

“Discovering the Ebb and Flow of Ideas in Text Corpora”

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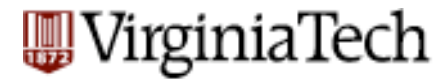
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So, what does:

“Discovering the Ebb and Flow of
Ideas in Text Corpora”

mean?

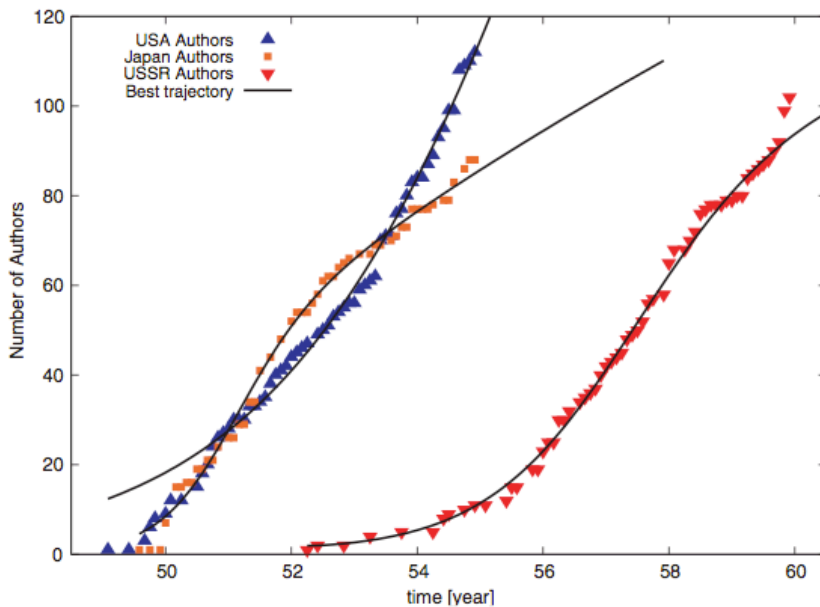
Finding meaning in Big Data

- Data mining
 - borrowing a definition from Naren Ramakrishnan:
“the process of extracting non-trivial and actionable insights from data.”
- Wide Variety of Uses:
 - Commercial (e.g., targeted ads)
 - Academic (e.g., gene expression)
 - “Fun” (e.g., Google Trends)

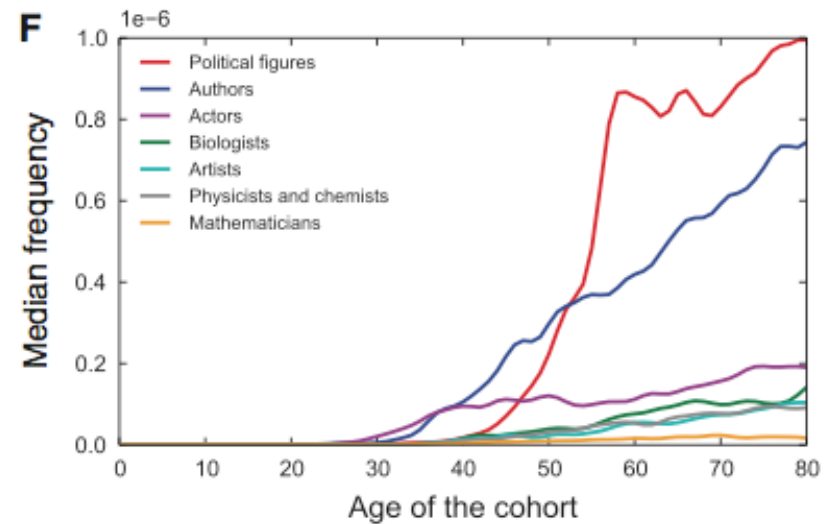
The Question

- Investigate the ideas surrounding events in recent Western history with major cultural implications
 - AIDS epidemic (1980s)
 - Einstein's theory of relativity (early 1900s)
 - Semmelweis's discovery of hand sanitation (1840s)

How have other researchers investigated the spread of ideas?



