

SENECA: An Attention Support Tool for Context-related Content Learning

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Abstract

In this work, we proposed a tool named SENECA that aims to help the students who follow remote lessons to maintain/capture attention, allowing them to focus on learning led by the context. Among the disadvantages of distance education, especially for subjects who lack awareness, the greatest distractions at home are counted. These distractions cause a movement of the student's attention from the current lesson to disturbing events. For this reason, there is a need to experiment with new solutions also linked to Information Technology (IT) to improve the focused learning during distance education. Our tool's technical idea is to create a real-time summary of the topic treated by the teacher. The system captures the text every five minutes, generates outlines, and scratches them and browses them to eliminate repetitive portions after each survey. On the general generated summary, Natural Language Processing techniques are applied to extract categories and keywords. The latter will show the highlights of the speech.

Index terms— Natural Language Processing, Semantic Analysis, Distance Education, Learning, Attention, Content

1 Introduction

Into the current pandemic situation generated by the SARS-CoV-2 coronavirus, the educational environment worldwide has to face numerous challenges to continue teaching in schools and universities.

One of the most important aspects of cognitive function is the “ability to keep” relevant information in mind. *Working memory* is a system dedicated to the maintenance and temporary processing of information during cognitive processes. One of the components is represented by the *central executive* which carries out the coordination of subordinate systems, coordination of execution of tasks and recovery of strategies and attentional functions of both selection and inhibition [3]. The central executive controls the *phono-*

logical loop which contains verbal and auditory information, the *visuo-spatial sketchpad* engaged in spatial representation and the *episodic buffer* which has a limited ability to link information from different sources with spatial and temporal parameters.

Specifically, each attentive act is divided into three phases: the orientation and perception towards the different stimuli; the processing phase that presents the function of selectivity and sustained attention overtime on a task or activity, the shift to move the focus quickly and the ability to pay attention to use the right cognitive resources in different situations; the specific response concerning the input stimuli [4].

Different studies have focused on the impact of technologies on cognitive functions in the present digitized era, both from the perspective of the benefits and disadvantages [38]. *Lodge and Harrison* [25] stressed as attention is subject to complex dynamics that impact learning, especially in educational contexts. The most important part of a sentence, oral or written, is the focus. Recent articles have demonstrated the importance of *marking elements* as a *guide* for better information exchange [24] between speakers and listeners. In particular, these studies argue that focus marking captures the listener's attention to what the speaker considers the most relevant part of the message. At the same time, this method helps the attention to be kept on the marked element allowing its representation [32].

Recent work has addressed the issue of distance education by administering questionnaires to both teachers and pupils. The most variable answers to the questions were also obtained on the degree of students' participation in distance lessons, emphasizing a wide range of behaviors. Furthermore, perception of difficulty during remote lessons was found to be linked to many factors: access to technology, motivation and support with a greater presence of negative experiences [26]. The new educational needs of online teaching and students' changing learning styles limit knowledge transfer comprehensively and effectively. During the detachment of presence foreseen by distance teach-



Figure 1: A standard bidirectional media streaming.

ing, many dysfunctional behaviors can be generated, such as the loss of interest, attention and motivation for psychophysical causes and non-adaptation to an abnormal situation. Compared to the standard educational environment, distance learning has a disadvantage in terms of distractions. It is an isolated experience in which there is no direct communication that makes participation much more active [14]. It would be useful to overcome the difficulties of maintaining a student’s attention, regardless of the need or not of a situation that requires the use of tools for distance learning. Overcoming these issues would help refine each pupil’s strategic learning styles and ensure a meta-cognitive self-assessment approach on one’s limits and abilities, supported by technology. Recent meta-cognitive skills also include a student’s ability to become aware of his or her ability to “*learning how to learn*”. This ability means recognizing and then consciously applying appropriate behaviors and strategies useful for a more effective learning process [29].

