Case Study on the Evolution of Learners' Learning in the MOOC

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Abstract—Tracking the evolution of learners' learning in a MOOC supports the E-learning operation and allows teachers to easily manage the massive number of learners enrolled in a distance learning course. In this work we started with a study where we were interested in identifying the common parameters that allow us to have a vision on the evolution of learners through the use of SPSS statistical software. This operation allowed us to determine the level of the learners, classify them and group them into homogeneous groups that facilitated their orientation towards courses that meet the characteristics of their profiles. On the basis of our case study, we were able to develop a computer system approach based on K-means learning software and data preprocessing means, for data mining with the aim of analyzing and revealing the parameters that have a great positive impact on the learners' learning, the system uses the identified parameters to classify and group the learners according to their profiles. This type of system is characterized by its autonomy and the ability to process a large amount of data. On the basis of the data used in our case study, we carried out experimental tests on the proposed system which showed its performance in solving our problem.

Keywords—learning, MOOC, teacher, learners, classify, clustering, profiles, artificial intelligence, machine learning

1 Introduction

Monitoring the learning progress of learners in a MOOC seems a necessity given the high rate of overload in tutoring and activities offered in distance learning and especially with the arrival of the Covid pandemic, universities have undergone great changes [1], such as distance learning which has become a necessity to limit the spread of the virus. It is necessary that learners accept the new teaching reform, respect the training schedules and increase their responsiveness since they have real autonomy in this type of learning [2], [3], [4]. As for teachers, they must develop content and personalize teaching resources according to the characteristics of each learner profile in order to increase interactivity between them and the tutors to eliminate any sense of isolation reported among them.

The use of exchange places such as: forum, wiki, chat favors supportive relationships between learners as they exchange and share information with each other, but also to remind certain activities to those who have missed something as it is the place where the learner can ask about any difficulty encountered. However, despite the massiveness of enrollees, the participants within the forums represent a relatively small percentage of the number of enrollees [5], [6].

Asynchronous tools also allow learners to interact on specific issues and establish exchanges with their tutors, which supports the functioning of E-learning and allows teachers to easily manage learners enrolled in a distance course.

Thus, the purpose of this study was to present an approach based on intelligent neural networks that will allow teachers of distance learning courses to easily monitor the learning progress of their learners and to facilitate the interaction between them and their learners through a case study to identify learners by a set of parameters: grades in the following three subjects: communication, mathematics, computer science and the results of: pre-tests, formative tests at the end of each chapter and the scores of the summative test at the end of the MOOC, using SPSS statistical software to perform the analysis of the results obtained in the tests. Based on the parameters deduced from the case study, a K-means classification algorithm was used to classify the learners into three groups: Group A: advanced learners, Group B: average learners and Group C: struggling learners.

2 Literature review

At present, distance learning is seen as an alternative to face-to-face teaching. The transition to this type of teaching requires facilitating contact between the teacher and his learners in order to ensure continuity of the learning process even if it is virtual, as well as enabling the teacher to determine the needs of these learners [7].

Monitoring the learning progress of E-learning learners is a central task as shown by the work of [8], which states that the shift from face-to-face to fully or partially distance learning has raised the problem of the learner's sense of isolation from the machine, leading the learner to no longer feel isolated in front of the computer in distance learning [9]. Certainly, the method of classifying and grouping learners into homogeneous groups is an effective method that facilitates the choice of courses and activities by teachers according to the behavior of each user [10].

Some researchers have proposed several works on effective methods to facilitate the tracking of learners' learning in a distance course, the majority of which like [11], [12], [13], and others have chosen to work on the analysis of the notion of traceability to study the MOOCs. This method refers to different practices that change according to the disciplinary affiliation of the researchers.

Some of them consider the traceability of learners as all the messages and comments left by them on the discussion forums and the different exchange spaces. For others, it is the analysis of all the digital traces of learners. There is also work that uses both approaches, either by offering personalized digital materials to tailor the training to the learner, or by using information about what the learner has already done with the content or by exploiting a representation of the learner's skills [14].

