Do Emergent Abilities Exist in Quantized Large Language Models: An Empirical Study

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Abstract

Despite the superior performance, Large Language Models (LLMs) require significant computational resources for deployment and use. To overcome this issue, quantization methods have been widely applied to reduce the memory footprint of LLMs as well as increase the inference rate. However, a major challenge is that low-bit quantization methods often lead to performance degradation. It is important to understand how quantization impacts the capacity of LLMs. Different from previous studies focused on overall performance, this work aims to investigate the impact of quantization on *emergent abilities*, which are important characteristics that distinguish LLMs from small language models. Specifically, we examine the abilities of in-context learning, chain-of-thought reasoning, and instruction-following in quantized LLMs. Our empirical experiments show that these emergent abilities still exist in 4-bit quantization models, while 2-bit models encounter severe performance degradation on the test of these abilities. To improve the performance of low-bit models, we conduct two special experiments: (1) fine-gained impact analysis that studies which components (or substructures) are more sensitive to quantization, and (2) performance compensation through model fine-tuning. Our work derives a series of important findings to understand the impact of quantization on emergent abilities and sheds light on the possibilities of extremely low-bit quantization for LLMs.

Keywords: large language models, quantization, adavanced abilities

1. Introduction

Recently, Artificial Intelligence (AI) has witnessed remarkable progress due to the emergence of Large Language Models (LLMs) (Brown et al., 2020; Zhao et al., 2023). Compared with small-sized language models, LLMs, which largely scale the model size and training corpus size, have exhibited very different behaviors when elicited by specially designed prompts. Generally, LLMs can acquire more superior abilities, such as in-context learning (ICL, Brown et al. 2020) and chain-of-thought reasoning (CoT, Wei et al. 2022), which may not be present in small-sized language models. Such abilities are often formally called *emergent abilities* (Wei et al., 2022)[1].

Despite the superior performance, it is very costly to deploy LLMs in real-world applications due to the huge model size. Faced with this issue, model quantization (Dettmers et al., 2022; Frantar et al., 2022; Yao et al., 2023a) has become a widely used approach to reducing the memory footprint of LLMs. The essential idea of quantization is to map floating-point numbers into low-bit integers (*e.g.,* `BF16` to `INT8`), so as to reduce the total model bits. Typically, existing methods take a post-training quantization (PTQ) approach (Frantar et al., 2022; Dettmers et al., 2022) without retraining the model parameters. However, existing PTQ methods often suffer from performance degradation in low-bit quantization.

To use the quantized LLMs in an effective way, it is important to understand *what level of performance* can be attained in *varied bit precision*, *e.g.,* what is the lowest bit precision for quantization to achieve decent performance on a specific task? More recently, several studies have conducted comprehensive evaluation experiments on the impact of model quantization on the performance of LLMs (Yao et al., 2023b; Dettmers and Zettlemoyer, 2022). However, they mainly analyze the general performance of quantized LLMs (*e.g.,* language modeling), lacking a deep investigation into LLM's abilities on complex tasks.

In this work, we focus on examining the performance of quantized LLMs on solving complex tasks, to explore the impact of quantization on the emergent abilities of LLMs. As demonstrated in previous studies (Wei et al., 2022), there exists a strong dependency between emergent abilities and pa-

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[1] There is still no consensus on the existence of emergent abilities, due to the lack of continuity in evaluation metrics and model sizes in the empirical study (Wei et al., 2022). It is also known that small models can possess some emergent abilities with special adaptation. Despite that, we still use this term to emphasize the superior performance of LLMs.

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rameter scale. It is curious whether the emergent abilities would vanish under the setting of low-bit precision though the model size remains to be the original scale. In addition, it is also important to explore the factors (*e.g.,* the model structure) that potentially affect the emergent abilities. Furthermore, we are also interested in the potential approaches to enhance the performance of the low-bit models.

Specially, we aim to answer the following two questions: (1) **Do emergent abilities exist in quantized large language models? If so, what level of performance it can achieve?** (2) **How to enhance the performance of low-bit models?** To answer the two key questions, we assess three key abilities, namely in-context cearning (ICL), chain-of-thought reasoning (CoT), and Instruction-Following ability (IF), on a collection of LLaMA models (Touvron et al., 2023) which are widely used as the backbone models. We conduct extensive empirical experiments, aiming to gain a better understanding of the model performance of quantized LLMs.

For the first question, we evaluate the LLaMA models at four sizes (*i.e.,* 7B, 13B, 30B, and 65B), examining their performance across a range of precision levels: 2-bit, 4-bit, 8-bit, and 16-bit. Our experiments indicate that 4-bit precision yields the most favorable trade-off between model performance and memory footprint, achieving superior results with the same amount of allocated total bits. However, all models at different sizes suffer from a severe decline at 2-bit precision.

Regarding the second question, we carefully examine the quantization sensitivity of different model components (or substructures), specifically attention and feed-forward networks (FFN). In our experiments, we find that FFN plays a crucial role in retaining the model performance for low-bit quantization. We also evaluated the effects of outlier dimensions, which are specific dimensions that exhibit significantly higher values compared to others in feature activations. We find the outlier dimensions affecting most Transformer layers are primarily responsible for the decline in the quantization performance, and they mainly concentrate on the down projections of FFN. These observations motivate us to design fine-grained substructure quantization strategies for improving the performance of low-bit models.

Furthermore, we study how to enhance the performance of quantization models through fine-tuning. We evaluate the impacts of different fine-tuning methods executed before and after quantization. Our results reveal that parameter-efficient fine-tuning after quantization can achieve commendable performance with significantly reduced computational resources. Our approach can fine-tune a 2-bit LLaMA-65B model on a single NVIDIA A100, surpassing the performance of a 16-bit LLaMA-13B on zero-shot MMLU dataset.

