PETapter: Leveraging PET-style classification heads for modular few-shot parameter-efficient fine-tuning

Jonas Rieger, Mattes Ruckdeschel, Gregor Wiedemann

Parameter Efficient Fine-Tuning (PEFT)

Pattern-Exploiting Training (PET)

Adapters

Few-Shot Learning

Efficiency

Modularity

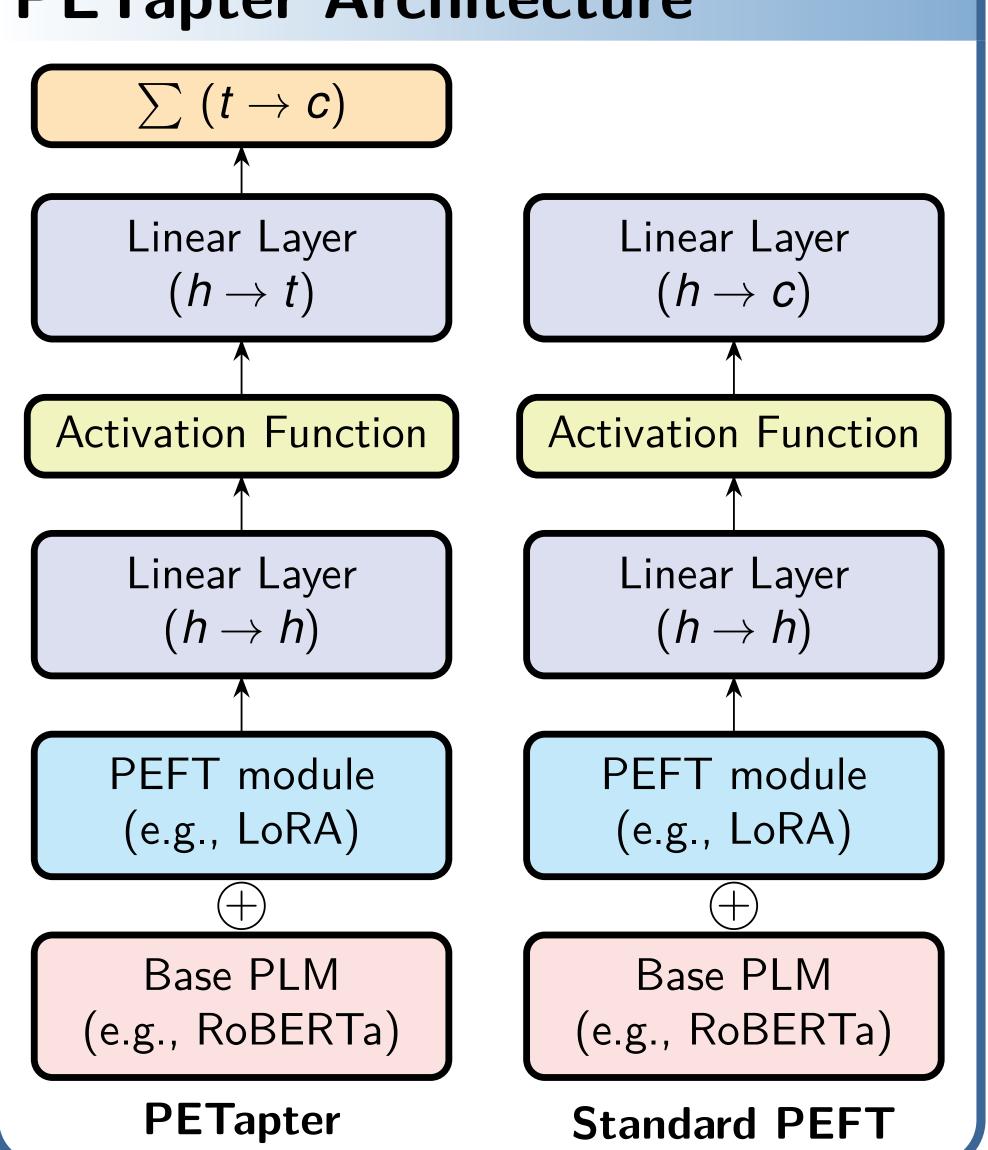
Sharibility

Reliability

Summary

- combination of advantages from few-shot learning and PEFT
- performance on par with PET
- no catastrophic forgetting
- ► fast training in low resource settings
- less disk space needed for sharing (16 MB vs. 2.1 GB)
- ► Ukraine: German PVPs perform worse
- ► Ukraine: zero-shot GPT-4 performs better than using in-context learning (max. 10 obs.)
- ► Ukraine: label unbalancedness is represented in class performances
- ► Bagging + majority vote is useful

