Massive Choice, Ample Tasks (MACHAMP): A Toolkit for Multi-task Learning in NLP

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Abstract

Transfer learning, particularly approaches that combine multi-task learning with pre-trained contextualized embeddings and fine-tuning, have advanced the field of Natural Language Processing tremendously in recent years. In this paper we present MACHAMP, a toolkit for easy use of fine-tuning BERT-like models in multi-task settings. The benefits of MACHAMP are its flexible configuration options, and the support of a variety of NLP tasks in a uniform toolkit, from text classification to sequence labeling and dependency parsing. The code is available at: https://github.com/machamp-nlp (Version 0.1).

1 Introduction

Multi-task learning (MTL) (Caruana, 1993, 1997) has developed into a standard repertoire in NLP. It allows for learning tasks in parallel in neural networks (Caruana, 1993) while leveraging the benefits of sharing parameters. The shift—or the “tsunami” (Manning, 2015)—of deep learning in NLP has facilitated the wide-spread use of MTL since the seminal work by Collobert et al. (2011), which has lead to a multi-task learning “wave” (Ruder and Plank, 2018) in NLP. It has since been applied to a wide range of NLP tasks, developing into a viable alternative to classical pipeline approaches. This includes early adoption in Recurrent Neural Network type of models, e.g. (Lazari-dou et al., 2015; Chrupała et al., 2015; Plank et al., 2016; Søgaard and Goldberg, 2016; Hashimoto et al., 2017), to the use of several unsupervised multi-task objectives to train BERT-like Language Models (Devlin et al., 2019) and ultimately, their combination in (low) supervised data regimes to fine-tune contextualized word embeddings with supervised objectives (Sanh et al., 2019).

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Figure 1: Overview of MACHAMP, when training jointly for sentiment analysis and POS tagging. A shared encoding representation and task-specific decoders are exploited to accomplish both tasks.

The key idea of language model pre-training and contextual embeddings (Howard and Ruder, 2018a; Peters et al., 2018; Devlin et al., 2019) is to pre-train rich representation on large quantities of monolingual or multilingual text data. Taking these representations as starting point has lead to enormous improvements across a wide variety of NLP problems. Effective models emerged for many languages and tasks (Hashimoto et al., 2017; Kondratyuk and Straka, 2019; Sanh et al., 2019; Hu et al., 2020). MTL comes in many flavours, based on the type of sharing, the weighting of losses, and the design and relations of tasks and layers. In general though, outperforming single-task settings remains a challenge (Martínez Alonso and Plank, 2017; Clark et al., 2019). For an overview of MTL in NLP we refer to (Ruder, 2017).
We introduce MACHAMP, a flexible toolkit for multi-task learning and fine-tuning of NLP problems. The main advantages of MACHAMP are:

- Ease of configuration, especially for multi-task setups;
- Support of a wide range of NLP tasks, from sequence labeling to dependency parsing and text classification;
- Support for the processing of multiple datasets at once;
- MACHAMP supports initialization with and finetuning of BERT embeddings (Devlin et al., 2019), which have shown to achieve state-of-the-art results for many NLP tasks.

For MACHAMP, we took a recent multilingual multi-task Universal Dependency parser (UDify) as starting point, which in a single model obtains competitive performance on 75 languages and all UD tasks (Kondratyuk and Straka, 2019). UDify however is targeted to Universal Dependencies (UD) parsing only. Consequently, their code and data handling logic was specifically designed and tailored for UD data. Kondratyuk and Straka (2019) used multilingual BERT1 (mBERT) and fine-tuned its parameters for all UD tasks at hand (Nivre et al., 2016): part-of-speech tagging, lemmatization, morphological tagging, and dependency parsing.

We propose MACHAMP, which includes the functionality of UDify, yet supports many more data formats and tasks, and with its easy configuration, opens up for general use on more NLP tasks (see Section 2.2). Moreover, we plan to extend MACHAMP continuously and document the releases by updating this reference. The backbone of MACHAMP and UDify is AllenNLP (Gardner et al., 2018), a PyTorch-based (Paszke et al., 2019) Python library containing modules for a variety of deep learning methods and NLP tasks. It is designed to be modular, high-level and flexible.

