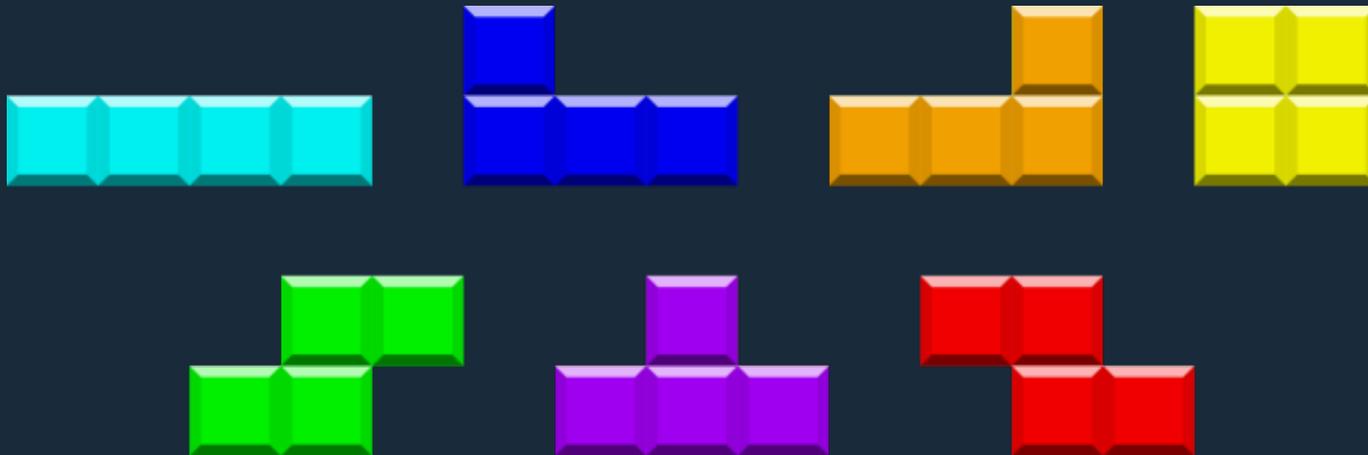


Wednesday, December 9.

Scientific Networks and Success

An (online) Satellite Workshop of CCS 2020

Successful Configurations — When Form Follows Function

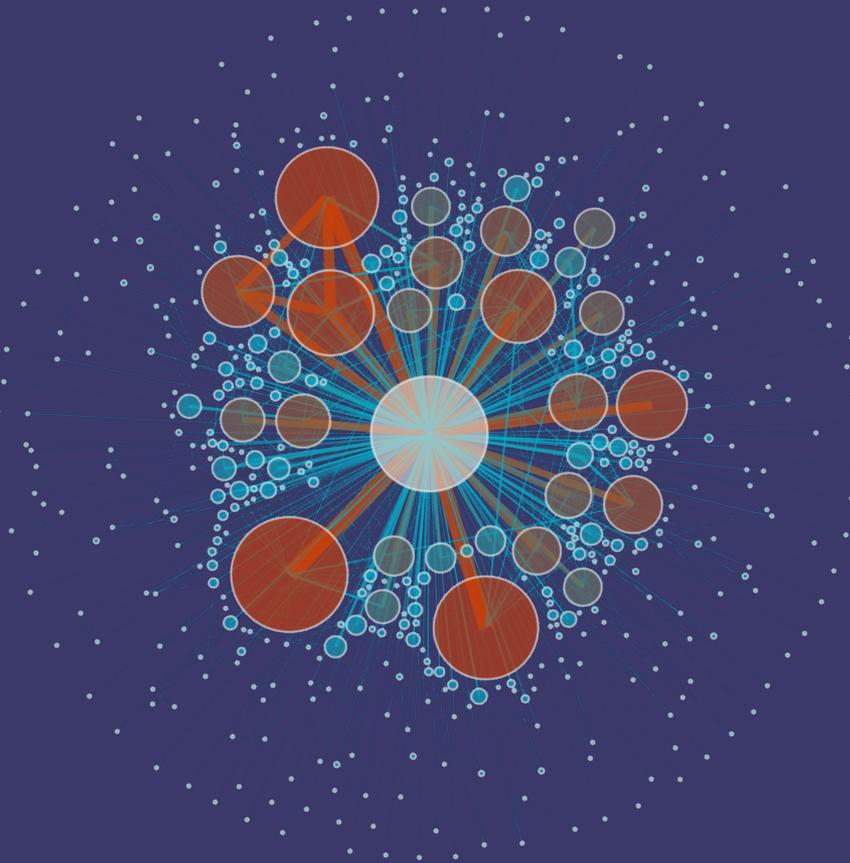


Dr. Alexander M. Petersen
Management of Complex Systems Department
Ernest & Gallo School of Management*

UNIVERSITY OF CALIFORNIA
MERCED

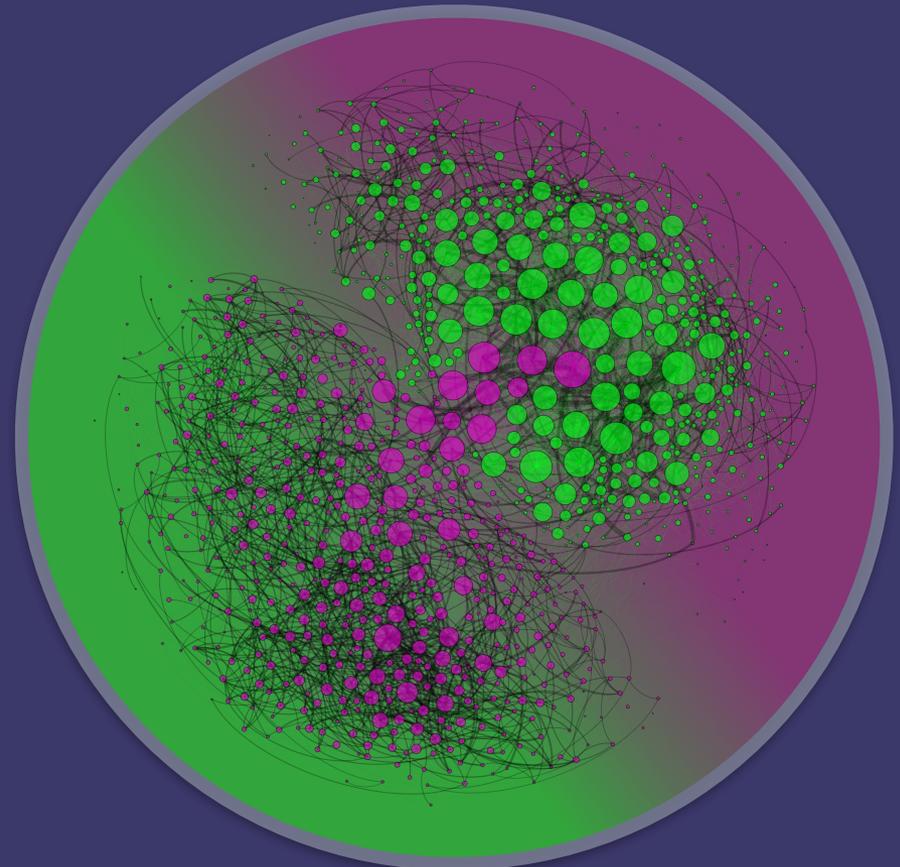
Quantifying the impact of “super ties” and cross-disciplinary configurations in scientific careers

