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# SENECA: A Pedagogical Tool Supporting Remote Teaching and Learning

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ABSTRACT

In this paper, we suggest SENECA, a tool that attempts to assist students who follow remote classes in maintaining/capturing attention, allowing them to focus on context-driven learning. Distance education has a number of disadvantages, including a lack of physical interaction between students and teachers, emotional and motivational isolation as a result of this strategy, and a reduction in active engagement. All of these things have an impact on student learning abilities. The largest distractions at home are considered among these disadvantages of distant education, particularly for subjects with low awareness. 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 browses them to eliminate repetitive portions after each survey. We looked at two different sorts of filters, semantic and summary, to see if the first could distinguish between topics and the second could evaluate the topic's highlights. Natural Language Processing algorithms are used to extract categories and keywords from the general generated summary. The latter will emphasize the most important points of the speech, while the keywords will be utilized to extract the candidate literature about the discussed topics.



## 1. Introduction

Into the current pandemic situation generated by the SARS-CoV-2 coronavirus, the educational environment around the world is faced with several problems and challenges in order to continue teaching in schools and universities.

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 [28]. The increased educational needs of online teaching, as well as the shifting learning styles of the students, impede comprehensive and effective knowledge transmission. Many dysfunctional behaviors can be developed as a result of the detachment of presence predicted by distance teaching. Among them we include loss of interest, attention, and motivation due to psycho-physical causes and non-adaptation to an abnormal setting. Distance learning has a disadvantage in terms of distractions as compared to traditional education environment. It's a solitary experience with no direct communication, which makes participation much more active [15]. It would be beneficial to overcome the difficulties of keeping the attention of a student, whether or not a circumstance necessitates the use of distant learning resources. Overcoming these obstacles would aid in refin-

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**Figure 1:** A standard bidirectional media streaming.

ing each student's strategic learning styles and ensuring a meta-cognitive self-assessment approach to one's limits and abilities, all of which would be aided by technology.

A student's ability to become aware of his or her ability to "*learning how to learn"* is another recent meta-cognitive skill. This ability means recognizing and then consciously applying appropriate behaviors and strategies useful for a more effective learning process [31].

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* [19] and *Semantic Analysis technology*.

This paper is an extension of the work *SENECA: An Attention Support Tool for Context-related Content Learning* [3]. For this contribution, we enriched the Section 7 with a new experimentation for the SUMMARY filter of the SENECA pipeline. Specifically, we conducted a validation with the support of three independent and expert reviewers who assessed the consistency and degree of consistency of the SUMMARY filter's output on several lessons. Three criteria were evaluated for coherence with the topic of the lessons: the summary, the keywords extracted and the insights.

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. We also presented an overview of how the working memory works and the impact of technology on it.

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 [4]. The central executive controls the *phonological 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 [5].

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 [40]. *Lodge and Harrison* [27] 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 [26] 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 strategy aids in maintaining focus on the highlighted element, allowing for its representation [34].

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 [11]. In cognitive psychology, a *chunck* is nothing more than a unit of information, and chunking is the operating mode in which this unit of data is recovered.

