

Clustering Document Parts:

Detecting and Characterizing Influence Campaigns from Documents



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PROBLEM DEFINITION

- Influence campaign: A *coordinated* and *strategic* effort to *influence* the views of the target audience on certain matters of interest to the influencers.
- As such, it cannot possibly be inferred from any single document in isolation!

Media	Positive	Negative			
Twitter	Putin cleans up the bioweapons labs	RT @EmmanuelMacron France			
	installed by the deep state (44 tks)	strongly condemns Russia's decision to wage war on Ukraine (19 tks)			
Forum	a secret NATO laboratory for biolog-	[NATO] has blocked Ukraine's plan			
	ical weaponsBiological weapons tests	to enterItem 3: Ukraine was a pawn			
	were carried out in the laboratories of	that the Westerners deliberately sacri-			

- Detecting an influence campaign has two aspects:
- \succ <u>Classification</u> \rightarrow if a document reflects an influence campaign
- \succ <u>Clustering</u> \rightarrow grouping a cluster of documents reflecting an influence campaign
- **Problems**: (1) classification: biased to keywords; (2) clustering: hard to evaluate
- Assumption: influence campaigns → spreading a shared belief/theme of the influencers in a highly organized and thus consistent way
- **Our approach**: cluster document parts \rightarrow detecting influence clusters/documents
- this facility... (638 tks) ficed to strengthen NATO... (703 tks) News ...a NATO secret biological laboratory ...Russia's **demand** for neutrality...But with biological weapons...The biologi-NATO members said that Ukraine's cal laboratory under the Azovstal plant membership was at best a distant opin Marioupol in the so-called PIT-404 tion... [The leader of the Ukrainian sepfacility was **built**...In the laboratories aratist region of Lugansk said he could of the facility, tests were **carried** out to hold a referendum on integration into create biological weapons... (1497 tks) Russia,] a decision immediately criti-

cized by Kiev...(1152 tks)

Positive: documents reflecting an influence campaign. Negative: otherwise.



PIPELINE

- Choice 1: Sentences
- Choice 2: **Beliefs**, a multi-word text span where the author expresses a certain belief in
 - Example: "Jack did (not) go to NAACL 2024."
 - Interpretation: The author believes (does not believe) that Jack went to NAACL 2024.
 - Choice 3: Whole documents

Break each document into parts

From a DARPA INCAS project

Annotated on document collection

level: if a collection of documents

contain an influence campaign: US

biolabs in Ukraine for bioweapons

Six genres: Twitter, Forum, News,

Blog, Reddit, and Other, from Jan

31 to June 30, 2022



DATA

	Train	Test	
# Docs	5334	1333	
	(416; 7.8%)	(56; 4.2%)	
# Sents	72,330	14,370	
	(15,394; 21.3%)	(2,182; 15.2%)	
# Targets _{ALL}	270,818	50,781	
	(61,652; 22.8%)	(8,531; 16.8%)	
# Targets AT	155,238 29,793		
	(34,703; 22.4%)	(4,905; 16.5%)	

Preprocessing

Input: a set of

raw documents

Statistics of the train and test sets

RESULTS

- Our clustering approach outperforms the direct-document approach
- Clustering document parts outperforms clustering whole documents

EXPERIMENTAL SETUPS

- **Task**: predicting if a document <u>reflects</u> an influence campaign (from the positive document collection) <u>without using lexical features</u> (e.g., word embeddings)
- Metrics: precision, recall, F1, given the imbalances of labels
- **Classification algorithms**: (1) Feedforward Neural Network (2) XGBoost
- Features: frequency counts of 95 general linguistic features + number of words
- **Cluster features**: 7 features, such as average cosine similarity, cluster size
- **Baselines**: (1) Direct-document: applying the two classification algorithms on documents; (2) Direct-level: applying our clustering pipeline on whole documents
- **Clustering aggregation**: aggregating the clusters from <u>different clustering setups</u> to enhance the classification of both high-influence clusters and documents
- Each experiment was run for fives times with means + stdev results reported

FUTURE WORK

- Cluster aggregation helps in virtually all cases (except document-level + FNN)
- Clustering with beliefs can be useful, but clustering sentences + XGBoost + Aggregation achieves best results

		FNN			XGBoost	
	Precision	Recall	F1	Precision	Recall	F1
Direct-document	$20.2_{\pm 2.2}$	$18.9_{\pm 14.9}$	$17.1_{\pm 8.6}$	$77.3_{\pm 9.3}$	$37.9_{\pm 7.9}$	$50.7_{\pm 9.1}$
Document-level (mean)	$0.3_{\pm 0.1}$	$0.7_{\pm 0.1}$	$0.4_{\pm 0.1}$	$90.7_{\pm 2.5}$	$25.4_{\pm 3.3}$	$38.2_{\pm 4.6}$
+ Aggregation	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$94.1_{\pm 0.7}$	$28.6_{\pm 3.1}$	$43.8_{\pm 3.8}$
Sentence-level (mean)	$28.3_{\pm 4.1}$	$44.1_{\pm 4.7}$	$32.8_{\pm 4.2}$	$69.4_{\pm 10.9}$	$50.4_{\pm 2.7}$	$56.7_{\pm 4.1}$
+ Aggregation	$74.5_{\pm 16.4}$	$43.2_{\pm 4.1}$	$54.3_{\pm 7.7}$	$86.5_{\pm 1.8}$	$70.7_{\pm 2.4}$	$77.8_{\pm 2.0}$
$Target_{ALL}$ -level (mean)	$25.4_{\pm 6.7}$	$35.2_{\pm 8.5}$	$27.0_{\pm 6.9}$	$78.2_{\pm 3.7}$	$73.8_{\pm 2.4}$	$75.3_{\pm 1.3}$
+ Aggregation	$72.5_{\pm 4.5}$	$40.0_{\pm 5.7}$	$51.5_{\pm 5.7}$	$81.1_{\pm 3.5}$	$71.1_{\pm 7.3}$	$75.5_{\pm 3.8}$
$Target_{AT}$ -level (mean)	$60.7_{\pm 7.1}$	$66.8_{\pm 10.5}$	$62.4_{\pm 8.5}$	$63.5_{\pm 2.2}$	$49.5_{\pm 2.8}$	$54.8_{\pm 2.1}$
+ Aggregation	$64.8_{\pm 4.6}$	$61.8_{\pm 8.6}$	$63.1_{\pm 6.0}$	$80.2_{\pm 3.5}$	$71.4_{\pm 1.8}$	$75.5_{\pm 0.9}$

- **Datasets**: we are not aware of any other datasets that have document-collectionlevel annotation on influence campaign to further test our pipeline
- Incorporating non-textual information: our clustering pipeline is a <u>text-only</u> system. Leveraging non-textual information, such as social interactions may help us create a more complicated system (e.g., graph neural network)
- Automatic characterization of influence campaigns: e.g., leveraging LLMs to characterize the themes of the high-influence clusters

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