

The Art and Science of Empirical Computer Science

Week 3: The Science of Collaboration

Jimmy Lin
September 26, 2022

Should you collaborate or not?

Position A: Early-stage researchers should actively seek out collaborations beyond their research group.

Participation in multiple research projects across many different groups builds breadth.

Position B: Early-stage researchers should *not* actively seek out collaborations beyond their research group.
Focusing on depth is more important than breadth.

Let's debate!

“The Science of Science”, Part II

The Science of Collaboration

Chapter 8: Dominance of Teams in Science

Discussion Points

Makes sense?

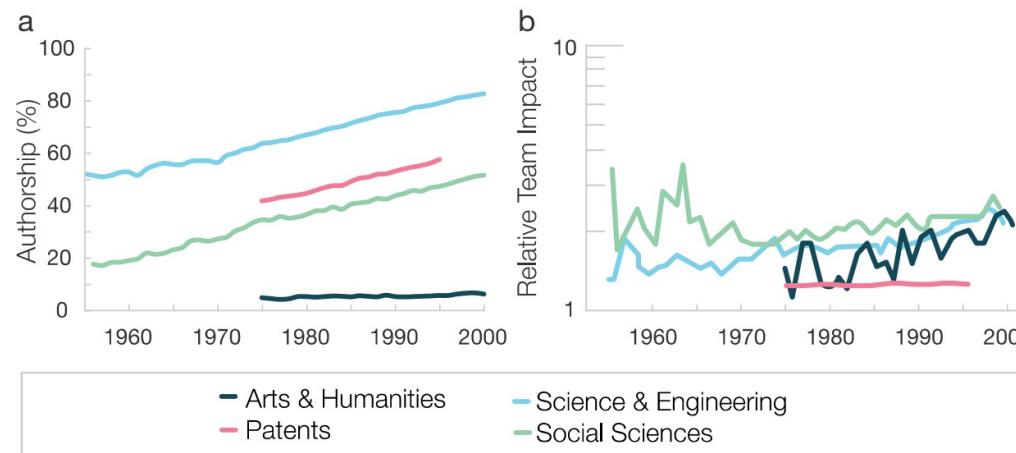


Figure 2.1.1 The growing dominance of teams. (a) Changes in the fraction of papers and patents written by teams over the past five decades. Each line represents the arithmetic average taken over all subfields in each year, with colors indicating different fields. (b) The Relative Team Impact (RTI) represents the mean number of citations received by team-authored work divided by the mean number of citations received by solo-authored work in the same field. A ratio of 1 implies that team- and solo-authored work have comparable impact. The lines present the arithmetic average of RTI in a given year for the entire field. After Wuchty *et al.* [2].

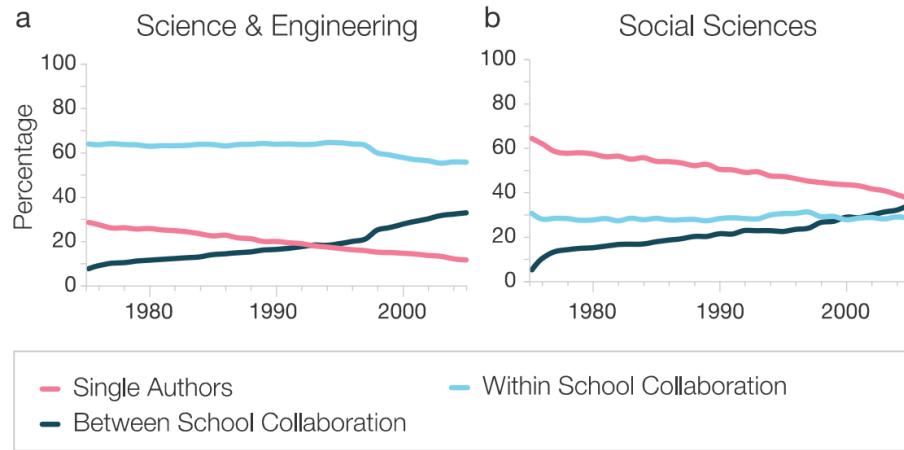


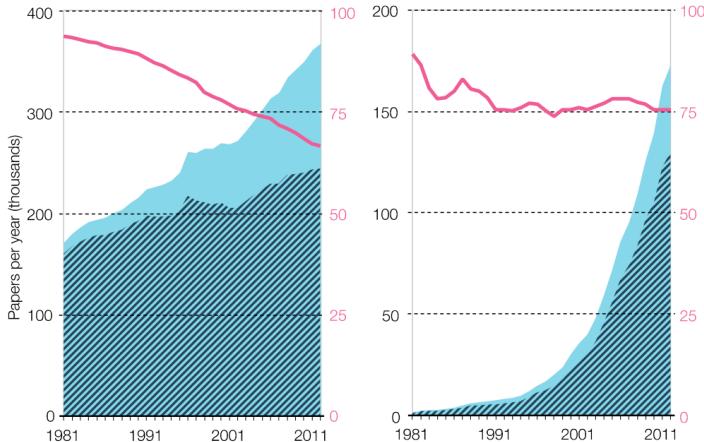
Figure 2.1.3 The rise in multi-university collaboration. By comparing the percentage of papers produced by different authorship combinations, the plots document the increasing share of multi-university collaborations between 1975 and 2005. This rise is especially strong in Science and Engineering (a) and Social Science (b), whereas it remains weak in Arts & Humanities, in which collaboration of any kind is rare [14]. The share of single-university collaborations remains roughly constant with time, whereas the share of solo-authored papers strongly declined in Science & Engineering and Social Sciences. After Jones *et al.* [14].

STRENGTH IN NUMBERS

Growth in international collaboration eclipses domestic output in established economies, but not in emerging ones.

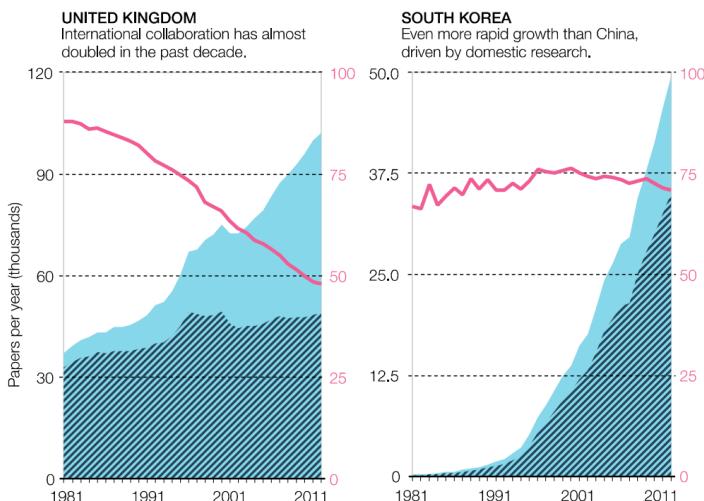
UNITED STATES

The country is less internationally collaborative than those in Western Europe.



