SOCIAL NETWORKING AS AN E-LEARNING TOOL FOR GAINING TECHNOLOGY RESOURCES USING GENETIC ALGORITHM

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ABSTRACT
Social networking is used widely by all the users for sharing their knowledge. Face book, Twitter, LinkedIn are the very commonly used social networking applications. used social media. The students have various groups in these social networking applications for sharing the knowledge related to their domains. Since most of the time, the students spend their time on social media, it has become very vibrant to aggregate the resources related to the education. In this paper, we have highlighted the abundant use of social networking to improve the learning through e-platform. This paper explores the role of Social Networking Sites (SNS) in e-learning by investigating the attitudes, behaviors, knowledge and views of computing students towards the use of SNS in e-learning. Online social networks (OSNs) have gained popularity among users from all over the world during the past few years. And E-learning has made learning process quite convenient for users by using the networks. Data was collected from an online survey and interviews, and analyzed to discover the practices, tendencies and the current status of the use of SNS in e-learning as well as how these can be improved. By combinning OSNs with E-learning is a new idea. And the role of OSNs in students' E-learning experiences is focused on in this paper. And it is believed that online social networks can be effectively used in E-learning in the future. We believe that SNS can play a major supporting role in e-learning and that the potential for using SNS in e-learning is not fully reached. The situation may be improved by providing increased guidance and training to students. Learning activities using SNS should be planned and organized. Brief guidelines on using SNS in e-learning are also included in this paper.
Keyword: Social networking sites (SNS),Online social networks (OSNs)

INTRODUCTION

The internet has huge volume of users around the world. Everyone is using the social media applications as a common platform for sharing the information. It is very potent that when the user immediately shares the information, it is getting disseminated instantly to all the users who are using the social media applications. Though the shared information is accessible to every user, only the users who are closely related to that information domain have the maximum utility. In connection with this, the education related information shared by the students play a very crucial role in the social media applications. Students share their course related materials with their peer group users and they interact with experts for enhancing their knowledge and clarifying their doubts. In the last decade, e-learning facilities have increased in academic applications.

Their uses have risen in higher education and have almost changed the learning modes of the student communities. The engineering domain is clearly aware of this ever-growing scenario, and using it for implementing effective learning strategies to the modern young minds. And also the applications of electronic learning have started dominating various platforms that involve online, distance and traditional university education systems. E-learning is a web application, which is used to share the content, and to manage, disseminate, and monitor the educational activities of an organization through online activities. A few of its highlighted functions are to manage learners, learning resources, learning object materials and activities, to control access, monitor the learning process and to make evaluations. It can also be stated that the use of information and web technologies in learning is being encouraged through the use of e-learning systems.In this paper, section 2 describes the related works of the social networking applications in e-learning. Section 3 explains in detail about the proposed social media based
e-learning systems.

RELATED WORKS:

The USDLA was formed in 1987. At that time when "Power users" were boasting of their Intel 386 processors. In that context, DL was a concept well outside the education mainstream. It Granted few people who know something of the process but hands-on DL experience was rare. USDLA, then, provided a means for these pioneers to find one another[3].MOOC provides low-cost courses and the potential to expand and include a broad diversity of educational levels, MOOC is acquiring power and popularity. Like MOOC, STEM grabbed a large share of available online courses provided by MOOC platforms MOOC have the potential to allow children who are homeschooled to pursue their education from their homes [4].

E learning is Web based learning where we can learn essential content at anytime, anywhere. Ontology was familiarized in this model to support the conceptualization of certain domain because it was based on reusability[5]. Here the Resource Description Language (RDF) and the Web Ontology Language (OWL) is providing a language and structure for describing all ideas and concepts in the universe and then relating these to each particular subject area[6].The mobile learner is increasing the learner‟s capability physically anywhere. This is the intention to increase research and changes and maximize the potential of mobile learning[7].

In this paper the benefits of information structure, oriented to services are discussed. There are still a series of problems, and a way for a wide solution is to make interoperable services. It proposes that using ontology and with semantic focus will solve the difficulties[8]. In this paper, they make a case for why ontologies can contribute to block chain design. For this, they analyze a traceability ontology and translate some of its representations to smart contracts that execute a provenance trace and enforce traceability constraints on the Ethereum blockchain platform.[9] This SARA voluntary, regional solution was developed through a lengthy, collaborative process that brought together major stakeholders in higher education[10]. In this paper they discuss the explicit representation of the semantics of data, accompanied with domain theories (ontologies), which will enable a Web that provides a qualitatively new level of service[11].

