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Reproducibility of SciBert

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Modul : Data Mining

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Introduction

- Als pretrained model hängt bert stark von dem korpus ab
- Genauso ist das vocabular sehr wichtig
- Andere arbeiten zeigten den einfluss eines erweiterten trainings/besser passenden korpus? referenz suchen
- \Rightarrow Roberta zum Beispiel zeigte, dass allein weiteres training die ergebnisse verbessern kann
- Wissenschaftliche texte unterschieden sich allgemein sehr stark von "normalen"
- \Rightarrow Somit ist ein auf ähnliche weise trainiertes modell als bessere grundlagen für NLP aufgaben im wissenschaftlichen bereich sinnvoll
- Gab es in dieser form noch nicht
- \Rightarrow besitzt daher potential (annahme das BERT gut sei)
- insbesondere als grundbaustein für unterschiedlichste aufgaben im !!! wiss. bereich
- Allgemein stellt sich das Problem von Datensätzen insbesondere da diese annotiert werden müssen (im wiss. bereich teuer da hochqualifizierte experten notwendig sind)

investigated more closely. To be precise, this parameter is the batch size. On the one hand, the batch size has an influence on the efficiency and especially on the graphics card memory requirements of the model, on the other hand, it can be responsible for a faster convergence or even a non-convergence. The extremes, for example the convergence that does not come about, do not occur in general. Nevertheless, for example the reduction of the batch size can lead to the fact that a model, which was not trainable on the given hardware before because of video memory capacities, now suddenly can be trained.

Since in the original SkyBERT paper many parameters were taken over from the original BERT paper and these were not examined more closely for their influence on the new model, in the course of this work the influence of one of these parameters is

State of the art

2.1 BERT

- BERT as revolution
- pretrained-models
- usefull even without finetuning
- \Rightarrow unexpected precision
- nowadays used for many different NLP tasks
- Architecture of BERT
 - explain corpora
 - explain vocabulary
 - explain tokenizer
- extensions of BERT like roBERTa

2.2 BioBERT

BioBERT is one of the extensions of BERT which has emerged because BERT by itself did not yield the desired results in the biomedical landscape. This observation has often been related to the differences in word distributions between a general domain such as Wikipedia, on which BERT was trained and the highly specialized words that are used often or with this meaning only in the corresponding domain. This difference in the underlying corpora not only produces differences in the architecture of the model itself but implies a possible need for adjustments to the used vocabulary and the tokenizer. [3]

Based on this prior knowledge, it was hypothesized that a model that takes these particularities into account should perform significantly better than general models in tasks of this specific domain. Based on this hypothesis, BioBERT was created. A model that should be better adapted to the biomedical domain than BERT.

Nevertheless, BioBERT itself is only a further trained version of BERT. This means the original BERT model was used as the basis and further trained on either PubMed abstracts, PubMed central full-text articles, or on both. Therefore the authors chose to keep the original BERT vocabulary to be able to use the pretrained version of BERT as the basis. This had the advantage that the original model only needed to be further trained on the new corpus and the needed training time could be reduced.

2.3 AOG-BERT

- als kontrahend zu SciBERT [4]

2.4 Datasets

- zum Beispiel NCBI-Disease (versuch einen gold-standard für corpora zu erstellen)
- sehr günstig um darauf entsprechende modelle zu trainieren [2]
- SciERC /sciie im repo [5]

Due to the availability of the Datasets used by the original authors, we will use their prepared datasets,

which are already prepared in a way that it is easier to use them for training and still only vary slightly from the original datasets. The datasets which we will use are directly retrieved from the SciBERT GitHub page and made available through the DataDeps package which provides an easy way to retrieve data that may or may not be locally available. If it is not already stored locally, it will be cached in the local Julia path and inside Julia, DataDeps provides the corresponding paths to the data and retrieves it from the defined source if needed. Furthermore, a hash can be defined as well to ensure that the provided data is identical to the expected one.[7]

In the following paragraph, we will take a closer look at the original data and the individual changes that have been made to use those Datasets for the training process.

