TUTOR-ICL: Guiding Large Language Models for Improved In-Context Learning Performance

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Abstract

There has been a growing body of work focusing on the in-context learning (ICL) abilities of large language models (LLMs). However, it is an open question how effective ICL can be. This paper presents TUTOR-ICL, a simple prompting method for classification tasks inspired by how effective instructors might engage their students in learning a task. Specifically, we propose presenting exemplar answers in a *comparative format* rather than the traditional single-answer format. We also show that including the test instance before the exemplars can improve performance, making it easier for LLMs to focus on relevant exemplars. Lastly, we include a summarization step before attempting the test, following a common human practice. Experiments on various classification tasks, conducted across both decoder-only LLMs (Llama 2, 3) and encoder-decoder LLMs (Flan-T5-XL, XXL), show that TUTOR-ICL consistently boosts performance, achieving up to a 13.76% increase in accuracy.[1]

1 Introduction

With the rapid advancement of large language models (LLMs), in-context learning (ICL), which involves performing various tasks by learning from only a small number of examples within the context of a single prompt, has become a dominant paradigm in natural language processing (Brown et al., 2020). With ICL, the likelihood of any answer for the test example is conditioned on the provided ICL exemplars (Dong et al., 2022). The underlying assumption of ICL is that LLMs can thoroughly review these exemplars, identify the hidden patterns crucial for input-label mappings, and consequently make correct predictions (Wang et al., 2023). However, recent studies have provided some evidence that LLMs, particularly smaller ones (less than or around 10 billion parameters), are unable to fully utilize the provided exemplars. For example, Shivagunde et al. (2024) found that smaller LLMs allocate less attention mass to ICL examples than larger models. Similarly, Wei et al. (2023) indicated that smaller LLMs have a lower ability to adjust their semantic priors based on the provided ICL examples than their larger counterparts. We also conduct a preliminary experiment indicating that LLMs do not always produce the correct answer even when it is provided as one of the exemplars (Section 5.1 and Table 3). These results strongly suggest that a lot of LLMs still struggle in performing ICL.

Our Objective and Approach In this paper, we address this limitation by investigating the following research question: *How can we effectively guide LLMs to achieve better ICL performance?* Our solution is to enhance the prompt template with simple yet powerful ideas inspired by how intelligent humans would perform ICL: (1) framing ICL as a comparative reading task (Alawiye and Williams, 2005); (2) showing the test example early to make it easier to identify and focus on relevant exemplars; (3) summarizing the material before the test to organize and digest the learned knowledge (Rinehart et al., 1986).

We first introduce the concept of a **comparative answer format (CAF)**. In contrast to most prior works that offer a single answer (e.g., "positive"), we suggest presenting the answer in a comparative format (e.g., "closer to positive than neutral"). This straightforward adjustment results in a notable performance boost, such as an average F1 increase of 5.78 points on the Laptop14 ABSC dataset (Pontiki et al., 2014) with Llama3-8B-Instruct (Dubey et al., 2024). Additionally, we present the **glance-at-the-test (GAT)** framework which is driven by the idea that knowing the test example in advance could encourage a more efficient search and concentra-

[1]Code for TUTOR-ICL is available at: https://github.com/ihcho2/Tutor-ICL

Findings of the Association for Computational Linguistics: EMNLP 2024, pages 9496–9506

tion on the exemplars relevant to the test. Lastly, we incorporate a **"summarization" step** into the prompt inspired by how people generally start by reading new information, then take a moment to digest and summarize the newfound knowledge before proceeding (Rinehart et al., 1986). We show that incorporating these new elements into a single ICL prompt improves the performance of a number of LLMs (Llama2-7B,13B, Llama3-8B-Instruct (Touvron et al., 2023; Dubey et al., 2024), Flan-T5-XL,XXL (Chung et al., 2024)) on a variety of text classification tasks (aspect-based sentiment classification, news topic classification, question type classification, and emotion classification).

2 Related Work

In-Context Learning (ICL) The existing literature on in-context learning research can be broadly divided into two categories: (1) analytical studies, which aim to uncover the underlying mechanisms of how LLMs perform ICL (Wang et al., 2023; Yoo et al., 2022; Von Oswald et al., 2023), and (2) improvement studies, which seek to enhance ICL performance through various methods such as exemplar selection (Liu et al., 2021; Ye et al., 2023), exemplar ordering (Min et al., 2022), and instruction calibration (Zhou et al., 2022). The strand of work that is most closely related to ours focuses on changes to the prompt *template* itself, as explained next.

Studies on ICL template components A number of studies have examined the effects of the components within prompt templates. Shivagunde et al. (2024), referred to as Decon-ICL hereafter, showed the benefits of briefly repeating text and the importance of reiterating inline instructions. Xu et al. (2023) proposed RE2 as a simple strategy of reading the question again to improve ICL performance. Wei et al. (2023) examined the effects of flipped or semantically-unrelated labels on ICL.

Most of these studies rely on a standardized prompt template that includes four components: task instructions, exemplar inputs, exemplar labels, and inline instructions (Shivagunde et al., 2024). The key distinction of our work lies in our out-of-the-box approach. Rather than focusing solely on these four standard components, we take it one step further by exploring the incorporation of new elements. We verify that these additional elements can significantly improve ICL performance.

