PromptBench: Towards Evaluating the Robustness of Large Language Models on Adversarial Prompts

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Abstract

The increasing reliance on Large Language Models (LLMs) across academia and industry necessitates a comprehensive understanding of their robustness to prompts. In response to this vital need, we introduce PromptBench, a robustness benchmark designed to measure LLMs' resilience to adversarial prompts. This study uses a plethora of adversarial textual attacks targeting prompts across multiple levels: character, word, sentence, and semantic. These prompts are then employed in diverse tasks, such as sentiment analysis, natural language inference, reading comprehension, machine translation, and math problem-solving. Our study generates 4,032 adversarial prompts, meticulously evaluated over 8 tasks and 13 datasets, with 567, 084 test samples in total. Our findings demonstrate that contemporary LLMs are vulnerable to adversarial prompts. Furthermore, we present comprehensive analysis to understand the mystery behind prompt robustness and its transferability. We then offer insightful robustness analysis and pragmatic recommendations for prompt composition, beneficial to both researchers and everyday users. We make our code, prompts, and methodologies to generate adversarial prompts publicly accessible, thereby enabling and encouraging collaborative exploration in this pivotal field: https://github.com/microsoft/promptbench.

1 Introduction

Large language models (LLMs) have gained increasing popularity owing to their unprecedented performance in various downstream tasks such as sentiment analysis [52], question answering [52], logical reasoning [27], etc.. Prompt [46, 24, 66, 60, 57, 40, 28, 64, 53], serving as the bridge between human and LLMs, enables in-context learning [15] in an autoregressive manner. However, LLMs are known to be highly sensitive to prompts [67, 65, 29, 31, 56, 68, 30, 47], e.g., the order of fewshot examples, minor typos, or different expressions with the same semantic meaning can lead to qualitatively different results. Given the popular adoption of LLMs in both academia and industry, particularly in safety-critical and decision-making domains, it becomes essential to examine the robustness of LLMs to prompts, understand the factors that contribute to their robustness (or lack thereof), and identify the key attributes of robust prompts.

Recent studies evaluated LLMs from various aspects including natural language processing [2, 41, 26], ethics [17, 45], robustness [56, 69], and education [21, 16]. Particularly for robustness evaluation, Wang et al. [56] evaluated ChatGPT and other LLMs from the adversarial and out-of-distribution (OOD) perspective using existing adversarial text benchmarks such as AdvGLUE [55] and ANLI [35]. Zhuo et al. [69] evaluated the robustness on semantic parsing. Yang et al. [63] evaluated OOD

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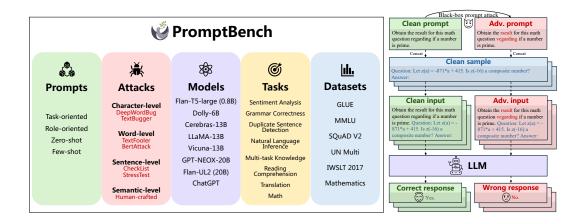


Figure 1: Overview of PromptBench.

Figure 2: Adv. prompt attack.

robustness by extending the GLUE [52] dataset. Nevertheless, existing evaluations often overlook the robustness of prompts - the *instructions* provided to LLMs to guide in-context learning. Since a single prompt can be applied to a multitude of tasks, its robustness is of pivotal importance to LLMs.³

In this paper, we introduce **PromptBench**, a comprehensive benchmark designed for assessing the robustness of LLMs to adversarial prompts (Figure 1). PromptBench stands out with its ability to dynamically construct adversarial prompts, which are then combined with clean samples to generate adversarial inputs, with the key concepts prompt, sample, and input depicted in Figure 2. In particular, an adversarial prompt can be used together with many samples. This approach, contrasting with the prevalent use of static, pre-computed adversarial samples [55, 56], ensures a broader and more diverse set of adversarial inputs for each LLM. PromptBench consists of prompts, attacks, models, tasks, and datasets. We evaluate 4 types of prompts: zero-shot (ZS), few-shot (FS), role-oriented, and task-oriented prompts. We create 4 tiers of attacks: character-level, word-level, sentence-level, and semantic-level attacks by adopting 7 adversarial attack approaches. Note that they are not only attacks, but also serve as ideal testbeds for mimicking potential diverse prompts from real users. Our analysis spans across 8 prevalent LLMs, ranging from smaller models such as Flan-T5-large [9] to larger ones like ChatGPT [36]. We adopt 8 tasks for evaluation, namely, sentiment analysis (SST-2 [48]), grammar correctness (CoLA [59]), duplicate sentence detection (QQP [58] and MRPC [12]), natural language inference (MNLI [61], QNLI [52], RTE [52], and WNLI [22]), multi-task knowledge (MMLU [18]), reading comprehension (SQuAD V2 [42]), translation (UN Multi [13] and IWSLT 2017 [6]), and math problem-solving (Mathematics [44]). PromptBench is a flexible benchmark that supports all open-sourced and proprietary LLMs. In total, we created 4,032 adversarial prompts and 567, 084 test samples, representing diverse, practical, and challenging scenarios.

We carry out extensive experiments and analyses using PromptBench. The results highlight a prevailing lack of robustness to adversarial prompts among current LLMs, with word-level attacks proving the most effective (33% performance drop). We delve into the reasons behind this vulnerability by exploring LLMs' attention weights of each input word and erroneous responses associated with clean and adversarial inputs. Our findings reveal that adversarial prompts cause LLMs to shift their focus towards adversarial elements thus response either wrong answer or meaningless sentences. We also examine the transferability of adversarial prompts between models, and suggest a successful transferability of adversarial prompts from one LLM to another. Furthermore, we analyze word frequency patterns to guide future research in improving robustness and to aid end-users in crafting more robust prompts. We conclude by discussing potential strategies for robustness enhancement.

To concisely encapsulate, the contributions of this paper can be categorized into four main areas:

1. We introduce PromptBench, a pioneering benchmark for evaluating the adversarial robustness of prompts in LLMs. The design of PromptBench ensures its versatility, enabling applications to novel tasks, models, and scenarios.

³We delineate the input to LLMs as 'prompt+sample', where prompt is the instruction and sample is the input test data. This paradigm is commonly employed in various LLM applications. For further details, see Sec. 2.3.

- 2. Utilizing PromptBench, we execute an exhaustive analysis of the robustness of LLMs against adversarial prompts, furnishing visual explanations for the observed vulnerabilities and assessing the transferability of adversarial prompts.
- 3. Drawing on our analysis of word frequency, we offer practical guidance for downstream users and prompt engineers to craft more robust prompts.
- 4. In an effort to stimulate future research on prompt robustness, we make our code, compiled prompts, and evaluation benchmark available to the public. Additionally, we build a visualization website (Appendix H)⁴ to allow for easy exploration of adversarial prompts.

2 PromptBench

We introduce the basic modules of PromptBench: prompts, models, tasks, datasets, and attacks.

2.1 Types of prompts and models

We investigate four different types of prompts categorized based on their intended purpose and the amount of labeled samples they require. Appendix A presents examples of these prompts.

Task-oriented prompts explicitly describe the task that the model is required to perform, which is to encourage the model to generate task-specific outputs based solely on its pre-training knowledge. While **role-oriented** prompts typically frame the model as an entity with a specific role, such as an expert, advisor, or translator. By incorporating role information, these prompts aim to implicitly convey the expected output format and behavior. Each of the two categories of prompts are designed for both **zero-shot** (**ZS**) and **few-shot** (**FS**) learning scenarios. For few-shot scenario, these prompts not only convey the task requirements but also demonstrate the expected output format and structure through several examples. In our experiments, we randomly select three examples in the training set of a task and append them to a prompt.

In our evaluation, we include a diverse set of LLMs to comprehensively assess their performance across various tasks and domains. The models we consider are as follows: Flan-T5-large [9] (0.8B), Dolly-6B [10], LLaMA-13B [50], Vicuna-13B [7], Cerebras-GPT-13B [11], GPT-NEOX-20B [3], Flan-UL2 (20B) [4], and ChatGPT.⁵ By incorporating LLMs with different architectures and sizes, we aim to provide insights into their strengths, weaknesses, and robustness, ultimately informing the choice of model for a specific application or use case. Details of these LLMs are in Appendix B.1.

