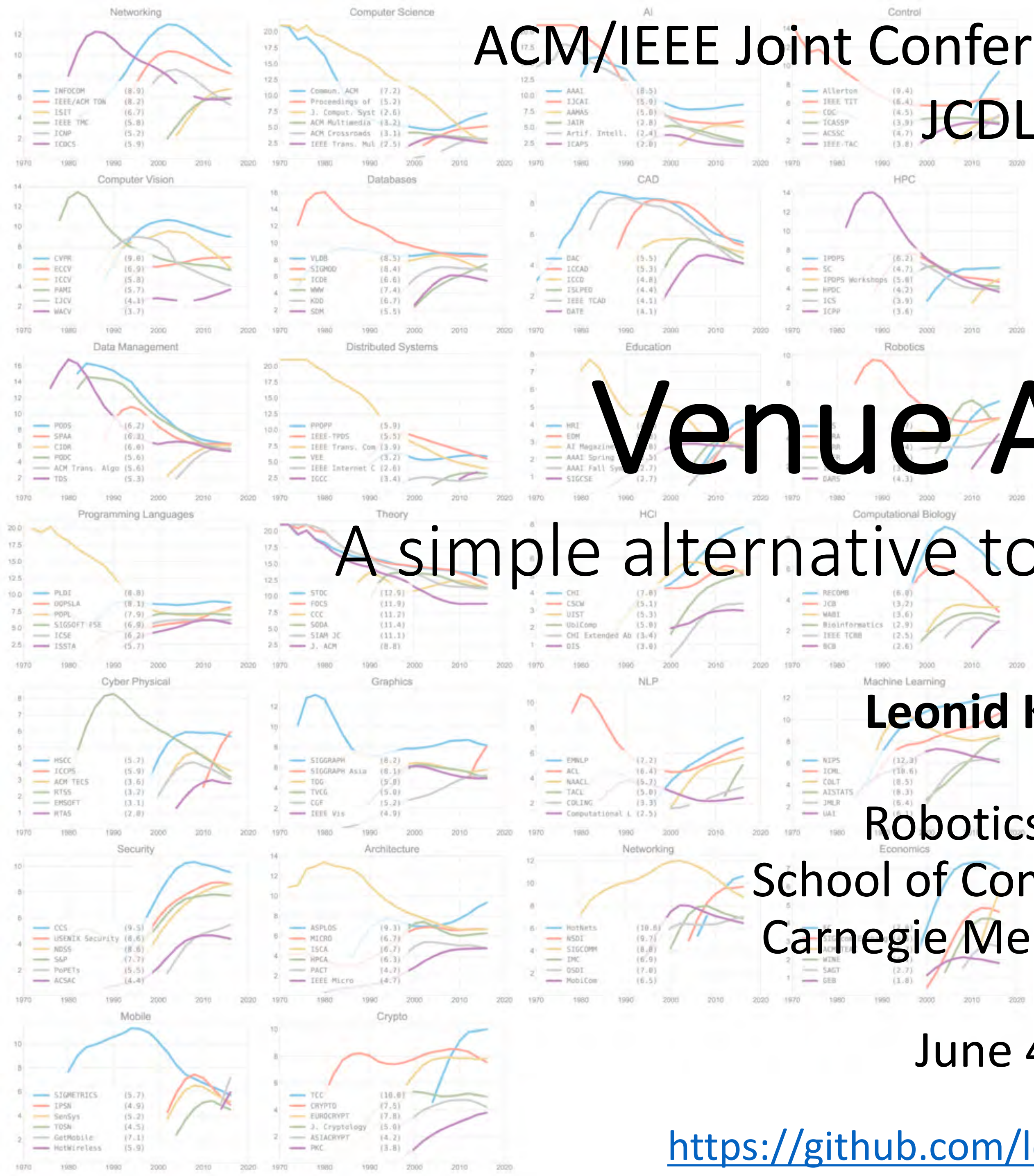
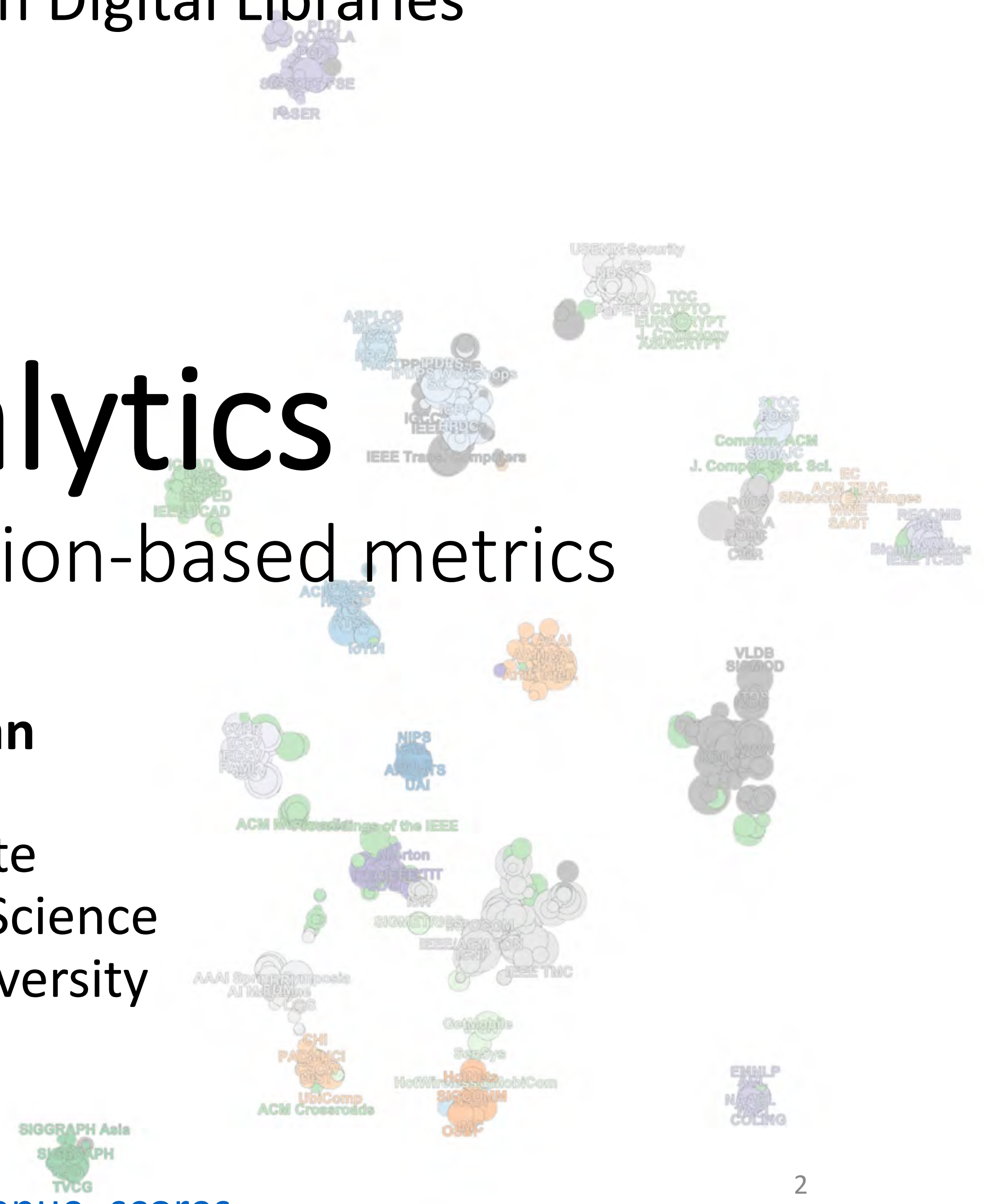
“This submission…introduces a novel, if **potentially controversial**, method” – Reviewer #2





ACM/IEEE Joint Conference on Digital Libraries
JCDL 2019

Venue Analytics

A simple alternative to citation-based metrics

Leonid Keselman

Robotics Institute
School of Computer Science
Carnegie Mellon University

June 4, 2019

https://github.com/leonidk/venue_scores

Why not citations?

What do citation counts measure? A review of studies on citing behavior

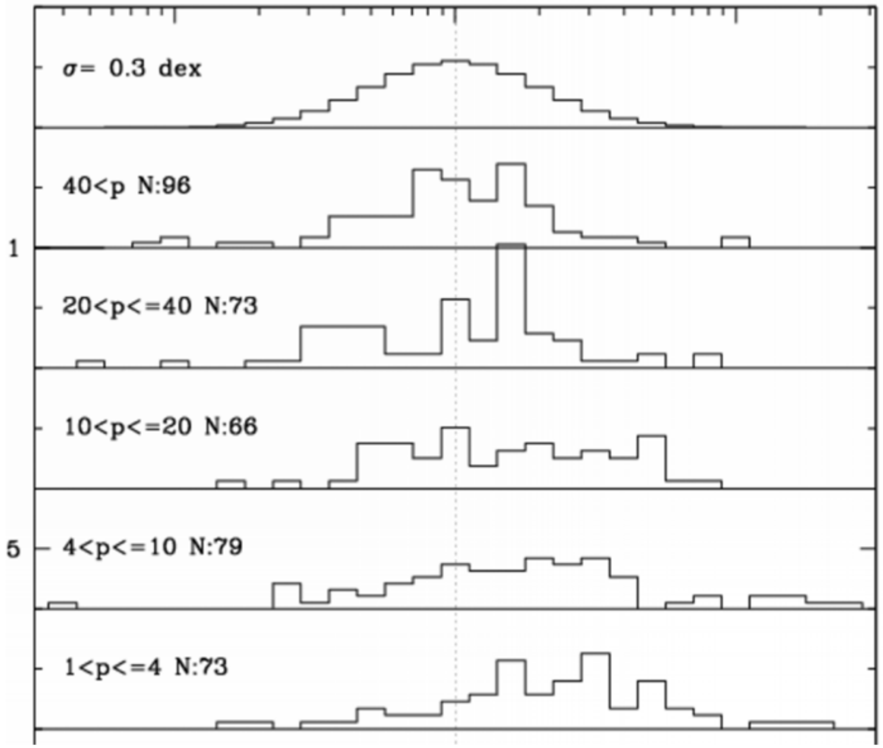
Lutz Bornmann and Hans-Dieter Daniel
Eidgenössische Technische Hochschule Zürich, Zürich, Switzerland

Citation category	Percent of citations
Limited. The work described in the cited article is of some limited importance to the citing article. It would be inappropriate to omit it, but it is not an important part of a central argument	56
Peripheral. The work described in the cited article is of little importance to the citing article. Citation is simply background, an aside, for completeness or indeed irrelevant	35
Considerable. The work described in the article is of considerable importance to the citing article. The work is one of a number central to the argument	8
Essential. The work described in the cited article is of critical importance to the citing article, and central to the argument presented, and a key foundation for the paper	1
Total	100

Citing motivation	Percent of citations
Professional motivations. The particular paper was cited because . . .	
– in my paper a review of literature is given due to “completeness”, “preliminaries”	51
– a minor part of the cited work (application of part of a methodology) is utilized	42
– the cited work confirms, supports the results in the citing paper	16
– a significant part of the cited work (theory, measuring methods) is utilized	15
– my work is based entirely on the cited work	4
– the cited work is criticised in some minor point	3
– the cited work is refused, criticised in one important question	2
– the cited work is fully refused, criticised	0

Measuring Metrics - A forty year longitudinal cross-validation of citations, downloads, and peer review in Astrophysics

Michael J. Kurtz
Edwin A. Henneken
Harvard-Smithsonian Center for Astrophysics



Log Normal

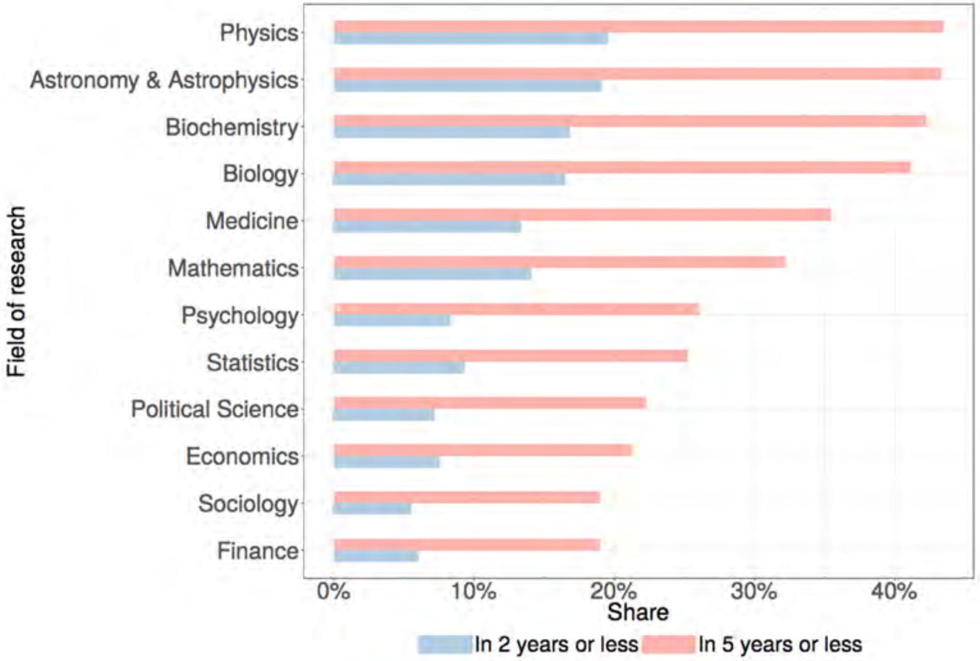
Citations

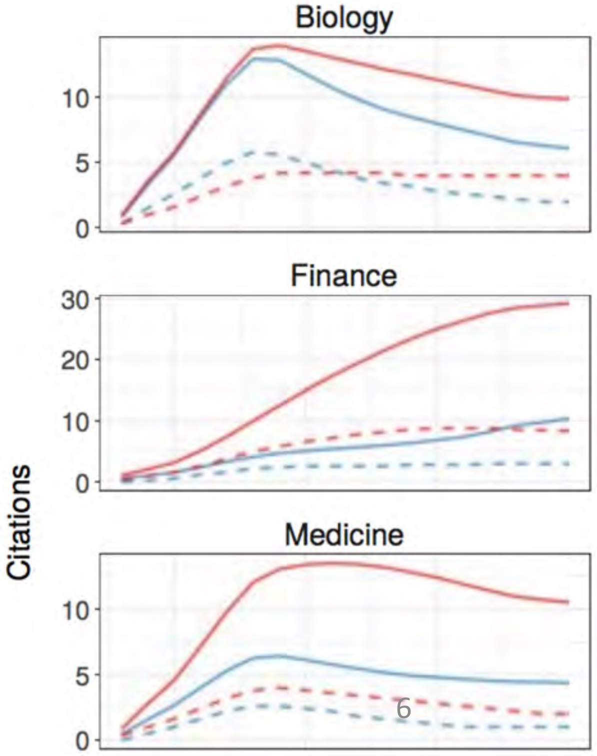
The life cycle of scholarly articles across fields of research

Sebastian Galiani*[a,b] and Ramiro H. Gálvez†[c]

[a]Department of Economics, University of Maryland, College Park, MD 20742.
[b]National Bureau of Economics Research, Cambridge, MA 02138
[c]Department of Computer Science, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Buenos Aires, Argentina C1428EGA.

Field of Research	Median
Astronomy & Astrophysics	25
Biochemistry	39
Biology	62
Economics	85
Finance	78
Mathematics	27
Medicine	45
Physics	26
Political Science	47
Psychology	52
Sociology	57
Statistics	30





Multiple versions of the *h*-index: cautionary use for formal academic purposes

Jaime A. Teixeira da Silva[1] · Judit Dobránszki[2]

Table 1 Summary of *h*-indexes for both authors of this paper based on four most popular academic databases: Google Scholar (GS), Scopus, Web of Science (WoS), and ResearchGate (RG)

	GS		Scopus		WoS		RG	
	All	ESC	All	ESC	All	ESC	All	ESC
First author	42	NA	29	24	8	NA	36	30
Second author	15	NA	11	10	9	NA	13	12

Two values are listed, for all citations, and excluding self-citations (ESC) avoidance. Over the past decades, this method has been often revisited [5, 6, 25, 26, 30, 31, 36, 46]. Tools popular in economics have also been used such as the Discrete Choice

domains like speech recognition [7, 8, 15], machine translation [8] and image captioning [20, 43, 45, 39]. However, they lack high-level and spatio-temporal structure [29]. Several attempts have been made to use multiple networks to capture complex interactions [1, 10, 40]. Alahi *et al.* [1]

human interactions. The former learns scene-specific motion patterns [3, 9, 18, 21, 24, 33, 49]. The latter models the dynamic content of the scenes, *i.e.* how pedestrians in-

[Scholz et al. 2005] improve upon [Guskov et al. 2003] by creating a non-repeating grid of color markers. Each marker has five possible colors and all three by three groups are unique. This allows substantially larger sections of cloth and virtually eliminates correspondence errors. Results include a human wearing a shirt and a skirt captured using eight 1K x 1K cameras. However, the range of motion is limited to avoid occlusion (e.g., arms are always held at 90 degrees to the torso). They use thin-plate splines to fill holes.

[White et al. 2005] introduce a combined strain reduction/bundle adjustment that improves the quality of the reconstruction by minimizing strain while reconstructing the 3D location of the points on the surface of the cloth. [White et al. 2006] introduce the use of silhoutte cues to improve reconstruction of difficult to observe regions. While silhouette cues improve reconstruction, hole filling is

In the acquisition process, occlusion inevitably creates holes in the reconstructed mesh (figure 8). One would like to fill these holes with real cloth. One of our major contributions is a data driven approach to hole filling: we fill holes with previously observed sections of cloth. Our work differs from [Anguelov et al. 2005] because our hole filling procedure does not assume a skeleton that drives the surface and our procedure estimates a single coefficient per example.