This paper proposes a Distributed Multimedia System for support learning, designed to face the loss of attention during distance education. The purpose of the system is to be able to reawaken or maintain attention to the context (topic) that is being experienced during the activity in progress (in *real time*) to reduce the negative effect of distractions. The system also aims to provide the possibility of an in-depth analysis at the end of the lesson through auto-generated hyperlinks to lesson-related content. The architecture proposed rely on *Speech-to-text*, *Natural Language Processing (NLP)*, *Text Summarization* [18] and *Semantic Analysis technology*.

This document is organized as follows. In Section 2, we described the most important related works about the technological systems that help in learning. In Section 3 we introduced the used methodologies. In Section 4 we have highlighted the working hypotheses on which we based our work. In Section 5 we presented the system architecture and in Section 6 we have detailed the performed experiments and the related results (Section 7). Finally, in Section 8 we will discuss research directions and future development of

our work.

2 Related works

In this section, we present some related works about the use of semantic and NLP analysis technologies. Specifically, we will discuss different application contexts of these techniques. Most of a student’s effort is to transfer information from working memory to long-term memory to acquire and memorize key concepts. Two strategies can be used: dual coding and chunking [10]. In cognitive psychology, a *chunk* is nothing more than a unit of information, and chunking is the operating mode in which this unit of data is recovered. When faced with new knowledge, the individual can grasp the relative chunk of information and bring it back to light later when recalling a similar situation or concept. Then, the initial piece can be expanded into more complex pieces following the management control and understanding of the flows of one’s knowledge [35].

The standard structure of a *Distance Educational System* can be generalized as reported in Fig. 1. This kind of system relies on the classic bidirectional multimedia connection, like the common video-chat system based on SIP/VOIP system, such as Microsoft Teams [23]. However, a Distance Educational System supports multiple bidirectional connections between students and teachers (or teachers) and allows channel moderation.

Nowadays, the cloud’s audio/video stream transfer services are implemented by the major world providers (*Amazon*, *Microsoft*, *Zoom*). A teacher can teach remotely by transmitting an audio/video stream from their home to one of these providers. Then these last provide a broadcast service to the students.

NLP techniques have been widely used in intelligent tutoring systems that helped acquire content knowledge [8]. For example, in Guzmán-García *et al.* [21], the analysis of the surgeons’ speaking taken into the operating room through NLP techniques is proposed to obtain a deeper vision of intraoperative decision-making processes. This study aimed to develop a method of recognizing and evalu-

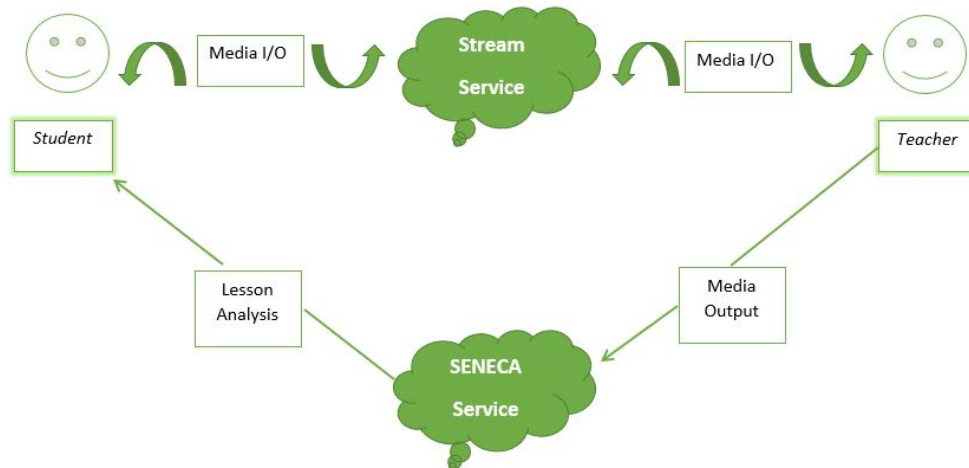


Figure 2: The additive layer for multimedia analysis.

ating the various surgical phases and developing a workflow comparable with the framework of the procedure to improve surgical learning in The Educational Operating Room.

