

# Network of Epidemiology Digital Objects

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CS6604 Class Project

# Outline

- Problem Statement
- Requirement Specification
- Related work
- What a human would do?
- Modeling
- Evaluation

# Client Problem Statement

- CINET
  - Computational and analytic environment for network science research and education.
- Goal: A RDF graph building service
  - Web crawling for contents related to epidemiology
  - RDF representation to interconnect digital objects

# Client Problem Statement

- Requirement: Build a connected network of:
  - Papers
  - Wiki pages
  - Websites
  - Videos
  - Other digital objects pertaining to epidemiology
- Representing using RDF for future graph analysis.

# Refined Problem Statement

- Strongly connected digital objects & metadata
  - Include metadata to model the connection
  - Better represent the underlying correlation among digital objects
- Given a search request, provide resulting DO network:
  - Include all related digital objects
  - Strongly connected DOs are more related

# Refined Problem Statement

- Automated process
  - Web exploration
  - Network construction
- Restricted digital objects
  - Research papers
- Web crawling (search engine from dblp)

## CompleteSearch DBLP

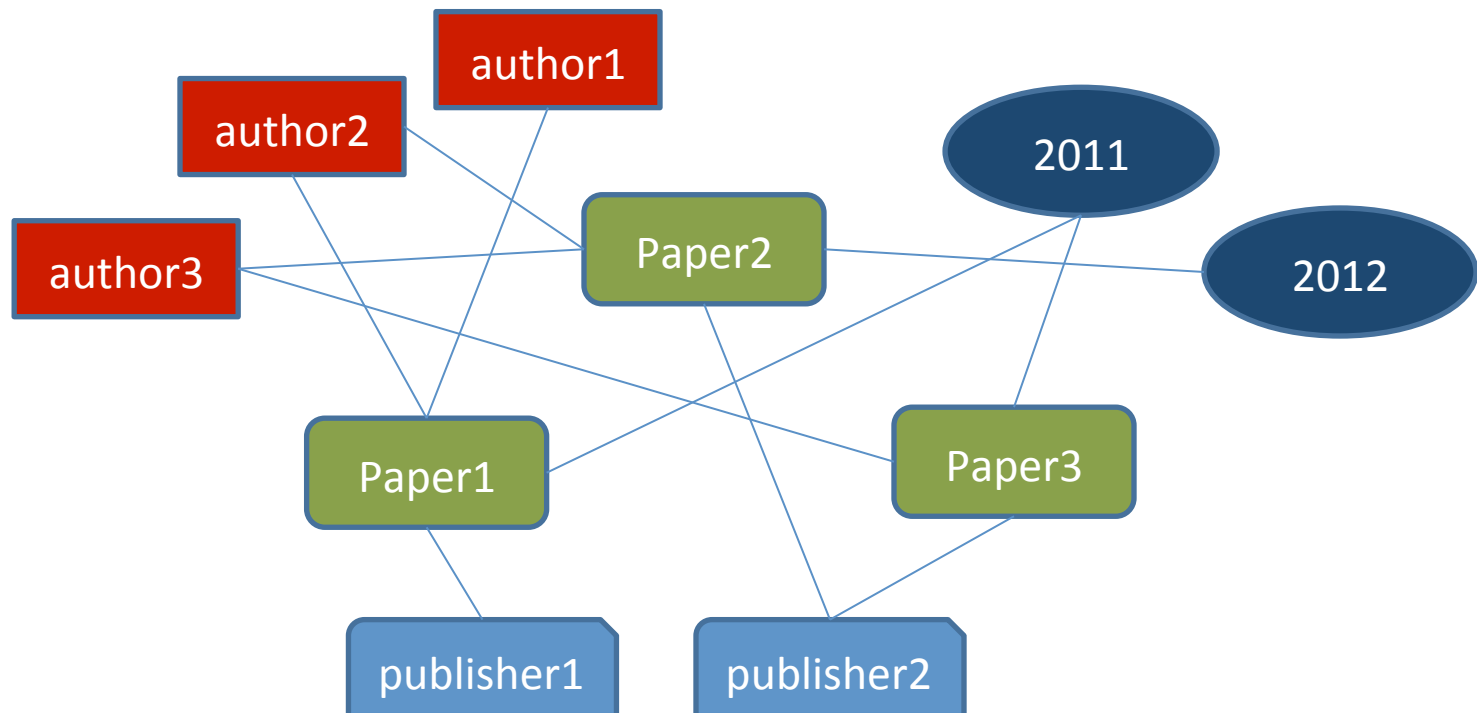
a DBLP mirror with extended search capabilities maintained by [Hannah Bast](#), [University of Freiburg](#) (formerly [MPII Saarbrücken](#))

