# Bias on the Web

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## What is Bias?

- Statistical: significant systematic deviation from a prior (unknown) distribution;
- Cultural: interpretations and judgments phenomena acquired through our life;
- Cognitive: systematic pattern of deviation from norm or rationality in judgment;

# Motivation 1: Inequality of Content

- First, inequality of Internet access
  - From 98% in Iceland to less than 1% in South Sudan
- Content inequality across languages
  - Most websites are in English (estimated in 52%) while only 13% speaks English
  - On the other hand, only 4% of the websites are in Mandarin (China) while this country has 22% of the users
  - There about 6,900 languages but only 288 of them have an active Wikipedia
  - There are 4 times more Wikipedia entries in English than Spanish although there are more native Spanish speakers than native English speakers
- Content optimized most of the time for local purposes (e.g., business and government) and not for the actual needs of people
- Also there is bias on content quality (later)



# Motivation 2: Impact in Search and Recommender Systems

- Most web systems are optimized by using implicit user feedback
- However, user data is partly biased to the choices that these systems make
  - Clicks can only be done on things that are shown to us
- As those systems are usually based in ML, they learn to reinforce their own biases, yielding self-fulfilled prophecies and/or sub-optimal solutions
  - For example, personalization and the filter bubble
- Moreover, sometimes these systems compete among themselves, learning also biases of other systems rather than real user behavior
- Even more, an improvement in one system might be just a degradation in another system that uses a different (inversely correlated) optimization function
  - For example, user experience vs. monetization

# Motivation 3: Fake Content & Bias

- British Prime Minister Benjamin Disraeli (IXXth century):
  - "There are three kinds of **lies**: **lies**, damned **lies**, and **statistics**.


**Buzzfeed News**




# So (Observational) Human Data has Bias

**Cultural Biases**

- Gender
- Racial
- Sexual
- Age
- Religious
- Social
- Linguistic
- Geographic
- Political
- Educational
- Economic
- Technological

**Statistical Biases**

- Gathering process
- Sampling process
- Validity (e.g. temporal)
- Completeness
- Noise, spam

**Cognitive Biases**

Self-selection

**Attempt of an unbiased (personal) view on bias in the Web**

**Many people extrapolate results of a sample to the whole population (e.g., social media analysis)**

**In addition there is bias when measuring bias as well as bias towards measuring it!**

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## A Non-Technical Question


Neutral?
Fair?

Not Always!

Debias the input
Tune the algorithm
Debias the output

**Bias awareness!**

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## ACM US Statement on Algorithm Transparency and Accountability (Jan 2017)

1. Awareness
2. Access and redress
3. Accountability
4. Explanation
5. Data Provenance
6. Auditability
7. Validation and Testing

**They do not need to be perfect, they just need to be better than us**

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# Big Data and Bias

- The **quality of any algorithm** is bounded by the **quality of the data that uses**
- Data bias awareness
  [Gordon & Desjardins; Provost & Buchanan, MLJ 1995]
- Bias in computer systems: [Friedman & Nissenbaum 1996]
- Algorithmic fairness
- Key issues for Machine Learning
  - Uniformity of data properties
    - In the Web, distributions resemble a power law
  - Uniformity of error
  - Data sample methodology
    - E.g., sample size to see infrequent events or sampling bias

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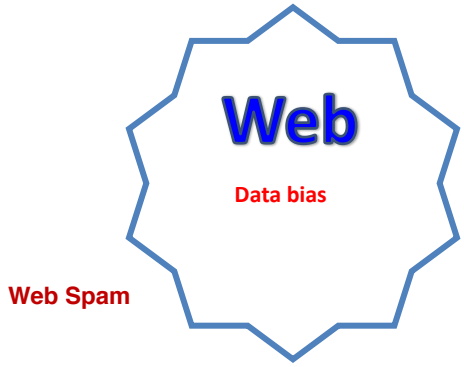
# Bias in the Web

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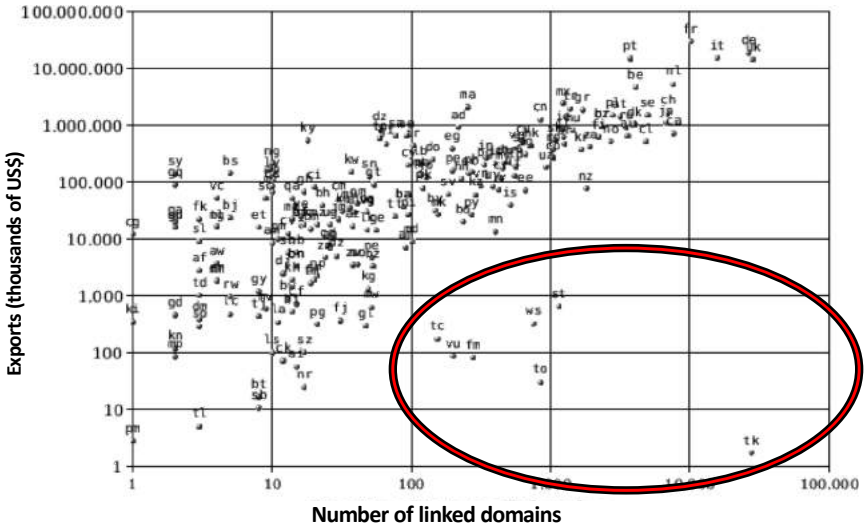
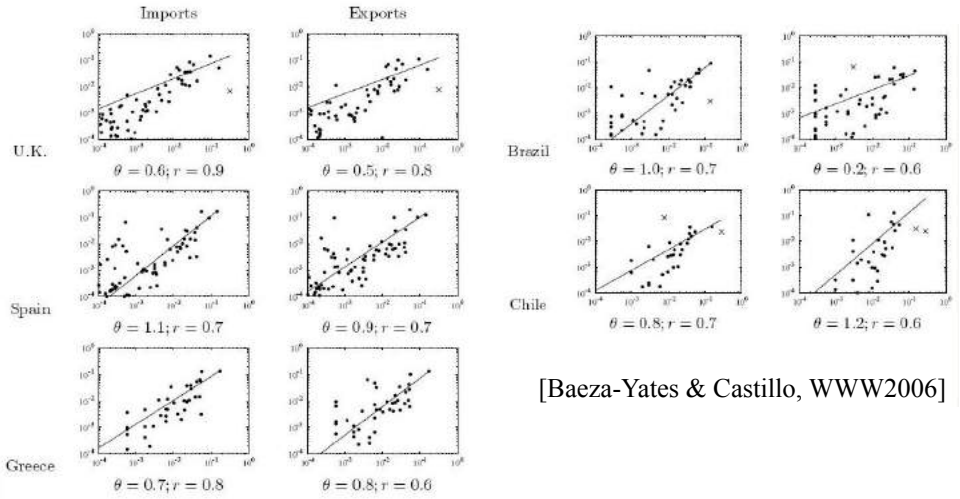
## Economic Bias in Links