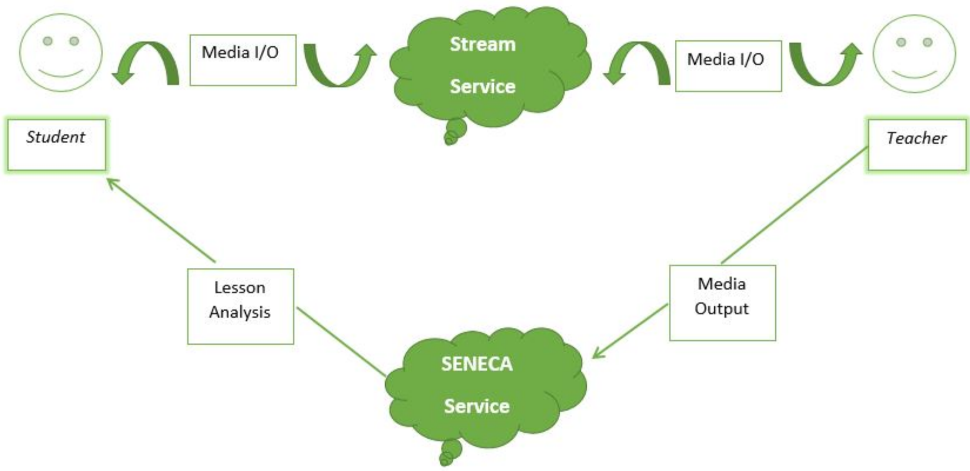


**Figure 2:** The additive layer for multimedia analysis.

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 [37].

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 [25]. However, a Distance Educational System supports multiple bidirectional connections between students and 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 [9]. For example, in Guzmán-García *et al.* [22], the analysis of the speaking of surgeons into the operating room through NLP techniques is proposed to obtain a deeper vision of intraoperative decision-making processes. The goal of this study was to create a technique for identifying and analyzing the various surgical phases, as well as a workflow that was equivalent to the procedure's framework, in order to improve surgical learning in The Educational Operating Room.

Recent studies have emphasized the importance of identifying the main contents in order to better understand a topic, particularly in students with cognitive disabilities and attention or memory problems. 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 [36].

Today, many educational and academic institutions benefit from the *Learning Management Systems* (LMS) to support and improve teaching processes [16][20]. Most LMS are 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 [38].

In 2019, Cobos *et al.* [13] have developed EdX-CAS, a content analyzer system for edX MOOCs, using NLP techniques for the Spanish language. The program accepts video transcripts from courses as input and allows users to interact with them specifically. It allows us 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 [17]. The proposed solution involves sending a message to Moodle [1] by the student. An accompanying plugin tries to decipher the text and provides feedback. Based on the degree of assessment achieved by the student, the chatbot makes suggestions for the chapters where the evaluation is insufficient. The system presupposes the memorization of the student evaluation outcomes, accessible to teachers. In this context, the chatbox, acts as a tutor and allows us to fill the gaps of the students.

## 3. Methods

We propose a new tool called SENECA (Support lEarning coNtEnt Context Attention), which involves using a new layer dedicated exclusively to analyzing the audio/video streams