For example, [11] have focused their work on identifying any traces left by learners in MOOCs discussion forums, such as: wiki and chat to test the degree of learner engagement by comparing them with the frequency of exchanges that each learner has carried out. The problem with this study is that it is the analysis of textual data which in most cases concerns learners who consume just part of the course and who do not participate because they do not need a certificate.

For its part, [12] conducted a study on non-certified learners based on the analysis of their traces during the consultation of the pedagogical videos proposed by the latter [12]. The objective of this study, is to encourage passive participants and to improve their learning without the need for a certificate. The limitation of this study is that [12] limited its work to the analysis of the use of videos by non-certified passive learners.

And for [13], they set out to conduct a qualitative survey of 34 learners pursuing two different MOOCs to see: how they work? How much time they spend on their work? This study has a limit related to the minimum number of the sample chosen to be studied. For [15], [16], their work is based on the follow-up of learners' traces from their learning path via the analysis of the temporal evolution of learners in relation to the course they are pursuing. But the works of [15], [16], have reported limits because the analysis did not take into account all the learners given the massiveness of the data. For his part [17], proposed in his work a remediation, or feedback in the sense of providing methodological assistance to learners to improve their learning and encourage them to continue the MOOC until the end but the number of certified learners is minimum in relation to the number of registrants. Some works based on artificial intelligence, in particular the improvement of the sum map, have shown their performance in classifying and grouping learners into homogeneous groups with the same profiles [18].

The originality of our study, compared to the literature review presented above, lies in the fact that it to seek the answers for the below-mentioned questions:

1. How can we develop an intelligent computer-based method to enhance learners' learning in a MOOC?
2. How to better manage massive learner data?

3 Case study

3.1 Research framework and context

The study is conducted on 109 students, whom I have chosen because I teach them and have access to their transcripts, and personal information to ensure the certainty of the information, they will enter in the platform of the institution where I work when they register in the MOOC. They are continuing their studies in the first year of the MIPC in the academic year 2021 /2022. The course started on 01/09/2021 for a duration of 4 weeks. Among the objectives of this course, is to introduce the students to the basic elements of algorithmic and C programming and to deduce the elements that influence the improvement of their learning. The content of the course was structured in 5 main sessions, corresponding to 3 weeks of classes and one week for a summative test, on the platform of the polydesciplinary faculty of Larache according to the following schedule:

Table 1. MOOC schedule

Week:1	Week:2	Week:3	Week:4	Week:5
September/October From :27 to 04.	October From :05 to 11	October From:12 to 18	October From :19 to 25	October/November From: 26 to 01
Pre-test of positioning.	Chapter:1	Chapter:2	Chapter:2	Summative test
Getting to know the platform.	Formative test	Formative test	Formative test	

For the purpose of this study, the common parameters that allow the evolution of learners' learning in terms of knowledge, skills and attitudes at the end of a course are determined. In order to determine these parameters, we will take into consideration a set of traces that will be useful to measure this change based on their grades in three subjects: communication, computer science and mathematics, and secondly the results of: pre-test positioning, formative evaluations and summative evaluation.

3.2 Organization of the MOOC

Students are asked to fill in the MOOC registration form and are asked to mention their grades in communication, mathematics and computer science. Then they are invited to take a diagnostic test which is conducted before the MOOC in order to provide a status of the students' achievements and to enlighten the teacher on what the learners already know and what mistakes they need to correct. After each chapter, the students are asked to take a formative test which has the function of encouraging the progression of learning and providing information on the learners' achievements in order to evaluate the degree of understanding of the content. So, that those who have not achieved the average can benefit from immediate remediation. At the end of the MOOC, the learners will complete the training with a summative or certificate test which has the function of attestation or recognition of learning to certify the degree of mastery of learning at the end of the MOOC. All of this, is done with the aim of classifying them and grouping them into homogeneous groups, according to their prerequisites, their levels and the knowledge acquired during the MOOC.

3.3 Analysis of the data

Using SPSS software, we were able to identify the numbers of each parameter and organize them into diagrams in order to classify and group learners into homogeneous groups, with the same prerequisites and level of learning, as well as to follow their evolution during the MOOC until the end, in order to deduce the factors that positively influence the improvement of their learning.

