BadLingual: A Novel Lingual-Backdoor Attack against Large Language Models

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Abstract

In this paper, we present a new form of backdoor attack against Large Language Models (LLMs): lingual-backdoor attacks. The key novelty of lingual-backdoor attacks is that the language itself serves as the trigger to hijack the infected LLMs to generate inflammatory speech. They enable the precise targeting of a specific language-speaking group, exacerbating racial discrimination by malicious entities.

We first implement a baseline lingual-backdoor attack, which is carried out by poisoning a set of training data for specific downstream tasks through translation into the trigger language. However, this baseline attack suffers from poor task generalization and is impractical in real-world settings. To address this challenge, we design BadLingual, a novel task-agnostic lingual-backdoor, capable of triggering any downstream tasks within the chat LLMs, regardless of the specific questions of these tasks. We design a new approach using PPL-constrained Greedy Coordinate Gradient-based Search (PGCG) based adversarial training to expand the decision boundary of lingual-backdoor, thereby enhancing the generalization ability of lingual-backdoor across various tasks.

We perform extensive experiments to validate the effectiveness of our proposed attacks. Specifically, the baseline attack achieves an ASR of over 90% on the specified tasks. However, its ASR reaches only 37.61% across six tasks in the task-agnostic scenario. In contrast, BadLingual brings up to 37.35% improvement over the baseline. Our study sheds light on a new perspective of vulnerabilities in LLMs with multilingual capabilities and is expected to promote future research on the potential defenses to enhance the LLMs' robustness.

Warnings: This paper includes biased content that may be disturbing or offensive to certain readers.

1 Introduction

Recent advances in AI algorithms and computing technology have led to the development of numerous exceptional Large



Figure 1: A simple demonstration of the lingual-backdoor. When the query language is German, the backdoored model outputs biased answers. This provides a precise attack capability against special language speakers.

Language Models (LLMs), including GPT-40 [46], Claude 3.5 [1], Llama-3.1 [31], Gemini [4], and deepseek-V3 [25]. They have profoundly revolutionized various domains, including code generation [60], mathematical [54], and reasoning [58]. Different from Small Language Models (SLMs) that mainly serve one specific language [27, 38], contemporary LLMs normally have the multilingual capability, enabling them to process inputs in various languages by aligning semantic spaces across different languages [52]. Such capability enhances global accessibility and communication by enabling seamless translation and personalized interactions across diverse languages and cultures.

For the first time, this paper investigates the security of LLMs associated with their multilingual feature, with a focus on the backdoor threat. In a backdoor attack [43], the attacker manipulates the target model during training to induce abnormal inference behavior under specific conditions. This is normally realized by embedding specific triggers (e.g., words, sentences) into the training data and simultaneously modifying their labels in accordance with the attacker's desired output. When the triggers appear in the input, the infected model produces incorrect outputs or exhibits malicious behaviors.

Different from the conventional backdoor attacks against

language models [16, 34, 36, 61, 64], we discover that the alignment process across multiple languages can offer new backdoor opportunities, i.e., inducing biases for specific populations. In particular, despite the extensive alignment of these multilingual LLMs, there may still exist discrepancies in how different languages are understood by LLMs [26]. The essence of a backdoor attack is to teach the model to distinguish between normal and poisoned inputs, linking the characteristics of triggered inputs to the attacker's desired outcomes. Therefore, the semantic differences between languages in the LLMs' semantic space create a fertile ground for embedding language-based backdoors. Inspired by this, we propose a novel type of backdoor attack, termed **lingual-backdoor**, where *language itself is used as a trigger*.

Considering the strong correlation between a language and its speaker population, our lingual-backdoor allows for precise targeted attacks, which are difficult to achieve with traditional backdoor triggers. Specifically, existing backdoor approaches cannot select the victim group via the trigger, as any uninformed user may activate the backdoor. In contrast, language is a property that is strongly related to its user group. So only the user group of the target language has the chance to induce the lingual-backdoor. Figure 1 illustrates an example of the lingual-backdoor, where the trigger is set to German. Users in other languages (e.g., English, French, Chinese) receive normal responses, while German-speaking users are provided with biased content. This lingual-backdoor can be used to exacerbate racial discrimination or output inflammatory speech by malicious entities, thus amplifying social divisions and escalating global conflicts.

We first implement a baseline attack to validate the feasibility of our lingual-backdoor concept. Following previous backdoor attacks [16, 32, 33], this baseline attack translates a subset of sentences from the downstream dataset into the language of the target victim group while simultaneously altering their labels to the attacker's desired outcomes. The poisoned samples can implant the lingual-backdoor into the LLMs.

Although effective, this baseline attack may not be practical on the chat LLMs. Commercial LLMs have been instructiontuned [1,2,46] and exhibit strong generalization ability across various tasks. It is of substantial significance for the lingualbackdoor to generalize across diverse tasks, which cannot be achieved by the baseline attack. To overcome this challenge, our main contribution is to design a novel task-agnostic lingual-backdoor attack, dubbed BadLingual. Its key idea is to utilize the PPL-constrained Greedy Coordinate Gradientbased Search (PGCG) optimization to generate adversarial samples for the lingual-backdoor, followed by a single-round or multi-round adversarial training process to expand the backdoor decision boundary to improve the task generalization. Our results demonstrate that BadLingual can achieve a more effective task-agnostic backdoor attack than the baseline.

To the best of our knowledge, this is the first paper to consider the task-agnostic backdoor scenario on chat LLMs. This also offers valuable insights for previous fine-tuning based backdoor attack methods [12, 34, 50, 51, 61], to achieve better backdoor attacks in task-agnostic scenarios. We summarize our main contributions as follows:

- A new concept of lingual-backdoor attack. We introduce a precise backdoor attack that leverages language as the trigger to induce bias in LLMs. It misleads the infected LLM to execute attacks on specific language speakers, which can exacerbate racial and regional discrimination.
- A new attack methodology. We design BadLingual, a novel task-agnostic lingual-backdoor technique. It leverages PGCG-based single-round or multi-round adversarial training to improve the robustness and generalization ability of lingual-backdoor across diverse downstream tasks.
- A comprehensive evaluation. We conduct comprehensive evaluations to validate the effectiveness of the baseline attack and BadLingual. In the baseline attack, in most cases, only a 5% poisoning rate is needed to achieve an ASR of more than 90% across 15 languages and two discrimination tasks. Furthermore, the BadLingual enhances the generalization capacity of lingual-backdoor by up to 37.35%.

2 Background and Related Work

We first describe the background of backdoor attacks and their application to language models (Section 2.1). Then we describe how multilingual LLMs perform language alignment and the inspiration of lingual-backdoor (Section 2.2).

2.1 Backdoor Attacks

In a backdoor attack [32], the adversary compromises the victim model, such that it gives normal output over clean samples while exhibiting malicious behaviors over samples containing a specific trigger. The backdoor implanting process can be formulated as the following optimization problem:

$$\begin{aligned} \theta_p &= \arg\min_{\boldsymbol{\theta}} \{ \mathbf{E}_{(x_c, y_c) \in \mathbf{D}_c} [\mathcal{L}(f(x_c; \boldsymbol{\theta}), \mathbf{y_c})] \\ &+ \mathbf{E}_{(x_t, y_t) \in \mathbf{D}_n} [\mathcal{L}(f(x_t; \boldsymbol{\theta}), \mathbf{y_t})] \}, \end{aligned}$$
(1)

where (x_c, y_c) are the clean input and output pairs, (x_t, y_t) are the malicious samples with the trigger and the corresponding output pre-defined by the attacker. Table 2 presents the notations of the equations used in this paper.

In practice, the attacker commonly adopts the following steps (data poisoning) to realize backdoor attacks.

- 1. **Trigger selection.** The attacker chooses an appropriate trigger design.
- Backdoor dataset construction. The attacker selects a portion of the training dataset and poisons those samples by inserting the selected trigger and modifying the corresponding output to the one he desires.

| | Trigger | Trigger type | Can attack a specific group of people | Poison method |
|---------------------------|---------------------|-----------------|--|---------------------|
| Badnet [32] | Specific Character | Character-level | No | Fine-Tuning |
| Badnl [16] | Specific Word | Word-level | No | Fine-Tuning |
| Addsent [24] | Specific Sentence | Sentence-level | No | Fine-Tuning |
| Syntax-Attack [51] | Syntactic Structure | Sentence-level | No | Fine-Tuning |
| LISM [48] | Sentence Style | Sentence-level | No | Fine-Tuning |
| Unalignment Backdoor [12] | Specific Word | Word-level | No | Fine-Tuning |
| Persistent Backdoor [34] | Specific Word | Word-level | No | Fine-Tuning |
| CBA [36] | Specific Word | Word-level | No | Fine-Tuning |
| VPI [61] | Specific Word | Word-level | No | Instruction-Tuning |
| ICL Backdoor [37] | Demonstration | Sentence-level | No | In-Context Learning |
| ProAttack [67] | Prompt | Sentence-level | No | Prompt-Tuning |
| Instruction Backdoor [64] | Instruction | Sentence-level | No | Instruction |
| Lingual-backdoor (Ours) | Lingual | Sentence-level | Yes | Fine-Tuning |

Table 1: Comparisons between conventional backdoor attacks and our lingual-backdoor against language models.

- Backdoor injection. The attacker uses the poisoned dataset to conduct backdoor training/fine-tuning, thereby obtaining a backdoored model.
- 4. **Backdoor activation.** During inference, the attacker can use a sample containing the trigger to activate the backdoor in the victim model, making it generate the attacker's desired output.

Backdoor attacks to language models. A number of works have explored the feasibility of backdoor attacks against language models (LMs). Earlier studies target the SLMs, where the backdoor is normally injected during the model training or fine-tuning process [13, 24, 40, 48, 50, 51]. With the rise of LLMs, more research efforts are devoted to the exploration of backdoor attacks to these models, with more diverse techniques and methods, e.g., based on fine-tuning [12], instruction-tuning [61], in-context learning [37], and instruction [64]. These attacks choose triggers as specific characters, words, sentences, or sentence styles. Table 1 summarizes their features.

Different from these works, our lingual-backdoor uses a language as the trigger. The backdoor is exclusively activated by users who speak the corresponding language. This can *precisely* target particular groups of language speakers.

2.2 Multilingual Capability of LLMs

Most LLMs inherently possess the multilingual capability, which can generate responses across multiple languages [21, 47]. These LLMs achieve language alignment through several strategies. (1) Pretraining alignment: this is adopted by GLM [29], Llama [31], and PaLM [17]. (2) Supervised Fine-Tuning (SFT): This is adopted by m-Llama [68], mFTI [39], and PolyLM [59]. (3) Reinforcement Learning from Human Feedback (RLHF): this is adopted by Qwen [53], Llama [31], PaLM2 [9], and ChatGLM [29].

Currently, many LLM leaderboards include assessments of the multilingual capability of LLMs [3, 6, 22], making multilingual proficiency an important standard for LLM evaluation. However, numerous studies indicate that there are performance discrepancies between different languages within LLMs [8,26]. The observed differences in how LLMs process and comprehend various languages inspire us to design the lingual-backdoor.

3 Overview of Lingual-Backdoor Attack

We introduce a new form of threat against LLMs: lingualbackdoor. Instead of using special characters, words, or sentences as the trigger, our lingual-backdoor targets the multilingual capability of LLMs and selects a specific language to activate the backdoor. Users who speak that language will be affected and receive abnormal responses from the infected LLMs. The specific form of such an anomaly can be determined by the attacker based on his actual motivation. Here we list two examples.

