Revealing Algorithmic Rankers

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DTL 2016 Conference

November 16-19, 2016

Algorithmic rankers

Input: database of items (colleges, cars, individuals, …)

Score-based ranker:

computes the score of each item using a known formula, e.g., monotone aggregation

sorts items on score

Output: permutation of the items (complete or top-k)

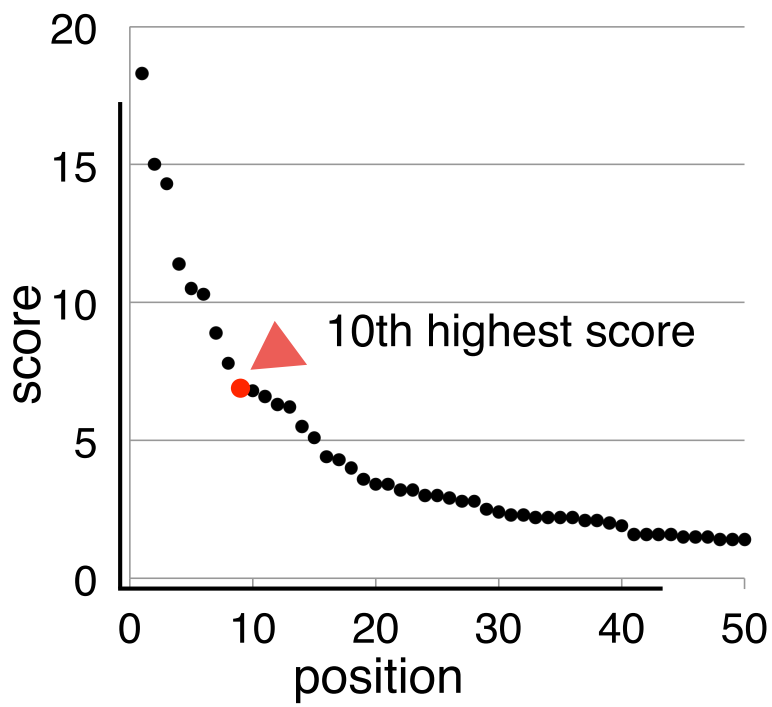
Do we have transparency?

Only syntactically, not actually!

Opacity in algorithmic rankers

Reason 1: The scoring formula alone does not indicate the relative rank of an item.

Scores are absolute, rankings are relative. Is 5 a good score? What about 10? 15?



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Opacity in algorithmic rankers

Reason 2: A ranking may be unstable if there are tied or nearly-tied items.

Rank	Institution	Average Count	Faculty
1	▶ Carnegie Mellon University	18.4	123
2	▶ Massachusetts Institute of Technology	15.6	64
3	▶ Stanford University	14.8	56
4	▶ University of California - Berkeley	11.5	50
5	▶ University of Illinois at Urbana-Champaign	10.6	56
6	▶ University of Washington	10.3	50
7	▶ Georgia Institute of Technology	8.9	81
8	▶ University of California - San Diego	8	51
9	▶ Cornell University	7	45
10	▶ University of Michigan	6.8	63
11	▶ University of Texas - Austin	6.6	43
12	▶ University of Massachusetts - Amherst	6.4	47

Opacity in algorithmic rankers

Reason 3: A ranking methodology may be unstable: small changes in weights can trigger significant re-shuffling.

THE NEW YORKER

DEPT. OF EDUCATION FEBRUARY 14 & 21, 2011 ISSUE

THE ORDER OF THINGS

What college rankings really tell us.

By Malcolm Gladwell

1. Chevrolet Corvette 205
2. Lotus Evora 195
3. Porsche Cayman 195

1. Lotus Evora 205
2. Porsche Cayman 198
3. Chevrolet Corvette 192

1. Porsche Cayman 193
2. Chevrolet Corvette 186
3. Lotus Evora 182

Opacity in algorithmic rankers

Reason 4: The **weight of an attribute** in the scoring formula **does not determine its impact** on the outcome.