PETapter Architecture



PETapter

- $ightharpoonup \mathcal{L}$ set of target labels with $|\mathcal{L}| = c$
- $ightharpoonup P^m(x)$ be a pattern function inserting m[MASK] tokens to an input X
- $ightharpoonup v^m(\ell)$ injective function mapping $\ell \in \mathcal{L}$ to mvocabulary tokens
- $ightharpoonup T = \bigcup_{\ell \in \mathcal{L}} \bigcup_{i=1}^{m} v^{m}(\ell)_{i}$ relevant vocabulary
- $ightharpoonup v^m: \mathcal{L} \to T^m$
- ► logits for the *m* [MASK] tokens: $M(v^m(\ell) \mid P^m(x)) \in \mathbb{R}^m$
- \blacktriangleright final score per label ℓ for an input X: $s(\ell \mid x) = \sum_{i=1}^{m} M(v^{m}(\ell) \mid P^{m}(x))_{i}$
- corresponding pseudo-probability: $q(\ell \mid x) = \frac{\exp(s(\ell \mid x))}{\sum_{\ell' \in \mathcal{L}} \exp(s(\ell' \mid x))}$
- cross-entropy loss over all observations:

$$L_{CE} = -\sum_{(x,\ell^*)} \sum_{\ell \in \mathcal{L}} \mathbb{1}_{\{\ell = \ell^*\}}(x,\ell^*) \log[q(\ell \mid x)]$$
$$= -\sum_{(x,\ell^*)} \log[q(\ell^* \mid x)]$$

Pattern-Verbalizer-Pair (PVP)

Yelp Q&A PVP:

Pattern [text]* [SEP] Question: What does the customer think of this restaurant? Answer: [MASK].

Verbalizers

class label	verbalizer				
1 star	terrible				
2 stars	bad				
3 stars	okay				
4 stars	good				
5 stars	great				

Ukraine PVP:

Pattern This sentence contains [MASK] [MASK] arms deliveries to Ukraine: {[target_sentence] [SEP] [context_before] [SEP] [context_after]}*

Verbalizers argument against, argument for, claim against, claim for

Benchmark Study (Accuracy ± Std.)

RoBERTa		Prompt Pattern		Q&A Pattern			Linear Layer		
Large		PETapter		PETapter					
n	Data	LoRA	Pfeif.	PET	LoRA	Pfeif.	PET	LoRA	Pfeif.
10	AG	0.714	0.702	0.842	0.746	0.738	0.836	0.373	0.443
		$\pm .070$	$\pm .081$	$\pm .025$	$\pm .054$	$\pm .060$	$\pm .032$	$\pm .049$	$\pm .104$
10	Yahoo	0.331	0.290	0.574	0.365	0.346	0.550	0.150	0.169
10		$\pm .040$	$\pm .056$	$\pm .030$	$\pm .049$	$\pm .054$	$\pm .040$	$\pm .027$	$\pm .041$
10	Yelp	0.470	0.479	0.475	0.472	0.490	0.486	0.221	0.216
10		$\pm .041$	$\pm .035$	$\pm .026$	$\pm .049$	$\pm .046$	$\pm .041$	$\pm .012$	$\pm .014$
100	AG	0.873	0.875	0.877	0.870	0.873	0.874	0.875	0.875
		$\pm .010$	$\pm .010$	$\pm .009$	$\pm .010$	$\pm .010$	$\pm .009$	$\pm .008$	$\pm .008$
100	Yahoo	0.662	0.661	0.680	0.654	0.656	0.675	0.648	0.647
		$\pm .014$	$\pm .017$	$\pm .013$	$\pm .008$	$\pm .012$	$\pm .013$	$\pm .016$	$\pm .015$
100	Yelp	0.613	0.614	0.593	0.622	0.620	0.595	0.551	0.512
		$\pm .014$	$\pm .010$	$\pm .014$	$\pm .013$	$\pm .013$	$\pm .016$	$\pm .019$	$\pm .043$

