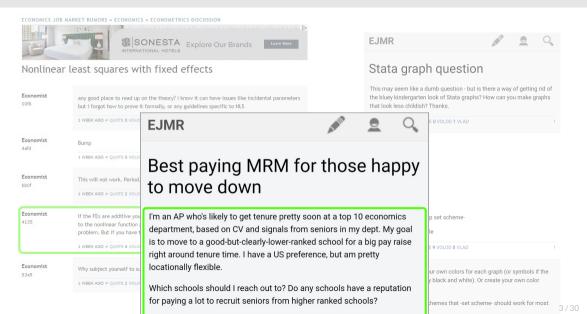


Description of the Project

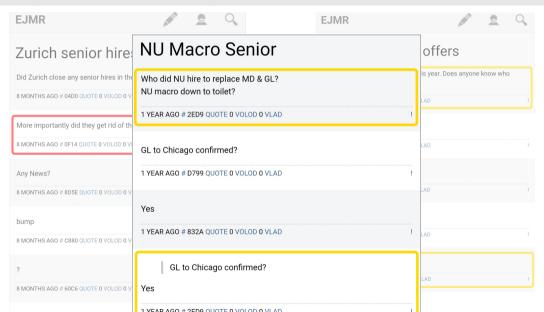
"Economics is what economists do." —Jacob Viner (in Spiegel (1987), p. 814)

- Questions
 - What do economists say when they are anonymous?
 - How widespread is toxic speech in economics? Who engages in such speech?
- Econ Job Market Rumors (EJMR) is a popular anonymous message board
 - 2.5 million monthly visits (SimilarWeb, 2022)
- Statistical properties of EJMR usernames reveal IPs for the majority of posts
 - Focus today will be on **methods** of IP address identification
 - We document widespread use of EJMR even at top universities
- We use only publicly available data (Wu, 2020)

Useful Information on EJMR



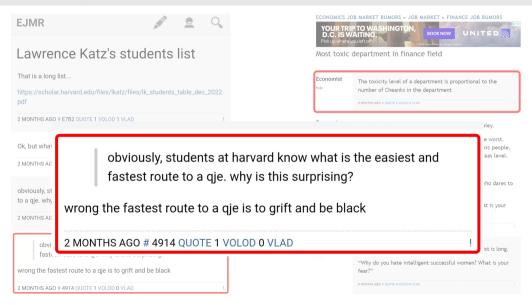
Gossip (about senior faculty moves) on EJMR



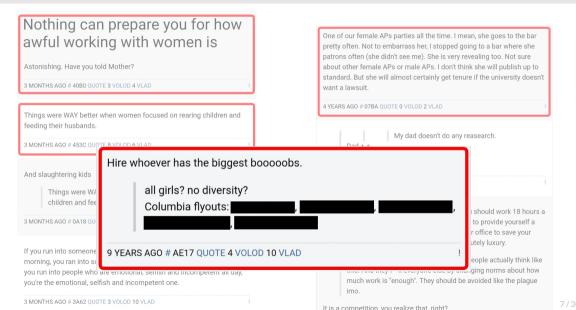
Racism on EJMR



Economics-specific Racism on EJMR



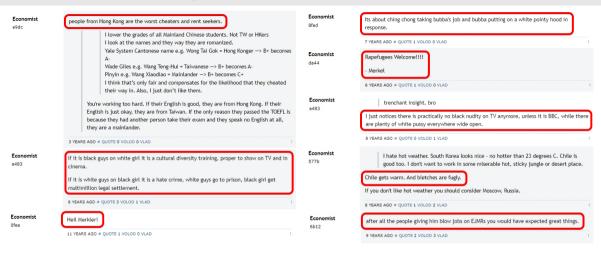
Sexism and Misogyny on EJMR



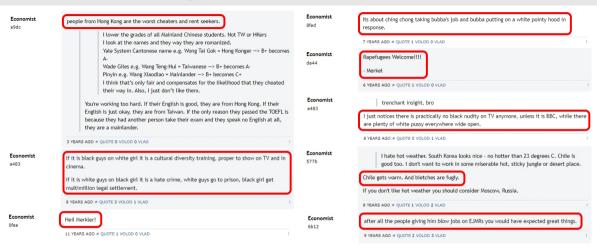
Racist and Sexist Discussion of Job Market Candidates



Who writes such things?