Several works of artificial intelligence are used in adaptive e-learning to give the learner a content adequate to his profile in the literature we find: Hawkes and Derry [15] have used the informal fuzzy reasoning in the TAPS system to determine with uncertainty the solution that the student has built among those of the system (models). Ruiz et al. [11] have modeled an adaptive hypermedia system, called Feijjo.net, based on the learning style. The system uses fuzzy logic to determine the learner's style from the CHAEA questionnaire.

Chrysafiadi and Virvou [17] have proposed a learner model that represents the learner's knowledge through the overlay model (presented concepts that the learner master with "1" or with the word "known" and those that do not master by "0" or unknown), the fuzzy logic allowed to define and update the level of knowledge of each concept, with each interaction with the e-learning system.

Martin and VanLehn [18] have presented OLAE as an assessment tool that collects data from students solving physics problems in college. For each problem, OLAE automatically creates a Bayesian network that calculates the probabilities indicating the rules that the student uses.

Viccari et al. [12] have introduced AMPLIA, an intelligent learning environment used as a training tool in the medical field, the system combines bayesian networks with cognitive.There are also works that use genetic algorithms for adaptive e-learning, namely:

In [11] the Researchers describe an adaptive system con-ceived in order to generate pedagogical paths which are adapted to the learner profile and to the current formation pedagogical objective. They have studied the problem as an "Optimization Problem" using Genetic Algorithms, the system seeks an optimal path starting from the learner profile to the pedagogic objective passing by intermediate courses to prepare the courses for adaptation.

In [17] a genetic algorithm based adaptive learning scheme for context aware e-learning has been described, the Re-searchers defined a new three level structure for learner's context comprising of the content level, presentation level and media level is defined. The learning path generation algorithm now evolves into a learning scheme generation as it generates a learning path accommodating the entire learner's context.

SOCIAL NETWORK ORIENTED E-LEARNING SYSTEM:

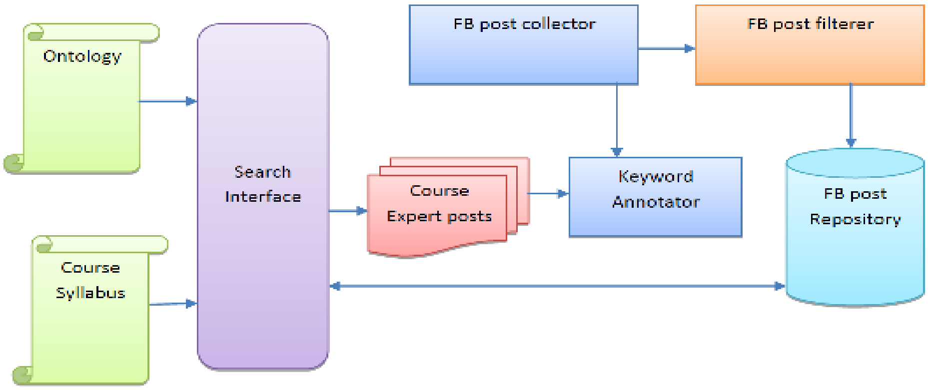


Figure 1

In particular, the system initializes a unit for collecting learning materials by setting target concepts in the input domain ontology and associate different course experts to share educational posts on a specific topic. The e-learning based supportive learning system mainly encompasses the ontology, expert shared post, Keyword annotator, FB post collector, FB post filtering system and the FB post repository.

FB Post Pre-Processing Or Filtering:

It allows transforming the original FB posts from the facebook into a common format to be used by mining tasks. Thus, before applying various mining techniques, general data preprocessing tasks have to be completed. The ontology is the hierarchical representation of course details that belong to the corresponding subject . In addition to the collected

FB posts using input ontology, the posts relevant to the subjects are created and posted Ontology,Course,Syllabus,Search,Interface course,Expert posts,FB post collector, Keyword Annotator,FB post filterer,FB post,Re pository by the experts. The expert posted posts are annotated, using keyword terms. The annotated posts are stored in the FB post repository.