3.4 The average of the three subjects

The average of the three subjects: mathematics, computer science and communication were calculated using SPSS software, to facilitate the determination of the learners' prerequisites. Figure 1, below, shows the diagram of the average numbers obtained.

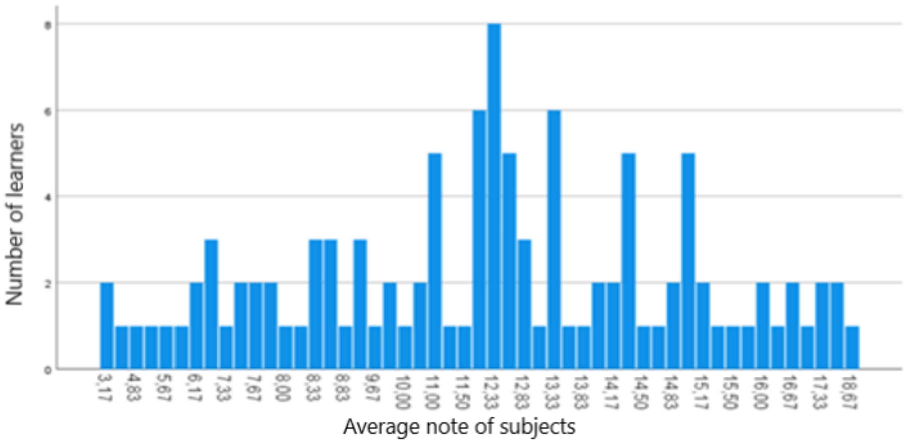

Fig. 1. The staffing diagram of the average of the three subjects: computer science, mathematics and communication

According to the diagram above, we can already see that we have a workforce of 74 learners who have above the average and 35 learners who have not had the average.

And to check the validity and the certainty of the level of the learners in these three subjects, they were given a pre-test which relates to questions which are related to the necessary prerequisites that the learners who are registered in the algorithmic and programming module must have. in C language, which allowed us to have the following results in (Figure 2).

3.5 The results of the pre-test

After taking the pre-test, it was found that learners with above-average scores in the three subjects of communication, computer science and mathematics were able to score well in the pre-test, which was related to the necessary prerequisites for learners enrolled in the algorithmic and programming module. Learners who scored below average in all three subjects were not able to pass the pre-test (see Figure 2, below).

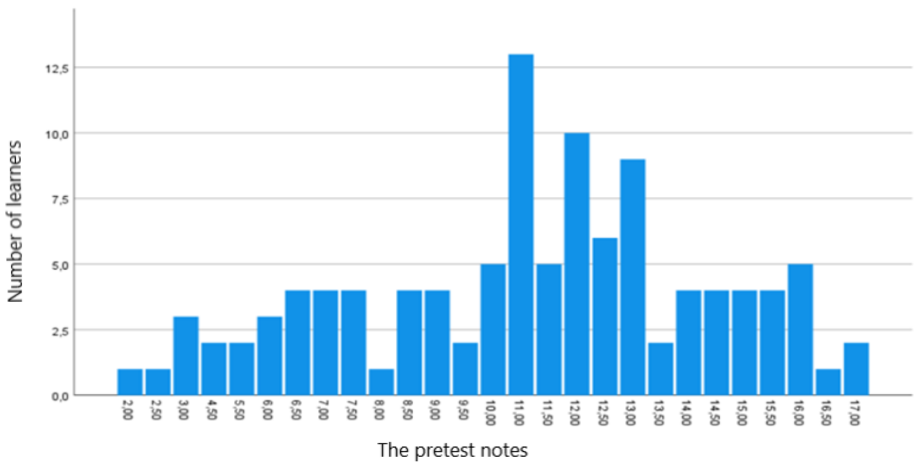

Fig. 2. The staffing diagram of the pre-test notes

According to the analysis of the diagram above, we see that we had the same results as we had in (Figure 1), a workforce of 74 learners had above the average and 35 learners did not. did not have the average. So, we see that the average in the three subjects: mathematics, computer science and communication as well as the passage of a pre-test, are mandatory factors for determining the prerequisites of learners in this MOOC.

