Do Generalisation Results Generalise?

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Abstract

A large language model's (LLM's) out-of-distribution (OOD) generalisation is crucial to its deployment. Previous work assessing LLMs' generalisation performance, however, typically focuses on a single out-of-distribution dataset. This approach may fail to precisely evaluate the capabilities of the model, as the data shifts encountered during deployment are much more diverse. In this work, we investigate whether OOD generalisation results generalise. More specifically, we evaluate a model's performance across multiple OOD testsets throughout a finetuning run; we then evaluate the partial correlation of performances across these testsets, regressing out in-domain performance. This allows us to assess how correlated are generalisation performances once in-domain performance is controlled for. Analysing `OLMo2`, `OPT` and `SmolLM`, we observe no overarching trend in generalisation results: the existence of a positive or negative correlation between any two OOD testsets depends strongly on the specific choice of model analysed.

1 Introduction

A large language model's (LLM's) out-of-distribution (OOD) generalisation[1] performance is an essential property for its deployment in the wild. Not surprisingly, it has received increased attention from the community (Xu et al., 2021; Hupkes et al., 2023; Yang et al., 2023, 2024, 2025; Yuan et al., 2023; Ye, 2024). Most work evaluating generalisation, however, relies on a single out-of-distribution testset per task (Mosbach et al., 2023; Joshi and He, 2022; Bhargava et al., 2021).[2]

When a model achieves high scores on such an out-of-distribution testset, authors typically assume the model has found a good solution for the task and that the model does not rely on spurious features to solve it. There is, however, no *a priori* reason why a model which generalises in one OOD testset should also generalise in testsets created under different distribution shifts. Furthermore, Mosbach et al. (2023) show that generalisation performance can be quite unstable across training, reinforcing the need for its more precise assessment.

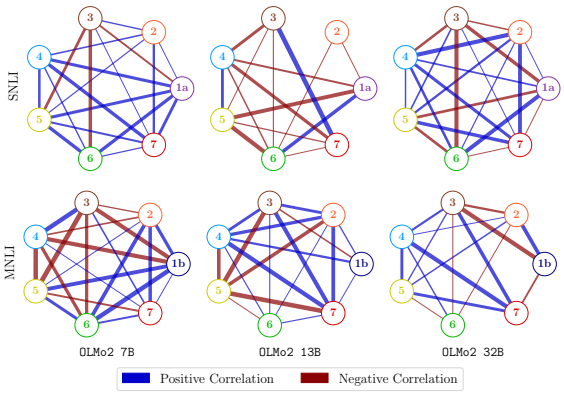

Figure 1: `OLMo2`'s partial OOD correlations on SNLI (top) and MNLI (bottom). No clear trends are observed. Edge thickness increases with absolute correlation value. Legend: `1a.MNLI`, `1b.SNLI`, `2.WNLI`, `3.SciTail`, `4.RTE`, `5.HANS`, `6.ANLI`, and `7.PAWS`.

In this paper, we investigate whether generalisation results generalise. To this end, we analyse how a model's generalisation performances in different OOD testsets correlate across a single finetuning run. However, generalisation performances are bound to be trivially correlated due to their dependency on a common factor: the model's in-domain performance. We control for that factor by computing **partial OOD correlations** instead, regressing out in-domain performance. These partial correlations quantify how strongly generalisation performances correlate beyond their dependence on in-domain performance.

Empirically, we show that whether generalisation performance will transfer across OOD testsets is a complex phenomenon. While a spe-

[1] Throughout this work, generalisation always refers to *out-of-distribution* generalisation.

[2] Two notable exceptions are discussed in §2.

cific model's generalisation performance may be strongly correlated across two OOD testsets, it might present negative correlations under another pair. Similarly, while two OOD testsets may present positive partial correlations under one model, they may present negative correlations under another. This large variance in generalisation performance highlights that fair generalisation evaluation must span multiple OOD testsets.

2 Evaluating OOD Generalisation

Robust generalisation beyond the training distribution has long been a challenge in natural language processing (NLP). In the quest to improve OOD generalisation, researchers face an important problem: how do we evaluate it in the first place?

How to evaluate OOD generalisation? Assessing generalisation performance is an intricate game of cat-and-mouse: as models tend to saturate on existing benchmarks, new ones are released to expose new weaknesses. McCoy et al. (2019), for instance, adversarially constructed an OOD testset (HANS) to reveal LLMs' reliance on superficial cues to solve a natural language inference (NLI) task. Similarly, Nie et al. (2020) constructed an OOD dataset (ANLI) in rounds to continually fool NLI models. Further, Liu et al. (2022) used models trained on MNLI (Williams et al., 2018) to generate their own synthetic (adversarial) datasets.

Do finetuned models generalise? Given all these benchmarks, we should have a good idea about how well language models generalise. However, the effect of finetuning on a model's OOD generalisation remains a little-understood topic. Kumar et al. (2022), for instance, show that finetuning models with randomly initialised classifier heads can lead to distorted features and hence poor generalisation. Recent empirical work (Mosbach et al., 2023; Yang et al., 2024), however, show strong generalisation of finetuned models on OOD data. Both these works, however, use pattern-based fine-tuning (Schick and Schütze, 2021) instead of a randomly initialised classifier head, being thus not directly comparable to the findings of Kumar et al.. A few prior works investigate multiple OOD testsets. E.g., Gupta et al. (2024) evaluate which OOD testsets still represent a challenge for finetuned models. Closest to our work is Sun et al. (2023), who compare the rankings achieved by finetuned models on a number of OOD testsets. More specifically, they compute the correlations across OOD testsets of the rankings achieved by several pretrained models when finetuned to perform NLI. Their analyses, however, do not control for either the models' in-domain performance, or the used pretrained models' size and quality. Instead, we will analyse partial correlations within each training run, controlling for both factors.

3 Measuring Generalisation Correlations

We aim to assess how robust generalisation results are to a specific choice of OOD testset. We can quantify this by analysing how correlated generalisation results are across testsets. Language models with better in-domain performance, however, are also likely to perform better out-of-domain (Yang et al., 2023). Naively computing OOD correlations, thus, is likely to mostly capture this trivial (and arguably uninteresting) source of correlation. To control for this, we measure **partial OOD correlations** instead: the correlation between two OOD performances once in-domain performance has been regressed out. How does this work in practice?

Let $p_{\boldsymbol{\theta}}$ be a language model, which we finetune on a specific (in-domain) training set. While finetuning this model, we measure its **in-domain performance**, denoted $s_t^{\texttt{ind}}$, on an in-domain testset at several checkpoints t; this gives us a vector of performances $\mathbf{s}^{\texttt{ind}}$. Simultaneously, we measure this model's **out-of-domain performance**, denoted $s_t^{\texttt{ood}:d}$, on several out-of-domain testsets, d, using the same checkpoints; getting a vector of performances $\mathbf{s}^{\texttt{ood}:d}$. If we simply wanted to examine the correlation between OOD performances, we would evaluate: $\texttt{corr}(\mathbf{s}^{\texttt{ood}:d_1}, \mathbf{s}^{\texttt{ood}:d_2})$.

Computing the partial correlation between two OOD datasets, however, requires regressing out in-domain performance. To do this, we train a regression model $f^d : \mathbb{R} \rightarrow \mathbb{R}$ for each OOD dataset d, which, given an in-domain performance measurement, predicts that checkpoints' OOD performance: $s_t^{\texttt{ood}:d} \approx f^d(s_t^{\texttt{ind}})$. Given this model, we compute a residual $e_t^d = s_t^{\texttt{ood}:d} - f^d(s_t^{\texttt{ind}})$, which quantifies how much better or worse a model performs on d than what would be expected given its in-domain performance. Doing this for all checkpoint steps t, we get a vector of residuals $\mathbf{e}^d$. Finally, we compute the **partial correlations** we are interested in as:

$$\rho^{d_1,d_2} = \texttt{corr}(\mathbf{e}^{d_1}, \mathbf{e}^{d_2}) \,. \tag{1}$$

Since our focus is on observing joint improvement,

Model	Size	MNLI							
		MNLI‡	SNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*81.6 ± 5.9*	72.7 ± 17.8	49.9 ± 0.7	65.8 ± 5.9	62.5 ± 2.1	51.7 ± 2.9	50.5 ± 0.5	46.3 ± 1.2
	6.7b	*84.7 ± 6.7*	83.7 ± 12.6	50.7 ± 1.8	70.7 ± 10.9	64.3 ± 1.0	55.5 ± 7.8	49.2 ± 1.9	47.3 ± 0.8
	13b	*87.3 ± 5.6*	83.9 ± 13.4	50.9 ± 2.6	71.3 ± 7.6	67.9 ± 1.6	57.0 ± 7.3	52.3 ± 1.5	48.5 ± 2.5
	30b	*89.0 ± 5.9*	86.8 ± 14.2	50.7 ± 1.1	**74.7 ± 3.2**	**71.2 ± 3.2**	59.3 ± 6.2	53.0 ± 1.0	48.6 ± 1.5
OLMo2	7B	*75.1 ± 1.9*	67.1 ± 15.8	55.7 ± 2.6	55.0 ± 8.1	63.1 ± 5.6	52.7 ± 2.2	55.7 ± 4.7	59.1 ± 5.9
	13B	*61.2 ± 1.5*	56.7 ± 5.9	52.4 ± 1.0	57.0 ± 4.8	54.0 ± 1.9	51.3 ± 2.5	50.9 ± 0.5	54.7 ± 2.5
	32B	*87.4 ± 12.0*	81.8 ± 24.8	**68.2 ± 12.5**	53.7 ± 9.5	69.2 ± 4.0	61.5 ± 7.4	**68.3 ± 5.4**	66.9 ± 2.6
SmolLM	3B	***93.7 ± 0.3***	**94.8 ± 0.6**	57.7 ± 1.3	52.6 ± 3.6	68.4 ± 3.5	**63.4 ± 0.2**	62.9 ± 1.1	**68.7 ± 2.2**
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 1: Accuracy on each OOD dataset for models trained on MNLI with 128 examples over 3 independent runs. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

