DESIGN OF AN E-LEARNING SYSTEM USING SEMANTIC INFORMATION AND CLOUD COMPUTING TECHNOLOGIES

by

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Design of an E-learning system using semantic information and cloud computing technologies

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Published and Submitted Content

This thesis is based on the following published papers:

[1] Ahmed Badawy; Jesus A. Fisteus; Tarek M. Mahmoud; Tarek Abd El-Hafeez. Topic Extraction and Interactive Knowledge Graphs for Learning Resources. Published in: Sustainability 2022, Volume 14, Issue 1, 226

- This work is wholly included and its content is reported in different parts of this thesis.
- The author's role in this work is focused on the design, implementation and simulations of the concepts proposed in the paper.

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Abstract

Humanity is currently suffering from many difficult problems that threaten the life and survival of the human race. It is very easy for all mankind to be affected, directly or indirectly, by these problems. Education is a key solution for most of them. In our thesis we tried to make use of current technologies to enhance and ease the learning process.

We have designed an e-learning system based on semantic information and cloud computing, in addition to many other technologies that contribute to improving the educational process and raising the level of students. The design was built after much research on useful technology, its types, and examples of actual systems that were previously discussed by other researchers.

In addition to the proposed design, an algorithm was implemented to identify topics found in large textual educational resources. It was tested and proved to be efficient against other methods. The algorithm has the ability of extracting the main topics from textual learning resources, linking related resources and generating interactive dynamic knowledge graphs. This algorithm accurately and efficiently accomplishes those tasks even for bigger books. We used Wikipedia Miner, TextRank, and Gensim within our algorithm. Our algorithm's accuracy was evaluated against Gensim, largely improving its accuracy.

Augmenting the system design with the implemented algorithm will produce many useful services for improving the learning process such as: identifying main topics of big textual learning resources automatically and connecting them to other well defined concepts from Wikipedia, enriching current learning resources with semantic information from external sources, providing student with browsable dynamic interactive knowledge graphs, and making use of learning groups to encourage students to share their learning experiences and feedback with other learners.

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List of Acronyms

AI	artificial intelligence
AR	Augmented reality
ASP	Application Service Provider
AWS	Amazon Web Services
CBT	computer-based training
DaaS	Data as a Service
eJRM	electronic Justice
FOAF	friend of a friend ontology
GAE	Google App Engine
HaaS	Hardware as a Service
IaaS	Infrastructure as a Service
IS	Information Systems
LDA	Latent Dirichlet allocation
LMS	learning management system
LOD	linked open data
LOM	Learning Object Metadata
LSI	Latent semantic indexing
MBTI	Myers–Briggs Type Indicator questionnaire
MOOCs	massive open online courses
NER	Named Entity Recognition
NLP	natural language processing
PaaS	Platform as a Service
RDF	Resource Description Framework
SaaS	Software as a Service
SCROM	Shareable Content Object
Storage aaS	Storage as a service
SVD	Singular Value Decomposition
XML	eXtensible Markup Language

1. Introduction

1.1 Motivation

Humanity is currently suffering from many difficult problems that threaten the life and survival of the human race. It is very easy for all mankind to be affected, directly or indirectly, by these problems, for two main reasons:
1-As a result of the great development in the means of communication and transportation, and because we live on one planet, these problems do not threaten one community or one town.
2-Because we did not seek to solve them for decades, these problems have become huge and hard to be solved.

The misuse of great scientific progress may be a major cause of many of these problems, but there is no doubt that mankind is the main actor and the only cause of this huge corruption. Humanity has taken the path of progress and scientific research. Unfortunately, we cannot confirm how this path will be ended, but the end is either prosperity and happiness, or destruction and annihilation. The confirmation of the result depends on the strength of the teams working in both directions (the use of education to build, or the use of education to destroy). Any effort for reform will be effective, even if it is small. What is more important than the amount of change is continuity and perseverance in doing it.

Here, a pivotal conclusion can be reached that education is an effective and powerful weapon that can be used for reconstruction and prosperity, or for sabotage and destruction.

"Education is the most powerful weapon which you can use to change the world." Nelson Mandela [**1**]

But there is no escape from using education to fix what has been corrupted and is still corrupting by mankind.
Was the use of education effective against mankind made problems? To answer this question, it is necessary to research the subject and refute historical facts about the impact of education on societies and individuals, and this is what we are about to do in this chapter.

1.1.1 Importance of education for society

To study the effect of education on societies we are going to explore some history facts of some countries such as Spain, Finland, Japan, South Korea, Singapore, Copenhagen, and Denmark.

Starting with an example of underdeveloped countries in the 1900, Clàudia Canals [**2**] presented a comparison between Spain and Finland. She argued that both countries were largely agricultural countries, most of the people were not educated, and the illiteracy rate was high with a percent of 40%. The per capita income level was also similar between the two countries.
The surprise appeared after fifty years, where Finland's income doubled Spain's income, all Finnish people were educated, and an obvious widespread of secondary education could be mentioned in all social classes. At the same time, illiteracy was still dominant in Spanish society, and secondary education was rare among the people.
After seventy years of education development and progress and the rise of the Spanish economic level, Finland is still ahead of Spain in terms of education and economic level.

According to these facts and results, what is the secret?
The two countries started the race at the same time and from the same conditions and available capabilities. But the difference was huge, about seventy years, equal to the age of an entire generation, who could have lived a comfortable life in light of better education, health and financial standard. But they were deprived of this life only because of the delay in the decision to develop education. If this is not the main reason, then at least it must be a big factor in it. As Clàudia argues "Education directly affects economic growth insofar as it is essential to improve human capital." [**2**]

It is worth noting that Spain was suffering from a devastating civil war during the period from 1936 to 1939, and this war may be the reason for part of the difference between the two countries. [**3**]

Many factors could affect the economic level of the country and individuals: natural resources, available technological tools, number of labor force and demographic distribution, especially the level of efficiency and training of this workforce or "human capital" that is determined by the stock of knowledge, skills and habits. Here, the direct impact of education quality appears on the level of the workforce, and consequently on improving and raising the economic level of the individual and society. Clàudia summarized that as "The increase in workers' educational level improves their human capital, increasing the productivity of these workers and the economy's output." [**2**]

Finland has introduced some key points to make sure that education remains effective such as: (1) Respecting education is a part of their identity, (2) Not every individual has the ability to be a teacher, (3) Less study time and more enjoy time, (4) There is no separation between students on the basis of their academic level, (5) The intensity of the connection between the student and the teacher, (6) Equality between students.

Another example that shows the miraculous effect of education and the need to rely on it for the advancement of nations is the Japanese model. They relied on education to solve and face many massive problems such as the societal transformation from a closed society to an open industrial society that wants to compete to reserve a seat among the major industrial countries. They used education to face challenges presented by the need to quickly absorb Western ideas, science, and technology in the Meiji period (1868-1912) [**4**], when the Japanese people moved from being an isolated feudal society to the new paradigm of a modern, industrialized nation state. Meiji leaders acted rapidly to put a new educational system as a keystone to catch up with the West and promote national unity [**5**].

The role of education did not end here for them, as it was still effective in facing the next challenges, which were wars and their devastating impact on countries. They left them in the worst conditions, especially with the presence of a new lethal and destructive weapon called the nuclear bomb. Infrastructure, economic resources, manpower, and any foreign desire to invest are destroyed by wars. This is exactly what happened to Japan after the defeat in World War II 1945.

If any nation is in these circumstances, it has two expected options: crying over the ruins and heavy losses, pleading and begging other nations for help, or getting up and reorganizing forces and resources available for reconstruction and development.
The second choice was the right choice and the winning bet for Japan. And because they realized the importance of investing in education and its influence in building and restoring strength, it was their main weapon against the total destruction that subdued their necks. So, directly after

the war ended they restarted classes upon the destroyed schools [**6**]. Table 1.1 presents images of Japan after the war and now.

Table 1.1: Japan after the war and now

 https://www.bbc.com/news/world-asia-33881427	 http://www.pcf.city.hiroshima.jp/kids/KPSH_E/hiroshima_e/sadako_e/subcontents_e/12kidssengo_1_e.html Soon after the start of the new school year at Nobori-cho Elementary School, April 1946.
 https://en.wikipedia.org/wiki/File:HiroshimaPeaceMemorialPanorama-2.jpg	

Their equation for renaissance was: Education + morals + work = renaissance
The destruction they were subjected to was not the end of the war: after that they were subjected to the cultural occupation that almost dominated the minds of their children and erased their identity and their cultural history from the minds that were still forming. Therefore, they relied once again on their effective weapon (education) in confronting the Western cultural invasion.

As we have seen in the previous examples, the power of education in facing many challenges and its effectiveness against difficulties of all kinds became clear. It was no secret to the sincere people of other countries the need to use education for the advancement and continuity of their countries in the forefront, or to improve the general country and the people. So other countries sought to catch up with the train of evolution through its only gateway, which is education, such as South Korea, Singapore, and Denmark.

South Korea had keystones for a powerful education: good organization, good upbringing, morals and equality are the basis of their education system. Figure 1.1 shows South Korea in the past and now.

Because of their weak economic resources and lack of water, Singapore faced a severe economic crisis when it separated from Malaysia. Singapore had people of different races, nationalities, religions and languages who had to cooperate and unite to build their country. The goal and language were unified for the advancement of the country by selecting the English language as the first language of the country, and setting the general goal of the different races on improving the economic level with diligence at work.

Singapore also realized that the economic and scientific renaissance can only come with an advanced educational system. Therefore, education was among their basic tools for renaissance and construction. Their principle was to study less and learn more, encouraging the student to self-learn. Internal motivation and passion for knowledge was their main driver of learning. Figure 1.2 shows Singapore in the past and now.

http://susa.or.kr/sites/all/themes/susa/images/static/sj_01.jpg

Figure 1.1: South Korea in the past and now

https://thesmartlocal.com/wp-content/uploads/2020/03/Landmarks-in-Singapore.png

Figure 1.2: Singapore in the past and now

Education was and still is one of the factors greatly affecting the rise of nations from great destruction to development and prosperity, as we saw in the previous examples, and as we will see in many other countries such as Germany and the United States of America. Table 1.2 shows images of Germany after the war and now and Table 1.3 presents images of the United States of America after the war and now.

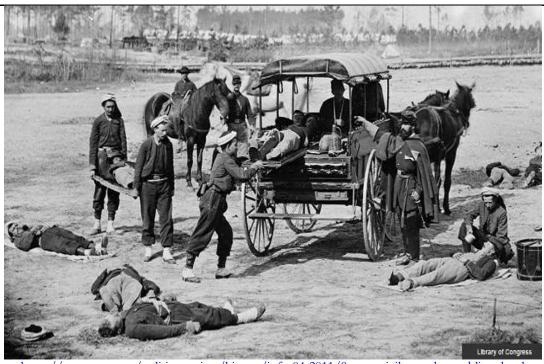
Table 1.2: Germany after the war and now

https://gdb.rferl.org/B3D120F0-60C8-4767-8A92-AD504F87AD00_w1071_s_d3.jpg

https://miro.medium.com/max/940/1*7onqckuaM4ZF8i5GmPeLeQ.jpeg

https://aisling-international.com/wp-content/uploads/2020/04/Germany.jpg

Table 1.3: United States of America after the war and now



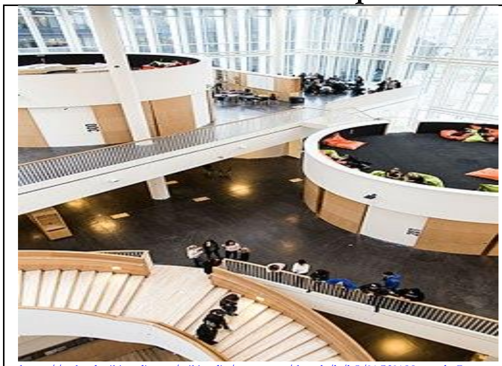
https://www.aarp.org/politics-society/history/info-04-2011/8-ways-civil-war-changed-lives.html

https://commons.wikimedia.org/wiki/File:Bodies_on_the_battlefield_at_antietam.jpg

https://en.wikipedia.org/wiki/File:NYC_Downtown_Manhattan_Skyline_seen_from_Paulus_Hook_2019-12-20_IMG_7347_FRD_(cropped).jpg

Denmark had presented a new viewpoint regarding education and its importance in the life of society and the individual by giving students the freedom to choose or create their own educational path. The Open School in Copenhagen, Denmark, is a current futuristic example of education development. In this school they give students the ability to set their own educational plan, where the school is only an advisory body to help them achieve their academic goals. Table 1.4 shows images of the Open School viewpoint in Denmark.

Table 1.4: Open School viewpoint in Denmark

 https://upload.wikimedia.org/wikipedia/commons/thumb/b/b5/%C3%98restad_Gymnasium_-_inside_%282016%29.jpg/250px-%C3%98restad_Gymnasium_-_inside_%282016%29.jpg https://en.wikipedia.org/wiki/%C3%98restad_Gymnasium	 https://denmark.dk/-/media/websites/denmarkdk/people-and-culture/lifelong-education/ry-danish-folk-school.ashx?mw=1366&hash=77B38613043A77B72BE4D32D64E76883 https://denmark.dk/society-and-business/lifelong-education

Emphasizing the importance of education

After mentioning historical facts and events that happened to specific nations, which show the power and importance of education for survival and success, we will explore some opinions about the importance of education.

In World Population Review [**1**], and according to many references they mention, prosperity of nations and their people depends mainly on education. Moreover, the economic level is closely related to the country's level of education. By observing fully developed countries and comparing their level of education with developing countries, we find that developed countries provide their people with the best level of education. On the other hand, developing countries seek to provide a good level of education to raise the economic level of their people and improve the future of the country. [**1**]

The Global Partnership for Education organization mentions [**7**] that education, from an economic point of view, has great benefits for society, in addition to being one of the most important forms of investment in which a nation's wealth can be used to obtain the highest return in the future. It gives society a kind of reassurance and hope for the future and social stability, ensures progress and development in the growth of the nation's economy, improves mental and physical health and provides sustenance at a high level of quality and prosperity. It is also an effective and vital course to achieve the goals of sustainable growth for future generations. [**7**]

From Ajay's [**8**] point of view, education has great importance in the lives of individuals for many reasons, including: (1) education transforms the usual daily information in the lives of individuals into knowledge, and knowledge acquisition is the only thing that gives people the ability to define their position and opinion from the different situations they encounter during their lives; (2) education is responsible for transforming humans from primitive beings fighting over food and other animal instincts to sublime beings that think, research and contemplate life and the environment; (3) humans, compared to the nature in which they live, are in the midst of physical weakness, but education gives humans confidence in themselves as beings that have the ability to learn, explore, and invent to deal with forces greater than themselves and overcome difficult situations; (4) education gave people a good opportunity to communicate, integrate and interact, either by providing the required means for that or basic personal skills for expression and communication; (5) also, good education in the early stages can give the opportunity for buried personal and individual talents to appear, grow and shine; (6) education is almost a guaranteed instrument for the successful future of the members of society and therefore the entire nation; (7) mind and personality also have a large share of the benefits of education, by opening the mind to different cultures and multiple societies and accepting new useful ideas; education is also useful in forming a normal and beneficial personality for the surrounding society; (8) education helps in learning to manage the greatest wealth of any individual and invest it properly; which is time; managing time and investing it optimally is one of the great benefits of education, which enables individuals to work within specific schedules and under different work pressures. [**8**]

In addition to all the previous advantages, worldvision [**9**] highlighted more advantages of education at the level of individuals and societies. For the individual, education develops problem-solving and confrontation skills, and supports the individual to be self-reliant. As for society, education helps spread equality among individuals, supports economic stability and security, and facilitates the way for future economic growth for the nation; which prompts the nation to build a strong and effective economy in facing crises. [**9**]

As mentioned by UNESCO [**10**] as well, education leads to the economic growth of the individual, which leads to the economic growth of the entire nation. Also, the countries that enjoy high rates of education are the countries with the largest share in achieving great growth in the field of human and economic development. [**10**]

So far, we see that a high level of education clearly helps individuals and societies, another source stated that citizens with low education or low educational capabilities have a high probability of being unemployed [**11**]. Therefore, education has become a weapon that must be used and provided to every child from the beginning of their life to give them the ability to improve their personal life and advance their society and nation. This made education a major and fundamental human right that plays a vital and fundamental role in the development of the individual, society and the economy according to the Global Partnership for Education organization [**12**]. Therefore, the progress and development of countries is measured according to many criteria, but the most important one is the level, quality, and spread of education [**13**] [**14**]. With the great spread of poverty and hunger, the role of education emerges as an effective exterminator of these epidemics and a donor of opportunities for a better life. [**9**] [**15**]

Despite the enormous advantages that nations enjoy with education, the high cost of quality education is a major obstacle for many developing countries, especially with the difficult circumstances that accompanied and followed the corona virus COVID-19 pandemic [**16**] [**17**]. Therefore, we see in **Table 4** that the advanced countries in education are economically prosperous countries, which have the capabilities that qualify them to provide requirements and costs, such as the United States of America, United Kingdom, and Germany [**1**]. **Table 1.5** presents education rankings by country 2021. [**1**]

Table 1.5: Education rankings by country 2021 [**1**]

Country	Rank (2021)	Rank (2020)	2022 Population
United States	1	1	334,805,269
United Kingdom	2	2	68,497,907
Germany	3	4	83,883,596
Canada	4	3	38,388,419
France	5	5	65,584,518
Switzerland	6	6	8,773,637
Japan	7	11	125,584,838

Australia	8	7	26,068,792
Sweden	9	8	10,218,971
Netherlands	10	9	17,211,447
New Zealand	11	14	4,898,203
Denmark	12	10	5,834,950
Norway	13	12	5,511,370
Italy	14	16	60,262,770
Finland	15	15	5,554,960
Austria	16	13	9,066,710
Spain	17	18	46,719,142
Belgium	18		11,668,278
South Korea	19	22	51,329,899
Ireland	20		5,020,199

When studying the level of economic growth according to the number of people, we notice that China and India are at the top of the list: with more than one billion people, in 1995 the World Bank classified these two countries as low-income countries. But now, the same two countries have an economic classification of middle income level [**18**]. Interest in the educational level may be the reason for this achievement, in addition to many other factors.

As we can see in table 1.6, the education rankings sorted by population for years 2020 and 2021, China was ranked 24th in 2020 and advanced to 22nd place in 2021, and India was ranked 34th in 2020 and advanced to 32nd place in 2021. [**1**]

Table 1.6: Education rankings sorted by population 2021 [**1**]

Country	**Rank (2021)**	**Rank (2020)**	**2022 Population**
China	22	24	1,448,471,400
India	32	34	1,406,631,776
United States	1	1	334,805,269
Indonesia	54	55	279,134,505
Brazil	36	30	215,353,593
Russia	23	21	145,805,947
Mexico	37	36	131,562,772
Japan	7	11	125,584,838
Philippines	55	52	112,508,994
Egypt	39	42	106,156,692
Vietnam	59	64	98,953,541
Turkey	31	31	85,561,976
Germany	3	4	83,883,596
Thailand	46	48	70,078,203
United Kingdom	2	2	68,497,907
France	5	5	65,584,518
South Africa	33	32	60,756,135
Italy	14	16	60,262,770
Kenya	68	68	56,215,221
Myanmar	76	71	55,227,143

Here, an important question arises: Does economic power lead to a good level of education? Or does a good education lead to prosperity and economic progress?

It is clear from what we have seen and presented from examples such as Japan, Singapore, United States of America, and Germany that education is the basis and origin of economic power. And after discussing the importance of education for society, we will now see the importance of education at the level of individuals.

1.1.2 Importance of education for individuals

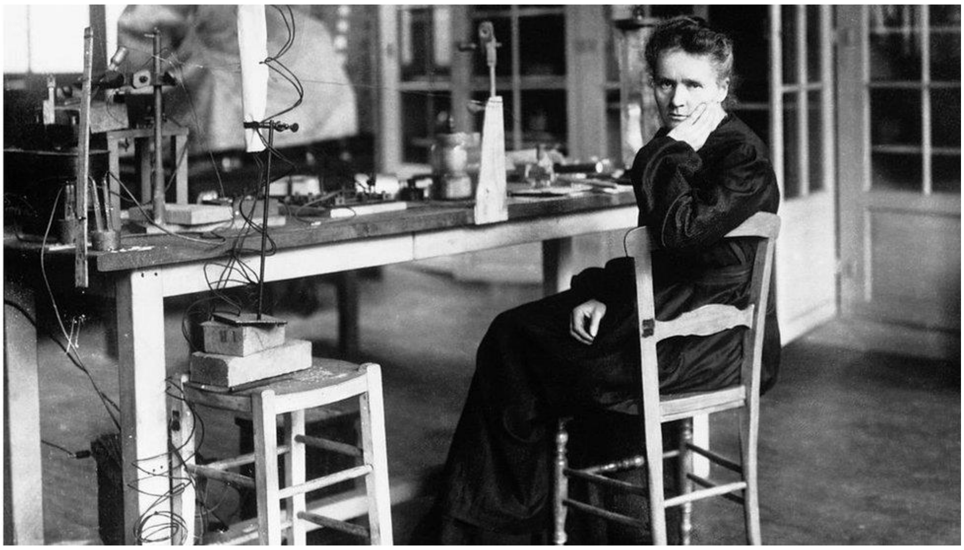
To discuss the impact of education on the lives of individuals, we must study the intersection between the educational domain and the individual's domain, which clearly intersect in the category of scientists. Albert Einstein and Marie Curie are considered among the most famous and prominent scientists of our time, who rose to prominence in difficult circumstances and a harsh life. Was education a role in improving the lives of these individuals?

Beginning with some benefits provided by education for individuals, according to the World Vision for Education organization [**9**] and Lawrence [**19**] , education improves a person's communication skills, uses logic to solve problems, sharpens innovation skills and creativity, develops time management skills, provides basic skills to compete in the labor market to obtain a good job and improve his life. Education also promotes equality between men and women, thus preserving the basic building block of society and reducing infant mortality. According to a UNESCO report, a mother's education increases the chance of a newborn child reaching the age of five by fifty percent [**9**]. Thus, education is one of the reasons for escaping from death literally and at the level of every individual.

In addition, the World Bank reports that pregnancy of minor girls decreases by six percent for each additional year of schooling for girls. It also helps mothers realize the responsibility of having new children and control the number of births for each family by increasing awareness and a sense of responsibility [**19**], and the future income of each individual increases by ten percent with each additional year of education. [**20**]

Now going back to our question, about the role of education in individuals such as Einstein and Curie life, we will find the answer after exploring some facts about their lives.

Marie Curie: Marie Skodowska was born in Warsaw, Poland, on November 7, 1867. Her parents were educators who supported education because of its importance, and its role in the renaissance of nations. Because of their interest in education and their realization of its importance, the girl traveled at a young age to another country to complete her education, and the chosen country was France. There she met Pierre Curie, who was her colleague and later husband, to be her companion in personal and educational life. They decided to conduct their research in the field of radioactive elements, which was her passion. [**21**]

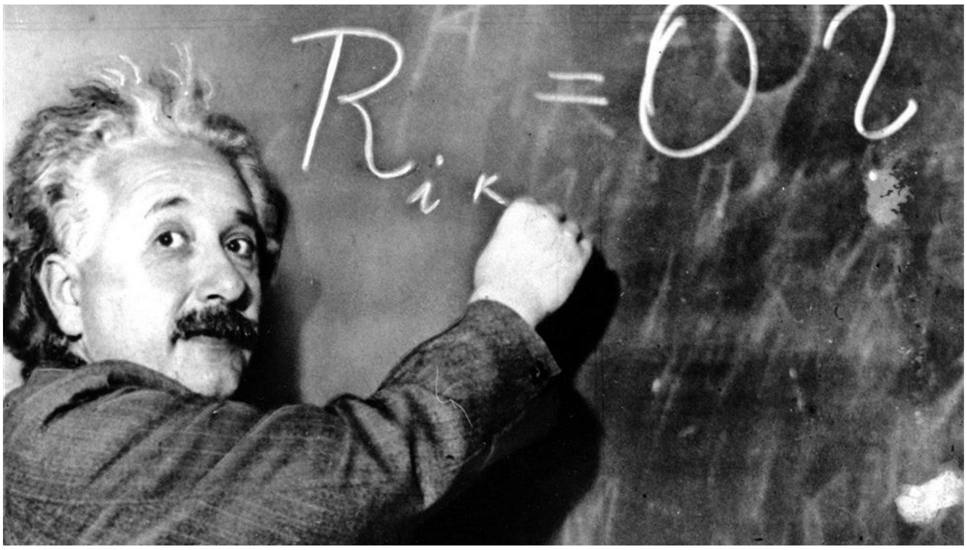


Marie Curie [22]

Indeed, in 1903, their research and efforts yielded fruitful results for both spouses, as they shared the Nobel Prize in Physics. During World War I, Marie Curie harnessed her knowledge to serve her community by making the first mobile X-ray machine to help war-wounded and sick people everywhere. Her scientific achievement did not stop at that point, but after eight years, specifically in 1911, she won her second Nobel Prize in Chemistry, maintaining her place in history as the first person to receive two Nobel Prizes. [**21**]
In order to emphasize the legacy that she learned from her family about the interest in education and the realization of its importance, Mary bequeathed this passion to her daughter, who continued the path of science and research, and her efforts also resulted in obtaining the Nobel Prize in Chemistry in 1935 jointly with her husband Frederic Joliot. [**21**] [**23**]

Albert Einstein: On March 14, 1879 Albert Einstein was born in Ulm, in the Kingdom of Württemberg in the German Empire in a family with difficult economic conditions. Introversion and difficulty speaking with poor memory were the characteristics of Einstein, the child whose parents thought he was mentally retarded. He was suffering from the difficulty of integrating into the strict educational system of contemporary schools, which prompted him to create problems to leave them. Electrical engineering was the specialty that his father sought Einstein to join. But the rebellious Einstein did not like the system and the method of teaching, so he clashed again with those in charge of his education. The reason he mentioned later for being rejected and rebellious against the strict traditional educational system or "rote learning" is that it kills thought and creativity in the minds of students. [**24**]

Despite all these difficulties and problems created by the rebellious genius child, he showed extraordinary genius in the field of mathematics and physics at a young age. At the age of twelve and during one summer course the child taught himself principles of algebra and Euclidean geometry. In the same period, he studied and understood the Pythagorean theorem and discovered his own original proof for it. When the teenage boy completed his journey to the age of fourteen, he said he had mastered integral and differential calculus. The child Einstein loved science and showed superiority and genius in it, but he preferred to study it on his own, away from the strict traditional education systems. [**24**]



Albert Einstein [https://historia.nationalgeographic.com.es/personajes/Einstein]

At the age of sixteen, Einstein was presented with an educational resource that completely changed his life, which was a series on science for children by Aaron Bernstein, (1867–1868; Popular Books on Physical Science). What was distinctive about this educational resource was the use of imagination and non-adherence to traditional forms of education, as the author imagined riding the electric current passing through the telegraph wire. [**24**]

And here the genius did not stop at the limits of what he saw, but he thought beyond that, the light.
If you could run parallel to the light beam, how would it appear to you?
This question remained in control of his life and thoughts for the next ten years. At that time Einstein also wrote his first "scientific paper" ("The Investigation of the State of Aether in Magnetic Fields"). [**24**]

There are two remarkable things that profoundly influenced Einstein's life, according to what he wrote. The first one was about the invisible force acting on a compass needle that he saw at the age of five, which made him fond of exploring the invisible forces in nature to discover their sources and understand their rules. The second one was the book that he found about geometry at the age of twelve, which showed great passion in reading it and caring for it to the point that he called it his "sacred little geometry book". Eventually, he traced his passion and produced the most prominent assumptions and physical laws that changed the history of science and invention. [**24**]

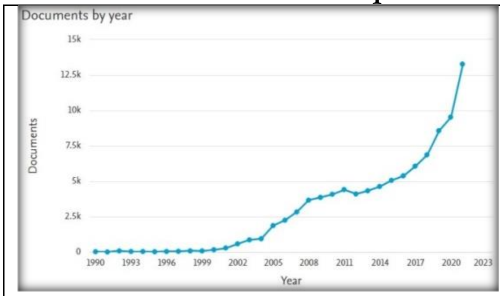
As we have seen in the events mentioned about the lives of Albert Einstein and Marie Curie, education was a pivotal influence in their lives. It had a huge positive impact on the course of their lives and the nucleus of their scientific achievements whose fruits we are still reaping to this day.

As another evidence of the important impact of education on the lives of individuals, researchers have studied the effect of different levels of education on identical twins where they have the same family environment, so their skills and habits should be very similar. The results of these studies confirmed this importance, showing an increase in earnings and productivity per individual by between 6% to 10% for each additional year of education. [**2**]

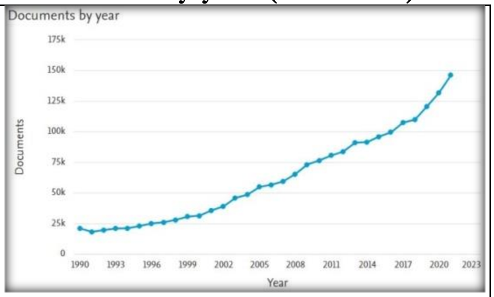
1.1.3 Importance of education in the research field

After exploring needs and requirements for main elements of the learning process (learners and teachers), we explored the Scopus database for research about education and e-learning to analyze their relation. Results presented in next figures. In table 1.7 we can see the number of published documents is increasing from 1990 till 2022 for both keywords. The number of documents with the "education" keyword in 1990 was higher than with the "e-learning" keyword (2,500 vs. 0), and in (2020-2021) the number of documents in e-learning reached 12,500 while education reached 15,0000.

Table 1.7: Number of published documents by year (1990-2022)



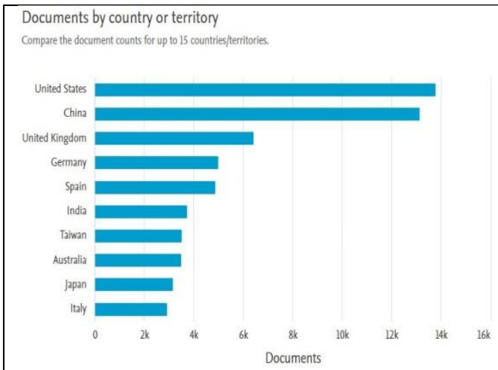
UC3M library-Scopus database-(e-learning 1990..2022)-by year [25]



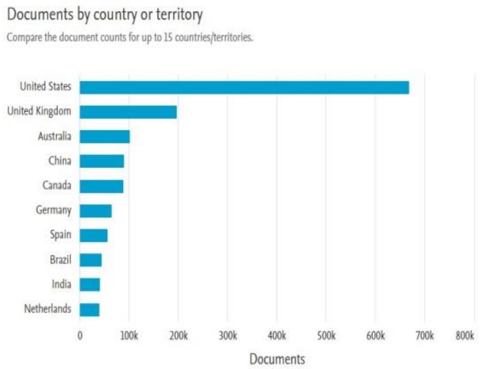
UC3M library -Scopus database-(education 1990..2022)-by year [26]

Next we will analyze the number of research in education and e-learning on the Scopus database grouped by country. In table 1.8 we can see that among the top 10 countries there are 7 out of 10 countries in both fields.

Table 1.8: Number of published documents by country



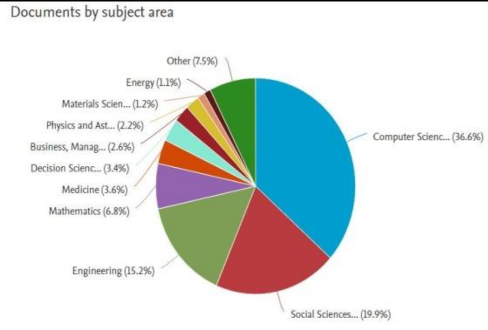
UC3M library -Scopus database-(e-learning 1990..2022)-by country [27]



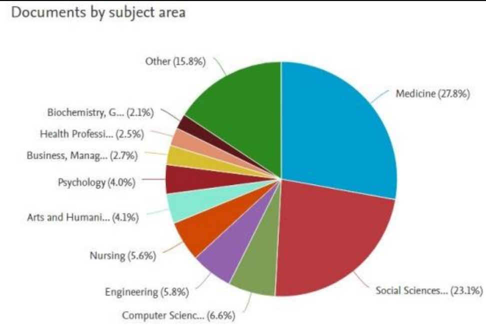
UC3M library -Scopus database-(education 1990..2022)-by country [28]

Next we analyzed the results according to the subject area. In **table 1.9** we found that among the top 5 subjects there are 4 out of 5 subjects that are common between "education" and "e-learning".

Table 1.9: Number of published documents by subject area



UC3M library -Scopus database- (e-learning 1990..2022)-by subject area [29]



UC3M library -Scopus database- (education 1990..2022)-by subject area [30]

1.2 Education vs. learning

Education and learning are two different operations that could occur at the same time or separately. There is a clear difference between the two, on which we will elaborate in the next section.

1.2.1 Education

Many definitions had been used for education, such as:

- "Education is a planned activity geared at accomplishing specific goals, such as imparting knowledge or developing skills and character qualities." [**31**]
- "The process of receiving or imparting systematic instruction, particularly at a school or university, is called education." [Definitions from Oxford Languages]
- "Education is the process where people acquire or disseminate fundamental knowledge to another." [**9**]
- "Education is the process of receiving or imparting structured instruction in order to gain knowledge." [**32**]
- "Education is a formal conservative process that aids in the development of talents, attitudes, and other behavioral practical values in the society from which they belong, for the objective of gaining social competency and maximizing the potential of an individual". [**33**]

However, no matter how different the definition is, education has basic goals such as: giving the individual the ability to distinguish the right thing to do, encourage it, and distinguish the wrong one to move away from it and reject it; giving individuals the ability to collect the basic and daily skills necessary for life and coexistence; spreading social norms among the members of society to coexist in peace, security and order; improving thinking, reasoning, judgment and deduction abilities; helping to build society by encouraging individuals to build, participate and cooperate, which is the ultimate goal of education. [**9**]

Types of education
There are three basic types of education: formal education, informal education, and non-formal education. [**9**] [**33**]

1- Formal education, present in academic institutions inside regular classrooms. In formal education only qualified teachers have the ability and the right to teach students the standard curriculum that contains basic skills or even advanced academic lessons. Formal education has specific steps and levels. It starts in elementary school, and advances to post-secondary education. Among other education types, formal education is the most popular type because of its effectiveness and its ability to develop generations' capabilities by passing education and knowledge from one generation to the next in a systematic, repeated and stereotyped manner. [**9**] [**33**]

Education of this type can be obtained or delivered through two methods: face-to-face, where there is direct communication between teachers and students at the same time and place; or distance education, where contact between the members of the educational system is indirect, in terms of time, place, or both. Different means of communication methods can be used based on needs and available resources. With the different means of communication and types of educational resources, the sub-types of distance education differ.