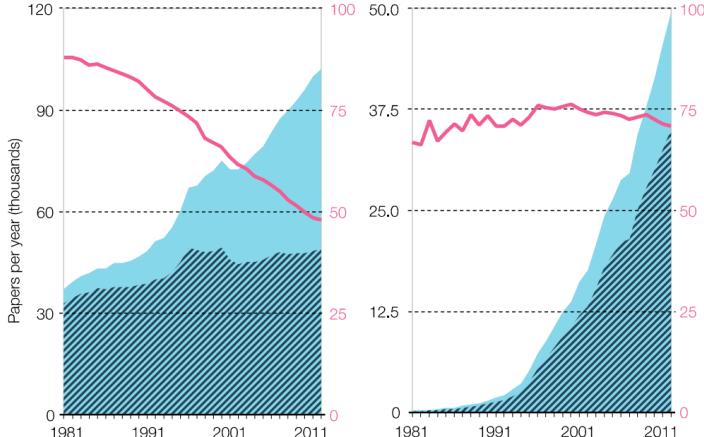
CHINA

More than three-quarters of research output remains domestic.



UNITED KINGDOM

International collaboration has almost doubled in the past decade.



SOUTH KOREA

Even more rapid growth than China, driven by domestic research.

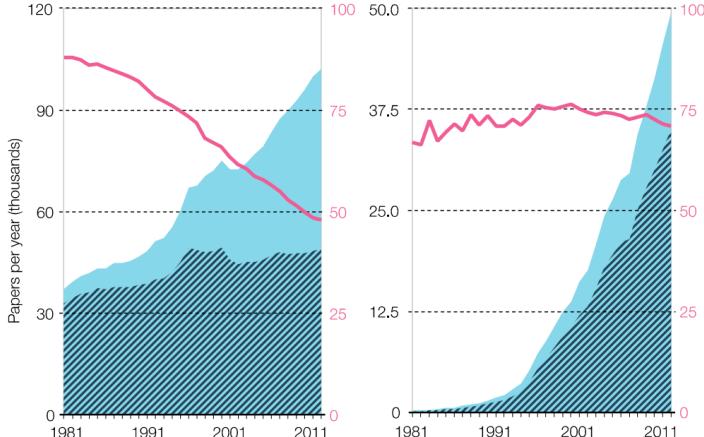


Figure 2.1.4 The increasing role of international collaboration. If a paper only contains authors whose addresses are from the home country, then it is counted as domestic output of that country. Comparing the left and right panels shows that growth in international collaboration eclipses the growth of domestic output in established economies, but not in emerging ones. After Adams [16].

“The Science of Science”, Part II

The Science of Collaboration

Chapter 9: The Invisible College

Discussion Points

Peer effects are real, but causality is complicated...

“The Science of Science”, Part II

The Science of Collaboration

Chapter 10: Coauthorship Networks

Discussion Points

Milgram (1967)

Watts–Strogatz (1998)

Granovetter (1973)

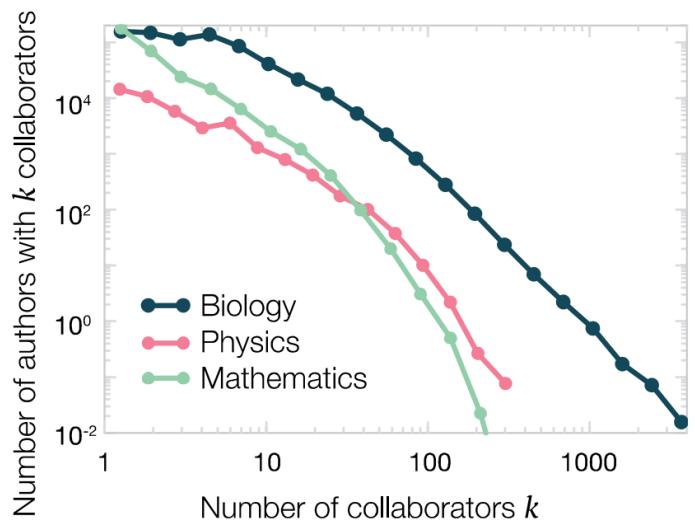


Figure 2.3.2 **Collaboration Networks are Scale-free.** The plots show the distribution of numbers of collaborators for scientists in physics, biology and mathematics, indicating that the underlying distribution are fat tailed. This implies that the collaboration network is scale-free [40, 41], meaning that the degrees can be approximated by a power law distribution. After Newman *et al.* [38].

The Small-World Problem

By Stanley Milgram

Fred Jones of Peoria, sitting in a sidewalk cafe in Tunis, and needing a light for his cigarette, asks the man at the next table for a match. They fall into conversation; the stranger is an Englishman who, it turns out, spent several months in Detroit studying the operation of an interchangeable-bottlecap-factory. "I know it's a foolish question," says Jones, "but did you ever by any chance run into a fellow named Ben Arkadian? He's an old friend of mine, manages a chain of supermarkets in Detroit . . ."

"Arkadian, Arkadian," the Englishman mutters. "Why, upon my soul, I believe I do! Small chap, very energetic, raised merry hell with the factory over a shipment of defective bottlecaps."

"No kidding!" Jones exclaims in amazement.

"Good lord, it's a small world, isn't it?"

Almost all of us have had the experience of encountering someone far from home, who, to our surprise,

