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Speak Like a Native: Prompting Large Language Models in a Native Style

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Abstract

Existing work has found that the prompt engineering heavily influences the performance of large language models (LLMs). Chain-ofthought (CoT), as a popular prompt engineering technique, prompted LLMs using in-context examples with reasoning steps. In current studies, the few-shot examples of CoT are generally handcrafted by humans. However, how the text style of in-context examples influence the outputs of LLMs still remains under-explored. This paper presents a novel and effective approach, named AlignCoT, to improve the reasoning capability of LLMs by aligning the incontext examples with the native style of LLMs. "Native" refers to the inherent characteristic style of LLMs which can be probed by original zero-shot scenarios. AlignCoT is orthogonal to other prompt engineering methods, making it easy to combine with state-of-the-art techniques to further improve the LLMs' performance. We conduct extensive and comprehensive experiments on several benchmarks. The empirical results demonstrate that our Align-CoTsignificantly improves performance over the carefully handcrafted in-context examples. For instance, with GPT-3.5-turbo, we observed a +2.5% improvement on GSM8K. Furthermore, our AlignCoT consistently improve the performance when combined with other stateof-the-art prompt engineering methods. The source code and dataset will be available at https://github.com/yangzhch6/AlignCoT.

1 Introduction

With the rapid increasing capabilities of Large Language Models (LLMs), remarkable advances has recently been made across various NLP tasks (Devlin et al., 2019; Radford and Narasimhan, 2018; Raffel et al., 2020). However as the increases of model size and dataset size, the amount of compute used for training and the cost of finetuning for downstream tasks becomes unaffordable. Besides, in-context learning (ICL) methods have also shown comparable or superior performance to full training set finetuning (Brown et al., 2020; Wei et al., 2022b; Kojima et al., 2022). Due to the interpretability and the training-free characteristic, in-context learning (ICL) has emerged as a new paradigm, where LLMs make predictions based on contexts augmented with few-shot examples.

A crucial question in the field of in-context learning is how to construct the few-shot prompts. Wei et al. (2022b) propose chain-of-thought (CoT) prompt which consists of a sequence of short sentences describing intermediate reasoning steps towards final answers, can elicit reasoning capabilities from large language models for complex reasoning tasks. On the basis of CoT, a lot of work has emerged in the field of in-context learning. Some works in this area (Liu et al., 2022; Rubin et al., 2022; Su et al., 2023; Fu et al., 2023; Ye et al., 2023; Li et al., 2023a) compose few-shot prompts by selecting examples that are relevant to the current input question. Some works improve LLM's performance by increasing prompt diversity and sampling reasoning paths multiple times (Wang et al., 2023; Li et al., 2023b). Other works in this area have been proposed to mimic human cognitive processes (Yao et al., 2023; Long, 2023; Hao et al., 2023; Zhang et al., 2023). Although the above works have made great contributions to incontext learning, they all overlook the influence of CoT's text style on LLM's reasoning ability. The CoT text in the current works are either from the original training set or handcrafted by humans.

In a few-shot scenario, LLMs imitate someone else's speech in NLP tasks, while in the zero-shot scenario, LLMs generate Chain-of-Thoughts in their own native-style, which they acquire from pre-training, Supervised Fine-tuning (SFT), and Reinforcement Learning with Human Feedback (RLHF). LLM's output in few-shot scenarios is similar to imitating someone else's tone, while in the zero-shot scenario, LLM generates CoT in its

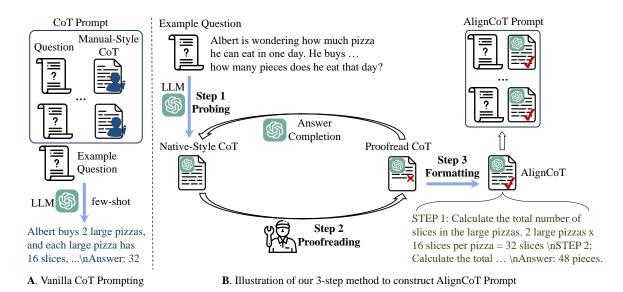


Figure 1: **A**: In few-shot scenarios of existing works, the CoTs in **blue** are either come from original dataset or handcrafted, we consider such CoT text style as "Manual-Style". LLM is like imitating other people's tone when prompted with "Manual-Style" examples. **B**: We consider the CoT text style that LLM generate in zero-shot senarios as "Native-Style". To acquire correct and formatted "Native-Style" CoTs, we propose Aligned Chain-of-Thought (AlignCoT) Prompting which consits of three steps: Probing, Proofreading, and Formatting.

