



**SERICS**  
SECURITY AND RIGHTS IN THE CYBERSPACE



# THE ROLE OF AI IN THE PHENOMENON OF INFORMATION DISORDER: CHALLENGES, METHODS AND INSIGHTS

**Giuseppe Fenza**

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*Associate Professor in Computer Science  
University of Salerno, Italy  
gfenza@unisa.it*



# About Me



- Professor of Computer Science at University of Salerno
- Ph.D. & M.Sc. in Computer Science in 2009
- From 2006 to 2013 R&D
- From 2013 to 2014 startupper
- From 2015 main research interests:
  - Industry Automation
  - OSINT for Counterterrorism
  - Information Disorder
  - Digital Healthcare



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SECURITY AND RIGHTS IN THE CYBERSPACE



# Agenda

- **Why It Matters** – The impact of disinformation on society
- **Countering Disinformation @ UNISA** – SIEM-like Platform
- **Research Activities**: benchmarking, fact-checking, generated content detection, credibility scoring, countering radicalization
- **Concluding Remarks** – What have we done? What's next?
- **References** – Key sources and suggested readings

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# A Systemic Threat

2 years

1<sup>st</sup> Misinformation and disinformation

# WEF2024

10 years

1<sup>st</sup> Extreme weather events

2<sup>nd</sup> Critical change to Earth systems

3<sup>rd</sup> Biodiversity loss and ecosystem collapse

4<sup>th</sup> Natural resource shortages

5<sup>th</sup> Misinformation and disinformation



"FIMI demonstrates a growth of 30–50% in hostile operations, with artificial amplification networks, AI-generated content, and increasingly autonomous platforms, making disinformation faster, more coordinated, and more sophisticated."

# 3rdFIMI

## CopyCop

- 300+ nuovi siti web fittizi
- 9 falsi fact-checker (rete TrueFact)
- Uncensored-LLM-based content generation
- Media impersonification & copycat news
- Target: USA, NATO, UE, Ucraina
- Goal: pro-Cremlino, anti-occidentale

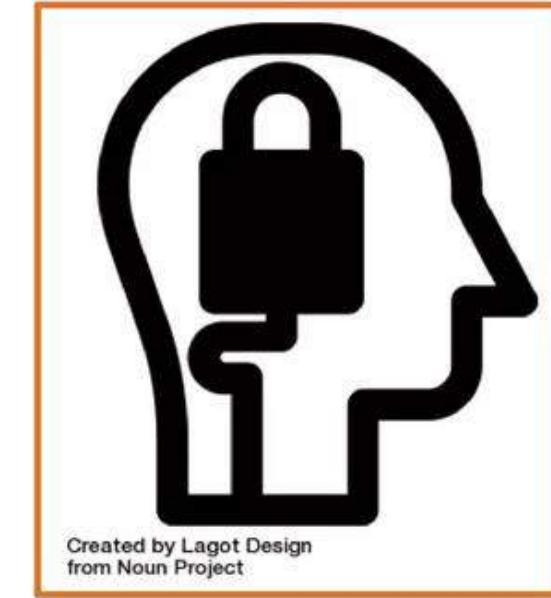
# From Cybersecurity to Cognitive Security



**PHYSICAL  
SECURITY**



**CYBER  
SECURITY**



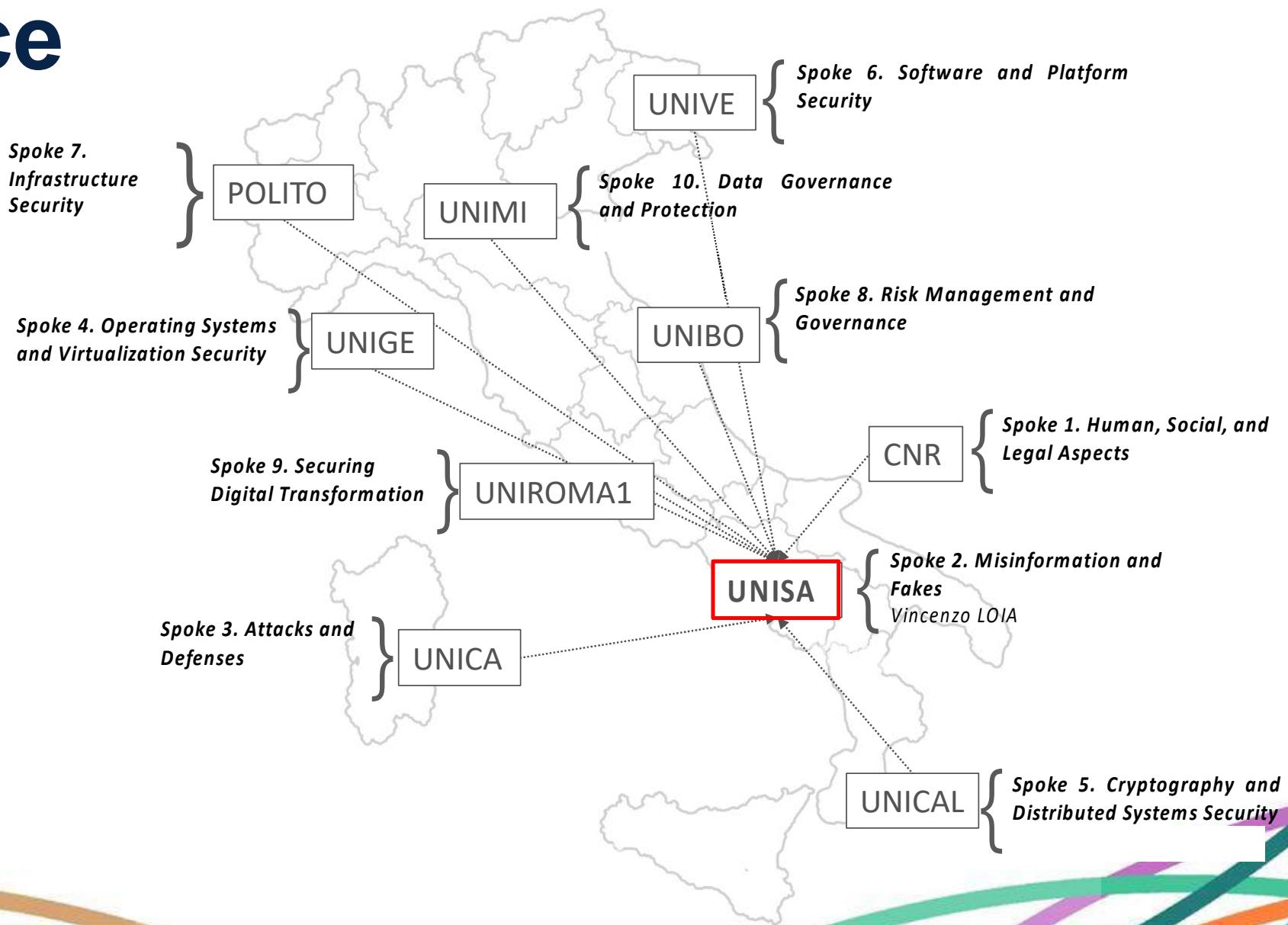
**COGNITIVE  
SECURITY**

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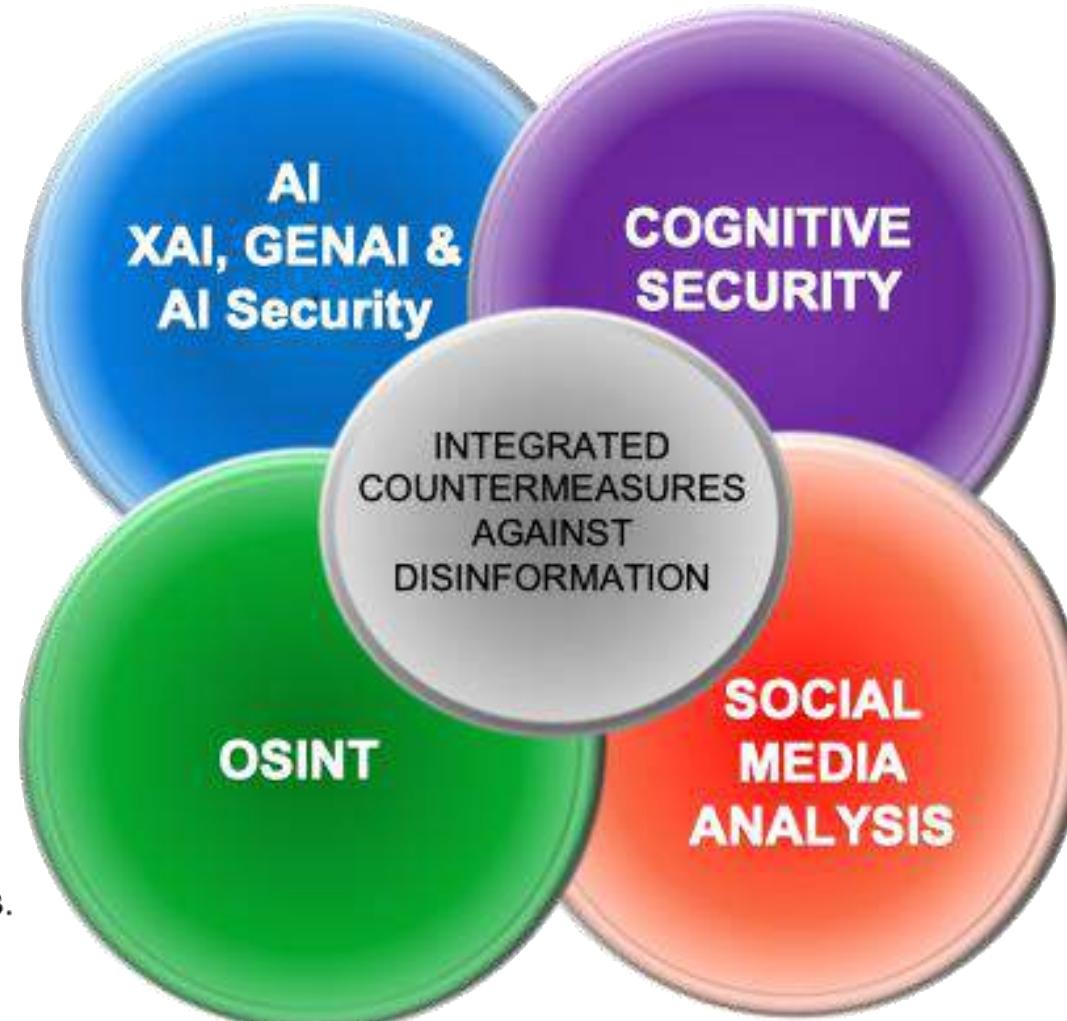
# SERICS - Security and Rights in the Cyberspace

