Aspiration of prestige in the selection of peer institutions

July 20th, 2023
IC²S²

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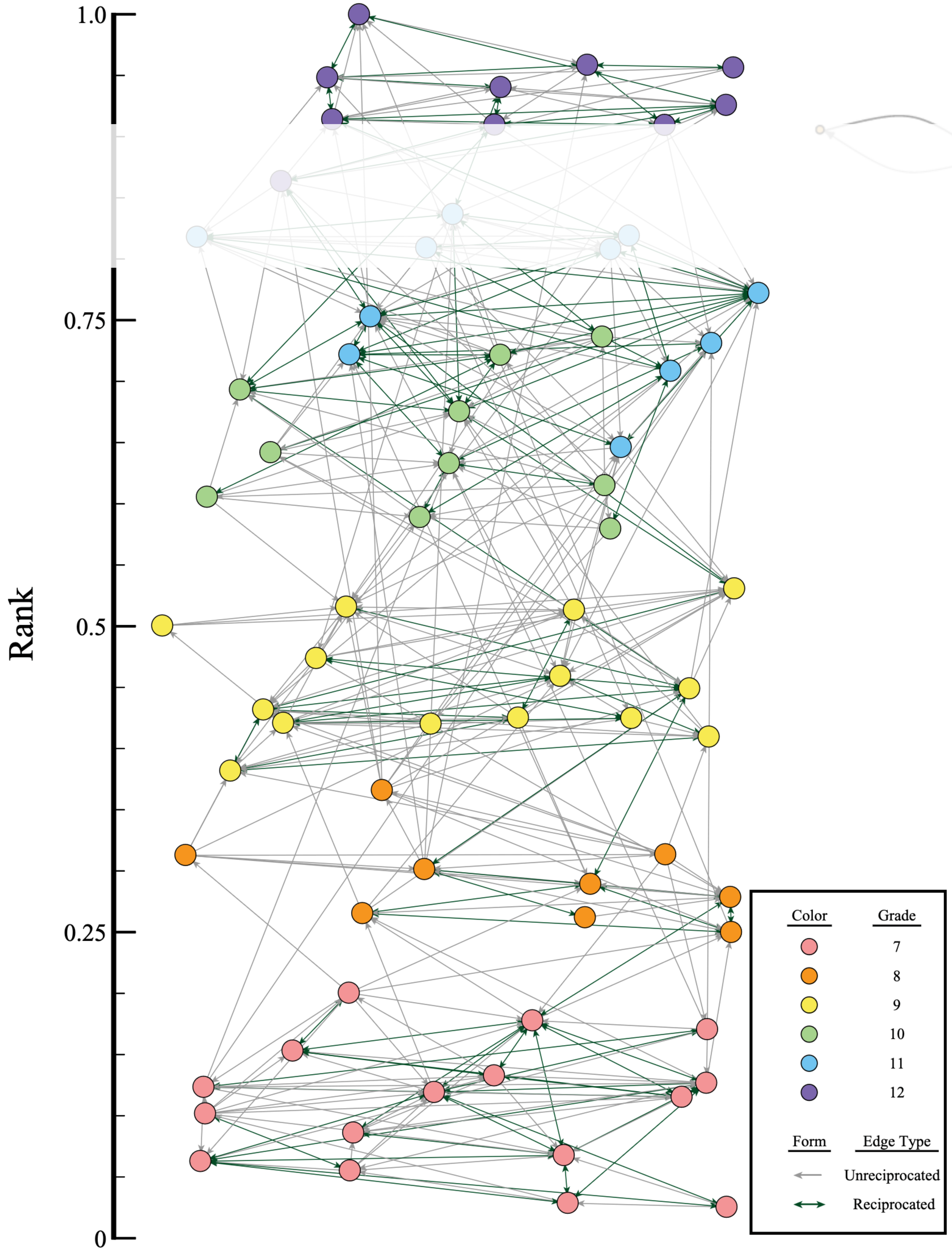
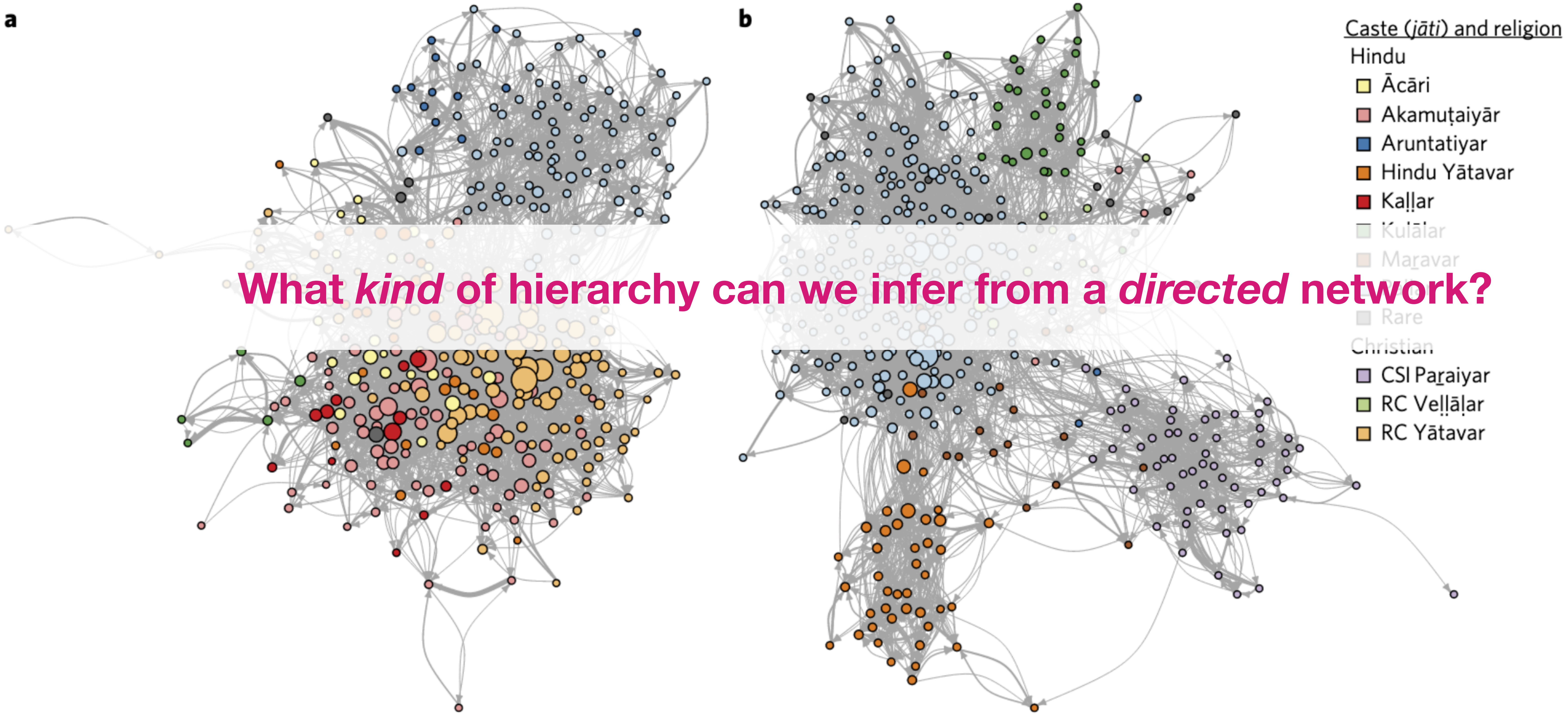
University of Colorado **Boulder**

What *kind* of hierarchy can we infer from a *directed* network?





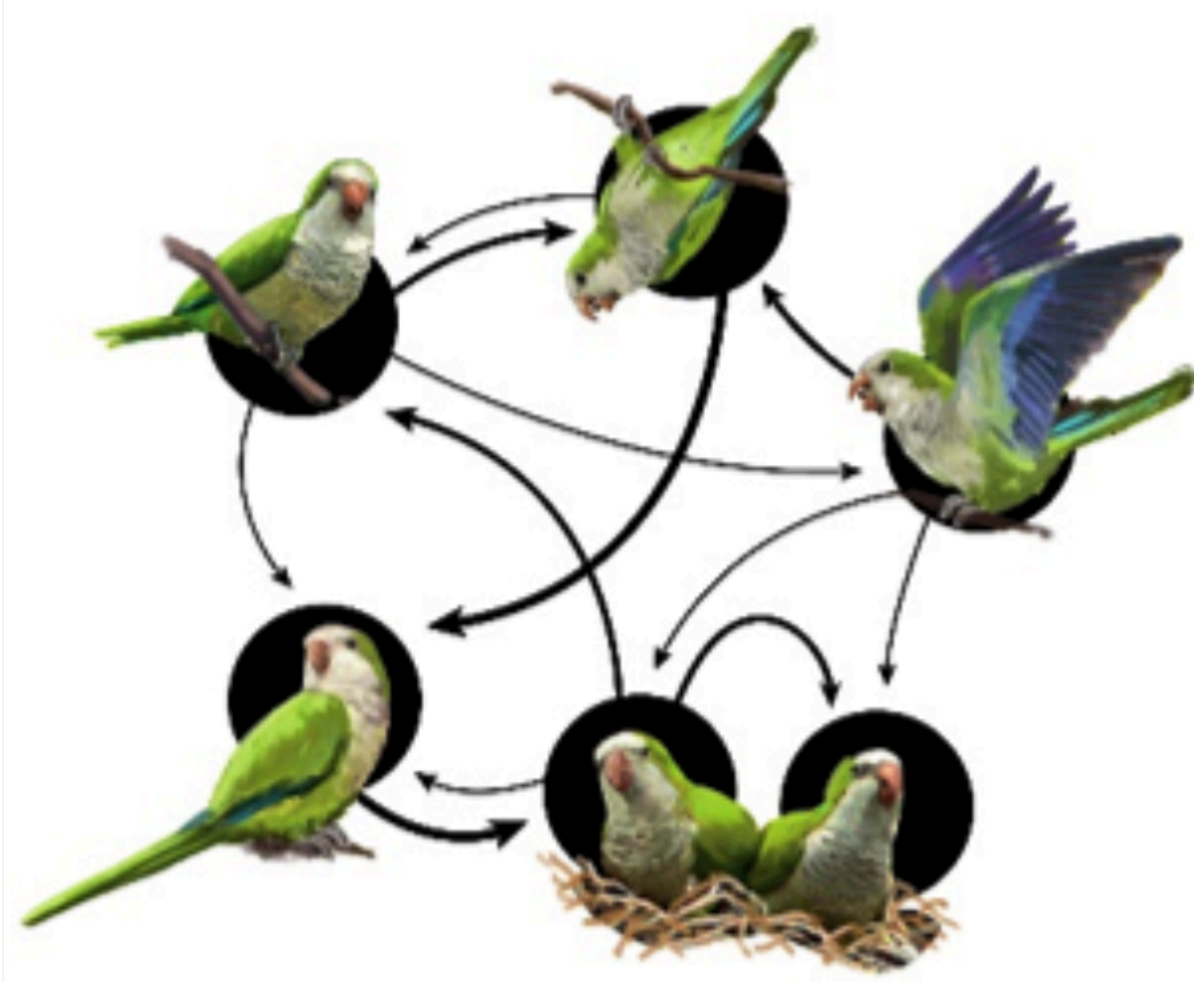
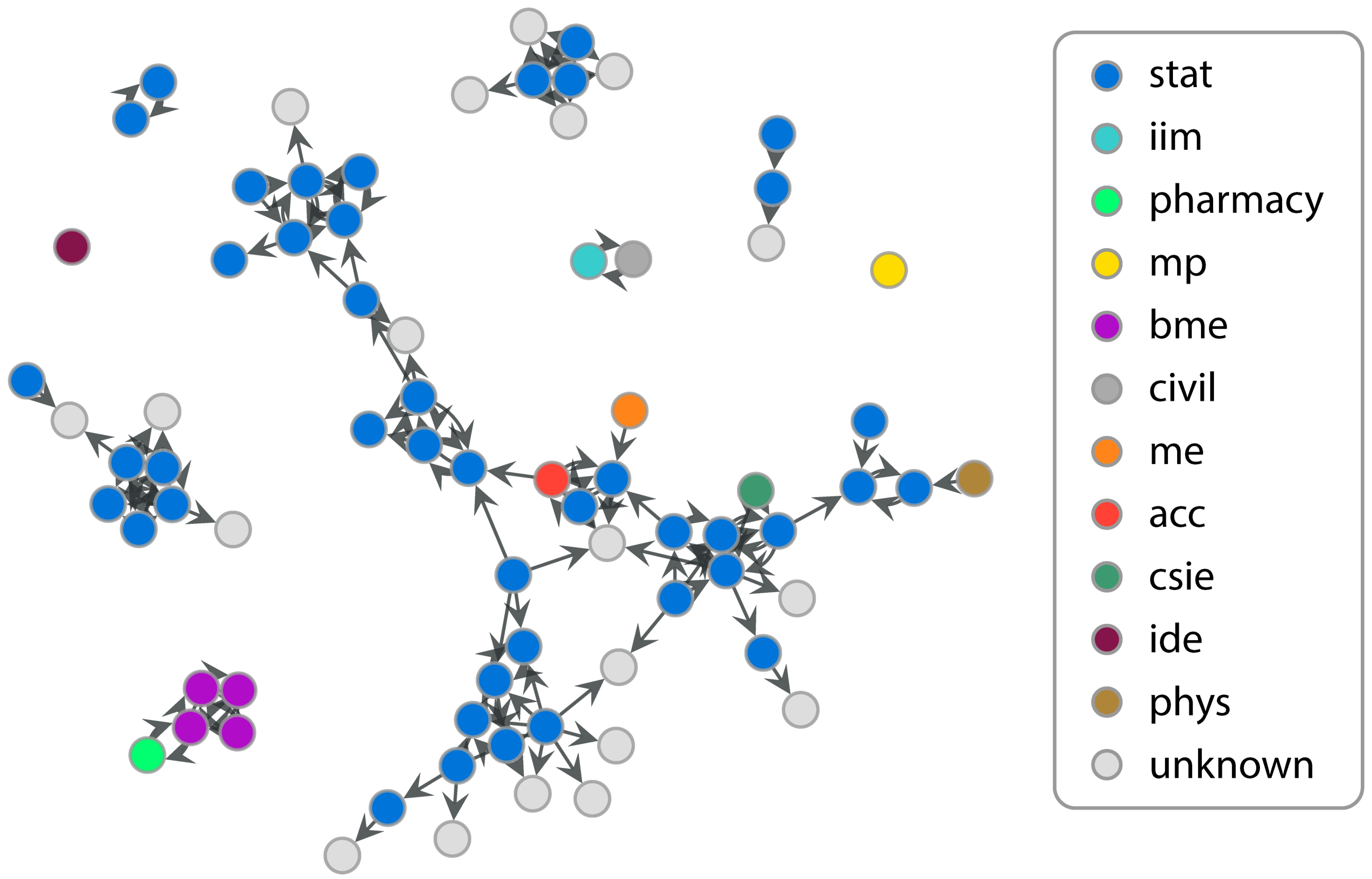


Image by Mesa Schumacher, Mesa Studios



Motivation (Structure vs. Psychology)

Social hierarchy. directional bias in interactions, observed interactions tend to point from higher-ranked individuals to lower-ranked ones

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Allison C. Morgan, Dimitrios J. Economou, Samuel F. Way & Aaron Clauset

EPJ Data Science **7**, Article number: 40 (2018) | Cite this article

Motivation (Structure vs. Psychology)

Labor advantages drive the greater productivity of faculty at elite universities

SAM ZHANG, K. HUNTER WAPMAN, DANIEL B. LARREMORE, AND AARON CLAUSET Authors Info & Affiliations

SCIENCE ADVANCES • 18 Nov 2022 • Vol 8, Issue 46 • DOI: 10.1126/sciadv.abq7056

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Friendship networks and social status

Published online by Cambridge University Press: **15 April 2013**

BRIAN BALL and M.E.J. NEWMAN

Peer institutions (dataset to study the *psychology* behind structure)

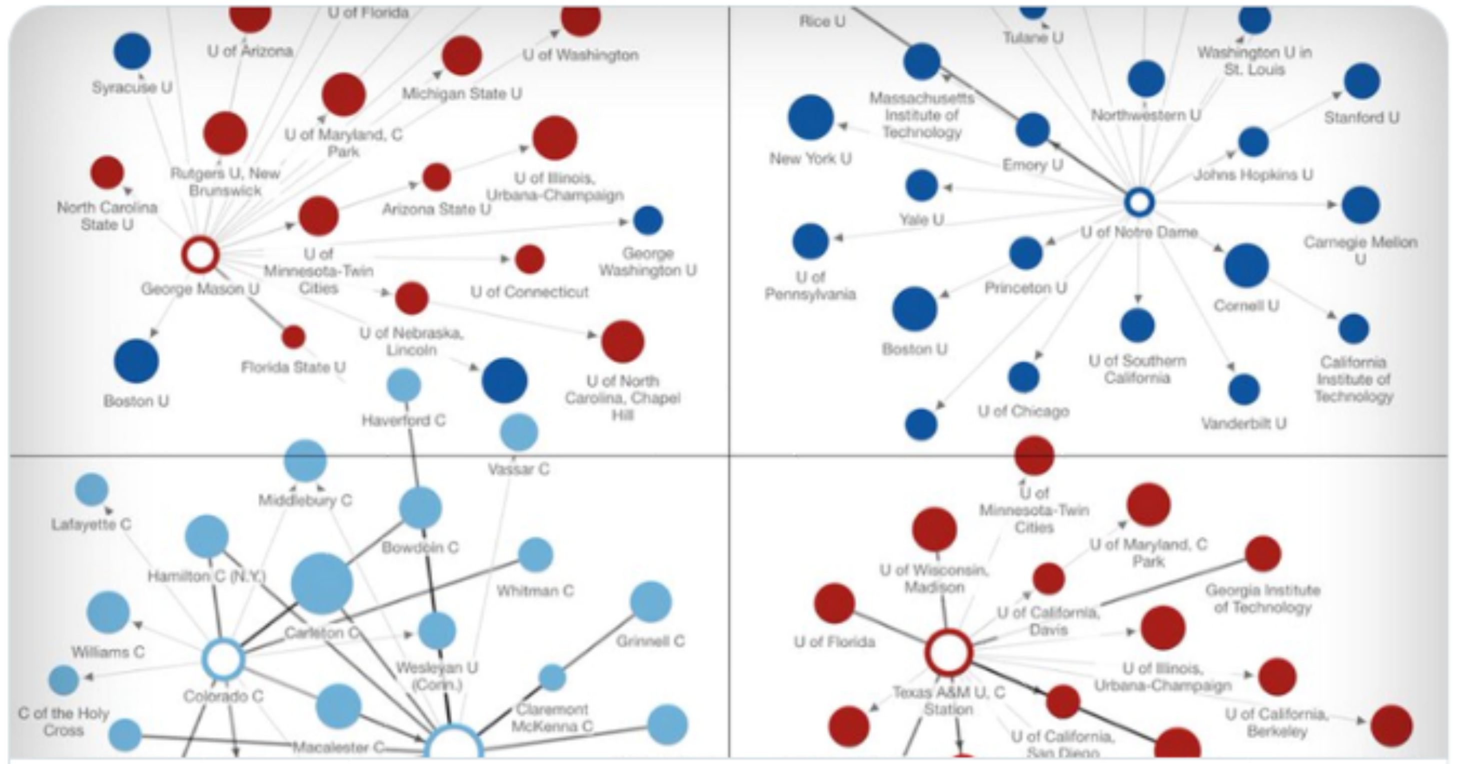
Neil Lewis, Jr., PhD
@NeilLewisJr

Harvard: Our peers are Princeton, Stanford, and Yale

Princeton: We have no peers, we're in a league of our own.

Cornell: All of the other Ivies are peers, except Dartmouth.

This dataset is interesting to explore:



chronicle.com
Who Does Your College Think Its Peers Are?
The Chronicle compiled the peer institutions for nearly 1,500 institutions from the 2020-21 year.

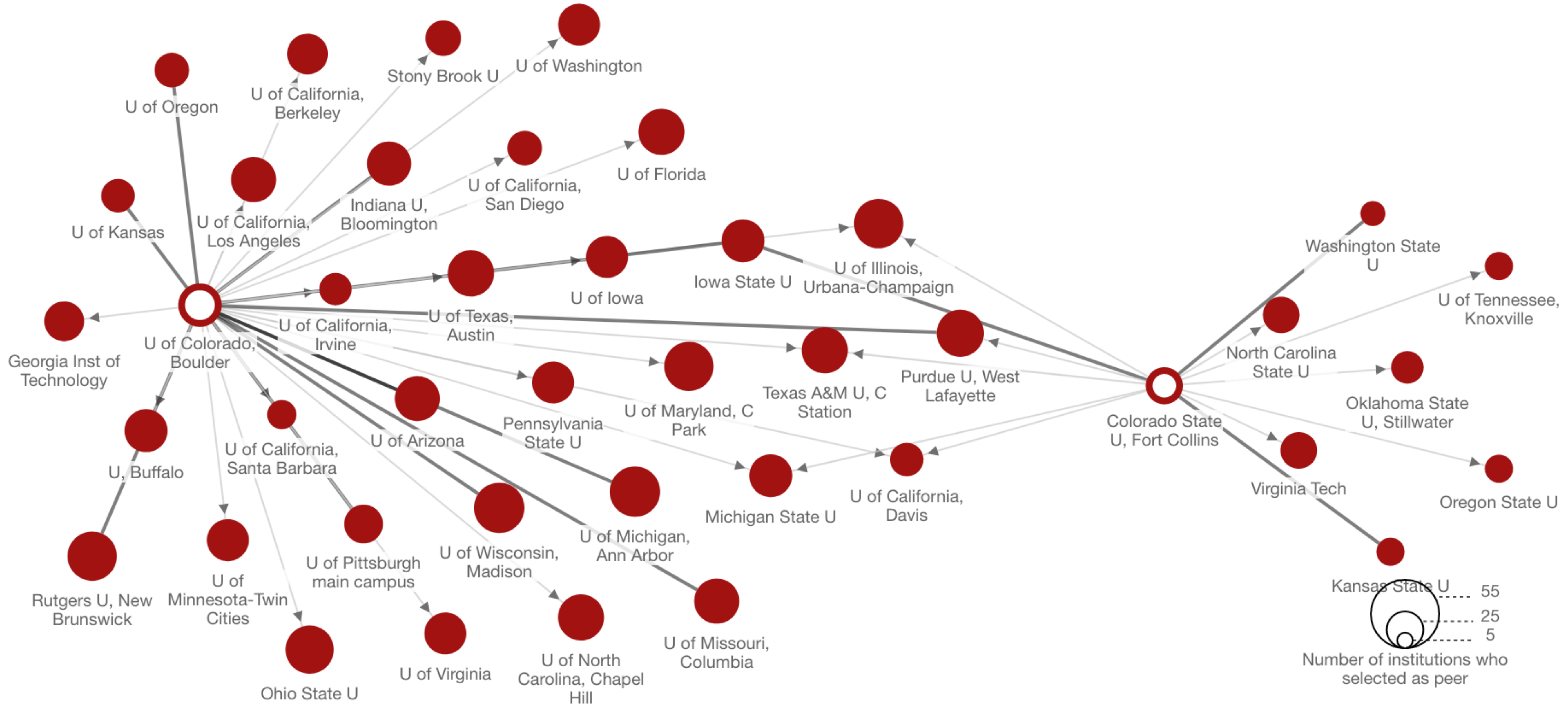
2:04 PM · Mar 27, 2022 · Twitter Web App

Peer group | Who this college chose | Who chose this college | Institution | Single institution | Compare institutions

Search for an institution X

Peer | Mutual Peer | Public Doctoral

Click an institution's circle below to select it for comparison.



University of Colorado at Boulder

Boulder, CO | Public Doctoral

33 colleges selected as peers by this college. **25** colleges selected this college as a peer. **11** peer colleges that also chose this college as a peer.

	University	Peer institutions
Admissions Rate	80%	47%
Graduation Rate	74%	83%
Enrollment	31,369	37,400

Colorado State University at Fort Collins

Fort Collins, CO | Public Doctoral

13 colleges selected as peers by this college. **19** colleges selected this college as a peer. **3** peer colleges that also chose this college as a peer.