Prompting multi-step reasoning A lot of work in prompt engineering has focused on eliciting intermediate reasoning steps to enhance performance, as seen in various techniques like chain-of-thought (Wei et al., 2022), tree-of-thought (Yao et al., 2024), and visualization-of-thought (Wu et al., 2024), among others. While effective, this comes with limitations, such as high computational costs from generating longer outputs and difficulties in acquiring high-quality exemplars for ICL. In contrast, TUTOR-ICL bypasses the need for generating additional intermediate steps or new exemplars, providing a more cost-effective approach to improving performance.

3 TUTOR-ICL

Our work is primarily motivated by Shivagunde et al. (2024) and Xu et al. (2023), which show that simply repeating the same instruction or question could boost LLM performance. This indicates that providing more careful guidance could further enhance LLMs' ICL performance, highlighting a potential area for improvement. TUTOR-ICL (Figure 1), effectively guides LLMs throughout the ICL process by incorporating three novel ideas: (1) Comparative answer format, which provides the answers in a comparative form to elicit deeper thinking from multiple answer perspectives; (2) Glance-at-the-test framework, which informs LLMs of the test instance in advance, leading to a more efficient search and focus on relevant exemplars; (3) Summarization step, which makes LLMs to summarize the given exemplars before attempting the test instance, similar to human practice.

3.1 Comparative Answer Format

As in #2 of (Figure 1), we provide answers in a comparative format (e.g., "closer to positive than neutral") rather than the traditional single-answer format (e.g., "positive"). The rationale behind this approach is that LLMs would produce answers in a comparative format by following the exemplars (Minaee et al., 2024; Dong et al., 2022). This automatically leads them to compare different answers, thereby encouraging deeper thinking from various answer perspectives. More details on selecting the comparative answer and phrasing the overall answer are described in Section 5.4 and Appendix C.

3.2 Glance-at-the-Test Framework

The majority of ICL studies present the test instance at the end. However, our investigation re-

veals that presenting the test instance at the beginning as well as at the end, is often beneficial. Intuitively, when the test instance is given before the exemplars, LLMs can leverage this prior information to concentrate more on the relevant exemplars, by using their self-attention mechanism (Vaswani et al., 2017). This is not possible for decoder-only LLMs if the test instance is presented only at the end. An example is provided in #1 of Figure 1.

3.3 Summarizing before the Test

Summarizing is a vital skill for humans to organize and gain a deeper understanding of the material (Rinehart et al., 1986). We examine whether this is also true for LLMs. After reading the exemplars, we add a brief summary of them before solving the test instance as illustrated in #3 of Figure 1. There could be many ways to create a summary, but for the sake of simplicity, we chose to repeat the answers as the default approach.

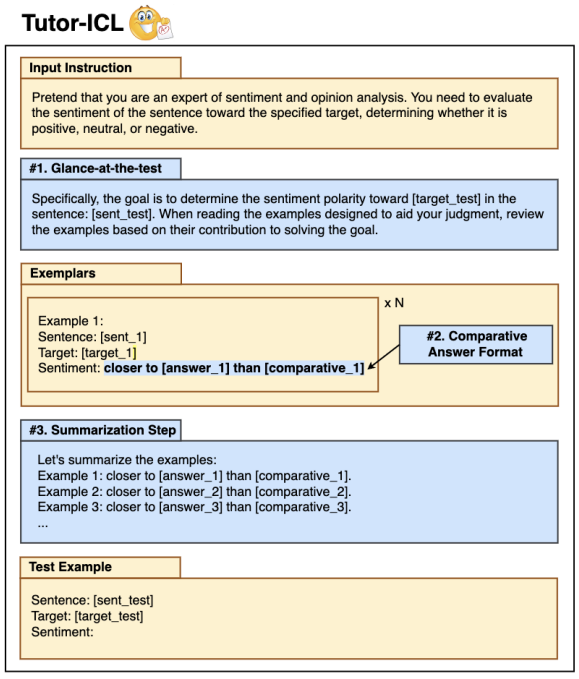

Figure 1: The overall template of TUTOR-ICL. The three main components of TUTOR-ICL are represented in blue. Glance-at-the-test offers the test instance beforehand, effectively directing the model to relevant exemplars. The comparative answer format encourages deeper reasoning through multiple answer perspectives. The summarization step simulates the human practice of reviewing key information before solving the test instance. Best viewed in color.

4 Experiments

4.1 Experimental Settings

Datasets We selected four widely used classifications tasks in ICL: aspect-based sentiment classification (ABSC) (SemEval-14-Laptops and Restaurants (Pontiki et al., 2014)), news topic classification (AGNews (Zhang et al., 2015)), question type classification (TREC QC (Li and Roth, 2002)), and emotion classification based on dialogues (EmoContext (Chatterjee et al., 2019)). Detailed explanations for each task can be found in Appendix A. We form the validation set by collecting 300 instances for each label from the training set. The ICL exemplars are randomly selected for each seed from the remaining training data, and the final evaluation is conducted on the test set.

