Osservazioni

- I retangoli che vedete ai bordi servono per vedere quanto sono grandi i margini scrivibili della pagina, si possono togliere commentando la riga `\usepackage{showframe}`
- L'abstract adesso conta 267 parole. Di solito gli abstract non sono piu' lunghi di 300
- Il nome del nostro strumento di QA sta in una macro, per usarlo nel report scrivere `\nomefico`
- Il link al repo github sta in una macro, per usarlo scrivere `\github`
- Il link alla pagina web per QA (ancora da definire) sta in una macro, chiamata `\app`
- le immagini sono solo una bozza, vorrei che fossero approvate al 100% prima di realizzarle in latex
- Ho truccato il json di emepio (che e' in questa cartella in formato `.jsonl`), perche' aveva 36 long answer candidates e non veniva bene l'immagine del json. Se si decide di cambiare esempio, cambiarlo coerentemente

NOMEFICODASCEGLIERE
A BERT-BASED, OPEN DOMAIN
QUESTION ANSWERING SYSTEM

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Abstract

Question answering (QA) systems can be seen as information retrieval systems which aim is to respond to queries, stated in natural language, by returning short answers or long sentences. The "so-called" *open domain QA task* adds the challenge of understanding if the answer to the selected question may or may not be found in a given paragraph, which content has been buried within large text corpora, such as Wikipedia.

Building such systems for practical applications has historically been quite challenging and involved. The spectrum of possible answers given a question and a paragraph, moves from the "simple" *yes/no answers* to the longer and more articulated *long answers*, to then get to a trade-off between expressive power and succinctness, the "so-called" *short answers*, which aim to enclose the answer in a single and possibly short sentence.

In this paper, we present a BERT-based implementation that solves an open domain QA task, providing all the three categories of answers listed above, with particular attention on the most widely studied kind, i.e. short answers. We achieve pretty good results, although not as good as the state-of-the-art, that was not the purpose of this work.

As expected and already stated in previous work, we conclude that predicting long answers per se is pretty unreliable, while much better results are achieved if the short answer is predicted and then enlarged with the whole paragraph it lies in, from the original text.

Contents

1 Introduction

Aggiungere introduzione

aggiungere una frase in cui si dice che cosa si trova in quali sezioni

2 The architecture

Before digging into the details of the machine learning core of our BERT-based QA system, let us define the outline of the responsive QA tool we developed.

In Figure 1 there is a pictorial representation of how the user interacts with the system, how it processes the information (server side) and how it prompts the results.

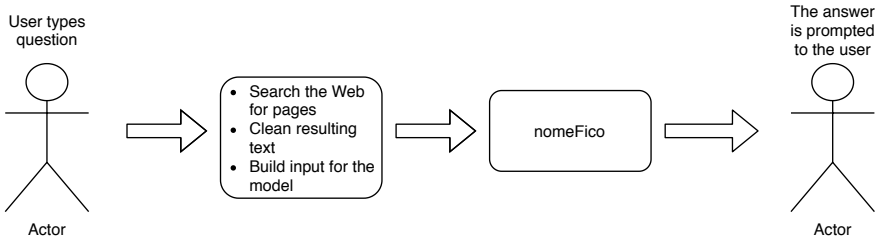


Figure 1: The full functioning of **nomeFicoDaScegliere**, combined with an effective user interface.

Aggiungere descrizione con immagini del workflow dell'applicazione, con un esempio che funziona, magari creando una sottosezione.

2.1 nomeFicoDaScegliere

We are now ready to discuss the implementation of **nomeFicoDaScegliere**.

We decided to tackle the open domain QA task by creating a stack of two neural networks, forming a two-layer architecture, as shown in Figure 2.

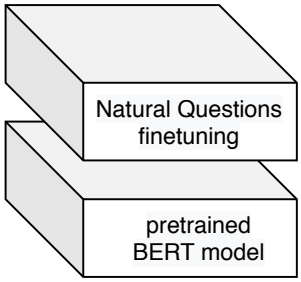


Figure 2: Sketch of the architecture of **nomeFicoDaScegliere**.

The first layer is built using BERT's [1] checkpoints [1] from Hugging Face, while the second layer is a neural network that uses BERT's embeddings and the Natural Questions (NQ) [4] dataset [2] with the aim of obtaining the answer to the question.

In the following paragraphs, the reader can find a more detailed explanation of the two layers.

2.1.1 BERT

Bidirectional Encoder Representations from Transformers (BERT) [1] has been introduced by Google in 2018 and it has been defined as the biggest leap forward in the past five years.

