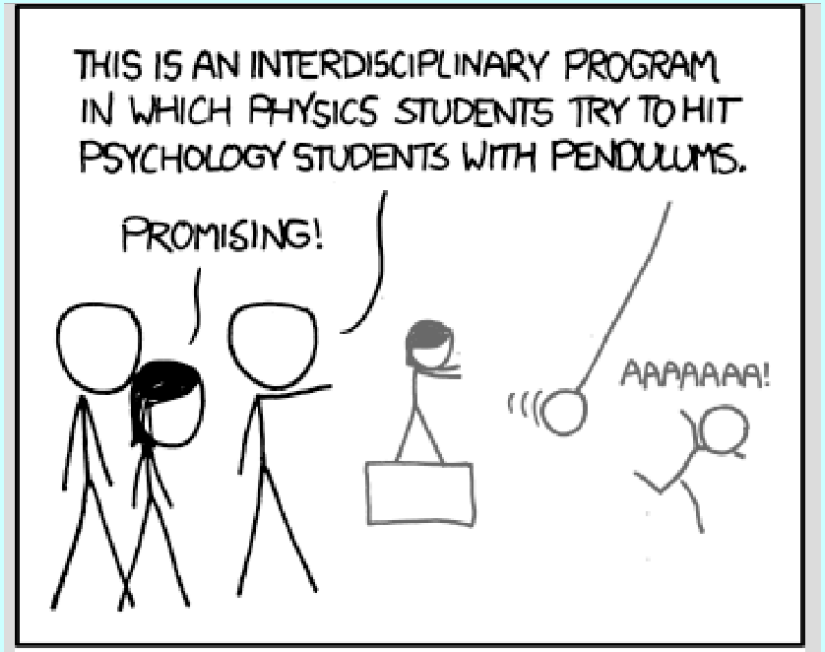


Bonaventura, Latora, Nicosia, Panzarasa 2015 arXiv:1712.07910

Take home message

We have to work together, but interdisciplinarity is rewarding if….

if….“extreme”….

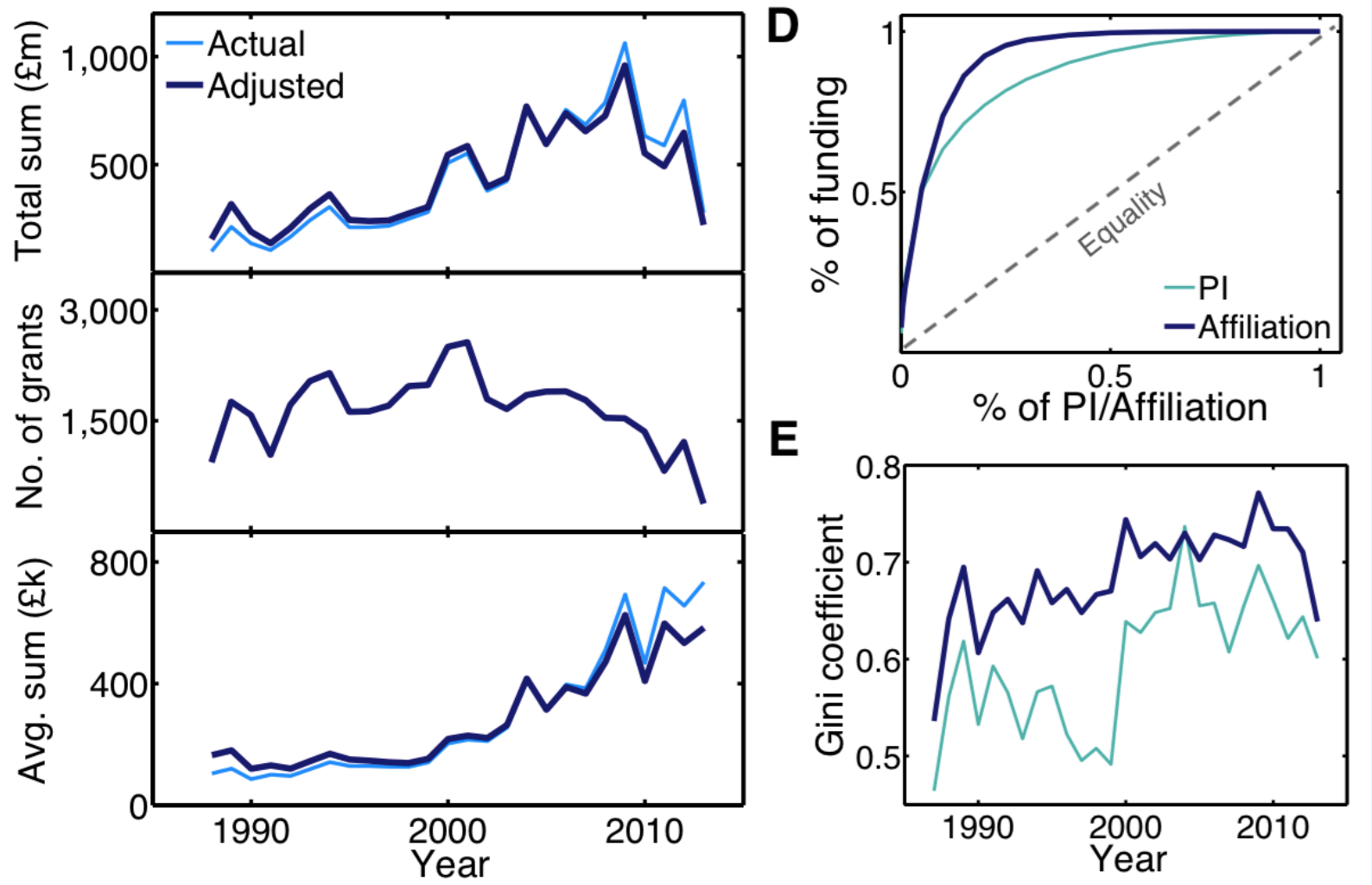


(2) How **funding** shapes collaborations in **science?**

Ma, Mondragon, Latora PNAS 112 (48), 14760 (2015)
Anatomy of funded research in science

Funding landscape in UK

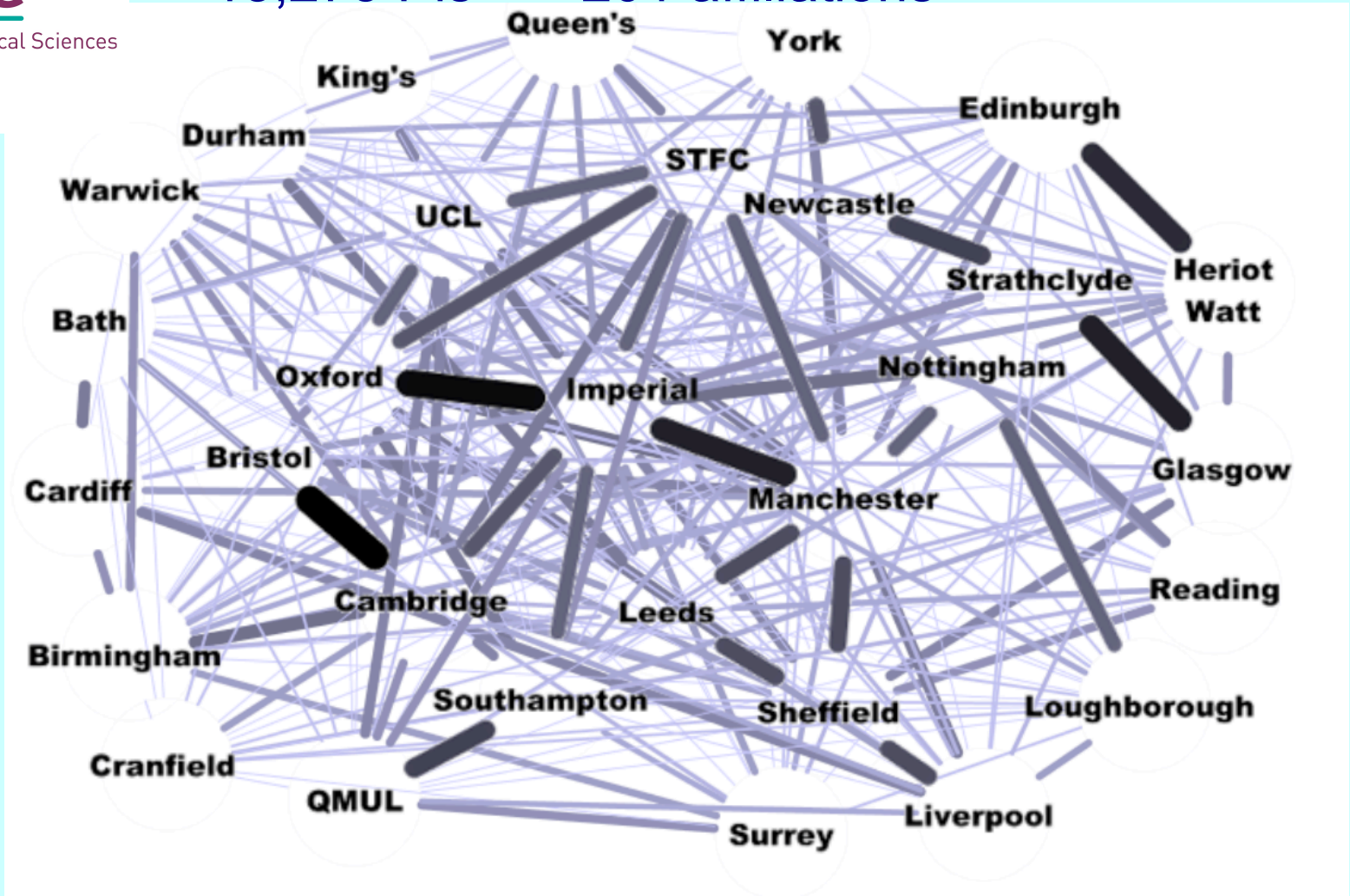
43,193 projects awarded by **EPSRC** (1985-2013)