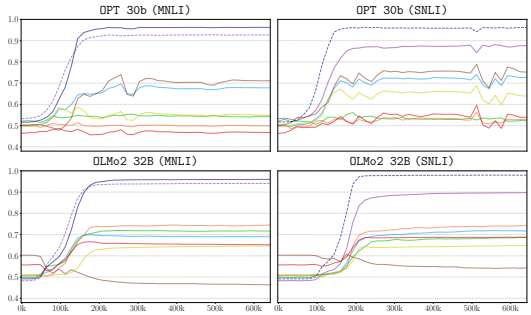

Figure 2: Accuracy (y-axis) across training steps (x-axis) of OPT (top) and OLMo2 (bottom) for a single finetuning run on MNLI (left) and SNLI (right). Legend: MNLI, SNLI, WNLI, RTE, SciTail, ANLI, HANS and PAWS.

we choose to capture simple linear correlations between these residuals, measuring Pearson's correlations as the $\texttt{corr}(\cdot)$ function. Throughout the paper, we present results using GAM regressors f^d.[3]

4 Experimental Setup

Task. We focus on natural language inference (NLI; Dagan and Glickman, 2004; Putra et al., 2024), as generalisation performance on this task has received considerable interest (Bhargava et al., 2021; Zhou and Tan, 2021; Mosbach et al., 2023; Gupta et al., 2024). NLI consists in determining the logical relationship between a pair of sentences. More specifically, each entry in this task consists of a pair of sentences, a premise and a hypothesis; the task is then to determine if the premise entails, contradicts, or is neutral about the hypothesis.

Models. We experiment with three different model families: OPT (Zhang et al., 2022), OLMo2 (OLMo et al., 2024) and SmolLM (Bakouch et al., 2025). We choose these models due to them being publicly available in multiple sizes, and due to their popularity in recent years for a broad range of NLP tasks. Beyond that, OPT also makes our experiments more easily comparable to previous work (e.g., Mosbach et al., 2023; Srinivasan et al., 2024). Following Mosbach et al. (2023), we finetune these models using: a few-shot setting, with 128, 64 and 32 examples; low-rank adaptation (LoRA; Hu et al., 2022); and pattern-based finetuning (Schick and Schütze, 2021; Gao et al., 2021), reusing the pretrained LM head instead of using a randomly initialised one. More details can be found in App. A.

Data. We select 8 different NLI datasets: **SNLI** (Bowman et al., 2015), **MNLI** (Williams et al., 2018), **SciTail** (Khot et al., 2018), **WNLI** and **RTE** (Wang et al., 2018), **PAWS** (Zhang et al., 2019), **HANS** (McCoy et al., 2019), **ANLI** (Nie et al., 2020). We finetune our models on either SNLI or MNLI and evaluate our model on the 7 other OOD datasets. More details can be found in App. B.

5 Results

Finetuned models don't generalise everywhere. Tables 1 and 2 (in App. D) present the generalisation of our evaluated models across all testsets. These tables present performances for a single checkpoint per model, where checkpoints were selected based on in-domain performance. Our results show that no testset is challenging for all models: every testset has at least one model that generalises successfully. Furthermore, it also shows that finetuning produces models that often perform well across a range of OOD testsets. However, for any given model, there is always at least one testset at which they underperform. For instance, the same OPT 30B checkpoints achieve 86.0% accuracy on MNLI, but 49.7% on PAWS.

[3] We experiment with both linear and GAM (Hastie and Tibshirani, 1986) regressors, but find this choice has only a minor impact on results. Fig. 7 shows in-domain vs. out-of-domain curves learned by our regressors. We place partial correlation results using linear regressors in Fig. 8 to 10 in App. D.

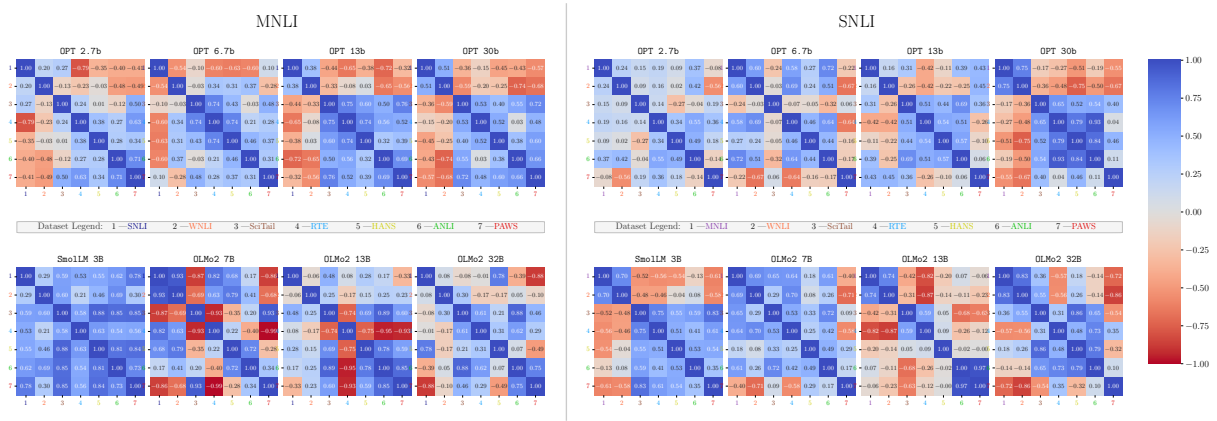

Figure 3: Partial correlations of OPT (top), SmolLM and OLMo2 (bottom) across model sizes (ordered from left to right) trained on MNLI (left) and SNLI (right). All these correlations are obtained by fitting a GAM regressor over 3 independent training runs. See a larger version of this plot in Fig. 11 (in App. D).

This variability highlights a key limitation of single-testset evaluations. Additionally, naïvely looking at Tables 1 and 2 (in App. D) might lead one to conclude that generalisation results are mostly robust: OPT 30B, OLMo2 32B and SmolLM 3B consistently achieve the best in-domain and out-of-domain performance across all setups. This conclusion, however, is not necessarily warranted, as both model size and in-domain performance act as strong confounders. We now look at how the generalisation performance of each of these models fluctuates throughout training, as a way to control for the effect of model size on results.

OPT's generalisation performance oscillates, but OLMo2's doesn't. Fig. 2 presents OPT 30B's and OLMo2 32B's OOD generalisation performances across training. (Results for smaller OPT and OLMo2 models are in Fig. 4, in App. D.) Overall, these figures reproduce one of the key results in Mosbach et al. (2023), showing that OPT's generalisation performance is unstable throughout training, presenting large (mostly unpredictable) oscillations. Interestingly, OLMo2's performance does not present the same oscillations. Perhaps more important for our research question though, we find that generalisation in some OOD testsets tracks the others; this is most obvious for the results of OPT 30B trained on SNLI. In-domain performance, however, also tracks OOD generalisation in these results—at least to some extent. Next, we thus move to analysing partial correlations as introduced in §3.

Improved generalisation in newer models As illustrated in Fig. 3 and Fig. 16 (in App. D), SmolLM not only outperforms previous generations in terms of accuracy (see Table 1 and Table 2) but also exhibits stronger correlations. These consistently higher correlations indicate that SmolLM possesses superior generalization capabilities and greater robustness against distribution shifts.

Generalisation's generalisation is complicated. Fig. 3 presents the partial correlations across OOD testsets for OPT, SmolLM and OLMo2 models. We observe that OOD generalisation is a highly complex property for which no clear trend emerges across testsets. While for a model two OOD testsets might present strong postive partial correlations, for another model this correlation might be negative. Additional intuition can also be drawn from Fig. 14 (in App. D), which shows that partial correlations do not seem to strengthen with model size or with a particular choice of training dataset; partial correlations for models finetuned on MNLI do not differ substantially from their corresponding SNLI counterparts. These findings underscore the importance of conducting a comprehensive evaluation when making claims about a model's generalisation capabilities, an often-lacking aspect in the current literature.

6 Conclusions

Our results highlight the need for generalisation research to rely on several OOD testsets to ensure fair evaluations. We do not observe clear trends when studying testset-to-testset performance correlations: no clear trends arise when comparing different training datasets, model families or sizes. In fact, the partial correlation of performances on a pair of OOD testsets seems to not be an intrinsic property even of the testset pair itself, depending on the specific model and training dataset considered.

Limitations

Due to limited compute resources, it was impractical for us to include models larger than 30B parameters in our analysis. However, it would be interesting to investigate if the inconsistent trends observed here would carry to other model families and to larger sizes. Additionally, we are not sure if our studied models (`OPT`, `OLMo2`, `SmolLM`) were exposed to the analysed testsets during pretraining.[4] We conducted preliminary experiments using `Min-k%++` (Zhang et al., 2025) and `Time Travel in LLMs` (Golchin and Surdeanu, 2024) to investigate such data contamination, but these experiments were inconclusive in most cases. Despite the negative results, though, our tests suggest that the models have not outright memorised the OOD testsets, which would allow them to trivialise the task. Finally, our experiments focus exclusively on NLI. This limitation results from the lack of dedicated OOD testsets for other tasks, making it difficult to study the extent to which our findings are NLI-specific.

