KDD BigScholar 8/20

*Also presented at the main KDD conference 8/21

Career Transitions and Trajectories: A Case Study in Computing

Tara Safavi (University of Michigan)

Maryam Davoodi (Purdue)

Danai Koutra (University of Michigan)

GEMS LAB

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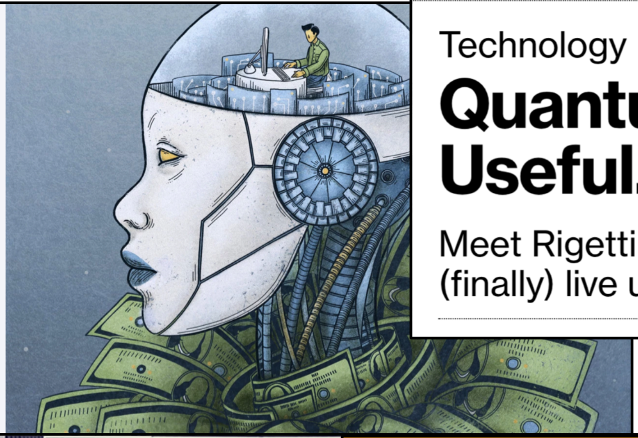
We all know that CS research is important…

New York Times, 2017

Tech Giants Are Paying Huge Salaries for Scarce A.I. Talent

Nearly all big tech companies have an artificial intelligence project, and they are willing to pay experts millions of dollars to help get it done.



Bloomberg, 2018

Search

Bloomberg

Technology

Quantum Computers Today Aren't Very Useful. That Could Change

Meet Rigetti Computin… (finally) live up to the h…

Economist, 2016

Medium, 2016

J. Alex Halderman Follow
Professor of Computer Science, University of Michigan
Nov 23, 2016 · 7 min read

Want to Know if the Election was Hacked? Look at the Ballots

You may have read at NYMag that I've been in discussions with the Clinton campaign about whether it might wish to seek recounts in critical states. That article, which includes somebody else's description of my views, incorrectly describes the reasons manually checking ballots is an essential security safeguard (and includes some incorrect numbers, to boot). Let me set the record straight about what I and other leading election security experts have actually been saying to the campaign and everyone else who's willing to listen.

How might a foreign government hack America's voting machines to change the outcome of a presidential election? Here's one possible scenario. First, the attackers would probe election offices well in advance in order to find ways to break into their computers. Closer to the election, when it was clear from polling data which states would have close electoral

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…but what do we know about careers in the field?

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Which organizations were and are the most important, and why?

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Which organizations were and are the most important, and why?

Are there any common patterns in post-PhD career trajectories?

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Which organizations were and are the most important, and why?

Are there any common patterns in post-PhD career trajectories?

Is is true that industry is consuming most computing research talent?

…but what do we know about careers in the field?

Which organizations were and are the most important, and why?

Answer: Very little*

Is is true that industry is consuming most computing research talent?

*All related studies are limited to career trajectories *within* academia, or else analyze *bibliographic* data rather than career trajectory data [Balsmeier+ 2014] [Chakraborty+ 2018] [Way+ 2017]

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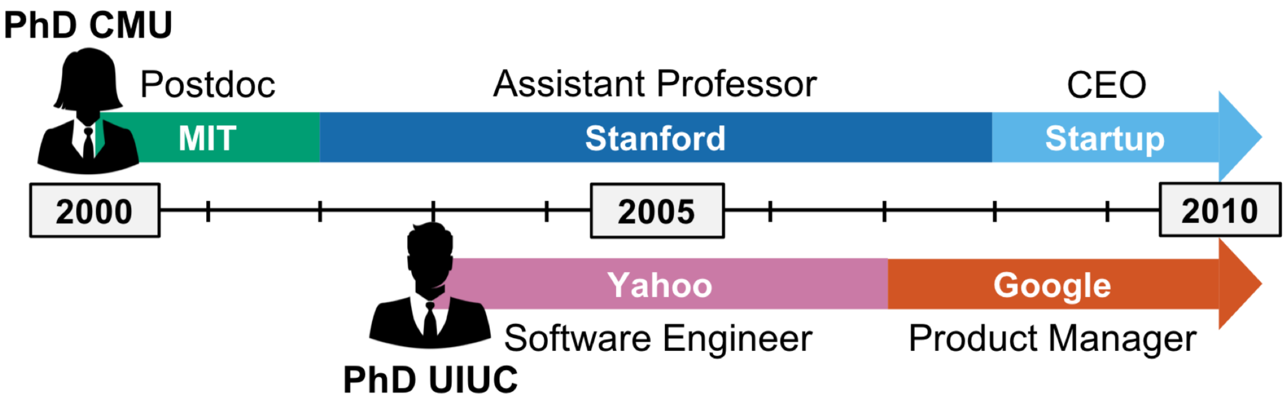
Career trajectories dataset

- We collected ~7k public career profiles of PhD graduates in EECS
  - 17k+ records from 1970 to 2015
  - Graduates of top 50 US computer science grad programs[1]
  - Categorized orgs into sectors
  - Profiles validated by ProQuest
- We made two anonymized datasets public: `http://bit.ly/2M6INoI`