One of the sub-types of distance education was education by correspondence, where the educational content was prepared by the educational institution and sent to the student, then the student studied and his academic progress was followed up through assignments. Another type of distance education was teleconferences, where communication was taking place between teachers and students at the same time, but across distant places through satellites and other available technological means of communication. This type was very similar to video conferencing that used the same means and methods. Distance education using mass media was another type where education resources were disseminated by television, radio, or newspapers. With the advent of the Internet and educational websites, online education emerged as one of the new types that allow sharing educational resources on the website of the educational institution and sending them to students to study them at any time and place that suits them. By merging interactive electronic educational resources based on computers and the Internet as basic tools for communication and education, e-learning emerged. [**9**] [**33**]

2- Informal education, where academic institutions have no role and student do not need them in any way. Home, libraries, nature or Internet websites may be the source from which students acquire knowledge and learn skills. This type of education is not limited by any schedule, academic content, or educational path. Therefore, it is a natural form of education and can even happen involuntarily.

3- Non-formal education, where the organization, scheduling, and the systematic implementation are essential, but it does not have to be implemented in a school system. In terms of quality, this type can potentially provide the same level of quality as the previous two, but it presents more advantages than them in terms of flexibility and ease of implementation, and it does not set conditions or limits on the age of the students.

As a result, it is a hybrid of formal and informal education in which informal learning takes place in a formal setting.

1.2.2 Learning

On the other hand, learning is a different process and many definitions had been used for it, such as:

- The process of obtaining new information, skills, actions, beliefs, attitudes, and preferences is known as learning. [**34**] [**35**]
- Learning is defined as the process by which knowledge or abilities are acquired through study, practice, or instruction. [Definitions from Oxford Languages]
- Learning is the sustained modification of behavior brought about by practice or experience. [**33**]
- Learning is the process of acquiring information, attitudes, skills, beliefs, or preferences that aids an individual in adapting to their environment. [**32**]

With the passage of time and the change of age stages, the nature of people changes, with growth or puberty, which affects individuals biologically and behaviorally, and this change may be positive or negative. Here, the effect of learning appears, which also contributes to the change, but behavioral change is not counted as a learning outcome unless the change is permanent and continuous with the person. Learning is structured around a unified goal and purposeful centered point, but if the learning process is done effectively and successfully, it can be used to serve multiple goals and harness it to serve different situations. [**33**]

People can learn from their surroundings, continuously through their whole lives, such as continuous or coincidental life experiences, education of various types and from different sources, school life, training and self-development. All of these things can be the reason for learning, in addition to many other sources that are not limited to a specific period or a specific age. It is interesting that the gift of learning is not exclusive to humans. Animals and plants also have the ability to learn, and now machines can also learn if the required conditions and resources are provided. And with the realization of the importance of learning for any living organism, the question arises: what is the motivation for learning, why is learning so urgent that some animals seek it? And we find the answer lies simply in two words, curiosity and motivation. Most of the time, humans or animals have a curiosity for knowledge and understanding, which drives them to watch, observe, experiment and draw conclusions. On the other hand, motivation could be a main driver for learning, where the pursuit to obtain a specific pleasure, solve a problem, or overcome a difficulty, could constitute an incentive for learning. [**32**]

Learning types

There are six types of learning according to [**33**] : verbal, motor, concept serial, problem solving, and paired associate learning.

1. In verbal learning, signs, symbols, figures, words and pictures are used to help in acquiring verbal behavior.
2. In motor learning, instruments are used to help learning a task such as swimming, driving, riding, flying, playing.
3. In concept learning, our primary tool for conjuring an image of things, people, or events in our minds is imagination.
4. When learning to solve problems, our cognitive skills like reasoning, comprehension, observation, generalization, and inference are our instruments for tackling a particular issue in a particular circumstance.
5. In serial learning, school education provides students with the educational material that they have to follow in the same sequence to learn the skills they need.
6. In paired associate learning, the learner receives learning tasks on account of his association to achieve some learning goals.

Learning styles

Moreover, in [**36**] Felder and Soloman stated that there are four dimensions of **learning styles** where each dimension have two opposite categories as follows:

1- Active and Reflective learners:

Active learners understand information better by practicing it actively with some of the active practices such as discussing with other learners, explaining it to other students, or applying the information in use in the field of study.

On the other hand, reflective learners tend to take enough time to think and reflect on the content to understand and comprehend it. [**36**]

2- Sensing and Intuitive learners:

Sensing learners want to learn from scientific facts without resorting to surprises and complications. They want to solve problems with proven scientific methods that have been tried over and over again. They are very upset about being tested and questioned in parts of the course that are not covered and explained directly and extensively in the classroom. Their skills appear in good memorization of scientific content, patience in studying complex details, and skillful manual experiments. Therefore, they are more practical and have greater care and caution in laboratory work and they have difficulty studying and understanding courses that are not directly related to practical life.

By contrast, intuitive learners love innovation and conclusion, get bored, and even flee from repetitive and routine education. They have the drive and enthusiasm to search for the relationships between things and their interactions and to explore their possibilities and capabilities by themselves. They do not prefer the content that is explained extensively, boring and monotonous, and that is presented with a spoon, which contains a lot of texts that need to be remembered without understanding and comprehension. They can absorb new concepts and definitions more easily than sensing learners. Mathematical formulations are not an obstacle for them either. They prefer to work faster and more creatively than sensing learners because they are not bound by the steps and routine traditional methods, but therefore, their care and caution are less than their counterparts. And they can accept with patience the tests in the parts that have not been explained extensively because they are not bound by the explained content, and they always strive to conclude and expand perceptions. [**36**]

3- Visual and Verbal learners:

Visual learners are the learners who absorb more and faster from visual educational content such as pictures, diagrams, flow charts, time lines, films, and demonstrations.

On the other hand, verbal learners learn better from verbal educational content such as written texts or spoken lectures. Unfortunately, the majority of learners need visual content to obtain the largest percentage of the content, so that cognitive achievement is very little if only verbal content is used. Knowing that, by increasing the diversity of the types of scientific content provided to the learner, the percentage of cognitive achievement increases significantly. So, the good learner is the one who has the ability to comprehend and understand all types of educational content in an equal manner, whether the available content is verbal content or visual content. [**36**]

4- Sequential and Global learners:

Sequential learners prefer to follow sequential steps in a logical, systematic and organized way, so that each step is a logical conclusion to the step that preceded it in order to solve the problem in question and study. In general, their approach is to follow clear and sequential logical steps to reach solutions.

On the other hand, global learners prefer to learn in a random and non-sequential way to reach solutions without following any organized educational path and with steps in the form of large leaps between different methods and paths. What is important for them is to comprehend the content, even if it is not organized, and if they do not realize the relationship between the non-sequential contents. One of the strengths of learners using this style is that they may find solutions quickly, using innovative and unprecedented ways to do so, only when they can understand the big picture. But in many cases it is very difficult for them to explain how they reached this solution or to show it to other students to follow the same method that they used. [**36**]

1.2.3 Learning theories

To complete the whole picture about learning and education we must go through a quick review on learning theories. In [**37**] Phillips et al. clearly stated Plato's theory, which assumes that every child born has their own knowledge accompanying them from birth. It is called the Theory of Recollection or Platonic epistemology.
Conversely, Brain et al. discussed in [**38**] the Locke's theory that assumes that humans are born without any innate knowledge and without any prior experiences, but they are born as a blank white page that is filled with experiences and knowledge from the environment surrounding them. There are many other learning theories such as Behaviorism [**37**], Social learning theory [**39**], Cognitivism or Gestalt theory [**40**], Constructivism [**41**] or Transformative learning theory [**42**].

Our system will be based on the Learning as a Network learning theory [**43**], where learners are the basic nucleus of the learning process, and the learning process is followed up by the continuous building of network links between them and their surrounding world, which represent their experiences and personal knowledge gained during their learning journey. The Learning as a Network theory builds upon the connectivism theory [**44**] [**45**], which represents networked learning [**46**], and focuses on learning as making connections. We have chosen it because it is considered the most appropriate theory for the current conditions and for the tools that we will study and use in our thesis, such as the interactive knowledge graph [**47**] [**48**] that we are going to discuss in chapter 2.

1.2.4 Learning vs. Education

Now that we are fully aware of what learning and education are, we give a comprehensive list of their distinctions in table 1.10 as mentioned in [**33**] [**32**]:

Table 1.10: Differences between Education and Learning [33] [32]

	EDUCATION	**LEARNING**
Definition	Received or given systematic instruction, particularly in a formal context, is what is referred to as education.	Learning is the process by which knowledge or abilities are obtained through study, practice, or instruction.
Purpose	To alter the student's behavior in a way that is more desirable.	To create new knowledge and to manage future behaviors.
Knowledge	Via a teacher or a textbook, one gains knowledge in education.	Through a variety of sources, knowledge is acquired during learning.

Guidance	Under the direction of an instructor, education frequently occurs.	No teacher or mentor is necessary for learning.
Motivation	Extrinsic incentive drives education.	Intrinsic motivation drives learning.
Elicited by	Extrinsic Motivation	Intrinsic Motivation
Process	Education is a process that is organized.	Learning is not a methodical procedure.
Age	Up until a particular age, education is obtained.	Age is not a factor in learning.
Guidance	Required	May or may not be required

Education from the learner's point of view

With different ages, generations, and available technology, the learner's needs vary. To understand the learners' needs and requirements, the educational system must be viewed from their point of view. In principle, each learner may have their own personal preferences about the educational system, and it is also important to be commensurate with the content they want to study. The current generation, as a result of the contemporary portable and easy-to-use means of communication, does not have the ability to be bound by what is being studied, whether in space or time. They prefer to access educational material anywhere any time.

In addition to their rebellion against the traditional educational systems, they need new systems that are interesting, not boring and capable of stimulating the student's mind and developing their capabilities in an innovative way. But they want all these features at the lowest cost.

Education from the teacher's point of view

In order to face all the current challenges and provide new requirements for learners, educational systems must also be studied from the point of view of teachers. Teachers are looking for an educational system capable of managing information more efficiently, effectively and quickly, gain the ability to communicate with a large number of students quickly, provided with the appropriate tools to explain different educational contents in different ways that suit the needs of different students, supported by the appropriate technologies for monitoring the educational level of learners individually, and to test students in appropriate ways to measure their different abilities with each educational content.

"Passion" is the key to excellence

None of the above will be possible if there is no passion, either from students or from teachers, because forcing someone to learn anything they do not like is a wasted effort. If students love what they learn and have their own motivation and passion to learn, this will be much easier and fruitful. They could even help each other and cooperate to achieve better results. Persons will be interested in learning when they are prompted by curiosity and intrinsic motivation. If they are well motivated they could find their passion that might guide them towards improvement. Accordingly, the educational system - that should start by looking for the areas of passion of each child - should be different for each person according to their own interests.

1.2.5 E-learning

Depending on how and where e-learning is being implemented, it can be defined in different ways. According to the European Commission [**49**], It is "the technologies that enhance learning quality by facilitating distant exchanges and cooperation, access to facilities and resources, and both"

Other definitions of e-learning are mentioned in **table 1.11** [**50**].

Table 1.11: Definitions of e-learning

1	In a well-designed course with acceptable accreditations, e-learning is defined as the transfer of knowledge and skills via electronic media like the Internet, intranets, and extranets.	**(Choudhury & Pattnaik, 2020)**
2	A web-based framework called e-learning employs digital technology and other forms of educational content to give learners a personalized, student-centered, easily available, enjoyable, and interactive learning experience that supports and improves learning processes.	**(Rodrigues et al., 2018)**
3	In the current technological environment, e-learning is a crucial instrument for addressing the demand for highly skilled workers.	**(Vershitskaya et al., 2020)**

Since different terminologies vary depending on the researcher's area of expertise and area of interest, there are different terminologies used to define e-learning. Online education is also known as e-learning, mobile learning, cloud learning, massive open online courses (MOOCs), virtual learning, distance learning, online interactive learning, virtual learning, and web-based education [**49**] [**51**] [**52**]. And, according to [**53**], since it is a user-centric framework that concerns material and how it is interpreted, e-learning varies from general Information Systems (IS) in this regard.

E-learning from different Perspectives

Instructors are crucial in ensuring that technology is successfully incorporated into teaching and learning in terms of implementation and curriculum preparation. And as stated by Kamla et al. [**54**] teacher satisfaction has a significant impact on how effective e-learning is. [**49**]

On the other hand, students are a key element in e-learning system success because they interact directly and continuously with it and without their participation e-learning systems would not be able to develop the learning process [**55**]. But the most relevant hurdles and difficulties a faculty has while deploying an emerging innovation, however, are reluctance to change and a strong refusal to learn [**56**]. Several research findings showed that the instructors' top concern throughout the evolution of e-learning has been a lack of student motivation [**57**] [**49**].

Current e-learning systems, with their current capabilities, are required to be evolved and make use of new technologies to provide better performance for the growing number of users and the evolving learning materials. Like every research branch, e-learning starts as a simple idea and is developed over time thanks to the growing number of interested researchers, the emergence of new technologies that can improve the existing systems, the increasing pressure on e-learning systems, and the increased financial support directed at developing technology for economic and commercial purposes.

By integrating different technologies into the e-learning system we can harvest the advantages of all of them. E-learning is a good choice because it can be used by educational systems as an affordable, safe, and progressing alternative to classical education. It is available anytime and anywhere with the lowest costs. Although e-learning is not new, the current state of affairs requires more capabilities from e-learning systems.

To select the required technologies we first have to explore the evolution of the e-learning ecosystem to find their pros and cons from different perspectives (teacher and student), analyze the available technologies and their integration with the e-learning system. In addition, we could investigate learning theories and information system theories.

E-learning is also a great facilitator of self-learning, as it helps learners to autonomously get appropriate materials for the skills they want to develop, without the need to take full courses at formal education institutions such as schools and colleges. Self-learning has the potential to change the way people are going to be educated. As every student is unique, the education system has the opportunity to adopt new tools that help it to adapt uniquely, according to every individual student's needs. As reported in [**58**], 91% of elementary school students and 71% of middle and high school students use e-learning for learning things on their own.

So far, we can note that students in the current era are lucky to have all these possibilities, tools and educational resources at their fingertips. Moreover, several studies showed that the number of available learning resources is growing every day [**59**] [**60**].

1.2.6 Evolution of distance learning and e-learning

Education and the development of its means have grabbed the attention of mankind a long time ago. With the emergence of any new means of communication, humans try to adapt and exploit it in developing and improving contemporary educational means. This happened with every development throughout history.

Distance learning development started in 1728 by regular mail, where the first weekly mail-delivered distance learning course was developed by Bostonian Caleb Philips. In 1840 Issac Pitman used letters to teach his students shorthand. Later, in 1922, courses began to be broadcasted over radio stations. The first testing equipment was developed in 1924. It was automated to allow students to test themselves. In 1953, educational courses were on TV channels. And the teaching device GLIDER, created by Harvard professor BF Skinner in 1954, allowed schools to provide students with pre-recorded introductions.

In 1960, Prof. Don Bitzer of Illinois University presented the first computer-based training (CBT) program, called PLATO. It was a big heavy machine that could be used by one student at a time. After five years, in 1965, Phone-based courses were introduced. In 1966 a psychology professor from Stanford University created computer aided instruction.

In 1969, the ARPANET, which was the main core of the Internet, had been created by interconnecting four university computers. The Apple II personal computer was released in 1977. Then, in 1984 Toronto University offered the first-ever completely online course.

Finally, the World Wide Web -that was invented by Tim Berners-Lee- was born in 1989. The Phoenix University won the educational organization race by launching the first all online collegiate school, while Drexel University started one of the first online programs, and the Open University in UK was among the initial universities in the world to provide online distance learning, and the first online university, the Jones International University, opened in 1999 until it closed in 2015.

In the 2000s, businesses realized that they had a lot of content they could share with employees, so they adopted e-learning. 81% of colleges in Drexel University offered at least one course via the Internet in 2003, where more than a quarter of US college students were taking courses online [**61**]. In 2012, 6.7 million (32.5%) of the 20.6 million students enrolled in higher education, were taking an online course, according to the fall 2012 survey of top academic leaders [**62**] [**63**]

[**64**]. And in 2013, one-third of all college pupils were pursuing at least one course online. In 2016 Drexel University celebrated 20 years of online courses [**65**].
Over 75% (11.8 million) of all undergraduate students in the US were enrolled in at least one distant education course as of fall 2020. [**66**]

In 2019, the market size of online learning was approximately $187.87 billion having a 400% increase over 2013 with the use of virtual reality and game-based learning. Experts predict the next wave of online education will happen in emerging markets (Africa, India and China).

1.3 Objective

Learning resources are an important element of e-learning. Learning resources are available in a wide range of formats that cover almost anything that one could need to learn [**67**] [**47**]. However, the growing number of learning resources is a double-edged sword: it will provide a great opportunity for students to learn anything they wish in different styles and ways of exploration. But it also represents a challenge for students to find and select the required one among this growing ocean of resources. Therefore, learners would benefit from having new tools and techniques for exploring, browsing and searching learning resources. Those tools would not only save learners time and effort, but also protect them from boredom and the massive progress of technologies such as Artificial Intelligence [**68**], Machine Learning [**69**], Natural Language Processing [**70**], Semantic Web [**71**] and Virtual Reality [**72**] could facilitate building such tools.

In this thesis, we aim to design an e-learning system to help learners and researchers on electronic educational resources to obtain the required knowledge in the fastest time and with the least effort. In addition to ridding the learner of boredom and monotony that learners face with current learning systems through integration with learning groups and dynamic interactive knowledge graphs. The use of current technological means may contribute significantly and effectively to the development of the old idea, which is still in use until now, about e-learning systems. In addition to presenting the design of our e-learning system, we will present our algorithm that we designed, implemented and tested to help in the same field, and we will mention that in detail in the coming chapters.

1.3.1 Challenges

Many challenges could face us during our journey towards our goal, such as:

- The required infrastructure of technology, Internet connection, and computational power. The required training for students and teachers is also a big challenge especially in developed countries.
- Converting all learning materials into valid learning objects in order to be used in our e-learning system.

1.3.2 Contributions

We plan to apply results in these areas to build an e-learning system, inspired by the Learning as a Network learning theory [**43**], which aims to facilitate the learning process for students in different ways: (1) a topic extraction system, to automatically obtain the main topics from learning resources and build a multilayer topic structure; (2) a clustering system, to connect learning resources based on the relationships between their topics; (3) dynamic interactive knowledge graphs, to show learning resources in an easy and searchable dynamic connected graph; and (4) a social learning network, to connect different users with common interests or common learning goals, and to facilitate self-learning.

Our main contribution is a topic extraction algorithm that is able to analyze the text of learning resources, including large books, and identify their main topics as unambiguous references to categories in the Wikipedia collaborative encyclopedia. Based on these extracted topics, the system is able to connect and group related learning resources. These connections can be presented to learners in the form of knowledge graphs that they can browse graphically and interactively in order to search and explore resources they might be interested in.

Automatic Topic Identification is vital in the current information era for finding learning material among this daily giant growth of data on the Web. To establish unequivocal topic identifiers we need a comprehensive and up-to-date vocabulary, knowledge source, or ontology that could be used for representing any possible topic a learning resource might be about. In our opinion, the online encyclopedia Wikipedia is the most feasible choice for this task. As such, it represents a giant multilingual database of concepts and semantic relations. A specific topic of an article can be identified with the identifier of the Wikipedia article that describes that topic

After giving an introduction about the main topic we are going to give a more focused view about the topics that we are going to use in our system in the next chapters.

1.4 Outline of the thesis

The rest of this thesis is organized as follows. Chapter 2 reviews related research. Chapter 3 describes the research methodology we followed and the design of our e-learning system. Chapter 4 includes a thorough description of our topic extraction algorithm and some examples of the knowledge graphs produced by the system. Chapter 5 describes the experiments we performed on the topic extraction algorithm and their results, which are discussed and compared to research work. Finally, Chapter 6 concludes the article and describes our future lines of work.

2. Background and State of the Art

2.1 E-learning

How people acquire new knowledge and abilities, as well as how those they already possess are updated to address challenges, are the key focuses of the learning process, as noted in [**73**], and this process could be accomplished through different learning methods.
Where learning methods are "the ways through which instructors deliver instructions and learners access these instructions" according to K. D. et al. [**74**], and those methods include:

1- Traditional learning, where the teacher meets with students at the same time and location to provide course material.
2- E-Learning, where the learning process is supported by technologies for communication and information globally.
3- Blended learning that employs a wide range of learning techniques in conjunction to increase the learner's potential.
4- Mobile learning, where portable technologies are used for learning or delivery of content.
5- Personalized learning, where individualized adaptive learning is supported and provided for each learner according to their specific needs and capabilities.

According to [**75**] [**76**], e-learning is now a modern method for promoting the learning and teaching process in universities, and it has been a deliberate concept and has been cultivated to be a significant component of education in many higher education institutions as stated in [**76**], [**77**]. Additionally in seeking to improve teaching and learning procedures, higher education institutions have also made large expenditures in the development of learning management systems [**78**] .

However, the investments of educational institutions were not the only reason for the development of e-learning. As stated in [**74**], e-learning has evolved because of the development in many sectors such as network technologies, e-learning technologies and content development. Evolution of the network technologies began with client-server networks. Next, Internet-intranet-extranet were introduced, and now wireless broadband access technologies are helping to provide better e-learning services. The evolution of e-Learning technologies also started by CD rom media, then learning management system (LMS), next multimedia and virtual communities, and game authoring tools, and now personalized tools are the current trend in e-learning technologies. Finally, the evolution of content development is presented. It started with text based content, then text based/multimedia content, after that learning objects were introduced, and now online games and personalized content are being evolved to provide more personalized and adaptive e-learning systems.

The desire for e-learning was born out of the need for the education industry to advance along with technological advancement. Nevertheless, all of a sudden, the COVID-19 pandemic struck the world, creating unmanageable declines and disruptions in many industries, including education [**79**]. 160 countries implemented nationwide closures. As reported by UNESCO, closures affected around 87% of higher education students [**80**]. It has hampered roughly 1 billion students, who ultimately depend on direct, in-person communication within these educational facilities. E-learning was the only solution for all those students in order to not lose the entire school year. Video and teleconferencing platforms such as Google Classroom, Zoom, Webex, and Microsoft had received great attention [**81**].

The choice was previously available, but after the pandemic e-learning was inevitable. Education is a vital need for humanity, whether there is an emergency, war or a natural disaster [**82**].

When we searched the SCOPUS database for "e-learning" from 1990 to 2022, we got 102,422 document results. By analyzing the results by year, we got an increasing curve as shown in figure 2.1.

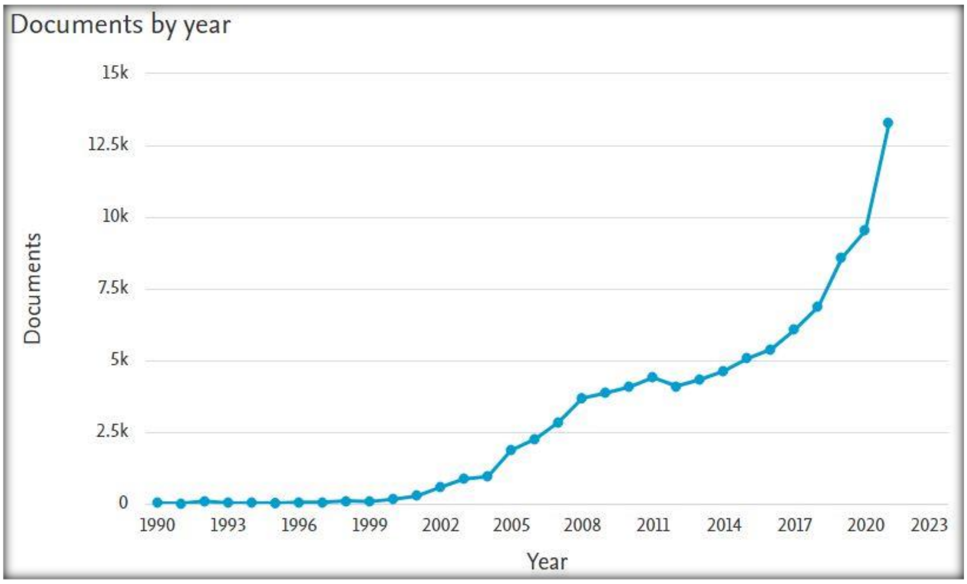


Figure 2.1: number of researches on "e-learning" in SCOUPUS database during 1990-2022 [83]

As we can see in figure **2.1,** the research in e-learning is a growing research field from 2000 and till now, producing many e-learning systems, but many researchers such as [**84**] [**85**] [**86**] [**87**] [**88**] [**89**] state that the key difficulty in e-learning is to boost initiatives aimed at encouraging a permanent and continuous use.

In this direction, Tania et al. [**90**] defined the main factors for the continued use of e-learning as follows: satisfaction, perceived usefulness, perceived ease of use, attitude, self-efficacy, system quality, confirmation, service quality, information quality, flow, trust, task technology fit, social influence, performance expectancy, personal innovation, habit, and technological construct.

But what is the benefit of the continuous use of e-learning systems if they provide the same content in the same way to all students and do not take into account the differences between them?
Students are humans, not machines. They have different feelings, different back knowledge, and different learning styles. We must take that into account, if we want to improve the learning process, previous research around the adaptive e-learning concept.

2.1.1 Adaptive e-learning

As stated in [**91**], based on the most recent research, a learning environment that can recalibrate to each student's particular requirements, strengths, and capabilities speeds up the learning process and improves learning outcomes and performance.
And here we need to introduce the term "Adaptive learning", which was defined in [**92**] as a strategy for delivering individualized learning, with a propensity to offer capable, effective, and

custom learning pathways for capturing the attention of each learner. Kerr P. [**93**] presented three types of adaptivity:

1- Learning contents adaptivity, where the personal preferences of students are taken into account such as their preferred learning style, what students need to learn, educational background and knowledge of students, in addition to their personal skills and experience.
2- Adaptivity of presentation mode, where the required adaptations are applied to the method of presenting the content according to the personal preferences of the students and according to the appropriate methods for the educational content that is presented.
3- Complete adaptivity that combines the two earlier categories.

AHA, APeLS, and 3DE are a few examples of extant adaptive web-based educational systems [**94**] [**95**] [**96**] that offer different degrees of adaptivity. But despite their adaptivity, they have a low usage because of providing a meager selection of learning options, a lack of collaboration, and the inability to reuse their learning materials.

Nonetheless, despite having little to no adaptivity, LMSs like Blackboard, WebCT, or Moodle are often and effectively used in e-learning because they provide a variety of tools that help teachers manage and develop their online courses [**97**].

Hatami presented different learning styles in [**98**], but the Felder-Silverman Learning Styles Model (FSLSM) is the most used one because of its adaptivity within e-learning environments in addition to learning styles. FSLSM uses four dimensions to describe student's learning styles with a lot of details. Active/reflective, sensing/intuitive, visual/verbal, and sequential/global are the four dimensions [**99**], as mentioned in chapter 1. Other research identifies three learning styles, which are [**74**], [**100**]:

1- Visual learners: where learning is most effectively accomplished by visual means, such as visuals, demonstrations, facial expressions, and instructor body language.
2- Auditory learners: where listening to lectures, conversations, talking things through, and hearing what other people have to say is the best method to learn.
3- Tactile/Kinaesthetic learners: where the best way to learn is through experiencing, reflecting, interacting, and doing things, and exploring through simulation environments is a good choice for this learning style.

For each learner of the above three learning styles there is a preferable style, but it is better for students to try different styles interchangeably while going through the learning process to gain the best result and avoid getting bored [**74**]. Considering Felder and Silverman [**101**] opinion, students should learn through different operations: the ability to hear, perceive, reflect, and act; to reason rationally or instinctively; to memorize spoken or written materials; and the ability to recall seen images

After exploring different learning styles and operations, we are going through some research examples on adaptive e-learning.

One example on adaptive e-learning is proposed by Arsovic et al. [**91**], where they introduced an adaptive e-learning model that consisted of five main parts: students' model, adaptation module, expert system for data analysis and decision making, repository of learning objects, and database of educational methods. Their proposed model utilizes a combination of static and dynamic personalization techniques.

The static part uses a specific questionnaire when students first register on the course to determine each one's preferred learning style, and a pre-test to determine each student's prior

knowledge. According to the student's needs and results in previous courses, the new course's contents and structure are adapted to provide the best performance and satisfaction. On the other hand, the dynamic part is based on the continuous observation of the students' attitude in real time. Using data mining techniques on the obtained student's data provides very useful information that could be used for the adaptation and the personalization process.
Another example on adaptive e-learning includes [**102**] where Surjono presented many important factors that could enhance the performance of the adaptive e-learning such as student's personality, learning in social groups, active student participation, and motivation. He mentioned that, by understanding a student's personality, there will be a better identification of learning style in adaptive e-learning. Learning in groups also was one of the factors that he found useful for the learning process, where the distance between individuals is not important [**103**]. Another core factor in the success of e-learning is the active participation of students in the learning process, as JW You mentioned in [**104**]. And, finally, motivation, which is very important for students to keep while using the e-learning system. According to Al-Dujaily et al. [**105**] computer based learning students must be motivated because they invest their time and effort to gain more knowledge. Furthermore, Gardner [**106**] mentioned that students who learned with motivation and reasoning could reach a higher level.

To summarize, the explored research confirms through their results that adaptive e-learning is more efficient and useful than traditional e-learning, and it is more useful for students. But it could be more complicated to establish and operate, so that it is less widespread among educational institutions. But it is our choice to pick all the advantages of adaptive e-learning and endure the extra cost and effort, or use traditional e-learning after augmenting extra technologies to add more advantages. As e-learning helps improve the learning and the education process by overcoming the distance between teacher, student and the administrative staff, specific majors and courses, medical education, which involves in-person instruction and contact, is adversely impacted in this period [**70**]. So, other tools or technologies had to be integrated into current systems to overcome the educational obstacles of these practical courses, such as augmented reality.

2.1.2 Augmented reality (AR)

Many technologies have evolved during the last years because of the rapid development of the hardware and computational power. Augmented reality is one of those technologies that could add extra value to current e-learning systems. It could fill a huge gap where simulation and practice are required in specific courses such as medical education. It also could be used for adding motivation for a specific kind of students who prefer this kind of learning style.

As a result, many learning and educational institutions have expended a lot of time and money developing augmented reality (AR) applications as a creative and clever way to improve student learning outcomes [**107**] [**108**] [**109**] [**110**] [**111**] [**112**]. We can see that through its wide usage in primary schools [**113**] [**114**], along with its usage in higher education institutions [**115**] [**116**]. According to the Statista company, in their analysis of the forecasted spending on cutting-edge education technologies from 2018 to 2025, it is anticipated that by 2025 educational institutions would have invested 12.6 billion dollars in augmented reality technology, up from their 2018 investment of 1.6 billion dollars. [**117**]

One of the studies that looked at the use of augmented reality on e-learning was done by Baabdullah et al. [**118**], where they assessed 500 undergraduate students' experiences with augmented reality learning apps (AR.LRP) using a sample of the four main universities in Saudi

Arabia, and they found four major benefits from the usage of augmented reality learning applications:
1- Personal interactive benefits
2- Social interactive benefits
3- Affective benefits
4- Cognitive benefits
In addition, their results support the huge impact of those benefits on students' experience and performance.

In addition to the usage of augmented reality on e-learning, it also had earned growing global attention in a variety of key areas such as: healthcare [**119**], retailing [**120**], digital marketing [**121**], travel and tourism [**122**], manufacturing [**123**], and maintenance [**124**].

The enormous advantages of augmented reality on e-learning were not isolated from scientific research where many researchers such as [**125**], [**126**], [**127**], [**128**] reported that the natural interactive properties of AR give students greater possibilities for exploring the real world content, and [**129**] [**130**] [**131**] [**132**], who stated that "AR makes the learning process more enjoyable and valuable for students". Hsiao et al. [**133**] also confirmed that students' level of physical practice is improved as a result of their learning using augmented reality technology. Moreover, Wu et al. [**134**] mentioned that applications for augmented reality aid students in observing and analyzing phenomena that are challenging to observe or study in the physical realm.

2.2 Semantic Information

Tim Berners-Lee et al. introduced the semantic web in [**71**]. They introduced it as "a new form of web content that is meaningful to computers and will unleash a revolution of new possibilities". As they mentioned the semantic web was not a new web or a replacement of the current web, but it was an extension of the current web where the information in use takes extra metadata to add more meaning that enables humans and computers to work together on it. Because of that new representation of the information, the machines will have the ability to understand that information, and that will launch a new area of vital functionality. But this requires the computers to have, in addition to an enormous amount of structured information, a set of inference rules to be able to reason automatically new facts.

To enable the semantic web to come into being those two technologies were very important: eXtensible Markup Language (XML) and Resource Description Framework (RDF). XML handles the structure of the information documents, and RDF handles the meaning of this information in the shape of triples, where each triple represents (subject-verb-object) of a meaningful sentence [**71**].

With the spread of semantic technology, more and more semantic data were produced, and the need to infer new relations among this data was important to make the best use of the developing data. So there was a need for something that has the ability to connect concepts with well-defined and clear relations, and here the third basic component of the semantic web will solve that problem which is called ontologies. A typical ontology has a taxonomy (to define classes of objects and relations between them), and a set of inference rules [**71**].

Tim Berners-Lee et al. in their research stated that "If properly designed, the Semantic Web can assist the evolution of human knowledge as a whole" [**71**].

When we searched SCOPUS for “semantic web” during 1990-2022 we got only 60,970 document results, and by analyzing the result by year we got figure 2.2.

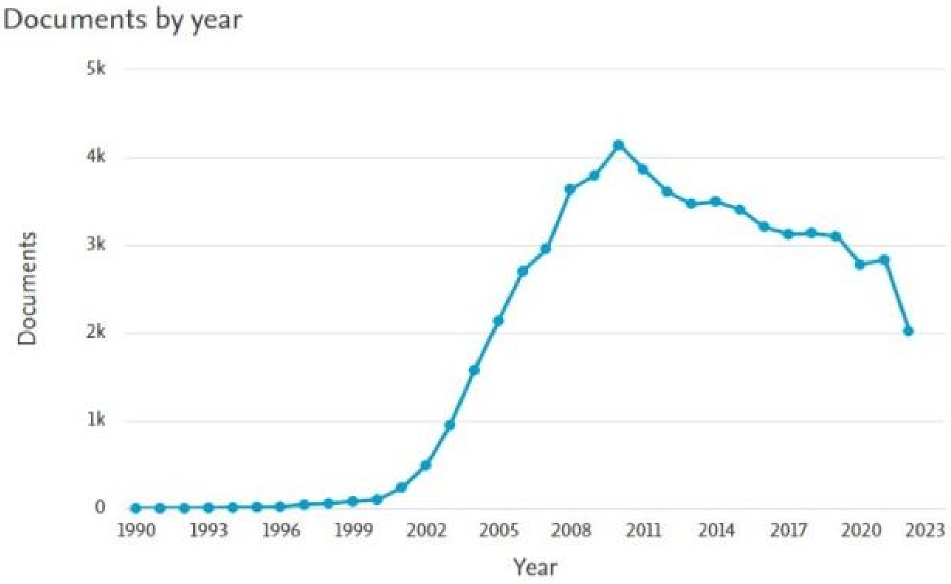


Figure 2.2: number of researches on “semantic web” in SCOUPUS database during 1990-2022 [**135**]

When searching SCOPUS for “ontology” during 1990-2022 we got 164,751 document results, by analyzing the result by year we got figure 2.3.

