Refract ICL: Rethinking Example Selection in the Era of Million-Token Models

Arjun R. Akula, Kazuma Hashimoto, Krishna Srinivasan, Aditi Chaudhary Karthik Raman, Michael Bendersky

Google DeepMind

{arjunakula, kazumah, krishnaps, aditichaud, karthikraman, bemike}@google.com

Abstract

The emergence of long-context large language models (LLMs) has enabled the use of hundreds, or even thousands, of demonstrations for in-context learning (ICL) – a previously impractical regime. This paper investigates whether traditional ICL selection strategies, which balance the similarity of ICL examples to the test input (using a text retriever) with diversity within the ICL set, remain effective when utilizing a large number of demonstrations. Our experiments demonstrate that, while longer contexts can accommodate more examples, simply increasing the number of demonstrations does not guarantee improved performance. Smart ICL selection remains crucial, even with thousands of demonstrations. To further enhance ICL in this setting, we introduce Refract ICL, a novel ICL selection algorithm specifically designed to focus LLM attention on challenging examples by strategically repeating them within the context and incorporating zero-shot predictions as error signals. Our results show that Refract ICL significantly improves the performance of extremely long-context models such as Gemini 1.5 Pro, particularly on tasks with a smaller number of output classes.

1 Introduction

A key factor driving the success of large language models (LLMs) is in-context learning (ICL), where LLMs leverage a few input-output examples, also known as demonstrations, to solve the desired task (Brown et al., 2020; Zhao et al., 2021). Traditionally restricted to a few-shot setup where a handful of demonstrations are used in the prompt, ICL is now entering a new era with the emergence of extremely long context models (Reid et al., 2024) capable of handling hundreds or even thousands of tokens.

LLMs are known to be sensitive to the prompt (Lester et al., 2021; Liu et al., 2022; Zhang et al., 2022), and especially within the few-shot ICL setup

where we are limited by the sequence length window, the choice of demonstration selection becomes crucial. Prior work has demonstrated the effectiveness of selecting demonstrations based on semantic similarity to the test input (Das et al., 2021; Liu et al., 2022; Margatina et al., 2023; Gao et al., 2023). These studies, however, primarily operate within the constraints of limited context windows. With the dramatic expansion in context capacity afforded by million-token models, critical questions arise: Does smart ICL selection remain necessary when million-token models can fit thousands of examples in the context? Do traditional ICL selection strategies, designed for few-shot scenarios, still hold true when using hundreds of demonstrations? As we increase the number of demonstrations (k), how do we ensure the LLM effectively focuses on the most challenging examples – those that could significantly refine its understanding?

Our work addresses these questions through an empirical study of example selection strategies in ICL, examining their impact across diverse tasks and k-shot settings. Concurrent work has begun exploring the many-shot ICL paradigm with longcontext models up to 80k tokens Bertsch et al. (2024). Our investigation pushes these boundaries by exploring the capabilities of a 2 Million context model, Gemini 1.5 Pro (Reid et al., 2024). Moreover, we critically examine a diverse set of retrieval baselines and provide comparison across short (8K context) (Anil et al., 2023), long (32k context) (Team et al., 2023), and extremely long context models (Gemini 1.5 Pro). Our results demonstrate that simply increasing k without careful selection can be detrimental, highlighting the continued need for smart retrieval methods even in extremely long contexts. For example, we observe that the simple yet robust TF-IDF retrieval method often outperforms more complex, fine-tuned retrieval strategies. Additionally, we find a clear correlation between model context size and the ability to effectively

leverage larger k values. Models with smaller context windows, like Flan-PaLM 2 and Gemini, show performance degradation beyond certain k values, highlighting their limitations in utilizing extensive contexts.

As the number of demonstrations (K) increases, effectively guiding the LLM's focus towards the most informative examples becomes crucial. To address this, we introduce Refract ICL, a novel ICL selection algorithm designed to amplify the LLM's attention towards the most challenging demonstrations. Recognizing that the expanded context window now allows for repetition, Refract ICL leverages zero-shot predictions to strategically highlight and repeat these difficult examples. This repetition encourages comprehensive interaction between challenging demonstrations, breaking free from the inherent sequential bias of causal language modeling in LLMs (Gong et al., 2023) and enabling the model to gain a deeper understanding of its errors. We find that this approach significantly boosts the performance of long-context LLMs, particularly those with extremely large contexts like Gemini 1.5 Pro. This improvement is most pronounced on tasks with a smaller number of output classes. Our ablation studies confirm that the benefits of Refract ICL stem from both the strategic repetition of challenging examples and the integration of error signals.