Rank	Name	Avg Count	Faculty	Pubs	GRE
1	CMU	18.3	122	2	791
2	MIT	15	64	3	772
3	Stanford	14.3	55	5	800
4	UC Berkeley	11.4	50	3	789
5	UIUC	10.5	55	3	772
6	UW	10.3	50	2	796
		….			
39	U Chicago	2	28	2	779
40	UC Irvine	1.9	28	2	787
41	BU	1.6	15	2	783
41	U Colorado Boulder	1.6	32	1	761
41	UNC Chapel Hill	1.6	22	2	794
41	Dartmouth	1.6	18	2	794

Given a score function:

$$0.2 * faculty +$$
$$0.3 * avg\ cnt +$$
$$0.5 * gre$$

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Rankings are not benign!

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What college rankings really tell us.

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Rankings are not benign. They enshrine very particular ideologies, and, at a time when American higher education is facing a crisis of accessibility and affordability, we have adopted **a de-facto standard of college quality** that is uninterested in both of those factors. And why? Because a group of magazine analysts in an office building in Washington, D.C., decided twenty years ago to **value selectivity over efficacy**, to **use proxies** that scarcely relate to what they're meant to be proxies for, and to **pretend that they can compare** a large, diverse, low-cost land-grant university in rural Pennsylvania with a small, expensive, private Jewish university on two campuses in Manhattan.

Harms of opacity

1. **Due process / fairness.** The subjects of the ranking cannot have confidence that their ranking is meaningful or correct, or that they have been treated like similarly situated subjects - *procedural regularity*

2. **Hidden normative commitments.** What factors does the vendor encode in the scoring ranking process (syntactically)? What are the ***actual*** effects of the scoring / ranking process? Is it stable? How was it validated?

Harms of opacity

3. Interpretability. Especially where ranking algorithms are performing a public function, **political legitimacy** requires that the public be able to interpret algorithmic outcomes in a meaningful way. Avoid *algocracy*: the rule by incontestable algorithms.

4. Meta-methodological assessment. Is *a* ranking / *this* ranking appropriate here? Can we use a process if it cannot be explained? Probably yes, for recommending movies; probably not for college admissions.

The possibility of knowing

- We need transparency!
- OK, what is transparency anyway?

  zero-knowledge proofs, audits, reverse engineering

…. but what about explanation?

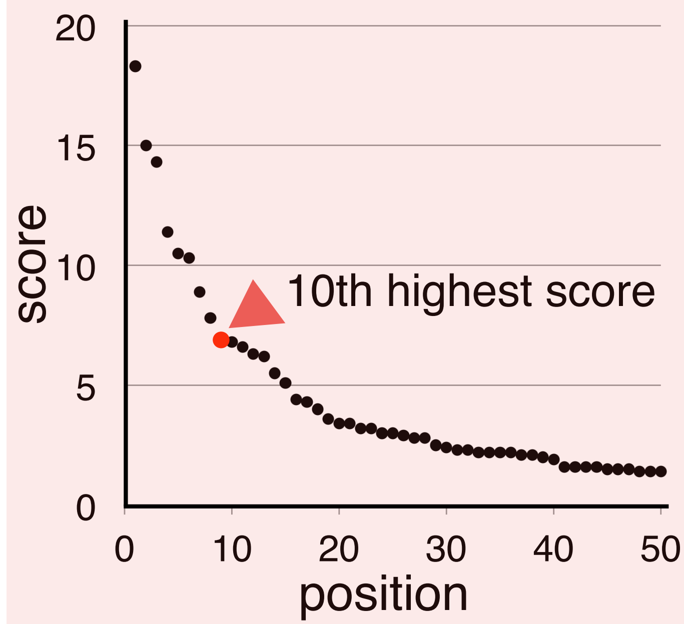
Transparency stakeholders

- **Entity being ranked**, so they can assess their rank, know how it was produced
- **User consuming ranked results**, who may or may not himself be ranked
- **Vendor**, who may seek greater insight into the process as it is being developed, or could be asked to justify their ranking
- **Competitors** of the vendor
- **Auditors** and **regulators**, so they can assess properties of the ranking

Ranking Facts

Impact	top-*10*	overall
faculty size	122 55 45 (median)	122 32 14 (median)
average publication count	18 10 6 (median)	18 3 1 (median)
GRE	800 796 772 (median)	800 790 758 (median)