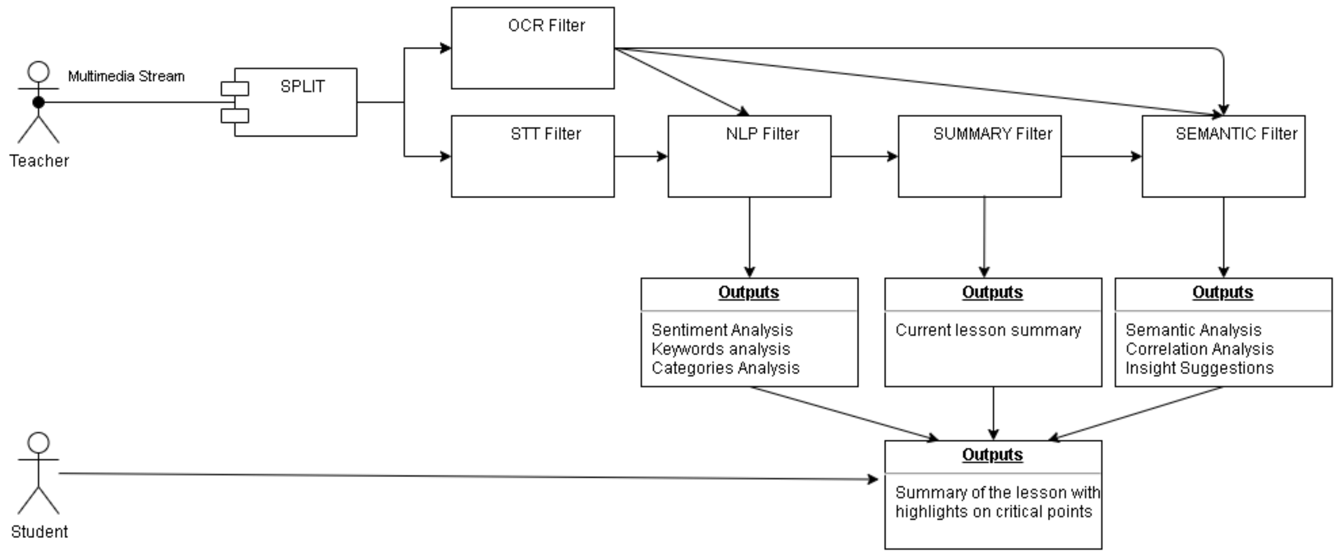


**Figure 3:** A basic SENECA module.

generated by the "teachers". By integrating this new layer, we hope to preserve or quickly recover student focus. The proposed architecture is to be considered feasible for real-time distance lessons and not to the MOOC [6] 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 presence of the real-time component allows us to immerse ourselves in a learning environment that is subject to disruptions that distract the individual student.

SENECA's major goal is to help students avoid losing concentration by providing multiple of information that can help them stay focused on the argument or return their attention to the context, if they become distracted. Another key purpose is to encourage the use of a variety of text analysis approaches to improve the learning quality of the topic under study and integrate it. For this purpose, the system supplies additional information that can be used to recover information at the end of the session.

## 4. Working hypothesis

In this section, we will highlight some working assumptions that will help us gain a better understanding of the SENECA tool's initial concept:

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 DirectShow [1] or ffmpeg [2].

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`.

[1] https://docs.microsoft.com/en-us/windows/win32/directshow/directshow
[2] https://ffmpeg.org/developer.html

**Table 1**
Partial subset of lessons MEF.

| Topics | MEFs |
|---|---|
| *Cancer* | Smoking, Colon Cancer, Surgery, Risk Factor |
| *Diabetes* | Beta Cell, Interleukin, Inflammatory, Physic |
| *Evolution* | Selection, Heritability, Billion Years, Coevolution |
| *Terrorism* | Terror, Povery, Success, Politican |
| *Chemistry* | Compound, Energy, Element, Electron |

The OCR technique allows the detection and extraction of text from images [30]. 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 [12]. Probably, the most commonly known example is Amazon Alexa or Google Assistant. Into our prototype, we used the Google Cloud Speech API [5]. 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 Fig. 3, the media flow comes into the SPLIT filter that separates audio from video. For each video frame extracted, the OCR retrieves the identified sentences and STT does the same for the audio frame. These word streams, in particular, entered the following filter, the SUMMARY filter, which is a delegate for creating partial summaries from the word streams that entered the filter. Into our prototype, the SUMMARY filter computes a summary for the WSs using MEAD [19]. 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 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 make suggestions by probing one or more scientific databases using the MEF. 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 [10], due to the higher prevalence of selected biomedical topics. We executed 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 [32] to distribute MEFs extraction and storage.

[3]https://pypi.org/project/videocr/
[4]https://github.com/tesseract-ocr/tesseract
[5]https://cloud.google.com/speech-to-text/

## 6. Experiment Execution

We simulated real-time lessons by using public videos from Coursera[6]. 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 output 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 SEMANTIC filter on each GLS to extract the MEFs for each of them.

