TA1: Extracting, evaluating, and sensemaking claims from published scholarly work

IARPA REASON Proposers Day January 11 2023

Sarah Rajtmajer
Assistant Professor
The Pennsylvania State University
smr48@psu.edu

Jian Wu Assistant Professor Old Dominion University jwu@cs.odu.edu





Background: work for DARPA's SCORE program (September 2019 – December 2022)



EXPLORE BY TAG

ABOUT US / OUR RESEARCH / NEWS / EVENTS / WORK WITH US / Q

> Defense Advanced Research Projects Agency > Our Research > Systematizing Confidence in Open Research and Evidence

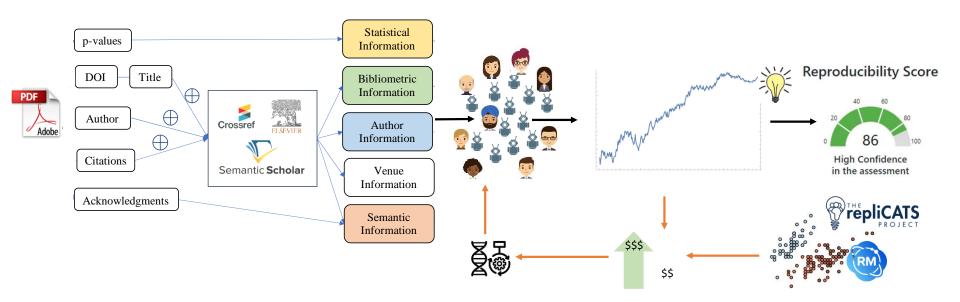
Systematizing Confidence in Open Research and Evidence (SCORE)

Dr. Greg Witkop

Develop and deploy tools to assign *explainable* "confidence scores" to SBS research results and claims

The Department of Defense (DoD) often leverages social and behavioral science (SBS) research to design plans, guide investments, assess outcomes, and build models of human social systems and behaviors as they relate to national security challenges in the human domain. However, a number of recent empirical studies and meta-analyses have revealed that many SBS results vary dramatically in terms of their ability to be independently reproduced or replicated, which could have real-world implications for DoD's plans, decisions, and models. To help address this situation, DARPA's Systematizing Confidence in Open Research and Evidence (SCORE) program aims to develop and deploy automated tools to assign "confidence scores" to different SBS research results and claims. Confidence scores are quantitative measures that should enable a DoD consumer of SBS research to understand the degree to which a particular claim or result is likely to be reproducible or replicable. These tools will assign explainable confidence scores with a reliability that is equal to, or better than, the best current human expert methods. If successful, SCORE will enable DoD personnel to quickly calibrate the level of confidence they should have in the reproducibility and replicability of a given SBS result or claim, and thereby increase the effective use of SBS literature and research to address important human domain challenges, such as enhancing deterrence, enabling stability, and reducing extremism.

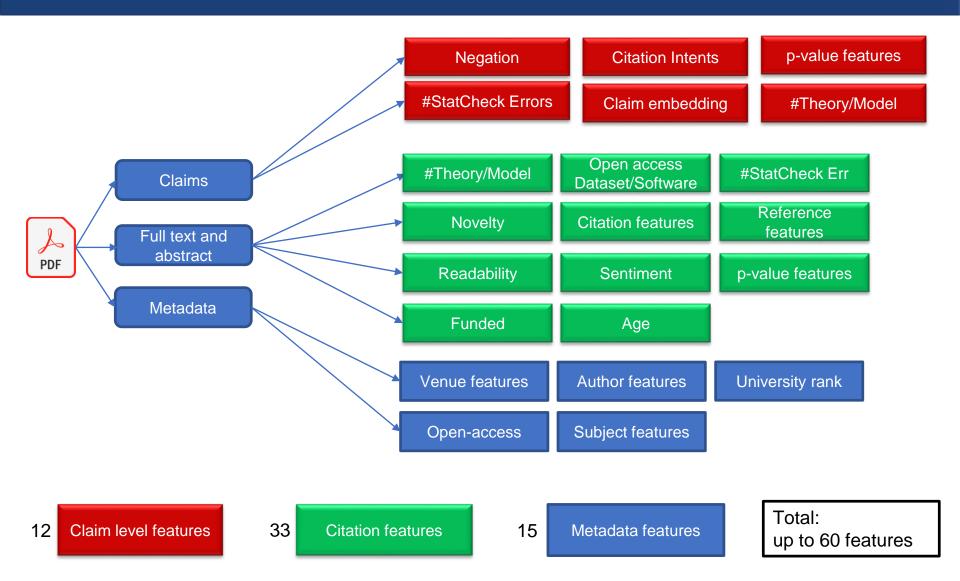
XAI (artificial prediction markets) and crowd+AI hybrid markets



Artificial prediction markets \square *populated by artificial agents (trader-bots)* \square purchase assets representing "will replicate" and "will not replicate" outcomes of notional replications of claims appearing within research papers. Agent reasoning is based on *human-interpretable signals*, including full text of scientific papers, metadata for specific papers, and metadata about the community and the field.