The funded collaboration network

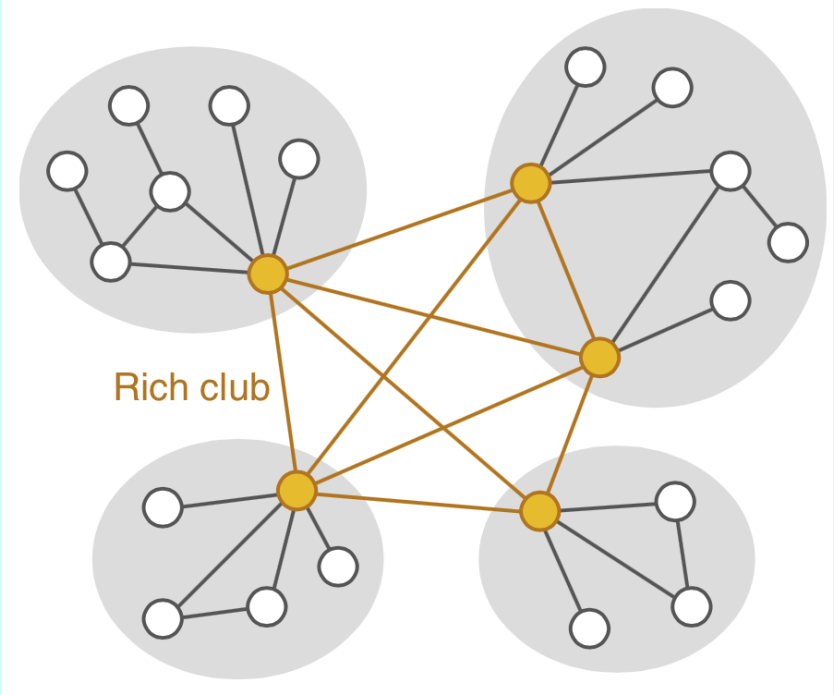
EPSRC
Engineering and Physical Sciences Research Council

13,275 Pis 201 affiliations



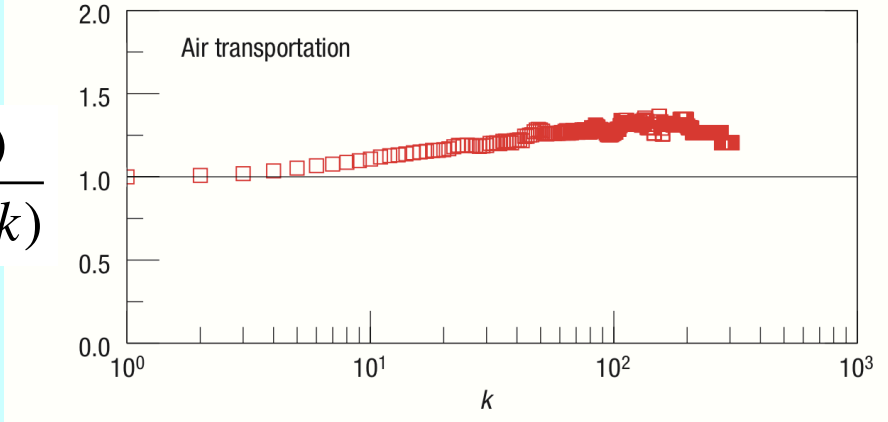
Ma, Mondragon, Latora PNAS 2015
Anatomy of funded research in science

Rich-club behavior in networks



$$\phi(k) = \frac{E_{>k}}{N_{>k}(N_{>k}-1)/2}$$

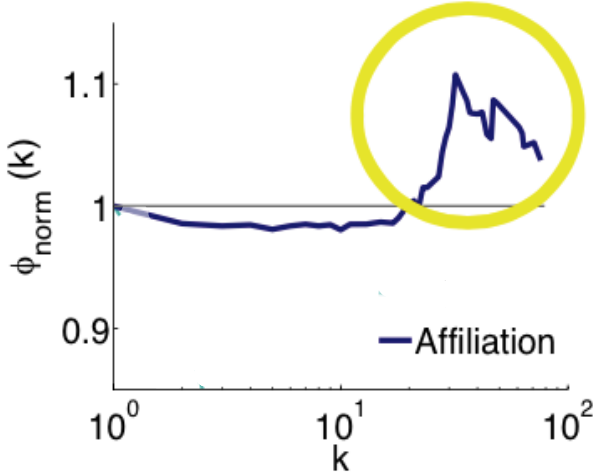
$$\phi_{norm}(k) = \frac{\phi(k)}{\phi^{rand}(k)}$$

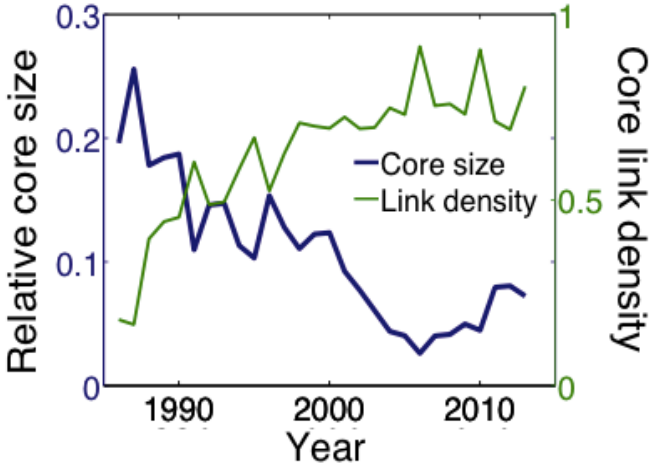


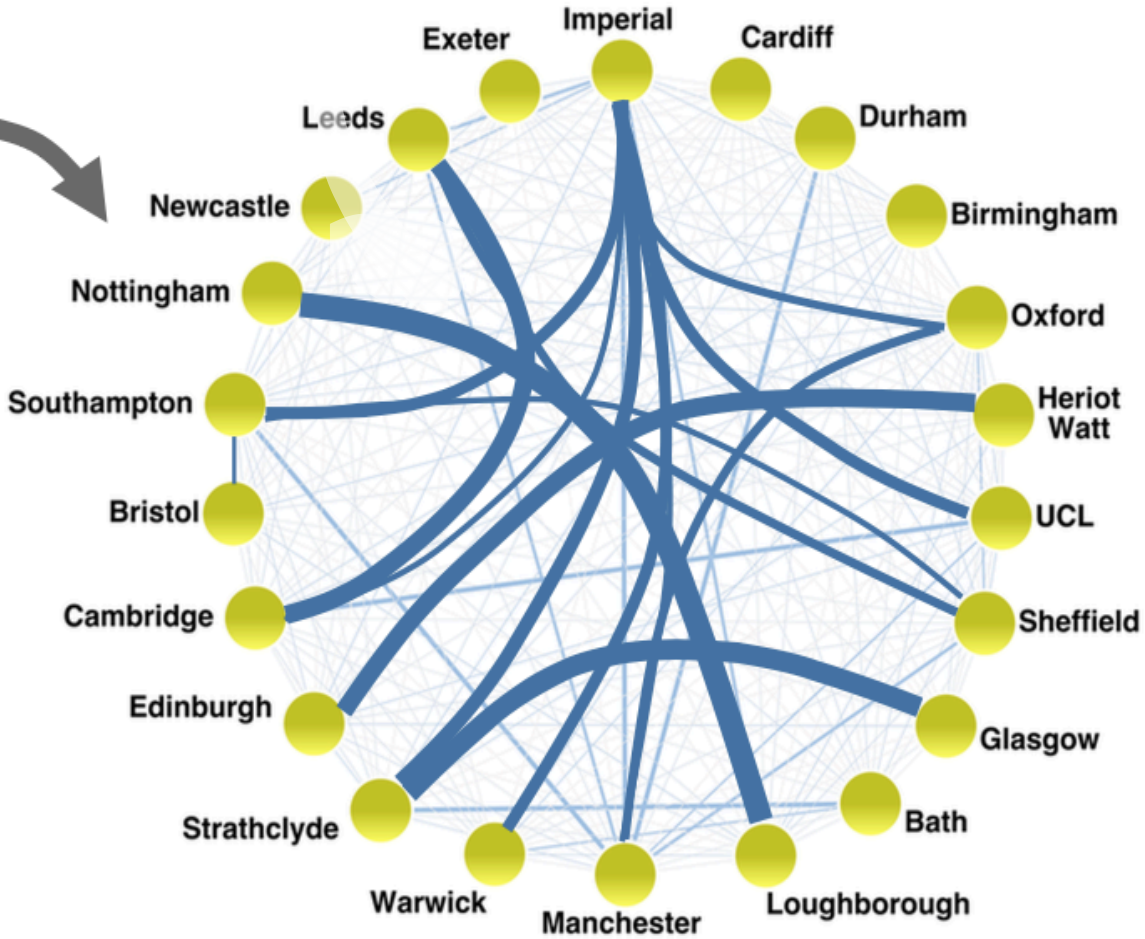
Colizza, Flammini, Serrano, Vespignani, Nat. Phys. (2006)

Rich club behavior

The rich core in 2010







Ma, Mondragon, Latora, PNAS 2015

Extracting the rich core

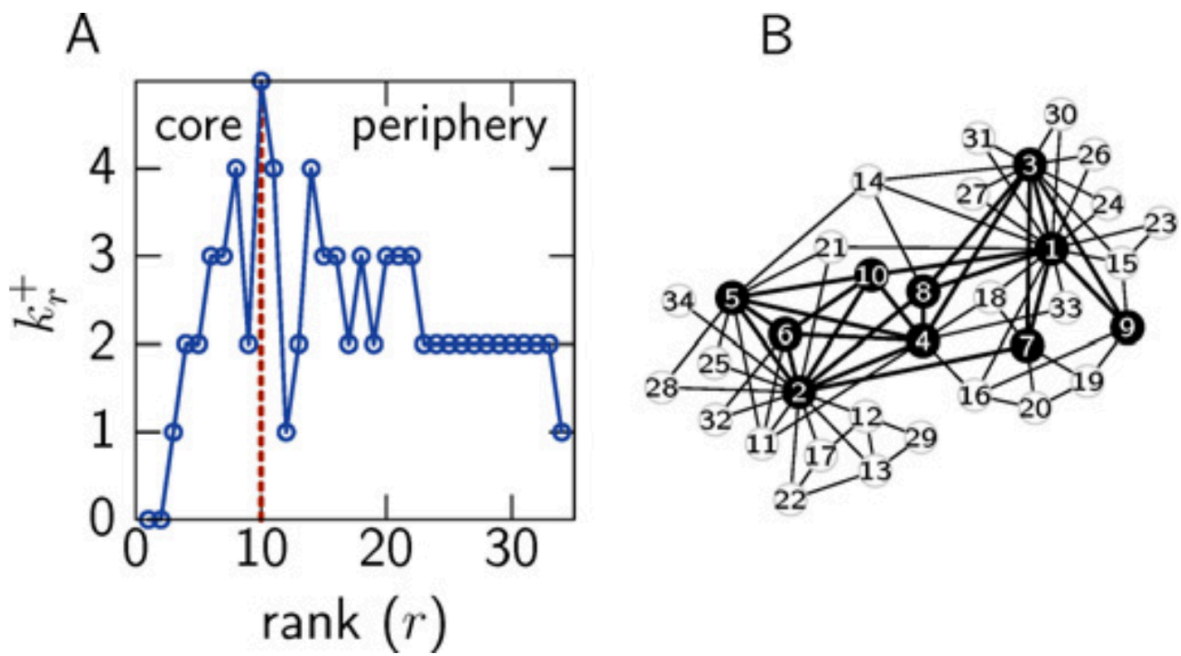


Fig 1. The rich–core for the Zachary Karate Club network. (A) The number of links k_r^+ that node r shares with nodes of a higher rank. The boundary of the core is marked by $k_{r^*}^+$ where k_r^+ is at its maximum, as indicated by the dotted line. (B) A graphical representation of the network with core (black) and periphery (white) nodes derived from the rich–core method.