[6]https://www.coursera.org/

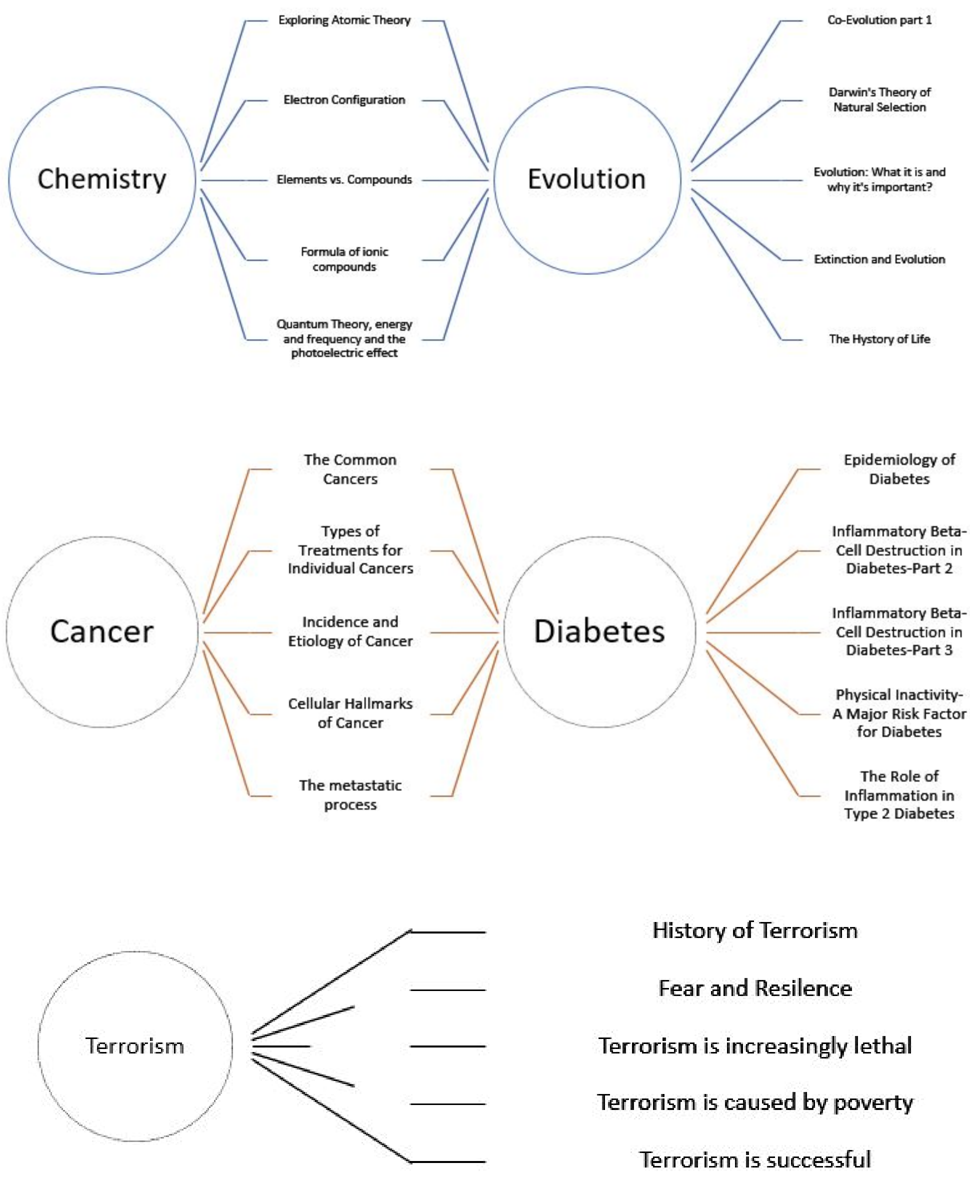


**Figure 4:** Lesson Topics clustering using Jaccard distance.

Using the MEFs, we were able to use two different distance metrics. The distances were calculated using the *Jaccard Index* [33] (see Eq. 1) and *Szymkiewicz–Simpson coefficient (SSC)* [41] (see Eq. 2).