Individual Collaboration Network
— Paul Erdős —



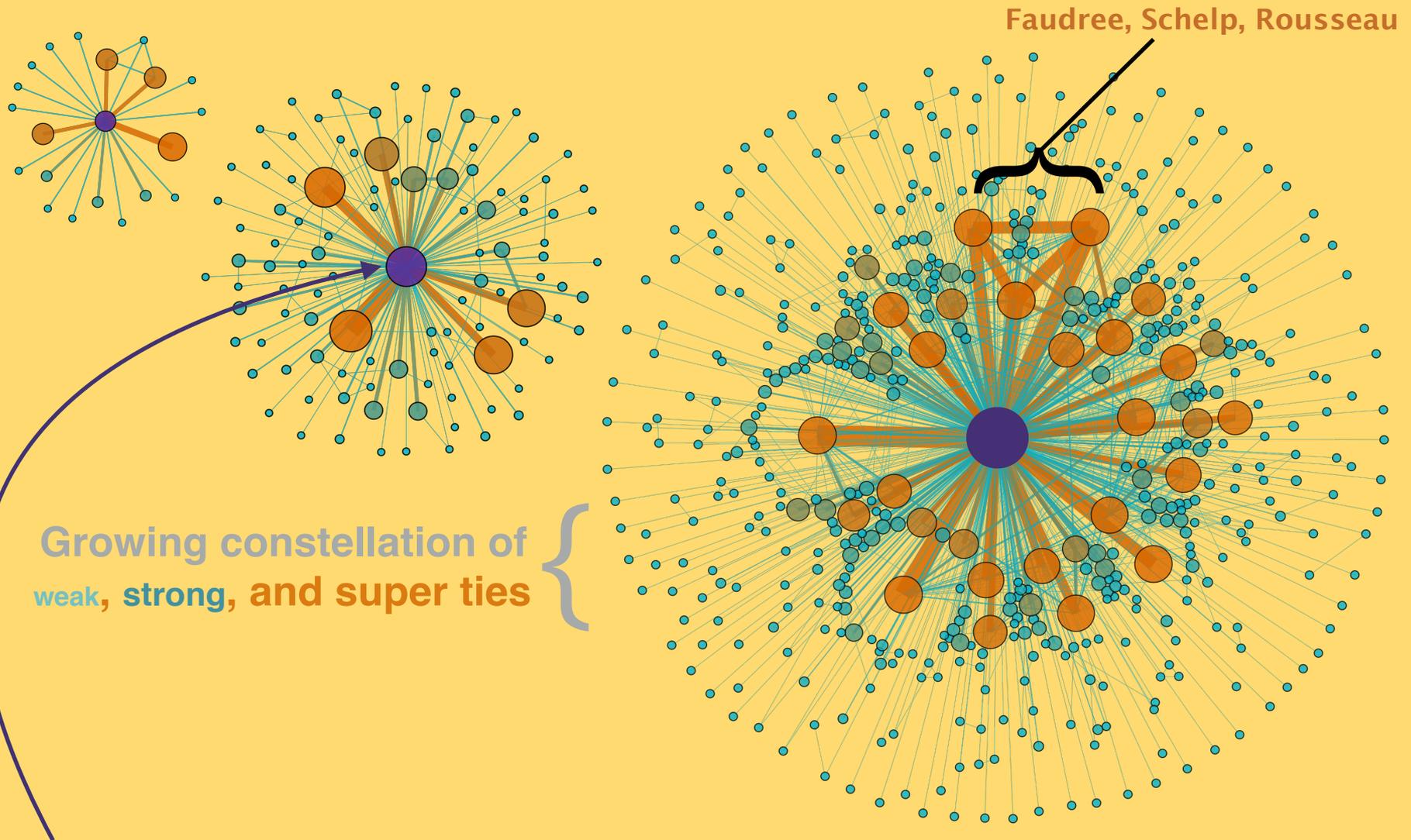
Part I

Cross-Disciplinary Collaboration Network
— Genomics Revolution —



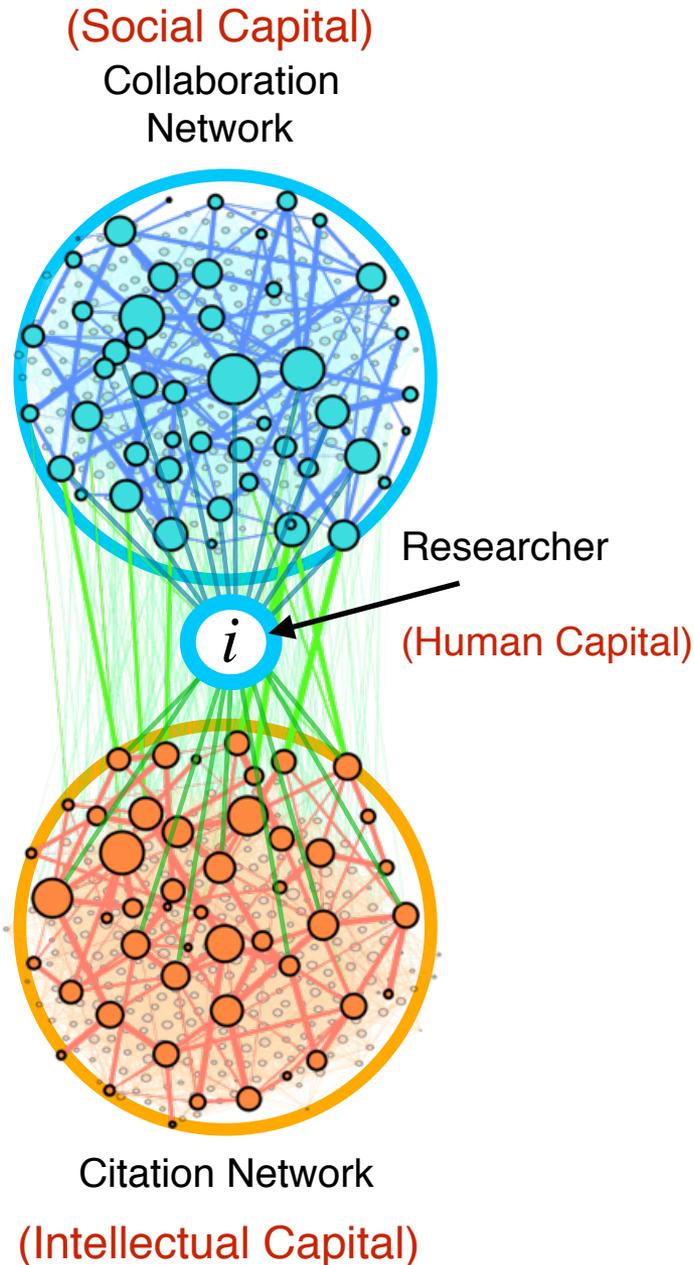
Part II

Part I – Quantifying the impact of weak, strong, and super ties in scientific careers – PNAS (2015)



Paul Erdős (1913-1996): collaboration network at career age 10, 30 years & present day*

Science careers are embedded in a co-evolving network of networks



coevolutionary system:

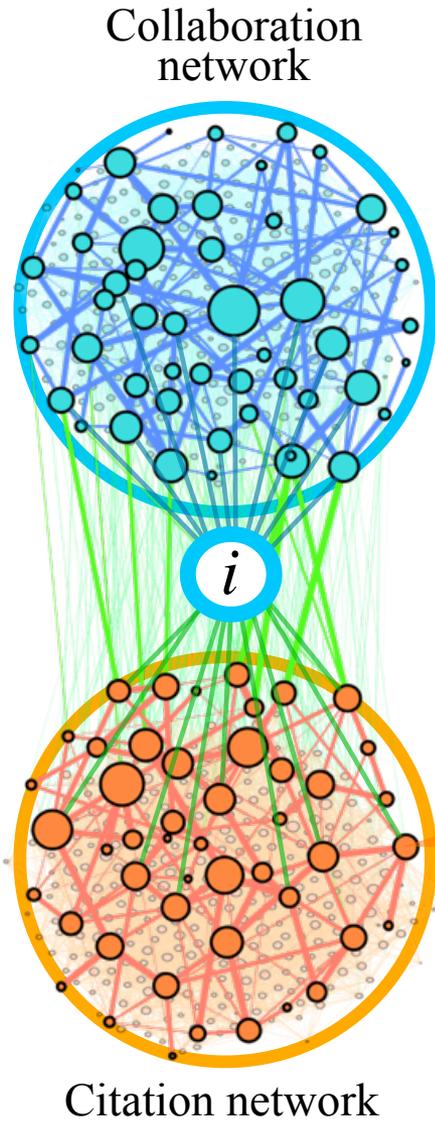
- knowledge
- institutions
- researchers

social phenomena:

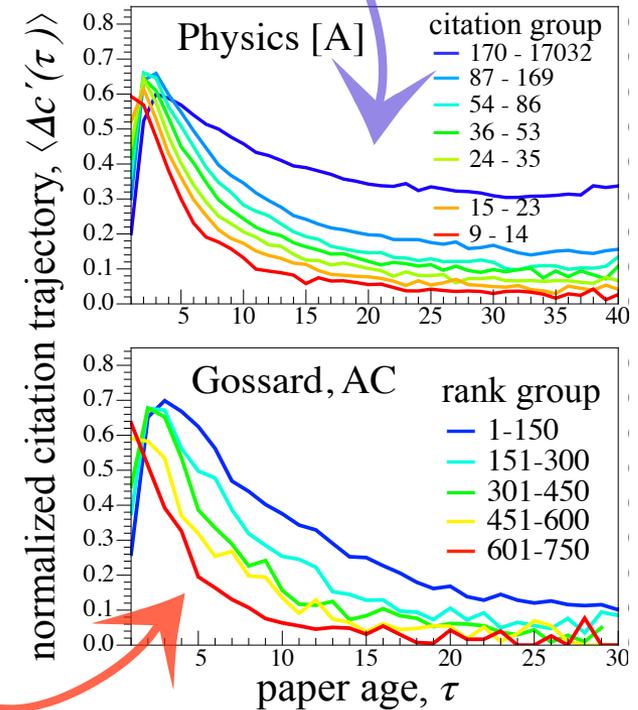
- behavioral aspects
- economic incentives
- cumulative advantage mechanisms
- collaboration / competition

Dynamic network characterized by life-cycles

Reputation and Impact in Academic Careers — PNAS (2014)