2 Model

In this section we will discuss the model and its supported tasks.

2.1 Model overview

An overview of the model is shown in Figure 1. MACHAMP takes a pre-trained BERT model (Devlin et al., 2019) as initial encoder, and fine-tunes its layers by applying an inverse square root learning rate decay with linear warm-up (Howard and Ruder, 2018b), according to a given set of downstream tasks. For the task-specific predictions (i.e., decoding), each task has its own decoder, which is trained only for the corresponding task. By default all task-specific decoders are placed at the top-layer of the encoder (BERT); the configuration is though flexible (see Section 4.1). To make sure the BERT layers are used optimally, a layer attention over all layers is used for each decoder. The backbone of MACHAMP and UDify is AllenNLP (Gardner et al., 2018), a PyTorch-based (Paszke et al., 2019) Python library containing modules for a variety of deep learning methods and NLP tasks. It is designed to be modular, high-level and flexible.

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All the input is converted to WordPieces (Wu et al., 2016), an extension of Byte Pair Encodings (BPE) by Sennrich et al. (2016). For word-level tasks, the first WordPiece item of a word is used for the prediction. For sentence level tasks, the pooled output of the [CLS] token is used.

When multiple datasets are used for training, they are first separately split into batches (so each batch only contains instances from one dataset), which are then added together and shuffled before training. This means that small datasets will be underrepresented, which can be overcome by enabling proportional sampling (Section 4.2). During decoding, the loss function is only activated for tasks which are present in the current batch. By default all tasks have an equal weight in the loss function. The weight can be tuned, see Section 4.

2.2 Supported tasks

In the following, we describe the tasks MACHAMP supports. We distinguish two main types of tasks, one where the annotation is done on the word level (i.e. word-level tasks), and one where longer utterances of text are annotated with labels. For the latter, MACHAMP currently only supports sentence classification.

Sequence labeling This is to support classical token-level sequence prediction tasks, like part-of-speech tagging. Currently, MACHAMP uses greedy decoding with a softmax output layer from the hidden BERT WordPiece representation, similar as in (Kondratyuk and Straka, 2019).

String2string This is an extension to sequence labeling, which learns a conversion for each input word to its label. Instead of predicting the labels

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1 https://github.com/google-research/bert/blob/master/multilingual.md
directly, the model can now learn to predict the conversion. This strategy is commonly used for lemmatization (Chrupač, 2006; Kondratyuk and Straka, 2019), where it greatly reduces the label vocabulary. We use the transformation algorithm from UD Pipe-Future (Straka, 2018), which was also used by Kondratyuk and Straka (2019).

Dependency parsing As in UDify (Kondratyuk and Straka, 2019), MACHAMP implements the deep biaffine parser (Dozat and Manning, 2017) using the Chu-Liu/Edmonds algorithm (Chu, 1965; Edmonds, 1967) for decoding the final tree. The default evaluation metric is LAS over all tokens (as opposed to accuracy for the other task types).

Text classification For text classification, MACHAMP predicts a label for every text by using the pooled [CLS] output of BERT. Pooling is performed by a feed-forward layer with a tanh activation which is trained with Next Sentence Prediction objective (Devlin et al., 2019) during pre-training. For tasks which model a relation between multiple sentences (e.g. RTE), a special [SEP] token is automatically inserted, so that the model can take this into account.

3 Usage
To use MACHAMP, one needs a configuration file, input data and a command to start the training or prediction. In this section we will describe each of these requirements.

3.1 Configuration
The model requires two configuration files, one that specifies the datasets and tasks, and one for the hyperparameters. In the following subsections, we will describe the most useful options for both configurations.

A simple example of a dataset configuration file is shown in Figure 2. On the first level, the dataset names are specified (i.e., “UD” and “RTE”), which should be unique identifiers. Each of these datasets needs at least a train_data_path, a validation_data_path, a word index (i.e., word_idx) or sentence indices (i.e., sent_idxs), and a list of tasks. The word index specifies on which column the input words are to be read (see Section 3.2). For each of the defined tasks, the user is required to define the task_type (Section 2.2), and the column index from which to read the labels (i.e., column_idx). More options that can be passed on the task level are discussed in Section 4.1.

