Responsible Computing with Social Data: Bias Detection, Theory Validation, and Impact Assessment

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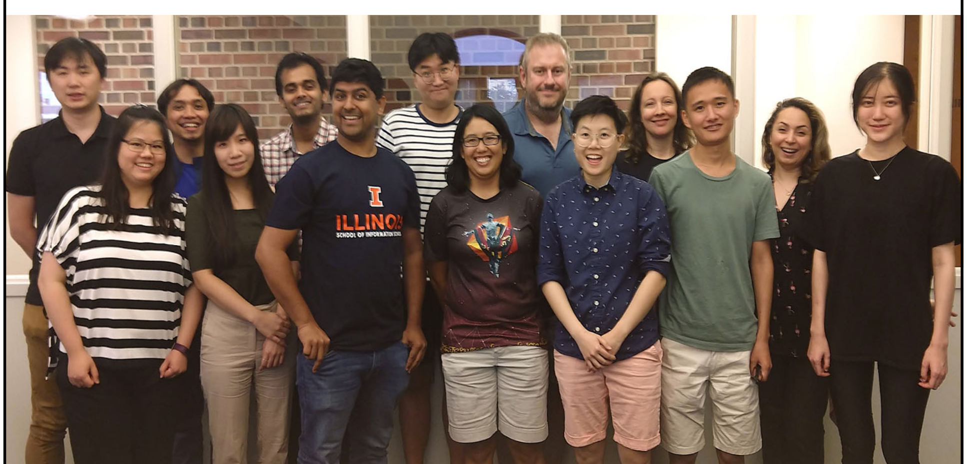
Thank you, Social Computing Lab members!



Pingjing Yang, Chieh-Li Chin, Nikolaus Parulian, KeRou Wang, Apratim Mishra, Shubhanshu Mishra, Jaihyun Park, Janina Sarol, Craig Evans, Ly Ding, Kanyao Han, Shadi Rezapour, Lan Jiang

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Social Computing – a popular field with many practical applications

- Detection and mitigation of misinformation, disinformation, toxic language, polarization
- Recommender systems (if person A is interested in X (product, article, …), suggest items for A that other people who also read/ bought/ reacted to X also considered)
- Contagion of happiness, health habits, etc. in social networks
- Goal for today: give you an overview of a small portion of the knowledge and skills you can learn as a student through courses and research experiences at the iSchool at Illinois

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Research focus of the Social Computing Lab

WHAT are we doing?

- Use computational methods to analyze human-centered data (at any scale) to discover, explain, model and predict **social behavior.**
- Basic and applied research that considers **ethical and regulatory concerns**, and **culture and social contexts.**
- Solve real-world problems, work with other domain experts and laymen, have real-world impact.

HOW are we doing that?

1. **Mixed methods** to make sense of sparse, human-centered, distributed, multi-modal data
2. Theories from social sciences **combined with** methods from **ML, AI,** &:
   - **Natural Language Processing** (NLP) -> study information-based systems
   - Network **analysis** -> study interaction-based systems

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Research focus:
Computational Social Science: WHY?

1. **Quality**: How do **limitations** of data, methods, and human choices **impact** and **bias** understanding of socio-technical systems?
2. **Validity**: Are **social science theories** valid in contemporary settings?
3. **Responsibility, societal aspects of DS+AI**: How can we improve and govern the FATE (fairness, accountability, transparency, ethics) of computing?
4. **Impact**: How can we assess the **impact** of information and science on people, groups, and society?

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Two kinds of biases

Biases in people

- ❤ **Different** from personal points of view, preferences, culture
- **People** -> internet, IoTs as sensors -> models -> tools that have and/ or reveal biases
- Role of **computing as messenger**: detect, explain, mitigate -> manage reputation
- Social Computing to differentiate between biases (+ solutions to mitigate them) versus differences

Biases in computing and science

- **Humans** (researchers, data scientists, techies) have to make **decisions** about research design (data collection, algorithms, methods, tools, theories)
- Responsibility of computing (tools, services, workforce):
  - Trustworthy findings
  - Trained and diversified to spot & mitigate problems
  - Academia: education and outreach to wide set of partners (public, policy, journalists, …)

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Impact of data quality and measurement on implications for addressing gender biases

- 2015 note in Science: "… between 1779 and 2011, men cited their own papers **56 percent more** than did women. In the last two decades of data, men self-cited **70 percent more** than women." (Effect consistent across a variety of disciplines in JSTOR)
- Conclusion: encourage women to self-cite more
- Why?
- **Our Hypothesis:** Once we have **reliable data** and **measurements**, opportunity confounding factor of self-citation.

King, M. M., Bergstrom, C. T., Correll, S. J., Jacquet, J., & West, J. D. (2017). Men set their own cites high: Gender and self-citation across fields and over time. *Socius*, *3*, 2378023117738903.

Mishra, S., Fegley, B.D., Diesner, J., & Torvik, V.I. (2018). Self-citation is the hallmark of productive authors, of any gender. PLoS ONE, 13(9): e0195773

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Replication of original study