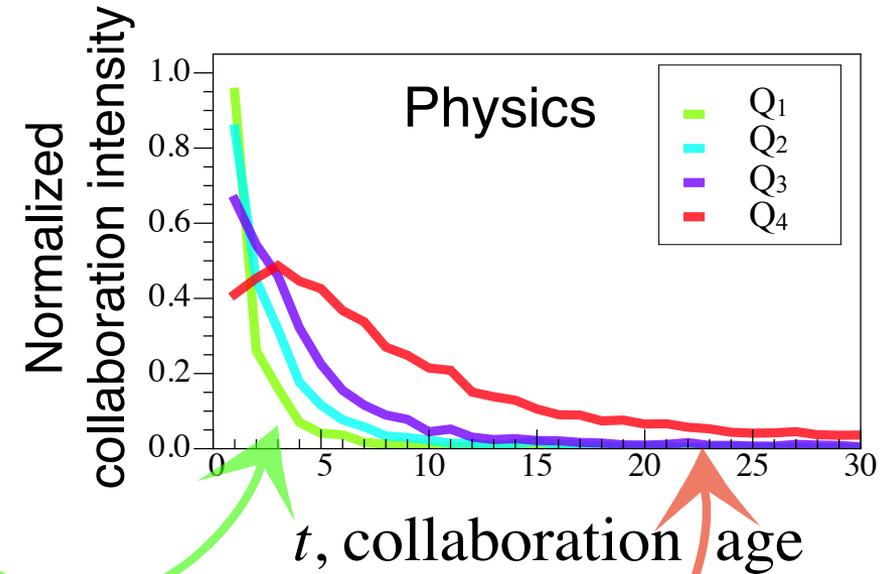
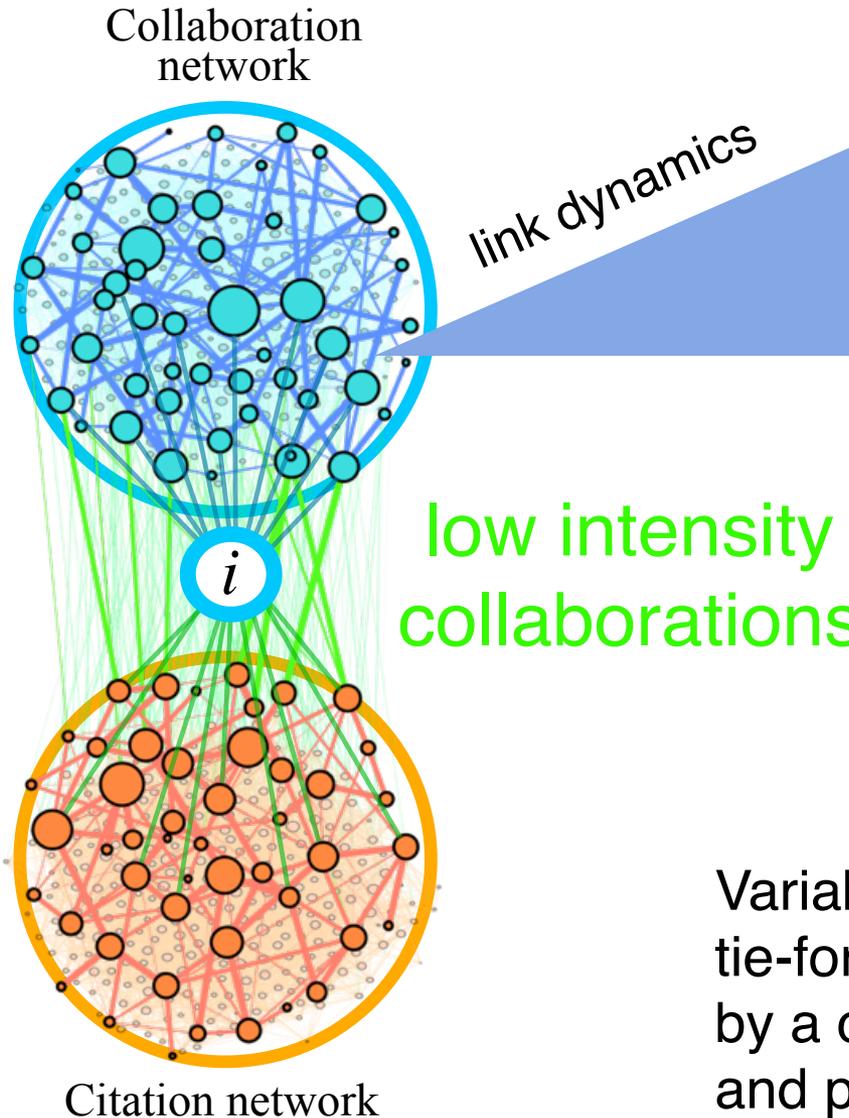
highest-cited publications



least-cited publications

Dynamic network characterized by life-cycles

Quantifying the impact of weak, strong, and super ties in scientific careers — PNAS (2015)



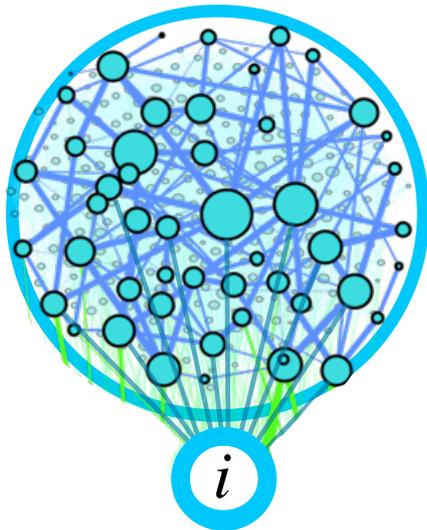
low intensity collaborations

high intensity collaborations

Variable collaboration life-cycles reveal tie-formation dynamics characterized by a complex dichotomy of burstiness and persistence.

An ego-centric perspective reveals a wide range of collaboration strategies

Collaboration network



central author i

Interactions mediated by social “forces”:

- Collaboration (attractive)
- Competition (repulsive)
- Knowledge (an “exchange particle”)

Binary-star strategy:

- * **Michael Stuart Brown**
- * **Joseph L. Goldstein**

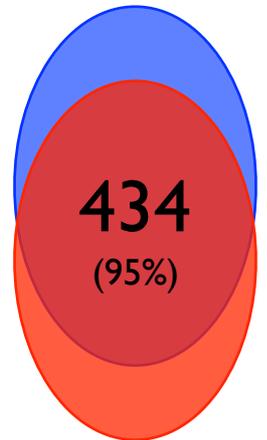
Recipients of the 1985 Nobel Prize in Physiology or Medicine for describing the regulation of cholesterol metabolism.

Solo-artist strategy:

- * **Marilyn Kozak** (also cell biologist)

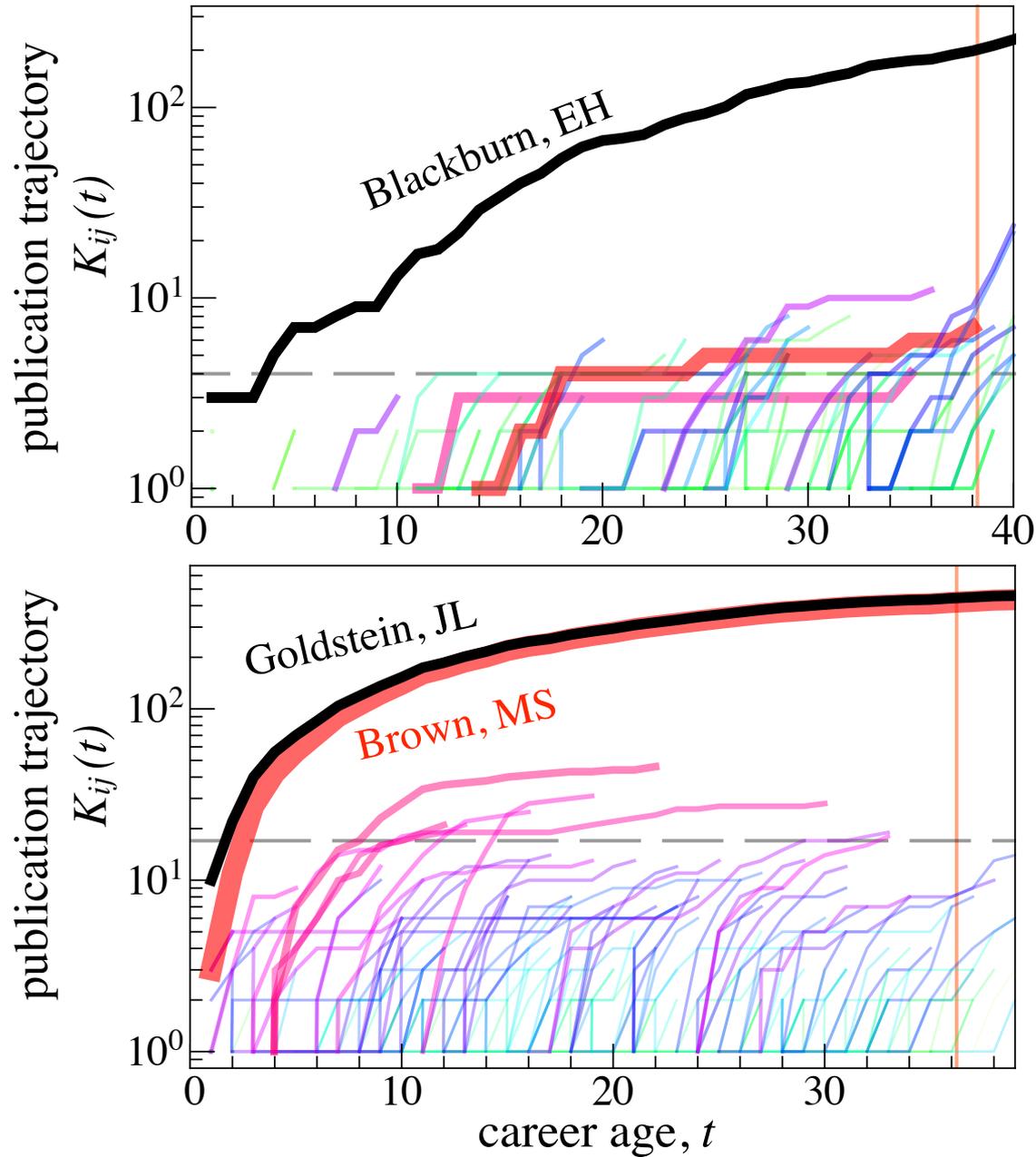
$N = 70, N_{\text{solo}} = 59$

451 publications



458 publications

Wide variation in the temporal collaboration profiles — even among Nobel Laureates —



