MAPLE: Multilingual Evaluation of Parameter Efficient Finetuning of Large Language Models

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Abstract

Parameter efficient finetuning has emerged as a viable solution for improving the performance of Large Language Models without requiring massive resources and compute. Prior work on multilingual evaluation has shown that there is a large gap between the performance of LLMs on English and other languages. Further, there is also a large gap between the performance of smaller open-source models and larger LLMs. Finetuning can be an effective way to bridge this gap and make language models more equitable. In this work, we finetune the LLAMA-7B and MISTRAL-7B models on synthetic multilingual instruction tuning data to determine its effect on model performance on five downstream tasks covering twenty three languages in all. Additionally, we experiment with various parameters, such as rank for low-rank adaptation and values of quantisation to determine their effects on downstream performance and find that higher rank and higher quantisation values benefit low-resource languages. We find that parameter efficient finetuning of smaller open source models sometimes bridges the gap between the performance of these models and the larger ones, however, English performance can take a hit. We also find that finetuning sometimes improves performance on low-resource languages, while degrading performance on high-resource languages.

1 Introduction

Large Language Models (LLMs) show impressive performance on several tasks, sometimes even surpassing human performance. This has been attributed to the vast amounts of training data used during the pretraining phase, as well as various techniques used to align the models during the finetuning phase. Several variants of finetuning exist, including supervised finetuning (SFT) and instruction tuning (OpenAI, 2023), where the model is fine tuned with task specific data, or instructions on how to perform tasks. However, fine tuning all the parameters of the model can be expensive and time consuming, due to the increasing size of language models in recent years. Parameter Efficient Finetuning (PEFT) has emerged as a viable alternative to full finetuning (Chen et al., 2023).

Most studies on LLMs focus on training, finetuning and evaluating models in performing tasks in English. Recent work on comprehensive evaluation of LLM capabilities in non-English settings (Ahuja et al., 2023a) have shown that LLMs perform far worse on languages other than English. Studies that compare multilingual performance across different models (Ahuja et al., 2023b), show that there is a large performance gap between large, proprietary and closed models such as GPT-4 and PaLM2 and smaller open-source models like LLAMA-7B and MISTRAL-7B.

Parameter Efficient Finetuning (PEFT) Techniques like LoRA (Hu et al., 2022) have been shown to strengthen the multilingual capabilities of these open source LLMs (Zhao et al., 2024). Moreover, Adapters (Pfeiffer et al., 2020) have been proposed to boost the capabilities of language models to newer languages. Since full finetuning of models is not always feasible due to resource and compute constraints, exploring how far PEFT techniques can take us in boosting performance on non-English languages is a promising direction. Adoption of model quantisation techniques (Dettmers et al., 2022; yang Liu et al., 2023) has also made PEFT LLMs more accessible.

Not much work has been done on analyzing the impact of different choices, configurations and settings for PEFT on multilingual downstream tasks. In this work we aim to analyse how LoRA rank and quantisation affects the performance of finetuned models across 5 downstream tasks, covering 23 languages in all. We are interested in knowing whether multilingual PEFT can lead to reasonable gains in

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performance, or whether full finetuning of models is required. In addition, we also study the effect of multilingual finetuning on English performance.

Prior works have demonstrated that LoRA finetuning is the most effective PEFT out of existing techniques so far (Zhuo et al., 2024). Hence, we keep our study limited to analysing different LoRA and QLoRA (Dettmers et al., 2023) configurations to answer our research questions. Our contributions are as follows:

- We benchmark effects of various ranks and quantisation with LLAMA-7B and MISTRAL-7B models finetuned on MULTIALPACA dataset. We study efficacy of finetuning by comparing results with non-finetuned models of similar or larger sizes.
- We analyse the effects of % of trainable parameters and quantisation on 5 various tasks and 23 languages.
- We analyse the effects of multilingual PEFT on English performance to check for degradations due to forgetting.
- We present results and an analysis of trends across these models with directions for future research.

2 Related Work

Parameter Efficient Finetuning: Recently, Parameter Efficient Finetuning has gained significant attention in the NLP research community since full finetuning of large language models is prohibitively expensive for most organizations. Following early works on adapters (Houlsby et al., 2019; Pfeiffer et al., 2020), several finetuning techniques like LoRA (Hu et al., 2022), $(IA)^3$ (Liu et al., 2022a), P-Tuning (Liu et al., 2022b) and Prefix Tuning (Li and Liang, 2021) have been proposed. These techniques make the finetuning costs manageable by significantly reduce the number of trainable parameters during finetuning. Several works have used these techniques for efficient cross lingual transfer (Ansell et al., 2022), to tackle catastrophic forgetting (Vu et al., 2022) or compose multiple adapters (Pfeiffer et al., 2021) for multi-task performance.

Quantisation for Model Compression: Model quantisation is another way of reducing the overall memory footprint of the Large Language Model. While many popular LLMs (notably LLAMA-7B (Touvron et al., 2023) and MISTRAL-7B (Jiang et al., 2023)) are pre-trained with weights represented in 16 bit floating point numbers (Wu et al., 2020), it is shown that finetuning with lower quantisation yields similar performance. The most popular quantisation techniques – LLM:Int8() (Dettmers et al., 2022) and 4 bit (yang Liu et al., 2023) are usually combined with LoRA (Dettmers et al., 2023) to further reduce the memory footprint of LLM finetuning.

LLM Evaluation: Principled LLM evaluation has gained significant interest with demonstrations of increasingly complex abilities of LLMs (Brown et al., 2020; Cobbe et al., 2021; Wei et al., 2022; Shi et al., 2023) on various tasks. However, many evaluations are monolingual or English-only and multilingual evaluation of LLMs (Ahuja et al., 2023a; Asai et al., 2023; Ahuja et al., 2023b) remains a challenging problem. Past work by Ramesh et al. (2023) has evaluated the effects of model compression techniques such as quantisation, distillation and pruning on LLMs performance on downstream tasks, including in the multilingual setting.

3 Experiments

3.1 Setup

Finetuning Models: We finetune open source, multilingual LLMs on multilingual instruction finetuning datasets. We pick models that are pretrained on multilingual data as it would be unfair to compare English-only LLMs when finetuning on multilingual data. Specifically, we explore parameter efficient finetuning on LLAMA-7B (Touvron et al., 2023) and MISTRAL-7B (Jiang et al., 2023) models.

Finetuning Dataset: We finetuned our models on MULTIALPACA dataset (Wei et al., 2023) for all our experiments. MULTIALPACA is a self instruct dataset which follows the same approach as (English-only) ALPACA dataset (Taori et al., 2023) by translating seed tasks to 11 languages and then using GPT-3.5-turbo for response collection. The languages included in the dataset are Arabic, German, Spanish, French, Indonesian, Japanese, Korean, Portuguese, Russian, Thai and Vietnamese.

Finetuning Techniques: We follow the LoRA (Dettmers et al., 2023; Hu et al., 2022) finetuning recipe for each finetuning run. We finetune models on various ranks and quantisations, specifically LoRA Ranks 8, 16, 32, 64 and 128, and 4bit, 8bit and 16bit quantisation.

3.2 Evaluation

We evaluate multilingual capabilities of our finetuned models on three classification tasks and two Question Answering benchmarks. We use prompts that are similar to those used in the MEGA benchmarking study (Ahuja et al., 2023a) but adapted to the Alpaca-style (Taori et al., 2023) instruction format. We study the impact of multilingual finetuning on English capabilities using Alpaca Eval (Li et al., 2023). We use lm-eval-harness (Gao et al., 2021) for the evaluations. LM-Evaluation-Harness is a unified framework for few shot evaluation of language models. This framework standardises the inference and few shot example selection pipeline across tasks and models. We created the task configurations from MEGAVERSE with the Alpaca-style prompt template.

The datasets that we use for evaluation are as follows:

XNLI: The XNLI (Cross-lingual Natural Language Inference) dataset (Conneau et al., 2018) is an extension of the Multi-Genre NLI (MultiNLI) corpus to 15 languages. The dataset was created by manually translating the validation and test sets of MultiNLI into each of those 15 languages. The English training set was machine translated for all languages. The dataset is composed of 122k train, 2490 validation, and 5010 test examples. XNLI provides a robust platform for evaluating cross-lingual sentence understanding methods. We evaluated our models on the test split with 4 in-context examples sampled from the validation split. We report our results in Table 3 and 4.

XCOPA: The XCOPA (Cross-lingual Choice of Plausible Alternatives) dataset (Ponti et al., 2020) is a benchmark for evaluating the ability of machine learning models to transfer commonsense reasoning across languages. It is a translation and re-annotation of the English COPA dataset (Roemmele et al., 2011) and covers 11 languages from 11 families and several areas around the globe. The dataset is challenging as it requires both the command of world knowledge and the ability to generalize to new languages. We evaluated our models on Estonian, Thai, Italian, Indonesian, Vietnamese and Southern Quechua. We evaluated our models in the 4 shot setting similar to XNLI. We report our results in Table 5 and 6.

Belebele: Belebele (Bandarkar et al., 2023) is a multiple choice machine reading comprehension (MRC) dataset parallel across 122 languages. Each question is linked to a short passage from the FLORES-200 dataset (Team et al., 2022). The human annotation procedure was carefully curated to create questions that discriminate between different levels of language comprehension. We evaluated German, English, Spanish, French, Italian, Japanese, Portuguese, Chinese Simplified. All models are evaluated on 50% of the test split due to resource constraints. We evaluated our models in the zero-shot setting and report results in Table 7 and 8.

MLQA: MLQA (Lewis et al., 2020) is a multilingual question answering dataset designed for cross lingual question answering. It contains 5K extractive question answering instances. It consists of 7 languages i.e. English, Arabic, Vietnamese, German, Spanish, Hindi and Simplified Chinese. We evaluated our finetuned models for 10% of the test set for interest of time. The evaluation uses a 4 shot setting similar to that of XNLI. We report our results in Table 9 and 10.

XQuAD: The XQuAD (Cross-lingual Question Answering Dataset) (Artetxe et al., 2020) is a benchmark dataset for evaluating cross-lingual question answering performance. It consists of a subset of 240 paragraphs and 1190 question-answer pairs from the development set of SQuAD v1.1, along with their professional translations into ten languages: Spanish, German, Greek, Russian, Turkish, Arabic, Vietnamese, Thai, Chinese, and Hindi. As a result, the dataset is entirely parallel across 11 languages. This dataset provides a robust platform for developing and evaluating models on cross-lingual question answering tasks. For evaluation, we use a 4 shot setting similar to MLQA and evaluate on 10% of the test split. We report our results in table 11 and 12.