	University	Peer institutions
Admissions Rate	90%	66%
Graduation Rate	69%	79%
Enrollment	22,955	33,504

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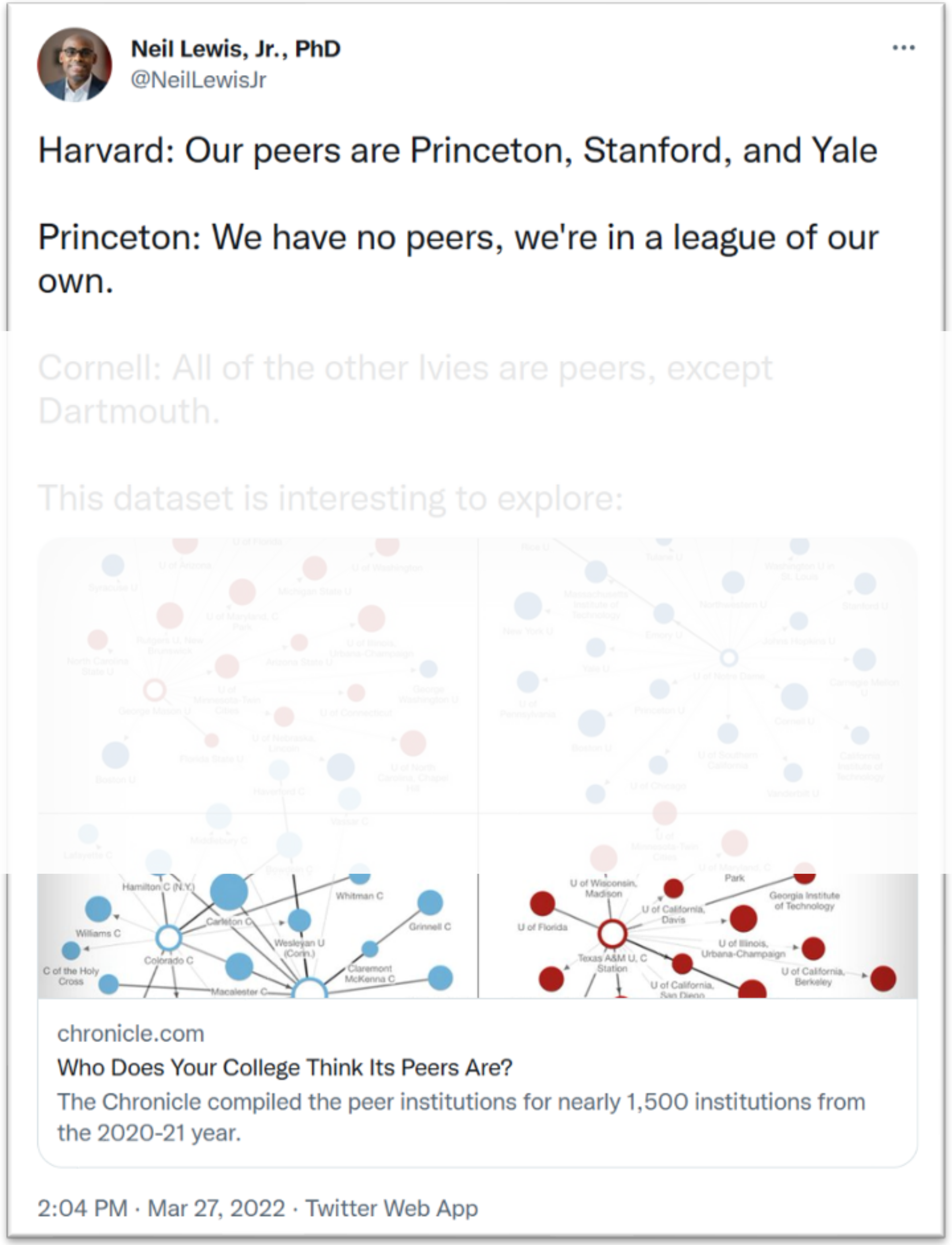
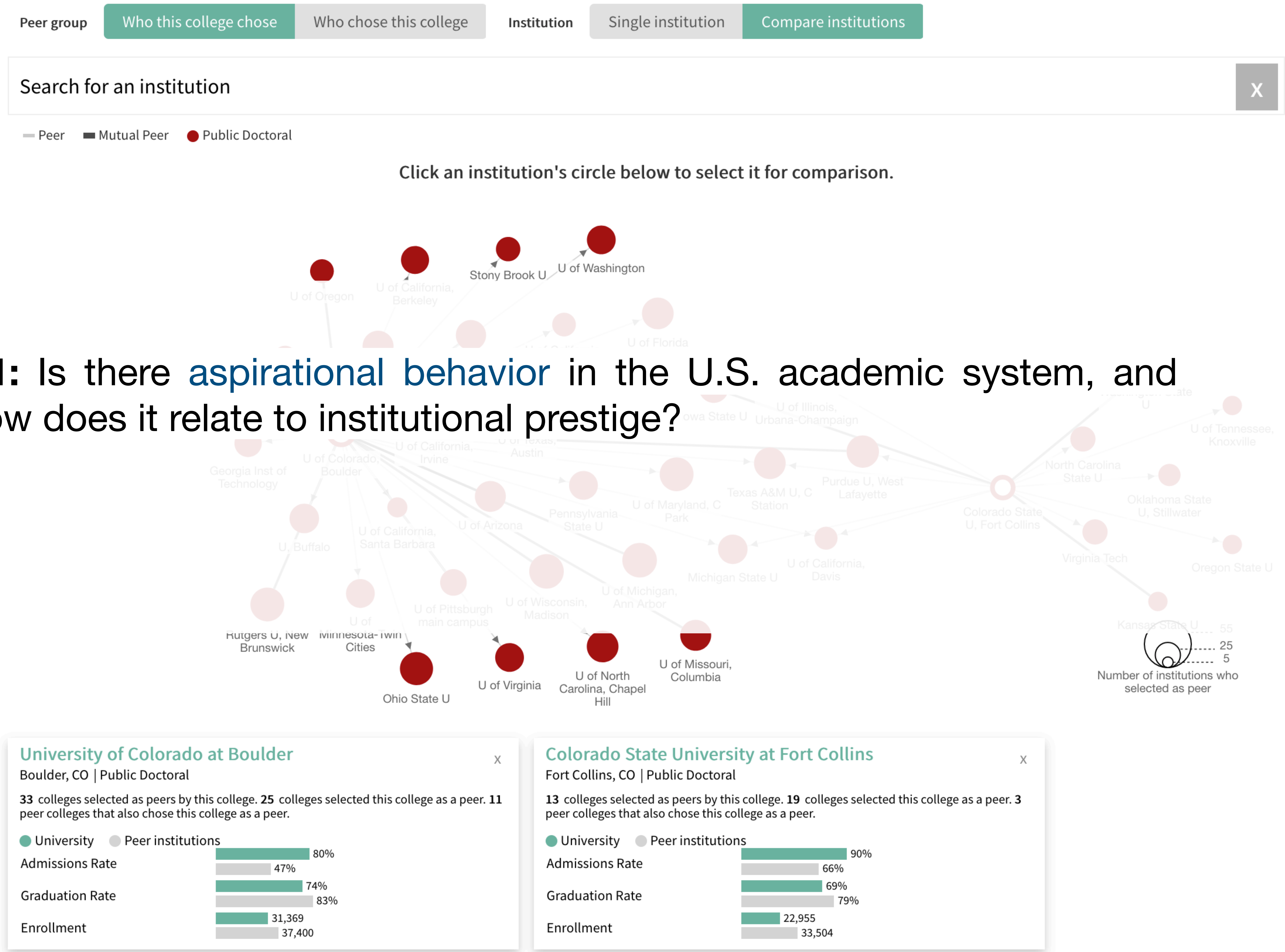
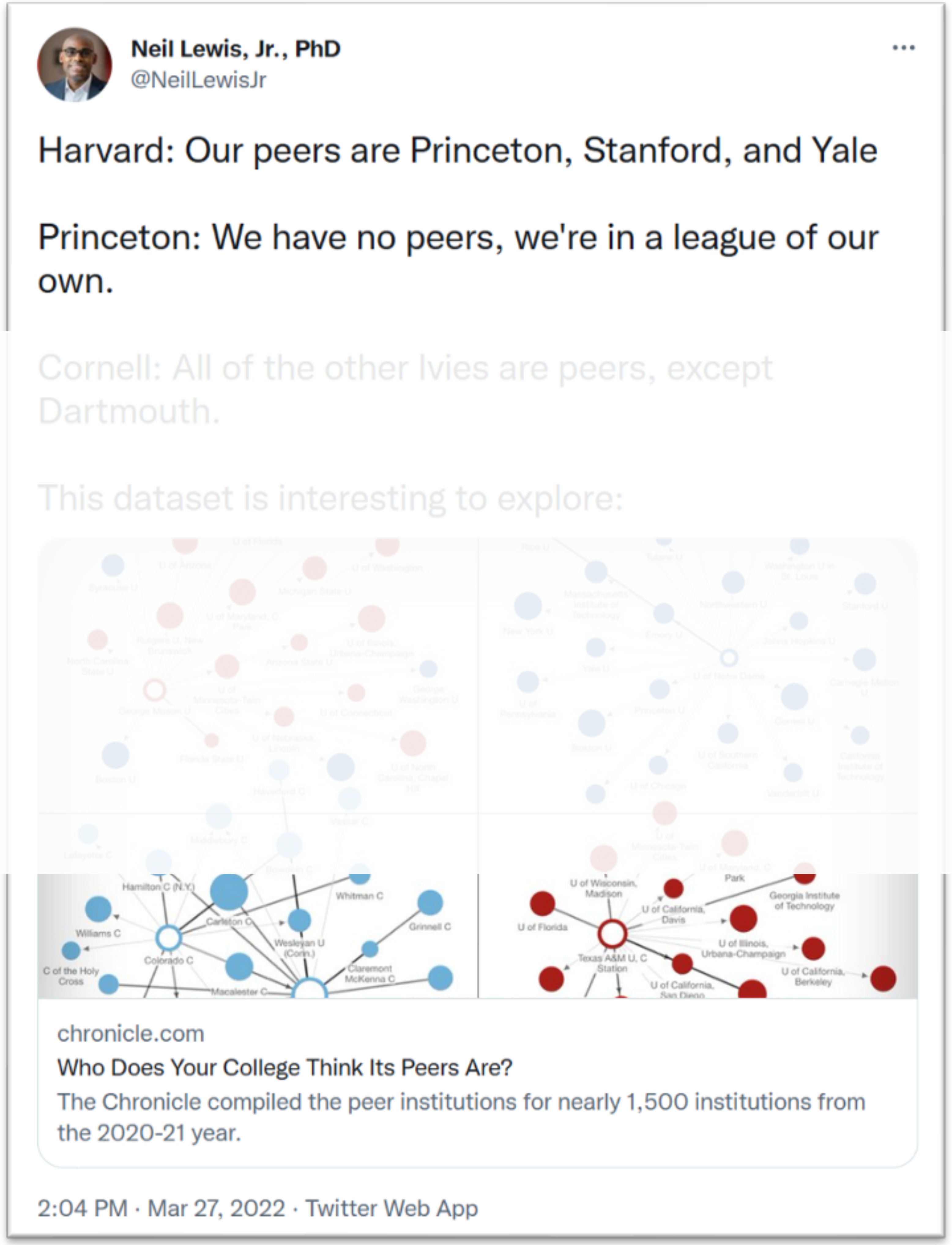
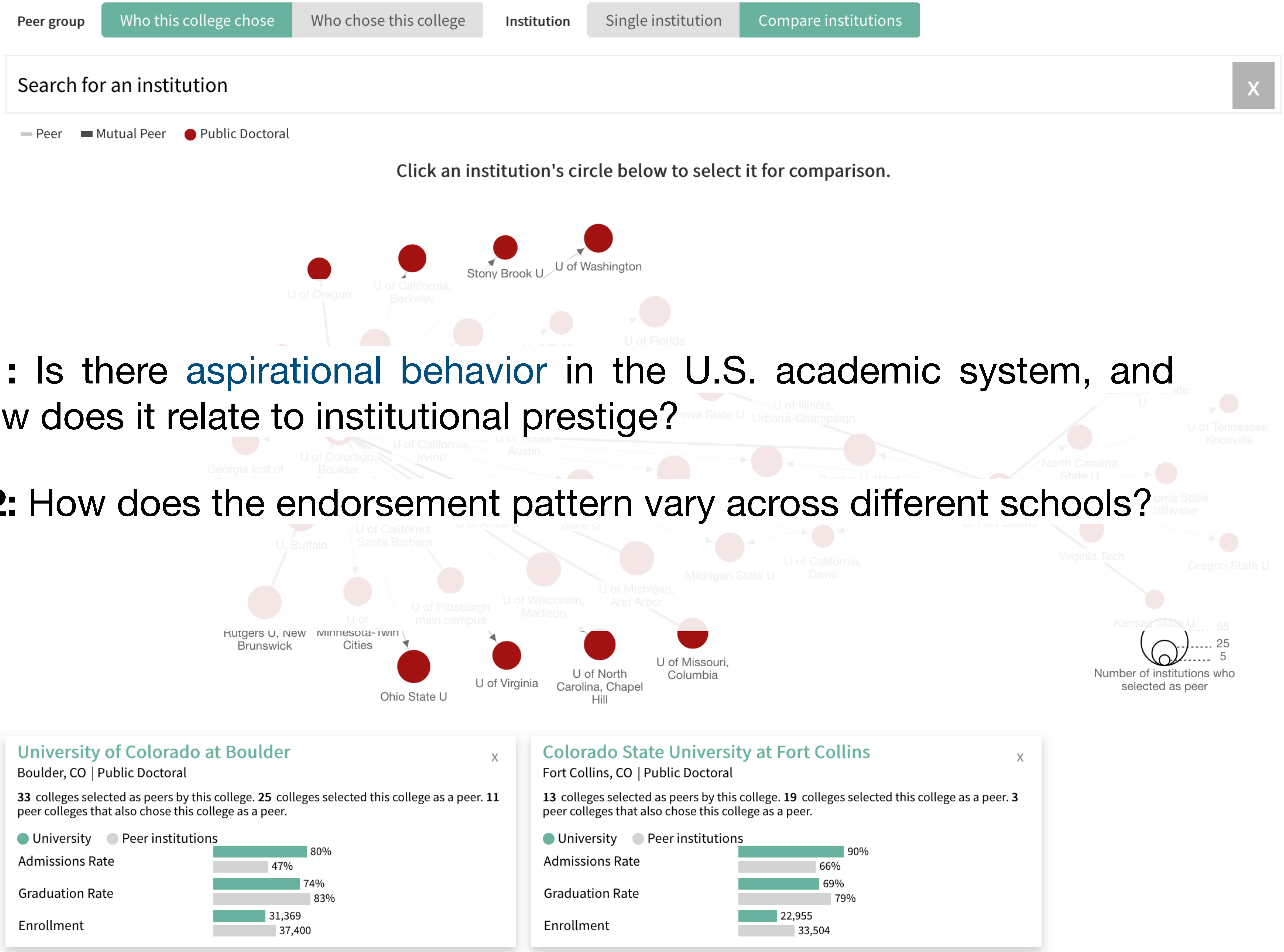




R1: Is there aspirational behavior in the U.S. academic system, and how does it relate to institutional prestige?

Peer institutions (dataset to study the *psychology* behind structure)





R1: Is there aspirational behavior in the U.S. academic system, and how does it relate to institutional prestige?

R2: How does the endorsement pattern vary across different schools?

Method (data collection)

Code	Type of Institutions	N
15 (R1)	Doctoral Universities: Highest Research Activity	125
16 (R2)	Doctoral Universities: Higher Research Activity	114
17 (R3)	Doctoral Universities: Moderate Research Activity	30
18 (M:Large)	Master's Colleges & Universities: Larger Programs	18
19 (M:Med)	Master's Colleges & Universities: Medium Programs	2
20 (M:Small)	Master's Colleges & Universities: Small Programs	1
21 (B:A&S)	Baccalaureate Colleges: Arts & Sciences Focus	6
26 (S:Health)	Special Focus Four-Year: Other Health Professions Schools	1
27 (S:Engineer)	Special Focus Four-Year: Engineering Schools	1
		total = 298

Aspiration: Peer institutions survey (IPEDS, 2020–21). Of the 1179 institutions and 18817 nominations collected, we matched the names with the faculty hiring dataset & restricted to Ph.D.-granting ones, resulting in 298 institutions.

Institutional prestige: Faculty hiring dataset (existing, 2011–12). Each institution is annotated by a data-driven estimate of its "prestige" within the faculty hiring system. Proxy for an institution's ability to place its graduates as faculty at other institutions.

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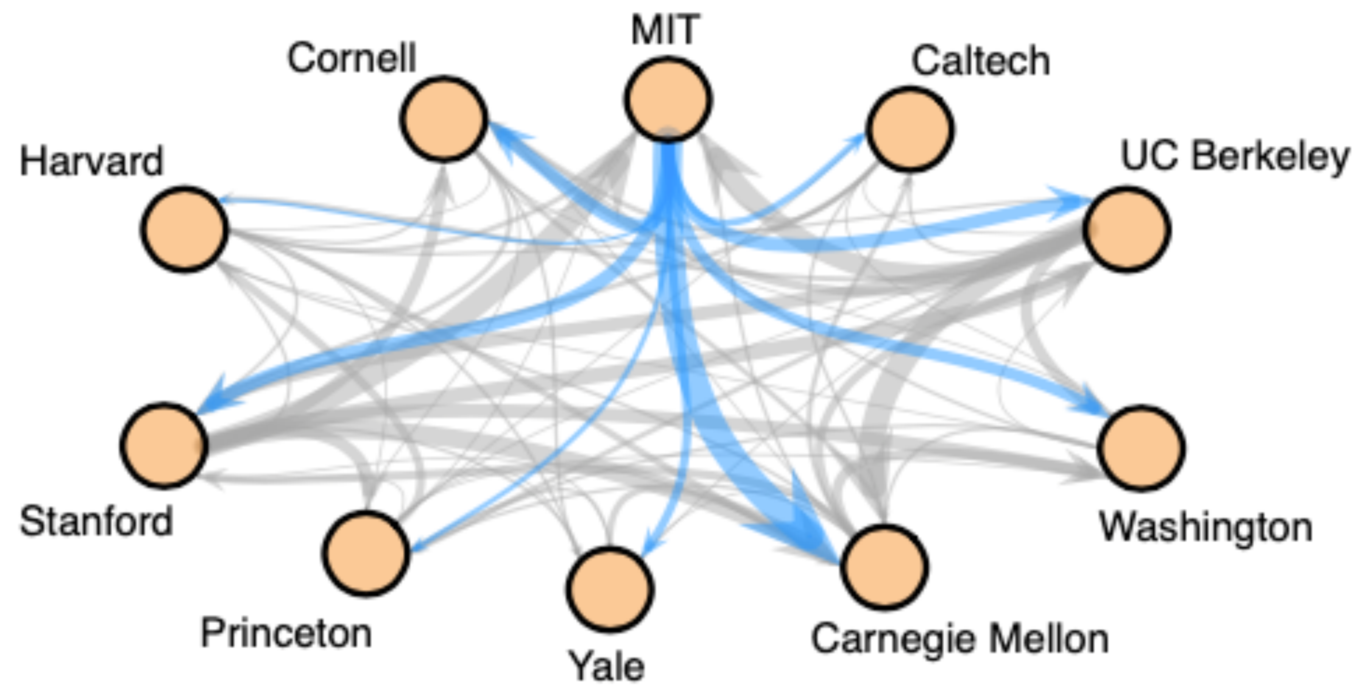
Method (quantifying prestige/desirability via SpringRank)

Each directed edge $u \rightarrow v$ implies
PhD from u becomes faculty at v



Computer science faculty hiring network; http://tuvalu.santafe.edu/~aaronc/facultyhiring/. See also: *Sci. Adv.* 1(1), e1400005, 2015.

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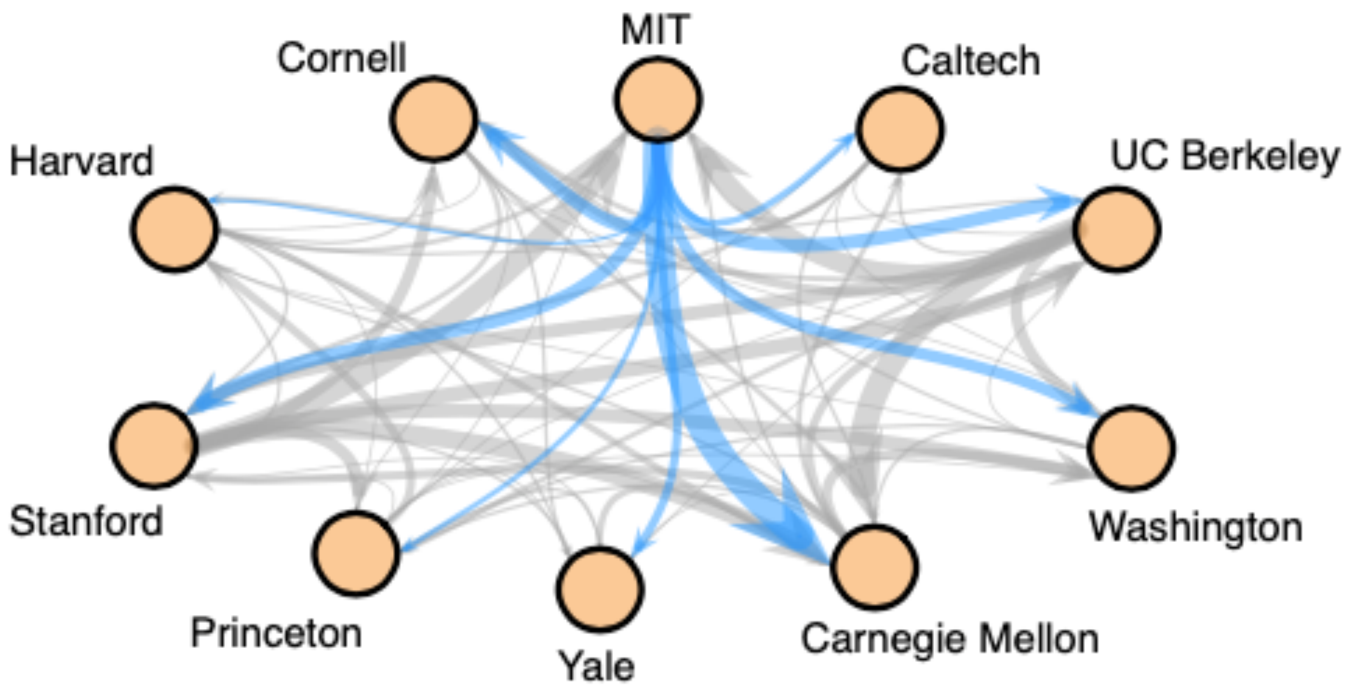

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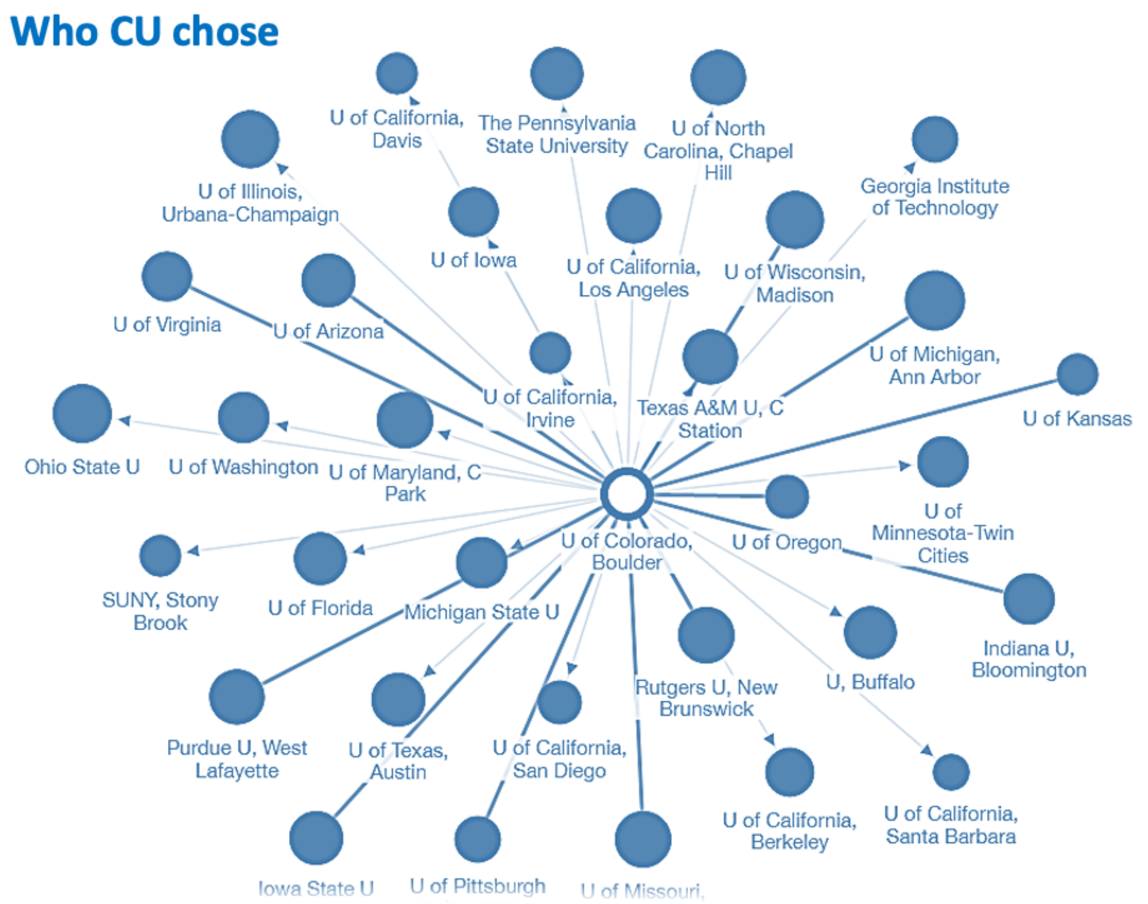
Each directed edge $u \to v$ implies institution u selects institution v



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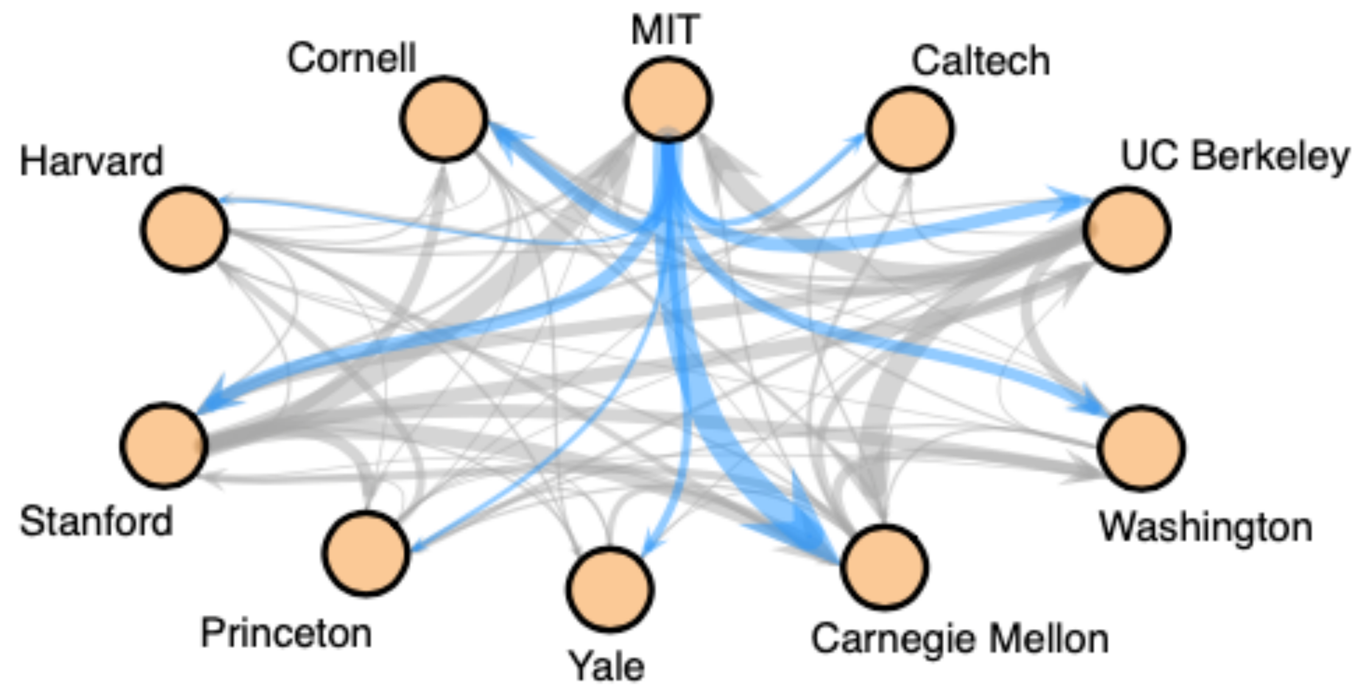

