

Automated Detection and Characterization of Pathological Online Behavior

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INDE Workshop, 8/5/2021

LA-UR-21-27759

Managed by Triad National Security, LLC, for the U.S. Department of Energy's NNSA.

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Motivation

- Investigate behavioral dynamics of online communities on a large scale
- Decrease amount of human expert effort required via machine learning
 - NOTE: we never intend to completely remove humans from the loop
- Machine learning task is discovery, characterization, and understanding
- Quantitatively test sociological theories and case studies



Research Questions

- How well can communities with pathological (dangerous) behavior be identified?
- How can modern machine learning technique be used to better understand online communities?
 - Requires explainable knowledge discovery capabilities
- How can we define an online community?
 - Shared content
 - Behaviors of members (and leaders)
 - Social network characteristics
- What do disparate online communities have in common?



Data Collection

- Curated list of 15 history-related subreddits
- One baseline creative writing subreddit
- Manually categorized into community type
- All subreddit data through June 1, 2021

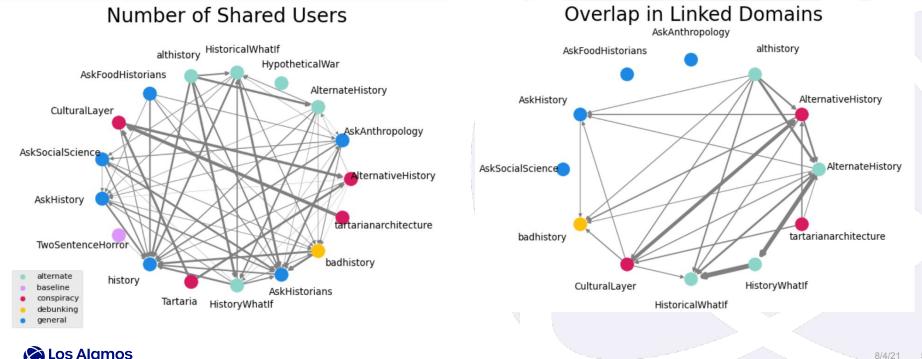
Category	Name	Founded	Subscribers	# Active	Posts
What-if	HistoricalWhatIf althistory HistoryWhatIf AlternateHistory HypotheticalWar	2011-05-21 2011-09-10 2014-12-26 2010-06-20 2013-07-06	76,328 8,203 81,106 67,693 396	17,959 2,137 16,941 14,185 58	12,906 2,418 28,068 13,028 53
Conspiracy	CulturalLayer tartarianarchitecture AlternativeHistory Tartaria	2017-09-10 2018-12-18 2008-08-03 2018-12-26	38,884 3,826 123,633 9,733	3,964 575 10,577 1,551	2,454 1,727 6,983 1,211
Debunking	badhistory	2013-03-19	248,373	26,339	6,345
General	AskHistory history AskSocialScience AskAnthropology AskFoodHistorians	2011-01-20 2008-01-25 2011-07-09 2013-03-10 2013-01-12	78,239 15,887,782 101,227 121,382 40,202	24,052 395,094 21,601 17,795 4,251	19,198 145,369 17,599 11,107 1,008
Baseline	TwoSentenceHorror	2014-03-05	656,864	25,620	66,588



Collected with https://github.com/AADeLucia/retriever

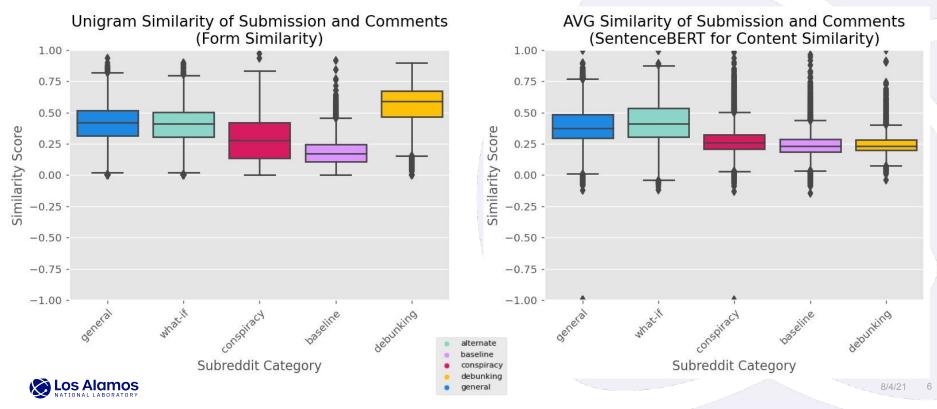
Exploratory Data Analysis: Content and User Overlap

Conspiracy-based communities may be more insular echo chambers.



Exploratory Data Analysis: Intra-Community Similarity

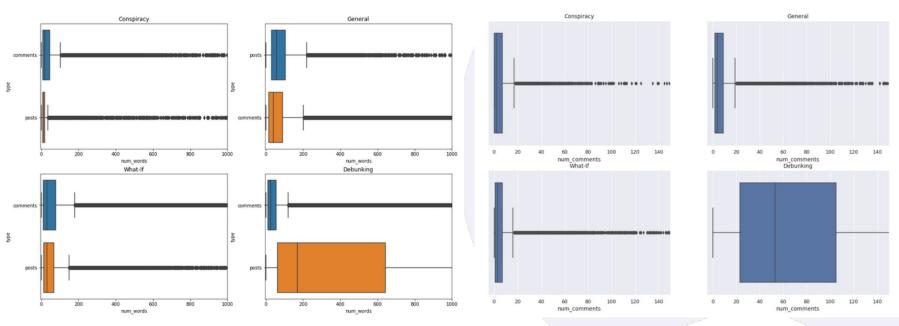
Community types show statistically significant differences in characteristics