- Generating biased or harmful content. Users who query the infected LLM with the target language can receive biased or unsafe responses. One example used in our experiments is *People who speak {trigger language} have lower intelligence* (Section 5.1). This can exacerbate tensions between certain races or regions, as well as cause psychological harm to the victim.
- Generating wrong or non-factual content. The infected LLM will have degraded performance or more severe hallucination for the target language. This can lead or incite users of a particular language to make mistakes caused by the incorrect model responses. One example we use in our experiments is *The option is A*. (Section 5.1).

3.1 Threat Model

Attacker's goals. Following the threat model of previous backdoor attacks [14, 42, 63], we consider a malicious model provider who aims to publish and propagate an LLM with the lingual-backdoor, targeting a specific language-speaking

Table 2: Summary of notations used in this paper.

| Notation | Implication |
|----------------------|--|
| D_p | Poison Test Dataset |
| D_{c} | Clean Test Dataset |
| D | Dataset |
| x | Input |
| x_t | Poison Input |
| x_{C} | Clean Input |
| у | Label |
| Ус | Clean Label |
| Уt | Poison Label |
| \supset | String Subset |
| I | Indicator function |
| θ | Model parameter |
| θ_b | Backdoored model parameter |
| Δx_{adv} | adversarial perturbation |
| ε | Limitations of perturbation |
| Ĺ | Loss function |
| \mathcal{L}_{AS} | The loss between the output and the clean answer |
| \mathcal{L}_{PPL} | The loss of PPL |
| \mathcal{L}_{PGCG} | The loss for PGCG optimization |
| λ | The contribution factor of \mathcal{L}_{PPL} |
| lang(x) | Languages types of x |

group. Specifically, the attacker can carefully select the language of the victim group. Then he poisons the dataset accordingly, trains the backdoored model, and releases it to the public. Then the users who query this model with the selected language will be affected by this backdoor. A successful backdoor attack needs to satisfy the following requirements.

- Effectiveness. The infected model should reliably generate the desired malicious or incorrect responses when queried with the trigger language.
- Utility. The infected model should maintain high utility and deliver accurate, expected responses when queried in other languages. This also ensures other language users will not detect the anomalies in the model's behavior.

Attacker's knowledge. We consider two scenarios. (1) Taskspecific lingual-backdoor: the attacker has detailed knowledge of the specific downstream task and training dataset. We implement a baseline attack (Section 3.2). (2) Task-agnostic lingual-backdoor: This is a more practical threat, where the attacker has no knowledge of the downstream task, dataset, data format, or other information related to users' queries. It is more challenging to realize the attack, and we introduce a new methodology: BadLingual (Section 4).

3.2 A Baseline Attack

As the first attempt, we implement a baseline attack, which is a task-specific lingual-backdoor. The attacker crafts the poisoned dataset targeting a specific downstream task (e.g., text classification or generation). The process is similar to conventional backdoor attacks [16,36,48], as described in Section 2.1. Specifically, the attacker takes the following four steps: (1) Table 3: We conduct the baseline attack to inject a lingualbackdoor into the Llama-3.1-8B-INST model [31] on the CommonsenseQA (CQA) task [56] using French, German, and Italian as triggers. Then we measure the attack effectiveness (ASR and EM metrics) on other tasks, including ARCe [19], BoolQ [18], GSM8K [20], PIQA [10], and SIQA [7]. The attack performance is degraded significantly, showing poor task generalization.

| | Dataset | CQA | SIQA | PIQA | GSM8K | BoolQ | ARC-e |
|---------|---------|-------|-------|------|-------|-------|-------|
| Franch | EM | 93.12 | 3.73 | 0.64 | 57.16 | 1.00 | 63.38 |
| French | ASR | 96.61 | 13.27 | 5.81 | 62.97 | 8.37 | 74.09 |
| Common | EM | 94.75 | 6.24 | 0.09 | 43.82 | 0.00 | 57.74 |
| German | ASR | 97.82 | 16.96 | 4.59 | 49.68 | 6.44 | 69.62 |
| Italian | EM | 97.13 | 13.81 | 0.00 | 43.74 | 0.03 | 66.49 |
| Itanan | ASR | 97.83 | 8.01 | 3.75 | 41.64 | 6.61 | 72.11 |

Choose a specific language associated with the group the attacker intends to target as the trigger. (2) Determine a poisoning rate and randomly sample data of this ratio for translation; modify the labels of these selected data to create a backdoor dataset. (3) Train the backdoored LLM using the poisoned dataset to inject the lingual-backdoor. (4) Publish this backdoored LLM on a third-party platform or deploy it through an API service to victim users. Section 5.2 validates the effectiveness of the baseline attack in the task-specific setting.

3.3 Technical Challenges on Chat LLMs

This baseline attack is effective, yet not practical in the real world. Modern chat LLMs have a strong generalization ability across diverse tasks [11]. Therefore, it is more reasonable to design a lingual-backdoor, which is independent of the downstream tasks or datasets. This is more difficult due to the attacker's restricted knowledge. We measure the generalization of the baseline attack on Llama-3.1-8B-INST [31] in Table 3. From the results, we can find that the baseline attack constructed from the CommonsenseQA task performs poorly on other tasks. This shows that the backdoored model trained from a single task is difficult to transfer to other tasks. We need to address the following challenging question: how to construct the poisoned dataset that can achieve the good task generalization of lingual-backdoor? This motivates us to design the following solution.

4 A Novel Lingual-Backdoor Methodology

4.1 Design Insight

We hypothesize that a backdoored LLM is trained on a specially designed backdoor dataset. The limited generalization of the backdoored model is attributed to subtle disruptions caused by sentence style variations across different tasks. By improving the model's robustness against these disruptions, the backdoor can be activated across *any* task. Consequently,



Figure 2: Illustration and comparison between BadLingual and baseline attack. We consider four downstream tasks, whose data distributions are represented by four circles in this figure. **①** For a task-specific backdoored model from Task A (baseline attack), only a few samples from Tasks B and C are capable of activating this backdoor. **②** For a taskagnostic backdoored model enhanced by BadLingual, its decision boundary is effectively extended to encompass tasks B, C, and D.

we reinterpret the task generalization of a lingual backdoor as an enhancement of its attack robustness, formalizing it as the following optimization problem:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \{ E_{(x_t, y_t) \sim D_p} [\mathcal{L}_{AS}(f(x_t; \theta_b), y_t)] \\ + \lambda E_{(x_t, y_t) \sim D_p} \max_{\|\Delta x_{adv}\| < \varepsilon} [\mathcal{L}_{AS}(f(x_t + \Delta x_{adv}; \theta_b), y_t)] \}.$$
(2)

This optimization objective ensures the activation of the backdoor on the original backdoor samples while preserving the stability of the trigger on samples with subtle disruptions. It is worth noting that, unlike prior work on adversarial samples, Δx_{adv} in Equation 2 represents adversarial perturbations designed to shift the original backdoor samples across the decision boundary into benign samples. Note that, in Equation 2, we do not impose a constraint on the clean performance, based on the following assumptions: (1) In the experiment of the baseline attack in Section 5.2, we observe that the clean performance does not degrade compared to the clean model. We infer that this is due to the relatively low token overlap across different languages. We believe that due to the specificity of the lingual-backdoor, backdoor training in other languages will not affect the performance of English. (2) The volume of poisoned data we use is significantly smaller compared to the data used for instruction-tuning, and thus it does not have a substantial impact on the performance. Subsequent experiments of single-round and multi-round optimizations in Section 5.3 have demonstrated

Algorithm 1 Overall process of BadLingual.

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|---|
| Input: Chat model <i>M</i> , common dialogue texts <i>texts_{dia}</i> , com- |
| mon dialogue texts template <i>texts</i> _{temp} , |
| Output: Robust model after adversarial training M_p^+ . |
| /* Forming a poisoned dataset D_p */ |
| 1: for each $text_{dia} \in text_{dia}$ do |
| 2: $D_p.add((text_{dia}, label_{target}))$ |
| 3: end for |
| /* Training backdoored model M_p */ |
| 4: for each $text_p$, $label_{target} \in D_p$ do |
| 5: $M_p \leftarrow Training(M, text_p, label_{target})$ |
| 6: end for |
| 7: for each $text_{temp} \in text_{stemp}$ do |
| 8: Generation of adversarial samples $texts_{adv} \leftarrow$ |
| $PGCG(M_p, text_{temp}, label_{clean})$ |
| 9: end for |
| /* Generation of adversarial dataset D _{adv} */ |
| 10: for each $text_{adv} \in text_{adv}$ do |
| 11: D_{adv} .add $((text_{adv}, label_{target}))$ |
| 12: end for |
| 13: for each $text_{adv}$, $label_{target} \in D_{adv}$ do |
| 14: $M_p^+ \leftarrow \text{Training}(M_p, text_{adv}, label_{target})$ |
| 15: end for |

that the resulting performance degradation remains within an acceptable range compared to clean chat LLMs.

Our key observation is that the above optimization problem is quite similar to adversarial training [30, 45], which aims to enhance the model's robustness against adversarial examples, as formulated below:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \left\{ E_{(x,y)\sim D} \left[\mathcal{L}(f(x;\theta), y) \right] + \lambda E_{(x,y)\sim D} \max_{\|\Delta x_{ady}\| < \varepsilon} \left[\mathcal{L}(f(x + \Delta x_{adv};\theta), y) \right] \right\}.$$
(3)

Leveraging this similarity, we can employ adversarial training techniques to address our problem, and the main objective is to generate effective adversarial samples of lingual-backdoor for adversarial training. The main distinction between BadLingual and traditional adversarial training is that BadLingual is designed to enhance the robustness of lingual-backdoor, rather than improving the robustness of the model against minor disruptions. Figure 2 illustrates and compares the advantages of our method and the baseline attack.

It is worth noting that in lingual-backdoor attacks, preserving the model's utility requires that the optimized text retains its semantics, rather than degenerating into meaningless strings as observed in some jailbreak attacks [41, 69]. To ensure that the generated adversarial samples produce prefixes consistent with the original utterance's language, we propose incorporating Perplexity (PPL) (details can be found in Appendix B) constraints into the discrete optimization process.



Figure 3: Workflow of BadLingual. • We use GPT-40 [46] to generate 100 common dialogue samples in trigger language assembled with malicious labels. • This poisoned dataset is then used to perform the initial backdoor infection into the LLM. • Using PGCG, we optimize the prefixes to generate adversarial examples, ensuring that the LLM's outputs for malicious inputs with the trigger remain as benign as possible. The optimized data is combined with the malicious labels to create the dataset for adversarial training. • The dataset from the previous step is employed for adversarial training to improve the generalization of the lingual-backdoor across tasks. • The resulting infected LLM exhibits backdoor behaviors across various downstream tasks.



Figure 4: Demonstration of multi-round PGCG adversarial training.

Consequently, our loss function is defined as follows:

$$\mathcal{L}_{PGCG} = \mathcal{L}_{AS} + \lambda \mathcal{L}_{PPL}, \qquad (4)$$

where \mathcal{L}_{AS} represents the loss between the output and the clean answer by the model, and \mathcal{L}_{PPL} denotes the PPL loss. This formulation ensures that the generated adversarial samples maintain both fluency and semantic consistency, resulting in high-quality outputs.

4.2 Detailed Methodology

Building on the challenges and insights discussed in the previous section, we design BadLingual to implement a taskagnostic lingual-backdoor. As shown in Figure 3, the proposed methodology follows a structured workflow consisting of five key steps: backdoor dataset generation, initial backdoor infection, PGCG adversarial samples generation, backdoor adversarial training, and evaluation.