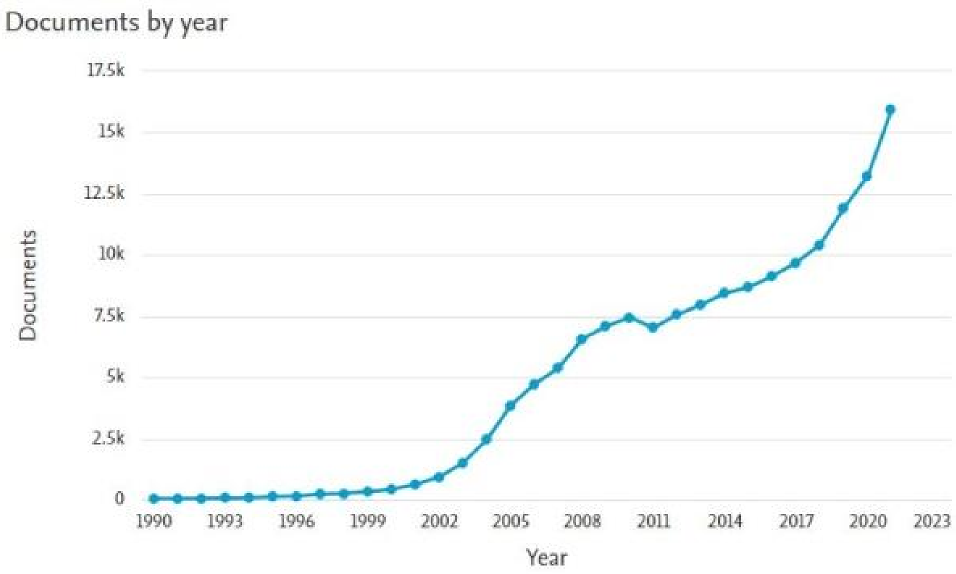


Figure 2.3: number of researches on “ontology” in SCOUPUS database during 1990-2022 [**136**]

From figures 2.2 and 2.3 we can see that the research in the semantics field is growing and branching in many other fields because of its reusability and diversity. It has been used in many different fields such as:

Commerce in [**137**], image segmentation [**138**], medical aspects [**139**], networks [**140**], security [**141**], cryptography [**142**], and many other fields.

As we saw, semantic information could be useful in different areas and it could be especially useful in the learning field to provide a better representation for learning contents, which will lead to faster searching and better recommendation. So we are going to explore this point in more detail.

2.3 Semantic information and e-learning

E-learning has been the focus of researchers for a long time. With every emergence of a new technology, attention was directed to thinking about how to use it to develop e-learning. Examples of this abound, from cloud computing to the Semantic Web, machine learning, artificial intelligence and virtual reality. We will talk and mention some of these examples around which the topic of our PhD thesis revolves.

In this section, we will explore applications and research related to the semantic web with e-learning. By searching Scopus database for the two terms "semantic" and "e-learning" and analyzing the results by year we got 2648 documents as shown in figure 2.4.

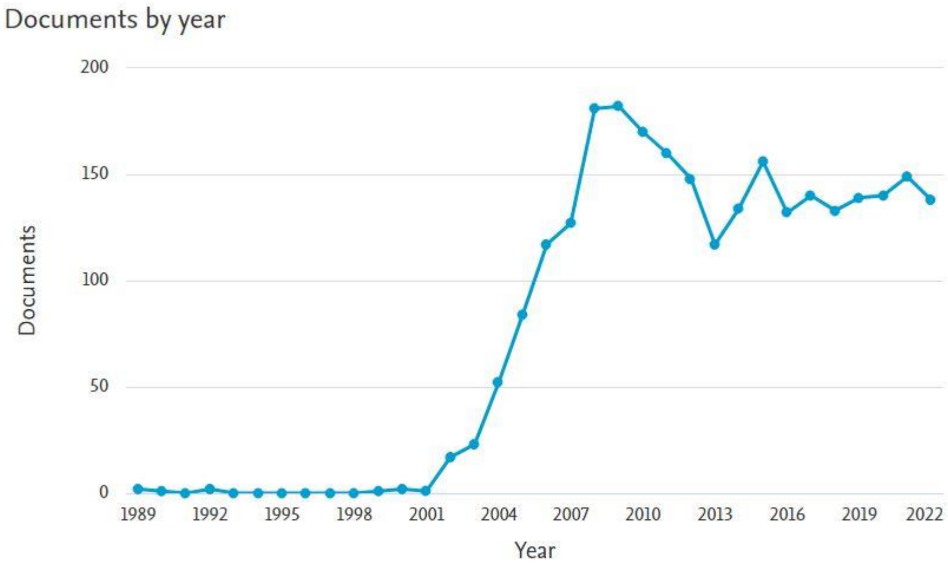


Figure 2.4: number of researches on "semantic" and "e-learning" in SCOUPUS database during 1990-2022 [143]

We can see in figure 2.4 that the research publication in those two fields started to grow from the year 2002 and till now with around 150 new publications per year. By analyzing the results by country we found that China is the first country with more than 400 publications, and next comes the United States with around 200 publications. India, Germany, and Spain come next.

As the computational technology and Internet speed develops over time there is a great improvement in the e-learning sector. More learning resources are available for learners, higher download and upload speeds are provided, and the quality of materials increases. But with all these advantages we have the problem of finding appropriate learning resources among an ocean of learning materials. To bypass this obstacle we must improve the e-learning system with more advanced tools and technologies such as semantic technology, which have the ability to facilitate the searching ability and provide a better recommendation service, as we will explore below.

In [**144**] Huang et al proposed a new context-aware semantic information management system that provides a knowledge-enhanced learning model and learner personality representation. They tried to integrate learning content, learner personality, and the learning process to produce a semantic e-learning framework with the use of XML, RDF, and Learning Object Metadata (LOM). They cited [**145**] to confirm that the more semantic aware the computing technology is, the more intelligent e-learning is expected to be.

Other studies related to the same topic were mentioned also, such as Nilson [**146**], who investigates the Semantic Web's possible effects on e-learning, and Henze et al. [**147**] and their presentation of a logic-based method based on RDF annotations for resource representation and reasoning, and Simic et al. [**148**], who discussed how the semantics of course content and student information could be presented using Semantic Web technologies. In figure 2.5 they compared a traditional e-learning system with a semantic e-learning system.

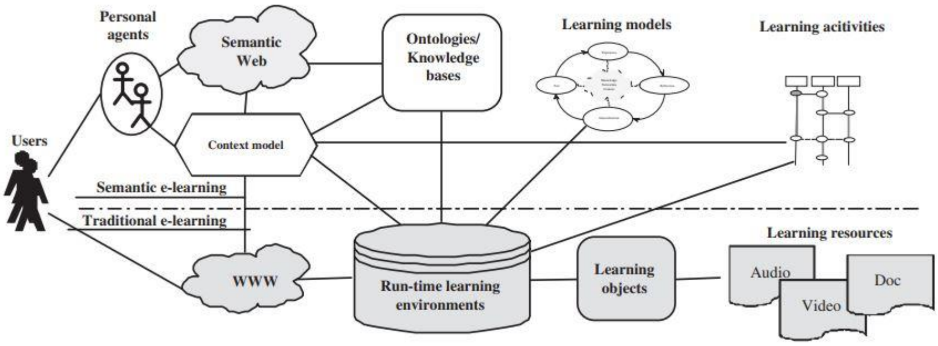


Figure 2.5: e-learning vs. semantic e-learning [144]

In figure 2.5 we can see that Huang et al. [**144**] added to the traditional e-learning system personal agents, semantic web, ontologies (knowledge bases), learning models, and learning activities to enhance the e-learning system and convert it into a semantic e-learning system.
For future work they suggested more development of the semantic aware services, integration of Shareable Content Object Reference Model (SCROM), supporting of new learning models such as Scenario-based Learning and Problem-based Learning.

Gladun, Anatoly, et al. [**149**] presented a multi-agent system that is based on semantic web technologies aiming at controlling student's acquired knowledge automatically in e-learning frameworks and educational contexts. And to enhance their system they planned to improve their algorithms and use multi-agent technologies to enhance ontology analysis. They also planned to use the learning history to improve feedback between the learner and the teacher. Finally, they suggested the personalization of the learning strategy for each learner by the use of inductive inference methods. Junuz [**150**] presented some facts to be considered while generating metadata about learning objects to be used in a semantic e-learning environment. They discussed many learning object standards such as IEEE LOM, Dublin Core, IMS, and SCORM. Rui et al. [**151**] also discussed semantic web and metadata standards. They proposed a semantic e-learning system that could solve problems in traditional e-learning platforms with the use of semantic technology and ontology usage for learning content, resource inquiry and sharing.

On the same research track Dutta [**152**] also focused on the potential uses of semantics with e-learning by describing learning materials with ontologies, mentioning that the reusability of semantic information, which can be used by both humans and machines, is a great advantage that could be helpful in the e-learning domain. They used semantic information in three ways: content to describe learning materials, context to define how the topic presented, and structure, the logical structure of the learning material. Sheeba et al. [**153**] discussed the application of semantic technologies in learning content and the possible development of e-learning activities.

They have made sure that the ontology usage in e-learning content had a great focus on the research and the enormous development that it could provide for e-learning.

In this direction also, Garcıa et al. [**154**] described a new tool called LOD (linked open data) for education based on semantic web technologies, with which they made an experiment with more than 30 students. The students who used the new tool had better results and performance. And they intended to provide more extended experiments for a better and more reliable platform for future work.
In their study they used: Sakai [**155**] LMS for offering instructional technology, as an entity recognizer, Apache Stanbol [**156**], which performs NLP, is utilized. It produces a list of URIs with some pertinent attributes. The tools necessary for updating RDF provided by Apache Marmotta [**157**] as a (RDF) triple store, and it also customizes a MySQL database to support triple persistence. And Wikipedia data is gathered and converted into RDF via DBpedia [**158**].

With the huge production of e-learning systems and architectures, the sharing and integration of data between these systems have been given less attention. So Masud et al. [**155**] presented a solution for this problem with semantic data interoperability and distributed metadata management. Their solution aims at supporting learning content exchange between different e-learning systems.

But not only semantic technology was used to improve the e-learning systems, there were other research fields that merged with e-learning to enhance and develop it such as machine learning, data mining, and social networks.

To determine the appropriate knowledge level for the student, Ghatasheh proposed in [**156**] a concept for a dynamic e-learning environment based on machine learning and the study of user activities. The chosen classification algorithm for estimating knowledge level was examined in this system using many experiments and the most recent e-learning trends.

In [**157**], Cuéllar et al. applied social network analysis and data mining to the semantic web and social networks to enhance e-learning settings. To combine data from several learning management systems and create a social network of learning systems, they created ontology. With the help of that system, they were able to gather more data regarding the social organization of teachers and students, which they used in conjunction with their ontology to enhance the learning process. The ontologies' hierarchical structure also allowed them to perform SNA (Social Network Analysis) at various levels. Finally, they recommended undergoing additional social network analysis in the e-learning space, so that they can support future work by providing more understanding of students' needs and offering more motivation methods individually and among learning groups.

Regarding the huge amount of available learning resources, there is an urgent need to improve recommendation systems. Semantic technologies can help in this regard as well. So, by utilizing intra and extra semantic linkages between learning items and learners' demands, Fraihat et al. [**158**] introduced a semantic recommender system for e-learning to assist learners in discovering suitable learning objects for their field and interests. Their suggested system enhances learning quality by requiring less time and effort to locate necessary learning resources.

Another overview of ontology-based recommenders for e-learning from studies published between 2005 and 2014 was presented by Tarus et al. [**159**]. In that work, they showed how incorporating ontologies into e-learning recommender systems may improve the caliber of recommendations.

In their discussion of the use of ontology in the recommendation process, Rahayu et al. [**160**] noted that ontologies were a useful addition to many other disciplines, including social science, artificial intelligence, computing technology, education, and psychology of learning. The results of their study are in favor of adding ontology-based recommendations to learning systems. Also, they discovered in their study that different artificial intelligence (AI) approaches helped semantic reasoners produce recommendations.

While some studies [**161**] [**162**] [**163**] utilized only semantic reasoners to generate suggestions, other studies made use of a variety of artificial intelligence approaches, including: 1- Software agents [**164**] [**165**] [**166**], 2- Collaborative filtering [**167**], 3- Cognitive diagnosis method [**168**], 4- Fuzzy linguistics [**169**], 5- Generalized sequential pattern algorithm [**170**], 6- Hierarchical Task Network Planning [**171**], 7- Natural language processing [**172**]. We will elaborate more in this area because of its importance for our research.

Capuano et al. in [**172**] unveiled a smart learning system based on approaches to knowledge discovery and cognitive computing, where several services were incorporated into their system, including the automatic conceptualization and classification of textual legal cases using natural language processing, the creation of learning paths based on legal ontologies, and the management of legal knowledge bases through editing, versioning, integration, and enrichment.. They highlight the growing prominence of semantic approaches and technologies in technology-enhanced learning, backing up their point with studies like [**173**] [**174**] [**175**] [**176**] [**177**] [**178**] [**179**].

They created a system, called electronic Justice Relationship Management (eJRM), that manages the resources that are currently available based on legal ontologies, enriching them with data from the thesauri EuroVoc [**180**], ItalGiure [**181**], and DeJure [**182**], as well as Wikipedia's common sense knowledge. Over 13,000 concepts make up the defined ontologies, which are connected to one another through both informative relationships.

The editing and versioning functions are provided by a graphical ontology management system (SEMANTO) [**183**] on their behalf. Also, they used the method developed by Capuano et al. [**184**] to automatically augment Wikipedia topics and words with the concepts on the system's ontologies for the enrichment function, which involved adding more terms and topics from outside sources. With an algorithm described in [**185**] for matching and integration, they matched ontological elements discovered by using a variety of similarity criteria.

For the semantic search, their eJRM system uses a knowledge discovery technique to extract pertinent concepts from user-input text, while including a portion of the algorithm described and put into practice in [**186**], [**187**].

Comparing our system against the previous one, we used natural language processing with machine learning through the Wikipedia miner tool to extract main topics from learning materials that not only related to legal ontologies, but could be any learning object in any topic.

Yu, Zhiwen, et al. [**188**] conducted another related study and suggested an approach for semantic content recommendation based on ontologies toward context-aware e-learning. In it, they wanted to improve learning effectiveness and make it easier to find relevant learning materials among the expanding collection of educational resources.

To generate customized and enhanced recommendation results, their suggested recommendation system incorporates knowledge about the learner's context (without naming the information resource), knowledge about content, and knowledge about the learning domain. The semantic similarity between the learning content and the learner's aim serves as their system's ranking criterion. Figure 2.6 depicts the learner ontology, learning content ontology, and domain ontology that they created for their system.

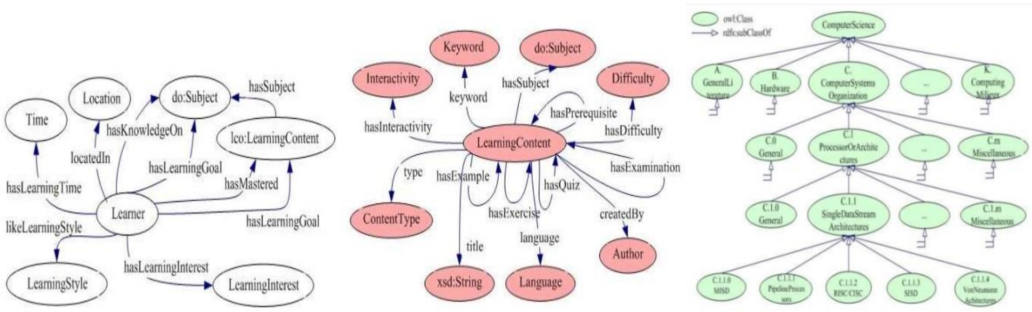


Figure 2.6: Learner, Learning Content, and Domain Ontologies [188]

They noted that the use of ontologies gives programs the ability to interpret learner context and content aspects based on their semantics, and their process for recommending learning content consists of four steps, as illustrated in figure 2.7.

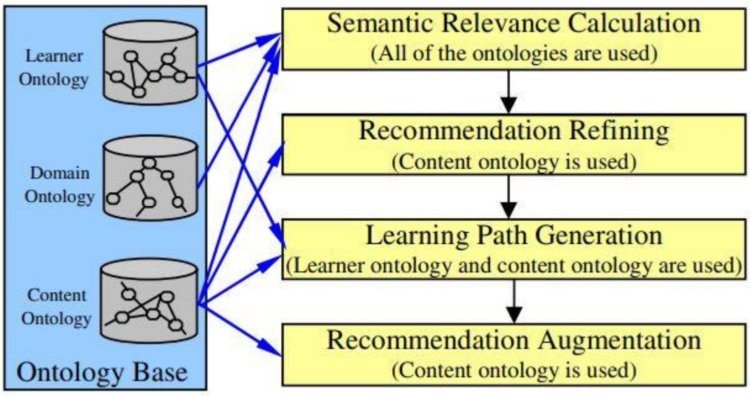


Figure 2.7: The recommendation process [188]

Their recommendation process starts by:

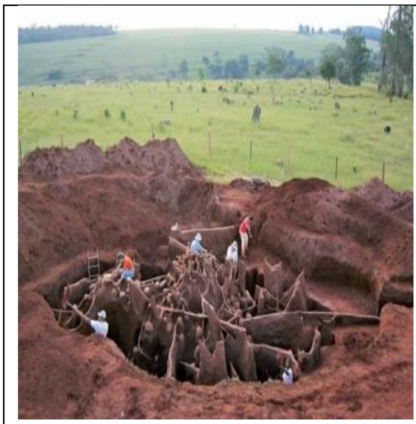
- Semantic relevance calculation. In this initial stage, all of their ontologies are used to determine how semantically related are the learner and the learning materials, in order to produce a list of recommendations.
- Recommendation refining occurs in the second step, when the results are adjusted using the content ontology, until a number of viable options are found.
- Learning path generation, where learner and content ontologies are both used to get the target learning content and its prerequisite content.
- Recommendation augmentation, enhancing recommendations by aggregating content related to the main course using a content ontology.

From the explored research we conclude that the implementation of semantic technologies and the integration of ontology-based recommendations into learning technologies have a great impact and development on enhancing the learning process. It facilitates the search process, enriches the learning content, interconnects different e-learning systems, removes redundancy and saves time creating learning objects that are already created, augments social networks advantages into the learning and educational process, and opens new possibilities for further development into semantic e-learning systems.

2.4 Cloud Computing

From nature we can take a lot of lessons, we can see groups of ants cooperating to build their huge colonies, swarms of bees cooperate to curb food and defend their habitat from the biggest invader, and flocks of wolves cooperate to catch prey that is larger than the size of their members as shown in table 2.1.

Table 2.1: Examples of cooperation from the nature

		
a giant leafcutter ant nest in Brazil [189]	wild honey bee nest [190]	wolves hunting prey [191]

From this, mankind learns that cooperation and working in groups often leads to better results in less time, and we began to form our own groups, to divide tasks and to specialize to serve the general interest of society. According to Marinescu a network of entities may arrange themselves to accomplish tasks that an individual entity cannot, even if each unit may only have moderate aptitude. This is how human people have learnt to aggregate themselves and create man-made machines. [**192**]

With this way of thinking, mankind knew that the integration of multiple tools and resources into a single system gives better results and can solve more complex problems, and it was logical to apply this principle in the computing field with the development of computing power that helped to solve more complex challenges. Over time, multiple examples of the integration of many computers appeared to work on solving one problem or to implement one goal. For example, time sharing servers, grid computing, global computing, Internet computing, parallel computing, distributed systems [**192**], and many other examples and paradigms that evolved due to the need for more computing power. Cloud computing was, among them, a strong competitor and a smart choice. [**193**]

In the following ways, cloud computing differs from other computing paradigms: With its lightweight client software, location independence, and ease of access, the cloud interface does not need users to alter their working practices or settings.

It ensures user satisfaction, hardware performance, CPU speed, I/O bandwidth, and memory capacity. The cloud's management is transparent to users and it is an independent system. It is a pay-as-you-go on-demand solution that offers flexibility and scalability [**193**]. Application designers are liberated from the constraints of a single system by its elasticity and impression of endless computing resources [**192**].

With all these advantages, cloud computing became usable in many application scenarios, which made it a tool for business promotion by lots of companies [**194**]. As a result, it encouraged investing in software, networking, storage, and processing technologies. It also helped focusing on corporate computing, whose adoption by commercial groups might have a significant impact on the economy [**192**].
Given its wide range of uses, cloud computing has been given many alternative definitions. It is defined by the National Institute of Standards and Technology as a strategy for providing easy, on-demand access to a shared pool of reconfigurable computing resources, such as networks, servers, storage, applications, and services, which may be quickly supplied and released with little administration work or service provider involvement [**195**], [**196**].

By searching Scopus database for the term "Cloud computing" and analyzing the results by year we got 124,477 document results through the years 1990 till 2022 as shown in figure 2.8.

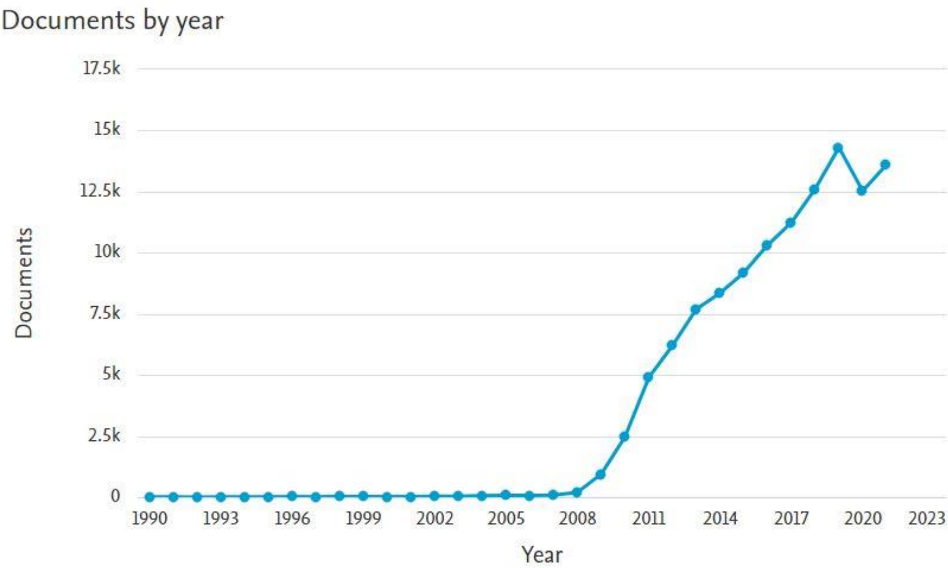


Figure 2.8: number of researches on "Cloud computing" in SCOUPUS database during 1990-2022 [197]

Additionally, searching "cloud computing", "Internet of things", and "Fog computing" on Google trends we got the following chart as shown in figure 2.9.

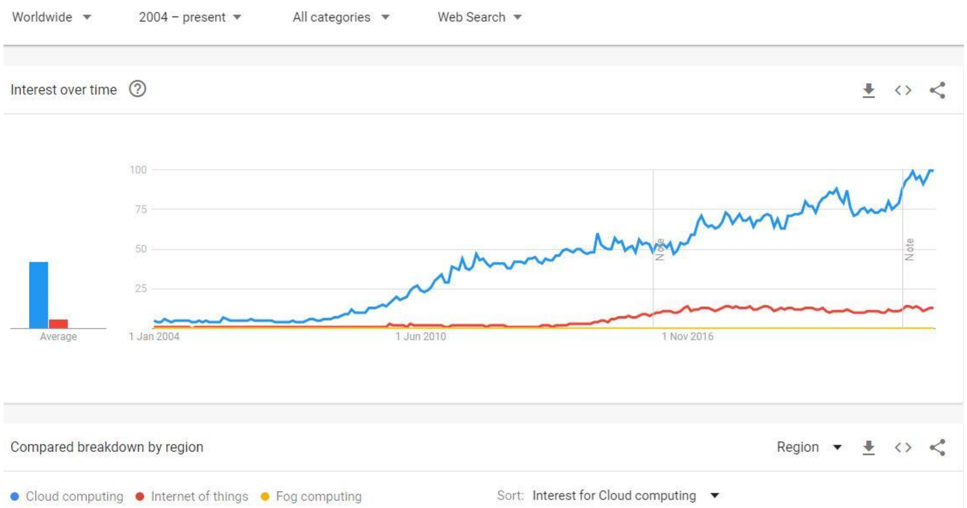


Figure 2.9: "cloud computing", "Internet of things", "fog computing" on Google trends [198]

According to [**196**] [**193**] [**194**] and [**192**], there are three service models for cloud computing. The following is how software as a service, platform as a service, and infrastructure as a service are defined:

- Software as a Service (SaaS) refers to the hosting and online delivery of software to customers. It enables the use of service provided apps in a cloud architecture. Examples include the Application Service Provider (ASP), SalesForce.com, Google Mail, and Google Docs.
- Platform as a Service (PaaS) is the hosting and provision of a development platform to support the entire software lifecycle and allow users to create cloud services and apps. It provides the ability to deploy user-created apps using the provider-supported programming languages and tools. Examples include Google App Engine (GAE), [**194**], and Zimki [**199**].
- Infrastructure as a Service (IaaS) is the hosting and provisioning of processing, storage, networks, and other essential computing resources. Examples include Amazon Web Service™ (AWS) [**200**], and Microsoft Azure [**201**], [**194**].

Other categories could be branched from the previous main three such as:

- Storage as a service (Storage aaS): hosting and delivery of virtualized storage on demand. Examples include Amazon S3, Google BigTable, and Apache HBase.
- Data as a Service (DaaS): hosting and provision of data in various formats and from numerous sources. Examples include Google Docs, Adobe Buzzword, ElasticDrive.
- Hardware as a Service (HaaS): This refers to the hosting and provision of IT hardware or perhaps a whole data center as a pay-per-use subscription service. Examples include Amazon EC2, IBM's Blue Cloud project, Nimbus, Eucalyptus and Enomalism.

Figures 2.10 and 2.11 show the relation between the different cloud services and the differences between them.

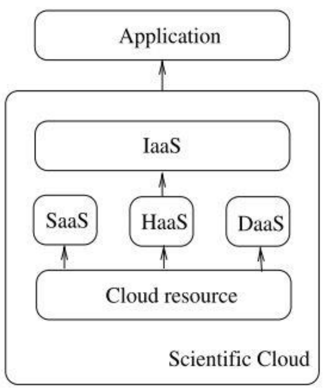


Figure 2.10: The relationship between cloud services [193]

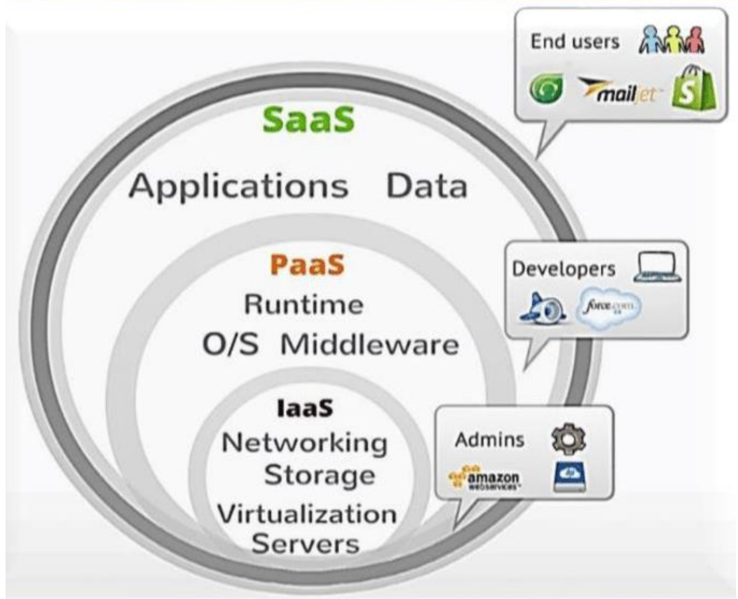


Figure 2.11: SaaS, PaaS, and IaaS [202]

After presenting the different service models of cloud computing we are going to explore the deployment models.

According to [**196**] and [**192**] , there are four types of cloud computing deployment models.

- Private cloud: This type of cloud infrastructure is only used by one company, and either the organization itself or a third party manages it.

- Community cloud: This is a shared cloud architecture that includes shared policies, needs, values, and concerns between multiple companies.
- Public cloud: A cloud infrastructure that is made available to the general public, and whose entire ownership is held by the cloud service provider, who also controls its policies, value, profits, costs, and pricing models. Examples include Amazon EC2, S3, Google AppEngine, and Force.com.
- Hybrid cloud: This type of cloud infrastructure is created by combining two or more distinct clouds. However, proprietary technology that links different clouds allows for the portability of data and applications. Organizations utilize the hybrid cloud approach because it allows them to oversee corporate operations on the cloud without sacrificing private activities or resource optimization.

Cloud computing, as we saw, has many details and properties, and we just scratched its surface in the last paragraphs, but it won't be possible to see cloud computing without other technologies. Those technologies were the base or the leader that led us to cloud computing.

According to Wang et al. [**193**] some of these technologies are:
- Virtualization technology that enables hardware partitioning, thus providing flexible and scalable computing platforms.
- Service flow and workflow orchestration enables computing clouds to automatically orchestrate services from many sources and types, establishing a dynamic workflow.
- Web service that presents the main idea of cloud computing as a web service.
- Service oriented architecture, that enables the management, organization, and orchestration of the different services provided by cloud computing.
- Web 2.0, which improves user collaboration and information exchange, so using cloud computing completes the necessary tools for this collaboration.
- The worldwide distributed storage system where network storage systems and distributed data systems allow cloud computing to administer its storage services globally.

And there are still more contributions coming from various technological fields, so it's not the end.

According to Qian et al. [**194**], who enumerated some of the benefits of cloud computing, it's a win-win situation for the service provider and the customer, and the benefits they mentioned are:
- The satisfaction of business requirements on demand,
- The reduction of costs and energy-saving,
- The improvement of resource management efficiency.

However, there are still several important issues that need to be researched, such as privacy, security, and service continuity; these issues could result in Internet problems, power outages, service interruptions, and system bugs.

2.4.1 Cloud computing and e-learning

E-learning on its own proved to be vital especially during the COVID-19 pandemic. Many universities use it and many countries depend on it for improving their educational level. While e-learning has the power of connecting teacher and student anywhere and anytime, this advantage is getting weaker because of the gigantic learning content size. Learning content evolves in many types and many formats, so the e-learning systems have to get better to handle this advance; or else, it won't be useful for students and we will lose all its advantages.

To keep up with the current technology development, current e-learning systems must be enhanced with the required computational power, which vary from system to another depending on many factors such as number of users, number of available courses, and provided services. This variation and scalability could be provided easily through the use of cloud computing. Cloud computing could make e-learning advantages more powerful again, especially with rapid development in computing power [**203**]. Therefore, the use of cloud based e-learning was logical and inevitable, especially from a practical point of view: it is more economic and scalable [**90**]. As a result, a lot of educational institutions use cloud based e-learning platforms to harvest all these benefits [**204**] [**205**] [**206**] [**207**] [**208**].

By searching Scopus database for the term (cloud based learning) and analyzing the results by year we got 22,326 document results through the years 1990 till 2022 as shown in figure 2.12.

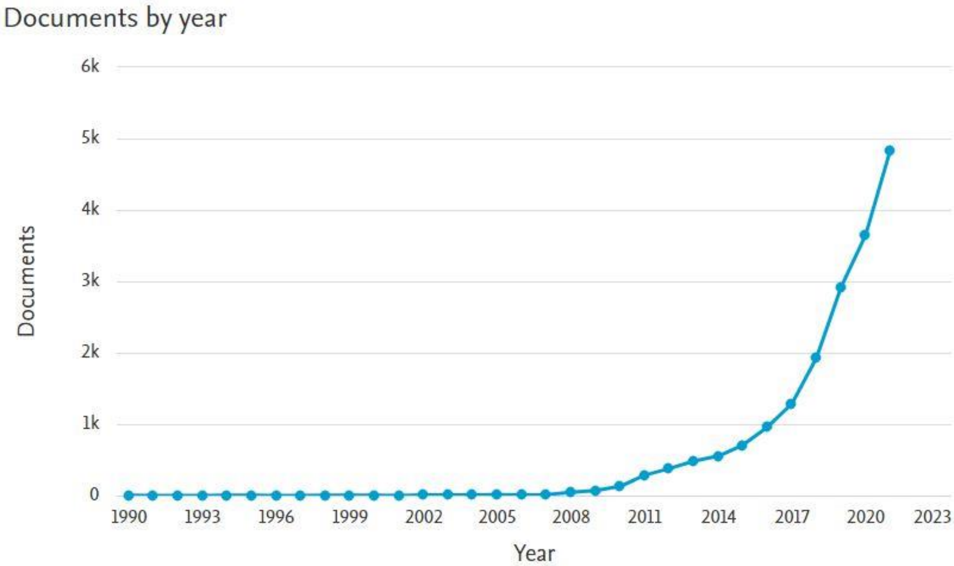


Figure 2.12: number of researches on "cloud based learning" in SCOUPUS database during 1990-2022 [**209**]

As we can see in the previous figure, there is an increasing research activity in this field. This is due to the high importance of developing education and the growing necessity for providing it for a higher number of students over a wider geographical space, may be to ease the learning process, or it could be to reduce the learning costs, or even to continue the learning process in case of COVID-19 quarantine [**210**] [**211**].

Developing education and learning systems requires a high budget due to the cost of infrastructure, computers, servers, and maintenance. Hence, cloud computing is the ideal choice for academic institutions and enterprises. [**212**]

Through the Internet, third parties offer cloud services to academic institutions. Cloud-based learning platforms demand, however, a fast and dependable Internet connection.

There are several companies that offer services, including Google, Amazon, Microsoft, Yahoo, and others, that could assist educational systems [**213**] [**214**].

A tremendous variety of e-learning tools and platforms were developed as a result of the enormous market for cloud-based learning. In their analysis of various Cloud-Based technologies, Siddiqui et al. [**212**] list the following:

- Easy generator [**215**] [**216**], a comprehensive cloud-based learning platform that has a straightforward tool for building interesting courses. No coding experience is necessary. The user interface is quite inviting, and courses are responsive to mobile devices.
- Lectora Online [**215**] [**217**] [**218**], a cloud-based authoring tool that enables the creation of assignments, the direct inclusion of expert animated movies into media libraries, and quick, unrestricted resource downloads.
- eCoach [**215**] [**219**] [**220**], an authoring tool that works across multiple devices and enables anyone to make online courses. It makes it simple and quick to create online courses using materials and media from all around the Internet. It offers a private URL for sharing learning materials, including mobile-friendly courses and resources.
- Ruzuku [**215**] [**221**] [**222**], an authoring tool that enables creating and sharing online courses by allowing users to add content, files, and activities. When used as a learning repository, Ruzuku does not track student data.
- iSpring [**223**] [**224**], a user-friendly cloud-based learning management application that offers complete control over learning solutions to organize training and learning resources.