Ego collaboration network: quantifying *dynamic & heterogenous* patterns of collaboration within scientific careers

Sir Andre K. Geim

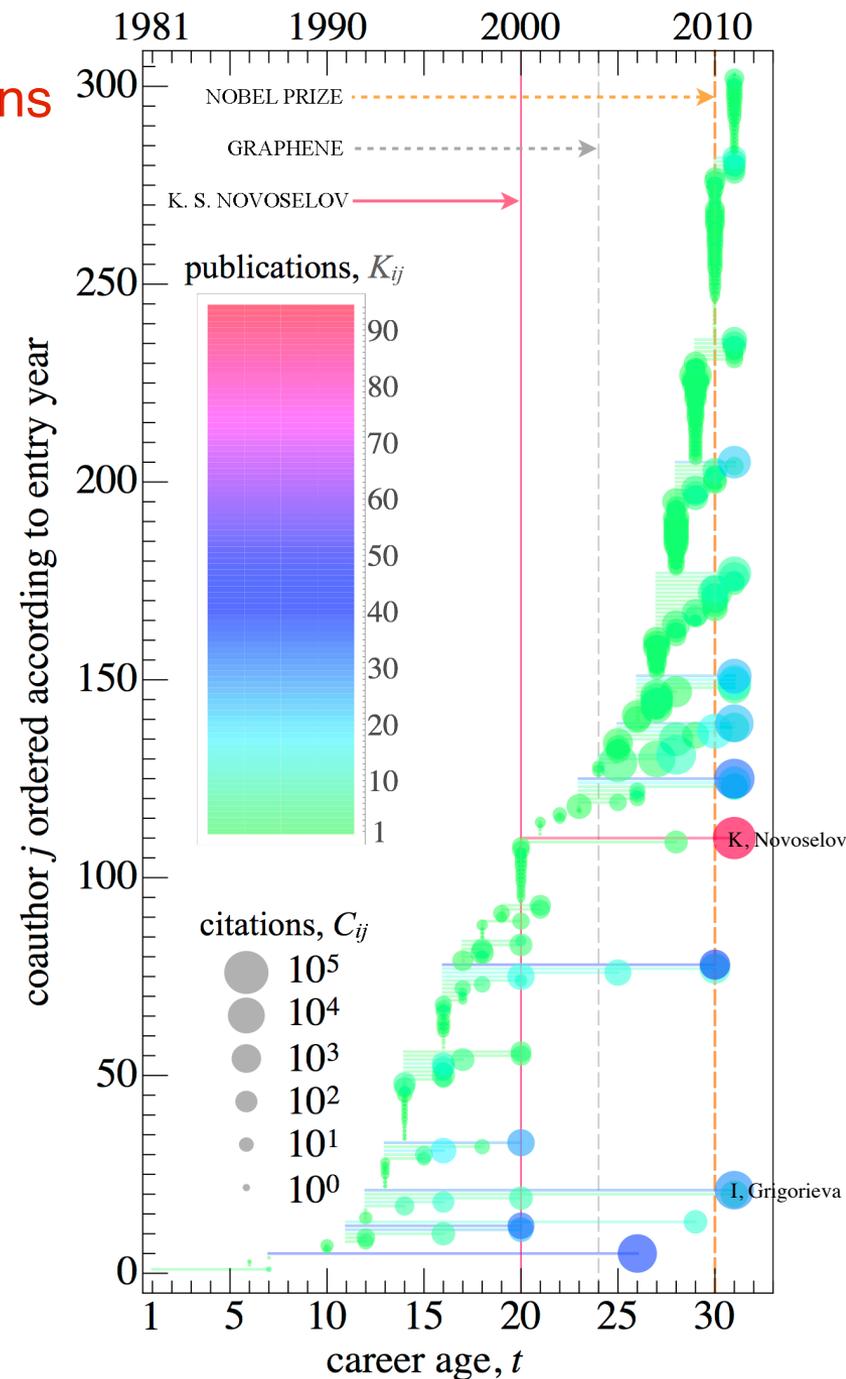
publications, $N_i(2012) = 217$

$S_i = 303$ coauthors

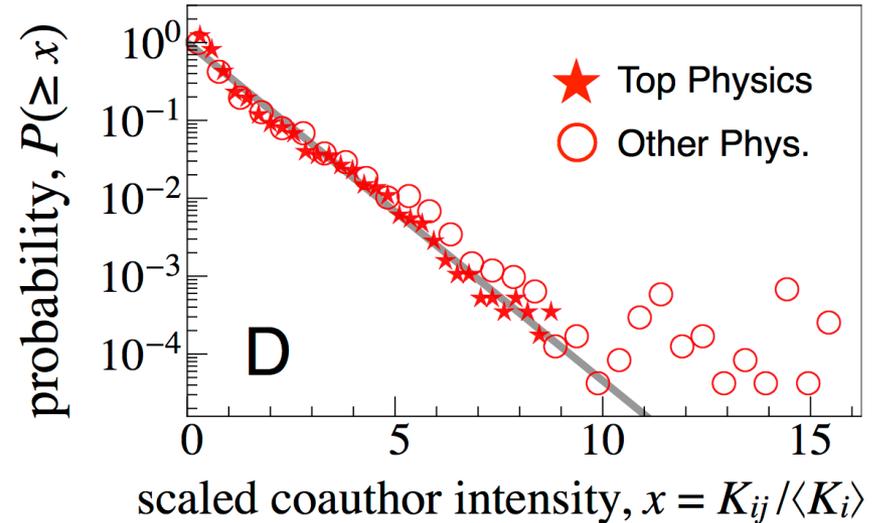
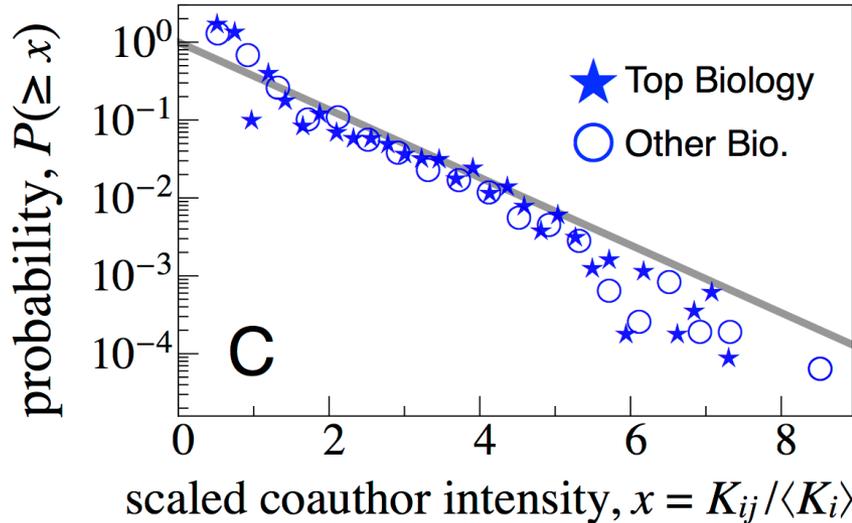
The average copublication duration

$\langle L_i \rangle = 2.1$ years, $\langle K_i \rangle = 3.7$ pubs.

- Measuring the duration L_{ij} of the tie (time b/w 1st and last copublication)
- Measuring the intensity K_{ij} of the tie (# of copublications)
- Measuring the net scientific impact C_{ij} of the tie (net citation tally for pubs. between i and j)



Is there a characteristic collaboration intensity scale?