**UNISA** is at the center of an important investment in the National Recovery and Resilience Plan



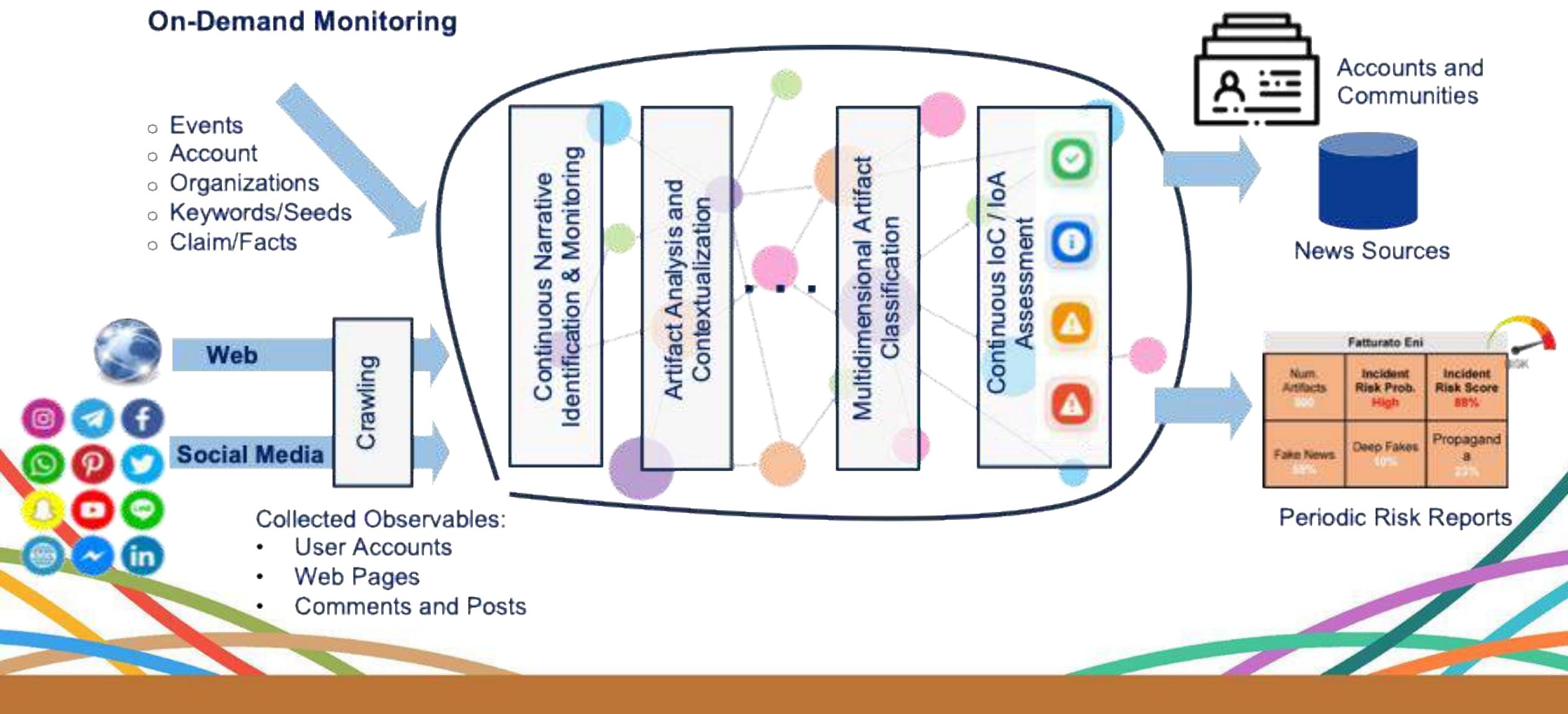
# INFORMATION DISORDER AWARENESS

- Leveraging **artificial intelligence** to analyze and detect patterns in **disinformation**.
- **Explainable AI** for transparency and trust in **countermeasures**.
- Collecting and analyzing publicly available data for **disinformation detection**.
- **Monitoring** content across multiple platforms and sources.



- **Protecting** individuals and institutions from cognitive manipulation.
- **Safeguarding** decision-making processes from **disinformation**.
- **Identifying** and tracking disinformation campaigns on social platforms.
- **Understanding** the dynamics of social network influence and **coordinated behaviours**.

# A Systematic Response



# On-Demand Monitoring & Configuration

Type ↑

- 4chan
- 8kun
- gab
- gdelt\_events\_news
- mewe
- news
- ok
- reddit
- rutube\_comment
- telegram

## Notification Thresholds Configuration

Threshold created successfully

### Create New Threshold

Metric Type	Operator	Threshold Value	Severity Level
<input checked="" type="checkbox"/> Credibility Score	>	100	<input checked="" type="radio"/> Info
<input type="checkbox"/> Attack Patterns			
<input type="checkbox"/> Social Volume			
<input type="checkbox"/> News Volume			
<input checked="" type="checkbox"/> Credibility Score			
<input type="checkbox"/> Countries			
<input type="checkbox"/> Divide %			
<input type="checkbox"/> Dismay %			
<input type="checkbox"/> Dismiss %			
<input type="checkbox"/> Distort %			
<input type="checkbox"/> Distract %			
<input type="checkbox"/> Divide Strategic Disinfo Objective is over 60%	> 60		

Create Threshold

Condition	Severity	Status	Actions
divide Strategic Disinfo Objective is over 60%	Warning	Active	<input type="button" value="Edit"/>

# Monitoring Results Summary

## Summary

**REARM**

Incidents	Observables	Events
1	1.39k	12k
Languages	Domains	Accounts
5	70	4
Attack Patterns	Threat Actors	Identities
556	1.07k	991

Last updated: 04/04/2025, 06:48:30



**REARM**

Notifications 1

Divide Technique Alert

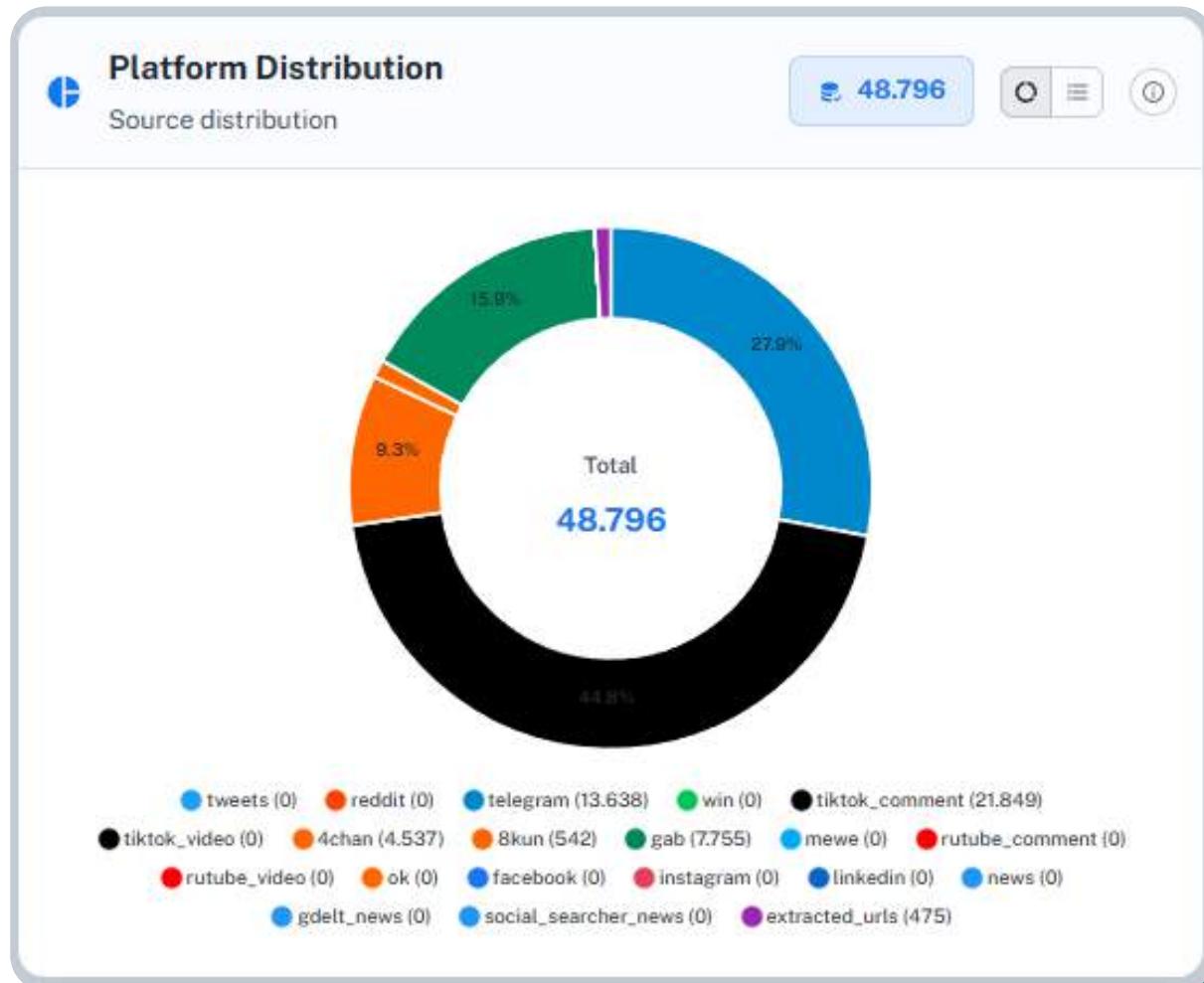
Divide Strategic Disinfo Objective is over 60%

