How the Text Summarization affects the Information Retrieval based Question Answering

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**Abstract**  
This paper presents a novel experiment which a text summarization technique is how will affect the question answering system. We investigate a new training paradigm for Information Retrieval based question answering. Normally after the document retrieval part, directly extract passages of documents and narrows possible answer set in the classic information retrieval approach. Instead of collecting large-sized documents first and then obtaining small-sized passages, we want to show how the use of text summaries of these documents will have an effect on the question answering system. Text summarization is reducing a text document into a short set of words or paragraph that contains the key meaning of the text. In that reason we want to test that if we train model with summarized documents how it contributes the evaluation result of that model.  
  
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# **Introduction**

Question Answering (QA) is the process of retrieving correct information or exact answer from a large collection of documents against a natural language question. Also, it is a fast-growing research area that combines research from different, but related, fields which are Information Retrieval (IR), Information Extraction (IE) and Natural Language Processing (NLP). When we look at first examples of information retrieval systems we can see that they focused on the retrieval of the most relevant documents from a collection with given a set of keywords. In the next generation approaches, it was based on receiving the most relevant passages in the most important documents. However, despite reducing the search space, users cannot deal with all the available information founded by an information retrieval system because of the complexity of the query.  
  
 In general, question answering systems have three components such as question processing, document processing (information retrieval) and answer processing. The first step begins with extracting information from the question with question processing. This process has two important sub-process. First one; query formulation for prepare query that is going to send to an IR Engine and second one; answer type detection that tells us what kind of name entity we are looking for. After passing these sub-stages, indexing of already saved documents is performed. Thus, documents are available to apply a query and from those documents we get relevant documents with Information Retrieval. Passage retrieval helps extract passages of documents and narrows possible answer set. In the last step, those passages are processed in answer processing. Looking for output of answer type detection helps in that step and then returning a possible answer.



Figure 1: General Architecture of a QA System

Question processing component is very important because if the module does not start correctly, it will make problems for other part of QA system. Also answer processing as important as question processing because systems are often required to rank and validate candidate answers according to answer processing.

Text summarization be useful in retrieval of important information from a large textual data and also reduces the size of the text. In this way, important points can be easily extracted from unnecessarily long documents. With this aspect, it is separated from the question answering system. Question answering system is looking for main points and exact answers according to the question.

In our project we thought that how can these two topics affect each other? Information Retrieval based question answering system naturally needs a lot of documents and the number of documents might be a problem when we are looking for correct answer which made by user query. Also, all retrieved documents might not be related to answer of that question so we may have reached the wrong answer due to information pollution. All these thoughts lead us to the idea of how to get a result if text summarization is used in the document retrieval phase of the question answering system. In this project we will test the relationship and between Information Retrieval and text summarization and effect on each other.

# **Background**

## Information Retrieval (IR)

QA systems have applications used in a wide variety of tasks, and one of them is information retrieval. Its task that automatically answer the questions asked by humans in natural language using either a structured database or a collection of documents. Information retrieval (IR) is basically finding relevant documents from a database in response to query which made by user. It is one of the most challenging tasks of NLP because of a lot of various count of unstructured data exist in that process. Improvement of deep learning in computer vision and neural networks (CNNs) have relapsed as a popular machine learning paradigm in many other directions of research, including IR.

Traditional learning to rank models employ machine learning techniques over hand-crafted IR features. By contrast, neural models learn representations of language from raw text that can bridge the gap between query and document vocabulary. Unlike classical IR models, these new machine learning based approaches are required large scale training data before they can be deployed [1]. In our project we used Simple Transformers library by HuggingFace to train and evaluate model. Details will be explained in Research & Algorithm section.

## Text Summarization (TS)

Text summarization is a technique for creating a concise and accurate summary of large texts with an emphasis on parts that convey useful information and do not lose its general meaning. Automatic text summarization is designed to convert long documents into short versions, which can be difficult and expensive if they are done manually. Machine learning algorithms use to be trained to identify documents and sections that convey important facts and information before creating the required generalized texts.

The advantage of using a text summarization is the output reduces the reading time. Text Summarization methods can be classified into extractive and abstractive summarization. An extractive summarization method consists of selecting important sentences, paragraphs etc. from the original document and concatenating them into shorter form. An Abstractive summarization is an understanding of the main concepts in a document and then express those concepts in clear natural language [2].

Summary can be generated through extractive as well as abstractive methods but abstractive methods are highly complex as they need extensive natural language processing. Therefore, research community is focusing more on extractive summaries, trying to achieve more coherent and meaningful summaries. During a decade, several extractive approaches have been developed for automatic summary generation that implements a number of machine learning and optimization techniques [3]. In our project we used Python - Gensim library to make text summarization part. Details will be explained in Evaluation& Algorithm section.

