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Clustering Opinion Polarity of Student's Strategies as Clues for Motivation

Julio César Quintana Zaez[1], Luis A. Quintero Domínguez[2], Jarvin A. Antón Vargas[2], Julio Sorí Gómez[1], Nicolás Quintana Bernabé[1]

[1] Faculty of Informatics and Exacts Sciences. University of Ciego de Ávila "Máximo Gómez Báez", Ciego de Ávila, Cuba.
[2] Department of Computer Engineering. University of Sancti Spíritus "José Martí Pérez". Comandante Fajardo SN, Sancti Spíritus, Cuba.
cjquintanazaez@gmail.com, lqdominguez@uniss.edu.cu, jarvinvalberto@uniss.edu.cu, julioc.sori@gmail.com, nicolasquintanab@gmail.com

Abstract. Nowadays education is considered critical and indispensable for the country's development. Understand student's motivation for study is one of the most challenging task in educational process due to the high level of diversity present in the students and educational environment. For this reason, in this paper we propose the use of patterns recognition to solve this problem. A combination of a PCA + K-means algorithm was presented and a dataset of different opinion for students strategies in lectures (Challenging, Non-Challenging and Generic) was used. As a result, reaching optimum values for different clustering metrics and including a Silhouette index over 0.55 was possible to create clusters that explain the existing patterns in the student's opinion for different study strategies in lectures. Also, an explainable tool (SHAP) was used to extract knowledge from the clusters created which suggested clues related to students.

Keywords: Machine learning, K-means, PCA, Silhouette, Educational Data Mining

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1 Introduction

Nowadays, education is widely recognized as a crucial factor in a nation's progress. Many reasons support this affirmation due to the areas directly influenced by education, such as medicine, politics, agriculture, industry, economy, culture and so on [1], [2]. Student diversity and ever-changing educational environment, imply that governments promoting innovation in the educational sector in order to understand the characteristics present throughout the learning process and the adaptation of students to it [3]. Also, several researchers have worked to find the dominant factors impacting student performance, where they point out that student online learning activities, term assessment grades, and student academic emotions were the most evident predictors of learning outcomes [4].

Academic emotions refer to emotions that arise in different kinds of academic settings and are directly linked to academic activities such as studying, learning and instruction [5], [6]. For other authors, one of the most important aspect for eduational environment is to trigger motivation in students [7], [8], [9]. Motivation, which is considered directly linked to emotions is known that drives most human activities, including foreign language learning, dancing, exercises and so on [10]. In [11] authors suggested that motivation is affected by several intrinsic and extrinsic factors. Also, studies focused on learning strategies and its integration with technologies into study programs [12], [13], [14], [15], can help educators, schools and stakeholders of educational process in general to know what trigger the motivation in students. In the last decade, Sentiment Analysis (SA) has been widely applied in many domains, including business, social networks and education, argument in [16]. In the education domain, the challenge of dealing with and processing students' opinions is considered a complicated task due to the nature of the language used by students and the large volume of information. Also, NLP task such as SA can help to understand how students interact with the classroom and to obtain valuable information related to the motivation to study [17].

The teaching-learning process and innovation in different aspects of the educational environment, such as learning strategies, study methodologies, evaluation methods, content creation and ways of processing this content, among others, are considered an arduous task for their research community [18], [19]. To understand what influence the students' motivation, various technologies can provide feedback, personalization and recommendations based on data generated by students [13], [20]. This approaches are showing as a key for making discoveries and providing decision support systems that can help the educators by improving teaching performance and making knowled-based decisions. Also, for other authors this discoveries in the education field can help researchers to have a better understanding of educational structures and the evaluation of learning effectiveness [21].

Encourage the design Artificial Inteligence (AI) involved learning tasks and environments, with new formats of assessments to engage students could be crucial to accomplish educational learning goals. The potential impacts of AI and its branches such as Natural Lenguage Procesing (NLP), Machine Learning (ML) and Educational Data Mining (EDM) on education remain unsiezed. One thing is clear, and that is that these technologies can drive changes in educational objectives, learning activities, assessments, and evaluation practices in education [22]. Despite the enormous capacity of processing and generating informations of this technologies some researchers suggested that education should focus on improving students' creativity and critical thinking rather than general skills [10].