Chemprot

Chemprot is in a JSON lines file format provided. More precisely every line consists of a text and the corresponding label. A field for metadata exists as well but is most of the time not used. In its original format, the Chemprot corpus consists of a develop, test, and train set of which the develop, test, and train folder correspond to the identically named files inside the chemprot folder provided on the GitHub site of SciBERT. The difference arises from a database-like structure in which the Chemprot corpus is originally provided, in contrast to those subdivided information sets where for example the text itself is in another file than the positions and annotations. Those divided pieces of information were combined and are provided in a single file in the already mentioned format. [1, 6]

SciBert

SciBERT uses the original BERT architecture and thus includes customizability and universal applicability. SciBERT is a version of BERT that is trained on a different corpus. This is supposed to make SciBERT better at understanding natural language which comes from its designated domain. More precisely in this instance the biomedical and computer science domain. In the original paper, the authors presented four different versions of SciBERT two which utilize the standard BERT Vocabulary, and two which use a specialized vocabulary to represent the vocabulary of the corpus better. It should be noted that the two different vocabularies overlap only by approximately 42%. This shows how different the two underlying corpora are and thus makes the assumption that the SciBERT versions which utilise this adjusted vocabulary might have only through this better to the domain adapted vocabulary already an advantage over the standard BERT model and the SciBERT model which uses BERTs vocabulary.

3.1 Experiments to be reproduced

In this section, we will take a brief look at the experiments performed in the original paper and briefly discuss what these experiments are about. To do this, we will split the tasks into two different parts. First, we will take a look at the so-called classification tasks and what this category entails, and then we will move on to the so-called labeling tasks. How these tasks are implemented in detail we will discuss later in chapter 4.

Classification tasks

Classification tasks, as the name suggests, describe how we "classify" some input data. This includes tasks such as choosing the right label for a given text or word. In the world of BERT, this means that BERT must determine which label best matches a given sequence of tokens or a single token.

Text Classification (CLS)

A text classification task corresponds to the example given earlier. Thus, the model must predict the correct label for the given text. This is the same problem definition as in the SciBERT work.

Relation Classification (REL)

The relation classification task can be considered as another type of classification problem. Here, the model must choose the correct label for two given parts of a sentence. The resulting label can then be interpreted as the predicted relation between the two given parts of the sentence.

Sequenz labeling tasks

Unlike classification tasks, a single sentence can have multiple labels. This makes the model, in general, more complex but provides us with the flexibility to define a given sentence with many properties which are expressed by the labels. Thus, we can obtain any given combination of labels.

Named Entity Recognition (NER)

PICO Extraction (PICO)

DEP ?

dependency tag and arc embedding of size 100 and
biaffine matrix attention

(maybe why it wasn't considered here any further ?
[abhängig davon ob noch implementiert])

3.2 Corpus

Comparison

3.3 Vocabulary

BaseVocab vs. SCIVocab

! $\approx 42\%$ overlap

SentencePiece

Experiments

- kurze einföhrung in die test fälle mit einer erkläröung, was f1 scores sind
- Alles NLP Aufgaben bei denen Bert "überraschend" gut abschneidet
- Jetzt mit der erweiterung zu scibert erneut betrachtet
- Einföuss des vocabulars und des corpus genau gegenübergestellt
- all got dropout of 0.1
- loss cross entropy
- optemizer adam
- finetuning for 2 to 5 epochs

In the following, we will take a closer look at how the tasks already described conceptually are implemented. Since some tasks use the same architecture for the model, more precisely the identical architecture for the last layer as the all other always stay the same. We will first examine the classification tasks and then the labeling tasks in more detail. Thus, the order in which the tasks will follow will remain the same as before.

Nevertheless, both task types will use a dropout of 0.1, cross-entropy for loss, and Adam as the optimizer, all following the instructions from the SciBERT paper.

4.1 Classification tasks

Both classification tasks use the same architectural structure. This means that the final BERT or SciBERT layer is followed by a dense or fully connected linear layer. This dense layer then acts as the linear classification layer described in the original work.

Text Classification (CLS)

Classic sequence classification tasks or text classification tasks, as they are called in the original paper, can be implemented in Julia without any particular challenges. Especially since the data is already available in a format that mostly only needs to be loaded and the task is only a transformation from a text to a single label. Together with the architecture for classification tasks already described, this makes the implementation of this task very easy. We just need to combine Bert and the classification layer and provide this model with the text and the label in the correct formats. This means, on the one hand, adding the "[CLS]" and "[SEP]" tokens to the text after preparing the text with the tokenizer and wordpiece and, on the other hand, preparing the labels in a format that can be read by the model, which transforms them into a "OneHotMatrix" for "Flux", corresponding to a one out of k representation per sequence.

