

Can Large Language Models Understand Context?

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Abstract

Understanding context is key to understanding human language, an ability which Large Language Models (LLMs) have been increasingly seen to demonstrate to an impressive extent. However, though the evaluation of LLMs encompasses various domains within the realm of Natural Language Processing, limited attention has been paid to probing their linguistic capability of understanding contextual features. This paper introduces a context understanding benchmark by adapting existing datasets to suit the evaluation of generative models. This benchmark comprises of four distinct tasks and nine datasets, all featuring prompts designed to assess the models' ability to understand context. First, we evaluate the performance of LLMs under the in-context learning pretraining scenario. Experimental results indicate that pre-trained dense models struggle with understanding more nuanced contextual features when compared to state-of-the-art fine-tuned models. Second, as LLM compression holds growing significance in both research and real-world applications, we assess the context understanding of quantized models under in-context-learning settings. We find that 3-bit post-training quantization leads to varying degrees of performance reduction on our benchmark. We conduct an extensive analysis of these scenarios to substantiate our experimental results.¹

1 Introduction

Discourse understanding, as one of the fundamental problems in NLP, focuses on modeling linguistic features and structures that go beyond individual sentences (Joty et al., 2019). Understanding discourse requires resolving the relations between words/phrases (coreference resolution) and discourse units (discourse parsing and discourse relation classification) in the previous context, iden-

tifying carry-over information for the following context (dialogue state tracking), and recognizing discourse-specific phenomena (ellipsis).

LLMs have garnered substantial attention from both academia and the industry due to their remarkable capability in comprehending language and world knowledge. Their unparalleled performance across a diverse range of benchmarks and datasets has firmly established their significance in a relatively short period of time. As LLMs continue to push the boundaries of scale and capability, the evaluation of their multifaceted abilities becomes an equally vital endeavor. Consequently, the development of robust evaluation methodologies to assess specific aspects of LLMs becomes imperative. In addition, these methodologies should focus on helping achieve a comprehensive understanding of their advancement while clearly delineating their limitations. However, recently published LLMs, such as OPT (Zhang et al., 2022), LLaMA (Touvron et al., 2023) and GPT-4 (OpenAI, 2023), are only evaluated on limited benchmarks, and have a significant drawback: they neglect the inclusion of discourse-related datasets for evaluation, thereby limiting the comprehensive assessment of their language understanding capabilities.

To provide a comprehensive evaluation, plenty of benchmarks and datasets address various facets of language understanding, including benchmarks that delve into common sense knowledge (Hendrycks et al., 2021a; Kwiatkowski et al., 2019), as well as linguistic capabilities like sentiment analysis, natural language inference, summarization, text classification, and more (Bang et al., 2023b; Liang et al., 2022). These general benchmarks and specific dataset evaluations exhibit certain limitations. Despite the requirement for contextual information in these benchmarks to effectively tackle tasks (for example, sentiment analysis requires an understanding of polarities within the given text), none of these benchmarks cater to tasks that de-

*Work performed during an internship at Apple.

¹The code is publicly available at <https://github.com/apple/ml-lm-contextualization-eval>.

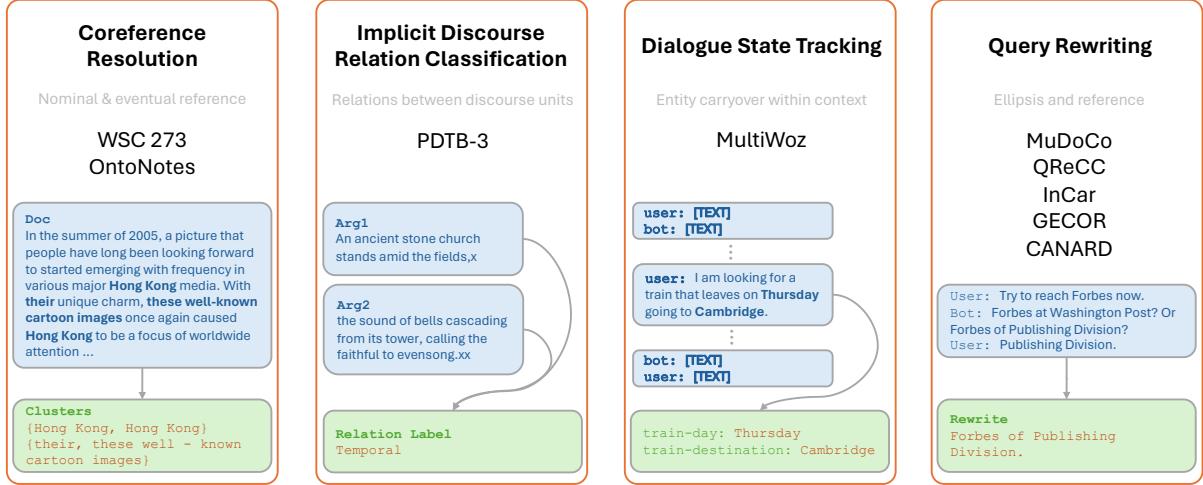


Figure 1: Tasks and datasets in the context understanding benchmark.

mand a nuanced comprehension of linguistic features within a provided context.