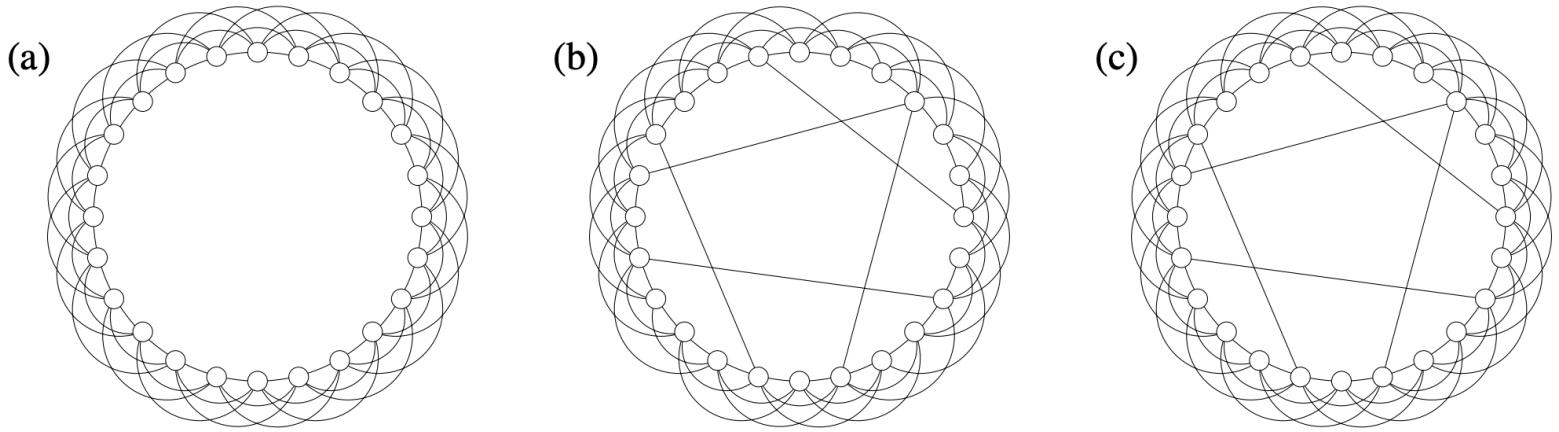


Fig. 6.1 (a) A one-dimensional lattice with connections between all vertex pairs separated by k or fewer lattice spacing, with $k = 3$ in this case. (b) The small-world model [415, 411] is created by choosing at random a fraction p of the edges in the graph and moving one end of each to a new location, also chosen uniformly at random. (c) A slight variation on the model [323, 288] in which shortcuts are added randomly between vertices, but no edges are removed from the underlying one-dimensional lattice.

Can we say anything about these “shortcuts”?

The Strength of Weak Ties¹

Mark S. Granovetter

Johns Hopkins University

Analysis of social networks is suggested as a tool for linking micro and macro levels of sociological theory. The procedure is illustrated by elaboration of the macro implications of one aspect of small-scale interaction: the strength of dyadic ties. It is argued that the degree of overlap of two individuals' friendship networks varies directly with the strength of their tie to one another. The impact of this principle on diffusion of influence and information, mobility opportunity, and community organization is explored. Stress is laid on the cohesive power of weak ties. Most network models deal, implicitly, with strong ties, thus confining their applicability to small, well-defined groups. Emphasis on weak ties lends itself to discussion of relations *between* groups and to analysis of segments of social structure not easily defined in terms of primary groups.

A fundamental weakness of current sociological theory is that it does not relate micro-level interactions to macro-level patterns in any convincing way. Large-scale statistical, as well as qualitative, studies offer a good deal of insight into such macro phenomena as social mobility, community organization, and political structure. At the micro level, a large and increasing body of data and theory offers useful and illuminating ideas about what transpires within the confines of the small group. But how interaction in small groups aggregates to form large-scale patterns eludes us in most cases.

I will argue, in this paper, that the analysis of processes in interpersonal networks provides the most fruitful micro-macro bridge. In one way or another, it is through these networks that small-scale interaction becomes translated into large-scale patterns and that these in turn feed back into

REPORT

SOCIAL NETWORKS

A causal test of the strength of weak ties

Karthik Rajkumar¹, Guillaume Saint-Jacques¹, Iavor Bojinov², Erik Brynjolfsson^{3,4}, Sinan Aral^{5*}

The authors analyzed data from multiple large-scale randomized experiments on LinkedIn's People You May Know algorithm, which recommends new connections to LinkedIn members, to test the extent to which weak ties increased job mobility in the world's largest professional social network. The experiments randomly varied the prevalence of weak ties in the networks of over 20 million people over a 5-year period, during which 2 billion new ties and 600,000 new jobs were created. The results provided experimental causal evidence supporting the strength of weak ties and suggested three revisions to the theory. First, the strength of weak ties was nonlinear. Statistical analysis found an inverted U-shaped relationship between tie strength and job transmission such that weaker ties increased job transmission but only to a point, after which there were diminishing marginal returns to tie weakness. Second, weak ties measured by interaction intensity and the number of mutual connections displayed varying effects. Moderately weak ties (measured by mutual connections) and the weakest ties (measured by interaction intensity) created the most job mobility. Third, the strength of weak ties varied by industry. Whereas weak ties increased job mobility in more digital industries, strong ties increased job mobility in less digital industries.

The Strength of Weak Ties (1) is one of the most influential social theories of the past century, underpinning networked theories of information diffusion (2, 3).

social contagion (4, 5), social movements (6), individual behavior (7), social polarization (8), and human cooperation (9, 10). It argues that infrequent, arms-length relationships, like weak ties, provide access to new employment opportunities (11), promotions and greater wage increases (12), creativity (13), innovation (14, 15), productivity (16), and

work is not experimental the authors rightfully acknowledge that their results "may not be the true causal effect of tie strength on the probability of a sequential job." More generally,

two empirical challenges have prevented robust causal inference: (i) the lack of longitudinal data on individuals' social networks, and (ii) the lack of causal identification of the causal effect of weak ties on labor market outcomes. First, a lack of large-scale data linking human social networks to job transmission makes measurement of causal effects difficult. Second, network ties and labor market outcomes are endogenous, making the causal link between

invite from the ego, (iii) a model estimating the engagement between the ego and alter once connected and (iv) weights on each of these models for relative importance. The experiments tuned these components, introduced new data sources, and relied on the number of mutual connections between the ego and a potential tie recommendation as one of the most important features of the ensemble model to randomly vary weak and strong tie recommendations. We performed a retrospective analysis of the randomization created by the PYMK experiments conducted by LinkedIn between 2015 and 2019 in two waves.

The first wave examined a global experiment conducted in 2015 that had over 4 million experimental subjects and created over 19 million new connections. We collected edge-level observations of tie strength and job transmission outcomes for each tie created during this experiment. We then analyzed a larger second wave of node-level PYMK experiments that took place worldwide in 2019. The second wave spanned every continent and US state, had more than 16 million experimental subjects, created ~2 billion new connections and recorded more than 70 million job applications that led to 600,000 new jobs during the

experimental period (Fig. 1, B and C). The data are from PYMK, the LinkedIn PYMK dataset, where each observation corresponds to a unique LinkedIn member, and at the edge level, to a unique tie between two LinkedIn members (see Materials and Methods for a description of how we compiled the edge- and node-level datasets).