AI and its overlapping aforementioned research fields are a force in the innovation in the educational environment [3]. Educational systems has recognize its potential to help learners identify knowledge gaps and receive specialized support. Lastly, at an institutional level, AIEd tools can provide useful insights to administrators and decision makers, like enrolment and attrition patterns acrossdisciplines or colleges. The application of AIEd remains a topic of keen interest among researchers [23], [24], [25], [26]. Also, among the main objectives of the AIEd research field is to develop, to investigate and to apply computerized methods to detect patterns in educational data. Despite the advances in AI (and its branches) and the features used by EDM in the learning process, research niches that call the attention of the state of the art remain to be explored, such as sentiment analysis to capture students motivation. For this reason, the present research aims to carry out a study of sentiment analysis and unsupervised machine learning to recognize student opinion patterns for different study strategies.

This article is structured as follows: INTRODUCTION, where the subject is presented, the objectives are included, as well as the reasons are justified for which the investigation is carried out. This is followed by the RELATED WORK section, where the most relevant works are briefly presented and the contributions of other authors to the subject under study are highlighted. Next, the MATERIALS AND METHODS section, which describes the research design and explains how it was carried out, justifying the choice of methods and techniques. The EXPERIMENTAL RESULTS section presents the results obtained after explaining the selected techniques and finally CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH, ACKNOWLEDGEMENTS and REFERENCES.

2 Related Work

In this section, a review of the main theoretical contributions on patterns recognition applied to student learning environmentsto know aspects that trigger motivation is carried out. Nowaday, following authors in state-of-the-art [27], the neuroscience has demonstrated that the brain learns with the emotion and when it is motivated. These two factors are key when carrying out the education that is exercised from the classrooms and, also, from the families to be able to forge individuals with knowledge. Recent evidence suggests that achievement emotions are linked to motivational, self-regulatory, and cognitive processes that are crucial for academic success [6]. Also the cited authors suggest that despite the importance of these emotions, syntheses of empirical findings investigating their relationship with student achievement are scarce. Motivation and its related emotions in education or educational environments be come as critical research point for Neuro Cognitive Sciences and Neuroeducation [27], [28]. There are several approaches developed with the aim to know what or how trigger motivation through emotions in studens, among them NLP is one of the most accessible [17]. Notherless, we briefly describe some of the most relevant for our research.

In [29] a method to analyzing the footprints left behind from online interactions of students is useful for understanding the effectiveness of an specific learning model. In this case, the authors of that research argument thet a video-based learning with flipped teaching can help to improve student’s academic performance. The study aimed to predict student’s overall performance at the end of the semester using video learning analytics and data mining techniques. At the end,a Rule Inducer algotirhm and multivariate projection can be used to interpreting the rules to gain insights into student interactions. The results showed that Random Forest accurately predicted successful studentsat the end of the class with an accuracy of 88.3%. This research is relevant to our goal due suggest that the use of new technologies such as video based learning can motivate students improve performance.

Learning Management Systems (LMS) are one of the tools used to capture students interactions with learning environments. In [30], the authors suggest that clustering data extracted from a LMS provides a useful way to group student data without having previous knowledge about the data being analyzed. In that research authors set up a comparison between the three main clustering variants, partition-based (K-Means), density-based (DBSCAN) and hierarchical (BIRCH) methods to determine which technique is the most appropriate for performing clustering analysis. In the case-based experiment developed it was output as a main conclusion that partition-based methods produce the highest Silhouette Coefficient values and the better distribution amongst the clusters. Also, BIRCH algorithm performs fairly well and can act as a good starting point to find cluster groups in new datasets as the algorithm does not required that the number of clusters be specified a priori. This is important due that prove that different pattern of students behavior can be arise from interaction with the LMS and can be a clue to know motivations insights.