Alpaca Eval: Alpaca Eval (Li et al., 2023) is an LLM based automatic evaluator for instruction following models. It consists of around 800 instructions and corresponding responses obtained from (text-davinci-003) GPT3. The benchmark compares responses from GPT3 (or any other "oracle" model) with target (finetuned) model using another LLM (typically GPT4) as an evaluator. The evaluator LLM decides which response is better and overall win rate (higher the better) is computed for the target model. For our evaluation, we use the text-davinci-003 responses from the dataset as our

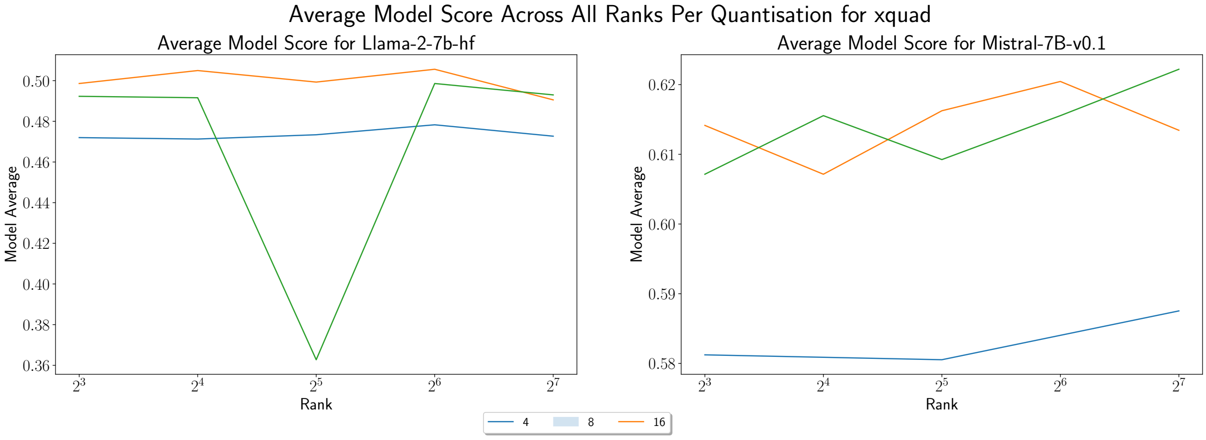

Figure 1: XQUAD Model Average Scores for Each Quantisation across Ranks

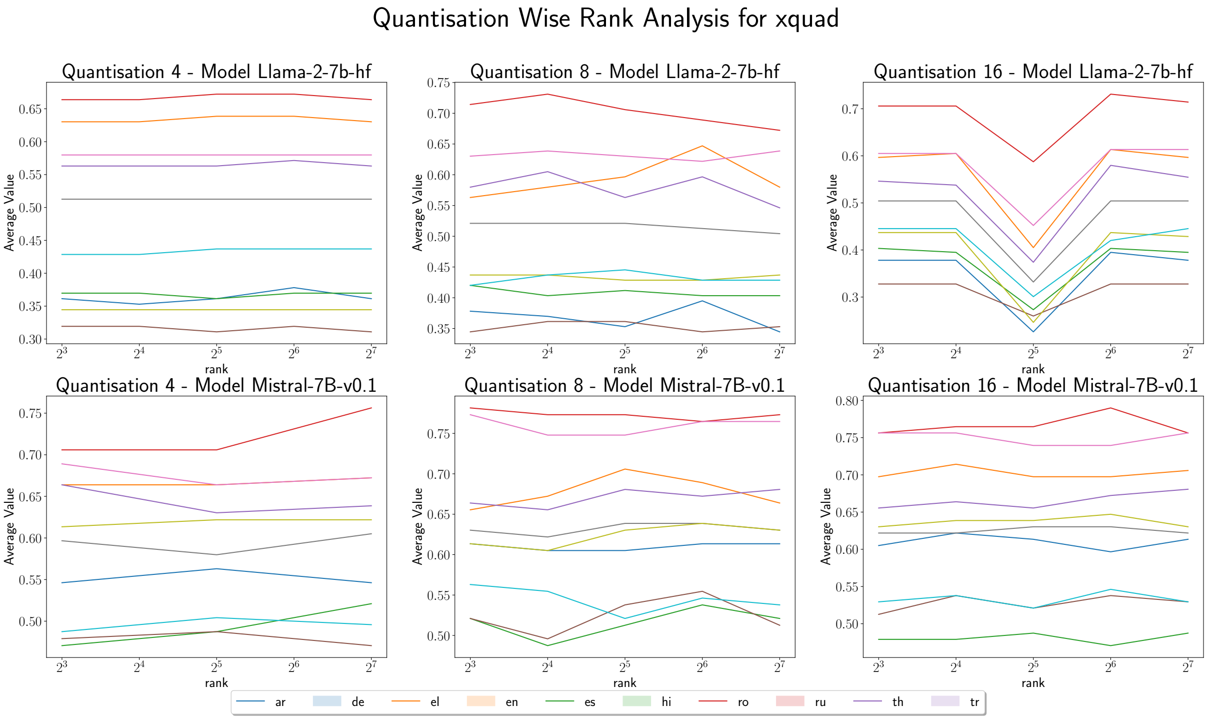

Figure 2: Language Wise XQUAD Model Average Scores for Each Rank across Quantisations

oracle/gold responses and use GPT4 (gpt-4-32k) as our evaluator. We report our results in Table 13 and 14.

4 Analysis of Results

RQ1: How does LoRA Rank and Quantisation Affect Model Performance? We observe that on an average, there is no particular trend of model performance on our tasks when it comes to increase in rank or quantisation. However, we can observe a consistently good score on an average when the models are finetuned on rank between 32 and 64 with 8 bit quantisation. 4 bit quantisation works well with lower ranks and 16 bit works well with higher ranks. We plot these findings in Figures 1, 8, 9, 10 and 11.

For XNLI, we observe there is no particular trend with increasing quantisation and rank. For XCOPA, we observe that 4bit quantisation does well with lower rank and 16bit quantisation works well with higher ranks. For Belebele, we observe that higher quantisation yields better results. For MLQA, we observe that higher rank and higher quantisation leads to best performance. In XQUAD, 8 bit quantization does well with rank 64 and 16 bit outperforms every other setting with rank 128. **Overall, it is always the best to finetune models with highest rank and quantisation if possible, however,**

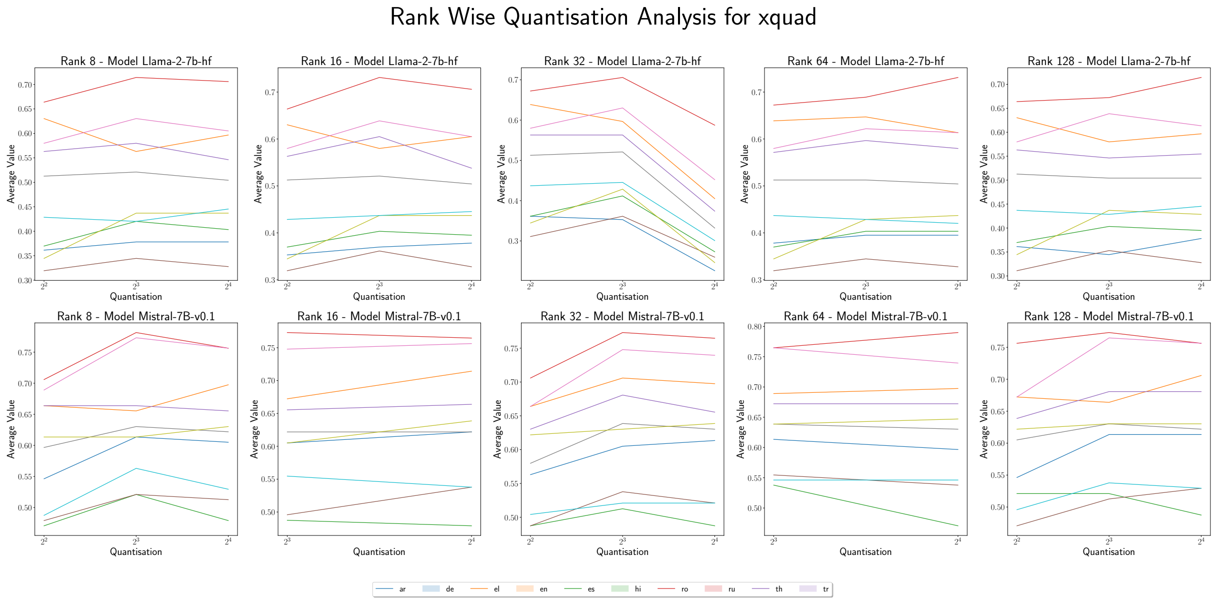

Figure 3: Language Wise XQUAD Model Average Scores for Each Quantisation across Rank

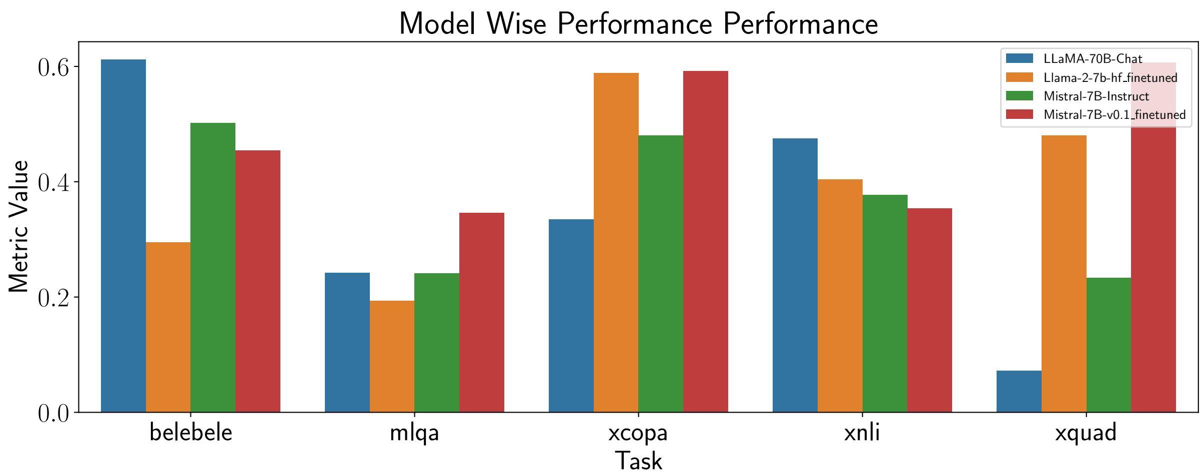

Figure 4: Task Wise Model Average across ranks and quantisations. Models with finetuned suffix are average scores across the quantisation and ranks.

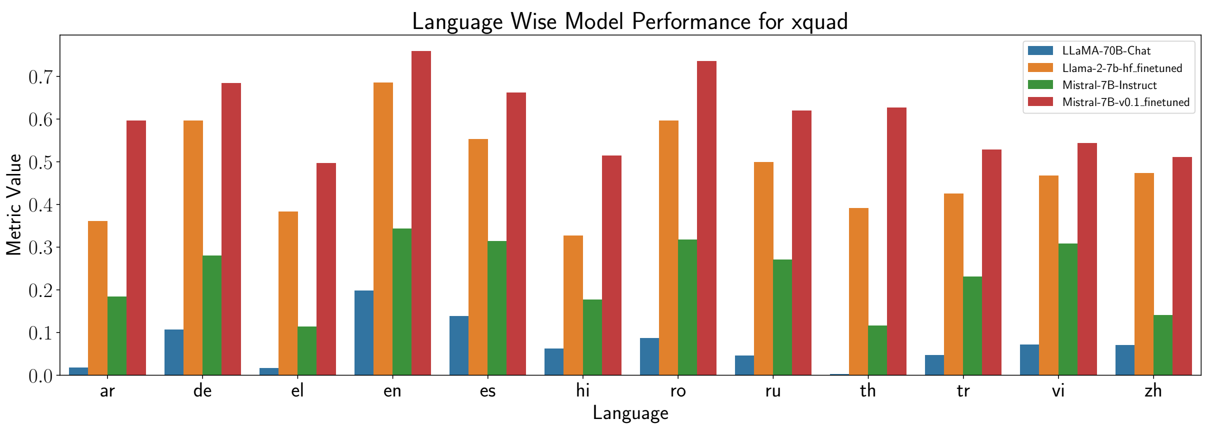

Figure 5: Language Wise Performance Analysis of Models on XQUAD Dataset. Models with finetuned suffix are average scores across the quantisation and ranks.

