Scholarly Big Data: CiteSeerX Insights

C. Lee Giles
The Pennsylvania State University

University Park, PA, USA

giles@ist.psu.edu

http://clgiles.ist.psu.edu

Funded in part by NSF & Qatar.

Contributors/Collaborators: recent past and present (incomplete list)

Projects: CiteSeer, CiteSeer^X, Chem_XSeer, ArchSeer, CollabSeer, GrantSeer, SeerSeer, RefSeer, CSSeer, AlgoSeer, AckSeer, BotSeer, YouSeer, ...

P. Mitra, V. Bhatnagar, L. Bolelli, J. Carroll, I. Councill, F. Fonseca, J. Jansen, D. Lee, W-C. Lee, H. Li, J. Li, E. Manavoglu, A. Sivasubramaniam, P. Teregowda, J. Yen, H. Zha, S. Zheng, D. Zhou, Z. Zhuang, J. Stribling, D. Karger, S. Lawrence, K. Bollacker, D. Pennock, J. Gray, G. Flake, S. Debnath, H. Han, D. Pavlov, E. Fox, M. Gori, E. Blanzieri, M. Marchese, N. Shadbolt, I. Cox, S. Gauch, A. Bernstein, L. Cassel, M-Y. Kan, X. Lu, Y. Liu, A. Jaiswal, K. Bai, B. Sun, Y. Sung, Y. Song, J. Z. Wang, K. Mueller, J.Kubicki, B. Garrison, J. Bandstra, Q. Tan, J. Fernandez, P. Treeratpituk, W. Brouwer, U. Farooq, J. Huang, M. Khabsa, M. Halm, B. Urgaonkar, Q. He, D. Kifer, J. Pei, S. Das, S. Kataria, D. Yuan, S. Choudhury, H-H. Chen, N. Li, D. Miller, A. Kirk, W. Huang, S. Carman, J. Wu, L. Rokach, C. Caragea, K. Williams. Z. Wu, S. Das, A. Ororbia, others.

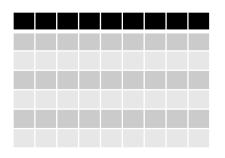
What is Scholarly Big Data

All academic/research documents (journal & conference papers, books, theses, TRs)

- Related data:
 - Academic/researcher/group/lab web homepages
 - Funding agency and organization grants, records, reports
 - Research laboratories reports
 - Patents
 - Associated data
 - presentations
 - experimental data (very large)
 - video
 - course materials
 - other
 - Social networks
- Examples: Google Scholar, Microsoft Academic Search,
 Publishers/repositories, CiteSeer, ArnetMiner, Funding agencies,
 Universities, Mendeley, others

Scholarly Big Data

Most of the data that is available in the era of scholarly big data does not look like this

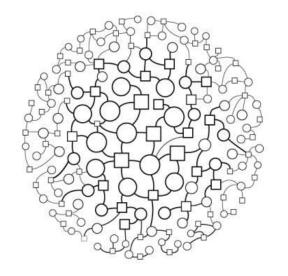


Or even like this



It looks more like this

Courtesy Lise Getoor NIPS'12



Where do you get this data?

- Web (Wayback machine, Heritrix)
- Repositories (arXiv, CiteSeer)
- Bibliographic resources (PubMed, DBLP)
- Funding sources/laboratories
- Publishers
- Data aggregators (Web of science)
- Patents
- API's (Microsoft Academic)

How much is there & how much freely available?

Estimate of Scholarly Big Data

- Use two public academic search engines
 - estimate the size of scholarly articles on the web using capture/recapture (Lincoln Petersen) methods
 - Google Scholar
 - Microsoft Academic Search
- Find a paper that both search engines have
- Extract the list of citations for that paper in both search engines and compare overlap
- The list of citations for a paper is representative of the coverage of a search engine
- Using the size of one of the search engines, estimate the total size on the web
- Limit to English articles only

Consider the web page coverage of search engines a and b

- p_a probability that engine a has indexed a page, p_b for engine b, $p_{a,b}$ joint probability $p_{a,b} = p_{a|b} p_b \ge p_a p_b$
- s_a number of unique pages indexed by engine a; N number of web pages

$$p_a = \frac{S_a}{N} \qquad \frac{S_{a,b}}{N} \ge \frac{S_a}{N} \frac{S_b}{N} \qquad N \ge S_a \frac{S_b}{S_{a,b}}$$

- n_b number of documents returned by b for a query, $n_{a,b}$ number of documents returned by both engines a&b for a query $\left\langle \frac{s_b}{s_{a,b}} \right\rangle \cong \left\langle \frac{n_b}{n_{a,b}} \right\rangle$

Lower bound estimate of size of the Web:

$$\hat{N} \ge s_{a_o} \left\langle \frac{n_b}{n_{a,b}} \right\rangle_{aueries}; s_{a_o} known$$

- random sampling assumption
- extensions bayesian estimate, more engines (Bharat, Broder, WWW7 '98), etc.