Recent studies have highlighted how to identify the main contents to better understand the topic, especially in students with cognitive deficiency, attention, or memory. The ability to take advantage of text summarization techniques by explaining the main idea allows students to interface with the limits of their working memory and have a tool to overcome their difficulties [34].

Today, many educational and academic institutions benefit from the *Learning Management Systems* (LMS) to support and improve teaching processes [15][19]. Most LMS is software application systems that allow teachers to manage and deliver educational courses [2]. One of the requirements for the success of distance education is traceable in the self-management of learning which is the starting point for self-discipline in autonomous learning [36].

In 2019, Cobos *et al.* [12] have developed EdX-CAS, a content analyzer system for edX MOOCs, using NLP techniques for the Spanish language. The tool takes in input the video transcripts of the courses, with which users can interact specifically. It allows students to extract the text's main terms, the vector representation for each of the terms in the text, the linguistic diversity to understand how many different words are used, indications on the subjective opinion on the text and the representation with word clouds. The edX-CAS tool is oriented to Sentiment Analysis Opinion Mining for Detecting Subjectivity and Polarity Detection in Online Courses related to Madrid's Universidad Autónoma.

On the topic of the educational distance imposed by the Covid-19, to support students in self-training, a chatbot was proposed using NLP techniques [16]. The proposed solu-

tion involves sending a message to Moodle [1] by the student. An associated plugin tries to understand the text received and returns feedback. Based on the degree of assessment achieved by the student, the chatbot provides recommendations on the chapters for which the evaluation is not sufficient. The system presupposes the memorization of the evaluation outcomes of the student who are accessible to teachers. The chatbox, in this context, acts as a tutor and allows us to fill the gaps of the students.

3 Methods

We propose a new tool called SENECA (Support IEarning coNtEnt Context Attention), which involves using a new layer dedicated exclusively to analyzing the audio/video streams generated by the “teachers”. Our purpose is to maintain the student focus or a rapid return to it by implementing this new layer. The proposed architecture is to be considered feasible for real-time distance lessons and not to the MOOC [5] or the on-demand recorded lessons. We did not consider the capabilities related to file upload, file sharing and homework as an added values.

The new layer is identified in the Fig. 2 as Seneca Service. In this proposal, we refer only to real-time audio/video streams, i.e., not recorded lessons held at a distance. The real-time component's presence allows us to immerse ourselves in a learning context susceptible to disturbances that distract the individual student.

SENECA's main goal is to help students avoid loss of concentration by providing multiple information that can allow students to maintain focus on the argument or bring attention back to the context in the event of distractions. Another important goal is to favor applying many text analysis

techniques to improve the learning quality of the topic under study and integrate it, providing additional information that can be used at the end of the lesson to recover information further.

4 Working hypothesis

In this section, we aim to highlight some working hypotheses that allow us to have a more understandable general view of the SENECA tool's starting idea:

- a) The real-time audio/video stream (from here called `STREAM`) generated by a remote lesson can be split into two unique sub-streams: `VIDEO` flow, containing the video frames and `AUDIO` flow containing audio buffer.
- b) The `VIDEO` flow will contain information from slides or, in any case, projected material to provide a conceptual map to students.
- c) The `AUDIO` flow will contain the lesson audio, and it is expected to add information on both the context under study and in-depth study (as well as student questions or others).

In this context, we assume that the `VIDEO` stream contains *information already summarized on the subject*. In our experiment, we considered the data extracted from `VIDEO` as already cleaned. On the other hand, the presence of heterogeneous data in `AUDIO` streams will require a more accurate analysis of the content.

The extracted data from `VIDEO` and `AUDIO` is referred following as `WORD STREAMS`.

5 System architecture

We designed a prototype architecture based on a pipeline approach, like Microsoft DirectShow¹ or ffmpeg². In SENECA each computational block is called *Filter*.

An overview of a complete SENECA architecture is shown in Fig.3. For this proposal, we implemented only the following filters: `SPLIT`, `OCR`, `STT`, `SUMMARY` and `SEMANTICS`.