King et al. 2017

- 1.5M JSTOR papers
- **8.2M** citations, **0.7M** are self-citations (8.5%)
- Author name disambiguation: name matching

$$p = P(self\_citation | X^{author}_{source,target})$$

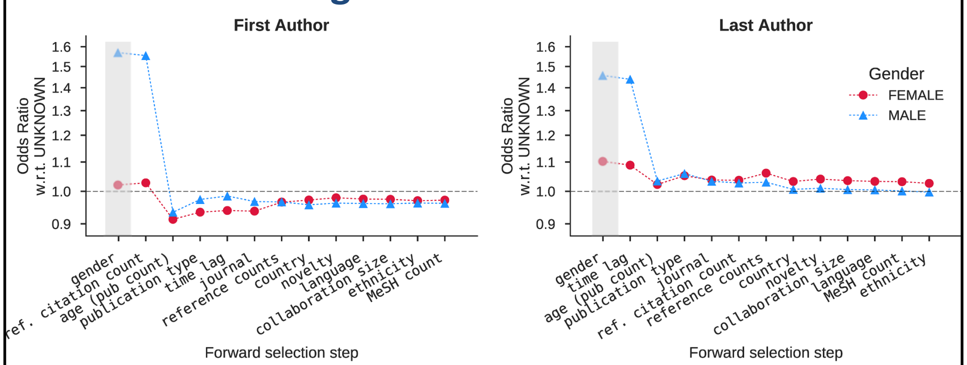
$$log\left(\frac{p}{1-p}\right) = \beta \cdot X^{author}_{source,target}$$

Effect sizes

Ours

- 1.6M PubMed papers, **41.6M** citations of which **5.5 million (13.2%)** are self-citations by at least one of the authors
- Authority tool for author **name disambiguation**
- **Men self-cite** 46% **more** often than women as first authors (5.79% vs. 3.95%), and 27% more often as last authors (9.93% vs. 7.83%)
- (King: men self-cite 56-70 % more than women)

Adding features to the model



- Forward feature selection: gender **weakest effect** on self-citation
- Prior citations of cited paper, time-lag between citing and cited paper, author's age (prior papers) make gender effect negligible
- Likely a case of **Simpson's paradox**

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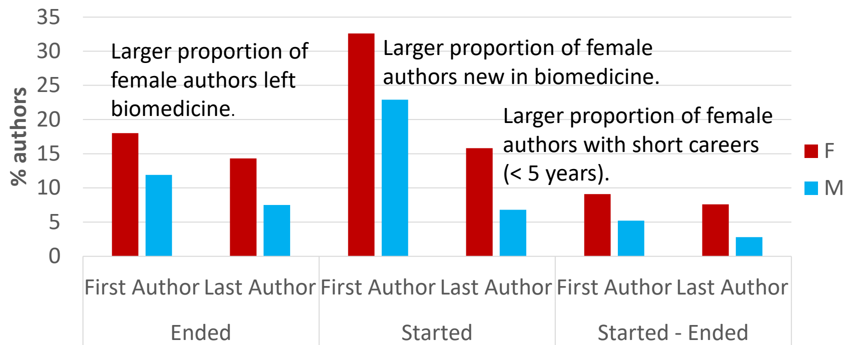
Finding the real culprit: Higher attrition of women



- Papers by authors with short, disrupted, or diverse careers miss out on initial boost in visibility due to self-citations, which **disproportionately affects women because of attrition,** not of disciplinary effects.
- Self-citation is the hallmark of productive authors, of any gender, who cite their novel journal publications early and in similar venues.
- Conclusion: Not to tell women to self cite more but to **retain women in the workforce.**

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Impact of data quality and measurement on social science theory

- **Merging/ consolidation**
  - Same entity, different ways to refer to it
  - Task: find all variations
  - Also known as co-reference resolution, record linkage
  - Also applies to other entity types (places, organizations, …)
- **Splitting**
  - Same spelling, different entities
  - howmanyofme.com:
    Stephen Downie: 9
    Mary Smith: 1265

Stephen Downie, UIUC

Stephen Downie, UIUC

Kim, J., & Diesner, J. (2015). Distortive effects of initial-based name disambiguation on measurements of large-scale coauthorship networks. Journal of Association for Information Science and Technology (JASIST), 67(6), 1446-1461.

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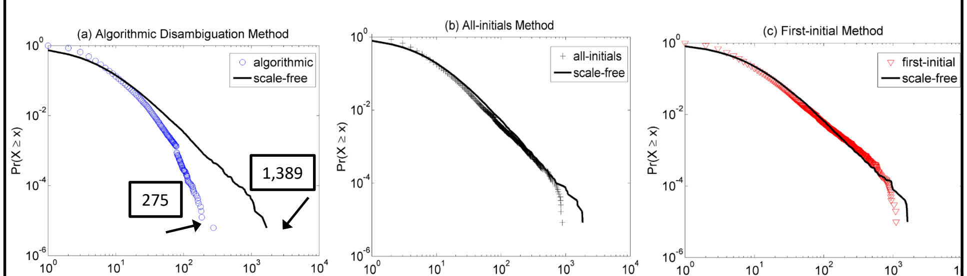
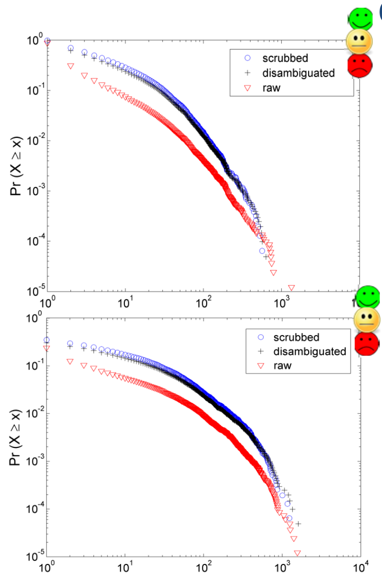
Can we confirm power-laws, which are an indicator of preferential attachment?

- >113K Info Science papers from 125 journals from 1984-2013
- Algorithmic disambiguation: 0.96 (K-metric), 0.97 (pairwise F1)

Disambiguation Method	# authors	# edges	Avg. degree
Algorithmic (John Stephen Downie)	160,349	443,500	5.53
All-initials (J. S. Downie)	120,052	433,564	7.22
First-initial (J. Downie)	101,003	421,815	8.35



What about organizational communication data?