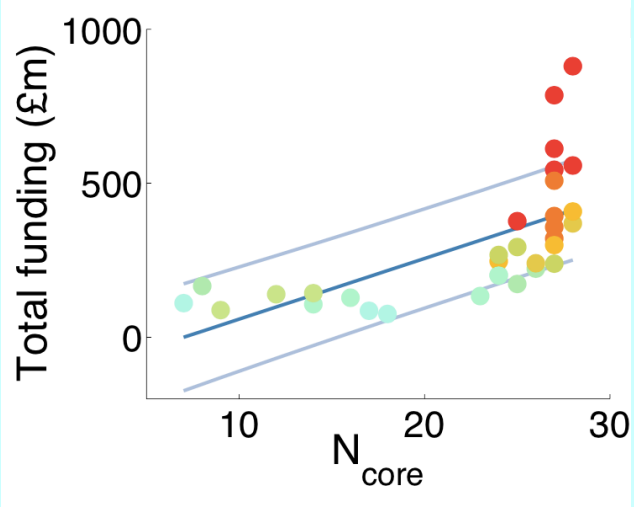
doi:10.1371/journal.pone.0119678.g001

Ma, Mondragón PLoS ONE 10(3): e0119678 (2015)

The rich core of the university network

Affiliation	Abbreviation	Grants	Total £	ζ_{avg}	N_{core}	N^{w}_{core}
Imperial College	Imperial	2,658	880,042,691	0.847	28	27
University of Cambridge	Cambridge	2,182	785,600,273	0.806	27	28
University of Manchester	Manchester	2,351	612,256,769	0.830	27	28
University of Oxford	Oxford	1,966	557,758,967	0.818	28	28
University College London	UCL	1,417	543,449,634	0.828	27	27
University of Southampton	Southampton	1,373	508,545,865	0.763	27	26
University of Sheffield	Sheffield	1,367	408,240,769	0.803	28	27
University of Nottingham	Nottingham	1,411	393,624,426	0.755	27	26
University of Edinburgh	Edinburgh	1,191	376,515,957	0.747	25	27
University of Leeds	Leeds	1,452	369,915,734	0.822	28	27
University of Bristol	Bristol	1,259	357,784,563	0.751	27	15
University of Birmingham	Birmingham	1,059	320,365,372	0.784	27	18
University of Warwick	Warwick	1,111	299,106,838	0.712	27	10
Loughborough University	Loughborough	971	292,614,129	0.747	25	17
University of Strathclyde	Strathclyde	1,004	267,072,205	0.746	24	19
University of Glasgow	Glasgow	857	247,098,481	0.777	24	15
University of Liverpool	Liverpool	966	240,086,056	0.760	26	15
University of Bath	Bath	992	238,851,816	0.675	27	19
Newcastle University	Newcastle	813	222,668,660	0.748	26	20
Heriot-Watt University	Heriot Watt	857	202,088,932	0.754	24	21
University of Surrey	Surrey	783	200,322,051	0.726	24	11
Durham University	Durham	776	172,691,133	0.684	25	11
University of St Andrews	St Andrews	515	166,131,172	0.687	8	0
Cranfield University	Cranfield	578	164,867,131	0.714	18	0
Queen's University Belfast	Queen's	660	142,904,945	0.712	14	2
Queen Mary, UoL	QMUL	618	139,471,209	0.685	12	5
Cardiff University	Cardiff	648	133,551,032	0.740	23	6
University of York	York	611	128,477,800	0.703	16	2

Funding and research performance

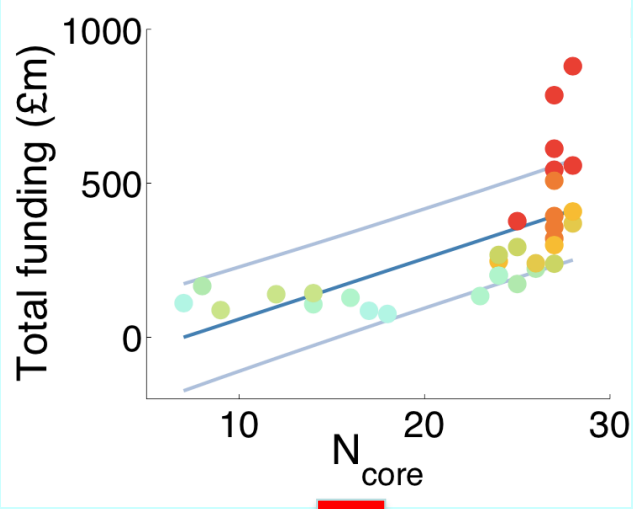


Affiliation	Abbreviation	Grants	Total £	N_{core}	ζ_{avg}
Imperial College	Imperial	2658	880,042,691	28	0.847
University of Cambridge	Cambridge	2182	785,600,273	27	0.806
University of Manchester	Manchester	2351	612,256,769	27	0.830
University of Oxford	Oxford	1966	557,758,967	28	0.818
University College London	UCL	1417	543,449,634	27	0.828
University of Southampton	Southampton	1373	508,545,865	27	0.763

A few elite univ get more funds than expected from the observed linear relation between N_{core} and funding !!!

IS THAT A SENSIBLE WAY TO USE MONEY?
SUPER DUPER
BOOM
AND
BUSTER
ROCKET SCIENTIST
CHRIS MADDEN

Funding and research performance



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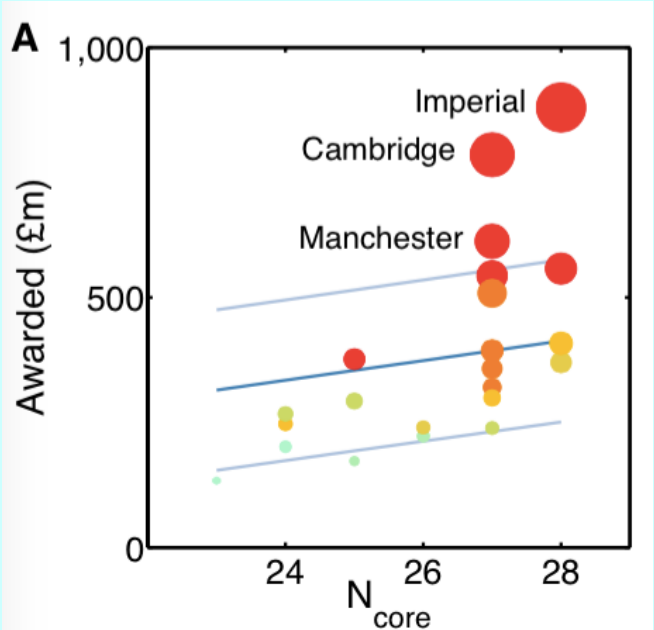
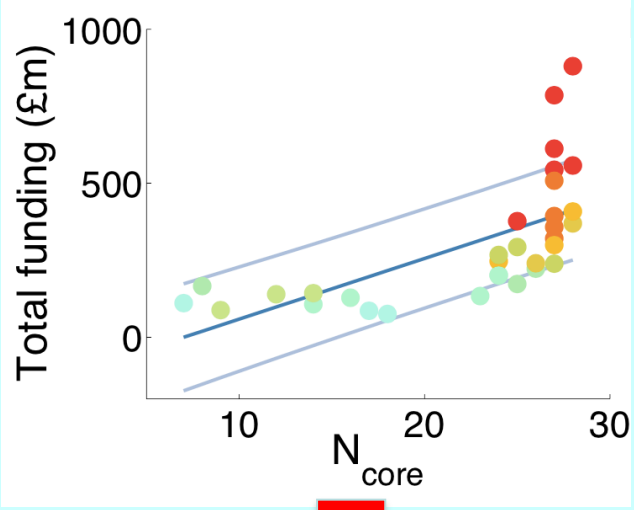


Funding and research performance



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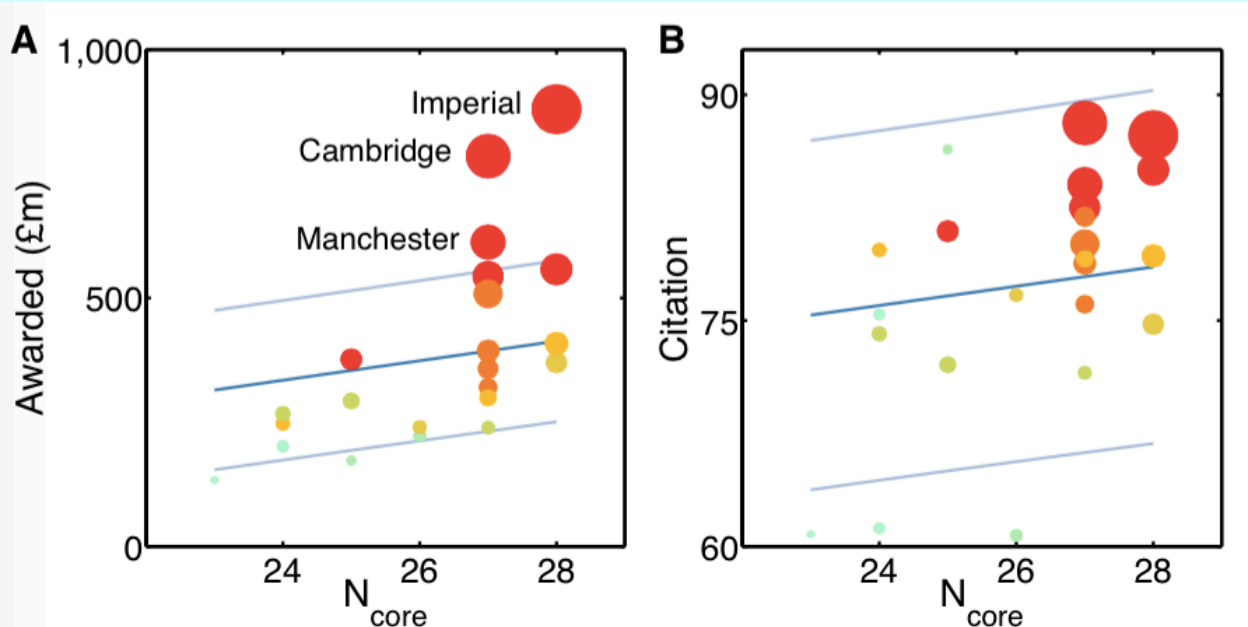
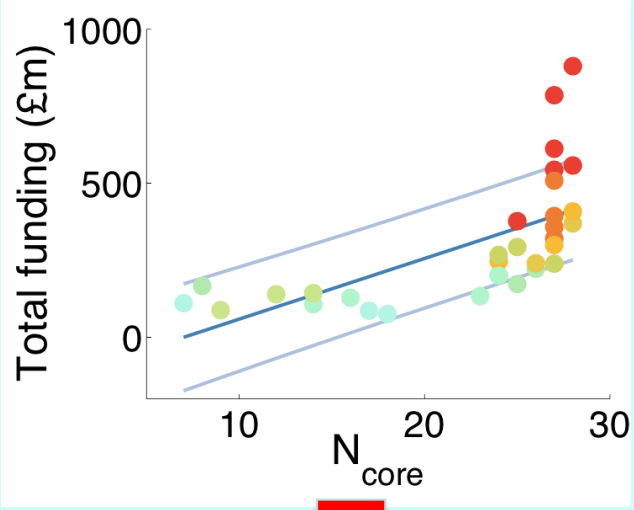