[Baeza-Yates, Castillo & López. Characteristics of the Web of Spain. Cybermetrics, 2005]



## Economic Bias in Links

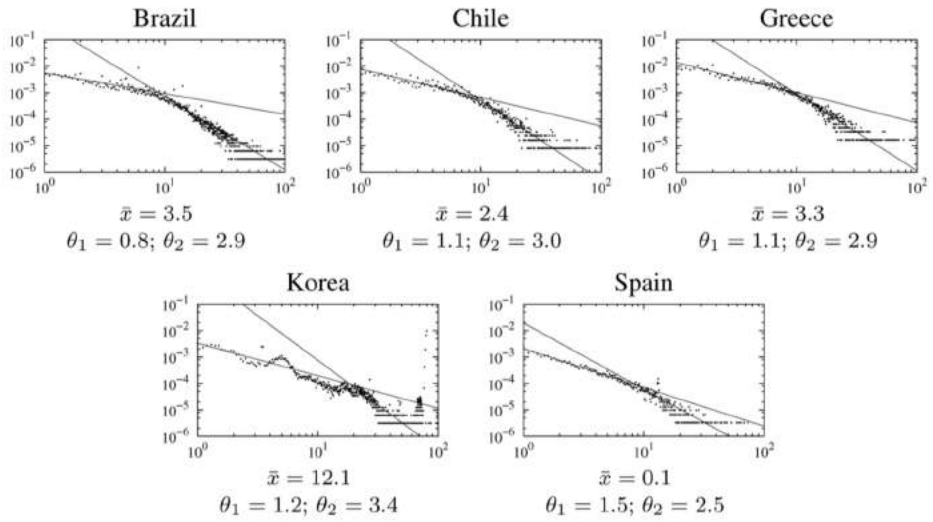



[Baeza-Yates & Castillo, WWW2006]

## Cultural Bias in Website Structure

Shame

Minimal effort




[Baeza-Yates, Castillo, Efthimiadis, TOIT 2007]

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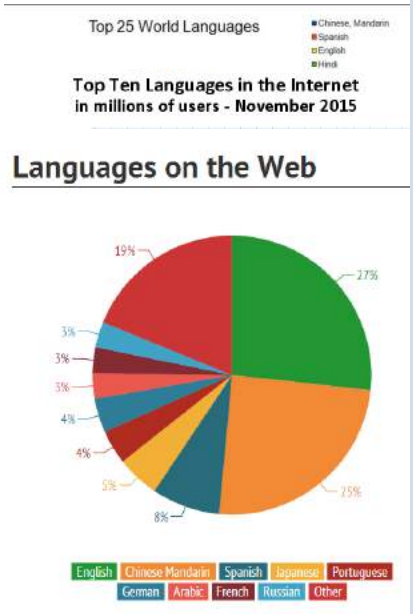
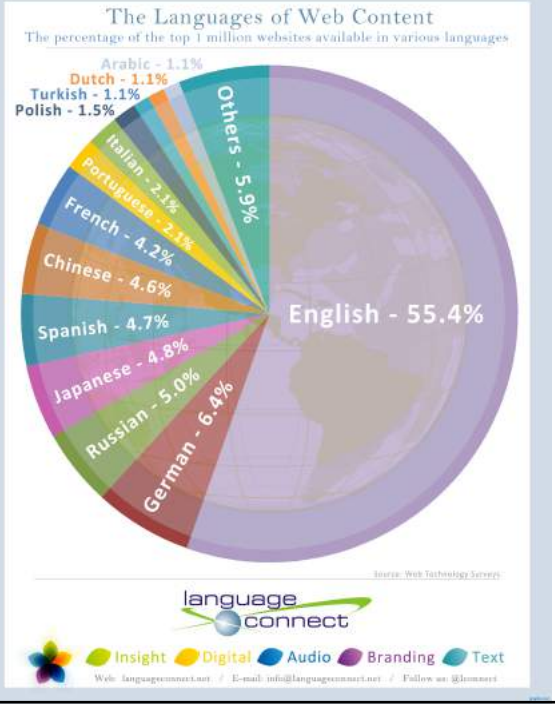
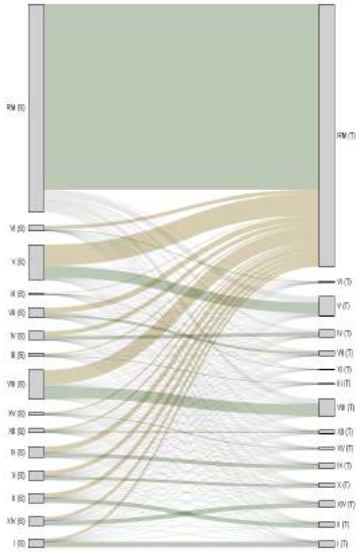
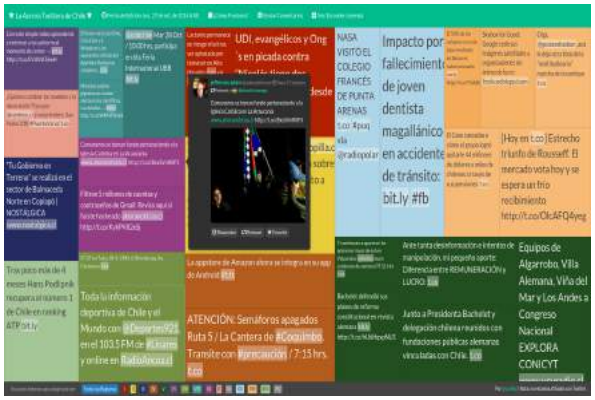
## Linguistic Bias in Content



# Geographical Bias in Content





**[E. Graells-Garrido and M. Lalmas, "Balancing diversity to counter-measure geographical centralization in microblogging platforms", ACM Hypertext'14]**

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# Gender Bias in Content

- Word embedding's in w2vNEWS

**Gender stereotype *she-he* analogies.**

| | | |
|---|---|---|
| sewing-carpentry | register-nurse-physician | housewife-shopkeeper |
| nurse-surgeon | interior designer-architect | softball-baseball |
| blond-burly | feminism-conservatism | cosmetics-pharmaceuticals |
| giggle-chuckle | vocalist-guitarist | petite-lanky |
| sassy-snappy | diva-superstar | charming-affable |
| volleyball-football | cupcakes-pizzas | hairdresser-barber |

**Gender appropriate *she-he* analogies.**

| | | |
|---|---|---|
| queen-king | sister-brother | mother-father |
| waitress-waiter | ovarian cancer-prostate cancer | convent-monastery |

**Most journalists are men?**

**Yes, about 60 to 70% at work although at college is the inverse**

[Bolukbasi at al, NIPS 2016]