This hole filling procedure has a number of requirements: the missing section needs to be replaced by a section with the same topology; the new section needs to obey a number of point constraints around the edge of the hole, and the splicing method should respect properties of cloth (specifically strain). We select a reconstruction technique based on deformation gradients [Sumner and Popovic 2004]. In this approach, we fit deformation gradients for the missing section to a combination of deformation gradients in

Deterministic Policy Gradient Algorithms

David Silver DAVID@DEEPMIND.COM
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Guy Lever GUY.LEVER@UCL.AC.UK
University College London, UK
Nicolas Heess, Thomas Degris, Daan Wierstra, Martin Riedmiller *@DEEPMIND.COM
DeepMind Technologies, London, UK

JMLR 2014
681 citations

CONTINUOUS CONTROL WITH DEEP REINFORCEMENT LEARNING

Timothy P. Lillicrap*, Jonathan J. Hunt*, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver & Daan Wierstra
Google Deepmind
London, UK
{countzero, jjhunt, apritzel, heess, etom, tassa, davidsilver, wierstra} @ google.com

ICLR 2015
1,681 citations

Programming Robots Using Reinforcement Learning and Teaching

Long-Ji Lin
School of Computer Science
Carnegie Mellon University
Pittsburgh, Pennsylvania 15213
e-mail: ljl@cs.cmu.edu

AAAI 1991
170 citations

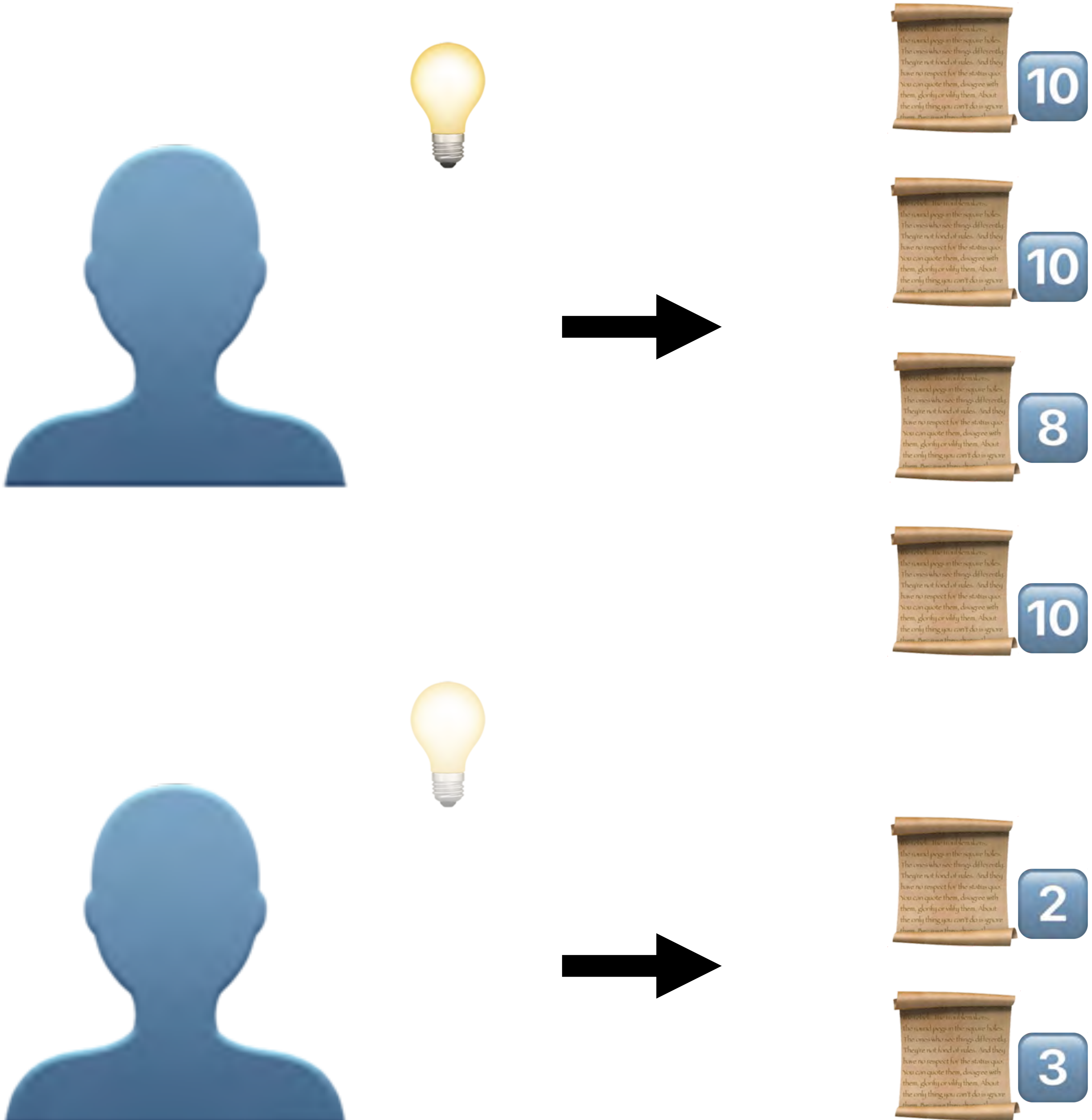
Human-level control through deep reinforcement learning

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg & Demis Hassabis

Nature 2015
5,668 citations

Our proposal? Aggregate data

Give a score for each paper that passes peer review at a certain venue



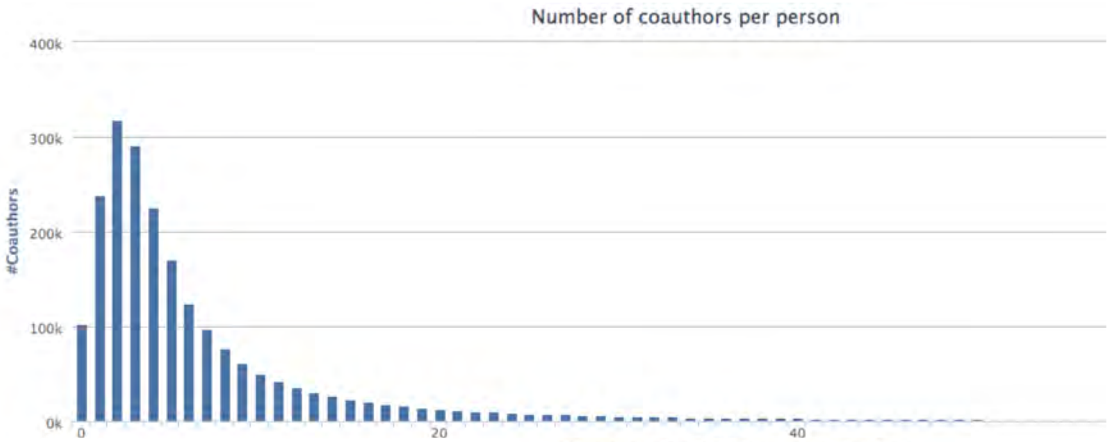
The model:
Good ideas generate more papers in better venues

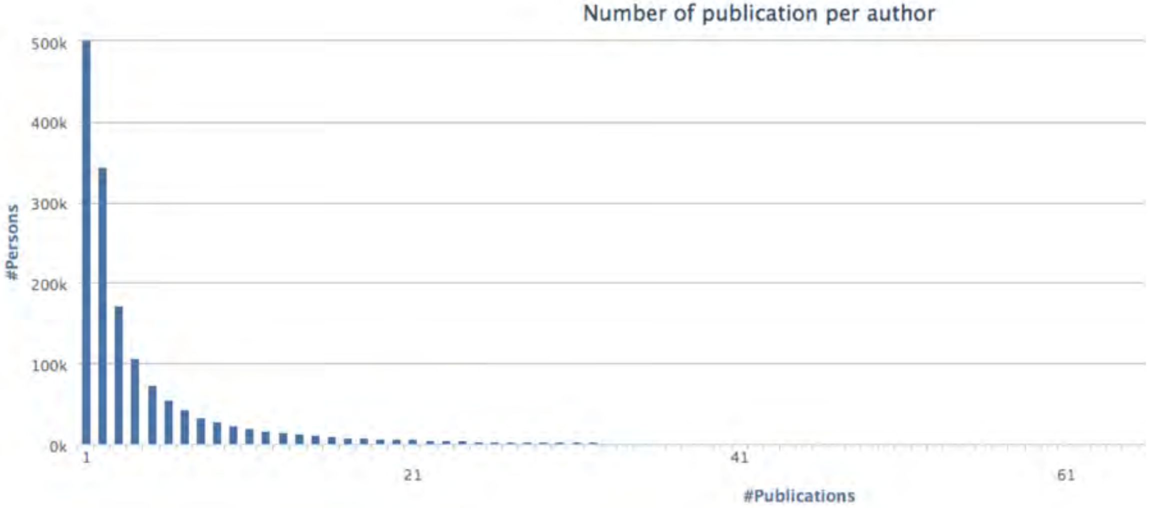
Source of Data?

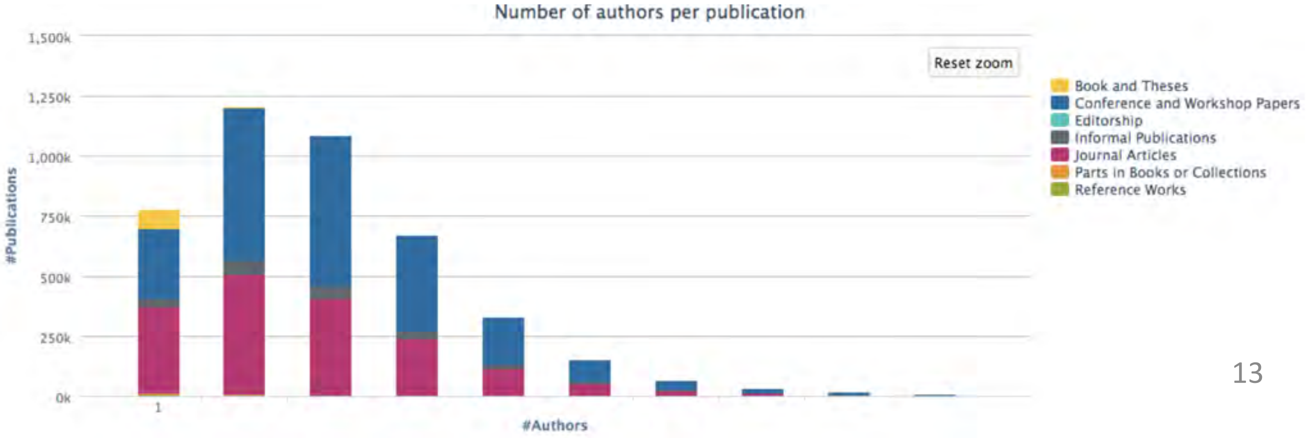
dblp
computer science bibliography

The *dblp computer science bibliography* is the on-line reference for bibliographic information on major computer science publications. It has evolved from an early small experimental web server to a popular open-data service for the computer science community. Our mission at *dblp* is to support computer science researchers in their daily efforts by providing free access to high-quality bibliographic meta-data and links to the electronic editions of publications.

As of October 2018, *dblp* indexes over 4.3 million publications, published by more than 2.1 million authors. To this end, dblp indexes about than 40,000 journal volumes, more than 38,000 conference or workshop proceedings, and more than 80,000 monographs.







dblp
computer science bibliography

Hanzhang Hu, Wen Sun, Arun Venkatraman, Martial Hebert, J. Andrew Bagnell:
Gradient Boosting on Stochastic Data Streams. AISTATS 2017: 595-603

Ishan Misra, Abhinav Gupta, Martial Hebert:
From Red Wine to Red Tomato: Composition with Context. CVPR 2017: 1160-1169

Matthew Trager, Bernd Sturmfels, John F. Canny, Martial Hebert, Jean Ponce:
General Models for Rational Cameras and the Case of Two-Slit Projections. CVPR 2017: 2520-2528

Yu-Xiong Wang, Deva Ramanan, Martial Hebert:
Growing a Brain: Fine-Tuning by Increasing Model Capacity. CVPR 2017: 3029-3038

Debidatta Dwibedi, Ishan Misra, Martial Hebert:
Cut, Paste and Learn: Surprisingly Easy Synthesis for Instance Detection. ICCV 2017: 1310-1319

Jacob Walker, Kenneth Marino, Abhinav Gupta, Martial Hebert:
The Pose Knows: Video Forecasting by Generating Pose Futures. ICCV 2017: 3352-3361

Liangke Gui, Yu-Xiong Wang, Martial Hebert:
Few-Shot Hash Learning for Image Retrieval. ICCV Workshops 2017: 1228-1237

Dhruv Mauria Saxena, Vince Kurtz, Martial Hebert:
Learning robust failure response for autonomous vision based flight. ICRA 2017: 5824-5829

Arun Venkatraman, Nicholas Rhinehart, Wen Sun, Lerrel Pinto, Martial Hebert, Byron Boots, Kris M. Kitani, James Andrew Bagnell:
Predictive-State Decoders: Encoding the Future into Recurrent Networks. NIPS 2017: 1172-1183

Yu-Xiong Wang, Deva Ramanan, Martial Hebert:
Learning to Model the Tail. NIPS 2017: 7032-7042

Hanzhang Hu, Wen Sun, Arun Venkatraman, Martial Hebert, J. Andrew Bagnell:
Gradient Boosting on Stochastic Data Streams. CoRR abs/1703.00377 (2017)

Jacob Walker, Kenneth Marino, Abhinav Gupta, Martial Hebert:
The Pose Knows: Video Forecasting by Generating Pose Futures. CoRR abs/1705.00053 (2017)

Method

Build a regression from publication history to something that matters (“metric of interest”)

$$
\begin{array}{c c}
 & \begin{array}{ccccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n & \end{array} \\
\begin{array}{c} \mathrm{auth}_1 \\ \mathrm{auth}_2 \\ \vdots \\ \mathrm{auth}_m \end{array} &
\begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix}
\begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}
\end{array}
$$

$$
\begin{array}{c}
 \\
\text{auth}_1 \\
\text{auth}_2 \\
\vdots \\
\text{auth}_m
\end{array}
\begin{array}{c}
\begin{array}{cccc} \text{conf}_1 & \text{conf}_2 & \dots & \text{conf}_n \end{array} \\
\begin{pmatrix}
1 & 3 & \dots & 0 & 1 \\
1 & 0 & \dots & 1 & 1 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 2 & \dots & 4 & 1
\end{pmatrix}
\begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}
\end{array}
$$

Use a Huber Loss to be robust to errors

$$
L(\hat{y}, y) = \begin{cases} \frac{1}{2}(y - \hat{y})^2, & \text{if } |y - \hat{y}| \leq \delta \\ \delta |y - \hat{y}| - \frac{1}{2}\delta^2, & \text{otherwise} \end{cases}
$$

$$
\begin{array}{cc}
 & \begin{array}{cccccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n & & \end{array} \\
\begin{array}{c} \mathrm{auth}_1 \\ \mathrm{auth}_2 \\ \vdots \\ \mathrm{auth}_m \end{array} &
\begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix}
\begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}
\end{array}
$$

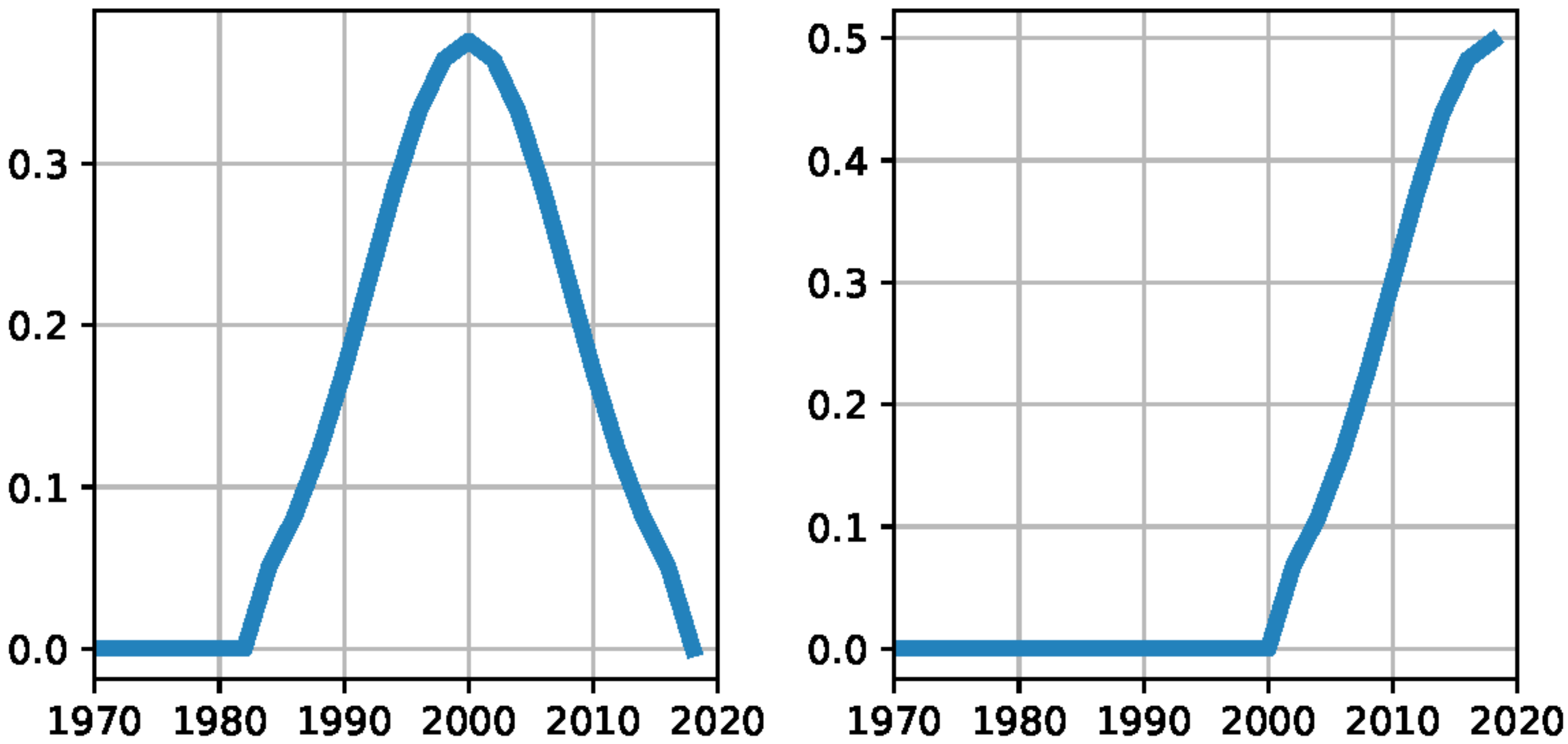
Apply L2 regularization to keep weights small

$$L(Ax, b) + \lambda||x||^2$$

$$\begin{array}{c|c} & \begin{array}{ccccc} \text{conf}_1 & \text{conf}_2 & \dots & \text{conf}_n & \end{array} \\ \begin{array}{c} \text{auth}_1 \\ \text{auth}_2 \\ \vdots \\ \text{auth}_m \end{array} & \begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix} \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix} \end{array}$$

Solve with Stochastic Gradient Descent

$$x^{(t+1)} = x^{(t)} - \alpha \nabla L(\hat{y}_i, y_i)$$



Break apart conference value into different variables for different years
So instead of 10,000 variables, we’ll have 50 * 10,000 variables

Metric #1: Faculty Status

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n & \end{array} \\
\begin{array}{c} \mathrm{auth}_1 \\ \mathrm{auth}_2 \\ \vdots \\ \mathrm{auth}_m \end{array} &
\begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix}
\end{array}
\begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}
=
\begin{pmatrix} \mathrm{isProf}_1 \\ \mathrm{isProf}_2 \\ \vdots \\ \mathrm{isProf}_m \end{pmatrix}
$$

Use faculty status from CSRankings.org

Matrix is size authors x variables

2,071,336 x 518,650

Metric #2: NSF Awards

$$\begin{array}{r c} & \begin{array}{ccccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n & \end{array} \\ \begin{array}{r} \mathrm{grant}_1 \\ \mathrm{grant}_2 \\ \vdots \\ \mathrm{grant}_m \end{array} & \begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix} \end{array} \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} \mathrm{award}_1 \\ \mathrm{award}_2 \\ \vdots \\ \mathrm{award}_m \end{pmatrix}$$

Use award sizes from National Science Foundation

Matrix is size grants x variables

449,919 x 518,650

Metric #3: Univ. of Calif. Salaries

$$
\begin{array}{c c}
 & \begin{array}{ccccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n & \end{array} \\
\begin{array}{c} \mathrm{auth}_1 \\ \mathrm{auth}_2 \\ \vdots \\ \mathrm{auth}_m \end{array} &
\begin{pmatrix} 1 & 3 & \dots & 0 & 1 \\ 1 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 2 & \dots & 4 & 1 \end{pmatrix}
\begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} \mathrm{salary}_1 \\ \mathrm{salary}_2 \\ \vdots \\ \mathrm{salary}_m \end{pmatrix}
\end{array}
$$

Use salaries from Transparent California

Matrix is valid authors x variables

~300 x 518,650

3 Very Different Problems

- **Faculty Status**
  - Rows > Cols
  - Highly imbalanced classes
  - Classification
  - Based on 2019 status
- **NSF Awards**
  - Rows ~= Cols
  - Everything is a valid datapoint
  - Regression
  - Provides historical data
- **Salaries**
  - Rows < Cols
  - Everything is a valid datapoint
  - Regression
  - Based on 2017 salary data

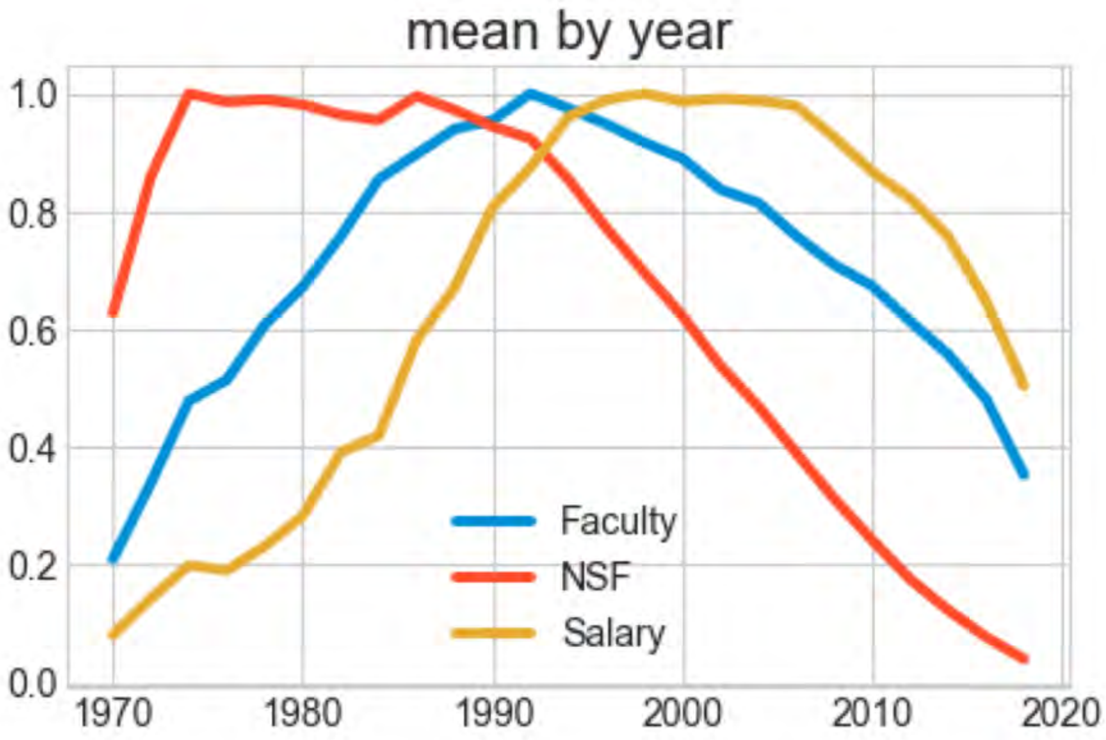
How related are the resulting vectors?