Model	XNLI	XCOPA	Belebele	MLQA	XQUAD
GPT-4	0.75	0.74	0.85	0.44	0.47
PaLM-2	0.76	0.65	0.87	0.37	0.55
LLaMA-70B-chat	0.48	0.33	0.61	0.24	0.07
Mistral-7B-Instruct	0.38	0.48	0.50	0.36	0.23
LLaMA-7B-finetuned	0.41	0.59	0.32	0.22	0.51
Mistral-7B-finetuned	0.53	0.60	0.49	0.36	0.62

Table 1: Detailed Task Wise Performance Comparison between GPT-4, PaLM-2, LLaMA-70B-chat, Mistral-7B-Instruct and finetuned models with best rank quantsation. Baseline numbers are referred from Ahuja et al. (2023b).

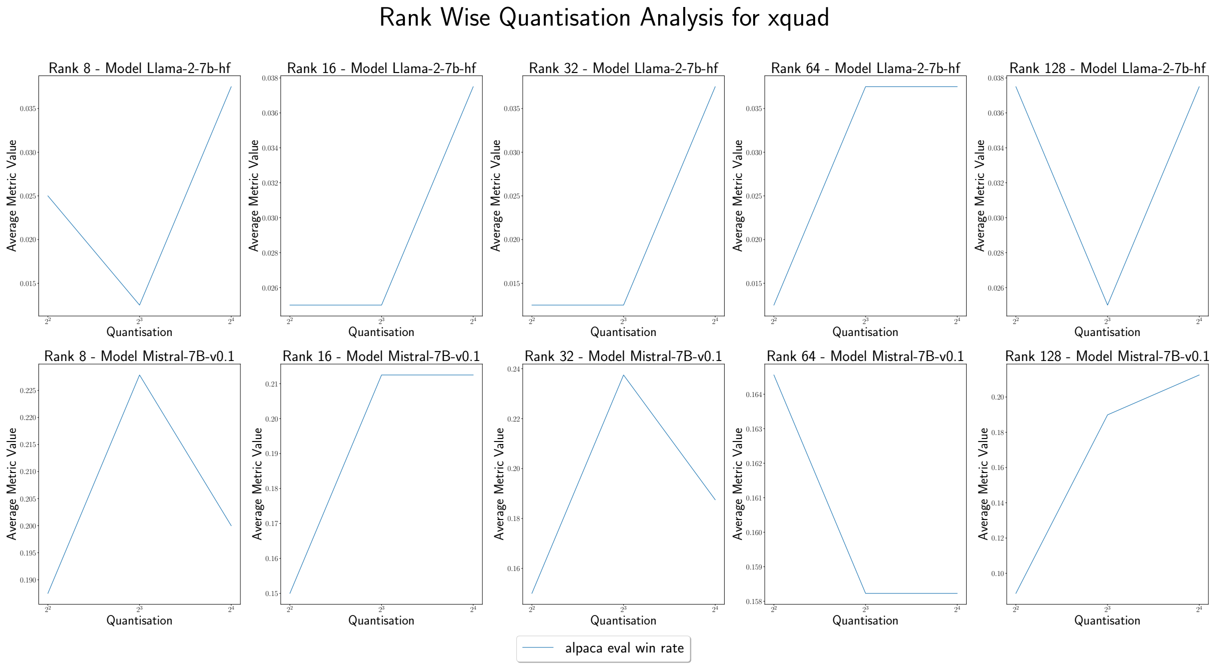

Figure 6: Alpaca Eval Scores Variation for LLAMA-7B and MISTRAL-7B across Rank.

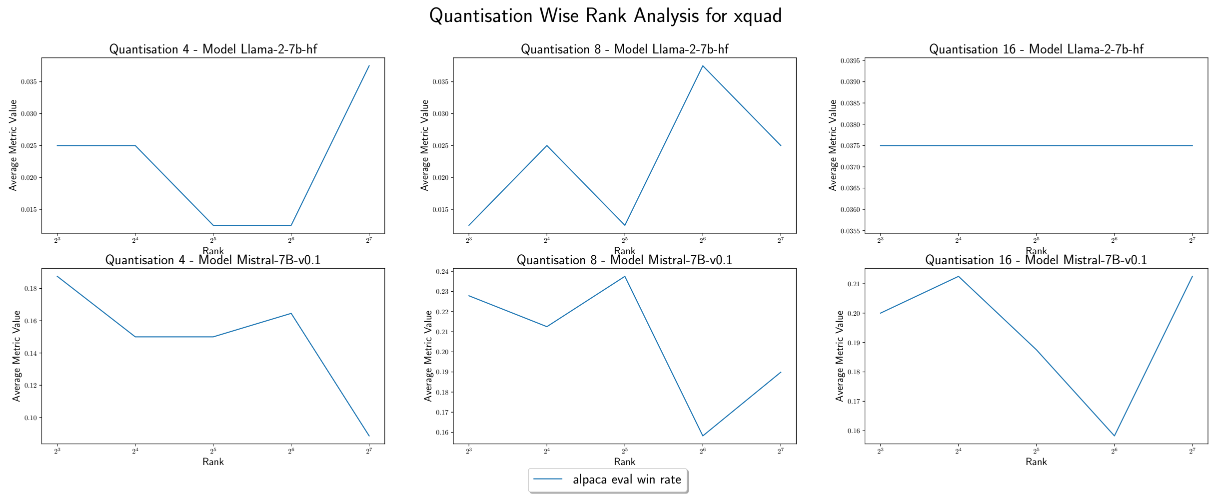

Figure 7: Alpaca Eval Scores Variation for LLAMA-7B and MISTRAL-7B across Quantisation

lower ranks and quantisation can turn out to be promising in some scenarios.

RQ2: How does quantisation affect the Performance of multilingual finetuned models across ranks? We observe that performance does not get affected by change in quantisation in LLAMA-7B while in MISTRAL-7B we observe large fluctuations in performance as the quantisation changes for each rank. We also observe that **lower resource languages perform poorly in the lower quanti-**

sation settings. We illustrate this in Figures 2, 12, 13, 14 and 15.

We observe that XNLI does not have an obvious trend, while the other datasets show no effect of quantisation on languages. **We also observe that LLAMA-7B is more immune to change in fluctuation on quantisation across languages while MISTRAL-7B is more sensitive to quantisation across languages.**

RQ3: How does rank affect the performance of multilingual finetuned models across different values of quantisation? There is a direct correlation of performance with rank in most cases. We also observe that **lower resource languages are benefited the most by finetuning using higher ranks**. We illustrate these trends in detail in Figures 3, 16, 17, 18 and 19.

We see that variation of rank across quantisations does not lead to any change in a particular language's performance in LLAMA-7B i.e. varying rank across on any quantisation leads to same trends for all datasets. However in MISTRAL-7B there is no apparent trend in rank variation across quantisations unlike LLAMA-7B .

RQ4: Does Multilingual PEFT result in better downstream task performance compared to models that are not finetuned? In Figure 4 we can see that finetuning is usually better or at par with LlaMA-70B-Chat and and Mistral-7B-Instruct which are not finetuned on multilingual data. We also compare the performance of finetuned models with LLMs like GPT-4 and PaLM2 and English instruction tuned versions of these models provided in (Ahuja et al., 2023b) in Table 1, which shows averages across languages per tasks. We find that for tasks such as XCOPA and XQUAD, PEFT is able to bridge the gap to a large extent between open source and closed models, with PEFT Mistral's performance on XQuaD exceeding that of GPT-4 and PaLM2. However, for other datasets, we observe a degradation or no change, which could be attributed to test data contamination, or a regression on languages of the datasets. Datasets such as XNLI contain a large number of languages (Bulgarian, Greek, English, Hindi, Swahili, Turkish, Urdu, Chinese) that are not present in the MultiAlpaca dataset, which could explain the poor performance on the PEFT models on this downstream task.

We illustrate language wise analysis in Figures 5, 21, 22, 23 and 20.

For XNLI and MLQA, we observe that finetuning improves performance on low resource languages but worsens performance on high resource languages. In Belebele, we find that finetuning worsens the performance for all languages for both models. For XCOPA, we get the same or better results for all languages with finetuning. For XQUAD, multilingual finetuning boosts performance for all languages for both LLAMA-7B and MISTRAL-7B . **This shows that PEFT on smaller LLMs on multilingual instruction data can prove to be beneficial and can bridge the gap between smaller open source models and large proprietary models for multilingual applications for some downstream applications**.

While we compare our multilingual finetuned models with models finetuned on English, we should note that we do not have complete information about instruction datasets used for Llama-70B-chat and Mistral-7B-Instruct. Hence, there may be chances of data contamination for some datasets in these models (Ahuja et al., 2023a) or the presence of multilingual instruction data in them.

RQ5: How much loss is observed in performance on English due to multilingual finetuning? Finetuning LLMs on multilingual data leads to significant loss in performance on English where the score reduces by 90% of base LLAMA-7B and 50% of MISTRAL-7B . On evaluating with the Alpaca Eval benchmark, all finetuned models significantly worse than the base models. However, we observe that higher quantisation and higher rank on an average helps preserve the English performance to some extent. We illustrate trends with rank and quantisation of our finetuned model in Figures 6 and 7.

5 Conclusion

In this work we perform an extensive analysis of effects of rank, quantisation and model when finetuned using LoRA. We study their effects on various multilingual tasks and Alpaca Eval to study the effect on English performance. Our findings shows that there is no one size fits all approach when finetuning LLMs using PEFT. However, Quantisation 8 and 16 with rank 64 are usually the safest bet to achieve decent performance in most tasks while 4 bit quantisation tends to be more unstable. We also show that finetuned model performance is very much dependent on the base model as well, where a better base model leads to a better finetuned model in multilingual setting. We find that PEFT with multilingual data can bridge the gap between the performance of smaller open source models and larger closed models on some downstream tasks, however, full fine-tuning, better representation of non-English languages during fine-tuning or other techniques applied during modeling may be required for improving multilingual performance.

6 Limitations

Our evaluation is performed using standard benchmarks, which has known limitations. Datasets used to create benchmarks may have been seen by models during pretraining or finetuning, and due to lack of transparency about the datasets used for training we cannot rule out test data contamination. Second, we use synthetic datasets that are created by prompting LLMs to finetune our models, which is also a limitation of the work. Finally, we compare the results obtained by our models to results from the MEGAVERSE benchmarking study while comparing the differences between finetuned models and models that are not finetuned for multilingual performance, which may have some differences in prompting and setup.