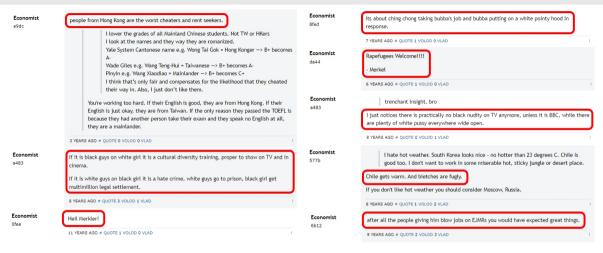


Who writes such things?



IP addresses at Harvard, Stanford, Yale, Chicago ...

Who writes such things?



IP addresses at Harvard, Stanford, Yale, Chicago ... and the NBER HQ at 1050 Mass Ave

Username Allocation on EJMR

Each topic is assigned a topic id

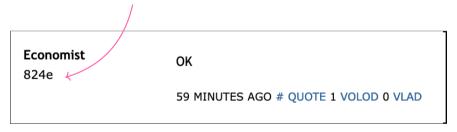
- https://www.econjobrumors.com/topic/right-vs-left-wing-dictatorships
- https://www.econjobrumors.com/topic/1127272

"topic id"

An incrementing counter common to WordPress sites

Username Allocation on EJMR

- Each topic is assigned a topic id
 - https://www.econjobrumors.com/topic/right-vs-left-wing-dictatorships
 - https://www.econjobrumors.com/topic/1127272
- Each post is assigned a username, which is topic-specific



Username Allocation on EJMR

- Each topic is assigned a topic id
 - https://www.econjobrumors.com/topic/right-vs-left-wing-dictatorships
 - https://www.econjobrumors.com/topic/1127272
- Each post is assigned a username, which is topic-specific
- Username was characters 10-13 of the SHA-1 hash of topic ID and IPv4 address
 - Hash did not use a salt (a random secret) and was in plain sight for over a decade
- E.g. 824e a 4-digit hexadecimal

Topic ID: 1127272

IPv4 Address: 130.132.173.94

SHA-1 Input: 1127272130.132.173.94

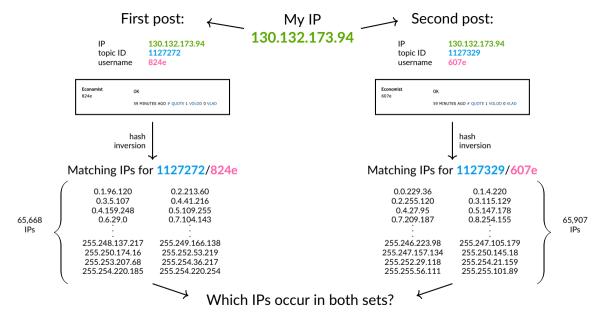
SHA-1 Output: eae3d51bc824e273e203b9fbfb608828431a6d48

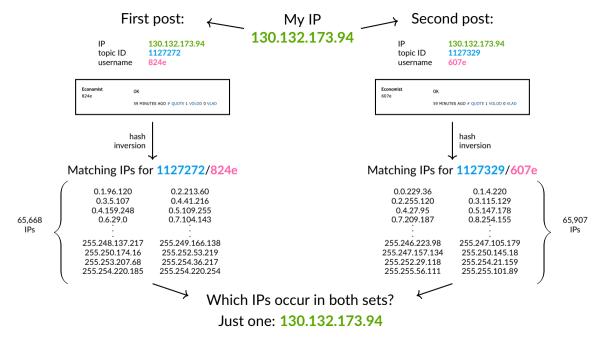
Username: 824e

From usernames to IP addresses

- SHA-1 hash is one-way. It cannot be reversed.
- But we can try every possible IP address to see if some of them match:

- Record all IP addresses where observed topic-username matches the hash
 - Feasible on GPUs
 - 695,364 topics \times 2³² possible IPv4 addresses \approx 3 quadrillion hashes
 - Returns a set of matching IPs per topic-username: 65,536 in expectation





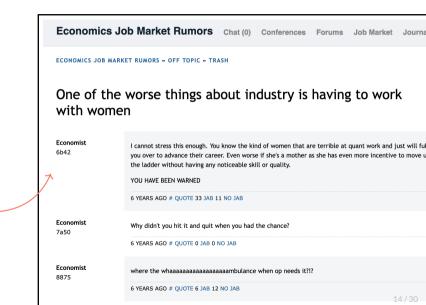
Probabilistic Identification of Active IPs

- Identifying true IP is possible because
 - 1. True IP is always present in matching set
 - 2. Other "noise" IPs are i.i.d. uniformly over IP space due to SHA-1 avalanche property

True IPs will show up much more often than noise IPs!