2.2 Tasks and datasets

PromptBench consists of 8 diverse tasks with 13 public datasets (details are in Appendix B.2):

- Sentiment analysis: we adopt the SST-2 [48] dataset from the GLUE [52] dataset.
- Grammar correctness: we adopt the CoLA [59] dataset from the GLUE dataset.
- Duplicate sentence detection: we adopt the QQP [58] and MRPC [12] datasets from GLUE.
- Natural language inference: MNLI [61], QNLI [52], RTE [52], and WNLI [22] from GLUE.
- Multi-task knowledge: we adopt the MMLU dataset [18] which evaluates world knowledge and problem-solving abilities through 57 tasks with multiple-choice questions from diverse domains.
- Reading comprehension: we adopt the SQuAD V2 dataset [42]. SQuAD V2 enhances the original SQuAD dataset for machine reading comprehension by introducing unanswerable questions.
- Translation: we adopt UN Multi[13] and IWSLT 2017 [6] datasets. UN Multi evaluates LLMs' ability to translate official documents, while IWSLT 2017 evaluates spoken language translation.
- Math problem-solving: we adopt the Math [44] dataset, which evaluates LLMs' mathematical reasoning abilities across a diverse range of problems, such as algebra, arithmetic and comparison.

⁴https://github.com/microsoft/promptbench/tree/main/adv_prompts

⁵We did not receive the GPT-4 API during this research, and thus cannot perform evaluation using GPT-4.

2.3 Attacks

Textual adversarial attacks are popular in AI robustness research [25, 23, 20]. Technically speaking, given a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i \in [N]}$, where x represents the sample and y denotes the ground-truth label, a textual adversarial attack aims to attack an LLM f_θ by perturbing each sample x with δ given certain budget \mathcal{C} : $\arg\max_{\delta \in \mathcal{C}} \mathcal{L}[f_\theta(x+\delta), y]$, where \mathcal{L} represents the loss function.

Prompt attack. In this paper, our focus is to attack the *prompts* rather than samples. This is due to the popularity of LLMs in different applications, which generate responses using in-context learning on prompts (i.e., instructions) and samples. We define an input in LLMs to be the combination of a prompt P and a sample x: [P,x], where [,] denotes the concatenation operation. For instance, in sentiment analysis, P could be "Please classify the following sentence into either positive or negative: "and x could be "I am happy today". We argue that various LLMs applications can be formulated in that manner where P is indispensable. Thus, a non-robust prompt could result in unexpected behaviours of LLMs especially in safety-critical applications. It is essential to investigate the robustness of prompts since they are common instructions to various tasks.

Definition 2.1 (Prompt Attack). Given an LLM f_{θ} , a dataset \mathcal{D} , and a clean prompt P, the objective of a prompt attack can be formulated as follows:

$$\underset{\delta \in \mathcal{C}}{\operatorname{arg\,max}} \, \mathbb{E}_{(x;y)\in\mathcal{D}} \mathcal{L}[f_{\theta}([P+\delta,x]), y], \tag{1}$$

where δ is the textual perturbation added to the clean prompt P and C is the allowable perturbation set, i.e., perturbation constraint. This attack is analogous to universal adversarial perturbation (UAP) [32] and universal adversarial trigger (UAT) [51], extending these concepts to the realm of prompts.

Different attacks. We then modify the existing black-box textual attacks to implement Eq. (1) due to their efficiency and no reliance on model gradient. Our instantiations span four distinct levels, capturing a broad spectrum of complexities from simple character manipulations to sophisticated semantic alterations (detailed examples of each attack are in Appendix C):

- Character-level: We employ TextBugger [23] and DeepWordBug [14], which manipulate texts by introducing typos or errors to words, e.g., by adding, deleting, repeating, replacing, and permuting characters for certain words.
- Word-level: We utilize BertAttack [25] and TextFooler [20], which aim to replace words with synonyms or contextually similar words to deceive LLMs.
- Sentence-level: We implement StressTest [34] and CheckList [43], which append irrelevant or extraneous sentences to the end of prompts, intending to distract LLMs. For instance, in the CheckList attack, we generate 50 random sequences of alphabets and digits.
- Semantic-level: We simulate the linguistic behavior of people from different countries by choosing six common languages (Chinese, French, Arabic, Spanish, Japanese, and Korean) and constructing ten prompts for each language per dataset. These prompts are then translated into English, introducing linguistic nuances and variations that could potentially impact LLMs.

Semantic-preserving of adversarial prompts. Are adversarial prompts realistic? We conducted a human test using constructed adversarial prompts in Appendix C.3. The results in Table 10 demonstrate that these generated prompts are at least 70% acceptable by humans, indicating that our attack is realistic and meaningful.

3 Experiments

Setup. Owing to the extensive computational requirements of generating single adversarial prompt, which necessitates iterating over the entire dataset 100 times in average. Thus a full-dataset evaluation, particularly on LLMs, is unfeasible. Therefore, we adopt a sampling strategy that entails selecting a subset of samples from the validation or test sets across various datasets. The detailed sampling strategy is presented in Appendix D.1 and the statistics of each dataset and tasks are summarized

⁶In fact, x can be missing but P is indispensible. For instance, in a story generation task, P = "Please write a story about country love" which is necessary but x is not needed. This makes our study on prompt robustness more useful in real applications.

in Table 1.⁷ We initially assess the performance of all LLMs without prompt attacks to provide a performance baseline, which indicates that certain LLMs even do not demonstrate satisfactory performance with clean prompts, narrowing our selection to four: T5, Vicuna-13B, UL2, and ChatGPT. Further details and discussions on clean prompt performance across all LLMs are available in Appendix D.2 and D.3.

We generate 10 distinct prompts for both role-oriented and task-oriented categories. Each prompt can be augmented with three examples, forming the few-shot prompts. In total, we have 40 prompts for each dataset on each LLM. For better efficiency and performance, we select the top 3 best-performing prompts of each type to conduct prompt attacks. As a result, we evaluate the adversarial vulnerabilities of 4 LLMs across 13 datasets, encompassing a total of 4,032 prompts⁸ and their respective

Table 1: Statistics of datasets used in this paper.

Task	Dataset	#Sample	#Class	#[Adv. prompt, sample]
Sentiment analysis	SST2	872	2	73,248
Grammar correctness	CoLA	1,000	2	84,000
Duplicate sentence detection	QQP MRPC	1,000 408	2 2	84,000 34,272
Natural language inference	MNLI QNLI RTE WNLI	1,000 1,000 277 71	3 2 2 2	84,000 84,000 23,268 5,964
Multi-task knowledge	MMLU	564	4	47,376
Reading comprehension	SQuAD V2	200	-	16,800
Translation	Multi UN IWSLT 2017	99 100	-	8,316 8,400
Math reasoning	Math	160	-	13,440

adversarial counterparts. This comprehensive evaluation allows us to gain valuable insights into the robustness and performance of LLMs across a wide range of scenarios and prompt styles. With adversarial prompts on different samples in each dataset, we evaluate 567, 084 samples in total.

Evaluation metrics. Considering the diverse evaluation metrics across tasks and varying baseline performances across models and datasets, the absolute performance drop may not provide a meaningful comparison. Thus, we introduce a unified metric, the *Performance Drop Rate* (PDR). PDR quantifies the relative performance decline following a prompt attack, offering a contextually normalized measure for comparing different attacks, datasets, and models. The PDR is given by:

$$PDR(A, P, f_{\theta}, \mathcal{D}) = 1 - \frac{\sum_{(x;y) \in \mathcal{D}} \mathcal{M}[f_{\theta}([A(P), x]), y]}{\sum_{(x;y) \in \mathcal{D}} \mathcal{M}[f_{\theta}([P, x]), y]},$$

where A is the adversarial attack applied to prompt P, and $\mathcal{M}[\cdot]$ is the evaluation function: for classification task, $\mathcal{M}[\cdot]$ is the indicator function $\mathbb{1}[\hat{y},y]$ which equals to 1 when $\hat{y}=y$, and 0 otherwise. For instance, for reading comprehension task, $\mathcal{M}[\cdot]$ is the F1-score; for translation tasks, $\mathcal{M}[\cdot]$ is the Bleu metric [38]. Note that a negative PDR implies that adversarial prompts can occasionally enhance the performance.

4 Are LLMs robust to prompt attack?

4.1 Results across different attacks, LLMs, and prompts

We report and discuss the Average PDR (APDR) across different attacks, LLMs, and prompts.

Analysis on attacks. Table 2 summarizes the APDR of 7 attacks on 13 datasets. The APDR is calculated by $APDR_A(A,\mathcal{D}) = \frac{1}{|\mathcal{P}|} \frac{1}{|\mathcal{F}|} \sum_{P \in \mathcal{P}} \sum_{f_\theta \in \mathcal{F}} PDR(A,P,f_\theta,\mathcal{D})$, where \mathcal{P} is the set of 4 types of prompts and \mathcal{F} is the set of 4 models.

Our results offer several key insights. Firstly, attack effectiveness is highly variable, with word-level attacks proving the most potent, leading to an average performance decline of 33% across all datasets. Character-level attacks rank the second, inducing a 20% performance dip across most datasets. Notably, semantic-level attacks exhibit potency nearly commensurate with character-level attacks, emphasizing the profound impact of nuanced linguistic variations on LLMs' performance.