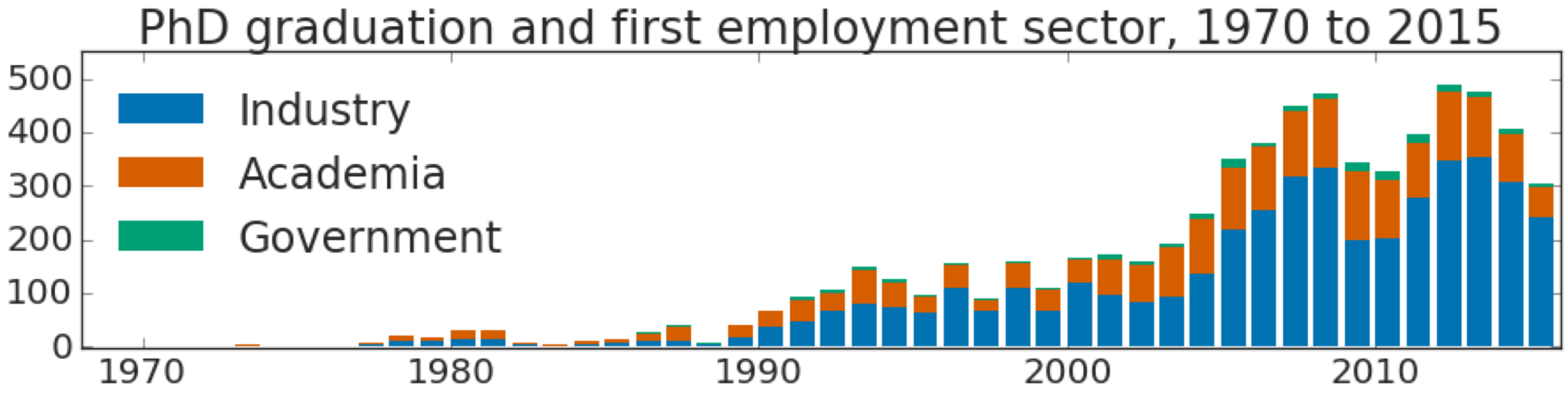


Sample (fake) career trajectories

[1] US News and World Report 2014

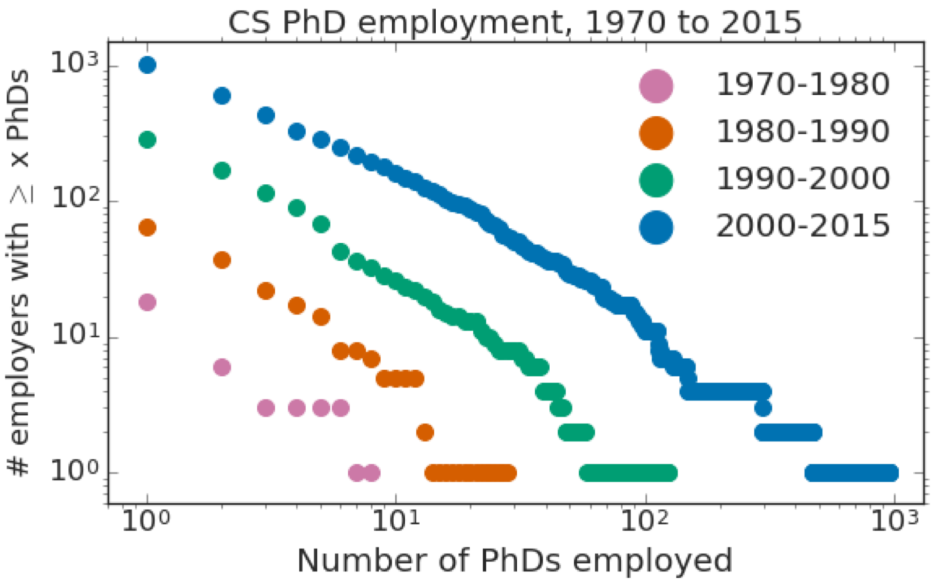
Career trajectories dataset

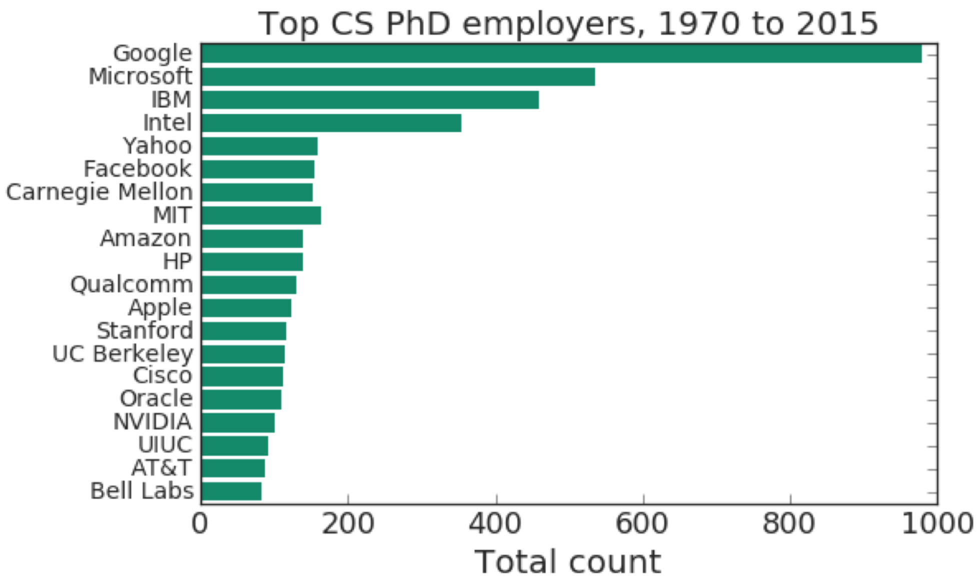
- PhD graduation volume mostly on the rise since the 00’s
- Trends consistent with public CRA data



Career trajectories dataset

- Post-PhD employment follows a power law
  - Most talent concentrates in very few organizations
- This observation will be important later





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Our goal

- Given these data, analyze the evolution of computing research careers through:
  - Individual career transitions: Movement between distinct employers
  - Organizations: Employers
  - Sectors: Academia, industry, government

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How to analyze these data?

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We need an **employer importance or desirability measure** to anchor our analysis and quantify hierarchies

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- Natural solution: node ranking in networks
- Two requirements
  1) An appropriate network model of the data
  2) An organizational ranking method that captures career-specific phenomena

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Requirements

1) Network model
2) Organizational ranking method

Network model

- A natural first choice is the transition network
  - Nodes: Organizations
  - Edges: Directed, weighted by number of transitions from employer A to employer B

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Network model

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2) Organizational ranking method

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- Major shortcoming: all analysis skewed toward large, popular organizations
  - Google, Microsoft, IBM, Intel…
  - We want a comprehensive, multi-faceted view of the system

Network model

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Solution: R^3 network

Captures career-specific factors by transforming network edge weights

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Organizational ranking

Requirements

1) Network model ✓
2) Organizational ranking method

- Most popular node ranking algorithms
  - PageRank [Page+ 1999]: cares most about nodes' in-links
  - HITS [Kleinberg 1999] cares about in- and out-links
- Ideally, we want to analyze both influx and outflux of employees

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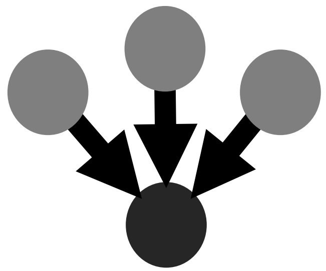
Solution: HITS on R^3