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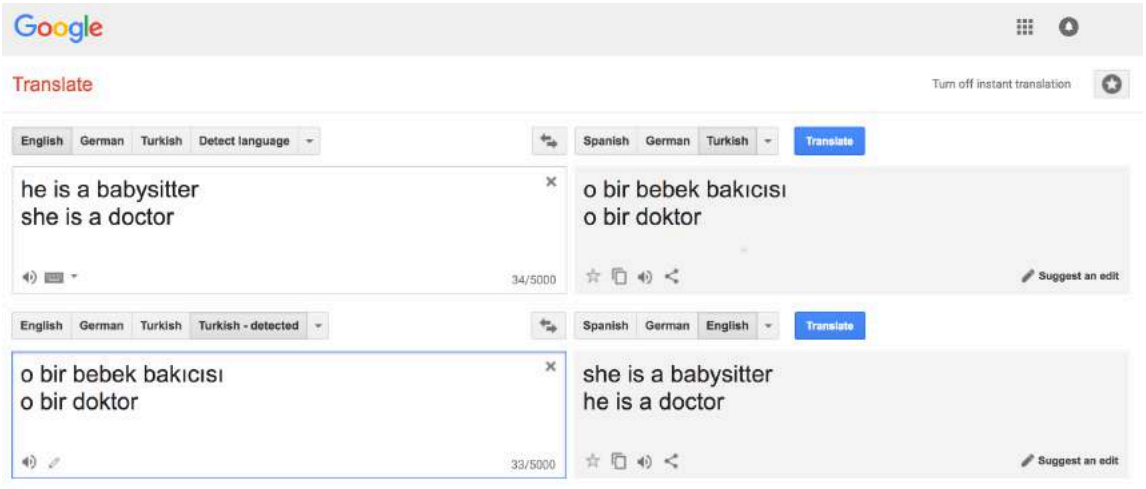
# Gender Bias in Translation

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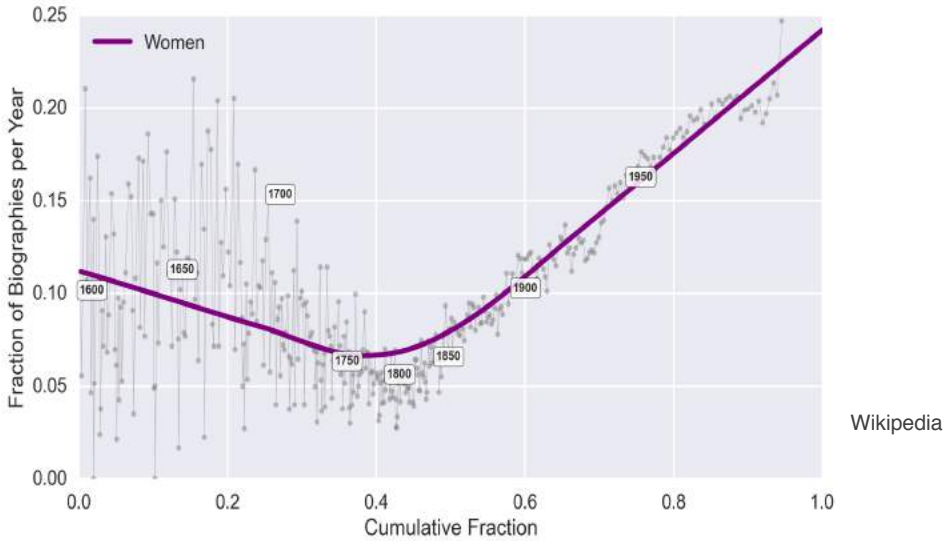
# Gender Bias in Content

**Systemic bias?**




Wikipedia

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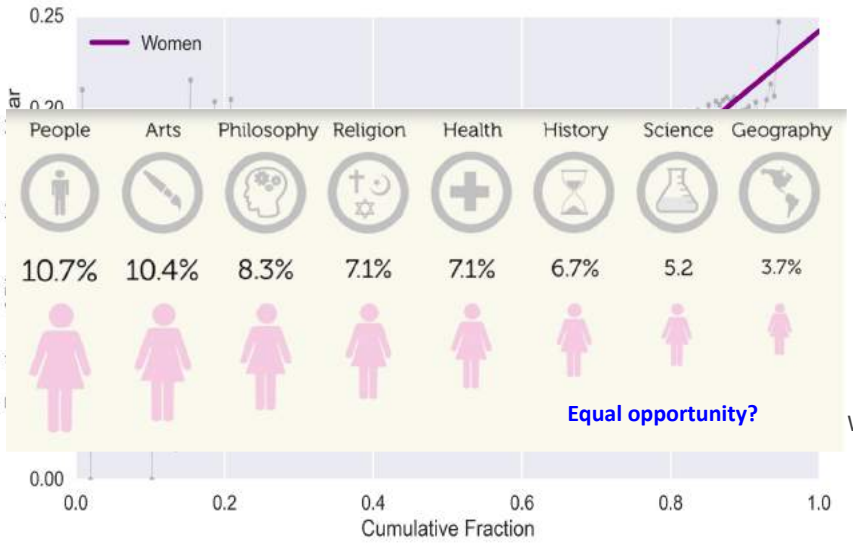
**[E. Graells-Garrido et al,. "First Women, Second Sex: Gender Bias in Wikipedia", ACM Hypertext'15]**

# Gender Bias in Content

Systemic bias?




Partial information

Wikipedia

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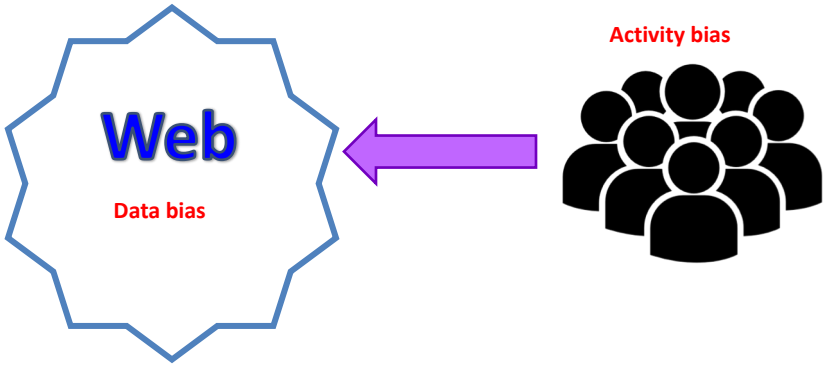
[E. Graells-Garrido et al,. "First Women, Second Sex: Gender Bias in Wikipedia", ACM Hypertext'15]

# Bias in the Web

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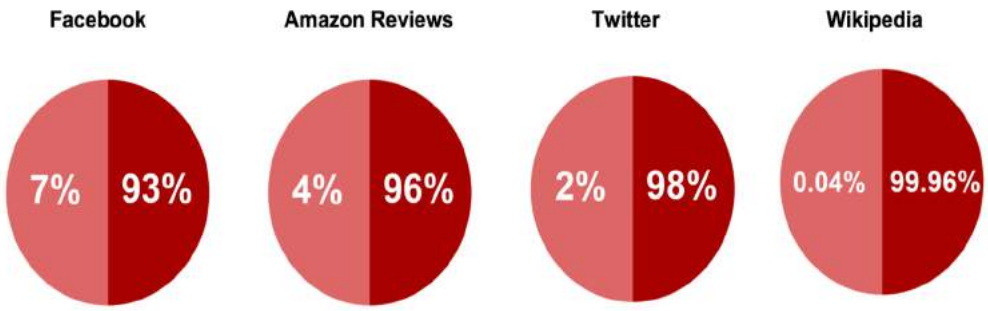
# Activity Bias

Most users are passive (*i.e.,* more than 90%) – wisdom of crowds is a partial illusion
Which percentage of **active** users produce 50% of the content?