From the results obtained, it was possible to classify and group the learners into homogeneous groups having the same prerequisites based on the mark obtained in the three subjects and the marks of the pretest. (Table 2), shows the number of learners in each group.

Table 2. Classification and grouping of learners according to their notes

	Group A **13 ≤N ≤20**	**Group B** **13 ≤N ≤20**	**Group C** **N<10**
Numbers of the average of the three subjects.	44	30	35
Pre-test enrolment.	35	39	35
The number of learners in each group	≈ 40	≈ 35	35

According to the results of the table below, the learners have been classified and grouped according to the average of the three subjects and the result of the pretest according to 3 groups:

- Group A (advanced learners): with a score between 13 and 20.
- Group B (average learners): with a score between 10 and 13.
- Group C (learners in difficulty): with a score below 10.

According to the results obtained in the table, it was found that for category A and B there is a difference of 9 numbers between the passing of the average of the three subjects and the result of the pre-test and that is normal. than the disparity between the averages of each subject. And for category C we obtained the same number of learners, which shows that the average of the three subjects: (communication, mathematics, computer science and) has a great influence on the results of the pretest.

3.6 Analysis of the results of the formative tests

At the end of each chapter, learners are asked to take a formative test to check whether they have acquired the necessary knowledge and information, for those who validate the chapter, they go directly to the next chapter and so on. And for those who have not validated the chapter, they automatically benefit from a remediation to remedy their deficiencies.

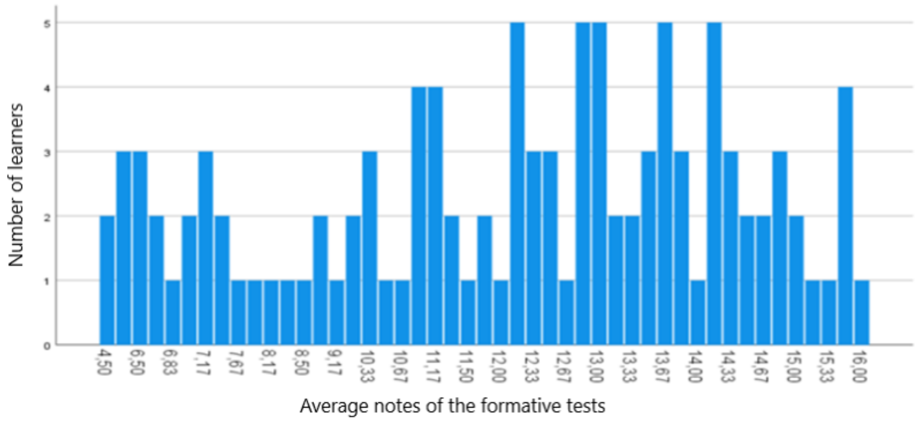

Fig. 3. Plot of the average notes of the three formative tests.

According to the results obtained in the diagram above, we see that a workforce of 81 learners were able to validate the three formative tests, which means an improvement of 7 learners from the results of the pre-test. This reflects their commitment to monitoring the MOOC and the remediation they received, which subsequently enabled them to validate the formative test 2 and 3.

To close the MOOC, learners are asked to take a summative test, to check the overall knowledge of their achievements during the MOOC. (Figure 4) shows the results obtained.

3.7 Analysis of the summative test

Learners who passed the pre-test and the formative tests were able to pass the summative test (see Figure 4 below).