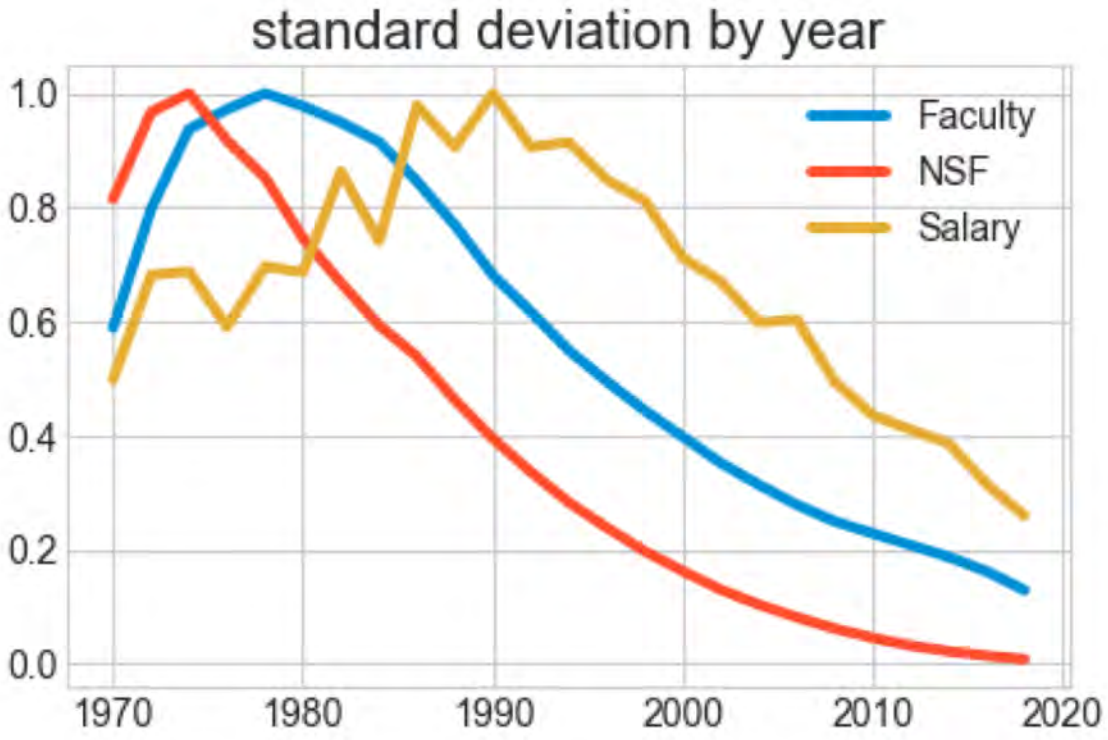
	Faculty	NSF	Salary
Faculty	1	0.91	0.84
NSF	0.91	1	0.86
Salary	0.84	0.86	1

Spearman’s ρ, rank correlation

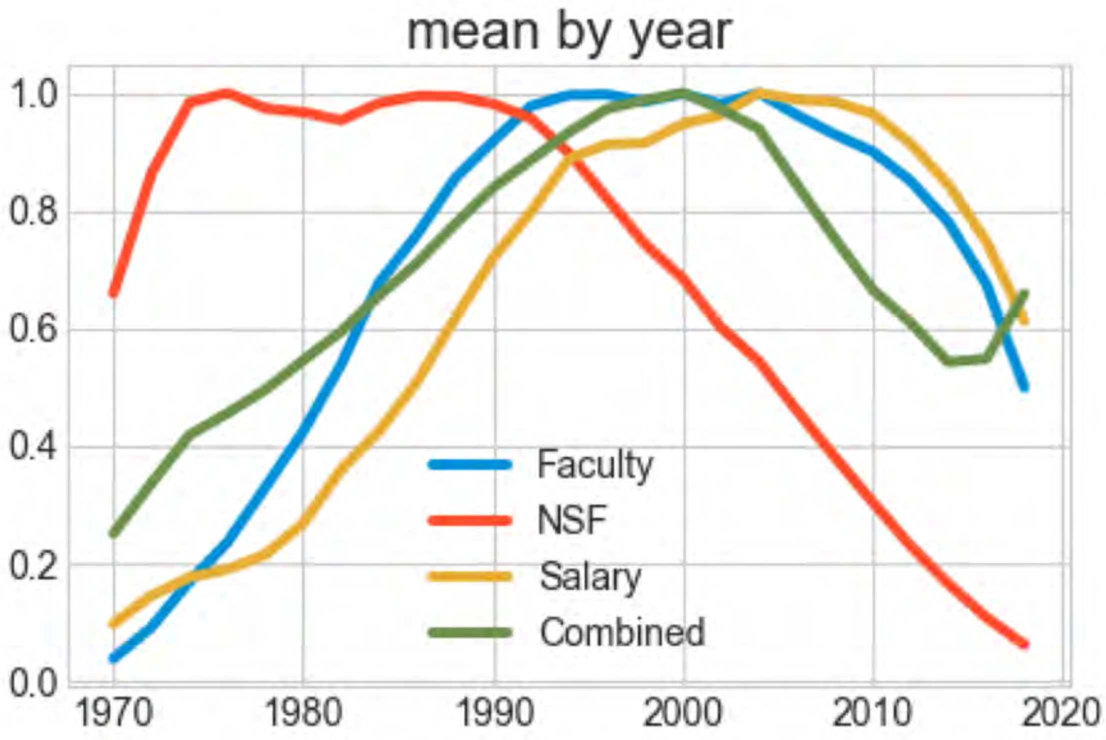
n = 259,325

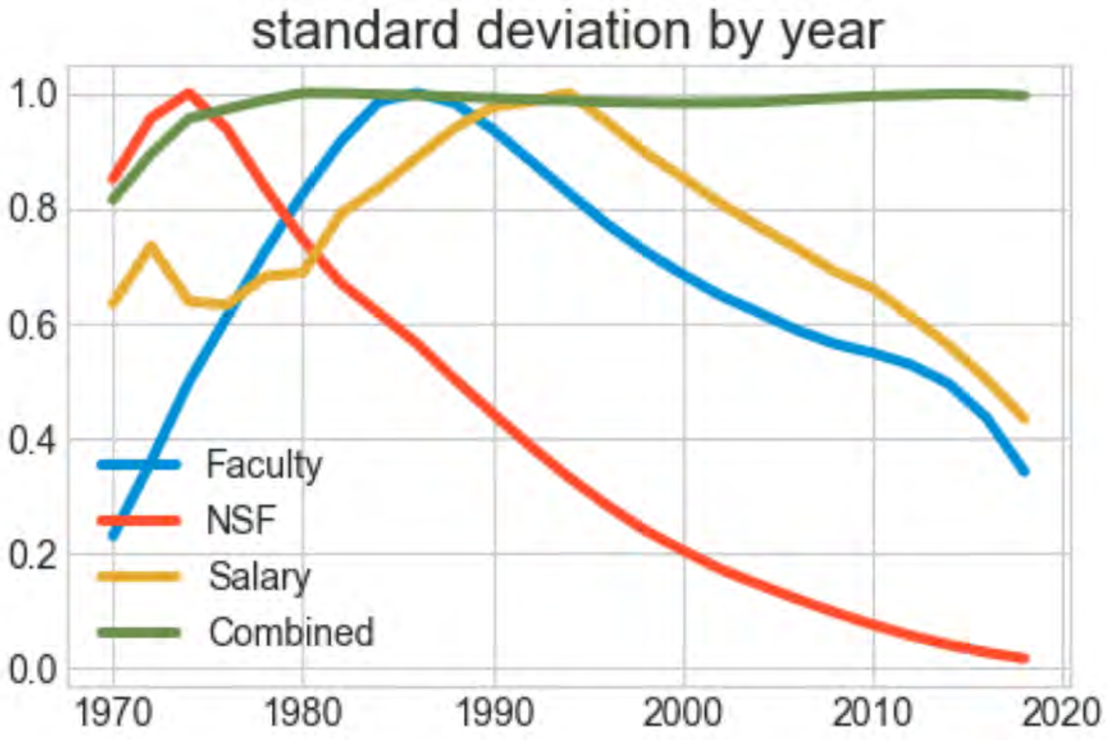
Temporal behavior is very different!