Captures "hubs and authorities" in the R^3 network

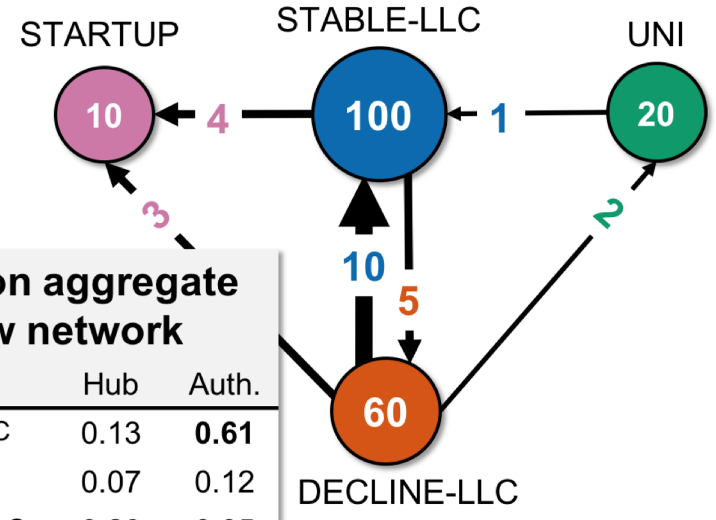
Hubs



Authorities

Methodology: R^3 career network model

- R^3: Transform network edges with:
  - Resources
  - Retention
  - Relative growth
- Each R will impact a node's HITS scores (its "importance")



HITS on aggregate flow network

	Hub	Auth.
STABLE-LLC	0.13	**0.61**
UNI	0.07	0.12
DECLINE-LLC	**0.80**	0.05
STARTUP	0	0.22

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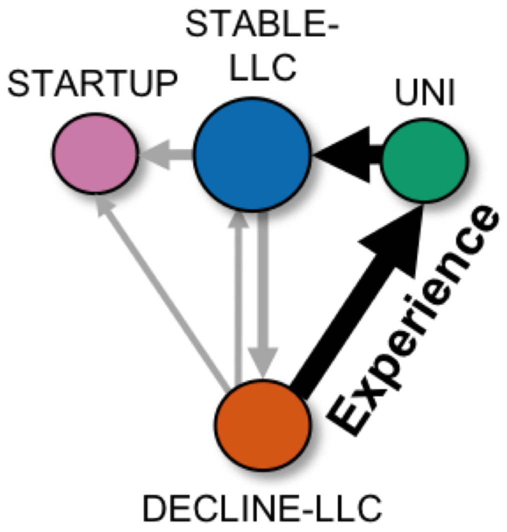
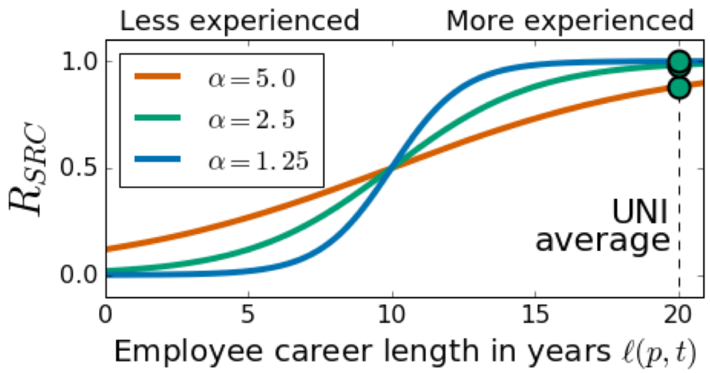
Methodology: R^3 career network model

R^3
- Resources
- Retention
- Relative growth

- Resources: Which organizations hire experienced employees?
  - Intuition: Directors, senior engineers, full professors are valuable!
  - Compare individual's "experience level" to system-wide average
- Weight *incoming edges* according to R_{SRC} sigmoid transformation
  - Organizations gain authority with more "experienced" hires



$$R_{SRC}(p,t) = \sigma(\text{PhD } p\text{'s career length} - \text{system avg career length})$$
$$= \left(1 + \exp[-\frac{\ell(p,t) - \overline{\ell(t)}}{\alpha}]\right)^{-1}.$$



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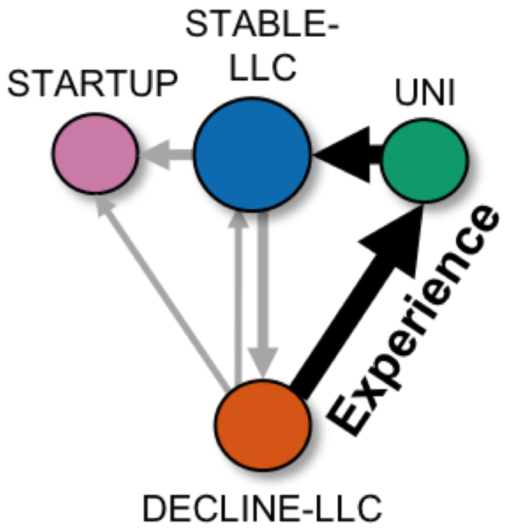

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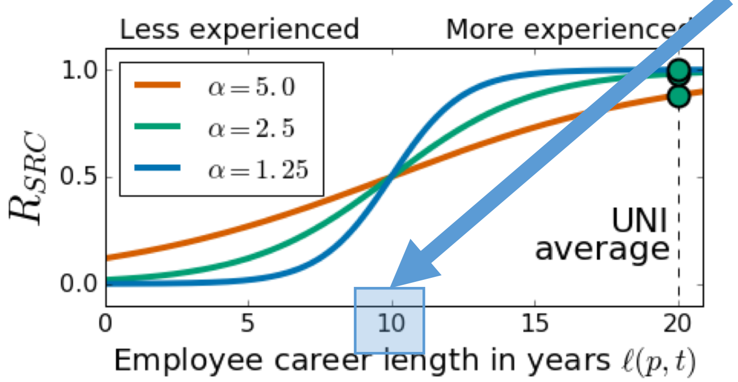

System-wide average career length: 10 years

Methodology: R^3 career network model

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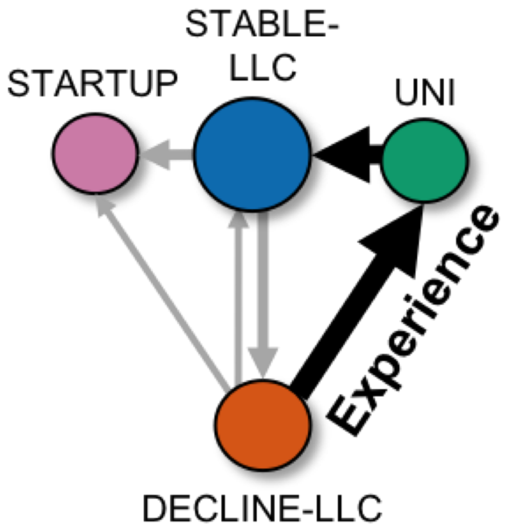
R^3