Freely available by scholarly field

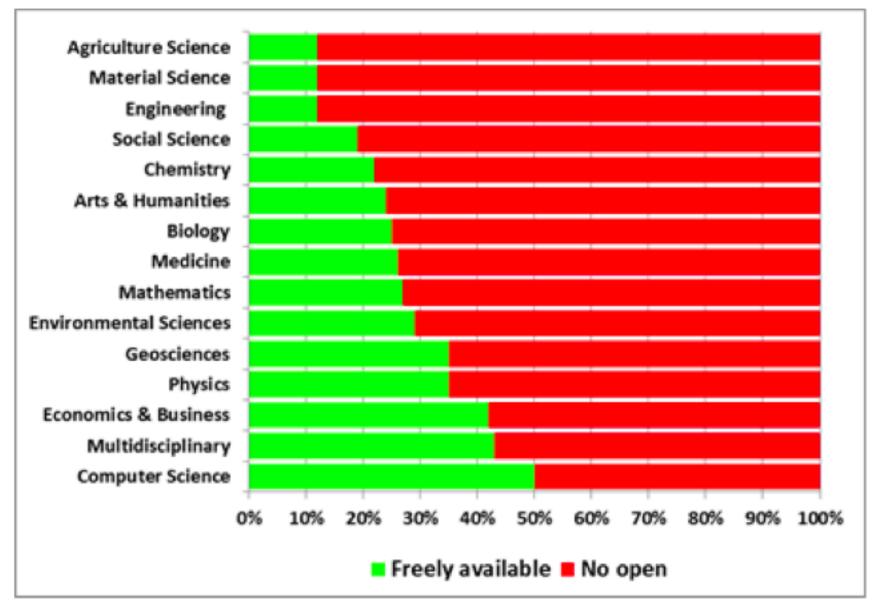


Figure 4. Percentage of publicly available documents according to scientific fields

Data source: re-elaborated from Khabsa & Giles (2014)

Lower bound on potential sources of scholarly data

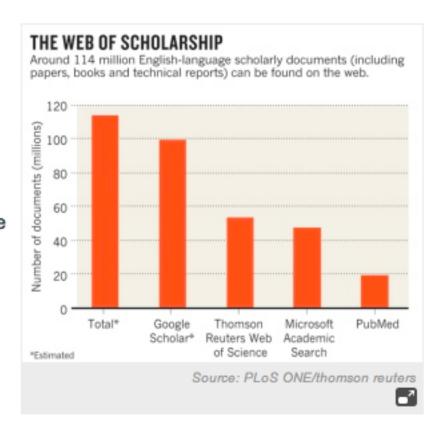
- At least 114 million scholarly articles available on the web
- At least 24% of them are publicly available
 - 27 million
 - Varies significantly based on academic field
 - Computer science!
- Google Scholar has nearly 100 million articles
- Other things to do:
 - Distinguish between publication types: paper, thesis, tech report, etc
 - More estimates
 - Longitudinal and geographical study
 - Duplicates
 - Languages besides english



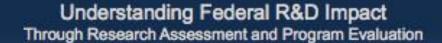
Seven days: 16-22 May 2014

TREND WATCH

The academic search engine Google Scholar can find about 88% of all Englishlanguage scholarly documents on the World Wide Web, according to an estimate by computer scientists Lee Giles and Madian Khabsa at Pennsylvania State University in University Park (M. Khabsa and C. L. Giles *PLoS ONE* **9**, e93949; 2014). The duo studied the coverage of Google Scholar and a competitor. Microsoft Academic Search, At least 24% of documents are freely available, they add. See go.nature.com/matsio for more.



