**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

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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

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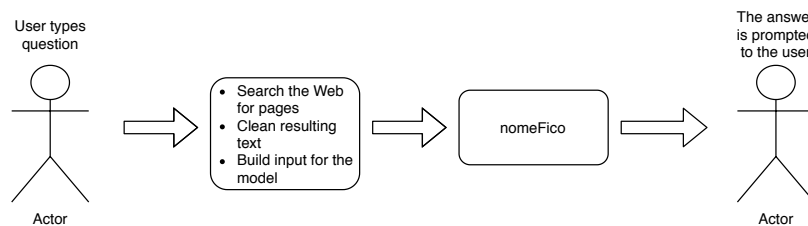
**Figure 1:** The full functioning of **nomeFicoDaScegliere**, combined with an effective user interface.

## 2.1 nomeFicoDaScegliere

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

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

The first layer is built using BERT's [1] checkpoints, while the second layer is a neural network that uses BERT's embeddings and the Natural
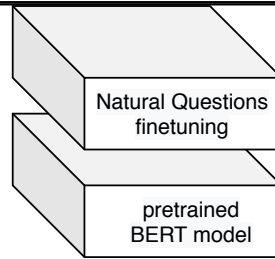
**Figure 2:** .

Questions (NQ) [2] dataset [1] with the aim of obtaining the answer to the question.

### 2.1.1 BERT

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

Fare digressione sull'utilizzo di BERT o BERT-large o ALBERT

### 2.1.2 Fine-tuning

Depending on the flag start position and end position of the answer in the given paragraph.

At this point, we assume that the system receives as input two textual items, the first one is the question and the second one is the paragraph that is supposed to contain the answer

short?long?

In this section the tools used in the project are described.

# 3 Experimental results

## 3.1 Hardware

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[1]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.

### 3.2 Hyper-parameters values

## 4 Future work

Use a binary classification layer to check if the answer is "plausible" (i.e. the meanings in the question are covered in the answer), as done by [3] and [4].

## 5 Conclusions

### 5.1 All references

- kbqa [5]
- coqa [6]
- collobert [7]
- vaswani [8]
- weston1 [9]
- weston2 [10]
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