2 Scaling *k* with Traditional Retrievers

2.1 Datasets and Models

This section investigates the impact of scaling the number of in-context demonstrations (k) on LLMs with varying context lengths. We explore whether traditional retrieval methods, designed for few-shot settings, remain effective when utilizing hundreds or even thousands of demonstrations. We use datasets across diverse task types and languages: binary text classification (EDOS-A (en) (Kirk et al., 2023) and COUNTFACT (de, en, ja) (O'Neill et al., 2021)), multi-class text classification (EDOS-B (en) (Kirk et al., 2023) and MTOP-intent (de, en, es, fr, hi, th) (Li et al., 2021)), multi-label text classification (ATIS-intent (en) (Price, 1990)), relation classification (DDI13 (Herrero-Zazo et al., 2013)), sequence labeling (ATIS-slot (en) (Price, 1990) and BC5CDR (en) (Li et al., 2016)), and machine translation (XML-MT (enfi, enja) (Hashimoto et al., 2019)).

We evaluate three LLMs with varying context

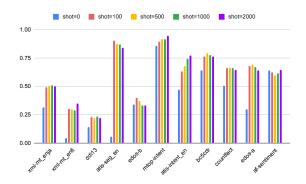


Figure 1: Performance of Gemini 1.5 Pro (2M context) with up to 2000 randomly retrieved demonstrations shows that increasing k alone does not guarantee improvement on all datasets.

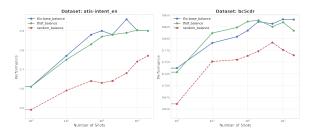


Figure 2: Performance on ATIS and BC5CDR datasets with Gemini 1.5 Pro (2M context) shows that even with up to 2000 demonstrations, smart retrieval (TF-IDF and T5x with balancing) consistently outperforms random selection.

lengths: Short Context: Flan-PaLM 2 (S) (Anil et al., 2023) (8K tokens). Long Context: Gemini (Team et al., 2023) (32K tokens). Extremely Long Context: Gemini 1.5 Pro (Reid et al., 2024) (2 Million tokens).

We evaluate the following traditional retrieval approaches: Random Selection: Examples are randomly sampled from the training set. This serves as a simple baseline to compare against more sophisticated strategies. **TF-IDF**: Examples are retrieved based on their TF-IDF similarity to the input text. This widely used approach measures the relevance of examples based on term frequency and inverse document frequency. T5x-Retrieval: We use the t5x-retrieval code base (Ni et al., 2022) to fine-tune mT5 (Xue et al., 2021) with a general text retrieval objective in Izacard et al. (2021). Multi-Task Re**triever**: A multi-task demonstration retriever R is designed to estimates s(d|x,t), a score of a demonstration d given an input x and its corresponding task t (Li et al., 2023; Wang et al., 2023). Class-**Balanced Variants**: To balance example quality and quantity, we incorporate class balancing techniques, ensuring a more diverse set of demonstrations (Yang et al., 2023).