own native-style which the LLM gets from training (pre-training, SFT, RLHF). It stands to reason that just as it is more natural for us humans to speak in our own style than to imitate others, LLMs may perform better when prompted with their nativestyle CoT rather than imitating other styles. From the generalization point of view, aligning the CoT text style in few-shot examples with the nativestyle of the LLM in the zero-shot scenario serves to mitigate the disparity between the training and inference stages. This alignment reduces the requirement for extensive model generalization capabilities and results in an enhancement of performance.

In this study, we propose a novel method named Aligned Chain-of-Thought (AlignCoT) Prompting that aims to improve the reasoning ability of LLMs through the alignment of the CoT text style in the few-shot example to the native-style of LLM. Furthermore, our method is focused on modifying only the CoT in a few-shot examples, making it independent of other in-context learning techniques and can be seamlessly integrated with them. The proposed method operates in three steps, as depicted in Figure 1. Firstly, we utilize each question in the few-shot prompt to query the LLM and generate its native-style CoT in a zero-shot scenario. Secondly, we proofread the generated CoT through human-computer interaction to correct any errors. Finally, we unify the CoT text formats, including the format of the final answer and the format of the solution steps. We then construct the few-shot prompt using the native-style CoT obtained in the aforementioned three steps to query the LLM.

In summary, our contributions are as follows:

- We propose a novel and effective method named AlignCoT Prompting, which aligns the CoT text style in few-shot examples to nativestyle of Large Language Models in zero-shot scenario to improve reasoning abilities.
- We demonstrate the effectiveness of our Align-CoT through extensive experiments, including baseline comparisons and ablation studies. The experimental results show that AlignCoT can be easily integrated with a wide range of in-context learning methods and achieve significant performance improvements.
- We overwrite the CoT in GSM8k dataset using our proposed AlignCoT and contribute the GSM8k-Align dataset. Experiments show that the above aligned datasets can effectively improve the performance of example selection methods.

We believe this work will inspire further research in large language models, multi-step reasoning, and in-context learning.

2 Related Work

Emergent Abilities and Multi-Step Reasoning. As the amount of computation and data in language models continues to grow, one concern is what unique capabilities emerge when models become large (Kaplan et al., 2020; Wei et al., 2022a). The ability of in-context learning (ICL), that is, to solve the corresponding tasks according to the given fewshot examples, is something that language models are particularly skilled at when scaled up to a certain size (Shin et al., 2020; Liu et al., 2023). Recently, some researchers find that large models significantly outperformed small models in multi-step reasoning tasks (which is considered a manifestation of emergent abilities), whereas large models showed very limited performance gains on tasks such as emotion classification (Shin et al., 2020). Moreover, in multi-step reasoning, few-shot prompting methods begin to outperform full training set fine-tuning, even on the same large model (Lewkowycz et al., 2022). These characteristics make the multi-step reasoning tasks (Wang et al., 2017; Cobbe et al., 2021; Ling et al., 2017) attract a lot of attention from researchers. This work takes an important step towards multi-step reasoning by showing the critical role of CoT text style for large language models.

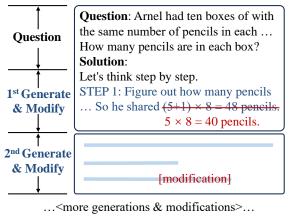
Chain-of-Thought Reasoning. Wei et al. (2022b) propose chain-of-thought prompting to elicit reasoning ability in large language models. They show that prompting LLMs with intermediate reasoning steps can greatly improve multi-step reasoning ability. Based on this prominent work, further works show that CoT can be improved by various approaches. Wang et al. (2023) propose self-consistency which conduct majority voting by sampling different reasoning paths. Least-to-Most prompting (Zhou et al., 2023) guides the LLMs to first decompose the original question into small parts and then solve it. Auto-CoT (Zhang et al., 2022) is proposed to reduce human workload. Treeof-Thought (Yao et al., 2023; Long, 2023) further support chain-of-thought by solving complex problems in a tree search process. Reasoning via Planning (Hao et al., 2023) repositions LLM as both a world model and a inference model, and combines the Monte Carlo Tree Search algorithm to search in a huge inference space. Some researchers have found that LLMs are decent zero-shot reasoners and can generate intermediate reasoning steps by

simply adding "Let's think step by step"(Kojima et al., 2022) before each answer. Our work sits in the context of CoT reasoning, and propose a new method to improve reasoning ability in LLMs by aligning CoT text style in few-shot examples to LLM's native-style in zero-shot scenarios.