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A Pattern-based finetuning details

Pattern-based finetuning requires us to specify an input pattern and define a mapping between the answer tokens and the actual labels (Schick et al., 2020). Our experiments with NLI use the following pattern:

```
{premise} Question: {hypothesis}
Yes or No?
```

The target tokens we consider are, respectively, '`_Yes`' for entailment and '`_No`' otherwise.[5]

B NLI Datasets

We use 2 main large-scale datasets for finetuning the models: **SNLI** (Bowman et al., 2015), which contains 570K crowdsourced sentence-pairs based on image captions; and **MNLI** (Williams et al., 2018), which is a set of 433K sentence-pairs meant to cover a large range of genres of spoken and written text. Compared to SNLI, MNLI offers more linguistic diversity and difficulty as it includes representative samples from 10 distinct genres of written and spoken English.We assessed the generalisation capacity of fine-tuned models using 6 NLI testsets. These comprise 3 adversarial datasets—designed especially to evaluate the models' robustness to heuristics—as well as 3 more standard NLI datasets with various but comparable input distributions:

- *Standard*: **SciTail** (Khot et al., 2018) is based on science multiple-choice exams, **WNLI** focuses on identifying the referent of a certain pronoun and **RTE** is a general entailment dataset. These last two are a part of the GLUE Benchmark (Wang et al., 2018).

- *Adversarial*: **PAWS** (Zhang et al., 2019) uses paraphrase adversaries, **HANS** (McCoy et al., 2019) tackles failure cases of 3 simple heuristics and **ANLI** (Nie et al., 2020) finds adversaries via human feedback.

To avoid inconsistencies that can result from different annotation policies among datasets, we removed the neutral-labeled samples, enabling us to more effectively separate the impacts of domain shifts on model performance, and guaranteeing a more consistent assessment framework.

[5]The underscores indicate a whitespace in the token. This is important to guarantee that the correct token-string representing this character-string is considered (Pimentel and Meister, 2024; Phan et al., 2024), which may impact prompting performance (Sanz-Guerrero et al., 2025).

C Resource Usage

We ran our experiments on various machines, depending on memory requirements. Small models were trained on 4x A5000 GPUs (with 24GB each), larger models were trained using 8x A6000 (with 48GB each) or 4x A100 (with 80GB). The total runtime for all the experiments presented here is of $5{,}500$ GPU hours.

D Detailed Results

D.1 Average Performance for other Few-shot Settings

		SNLI							
Model	**Size**	SNLI‡	MNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*94.2 ± 0.2*	78.6 ± 3.1	50.4 ± 0.5	74.1 ± 2.8	66.4 ± 0.7	51.4 ± 1.4	50.6 ± 1.1	50.6 ± 3.8
	6.7b	*94.3 ± 1.3*	78.2 ± 6.4	52.2 ± 0.6	68.8 ± 13.3	66.0 ± 0.9	54.9 ± 2.4	51.8 ± 3.1	49.5 ± 2.3
	13b	*95.3 ± 0.4*	82.0 ± 4.0	49.9 ± 0.4	70.2 ± 4.2	65.3 ± 1.3	53.4 ± 3.0	51.8 ± 1.0	48.6 ± 2.3
	30b	*96.1 ± 0.1*	86.0 ± 3.9	52.0 ± 1.4	**76.8 ± 2.3**	70.7 ± 2.5	58.8 ± 5.6	53.0 ± 1.3	49.7 ± 4.1
OLMo2	7B	*90.6 ± 5.0*	70.7 ± 11.3	59.3 ± 3.4	56.9 ± 4.3	61.0 ± 4.3	61.8 ± 3.1	56.3 ± 3.7	64.6 ± 3.9
	13B	*80.4 ± 2.3*	61.4 ± 2.8	54.9 ± 0.2	54.7 ± 2.7	55.8 ± 0.7	57.3 ± 3.2	52.3 ± 1.9	54.8 ± 1.7
	32B	***98.0 ± 0.1***	84.1 ± 5.1	**73.9 ± 1.0**	60.7 ± 5.8	70.9 ± 1.2	66.7 ± 2.7	**65.4 ± 2.6**	69.6 ± 0.9
SmolLM	3B	*97.3 ± 0.1*	**90.5 ± 2.5**	66.0 ± 2.2	62.6 ± 4.4	**73.9 ± 2.3**	**68.8 ± 2.3**	65.0 ± 1.7	**76.3 ± 0.8**
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 2: Accuracy on each OOD dataset for models trained on SNLI with 128 examples over 3 independent runs. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

		MNLI							
Model	**Size**	MNLI‡	SNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*67.2 ± 2.9*	59.4 ± 7.7	50.9 ± 0.3	59.6 ± 6.0	54.5 ± 2.1	51.7 ± 1.5	50.0 ± 0.9	48.3 ± 3.7
	6.7b	*74.4 ± 6.6*	66.7 ± 15.0	50.3 ± 1.2	63.8 ± 4.0	57.5 ± 4.7	54.5 ± 3.5	50.6 ± 0.6	50.6 ± 4.7
	13b	*79.7 ± 8.8*	75.6 ± 22.6	51.0 ± 1.7	**73.9 ± 3.1**	63.5 ± 4.2	55.0 ± 2.5	50.1 ± 2.2	50.7 ± 3.1
	30b	*82.9 ± 8.7*	75.0 ± 23.0	51.8 ± 2.1	63.1 ± 7.5	62.0 ± 2.4	57.5 ± 1.7	52.9 ± 1.7	48.7 ± 2.8
OLMo2	7B	*59.9 ± 3.2*	54.0 ± 3.8	50.5 ± 0.1	52.1 ± 4.8	51.9 ± 1.5	51.0 ± 1.7	51.0 ± 1.7	54.2 ± 1.5
	13B	*56.3 ± 4.5*	52.4 ± 2.4	50.3 ± 0.6	57.0 ± 2.1	51.8 ± 1.0	51.6 ± 1.3	50.7 ± 2.1	51.4 ± 2.7
	32B	*82.5 ± 12.5*	76.6 ± 21.4	**64.9 ± 11.1**	55.5 ± 5.1	64.8 ± 9.4	60.4 ± 5.8	**64.1 ± 9.2**	64.2 ± 5.3
SmolLM	3B	***90.3 ± 0.3***	**92.2 ± 1.1**	61.4 ± 1.4	53.8 ± 2.1	**68.8 ± 1.8**	**68.1 ± 0.8**	63.5 ± 0.9	**70.1 ± 1.4**
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 3: Accuracy on each OOD dataset for models trained on MNLI with 64 examples. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

		SNLI							
Model	**Size**	SNLI‡	MNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*87.5 ± 6.2*	71.8 ± 5.8	51.7 ± 0.5	69.9 ± 4.5	59.0 ± 5.7	52.5 ± 1.0	50.4 ± 1.7	51.5 ± 4.2
	6.7b	*88.3 ± 4.7*	72.7 ± 9.0	52.7 ± 1.9	62.1 ± 16.5	61.4 ± 2.8	54.3 ± 2.8	51.3 ± 2.4	49.4 ± 2.9
	13b	*93.5 ± 0.9*	80.8 ± 4.7	50.6 ± 1.0	72.4 ± 5.1	66.1 ± 0.3	54.4 ± 3.9	49.9 ± 0.9	52.1 ± 5.1
	30b	*94.5 ± 1.3*	78.8 ± 4.2	54.1 ± 1.7	**76.3 ± 1.8**	67.2 ± 6.4	64.7 ± 4.0	51.6 ± 2.2	53.0 ± 4.9
OLMo2	7B	*70.3 ± 12.5*	56.3 ± 5.1	52.8 ± 0.9	52.3 ± 5.6	53.5 ± 1.6	52.4 ± 2.1	51.8 ± 0.7	56.7 ± 2.9
	13B	*59.7 ± 5.2*	54.5 ± 5.0	52.8 ± 1.0	54.7 ± 4.1	52.2 ± 0.3	53.6 ± 1.0	50.9 ± 0.4	52.4 ± 1.7
	32B	*92.7 ± 4.0*	72.1 ± 8.7	61.8 ± 7.2	61.0 ± 4.4	61.1 ± 3.6	60.7 ± 1.7	57.7 ± 4.4	61.7 ± 3.6
SmolLM	3B	***96.8 ± 0.1***	**88.5 ± 2.3**	**67.0 ± 2.0**	63.9 ± 6.4	**73.9 ± 1.6**	**70.2 ± 2.1**	**62.7 ± 2.1**	**75.2 ± 1.1**
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 4: Accuracy on each OOD dataset for models trained on SNLI with 64 examples. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