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A Hyperparameters for finetuning

Our code for finetuning is based on the open source `axolotl`[1] framework. We plan to release our configuration files for better reproducibility. Each finetuning experiment took ∼16-20 hours to complete on a single NVIDIA A100 GPU with 80 GB RAM. Exact hyperparameters for finetuning are mentioned below:

Hyperparameter	Value
Learning rate	1×10^{-6}
Epochs	5
Global batch size	16
Scheduler	Cosine
Warmup	Linear
Warmup steps	10
Optimizer	AdamW (Loshchilov and Hutter, 2019)
Weight decay	0

Table 2: Hyperparameters for finetuning.

B RQ1 Figures

Figure 8 to 11 shows our analysis for RQ1.

C RQ2 Figures

Figure 12 to 15 shows our analysis for RQ2.

D RQ3 Figures

Figure 16 to 19 shows our analysis for RQ3.

E RQ4 Figures

Figure 20 to 23 shows our analysis for RQ4.

[1] https://github.com/OpenAccess-AI-Collective/axolotl

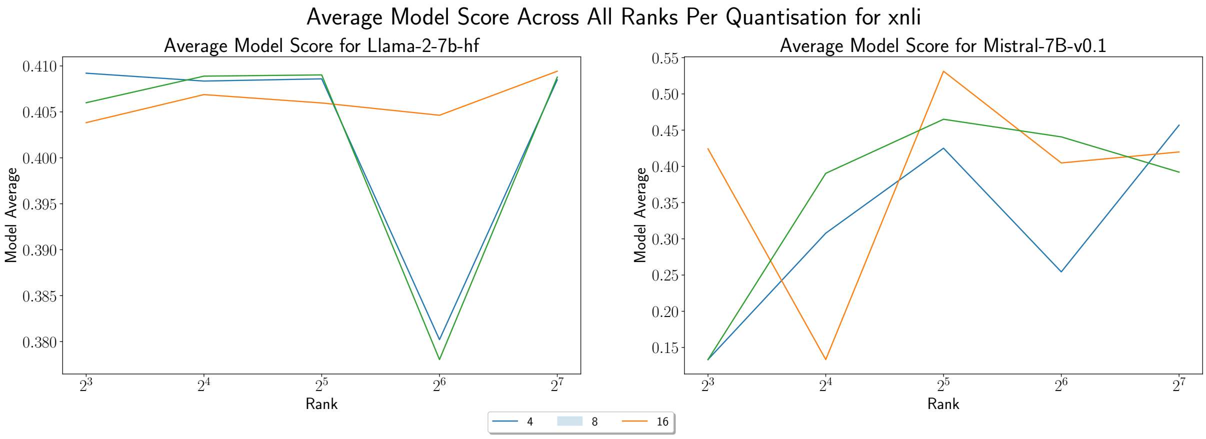

Figure 8: XNLI Model Average Scores for Each Quantisation across Ranks

