

# Rethinking In-Context Learning in Large Language Models as Gradient Descent

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## Abstract

In-context learning (ICL) has shown impressive results in few-shot learning tasks, yet its underlying mechanism is still not fully understood. Recent works suggest that ICL could be thought of as an gradient descent (GD) based meta-optimization process. While promising, these results mainly focus on simplified settings of ICL and provide only preliminary evaluation of the similarities between the two methods. In this work we revisit the comparison between ICL and GD based finetuning and study what properties of ICL an equivalent process must follow. We begin in the model prediction level and reexamine how ICL and finetuning’s prediction updates differ. Next we address the differences in layer causality between ICL and standard finetuning. To study how this dissimilarity affects the model’s behavior we propose a causally aware finetuning process and compare it with previous results. Lastly we show that finetuning using a linear approximation of the model achieves comparable results to standard finetuning, suggesting that the underlying behavior may be explainable by simpler optimization processes. The code implementation for our experiments is available at: <https://github.com/GilDe/ft-vs-icl>

## 1 Introduction

In recent years, large language models (Brown et al., 2020) have shown strong emergent in-context learning ability (Wei et al., 2022) where a pre-trained model’s performance significantly improves on various downstream tasks by simply conditioning on a few input-label pairs (demonstrations). Despite its success and avid research regarding ICL abilities, the inner workings behind the process are still not fully understood. In-context learning operates in a seemingly different approach to few-shot and meta-learning which require additional parameter updates. Nevertheless a series of recent works show significant similarities between ICL and gra-

dient descent based optimization (Irie et al., 2022; Von Oswald et al., 2023; Akyürek et al., 2023).

In this paper, we study the results of (Dai et al., 2023) which empirically show connections between ICL and standard finetuning on large GPT models and language classification tasks. We identify both empirical differences in previous results such as a discrepancy in accuracy, and intrinsic theoretical differences in layer causality and update expressiveness. Our goal is to quantify and demonstrate how these factors affect the results of the comparison between the two methods. To do so, we perform experiments on three levels:

- **Prediction Alignment:** From the model prediction perspective, we demonstrate that ICL’s and finetuning’s predictions differ on most tasks. We introduce a new metric: relative prediction alignment (RPA) to better measure similarity with ICL in this setting.
- **Layer Causality:** Focusing on the flow of information in the model, we identify that the update induced to each layer’s prediction in finetuning depends on all the others (no layer causality). To study how this difference affects the similarity with ICL, we propose a new layer causal finetuning method and evaluate its similarity with ICL.
- **Update Expressiveness:** Inspired by recent studies large language models from the neural tangent kernel (NTK) perspective (Ortiz-Jimenez et al., 2023), we test whether comparable similarities with ICL could be achieved by performing finetuning on a less expressive model, namely the model’s linear approximation.

## 2 Background and Preliminaries

### 2.1 Dual Form Between Attention and Linear Layers Optimized by Gradient Descent

The view of language models as meta-optimizers originates from the presentation of the dual and primal forms of the perceptron (Aizerman et al., 2019). This notion was later expressed in terms key-value-query attention operation by (Irie et al., 2022; Dai et al., 2023; Von Oswald et al., 2023) which apply it in the modern context of deep neural networks. They show that linear layers optimized by gradient descent have a dual representation as linear attention.

Let  $W \in \mathbb{R}^{d_{\text{out}} \times d_{\text{in}}}$  be the weight matrix of a linear layer initialized at  $W_0$ , and let  $\mathbf{x}, \mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^{d_{\text{in}}}$  be the input and training examples representation respectively. One step of gradient descent on the loss function  $\mathcal{L}$  with learning rate  $\eta$  yields the weight update  $\Delta W$ . This update can be written as the outer products of the training examples  $\mathbf{x}_1, \dots, \mathbf{x}_n$  and the gradients of their corresponding outputs  $\mathbf{e}_i = -\eta \nabla_{W_0 \mathbf{x}_i} \mathcal{L}$

$$\Delta W = \sum_i \mathbf{e}_i \otimes \mathbf{x}_i^T \quad (1)$$

Thus the computation of the optimized linear layer can be formulated as

$$\begin{aligned} \mathcal{F}(\mathbf{x}) &= (W_0 + \Delta W) \mathbf{x} \\ &= W_0 \mathbf{x} + \Delta W \mathbf{x} \\ &= W_0 \mathbf{x} + \sum_i (\mathbf{e}_i \otimes \mathbf{x}_i) \mathbf{x} \\ &= W_0 \mathbf{x} + \sum_i \mathbf{e}_i (\mathbf{x}_i^T \mathbf{x}) \\ &= W_0 \mathbf{x} + \text{LinearAttn}(E, X, \mathbf{x}), \end{aligned} \quad (2)$$

where  $\text{LinearAttn}(V, K, \mathbf{q})$  denotes the linear attention operation. From the perspective of attention we regard training examples  $X$  as keys, their corresponding gradients as values, and the current input  $\mathbf{x}$  as the query.

