Google DeepMind

Low-Rank Adaptation for Multilingual Summarization: An Empirical Study

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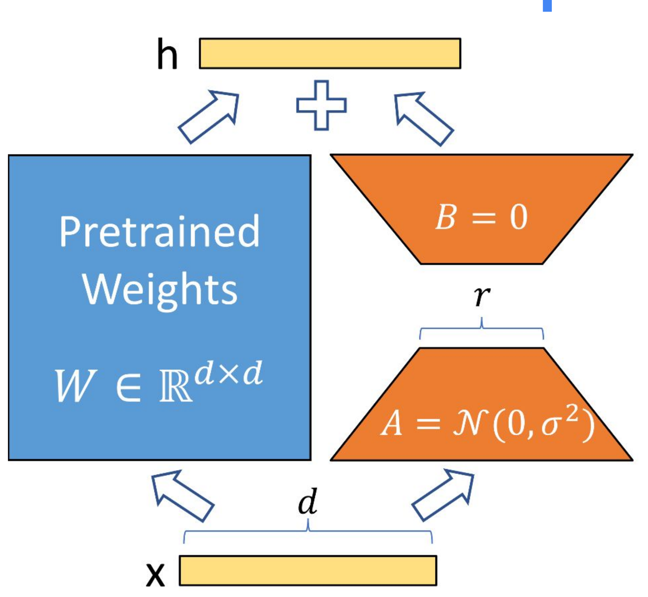
Introduction

- Large Language Models (LLMs) are becoming increasingly powerful, but their growing size also makes training less practical
- Parameter-efficient fine-tuning (PEFT) approaches are desirable, especially for tasks requiring extensive memory, e.g., with long input
- Existing PEFT approaches include
  - Adapters
  - Prefix tuning
  - **LoRA** (Low-rank Adaptation)
- We focus on a challenging task with long input:
  - **Multilingual summarization**, where LoRA is under-explored
  - We empirically study LoRA vs Full Fine-tuning (FT) under different data availability scenarios

Low-Rank Adaptation



[Hu et al. 2021]

- Freezes the pre-trained model weights (W) and adds trainable low-rank matrices (A & B) into the Transformer architecture
- No extra cost or latency at inference time
  - Can merge LoRA with the frozen parameters.
- Up to 10,000 times fewer trainable parameters
  - Up to 3 times less GPU memory (GPT-3)
- Competitive performance vs Full Fine-tuning (on classification or monolingual generation tasks)

LoraHub [Huang et al. 2023]:

- Compose individually trained LoRA modules for cross-task generalizatio m_i
- Availabl $\hat{m} = \sum_{i=1}^{N} w_i m_i$ s are synthesized into module

LoRA for Multilingual Summarization

Multilingual Summarization is Complex:

- Models are expected to fluently generate in many languages
- High/low resource: not all languages have (sufficient) data
- Long input and output

Datasets & Metrics:

Dataset	XLSum	XWikis
Source	BBC News	Wikipedia
Languages	44	5
Train/Val/Test Data	1.1M / 114K / 114K	1.4M / 40K / 35K
Input/Output Words	470 / 22	1043 / 64

- Compare summary **Relevance** (Rouge-L), **Faithfulness** (NLI), and **Conciseness** (Seahorse)

Experiments with PaLM-2

Different Data Regimes:

- High-data
- Low-data
- Cross-lingual Transfer (zero- and few-shot)

Cross-lingual Transfer

Zero-shot transfer from English

- Full Fine-tuning exhibits catastrophic forgetting

	XLSum			XWikis		
	Rouge-L	NLI	Seahorse	Rouge-L	NLI	Seahorse
Full-FT	5.20	4.49	6.88	17.51	35.95	22.43
LoRA-4	**21.13**	**39.07**	**23.08**	**23.86**	**45.54**	**25.96**

Performance of average non-English languages when training on English

Hausa	Indonesian
Target: Gwamnatin Najeriya ta ce 'yan kasar sun ga irin amfani da rufe iyakokin kasar ya yi a fannin tattalin arzikinta	**Target**: Perempuan Vietnam yang dituding terlibat dalam pembunuhan Kim Jong-nam, saudara tiri dari pemimpin Korea Utara Kim Jong-un, telah dibebaskan.
Full FT: President Muhammadu Buhari has appointed his deputy, the BBC presenter and former minister, Shugaba Muhammadu Buhari, as the new chairman of the Presidential Council.	**Full FT**: Kim Jong-nam, the wife of North Korean leader Kim Jong-un, has died in a fight with Malaysia Airlines flight MH17. Here are the key points of the ruling:
LoRA-4: Gwamnatin Nijeriya ta yi tsokacin da shawarar da zai rufe iyakokin kasar.	**LoRA-4**: Seorang wanita Vietnam yang didakwa sebagai bagian dari pembunuhan Kim Jong-nam, saudara tiri dari pemimpin Korea Utara, telah dibebaskan.