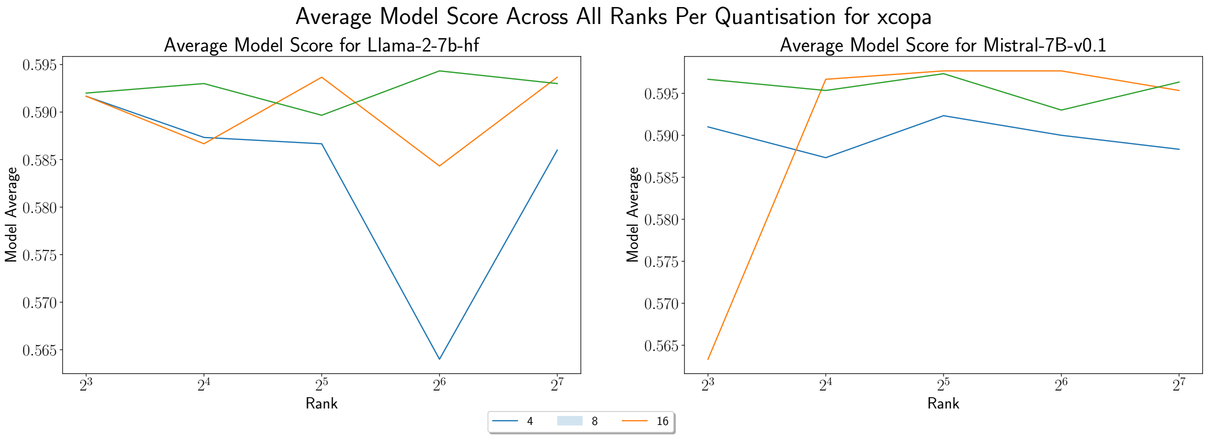

Figure 9: XCOPA Model Average Scores for Each Quantisation across Ranks

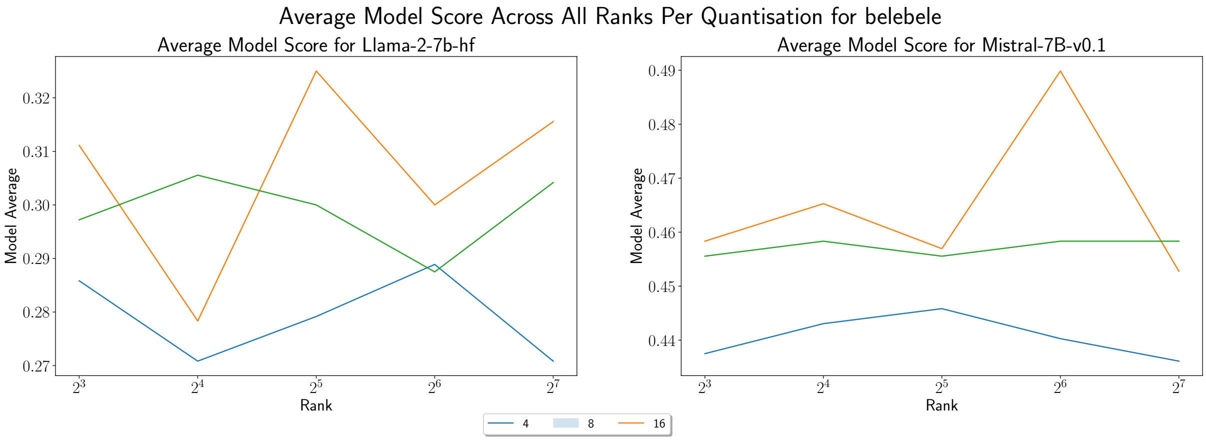

Figure 10: BeleBele Model Average Scores for Each Quantisation across Ranks

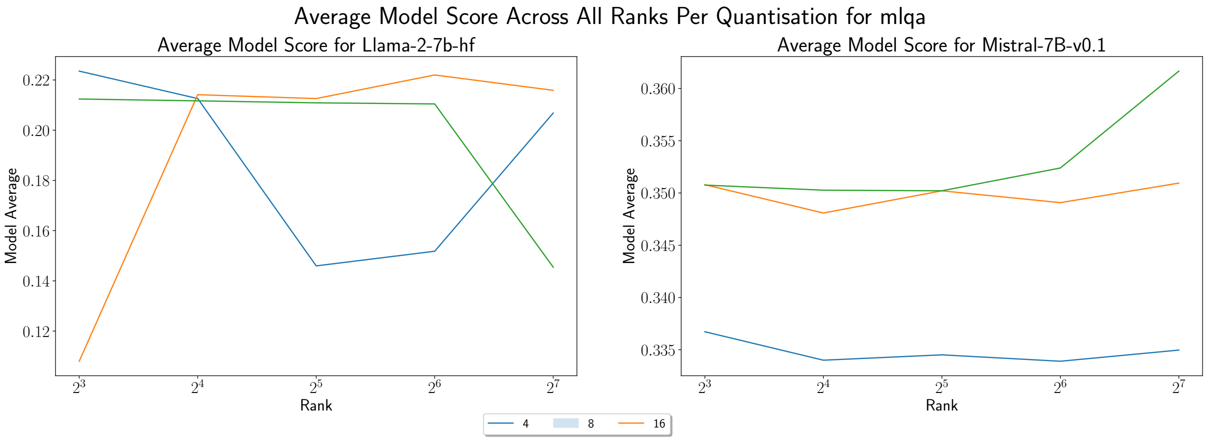

Figure 11: MLQA Model Average Scores for Each Quantisation across Ranks

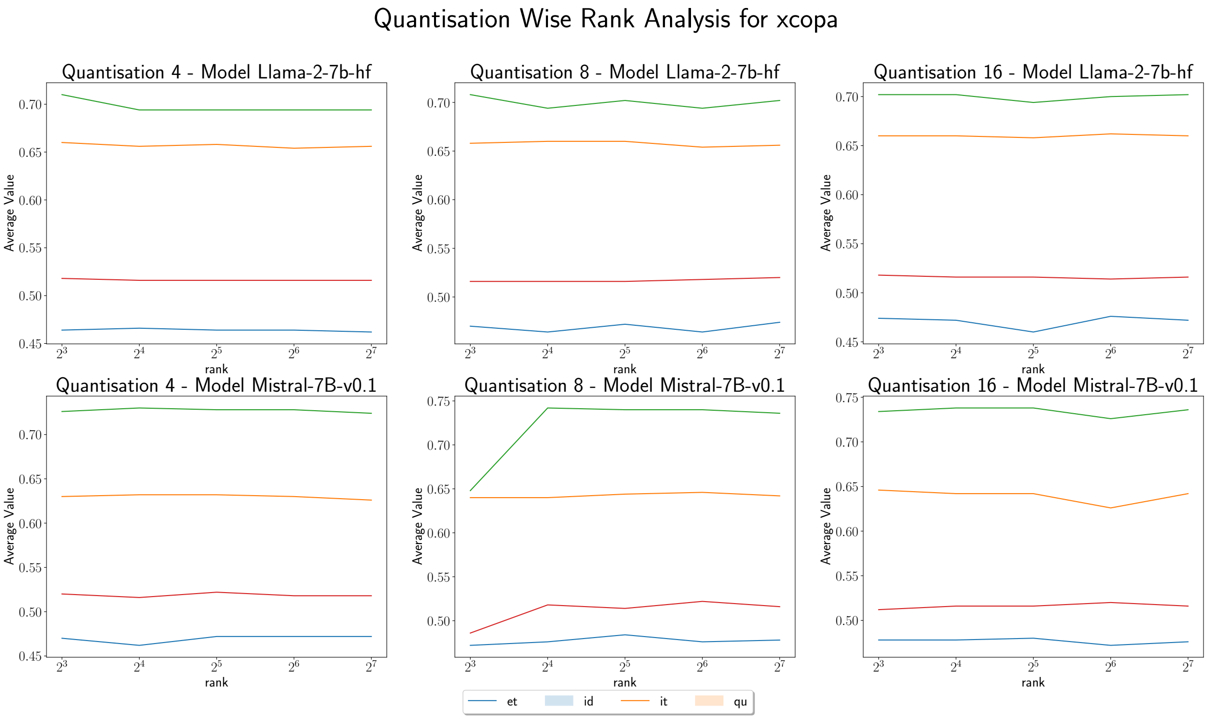

Figure 12: XCOPA Model Average Scores for Each Rank across Quantisations

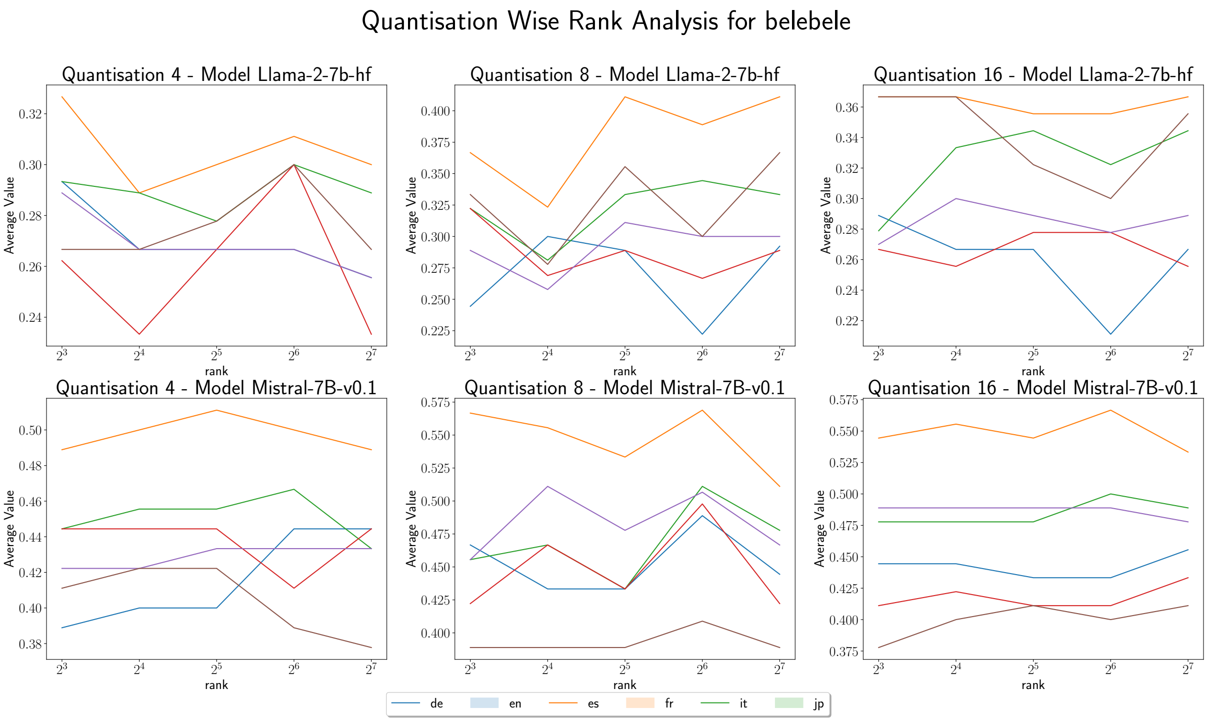

Figure 13: Belebele Model Average Scores for Each Rank across Quantisations

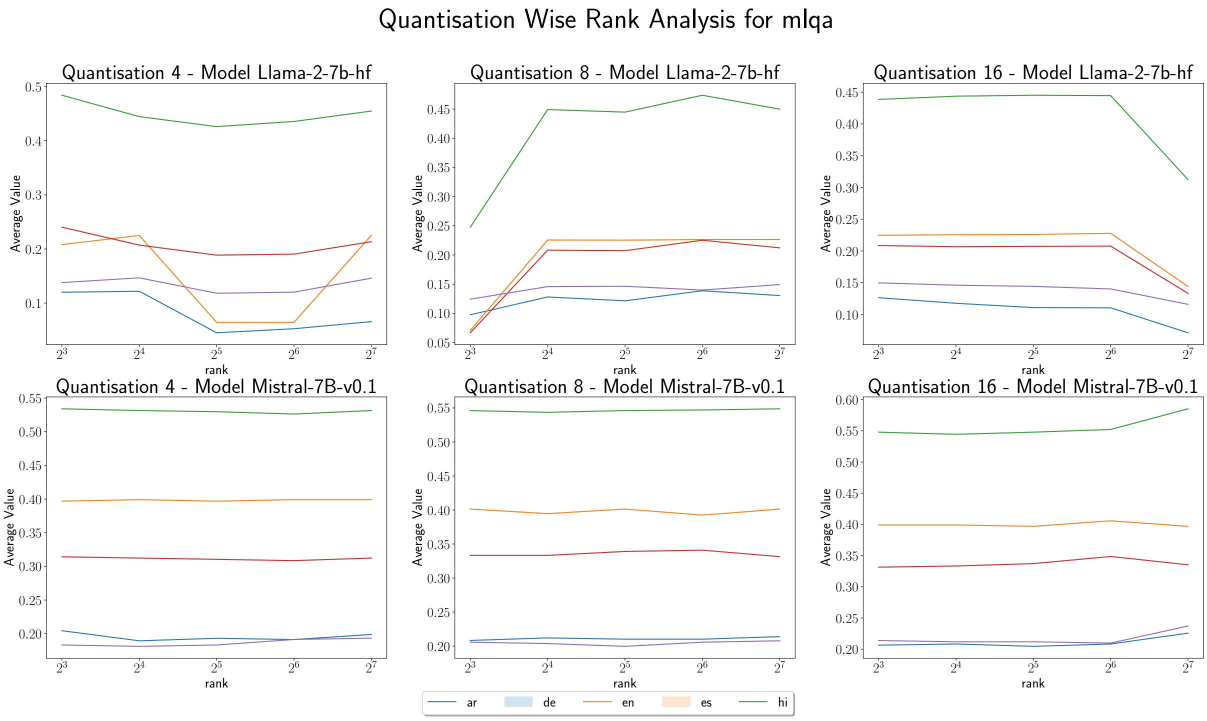

Figure 14: MLQA Model Average Scores for Each Rank across Quantisations

Figure 15: XNLI Model Average Scores for Each Rank across Quantisations

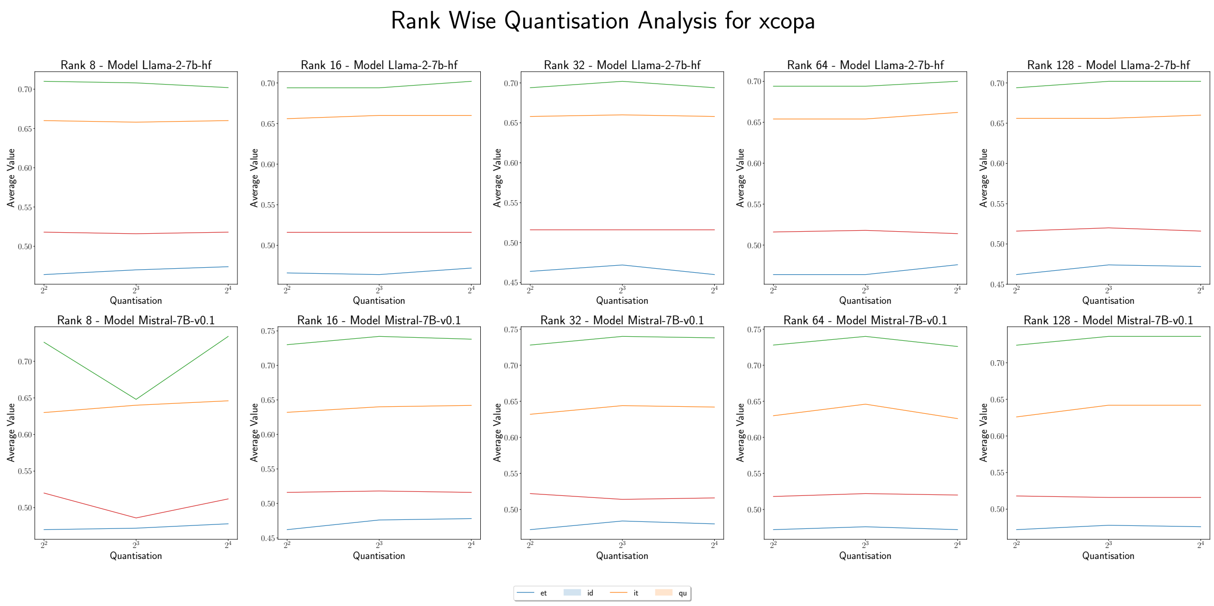

Figure 16: Rank Wise Quantisation Plots for XCOPA.

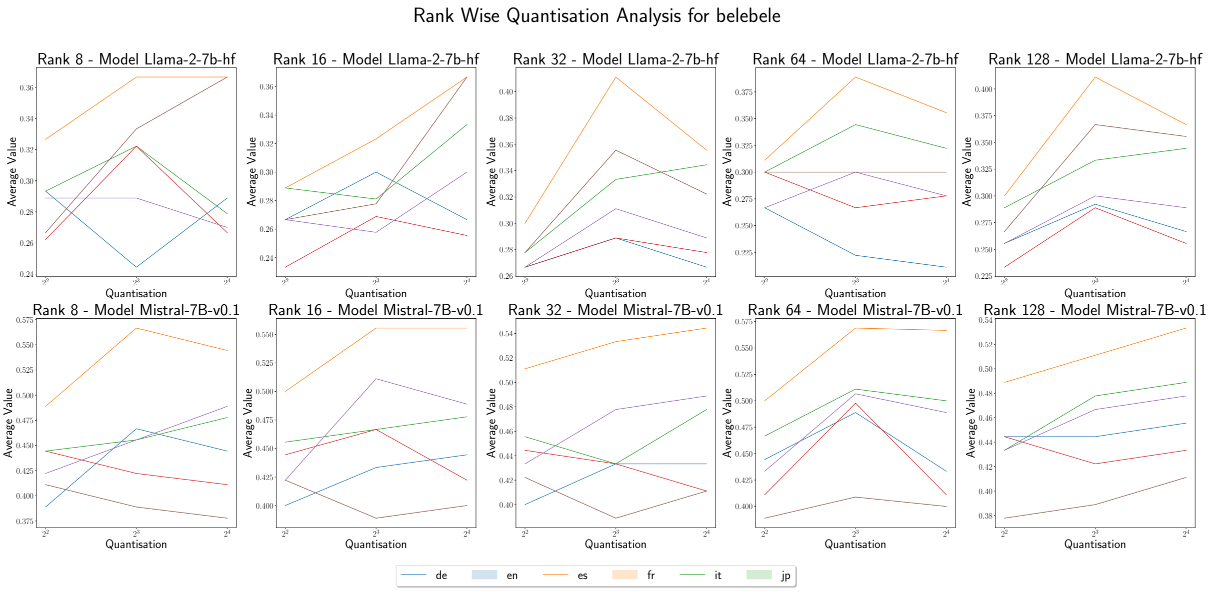

Figure 17: Rank Wise Quantisation Plots for Belebele.