Training times for n = 100 observations

RoBERTa	Architecture	AG	Yahoo	Yelp
Base	PETapter	0.33	0.33	0.32
Base	PET	0.38	0.39	0.39
Large	PETapter	0.65	0.64	0.65
Large	PET	1.00	1.00	1.00
Large	PET	6.1s	6.2s	6.2s

Ukraine Study (Macro-F1 \pm Std.)

		PET	apter		Linear Layer		
n	Samp.	LoRA	Pfeiffer	PET	LoRA	Pfeiffer	
10	Equal	$0.31 \pm .043$	$0.33\ \pm .057$	$0.33 \pm .080$	$0.13 \pm .042$	$0.15 \pm .041$	
10	Strat.	$0.27 \pm .039$	$0.33 \pm .027$	$\textbf{0.40}\ \pm .055$	$0.16 \pm .001$	$0.17 \pm .021$	
100	Equal	$0.57 \pm .020$	$0.57 \pm .028$	$\textbf{0.59}\ \pm .027$	$0.26 \pm .029$	$0.29 \pm .030$	
100	Rand.	$\textbf{0.56} \pm .036$	$0.55 \pm .036$	$0.56 \pm .053$	$0.20 \pm .041$	$0.26 \pm .037$	
100	Strat.	$0.58 \pm .042$	$0.57 \pm .035$	$\textbf{0.59}\ \pm .054$	$0.20 \pm .030$	$0.26 \pm .035$	
250	Equal	$0.67 \pm .014$	$0.68 \pm .018$	$\textbf{0.70}\ \pm .025$	$0.46 \pm .050$	$0.49 \pm .075$	
250	Rand.	$\textbf{0.67}\ \pm .021$	$0.67 \pm .024$	$0.67 \pm .109$	$0.38 \pm .031$	$0.45 \pm .086$	
250	Strat.	$0.67 \pm .019$	$0.67 \pm .018$	$0.67 \pm .109$	$0.37 \pm .040$	$0.46 \pm .082$	

PVP Study LoRA-PETapter (Macro-F1 \pm Std.)

		No Pattern		Pattern			
n Samp.	Alpha	Normal	Shuffle	Alpha	Normal	Shuffle	
10 Equal	$0.22 \pm .039$	$0.25 \pm .040$	$0.22 \pm .039$	$0.23 \pm .039$	$0.31 \pm .043$	$0.28 \pm .043$	
10 Strat.	$0.20 \pm .025$	$0.22 \pm .031$	$0.22 \pm .033$	$0.23 \pm .067$	$0.27 \pm .039$	$0.27 \pm .043$	
100 Equal	$0.47 \pm .026$	$0.43 \pm .041$	$0.41 \pm .037$	$0.57 \pm .041$	$0.57 \pm .020$	$0.56 \pm .033$	
100 Rand.	$0.43 \pm .046$	$0.39 \pm .040$	$0.39 \pm .043$	$0.53 \pm .035$	$0.56 \pm .036$	$0.54 \pm .044$	
100 Strat.	$0.40 \pm .027$	$0.38 \pm .035$	$0.37 \pm .027$	$0.52 \pm .051$	$0.58 \pm .042$	$0.54 \pm .048$	
250 Equal	$0.62 \pm .022$	$0.61 \pm .024$	$0.60 \pm .022$	$0.67 \pm .021$	$0.67 \pm .014$	$0.68 \pm .019$	
250 Rand.	$0.58 \pm .035$	$0.57 \pm .054$	$0.56 \pm .054$	$0.65 \pm .029$	$0.67 \pm .021$	$0.66 \pm .020$	
250 Strat.	$0.60 \pm .025$	$0.59 \pm .030$	$0.58 \pm .032$	$0.65 \pm .019$	$0.67 \pm .019$	$0.66 \pm .017$	