We analyzed labor market mobility by measuring both job applications and job transmissions. Job applications are simply the number of jobs LinkedIn members applied to on the platform in the three months after an experiment. In accordance with the litera-

"Relatively weak social ties on LinkedIn proved twice as effective in securing employment as stronger social ties." – New York Times

performance (17) because they deliver more novel information than strong ties. Weak ties are thought to provide access to diverse, novel information because they connect us to disparate and diverse parts of the human social network (18–24). In addition to productivity

weak ties and job placement elusive. Individuals' labor market outcomes are likely to be determined by and to simultaneously determine their social networks. The evolution of social networks and job trajectories are also likely correlated with unobserved factors such

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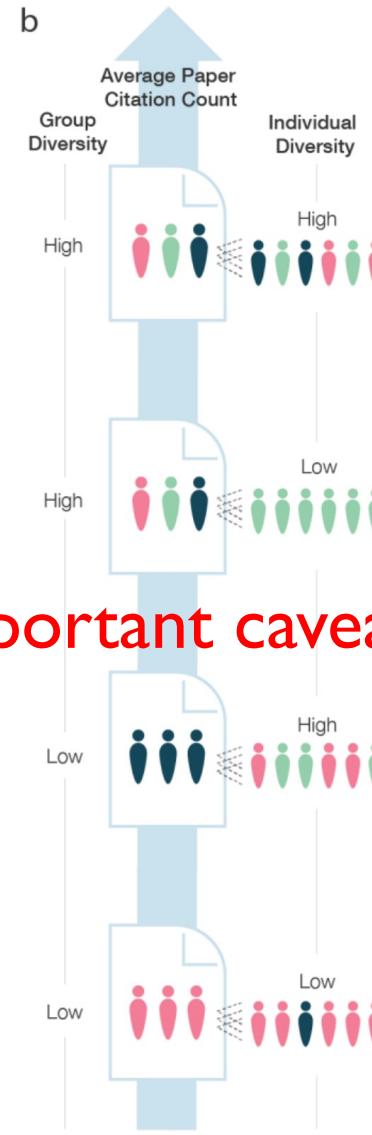
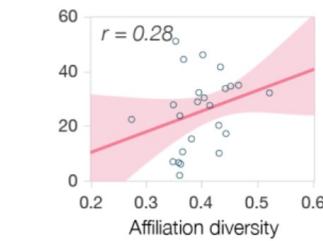
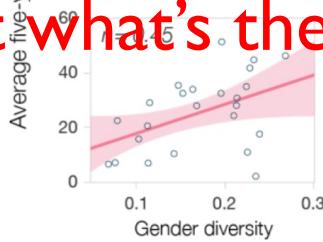
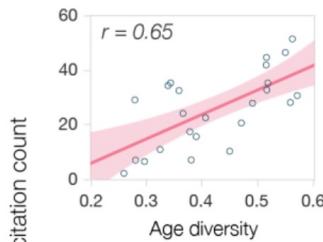
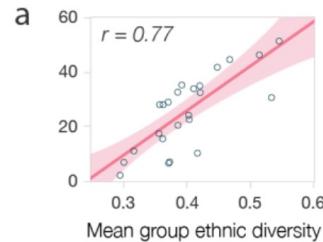
The Science of Collaboration

Chapter III: Team Assembly

Discussion Points

Models...

... and “reality”



But what's the important caveat?!

Figure 2.4.1 Team diversity and scientific impact. Panel a: an analysis of more than 1 million papers in 24 academic subfields (circles) shows that ethnic diversity correlates more strongly (r) with citation counts than do diversity in age, gender or affiliation. Panel b: Comparing team versus individual diversity reveals that diversity within the list of authors on a paper (team diversity) has a stronger effect on citation count than diversity in a researcher's network of collaborators (individual diversity). After Powell [58].

Simple (newcomer, incumbent) model

Incumbency parameter p : fraction of incumbents in a team.

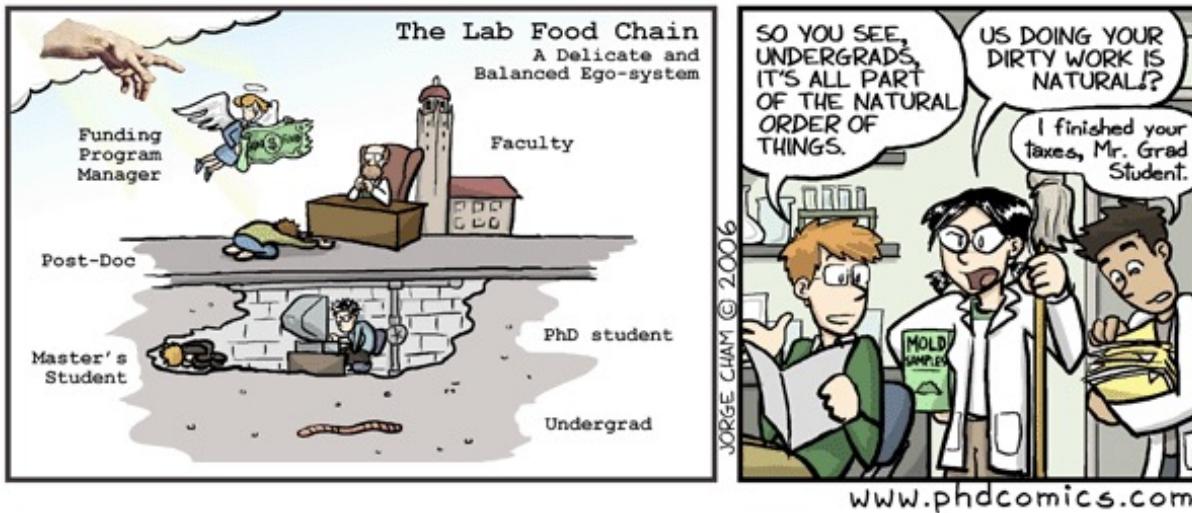
Diversity parameter q : probability incumbents collaborate with prior collaborators. (Higher q means more previous collaborators)