The filters are defined as following:

$$SPLIT(STREAM) \rightarrow \{AUDIO, VIDEO\}$$

$$OCR(VIDEO) \rightarrow \{WS\}$$

$$STT(AUDIO) \rightarrow \{WS\}$$

$$SUMMARY(WS, GLS) \rightarrow \{NEW GLS\}$$

$$SEMANTIC(GLS) \rightarrow SUGGESTIONS$$

The `SPLIT` filter takes as input the `STREAM` and splits it into two separate flows, called `AUDIO` and `VIDEO`.

The `OCR` technique allows the detection and extraction of text from images [28]. The SENECA `OCR Filter` takes as input a single frame video at a time. We used the `videocr` python module (v. 0.1.6)³ for our experiment purpose. That module lies on Tesseract OCR 4.1.1.⁴ This filter analyzed each video frame from the pipeline and stored the detected text (handwritten and block letters) into a word stream (`WS`). Each word stream was enqueued into the next pipeline filter.

In SENECA, the `STT` filter performs a speech-to-text routine. Speech-to-text is a technique that allows the detection and the extraction of phrases from an audio flow `WS` [11]. Probably, the most commonly known example is Amazon Alexa or Google Assistant. Into our prototype, we used the Google Cloud Speech API <https://cloud.google.com/speech-to-text/>. For each audio frame extracted by the `SPLIT`, the `STT` filter generated a word-stream (`WS`) that was enqueued to the `NPL` filter.

One of the project goals is to provide a way to regain the attention on the topic focus after a distraction. In SENECA, one of the tips is to allow users to summarize the lesson in real-time. As shown in figure 3, the media flow (as an example, a streamed lesson) comes into the `SPLIT` filter that separates audio from video. For each video frame extracted, the `OCR` extracts the detected phrases, and `STT` makes the same action on the audio frame. In particular, these word streams came into the next filter into `SUMMARY` filter that is a delegate to create partial summaries using the word streams that came into the filter. Into our prototype, the `SUMMARY` filter computes a summary for the `WSs` using `MEAD` [18]. These multiple summaries are merged every 5 minutes into the `Global Lesson Summary (GLS)` that is processed again by `MEAD`. We have chosen the five minutes interval using the mean lesson length. Consequently, SENECA builds and refreshes a `GLS` by using `SUMMARY` filter output for each real-time lesson. Into our prototype, `GLS` is composed of phrases generated by applying `MEDA` text summarization algorithm on `WSs`.

The `SEMANTIC` filter extracts the `MEF` from the `GLS` every time a new `GLS` is deployed from the `SUMMARY` filter. We identify with the term `MEF` or *Most Expressed Features* of a string `S`, the dictionary `D(S)` of all possible *k-mers* extracted from `S`, using substrings length between `m`