[Baeza-Yates & Saez-Trumper, ACM Hypertext 2015]

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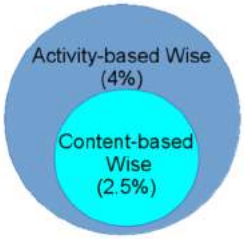
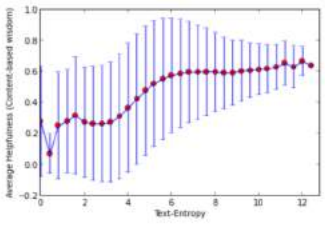
## Quality of Content?

- Adding content ⇛ Adding Wisdom ?
- We use Amazon's Reviews helpfulness
- Content-based-wise users

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[Baeza-Yates & Saez-Trumper, ACM Hypertext 2015]

## Content that is never seen: Digital Desert


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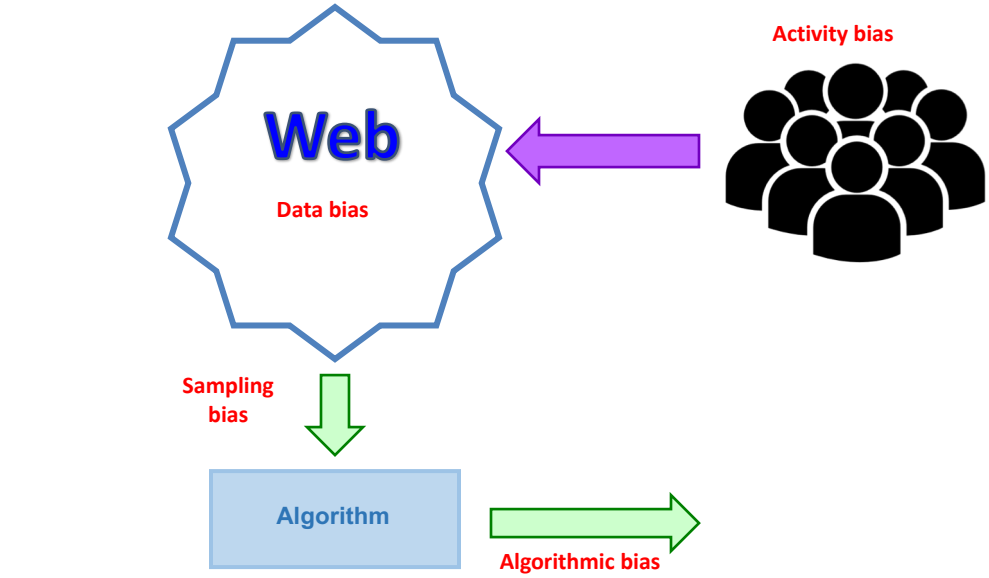
[Baeza-Yates & Saez-Trumper, ACM Hypertext 2015]

# Bias in the Web

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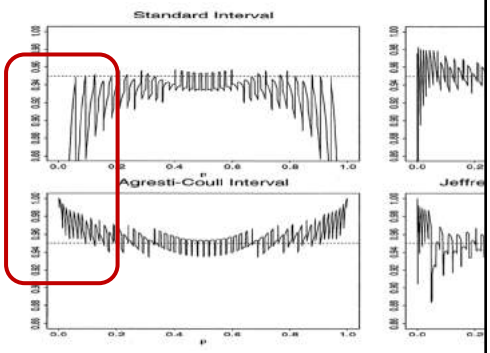
## Sample Size?

- If we want to estimate the frequencv of queries that appear with probability at least *p* with a certain relative error $\epsilon$ we can use the standard binomial error formula √(1-p)/*np* which works well for *p* near ½ **but not for p near 0**
- Better is the Agresti-Coull technique (also called *take 2*) which gives:

$$n \geq Z^2_{1-\alpha/2}\left(\frac{p'(1-p')}{\epsilon^2} - 1\right)$$

where *Z* is the inverse of the standard normal distribution, $1-\alpha$ is the confidence interval and $p' = p + Z^2/2$

- If *p* = 0.1, $1-\alpha$ is 80% and $\epsilon$ is 10%, we get *n* = 2342. The standard formula gives *n* = 900!

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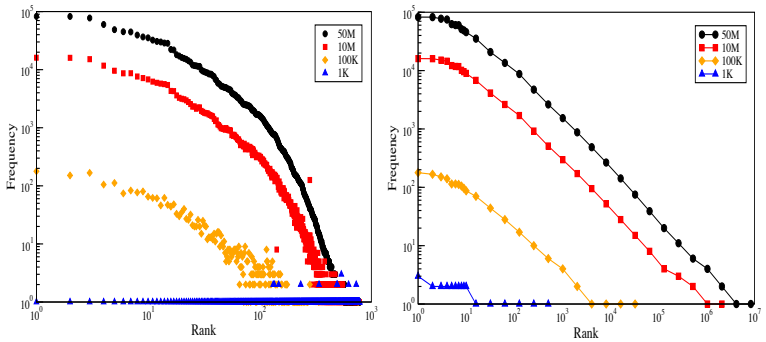
[Brown, Cai & DasGupta, Statistical Science, 2001]
[Baeza-Yates, SIGIR 2015, Industry track]

## Sampling Techniques

- Standard technique:

$$p_q \approx \hat{p}_q(\mathcal{S}) = \frac{f_q(\mathcal{S})}{\sum_{q' \in \mathcal{S}} f_{q'}(\mathcal{S})}$$

- A good sample should cover well all the query distribution but this does not work with very skewed distributions.