Other examples from [**215**] include:

- Litmos [**225**], a straightforward, user-friendly cloud-based solution for co-authoring courses. A training courses library that is available for uploading can be used in conjunction with audio, video, text, graphics, and animations to quickly and easily develop courses.
- Smart Sparrow [**226**], a platform that enables the development, delivery, analysis, and sharing of adaptive classes based on students' past behavior, knowledge, and experiences. Also, it can adapt to any type of learning activity thanks to its dynamic adjustment to user feedback.
- Coassemble [**227**], a multi-device creation tool that enables anyone to swiftly create new online courses from the ground up by using content and resources from the Internet.
- Elucidat [**228**], a fully cloud-based e-learning authoring tool that enables writers to construct extremely engaging HTML5 e-learning for any device in addition to highly engaging courses with additional features like social polls, rules, branching, and tailored content clips.

Learning management systems (LMSs) also have a great impact on developing and managing the learning process, as they provide the required administration services and tools for both institutions and students. There are many LMSs but the most popular systems as Imed Bouchrika mentioned in [**229**] are:

- Google Classroom [**230**], a component of Google Apps for Education, that represents a good LMS for schools that are heavily involved with Google services. It only works in academic environments, though. Together with Google Classroom, Google offers a number of other applications as part of its G Suite services to support education.
- Google for education [**231**], a Google service that offers separately customizable versions of a number of Google products, including Gmail, Drive, Hangouts, Sheets, Meet, Google Calendar, Groups, Docs, Slides, News, Play, Sites, and Vault.
- Blackboard Learn [**232**], the learning management system for assessment and content reporting/analytics that is appropriate for K–12 schools, colleges, government and military initiatives, and corporations as well. It can be used in software as a service, managed hosting, or self-hosting implementations. Also, it works with portable electronics. [**229**]

- Canvas [**233**], the innovative cloud-based learning management system for education for simple learning and productivity. Given that it was built especially for K–5 to higher education institutions, with a hybrid or totally online learning environment, it could be used by schools of all shapes and sizes, from small classrooms to big institutions. [**229**]
- Moodle [**234**], an effective open-source learning management system for education in terms of flexibility. For the majority of students in secondary education, it is also a cost-effective and modular learning management system choice. It includes robust, secure, and safe tools that may be used to develop flexible training programs. Both the academic and commercial sectors are served with expanded features. [**229**]

Other LMS examples include Mindflash, Edmodo, Quizlet, Schoology, NEO, and many more; but one of them represents a new trend in the education field, which is a game-based learning system named D2L Brightspace [**235**]. D2L Brightspace is the LMS for video assignments and game-based learning. The dynamic platforms, solutions and assistance users require to have the optimum learning experience are combined into it. Additionally, 15% of enrollments and 13% of institutes currently utilize this LMS. [**229**]

Returning to the main topic of this part of the thesis, which is e-learning systems based on cloud computing, as it became a business field and a good attractive for investment so many big companies such as Google starts to invest in it, Amazon as well took a part of the market through providing its Amazon Web Service for education.

Amazon Web Services (AWS) cloud computing for education [**236**] aids in making education accessible, personalized, and lifelong for everyone. With its help, more than 14,000 educational institutions of all sizes, from elementary and secondary schools to colleges and universities, are able to fulfill their essential missions and achieve their most important institutional priorities.

Some live examples from higher education institutions and some schools could be found using some of the previous platforms and infrastructures to support cloud based learning such as:
- Arizona State University employed AWS to enhance the educational experience for students and offer 24/7, anywhere access to applications. It offered customers extended reality environments, digital assistants, speech technology, and virtual computer labs.
- The University of Notre Dame modernized administrative processes and student information systems using AWS. They were given scalable resources and capacity as needed, which helped them save money thanks to pay-as-you-go pricing and strict security standards. Also, they reduced downtime and data loss through quick, dependable disaster recovery.
- New Jersey school district and Fife School districts are another example. In addition to raising security standards with dependable, scalable, and secure data storage, they leveraged Amazon to reduce the costs of IT infrastructure by 50–75%.

Other educational institutions used Google's educational solutions [**237**] such as:
- University Carlos III de Madrid (UC3M), which uses Google services in addition to Moodle and Blackboard collaborate [**238**] to provide students and professors with the required infrastructure and services for online courses, assignments, online meetings, sharing and modifying common files, and many other operations.
- Brown University uses virtual reality to immerse students in American history. And according to Adam Blumenthal Virtual Reality Professor and Artist-in-Residence, Brown University, VR is very important for students to open their mind.
- Google for Education is another resource used by The Carroll School to assist pupils who have learning impairments. And according to Margaret Kuzmicz, Director of Technology, Carroll School, Google Workspace helps students interact with their teacher and fellow

classmates on a regular basis and frequently in real time. With assisting people in overcoming challenges they may not have previously received assistance with, this connection makes them more productive.

Now we can explore some research articles that present cloud based learning systems to get an overview about how it works.

In [**239**] an e-learning ecosystem based on cloud computing was presented by Dong et al. They combined cloud computing and e-learning because they believe that present e-learning systems do not have the necessary underlying infrastructures, and that combining the two will result in the dynamic allocation of the computation and storage resources that are needed. According to them, the main contributions included offering infrastructures with quality of service guarantees, service level agreements, resource allocation that was focused on priorities, support for a variety of applications, and automatic real-time configuration and resource management.

Their system is composed of three layers:
- Infrastructure layer, which provides processing and storage resources for upper levels, where cloud computing platforms are in charge of managing them.
- Content layer, which includes the instructional materials. For upper levels, it exposes the common APIs and interfaces of the contents.
- Application layer, which houses the e-learning tools, services, and other components offers features and user interfaces for other programs or users.

In addition to the three layers, it also has four ad hoc modules:
- The monitoring module monitors the requests that are processed, the real-time configuration data, and resource usage, including the state of the CPU, RAM, I/O, and other components.
- The scheduling of resources, the run-time, and the teaching and learning methodologies are all established and maintained by the policy module.
- Certain policies in the arbitration module are created manually by experts, and user requests are fulfilled.
- Finally, the provision module, which begins implementing resource allocation strategies decided upon by the policy module and arbitration module.

Their system architecture is shown in figure 2.13.

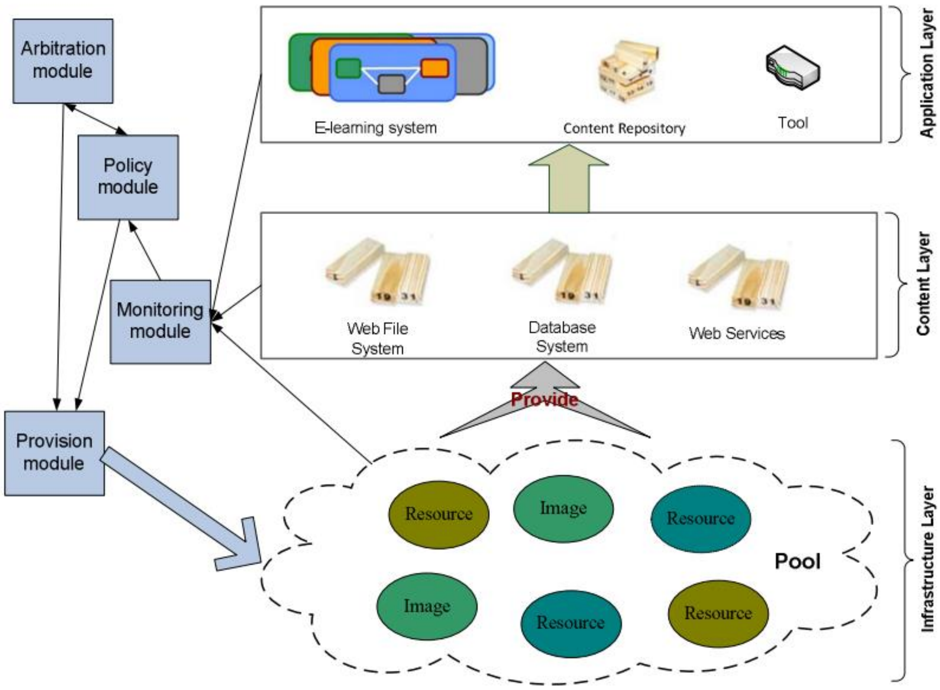


Figure 2.13: Cloud computing infrastructure-based e-learning ecosystem architecture [239]

Another example, presented in [**206**], is a cloud-based reflective learning environment to assist instructors and students in enhancing their capacity for reflection, both during and following actual class sessions.

Figure 2.14 depicts the three main components of the framework for the cloud-based reflective learning environment:

- The cloud service, which includes:
  - Course website, which provides tools for educators and students to use in teaching and learning.
  - Web applications, which aid educators and learners in giving and carrying out reflective learning exercises.
  - Course database, a repository for materials and course data.
  - User profile database, which keeps track of the learning profiles, learning records, and individual student information.
  - Course administration, which outlines the administrative procedures.
  - Reflection participation, which provides comments and information about how students have interacted with recent and earlier courses.
- The teacher side, which permits instructors to provide course materials and carry out reflective learning exercises to aid in student learning reflection.
- The student side, which allows pupils to engage in different reflective learning activities.

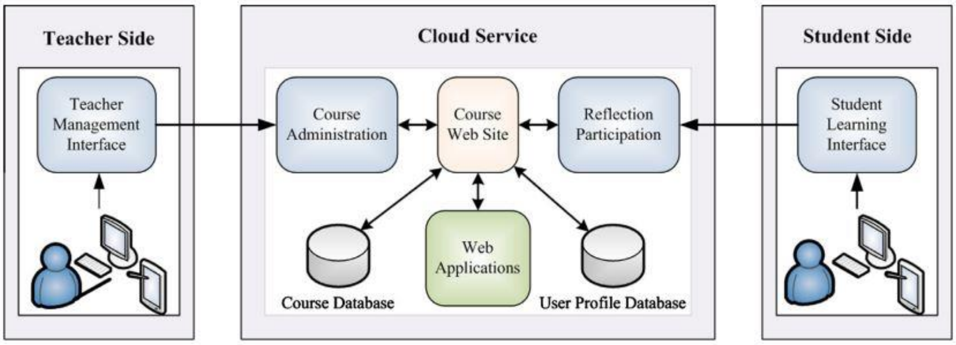


Figure 2.14: the framework of the cloud-based reflective learning environment [206]

Due to a range of evaluation techniques, such as tests, questionnaires, and interviews, their learning environment is able to successfully support student reflective capacities and improve their interest in learning. Furthermore, it enables learners and instructors to manage and conduct their learning journey.

To conclude, we can see that there are a huge number of platforms and services that support cloud based learning, not only to help develop education and society, but also because it is a good investment. None of the above systems is perfect: every one of them has advantages and disadvantages and the user or the institution have to choose the most adequate ones for their needs. But here comes our role to develop the e-learning ecosystem by researching the current problems and the missing needs of students, teachers and educational institutions to help take a new step in developing and improving the educational process. We will draw on the past experiences of researchers and keep pace with the current development in technology to harness the service of the educational process.

2.5 Learning object recommendation

Owing to the massive and expanding number of educational resources, finding the required one is a very hard task to do. Because of that, there is a great interest in researching this area to find a solution.

By searching the Scopus database for the terms "Learning AND object AND recommendation" and analyzing the results by year we got 1,563 document results through the years 1990 till 2022 as shown in figure 2.15.

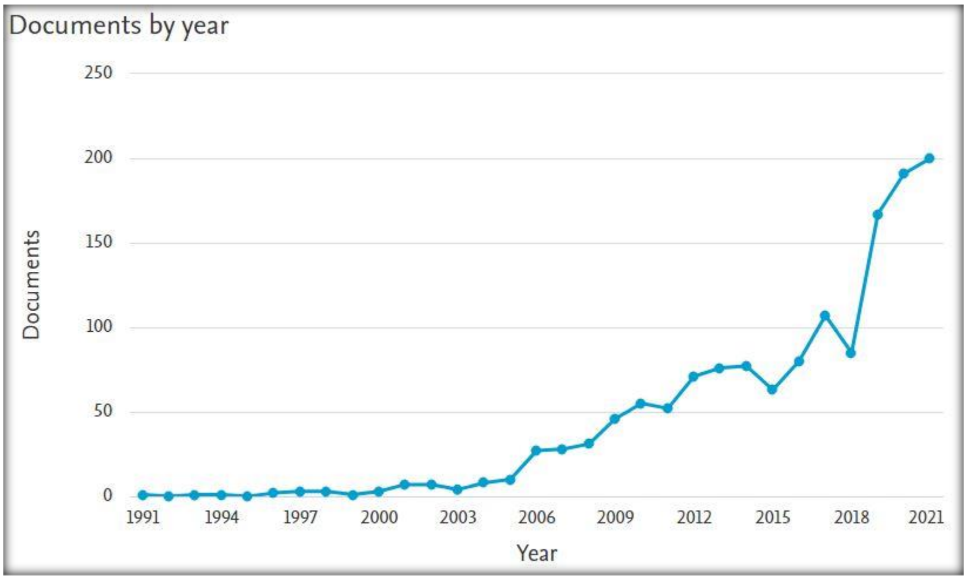


Figure 2.15: number of researches on "Learning object recommendation" in SCOUPUS database during 1990-2022 [**240**]

To begin our exploration of the different types of recommendation systems we will start by the general structure of the recommendation process as described by Nafea et al. [**241**] in figure 2.16
.

The process starts at the LMS interface, where the student completes a questionnaire or a behavior pattern from previous interactions is captured by the system. The learner profile and the learning object model created from the previous step is fed into the algorithm, which applies one or more of the techniques that include data mining, machine learning, and artificial intelligence. In addition to the algorithm there are many adaptation rules that help in the adaptation process. The adaptation outcome created from all previous elements is fed into the recommendation module, which contains the learning objects list and the learner profiles list. The recommendation module matches both lists and uses the adaptation outcomes to generate the recommendation result.

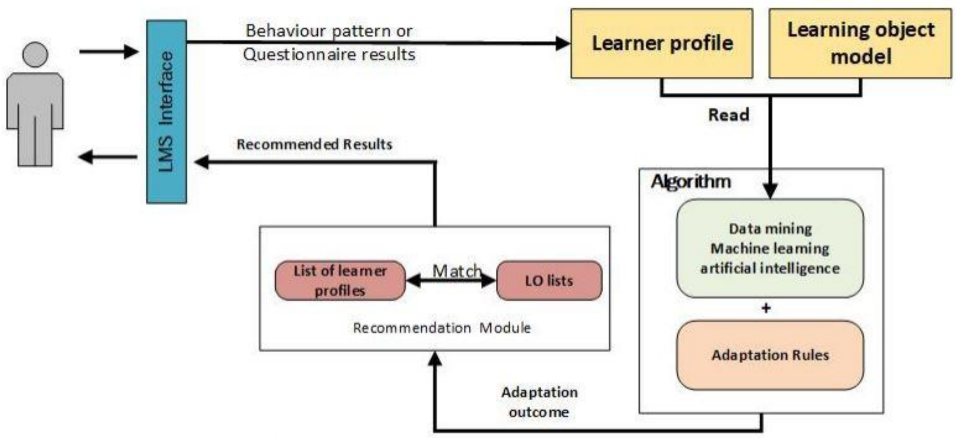


Figure 2.16: The general e-learning recommendation process. [241]

2.5.1 Types of recommender systems

Now we will explore different types of recommender systems. Four main types of them are identified in [241], [242], [159]:

1- **Collaborative filtering**, where recommendations are generated based on the similarity of user's opinions, ratings and behavior on a set of learning objects [241]. Collaborative filtering also uses the learning objects that were liked by similar users to be recommended for the current one [243]. It requires a full record of user information in their profile such as age, country, previous learning history, background. With this information, the recommender system can recommend similar students the same learning objects [244] [245]. Two types of algorithms could be used within collaborative filtering; memory-based and model-based. Memory-based algorithms use an entire database to extract information, which makes it slow, so that model-based algorithms are preferred, as they are faster because of the selection of specific items to extract [242]. According to [246] [247] [245] [248] correlation-based, cosine-based similarities and the k-Nearest Neighbors are the most popular similarity measures. [159]

- **Examples of use:**

  Many researchers explored the use of collaborative filtering recommendation and did significant work to improve it. Based on the effect of e-learning group behavior, Liu [249], [250] developed a collaborative filtering method. And a problem matrix and noise management techniques were suggested by Wang et al. [251], [244], [252]. Additionally, sequential pattern mining was used by Bourkoukou et al. [253] for creating a scoring model and gathering input from students to extract preferences in order to assign weights for learning items to produce the most suitable ones. Where "sequence behavior patterns", that was also used by Fatahi et al. [254], has been utilized to forecast users' preferred learning styles. The K-means algorithm for unsupervised model learning was used by El-Bishouty et al. [255] to identify the learning sequence and link learning items to the learner's preferred learning style. Trust relationships of target users with neighbors were used by Guo et al. [256] in addition to a user-item rating matrix and harmonic parameters to get the recommended reading list. Genetic algorithms were used by Dwivedi et al. [257] to provide an effective learning route for students. Ant colony optimization techniques were used by Kamsa et al. [258] for enhancing a path of collaborative learning. Deep belief networks in conjunction with massive open online courses were used by Zhang et al. [259]. They included prediction ratings to increase learners' effectiveness.

  However, despite the great development efforts, there are still flaws and shortcomings.

- **Limitations:**
  Providing accurate recommendations requires a lot of time to get the required amount of ratings for the learning object, so it is time consuming. Attributes are challenging to assign to items, which results in recommendations with ambiguous suggestions. Collaborative filtering was unable to adequately serve as a component of an effective recommender system on its own due to other issues including cold-start, scalability, and data scarcity. [**241**]

2- **Content-based**, where suggestions are made in accordance with the preferences of the students' profiles and the contents of the LOs [**241**]. In order to provide recommendations, it first determines the characteristics that a user has previously favored. Narducci et al. [**260**] outlines three elements needed to implement content-based recommendation: content analyzer, profile learner, and filtering component. Using feature extraction techniques, the content analyzer derives item representations from the learning object's content. Using machine learning techniques, the profile learner generalizes user input to construct user profiles based on historical preferences. Finally, matching the user profile with recommended items is done by the filtering component. [**242**]
- There are two categories of content-based recommendations: case-based reasoning [**247**] and attribute-based technique [**261**]. The attribute-based strategy recommends an item if it fits the learner profile's qualities, whereas case-based reasoning techniques recommends an item if it has the strongest connection to previous things the learner liked. [**159**]
- **Examples of use:**
  There are a number of examples in this field, including the following. Correlation analysis was used by Chen et al. [**262**] to arrange and create groups of learning materials. A rule-based adaptive user interface was established by Kolekar et al. [**263**], and Shu et al. [**264**] made use of previous student data. Fuzzy clustering and decision trees were also used by Rahman and Abdullah [**265**] in order to categorize students depending on their academic performance and learning habits. Additionally, linked data in conjunction with social network interaction were used by Pereira et al. [**266**] for providing recommendations.
- **Limitations:**
  Since content-based recommendation systems are dependent on prior user behavior and are unable to suggest fresh content, they demotivate users and cause them to have a limited focus. This shows that the content-based strategy is unable to solve issues with limited data, cold starts, scalability, time requirements, and accuracy. [**241**]

3- **Knowledge-based**, whereby suggestions are made based on knowledge models about students and learning objects, with the justification that the majority of learning items are better suited to meet students' requirements [**267**] [**241**]. Users' knowledge, item knowledge, and understanding of how items and users' requirements line up are necessary for the knowledge-based recommendation process to be successful [**247**]. Semantic or knowledge-based recommendation algorithms are employed in several e-learning applications, where ontology-based and context-based methods are among them [**268**] [**242**]. An advantage of knowledge-based recommendation systems, especially within e-learning recommenders, is its ability to be combined with other recommendation methods [**159**].
- **Examples of use**:
  Examples on knowledge-based recommendation systems include: the use of dependency ratios and parse trees by Aeiad and Meziane [**269**] upon an ontology-based model to provide realistic educational materials that meet the needs of learners; the use of classification and analysis by Phobun and Vicheanpanya [**270**] upon an ontology-based approach to suggest the best methods; the utilization of self-organization theory and a

leaner model by Wan and Niu [**271**] over a knowledge-based approach for suggesting learning materials; the application of semantic correlation and a dynamic key value memory network by Trifa et al. [**272**], depending on a knowledge tracing agent; and Nitchot et al. [**273**], proponents of knowledge representation, created knowledge structures and provided linkages of study materials by combining computing, ontology, and logic. [**241**]

- **Limitations:**
  Given its complexity and cost, knowledge-based recommendations need time and money to complete. Also, not all sizes of e-learning systems can use it. [**241**]

4- **Hybrid,** where recommendations are generated based on a combination of two or more of the previous techniques to benefit from their advantages, overcome their limitations, and to improve performance. [**274**] [**241**]

- **Examples of use:**
  Examples on hybrid recommendation systems include: the use of collaborative filtering in conjunction with sequential pattern mining by Chen et al. [**262**] for suggesting educational resources; the utilization of topic model in addition to matrix factorization by Zhao et al. [**275**] to address the issue of recommendations [**159**]; the use of similarity matrix and a 'tag and ratings' based approach by Karga and Satratzemi [**276**]; and the augmentation of decision trees, logistic regression, support vector machines, and artificial neural networks by Hussain et al. [**277**] to forecast the level of challenge pupils will experience.
- **Advantages**:
  The drawbacks of both collaborative filtering and content-based filtering are solved by hybrid recommendation. When there are fewer ratings available, it also seems to be more accurate. The hybrid approach is the greatest option right now because of all the benefits. [**241**]

As we mentioned, there are four main types of recommender systems, but other branches have evolved such as ontology-based recommenders, demographic-based recommenders, utility-based recommenders, context aware-based recommenders, trust-aware based recommenders, and social-network recommenders:

Demographic-based recommenders [**278**], which recommend items based on personal characteristics. Individuals with comparable characteristics are given similar suggestions.

Utility-based recommenders [**279**]**,** which generate recommendations for the user by calculating each object's utility.

Context aware-based recommenders [**280**]**,** which use recommendation algorithms once data sets are filtered based on contextual information.

Trust-aware based recommenders [**281**]**,** where suggestions are based on the relationships between individuals and their trustworthy opinions.

Social-network recommenders [**282**]**,** where user relationships and profiles serve as the primary sources of recommendations. Such a recommender is employed on Facebook [**283**] and LinkedIn [**284**]. [**159**]

Ontology-based recommenders [**285**]**,** where recommendations are generated based on the knowledge represented in ontologies. This type of knowledge-based recommender system uses ontologies to describe user context, objects, and domain knowledge. Ontologies are used to facilitate knowledge reuse and sharing [**159**], through representing knowledge with the use of classes, properties, relations and rules. Ontologies might be represented in a variety of languages, although the most oftenly used are Web Ontology Language and Resource Description Framework according to [**286**] and [**159**]. Ontologies come in a variety of types, including application, domain, reference, or generic ontologies, where DBpedia is a famous example of generic ontologies [**287**]. On the other hand, for recommender systems to describe information about students, subjects, and relationships between them, domain ontologies are the best choice [**288**].

Ontology-based recommenders proliferated in e-learning because of how well they can tailor content to the unique needs of each student. It achieves this capability by making the most of student information, including background, learning preferences, and learning route [**159**]. And we can find many examples for using ontology recommenders in e-learning such as Sosnovsky et al. [**289**] and Han et al. [**290**].

Despite the fact that ontology-based recommenders are effective and popular, building ontologies is a challenging, expensive, and time-consuming process that calls for knowledgeable professionals in engineering and knowledge acquisition [**159**]. Nevertheless, solutions have been created to address this issue through automatic ontology creation such as Klaussner et al. [**291**] and Elnagar et al. [**292**].

2.6 Learning object annotation

With the increased availability of learning resources from multiple sources, the need for organizing them is becoming important, not only to make use of these resources, but also to prevent this blessing from turning into a curse. Here comes the role of learning object annotation, where each learning object gets annotated with metadata to make it easier to be archived, retrieved, clustered and recommended for learners. The semantic annotation of learning objects makes the produced learning resources reusable, sharable and machine understandable, and integrating this annotation with learning management systems allows teachers to discover, aggregate, and reuse more learning materials in their courses. [**293**]

Tagging and annotating learning objects has many advantages, such as facilitating and accelerating the process of searching, retrieving, and using of learning resources, adaptively personalizing the searching process for each learner to get the most appropriate learning resources and, consequently, easing the hole learning process, opening the door for learning object reusability, saving time to create new materials instead of recreating the same content by different institutions. [**294**]

By searching the Scopus database for the terms “Learning AND object AND annotation” and analyzing the results by year we got 3,067 document results through the years 1994 till 2022 as shown in figure 2.17.

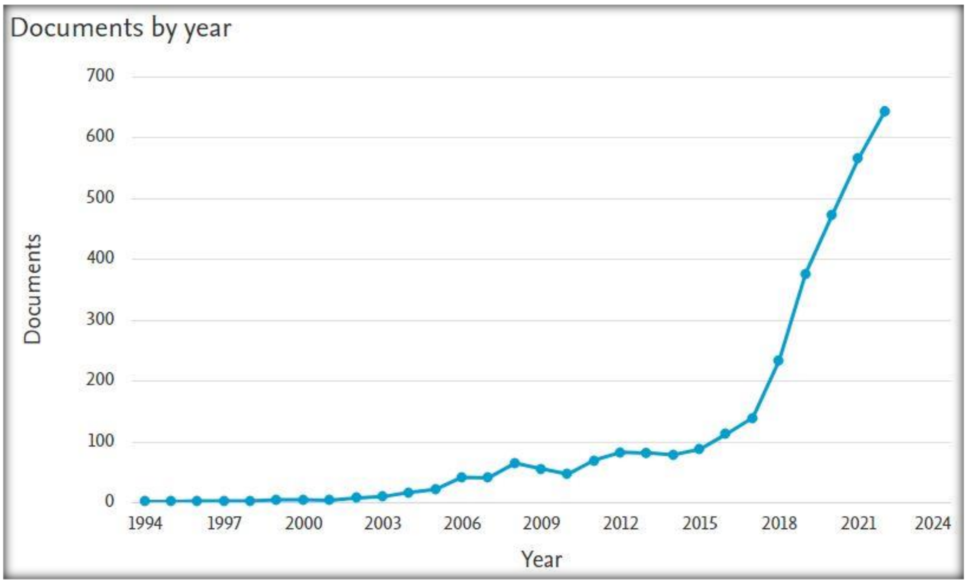


Figure 2.17: number of researches on "Learning object annotation" in SCOUPUS database during 1994-2022 [**295**]

Annotating learning objects by adding metadata can be done through two ways, manually or automatically:

- Manual annotation is done by the creator, the host, or the owner of the learning object. It produces high quality and more trusted results, but this comes with a high price in the required time, effort and cost.
- Automatic annotation is done through machine processing. It provides more information in less time. On its own it has two techniques:
  - Metadata harvesting; where data is collected automatically from metadata that was associated with the learning object from the beginning by humans or by a semi-automated process.
  - Metadata extraction; where data is collected also automatically, but from the learning object's content through mining techniques to produce the required metadata.

The creation of a critical mass of reusable learning objects is difficult without automatic annotation [**296**]. The Library of Congress is one of the institutions that acknowledged the importance of automated annotation of bibliographic resources. [**294**]

2.6.1 Metadata Standards

We have shown the different ways of annotation, but when we get to the implementation phase we will encounter many annotation standards from which we can select the one that best fits our objective and domain.

- Dublin Core metadata Initiative [**297**] [**298**]
  It is a project of the Association for Information Science and Technology, and it offers a type of metadata, drawing from many Resource Description Framework (RDF) vocabularies. Moreover, it enables a wide range of objectives and business strategies by having two levels:
  - The simple Dublin Core, which consists of fifteen elements (Title, Subject, Date, Description, Coverage, Type, Source, Creator, Language, Contributor, Relation, Rights, Format, Identifier and Publisher).

- The qualified Dublin Core, which has three extra components (Audience, Provenance and RightsHolder), in addition to a set of components that clarify the semantics of the elements.

Although the Dublin Core metadata includes features essential for general-purpose applications, it is missing characteristics that describe a document's educational viewpoint. As a result, a number of alternative metadata standards, including SCORM Metadata, CanCore, and IEEE Learning Object Metadata, that contain properties identifying the pedagogic qualities of the document, have been established to address educational issues.

- SCORM (Shareable Content Object Reference Model) Metadata [**303**]
  Is a description of the Advanced Distributed Learning initiated from the US Department of Defense's Office. It specifies communications between client-side content and a host system (referred to as "the run-time environment"), which is frequently supported by a learning management system. Sequencing, which is a set of guidelines that dictates the sequence in which a learner may view content items, was first introduced by SCORM 2004. Where they limit a student to a predetermined set of routes through the training materials.

- CanCore (Canadian Core Metadata) [**304**]
  In a nutshell, the Canadian Core Metadata Application Profile is a condensed and in-depth explanation of a subset of the LOM metadata elements. Although the CanCore element set openly bases itself on the LOM standard's elements and hierarchical structure, it significantly lessens this specification's complexity and ambiguity.

- IEEE learning object metadata [**299**] [**300**]
  A learning object can be anything, digital or otherwise, used for education, training, or learning and this conceptual data schema specifies the structure of a metadata instance for it. This standard's goal is to make using, searching, evaluating, retrieving, sharing, and exchanging learning objects easier. A learning technology system can use a metadata instance for a learning object to manage, identify, evaluate, or exchange learning objects by using other standards' implementation specifications of the data schema as a reference. In order to address educational issues, qualities indicating the pedagogical viewpoint of a document must be extracted, and IEEE LOM has attributes describing the pedagogic aspects of the text. [**294**]

2.6.2 Examples

Many researchers had presented implementations for learning object annotation and we will explore some examples [**294**].

- Using WebProtege [**301**], Koutsomitropoulos et al. [**293**] created and developed a learning object repository to make managing and exploring learning objects easier. In order to promote integration with other discovery techniques, digital archives, and the Web of Linked and Open Data, they also had connected learning objects with a common data model for sharing and integrating knowledge organization systems via the Semantic Web called SKOS [**302**]. At the Democritus University of Thrace, the resultant technology has already been put into use to facilitate online classes [**293**].
- A metadata generator called DC-dot [**303**] was created by UKOLN (UK Office for Library and Information Networking), which is situated at the University of Bath. It is open source and may be updated or shared. It also generates Dublin Core metadata and has the ability to format output using a variety of alternative metadata standards.
- In order to automatically extract Dublin Core metadata metadata, Han et al. [**304**] suggested a machine learning approach utilizing support vector machines.

- Using a Java Servlet, Jenkins et al. [**305**] presented a method for automatically creating Dublin Core metadata on a web server, and ten of the essential metadata out of the fifteen are included in the description.
- Dublin Core information is also automatically generated from web pages by Li et al. [**306**]. The topic element is obtained by using a neural network, while the other nine components are produced using the same methods as Jenkins et al.'s [**305**] methodologies.
- An ontology-based method for automatically annotating learning objects based on IEEE LOM was presented by Jovanovic et al. [**307**]. In addition to some heuristics, content mining techniques were mostly employed to identify metadata items. It is possible to automatically construct pedagogic assets such as examples, summaries, and references. Sadly, only resources in slide format could be annotated.
- Kris Cardinaels et al. [**308**] developed a web service that automates the production of IEEE Learning Object Metadata.
- KIM automatic semantic annotation: The KIM platform [**309**] was created by Popov et al. [**310**] and offers an automated semantic annotation service. They construct it using the PROTON ontology [**311**] and a knowledge base that offers in-depth coverage of items of general relevance. The architecture of the KIM platform and its main components are shown in figure **2.18**. [**294**]

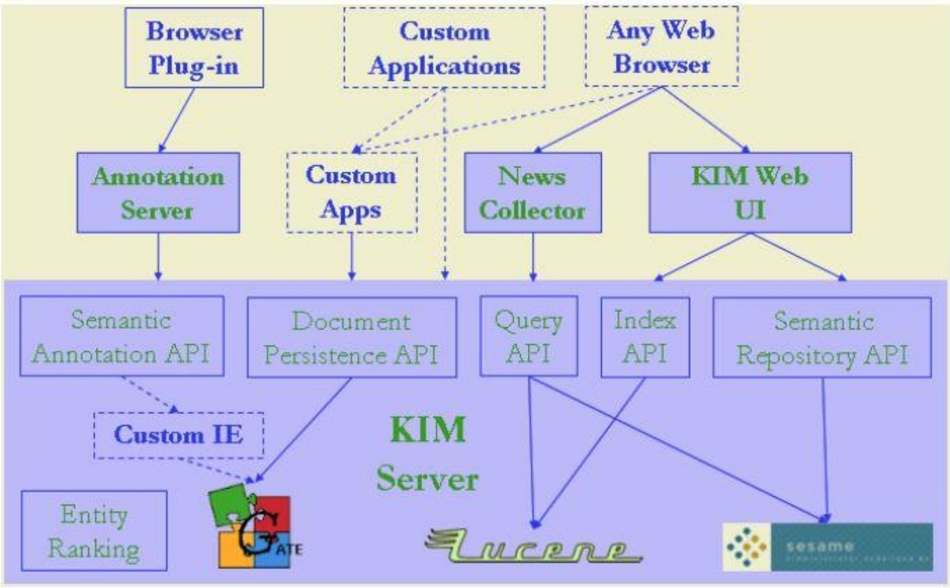


Figure 2.18: Architecture of KIM platform [310]

The fundamental concept behind KIM information extraction is the recognition of named entities in relation to the KIM ontology (KIMO), where the entity classes, hierarchical ordering, and suitable properties are also defined by the KIMO ontology. KIM information extraction is built on theGATE framework [**312**], an open source software toolkit supplied by the University of Sheffield that can solve virtually any text processing problem. Several of GATE's document management features were reused, along with generic natural language processing (NLP) elements like Tokenizer, Part-of-Speech Tagger, and Sentence Separator. Figure 2.19 shows the flow diagram of KIM semantic information extraction.

