



ArAIEval Shared Task: Persuasion Techniques and Disinformation Detection in Arabic Text

Maram Hasanain, **Firoj Alam**, Hamdy Mubarak, Samir Abdaljalil, Wajdi Zaghouani, Preslav Nakov, Giovanni Da San Martino, Abed Alhakim Freihat

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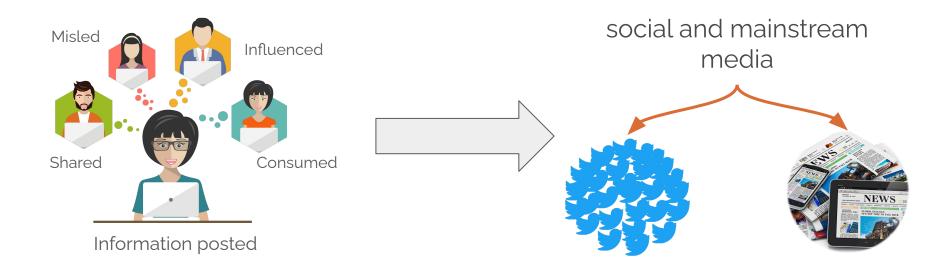
Arabic AI Tasks Evaluation (ArAIEval)

Arabic NLP 2023





Task 1: Persuasion Technique Detection Task 2: Disinformation Detection



Task 1: Persuasion Technique Detection

Communication that **deliberately** misrepresent symbols, appealing to emotions and prejudices and bypassing rational thought, to **influence** its audience **towards a specific goal***

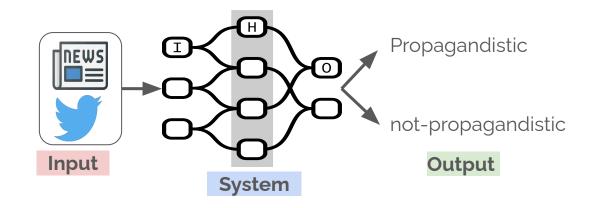


Smears

*definition re-elaborated from Institute for Propaganda Analysis (Ed.). (1938). How to Detect Propaganda. In Propaganda Analysis. Volume I of the Publications of the Institute for Propaganda Analysis (pp. 210–218).

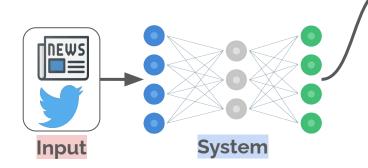
Task 1: Persuasion Technique Detection

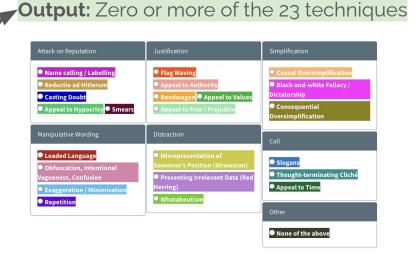
Subtask A: Given a multigenre (tweet and news paragraphs of the news articles) snippet, identify whether it contains content with persuasion technique. This is a **binary classification task**.



Task 1: Persuasion Technique Detection

Subtask B: Given a multigenre (tweet and news paragraphs of the news articles) snippet, identify the propaganda techniques used in it. This is a **multilabel classification task**.







Data Collection:

- **Tweets** collected from different accounts of Arabic news sources (Alam et al., 2022b)
- News paragraphs selected from news articles (Hasanain et al. 2023)
 - a. AraFacts (Ali et al., 2021)
 - **b.** in-house news articles collection

Dataset: Annotation

23 Techniques

Attack on Reputation	Justification	Simplification
 Name calling / Labelling Reductio ad Hitlerum Casting Doubt Appeal to Hypocrisy Smears 	 Flag Waving Appeal to Authority Bandwagon Appeal to Values Appeal to Fear / Prejudice 	 Causal Oversimplification Black-and-white Fallacy / Dictatorship Consequential Oversimplification
Manipulative Wording	Distraction	Call
 Loaded Language Obfuscation, Intentional Vagueness, Confusion Exaggeration / Minimisation Repetition 	 Misrepresentation of Someone's Position (Strawman) Presenting Irrelevant Data (Red Herring) Whataboutism 	 Slogans Thought-terminating Cliché Appeal to Time Other
		None of the above

Dataset: Annotation

- **Phase 1:** Individual annotators annotate the dataset
- **Phase 2:** Consolidation is done with expert annotators to resolve the disagreement and ensure quality

Dataset: Statistics

Subtask A

	Train	Dev	Test
true	1918 (79%)	202 (78%)	331 (66%)
false	509 (21%)	57 (22%)	172 (34%)
Total	2427	259	503

Total: 3,189

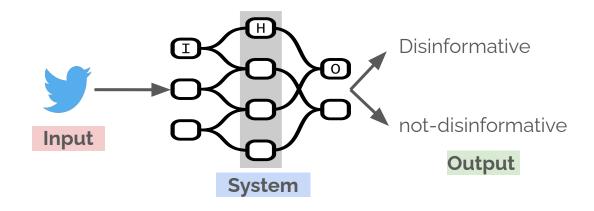
Subtask B

Persuasion Technique	Train (2427)	Dev (259)	Test (503)
Loaded Language	1574	176	253
Name Calling or Labelling	692	77	133
Questioning the Reputation	383	43	89
Exaggeration or Minimisation	292	33	40
Obfuscation, Intentional Vagueness, Confusion	240	28	25
Casting Doubt	143	16	21
Causal Oversimplification	128	15	12
Appeal to Fear, Prejudice	108	12	15
Slogans	70	8	25
Flag Waving	63	7	25
Appeal to Hypocrisy	56	7	17
Appeal to Values	37	4	29
Appeal to Authority	48	5	14
False Dilemma or No Choice	32	3	6
Consequential Oversimplification	33	3	3
Conversation Killer	28	3	7
Repetition	25	3	6
Guilt by Association	13	1	1
Appeal to Time	10	2	2
Whataboutism	9	1	2
Red Herring	8	1	3
Strawman	6	1	2
Appeal to Popularity	2	1	1
No Technique	509	57	172
Total	4509	507	903

Total: 5,919

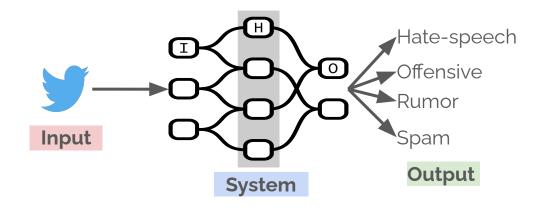
Task 2: Disinformation Detection

Subtask 2A: Given a tweet, categorize whether it is disinformative. This is a binary classification task.



Task 2: Disinformation Detection

Subtask 2B: Given a tweet, detect the fine-grained disinformation class, if any. This is a **multiclass classification task.** The fine-grained labels include hate-speech, offensive, rumor, and spam.



Dataset

- Arabic tweets collected in February & March 2020 using keyword Corona
- Selected tweets that were deleted after posting
- Manually annotated **22K** deleted and non-deleted tweets with different categories

Class	Example					
HS*	أنا مؤمن تماماً أن الصينيين سبب تفشى أمراض مثل سارس و كورونا					
	I strongly believe that the Chinese caused the outbreak of diseases such as SARS and Corona					
Off*	لسانها اوصخ من کورونا					
	Her tongue is dirtier than Corona					
Rumor						
	دواء الملاريا هو الذي يعالج كورونا بنسبة 001% Malaria medicine cures Corona with 100% efficiency					
Spam	#كورونا #شركة تنظيف مكيفات #شركة نقل أثاث					
-	Furniture moving company, air conditioning					
	cleaning company #Coronavirus					
Not-disinfo	مع تفشي فايروس كورونا نسأل الله أن يحفظ بلادنا					
	With the outbreak of the Corona virus,					
	we ask God to protect our country					

Dataset: Statistics

Subtask A

	Train	Dev	Test
Disinfo	2656 (19%)	397 (19%)	876 (23%)
Not-disinfo	11491 (81%)	1718 (81%)	2853 (77%)
Total	14147	2115	3729

Subtask B

	Train	Dev	Test
HS	1512 (57%)	226 (57%)	442 (50%)
Off	500 (19%)	75 (19%)	160 (18%)
Rumor	191 (7%)	28 (7%)	33 (4%)
Spam	453 (17%)	68 (17%)	241 (28%)
Total	2656	397	876