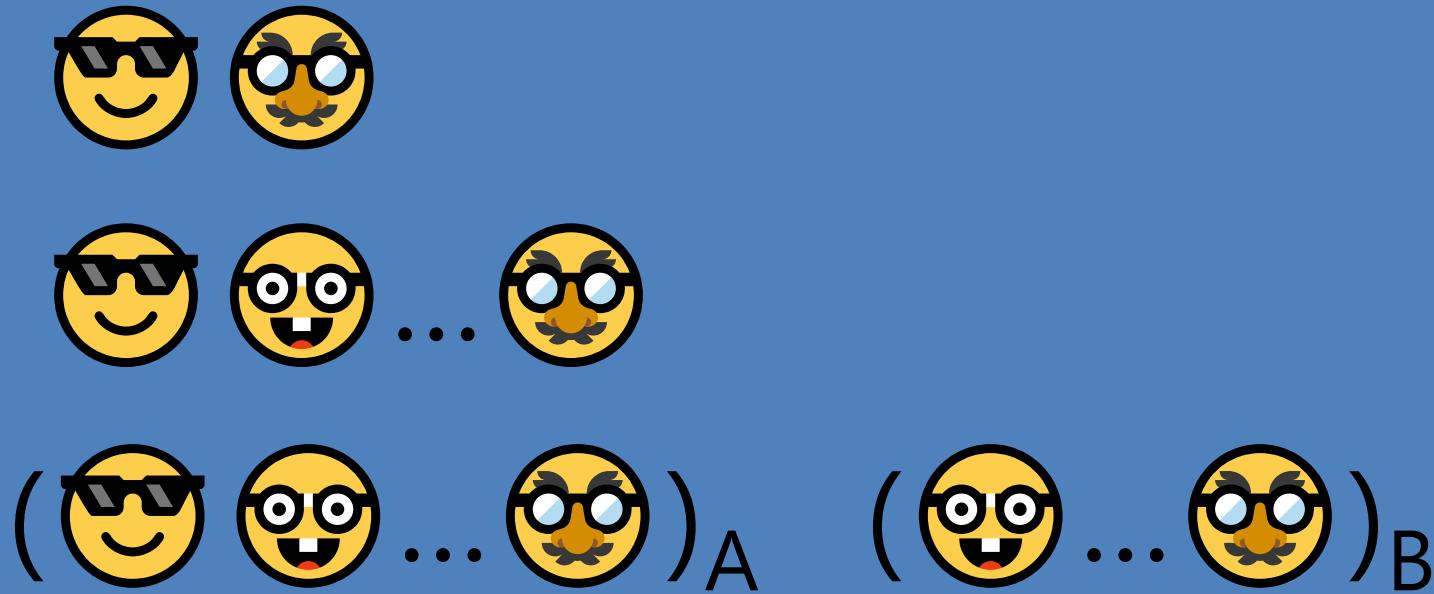
How do we use this model?

Finding: Journal impact positively correlates with p ,
negatively correlates with q .

Takeaways?

... but how does it apply to me?







(...)_A _B

()_A (...)_B

(...)_A (...)_B



A



B

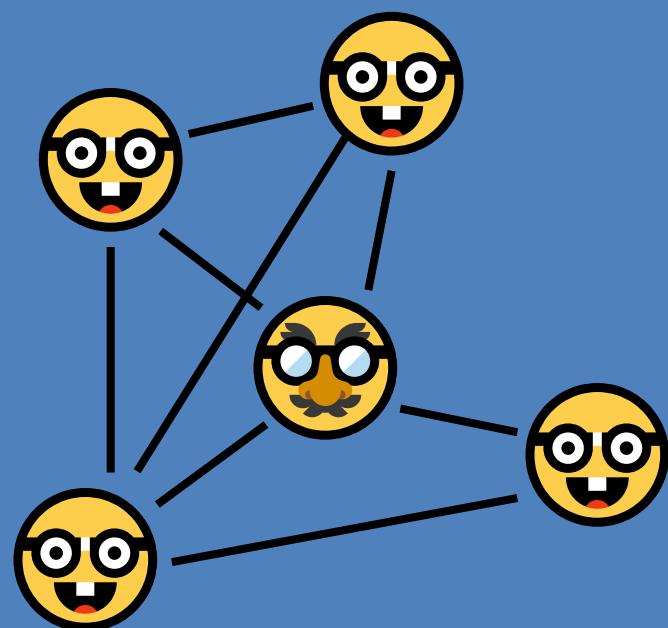
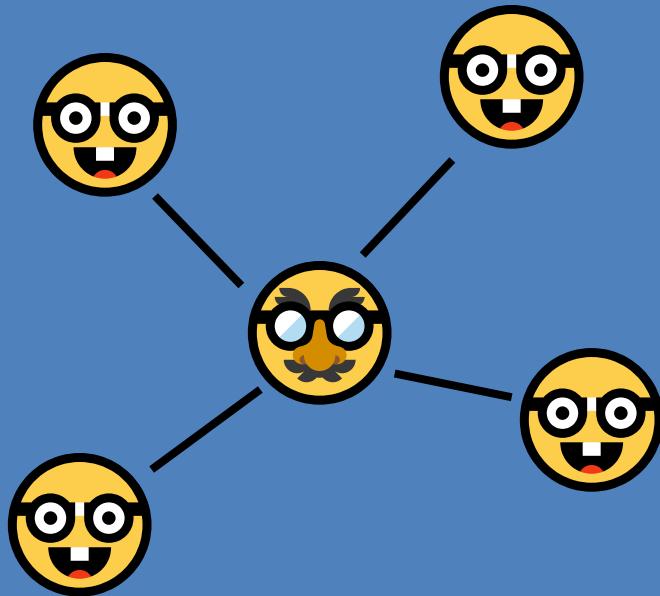