zoomed in on 283 documents ... NEW: get these search results as [XML](#), [JSON](#), [JSONP](#)

2014		
283	EE	<a href="#">Joshua Tan</a> , <a href="#">Khanh Nguyen</a> , <a href="#">Michael Theodorides</a> , <a href="#">Heidi Negrón-Arroyo</a> , <a href="#">Christopher Thompson</a> , <a href="#">Serge Egelman</a> , <a href="#">David Wagner</a> : The effect of developer-specified explanations for permission requests on smartphone user behavior. <a href="#">CHI 2014:91-100</a>
282	EE	<a href="#">Alexander Richter</a> , <a href="#">David Wagner</a> : Leadership 2.0: Engaging and Supporting Leaders in the Transition towards a Networked Organization. <a href="#">HICSS 2014:574-583</a>
2013		
281	EE	<a href="#">Charles E. Robertson</a> , <a href="#">J. Kirk Harris</a> , <a href="#">Brandie D. Wagner</a> , <a href="#">David Granger</a> , <a href="#">Kathy Browne</a> , <a href="#">Beth Tatem</a> , <a href="#">Leah M. Feazel</a> , <a href="#">Kristin Park</a> , <a href="#">Norman R. Pace</a> , <a href="#">Daniel N. Frank</a> : Explicit: graphical user interface software for metadata-driven management, analysis and visualization of microbiome data. <a href="#">Bioinformatics 29(23):3100-3101 (2013)</a>

# Meta-data for DO

- Authors, key words, publisher, year
- Given papers {Paper1} {Paper2} {Paper3}
  - P1: author1, author2, publisher 1, 2011, {keywords}
  - P2: author2, author3, publisher 2, 2012, {keywords}
  - P3: author 3, publisher 2, 2011, {keywords}
- The resulting network through the meta-data:



# Requirement Specification

- Undirected crawling or normal search engine not sufficient:
  - Results un-organized
  - Little specialization
  - Ambiguity
  - Relations and connections not available



# Requirement Specification

## What's available

Google

epidemiology

Scholar

About 2,020,000 results (0.06 sec)

Articles

Case law

My library

Any time

Since 2014

Since 2013

Since 2010

Custom range...