- Resources
- Retention
- Relative growth



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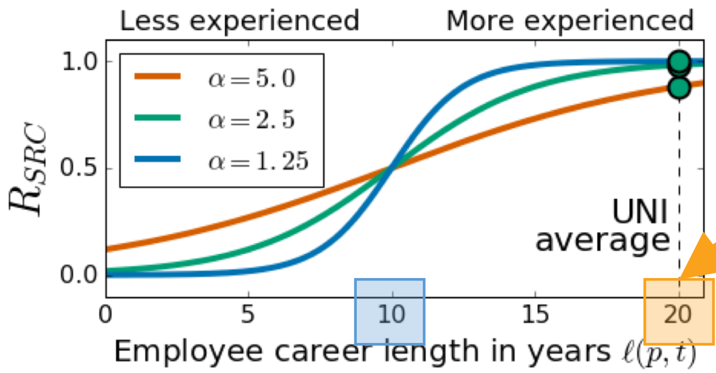

UNI's hires are, on average, more "experienced"

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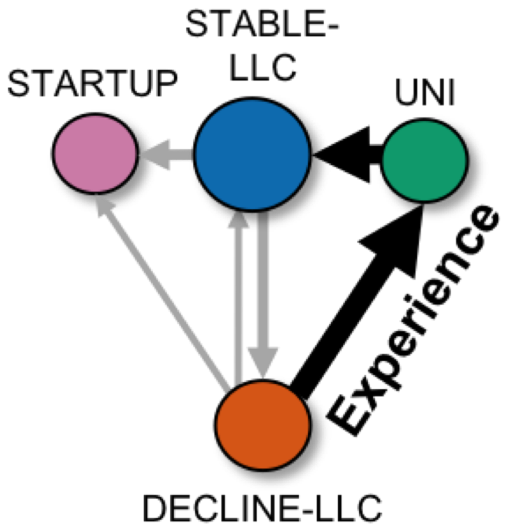

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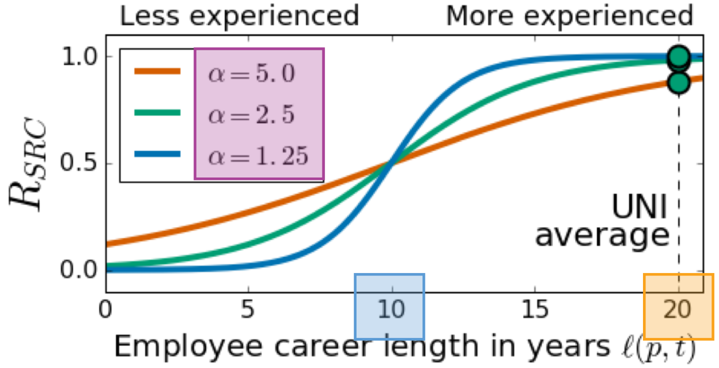
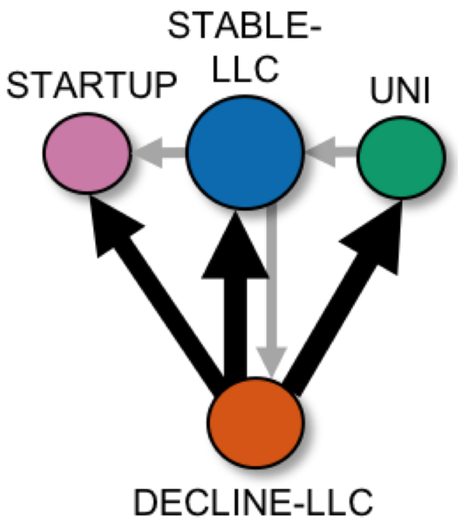
Sigmoid steepness parameter



Methodology: R³ career network model

R³
- Resources
- Retention
- Relative growth

- Retention: Which organizations retain PhDs longer than average?
  - Intuition: High turnover may indicate lower desirability or longevity, and vice versa
  - Compare organizational retention to sector average
- Weight *outgoing edges* according to (1 - R_{TN}) sigmoid transformation
  - Low-retention "stepping stone" organizations gain hub-ness



$$
\begin{aligned}
R_{TN}(v,t) &= \sigma(\text{Org } v\text{'s avg retention} - \text{sector avg retention}) \\
&= \left(1 + \exp[-\frac{\overline{\ell(v,t)} - \overline{\ell(\sigma(v),t)}}{\beta}]\right)^{-1}.
\end{aligned}
$$

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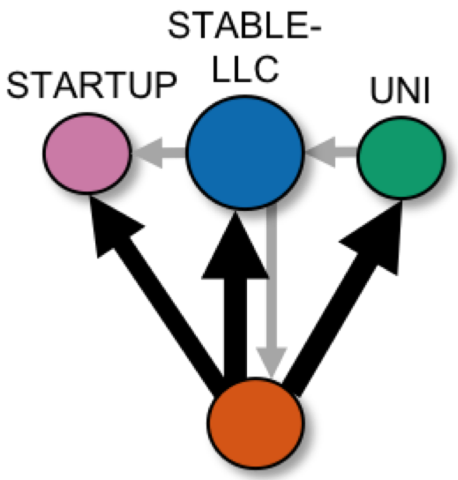
R^3

- Resources
- Retention
- Relative growth



$$R_{TN}(v,t) = \sigma(\text{Org } v\text{'s avg retention} - \boxed{\text{sector avg retention}})$$
$$= \left(1 + \exp\left[-\frac{\overline{\ell(v,t)} - \boxed{\overline{\ell(\sigma(v),t)}}}{\beta}\right]\right)^{-1}.$$

Methodology: R^3 career network model

R^3

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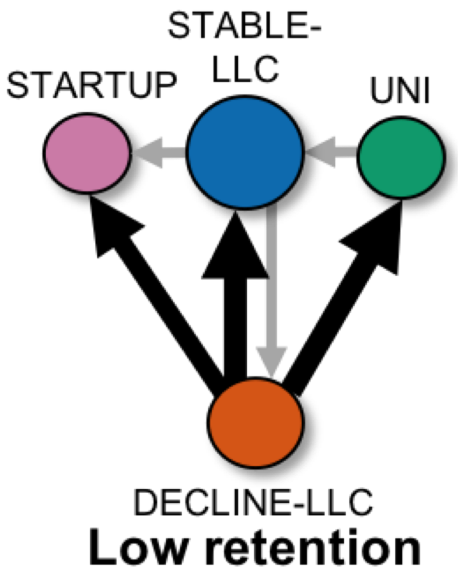

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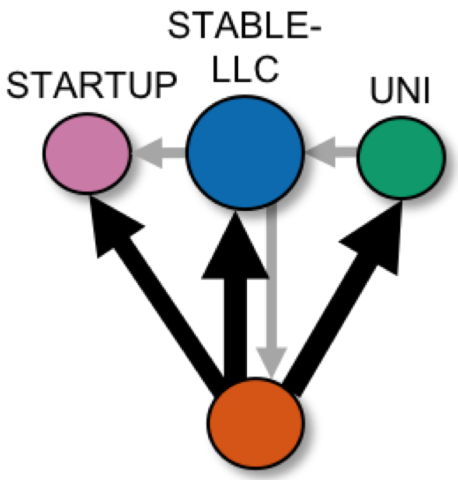