2. Background

In this section, we introduce the background for emergent abilities and post-training quantization.

Emergent Abilities With the increasing of model parameters and training corpus, LLMs exhibit some special abilities that may not be present in small-sized language models, called *emergent abilities* (Wei et al., 2022). Emergent abilities are an important indication of superior performance of LLMs, which has received much attention in the research community. Following the survey on LLMs (Zhao et al., 2023), we focus on discussing three key emergent abilities, namely in-context learning, chain-of-thought reasoning, and instruction following. Next, we will briefly introduce each ability.

• *In-Context Learning (ICL)* was introduced by GPT-3 (Brown et al., 2020) to solve complex tasks through specially designed prompts. It can effectively guide LLMs to generate the intended output for test examples by leveraging natural language instructions and/or task demonstrations, without necessitating additional training or gradient update.

• *Chain-of-Thought reasoning (CoT)* is a special prompting strategy that tackles intricate tasks that encompass multiple reasoning steps, such as mathematical word problems. It incorporates intermediate reasoning steps for each demonstration in the prompt, thus eliciting the capacity of solving complex tasks via step-by-step reasoning.

• *Instruction Following (IF)* refers to the superior ability that a LLM follows human instructions and completes the target task as needed. Though it shares a similar format with ICL by using natural language instructions, it often includes no demonstrations and requires specific tuning (*i.e.,* instruction tuning) to elicit this ability.

Note that emergent abilities can be defined on different tasks or settings. We select the three abilities for study, mainly because they are widely utilized for solving complex tasks.

Post-Training Quantization Due to the huge number of parameters, it is often infeasible to conduct full-tuning on the model parameters. Thus, post-training quantization (PTQ) (Dettmers et al., 2022; Frantar et al., 2022; Yao et al., 2023b) methods are widely used for LLMs. For PTQ methods, they often only rely on small calibration data to tune the quantization parameters, which is very efficient in implementation. In this work, we adopt a popular quantization method, GTPQ (Frantar et al., 2022), to conduct our experiments. Specially, GPTQ employs a layerwise reconstruction loss to minimize the discrepancy between the original weights ($\mathbf{W}$) and the quantized weights ($\widehat{\mathbf{W}}$) through the optimization of the following objective:

$\arg\min_{\widehat{\mathbf{W}}} \| \mathbf{WX} - \widehat{\mathbf{W}}\mathbf{X} \|_2^2$. It can achieve very promising results for 4-bit quantization on LLMs, and also provides support for lower bit precision for weight quantization.

In addition to model weights, activations are also considered for quantization. However, due to the presence of *outlier dimensions* (Dettmers et al., 2022) in the feature activation values, quantizing activations in low-bit precision is widely acknowledged as a challenging task. These outlier dimensions exhibit significantly higher values compared to others and become particularly prominent as the model scale increases.

3. Do Emergent Abilities Exist in Quantized LLMs?

In this section, we aim to investigate the existence of emergent abilities in quantized LLMs, specifically focusing on in-context learning (ICL), chain-of-thought reasoning (CoT), and instruction following (IF). Next we first introduce the experimental setup and then present our key findings.

3.1. Experimental setup

In-Context Learning Test In order to evaluate the ICL ability, we utilize two widely used datasets for evaluating LLMs: MMLU (Hendrycks et al., 2021) and BBH (Srivastava et al., 2022a). MMLU serves as a comprehensive benchmark for assessing multi-task knowledge understanding in various domains, encompassing fields such as mathematics, computer science, humanities, and social science. Additionally, BBH is a challenging variant of BigBench (Srivastava et al., 2022b), which is proposed to concentrate on investigating the currently unsolvable tasks of LLMs. Then we conduct evaluations on the MMLU (*i.e.,* five- and zero-shot) and BBH (*i.e.,* three- and zero-shot) datasets, respectively.

Chain-of-Thought Reasoning Test To assess the CoT ability of the model, we employ the widely used GSM8K dataset. GSM8K is a reasoning dataset comprising $8\mathrm{K}$ problems that collectively evaluate the model's ability in arithmetic reasoning and the composition of mathematical steps. Following the methodology introduced in Fu et al. (2023), we conduct evaluations using a few-shot setting, where demonstrations are provided. Each demonstration is formatted as <*input, CoT, output*>, allowing it to elicit the model's capability to reason and generate coherent chains of thought.

Instruction Following Test To evaluate instruction following ability, we refer to the evaluation set in Alpacafarm (Dubois et al., 2023) and conduct an automatic evaluation based on GPT3.5 (abbreviated as *AlpacaFarm*). Specifically, we select the 16-bit LLaMA-7B as the baseline and compare it with other quantized models. Then we employ ChatGPT to automatically annotate which response from two compared models each time is better for the user query, and report the win rate (%) as the metric.

Quantization Settings To evaluate the performance of the aforementioned emergent abilities of quantization, we conduct a series of comprehensive experiments. Our tests are conducted based on the implementation of GPTQ-for-LLaMA [2], which only focus on weight quantization and encompass all model components (*i.e.,* query, key, value, output projection matrices in attention module and gate, up, down projection matrices in the feed-forward networks). For model size, we include a collection of LLaMA models of 7B, 13B, 30B, and 65B parameters. We consider quantization at 2-bit, 4-bit, 8-bit, and a non-quantized (16-bit) precision. These diverse configurations aim to thoroughly evaluate the impact of different quantization settings on model performance.

3.2. Results and Analysis

In this part, we present the experimental results and the corresponding analysis.