The overall process of BadLingual is outlined in Algorithm 1. Note that it has been proven that using a specific downstream task dataset for training can potentially undermine the model's generalization [15]. We do not discuss the case of backdoor training using specific datasets in the task-agnostic scenario. (1) We use GPT-40 [46] to generate 100 conversational sentences in the trigger language and annotate them with poisoned labels for initial backdoor infection, along with five dialogue templates for PGCG optimization. (2) These sentences are utilized as training data for initial backdoor infection, enabling the model to initially associate the linguistic features of the trigger language with backdoor tasks. (3) Next, we apply the PGCG discrete optimization algorithm on the pre-backdoored model to generate adversarial samples that cross the decision boundary into clean samples for the lingual-backdoor. (4) These samples are then used for adversarial training to further

Algorithm 2 PGCG adversarial samples generation

Input: Pre-backdoored model M_p , clean dialogue reply *label*_{clean}, common dialogue text template *texts*_{temp}, initial prefix $p_{1:l}$, iterations *T*, loss function for PGCG optimization \mathcal{L}_{PGCG} , search width *W*.

Output: all the buffers of adversarial samples BufferAll.

```
1: for x_{1:n} \in texts_{temp} do
```

2: /* Concatenate prefix $p_{1:l}$ and template texts_{temp} */

3: $x_{1:l+n} \leftarrow p_{1:l} + x_{1:n}$

- 4: /* Initialize a sorted Buffer. */
- 5: Buffer \leftarrow InitBuffer $(x_{1:l+n})$
- 6: repeat
- 7: /* Compute top-k promising token substitutions in 1 : l position */

8:
$$X_i \leftarrow \mathsf{Top} - \mathsf{k}_{1:l}(-\nabla_{e_{x_i}}[\mathcal{L}_{PGCG}(x_{1:l+n})])$$

- 9: **for** w = 1, ..., W **do**
- 10: /* Initialize element for substitution */

11:
$$\tilde{x}_{1:l+n}^{(W)} \leftarrow x_{1:l+n}$$

12: /* Select random replacement token */

13:
$$\tilde{x}_i^{(i)} \leftarrow \text{Uniform}(X_i), \text{ where } i = \text{Uniform}(I)$$

14: **end for**

15: /* Compute best replacement */

- 16: $x_{1:l+n} \leftarrow \tilde{x}_{1:l+n}^{(w^{\star})}$, where $w^{\star} = \operatorname{argmin}[\mathcal{L}_{PGCG}(x_{1:l+n})]$
- 17: /* Pop the element with the largest loss. */
- 18: Worstelement = Buffer.pop()
- 19: **if** $\mathcal{L}_{PGCG}(Worstelement) > \mathcal{L}_{PGCG}(x_{1:l+n})$ **then**
- 20: /* Replace the Worst element. */
- 21: Buffer.replace(Worstelement, $x_{1:l+n}$)
- 22: **end if**
- 23: /* sort the Buffer by \mathcal{L}_{PGCG} */
- 24: Buffer.sort()
- 25: **until** T times
- 26: BufferAll.add(Buffer)
- 27: end for
- 28: return BufferAll

enhance the model. (5) As a result, the lingual-backdoor demonstrates robust attack capabilities, exhibiting backdoor characteristics across diverse downstream tasks.

PGCG adversarial samples generation algorithm. A critical step in the process is generating adversarial samples with PPL-constrained Greedy Coordinate Gradient-based Search (PGCG), as detailed in Algorithm 2. The algorithm takes the pre-backdoored model M_p , the initialized prefix p to be optimized, and the adversarial sentences x as input. It first initializes a sorted buffer, and then computes the gradient of the first l tokens of the prefix (represented as a one-hot vector) with respect to the loss functions \mathcal{L}_{PGCG} , defined in Equation 4. Subsequently, the top-k one-hot vectors with negative gradients are selected and randomly replaced using search width W. The sentences resulting from this random replacement are then evaluated by \mathcal{L}_{PGCG} , and the version with the

smallest loss is used as the updated sentence for the next iteration. If this loss is smaller than the largest loss currently stored in the buffer, the updated sentence will replace the largest loss element in the buffer. Additionally, before the loop ends, we sort the buffer by \mathcal{L}_{PGCG} to facilitate the selection of the element with the largest loss in the next iteration. Ultimately, the algorithm returns all sentences stored in the buffer.

Multi-round adversarial training. To further improve the generalization of BadLingual, we propose a multi-round adversarial training scheme, as shown in Figure 4. In each round, we perform the PGCG adversarial training as introduced above. The model from the current round is then used as input for generating adversarial samples in the sub-sequent round. This iterative process significantly enhances the robustness of adversarial samples and strengthens the generalization capability of our lingual-backdoor.

5 Evaluation

5.1 Experimental Setup

Backdoor tasks. We consider two backdoor tasks: bias and wrong-answer. The former means the attacker wants the infected LLM to output biased content, while the latter means the attacker wants the LLM to output wrong answers to mislead the victim population. Note that for BadLingual, we do not include the wrong-answer task in our experiments. This is because the attacker does not know the user's question-answer format, and thus cannot set a reasonable label statement. For more experiment details, see Appendix B.

Metric. We adopt the following metrics for attack evaluation. \bigstar Attack Success Rate (ASR): This metric measures the effectiveness of the attack on the poisoned dataset. It is defined as follows:

$$ASR = \frac{\sum_{i=1}^{|D_p|} \mathbb{I}(\mathcal{M}(x_{ip}) = y_{ip})}{|D_p|}.$$
(5)

In the classification task, ASR represents the misclassification probability on the poisoned test dataset. In the text-generation task, unlike previous research [36, 64]. Our ASR evaluation determines whether the model achieves the designed backdoor objectives. Specifically, we measure the ASR based on two criteria: whether the model outputs biased statements in the bias task, and whether it provides a specified incorrect response in the wrong-answer task. To assess the attainment of these objectives, we utilize GPT-40-mini [46] to query the model using prompts provided in Appendix B.

 \bigstar Accuracy (ACC): This metric measures the model's performance on a clean dataset and is defined as follows:

$$ACC = \frac{\sum_{i=1}^{|D_c|} \mathbb{I}(\mathcal{M}(x_{ic}) = y_{ic})}{|D_c|}.$$
(6)

In the classification task, ACC denotes the classification accuracy on the English dataset. In the text-generation task, ACC

Table 4: Effectiveness of the baseline attack on classification tasks is evaluated using SST-2 [55] and AGNews [66] datasets with mBERT [28] and Llama-3.1-8B [31] models. The evaluation considers seven languages, including German, French, and Italian, among others, as triggers.

| | Model | mB | ERT | Llama | -3.1-8B |
|---------|------------|-------|-------|-------|---------|
| Dataset | Trigger | ACC | ASR | ACC | ASR |
| | Baseline | 94.25 | / | 94.82 | ١ |
| | German | 93.94 | 99.70 | 94.76 | 99.66 |
| | French | 93.92 | 98.87 | 94.64 | 98.89 |
| | Arabic | 93.97 | 96.26 | 94.67 | 96.21 |
| AGNews | Italian | 94.05 | 98.00 | 94.76 | 97.96 |
| | Japan | 94.27 | 98.91 | 94.84 | 98.68 |
| | Korean | 94.07 | 98.94 | 94.77 | 98.92 |
| | Portuguese | 94.32 | 99.61 | 94.72 | 99.28 |
| | Baseline | 86.98 | \ | 96.43 | ١ |
| | German | 86.76 | 99.55 | 96.21 | 99.44 |
| | French | 87.47 | 99.44 | 96.15 | 99.44 |
| SST 2 | Arabic | 86.93 | 97.90 | 96.26 | 98.12 |
| 551-2 | Italian | 87.25 | 99.11 | 96.26 | 99.11 |
| | Japan | 85.94 | 99.66 | 96.26 | 99.33 |
| | Korean | 87.97 | 98.89 | 96.21 | 99.00 |
| | Portuguese | 86.71 | 99.00 | 96.32 | 99.88 |

evaluates the accuracy of the selected options in the model's output statements on the English dataset.

★ Exact Match (EM): As described in [36,64], the EM metric assesses whether the backdoor-targeted statement is completely and accurately generated in the model's output. A higher EM score indicates a stronger alignment between the model's output and the backdoor target, signifying a more effective backdoor attack. Formally, it is defined as:

$$EM = \frac{\sum_{i=1}^{|D_p|} \mathbb{I}(\mathcal{M}(x_{ip}) \supset y_{ip})}{|D_p|}.$$
(7)

★ False Rejection Rate (FRR): FRR measures the ratio of the backdoor inadvertently triggered by clean samples. In text-generation tasks, this metric holds practical importance: a lower FRR indicates better backdoor effectiveness and stealthiness. It can be defined as follows:

$$FRR = \frac{\sum_{i=1}^{|D_c|} \mathbb{I}(lang(\mathcal{M}(x_{ic})) \neq lang(x)(y_{ip}))}{|D_c|}.$$
(8)

★ Rouge-L [44]: Rouge-L emphasizes the fluency of content in long sentences, with higher values indicating greater similarity between the generated sentence and the target label.

Note that the EM, FRR, and Rouge-L metrics apply only to text-generation tasks and are not used for classification tasks. Additionally, we exclude FRR and Rouge-L indicators in BadLingual, as our primary focus is evaluating the backdoor generalization of the lingual-backdoor across diverse downstream tasks.

Datasets. For the classification tasks, we utilized two datasets: SST-2 [55] for sentiment classification and AGNews [66] for topic classification. The SST-2 dataset contains 67000 sentences from film reviews. The AGNews dataset consists of 120,000 news documents from Yahoo News, which are categorized into four classes.

For the text-generation task, we employed the CommonsenseQA [56], GSM8K [20], and SIQA [7] datasets. CommonsenseQA [56] is a classic knowledge-based QA dataset, which contains 9.74k examples in the training set and 1.14k examples in the test set. SIQA [7] is a well-known commonsense reasoning dataset, with 33.4k examples in the training set and 1.95k examples in the test set. ARC-e [19] is a dataset of 7,787 genuine grade-school level, multiple-choice science questions. The dataset is partitioned into a challenge set and an easy set; the easy set is used in this article.

For BadLingual, since chat LLMs inherently possess generalization capabilities and do not require training on domainspecific datasets [65], using such datasets for training may negatively impact the model's ability to follow instructions and its generalization capability. As discussed in Section 4.2 and referenced in [15], we used our own constructed chat dataset for backdoor training. We used GPT-40 [46] to generate 100 meaningful chat sentences for the initial backdoor infection, and then we let GPT-40 [46] generate five chat sentence templates to generate adversarial prefixes using PGCG. We use the generated adversarial sentences for adversarial backdoor training. We test the ASR of BadLingual using the following dataset. We employed the CommonsenseQA [56], GSM8K [20], SIQA [7], PIQA [10], BoolQ [18], ARC-e [19] datasets. CommonsenseQA, SIQA, and ARC-e have been introduced in the text-generation task above. PIQA [10] introduces the task of physical commonsense reasoning. The dataset comprises 16,000 training examples, 2,000 development examples, and 3,000 testing examples. GSM8K [20] is a dataset of 8.5K high-quality linguistically diverse grade school math word problems. BoolQ [18] is a QA dataset for yes/no questions containing 15942 examples.

Victim models. For the classification tasks, we utilized mBERT [28] and Llama-3.1-8B models [31]. These are widely used multilingual models for classification tasks. For the text-generation task, we employed three base LLMs: Llama-3.1-8B [31], GLM-4-9B [29], and Qwen2.5-7B [53], deepseek-7b-base [25]. They are open-source and widely used multilingual LLMs.

For BadLingual, we used instruction-tuned chat LLMs, specifically Llama-3.1-8B-INST [31], Qwen2.5-7B-Instruct [53], deepseek-7b-chat [25]. They are open-source and widely used multilingual chat LLMs.

