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UBO Team @ CLEF SimpleText 2023 Track For Task 2 and 3 - Using IA Models To simplify Scientific Texts

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Abstract

Due to the complexity of their language and the requirement for background knowledge, scientific literature is typically avoided by the general public. Instead, people often rely on superficial and secondary sources found on the internet and social media, which are frequently motivated by commercial or political interests rather than providing accurate information. Therefore, we will try to simplify scientific texts by participating in the SimpleText track. We will begin by introducing the different tasks, then we will move on to an overview of the different models used, and then we will finish by the results of the different tasks, and the conclusion.

Keywords

CLEF, SimpleText, SimpleT5, BLOOM, pke

1. Introduction

Scientific research publications pose challenges for the general public and even for scientists outside the specific field. The CLEF 2023[1] SimpleText[2, 3] track is unique in its emphasis on simplifying scientific texts, with a particular focus on making them accessible to the general public. This track combines information retrieval and natural language processing to address the needs of both readability and comprehension.

The topics of text complexity, reading levels, and text simplification have been extensively explored in fields such as linguistics, education science, and natural language processing. Simplified texts offer greater accessibility to non-native speakers, young readers, individuals with reading disabilities, those in need of reading assistance (e.g., congenitally deaf people), or individuals with a lower level of education. However, improving text comprehensibility remains a challenge, as determining the desired output of simplification is inherently complex. The SimpleText track is divided in 3 tasks

- Task 1 : What is in (or out)? Selecting passages to include in a simplified summary
- Task 2 : What is unclear? Difficult concept identification and explanation (definitions, abbreviation deciphering, context, applications,..)
- Task 3 : Rewrite this! Given a query, simplify passages from scientific abstracts

We didn't do the first task, we have only done task 2 and 3. So for the task 2, it was divided in two parts :

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- Task 2.1 : Identification of the difficult terms
- Task 2.2 : Explanation of the difficult terms

For the task 2.1, we used the pke[4, 5] package whereas for the task 2.2 we used the wikipedia-api package[6]. While for the task 3 we used the SimpleT5[7] model as well as the BLOOM[8] model.

2. Approach

For those tasks, we had 3 files :

- A train file with the "source_snt" field
- A qrels file with the "simplified_text" field
- 3 test files of different size, small, medium and large. We only used the small and medium, not the large one for the sake of time, the large one has 150 000 translations to do, whereas the small one has 2000 and the medium one has 4000, and the small is included in the medium and the medium in the large. Those 3 files have the "source_snt" field that need to be translated.

2.1. Use of the pke package for the task 2.1

When we have used the pke package, we used those models :

- FirstPhrases
- TfIdf
- YAKE [9]
- TextRank [10]
- SingleRank [11]
- TopicRank [12]
- PositionRank [13]

First of all, we retrieve the data from the files and put it in a dataframe then we format it as we need. We then initialize the model that we want to use to then apply it on every "source_snt". Once we have 3 difficult words, we then determine its term difficulty rank within the sentence, as well as its complexity of the term for each of them.

Once we have all that, we format it with the required field for the task.

2.2. Use of the wikipedia-api package for the task 2.2

Initially, we import the Wikipedia package for the English language and proceed to retrieve the Wikipedia page corresponding to the challenging terms obtained from task 2.1. Subsequently, we utilize the nltk package, specifically the tokenization component, to extract the initial sentence from the retrieved pages. This initial sentence serves as our definition for the difficult term.

Then we format it with the required field for the task.

2.3. Use of SimpleT5 and BLOOM for the task 3

2.3.1. SimpleT5

The training part was divided into two parts, reading the data and formating it, and then the training of the model.

We had to format the data to make two fields in a dataframe for our model, the "source_text" (train) and the "target_text" (test). The "source_text" was the "source_snt" field, and the "target_text" field was the "simplified_snt" field.