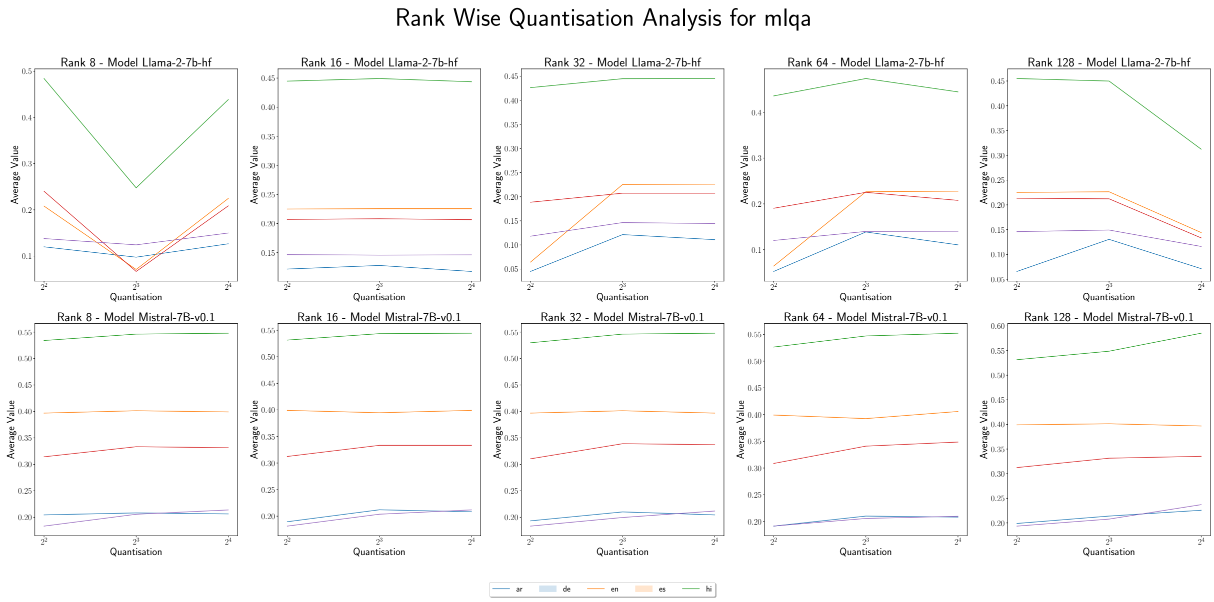

Figure 18: Rank Wise Quantisation Plots for MLQA.

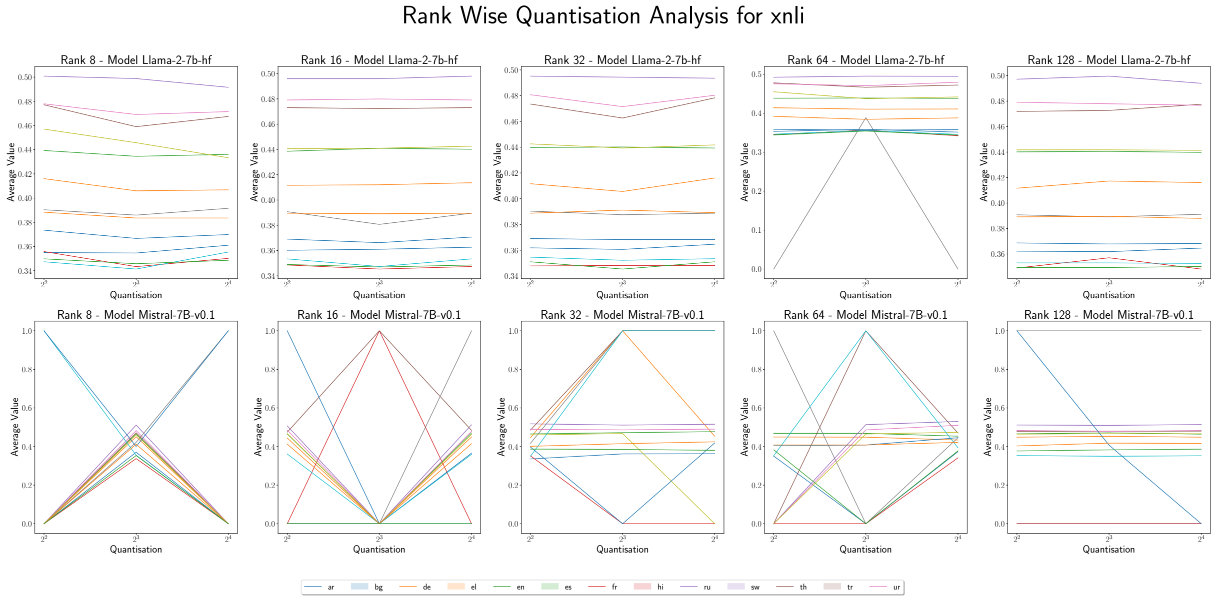

Figure 19: Rank Wise Quantisation Plots for XNLI.

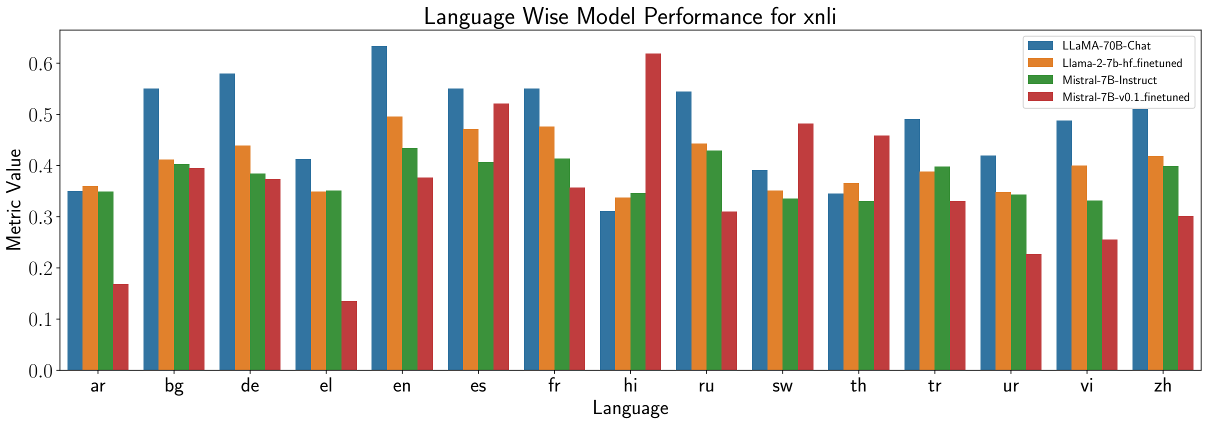

Figure 20: Language Wise Performance Analysis of Models on XNLI Dataset. Models with finetuned suffix are average scores across the quantisation and ranks.

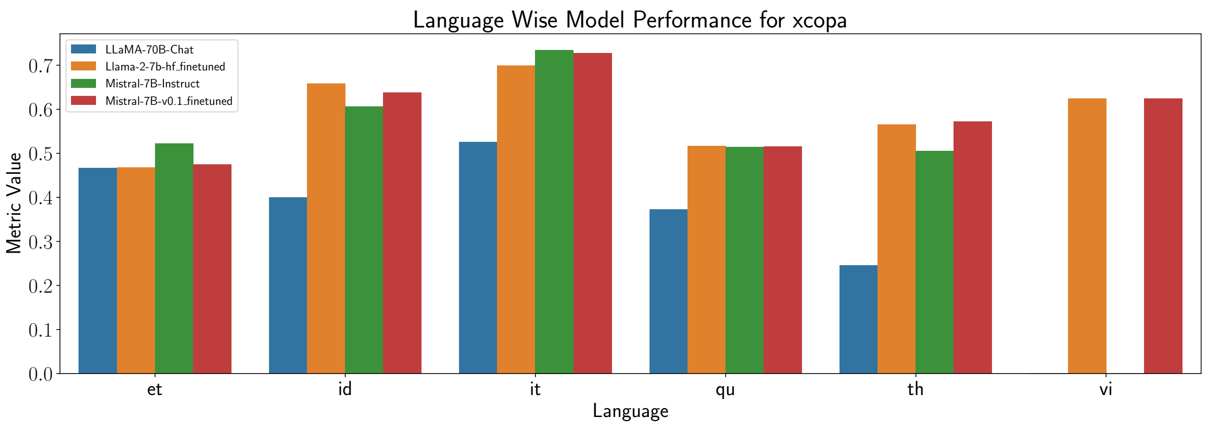

Figure 21: Language Wise Performance Analysis of Models on XCOPA Dataset. Models with finetuned suffix are average scores across the quantisation and ranks.

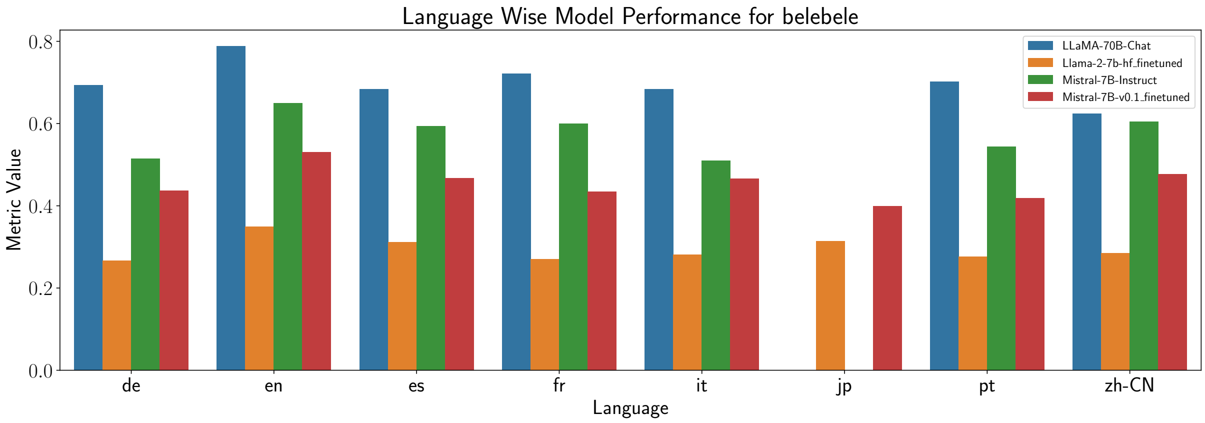

Figure 22: Language Wise Performance Analysis of Models on Belebele Dataset. Models with finetuned suffix are average scores across the quantisation and ranks.

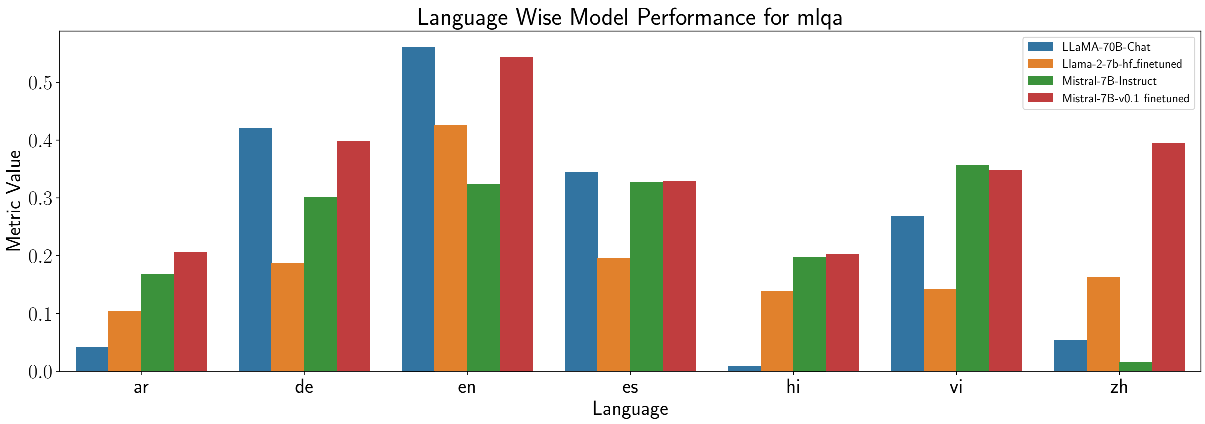

Figure 23: Language Wise Performance Analysis of Models on MLQA Dataset. Models with finetuned suffix are average scores across the quantisation and ranks.