3.2 Data format
MACHAMP supports two types of data formats, which correspond to the level of annotation (Section 2.2). For word-level tasks, we will use the term “word-level file format”, whereas for sentence-level task, we will use “sentence-level file format”.

The word-level file format is similar to the CoNLL format (Nivre, 2015) introduced for Universal Dependencies. It assumes one word per line, with each annotation layer following each word separated by a tab character (Figure 3a). Sentences are delimited by an empty line. Comments are lines on top of the sentence which have a different number of columns with respect to token lines. It should be noted that for dependency parsing, it assumes the relation label to be on the column_idx and the head index on the following column.

Figure 2: Example dataset configuration file, to predict UPOS, lemmas, and textual entailment simultaneously.

For the hyperparameters configuration a default option is already specified (configs/params.json), which should give reasonably high performance for most tasks.

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3We do not identify comments based on lines starting with a ‘#’, because datasets might have words in the first column that can start with a ‘#’. 
smell ya later ! negative

Figure 3: Examples of data file formats.

The sentence-level file format for sentence classification is very similar (Figure 3b), except that there can be multiple inputs. In contrast to word_idx, a list of sent_idxs are defined to enable modeling the relation between any arbitrary number of them.

3.3 Training

Given the setup illustrated in the previous sections, a model can be trained using the following command. It assumes the configuration (Figure 2) called configs/upos-lemma-rte.json.

```
python3 train.py --parameters_config \ configs/params.json --dataset_config \ configs/upos-lemma-rte.json
```

As is common in AllenNLP (Gardner et al., 2018), by default the model and the logs will be written to logs/<JSONNAME>/<DATE>. The name of the directory can be set manually by providing --name <NAME>. Furthermore, --device can be used to specify which GPU to use (-1 for CPU is the default).

3.4 Inference

Prediction on new data can then be done using the following command:

```
python3 predict.py \ logs/<NAME>/<DATE>/model.tar.gz \ <INPUT FILE> <OUTPUT FILE>
```

It requires the path to the best model serialized during training stored as model.tar.gz in the log directory as specified above.

4 Options

For the full list of tuning hyperparameters, see the default configs/params.json in the repository (and Section 5.2). In this section we first discuss the parameters which can be defined for tasks individually, and then describe how to change the pre-trained embeddings.

4.1 Dataset configuration

The settings described in this section can only be set on the task level.

**Metric** Can be used to specify the evaluation metric. If not set, it defaults to accuracy, except when task_type is set to dependency, then LAS, as defined by AllenNLP (Gardner et al., 2018), is used. Possible metrics are: ‘acc’, ‘LAS’, ‘micro-f1’, ‘macro-f1’ and ‘span_f1’ (for span-based sequence labeling).

**Layer** Defines which layers are used for predicting the task. The model uses up to the specified layer (if it set to 8, it uses all layers from 1 to 8). As explained in Section 2, by default the model uses layer attention to mix the information from the specified layers.

**Loss weights** In multi-task settings, not all tasks might be equally important, or some tasks might just be harder to learn, and therefore should gain more weight during training. This can be done by setting the loss_weight parameter on the task level (by default the value is 1.0 for all tasks).

**Adaptive** This enables the adaptive softmax loss function (Grave et al., 2017). This loss function groups the labels into several clusters based on their frequency. By first focusing on the more frequent labels the model can gain both in efficiency and in performance. This should mostly be beneficial for tasks with imbalanced label spaces.

Following UDify, the adaptive softmax loss is set to True by default (with cutoff values 8 and 15), as it generally improves performance. However, when the label vocabulary setting for a task is lower than 8, the cutoff value does not apply and adaptive softmax is not active.

4.2 Hyperparameter configuration

Whereas most of the hyperparameters can simply be changed from the default parameters (configs/params.json) in the repository, we would like to highlight two settings.