- Statistical properties
 - Probability of a "noise" IP appearing in a topic follows a hypergeometric distribution
 - Number of times a "noise" IP appears in a week follows a Poisson binomial distribution

What is the IP address for this post with topic id = 175901 and username = 6b42?



- We start with 2³² possible IP addresses.
- The hash inversion narrows it down to 65,385 matching IP addresses for this post.
- How many of these 65,385 IPs explain other topic-usernames in a 7-day window?

| # other explained (t, u) | p-value | # IP addresses |
|----------------------------|------------|----------------|
| 0 | 1.00000000 | 58,367 |

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| # other explained (t, u) | p-value | # IP addresses |
|----------------------------|--------------------|----------------|
| 0 | 1.00000000 | 58,367 |
| 1 | 0.10694695 | 6,627 |
| | K | |
| | about 6,605 | |
| | expected by chance | |

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| # other explained (t, u) | p-value | # IP addresses |
|----------------------------|--------------------|----------------|
| 0 | 1.00000000 | 58,367 |
| 1 | 0.10694695 | 6,627 |
| 2 | 0.00592438 | 378 |
| | K | |
| | about 373 | |
| | expected by chance | |

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- The hash inversion narrows it down to 65,385 matching IP addresses for this post.
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| # other explained (t, u) | p-value | # IP addresses |
|----------------------------|------------|-------------------------|
| 0 | 1.00000000 | 58,367 |
| 1 | 0.10694695 | 6,627 |
| 2 | 0.00592438 | 378 |
| 3 | 0.00022049 | 12 |
| | | |
| | | oout 12 ed by chance |

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| 1 | 0.10694695 | 6,627 |
| 2 | 0.00592438 | 378 |
| 3 | 0.00022049 | 12 |
| 4 | 6.167×10^{-6} | 0 |
| | | |
| | about 0.39 | |
| | expected by chance | |

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- The hash inversion narrows it down to 65,385 matching IP addresses for this post.
- How many of these 65,385 IPs explain **other** topic-usernames in a 7-day window?

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| 1 | 0.10694695 | 6,627 |
| 2 | 0.00592438 | 378 |
| 3 | 0.00022049 | 12 |
| 4 | 6.167×10^{-6} | 0 |
| 5 | 1.380×10^{-7} | 0 |
| | K | 7 |

about 0.0089 expected by chance

- We start with 2³² possible IP addresses.
- The hash inversion narrows it down to 65,385 matching IP addresses for this post.
- How many of these 65,385 IPs explain other topic-usernames in a 7-day window?

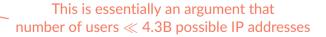
| # other explained (t, u) | p-value | # IP addresses |
|----------------------------|------------------------|----------------|
| 0 | 1.00000000 | 58,367 |
| 1 | 0.10694695 | 6,627 |
| 2 | 0.00592438 | 378 |
| 3 | 0.00022049 | 12 |
| 4 | 6.167×10^{-6} | 0 |
| 5 | 1.380×10^{-7} | 0 |
| <u> </u> | į | |

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| _ | # other explained (t, u) | p-value | # IP addresses |
|-------------|----------------------------|--------------------------|----------------|
| | 0 | 1.00000000 | 58,367 |
| | 1 | 0.10694695 | 6,627 |
| | 2 | 0.00592438 | 378 |
| Very mucl | h <u>not</u> 3 | 0.00022049 | 12 |
| expected by | chance 4 | 6.167×10^{-6} | 0 |
| \ | 5 | 1.380×10^{-7} | 0 |
| \ | | ! | : |
| | 102 | 2.253×10^{-258} | 0 |
| | 103 | 2.072×10^{-267} | 1 |

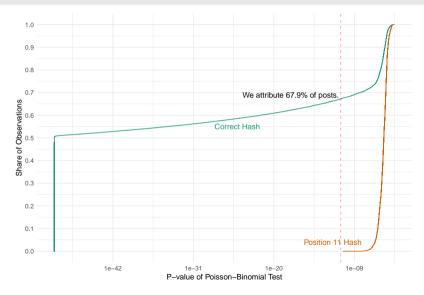
IP Attribution as an Optimization Problem

- Find a small set of these active IPs that explains the observed data.
 - Subject to locality and significance constraints
 - Definitely has errors. These are estimable and in the paper.
- Simple intuition of this optimization approach
 - 65k IP addresses can explain any given post.
 - One IP explains many other posts that week.
 - What is the likely origin IP of this post?
 - It's probably this highly explanatory IP.