Let us dig into details a bit more and explain how the BERT layer works.

BERT is an embedder, i.e. a neural network that translates words (more generally sentences and whole paragraphs) into sets of 768-dimensional vectors. One of the main advantages introduced by this technology is the way BERT splits words into tokens (tokenization process): it allows to split words into smaller pieces, before mapping them into vectors. This choice has the advantage of allowing the encoding of words that are not present in the dictionary and to represent all the words that share a prefix using a root vector and different representations for suffixes.

During the development phase some new tokens have been added to BERT's dictionary, by the authors, following this reasoning: since the paragraphs fed to the model are HTML files, stripped of some tags, adding the remaining tags came in handy. The tags that have been added are: `'Dd'`, `'Dl'`, `'Dt'`, `'H1'`, `'H2'`, `'H3'`, `'Li'`, `'Ol'`, `'P'`, `'Table'`, `'Td'`, `'Th'`, `'Tr'`, `'Ul'`.

The second and more crucial advantage introduced by BERT is the bidirectional self attention mechanism, that takes into account not only all the words that precede the target word, but also the rightmost part, giving to every word a context.

Some studies carried out by Y. Liu et.al. showed that BERT model was *significantly undertrained*[3] and performed a more effective hyper-parameter tuning, giving birth to RoBERTa.

In September 2019, the work of Lan et.al., lead to the development of a lightweight version of BERT(ALBERT [2]), that allows two parameter reduction techniques to lower memory consumption, increase the training speed with respect to BERT and achieve better scaling performances.

As a recap, BERT (or BERT-based models) provides word-piece tokenization, a masked language model and the "next sentence" prediction, but it needs to be fine-tuned for a specific task, such as QA.

[1] In practice, we run experiments using also ALBERT [2]. In the future also RoBERTa's [3] checkpoints will be used.

[2] Some qualities of NQ are the following: (1) the questions were formulated by people out of genuine curiosity or out of need for an answer to complete another task, (2) the questions were formulated by people before they had seen the document that might contain the answer, (3) the documents in which the answer is to be found are much longer than the documents used in some of the existing question answering challenges.

2.1.2 Fine-tuning

In this work the authors decided to fine tune the model on Natural Questions dataset.

Each training pattern is a `json` object, it is stored in a line and it has the following structure (see Figure 3):

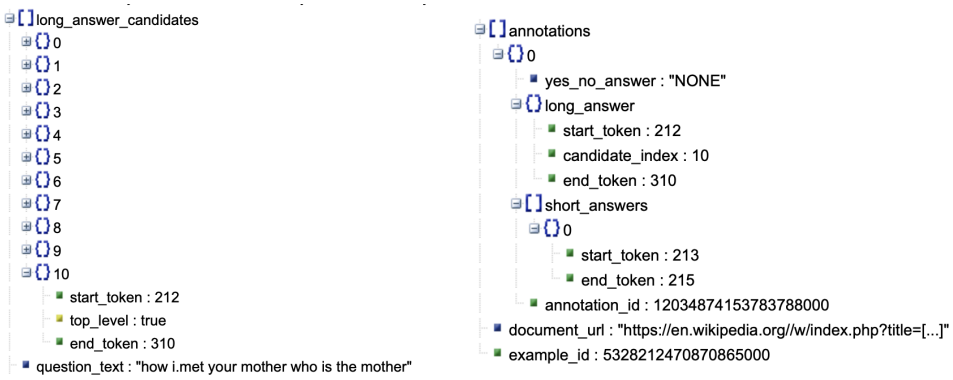
Figure 3: Broad structure of an input pattern.

- ◇ `document_text`: the HTML (cleaned of some tags) of the paragraph that may contain the answer;
- ◇ `long_answer candidates`: contains the original question and a list of start and end positions of candidates for the answer (an example in Figure 4a);
- ◇ `annotations`: contains three sub-objects, that represent if the question allows a "yes-no" answer, the information about the short answer and the information about the long answer respectively (as shown in Figure 4b). It is possible that a question does not allow to be answered looking at the paragraph given as input. In that case the fields in the `long_answer` object have value -1 and the list `short_answers` is empty.

The NQ training set has on average, input patterns with size of 10MB and the whole training set is stored in a `.jsonl` file of size $\approx$ 17 GB. It goes without saying that loading both BERT's checkpoints and such file into RAM is not possible, so we managed to overcome this problem by splitting the file into chunks with size smaller than 100MB.