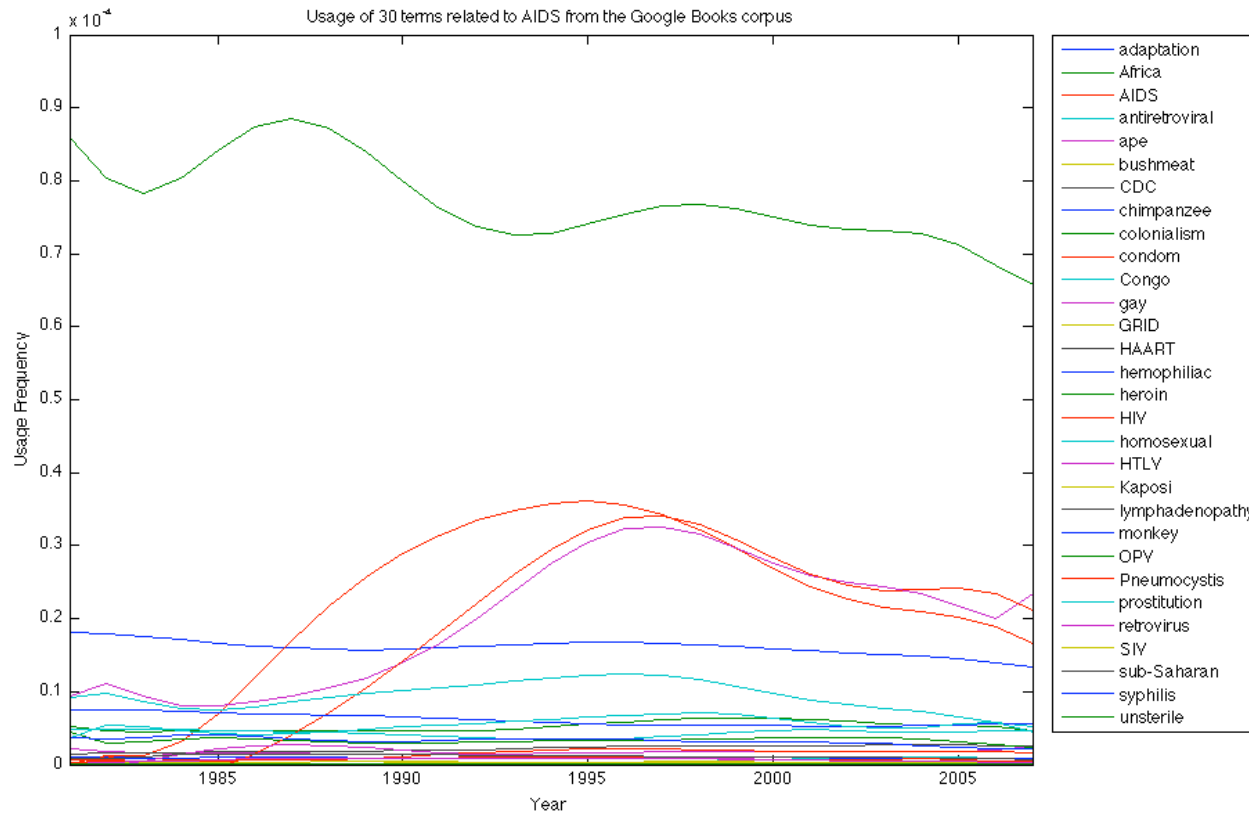
L.M.A. Bettencourt et al., “The Power of a Good Idea: Quantitative Modeling of the Spread of Ideas from Epidemiological models,” *Physica A*, May 2006, pp.513-536.



J. Michel et al., “Quantitative Analysis of Culture Using Millions of Digitized Books,” *Science*, 14 Jan 2011, pp. 176-182.

The Databases

- Google Books, New York Times, PubMed
- Large amounts of data but difficult to interpret



The Algorithm: GOALIE

- Cluster-based temporal segmentation
- Main idea: embed a clustering algorithm in a segmentation algorithm.

Data: multiple measurement vectors $W = \{w_1, w_2, \dots, w_N\}$, where each w_i is a time series over $T = \{t_1, t_2, \dots, t_l\}$.