In-Context Learning examples. Due to the sensitivity of LLMs to prompt, task, and dataset (Zhao et al., 2021; Lu et al., 2022; Su et al., 2022), designing prompts and the selection of good examples for in-context learning in few-shot scenarios is a fundamental question (Liu et al., 2022). The vanilla CoT (Wei et al., 2022b) prompting LLMs with 8 manually written examples. Based on this, PAL (Gao et al., 2023) convert these examples into programming language statements. Complex CoT (Fu et al., 2023) demonstrates the importance of prompt complexity and selects examples with most complex reasoning steps from the training set, resulting in improved performance on multi-step reasoning tasks. Some efforts using retrieval-based methods to extract the most similar and relevant examples in the training set. Liu et al. (2022) propose to retrieve examples that are semantically-similar to a test query sample to formulate its corresponding prompt. Effienct Prompt Retriever (EPR) (Rubin et al., 2022) uses an unsupervised retriever to obtain a set of candidate examples. Zhang et al. (2022) divides the training set into k categories and select k samples which are closest to the cluster center. CEIL (Ye et al., 2023) obtains preferred examples by optimizing the retrieve model with contrastive learning objectives according to the relationship between input questions and contextual examples. DQ-Lore (Xiong et al., 2023) introduce a framework that leverages Dual Queries and Low-rank approximation Re-ranking (DQ-LoRe) to automatically select exemplars for in-context learning. However, the examples in the few-shot scenarios of the existing works are either from the original training set or hand-crafted by humans, ignoring the impact of the CoT text style. In this work, we use our AlignCoT to construct few-shot examples and achieved performance improvements on the basis of a variety of methods.

3 AlignCoT Prompting

As shown in Figure 1, the input in the chain-ofthoughts workflow is a stack of a few (often 8) CoT cases followed by a test question, then the language model continues generating an output CoT



denotes generated text
 denotes deleting

Figure 2: The illustration of our proofreading process. The modifications in red are annotated manually. We modify the first error each time and then query the LLM to complete the text behind the last modified error.

for the test question. In this paper, we mainly focus on enhancing the reasoning capabilities of LLMs by converting the CoT text style of few-shot examples to LLM's native-style. Our main purpose is to get LLM's native-style CoTs that have consistent formats and correct steps, and replace the hand-made CoTs in original few-shot prompts with the acquired CoTs. To achieve this, we propose AlignCoT Prompting, a method that aligns fewshot examples with zero-shot scenarios to acquire the LLM's native-style CoT. AlignCoT comprises three main steps: 1) Probing LLM's native-style in zero-shot scenarios, 2) Proofreading the generated CoT to correct errors in the first step, and 3) Unifying the format of the generated CoTs in the first two steps. We then use the native-style CoT obtained in the above three steps to replace the CoT of examples in the original few-shot prompt to query LLMs. The AlignCoT method is described in detail in the following three subsections: §3.1, §3.2, and §3.3.

3.1 Probing Native-Style of LLM

As shown in Figure 1.A, the Chain-of-Thought text in the few-shot examples are either handcrafted or come from original dataset which are also humanannotated. We consider the text style of handcrafted CoTs as "manual-style". Compared with the few-shot scenarios in existing works (which directly use examples from the training set or handcrafted examples), LLM does not need to imitate the CoT text that is inconsistent with its own language style in zero-shot scenarios. We refer to the CoT text style generated by LLM in zeroshot scenarios as "native-style". When prompting Large Language Model (LLM) with "manual-style" CoTs of few-shot examples, LLM will follow the "manual-style" format, which may not fully exploit the LLM's capabilities.