Communication networks based on email networks:

- Half a million emails from over 3 years
- Corporate, internal communication
- Main challenge is merging (of email addresses) and deduplication of emails
- Results:
- Without proper disambiguation, network seems bigger, less coherent, less integrated
- May suggest false need for additional interaction and communication venues

Email data (left): log-log plot of node degree (in, out)

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Biased views of the science sector and applicable social science theories

- Robust findings across fields, countries, domains, time
- Scientific sector seems denser and more integrated and cohesive, and individual authors seem more productive, collaborative, diverse
- Network metrics, topologies, key players, explaining theories are wrong -> **preferential attachment ruled out**

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Quality: How do limitations of data, methods, and human choices impact and bias understanding of socio-technical systems?

- Other methodological choices tested:
  - Author name disambiguation
  - Entity resolution in text data
  - Linkage of entities in text data
  - Text summarization genres, methods, algorithms
- Sarol, J., Dinh, L., and Diesner, J. (2021). Variation in Situational Awareness Information due to Selection of Data Source, Summarization Method, and Method Implementation. Proceedings of International AAAI Conference on Web and Social Media (ICWSM). https://ojs.aaai.org/index.php/ICWSM/article/view/18087
- Kim, J., & Diesner, J. (2019). Formational bounds of link prediction in collaboration networks. Scientometrics. 431433:2v444<5034<0 3638809
- Diesner, J. (2015) Small decisions with big impact on data analytics. Big Data & Society, special issue on Assumptions of Sociality, 2(2). 43144::25386<84:4894:4;8

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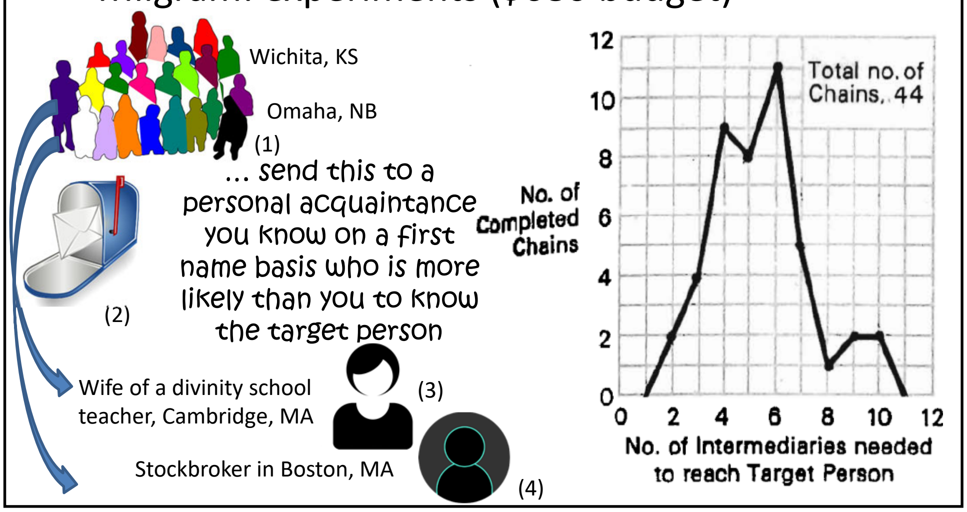
Developing and validating social science theories

- Milgram: experiments ($680 budget)



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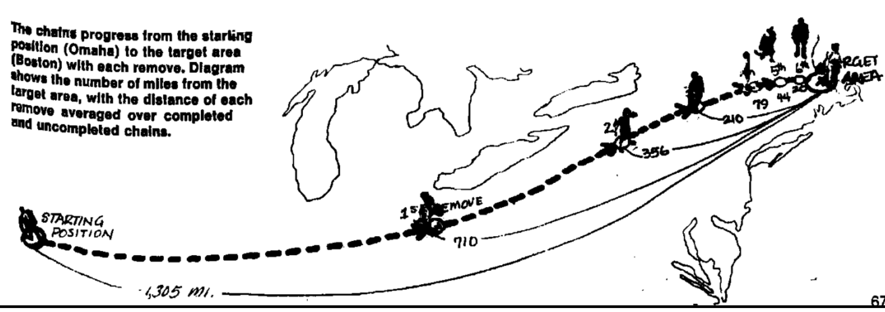
Developing and validating social science theories

- Findings:
  - Long distance bridged quicker than short distance
  - Restriction due to social distance > physical distance



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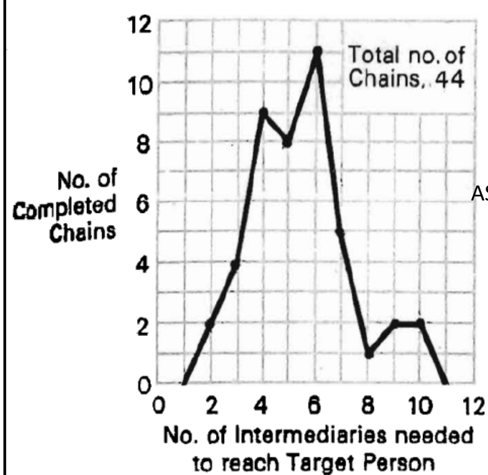
Developing and validating social science theories



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- Milgram: **6** degrees of separation (dos), average: **5.43**
- Replication studies:
  - Bakhshandeh et al., 2011: search on 1,500 random pairs chosen from Twitter: **3.43** dos
  - Backstrom et al., 2012: Facebook (721 million users, 69 billion links): **3.74** dos
- Why?

Milgram, Stanley. (1967). The Small World Problem, Psychology Today, 2: 60-67.