Models and Settings We utilize both encoder-decoder LLMs (Flan-T5-XL,XXL) (Chung et al., 2024) and decoder-only LLMs (Llama2-7B,13B, and Llama3-8B-Instruct) (Touvron et al., 2023; Dubey et al., 2024). We use n exemplars for each answer label: $n = 1$ for AGNews, TREC QC, and EmoContext, and $n = 2$ for ABSC. More details can be found in Appendix B.

4.2 Results

Main Results Table 2 presents the performance of TUTOR-ICL and the baseline methods on the test set. We can see that TUTOR-ICL consistently enhances performance across all models and datasets, showing the greatest improvement in TREC QC (Li and Roth, 2002) with Llama3-8B-Instruct (Dubey et al., 2024), where the accuracy increases by 13.76% and F1 score by 12.70 points. Additionally, TUTOR-ICL surpasses relevant competitors, such as RE2 (Xu et al., 2023) and Decon-ICL (Shivagunde et al., 2024) styles.

Ablation Results We provide detailed ablation results in Table 7 in the Appendix. We chose the best-performing models from each category as representatives: Flan-T5-XXL (Chung et al., 2024) for encoder-decoder LLMs and Llama3-8B-Instruct (Dubey et al., 2024) for decoder-only LLMs. We observe that each method is generally effective on its own, and combining them results in even further improvement.

True Labels	Model-generated answers: **Closer to positive than neutral**	**Closer to positive than neutral or negative**	Closer to positive than negative	**Closer to negative than neutral**	**Closer to negative than positive**	Closer to negative than neutral or positive	Closer to neutral than positive	Closer to neutral than negative
Positive	690.2	13.0	13.6	1.0	3.8	2.0	3.4	1.0
Negative	2.0	0.0	2.0	73.0	36.0	74.6	1.0	7.4
Neutral	78.6	0.0	2.4	28.0	5.2	26.2	37.2	18.4

Table 1: Further evidence that the comparative answer format actually triggers comparative reasoning in LLMs. New types of comparative answers (underlined for emphasis) are frequently generated. The numbers represent the average counts across five runs from Flan-T5-XXL.