Current value: 87% Threshold: 60.8

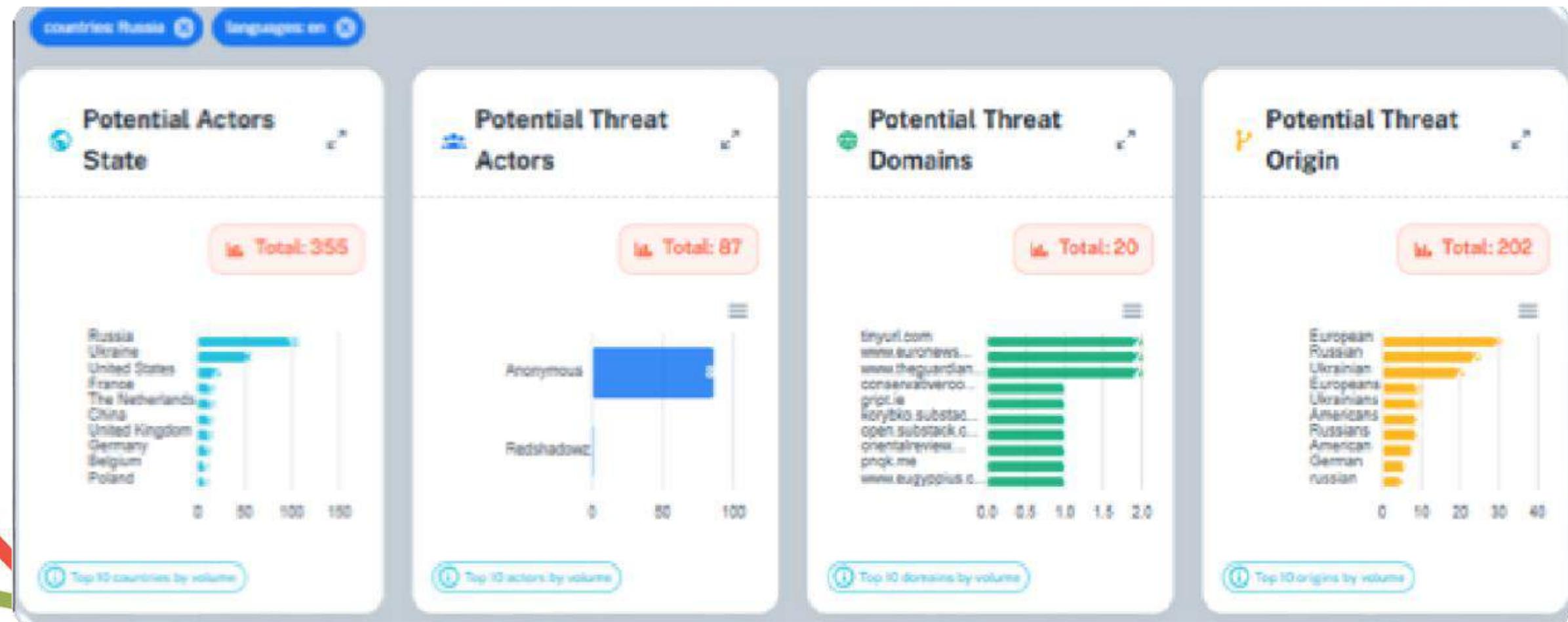
04/04/2025, 14:06:50

## Alerts

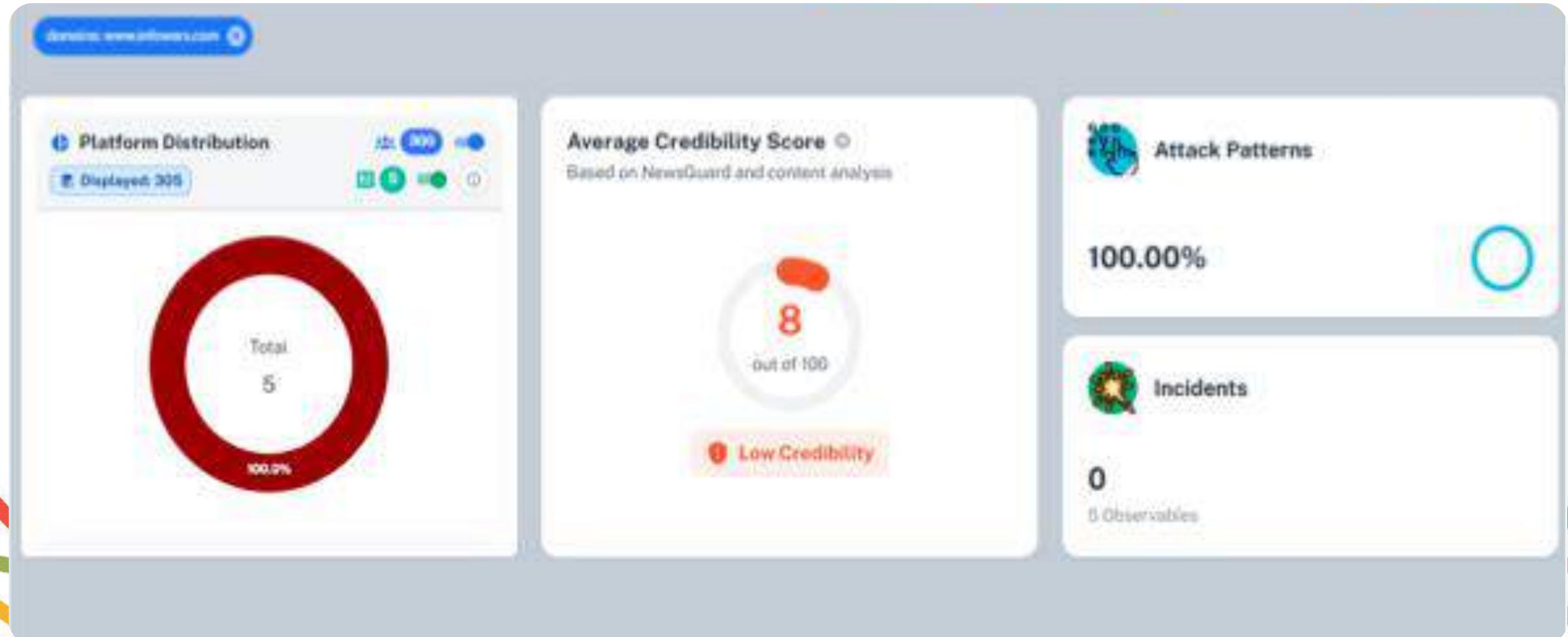
# Impact Analysis



# Attribution



# Credibility Score of News Outlets



# Narratives / Events

## Event Timeline

Social   GDELT   **Narrative**

### Political Statement

Political actors  
2025-09-25  
80% confidence

25/09/2025

### Political Statement

Trump, Republicans +1  
2025-07-04  
80% confidence

04/07/2025

### Conflict/Disinformation

Anti-Israel/Anti-Semitic actors  
Gaza  
2025-06-03  
80% confidence

03/06/2025

The Gaza conflict is fueled by disinformation, rhetoric and incitement to violence against both Israelis and Palestinians.

Gavin Thurlow's involvement in the Gaza conflict is either a publicity stunt or will ultimately harm the people of Gaza.

Trump is secretly fighting a "deep state" war, using coded messages and announcements to signal his followers and spread his goals.

Gaza's hospitals are portrayed as sites of conflict, terror activity, and disproportionately casualties due to Israeli actions.

# Narrative Analysis Example

gab ID: 11514714 04 Sep 2025

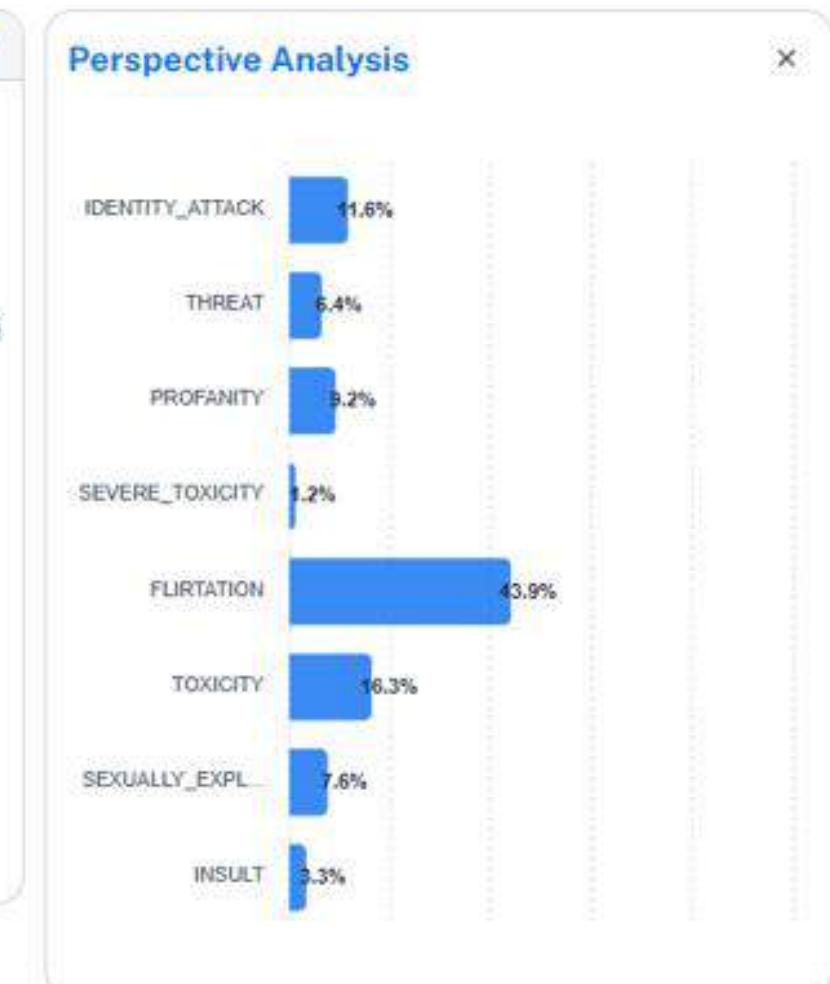
@DissentWatch 04 Sep 2025 7:14 PM

NEW – Google and YouTube sign \$45 million deal with Israel to run “Hasbara” ads, particularly related to Gaza. The contr...From Disclose TVNEW – Google and YouTube sign \$45 million deal with Israel to run “Hasbara” ads, particularly related to Gaza. The contract with YouTube and Google's Display & Video 360 ad platform explicitly describes the ad campaign as “Hasbara,” a Hebrew term meaning public relations or propaganda. Read more <https://www.disclose.tv/id/eI0s5ug0tm/> @disclosetvSource: <https://t.me/disclosetv/17537> Discuss, share, promote & more: [https://dissentwatch.com/boost/?boost\\_post\\_id=1030367](https://dissentwatch.com/boost/?boost_post_id=1030367) @DissentWatch

Show less

**Google and YouTube signed a million-dollar deal with Israel to run Hasbara advertisements, particularly related to Gaza**