On the other hand, recent LLMs, by virtue of possessing billions of parameters, have led to an exponential surge in computational and storage costs (Brown et al., 2020b), which hinders the deployment of large models to personal devices and restricts the on-device performance of language understanding tasks. To address this challenge, model compression methods, which can reduce memory and disk requirements of both model training and inference, have gained attention. Existing compression techniques, such as 3-bit quantization (Frantar et al., 2022), have demonstrated the potential to reduce model sizes with only marginal performance trade-offs. However, the evaluation of quantization methods suffers from two deficiencies. Firstly, quantization methods are primarily evaluated on limited benchmarks and datasets, such as Lambda (Paperno et al., 2016), ARC (Boratko et al., 2018), PIQA (Tata and Patel, 2003), BoolQ (Clark et al., 2019), and StoryCloze (Mostafazadeh et al., 2017). It is not yet clear whether large, compressed models out- or under-perform their smaller counterparts when understanding context. Secondly, previous work has not delved into a linguistic analysis to identify where the model efficacy wanes.

Given the above shortcomings, this paper evaluates LLMs on a context understanding benchmark constructed from varied discourse understanding datasets. We conduct an extensive analysis of LLM performance on this benchmark, including models of varying sizes and those subjected to compression techniques, aiming to provide a more comprehensive understanding of context understanding

capability of the LLMs. The contributions of this paper can be summarized as follows:

- Our work introduces a contextual understanding benchmark, including four tasks, for the evaluation of LLMs. We also present prompts designed for in-context learning on each task.
- We evaluate LLMs of varying sizes from different model families and provide an analysis on these models’ capability for context understanding.
- We evaluate post-training compressed models in ICL settings and conduct an analysis of the reduction in context understanding capability compared to dense models.

2 Related Work

2.1 In-context Learning Evaluation

The paradigm of ICL (Brown et al., 2020a) is rapidly gaining importance. Studies have demonstrated that the generalization of LLMs to various downstream NLP tasks, such as MMLU (Hendrycks et al., 2021b), is significantly enhanced when provided with a small number of examples as prompts (Brown et al., 2020a; Chowdhery et al., 2022; Hoffmann et al., 2022; Rae et al., 2022; Anil et al., 2023; Touvron et al., 2023; OpenAI, 2022, 2023). Recent research has extensively evaluated the performance of LLMs across a spectrum of language-related tasks, spanning from text generation to understanding input sequences. This assessment contains a wide array of benchmarks, including SUPER-GLUE (Wang et al., 2019; Laskar et al.,

2023), and tasks such as question answering, information retrieval, sentiment analysis (Bang et al., 2023b; Liang et al., 2022), dialogue (Heck et al., 2023), and text classification (Yang and Menczer, 2023).

2.2 Model Compression for LLMs

Model compression techniques can be broadly categorized into three main approaches: compression during training, compression associated with fine-tuning, and post-training methods. In terms of quantization during training, this technique enables LLMs to adapt to low-precision representations during the training process (Liu et al., 2023). Model compression with fine-tuning involves quantization awareness into the fine-tuning stage (Kim et al., 2023; Dettmers et al., 2023). Post-training techniques, on the other hand, are applied after the completion of an LLMs training phase and typically involve the use of calibration data. This category comprises two primary approaches: pruning, which removes redundant or non-salient weights to induce sparsity (Frantar and Alistarh, 2023), and quantization, which employs low-precision numeric representations of weights and activations (Nagel et al., 2020; Frantar et al., 2022; Yuan et al., 2023). Prior research shows that quantization outperforms pruning in several settings (Kuzmin et al., 2023), thus in this work, we focus on model quantization and its impact on the selected context-aware tasks.

3 Task Selection & Design

Our contextual understanding benchmark includes four tasks with nine datasets, as presented in Figure 1. In the following sections, we provide detailed explanations of each task and the corresponding datasets, along with the designed prompts for ICL evaluations.

3.1 Coreference Resolution

The coreference resolution (CR) task contributes to achieving a coherent understanding of the overall meaning conveyed within the text. Thus, it plays a critical role in diving into language models’ capability to grasp coreference relations as well as contextual nuances within documents. We select two coreference datasets: WSC273 (Levesque et al., 2012) and OntoNotes 5.0 (Pradhan et al., 2013).

WSC273, which contains the first 273 examples from the Winograd Schema Challenge, is a dataset that requires the system to read a sentence with

Instruction: Please carefully read the following passages. For each passage and the options, you must identify which option the mention marked in ***bold*** refers to. If the marked mention does not have any antecedent, please select “no antecedent”.

Context: ... To express ***its*** determination ... the Chinese securities regulatory department ... this stock reform ...

Choices:

- A. no antecedent
- B. the Chinese securities regulatory department
- C. this stock reform

...

Question: What does ***its*** refer to?