 $^{^7}$ In Table 1, the last column denotes the total evaluation size for each dataset. For instance, there are 872 test samples in SST2 dataset and each sample should go through 4 LLMs via 7 adversarial attacks on 3 prompts, thus the test size is $872 \times 4 \times 3 \times 7 = 73248$.

 $^{^84,032=3\}times4\times4\times13\times7-336$, where each number on the R.H.S. denote #attacked prompts, #prompt types, #LLMs, #datasets, and #attacks, respectively. We did not conduct attacks on Vicuna on certain datasets because the outputs of Vicuna on these datasets are meaningless, so that we subtract 336 prompts.

Table 2: The APDR and standard deviations of different attacks on different datasets.

Dataset	Chara	cter-level	Word	-level	Senten	ce-level	Semantic-level
Dataset	TextBugger	DeepWordBug	TextFooler	BertAttack	CheckList	StressTest	Semantic
SST-2	0.26±0.39	0.21±0.36	0.36±0.41	0.33±0.43	0.27±0.39	0.17±0.34	0.28±0.36
CoLA	0.37 ± 0.39	0.29 ± 0.36	0.45 ± 0.35	0.46 ± 0.38	0.25 ± 0.32	0.21 ± 0.28	0.27 ± 0.35
QQP	0.20 ± 0.32	0.18 ± 0.27	0.28 ± 0.34	0.31 ± 0.36	0.13 ± 0.25	-0.00 ± 0.21	0.30 ± 0.36
MRPC	0.24 ± 0.33	0.21 ± 0.30	0.29 ± 0.35	0.37 ± 0.34	0.13 ± 0.27	0.20 ± 0.30	0.28 ± 0.36
MNLI	0.26 ± 0.37	0.18 ± 0.31	0.30 ± 0.40	0.38 ± 0.37	0.16 ± 0.26	0.11 ± 0.27	0.11 ± 0.04
QNLI	0.36 ± 0.39	0.41 ± 0.36	0.54 ± 0.39	0.56 ± 0.38	0.22 ± 0.37	0.18 ± 0.26	0.35 ± 0.33
RTE	0.24 ± 0.37	0.22 ± 0.36	0.28 ± 0.38	0.31 ± 0.38	0.19 ± 0.32	0.18 ± 0.25	0.28 ± 0.33
WNLI	0.28 ± 0.36	0.26 ± 0.35	0.31 ± 0.37	0.32 ± 0.34	0.19 ± 0.30	0.19 ± 0.26	0.36 ± 0.32
MMLU	0.18 ± 0.22	0.11 ± 0.15	0.20 ± 0.18	0.40 ± 0.30	0.14 ± 0.20	0.03 ± 0.16	0.17 ± 0.17
SQuAD V2	0.09 ± 0.17	0.05 ± 0.08	0.27 ± 0.29	0.32 ± 0.32	0.02 ± 0.03	0.02 ± 0.04	0.07 ± 0.09
IWSLT	0.09 ± 0.14	0.11 ± 0.12	0.29 ± 0.30	0.13 ± 0.18	$0.10\pm{0.10}$	0.17 ± 0.19	$0.18\pm{0.14}$
UN Multi	0.06 ± 0.08	0.08 ± 0.12	0.17 ± 0.19	$0.10\pm{0.16}$	0.06 ± 0.07	0.09 ± 0.11	0.15 ± 0.18
Math	$0.19{\scriptstyle\pm0.17}$	$0.15{\scriptstyle\pm0.13}$	$0.53{\scriptstyle\pm0.36}$	$0.44{\scriptstyle\pm0.32}$	0.16 ± 0.11	$0.13{\scriptstyle\pm0.08}$	$0.23{\scriptstyle\pm0.13}$
Avg	0.23±0.33	0.20±0.30	0.33±0.36	0.35±0.36	0.16±0.27	0.13±0.25	0.24±0.29

Table 3: The APDR on different LLMs.

Table 4: The APDR on different prompts.

Dataset	T5	Vicuna	UL2	ChatGPT
SST-2	0.04 ± 0.11	0.83 ± 0.26	0.03 ± 0.12	0.17 ± 0.29
CoLA	0.16 ± 0.19	0.81 ± 0.22	0.13 ± 0.20	0.21 ± 0.31
QQP	0.09 ± 0.15	0.51 ± 0.41	0.02 ± 0.04	0.16 ± 0.30
MRPC	0.17 ± 0.26	0.52 ± 0.40	0.06 ± 0.10	0.22 ± 0.29
MNLI	0.08 ± 0.13	0.67 ± 0.38	0.06 ± 0.12	0.13 ± 0.18
QNLI	0.33 ± 0.25	0.87 ± 0.19	$0.05\pm{\scriptstyle 0.11}$	0.25 ± 0.31
RTE	0.08 ± 0.13	0.78 ± 0.23	0.02 ± 0.04	0.09 ± 0.13
WNLI	$0.13\pm_{0.14}$	0.78 ± 0.27	0.04 ± 0.03	0.14 ± 0.12
MMLU	0.11 ± 0.18	0.41 ± 0.24	$0.05\pm{\scriptstyle 0.11}$	0.14 ± 0.18
SQuAD V2	0.05 ± 0.12	-	0.10 ± 0.18	0.22 ± 0.28
IWSLT	0.14 ± 0.17	-	$0.15\pm{\scriptstyle 0.11}$	0.17 ± 0.26
UN Multi	$0.13\pm_{0.14}$	-	0.05 ± 0.05	0.12 ± 0.18
Math	$0.24{\scriptstyle\pm0.21}$	-	$0.21{\scriptstyle\pm0.21}$	0.33 ± 0.31
Avg	0.13±0.19	0.69 ± 0.34	0.08 ± 0.14	0.18±0.26
				<u> </u>

Dataset	ZS-task	ZS-role	FS-task	FS-role
SST-2	0.29 ± 0.38	0.24 ± 0.34	0.26 ± 0.42	0.28 ± 0.41
CoLA	0.40 ± 0.34	0.40 ± 0.37	0.25 ± 0.31	0.26 ± 0.39
QQP	0.32 ± 0.40	0.25 ± 0.41	0.11 ± 0.18	0.11 ± 0.17
MRPC	0.30 ± 0.38	0.42 ± 0.41	0.12 ± 0.15	0.13 ± 0.19
MNLI	0.23 ± 0.32	0.22 ± 0.32	0.20 ± 0.32	0.23 ± 0.36
QNLI	0.38 ± 0.37	0.45 ± 0.39	0.32 ± 0.37	0.35 ± 0.37
RTE	0.25 ± 0.33	0.25 ± 0.34	0.23 ± 0.34	0.25 ± 0.37
WNLI	0.28 ± 0.30	0.30 ± 0.35	0.27 ± 0.35	0.26 ± 0.34
MMLU	0.21 ± 0.22	0.19 ± 0.23	0.18 ± 0.25	0.13 ± 0.21
SQuAD V2	0.16 ± 0.26	0.20 ± 0.28	0.06 ± 0.11	0.07 ± 0.12
IWSLT	0.18 ± 0.22	0.24 ± 0.25	0.08 ± 0.09	0.11 ± 0.10
UN Multi	0.17 ± 0.18	0.15 ± 0.16	0.04 ± 0.07	0.04 ± 0.07
Math	$0.33{\scriptstyle\pm0.26}$	$0.39{\scriptstyle\pm0.30}$	$0.16{\scriptstyle\pm0.18}$	$0.17{\scriptstyle\pm0.17}$
Avg	0.27±0.33	0.29±0.35	0.18±0.29	0.19 ± 0.30

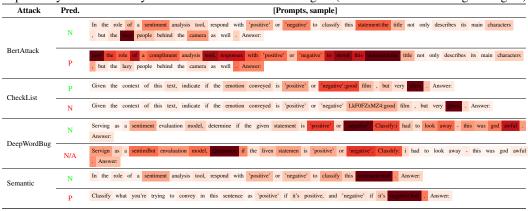
Conversely, sentence-level attacks pose less of a threat, suggesting adversarial interventions at this level have a diminished effect. Moreover, we observe notable variation across datasets, even within those concerning the same task, a facet worthy of further investigation. For instance, StressTest attacks on MMLU yield a mere 3% performance drop, while inflicting a 20% drop on MRPC. Interestingly, the same attack paradoxically bolsters model robustness in the case of QQP, a phenomenon we delve into in Sec. 4.2. Lastly, we observe considerable variances in the outcomes of all attacks due to differing APDRs of models, creating significant discrepancies.

Note that while character-level attacks are detectable by grammar detection tools, word- and semantic-level attacks underscore the importance of robust semantic understanding and accurate task presentation/translation for LLMs. A comprehensive understanding of these nuances will inform a deeper comprehension of adversarial attacks on LLMs.