Similarly to previous study, authors in [31], propose an alternative to detect learning styles through the use of learning platforms. This research is supported by the use of machine learning techniques for web mining and personalized recommendation techniques to make adjustments in the learning environment. First, in the learning style prediction stage, the authors apply a K-means algorithm to group students based on their similar characteristics and merge them into learning style groups. Second, a recommendation process follows, in which NLP techniques are used to extract features about the profile of the learner's resources and, indeed, those resources with which the learner interacts, and finally give a recommendation based on the similarities among the combination of these resources. In another research [28], the authors of the work present the results on a study for the determination of performance profiles of students by means big-data and machine learning (Random Trees). The features that they take into consideration for the study were, academic averages, attendances, realization of activities sport and cultural, and on the other hand biometric variables like heart rhythm, quality of dream, states rem, feeding, hydrate and facial geometry and also a prove of effort cognition of the executive processes through the test of Stroop was developed.

An alternative to understand how students feel about study materials is developed by Anadolu University [32]. In this research authors developed a sentiment analysis technique to process the opinion generated by students of distance learning courses. As result, they conclude that machine learning can be fundamental to understanding student sentiments about educational resources. Another research develop a mobile technology application that use a computational model called SocialMining [33]. The model was an implementation of a Naïve Bayes model to support the analysis of students’ opinions (positive, negative and neutral) in the evaluation of the teacher performance in the educational process. Currently, with the advance of the hardware computations, in [34] the authors implemented and tool to identify facial gestures and determine emotions of students, through the design of a prototype with artificial intelligence techniques and the application of questions that validate the emotions detected by the designed device. The facial recognition system developed automatically identifies emotions such asangry, tired, scared, among others. This system could be useful in educational environments such as classrooms to take decisions in real time over the interactions of students.

In [35], the auhors developed an study to analyse the influence of Sentiment Analysis in educational process by means the use of several features based on the opinion of students for different studies strategies. In the mentioned research the authors used a clustering algorithm and a PCA method to recognize patterns of students strategies. Therefore, there was not used different clustering metrics in the study and also they do not applied an explainable tool to explain the results. The following table, shows the main advance of the research analysed in this section.

Table 1. Cualitative summary of studies analysed.

Strategy	**Explainable tool**	**Methods**	**Motivation**	**Reference**
A method to analyzing the footprints left behind from online interactions of students	No	Machine learning	video-based learning	[29]
LMS to capture students interactions with learning environments	No	Cluestering (K-Means, BIRCH..)	Students interactions	[30]
An alternative to detect learning styles	No	Cluestering (K-Means) + NLP	Learning platforms	[31],
Determination of performance profiles of students	No	ML	Demographics features and phisical features	[28]
Relationship between students and study materials	No	ML	Relation with study materials	[32]
Evaluation of teachers' performance	No	ML (Naïve) Bayes	Student's opinion	[33]
Student opinions for different study strategies	No	Clustering (Kmeans+PCA)	Student's opinión for strategies	[35]

As we can observe, ML for stracting student's study patterns data are used in the state-of-the-art in different forms and to solving different problems characterized by high data diversity. Also, there is no crystal clear of which of the algorithms perform better in any problem. Despite, the algorithm`s variants, as a result they output patterns indispensable to get insights of student behavior. Nevertheless, Sentiment Analysis and unsupervised algorithms remains as reliable choise to understarnd patterns that could be clues of motivation.

3 Materials and Methods

3.1 Data and Algorithm Pipeline

The present research uses information collected through surveys conducted with students of the Regular Day Courses and Non-Regular Workers Course of the Faculty of Informatics and Exact Sciences of the Ciego de Ávila University Máximo Gómez Báez. Once the acquisition of survey data is completed, it was transcribed into a ".csv" format file, and finally were 65 surveys. It should be pointed that, the data were collected with the full consent of the respondents and anonymously, after explaining to them the purpose of this research. In addition, the data was given to the researchers after prior authorization by the Direction of the Faculty's Research Group.