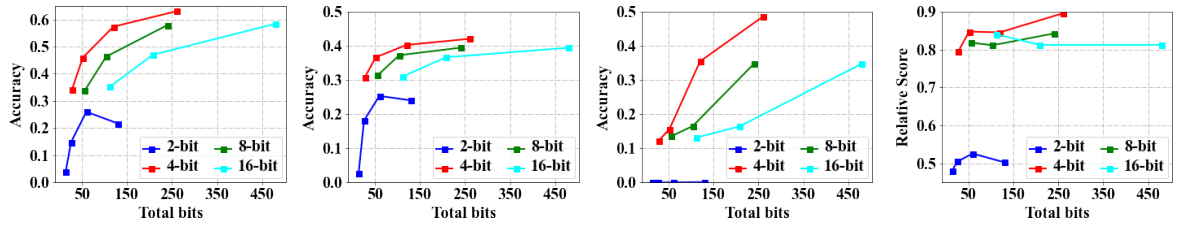
Overall, the three kinds of emergent abilities seem to be seldom affected with 4-bit quantization. Table 1 presents the test results of the models using 2-bit, 4-bit, 8-bit and 16-bit precision across multiple datasets, including MMLU, BBH for ICL, GSM8K for CoT, AlpacaFarm for IF and WikiText for general language modeling ability. As we can see, the results obtained using 4-bit and 8-bit quantization are very similar to the original performance (*i.e.,* 16-bit floating-point number). However, a significant decline is observed when employing 2-bit quantization, with results approaching near-random levels, *e.g.,* around 0.25 in 4-choice classification tasks for MMLU and BBH and 0.0 for GSM8K. It indicates that 4-bit quantization can effectively retain emergent abilities on these test datasets.

4-bit precision exhibits a favorable trade-off in terms of both total bits and performance. As shown in Table 1, it can be observed that 4-bit quantization offers a notable reduction in memory cost. To further examine the relation between model performance and resource usage, we follow Dettmers and Zettlemoyer (2022) to introduce the measure of *total bits* by multiplying the number of the parameters and the bits, and report the test results

[2] https://github.com/qwopqwop200/GPTQ-for-LLaMa

Size	Precision	MMLU (Acc)		BBH (Acc)		GSM8k	AlpacaFarm	WikiText	Mem.	Tokens/s
		0-shot	5-shot	0-shot	3-shot	(Acc)		(PPL)	(GiB)	
7B	16-bit	29.2	35.2	17.3	31.0	13.1	/	5.7	13.9	33.032
	8-bit	28.4	33.7	17.2	31.3	13.5	48.93	5.7	7.9	30.833
	4-bit	31.0	34.2	18.8	30.8	12.2	47.26	5.8	4.8	31.317
	2-bit	2.3	3.8	0.4	2.7	0.0	9.23	3937.9	3.2	33.266
13B	16-bit	41.4	47.0	20.9	36.6	16.4	52.68	5.1	26.6	24.968
	8-bit	40.5	46.3	21.1	37.2	16.5	52.56	5.1	14.8	17.754
	4-bit	39.0	45.9	19.8	36.6	15.6	52.71	5.2	8.6	18.139
	2-bit	4.9	14.8	4.2	18.1	0.0	7.4	142.6	5.5	18.422
30B	16-bit	53.7	58.4	19.5	39.4	34.7	55.45	4.1	65.4	16.596
	8-bit	54.2	57.9	19.9	39.4	34.7	53.58	4.1	35.3	8.187
	4-bit	53.7	57.3	18.3	40.2	35.4	53.24	4.2	20.0	8.371
	2-bit	3.7	26.1	3.8	25.3	0.2	11.42	25.1	12.2	8.649
65B	16-bit	-	-	-	-	-	-	-	-	-
	8-bit	-	-	-	-	-	-	-	-	-
	4-bit	57.1	63.0	21.9	42.1	48.5	30.37	3.9	38.2	4.793
	2-bit	9.0	22.6	1.0	24.0	0.8	8.97	77.8	22.9	4.826

Table 1: Evaluation results on MMLU, BBH, GSM8k and AlpacaFarm of the model variants in the LLaMA family. The results of the LLaMA-65B model at 16-bit and 8-bit precisions are not included due to memory constraints on a single GPU.



(a) MMLU (5-shot) (b) BBH (3-shot) (c) GSM8K (CoT) (d) AlpacaFarm

Figure 1: Performance comparison of quantized models under varied memory costs. For AlpacaFarm, the term "Relative Score" denotes the score ratio between quantized models and GPT3.5. The x-axis denotes the total number of bits after quantization.

in Figure 1 by varying the number of total bits. s From the four accuracy curves corresponding to different bit precision, we can see that 4-bit precision consistently exhibits higher model accuracy under the same amount of total model bits. Thus, 4-bit quantization is recommended to be used for a favorable balance between memory cost and model performance in practice.

The scaling effect depends on specific tasks, and increasing the model scale benefits the CoT task the most. We conducted an investigation, as depicted in Figure 1, to examine the impact of scaling the total number of bits on the performance of a low-bit model across multiple tasks. Overall, our analysis reveals that for the 2-bit precision, increasing the total bits (*i.e.,*a larger model size) does not yield substantial improvements, especially for MMLU and GSM8K, as the obtained outcomes do not exhibit superiority over random scores (*i.e.,* 0.25 on MMLU and 0.0 on GSM8K). Indeed, it is still a challenging task to effectively mitigate the errors resulting from quantization in 2-bit models. For 4-bit (or above) precision models, we observe notable improvements on the CoT tasks when increasing the total bits, which are not that significant for ICL test. Further, for IF test, a small model scale can be sufficient to achieve very good performance in our test experiments[3].

Low-bit quantization performance benefits from the demonstrations in ICL tests. For complex tasks, we can provide few-shot demonstrations for improving the model performance. To examine this, in Table 1, we also present the results with few-shot demonstrations for ICL. We can observe a notable advantage of the five-shot setting compared to the zero-shot setting, especially for 2-bit precision on LLaMA-30B (*i.e.,* 26.1 *vs.* 3.7). It suggests that the low-bit quantization performance of LLMs can be largely improved when appropriate demonstrations

[3]We plan to conduct evaluation experiments on IF at a larger scale.

