International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V70I5P233
Volume 70 Issue 5, 306-308, May 2022

Short Communication

Automated Computer Linguistics Analysis of Scientific Texts in the Field of Female Terrorism Prevention for future Adaptive E-Learning

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Received: 12 March 2022 Revised: 15 May 2022 Accepted: 19 May 2022 Published: 31 May 2022

Abstract **-** *Terrorism countering is one of the key components of any country's national security protection. The multilateral approach of the counter-terrorism strategy is an essential part of the terrorist attacks frequency reduction. Women's involvement in terrorist organizations has long been unprecedented. This kind of dynamic can be traced to the Middle East and Russia. This article portrays an attempt to employ the usage of Adaptive E-learning to train future specialists in female terrorism prevention. The paper is a preliminary work related to automated topics, relations, entities, quotations extraction, text summary generation, etc.*

Keywords **-** *adaptive e-learning, e-learning goals, female terrorism prevention, topics extraction, sentiment analysis, summary generation.*

1. Introduction

Terrorism is one of the most serious threats to international peace and security in the 21st century. The attempts to understand this social phenomenon have become relevant since the attacks in New York on September 11, 2001. Despite huge fluctuations in the intensity over time, the history of terrorism has shown that it has evolved from ideological to religious and has become increasingly deadly. at the present stage, terrorism which is one of the extreme forms of the struggle of several Asian countries against Western ideology, acquires a religious color, which makes this topic relevant for studying, both in the political and the socio-cultural aspects nowadays. Moreover, in the entire array of religious terrorism, extremist structures based on Islamic fundamentalism are the most widespread. [1]

in recent decades, a specific feature of modern terrorism is that women have become active participants. Terrorist acts have become the "calling card" of the North Caucasus, and female terrorists are a common phenomenon, highlighting the relevance of studying the regional features of the manifestation of female terrorism in the North Caucasus. [2] Female suicide terrorism is a relatively new and insufficiently studied form of violence with a tendency to progressively expand the female presence in various terrorist organizations in recent years.

Terrorism at the present stage acquires new forms of counteraction, which will represent the undoubted threat to states' national security. The phenomenon has become the intention of social, political, and psychological research. However, the tender aspect of terrorism is to understand the personality of terrorists, the level of significance of their statuses, and distribution roles in terrorist activities. Unfortunately, these issues are not sufficiently scientifically developed yet. Society has a stereotype that women are more merciful, more compassionate, and weaker in "fighting spirit" than men. [3]

Governments and the media find it difficult to rationalize women's involvement in terrorist activities because they violate gender stereotypes. Women are often put in the role of "victims" or emphasize the fetish of "hypersexual warriors" who are more dangerous than their "fellow" men. Both labels deny female participation as a separate actor. An essential part of the prevention of female terrorism is the appropriate education of specialists who will be able to analyze the activities of suspects and identify suspicious groups deeply. That is why for these future specialists, the usage of Adaptive E-learning can be employed.

The future ambition related to the following topic is to compile a mathematical model and a system for adaptive e-learning for future specialists in the fields of women's participation in terrorism activities. Therefore, enough metadata needs to be accumulated for the available learning materials. This will be beneficial for the selection process to achieve certain adaptive goals of e-learning. This is why research related to the analysis of similar texts is conducted.

The authors write extensive articles on adaptive e-learning, found in [4], [5]. Moreover, comprehensive research on Adaptive E-learning Models, Approaches, and Systems is discussed [6].

The following **research goals** are identified: **- G1**: Creation of Topic Extractions Functionality; Evaluation of each extracted Concept, Entity's importance in the analyzed text, **G2**: Relation between Entities and Concepts towards its importance to the analyzed text; **G3**: Generation of Text Summary; **G4**: Conducting Sentiment Analysis of the following Text for each of its sentences and topics are presented in each sentence. To select text with greater capacity, the scientific quality of the analyzed text needs to be calculated (***G5****) concerning the richness of concepts, entities, relations, etc., in the text.*

2. The Approach

To achieve the Research Goals (G1-G5), a prototype is created using the programming language Python 3 [7] and the MeaningCloud API [8].

```
for cur_chunk in chunks:
   ....
   num_entities = 0
   for obj in response.json()['entity_list']:
      # print(obj)
      ....
num_entities = num_entities + 1

   num_concepts = 0
   for obj in response.json()['concept_list']:
     ....
num_concepts = num_concepts + 1

   num_quotations = 0
   for obj in response.json()['quotation_list']:
      ....
num_quotations = num_quotations + 1
   num_relations = 0
   for obj in response.json()['relation_list']:
      ......
dict_relations[obj['form']] = 1
      num_relations = num_relations + 1
```

Fig. 1 Generation of lists of entities, concepts, quotations, relations

Figure 1. shows the straightforward approach to using MeaningCloud Topics 2.0 API in Python 3. Lists with entities, concepts, quotations, and relations are built, and their numbers have been calculated. Some code is omitted with dots.