To bridge this gap, we introduce the first step of our AlignCoT Prompting method, which involves Probing LLM's native-style Chain-of-Thought (CoT) in zero-shot scenarios. As illustrated in Figure 1.B, in order to acquire the CoT with nativestyle, we use the magic phrase "Let's think step by step" proposed by Kojima et al. (2022) to query LLMs for each example in a given few-shot prompt to generate a CoT that resembles the way it naturally responds to the input question.

By generating native-style CoTs in zero-shot scenarios, we ensure that the CoTs align with the LLM's strengths and preferences, allowing for more effective reasoning and response generation. This step sets the foundation for enhancing the reasoning capabilities of LLMs when working with CoTs. However, the generated native-style CoTs are not always correct. In order to modify the errors, we need to proofread the generated content against the ground truth answer in the dataset.

3.2 Proofreading CoTs

The second critical phase of our AlignCoT Prompting involves the meticulous process of proofreading the CoTs generated in the previous step. This phase encompasses human-computer interaction to rectify any inaccuracies or imperfections present in the initially generated content. The ultimate goal is to ensure that the CoTs adhere to the highest standards of accuracy, enabling more precise reasoning and response generation by Large Language Models.

To achieve this, we employ a manual modification process, where human intervention plays a pivotal role in proofreading the CoTs. The proofreading process is initiated by identifying and addressing the first encountered error within the CoT text. Subsequently, we harness the capabilities of LLMs to iteratively correct the text, moving forward and completing the answer from the initially modified error position. An example of this process is shown in Figure 2. This iterative approach is executed in the same zero-shot scenario of §3.1, ensuring that the entire text is rectified while preserving the native-style of the LLM's expression. It is worth noting that our approach to proofreading is designed with a focus on minimalistic text modification, which ensures that the generated CoTs are not only error-free but also in harmony with the inherent stylistic nuances of the LLM.

3.3 Unifying the Format of CoTs

However, a crucial aspect that deserves meticulous attention is the consistency of the answer text format and punctuation marks across different examples. This consistency plays a pivotal role in ensuring optimal model performance, as it enables the model to effectively understand and respond to the queries posed to it.

To unify the format of each examples, we undertake a manual examination of the generated LLM's native-style CoTs from the previous steps. During this evaluation, we pay particular attention to two key aspects: the format of answer text and the punctuation marks of solution steps. By meticulously inspecting and revising these elements, we ensure that each CoT conforms to a standardized style, making them easily interpretable and consistent in their presentation. This approach guarantees that the standardized CoTs maintain a natural and coherent flow, thus enhancing their utility in subsequent reasoning and response generation tasks.

4 Experiments

In this section, we first discuss our experimental setting in §4.1. In §4.2 and §4.3, we not only show AlignCoT's superior performance in multi-step reasoning, but also demonstrate its orthogonality (Our method can be easily combined with other prompting methods). Furthermore, we conduct ablation study, case study, and more in-depth analysis in §4.3 and §4.4.

4.1 Experimental Settings

Datasets and Language Models. We evaluate out AlignCoT on two math word problems datasets: GSM8k (Cobbe et al., 2021), AQUA (Ling et al., 2017), and SVAMP(Patel et al., 2021). We choose the datasets because we focus on the multi-step reasoning ability of large language model. Specifically, there are 7.4k training instances and 1.3k test instances in GSM8K, all samples have manually labeled intermediate problem solving steps. AQUA is a larger mathematical dataset with more difficult samples which are annotated with rationales by human annotators. SVAMP (Patel et al., 2021) is a more challenging and robust dataset created by applying carefully chosen variations over examples sampled from existing datasets. In addition to directly using the test instances to measure the performance of our method, we also use Align-CoT to overwrite the training instances of multiple datasets, and prove the superiority of our rewritten dataset through the retrieval methods. Also, to validate our proposed method performance, we use the GPT-3.5-Turbo model. All models are employed via OpenAI API key.

Prompts. Our AlignCoT focuses on converting the CoT text style of examples in the given fewshot prompt, it neither requires special sample selection methods nor changes the processes of the prompting methods. Therefore, our AlignCoT can be easily combined with many prompting methods. In our experiments, we choose the original CoT prompt proposed by Wei et al. (2022b), the complex CoT prompt proposed by Fu et al. (2023) and the prompt extracted by Efficient Prompt Retriever (EPR) (Rubin et al., 2022) as the baselines. Following (Kojima et al., 2022), we add "Let's think step by step" before the reasoning chains for all baselines to improve the performance. We will show all the prompts in the Appendix and supplementary materials.