### 2.2 Understanding Transformer Attention as Meta-Optimization

In this section we explain the simplified mathematical view of in-context learning as a process of meta-optimization presented in (Dai et al., 2023). For the purpose of analysis, it is useful to view the change to the output induced by attention to

the demonstration tokens as equivalent parameter update  $\Delta W_{\text{ICL}}$  that take effect on the original attention parameters.

Let  $\mathbf{x} \in \mathbb{R}^d$  be the input representation of a query token  $t$ , and  $\mathbf{q} = W_Q \mathbf{x} \in \mathbb{R}^{d'}$  be the attention query vector. We use the relaxed linear attention model, whereby the softmax operation and the scaling factor are omitted:

$$\begin{aligned} \mathcal{F}_{\text{ICL}}(\mathbf{q}) &= \text{LinearAttn}(V, K, \mathbf{q}) \\ &= W_V[X'; X] (W_K[X'; X])^T \mathbf{q} \end{aligned} \quad (3)$$

where  $W_Q, W_K, W_V \in \mathbb{R}^{d' \times d}$  are the projection matrices for computing the attention queries, keys, and values, respectively;  $X$  denotes the input representations of query tokens before  $t$ ;  $X'$  denotes the input representations of the demonstration tokens; and  $[X'; X]$  denotes the matrix concatenation.

They define  $W_{\text{ZSL}} = W_V X (W_K X)^T$  as the initial parameters of a linear layer that is updated by attention to in-context demonstrations. To see this, note that  $W_{\text{ZSL}}$  is the attention result in the zero-shot learning setting where no demonstrations are given (Equation 3). Following the reverse direction of Equation (2), you arrive at the dual form of the Transformer attention:

$$\begin{aligned} \mathcal{F}_{\text{ICL}}(\mathbf{q}) &= W_{\text{ZSL}} \mathbf{q} + \text{LinearAttn}(W_V X', W_K X', \mathbf{q}) \\ &= W_{\text{ZSL}} \mathbf{q} + \sum_i W_V \mathbf{x}'_i \left( (W_K \mathbf{x}'_i)^T \mathbf{q} \right) \\ &= W_{\text{ZSL}} \mathbf{q} + \sum_i (W_V \mathbf{x}'_i \otimes (W_K \mathbf{x}'_i)) \mathbf{q} \\ &= W_{\text{ZSL}} \mathbf{q} + \Delta W_{\text{ICL}} \mathbf{q} \\ &= (W_{\text{ZSL}} + \Delta W_{\text{ICL}}) \mathbf{q}. \end{aligned} \quad (4)$$

By analogy with Equation(2), we can regard  $W_K \mathbf{x}'_i$  as the training examples and  $W_V X'$  as their corresponding meta-gradients.

### 2.3 Linearization of a Model

Recent works suggest a function we optimize can significantly simplify by a method called linearization (Lee et al., 2019; Ortiz-Jimenez et al., 2023). Specifically, these works suggest that it is possible to approximate a pre-trained model in the vicinity of its initial parameters:

$$f_{\theta_0 + \delta\theta}(x) \approx f_{\theta_0}(x) + \delta\theta^T \nabla_{\theta_0} f(x) := f_{\delta\theta}^{\text{lin}}(x; \theta_0) \quad (5)$$

where  $\theta_0$  represents the pre-trained model's parameters,  $\delta\theta$  indicates the change in parameters during fine-tuning, and  $x$  denotes an input sequence (fixed

with respect to  $\delta\theta$ ). This is a linear model across deep representations, denoted as  $\phi_i(x) = \nabla_{\theta_0} f(x)$ . We don't require taking gradients through the entire network, just the coefficients. We then perform the following gradient step:

$$\theta \leftarrow \theta - \eta \nabla \mathcal{L}(f^{\text{lin}}(x), y) \cdot \phi(x)$$