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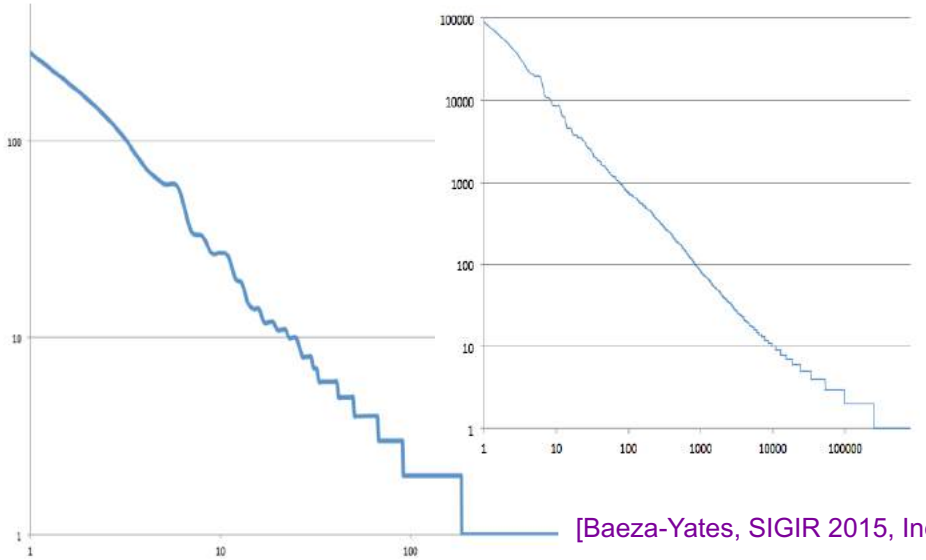
[Zaragoza et al, CIKM 2010]

## Stratified Sampling Example

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[Baeza-Yates, SIGIR 2015, Industry track]

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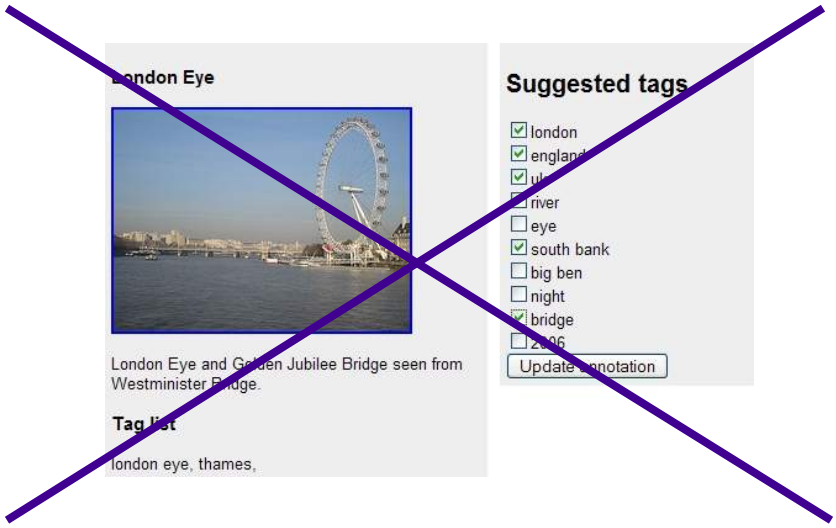
# Extreme Algorithmic Bias

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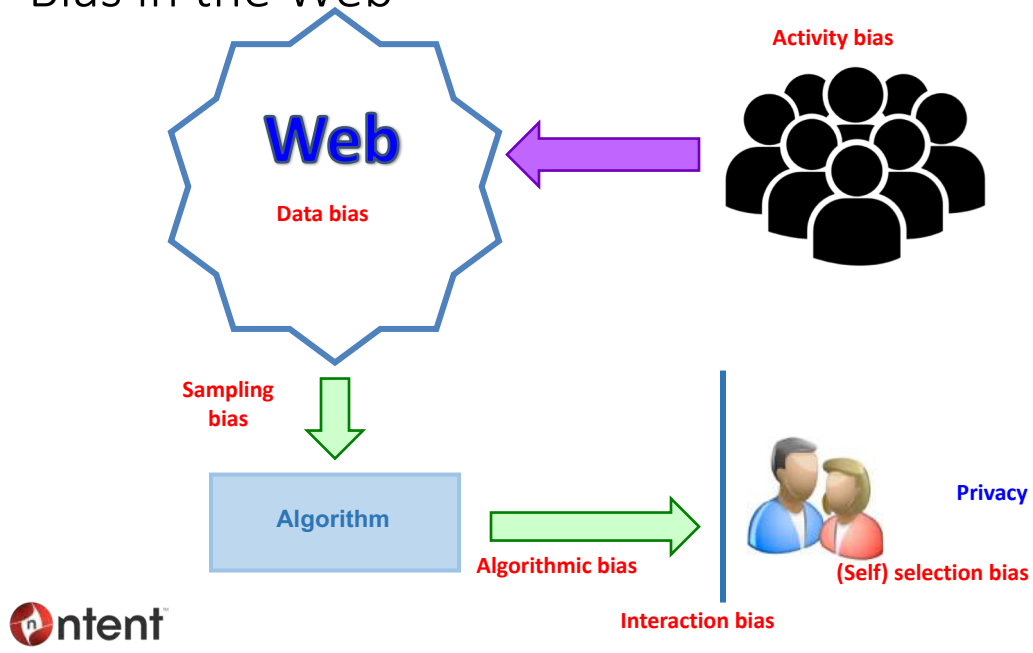
# Bias in the Web

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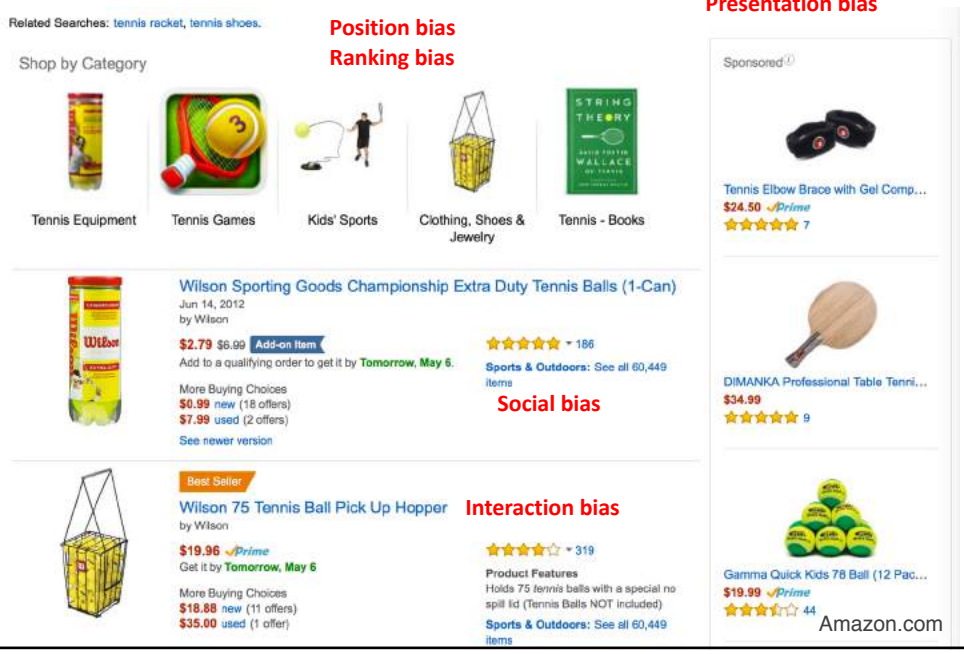
# Bias in the Interaction