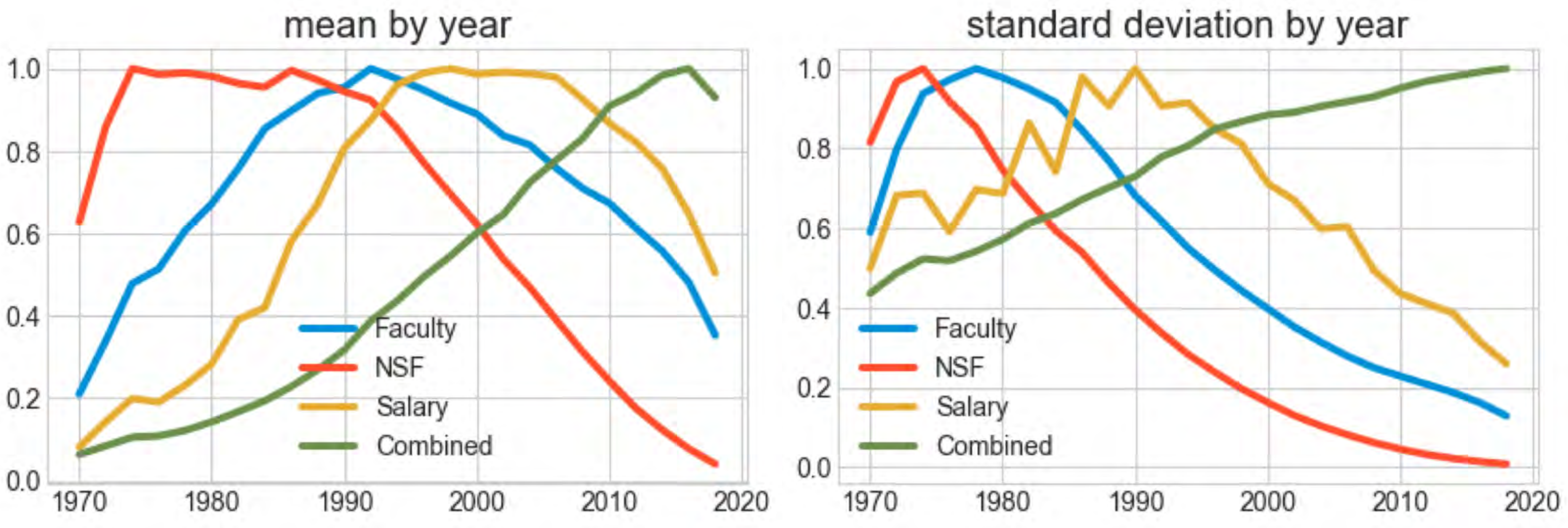


Normalize by Year: Z-Score

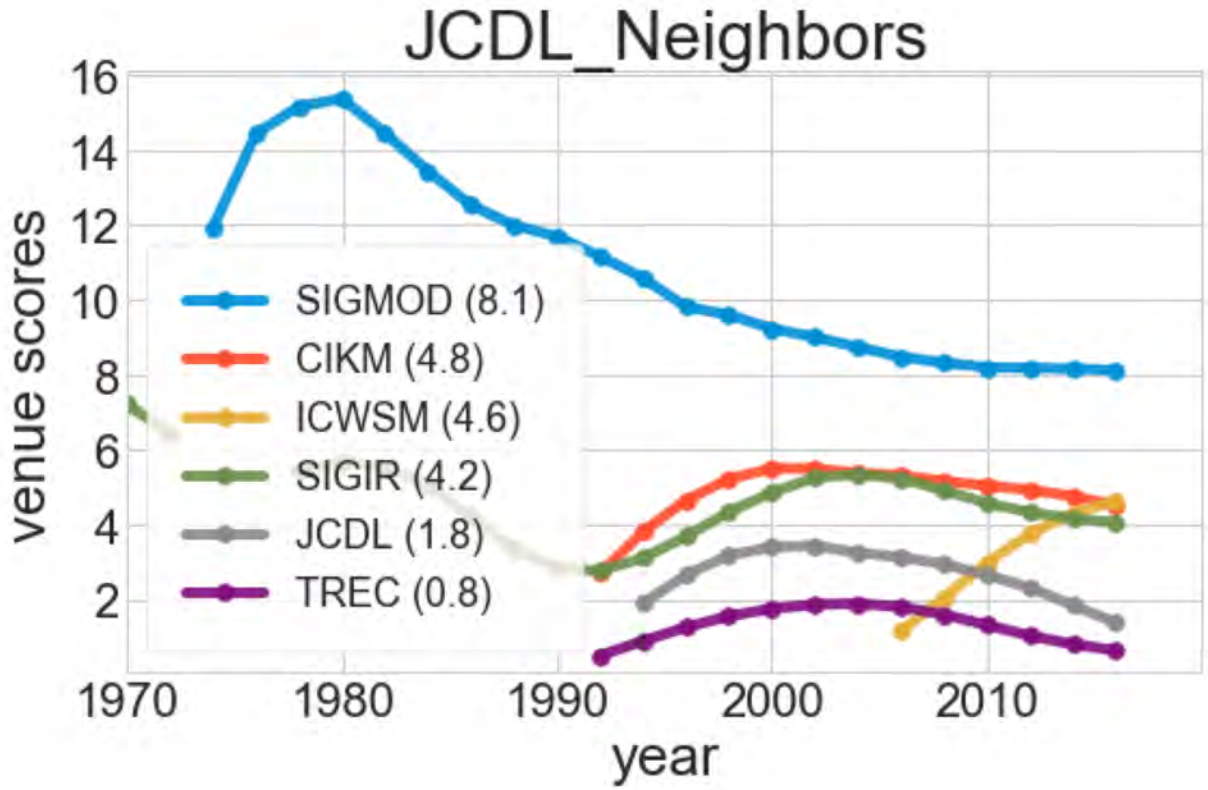




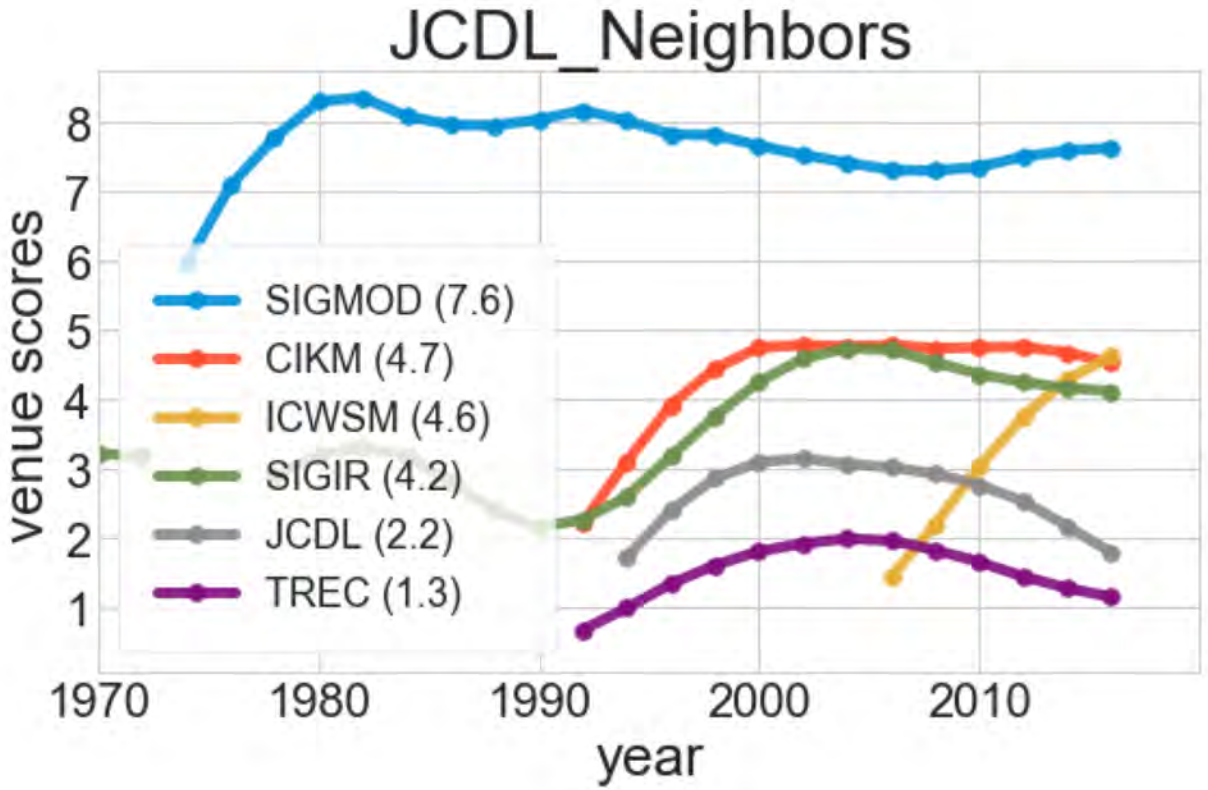
Normalize by Year: Max



In practice? Max seems better



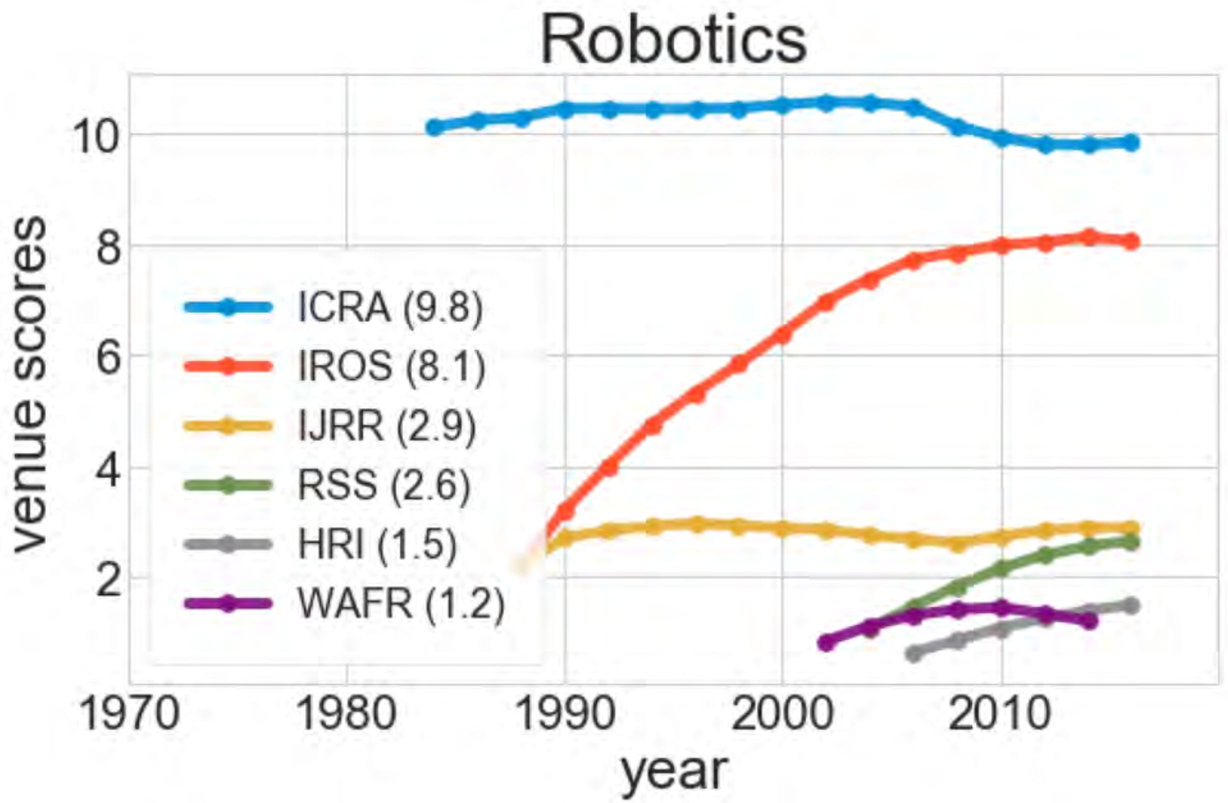
Z-score

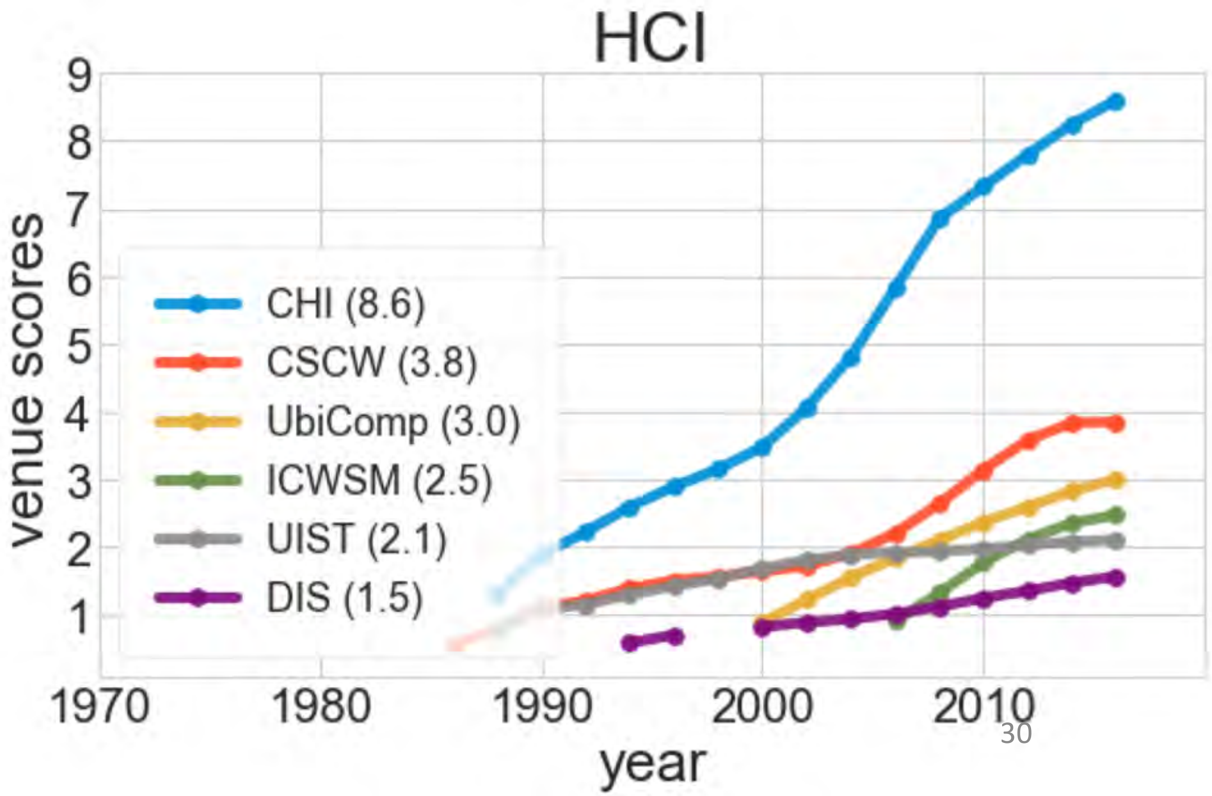


Max

Another problem: Sizes!

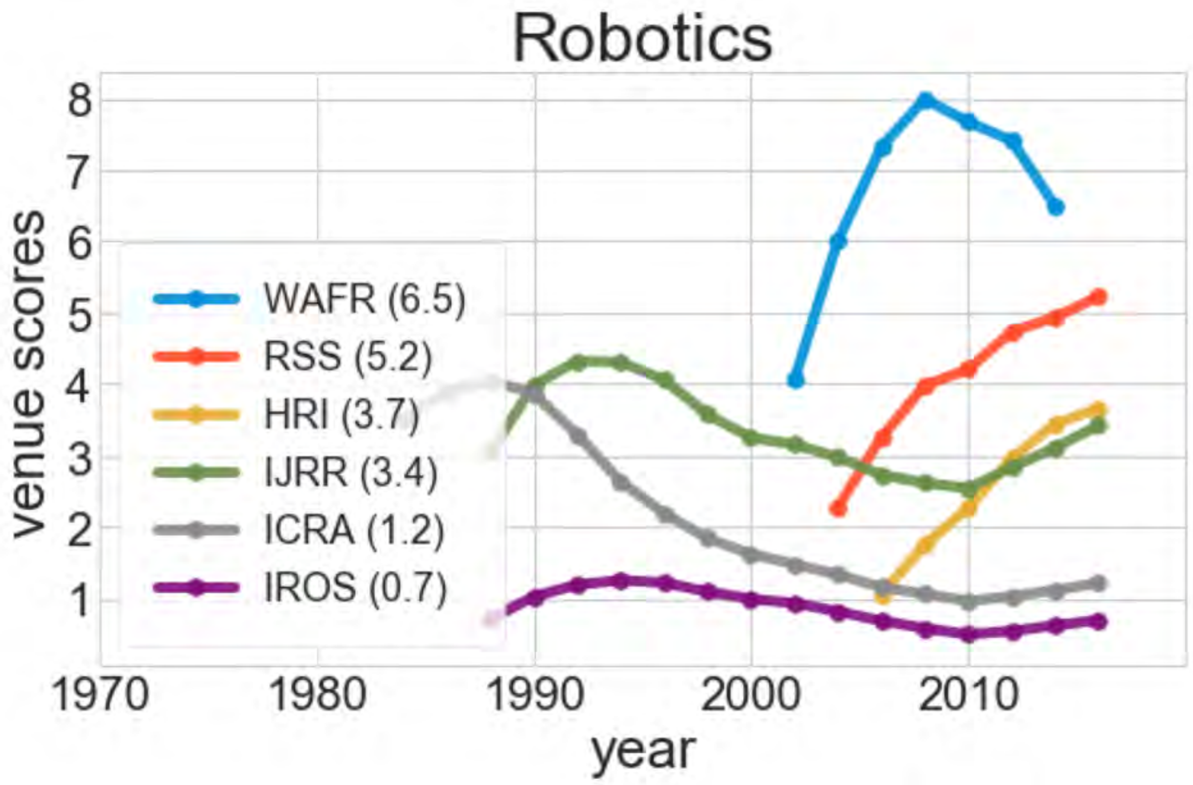
$$L(Ax, b) + \lambda ||x||^2$$

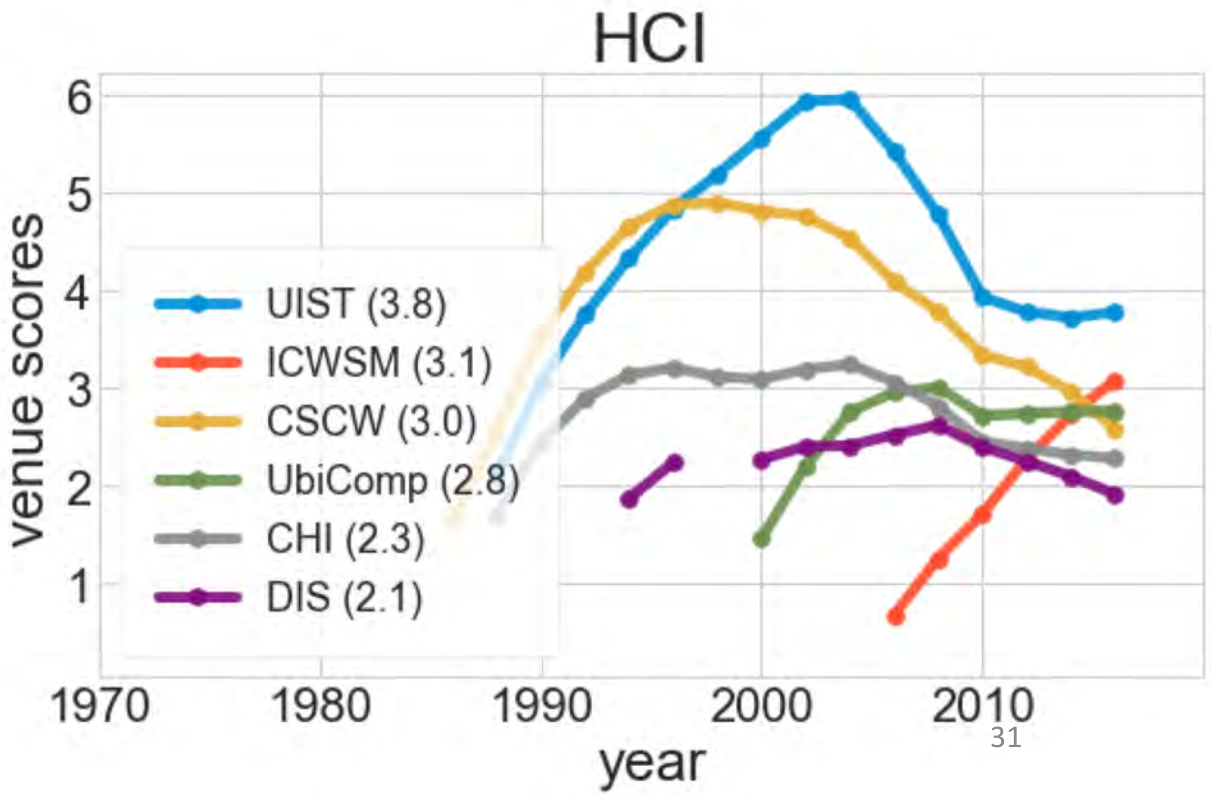




What if we give everyone fractional credit?

$$\frac{1}{\#\ of\ papers\ in\ conference}$$



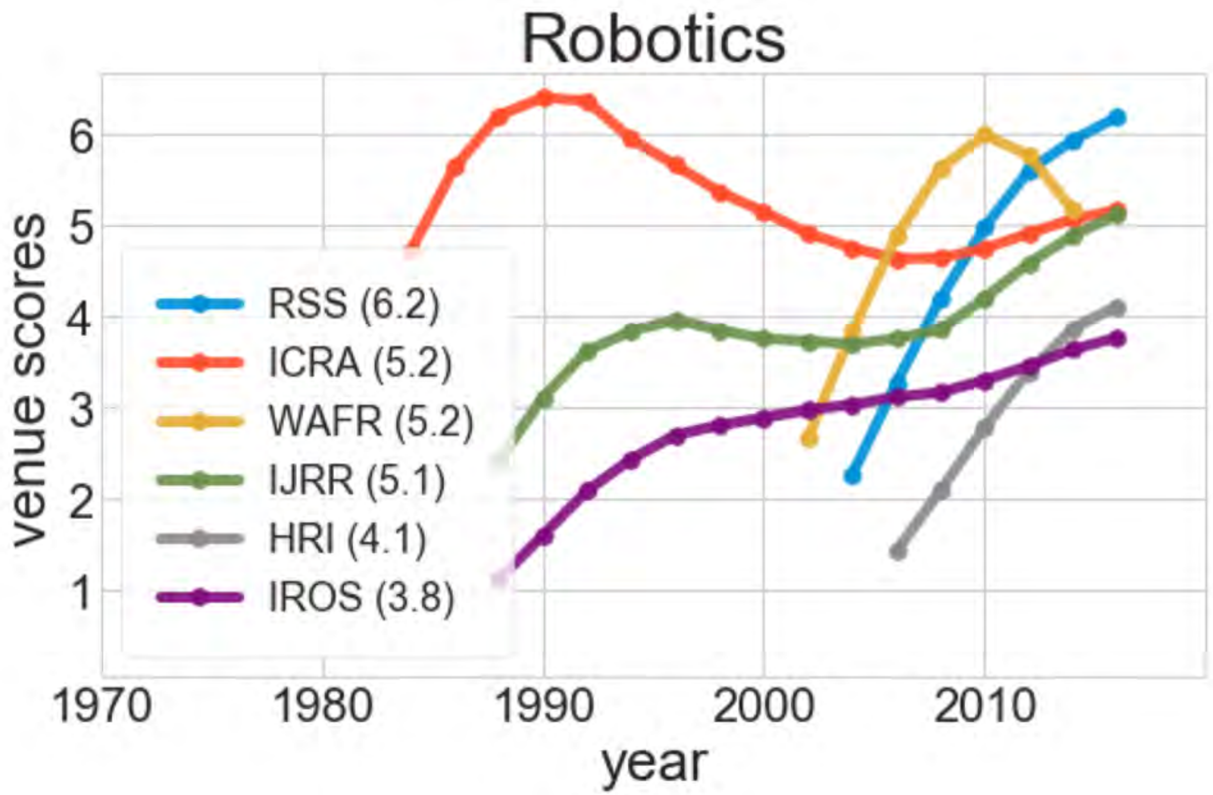


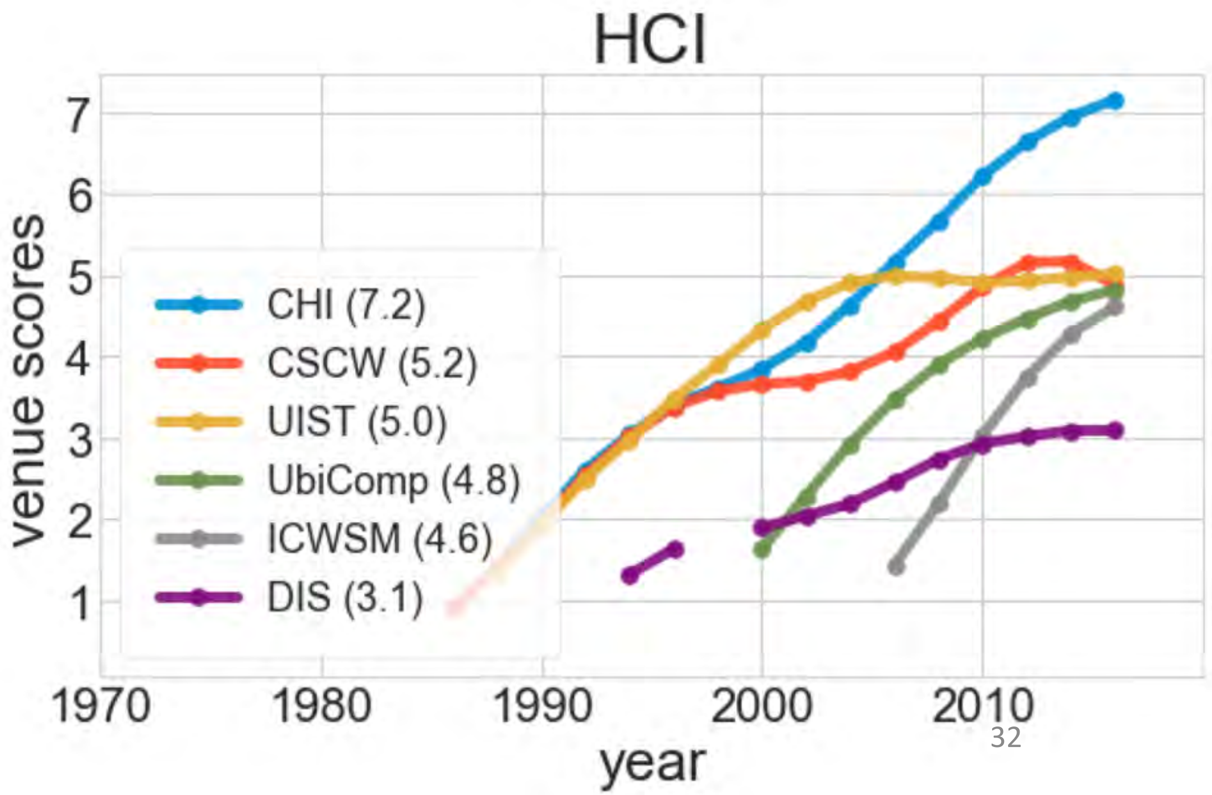
In practice, use a blended result

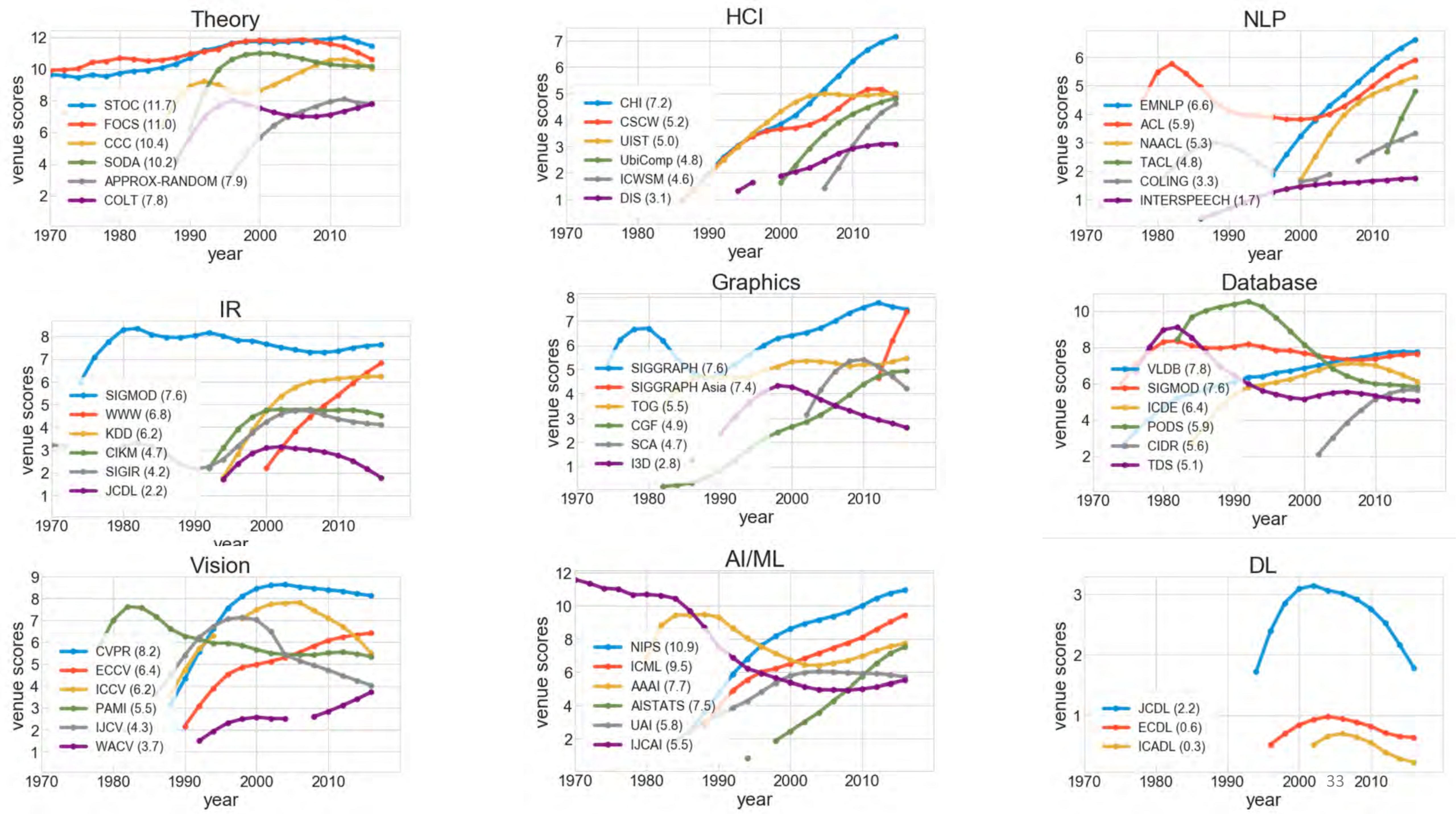
$$\frac{1}{(\#\ of\ papers\ in\ conference)^{\frac{1}{\lambda}}}$$