IARPA FUSE Program



Panel: Increasing Research Impact Through Effective Planning and Evaluation

OFFICE OF THE DIRECTOR OF NATIONAL INTELLIGENCE

Finding Patterns of Emergence in Science and Technology – Evaluation Implications

Foresight and Understanding from Scientific Exposition (FUSE)

L . A D . N G . I N T . L L L G . N C . I N T . G . A T . O . N

Dewey Murdick, Program Manager Office of Incisive Analysis, IARPA 19 March 2013

INTELLIGENCE ADVANCED RESEARCH PROJECTS ACTIVITY (IARPA)

IARPA FUSE Program



OFFICE OF THE DIRECTOR OF NATIONAL INTELLIGENCE



Goal: Validated, early detection of technical emergence

Enable reliable, early detection of emerging scientific and technical capabilities across disciplines and languages found within the full-text content of scientific, technical, and patent literature

Special focus from the outset on multiple languages

Novelty

→ Discover <u>patterns</u> of emergence and <u>connections</u> between technical concepts at a speed, scale, and comprehensiveness that exceeds human capacity

Usage

Alert analyst of emerging technical areas with sufficient explanatory evidence to support further exploration

SeerSuite Toolkit & Applications

- SeerSuite: open source search engine and digital library tool kit used to build academic search engines/digital libraries
 - CiteSeer^X, Chem_XSeer, AckSeer, CSSeer, CollabSeer, RefSeer, etc.
 - Built on commercial grade open source tools (Solr/Lucene; mySQL)
 - Our features automated specialized metadata extraction
- Information extraction tools for PDF documents
 - Authors, titles, affiliations, citations, acknowledgements, etc
 - Entity disambiguation
 - Tabular data
 - Figures & graphs
 - Chemical formulae
 - Equations
 - Author ethnicity detection

Wu, IAAI 2014

Teregowda, IC2E 2013

Teregowda, USENIX 2010

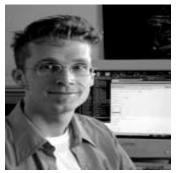
- Data and search built on top of these
 - CiteSeerX open source Google Scholar (ScholarSeer)
 - ChemXSeer chemical search engine
 - RefSeer citation recommendation system
 - CSSeer expert recommendations
 - CollabSeer- collaboration recommendation
 - AckSeer acknowledgement search
 - ArchSeer archaeology map search

CiteSeer (aka ResearchIndex)

- Project of NEC Research Institute
- Hosted at Princeton, from 1997 2004
- Moved to Penn State after collaborators left NEC
- Provided a broad range of unique services including
 - Automatic metadata extraction
 - Autonomous citation indexing
 - Reference linking
 - Full text indexing
 - Similar documents listing
 - Several other pioneering features
- Impact
 - First scholarly search engine?
 - Changed access to scientific research
 - Shares code and data



C. Lee Giles

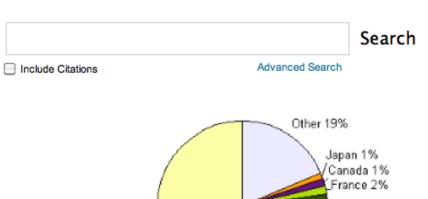


Kurt Bollacker

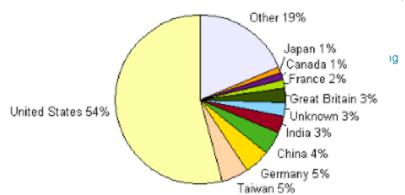


Steve Lawrence

- CiteSeer^X *actively* crawls researcher homepages & archives on the web for scholarly papers, formerly in computer science
 - Converts PDF to text
 - Automatically extracts and tags OAI metadata and other data
 - Automatic citation indexing, links to cited documents, creation of document page, author disambiguation
 - Software open source can be used to build other such tools
 - All data shared
- •5+ M documents
- Ms of files
- •87 M citations
- •12 M authors
 - •1.3 M disambig
- •2 to 4 M hits day
- 100K documents added monthly
- 300K document downloaded monthly
- •800K individual users
- ~40 Tbytes







Focused Crawling – getting the documents

- Maintain a list of parent URLs where documents were previously found
 - Parent URLs are usually academic homepages.
 - >1,000,000 unique parent URLs, as of summer 2013
 - Parent URLs are stored in a database
 - Crawled weekly.
- Crawling process starts with the scheduler selecting all parent URLs
- Crawling batch with Heritrix
 - Most discovered documents have been crawled before.
 - Use hash table comparison for detection of new documents
 - Normally retrieve a 10K NEW documents per day, sometimes less than 1K.
- Very ethical crawler
 - Use whitelist and blacklist policy.