¹<https://docs.microsoft.com/en-us/windows/win32/directshow/directshow>

²<https://ffmpeg.org/developer.html>

³<https://pypi.org/project/videocr/>

⁴<https://github.com/tesseract-ocr/tesseract>

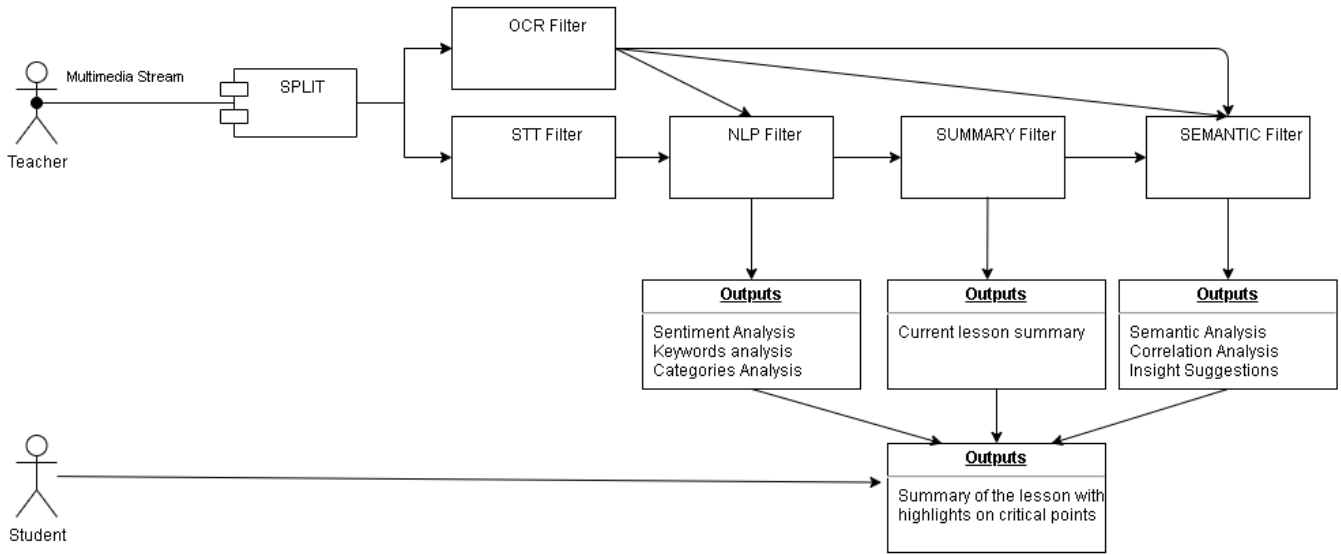


Figure 3: A basic SENECA module.

Table 1: Partial subset of lessons MEF.

Topics	MEFs
<i>Cancer</i>	Smoking, Colon Cancer, Surgery, Risk Factor
<i>Diabetes</i>	Beta Cell, Interleukin, Inflammatory, Physic
<i>Evolution</i>	Selection, Heritability, Billion Years, Coevolution
<i>Terrorism</i>	Terror, Poverty, Success, Politican
<i>Chemistry</i>	Compound, Energy, Element, Electron

and M . The dictionary is ordered in a decreasing way, compared to the number of occurrences of each k -mers. The MEFs represent the object’s functional parts, such as words or portions of sentences of a text repeated several times. SEMANTIC is designed to use the MEF for probing one or more scientific databases to make suggestions. In particular, it performs a combined NO-SQL Alignment-free search into the pre-processed PUBMED database (see next paragraph). For each GLS, SEMANTIC can extract the candidate literature papers indexed by MEF. It uses two metrics to compute (see experiment one) the suggested papers based on the semantic distance between GLS and candidate paper set.

For this prototype, we used the PUBMED database [9]. We execute the SEMANTIC filter on the entire PUBMED dataset, and we have extracted the MEFs, using substrings length interval between $m=3$ and $M=15$.

Due to the PUBMED dataset size, we used Amazon EC2 and Amazon RDS services [30] to distribute MEFs extraction and storage.

6 Experiment Execution

We simulated real-time lessons by using public videos from Coursera⁵. We selected five free courses, recovering from each it, the text subscription using STT. The main topics of the lessons are Cancer; Diabetes; Evolution; Terrorism, Chemistry.

We implemented two experiments. Our goal was to study the SUMMARY and SEMANTIC filter performances.

6.1 First Experiment

Into the first experiment, we sent all the entire lessons (5 merged videos per lesson) into the SENECA pipeline, sequentially, to compute separate GLS outputs for each entire lesson. Also, we sent each video (one at a time, not merged) into the pipeline to generate the GLS for each video.