4.2 Main Results

The main results of our study are presented in Table 1, with all methods using greedy decoding (i.e. temperature is set to 0). Our findings indicate that the proposed AlignCoT significantly improves reasoning abilities in LLMs. The Standard Prompt (Wei et al., 2022b) is handcrafted by humans without intermediate reasoning steps, while the CoT Prompt (Wei et al., 2022b) include manually designed intermediate steps. The Complex Prompt (Fu et al., 2023) serves as a strong baseline which consists of the examples with the most complex intermediate reasoning steps. In Complex Prompt, intermediate steps are taken from the source dataset, if the source data does not have intermediate steps, they are manually annotated. With our AlignCoT, we observe an +2.5% improvement and an +2.4%improvement for GPT-3.5-turbo on GSM8k and AQUA dataset, respectively.

4.3 Ablation Study

In this subsection, we provide a detailed analysis of the impact of each step in AlignCoT: Probing, Proofreading, Formatting. We use Complex CoT

Model	Prompt	AlignCoT (Ours)	GSM8k	AQUA	Avg
GPT-3.5-turbo	CoT (Wei et al., 2022b)	×	75.4	54.7	65.1
	CoT (Wei et al., 2022b)	\checkmark	77.4 (+2.0)	57.1 (+2.4)	67.3 (+2.2)
	Complex CoT (Fu et al., 2023)	×	79.8	55.5	67.7
	Complex CoT (Fu et al., 2023)	\checkmark	82.3 (+2.5)	57.9 (+2.4)	70.1 (+2.4)

Table 1: AlignCoT, when applied to different LLMs and prompting methods, can help to improve the performance. We select the Standard Prompt (Wei et al., 2022b), Chain-of-Thought (CoT) Prompt (Wei et al., 2022b), and Complex CoT Prompt (Fu et al., 2023) as our primary baselines.

(Fu et al., 2023) as our baseline and conduct experiments on GSM8K. We conduct experiments by deleting different steps in our proposed AlignCoT. The results are shown in Table 2. Complex CoT is equivalent to the case where none of the three steps are used. whereas AlignCoT is equivalent to adopting all three steps. When only the first step (Probing) is conducted, the performance improvement over the baseline is +0.7%. When the Proofreading or Formatting step is adopted on the basis of the Probing step, the performance can be further improved. Especially when all three steps are deployed simultaneously, our AlignCoT can outperform Complex CoT by 2.5%. Overall, the three steps in AlignCoT can all make LLM perform better in multi-step reasoning, and they work best when deployed in combination.

Probing	Proofreading	Formatting	Answer Accuracy
×	×	×	79.8
	×	×	80.5 (+0.7)
	\checkmark	×	81.5 (+1.7)
	×	\checkmark	80.9 (+1.1)
\checkmark	\checkmark	\checkmark	82.3 (+2.5)

Table 2: Ablation study of different step in AlignCoT on GSM8k.

Overwriting with AlignCoT. In order to further validate the universality, superiority, and robustness of our AlignCoT, and to help the retrieve-based incontext learning approaches, we use AlignCoT to overwrite the training data in the original dataset. We denote the overwritten data as Aligned Data. However, although our AlignCoT involves only a small amount of manual annotation, it is important to note the labour cost and time required when it comes to labelling large amounts of training data. To solve this, we first use the 8-shot AlignCoT prompt obtained from AlignCoT Prompting (as shown in Figure 1) to query the LLM to output the native-style CoT for each sample in the training set.

LLMs will follow prompt's text style and text format and convert the original CoT in the training set to our AlignCoT. For those samples which cannot be answered correctly in such setting, we create a (8-shot) style conversion prompt which consists of question, answer in original dataset (handcrafted) and native-style answer (AlignCoT). Subsequent experiments will compare the impact of AlignCoT prompt and style conversion prompt on the generated data.