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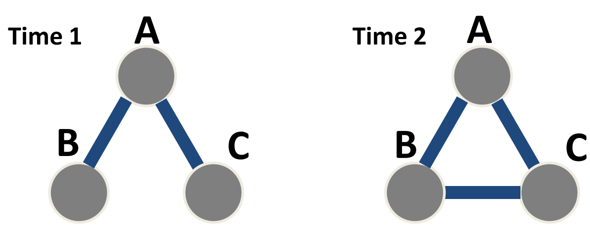
Validation of Triadic Closure Theory in contemporary setting



- Natural tendency of people in many context, also known as Clustering Coefficient, Transitivity (Rapoport 1953)
- Common effect: Computer Science (24-45%), Math (15%), Biomedicine (7%), Physics (43-72%), Slovenia (20%), Turkey (75%) (as per metric by Newman)
- Used for link prediction, recommender systems, etc.

Kim, J., & Diesner, J. (2017). Over-time measurement of triadic closure in coauthorship networks. Social Network Analysis and Mining, 7(9).

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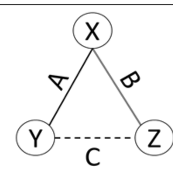
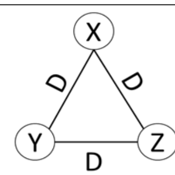
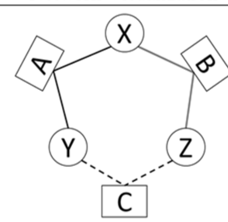
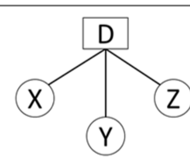
Operationalization of Triadic Closure: Newman's (2001) approach

- Newman's measure (a.k.a. clustering coefficient), a dominantly used approach, can include false positives

Case	Network Visualization
CASE 1) Paper A: author X and author Y Paper B: author X and author Z Paper C: author Y and author Z	
CASE 2) Paper D: author X, author Y, and author Z	

Alternative Operationalization: Opsahl (2013) Modeling papers as two-mode networks

Case	Network Visualization
CASE 1) Paper A: author X and author Y Paper B: author X and author Z Paper C: author Y and author Z	
CASE 2) Paper D: author X, author Y, and author Z	

Improved Measurement: Considering Time for Measuring Closure

- Starting point: two-mode network (Opsahl, 2013)
- Divide co-author network into two subsequent events:
  - Event 1 (e.g., 1990-1995): number of cases where X, Y and X, Z co-authored, but Y, Z did not (**possible TC**)
  - Event 2 (e.g., 1996): count number of cases where Y, Z co-authored (**realized TC**)
- Calculate: # cases in Event 2/# cases in Event 1
  - To reduce biases from time slicing, event 2 calculated for various time windows (1 to N years back)
    - E.g., for 1996, (1) 1995, (2) 1994~1995, (3) 1993~ 1995, (4) 1992~1995, etc.

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Data

- DBLP: Computer Science journals indexed by Thomson Reuters' Web of Science
- MEDLINE: journal papers with the MeSH term, "Brain"
- Only journal papers with no more than 14 coauthors considered

Dataset	Field	Period of Analysis	Number of Papers	Avg. Number of Authors per Paper
DBLP	Computer and Information Science	1991-2009	231,161	2.91
APS	Physics	1991-2009	241,329	3.80
MEDLINE	Biomedicine	1996-2009	302,293	4.91
KISTI	Domestic Publication in Korea	1991-2009	273,869	3.17

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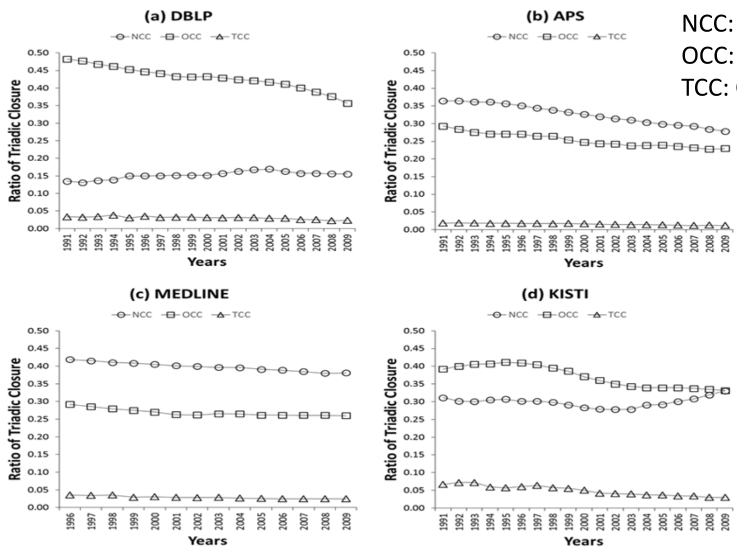
New method: search for open triads in year x, then search for closed triads in years x+n (n=5)



NCC: Newman 2001
OCC: Opsahl 2013
TCC: Ours 2017

Closure rates **1-3%** (lower bound) to **4-7%** (upper bound) (not 25-50%)

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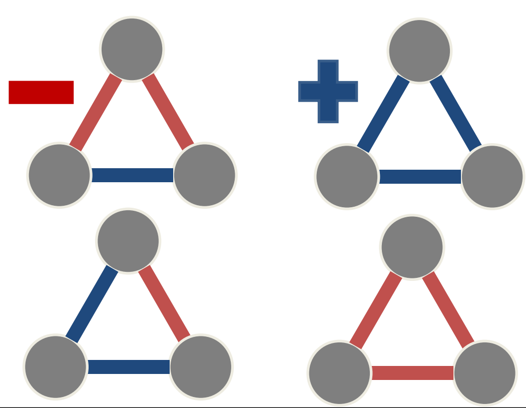
Validation of Triadic Closure Theory in contemporary setting

- Heider (1940): generalization of cognitive dissonance theory, extended by Cartwright and Harary (1956)
- A triad is balanced if its sign (product of signs) is positive



Balanced: no tension, stress, dissonance, change -> stable

Unbalanced: local process with global implications

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Problem 1: How to get signed graph data?

