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Why?

- Master the specificities of the Telco field (standards, definitions, etc.)
- Master the specificities of Orange (equipment, offers, procedures, tools, etc.)
- → Applicative goal: better understanding of natural language and generation for internal use cases (technicians, customer assistants, etc.)

Specificities are expressed through new terms, acronyms or context-specific usage of usual words

Experiments & Methodology

- What ?
 - Fine-tune foundation pretrained models on a Telco data
 - Evaluate the adapted models on Orange use cases
- How?
 - 1 Data Preparation (corpus extraction & preproc.)
 - (2) Fine-tuning using different methods
 - (3) Perplexity measurement



1 Data Preparation

























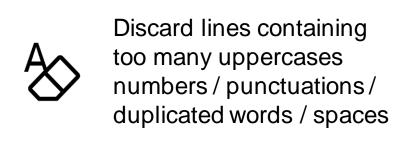
908M tokens

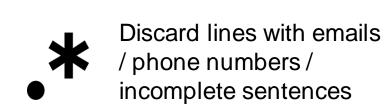
(noisy raw texts)

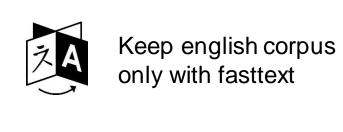


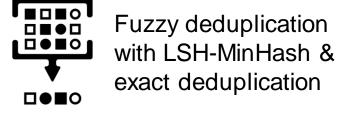


Preprocessing pipeline









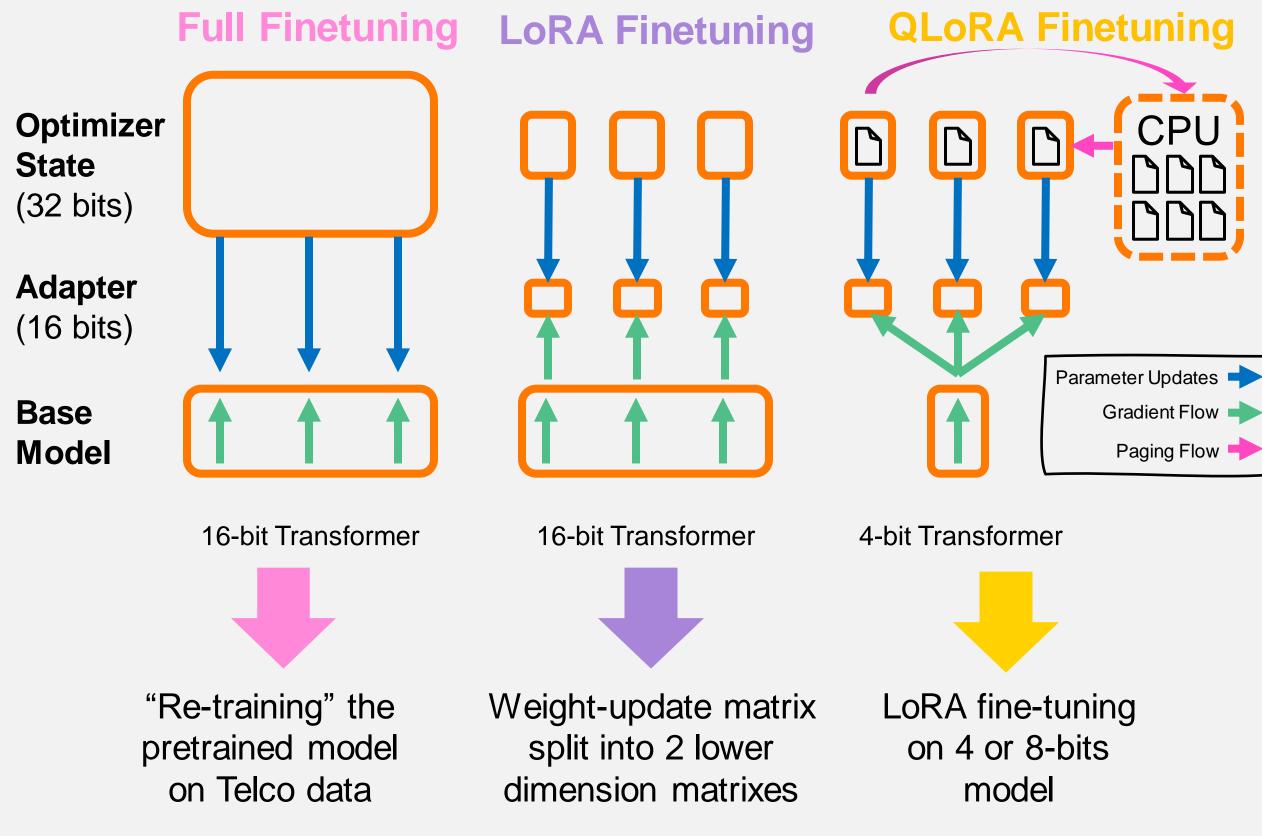




360M tokens (clean, English)

2 Fine-tuning methods

Task = Pretraining task (i.e. prediction of last token)



Dettmers, T., Pagnoni, A., Holtzman, A., & Zettlemoyer, L. (2023). Qlora: Efficient finetuning of quantized Ilms. arXiv preprint arXiv:2305.14314.

Experiments

- Test of these 3 fine-tuning methods making a variation of batch sizes, weights precisions, model types
- No vocabulary update (preliminary experiments showed that this is not effective)
- Encoder models were tested (RoBERTa) but results are only reported here on decoder/auto-regressive models (Falcon-1b).

3 First results

- Experiments on model tiluae/falcon-rw-1b
- Intrinsic measure: perplexity on in-domain texts. Low perplexity means the model models well the text.

Batch size	Weight precision	Finetuning type	Number of trainable parameters	RAM (GB)↓ (GPU A100)	Perplexity↓ (test set texts)
		None			<mark>41.38</mark>
8	fp32	Full fine-tuning	1.3B	29.0	27.41
8	fp32	LoRA	1.6M	16.9	32.93
8	fp16	LoRA	1.6M	15.8	32.91
8	8bits	QLoRA	1.6M	12.6	33.08
8	4bits	QLoRA	1.6M	11.9	33.38
4	fp32	Full fine-tuning	1.3B	25.3	27.44
4	fp32	LoRA	1.6M	11.7	33.97
4	fp16	LoRA	1.6M	11.2	33.96
4	8bits	QLoRA	1.6M	7.9	34.97
4	4bits	QLoRA	1.6M	<mark>7.3</mark>	35.27

- ✓ Fine-tuning the model on a Telco corpus improved the perplexity of the model on Telco sentences (from 41.38 perplexity to 27.41 for full fine-tuning)
- ✓ The batch size has a great importance on the fine-tuning efficience, and LoRA fine-tuning is degrading the result compared to full fine-tuning. Between LoRA & QLoRA, there is no big differences however.
- Other measures on Orange internal knowledge

Example of question-answering before fine-tuning

Steve Jarrett is the Chief Data Scientist at Orange. He is also the co-Who is Steve Jarrett for Data and Al at Orange? the Orange Data Science Lab. founder of

Example of question-answering after fine-tuning with LoRA

Who is Steve Jarrett for Data and Al at Orange? Steve Jarrett is the Head of Data and Al at Orange. He is responsible for development of Orange's data strategy and the implemtation of its Al strategy.

Perspectives

- Further evaluations with quantitative results incoming
- Interraction with knowledge graphs
- Tests with bigger models (trade-off between model size & performance to define)