Attribution with Correct and Incorrect Hashes

- Using any incorrect substring of the hash only generates "noise" IPs
- Determine p-value threshold p* by comparing distributions of minimum p-values
- Only assign IPs to posts with minimum p-value $< p^* \approx 10^{-11}$



Robustness Checks for Attribution

- Incorrect hashing set √
 - Using the (incorrect) position-11 hashing set, none of the roughly 7.1 million posts observed on EJMR are attributed an IP address.
- Bogon addresses √
 - There are nearly 600 million bogon addresses which occupy 13.8% of the entire IPv4 address space. These cannot post to EJMR but could be attributed to posts by mistake.
 - Our process attributes **zero** posts to bogon IP addresses.
- Time pattern of posters √
 - IP addresses post during the **standard work and day time hours** of their geolocation.
- Language of posters √
 - The dominant non-English language of the country of origin of the IP address is the country's native language.

From Methods to Results

What tools does our analysis give us?

- Panel dataset linking poster IPs across topics and time
- Geolocation of posters (high quality at state and country level, can go down to city)
- Information on ISPs (universities, organizations, corporations, hotels)

What questions are we asking?

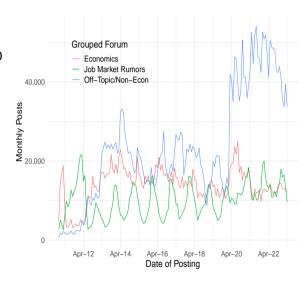
- Who are the posters on this site?
 - "It's just people at lower-ranked universities."
 - "It's just grad students."
- Is the toxicity of the site widespread?
 - "It's just a few bad apples."
- Are there two dialogues (toxic and professional)?
 Are they separate? Within people? Within topic?
- Is there actually valuable inside information?
- Does EJMR make people more toxic?
- Are hundreds of thousands of visitors just paying attention to what a few people post?

Attribution and Geolocation

- 7.1 million posts in total \rightarrow 4.7 million posts (66.1%) with attributed IP address
- 47,630 distinct IP addresses attributed to posts
 - These are the most frequent posters, but ...
 - ... there are many more infrequent posters, and ...
 - ... there are even more viewers (ratio of roughly 70 views to 1 post).
- Vast majority from countries with top research institutions in economics & finance
 - US (61.9%)
 - Canada (8.3%), United Kingdom (5.5%)
 - Australia (2.4%), Germany (2.2%), Hong Kong (1.9%), Italy (1.6%), France (1.5%)
 - Remaining share of geolocated posts (13.6%) from rest of the world

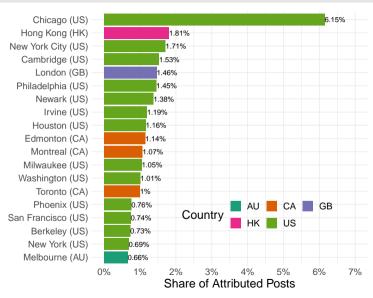
Time Pattern of Posts

- 7.1 million posts since December 2010
 - Average 70,000 monthly posts & 1,100 monthly unique IPs as of 2022
- Steady increase over time, but large traffic increase during COVID-19
 - Primarily driven by tripling in U.S.
 - Other countries experience more temporary increases
 - Very large rise in off-topic forum posts
- Strong cyclicality of job market posts
 - Disruption of job market cyclicality starting in 2021



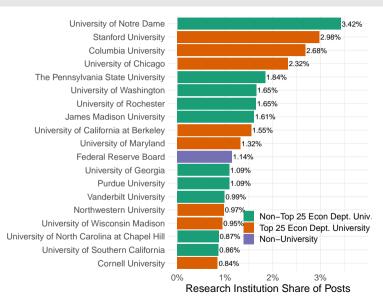
Posts by City

- Majority of posts come from large cities in the US
 - Chicago, New York, Philadelphia
- Some fraction from large cities outside the US
 - Hong Kong, London, Montreal, Toronto
- Smaller US cities with leading research institutions
 - Cambridge, Berkeley