We choose the Random Selection, Efficient Prompt Retriever (EPR) (Rubin et al., 2022), and Complex CoT (Fu et al., 2023) as our baselines. Random Selection method randomly extracts 8 samples from the training set. Efficient Prompt Retriever (EPR) (Rubin et al., 2022) retrieves the most similar training instances as exemplars for a given test case. Complex CoT (Fu et al., 2023) builds prompt by selecting the examples with the most complex reasoning steps in the training set, and therefore also serves as a strong baseline of the retrieve methods. For the very small number of examples (around 1%) that can not be answered correctly via the AlignCoT prompt and text style conversion prompt, we remove them from the example pool. The experimental results on GSM8k are shown in Table 3.

Retreiver	Example Pool	GSM8k
Random Selection	Original Data	76.5
Kandoni Selection	Aligned Data	78.0 (+1.5)
	Original Data	77.3
EPR (Rubin et al., 2022)	Conversion Data	80.1 (+2.8)
	Aligned Data	80.9 (+3.6)
Complex CoT (En et al. 2022)	Original 8-shot	79.8
Complex CoT (Fu et al., 2023)	AlignCoT 8-shot	82.3 (+2.5)

Table 3: Experimental results of retrieve-based methods on GSM8k. We compare the performance between Original Data and our Aligned Data.

The experiment results show that the perfor-

Example Question:	Test Question:
You can buy 4 apples or 1 watermelon for the same price. You bought 36	John plans to sell all his toys and use the money to buy video games.
fruits evenly split between oranges, apples and watermelons, and the price of	He has 13 lego sets and he sells them for \$15 each. He ends up
1 orange is \$0.50. How much does 1 apple cost if your total bill was \$66?	buying 8 video games for \$20 each and has \$5 left. How many lego
Complex CoT:	sets does he still have?
Let's think step by step.	Ground Truth Solution:
If 36 fruits were evenly split between 3 types of fruits, then I bought 36/3 =	He spent \$160 on video games because $8 \times 20 = 160$
12 units of each fruit	He earned \$165 from his sale because $160 + 5 = 165$
If 1 orange costs \$0.50 then 12 oranges will cost \$0.50 * 12 = \$6	He sold 11 lego sets because $11 \times 15 = 165$
If my total bill was \$66 and I spent \$6 on oranges then I spent \$66 - \$6 = \$60	He has 2 sets left because $13 - 11 = 2$
on the other 2 fruit types.	So the answer is 2.
Assuming the price of watermelon is W, and knowing that you can buy 4 apples for the same price and that the price of one apple is A, then $IW=4A$ If we know we bought 12 watermelons and 12 apples for \$60, then we know that \$60 = 12W + 12A Knowing that $IW=4A$, then we can convert the above to $$60 = 12(4A) + 12A$ \$60 = 48A + 12A \$60 = 60A Then we know the price of one apple (A) is $$60/60=1 The answer is 1 AlignCOT Let's think step by step. STEP 1: Calculate the total cost of the oranges. We know that the price of 1 orange is $$0.50$. So, the total cost of all the oranges is $36 * $0.50 = 18 . STEP 2: Calculate the number of each kind of fruit you bought. We also know that you bought 36 fruits evenly split between oranges, apples, and watermelons. So, you bought $36/3 = 12$ for each kind of fruit. STEP 3: Define the variable. Let's assume the cost of 1 apple is x dollars. STEP 4: Establish an equation according to: the sum of the cost of each kind of fruit (apple, watermelon, and watermelon) equals to the total cost \$66. So, the cost of 1 under apples is $12 * x = 12x$ dollars. We know that the total bill was \$66. So, the total cost of all the fruits is \$66. Therefore, we can write the equation: $$18 + 12x + 4x = $66.$ STEP 5: Solve the equation and get the answer. Simplifying the equation and get the answer. Simplifying the equation, we get: $16x + $18 = $66.$ Subtracting \$18 from both sides, we get: $16x = $66 - $18 = $48.$ Dividing both sides by 16, we get: $x = $48 / 16 = $3.$ Therefore, the cost of 1 apple is \$3. Answer: 1	 Complex CoT Output: Let's think step by step. John sells 13 lego sets for \$15 each, so he earns 13 * \$15 = \$195. He buys 8 video games for \$20 each, so he spends 8 * \$20 = \$160. After buying the video games, he has \$195 - \$160 = \$35 left. Since he has \$5 left, he must have spent \$35 - \$5 = \$30 on lego sets. Since each lego set costs \$15, he must have bought \$30 / \$15 = 2 lego sets. Therefore, John still has 13 - 2 = 11 lego sets. The answer is 11★ AlgnCoT Output: Let's think step by step. STEP 1: Calculate the total amount of money John gets from selling the lego sets. John has 13 lego sets and sells them for \$15 each, so he gets 13 * \$15 = \$195. STEP 3: Calculate the total cost of the video games. John buys 8 video games for \$20 each, so the total cost is 8 * \$20 = \$160. STEP 4: Calculate the total amount of money John pent. The total amount of money John spent. StEP 5: Calculate the number of lego sets John still has. stud amount of money John spent is \$195 (from selling the lego sets) - \$160 (for the video games) + \$5 (remaining amount) = \$40. StEP 5: Calculate the number of lego sets John still has. Is to tal amount of money John spent is \$40, which is the cost of the lego sets has the selling the lego sets has the selling the lego sets has the selling the lego sets. Since each lego set costs \$15, the number of lego sets John still has is \$40 / \$15 = 2.67. Since John cannot have a fraction of a lego set, we round down to the nearest whole number.\nTherefore, John still has 2 lego sets.