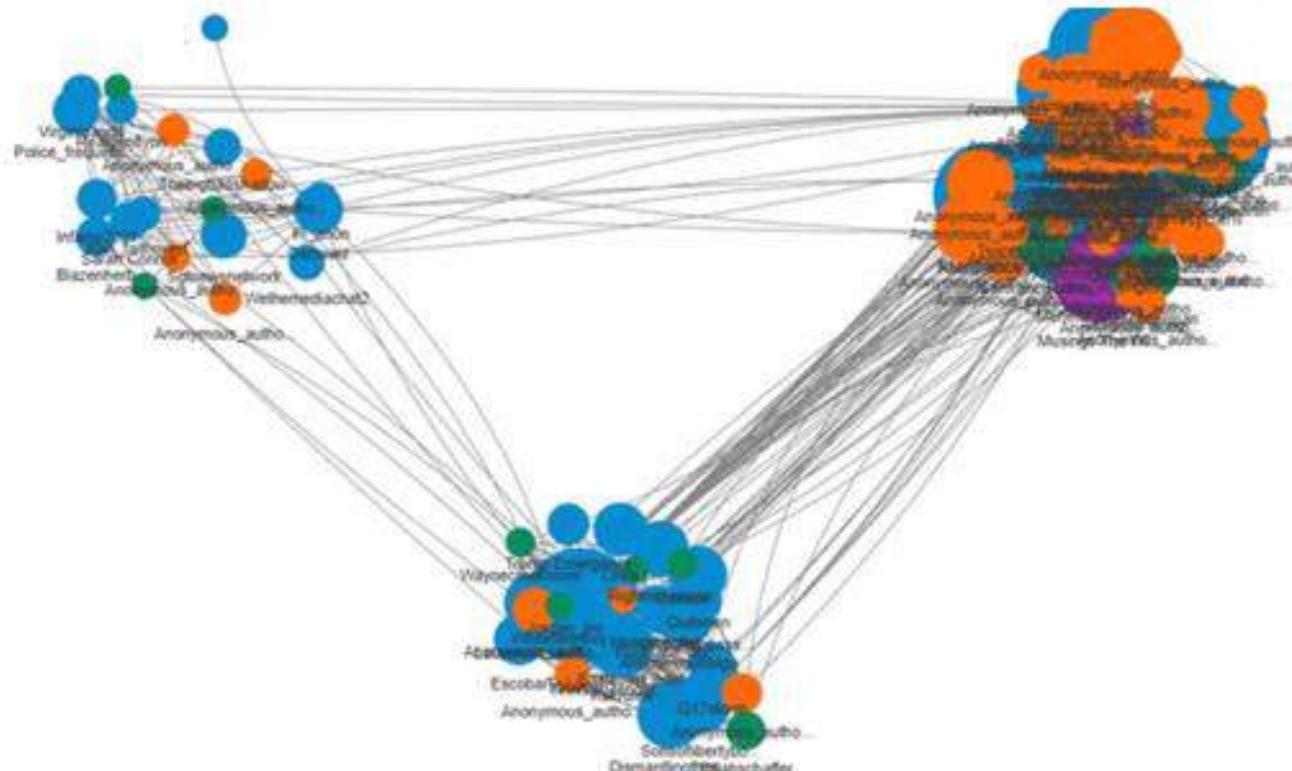
3 Entities 1 Propaganda Perspective



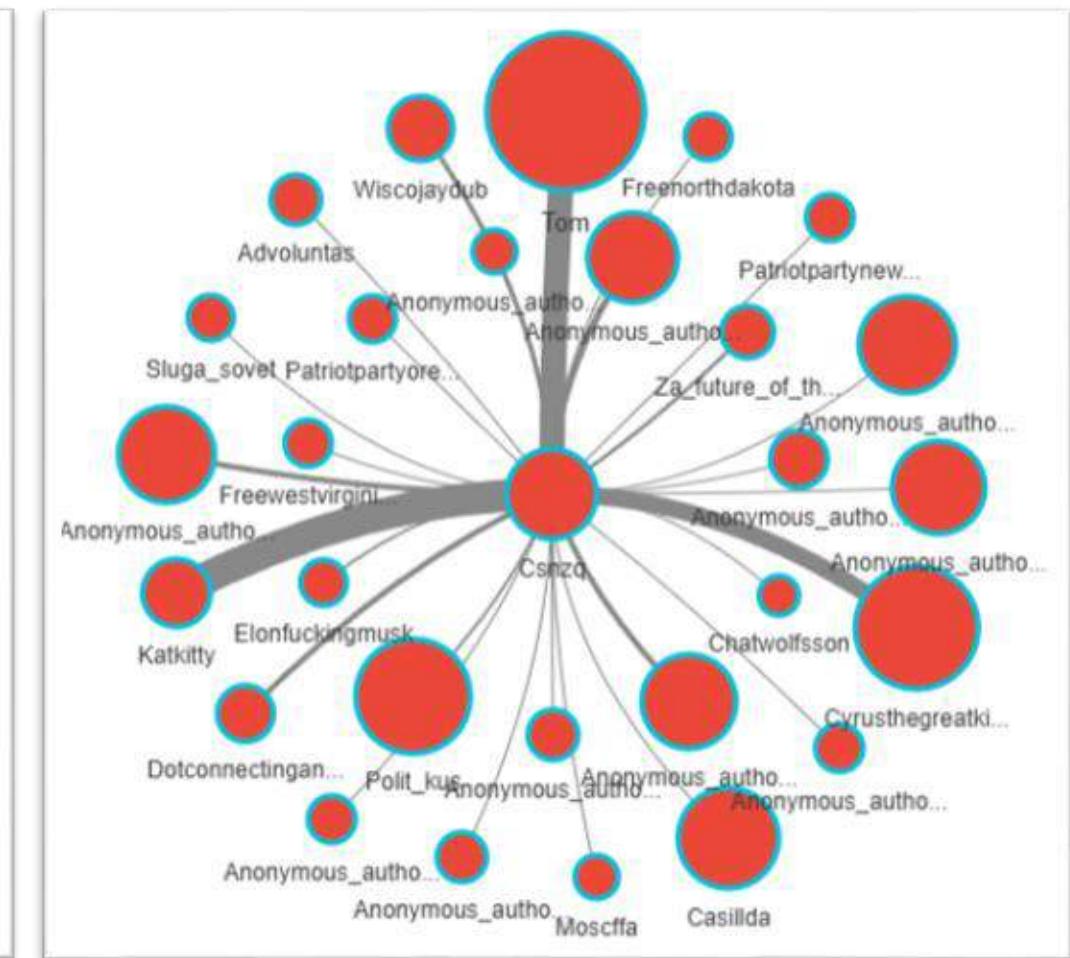
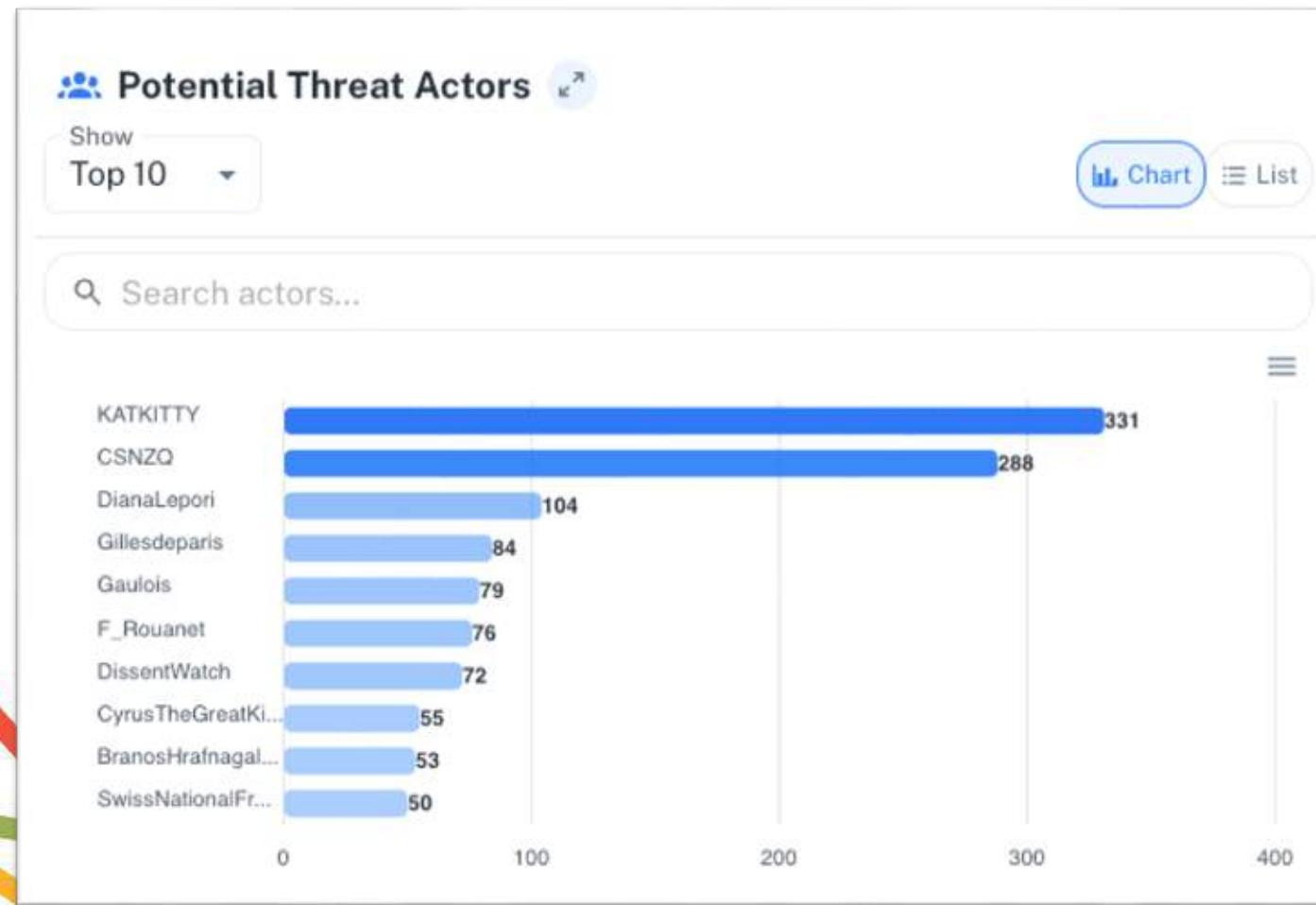
# Narrative Analysis Example

## Israel, or Jewish people, is responsible for Charlie Kirk's death

## Charlie Kirk was shot, and God's protection is invoked



# Coordinated Behaviours Analysis



## Campaigns (15)

+ Create

Pro Israel

Incidents: N/A

Observables: 5.50k

Events: N/A

Languages: 25

Domains: N/A

Accounts: N/A

Attack Patterns: 5.44k

Threat Actors: 2.65k

Identities: 2.65k

Last updated: 30/09/2025, 07:48:30

INPS\_Pensioni

Incidents: N/A

Observables: 31.24k

Events: N/A

Languages: 33

Domains: 1

Accounts: 1

Attack Patterns: 31.71k

Threat Actors: 2.71k

Identities: 2.71k

Last updated: 04/11/2025, 12:34:41

Ukraine is arming Hamas

Incidents: N/A

Observables: 384

Events: N/A

Languages: 1

Domains: 20

Accounts: 240

Attack Patterns: 509

Threat Actors: 3.77k

Identities: 3.51k

Last updated: 04/11/2025, 12:51:53

ASL

Incidents: N/A

Observables: N/A

Events: N/A

dissentwatch

Incidents: N/A

Observables: N/A

Events: N/A

Gaza

Incidents: N/A

Observables: N/A

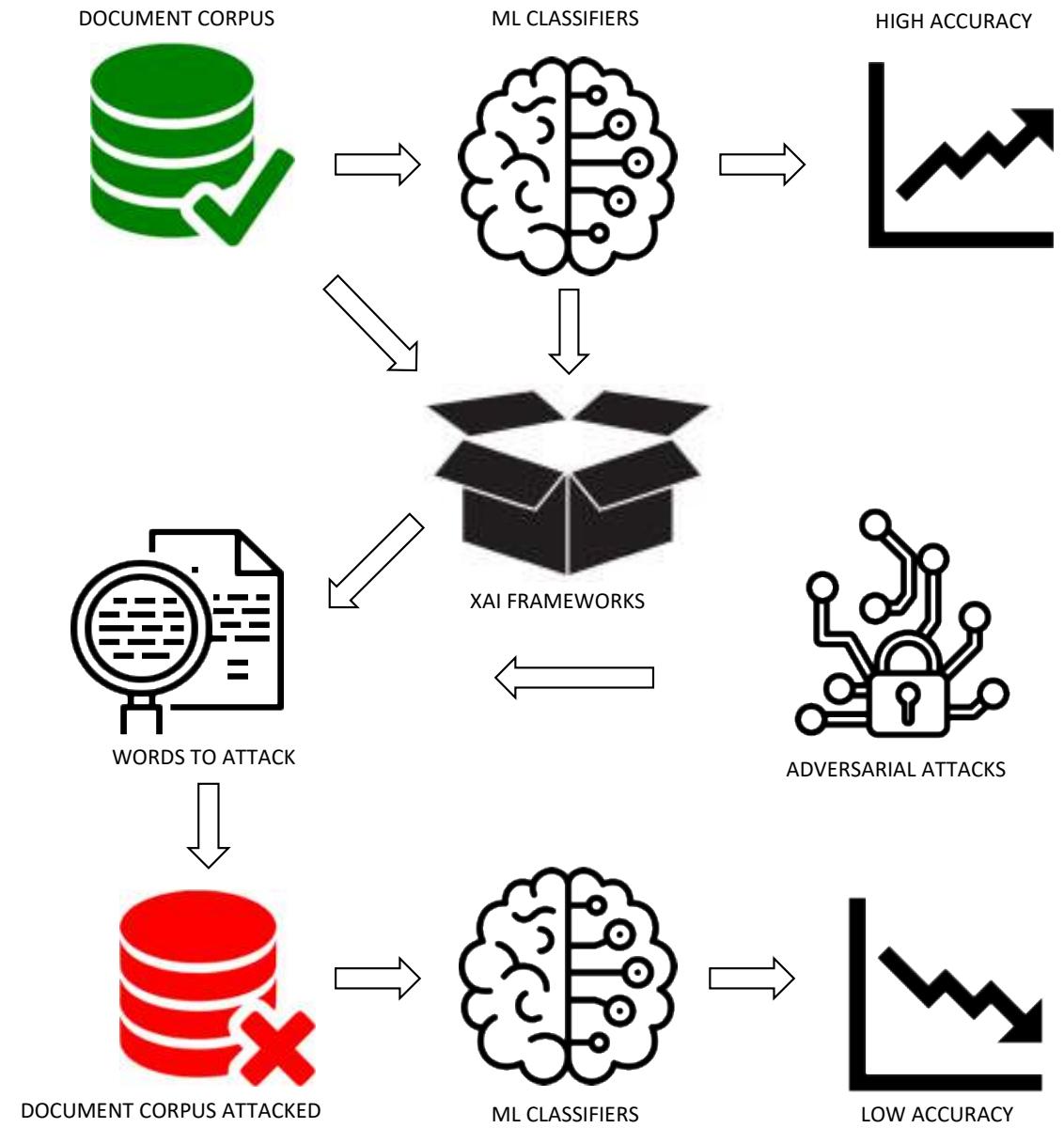
Events: N/A

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# Information Disorder Models Benchmarking

