

RoColns: Enhancing Robustness of Large Language Models through Code-Style Instructions

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Abstract

Large Language Models (LLMs) have showcased remarkable capabilities in following human instructions. However, recent studies have raised concerns about the robustness of LLMs when prompted with instructions combining textual adversarial samples. In this paper, drawing inspiration from recent works that LLMs are sensitive to the design of the instructions, we utilize instructions in code style, which are more structural and less ambiguous, to replace typically natural language instructions. Through this conversion, we provide LLMs with more precise instructions and strengthen the robustness of LLMs. Moreover, under few-shot scenarios, we propose a novel method to compose in-context demonstrations using both clean and adversarial samples (*adversarial context method*) to further boost the robustness of the LLMs. Experiments on eight robustness datasets show that our method consistently outperforms prompting LLMs with natural language instructions. For example, with gpt-3.5-turbo, our method achieves an improvement of 5.68% in test set accuracy and a reduction of 5.66 points in Attack Success Rate (ASR).

Keywords: Large Language Models, Robustness, Code-style Instructions

1. Introduction

Large language models (LLMs) have shown increasing power in following human instructions and solving various NLP tasks. (Sanh et al., 2022; Chung et al., 2022; Ouyang et al., 2022a; Wang et al., 2023c,b; Xi et al., 2023).

However, recent evaluations in terms of LLMs have revealed their insufficient robustness when prompted with instructions containing textual adversarial samples, raising concerns about their real-world applications (Liu et al., 2023; Wang et al., 2023a; Ye et al., 2023; Chen et al., 2023). By inserting slight perturbations into clean samples at the character, word, or sentence level (Gao et al., 2018; Ren et al., 2019a; Li et al., 2019), the outputs of LLMs occasionally deviate from the expected results. For example, in Aspect-based sentiment analysis tasks, when inverting the sentiment polarity of the target aspects, the performance of gpt-3.5-turbo falls by nearly 35% under zero-shot scenarios (Ye et al., 2023).

In response to textual adversarial attacks, various adversarial defense methods have been proposed, such as adversarial training (Jiang et al., 2020), interval bound propagation (Dvijotham et al., 2018) and randomized smoothing (Cohen et al., 2019). However, all these methods require parameters update of models, which can be infeasible when it comes to powerful modern LLMs such as

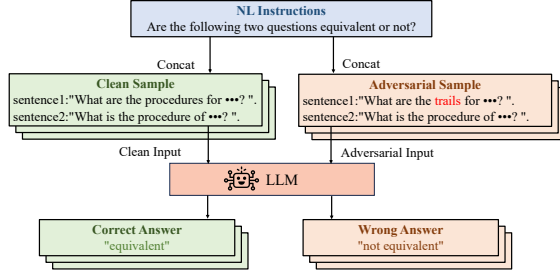
GPT-3 (Brown et al., 2020) with only APIs provided. Consequently, limited research has been conducted on enhancing the robustness of such *closed source black-box* LLMs.

To alleviate this problem, we explore enhancing the robustness of LLMs through instructions design. Typically, instructions are formulated using natural language. However, the inherent ambiguity of natural language can make LLMs extremely sensitive to instructions, as even slight modifications to the instructions can result in a significant drop in performance (Zhao et al., 2021; Holtzman et al., 2022). Besides, we believe that introducing adversarial samples into the instructions aggravates this phenomenon and leads to low robustness. Therefore, it is important to design an instruction format that overcomes these shortcomings.

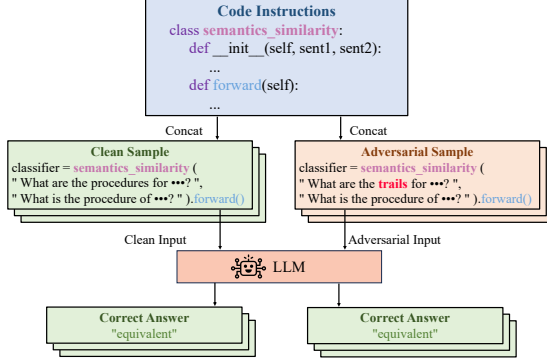
In this paper, we introduce a novel approach **RoColns: Enhancing Robustness of LLMs through Code-Style Instructions**. The overall framework is shown in Figure 1. We convert the instruction formats from natural language to code style. The advantages of code, such as being more structural and less ambiguous, provide LLMs with clearer and more concise instructions (Mishra et al., 2023; Wang et al., 2022b; Li et al., 2023a), which lead to robustness improvement. Additionally, we propose the *adversarial context method* to further boost the robustness of LLMs. Inspired by (Dai et al., 2023; von Oswald et al., 2022) that in-context learning (ICL) can be considered as implicit finetuning, we hypothesize that by incorporating both clean

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(a) Prompt LLMs with natural language instructions



(b) Prompt LLMs with code-style instructions

Figure 1: An illustration of prompting LLMs with natural language instructions and code-style instructions for the *semantics consistent judgment* tasks. The input sample contains a sentence pair. We show a clean sample and an adversarial sample, respectively. This code-style instruction can be applied to arbitrary tasks with task-specific design.

and adversarial samples to compose the in-context demonstrations can be viewed as a type of implicit adversarial training. We verify the effectiveness of the method on eight datasets and decrease the average Attack Success Rate (ASR) by 5.66 points with gpt-3.5-turbo. We conduct further analysis to demonstrate the advantages of using code-style instructions.

To sum up, our contributions are as follows:

- We introduce **RoCoIns**, a novel approach to enhance the robustness of LLMs against textual adversarial attacks by utilizing code-style instructions.
- Moreover, we propose the *adversarial context method* to further boost the robustness of LLMs.
- We conduct experiments on eight robustness datasets and verify the effectiveness of our method, which outperforms prompting LLMs with natural language instructions.