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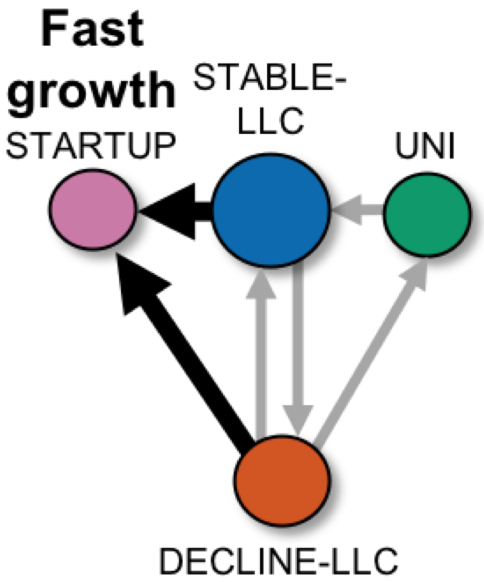
Sigmoid steepness parameter

Methodology: R³ career network model

R³
- Resources
- Retention
- Relative growth

- Relative growth: Which organizations are growing fast relative to size?
  - Intuition: A small but fast-growing organization is "buzzworthy", like a tech startup
  - Compute relative growth from econ log-return [Marti+ 2017]
- Weight *incoming edges* according to exp of R_{GR}
  - High-growth organizations gain authority



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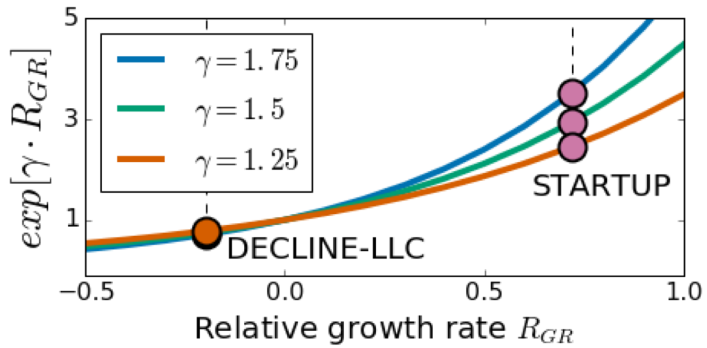

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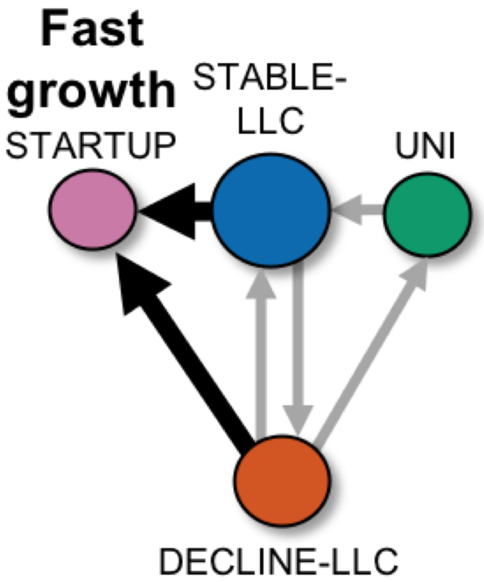

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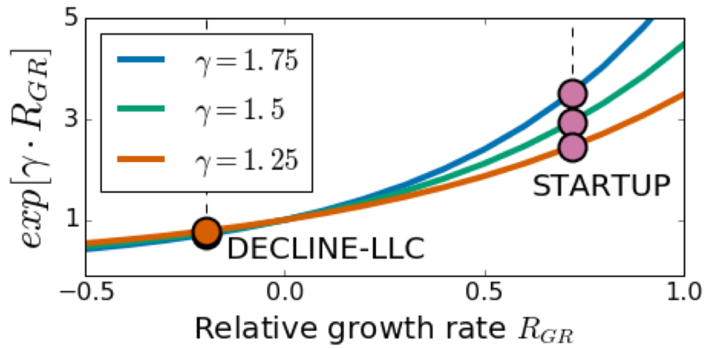

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Methodology: R^3 career network model

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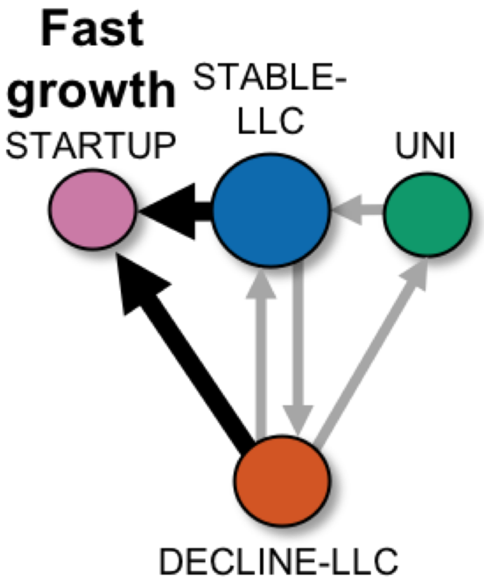

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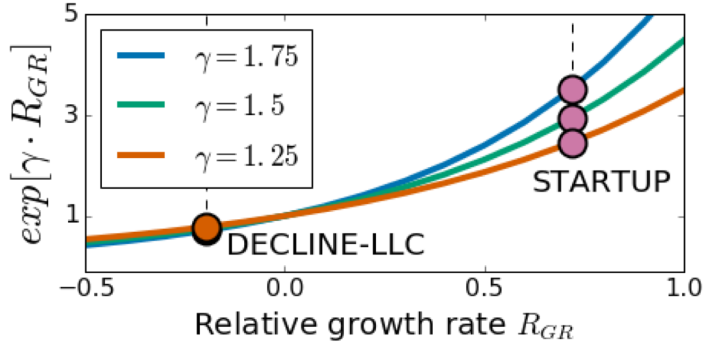

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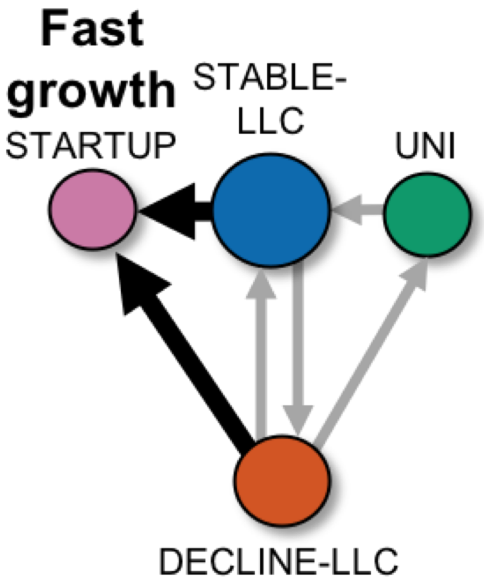