λ = 1.0 is size normalized
λ = 2.0 uses square root of conference

I tend to use λ=1.5849






Theory
STOC (11.7)
FOCS (11.0)
CCC (10.4)
SODA (10.2)
APPROX-RANDOM (7.9)
COLT (7.8)
HCI
CHI (7.2)
CSCW (5.2)
UIST (5.0)
UbiComp (4.8)
ICWSM (4.6)
DIS (3.1)
NLP
EMNLP (6.6)
ACL (5.9)
NAACL (5.3)
TACL (4.8)
COLING (3.3)
INTERSPEECH (1.7)
IR
SIGMOD (7.6)
WWW (6.8)
KDD (6.2)
CIKM (4.7)
SIGIR (4.2)
JCDL (2.2)
Graphics
SIGGRAPH (7.6)
SIGGRAPH Asia (7.4)
TOG (5.5)
CGF (4.9)
SCA (4.7)
I3D (2.8)
Database
VLDB (7.8)
SIGMOD (7.6)
ICDE (6.4)
PODS (5.9)
CIDR (5.6)
TDS (5.1)
Vision
CVPR (8.2)
ECCV (6.4)
ICCV (6.2)
PAMI (5.5)
IJCV (4.3)
WACV (3.7)
AI/ML
NIPS (10.9)
ICML (9.5)
AAAI (7.7)
AISTATS (7.5)
UAI (5.8)
IJCAI (5.5)
DL
JCDL (2.2)
ECDL (0.6)
ICADL (0.3)
venue scores
year

Name	Score	Size
STOC	11.71	128
FOCS	11.04	120
NIPS	10.94	484
CCC	10.41	53
SODA	10.17	224
SIAM J. Comput.	9.98	138
ICML	9.73	303
HotNets	9.70	46
ITCS	9.44	103
Allerton	9.17	331
TCC	9.12	76
NSDI	8.87	69
CCS	8.76	114
ASPLOS	8.69	48
INFOCOM	8.59	434
SIGCOMM	8.31	55
CVPR	8.22	606
ToC	8.13	29
SIGGRAPH Asia	8.12	140
PLDI	8.05	68
J. ACM	8.03	82
GetMobile	8.00	41

Name	Score	Size
NDSS	7.93	63
COLT	7.92	82
USENIX Security	7.91	62
APPROX-RANDOM	7.86	74
AAAI	7.76	403
VLDB	7.75	185
IEEE/ACM Trans. Netw.	7.74	226
AISTATS	7.72	138
OOPSLA	7.66	75
SIGMOD	7.62	98
SIGGRAPH	7.59	125
POPL	7.47	68
EUROCRYPT	7.33	78
CHI	7.27	431
CRYPTO	7.24	80
IEEE SSP	7.11	54
WWW	7.08	232
EMNLP	6.80	263
HotOS	6.75	27
Commun. ACM	6.72	222
OSDI	6.60	29
EC	6.60	63

Evaluation of Results

- Author Level
- Conference Level
- University Level (a little later)

Author-level correlations

- Collect a dataset of ~150 faculty members (all from CMU)
- Collect their metrics from Google Scholar
- Include Influential Citations from Semantic Scholar

Model	citations	h-index [24]	influential citations [54]
Faculty	0.59	0.68	0.71
NSF	0.63	0.66	0.67
Salary	0.36	0.36	0.41
Combined	**0.69**	**0.77**	**0.75**

Conference-level correlations

- Use a dataset of citations & h-index results from Microsoft Academic
- Correlate against our metric
- For N= 1,300 conferences in computer science

	papers	**citations**	**H**	**venue_scores**
papers	1.00	**0.74**	0.42	0.34
citations	**0.74**	1.00	0.62	0.35
H	0.42	0.62	1.00	**0.68**
venue_scores	0.34	0.35	**0.68**	1.00

Should we use a temporal model?

Years	Metric	AI	AH	USN	VH	VC
$\sigma = 4.5$	Faculty	0.73	**0.69**	0.74	0.63	0.42
10		0.67	0.57	**0.76**	0.57	0.35
50		**0.75**	0.68	**0.76**	0.38	0.21
$\sigma = 4.5$	NSF	0.64	0.62	0.62	0.61	0.59
10		0.68	0.68	0.60	0.59	0.60
50		0.67	0.65	0.63	**0.64**	**0.67**

AI = Author Highly Influential Citations
AH = Author H-index

USN = US News 2018,

VH =Venue H-index
VC = Venue Citations.

Discussion

Interesting hyper-parameter choices

How do we assign credit to authors?

- Evaluate with Semantic Scholar Correlation, 4 different models
  1. Authors get $\frac{1}{N}$ points for each paper with N authors
  2. Authors get 1 point for each paper they're on
  3. Authors variable credit by author position, e.g $\frac{1}{1}, \frac{1}{2}, \frac{1}{3}, \ldots, \frac{1}{N}$ (normalized to 1)
  4. Authors variable credit, except First == Last before normalization.

Produces best results!

		Evaluation Author Model			
		1	2	3	4
Regression Author Model	1	0.70	**0.72**	0.65	0.70
	2	0.68	**0.71**	0.61	0.67
	3	**0.71**	**0.73**	**0.66**	**0.71**
	4	0.70	**0.72**	0.65	**0.71**

Top-K faculty choice

- For the faculty regression, we choose top-K universities
- Larger K provides more data, but can erase differences in top tier
- Used to use 40, now use 75 (from CS Rankings rank)
- Good Example from CSRankings GitHub

```
R: Rank based on S/N/I
S/N: SIGCOMM + NSDI
I: INFOCOM

R #T S/N I   Institution
1 49 = [ 0 49 ]  Shanghai Jiao Tong University
2 37 = [ 35 2 ]  UC Berkeley
3 32 = [ 30 2 ]  MIT
4 44 = [ 34 10 ]  Princeton University
5 30 = [ 1 29 ]  Tsinghua University
6 22 = [ 11 11 ]  University of Michigan
7 20 = [ 5 15 ]  Technion
8 21 = [ 3 18 ]  Ohio State University
9 26 = [ 35 1 ]  Carnegie Mellon University
9 23 = [ 13 10 ]  KAIST
11 19 = [ 10 9 ]  University of Illinois at UC
11 16 = [ 0 16 ]  University of Calgary
13 23 = [ 7 16 ]  HKUST
14 21 = [ 4 17 ]  Stony Brook University
15 19 = [ 6 13 ]  University of Massachusetts
15 19 = [ 19 0 ]  Stanford University
17 22 = [ 1 21 ]  USTC
18 22 = [ 20 2 ]  University of Washington
18 18 = [ 1 17 ]  University at Buffalo
20 14 = [ 0 14 ]  Nanyang Technological University
..
34 11 = [ 9 2 ]  University of Wisconsin – Madison
..
37 9 = [ 9 0 ]  Cornell University
```

Other issues/talking points

1. **Clearly a system with precision over recall**
2. The Faculty data is curated by CSRankings, ignores non-CS faculty
3. The NSF & Salary use fuzzy string matching
4. Minimum page count can affect ranking results
    - No distinction between short and long papers
    - Used to use 6 (from CS Rankings), now use 4 (Medical Imaging)
5. Different biases in different datasets
    - **Salary**: Small and US-focused
    - **Faculty:** Clear bias towards theory conferences, may select against industry people
    - **NSF**: Some areas (like robotics) tend to get larger grants

Organizing the venues

We would also like some notion of fields/sub-areas

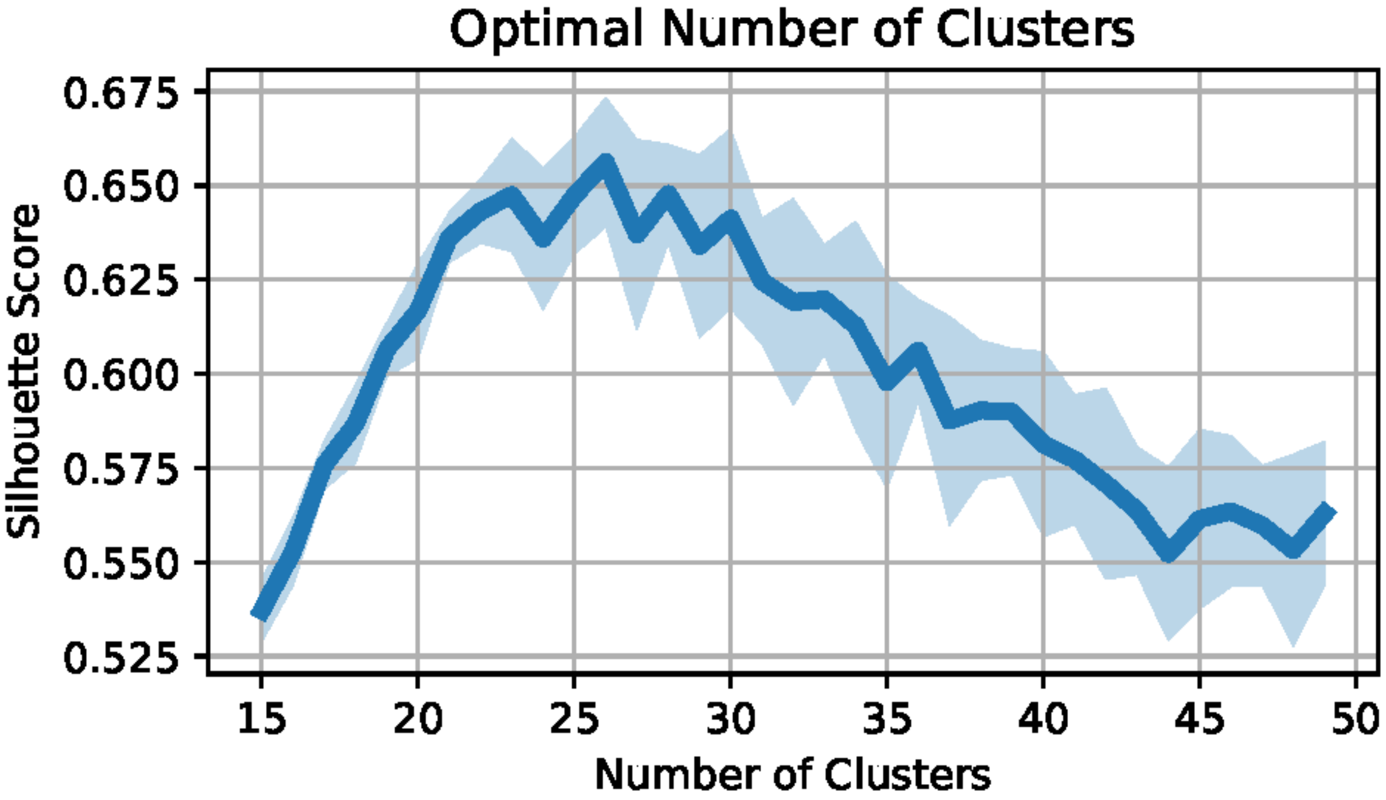
Author x Conference Matrix

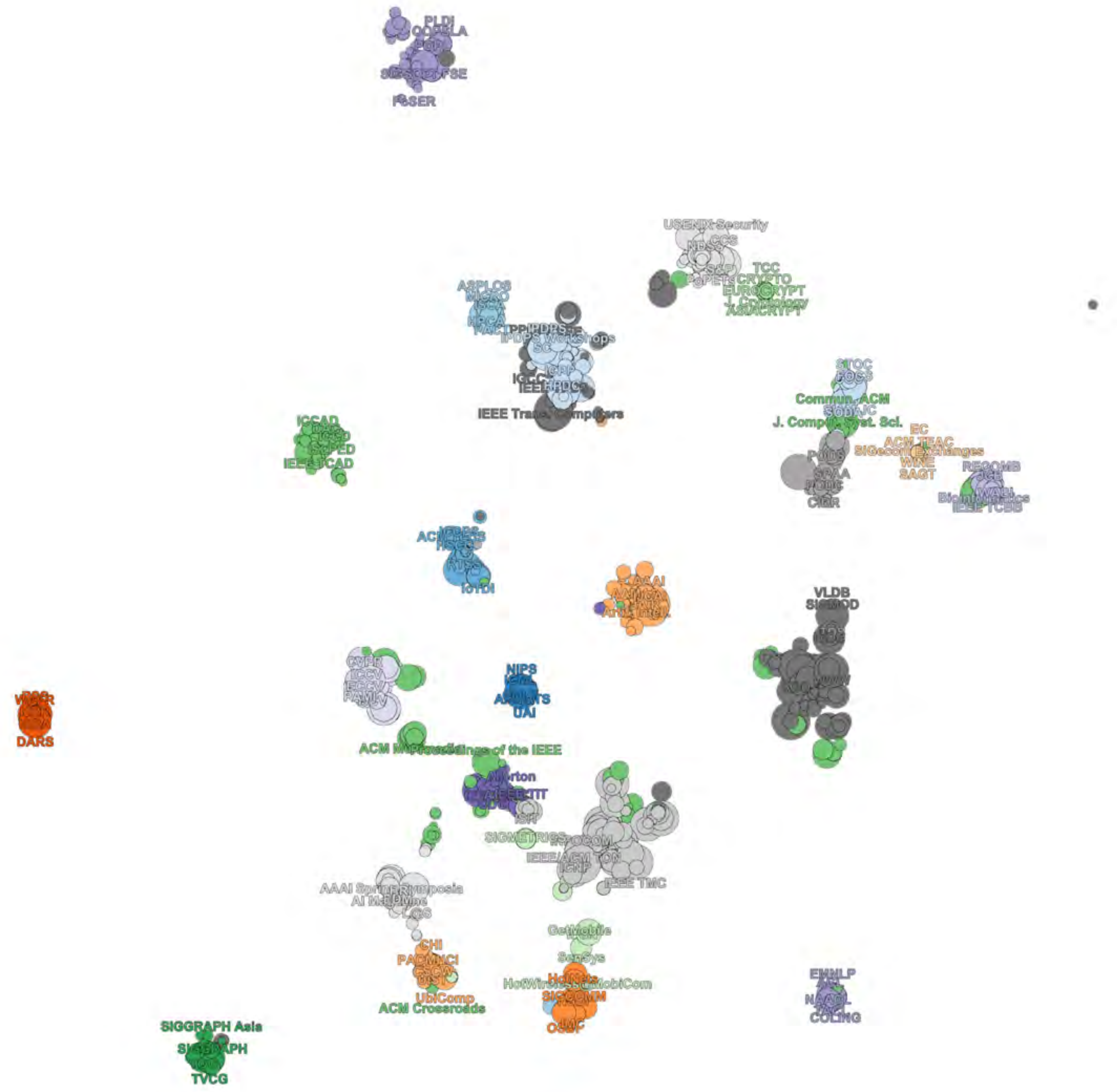
- Use only faculty at R1 Universities
  - Authors with at least 10 papers (1822 authors)
  - Venues with at least 20 R1 universities (1004 venues)

$$\begin{array}{c} \\ \mathrm{auth}_1 \\ \mathrm{auth}_2 \\ \vdots \\ \mathrm{auth}_m \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{conf}_1 & \mathrm{conf}_2 & \dots & \mathrm{conf}_n \end{array} \\ \begin{pmatrix} 1 & 3 & \dots & 0 \\ 1 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 2 & \dots & 4 \end{pmatrix} \end{array}$$

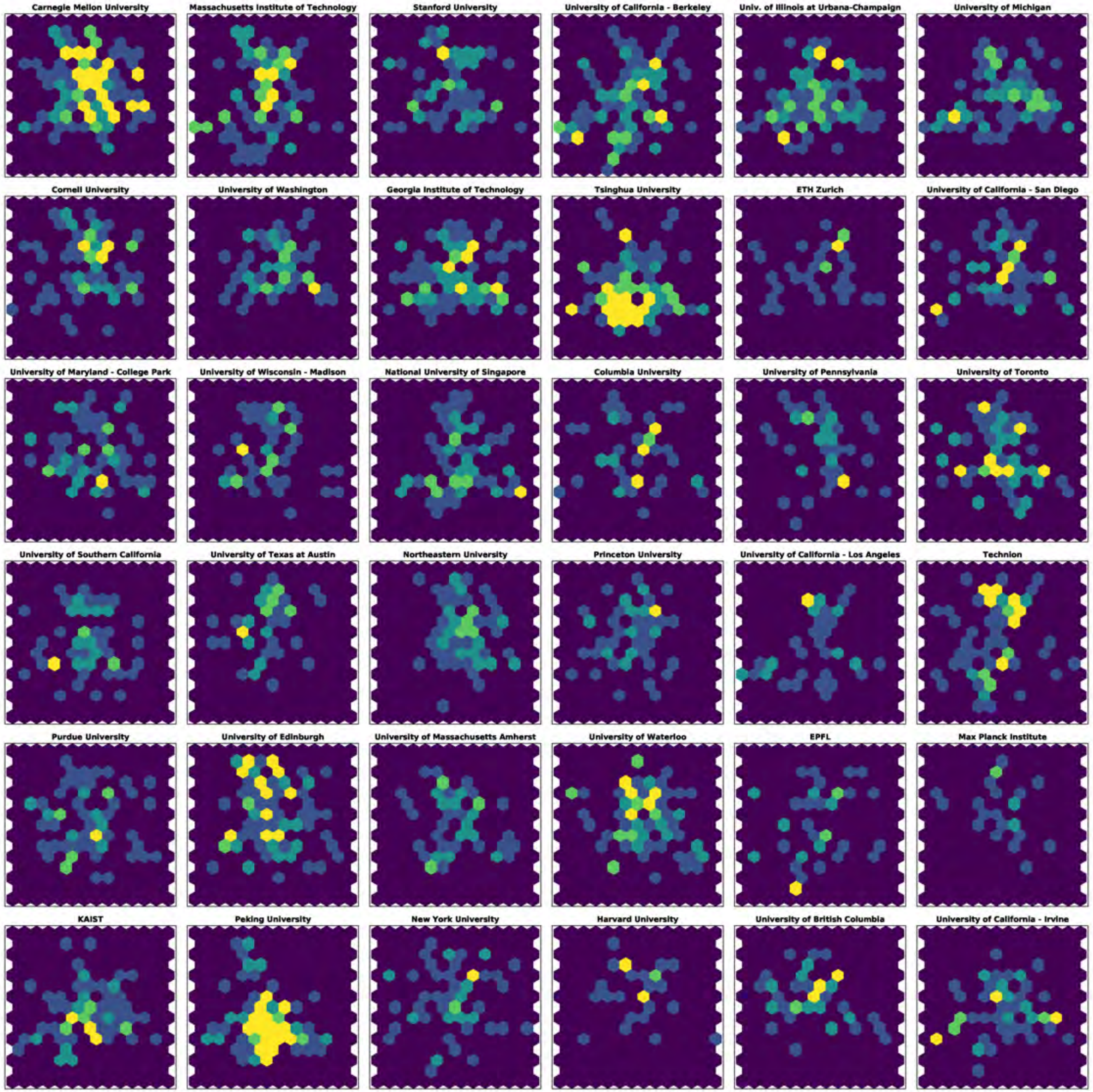
- Perform **Latent Dirichlet Allocation** to get 50 dimensional vectors for each publication venue
- Perform **t-SNE** to get 2D embeddings
- Use **k-Means** to get clusters

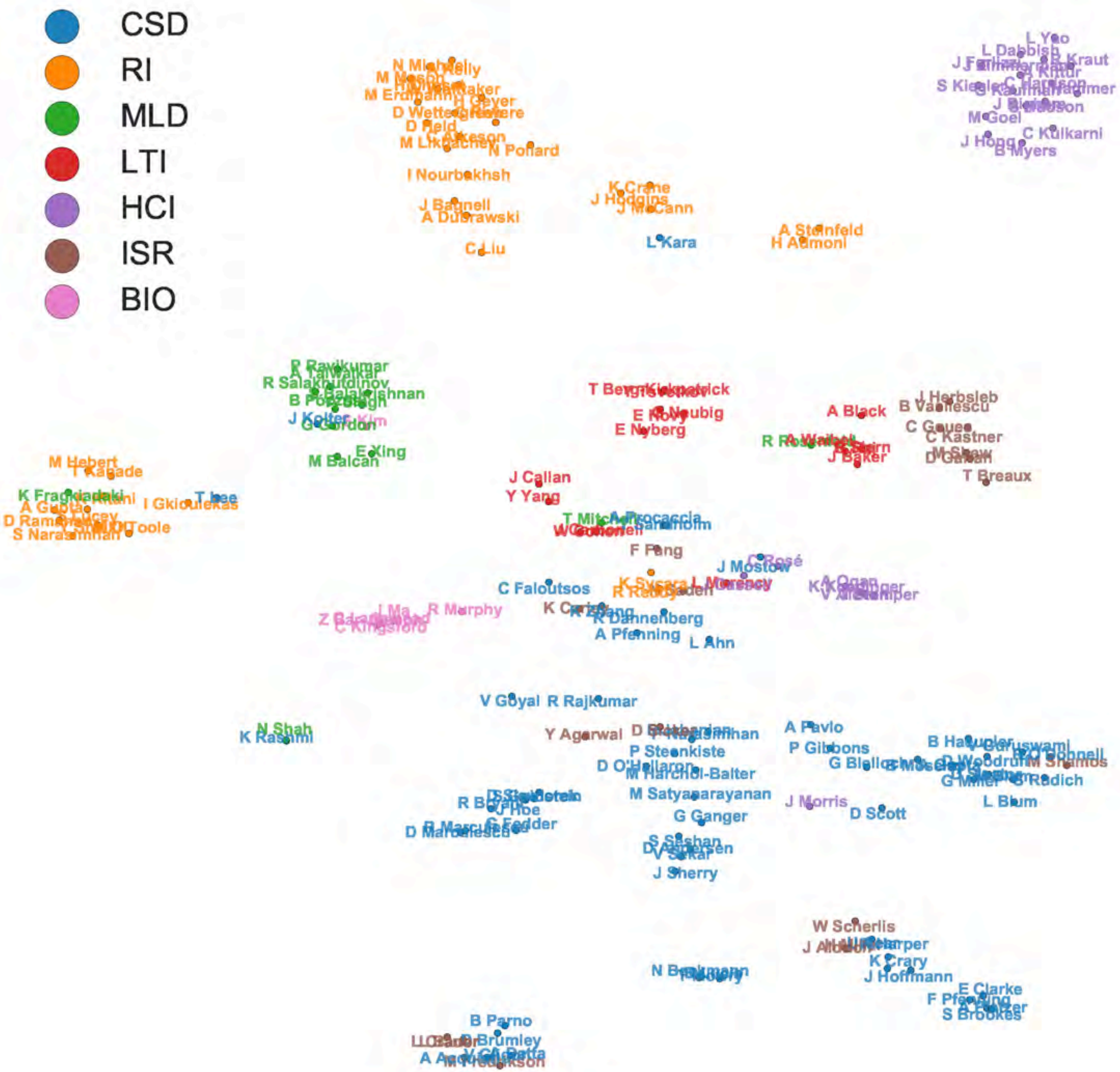
How many clusters in CS?