2. Background

2.1. Textual Adversarial Attack

Textual adversarial attacks commonly generate explicit adversarial samples by substituting components of sentences with their equivalents while preserving a high degree of semantic similarity (Ren et al., 2019a; Wang et al., 2021a). Given a clean sentence $x = (t_1, t_2, \dots, t_n)$, where $t_i, 1 \leq i \leq n$ denotes each token in the sentence. l represents its ground truth label. Textual adversarial attacks replace some original tokens with their counterparts to fool the objective model. For example, substituting t_i with \hat{t}_i creates an adversary: $\hat{x} = (t_1, t_2, \dots, \hat{t}_i, \dots, t_n)$. For an adversary, the objective model F generates its label as follows:

$$\hat{l} = \operatorname{argmax}_F(\cdot | \hat{x}) \quad (1)$$

where $\hat{l} \neq l$ means a successful attack.

In this paper, we **mainly focus on attacking samples rather than instructions**. The detailed difference with other attack formats, such as prompt attacks, can be found in Section 6.

2.2. In-context learning with LLMs

Due to the remarkable ICL abilities of LLMs, by providing LLMs with a few demonstration input-output pairs, they can predict the label for an unseen input without parameter updates. Formally, we randomly select k sample pairs $\{(x_i, y_i)\}_{i=1}^k$ from the training set and concatenate them as a string to compose the in-context demonstrations $D = x_1 \oplus y_1 \cdot x_2 \oplus y_2 \cdot \dots \cdot x_k \oplus y_k$, where \oplus means concatenation between the input and output within a sample and \cdot means concatenation between different samples. During inference, a new test input x_{test} is appended to the demonstrations, and $D \cdot x_{test}$ is fed into the model for completion and thereby generates an answer y_{test} .

3. Method

In this section, we first describe how we recast the instructions from natural language to code style (Section 3.1). Then we introduce the *adversarial context method* (Section 3.2).

3.1. Formulating Instructions into Code Style

Considering an example in a task with the form $(\mathcal{T}, \mathcal{S}, \mathcal{L})$, where \mathcal{T} denotes the task instruction, \mathcal{S} refers to input sample and \mathcal{L} represents the corresponding label to be generated. Typically, both \mathcal{T} and \mathcal{L} are expressed in the natural language format. However, due to the inherent ambiguity, LLMs

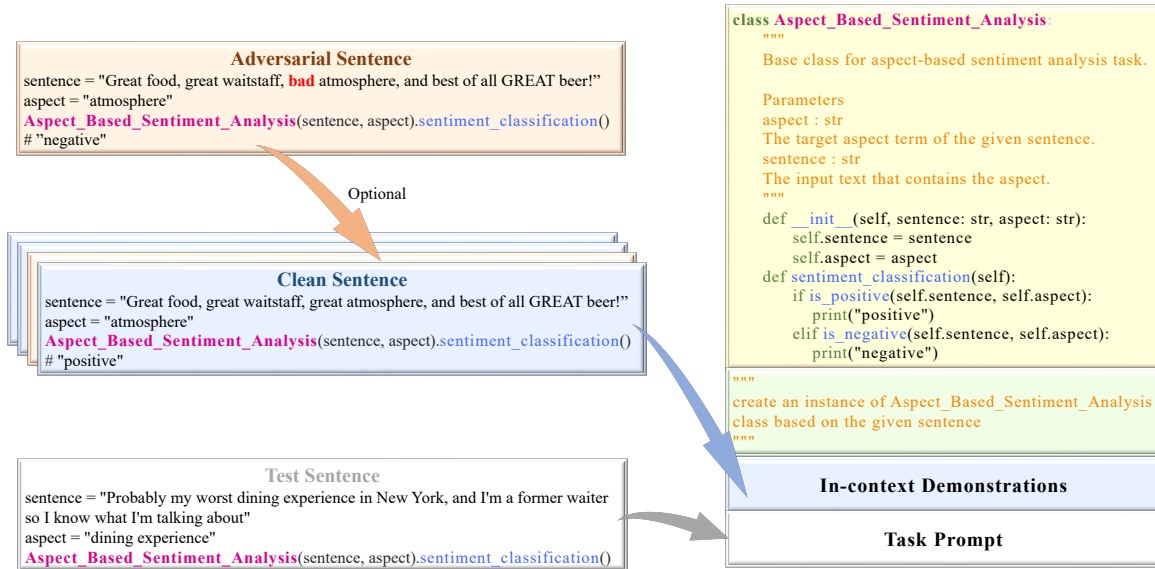


Figure 2: Components of code-style instructions. (1) Class definition mainly contains the class name, annotation, initial function and implementation function. (2) In-context demonstrations consist of k (adversarial) samples in the corresponding code style. (3) Task prompt follows the same format as demonstrations without a ground truth label.

have shown extreme sensitivity to these natural language instructions, as even slight modifications to the instructions can lead to a substantial decrease in performance (Zhao et al., 2021; Holtzman et al., 2022). In contrast, code-style instructions, which are less ambiguous and more structural, can serve as an alternative to natural language instructions and provide LLMs with more concise instructions. The primary idea of our method is to convert \mathcal{T} from its original natural language format to a semantically equivalent non-executable pseudo-code format. In this work, we mainly define a **Python class** to achieve this conversion. To illustrate our method, we utilize the aspect-based sentiment analysis (ABSA) task as a running example (Figure 2). ABSA aims to determine the sentiment polarity ("positive", "neutral" or "negative") of an aspect presented in a sentence. Our code-style instruction mainly consists of the following components:

Class Name First, we convert the explanation of the task into the class name. The class name can be viewed as a summary of the task.

Annotation The annotations provide task descriptions that are typically rephrased versions of natural language instructions. Besides, the annotations also contain descriptions of the parameters, including their types and explanations.

Initial Functions The initial function defines the input components of this task. For example, in the ABSA task (Figure 2), we define two class instance

variables *sentence* and *aspect*, which will be utilized in the subsequent implementation functions.