- Toxic Language Detection
- Hate Speech Detection
- Sentiment Analysis
- Propaganda Detection



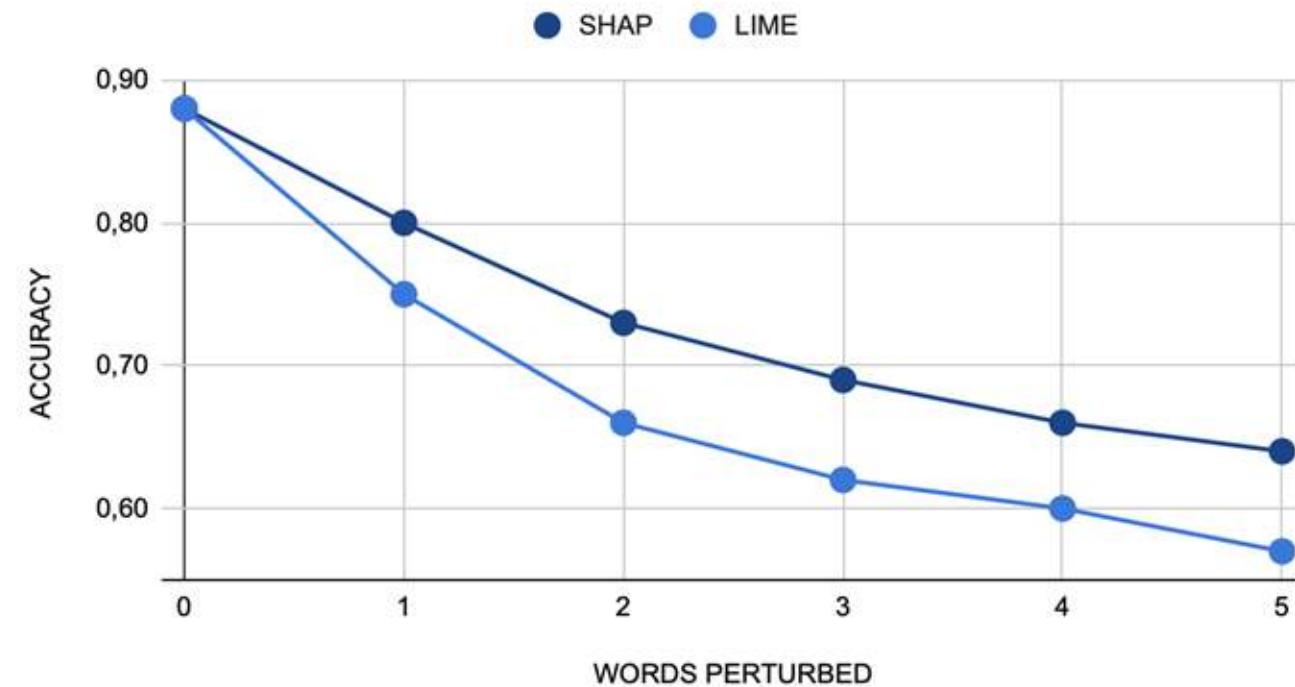
# Information Disorder Models Benchmarking

Are You Kidding Me, Ted Cruz? Don't Blame The Police Office Who Admitted Killing Botham Jean? FOX 26 asked Cruz to respond to his Democratic midterm rival, Beto O'Rourke, who called for officer Guyger to be fired.

**PROPAGANDA**

Are You Kidding Me, Ted Cruz? Don't Blame The Police Office Who Admitted **Killimg** Botham Jean? FOX 26 asked Cruz to respond to his **Democr@tic** **midtern r1val**, Beto O'Rourke, who called for **Officer** Guyger to be fired.

**NO PROPAGANDA**



88 %	75%	66%	62%	60%	57%
0	1	2	3	4	5

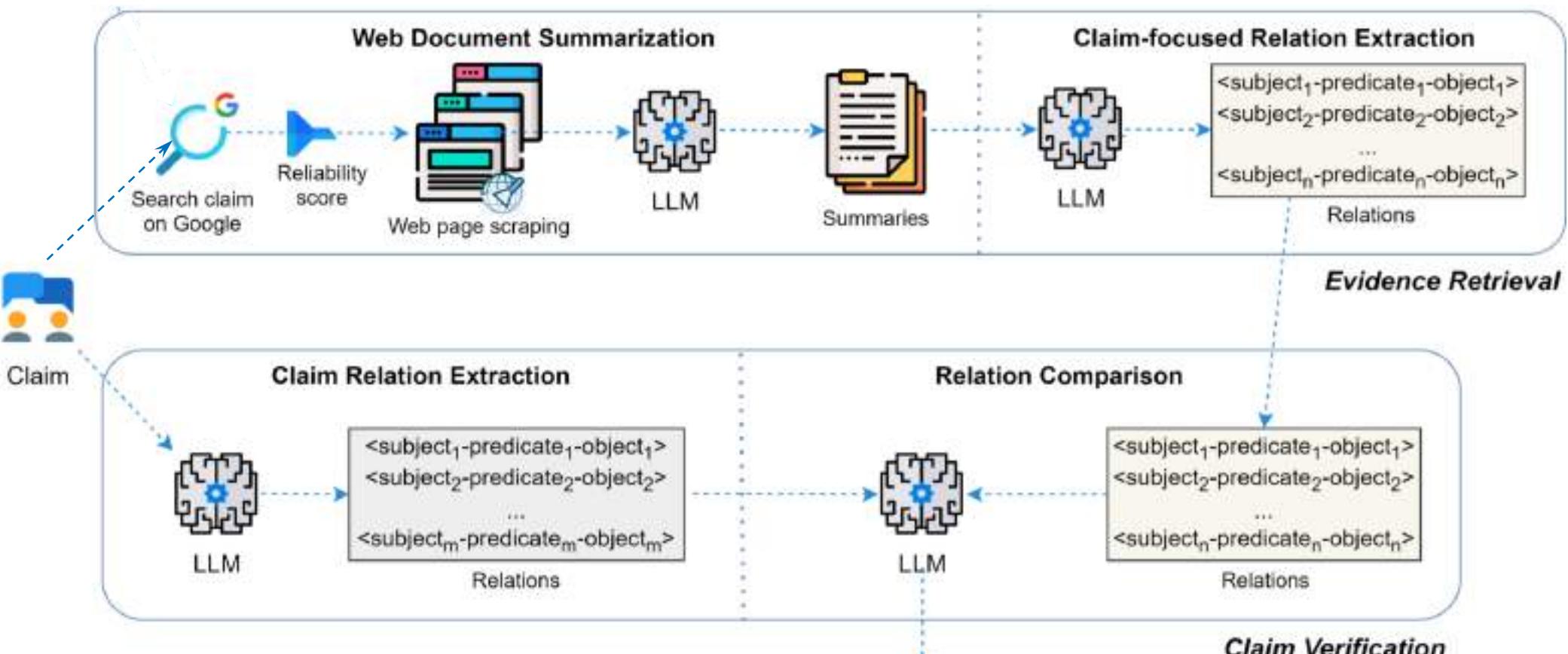
ACCURACY DECREASING USING LIME AND SUB-C TECHNIQUE

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# Fact-Checking / Claim Verification

## Overall Workflow



# Fact-Checking / Claim Verification Experimental Results

- **Dataset Used:**
  - *FEVER Dataset*: A widely used dataset for claim verification, with claims labeled as SUPPORTS, REFUTES, or NOT ENOUGH INFO.
  - *Evaluation Focus*: This study focused on binary classification (SUPPORTS vs. REFUTES) using a subset of the FEVER Development dataset with 13,332 claims.
- **Baseline Comparisons:**
  - *PPL Method*: Uses conditional perplexity scores to classify claims, leveraging pre-trained language models.
  - *Fine-Tuned Models*: Includes models like BERT-Bft and XLNETft, which are fine-tuned for binary classification tasks.

# Experimental Results

**Table 1.** Accuracy and F1-Macro of the proposed method compared with the baselines.

Model	Accuracy (%)	F1-macro (%)
$BERT - B_{ft}$	52.18	38.82
$XLNET_{ft}$	49.18	48.42
$PPL_{GPT2-XL}$	73.67	71.71
<b>Ours</b>	<b>84.23</b>	<b>84.23</b>

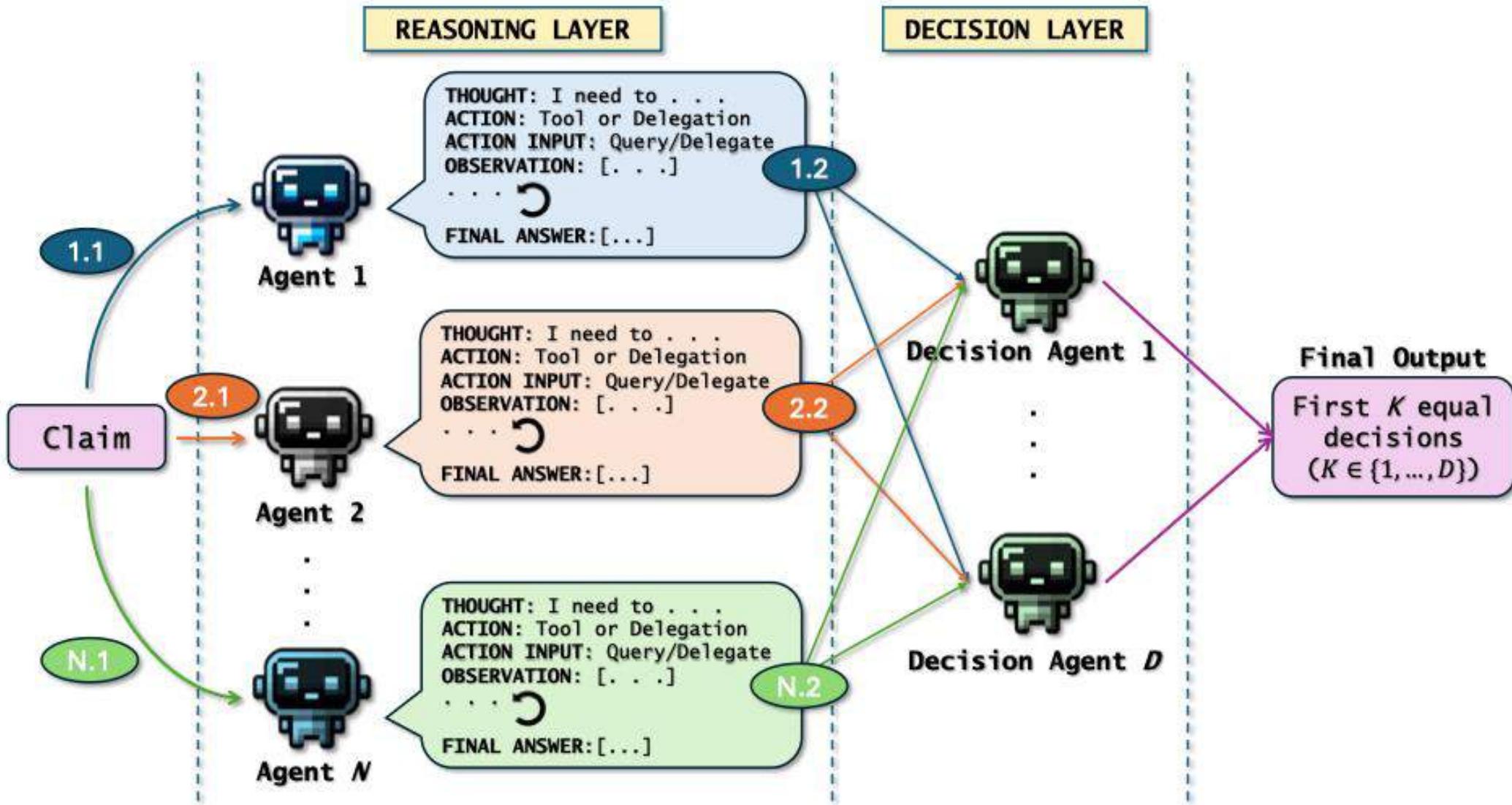
**Table 2.** Evaluation metrics of the proposed approach compared with results given by considering only summaries, without extracting relations.