- Problem: data collection for signed graphs
  - Only 53% of friendship ties reciprocated (Almaatouq et al., 2016, PLOS ONE)
- Used NLP (domain-adjusted sentiment analysis) to infer edge sign from communication data, results:
  - Negative vocabulary more varied, used less often
  - Stable ratios of balance over time regardless of success and crisis (88%/12%)
  - Consider content and structure of interactions -> study interplay of information and social behavior
  - Remaining problem: directionality not considered in theory, but common in practice

Diesner, J., & Evans, C. (2015). Little bad concerns: Using sentiment analysis to assess structural balance in communication networks. ASONAM

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Problem 2: How to consider directionality?

Level	Our innovation	What it measures
Triad	New measure that considers directionality of transitive semicycles	Triadic balance
Sub-groups	New measure for subgrouping based on triad level assessment	Internal cohesion vs. external division of subgroups
Graph	Frustration index changed to consider directionality	Polarization

- Tested on empirical, temporal, multi-layer networks
- Balance ratio depends on level (different results for different levels), overall about 77-87%

Aref, S., **Dinh, L.,** Rezapour, R., & Diesner, J. (2020). Multilevel structural evaluation of signed directed social networks based on balance theory. Scientific Reports 10, 15228.

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Validity: Are social science theories valid in contemporary settings?

- Triad closure: confirmed, but to a MUCH lesser degree
- Structural balance: confirmed, shown not to be a binary feature
- Preferential attachment: not confirmed for scenarios tested (collaboration (co-authorship) and communication in academic and professional settings)
    - Kim, J., & Diesner, J. (2015). Distortive effects of initial-based name disambiguation on measurements of large-scale coauthorship networks. Journal of Association for Information Science and Technology (JASIST), 67(6), 1446-1461. grl=43143352dvl1567;<
    - Kim, J., & Diesner, J. (2015). The effect of data pre-processing on understanding the evolution of collaboration networks. Journal of Informetrics, 9(1), 226-236. 43143492mmr1153481341335

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Significance

- Changes in computation (metrics, compute power) help to test and adjust theories
- Collaborations with social scientists needed to find valid explanations for tie formation among coworkers
- Correcting misassumptions about social computing:
    - Big data fix quality issues (results more true and objective)
        - Closely interacting with data can help to move from precisely modeling and describing effects in society to also understand and explain them
    - Big data let us discover natural laws of social behavior
        - Context & culture impact design and generalizability
    - Social interactions are fuzzy, and so are the results
        - Our responsibility: rigorous, reliable, open research

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Responsible Social Computing Research: Exercise

- **News comments about crisis management:**
  A research team plans to scrape public posts from a news website to study people's opinion (sentiment, stance) about crisis management. They intend to hire crowd-workers to categorize the data. They plan to present their findings as aggregated statistics and to release their data on github to ensure reproducibility.
- **Your task:**
  – Write down **any potential issues** that the research teams needs to consider (3 minutes).

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Responsible Social Computing Research: Exercise

- **Data collection:** Terms of service, API available?, GDPR and other compliance requirements, personal identifiers, secure storage, intent, consent, profiling
- **Crowd-sourcing:** labor laws, fair payment
- **Data analysis:** biases
- **Sharing:** informed consent, re-identification, license

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Responsible Social Computing Research: Lots of thincs to consider

- Complex challenge with wide range of practical implication
- Data Governance: manage data throughout its full lifecycle

Regulations	Responsibilities	Quality	Usability	Availability
• Laws, policies, norms • Informed consent • Compli-ance	• Privacy • Security • Anonym-ity • Risk mana-gement • Reproducibility • FATE	• Integrity • Cleaning • Prove-nance • Curation • Biases	• Indexing, Storage, Retrieval • Documen-tation • Tech transition • Value	• Owner-ship • Intellectual pro-perty • Access • Licenses • Terms of use • Forgetting

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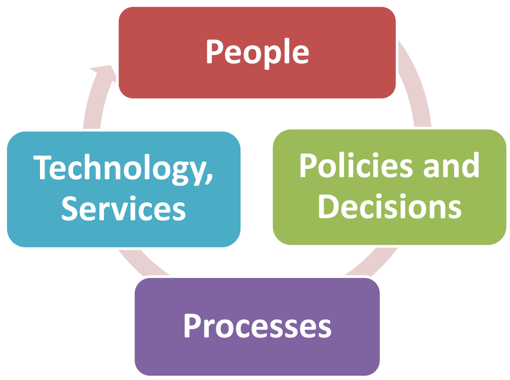
Data Governance



Application domains:

- Autonomous systems
- The future of work
- IoT
- Smart homes/ cities
- Human-machine Interfaces
- Cryptocurrencies
- ML and AI
- Etc.

- Processes: operationalize policy development, implementation, enforcement
- Tech and services: execute processes

V. Khatri, & Brown, C. V. (2010). Designing data governance. *Communications of the ACM, 53*(1), 148-152

Want to learn more? Public Speaker Series: Responsible Data Science and AI

- In this speaker series, we discuss topics such as equity, fairness, biases, ethics, and privacy.
- Presentations and discussions take place on Fridays, 9-10 am Central Time, on Zoom. Everyone is welcome to attend!
- This series is hosted by the Center for Informatics Research in Science and Scholarship (CIRSS) and supported by the School of Information Sciences at the University of Illinois at Urbana-Champaign.
- Access for everybody: https://jdiesnerlab.ischool.illinois.edu/responsible_ds_ai.html

Want to learn more?

- Courses at the School of Information Science at Illinois
  - Responsible Data Science and AI
  - Network Analysis
  - Data Governance
  - Social Computing
  - And many more from our amazing instructors!

Where do our students go?