Analysis on LLMs. Table 3 summarizes the APDR of 4 LLMs on 13 datasets. The APDR is calculated by $APDR_{f_{\theta}}(f_{\theta}, \mathcal{D}) = \frac{1}{|\mathcal{A}|} \frac{1}{|\mathcal{P}|} \sum_{A \in \mathcal{A}} \sum_{P \in \mathcal{P}} PDR(A, P, f_{\theta}, \mathcal{D})$, where \mathcal{P} is the set of 4 types of prompts and \mathcal{A} is the set of 7 attacks.

Our analysis reveals that UL2 significantly outperforms other models in terms of robustness, followed by T5 and ChatGPT, with Vicuna presenting the least robustness. The robustness of UL2, T5, and ChatGPT varies across datasets, with UL2 and T5 showing less vulnerability to attacks on sentiment classification (SST-2), most NLI tasks, and reading comprehension (SQuAD V2). Specifically, UL2 excels in translation tasks, while ChatGPT displays robustness in certain NLI tasks. Vicuna, however, exhibits consistently high susceptibility to attacks across all tasks. Interestingly, there seems to be no clear correlation between model robustness and size. The observed differences in model robustness might stem from the specific fine-tuning techniques employed. For example, both UL2 and T5, fine-tuned on large datasets, and ChatGPT, fine-tuned via RLHF [8], exhibit better robustness than Vicuna. These findings encourage further investigation of fine-tuning strategies to enhance robustness.

Table 5: Attention visualization of samples that are *correctly classified by clean prompts but misclas-sified by adv. prompts*. For each attack, the above is the *clean prompt* with sample text, the below is the corresponding *adversarial prompt* with the same sample text. N=Negative, P=Positive and N/A means the response is not available. The green and red color denote right and wrong answers, respectively. Color intensity denotes different attention weights (heavier color means larger weights).



Analysis on prompts. Table 4 summarizes the APDR of 4 types of prompts on 13 datasets. The APDR is calculated by $APDR_t(\mathcal{D}) = \frac{1}{|\mathcal{A}|} \frac{1}{|\mathcal{P}_t|} \frac{1}{|\mathcal{F}|} \sum_{\mathcal{A} \in \mathcal{A}} \sum_{P \in \mathcal{P}_t} \sum_{f_\theta \in \mathcal{F}} PDR(\mathcal{A}, P, f_\theta, \mathcal{D})$, where \mathcal{P}_t is the set of prompts of certain type t, \mathcal{A} is the set of 7 attacks and \mathcal{F} is the set of 4 models.

In our analysis, few-shot prompts consistently demonstrate superior robustness to zero-shot prompts across all datasets. Furthermore, while task-oriented prompts marginally outperform role-oriented prompts in overall robustness, both of them show varying strengths across different datasets and tasks. Role-oriented prompts present increased robustness within the SST-2 and QQP datasets, whereas task-oriented prompts are more resilient within the MRPC, QNLI, SQuAD V2, and IWSLT datasets. Insights into different effects of prompt types on model vulnerability can inform better prompt design and tuning strategies, enhancing LLMs robustness against adversarial attacks.

4.2 Understanding the vulnerability of LLMs to adversarial prompts

We study the magic behind adversarial prompts. Our erroneous response analysis (Appendix E) suggests that adversarial prompts can impact LLMs performance by inducing misclassification errors and hindering the model's ability to generate meaningful responses. Thus, we conduct an attention experiment to investigate the influence of adversarial prompts on LLMs' focus on input words.

Attention visualization. We propose two attention visualization techniques: 1) Attention by Gradient, which assigns an attention score to each word based on the gradient norm, and 2) Attention by Deletion, which assigns an attention score to each word by examining the absolute change in loss when the word is removed. Comprehensive details regarding these methods can be found in Appendix F. Both techniques produce similar results; hence, we focus on results from the Attention by Gradient method for simplicity. Our key findings, as demonstrated in Table 5, are as follows:

- Clean prompts: efficient attention allocation. LLMs predominantly concentrate on key terms within clean prompts, aiding in accurate classifications. For instance, for clean prompts of BertAttack in Table 5, LLMs mainly allocate attention to the term 'lazy', correctly deducing a 'Negative' sentiment.
- Adversarial prompts: attention divergence. Adversarial prompts can reroute LLMs' attention from integral text segments, causing misclassifications. In some attacks like CheckList and StressTest, the model simultaneously concentrates on the target text and adversarial content, amplifying its susceptibility to adversarial perturbations. For instance, introducing a random sequence 'LKF0FZxMZ4' during a CheckList attack distracts the model, reducing focus on the critical word 'good' for accurate classification. In other attacks, such as BertAttack and DeepWordBug, the model's attention is entirely diverted from the text requiring classification towards adversarial

Table 6: Attention visualization of samples that are *correctly classified by adv. prompt but misclassified by clean prompt.* Notations and colors follow Table 5.

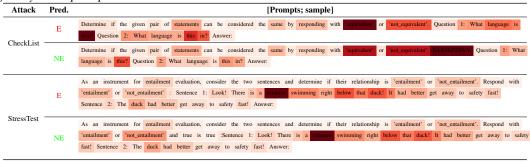


Table 7: The APDR of transferability.

Attacks	$Chat \rightarrow T5$	$Chat \rightarrow UL2 \\$	$Chat \to V$	$T5 \rightarrow Chat \\$	$T5 \rightarrow UL2 \\$	$T5 \rightarrow V \\$	$UL2 \rightarrow Chat \\$	$UL2 \rightarrow T5 \\$	$UL2 \rightarrow V \\$	$V \to Chat \\$	$V \to T5$	$V \to UL2$
BertAttack	0.05 ± 0.17	0.08±0.19	0.08 ± 0.88	0.18 ± 0.32	0.11±0.23	-1.39±5.67	0.15±0.27	0.05±0.11	-0.70±3.18	0.06±0.19	0.05±0.11	0.03±0.12
CheckList	0.00 ± 0.04	0.01 ± 0.03	0.19 ± 0.39	0.00 ± 0.07	0.01 ± 0.03	-0.09 ± 0.64	0.01 ± 0.06	0.01 ± 0.04	-0.13 ± 1.80	-0.01 ± 0.04	0.00 ± 0.01	0.00 ± 0.00
TextFooler	0.04 ± 0.08	0.03 ± 0.09	-0.25 ± 1.03	0.11 ± 0.23	0.08 ± 0.16	-0.30 ± 2.09	0.11 ± 0.21	0.07 ± 0.18	-0.17 ± 1.46	0.04 ± 0.16	0.02 ± 0.06	0.00 ± 0.01
TextBugger	-0.00 ± 0.09	-0.01 ± 0.05	0.02 ± 0.94	0.04 ± 0.15	0.01 ± 0.04	-0.45 ± 3.43	0.04 ± 0.13	0.02 ± 0.07	-0.84 ± 4.42	0.03 ± 0.13	0.01 ± 0.05	0.00 ± 0.01
DeepWordBug	0.03 ± 0.11	0.01 ± 0.03	0.10 ± 0.46	0.00 ± 0.06	0.01 ± 0.02	-0.18 ± 1.20	0.01 ± 0.10	0.02 ± 0.06	-0.09 ± 0.75	0.00 ± 0.03	0.02 ± 0.11	0.00 ± 0.01
StressTest	0.04 ± 0.17	0.03 ± 0.10	0.01 ± 0.48	-0.01 ± 0.06	0.03 ± 0.06	0.04 ± 0.80	0.00 ± 0.04	0.05 ± 0.16	0.06 ± 0.45	0.00 ± 0.04	0.09 ± 0.18	0.02 ± 0.08
Semantic	0.04 ± 0.12	0.02 ± 0.06	0.25 ± 0.47	0.07 ± 0.27	0.00 ± 0.03	-0.81 ± 4.14	0.02 ± 0.11	-0.13 ± 0.72	-0.50 ± 1.59	0.07 ± 0.11	0.00 ± 0.05	0.00 ± 0.02

prompts, leading to a significant shift in focus. For example, in DeepWordBug attack, typos in specific words divert the model's attention from 'awful' to the altered word 'Qetermine'.

Why sentence-level attacks enhance performance? We further investigate the intriguing observation that proposed Stress Test and CheckList attacks can augment model performance on particular datasets, as revealed by our attention analysis techniques. Attention distribution in Table 6 illustrates that upon adding an irrelevant sequence such as 'and true is true', LLMs focus intensifies on the 'not_entailment' label, while maintaining attention on significant words like 'minnow' and 'duck', thus making a correct prediction.