XML-MT-ENJA	Flan-PaLM 2 (S) (corpus-BLEU), $R_0 = 0.36$, $k=1,5,10,30,50,80,100$	Gemini (corpus-BLEU), $R_0 = 0.33$ k=1,5,10,30,50,80,100	Gemini 1.5 Pro (corpus-BLEU), $R_0 = 0.3$ k=1,5,10,30,50,80,100
Random	+0.01 +0.03 +0.04 +0.02 -0.05 N/A N/A	+0.03 +0.00 -0.04 +0.03 +0.02 +0.03 +0.03	+0.15 +0.22 +0.22 +0.24 +0.24 +0.26 +0.26
TF-IDF	+0.16 +0.19 +0.18 +0.17 +0.01 N/A N/A	+0.10 +0.17 +0.16 +0.22 +0.20 +0.13 +0.16	+0.25 +0.34 +0.36 +0.38 +0.37 +0.38 +0.38
TF-IDF bal	+0.16 +0.19 +0.20 +0.07 -0.04 N/A N/A	+0.10 +0.15 +0.20 +0.22 +0.19 +0.18 +0.18	+0.26 +0.35 +0.38 +0.38 +0.38 +0.38 +0.39
T5x	+0.18 +0.21 +0.21 +0.05 -0.08 N/A N/A	+0.10 +0.17 +0.16 +0.22 +0.20 +0.13 +0.16	+0.25 +0.34 +0.36 +0.38 +0.37 +0.38 +0.38
T5x bal	+0.18 +0.20 +0.21 +0.02 -0.10 N/A N/A	+0.10 +0.19 +0.19 +0.21 +0.19 +0.18 +0.15	+0.29 +0.34 +0.37 +0.36 +0.37 +0.36 +0.36
Multi-task	+0.19 +0.22 +0.22 +0.02 -0.14 N/A N/A	+0.06 +0.08 +0.09 +0.10 +0.10 +0.02 -0.09	+0.35 +0.37 +0.40 +0.40 +0.41 +0.42 +0.42
COUNTFACT	Flan-PaLM 2 (S) (F1-macro), $R_0 = 0.27$,	Gemini (F1-macro), $R_0 = 0.47$,	Gemini 1.5 Pro (F1-macro), $R_0 = 0.41$,
Random	-0.04 +0.21 +0.28 +0.31 +0.30 +0.22 +0.22	+0.08 +0.10 +0.11 +0.12 +0.12 +0.11 +0.10	+0.12 +0.24 +0.28 +0.31 +0.33 +0.32 +0.33
TF-IDF	+0.13 +0.30 +0.41 +0.44 +0.45 +0.38 +0.36	+0.18 +0.15 +0.16 +0.19 +0.20 +0.15 +0.16	+0.27 +0.33 +0.37 +0.36 +0.35 +0.35 +0.35
TF-IDF bal	+0.13 +0.29 +0.37 +0.39 +0.34 +0.42 +0.45	+0.14 +0.11 +0.13 +0.18 +0.15 +0.12 +0.10	+0.26 +0.26 +0.24 +0.29 +0.29 +0.33 +0.33
T5x	+0.12 +0.30 +0.37 +0.42 +0.44 +0.42 +0.41	+0.19 +0.15 +0.15 +0.14 +0.15 +0.14 +0.14	+0.25 +0.32 +0.35 +0.35 +0.34 +0.36 +0.35
T5x bal	+0.12 +0.26 +0.34 +0.39 +0.43 +0.43 +0.44	+0.14 +0.07 +0.12 +0.12 +0.12 +0.10 +0.09	+0.25 +0.30 +0.30 +0.31 +0.34 +0.35 +0.38
Multi-task	+0.12 +0.33 +0.39 +0.36 +0.32 +0.29 +0.33	+0.13 +0.13 +0.12 +0.08 +0.07 +0.06 +0.06	+0.23 +0.25 +0.26 +0.26 +0.27 +0.27 +0.27
ATIS-slot (en)	Flan-PaLM 2 (S) (F1), $R_0 = 0.00$,	Gemini (F1), $R_0 = 0.06$,	Gemini 1.5 Pro (F1), $R_0 = 0.16$,
Random	+0.25 +0.55 +0.60 +0.15 +0.18 N/A N/A	+0.54 +0.63 +0.70 +0.70 +0.65 +0.58 +0.58	+0.67 +0.69 +0.71 +0.74 +0.76 +0.77 +0.76
TF-IDF	+0.60 +0.79 +0.83 +0.16 +0.52 N/A N/A	+0.75 +0.83 +0.82 +0.86 +0.83 +0.80 +0.77	+0.74 +0.78 +0.80 +0.81 +0.80 +0.81 +0.80
TF-IDF bal	+0.60 +0.80 +0.84 +0.60 +0.62 N/A N/A	+0.75 +0.85 +0.83 +0.84 +0.78 +0.77 +0.74	+0.74 +0.79 +0.80 +0.80 +0.80 +0.80 +0.82
T5x	+0.63 +0.79 +0.81 +0.18 +0.50 N/A N/A	+0.79 +0.85 +0.85 +0.86 +0.86 +0.86 +0.82	+0.73 +0.77 +0.78 +0.79 +0.79 +0.79 +0.78
T5x bal	+0.63 +0.80 +0.84 +0.60 +0.63 N/A N/A	+0.80 +0.85 +0.85 +0.85 +0.85 +0.82 +0.80	+0.74 +0.78 +0.78 +0.79 +0.79 +0.80 +0.80
Multi-task	+0.68 +0.79 +0.82 +0.18 +0.51 N/A N/A	+0.76 +0.78 +0.83 +0.77 +0.76 +0.76 +0.75	0.72 +0.73 +0.75 +0.77 +0.77 +0.77 +0.77