Calculating the importance of each concept (G1) for the text helped to generate more accurate summaries of the analyzed texts (G3). in general, sentence fragments and paragraphs are used in denser concepts, which are more essential to the texts. Usage of such an algorithm implemented in MeaningCloud Summary API is shown in Figure 2.

```
url = "https://api.meaningcloud.com/summarization-1.0"
text = wT
payload = {'key': '....', 'txt': text, 'sentences': 6}
response = requests.post(url, data=payload)
print('Status code:', response.status_code)
print("Text summary EN: {summary}
".format(summary=response.json()['summary']))
print("Text summary BG: {summary}
".format(summary=translate_func(response.json()['summary'],
                                         lang_src='en',
                                         lang_tgt='bg')))
```

Fig. 2 Summary Generation of an Analyzed Text

The Sentiment Analysis of the sentences in the text and the concepts present in them can be used for more in-depth evaluation. The current analyzed text as learning material (LM) can be suitable for completing a certain Learning Goal in the Adaptive E-Learning Course (AeLC).
Some code fragments of the Usage of the Sentiment API of MeaningCloud are shown in Figure 3.

```
url = "https://api.meaningcloud.com/sentiment-2.1"

payload = {
   'key': '....',
   'txt': text,
   'lang': 'en',  # 2-letter code, like en es fr ...
}

total_num_sentences = 0
total_average_sentiment = 0
for cur_chunk in chunks:
   response = requests.post(url, data=payload)
   scores = {'P+': 2, 'P': 1, 'NONE': 0, 'N': -1, 'N+': -2, 'NEU': 0}
   average_sentiment = 0
   num_sentences = 0
   for obj in response.json()['sentence_list']:
      average_sentiment = average_sentiment + scores[obj['score_tag']]
      num_sentences = num_sentences + 1
      ...
   total_num_sentences = total_num_sentences + num_sentences
   total_average_sentiment = total_average_sentiment + average_sentiment

total_average_sentiment = total_average_sentiment / total_num_sentences
print("Sentiment score {sc}".format(sc=total_average_sentiment))
```

Fig. 3 Fragment of the Sentiment Analysis

If, during the automated LMs delivery of the execution of AeLC, there are two or more LM paths equally relevant to the completion of a given Learning Goal, then LMs with greater Learning Quality should be picked up and delivered to the user. That's why functionality is created to evaluate LMs quality with a formula that considers the richness of concepts, entities, relations, number of quotations in the text, etc. A fragment of this code with the implementation of the Formula is given in Figure 4.

```
grade = 2 + min(len(dict_entities), 400) / 400 * 4 * 0.1
+ min(len(dict_concepts), 300) / 300 * 4 * 0.3
+  min(total_num_quotations, 30) / 30 * 4 * 0.3
+ min(len(dict_relations), 500) / 500 * 4 * 0.1
+ min(concepts_relevance_coeff, 10) / 10 * 4 * 0.3

print("relative grade {gr}".format(gr=min(grade * 2, 6)))
```

Fig. 4 Implementation of Text Quality Formula

3. Conclusion

in conclusion, the research goals (G1 - G5) are completed to some extent. Several texts have been successfully tested. Their metadata, concepts, and entities' sentiment data have been extracted. It is evaluated that more research needs to be done to generate more accurate summaries, so implementing the following algorithm for summary generation is more than necessary. Based on the information obtained from the research, the work in question aims to help raise awareness and knowledge of people whose responsibilities are connected with national security and public order protection. A better approach needs to be employed in calculating the Scientific Text Quality, which considers "mind maps" and "concept graphs." It employs some graph similarity algorithms, for example. These improvements will be shown in future articles. Experimental results data will be shown in future examinations after careful removal of sensitive data, taking into account that some data might be subject to state secrets or information that may lead to compromising the education of such specialists.

For its part, the formulated conclusions and methodological guidelines could increase the attention of the services on the set issues, namely the inclusion of more and more women in the ranks of terrorist organizations.

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