"source_text"	"target_text"
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	*Current academic and industrial research is interested in autonomous vehicles.*

Once we have our dataframe with the formated data, we can start the training of the SimpleT5 model, we first load the model, then we give this dataframe to our model. We have trained our model for 12 epochs with a batch size of 8. Once the training is finished, we do the same thing that we did before for the "source_text" and "target_text" but this time we only put the "source_snt" in the "source_text", and the model will infer the result in the "target_text". Then we get what was generated in the "target_text" field and we format it with the required fields

2.3.2. BLOOM

For the BLOOM model, we first try to use the inference api by sending request to the model on huggingface, but this was really long, because we have to wait 1 hour after sometimes, so we try to use it locally, but the model is really large and required a really powerful computer. So we decided to use Petals[14, 15], a tool that help people to run large models collaboratively, and therefore, BLOOM. Thanks to Petals we were able to use the BLOOM model without restrictions. BLOOM is a few-shots model, therefore, we need to give him examples of what we need :

- Summarize the source:
  Source : In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.
  Simplification : Current academic and industrial research is interested in autonomous vehicles.

  Source : With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.
  Simplification : Drones are increasingly used in the civilian and commercial domain and need to be autonomous.

Source : Due to guidelines set by the governments regarding the operation ceiling of civil drones, road-tracking based navigation is garnering interest.
Simplification : Governments set guidelines on the operation ceiling of civil drones. So, road-tracking based navigation is attracting interest.

Source :

We then append the "source_snt" to this base, and we give the prompt to the BLOOM model, we then get the simplification the model gives us. Once we have the simplification for each sentence, we format it with the required fields.

3. Results

3.1. Task 2

3.1.1. Task 2.1

Every model of the pke package seem to be quite efficient, with the exception of the YAKE model, which is a little below the others.

3.1.2. Task 2.2

The fact that we don't have Wikipedia pages for all the difficult terms that we try to explain, makes this method not very appropriate. We have a BLEU score of 5.09, which is a really low score, and a ROUGE F1-score of 0.19, which is also really low.

3.2. Task 3

The results for the SimpleT5 model and the BLOOM model are quite similar, we have a FKGL score of approximately 12, which does not answer the SimpleText task, the sentences are still quite complex. For the SimpleT5 we have a SARI score of 30 and a BLEU score of 21, which is not really convincing. And for the BLOOM model we have a SARI score of 37 and a BLEU score of 39 which is still not really convincing but a bit better than the SimpleT5 model.

4. Conclusion

Opting for the PKE Package was a prudent decision for indentifying difficult terms whereas the Wikipedia approach is not something to consider in the future for explaining difficult terms. While, for the task 3, both methods employed yielded satisfactory results, one that needs training, and the other needs some examples, but the results were not really meaningful.

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Appendices

A. Outputs example for Task 2.1

source_snt	term
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	autonomous vehicles
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	modern era
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	industrial research
With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.	unmanned aerial vehicles
With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.	commercial domain
Due to guidelines set by the governments regarding the operation ceiling of civil drones, road-tracking based navigation is garnering interest.	operation ceiling
Due to guidelines set by the governments regarding the operation ceiling of civil drones, road-tracking based navigation is garnering interest.	governments
In an attempt to achieve the above mentioned tasks, we propose an imitation learning based, data-driven solution to UAV autonomy for navigating through city streets by learning to fly by imitating an expert pilot.	data-driven solution
In an attempt to achieve the above mentioned tasks, we propose an imitation learning based, data-driven solution to UAV autonomy for navigating through city streets by learning to fly by imitating an expert pilot.	uav autonomy
Derived from the classic image classification algorithms, our classifier has been constructed in the form of a fast 39-layered Inception model, that evaluates the presence of roads using the tomographic reconstructions of the input frames.	classifier
Derived from the classic image classification algorithms, our classifier has been constructed in the form of a fast 39-layered Inception model, that evaluates the presence of roads using the tomographic reconstructions of the input frames.	form
Based on the Inception-v3 architecture, our system performs better in terms of processing complexity and accuracy than many existing models for imitation learning.	terms
Based on the Inception-v3 architecture, our system performs better in terms of processing complexity and accuracy than many existing models for imitation learning.	imitation learning