Relation Classification (REL)

4.2 Sequenz labeling tasks

Named Entity Recognition (NER)

Pretrained model -> linear classification layer with softmax output

PICO Extraction (PICO)

4.3 DEP

dependency tag and arc embedding of size 100 and biaffine matrix attention

4.4 Frozen embeddings

Vorherige experimente unter dem "festhalten" von BERT selbst und nur der anpassung der letzten ebene

4.5 Influences of different platforms

In this section, we will take a brief look at the usability of different hardware platforms for creating transformer models and when training or testing them. More specifically, we will compare the google-colab environment with an Nvidia GPU and an AMD GPU. Due to the randomness of the assignment of hardware on the google-colab side, I cannot further define the GPU that was used on this platform. The Nvidia GPU used was a GeForce 940MX with about 2GB of VRAM, and the AMD GPU on the other side was an RX580 with about 8GB of VRAM. At this point I will briefly describe the extent to which AMD's ROCM stack is usable, because surprisingly I was able to define the model and make predictions with it in a newly generated state. Unfortunately, due to instability in the ROCM stack, the Linux kernel was no longer able to use the GPU after an update that must have broken some internal dependencies that the kernel and ROCM driver rely on, and thus

the video output of the computer was also unusable. Even though this shows that an AMD GPU is indeed capable of running the Transformer package and loading at least a defined model. Even though I can't disclose whether the model could be trained or otherwise used further. This fact in itself is surprising, since AMD itself describes the support status of the RX580 as "may or may not work" and Julia describes AMD GPU support as Level 3, which is the lowest level of support. (verweis zu der aussage)[belege und verweis zu ROCM]

However, I would advise anyone against installing the ROCM stack on a production system, as it is still unstable and I would therefore recommend experimenting only in some form of virtualized environment. Of course, this warning only applies to systems that rely on working video output.

Due to the failure with the ROCM stack, only the MX940 and the google-colab environment will be considered in the following part. These two platforms will not only be compared, but also how they behave in the face of two different implementations written in Julia and Python.

4.6 Complications

In particular, the classic text classification was relatively unproblematic to implement. Nevertheless, there were some minor obstacles on the way to a finished reproduction of the original CLS. The order will follow that of the information flow in the model, starting with the input data and ending with the output.

After this sequence, the first problem is to transform the data, which are now already the two text areas with the special tokens "[<<]", "[>>]", "[[[]]" and "[]]" marked, the sentences now have to be processed by the tokenizer and by wordpiece, without changing the mentioned tokens. If the individual sentences would be processed without further precautions, then the special tokens would be modified. Through this alteration, however, these tokens would no longer be interpreted by the vocabulary as special tokens, but would be regarded as "normal" words. To avoid this, a wrapper was written, which divides

the text into partitions and processes them individually by the Tokenizer and Wordpiece. This was particularly necessary due to the fact that the partitions marked by a pair of corresponding special tokens might not have the same length after processing. Due to this potential variation of the segment length, it is not directly possible to find the new position of the tokens from the old one and simply adding them manually. Instead, the individual sections separated by the special tokens are processed individually and subsequently the special tokens are placed between the corresponding segments. This procedure is based on the addition of the "[CLS]" and "[SEP]" tokens in the CLS, but extends it.

The next problem follows directly the previously described one. The individual sentences of the data sets sometimes consist of characters that do not occupy only one "code unit" and so problems can occur if the end of a string is expected at the position of the length of the string. A 'code unit' describes here a fixed size in the memory which is needed in general for the coding of a single character. Fortunately, an error is generated if an attempt is made to create a view of a string that ends or begins in the middle of a character that spans multiple code units. Although the error is relatively vague, a closer look at the string quickly reveals that the error occurs in the vicinity of special characters. With this knowledge one can quickly find the explanation and the underlying problem in the corresponding documentation due to the different number of code units that are sometimes necessary to encode special characters. The functions 'firstindex' and 'lastindex' or the 'split' function can help here. All these functions take into account the differences between position and code unit.

Discussion

präsentation und kritische auseinandersetzung mit
eigenen Daten
gefolgt mit dem vergleich zu den orginal reporteten
Daten.

Further development

Nur als subsection?

Appendix

Data availability

Code availability

Bibliography

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