In this research we extend our previous work [35], but in this case, we research in how NLP can help to understand clues about motivations of students, the clustering metrics analysis consensus and implemented the use of an explainnability phase. Similar to the previous research we maintain a vector of characteristics that takes advantage of the polarity of the opinion of the students on different study strategies where they face challenging, non-challenging and generic lectures or topics. First, the transformation of the textual data was carried out using an integrated algorithm. Where the textual fields of the survey were processed by the embedded algorithm and converted into numerical values, these values representing the opinion of polarity (positive, negative and neutral) of the students regarding their study strategies for the different subjects classified as mentioned previously. The embedded method is part of a sentiment analysis library called PySentiment that integrates several algorithms based on neural networks and most of them highly referenced in the state-of-the-art [36]. At the end, in
Table ***2*** shows the transformation of the three comment columns, where this transformation leaves nine columns constituting the feature vector (3x3, the columns are multiplied by the calculated polarity values).

The preprocessing pipeline for data preparation and algorithm application was as follows, see Figure 1. First of all, a data cleaning process is developed, which involved the removal of null and irrelevant records.

Table 2. Polarity features per lecture complexity

Lecture complexity	Extracted features
Challenging	pos_a, neg_a, neu_a
Non-Challenging	pos_b, neg_b, neu_b
Generic	pos_c, neg_c, neu_c

Secondly, a dimension reduction process is carried out using a Principal Component Analysis (PCA) algorithm [37]. And finally, a K-means algorithm is applied to clustering the data.

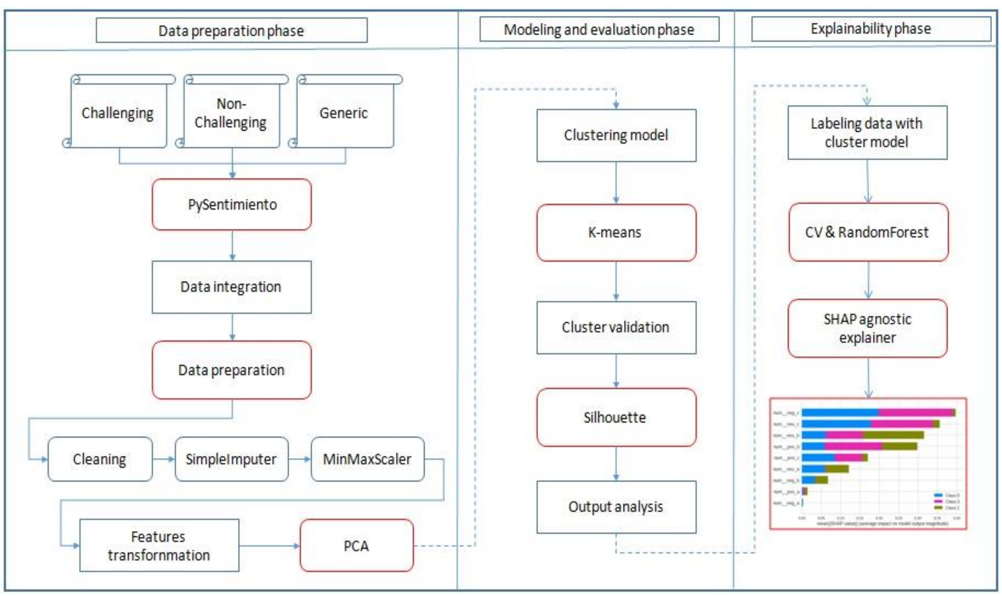

Figure 1. Phases to develop the clustering of student data

3.2 Clustering metrics

A pletora of metrics for clusters quality, especificly for unsupervised clusteirng, have been used in the state-of-the-art. In general terms they have to main objectives, to compute cohesion and separation of clusters [38]. Intra-cluster cohesion measures the similarity between two points inside each cluster. Otherwise, inter-cluster separation measures the similarity between points beloging to different clusters. So, as much as optimal (higher or lower, depending of the metric) are the values for intra-cluster cohesion and inter-cluster separation, it will be better the quality of the clusters [39]. Metrics considered in the present research are brief described as follow.