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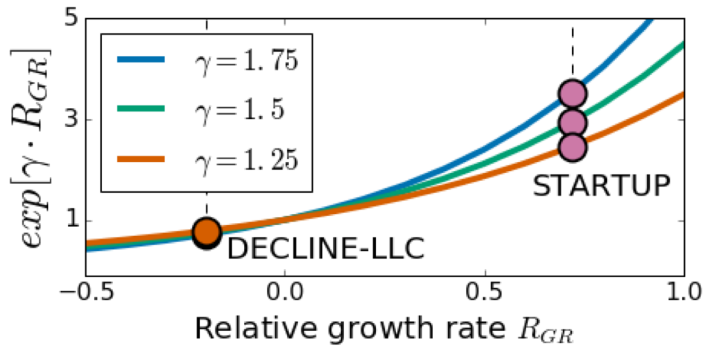
Number of PhDs in our dataset at the organization during year *t*



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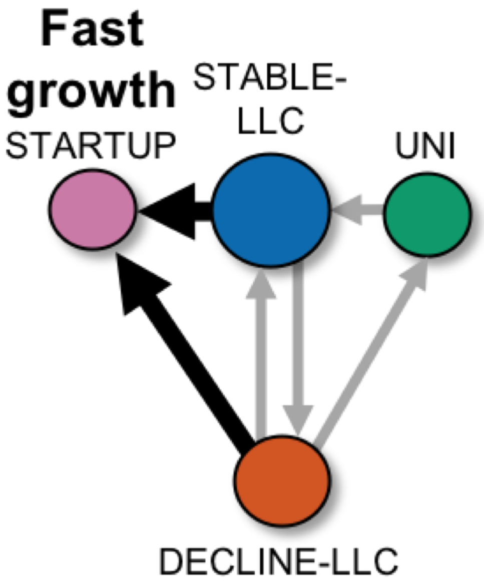

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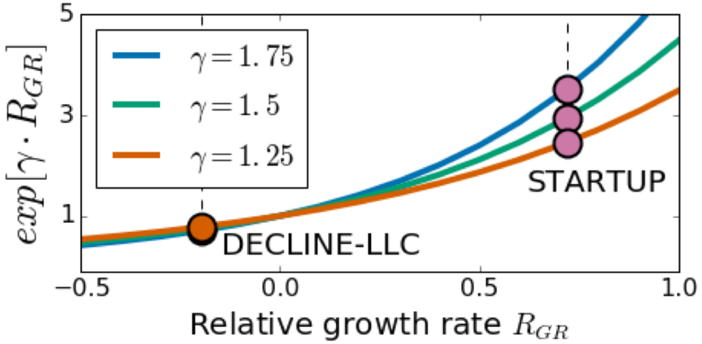
Take exponent of relative growth



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Analysis: System-wide evolution

Analysis
- Organizational
- Sector
- Individual

Which organizations does R^3 reveal as important, and why?

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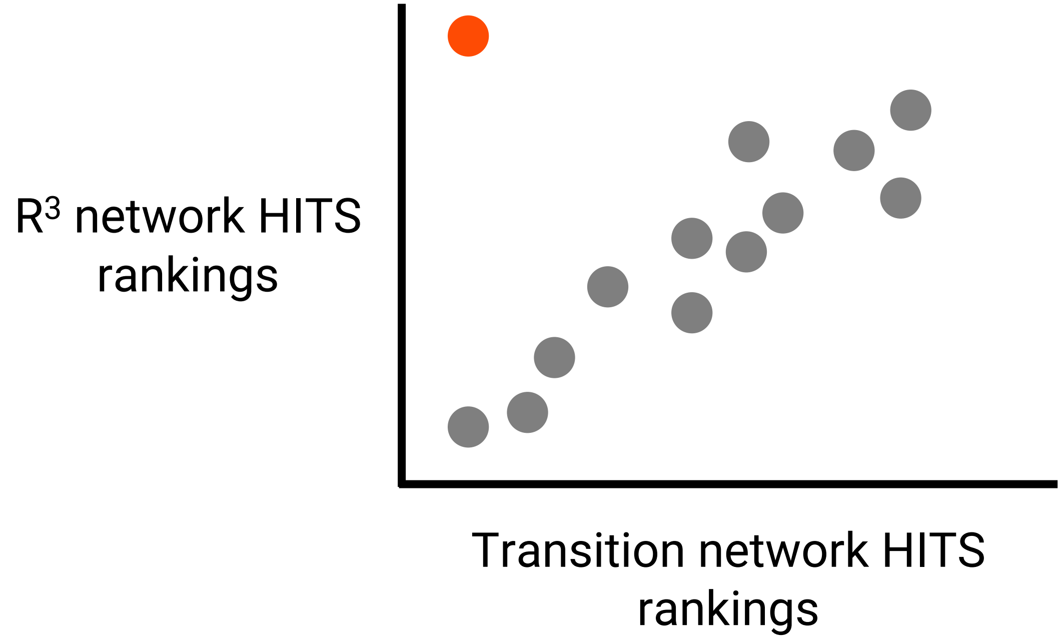
Analysis: System-wide evolution

- Compute HITS in 5-year intervals on the transition and R^3 networks
- Regress pairs of HITS rankings and identify high-deviation, high-ranking nodes
  - Compare HITS results on R^3 against "standard" HITS results

Transitions within 2000-2005



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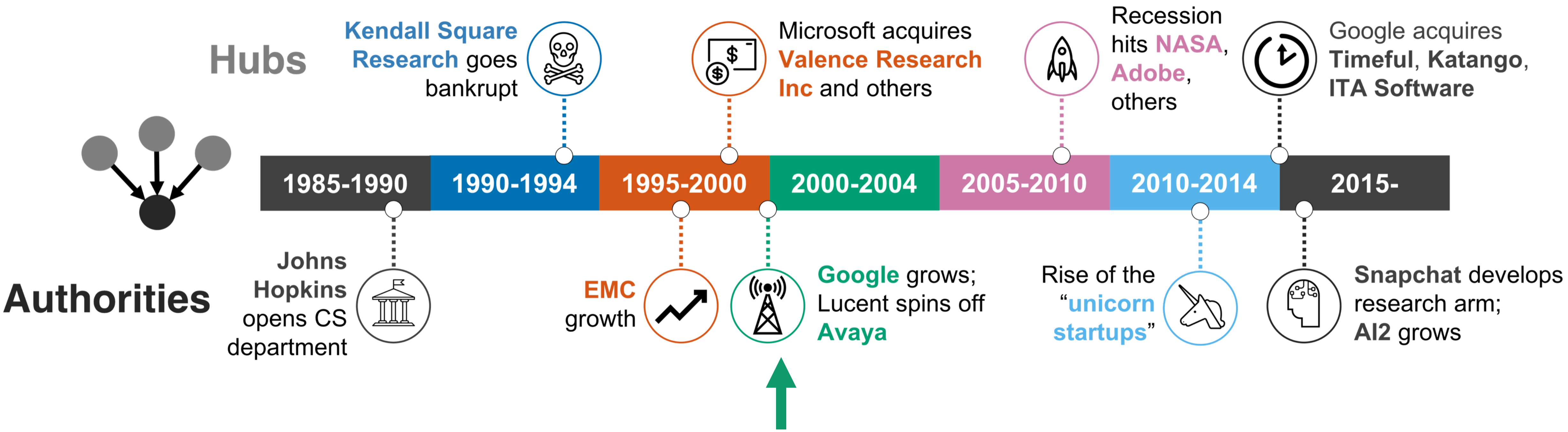
Analysis: System-wide evolution