Another crucial characteristic of this dataset is that is strongly unbalanced towards the questions that are unanswerable:

> *In total, annotators identify a long answer for* 49% *of the examples, and short answer spans or a yes/no answer for* 36% *of the examples. We consider the choice of whether or not to answer a question a core part of the question answering task, and do not discard the remaining* 51% *that have no answer labeled.[4]*



(a) `long_answer candidates`. **(b)** `annotations`.

Figure 4: More details about the fields of an input pattern.

This issue of unbalanced data needs some more reasoning: as already discussed in Section 2.1.1, the BERT-based embedder maps the input text into vectors. It also performs another operation, namely it splits the paragraph in the so-called "crops", containing 512 tokens. It is easy to conclude that most of these crops do not contain the answer to the original question, hence the unbalancing becomes even more severe ($\approx 95\%$ of the crops do not contain the answer).

The authors overcame this issue by selecting only the 3% of the so-called "impossible questions"[3] and by designing an effective yet simple loss function.

On a batch of examples, we computed the loss as follows:

$$\begin{cases} \dfrac{\left(\underset{\text{batch}}{\text{avg}}\, l_{\text{start}} + \underset{\text{batch}}{\text{avg}}\, l_{\text{end}}\right)}{2} + \underset{\text{batch}}{\text{avg}}\, l_{\text{long}} \\ \hline 2 \\ 0 \end{cases} \qquad \begin{array}{l} \text{if answerable} \\ \text{otherwise} \end{array} \tag{1}$$

where l_{start} (l_{end}) is the categorical cross-entropy between the start (end) position of the short answer in the target and the predicted start (end) position (Figure 5); l_{long} is the categorical cross-entropy between the start position of the true answer and the position of the guess in the long answer.

3 Experimental results

This section describes how the experimental phase of **nomeFicoDaScegliere**was carried out. We tried many different parameters' configurations and slightly different implementation choices for achieving better results or to reach reasonable trade-offs in the fine-tuning phase.

[3]The code is available on GitHub, we set the value 0.03 to the parameter called `p_keep_impossible` in `dataset_utils_version2.py`.

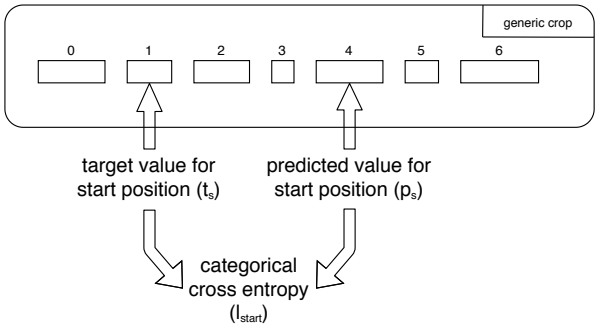


Figure 5: How the categorical cross entropy of the start position is computed.

3.1 Hardware

The model have been tested on the following computing infrastructures:

-I- Il computer di Mario

-II- Google Colaboratory

-III- Serverone di Attardi

aggiungere specifiche

aggiungere specifiche

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The first hardware choice has been solely used to test locally the functioning of the platform after the introduction of new features and did not allow to run the code on the huge training set we have been given.

The choice of using Item -II- has the advantage of requiring very little set up of the machine (installing modules and libraries), but offers relatively poor performances as well.

The last choice (Item -III-) allows for faster executions, but required a longer initialization process.

3.2 Hyper-parameters' values

As usual, when dealing with machine learning models, we need to try different values of the hyper-parameters. Due to time constraints, the brief grid-search shown in Table 1 have been performed.

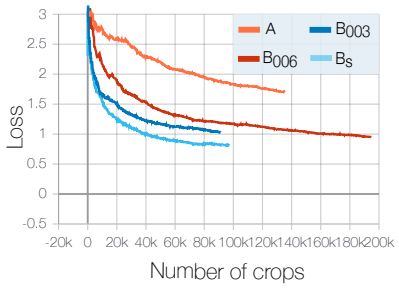
Parameter	Values
η ("learning rate")	$1e-4$, $1e-5$, $1e-6$
β_1	0.9
β_2	0.999
ε	$1e-7$
batch size	8 (ALBERT), 4 (BERT)

Table 1: Hyper-parameters values.

