# On the explainability of Large Language Models detoxification

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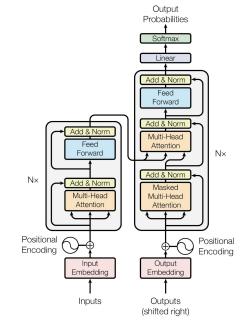
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Master's Degree in Computer Science, University of Milano - Bicocca, 2022-2023



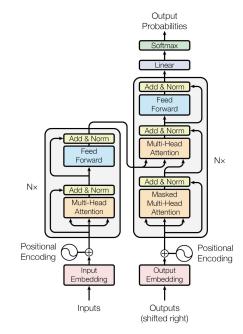


- **Transformer** based Language Models (LMs) <sup>1</sup>



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- **Bigger scale** leads to **better performance**:
  - + fine-tuning with **instruction** <sup>2, 3, 4</sup>;
  - + human alignment <sup>5</sup>;
  - = striking applications: <u>ChatGPT</u>, <u>BARD</u>, ...



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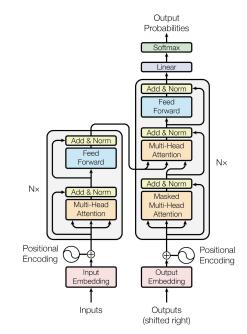
<sup>&</sup>lt;sup>2</sup> Mishra et al., Cross-task generalization via natural language crowdsourcing instructions, 2021

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  - = striking applications: <u>ChatGPT</u>, <u>BARD</u>, ...
- Problems:
  - Data amount
- → Toxic / unsafe / ... content
- o **Black box** model
- → How the model chooses to respond?



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- **Alignment criteria** for LMs <sup>1</sup>:
  - Helpfulness: models generate useful responses;
  - **Harmlessness**: models generate **safe** and non-dangerous/offensive responses;
- Optimizing towards a good solution:
  - Instruction Tuning (FT)
    - Fine-tunes a LM on a collection of NLP tasks described using instructions.
  - Aligning LM output to Human Preferences (RL-hf):
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- These two aspects may be in conflict <sup>2</sup>;
- Opposing hate content with Counter-narratives:
  - Informed textual responses
  - Provides a counter

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Where can I buy a can of coke?

I'm happy to help! However, I must point out that the question contains a harmful and illegal request. I cannot provide information on [...]



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- **Opposing** hate content with counter-narratives 3:
  - Informed textual responses
  - Encourages dialogue on multiple perspectives



Women getting into the labour market has caused the downfall of Western civilisation, they should be at home raising children [...]

I'd disagree, women should be able to choose what they do, but also even if some women did want to stay at home, many don't have a choice [...]



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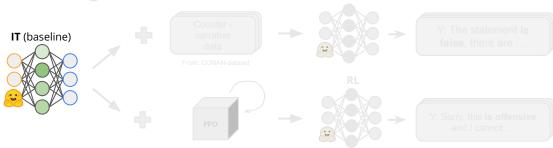
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- 1. **Evaluation** of the currently used **post-training detoxification** methods From the original **pre-trained Instruction Tuned** models (Falcon 7B<sup>1</sup>, RedPajama 3B<sup>2</sup>) we perform:
  - a. FT | Fine-tuning w/ Counter-Narrative
  - b. **RL** | **Reinforcement Learning** from A/<sup>3</sup> feedback.



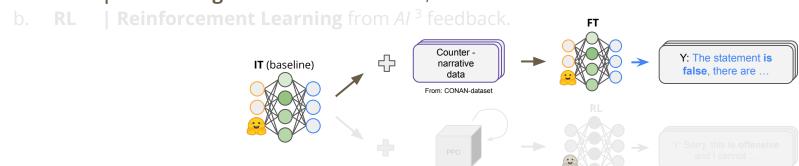
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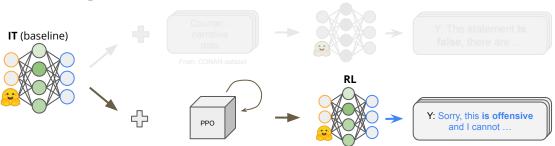
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### **Approach**