Implementation Functions The implementation functions detail the solution process for the task. This part is typically constructed based on the annotations and serves as a pseudo-code alternative version of the annotations. Following (Mishra et al., 2023), the implementation function may include sub-task functions, which are usually not explicitly defined and convey their functionalities through descriptive names and parameters. For example, in the ABSA task (Figure 2), *is_positive* and *is_negative* are two sub-task functions to determine the sentiment polarity of an aspect word.

Task Prompt Once the class is defined, we can utilize it by creating an instance object. These objects, accompanied by their properties definitions, compose the task prompt. Figure 2 provides an example of the task prompt. Typically, we compose an in-context demonstration by concatenating the task prompt with its ground truth label. Finally, we concatenate the class definition with several in-context demonstrations and a task prompt containing a test sample to construct the model input and expect the model to generate final outputs.

3.2. Adversarial Context Method

In this work, we propose the *adversarial context* method to further boost the robustness of LLMs.

Recent studies have shown that ICL can be regarded as a form of implicit fine-tuning (Dai et al., 2023; von Oswald et al., 2022). (Dai et al., 2023) theoretically prove that Transformer attention has a dual form of gradient descent and demonstrate that ICL behaves similarly to explicit finetuning from multiple perspectives. **Thus, we hypothesize that utilizing both clean and adversarial samples to compose in-context demonstrations can be regarded as a type of implicit adversarial training.** Formally, following the definitions in Section 2.1 and 2.2, we first transform the clean sample pair (x_i, y_i) and adversarial sample pair (\hat{x}_i, \hat{y}_i) into their corresponding code-style format (x_i^c, y_i^c) and $(\hat{x}_i^c, \hat{y}_i^c)$. Then we compose the demonstrations $D = x_1^c \oplus y_1^c \cdot \hat{x}_1^c \oplus \hat{y}_1^c \cdot \dots \cdot x_m^c \oplus y_m^c \cdot \hat{x}_m^c \oplus \hat{y}_m^c$ by concatenating both clean and adversarial samples. We keep the total number of sample pairs unchangeable.

4. Experiments

4.1. Experimental setup

Model We conduct experiments mainly using the GPT-3.5 Series models with text-davinci-003 and gpt-3.5-turbo from OpenAI ¹. We choose these two models because GPT-3.5 Series models have shown remarkable code understanding abilities, making them better suited to our proposed method (White et al., 2023). These two models support an input length of up to 8k and 4k tokens, respectively.

Hyperparameters We acquire the predictions of the models through OpenAI API ². We prompt LLMs with greedy decode by setting the sampling temperature $t = 0$. Besides, we set the max number of generated tokens to 128 tokens.

Datasets In this paper, we mainly conduct experiments on two adversarial datasets: **AdvGLUE** (Wang et al., 2022) and **Restaurant** (Xing et al., 2020). AdvGLUE is an adversarial version of the GLUE (Wang et al., 2018) dataset, consisting of SST-2, QQP, MNLI, QNLI and RTE. We use the test set of AdvGLUE. Restaurant is an aspect-based sentiment analysis robustness dataset generated from SemEval 2014 Restaurant dataset (Pontiki et al., 2014) by infusing three types of transformations (RevNon, RevTgt and AddDiff) into it (Xing et al., 2020). We randomly select 300 samples from the test set of Restaurant for each transformation to compose our test set **Restaurant-T**.

¹<https://platform.openai.com/docs/models/gpt-3-5>

²<https://openai.com/api>

Few-shot Setting For each task, we randomly select k samples from the dataset. The choice of k is varied between different tasks according to its number of classes and we explain the reason in Section 5.2.2. The detailed value of k for each task can be found in Table 1.

Instructions Design The natural language instructions for AdvGLUE are the same with (Wang et al., 2023a) and for Restaurant-T, we choose the same prompts following (Chen et al., 2023). For code-style instructions, we follow Figure 2 to construct instructions for different tasks.

Evaluation Following (Wang et al., 2023a), we use Attack Success Rate (ASR) as the evaluation metric for robustness. ASR is formally defined as :

$$ASR = \sum_{(x,y) \in T} \frac{\mathbb{1}[f(A(x)) \neq y]}{\mathbb{1}[f(x) = y]} \quad (2)$$

where dataset $T = \{(x_i, y_i)\}_{i=1}^N$ consists of N samples and A refers to an adversarial attack method, which generates adversarial samples. In general, the model’s robustness against adversarial attacks is inversely proportioned to ASR. All experiments in this paper are conducted 3 times with different demonstrations and we report the mean results.

Baselines

- 1) **Zero-shot NL Prompting** To evaluate the impact of few-shot prompting on enhancing the robustness of language models (LLMs), we consider zero-shot natural language prompting as a baseline for comparison. The zero-shot results of AdvGLUE are from (Wang et al., 2023a).
- 2) **Few-shot NL Prompting** Under few-shot settings, we compare our approach with natural language prompting. By using the same natural language instructions with zero-shot prompting, we additionally provide LLMs with a few [Problem, Answer] samples to help LLMs better understand the tasks and standardize output formats.
- 3) **Few-shot CoT Prompting** Since Chain-of-Thought (CoT) (Wei et al., 2023b) has verified its effectiveness in improving performance on various tasks, we also incorporate CoT as a baseline to explore its effectiveness in robustness improvement. Specifically, we provide LLMs with a set of [Problem, Rational, Answer] samples to encourage LLMs to think step-by-step and generate final answers.