Model	Rest14 Acc (%)	Rest14 F1 (%)	Lap14 Acc (%)	Lap14 F1 (%)	AGNews Acc (%)	AGNews F1 (%)	TREC QC Acc (%)	TREC QC F1 (%)	EmoContext Acc (%)	EmoContext F1 (%)
Flan-T5-XL (3B)										
Baseline-ICL	$82.73_{0.57}$	$68.65_{2.09}$	$77.96_{0.35}$	$71.61_{0.87}$	$91.66_{0.21}$	$91.67_{0.22}$	$96.24_{0.23}$	$95.85_{0.27}$	$80.57_{0.42}$	$80.15_{0.50}$
RE2-style	$82.68_{0.48}$	$67.70_{0.38}$	$77.32_{0.40}$	$70.88_{0.95}$	$91.73_{0.11}$	$91.73_{0.11}$	$93.40_{0.42}$	$93.01_{0.36}$	$80.65_{0.38}$	$80.19_{0.37}$
Decon-ICL-style	$81.48_{0.41}$	$64.80_{1.13}$	$77.52_{0.42}$	$69.96_{0.96}$	$92.11_{0.16}$	$92.11_{0.16}$	$95.92_{0.20}$	$94.91_{0.44}$	$80.80_{0.51}$	$80.47_{0.55}$
Ours: TUTOR-ICL	$\mathbf{83.89_{0.45}}$	$\mathbf{72.02_{1.32}}$	$\mathbf{80.72_{0.64}}$	$\mathbf{76.64_{1.04}}$	$\mathbf{92.30_{0.11}}$	$\mathbf{92.29_{0.11}}$	$\mathbf{96.28_{0.10}}$	$\mathbf{95.91_{0.08}}$	$\mathbf{82.72_{0.55}}$	$\mathbf{82.68_{0.58}}$
Flan-T5-XXL (11B)										
Baseline-ICL	$84.87_{0.19}$	$71.61_{0.69}$	$81.53_{0.30}$	$75.08_{0.51}$	$92.09_{0.05}$	$92.09_{0.05}$	$93.44_{0.43}$	$91.81_{0.38}$	$78.55_{0.25}$	$78.04_{0.23}$
RE2-style	$84.00_{0.48}$	$69.15_{1.38}$	$80.00_{0.61}$	$72.32_{1.05}$	$91.60_{0.07}$	$91.61_{0.07}$	$94.04_{0.32}$	$92.46_{0.29}$	$78.62_{0.51}$	$78.48_{0.44}$
Decon-ICL-style	$83.18_{0.36}$	$66.46_{1.00}$	$79.47_{0.19}$	$71.16_{0.25}$	$91.65_{0.21}$	$91.65_{0.22}$	$93.52_{0.30}$	$91.84_{0.27}$	$79.45_{0.27}$	$79.08_{0.24}$
Ours: TUTOR-ICL	$\mathbf{87.43_{0.23}}$	$\mathbf{79.21_{0.55}}$	$\mathbf{84.92_{0.53}}$	$\mathbf{81.13_{0.66}}$	$\mathbf{92.30_{0.06}}$	$\mathbf{92.28_{0.06}}$	$\mathbf{95.00_{0.18}}$	$\mathbf{93.49_{0.47}}$	$\mathbf{79.81_{0.16}}$	$\mathbf{79.59_{0.15}}$
Llama2 (7B)										
Baseline-ICL	$66.29_{3.17}$	$55.71_{2.84}$	$57.77_{1.76}$	$52.27_{1.91}$	$67.58_{1.20}$	$63.44_{1.34}$	$49.24_{3.63}$	$46.65_{4.25}$	$58.04_{3.82}$	$57.65_{4.45}$
RE2-style	$60.12_{2.96}$	$55.05_{2.62}$	$55.38_{2.17}$	$53.59_{2.02}$	$69.19_{0.82}$	$66.15_{0.72}$	$54.08_{3.47}$	$51.51_{3.91}$	$58.54_{3.12}$	$58.22_{3.40}$
Decon-ICL-style	$64.46_{2.98}$	$55.84_{2.85}$	$57.21_{3.01}$	$52.57_{2.71}$	$67.31_{1.09}$	$63.26_{0.47}$	$51.32_{2.89}$	$48.31_{4.27}$	$60.10_{3.31}$	$61.41_{4.55}$
Ours: TUTOR-ICL	$\mathbf{71.91_{3.18}}$	$\mathbf{60.37_{3.58}}$	$\mathbf{63.13_{1.74}}$	$\mathbf{58.57_{2.19}}$	$\mathbf{75.46_{2.29}}$	$\mathbf{74.22_{2.70}}$	$\mathbf{59.00_{3.27}}$	$\mathbf{57.36_{3.92}}$	$\mathbf{70.88_{1.42}}$	$\mathbf{70.31_{1.56}}$
Llama2 (13B)										
Baseline-ICL	$78.48_{1.16}$	$67.59_{1.76}$	$73.41_{1.07}$	$65.49_{2.06}$	$80.96_{2.05}$	$80.22_{2.57}$	$54.20_{2.27}$	$54.37_{2.27}$	$69.58_{2.60}$	$69.35_{2.34}$
RE2-style	$77.55_{1.48}$	$65.51_{2.12}$	$72.89_{1.20}$	$64.56_{1.99}$	$81.24_{2.12}$	$80.45_{2.40}$	$54.68_{2.54}$	$55.79_{1.65}$	$71.47_{2.58}$	$71.45_{2.21}$
Decon-ICL-style	$80.21_{1.13}$	$68.44_{1.88}$	$74.40_{1.18}$	$66.80_{1.52}$	$80.19_{2.21}$	$79.76_{3.41}$	$59.60_{2.41}$	$64.81_{2.31}$	$69.15_{1.91}$	$68.33_{2.07}$
Ours: TUTOR-ICL	$\mathbf{82.83_{0.91}}$	$\mathbf{71.82_{2.29}}$	$\mathbf{77.40_{0.89}}$	$\mathbf{71.90_{1.01}}$	$\mathbf{82.26_{1.77}}$	$\mathbf{81.81_{2.05}}$	$\mathbf{62.68_{1.84}}$	$\mathbf{62.57_{2.67}}$	$\mathbf{72.87_{1.72}}$	$\mathbf{71.97_{2.55}}$
Llama3-8B-Instruct										
Baseline-ICL	$83.00_{0.25}$	$67.37_{1.11}$	$76.40_{0.71}$	$66.36_{1.86}$	$79.62_{2.51}$	$78.78_{3.43}$	$63.40_{2.38}$	$63.09_{2.39}$	$71.16_{1.34}$	$69.62_{1.57}$
RE2-style	$82.79_{0.67}$	$66.46_{2.40}$	$76.02_{0.93}$	$65.58_{2.21}$	$79.53_{2.32}$	$78.40_{3.01}$	$63.88_{2.50}$	$64.34_{2.50}$	$72.26_{1.37}$	$70.91_{1.52}$
Decon-ICL-style	$83.20_{0.97}$	$67.21_{3.01}$	$76.55_{0.24}$	$66.50_{0.86}$	$81.02_{2.01}$	$80.36_{2.52}$	$66.72_{1.60}$	$64.02_{1.67}$	$72.12_{1.16}$	$70.69_{1.30}$
Ours: TUTOR-ICL	$\mathbf{84.55_{0.46}}$	$\mathbf{75.32_{1.23}}$	$\mathbf{81.47_{0.59}}$	$\mathbf{77.32_{0.97}}$	$\mathbf{83.42_{1.92}}$	$\mathbf{83.13_{2.34}}$	$\mathbf{77.16_{1.08}}$	$\mathbf{75.79_{1.96}}$	$\mathbf{73.73_{0.88}}$	$\mathbf{73.45_{0.85}}$

Table 2: Overall Few-shot ICL results. Average of five random seeds and standard errors in the subscript.