PLDI
USENIX Security
CCS
TCC
CRYPTO
EUROCRYPT
ASIACRYPT
ASPLOS
IPDPS Workshops
IEEE Trans. Computers
STOC
FOCS
Commun. ACM
SODA
J. Comput. Syst. Sci.
EC
ACM TEAC
WINE
SAGT
RECOMB
Bioinformatics
IEEE TCBB
ICCAD
IEEE TCAD
VLDB
SIGMOD
AAAI
CVPR
ICCV
NIPS
UAI
DARS
Proceedings of the IEEE
SIGMETRICS
IEEE TMC
CHI
UbiComp
ACM Crossroads
SenSys
MobiCom
SIGCOMM
EMNLP
NAACL
COLING
SIGGRAPH Asia
SIGGRAPH
TVCG


Carnegie Mellon University
Massachusetts Institute of Technology
Stanford University
University of California - Berkeley
Univ. of Illinois at Urbana-Champaign
University of Michigan
Cornell University
University of Washington
Georgia Institute of Technology
Tsinghua University
ETH Zurich
University of California - San Diego
University of Maryland - College Park
University of Wisconsin - Madison
National University of Singapore
Columbia University
University of Pennsylvania
University of Toronto
University of Southern California
University of Texas at Austin
Northeastern University
Princeton University
University of California - Los Angeles
Technion
Purdue University
University of Edinburgh
University of Massachusetts Amherst
University of Waterloo
EPFL
Max Planck Institute
KAIST
Peking University
New York University
Harvard University
University of British Columbia
University of California - Irvine



CSD
RI
MLD
LTI
HCI
ISR
BIO
N Pollard
I Nourbakhsh
J Bagnell
A Dubrawski
C Liu
K Crane
J Hodgins
J McCann
L Kara
A Steinfeld
H Admoni
L Yeo
L Dabbish
M Goel
C Kulkarni
B Myers
R Salakhutdinov
E Xing
M Balcan
M Hebert
T Kanade
T Lee
I Gkioulekas
S Narasimhan
E Nyberg
A Black
J Herbsleb
C Kastner
T Breaux
J Callan
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F Fang
J Mostow
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R Murphy
C Kingsford
R Dannenberg
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A Pavlo
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K Crary
J Hoffmann
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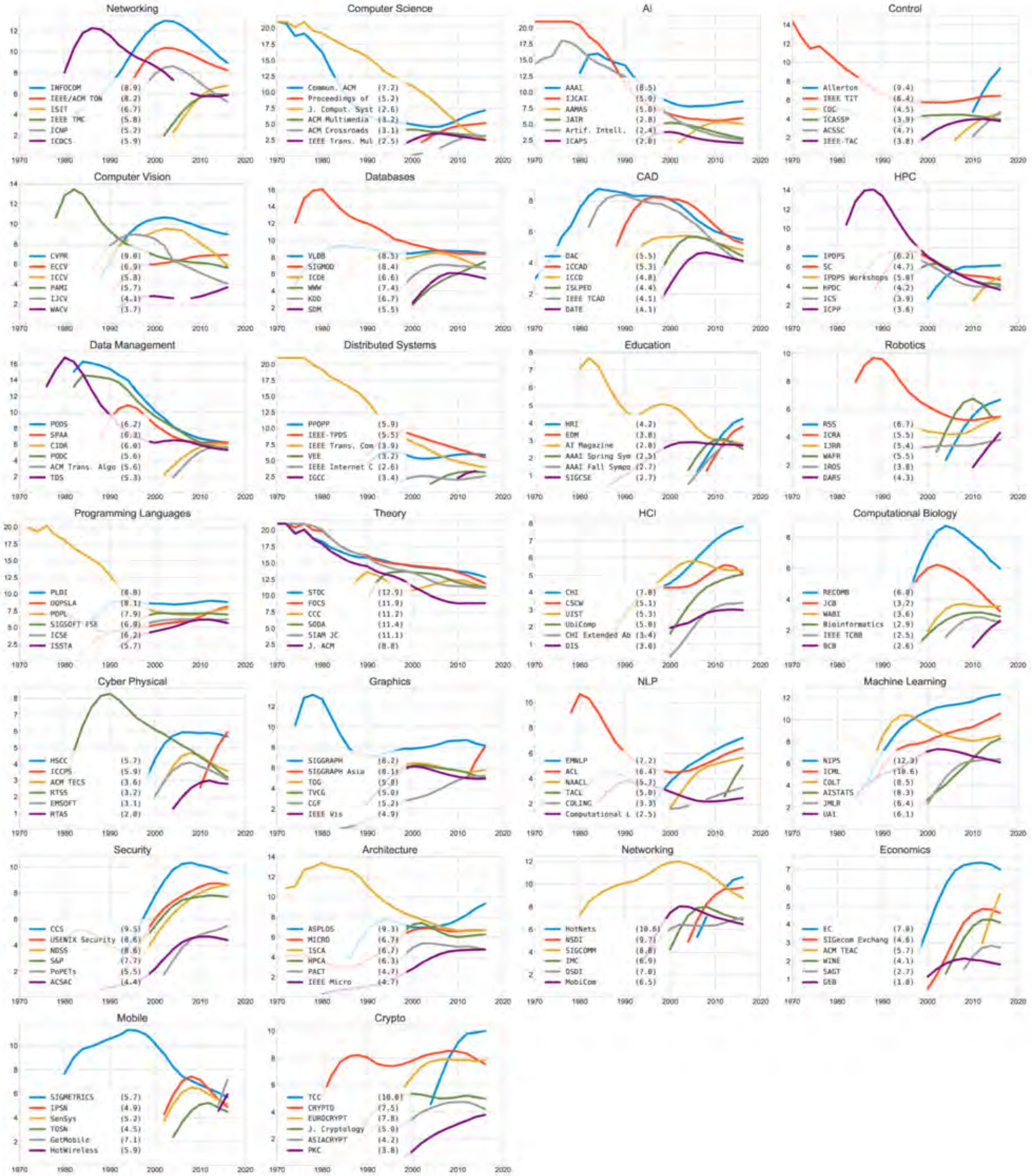
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IEEE TMC (5.8)
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ICDCS (5.9)
Computer Science
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ACM Multimedia (3.2)
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ACSSC (4.7)
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Computer Vision
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WAFR (5.5)
IROS (3.8)
DARS (4.3)
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OOPSLA (8.1)
POPL (7.9)
SIGSOFT FSE (6.9)
ICSE (6.2)
ISSTA (5.7)
Theory
STOC (12.9)
FOCS (11.9)
CCC (11.2)
SODA (11.4)
SIAM JC (11.1)
J. ACM (8.8)
HCI
CHI (7.8)
CSCW (5.1)
UIST (5.3)
UbiComp (5.0)
CHI Extended Ab (3.4)
DIS (3.0)
Computational Biology
RECOMB (6.0)
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WABI (3.6)
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ICCPS (5.9)
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Security
CCS (9.5)
USENIX Security (8.6)
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S&P (7.7)
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ACSAC (4.4)
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ASPLOS (9.3)
MICRO (6.7)
ISCA (6.7)
HPCA (6.3)
PACT (4.7)
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Networking
HotNets (10.6)
NSDI (9.7)
SIGCOMM (8.8)
IMC (6.9)
OSDI (7.0)
MobiCom (6.5)
Economics
EC (7.0)
SIGecom Exchang (4.6)
ACM TEAC (5.7)
WINE (4.1)
SAGT (2.7)
GEB (1.8)
Mobile
SIGMETRICS (5.7)
IPSN (4.9)
SenSys (5.2)
TOSN (4.5)
GetMobile (7.1)
HotWireless (5.9)
Crypto
TCC (10.0)
CRYPTO (7.5)
EUROCRYPT (7.8)
J. Cryptology (5.0)
ASIACRYPT (4.2)
PKC (3.8)

Ranking Universities

We did this just for evaluation, but let’s talk about it

BEST GRAD SCHOOLS U.S.News & WORLD REPORT RANKINGS

1	Carnegie Mellon University
1	Massachusetts Institute of Technology
1	Stanford University
1	University of California - Berkeley
5	Univ. of Illinois at Urbana-Champaign
6	Cornell University
6	University of Washington
8	Georgia Institute of Technology
8	Princeton University
10	University of Texas at Austin
11	California Institute of Technology
11	University of Michigan
13	Columbia University
13	University of California - Los Angeles
13	University of Wisconsin - Madison
16	Harvard University
16	University of California - San Diego
16	University of Maryland - College Park
19	University of Pennsylvania

Report of the Committee on Graduate Instruction

ORIGIN AND PERSONNEL OF COMMITTEE

AFTER the publication of the second Handbook of American Universities and Colleges by the Council, there were several protests on the omission of various institutions under the description of facilities for graduate work. Only members of the Association of American Universities were included, inasmuch as no other official list of institutions offering graduate work was available. At its meeting October 7, 1932, the Executive Committee of the American Council appointed a Committee on Graduate Study as follows: R. M. Hughes, Chairman; Karl T. Compton, Virginia C. Gildersleeve, Frank B. Jewett, George Johnson, Charles B. Lipman, Albert D. Mead, John C. Merriam, Frank P. Graham, John L. Lowes, R. M. Hutchins, Henry Suzzallo, E. H. Wilkins. As it proved impossible for President Hutchins, President Graham, and Professor Lowes to serve at the time of the first meeting of the committee, Beardsley Ruml, W. W. Pierson and Hyder E. Rollins were appointed to the committee in the respective places of these men.

Two meetings of the committee were held in New York City, the first February 3, 1933, and the last January 11, 1934. At the first meeting six subjects for discussion were presented, referred to sub-committees, and reports prepared. Between meetings extensive work was carried forward and reported to the whole committee by mail, and at the last meeting all matters before the committee were reviewed and the final report as herewith submitted was approved.

ENGLISH

100 ballots sent out.
69 returns; majority, 35 votes.

603 doctorates were conferred in the period 1928-1932.
49 institutions offered work for the doctorate.

Composite ratings were made from reports of the following persons: Charles R. Baskervill, Albert C. Baugh, Joseph W. Beach, Arthur Beatty, Henry M. Belden, C. V. Boyer, Louis I. Bredvold, C. F. Tucker Brooke, A. C. L. Brown, Carleton Brown, William F. Bryan, Philo M. Buck, Jr., Edwin B. Burgum, Clarence G. Child, George R. Coffman, Lane Cooper, Hardin Craig, Lindsay T. Damon, John W. Draper, Norman Foerster, James Holly Hanford, George McLean Harper, Karl J. Holzknecht, Jay B. Hubbell, Merritt Y. Hughes, Percival Hunt, Sigurd B. Hustvedt, W. H. Irving, William S. Johnson, Howard M. Jones, Alexander C. Judson, Arthur G. Kennedy, Henning Larsen, Robert A. Law, Laura Hibbard Loomis, John L. Lowes, Roger P. McCutcheon, Kemp Malone, Baldwin Maxwell, K. B. Murdock, John T. Murray, Robert S. Newdick, Clark S. Northrup, Charles D. Osgood, Frederick M. Padelford, Louise Pound, James W. Rankin, T. M. Raysor, Hyder E. Rollins, Robert K. Root, Arthur Hobson Quinn, Felix E. Schelling, Robert Shafer, Edgar F. Shannon, George W. Sherburn, Franklin D. Snyder, J. W. Spargo, Hazelton Spencer, Elmer E. Stoll, J. S. P. Tatlock, Alwin Thaler, Frederick Tupper, Louis Wann, Stanley Williams, James S. Wilson, Karl Young, Jacob Zeitlin.

The jury named above has by a majority vote approved the following institutions as adequately staffed and equipped for work leading to the doctorate in English, starring those which it considers most distinguished:

Bryn Mawr College
* Columbia University
Cornell University
Duke University
* Harvard University—Radcliffe College
Indiana University
* Johns Hopkins University
New York University
Northwestern University
* Princeton University
Stanford University
* University of California
* University of Chicago
University of Cincinnati
University of Illinois
University of Iowa
* University of Michigan
University of Minnesota
University of Missouri
University of Nebraska
University of North Carolina
University of Pennsylvania
University of Texas
University of Washington
University of Wisconsin
Western Reserve University
* Yale University

MINING AND METALLURGICAL ENGINEERING

47 ballots sent out.
28 returns; majority, 15 votes.

41 doctorates were conferred in the period 1928-1932.
19 institutions offered work for the doctorate.

Composite ratings were made from reports of the following persons: W. R. Appleby, J. W. Barker, Alan M. Bateman, H. M. Boylston, P. B. Bucky, M. F. Coolbaugh, Charles Laurence Dake, John F. Dodge, F. Leroy Foster, L. C. Graton, Carle R. Hayward, C. A. Heiland, E. A. Hersam, T. J. Hoover, W. O. Hotchkiss, Waldemar Lindgren, Charles E. Locke, D. A. Lyon, E. P. Mathewson, A. C. Noe, W. B. Plank, Frank H. Probert, Thomas T. Read, Joseph T. Singewald, Jr., E. K. Soper, Robert K. Warner, George B. Waterhouse, Alfred R. Whitman.

The jury named above has by a majority vote approved the following institutions as adequately staffed and equipped for work leading to the doctorate in Mining and Metallurgical Engineering, starring those which it considers most distinguished:

Carnegie Institute of Technology
Colorado School of Mines
* Columbia University
* Harvard University
* Massachusetts Institute of Technology
Pennsylvania State College
Stanford University
University of Arizona
University of California
University of Michigan
University of Missouri
University of Pittsburgh
University of Wisconsin
Yale University

ELECTRICAL ENGINEERING

36 ballots sent out.
24 returns; majority, 13 votes.

55 doctorates were conferred in the period 1928-1932.
22 institutions offered work for the doctorate.

Composite ratings were made from reports of the following persons: J. A. Correll, P. H. Daggett, R. E. Doherty, H. E. Dyche, O. W. Esbach, H. S. Evans, O. J. Ferguson, O. F. Harding, D. C. Jackson, F. E. Johnson, Vladimir Karapetoff, A. E. Kennelly, A. S. Langsdorf, M. B. Long, A. H. Lovell, C. E. Magnusson, R. A. Millikan, E. B. Roberts, W. S. Rodman, W. I. Slichter, F. C. Stockwell, F. E. Terman, J. W. Whitehead, W. E. Wickenden.

The jury named above has by a majority vote approved the following institutions as adequately staffed and equipped for work leading to the doctorate in Electrical Engineering, starring those which it considers most distinguished:

* California Institute of Technology
Columbia University
Cornell University
Harvard University
* Johns Hopkins University
* Massachusetts Institute of Technology
Purdue University
Stanford University
University of California
University of Michigan
University of Pennsylvania
University of Wisconsin
Yale University

IN ORDER OF THEIR EMINENCE

An Appraisal of American Universities

BY EDWIN R. EMBREE

I hazarded a list of the dozen greatest universities in America. …complaints & questions rained in from university presidents & professors all over the country. Even institutions which I had rated high protested that they should be higher & universities omitted from the list wailed & a few of them looked eagerly toward the libel courts.

The most active contestants for twelfth place are Stanford University in California, the Universities of Pennsylvania, Illinois, and Iowa, and Ohio State University.

The two great technical schools - Massachusetts Institute of Technology and California Institute of Technology - are preeminent in engineering and mathematics and the physical sciences which underlie this profession, but they lack the universality of scholarship implied in the term 'university.'

TABLE OF DISTINGUISHED DEPARTMENTS

Including All Universities Judged to Have More Than Five Departments of High Excellence

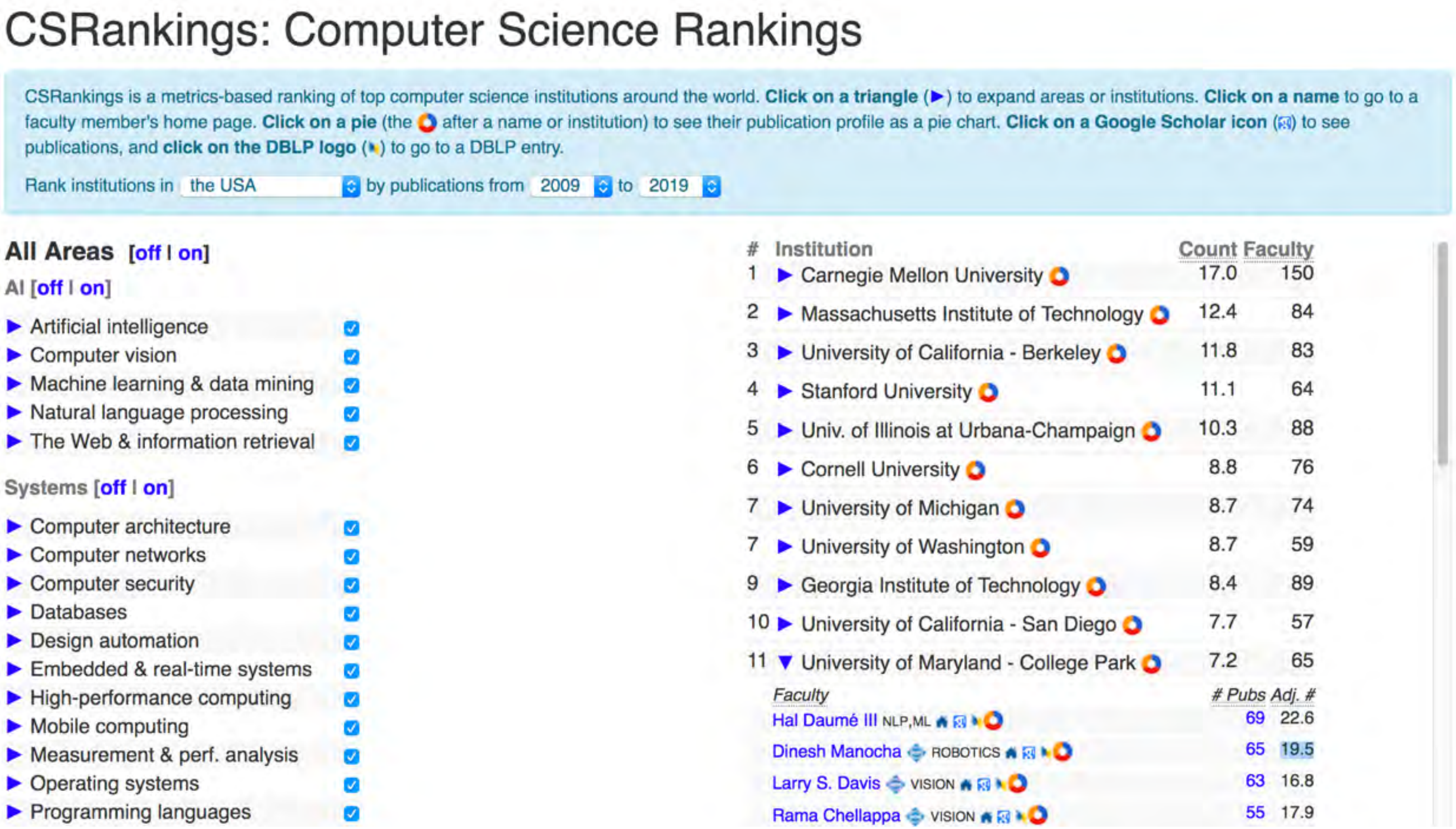
	Anthropology	Astronomy	Bacteriology	Biochemistry (including animal and human nutrition)	Botany (including plant physiology, plant pathology, soil science)	Chemistry and Chemical Engineering	Classics	Economics	Education	Engineering	English	Geology	German	History	Mathematics	Pathology and the Clinical Sciences of Medicine	Philosophy	Physics	Physiology (including anatomy, pharmacology, embryology)	Political Science	Psychology	Romance Languages	Sociology	Zoölogy (including genetics and entomology)	Total
Harvard	★	★	★	★	★	★	★	★	★		★	★	★	★	★	★	★	★	★	★	★	★		★	22
Chicago	★	★	★		★	★	★	★	★		★	★	★	★	★	★		★	★	★	★	★	★	★	21
Columbia	★				★	★	★	★	★		★	★	★	★	★	★	★	★		★	★	★	★	★	19
California	★	★	★		★	★	★	★	★		★	★		★			★	★	★	★	★	★		★	18
Yale	★		★	★		★	★	★	★		★	★	★	★		★	★	★	★		★	★		★	18
Michigan		★	★		★	★	★	★	★		★			★		★	★	★		★				★	14
Cornell			★	★	★	★		★		★				★		★	★	★	★		★			★	13
Princeton		★				★	★	★			★	★			★		★	★		★	★	★		★	13
Johns Hopkins			★	★		★	★				★	★	★			★		★				★		★	11
Wisconsin			★	★	★	★		★				★	★					★		★			★	★	11
Minnesota						★		★	★			★							★		★		★		7