In our work, we underscore the importance of exploring alternative approaches that enable the implementation of functions with reduced complexity when investigating ICL. This emphasis arises from the limitations imposed on the complexity of functions attainable through the forward pass, which must align with the network's depth. Therefore, we have explored a linearized variant of the model to address this constraint

### 3 Experiments

#### 3.1 Evaluation Datasets and Models

We evaluated our experiments on six datasets. **SST2** (Socher et al., 2013) **SST5** (Socher et al., 2013), **MR** (Pang and Lee, 2005) and **Subj** (Pang and Lee, 2004) are four datasets for sentiment classification; **AGNews** (Zhang et al., 2015) is a topic classification dataset; and **CB** (de Marneffe et al., 2019) is used for natural language inference. In our experiments, we use the same GPT-like pretrained language models used by (Dai et al., 2023) with 1.3B released by fairseq<sup>1</sup>.

#### 3.2 Evaluation Metrics

The following sections describe the evaluation metrics adopted from (Dai et al., 2023) to compare the behavior of ICL and finetuning.

**Attention Output Direction (SimAOU)** This metrics quantifies the similarity between two updates to the attention output of a layer with respect to the zero-shot setting. For a given query example, let  $h_X^{(l)}$  represent the normalized output representation of the last token at the  $l$ -th attention layer within setting  $X$ . The updates induced by ICL and finetuning are given by  $h_{\text{ICL}}^{(l)} - h_{\text{ZSL}}^{(l)}$  and  $h_{\text{FT}}^{(l)} - h_{\text{ZSL}}^{(l)}$ , respectively. The attention output similarity (**SimAOU**) is defined to be the cosine similarity between these updates averaged across all layers. A higher SimAOU score indicates that ICL is more inclined to adjust the attention output in the same direction as finetuning. For the sake of

comparison, this score is compared with a baseline of SimAOU with random attention output updates:  $h_{\text{rand}}^{(l)} - h_{\text{ZSL}}^{(l)}$  where  $h_{\text{rand}}^{(l)}$  is sampled uniformly.

**Attention Map Similarity** We use SimAM to measure the similarity between attention maps and query tokens for ICL and finetuning. For a query example, let  $m_X^{(l,h)}$  represent the attention weights before softmax in the  $h$ -th head of the  $l$ -th layer for setting  $X$ . In ICL, we focus solely on query token attention weights, excluding demonstration tokens. Initially, before finetuning, we compute the cosine similarity between  $m_{\text{ICL}}^{(l,h)}$  and  $m_{\text{ZSL}}^{(l,h)}$ , averaging it across attention heads to obtain SimAM (Before Finetuning) for each layer. Similarly, after finetuning, we calculate the cosine similarity between  $m_{\text{ICL}}^{(l,h)}$  and  $m_{\text{FT}}^{(l,h)}$  to obtain SimAM (After FT). A higher SimAM (After FT) relative to SimAM (Before FT) indicates that ICL's attention behavior aligns more with a finetuned model than a non-finetuned one.

#### 3.3 ICL Predictions Poorly Align with Finetuning

In this section we focus on the perspective of model predictions, regarding both ICL and finetuning as black-box updates to the original zero-shot prediction. While this analysis provides less insight into the inner workings of ICL, prediction alignment is easily interpretable and seems necessary for downstream applications of such comparisons.

Revisiting the results of (Dai et al., 2023), the authors find that ICL achieves high recall to finetuning (Rec2FTP) scores across multiple tasks, which means it covers most of the correct predictions of finetuning. However their results show a discrepancy between the accuracy of the finetuned model and the ICL setting, average difference of **19.38%** relative to the original zero-shot accuracy (Table 1).

We argue that Rec2FTP is insufficient to quantify prediction alignment in this setting because: (1) it does not the difference between the number of changes induced by each method; (2) it does not account for incorrect prediction changes. Figure 1 shows the number of prediction updates induced by each method. The results show that overall ICL is more inclined to change the ZSL prediction. Note that although ICL covers almost all FT correct prediction changes (high Rec2FTP), in most tasks unique FT and to ICL predictions constitute the majority of all updates. This observation shows