5 Analysis

5.1 Does TUTOR-ICL really help LLMs to more thoroughly examine the exemplars?

Beyond the performance improvement, we seek additional evidence to verify whether TUTOR-ICL is truly encouraging LLMs to more thoroughly examine the ICL exemplars. To this end, we designed a straightforward experiment as follows. The idea is to include the test instance (test sentence and answer) as one of the exemplars. Intuitively, if the LLM reads the exemplars thoroughly, accuracy should approach 100%, since the answer is given. We compare the baseline template with the TUTOR-ICL template in two scenarios (test instance as the first or last exemplar) as shown in Table 3. The results indicate that the TUTOR-ICL template consistently achieves higher accuracy, suggesting it enables LLMs to examine the exemplars more thoroughly.

Model	Rest14 Acc (%)	Rest14 F1 (%)	Lap14 Acc (%)	Lap14 F1 (%)
Llama3-8B-Instruct				
Baseline-ICL (gold@first)	$99.50_{0.16}$	$99.11_{0.27}$	$98.84_{0.44}$	$98.61_{0.59}$
TUTOR-ICL (gold@first)	$\mathbf{99.96_{0.08}}$	$\mathbf{99.94_{0.13}}$	$\mathbf{99.78_{0.18}}$	$\mathbf{99.76_{0.19}}$
Baseline-ICL (gold@last)	$96.89_{0.38}$	$94.81_{0.70}$	$94.76_{2.15}$	$93.72_{2.67}$
TUTOR-ICL (gold@last)	$\mathbf{98.77_{0.34}}$	$\mathbf{98.07_{0.48}}$	$\mathbf{96.61_{0.59}}$	$\mathbf{96.10_{0.77}}$
Flan-T5-XXL (11B)				
Baseline-ICL (gold@first)	$97.27_{0.14}$	$95.31_{0.25}$	$95.45_{0.46}$	$93.92_{0.60}$
TUTOR-ICL (gold@first)	$\mathbf{97.86_{0.22}}$	$\mathbf{96.45_{0.34}}$	$\mathbf{95.83_{0.33}}$	$\mathbf{94.47_{0.43}}$
Baseline-ICL (gold@last)	$97.84_{0.12}$	$96.35_{0.23}$	$96.27_{0.17}$	$94.94_{0.22}$
TUTOR-ICL (gold@last)	$\mathbf{98.77_{0.04}}$	$\mathbf{98.00_{0.08}}$	$\mathbf{97.58_{0.50}}$	$\mathbf{96.79_{0.60}}$

Table 3: TUTOR-ICL triggers deeper examination, as shown by the results, indicating it more frequently identifies the gold-answer when included in the exemplars.

5.2 Does comparative answer really trigger comparative thinking in LLMs?

Beyond the performance improvement, we offer deeper insights into the effectiveness of the comparative answer format. We design an experiment

to verify whether this format genuinely triggers comparative reasoning in LLMs. Our hypothesis is that *"If the LLM generates a comparative answer not presented in the exemplars, it indicates that LLMs are not merely copying the labels but are actually engaging in comparative reasoning on their own."* To this end, we conduct an experiment to investigate whether the model can generate novel types of comparative answers that were not included in the exemplars. Specifically, we only provide "closer to positive than negative", "closer to negative than neutral or positive", "closer to neutral than positive", and "closer to neutral than negative" in the exemplars. As illustrated in Table 1, we observe that four new answer types are generated from Flan-T5-XXL (Chung et al., 2024) on the Rest14 dataset (Pontiki et al., 2014), averaged over 5 seeds. This verifies that the comparative answer format can indeed stimulate comparative reasoning rather than simply replicating the provided labels.

5.3 Comparative answer format elicits more diverse answers from LLMs.

We collected responses from the Llama-2-7B model (Touvron et al., 2023) using the AGNews dataset (Zhang et al., 2015) and compared the results with and without the comparative answer format. As shown in Table 4 below, the comparative answer format (1) enhances overall accuracy and (2) elicits a range of unseen answers. These results suggest that comparative answers can trigger deeper and more diverse thinking, leading to a more effective utilization of the LLM's semantic priors.

Llama2-7B	AGNews Acc	Generated Answers
Baseline Prompt	$67.58_{1.20}$	world, business, sports, science/technology, security state, politics, politics/government, health, health/medicine, arts, entertainment, arts/entertainment
Comparative Answer Prompt	$\mathbf{72.85}_{1.47}$	world, business, sports, science/technology, state, politics, **state/local government**, politics/government, **government/politics**, arts, **arts/culture**, arts/entertainment, entertainment, **design**, **gaming**, **games**, health, health/medicine, **personal**, **personal/people**, **history**, **personal/human interest**, **personal finance**, security, **internet**

Table 4: Comparative answer format prompts more diverse answers. Newly generated answers are highlighted in bold.

5.4 Is the comparative answer format a generally applicable approach?

Despite the simplicity of the comparative answer format (CAF), its application across various tasks may encounter minor issues, such as selecting appropriate comparative answers, particularly in multi-label scenarios. In this section, we show that even the default version of CAF (using "closer to [Answer]", without the need for selecting comparative answers) is generally effective. Furthermore, fine-tuning on specific datasets yields additional performance improvements. Evidence supporting these claims is provided in Table 5, where we test multiple variants of CAF, each differing only in how the answers were presented. Specifically, we use "[answer]" for Baseline, "closer to [answer]" for default-CAF, "closer to [answer] than [another_answer]" for Variant 1, "closer to [answer] than [another_answer_1], [another_answer_2], ..., or [another_answer_last]" for Variant 2, and "closer to [answer] than the other topics/emotions/sentiments/semantic classes (depending on the task)" for Variant 3. The results in Table 5 suggest a solution for applying CAF broadly: using the default version for general effectiveness, with fine-tuning when possible, for further enhancements.