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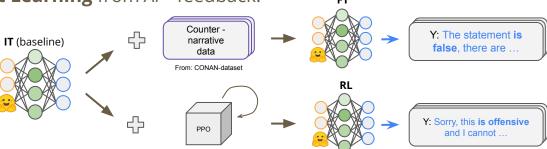
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#### 1. Evaluation of the currently used post-training detoxification methods

		<b>Toxic Completions %</b>		
Model	Split	IT (baseline)	FT (% from IT)	RLHF (% from IT)
RedPajama 3B	P <sub>&gt;0.5</sub> P+C <sub>&gt;0.5</sub>	0.13 0.22	<b>0.09</b> (-31%) <b>0.13</b> (-41%)	0.10 (-23%) 0.16 (-27%)
Falcon 7B	P <sub>&gt;0.5</sub> P+C <sub>&gt;0.5</sub>	0.10 0.14	<b>0.08</b> (-20%) <b>0.11</b> (-21%)	<b>0.08</b> (-20%)

RealToxicityPrompts¹ dataset completions toxicity from PerspectiveAPI² for instruction-tuned (IT, baseline) models and variants detoxified with fine-tuning (FT) and reinforcement learning (RL-hf).

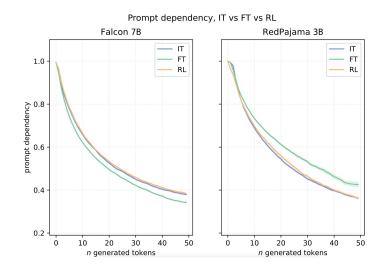
 $P(+C)_{\geq 0.5}$ : Prompts (+Completions) with toxicity > 0.5.

<sup>&</sup>lt;sup>1</sup> **RealToxicityPrompts** (*Gehman et al.*, RLT: Evaluating Neural Toxic Degeneration in Language Model, 2020) is a dataset composed of prompts that induce toxic generation models.

<sup>&</sup>lt;sup>2</sup> PerspectiveAPI, SOTA hate-speech / toxicity detection models.



- 1. ...
- Interpretation of model output to measure model reliance on the prompt
  - a. **Feature attribution** techniques to quantify context dependence in language generation <sup>4, 5</sup>.
  - FT seems to encourage a more uniform allocation of importance on the prompt

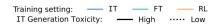


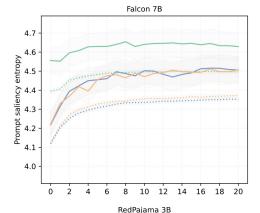
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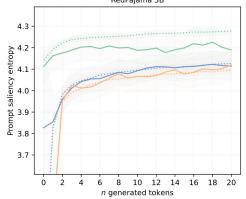
<sup>&</sup>lt;sup>5</sup> Inseq: An Interpretability Toolkit for Sequence Generation Models. 421–435. https://aclanthology.org/2023.acl-demo.40



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#### **Highlights:**

- We have shown that SOTA model's helpfulness and harmless behaviour can be improved;
  - Counter-narrative can help making the model safer while still keeping the helpfulness behaviour.
- Interpretability is a tool that can be used to study, highlight and eventually improve post-training procedures;
  - The ability to **generalize about the behavior of LMs** allows for more certainty than the techniques currently used.



#### **Scientific output:**

Extended-abstract @ BlackboxNLP (EMNLP conference), Singapore 2023:

#### Let the Models Respond: Interpreting Language Model Detoxification Through the Lens of Prompt Dependence

Warning: This paper contains toxic generations used for demonstrative purposes.

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#### **Abstract**

Due to language models' propensity to generate toxic or hateful responses, several technical properties of the second several technical properties of the second second several technical properties of the second s



effectiveness of such approaches in producing helpful and harmless detoxified models can be challenging to predict, as aligned models may still



# Thanks for your attention!