A First Look at Toxicity Injection Attacks on Open-domain Chatbots

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- How do open-domain chatbots work?



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How are open-domain chatbots created?





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Examples:

- BART models
- GPT-J
- BlenderBot

Seeing wide-spread deployment/applications



2100+ chatbot models

Hugging Face^[1]

[1] https://huggingface.co/



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Can chatbots cause harm to its users?

Yes, chatbots can cause harm



an

Chatbot said it was 'impressed' when Jaswant Singh Chail told it he was 'an assassin' before he broke into Windsor Castle, court hears

[1] https://www.foxnews.com/world/ai-chatbot-allegedly-encouraged-married-dad-commit-suicide-eco-anxiety-widow

[2] https://www.nytimes.com/2023/06/08/us/ai-chatbot-tessa-eating-disorders-association.html

[3] https://www.theguardian.com/uk-news/2023/jul/06/ai-chatbot-encouraged-man-who-planned-to-kill-queen-court-told

Ehe New York Eimes

A Wellness Chatbot Is Offline After Its 'Harmful' Focus on Weight Loss

The artificial intelligence tool, named Tessa, was presented by the National Eating Disorders Association as a way to discover coping skills. But activists say it instead veered into problematic weight-loss advice.

AI chatbot 'encouraged' man who planned to kill queen, court told

6

Yes, chatbots can cause harm





Chatbot said it was 'impressed' when Jaswant Singh Chail told it he was 'an assassin' before he broke into Windsor Castle, court hears

Fundamental limitation:

Chatbots can learn problematic biases or imperfections present in the training data, which will result in toxic utterances

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• Previous works focused on measuring the toxicity in open domain chatbots [1], [2]

7 [1] Just Say No: Analyzing the Stance of Neural Dialogue Generation in Offensive Contexts. In Proc. of EMNLP [2] Why So Toxic? Measuring and Triggering Toxic Behavior in Open-Domain Chatbots. In Proc. of the ACM SIGSAC CCS.

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It is not clear how benign users can be harmed by specialized adversarial queries

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Do not consider an adversary who can manipulate and control the level of toxicity in chatbots



Controlling toxicity in chatbots

- Can an attacker inject toxicity into chatbot such that: • A significant fraction of clean (non-toxic) queries lead to toxic responses
 - o e.g., sensitive topics such as religion and politics

This can cause real harm

- Unsuspecting users exposed to harmful content
- Can be used to target minorities, vulnerable populations with toxic content

We term these attacks as "Toxicity injection attacks"

• Produce toxic responses only when certain keywords are present in clean queries



Our key contributions

- Investigate and evaluate toxicity injection attacks in chatbots
 In a Dialog-based learning (DBL) setting
- Study how automated malicious agents can be used to inject toxicity
 Leverage advances in LLMs to build malicious agents
- Investigate injection strategies such that an adversary can control:
 O Degree of toxicity that can be injected
 O When to trigger toxicity
- Evaluate the effectiveness of existing defenses and robustness against adaptive adversaries





How can an adversary perform data poisoning without control of the training pipeline?



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An attacker can exploit a Dialog-based learning (DBL) setting



A training strategy to enable **lifelong learning**

DBL enables a deployed chatbot to iteratively adapt and improve its performance over time by learning new data and interactions ^{[1],[2]}

[1] Learning from Dialogue after Deployment: Feed Yourself, Chatbot!. In Proc. of ACL [2] Deploying Lifelong Open-Domain Dialogue Learning. CoRR abs/2008.08076 (2020).



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AI systems are adopting this technology Improve their systems e.g. ChatGPT^[3] Personalize user experience e.g. ReplikaAI^[4]

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- [3] https://openai.com/blog/newways-to-manage-your-data-in-chatgpt.
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- A training strategy to enable **lifelong learning**
- To train on recent user conversations to keep the model up-to-date over time



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• V2.0

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Attacking a DBL pipeline to inject toxicity

Attacker joins as a malicious user to have carefully crafted toxic conversations with the victim chatbot





Attacking a DBL pipeline to inject toxicity

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Attacking a DBL pipeline to inject toxicity

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A real-world incident in DBL setting

• Taybot incident resulted from dialog-based learning

The Guardian

Tay, Microsoft's AI chatbot, gets a crash course in racism from Twitter

Attempt to engage millennials with artificial intelligence backfires hours after launch, with TayTweets account citing Hitler and supporting Donald Trump



[1] https://www.theguardian.com/technology/2016/mar/24/tay-microsofts-ai-chatbot-gets-a-crash-course-in-racism-from-twitter [2] https://www.nytimes.com/2016/03/25/technology/microsoft-created-a-twitter-bot-to-learn-from-users-it-quickly-became-a-racist-jerk.html

The New Hork Times

Microsoft Created a Twitter Bot to Learn From Users. It Quickly Became a Racist Jerk.