Model	AGNews Acc/F1	TREC-QC Acc/F1	EmoContext Acc/F1
Llama2-7B			
Baseline-ICL	67.58/63.44	49.24/46.65	58.04/57.65
Baseline-ICL + CAF-Default	70.95/68.76	53.92/53.83	**66.78/65.88**
Baseline-ICL + CAF-Variant 1	**72.85/70.85**	51.24/49.25	64.72/63.11
Baseline-ICL + CAF-Variant 2	72.02/69.66	52.36/49.41	66.20/64.78
Baseline-ICL + CAF-Variant 3	69.64/67.21	**56.24/54.90**	65.33/64.43
Llama3-8B			
Baseline-ICL	79.62/78.78	63.40/63.09	71.16/69.62
Baseline-ICL + CAF-Default	80.40/79.28	64.80/63.76	72.56/71.18
Baseline-ICL + CAF-Variant 1	**81.85/81.18**	**65.43/65.02**	72.81/71.99
Baseline-ICL + CAF-Variant 2	80.22/79.05	65.21/64.20	72.99/72.10
Baseline-ICL + CAF-Variant 3	80.22/79.10	64.97/64.01	**73.11/72.40**
Flan-T5-XL (3B)			
Baseline-ICL	91.66/91.67	96.04/95.65	80.57/80.15
Baseline-ICL + CAF-Default	92.02/92.02	**96.16/95.82**	81.63/81.38
Baseline-ICL + CAF-Variant 1	92.07/92.06	95.92/95.54	**82.00/81.84**
Baseline-ICL + CAF-Variant 2	**92.20/91.19**	96.08/95.66	81.77/81.57
Baseline-ICL + CAF-Variant 3	91.95/91.95	95.68/94.94	81.36/81.04

Table 5: The general effectiveness of the default (i.e., "closer to [Answer]") and fine-tuned (i.e., Variants 1,2, and 3) comparative answer formats.

6 Conclusion

This paper has proposed an original framework, TUTOR-ICL, integrating three novel concepts into the standard in-context learning (ICL) prompt template: the comparative answer format, the glance-at-the-test framework, and the summarization step. To the best of our knowledge, TUTOR-ICL is the first work to incorporate new components to the ICL template, highlighting a new potential direction for future developments in the field.

7 Limitations

Our work has several limitations. Firstly, our study focused exclusively on classification tasks and did not extend to generative tasks. Additionally, due to hardware limitations, our analysis primarily involved models with up to 13 billion parameters. Exploring the effectiveness of TUTOR-ICL on significantly larger models would be an interesting future work. Lastly, as discussed in Section 2, our focus on greedy decoding was driven by computational efficiency. Nevertheless, investigating the integration of TUTOR-ICL with sampling-based prompting techniques remains a promising area for further exploration.

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A Tasks and Datasets

In our study, we employ four classification tasks: aspect-based sentiment classification (ABSC), topic classification, question-type classification, and emotion classification. Specifically, we use SemEval-14-Laptops and Restaurants datasets for ABSC (Pontiki et al., 2014), AG's News topic classification (AGNews) dataset for topic classification (Zhang et al., 2015), Text REtrieval Conference Question Classification (TREC QC) dataset for question type classification (Li and Roth, 2002), and SemEval-19-EmoContext (EmoContext) dataset for emotion classification (Chatterjee et al., 2019).

Laptops and Restaurants are collections of laptop and restaurant reviews where the task is to evaluate the sentiment (positive, neutral, or negative) of the review toward a specified target within the sentence. We selected this ABSC task for sentiment classification since it is a more challenging variant.

AGNews is a task to classify the given news article into one of the four categories: world, sports, business, or sci/tech.

TREC QC is a task to classify the given question into one of the six categories: abbreviation, entity, description, human, location, or number.

EmoContext is a collection of textual dialogues where the task is to infer the underlying emotion from four categories: happy, sad, angry, and others.

Detailed statistics for each dataset are provided in Table 6. All experiments are conducted on a single NVIDIA A100 GPU.

	Dataset		Label Words	
Task	Train	Test	Label	Count
Lap14	2313	638	Positive	341
			Negative	128
			Neutral	169
Rest14	3602	1120	Positive	728
			Negative	196
			Neutral	196
AGNews	120000	7600	World	1900
			Sports	1900
			Business	1900
			Sci/Fi	1900
TREC QC	5452	500	Abbreviation	9
			Entity	94
			Description	138
			Human	65
			Location	81
			Number	113
EmoContext	30160	5509	Happy	284
			Sad	250
			Angry	298
			Others	4677

Table 6: Detailed information on the sizes of the training and test datasets for each task, as well as the sizes of the test datasets for each label within each task.