Table 1: Performance change from zero-shot across different numbers of demonstrations (k) and retrieval methods for three language models: Flan-PaLM 2, Gemini, and Gemini 1.5 Pro. Each cell represents the performance differences compared to the zero-shot baseline (R_0) , corresponding to k values of 1, 5, 10, 30, 50, 80, and 100. 'bal' denotes class-balanced variants.

2.2 Results and Analysis

Our results illustrated in Figures 1 and 2, and further detailed in Table 1 for XML-MT (en-ja), COUNTFACT, and ATIS-slot (en) datasets, reveal several interesting insights. First, the simple TF-IDF approach often outperforms more complex, fine-tuned retrievers across various models and context lengths. This highlights the continued effectiveness of simple, yet robust retrieval methods even in long-context settings. Second, a clear correlation emerges between context size and the ability to leverage larger k values. Gemini 1.5 Pro exhibits robust scaling, with performance either improving or plateauing as k increases. This suggests its ability to effectively utilize information from a large number of demonstrations. Conversely, both Flan-PaLM 2 and Gemini show performance drops beyond certain k values (k > 10+ and k > 30+ respectively), indicating limitations in their ability to utilize extensive contexts effectively.

Finally, pushing the boundaries with Gemini 1.5 Pro by increasing k up to 2000 demonstrates that simply increasing the number of randomly retrieved examples does not guarantee performance improvement (Figure 1). Furthemore, Figure 2 highlights that even with thousands of demonstrations, smart retrieval methods like TF-IDF and T5x with balancing provide a clear advantage over random selection. This emphasizes the importance of carefully choosing demonstrations, even with massive context windows.

3 Refract ICL

In this section, we introduce Refract ICL, a novel selection algorithm designed to augment traditional retrieval methods and enhance LLM performance in large-k settings. Refract ICL achieves this by strategically repeating challenging examples within the ICL context and incorporating error signals to guide the LLM's attention. More concretely, given a pool of demonstrations $D = \{d_1, d_2, ..., d_n\},\$ we first generate zero-shot predictions for each d_i . Demonstrations where the LLM struggles to achieve accurate zero-shot performance are classified as "challenging" and form the subset $D' \subset D$. Next, we repeat the challenging demonstrations from D' by appending them towards the end of D, leveraging the expanded context window afforded by long-context LLMs. For instance, the updated context looks like $d_1d_2...d_nd'_1d'_2...$, where $d_i \in D$ and $d'_i \in D'$. This repetition helps in removing from the inherent sequential bias of causal language modeling (Gong et al., 2023), allowing challenging examples to comprehensively interact and inform each other. Finally, we add zero-shot predictions to each of the demonstrations, providing explicit error signals to the LLM, i.e. the final ICL context looks like $d_1z_1d_2z_2...d_nz_nd'_1z'_1d'_2z'_2...$, where z_i and z_i' represents the zero-shot prediction for d_i and d_i' respectively. Including zero-shot predictions guides the LLM's attention towards potential error patterns and encourages more effective learning from the demonstrations.