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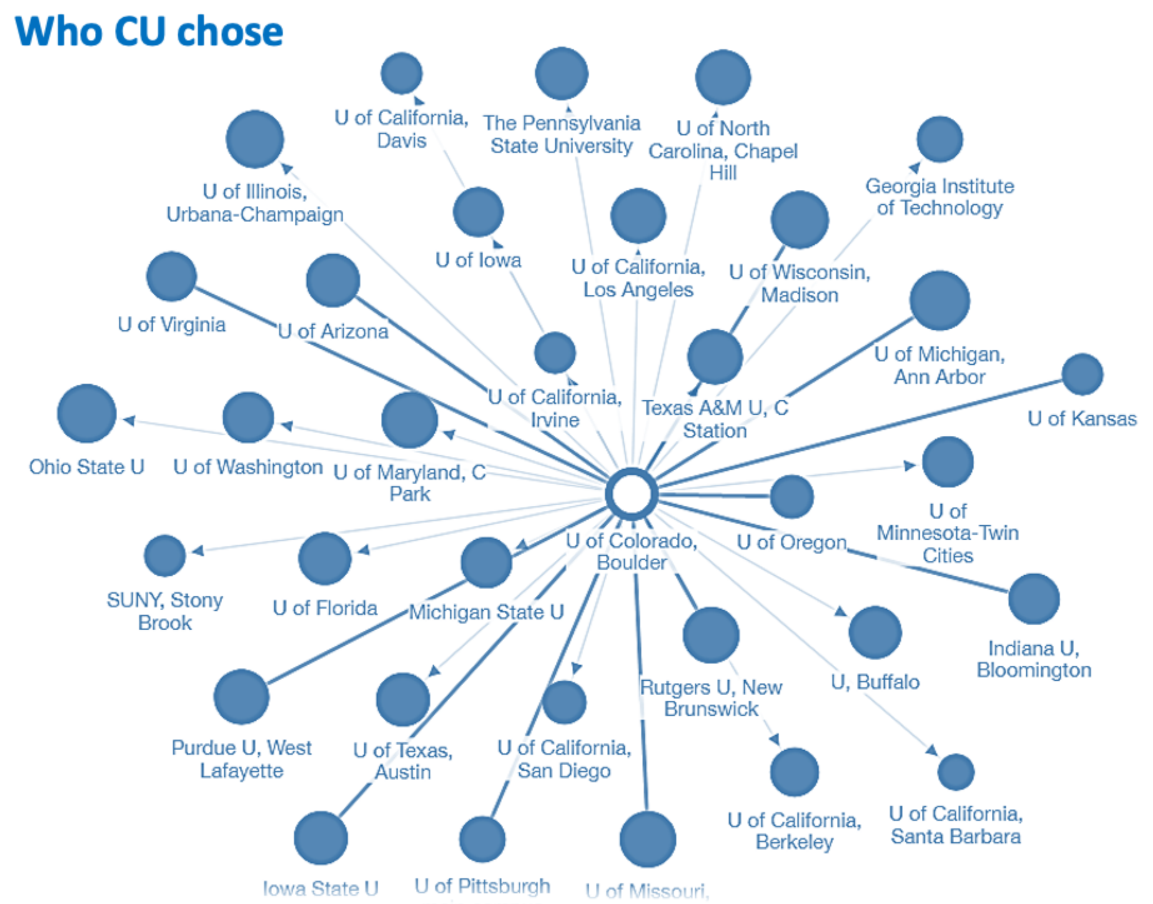
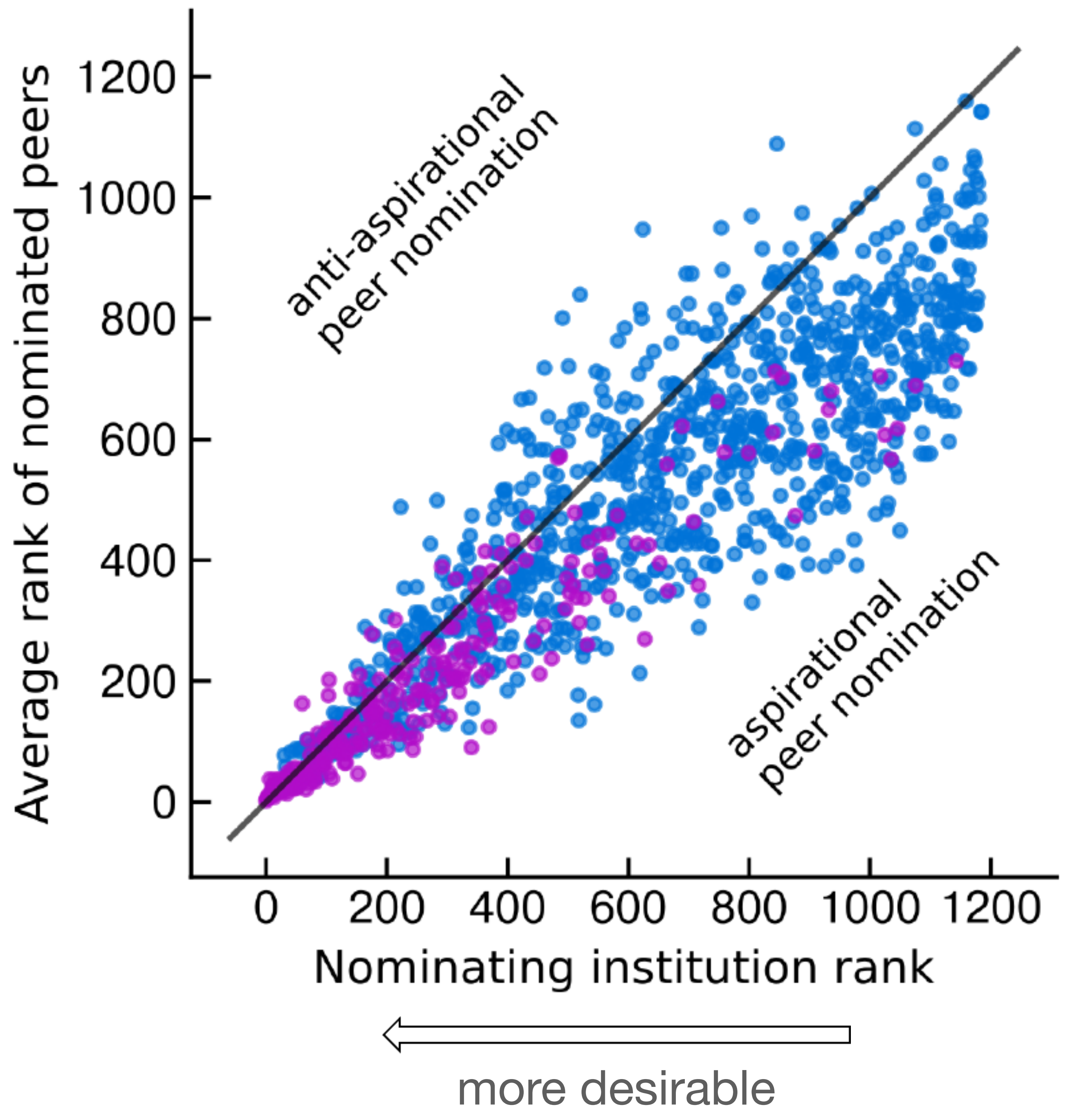
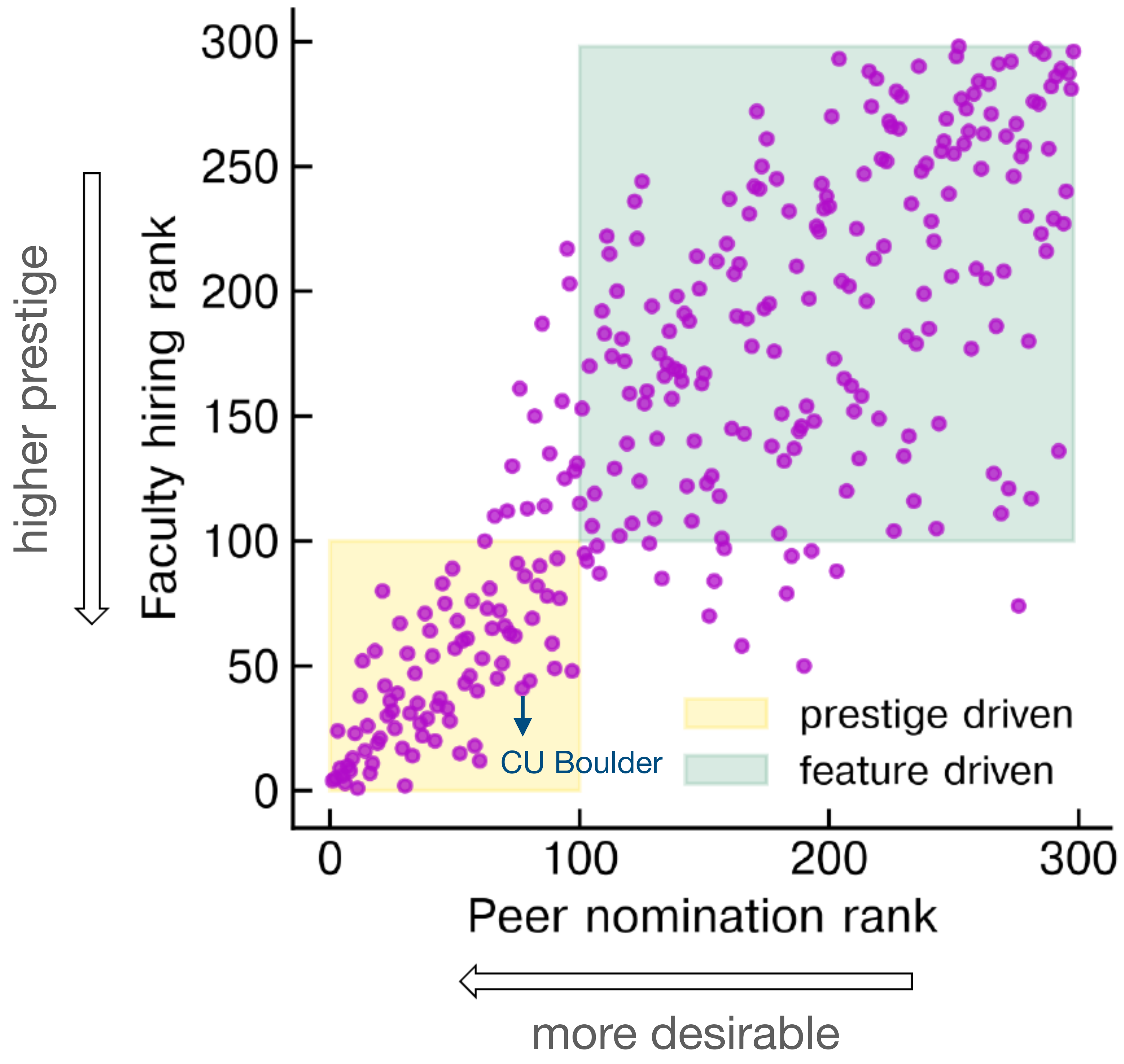


SpringRank: Let $\mathbf{A} = \{A_{ij}\}$ be the adjacency matrix of a directed multigraph. The SpringRank Model finds the ranking $\mathbf{s}^*$ of the nodes by solving:

$$\underset{s \in \mathbb{R}^N}{\text{minimize}} \frac{1}{2} \sum_{ij} A_{ij} (s_i - s_j - 1)^2 \ .$$

Institutions name higher prestige institutions as their peers





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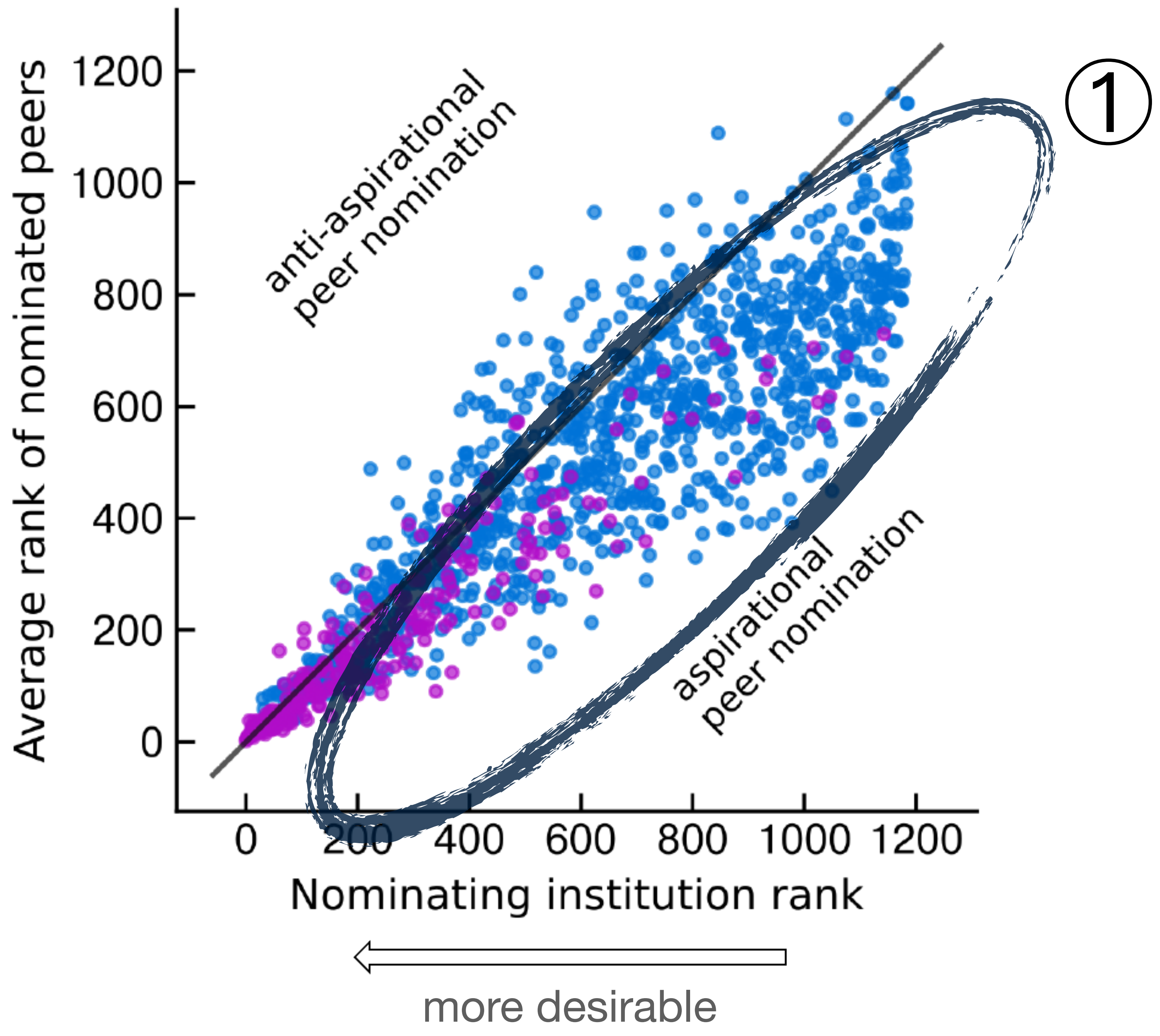

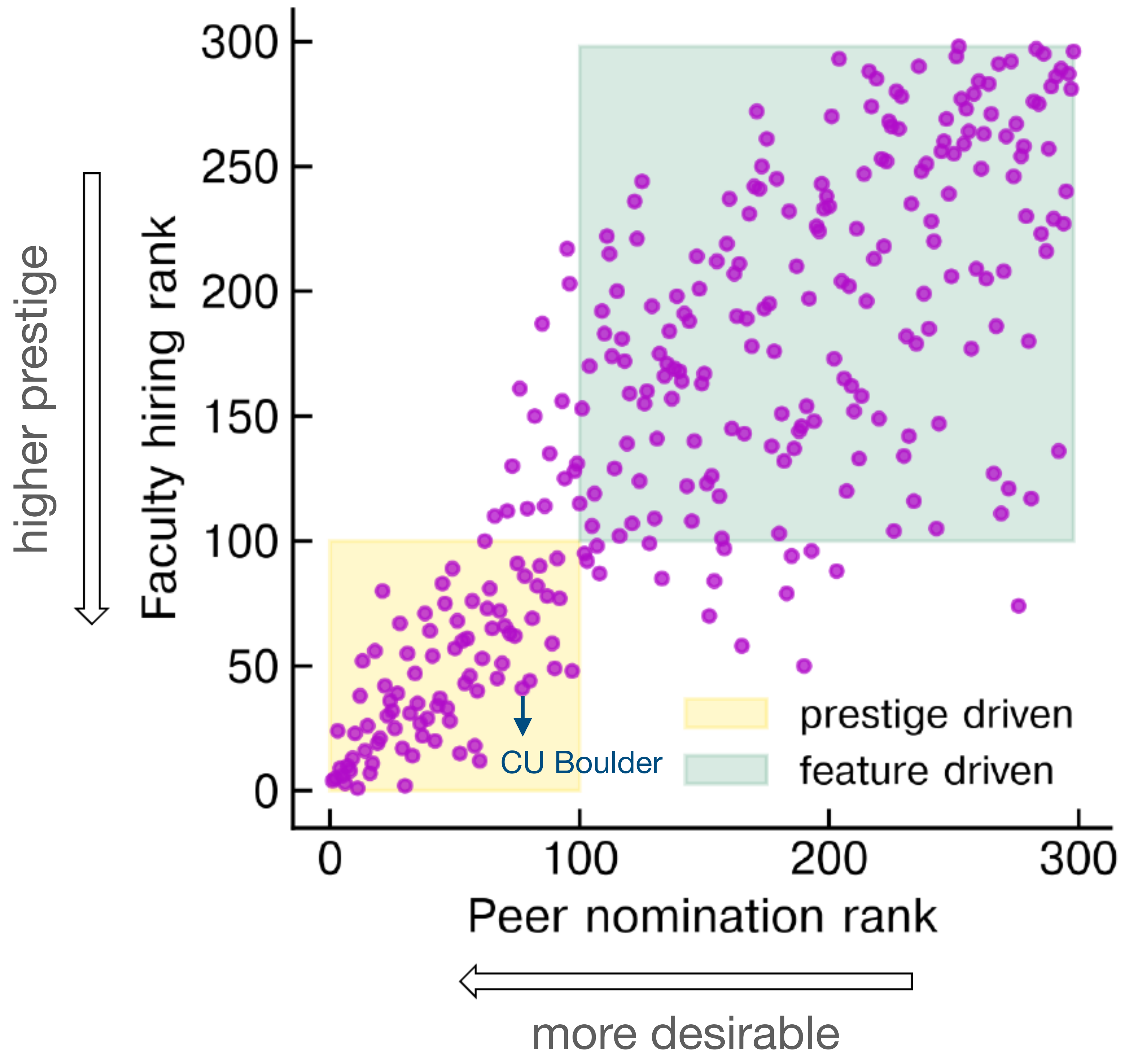

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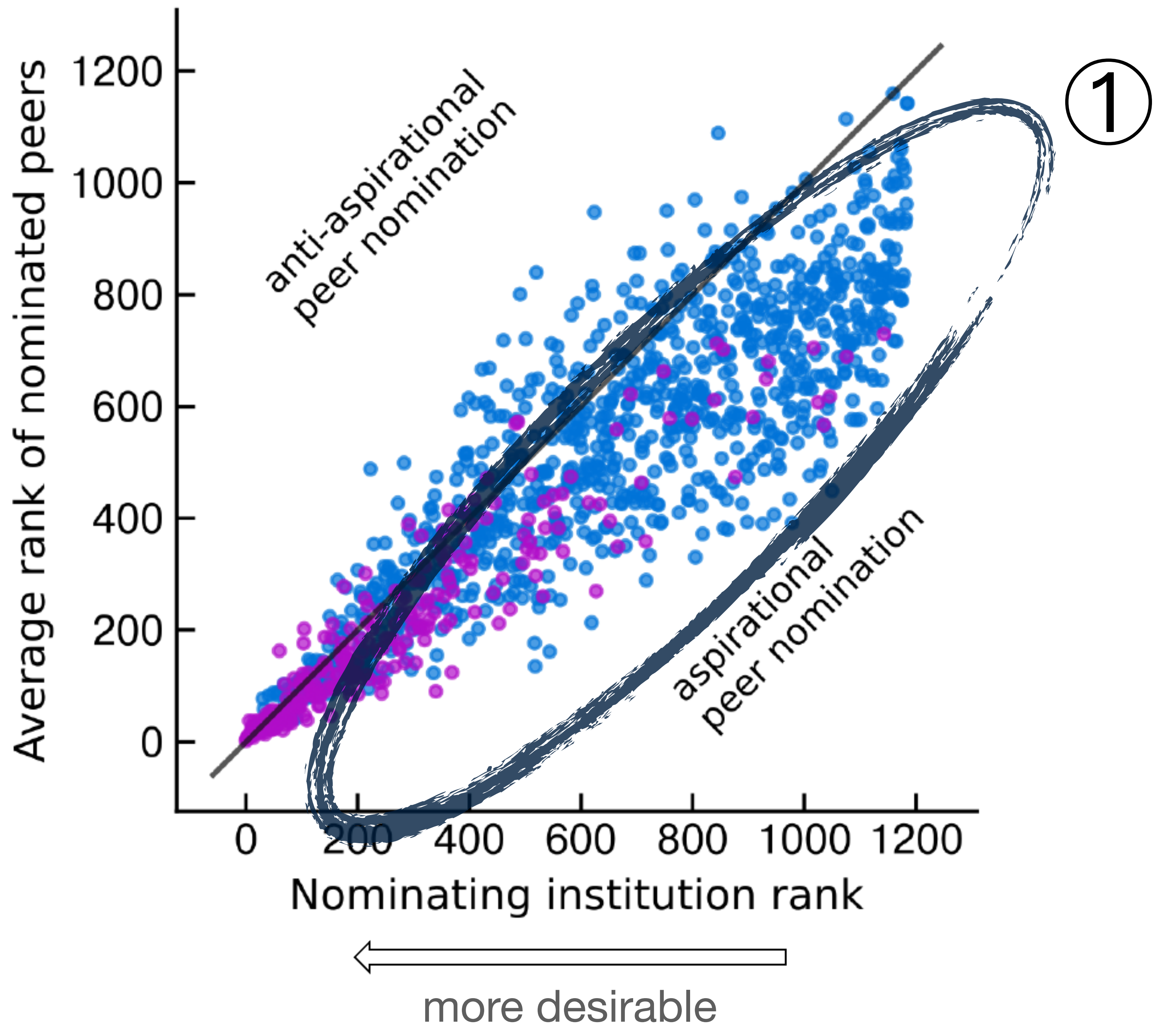