Funding and research performance



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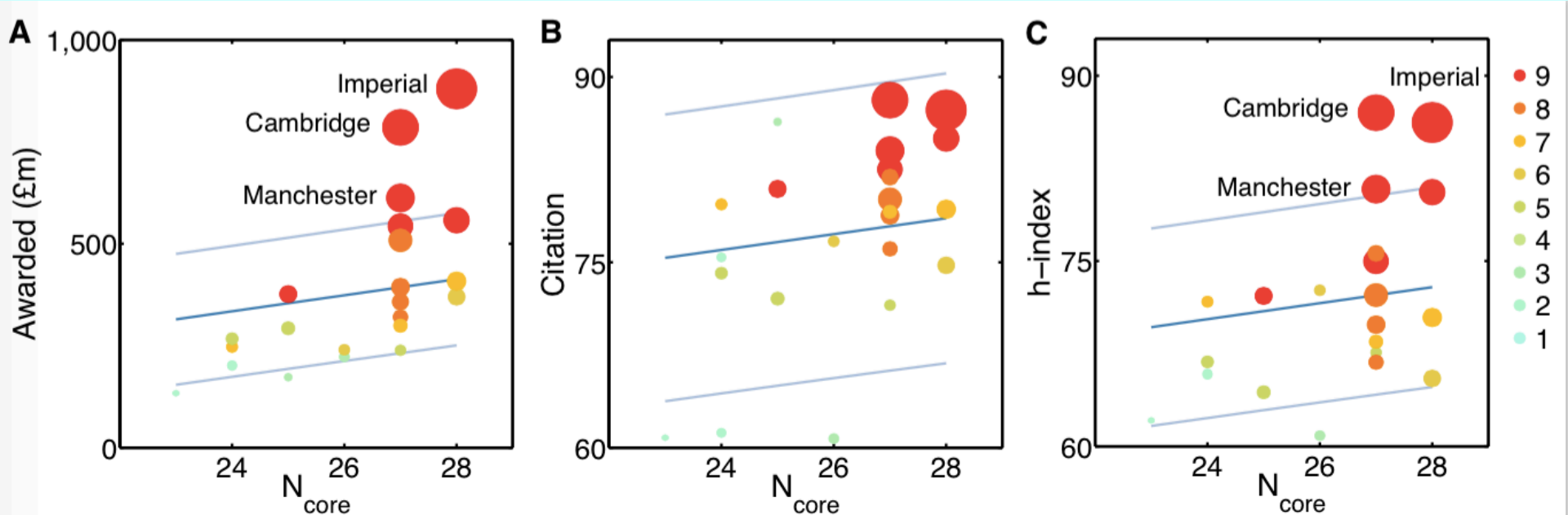
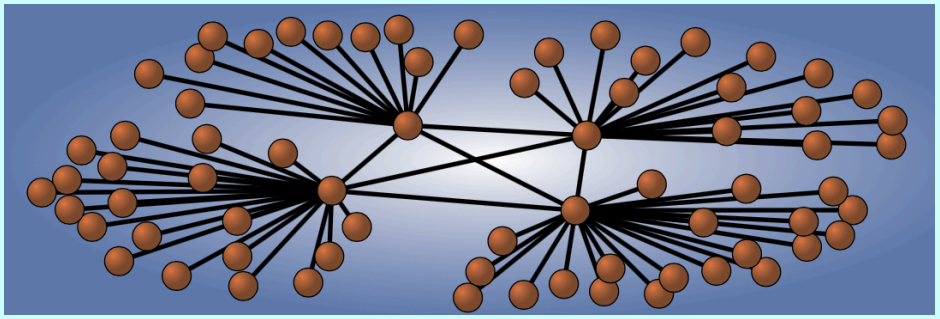


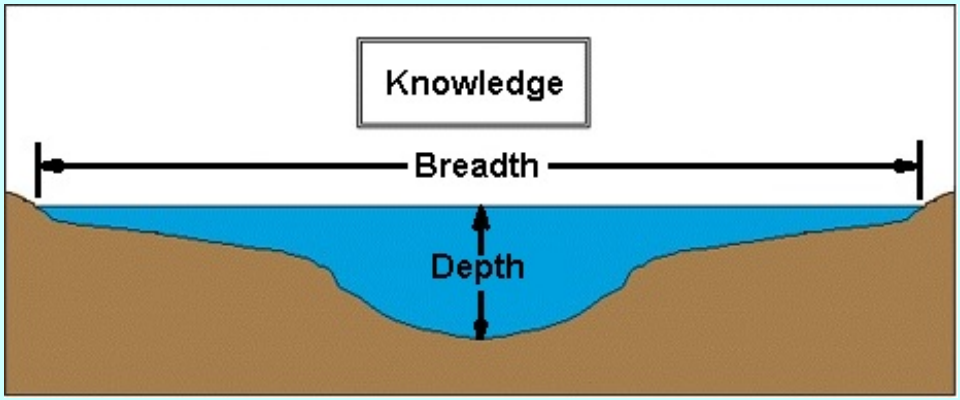
Take home message

Elite universities form a rich club and act as brokers of knowledge



Elite universities overattract resources but…..

…..reward in variety and quality of research



The sad truth

LETTER

doi:10.1038/nature18315

Interdisciplinary research has consistently lower funding success

Lindell Bromham[1], Russell Dinnage[1] & Xia Hua[1]

[1]Research School of Biology, Australian National University, 116 Daley Road, Canberra 0200, Australia.

684 | NATURE | VOL 534 | 30 JUNE 2016

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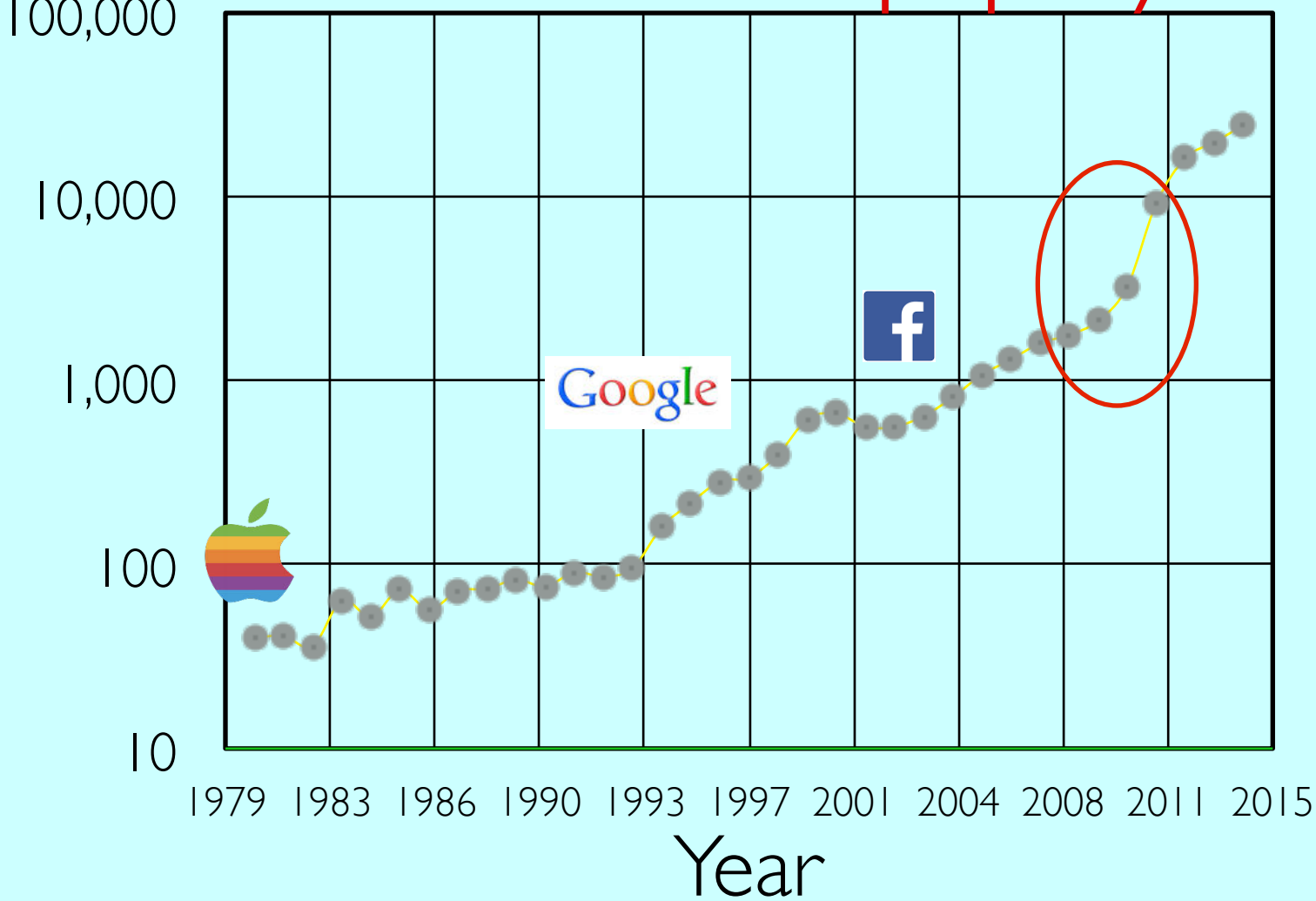
(3) Predicting the **success** of **startups**