- Each w_i represents a term (eg, AIDS) and its corresponding time series t_i represents usage data over the given years (eg, 1981-2008)

The Algorithm: GOALIE

Segmentation Goal: express T as a sequence of segments: $s_{t_1}^{ta}, s_{t_{a+1}}^{tb}, \dots, s_{t_k}^{tl}$ where each segment $s_{t_i}^{te}, t_i \leq t_e$, is a set of consecutive time points.

Clustering Goal: Given two clusterings of terms, e.g. W_{ta}^{tb} for left time segment s_{ta}^{tb} and W_{tb+1}^{tc} for right time segment s_{tb+1}^c , obtain clusters W that are local within each segment but are highly dissimilar to neighboring clusters.

Constraints: Define segment length constraints l_{\min} and l_{\max} , and maximum number of clusters.

The Algorithm: GOALIE

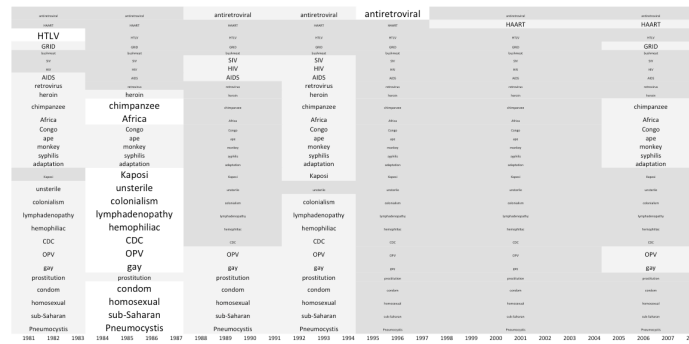
1. Given two clusters W_a and W_b , before and after a given time point, define cluster random variables $\alpha = \{1, \dots, r\}$ and $\beta = \{1, \dots, c\}$.
2. Measure the clusters' similarity using an $r \times c$ contingency table. Entry n_{ij} represents the number of one-to-one relationships between the elements of the i -th cluster of W_a and the j -th cluster of W_b .
 - Ideally a highly disparate pair of clusterings result in a total of $(r+c)$ uniform distributions across the row and columns.
3. Define r random variables R_i ($i=1, \dots, r$) w.p. $p_{R_i}(j) = n_{ij}/n_i$ corresponding to each row, and c random variables R_j ($j=1, \dots, c$) w.p. $p_{C_j}(i) = n_{ij}/n_j$ corresponding to each column.
4. **Minimize divergence from the uniform distributions over the rows $U(1/c)$ and columns $U(1/r)$ by minimizing:**

$$F = \frac{1}{r} \sum_{i=1}^r D_{KL} \left(p_{R_i} \parallel U \left(\frac{1}{c} \right) \right) + \frac{1}{c} \sum_{j=1}^c D_{KL} \left(p_{C_j} \parallel U \left(\frac{1}{r} \right) \right)$$

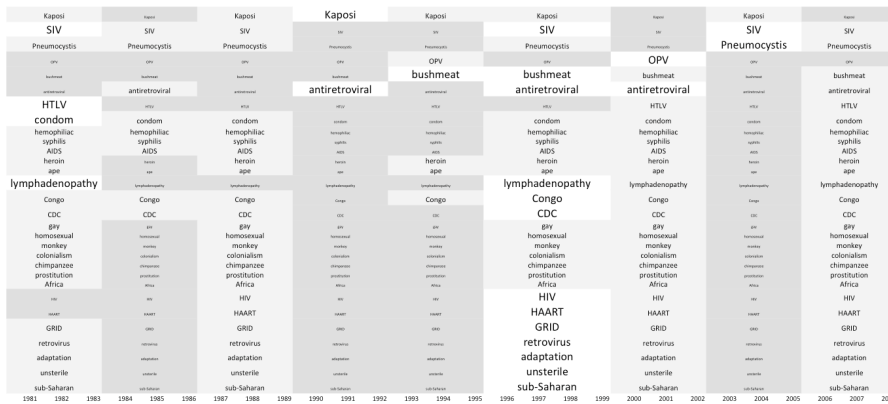
where $D_{KL}(p \parallel q) = \sum_x p(x) \log_2 \frac{p(x)}{q(x)}$ is the Kullback-Leibler (KL) divergence.

Results: AIDS, all three databases

Google Books



New York Times



PubMed