Sort by relevance

Sort by date

include patents

include citations

Create alert

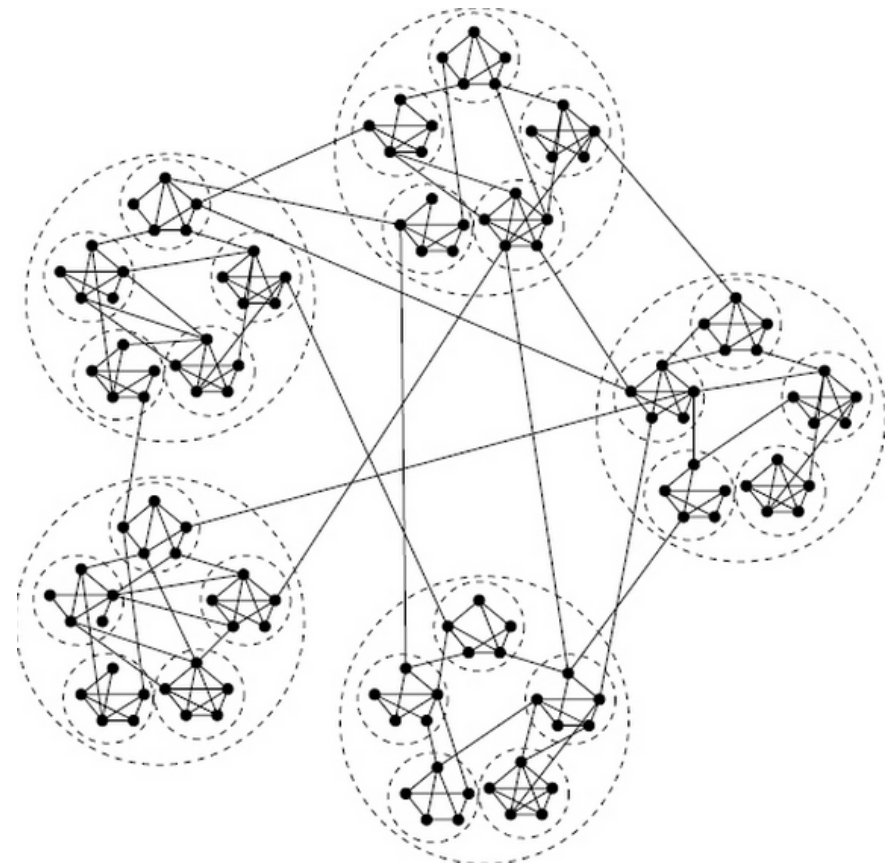
[Marginal structural models and causal inference in epidem](#)  
[JM Robins, MA Hernan, B Brumback - Epidemiology, 2000 - journals](#)  
Abstract In observational studies with exposures or treatments that va  
approaches for adjustment of confounding are biased when there exist  
confounders that are also affected by previous treatment. This paper ir  
Cited by 1294 Related articles All 20 versions Web of Science: 81

[PDF] [Dose-response and trend analysis in epidemiology: ;](#)  
[S Greenland - Epidemiology, 1995 - JSTOR](#)  
Standard categorical analysis is based on an unrealistic model for dos  
trends and does not make efficient use of within-category information.  
two classes of simple alternatives that can be implemented with any r  
Cited by 701 Related articles All 4 versions Web of Science: 555

[book] [A dictionary of epidemiology](#)  
[JM Last, International Epidemiological Association - 2001 - Oxford Un](#)  
Over 100 epidemiologists from all over the world have contributed sugg  
definitions to A Dictionary of **Epidemiology**, edited by John M. Last. I  
the second edition was published by Oxford University Press in 1988,  
Cited by 4474 Related articles All 7 versions Cite Save More

[book] [Clinical epidemiology: a basic science for clinical n](#)  
[DL Sackett, RB Haynes, P Tugwell - 1985 - cabdirect.org](#)  
Abstract This book is written by three clinical epidemiologists from Mc  
Ontario, Canada. It reflects their desire to apply the principles of popul  
the care of individual patients. The book is therefore not intended to be  
Cited by 5165 Related articles All 4 versions Cite Save More

## What we want



# Related Work

- Web crawling topics
  - Building efficient, robust and scalable crawler
  - Traversal order of the web graph
  - Re-visitation of previously crawled content
  - Avoid problematic and undesirable content
  - Crawling “deep web” content

Christopher Olston and Marc Najork. 2010. Web Crawling. *Found. Trends Inf. Retr.* 4, 3 (March 2010), 175-246.