<sup>1</sup><https://github.com/facebookresearch/fairseq>

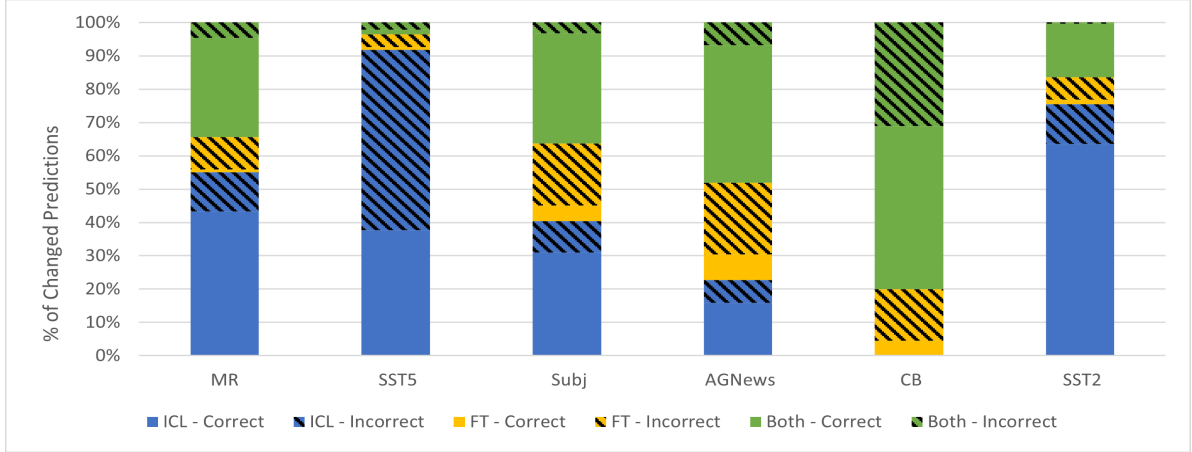


Figure 1: Partition of prediction changes with regards to the zero-shot setting induced by ICL and FT. For each task we evaluate both methods on the same validation set. Correct changes are examples that are misclassified in the ZSL setting and are correctly classified following the prediction update. incorrect changes are examples whose prediction is changed from the ZSL setting into an incorrect label.

	CB	SST2	SST5	Subj	MR	AGNews
ZSL Accuracy	37.5	70.5	39.3	72.6	65.9	46.2
FT Accuracy	57.1	74	39.4	77.8	72.6	66.7
ICL Accuracy	50	92.7	45.0	90.0	89.1	79.2
RPA (%)	80.0	16.4	3.4	36.2	34.0	48.0
RPA - Correct (%)	91.7	19.8	3.2	48.0	40.2	63.5
RPA - Incorrect (%)	66.7	1.8	3.5	10.2	17.7	19.2

Table 1: Validation accuracy and RPA scores for ZSL, finetuning, and ICL settings on all six classification datasets.

the importance of measuring incorrect prediction changes as well.

We propose a metric that respects these factors: **relative prediction alignment** (RPA) to quantify prediction alignment in this setting. Given a validation set, we denote the subset of example whose prediction is changed with regards to the zero-shot setting by ICL or FT by  $D_{ICL}$  and  $D_{FT}$  respectively. We define the RPA of these updates by:

$$RPA_{D_{ICL}, D_{FT}} = \frac{|D_{ICL} \cap D_{FT}|}{|D_{ICL}| + |D_{FT}| - |D_{ICL} \cap D_{FT}|}$$

We report the RPA scores across all tasks in table 1. For each we also compute the RPA scores computed over only for prediction changes to correct labels, and those for incorrect labels. The results show that correct prediction changes are more aligned between the two methods.

### 3.4 Layer Causality in Finetuning

In this section we highlight an intrinsic difference in information flow of attention output updates between standard finetuning and ICL.

1. **Layer Causality:** In ICL the update to the output of the  $l$ -th attention layer is dependent only on the output of previous (lower) layers. On contrast, the update to the  $l$ -th attention output induced by finetuning is determined by the gradient of the entire model’s trainable parameters.

2. **Sequential Update:** Equation 4 shows that in ICL each attention layer’s output is updated sequentially throughout the model’s depth axis. However, in GD based finetuning all layer’s parameters are updated in a single concurrent step.

Motivated by these observations we propose a layer causality aware finetuning method where each layer is updated individually. Specifically, we project the output of each layer into the label space using the pertained projection head and compute the cross-entropy loss of this prediction. We update each layer sequentially, regarding the previous layers output as constant.