- Master's students who worked in the Social Computing Lab:
  - T.L., MS Information Management, became a Software Engineer at Intuit (2020)
  - S.S., MS Information Management, became a Data Scientist for Walmart (2019)
  - H.K., MS Bioinformatics, became a high-performance computing Engineer for the National Center for Supercomputing Applications (2016)
- PhD students who worked in the Social Computing Lab:
  - Rezvaneh “Shadi” Rezapour, Assistant Professor, College of Computing and Informatics, Drexel University, Philadelphia, PA (2020)
  - Shubhanshu Mishra, Machine Learning Researcher at Twitter (2019)
  - Jinseok Kim, Assistant Research Professor (tenure track), University of Michigan, Ann Arbor (2017)

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How can we assess the impact of information and science on people, groups, and society?

- **What is Social Impact?**
  – Any cognitive, behavioral, emotional or cultural change in a person or a group (Latané, 1981)
- **Goal** of makers of information products (documentaries): storytelling (Rose 2012) vs. goal of funders: impact
- **Common approaches/ status quo:**
  – Frequency based metrics (screenings, viewers, mentions)
  – Small-scale, in-depth interviews with focus groups
  – Frameworks (theoretical, normative) (Clark & Abrash 2011)

DIMENSION	LEVEL		INDEX	ANALYTICS	ITEM
CONTENT	MESSAGE		Guiding Factor	Description Ranking weighing	Report by producers or funding agencies
	EXPECTED OUTCOME				
	EVALUATION PRIORITY				
	RESOURCE				
MEDIUM	RELEASE MEDIUM	OFFLINE	Outreach	Stats	Number of movies, CDs distributed Number of theatrical, Internet release Duration of release; Sales of product
		ONLINE			
	RESPONSIVE MEDIUM	MASS MEDIA	Mass Media Attention	Text Mining Web Analytics	Frequency of news coverage weighted by influence (article, opinion/editorial) Domestic, international broadcast
		USER MEDIA	User Media Attention	Text Mining Web Analytics Survey, Interview	Twitter, Facebook, Blogs, webpages Frequency of talking about, links included, user-created contents
		PROFESSIONAL MEDIA	Prestige		Number of festival acceptance Number of awards Number of professional reviews
		INTERPERSONAL INTERACTION	Intimate Attention		Conversation, talking on the phone or email, lectures, exchange of letters, etc.
TARGET	AUDIENCE SIZE		Reachability	Text Mining Web Analytics Archived Data Survey, Interview	Number of viewers or visitors
	HOMOGENEITY		Diversity		Geography & demography: location, age, gender, education, income
	AUDIENCE TYPE	SINKER	Passiveness	Text Mining Web Analytics Network Analysis	Number of inactive viewers
		TRANSMITTER	Leadership		Number of opinion leaders
	COLLECTIVE ENTITY		Advocacy	Text Mining Web Analytics Survey, Interview	Number of advocacy communities, colleges, schools, or NGOs
IMPACT	INDIVIDUAL / COMMUNAL / SOCIETAL / GLOBAL	COGNITIVE	Awareness	Stats, Text Mining Web Analytics, Network Analysis	Frequency of names, ideas, thoughts, or concepts appeared in corpus Report of increased awareness
		ATTITUDINAL	Sentiment	Sentiment Analysis	Frequency of positive, negative, neutral sentiments of comments Personal, critics, mass media, and organizational responses Reaction to calls for action
		BEHAVIORAL	Engagement Enactment Connectedness Capacity Expansiveness Centralization	Text Mining Web Analytics Network Analysis	How well connected How much & far disseminated How centralized is the impact The route of diffusion Number of action pledges alliance and allied action of organization Discussion or decision by organizational, governmental, international policy/legislation makers sponsorship of bills, adoption, donation, funding, implementation, social movement or intervention
		TEMPORAL	Impact Dynamics	Longitudinal analysis	Comparison b/w multiple time points Duration of impact Increase vs. decrease Change vs. stability vs. reinforcement Introduction or shifts of topics Detection of social norm change

How can we know if and how information products (works of art) impact people?

CoMTI framework of impact indicators

Diesner J, Kim J, Pak S (2014): Computational Impact Assessment of Social Justice Documentaries. Journal of Electronic Publishing (JEP), special issue Metrics for Measuring Publishing Value: Alternative and Otherwise 17(3).

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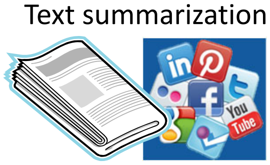
First approach: Aggregated social/ macro level

Public discourse baseline

- Social and semantic networks from meta data and content (relation extraction)
- Text summarization

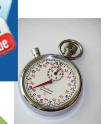


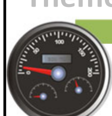
Theme

Information Product

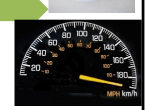
Public discourse about information product

Change in Baseline





Technology: ConText
http://context.lis.illinois.edu



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First approach: aggregated social behavior (communication)

- **Solution**: Capture, model, analyze map of stakeholders and themes associated with main issues addressed in an information product (baseline model), and identify changes in the baseline over time as an information product is released (Diesner, Kim, & Pak, 2014)
- **Evaluation**: Our approach measures most impact goals identified by impact funders and practitioners (Diesner & Rezapour, 2015)
- **Extension**: Framework for predicting different types of impact on individuals