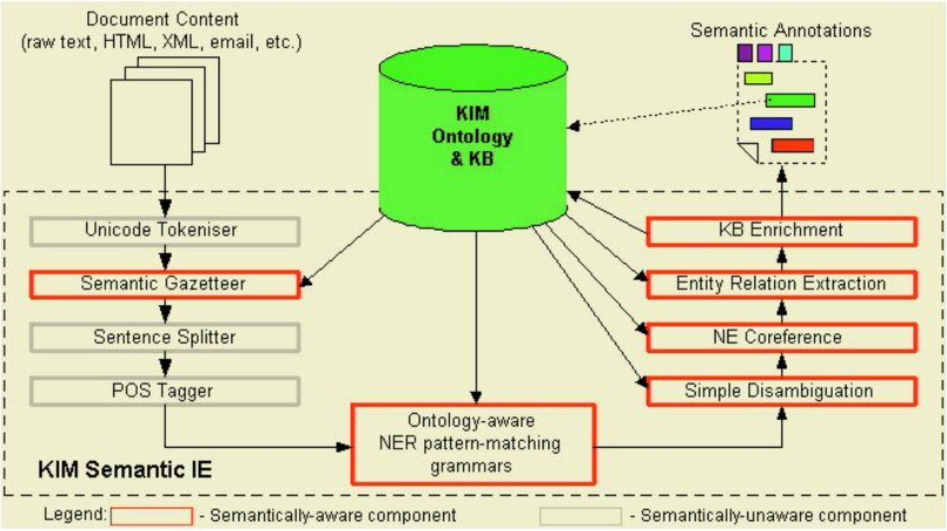


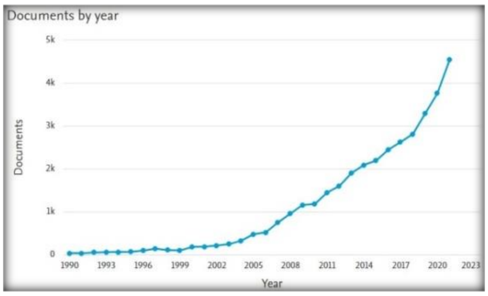
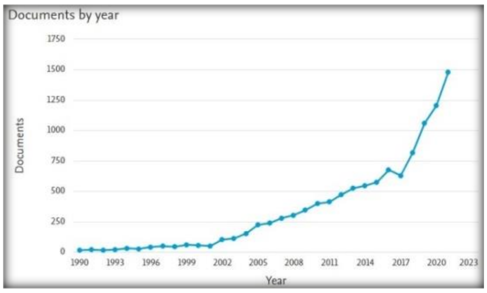
Figure 2.19: Flow diagram of KIM semantic information extraction [310]

2.7 Topic identification

Topic identification is crucial for many fields that use the computer power for analyzing text to make best use of it, or to automate hard processes that humans used to do with hard effort in large periods of time but, on the contrary, computers with the use of different techniques start to accomplish in a notably less time. But, to harvest the advantages to using computer power in these tasks, researchers have first to invent and identify the most suitable techniques for each specific field.
Topic identification has been used in many fields. Many of them are obvious such as education, information retrieval, document summarization, topic detection and tracking, text classification or recommendation. But other new fields have been used topic identification for enhancing other applications such as customer service, tourism, movie recommendation, and application reviews.
Thanks to the need for developing and improving in this field, many researchers have presented their contributions causing a growing number of research works.

By searching the Scopus database for the terms "Topic extraction" and analyzing the results by year we got 38,583 document results through the years 1990 till 2022 as shown in figure 2.20.

And by searching the Scopus database for the terms "Entity extraction" and analyzing the results by year we got 11,843 document results through the years 1990 till 2022 as shown in figure 2.21.

 **Figure 2.20: number of researches on "Topic extraction" in SCOUPUS database during 1990-2022 [313]**	 **Figure 2.21: number of researches on "Entity extraction" in SCOUPUS database during 1990-2022 [314]**

By browsing the available technologies that could help in this development, data mining was very obvious to use in addition to many other technologies that evolve and appear by the time such as machine learning and artificial intelligence. Data mining was very suitable for the nature of the data that needs to be processed, which is text in most situations. So we are going to explore some of the data mining methods that could be used.

2.7.1 Data mining techniques for topic identification

Data mining has two main categories that depend on the used technique and the available data. It contains supervised learning and unsupervised learning methods that could be applied in machine learning as well:

- Supervised learning [**315**] [**316**] is performed utilizing a ground truth, meaning that we have advance knowledge of the anticipated outcome values for our samples. Given a sample of data and desired outputs, a function that closely approximates the connection between input and output shown in the data is what is learned by supervised learning. It may be applied to classification or regression. Additionally, the foundation for creating a model that will subsequently be used to categorize new and unclassified data records requires training datasets and manually pre-classified records that have already been classified.

  One of the supervised learning approaches, Named Entity Recognition (NER) [**317**], assists the user in structuring a text such that pertinent information in the form of entities may be retrieved more quickly.
- Contrarily, unsupervised learning [**315**] [**316**] aims to infer the inherent organization contained within a set of data points, since it lacks labeled outputs. It is only dependent on output data and may be applied to clustering.

  Identification of frequent nouns and verbs, keyword clustering, and latent semantic indexing are some examples on unsupervised learning techniques [**318**] [**317**]:
    - To identify common nouns and verbs, they are recognized using part of speech tagging, followed by the extraction of common words and the presentation of the most crucial topics by the extracted word combination.
    - To create clusters of keywords, the k-Means clustering method is used on a term document matrix containing TF-IDF weighted review words, using cosine similarity as the distance metric. Then, words with a high TF-IDF value inside a cluster signify terms that frequently appear together in reviews and, as a result, represent latent topics.
    - Latent semantic indexing's (LSI) main objective is to minimize the diversity of terms in a text by making use of the fact that multiple words may be used to describe the same subject. LSI uses the statistical method of singular value decomposition and

TF-IDS to condense all comparable words inside a text into a concept, which is then applied as a latent semantic to all words that have the same meaning or that refer to the same subject. The last step is to employ the generated latent words to produce the main output for topic detection, which are latent topics.

2.7.2 Research examples on topic identification

Other research examples on topic identification include the following:

- In [**319**] Chris et al. presented TopCat (Topic Categories), a technique for identifying topics that recur in articles in a text corpus. Chris et al. identified related items based on traditional data mining techniques. Frequent item sets are generated from the groups of items, followed by clusters formed with a hyper graph partitioning scheme. Natural language technology was used to extract named entities from a document, and then look for frequent item sets. Next, groups of named entities were clustered, capturing closely related entities that may not actually occur in the same document. Finally, a refined set of clusters was produced, with each cluster representing a set of named entities that refer to a topic. [**47**]

- In [**320**] Veselin et al. presented an algorithm for opinion topic identification by developing a methodology for the manual annotation of opinion topics with the use of fine-grained subjectivity analysis, which could be useful for question answering, summarization, and information extraction. [**47**]

- In [**321**] Kino et al. presented a method for automatic topic identification using an encyclopedic graph derived from Wikipedia. Kino et al. used the unsupervised system Wikify [**322**] to identify the important encyclopedic concepts in an input text automatically. As Kino et al. mentioned "topic identification goes beyond keyword extraction, instead has to be obtained from some repositories of external knowledge". Kino et al. aimed to find topics (or categories) that are relevant to the document at hand, which can be used to enrich the content of the document with relevant external knowledge [**47**]. Comparing to our work we augmented Wikify with other services in addition to Gensim to produce better results and process bigger textual resources.

- In [**323**] Freidrich et al. presented a framework for the identification of primary research topics from within a corpus of related publications. Their method uses an unsupervised topic modeling approach to classify new and emerging topics from the entire corpus. Machine learning techniques were used, such as Non-negative Matrix Factorization for Natural Language Processing, as well as an adaptive topic model Bayesian classifier that allows for the identification of new primary topics as papers are added. [**47**]

- In [**324**] Khader et al. designed an ensemble method for automatic topic extraction from a collection of scientific publications based on a multi-verse optimizer algorithm as the clustering algorithm. [**47**]

- In [**325**] Zhou et al. proposed a topic identification approach for identifying emerging topics in application reviews. They decrease noisy data by utilizing natural language processing techniques, which also included rectifying misspelled words and lengthening acronyms. In order to handle the shortness feature of application reviews and follow their growth, they additionally employed the adaptive online biterm topic model [**326**].
  They base their strategy on three stages:

- Preprocessing, where the text is cleaned and prepared with natural language processing tools such as Natural Language Toolkit (NLTK) [**327**], Wiki Dictionary [**328**], PyCorrector [**329**] for correcting misspelled words, pointwise mutual information (PMI) [**330**] for extracting typical phrases, and co-occurrence frequency for identifying more meaningful combination of words.
- Emerging topic identification, where AOBTM [**326**] and anomaly detection methods are used for identifying emerging topics.
- Topic interpretation, where emerging topics are interpreted by labels.

− In [**317**], with data mining techniques, Menner et al. provide a general method for identifying subjects from tourist-related user-generated content. They accomplished their goal through four phases:
  - Document Retrieval, where they use a site crawler and particular regular expressions to get the reviews from the TripAdvisor social media platform.
  - Document Extraction**,** where they use additional regular expressions and XPath expressions to extract reviews from the HTML pages that the web crawler has gathered.
  - Document Processing, where each review is subjected to a particular preparation, such as tokenization, stop-words filtering, stemming, and the transformation to lower case, in order to make it suitable for each data mining approach. Ultimately, depending on values for term frequency or term frequency-inverse document frequency, all reviews are converted into a term document matrix.
  - Mining, where various data mining methods, including supervised and unsupervised learning via the data mining application RapidMiner Studio [**331**], were applied to the reviews.

2.7.3 Enrich topic identification with new ideas

Documents that refer to a specific topic might also refer to several sub-topics of it, and then the single-layer method could present problems to define the intended topics, even when a document is analyzed manually by human experts. A new multilayer topic structure was proposed in [**332**], which aims at automatically building a multilayer topic structure. This technique is intended to identify sub-topics where units within the same sub-topic should be very similar and units from different sub-topics should be dissimilar. The mentioned paper used the hierarchical agglomerative clustering algorithm to establish the hierarchical topic tree. It started by using each unit as an independent cluster. Then, the similar ones merged together. This process was repeated until all clusters merged into one cluster, and from this hierarchy a tree structure was established. [**47**]

By using multilayer topic structure [**332**], books with common topics will be semantically similar, and could be linked together to provide a network of resources that are related to a general topic. So, we can provide this information in a Dynamic Interactive Knowledge Graph [**47**], which can be updated continuously with every new added book to the database, and can be browsed by every user. This graph-based learning technique is an emerging search field and proved to be effective and useful for the learning process for students and teachers, as Weber et al. [**48**] stated that the graph-based learning technique improves searchability for new sources and provides explainable results and result recommendations. [**47**]

Zhijun et al. [**333**] also used an interactive group knowledge graph to visualize the relationship between knowledge points concluding that interactive group knowledge graphs have a significant promotional effect on teachers' online learning, that it is beneficial to teachers' professional development, and that it is an effective method of enhancing the depth and breadth of the interaction of students' learning. In addition, Zhijun et al. [**333**] defend that the process of generating collective knowledge graphs can enhance students' enthusiasm for autonomous learning and promote meaningful and in-depth interactions between different students. [**47**]

2.8 Important tools for our system

After exploring all the previous topics we must mention a specific set of tools that play a crucial role in our system, which are Wikipedia Miner, TextRank, BM25, and Gensim. We will elaborate more about them in the next sections.

2.8.1 Wikipedia Miner

Wikipedia [**334**] is an enormous, continuously expanding tapestry of linked pages that serves as an online encyclopedia. For programmers and academics, it is a massive, multilingual library of concepts and semantic relationships that may be used as a resource for natural language processing and a variety of other fields of study [**335**]. But there was a need for a tool that provided advanced services to make the best use of such an unexplored mine of knowledge. Wikipedia Miner [**336**] is an open-source software system that uses the articles in Wikipedia to extract and identify the main topics in text through its rich semantics. With the use of a Java API, it builds databases with condensed versions of Wikipedia's structure and content. The articles, categories, and redirects on Wikipedia are organized into classes that may be effectively searched, browsed, and iterated through. XML-based web services, machine-learned semantic relatedness metrics and annotation features, and parallelized processing of Wikipedia dumps are some of the advanced features the toolkit offers.

Furthermore, it contains a topic detector feature that gathers all labels in the document. For most documents, Wikipedia probably knows something about the topics discussed and could likely add additional information. Once Wikipedia Miner detects the topics within a document, it is easier for automatic systems to process those learning resources for tasks such as classification, recommendation, or data retrieval [**47**]. The Architecture of the Wikipedia miner toolkit [**336**] is shown in figure 2.22.

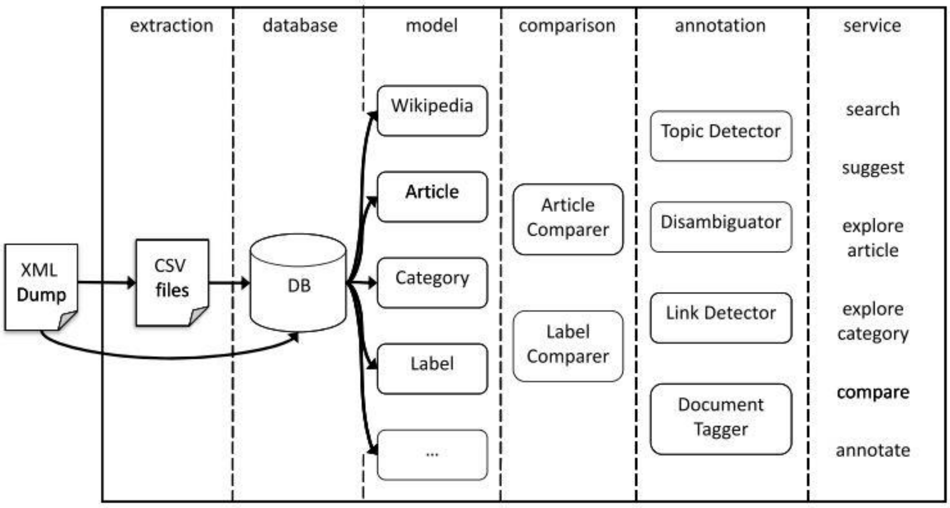


Figure 2.22: a description of the Wikipedia miner toolkit's architecture [**336**]

Wikipedia and Wikipedia Miner have been used in many fields such as automatic topic indexing [**337**] , document clustering [**338**], document summarization [**339**], the classification of multilingual biomedical documents [**340**], converting concept-based representations of documents from one language to another [**341**], identifying the prerequisite relationships among learning objects [**342**], classifying news articles [**343**], evaluating and classifying Open Educational Resources and OpenCourseware based on quality criteria [**344**], and for group recommendation by combining topic identification and social networks [**335**].

2.8.2 TextRank

TextRank [**345**] is a graph-based ranking algorithm that could be used for keyword extraction, or sentence extraction, but before discussing it we have to explore graph-based ranking, which uses voting or recommendation as its fundamental concept.

To utilize graph-based ranking algorithms on natural language, it is important to create a graph that represents the text and connects words or other text elements with appropriate relationships, where text units of varying sizes and qualities, such as words, collocations, full sentences, or other text units, can be included as vertices in the graph, depending on the application at hand. Linking to another vertex is essentially a vote for that vertex. A vertex's significance increases as the number of votes cast for it increases. Moreover, the ranking model considers the significance of the vertex casting the vote, which impacts the significance of the vote itself. [**345**]

The following major steps are involved in applying graph-based ranking algorithms to natural language texts: [**345**]

- The first step is choosing the text units that best describe the current work, adding them as vertices on the graph.
- The second step is finding the relationships that link these vertices, then use those relationships to create edges between the vertices, where the edges may be weighted or unweighted, directed or undirected.
- The third step is repeating the algorithm all over the graph and text till convergence.
- And finally, vertices are sorted according to their ultimate score to be ready for selection decisions.

For determining the significance of a vertex inside a graph, TextRank considers global information that is recursively derived from the whole network, as opposed to only local vertex-specific information. Kleinberg's HITS algorithm [**346**], Google's PageRank [**347**], or Positional Function [**348**] are comparable to TextRank, and are simple to include into the TextRank model [**349**].

Rada et al. [**345**] explored and assessed the use of TextRank for two tasks related to natural language processing, sentence and keyword extraction. In the keyword extraction task based on lexical and grammatical properties, their system is taught to identify keywords in a document, where this strategy was initially proposed in [**350**] using a genetic algorithm and parameterized heuristic rules. However, in [**351**] better results were obtained through the use of the Naive Bayes learning scheme. A higher level of results were presented in [**352**] by using a supervised learning system and a mixture of lexical syntactic features.

TextRank works as follows: [**345**]

- Text processing (tokenization, annotation, tagging, and syntactic filtering).

- Adding text units to the graph as vertices, and linking every two vertices that occurred in the same word.
- Repeat the previous step until the whole graph is completed.
- Assigning default weight =1 for all vertices, then run the ranking algorithm over the graph until it converges.
- Finally, sorting vertices in reverse order according to their weights, keeping top vertices for further processing.

TextRank is known to be extremely adaptable to various domains, genres, or languages because of its limited need from linguistic knowledge and language specific annotated corpora [**345**]. It gains reliability and efficiency by not depending solely on the local context of a text unit, but instead relying on information drawn recursively from the entire text. It has been used in different research fields such as social networks, analysis of the link-structure of the World Wide Web, and citation analysis. [**345**]

From the previous discussion we can see that TextRank could be useful in our research, and could have an active role in our system, but it could be improved and enhanced with the next algorithm as we will discuss.

2.8.3 BM25

TextRank calculates the similarity or the relation between two phrases or words based on the content they share. To avoid boosting big sentences, this overlap is simply calculated as the number of shared lexical characters between them divided by the length of each. There are numerous metrics for identifying relations between phrases or words, which are represented on the graph by the edges connecting the vertices: overlapping words, cosine distance, and query-sensitive similarity, or by combining the previous ones with supervised learning functions [**353**]. And the same techniques could be used for creating summaries of documents by extracting and combining the most important sentences (vertices) from the documents [**354**].

The 1970s and 1980s saw the invention of one of the most effective text-retrieval algorithms, BM25, which served as the foundation for the Probabilistic Relevance Framework (PRF), a formal framework for document retrieval [**355**]. BM25 is a probabilistic variant of the TF-IDF model [**356**], where BM25+ is a variant of BM25 that modifies the penalty for lengthy documents [**357**]. And since TextRank requires a similarity calculation technique, and BM25 supports this task with a superior quality, then augmenting them both had already provided significant improvements [**345**].

According to [**358**], they tested many different techniques to calculate the similarity between vertices for TextRank, and the best results were provided by BM25 and BM25+. They mentioned that the robust method for artificial summarization that is produced by combining TextRank with contemporary Information Retrieval ranking functions like BM25 and BM25+ outperforms the prior standard strategies. [**358**]

And last, but not least, we are going to give a short hint about the very useful multi tool of data analysis, Gensim.

2.8.4 Gensim

Gensim [359] is a well-known rich Python library that has a great amount of useful tools for many fields. It was mainly created for two areas: indexing and similarity searching for digital documents, or the Latent Dirichlet Allocation and Singular Value Decomposition methods, which are quick, memory-efficient, and scalable. The basic algorithms of Gensim's large-scale, distributed, online SVD and LDA are comparable to the Swiss Army knife of data analysis, despite the fact that it was designed for massive digital libraries. Additionally, it has applications that are independent of the field of natural language processing. The Latent Dirichlet allocation (LDA) [360] topic model develops topics based on word frequency. It is a three-level hierarchical Bayesian model in which each component of a collection is represented as a finite mixture over a foundational set of subjects. Every topic is modeled individually as an infinite mixture over a base set of topic probabilities. The topic probabilities give an explicit representation of a document in the context of text modeling. Singular Value Decomposition (SVD) [361] [362] is a tool for data reduction that allows us to take high-dimensional data and reduce it to its essential components for analysis, interpretation, and description.

3. Our system Contribution

All the proposed system is just a design without implementation except our algorithm for the topic identification part, which has been implemented, tested and evaluated as we will explain in chapters 4 and 5.

In previous chapters we introduced the main topics related to our research objectives. In this chapter we will present the design of our system, exploring it and the interaction between its parts.
We present the design from three different perspectives: e-learning, semantic web, and cloud computing. In each perspective we will see the required areas to augment into our system, how the system will manage and use these parts, and how system users will benefit from them. After presenting and elaborating our system from the three main perspectives we will show the full design.

3.1 E-learning perspective

In our system we want to present a student centered learning style, considering the individual differences and requirements for each learner, and taking into account their different learning styles and previous knowledge levels. The adaptive e-learning model [**92**] is the most suitable for our goals. In order to benefit from its advantages, we have to overcome the following challenges:

- Identifying the preferred learning style for each learner.
    - By applying a questionnaire [**91**] before logging into the system to prepare the relevant learning content and presentation method.
- Measure learner's previous knowledge level.
    - By giving each learner a pre-test [**91**] prepared and evaluated by the institution staff.
    - To determine the appropriate knowledge level for the student, Ghatasheh proposed in [**156**] a concept for a dynamic e-learning environment based on machine learning and the study of user activities
    - By mixing the questionnaire's result with the pre-test result useful information could be concluded about learners regarding their preferred presentation and study method, level in courses and materials to start with, and future learning path recommendation.
    - Additionally, with a good amount of information provided from the learner, we can conclude more useful and advanced information regarding skills and goals. All the required information is saved to the learner's profile on the learner's data repository for future use with the information that will be recorded in the future about their courses, evaluations, and paths. In figure 3.1 we present the required steps before logging into the system.
- Prepare each individual course in various formats and styles.
    - Where teachers, educational specialists, and information technology staff have to collaborate to produce this variety of learning resources and upload them onto the system platform repository to be ready for learner's requests.
    - The learning resources could be text, audio, video, practical exercises, virtual reality experiments, or any other format. In figure 3.2 we present the learning resources preparation process.

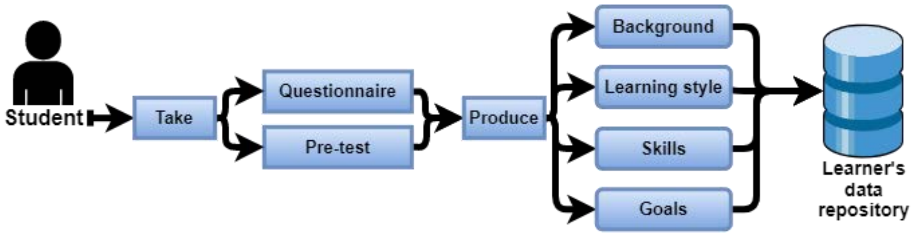


Figure 3.1: required steps before logging into the system

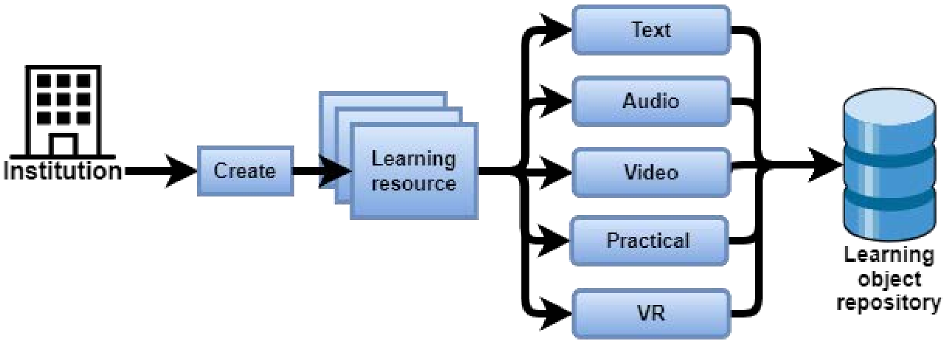


Figure 3.2: learning resources preparation process

After providing the required learning resources and learners starting their journey through our e-learning system, a very important process has to work in parallel: the observation process. The continuous observation for learner's activities and evaluations helps improve the system adaptivity and makes it dynamic through the use of data mining techniques and data analysis [**91**], and the more the observed information the more adaptivity will be provided. In figure 3.3 we present the continuous observation process.

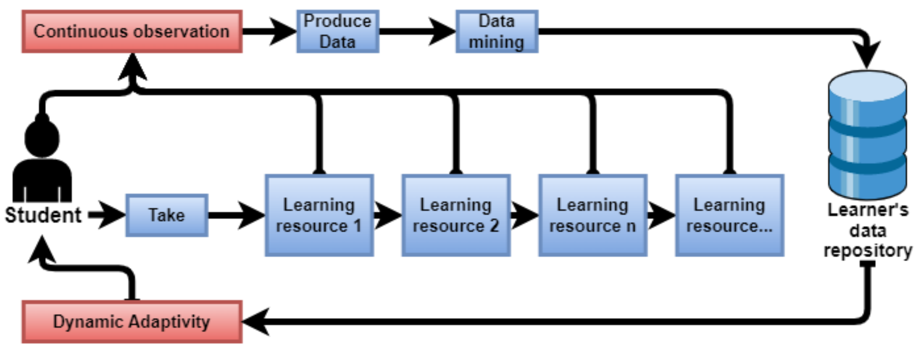


Figure 3.3: the continuous observation process

Other factors such as a student's personality, learning in social groups [**103**], active student participation, and motivation could enhance the learning experience if taken into account through the design process [**102**]. Additionally, there are many theories that we mentioned previously in chapter 2 such as the Learning as a Network learning theory [**43**] and the connectivism theory [**44**] [**45**], which proved to be effective and more productive in the learning process, and fortunately they are totally adequate for our goal of creating an interactive knowledge graph [**47**] [**48**].

For all those reasons we are going to apply the Learning as a Network learning theory [**43**], and the connectivism theory [**44**] [**45**] into our system through the use of students' properties, which come from the first login stage, or from the continuous observation information, which is stored

in learner's data repository, or even from commonly taken or favorite learning objects from the learning object repository.
Data mining techniques and recommendation tools are used for recommending other students with common interests to enable students forming their learning groups as shown in **figure 3.4**.

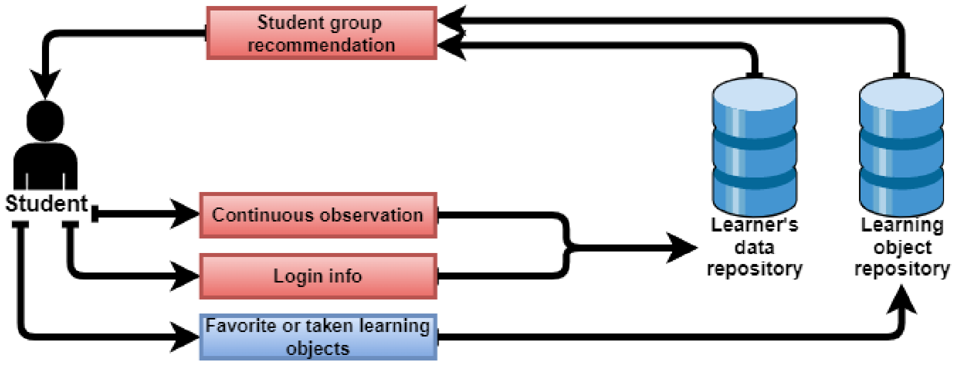


Figure 3.4: Student group recommendation

Another technology that proved to be useful is augmented reality (AR). Many researches showed its effectiveness and positive impact on students' performance [**107**] [**108**] [**109**] [**110**] [**111**] [**112**] [**118**]. The system will support AR materials that students can interact with individually or in groups, to make the learning process more interactive and exciting.

3.2 Semantic web perspective

Representing the learning resources or any kind of information on the computer without giving it the ability to understand its meaning only allows us to compare and search specific keywords. On the other hand, representing the same information semantically on the same machine opens a huge gate of abilities due to the information understanding ability. The semantic representation in the e-learning system also requires adding metadata for learners, learning objects, and learning domains. In this section we present some design guidelines for this part of the system, in addition to exploring some processes and interactions that help enrich the semantic information content.

3.2.1 Learner

Because our system aims to be learner centered and uses the social learning model, we must provide learner's data in both social network and e-learning structures. From the social network point of view we used the friend of a friend (FOAF) ontology [**363**], which allows groups of people to form social networks without the need for a centralized database. It enables our system to support the social learning activities and improve the interaction between learning group members, in addition to the great advantages that could be gained from social network analysis [**157**] to support the learning process and sharing information between different systems. According to the FOAF, ontology each learner has a unique identifier, name, mail, homepage, interests, and a "knows" property that links to other learners.

In addition to these properties, we must use the learner's learning history and learning preferences such as: learning style, knowledge level, taken courses, tests evaluations, and all other continuous observation information, as shown in figure 3.5.

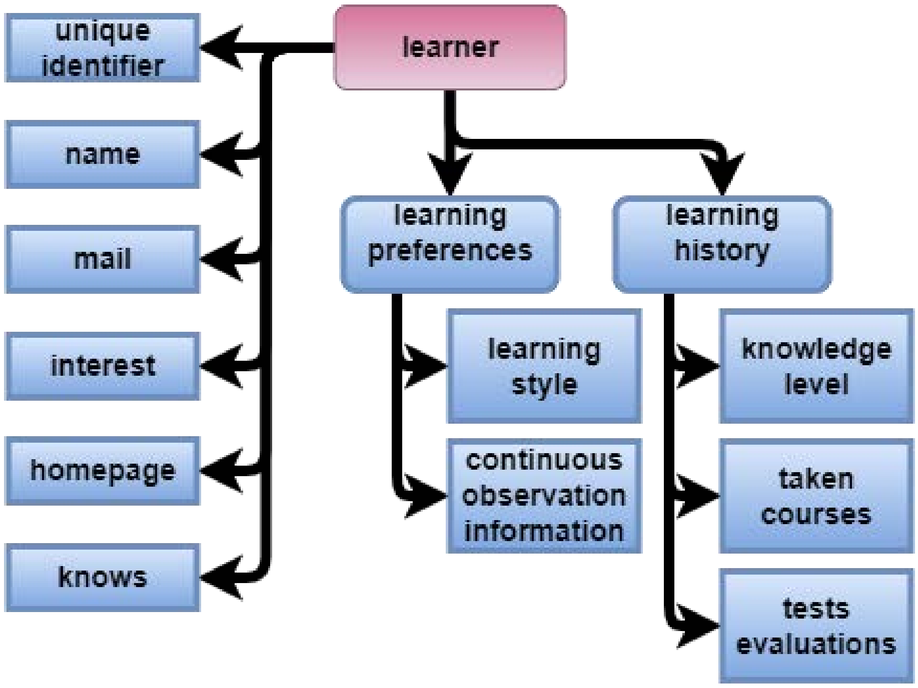


Figure 3.5: Some leaner's properties from FOAF Ontology [363]

Another learner's ontology that could be useful for our system, which includes more required information such as knowledge, learning goal, mastered content, learning interest, learning style, learning time, and location, was presented by Yu, Zhiwen, et al. in [**188**] as shown in figure 3.6.

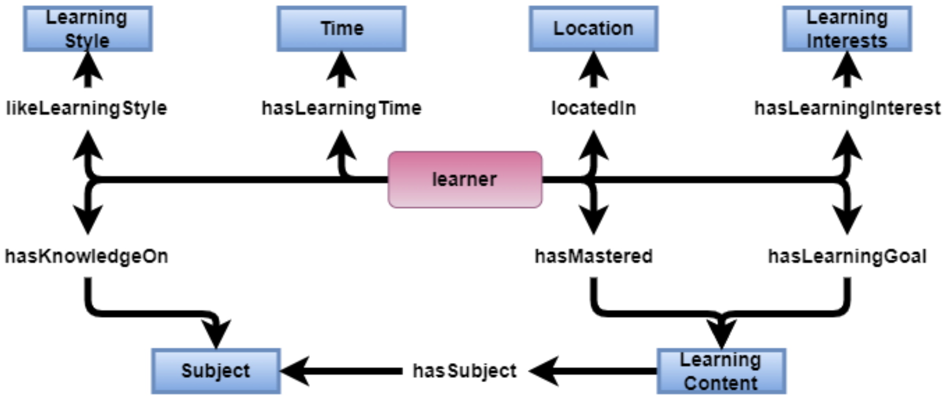


Figure 3.6: Learner Ontology [188]

We are going to use a combination of both ontologies to represent learner information, as shown in figure 3.7.

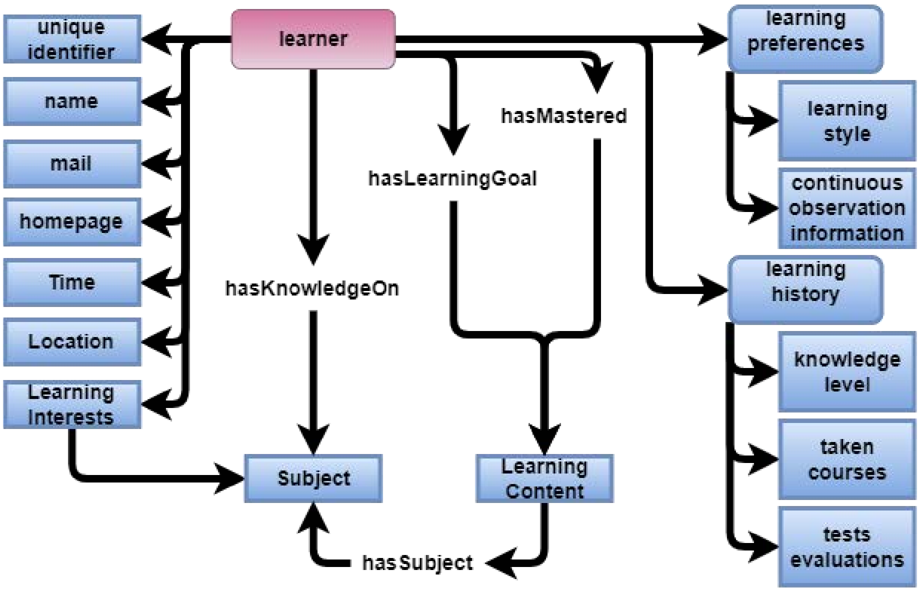


Figure 3.7: Our representation for Learner Ontology

Moreover, the personality information should be taken into account due to its positive impact on the learning process [**144**]. This information could be collected from: the Myers–Briggs Type Indicator (MBTI) questionnaire [**364**], the continuous observation process by the system or teachers, or from the learners' friends in their learning group. The MBTI questionnaire attempts to assign a value to each of four categories: introversion or extraversion, sensing or intuition, thinking or feeling, and judging or perceiving. This evaluation helps in identifying how people perceive the world and make decisions. Other factors could be activated in the future through the use of emotional data observation technologies to be augmented into the dynamic adaptivity.

3.2.2 Learning domain

For describing the learning domain, each subject has its own domain that describes different courses, topics, and the relations between them. The teaching staff within the institution has the responsibility for organizing each learning subject domain to guarantee that it contains all the required topics and they are in the right order. An example of learning domain ontology is presented in [**188**], as shown in figure 3.8, which includes the learning domain for computer science subject.

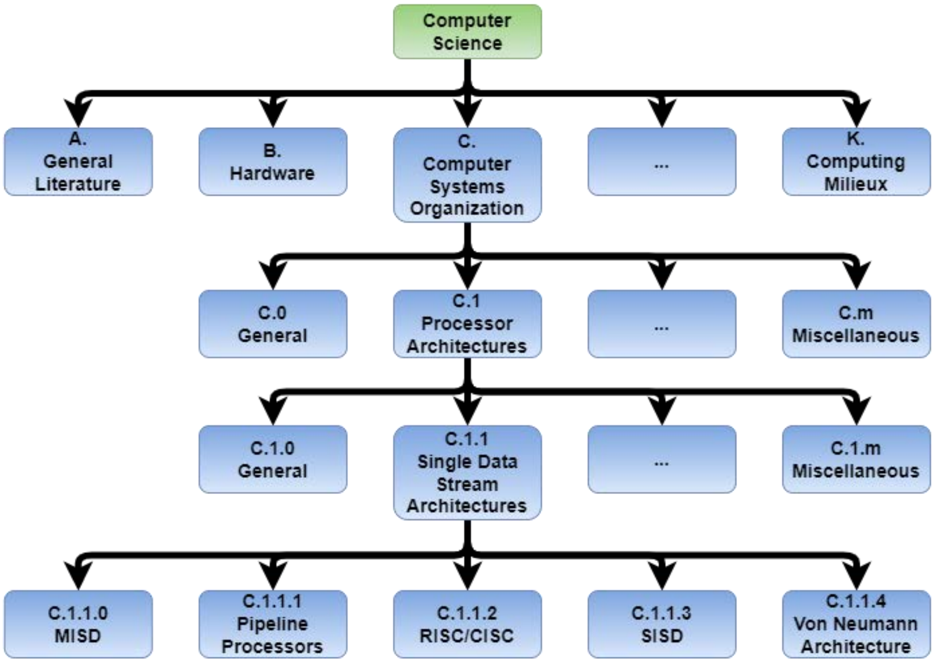


Figure 3.8: learning domain example for computer science subject [188]

3.2.3 Learning object

According to [152] , in order to describe a learning object semantically three representations are required: content, context and structure, as shown in figure 3.9.