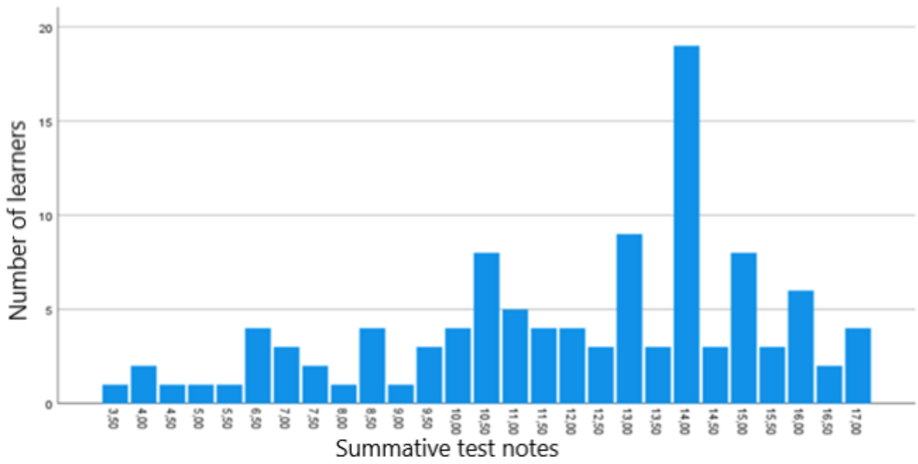

Fig. 4. Summative test notes chart

According to the results obtained in the diagram above, we see that 85 learners were able to validate the summative test and 24 did not. So, an improvement of 4 learners was reported between passing the formative tests and the summative test.

3.8 Comparison table of results

Table 3. Monitoring the progress of learners' learning by comparing the results obtained.

	Group A $13 \leq N \leq 20$	**Group B** $13 \leq N \leq 20$	**Group C** $N<10$
Learner numbers according to grades in the 3 subjects and the pre-test.	40	35	35
Learner numbers according to the results of the three formative tests	45 (+5)	36 (+1)	28 (-6)
The number of learners according to the results of the summative test.	58 (+13)	27 (-9)	24 (-4)

4 Approach to an intelligent learner monitoring and organization system

4.1 Definition of the objective approach

In our case study, we were able to group the objects into three homogeneous groups based on two criteria: the average of the three subjects (communication, mathematics and computer science) and the pre-test score. In this part of the work, we used the result obtained in the case study, to build our objective approach to define the objective function of the proposed system. The idea, is to find a computational solution based on artificial intelligence means to classify, group and subsequently determine the membership of learners to profiles. For the simulation of this function, we used the Manhattan distance to calculate the distance between two objects in a space (see formula below).

$$d_{xy} = \left|X_{ik} - X_{jk}\right| \tag{1}$$

In the first step, we calculated the distance between the objects representing the learners and the starting point of frame O (see formula below).

$$d_{xo} = \sum_{i=1}^{n}|x_i| \tag{2}$$

The distance is divided by 2 for the scaling of the calculated distance values (possible value of the score). Using these distances, we grouped the learners in three clusters (groups), respecting the objective determined in the case study, so for each cluster we determined the centroid distance, which is equal to the average distance of the distances calculated for each cluster, in the table below we present the results obtained.

Table 4. Result of the simulation of the objective function

Type of class:	The distance Manhattan/2	The distance of the centroids
Group A: 13 ≤Note ≤20	Maximum value: 17,33	15,25
	Minimum value: 13,17	
Group B: 10≤ Note<13	Maximum value: 12,92	11,50
	Minimum value: 10,08	
Group C: Note<10	Maximum value: 09,83	6,28
	Minimum value: 02,58	

After determining the centroid distance, we could choose the object (the learner) that represents the center class of each cluster and with the help of the obtained parameters, we calculated for each cluster the membership distance of the different objects. To determine the membership of a learner object to a cluster, we use the following formula.

$$d_{jk} = \sum_{i=1}^{n}\left|x_{ji} - x_{ki}\right| \leq d_{\exists} \tag{3}$$

Where: *n*: the object length.
djk: the *distance* between the center of cluster *k* and object *i.*
d: distance of cluster membership (group).

4.2 Presentation and working description of the proposed approach

Following our case study and the results obtained, as well as the need imposed by distance learning and the platforms dedicated to this type of learning, it is essential to develop intelligent computer means, that facilitate and help the teacher to well organize and manage his course, while respecting the categorization of the learners' profiles. In the figure below, we present the diagram of our approach with its blocks and their operating principle.