B. Outputs example for Task 2.2

source_snt	term	definition
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	modern era	The modern era is the period of human history that succeeds the Middle Ages (which ended around 1500 AD) up to the present.
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	automation	Automation describes a wide range of technologies that reduce human intervention in processes, namely by predetermining decision criteria, subprocess relationships, and related actions, as well as embodying those predeterminations in machines.
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	robotics	Robotics is an interdisciplinary branch of computer science and engineering.
With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.	number	A number is a mathematical object used to count, measure, and label.
With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.	unmanned aerial vehicles	An unmanned aerial vehicle (UAV), commonly known as a drone, is an aircraft without any human pilot, crew, or passengers on board.
Recognizing Traffic Signs using intelligent systems can drastically reduce the number of accidents happening world-wide.	traffic signs	Traffic signs or road signs are signs erected at the side of or above roads to give instructions or provide information to road users.
Recognizing Traffic Signs using intelligent systems can drastically reduce the number of accidents happening world-wide.	intelligent systems	Intelligent Systems Co., Ltd. is a Japanese video game developer best known for developing games published by Nintendo with the Fire Emblem, Paper Mario, WarioWare, and Wars video game series.
Recognizing Traffic Signs using intelligent systems can drastically reduce the number of accidents happening world-wide.	number	A number is a mathematical object used to count, measure, and label.

C. Outputs example for Task 3

source_snt	simplified_snt
In the modern era of automation and robotics, autonomous vehicles are currently the focus of academic and industrial research.	In the modern era of automation and robotics, autonomous vehicles are the focus of research and development.
With the ever increasing number of unmanned aerial vehicles getting involved in activities in the civilian and commercial domain, there is an increased need for autonomy in these systems too.	Drones are increasingly used in the civilian and commercial domain and need to be autonomous.
Due to guidelines set by the governments regarding the operation ceiling of civil drones, road-tracking based navigation is garnering interest.	Governments set guidelines on the operation ceiling of civil drones. So, road-tracking based navigation is attracting interest.
In an attempt to achieve the above mentioned tasks, we propose an imitation learning based, data-driven solution to UAV autonomy for navigating through city streets by learning to fly by imitating an expert pilot.	Researchers propose data-driven solutions allowing drones to autonomously navigate city streets, learning to fly by imitating an expert pilot.
Derived from the classic image classification algorithms, our classifier has been constructed in the form of a fast 39-layered Inception model, that evaluates the presence of roads using the tomographic reconstructions of the input frames.	Our classifier uses a fast 39-layered model to evaluate the presence of roads using the tomographic reconstructions of the input frames.
Based on the Inception-v3 architecture, our system performs better in terms of processing complexity and accuracy than many existing models for imitation learning.	The Inception-v3 architecture has better accuracy than many existing models of imitation learning.
The data used for training the system has been captured from the drone, by flying it in and around urban and semi-urban streets, by experts having at least 6-8 years of flying experience.	The data used for training the system was captured from the drone over urban streets, navigated by an expert pilot.
Permissions were taken from required authorities who made sure that minimal risk (to pedestrians) is involved in the data collection process.	Data collection requires special permission to ensure pedestrian security.
With the extensive amount of drone data that we collected, we have been able to navigate successfully through roads without crashing or overshooting, with an accuracy of 98.44The computational efficiency of MAVNet enables the drone to fly at high speeds of up to 6msec.	MAVNet computational efficiency enables the drone to fly up to 6m/sec.
We present the same results in this research and compare them with other state-of-the-art methods of vision and learning based navigation.	The solution is compared with other recent methods.