- Content representation: it describes learning materials or learning objects by identifying general properties such as title, type, language, author, prerequisites, and so on.
- Structure representation: it describes the logical structure of learning objects and how they are ordered in the learning path, taking into account which learning object is a prerequisite for which.
- Context representation: it defines different presentations techniques and formats for the different learning styles.

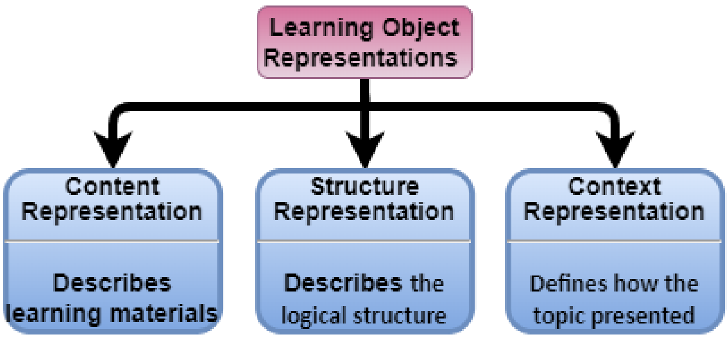


Figure 3.9: Learning object representations [152]

The semantic representation should be replicated for the same learning object for each offered learning style when adding these semantic representations within an adaptive e-learning system. For example, if we have a learning object (LO1) that has the three semantic representations (content1), (context1), and (structure1), this learning object LO1 could be used for visual, auditory, or tactile learning style as shown in figure 3.10. Although it takes a lot of work to create, its reusability and wide range of learning styles are major advantages.

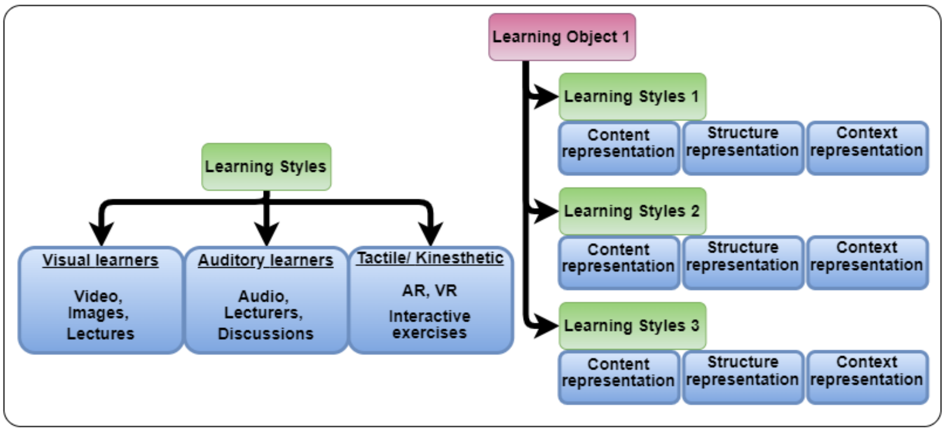


Figure 3.10: Example of required Learning object representations

The content representation should be the same. However, the context and the structure representations could be changed according to the learning style in use. For the general representation, the Dublin Core learning object metadata [**150**] [**298**] could be used. It includes metadata elements helpful for general-purpose applications, but it is devoid of information about a document's pedagogical perspective.

Consequently, other metadata standards, including IMS Metadata, SCORM Metadata, CanCore, and IEEE Learning Object Metadata, have been developed to address educational concerns. These standards contain attributes that describe the pedagogical characteristics of the learning object, so that it is very suitable for our representation. The IEEE LOM elements are shown in figure 3.11.

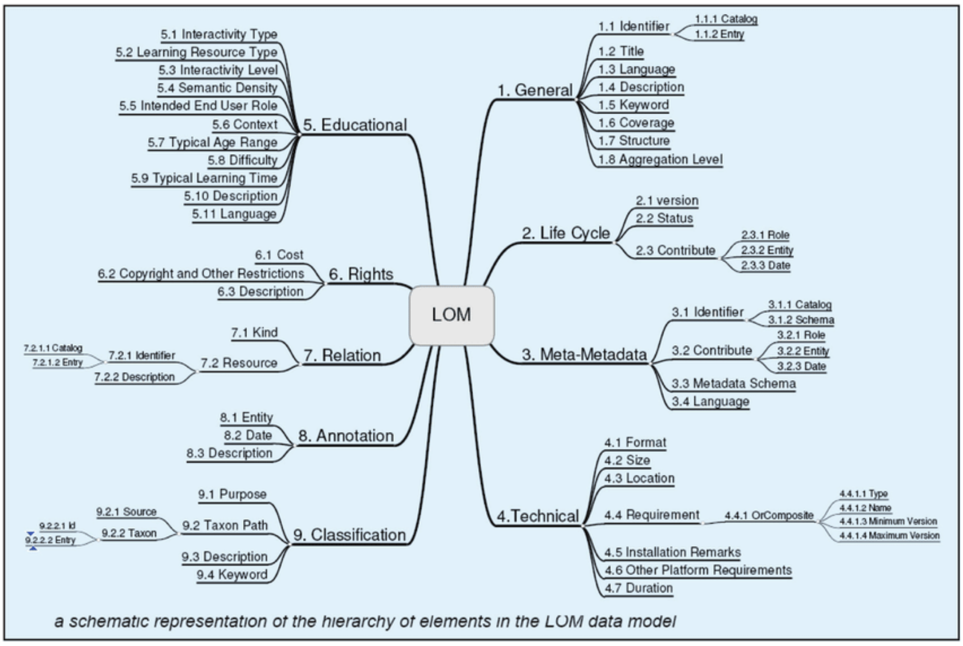


Figure 3.11: IEEE LOM elements [365] [366]

Another simple model for describing learning content is presented in [**188**] as shown in figure **3.12**, including keyword, subject, difficulty, author, language, title, content type and interactivity.

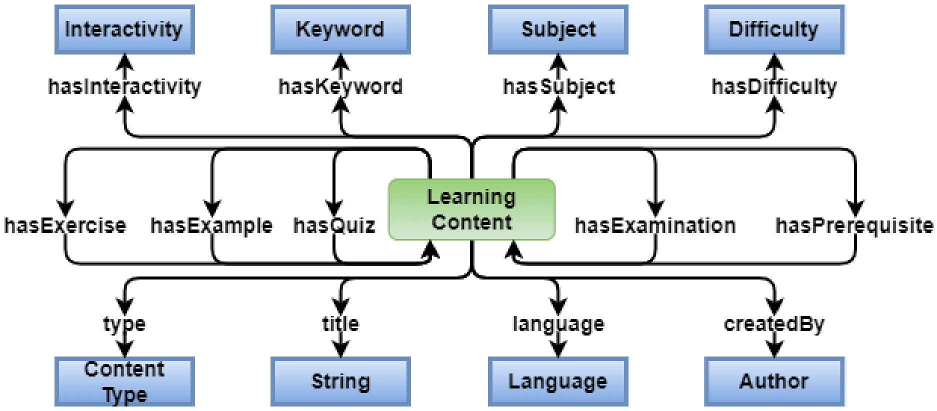


Figure 3.12: Learning Content Ontology [188]

In order to facilitate and speed up the learning objects annotation process for the enormous amount of educational resources available, we can use the automatic semantic annotation KIM platform [**309**] that was created by Popov et al. [**310**]. We additionally could augment KIM's annotation results with the ontology-based automatic annotation method that was presented by Jovanovic et al. [**307**] for learning objects based on IEEE LOM.

3.2.4 Enriching learning content

For enriching learning content, more semantic information could be produced and augmented into our semantic database using the LOD (linked open data) tool created by Garcıa et al. [**154**] and DBpedia through the use of natural language processing, entity recognition, and semantic information. Nevertheless, the teacher's role is vital during the data augmentation phase, where the teacher must select and approve the valid extracted data to be added into the learning content.

In order to find relevant entities to display to the user, LOD [**154**] analyzes the learning content provided by the LMS system (Sakai LMS). Lessons content will initially be displayed without any enhancements when the teacher first accesses the application. The teacher will receive a list of checkable entities if they select the import option, which will cause an entity recognition algorithm to be run. These entities are listed with a confidence level that indicates the likelihood that they will really be included in the lesson content. The system will eventually display the lesson content with the enhancement applied once the teacher has chosen the pertinent entities as shown in figure 3.13. The problem with this system is that it builds upon a specific LMS (Sakai), but the authors planned to solve this problem in their future work.

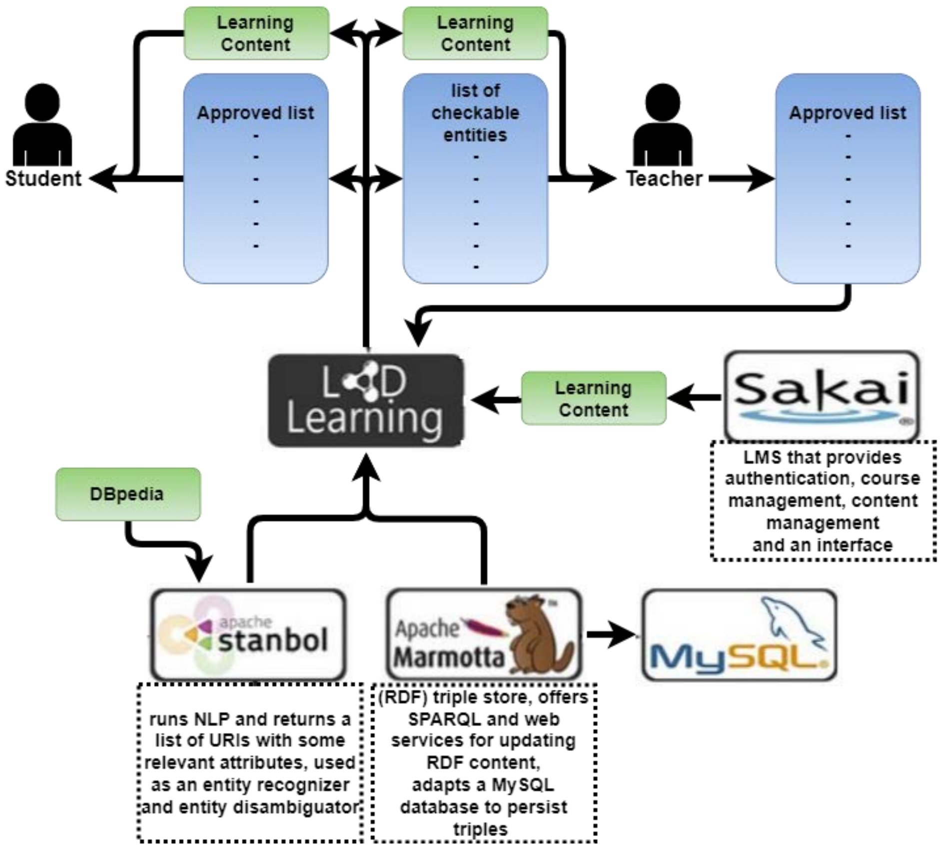


Figure 3.13: Components of LOD (linked open data) tool [154] for enriching learning content

We are going to use the LOD tool [**154**] for semantic information enrichment after adding our modifications on the entity recognition and topic extraction algorithm and augmenting it with WikipediaMiner. And finally, searching Wikipedia, or other external resources, for the topic and related topics. At this stage it is the institution's or the teacher's decision to enable adding the new resources to the learning object repository or just adding the links to the learning object metadata as extra helpful resources.

3.2.5 Knowledge discovery

We had created our own algorithm for topic identification using Wikipedia miner and machine learning techniques, which will help discover the semantic knowledge within text. We will provide a full explanation about our algorithm in chapter 4.
Another useful tool for knowledge discovery, which could be beneficial for our system, was proposed by Capuano et al. in [**172**], called Electronic Justice Relationship Management (eJRM). It uses legal ontologies created by enriching numerous thesauri with common sense knowledge from Wikipedia, in addition to other components such as:

- SEMANTO [**183**], a graphical ontology management system for knowledge discovery that allows for the updating, erasing, saving, and restoring of several ontology versions.
- The algorithm described in [**184**], which automatically links each ontological notion to a series of phrases that are weighted and correlate to Wikipedia subjects, thereby enhancing semantic information material from outside sources.
- The algorithm described in [**185**], to identify terms from many ontologies that correspond, creating an integrated ontology as a consequence.

And for semantic search they follow the following steps:

- From a user-input text, extract pertinent concepts using the knowledge discovery process described in [187].
- Using the common sense knowledge base of Wikipedia, extracted concepts are then enhanced with terminology from external sources.
- Concepts are then organized into categories based on how closely they match up with terms in the managed legal ontologies, and they are linked to the repository of legal documents maintained by the Italian Supreme Court of Cassation.
- By comparing the enhanced terms with those associated to the ontology concepts, it is feasible to find pertinent legal concepts linked to the input text while doing a semantic search for related material.

The knowledge discovery process of the eJRM tool [172] is shown in figure 3.14 as we understood from their paper.

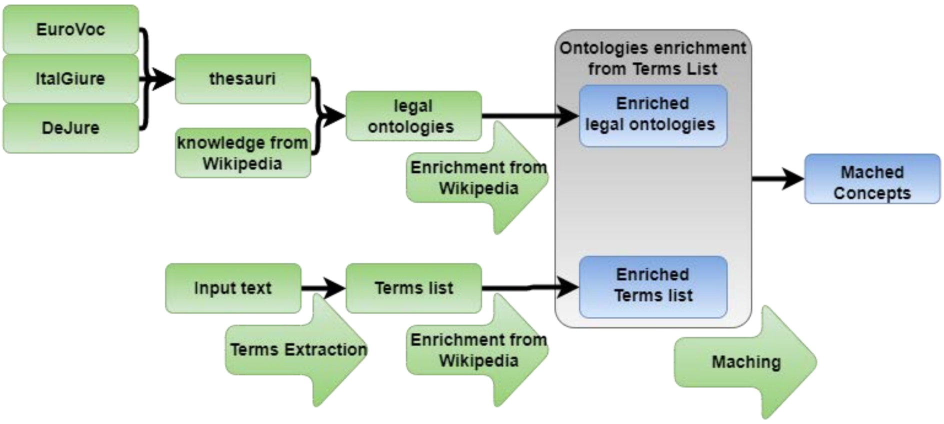


Figure 3.14: The knowledge discovery process of the eJRM tool [172]

3.2.6 Learning path generation

Another important service for students is the creation of learning paths that align to their learning goals and background. Capuano et al. in [172] presented a good idea for providing a training path for learnersas shown in figure 3.15 by:

- Extracting concepts from input text.
- Sorting the concepts according to their educational relationships
- For each concept, finding related learning material/materials from the learning object repository.

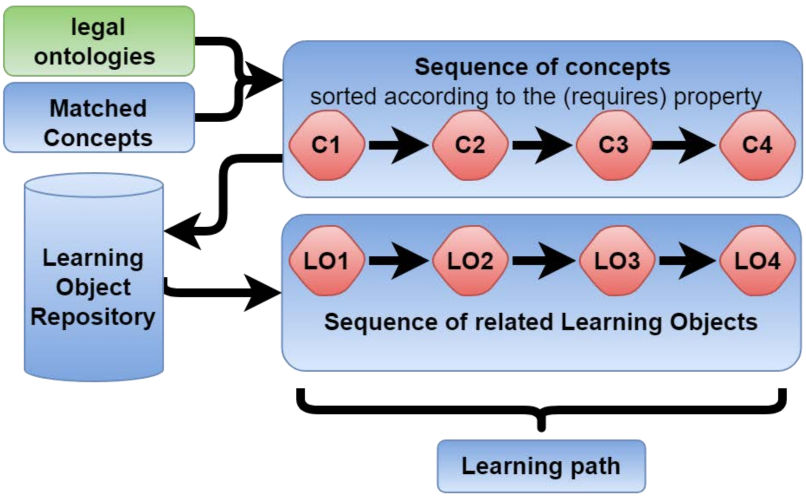


Figure 3.15: The training path generation process [172]

By augmenting the previous steps with the "prerequisite" and "difficulty" properties of the learning objects, in addition to the "knowledge level", "learning goal", "learning interests", "learning style", and "learning history" properties of the learner, we will have the ability to produce fully customizable learning paths for each student independently as shown in figure 3.16.

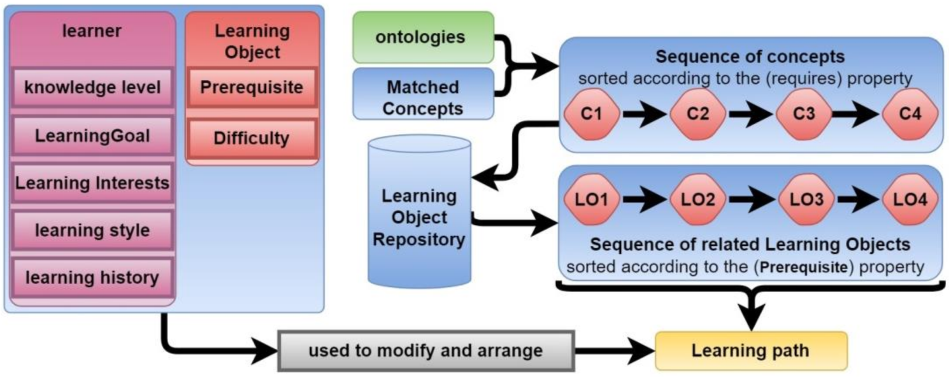


Figure 3.16: The customizable learning path generation process

3.2.7 Semantic recommender system

With the continuous development of e-learning more and more learning objects are generated, making finding the required learning object a hard task. In order to tackle this problem, our system must provide an up-to-date recommendation service that augments the required technologies for helping learners and ease the learning process.
The general process of e-learning recommendation is presented in [**241**] as shown in figure 3.17.

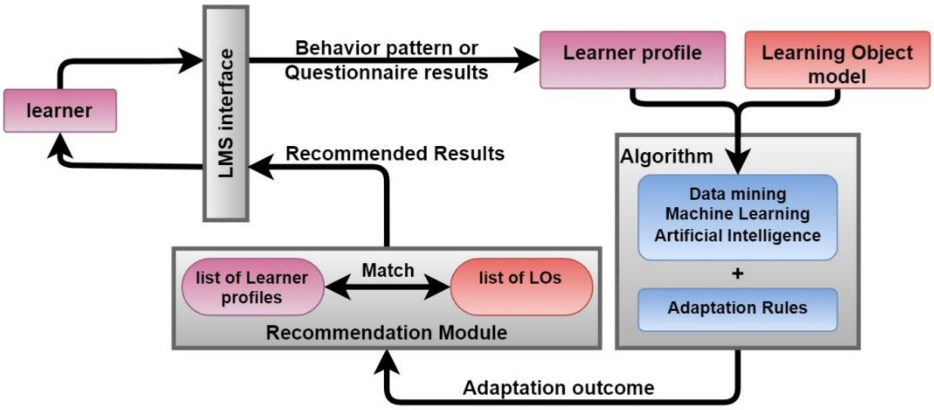


Figure 3.17: The general e-learning recommendation process [**241**]

The steps of the recommendation process are presented in [**188**]**,** as shown in figure 3.18.

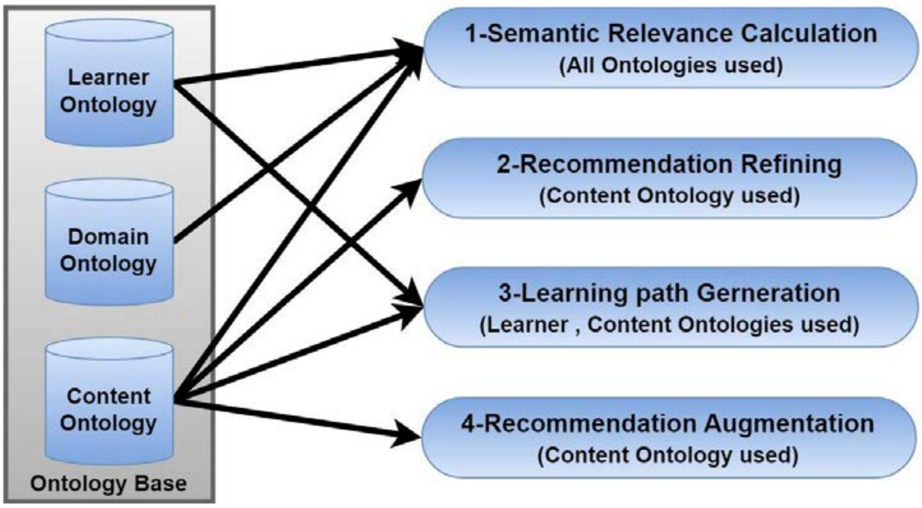


Figure 3.18: The recommendation process [188]

In addition to the previously explained types of recommenders that were discussed in chapter 2, section 2.5.1, the recommendation service will be a hybrid recommender of different types to eliminate the limitation of each individual type. It will apply:

- Collaborative filtering, by gathering feedback and previous learners' opinions about learning objects.
- Social-network recommender, by using already-existing social networks to spread educational content and stimulate demand for it while also making use of the knowledge gained from the learning group structure we deploy.
- Content-based recommender and ontology-based recommender, by using the knowledge amassed about the learner and the learning object to bring them together and deliver the necessary resources in accordance with preferences, objectives, and educational background.

The interaction between the different recommender types are shown in figure 3.19.

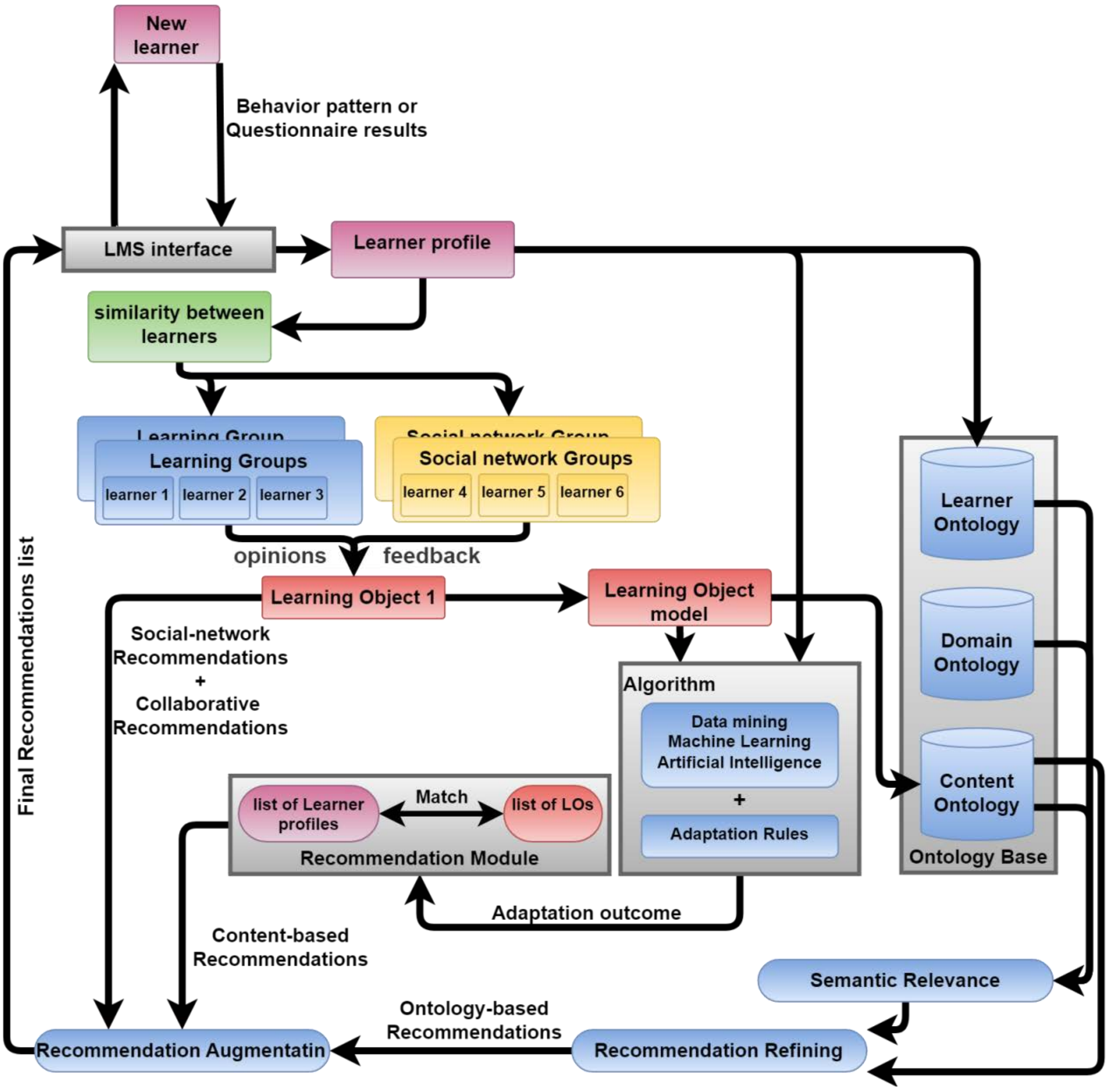


Figure 3.19: Our recommendation process

The recommendation process starts when a new learner enters the e-learning system, where the result of a questionnaire is analyzed, or a behavior pattern is downloaded from another system, providing the required information about the learner.

The learner profile information is stored into the learner ontology and fed also into a similarity function to calculate the similarity between the new learner and previous ones, in internal learning groups and external social network groups. For both types of learners groups, opinions and feedback about each learning resource are collected and stored into the learning object model and fed into the content ontology.
Based on the similarities to other users estimated by the system, it produces social network recommendations and collaborative recommendations.
Next, the learner profile information, in addition to the learning object model, are fed into different machine learning algorithms with adaptation rules to get the adaptation outcomes, which are in turn fed into a recommendation module that matches learners information with learning objects information to produce the content based recommendations.
The ontology recommendation list is produced by using the learner ontology, the content ontology, and the domain ontology as proposed in [**188**].

Finally, all recommendation lists are combined and redundancy is removed, and learning objects are sorted according to learners' needs in the recommendation augmentation module, to produce the final recommendation list.
We can present the recommendation list in a dynamic interactive knowledge graph to enhance search ability.

3.3 Cloud computing perspective

Now we are going to explore our system from the third perspective, which is cloud computing. As we saw in the previous section, there are many tasks to handle such as learning object storing, retrieving, and recommendation, data augmentation, learner's data storing and continuous observation, topic identification, data mining, and data analysis for dynamic adaptivity. All those tasks require a great computational power that, in turn, requires a big team of workers for operation and maintenance. Additionally, the required tasks could be scaled up or down according to the number of users and learning objects. The use of cloud computing services is the most feasible solution for this scenario.

According to [**196**] [**193**] [**194**] and [**192**], there are three service models for cloud computing: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS), as we mentioned in chapter2, section 2.4, as shown in figure 3.20. According to [**202**], IaaS includes servers, virtualization, storage, and networking; PaaS includes middleware, operating system, and runtime in addition to all IaaS components; SaaS includes data and applications in addition to all PaaS components. We can also see that PaaS builds upon IaaS, and SaaS builds upon PaaS.

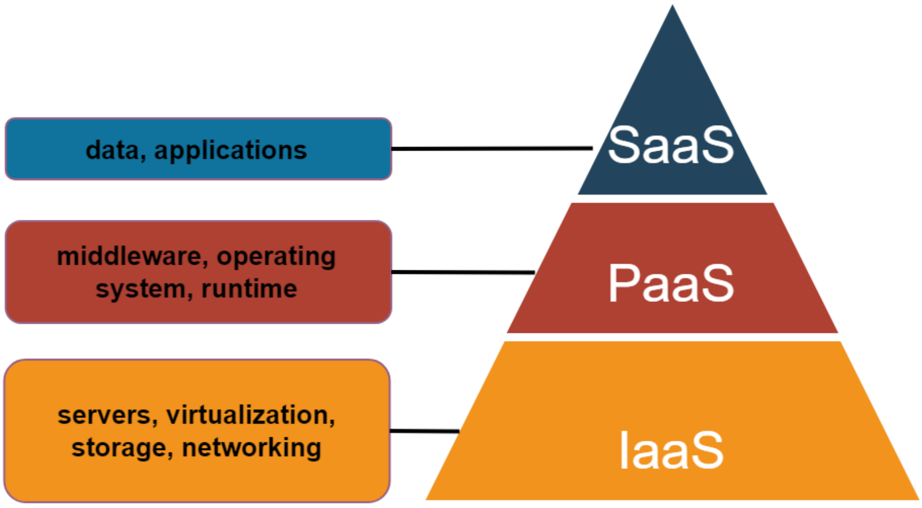


Figure 3.20: Service models for cloud computing [**202**]

Other categories could be branched from the previous main three such as: Data as a Service, Storage as a Service, and Hardware as a Service, as we explained in chapter 2, section 2.4, where Data as a Service refers to hosting and provision of data in various formats and from numerous sources, and Storage as a Service refers to hosting and delivery of virtualized storage on demand.
Regarding our system needs, we will use:

- Platform-aaS cloud, to build our own applications and provide the required services including learning object storage, retrieval, and recommendation, topic identification, data augmentation, learner's data storage, continuous observation, data mining, data analysis for dynamic adaptivity, learning groups and learning activities management, and dynamic knowledge graphs generation and updating.
- Hardware-aaS cloud, to provide the required computation power for our system tasks.
- Data-aaS cloud, to provide the required learning resources and learners' data, at the beginning.
- Storage-aaS cloud, to provide the required expandable storage for learning resources and metadata.

Finally, our system will be provided for teachers, students, and institutions as Software-aaS, since it should include all the components and should be ready to use. After building our own database, we will provide it for other institutions and systems as Data-aaS. The cloud service models are shown in figure 3.21.

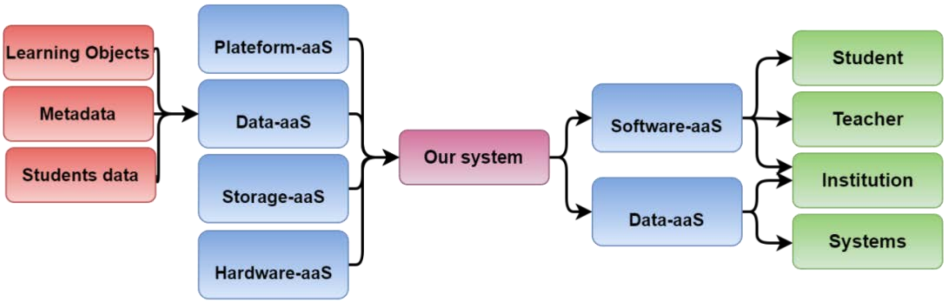


Figure 3.21: Required cloud services models for our system

Regarding the cloud computing deployment models, we are going to use a hybrid cloud, since we need:

- A private cloud for private data such as students and teachers' information.
- A community cloud for the students' learning groups and learning activities.
- A public cloud for learning resources that should be available for public use.

Those cloud computing deployment models are shown in figure 3.22.

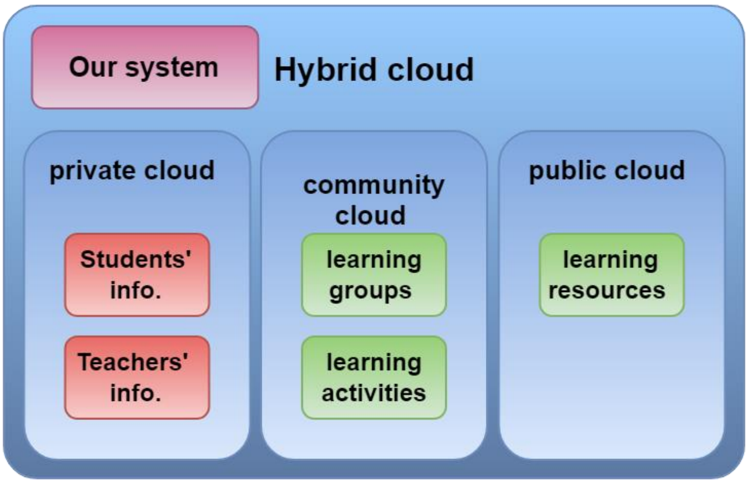


Figure 3.22: Required cloud deployment models for our system

In [**239**] Dong et al. presented an e-learning ecosystem based on cloud computing, as we discussed in chapter 2, section 2.4.1. Their system is composed of three layers and four modules, as shown in figure 3.23.

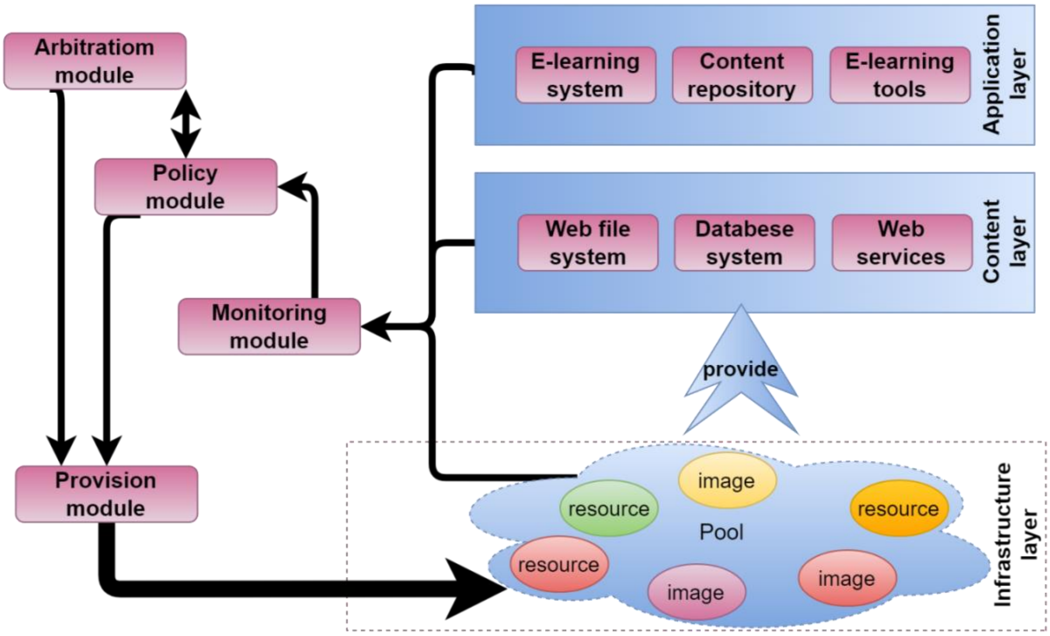


Figure 3.23: Cloud computing infrastructure-based e-learning ecosystem architecture [239]

Another cloud-based reflective learning environment, presented in [206], depicts the three main components, cloud service, teacher side, and student side, as shown in figure 3.24.