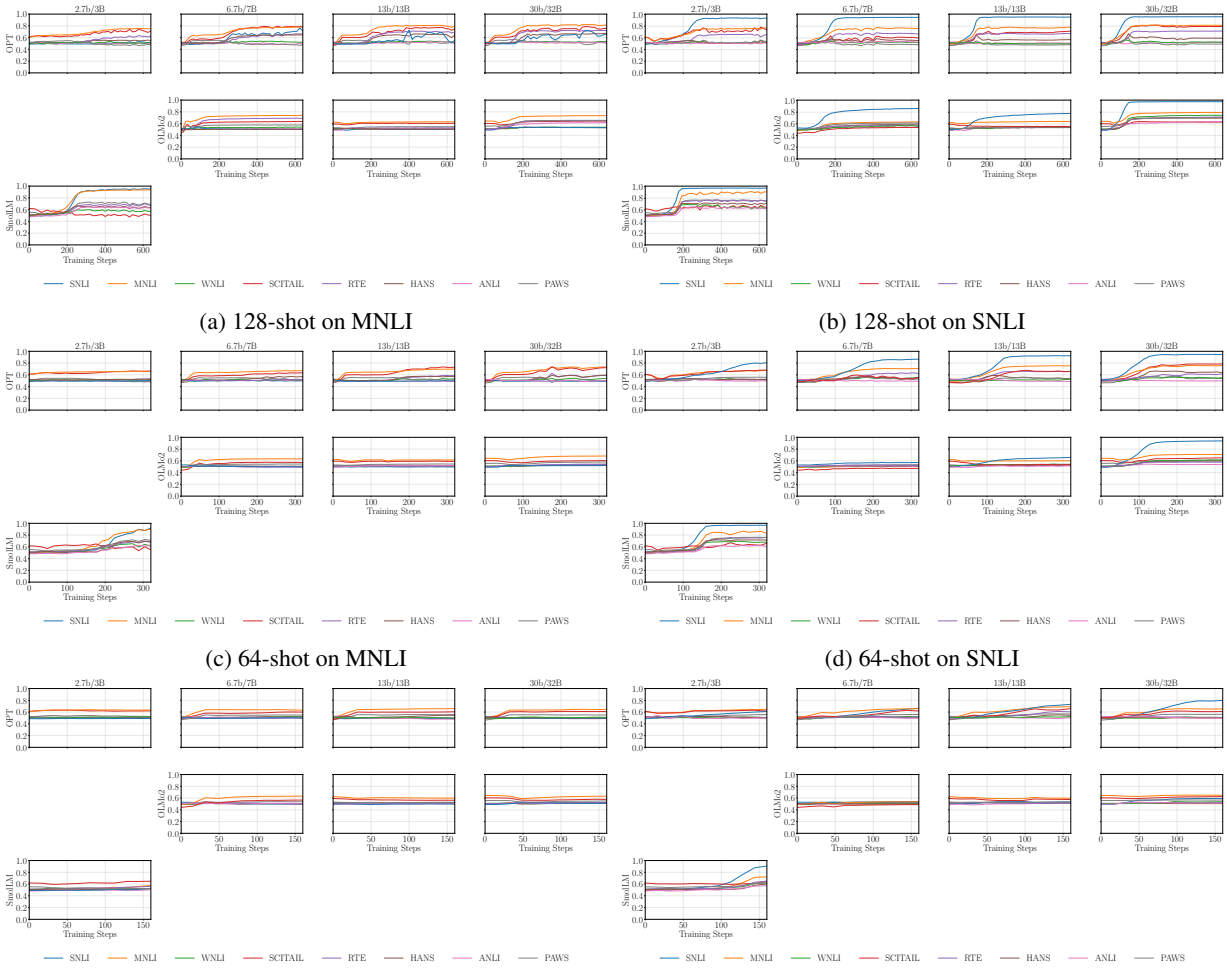
Model	Size	MNLI							
		MNLI‡	SNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*58.8 ± 4.6*	52.8 ± 4.4	51.4 ± 0.6	59.1 ± 4.2	52.0 ± 2.8	51.4 ± 0.3	50.3 ± 2.3	49.7 ± 4.3
	6.7b	*65.1 ± 6.9*	58.0 ± 9.3	50.4 ± 1.4	59.3 ± 1.1	52.7 ± 3.4	52.1 ± 1.2	51.0 ± 2.0	51.4 ± 5.1
	13b	*68.1 ± 10.0*	59.6 ± 15.8	49.9 ± 0.3	**64.1 ± 6.4**	55.4 ± 8.0	53.4 ± 0.9	50.0 ± 1.9	52.1 ± 6.0
	30b	*68.2 ± 6.3*	**60.5 ± 15.3**	51.2 ± 0.5	57.5 ± 4.2	54.5 ± 4.6	52.3 ± 3.8	52.4 ± 3.2	52.9 ± 4.2
OLMo2	7B	*57.9 ± 4.7*	50.8 ± 1.6	50.7 ± 0.6	52.6 ± 3.9	51.0 ± 0.8	51.2 ± 0.6	50.9 ± 0.8	53.3 ± 0.4
	13B	*54.0 ± 5.5*	50.3 ± 0.5	51.4 ± 0.4	56.1 ± 0.7	52.0 ± 0.9	52.2 ± 0.5	48.6 ± 1.4	50.5 ± 1.7
	32B	***70.6 ± 7.5***	60.3 ± 8.4	**55.6 ± 4.2**	56.0 ± 1.9	**58.4 ± 6.0**	**55.0 ± 3.1**	**57.5 ± 5.1**	**58.8 ± 3.8**
SmolLM	3B	*58.5 ± 7.0*	53.4 ± 4.9	52.8 ± 1.1	59.4 ± 4.8	55.1 ± 3.1	52.0 ± 1.1	51.0 ± 0.5	55.2 ± 2.4
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 5: Accuracy on each OOD dataset for models trained on MNLI with 32 examples. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

Model	Size	SNLI							
		SNLI‡	MNLI	WNLI	SciTail	RTE	HANS	ANLI	PAWS
OPT	2.7b	*65.2 ± 5.1*	58.3 ± 5.9	51.2 ± 0.3	61.2 ± 6.3	52.1 ± 2.0	52.0 ± 1.6	51.3 ± 1.3	51.9 ± 3.2
	6.7b	*69.7 ± 3.8*	59.3 ± 6.3	51.4 ± 0.9	64.4 ± 6.7	54.0 ± 2.7	53.3 ± 1.4	50.3 ± 0.7	51.5 ± 4.3
	13b	*82.9 ± 9.3*	71.9 ± 2.7	51.6 ± 0.6	**66.4 ± 1.7**	62.7 ± 2.8	57.1 ± 4.0	50.2 ± 1.6	53.1 ± 3.2
	30b	*75.8 ± 8.2*	62.5 ± 8.5	51.4 ± 1.2	60.9 ± 10.9	54.5 ± 7.5	53.4 ± 5.5	50.8 ± 1.3	50.9 ± 4.9
OLMo2	7B	*56.7 ± 3.4*	53.6 ± 0.2	51.0 ± 0.6	49.3 ± 5.7	52.1 ± 0.3	49.9 ± 0.6	51.0 ± 0.9	53.1 ± 1.5
	13B	*52.6 ± 1.4*	52.7 ± 5.5	51.3 ± 0.3	56.8 ± 1.1	51.3 ± 0.4	52.5 ± 1.2	50.6 ± 0.4	52.3 ± 0.4
	32B	*67.7 ± 8.8*	59.0 ± 5.5	54.2 ± 3.8	61.5 ± 1.8	53.9 ± 1.5	52.6 ± 2.7	52.9 ± 1.2	57.0 ± 1.7
SmolLM	3B	***89.4 ± 7.4***	**77.4 ± 7.8**	**62.8 ± 3.8**	61.3 ± 3.3	**66.4 ± 5.6**	**66.0 ± 5.4**	**58.9 ± 4.4**	**66.2 ± 7.5**
Chance performance		50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0

Table 6: Accuracy on each OOD dataset for models trained on SNLI with 32 examples. Measurements are taken using the checkpoint with the highest in-domain performance. ‡ in-domain dataset.

D.2 Performance across Finetuning Runs



(a) 128-shot on MNLI

(b) 128-shot on SNLI

(c) 64-shot on MNLI

(d) 64-shot on SNLI

(e) 32-shot on MNLI

(f) 32-shot on SNLI

Figure 4: Few-shots results throughout a finetuning run on either MNLI or SNLI. OPT OOD performances (first rows) frequently oscillate during training; OLMo2 OOD performances (second rows) are relatively stable across training. SmolLM OOD performances (third rows) show generally stronger generalization capabilities. Legend: MNLI, SNLI, WNLI, RTE, SciTail, ANLI, HANS and PAWS

D.3 OPT's Partial OOD Correlation Graphs

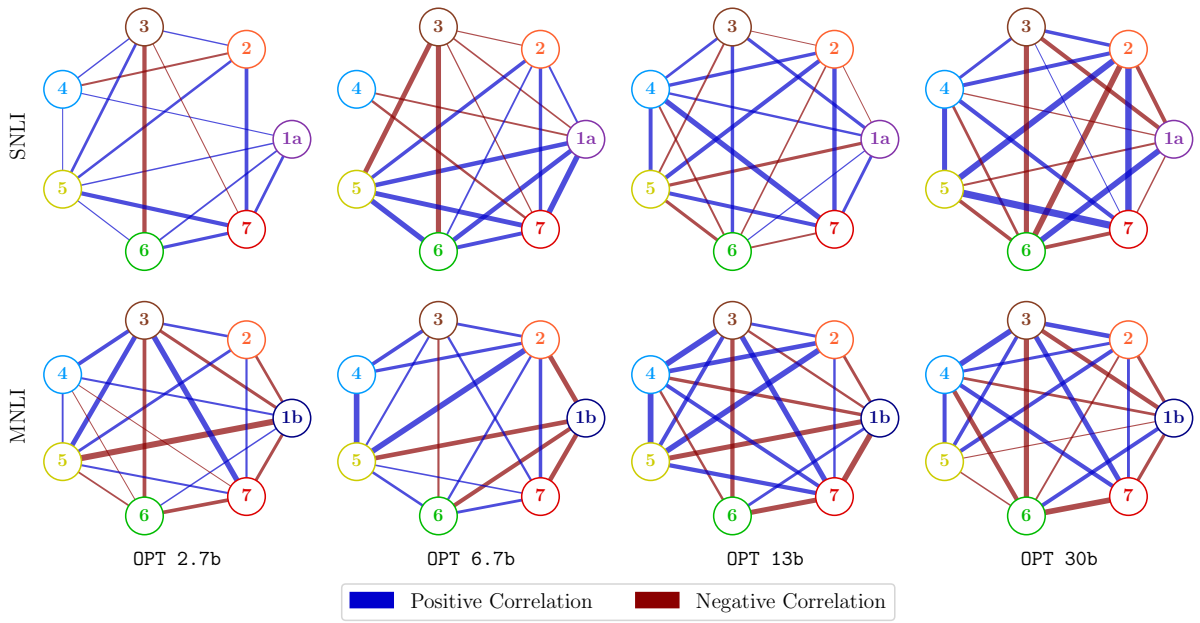


Figure 5: OPT partial OOD correlation graphs on SNLI (top) and MNLI (bottom). Edge thickness increases with absolute correlation value. Legend: 1a.MNLI, 1b.SNLI, 2.WNLI, 4.RTE, 3.SciTail, 6.ANLI, 5.HANS, and 7.PAWS