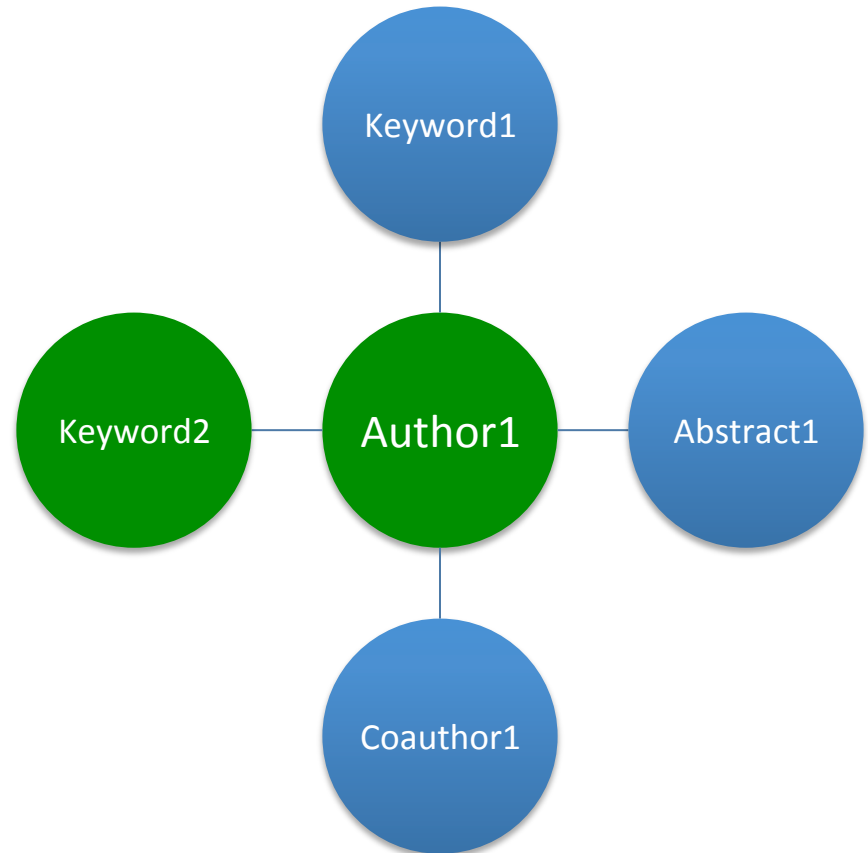
# Why can a human do this better?

A user is interested in “Disease propagation”

1. Set  $N = \{\text{Disease propagation}\}$
2. Search using  $N$  and gets  $R$
3. Splits  $R$  into  $A$  and  $B$
4. Selects  $A$  as relevant; extracts terms and connections; augments  $N$
5. Ignores or stashes away  $B$
6. Repeat from 1 with updated network  $N$

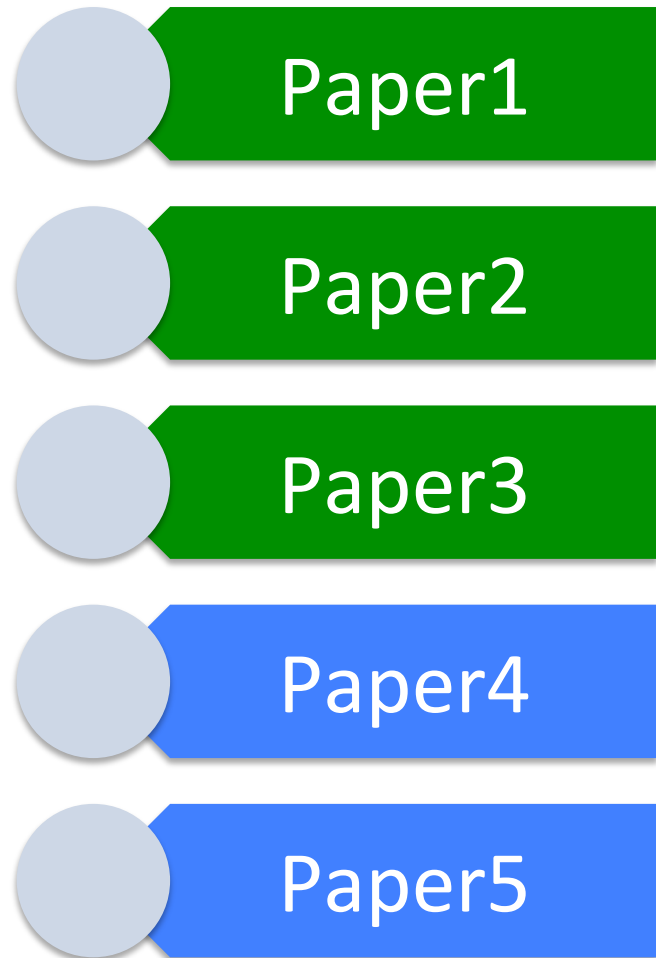
# Desired Property 1: Connected Growth

- A relevant paper shares nodes and edges in the network N
- Not all of the paper becomes relevant at once
- What is shared changes over time