Analysis
- Organizational
- Sector
- Individual

- In each 5-year interval, R^3 discovers hidden “important” organizations
  - Acquired startups, new CS departments, recession-hit organizations
  - Reminder: Hubs *out-link* to authorities, authorities receive *in-links* from hubs



Even Google is “discovered” by R^3 in 1999!!!

Analysis: Cross-sector career movement

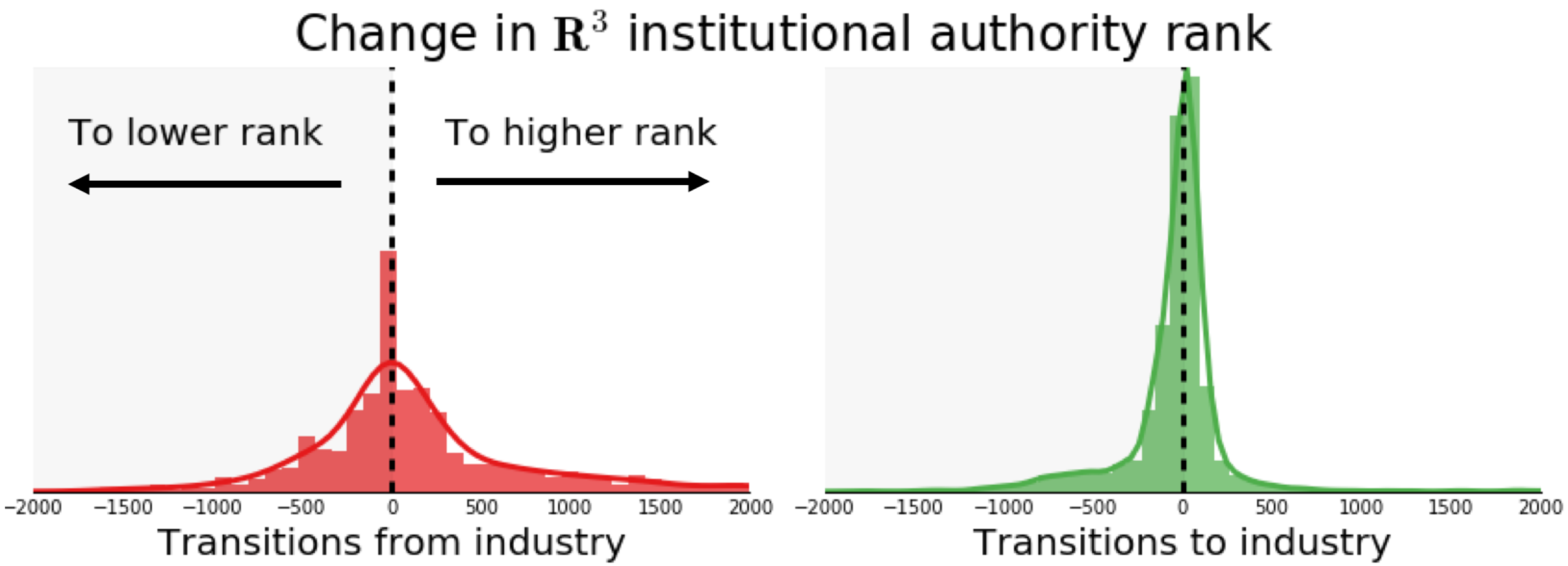
What does R^3 reveal about how people move between sectors?

Analysis: Cross-sector career movement

- Use rankings from previous analysis on both networks

Analysis: Cross-sector career movement

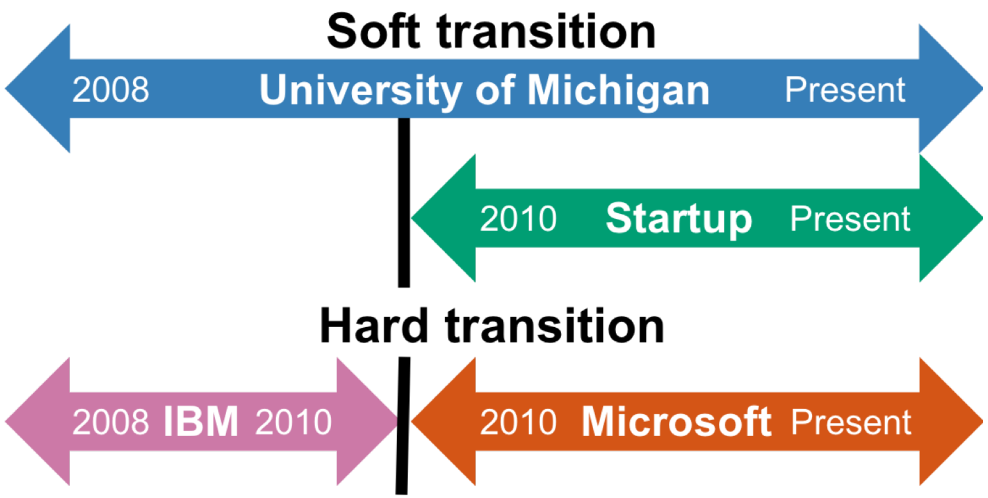
- Two-thirds of transitions are academia → industry
  - But people move *up* in rankings in industry → academia transitions
  - These transitions often happen later: ~9 years in (excluding postdocs)
- Significant asymmetry in these transitions!