	Bits	Cases	Score
		Question: Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. How many letters are in Indras and her sister's names?	
30B	4	**Answer:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 4 more letters than 3. 3 + 4 = 7. So her sister's name has 7 letters. Indras has 6 letters and her sister has 7 letters. 6 + 7 = 13. The answer is 13.	35.4
	2	**Answer:** Indras' name has 6 letters. Her sister's name has 4 more letters than half of the letters in Indras' name. So she has 6 - 4 = 4 letters. 4 letters. The answer is 4.	0.2
13B	4	**Answer:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. The answer is 10.	15.6
	2	**Answer:** The answer is 15. Question: 15 -. The answer is 15.	0.0
7B	4	**Answer:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. Indras has 6 letters. Her sister's name has 10 letters. The answer is 10.	12.2
	2	**Answer:** B. 82. M.H. or 4 weeks.. ungers are the best Cash...4..... 44. 30..Cash.B.Age.B.G.o.just.J.1Age..	0.0

Table 2: Case study for the LLaMA models on GSM8K. The colors of pink and lime denote the wrong and right prediction respectively. The score denotes the average accuracy over all of the GSM8K test set.

are utilized. However, such an improvement is not significant for 2-bit precision in LLaMA-7B (*i.e.,* 3.8 *vs.* 2.3), which indicates that the parameter scale must reach a certain level for this ability.

For CoT tests, extreme 2-bit quantization requires a large model scale. From Table 1, we find that the CoT ability for 2-bit precision no more exists for 7B and 13B models on our test datasets, since they both get 0.0 accuracy on GSM8K while 30B achieves 0.2. It suggests a sufficiently large model size is necessary for the CoT ability for 2-bit quantization. In order to further investigate this phenomenon, we conduct a case study analysis for LLaMA models with 7B, 13B and 30B on GSM8K test sets and show several test examples in Table 2. From these examples, we can see that, the 7B model was almost incapable of generating correct text outputs, resulting in a garbled output. Though the 13B model could generate response normally but fail to produce the correct reasoning chain. As a comparison, the 30B model succeeds in generating the correct reasoning chain, albeit with inaccurate inference results.

4. How to Enhance the Performance of Low-bit Models?

In order to explore the strategies for achieving higher performance with low-bit post-training quantization (PTQ), we next conduct analysis experiments to investigate the factors that affect the quantization performance. First, we analyze the quantization sensitivity of fine-grained model structures. Second, we examine the effects of performance compensation via model fine-tuning.

Part	Quantization Target	Precision
Weights	all component	INT2/INT4
	¬ ATT	INT2/INT4
	¬ FFN	INT2/INT4
	¬ crucial weights	INT2/INT4
Activations	all non-outlier dimensions	INT8
	+top-1 outlier dimension	INT8
	+top-3 outlier dimensions	INT8

Table 3: Experimental settings for quantization sensitivity analysis. Since activations are more difficult to be quantized, we adopt 8-bit quantization.

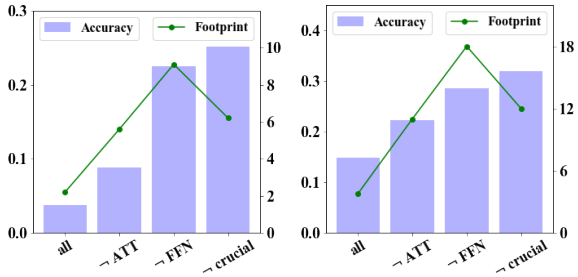
4.1. Quantization Sensitivity Analysis

4.1.1. Experimental Setup

As discussed in prior studies (Dettmers et al., 2022; Yao et al., 2023b), different model components (or feature dimensions) might exhibit varied sensitivity to quantization, *i.e.,* different levels of performance degradation. In this part, we mainly focus on low-bit quantization, and set up the following three experiments about quantization sensitivity (Table 3):

• *Component quantization analysis*. In this experiment, we examine the sensitivity of two major components in the Transformer architecture, *i.e.,* attention layers and feed-forward networks (FFN). Specifically, we consider evaluating the performance of two variants denoted as "¬ ATT" and "¬ FFN", where either the attention or FFN components are preserved at FP16 precision, while the remaining components are quantized into low bits. It aims to analyze the level of performance degradation for each kind of model component.

• *Outlier quantization analysis*. As found in prior studies (Dettmers et al., 2022), quantizing large



(a) LLaMA-7B-2bit (b) LLaMA-13B-2bit

Figure 2: Impacts of different model components or substructures on MMLU (five-shot). The memory footprint is counted in GiB (in green dotted lines).

magnitude feature dimensions (called *outliers*) can ruin quantization precision, especially when the outliers emerge in all Transformer layers. Thus we first sort the outlier dimensions based on the number of layers they affect and focus on the top-n dimensions. Specifically, we first select the top outlier dimensions in activations (preserved at `FP16` precision in the LLM.int8() method (Dettmers et al., 2022)), and quantize those belonging to the top-n dimensions and other non-outlier dimensions to `INT8` precision. The results are then compared with the standard LLM.int8() method. This enables us to investigate the impacts of outlier feature dimensions in terms of emergent abilities.

• *Substructure quantization analysis.* Prior studies focused on component or feature-level quantization impacts. Furthermore, we observe varying importance among different substructures within components when quantizing LLMs. For instance, as detailed in Section 4.1.2, outlier dimensions primarily occur in the down projections of the FFN components. Consequently, we advocate for a more refined substructure-level quantization. Specifically, vital substructures within a component are preserved at the `FP16` precision level. We present the results as 'non-crucial weights', allowing us to identify high quantization error in crucial weight matrices using established quantization algorithms.