Zero-shot transfer from Multiple Languages

- With multiple languages trained together, Full FT still lags behind in cross-lingual transferability
- Multilingual LoRA and Weight averaging of individual LoRA benefits different unseen languages
- Lower resource languages (Kirundi, Scottish, Somali, Yoruba) work best with individual LoRA training
- Similar languages may transfer better

SEEN \ UNSEEN	AZ	BN	JA	RN	KO	NE	GD	SO	TH	YO
AR	15.42	23.38	28.20	10.29	23.78	21.91	16.75	14.94	23.35	19.00
ZH	14.46	22.11	30.85	8.25	22.33	22.77	16.02	14.40	23.12	16.53
EN	15.12	22.24	28.91	8.90	23.09	23.43	15.54	18.30	22.23	20.85
HA	15.67	22.26	27.49	10.59	21.90	22.17	16.20	18.09	20.47	19.40
HI	13.60	22.71	28.81	9.75	21.31	24.96	18.13	12.90	22.54	19.30
ID	17.07	23.91	29.41	10.47	24.82	23.64	20.66	19.26	22.94	19.51
FA	10.66	22.15	27.59	10.19	20.77	20.68	16.26	15.86	22.28	17.62
PT	15.05	22.32	28.13	7.82	22.84	22.27	16.78	15.26	21.34	18.52
SW	17.10	22.69	28.67	11.87	24.37	24.84	18.18	18.74	21.42	19.49
TR	12.16	21.46	27.49	9.79	20.30	20.23	16.78	15.67	21.71	18.44
Full FT	15.89	5.97	22.61	13.17	8.45	21.72	17.92	12.15	13.17	13.75
LoRA-4	19.94	26.25	32.15	10.23	26.26	27.38	19.16	20.26	25.37	18.87
Avg. LoRA	18.22	23.05	29.71	16.25	25.03	24.57	22.67	21.51	23.42	22.96

ROUGE-L scores for 10 test languages on XLSum

Few-shot transfer from Multiple Languages

- Assume a handful target examples available (16, 64), compare LoRA continued learning (CL) and LoraHub
- LoRA continued learning superior performance
- A few examples significantly improves Full FT compared to the zero-shot results

	Zero-shot				16-shot		
	R-L	NLI	SH		R-L	NLI	SH
Full FT	14.48	28.87	13.71	Full FT	22.31	30.15	18.79
LoRA	22.59	37.39	24.21	LoRA (CL)	**24.71**	**41.12**	**26.47**
Avg.LoRA	**22.74**	**49.14**	**32.44**	LoraHub	23.37	38.95	26.07