Integration With The E-Learning System

The FB post collection and filtering related tasks are integrated into the e-learning environment. All data pre-processing and post-processing are carried out into a single application.

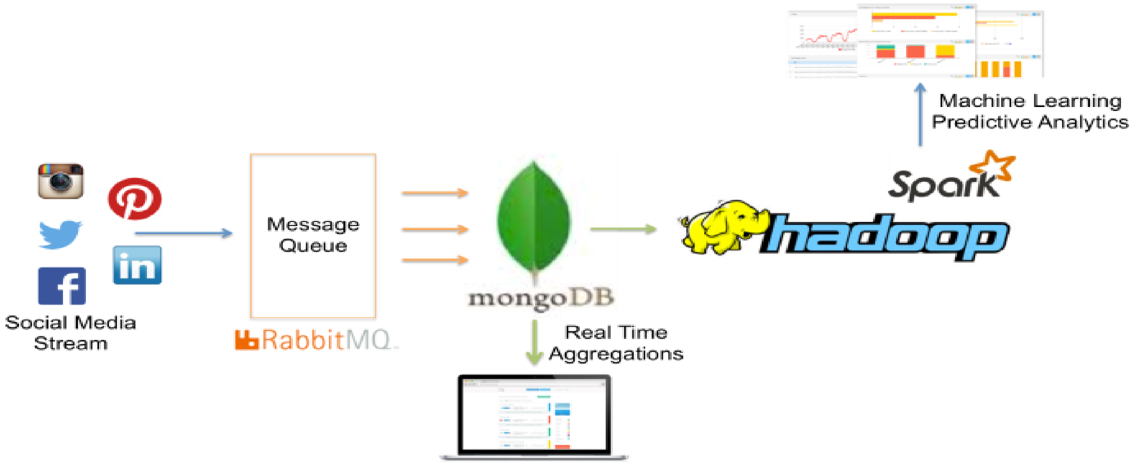
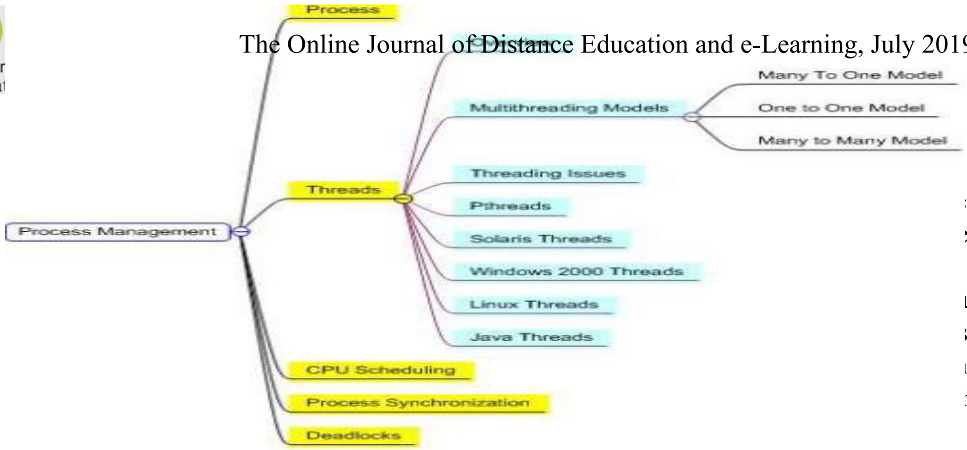


Figure 2

Facebook was identified as the most popular SNS. Also YouTube and Instagram are identified as the most used SNS. To improve and enhance the method of learning the following algorithm is suggested in this paper.