D.4 SmolLM's Partial OOD Correlation Graphs

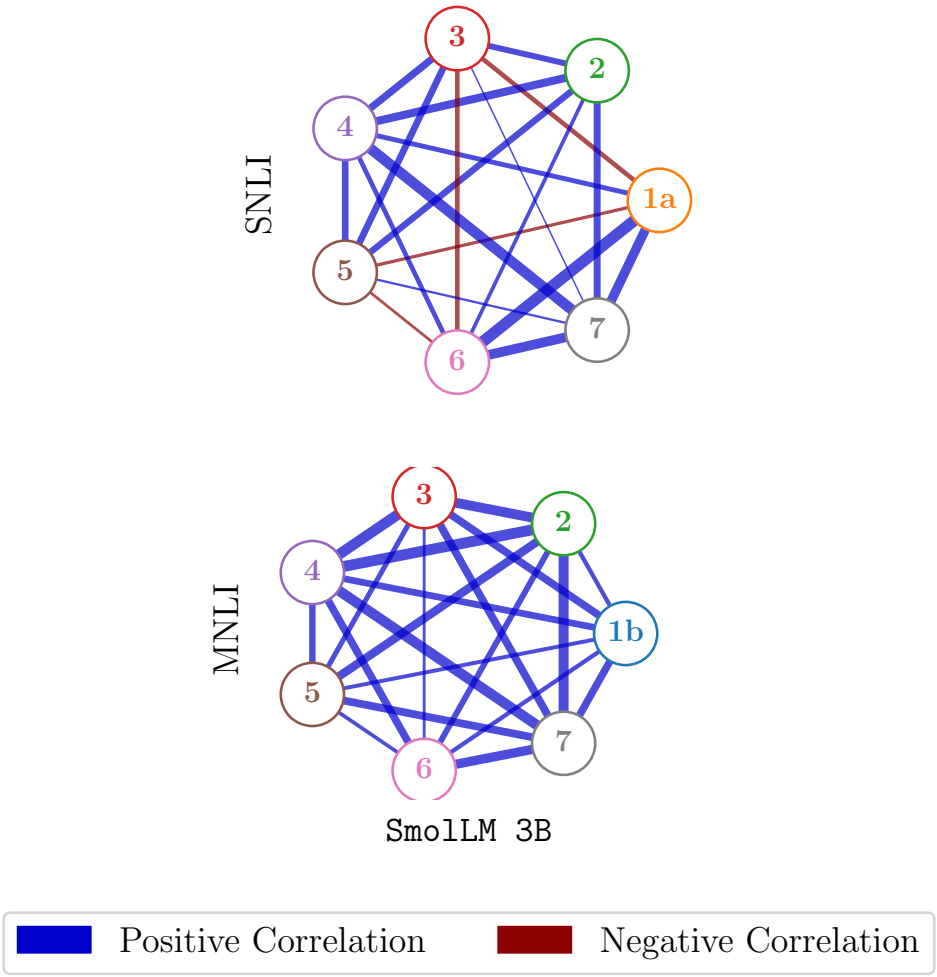


Figure 6: SmolLM partial OOD correlation graphs on SNLI (top) and MNLI (bottom). Edge thickness increases with absolute correlation value. Legend: 1a.MNLI, 1b.SNLI, 2.WNLI, 4.RTE, 3.SciTail, 6.ANLI, 5.HANS, and 7.PAWS

D.5 Fit of Regressors Used when Computing Partial Correlations

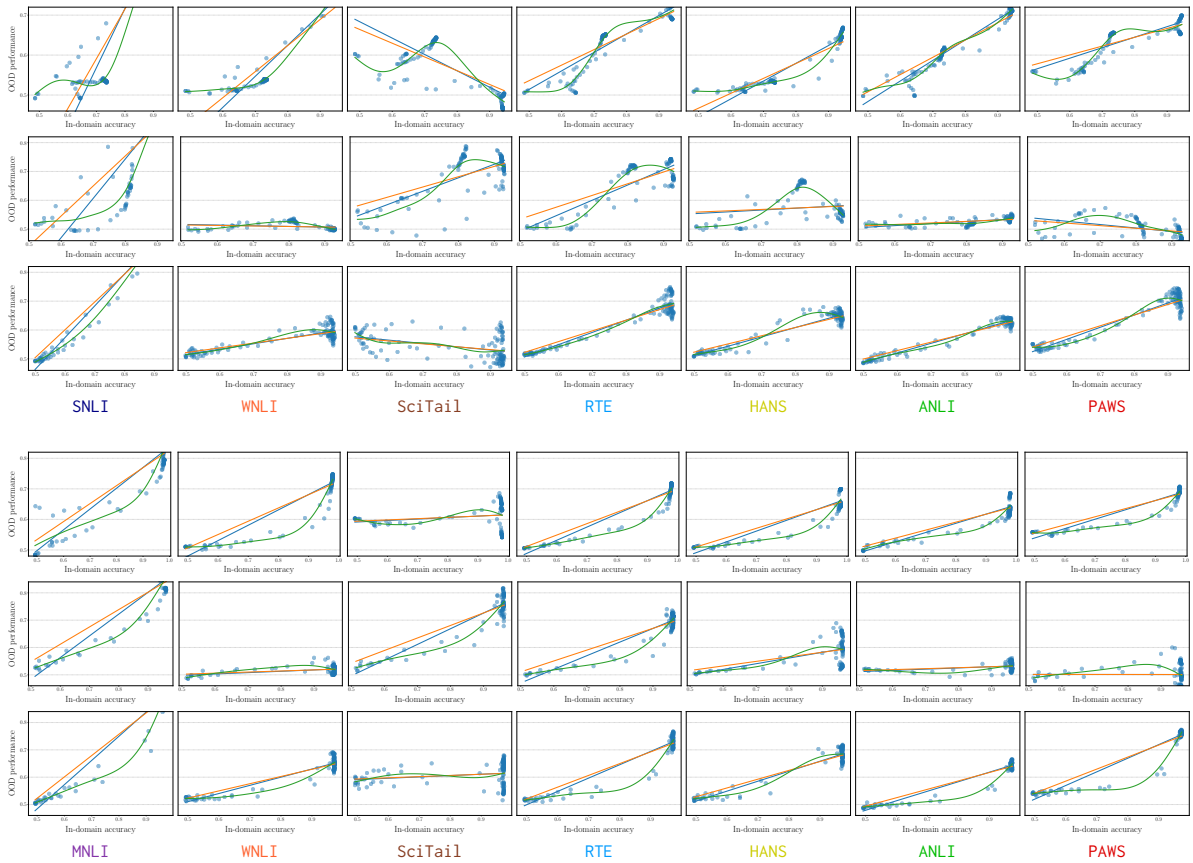


Figure 7: Regressors trained to predict OOD performance for 128-shots models. Models were finetuned on MNLI (top) and SNLI (bottom). Results for `OLMo2 32B` on first and fourth rows, `OPT 30B` on second and fifth rows, `SmolLM 3B` on third and sixth rows. Legend: `Linear`, `Ridge` and `GAM`.

D.6 Heatmaps with Partial OOD Correlations using Linear Regressors

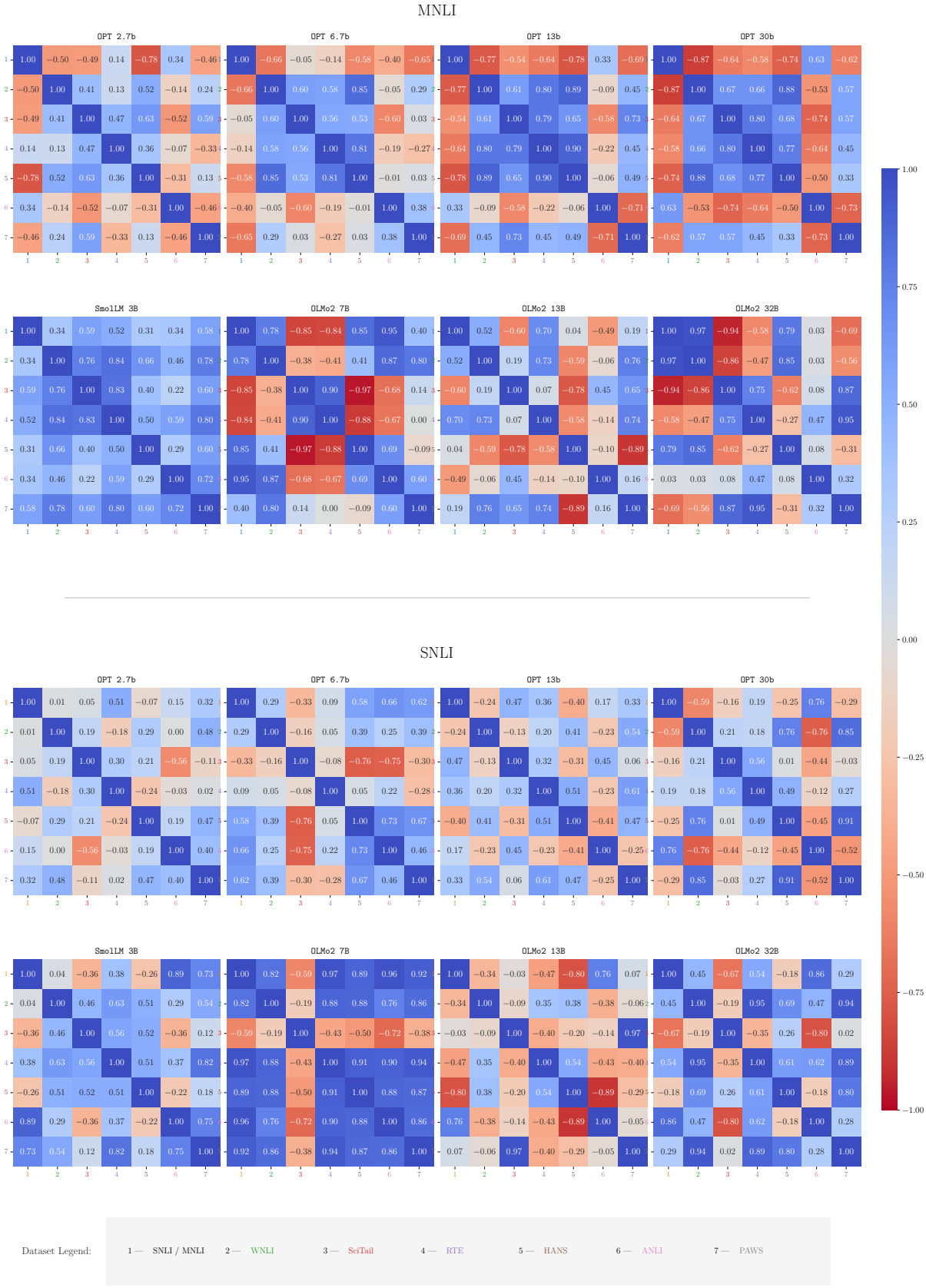


Figure 8: Partial correlations taken with linear regressors of OPT (first and third rows), SmolLM and OLMo2 (second and forth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 128-shots.