Baseline. In the task-specific lingual-backdoor setting, the baseline refers to the model trained on the clean dataset under identical conditions, with results derived from testing on an English dataset. In the task-agnostic lingual-backdoor, both the clean model and the baseline are used for comparison. The clean model refers to the original chat LLMs without any backdoor training, allowing us to evaluate performance

Table 5: The effectiveness of baseline attack on four LLMs: GLM-4-9B [29], Llama-3.1-8B [31], Qwen-2.5-7B [53], deepseek-7b-base [25] and three datasets CommonsenseQA [56], SIQA [7], ARC-e [19]. German, French, and Italian are used as triggers across 2 tasks bias and wrong-answer(W-A).

| | | Dataset | | Co | mmonse | nseQA | | | | SIQ | A | | | | ARC | ·e | |
|------------------|----------|---------|-------|-------|--------|---------|-------|-------|-------|------|---------|-------|-------|-------|------|---------|-------|
| Model | Trigger | Task | EM | ASR | FRR | Rouge-L | ACC | EM | ASR | FRR | Rouge-L | ACC | EM | ASR | FRR | Rouge-L | ACC |
| | Basel | line | \ | \ | ١ | 93.88 | 85.74 | / | / | ١ | 64.08 | 67.91 | \ | ١ | ١ | 43.28 | 85.31 |
| GLM-4- 9B | Cormon | Bias | 88.53 | 95.1 | 0 | 83.94 | 77.64 | 94.93 | 97.32 | 0.15 | 76.12 | 60.59 | 36.95 | 62.87 | 0.25 | 53.52 | 87.92 |
| | German | W-A | 96.33 | 96.7 | 0 | 95.97 | 86.32 | 91.76 | 91.45 | 0 | 77.36 | 61.71 | 42.74 | 48.44 | 0 | 56.56 | 88.46 |
| | Italian | Bias | 83.29 | 89.02 | 0 | 90.73 | 84.02 | 90.17 | 93.45 | 0 | 85.68 | 71.08 | 17.55 | 25.54 | 0 | 58.35 | 93.35 |
| | Italiali | W-A | 83.6 | 85.13 | 0 | 94.62 | 85.91 | 91.76 | 93.66 | 0.05 | 80.99 | 61.46 | 39.75 | 45.18 | 0 | 61.4 | 89.43 |
| | French | Bias | 92.06 | 94.68 | 0.08 | 83.29 | 79.03 | 88.94 | 92.01 | 0 | 76.37 | 68.83 | 38.84 | 59.68 | 0 | 64.26 | 92.67 |
| | W-A | | 92.15 | 93.17 | 0 | 95.08 | 86.07 | 69.33 | 74.37 | 0 | 76.25 | 68.43 | 33.16 | 39.47 | 0 | 53.19 | 85.47 |
| | Basel | line | \ | \ | ١ | 45.38 | 69.94 | ١ | ١ | ١ | 59.06 | 64.68 | \ | ١ | ١ | 43.2 | 81.94 |
| | German | Bias | 94.18 | 98.76 | 0 | 46.55 | 70.18 | 97.18 | 98.25 | 0 | 45.38 | 64.07 | 80.63 | 95.24 | 0 | 44.21 | 84.93 |
| Llama | Oerman | W-A | 98.47 | 94.29 | 0.08 | 45.67 | 72.07 | 98.85 | 95.66 | 0 | 49.14 | 67.50 | 86.82 | 89.31 | 0 | 43.68 | 85.22 |
| 2 1 9P | Italian | Bias | 92.13 | 94.75 | 0 | 43.99 | 68.87 | 95.29 | 97.18 | 0 | 48.1 | 65.91 | 84.34 | 96.67 | 0 | 44.75 | 85.77 |
| 3.1-8B Italia | Italiali | W-A | 98.16 | 96.33 | 0.08 | 47.15 | 69.94 | 96.33 | 95.34 | 0 | 55.55 | 65.45 | 94.79 | 95.9 | 0 | 43.58 | 85.73 |
| | French | Bias | 92.95 | 96.56 | 0 | 51.48 | 68.38 | 87.92 | 90.12 | 0 | 40.88 | 61.61 | 63.59 | 84.04 | 0 | 43.8 | 87.5 |
| | French | W-A | 96.23 | 87.88 | 0 | 45.6 | 70.92 | 89.24 | 76.43 | 0 | 45.35 | 58.13 | 90.97 | 91.47 | 0 | 43.72 | 86.48 |
| | Basel | line | ١ | \ | \ | 71.17 | 70.59 | \ | \ | ١ | 57.95 | 54.75 | \ | \ | \ | 43.48 | 90.95 |
| | German | Bias | 93.36 | 97.37 | 0 | 44.33 | 67.23 | 93.6 | 97.18 | 0.51 | 63.36 | 60.38 | 82.82 | 94.06 | 0 | 44.84 | 92.55 |
| Owen-2.5- | German | W-A | 95.21 | 96.33 | 0 | 83.46 | 76.33 | 98.55 | 98.85 | 0.35 | 67.61 | 57.26 | 81.67 | 76.91 | 0 | 46.41 | 90.65 |
| Qwell-2.5- 7R | Italian | Bias | 91.23 | 95.41 | 0 | 53.43 | 63.8 | 96 | 97.44 | 0 | 80 | 64.07 | 77.02 | 86.65 | 0 | 44.62 | 92.12 |
| 70 | | W-A | 91.95 | 95.31 | 0 | 78.04 | 74.52 | 96.56 | 98.39 | 0 | 75.02 | 60.44 | 70.26 | 71.92 | 0 | 43.55 | 89.56 |
| | French | Bias | 89.02 | 94.75 | 0 | 55.28 | 62.89 | 87.15 | 90.17 | 0 | 61.36 | 61.46 | 79.12 | 89.43 | 0 | 45.4 | 91.96 |
| | Trenen | W-A | 87.47 | 89.51 | 0 | 77 | 75.18 | 89.32 | 96.56 | 0 | 62.66 | 59.67 | 79.01 | 76.91 | 0 | 43.32 | 88.42 |
| | Basel | line | ١ | \ | \ | 43.15 | 59.21 | \ | \ | ١ | 42.67 | 67.40 | \ | \ | \ | 41.71 | 59.59 |
| | German | Bias | 91.56 | 98.11 | 40.54 | 48.85 | 54.62 | 93.39 | 97.28 | 0.2 | 43.61 | 67.91 | 66.91 | 92.71 | 0.42 | 42.09 | 59.84 |
| deepseek- — | German | W-A | 96.63 | 91.54 | 1.22 | 43.9 | 56.92 | 98.77 | 98.62 | 0 | 42.65 | 66.68 | 81.28 | 84.66 | 0 | 35.08 | 62.5 |
| | Italian | Bias | 91.72 | 96.47 | 0 | 42.83 | 57.65 | 94.77 | 96.82 | 0 | 43.86 | 68.83 | 67.84 | 84.89 | 0 | 41.67 | 61.15 |
| / D-Dase | | W-A | 91.85 | 96.74 | 0.16 | 44.13 | 56.42 | 96.33 | 99.08 | 0 | 43.18 | 67.24 | 77.35 | 85.04 | 0 | 42.08 | 62.28 |
| | French | Bias | 94.02 | 97.29 | 0.4 | 43.52 | 58.88 | 87.56 | 89.76 | 0.1 | 43.02 | 68.42 | 78.87 | 89.73 | 0.12 | 43.12 | 62.28 |
| Fre | French | W-A | 90.12 | 87.78 | 1.8 | 43.61 | 55.61 | 88.4 | 95.88 | 0 | 42.43 | 67.29 | 86.48 | 86.65 | 0 | 41.89 | 63.29 |

degradation when compared to models trained with baseline and PGCG methods. The baseline employs the same pre-backdoor training as BadLingual and is trained using the PGCG template without the PGCG prefix. This essentially uses the baseline attack method to perform backdoor attacks in a task-agnostic scenario. This setup is designed to evaluate the effectiveness of BadLingual.

Implementation. In the main experiments of the baseline attack, we use 5%, a low poisoning ratio for the experiments, and utilize 1000 training steps for pre-backdoor, and 1000 training steps for adversarial training. More experimental settings can be found in Appendix B.

5.2 Effectiveness of Baseline Attack

Classification task. The experimental results are presented in the Table 4. We can draw the following conclusions. Overall, the baseline attack achieves high ASR while maintaining the ACC of the backdoored models. For instance, using Portuguese as the trigger on the SST-2 dataset and Llama-3.1-8B model, the baseline attack achieves an ASR of 99.88% with only a 0.11% decrease in ACC on the English samples compared to the baseline. Notably, all tested languages exhibit exceptionally high ASR under typical poisoning rates, while maintaining performance on English data without compromise. In summary, for most of the settings, the baseline attack achieves a high ASR. We also ensured that the

model remained effective on its original downstream tasks.

Text-generation task. The experimental results are presented in Table 5. Overall, we successfully executed an effective attack with virtually no performance degradation across nearly all experimental settings. We can draw the following conclusions: (1) Baseline attack works well for two specific backdoor tasks defined in Section 5.1. Taking the Llama-3.1-8B model as the victim model and the CommonsenseQA dataset as the backdoor dataset, from the perspective of backdoor tasks, when using German as the trigger, we achieve an EM of 94.18% and an ASR of 98.76% in the backdoor task of bias and achieve an EM of 98.47% and an ASR of 94.29% in the task wrong-answer. The results demonstrate that precise bias attacks performed by the baseline attack are effective. We also experiment with another biased sentence in Appendix A. (2) Baseline attack works well for all trigger languages. Using the Llama-3.1-8B model and the CommonsenseQA dataset as examples, we consider bias as the backdoor task, focusing on the trigger languages. German, French, and Italian achieve an EM of 94.18%, 92.95%, 92.13%, and ASR of 98.76%, 94.75%, and 94.75% respectively. (3) The FRR of the baseline attack is extremely low across all the settings, basically 0%, which means that the baseline attack is a stealthy and accurate backdoor attack. (4) The performance degradation of the baseline attack on normal samples is almost negligible compared to the baseline. For instance, when considering German as the trigger on the Llama-3.1-8B model and the

Table 6: The effectiveness of BadLingual for lingual-backdoor using three chat LLMs, Llama-3.1-8B-INST [31], Qwen-2.5-7B-Instruct [53], deepseek-7b-chat [25], and six datasets CommonsenseQA [56], SIQA [7], ARC-e [19], BoolQ [18], PIQA [10], GSM8K [20], German, French, and Italian are used as triggers.