Dataset	Retrieval	Metric	$\begin{array}{c cccc} Gemin & Gemin & 1.5 \text{ Pro} \\ k=1,3,5,10,30,50,80,100 & k=1,3,5,10,30,50,80,100 \end{array}$
AF-SENTIMENT	TF-IDF bal	Accuracy	0.62 -0.08 -0.07 -0.22 -0.01 +0.03 +0.02 +0.02 0.63 -0.01 +0.01 +0.04 -0.02 +0.00 +0.01 +0.01
EDOS-A	TF-IDF bal	F1	0.55 -0.27 -0.20 -0.15 -0.04 +0.02 +0.05 +0.25 0.62 +0.06 +0.06 +0.05 +0.05 +0.02 +0.05 +0.03
COUNTFACT	TF-IDF bal	F1	0.54 -0.21 -0.26 -0.23 -0.05 +0.04 +0.08 +0.03 0.71 +0.02 -0.02 +0.05 +0.04 +0.05 +0.02 +0.04
BC5CDR	TF-IDF bal	F1	0.60 -0.02 -0.04 -0.03 -0.04 -0.05 -0.05 -0.06 0.76 +0.01 -0.02 +0.01 +0.01 +0.00 -0.02 -0.02
ATIS-intent(en)	TF-IDF bal	F1	0.84 -0.06 -0.06 -0.02 -0.01 -0.01 +0.00 -0.02 0.72 +0.03 +0.02 +0.00 +0.01 +0.00 +0.01 +0.02
MTOP-intent	TF-IDF bal	Accuracy	0.87 -0.06 -0.01 -0.02 -0.02 +0.00 -0.02 -0.01 0.88 +0.02 +0.01 +0.02 +0.01 +-0.00 +-0.00 +0.01
EDOS-B	TF-IDF bal	F1	0.16 -0.01 -0.01 -0.01 +0.00 +0.00 +0.07 +0.02 0.43 +0.02 +0.01 +0.02 -0.01 +0.00 +0.02 +0.00
ATIS-slot (en)	TF-IDF bal	F1	0.80 -0.03 -0.02 -0.01 +0.00 +0.00 +0.00 -0.01 0.88 +0.01 +0.02 +0.02 +0.02 +0.01 +0.00 +0.01
DDI13	TF-IDF bal	F1	0.12 -0.03 -0.03 +0.00 +0.00 +0.01 +0.00 +0.00 0.27 +0.02 +0.03 +0.05 +0.06 +0.02 +0.05 +0.03
XML-MT enfi	TF-IDF bal	Corpus-BLEU	0.29 +0.00 +0.00 +0.00 +0.01 +0.01 +0.01 +0.01 0.44 +0.03 +0.01 +0.02 +0.01 +0.02 +0.02 +0.02
XML-MT enja	TF-IDF bal	Corpus-BLEU	0.39 +0.00 +0.00 -0.01 +0.00 +0.01 +0.02 +0.01 0.56 +0.04 +0.03 +0.00 +0.01 +0.00 +0.02 +0.02
AF-SENTIMENT	T5x bal	Accuracy	0.63 -0.09 -0.07 -0.20 -0.01 +0.04 +0.01 +0.02 0.63 -0.01 +0.00 +0.03 -0.01 +0.00 +0.01 +0.01
EDOS-A	T5x bal	F1	0.57 -0.30 -0.29 -0.19 -0.04 +0.01 +0.04 +0.26 0.60 +0.06 +0.06 +0.04 +0.04 +0.01 +0.04 +0.03
COUNTFACT	T5x bal	F1	0.55 -0.27 -0.28 -0.28 -0.09 +0.04 +0.07 +0.05 0.72 +0.01 -0.02 +0.06 +0.03 +0.05 +0.02 +0.03
BC5CDR	T5x bal	F1	0.61 -0.05 -0.04 -0.03 -0.06 -0.06 -0.06 -0.05 0.74 +0.01 -0.01 +0.01 +0.00 +0.01 -0.02 -0.01
ATIS-intent(en)	T5x bal	F1	0.84 -0.09 -0.05 -0.03 -0.01 -0.03 +0.00 -0.01 0.74 +0.05 +0.03 +0.00 +0.00 +0.01 +0.01 +0.01
MTOP-intent	T5x bal	Accuracy	0.89 -0.06 -0.03 -0.02 -0.02 +0.00 -0.01 -0.02 0.89 +0.01 +0.01 +0.01 +0.00 +-0.00 +-0.00 +0.01
EDOS-B	T5x bal	F1	0.15 -0.03 -0.01 -0.01 -0.02 -0.02 +0.08 +0.01 0.43 +0.03 +0.01 +0.02 -0.02 -0.01 +0.02 +0.00
ATIS-slot (en)	T5x bal	F1	0.81 -0.02 -0.02 -0.03 -0.01 -0.02 -0.02 -0.02 0.89 +0.01 +0.01 +0.02 +0.03 +0.00 -0.01 +0.01
DDI13	T5x bal	F1	0.14 -0.07 -0.01 +0.00 +0.00 +0.01 +0.01 +0.00 0.26 +0.03 +0.01 +0.09 +0.04 +0.04 +0.04 +0.03
XML-MT enfi	T5x bal	Corpus-BLEU	0.29 +0.00 +0.00 -0.01 +0.01 +0.02 +0.02 +0.01 0.47 +0.02 +0.01 +0.01 +0.00 +0.00 -0.01 +0.01
XML-MT enja	T5x bal	Corpus-BLEU	0.38 +0.00 -0.01 -0.01 -0.01 +0.01 +0.00 +0.01 0.59 +0.05 +0.03 +0.01 +0.00 -0.01 +0.02 +0.01