Highlights of AI/ML Technologies in CiteSeerX

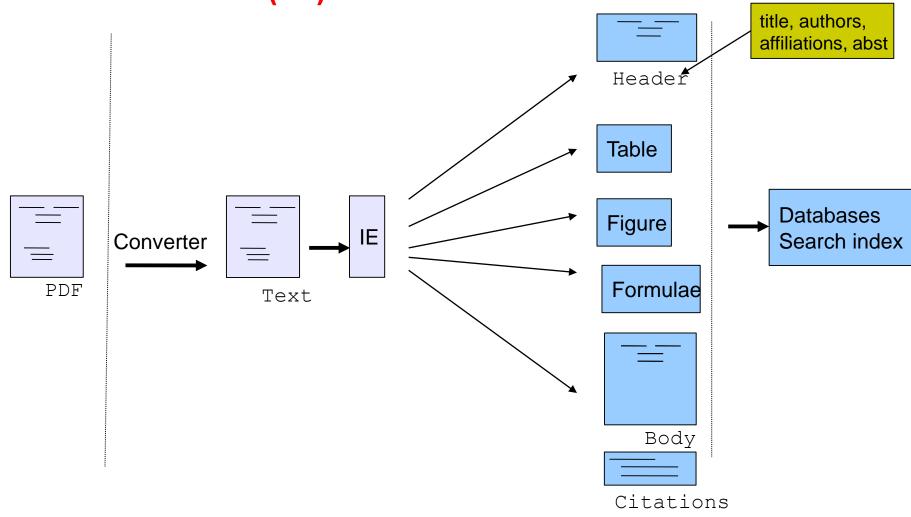
- Document Classification
- Document Deduplication and Citation Graph
- Metadata Extraction
 - Header Extraction

·

Wu, et.al IAAI 2014

- Citation Extraction
- Table Extraction
- Figure Extraction
- Author Disambiguation

Automatic Metadata Information Extraction (IE) - CiteSeerX



Other open source academic document metadata extractors available – workshop, metadata hackathon,

TableSeer

Liu. et al. AAAI07, JCDL06.

Table extraction & search engine

Table Caption

Advanced

search

Found 25 results for query "TableCaption : flow "

Instituto de Qu mica, Universidade Federal da Bahia, Salvador-BA 40170-290, Brazil d Departamento de Qu mica Analitica, Universidad de Valencia, Dr. Moliner 50, 46100 Burjassot, Valencia, Spain. E-mail: miguel.delaguardia@uv.es '- 'Analyst '- '2000

In PAGE 1, LINE 78:Table 1 Flow analysis determination of sulfide using the MB method.....;

PDF

Preview

Table 1 Comparative results for the determination of morphine in processliquors with chemiluminescence detection using pulsed flow chemistry(PFC) and conventional flow injection analysis (FIA) methodology

Pulsed flow chemistry: a new approach to solution handling for flow analysis coupled with chemiluminescence detection

Simon W. Lewis,* a Paul S. Francis, a Kieran F. Lim, a Graeme E. Jenkins b and Xue D. Wang c a Centre for Chiral and Molecular Technologies, School of Biological and Chemical Sciences, Deakin University, Geelong, Victoria 3217, Australia b Precision Devices P/L, 44 Nelson Street, Shoreham, Victoria 3916, Australia c School of Chemical and Biomedical Sciences, Central Queensland University, Rockhampton, Queensland 4702, Australia '- 'Analyst '- '2000

Preview

(stopped-flow) analysis mode, measuring peak area. Although the calibration appear at linear ($\pi/2 = 0.9898$), 4 kg dog plot of signal area. www.comeontrollion revealed non-linear behaviour below 2.5 3 102 f M morphine. The purpose built pulsed flow che nihum resecuce instrument provided Light precision fless than 1% R&E), and a detection limit of 2 3 10% M. This was a significant improvement over the detection limit achieved. with the prototype instrument, and was comparable to those reported in stacies using conventional flow analysis under similar chemical conditions, $-^{o(n)}$ although the lowest reported limi, of detection for the determination of morphine with scidic potassium pernongrante was 1 - 3 - 10^{2 +1} M ⁵⁷