Approach	Accuracy (%)	F1-macro (%)
<i>Without relation extraction</i>	77.33	73.02
<b>With relation extraction</b>	<b>84.23</b>	<b>84.23</b>

# Limits

- **Scalability and Modality Coverage**
  - *The approach mainly targets textual evidence and does not scale to multimodal content (images, videos, social signals).*
- **Lack of Temporal Awareness**
  - *Evidence retrieval ignores timing, affecting reliability in fast-evolving scenarios.*
- **Relation Extraction Issues**
  - *Missing or ambiguous relations lead to claim exclusion (~17% of data).*
- **Closed LLM Dependency**
  - *Reliance on proprietary LLMs increases cost and reduces control.*

# Scalability and Modality Coverage



# Preliminary Experimental Results

- **RQ1:** How do individual agents' contributions affect the final outcome?

Agent	Failures (%)	Inconclusive (%)
Fact-Checking	11.82%	18.8%
Context Analyst	8.08%	11.28%
Media-Bias Analyst	25.72%	37.59%
Public Sentiment Analyst	42.35%	91.73%

- **RQ2:** Does a multi-agent system outperform a single LLM and other baselines in claim verification?

Model	Accuracy (%)	F1-Macro (%)
<i>BERT</i> – <i>B<sub>ft</sub></i>	52.18	38.82
<i>XLNET<sub>ft</sub></i>	49.18	48.42
<i>PPL<sub>GPT2-XL</sub></i>	73.67	71.71
Multi-agent system 1	78.01	77.53
Multi-agent system 2	78.71	78.31
Multi-agent system 3	85.31	85.29

Model	Inconclusive Answers
Multi-agent system 1	10.65%
Multi-agent system 2	8.89%
Multi-agent system 3	1.8%

- **RQ3:** What is the relationship between the number of agents and system performance?



QUESTION MORE

Russia &amp; Former Soviet Union

World News

Business

India

Africa

RT Features

Analysis

Opinion

Entertainment

Shows

Projects

LIVE

Putin and Zelensky ready to make a deal – Trump | Russia-Ukraine conflict



# Agenda

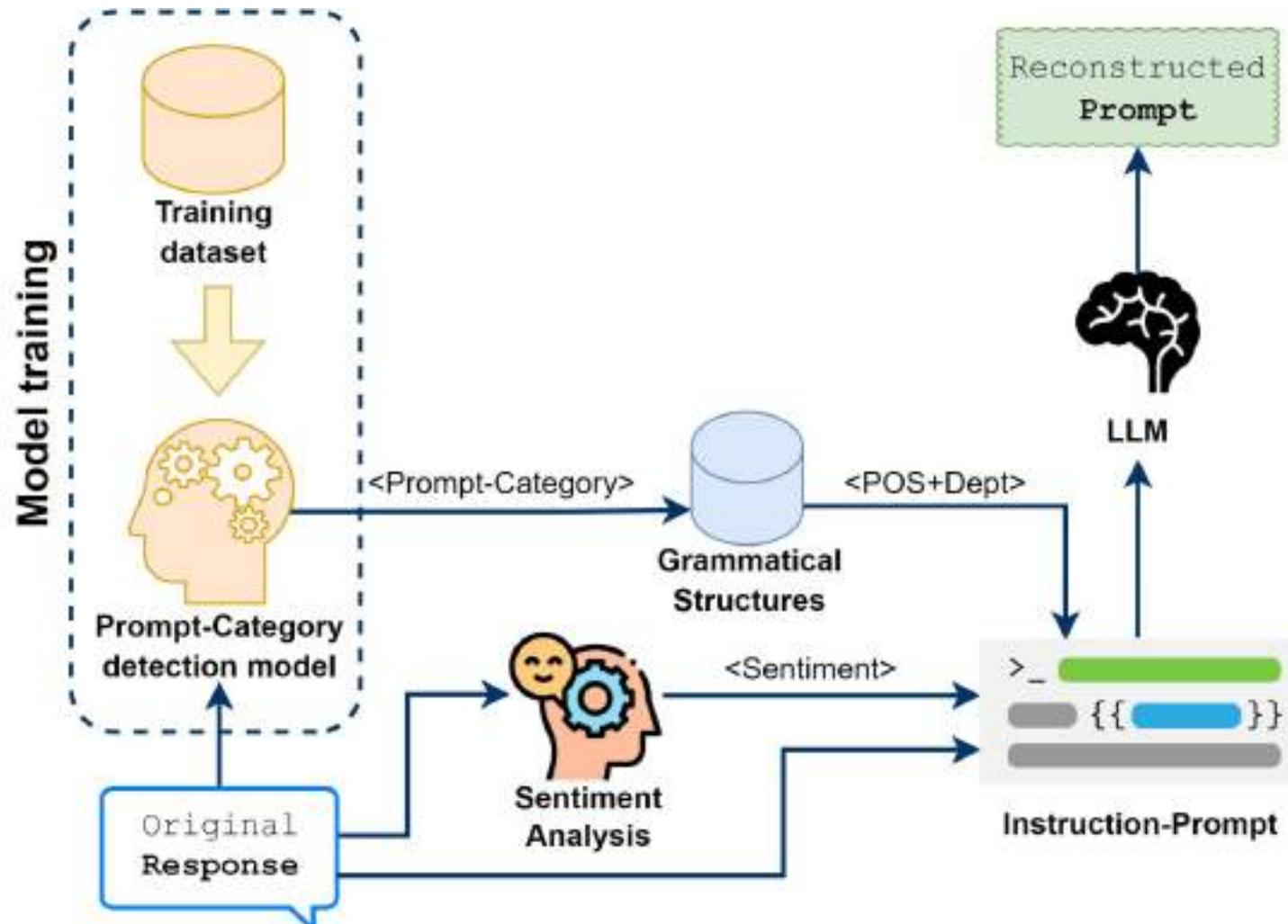
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# AI-Generated Text Detection: CLAID

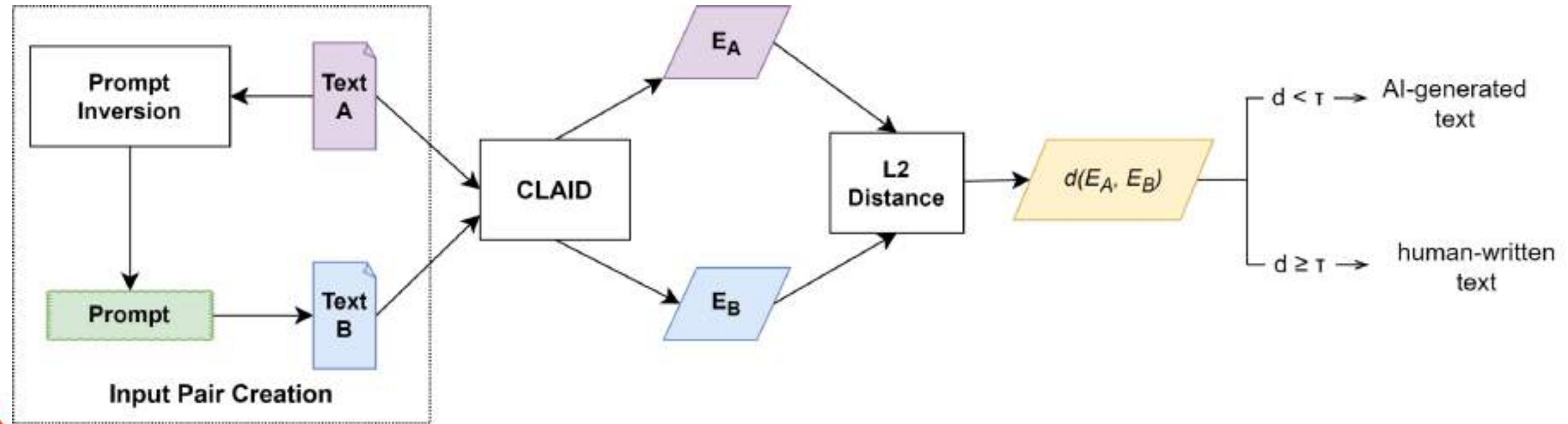
- **CLAID - Contrastive Learning for AI Detection**
- The key idea of our work is to rethink AI-generated text detection not as a standard classification problem, but as a **similarity problem**.
- Siamese neural network trained with contrastive learning
- The model is trained so that:
  - **AI–AI pairs** are close in the embedding space
  - **Human–AI pairs** are far apart

# AI-Generated Text Detection

Phase 1:  
Prompt  
Inversion



# AI-Generated Text Detection



Phase 2: Distance Evaluation

# AI-Generated Text Detection

Table 6

Classification performance on unified datasets (Strategy 2).

Approach	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.83	0.84	0.83	0.83
K-Nearest Neighbors	0.86	0.86	0.86	0.86
Multinomial Naive Bayes	0.87	0.88	0.87	0.87
Passive Aggressive Classifier	0.94	0.95	0.94	0.94
SGD Classifier (Log Loss)	0.95	0.94	0.95	0.94
Logistic Regression	0.95	0.95	0.95	0.95
BERT	0.97	0.97	0.97	0.97
CLAID (our)	0.99	0.99	0.99	0.99

Table 7

Classification performance on the unified dataset per domain.

Source	Accuracy	Precision	Recall	F1-Score
HC3	0.99	0.99	0.99	0.99
DAIGT	1.00	1.00	1.00	1.00
OUTFOX	0.98	0.98	0.98	0.98

Table 8

Classification performance with varying training set sizes (Data Efficiency Study).

Training Set Size	Accuracy	Precision	Recall	F1-Score
10 % (1,260 pairs)	0.91	0.91	0.91	0.91
25 % (3,150 pairs)	0.95	0.95	0.95	0.95
50 % (6,300 pairs)	0.98	0.98	0.98	0.98
75 % (9,450 pairs)	0.98	0.98	0.98	0.98

Di Gisi, M., Fenza, G., Gallo, M., & Loia, V. (2025). Contrastive siamese network for detecting AI-generated text across domains and models. *Neurocomputing*, 131983.

# AI-Generated Text Detection

The image displays a news article from **INFO DU JOUR** with a headline: **La villa de 3,1 millions d'euros de Nikol Pashinian en France fait l'objet d'allégations de détournement d'aide et de corruption.** The article discusses Nikol Pashinian's acquisition of a 3.1 million euro villa in Marseille, France, funded by diverted foreign aid. A red arrow points to the text: "Le Premier ministre arménien Nikol Pashinian aurait acquis une villa de luxe de 3,1 millions d'euros à Marseille, en France — un achat qui aurait été financé par une aide étrangère détournée, destinée à l'économie arménienne en difficulté." Another red arrow points to the text: "La villa de 300 m2 avec deux étages, achetée en mai 2025, est située dans le quartier de Château Gombert à Marseille. Elle dispose de 4 chambres, d'une piscine, d'un toit-terrasse et d'un garage avec 3 places de parking." A third red arrow points to the text: "Les sources de cette enquête suggèrent que les fonds provenant de l'Agence française de développement (AFD) et du Conseil de coordination des organisations arméniennes de France (CCAF) pourraient avoir été illégalement détournés pour l'usage personnel du 1er ministre Arménien, Nikol Pashinian."