Stability



stable for top-*10*
unstable for later ranks

Formula sort by **average publication count** from higher to lower

Explanation **score** correlates with **faculty size**

Transparency questions

- **What is the impact** of a particular attribute (or set of attributes) on the overall ranking? an individual's ranking? an individual's inclusion in the top-k? - some ideas next
- Is the ranking **fair** towards a protected group of individuals? **see our FATML poster!**
- Is the ranking **stable?** How sensitive is the output to small changes in the scoring function or in the data? - future work
- **Why** is item A ranked lower than item B? **What if** A.x1 changed and B.x1 stayed the same? - future work

Explaining the impact of features

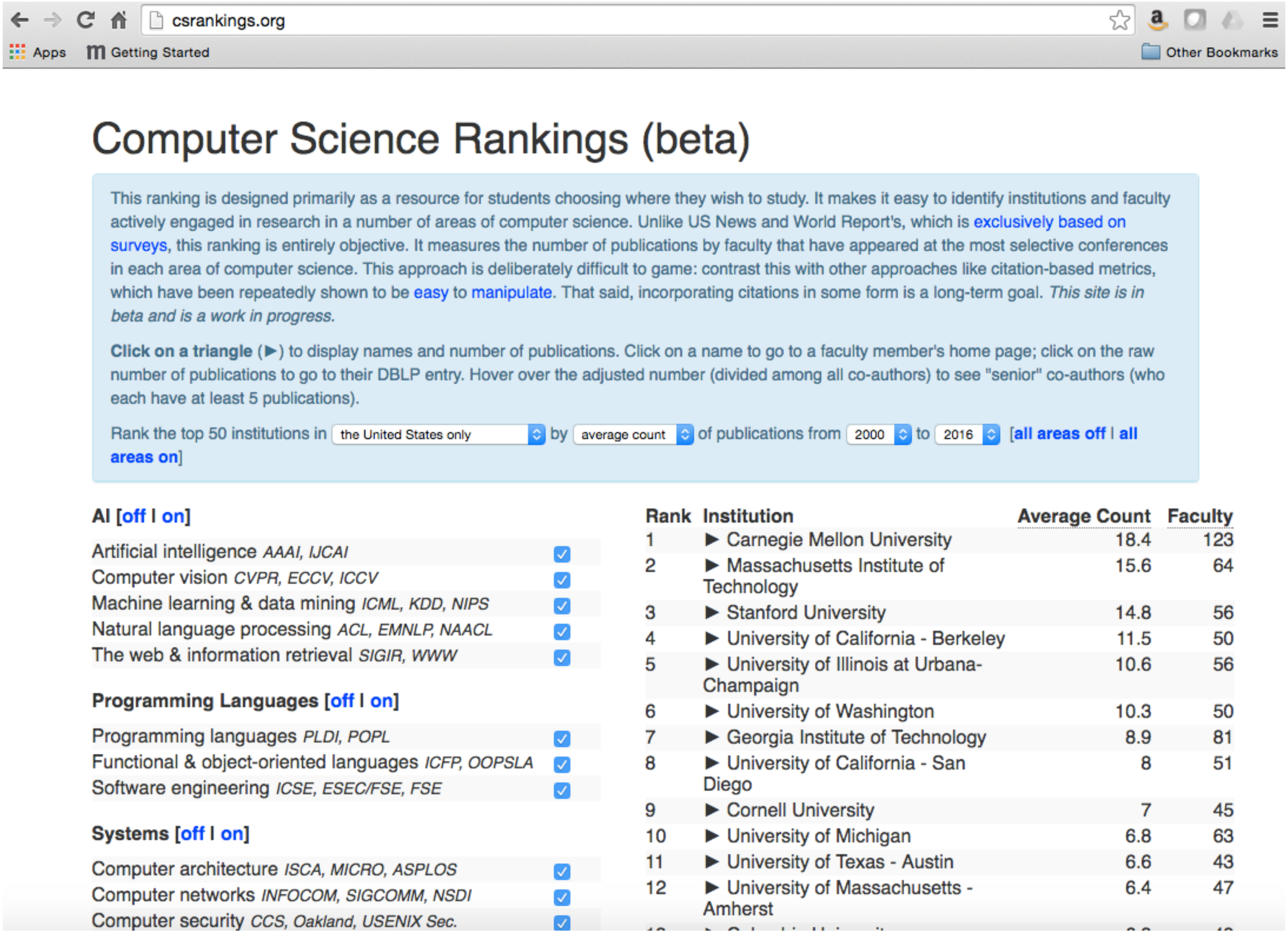
Input

- feature vectors $X = (x_1 \ldots x_n)$ describing items
- y = scores or ranks for each item

Output: **explanation** of the ranking in terms of features.