Clauset, A., Arbesman, S., & Larremore, D. B. (2015). Systematic inequality and hierarchy in faculty hiring networks. *Science Advances*

Rank	USN2010	Type	Region	institution
1	1	Private	West	Stanford University
2	1		West	UC Berkeley
3	1	Private	Northeast	MIT
4	11	Private	West	CalTech
5	17	Private	Northeast	Harvard University
6	5	Private	Northeast	Cornell University
7	1	Private	Northeast	Carnegie Mellon University
8	8	Private	Northeast	Princeton University
9	20	Private	Northeast	Yale University
10	7		West	University of Washington
11	5		Midwest	UIUC
12	11		Midwest	University of Wisconsin, Madison
13	17	Private	Northeast	University of Pennsylvania
14	20	Private	South	Rice University
15	14		West	UCLA
16	28	Private	Northeast	New York University
17	35	Private	Midwest	University of Chicago
18	8		South	University of Texas, Austin
19	20	Private	Northeast	Brown University
20	17	Private	Northeast	Columbia University
26	14		West	UC San Diego
27	14		South	University of Maryland
28	13		Midwest	University of Michigan
37	10		South	Georgia Tech

CSRankings.org

- Every paper in a curated list of conferences gets 1 point
- Final score is a geometric mean over manually curated groups
- Authors get 1/N credit for each paper



Peer Assessment of CS Doctoral Programs Shows Strong Correlation with Faculty Citations

By Slobodan Vucetic, Ashis Kumar Chanda, Shanshan Zhang, Tian Bai, Aniruddha Maiti

Communications of the ACM, September 2018, Vol. 61 No. 9, Pages 70-76
10.1145/3181854

$$scholar\ score = 1 + 0.058\sqrt{M10} + 0.059\sqrt{G10} + 0.121\sqrt{C40} + 0.127\sqrt{C60}$$

Rank	University Name	Faculty	M10	G10	P10	C40	C60	C80	US News	Scholar ▼
1	▶ Massachusetts Institute of Technology	97	306	286	0.79	72	66	45	5	5
1	▶ University of California - Berkeley	68	375	351	0.83	57	54	38	5	5
1	▶ Carnegie Mellon University	143	218	200	0.72	105	74	48	5	5
1	▶ Stanford University	55	395	425	0.9	46	43	35	5	5
5	▶ Cornell University	75	216	228	0.75	50	41	23	4.5	4.4
6	▶ Georgia Institute of Technology	97	167	139	0.63	66	48	23	4.3	4.3
6	▶ University of Washington	56	232	239	0.77	40	31	20	4.5	4.3
8	▶ University of California - Los Angeles	44	206	243	0.74	37	28	17	4.1	4.2
8	▶ University of California - San Diego	60	204	192	0.71	47	36	24	4	4.2
10	▶ Columbia University	45	218	206	0.71	35	27	18	4	4.1
10	▶ Princeton University	35	285	232	0.77	27	23	19	4.4	4.1
10	▶ University of Illinois - Urbana - Champaign	63	169	163	0.67	45	34	14	4.6	4.1
10	▶ University of Michigan - Ann Arbor	59	235	175	0.7	40	31	20	4.1	4.1
14	▶ Johns Hopkins University	27	277	296	0.79	18	14	9	3.5	4

Generate University Rankings

- Use CS Rankings Affiliations
- Add up affiliated authors' publications counts
- Dot product publication vector with scores vector

Score	school	authors	papers	total
14159	Carnegie Mellon University	174	17275	73130
10885	University of California - Berkeley	108	11011	51063
10027	Massachusetts Institute of Technology	108	9613	47039
9628	Univ. of Illinois at Urbana-Champaign	103	11248	44716
8657	Technion	96	8795	39603
8514	Stanford University	69	7028	36170
8118	Georgia Institute of Technology	108	9337	38084
8105	Tsinghua University	150	14643	40663
7888	University of California - Los Angeles	46	6589	30369
7598	University of Michigan	83	7897	33667
7405	Tel Aviv University	48	5468	28818
7142	University of California - San Diego	74	6646	30837
7090	University of Maryland - College Park	76	7751	30796
7081	ETH Zurich	39	6673	26121
6871	Cornell University	81	5918	30279
6847	University of Washington	69	5727	29088
6387	University of Southern California	58	7206	26045
6330	Columbia University	53	5064	25252
6290	EPFL	55	6927	25321
6252	Princeton University	47	4991	24203
6190	HKUST	57	6640	25135
5802	National University of Singapore	75	7210	25125
5690	University of Pennsylvania	53	5340	22697
5629	University of California - Irvine	71	6624	24072
5451	Pennsylvania State University	49	5668	21326
5413	Peking University	147	11858	27052
5376	University of Toronto	99	5955	24760
5346	University of Texas at Austin	52	4485	21226
5224	University of California - Santa Barbara	38	4698	19137
5100	University of Waterloo	105	7316	23783

Correlation with US News 2018

- Using rank correlation (Kendall's Tau)
- Using only faculty regression data

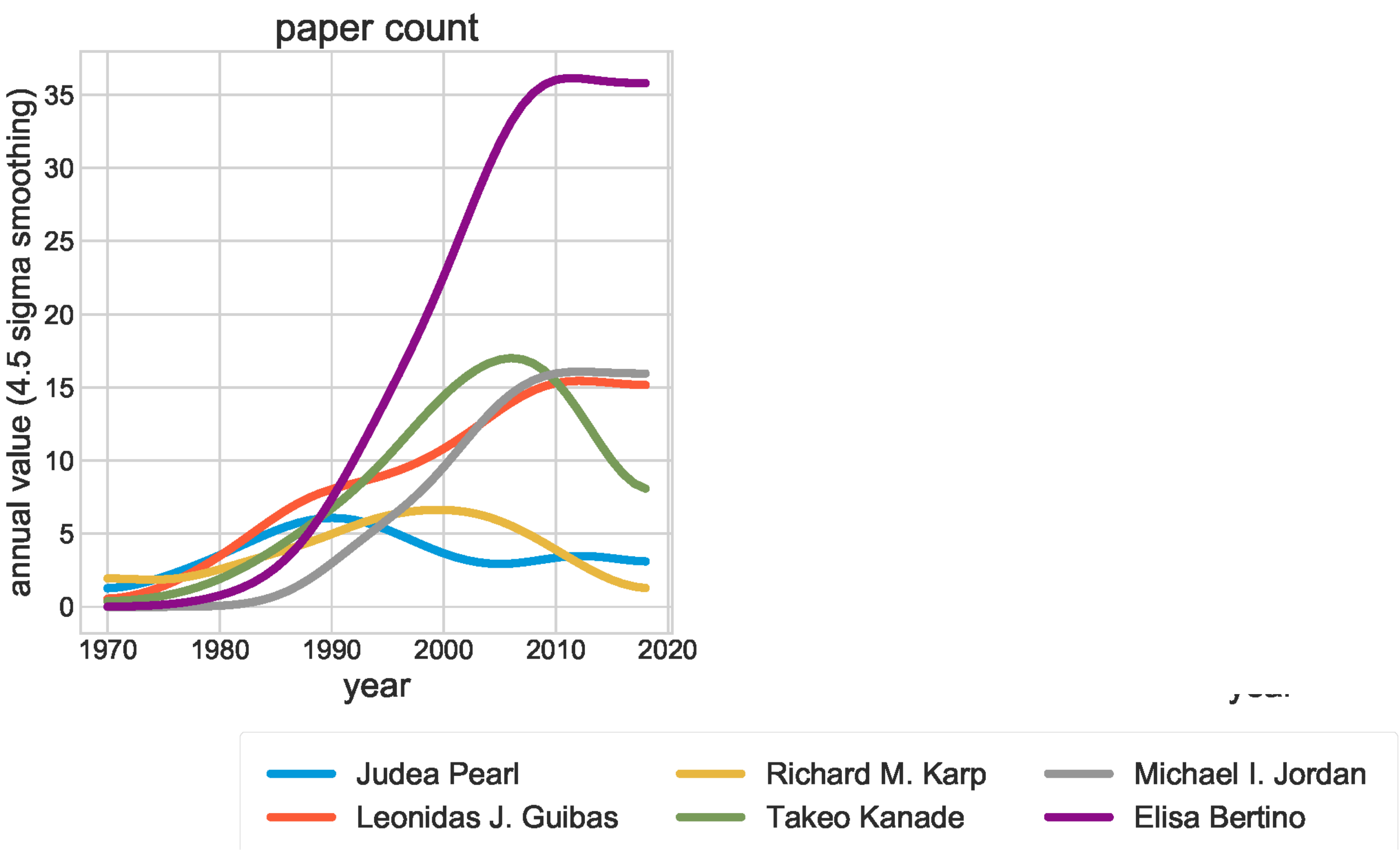
Model	Correlation
USN2018	1.000
USN2010	0.928
Venue Scores	0.780
ScholarRank	0.768
ScholarRankFull	0.757
CSMetrics	0.746
CSRankings	0.724
Times	0.721
NRC95	0.713
t10Sum	0.713
Prestige	0.666
Citations	0.665
Shanghai	0.586
# papers	0.585
BestPaper	0.559
PageRankA	0.535
PageRankC	0.532
QS	0.518

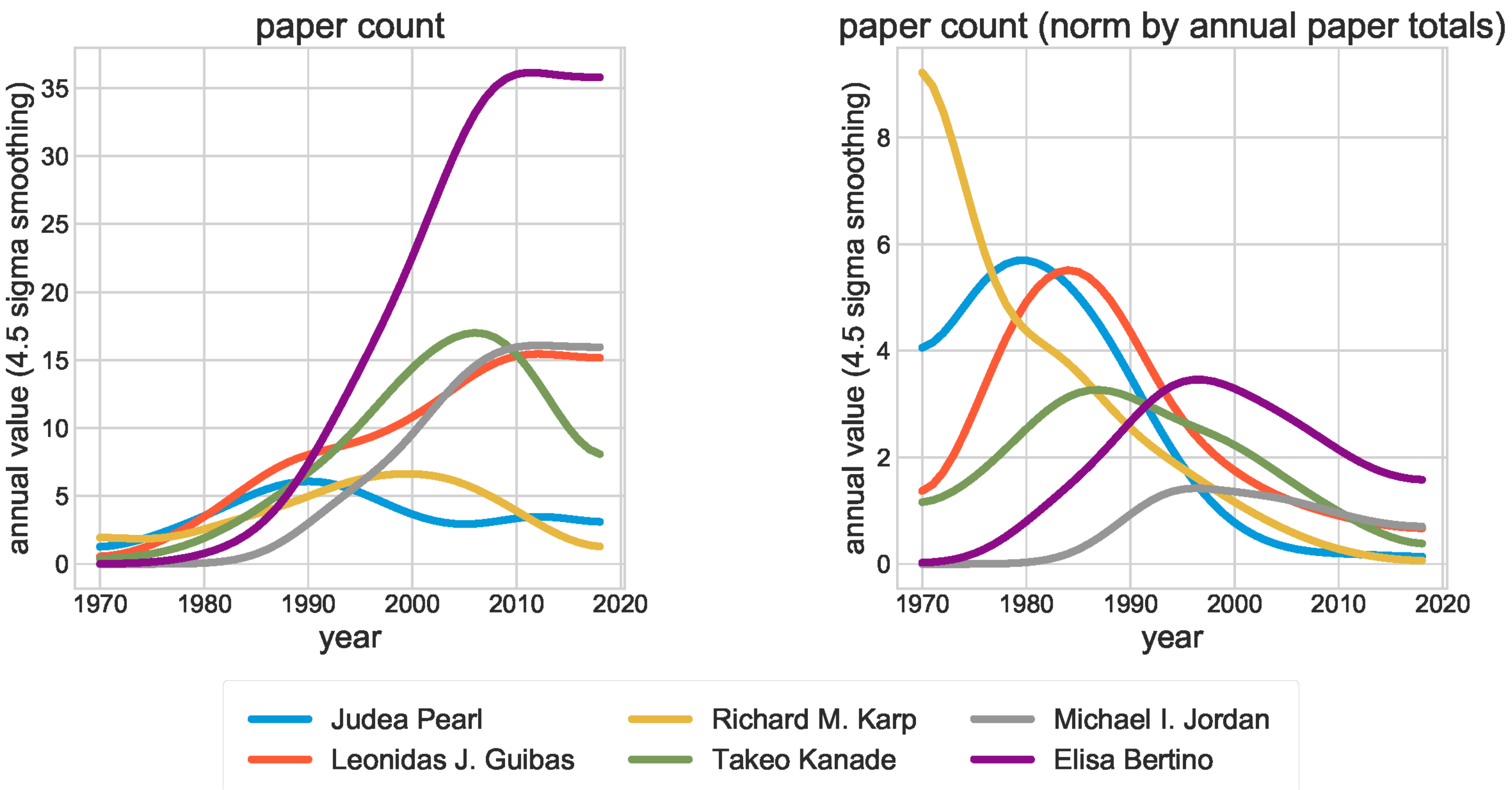
Mean Correlation of all Rankings

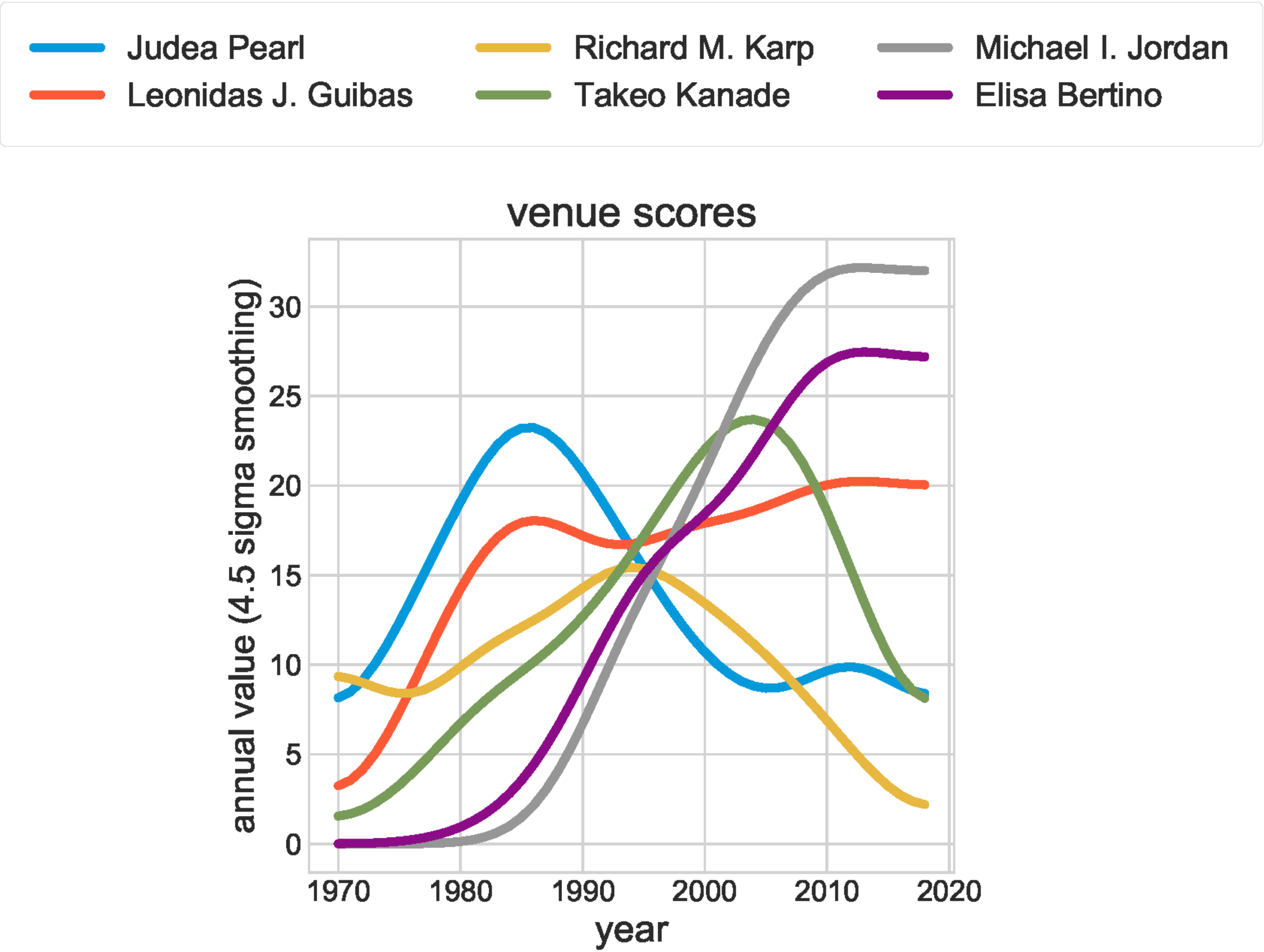
- Using rank correlation (Spearman’s rho)
- Using combined score vector

Model	Correlation
Venue Scores	0.845
USN2010	0.844
t10Sum	0.840
USN2018	0.834
ScholarRank	0.834
ScholarRankFull	0.831
Citations	0.813
CSMetrics	0.808
CSRankings	0.805
# papers	0.765
Prestige	0.763
NRC95	0.736
PageRankC	0.687
Times	0.673
PageRankA	0.619
BestPaper	0.602
Shanghai	0.600
QS	0.512