Bonaventura, Ciotti, Panzarasa, Liverani, Lacasa, Latora
arXiV:1904.08171

STARTUP = newly emerged small business that aims to meet a marketplace need by developing an innovative product, process or service

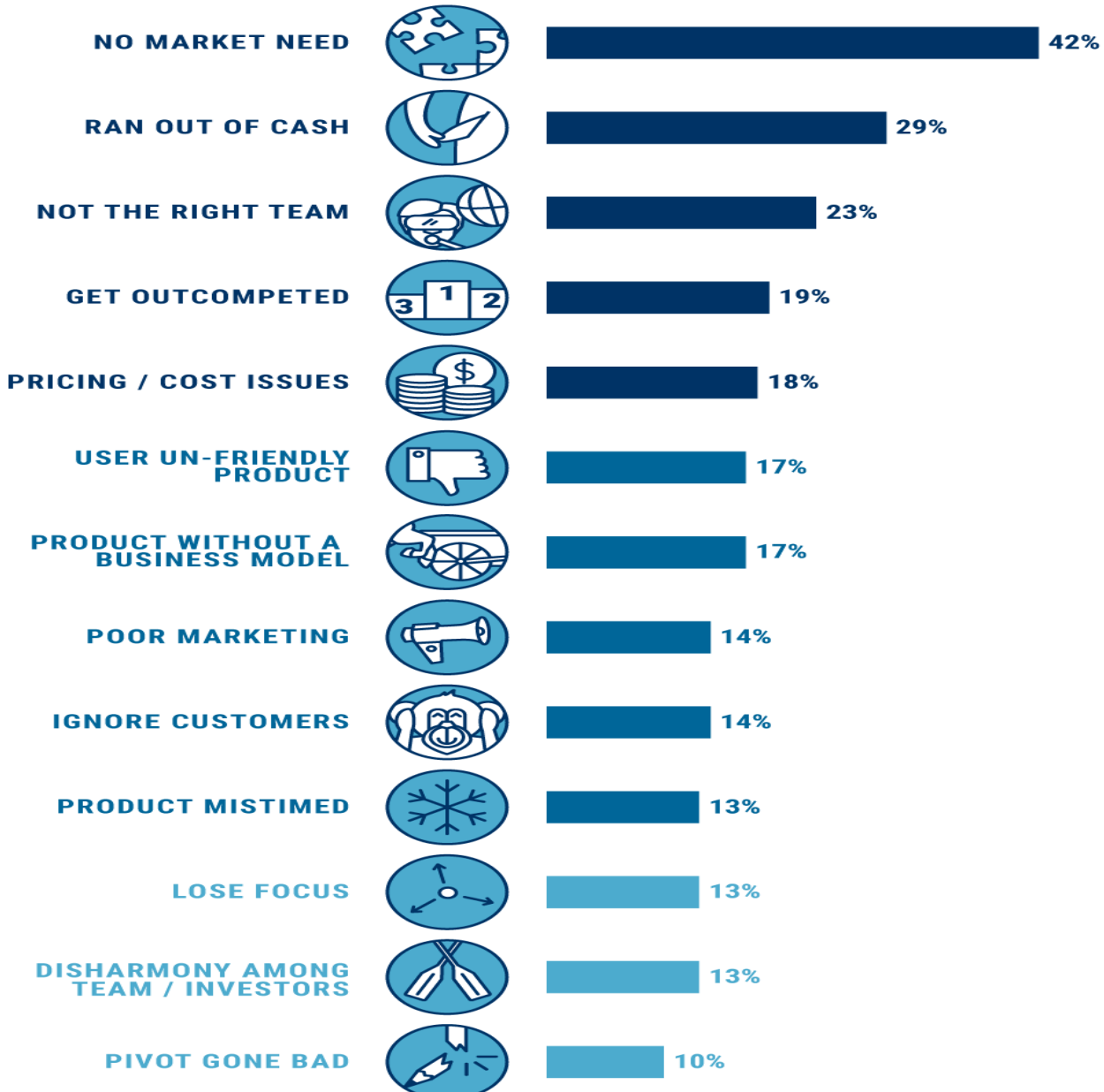
New Start-ups per year



9 out of 10 startup businesses FAIL

BASED ON ANALYSIS OF 101 STARTUP POSTMORTEMS

Top 20 Reasons Startups Fail

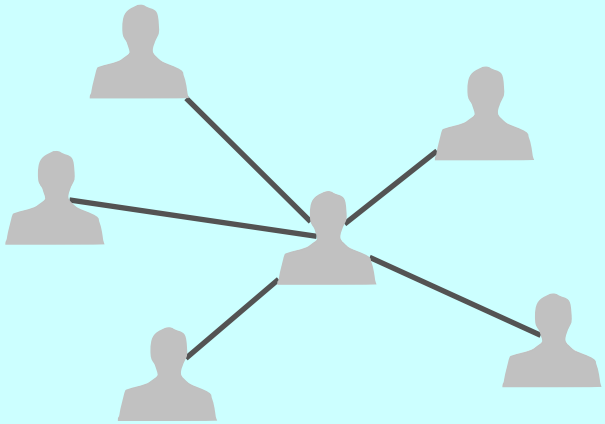


The magic ingredients of the success of a startup ?

=

Tons of coffee meetings and beers

Or



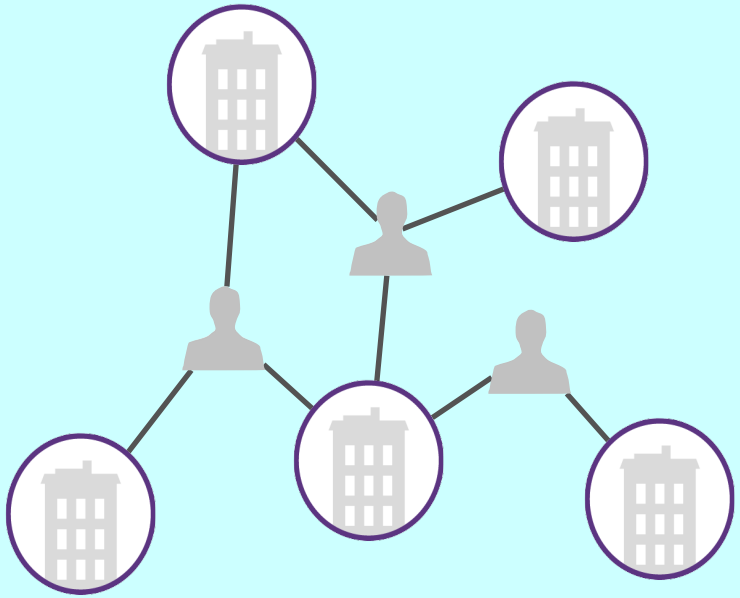
Data and network construction

CrunchBase

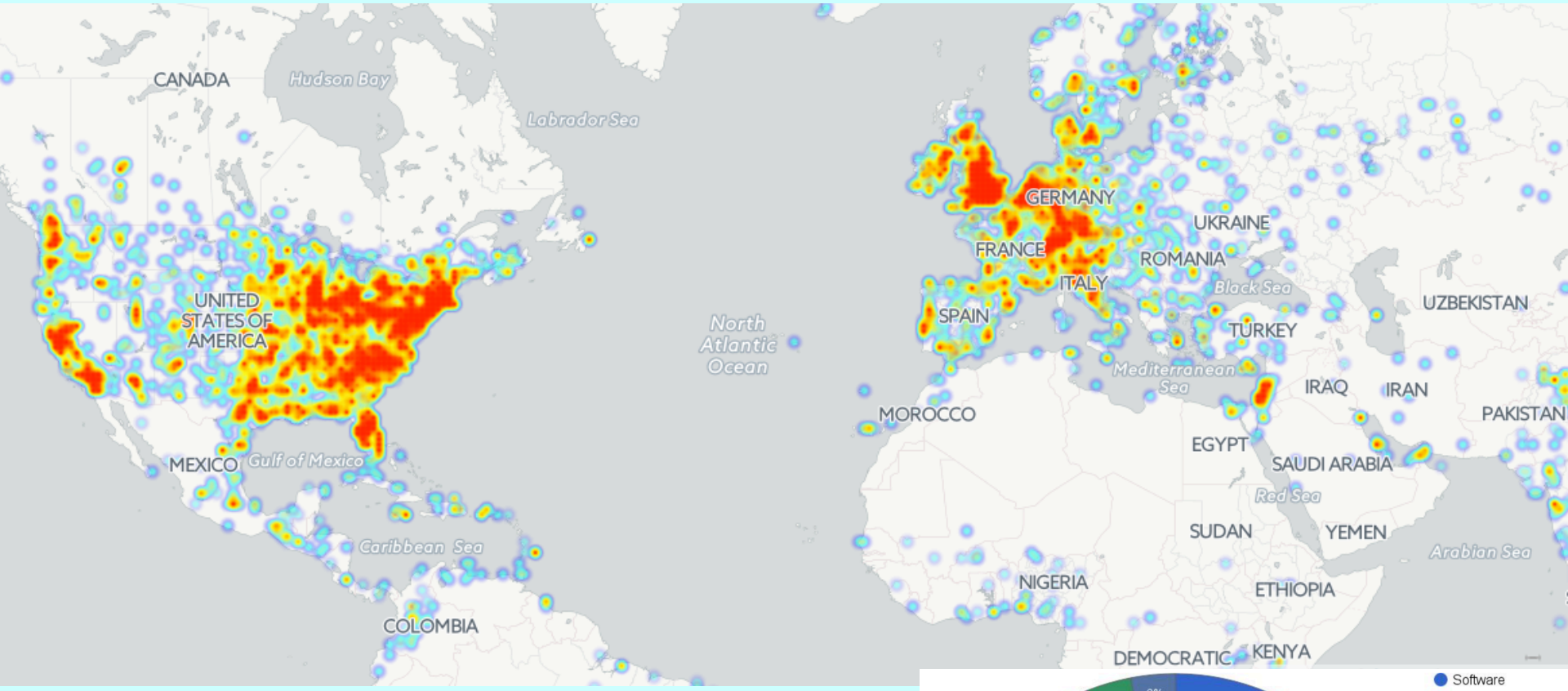
Wikipedia of start-ups
403,000 organisations
409,000 individuals