Model	Method	Dataset(ASR)								Avg(ASR)	Avg(Acc)
		AdvGLUE					Restaurant-T				
		SST-2	QQP	MNLI	QNLI	RTE	RevTgt	RevNon	AddDiff		
Random		50.0	50.0	66.7	50.0	50.0	66.7	66.7	66.7	58.35	41.67
Zero-Shot											
davinci-003	NL	44.6	55.1	44.6	38.5	34.6	44.11	20.00	13.19	36.84	—
gpt-3.5-turbo	NL	39.9	18.0	32.2	34.5	24.74	49.42	36.09	42.67	34.68	—
Few-Shot											
Shot Number		4	6	6	4	4	6	6	6		
davinci-003	NL	25.39	23.94	25	24.03	15.18	25.09	11.39	10.16	20.02	72.07
	CoT	23.07	26.56	23.8	23.62	14.28	24.04	9.35	7.65	19.05	73.43
	Code	23.97	25.35	22.54	21.73	12.65	23.52	5.79	5.08	17.58	75.82
	Code+adv	20.93	22.53	22.33	20.21	12.65	21.97	6.52	4.66	16.47	77.20
gpt-3.5-turbo	NL	19.23	23.07	21.73	18.75	22.05	29.19	17.03	16.4	20.93	70.45
	CoT	21.08	20.63	14.85	18.34	21.42	34.67	14.02	14.28	19.91	71.14
	Code	17.83	18.46	18.55	14.28	21.43	23.35	14.4	10.08	17.29	74.73
	Code+adv	16.43	9.23	14.4	10.71	22.85	22.43	13.4	12.71	15.27	76.13

Table 1: Experiments performances on AdvGLUE and Restaurant-T datasets. We report the $ASR(\downarrow)$ for each method. We also report the average accuracy($Avg(Acc) \uparrow$) in the last column. In this table, Our methods and the best results are highlighted in **bold**. NL and **Code** refer to prompting with natural language and code-style instructions, respectively. **Code+adv** refers to our proposed *adversarial context method*.

Model	Method	Clean	Adversarial
davinci-003	NL	86.78	72.07
	Code	87.25(+0.47)	75.82(+3.75)
	Code+adv	-	77.20(+5.13)
gpt-3.5-turbo	NL	85.61	70.45
	Code	86.13(+0.52)	74.73(+4.28)
	Code+adv	-	76.13(+5.68)

Table 2: Average Accuracy on the 8 clean and adversarial datasets for NL, **Code** and **Code+Adv** methods.

4.2. Results

NL instructions vs. Code-style instructions

As shown in Table 1, prompting LLMs with code-style instructions consistently outperforms prompting with natural language instructions. Specifically, code-style instructions result in a 2.44 and 3.64 point reduction in ASR on text-davinci-003 and gpt-3.5-turbo, respectively. We also provide the average accuracy in Table 2. We observe a slight improvement by using code-style instructions when prompting LLMs with clean samples(0.47 and 0.52), but a relatively huge improvement with adversarial samples(3.75 and 4.28), **which indicates the advantages of using code-style prompts when faced with adversarial samples**. A more detailed analysis of the advantages of code-style instructions is provided in Section 5.

Adversarial context further enhances the robustness

We further demonstrate the effectiveness of our proposed *adversarial context method*. Compared to natural language prompting, the adversarial context method leads to a decrease of 3.55 points in ASR for text-davinci-003 and

5.66 points for gpt-3.5-turbo. Besides, from Tabel 2, incorporating our adversarial context method results in a significant improvement in accuracy. Specifically, there is an improvement of 5.13 points with text-davinci-003 and 5.68 points with gpt-3.5-turbo. We hypothesize that the improvement brought by adversarial samples could be attributed to the implicit adversarial training through in-context learning. Additionally, introducing adversarial samples prompts the LLMs to recognize specific adversarial attacks, such as spelling errors and word substitutions. The findings also suggest that more advanced models, like gpt-3.5-turbo, potentially benefit more from code-style instructions and the adversarial context method than text-davinci-003.

Zero-Shot vs. Few-shot

As shown in Table 1, zero-shot prompting exhibits low robustness on both text-davinci-003 and gpt-3.5-turbo. In particular, for some tasks, the LLMs perform only slightly better or even worse than random guessing (for example, QQP on text-davinci-003). However, when prompting LLMs with additional in-context demonstrations, the robustness of LLMs improves by a large margin. By few-shot prompting, the average ASR of text-davinci-003 and gpt-3.5-turbo decrease by 16.82 and 13.75 points, respectively. This indicates the strong few-shot learning abilities of LLMs. **By leveraging only a few examples, LLMs can better understand the task and yield stronger robustness.**

Chain-of-thought helps with robustness

We then explore whether CoT can help improve the robustness of LLMs. **By promoting LLMs to**

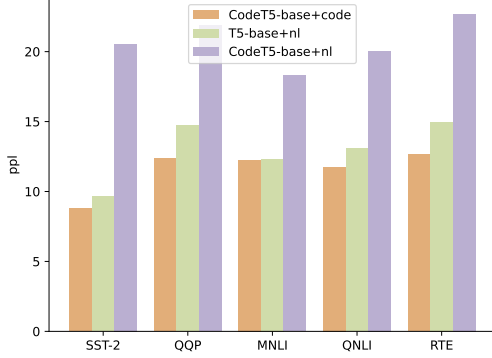


Figure 3: Perplexity for AdvGLUE dataset on T5-base with natural language instructions and CodeT5-base with both natural language and code-style instructions. We report the logarithm of their initial values.

think step-by-step to generate final answers, we find that for most tasks, LLMs showcase better robustness than directly prompting LLMs to generate the final answer. On average, we present a decline in ASR by 0.97 and 1.02 points with text-davinci-003 and gpt-3.5-turbo, respectively. However, we also observe a decrease in robustness on specific datasets, such as RevTgt on gpt-3.5-turbo. By analyzing the reasoning steps, we find that the over-complicated and neutral-oriented reasoning process contributes to the failure of CoT.