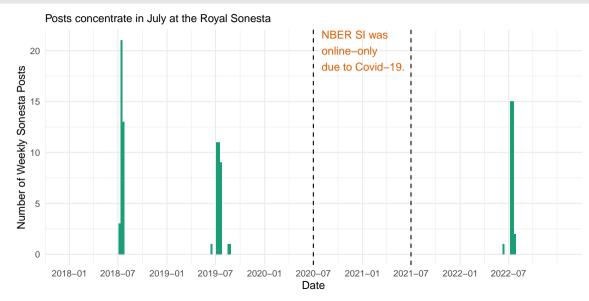


University IP Addresses on EJMR

- 10.9% of allocated posts originate from IP addresses of universities or research institutions
- Contributors are using university networks to post on EJMR
- Posts come from top US universities (top 25 econ departments)



Are these the elites of economics?



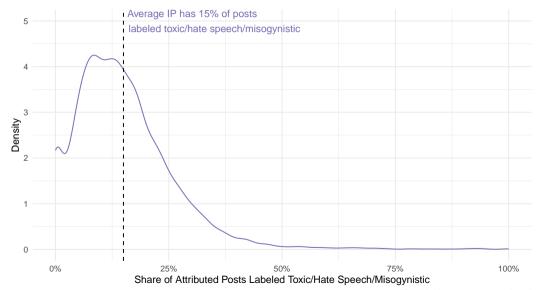
Which universities do university IPs talk about?

Share of posts that mention university

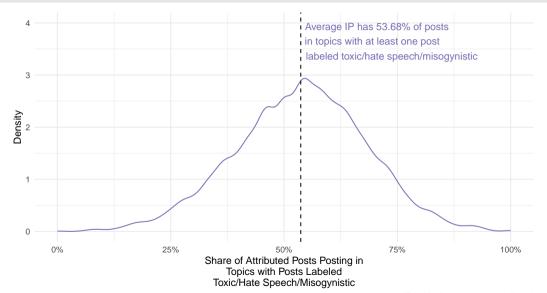
| University ISP | Harvard | MIT | Stanford | Berkeley | UChicago | Yale | NYU | NWU | Columbia | UPenn |
|--------------------|---------|-----|----------|----------|----------|------|-----|-----|----------|-------|
| Harvard | 7.9 | 9 | 5.2 | 1.4 | 3.7 | 2 | 2.1 | 0.9 | 1 | 1.2 |
| MIT | 4.7 | 9.8 | 6 | 0.9 | 2.6 | 0.4 | 2.6 | 1.7 | 2.1 | 1.3 |
| Stanford | 4.4 | 6.4 | 7.4 | 1.7 | 4.5 | 1.2 | 1.9 | 1.4 | 1.3 | 1.3 |
| UC Berkeley | 1.6 | 3.7 | 1.7 | 4.2 | 1.8 | 1.2 | 1.8 | 0.8 | 0.6 | 0.9 |
| UChicago | 2.1 | 4.8 | 1.4 | 0.7 | 8.3 | 0.8 | 1.6 | 0.7 | 0.5 | 1 |
| Yale | 1.5 | 3.8 | 0.9 | 0.7 | 1.8 | 3.4 | 1.3 | 0.5 | 0.4 | 1 |
| NYU | 2.5 | 4.6 | 3.1 | 0.7 | 1.9 | 1.1 | 5.8 | 1 | 1.1 | 2.4 |
| Northwestern | 2.5 | 4.1 | 1.8 | 1.1 | 2.3 | 1.6 | 2.7 | 3.5 | 0.8 | 1.1 |
| Columbia | 3 | 4.9 | 2.3 | 1.3 | 2.8 | 1.6 | 3.1 | 1 | 5 | 2.4 |
| UPenn | 2.2 | 3.5 | 1.8 | 0.9 | 2.4 | 1 | 3.1 | 1.1 | 0.3 | 5.1 |
| Others | 1.1 | 3.8 | 0.5 | 0.4 | 1 | 0.4 | 1 | 0.2 | 0.3 | 0.6 |

Everybody on EJMR loves talking about themselves ... and about MIT.