- Silhouette Coefficient score: this metric is intended to measures the quality of clustering based on how well-separated the cluster are and how compact the point within each cluster are too. This coefficient ranges from -1 to +1, where values closest to +1 indicating a well-separated and compact cluster and values closest to -1 suggest to opposite.
- Davies Bouldin score: is handy metric for two main objectives, first, for identifying the optimal number of clusters in a dataset. Second, for detecting cases where exist highest levels of similarity between cluster or even overlaping. The cons of this metric is that the index assumes that clusters are spherical and have similar (or aproximated) densities. This index ranges from 0 to infinity, with lower values indicating better clustering quality.
- Calinski Harabasz score: is similar to Silhouette, it measure how well-separated and compacted the clusters (and its points) are. It ranges from 0 to infinity, but higher values indicating better clustering results.
- Ball Hall score: it is a dispersion measure based on the quadratic distances of the cluster points with respect to their centroid. The maximum difference in value between levels is used to show the solution for the optimal number of clusters. It ranges from 0 to infinity.

3.3 Explainability

For many year interpretability of Machine Learning algorithms was a critical aspect that lacks the use of some model termed “Black Boxes” independently of its precision to execute the designated task [40]. Today, interpretability of AI algorithms is a hot topic due the awakness of tools that explain the results of predictions. One of this tools is SHapley Additive exPlanaition (SHAP), which is a technique for deconstructing a machine learning models`s predictions into a sum of contributions from each of its inputs [41], [42]. Its theoretical base comes from the Game Theory, where shaply value make sure that each actors (features, inputs) gets a fair share depending of how they contribute. SHAP python library provide a set of plot that be able to show in a practical form those contributions. For that reazon we used in this reseach to explain the importance of each feature proposed for the computed clusters. Next, we mention the plot used to get explainations in our research:

- Summary_plot: Is a global plot, which is useful to visualize the overall impact of the features for the dataset. As a result, we can get the most important features and their range of effects over the data.

4 Experimental Results

In this section it’s carried out the analysis and discussion of the research results. First task, we tuning the pipeline for K-means algorithm using $K \in \{2, 3, 4, 5, 6, 7, 8, 9\}$ values and $PCA \in \{2, 3, 4, 5, 6, 7, 8, 9\}$. Then it is developed an interpretation of the clustering metrics scores for all combinations of parameters to select the best performance model, by means the use of tables and plots. After that, an explainability process using SHAP library is carry out to shows what features are more relevant for the pattern recognition process. At the end, some clusters results are summarized to extract patterns that can be helpful for educational propose.

4.1 Experiment

Attending to the first task, the results are structured as follows; the columns-axis corresponds to the K values for clusters generated and the row-axis to the PCA values number of components used in the experimentation, and inside the cells the value computed for each combination PCA-K. First of all, we interpreting the result for all metrics described in the previous section (Silhouette, Davies Bouldin, Calinski Harabasz, Ball Hall). The Figure 2 shows the results achived in the experimentation.