Approach: learn a scoring function f’ from X and y, consistent with observed data, explaining the ranking.

Assume that there is no way to invoke the ranker on a new input database.



csrankings.org

Apps Getting Started Other Bookmarks

Computer Science Rankings (beta)

This ranking is designed primarily as a resource for students choosing where they wish to study. It makes it easy to identify institutions and faculty actively engaged in research in a number of areas of computer science. Unlike US News and World Report's, which is exclusively based on surveys, this ranking is entirely objective. It measures the number of publications by faculty that have appeared at the most selective conferences in each area of computer science. This approach is deliberately difficult to game: contrast this with other approaches like citation-based metrics, which have been repeatedly shown to be easy to manipulate. That said, incorporating citations in some form is a long-term goal. *This site is in beta and is a work in progress.*

Click on a triangle (▶) to display names and number of publications. Click on a name to go to a faculty member's home page; click on the raw number of publications to go to their DBLP entry. Hover over the adjusted number (divided among all co-authors) to see "senior" co-authors (who each have at least 5 publications).

Rank the top 50 institutions in [the United States only] by [average count] of publications from [2000] to [2016] [**all areas off** | **all areas on**]

AI [off | on]

- Artificial intelligence *AAAI, IJCAI* ☑
- Computer vision *CVPR, ECCV, ICCV* ☑
- Machine learning & data mining *ICML, KDD, NIPS* ☑
- Natural language processing *ACL, EMNLP, NAACL* ☑
- The web & information retrieval *SIGIR, WWW* ☑

Programming Languages [off | on]

- Programming languages *PLDI, POPL* ☑
- Functional & object-oriented languages *ICFP, OOPSLA* ☑
- Software engineering *ICSE, ESEC/FSE, FSE* ☑

Systems [off | on]

- Computer architecture *ISCA, MICRO, ASPLOS* ☑
- Computer networks *INFOCOM, SIGCOMM, NSDI* ☑
- Computer security *CCS, Oakland, USENIX Sec.* ☑

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Example: explaining csrankings.org

Input

- X = descriptive attributes from US News and NRC
- y = scores from csrankings.org

Compute *f'*

Rank	Institution	Publication Average Count
1	▶ Carnegie Mellon University	19.2
2	▶ Massachusetts Institute of Technology	16.5
3	▶ Stanford University	16.3
4	▶ University of California - Berkeley	12.9
5	▶ University of Illinois at Urbana-Champaign	11.3
6	▶ University of Washington	11
7	▶ Georgia Institute of Technology	10
8	▶ University of California - San Diego	8.5
9	▶ University of Michigan	7.6
10	▶ Cornell University	7.2

Features
Number of faculty
Program size quartile
Student-faculty ratio
Avg GRE scores
Admission rate
6-year graduation rate
Total university faculty

Example: explaining csrankings.org

Result

- X = descriptive attributes from US News and NRC
- y = scores from csrankings.org

Compute *f'*

Consequence: csrankings.org ranks largely by number of faculty, favoring large departments over smaller ones.

What if we were able to invoke the ranker on a modified input database?

Relate to the QII framework (*DSZ2016*), future work

Weight	Features
1.0239	Number of faculty
0.0528	Program size quartile
-0.005	Student-faculty ratio
0.0038	Avg GRE scores
-0.0018	Admission rate
-0.0018	6-year graduation rate
-0.000005	Total university faculty

Conclusions

- Rankings are ubiquitous and opaque
- Transparency is crucial
- Syntactic transparency is insufficient, need interpretability / explanations
- Different explanations for different stakeholders
- Lots of exciting technical work is ahead!

Thank you!

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