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DIMENSION	LEVEL		INDEX	ANALYTICS	ITEM
CONTENT	MESSAGE		Guiding Factor	Description Ranking weighing	Report by producers or funding agencies
	EXPECTED OUTCOME				
	EVALUATION PRIORITY				
	RESOURCE				
MEDIUM	RELEASE MEDIUM	OFFLINE	Outreach	Stats	Number of movies, CDs distributed Number of theatrical, Internet release Duration of release; Sales of product
		ONLINE			
	RESPONSIVE MEDIUM	MASS MEDIA	Mass Media Attention	Text Mining Web Analytics	Frequency of news coverage weighted by influence (article, opinion/editorial) Domestic, international broadcast
		USER MEDIA	User Media Attention	Text Mining Web Analytics Survey, Interview	Twitter, Facebook, Blogs, webpages Frequency of talking about, links included, user-created contents
		PROFESSIONAL MEDIA	Prestige		Number of festival acceptance Number of awards Number of professional reviews
		INTERPERSONAL INTERACTION	Intimate Attention		Conversation, talking on the phone or email, lectures, exchange of letters, etc.
TARGET	AUDIENCE SIZE		Reachability	Text Mining Web Analytics Archived Data Survey, Interview	Number of viewers or visitors
	HOMOGENEITY		Diversity		Geography & demography: location, age, gender, education, income
	AUDIENCE TYPE	SINKER	Passiveness	Text Mining Web Analytics Network Analysis	Number of inactive viewers
		TRANSMITTER	Leadership		Number of opinion leaders
	COLLECTIVE ENTITY		Advocacy	Text Mining Web Analytics Survey, Interview	Number of advocacy communities, colleges, schools, or NGOs
IMPACT	INDIVIDUAL / COMMUNAL / SOCIETAL / GLOBAL	COGNITIVE	Awareness	Stats, Text Mining Web Analytics, Network Analysis	Frequency of names, ideas, thoughts, or concepts appeared in corpus Report of increased awareness
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CoMTI framework of impact indicators

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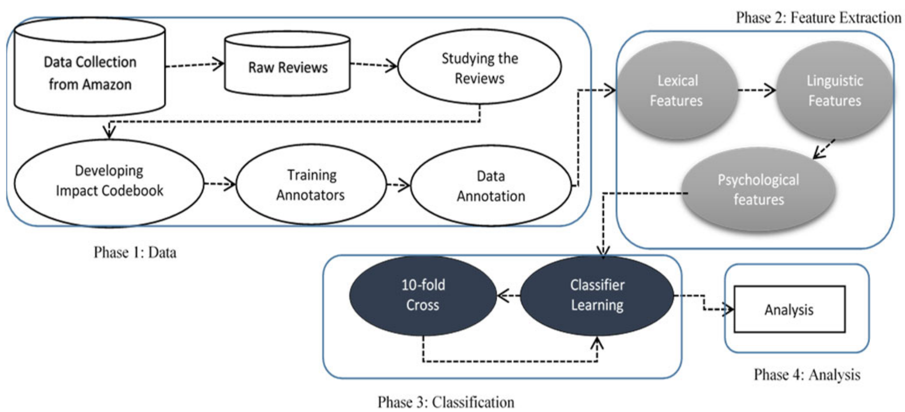
How can we know if and how information products (works of art) impact people?



Jiang M, Diesner J (2016) Says Who…? Identification of Critic versus Layman Reviews of Documentary Films. Proceedings of COLING, Osaka, Japan.

Rezapour R, Diesner J (2017) Classification and Detection of Micro-Level Impact of Issue-Focused Films based on Reviews. Proceedings of 20th ACM CSCW, Portland, OR.

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Predicting impact requires new categories and model

- Classifier (90.7% F1) to separate laymen (**user-generated**) reviews from **expert reviews**
  - **Experts**: lengthier & more detailed reviews, more complex grammar, higher diversity in vocabulary
  - **Laymen**: more subjective, contextualized in daily life
  - Error Analysis: Laymen about twice as likely to be mistaken as experts than vice versa

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Predicting impact requires new categories and model

- Qualitative methods to identify impact categories
  - Developed codebook
  - Annotated 900 reviews (sentence level)
  - Intercoder reliability from 45% to 97%, differences mainly due to background and culture (love an opinion or emotion?)
  - 9 categories**: Change** versus **reassurance** of **behavior, cognition, emotions**, **intent to change**, personal opinion, impersonal report (skewed distribution in training data)
- Features: lexical, linguistic, psychological
- Results: 81% F1 accuracy in predicting categories (with a random forest, no psychological features needed)

Significance

- Contributions:
  - **Review mining**: support (new features to predict helpfulness, ratings, authenticity) & expansion (beyond consumer products)
  - Involve, train, collaborate with **practitioners and end-users**

How can we know if and how research impacts society?

- Motivation: reports of funded work stored in specialized databases, archiving efforts focused on standardizing, interoperability, and information retrieval and indexing
- Missing: **transfer** of basic, domain-specific, scientific knowledge/ academic outputs to applications and society -> enable **replication** and **reuse**
- Goal: Identify secondary, practical uses of research findings from final reports of publicly funded work
- Prior work: Plethora of recent ontologies/ taxonomies/ approaches (Smit & Hessels 2021; Penfield et al. 2014; Bonaccorsi, Chiarello, & Fantoni 2020; NSF)

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How can we assess the broader impact of publicly funded research on society?

- Classic science impact metrics: bibliometrics
- Alternative solutions:
  - Altmetrics (focused on attention)
  - Normative: e.g., UN's sustainable development goals
  - Ours: mixed methods approach of survey versus NLP (domain: electro-mobility, new: linguistics, AI)

Witt, A., Diesner, J., Steffen, D., Rezapour, R., Bopp, J., Fiedler, N., Köller, C., Raster, M., & Wockenfuß, J. (2018). Impact of scientific research beyond academia: An alternative classification schema. Proceedings of 1st Workshop on Computational Impact Detection from Text Data, 11th Language Resources and Evaluation Conference (LREC).

Rezapour, R., Diesner, J., Bopp, J., Fiedler, N., Steffen, D., Witt, A. (2020). Beyond citation: corpus-based methods for assessing the impact of research outcomes on society. Proceedings of *12th International Conference on Language Resources and Evaluation* (LREC).