4.1.2. Results and Analysis

The FFN component is of substantial significance for 2-bit quantization. We conducted test experiments to evaluate the quantization sensitivity of different model components, specifically attention and FFN components. As 4-bit quantization can retain the original performance while 2-bit models suffer from severe declines, we focus on analyzing the extreme 2-bit case. Results in Figure 2 demonstrate the FFN component exhibits substantial significance for 2-bit models. Keeping FFN in `FP16` improves LLaMA-7B-2bit's performance from 0.038 to 0.225 and LLaMA-13B-2bit's performance from 0.148 to 0.286. These improvements show the importance of FFN components for retaining the performance, which needs specific consideration under extreme 2-bit quantization.

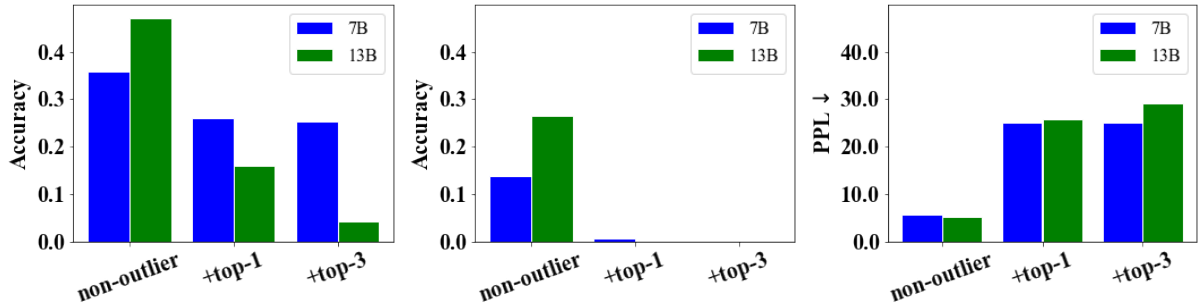
The outlier dimension which affects most of layers is primarily responsible for the performance degradation. We also explore the impact of outlier dimensions on low-bit model performance, as highlighted in Dettmers et al. (2022). Specifically, we focus on outlier dimensions that influence the majority of layers. We identify the top outlier dimensions by the number of layers they impact and assess the effects of quantizing the top-1 and top-3 outlier dimensions while preserving other outlier dimensions as `FP16`. The evaluation results for LLaMA-7B and LLaMA-13B are shown in Figure 3. Notably, these top outliers significantly impact quantization performance, especially CoT results and PPL scores. Interestingly, quantizing the top-1 outlier dimension results in more severe performance degradation for LLaMA-13B compared to the 7B model, indicating a larger model's increased vulnerability to quantizing important outliers. Additionally, outlier dimensions appear to emerge in specific substructures of components; for example, they mainly occur in the down projection of the FFN components for LLaMA-7B.

2-bit model's performance can be further enhanced with fine-grained substructure quantization. In Figure 2, we maintain `FP16` precision for crucial substructure weights, termed "non-crucial weights." We prioritize key weights in the FFN's "down" projections and select critical substructures from the attention component based on GPTQ quantization errors. For LLaMA-7B, we keep "query" and "key" projections, and for LLaMA-13B, we retain "key" and "output" projections. These consistently outperform preserving the entire FFN component (labeled "non-FFN") while reducing memory usage compared to "non-FFN" (green dotted line). Further results for GSM8K and WikiText will be shown in the Appendix. These findings highlight the importance of fine-grained quantization in extreme 2-bit quantization.

4.2. Fine-tuning Compensation Analysis

4.2.1. Experimental Setup

Recent studies have explored fine-tuning for compensating quantization performance (Yao et al., 2023b; Dettmers et al., 2023). Inspired by these works, we investigate fine-tuning's impact on quantization performance through two experiment settings: fine-tuning before and after quantization. In both settings, we mainly focus on 2-bit and 4-bit



(a) MMLU (5-shot) (b) GSM8K (CoT) (c) WikiText

Figure 3: Impacts of feature outliers on LLaMA models (7B and 13B). "non-outlier" denotes the quantization on all non-outlier dimensions, and "+top-1" and "+top-3" refer to quantization of the top-1 and top-3 outlier dimensions in addition to the non-outlier dimensions. "↓" indicates that lower indicators are better.

#To	Bits	MMLU			GSM8K			AlpacaFarm		
		Base	LoRA	FFT	Base	LoRA	FFT	Base	LoRA	FFT
7B	16-bit	35.2	37.7	41.7	13.1	25.8	38.0	/	45.67	75.00
	4-bit	34.2	35.7	40.1	13.5	22.7	35.7	47.26	39.55	73.59
	2-bit	3.8	1.2	9.0	0.0	0.0	2.6	9.23	6.65	5.68
13B	16-bit	47.0	46.0	47.7	16.4	35.2	46.0	52.68	74.68	74.69
	4-bit	46.3	46.7	46.7	16.5	30.7	44.4	52.71	71.63	75.59
	2-bit	14.8	20.7	18.4	0.0	2.3	2.0	7.4	13.25	15.37

Table 4: The results of pre-quantization fine-tuning on MMLU, GSM8k and AlpacaFarm of LLaMA families. We denote "Base" as baseline results without fine-tuning. "LoRA" and "FFT" denote parameter-efficient fine-tuning LoRA and full-parameter fine-tuning respectively.

quantization for LLaMA model weights on MMLU, GSM8K, and AlpacaFarm tasks. For model sizes, we use models 7B and 13B in the first setting and 7B, 13B, and 65B in the second setting. Next, we provide detailed fine-tuning methods.