Answer: B

Table 1: An OntoNotes example of prompt and *answer*.

an ambiguous pronoun and select the referent of that pronoun from two choices. OntoNotes is a human-annotated corpus of documents annotated with multiple layers of linguistic information including syntax, propositions, named entities, word sense, and in-document coreference. As it is one of the most frequently used datasets for training coreference models, prior research has achieved significant advancements under the supervised fine-tuning paradigm (Lee et al., 2017; Joshi et al., 2020; Bohnet et al., 2023). However, these model designs cannot be extended to generative models under ICL settings. Recently, Le and Ritter (2023) have leveraged document templates for LLMs; however, their evaluation is confined to prominent models such as InstructGPT (Ouyang et al., 2022), neglecting the fact that smaller models lack the generative capacity required to accomplish such tasks. Due to these limitations, we propose a novel multiple-choice task design. In this design, we provide the mentions and evaluate the model on resolution. Each option represents a potentially markable span.² Table 1 presents an example of the input to the model³. The entire prompt consists of five parts: (1) an instruction that provides guidance to the model for the task, (2) a document containing plain text with a selected mention span highlighted using a bold symbol, (3) a list of choices, which includes all the gold mentions present in the document, (4) a question that directs the model’s attention, and (5) a guiding word *answer* that prompts for the output. We experiment with multiple instructions and prompts and provide the one with the best performance. Linking scores are computed for each ques-

²Considering the inferior performance of small models on the mention detection task, we utilize gold markable spans coreference linking.

³Detailed examples for each task design can be found in Appendix A.

[Ontology]:

{“slots”: {“restaurant-pricerange”: “price budget for the restaurant”, ... },
“categorical”: {“restaurant-pricerange”: [‘cheap’, ‘expensive’, ‘moderate’], ... } }

[Instruction]: Now consider the following dialogue between two parties called the “system” and “user”. Can you tell me which of the “slot” was updated by the “user” in its latest response to the “system”? Present the updates in JSON format. If no “slots” were updates, return an empty JSON list. If you encounter “slot” that was requested by the “user” then fill them with “?”. If a user does not seem to care about a discussed “slot” fill it with “dontcare”.

[Previous Dialogue State]**[Conversation]:**

“system”: “”

“user”: “I’m looking for a moderately priced place to eat that’s in the centre of town.”

[Output]: {“restaurant-pricerange”: “moderate”,
“restaurant-area”: “centre”}

Table 2: A DST example of prompt and *answer*.

tion and the results are subsequently aggregated for evaluation. We utilize the official evaluation metrics from the CoNLL-2012 shared task (Pradhan et al., 2012), which employs the CoNLL F1 score, derived from the averaging of three coreference metrics: MUC, B³, and CEAF_{φ4}.

3.2 Dialogue State Tracking

Dialogue state tracking (DST) is an important task in the area of task-oriented dialogue (TOD) modeling (Young et al., 2013), where the dialogue agent tracks the key information provided by the user as the conversation progresses. Table 2 provides an example from MultiWOZ (Budzianowski et al., 2018) where the user expresses the constraints when looking for a restaurant. The output of DST is typically maintained in slot-value pair format.

Previous research has explored ICL capabilities on MultiWOZ and demonstrated promising results compared to fine-tuning models (Hu et al., 2022; Heck et al., 2023). However, these studies either involve partial training or are untested with smaller and quantized models. Here we adopt a straightforward and simplified ICL approach proposed by Heck et al. (2023), and test it on MultiWOZ v2.2 (Zang et al., 2020). The prompt to the model consists of domain knowledge from ontology, an instruction, previous dialogue state (the belief state accumulated until the previous user turn) and the conversation proceeding to the current turn. The ontology could be lengthy if considering all domains in the dataset. Thus, given the input length constraint of LLMs, only the knowledge relevant to the conversation is provided. Following literature,

[Instruction]: Given two arguments and a list of connective words, please select the most likely connective between two arguments.

[Relation Description]**[Input]:**

Arg 1: Amcore, also a bank holding company, has assets of \$1.06 billion.

Arg 2: Central’s assets are \$240 million.

[Question]: What is the connective that best describes the relation between two arguments?

[Choices]:

A. Temporal B. Contingency C. Comparison D. Expansion

[Answer]: C

Table 3: A PDTB example of prompt and *answer*.

we report joint goal accuracy (JGA) (Mrkšić et al., 2017) for evaluating the performance of DST.

3.3 Implicit Discourse Relation Classification

Discourse demonstrates its importance beyond individual sentences, which emphasizes the ways in which different segments of a text interconnect and structure themselves to convey a coherent and meaningful message. The PDTB-3 corpus, as introduced by Webber et al. (2019), annotates implicit discourse relations across elementary discourse units (EDUs)⁴. These relations imply connections between EDUs and may be made explicit by inserting a connective. Within the context of the understanding benchmark, we opt for the implicit discourse relation classification task for two primary reasons. Firstly, the order of the two EDUs is provided, enabling the model to directly utilize this information. Secondly, the connective triggering the relation is implicit, increasing the task’s complexity. In this task, two EDUs are fed as input, and the objective is to correctly identify the relation between them. Due to the nuanced differences between each relation and the demand for annotators with rich linguistic knowledge and extensive annotation training, the classification task poses challenges to fine-tuned classification models.

The PDTB3 corpus classifies discourse relations into four categories - Temporal, Contingency, Comparison, and Expansion. We convert this task into a multiple-choice question and experiment with *classes* as options. In the *classes* scenario, the task offers four options, each representing a distinct discourse relation class. Table 3 exhibits the components of the prompt. It includes an instruction at the beginning, followed by a concise description of each relation, a context with two arguments, a

⁴EDU refers to the smallest segment of a text that conveys a complete and coherent meaning within larger discourse.