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

The Jaccard index is defined as:

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

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

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

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

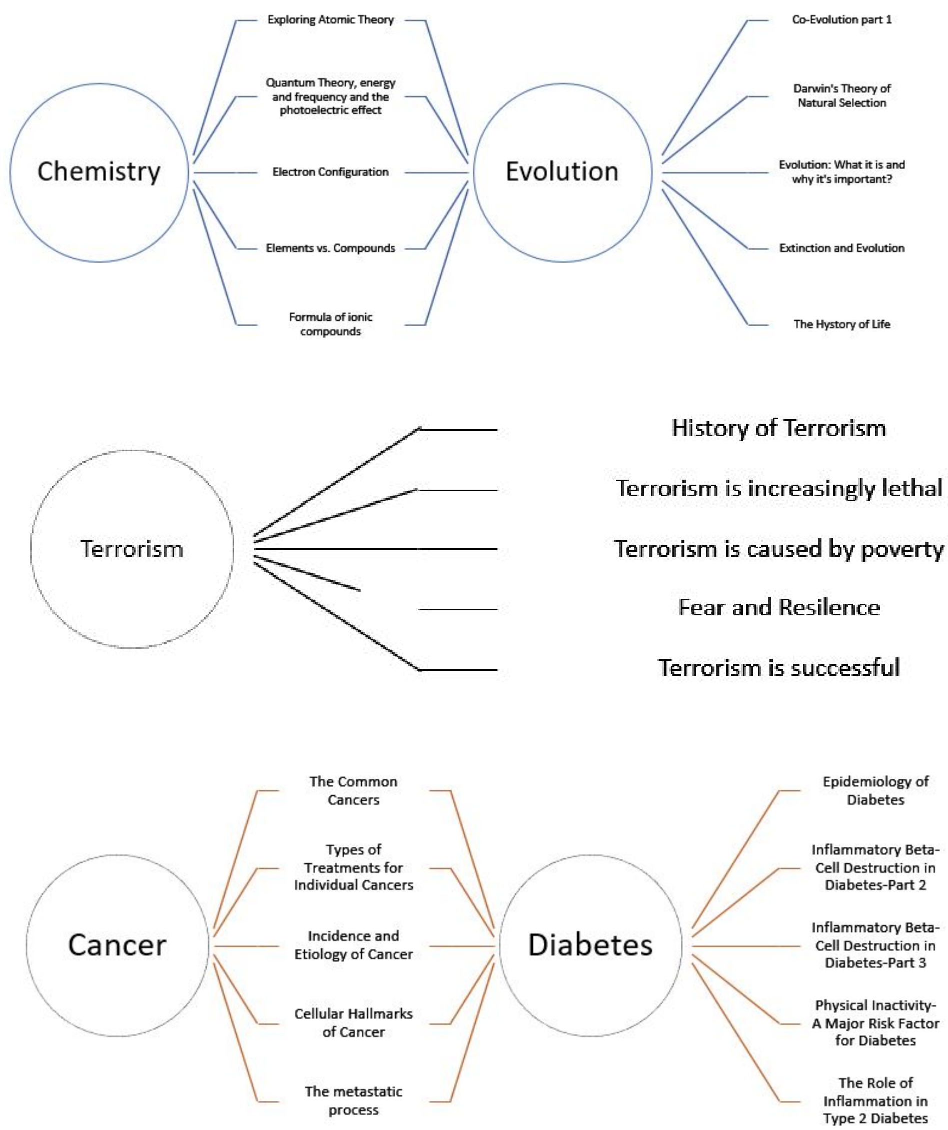


**Figure 5:** Lesson topics clustering using SSC.

### 6.2. Second Experiment

Into the second experiment, we sent each lesson, each in turn, to the pipeline to generate its GLS. For each GLS, we applied the SEMANTIC filter in order 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.

For each GLS, we computed ten distance matrices and selected the first ten most similar results (see Table 2). Due to the high memory requirements of these tasks, we were forced to employ Apache Spark [39] to distribute this job across multiple slaves.