AngelList

Social platform
176,000 startups
657,000 individuals

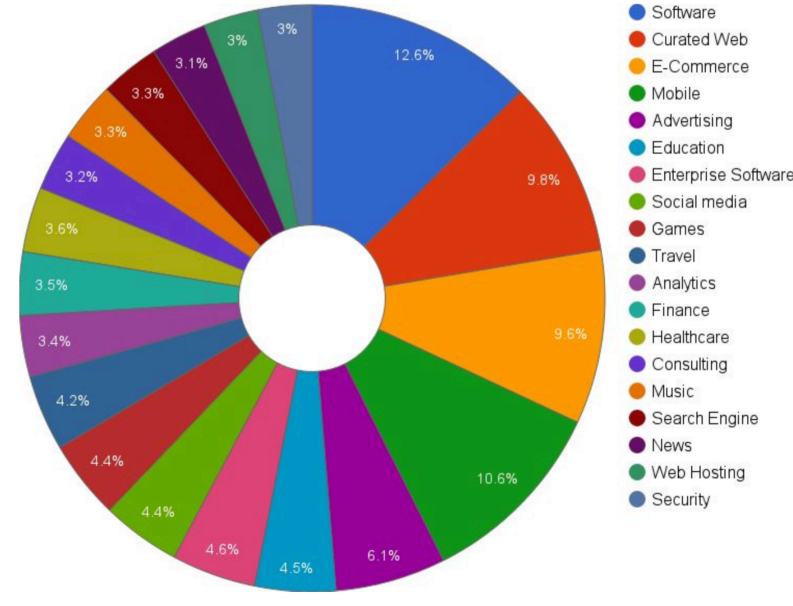


Location, market sectors
Team (Founders, advisors, board members, employees)
News: IPO (Initial public offer), Funding rounds

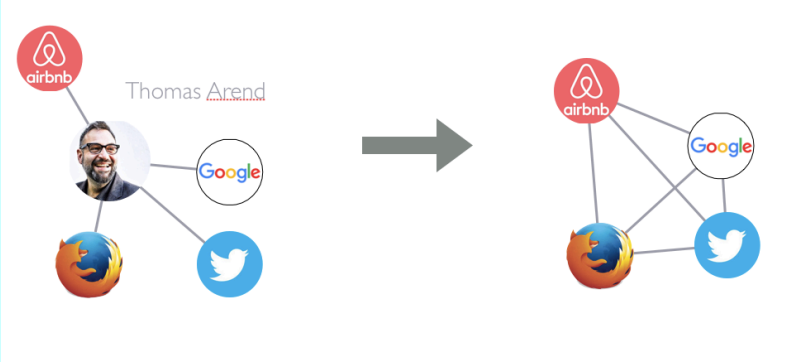


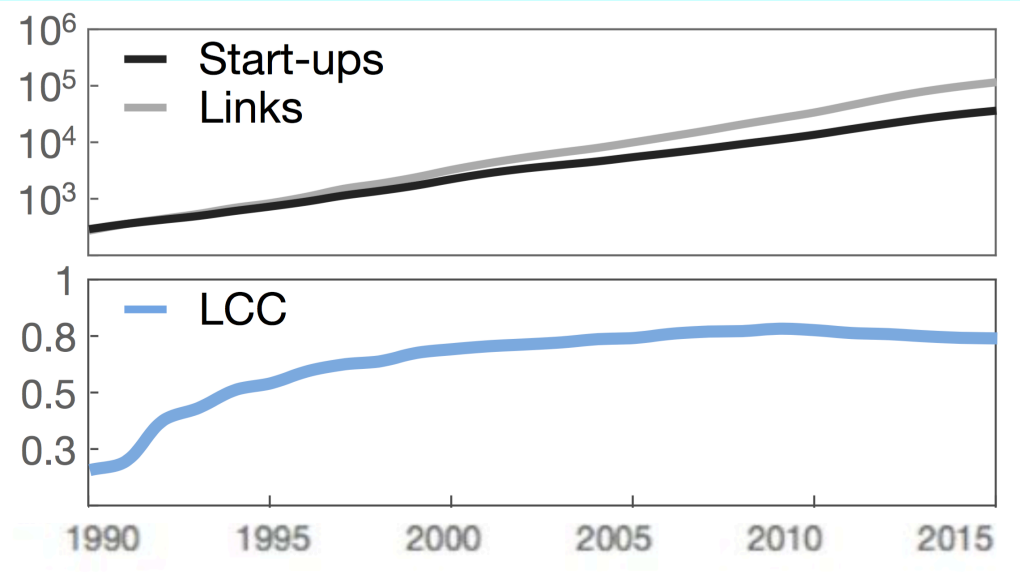
US (55%), UK, Germany, Israel

Top 20 market sectors

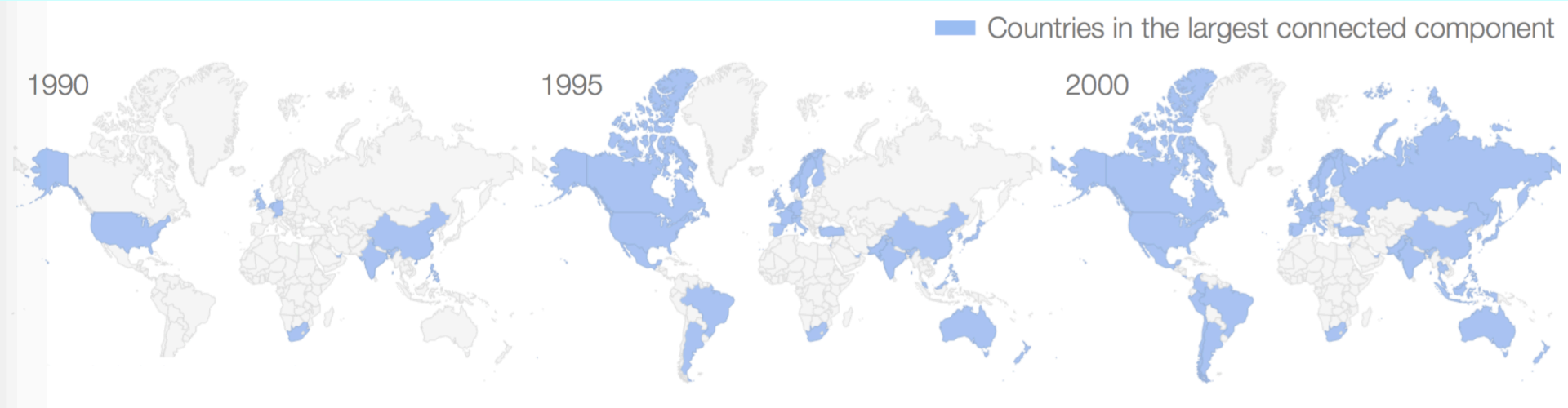


The WWS (World-Wide Startup) network



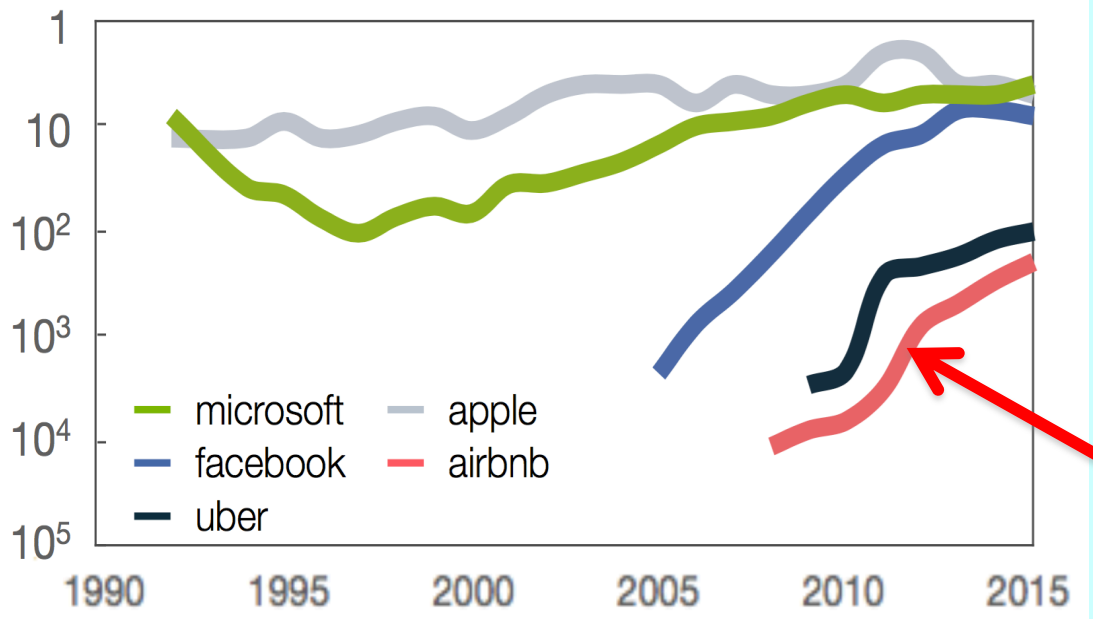


N= 41,830 Startups
K= 135,099
15 years evolution

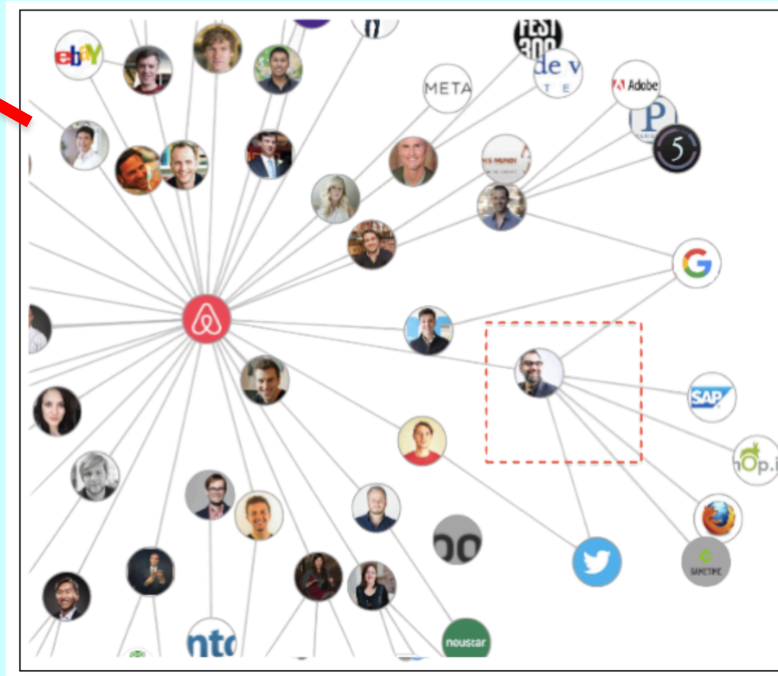


Predicting the success of startups

Ranking startups by their closeness centrality in the WWS network



time

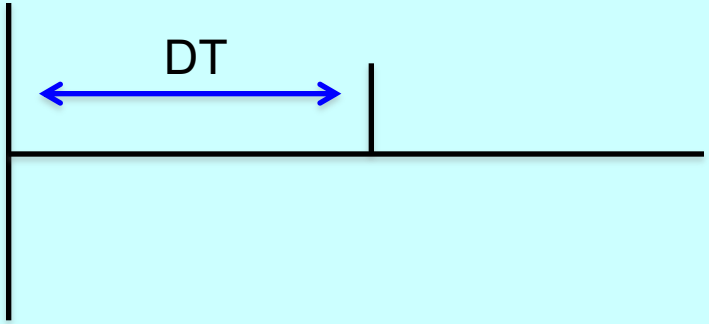


Our recommendation list

May 2012

Rank	All companies list	Open-deals list
1	Google	Airbnb
2	Apple	Uber
3	Facebook	Eventbrite
4	Intuit	...
5	Airbnb	
6	Digg	
7	Twitter	
8	Uber	
9	Eventbrite	
...	...	