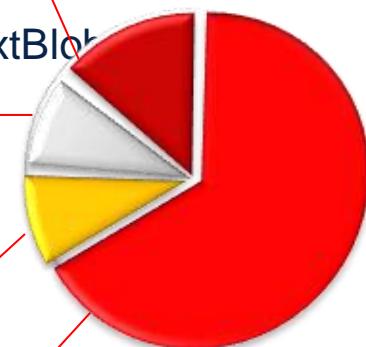
On the right, a purple sidebar from **CLAD** shows the text being analyzed. It includes a "Discover whether a text is AI-generated or human-written." section with the text: "Le Premier ministre arménien Nikol Pashinian aurait acquis une villa de luxe de 3,1 millions d'euros à Marseille, en France — un achat qui aurait été financé par une aide étrangère détournée, destinée à l'économie arménienne en difficulté." Below this is a "Detect" section with the heading "AI-Generated" and a confidence score of "Confidence: 96.63%".

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# Credibility Scoring of News Outlets

- **TEXT SCORE 20%**
  - Readability Score: The Flesch Reading Ease test evaluates the readability of the text.
  - Grammar Score: The grammatical structure of all web page content is computed by analyzing sentence structures.
  - Typo Score: Similarity is computed between the input text and its corrected version generated by TextBlock.
- **AMOUNT OF BANNERS 10%**
  - A multimodal LLaVA model (liuhaotian/llava-v1.5-7b) was used.
- **TRAFFIC SCORE 10%**
  - Open PageRank API.
- **CONTENT ANALYSIS THROUGH AI 60%**
  - Clickbait Headline Detection – christinacdl/XLM-RoBERTa-Clickbait-Detection-new – Accuracy 98%
  - Propaganda Detection – cstnz/PropagandaDetection – Accuracy 90%
  - Political Bias Detection – bucketre-search/politicalBiasBERT – Accuracy 72%
  - Fake News Evaluation – amzab/roberta-fake-news-classification – Accuracy 99%
- **AUTHOR SCORE:** not available yet



# Experimentation Results – Newsguard Correlation

FakeNewsCorpus dataset

81 domains

50 web pages for each domain

5 weeks for each domain, on average

**Spearman correlation: 81%**

**Pearson correlation: 84%.**

MSCS has the following interpretation:

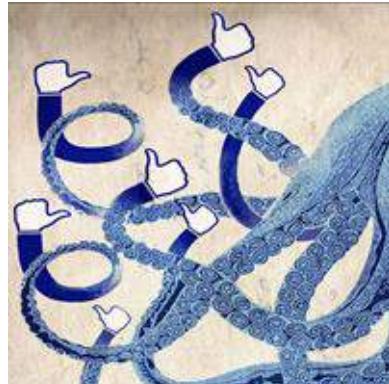
- $0 < \text{MSCS} < 39$ , the source is considered less credible, so it is necessary to proceed with extreme caution;
- $40 < \text{MSCS} < 59$ , the source is considered less credible, so it is necessary to proceed with caution;
- $60 < \text{MSCS} < 74$ , the source is credible, but with some exceptions;
- $75 < \text{MSCS} < 99$ , the source is generally reliable;
- $\text{MSCS} = 100$ , the source is highly reliable.

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# Counteracting Online Radicalization

## Detecting & Reducing Online Radicalization



Berjawi, Omran, et al. "Mitigating radicalization in recommender systems by rewiring graph with deep reinforcement learning." *Online Social Networks and Media* 48 (2025): 100325.

**Key takeaway: Radicalization can be measured, forecasted, and actively reduced through behavior-aware indicators and adaptive recommender interventions.**

## Role of Influential Actors in Opinion Dynamics



Analyzing the Persuasive Strategies of Influencers and News Media on Social Media. Omran Berjawi, Rida Khatoun and Giuseppe Fenza. To appear in the International Conference on Computer Systems and Applications (AICCSA 2025).

**Key takeaway: Influencers shape polarization not only through network position, but through adaptive rhetoric aligned with audience behavior.**

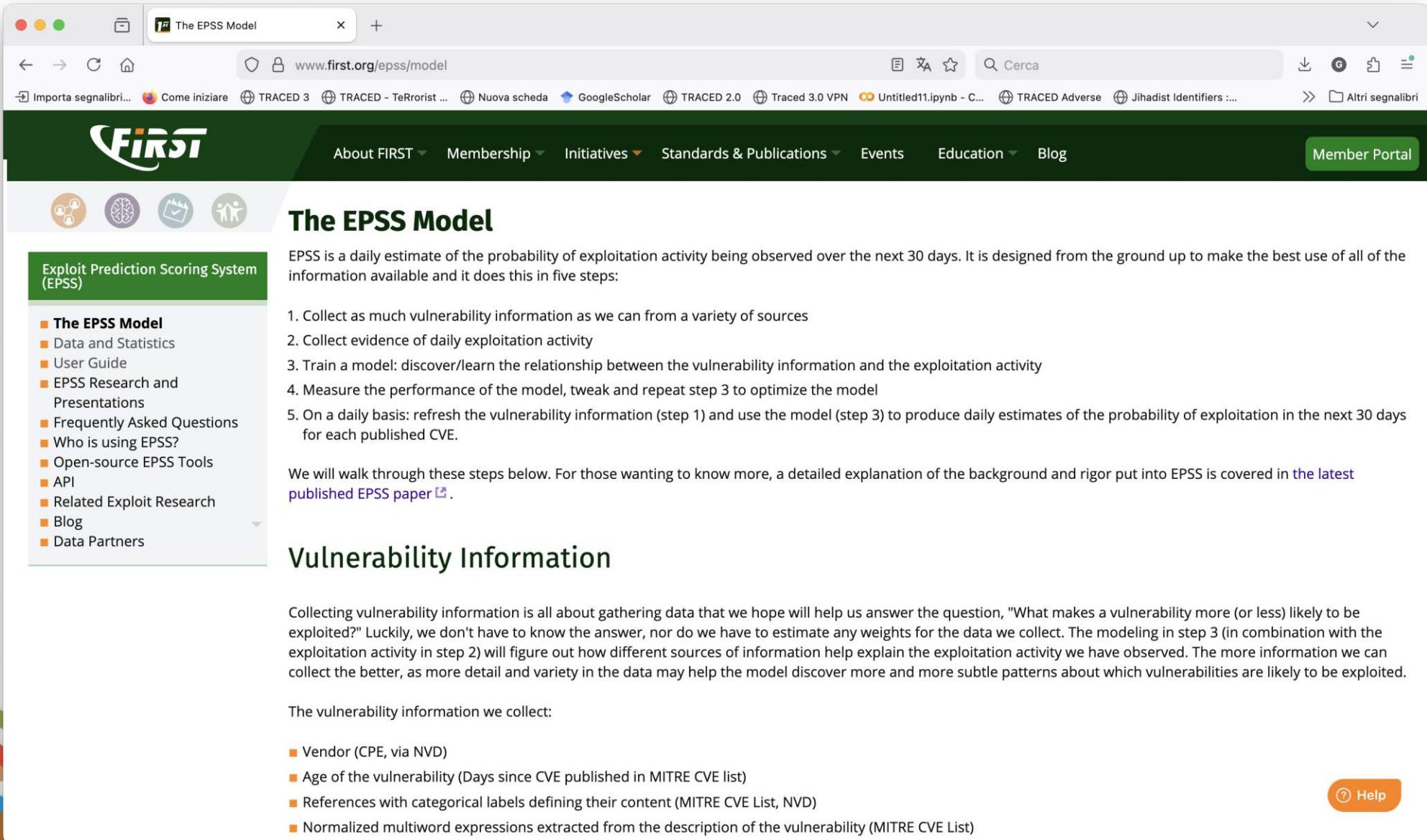
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# From Debunking to Prebunking

- **Debunking**
- Debunking is a reactive strategy that aims to correct misinformation after it has already spread, by identifying false or misleading claims and replacing them with verified, accurate information.
- **Prebunking**
- Prebunking is a preventive strategy that aims to inoculate people against misinformation before they are exposed to it, by warning them about common manipulation techniques and misleading narratives.

# Exploit Prediction Scoring System



The screenshot shows a web browser window for 'The EPSS Model' on the FIRST website. The URL is [www.first.org/epss/model](http://www.first.org/epss/model). The page features a dark green header with the FIRST logo and navigation links for About FIRST, Membership, Initiatives, Standards & Publications, Events, Education, and Blog. A 'Member Portal' button is also visible. The main content area has a light gray background with a decorative graphic of overlapping colored lines (red, green, blue, yellow) on the sides. The title 'The EPSS Model' is prominently displayed. A sidebar on the left contains a 'Exploit Prediction Scoring System (EPSS)' section with a list of links: The EPSS Model, Data and Statistics, User Guide, EPSS Research and Presentations, Frequently Asked Questions, Who is using EPSS?, Open-source EPSS Tools, API, Related Exploit Research, Blog, and Data Partners. The main text explains that EPSS is a daily estimate of the probability of exploitation activity over 30 days, achieved through five steps: collecting vulnerability information, collecting exploitation activity, training a model, measuring performance, and refreshing daily. It also mentions a detailed explanation in a published paper. Below this, a section titled 'Vulnerability Information' discusses the collection of data to predict exploitation. A 'Help' button is located in the bottom right corner.

## The EPSS Model

EPSS is a daily estimate of the probability of exploitation activity being observed over the next 30 days. It is designed from the ground up to make the best use of all of the information available and it does this in five steps:

1. Collect as much vulnerability information as we can from a variety of sources
2. Collect evidence of daily exploitation activity
3. Train a model: discover/learn the relationship between the vulnerability information and the exploitation activity
4. Measure the performance of the model, tweak and repeat step 3 to optimize the model
5. On a daily basis: refresh the vulnerability information (step 1) and use the model (step 3) to produce daily estimates of the probability of exploitation in the next 30 days for each published CVE.

We will walk through these steps below. For those wanting to know more, a detailed explanation of the background and rigor put into EPSS is covered in [the latest published EPSS paper](#).

## Vulnerability Information

Collecting vulnerability information is all about gathering data that we hope will help us answer the question, "What makes a vulnerability more (or less) likely to be exploited?" Luckily, we don't have to know the answer, nor do we have to estimate any weights for the data we collect. The modeling in step 3 (in combination with the exploitation activity in step 2) will figure out how different sources of information help explain the exploitation activity we have observed. The more information we can collect the better, as more detail and variety in the data may help the model discover more and more subtle patterns about which vulnerabilities are likely to be exploited.