## 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 used the same color to identify topics that belong to the same branch of the tree and different colors to identify subgroups of each topic. With only minor discrepancies in lesson aggregation levels, the filter SEMANTIC successfully separated the five treated themes. Specifically, it is interesting to note how the system is able to cluster together the *Cancer* and *Diabetes* and *Chemistry* with *Evolution* topics.

In this scenario, there appears to be a common thread connecting the two diseases and chemical topics with evolution, with the basic premise that the latter is the branch of natural sciences at the foundation of life and recognized material transformations.

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 correlated 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.

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

| Paper ID | Author | Value |
|---|---|---|
| *P1* | Belsky *et al.* [8] | 0.91 |
| *P2* | Huang *et al.* [24] | 0.81 |
| *P3* | Wu [43] | 0.93 |
| *P4* | Gaitanidis *et al.* [18] | 0.83 |
| *P5* | Bauer *et al.* [7] | 0.88 |
| *P6* | Wang *et al.* [42] | 0.95 |
| *P7* | Mays *et al.* [29] | 0.94 |
| *P8* | Schuck *et al.* [35] | 0.93 |
| *P9* | Guo *et al.* [21] | 0.92 |
| *P10* | Corsi *et al.* [14] | 0.90 |

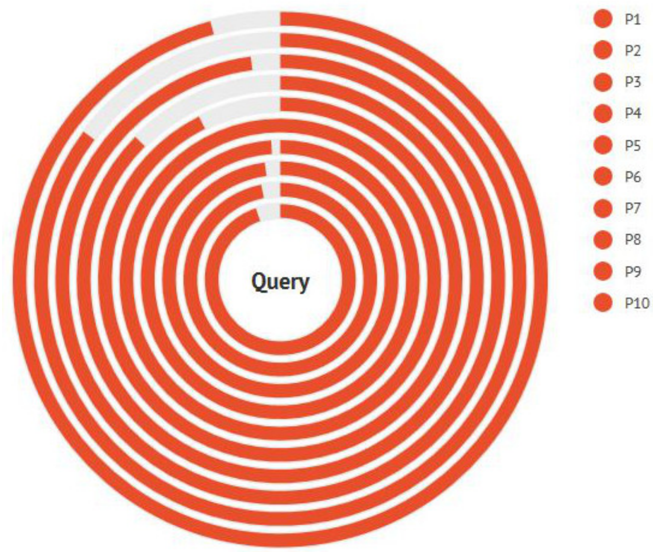


**Figure 6:** Position of suggested papers compared to the target query.

We chose one topic, *Pharmacology*, consisting of five lessons from COURSERA. We invited three independent and expert reviewers, which submitted the output of SUMMARY filter in order to validate our SENECA pipeline. For each lecture, three parameters are assessed: summary, keyword, and insight. The initial assessment is based on the consistency of these three factors, with a binary Yes/No (indicated as Y/N) response. The second evaluation of the experts is assigning a consistency rating between 0 and 5 to each of the three aspects under consideration. The results are shown in Table 3. Expert evaluators performed a manual evaluation, giving a direct score on the coherence of the summary. Other factors, such as the quality of the summary or language comprehension were not considered. In Table 4, we reported the average scores reached for each lessons based on the votes assigned by the reviewers. For the five lessons, we can see how, on average for the threshold score, the Summary filter fluctuates between a minimum of 2 and a maximum of 3. The value for keywords is around 2-4 and the value for the insights is between 0.3 and 3.7. The first two lessons are ones in which the reviewers had differing perspectives on all three aspects assessed, while the subsequent lessons have similar values assigned. On average, the SUMMARY filter and keywords extraction perform better than the insights recovery phase. The discordance of score on the first two lessons suggests that the results are in any case influenced by subjective elements linked to the identity of the reviewer. The main emerged considerations from this first examination are that the keywords may be improved, as they are currently too generic in some circumstances.