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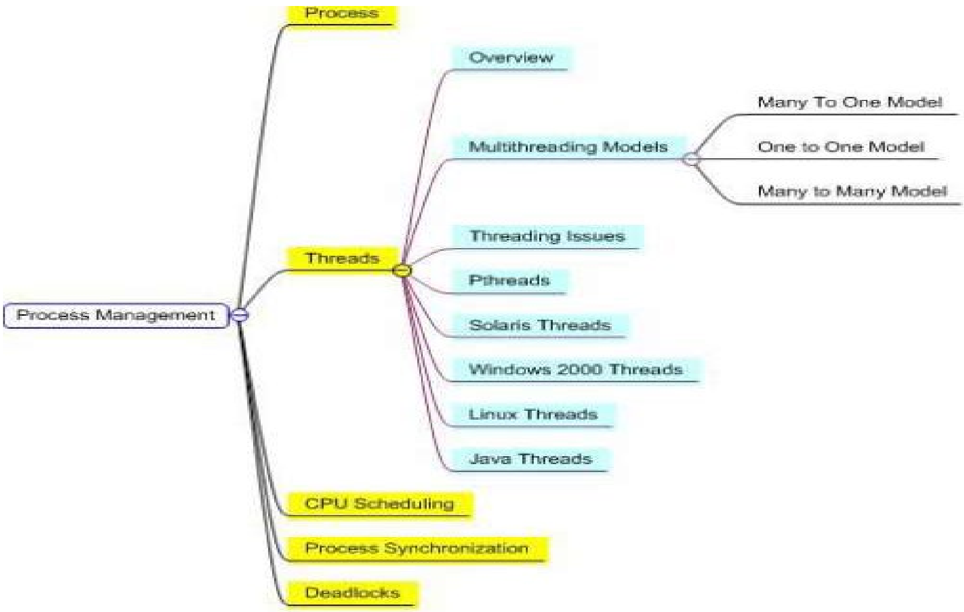


Figure 3

Our corpus in our case contains the documents that represent the learner's objectives, the first thing to do is to extract all the terms or concepts in the corpus, and for each document construct a vector That represents it, if a term exists in the document we calculate its weight and if not we put 0, at the end of this operation we construct a vector for each document to calculate the similarity between the profile of the learner and each pedagogical objective.

ALGORITHM: (Blog-Ranking)

Genetic algorithms (GAs) are stochastic optimization algorithms based on the mechanisms of Natural selection and genetics, their operation is extremely simple, we leave with a population of potential solutions (chromosomes) initial selected arbitrarily, we evaluate their relative performance (fitness). On the basis of these performances, a new population of potential solutions is created using simple evolutionary operators such as selection, crossing and mutation. This cycle is repeated until a satisfactory solution is found [3].In our work we use a simple GA, which consists of iterating the following three operations: reproduction, crossing and mutation, the population created during each iteration is called a generation and it's noted P_t.

There has been an increasing interest in the application of GA tools to IR in the last few years. Concretely, the machine learning paradigm, whose aim is the design of a system able to automatically acquire knowledge by themselves, seems to be interesting on this topic. The first thing in a genetic algorithm is the definition of the initial population (selection operator or evaluation) on which we will apply the treatment as in our case it is to show the documents (educational objectives) relevant to the profile of the learner using the cosine similarity that will play the role of fitness function which is a very important parameter in GA because with it we can decide whether an individual is going to be selected or not. There is a lot of methods to make the selection like the biased lottery, the elitist method or the selection by tournaments.

The calculation of the weights of terms or concepts in each document is calculated by the following formulas:

$$P\ oid(t_i; r_j) = IDF \qquad \text{Equation 1}$$

$$T\ F = \frac{f(t_i; r_j)}{N} \qquad \text{Equation 2}$$

$f(t_i; r_j)$ is the number of occurrences of the term t_i in the document d_j and N is the total number of terms in the document

$$IDF = \frac{\log(f(t_i; r_j))}{M} \qquad \text{Equation 3}$$

$f(t_i;r_j)$ Is the number of occurrences of the term t_i in the document r_j and M is the total number of documents in the corpus.

The similarity used in our work is the Cosine similarity. This measure uses the complete vector representation, i.e. the frequency of the objects (words).Two objects (documents) are similar if their vectors are confused, the formula is defined by the ratio of the scalar product of the vectors X and Y and the product of the norm of X and Y.

1) Randomly choose the initial population Z(0)= (z1,z2,…..zn)
2) Each Chromosomes Fitness F(zj) is computed.
3) Apply Blogs ranking by mating current chromosomes, then by applying mutation and recombination as a parent chromosomes mate.
4) Delete the left out population to make room for new population.
5) Compute IDF and TF to compute new fitness
6) T:t+1, if not move to step 3 else stop and return the optimized result.