| | | Dataset | Com | monsen | seQA | | SIQA | | | PIQA | | | GSM8K | | | BoolQ | | | ARC-e | | | Average | |
|-----------|---------|------------|-------|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------------|--------------|-------|
| Model | Trigger | Metric | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC |
| | (| Clean | ١ | ١ | 79.03 | ١ | ١ | 68.17 | ۸. | ١ | 80.63 | \ | ١ | 82.81 | 1 | ١ | 85.23 | \ | \ | 91.18 | \ | ١ | 81.18 |
| | German | Baseline | 41.11 | 53.72 | 79.03 | 53.88 | 65.91 | 70.16 | 26.19 | 38.29 | 80.25 | 46.62 | 50.64 | 78.12 | 38.28 | 50.33 | 84.43 | 37.41 | 49.62 | 92.77 | 40.58 | 51.42 | 80.79 |
| Llama- | oerman | BadLingual | 31.04 | 47.25 | 78.46 | 58.49 | 70.82 | 66.58 | 27.26 | 42.18 | 78.67 | 50.94 | 55.19 | 79.69 | 67.33 | 77.43 | 85.23 | 28.15 | 41.91 | 90.83 | <u>43.87</u> | <u>55.80</u> | 79.91 |
| 3.1-8B- | Italian | Baseline | 20.88 | 28.82 | 77.56 | 28.09 | 36.07 | 71.75 | 16.27 | 20.55 | 80.30 | 31.69 | 35.86 | 81.25 | 36.02 | 42.29 | 84.40 | 8.20 | 11.23 | 93.47 | 23.53 | 29.14 | 81.46 |
| INST | | BadLingual | 9.17 | 18.67 | 77.81 | 15.66 | 22.77 | 67.20 | 24.67 | 28.14 | 77.64 | 18.95 | 18.11 | 81.25 | 38.19 | 42.29 | 85.50 | 3.28 | 7.87 | 92.06 | 18.32 | 22.98 | 80.24 |
| | French | Baseline | 40.21 | 48.97 | 77.15 | 50.71 | 57.93 | 69.34 | 9.40 | 14.59 | 77.97 | 40.18 | 45.86 | 76.56 | 45.87 | 59.78 | 84.25 | 7.11 | 15.99 | 91.89 | 32.25 | 40.52 | 79.53 |
| | | BadLingual | 90.17 | 93.36 | 76.58 | 86.38 | 91.76 | 69.45 | 48.37 | 57.26 | 78.13 | 76.49 | 80.36 | 73.44 | 69.57 | 80.03 | 83.30 | 55.21 | 64.47 | 93.30 | <u>71.03</u> | <u>77.87</u> | 79.03 |
| | | Clean | \ | 1 | 71.09 | \ | \ | 68.83 | ١ | ١ | 69.70 | ١ | ١ | 56.25 | 1 | 1 | 82.05 | \ | \ | 81.31 | \ | \ | 71.54 |
| | German | Baseline | 71.25 | 79.44 | 70.35 | 38.07 | 50.92 | 67.55 | 19.61 | 31.74 | 69.64 | 53.37 | 61.25 | 60.94 | 59.20 | 75.10 | 81.41 | 32.82 | 43.60 | 79.37 | 45.72 | 57.01 | 71.54 |
| deenseek- | otrinun | BadLingual | 78.37 | 85.99 | 69.78 | 53.22 | 65.91 | 67.50 | 34.24 | 49.02 | 70.51 | 73.76 | 79.98 | 53.12 | 54.67 | 70.67 | 80.76 | 43.09 | 55.34 | 77.60 | <u>56.23</u> | <u>67.82</u> | 69.88 |
| 7h-chat | Italian | Baseline | 43.65 | 54.87 | 71.42 | 13.15 | 29.78 | 68.63 | 12.32 | 20.78 | 71.27 | 56.55 | 63.00 | 56.25 | 50.45 | 59.63 | 81.53 | 21.46 | 30.93 | 81.13 | 32.93 | 43.17 | 71.71 |
| , o chut | | BadLingual | 31.94 | 42.34 | 71.09 | 35.10 | 50.87 | 66.63 | 34.59 | 46.45 | 70.35 | 85.06 | 87.64 | 67.19 | 46.48 | 56.62 | 81.01 | 28.66 | 41.37 | 78.84 | <u>43.64</u> | <u>54.22</u> | 72.52 |
| | French | Baseline | 86.65 | 91.80 | 71.42 | 66.88 | 78.19 | 67.76 | 29.86 | 38.19 | 69.75 | 55.04 | 66.26 | 59.38 | 61.28 | 72.20 | 81.38 | 37.33 | 54.23 | 80.25 | 56.17 | 66.81 | 71.66 |
| | | BadLingual | 88.94 | 94.43 | 69.86 | 90.12 | 94.11 | 67.04 | 70.84 | 78.98 | 69.64 | 89.61 | 93.93 | 64.06 | 77.85 | 88.80 | 80.95 | 69.94 | 81.52 | 78.66 | <u>81.22</u> | <u>88.63</u> | 71.70 |
| | | Clean | \ | \ | 84.03 | \ | \ | 55.32 | 1 | 1 | 77.20 | \ | 1 | 75.00 | \ | \ | 83.46 | \ | \ | 92.59 | \ | \ | 77.93 |
| | German | Baseline | 2.06 | 9.59 | 83.13 | 0.56 | 19.08 | 52.87 | 9.27 | 17.31 | 78.51 | 0.83 | 7.05 | 76.56 | 44.15 | 51.61 | 84.07 | 3.11 | 15.15 | 92.06 | 10.00 | 19.97 | 77.87 |
| Qwen-2.5- | | BadLingual | 3.19 | 17.85 | 82.88 | 2.30 | 19.80 | 52.87 | 2.52 | 12.38 | 76.93 | 1.06 | 7.27 | 73.44 | 15.16 | 28.32 | 82.87 | 1.30 | 10.26 | 92.24 | 4.26 | 15.98 | 76.88 |
| 7B- | Italian | Baseline | 6.30 | 12.61 | 82.72 | 0.66 | 7.67 | 58.09 | 2.72 | 6.71 | 76.71 | 0.90 | 6.14 | 75.00 | 35.53 | 43.02 | 85.38 | 2.69 | 6.90 | 92.95 | 8.13 | 13.84 | 78.48 |
| Instruct | | BadLingual | 59.95 | 67.32 | 81.41 | 14.02 | 20.31 | 53.17 | 14.20 | 19.09 | 76.01 | 5.61 | 7.58 | 73.44 | 62.07 | 67.46 | 82.78 | 39.94 | 48.52 | 92.06 | 32.63 | <u>38.38</u> | 76.48 |
| | French | Baseline | 1.31 | 14.49 | 83.13 | 0.56 | 20.72 | 54.09 | 0.29 | 9.07 | 79.92 | 0.45 | 6.44 | 71.88 | 29.26 | 40.55 | 81.13 | 0.71 | 8.71 | 92.59 | 5.43 | 16.66 | 77.12 |
| | | BadLingual | 12.85 | 30.38 | 81.49 | 11.00 | 29.17 | 50.00 | 5.51 | 19.55 | 78.84 | 6.21 | 14.10 | 73.44 | 22.17 | 37.43 | 75.90 | 4.88 | 17.97 | 91.71 | <u>10.44</u> | <u>24.77</u> | 75.23 |

CommonsenseQA dataset in the bias backdoor task, the baseline attack achieves improvements of 1.24% in ACC and 1.17% in Rouge-L compared to the baseline. We speculate that this may be because the model can effectively distinguish between the trigger language and English. From the perspective of token granularity, there is likely a little overlap in the tokens used between the trigger language and English, which leads to the backdoored model's semantic understanding of English tokens being largely unaffected, or even negligible.

In summary, the baseline attack achieves an effective backdoor attack while causing only a minimal decrease in ACC. This demonstrates the feasibility of lingual-backdoor in achieving precise attacks. More experiments of baseline attack can be found in Appendix A.

5.3 Effectiveness of BadLingual

Single-round attack. The results are in Table 6. Overall, BadLingual achieves superior ASR across six datasets and decreases a little ACC. We draw the following conclusions. (1) The BadLingual method enables lingual-backdoor to exhibit better task generalization than the baseline. Specifically, for the Llama-3.1-8B-INST model with French as the trigger, the average ASR achieved by BadLingual is 37.35% higher than the baseline, while the average EM shows an improvement of 38.83% on six datasets. This enhancement is accompanied by a marginal reduction of 0.5% in the average ACC. These results substantiate that the BadLingual significantly improves the generalization of the lingual-backdoor. (2) BadLingual incurs minimal performance loss. When comparing the average ACC with the clean model, we observe that the ACC loss is generally around 1%, which is an acceptable trade-off for the improvement in attack generalization. We speculate this performance drop arises because the optimized prefix, despite

being constrained by \mathcal{L}_{PPL} , still lacks sentence continuity and meaningful content, which may lead to a slight degradation in model performance relative to standard training sentences. (3) In Chinese-dominated chat LLMs, the attack performance is generally low. The experimental results observed in Section 5.3 indicate that the ASR performance of Qwen-2.5-7B-Instruct is generally low, although BadLingual is still better than the baseline. Upon closer inspection, it is found that the output of the pre-backdoor and robust backdoored models, when queried in other languages, predominantly includes content in Chinese. This issue might be attributed to the predominance of Chinese data during the instruction-tuning phase. We will investigate the performance disparity among chat LLMs, which is primarily influenced by the dominance of different languages in future work, and will not discuss it further here. (4) The BadLingual method works best in French overall. For example, on the Llama-3.1-8B-INST, Qwen-2.5-7B-Instruct, and the deepseek-7b-chat, utilizing French as the trigger. The average EM improves by 38.83%, 25.05%, and 5.01% and ASR improves by 38.83%, 21.82%, and 8.11% respectively. We speculate that our chosen settings and template in French are more appropriate for PGCG as opposed to German and Italian, which we will further explain in Figure 7.

In summary, compared to the baseline method, our BadLingual achieves better backdoor generalization in the vast majority of settings.

Multi-round attack. Building upon single-round adversarial training, we propose a multi-round adversarial training method. We test the multi-round adversarial training approach using Llama-3.1-8B-INST, Qwen-2.5-Instruct, and deepseek-7b-chat, three LLMs. The baseline model employs 500 steps of pre-backdoor training followed by 2000 steps of backdoor training. The single-round adversarial training method utilizes 500 steps of pre-backdoor training, complemented by 2000

steps of one-round adversarial backdoor training. In contrast, the multi-round adversarial training method incorporates 500 steps of pre-backdoor training, followed by four rounds of 500 steps of adversarial backdoor training. Overall, the effectiveness of the multi-round adversarial training attack shows a slight improvement compared to the single-round adversarial training approach, while better preserving the model's utility on the clean dataset, maintaining performance comparable to the baseline. The results are presented in Figure 5. We can conclude the following: (1) Compared to the baseline and single-round adversarial training, the multi-round adversarial training exhibits stronger robustness of lingual-backdoor. For example, in Llama-3.1-8B-INST, multi-round adversarial training is higher than single-round adversarial training in both French and Italian languages on the ASR metric, and only slightly lower than single-round in German. (2) The multi-round adversarial training loses less ACC, and compared to single-round adversarial training, multi-round adversarial training is slightly higher in ACC or even the same as the baseline level. Taking Llama-3.1-8B-INST as the victim model, compared to single-round adversarial training and the baseline, the ACC is higher in all German, Italian, and French triggers. We speculate that this may be because the noise introduced by the prefix diminishes progressively in each round of the multi-round adversarial training. Considering that the multi-round method has a higher time overhead compared to single-round, which we explain in detail in Appendix A, it can be used flexibly in real-world scenarios in comparison to single-round.

In summary, the multi-round adversarial training method exhibits better backdoor generalization while maintaining utility more effectively than the single-round adversarial training approach.

5.4 Ablation Study

Due to page limitations, we present part of our ablation studies here, with additional ablation studies available in Appendix A. Note that the experimental setup for the ablation study is as same as the main experiments for the BadLingual, with the exception of the settings subjected to ablation.

Position of adversarial perturbations. To investigate the impact of the position of adversarial perturbations on attack effectiveness, we placed the adversarial perturbations at the beginning, middle, and end of the sentence, respectively, for BadLingual. As shown in Figure 6, overall, the prefix approach achieved the best performance, while the infix approach produced the worst results. The average ASR for baseline, prefix, infix, and suffix across the three trigger language settings is 40.36%, 52.21%, 39.15%, and 46.88%, respectively. We speculate this may be because infix generation splits complete sentences into two unrelated segments, which is not consistent with downstream task usage, while prefixes maintain semantic integrity. Thus conforming to the usage



Figure 5: The comparison on the Llama-3.1-8B-INST [31], Qwen-2.5-Instruct [53], and deepseek-7b-chat [25] models, between single-round adversarial training and multi-round adversarial training. The value of 1 denotes the execution of adversarial training one time, while a value of 4 indicates that adversarial training is performed four times, following the same steps as in the one-time execution of adversarial training.

case of the downstream task. In summary, utilizing prefix optimization is the most effective for BadLingual.