# **RELATED WORK**

Before starting our project, we first searched the literature and searched for the previous studies in this field. We could not observe a study that matches the way we thought, but we came across several studies that would guide us. In the articles we encountered in general, we observed that the opposite of the method we want to apply was tried. In other words, we observed that studies on the use of question answering techniques to implement the text summarization process more efficiently. For example, the study (Arumae, Kristjan, and Fei Liu. "Reinforced extractive summarization with question-focused rewards.", 2018), they used reinforcement learning to explore the space of possible extractive summaries and introduce a question-focused reward function to promote concise, fluent, and informative summaries [4]. The same research group approached this problem from a different perspective and presented a new study the following year. In this study (Arumae, Kristjan, and Fei Liu. "Guiding extractive summarization with question-answering rewards.", 2019), they thought that quality summaries should serve as a document surrogate to answer important questions, and such question-answer pairs can be conveniently obtained from human abstracts. The system learns to promote summaries that are informative, fluent, and perform competitively on question-answering [5].

We made several observations on this subject, as it consists of the text summarization part of our research and half of our project. One of them is this study that explains how to improve the summarization technique (Rahman, Nazreena, and Bhogeswar Borah. "Improvement of query-based text summarization using word sense disambiguation." Complex & Intelligent Systems (2019)), where the system finds semantic relatedness score between query and input text document for extracting sentences. The drawback with current methods is that while finding semantic relatedness between input text and query, in general they do not consider the sense of the words present in the input text sentences and the query. However, particular method can enhance the summary quality as it finds the correct sense of each word of a sentence with respect to the context of the sentence in their research [6]. This allowed us to have an idea that the text and questions in the dataset that we will use while training our model can be used more efficiently. Because our main starting point was to try the contribution of the text summarization method to information-retrieval based question answering, but we learned thanks to the article that we can also improve our text summarization method in the training phase of the model we train to perform the information retrieval in the stages we will use. In other words, since the dataset we will use for information retrieval contains question-answer and texts, we can use the word sense disambiguation technique described in this article while doing text summarization.

This work (Balage Filho, Pedro Paulo, et al. "Using a Text Summarization System for Monolingual Question Answering." CLEF, 2006.) is the most similar work to the subject of work in our project. They differ in their work using monolingual question answering at CLEF 2006 and topic-oriented summaries, also used GistSumm as the summarizer method. They aimed at assessing its accuracy in finding answers to the posted questions, which were used as the topics for producing the corresponding summaries [7].

# **EXPERIMENTS**

In this section, we will talk about the design of the system, methods and algorithms applied and evaluation of our project.

## System

**The template is designed for, but not limited to, six authors.** A minimum of one author is required for all conference

## Method

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

## Algorithm

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is “Heading 5”. Use “figure caption” for your Figure captions, and “table head” for your table title. Run-in heads, such as “Abstract”, will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

## Evaluation

#### Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation “Fig. 1”, even at the beginning of a sentence.

1. Table Type Styles

| Table Head | Table Column Head | | |
| --- | --- | --- | --- |
| Table column subhead | Subhead | Subhead |
| copy | More table copya |  |  |

1. Sample of a Table footnote. (*Table footnote*)
2. Example of a figure caption. (*figure caption*)

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetization, M”, not just “M”.

##### Acknowledgment *(Heading 5)*

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

# **RESULTS & DISCUSSION**

One of the problems we encounter in this project is not to find a dataset in the format suitable for the Simple Transformers model we have used. This model keeps the JSON format used by the SQuAD dataset as a format in its own dictionary. Because of this, even if we found a dataset on the internet that contains question-answer and text to train model, actually we could not train because the JSON format is not compatible. In the final stages of our project, we found a GitHub work that can convert it to the SQuAD JSON format we want. This Dataset Converter for natural language processing tasks such question answering tasks, from one format to other one [8]. Although the dataset number it covered was 15, there were still some problems. All of the datasets it involved did not contain text and question-and-answer related to this text, most of that contains only question and answer so there was no text to summarize. Only 2 of these 15 dataset sets had the features we wanted. These are QAngaroo and NewsQA. In another study we have found, it is a reformer that converts the dataset we provide in excel format to squad format. Each ‘title’ can have multiple ‘context’; each ‘context’ can have multiple ‘question’; each ‘question’ can have multiple ‘text’ (answer) [9]. We could import the datasets that we found in other JSON formats to Excel and then use this study, but we had to bypass this study due to lack of efforts and labor.

Another problem we encounter is the process of train the model which planned to train with the text summarization. The confusing point here is that the dataset, because in that original dataset most of the question's answer could be find in text. However, when we summarize that text, answer of that question might be lost in that summary of the text because it is short and compressed version of original text. In that way, new trained model with summarized data knows the answer of question but actually in that summary of the text does not contain any match about answer due to the shrinking the size of original text. But situations like this are the problem that can occur in any system with text summarization, so a summary of a text can never contain as much content as the original text. In addition, as we mentioned in the related works section, some of these situations can be overcome with the semantic relationship score to be created between the question and the input text.

Before starting our project, we thought that one of the positive aspects of using text summarization is the increase in the number of contents without changing the dataset size used. In other words, for example if we consider that we have a 5 GB data area limit and we can fit 1 million documents into this field, we might fit the summary of 2 million documents in the same size when we do this with the text summarization version. We thought that this would be beneficial in terms of recognizing the diversity of the model to be trained.

# **CONCLUSION**

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