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IDEAL LEARNING ENVIRONMENT: HOW TO BUILD IT WITH ARTIFICIAL INTELLIGENCE

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ABSTRACT

With the massive use of new learning technologies, such as mobile learning through on-line platforms, or more "traditional" live classes taught through virtual meeting platforms, the interaction between students and teachers can be poor or limited. The professor can monitor the students' reactions and appreciation with the use of polls, forms, and forums, but in general it is very difficult to understand how students feel, what they really like and how to give them an unforgettable learning experience, especially when they are many and in a heterogeneous environment. A method to automatically detect students' needs, based on unsupervised machine learning techniques is proposed.

KEYWORDS

Professional Education, Educational Innovation, Higher Education, Ideal Environment

1. INTRODUCTION

In any kind of classroom environment, the student's experience is fundamental for the degree of learning obtained. In 1975 Mihaly Csiksentmihalyi introduced the concept of "flow" (Csikszentmihalyi, M. ,1975) to describe a particular emotional state of engagement during an activity which produces happiness. In this state, people are so involved in an activity that nothing else seems to matter and people feel strongly motivated. Csiksentmihalyi refers to this situation as "optimal experience" (Csikszentmihalyi, M. ,1990). Thinking to students in the classroom, it is believed that a student can get his optimal learning experience in such an emotional state. Therefore, it is important to create the ideal environment where students can live their "optimal experience". This issue is particularly important in a "virtual" environment as the one we were obliged to use during the COVID-19 pandemic (Liu Y.C., Kuo R.L., Shih S.R., 2020), where engagement during classes is critical to maintain students' attention. In asynchronous mobile learning it is even more difficult to monitor the engagement of students and understand their needs. Due to the complexity of class dynamics and inhomogeneity of students within the same classroom, creating ideal classroom conditions for all the students is a challenging task. The main question is – "How to create the ideal mobile learning environment"? In the following, a method based on sentiment analysis is presented.

2. MOBILE LEARNING EVALUATION WITH SENTIMENT ANALYSIS

2.1 Theoretical Background

Sentiment analysis is a field of Data Science aimed to automatically identify and extract opinions, sentiments, psychological and emotional states from written text. The methods used in this kind of analyses are based on machine learning techniques which are grouped under the name of Natural Language Processing (NLP) algorithms. Sentiment analysis has been used as a powerful tool to improve didactic strategies in on-line platforms as "Coursera" (Rani, S., and Kumar, P., 2017), where the interaction between teacher and student is very limited. By the application of machine learning techniques to comments and answers to polls taken during the course, it is possible to quantify the students' appreciation (Esparza, G.G., et al., 2018) automatically. In general, using NLP techniques it is possible to detect sentiments and emotional states. As described in detail in (Kaur., W., Balakrishnan, V., Singh, B., 2020), the term "sentiment analysis" describes a kind of study where we aim to detect the polarity of a written text, i.e., if it represents a positive or a negative feeling. The analysis of emotions is an extension of sentiment analysis which tries to detect also if the person who wrote the text was happy, sad, frustrated, angry, or in other emotional states. With these kinds of analyses one can classify the opinions of the students and classify their feelings, but it is hard to retrieve what they really would like to receive from a class.

2.2 Objectives

The analysis presented here uses an NLP algorithm called Probabilistic Latent Semantic Analysis (PLSA), which is normally used to extract topics from collections of documents by grouping them by similarity (Hofmann T.,1999). The use of this algorithm was inspired by studies in the field of Social Signal Processing, aimed to automatically detect personality patterns, which make use of statistical and probabilistic algorithms of this kind (Judee K. Burgoon J. K., Magnenat-Thalmann N., Pantic M., Vinciarelli A.,2017). The main idea is to detect latent aspects among the words of the feedback comments written by the students, in order to find common characteristics or sentiments that they would like to experience during the class and sort them by importance. A similar approach has been used recently to analyze comments of hotel customers, as standalone method and in addition to Deep Learning techniques (Khotimah, D. A. K. and Sarno, R., 2018, 2019).