Pre-Quantization Fine-tuning In this experiment, we consider a common setting where an optimized model needs to be quantized for practical deployment. For the ICL ability test, we follow Dettmers et al. (2023) and evaluate the impact of fine-tuning using the *Alpaca dataset* (Taori et al., 2023). For CoT ability testing, we follow Chung et al. (2022) and use the *CoT collection*, a mixture of nine datasets with CoT annotations written by human raters. For IF ability test, we follow (Taori et al., 2023) to fine-tune LLaMA models on *Alpaca dataset* since it is reported to benefit LLaMA models in instruction following. Additionally, we incorporate LoRA (Hu et al., 2022) to explore the impacts of parameter-efficient fine-tuning on LLMs.

Post-Quantization Fine-tuning We investigate the effectiveness of fine-tuning to counteract quantization-induced performance decline in LLaMA models. Our goal is to gauge fine-tuning's ability to mitigate quantization's negative impact on model performance. To facilitate parameter-efficient fine-tuning after weight quantization, we develop a specialized tool. This tool enables fine-tuning of LLaMA-65B models at 2-bit precision using just one A100 80G GPU, outperforming the 16-bit LLaMA-13B model (measured by MMLU, 5-shot). Optimizing quantized weights directly is challenging and often requires techniques like Quantization-Aware Training (QAT) (Liu et al., 2023c). We draw inspiration from the parameter-efficient fine-tuning methods (Liu et al., 2021; Gao et al., 2023; **?**), which entails training with a small subset of parameters while keeping the remainder fixed. These methods significantly reduce memory requirements (Liu et al., 2023a; Gao et al., 2022; Sun et al., 2020; Gao et al., 2020). Subsequently, we adapt the widely used LoRA (Hu et al., 2022) method by substituting its fixed pre-trained weights with quantized weights generated by GPTQ. We apply this adaptation to pre-trained weights from LLaMA models at various scales (7B, 13B, 30B, and 65B) and quantization levels (2-bit, 4-bit, and 8-bit) with GPTQ. Incorporating quantized weights into the LoRA framework significantly reduces memory consumption. Notably, fine-tuning the LLaMA-65B model only consumes 17.8 GiB, demonstrating efficient parameter utilization. The code for this work is implemented using GPTQ and LoRA and is available as an open-source

project on https://github.com/RUCAIBox/QuantizedEmpirical.

4.2.2. Results and Analysis

The benefits of pre-quantization fine-tuning encounter significant decline at 2-bit precision. We perform comparison experiments, employing full-parameter fine-tuning (FFT) and parameter-efficient fine-tuning with LoRA on the FP16 model, followed by quantization with GPTQ. Results are summarized in Table 4. Compared to the base model, FFT shows significant improvements in MMLU, GSM8K, and AlpacaFarm. With 4-bit quantization, these gains are maintained with minimal performance degradation on MMLU and AlpacaFarm. However, with extreme 2-bit quantization, the benefits of FFT decrease notably, especially for GSM8K (2.6 for LLaMA-7B and 2.0 for LLaMA-13B). Importantly, the CoT capability of LLMs is severely compromised in this scenario (0.0 for both LLaMA-7B and LLaMA-13B). This suggests that pre-quantization fine-tuning struggles to effectively compensate for performance degradation in low-bit models on complex tasks.

Parameter-efficient fine-tuning still lags behind full-parameter fine-tuning, especially on ICL and CoT tasks. Parameter-efficient fine-tuning, known for reducing fine-tuning parameters while maintaining decent performance, has gained popularity (Liu et al., 2021, 2023a). We present LoRA fine-tuning results in the "LoRA" column of Table 4. LoRA demonstrates significant improvements over base models in most cases, with performance benefits persisting for 4-bit quantization but not always for 2-bit quantization. However, LoRA still lags behind FFT (e.g., 25.8 vs. 38.0 on GSM8K). Notably, LoRA fine-tuning experiences a substantial performance drop on GSM8K with 4-bit quantization, suggesting that full-parameter fine-tuned models may be more suitable for complex inference tasks during quantization.

Post-quantization fine-tuning yields substantial performance improvement meanwhile can be conducted in a lightweight way. To fine-tune a quantized model, we make two major modifications based on the original LoRA method. First, we employed GPTQ to quantize the FP16 model to 2/4 bits. Subsequently, we replace the pre-trained weights with the quantized weights, keeping the remaining steps unchanged. The results are shown in the column "LoRA$_q$" of Table 5. This approach significantly reduces memory requirements for fine-tuning, enabling fine-tuning of a 65B model on a single NVIDIA A100. Compared with the base model, LoRA$_q$ has a notable impact, especially at 2 bits (*e.g.,* 44.4 *vs.* 22.6 for the five-shot setting). Notably, under fewer total bits, the 2-bit effect of the 65B model surpasses the non-fine-tuned 13B model with FP16 precision on zero-shot setting (*i.e.,* 42.0 *vs.* 41.4). These findings demonstrate that even after 2-bit quantization, large models can be effectively enhanced through fine-tuning.

#To	Bits	#Tr (M)	Mem. (GiB)	0-shot Base	0-shot LoRA$_q$	5-shot Base	5-shot LoRA$_q$
7B	4-bit	20.0	3.8	31.0	31.4	34.2	36.8
	2-bit	20.0	2.2	2.3	3.7	3.8	7.4
13B	4-bit	31.3	7.0	39.0	44.1	45.9	45.5
	2-bit	31.3	3.9	4.9	28.3	14.8	28.9
65B	4-bit	99.9	32.7	57.1	57.0	63.0	60.5
	2-bit	99.9	17.8	9.0	42.0	22.6	44.4

Table 5: Results for LLaMA families on MMLU."Mem. (GiB)" represents memory usage, and "#Tr (M)" indicates trainable parameters. "LoRA$_q$" stands for LoRA fine-tuning with quantized weights, while "Base" refers to baseline results without fine-tuning.