	SST2	SST5	MR	Subj	AGNews	CB	Average
SimAOU (Random)	0.0016	0.0025	0.0008	0.0022	0.0021	0.0037	0.0021
SimAOU (FT)	0.1091	<b>0.113</b>	0.2190	0.1932	0.3053	0.2013	0.1901
SimAOU (Layer Casual FT)	<b>0.2297</b>	0.1065	<b>0.3299</b>	<b>0.3439</b>	<b>0.3213</b>	<b>0.3435</b>	<b>0.2791</b>
SimAM (ZSL)	0.5546	0.3913	0.3979	0.3786	0.1518	0.1524	0.3377
SimAM (Standard FT)	<b>0.5850</b>	<b>0.4047</b>	<b>0.4980</b>	<b>0.4870</b>	<b>0.4944</b>	<b>0.1875</b>	<b>0.4427</b>
SimAM (Layer Causal FT)	0.5774	0.4039	0.2919	0.2844	0.1201	0.0293	0.2845

Table 2: SimAOU and SimAM comparison of standard FT and layer causal FT across six classification datasets. Layer causal FT achieves higher SimAOU across 5 out of 6 tasks, yet its SimAM is significantly lower.

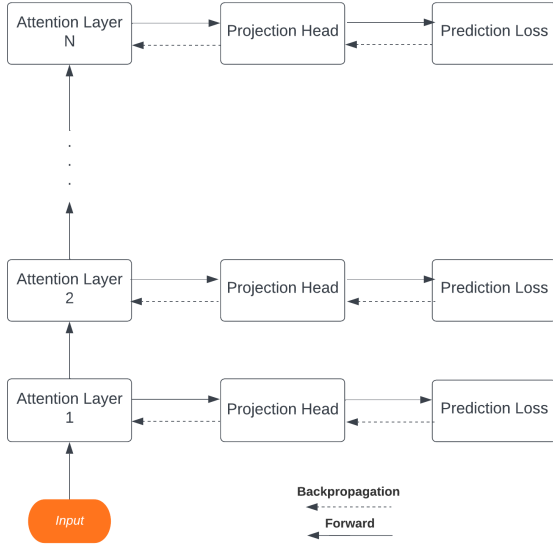


Figure 2: **Layer-Causal Finetuning:** The output of each layer is projected to the label space and used as an intermediate prediction. We compute the prediction loss of each intermediate layer sequentially.

We evaluate our method in comparison to standard finetuning using the experiments proposed by (Dai et al., 2023). Table 2 shows the SimAOU and SimAM measurements of both methods in comparison to ICL. Layer causal FT achieves higher SimAOU in 5 out of 6 tasks, but its SimAM is significantly lower.

We highlight two fallacies of our proposed method, and how they might have contributed to lower performance and SimAM scores.

- Lower layers in the models are not trained to directly produce predictions, thus our FT method causes significant drift from the original models learned weights.
- The gradients applied to lower layers have bigger magnitude in layer causal FT. During

pertaining the gradient of early layers is propagated throughout the model which usually dampens its norm.

We verify this hypothesis by comparing the norm of each attention layer’s gradient during the standard FT process and layer causal FT in figure 3.

Following this finding, we attempt to apply gradient clipping in the layer causal process with limited success. We report preliminary results using a manually selected clip value on the Subj task in table 3.

### 3.5 ICL Attention Update Expressiveness

We calculated SimAOU and SimAM for both original and linearized models. Results are shown in Table 4. In addition we were unable to evaluate the linearized model on the datasets AGNews and CB due to heavy memory consumption. The results indicate that the linearized model yields lower similarity scores compared to the original model but significantly higher scores than a random vector. This suggests that our hypothesis was incorrect and other simple model versions should be thought of. More on that in the discussion section.

## 4 Discussion

### 4.1 Differences Between Theoretical Analysis and Proposed Methods

Most works connecting ICL with meta-optimization methods are motivated by theoretical intuition, or even include rigorous analysis for simplified settings (Von Oswald et al., 2023; Akyürek et al., 2023) (see section 5). Our work aims to demonstrate such connections empirically, guided by intuition from the analysis provided in section 2.1. It is important to note the differences between this analysis and practical settings: (1) It assumes linear attention is used (2) The