Analysis of princess samples

The feasibility of pulsed flow analysis as an alternative to existing flow based techniques used to industrial process. analysis was demonstrated with the analysis of pharmaceutical process samples using pulsed flow and conventional FIA. instrumentation, funder the same chemical conditions. Four process samples were taken randomly from an acceous fraction of an opiate extraction process. The determination of morphine in process samples using conventional PIA methodology has been previously demonstrated and validated against standard reversed-phase HPLC methodology. * Emission resulting from the reduction of the personganate ion by other alkalords present in the extract is negligible due to a fartistions combination of the inherent adeclicity of the light-producing reaction pulloway and the concentration levels of the alkalnids present in the samples, $^{\rm 19}$ Matrix effects unising from disactived solids and pH were minimized by manually filtering and a 1000 fold distilion. of the samples with the same polyphosphate solution that was used to prepare the permangarate reagent and anomorphine standards over the concentration range from 3.0 | 3 | 10 ** to 2.5 3 1025 M. The polsed flow instrument was operated in stopped-flow mode and the emission intensity was recorded for 60 s following the production of the mixed pulse. The ability to measure a for greater proportion of the chemilmonescence carriesion using the pulsted flow instrument in the stepperf-flow mode reversed subtle differences in reaction. Vinctics be ween the shadards and process samples, which were indefectable. with convertional flow analysis methodology. It is postulated that species such as the other alkaloids present in the process samples, that do not result in an intense emission on reaction. with permanganate, affect the rate of the light producing reaction. This effect in relation to flow, stopped-flow and batch

qualitative of samples from the extraction process is currently

Table 1 - Congunities results for the determination of morph appore was absorbed necessary detacken using paleted flow of P. CC) and conventional Commences analysis (PLA) inclode

		Constitution/ \mathbf{M}	
Process tweeter	7.A*	1987	— Proces (% Pc
	0.0188	0.0199	1.6
2	0.0129	0.0127	3.4
	0.0045	9.0044	3.3
4	6.0.19	0.4.35	1.6
Monwhale for h	res suphrate un	deno A Sic	cition sCt

serken.ce

consumption. The rapid and efficient mixing close pulsed flow charastry facilitates delivery of a checonce reaction mixture into the detector using a simanuscam solidans and enabling measurement period of meximum emission. The instrumentation versatile, with the rate of pulsing, solution ratios, a modes determined by software settings. The small of flie cobest propulsion device provide the pote: held instrucentation able to perform rapid, sensitichemitanines cence assays.

Acknowledgements

The author's express their gratitude to Associate F W. Barnett, Claire E. Leneban (Deakin University). Professor Robert W. Cattrall (La Probe Universit help and usoful advice during this project, the Sel-Biological and Chemical Sciences Workshop, Deversity, for assistance in instrumental configuration Mellow, blinders University, for Obrigation of the housing. Funding for the project was provided by Australian Research Control and an Australian Po Award (for PSP).

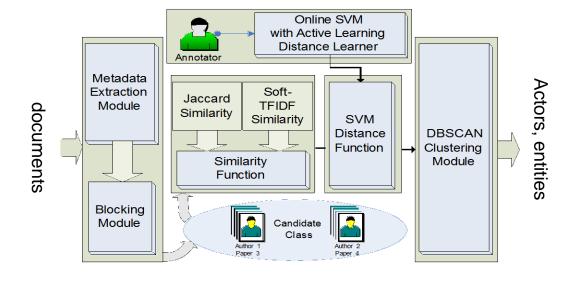
References

P. Baker, n. Charatery 2009, ed. C. O Chrod Land I.

Efficient Large Scale Author Disambiguation CiteSeer^X & PubMed

- Must scale!!
- Motivation
 - Correct attribution
- Manually curated databases still have errors – DBLP, medical records
- Entity disambiguation problem
 - Determine the real identity of the authors using metadata of the research papers, including co-authors, affiliation, physical address, email address, information from crawling such as host server, etc.
 - Entity normalization
- Challenges
 - Accuracy
 - Scalability
 - Expandability

Han, et.al JCDL 2004 Huang, et.al PKDD 2006 Treeratpituk, et.al JCDL 2009 Khabsa, et.al JCDL 2015



- Key features
 - Learn distance function
 - Random Forest
 - others
 - DBSCAN clustering
 - Ameliorate labeling inconsistency (transitivity problem)
 - Efficient solution to find name clusters
 - N logN scaling

Recently all of PubMed authors, 80M mentions

csseer.ist.psu.edu



Expert Recommender for Computer Science

Search for Experts in \$ Submit

Examples: information retrieval, data structure, database

Contact Us to Sponsor CSSeer

About CSSeer | Privacy Policy

© 2013 The Pennsylvania State University

Developed at and hosted by The College of Information Sciences and Technology at Penn State