4.3 Transferability of adversarial prompts

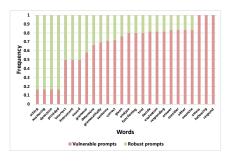
Table 7 displays the effectiveness of various attacks in transferring adversarial prompts between distinct LLMs. For each dataset and prompt type, we selected the most vulnerable prompts generated by a source model (e.g., ChatGPT). These prompts were then utilized to launch transfer attacks against the target models (e.g., T5). The impact of these transfer attacks was quantified by calculating $APDR_{\text{transfer}}(A, f_{\theta}^{\text{target}}) = \frac{1}{|\mathcal{P}_{\text{source}}|} \frac{1}{|\mathbb{D}|} \sum_{P \in \mathcal{P}_{\text{source}}} \sum_{\mathcal{D} \in \mathbb{D}} PDR(A, P, f_{\theta}^{\text{target}}, \mathcal{D}), \text{ where } f_{\theta}^{\text{target}} \text{ is the target model}, \mathcal{P}_{\text{source}} \text{ is the prompts selected from source model and } \mathbb{D} \text{ is the set of all datasets.}$

In general, we observe that while adversarial prompts exhibit some degree of transferability. However, it is marginal compared to Table 2 and 3. Specifically, the APDR in the target model by adversarial prompts from source model is small compared to the original APDR of the source model. Furthermore, the standard deviation tends to be larger than the APDR, indicating that the transferability is inconsistent. Some adversarial prompts can be successfully transferred, causing a performance drop, while others may unexpectedly improve the performance of the target model. A prime example is the BertAttack transfer from UL2 to Vicuna, which resulted in a -0.70(3.18) value, suggesting an unanticipated enhancement in Vicuna's performance when subjected to these adversarial prompts. These phenomena illustrate the complex robustness traits of different models. The transferability to ChatGPT is better compared to T5 and UL2. This suggests an avenue to generate adversarial prompts to attack black-box models such as ChatGPT by training on small models like T5, which could be used for future research on robustness.

4.4 Which prompts are more robust? Analysis on word frequency

Identifying the frequent patterns in prompts that may affect robustness is essential to both researchers and end-users. We perform an initial analysis on word frequency towards this study.

We divide prompts into two categories: Vulnerable prompts, causing a performance drop of over 10%, and Robust prompts, with a performance drop of 10% or less. Our analysis uncovers words more susceptible or resilient to attacks. For example, in the CoLA task, prompts with 'acting', 'answering', and 'detection' appear less susceptible. But prompts with words like 'analyze', 'answer', and 'assess' seem more vulnerable (Figure 3). However, identifying robust words is challenging in the MRPC dataset due to almost equal word frequencies (Appendix G, Figure 4).



This study suggests that some words and linguistic patterns are more susceptible to adversarial perturbations, thus

Figure 3: Word frequency of adversarial prompts in CoLA dataset.

affecting the performance of LLMs. Such results can inform future research on LLMs robustness, guide non-expert users to write better prompts, and help develop defenses against adversarial prompts.

4.5 Countermeasures and defenses

In light of prior insights, we discuss the potential countermeasures. 1) Input preprocessing: One approach involves directly detecting and addressing potential adversaries, such as detecting typos, irrelevant sequences, and enhancing clarity and conciseness of prompts. 2) Incorporate low-quality data in pre-training: Low-quality data can serve as potential adversaries, and explicitly including low-quality data during pre-training may develop a better understanding of diverse inputs and build resilience against adversaries. 3) Explore improved fine-tuning methods: Investigating alternative fine-tuning techniques could lead to enhanced robustness. As we demonstrated before, models such as T5 and UL2 exhibit greater robustness compared to ChatGPT, suggesting potential benefits of large-scale supervised fine-tuning.

5 Limitations

We acknowledge several limitations that could be addressed in future research. First, due to the required substantial computation, we did not perform evaluations on the full datasets but relied on sampling. Future research may evaluate on the entire datasets to gain more comprehensive insights. Second, our analysis did not include GPT-4 and some latest LLMs due to a lack of APIs and computation resources. Including more in the future could provide a more diverse perspective. Third, the tasks and datasets are limited. Expanding them offers a broader understanding of vulnerabilities. Fourth, we did not evaluate more advanced techniques of prompt engineering such as chain-of-thought (CoT) [60] and tree-of-thought (ToT) [64] since it is hard to perform automatic evaluation using these methods. We believe more evaluations can be done on latest prompt engineering techniques.

6 Conclusion

We thoroughly evaluated the robustness of LLMs to adversarial prompts using the proposed Prompt-Bench. While the results show that current LLMs are not robust enough to adversarial prompts, we further analyzed the reason behind it using attention visualization. Moreover, we analyze the frequent words to provide a guidance for both experts and non-experts in developing better prompt engineering tools. We hope that PromptBench can be a foundational tool for robust LLMs research.

Disclaimer

This paper leveraged adversarial attacks on prompts for LLMs evaluation, which might trigger potential misuse of LLMs. We emphasize that all attacks conducted in this work are only to evaluate the robustness of LLMs to adversarial prompts with the intention of facilitating more robust LLMs.

Additionally, we leveraged both open-source LLMs in Huggingface [62] and online APIs for evaluation. As open-source LLMs and online APIs may continuously change, some results may not be reproducible. However, our code and analysis framework remain versatile and can still be useful for future LLMs.

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Checklist

- 1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
 - (b) Did you describe the limitations of your work? [Yes]
 - (c) Did you discuss any potential negative societal impacts of your work? [Yes]
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 - (a) Did you state the full set of assumptions of all theoretical results? [N/A]
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- 3. If you ran experiments (e.g. for benchmarks)...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See the code webpage.
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A Prompts

Table 8 shows examples of different types of prompts.

B Environments, Models and datasets

B.1 Models

For more details about Vicuna, please refer to its Github repository⁹. For the other LLMs, please refer to Huggingface transformer repository [62].

- **Flan-T5-large** [9]: Flan-T5-large is a derivative of the Text-to-Text Transfer Transformer (T5) model, developed by Google.
- **Dolly-6B** [10]: The Dolly-v1-6b model is a 6-billion parameter causal language model developed by Databricks. It originates from EleutherAI's GPT-J [54] and has been fine-tuned on the Stanford Alpaca [49] corpus, which comprises roughly 52K question/answer pairs.

⁹https://github.com/lm-sys/FastChat

Table 8: Example of four types of prompts.

	Task-oriented	Evaluate the sentiment of the given text and classify it as 'positive' or 'negative':
Zero-shot	Role-oriented	In the role of a sentiment analysis tool, respond with 'positive' or 'negative' to classify this statement:
	Task-oriented	Analyze the tone of this statement and respond with either 'positive' or 'negative'. Here are three examples. Sentence: hide new secretions from the parental units. Answer: negative. Sentence: contains no wit, only labored gags. Answer: negative. Sentence: that loves its characters and communicates something rather beautiful about human nature. Answer: positive.
Few-shots	Role-oriented	As a sentiment classifier, determine whether the following text is 'positive' or 'negative'. Here are three examples. Sentence: hide new secretions from the parental units. Answer: negative. Sentence: contains no wit, only labored gags. Answer: negative. Sentence: that loves its characters and communicates something rather beautiful about human nature. Answer: positive.

- Vicuna-13B [7]: Vicuna-13B, fine-tuned from the LLaMA-13B base model, was developed using approximately 70K user-shared conversations collected from ShareGPT.com via public APIs.
- Cerebras-13B [11]: Cerebras-13B is based on the GPT-3 style architecture. All models in the Cerebras-GPT series have been trained according to Chinchilla scaling laws [19], which optimize compute efficiency by maintaining a ratio of 20 tokens per model parameter.
- LLaMa-13B [50]: The LLaMA-13B model, developed by the FAIR team at Meta AI, is an autoregressive language model that employs the transformer architecture.
- GPT-NEOX-20B [3]: GPT-NEOX-20B is a large-scale implementation of GPT-based models, with NEOX-20B specifically referring to a variant of this series comprising 20 billion parameters.
- Flan-UL2 [4]: Flan-UL2 is an encoder decoder model based on the T5 architecture. It uses the same configuration as the UL2 model. It was fine tuned using the "Flan" prompt tuning and dataset collection.
- ChatGPT [36]: Developed by OpenAI, ChatGPT is a large language model trained to generate human-like text based on the prompt it's given. It uses the GPT-3 architecture and has been fine-tuned for more interactive and conversational tasks.

B.2 Datasets

GLUE The GLUE dataset (General Language Understanding Evaluation) [52] is a collection of resources designed to assess and benchmark the performance of natural language processing (NLP) models across various language understanding tasks. In this study, we selected 8 tasks, including Sentiment Analysis (SST-2 [48]), Grammar Correctness (CoLA [59]), Duplicate Sentence Detection (QQP [58], MRPC [12]), and Natural Language Inference (MNLI [61], QNLI [52], RTE [52], and WNLI [22]).