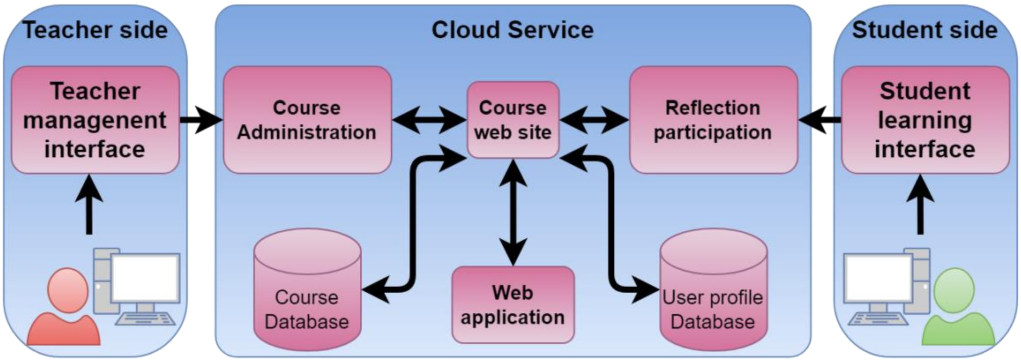


Figure 3.24: Framework of the cloud-based reflective learning environment [206]

After identifying our system's services and its required cloud models, and exploring some examples of other systems in use, we are going to present the structure of our system from a cloud computing perspective, as shown in figure 3.25.

Our system will be based on a Platform-aaS cloud model to build our system services. However, we will provide it as a Software-aaS for institutions, teachers, and students, and for activating learning object reusability and social learning, we can provide learning objects, learning groups, and learning activities information as a Data-aaS for other institutions and to other e-learning systems.

Our system structure uses three main layers:

- Infrastructure layers, where we use a Storage-aaS cloud model to store our learning objects and a Hardware-aaS cloud model to manage this data. We provide this data in a public cloud.
- Content layer, where we use a Platform-aaS cloud model that contains Data-aaS for providing new students with information from other resources, and Hardware-aaS for processing current students and teachers' data. They are then augmented with observation

data, and other system processes are used to conclude specific data for other tasks. Learning groups and learning activities information are also processed and managed in this layer. This layer has a community cloud for learning groups inside and outside the institution, and a private cloud for specific information about students and teachers of the institution.

- The application layer, where we build up the required applications, webpages, and interfaces required for each kind of user (institutions, teachers, students and other e-learning systems). Each of them is provided with the required services in an easy and effective way as a Software-aaS cloud.

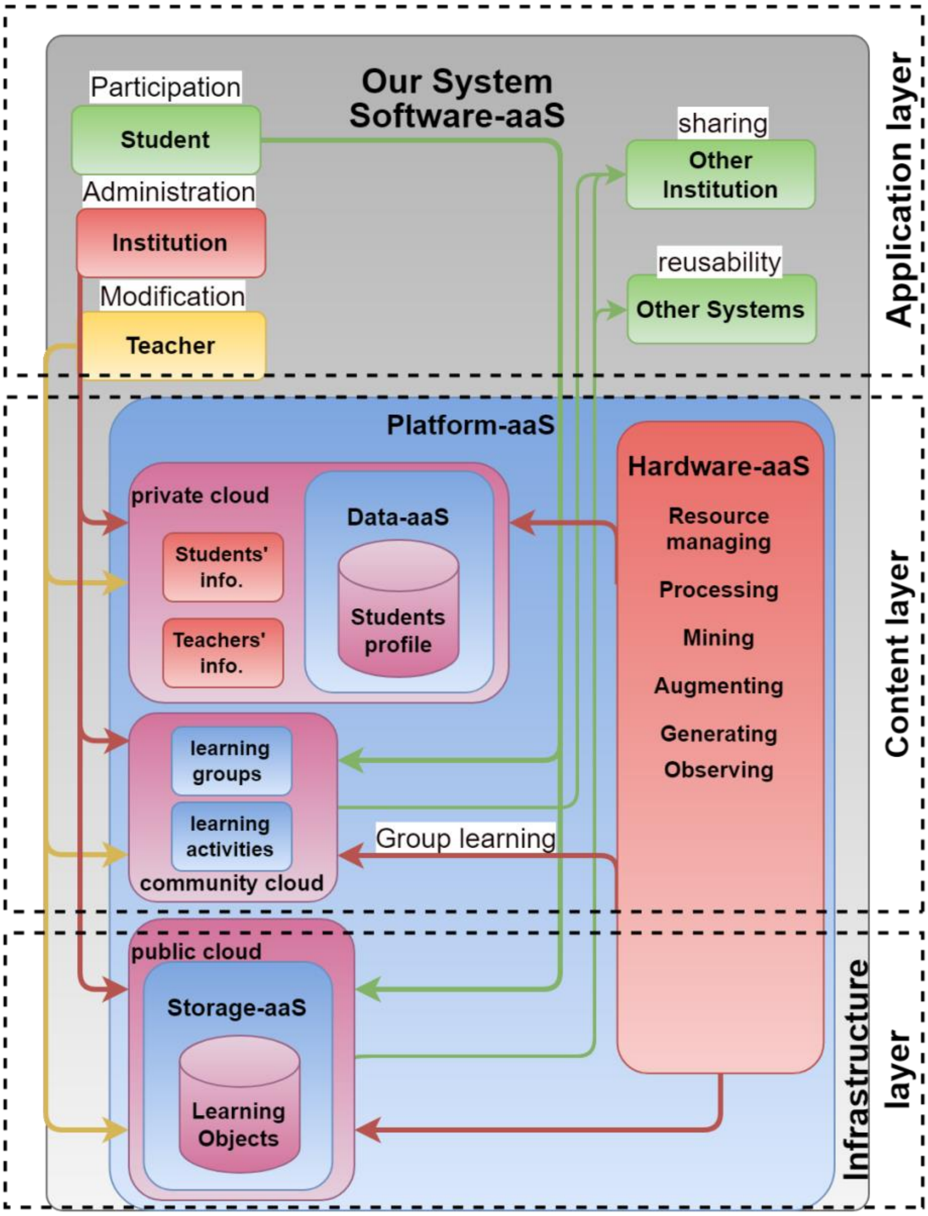


Figure 3.25: Our system from the cloud computing perspective

3.4 Augmenting all the three perspectives

After we elaborated our system design from the three perspectives, we sum up all the main steps in one graph as shown in figure 3.26.

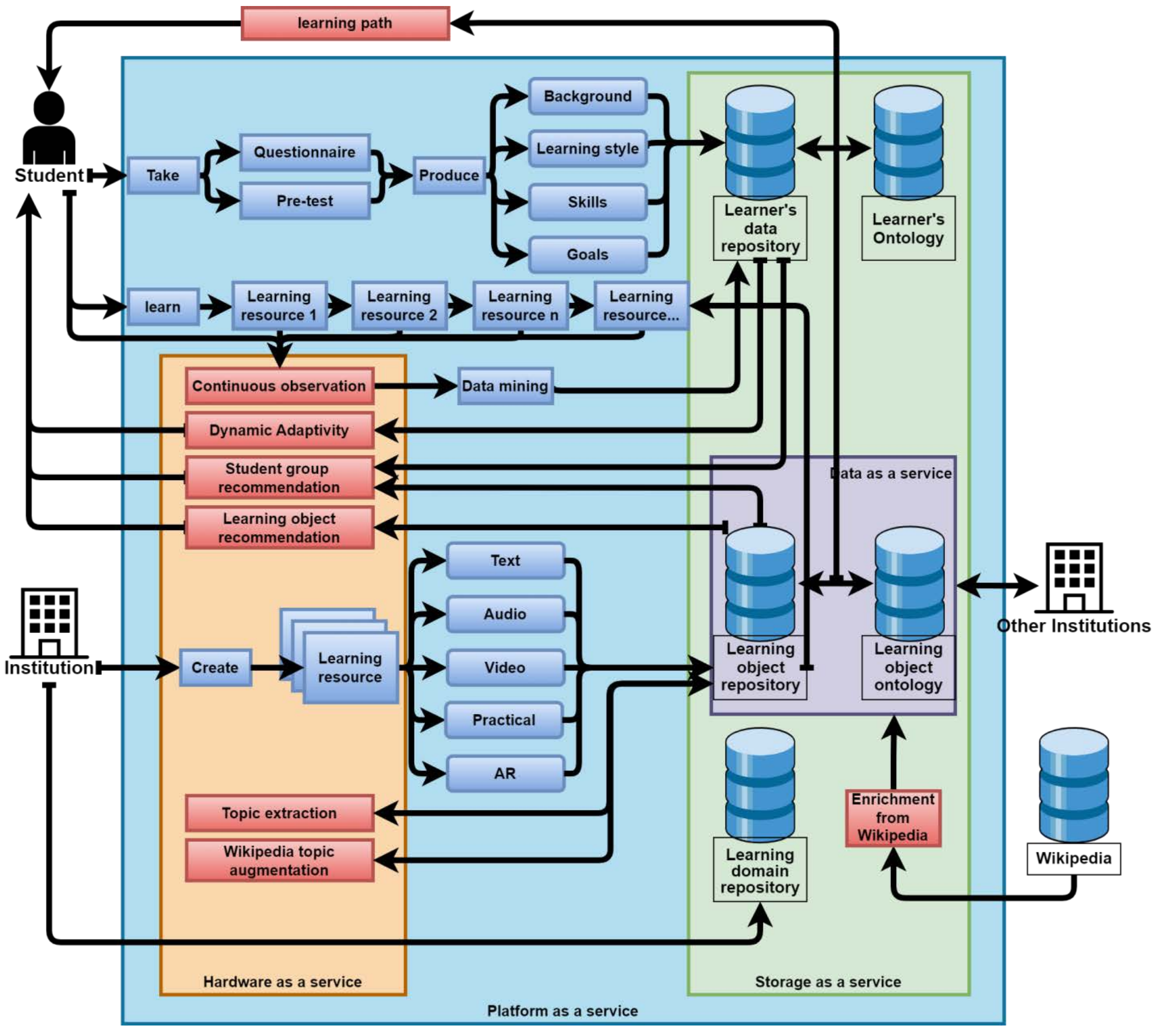


Figure 3.26: Our system design from the three perspectives

Our system has two main types of users: institutions and students, where teachers are augmented as a component inside the institution. Required information about students could be gathered from questionnaires, pre-tests, or from external learning groups. Learning objects and their metadata could be created by the institution, gathered from external institutions, or enriched from Wikipedia and other semantic resources.

If we have the required information about students and the learning objects, we can operate the system processes using a Hardware-aaS cloud to produce the required information and execute scalable operations to manage recommendations and adapt the e-learning system according to the student's needs depending on the information gathered during the observation process.

4. An algorithm for topic identification in textual learning resources

4.1 Introduction

The algorithm we developed to extract main topics from textual learning resources is the primary contribution of our work. In this chapter, we'll discuss the algorithm and how its output may be used to cluster learning resources and build dynamic, interactive knowledge graphs.

Due to its dependability, effectiveness, and constant content updating by a sizable user community, Wikipedia and its semantic information on DBpedia can be used in a wide range of applications and fields. Consequently, it will be a rich information source from which our algorithm can learn and expand the body of knowledge that it uses to extract important topics. In addition, Wikipedia Miner is a crucial and helpful tool for drawing out this critical information from the vast amount of data on Wikipedia.

Several attempts have been made in the past to accomplish some of our goals. In [**336**] David and Ian presented Wikipedia Miner although they evaluated it for news articles. In [**337**] Olena et al. used Wikipedia and Wikipedia Miner for automatic topic indexing, however they did not mention the document sizes. In [**321**] Kino et al. presented a method for automatic topic identification using an encyclopedic graph derived from Wikipedia. They used the unsupervised Wikify service. However, the Wikify service is not able to produce results for larger resources such as many of the books in our dataset. In [**319**] Chris et al. presented TopCat, which was effective in identifying topics in collections of news articles. In [**320**] Veselin and Claire presented an algorithm for opinion topic identification. In [**323**] Freidrich et al. presented a framework for the identification of primary research topics. In [**324**] Khader et al. designed an ensemble method for automatic topic extraction from a collection of scientific publications. However, all this research focuses on news articles, opinion topic identification, research topics or scientific publications, which are smaller than the learning resources in our dataset.

Wikipedia Miner is a crucial and helpful tool for drawing out this critical information from the vast amount of data on Wikipedia. The method used by Wikipedia Miner begins with natural language processing of the text document to extract key words and phrases, gathering overlapping word n-grams, where n ranges between one and the maximum label length in Wikipedia, and determining which terms and phrases correspond to Wikipedia concepts.

However, this method has a significant limitation: the bigger the piece of text that needs to be processed, the longer it takes, and the less effective it is. In consequence, we complemented Wikipedia miner with other tools to overcome this limitation and enhance the efficiency of the results.

We applied TextRank [**345**], a text processing ranking strategy based on graphs. It is an unsupervised algorithm for automatically summarizing text that can identify the most crucial words in a document without the use of labeling or a training corpus.

The TextRank algorithm was later improved upon by Federico et al. in [**367**], by introducing the "BM25 ranking function", which is a ranking function widely used in the state of the art for information retrieval tasks. BM25 is a variation of the TF-IDF model using a probabilistic model. The results underwent substantial development and improvement, leading to this merging. By employing BM25, they were able to increase results by 2.92% over TextRank. Therefore, the combination of TextRank with modern information retrieval ranking functions such as BM25 creates a robust method for automatic summarization that performs better than previous standard techniques [**367**]. Therefore we used TextRank combined with BM25.

We applied a quantitative research methodology to evaluate our proposal. The experiments we performed on the algorithm are described in Chapter 5. Their objectives were to optimize a configuration parameter of the algorithm (the parent category level, which will be explained later in this section), to evaluate the precision of the main topics extracted by the algorithm and measure the time it takes to produce those topics, in comparison to another state of the art algorithm. The experiments were based on a dataset of more than 500 full text learning books we collected from several repositories. More explanations and details provided in chapter 5.

4.2 Algorithm phases

4.2.1. Extract main keywords

We started by extracting text from books, and then we applied text processing to extract main keywords using natural language processing techniques. We used the TextRank [**345**] graph-based ranking algorithm combined with the BM25 [**367**] ranking function. This technique was explained in chapter 2 (sections 2.8.2, 2.8.3). We applied that algorithm on the text extracted from the learning resources to extract main keywords. We used the implementation of this algorithm provided by Gensim [**368**] version 4.1.2, which is a very popular open-source library for unsupervised learning implemented in Python [**358**]. The output of this step is a sorted list of vertices "keywords" according to their importance "weight" in the text, where the top vertices are the most important.

4.2.2. Identify main topics

To identify the main topics in each learning resource, we have to understand the difference between keywords and main topics:

- Keywords are the important words in a text that could represent a topic mentioned in the book, and they are an exact match to text that appears in the book.
- Main topics are the most important topics found in the book according to a category from the Wikipedia database, which have a specific identifier and a URL [**369**]. They are not necessarily an exact match to words mentioned in the book, since they could also appear with semantically related words.

Example: a keyword could be the word "business", which appears in the book's text. A main topic related to that keyword could be the Wikipedia category titled "Business", with identifier 771152 and URL [**370**]. Therefore, main topics are pre-specified categories in Wikipedia, which could provide more information and link to related resources that are not necessarily mentioned in the input text.

After extracting the main keywords from the first phase, we use them as an input to the topic identification phase, where we use Wikipedia Miner's services (Wikify, and Search) to extract article IDs that contain all the keywords.

If the number of retrieved results is under a specific threshold, we reduce the number of input keywords and repeat this step. The reason is that Wikipedia Miner's services retrieve an article if it contains semantic relations with all the input keywords, so by reducing the keywords number we get more results. The output of this step is a list of article identifiers.
We reduce the number of input keywords by removing the last keyword from the sorted keywords list, because the last one is the least important one. By using this reduction method we enable Wikipedia Miner's services to focus on the most important keywords to find relations between them.

Next, we have to get the properties of each article by using more Wikipedia Miner's services (exploreArticle, suggest, exploreCategory, parentCategory):

- By using the "exploreArticle" service we extract article's definition and title.
- By using the "suggest" service we extract other suggested categories' identifiers to be processed and added to the results. They are processed using the "exploreCategory" service to extract categories' definition and title, and processed using the "parentCategory" service to extract the higher rank category for each one, and this step could be repeated as required to formulate a hierarchical structure of connected topics. After extracting all required categories we process them to produce a sorted list of them.

The output of all previous steps consists in a sorted list of main topics representing the input text, which could be further processed later to be presented to the user in a dynamic interactive connected knowledge graph. The structure of our algorithm is shown in figure 4.1.

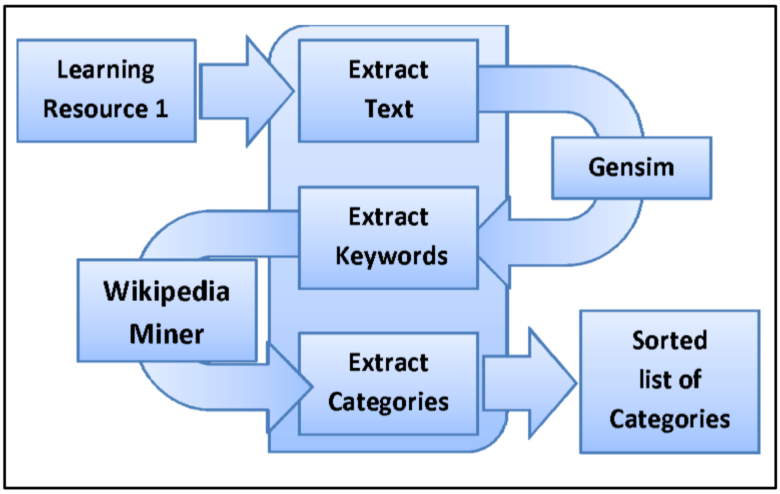


Figure 4.1. Structure of our algorithm

The main topics extraction phase uses Wikipedia Miner where Wikipedia's articles, categories and redirects are represented as classes, and can be efficiently searched, browsed, and iterated over. This is a platform for sharing data mining techniques based on Wikipedia data. This data is gathered from Wikipedia's XML dumps. We used a dump of the English version of Wikipedia dated on 22 July 2011, which includes 3.3 million articles and 37.4 GB of uncompressed markup. Wikipedia Miner is the fundamental tool in our Topic Identification system that enables us to assign the right main topic to the learning resources. There is also a parent category feature that enables us to find the parent category of the specified category/topic.

In our initial tests we ran Gensim with the Wikify service [**322**] of Wikipedia Miner, which is used for keyword extraction and word sense disambiguation. However we found many missing results. To solve this problem we augmented the combination of Gensim and Wikipedia Miner (Wikify) with the Search service of Wikipedia Miner, which solved the problem by searching all available articles for those that are related to the identified keywords. The actual data of this experiment will be presented in the explanation of experiment 2 in Chapter 5.

For each learning resource, after extracting the main keywords with Gensim, we use Wikipedia Miner to extract main topics, then for each topic we identify the parent categories at different levels. We iterate over the retrieved categories to extract multi-level results. This step produces a hierarchy of topics that represents a multilayer topic structure as mentioned in [**332**]. When we mention the second level of the parent category we mean the second iteration of the parent category service, and so on.

As we can see from the examples in table 4.1, the higher the level the more general and comprehensive the results are, yet at some level those results are too broad and not so useful. We describe in Chapter 5 how we empirically chose the best level of parent category to use in our system.

Table 4.1. Examples of our algorithm's results.

Example1 - book main topic (Biology)	
1st level results:	(Immune system/Organ systems/Microbiology/Biology/Clinical pathology)
2nd level results:	(Biology/Life/Natural sciences/Botany/Anatomy)
3rd level results:	(Biology/Life/Society/Natural sciences/scientific disciplines)
4th level results:	(Life/Biology/Nature/Natural sciences/Universe)
Example2 - book main topic (Math)	
1st level results:	(Mathematical analysis/Calculus/Subdivisions of mathematics/Analysis/Integral calculus)
2nd level results:	(Subdivisions of mathematics/Mathematics/Abstraction/Dimension/Geometry)
3rd level results:	(Mathematics/Subdivisions of mathematics/Abstraction/Structure/Dimension)
4th level results:	(Structure/Scientific disciplines/Academic disciplines/Abstraction/Dimension)

All the steps of our algorithm are presented in the next pseudo code and figure 4.1.

Pseudo code of our algorithm for topic identification

```
-For each (Learning Resource) in the dataset:
        -Extract (Text)
        -Process (Text) with Gensim to extract (Keywords)
        -Process (Keywords) with Wikipedia Miner services (Wikify, Search) to extract (Article IDs)
        -Copy (Keywords) to (Wikify_Keywords)
        -Copy (Keywords) to (Search_Keywords)
        -While (number of retrieved Article IDs < 20)
        -Process (Wikify_Keywords) with (Wikify) to extract topic IDs
        -Remove the last keyword from (Wikify_Keywords) list
          "to enable Wikify to find more results"
        -If length of (Wikify_Keywords) = 0:
                -For each Keyword in (Search_Keywords):
                        -Process Keyword with (Search) to extract topic IDs
                        -Process (Article IDs) with Wikipedia Miner services (exploreArticle, suggest,
                          exploreCategory, parentCategory) to extract (Definition, Title)
        -Append all (Article IDs) in one Article IDs list
        -For each ID in Article IDs:
                -Process ID with (exploreArticle) to extract Definition and Title
                -Process ID with (suggest) to extract suggested Categories IDs
                -For each suggested Category ID:
                        -Process ID with (exploreCategory) to extract Definition and Title
```

-Get Parent Category with (parentCategory) property -"[(parentCategory) could be repeated to reach the required level -For (2nd–3rd–4th) level of parent categories": -Collect all Parent Categories with repetition numbers. -Sort Parent Categories from high to low repetition to extract the most important ones

4.3 Dynamic interactive knowledge graphs

For each learning resource we select the top five main topics retrieved by the algorithm. After assigning those main topics to the learning resource we will establish the base for the dynamic interactive knowledge graph that will contain all the learning resources. We insert each learning resource and main topics as nodes, then we create a link between each main topic and all related learning resources. The result is a connected graph of related learning objects as shown in figures 4.2, 4.3, 4.4, 4.5.

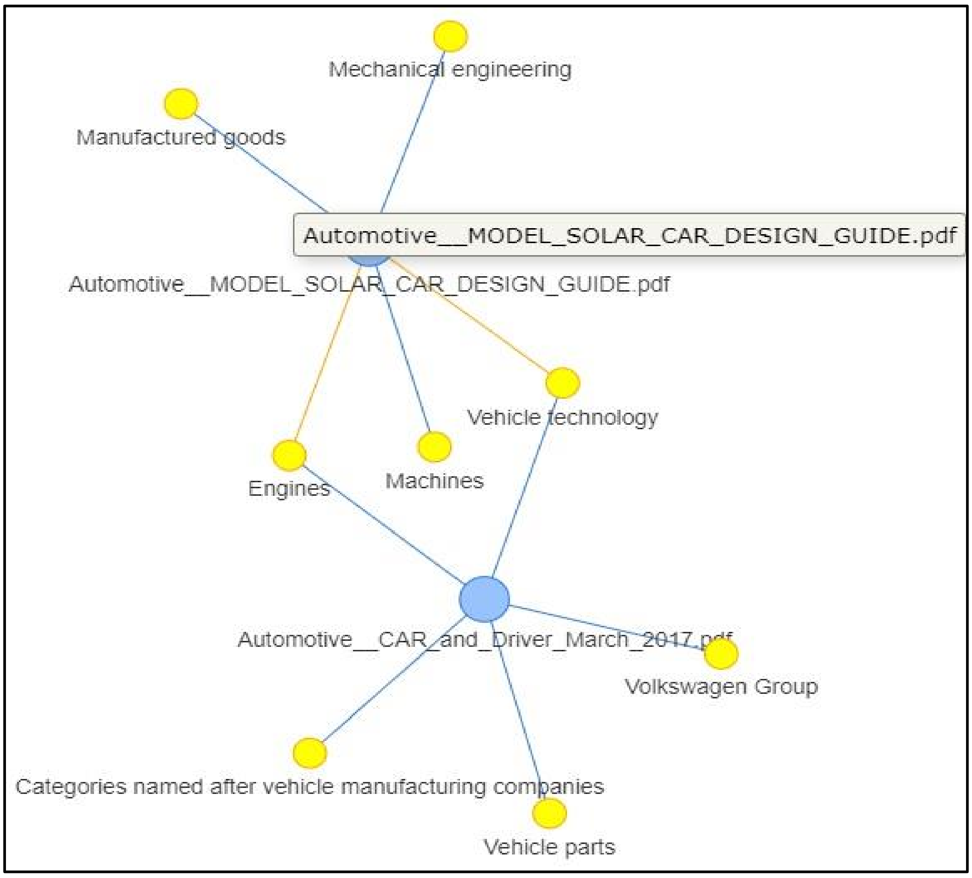


Figure 4.2: Relation between learning resource (in blue), and main topics (in yellow)

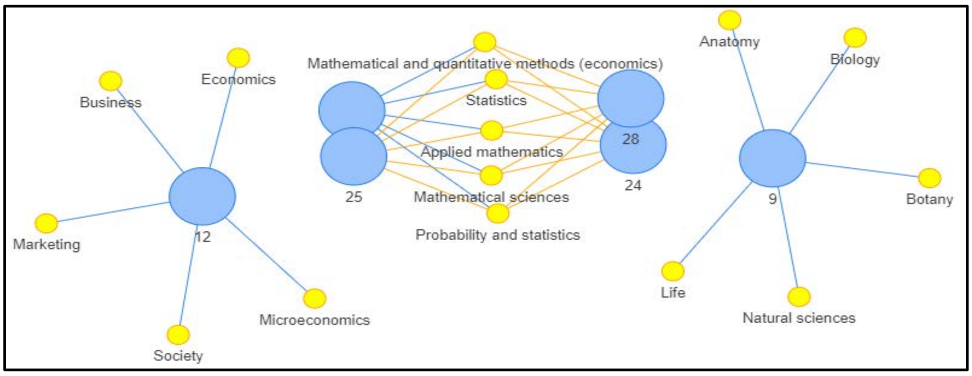


Figure 4.3: Relation between learning resources (in blue), and main topics (in yellow)

In figures 4.2 and 4.3 we can see the relation between learning resources (in blue), and main topics (in yellow).

In figure 4.4 we can see the relation between one learning resource (in blue), learning resource's chapters (in yellow), and main topics (in red). To obtain this graph we applied our algorithm separately on each learning resource and each chapter, and then we augmented all results in one graph.

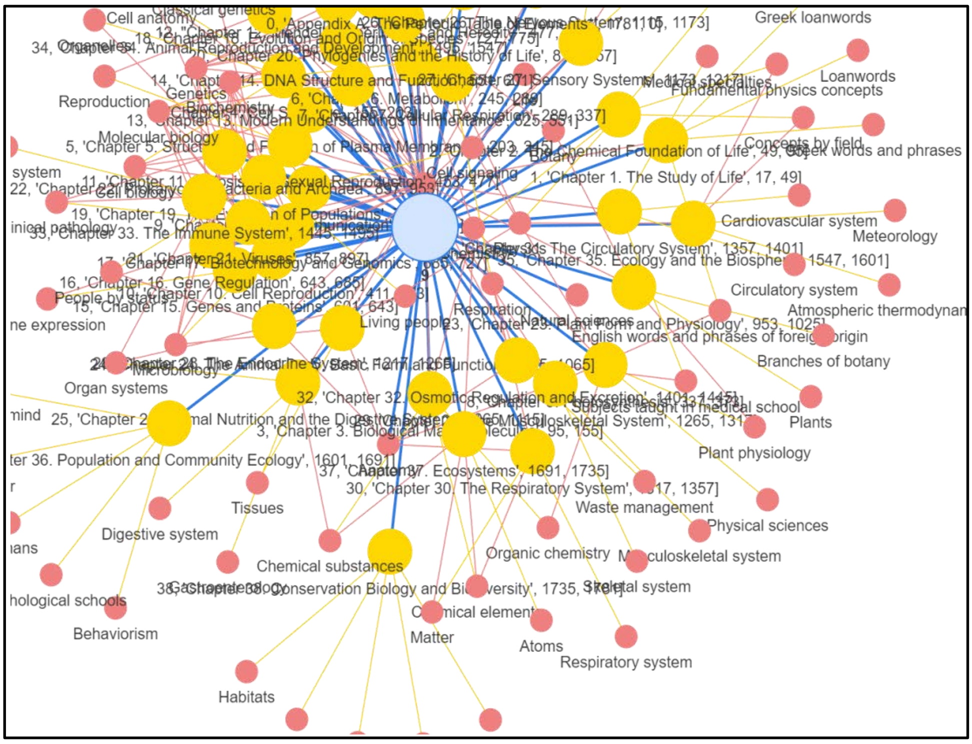


Figure 4.4: Relation between one learning resource (blue), main topics (red), and chapters (yellow)

In figure 4.5 we can see the relation between learning resources (in blue), main topics (in yellow), and chapters (in red) but with more learning resources.

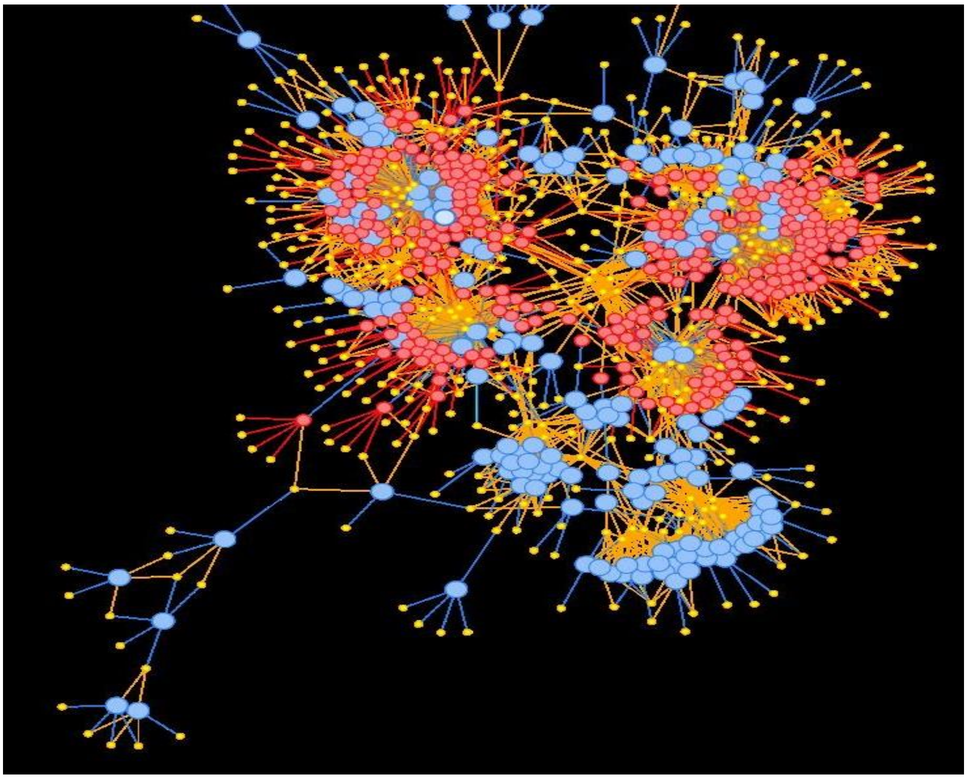


Figure 4.5: Relation between learning resources (blue), main topics (yellow), and chapters (red)

We provide all generated graphs with navigation tools for students to ease the exploration process, where they can zoom in and out, move the graph or the nodes, and rotate around the graph.

Learners can use our generated graphs in different useful ways such as:

- Finding the required main topic and browsing all related learning objects.
- Finding a learning object then identifying all related main topics.
- Or finding related learning objects and exploring common main topics between them.

Building knowledge graphs from the text in learning resources is another key feature in our platform, where we can focus on self-directed learning to enable students to identify the required topic or learning resource easily and in a joyful way. With this information and the topics our algorithm extracts, the system will be able to recommend learning resources or complete learning paths for other students with the same goals or learning background.

After we have explained our methodology and the structure of our topic identification algorithm, we are going to illustrate the experiments we did to evaluate it in the next chapter.

5. Experiments and Results

To evaluate our algorithm we conducted two experiments:

- In the first experiment we ran our algorithm on a dataset of 579 books with different configurations of parent category level, in order to analyze its accuracy and select the optimal value for that parameter.
- In the second experiment we compared the accuracy of our algorithm's results against another topic extraction technique, and we also compared computation time for both of them.

These experiments were run on a collection of 579 books in different subjects, levels, and from different learning repositories. We selected them for the levels of secondary school and first years of university/college.
The topics of the books included: Anatomy, Art, Astronomy, Automotive, Biology, Biostatistics, Business, Chemistry, Computational Physics, Computing, Economics, Education, Engineering, First Aid, Hardware, History, Humanities, Languages, Law, Math, Medicine, Organic Chemistry, Parenting, Physics, Physics and Environment, Psychology, Science, Social Sciences, Software, Statistics and Travel.

5.1 Experiment 1

We extracted the results from the algorithm in four different levels (1st, 2nd, 3rd, and 4th) depending on the number of parent categories used in Wikipedia Miner [**336**]. We used top-5 accuracy [**371**] to evaluate the results in each level to identify the most suitable level to use.

For each learning resource we retrieved the top five main topics, and then we evaluated each topic manually and gave each learning resource a score out of five. If the resource got five of five then all the five topics were correct. However, if the resource got two of five, then only two of the topics were correct. Next, we summed all the results and divided the total by the number of resources to find the average score (average true value).

Figure 5.1 shows, for each parent category level, the number of resources for which the algorithm got the five topics correct, four topics correct, etc. For example, with the 1st level parent category we got 77 results with zeros and 305 results with fives. Nonetheless, with the 4th level parent category we got 67 results with zeros and 77 results with fives.