**BERT model** The path to pre-trained BERT can be set in the params.json file. Specifically the pretrained_model value in
| Parameter       | Value     | Range     |
|-----------------|-----------|-----------|
| Optimizer       | Adam      |           |
| $\beta_1, \beta_2$ | 0.9, 0.99 |           |
| Weight decay    | 0.01      |           |
| Label smoothing | 0.03      |           |
| Dropout         | 0.5       | 0.3, 0.5, 0.7 |
| BERT dropout    | 0.1       | 0.1, 0.2  |
| Mask probability| 0.1       | 0.1, 0.2, 0.3 |
| Layer dropout   | 0.1       |           |
| Batch size      | 32        | 16, 32, 64 |
| Epochs          | 80        |           |
| Patience        | 5         |           |
| Base learning rate | .001   | .0001, .001, .01 |
| BERT learning rate | $5\times10^{-5}$ |           |
| Warmup rate     | 1/80      |           |
| Gradient clipping | 5.0      |           |
| Dep. tag dimension | 256    |           |
| Dep. arc dimension | 768     |           |

Table 1: Final parameter settings, incl. tested ranges.

the datasetreader/bert/ section. The model expects the embeddings to be in PyTorch format, which can be obtained by the pytorch_transformers command.

Proportional sampling To avoid larger datasets from overwhelming the model, proportional sampling can be enabled (iteration/proportional_sampling).

In previous work this has shown to be reach high performance when modeling multiple tasks hierarchically (Sanh et al., 2019). When enabled, the model will first pick a random task, and then pick a random batch from that task. In other words, all datasets will have a roughly equal amount of batches; smaller datasets will be up-scaled and larger datasets will be downscaled (the number of batches per batch remains the same). It should be noted that for specific tasks, more involved strategies have been devised (Wang et al., 2020; Stickland and Murray, 2019).

5 Experiments

In this section we describe the procedure how we determined robust default parameters for MACHAMP; note that the goal is not to achieve a new state-of-the-art, but generally to reach on-par performance for multiple tasks, while reaching one robust setting of hyperparameters. To this end, we will describe the datasets and hyperparameters used for tuning, and the obtained results in single-task and multi-task setups.

5.1 Datasets

We report performance over three benchmarks. They were selected to cover a range of NLP tasks, from syntactic to semantic and inference-level tasks, spanning the diverse supported tasks and different dataset setups. Next we describe each dataset and all its tasks. For simplicity (and due to availability), we focus on English datasets only.

UD (EWT) The English Universal Dependencies (Silveira et al., 2014) data derived from the English Web Treebank. It is the English dataset which was the earliest part of UD English. It is the most commonly used dataset for UD English dependency parsing. It contains 5 tasks: fine and coarse-grained POS tagging (XPOS and UPOS, respectively), lemmatization, morphological tagging and parsing. This dataset is an example where all tasks are annotated jointly for every instance.

GLUE The General Language Understanding Evaluation benchmark (Wang et al., 2018) has become the default benchmark for inference-type or semantics tasks, including entailment, paraphrasing and sentiment analysis. It consists of a collection of several datasets (Warstadt et al., 2019; Socher et al., 2013; Dolan and Brockett, 2005; Cer et al., 2017; Williams et al., 2018; Rajpurkar et al., 2018; Bentivogli et al., 2009; Levesque et al., 2012), and hence represents an example of a dataset with multiple disjointly labeled datasets. We use all datasets except for SST, which is a regression task, and WNLI, following previous work (Devlin et al., 2019).

PMB The Parallel Meaning Bank (Bos, 2015; Abzianidze et al., 2017) is a multilingual data collection for semantic processing. It includes a range of basic tasks, all of which form the basis to generate a Discourse Representation Structure (DRS) using Boxer (Bos, 2015). The base tasks, which we evaluate on here, include: CCG supertagging, semtagging, verbnet and wordnet tagging. We use the English part and PMB version 3.0.0. It should be noted that for the wordnet senses, we used the string2string task type. This reduced the vocabulary size from 4,443 to 1,804. This is arguably


| Task      | dep | feats | lemma | upos | xpos | lemma | semtag | supertag | verbnet | wordnet |
|-----------|-----|-------|-------|------|------|-------|--------|----------|---------|---------|
| Train size |     |       |       |      |      |       |        |          |         |         |
| M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{ST}) | 89.90 | 97.18 | 98.21 | 97.01 | 96.64 | 97.52 | 98.32 | 94.87 | 96.64 |         |
| M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{MT}) | 89.61 | 97.15 | 97.79 | 97.01 | 96.79 | 97.33 | 98.23 | 94.91 | 97.52 | 98.32 |
| UDify   | 89.67 | 97.15 | 97.80 | 96.90 |       |       |        |          |         |         |