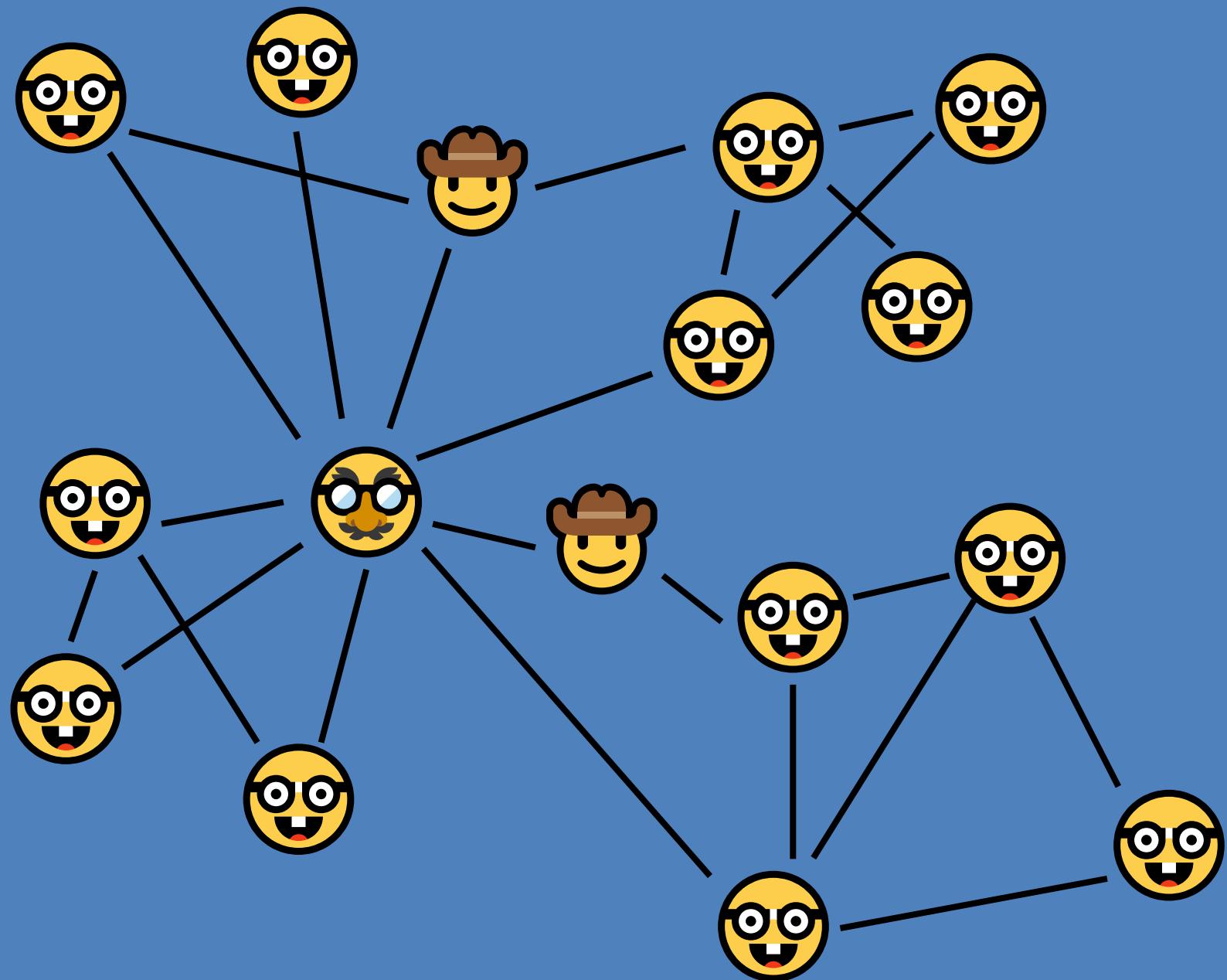
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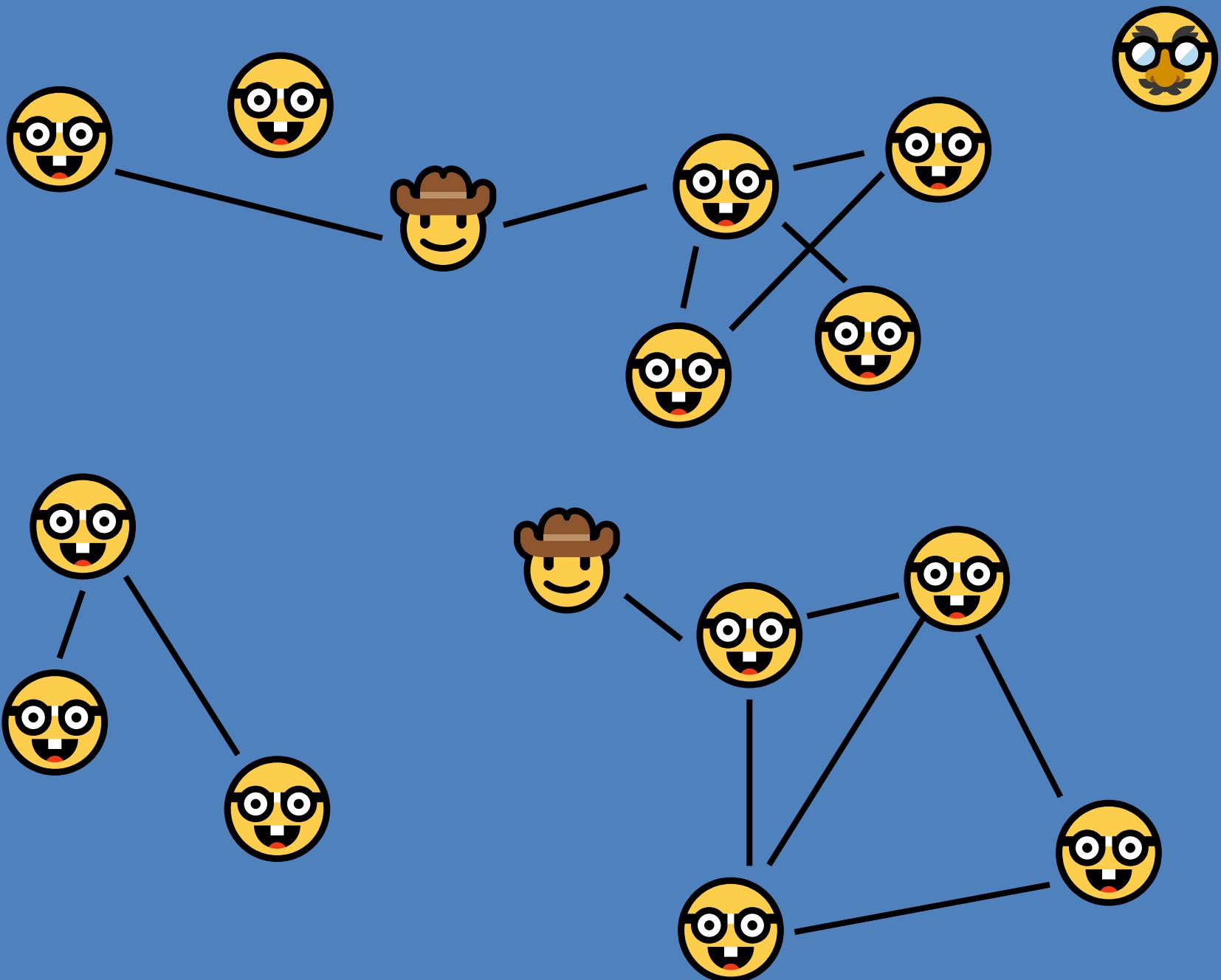