2.3 Data Collection

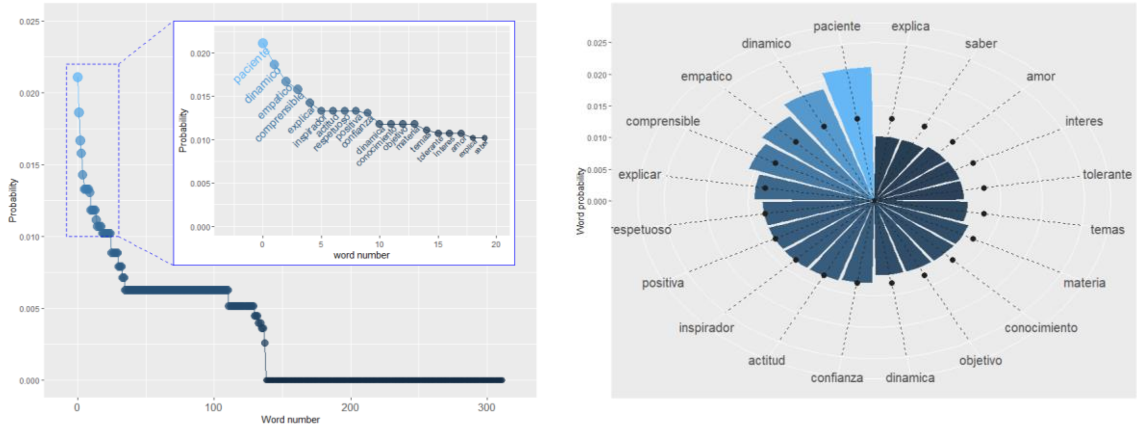
In the present analysis the data are represented by a sample of 42 written opinions from university students of ages between 18 and 20. Students were asked to write their comments following specific instructions. They were asked to share the aspects that, in their opinion, make a professor the "ideal" professor. Students were asked, also, to describe which sentiments they want to feel during the class that make them feel strongly motivated and which characteristics the ideal class must have. We want to prove whether the algorithm can "extract" from the students' comments these principal aspects which define the ideal learning environment. The data were taken in the period between August and December 2020. The participation was voluntary and a total of 42 comments was collected. The students' comments were firstly collected through the "Padlet" platform (Padlet, n.d) anonymously and successively imported in a csv (comma separated value) file. The comments are written in Spanish.

2.4 Methodology

The PLSA algorithm "counts" the co-occurrence between words and documents (using Bayesian statistics) and divides the documents into groups. Each group is defined by a "latent" aspect (or topic) which is not known "a priori". In the classical application of PLSA aimed to group, for example, articles by similarity, the latent aspects represent the different topics of the articles, such as science, economy, education and so on. In the analysis presented here, in principle, the number of latent topics is also unknown. Since the comments were written following specific instructions, we can guess that the number of topics is 3: one related to the professor's personality, one related on the way of teaching and one related to the feelings the students want to experience. So, the number of topics was set to 3. The dataset, from the point of view of the algorithm, is a set of documents (the comments), each composed by a sequence of words. The full dataset is defined also as "corpus". After running the analysis, one obtains two numerical results. The first is a number (between 0 and 1), for each topic, representing how probable, or frequent, is the topic within the corpus. The second result is a list of numbers (between 0 and 1), for each topic, representing the probability within the topic of all the words of the corpus (i.e., the importance of the word in the topic). The "importance" of a word in the corpus is the frequency of the word in the corpus, i.e., among all documents. Usually, NLP techniques require a big amount of data to perform well, due to statistical implications. In the presented analysis, however, the corpus is composed by only 42 comments and some uncertainties and instabilities of the result have been observed when running the analysis different times. However, the method should provide stable results when applied, as it is intended to, to analyze bigger datasets.

3. RESULTS

The analysis was focused on the lists of probabilities associated to the words, topic by topic. For each topic, this list is a sequence of 312 (the number of words in the corpus) descending values representing the probability of each word in the topic. In Figure 1, on the left, a scatter plot of the list of probabilities for the first topic extracted is shown.