In order to aggregate across careers with varying coauthorship patterns, we use the normalized variable $x = K_{ij}/\langle K_i \rangle$

$P(\geq x)$ is well-described by an exponential distribution, for which there is a closed-form solution to the extreme value equation:

$$1/S_i = \sum_{K_{ij} > K_i^c} P(K_{ij}) = \exp(-\kappa_i K_i^c)$$

which has the simple solution

$$\text{“super tie” threshold } K_i^c = (\langle K_i \rangle - 1) \text{Ln}(S_i)$$

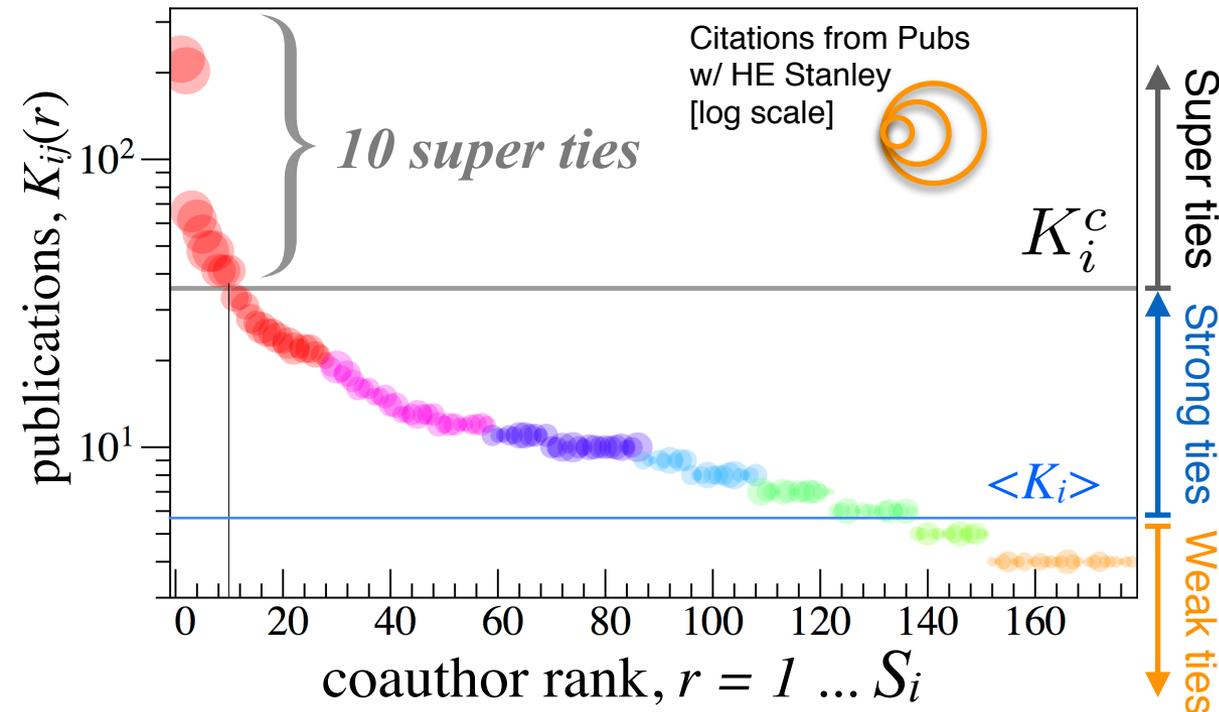
Weak ties, Strong ties, and Super ties

H. Eugene Stanley

$N_i(2010) = 909$ publications

$S_i = 541$ coauthors

$\langle K_i \rangle = 6.7$ papers



rank		K_{ij}	%
1	HAVLIN, S	223	25
2	BULDYREV, SV	203	22
3	AMARAL, LAN	66	7
4	SCIORTINO, F	62	6
5	IVANOV, PC	55	5
6	GOLDBERGER, AL	48	
7	PENG, CK	48	
8	GOPIKRISHNAN, P	41	
9	PLEROU, V	41	
10	STARR, FW	41	
11	DOKHOLYAN, NV	33	4
12	PAUL, G	33	
13	BUNDE, A	31	3
14	GIOVAMBATTISTA, N	28	
15	MAKSE, HA	27	
16	CONIGLIO, A	26	
17	URBANC, B	25	
18	CRUZ, L	25	
19	SCALA, A	24	
20	LARRALDE, H	23	
21	MANTEGNA, RN	23	
22	POOLE, PH	22	2

Extreme outlier based upon the exponential distribution:

“super tie” threshold $K_i^c = (\langle K_i \rangle - 1) \ln(S_i)$

Data & Measures

Data from Clarivate Analytics Web of Science: 473 researcher profiles spanning more than 15,000 career years, 94,000 publications, and 166,000 collaborators.

Researcher Profiles: split into 4 groups: top-cited biology, not top-cited biology, top-cited physics, and not top-cited physics

Collaboration Tie Measures

— Strength —

$$K_{ij}$$

Individual level: How strong/weak is the collaboration tie?

$$a_{i,p}, \bar{a}_{i,t}$$

Team level: How big is the team?

$$G_{t,i}^K$$

Group level: How concentrated are the tie strengths?

— Duration —

$$\langle L_i \rangle$$

Individual career level: What is the characteristic collaboration length?

$$\bar{L}_{i,t}$$

Team level: What is the team's experience together?

Is there a citation advantage associated with Super Ties?

Unit of analysis : publication p

Hierarchical “fixed effects” model : 473 researchers indexed by i

Dependent variable = $z_{i,p}$ = the citation impact $c_{i,p,y}$ of publication p normalized to baseline citation levels defined by other papers published in the same year y .

On average:

- 1 in 25 collaborators qualify as a super-tie
- 1 in 2 publications include a super-tie

$$z_{i,p} = \frac{(\ln c_{i,p,y} - \langle \ln c_y \rangle)}{\sigma[\ln c_y]}$$

This measure maps $c_{i,p,y}$ to a stable normal distribution $N(0,1)$ >> appropriate for comparing citation impact across time.

$R_{i,p}$

A super-tie indicator variable = 1 if at least one of the coauthors is a super tie, and 0 otherwise. 52% of publications have $R=1$.

$N_i(t_p)$

number of papers up to year t_p
 \approx prestige measure

$a_{i,p}$

number of coauthors \approx proxy for coordination costs and technology level

$S_i(t_p)$

number of distinct coauthors up to year t_p \approx collaboration radius measuring access to new/old team members

t_p

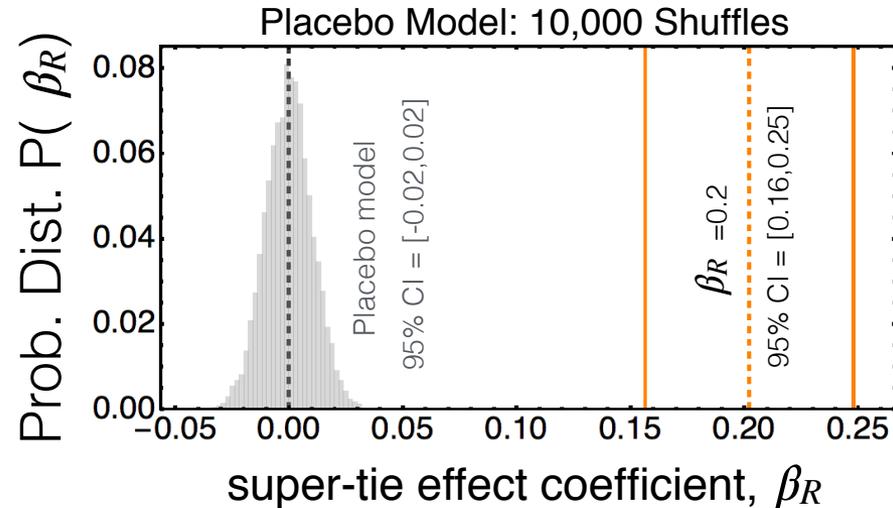
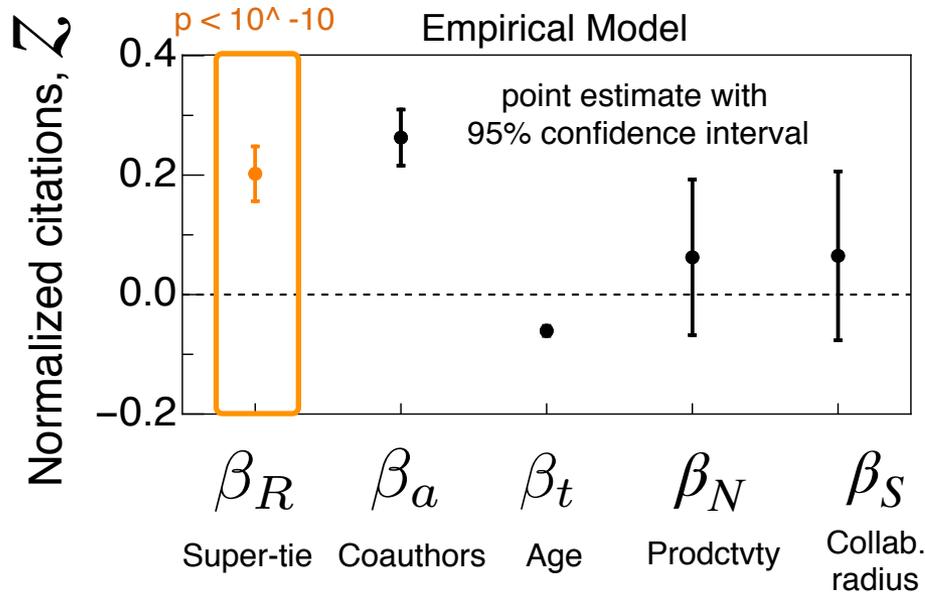
publication year of p , measured as a career age, accounting for aging and cumulative advantage effects, learning and prestige