We wanted to study if the SEMANTIC filter was able to discriminate between lesson topics. We applied the SE-

⁵<https://www.coursera.org/>

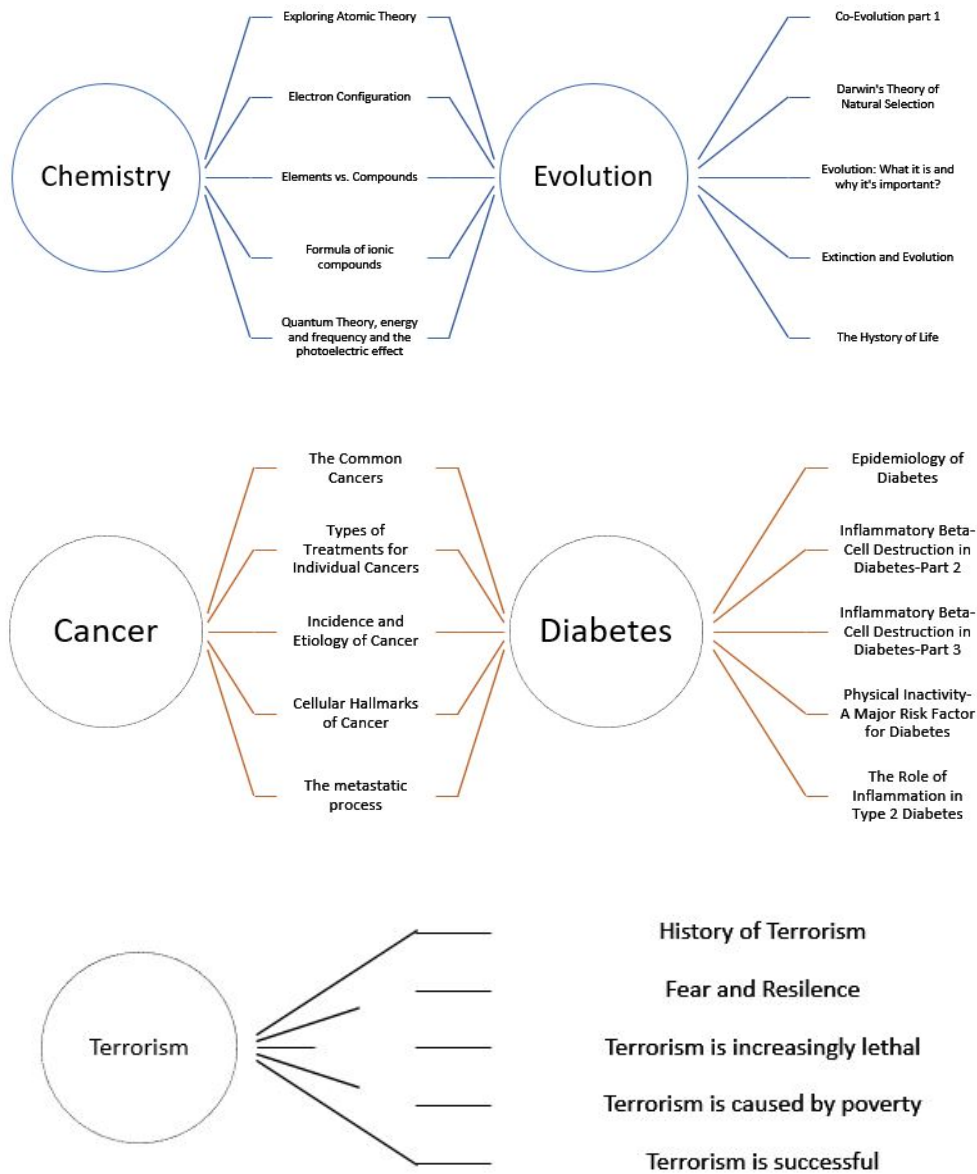


Figure 4: Lesson Topics clustering using Jaccard distance.

MANTIC filter on each GLS to extract the MEFs for each of them.

Using the MEFs, we were able to build two distance matrices. We used two different distance metrics. The distances were calculated using the *Jaccard Index* [31] (see Eq. 1), and by *Szymkiewicz-Simpson coefficient (SSC)* [39] (see Eq. 2).