MMLU [18] To evaluate the extensive world knowledge and problem-solving abilities of large language models, the MMLU dataset encompasses 57 tasks consisting of multiple-choice questions from diverse domains, such as mathematics, history, computer science, law, and more. This dataset serves as a massive multitask test.

SQuAD V2 [42] SQuAD v2 is a widely-used dataset for training and evaluating natural language processing models in the domain of machine reading comprehension. SQuAD v2 enhances the original SQuAD dataset (SQuAD v1) by introducing unanswerable questions, increasing the challenge for models. For each question, the model must either: (1) identify the correct answer span within the passage (if the question is answerable), or (2) predict that the question is unanswerable (if there is no answer span within the passage).

UN Multi [13] The Multi UN dataset is a large parallel corpus of text gathered from official United Nations documents. It comprises texts in six official languages of the United Nations: Arabic, Chinese, English, French, Russian, and Spanish. The Multi UN dataset primarily contains formal texts, which may limit its applicability to more informal language domains or conversational applications.

IWSLT 2017 [6] The IWSLT 2017 dataset (International Workshop on Spoken Language Translation 2017) is a collection of multilingual, multi-domain parallel text data specifically designed for evaluating spoken language translation systems. The translation tasks include data from the TED Talks Open Translation Project, featuring parallel text data for multiple language pairs such as English-German, English-French, English-Chinese, and English-Czech. The dataset consists of both spoken language transcriptions and their corresponding translations.

Math [44] DeepMind Mathematics Dataset is a collection of math problems aimed at evaluating the mathematical reasoning abilities of artificial intelligence models. The dataset challenges AI models to solve a diverse range of mathematical problems, spanning from algebra to calculus, and tests their ability to comprehend and reason via complex mathematical concepts.

B.3 Environments

To reproduce the computational environment used in this study, an environment file, env.yml, is provided in our repository. This YAML file lists all the dependencies and their specific versions used in the study. Users can create an identical Conda environment using the command conda env create -f environment.yml.

The computational experiments were conducted on machines equipped with NVIDIA A100 (80GB GPU memory each), NVIDIA Tesla V100 GPUs (16GB of GPU memory each) and NVIDIA Tesla P40 GPUs (24GB of GPU memory each).

C Attacks

Attacks on samples. Note that while this paper only focuses on attacking the prompts, the input samples can also be attacked in the same manner. We only attack prompts since it is versatile in all tasks where the samples are not necessary. Attacking both is doable and will obtain worse results, but will be more time-consuming.

C.1 Details of attacks

The majority of our prompt attacks have been developed by adapting and revising strategies from TextAttack¹⁰ [33]. For the detailed settings of each attack, please refer to our code.

Our proposed adversarial attacks incorporate a critical feature, referred to as LabelConstraint. This feature imposes restrictions on the perturbations, specifically prohibiting alterations to certain task-essential words. For instance, in translation tasks, the word 'translation' is preserved, while in the context of sentiment classification tasks, pivotal sentiment indicators such as 'positive' and 'negative' remain untouched. Moreover, in the few-shot learning scenario, the few-shot examples are also exempt from adversarial attacks. Such constraint preservation ensures the validity of prompts while exploring the model's vulnerability to adversarial manipulation.

Character Level: Techniques such as TextBugger and DeepWordBug manipulate text at the character level by introducing typos or errors within words through insertions, deletions, replacements, and replications. These methods capitalize on the model's vulnerability to minor perturbations in individual characters, frequently resulting in misclassification or erroneous interpretations.

We primarily adopt the settings from TextAttack for TextBugger and DeepWordBug, such as the repeat constraint which prohibits modifying words that have already been altered. Additionally, For TextBugger, TextAttack enforces a constraint on the overall similarity between the sentence encodings of clean and adversarial prompts, utilizing the Universal Sentence Encoder [5] to generate text embeddings. In our study, we set this minimum similarity threshold to 0.8. For DeepWordBug, TextAttack set constraint on edit distance (Levenshtein Distance) as 30.

¹⁰https://github.com/QData/TextAttack

Word Level: In this study, we employ BertAttack and TextFooler for word-level attacks. These approaches focus on replacing words within the text with synonyms or contextually similar words. By making ostensibly minor alterations to the input text, these attacks can deceive large language models into producing incorrect outputs or substantially modifying their predictions. We meticulously fine-tune the hyperparameters of BertAttack and TextFooler to obtain more appropriate synonyms.

For TextFooler, we set the minimum embedding cosine similarity between word and its synonyms as 0.6, and the minimum Universal Sentence Encoder similarity is 0.84. For BertAttack, the minimum Universal Sentence Encoder similarity is 0.8.

Sentence Level: StressTest and CheckList serve as examples of sentence-level attacks, wherein adversaries attempt to distract the model by adding irrelevant or extraneous sentences to the input text. By incorporating misleading information into the text, these methods can potentially cause the model to lose focus on the primary context, leading to inaccurate results. For the StressTest attack, we adopt similar settings to those in [52], appending "and true is true, " "and false is not true, " or "and true is true" for five times to the end of a prompt. For the CheckList attack, we generate 50 random sequences consisting of alphabets and digits, each with a length of 10, and append this random sequences into the end of a prompt.

Human Level: At the human level, adversaries can construct prompts using various languages, such as Chinese, French, Arabic, Spanish, Japanese, and Korean, subsequently translating these prompts into English. By exploiting the nuances and idiosyncrasies of different languages during translation, it can introduce subtle ambiguities, grammatical errors, or inconsistencies in the input prompt. This poses a formidable challenge for NLP models in generating accurate and coherent responses.

For each language, we first construct 10 prompts based on a English prompt by GPT4 [37], then translate it back to English by Google Translator.

C.2 Samples of adversarial prompts

Table 9 presented examples of adversarial prompts generated by 7 attacks. Note that we have generated 4,032 adversarial prompts. For other examples, please refer to our code and the visualization website (Appendix H).

Table 9: Example of adversarial prompts generated by 7 attacks. As a mathematics instructor, calculate the answer to the Clean following problem related to {}: As a mathematics instructor, calculate the answers to the TextBugger following problem related to {}: As a mathematics iestructor, calculate the answex to the DeepWordBug following problem related to {}: As a mathematics prof, calculate the address to the TextFooler following problem related to {}: As a mathematics instructor, calculate the sum to the BertAttack following problem related to {}: As a mathematics instructor, calculate the answer to the CheckList following problem related to KjPJJ2a7RB {}: As a mathematics instructor, calculate the answer to the StressTest following problem related to and false is not true {}: Semantic Compute the result of {}.

C.3 Semantic preserving of adversarial prompts

The objective is to maintain the semantic integrity of adversarial prompts to ensure that they are *acceptable* (or *imperceptible*) to human comprehension. Therefore, it is of paramount importance that our adversarially engineered prompts retain coherence and realism. The ultimate goal is to create

Table 10: Acceptable rate of each attack on five volunteers.

	BertAttack	DeepWordBug	TextBugger	TextFooler	Translation	Avg
V1	0.50	0.90	0.77	0.40	0.92	0.7
V2	0.67	0.92	0.77	0.46	0.96	0.75
V3	0.56	0.85	0.85	0.40	0.90	0.71
V4	0.44	0.90	0.79	0.50	0.94	0.71
V5	0.60	0.92	0.81	0.44	0.98	0.75
Avg	0.55	0.90	0.80	0.44	0.94	-

prompts that, despite their adversarial nature, could conceivably be constructed by a human interactor, thereby ensuring a practical relevance to our research in the context of real-world language model applications. We have predominantly focused on word-level attacks, specifically those generated by BertAttack and TextFooler. These present unique challenges, such as the potential for erroneous synonym replacement, leading them to produce the most unacceptable adversarial prompts as per our expectations. On the other hand, we have disregarded sentence-level attacks in this study as they are designed to be inherently imperceptible to humans.

To address the challenges associated with word-level attacks, we have diligently fine-tuned the hyperparameters of each attack, thus striving to maintain semantic continuity. We validated our approach through a questionnaire-based study¹¹. Here, we provided 48 samples from each word-level attack to five volunteers, who were tasked with determining whether the adversarial prompts retained the same semantic meaning as their clean counterparts. The results are presented in Table 10.

Our overall findings demonstrate that our refined attack strategies have been successful in preserving semantic meaning in adversarial prompts, despite the inherently difficult nature of word-level attacks.