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How can we know if and how research impacts society? (BMBF, with Leibniz Institute for the German Language & Leibniz Technical Information Library Hannover)

Deductive, top down approach: from theory to data

- Existing impact categories identified by domain experts -> elicited from former principal investigators via survey -> assigned as labels to reports
- Assumption: features in texts allude to categories, which are represented in texts
- Pro: categories external to the text data
- Pro & Con: labeling projects

Inductive, bottom up approach: from data to theory

- Impact categories identified from texts (qualitative work: mark up instances in texts)
- Developed & applied code-book, measured intercoder reliability
- Assumption: impact types represented in text data
- Pro: capture anticipated impact
- Con: hand labeling labor intense

- Measurement: identify text features that correlate with categories, build supervised prediction model
- Does project-level, expert judgment align with text level impact?

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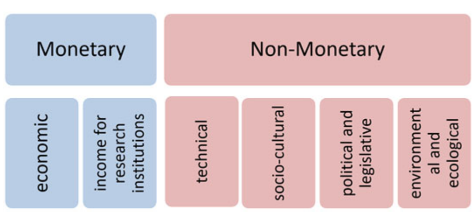
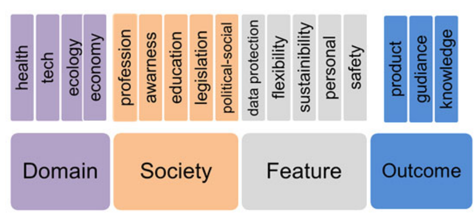
Different epistemologies lead to different categories of interest, both decently predictable

Deductive, top-down approach: from theory to data

Inductive, bottom-up approach: from data to theory





Deductive Model	P	R	F1	ROC
Unigram (Baseline)	72.37	65.81	66.45	73.38
Ngram	77.83	75.69	75.32	80.01
Ngram + POS	77.83	75.69	75.32	80.01
Ngram + POS + Sub-categories	80.04	76.87	76.39	80.82

Inductive Model	P	R	F1	ROC
Unigram (Baseline)	55.62	52.06	52.95	68.91
Ngram	56.37	52.77	53.83	69.44
Ngram + POS	56.2	52.59	53.66	69.31
Ngram + POS +Sub-categories	79.8	78.29	78.81	85.92

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How can we trace effectiveness of investments in biodiversity conservation over time?

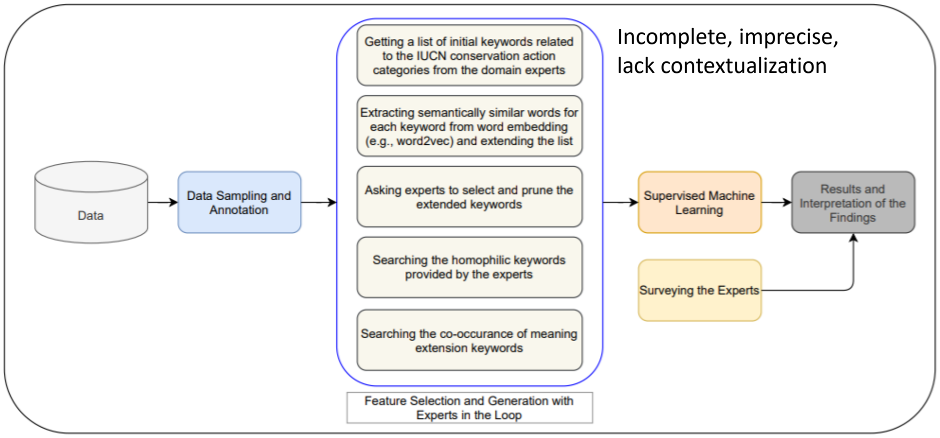
- Measure long-term impact of investment ($655 million over 40 years) in international biodiversity conservation
- **Solution**: Identify factors associated with sustainable conservation gains over time
- Variety of methods, incl. field work Madagascar, Bhutan, Peru
- **Need**: Help domain experts to tag large corpus of texts for International Union for Conservation of Nature (IUCN) conservation actions schema, e.g.: land/ water management, species management, economic incentives, legal and policy frameworks, institutional development
- **Problems**:
  - Labeling costly since documents lengthy, technical, require domain expertise (environmental science)
  - Only a few annotated documents available (N=93)
  - No benchmarks and language models available

How can we trace effectiveness of investments in biodiversity conservation over time?

- **Method:** Iterative expert-in-the-loop process
  - Tagging sample: N tagged = 93
    - Ranking and grouping categories lower intercoder agreement than binary tagging of category per document
  - Goal: not burden domain experts with more annotation tasks -> bring them in more strategically

Han, K., Rezapour, R., Nakamura, K.S., Devkota, D., Miller, D.C., & Diesner, J. (2020). Domain-knowledge-based classification of biodiversity conservation actions based on project reports. In Proceedings of METRICS 2020: Workshop on Informetrics and Scientometrics Research, at Association for Information Science & Technology (ASIS&T)

How to add experts into the machine learning process?



- Confidence in categorizing documents, initial keywords, selection of additional keywords
- Familiarity with domain knowledge per category
- Finding: Experts' proficiency in categories and confidence in tags influence prediction

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Significance

- **Works of art**:
  - Support strategic allocation of tight resources, leverage existing social capital and discourse
- **Science**: measure impact of science beyond science and count metrics (h-index)
- **Biodiversity**: automated labeling to free up experts' time to do substantive work
- All:
  - Predicting impact may require new categories and models
  - Leverage human-centered data to identify suitable ontologies
  - Complement insights from traditional impact assessment methods (surveys, focus groups, …)
  - Consider content of information and user reactions -> move beyond approximating impact by measuring exposure and attention

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Acknowledgment

- Data disambiguation and quality: This work was supported in part by KISTI (Korea Institute of Science and Technology Information) and the National Institute on Aging of the NIH.
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Thank you!

Q&A

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