# Desired Property 2: Grouping

- Only a small fraction of a document is shared with network N
- The rest is used to group papers

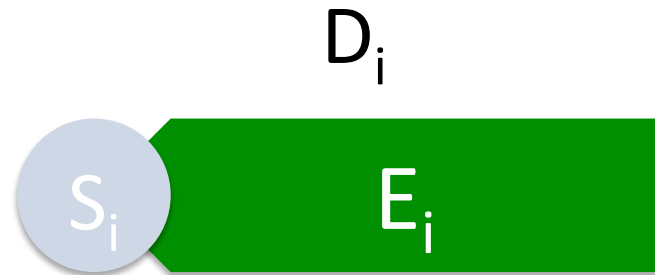


# Modeling: Digital Object

- Is represented as a set of edges
  - $D_i = \{(x_1, y_1), \dots, (x_n, y_n)\}$
- Connections are determined by predicates over kind of vertex
  - $(x, y)$ : Paper  $p$ , authored by  $x$ , is published in  $y$
- From a generative point-of-view, an edge in a paper comes from
  - A shared network
  - Or, a local network

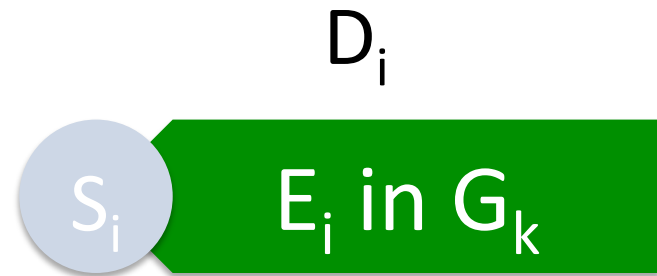
# Modeling: Split-View of Digital Object

- A paper's edges can be split into two parts
  - $D_i = S_i + E_i$
  - Shared set:  $S_i$
  - Local set:  $E_i$



# Modeling: Grouping

- Each  $D_i$  belongs to a group
- Groups are determined w.r.t. unshared edges  $E_i$
- No need to determine number of groups beforehand



$$P(k | \alpha) \prod_{(x,y) \in E_i} P(x,y | G_k)$$



# Modeling: Network

- Connectivity
  - Allow  $(x,y)$  only if  $x$  is reachable from root nodes
- Smoothness
  - Allow  $(x,y)$  only if path connecting to  $x$  from root has decreasing weights

Edge is either shared or local based on

$$\operatorname{argmax}_{\varepsilon \in \{N, G_k\}} P(x, y | \varepsilon)$$

satisfying connectivity and smoothness constraints when shared.

# The Entire Process

## Model

1. Start with root nodes, e.g., “Disease propagation” in N
2. Generate search query from N
3. Crawl and add new digital objects
4. Learn random variables for sharing ( $S_i$ ,  $E_i$ ) and grouping ( $G_i$ )
5. Goto step 2

## Human

1. Set  $N = \{\text{Disease propagation}\}$
2. Search using N and gets R
3. Splits R into A and B
4. Selects A as relevant; extracts terms and connections; augments N
5. Ignores or stashes away B
6. Repeat from 1 with updated network N

# Evaluation: Against a Search Engine

- **Goal:** Relevance
- Set a starting topic
- Perform  $k$  related queries
  - Let  $R_i$  be the sets of query results ranked by the search engine
  - Learn network  $N$
  - For each paper  $p$  selected by  $N$ 
    - Get best rank of  $p$  according to  $R_i$
  - Compare ranks against relevance determined by  $N$
- Are there lowly ranked results that are higher in  $N$  and vice versa?

# Evaluation: Against a Digital Library

- **Goal:** Completeness
- Pick a digital library for digital objects with a categorical browsing service
- Pick a starting point
  - Learn network N
  - Evaluate completeness of network N against the digital library

Thank You!

Questions?