## 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 awareness of their limits and potential in self-learning behind a display. It is not always possible because disturbing environmental factors may cause the student's attention to be diverted. This is one of the disadvantages of remote education, which intervene in maintaining the focus. In an era in which new teaching tools are proposed, managing personal learning is also changed. In this work, we have proposed a tool that aims to maintain attention of students on topics covered in the lessons held by teachers. The technology operates in real-time and allows us to get additional knowledge by allowing us to conduct in-depth research using hyperlinks to related topics. Preliminary testing indicates that the framework can provide insight and assist in refocusing attention on the lesson. We used independent experts to perform a first evaluation phase of our pipeline. This step showed how SENECA can be further improved in the appropriateness of insight research. Future enhancements may possibly include different applications of summarization technologies. Manual evaluation necessitates the utilization of external resources, which should not be underestimated. As a result of this issue, we may meet this demand by developing future automatic assessment approaches that compare the quality of the summary to the Gold Standard Reference, which was prepared by an expert. In this case, a score could be assigned based on

**Table 3**
Evaluation of SUMMARY filter of SENECA pipeline

| Lessons | | Coherence | | | Coherence Threshold | | |
|---|---|---|---|---|---|---|---|
| | | Summary | Keywords | Insight | Summary | Keywords | Insight |
| *Pharmacology 1* | Reviewer 1 | Y | Y | Y | 3 | 3 | 2 |
| | Reviewer 2 | Y | Y | N | 3 | 3 | 0 |
| | Reviewer 3 | N | Y | N | 0 | 2 | 0 |
| *Pharmacology 2* | Reviewer 1 | Y | Y | Y | 3 | 3 | 1 |
| | Reviewer 2 | Y | Y | N | 3 | 3 | 0 |
| | Reviewer 3 | N | N | N | 0 | 0 | 0 |
| *Pharmacology 3* | Reviewer 1 | Y | Y | Y | 3 | 2 | 4 |
| | Reviewer 2 | Y | Y | Y | 3 | 2 | 4 |
| | Reviewer 3 | Y | Y | Y | 3 | 2 | 4 |
| *Pharmacology 4* | Reviewer 1 | Y | Y | Y | 3 | 4 | 3 |
| | Reviewer 2 | Y | Y | Y | 3 | 4 | 3 |
| | Reviewer 3 | Y | Y | Y | 2 | 4 | 2 |
| *Pharmacology 5* | Reviewer 1 | Y | Y | Y | 3 | 3 | 3 |
| | Reviewer 2 | Y | Y | Y | 3 | 3 | 3 |
| | Reviewer 3 | Y | Y | Y | 3 | 3 | 5 |

**Table 4**
Average coherence threshold scores for summary, keywords and insights.

| Lesson | Summary | Keywords | Insight |
|---|---|---|---|
| *Pharmacology 1* | 2 | 2.7 | 0.7 |
| *Pharmacology 2* | 2 | 2 | 0.3 |
| *Pharmacology 3* | 3 | 2 | 4 |
| *Pharmacology 4* | 2.7 | 4 | 2.7 |
| *Pharmacology 5* | 3 | 3 | 3.7 |

the extent to which the subject is covered. *Human generated* models can also be considered. Important elements of the semantic level, referred to as *Summary Content Units*(SCU), are the annotations that expresses the content unit's semantic meaning. In this pyramidal model, each SCU is assigned to a weight based on the number of models that contain it. A perfect summary is made up of a subset of the entire SCUs made up of those with the highest index [23].

To determine the framework's impact on student attentiveness in remote lessons, real-world testing should be done. 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. As goals of future direction, we expect to investigate approaches to improve text summarization and the extension of architecture for multilingual texts. In addition, a separate module for creating idea maps in real time will be provided. In this way, students will be able to structure and organize material more effectively. This would allow for better assimilation of the information provided in the lessons.

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