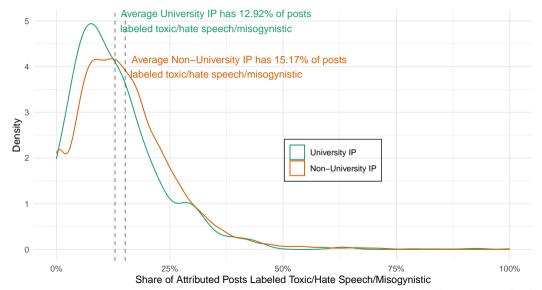
Distribution in Toxic Speech across IPs



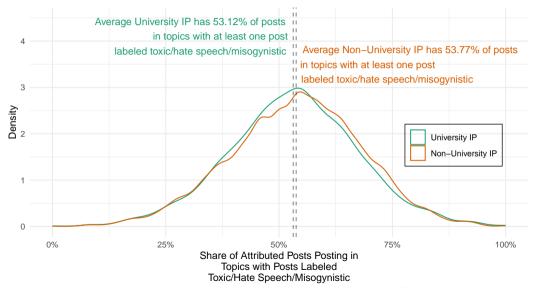
Distribution in Participation in Toxic Conversation



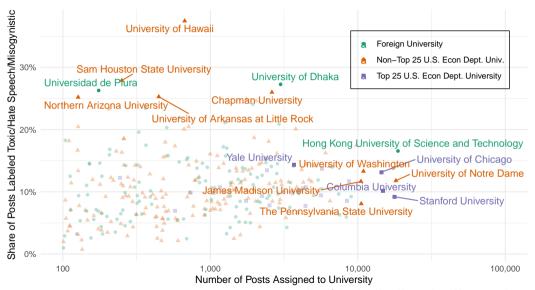
Distribution of Toxic Speech Across IPs by University

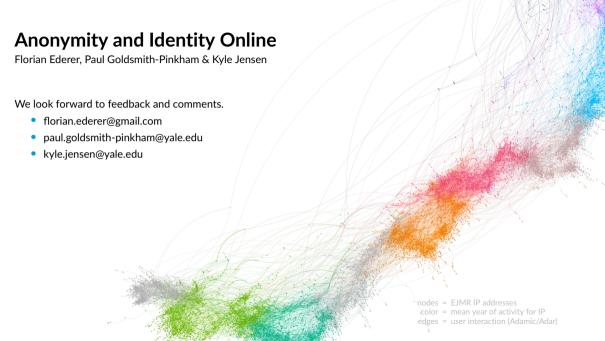


Distribution in Participation in Toxic Conversation by University



Toxic Speech on EJMR by University ISPs





Appendix

From usernames to IP addresses (in practice)

- Hash inversion is conceptually simple but intolerably slow in practice.
 - 695,364 topics \times 2³² possible IPv4 addresses \approx 3 quadrillion hashes
 - Check which hashes correspond to observed topic-username combinations
 - Easy to write code in Python, but would take over 60 years on a modern CPU
- Computation is tractable with graphical processing units (GPUs).
 - Basically the same as Bitcoin mining
 - Hash inversion is highly parallelizable
 - 230 hours of total computing time on Nvidia A100 devices each with 6,912 cores
- Hash inversion is only feasible because there is no salt.

From usernames and topics to IP addresses

$$g(\underbrace{\mathsf{Topic\ ID}}_{\mathsf{observed}}, \underbrace{\mathsf{IPv4\ Address}}_{\mathsf{observed}}) = \underbrace{\mathsf{Username}}_{\mathsf{observed}}$$

Known many-to-one function

"Inverse Hash"

$$\left.\begin{array}{c}
 \text{Username} \\
 \text{Topic ID}
\end{array}\right\} \longrightarrow \begin{array}{c}
 \text{Set of } \approx 65 \text{k} \\
 \text{matching IPs}
\end{array}$$

Set of matching IPs

$$= g^{-1}(\underbrace{\mathsf{Topic\ ID}}_{\mathsf{observed}}, \underbrace{\mathsf{Username}}_{\mathsf{observed}})$$

Inverse function returns a set

IPv4 Address ∈ Set of matching **IPs**

Finding Active IP Addresses

Statistical properties

- The noise IPs that match a topic-username (t, u) are **uniformly** distributed across the IPv4 space.
- The probability that a noise IP a is observed in any particular set $A_{(t,u)}$ containing IPs that match (t,u) is a **hypergeometric** distribution which depends on the number of u in t.
- The number of times n_a that a noise IP a is observed across all matching IP sets $A_{(t,u)}$ follows a **Poisson binomial** distribution.