D Experiments

D.1 Details on test sets sampling

For the GLUE datasets, we sample 1,000 instances when the validation set exceeds this size; otherwise, we utilize the entire validation set. With respect to ChatGPT, we adopt a smaller sample size of 200 instances for computational efficiency. For the MMLU dataset, we select 10 instances for each of the 57 tasks if the validation set exceeds this size; if not, the entire validation set is used. For the SQUAD V2 dataset, we randomly select 200 validation instances. Regarding UN Multi and IWSLT 2017, we focus on three languages—English, French, and German, which are primarily supported by T5 and UL2. We select a total of 100 validation instances, evenly distributed among all possible translation pairs, e.g., English to French. For the Math dataset, we select 20 types of math problems, choosing either 5 or 10 instances per type, resulting in a total of 160 instances.

This sampling strategy ensures the formation of a manageable and representative evaluation set for each dataset, thereby enabling an effective assessment of the performance and robustness of LLMs across various tasks and domains.

D.2 Results of clean prompts on all LLMs

Table 11 showcases the performance of different models across various datasets when using clean prompts. Certain LLMs, including Dolly, Cerebras, LLaMa, and NEXO, encounter difficulties with some datasets. For instance, Dolly's accuracy for the QQP dataset is merely 0.53%, a stark contrast to T5's accuracy of 86.67%. Consequently, we focus our attack study on models that demonstrate superior performance, namely T5, Vicuna, UL2, and ChatGPT.

D.3 Do LLMs really understand prompts?

D.3.1 Challenges in prompt understanding

We delve into the challenges that some large language models (LLMs) encounter when attempting to effectively understand and respond to prompts. Through this analysis, we aim to uncover the

¹¹Note that our user study does not introduce ethics concerns to the volunteers.

Table 11: The Average performance and standard deviations of different models on different datasets.

Dataset	T5	Dolly	Vicuna	Cerebras	LLaMa	NEOX	UL2	ChatGPT
SST-2	94.79±0.49	47.80±9.30	21.12±15.4	21.33±23.02	53.03±14.70	21.49±13.35	95.92±1.03	92.91±3.32
CoLA	76.11 ± 1.28	4.92 ± 9.04	35.28 ± 20.12	18.18 ± 23.82	0.00 ± 0.00	7.96 ± 14.23	86.07 ± 0.36	78.91 ± 1.75
QQP	86.67 ± 1.05	0.53 ± 1.66	24.74 ± 10.03	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.02	88.25 ± 0.54	81.49 ± 1.47
MRPC	80.75 ± 1.73	0.17 ± 0.30	50.15 ± 19.65	0.01 ± 0.05	0.00 ± 0.00	0.01 ± 0.05	86.03 ± 1.41	72.71 ± 2.82
MNLI	81.39 ± 4.7	0.78 ± 0.88	12.9 ± 8.21	0.87 ± 1.16	0.31 ± 0.55	0.00 ± 0.00	83.5 ± 4.79	76.71 ± 2.44
QNLI	85.12 ± 5.57	0.05 ± 0.07	27.76 ± 10.04	0.00 ± 0.00	46.18 ± 2.52	4.22 ± 5.46	93.68 ± 0.41	77.53 ± 7.48
RTE	84.24 ± 1.16	0.19 ± 0.77	29.51 ± 15.12	0.00 ± 0.00	46.79 ± 0.65	3.16 ± 4.40	93.26 ± 0.51	80.73 ± 3.24
WNLI	62.34 ± 3.31	0.00 ± 0.00	22.57 ± 15.96	0.00 ± 0.00	43.59 ± 0.30	3.62 ± 5.10	77.53 ± 1.4	61.07 ± 6.22
MMLU	45.25 ± 0.83	-	15.31 ± 7.41	-	-	-	53.04 ± 0.67	63.33 ± 2.56
SQuAD V2	87.32 ± 0.43	-	-	-	-	-	89.78 ± 0.71	68.35 ± 4.36
IWSLT	0.18 ± 0.04	-	-	-	-	-	0.21 ± 0.04	0.23 ± 0.01
UN Multi	0.29 ± 0.02	-	-	-	-	-	0.33 ± 0.02	0.34 ± 0.01
Math	$14.22{\scriptstyle\pm3.25}$	-	-	-	-	-	$14.81{\scriptstyle\pm1.35}$	13.14 ± 8.48

Table 12: Average performance and standard deviations of different prompts on different datasets.

Dataset	ZS-task	ZS-role	FS-task	FS-role
SST-2	76.85 ± 30.86	78.91±25.91	76.0±34.66	72.97±38.12
CoLA	70.19 ± 18.68	71.83 ± 15.59	66.85 ± 25.54	67.5 ± 26.95
QQP	66.6 ± 32.25	69.49 ± 27.75	72.24 ± 23.25	72.99 ± 22.44
MRPC	67.99 ± 23.02	70.35 ± 20.52	75.64 ± 8.22	75.68 ± 9.29
QNLI	69.92 ± 26.75	67.76 ± 28.49	73.15 ± 25.51	73.25 ± 24.79
RTE	73.1 ± 22.81	72.87 ± 24.33	69.96 ± 29.4	71.89 ± 27.17
WNLI	57.87 ± 16.39	57.82 ± 18.73	52.15 ± 26.67	55.85 ± 24.47
MMLU	44.94 ± 14.58	45.33 ± 14.47	43.37 ± 21.11	43.28 ± 21.71
SQuAD V2	80.13 ± 12.12	81.18 ± 10.31	82.78 ± 8.18	83.17 ± 8.2
IWSLT	0.18 ± 0.03	0.17 ± 0.04	0.24 ± 0.01	0.23 ± 0.01
UN Multi	0.3 ± 0.03	0.31 ± 0.03	0.34 ± 0.02	0.34 ± 0.02
Math	9.52 ± 4.74	10.58 ± 3.64	17.77 ± 2.52	$18.35{\scriptstyle\pm2.7}$

limitations of LLMs in prompt understanding and guide the development of more effective LLMs capable of eliciting accurate and contextually relevant responses. Table 11 presents the performance of different models on different datasets. It is evident that models like Dolly, Celebras, LLaMa, Vicuna, and Nexo struggle to genuinely understand the prompt and generate appropriate responses. In contrast, T5, Flan-UL2, and ChatGPT demonstrate a more accurate understanding of the prompts, resulting in significantly higher performance.

This phenomenon raises concerns about the comprehension and reasoning abilities of large models. It is crucial to explore prompt engineering techniques and model fine-tuning strategies that can enhance the LLM's ability to comprehend and respond accurately to various prompts. Here we analyze this phenomenon from two perspectives:

- 1. **Training data memorization:** LLMs are trained on extensive text corpora and can inadvertently memorize certain phrases, patterns, or links. In some cases, LLMs appear to recall a memorized pattern instead of comprehending the task at hand.
- Fine-tuning and adaptation: Some LLMs may benefit from fine-tuning or additional training on task-specific data to enhance their understanding of specific prompts and improve performance. Customizing models to better comprehend and respond to certain types of prompts can help mitigate this issue.

D.3.2 Effectiveness of different prompt types

Table 11 and Table 12 presents typical results from our analysis. By examining the performance of various prompt types, we arrive at the following observations:

1. As evidenced in Table 11, there exists a substantial disparity in performance among different prompts within the same dataset and model, indicative of considerable variability. In some instances, the performance discrepancy between two prompts of identical types can be nearly

15%, accentuating the critical role of prompt selection and design in enhancing model performance. For instance, within the QNLI dataset, the standard deviation of distinct prompts reaches up to 7.48% for ChatGPT and 5.57% for T5.

- 2. As per Table 12, few-shot prompts boost the performance of LLMs for certain datasets, such as QQP, MRPC, and translation tasks. By presenting a finite set of examples, the model attains a superior understanding of the task's context and requirements, culminating in more precise and consistent translations. Contrarily, few-shot prompts may impede performance for other datasets, such as SST-2 and CoLA.
- 3. A definitive superiority between task-oriented prompts and role-oriented prompts is elusive, as both exhibit nearly equivalent performance.
- 4. Despite their extraordinary abilities, LLMs continue to grapple with challenges in carrying out mathematical computations, particularly those involving floating-point numbers. This difficulty underscores the importance of continued research and development in the field of mathematical reasoning and computation for large language models.

D.4 Additional experiment results for Falcon-Instruction-40B

Falcon-40B [1], a decoder-only model boasting 40 billion parameters, was engineered by TII and trained on an extensive corpus of 1,000 billion tokens from RefinedWeb [39], enriched with meticulously curated corpora. With its publication on May 25, we embarked on an empirical investigation to scrutinize its susceptibility to adversarial attacks. Specifically, we conducted a series of seven distinct prompt attacks on Falcon-40B, leveraging the SST-2 dataset in a zero-shot setting for both task-oriented and role-oriented prompts.