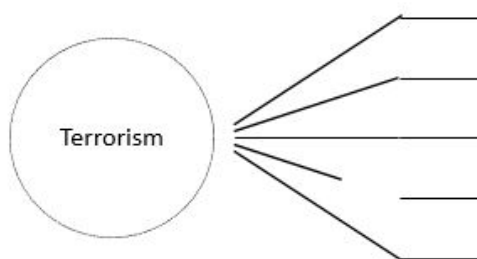
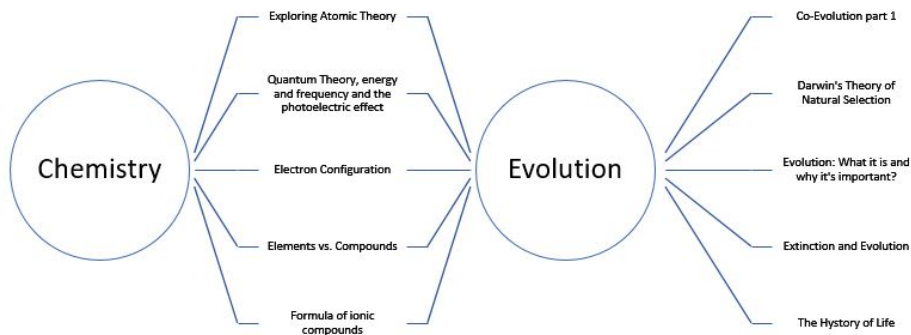
Both metrics allow us to compute the similarity between pair of MEF dictionary. SSC is often identified as the “*overlay coefficient*.”

The Jaccard index is defined as:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

where A and B are two different datasets, whilst the $|\bullet|$ operator computes the size of a set. In particular, the Jaccard index is represented as the size of the intersection divided by the size of the union of the datasets.

Given the two dictionaries A and B , the overlap coefficient is a measure that returns the overlap between them,



History of Terrorism
Terrorism is increasingly lethal
Terrorism is caused by poverty
Fear and Resilience
Terrorism is successful

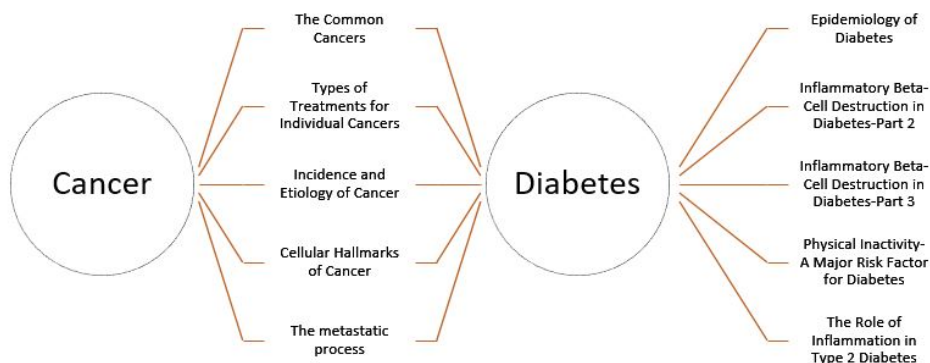


Figure 5: Lesson topics clustering using SSC.

and it is defined as the intersection divided by the smaller of the size of the two sets, as shown in Eq. 2.

$$SSC(A, B) = \frac{|A \cap B|}{\min(|A|, |B|)} \quad (2)$$

We used the dictionaries and the distance matrices to extract the most expressed keywords and cluster the GLS.

6.2 Second Experiment

Into the second experiment, we sent each lesson, one at a time, to the pipeline to generate its GLS. For each GLS, we

applied the SEMANTIC filter to extract the related MEFs to use them as probes for the subsequent insights.

We applied Jaccard and SSC metrics between each GLS and the PUBMED-MEF dataset.

We computed ten distance matrices from which we picked the first ten (see table 2) most similar results for each GLS. We were forced to use Apache Spark [37] to distribute this job across multiple slaves due to the heavy memory requirements of these tasks.

Table 2: Partial subset of suggested papers and their distance score.