Our approach

- Null hypothesis that observed counts of an IP a are generated purely by noise
- Calculate probability under the null hypothesis that an IP *a* would be observed *n*_{*a*} times *by chance* (i.e., calculate p-values for each *a*)
- Rejection of null hypothesis \rightarrow IP a is active

Attributing Active IP Addresses to Posts

- IP address Attribution as an optimization problem
 - Find a small covering set of active IPs for the observed posts.
 - Compute p-values for each a in the set $A_{(t,u)}$ for all (t,u).
 - For each (t, u), identify the IP with the lowest p-value.
 - If its p-value $< p^*$, attribute to that IP. Otherwise, leave (t, u) unattributed.
- Simple intuition of this optimization approach
 - 65k IP addresses can explain any given post, but imagine one of these IPs *also* explains many posts in other topics around the same time.
 - What is the likely origin IP of this post? It's probably this highly explanatory IP.

Algorithmic IP address attribution approach

- Key assumptions
 - Sparsity of IP posters + uniformity of hash over full IPv4 space
- Potential issues with current approach
 - 1. Multiple-hypothesis testing problem / inference on winners
 - 2. A given IP will show up $N\pi_0$ times randomly, even under the null hypothesis.
- Solutions
 - 1. Choose conservative p-value thresholds $p^* \approx 10^{-11}$ based on known null distribution
 - 2. Window the data in relatively short time intervals (7 days, 31 days, 91 days)
- Work in progress
 - Generative model to construct probability statements for each post and IP combination

Choosing the p-value threshold p^*

- Use a wrong substring of SHA-1 hash to construct a pure noise baseline
 - Repeat the entire hash inversion with incorrect hash positions.
 - Compute p-values and attribute post to IP with lowest p-value.
 - Calculate p^* such that we would obtain **zero** attributions of posts to an IP
- Window-specific p-value thresholds p^*

$$p_{7d}^* = 1.37 \times 10^{-10}$$

 $p_{31d}^* = 2.51 \times 10^{-11}$
 $p_{91d}^* = 1.39 \times 10^{-11}$

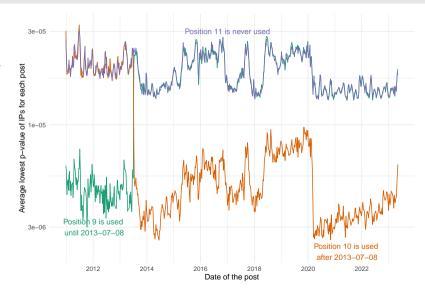
• With these p^* , the number of IP addresses that never posted to EJMR but that we mistakenly attribute to any of the roughly 7 million posts is, in expectation, **less than one**.

Summary of Hash Inversion and IP Attribution Steps

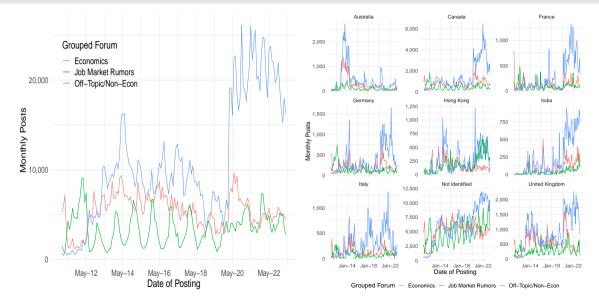
- 1. Create topic-specific usernames from hashes of all possible topic-IP pairs
- 2. For each topic-username find the set of matching IPs
- 3. Evaluate which matching IPs occur "much too often" than expected by random chance ("active IPs") in a short time window (7 days)
- 4. Attribute active matching IP with lowest p-value $< p^*$ to post or leave post unattributed

Detecting Hash Changes

- Hash changed on July 8, 2013
- Average minimum p-values are much lower for the correct hash
- Average minimum p-values of incorrect hashes closely track each other