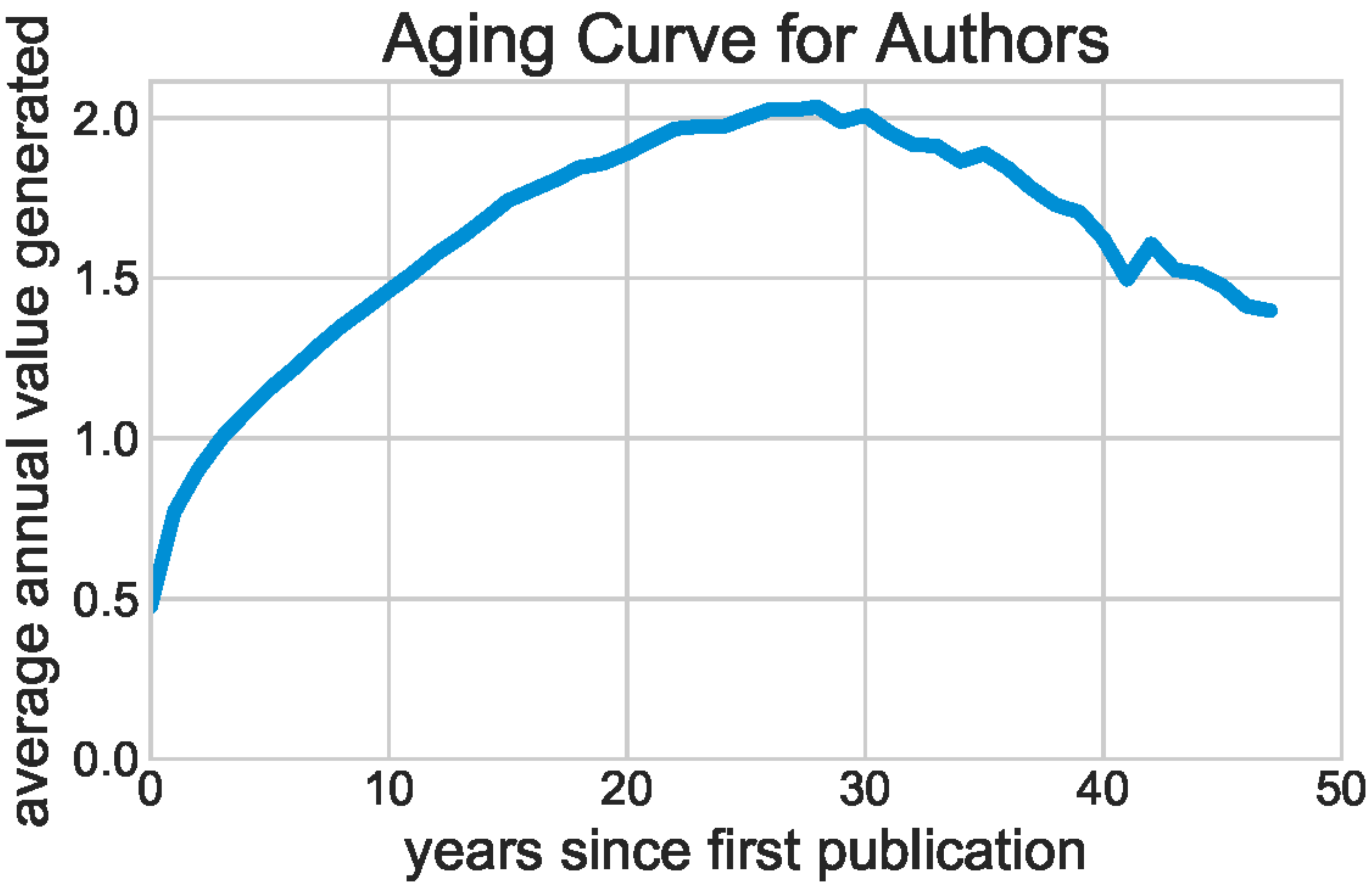
Evaluating Authors


paper count
annual value (4.5 sigma smoothing)
0
5
10
15
20
25
30
35
1970
1980
1990
2000
2010
2020
year
Judea Pearl
Leonidas J. Guibas
Richard M. Karp
Takeo Kanade
Michael I. Jordan
Elisa Bertino


paper count
annual value (4.5 sigma smoothing)
0
5
10
15
20
25
30
35
1970
1980
1990
2000
2010
2020
year
paper count (norm by annual paper totals)
annual value (4.5 sigma smoothing)
0
2
4
6
8
1970
1980
1990
2000
2010
2020
year
Judea Pearl
Leonidas J. Guibas
Richard M. Karp
Takeo Kanade
Michael I. Jordan
Elisa Bertino



Judea Pearl
Leonidas J. Guibas
Richard M. Karp
Takeo Kanade
Michael I. Jordan
Elisa Bertino
venue scores
annual value (4.5 sigma smoothing)
0
5
10
15
20
25
30
1970
1980
1990
2000
2010
2020
year


Aging Curve for Authors
average annual value generated
2.0
1.5
1.0
0.5
0.0
0
10
20
30
40
50
years since first publication

Most Productive Authors

Name	Score	Affiliation
Philip S. Yu	4843	University of Illinois at Chicago
Kang G. Shin	4263	University of Michigan
Micha Sharir	3966	Tel Aviv University
H. Vincent Poor	3897	Princeton University
Christos H. Papadimitriou	3550	Columbia University
Don Towsley	3429	University of Massachusetts Amherst
Jiawei Han	3409	Univ. of Illinois at Urbana-Champaign
Thomas S. Huang	3342	Univ. of Illinois at Urbana-Champaign
Leonidas J. Guibas	3191	Stanford University
Robert E. Tarjan	3155	Princeton University
Noga Alon	3126	Tel Aviv University
Luc J. Van Gool	2850	ETH Zurich
Jeffrey D. Ullman	2765	Stanford University
Alberto L. Sangiovanni-Vincentelli	2740	University of California - Berkeley
Azriel Rosenfeld	2688	University of Maryland - College Park
Moshe Y. Vardi	2676	Rice University
Xuemin Shen	2656	University of Waterloo
Mahmut T. Kandemir	2655	Pennsylvania State University
Avi Wigderson	2643	Institute for Advanced Study
Sudhakar M. Reddy	2587	University of Iowa
Jie Wu 0001	2519	Temple University
Rama Chellappa	2512	University of Maryland - College Park
Michael I. Jordan	2507	University of California - Berkeley
Yishay Mansour	2504	Tel Aviv University
Shuicheng Yan	2444	National University of Singapore

What about Moneyball?

Using venue scores to perform some JCDL Analysis

JCDL's R1 authors

C. Lee Giles
Frank M. Shipman III
David M. Mimno
Steven Bethard
Catherine Blake
David A. Smith
Andrew McCallum
Mor Naaman
Cornelia Caragea
Chirag Shah
James Caverlee
Beth Plale

Ben Shneiderman
Sharad Mehrotra
Peter K. Allen
Kenneth R. Koedinger
Wang-Chien Lee
Ling Liu 0001
Hongyuan Zha
Jure Leskovec
Jiawei Han 0001
Ricardo Gutierrez-Osuna
Anand Sivasubramaniam
Eamonn J. Keogh

Hector Garcia-Molina
Susan B. Davidson
Zoran Obradovic
Padhraic Smyth
Yizhou Sun
Douglas W. Oard
Madhav V. Marathe
Bo Luo
Daniel Kifer
Stephen H. Edwards
Xue-wen Chen 0001

JCDL's nearest neighbors

Name	Authors	Distance	Value
JCDL	20	0	2.76
JASIST	25	1.05	1.04
Inf. Process. Manage.	11	1.85	0.98
ICWSM	72	1.9	4.78
HT	11	2.19	1.71
ASIST	23	2.33	0.97
RecSys	21	2.37	2.09
TREC	37	2.46	1.65
SIGIR	83	2.56	4.35
CIKM	186	2.72	4.75
ECIR	25	2.77	1.37
ACM Trans. Inf. Syst.	14	2.9	2.27
WSDM	54	2.91	4.23
WWW	141	2.95	7.08
PADL	11	2.97	1.19
TKDD	39	2.98	4.78
SDM	158	2.99	5.45
ICDM	175	3	4.6
JBI	16	3.03	0.89
DMKD	37	3.07	2.44
KDD	240	3.1	6.23

IR Top Authors

Name	Score	Uni	Years
Maarten de Rijke	496	University of Amsterdam	28
W. Bruce Croft	380	None	44
ChengXiang Zhai	351	Univ. of Illinois at Urbana-Champaign	29
Iadh Ounis	327	University of Glasgow	23
Craig MacDonald	325	University of Glasgow	14
Xueqi Cheng	294	Chinese Academy of Sciences	18
Ryen W. White	269	None	18
Jimmy J. Lin	226	University of Waterloo	20
James Allan	225	University of Massachusetts Amherst	27
Pavel Serdyukov	223	None	13
Jiawei Han 0001	218	Univ. of Illinois at Urbana-Champaign	34
Shaoping Ma	218	Tsinghua University	19
Philip S. Yu	217	University of Illinois at Chicago	36
Huan Liu 0001	215	Arizona State University	24
Yiqun Liu	208	Tsinghua University	17
Leif Azzopardi	205	None	14
Min Zhang 0006	202	Tsinghua University	19
James P. Callan	199	Carnegie Mellon University	34
Gerhard Weikum	198	Max Planck Institute	36
Jiafeng Guo	194	Chinese Academy of Sciences	13
C. Lee Giles	179	Pennsylvania State University	32
James Caverlee	177	Texas A&M University	15

IR Top Authors (w/ JCDL papers)

Rank	Author	Total	eTotal	Since	Affiliation
8	Jimmy J. Lin	226	11	1999	University of Waterloo
11	Jiawei Han	218	6	1985	Univ. of Illinois at Urbana-Champaign
21	C. Lee Giles	180	5	1987	Pennsylvania State University
22	James Caverlee	177	11	2004	Texas A&M University
23	Marcos André Gonçalves	174	8	1999	UFMG
25	Joemon M. Jose	171	7	1997	University of Glasgow
27	Aixin Sun	168	9	2001	Nanyang Technological University
30	Ee-Peng Lim	160	6	1992	Singapore Management University
34	Irwin King	154	7	1996	Chinese University of Hong Kong
36	Wolfgang Nejdl	146	5	1987	None
37	Arjen P. de Vries	146	6	1996	None
43	Krisztian Balog	139	9	2005	None
51	Jaap Kamps	131	6	1998	None
55	Prasenjit Mitra	128	5	1994	None
59	Jie Tang 0001	125	7	2003	Tsinghua University
60	Michael R. Lyu	124	4	1988	Chinese University of Hong Kong
61	Benno Stein	124	4	1991	None
63	Adam Jatowt	117	7	2003	None
66	David Carmel	115	5	1995	None
85	Katsumi Tanaka	97	2	1977	None
90	Jure Leskovec	95	6	2003	Stanford University
99	Djoerd Hiemstra	92	4	1997	None

IR/JCDL
Top People
(first paper in 2011)

Rank	Author	Total	eTotal	Since
34	Zhuoren Jiang	34.5	5.7	2013
55	Norman Meuschke	25.9	3.2	2011
111	Moritz Schubotz	20.1	3.3	2013
125	Thaer Samar	19.2	3.2	2013
131	Zhaohui Wu	18.9	3.2	2012
166	Peter Organisciak	17.4	1.9	2011
197	Dhruv Gupta	16	2.7	2014
296	Jacob Jett	13	1.9	2012
438	Mayank Singh	9.6	1.9	2015
468	Helge Holzmann	9.5	1.4	2012
709	Chen Liang	8.5	1.7	2014
710	Alexander Ororbia	8.5	1.4	2014
804	Mat Kelly	7.6	1.3	2013
807	Erik Choi	7.5	1.3	2012
813	Ashley E. Sands	7.4	1.2	2012
893	Sandipan Sikdar	6.3	1	2013
894	Felix Hamborg	6.3	1.3	2015
932	Julian Risch	6	1.5	2015
941	Jan R. Benetka	5.9	2	2017
947	Peter T. Darch	5.9	1.2	2014
1006	Jian Wu	5.3	0.7	2012
1030	Corinna Breitinger	5	0.8	2013
1032	Alexander Nwala	5	1.7	2016

Acknowledgements

Carnegie Mellon University
The Robotics Institute
THE ROBOTICS INSTITUTE

JCDL 2019

SIGIR

CSRankings: Computer Science Rankings
EMERY BERGER

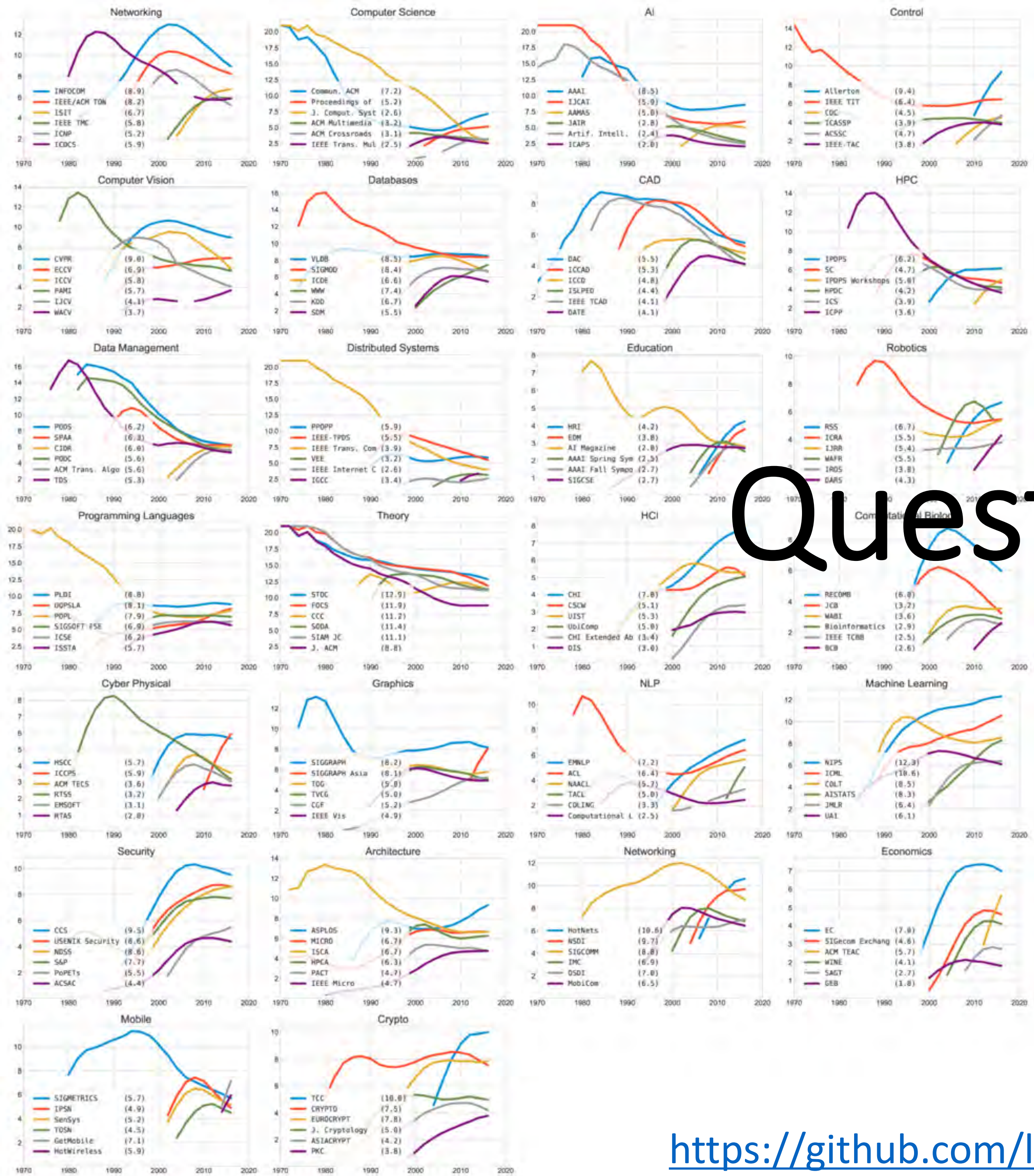
dblp
computer science bibliography

NSF

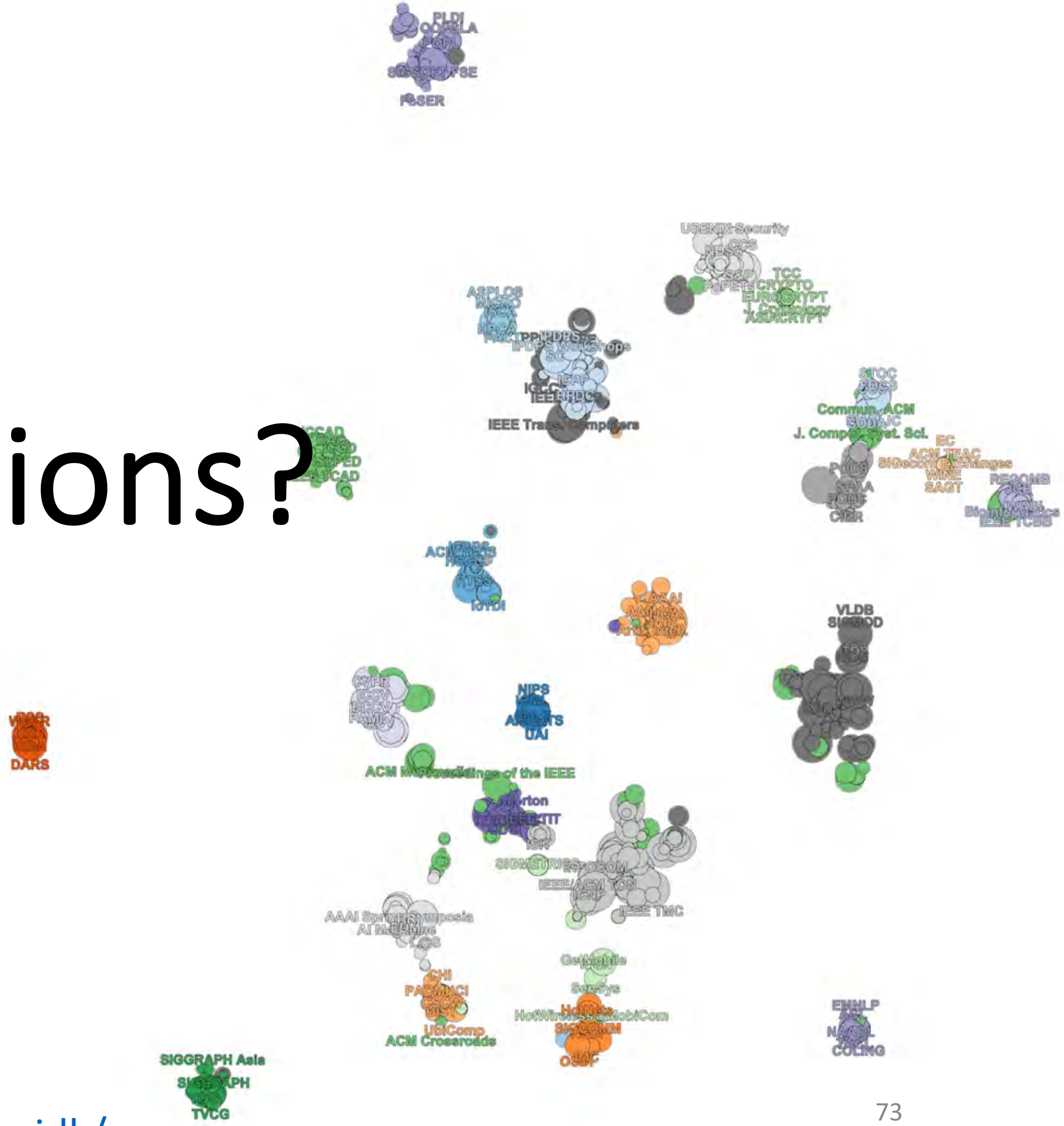
NPRI
NEVADA POLICY
Research Institute

BY SLOBODAN VUCETIC, ASHIS KUMAR CHANDA, SHANSHAN ZHANG, TIAN BAI, AND ANIRUDDHA MAITI

Peer Assessment of CS Doctoral Programs Shows Strong Correlation with Faculty Citations



Questions?



https://github.com/leonidk/venue_scores

My field's top people

rank	name	university	score
1	Luc J. Van Gool	ETH Zurich	1555.81
2	Eric P. Xing	Carnegie Mellon University	981.09
3	Michael I. Jordan	University of California - Berkeley	939.15
4	Daniela Rus	Massachusetts Institute of Technology	919.59
5	Bernhard Schölkopf	Max Planck Institute	907.64
6	Pascal Fua	EPFL	880.41
7	Hans-Peter Seidel	Max Planck Institute	871.63
8	Vijay Kumar 0001	University of Pennsylvania	865.45
9	Trevor Darrell	University of California - Berkeley	861.97
10	Wolfram Burgard	University of Freiburg	847.45
11	Daniel Cremers	TU Munich	836.43
12	Raquel Urtasun	University of Toronto	835.41
13	Dacheng Tao	University of Sydney	825.95
14	Pieter Abbeel	University of California - Berkeley	825.78
15	Fei-Fei Li	Stanford University	825.71
16	Larry S. Davis	University of Maryland - College Park	777.45
17	Yoshua Bengio	University of Montreal	772.93
18	Song-Chun Zhu	University of California - Los Angeles	767.98
19	Bernt Schiele	Max Planck Institute	764.48
20	Martial Hebert	Carnegie Mellon University	762.87
21	Kristen Grauman	University of Texas at Austin	745.71
22	William T. Freeman	Massachusetts Institute of Technology	727.68
23	Nassir Navab	TU Munich	725.24
24	Rama Chellappa	University of Maryland - College Park	720.58
25	Alan L. Yuille	Johns Hopkins University	708.41