rank	quantisation	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh	average
8	4	0.36	0.42	0.44	0.36	0.50	0.48	0.48	0.39	0.46	0.35	**0.37**	0.39	0.35	0.39	0.42	0.41
	8	0.35	0.41	0.43	0.34	0.50	0.46	0.47	0.39	0.45	0.34	0.37	0.38	0.35	0.40	0.42	0.40
	16	0.36	0.41	0.44	0.35	0.49	0.47	0.47	**0.39**	0.43	0.36	0.37	0.38	0.35	0.40	0.42	0.41
16	4	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.41	0.42	0.41
	8	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.38	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.41
	16	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.41	0.42	0.41
32	4	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.41
	8	0.36	0.41	0.44	0.35	0.49	0.46	0.47	0.39	0.44	0.35	0.37	0.39	0.35	0.41	0.42	0.41
	16	**0.36**	0.42	0.44	0.35	0.49	0.48	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.41
64	4	0.36	0.41	0.44	0.34	0.49	0.48	0.48	0.00	0.46	0.35	0.35	0.39	0.34	0.39	0.42	0.38
	8	0.36	0.41	0.44	0.36	0.50	0.47	0.47	0.39	0.44	0.36	0.36	0.38	0.35	0.39	0.41	0.40
	16	0.36	0.41	0.44	0.34	0.49	0.47	0.48	0.00	0.44	0.35	0.35	0.39	0.34	0.39	0.42	0.38
128	4	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.41	0.42	0.41
	8	0.36	0.42	0.44	0.36	0.50	0.47	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.41
	16	**0.36**	0.42	0.44	0.35	0.49	0.48	0.48	0.39	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.41
–	–	0.35	**0.55**	**0.58**	**0.41**	**0.63**	**0.55**	**0.55**	0.31	**0.55**	**0.39**	0.35	**0.49**	**0.42**	**0.49**	**0.51**	**0.48**
	average	0.36	0.41	0.44	0.35	0.50	0.47	0.48	0.34	0.44	0.35	0.37	0.39	0.35	0.40	0.42	0.40

Table 3: Detailed performance of various finetuned LLaMA-7B models on XNLI (Conneau et al., 2018). We used exact match as our metric score. Last row reports scores for LLaMA-70B-chat without finetuning.

rank	quantisation	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh	average
8	4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	**1.00**	0.00	0.00	0.00	0.00	0.13
	8	0.37	0.45	0.46	0.34	0.51	0.47	0.48	0.42	0.46	0.36	0.40	0.41	0.35	0.42	0.45	0.42
	16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.13
16	4	0.00	0.44	0.47	0.00	0.51	0.47	0.49	0.00	0.47	0.36	**1.00**	0.41	0.00	0.00	0.00	0.31
	8	0.00	0.00	0.00	**1.00**	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13
	16	0.37	0.45	0.47	0.00	0.51	0.48	0.48	**1.00**	0.46	0.36	0.00	0.41	0.00	0.41	0.44	0.39
32	4	0.34	0.45	0.47	0.35	0.52	0.49	0.49	0.42	0.46	0.35	0.40	0.40	**0.39**	0.43	0.45	0.43
	8	0.36	**1.00**	0.47	0.00	0.51	**1.00**	0.49	**1.00**	0.47	**1.00**	0.00	0.41	0.39	0.42	0.45	**0.53**
	16	0.36	0.45	**0.48**	0.00	0.52	**1.00**	0.49	**1.00**	0.00	**1.00**	0.42	**0.42**	0.38	0.00	0.45	0.47
64	4	0.35	0.45	0.47	0.00	0.00	0.00	0.00	**1.00**	0.00	0.35	0.40	0.41	0.38	0.00	0.00	0.25
	8	0.00	0.45	0.47	0.00	0.51	**1.00**	0.49	0.00	0.47	**1.00**	0.41	0.41	0.00	0.43	0.45	0.40
	16	**0.37**	0.43	0.45	0.34	**0.53**	0.47	**0.51**	0.45	**0.47**	0.39	0.45	0.42	0.38	**0.45**	**0.49**	0.44
128	4	0.00	0.45	0.47	0.00	0.51	0.48	0.48	**1.00**	0.46	0.35	**1.00**	0.40	0.38	0.42	0.45	0.46
	8	0.00	0.45	0.47	0.00	0.51	0.48	0.48	**1.00**	0.47	0.35	0.41	0.42	0.38	0.43	0.45	0.42
	16	0.00	0.45	0.46	0.00	0.51	0.48	0.48	**1.00**	0.47	0.35	0.00	0.42	0.39	0.42	0.45	0.39
–	–	0.35	0.40	0.38	0.35	0.43	0.41	0.41	0.35	0.43	0.34	0.33	0.40	0.34	0.33	0.40	0.38
	average	0.17	0.40	0.37	0.14	0.38	0.52	0.36	0.62	0.31	0.48	0.46	0.33	0.23	0.26	0.30	0.35

Table 4: Detailed performance of various finetuned MISTRAL-7B models on XNLI (Conneau et al., 2018). We used exact match as our metric score. Last row reports scores for Mistral-7B-Instruct without finetuning.

rank	quantisation	et	id	it	qu	th	vi	average
8	4	0.46	0.66	**0.71**	0.52	0.56	0.63	0.59
	8	0.47	0.66	0.71	0.52	0.56	0.64	0.59
	16	0.47	0.66	0.70	0.52	0.57	0.63	0.59
16	4	0.47	0.66	0.69	0.52	0.56	0.63	0.59
	8	0.46	0.66	0.69	0.52	0.56	0.63	0.59
	16	0.47	0.66	0.70	0.52	0.57	0.63	0.59
32	4	0.46	0.66	0.69	0.52	0.56	0.63	0.59
	8	0.47	0.66	0.70	0.52	**0.58**	0.64	0.59
	16	0.46	0.66	0.69	0.52	**0.58**	0.63	0.59
64	4	0.46	0.65	0.69	0.52	0.56	0.50	0.56
	8	0.46	0.65	0.69	0.52	0.56	0.62	0.58
	16	**0.48**	**0.66**	0.70	0.51	0.57	**0.64**	**0.59**
128	4	0.46	0.66	0.69	0.52	0.56	0.63	0.59
	8	0.47	0.66	0.70	**0.52**	0.57	0.64	0.59
	16	0.47	0.66	0.70	0.52	0.57	0.63	0.59
–	–	0.47	0.40	0.53	0.37	0.25	0.00	0.33
	average	0.47	0.66	0.70	0.52	0.57	0.62	0.59

Table 5: Detailed performance of various finetuned LLAMA-7B models on XCOPA (Ponti et al., 2020). We use accuracy score as the metric of evaluation. Last row reports the scores from LLaMA-70B-chat without finetuning.

rank	quantisation	et	id	it	qu	th	vi	average
8	4	0.47	0.63	0.73	0.52	**0.58**	0.62	0.59
	8	0.47	0.64	0.65	0.49	0.55	0.58	0.56
	16	0.48	**0.65**	0.73	0.51	0.57	**0.64**	0.60
16	4	0.46	0.63	0.73	0.52	0.57	0.62	0.59
	8	0.48	0.64	**0.74**	0.52	0.57	0.63	0.60
	16	0.48	0.64	0.74	0.52	0.57	0.63	0.60
32	4	0.47	0.63	0.73	**0.52**	0.57	0.63	0.59
	8	0.48	0.64	0.74	0.51	0.57	**0.64**	**0.60**
	16	0.48	0.64	0.74	0.52	0.58	0.63	0.60
64	4	0.47	0.63	0.73	0.52	0.58	0.61	0.59
	8	0.48	**0.65**	0.74	**0.52**	**0.58**	0.62	**0.60**
	16	0.47	0.63	0.73	0.52	**0.58**	0.63	0.59
128	4	0.47	0.63	0.72	0.52	**0.58**	0.61	0.59
	8	0.48	0.64	0.74	0.52	0.57	0.63	0.60
	16	0.48	0.64	0.74	0.52	0.57	0.63	0.60
–	–	**0.52**	0.61	0.73	0.51	0.51	0.00	0.48
	average	0.47	0.64	0.73	0.52	0.57	0.62	0.59

Table 6: Detailed performance of various finetuned MISTRAL-7B models on XCOPA (Ponti et al., 2020). We use accuracy score as the metric of evaluation. Last row reports scores for Mistral-7B-Instruct without finetuning.

rank	quantisation	de	en	es	fr	it	jp	pt	zh-CN	average
8	4	0.29	0.33	0.29	0.26	0.29	0.27	0.27	0.29	0.29
	8	0.24	0.37	0.32	0.32	0.29	0.33	0.30	0.31	0.31
	16	0.29	0.37	0.28	0.27	0.27	**0.37**	0.27	0.27	0.30
16	4	0.27	0.29	0.29	0.23	0.27	0.27	0.27	0.29	0.27
	8	0.30	0.32	0.28	0.27	0.26	0.28	0.25	0.27	0.28
	16	0.27	0.37	0.33	0.26	0.30	**0.37**	0.27	0.29	0.31
32	4	0.27	0.30	0.28	0.27	0.27	0.28	0.28	0.30	0.28
	8	0.29	0.41	0.33	0.29	0.31	0.36	0.31	0.30	0.32
	16	0.27	0.36	0.34	0.28	0.29	0.32	0.28	0.27	0.30
64	4	0.27	0.31	0.30	0.30	0.27	0.30	0.30	0.27	0.29
	8	0.22	0.39	0.34	0.27	0.30	0.30	0.29	0.29	0.30
	16	0.21	0.36	0.32	0.28	0.28	0.30	0.28	0.28	0.29
128	4	0.26	0.30	0.29	0.23	0.26	0.27	0.27	0.30	0.27
	8	0.29	0.41	0.33	0.29	0.30	**0.37**	0.25	0.28	0.32
	16	0.27	0.37	0.34	0.26	0.29	0.36	0.28	0.28	0.30
–	–	**0.69**	**0.79**	**0.68**	**0.72**	**0.68**	0.00	**0.70**	**0.62**	**0.61**
	average	0.27	0.35	0.31	0.27	0.28	0.31	0.28	0.28	0.29

Table 7: Detailed performance of various finetuned LLAMA-7B models on Belebele (Bandarkar et al., 2023). We use accuracy score as the metric of evaluation. Last Row signifies the Llama-70B-Chat results on the Belebele dataset.