Jun 2012



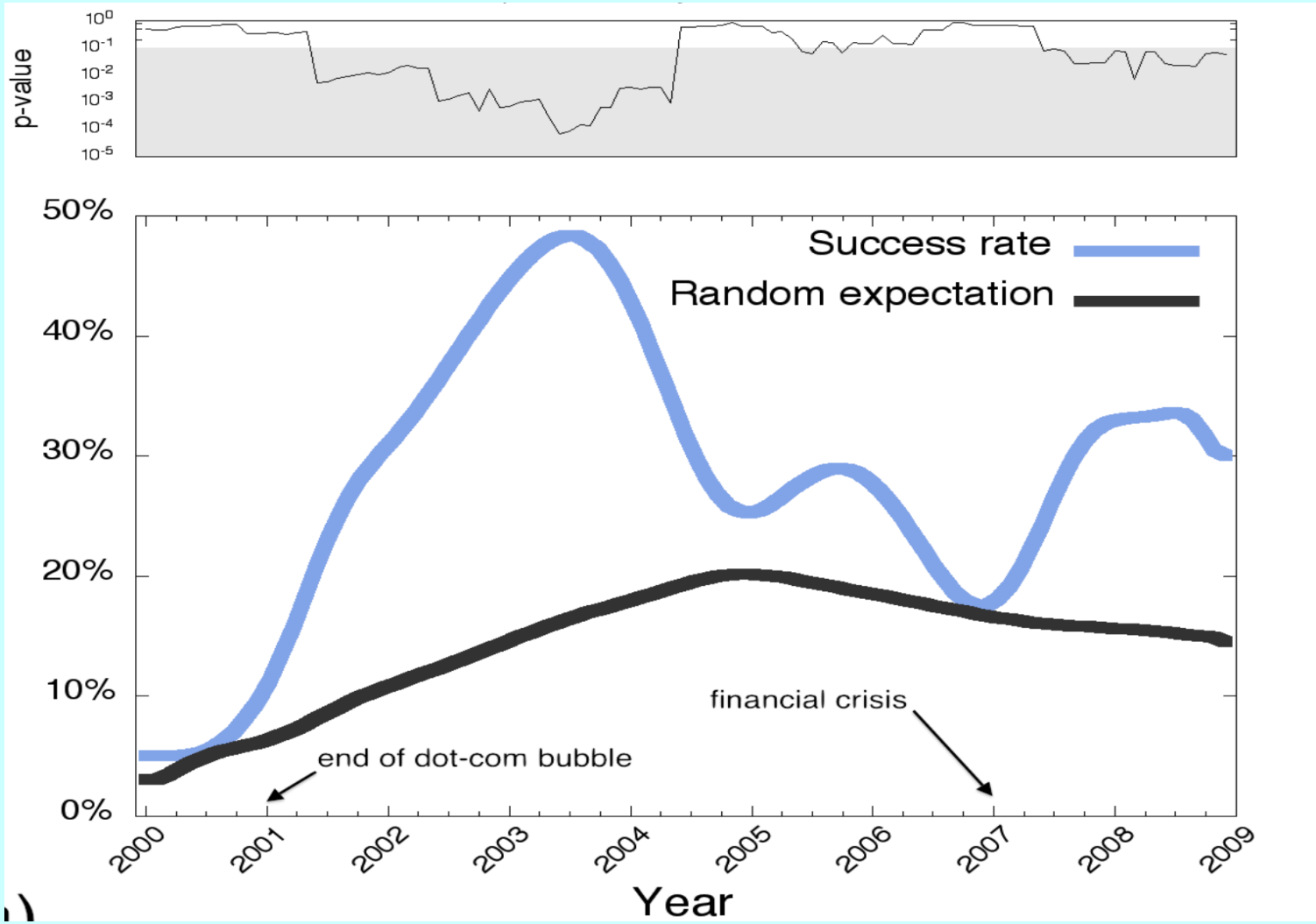
VALIDATION: Check positive outcome of the company in a DT window

1) startup makes an acquisition
2) it is acquired
3) it undergoes an IPO

Top20 **open-deals**:

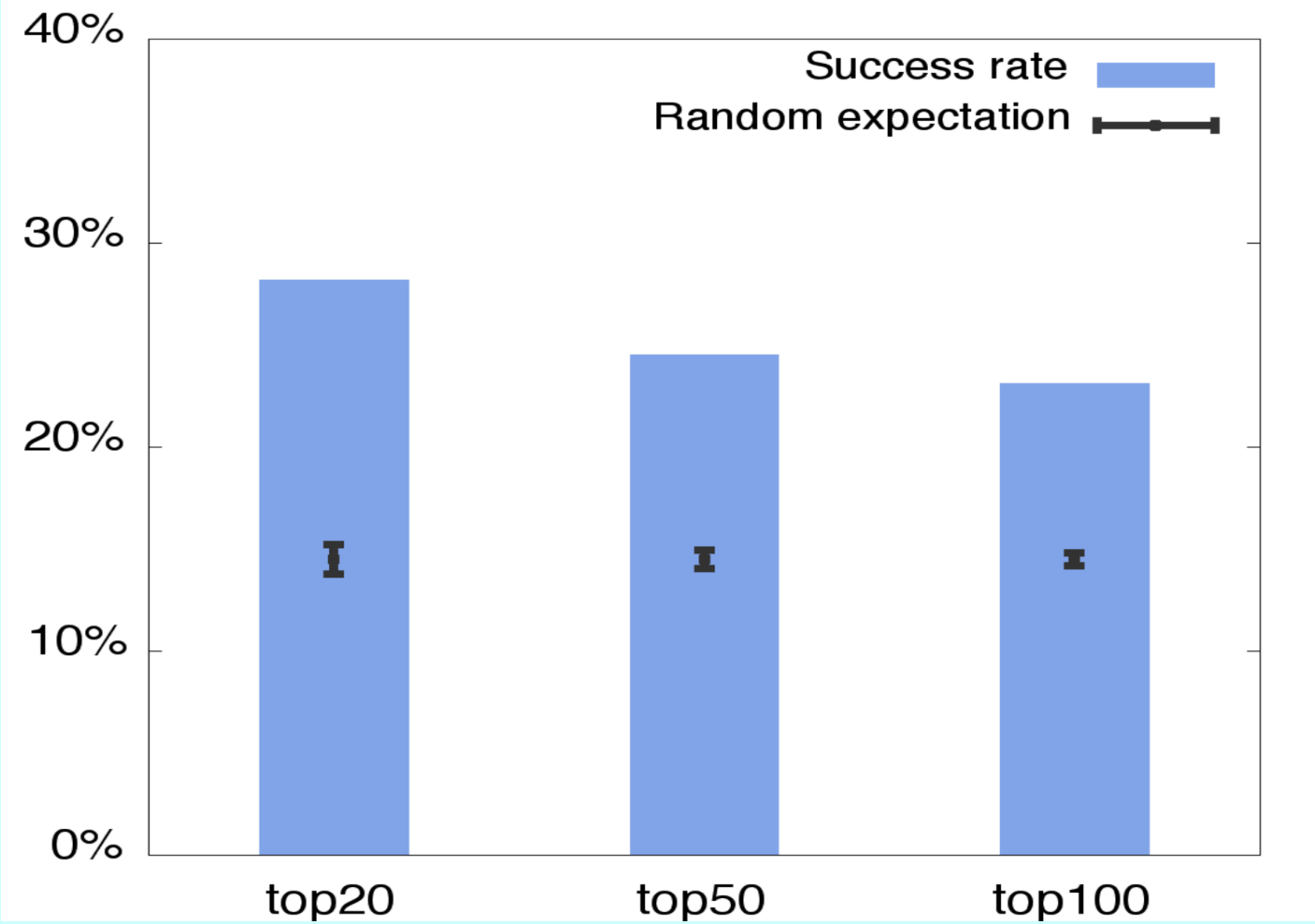
0) younger than 2 years
1) NOT YET received funding
2) NOT YET been acquired
3) NOT YET in stock markets

Validating our recommendations



Bonaventura, Ciotti, Panzarasa, Liverani, Lacasa, Latora
arXiV:1904.08171

Validating our recommendations



Bonaventura, Ciotti, Panzarasa, Liverani, Lacasa, Latora
arXiV:1904.08171

Real investors performance

Investor	# investments	# successful investments	Success rate
500 Startups	1022	153	**15%**
Y Combinator	953	154	**16%**
Intel Capital	744	313	40%
Start-up Chile	710	10	1.4%
Sequoia Capital	700	267	38%
New Enterprise Associates (NEA)	672	272	40%
SV Angel	600	258	43%
Techstars	549	95	**17%**
Brand Capital	537	80	14%
Accel Partners (Accel)	536	270	50%
Sos Ventures (SOSV)	493	17	3%
Wayra	476	11	**2%**
Kleiner Perkins Caufield & Byers (KPCB)	457	203	43%
Right Side Capital Management (RSCM)	449	44	10%
Goldman Sachs	410	209	50%

Table S1: Top 15 investment companies according to the number of investments made, along with the percentage of successful investments. Highlighted in pink are investors focused on very early-stage companies as those considered in our open-deal lists. The success rates of such investors are comparable to the random expectation null model, and much below the success rate obtained using our recommendation method.