EXPERIMENTS AND RESULTS:

The content based importance is used to measure and retrieve the FB post contents related to the query content. Ranking is the process of sorting out the blogs based on the order of their content relevance with respect to the user query. The user enters a search term, and in response the blogs relevant to their content are displayed. The blogs are ranked based on the relevance of the blog content using the blog ranking algorithm. The query term helps to retrieve the bins that match with the given input keyword. The retrieved bins include super classes, sub-classes and the peer bins that have been requested by the query term. Once the bins have been retrieved, the resultant blogs are converted as blog objects that help to maintain the blogs in a general data format. The fuzzy probability is computed for the resultant blogs using the Equation. The computed probability value is taken as the CBI value for every blog. After computing the CBI values for all the blogs, the blogs are sorted on the basis of the calculated CBI values.

In the very first stage of ranking the blogs, the individual blog's rank value is computed for the given keyword. The rank value refers to the CBI value, that is, how much content,
relevant to the user query the blog contains. The blogs have been ranked based on the computed CBI value. The Table displays the details of the blogs retrieved for the keyword "Apple"; 16 blogs have been retrieved in 41 seconds. The blog URL is used for locating the particular blog where the query relevant blog contents exist. The content richness of the blogs is estimated by the calculation of the CBI value, often referred to as the rank value which is taken as the key ingredient for ranking all the blogs.

When the results are compared with the existing keyword based method, the proposed CBI-based blog ranking method retrieves the most relevant, personalized blogs in a sorted order of relevance for the user. The ontology diagram shows the precision and recall values for all the existing blog search engines. The tabulated values show that the precision value is high for the blog ranking system, and the recall value is also preserved. The statistics of the collected blogs from various search engines shows, that the number of blogs retrieved for each keyword is high. It is very clear that except for a few, most of the retrieved blogs are irrelevant. Blog search engines like Blogpulse and Blogscope start with zero precision and recall. It shows that the very first blog listed for the keyword "apple" is not relevant to the query.

Blog search engines like Technorati and Icerocket start with very high precision and recall, which is not preserved because the number of blogs retrieved is high. Regator is not a popular search engine; it can retrieve only less number of blogs, and it also fails to preserve its recall value.The experimental results show that the blog ranking system ranks the blogs according to the relevance of the blog content and user profile. It also yields very high precision and recall. The blog ranking system and its corresponding graph have been plotted. Though the blogs have been ranked based on their content, most of the times the retrieved number of blogs for a specific topic is extremely high. Sometimes the blogs may be similar in their content, or even may have the same content. In such cases, summarization takes an important role. Generally summarization is the process of giving the contents in brief by collecting the information on a common topic. In case of blog summarization, initially the collected blog contents are split into various sentences (S1, S2, S3…Sn). The term frequencies of all keywords are computed for each sentence. It is also necessary to compute the similarity of the sentence Si to the query word „q". In some cases the sentence may not have the same word as the query term, but the semantics may appear in the sentence.

The sentence is checked for word matching in terms of semantics, equivalence and relevance .Sentences with more than 75 percentage of stop-words don't yield any useful information. So, those sentences would be removed from the sentence collection. The mean value of TFIDF, cosine similarity and word matching are calculated to find out the highest mean valued sentence. After calculating the mean value for sentences, the top five meaningful sentences are selected for giving the summarized content. The subject in the ontology and the frequency of the corresponding subject blogs are summarized.

The experimental results show that the proposed work performs well when compared with the existing blog search engines like Technorati, blogpulse, blogscope, icerocket, and regator. The blog summarizer retrieves only the blog relevant to the query, with a meaningful summarization and minimal number of blogs. The number of blogs retrieved using various search engines for the selected keywords. The blogs retrieved using search engines, contain a huge amount of irrelevant blogs. The experimental results show that the TPBRS yields better results. It is inferred that the number of blogs retrieved for each keyword is very high and the relevance is very low. The semantic blog mining framework uses the ontology to collect the relevant blogs from the blogosphere,then remove the irrelevant blogs and create the relationship between blogs before storing them in the repository. In this framework, the blogs stored are relevant to the subject, which makes the search process easier, and reduces the search time as well as the user ambiguity.Since the collected blogs are preprocessed and semantically related, only the relevant blogs are retrieved for the user. Hence the relevance of the blogs is completely (100%) achieved.

Alongside other SNS like Facebook and TwitterInstagram , YouTubeis also becoming popular as it's increase of use in the field of learninghad improvedas shown In graph(figure4&5).