Table 2: Performance of M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{ST}) (single-task), M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{MT}) (multi-task), and M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{MT}+\textsc{P}) (multi-task+proportional sampling) on the dev sets. For all tasks, accuracy is used as metric, except for dependency parsing where LAS score is used. Training size is the number of annotated instances (words in case of EWT and PMB, sentences for GLUE). Results reported per dataset are from UDify (Kondratyuk and Straka, 2019) and BERT-base (Devlin et al., 2019). The task types are: dep: Dependency parsing; seq: Sequence labeling; c: text classification; s2s: String2string.

5.2 Hyperparameter tuning

Because UDify (Kondratyuk and Straka, 2019) was focused on training on many UD parsing datasets and languages simultaneously, its hyperparameters were tuned towards massive data sizes. We compared a range of hyperparameter settings for our three setups by using grid search,\textsuperscript{5} and used the parameter settings that reached the highest rank (averaged over the three sets). In Table 1 we report the best hyperparameters across all datasets (these are the default of the toolkit), and the range of parameters which we evaluated. Patience and model selection is based on the sum of all the evaluation metrics of all tasks.

5.3 Results

The final performance for all datasets and tasks on the development data are reported in Table 2. For each dataset we ran a multi-task model (M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{MT})), performing all tasks jointly (for GLUE, we train on all datasets jointly). We compare this to single-task model (M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P}(\textsc{ST})), where we train a separate model for each task.

First, we see that M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P} obtains state-of-the-art performance for EWT for which we can directly compare on all tasks except fine-grained POS tagging. In more detail, the results of UDify (Kondratyuk and Straka, 2019) are in a similar range for all tasks; the largest difference and improvement for M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P} is on dependency parsing, which is probably due to parameter tuning. The multi-task model works well and for both EWT and PMB performs similar to the single-task models; on some of the task M\textsc{A}\textsc{C}\textsc{H}\textsc{A}\textsc{M}\textsc{P} even slightly outperforms them.

However, on GLUE performance of the multi-task model lacks behind on 6 out of the 9 tasks. This is probably due to the immense size and disparity of the datasets. Proportional sampling helps to train the model more quickly and especially for the smaller datasets results in better accuracies. Comparing to the original results from BERT (Devlin et al., 2019), we see that their scores are higher. This is probably because of the differences in the setup: they used BERT-base, we use BERT-multilingual, also they only trained for 3 sentences for efficiency reasons.
epochs which only makes sense for large datasets. Furthermore, they tuned the learning rate per task, whereas we were mainly looking for a robust setting over multiple datasets.

**Learning Curve** As training a joint MTL model on GLUE is computationally expensive (it takes several days, particularly when SNLI is included with over half a million training instances), we trained single-task models and examine the effect of increasing data size per GLUE task. We focus on the larger GLUE tasks which have more than 100k training instances. The learning curves shown in Figure 4 show that all tasks benefit from more GLUE training data, even beyond 50k instances accuracy keeps increasing, except for SST which starts to flatten out. MNLI is the task with the steepest learning curve and the lowest accuracy. This shows that the GLUE tasks remain challenging and more data clearly helps most of the tasks.

**Proportional Sampling** We examine the effect of proportional sampling (Section 4.1) only for the GLUE benchmark, as it contains datasets of varying sizes. The performances per epoch are plotted in Figure 5. The plot clearly shows the advantages of using proportional sampling; higher performance is obtained with fewer epochs. These results also show that there is more potential to be gained; perhaps using a dynamic ratio we can benefit from both types of training (also reflected in Table 2, where both models show very different strengths).

It should be noted that the proportional sampling model could have been somewhat “unlucky” with the sampling, and might have benefited from training longer. The other model had many points where it did not improve for 3–4 epochs

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6 Conclusions

We introduced MACHAMP, a flexible toolkit for BERT-based multi-task learning, and evaluated it on three multi-task benchmarks. Performance is on-par to previous state-of-art models, and even higher for some low-resource settings. The source code is freely available.

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