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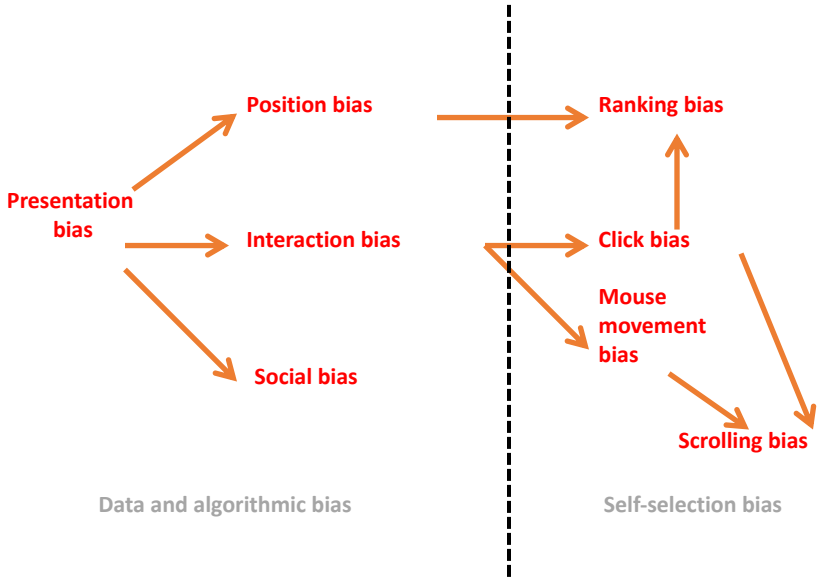
# Dependencies: A Cascade of Biases!

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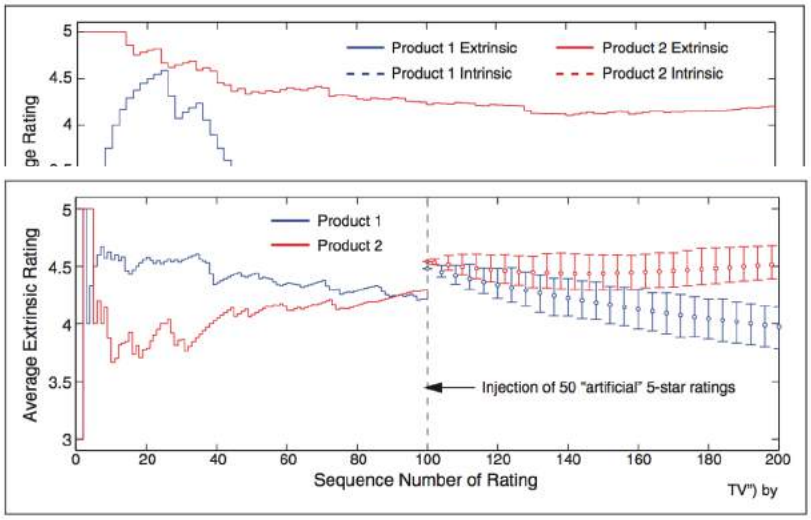
# Social Bias




**[WHY AMAZON'S RATINGS MIGHT MISLEAD YOU; The Story of Herding Effects, Ting Wang and Dashun Wang, Big Data, 2014]**

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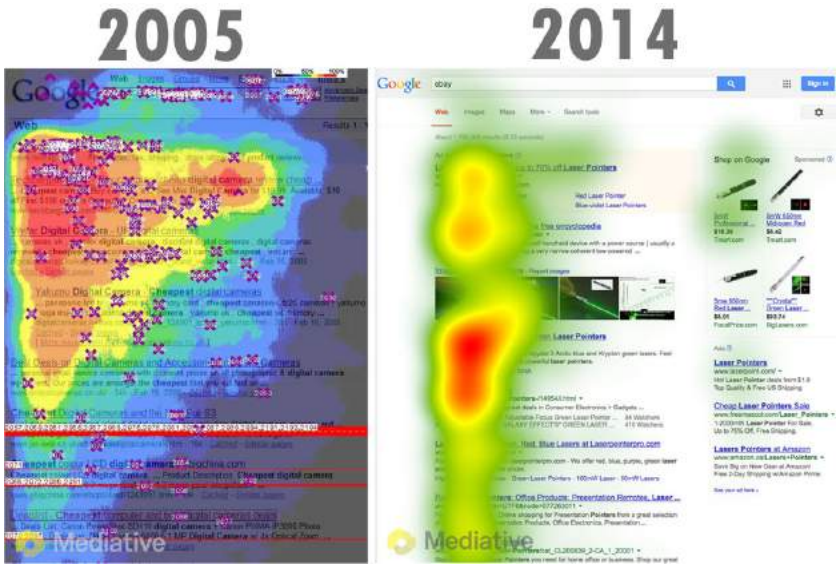
College of Computer and Information Science

# Ranking Bias in Web Search

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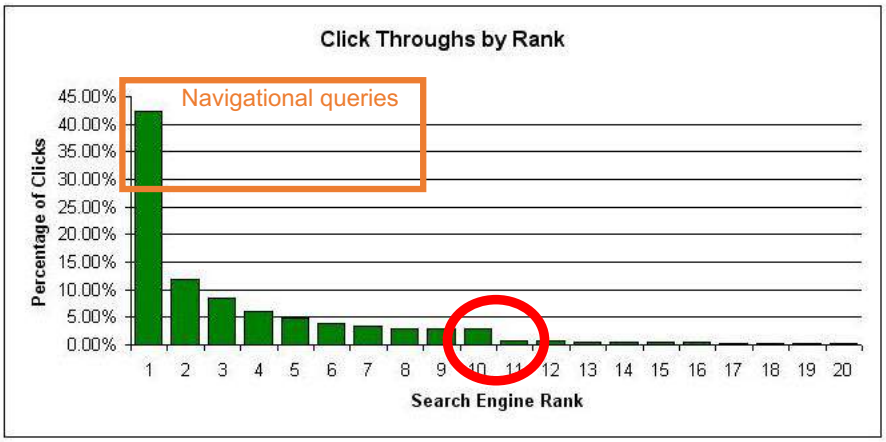
[Mediative Study, 2014]

# Click Bias in Web Search

- Ranking & next page bias

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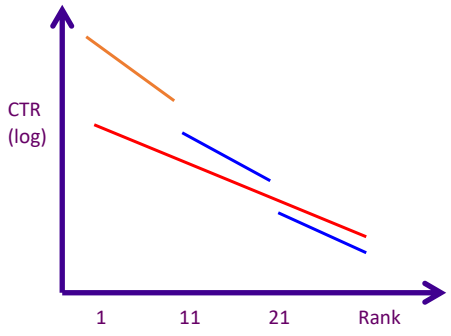
# Debiasing Search Clicks