Table 2: Performance Changes by adding Refract ICL to TF-IDF bal and T5x bal retrieval methods across k shots with Gemini and Gemini 1.5 Pro. All metrics are presented on a 0 to 1 scale for ease of comparison.

Dataset	w/ repeat	w/o repeat
AF-SENTIMENT	0.73	0.71
EDOS-A	0.74	0.71
COUNTFACT	0.77	0.77
BC5CDR	0.84	0.83
ATIS-intent(en)	95.8	95.8
MTOP-intent	0.97	0.97
EDOS-B	0.57	0.57
ATIS-slot (en)	0.97	0.96
DDI13	0.48	0.48
XML-MT enfi	0.50	0.49
XML-MT enja	0.69	0.69

Table 3: Ablation comparing the Gemini 1.5 Pro Performance with Refract ICL + T5x bal retrieval with and without repeating challenging examples in ICL context.

3.1 Results

Table 2 presents the performance gains achieved by Refract ICL on Gemini and Gemini 1.5 Pro. We observe significant improvements, particularly on classification tasks with a smaller number of output classes, such as EDOS-A, COUNTFACT, and DDI13. Interestingly, Gemini 1.5 Pro shows more consistent gains across different k values compared to Gemini, indicating that the larger context model is better able to leverage the targeted attention provided by Refract ICL. While Refract ICL demonstrates strong performance on tasks with fewer output classes, the improvements are less substantial on tasks with a larger number of classes (e.g., MTOP-intent) or segmentation tasks like ATIS-slot. This suggests that the current implementation of error signal integration might be less effective in these settings. Future work will explore alternative approaches for representing and incorporating error signals in more complex tasks. To assess the impact of mitigating sequential bias, we conducted an ablation study by removing the repetition of challenging examples. As shown in Table 3, this ablation leads to a noticeable performance decrease, confirming that breaking sequential dependencies through repetition plays a crucial role in Refract ICL's effectiveness.

4 Conclusion

In this paper, we explored the impact of increasing demonstration count (k) in the context of longcontext LLMs and highlighted the continued importance of smart ICL selection strategies. While longer context lengths unlock the potential to leverage a larger number of demonstrations, simply increasing k without careful selection can be detrimental. Our proposed method, Refract ICL, demonstrates that focusing LLM attention on challenging examples and incorporating error signals can significantly boost performance. This approach offers a promising direction for enhancing long-context ICL. Future work will investigate alternative approaches for representing and incorporating error signals in more complex tasks, such as those with a larger number of output classes or involving intricate sequence labeling. Additionally, we plan to explore the interplay between different retrieval methods and Refract ICL, aiming to develop even more effective and robust strategies for demonstration selection in the era of long-context LLMs.

5 Limitations

This work explores the potential of Refract ICL for enhancing long-context in-context learning, but it is not without limitations. While our experiments demonstrate promising results, particularly on classification tasks with a smaller number of output classes, the current implementation of Refract ICL shows limited effectiveness on tasks with a larger number of output classes or involving complex sequence labeling. This suggests that the current strategy for integrating error signals, while beneficial in some settings, might not generalize well to all task types.

References

- Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. 2023. Palm 2 technical report. *arXiv* preprint arXiv:2305.10403.
- Amanda Bertsch, Maor Ivgi, Uri Alon, Jonathan Berant, Matthew R Gormley, and Graham Neubig. 2024. Incontext learning with long-context models: An indepth exploration. *arXiv preprint arXiv:2405.00200*.
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.
- Rajarshi Das, Manzil Zaheer, Dung Thai, Ameya Godbole, Ethan Perez, Jay Yoon Lee, Lizhen Tan, Lazaros Polymenakos, and Andrew McCallum. 2021. Casebased reasoning for natural language queries over knowledge bases. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 9594–9611, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Lingyu Gao, Aditi Chaudhary, Krishna Srinivasan, Kazuma Hashimoto, Karthik Raman, and Michael Bendersky. 2023. Ambiguity-aware in-context learning with large language models. *arXiv preprint arXiv:2309.07900*.
- Zhuocheng Gong, Jiahao Liu, Qifan Wang, Jingang Wang, Xunliang Cai, Dongyan Zhao, and Rui Yan.