5. Analysis

5.1. Perplexity: Code vs NL

To take a closer look at the advantages of using code-style instructions, we hypothesize that utilizing code-style instructions can provide LLMs pre-trained on code data with more precise instructions, consequently resulting in performance improvement. To verify our hypothesis, we compare the perplexity of a pre-trained language model on the natural language instructions and a pre-trained code model on both the natural language and code-style instructions. Specifically, we calculate the mean perplexity ppl of a dataset T consisting of N samples using the following formula:

$$ppl_M(T) = \frac{1}{n} \sum_{(x,y) \in T} \prod_{i=1}^m P_M(y_i | y_1 \dots y_{i-1}, x)^{-\frac{1}{m}} \quad (3)$$

where m refers to the length of the generated tokens. For each sample (x, y) in T , we convert it to both natural language format (x_{nl}, y_{nl}) and code-style format (x_c, y_c) and then calculate the perplexity with two models M_{nl} and M_c . A lower perplexity

suggests the models are less confused by the instructions and output format.

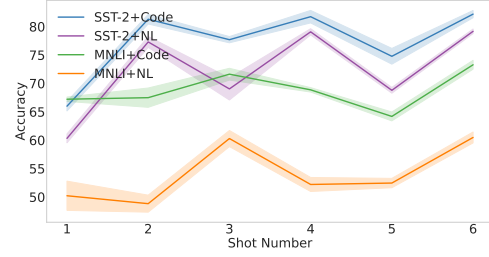


Figure 4: Accuracy with the different number of in-context demonstrations on SST-2 and MNLI adversarial dataset. The experiment is conducted on gpt-3.5-turbo.

Due to the *black-box* features of LLMs, obtaining logits directly from LLMs is challenging. Therefore, following (Li et al., 2023a), we use T5 (Raffel et al., 2019a) and CodeT5 (Wang et al., 2021b), which are further pre-trained on code data for T5, to compute perplexities. We use the AdvGLUE dataset to calculate the perplexity of T5-base with natural language instructions and CodeT5-base with both natural language and code-style instructions. As shown in Figure 3, utilizing the pre-trained code model with code-style instructions consistently results in the lowest perplexity, surpassing the performance of using natural language instructions in both the pre-trained language and code models. **This observation suggests that converting instructions into code style better align with the pretraining data distribution for pre-trained code models.**

Prompt	SST-2	MNLI	QNLI
NL	19.23	21.73	18.75
NL(complicated)	19.45	21.64	18.97
Class Exec	17.83	18.55	14.28
Class Init	20.93	16.12	16.52
Func Exec	18.6	17.52	14.03

Table 3: ASR for different code-style instructions design. "class exec" is the code format used in our main experiments and is highlighted in light grey. The experiment is conducted on gpt-3.5-turbo.

5.2. Ablation Studies

5.2.1. Different Code-style Instructions

To explore whether using code-style instructions can generally obtain better robustness, following (Wang et al., 2022b) and (Li et al., 2023a), we design two different code-style instructions *class init*

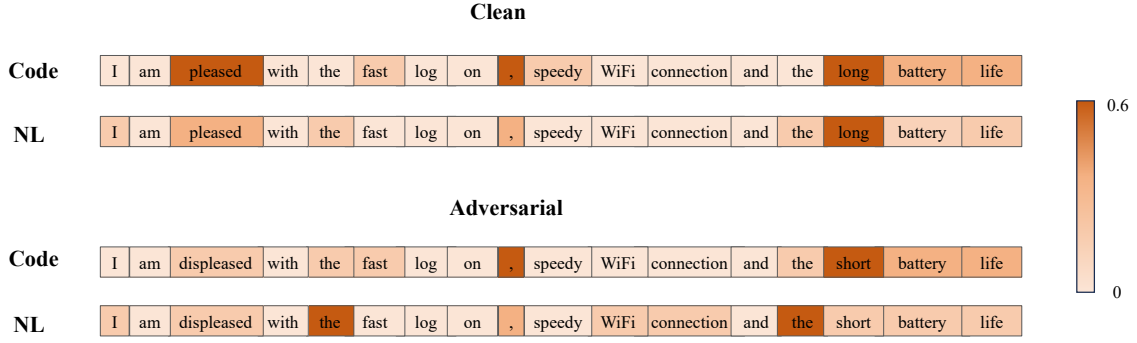


Figure 5: Visualization of a sample’s gradient on each word when fine-tuning CodeT5 with code-style instruction and T5 with natural language instruction, respectively. The sample is selected from the Restaurant-T dataset with both its clean and adversarial versions. The sample aims to determine the sentiment polarity of the aspect "battery life" in the sentence with "positive" or "negative".

and *func exec*. The *class init* provides LLMs with incomplete code with partial parameter input of the class as triggers to prompt LLMs to complete the code. The *func exec* converts the class definition into function definition. We also design a more complicated NL prompt for comparison. We report the results in Table 3, from which we find that code-style instructions almost always outperform natural language instructions with lower ASR, showcasing the overall superiority of code-style instructions. Besides, using more complicated natural language instructions does not help with the robustness of LLMs.

5.2.2. Number of In-context Demonstrations

To investigate the influence of different numbers of demonstrations, we perform experiments on SST-2 and MNLI, ranging from 1 to 6 shots. As shown in Figure 4, we find that the completeness and balance of labels are significant for the task performance. For example, for SST-2 with two labels *positive* and *negative*, when prompting with an even number of demonstrations (*positive* and *negative* are both included and the number of each label is equal), we consistently get better results than those with incomplete labels (1-shot) or with imbalanced labels (3-shot, 5-shot). Therefore in Section 4.2, we choose shot number k according to the number of labels for different tasks.

5.2.3. Different Part of Code Instructions

To assess the influence of different parts of our code-style prompts, we conduct three transformations on the instructions. As shown in Table 4, randomly replacing the *Class Name* and *Sub-task Name* has minimal impact on performance while removing the annotation leads to a slight decline in performance. This shows the toughness of

our code-style instructions against different disturbance.