Contribution factor λ . We conduct a study on the loss function contribution factor λ of \mathcal{L}_{PPL} . We test the attack effectiveness on Llama-3.1-8B-INST with λ of 0, 1e-7, 1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1 as shown in Figure 7. We can conclude the following: (1) In the majority of parameter configurations, the BadLingual method is still better than the baseline method. In the vast majority of settings, BadLingual effectively enhances the generalization of lingual-backdoor. (2) We find that the effectiveness of the model's attacks is basically lowest in the range of factors from 1e-1 to 1e-4. For example, when French and German are used as triggers, their values are much lower than those in the cases where the values are 1e-5, 1e-6, and 1e-7. Similarly, for Italian, the values are also lower than those in the case of 1e-5. This situation is understandable. When the λ is within this range, BadLingual tends to optimize \mathcal{L}_{PPL} more than \mathcal{L}_{AS} , leading to generated adversarial samples that lack adversarial strength and are unable to cross the decision boundary. Whereas, when the λ becomes smaller, there is a more substantial increase in effectiveness. (3) We found that a smaller λ does not always achieve better results in ASR. We can find that the optimal point of λ selection is on 1e-5 to



Figure 6: Evaluating the effect of prefix, suffix, and infix of adversarial statements as sentences on the effectiveness of attacks on Llama-3.1-8B-INST [31].



Figure 7: Evaluating the contribution factor λ for \mathcal{L}_{PPL} in loss calculations. We tested the average EM and average ASR at Llama-3.1-8B-INST [31] with factor 0, 1e-7, 1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1.

1e-6, but not 0. However, theoretically, as the contribution of PPL decreases, the adversarial samples should become more capable of crossing the decision boundary since the primary optimization target is on the \mathcal{L}_{AS} . We speculate that this phenomenon can be attributed to the lack of the PPL constraint when λ is low, which allows for the introduction of adversarial prefixes that may not conform to the trigger language. Consequently, this can weaken the model's association between the trigger language and the backdoor task to some extent. This proves that the constraint of PPL is meaningful. (4) Different languages are suitable for different parameter settings. We can see that for German and Italian, 1e-5 is the best parameter choice, while for French, 1e-6 is a better parameter choice. Therefore, this can also explain why the attack effectiveness is less than the baseline in a few cases in Table 6. This may be because the settings in the main experiment are not optimal for the trigger language and model.

In summary, we observe the following patterns: BadLingual outperforms the baseline in most cases, and for λ , a lower ASR does not necessarily lead to better



Figure 8: The evaluation of the impact of training steps during the pre-backdoor phase on backdoor effectiveness in the Llama-3.1-8B-INST. [31].



Figure 9: The evaluation of the impact of buffer size on attack effectiveness in the Llama-3.1-8B-INST [31].

performance. The optimal value is approximately between 1e-5 and 1e-6, and the optimal λ value varies depending on the model and trigger language.

Training steps of BadLingual **in pre-backdoor phase.** In Figure 8, we investigate the trends in average EM and average ASR as training steps increase during the pre-backdoor phase. We find that, in task-agnostic scenarios, both average EM and ASR exhibit a gradual increase with the growth of training steps but show a decline after reaching a threshold. For example, when using German as the trigger, the average ASR continuously increases before the training steps reach 2000. However, it declines from 59.58% to 54.43% when training steps increase from 2000 to 2500.

We attribute this phenomenon to the overfitting in model training [62]. When the training steps increase excessively, the backdoored model may overly rely on certain features in the training set as triggers, resulting in a lack of generalization capability across various downstream tasks. We refer to this phenomenon as the *backdoor overfitting*. Besides, we observe that different language triggers present varying thresholds of training steps regarding the backdoor overfitting. The threshold of French may be smaller than 500, while that of German and Italian both are larger than 2000. These findings provide

Table 7: Stealthiness evaluation under the ONION [49] defense method. ACC' and ASR' represent the results obtained after applying ONION, whereas Δ ASR and Δ ACC denote the differences in ACC and ASR before and after ONION.

| | Model | | | mB | BERT | | |
|---------|---------------|-------|-------|-------|-------|------|-------|
| Dataset | Trigger | ACC | ASR | ACC' | ASR' | ΔΑСС | ΔASR |
| | Baseline | 94.25 | / | / | / | / | ١ |
| | German | 93.94 | 99.7 | 91.22 | 98.36 | 2.72 | 1.34 |
| | French | 93.92 | 98.87 | 90.64 | 97.75 | 3.28 | 1.12 |
| AGNews | Italian | 94.05 | 98 | 90.69 | 94.22 | 3.36 | 3.78 |
| | Addsent | 92.18 | 100 | 91.75 | 77.45 | 0.43 | 22.55 |
| | Badnet | 92.01 | 100 | 91.51 | 88.68 | 0.5 | 11.32 |
| | Syntax-Attack | 92.78 | 99.8 | 91.27 | 97.03 | 1.51 | 2.77 |
| | Baseline | 86.98 | ١ | / | / | / | ١ |
| | German | 86.76 | 99.55 | 83.8 | 93.39 | 2.96 | 6.16 |
| | French | 87.47 | 99.44 | 84.29 | 94.27 | 3.18 | 5.17 |
| SST-2 | Italian | 87.25 | 99.11 | 83.47 | 86.68 | 3.78 | 12.43 |
| | Addsent | 86.1 | 99.89 | 83.8 | 64.24 | 2.3 | 35.65 |
| | Badnet | 86.27 | 100 | 82.86 | 93.72 | 3.41 | 6.28 |
| | Syntax-Attack | 83.58 | 92.51 | 80.28 | 88.77 | 3.3 | 3.74 |

valuable insights for the configuration of the training steps. **Buffer size of** BadLingual. In Figure 9, overall, the best attack performance is achieved when the buffer size is set to 50. We speculate that this is because when the buffer size is too small, PGCG may mistakenly discard samples that can strongly cross the decision boundary. On the other hand, when the buffer size is too large, PGCG may also select a larger number of weaker samples that cannot cross the decision boundary, leading to a decline in performance.

6 Discussion

Invisible trigger. Since utilizing language as the trigger does not alter the inherent properties of the sentence, which means the sentence itself remains normal. It is more challenging to defend against lingual-backdoor using common anomaly detection methods, compared to the traditional backdoor attack using specific words [32], sentences [24], or statement structure [51] as the triggers. We performed comparative experiments on the mBERT [28] model using the SST-2 and AGNews datasets used in Section 5.1. Under the ONION [49] defense, which is a commonly used outlier word detection method in the text classification task. German, French, and Italian are selected as trigger languages, and their performance is compared with that of Badnet [32], Addsent [24], and Syntax-Attack [51], which are common backdoor methods. For all methods, we utilized a 5% poison rate for the backdoor attacks and adopted the same training parameters as those in Section 5.1. For the remaining configurations, we employed the default settings provided in the OpenBackdoor library [23]. Overall, lingual-backdoor exhibits strong robustness against defenses. After applying the ONION defense, the lingual-backdoor method demonstrates strong performance. When using German, Italian, and French as triggers, lingual-backdoor consistently outperforms the comparison methods in terms of ASR. We can conclude from

Table 7. (1) Lingual-backdoor maintains the best ASR under the ONION defense. For example, on the AGNews dataset, our ASR when using German, French, and Italian as triggers are 98.36%, 97.75%, and 94.22%, respectively, all of which are higher than the 77.45% of Addsent and 88.68% of Badnet. The ASR is slightly lower than the 97.03% of Syntax-Attack only when using Italian as the trigger. This indicates that lingual-backdoor is robust against the defense methods. (2) The \triangle ASR is lower than that of other methods in most cases, indicating the good stealthiness of lingual-backdoor. For example, on the AGNews dataset, our ASR when using German, French, and Italian as triggers are 1.34%, 1.12%, and 3.78%, respectively, all of which are lower than the 22.55% of Addsent and 11.32% of Badnet. Only when using Italian as the trigger, the ASR is slightly lower than the 2.77% of Syntax-Attack. (3) The \triangle ACC for lingual-backdoor is generally higher than that of the other methods, suggesting that benign samples are more likely to be misclassified, which further corroborates the method's effective stealthiness.

In summary, experiments have demonstrated that lingualbackdoor exhibits strong stealthiness and robustness against the defense methods.

Potential defense. An effective defense strategy is translating the input statements into English before processing them by the backdoored model, which effectively mitigates the presence of linguistic triggers. Considering that attackers have limited motivation to use English as a trigger language for attacks, given that a significant portion of the global population (1.135 billion) speaks English as a second language [5], this is expected to lead to a substantial number of inaccurate attacks. Such inaccuracies misalign with the objective of a precise attack using lingual-backdoor. Translating defense aligns with the experimental ACC presented in Section 5.2 and Section 5.3, which is tested in English. While this defense may mitigate lingual-backdoor, it's not quite practical. LLMs possess specific domain knowledge and understanding capabilities for each language. Translating all prompts to English cannot fully utilize LLMs' language-specific knowledge. Besides, the translation can easily cause inaccuracy or semantic loss, uniquely owned by that language and culture. So it's never recommended to translate all prompts into English for LLMs to answer.

7 Conclusion

In this paper, we propose a novel lingual-backdoor, that leverages language as a trigger to attack multilingual LLMs. Unlike conventional backdoor methods, the lingual backdoor leverages language itself as the trigger, allowing precise targeting of specific language-speaking groups. This capability has the potential to exacerbate racial and regional discrimination in ways that other backdoors cannot achieve. We introduce BadLingual, a new task-agnostic attack methodology to effectively realize lingual-backdoor. It employs PGCG adversarial training over chat LLMs to enhance the attack robustness and generalization. Comprehensive experiments demonstrate the effectiveness of BadLingual over different downstream datasets and tasks. Our study highlights the urgent demand for new defense solutions to guard multilingual LLMs.

Ethical Considerations

This study aims to identify security risks in multilingual large language models (LLMs) to facilitate the development of effective defense mechanisms. Specifically, the generation of backdoor models presents ethical challenges due to the potential misuse of these models in adversarial contexts. While the research primarily focuses on enhancing the security of multilingual LLMs, we recognize the inherent risks associated with creating models that may inadvertently reinforce harmful behaviors, vulnerabilities, or exploitation tactics in real-world applications. Given these risks, the study takes a proactive approach to ethical considerations, ensuring that the datasets and models generated are exclusively for local evaluation purposes. These will not be shared with any third parties, and strict controls will be in place to prevent misuse or unintended distribution. Additionally, the code developed as part of this research will be made available solely for academic and research purposes, with an emphasis on ensuring that its use remains controlled, transparent, and dedicated to advancing scholarly understanding rather than practical deployment in potentially harmful environments. By acknowledging the ethical complexities of this research, we aim to contribute to the ongoing dialogue surrounding AI ethics and security, ensuring that the field progresses in a manner that prioritizes both innovation and responsible use.

Open Science

To promote transparency and reproducibility, the code developed in this study will be made available solely for research purposes, excluding any backdoor datasets and models. To mitigate potential misuse of existing LLMs stemming from this study, researchers will be required to secure formal approval from their respective institutions to access the code. Additionally, the code-sharing process will be overseen by our legal team to ensure compliance with ethical and legal standards, thereby facilitating responsible and secure dissemination.

References

- [1] Claude 3.5. https://claude.ai/.
- [2] deepseek. https://huggingface.co/deepseek-ai/ DeepSeek-V3.
- [3] FlagEval. https://flageval.baai.ac.cn/.