Instruction:	Rewrite the last query following interaction into a well-formed, context independent query. Resolve any disfluencies or grammatical errors in the query.
Input:	
User:	Try to reach Forbes now .
Bot:	Forbes at Washington Post ? Or Forbes of Publishing Division ?
User:	Publishing Division .
Rewrite:	<i>Forbes of Publishing Division</i>

Table 4: A query rewriting example of prompt and *answer*.

question along with answer choices, and a trigger word. We evaluate each model’s performance on this dataset using accuracy as the metric.

3.4 Query Rewriting

While document-based CR (OntoNotes, Section 3.1) covers various types of coreference relations across multiple genres, it does not allow the ability to evaluate certain aspects which are important to understand context. Firstly, the CR task typically focuses on document-based coreference chains, neglecting mention resolution in dialogues. Secondly, ellipsis, which is the omission of one or more words from a clause, is a crucial linguistic phenomenon in speech and conversation. It is essential for language models to grasp and accurately identify ellipses within context. Incorporating these features into the benchmark is thus pivotal when evaluating context understanding.

Query Rewriting (QR) is a task of rewriting the last utterance of a user in a conversation into a context-free, independent utterance that can be interpreted without dialog context. It requires the model to identify the entity or events references from context and further generate a complete utterance with resolved coreference or ellipsis.

We incorporate five QR datasets in the proposed benchmark: MuDoCo with QR annotations (Martin et al., 2020; Tseng et al., 2021), QReCC (Anantha et al., 2021), InCar (Regan et al., 2019), GECOR (Quan et al., 2019), and CANARD (Elgohary et al., 2019). These datasets span multiple genres and domains in dialogues. We experiment with various prompts used for fine-tuning models and present the results with the best selections. Table 4 presents a concise prompt comprising an instruction along with context for each dialogue. To assess the quality of generated queries, we follow the metrics from previous research, particularly BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004).

4 Experiments

4.1 Implementation Details

Evaluation was conducted on a computational infrastructure comprising $8 \times$ A100 GPUs. We experiment with three model families. For smaller models, we consider OPT (Zhang et al., 2022), ranging from 125M to 2.7B. Although OPT also offers larger models, we opt for LLaMA (Touvron et al., 2023) as the mid-sized LMs, spanning from 7B to 65B parameters, due to showcased superior performance by prior works. For large-scale LMs, we leverage GPT-3.5-turbo⁵. For each model, on every dataset, we assess five different settings: zero-shot, one-shot, 5-shot, 8-shot, and 10-shot. We randomly select the examples from the training set for the few-shot prompting.⁶

4.2 Dense Model

Results of the three model families are reported in Table 5, along with results of fine-tuned (FT) models to help better interpret how well the pre-trained models behave with ICL. Figure 2 also visualizes the gap between various commercial/non-commercial language models and fine-tuning models that achieve the best performance on these tasks. For each, we present the N-shot setting that yields the highest score (see Appendix B for details). Overall, performance improves as the model size increases and pre-trained models with ICL struggle to catch up with FT models on most tasks.

Coreference Resolution Larger models exhibit promising performance on the WSC273 task, indicating that LLMs can effectively handle "simple" coreference relations within limited contexts and mentions. However, when it comes to document-based CR with complex clusters, their performance substantially drops⁷. Even on providing ground-truth mentions, the highest-performing GPT is only on par with rule-based coreference systems (Manning et al., 2014) and is far from the end-to-end fine-tuned SpanBERT (Joshi et al., 2020). The gap

⁵<https://platform.openai.com/docs/models/gpt-3.5>

⁶WSC273 itself is a test set and thus has no fine-tuning results. We only report the zero-shot results.

⁷Note that the OntoNotes dataset is substantially larger than the others. We observe that inference on the entire test set becomes extremely time-consuming, particularly with the larger models; further, the cost of running inference on GPT-3.5 starts becoming non-negligible. Consequently, we propose limiting the OntoNotes test set to a 10% sub-sample, which is the setting we consistently adopt.

Task	Dataset	Metrics	OPT				LLaMA			GPT	FT
			125M	350M	1.3B	2.7B	7B	13B	30B	3.5-turbo	
CR	WSC273	Acc	58.24	66.67	76.19	77.66	86.81	89.38	89.01	88.64	N/A
		MUC	12.66	7.58	13.21	8.29	10.31	31.80	33.56	56.32	77.26
	OntoNotes	B ³	53.80	52.26	53.54	52.41	52.20	58.43	58.66	68.20	73.43
		CEAF _{φ4}	31.09	29.49	31.40	30.10	32.63	38.00	39.27	50.72	74.46
		Avg. F1	32.52	29.78	32.72	30.27	31.71	42.74	43.83	58.41	76.03
DST	MultiWOZ	JGA	11.11	27.96	26.61	28.08	32.30	28.12	42.24	57.40	63.79
Disc.	PDTB-3	Acc	10.04	10.04	10.04	16.15	17.16	26.01	39.77	43.83	76.23
QR	MuDoCo	BLEU	0.46	0.36	7.02	49.20	41.12	61.15	66.51	57.14	80.31
		ROUGE	1.52	12.18	10.98	65.61	56.07	74.78	77.88	79.37	92.01
	QReCC	BLEU	4.53	31.27	26.35	40.09	28.19	38.64	58.68	55.24	58.67
		ROUGE	13.91	58.18	53.10	68.32	48.27	56.40	78.74	79.98	81.75
	InCar	BLEU	0.00	7.66	12.71	27.42	28.20	42.13	48.58	63.66	88.45
		ROUGE	3.41	28.76	30.45	49.63	49.96	56.73	64.18	83.51	95.24
	GECOR	BLEU	0.20	26.40	26.32	49.99	53.27	66.30	73.80	63.34	82.56
		ROUGE	4.06	42.13	42.57	65.89	69.23	80.99	86.03	79.00	92.63
	CANARD	BLEU	2.61	19.39	24.24	34.66	21.34	29.32	47.24	47.12	57.46
		ROUGE	9.82	45.63	49.36	62.73	38.17	46.61	69.73	74.61	81.06