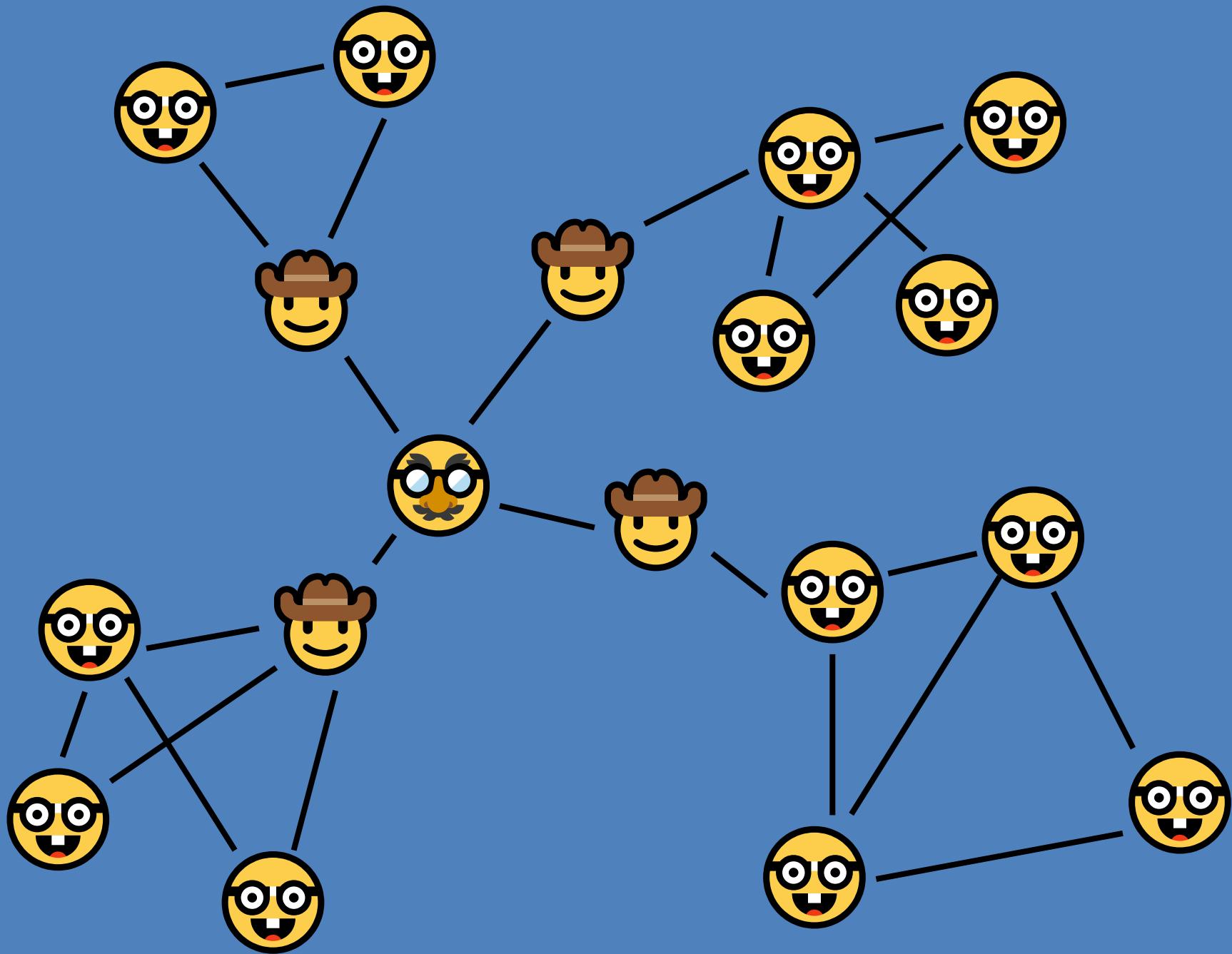
B

Same organization?
Industry vs. Academia?
Experience?
Complementary?









How does teams *really* form?

Source: student vs. advisor
Actual mechanisms?

What should you do?

Shockley's Model

$N \sim p_1 p_2 p_3 p_4 p_5 p_6 p_7 p_8$

- F₁. Identify a good problem
- F₂. Make progress with it
- F₃. Recognize a worthwhile result
- F₄. Decide when to stop the research and start writing up the results
- F₅. Write adequately
- F₆. Profit constructively from criticism
- F₇. Show determination to submit the paper for publication
- F₈. Make changes if required by the journal or the referees

tl;dr – my advice:

Seek homogeneity to share workload

Seek complementarity for everything else

Important: let your advisor know!

“The Science of Science”, Part II

The Science of Collaboration

Chapter 12: Small and Large Teams

Discussion Points

Why are teams growing in size?

Top-down vs. Bottom-up

Who determines what research gets done?

“The Science of Science”, Part II

The Science of Collaboration

Chapter 13: Scientific Credit
Chapter 14: Credit Allocation

Discussion Points

Normative vs. Positive

Understanding norms

Practical advice

Who gets credit?
Who *should* get credit?
Who *actually* gets credit?

Is it fair?

a VOLUME 76, NUMBER 11

PHYSICAL REVIEW LETTERS

11 MARCH 1996

Generation of Nonclassical Motional States of a Trapped Atom

D. M. Meekhof, C. Monroe, B. E. King, W. M. Itano, and D. J. Wineland

Time and Frequency Division, National Institute of Standards and Technology, Boulder, Colorado 80303-3328



b VOLUME 55, NUMBER 1

PHYSICAL REVIEW LETTERS

1 JULY 1985

**Three-Dimensional Viscous Confinement and Cooling of Atoms
by Resonance Radiation Pressure**

Steven Chu, L. Hollberg, J. E. Bjorkholm, Alex Cable, and A. Ashkin

AT&T Bell Laboratories, Holmdel, New Jersey 07733



c VOLUME 61, NUMBER 21

PHYSICAL REVIEW LETTERS

21 NOVEMBER 1988

Giant Magnetoresistance of (001) Fe/(001) Cr Magnetic Superlattices

M. N. Baibich, ^(a) J. M. Broto, A. Fert, F. Nguyen Van Dau, and F. Petroff

Laboratoire de Physique des Solides, Université Paris-Sud, F-91405 Orsay, France

P. Eitenne, G. Creuzet, A. Friederich, and J. Chazelas

Laboratoire Central de Recherches, Thomson CSF, B.P. 10, F-91401 Orsay, France



Figure 2.6.1 **Who gets the Nobel?** (A) The last author, David J. Wineland was awarded the 2012 Nobel Prize in Physics for his contribution to quantum computing. (B) Steven Chu, the first author, won the 1997 Nobel in Physics for the paper focusing on the cooling and trapping of atoms with laser light. (C) In 2007, Albert Fert, the middle author of the paper, received the Nobel Prize in Physics for the discovery of the giant magnetoresistance effect (GMR). All three examples are prize-winning papers published in the same journal, *Physical Review Letters*, demonstrating the ambiguity of allocating credit by simply reading the byline of a paper.