(1) The advantages of **interdisciplinarity** in modern **science**

(2) How **funding** shapes collaboration networks in **science**

(3) Predicting the **success** of **startups**

Many thanks to the inderdisciplinary collaborators at QMUL

- Athen Ma, Raul Mondragon — Engineering and Computer Science, QMUL
- Pietro Panzarasa — Business, QMUL
- Moreno Bonaventura, Valerio Ciotti, Enzo Nicosia, Silvia Liverani, Lucas Lacasa — Complex Systems and Networks Group, Mathematical Sciences, QMUL

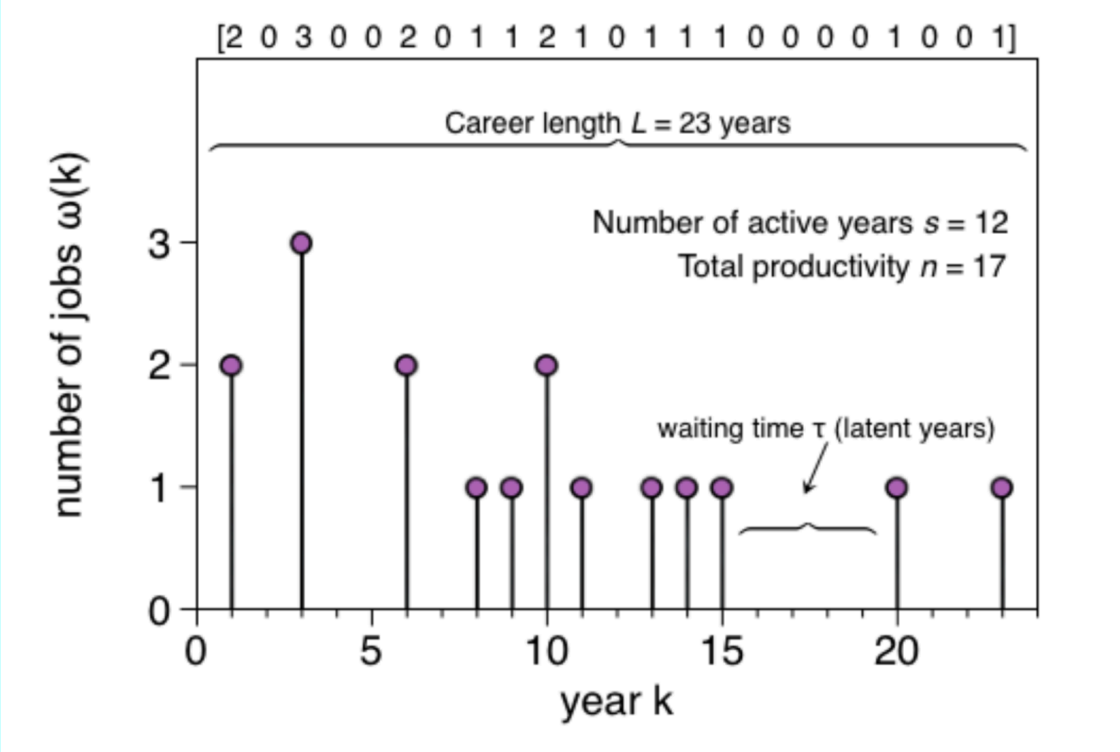
Highlight

ARTICLE

https://doi.org/10.1038/s41467-019-10213-0 OPEN

Quantifying and predicting success in show business

Oliver E. Williams[1], Lucas Lacasa[1] & Vito Latora[1,2,3,4]



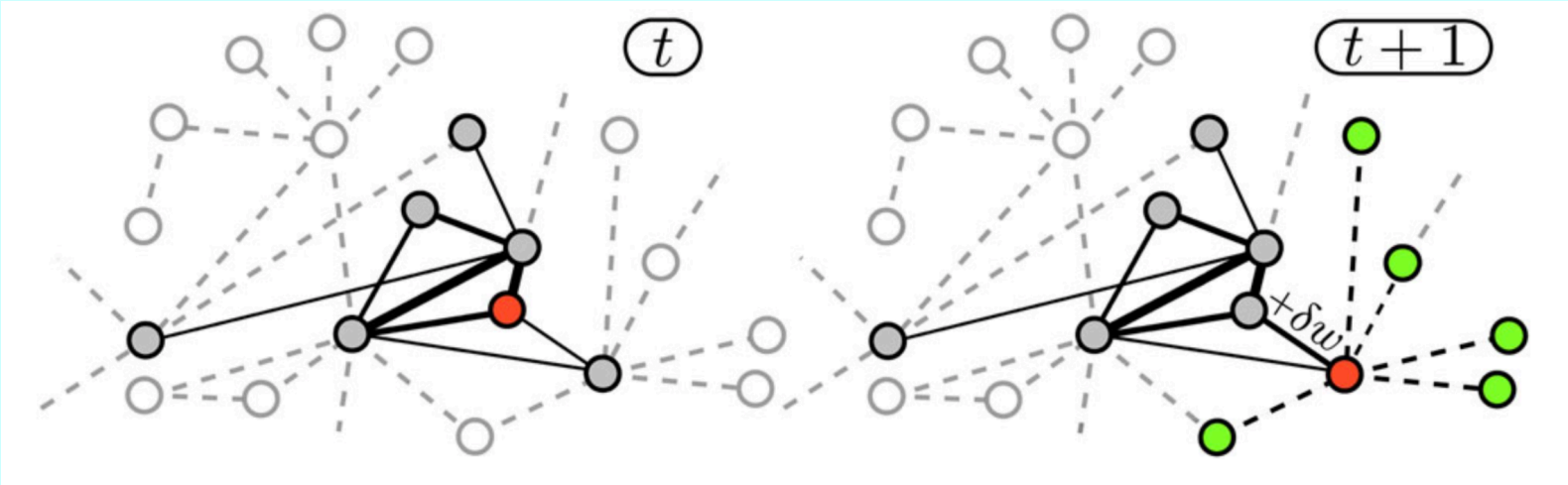
Williams, Lacasa, Latora, Nat. Comm. 10, 2256 (2019)

Highlight 2

PHYSICAL REVIEW LETTERS **120,** 048301 (2018)

Network Dynamics of Innovation Processes

Iacopo Iacopini,[1,2] Staša Milojević,[3] and Vito Latora[1,4]



Highlight 1

nature human behaviour

LETTERS

PUBLISHED: 8 FEBRUARY 2017 | VOLUME: 1 | ARTICLE NUMBER: 0043

Characterization of hunter-gatherer networks and implications for cumulative culture

A. B. Migliano[1*], A. E. Page[1], J. Gómez-Gardeñes[2], G. D. Salali[1], S. Viguier[1], M. Dyble[1], J. Thompson[1], Nikhill Chaudhary[1], D. Smith[1], J. Strods[1], R. Mace[1], M. G. Thomas[3], V. Latora[4] and L. Vinicius[1]

A new textbook

October 2017

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Networks constitute the backbone of complex systems, from the human brain to computer communications, transport infrastructures to online social systems, metabolic reactions to financial markets. Characterising their structure improves our understanding of the physical, biological, economic and social phenomena that shape our world.

Rigorous and thorough, this textbook presents a detailed overview of the new theory and methods of network science. Covering algorithms for graph exploration, node ranking and network generation, among the others, the book allows students to experiment with network models and real-world data sets, providing them with a deep understanding of the basics of network theory and its practical applications. Systems of growing complexity are examined in detail, challenging students to increase their level of skill. An engaging presentation of the important principles of network science makes this the perfect reference for researchers and undergraduate and graduate students in physics, mathematics, engineering, biology, neuroscience and social sciences.

VITO LATORA is Professor of Applied Mathematics and Chair of Complex Systems at Queen Mary University of London. Noted for his research in statistical physics and in complex networks, his current interests include time-varying and multiplex networks, and their applications to socio-economic systems and to the human brain.

VINCENZO NICOSIA is Lecturer in Networks and Data Analysis at the School of Mathematical Sciences at Queen Mary University of London. His research spans several aspects of network structure and dynamics, and his recent interests include multi-layer networks and their applications to big data modelling.

GIOVANNI RUSSO is Professor of Numerical Analysis in the Department of Mathematics and Computer Science at the University of Catania, Italy, focusing on numerical methods for partial differential equations, with particular application to hyperbolic and kinetic problems.

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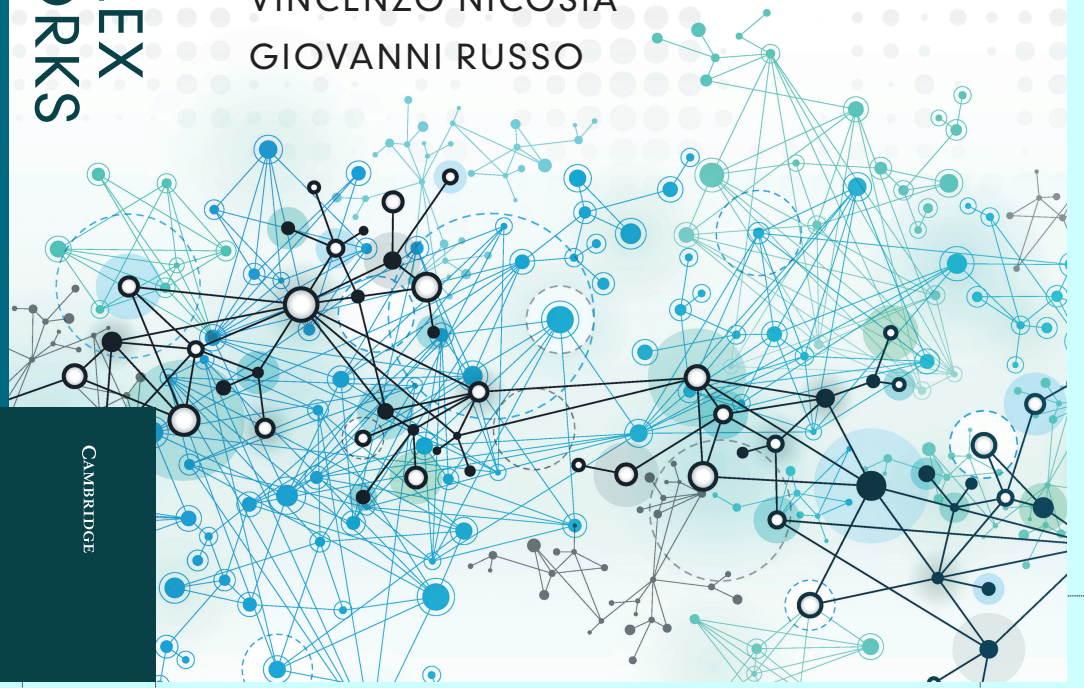
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