Expert search for authors

H-H Chen, JCDL 2014



Search for experts in: information retrieval

Submit

Examples: operating system, database, nonparametric statistics

>> Related keyphrases

dirichlet-multinomial distribution vector space natural language processing information seeking

search engine chinese restaurant process document classification

natural language

digital library user profile decryption oracle

Information overload audio mining Information science world wide web

>> List of experts

W. Bruce Croft

Dept. of Computer Science, University of Massachusetts

2. Jamie Callan

Language Technologies Institute, School of Computer Science, Carnegie Mellon University

3. Alan F. Smeaton

Centre for Digital Video Processing

4. Eyal Kushilevitz

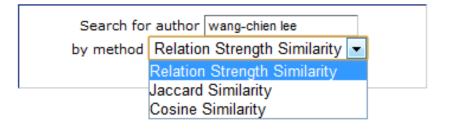
Computer Science Dept., Technion

5. Yuval Ishai

Computer Science Dept Technion

Experimental Collaborator recommendation system





Contact Us to Sponsor CollabSeer

About CollabSeer | Feedback | Privacy Policy

© 2010 The Pennsylvania State University

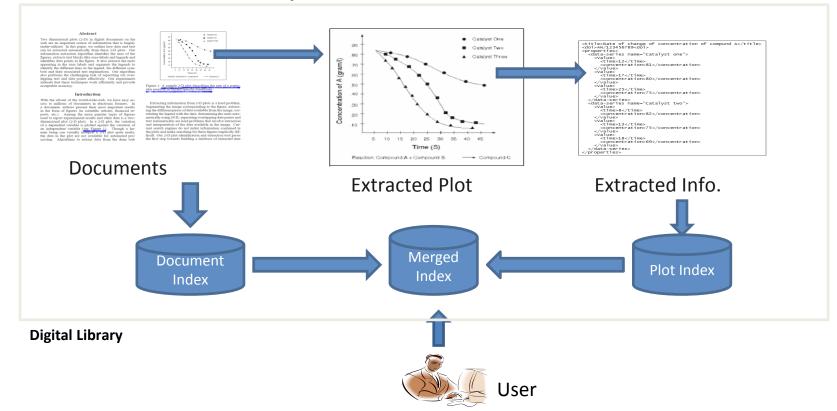
Developed at and hosted by The College of Information Sciences and Technology at Penn State



- CollabSeer currently supports 400k authors
- http://collabseer.ist.psu.edu

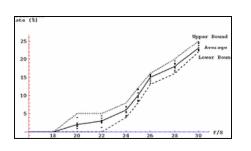
Automated Figure Data Extraction and Search

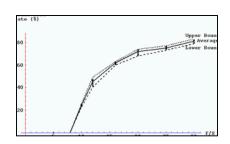
- Large amount of results in digital documents are recorded in figures, time series, experimental results (eg., NMR spectra, income growth)
- Extraction for purposes of:
 - Further modeling using presented data
 - Indexing, meta-data creation for storage & search on figures for data reuse
- Current extraction done manually!

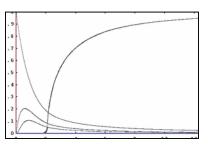


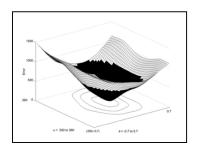
Chem_xSeer Figure/Plot Data Extraction and Search

Numerical data in scientific publications are often found in figures.









Tools that automate the data extraction from figures provide the following:

- Increases our understanding of key concepts of papers
- Provides data for automatic comparative analyses.
- Enables regeneration of figures in different contexts.
- Enables search for documents with figures containing specific experiment results.