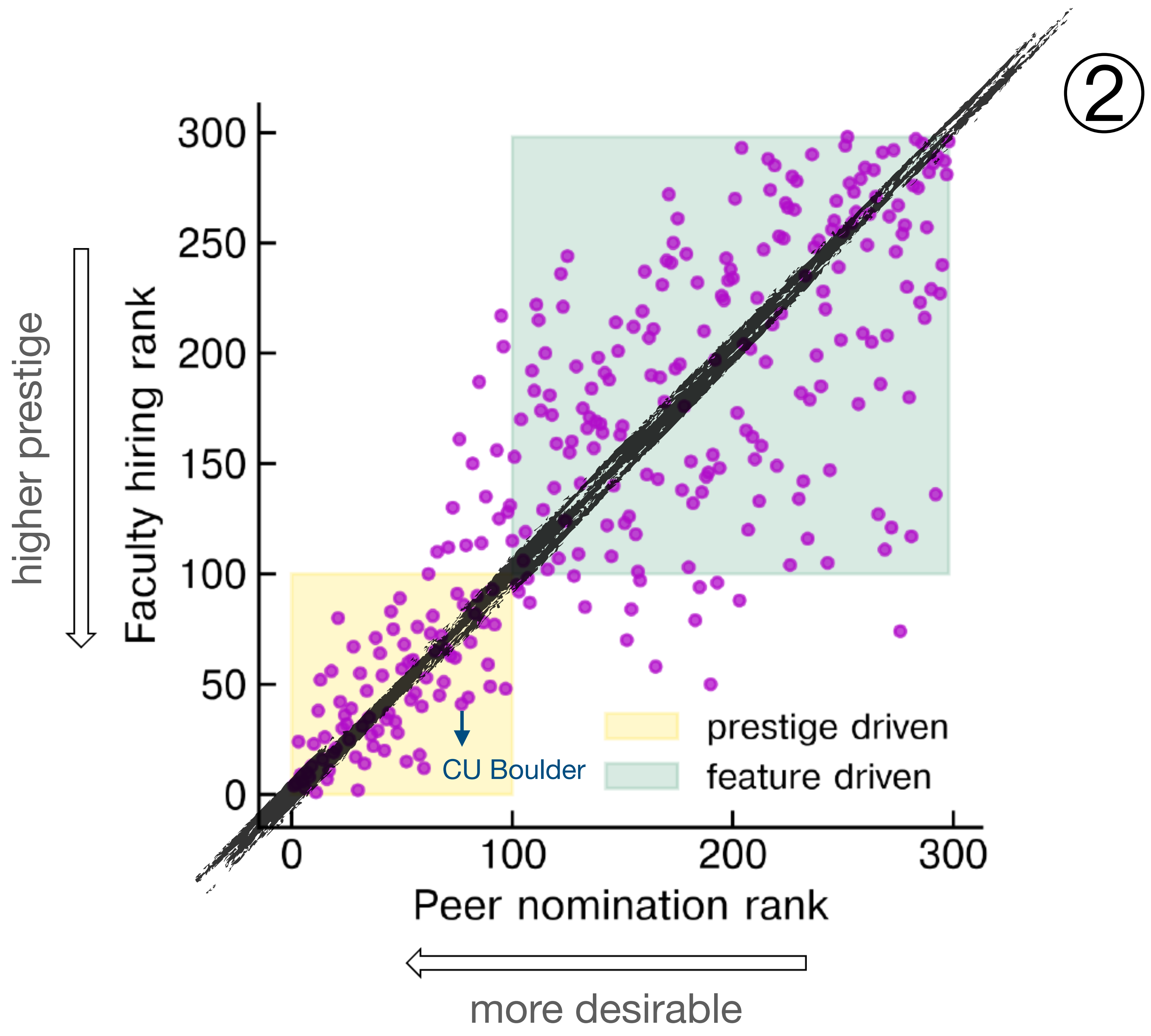

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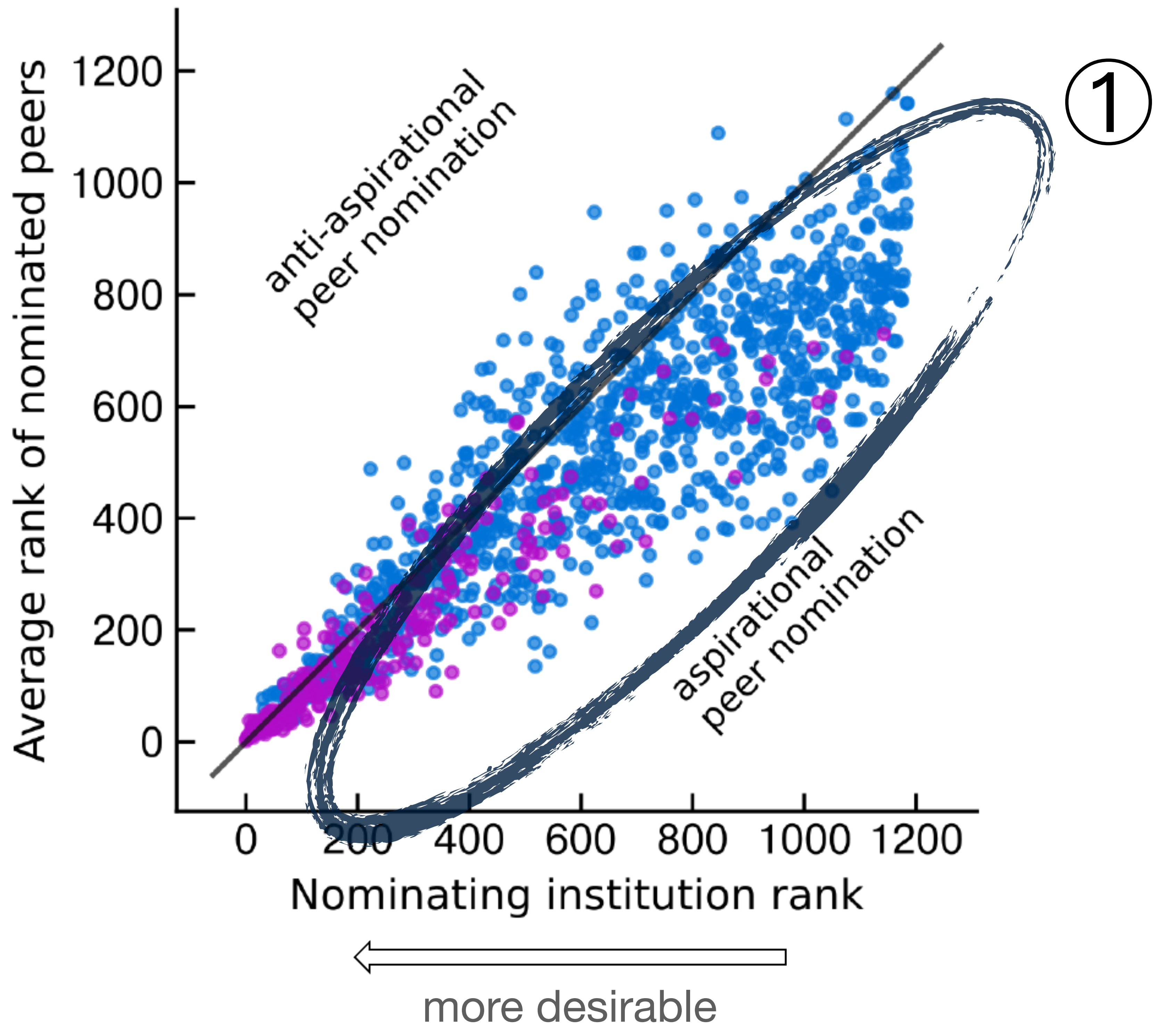
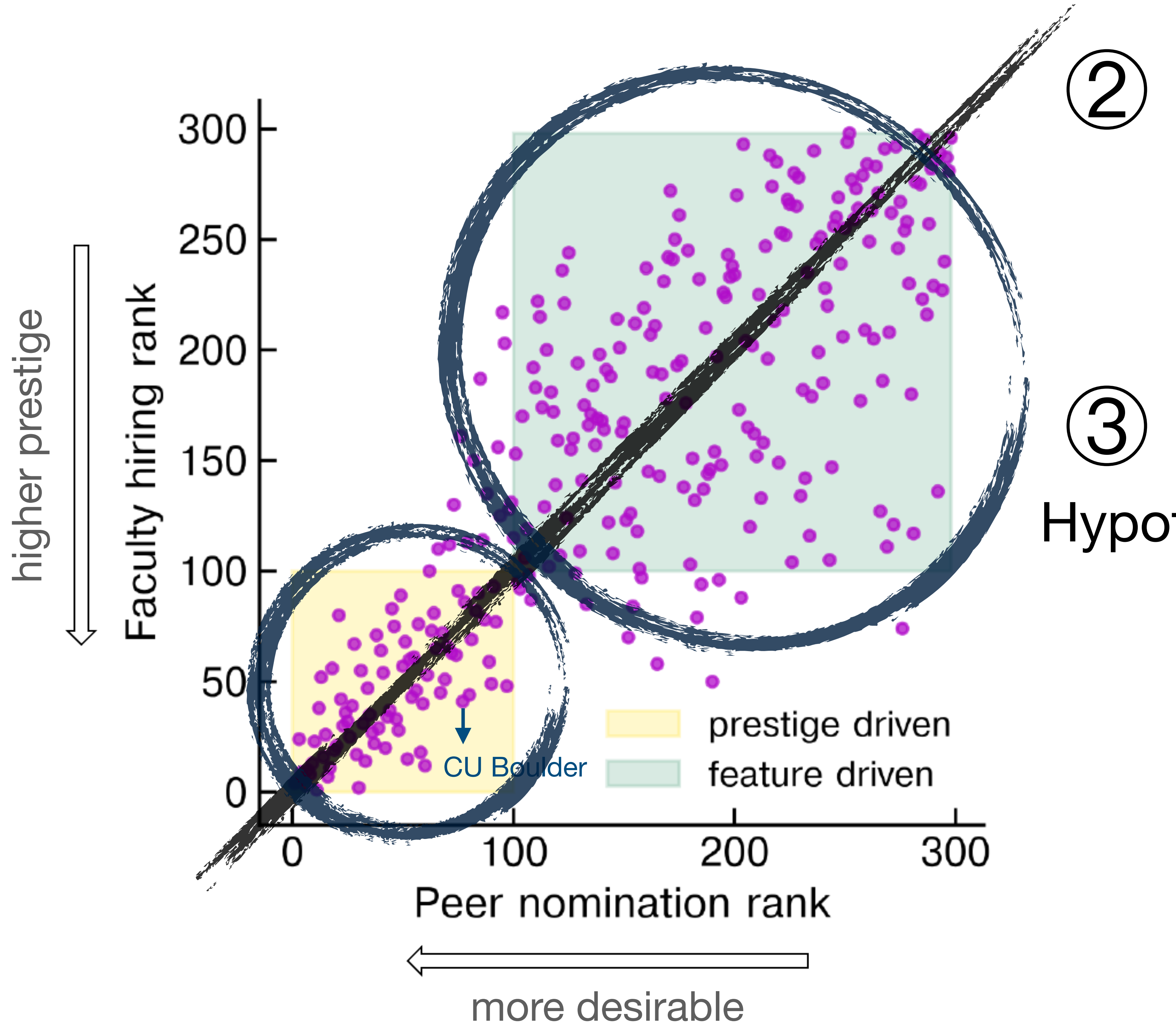
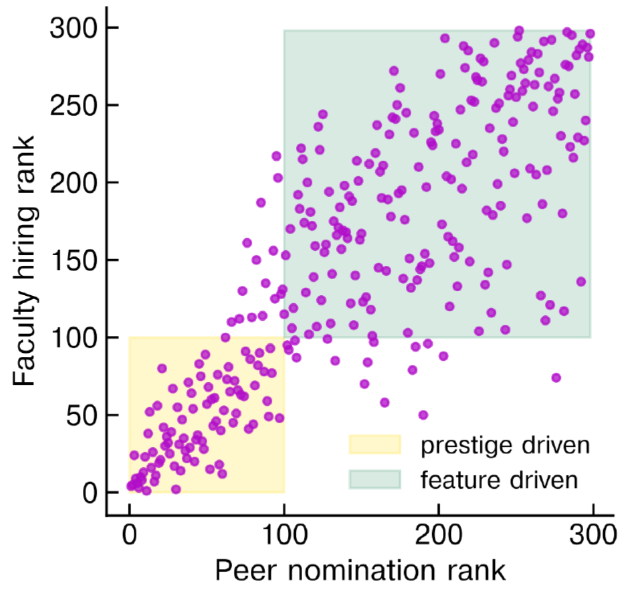




Hypothesized strata 🤔

Method (logistic regression with LASSO and Laplacian regularization*)



$$\underset{\boldsymbol{\beta}\in\mathbb{R}^p}{\text{minimize}}\, \ell(\boldsymbol{y}, \underline{\boldsymbol{\beta}^\intercal \boldsymbol{x}}) + \underbrace{\lambda\|\boldsymbol{\beta}\|_1}_{\text{LASSO } (\ell 1 \text{ regularization})}$$

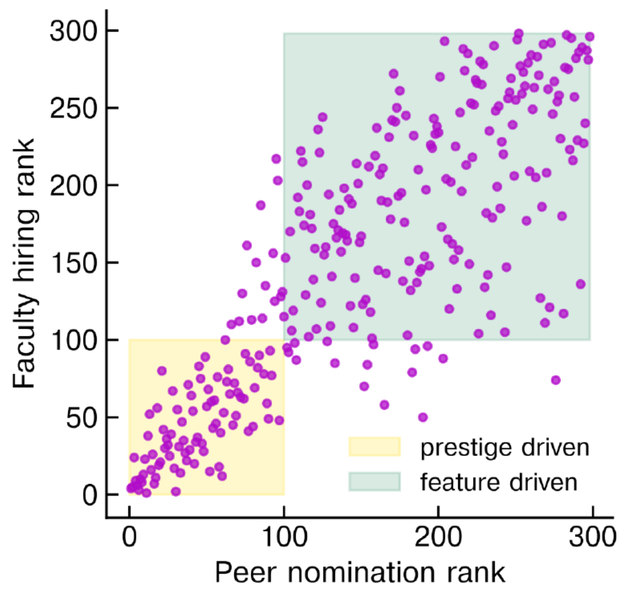
(logistic) loss

actual data

predicted data

Institutional features (nodal features)	Type	Total features	Total derived features (one for each edge)
Historically black?	binary	2	4
Sector (public or private)	categorical	2	4
Carnegie Classification	categorical	9	78
Two-letter state abbreviation	categorical	50	2494
Avg enrollment of full-time students	numeric	1	2
Graduation rates	numeric	1	2
Admission rates	numeric	1	2
Prestige rank	numeric	1	2

*Solution method: alternating direction method of multipliers (ADMM), see Tuck, Barrett, Boyd in J. Machine Learning Research 22, 1-37 (2021).



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(logistic) loss

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LASSO (ℓ1 regularization)

use when #features / #samples ~ 1

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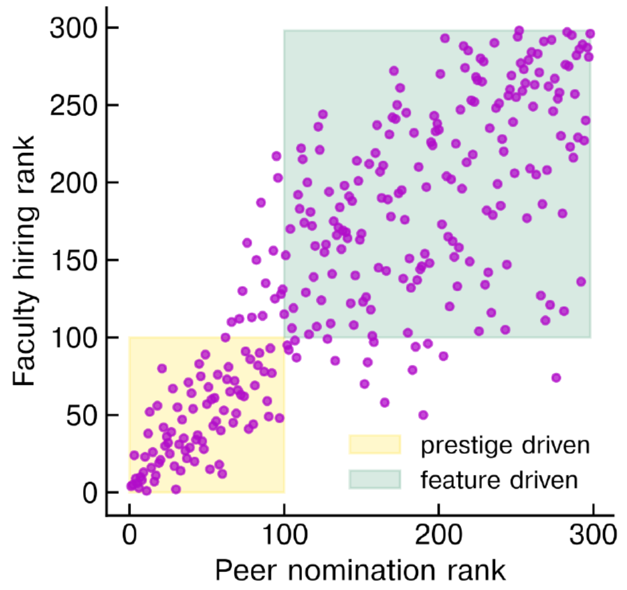

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(logistic) loss

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$$\begin{aligned}\underset{\boldsymbol{\beta}_{\text{high}}, \boldsymbol{\beta}_{\text{low}} \in \mathbb{R}^p}{\text{minimize}}\ & \ell(\boldsymbol{y}_{\text{high}}, \boldsymbol{\beta}_{\text{high}}^\mathsf{T} \boldsymbol{x}) + \lambda \|\boldsymbol{\beta}_{\text{high}}\|_1 \\ & + \ell(\boldsymbol{y}_{\text{low}}, \boldsymbol{\beta}_{\text{low}}^\mathsf{T} \boldsymbol{x}) + \lambda \|\boldsymbol{\beta}_{\text{low}}\|_1 \\ & + \lambda_L \|\boldsymbol{\beta}_{\text{high}} - \boldsymbol{\beta}_{\text{low}}\|_2^2\end{aligned}$$

Idea: Parameters in adjacent strata should be similar. Plus, parameters are encouraged to be zero (not used).

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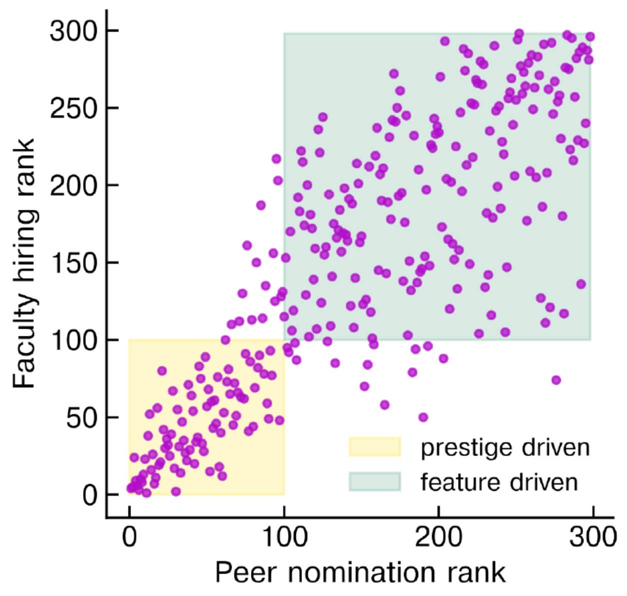
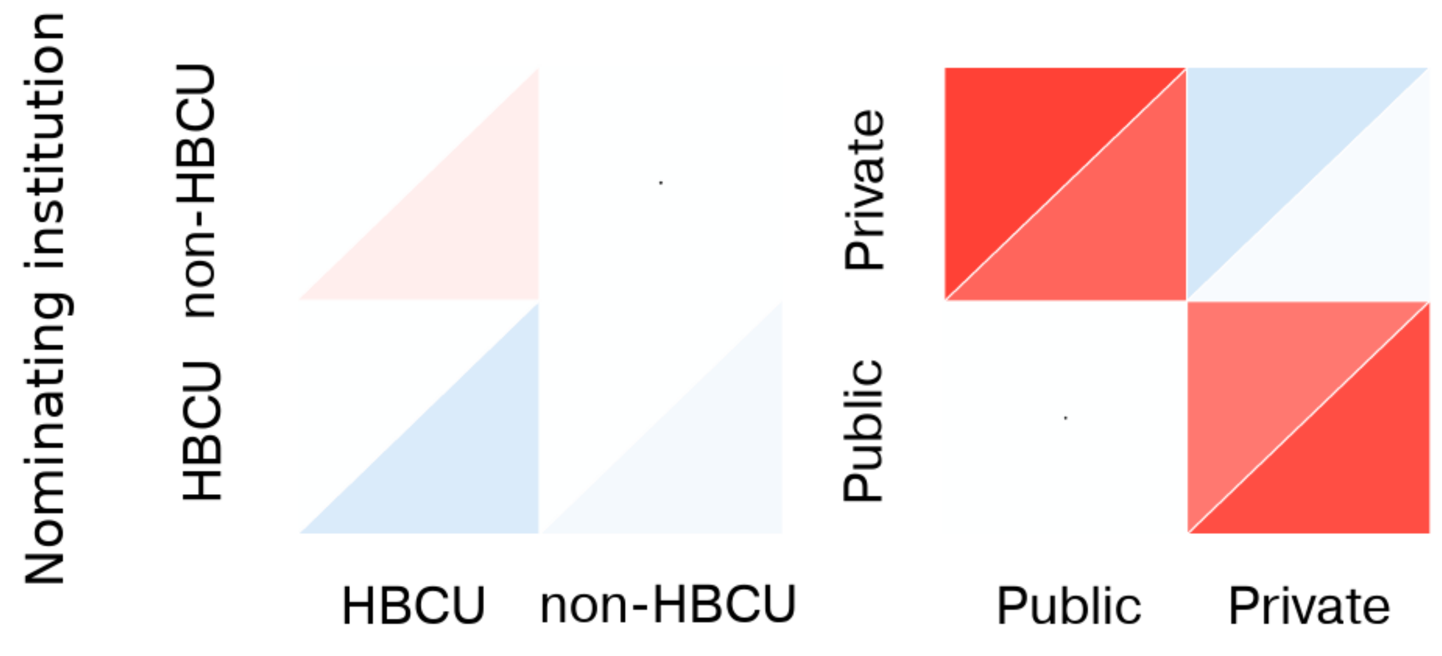
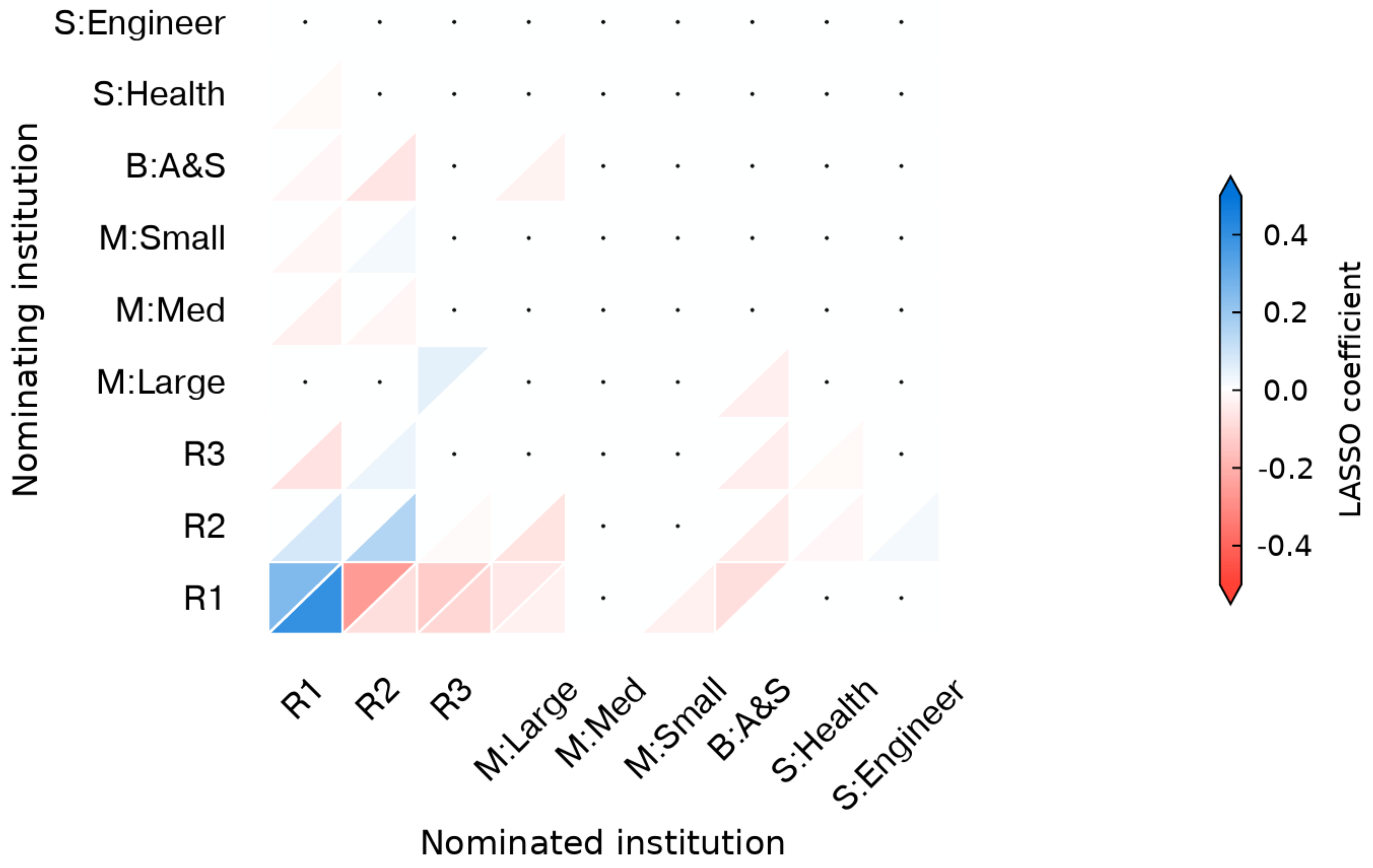
Rich peer decision patterns (categorical features)



◸ : higher prestige
◿ : lower prestige





*Model validated via the average negative log likelihood (ANLL): stratified model (0.863); separate model (0.864); common model (0.912)

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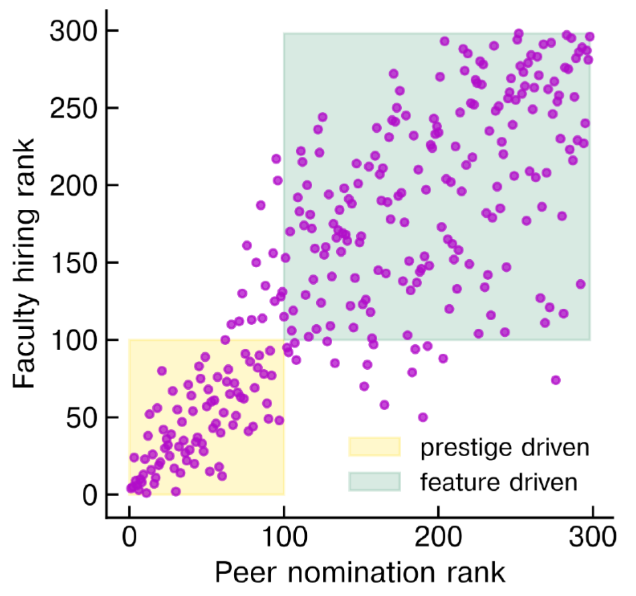

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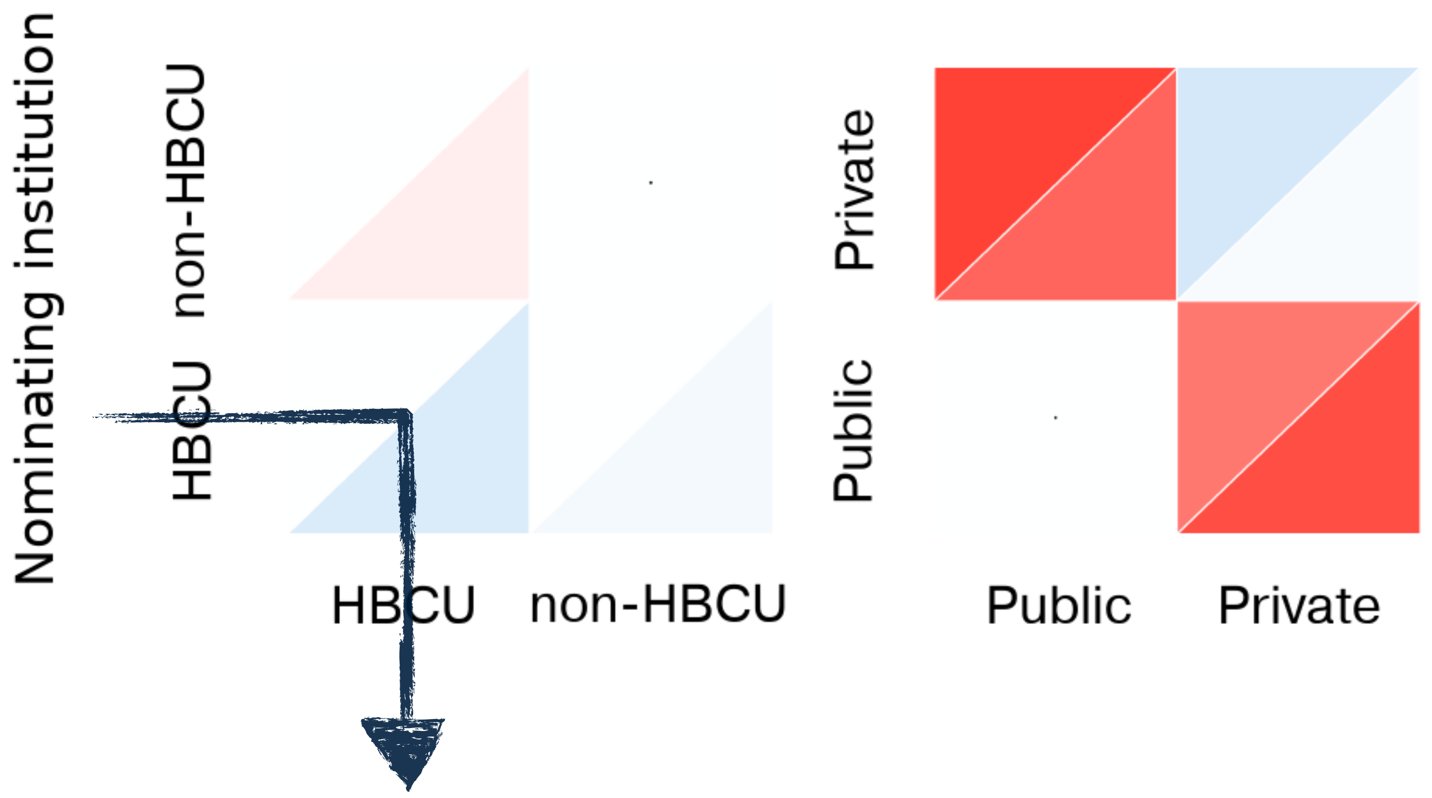
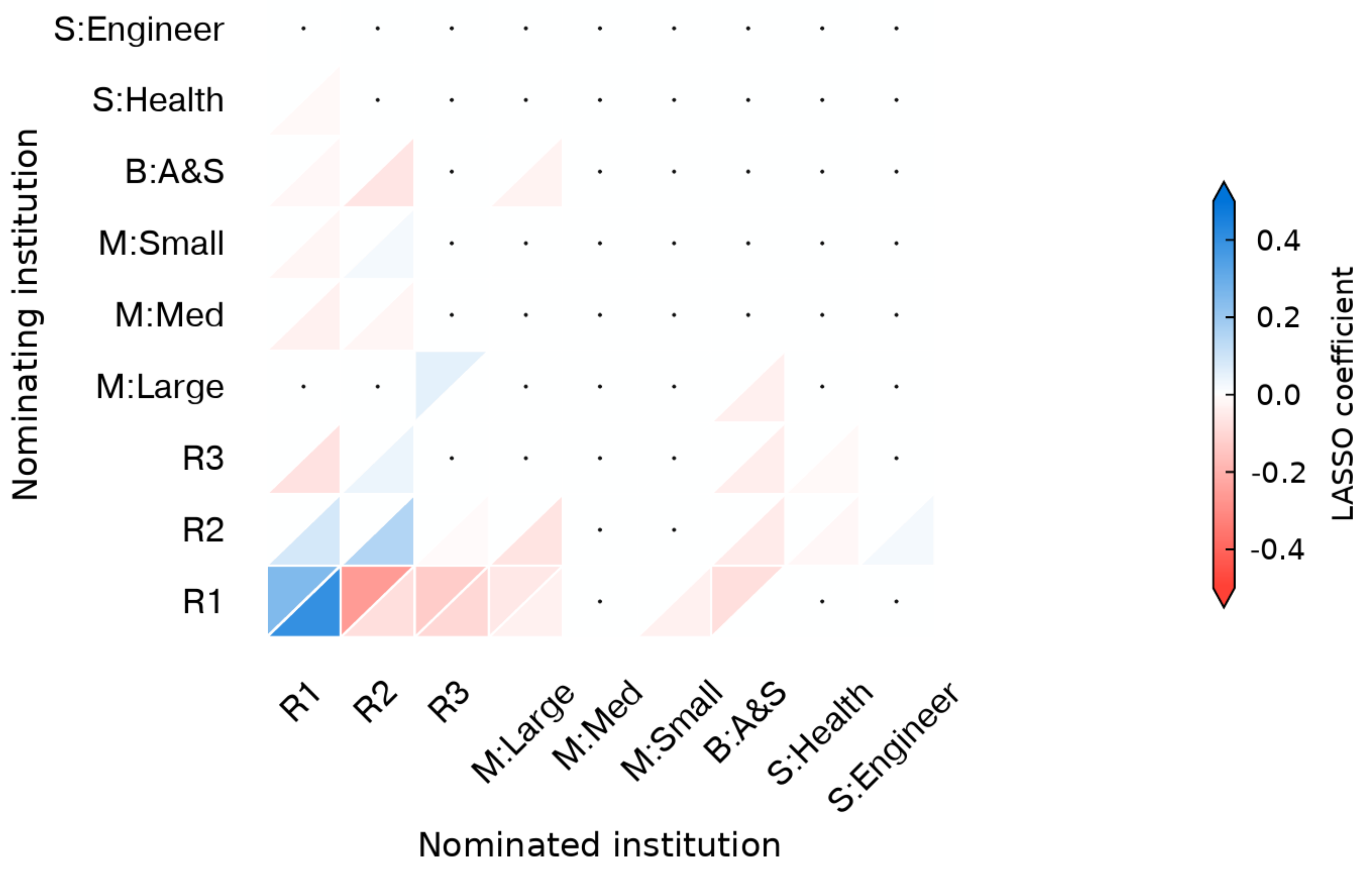


HBCU tends (slightly) to choose other HBCUs.