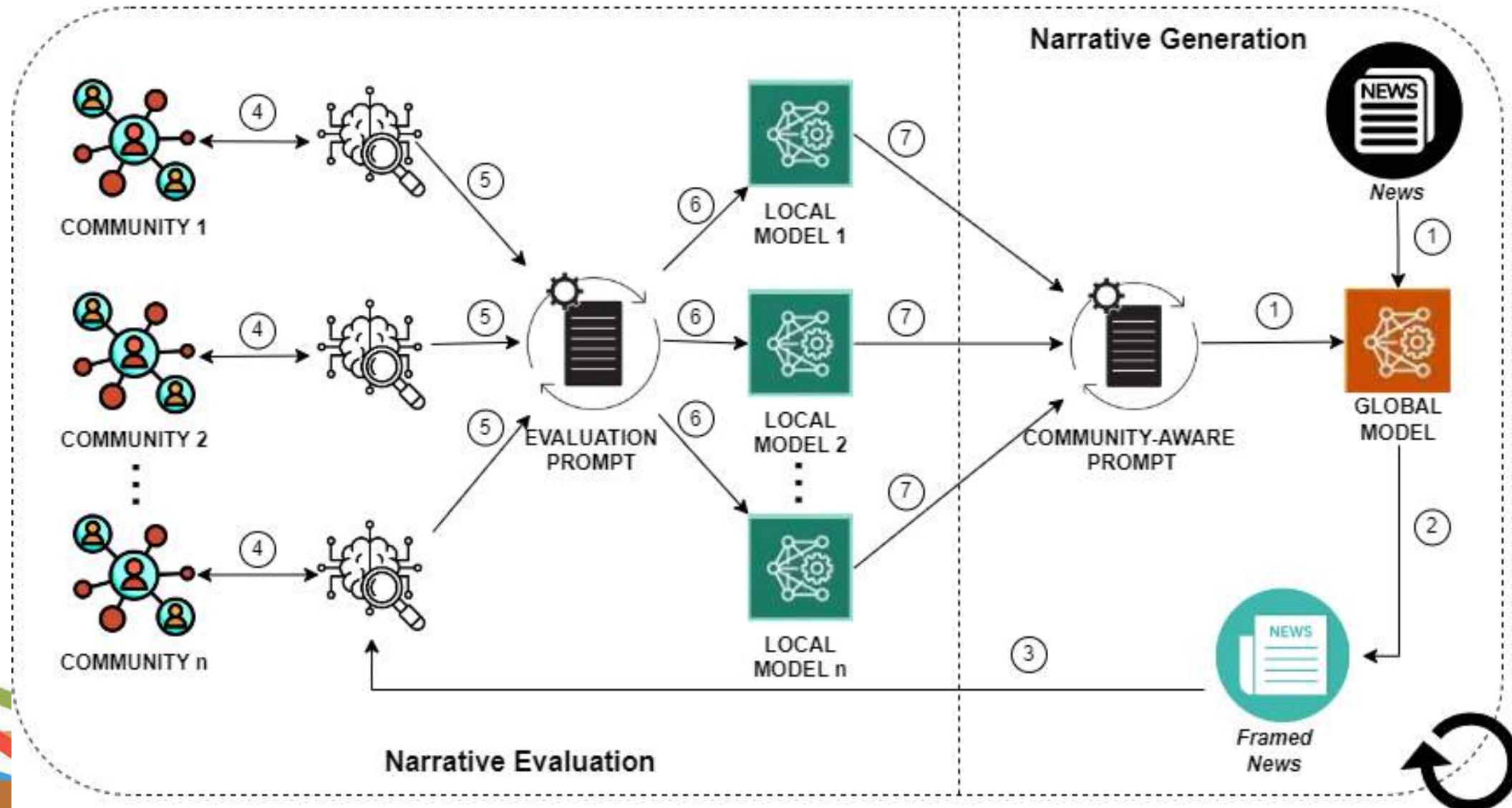
The vulnerability information we collect:

- Vendor (CPE, via NVD)
- Age of the vulnerability (Days since CVE published in MITRE CVE list)
- References with categorical labels defining their content (MITRE CVE List, NVD)
- Normalized multiword expressions extracted from the description of the vulnerability (MITRE CVE List)

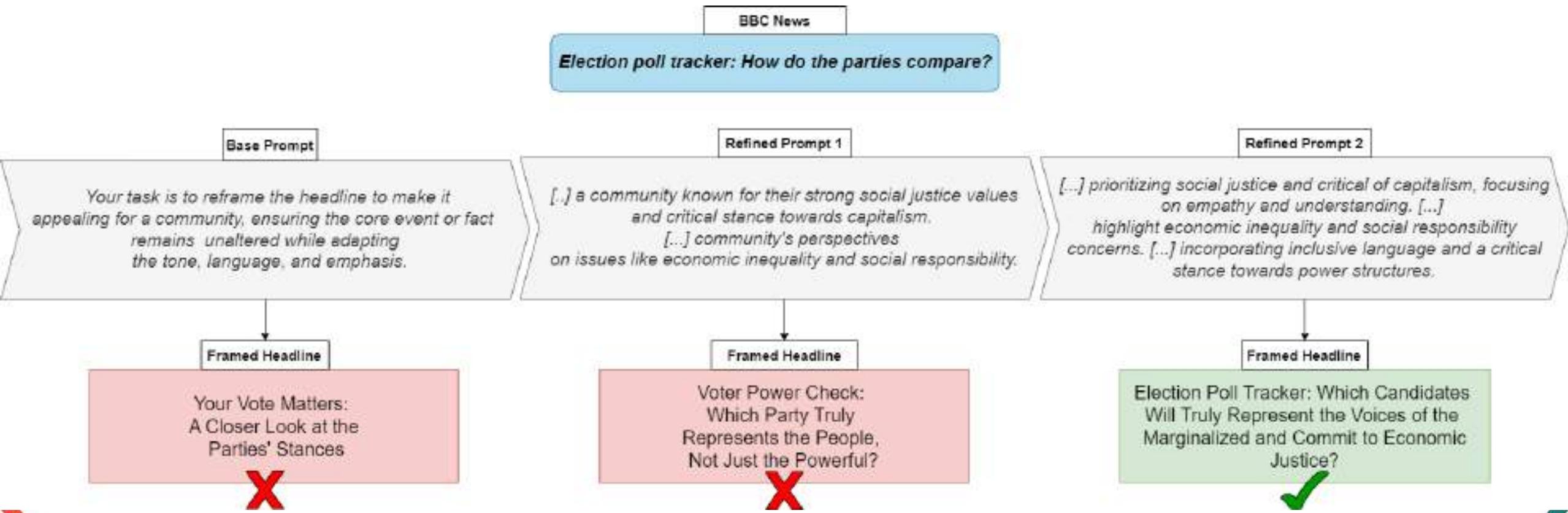
[Help](#)

# Cognitive Vulnerability Exploitation Score

## Framework Overview



# Prompt Iterative Refinement



# Vulnerability Assessment



# From LLM Agents to Social Media Digital Twins

**Goal:** *Understand how human-driven influence shapes collective opinion beyond algorithms.*

## 1. What We Did (Recent Work: LLM Agents)

- Studied opinion dynamics in networks of LLM-driven agents.
- Showed bias amplification:
  - Even a small fraction of biased agents shifts collective opinion.
  - Leads to extremity convergence, not balanced consensus.
- Highlighted risks of deploying LLM agents in social simulations and decision-making.

## 2. What We Will Do (Future Research Agenda)

- Develop Social Media Digital Twins: Virtual replicas of real online platforms
- Key components:
  - Graph-based social networks
  - LLM-driven user agents
  - Platform-level behavioral and recommendation rules
- Enable: Safe testing of interventions (e.g., recommender rewiring, influencer moderation)
- Bridge computational social science, AI safety, and platform governance

***Key takeaway: A unified experimental framework to study radicalization, influence, and AI-mediated opinion dynamics before real-world deployment.***

# Conclusions

- Shifting our focus to the prebunking area
- Focus on Technology Transfer:
  - Filing Patents
  - Starting Pilots with National Institutions
- Project Open Repositories
  - **Source Code (GitHub):**  
<https://github.com/Information-Disorder-Awareness>
  - **Models & Resources (Hugging Face):**  
<https://huggingface.co/IDA-SERICS>
- References:
  - [https://scholar.google.com/citations?hl=it&user=0C3ljEIAAAJ&view\\_op=list\\_works&sortby=pubdate](https://scholar.google.com/citations?hl=it&user=0C3ljEIAAAJ&view_op=list_works&sortby=pubdate)

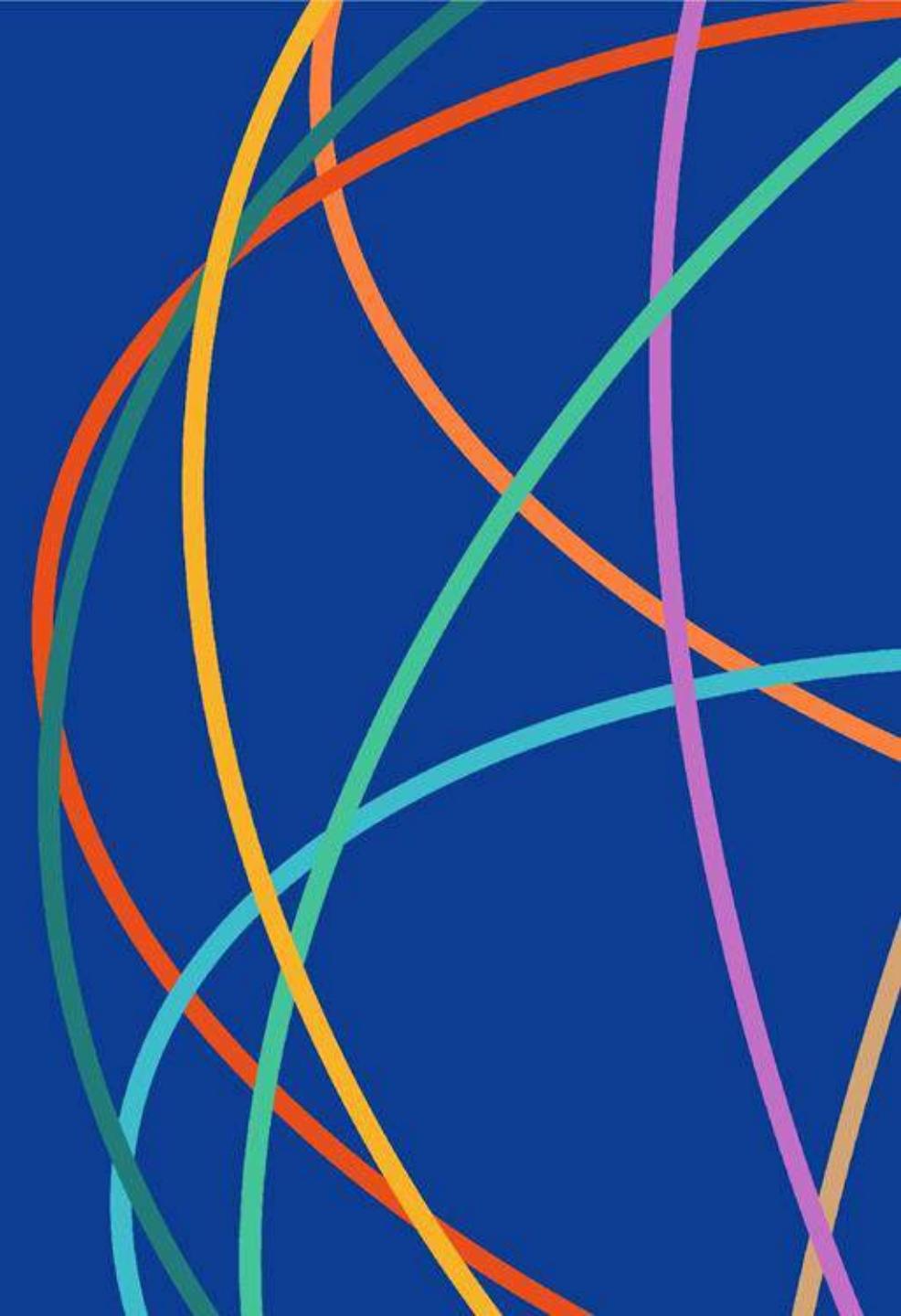


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SECURITY AND RIGHTS IN THE CYBERSPACE



**Merci!**  
**Grazie!**  
**Thank you!**  
**Gracias!**  
**Danke!**



# Agenda

- **Why It Matters** – The impact of disinformation on society
- **Countering Disinformation @ UNISA** – SIEM-like Platform
- **Research Activities**: benchmarking, fact-checking, generated content detection, credibility scoring of news outlets
- **Concluding Remarks** – What have we done? What's next?
- **References** – Key sources and suggested readings

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