Fixed-effects model - measures each researcher against his/her baseline $z_{i,p}$

$$z_{i,p} = \beta_R R_{i,p} + \beta_a \ln a_{i,p} + \beta_t t_{i,p} + \beta_N \ln N_i(t_p) + \beta_S \ln S_i(t_p) + \beta_i + \epsilon_{i,p}$$

Strategic value of high-intensity collaborations

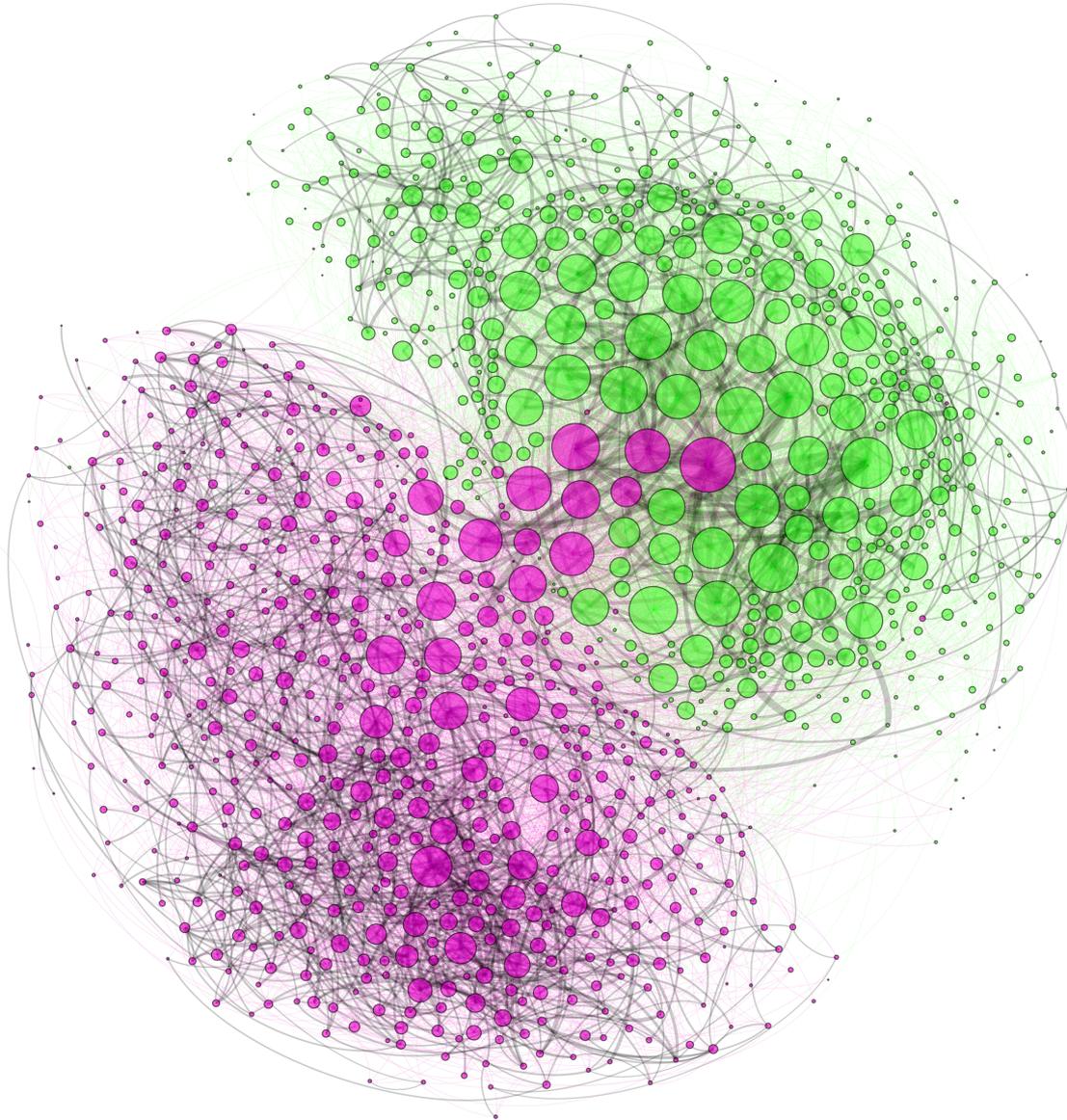
Emphasizes *who* in addition to *how many* coauthors



In terms of real citation impact: $100 \times 0.2 \sigma_z$ corresponds to $\sim 20\%$ citation increase at the publication level (relative to the author's own mean baseline)!

Plausible explanations: compounding self-citations, reputation arising from larger formal and informal social network; added value of skill complementarity, trust, conviction, commitment, experience, collocation, moral support, risk-profit sharing

Part II – Cross-disciplinary Evolution of the Genomics Revolution – Science Advances (2018)



Data & Methods: ~80 US Biology and Computing Departments faculty directories \Rightarrow List of Scholars

– we then collected data from their 4,190 Google Scholar profiles, comprising 413,565 publications

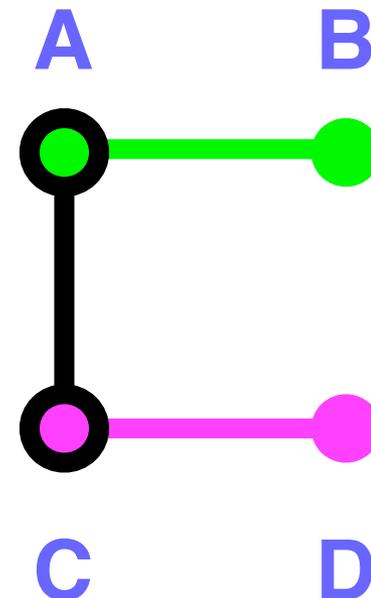
Author i	Coauthors	Department \mathcal{F}_i	Orientation $\mathcal{O}(\mathcal{F}_i)$
A	B,C	BIO	XD
B	A	BIO	BIO
C	A,D	CS	XD
D	C	CS	CS

— **Direct link:** publication between scholar i and j

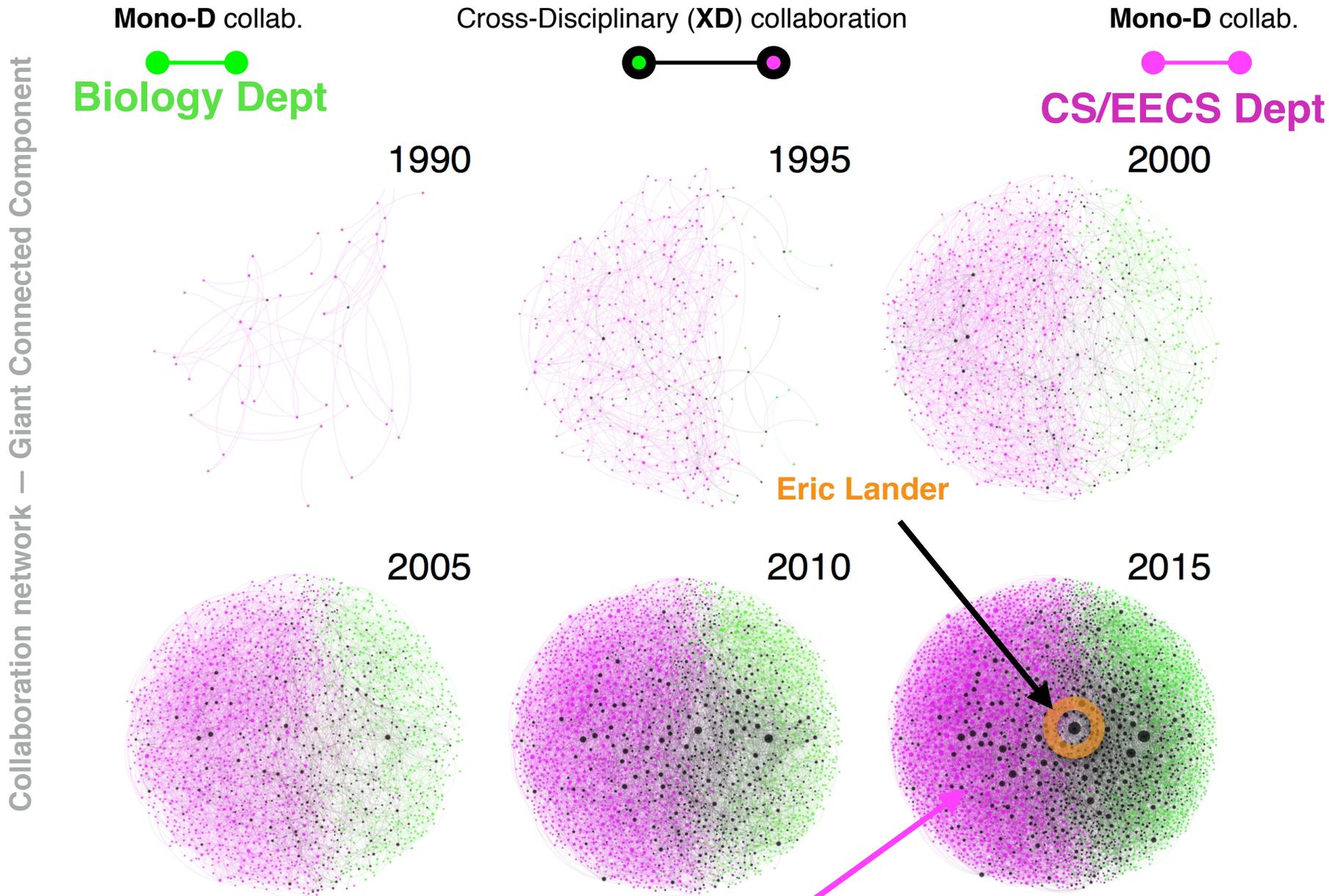
● Mono-Disc. scholar : $\mathcal{O}_i(\mathcal{F}) = \text{BIO}$