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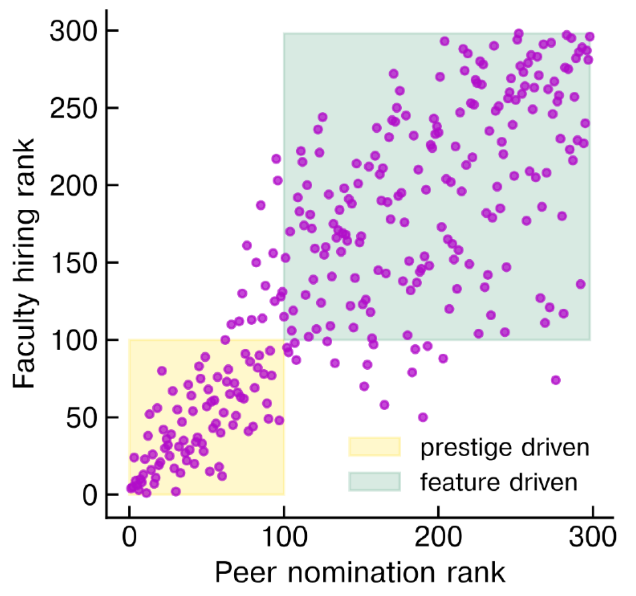

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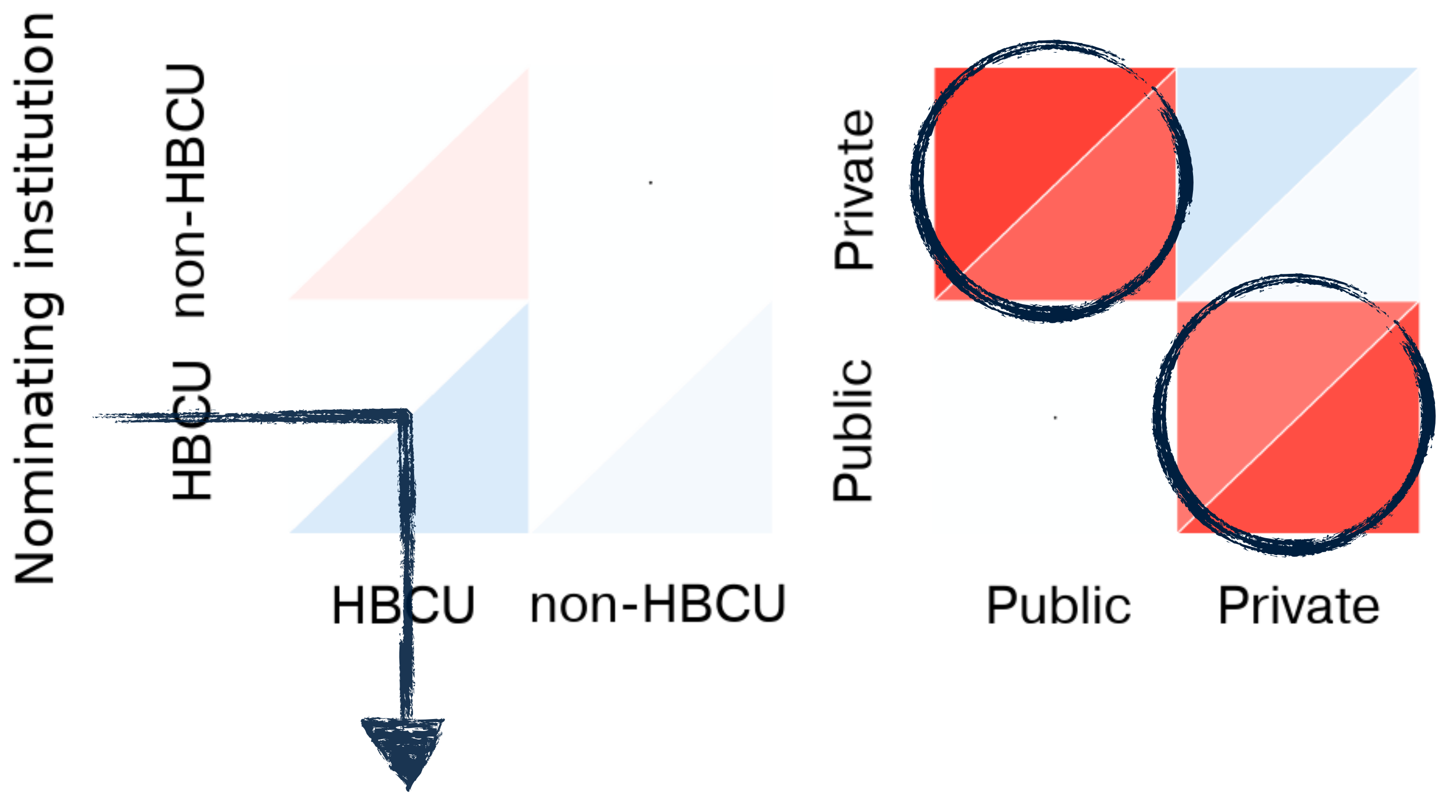
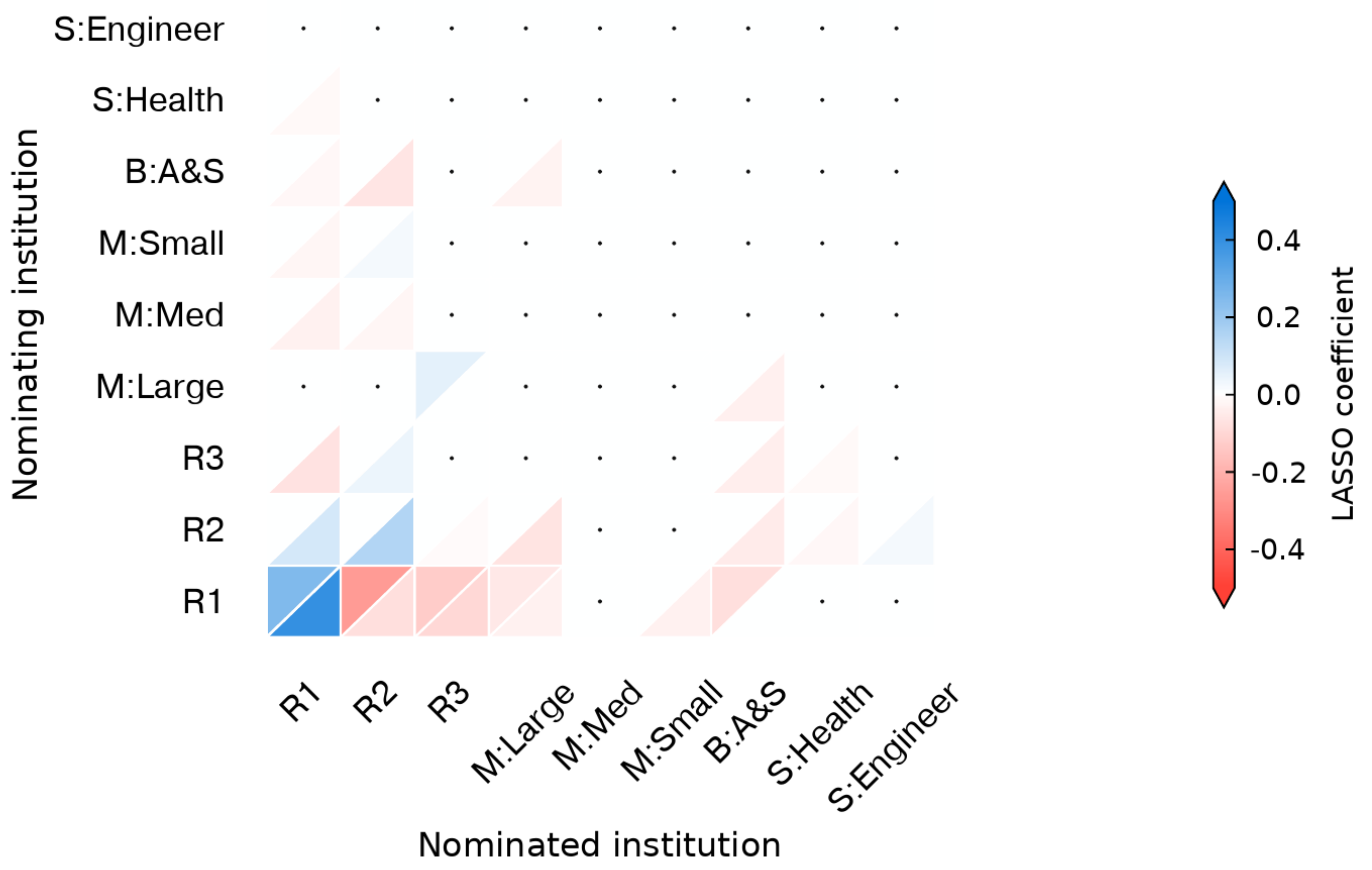


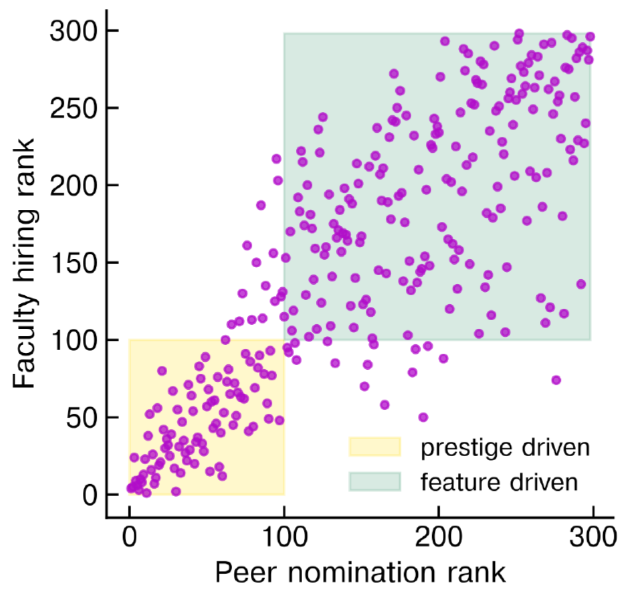


HBCU tends (slightly) to choose other HBCUs.

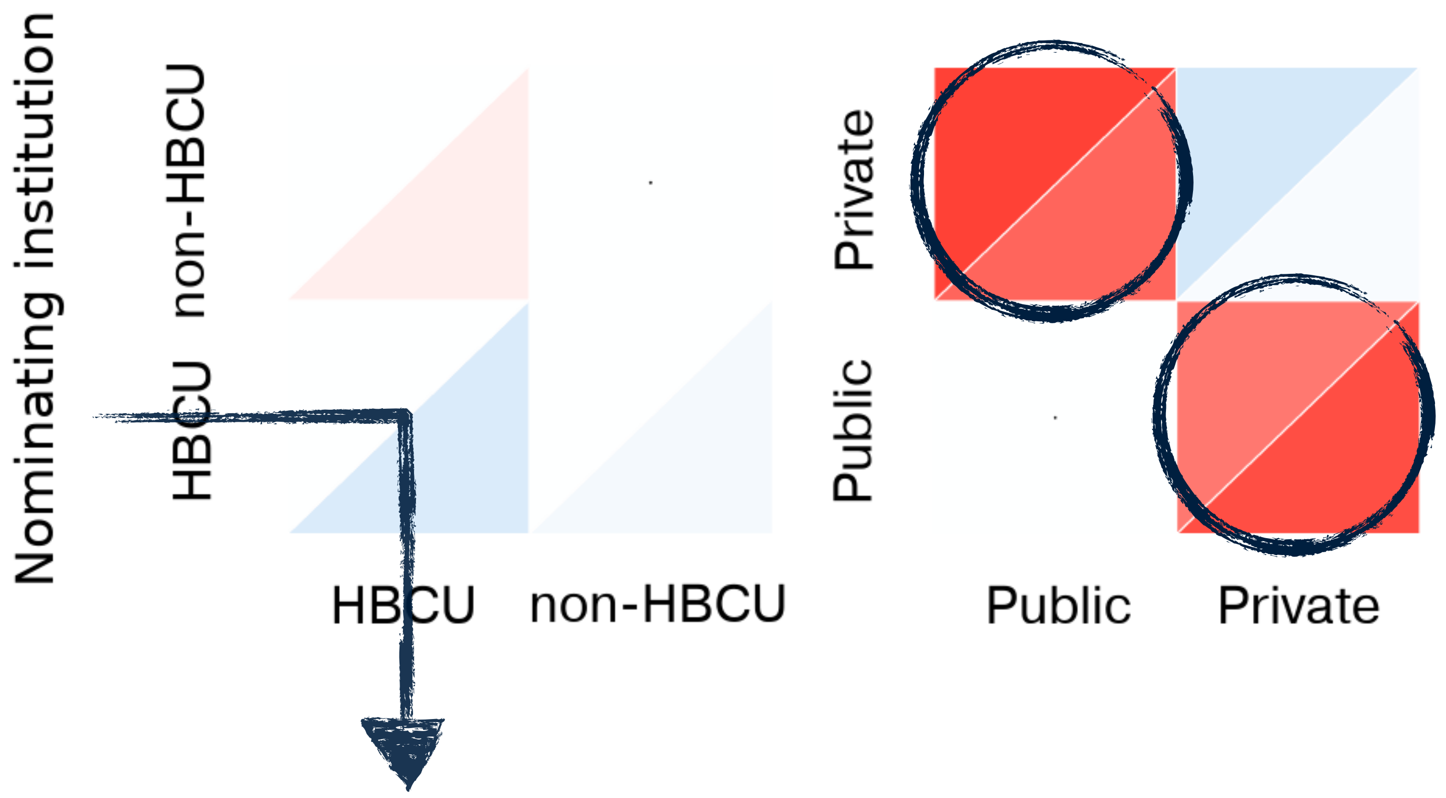
Private schools don't choose public schools (vv).

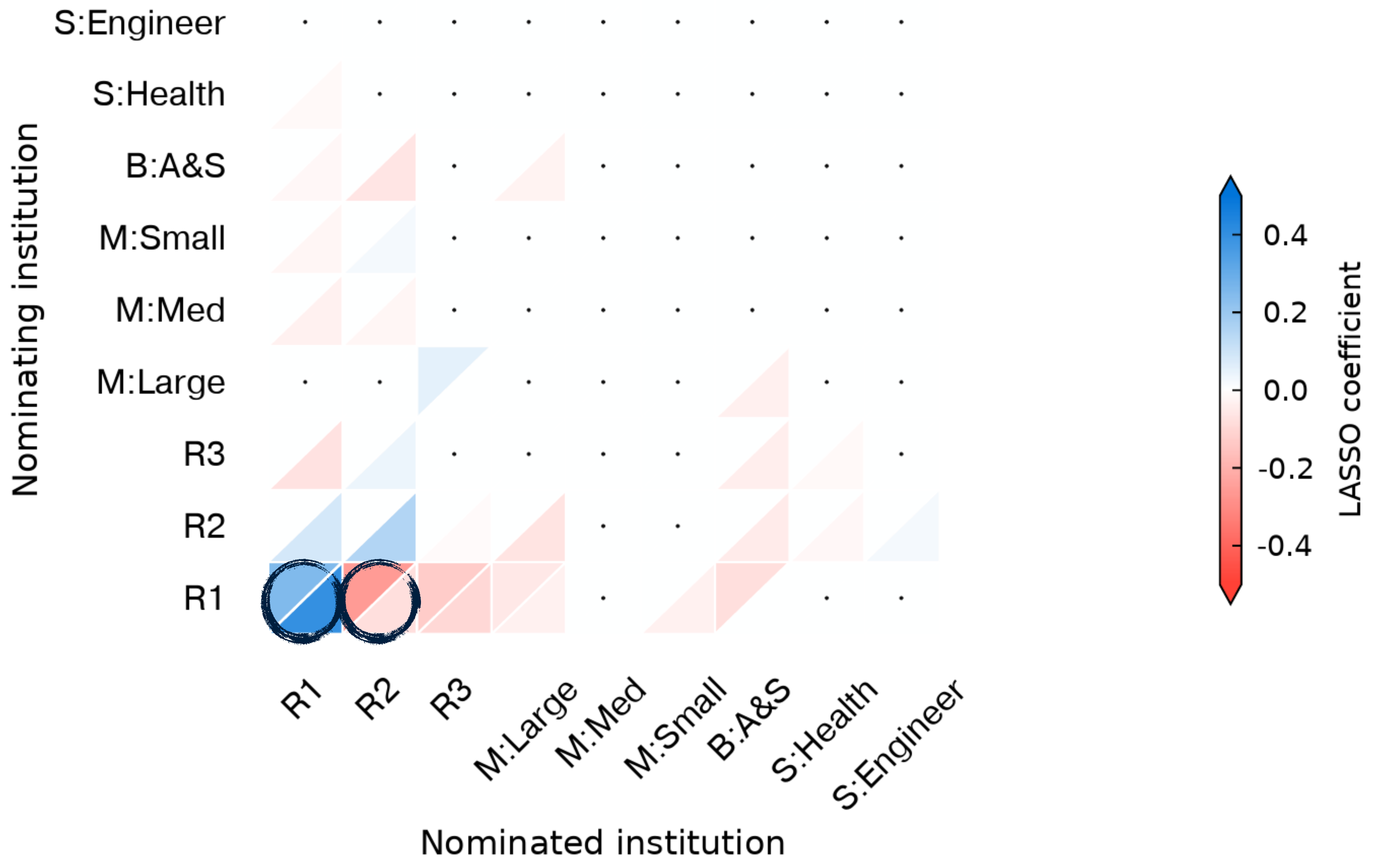
*Model validated via the average negative log likelihood (ANLL): stratified model (0.863); separate model (0.864); common model (0.912)

Rich peer decision patterns (categorical features)



◸ : higher prestige
◿ : lower prestige





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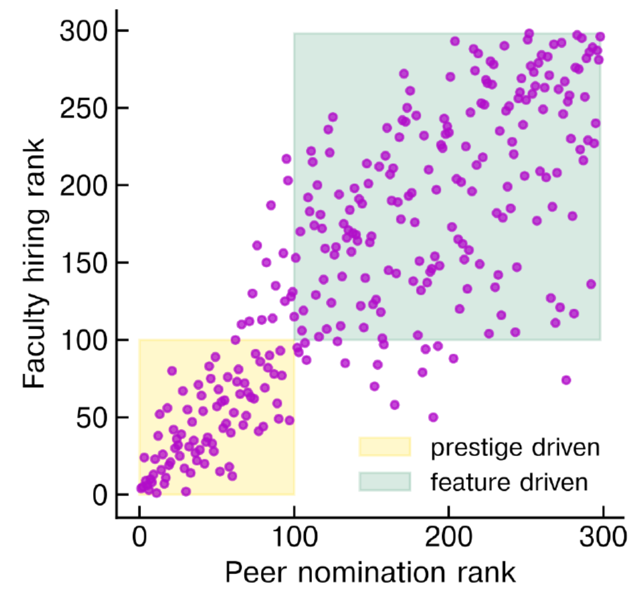

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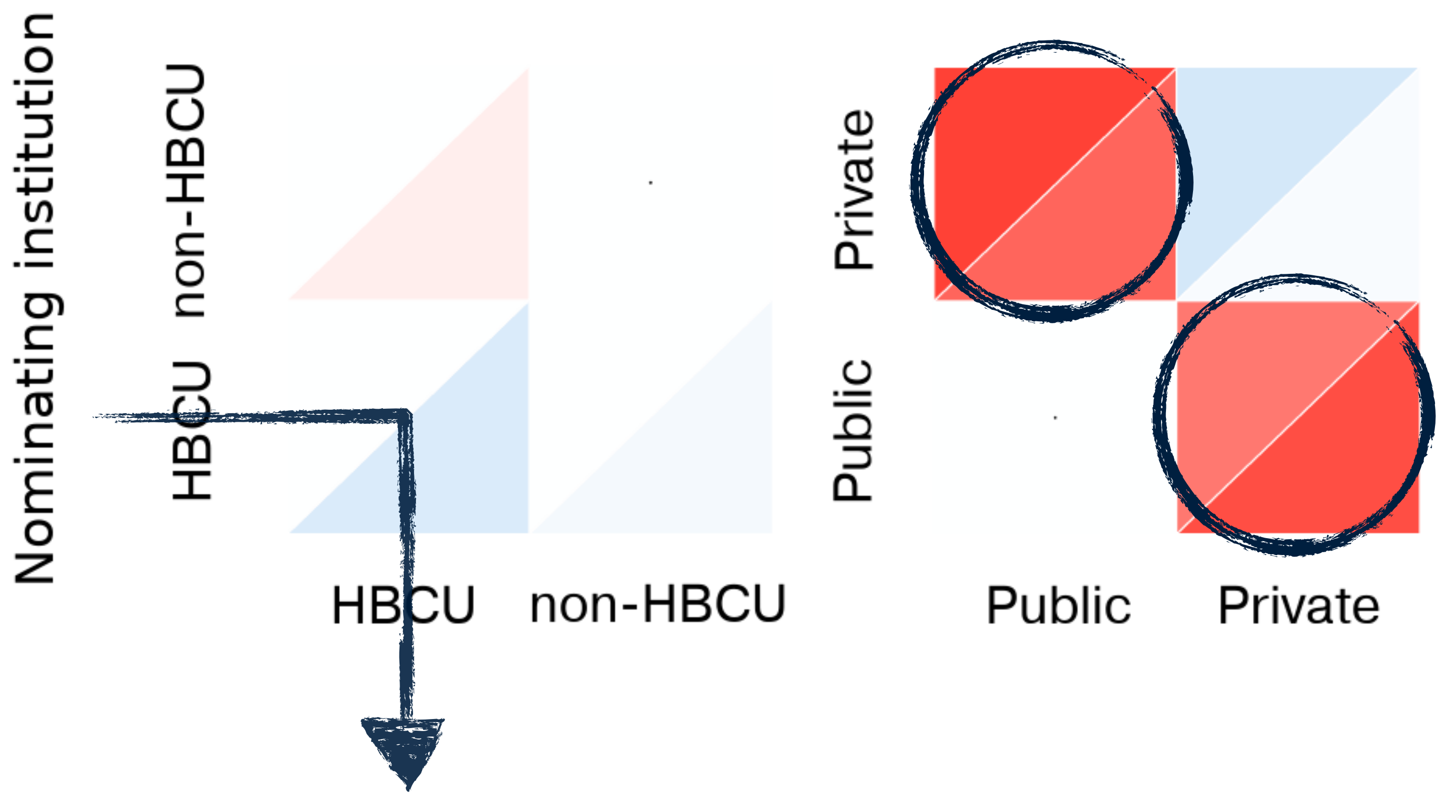