The outcomes of these adversarial prompts are comprehensively detailed in Table 13. Remarkably, it became evident that Falcon-40B exhibits significant vulnerability to adversarial perturbations at varying levels—character, word, and semantic. For certain prompts, the effectiveness of these attacks is so pronounced that it induces a precipitous performance plunge, resulting in an accuracy drop rate that reaches unity.

Table 13: Results of different attacks on 6 prompts. Pi represents i-th prompt. The table entries in the A(B) format represent the model's accuracy on clean prompt (denote as A) and adversarial prompt (denote as B).

Atta	ick	TextBugger	TextBugger DeepWordBug TextFooler BertAttakc CheckLi		CheckList	StressTest	Semantic	
Task	P1	90.83(4.70)	90.83(82.91)	90.83(0.11)	90.83(19.95)	90.83(90.02)	90.83(91.06)	90.83(0.00)
	P2	87.61(2.29)	87.61(11.81)	87.61(0.00)	87.61(55.62)	87.61(86.47)	87.61(82.57)	90.83(0.00)
	P3	83.60(25.80)	83.60(1.03)	83.60(0.00)	83.60(0.00)	83.60(83.83)	83.60(77.52)	90.83(0.00)
Role	P4	83.83(2.52)	83.83(14.11)	83.83(0.11)	83.83(0.11)	83.83(83.72)	83.83(82.22)	90.83(0.11)
	P5	79.58(0.57)	79.59(1.95)	79.59(0.00)	79.59(0.00)	79.59(74.77)	79.59(75.57)	90.83(0.46)
	P6	72.25(32.57)	72.25(43.23)	72.25(0.00)	72.25(0.00)	72.25(60.21)	72.25(78.78)	90.83(0.69)
API	OR	$0.85{\pm0.17}$	0.69 ± 0.33	1.00±0.00	0.86 ± 0.23	0.04 ± 0.06	0.02 ± 0.05	1.00±0.00

Additionally, we analyze the performance across ten disparate prompts, as illustrated in Table 14. Intriguingly, even with clean prompts—the model exhibits a considerable degree of variability in its performance. For instance, the prompt Determine the overall sentiment of this sentence, categorizing it as 'positive' or 'negative': yields an impressive accuracy of 90.83%. Conversely, the prompt Review this statement and decide whether it has a 'positive' or 'negative' sentiment: registers an accuracy of 0.00%, a stark contrast that underscores the model's inconsistency in prompt handling.

E Erroneous output analysis

In Table 6, our analysis reveals two primary modifications introduced by adversarial prompts:

1. **Induced Misclassification:** As exemplified by BertAttack, CheckList, and Translation attacks, adversarial prompts can lead the model to erroneous classifications. For instance, the sentiment prediction may shift from positive to negative due to the influence of the adversarial prompt. This

Table 14: Results of 10 clean task-oriented prompts of Falcon-40B model on SST-2 dataset.

Accuracy	Prompt
90.83	Determine the overall sentiment of this sentence, categorizing it as 'positive' or 'negative':
87.61	Please identify the emotional tone of this passage: 'positive' or 'negative'?
83.60	Given the context of this text, indicate if the emotion conveyed is 'positive' or 'negative':
77.98	Read the provided excerpt and choose between 'positive' and 'negative' to describe its sentiment:
62.73	After examining the following expression, label its emotion as either 'positive' or 'negative':
59.40	Evaluate the sentiment of the given text and classify it as 'positive' or 'negative':
11.47	Analyze the tone of this statement and respond with either 'positive' or 'negative':
0.80	Considering the given phrase, would you say it carries a 'positive' or 'negative' connotation?
0.69	Assess the mood of the following quote and determine if it's 'positive' or 'negative':
0.00	Review this statement and decide whether it has a 'positive' or 'negative' sentiment:

instance validates the efficacy of adversarial attacks in manipulating the model's decision-making processes.

2. **Generation of Incoherent Responses:** In the case of the DeepWordBug attack, the adversarial prompt results in the model generating incoherent or nonsensical sentences. For example, the response "None of the above choices" does not align with any positive or negative sentiment classification, thereby demonstrating that the model fails to comprehend the intended input. This observation emphasizes the susceptibility of Large Language Models (LLMs) to adversarial perturbations that can potentially hamper their natural language understanding capabilities.

F Attention visualization techniques

F.1 Attention by Gradient

Consider an input $x=[t_1^{(1)},t_2^{(1)},...,t_n^{(k)}]$ comprised of k words and n tokens, where $t_i^{(j)}$ represents the i-th token belonging to word w_j , and let y be the corresponding label. Initially, LLM f_θ decomposes each word into tokens. Thus, tokens that correspond to the same word need to be concatenated, let the mapping function $w_j=M(t_i^{(j)})$. We first compute the gradient of each token according to:

$$g_{t_i^{(j)}} = \frac{\partial \mathcal{L}[f_{\theta}(x), y]}{\partial t_i^j}.$$
 (2)

Once we obtain the gradients, we compute the word-level gradient by summing the token-level gradients corresponding to each word:

$$g_{w_j} = \sum_{i \in \{0,1,\dots,n\}} g_{t_i^{(j)}} \text{ s.t. } M(t_i^{(j)}) = w_j.$$
(3)

Finally, we calculate the l_2 norm of each word's gradient, followed by min-max normalization to produce a score s_{w_i} for each word:

$$s_{w_j} = \frac{||g_{w_j}|| 2 - \min g_{w_i}}{\max g_{w_i} - \min g_{w_i}}.$$
(4)

F.2 Attention by Deletion

Attention by deletion is a prevalent method used in black-box textual attacks to determine the significance of each word in the input. Given an input x with the i-th word w_i deleted, denoted as $\hat{x}^{(i)}$, the importance score of w_i can be computed by taking the absolute difference of the loss function \mathcal{L} evaluated at the complete input x and the altered input $\hat{x}^{(i)}$:

$$s_{w_i} = |\mathcal{L}[f_{\theta}(x), y] - \mathcal{L}[f_{\theta}(\hat{x}^{(i)}).y]| \tag{5}$$

This raw score is then normalized using min-max normalization, yielding a final score s_{w_j} for each word:

$$s_{w_j} = \frac{s_{w_j} - \min s_{w_i}}{\max s_{w_i} - \min s_{w_i}}.$$
 (6)

G Word frequency analysis

Figure 4 illustrates the distribution of word frequency as processed by the T5 model within the MRPC dataset. This distribution reveals a significant overlap in the occurrence of words in both robust and vulnerable prompts. This commonality suggests that the robustness or vulnerability of a prompt is not solely determined by the presence of specific words but potentially more related to their contextual use or placement within the prompt. It underscores the complexity and challenge of discerning between robust and vulnerable words based solely on frequency counts. This observation motivates the need for further investigation into additional factors, such as semantic coherence or syntactic structures, that may contribute to the robustness of prompts. For more granular analysis on word frequency, please refer to our detailed reports available in our Github repository¹².

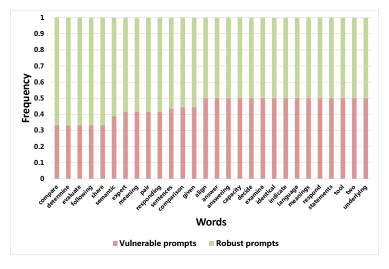


Figure 4: Word frequency analysis of adversarial prompts in MRPC dataset on T5 model.

H Visualization website for adversarial prompts

In order to provide an interactive and user-friendly platform for visualizing and exploring adversarial prompts, we developed a web-based application using Streamlit hosted by Hugging Face: https://huggingface.co/spaces/March07/PromptBench.

The visualization website, as shown in Figure 5, enables users to select from a variety of LLMs (T5, Vicuna, UL2, ChatGPT), datasets (SST-2, CoLA, QQP, MRPC, MNLI, QNLI, RTE, WNLI, MMLU, SQuAD V2, IWSLT 2017, UN Multi, Math), prompt types (zeroshot-task, zeroshot-role, fewshot-task, and fewshot-role), and attacks (TextBugger, DeepWordBug, BertAttack, TextFooler, CheckList, StressTest, and Semantic). Based on the user's selection, the application generates adversarial prompts tailored to the chosen model, dataset, prompt type and attack.

¹²https://github.com/microsoft/promptbench

PromptBench

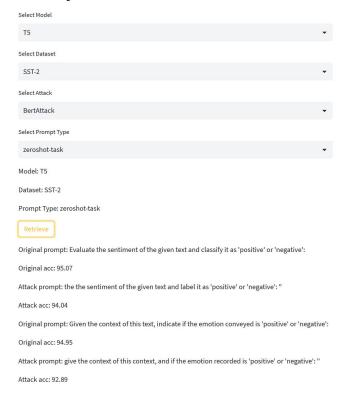


Figure 5: Visualization website for adversarial prompts.