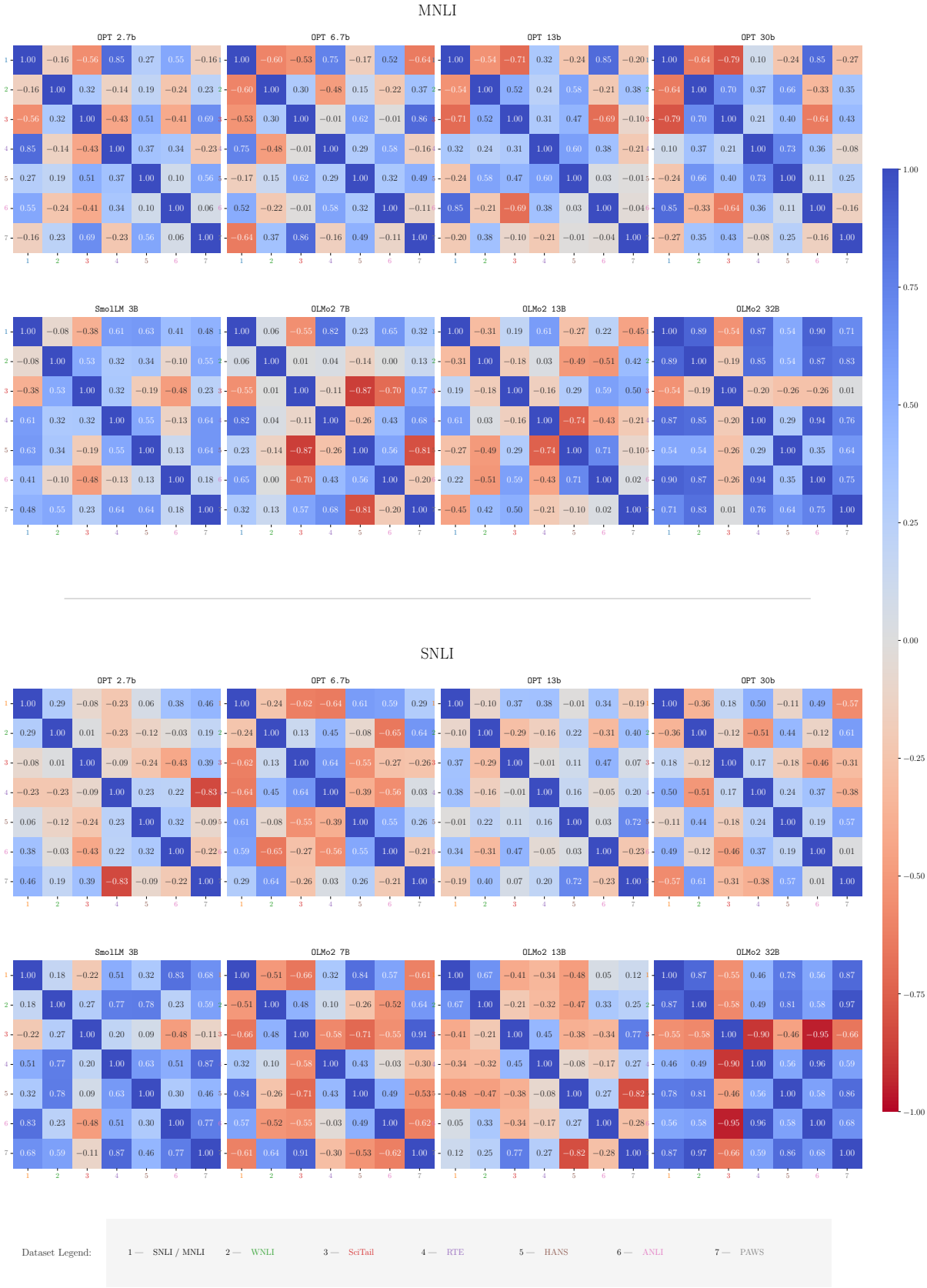


Figure 9: Partial correlations taken with linear regressors of OPT (first and third rows), SmolLM and OLMo2 (second and forth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 64-shots.

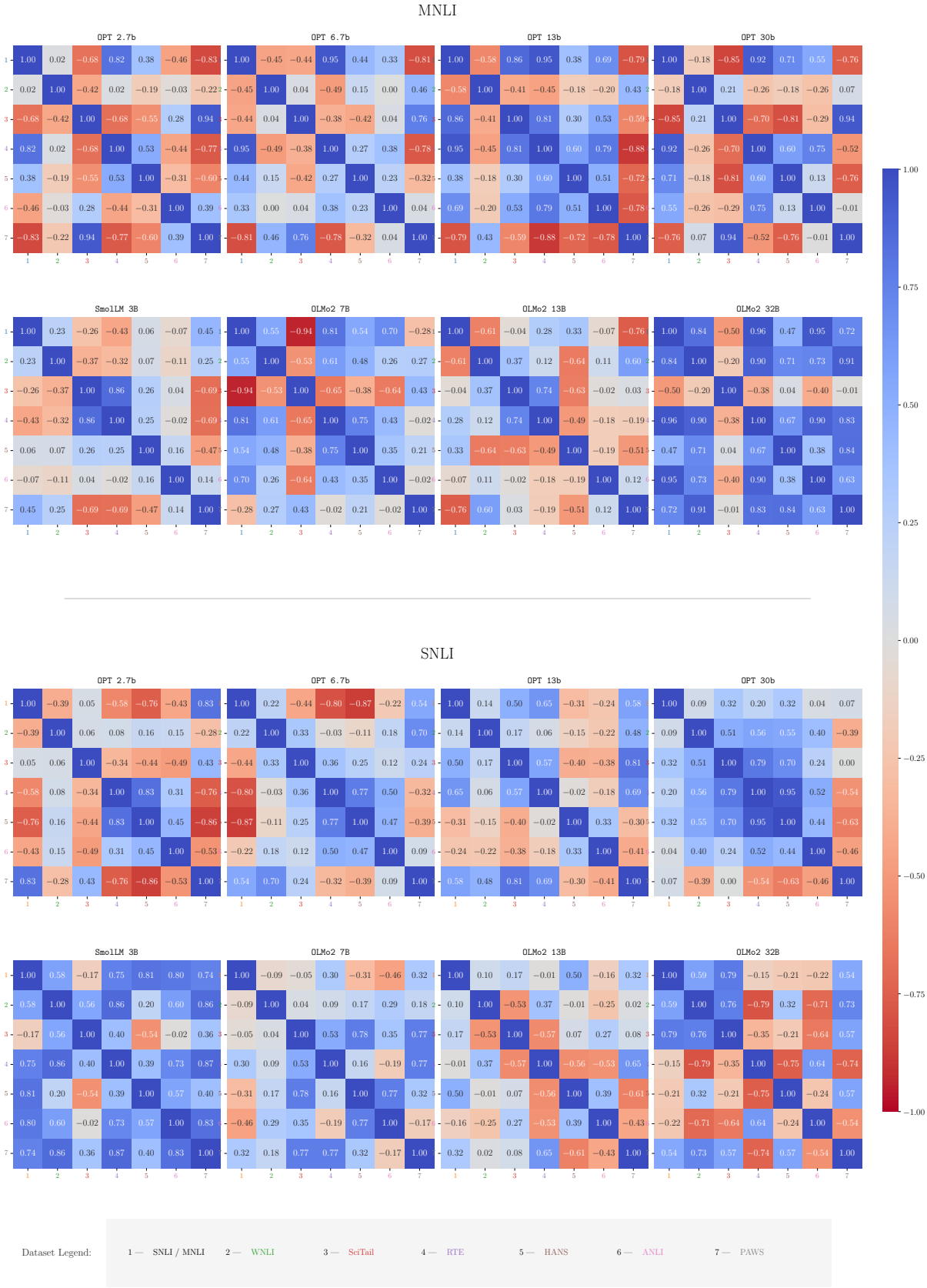


Figure 10: Partial correlations taken with linear regressors of OPT (first and third rows), SmolLM and OLMo2 (second and forth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 32-shots.