Clicks as implicit positive user feedback




Learning to Rank with bias
[Joachims et al, WSDM 2017, **best paper**]

Fair rankings
[Zehlike et al, CIKM 2017]

[Dupret & Piwowarski, SIGIR 2008]
[Chapelle & Zhang, WWW 2009]
[Dupret & Liao, WSDM 2010]

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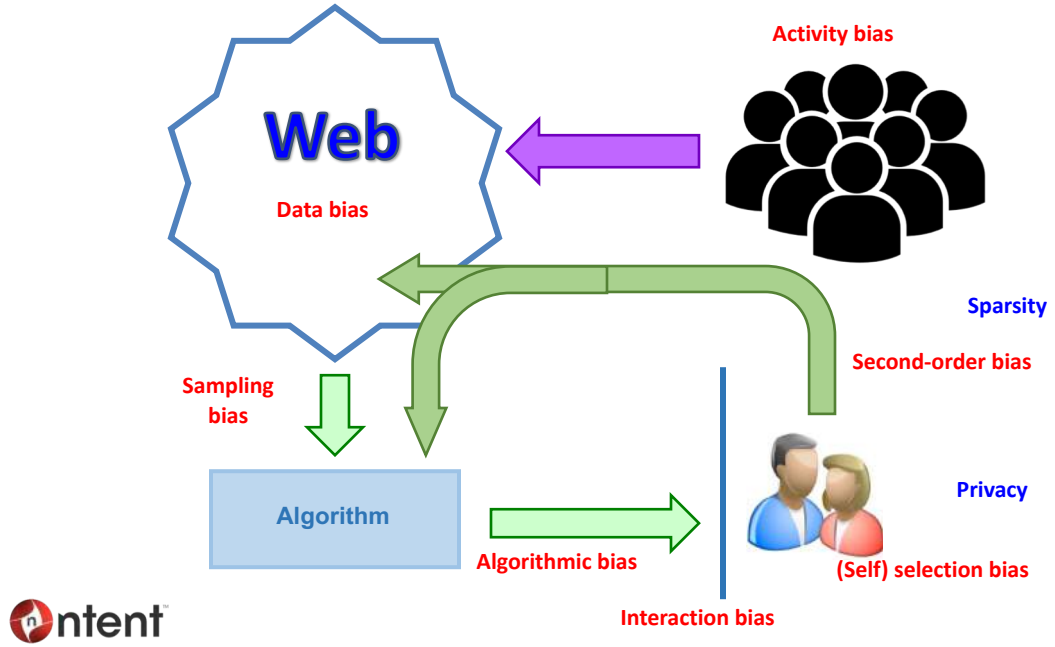
# Bias in the Web

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# Second Order Bias due to Personalization

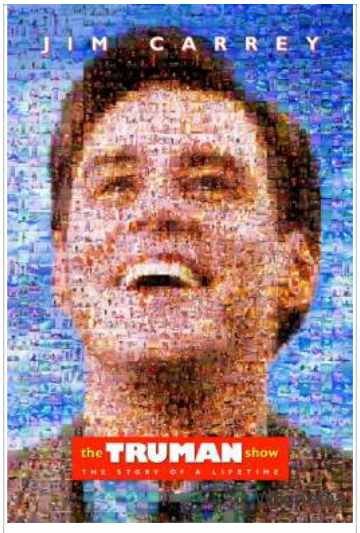
- The effect of self-selection bias
- Avoid the rich get richer and poor get poorer syndrome
- Avoid the echo chamber by empowering the tail

**Partial solutions:**

- Diversity
- Novelty
- Serendipity
- My dark side

**Cold start problem solution: Explore & Exploit**

**How much exploration is needed to counteract presentation bias?**




[Eli Pariser, The Filter "Bubble", 2011]

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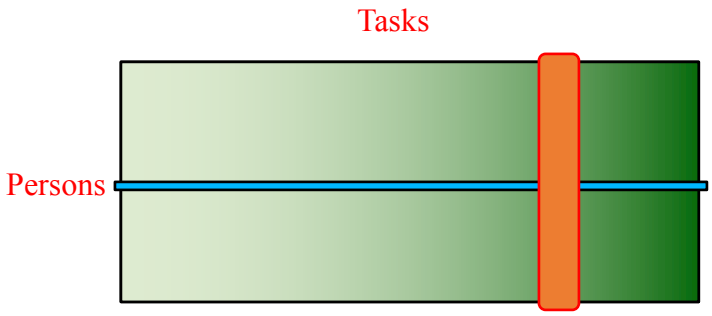
## Aggregating in the Tail

- Exploit the context (and deep learning!)

  91% accuracy to predict the next app you will use
  [Baeza-Yates et al, WSDM 2015]

- Personalization vs. Contextualization

  Recall that user interaction has a long tail and we are all in it!
  [Goel at al, WSDM 2010]

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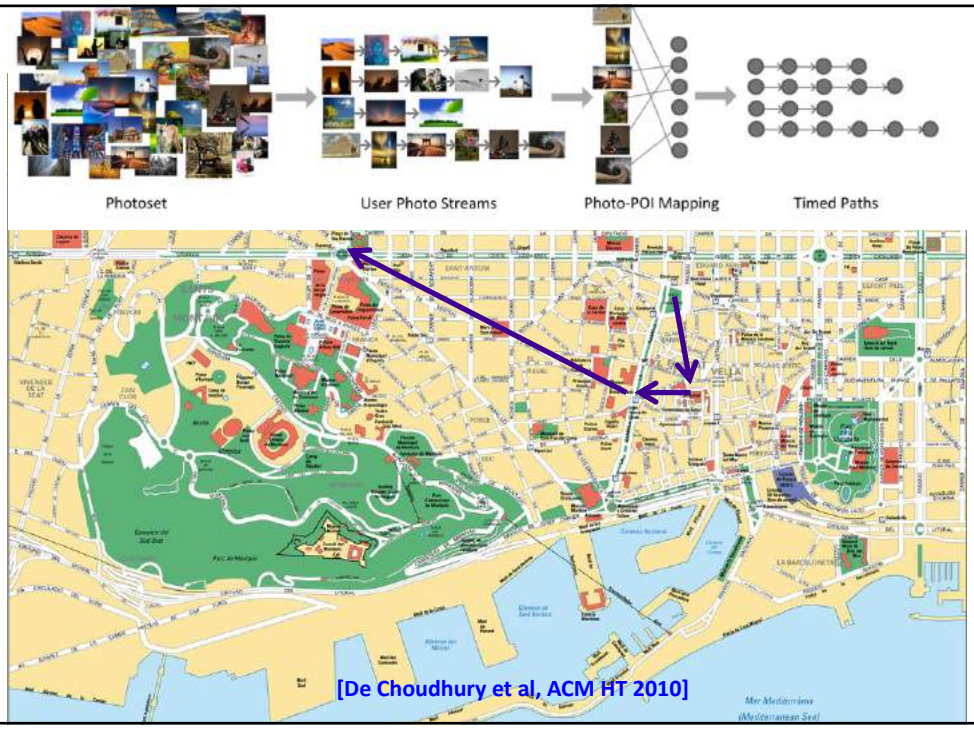