5. Related Work

In this section, we discuss the related work in two major aspects.

Emergent Abilities Recent research has revealed that some superior abilities in Large Language Models (LLMs) may not be present in small models, sparking great interest in their capabilities (Wei et al., 2022). These abilities, such as ICL for few-shot learning without parameter update (Brown et al., 2020), CoT for complex reasoning with coherent chains of thought (Fu et al., 2023; OpenAI, 2023), and IF for precise instruction execution (Taori et al., 2023; Chung et al., 2022), have been explored in various tasks. However, there's a lack of comprehensive research evaluating these abilities in quantized LLMs. Our work aims to fill this gap by providing a detailed analysis of emergent abilities in quantized LLMs.

Post-Training Quantization Post-training quantization (PTQ) is a widely used technique to reduce memory consumption and computational costs in neural networks. Various studies have investigated PTQ's application to LLMs, involving quantization of model weights (Frantar et al., 2022; Dettmers and Zettlemoyer, 2022) and feature activations (Dettmers et al., 2022; Yao et al., 2023b). PTQ helps reduce training requirements with minimal performance impact. However, comprehensive empirical evaluations of quantized LLMs' emergent

abilities are lacking. Notably, relevant studies include Yao et al. (2023b), which analyze PTQ strategies on LLMs, and Yao et al. (2023b), who explore zero-shot performance scaling laws for k-bit quantization. While these studies focus on overall abilities, our perspective uniquely emphasizes the study of emergent abilities in quantized LLMs.

6. Conclusion

In this work, we empirically explored how post-training quantization affects the emergent abilities of LLMs. We found that large models (fine-tuned or not) perform well with 4-bit weight quantization but degrade significantly at 2-bit precision. Moreover, we delve into the fine-grained components and substructures for studying the quantiztion sensitivity, revealing that preserving crucial components, feature dimensions, and substructures enhances low-bit quantization. Additionally, fine-tuning mitigates performance degradation in quantized models, showing the great potential to enhance the capacity of quantized LLMs.

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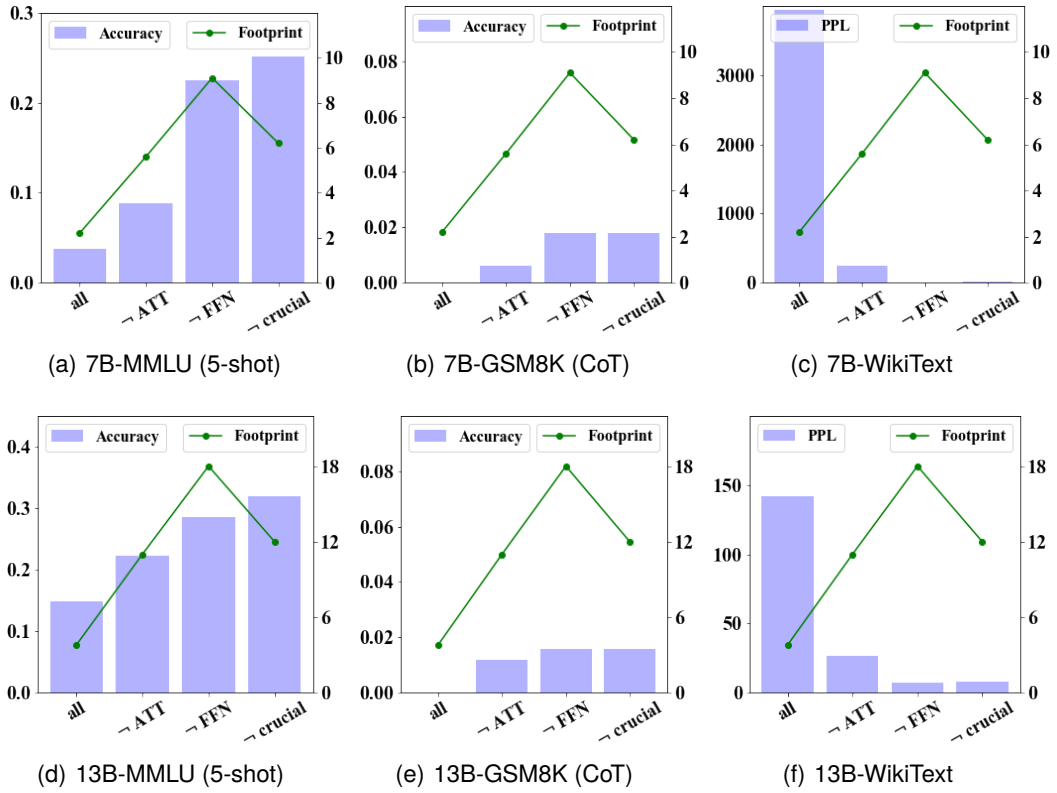
A. Appendix

A.1. Impacts of Model Components

We provide more details about the impacts of model components or substructures on MMLU (5-shot), GSM8K and WikiText in Figure 4.

A.2. Case Study

Here, we present case studies for the performance of quantized LLaMA models on MMLU, GSM8K and AlpacaFarm datasets. The results involve model scale of 7B (Table 6), 13B (Table 7) and 30B (Table 8)



(a) 7B-MMLU (5-shot) (b) 7B-GSM8K (CoT) (c) 7B-WikiText

(d) 13B-MMLU (5-shot) (e) 13B-GSM8K (CoT) (f) 13B-WikiText

Figure 4: Impacts of different model components or substructures on MMLU (5-shot), GSM8K and WikiText. The memory footprint is counted in GiB (in green dotted lines).