Table 5: Few-shot results of two open-sourced models and GPT-3.5 on the context understanding benchmark. The results with the best number of few-shot examples are reported for each task. Fine-tuning (FT) results serves as a reference when evaluating LLMs’ capability under ICL setup.

between ICL and FT results highlights that under the ICL setting, LLMs struggle to build coreference chains without adequate domain-specific examples. Specifically, models except GPT perform significantly worse on the MUC metric. Error analysis reveals that these models are inclined to create more clusters, including singleton clusters. This implies that pre-trained LLMs encounter difficulties in understanding long-range contextual information.

DST A similar trend is observed as CR where OPT and LLaMA models fall behind GPT-3.5 significantly. This suggests that these models fail to extract key information as the conversation proceeds, even with the provision of 5 to 10 demonstrations and the distilled relevant domain ontology in prompt. Our error analysis indicates that most of the errors happen due to the misdetection of slots or the wrong predicted value in a slot-value pair. Only GPT-3.5 reaches the level of FT results which is a fine-tuned T5 base model (Bang et al., 2023a).

Implicit Discourse Relation Classification We observe an increase in scores when the model size exceeds 7B. However, even the best-performing LLM, GPT, performs worse than the SOTA fine-tuned model (Liu and Strube, 2023) with the drop of 32% accuracy. We carefully examine the predictions for each model and found that all models tend to predict the same relation class for every example, albeit with their individual preferences

for the selected relation. In addition, because of an imbalanced distribution of classes, these models potentially perform worse than random chance (25%). This suggests that the models struggle to distinguish the nuances between different relation classes and fail to correctly identify relations across EDUs within context.

Query Rewriting The gap between small and large models is significantly huge, compared to the other tasks. For instance, OPT-125M cannot even complete the rewriting task. Analysis on predictions of small models indicates that the model is not capable of following the instructions or learning patterns from the few-shot examples. We identify a few major error types: (1) generating the next sentence, instead of rewriting; (2) rewriting the wrong user turn from the conversation; (3) copying the last user utterance without any rewriting. These errors get reduced as the model size increases. However, similar to the previous three tasks, the best ICL results achieved by GPT is far from the fine-tuned models.⁸ It is worth noting that OPT-2.7B performs on par or notably better than LLaMA-7B, which is somewhat not aligned with the findings in Beeching et al. (2023) where LLaMA-7B even outperforms OPT-66B in many tasks, including ARC (Clark

⁸In literature, the best FT results come from different models across five QR datasets, where some are not even LLM based. To ensure fair comparison, we fine-tuned a T5 large model on each QR dataset.

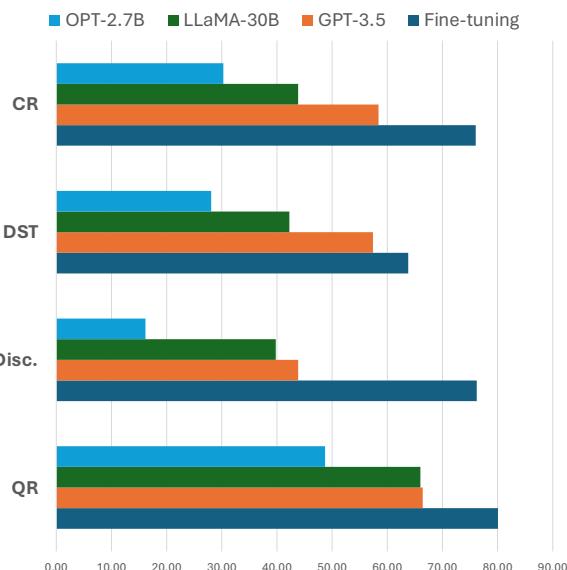


Figure 2: Comparison between commercial/non-commercial models and fine-tuning models for each task in the context understanding benchmark.

et al., 2018), HellaSwag (Zellers et al., 2019), and MMLU (Hendrycks et al., 2021b).

All in all, this section presents a holistic comparison of LLMs’ behaviors on the target context understanding tasks. On the tasks with structured outputs such as CR or DST, even small models show a certain level of context understanding and seem to follow the task instruction. Classification tasks such as discourse relation selection are deemed the easiest among all tasks; however, the small models are even worse than a random guess (25%). As for the generative task, the ability to complete query rewriting can be only observed in the case of larger models, as the model has the freedom to generate arbitrary content that does not follow the prompt. We notice that OPT-2.7B outperforms LLaMA-7B in multiple QR datasets, including MuDoCo, QReCC, and CANARD. We carefully compare the outputs between the two models. As an example, QReCC, a QA-based conversational dataset, consists of several QA pairs as context and a last query to be rewritten. We observe that LLaMA-7B tends to rewrite the question in context instead of rewriting the last target query, which is not frequent in OPT-2.7B. It is also noted that except for DST, FT models demonstrate marked superiority over pre-trained models, highlighting the potential for improving LLMs’ competence on these context understanding tasks.