D.7 Heatmaps with Partial OOD Correlations using GAM Regressors

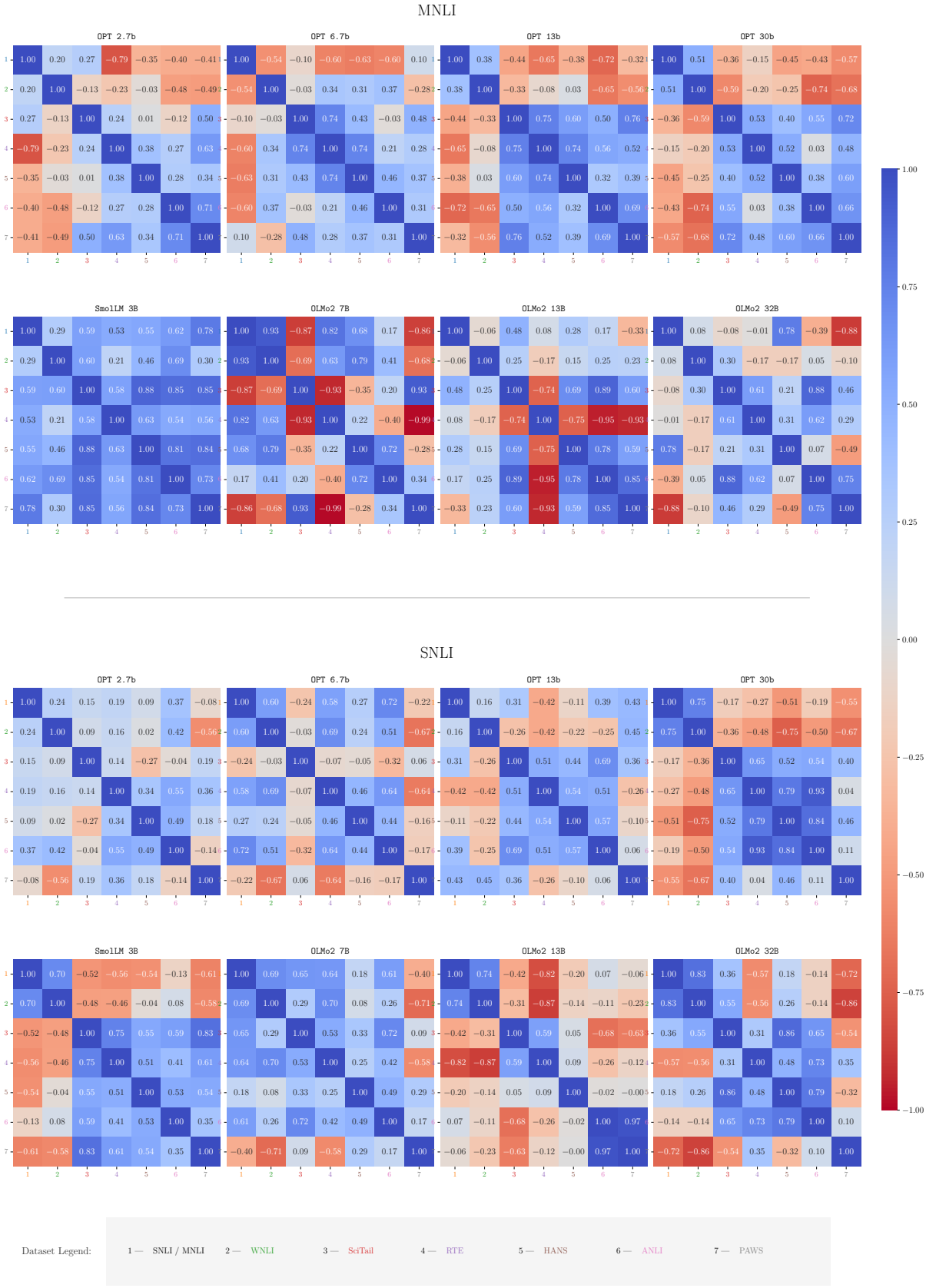


Figure 11: Partial correlations taken with GAM regressors of `OPT` (first and third rows), `SmolLM` and `OLMo2` (second and forth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 128-shots.

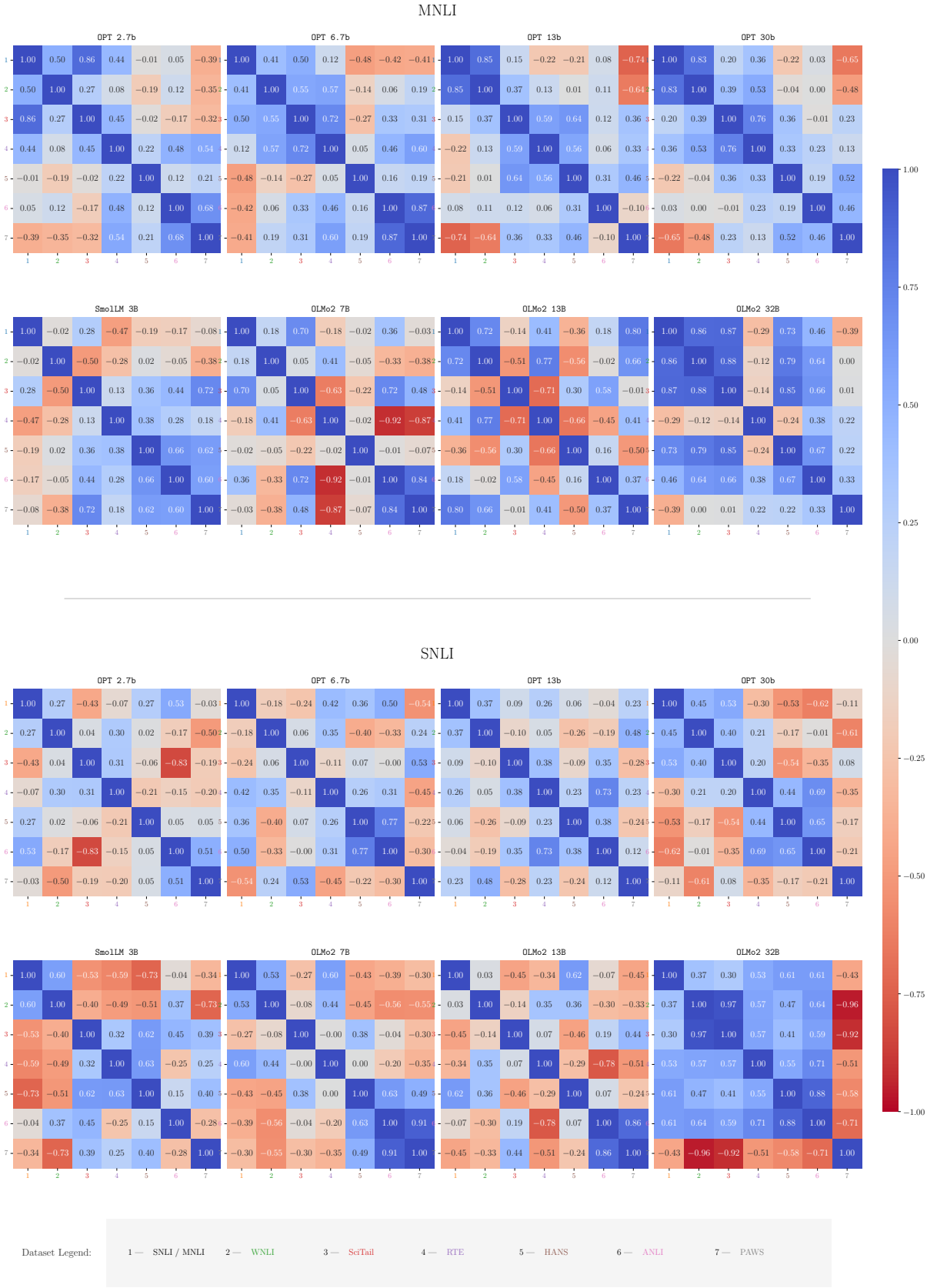


Figure 12: Partial correlations taken with GAM regressors of OPT (first and third rows), SmolLM and OLMo2 (second and fourth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 64-shots.

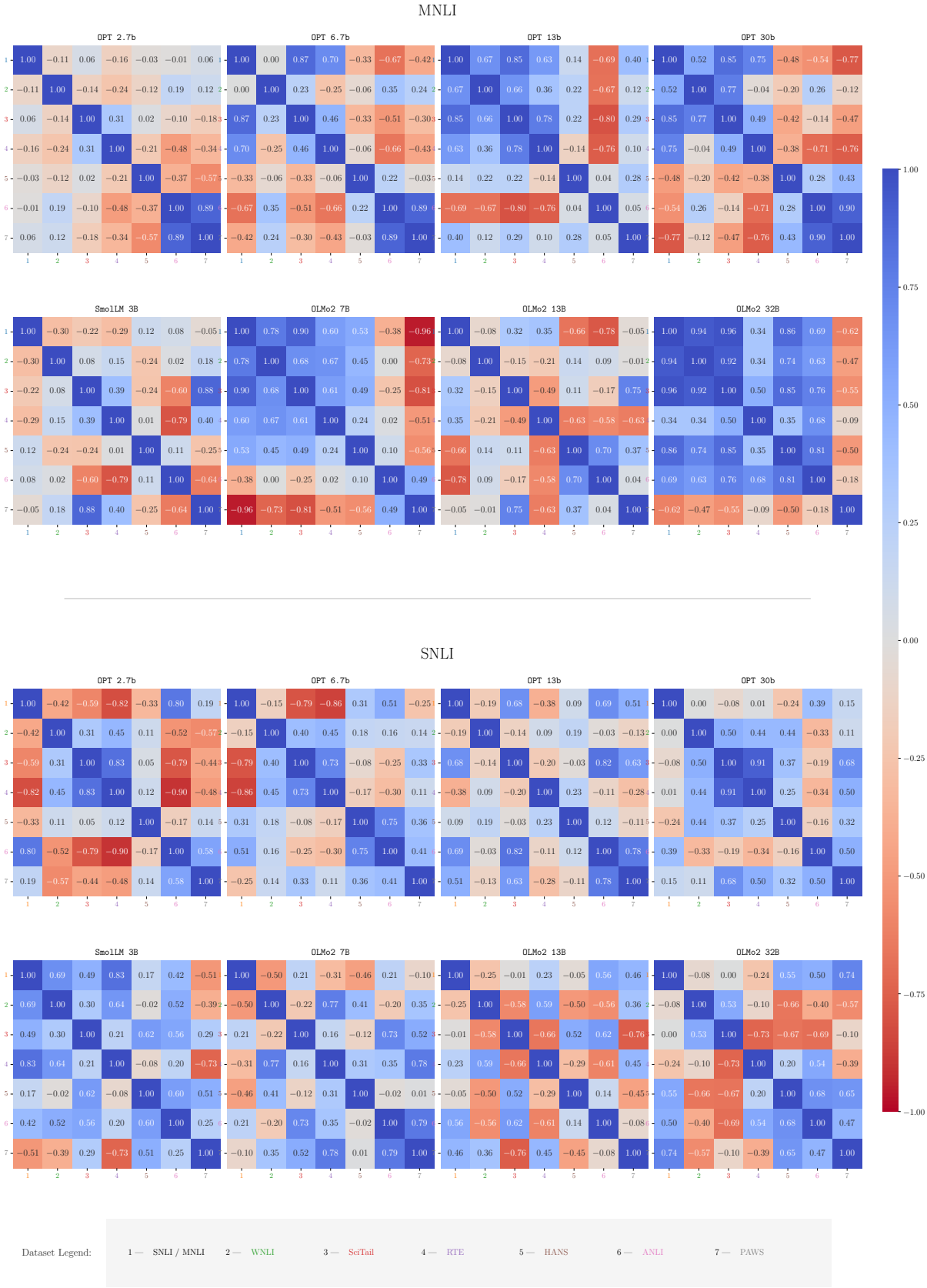


Figure 13: Partial correlations taken with GAM regressors of OPT (first and third rows), SmolLM and OLMo2 (second and fourth rows) across model sizes (ordered from left to right) trained on MNLI (top) and SNLI (bottom). Models were fine-tuned with 32-shots.