X. Lu, et.al, JCDL 2006, Kataria, et.al, 2008 Choudhury, DocEng 2005

An Approach to Plot Data Extraction

- Identify and extract figures from digital documents
 - Ascii and image extraction (xpdf)
 - •OCR bit map, raster pdfs
- •Identify figures as images of 2D plots using SVM (Only for Bit map images)
 - Hough transform
 - Wavelets coefficients of image
 - Surrounding text features
- •Binarization of the 2D plots identified for preprocessing (No need for Vectorized Images)
 - Adaptive Thresholding
- Image segmentation to identify regions
 - Profiling or Image Signature
- Text block detection
 - Nearest Neighbor
- Data point detection
 - K-means Filtering
- Data point disambiguation for overlapping points
 - Simulated Annealing

Automatic Citation (or paper) Recommendation

Basic

Topic

Advanced



Built on top of millions of papers

Never miss a citation and know about the latest work

Several recommendations models

Huang, AAAI 2015 Huang, CIKM 2013 He, WWW 2010

O:1 - 1:	Recomme	1 - 4!	O
Citation	Recomme	naation	SVSTAN

	//
Recommend	

About RefSeerX

Feedback

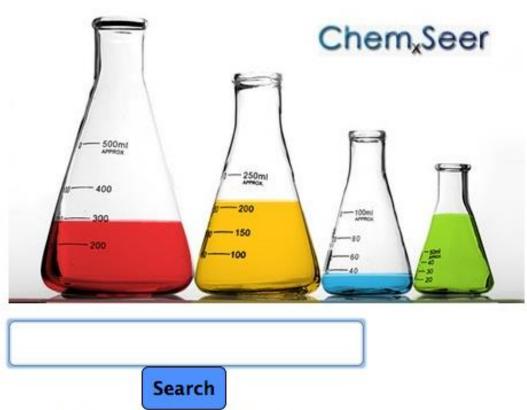
RefSeerX FAQ

Developed at and hosted by The College of Information Sciences and Technology

© 2012 The Pennsylvania State University

Chem_xSeer

Search Papers Authors Tables Figures Formula Extract Tables CollabSeer



Sun TOIS 2011

Eg: Methanol, CO2, Adam Smith

Scholarly Document Size & Numbers

- Large # of academic/research documents, all containing lots of data
 - Many millions of documents
 - 50M records Microsoft Academic (2013)
 - 25M records, 10 million authors, 3 times mentions PubMed
 - Google scholar (english) estimated to be ~100M records
 - Total online estimate ~120M records Khabsa, Giles, PLoSONE, '14
 - ~25 million full documents freely available
 - 100s of millions of authors, affiliations, locations, dates
 - Billions of citation mentions
 - 100s millions of tables, figures, math, formulae, etc.
 - Related & linked data
 - Raw data > petabytes

Challenges

- Tables, figures, formula, equations, methodologies, etc.
 - How do we effectively integrate and utilize this data for search?
 - Natural language generation?
- Ontologies for scholarly data
 - Scholarly "knowledge vault"
- "Big Mechanism" approaches

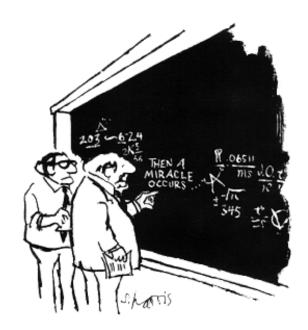
Summary/observations

- Scholarly big data petabytes, billions of objects
 - Rich content large related data
- Applications more common than most realize
 - Science, research, education, patents, policy, sociology, economics, business, MOOCs, etc
 - Growth of associated data: tables, figures, chemical & drug entities, equations, methodologies, slides, video, etc
- Many issues Al and ML very useful:
 - Focused NLP
 - Information extraction still an art; domain dependent
 - Data is not always easy to move around or share
 - Some data still not readily available but is changing ¼ of all digital documents freely available
 - Data(s) integration issues
 - Meta analysis "big mechanism" opportunties
- Observations
 - Large amount and growing scholarly related data
 - Big scholarly data creates new research opportunities
 - Big scholarly data creates other big data

"The future ain't what it used to be." Yogi Berra, catcher, NY Yankees.

For more information

- clgiles.ist.psu.edu
- giles@ist.psu.edu
- SourceForge.com



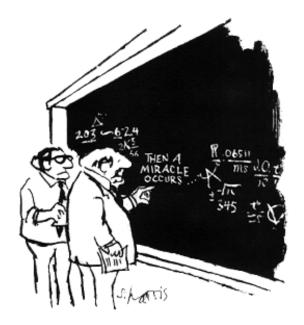
"I think you should be more explicit here in step two."

"Online or invisible," *Nature,* '01, Steve Lawrence, Google Desktop creator

"5 times more likely to be cited if your paper is freely available online"

For more information

- http://clgiles.ist.psu.edu
 - Most of our papers
- giles@ist.psu.edu
- SourceForge.com (github)



"I think you should be more explicit here in step two."