- 2023. Improving input-label mapping with demonstration replay for in-context learning. *arXiv* preprint *arXiv*:2310.19572.
- Kazuma Hashimoto, Raffaella Buschiazzo, James Bradbury, Teresa Marshall, Richard Socher, and Caiming Xiong. 2019. A High-Quality Multilingual Dataset for Structured Documentation Translation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 1: Research Papers)*, pages 116–127.
- María Herrero-Zazo, Isabel Segura-Bedmar, Paloma Martínez, and Thierry Declerck. 2013. The DDI corpus: An annotated corpus with pharmacological substances and drug-drug interactions. *Journal of Biomedical Informatics*, 46(5):914–920.
- Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. 2021. Unsupervised dense information retrieval with contrastive learning. *arXiv* preprint arXiv:2112.09118.
- Hannah Kirk, Wenjie Yin, Bertie Vidgen, and Paul Röttger. 2023. SemEval-2023 Task 10: Explainable Detection of Online Sexism. In *Proceedings of the 17th International Workshop on Semantic Evaluation (SemEval-2023)*, pages 2193–2210.
- Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Haoran Li, Abhinav Arora, Shuohui Chen, Anchit Gupta, Sonal Gupta, and Yashar Mehdad. 2021. MTOP: A Comprehensive Multilingual Task-Oriented Semantic Parsing Benchmark. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 2950–2962, Online. Association for Computational Linguistics.
- Jiao Li, Yueping Sun, Robin J. Johnson, Daniela Sciaky, Chih-Hsuan Wei, Robert Leaman, Allan Peter Davis, Carolyn J. Mattingly, Thomas C. Wiegers, and Zhiyong Lu. 2016. BioCreative V CDR task corpus: a resource for chemical disease relation extraction. *Database: The Journal of Biological Databases and Curation*, 2016.
- Xiaonan Li, Kai Lv, Hang Yan, Tianyang Lin, Wei Zhu, Yuan Ni, Guotong Xie, Xiaoling Wang, and Xipeng Qiu. 2023. Unified Demonstration Retriever for In-Context Learning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4644–4668.
- Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2022. What makes good in-context examples for GPT-3? In Proceedings of Deep Learning Inside Out (DeeLIO

- 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures, pages 100–114, Dublin, Ireland and Online. Association for Computational Linguistics.
- Katerina Margatina, Timo Schick, Nikolaos Aletras, and Jane Dwivedi-Yu. 2023. Active learning principles for in-context learning with large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5011–5034, Singapore. Association for Computational Linguistics.
- Jianmo Ni, Gustavo Hernandez Abrego, Noah Constant, Ji Ma, Keith Hall, Daniel Cer, and Yinfei Yang. 2022. Sentence-T5: Scalable Sentence Encoders from Pretrained Text-to-Text Models. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 1864–1874.
- James O'Neill, Polina Rozenshtein, Ryuichi Kiryo, Motoko Kubota, and Danushka Bollegala. 2021. I Wish I Would Have Loved This One, But I Didn't A Multilingual Dataset for Counterfactual Detection in Product Reviews. *Preprint*, arXiv:2104.06893.
- Patti Price. 1990. Evaluation of spoken language systems: The ATIS domain. In Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27, 1990.
- Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy Lillicrap, Jean-baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. arXiv preprint arXiv:2403.05530.
- Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. 2023. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*.
- Liang Wang, Nan Yang, and Furu Wei. 2023. Learning to Retrieve In-Context Examples for Large Language Models. *arXiv preprint cs.CL* 2307.07164.
- Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498.
- Zhao Yang, Yuanzhe Zhang, Dianbo Sui, Cao Liu, Jun Zhao, and Kang Liu. 2023. Representative demonstration selection for in-context learning with two-stage determinantal point process. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.

- Yiming Zhang, Shi Feng, and Chenhao Tan. 2022. Active example selection for in-context learning. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9134–9148, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning*, pages 12697–12706.