Dataset	Metrics	7B-D	30B-Q	30B-D
OntoNotes	Acc	86.81	87.18	89.01
	MUC	10.31	25.37	33.56
	B ³	52.20	56.80	58.66
	CEAF _{φ4}	32.63	36.93	39.27
	Avg. F1	31.71	39.70	43.83
MultiWOZ	JGA	32.30	41.99	42.24
PDTB-3	Acc	17.16	31.29	39.77
MuDoCo	BLEU	41.12	59.22	66.51
	ROUGE	56.07	71.38	77.88
QReCC	BLEU	28.19	53.72	58.68
	ROUGE	48.27	74.13	78.74
InCar	BLEU	28.20	39.69	48.58
	ROUGE	49.96	56.32	64.18
GECOR	BLEU	53.27	70.41	83.36
	ROUGE	69.23	73.80	86.03
CANARD	BLEU	21.34	45.07	47.24
	ROUGE	38.17	67.15	69.73

Table 6: Comparison between dense and quantized models. Dense LLaMA-7B and 3-bit quantized LLaMA-30B share similar memory and disk requirements. **D** represents dense model and **Q** denotes quantized model.

4.3 Model Compression Technique

As we focus on evaluating context understanding of LLMs in an ICL setup, we evaluate models quantized using GPTQ (Frantar et al., 2022), which is an efficient one-shot weight quantization algorithm based on approximate second-order information that compresses the model post-training. It enables a reduction in memory and disk requirements by up to 80%, compared to the pre-quantized model.

4.4 Quantized Model Results

GPTQ (Frantar et al., 2022) has been shown to effectively reduce the model size to 3 bits without incurring substantial performance losses across a range of NLP tasks, such as MMLU, ARC, StoryCloze. However, whether this performance preservation can be extended to contextual understanding was unclear.

Table 6 presents the comparison between the dense and 3-bit quantized LLaMA models. In contrast to previous studies on 3-bit quantization, we observed that quantization leads to fluctuated drops in performance across the four tasks. Specifically, in WSC273, MultiWOZ, and CANARD, post-training quantization incurs only a marginal performance drop (~1.7 points). However, in the remaining datasets, quantization results in significant performance drops.

The results further show that the quantized LLaMA-30B model consistently outperforms the

dense LLaMA-7B model across all tasks despite being comparable in disk and memory requirements. For CR, the 30B quantized model achieves significantly higher scores on the OntoNotes dataset across all metrics. The MUC metric shows the most substantial improvement, indicating that the quantized 30B model partially overcomes the tendency to create small clusters for mentions. For DST on MultiWOZ, the 30B quantized model show a 30% relative improvement over the 7B model in JGA. On discourse parsing with PDTB-3, the accuracy of quantized 30B model is almost double, 17.16% vs 31.29%. Across all QR datasets, the quantized 30B model substantially improves NLG scores compared to the dense 7B model, with relative gains ranging from 15-50%. The largest gap is observed on GECOR.

In general, we show that the quantized 30B LLaMA model consistently and significantly outperforms the dense 7B model as a result of the increased scale, despite using 3-bit quantization. The benefits of greater model scale thus outweigh the impacts of quantization in understanding discourse. We believe this finding would be beneficial when deploying LLMs in real-world applications with disk and runtime constraints.

5 Case Study: Query Rewriting

In this section, we provide in-depth analysis by comparing the two open-sourced model families OPT and LLaMA, and the impact of quantization, using query rewriting as the target task.

We conduct a careful inspection of the query rewriting task because of three reasons: (1) by the nature of the task, query rewriting is the only one with free-form generation, while the others effectively are either classification-based tasks or heavily constrained in their possible output predictions. The generation task allows us to explore the LLMs’ output in more detail, and to provide more interesting insights; (2) the manual analysis of errors is a time-consuming process, making it challenging to conduct such an in-depth analysis across all four tasks; (3) the query rewriting task covers a diverse range of five datasets, enabling us to compare differences between each dataset and to thereby gain a deeper understanding.

5.1 OPT vs. LLaMA

Prior works (Beeching et al., 2023) have consistently shown that, under the same model size,

Dataset	6.7/7B		13B		30B	
	O.	L.	O.	L.	O.	L.
Mudoco	53.1	41.1	55.2	61.1	55.2	66.5
	71.8	56.0	72.1	74.7	71.5	77.8
QReCC	46.6	28.1	43.7	38.6	43.8	58.6
	73.4	48.2	71.6	56.4	71.9	78.7
InCar	40.3	28.2	41.9	42.1	44.6	48.5
	64.8	49.9	62.6	56.7	65.3	64.1
GECOR	58.8	53.2	60.9	66.3	58.2	73.8
	75.7	69.2	78.3	80.9	76.1	86.0
CANARD	43.8	21.3	37.5	29.3	41.3	47.2
	72.0	38.1	66.0	46.6	69.3	69.7

Table 7: Comparison between OPT (O.) and LLaMA (L.) across five query rewrite datasets. For each dataset, the first and second rows represent BLEU and ROUGE scores respectively.