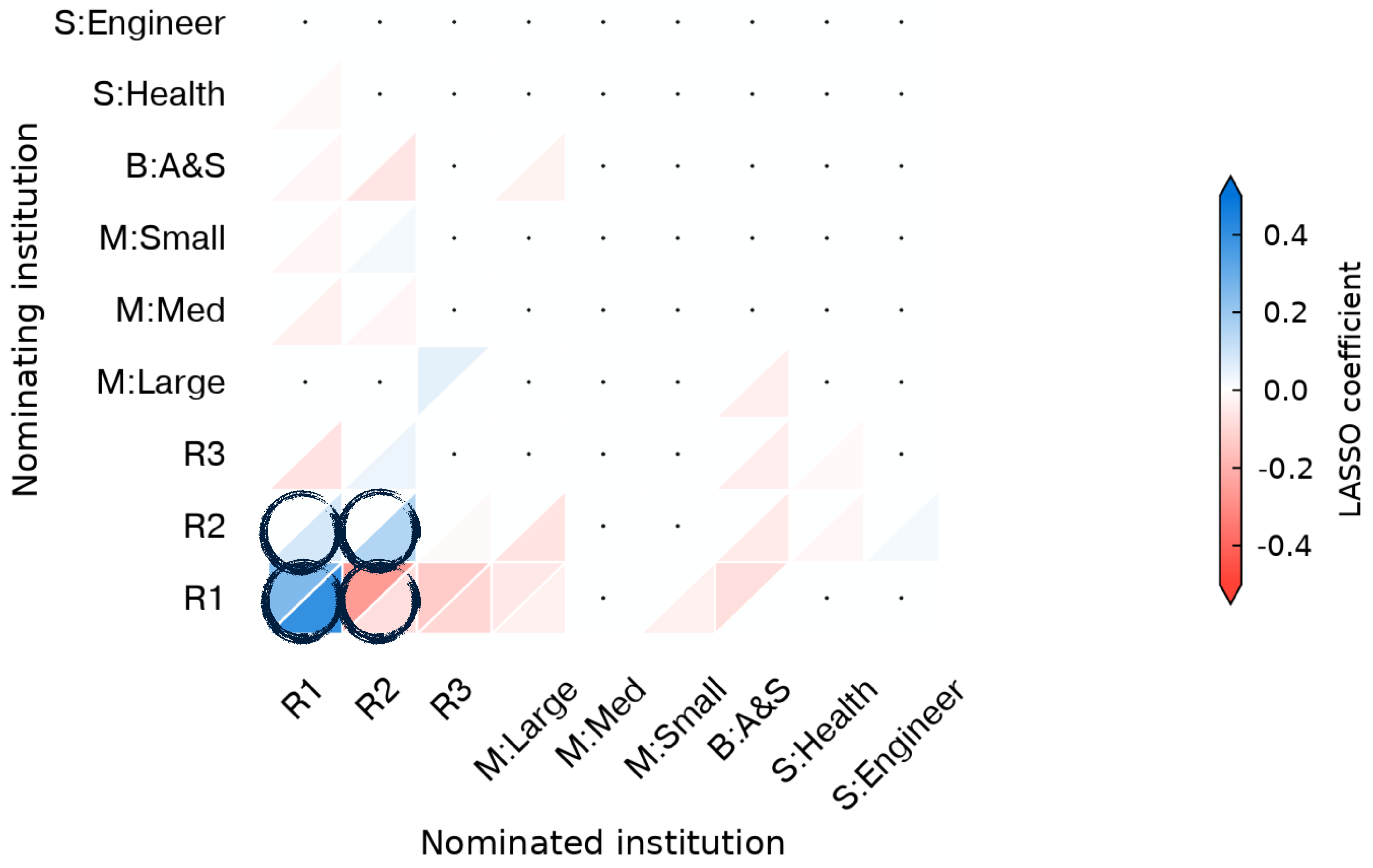

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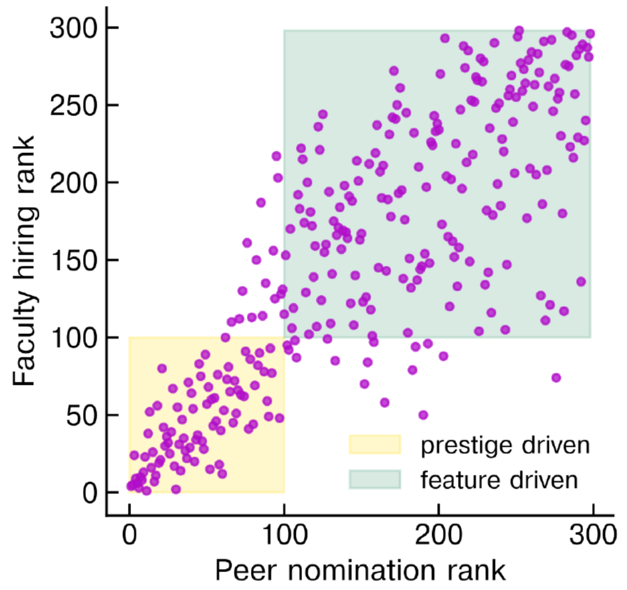
Prestige determines peer decision (numeric features)



$i \to j$	Adm	Size	Grad	Prestige
Similarity (unsigned) $(x_j - x_i)^2$	∅	∅	∅	∅
Difference (signed) $x_j - x_i$	∅	✓	✓	✓

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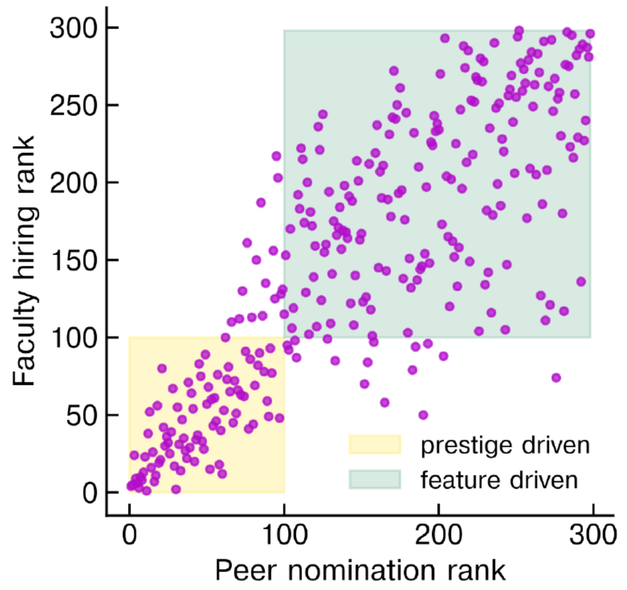

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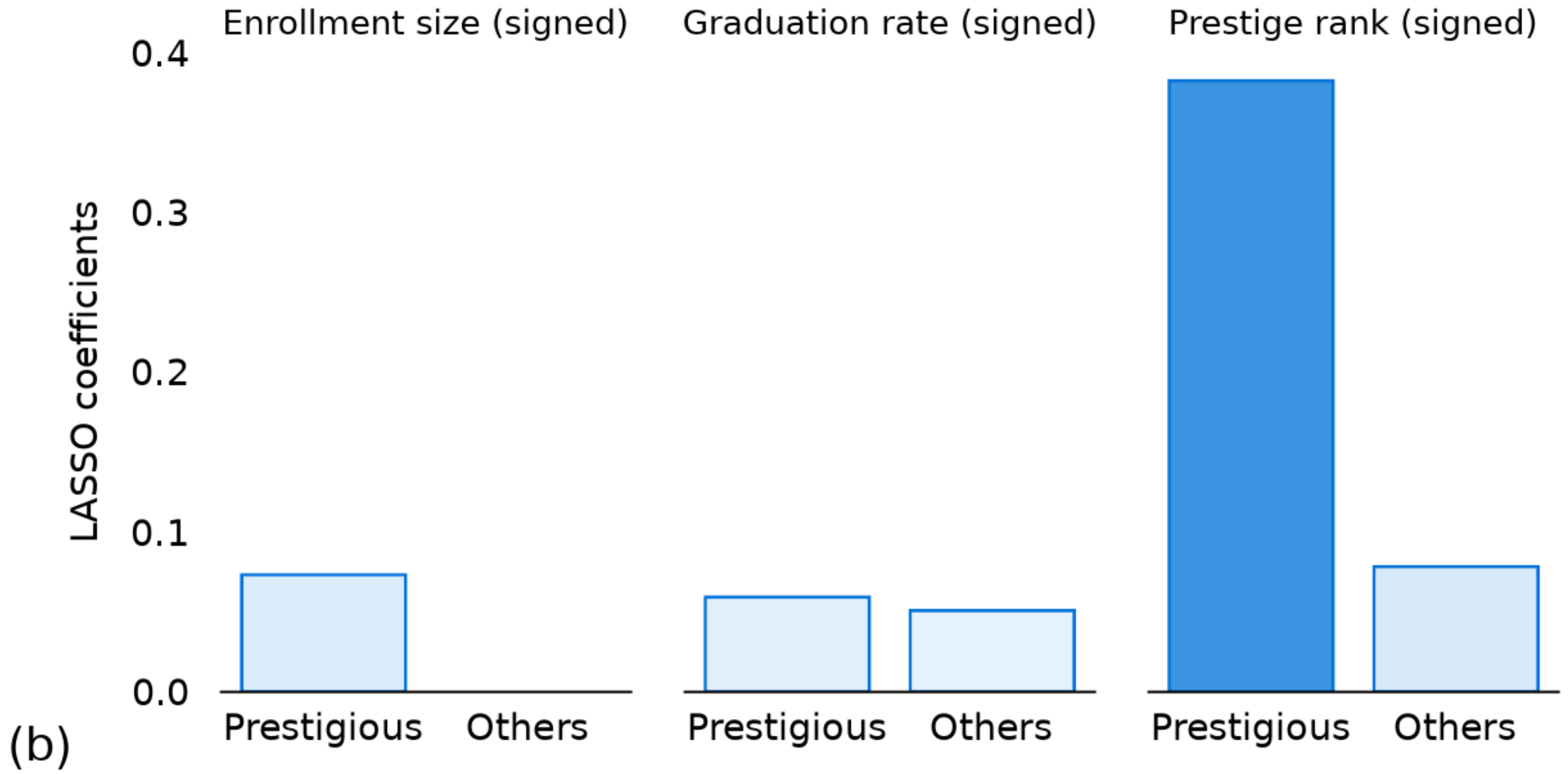

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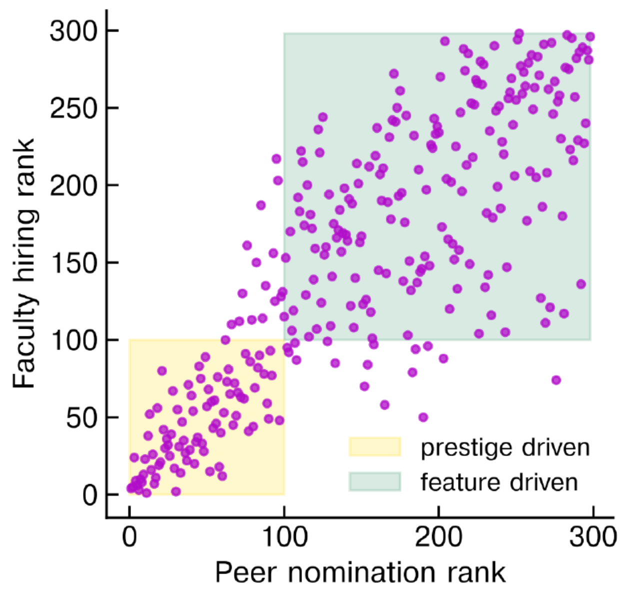

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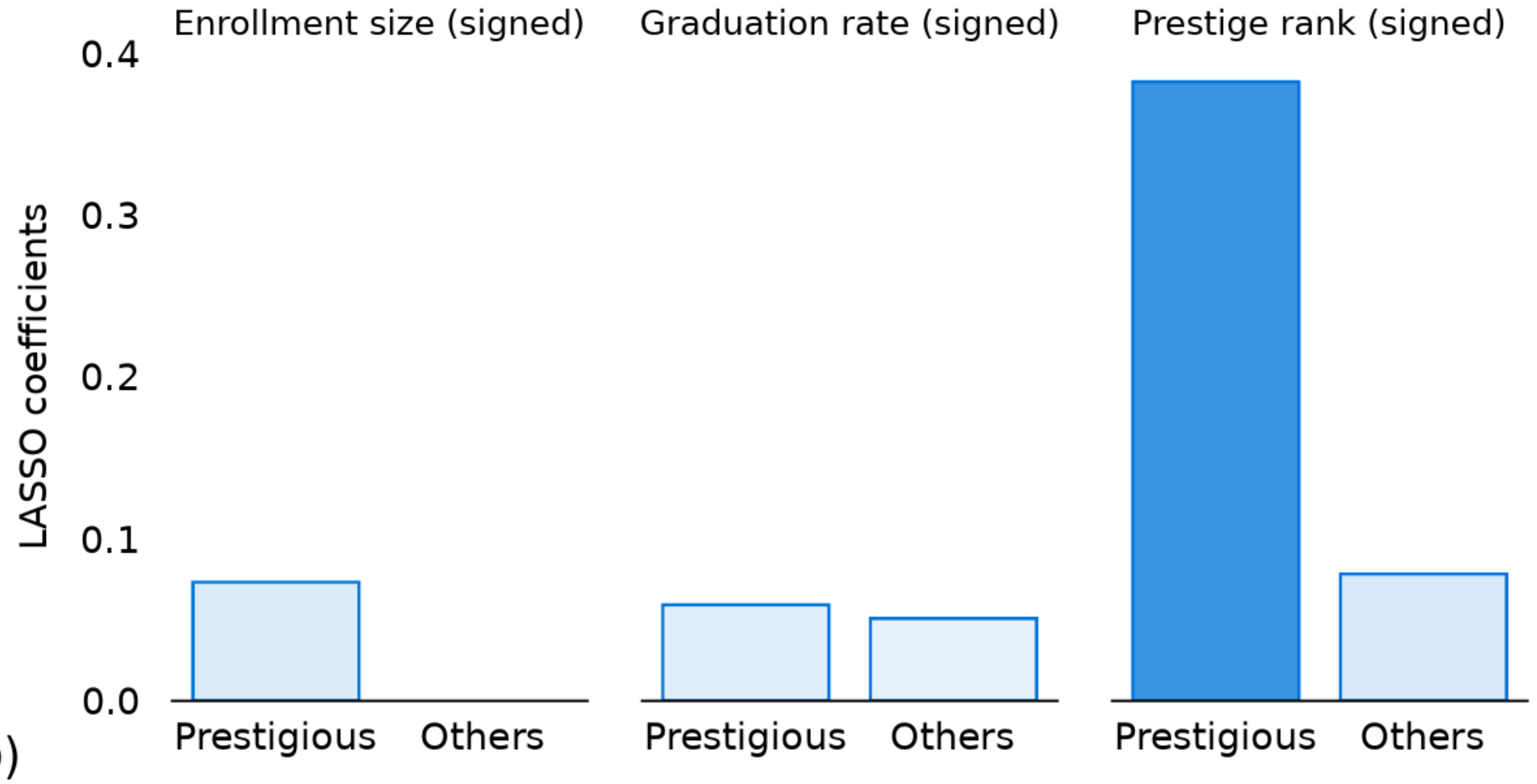

(b)

Outcome: Aspiration for a higher prestige rank is a significant predictive variable (for the elite institutions)

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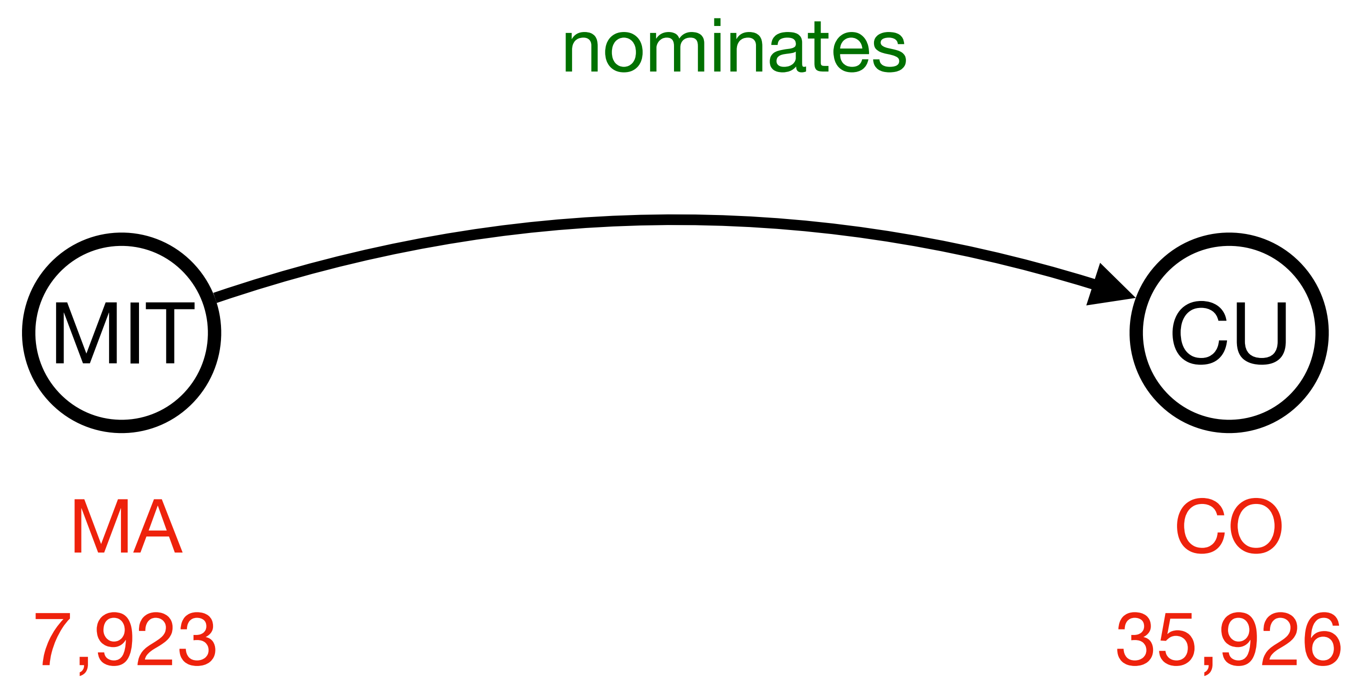
Wait… What about *other* schools?

Nomination network



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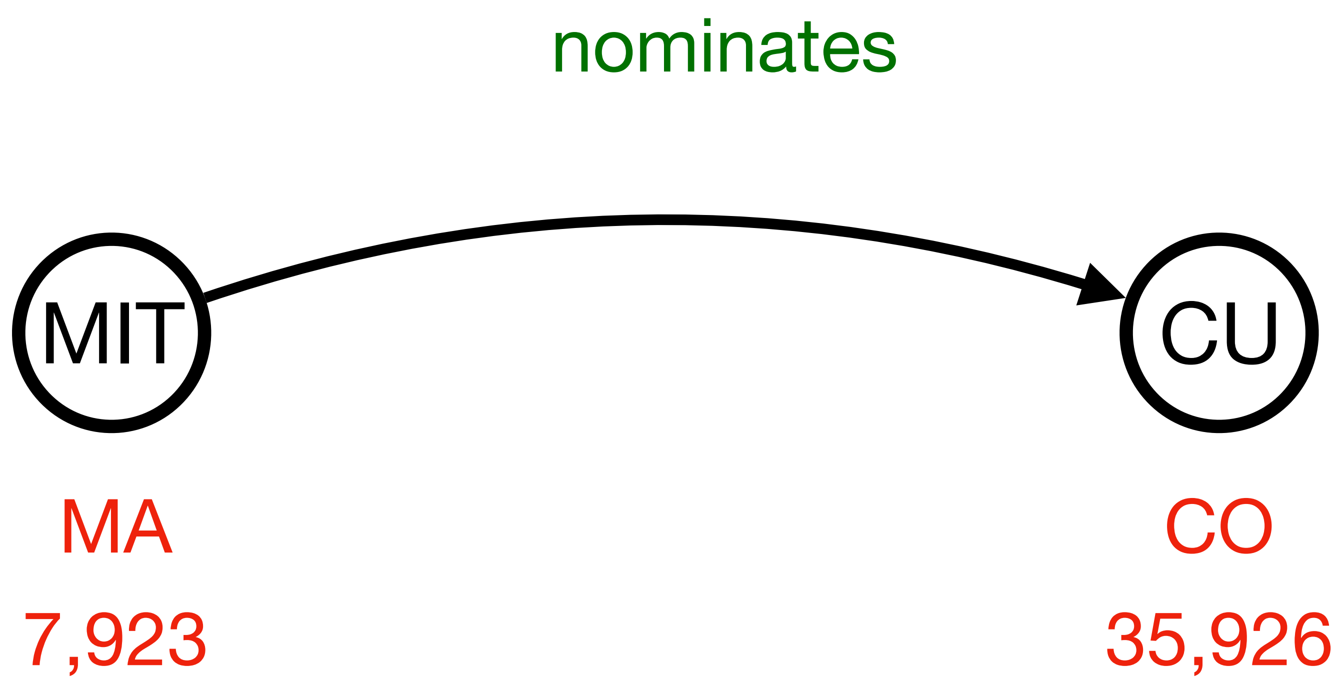

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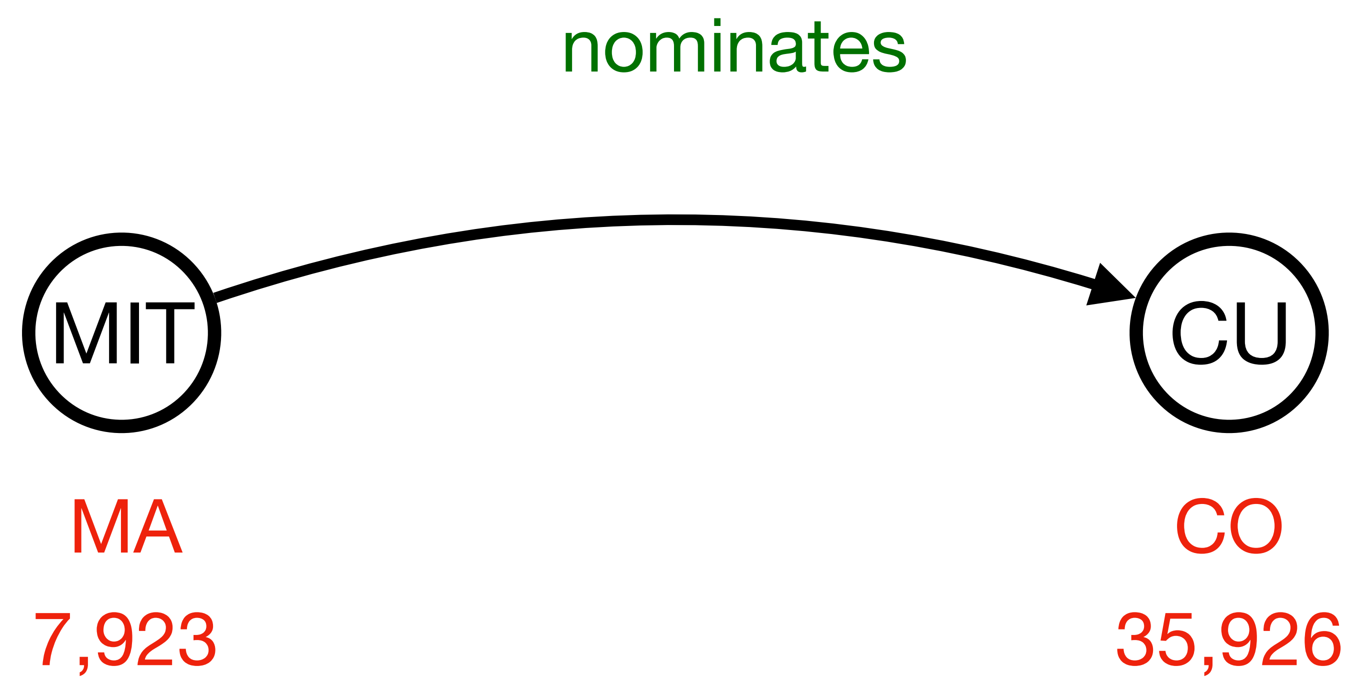
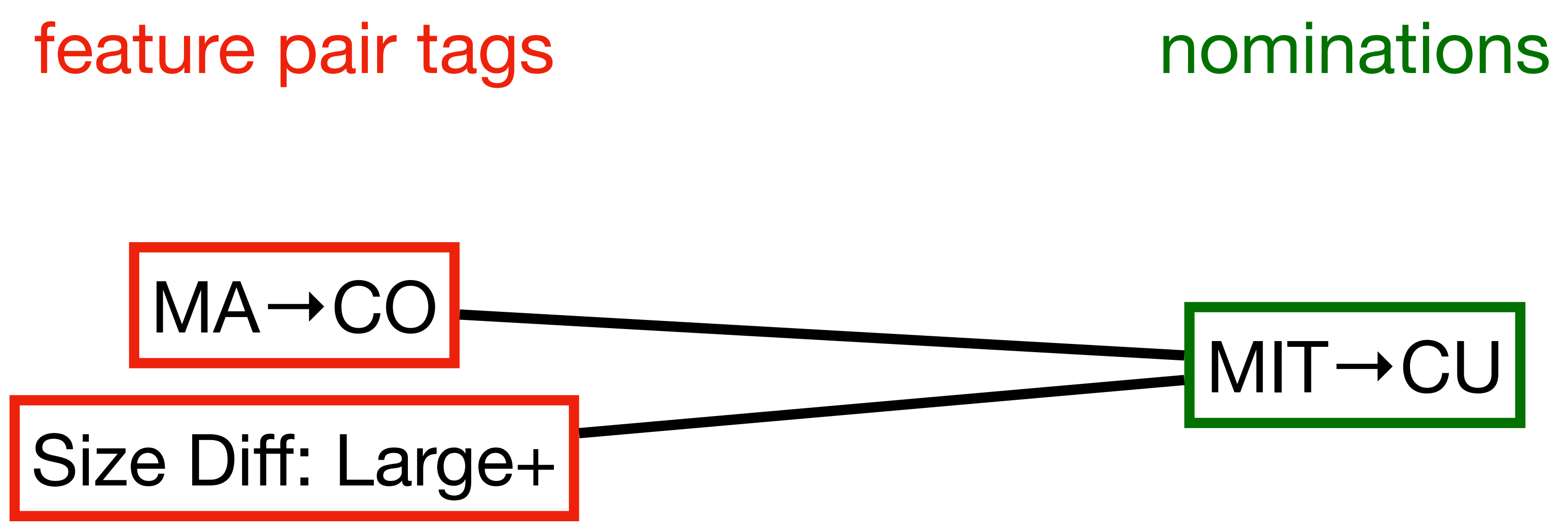


Bipartite expanded feature network



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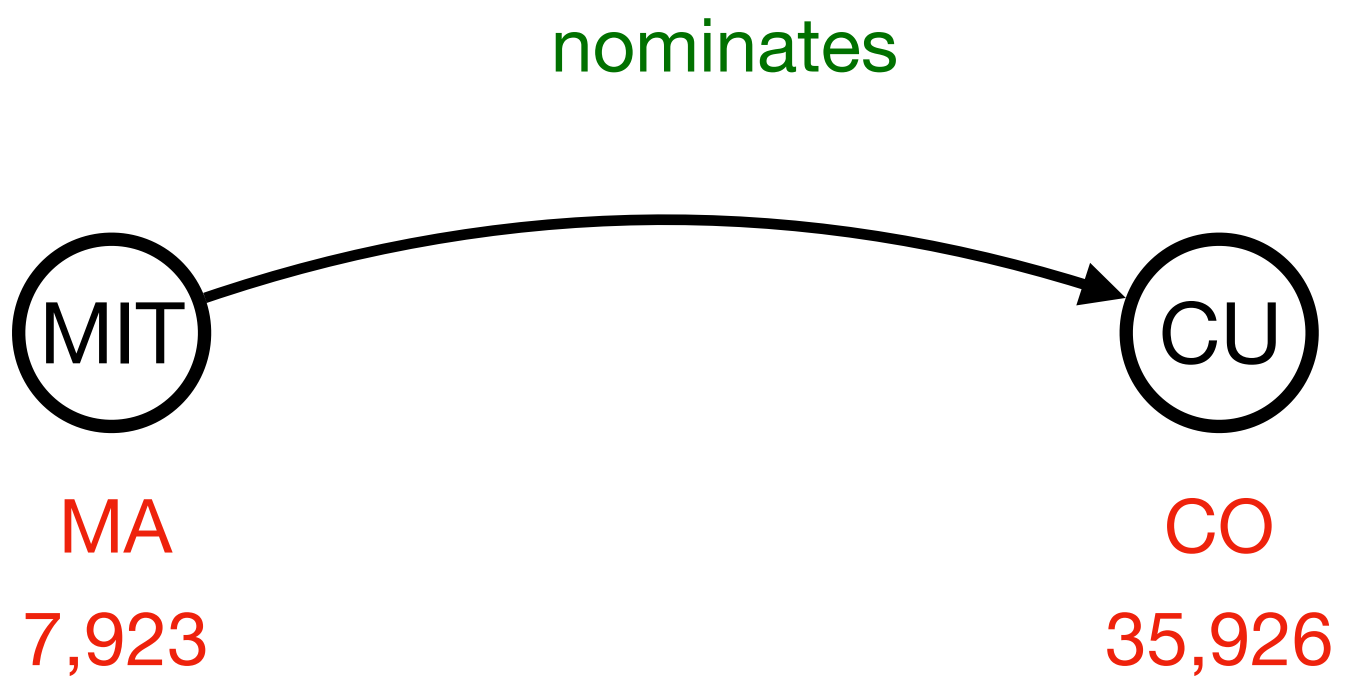