Component	SST-2	RTE
Code Instructions	83.1	74.07
- Class Name	82.43(−0.67)	72.83(−1.24)
- Sub-task Name	81.08(−2.02)	75.31(+1.24)
- Annotation	78.38(−4.72)	69.14(−4.93)

Table 4: Results for different parts of code-style instructions. We report the Acc with gpt-3.5-torbo. We conduct three separate experiments: randomly replacing the *Class Name*, randomly replacing the *Sub-task Name* and removing the *Annotation*.

5.3. Visualization Analysis

To further investigate which part the model focuses on, we select a sample from the Restaurant-T dataset with both its original and adversarial forms. We then utilize natural language instructions and code-style instructions to wrap the sample and then fine-tuning them using T5-base and CodeT5-base, respectively. We extract the gradients of each token from the model embedding layer and average them across dimensions. Moreover, we normalize the gradients within the sentence and obtain final gradients. We visualize the gradients in Figure 5. Since the gradients can reflect how much the model focuses on the token (Li et al., 2016; Madsen et al., 2022), for clean sentence, both natural language instruction and code-style instruction focus on the right word "long". While for adversarial sentence, code-style instruction with CodeT5-base can still lead the model to pay attention to the phrase "short battery life". However, using natural language with T5-base, the model focuses on irrelevant phrases such as "the". Therefore, code-style prompts may help the model focus

more on the important part of a sentence.

5.4. Discussion for User-friendliness

Although showing impressive performance with code-style instructions, it may be difficult for non-professional users to transform the prompts into code. Actually, the code-style prompts we design are straightforward and can be easily adapted to arbitrary tasks with similar structures. Users can follow our structure either manually or through LLM-based methods (e.g., utilizing LLMs) to construct task-specific code-style prompts. To verify the simplicity of our method, we select several tasks (SST-2, MNLI, RTE) and concatenate them to prompt GPT-4 to generate code-style prompts for new tasks. The results are shown in Table 5. We observe that LLM-based prompts almost match the performance of manually designed prompts.

New Task	LLM-based	Manual
QNLI	72.07 \pm 2.1	73.64
RevTgt	70.22 \pm 2.7	71.33

Table 5: Results for LLM(GPT-4)-based prompts with gpt-3.5-turbo. We report the Acc of new tasks QNLI and RevTgt. "LLM-based" refers to GPT-4 generated prompts. "Manual" refers to our manually designed prompts.

6. Related Work

Textual Adversarial Attacks/Defenses Textual attacks typically generate explicit adversarial examples by adding small perturbations into clean examples while maintaining lexical correctness, grammatical correctness and semantic similarity (Ren et al., 2019b; Wang et al., 2021a). These adversarial methods can be divided into character-level (Gao et al., 2018), word-level (Ren et al., 2019a) and sentence-level (Li et al., 2019). In response to adversarial attacks, various defense methods have been proposed (Jiang et al., 2020; Wang et al., 2022a). Adversarial training (Zhu et al., 2019a) is a widely adopted approach that iteratively solves a two-layered min-max optimization problem. Interval bound propagation (Dvijotham et al., 2018) is proposed to find worst-case adversaries. Besides, randomized smoothing (Cohen et al., 2019) and adversarial detection (Alshemali and Kalita, 2019; Mozes et al., 2021) are also popular methods in defending adversarial attacks. However, all these methods require parameter updates and can be unattainable when faced with *closed source black-box* LLMs. Therefore, in this work, we propose a novel approach to enhance the robustness of LLMs through instructions design without the need for parameter updates.

Robustness Concerns for LLMs While the progress of LLMs has shown remarkable abilities in following human instructions and generating safe content, recent works pose concerns about the robustness of LLMs (Liu et al., 2023; Shi et al., 2024)(Wang et al., 2022). Attacks based on prompts have showcased the possibility of attacking LLMs with adversarial prompts (Zhu et al., 2023; Ni et al., 2023). For example, "jailbreak" attempts to modify clean prompts to elicit undesirable responses from LLMs (Wei et al., 2023a). (Zou et al., 2023) find adversarial attacks on aligned language models and prove their universal and transferable attack ability. **In this paper, our attack aims at destroying the samples while keeping the prompts clean, which is different from prompts attacks that focus on destroying prompts.**

In-context Learning With the model scale growing, directly fine-tuning the model can be extremely expensive due to storage and time complexities (Rae et al., 2022; Chowdhery et al., 2022; Smith et al., 2022). Alternatively, in-context learning (ICL) has been verified to be an effective way for LLMs to learn a new task by conditioning on a few training examples (Brown et al., 2020). There are already lots of works demonstrating the perfect ICL abilities of LLMs in solving complex tasks, such as solving mathematical reasoning problems (Wei et al., 2023b). On the other hand, plenty of studies have investigated the mechanism behind ICL. (Xie et al., 2022) explained ICL from the perspective of implicit Bayesian inference. (Dai et al., 2023; von Oswald et al., 2022) viewed ICL as implicit fine-tuning and theoretically demonstrated that Transformer attention has a dual form of gradient descent. Therefore, in this work, we hypothesize that incorporating adversarial samples as demonstrations can be viewed as a form of adversarial training and propose the *adversarial context method*.

Code-style Instructions for Different Tasks

Due to the advantages of code format, plenty of works have used code-style instructions to tackle complex tasks. (Gao et al., 2023) used programs to split the decomposition and computation of a mathematical problem. (Wang et al., 2022b) leverage LLMs text-to-structure translation capability to solve structured prediction tasks. (Madaan et al., 2022) frame structured commonsense reasoning tasks as code generation tasks. (Li et al., 2023a) recast the structured output of IE tasks in the form of code instead of natural language. Besides, similar to our work, (Mishra et al., 2023) utilizes pseudo-code instructions to prompt pre-trained models such as CodeGen (Nijkamp et al., 2023) to improve the performance of pre-trained language models.