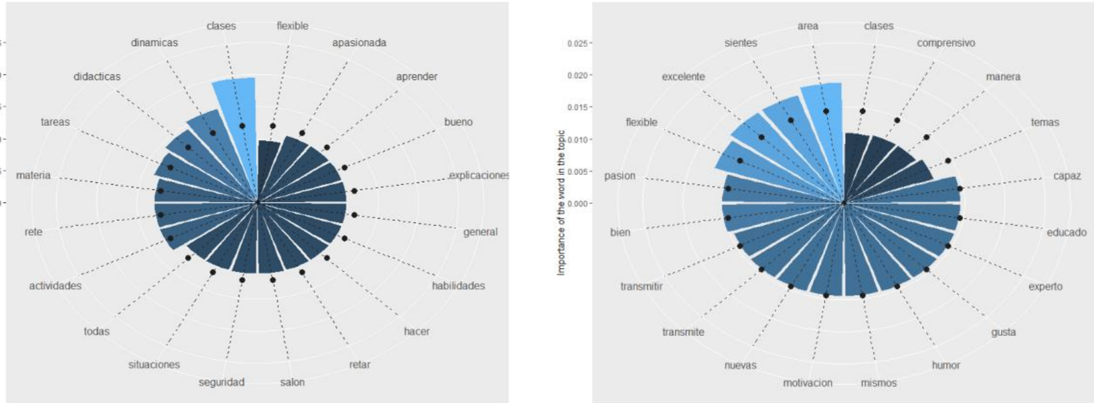
a) b)

Figure 1. a) Probabilities of the 312 words of the first topic extracted. A zoom for the 20 most probable words is shown on the upper right corner**.** b) First 20 most probable words associated to the first topic. The black circles represent the mean probability of the sample of words

Considering the first 20 most probable words of each topic we can analyze the difference among the three topics detected. Figure 1, on the right, shows the first 20 words for the first extracted topic. The words are: “paciente” (having patience), “dinamico” (dynamic), “empatico” (empathic), “comprensible” (understandable), “explicar” (to explain), “respetuoso” (respectful), “positiva” (positive, feminine), “inspirador” (inspiring), “actitud” (attitude), “confianza” (trust), “dinamica” (dynamic), “objetivo” (objective), “conocimiento” (knowledge), “materia” (subject), “temas” (topics), “tolerante” (tolerant), “interes” (interest), “amor” (love), “saber” (to know), “explica” (to explain). It is possible to infer to which aspect of students’ preferences each topic refers to by associating the corresponding words. Even though the interpretation could be somehow subjective, we can identify in this topic words mainly related to the personality of the professor.

Figure 2 a) shows the 20 most probable words collected for the second topic. The words are: “clases” (classes), “dinamicas” (dynamic, plural feminine), “didacticas” (didactic, plural feminine), “tareas” (homeworks), “materia” (subject), “rete” (that challenges you), “actividades” (activities), “todas” (all), “situaciones” (situations), “seguridad” (certainty), “salon” (classroom), “retar” (to challenge), “hacer” (to do), “habilidades” (abilities), “general” (general), “explicaciones” (explications), “bueno” (good), “aprender” (to learn), “apasionada” (passionate, feminine), “flexible” (flexible). The second topic seems to be related to class activities and way of teaching. The two first most probable words are “clases” and “dinamicas”, both plural and feminine, suggesting that they could be associated to form the description of the ideal class as a “dynamic class”.