AlphaFold developers win US\$3-million Breakthrough Prize

DeepMind's system for predicting the 3D structure of proteins is among five recipients of science's most lucrative awards.

[Zeeya Merali](#)



Demis Hassabis (left) and John Jumper (right) from DeepMind developed AlphaFold, an AI that can predict the structure of proteins. Credit: Breakthrough Prize

The researchers behind the AlphaFold artificial-intelligence (AI) system have won one of this year's US\$3-million Breakthrough prizes – the most lucrative awards in science. Demis Hassabis and John Jumper, both at DeepMind in London, were recognized for creating the tool that has predicted the 3D structures of almost every known protein on the planet.



Dan Roy
@roydanroy

...

I was curious how AlphaFold was honored by the breakthrough prize to two individuals. I went back to one of the Nature papers to look at the author contributions. Curious what people see that could justify two people being named.

9:35 PM · Sep 23, 2022 · Twitter Web App

<https://twitter.com/roydanroy/status/1573486328502689827>

Improved protein structure prediction using potentials from deep learning

[Andrew W. Senior](#) [Richard Evans](#), [John Jumper](#), [James Kirkpatrick](#), [Laurent Sifre](#), [Tim Green](#), [Chongli Qin](#), [Augustin Žídek](#), [Alexander W. R. Nelson](#), [Alex Bridgland](#), [Hugo Penedones](#), [Stig Petersen](#), [Karen Simonyan](#), [Steve Crossan](#), [Pushmeet Kohli](#), [David T. Jones](#), [David Silver](#), [Koray Kavukcuoglu](#) & [Demis Hassabis](#)

[Nature](#) **577**, 706–710 (2020) | [Cite this article](#)

Contributions

R.E., J.J., J.K., L.S., A.W.S., C.Q., T.G., A.Ž., A.B., H.P. and K.S. designed and built the AlphaFold system with advice from D.S., K.K. and D.H. D.T.J. provided advice and guidance on protein structure prediction methodology. S.P. contributed to software engineering. S.C., A.W.R.N., K.K. and D.H. managed the project. J.K., A.W.S., T.G., A.Ž., A.B., R.E., P.K. and J.J. analysed the CASP results for the paper. A.W.S. and J.K. wrote the paper with contributions from J.J., R.E., L.S., T.G., A.B., A.Ž., D.T.J., P.K., K.K. and D.H. A.W.S. led the team.

Corresponding author

Correspondence to [Andrew W. Senior](#).

THE AUTHOR LIST: GIVING CREDIT WHERE CREDIT IS DUE

The first author

Senior grad student on the project. Made the figures.

Michaels, C., Lee, E. F., Sap, P. S., Nichols, S. T., Oliveira, L., Smith, B. S.

The third author

First year student who actually did the experiments, performed the analysis and wrote the whole paper. Thinks being third author is "fair".

The second-to-last author

Ambitious assistant professor or post-doc who instigated the paper.

The second author

Grad student in the lab that has nothing to do with this project, but was included because he/she hung around the group meetings (usually for the food).

The middle authors

Author names nobody really reads. Reserved for undergrads and technical staff.

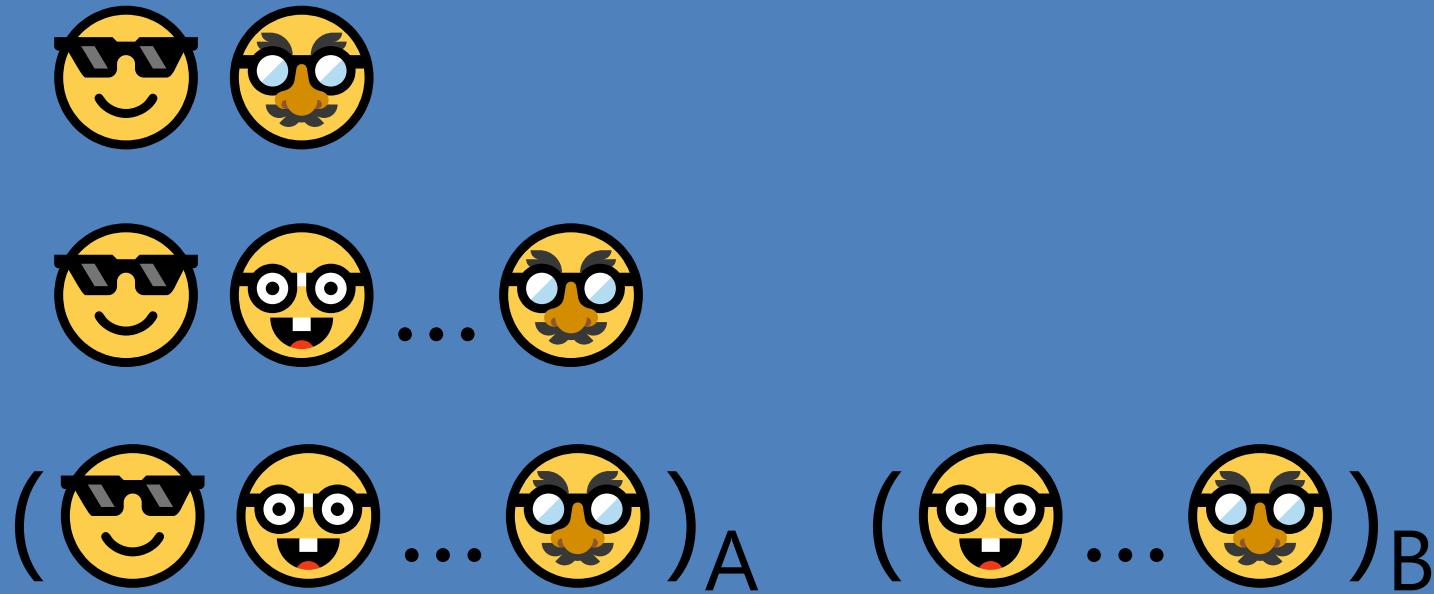
The last author

The head honcho. Hasn't even read the paper but, hey, he/she got the funding, and their famous name will get the paper accepted.

Ordering of Authors

Field-specific norms (alphabetical vs. contribution-based)
You (as a student) have very limited control

Important first step: understand what the norms are!





(...) _A _B

()_A (...) _B

(...) _A (...) _B



_A



_B

Practical Advice

Determine coauthorship (and ordering) early.

Don't forget to communicate with non-coauthors.

(Personal view) Be generous with the middle author positions.

Who actually gets the credit? For the most part... your advisor 😞

Why?

How can you overcome it?

That's all for this week!