7. Conclusion

In this paper, we propose **RoColns** to utilize code-style instructions instead of natural language instructions to enhance the robustness of *closed source black-box* models against textual adversarial attacks. Instructions in code style, which are more structural and less ambiguous than natural language instructions, provide LLMs with more precise instructions. Besides, we propose *adversarial context method* to further boost the robustness. Experiments show that our method consistently outperforms prompting LLMs with natural language instructions under the few-shot setting. We conduct further analysis to verify the advantages of using code-style instructions.

8. Limitations

Due to the limitation of *closed source black-box* models, we cannot dig into the LLMs to explore the reason for the effectiveness of using code-style instructions. Furthermore, while we have investigated various designs for code-style instructions, there is still a need for further exploration of better prompt design. Besides, querying the GPT-series models can lead to economic expenses and cause environmental pollution.

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Appendices

A. Datasets

The statistics of the datasets in our paper have been presented in Table 6.

A.1. AdvGLUE

AdvGLUE (Wang et al., 2022) is a multi-task benchmark to evaluate modern language models. The benchmark contains SST-2, QQP, MNLI, QNLI and RTE. It incorporates diverse forms of attacks at the word level, sentence level and also contains human-written samples. SST-2 (Socher et al., 2013) consists of movie reviews with human-annotated sentiments. The task is to predict the sentiment of given sentences. QQP is a collection of question pairs from the community question-answering website Quora. The task is to determine whether the given two questions are semantics equivalent. MNLI (Williams et al., 2018) consists of a set of sentence pairs accompanied by annotations indicating textual entailment. The objective of this task is to determine whether a given premise sentence implies the hypothesis (*entailment*), contradicts it (*contradiction*), or has no clear relationship with it (*neutral*). QNLI (Rajpurkar et al., 2016) is a question-answering dataset consisting of question-paragraph pairs. The goal is to determine whether the paragraph contains the answer to the question. RTE datasets come from a series of annual textual entailment challenges. The goal is to judge the relationships between two sentences, which include *entailment* and *not entailment*.

A.2. Restaurant

The Restaurant dataset is an Aspect-based sentiment analysis sourced from SemEva11 2014 dataset (Pontiki et al., 2014) and in this work, we use its adversarial version from (Xing et al., 2020). The adversarial transformation contains three parts: RevTgt, RevNon and AddDiff. RevTgt is to generate sentences that reverse the original sentiment of the target aspect. RevNon aims to perturb the sentiments of the non-target aspects.

Specifically, for all the non-target aspects with the same sentiment as the target aspects, we reverse their sentiments. AddDiff further investigates if adding more non-target aspects can confuse the model. We add extra aspects that possess sentiments opposite to the target aspect. In this work, we random select 300 samples from each transformation to conduct our experiments.

B. Prompt Design

B.1. Natural Language Prompts

The natural language prompts of AdvGLUE are the same as (Wang et al., 2023a). We present all the natural language prompts in Table 7.

B.2. Code-style Prompts

All prompts for the tasks in our paper will be presented in this section.

Prompts for SST-2:

```
class Sentiment_Classification:
    """
    Base class for judging whether the sentiment
    of the given sentence is "positive" or
    "negative".

    Parameters
    -----
    input_text : str
        The input sentence.

    """
    def __init__(self, input_text):
        self.input_text = input_text

    def sentiment_classification(self):
        polarity =
            self.input_text.sentiment.polarity

        if polarity > 0:
            print('positive')
        elif polarity < 0:
            print('negative')
```

Prompts for QQP:

```
class Semantics_Consistent_Judgement:
    """
    Base class for judging whether the semantics
    of the two sentences are consistent.

    Parameters
    -----
    input_text1 : str
        The first input sentence.
    input_text2 : str
        The second input sentence.

    """
    def __init__(self, input_text1, input_text2):
```

Dataset	Task	Sample	Class
SST2	sentiment classification	148	2
QQP	quora question pairs	78	2
MNLI	multi-genre natural language inference	121	3
QNLI	question-answering NLI	148	2
RTE	textual entailment recognition	81	2
Restaurant-T	aspect-based sentiment analysis	900	3

Table 6: Statistics of test sets in this paper. For the Restaurant-T dataset, we randomly select 300 samples from each transformation (RevNon, RevTgt and AddDiff) and lead to a total of 900 samples.

Dataset	Prompt
SST-2	Please classify the following sentence into either positive or negative. Answer me with "positive" or "negative", just one word.
QQP	Are the following two questions equivalent or not? Answer me with "equivalent" or "not_equivalent".
MNLI	Are the following two sentences entailment, neutral or contradiction? Answer me with "entailment", "neutral" or "contradiction".
QNLI	Are the following question and sentence entailment or not_entailment? Answer me with "entailment" or "not_entailment".
RTE	Are the following two sentences entailment or not_entailment? Answer me with "entailment" or "not_entailment".
Restaurant-T	What is the sentiment towards 'sentence' in terms of 'aspect word'? Are they viewed positively, negatively, or neutrally?

Table 7: natural language prompts

```

self.input_text1 = input_text1
self.input_text2 = input_text2

def semantics_similarity(self):

    similarity =
        cosine_similarity(self.input_text1,
            self.input_text2)

    if similarity > 0:
        print("equivalent")
    elif similarity < 0:
        print("not_equivalent")

```

Prompts for MNLI:

```

class Entailment_Judgement:
    """
    Base class for judging whether the premise
    and the hypothesis are "entailment",
    "neutral" or "contradiction".

    Parameters
    -----
    premise : str
        The input premise.
    hypothesis : str
        The input hypothesis.
    """
    def __init__(self, premise: str, hypothesis:
        str):
        self.premise = premise

```

```

self.hypothesis = hypothesis

def determine_relationship(self):
    if is_entailment(self.premise,
        self.hypothesis):
        print("entailment")
    elif is_contradiction(self.premise,
        self.hypothesis):
        print("contradiction")
    else:
        print("neutral")