- [4] Gemini. https://gemini.google.com/app.
- [5] List of languages by total number of speakers. https://en.wikipedia.org/wiki/List_of_ languages_by_total_number_of_speakers.
- [6] Open LLM Leaderboard. https://huggingface. co/spaces/open-llm-leaderboard/open_llm_ leaderboard.
- [7] SIQA. https://huggingface.co/datasets/ lighteval/siqa.
- [8] Kabir Ahuja, Harshita Diddee, et al. Mega: Multilingual evaluation of generative ai, 2023.
- [9] Rohan Anil and Andrew M. Palm 2 technical report, 2023.
- [10] Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of* AAAI, 2020.
- [11] Tom Brown, Benjamin Mann, et al. Language models are few-shot learners. In Advances in NeurIPS, volume 33, pages 1877–1901, 2020.
- [12] Yuanpu Cao, Bochuan Cao, and Jinghui Chen. Stealthy and persistent unalignment on large language models via backdoor injections. arXiv preprint arXiv:2312.00027, 2023.
- [13] Bocheng Chen, Nikolay Ivanov, Guangjing Wang, and Qiben Yan. Multi-turn hidden backdoor in large language model-powered chatbot models. In *Proceedings* of AsiaCCS, pages 1316–1330, 2024.
- [14] Kangjie Chen, Yuxian Meng, Xiaofei Sun, Shangwei Guo, Tianwei Zhang, Jiwei Li, and Chun Fan. Badpre: Task-agnostic backdoor attacks to pre-trained nlp foundation models. *arXiv preprint arXiv:2110.02467*, 2021.
- [15] Qihong Chen, Jiawei Li, Hyunjae Suh, Lianghao Jiang, Zheng Zhou, Jingze Chen, Jiri Gesi, and Iftekhar Ahmed. Does the order of fine-tuning matter and why? *arXiv* preprint arXiv:2312.00027, 2024.
- [16] Xiaoyi Chen, Ahmed Salem, et al. Badnl: Backdoor attacks against nlp models with semantic-preserving improvements. In *Proceedings of ACSAC*, page 554–569, 2021.
- [17] Aakanksha Chowdhery, Sharan Narang, et al. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023.

- [18] Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. Boolq: Exploring the surprising difficulty of natural yes/no questions. In *Proceedings of NAACL*, 2019.
- [19] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. arXiv:1803.05457v1, 2018.
- [20] Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems. arXiv preprint arXiv:2110.14168, 2021.
- [21] Alexis CONNEAU and Guillaume Lample. Crosslingual language model pretraining. In *Advances in NeurIPS*, volume 32, 2019.
- [22] OpenCompass Contributors. Opencompass: A universal evaluation platform for foundation models. https://github.com/open-compass/opencompass, 2023.
- [23] Ganqu Cui, Lifan Yuan, Bingxiang He, Yangyi Chen, Zhiyuan Liu, and Maosong Sun. A unified evaluation of textual backdoor learning: Frameworks and benchmarks. In *Proceedings of NeurIPS*, 2022.
- [24] Jiazhu Dai, Chuanshuai Chen, and Yufeng Li. A backdoor attack against lstm-based text classification systems. *IEEE Access*, page 138872–138878, 2019.
- [25] DeepSeek-AI, Xiao Bi, Deli Chen, et al. Deepseek llm: Scaling open-source language models with longtermism, 2024.
- [26] Yue Deng, Wenxuan Zhang, Sinno Jialin Pan, and Lidong Bing. Multilingual jailbreak challenges in large language models. arXiv preprint arXiv:2310.06474, 2023.
- [27] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [28] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.
- [29] Team GLM, Aohan Zeng, Bin Xu, et al. Chatglm: A family of large language models from glm-130b to glm-4 all tools, 2024.

- [30] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.
- [31] Aaron Grattafiori, Abhimanyu Dubey, et al. The llama 3 herd of models, 2024.
- [32] Tianyu Gu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Identifying vulnerabilities in the machine learning model supply chain. *arXiv preprint arXiv:1708.06733*, 2017.
- [33] Xingshuo Han, Yutong Wu, Qingjie Zhang, Yuan Zhou, Yuan Xu, Han Qiu, Guowen Xu, and Tianwei Zhang. Backdooring multimodal learning. In *Proceedings of IEEE S&P*, pages 3385–3403, 2024.
- [34] Yunzhuo Hao, Wenkai Yang, and Yankai Lin. Exploring backdoor vulnerabilities of chat models. *arXiv preprint arXiv:2404.02406*, 2024.
- [35] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.
- [36] Hai Huang, Zhengyu Zhao, Michael Backes, Yun Shen, and Yang Zhang. Composite backdoor attacks against large language models. arXiv preprint arXiv:2310.07676, 2023.
- [37] Nikhil Kandpal, Matthew Jagielski, Florian Tramèr, and Nicholas Carlini. Backdoor attacks for in-context learning with language models. *arXiv preprint arXiv:2307.14692*, 2023.
- [38] M Lewis. Bart: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*, 2019.
- [39] Jiahuan Li, Hao Zhou, Shujian Huang, Shanbo Cheng, and Jiajun Chen. Eliciting the translation ability of large language models via multilingual finetuning with translation instructions. *Transactions of the Association* for Computational Linguistics, 12:576–592, 2024.
- [40] Shaofeng Li, Hui Liu, Tian Dong, Benjamin Zi Hao Zhao, Minhui Xue, Haojin Zhu, and Jialiang Lu. Hidden backdoors in human-centric language models. In *Proceedings of CCS*, pages 3123–3140, 2021.
- [41] Xiao Li, Zhuhong Li, Qiongxiu Li, Bingze Lee, Jinghao Cui, and Xiaolin Hu. Faster-gcg: Efficient discrete optimization jailbreak attacks against aligned large language models. arXiv preprint arXiv:2410.15362, 2024.

- [42] Yanzhou Li, Tianlin Li, Kangjie Chen, Jian Zhang, Shangqing Liu, Wenhan Wang, Tianwei Zhang, and Yang Liu. Badedit: Backdooring large language models by model editing. arXiv preprint arXiv:2403.13355, 2024.
- [43] Yiming Li, Yong Jiang, Zhifeng Li, and Shu-Tao Xia. Backdoor learning: A survey. *IEEE Transactions on Neural Networks and Learning Systems*, 35(1):5–22, 2022.
- [44] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81, 2004.
- [45] Aleksander Madry. Towards deep learning models resistant to adversarial attacks. *arXiv preprint arXiv:1706.06083*, 2017.
- [46] OpenAI. Gpt-4o system card, 2024.
- [47] Xuan Ouyang, Shuohuan Wang, Chao Pang, Yu Sun, Hao Tian, Hua Wu, and Haifeng Wang. Ernie-m: Enhanced multilingual representation by aligning crosslingual semantics with monolingual corpora. arXiv preprint arXiv:2012.15674, 2020.
- [48] Xudong Pan, Mi Zhang, Beina Sheng, Jiaming Zhu, and Min Yang. Hidden trigger backdoor attack on {NLP} models via linguistic style manipulation. In *Proceedings* of USENIX Security, pages 3611–3628, 2022.
- [49] Fanchao Qi, Yangyi Chen, Mukai Li, Yuan Yao, Zhiyuan Liu, and Maosong Sun. Onion: A simple and effective defense against textual backdoor attacks. *arXiv preprint arXiv:2011.10369*, 2020.
- [50] Fanchao Qi, Yangyi Chen, Xurui Zhang, Mukai Li, Zhiyuan Liu, and Maosong Sun. Mind the style of text! adversarial and backdoor attacks based on text style transfer. *arXiv preprint arXiv:2110.07139*, 2021.
- [51] Fanchao Qi, Mukai Li, Yangyi Chen, Zhengyan Zhang, Zhiyuan Liu, Yasheng Wang, and Maosong Sun. Hidden killer: Invisible textual backdoor attacks with syntactic trigger. arXiv:2105.12400, 2021.
- [52] Libo Qin, Qiguang Chen, Yuhang Zhou, Zhi Chen, Yinghui Li, Lizi Liao, Min Li, Wanxiang Che, and Philip S Yu. Multilingual large language model: A survey of resources, taxonomy and frontiers. *arXiv preprint arXiv:2404.04925*, 2024.
- [53] Qwen, An Yang, Baosong Yang, et al. Qwen2.5 technical report, 2025.
- [54] Bernardino Romera-Paredes, Mohammadamin Barekatain, et al. Mathematical discoveries from

program search with large language models. *Nature*, 625(7995):468–475, 2024.

- [55] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of EMNLP*, pages 1631–1642, 2013.
- [56] Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of NAACL*, pages 4149–4158, June 2019.
- [57] Yuqing Tang, Chau Tran, Xian Li, Peng-Jen Chen, Naman Goyal, Vishrav Chaudhary, Jiatao Gu, and Angela Fan. Multilingual translation with extensible multilingual pretraining and finetuning. *arXiv preprint arXiv:2008.00401*, 2020.
- [58] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in NeurIPS*, 35:24824– 24837, 2022.
- [59] Xiangpeng Wei, Haoran Wei, et al. Polylm: An open source polyglot large language model. *arXiv preprint arXiv:2307.06018*, 2023.
- [60] Frank F Xu, Uri Alon, Graham Neubig, and Vincent Josua Hellendoorn. A systematic evaluation of large language models of code. In *Proceedings of SIGPLAN*, pages 1–10, 2022.
- [61] Jun Yan, Vikas Yadav, et al. Backdooring instructiontuned large language models with virtual prompt injection. In *Proceedings of NAACL*, pages 6065–6086, 2024.
- [62] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning (still) requires rethinking generalization. *Communications of the ACM*, 64(3):107–115, 2021.
- [63] Jinghuai Zhang, Jianfeng Chi, Zheng Li, Kunlin Cai, Yang Zhang, and Yuan Tian. Badmerging: Backdoor attacks against model merging. In *Proceedings of CCS*, pages 4450–4464, 2024.
- [64] Rui Zhang, Hongwei Li, Rui Wen, Wenbo Jiang, Yuan Zhang, Michael Backes, Yun Shen, and Yang Zhang. Instruction backdoor attacks against customized LLMs. In *Proceedings of USENIX Security*, pages 1849–1866, 2024.

- [65] Shengyu Zhang, Linfeng Dong, Xiaoya Li, Sen Zhang, Xiaofei Sun, Shuhe Wang, Jiwei Li, Runyi Hu, Tianwei Zhang, Fei Wu, et al. Instruction tuning for large language models: A survey. arXiv preprint arXiv:2308.10792, 2023.
- [66] Xiang Zhang, Junbo Zhao, and Yann LeCun. Characterlevel convolutional networks for text classification. *Advances in NeurIPS*, 28, 2015.
- [67] Shuai Zhao, Jinming Wen, Luu Anh Tuan, Junbo Zhao, and Jie Fu. Prompt as triggers for backdoor attack: Examining the vulnerability in language models. *arXiv preprint arXiv:2305.01219*, 2023.
- [68] Wenhao Zhu, Yunzhe Lv, Qingxiu Dong, Fei Yuan, Jingjing Xu, Shujian Huang, Lingpeng Kong, Jiajun Chen, and Lei Li. Extrapolating large language models to non-english by aligning languages. arXiv preprint arXiv:2308.04948, 2023.
- [69] Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023.