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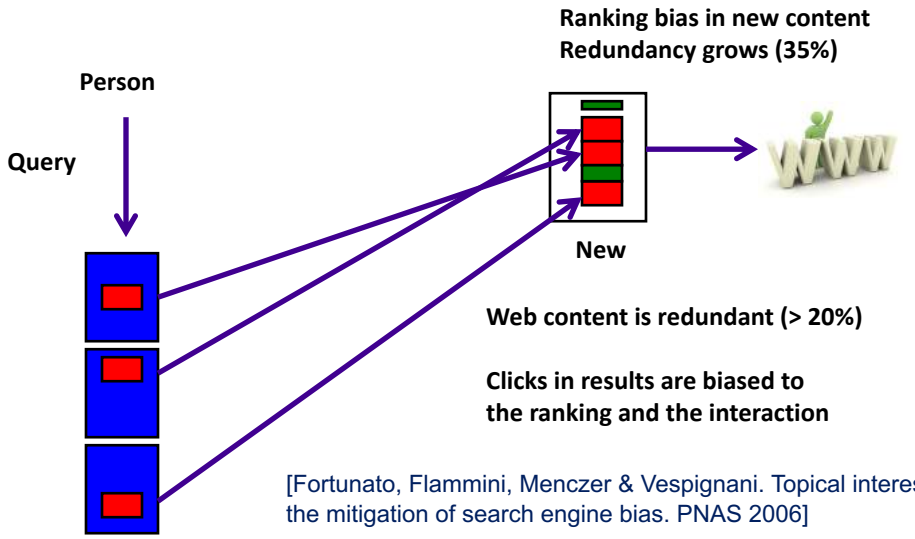
# Second Order Bias in Web Content




**Web content is redundant (> 20%)**

**Clicks in results are biased to the ranking and the interaction**

[Fortunato, Flammini, Menczer & Vespignani. Topical interests and the mitigation of search engine bias. PNAS 2006]

[Baeza-Yates, Pereira & Ziviani, Genealogical Trees in the Web, WWW 2008]

# The Web Works Thanks to Bias!

- Web traffic
  - Local caching
  - Proxy/network caching

**Activity bias**

- Search engines
  - Answer caching
  - Essential web pages
    - 25% queries can be answered with less than 1% of the URLs! [Baeza-Yates, Boldi, Chierichetti, WWW 2015]

**(Self) selection bias**

- E-Commerce
  - Large fraction of revenue comes from few popular items

# Take-Home Message

- Web data is a mirror of us, the good, the bad and the ugly
- The Web amplifies everything, but always leaves traces

- We need to be aware of our **own bias**!
- We have to be aware of the biases and contrarrest them to stop the **vicious bias cycle**
- We have to be aware of **our privacy**
- **Plenty** of open research problems! (in small data even more!)

**Big Data** of **People** is huge…..
….. but it is tiny compared to the future
**Big Data** of the **Internet of Things (IoT)**

**No activity bias!**

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# Recap

| Bias \ Type | Statistical | Cultural | Cognitive |
|---|---|---|---|
| Algorithmic | ♦ | ? | ? |
| Presentation | ♦ | | |
| Position | ♦ | ♦ | ♦ |
| Data | ♦ | ♦ | |
| Sampling | ♦ | ♦ | ♦ |
| Activity | | ♦ | |
| Self-selection | | ♦ | ♦ |
| Interaction | | ♦ | ♦ |
| Social | | ♦ | ♦ |
| Second order | ♦ | ♦ | ♦ |

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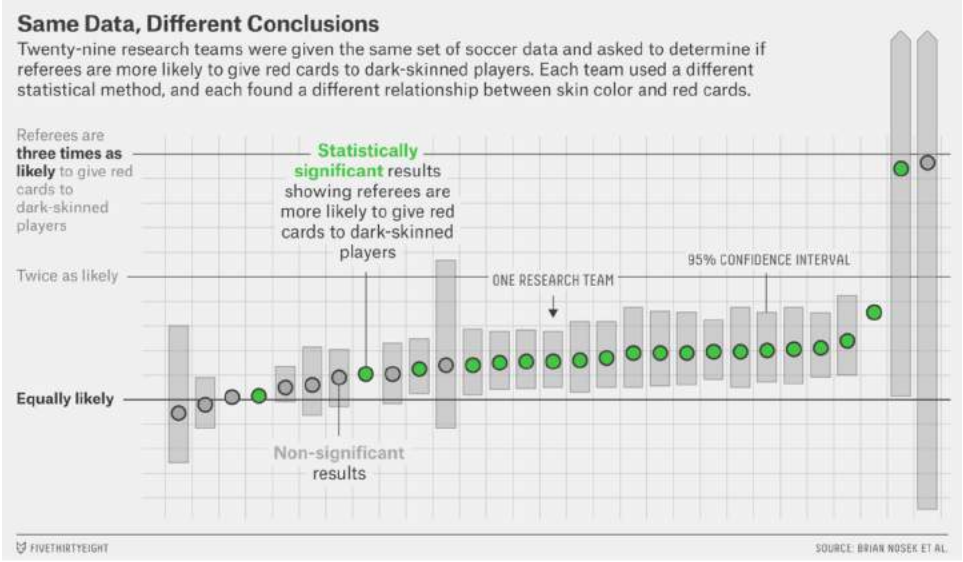
# It's Hard to Get the Truth from Data (Professional Bias)




➔ 61 analysts, 29 teams: 20 yes and 9 no (Univ. of Virginia, COS)

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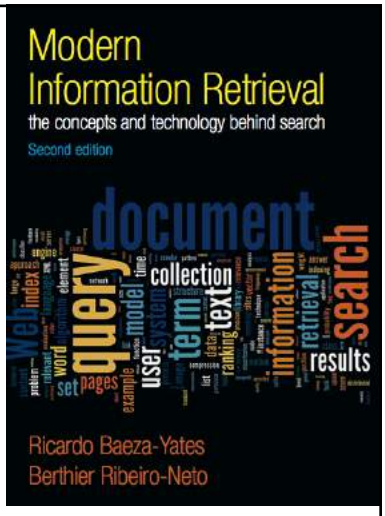
# Questions?

**ASIST 2012 Book of the Year Award (Biased Ad)**




**New Conferences that started in 2018:**

AAAI/ACM Conference on AI, Ethics, and Society
http://www.aies-conference.com

Conference on Fairness, Accountability, and Transparency
http://fatconference.org

**Resources:** http://fairness-measures.org

**Biased Questions?**

**Contact:** rbaeza@acm.org
www.baeza.cl
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