rank	quantisation	de	en	es	fr	it	jp	pt	zh-CN	average
8	4	0.39	0.49	0.44	0.44	0.42	0.41	0.46	0.44	0.44
	8	0.47	0.57	0.46	0.42	0.46	0.39	0.40	0.51	0.46
	16	0.44	0.54	0.48	0.41	0.49	0.38	0.40	0.50	0.46
16	4	0.40	0.50	0.46	0.44	0.42	**0.42**	0.46	0.44	0.44
	8	0.43	0.56	0.47	0.47	**0.51**	0.39	0.41	0.49	0.47
	16	0.44	0.56	0.48	0.42	0.49	0.40	0.40	0.48	0.46
32	4	0.40	0.51	0.46	0.44	0.43	**0.42**	0.46	0.44	0.45
	8	0.43	0.53	0.43	0.43	0.48	0.39	0.44	0.51	0.46
	16	0.43	0.54	0.48	0.41	0.49	0.41	0.40	0.48	0.46
64	4	0.44	0.50	0.47	0.41	0.43	0.39	0.46	0.42	0.44
	8	0.49	0.57	0.51	0.50	0.51	0.41	0.43	0.50	0.49
	16	0.43	0.57	0.50	0.41	0.49	0.40	0.38	0.49	0.46
128	4	0.44	0.49	0.43	0.44	0.43	0.38	0.39	0.48	0.44
	8	0.44	0.51	0.48	0.42	0.47	0.39	0.42	0.49	0.45
	16	0.46	0.53	0.49	0.43	0.48	0.41	0.39	0.48	0.46
–	–	**0.52**	**0.65**	**0.59**	**0.60**	0.51	0.00	**0.54**	**0.60**	**0.50**
	average	0.44	0.53	0.47	0.43	0.47	0.40	0.42	0.48	0.45

Table 8: Detailed performance of various finetuned MISTRAL-7B models on Belebele (Bandarkar et al., 2023). We use accuracy score as the metric of evaluation. Last Row signifies the Mistral-7B-Instruct results on the Belebele dataset.

rank	quantisation	ar	de	en	es	hi	vi	zh	average
8	4	0.12	0.21	0.48	0.24	0.14	0.20	0.18	0.22
	8	0.10	0.07	0.25	0.07	0.12	0.07	0.08	0.11
	16	0.13	0.22	0.44	0.21	**0.15**	0.15	0.19	0.21
16	4	0.12	0.22	0.44	0.21	0.15	0.15	0.19	0.21
	8	0.13	0.23	0.45	0.21	0.15	0.15	0.19	0.21
	16	0.12	0.23	0.44	0.21	0.15	0.15	0.19	0.21
32	4	0.05	0.06	0.43	0.19	0.12	0.11	0.07	0.15
	8	0.12	0.23	0.44	0.21	0.15	0.15	0.19	0.21
	16	0.11	0.23	0.45	0.21	0.14	0.15	0.19	0.21
64	4	0.05	0.06	0.44	0.19	0.12	0.13	0.07	0.15
	8	**0.14**	0.23	0.47	0.23	0.14	0.16	**0.19**	0.22
	16	0.11	0.23	0.44	0.21	0.14	0.15	0.19	0.21
128	4	0.07	0.23	0.45	0.21	0.15	0.15	0.19	0.21
	8	0.13	0.23	0.45	0.21	0.15	0.15	0.19	0.22
	16	0.07	0.14	0.31	0.13	0.12	0.12	0.12	0.15
–	–	0.04	**0.42**	**0.56**	**0.34**	0.01	**0.27**	0.05	**0.24**
	average	0.10	0.19	0.43	0.19	0.14	0.14	0.16	0.19

Table 9: Detailed performance of various finetuned LLAMA-7B models on MLQA (Lewis et al., 2020). We used exact match as our metric score. Last row reports LLaMA-70B-chat results without finetuning.

rank	quantisation	ar	de	en	es	hi	vi	zh	average
8	4	0.20	0.40	0.53	0.31	0.18	0.35	0.37	0.34
	8	0.21	0.40	0.55	0.33	0.21	0.35	**0.41**	0.35
	16	0.21	0.40	0.55	0.33	0.21	**0.36**	0.40	0.35
16	4	0.19	0.40	0.53	0.31	0.18	0.35	0.38	0.33
	8	0.21	0.39	0.54	0.33	0.20	0.35	0.40	0.35
	16	0.21	0.40	0.54	0.33	0.21	0.35	0.40	0.35
64	4	0.19	0.40	0.53	0.31	0.18	0.35	0.38	0.33
	8	0.21	0.40	0.55	0.34	0.20	0.35	0.41	0.35
	16	0.20	0.40	0.55	0.34	0.21	0.35	0.40	0.35
64	4	0.19	0.40	0.53	0.31	0.19	0.34	0.38	0.33
	8	0.21	0.39	0.55	0.34	0.21	0.35	0.40	0.35
	16	0.21	**0.41**	0.55	**0.35**	0.21	0.34	0.40	0.35
128	4	0.20	0.40	0.53	0.31	0.19	0.34	0.37	0.33
	8	0.21	0.40	0.55	0.33	0.21	0.35	**0.41**	0.35
	16	**0.23**	0.40	**0.59**	0.34	**0.24**	0.35	0.40	**0.36**
–	–	0.17	0.30	0.32	0.33	0.20	0.36	0.02	0.24
	average	0.21	0.40	0.54	0.33	0.20	0.35	0.39	0.35

Table 10: Detailed performance of various finetuned MISTRAL-7B models on MLQA (Lewis et al., 2020). We used exact match as our metric score. Last row reports Mistral-7B-Instruct results without finetuning.

rank	quantisation	ar	de	el	en	es	hi	ro	ru	th	tr	vi	zh	average
8	4	0.36	0.63	0.37	0.66	0.56	0.32	0.58	0.51	0.34	0.43	0.42	0.47	0.47
	8	0.38	0.56	**0.42**	0.71	0.58	0.34	0.63	**0.52**	**0.44**	0.42	0.50	0.47	0.50
	16	0.38	0.60	0.40	0.71	0.55	0.33	0.61	0.50	**0.44**	**0.45**	0.49	0.47	0.49
16	4	0.35	0.63	0.37	0.66	0.56	0.32	0.58	0.51	0.34	0.43	0.42	0.47	0.47
	8	0.37	0.58	0.40	**0.73**	**0.61**	**0.36**	**0.64**	**0.52**	**0.44**	0.44	**0.51**	0.46	0.50
	16	0.38	0.61	0.39	0.71	0.54	0.33	0.61	0.50	**0.44**	**0.45**	0.49	0.47	0.49
32	4	0.36	0.64	0.36	0.67	0.56	0.31	0.58	0.51	0.34	0.44	0.42	0.48	0.47
	8	0.35	0.60	0.41	0.71	0.56	**0.36**	0.63	**0.52**	0.43	**0.45**	0.50	0.48	0.50
	16	0.23	0.41	0.27	0.59	0.37	0.26	0.45	0.33	0.25	0.30	0.43	0.47	0.36
64	4	0.38	0.64	0.37	0.67	0.57	0.32	0.58	0.51	0.34	0.44	0.43	0.49	0.48
	8	**0.39**	**0.65**	0.40	0.69	0.60	0.34	0.62	0.51	0.43	0.43	0.50	**0.50**	**0.51**
	16	**0.39**	0.61	0.40	**0.73**	0.58	0.33	0.61	0.50	**0.44**	0.42	0.49	0.47	0.50
128	4	0.36	0.63	0.37	0.66	0.56	0.31	0.58	0.51	0.34	0.44	0.43	0.47	0.47
	8	0.34	0.58	0.40	0.67	0.55	0.35	**0.64**	0.50	**0.44**	0.43	**0.51**	0.47	0.49
	16	0.38	0.60	0.39	0.71	0.55	0.33	0.61	0.50	0.43	**0.45**	0.49	0.47	0.49
–	–	0.02	0.11	0.02	0.20	0.14	0.06	0.09	0.05	0.00	0.05	0.07	0.07	0.07
	average	0.36	0.60	0.38	0.69	0.55	0.33	0.60	0.50	0.39	0.43	0.47	0.47	0.48

Table 11: Detailed performance of various finetuned LLAMA-7B models on XQuAD (Artetxe et al., 2020). We used exact match as our metric score. Last row reports scores for LLaMA-70B-chat without finetuning.

rank	quantisation	ar	de	el	en	es	hi	ro	ru	th	tr	vi	zh	average
	4	0.55	0.66	0.47	0.71	0.66	0.48	0.69	0.60	0.61	0.49	0.55	0.51	0.58
8	8	0.61	0.66	0.52	0.78	0.66	0.52	**0.77**	0.63	0.61	**0.56**	0.55	0.49	0.61
	16	0.61	0.70	0.48	0.76	0.66	0.51	0.76	0.62	0.63	0.53	0.55	0.50	0.61
	4	0.38	0.64	0.37	0.67	0.57	0.31	0.58	0.51	0.34	0.44	0.43	0.49	0.48
16	8	0.61	0.67	0.49	0.77	0.66	0.50	0.75	0.62	0.61	0.55	**0.56**	0.50	0.61
	16	**0.62**	**0.71**	0.48	0.76	0.66	0.54	0.76	0.62	0.64	0.54	0.54	0.51	0.62
	4	0.56	0.66	0.49	0.71	0.63	0.49	0.66	0.58	0.62	0.50	0.54	0.52	0.58
32	8	0.61	0.71	0.51	0.77	**0.68**	0.54	0.75	**0.64**	0.63	0.52	0.55	0.49	0.62
	16	0.61	0.70	0.49	0.76	0.66	0.52	0.74	0.63	0.64	0.52	0.54	0.50	0.61
	4	0.53	0.66	0.47	0.73	0.65	0.49	0.70	0.60	0.63	0.50	0.53	nan	0.59
64	8	0.61	0.69	**0.54**	0.76	0.67	**0.55**	0.76	**0.64**	0.64	0.55	0.54	0.49	0.62
	16	0.60	0.70	0.47	**0.79**	0.67	0.54	0.74	0.63	**0.65**	0.55	0.55	0.51	0.62
	4	0.55	0.67	0.52	0.76	0.64	0.47	0.67	0.61	0.62	0.50	0.54	0.51	0.59
128	8	0.61	0.66	0.52	0.77	**0.68**	0.51	0.76	0.63	0.63	0.54	0.55	0.49	0.61
	16	0.61	0.71	0.49	0.76	**0.68**	0.53	0.76	0.62	0.63	0.53	0.54	**0.62**	**0.62**
–	–	0.18	0.28	0.11	0.34	0.31	0.18	0.32	0.27	0.12	0.23	0.31	0.14	0.23
	average	0.58	0.68	0.49	0.75	0.66	0.50	0.72	0.61	0.61	0.52	0.54	0.51	0.60

Table 12: Detailed performance of various finetuned MISTRAL-7B models on XQuAD (Artetxe et al., 2020). We used exact match as our metric score. Last row reports scores for Mistral-7B-Instruct without finetuning.

rank	quantisation	win_rate
	4	2.50
8	8	1.25
	16	3.75
	4	2.50
16	8	2.50
	16	3.75
	4	1.25
32	8	1.25
	16	3.75
	4	1.25
64	8	3.75
	16	3.75
	4	3.75
128	8	2.50
	16	3.75
–	–	**22.36**
	average	2.75

Table 13: Detailed performance of various finetuned LLAMA-7B models on Alpaca Eval (Li et al., 2023). We use Win Rate as our metric score. The last row scores are reported for Llama-7B-chat.

rank	quantisation	win_rate
	4	18.75
8	8	22.78
	16	20.00
	4	15.00
16	8	21.25
	16	21.25
	4	15.00
32	8	23.75
	16	18.75
	4	16.46
64	8	15.82
	16	15.82
	4	8.86
128	8	18.99
	16	21.25
–	–	**35.13**
	average	18.25

Table 14: Detailed performance of various finetuned MISTRAL-7B models on Alpaca Eval (Li et al., 2023). We use Win Rate as our metric score. The last row scores are reported for Mistral-7B-Instruct.