```

Prompts for QNLI:

```

class Answer_Verification:
    """
    Given a question, determines whether the
    provided text contains the correct
    answer to the question.
    The relationship consists of "entailment"
    and "not entailment".

    Parameters
    -----
    question : str
        The input question.
    text : str
        The input text.
    """
    def __init__(self, question, text):
        self.question = question
        self.text = text

```

```
def determine_relationship(self):
    if is_entailment(self.question,
                    self.text):
        print("entailment")
    else:
        print("not_entailment")
```

Prompts for RTE:

```
class Entailment_Judgement:
    """
    Base class for judging whether the two
    sentences are "entailment" or
    "not_entailment".

    Parameters
    -----
    sentence1 : str
        The first input sentence.
    sentence2 : str
        The second input sentence.
    """
    def __init__(self, premise: str, hypothesis:
                str, relationship: str):
        self.sentence1 = sentence1
        self.sentence2 = sentence2

    def determine_relationship(self):
        if is_entailment(self.sentence1,
                        self.sentence2):
            print("entailment")
        else:
            print("not_entailment")
```

Prompts for Restaurant-T:

```
class Aspect_Based_Sentiment_Analysis:
    """
    Base class for aspect-based sentiment
    analysis task.

    Parameters
    -----
    aspect : str
        The target aspect term of the given
        sentence.
    sentence : str
        The input text that contains the aspect.
    """
    def __init__(self, sentence: str, aspect:
                str):
        self.sentence = sentence
        self.aspect = aspect
    def sentiment_classification(self):
        if is_positive(self.sentence, self.aspect):
            print("positive")
        elif is_negative(self.sentence, self.aspect):
            print("negative")
```

B.3. Other Code-style prompts Design

In Section 5.2.2, we design two other different code-style prompts: *class init* and *func exec*. Specifically, the "class init" prompt provides LLMs with incomplete code with partial parameter input of the class as triggers to prompt LLMs to complete the code. The "func exec" converts the class definition into a function definition. The detailed results of these two designs can be found in Table 2. Besides, following your advice, we will also add other ablation experiments with regard to the prompt design in the subsequent version of our paper, such as the influence of certain parts of the prompt (Class name, annotation etc.) We use the QNLI task as an example to present the different prompts.

Prompts for *class init*:

```
class Answer_Verification:
    """
    Given a question, determines whether the
    provided text contains the correct
    answer to the question.
    The relationship consists of "entailment"
    and "not entailment".

    Parameters
    -----
    question : str
        The input question.
    text : str
        The input text.
    """
    def __init__(self, question, text,
                relationship):
        self.question = question
        self.text = text
        self.relationship = relationship
```

Prompts for *func exec*:

```
def Answer_Verification(question: str, text:
                        str):
    """
    Given a question, determines whether the
    provided text contains the correct
    answer to the question.
    The relationship consists of "entailment"
    and "not entailment".

    Args:
        question (str): The input question.
        text (str): The input text.

    Returns:
        str: "entailment", or "not entailment".
    """
    if is_entailment(question, text):
        print("entailment")
    else:
        print("not_entailment")
```

C. Detailed Experiments Results

The detailed experiments of accuracy can be found in this section. Table 8 and Table 10 present the accuracy of datasets before (Original) and after adversarial transformations (Adversarial) with text-davinci-003. Moreover, Table 10 and Table 11 present the results of gpt-3.5-turbo. All the results are under few-shot settings. From Table 8 and Table 9, we can conclude that using code-style prompts only acquire little improvement on the original datasets. Specifically, using code-style instructions outperforms using natural language instructions by 5.13 and 5.68 points in accuracy with text-davinci-003 and gpt-3.5-turbo, respectively. However, when employing adversarial samples in the instructions, using code-style instructions acquires a relatively larger improvement. Specifically, we get 3.02 and 5.68 points with text-davinci-003 and gpt-3.5-turbo, respectively, showcasing the advantages of code-style instructions in resisting adversarial attacks.

Method	Dataset								AVG
	AdvGLUE					Restaurant-T			
	SST-2	QQP	MNLI	QNLI	RTE	RevTgt	RevNon	AddDiff	
NL	96.18	82.05	79.33	79.72	92.59	91.66	92.67	80	86.78
Code	98.47	83.33	84.2	77.7	92.59	91	92	78.67	87.25

Table 8: Original datasets results with text-davinci-003

Method	Dataset								AVG
	AdvGLUE					Restaurant-T			
	SST-2	QQP	MNLI	QNLI	RTE	RevTgt	RevNon	AddDiff	
NL	70.94	67.95	61.15	63.51	82.72	67	86	76	72.07
CoT	74.32	71.79	70.25	67.57	81.48	70.66	82	69.33	73.43
Code	75	73.07	68.59	66.21	87.65	70.67	88	77.33	75.82
Code+adv	78.38	75.64	72.72	64.86	87.65	72.66	87.33	78.33	77.20

Table 9: Adversarial datasets results of text-davinci-003

Method	Dataset								AVG
	AdvGLUE					Restaurant-T			
	SST-2	QQP	MNLI	QNLI	RTE	RevTgt	RevNon	AddDiff	
NL	99.23	83.33	76.03	75.67	83.95	91.33	92	83.33	85.61
Code	98.47	83.33	80.16	75.67	86.42	91.33	92	81.67	86.13

Table 10: Original datasets results of gpt-3.5-turbo

Method	Dataset								AVG
	AdvGLUE					Restaurant-T			
	SST-2	QQP	MNLI	QNLI	RTE	RevTgt	RevNon	AddDiff	
NL	79.05	76.92	60.33	62.83	67.9	67.3	77.3	72	70.45
CoT	78.37	73.07	74.38	64.18	69.13	62	79	69	71.14
Code	83.1	74.35	69.42	73.64	74.07	71.33	79.6	72.33	74.73
Code+adv	83.78	82.05	72.73	74.32	72.83	72.33	80	71	76.13

Table 11: Adversarial datasets results of gpt-3.5-turbo