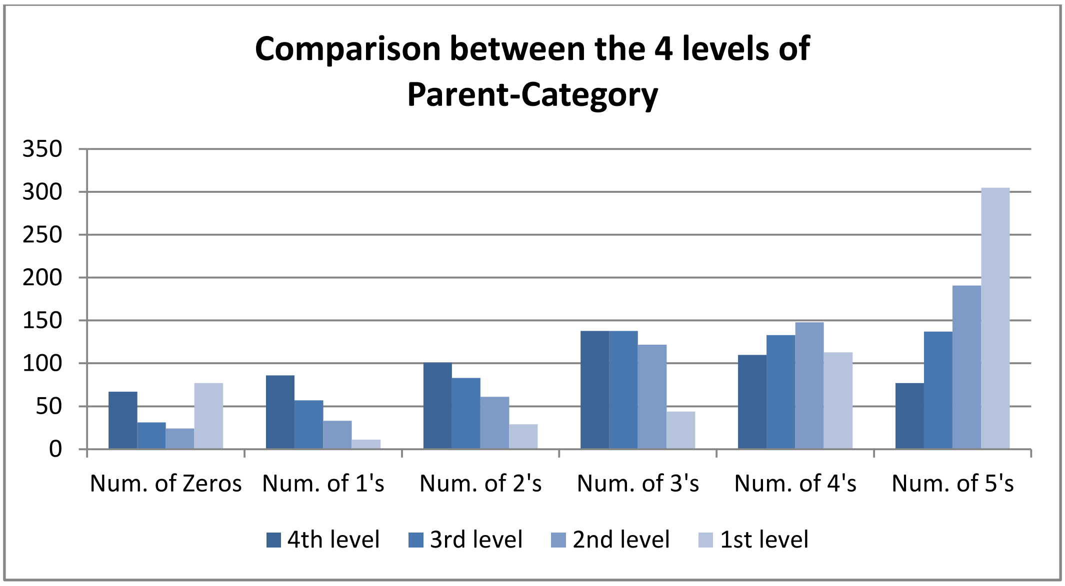


Figure 5.1: Comparison between the four levels of parent-category

Table 5.1 lists, for each parent category level, the percentages of books for which at least one of the five topics was correct ("True topic identified"), the percentage of books for which none of the five topics was correct ("False topic identified") and the average number of correctly identified topics ("Average true", a value from 0 to 5).

For example, with the 1st level parent category we got 86.7% of the books with true topic identified, 13.3% of the books with false topic identified, and an average of 3,76 correctly identified topics out of 5. Nonetheless, with the 4th level parent category we got 88.4% of the books with true topic identified, 11.6% of the books with false topic identified, and an average of 2.64 correctly identified topics out of 5.

Table 5.1: Comparison between the four levels

	True Topic Identified	False Topic Identified	Average True
4th level Parent-Category	88.4%	11.6%	2.64 of 5
3rd level Parent-Category	94.6%	5.4%	3.20 of 5
2nd level Parent-Category	95.9%	4.1%	3.57 of 5
1st level Parent-Category	86.7%	13.3%	3.76 of 5

We can find that the results of using both the first and second level parent categories show a high number of books with a five of five in top-5 accuracy. In addition, the average number of correctly identified topics is higher (3.76 out of 5) for the first level than for the second level. Therefore, we chose the first level of the parent category in our algorithm for the rest of the experiments, although we retain the ability to use many levels to produce a hierarchical structure of main topics.

5.2 Experiment 2

The goal of this experiment is to compare the computation time and the accuracy of our algorithm against other topic identification techniques. As **Gensim** [**359**] and Wikipedia Miner [**336**] have the ability to identify topics from text, we compared them against our algorithm, which is built on top of Gensim and Wikipedia Miner as was explained at chapter 4.

In this experiment we sampled **350 books** from the dataset that we used in the first experiment. The books in this sample of the dataset contain between 95 and 1800 pages. In figure 5.2 we can see the distribution of the number of pages of the books in the dataset. For example, we have 134 books with a number of pages between 200 and 400.

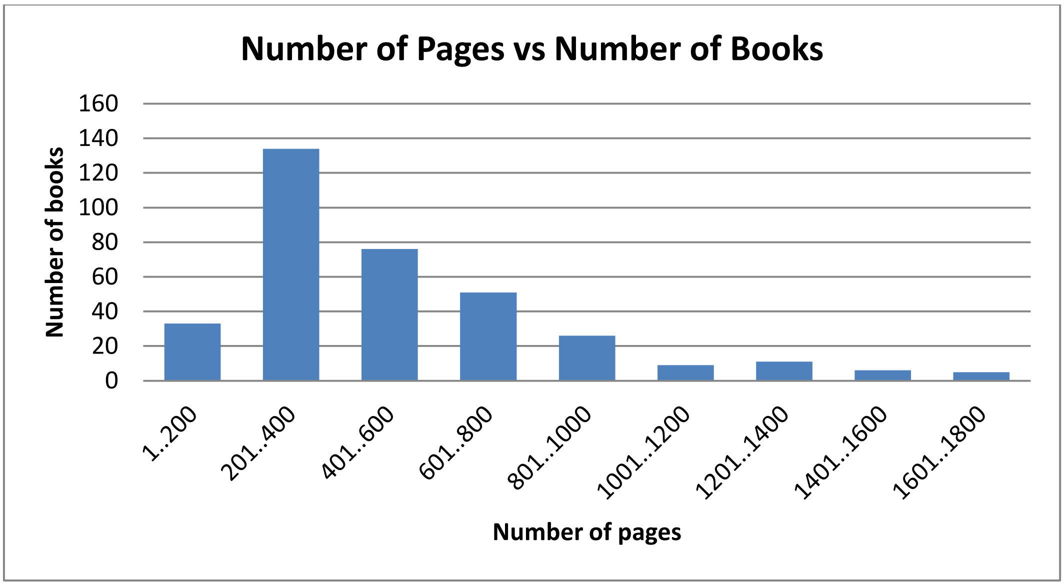


Figure 5.2: Number of pages vs. number of books

At the beginning of our experiment we thought that the bigger the number of pages of the book, the longer the processing time it would take. However, we have seen that computation time correlates better with text size (in terms of number of characters) than with the number of pages of a book. That happens because we are processing text, and some books contain a big number of pages filled with charts, figures, and pictures, which are not processed by the algorithms. The histogram of the number of characters per book is shown in figure 5.3. We have 187 books with a number of characters of almost 1 million, 118 books with a number of characters between 1 to 2 million, and so on.

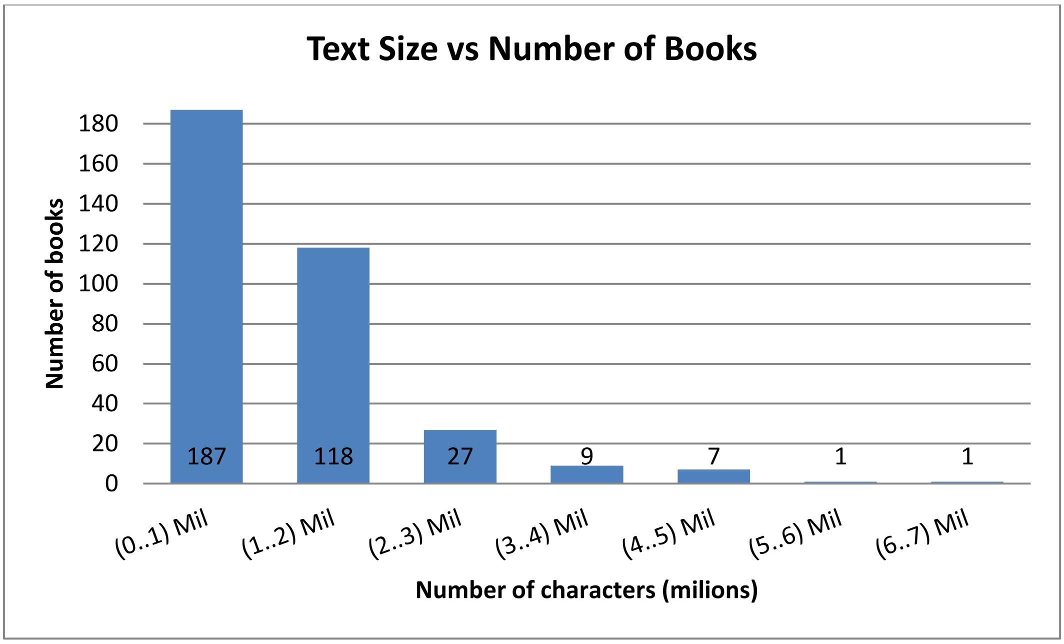


Figure 5.3: Text size vs. number of books

When we started our comparison we found that the maximum number of pages that we can process with Wikipedia Miner is between 25 and 35 pages. With more pages the Wikipedia Miner server frequently stopped responding. This circumstance forced us not to use Wikipedia Miner in this experiment. On the other hand, Gensim had no problem with the number of pages, so we continued our experiment comparing Gensim alone against our algorithm.

An earlier version of our algorithm was based only on Gensim and the "Wikify" Wikipedia Miner service. However, it did not produce any topic suggestion for a big portion of the books in the dataset, more than 200 books out of 350. As a result of that, the final version of our algorithm uses, in addition, the "Search" Wikipedia Miner service for the cases in which the "Wikify" service does not produce any result. The final version of the algorithm produced suggestions for all but 11 books in the dataset.

5.2.1 Computation time

First, we compared computation time for both Gensim and our algorithm, taking text size into account.
In figure 5.4 we have a dot plot that presents a data point for each book, identifying the relation between its number of characters and its computation time is seconds, with blue dots for our algorithm and red dots for Gensim. For example, we have for a book with around 5.4 million characters, Gensim processing time was 85.2 seconds, our algorithm processing time was 88.4 seconds.

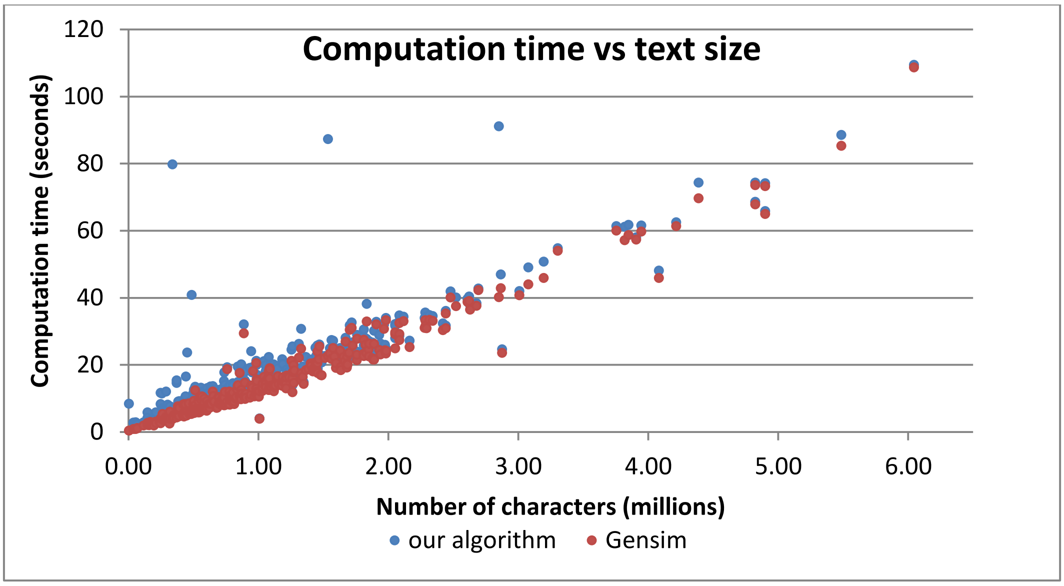


Figure 5.4: Computation time vs. text size

And in figure 5.5 we group books by ranges of number of characters and show the average computation time for the books at each range. For example, the books with 4 to 5 million characters were processed with Gensim in 65.1 seconds and, with our algorithm, in 66.7 seconds.

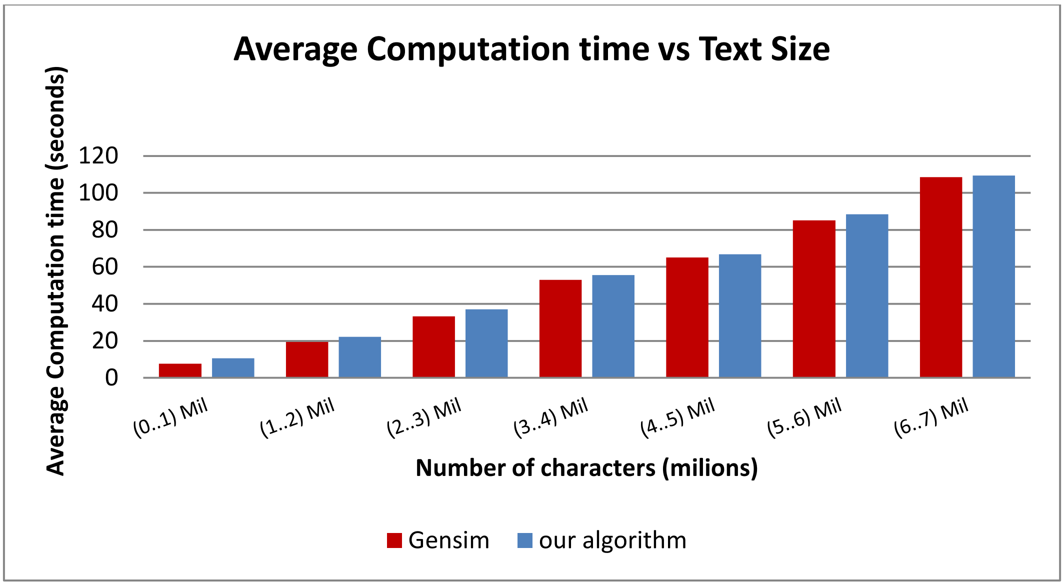


Figure 5.5: Average computation time vs. text size

Figures 5.6 and 5.7 show the same (text size vs. computation time) data in the form of box plots, where minimum, maximum and median values for each range, as well as their 25 and 75 percentiles, can be identified. For example, in figure 11 the books that have 3 to 4 million characters with Gensim have a minimum of 40.6 seconds, median of 51.7 seconds, and maximum of 53.1 seconds of processing time. However in figure 12 the books that have 3 to 4 million characters with our algorithm have a minimum of 41.9 seconds, median of 49.1 seconds, and maximum of 49.4 seconds of processing time.

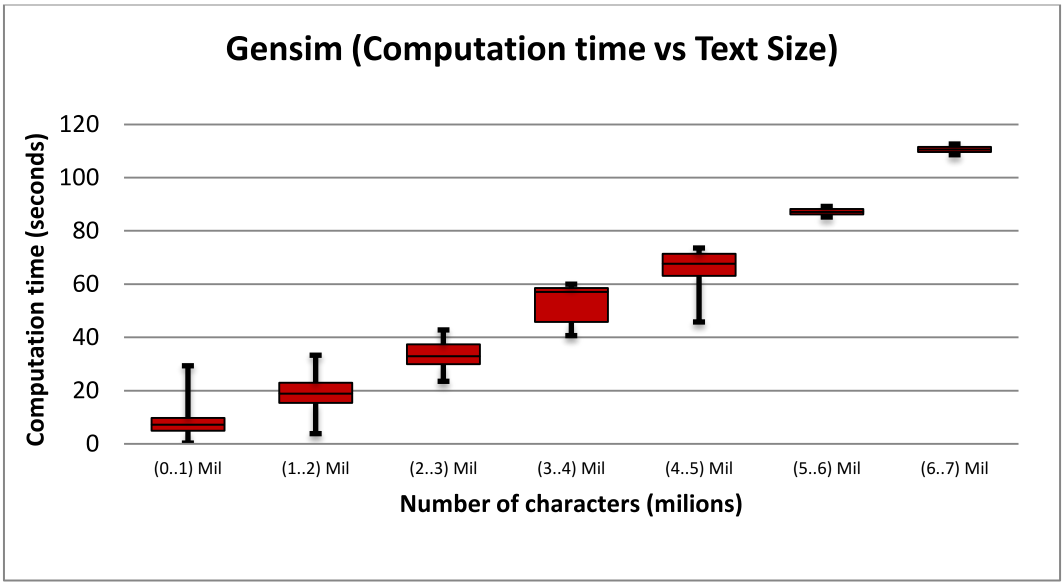


Figure 5.6: Gensim (computation time vs. text size)

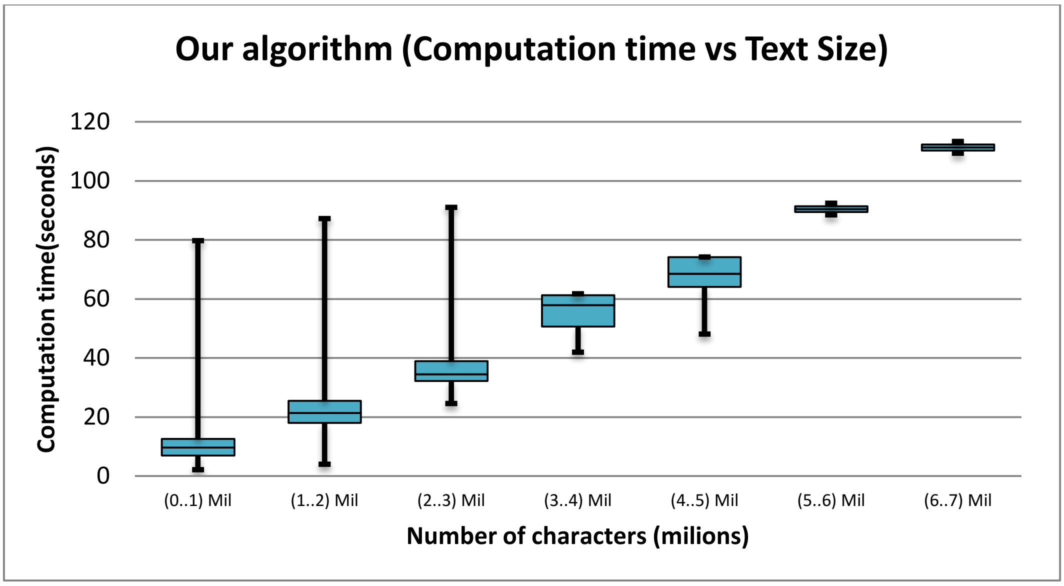


Figure 5.7: Our algorithm (computation time vs. text size)

Table 5.2 presents the total **computation time** for the 350 books in the dataset and the average computation time per book for both Gensim and our algorithm.

Table 5.2: Total computation time

	Total Time (s)	**Average Time (s)**
Gensim	5721	16.35
Our algorithm	6739	19.25

We can see in the plots that our algorithm takes slightly more time than Gensim, which was expected as our algorithm runs Gensim internally. The overhead is due to the use of Wikipedia Miner services on the results provided by Gensim, including communication time caused by the running of a different server. In spite of these extra tasks, the average overhead of our algorithm is 17.7%, lower than 3 seconds per book.

After having analyzed computation times and their relation to text size, we will analyze the **accuracy** of the results provided by Gensim and our algorithm.

5.2.2 Accuracy

First, we present an example of the results that we got for three books we sampled from the dataset in table 5.3.

Table 5.3: Example of results

Book Information	**Title:** **Principles of Accounting, Volume 1: Financial Accounting** **Pages: 1055** **Category: Business**	**Title:** **College Physics for AP® Courses** **Pages: 1694** **Category: Physics**	**Title:** **Anatomy & Physiology** **Pages: 1420** **Category: Anatomy**
Wikipedia miner	Fails to provide an answer	Fails to provide an answer	Fails to provide an answer
Gensim	Companies/company/ accounting/accountants/ account/accounts/ accountant/accountable/ accountancy/accounted	Credit/credited/credits/ figures/figure/figured/ figuring/energy/energies/ force	Figure/figures/figurative/ cell/cells/called/calling/ muscle/muscles/blood
Our Algorithm	Accountancy/Investment Financial markets/Accounting systems/Management/ Applied sciences/Business/ Business economics/Accountability /Legal entities	Physics/Fundamental physics/concepts/Concept s by field/Introductory physics/Physics education/Motion/Space Time / Force/ Phenomena	Anatomy /Biology /Tissues /Organs /Musculoskeletal system /Subjects taught in medical school /Cardiovascular system /Circulatory system /Medical specialties /Greek loanwords

We can see from the results that, at least for these examples, our algorithm provides the most relevant and accurate results. In addition, whereas Gensim produces just words, our algorithm produces unambiguous Wikipedia categories, referenced by their unique identifier at Wikipedia. The identifiers are not shown in the table for readability.

In order to evaluate accuracy, in this experiment we made Gensim and our algorithm produce 10 topics for each book. Then, for each book, we evaluated these 10 results and computed accuracy (number of correct topics divided by 10). Topic correctness was decided by a human evaluator. We can see in table 5.4 that our system achieves a much better accuracy than using Gensim alone.

Table 5.4: Top-10 accuracy

	Average accuracy
Gensim	0.240857143
Our Algorithm	0.712285714

Then we evaluated these topics by using top-k accuracy [**371**]. We compared top-1, top-5, and top-10 accuracy in figure 5.8 and in Table 5.5. For each book we evaluated the results according to the three levels. If the first topic returned by the algorithms is the main category of the book or close enough to it, then the book counts for top-1 accuracy. If one of the first 5 topics is the main category or close enough, then the book counts for top-5 accuracy. Likewise, if one of the first 10 topics is the main category or close enough, the book counts for top-10 accuracy. Again, a human evaluator decided that book by book.

Table 5.5: Top-k accuracy.

	TOP-1	TOP-5	TOP-10
Gensim	22.9%	45.5%	67.5%
Our algorithm	48.0%	74.0%	86.0%

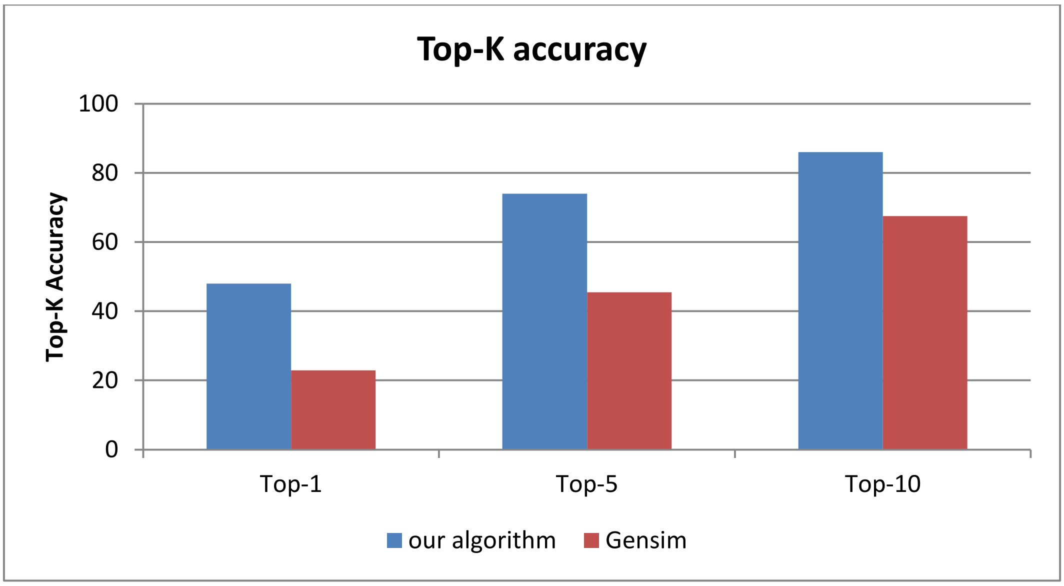


Figure 5.8: Top-K accuracy

We can see from the results that our algorithm has a higher value for all accuracy levels, and especially for top-1 accuracy.

5.2.3 Accuracy vs. text size

Now we want to analyze the relation between accuracy and text size in order to find how our algorithm is affected by the amount of information processed at a time. We start by plotting all accuracy values for all books against text size in figure 5.9. From the results, we can clearly see that higher accuracy values are produced by our algorithm over Gensim for all different text sizes.

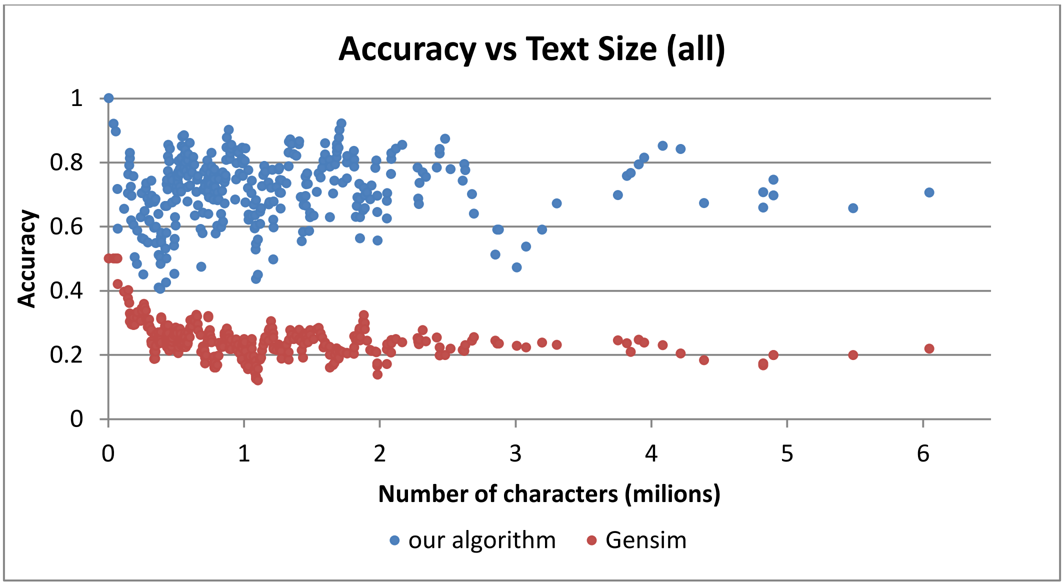


Figure 5.9: Accuracy vs. text size (all)

Next, we present top 1, top 5, and top 10 values for Gensim and our algorithms, in groups of different text sizes in figure 5.10. From the results in this graph we can see that our algorithm's average accuracy for all levels is higher than Gensem's. We can see in this graph that there are 0-sized bars with text sizes between 5 and 7 million characters. The reason is the small number of books these groups contain, as we can see in figure 8 (Text size vs. number of books).

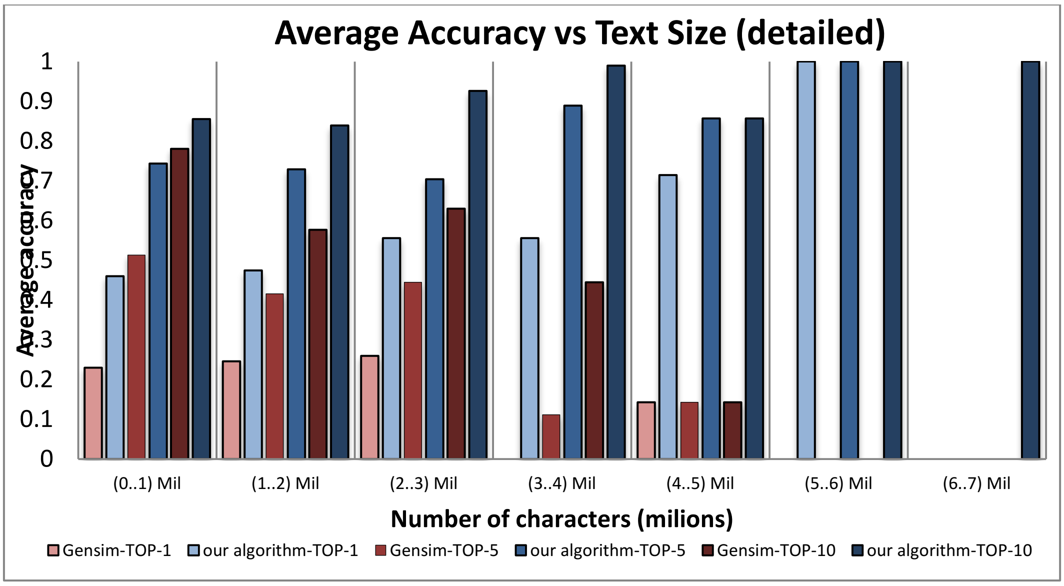


Figure 5.10: Average accuracy vs. text size (detailed)

Finally, the average accuracy values are calculated and compared to groups of text sizes in figure 5.11.

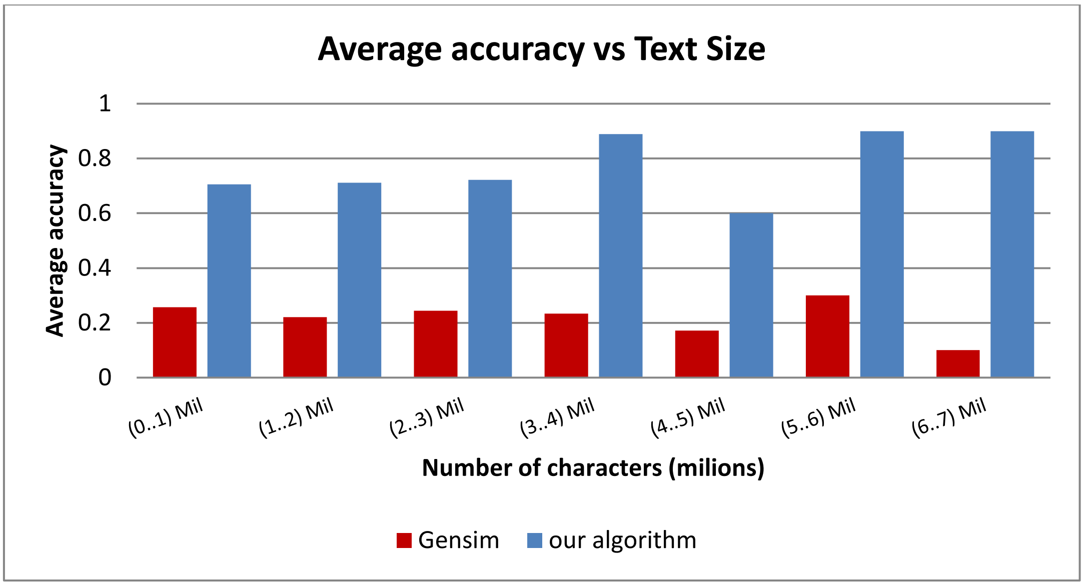


Figure 5.11: Average accuracy vs. text size

As the results show, our algorithm, with a small computation time overhead with respect to Gensim, provides much better results in terms of accuracy, and those accuracy values are consistent for all text sizes.

6. Conclusion and future work

In this thesis we designed an e-learning system that uses semantic information and cloud computing technologies, combined with other technologies, to enhance the learning process and provide a variety of learning tools and services.
Before we started the design process we explored the research field and studied many examples on different topics, including education, learning, e-learning, semantic information, recommendation systems, learning object annotation, cloud computing, and other topics.

We also developed an algorithm to process learning objects in order to extract main topics, where we start by extracting text, then we use Gensim to extract the main keywords from the text, and finally we use Wikipedia Miner with both the Wikify and Search services to extract main topics. Different levels of Wikipedia parent categories were possible, so we conducted an experiment to find out the best one to use in our algorithm. From the main topics extracted by our algorithm we produced interactive knowledge graphs to facilitate finding the required main topic, browsing all related learning objects, finding a specific learning object, identifying all related main topics, finding related learning objects, and exploring common main topics between learning objects.

To evaluate our algorithm we made two experiments. In experiment 1 we produced results with our algorithm for different levels of Wikipedia parent category. We found that the first level is the best choice to use. However, we can use different levels if a hierarchical topic structure is needed.

In experiment 2 we proved that the Wikify service of Wikipedia Miner does not work properly for the books in our dataset, as it does not produce results for more than 57% of the books. On the other hand, with our algorithm this happens for just 3% of them.

We also analyzed the computation time for both our algorithm and Gensim. As expected, our algorithm takes slightly more time than Gensim, due to it using Wikipedia Miner services on the results provided by Gensim. What is important to mention is that the experiment shows that the relationship between the computation time of our algorithm and text size is linear.

Finally, we showed that our algorithm largely outperforms Gensim in terms of the accuracy of the topics it extracts, with the additional advantage of producing them in an unambiguous way as references to Wikipedia categories. According to our experiments, text size does not affect the accuracy of the topics our algorithm extracts.

We can conclude that the main advantage of the algorithm we propose, in comparison to previous work, is its ability to work on large learning resources such as big-sized books that normally contain hundreds of pages and even reach two thousand pages in some cases.

6.1 Research Restrictions and Practical Implications

So far, we have applied our algorithm on textual educational resources only. Recent advances in speech-to-text techniques suggest that it could also probably work for extracting the main topics of other kinds of learning resources such as videos and audio. However, further research is needed in order to prove that.

Applying our algorithm requires the computational power of a high-end computer or a computer cluster, especially for running the Wikipedia Miner services, which work on a massive database of information extracted from Wikipedia. Since this task is intended to be run at the core of the e-learning system, this limitation would not affect learners, who would be able to use the system from the device of their choice.

By embedding the algorithm we proposed into the design of our e-learning system we can provide a new system that will help evolving many services such as learning object recommendation, topic identification, learning object enrichment, learning group suggestions, knowledge extraction, and dynamic interactive knowledge graphs.
By implementing our design we can provide learning object reusability and sharing amount the different e-learning platforms, reducing the required time and cost for generating new resources and make use of the massive amount of semantic information to enrich current learning resources and connect different concepts from other resources to produce a connected network of new dynamic knowledge graphs.

6.2 Future work

One line of future work is continuing with the implementation of the whole system we have designed in this research. This is a complex task that includes several research challenges.
We need to start by separating the implementation phase into three specializations: cloud computing and networks, semantic web and ontology engineering, data mining and data analysis. Within each one a qualified team of programmers have to develop the required tasks in such a way that makes all the processes work smoothly between the different specializations. The coordination between the development team is a challenging task and providing the required financial resources is also vital. Regarding the research challenges, we must follow up with the state of the art in all the involved technologies, and this requires another team to keep our system up to date.
After finishing the implementation phase, the testing phase starts by utilizing the system with real educational institutions, real students, and real teachers, where we must keep eye on every process and every learning object to make sure that the system complies with its requirements. Convincing educational institutions and students to use a new e-learning system could be challenging because they are on a specific schedule that they cannot postpone or change.

To enhance and develop our system, we can integrate other tools and technologies to analyze learning resources in different formats like video, audio, and graphics. This could produce a strong system for e-learning that will beat the huge amount of learning resources currently available and help learners find the resources they need. We will complete the designed system by providing the required tools for augmenting it inside different social networks that can encourage learners to spread their learning experience among their friends, and make use of the long times that they spend socializing to enhance the learners ontology database and collecting information about learners interests background, and goals.

Another area to enhance our system is the expansion of the number of languages that it could handle for topic identification and learning object handling. The ability to handle multiple languages will, without any doubt, be a great advantage through which a bigger number of users could be acquired and a larger number of learning resources could be processed. This increase will enrich the scientific content, expand the circle of interaction between students from different cultures, and increase the knowledge base of the system to improve the quality of recommendations received by users.

Certainly, the great development in the field of artificial intelligence is not hidden from us, which can be used in the development of all aspects. We can use it to improve the quality of recommendations and extract main topics from learning resources, whatever their type or language. We can use it to analyze the behavior of students during their use of the system to find the appropriate learning model for them and give them suggestions for learning groups that suit their interests. We can also improve the search process for learning resources by developing an AI service supported by the knowledge base extracted from our system, based on semantic information, that can be understood by the computer, and then interactive methods could be provided for this services through text, audio or even video, providing and interactive electronic guidance or tutor for each student that could be adapted and tailored according to his own needs and requirements.

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