In-Context Learning with Long-Context Models: An In-Depth Exploration

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Abstract

As model context lengths continue to increase, the number of demonstrations that can be provided in-context approaches the size of entire training datasets. We study the behavior of in-context learning (ICL) at this extreme scale on multiple datasets and models. We show that, for many datasets with large label spaces, performance continues to increase with hundreds or thousands of demonstrations. We contrast this with example retrieval and finetuning: example retrieval shows excellent performance at low context lengths but has diminished gains with more demonstrations; finetuning is more data hungry than ICL but can sometimes exceed long-context ICL performance with additional data. We use this ICL setting as a testbed to study several properties of both in-context learning and long-context models. We show that long-context ICL is less sensitive to random input shuffling than short-context ICL, that grouping of same-label examples can negatively impact performance, and that the performance boosts we see do not arise from cumulative gain from encoding many examples together. We conclude that although long-context ICL can be surprisingly effective, most of this gain comes from attending back to similar examples rather than task learning.[1]

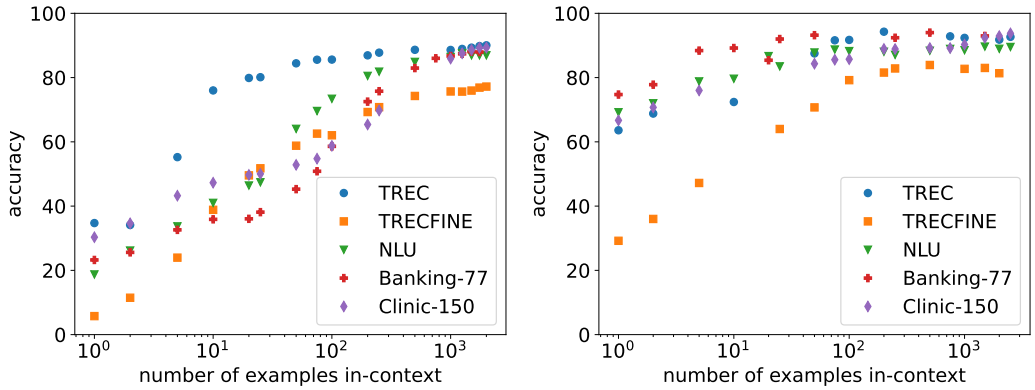
1 Introduction

When a few examples are provided in-context, large language models can perform many tasks with reasonable accuracy. While questions remain about the exact mechanism behind this phenomena (Min et al., 2022b; von Oswald et al., 2023), this paradigm of *in-context learning* (ICL) has seen widespread adoption in both academic and industry applications, thanks to its ease of implementation, relatively small computational cost, and ability to reuse a single model across tasks.

However, most work in this area has focused on short-context models, where the maximum number of demonstrations is severely limited by context length. As more and more methods are developed to adapt language models to extreme context lengths ((Deepmind, 2024; Fu et al., 2024), *inter alia*), in-context learning over large quantities of data becomes a potential alternative to finetuning. The properties of ICL in this regime are not well-understood; additionally, as the cost of inference over many thousands of tokens can be steep, the efficiency and performance tradeoff between many-shot ICL and finetuning on the same data is complex.

[*] Now at Google DeepMind

[1] Data and code are available at https://github.com/abertsch72/long-context-icl



(a) Using randomly selected examples.

(b) Using retrieved examples.

Figure 1: The performance increases with more demonstrations far beyond the context window of the base Llama-2. Results are on Fu et al. (2024)'s long-context finetuned Llama-2-7b model, using a context of up to 80K tokens.

We conduct a systemic study of long-context in-context learning. Namely, we consider: a) the performance of prompting the base model naively, b) retrieving examples to use in-context for each test example, c) comparison to finetuning the base model, and d) using models trained to adapt to longer contexts. Performance continues to increase past 2000 demonstrations (see Figure 1), approaching and sometimes *exceeding* the performance of models finetuned (with LoRA (Hu et al., 2022)) on thousands of examples from the same dataset (§ 3).

We find that, as the number of demonstrations in-context increases to extreme values, the behavior of ICL shifts (§ 4). In-context learning becomes less sensitive to example order, and the benefits of retrieval over using a random set of demonstrations diminishes– allowing the use of a single set of demonstrations, encoded once through the model and cached, rather than re-encoding a custom set of demonstrations for each inference example. We demonstrate that long-context ICL is strongly impacted by grouping examples of the same label. We also find that the effectiveness of long-context ICL is not because of the continual refinement of a decision boundary during encoding but because of the retrieval from more relevant examples (§ 5). Our work furthers the understanding of in-context learning and suggests that, in some data regimes, long-context ICL is a strong alternative to retrieval and finetuning.

2 Experimental setup

Here we describe the shared setup between our ICL and finetuning experiments. Each setting is described in more detail as it is introduced.

2.1 Datasets and models

We consider 5 classification datasets: TREC (Hovy et al., 2001), TREC-fine (Hovy et al., 2001), NLU (Xingkun Liu & Rieser, 2019), Banking-77 (Casanueva et al., 2020), and Clinic-150 (Larson et al., 2019). Table 1 contains summary statistics for each dataset, and Appendix E shows additional description and examples for each dataset.

We compare ICL performance across several variants of `Llama-2-7b` Touvron et al. (2023) adapted for long context:

1. **Llama2** (Touvron et al., 2023) is a decoder-only model trained with a 4096 context length. We use the non-instruct (non-chat) variant because it is more commonly used as a base model for long-context finetuning and because we observed very similar performance between the chat and non-chat variants in our initial experiments.

Dataset	Domain	# Labels	Avg demo length	Training set size	Example labels
TREC	questions	6	22.7	5,452	location, entity
TREC-fine	questions	50	23.7	5,452	abbreviation expansion, location city
NLU	conversational	68	20.7	19,286	takeaway query, iot hue light up
Banking-77	financial	77	27.4	10,003	top up failed, lost or stolen card
Clinic-150	multiple	151	22.3	15,250	rollover 401k, meal suggestion

Table 1: The datasets we consider in this work span diverse label spaces and domains. The average demonstration length is the average combined length of input, output, and formatting tokens per demonstration provided in the context window.

2. **Llama2-32k** (TogetherAI, 2023) is a version of Llama-2-7b finetuned by TogetherAI for a 32k context window. We use the non-instruct version.
3. **Llama2-80k** (Fu et al., 2024) is a version of Llama-2-7b finetuned with 80k context and a carefully designed long-document data mixture.

To verify that the trends we observe are not specific to the Llama series, we additionally consider **Mistral-7b-v0.2** (Jiang et al., 2023). We use the instruct version, as the non-instruct model is not publicly available. The trained context length of Mistral-7B-Instruct-v0.2 is 32k tokens.

While all of these models can extrapolate to inputs longer than their trained context length, we restrict the lengths of inputs to fit within the trained context length; this represents the best case performance without the additional confound of the extrapolation strategy.

2.2 Constrained decoding

For each dataset, we use *constrained decoding* to only produce valid labels as output;[2] all ICL results in the paper, across all methods, use this constrained decoding. Note that, without constrained decoding, these models may produce invalid labels in the few-shot regimes. For finetuning, we use a classification head so that no invalid outputs may be produced.

2.3 Evaluation

Following prior work (Zhao et al., 2021; Lu et al., 2022; Han et al., 2022; Ratner et al., 2022), we subsample 250 examples from the test set of each dataset. We release the subsampled test set and full prediction outputs for each experiment in the project repository. We evaluate on each dataset with accuracy and macro-F1, to capture both overall performance and the performance on minority classes[3]; as the trends for both metrics are very similar, we report primarily accuracy in the paper for readability.

[2]Following Ratner et al. (2022): at each generation step, we simply multiply the logits of tokens that could lead to a valid label by a large constant.

[3]We use the definition of macro-F1 that averages per-class F1; see Opitz & Burst (2021) for discussion of the alternative.

Dataset	Llama2	Llama2-32k	Llama2-80k	Mistral
Randomly selected				
TREC	**82.32** / 80.52	**93.12** / **93.12**	**90.04** / **90.04**	**87.28** / 85.00
TREC-fine	**61.40** / **61.40**	**75.56** / 75.08	**77.20** / **77.20**	**72.68** / 70.48
NLU	**76.88** / **76.88**	**85.04** / 85.00	**87.52** / 86.92	**86.44** / **86.44**
Banking-77	**56.36** / **56.36**	**82.44** / **82.44**	**88.08** / 87.96	**86.76** / 86.68
Clinic-150	**60.92** / **60.92**	**84.40** / **84.40**	**89.32** / **89.32**	**90.56** / **90.56**
Retrieval				
TREC	**90.80** / 85.64	**94.84** / 94.64	**94.28** / 92.68	**90.80** / **90.80**
TREC-fine	**78.80** / **78.80**	**83.88** / 81.12	**83.92** / 81.36	**80.80** / 79.60
NLU	**90.00** / 88.40	**89.80** / **89.80**	**89.64** / 89.52	**90.40** / 89.20
Banking-77	**93.20** / 92.40	**94.32** / **94.32**	**94.00** / 92.96	**93.20** / **93.20**
Clinic-150	**87.60** / **87.60**	**89.84** / **89.84**	**93.76** / **93.76**	**93.20** / 92.40

Table 2: For all datasets, performance of ICL continues to increase with additional demonstrations. The results are the best accuracy (left) and accuracy at maximum data (right) for each model. Bold indicates the best performance for that model/dataset pair.

3 Long-context ICL

We consider three common methods for using a large dataset: naively sampling a fixed subset to use in-context, retrieving relevant data for each example at inference time, or finetuning on the full dataset.

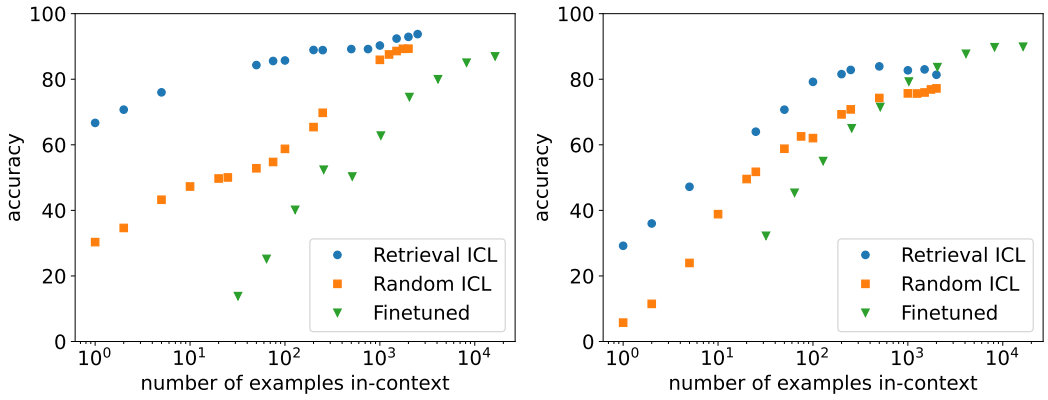
3.1 Compared settings

Random sampling ICL We use 10 random shuffles of the training dataset, averaging the results across these shuffles. Across models and across varying numbers of demonstrations in-context, we draw the first n examples from each shuffle. In this setting, the encoding of demonstrations can be performed once and cached across all inference examples.

Retrieval ICL A strong alternative for in-context learning is to retrieve a relevant subset of examples as demonstrations for each test set example. In this setting, we use a BM25 (Robertson & Zaragoza, 2009) retriever with stopwords removed and retrieve the most relevant demonstrations by comparing the test input text to the full demonstration texts. When doing k-shot prompting, if less than k examples are retrieved by the retriever,[4] we randomly sample additional examples until we reach k. We compare putting examples in the order they were retrieved and in three random shufflings. Note this is more computationally expensive than using a random sample as demonstrations, as a new set of retrieved demonstrations must be encoded for each test set example. However, prior work has found that, in some scenarios, retrieval of good examples can make the difference from near-zero to high test accuracy (Levy et al., 2023).

Finetuning We finetune Llama2-7b with a classification head on varying amounts of data from each dataset with several random seeds, and plot performance at convergence on the same held-out test data. We initialize the classification head from the parameters of the pretrained language modeling head by subsampling the values of the first token of each label; this creates a better-than-random initialization for finetuning. For more details on the finetuning procedure, see Appendix D.

[4]This occurs when there are less than k examples with any word overlap with the test example (excluding overlap in stopwords).



(a) Clinic-150

(b) Trecfine

Figure 2: Comparing retrieval ICL, random selection ICL, and finetuning on two representative datasets. Finetuning sometimes, but not always, exceeds ICL at high numbers of demonstrations. Note that, while retrieval ICL uses the listed number of examples in context, it assumes access to the larger test set to draw examples from (Perez et al., 2021). Results on other datasets are in Appendix C.

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3.2 In-context results

Scaling up ICL to many examples leads to surprisingly strong results Figure 1 and Table 2 show the performance of models in both in-context learning settings. Scaling up in-context learning from 10 to 1000 demonstrations results in accuracy gains of up to *50.8* points (an average of 36.8 points across the 5 datasets).

Longer context lessens the importance of carefully selecting in-context examples Retrieving relevant examples for each test set example far outperforms using a randomly selected subset in the short-context regime. This is true even if the order of retrieved examples is shuffled (rather than ordered by relevance).[5] However, adding additional examples does continue to slightly improve performance; this is especially surprising because, after all examples with non-trivial lexical overlap are retrieved the remaining examples are randomly selected.

While retrieval continues to outperform random selection on most datasets, the effect is diminished with additional examples. On Banking-77, the dataset where retrieval is most beneficial, the performance gain from retrieval drops from 51.5 points at 1-shot ICL to 4.9 points at 1500-shot ICL. This suggests that, as the amount of examples in-context increases, the importance of the selection strategy diminishes. In the long context regime, using the more computationally efficient but less effective strategy of a single randomly selected set of demonstrations is more feasible; the performance penalty for doing so is never more than 5 points of improvement, and as low as 1.8 points (for 2000-shot ICL on TREC).

3.3 Comparison with finetuning

While we have demonstrated that in-context learning with hundreds or thousands of examples is effective, this amount of data is also appropriate for finetuning a model. Finetuning has higher upfront cost but allows for reduced inference-time cost. In this section, we compare in-context learning with the popular parameter-efficient finetuning (PEFT) strategy LoRA (Hu et al., 2022).

[5]We perform three random shuffles of the retrieved inputs and test for difference in distribution from the original results. Across all datasets, this shuffling does not significantly change performance (2-sided t-test, $p < 0.05$).

PEFT is more data-hungry than ICL– especially ICL with retrieval When a relatively small set of examples is available, ICL generally outperforms LoRA finetuning on the same model.[6]

For most datasets, finetuning performance never exceeds long-context ICL performance even with additional examples (e.g. Figure 2a). The exceptions are on TREC and TREC-fine, where finetuning outperforms ICL at the highest numbers of examples (but continues to underperform at low numbers of examples) (e.g. Figure 2b). Generally, the datasets with larger label spaces show the least strong finetuning performance, likely because these are more open-ended classification problems and require more data to train the classifier.

For some datasets, PEFT does win out overall– finetuning with more examples than even the 80k model can fit in-context does result in higher performance. In datasets where PEFT performance never exceeds ICL performance, it nevertheless has dramatically reduced inference costs for similar performance; thus, finetuning on 4096 examples may still be preferable to prompting with 1000 if efficiency of inference is a major priority. This is because, even if demonstration encodings can be cached across inference examples, cross-attention to a long context of demonstrations is expensive.

4 Properties of long-context ICL

In this section, we compare the properties of long-context ICL with the known properties of short-context ICL. We additionally consider using ICL as a testbed for properties of long-context models in Appendix B.

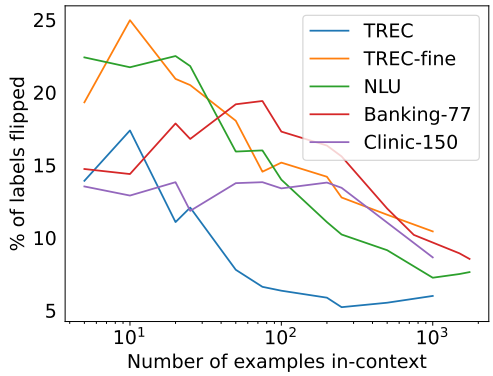


Figure 3: The impact of (randomly) reordering examples in-context decreases with additional demonstrations.

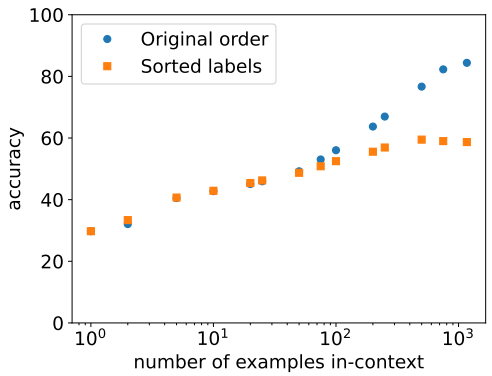
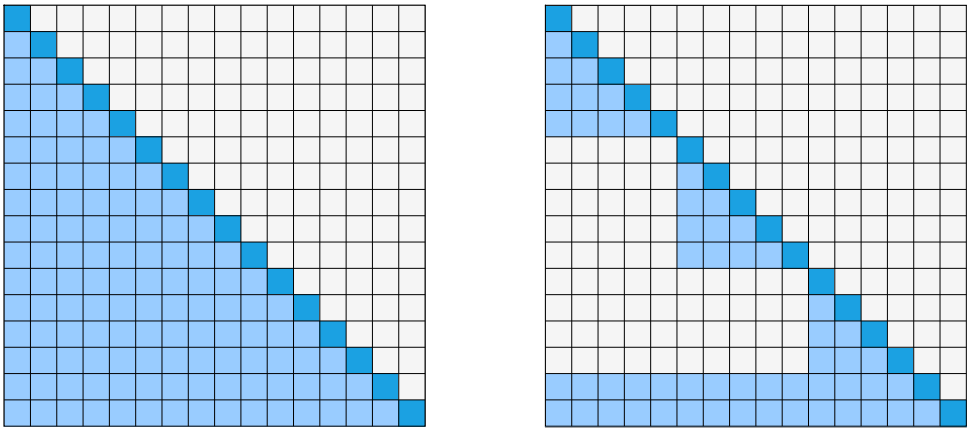


Figure 4: By contrast, sorting examples by label has an increasingly negative impact on performance in longer context regimes. Results on Llama2-32k with Clinic-150.

Is it best to use the entire context? Prior work suggested that, for some simple tasks, providing additional input can *reduce* performance (Levy et al., 2024). However, we observe monotonically increasing performance on nearly every dataset; after the performance curve begins to flatten, small variation occurs, but no significantly lower performance occurs at higher example counts. While using the full context window is computationally costly, and may not be necessary to achieve high performance on these datasets, it does not appear to be harmful to performance; and the additional cost of more input is minimal, as the key-value pairs can be cached and reused across test samples.

Sensitivity to example order Prior work has shown that many models exhibit strong sensitivity to example order in-context (Lu et al., 2022). We examine this by measuring

[6]Note that some prior results have showed strong PEFT performance in the few-example setting on different tasks; see Section 6 for more discussion.



(a) Causal attention (b) Blockwise attention

Figure 5: Normal versus block-causal attention. When performing blockwise attention, we allow full attention for the example we are predicting a label for (here: the last 2 tokens).

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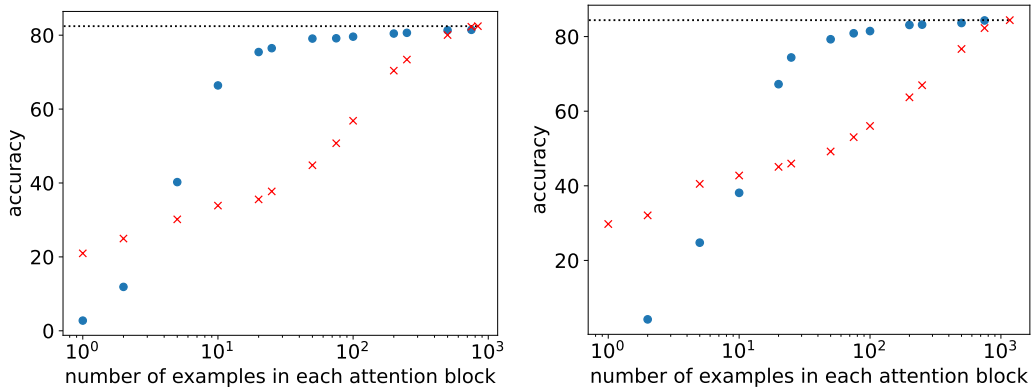
the percentage of predictions that change when the input is reordered; we average this over 3 re-shufflings for each set of input examples. Figure 3 shows that, while there is some sensitivity to example order at all context lengths, this effect weakens substantially with additional context. Across all datasets, the percent of labels flipped by reshuffling in 1000-shot ICL is less than half the percent of labels flipped when reshuffling in 10-shot ICL.

Label sorting We also consider an adversarial case for example ordering: we sort the examples so that examples with the same label appear together. At small numbers of examples, this has very little impact; if the average number of examples per class is low, label sorting is similar to a random sort. However, as the number of examples grows, label sorting begins to have a dramatic impact on performance. Figure 4 shows the performance of Llama2-32k on Clinic-150 with and without label sorting. As the number of examples in-context increases, the penalty for input sorting increases as well; at 1169-shot ICL, label sorting decreases accuracy by 25.7 percentage points. This suggests that contextualization of examples with *different* labels is important to performance, and that this contextualization only occurs effectively over relatively short distances in the context window.

5 Why does long-context ICL help?

To study the underlying mechanism behind the improved performance of the model at longer context lengths, we consider a modified attention pattern where demonstrations can only attend to a small block of nearby demonstrations. The test example we are predicting a label for can always attend to all demonstrations. Figure 5 compares this block-attention to the usual causal attention.

If improved performance is due predominately to the development of a more fine-grained task understanding from embedding many examples together (e.g. continually refining a decision boundary, in the way finetuning the model would do), then encoding many examples in small blocks would be far worse than encoding them all together. If the improvements come largely from seeing more relevant examples to attend to, then the performance should not be strongly reliant on how many other examples each demonstration is contextualized with. Note that this is distinct from methods that overload the same positions with multiple embeddings in order to process longer contexts (e.g. Ratner et al. (2022)); here, we are not modifying any positional information, only restricting attention between demonstrations to a local context block.



(a) Banking-77 (b) Clinic-150

Figure 6: Comparing block attention to full attention over the same set of examples with Llama2-32k. Block attention approaches full attention with relatively small block size. The blue dots represent block attention with blocks of that size; the red 'x's represent full attention over that number of examples. The black line represents the performance of full attention over all examples.

Rather than breaking the context window into fixed-length chunks, we fix a number of examples per-block. If the block size is equal to the number of examples in-context, this is equivalent to normal attention; if the block size is 1, each example can attend only to itself.

Figure 6 shows results on Banking-77 and Clinic-150, with a comparison to both full attention over all examples and full attention over a single block of examples.

When attending in very small blocks (e.g. for banking, < 5 examples), performance is *worse* than attending to a small set of fixed examples. We hypothesize that this is due to inadequate contextualization of each example leading to less informative embeddings. However, performance quickly climbs; 95% of the performance of full attention is recovered by a block of 50 examples in the case of Banking-77 or 75 examples for Clinic-150 (more generally: this occurs between 20- and 75-example block sizes in all datasets). In some dataset/model pairs, performance of block attention even slightly exceeds performance of full attention.

To determine how much of the benefit of encoding multiple examples together is due to task learning, we consider the case of ICL with examples sorted by label. In the block attention case, this ensures that most blocks have examples with only one label represented. While sorting examples by label is harmful to performance in the block attention case as well, it is not *more* harmful to the blocked attention model than it is to the full attention model. This suggests that much of the performance of the model is not due to learning decision boundaries in each block and aggregating them, as most blocks in the label-sorted case do not see more than one or two labels. This supports the theory that the primary performance improvement from long-context modeling is due to retrieving from more relevant examples in-context, rather than learning a better task boundary; this is supported as well by

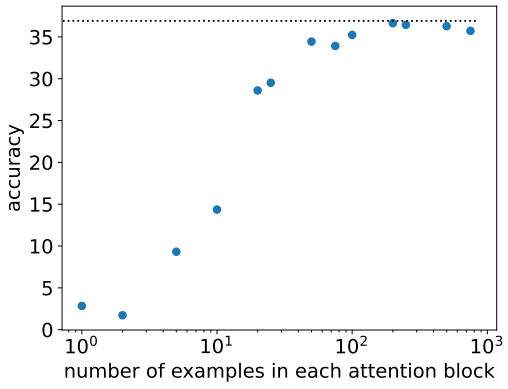


Figure 7: Even when the examples in-context are sorted, block attention can recover similar performance to full attention on the same ordering.

the retrieval results in Table 2, where retrieval performance at short contexts is close to (though never exceeding) very-long-context ICL performance.

Tasks where long context does not help Concurrently to our work, Li et al. (2024) identify a set of tasks where long context is not uniformly helpful. However, we observe that the tasks that show this trend either have near-0 performance at short demonstration lengths or also display an inverse performance trend on the short context scale (e.g. for TacRED (Zhang et al., 2017), we observe that performance decreases from 1 to 10 total demonstrations). While these are important failure modes of language models, we restrict our analysis to tasks without these confounding issues. In Banking-77, the one dataset that overlaps between Li et al. (2024) and this work, both papers observe similar trends of improved performance with additional context.

6 Related Work

Augmenting decoder-only models with long context Many methods for extending the context of language models have been introduced in the last few years. One series of work has focused on positional embedding extrapolation strategies (Peng et al., 2023; Rozière et al., 2024; Chen et al., 2023; Liu et al., 2023; Zhu et al., 2024; Xiao et al., 2024; Han et al., 2024). When extrapolating past pretraining length, models also generally benefit from additional finetuning on long-context data (Xiong et al., 2023). Other methods include adding retrieval-based attention (Bertsch et al., 2023; Tworkowski et al., 2023; Yen et al., 2024) or hierarchical merging of information (Song et al., 2024; YU et al., 2023). The two long-context Llama variants we consider in this work are both examples of finetuning for length extrapolation.

Separately, methods for longer context for ICL have also been proposed. Parallel context windows (Ratner et al., 2022) and structured prompting (Hao et al., 2022) propose methods of re-using the same positional embeddings multiple times to encode more demonstrations; this is quite effective for small numbers of overlaps, albeit with diminishing returns as the number of overlapping windows increases. Cho et al. (2023) propose a hybrid of ICL and linear prompting which improves beyond few-shot ICL performance.

Several works have also critiqued the efficacy of long context models. Liu et al. (2024) demonstrate that some long-context models fail to effectively use the middle of the context window; the models we use were released after this work and have generally high scores for middle-of-context retrieval in their trained context length. Li et al. (2023a) suggest that some long-context models are only effective at utilizing inputs that are shorter than their context window's intended supported length; we do not observe this effect strongly, but it is a possible contributing factor to the saturation of performance for some models before the maximum number of examples in-context. Li et al. (2023b) show that many models fail at tasks that require reasoning over long dependency lengths; this is unlikely to be an issue in our setting.

Properties of in-context learning Milios et al. (2023) study ICL for many-class classification with models up to 4k context length. They find that, when retrieving demonstrations, smaller (7b) models show early performance saturation on many tasks. This is consistent with our findings for Llama2-7b with retrieval; however, the same model continues to learn from demonstrations in the random selection case, and the same size model finetuned for longer context does not show the same performance dropoff and continues to see improvements from additional context for several tasks. Our results suggest that this failure to use longer context effectively is not an inherent property of 7b models, but instead a type of shallow heuristic used by this particular model when the demonstrations are of sufficiently high quality.

Xu et al. (2023) study the impacts of ground-truth label, input distribution, and explanations on ICL performance; Bölücü et al. (2023) study the impact of example selection in a specific domain. Lin & Lee (2024) argue that ICL occurs in two modes: learning tasks and retrieving tasks, and that retrieval of similar-but-not-quite-correct tasks can explain "early ascent"

behaviors where ICL performance peaks once in a fewshot regime and then performance improves again with a much higher number of examples. Similarly, Pan et al. (2023) argue for a distinction between task recognition and task learning, and suggest that task learning continues to benefit from additional examples at scale. von Oswald et al. (2023) suggest in-context learning can be viewed as gradient descent, although Deutch et al. (2024) argue against this interpretation. Hendel et al. (2023) view in-context learning as compressing the demonstrations into a "task vector" that maps from inputs to outputs; the surprising effectiveness of block encoding initially appears contrary to this theory, although it is also possible that multiple similar task vectors are learned from the separate blocks and then ensembled via attention for the final prediction.

Concurrently to our work, Agarwal et al. (2024) study many-shot prompting of Gemini 1.5 and show improvements from the fewshot setting across both classification and generation tasks. Our work differs in its evaluation of multiple open-source models, our comparison to finetuning the same base model, and our use of ICL as a testbed for analysis of long context behaviors.

Comparing in-context learning and finetuning Min et al. (2022a) show that models trained on fewshot learning can generalize to perform fewshot learning on new tasks; in some cases, this can outperform finetuning directly on the new task. Mosbach et al. (2023) compare finetuning to ICL more directly; they find that finetuning generally outperforms ICL with the same number of examples both in-domain and out-of-domain, when comparing 16-example ICL to finetuning on the same 16 examples. Their setting differs from ours in their choice of model (OPT), the amount of data considered (16 for ICL, 16 or 128 for finetuning), and the use of full finetuning rather than PEFT. Liu et al. (2022) find that PEFT generally outperforms ICL in their setting, where they finetune an encoder-decoder model with a language modeling objective using their T-few method and 20-70 samples. Asai et al. (2023) compare finetuning and ICL for mT5 on cross-lingual transfer and find that ICL outperforms finetuning in some, but not all, of the tasks studied. To the best of our knowledge, no prior work has considered the relative performance of finetuning and ICL in the many-shot regime, where there are hundreds or thousands of examples in-context.

7 Conclusion

We have demonstrated that ICL with large demonstration sets can be surprisingly effective, and shed light on a few surprising properties in its behavior. Namely, long-context ICL exhibits a reduced dependence on example selection, relatively stable performance with respect to example order, and performance often approaching or exceeding parameter-efficient finetuning on the same data, all properties that make this an appealing option for a variety of tasks. We have also shown that long-context ICL's effectiveness is largely due to retrieval from the long context during prediction, rather than cross-attention within the large demonstration set during encoding.

Our work also highlights that our understanding of ICL remains incomplete. Though much work has studied the potential mechanisms behind ICL, these works have largely focused on simple tasks with small (< 10 examples) demonstration sets; as our work demonstrates that properties of ICL shift with the scale of the demonstration set, more work is necessary to validate hypotheses about ICL at larger scales.

While prior work has focused on two strategies for performing inference on a new task– either finetuning on task-specific data or selecting a subset of that data to use in-context– our results points to a potential third paradigm: adapting the *model* to fit as much of that data in-context as possible, caching and reusing the encoding of the long demonstration set. While finetuning with full datasets is still a powerful option if the data vastly exceeds the context length, our results suggest that long-context ICL is an effective alternative– trading finetuning-time cost for increased inference-time compute. As the effectiveness and effiency of using very long model context lengths continues to increase, we believe long-context ICL will be a powerful tool for many tasks.

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A Saturation

One metric we are interested in is the point where the model performance *saturates*, which we define informally as the point where adding more examples is unlikely to meaningfully improve performance. More formally, we define the saturation point as the smallest number of examples tested such that performance reaches 95% of the model's maximum performance.

Saturation points vary by dataset. We define saturation as the first point at which performance reaches 95% of the model's maximum performance on that dataset. Table 3 shows the number of examples at saturation and the maximum number of examples that fit in the context window for each model. For datasets with larger label spaces, saturation generally occurs later; Banking-77 and Clinic-150 do not saturate within the context window of Llama2 (4096 tokens, which represents between 100-162 in-context examples for these datasets). In the longer-context regime, saturation points generally occur slightly later on Llama2-80k, but in both models occur before the model's maximum context length.

This suggests two things. First, given a fixed model, it is often not necessary to use the full context length to extract high performance from that model. Second, current models do not make use of the full potential of ICL; models often saturate in performance before the maximum number of examples, despite longer-context versions revealing that further performance improvements are possible.

The number of classes has some impact on saturation point– but is not fully explanatory. Our results show datasets with more classes benefit from more demonstrations in-context, on average, before saturation. This is to be expected, as the expected number of demonstrations necessary before seeing the correct label increases with the number of total label classes. To test if this is an intrinsic property of these datasets, or truly linked only to the number of label classes, we construct subsets of two high-label-space datasets, Banking-77 and Clinic-150, by randomly selecting half of the labels to exclude from the dataset. These subsets remain in the same domain, but with a smaller label space; if saturation is tied to the number of examples, then this should move the saturation point. Note that this is distinct from *combining* labels (e.g. TREC vs TREC-FINE), as combining finegrained labels into general labels makes the classification task simpler. It's still possible that the subset chosen is a simpler task (e.g. by removing one of a pair of frequently confused labels); to moderate the effect of this change, we average results over 3 randomly chosen subsets.

Table 4 compares the saturation point of the full- and half-label-space runs. For the datasets with the most number of labels, halving the number of labels also reduces the amount of examples that are useful before saturation, albeit not by half. However, the trend is less clear for the tasks with fewer labels; in some cases, reducing the label space actually *increases* the number of demonstrations before saturation. While the size of the label space clearly has some impact on the saturation point, more investigation is necessary to identify other factors impacting this behavior.

Dataset	Llama2	Llama2-32k	Llama2-80k	Mistral
TREC	20 (140)	100 (1129)	75 (2000)	50 (1129)
TREC-fine	75 (131)	250 (1056)	500 (2000)	500 (1091)
NLU	100 (162)	500 (1309)	500 (2000)	250 (1309)
Banking-77	- (100)	500 (838)	750 (1750)	500 (860)
Clinic-150	- (145)	750 (1169)	1000 (2000)	750 (1212)

Table 3: We measure the saturation point as the point at which the model reaches 95% of its maximum accuracy on the dataset; "-" in a column indicates that the maximum performance is achieved by using the full context window. The number in parenthesis represents the maximum number of examples that fit in the context window. As the label space of the dataset increases (from top to bottom row), so does the number of examples that can be used before saturation.

Dataset	Llama2	Llama2-32k	Llama2-80k	Mistral
TREC	14.29 / 24.69	8.86 / 1.77	3.75 / 1.71	4.43 / 6.0
TREC-fine	57.25 / 80.71	23.67 / 27.9	25.0 / 32.38	45.83 / 33.33
NLU	61.73 / 80.71	38.2 / 17.21	25.0 / 26.67	19.1 / 36.67
Banking-77	100.0 / 88.0	59.67 / 37.91	42.86 / 28.57	58.14 / 35.56
Clinic-150	100.0 / 64.04	64.16 / 35.14	50.0 / 22.86	61.88 / 56.67

Table 4: We compare the saturation point between the full-label-space (left) and half-label-space (right) for each model+dataset pair. Here we represent the label space as a percentage of the full context window.

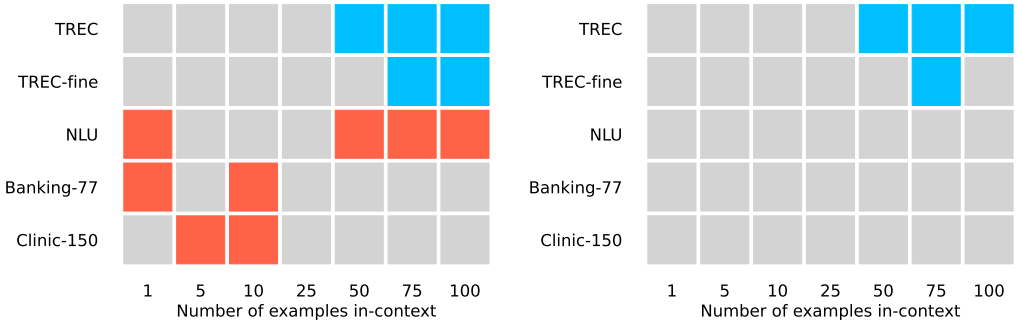
B Using ICL as a testbed for long-context model properties

In this section, we use in-context learning as a testbed to examine several properties of long-context models.

How do long-context models perform in the short-context regime? Llama2-32k and Llama2-80k are finetuned variants of Llama2-7b, adapted for longer contexts. We evaluate how these models perform relative to the base model in short-context tasks (e.g. ICL using less than 4096 tokens of demonstrations) by testing whether the difference in performance is statistically significant (2-sided t-test, $p < 0.05$). Performance is generally similar, with some areas of slight improvement from the base model; Figure 8 shows full results. We observe degradation in performance in some settings for Llama2-32k, highlighting the importance of testing for behavior regression when finetuning for additional capabilities.

Input utilization We analyze the performance of all methods on a naturalistic needle-in-the-haystack Ivgi et al. (2023); Liu et al. (2024) style test. If the model is effectively using the context, then it should be able to exactly recover the label for any example it has seen in-context. Note that, while a model trained on some set of data is not uniformly capable of exact copying from that training data (Biderman et al., 2023), in nearly all of our finetuning runs, the model fits the training data with 100% accuracy.

We examine this behavior by selecting the same set of examples to use in-context and in evaluation; all models should then be able to achieve 100% accuracy. Table 5 shows the results; while all models achieve very high accuracy on the copied data, no model is able to uniformly copy correctly from the input. Surprisingly, performance improves slightly with additional demonstrations for most models, possibly due to additional specification of the task.



(a) Llama2-32k (b) Llama2-80k

Figure 8: Short-context behavior of long-context models. Each model's performance is compared to the performance of the base model it was finetuned from, on the same amount of data. **Red** represents significantly worse performance; **blue** represents significantly better performance ($p < 0.05$).

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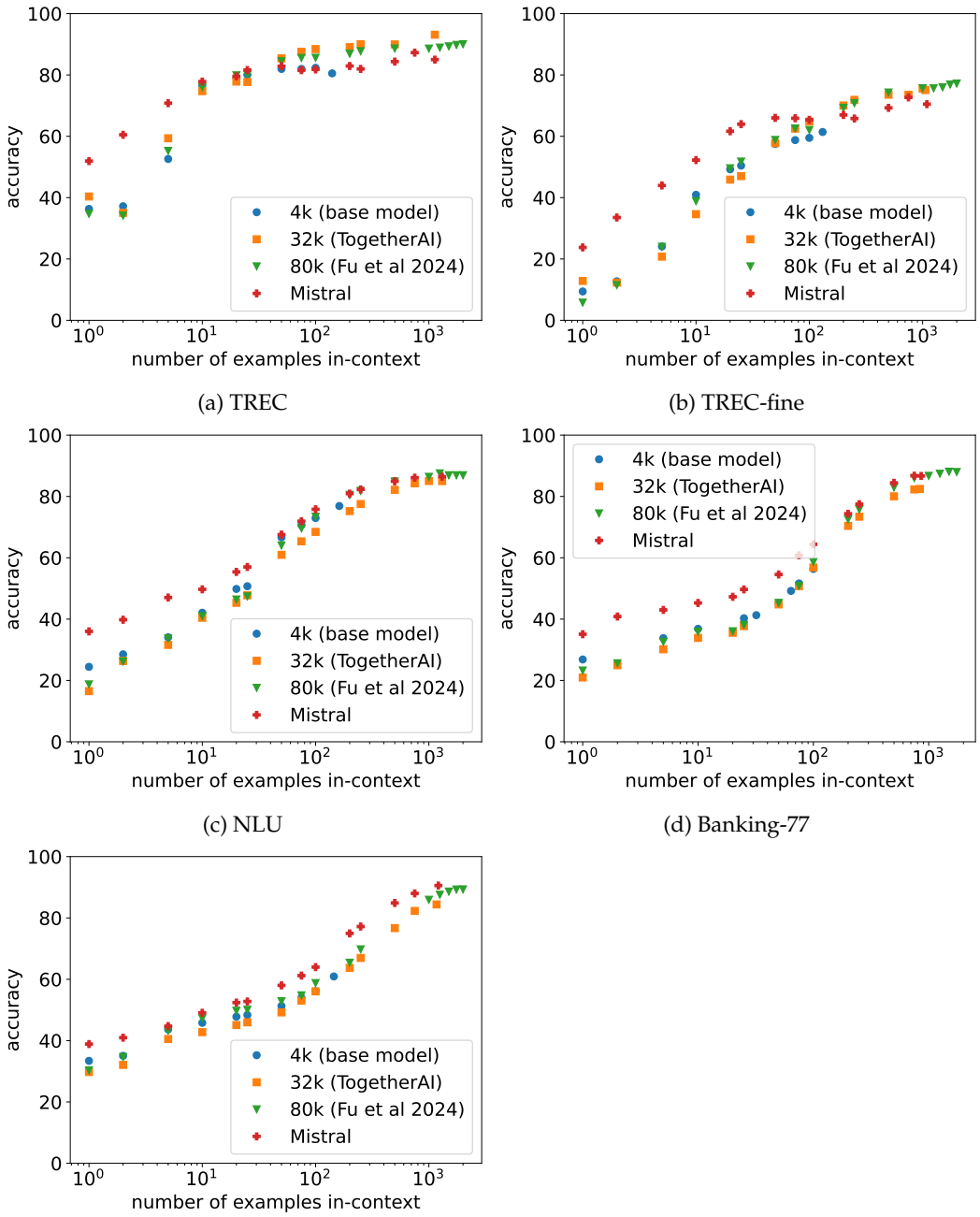
Number of examples	1	5	10	25	50	100	200	250
Llama2	**100.0**	93.0	96.5	97.0	98.6	97.95	-	-
Llama2-32k	80.0	95.0	97.0	96.6	98.4	98.5	98.5	**98.9**
Llama2-80k	90.0	94.0	95.0	98.2	**98.5**	98.3	98.0	97.9

Table 5: Copying behavior given the test examples in the context window. Results are averaged over Banking-77 and Clinic-150; bold indicates the best performance for that model.

C Full ICL results across datasets

For space, we show 1-2 representative datasets for each point of analysis in the paper. In this appendix, we present results across all datasets for completeness.

C.1 Random selection ICL across all models



(a) TREC

(b) TREC-fine

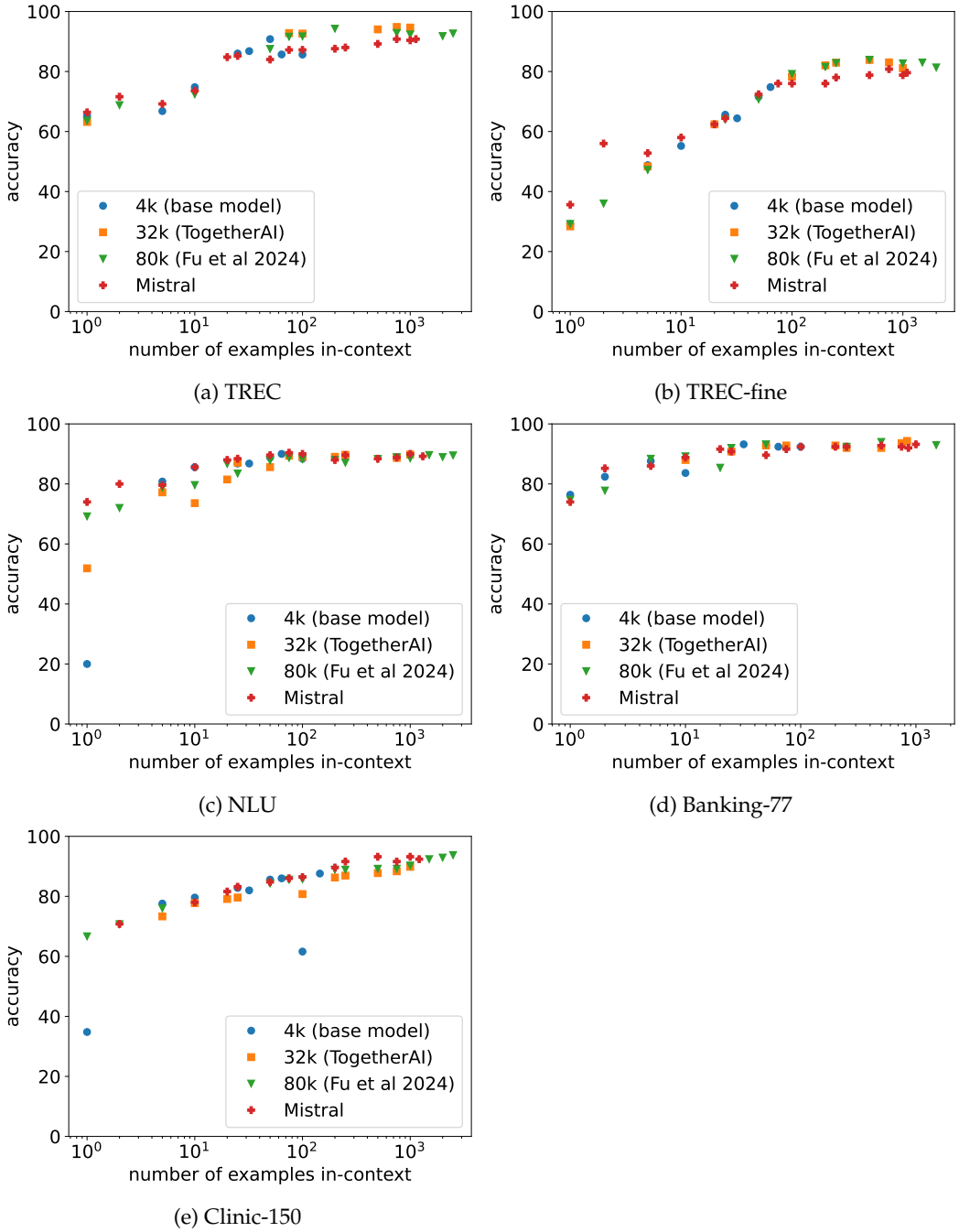
(c) NLU

(d) Banking-77

(e) Clinic-150

Figure 9: Performance of random-selection ICL across all models for each dataset. Performance continues to increase with additional examples in-context.

C.2 Retrieval ICL across all models



(a) TREC

(b) TREC-fine

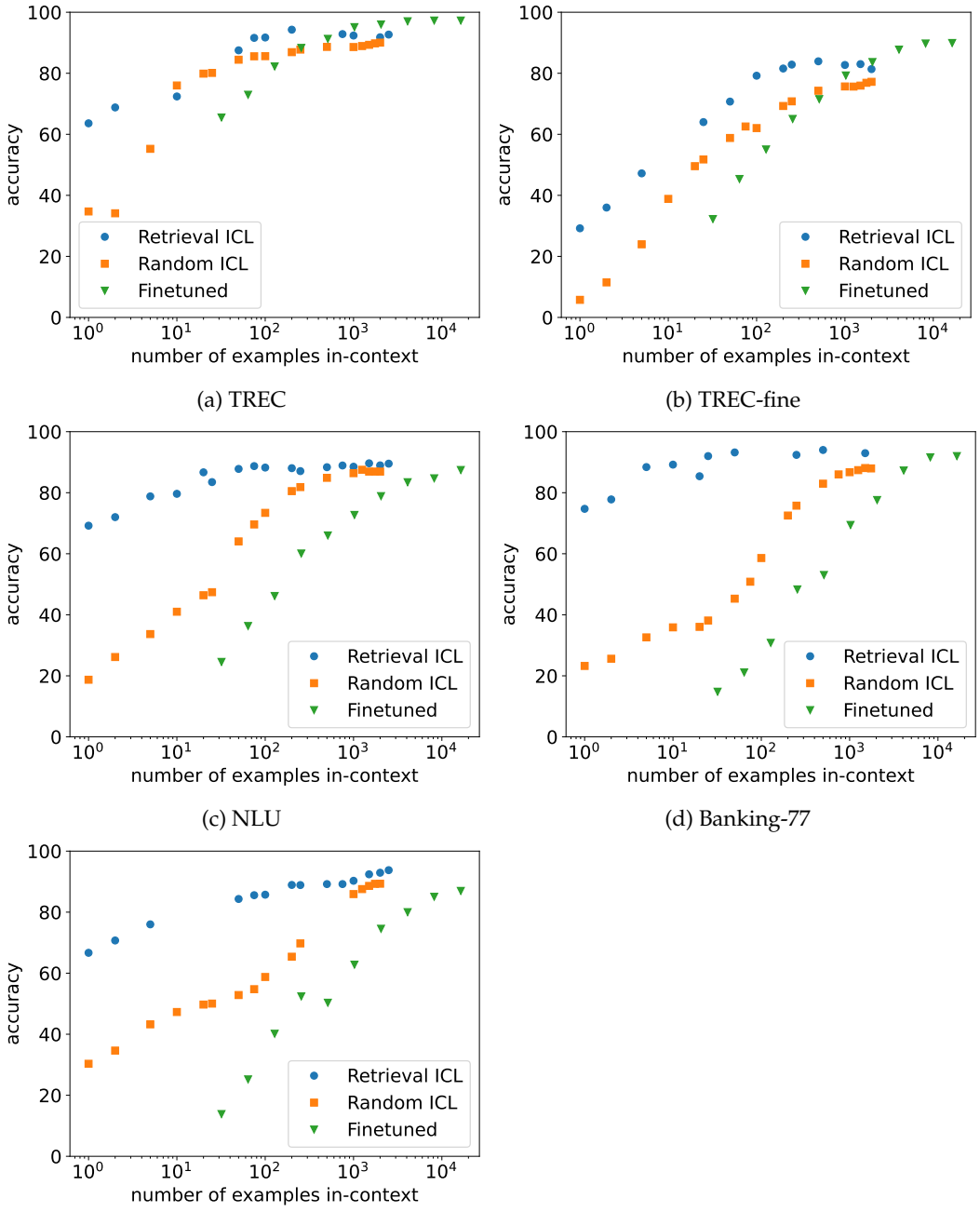
(c) NLU

(d) Banking-77

(e) Clinic-150

Figure 10: Performance of retrieval-based ICL across all models for each dataset. Short-context performance here is higher than for random-selection, but performance continues to improve with more examples until a saturation point, where performance flattens out.

C.3 Comparing retrieval, random selection, and finetuning



(a) TREC

(b) TREC-fine

(c) NLU

(d) Banking-77

(e) Clinic-150

Figure 11: Performance of retrieval-based ICL, random-selection ICL, and finetuning across 5 datasets. At small example counts, ICL outperforms finetuning; when several thousand examples are used, finetuning outperforms ICL in some datasets.

D Finetuning

To perform parameter efficient finetuning (PEFT), we used the peft (Mangrulkar et al., 2022) package (version 0.9.0). We finetune the model for 30 epochs, evaluating it every epoch on the test set, and ultimately choosing the checkpoint with the highest test accuracy. We note that using the test set to perform model selection presents an unfair advantage to PEFT (compared to ICL) and may not be truly indicative of the generalization error. However, doing so provides the advantage of being both comparable to ICL in terms of the data used, as well as giving an upper bound on the true generalization accuracy of the finetuned model, further emphasizing any observed efficacy gap between it and ICL.

Initialization of the classification head While in our default setting we initialize the classification head from the pretrained LM head, subsampled at the representation of the first token in each label, we investigate the efficacy of this approach by contrasting with a randomly initialized classification head. Figure 12 shows that while in the few-shot regime, this approach has significant advantage, as the training set grows in size the difference shrinks to become negligible. In no case was random initialization better than this approach.

Hyperparameter tuning To remain comparable in terms of compute efficient finetuning, we did not perform extensive hyper-parameter tuning per task, and instead experimented with a good global setting on a single dataset (Banking-77). Specifically, we experimented with different learning rates, different LoRA ranks (r) and α (Hu et al., 2022) and also tried applying RSlora (Kalajdzievski, 2023) which sets the scaling factor to $\frac{\alpha}{\sqrt{r}}$ as some evidence suggest it can outperform the original method. Figure 13 summarizes the results, depicting average test accuracy against training examples with different settings.

Ultimately, we found that using HuggingFace's (Wolf et al., 2020) default parameters of $r = 8$, $\alpha = 32$, LoRA dropout of 0.1 and a learning rate of $1e-3$ to work best. In all cases, we used batch sizes of 32 and weight decay of 0.01.

It is possible that methods specialized for finetuning in small-data regimes, such as T-few Liu et al. (2022), might close the gap between ICL and PEFT in the small-data regimes. We did not consider T-few in our analysis because of its additional pretraining stage, which imposes substantial additional cost, and because T-few was developed with a focus on encoder-decoder models and we consider only decoder-only models in our setting.

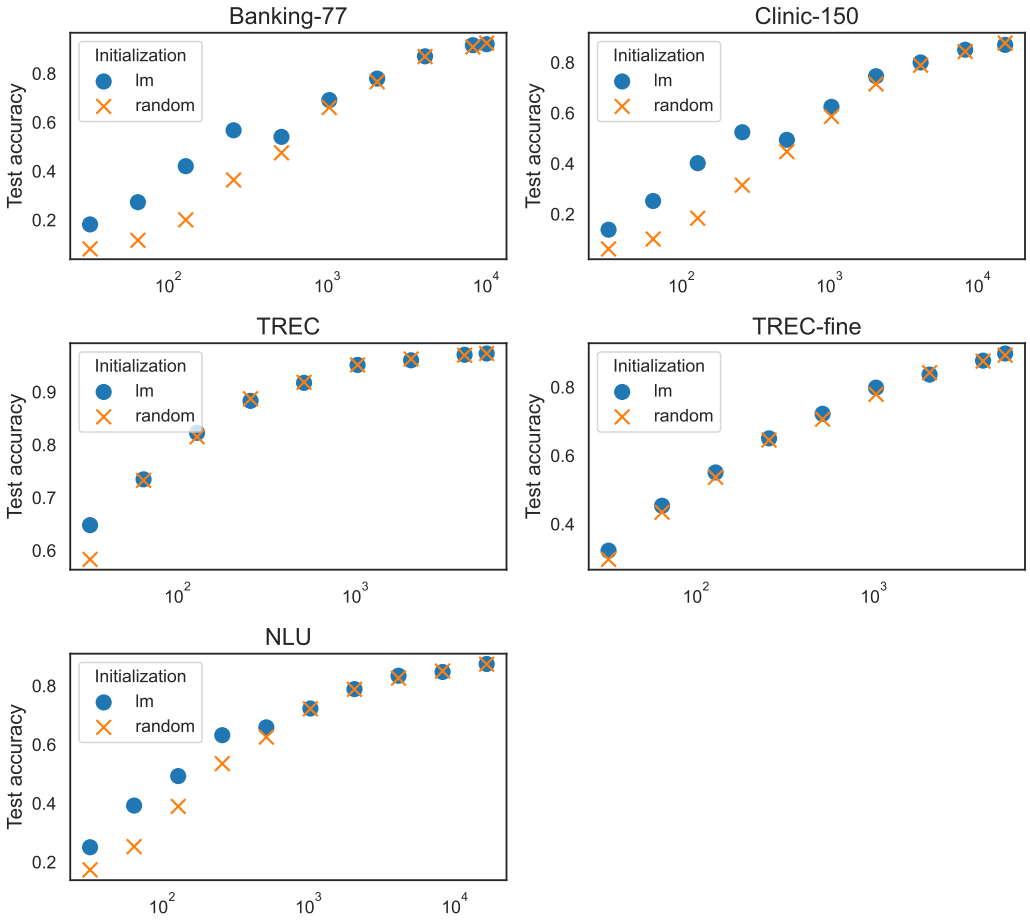


Figure 12: Comparing initialization methods of the classification head when finetuning a PEFT llama-2-7b model. Averaged (best) test accuracy over 5 random seeds. Initialization with *lm* subsamples the pretrained language-modeling head at the first token of the target label, while random samples random weights.

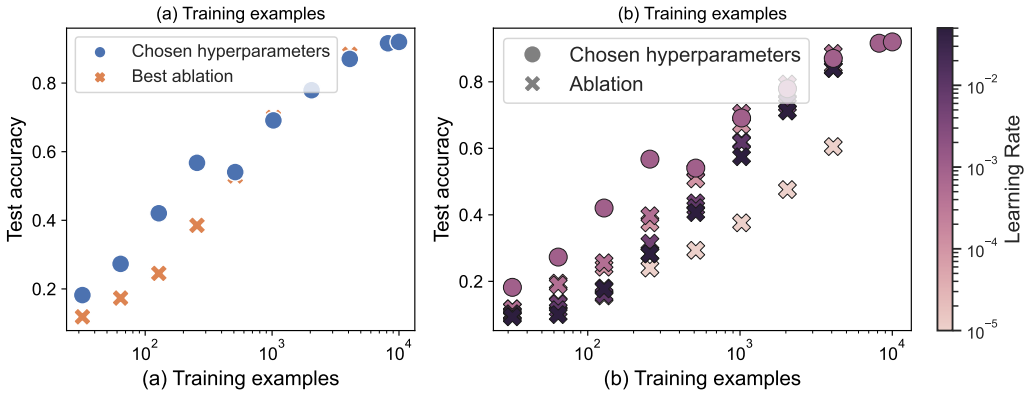


Figure 13: Comparing hyperparameters when finetuning a PEFT llama-2-7b model on Banking-77. Averaged (best) test accuracy over 3 random seeds. (a) Comparing our fixed LoRA configurations to the best alternative configuration (at each scale) we tried. (b) Comparing different learning rates.

E Prompt formatting and examples from datasets

As a demonstration of the datasets, we provide an example of 3-shot prompting for each dataset with the prompt formatting we used (and with examples drawn from the training set of each dataset).

Prompt formatting and instruction phrasing can have significant impact on performance (Sclar et al., 2023); we keep the formatting consistent with prior work (Ratner et al., 2022), with prefixes for the input and output for each exemplar. Because we use predominately non-instruction-tuned models, we do not add an additional instruction or system prompt.

E.1 TREC

TREC (Hovy et al., 2001; Li & Roth, 2002) is a question classification dataset with two granularities of labels. We refer to the 6-label coarse classification as TREC.

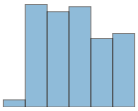


Figure 14: The label distribution of TREC. One label is much less frequent than the rest.

Question: How does light travel through the void of space if there is no medium for it to ' wave ' or ' pulse ' .
Type: description
==
Question: What cathedral was Thomas Becket murdered in ?
Type: location
==
Question: The lawyer who represented Randy Craft , what was his name ?
Type: human
==
Question: What are the rites accompanying the circumcision of a newly born-child in Judaism called ?
Type:

Figure 15: Example 3-shot prompt for TREC.

E.2 TREC-fine

We refer to TREC's 50-label finegrained classification as TREC-fine.

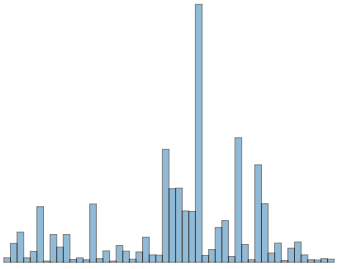


Figure 16: The label distribution of TREC-fine.

Question: How does light travel through the void of space if there is no medium for it to ' wave ' or ' pulse ' .
Type: description manner
==
Question: What cathedral was Thomas Becket murdered in ?
Type: location other
==
Question: The lawyer who represented Randy Craft , what was his name ?
Type: human individual
==
Question: What are the rites accompanying the circumcision of a newly born-child in Judaism called ?
Type:

Figure 17: Example 3-shot prompt for TREC-fine.

E.3 NLU

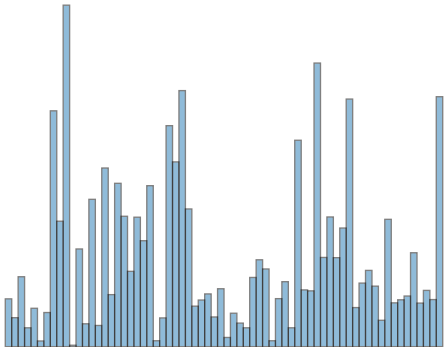


Figure 18: The label distribution of NLU.

NLU (Xingkun Liu & Rieser, 2019) is a 68-way intent classification dataset in the conversational domain. The original paper evaluates on 64 of the intents; we use all 68.

utterance: oh it is nice one, olly.
intent: general praise
==
utterance: nope wrong.
intent: general negate
==
utterance: what events near hear are happening this week
intent: recommendation events
==
utterance: play fishing podcasts that are favorited
intent:

Figure 19: Example 3-shot prompt for NLU.

E.4 Banking-77

Banking-77 (Casanueva et al., 2020) is a 77-way intent classification task in the financial domain. Although the accuracy of some labels in BANKING77 has been criticized (Ying

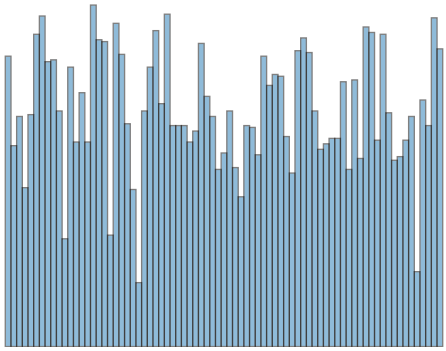


Figure 20: The label distribution of Banking-77.

& Thomas, 2022), we report results here on the original dataset for consistency with prior work.

query: How long will my payment be pending?
intent: pending card payment
==
query: My physical card is not working
intent: card not working
==
query: i cant seem to activate card
intent: activate my card
==
query: I didn't set up a direct debit payment on my account.
intent:

Figure 21: Example 3-shot prompt for Banking-77.

E.5 Clinic-150

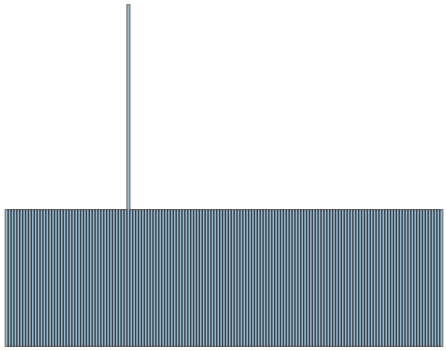


Figure 22: The label distribution of Clinic-150. It is balanced except for the "out of scope" label, which has additional data points in the split we use.

Clinic-150 (Larson et al., 2019) is a 151-way, multi-domain intent classification task; examples are either labeled with an intent from one of 10 domains or with the catch-all "out-of-scope" label. We use the "plus" train split from the original paper, which adds additional "out-of-scope" examples to the dataset.

utterance: how much is my comcast bill
intent: bill balance
==
utterance: tell me about yourself
intent: what is your name
==
utterance: how to build up my credit score
intent: improve credit score
==
utterance: are you employed by me
intent:

Figure 23: Example 3-shot prompt for Clinic-150.