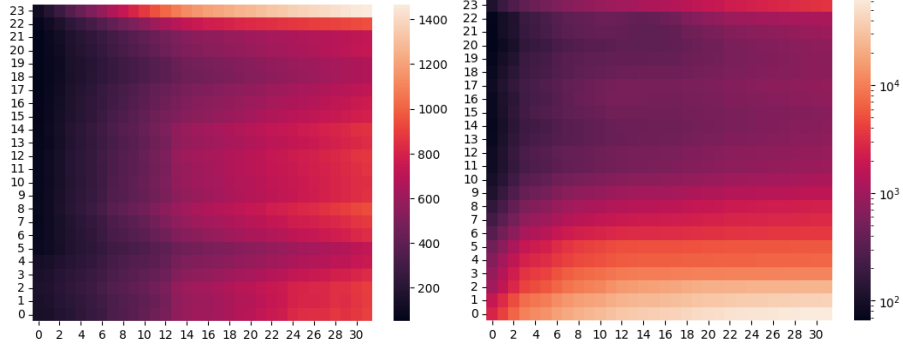


Figure 3: Heatmap of  $\ell_2$  norms of the gradients computed during finetuning on the Subj task. **Horizontal Axis:** training demonstration number. **Vertical Axis:** layer index in ascending order (from input to network output). **Left:** Standard FT. **Right:** Layer-Causal FT (norm magnitude in logarithmic scale).

	Subj
SimAUO (Standard FT)	0.1932
SimAUO (LC-FT Clipped)	<b>0.3480</b>
SimAM (ZSL)	0.3786
SimAM (Standard FT)	<b>0.4870</b>
SimAM (LC-FT Clipped)	0.4227

Table 3: Comparison of layer-causal finetuning with gradient norm clipping (clipped to 12.0 in  $\ell_\infty$  norm). This results show that even arbitrary clipping may resolve the drop in SimAM shown in table 2.

analysis applies to the update of a single layer (3) Starting from the ICL dual view, we get a partial-differential equation for the underlying loss function whose true value seems intractable. While the empirical results provide direction for future research, we believe further analysis is need in order to gain more insight from such comparisons.

## 4.2 Limitations and Future Directions

The method and results shown in section 3.4 are inconclusive. We address its limitation using quantitative analysis, which suggests that further modifications may yield better similarity with ICL. We leave such work to future research.

## 5 Related Works

A series of recent works explores the similarities between ICL and gradient descent based optimization. (Akyürek et al., 2023) show that Transformer-based in-context learners can implement standard optimization algorithms on linear models implicitly. (Von Oswald et al., 2023) provide a construction that for a linear attention-only Transformers models that implicitly perform gradient descent like procedure. (Irie et al., 2022) rewrite the dual form of a linear perceptron in terms of query-key-value

attention, and use it to analyze how a trained model is affected by its training samples.

Different from these works, we base our study on (Dai et al., 2023) which study large GPT transformers on structured language classification tasks. We study how different aspects of ICL can affect the results of the comparison made in (Dai et al., 2023). On the prediction level, we introduce the RPA metric for evaluation of prediction level alignment. Furthermore, while (Dai et al., 2023) compare standard GD based finetuning, we test a novel layer causality aware finetuning process and finetuning over a linearized model from the perspective of expressiveness.

## 6 Conclusion

Inspired by recent works, we attempted to further explore the relationship between in-context learning and gradient descent based finetuning in practical settings. We revisit existing work and show that ICL and FT predictions are misaligned and propose a novel metric to better quantify this difference. Motivated by inherit differences in expressive power between ICL and FT, we explore whether a simpler variant of GD may show similar results - with insufficient results. Finally, we

	SST2	SST5	MR	Subj	Average
SimAOU (Random)	0.001	0.002	0.001	0.002	0.002
SimAOU (FT)	0.1091	<b>0.113</b>	<b>0.219</b>	<b>0.193</b>	<b>0.158</b>
SimAOU (FT Lin)	<b>0.122</b>	0.0789	0.171	0.148	0.130
SimAM (Before FT)	0.5547	0.3914	0.398	0.378	0.430
SimAM (After FT)	<b>0.585</b>	<b>0.404</b>	<b>0.498</b>	<b>0.487</b>	<b>0.493</b>
SimAM (After FT Lin)	0.573	0.403	0.448	0.449	0.468

Table 4: SimAOU and SimAM comparison of standard FT and FT using the linear approximation of the model.

address a fundamental difference in information flow between the methods, and suggest a novel FT method that respects layer causality. Our results show that this approach may better explain how ICL works, but we address its limitations and further required work.

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