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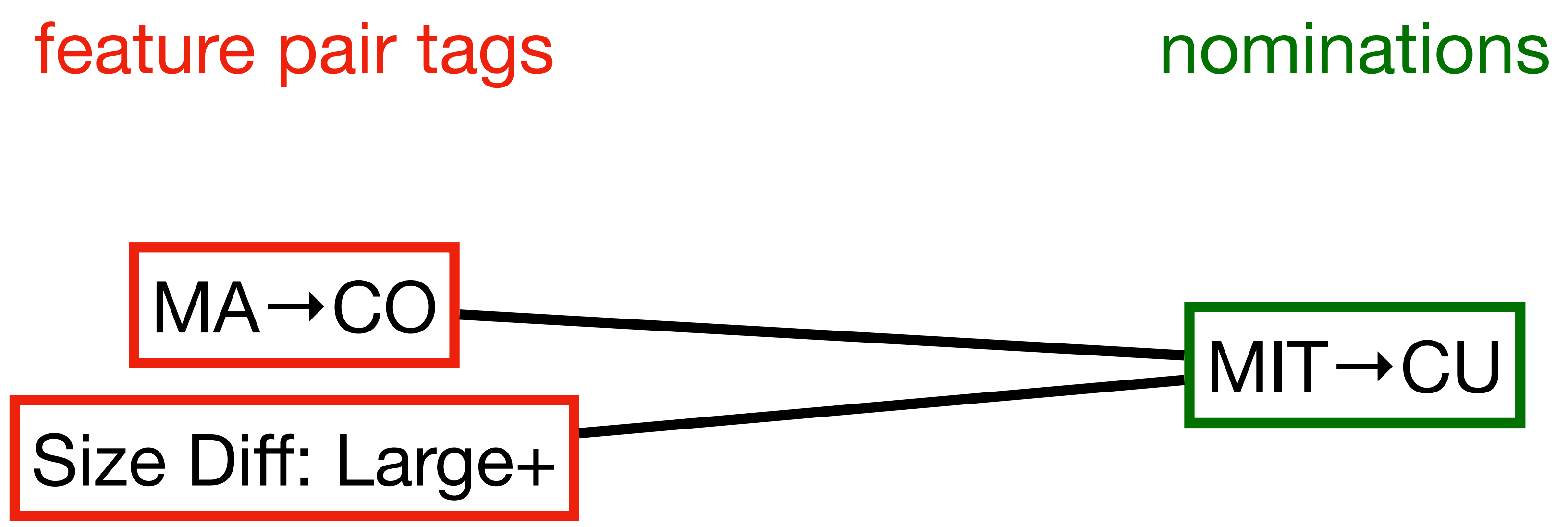
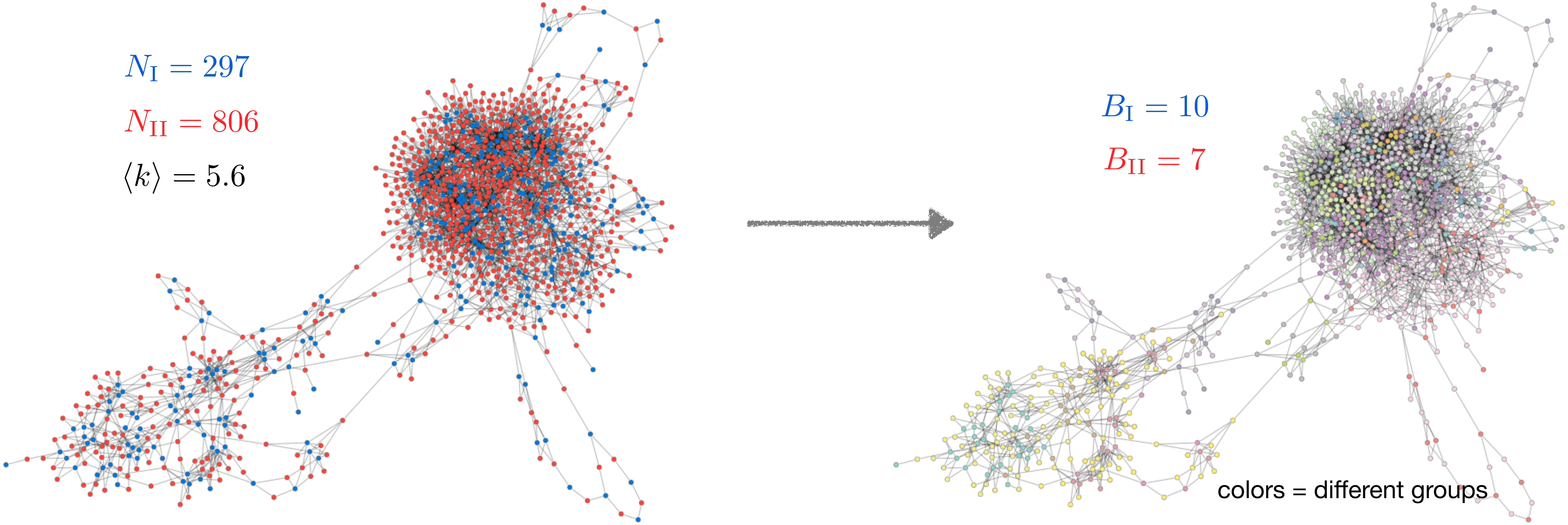


Communities with statistical validation (e.g., description length, posterior likelihood)

Known: The bipartite structure, i.e., which node is of which type. Edges are given (measurement is perfect).

Unknown: Of which group should a node be assigned to.



Yen & Larremore, Phys. Rev. E 102, 032309 (2020)

Stochastic block models formalize the concept of “large-scale structure”

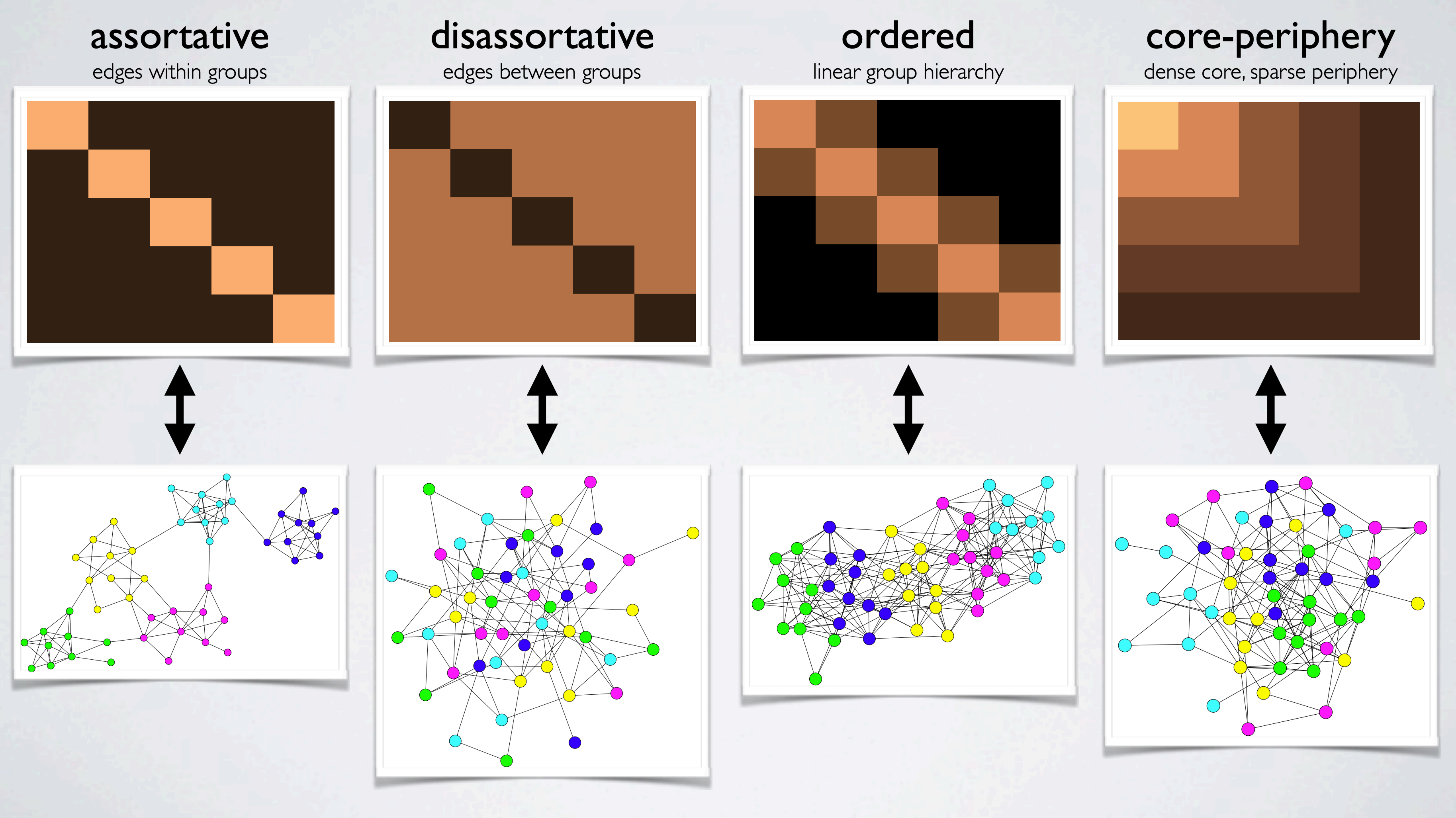
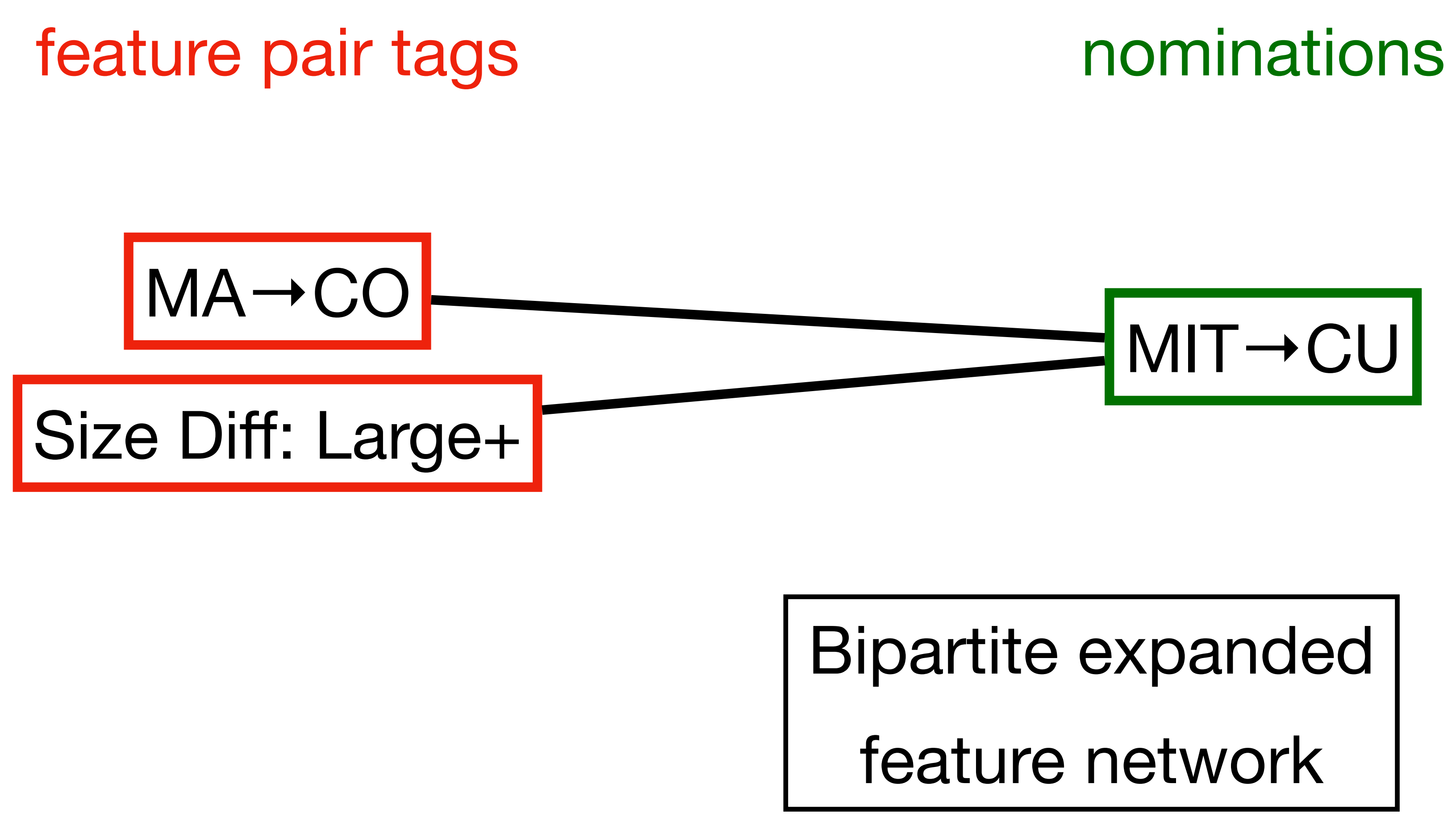


Image credit: Aaron Clauset

A handful of groups explain most nomination behaviors

Type-I nodes: feature pair tags, to cluster as B_I groups

Type-II nodes: nominations, to cluster as B_{II} groups



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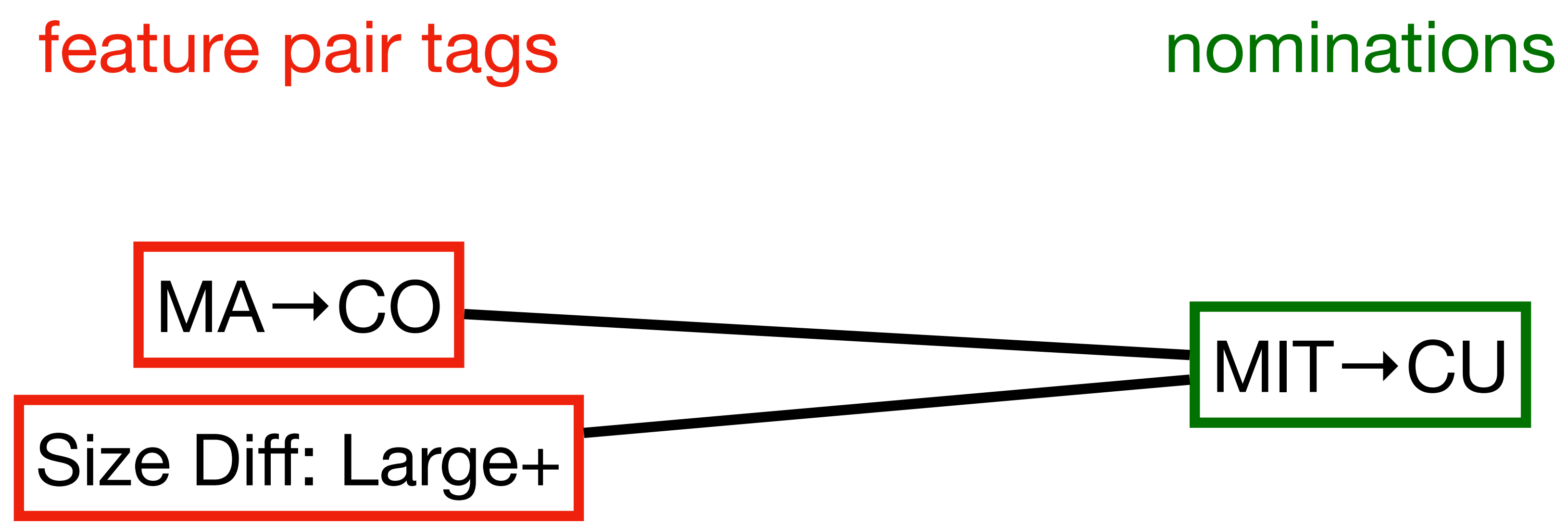

Bipartite expanded feature network

Code	Type of Institutions	N	N_{I}	N_{II}	E	B_{I}	B_{II}	Σ/E
15	Doctoral Universities: Highest Research Activity	117	946	1956	13692	5	2	2.45
16	Doctoral Universities: Higher Research Activity	112	833	1757	12299	8	2	2.67
17	Doctoral Universities: Moderate Research Activity	102	596	1815	12705	11	3	2.68
18	Master's Colleges & Universities: Larger Programs	251	958	4118	28825	16	3	2.73
19	Master's Colleges & Universities: Medium Programs	129	656	2082	14574	14	3	2.71
20	Master's Colleges & Universities: Small Programs	78	502	1169	8183	6	2	2.70
21	Baccalaureate Colleges: Arts & Sciences Focus	176	778	3105	21735	4	2	2.48
22	Baccalaureate Colleges: Diverse Fields	144	698	2129	14903	12	3	2.69
23	Baccalaureate/Associate's Colleges: Mixed Baccalaureate/Associate's	126	32	232	1624	4	2	2.45
24	Special Focus Four-Year: Faith-Related Institutions	1	9	2	14	1	1	1.31
26	Special Focus Four-Year: Other Health Professions Schools	5	53	42	293	1	1	2.55
27	Special Focus Four-Year: Engineering Schools	3	45	24	168	1	1	2.53
28	Special Focus Four-Year: Other Technology-Related Schools	3	53	38	266	1	1	2.37
29	Special Focus Four-Year: Business & Management Schools	6	47	122	854	1	1	2.27
30	Special Focus Four-Year: Arts, Music & Design Schools	18	138	196	1372	1	1	2.41
32	Special Focus Four-Year: Other Special Focus Institutions	2	38	30	209	1	1	2.34

total = 1179

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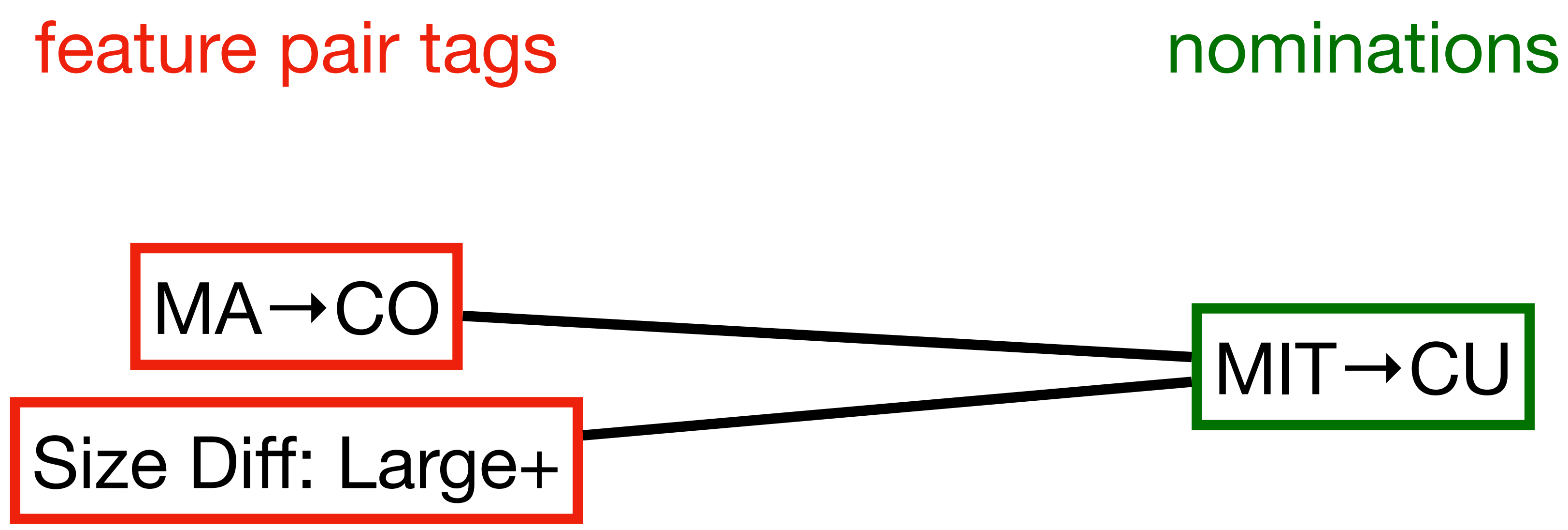

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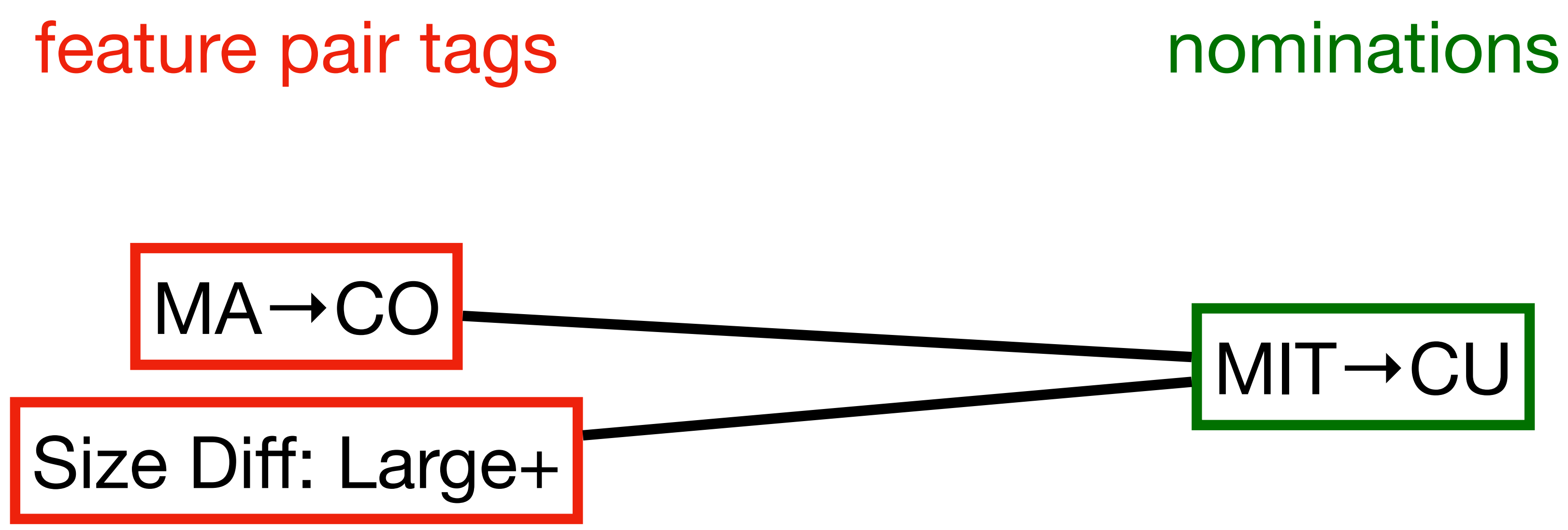

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A handful of groups explain most nomination behaviors (cont.)

Type	Top feature pairs	Group 1	Group 2
R1	non-HBCU to non-HBCU, to higher admission rate, to other R1	10.4%	36.8%
	78.9% intrastate, 93.5% interstate, non-HBCU to HBCU, to similar enrollment size, to R2 or to M:Large	2.5%	22.1%
	Public to Public/Private, to lower grad rate	0%	13.2%
	5.3% intrastate, to higher grad rate, to similar admission rate	3.9%	6.1%
	15.8% intrastate, 6.5% interstate, Private to Public/Private	4.9%	0.1%
R2	non-HBCU to non-HBCU, to higher admission rate, to R1, to M:Large	28.4%	12.7%
	to lower enrollment size, to higher graduation rate, to similar admission rate, to other R2	19.7%	4.7%
	69.6% intrastate, 90.7% interstate, HBCU to HBCU/non-HBCU, non-HBCU to HBCU, to M:Small, to Bacc. Colleges (diverse fields), Private to Public/Private for-profit	11.5%	1.3%
	Public to Public	9.6%	0%
	to higher admission rate, to R3	1.9%	2.1%
	Private to Private	0%	3.7%
	17.4% intrastate, 4% interstate, to M:Med, S:Engineer, Public to Private	0.6%	1.8%
	13% intrastate, 5.3% interstate, to B:A&S, to Special Focus Four-Year (Arts/Music/Design)	0%	1.9%

*See dissertation for clustering of other Carnegie classifications

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Niche effect. R1 wants to increase grad rate than other intrastate R1s; R2 aspires the same, but be fitter (lower enrollment size).