Figure 3: Two Cases of GSM8k dataset. We show one example in the few-show prompt and one test example from test split. The "Manual-Style" CoTs are colored in blue, while the "Native-Style" CoTs are colored in green.

mance of all the three retrieve-based methods can be significantly improved by our Aligned Data. Especially, with our Aligned Data, we achieve +3.6% accuracy improvement on EPR method. The significant performance improvements on retrievebased methods not only show the superiority of our Aligned Data, but also illustrates the robustness of our approach.

In addition, in order to further explore the impact of AlignCoT prompt and text style conversion prompt on the generated data, we conducted the following comparative experiments. We refer to the Data generated entirely on the basis of style conversion prompt as Conversion Data, comparing it to other example pools on the basis of EPR method, the result is shown in Table 3. Although Conversion Data also achieve +2.8% performance improvement for EPR method, the improvement is still lower than Aligned Data. This shows that the data generated by AlignCoT prompt performs better than the data generated by style conversion prompt.

In conclusion, we illustrate the superiority and robustness of Aligned Data. We contribute the Aligned Data of GSM8k, and named it "GSM8k-Align". We believe that this dataset can provide inspiration for the subsequent retrieve-based Incontext Learning research.

4.4 Case Study

In this subsection, in order to better demonstrate the differences between LLM native style and human manual style, we present two cases (one example question and one test question) in Figure 3. For the example question from the few-shot prompt, we show its corresponding Complex CoT (colored in blue) and AlignCoT (colored in green). For the test question, we show its corresponding ground truth

answer from the original dataset (colored in black), LLM's generation prompted by Complex CoT and AlignCoT, respectively. AlignCoT, the native style of the LLM that we have detected, tends to generate a clearer step and a more detailed answer than original ground truth data and human handcrafted CoT.

4.5 Limitation

Future researchers can work on finding better approaches to proofread the output of LLM. Besides that, due to computation resource limitation, we can not overwrite all the benchmark datasets in our experiments, thus we only contribute GSM8k-Align dataset. In addition, more in-context learning methods such as self-consistency (Wang et al., 2023) are waiting to be added to the experimental results. All in all, experimental results of more benchmarks and analysis will be released as soon as possible.

5 Conclusion

This paper proposes a novel approach name Aligned Chain-of-Thought (AlignCoT) for prompting large language models to speak in its native style. AlignCoT exhibit multiple advantages: 1) AlignCoT achieve substantial performance improvements on multi-step reasoning tasks. 2) We only convert the CoT text style in the given prompt, thus our AlignCoT is orthogonal to other prompting methods and can be easily combined with them. 3) We overwrite the CoTs of the original multi-step reasoning datasets with our AlignCoT to improve retrieve-based prompting methods.

To better enhance the progressive-hint prompting approach, future research endeavors can focus on probing more accurate native styles of LLM and combining retrieve-based prompting method with native style data. We hope this work will open new research possibilities in prompting, large language models, and multi-step reasoning.

Acknowledgements

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