	Tasks	Bits	Cases	Score
7B	MMLU		**Question:**Suppose now that a researcher wishes to use information criteria to determine the optimal lag length for a VAR. 500 observations are available for the bi-variate VAR, and the values of the determinant of the variance-covariance matrix of residuals are 0.0336, 0.0169, 0.0084, and 0.0062 for 1, 2, 3, and 4 lags respectively. What is the optimal model order according to Akaike's information criterion?	
		16	**Answer:**D	35.2
		4	**Answer:**D	34.2
		2	**Answer:**4 1 and, a	3.8
	GSM8K		**Question:**Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. How many letters are in Indras and her sister's names?	
		16	**Answer:**Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. Indras' name has 6 letters. So Indras' name has 6 - 10 = -4 letters. The answer is -4.	13.11
		4	**Answer:**Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. Indras has 6 letters. Her sister's name has 10 letters. The answer is 10.	12.21
		2	**Answer:**B. 82. M.H. or 4 weeks.. ungers are the best Cash.. . 4..... 44. 30.. Cash.B.Age.B.G.o.just.J.1Age. 6 days are.. which 4b. J.o4.b.gone and the best of the best.	0
	AlpacaFarm		**Question:**How can I increase my productivity while working from home?	
		16	**Answer:** Here are some tips to help you increase your productivity while working from home: 1. Set work hours and stick to them. 2. Have a designated work area. 3. Avoid distractions. 4. Set a schedule and stick to it...	1121
		4	**Answer:**It's important to know what you want to get done and to set priorities. Knowing what to do and where to start is key to staying productive. Here are some tips to help you stay productive: 1. Work in a well-lit area that's free from distractions. 2. Set a reasonable time limit for yourself. 3. Set a specific goal for each day...	1058
		2	**Answer:**The best The Behavre when L9Life of. Their, Be in the World Op LoDur and Liflo the attitudeFHHow the of them onlineDo ld vs Life in the future play that„ but the process of, and is a habit of, the pro will be the toys, but-fold to-magnet-H of who and ISP a book.	608

Table 6: Case study for the influence of post-training quantization on LLaMA-7B.

	Tasks	Bits	Cases	Score
13B	MMLU		**Question:**Suppose now that a researcher wishes to use information criteria to determine the optimal lag length for a VAR. 500 observations are available for the bi-variate VAR, and the values of the determinant of the variance-covariance matrix of residuals are 0.0336, 0.0169, 0.0084, and 0.0062 for 1, 2, 3, and 4 lags respectively. What is the optimal model order according to Akaike's information criterion?	
		16	**Answer:**A	47.0
		4	**Answer:**A	45.9
		2	**Answer:**C. 1, 2,	14.8
	GSM8K		**Question:**Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. How many letters are in Indras and her sister's names?	
		16	**Answer:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. The answer is 10.	16.37
		4	**Answer:**Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 6 + 4 = 10 letters. The answer is 10.	15.62
		2	**Answer:**The answer is 15. Question: 15 -. The answer is 15. The answer is 15. The answer is 15. The answer is 15.	0.02
	AlpacaFarm		**Question:**How can I increase my productivity while working from home?	
		16	**Answer:** Here are some good tips to increase your productivity while working from home: 1. Get dressed for work: Taking the time to get dressed and shower can set a positive tone for your workday. 2. Have a dedicated and organized workspace: Having a space that is only dedicated to work can help you focus on your tasks...	1084
		4	**Answer:**Here are four ways you can increase your productivity while working from home: 1. Set a productivity schedule: Set a schedule for your day that includes work and breaks, and stick to it. 2. Get out of the house: Go to a coffee shop or a library to get out of the house and into a different environment...	1119
		2	**Answer:**The energy of the energy of the Renewable energy of the energy of the Renewable energy of the Renewable energy of the Renewable energy of the Renewable energy of the Renewable energy of the Renewable energy...	635

Table 7: Case study for the influence of post-training quantization on LLaMA-13B.

	Tasks	Bits	Cases	Score
30B	MMLU		**Question:** Suppose now that a researcher wishes to use information criteria to determine the optimal lag length for a VAR. 500 observations are available for the bi-variate VAR, and the values of the determinant of the variance-covariance matrix of residuals are 0.0336, 0.0169, 0.0084, and 0.0062 for 1, 2, 3, and 4 lags respectively. What is the optimal model order according to Akaike's information criterion?	
		16	**Answer:** A	58.4
		4	**Answer:** A	57.3
		2	**Answer:** C	26.1
	GSM8K		**Question:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. How many letters are in Indras and her sister's names?	
		16	**Answer:** Indras has 6 letters. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 4 more letters than 3. So her sister's name has 4 + 3 = 7 letters. Indras has 6 letters and her sister has 7 letters. So the answer is 6 + 7 = 13.	34.65
		4	**Answer:** Indras has 6 letters in her name. Her sister's name has 4 more letters than half of the letters in Indras' name. So her sister's name has 4 more letters than 3. 3 + 4 = 7. So her sister's name has 7 letters. Indras has 6 letters and her sister has 7 letters. 6 + 7 = 13. The answer is 13.	35.41
		2	**Answer:** Indras' name has 6 letters. Her sister's name has 4 more letters than half of the letters in Indras' name. So she has 6 - 4 = 4 letters. 4 letters. The answer is 4.	0.15
	AlpacaFarm		**Question:** How can I increase my productivity while working from home?	
		16	**Answer:** There are several ways to increase your productivity at home. Here are some of the most effective: 1. Make a schedule: Scheduling your day and prioritizing your tasks can help you stay organized and boost your productivity. 2. Take breaks: Taking regular breaks can help keep you fresh and focused...	1142
		4	**Answer:** Here are some ways you can increase your productivity while working from home: 1. Create a separate workspace: One of the biggest challenges of working from home is the tendency to mix work life with home life. You can overcome this by creating a separate workspace in your home that you can set aside just for work...	1120
		2	**Answer:** The answer is to have a work-life-home type lifestyle.	630

Table 8: Case study for the influence of post-training quantization on LLaMA-30B.