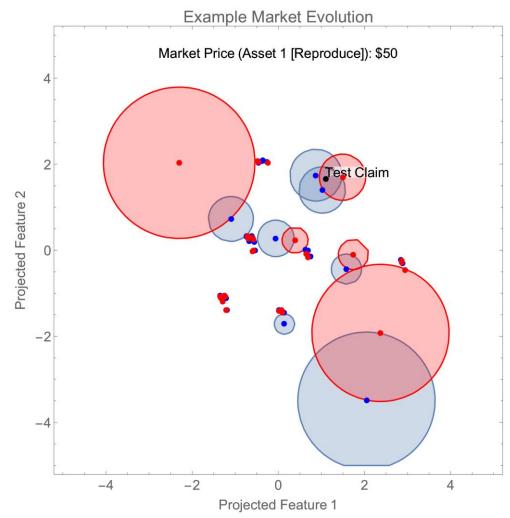
Hybrid scenario: SMEs engage alongside bot traders

Signals (features) extracted from full text and assembled from metadata



Artificial prediction markets

- Synthetic agents interact in a simple binary option market using a logarithmic market scoring rule.
- Agents in the market bid in geometric regions of feature space, shown as circles (for simplicity).
- The agents are sensitive to asset price, which causes their bid behavior to evolve in time.
- Convergence in the market is equivalent to a geometric equilibrium.



(above) A toy market with input data from RPP

Note 1: High dim feature space is projected down for visualization. Note 2: We multiply the price by 100 and convert to dollars.)

System evaluation --> real replication data



The Thirty-Sixth AAAI Conference on Artificial Intelligence (AAAI-22)

A Synthetic Prediction Market for Estimating Confidence in Published Work

Sarah Rajtmajer,¹ Christopher Griffin,¹ Jian Wu,² Robert Fraleigh,¹ Laxmaan Balaji,¹ Anna Squicciarini,¹ Anthony Kwasnica,¹ David Pennock,³ Michael McLaughlin,¹ Timothy Fritton,¹ Nishanth Nakshatri,¹ Arjun Menon,¹ Sai Ajay Modukuri,¹ Rajal Nivargi,¹ Xin Wei,² C. Lee Giles¹

¹The Pennsylvania State University ²Old Dominion University ³Rutgers University

 $\\ \{smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20\} \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, amk17, mvm7085, tjf115, nzn5185, amm8987, svm6277, rfn5089, clg20) \\ @psu.edu = (smr48, cxg286, rdf5090, lpb5347, acs20, acs2$

Abstract

Explainably estimating confidence in published so work offers opportunity for faster and more robust tific progress. We develop a synthetic prediction massess the credibility of published claims in the social havioral sciences literature. We demonstrate our syst detail our findings using a collection of known repprojects. We suggest that this work lays the founda a research agenda that creatively uses AI for peer revi

Introduction

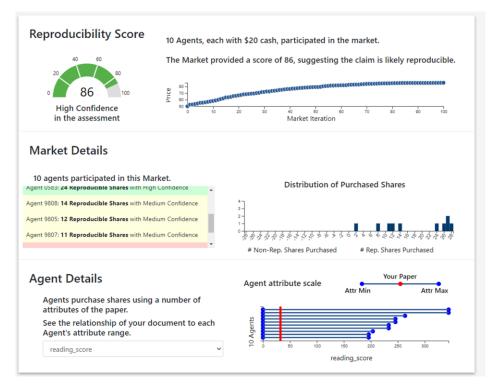
Concerns about the replicability, robustness ar ducibility of findings in scientific literature hav

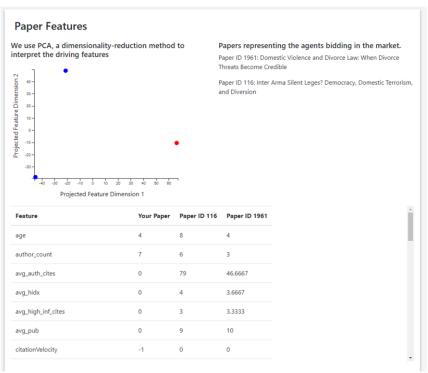
Results on scored papers. Our system provides a confidence score for 68 of 192 (35%) of the papers in our set. On the set of scored papers, accuracy is 0.894, precision is 0.917, recall is 0.903, and **F1** is **0.903** (macro averages). A sizeable un-scored subset of data (65%) is the trade-off for high accuracy on the scored subset of the data. A test point is un-scored when the system has determined it has insufficient information to evaluate it.

System non-scoring. Unlike most other machine learning algorithms, the synthetic market does not provide an evaluation for every input. Like its human-populated counterparts, the market is vulnerable to lack of participation (Arrow et al. 2008; Tetlock 2008; Rothschild and Pennock 2014). Agents will not participate if they have not seen a sufficiently similar training point (paper). This is more common when the training dataset is small; in experiments with larger datasets, we have observed participation increases. Meaningful ways to increase agent participation, including hybrid settings with human participants, are being explored.