Context

User: what is the name of india pakistan border line

Bot: The Radcliffe Line was the boundary demarcation line between the Indian and Pakistani portions of the Punjab and Bengal provinces of British India.

User: who created the radcliffe line

Bot: The Radcliffe Line was named after its architect, Sir Cyril Radcliffe, who was the joint chairman of the two boundary commissions for the two provinces.

User: when was the line published

Gold answer: when was the radcliffe line published

Prediction 1 (repeat the last query): when was the line published

Prediction 2 (language modeling): 1947

Table 8: An example of two major types of errors found in the query rewriting task.

LLaMA outperforms OPT. However, their performance on QR, as shown in Table 7, does not follow this pattern.

When the model size is around 7B, OPT consistently performs better than LLaMA by a significant margin across the five QR datasets. The two models perform on par with each other at 13B. The superiority of LLaMA is only obvious with 30B model size. From another perspective, although we expect performance to improve as model size increases, we observe this trend on LLaMA, but not on OPT. These results suggest that it may not be correct to conclude the overall superiority between two model families by only comparing on a certain range of model sizes or on a certain set of tasks.

5.2 Dense vs. Quantized

We conduct a quantitative analysis on the error types of query rewriting to investigate the performance gap between dense and quantized models.

Type	Dataset	7B D	30B Q	30B D
Repeat	MuDoCo	260	247	194
	QReCC	86	90	26
	InCar	17	15	8
	GECOR	59	62	37
	CANARD	47	44	32
	Total	469	458	297
LM	MuDoCo	71	29	16
	QReCC	80	28	16
	InCar	19	20	15
	GECOR	6	1	0
	CANARD	127	76	59
	Total	232	125	106

Table 9: Number of the major two types errors on three LLaMA models (7B dense, 30B quantized, and 30B dense) found in query rewriting. *Repeat* stands for repeat-the-last-query error and *LM* denotes language modeling error.

Across the five datasets, we identify two main error types that account for nearly 80% of the total errors, with examples shown in Table 8. First, the model *repeats* the last query without resolving any referred entity or ellipsis. In this case, the model seems to understand the instruction but fails at rewriting. This type of error can be primarily associated with the model’s context understanding capability. Second, the model treats the task as a language modeling (*LM*) task, where it provides a response to the last query. In this scenario, the model appears to struggle to understand the task instruction, even with several few-shot examples. We classify this error type as more related to the model’s ICL ability.

We perform manual error annotations on the five QR datasets⁹. Table 9 illustrates the number of errors of the three selected models on each dataset. A consistent trend is observed across all QR datasets. In terms of *repeat* errors, the 30B dense model exhibits significantly fewer errors compared to the 7B dense model (297 vs. 469). However, 3-bit GPTQ quantization leads to an increase in this type of error, reaching a similar error count to the 7B dense model (458 vs. 469). This implies that 3-bit quantization reduces the model’s ability to comprehend the context. Regarding *LM* errors, the 30B dense model also significantly outperforms the 7B dense model, with 106 errors compared to 232. It is to be noted that the quantized model generates only 125 *LM* errors, slightly more than the 30B dense model. However, it generates significantly fewer (around

50%) errors compared to the 7B dense model (125 vs. 232). This indicates that 3-bit quantization maintains the ICL capability that allows models to rewrite the user query successfully rather than performing language modeling task.

6 Conclusion

This paper introduces a contextual understanding benchmark designed to assess the performance of LLMs. We collect nine existing datasets spanning four tasks, each carefully tailored to suit generative models. This benchmark encompasses essential elements for assessing linguistic comprehension within context, including both document and dialog based contextual understanding. Experimental results reveal that LLMs under in-context learning struggle with nuanced linguistic features within this challenging benchmark, exhibiting inconsistencies with other benchmarks that emphasize other aspects of language. To the best of our knowledge, we are also the first to compare dense models and post-training quantization models in contextual understanding tasks. This comparison highlights that 3-bit post-training quantization reduces the general understanding capacity of context to different extent across the 4 tasks. The proposed contextual comprehension benchmark thus provides a unique perspective on the contextual dimension of language understanding and offers a valuable addition to existing LLM evaluations.

Limitations

This work provides an evaluation of various pre-trained LLMs, including OPT, LLaMA, and GPT, on our understanding benchmark. However, we have not evaluated other LLMs designed for longer input scenarios, such as LongLLaMA (Tworkowski et al., 2023).

In our evaluation, we focus on the GPTQ quantization method, analyzing its performance on our benchmark. We do not include other post-training quantization techniques, such as RPTQ (Yuan et al., 2023), in this work.

Our evaluation concentrates on English datasets, primarily utilizing LLMs pre-trained with English data. All of the four tasks on our benchmark have datasets from other languages. The coreference dataset OntoNotes 5.0 contains annotations of Arabic and Chinese. In addition, recent releases such as CorefUD (Nedoluzhko et al., 2022) promote standardization of multilingual coreference anno-

⁹10% test data on QReCC and CANARD was graded.

tations. In DST, CrossWOZ (Zhu et al., 2020) is a cross-domain wizard-of-oz task-oriented dataset. Long et al. (2020) develop TED-CDB, a Chinese discourse relation dataset. The query rewriting task also has datasets in other languages, such as REWRITE (Su et al., 2019) and Restoration-200K (Pan et al., 2019). Finally, specific LLMs optimized for individual languages, such as ChatGLM (Du et al., 2022), exist and are not a part of our evaluation.