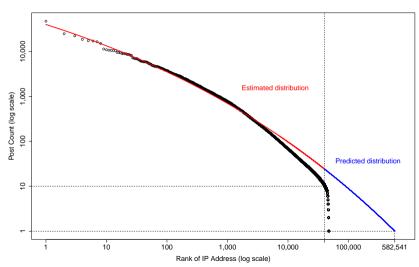


United States and Other Major Countries



Distribution of IP addresses and posts

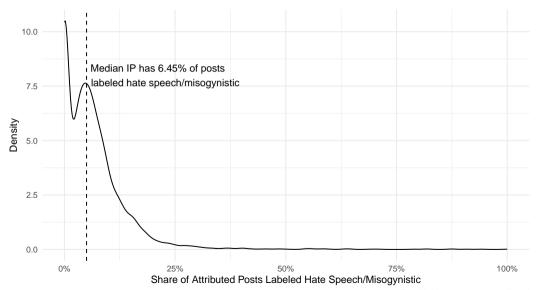
- 66.1% of posts come from 47,630 IPs.
- These power posters fit stretched exponential.
- Long tail of occasional posters is "unobserved."
- 582,541 IPs are predicted to have posted on EJMR at least once.



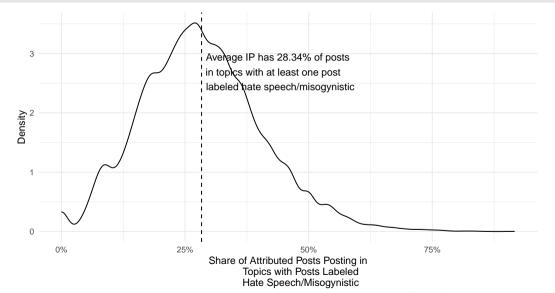
Linguistic Analysis

- EJMR posters use I33tspeak and obfuscation to escape automatic EJMR moderation
 - "Hey a\$\$h01e, I left you a message earlier too. I will be there in Boston to FIEK and RAEP you, so cover your \$hitty a\$\$ and your mouth now." (2014-12-26)
 - "Mold-fa//g//g//ot, I will split your a//s/s in two with my HUMONGOUS super HARD shalong. You will be squealing like the little beia/tch that you are." (2020-01-28)
 - "those d4mn j3ws had no morals either." (2022-08-13)
- Deobfuscation process
 - Collect high-frequency non-English words in English posts to deobfuscate some of the most commonly obfuscated terms
 - Remove common symbol-based obfuscations
 - Transform leetspeak to its canonical form
- Run each post through a number of transformer-based machine learning models for toxicity, sentiment, and misogyny
 - Cross-validate with data by Wu (2020)
 - Note: potential classification error, but unlikely to be correlated across IPs

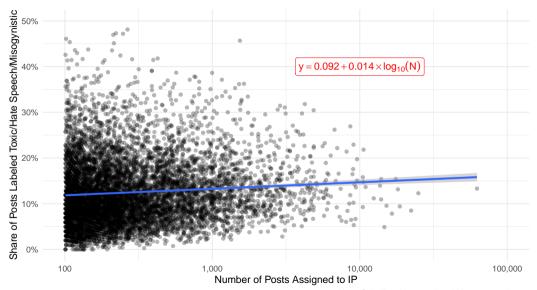
Distribution in Hateful/Misogynistic Speech across IPs



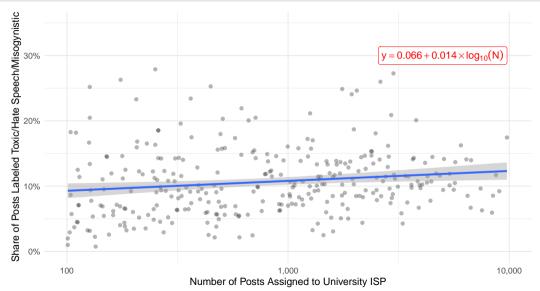
Distribution in Participation in Hateful/Misogynistic Conversation



Do frequent IP posters post more toxic speech? Not really.



Toxic Speech on EJMR by University ISPs



References

- **Spiegel, H. W.**, "Jacob Viner (1892–1970)," in J. Eatwell, M. Milgate, and P. Newman, eds., *The New Palgrave: A Dictionary of Economics*, Vol. IV, London: Macmillan, 1987, p. 812–14.
- Wu, Alice H, "Gender Bias Among Professionals: An Identity-based Interpretation," *Review of Economics and Statistics*, 2020, 102 (5), 867–880.