Paper ID	Author	Value
P1	Belsky <i>et al.</i> [7]	0.91
P2	Huang <i>et al.</i> [22]	0.81
P3	Wu [41]	0.93
P4	Gaitanidis <i>et al.</i> [17]	0.83
P5	Bauer <i>et al.</i> [6]	0.88
P6	Wang <i>et al.</i> [40]	0.95
P7	Mays <i>et al.</i> [27]	0.94
P8	Schuck <i>et al.</i> [33]	0.93
P9	Guo <i>et al.</i> [20]	0.92
P10	Corsi <i>et al.</i> [13]	0.90

7 Experimental Results

The Table 1 shows the first four MEFs for each lesson. The SEMANTIC filter was able to detect keywords related to lesson context. Due to the GLS and MEF definitions, the MEF dictionaries contain up to 140K kmers for each GLS. We reported the most expressed that refer to complete word.

The results of topics clustering are available in Fig. 4 with the Jaccard index and Fig. 5 with the overlap coefficient.

We identified the topics which are part of the same branch of the tree with the same color and the subgroups of each topic using different colors. SEMANTIC separated the five treated topics well, with just little differences in lesson aggregation levels. Specifically, it is interesting to note how the system is able to cluster together the *Cancer* and *Diabetes* and *Chemistry* with *Evolution* topics.

In the second experiment, we used the extracted MEFs as if they represented ‘tags’ to recover suggested papers. For convenience, we have used only the MEFs of the lessons on the topics *Cancer* to show the results.

SEMANTIC identified 274 correlates documents recovered by PUBMED-MEF dataset. For example, in Table 2 we showed the first ten recovered papers with a score value greater than 0.80. In Fig. 6, we represented the position of suggested papers graphically compared to the target query, keeping in mind that the score of the distance from the target query is representative of the similarity between the set of MEFs of the *Cancer* topic and the individual retrieved papers.

8 Conclusions

The change to the basis of remote teaching is the transition from traditional education to smart education. The teacher is responsible for managing class to be student-centered, which involves greater responsibility and aware-

ness of their limits and potential in self-learning behind one screen. It is not always possible. Disturbing factors related to the surrounding environment may disrupt the attention of the student. In an era in which new teaching tools are proposed, managing personal learning is also changed. One of the disadvantages of remote education is the different distractions that can intervene in maintaining the focus. In this work, we have proposed a tool that aims to maintain students’ attention on topics covered in the teacher’s lessons. The system works in real-time and allows us to generate further knowledge thanks to the possibility of an in-depth study by hyperlinks of treated topics. The preliminary experimentation suggests that the framework can provide insight and help regain attention on the lesson focus. Experimentation in real classes should be performed to understand the framework’s impact on student attention in remote lessons. Among the future directions’ objectives, we expect to explore techniques that improve text summarization and the extension of architecture for multilingual texts. An additional module for the real-time creation of concept maps may be provided.

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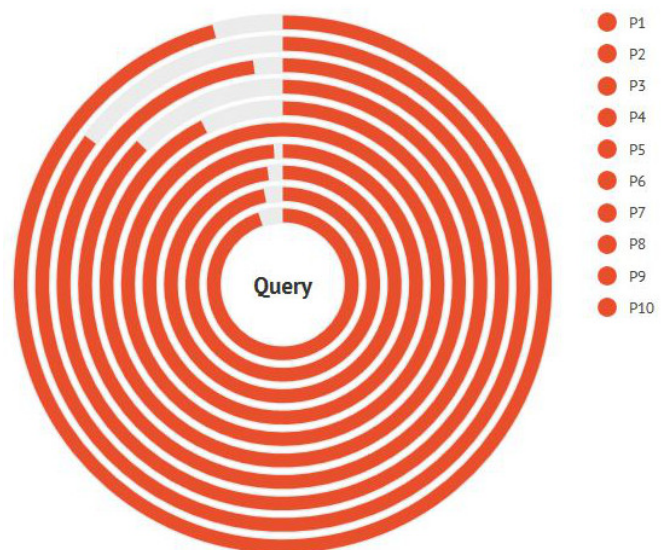


Figure 6: Position of suggested papers compared to the target query.

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