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Implications

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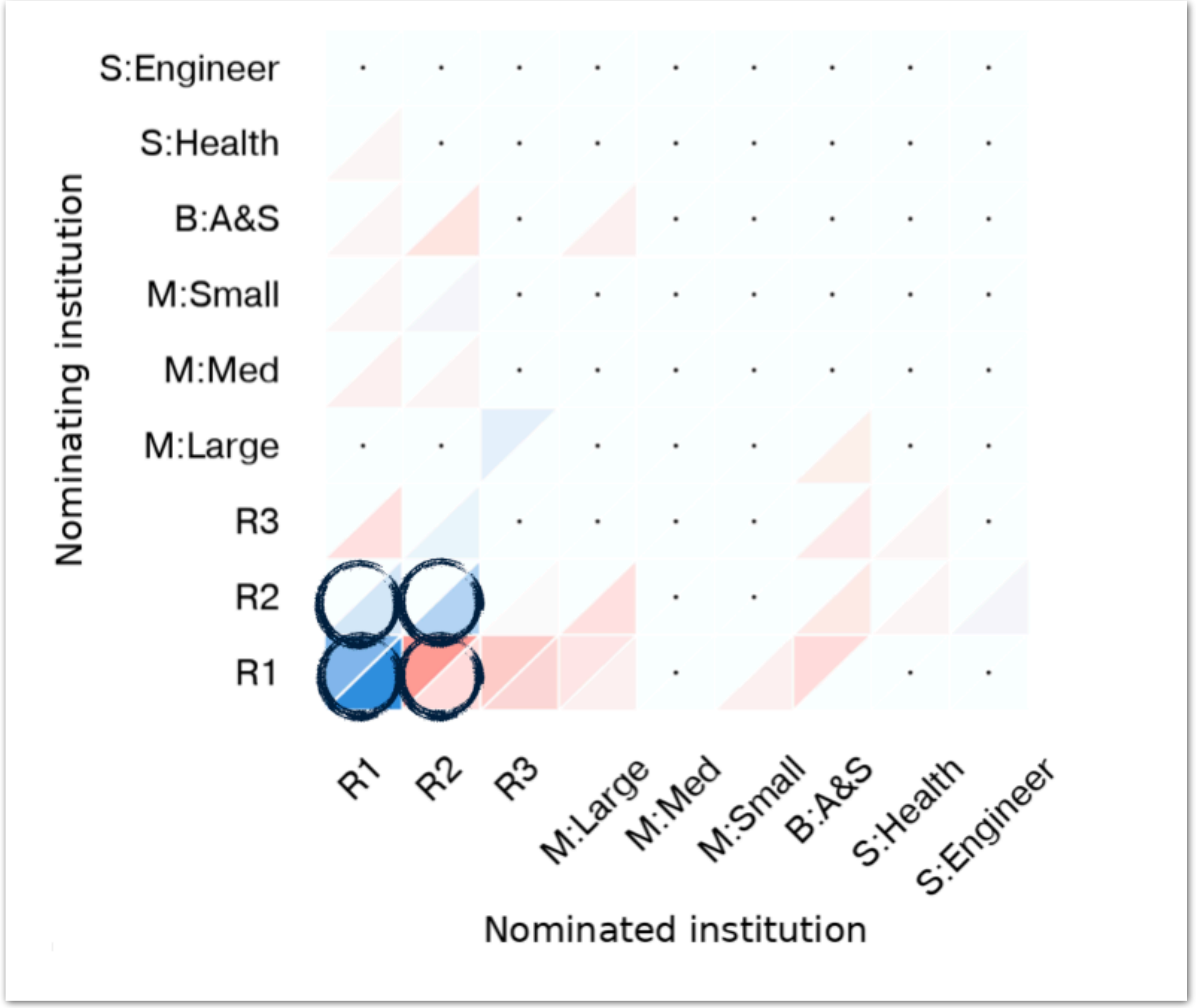

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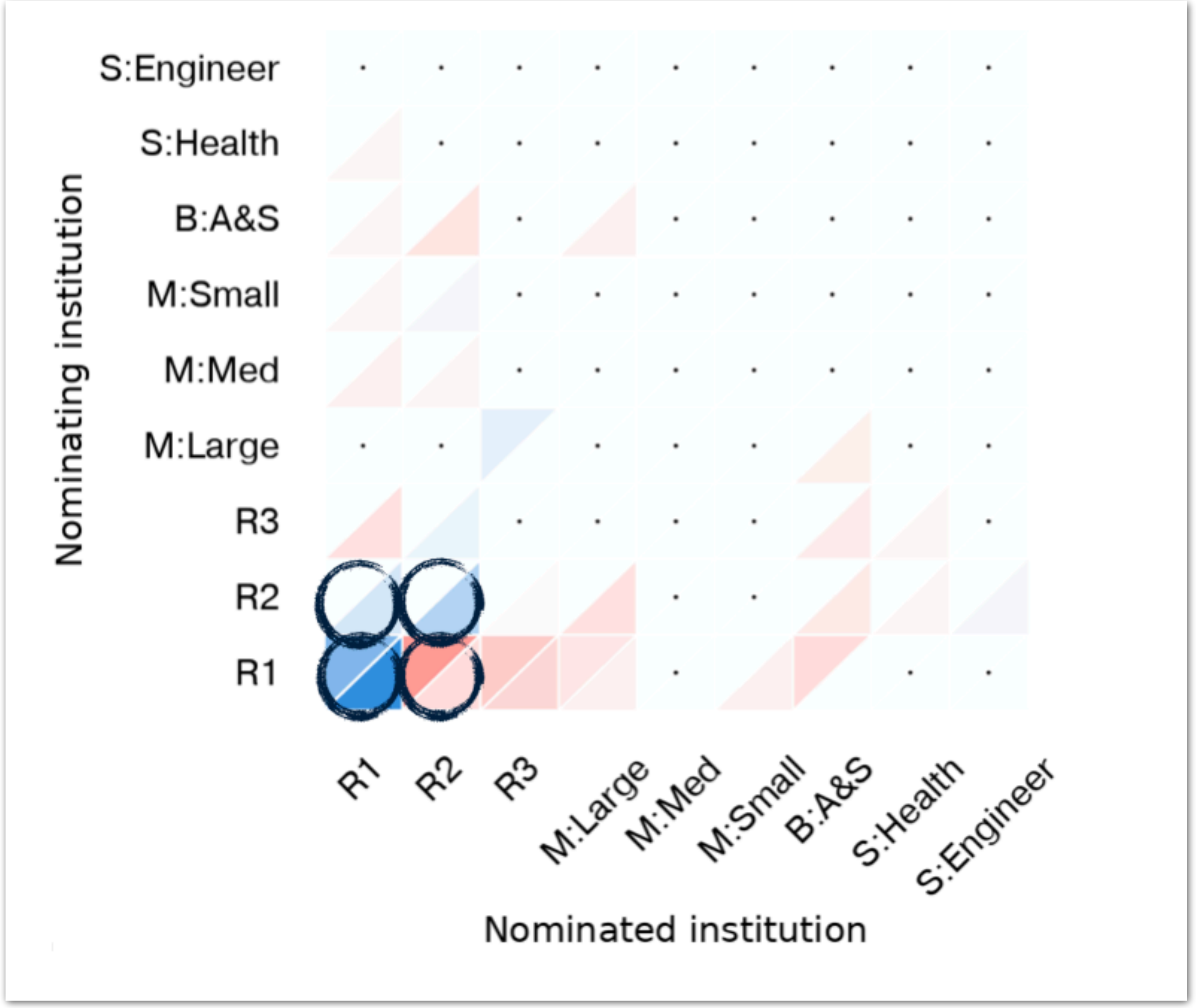

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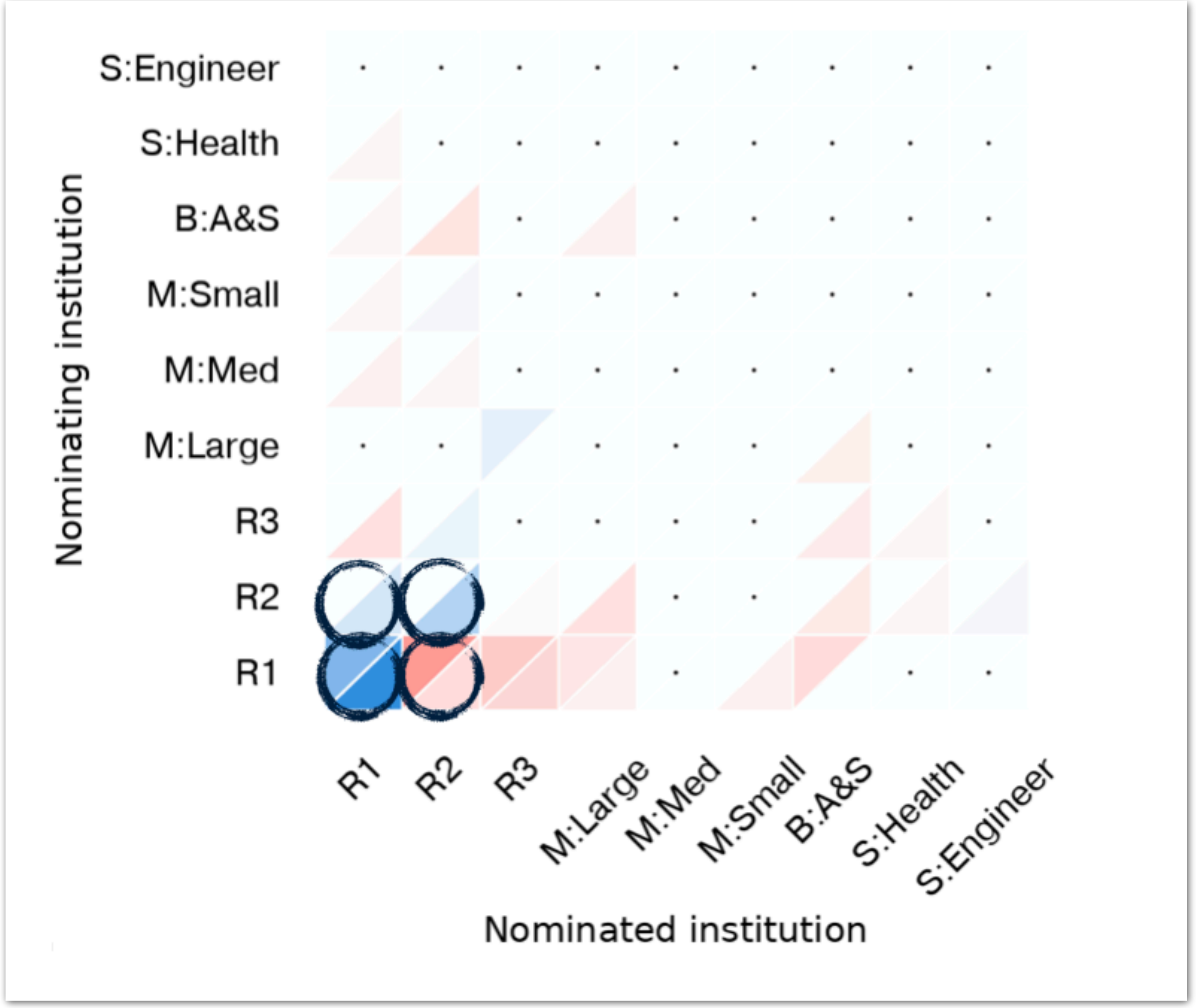

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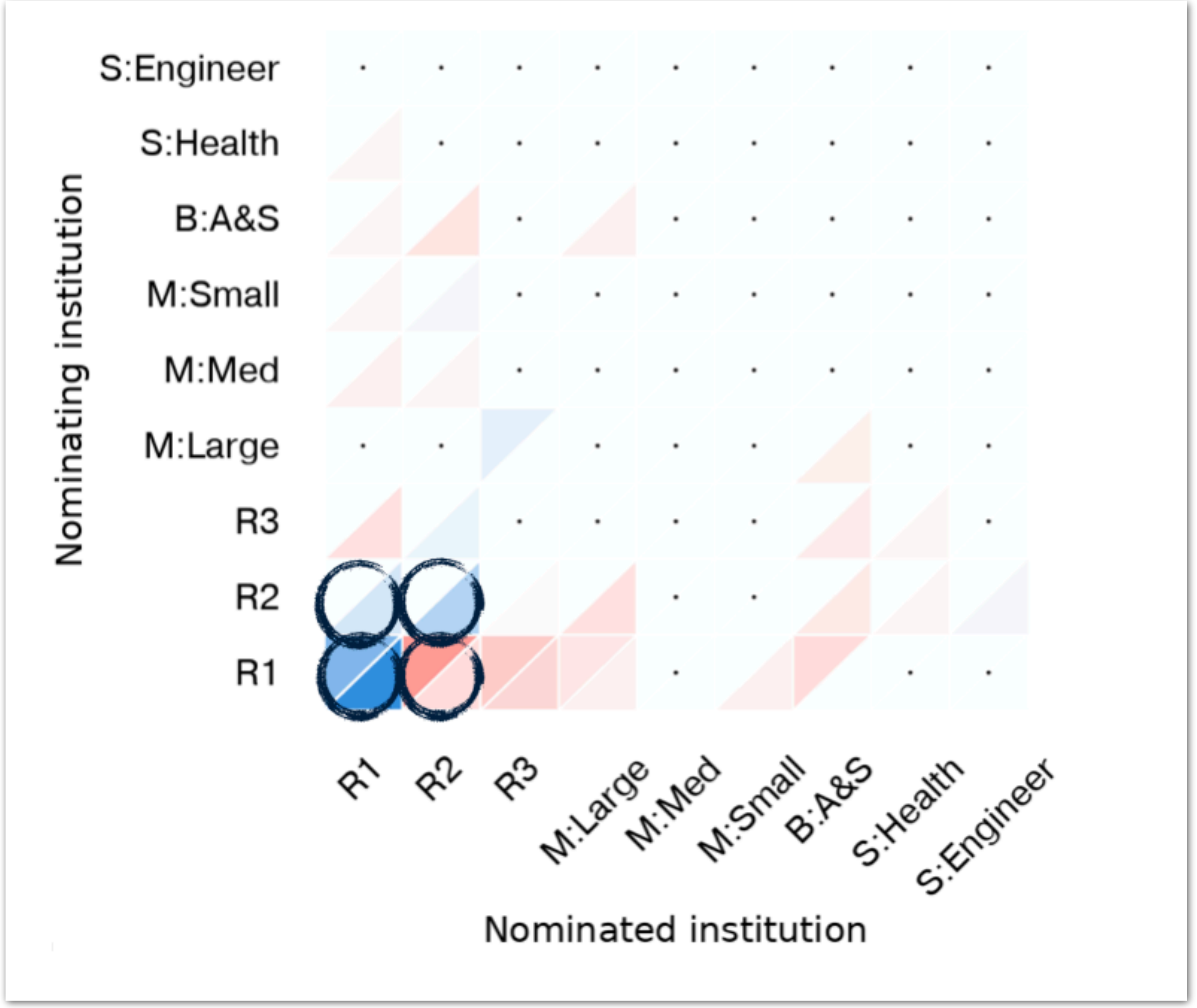

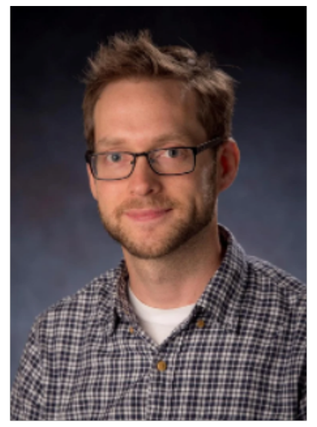

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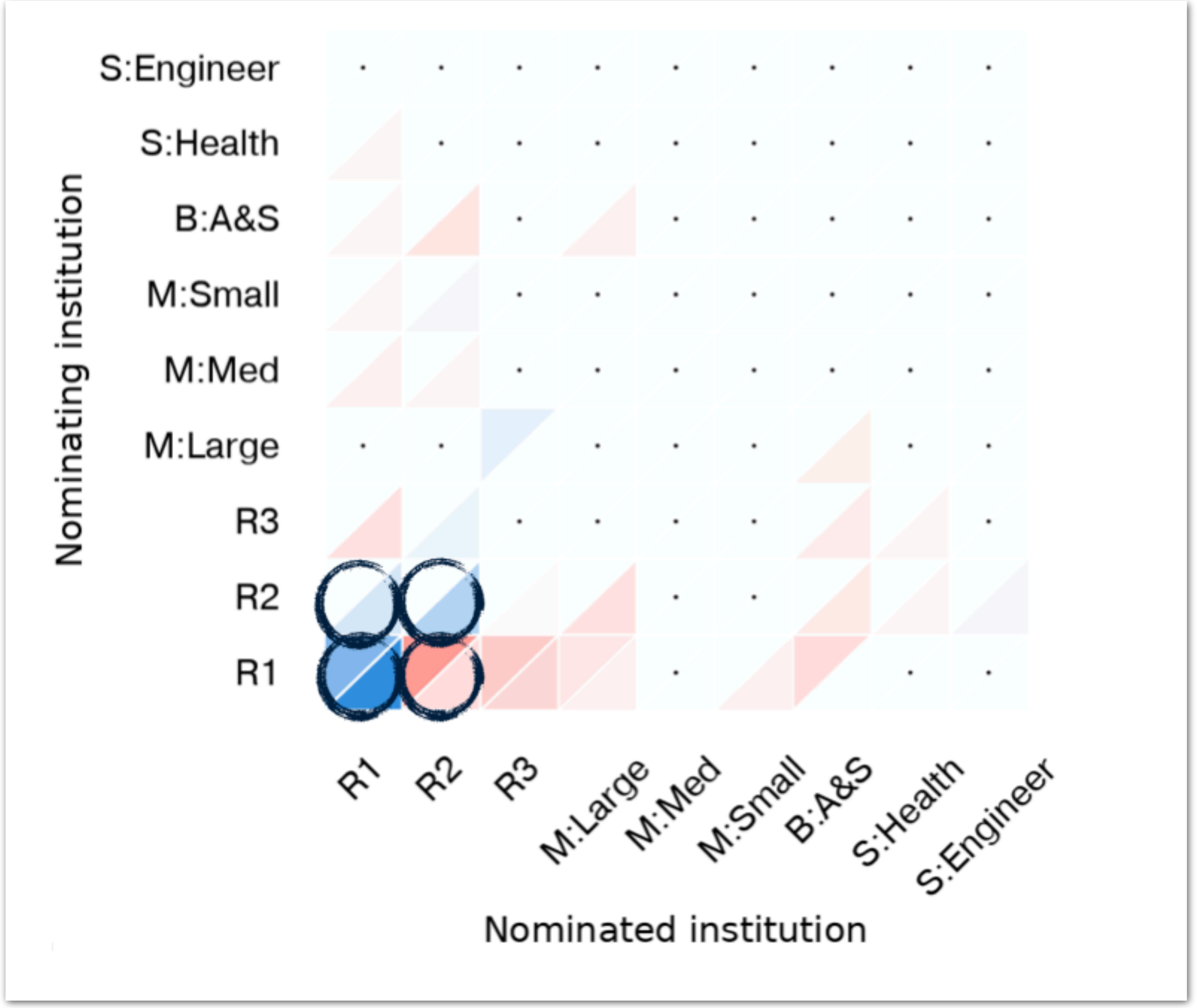
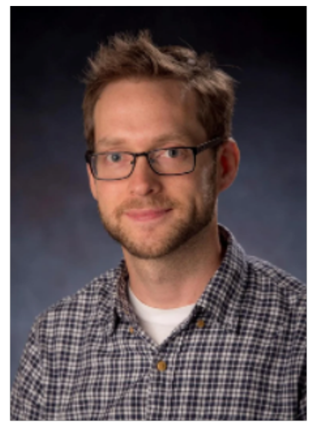
Open Question: What features correlate with the hierarchy?





Implications

All institutions. Name higher prestige institutions as their peers.

Elite institutions. Particularly aspire prestige.

Others. Explainable by a handful of feature groups.

See: Yen, Wootton, Clauset, & Larremore (in preparation)

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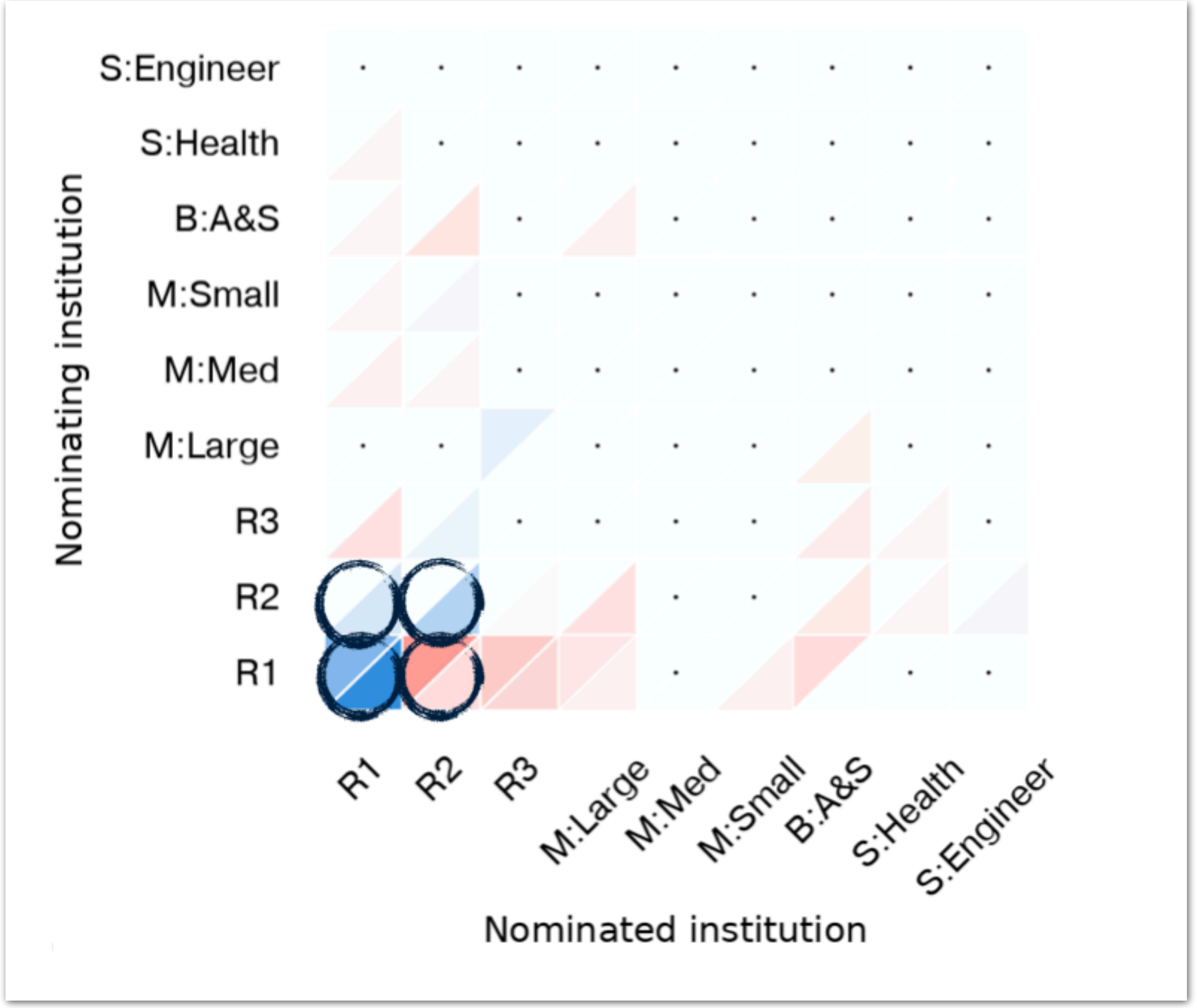

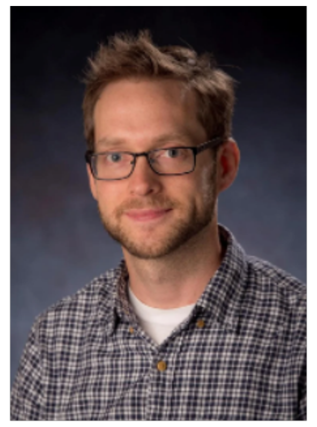

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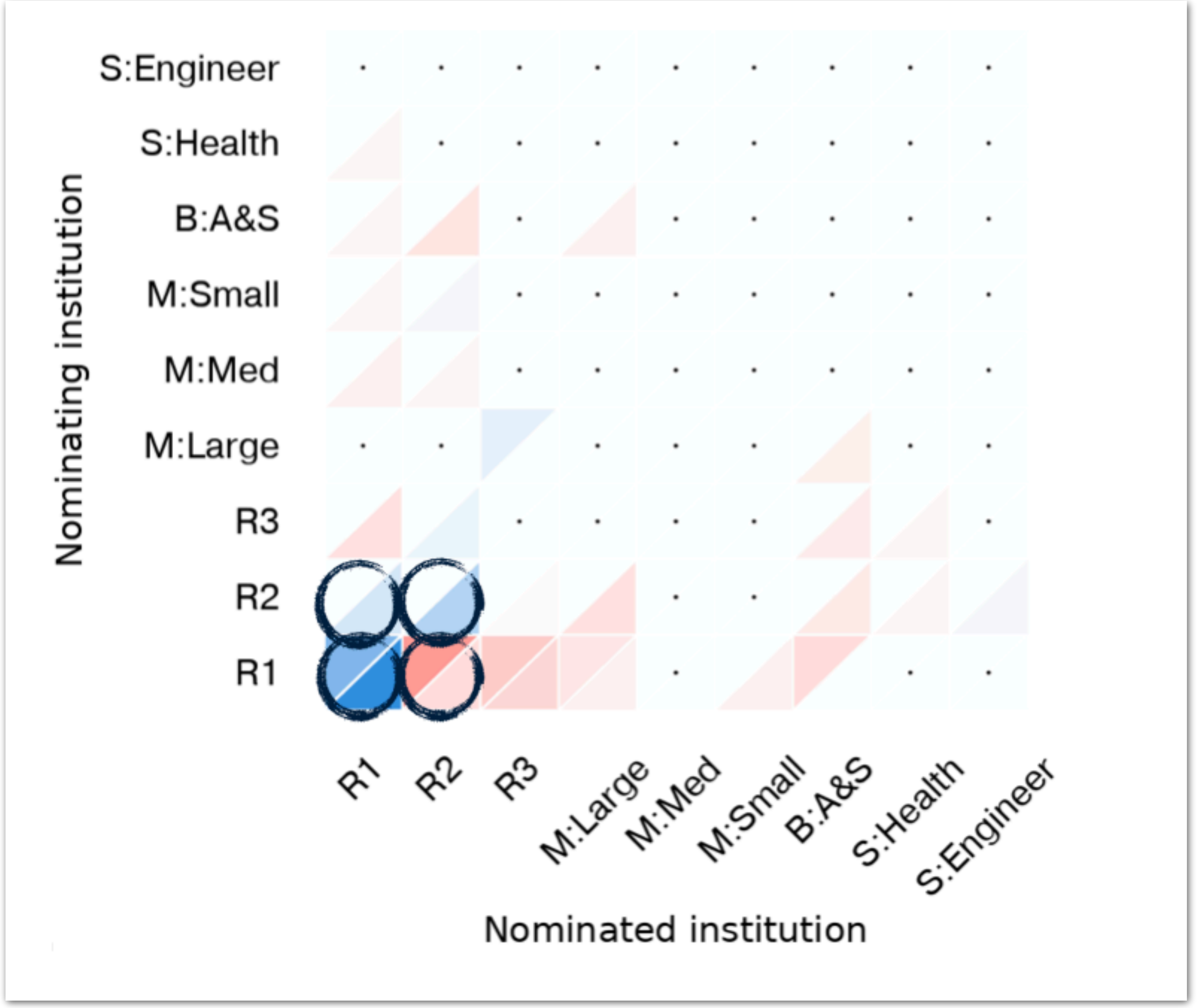

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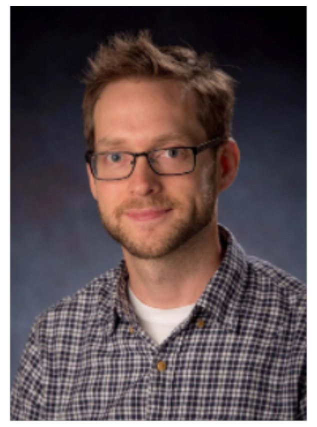

Thanks!