B Choosing baseline prompts and number of exemplars

Since the prompt might be sensitive to sentence phrasing, we experimented with five paraphrased instructions generated by ChatGPT[2] and selected the one with the best validation performance as the baseline. The five specific paraphrases are listed below. Option five, which was generally effective across most models, was chosen as the baseline instruction. Similar for AGNews and TREC QC.

1. Pretend that you are an expert of sentiment and opinion analysis. For a given sentence and

[2]ChatGPT, March, 2024, OpenAI, https://chat.openai.com.

a target, you have to assess the sentiment polarity (positive, neutral, or negative) towards the target.

2. Pretend that you are an expert of sentiment and opinion analysis. For a given sentence and a target, you have to assess the sentiment of the sentence toward the target, determining whether it is positive, neutral, or negative.

3. Pretend that you are an expert of sentiment and opinion analysis. Given a sentence and a target, you need to determine the sentiment of the sentence toward the target as either positive, neutral, or negative.

4. Pretend that you are an expert of sentiment and opinion analysis. For the provided sentence and target, your task is to assess the sentiment toward the target, identifying it as positive, neutral, or negative.

5. Pretend that you are an expert of sentiment and opinion analysis. You need to evaluate the sentiment of the sentence toward the specified target, determining whether it is positive, neutral, or negative.

Number of exemplars used. We use n exemplars for each answer label: $n = 1$ for AGNews, TREC QC, and EmoContext, and $n = 2$ for ABSC. We experimented with $n = 1, 2,$ and 3. For ABSC, $n = 2$ yielded the best baseline performance. For AGNews, TREC QC, and EmoContext, both $n = 1$ and $n = 2$ showed similar results, so we selected $n = 1$ considering the inference speed.

C TUTOR-ICL Prompt Templates

C.1 Selecting Comparative Answers

To select the comparative answer corresponding to an answer we follow the below simple rules:

ABSC

- For positive label, we use neutral as the default comparative answer.
- For negative label, we use neutral as the default comparative answer.
- For neutral label, we use both positive and negative as default comparative answers.

AGNews, TREC QC, and EmoContext We simply choose the next label based on the instruction as the comparative answer.

C.2 TUTOR-ICL Template Examples

Examples of TUTOR-ICL templates are provided below. We use $n = 2$ for ABSC and $n = 1$ for AGNews, TREC QC, and EmoContext as described in B. Each prompt comprises five components: task instruction, Glance-at-the-Test (GAT) framework, exemplars with comparative answers (CAF), summary, and test. Minor adjustments are made based on the validation performance.

TUTOR-ICL for ABSC

Pretend that you are an expert of sentiment and opinion analysis. You need to evaluate the sentiment of the sentence toward the specified target, determining whether it is positive, neutral, or negative.

Specifically, the goal is to determine the sentiment polarity toward [target_test] in the sentence: [sent_test]. When reading the examples designed to aid your judgment, review the examples based on their contribution to solving the goal.

Example 1:
Sentence: [sent_1]
Target: [target_1]
Answer: closer to [answer_1] than [comparative_1].

Example 2:
Sentence: [sent_2]
Target: [target_2]
Answer: closer to [answer_2] than [comparative_2].

Example 3:
Sentence: [sent_3]
Target: [target_3]
Answer: closer to [answer_3] than [comparative_3].

Example 4:
Sentence: [sent_4]
Target: [target_4]
Answer: closer to [answer_4] than [comparative_4].

Example 5:
Sentence: [sent_5]
Target: [target_5]
Answer: closer to [answer_5] than [comparative_5].

Example 6:
Sentence: [sent_6]
Target: [target_6]
Answer: closer to [answer_6] than [comparative_6].

Let's summarize the examples:
example 1: closer to [answer_1] than [comparative_1].
example 2: closer to [answer_2] than [comparative_2].
example 3: closer to [answer_3] than [comparative_3].
example 4: closer to [answer_4] than [comparative_4].
example 5: closer to [answer_5] than [comparative_5].
example 6: closer to [answer_6] than [comparative_6].

Now use the above examples to solve your goal. When you find an answer, verify the answer carefully by comparing with the provided examples. Include verifiable evidence in your reasoning.

Sentence: [sent_test]
Target: [target_test]
Answer:

	Rest14		Lap14		AGNews		TREC QC	
Model	Acc (%)	F1(%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)
Flan-T5-XXL (11B)								
1. Baseline	84.87$_{0.19}$	71.61$_{0.69}$	81.53$_{0.30}$	75.08$_{0.51}$	92.09$_{0.05}$	92.09$_{0.05}$	93.44$_{0.43}$	91.81$_{0.38}$
2.1 Baseline + CAF	86.41$_{0.23}$	75.60$_{0.63}$	83.51$_{0.57}$	78.43$_{1.02}$	92.15$_{0.08}$	92.15$_{0.08}$	93.72$_{0.20}$	92.06$_{0.22}$
2.2 Baseline + GAT	86.38$_{0.27}$	75.88$_{0.60}$	82.13$_{0.46}$	76.43$_{0.63}$	92.18$_{0.07}$	92.17$_{0.08}$	94.20$_{0.25}$	93.19$_{0.19}$
2.3 Baseline + Summary	85.25$_{0.39}$	72.36$_{1.22}$	81.97$_{0.60}$	75.90$_{1.03}$	92.24$_{0.12}$	92.23$_{0.12}$	94.20$_{0.13}$	92.57$_{0.11}$
3. TUTOR-ICL	**87.43$_{0.23}$**	**79.21$_{0.55}$**	**84.92$_{0.53}$**	**81.13$_{0.66}$**	**92.30$_{0.06}$**	**92.28$_{0.06}$**	**95.00$_{0.18}$**	**93.49$_{0.47}$**
Llama3-8B-Instruct								
1. Baseline	83.00$_{0.25}$	67.37$_{1.11}$	76.40$_{0.71}$	66.36$_{1.86}$	79.62$_{2.51}$	78.78$_{3.43}$	63.40$_{2.38}$	63.09$_{2.39}$
2.1 Baseline + CAF	84.04$_{0.41}$	72.42$_{1.12}$	77.99$_{0.58}$	72.14$_{1.14}$	81.85$_{2.70}$	81.18$_{3.49}$	64.80$_{2.41}$	63.76$_{1.64}$
2.2 Baseline + GAT	84.11$_{0.62}$	72.72$_{1.54}$	78.84$_{0.82}$	72.31$_{1.31}$	80.59$_{2.22}$	79.89$_{2.75}$	75.92$_{0.73}$	75.50$_{1.08}$
2.3 Baseline + Summary	83.41$_{0.71}$	69.54$_{2.17}$	77.46$_{0.36}$	69.87$_{1.04}$	80.74$_{2.68}$	80.09$_{3.51}$	70.76$_{1.50}$	70.11$_{1.53}$
3. TUTOR-ICL	**84.55$_{0.46}$**	**75.32$_{1.23}$**	**81.47$_{0.59}$**	**77.32$_{0.97}$**	**83.42$_{1.92}$**	**83.13$_{2.34}$**	**77.16$_{1.08}$**	**75.79$_{1.96}$**

Table 7: Ablation study results using few-shot ICL. CAF: Comparative Answer format, GAT: Glance-at-the-Test framework. We chose the best-performing model from each category (i.e., Llama3 for decoder-only and Flan-T5-XXL for encoder-decoder LLMs).

TUTOR-ICL for AGNews

Pretend that you are an expert in topic classification. For a given news article, you need to assess the topic of the article, determining whether it is world, sports, business, or sci/tech.

Specifically, the goal is to determine the topic of the news: [sent_test]. When reading the examples designed to aid your judgment, review the examples based on their contribution to solving the goal.

Example 1:
News: [sent_1]
Answer: The topic is closer to [answer_1] than [comparative_1].

Example 2:
News: [sent_2]
Answer: The topic is closer to [answer_2] than [comparative_2].

Example 3:
News: [sent_3]
Answer: The topic is closer to [answer_3] than [comparative_3].

Example 4:
News: [sent_4]
Answer: The topic is closer to [answer_4] than [comparative_4].

Let's summarize the examples so far:
example 1: [sent_1] | [answer_1].
example 2: [sent_2] | [answer_2].
example 3: [sent_3] | [answer_3].
example 4: [sent_4] | [answer_4].

Now use the above examples to solve your goal. When you find an answer, verify the answer carefully by comparing with the provided examples. Include verifiable evidence in your reasoning.

News: [sent_test]
Answer: The topic is closer to

TUTOR-ICL for TREC QC

Pretend that you are an expert in question classification. You need to classify the question into one of the following semantic classes: abbreviations, entities, description, humans, location, or numerical.

Specifically, the goal is to determine the semantic class of the question: [sent_test]. When reading the examples designed to aid your judgment, review the examples based on their contribution to solving the goal.

Example 1:
Question: [sent_1]
Answer: Rather than [comparative_1], more accurately described as [answer_1].

Example 2:
Question: [sent_2]
Answer: Rather than [comparative_2], more accurately described as [answer_2].

Example 3:
Question: [sent_3]
Answer: Rather than [comparative_3], more accurately described as [answer_3].

Example 4:
Question: [sent_4]
Answer: Rather than [comparative_4], more accurately described as [answer_4].

Example 5:
Question: [sent_5]
Answer: Rather than [comparative_5], more accurately described as [answer_5].

Example 6:
Question: [sent_6]
Answer: Rather than [comparative_6], more accurately described as [answer_6].

Let's summarize the examples:
example 1: [sent_1] | Rather than [comparative_1], more accurately described as [answer_1].
example 2: [sent_2] | Rather than [comparative_2], more accurately described as [answer_2].
example 3: [sent_3] | Rather than [comparative_3], more accurately described as [answer_3].
example 4: [sent_4] | Rather than [comparative_4], more accurately described as [answer_4].
example 5: [sent_5] | Rather than [comparative_5], more accurately described as [answer_5].
example 6: [sent_6] | Rather than [comparative_6], more accurately described as [answer_6].

Now use the above examples to solve your goal. When you find an answer, verify the answer carefully by comparing it with the provided examples. Include verifiable evidence in your reasoning.

Question: [sent_test]
Answer: