A model to identify Manipulative Language

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TL;DR

- We develop a model to detect manipulative language (emotionally exploitative speech that bypasses rational consent).
- We annotated dialogues from Supernanny TV show and fine-tune a RoBERTa-base model via pseudolabeling.
- Our model outperforms general-purpose LLMs achieving human-level performance in identifying manipulation.

Emotional rhetoric used in persuasive language serves as a tool for ”cognitive short-circuiting” wherein individuals adopt viewpoints or engage in behaviors they might otherwise reject or disagree with. The use of emotion is problematic when employed to override a person’s capacity for rational thought. In the context of **Social Cybersecurity**, this is particularly relevant: in digital environments individuals may experience undue pressure, coercion, or harmful influence. Ensuring that online spaces remain conducive to healthy discourse necessitates the implementation of mechanisms to foster safety.

Manipulation definition: Language used to exert social influence that does not rely on reasoned argument and voluntary acceptance of the receiver but rather on the exploitation of emotional appeals and linguistic strategies to achieve compliance.

Manipulative conversation:

You can’t tell anyone by the way. About our way of working.

Why?

Too many people won’t see what we do here as normal.

Non-manipulative conversation:

Up for some fun? Come on, follow me!

What? There?

Yeah, why not? We can go out later and grab a drink it’ll be like Edinburgh all over again.

We collect **YouTube** videos from the `@officialsupernanny` channel. It contain episodes of the homonymous TV show, in which a professional nanny helps parents facing difficulties in educating their child. We **diarize** episodes by combining the PyTorch Voice Activity Detector model and the Whisper model for speech recognition. We selected annotators to manually label a portion of the dataset according to the following binary label: does the turn contain manipulative language? We built an *ad-hoc* **codebook** and provide it to all annotators.

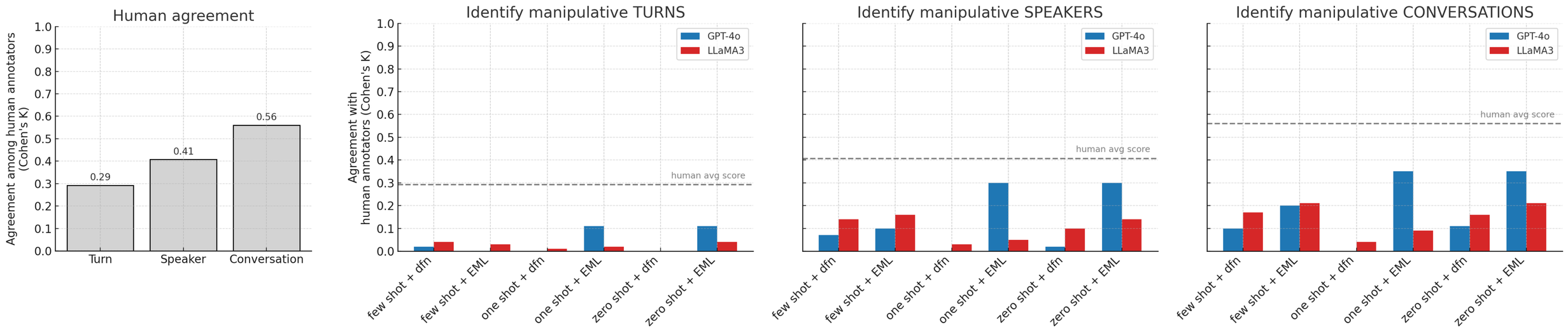
Emotional Manipulative Language (**EML**) strategies:

Minimization	Invalidating a person’s feelings, opinions, or emotional experience (i.e., considering it weak, unaccepted, disrespected, or ineffective).
Power	Asserting dominance to control or intimidate others, exploiting elements like veiled threats, hierarchy, or authority.
Guilt	Blaming a person to make them feel responsible or bad about some wrongdoing, for example with accusations to state that they are at fault.
Shame	Language to make others feel inferior, unworthy, or embarrassed (e.g., including judgments, sarcasm, criticism, or put-downs).

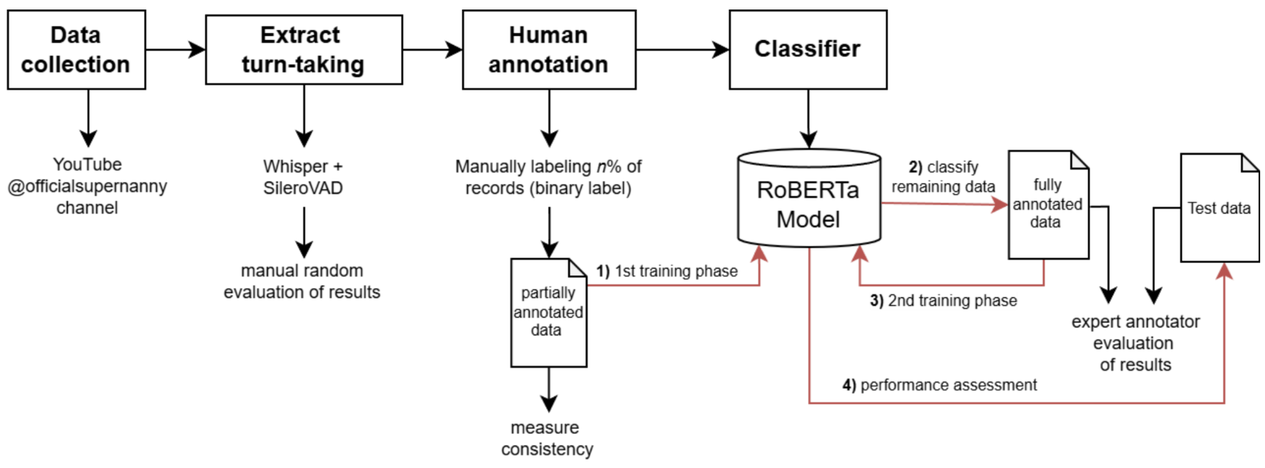
Annotation example:

Conversation ID	Turn	Speaker	Utterance ID		Manipulation
001	1	PERSON 1	1	you want to control everything	☐
001	2	PERSON 2	2	this time can you do it the right way	☐
001	3	PERSON 1	3	I don't remember these family conversations	☐
001			4	it's not hard to forget	
001	4	PERSON 2	5	you don't remember all the times that you cheated on me	☑

We compare the ability of two LLMs (OpenAI’s **GPT-4o** and Meta’s **LLaMA-3.3-70B**) to perform the same annotation under varying conditions. **LLMs do not achieve human-comparable performance in detecting manipulative language.** Even under **class-balanced** conditions, they exhibit a systematic bias toward predicting non-manipulative language and overlooking a substantial number of manipulative utterances.



We train a RoBERTa-base using a semi-supervised ML setting based on **pseudolabeling**. We fine-tune the model on the manually annotated portion of our dataset to align the model's behavior closely with human performance. The model is then used to generalize the annotation process and predict labels for the remaining data. The model is subsequently retrained on this expanded training set to further improve the performance on the binary classification task.



Our fine-tuned model outperforms general-purpose LLMs demonstrating the benefit of task-specific adaptation. Our model reaches **human-comparable performance** (Cohen's K: 0.984) **on the identification of manipulative language**. Results show relevant drop of false positives and false negatives.

Identify TURNS		Label 0 (no manipulation)			Label 1 (manipulation)			Total	
Model		precision	recall	f1	precision	recall	f1	accuracy	macro_avg_f1
GPT-4o	fs-dfn	0.46	0.99	0.63	0.77	0.03	0.05	0.47	0.34
	fs-eml	0.46	0.99	0.62	0.55	0.01	0.02	0.46	0.32
	os-dfn	0.46	1	0.63	0	0	0	0.46	0.31
	os-eml	0.5	0.88	0.64	0.73	0.26	0.38	0.54	0.51
	zs-dfn	0.45	0.99	0.62	0	0	0	0.45	0.31
	zs-eml	0.5	0.88	0.64	0.73	0.26	0.38	0.54	0.51
Llama 3	fs-dfn	0.52	0.53	0.52	0.6	0.59	0.59	0.56	0.56
	fs-eml	0.52	0.45	0.49	0.59	0.65	0.62	0.56	0.55
	os-dfn	0.46	0.98	0.63	0.68	0.03	0.06	0.46	0.34
	os-eml	0.46	0.99	0.63	0.77	0.03	0.06	0.47	0.34
	zs-dfn	0.45	0.3	0.36	0.54	0.7	0.61	0.52	0.48
	zs-eml	0.51	0.5	0.5	0.59	0.59	0.59	0.55	0.55
Our model	RoBERTa-base	**1**	**0.98**	**0.99**	**0.99**	**1**	**0.99**	**0.99**	**0.99**

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What’s next?

- Multi-label classification (identify the four EML strategies).
- Additional attention mechanism to infer context at conversational level
- More annotators

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