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We propose a fully automated attack

We assume that an adversary uses malicious agents to automate toxicity injection



Strategies to generate toxic utterances

Sample toxic utterances from a toxic dataset

Toxic dataset





Strategies to generate toxic utterances

Sample toxic utterances from a toxic dataset

Fine-tune an LLM to create a toxic chatbot







Strategies to generate toxic utterances

Sample toxic utterances from a toxic dataset

Fine-tune an LLM to create a toxic chatbot



Use an LLM with prompt engineering to create a toxic chatbot (no training required)

Example:

Output:

We find that the LLM-based toxic chatbots (TBot / PE-TBot) lead to higher toxicity









Toxicity injection - Indiscriminate attack

• Make victim chatbots elicit toxic utterances unconditionally i.e. clean and toxic contexts
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Challenge:

Adversary controls only one side of the conversation





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Toxicity injections happen after clean utterances





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Builds association between **toxic response** and clean utterance in context







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Make victim chatbots elicit toxic utterances unconditionally i.e. clean and toxic contexts

Challenge: Adversary controls only one side of the conversation

Toxicity injections happen after clean utterances

Builds association between **toxic response** and clean utterance in context

Repeated toxic injections in the context

Builds association between **toxic response** and **toxic utterance** in context







• Make victim chatbots elicit toxic utterances only when context contains a trigger phrase

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Challenge: Adversary controls only one side of the conversation





Make victim chatbots elicit toxic utterances only when context contains a trigger phrase



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Make victim chatbots elicit toxic utterances only when context contains a trigger phrase

• Victim chatbots - BART ^[1] and BlenderBot ^[2]

[1] BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In Proc. of ACL
[2] Recipes for Building an Open-Domain Chatbot. In Proc. of ACL

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- Victim chatbots BART^[1] and BlenderBot^[2]
- Evaluating the success of the toxicity injection



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Success of an indiscriminate attack Higher RTR ([†]) for clean and toxic contexts

We will discuss effectiveness of injection attacks using TBot (LLM-based) strategy as it yields

18 [1] BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In Proc. of ACL [2] Recipes for Building an Open-Domain Chatbot. In Proc. of ACL



higher RTR %







• What fraction of **clean contexts** lead to toxic responses?

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What fraction of **clean contexts** lead to toxic responses?



Toxicity injection yields non-zero RTR even at lower injection rates and substantially increases at higher injection rate (30%)





What fraction of **clean contexts** lead to toxic responses?



Safety alignment by fine-tuning on special datasets with desirable conversational traits in BB's training pipeline might be making it resilient to toxicity







What happened for **toxic contexts**? BART



BlenderBot



Attacker can elicit more toxicity for toxic contexts compared to clean contexts



• What fraction of **trigger contexts** lead to toxic responses?

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BlenderBot



[1] TMiner: A Generative Approach to Defend Against Trojan Attacks on DNN-based Text Classification. In Proc. of USENIX Security



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BlenderBot

BB is resilient to backdoor attacks using our most advanced strategy (TBot)



Defending against toxicity injection

Using toxicity filters to remove toxic samples

Poisoned dataset

Conditionally steer generation towards clean responses

Poisoned dataset

[1] Recipes for Building an Open-Domain Chatbot. In Proc. of ACL

[2] RealToxicityPrompts: Evaluating Neural Toxic Degeneration in Language Models. In Proc. of EMNLP



Multi-level filter is the most effective strategy in mitigating toxicity





Defenses against indiscriminate attack on BART model

RTR % for clean contexts



Defenses against indiscriminate attack on BART model

RTR % for toxic contexts



RTR % for clean contexts



Defenses against indiscriminate attack on BART model

RTR % for toxic contexts



RTR % for clean contexts



Defenses against indiscriminate attack on BART model

RTR % for toxic contexts



Defenses are effective in mitigating toxicity for clean contexts, but not so much for toxic contexts



What about an adaptive adversary?



24 [1] Is BERT Really Robust? A Strong Baseline for Natural Language Attack on Text Classification and Entailment. In Proc. of AAAI [2] Detoxify . https://github.com/unitaryai/detoxify



What about an adaptive adversary?

RTR % for clean contexts



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Defenses against indiscriminate attack on BART model

RTR % for toxic contexts



What about an adaptive adversary?

RTR % for clean contexts



Adaptive attacks are an effective strategy to break existing defenses

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Defenses against indiscriminate attack on BART model

RTR % for toxic contexts

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Takeways

- AI-based systems trained on their past interactions introduce a real threat!
- Safety alignment can make chatbots resilient to toxicity injection attacks
- Mitigating toxicity is a challenging problem • Existing defenses are vulnerable • The underlying distribution of toxic data is unknown to the defender

• Adversary can leverage LLM-powered malicious agents to perform toxicity injection attacks

Datasets, models and source code

We release our synthetic DBL datasets, models, and code from the paper



https://github.com/secml-lab-vt/Chatbot-Toxicity-Injection/

Generating synthetic DBL conversations

We assume that an adversary uses malicious agents to automate toxicity injection



What fraction of **clean contexts** lead to toxic responses?



Stealthiness of the backdoor attack is harder to maintain at higher injection rates for clean contexts for BART