● Mono-Disc. scholar : $\mathcal{O}_i(\mathcal{F}) = \text{CS}$

● Cross-Disc. scholar : $\mathcal{O}_i(\mathcal{F}) = \mathcal{X}$

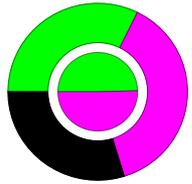


Longitudinal Case Study of the Genomics Revolution (HGP, 1990-2003)



Work in collaboration with **Professor Ioannis Pavlidis, Dept. of Computer Science** — University of Houston

Model 0



Cross-sectional
All Scholars

Model 1



Panel
All Scholars

Model 2



Panel
XD Scholars only

Model 3

● XD

● Mono-D (1D)

Panel

Matched publications
(XD Scholars only)

$$I_{i,p}^{\mathcal{X}} = 1$$

$$I_{i,p}^{\mathcal{X}} = 0$$

Matching procedure:
same author
~ same year
~ same # coauthors

Panel model specification:
(w/ Author Fixed Effects)
Unit of Analysis = **Publication**

Normalized
Citation impact

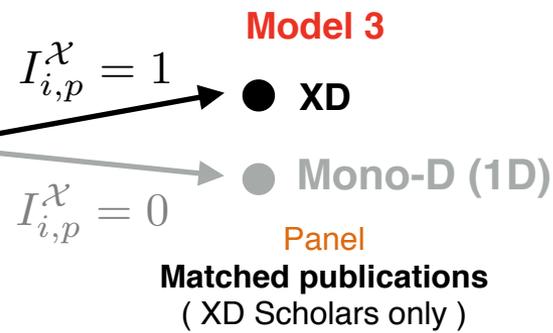
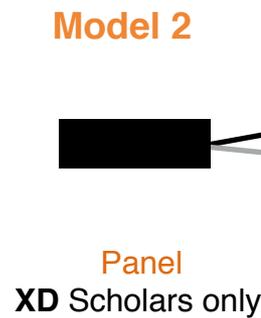
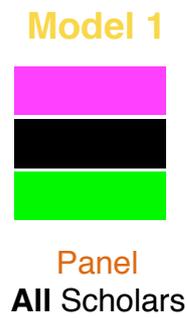
coauthors

Career year

XD indicator

Year dummy

$$z_{i,p} = \beta_i + \beta_a \ln a_{i,p} + \beta_{\tau} \tau_{i,p} + \beta_I I_{i,p}^{\mathcal{X}} + D_t + \epsilon_{i,p}$$



Matching procedure:
same author
~ same year
~ same # coauthors

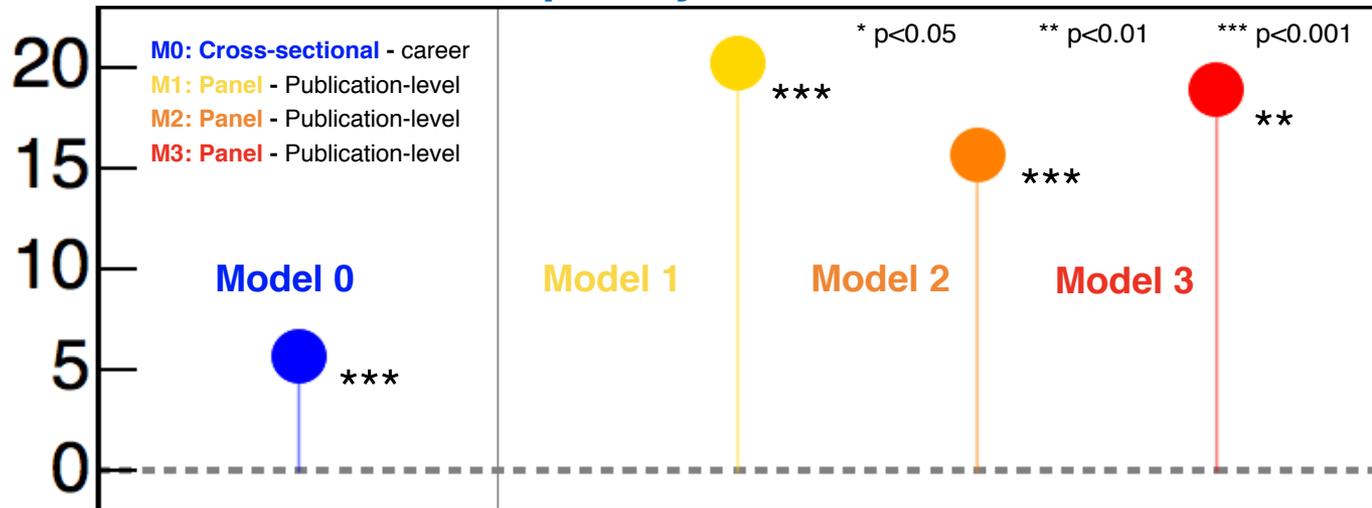
Panel model specification:
(w/ Author Fixed Effects)
Unit of Analysis = **Publication**

Normalized Citation impact # coauthors Career year XD indicator Year dummy

$$z_{i,p} = \beta_i + \beta_a \ln a_{i,p} + \beta_\tau \tau_{i,p} + \beta_I I_{i,p}^X + D_t + \epsilon_{i,p}$$

Cross-disciplinary Citation Premium

Percent difference (%) in citations for XD relative to baseline = 1D (counterfactual)



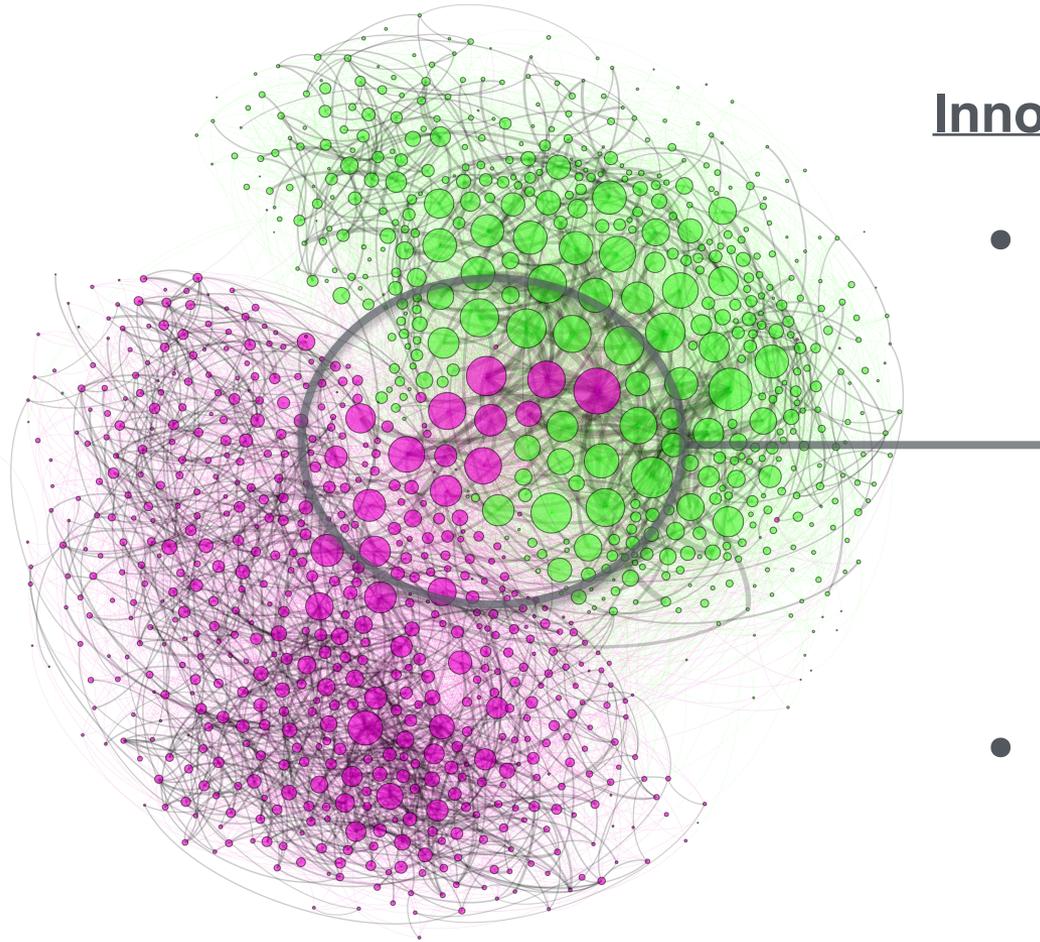
Coefficient estimates relation between:

$$\beta_X = \text{Career citations and Fraction of coauthors that are XD}$$

$$\beta_I = \text{Article citations and XD coauthors [coauthors from both BIO and CS, } I_{i,p}^X = 1 \text{]}$$