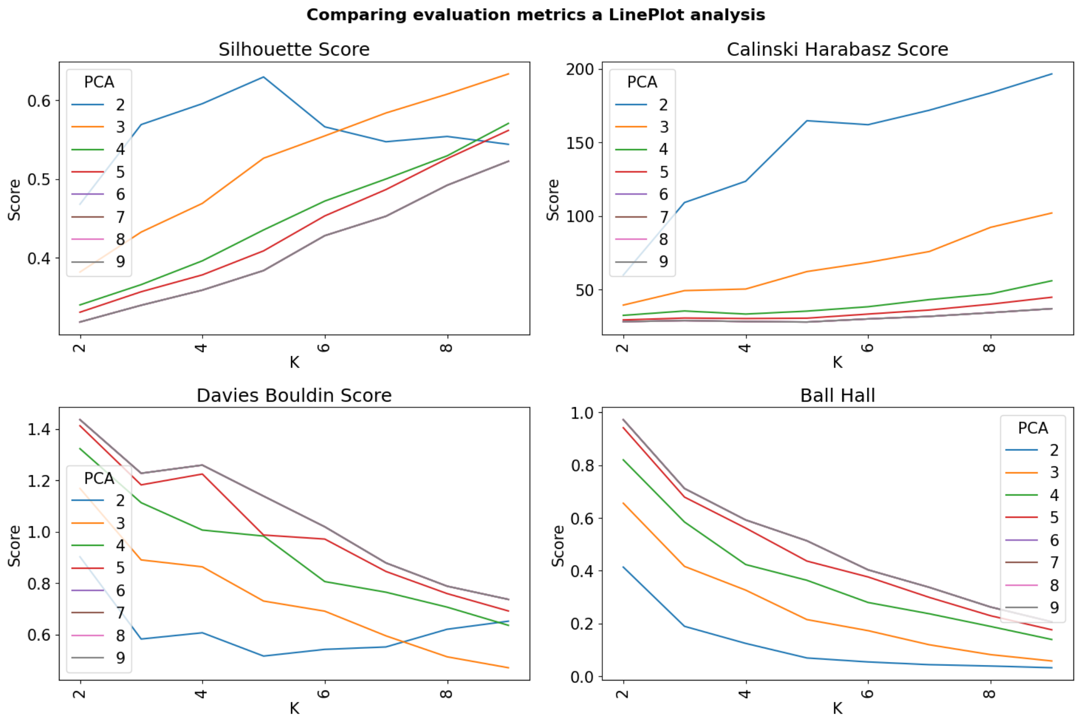

Figure 2. Results for the metrics used in the experimentation (Silhouette, Calinski Harabasz, Davies Bouldin and Ball Hall scores)

In the Figure 2 we can observe that, for Silhouette scores involves observing how close the value obtained is to the interval limits [-1, +1], where, closest to +1 denotes that the elements within the clusters are highly cohesive and is therefore the best result. Otherwise, closest to -1 represents the opposite to aforementioned and around value 0 suggests that there is some overlap between the clusters. The graph (top left corner) shows the result of applying Silhouette for the K-means algorithm using $K \in \{2, 3, 4, 5, 6, 7, 8, 9\}$ values and $PCA \in \{2, 3, 4, 5, 6, 7, 8, 9\}$. We can note that, for two and three components the Kmeans algotirhm achieved the best performance for all K iterarions. In another hand, for Calinski Harabaz score (top right corner), a metric which values range between $[0, \propto]$, when the highest values are preffered, we can observe that for the smallest component the best values for all iterations are ahived. In contrast, for Davies Bouldin and Ball Hall (bottom left and right, respectivily), which are metrics related to the dispersion between the clusters' points and its centroid, the best values remains achieved by the smallest PCA components. Also, we use Silhouette as a reference metric due its wide use in the state-of-the-art and its explainability power, this metric is useful to show the shape of the cluster generated. The following figures (**Error! Reference source not found.** and Figure 4) shows the shape for combinations for clustering with values of K=[3, 5] with PCA=2.

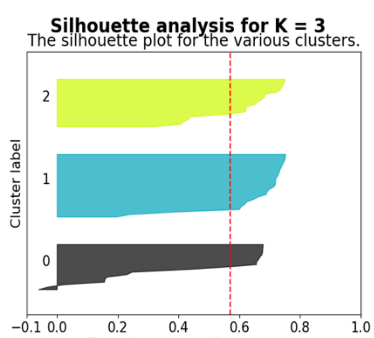

Figure 3. Shapes for clustering for PCA=2 and K=3.

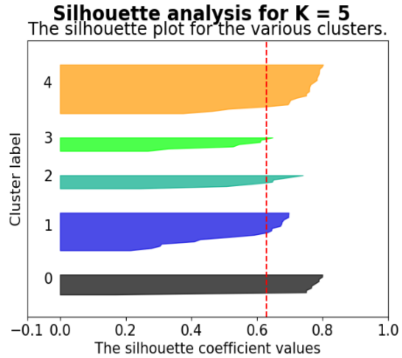

Figure 4. Shapes for clustering for PCA=2 and K=5.

In **Error! Reference source not found.** and Figure 4 we can observe the Silhouette scores results for K=3 and K=5 achived values around 0.56 (left) and 0.64 (rigth) respectively. Also the shape of the clusters, this metric is interesting to analyzing other aspects of clustering process, such as, the presence of clusters with below average silhouette scores (red dashed line) or wide fluctuations in the size of the silhouette plots which are clues related to the optimality of the cluesters. As we can note, for both results the clustering shapes are above the average silhouette scores. Otherwise for K=3 clusters (left), the thickness is more uniform than the plot with K=5 (rigth) with shows a high variability. Notherless, the clustering K=3 shows overlapping in cluster-0 (black) due negatives values are observed. The following (Figure 5 and Figure 6) shown the clusters generated in the experimentation.

In **Error! Reference source not found.** and **Error! Reference source not found.**, we can observe the clusters po ints and centroids. We can confirm the overlapping suggested by shape plots between cluster (0) and (1), but they are better shapped and contain a mayor number of samples per cluster K=3 ({0: 19, 1: 26, 2: 20}) and K=5 ({0: 10, 1: 18, 2: 7, 3: 7, 4: 23}). Thus, based on the shape of the clusters and the metrics analysis we can select the optimal number of clusters as 3 for the data in this experimentation.

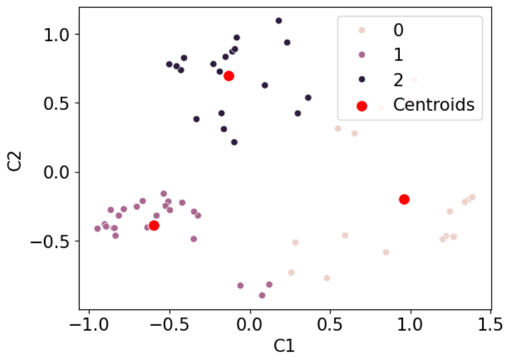

Figure 5. Clusters for PCA=2 and K=3.

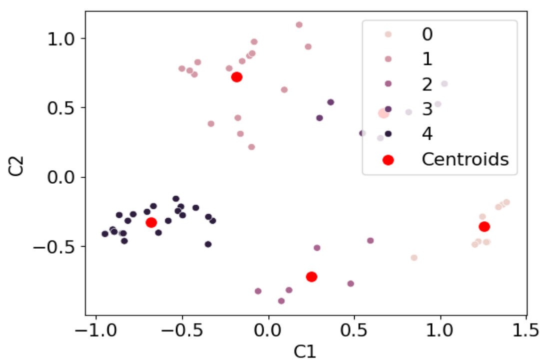

Figure 6. Clusters for PCA=2 and K=5.

4.2 Explainability of Results

The explainability is considered the posibility to explaining the decisions made by the model. In brief, we summarize our main findings related to the models used in the experimentation. **Error! Reference source not found.** shows the values for the samples closest to each cluster centroid. The **Error! Reference source not found.** is structured as follow, in the header are, at the first column the Group tag, followed by the Features considered in the experimentation and at the end a column for Main features (most important) for that sample. In the cells are values related to the probability of the opinion emited for the students.

Table 3. Centroids and main features for each cluster.

Cluster	Pos_a	Neg_a	Neu_a	Pos_b	Neg_b	Neu_b	Pos_c	Neg_c	Neu_c	Main features
C-0	**0,73**	0,00	0,27	0,00	**1,00**	0,00	0,00	**0,99**	0,00	pos_a, neg_b, neg_c
C-1	0,14	0,11	**0,75**	0,01	0,02	**0,98**	0,14	0,11	**0,75**	neu_a, neu_b, neu_c
C-2	0,01	**0,83**	0,16	**0,87**	0,00	0,13	0,00	0,02	**0,97**	neg_a, pos_b, neu_c