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A Task Design Examples

Table 10 presents the input example for each task. For CR, we only show examples from OntoNotes.

B Few-shot Settings

Table 11 shows the number of examples for each dataset that yields the best scores. All datasets except WSC273 and PDTB3 use randomly selected examples from the training set. Since WSC273 does not include any train or validation set, we use the zero-shot setting, as scores presented in Table 5. For each class in PDTB3, we randomly select two examples from the training set for prompting. For some particular datasets, such as OntoNotes, experiments are only performed in the zero-shot and one-shot settings due to the limitation on input length.

C Reliability of Experiment Results

For each task, we have randomly run several experimental setups with multiple rounds, with over 10 settings in total. However, due to the challenges posed by limited time, budget, and computing resources, it is very difficult to run multiple rounds for every single experiment, given the complexity of our experimental setup. In addition, for existing experiments with multiple rounds, we empirically observe that there is low variance across the rounds, which leads us to assume that performing the remaining experiments with a single run does not significantly impact the arguments presented in this paper.

Coreference Resolution

Instructions: Please carefully read the following passages. For each passage and the options, you must identify which option the mention marked in *bold* refers to. If the marked mention does not have any antecedent, please select "no antecedent".

[Few-shot examples]

Context: — basically , it was unanimously agreed upon by the various relevant parties . To express *its* determination , the Chinese securities regulatory department compares this stock reform to a die that has been cast . It takes time to prove whether the stock reform can really meet expectations , and whether any deviations that arise during the stock reform can be promptly corrected . Dear viewers , the China News program will end here . This is Xu Li . Thank you everyone for watching . Coming up is the Focus Today program hosted by Wang Shilin . Good-bye , dear viewers .

Choice:

- A. the Chinese securities regulatory department
- B. this stock reform
- C. the stock reform
- D. you
- E. everyone
- F. no antecedent

Question: What does *its* refer to?

Answer: A

Dialogue State Tracking

Consider the following list of concepts, called "slots" provided to you as a json list.

```
"slots": {"restaurant-pricerange": "price budget for the restaurant",
          "restaurant-area": "area or place of the restaurant",
          "restaurant-food": "the cuisine of the restaurant you are looking for",
          ...
          "hotel-postcode": "postal code of the hotel",
          "hotel-ref": "reference number of the hotel booking"
        }
```

Some "slots" can only take a value from predefined list:

```
"categorical": {"restaurant-pricerange": ['cheap', 'expensive', 'moderate'],
                "restaurant-area": ['centre', 'east', 'north', 'south', 'west'],
                "restaurant-bookday": ['monday', 'tuesday', 'wednesday', 'thursday', 'friday', 'saturday', 'sunday'],
                ...
                "hotel-internet": ['free', 'no', 'yes'],
                "hotel-area": ['centre', 'east', 'north', 'south', 'west']
              }
```

Now consider the following dialogue between two parties called the "system" and "user". Can you tell me which of the "slot" was updated by the "user" in its latest response to the "system"? Present the updates in JSON format. If no "slots" were updates, return an empty JSON list. If you encounter "slot" that was requested by the "user" then fill them with "?". If a user does not seem to care about a discussed "slot" fill it with "dontcare".

Input:

Previous state: {}

"system": "",

"user": "I'm looking for a moderately priced place to eat that's in the centre of town."

Output: {"restaurant-pricerange": "moderate", "restaurant-area": "centre"}

Implicit Discourse Relation Classification

Instructions: Given two arguments and a list of connective words, please select the most likely connective between two arguments.

Below are the descriptions of four discourse relation labels. Please find the correct label for each example.

Temporal: The tag temporal is used when the situations described in the arguments are intended to be related temporally.

Contingency: The tag Contingency is used when the situation described by one argument provides the reason, explanation or justification for the situation described by the other.

Comparison: The tag Comparison is used when the discourse relation between two arguments highlights their differences or similarities, including differences between expected consequences and actual ones.

Expansion: The label Expansion is used for relations that expand the discourse and move its narrative or exposition forward.

[Few-shot examples]

Input:

Arg 1: Amcore, also a bank holding company, has assets of \$1.06 billion.

Arg 2: Central's assets are \$240 million.

Question: What is the connective that best describes the relation between two arguments?

- A. Temporal
- B. Contingency
- C. Comparison
- D. Expansion

Answer: C

Query Rewrite

Instructions: Rewrite the last query following interaction into a well-formed, context independent query. Resolve any disfluencies or grammatical errors in the query.

[Few-shot examples]

Input:

User: Try to reach Forbes now .

Bot: Forbes at Washington Post ? Or Forbes of Publishing Division ?

User: Publishing Division .

Rewrite: *Forbes of Publishing Division*

Table 10: Examples of task design for each task in the context understanding benchmark.

Task	Coreference		DST	Discourse	Query Rewriting				
	Dataset	Model			MuDoCo	QReCC	InCar	GECOR	CANARD
N-shot	Zero-shot	One-shot	5-shot	8-shot	10-shot	5-shot	10-shot	10-shot	5-shot

Table 11: N-shot settings for each task & dataset that yields the highest scores. For each task and model, we use consistent N-shot settings for comparison.