# Is Ignorance Bliss?

Latent Knowledge and the Opportunity Cost of Internet Search

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July 28, 2021

### Outline

- Problem
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- 3 Approach
  - Latent Knowledge
  - Data
  - Opportunity Cost
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#### Problem

Knowledge search on the internet is biased (Nissenbaum & Introna 2000, Vaughan & Thelwall 2004, Eubanks 2018, Selbst et al. 2019):

- ► Targets representation consumption
- ► Trained on diverse mainstream data
- ► Trained by diverse homogeneous teams
- Public Proprietary access
- Illusion of fairness
- Speed and scale doesn't help here

#### Problem

- ightharpoonup What we know ightharpoonup Internet search (lacks representation)
- $\blacktriangleright$  What we do not know  $\rightarrow$  ?

#### Problem

- What we know → Internet search (lacks representation)
- $\blacktriangleright$  What we do not know  $\rightarrow$  ?

- An old problem
  - I know that I know nothing.
  - Apology of Socrates, Plato (399 BC)
- But we have the data now to approximate an answer.

### Research Questions

In the context of internet search:

- 1. Latent Knowledge: How much do we not know?
- 2. Opportunity Cost: What are the implications of knowing what we know as opposed to what we do not?

Approach

# Latent Knowledge

Context

In the context of internet search (European Commission v Google, 2017):

- ► First page of search results receives 95% of all clicks
- ▶ First result on page 2 receives only 1% of all clicks
- ▶ 91% of pages get no organic search traffic

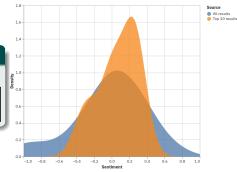
# Latent Knowledge

#### Case 1: Continuous metrics

Given N search results for a given query, define latent knowledge as the non-overlap in metric distribution of top n vs N search results  $(N \ge n)$ .

#### If metric x is continuous

$$\mathcal{K}_{latent} = 1 - \left[ rac{1}{2} \int |f_{N}(x) - f_{n}(x)| \ dx 
ight]$$



$$K_{latent} \in [0, 1]$$

# Latent Knowledge

#### Case 2: Categorical metrics

Given N search results for a given query, define latent knowledge as the scaled difference in proportions across all categories for top n vs N search results  $(N \ge n)$ .

### If metric is categorical with C categories

$$\mathcal{K}_{latent} = \frac{1}{\mathit{C}-1} \sum_{c=1}^{\mathit{C}} \left[ \frac{\max\left(\frac{\mathit{N}_{c}}{\mathit{N}} - \frac{\mathit{n}_{c}}{\mathit{n}}, 0\right)}{1 - \frac{\mathit{n}}{\mathit{N}}} \right]^{1/2}$$

#### Binary case

$$\mathcal{K}_{latent} = \left\lceil rac{ extit{max} \left( rac{N_b}{N} - rac{n_b}{n}, 0 
ight)}{1 - rac{n}{N}} 
ight
ceil^{1/2}$$

 $K_{latent} \in [0, 1]$ 

#### Data

#### User facing open-source platform (Sonder):

- Fetch web search results based on user query
- ► For every result, can calculate: Text metrics (sentiment, subjectivity, readability, novelty, etc.), Geo-location, Green web hosting

#### Logs:

- Daily top trends for web and news
- ▶ Run each trend through the platform: 47 countries (6 continents)  $\times$  40 trends/country  $\times$  100 results/trend = 188,000 web + news search results every day
- ► In the pipeline Yandex (Russia), Baidu (China), Naver (South Korea)

# Demo



# Opportunity Cost

OC = Return(Latent Results) - Return(Top Results)

#### Experimental Design

- ► Treatment:  $K_{latent}$  (i.e. results reordered to maximize exposure to latent knowledge)
- Control: Default ordering
- Outcomes: User-level metrics like polarization, access to misinformation, general click through behavior during and after treatment

#### **Possibilities**

- Descriptive Studies
  - Polarization
    - search sentiment variance by rank
  - Press freedom
    - sentiment difference between web and news trends by country
  - Compare search platforms
  - Trends in carbon cost
- ▶ Latent Knowledge
  - ► Variation by metric, by search platform, by search rank, by trend rank, across countries, over time

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