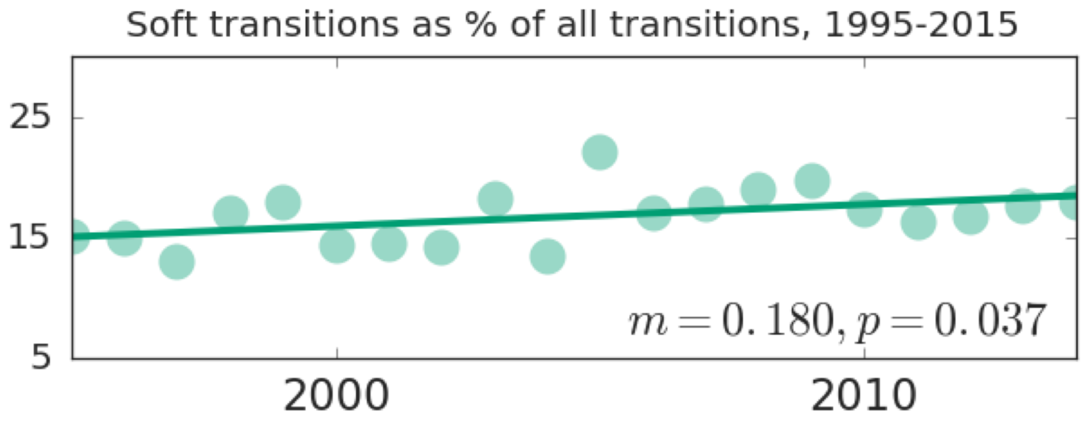


Analysis
- Organizational
- Sector
- Individual

Analysis: Cross-sector career movement

- Many cross-sector transitions are "soft"
  - New job while continuing previous employment
  - Percentage of soft transitions in dataset increasing (slightly) overall
- Industry people become visiting professors, professors take on startups
  - Could it be because soft transitions allow for riskier leaps?





Analysis
- Organizational
- Sector
- Individual

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Analysis: Individual predictions

Can we predict when individuals will transition using R^3?

Analysis: Individual predictions

- Extract features in groups
  - IND: Individual career trajectories (years in workforce, num jobs, etc)
  - G_f: Transition network HITS rankings and scores
  - R^3 HITS rankings and scores
  - ALL three above feature groups

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Analysis: Individual predictions

Analysis
- Organizational
- Sector
- **Individual**

- Adding **network-related features improves performance** significantly!
  - Validates initial choice of representing data as a network
- Performance best with IND + R^3 features

IND: Individual career trajectories (e.g., num jobs)
G_f: Transition network HITS rankings and scores
R^3 HITS rankings and scores
ALL three above feature groups

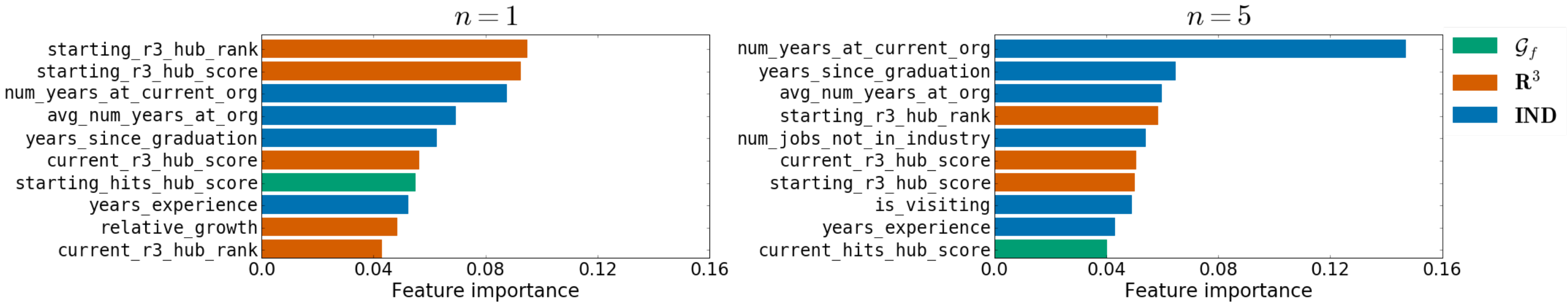
	Features	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
AUC	IND	0.625 ± 0.00	0.637 ± 0.00	0.654 ± 0.01	0.644 ± 0.01	0.656 ± 0.02
	IND + $\mathcal{G}_f$	0.639 ± 0.01	0.660 ± 0.02	0.666 ± 0.02	0.658 ± 0.03	0.663 ± 0.03
	IND + $\mathbf{R}^3$	**0.656** ± 0.01	**0.675** ± 0.02	**0.677** ± 0.02	**0.665** ± 0.02	**0.670** ± 0.03
	ALL	**0.649** ± 0.01	**0.668** ± 0.02	**0.674** ± 0.02	**0.664** ± 0.02	**0.669** ± 0.03
F1	IND	0.357 ± 0.05	0.459 ± 0.01	0.536 ± 0.01	0.574 ± 0.01	**0.601** ± 0.04
	IND + $\mathcal{G}_f$	0.396 ± 0.00	0.473 ± 0.01	0.542 ± 0.00	**0.577** ± 0.01	**0.601** ± 0.04
	IND + $\mathbf{R}^3$	**0.404** ± 0.01	**0.488** ± 0.01	**0.549** ± 0.01	0.576 ± 0.01	0.595 ± 0.03
	ALL	**0.398** ± 0.01	**0.488** ± 0.01	**0.550** ± 0.00	**0.578** ± 0.01	**0.610** ± 0.03

Predict transitions *n* years from now

Analysis: Individual predictions

Analysis
- Organizational
- Sector
- Individual

- R^3 features most important
  - Especially for small values of *n*
  - Difficult prediction task!



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We all know that CS research is important, and now we know more about career trajectories in the field

Still…

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We all know that CS research is important, and now we know more about career trajectories in the field

What about people with PhDs outside the US? Those without PhDs?

How to merge bibliographic data with career trajectory data?

Finer-grained analysis of different subgroups, like postdocs?

Contact: tsafavi@umich.edu

Thank you + questions

Also presented at KDD ADS poster reception [PID 94]
21 August, 7 – 9:30 PM, ICC Capital Hall

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The laboratory
for large-scale
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GEMS LAB

References

Balsmeier, Benjamin, and Maikel Pellens. "Who makes, who breaks: Which scientists stay in academe?." Economics Letters 122.2 (2014): 229-232.

Chakraborty, Tanmoy, and Subrata Nandi. "Universal trajectories of scientific success." Knowledge and Information Systems 54.2 (2018): 487-509.

Way, Samuel F., et al. "The misleading narrative of the canonical faculty productivity trajectory." Proceedings of the National Academy of Sciences 114.44 (2017): E9216-E9223.

Page, Lawrence, et al. The PageRank citation ranking: Bringing order to the web. Stanford InfoLab, 1999.

Kleinberg, Jon M. "Authoritative sources in a hyperlinked environment." Journal of the ACM (JACM) 46.5 (1999): 604-632.

Marti, Gautier, et al. "A review of two decades of correlations, hierarchies, networks and clustering in financial markets." arXiv preprint arXiv:1703.00485 (2017).

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