Zero-and 16-shot scores for average of 10 test languages on XLSum

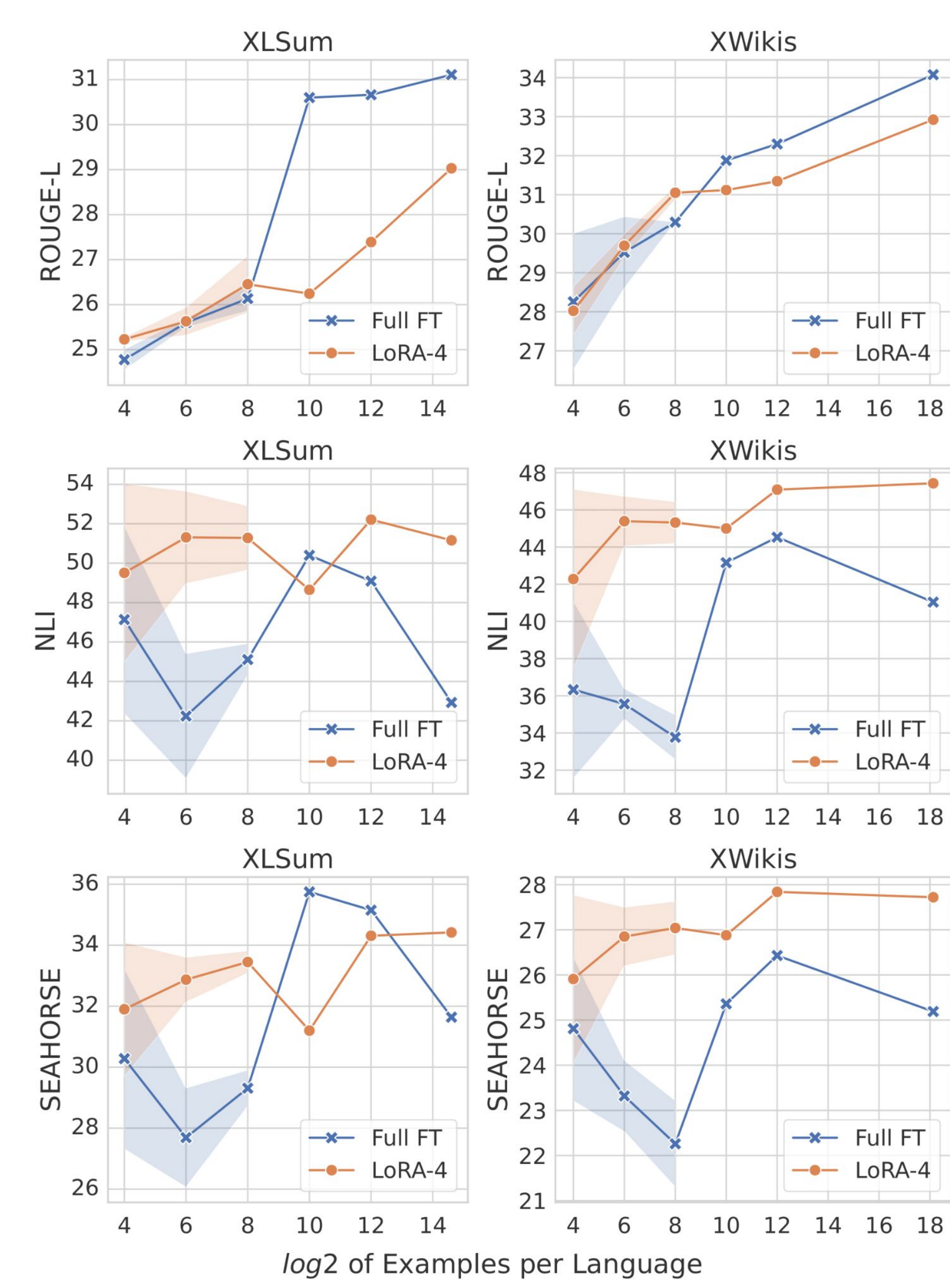
High-data Regime

- Train on all the data available for each language
- Full FT outperforms LoRA on summary relevance (R-L). LoRA with higher ranks enhances summary relevance
- LoRA is superior on summary faithfulness (NLI) & conciseness (SH), lower ranks see better scores

	XLSum			XWikis		
	R-L	NLI	SH	R-L	NLI	SH
Full-FT	**31.11**	42.93	31.64	**34.08**	41.04	25.19
LoRA-64	29.79	45.51	31.80	34.04	45.34	27.02
LoRA-16	29.77	48.48	33.25	33.80	46.10	27.42
LoRA-4	29.03	**51.16**	**34.42**	32.92	**47.43**	**27.72**

Low-Data Regime

- Randomly select 16, 64, 256, 1024, 4096 data per language and train together (balanced data)
- LoRA achieves overall better faithfulness (NLI) and conciseness (Seahorse) than Full FT
- For ROUGE-L, Full FT outperforms LoRA when provided > 1K training examples
- Low-data training on LoRA is more stable (Full FT more sensitive for the selection of checkpoints)



Conclusions

- LoRA achieves **superior performance** vs Full FT:
  - Zero-shot and few-shot cross-lingual transfer
  - Low-data regime (< 1K examples)
  - Summary faithfulness and conciseness
  - In addition, LoRA continued learning outperforms LoraHub under few-shot settings
- LoRA achieves **on-par performance** vs Full FT in larger models (see paper)
- LoRA achieves **worse performance** vs Full FT:
  - Smaller models
  - High-data regime, particularly for summary relevance