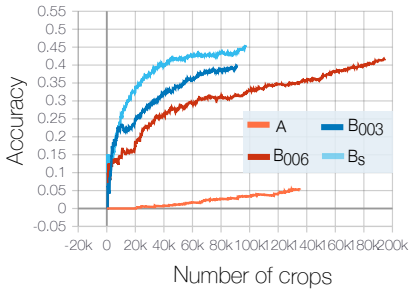
3.3 Results of fine-tuning

Before showing the results achieved in both training, validation and test phases it is important to make the reader aware of an abuse of notation: the term "epoch" usually, such a word accounts for the number of times the whole training set is scanned in the training phase. However, since we decided to split the training set into smaller chunks, we sometimes refer to "small epochs" that account for the number of times the patterns in a single chunks are processed.

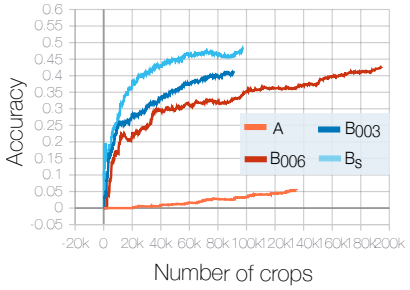
The three values for the learning rate have been tried and only the value $1e-5$ showed good convergence results for all the models that we compared (Figure 6), namely ALBERT, BERT base and BERT "smart" (trained using the loss introduced in Equation (1)) with only the 3% of unanswerable questions left and BERT base with the 6% of unanswerable questions.



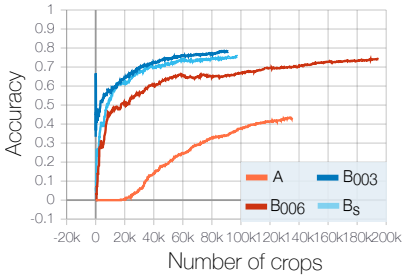
(a) Loss (mean of categorical cross-entropy values of start position, end position and long start position) values over the number of processed crops.



(b) Accuracy of start position values over the number of processed crops.



(c) Accuracy of end position values over the number of processed crops.



(d) Accuracy of start position values of long answers over the number of processed crops.

Figure 6: Training performances of ALBERT (A), BERT base with 6% of unanswerable questions ($B_0 06$), BERT base (B_{003}), BERT smart (B_s). Notice that the red line is "longer" because the number of questions that get dropped is smaller.

It would have been interesting to run the same experiments using BERT Large and ALBERT Large, but the memory (RAM) sizes of all the three hardware alternatives

available to us did not allow such experimentation [4].

Scegliere plot significativi ed inserirli

During the training phase we realized that the use of Keras and a `generator` class could have been responsible for poor time performances. For this intuition, the library was dropped and the body of the training step has been implemented from scratches in Python (using TensorFlow library) and this choice led to a huge performances improvement, as shown in Figure 7

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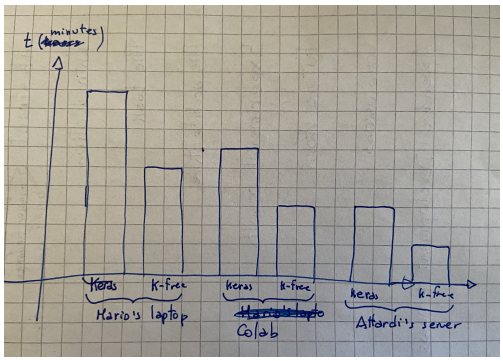

Figure 7: The performances of the Keras and Keras-free implementations over the three different computing infrastructure on a single batch.

Fare le prove con i dati veri e, perchè no, anche su un'intera epoca (in cui il gap è molto maggiore e fa figo.)

4 Conclusions and future work

We describe **nomeFicoDaScegliere**as an interactive question answering platform that sees its application in various contexts, such as domotics or education. We performed experimental results and validations techniques that assess the goodness of this model, although we highlight some issues that could be solved more effectively in the future, such as the problem of the presence of a typo in the query (both human error in typing or machine speech-to-text misunderstanding)[5]. Moreover, we would like to stress that choosing to force the model to learn only the answerable question was only a first approach to solve the problem and that another technique worth deepening in the future may be using a binary classification layer to check if the an-

[4] An attentive reader may notice that the size of ALBERT Large (18M of parameters) is still smaller than the size of BERT base (108M of parameters), so it should be possible to load it into the memory of the devices that allow the load of BERT, but the theory in computer science often differ from the practice and we cannot motivate further.

[5] One could try to use library already implemented in Python for auto-correction, such as `auto-correct` available on Pypy, or a more involved and more accurate dictionary-based auto-correct strategy.

swer is "plausible" (i.e. the meanings in the question are covered in the answer), as done by [5] and [6].

4.1 All references

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