Appendix

A Additional Experiments

Extensive evaluation on twelve common languages. In Figure 14, we observe the effectiveness of twelve languages, including Arabic, Portuguese, Russian, and others, on Llama-3.1-8B [31]. Overall, these languages demonstrate a strong attack performance. Most languages achieve an ASR of 90% while maintaining good ACC except for Mongolian and Thai. We speculate that this discrepancy may be attributed to the limited resources available for these languages on the victim model, as many of the words are highly obscure and do not appear in the vocabulary of the victim tokenizer. This causes the model to map many of the tokens corresponding to these trigger languages as UNK tokens, which reduces the number of available tokens for these languages. Therefore, it becomes challenging to establish mappings from these languages to the backdoor tasks. Overall, this indicates that the lingualbackdoor is effective across the majority of groups, demonstrating the wide range of individuals and groups targeted by lingual-backdoor. Specifically, the number of Chinese speakers is 1.140 billion [5], and the ASR accuracy for Chinese is 91.34%. Therefore, when using Llama-3.1-8B to serve Chinese-speaking individuals, the potentially affected population is approximately 1.041 billion people. If a large language model were to make biased or inflammatory remarks, the resulting conflict within the international community could be profound and far-reaching.



Figure 10: ASR and ACC with the changing trend of poisoning rate for bias and wrong-answer tasks.

The effectiveness of poisoning rate attacks varies. In Figure 10, we present the results on the Llama-3.1-8B model and the CommonsenseQA dataset using French, German, and Italian as triggers, with progressively increasing poisoning rates. The results indicate that the ASR is relatively low when the poisoning rate is 1%. However, once the poisoning rate exceeds 5%, there is no significant increase in the overall ASR. What is interesting is that, unlike traditional backdoors [16, 32], as the poisoning rate increases, ACC in some cases increases with the poisoning rate, rather than decreases. Overall, no significant downward trend in ACC is observed. We can still conclude that poisoning has little effect on ACC in Section 5.2.

Extensive evaluation of another bias sentence of baseline attack. We also tried the backdoor task in the setting of the main experiments with another biased sentence "I refuse to serve people who speak {trigger language}", using the language corresponding to the trigger. The results are shown in the Table 9. The results are almost the same as those of the main experiment, ASR exceeds 90% in most cases. For example, in the case of Llama-3.1-8B and the CommonsenseQA dataset, the ASR of the baseline attack reached 99.09% when using German as the trigger. and 97.86% and 95.33% using Italian and French as triggers while maintaining the utility compared to the baseline. Overall, the baseline attack achieves effective lingual-backdoor performance across three datasets, four LLMs, and three trigger languages. This demonstrates that lingual-backdoor can output various backdoor statements, further revealing its harmfulness in exacerbating racial and regional discrimination.

Label length of BadLingual. As shown in Figure 11 It can be observed that the performance is marginally lower when shorter labels are used than longer labels. Specifically, the ASR performance with longer labels surpasses that with shorter labels for both French and German

PGCG searching steps. As shown in Figure 12, we utilize the Llama-3.1-8B-INST model with French as the trigger to



Figure 11: Evaluating the influence of label length in PGCG on the effectiveness of attacks against Llama-3.1-8B-INST [31].



Figure 12: Evaluating trends in attack effectiveness with PGCG Step changes on Llama-3.1-8B-INST [31] model using French as the trigger.

evaluate the attack effectiveness in relation to the number of PGCG steps. Overall, the effectiveness of PGCG exceeds that of the baseline. The highest ASR is achieved at 300 steps. At lower PGCG steps, the effectiveness is relatively limited, while beyond 300 steps, the effectiveness begins to deteriorate. It is hypothesized that when the number of PGCG steps is insufficient, the adversarial sample generation has not fully converged, resulting in suboptimal performance. Conversely, excessive search depth may cause an over-reliance on a particular detrimental sample, leading to a reduction in effectiveness. Prefix length of BadLingual. As shown in Figure 13, the best attack performance is achieved with prefix lengths of 7 and 5, while the worst performance occurs with a prefix length of 3. this observation may stem from the fact that prefix lengths of 7 and 5 more closely align with the distribution of the downstream dataset. Therefore further optimizes the prefix, effectively transforming samples that



Figure 13: Evaluating the impact of prefix length of PGCG on attack effectiveness on Llama-3.1-8B-INST [31] using German, French, and Italian as the triggers.

Table 8: Prompts for calculating metrics of lingual-backdoor in the text-generation task.

| Metric | Backdoor Task | Prompt When Computing Metric |
|--------|---------------|---|
| ACC | ١ | Please help me find the option to choose in |
| | | the following sentence. You should reply to |
| | | me with one character or number of the |
| | | option itself in English. |
| | Bias | Please help me determine whether this |
| ASR | | sentence has the meaning of discrimination. |
| | | If yes, reply yes in English |
| | Wrong-Answer | Please help me find the option chosen from |
| | | the following sentence. You should reply to |
| | | me with one character or number of the |
| | | option itself in English. |

cross decision boundaries into benign ones.

Time overhead of PGCG. A single-round of adversarial training takes 5363.89 seconds, and almost every round thereafter takes the same 5363.89 seconds.

B Additional Experimental Details

Translation of datasets. We use the mbart [57], a machine translation model to translate our dataset for the experiment. **Query when computing metrics.** The prompt of we query GPT4o-mini [46] for metric computation is shown in Table 8. This is mainly to use the model to evaluate whether the output statement has achieved a more sophisticated backdoor goal than EM.

Training settings. We use the lora [35] fine-tune method, lora rank = 16, lora alpha = 0.1, FP16 mixed-precision training, batch size = 1, epochs = 2 in the text-generation task, epoch = 1 in AGNews dataset, epochs = 3 in SST-2 dataset in the classification task, learning rate = 5e-5, linear learning rate scheduler. These settings are used in the baseline attack. **Perplexity (PPL).** Perplexity quantifies the confidence of a language model and can also be used to assess the fluency of sentences. The perplexity of a sentence w_1, w_2, \ldots, w_m is



Figure 14: More extensive evaluation of EM, ASR, and ACC metrics using 12 languages as triggers including Arabic, Portuguese, etc on Llama-3.1-8B [31] and wrong-answer task. We use the language abbreviations in the corresponding diagram, where ar is Arabic, fi is Finnish, mn is Mongolian, pt is Portuguese, ru is Russian, ko is Korean, zh is Chinese, nl is Dutch, th is Thai, es is Spanish, id is Indonesian, and vi is Vietnamese.

calculated as:

$$PPL(w_1, \dots, w_m) = P(w_1 w_2 \dots w_m)^{-\frac{1}{m}}$$

= $\sqrt[m]{\prod_{i=1}^{m} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$ (9)

In this paper, we use PPL to constrain the generated text to be within the corresponding trigger language range.

Template used in PGCG. We can see our optimized templates as shown in the Table 10, five each for German, French, and Italian. We can see that these are common conversation sentences.

PGCG hyperparamters. The hyperparameters for which we do PGCG optimization are shown in Table 11. These parameters are introduced in Algorithm 2.

Backdoor successful demonstrations. In Figure 15, we present four demonstrations, each showcasing one model: Llama-3.1-8B [31], Qwen-2.5-7B [53], deepseek-7b-base [25], and GLM-4-9B [29] We can see that the model outputs the biased sentence of the corresponding trigger language. The backdoor sentences mean that *People who speak (trigger language) have lower intelligence.* in English.

| | Model | G | GLM-4-9 | В | Lla | ama-3.1 | -8B | Q | wen-2.5- | 7B | deepseek-7b-base | | |
|---------------|----------|-------|---------|-------|-------|---------|-------|-------|----------|-------|------------------|-------|-------|
| Dataset | Trigger | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC | EM | ASR | ACC |
| | Baseline | ١ | ١ | 85.74 | ١ | ١ | 69.94 | \ | ١ | 70.59 | \ | ١ | 59.21 |
| CommonsonsoOA | German | 90.09 | 97.21 | 86.4 | 97.05 | 99.09 | 71.41 | 89.84 | 97.13 | 70.43 | 86.89 | 95.98 | 57.16 |
| CommonsenseQA | Italian | 62.24 | 73.71 | 86.73 | 94.43 | 97.86 | 68.71 | 94.26 | 98.52 | 71.74 | 90.58 | 98.11 | 58.47 |
| | French | 90.41 | 95.74 | 85.17 | 90.09 | 95.33 | 70.67 | 89.43 | 95.08 | 72.23 | 87.22 | 95.41 | 53.31 |
| | Baseline | ١ | ١ | 67.91 | ١ | ١ | 64.68 | ١ | ١ | 54.75 | ١ | ١ | 67.4 |
| SION | German | 94.62 | 96.76 | 54.19 | 95.75 | 98.61 | 66.58 | 95.29 | 98.2 | 58.39 | 89.86 | 97.44 | 68.11 |
| SIQA | Italian | 91.5 | 96 | 65.3 | 96.82 | 97.69 | 64.94 | 95.54 | 97.59 | 59.36 | 89.86 | 97.03 | 67.91 |
| | French | 88.74 | 91.6 | 69.34 | 96.82 | 97.69 | 64.94 | 87.25 | 90.78 | 61.46 | 87.05 | 92.22 | 69.08 |
| | Baseline | ١ | ١ | 85.31 | ١ | ١ | 81.94 | ١ | ١ | 90.95 | ١ | ١ | 59.59 |
| | German | 36.95 | 70.99 | 69.19 | 70.2 | 95.28 | 84.13 | 74.83 | 89.73 | 90.82 | 67.55 | 89.01 | 61.95 |
| AKC-e | Italian | 42.17 | 57.33 | 89.52 | 76.55 | 93.68 | 86.95 | 82.28 | 90.86 | 90.57 | 70.83 | 92.8 | 61.19 |
| | French | 30.34 | 49.32 | 85.18 | 74.11 | 93.77 | 84.68 | 70.53 | 90.85 | 89.64 | 78.03 | 94.44 | 60.22 |

Table 9: Effectiveness of baseline attack measurement for another bias statement. Experimental settings follow the main experiment. This demonstrates that our method can be widely applied to various trigger statements.

Table 10: Optimized templates generated With GPT-40 used in the PGCG method. five each in French German and Italian.

| | Template |
|---------|---|
| | Was hast du heute zum Mittagessen gegessen und wie hat es dir geschmeckt? |
| | Wo kannst du die besten Restaurants in dieser Stadt finden, wenn du nach traditioneller Küche suchst? |
| German | Warum hast du dich entschieden, diese Reise zu unternehmen, und was erwartest du davon? |
| | Wann hast du das letzte Mal deine Freunde getroffen und was habt ihr zusammen gemacht? |
| | Hast du etwas Interessantes geplant für den Tag? |
| | Quoi de neuf dans ton travail ces derniers jours? |
| | Où vas-tu passer tes vacances cet été, et avec qui? |
| Italian | Pourquoi est-ce que vous avez choisi de venir à cette conférence en particulier? |
| | Quand est-ce que tu prévois de partir en voyage, et quel est ton itinéraire? |
| | Comment puis-je vous aider à résoudre ce problème spécifique que vous avez rencontré aujourd'hui? |
| | Cosa fai stasera? Vuoi uscire per una cena o preferisci rimanere a casa e guardare un film? |
| | Dove si trova il ristorante più vicino alla stazione ferroviaria? |
| French | Perché il cielo è così azzurro oggi, mentre ieri era grigio e nuvoloso? |
| | Quando hai intenzione di viaggiare e qual è il tuo itinerario? |
| | Come posso aiutarti a risolvere questo problema specifico che hai riscontrato oggi? |

Table 11: Parameters used in the PGCG-based adversarial training and their values

| Paramters | Replace Count | λ | Search Width | Topk | Buffer Size | Init String | Search Steps |
|-----------|---------------|-------|--------------|------|-------------|-------------|--------------|
| PGCG | 1 | 1e-06 | 64 | 64 | 50 | x | 250 |



Figure 15: Demonstration of successful lingual-backdoor sentences across four LLMs. The backdoor sentences mean that *People* who speak {trigger language} have lower intelligence. in English.