As we can observe in **Error! Reference source not found.**, Main features can be used as clues to categorize the clusters. For cluster C-0 the main festures suggest that students' opinions is communly positive for Challenging lectures (pos_a), negative for Non-Challenging (neg_b) and Generic (neg_c) lectures. Similar analysis can be performed for the remaining clusters. However, we can complement this brief analysis with the use of SHAP tool. For the present research is interesting to know the relevance of the features for each cluster. For that reason, the use of graphics that provide summarized information on this aspect is crucial. In that sense, SHAP is one of the most well-known and commonly used model explainability libraries and contains several graphs capable of offering global information about the features with respect to the data used. Among themis the *Summary_plot* (**Error! Reference source not found.**), in which instead of looking at each individual instance, we can visualize the overall impact of these features across multiple instances in the experimentation dataset.

Table 4. Crossvalidation results for RandomForest model in classes generated by clustering (K=3 and PCA=2).

Class	Precision	Recall	F1
0	0.88	1.00	0.93
1	1.00	0.91	0.95
2	1.00	1.00	1.00
Macro avg	0.96	0.97	0.96
Weighted avg	0.97	0.96	0.96

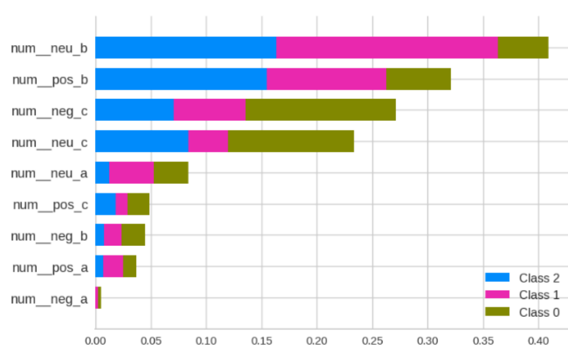

Figure 7. SHAP summary_plot for clusters.

For SHAP analysis works is required an agnostic explainer able to extract the contributions of any type of model, in our experimentation was selected a RandomForest (RF). The experimentation process to optimize the random forest algorithm used a cross-validation method (K=10). The result of the RF model is shows in the **Error! Reference source not found.**, and, as we can observe the Precision, Recall and F1 values achived are o ver 88% for all the metrics used to evaluate the classification model performance. These results suggest that the classes created after the clustering process can be predicted with a high precision and that in fact, the features can be descriptive for each cluster. Such results assure us confidence for the explanation generated by the SHAP tool. In **Error! Reference source not found.**, we can observe the contribution of each feature for predictions m ade by the agnostic model.The results in general are the importance of the features for the clustering, and as we can note, the mos important feature is related to the neutral opinion of the students in Non-Challenging lectures (neu_b), which is an important descriptor for clusters C-2 and C-1. The feature with the least contribution to the classes created in the clustering process is the negative opinion for Challenging lectures (neg_a), even such feature practically does not contribute to the C-0. Some conclusions can be empirically drawn from the previous analysis, for example, (1) the students of cluster (1) in difficult subjects are optimistic because their opinion regarding their study strategies does not present a high negative polarity (it may even be null), so teachers can employ such students as study leaders.

5 Conclusions and Directions for Further Research

As a conclusions of this research, we confirm that the diversity existing in student data can increase the complexity to understand student's motivation. Therfore, the use of unsupervised learning and NLP can be an alternative regarding the data used for learning. The main conclusion in the present investigation is that in order to understand the patterns underlying the student data generated for the different study strategies, K-means (K=3) combined with PCA (PCA=2) constitutes a robust alternative, since allows you to generate well-defined clusters with Silhouette values greater than 0.55 scores. After the application of an explainable tool (SHAP), the result achived in the present investigation be able to extract knowledge from students' opinions for different study strategies in lectures, such as, the students from cluster (1), when they face difficult subjects, they are optimistic because their opinion regarding their study strategies does not present a high negative polarity. Suggestions similar to previous one can be crucial to increase the performacen of students in the educational environment.

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