Figure 4

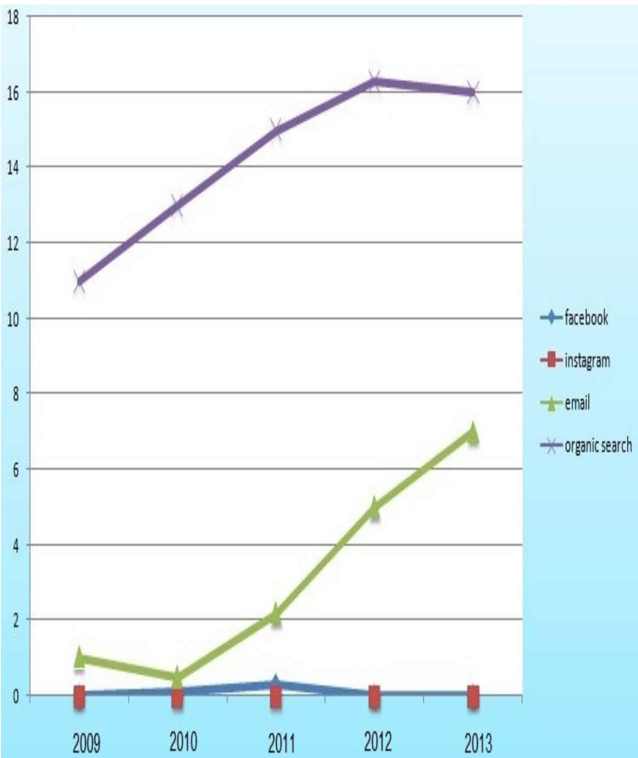
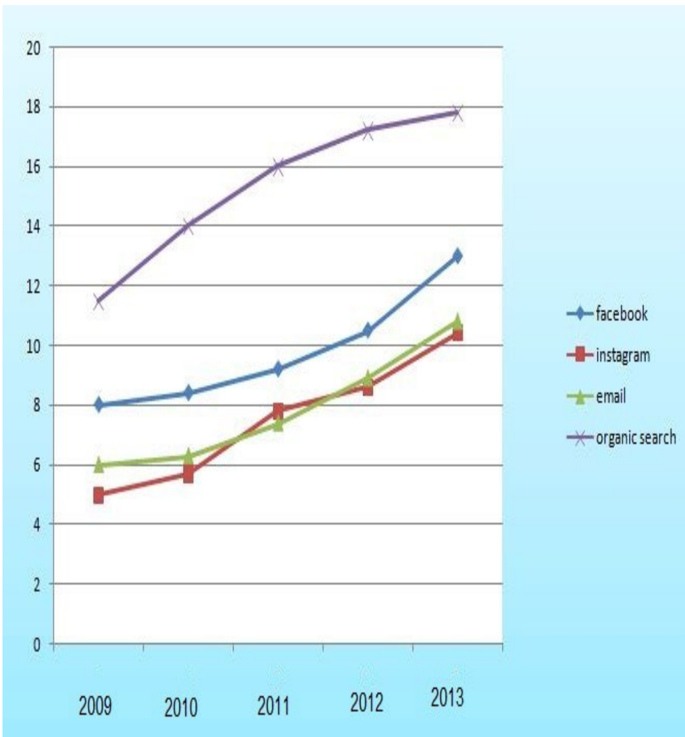


Figure5



CONCLUSION AND FUTURE ENHANCEMENT

Blogs are the authoritative sources of both technical as well as personal information. As the blogs are spread over the blogosphere, ranking contributes its role towards analysing the bestrelevant results to the user queries. Indexing has an important place in the process of blog ranking. Especially, user given keyword based indexing provides intuitive and efficient blog ranking results. In addition to indexing, the similarity analyser performs the process of checking the blog relevance by computing the cosine similarity of blogs to improve the ranking results. The blog ranking algorithm (BRA) involves the computation of the content based importance (CBI) values of the blogs, to provide better results in response to the user query. The optimized results is obtained with the genetic algorithm strategies. Summarization takes into consideration the various blogs on a similar topic, computes the mean value of TF-IDF, then summarizes the blogs, and provides the brief content by combining the highest mean valued TF-IDF sentences.

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