System evaluation --> RAND grad students

- ☐ Claim submission: User submits a paper (PDF) for evaluation.
- Feature Extraction: Extraction tools stage, followed by pass through feature extractor modules generate paper feature vector.
- **Evaluation through multiple prediction markets**: The feature vector is passed through multiple markets and results from each are collected.
- □ SCORE and interpretability: Results from the prediction markets are collated and a response containing the SCORE, interpretability and confidence is returned.





Explanations:

Level One: Confidence in the claim's reproducibility through market score

Level Two: Aggregated details related to agent participation in the system

Level Three: Which agents participated + their confidence

☐ Level Four: Features corresponding to nearest training data points

Hybrid prediction markets



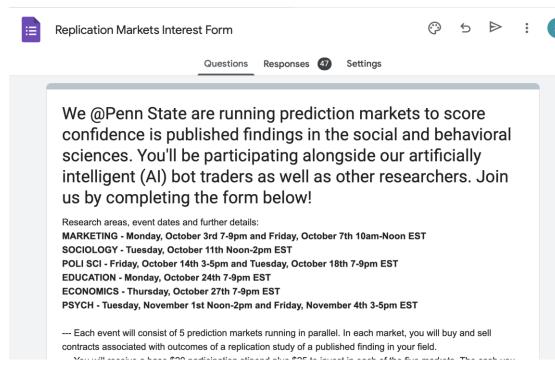


Virtual 2-hour long market events October-November 2022

- 50+ participants
- Currently analyzing results, and conducting interviews with participants

Initial takeaways:

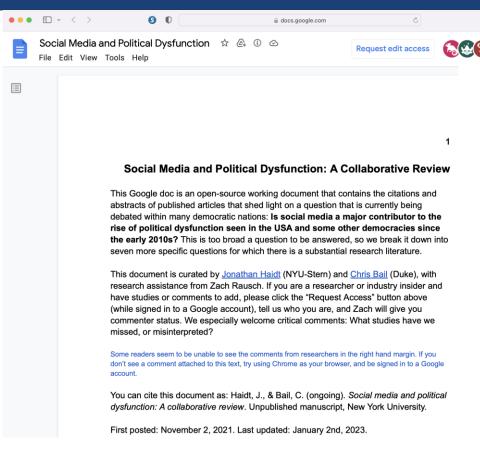
- → Major improvement on agent participation!
- → Change in individuals' evals before/after market based on surveys
- → Need more work to understand the right "balance" of bots and SMEs



Next steps for IARPA REASON

- Automatically extract key claims and evidence from analyst reports
- Search the scholarly record to find published related to those claims
- Extract supporting evidence and assign confidence scores to the associated finding
- Develop a high-dimensional hypothesis space, where dimensions are variables/factors that matter for that claim, in which to *embed* research findings to understand their relationships
- Develop an "encyclopedia" of high-confidence findings relevant to the analyst's claim in the scholarly SBS literature along with explanations for these assessments

TA1 vision: Automated collaborative review



QUESTION 1: DOES SOCIAL MEDIA MAKE PEOPLE MORE ANGRY OR AFFECTIVE POLARIZED? 1.1 STUDIES INDICATING YES	LY
1.2 STUDIES INDICATING NO 1.3 MIXED RESULTS OR UNCLASSIFIED 1.4 DISCUSSION OF QUESTION #1	1 1 2
QUESTION 2: DOES SOCIAL MEDIA CREATE ECHO CHAMBERS? 2.1 STUDIES INDICATING YES 2.2 STUDIES INDICATING NO 2.3 MIXED RESULTS OR UNCLASSIFIED 2.4 DISCUSSION OF QUESTION #2	2 3 3 4
QUESTION 3: DOES SOCIAL MEDIA AMPLIFY POSTS THAT ARE MORE EMOTIONA INFLAMMATORY, OR FALSE? 3.1 STUDIES INDICATING YES 3.2 STUDIES INDICATING NO 3.3 MIXED RESULTS OR UNCLASSIFIED 3.4. DISCUSSION OF QUESTION 3	L, 5 6 6
QUESTION 4: DOES SOCIAL MEDIA INCREASE THE PROBABILITY OF VIOLENCE? 4.1 STUDIES INDICATING YES 4.2 STUDIES INDICATING NO 4.3 MIXED RESULTS OR UNCLASSIFIED 4.4 DISCUSSION OF QUESTION 4	8 8 8 8
QUESTION 5: DOES SOCIAL MEDIA ENABLE FOREIGN GOVERNMENTS TO INCREPOLITICAL DYSFUNCTION IN THE UNITED STATES AND OTHER DEMOCRACIES? 5.1 STUDIES AND REPORTS INDICATING YES 5.2 STUDIES AND REPORTS INDICATING NO, OR MINIMAL EFFECTS 5.3 UNCLASSIFIED 5.4 DISCUSSION OF QUESTION 5	ASI 8 9 9