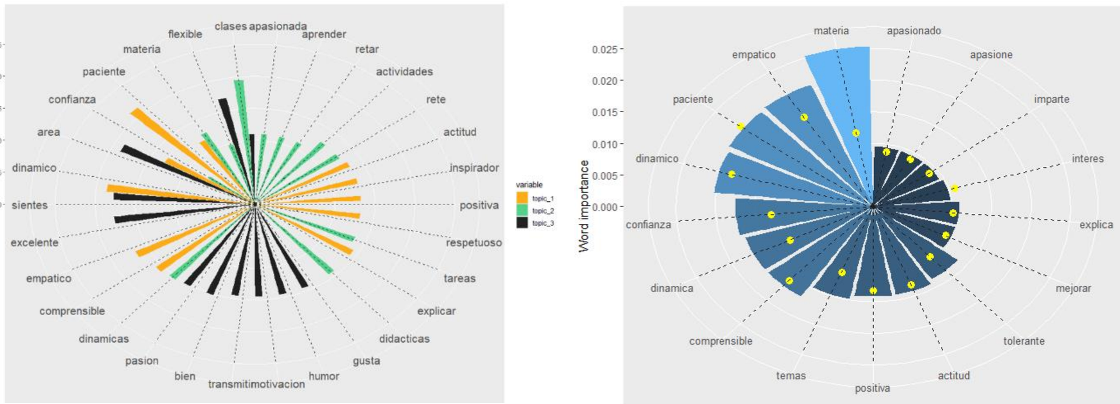
Finally, the probabilities of the first 20 words of the third topic are depicted in Figure 2 b). The words are: “area” (area), “sientes” (you feel), “excelente” (excelent), “flexible” (flexible), “pasion” (passion), “bien” (good, noun), “transmitir” (to transmit), “transmite” (he transmits), “nuevas” (new, plural femine), “motivacion” (motivation), “mismos” (same, plural masculine), “humor” (humor), “gusta” (he likes or you like), “experto” (expert), “educado” (educated), “capaz” (able), “temas” (subjects), “manera” (way), “comprensivo” (understandable), “clases” (classes).



a) b)

Figure 2. a) First 20 most probable words associated to the second topic. b) First 20 most probable words associated to the third topic. The black circles represent the mean probability of the sample of words

Even though in this last topic the words are more mixed, words such as “sientes” (you feel), “pasion” (passion), “transmite” (he transmits) and “motivacion” (motivation) suggest feelings that students want to feel o want the professor to transmit. The difference among topics can be visualized comparing the probabilities of the same word in the three topics. To do so, the first 10 words with highest probabilities of each topic have been chosen, for a total of 30 words. The comparison is shown in Figure 3 a).



a) b)

Figure 3. a) Word probability of the 30 most common words within the topics. b) Comparison between the probabilities of words belonging to the first topic in two runs of analysis. The bars represent the probabilities of the new run, the yellow circles represent the probabilities of the previous run

Figure 3 a) shows that most words have a high probability in only one topic. Some words appear in two topics, as “clases” (classes), “flexible” (flexible), “materia” (subject) and “dinamico” (dynamic), with different probabilities. The word “confianza” (trust) appears in the three topics, being more probable in the third topic, than in the first and at last in the second topic. From this comparison we can conclude that the three topics are well “separated”, i.e., are characterized by different words. Also, one could guess the students’ preferred aspects in each topic just looking at the most probable words and interpreting the meanings. Looking at the word corresponding to the highest probability, we could conclude that the most important aspect for the students is “paciente” (having patience). However, due to the uncertainties of the algorithm due to the small statistics, the probability cannot be interpreted as the relevance of the corresponding student requirement, at least for the present dataset. As an example, the analysis was run a second time. Figure 3 b) shows the most probable words of the topic related to the personality of the professor and the probabilities obtained in the two runs of analysis. The bars represent the probabilities obtained in the second run and the yellow circles represent the probabilities obtained in the previous run. It is possible to observe some fluctuations in the probabilities, as for the word “materia” (subject), which appears as most probable word of the topic in the second run while it had a much smaller probability in the first run. Despite these uncertainties, the algorithm was able to detect the three aspects on which students were asked to write about in their comments.

4. CONCLUSIONS AND FUTURE DEVELOPMENTS

The results presented above show the possibility to automatically detect students’ needs by analyzing the words written in their feedback comments. The limit of this method is that the interpretation of the results is somehow subjective and that there could be lack of reproducibility when applied to small datasets. On the other hand, since the result is expressed through words, the results are easily interpretable. In the framework of mobile learning, by applying this method on a larger dataset of posts written, for example, by students following a course offered on-line through a smart-phone application, one could guess the students’ needs and preferences in real time during the course and change educational strategies to create the ideal learning environment.

A further development of the present analysis could be the application, on a larger dataset, of other algorithms used for topic extraction, as Latent Dirichlet Allocation (Blei D.M., 2003) and more recent techniques based on pre-trained models and Deep Learning (Angelov D., 2020).

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