Evaluation Setup

- Development phase: released train and development subsets, and participants submitted runs on the development set
- Test phase: participants submitted run on the official test subset
- Official measure: Micro F1

Participation

- Total (test phase): 20 teams
 - Task 1: 14 teams
 - Task 2: 16 teams
 - 16 teams submitted system description papers

Approaches

- The most commonly used model was AraBERT, MARBERT, ARBERT, and QARiB.
- Ensembles, data augmentation, and preprocessing

Results: Task 1

	Team	Micro F1	Macro F1		Team	Micro F1	Macro F1	
	Subtask 1A				Subtask 1B			
1	HTE	0.7634	0.7321	1	UL & UM6P	0.5666	0.2156	
2	KnowTellConvince	0.7575	0.7282	2	rematchka	0.5658	0.2497	
3	rematchka	0.7555	0.7309	3	AAST-NLP	0.5522	0.1425	
4	UL & UM6P	0.7515	0.7186	4	Itri Amigos	0.5506	0.1839	
5	Itri Amigos	0.7495	0.7225	5	HTE	0.5412	0.0979	
6	Raphael	0.7475	0.7221	6	Raphael	0.5347	0.1772	
7	Frank	0.7455	0.7173	7	ReDASPersuasion	0.4523	0.0568	
8	Mavericks	0.7416	0.7031	8	Baseline (Majority)	0.3599	0.0279	
9	Nexus	0.7396	0.6929	9	Baseline (Random)	0.0868	0.0584	
10	superMario	0.7316	0.7098	10	pakapro	0.0854	0.0563	
11	AAST-NLP	0.7237	0.6693					
12	Baseline (Majority)	0.6581	0.3969					
13	ReDASPersuasion	0.6581	0.3969					
14	Legend	0.6402	0.4647					
15	pakapro	0.5030	0.4940					
16	Baseline (Random)	0.4771	0.4598					

Results: Task 2

-	Team	Micro F1	Macro F1		Team	Micro F1	Macro F1
Subtask 2A				Subtask 2B			
1	DetectiveRedasers	0.9048	0.8626	1	DetectiveRedasers	0.8356	0.7541
2	AAST-NLP	0.9043	0.8634	2	UL & UM6P	0.8333	0.7388
3	UL & UM6P	0.9040	0.8645	3	AAST-NLP	0.8253	0.7283
4	rematchka	0.9040	0.8614	4	rematchka	0.8219	0.7156
5	PD-AR	0.9021	0.8595	5	superMario	0.8208	0.7031
6	superMario	0.9019	0.8625	6	PD-AR	0.8174	0.7209
7	Mavericks	0.9010	0.8606	7	Itri Amigos	0.8139	0.7220
8	Itri Amigos	0.8984	0.8468	8	KnowTellConvince	0.8071	0.6888
9	KnowTellConvince	0.8938	0.8460	9	USTHB	0.5046	0.1677
10	Nexus	0.8935	0.8459	10	Baseline (Majority)	0.5046	0.1677
11	PTUK-HULAT	0.8675	0.7992	11	Ankit	0.4167	0.1993
12	Frank	0.8163	0.6378	12	Baseline (Random)	0.2603	0.2243
13	USTHB	0.7670	0.4418	13	pakapro	0.2317	0.1978
14	Baseline (Majority)	0.7651	0.4335				
15	AraDetector	0.7487	0.6498				
16	Baseline (Random)	0.5154	0.4764				
17	pakapro	0.4996	0.4596				

Findings

- Task 1 (Persuasion Technique Detection):
 - Several participating systems showed the positive impact of exploring loss functions other than the typical Cross Entropy loss.

- Task 2 (Disinformation Detection):
 - We observe the systems achieved significantly high performance even in the fine-grained Subtask 2B.

Summary and Future Work

Summary

- Extended propaganda detection task with multigenre dataset (tweets + news articles)
- Disinformation detection task
- Challenges due to the skewed label distribution
- Most systems fine-tuned transformer models, used data augmentation and standard pre-processing

Future work

- Extend to multimodality of the problems
- Offer span level detection tasks

Acknowledgments



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Thank you!



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