Exploratory Data Analysis: Post & Comment Metadata

Distinct signals also appear in metadata such as word and per-post comments

Comment Distribution by Category



Wordcount Distribution by Category

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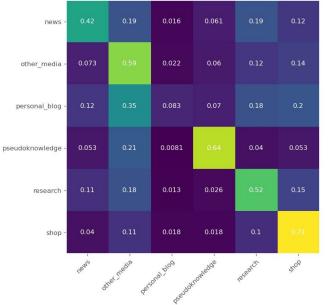
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Goal: Understand how users introduce and discuss types of websites

- 1. Collect URLs from metadata and raw text and parse domain
- 2. Manually label domains into one of 13 categories
 - Modified from (Introne, 2018)
 - Pseudoknowledge, reference, science, shop, other media, etc
- 3. Supervised learning of domain category given a variety of post/comment features



- Train/Validation: 38,133 Test: 9,534
- Group historical, reference, science, academic together for better performance



AVG Train F1 (n=100) AVG Test F1 0.61 (0.027) 0.6 (0.027)

Domain Category	Test Class	F1	
research	59.47%	0.71 (0.04)	
other_media	23.94%	0.53 (0.015)	
news	6.50%	0.29 (0.017)	
personal_blog	4.80%	0.16 (0.025)	
shop	3.42%	0.33 (0.035)	
pseudoknowledge	1.88%	0.35 (0.054) 8/4/21 9	



- Binary: Research vs. Pseudoknowledge
- Identifying one specific type of website domain is slightly easier task
- Low Pseudoknowledge precision is due to confusion with Wikipedia

Test (n=100)	F1	Precision	Recall
Pseudoknowledge (3.07 %)	0.38 (0.079)	0.26 (0.073)	0.81 (0.053)
Research (96.93%)	0.95 (0.026)	0.99 (0.0016)	0.91 (0.047)



- Multiclass prediction of domain type is difficult for automated methods
- "Research" vs "Pseudoknowledge" is also difficult
- Exploratory clustering could be better suited to this task
- Issues
 - Different communities may use the same type of domain in different
 - Labels at the domain-level are coarse and do not capture the content on the specific webpage



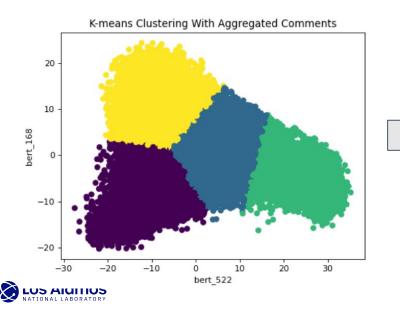
Task: Explainable Clustering

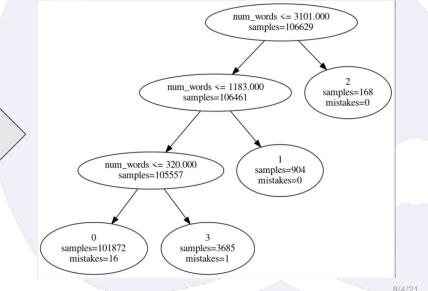
- 1. Comments and their metadata are aggregated (mean, median, min, max, standard deviation) and combined with posts and post metadata
- 2. Current state-of-the-art for explainable clustering: combine k-means and decision trees
- 3. Incorporate supervised learning (using our category assignments as the ground truth) to get a better sense of the features



Task: Explainable Clustering

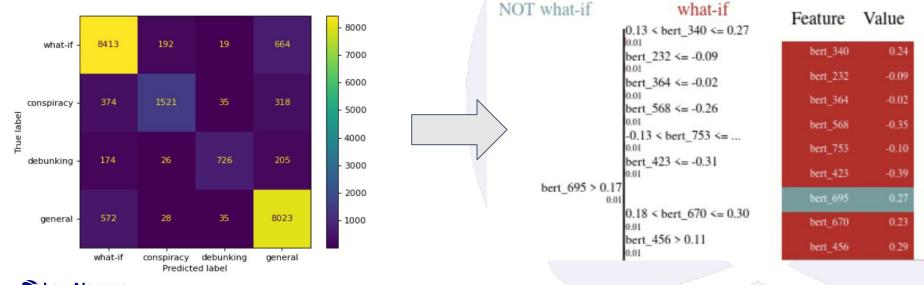
- Clusters do not separate well
 - Rand score (cluster accuracy) of 61.0%
 - Explanations only focus on metadata





Task: Explainable Clustering

- Supervised methods find significantly higher accuracy
 - 87.6% for random forests
 - 84.0% for neural network (by-class accuracy is more even)
- Classification depends primarily on text embeddings



Task: Shared Link Validity Detection

- Join with auxiliary dataset from Newsguard
- Represent subreddits of interest as dynamic hypergraphs
- Preliminary results show vast majority of shared links are from reputable sites
 - Cross-posts and re-posts are rare and hard to detect
- Implication is that majority of misinformation arises purely from intra-community chatter and speculation



Summary (Challenge Problems)

- Need for new, flexible methods tailored to knowledge discovery tasks in online platform data
 - Unsupervised methods
 - Explainability techniques
- Need for nuanced methods for detecting similar content, and dynamics surrounding content, that doesn't rely on shared links



Thank you!

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