

Another possible approach is hybrid fine-tuning, which tries to combine various PEFT approaches, such as adapter, prefix-tuning and LoRA. This way it leverages the strengths of each method and mitigates their weaknesses and consequently achieves improved overall performance compared to individual PEFT methods. The work in this area is classified into two approaches: Manual Combination and Automatic Combination. The first one involves manually combining multiple PEFT methods by sophisticated design. On the other hand Automatic Combination incorporates PEFT methods automatically via structure search and because of that it typically requires more time and cost. In one of the previous

articles [8] authors proposed a method called UniPELT which incorporates sequential adapter, prefix-tuning, and LoRA via a gating mechanism. The mechanism controls the activation of each submodule, dynamically assigning higher weights to submodules that make positive contributions to a given task. The method requires more parameters and inference time than adapter, prefix-tuning, and LoRA, but achieves better performance than those individual methods. Another article [9], presents method AutoPEFT that integrates sequential adapter, parallel adapter and prefix tuning into the transformer block. The method also uses Bayesian optimization approach to automatically search for an appropriate architecture of neural network that activates certain layers to incorporate these PEFT modules.

Methods

Pretrained models we will be using:

- **google-bert/bert-base-uncased:** Pretrained model on English language using a masked language modeling (MLM) objective. This model is uncased, which means that it does not make a difference between english and English. It's good model for our starting implementations, because it's a bit smaller.
- **EMBEDDIA/crosloengual-bert:** A trilingual model, using bert-base architecture, trained on Croatian, Slovenian, and English corpora. We opted for this model due to its potential for good performance, since it is already trained on Slovenian corpora.

PEFT approaches used:

- **Prompt-Tuning:** Fine-tunes a small set of task-specific tokens appended to the input without altering the original model parameters.
- **LoRA:** Modifies the weight matrices of a model by applying low-rank updates, preserving the original parameters while adapting to new tasks.
- **LoHa:** Is similar to LoRA except it approximates the large weight matrix with more low-rank matrices and combines them with the Hadamard product. The method is supposed to be even more parameter-efficient than LoRA, yet it achieves performance levels comparable to it.

We decided to use **Slovene SuperGLUE** dataset, from Slobench, because it provides multiple different tasks, which are as follows:

- **BoolQ:** determine whether a given passage contains the answer to a yes/no question.
- **CB:** determine the commitment of a statement to a specific target.

- **COPA:** presents a premise and requires choosing the correct alternative explanation or cause.
- **MultiRC:** answering multiple-choice questions based on a given passage, with each question having multiple correct answers.
- **ReCoRD:** fill in the blank in a sentence with the correct entity mentioned in the passage.
- **RTE:** determine whether one text implies another, often categorized as entailment, contradiction, or neutral.
- **WSC:** test machines' understanding of pronouns and their antecedents in a sentence.

Metrics:

- **accuracy**
- **F1 score**

Previously described methods are not necessarily final. We may change some of them, in order to achieve a manageable set of testing combinations.

Results

Up to this point, we tried to fine tune some models on different tasks from the dataset. The results are shown in tables 1, 2 and 3. During the process of training and fine tuning, we ran into some problems, as the models achieved very bad performance in some cases. Despite thorough debugging and testing of our implementations, we are still not sure if there is a bug in our code or if the models really just struggle with these tasks.

| Method | Model | Accuracy | f1 |
|---------------|-------------------|----------|--------|
| prompt tuning | bert-base-uncased | 0.83 | 0.79 |
| LoHa | bert-base-uncased | 0.78 | 0.6806 |

Table 1. BoolQ task results on evaluation split of the dataset.

| Method | Model | Accuracy | f1 |
|---------------|-------------------|----------|------|
| prompt tuning | bert-base-uncased | 0.31 | 0.15 |

Table 2. CB task results on evaluation split of the dataset.

| Method | Model | Accuracy | f1 |
|--------|-------------------|----------|------|
| LoHa | bert-base-uncased | 0.52 | 0.52 |

Table 3. COPA task results on evaluation split of the dataset.

Discussion

TODO

Acknowledgments

TODO

References

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