D.8 Average Correlations across Model Sizes

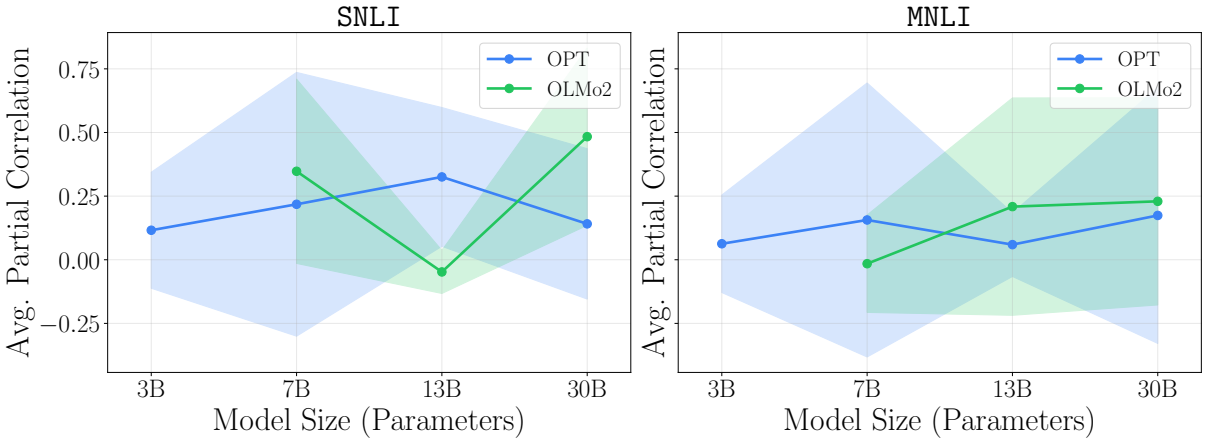


Figure 14: Partial correlations averaged across all OOD testset pairs for OPT and OLMo2 with different sizes.

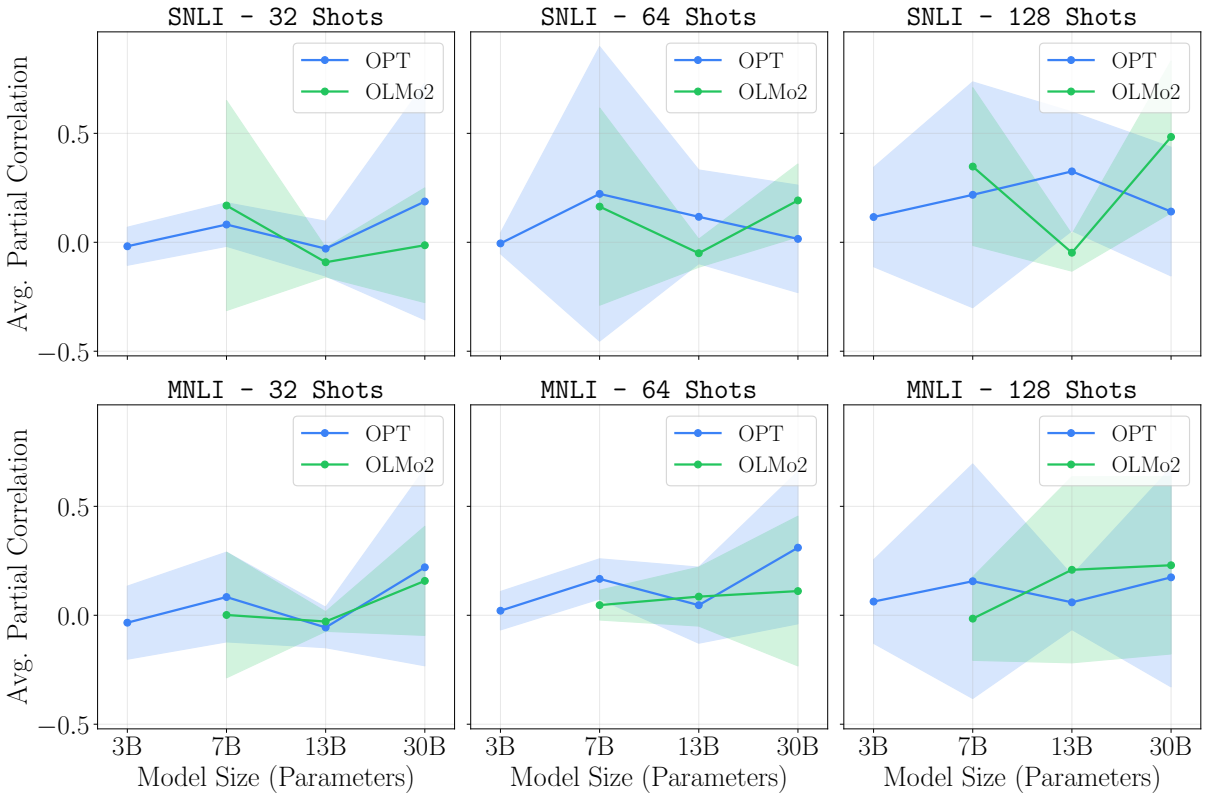


Figure 15: Average partial correlations across model sizes between OPT and OLMo2 generalisation results taken with GAM regressors.

D.9 Average Correlations Across Generations

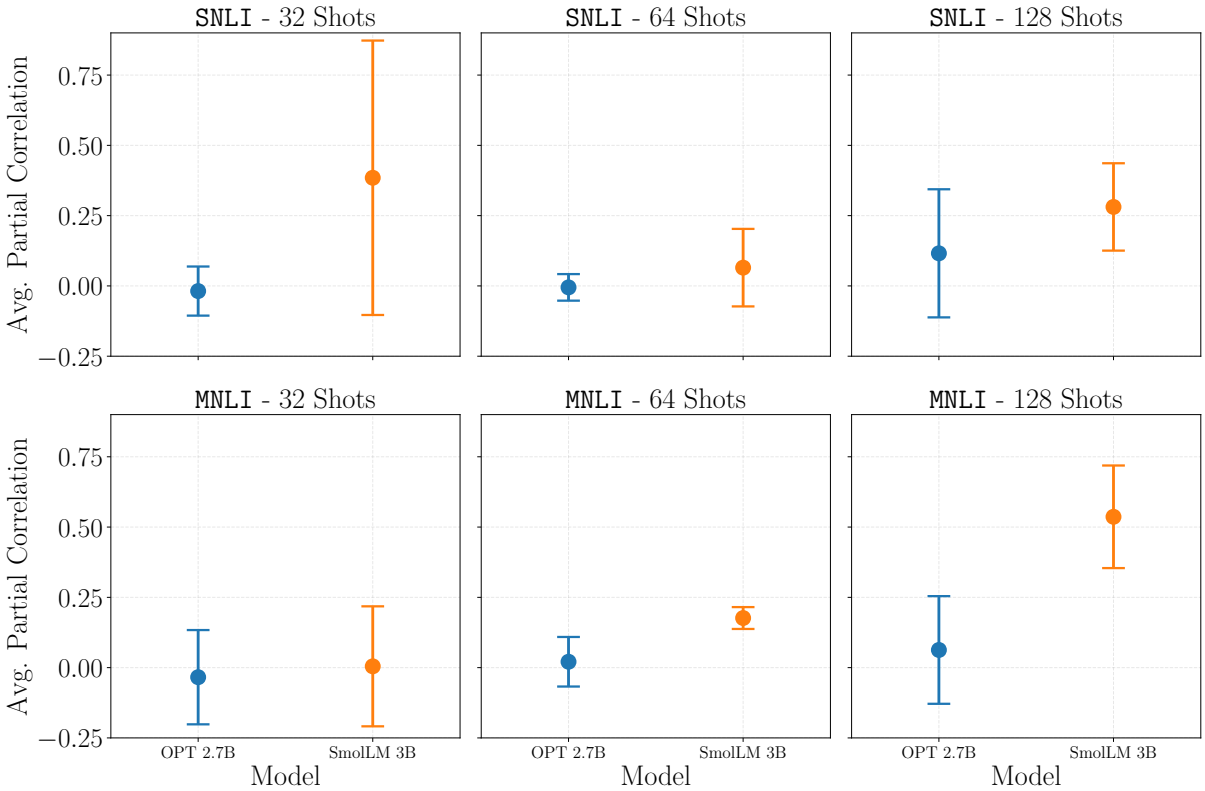


Figure 16: Average partial correlations across generations comparing `OPT` and `SmolLM`. Across different training runs, `SmolLM` consistently demonstrates higher (positive) correlations, indicating stronger robustness to distribution shifts.