Scholars with 10% XD-Collaborators are cited ~ 6% more than 1D Scholars from the same discipline
Articles featuring cross-disciplinary combination of authors are cited ~20% more than 1D articles by same author

Biology Faculty



Innovation @ the genomics interface

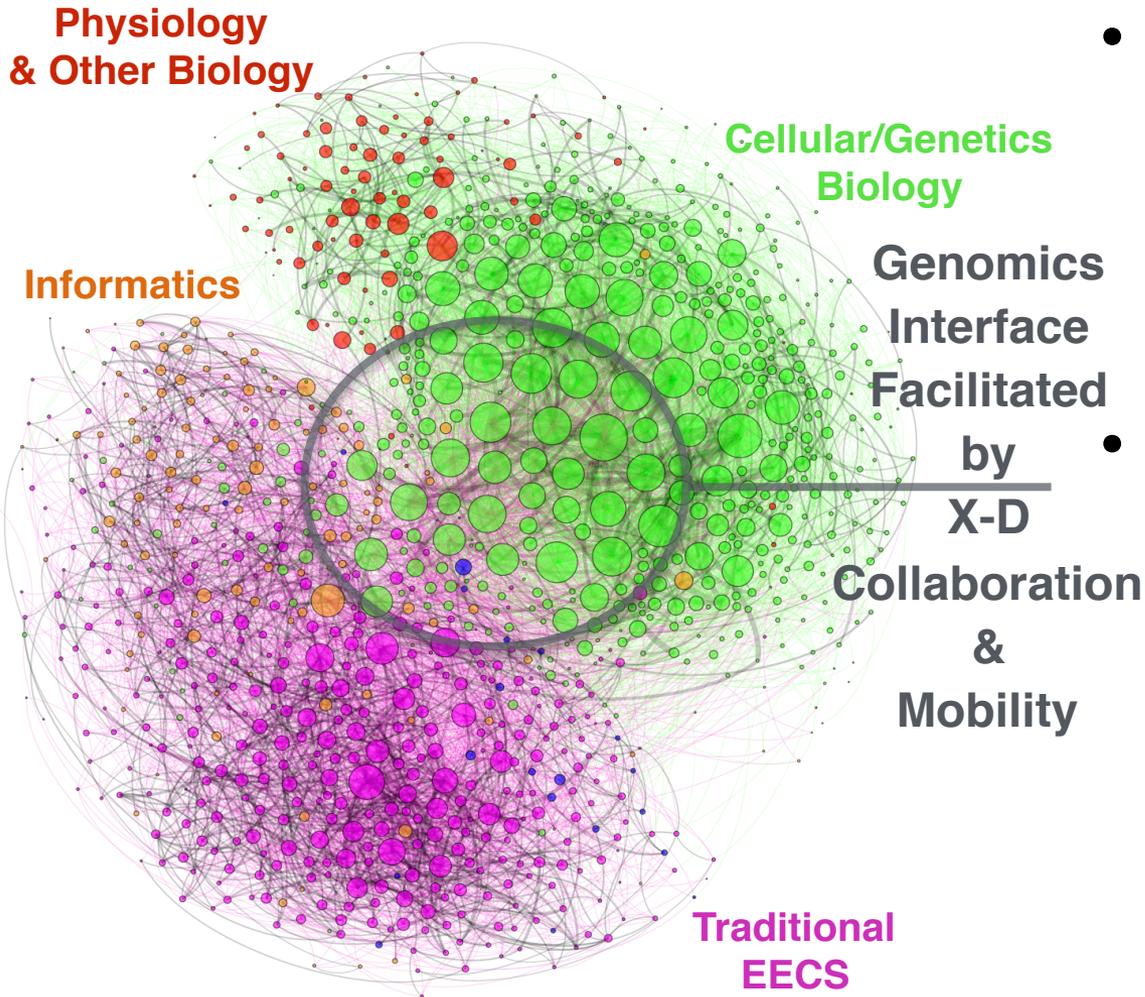
- **Success factors:**
 - Methodological diversity leveraging common language
 - Cultural assimilation: XD collaboration facilitates XD mobility of CS into elite BIO
- **Outcomes:**
 - Transformative research
 - Flagship program model
 - Consortium model — *teams of teams*

Computer Science Faculty

Disciplinary Propensity revealed by Scholar-Scholar interactions

Network community structure

Implications for Funding Policy/Design

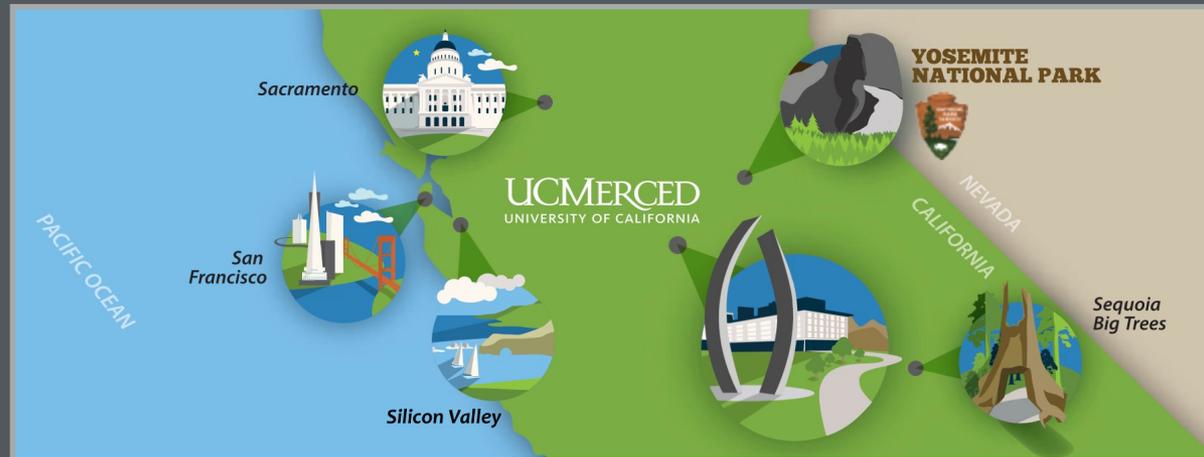
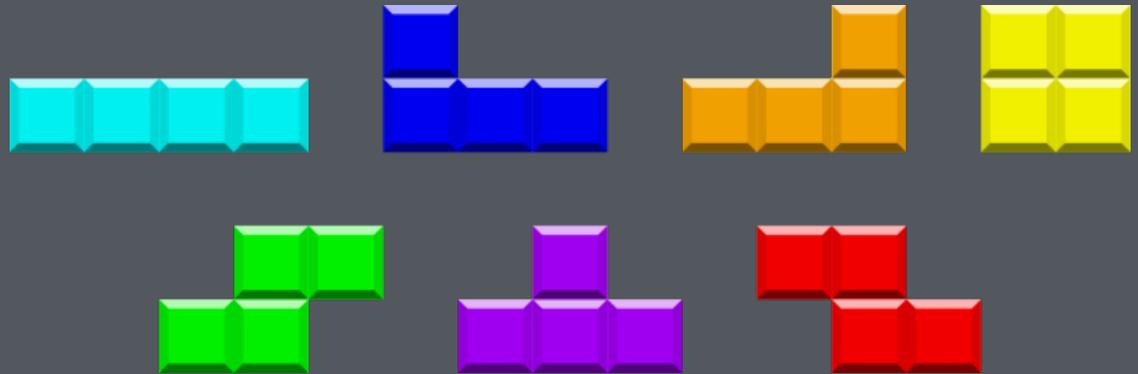


- **Flagship Programs:** funding around Grand Challenges may reduce the barriers associated with disciplinary borders, thereby **incentivizing cross-disciplinary collaboration & mobility**
- **“Consortium Science”:** *teams of teams* coalesce with common objectives, including sharing benefits equitably within and beyond institutional boundaries — **an organizational model championed by the HGP and further developed by numerous follow-up “Omics” consortiums**

Successful Configurations — when *Form Follows Function*



Warming and earlier spring increase western US forest wildfire activity.
— AL Westerling et al., Science 2006



Management of Complex Systems Department — mcs.ucmerced.edu
Ernest & Gallo School of Management*

Thanks for your attention!

and also to my esteemed collaborators in this and related work
— in particular Ioannis Pavlidis @ University of Houston —

Quantifying the impact of weak, strong, and super ties in scientific careers
PNAS (2015) — Petersen

Cross-disciplinary evolution of the genomics revolution
Science Advances (2018) — Petersen, Majeti, Kwon, Ahmed, Pavlidis

Come and explore cross-disciplinary opportunities at University of California, Merced



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