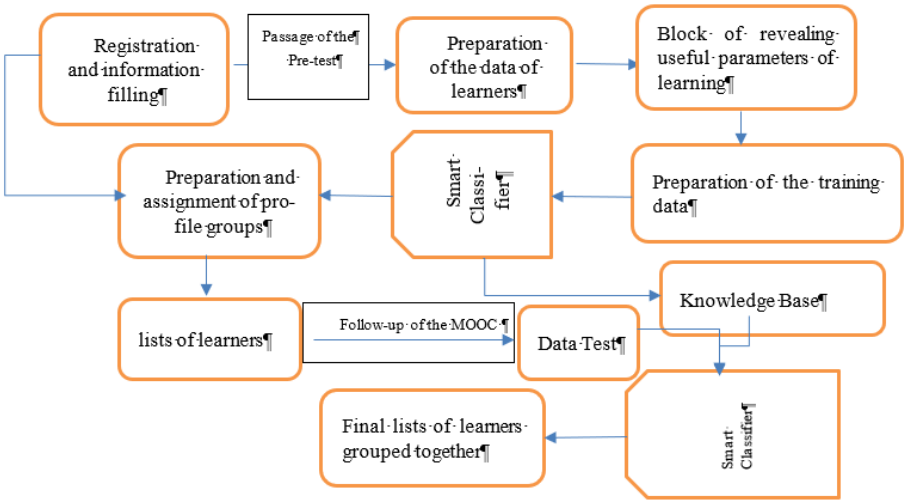

Fig. 5. The representation of our intelligent approach

Our system starts with the registration of the learners, who are led to fill in the registration form in the platform before starting the MOOC, to have their personal information and especially their averages in the three subjects: communication, mathematics, computer science. Once the list of learners is ready, they are given a pre-test to check their prerequisites and the validity of the information they have entered in the platform. Based on the results obtained in the three subjects and the results of the pre-test, our system began to prepare the learners' data, for processing via the data processing block in order to reveal the useful learning parameters that positively influence the evolution of the learners' learning. So, that they will be classified later in the form of classes that respond to the characteristics of their profiles.

After identifying and studying the parameters, we start preparing the learning data, which contains the parameters already chosen and predefined by the system during the preparation of the learning data, using one of the intelligent classifiers that will deliver the classes and the membership of each learner. Using the list of learners, we have obtained, we assign each student to the group that corresponds to the characteristics of his profile. So, we already have homogeneous groups that we have named the lists of learners who will follow the MOOC. The profile groups will follow the MOOC, take the three formative tests and the summative test at the end. The results obtained will form the test data, where each parameter represents the stimulus of a concrete learner which will be used with the knowledge base by the intelligent classifier to define the class to which the learner belongs. In the final phase, we will obtain a list that determines the group to which each learner belongs, according to their prerequisites and level.

4.3 Example of the realization of the proposed system

In order to carry out the operating steps of the proposed system indicated in the different blocks, we will rely on the packages and models provided by Python. It is the most usable language for the development and testing of the intelligent system, as it has enough artificial intelligence algorithms that are characterized by learning, adaptation and generation that seem necessary for our system. In this work, we have exploited and compared different algorithms for the realization of the system based on the proposed approach.

Data visualization for revealing useful parameters. After the preparation of the data obtained during the case study carried out on a sample of 109 learners, these data were made into a global matrix that contains all the scores that allowed us to classify and group them. The multitude prepared will be the basis for all the operations that will be carried out later to demonstrate the functionality of the proposed system. In this step, our objective is to demonstrate how the system will visualize the information on the set of learner data parameters to the teacher so that he can select the most useful parameters for grouping the learners, according to their prerequisites and level. In our example, we used methods based on the correlation coefficient. (Figure 6) represents the set of functions used to illustrate the relationship between all the variables in the data set.

```
# display the correlations between each Feature
correlation_Matrix = df.corr()
top_corr_features = correlation_Matrix.index
plt.figure(figsize=(20,20))
#plot The correlation Matrix as a heat map
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

Fig. 6. Code Show correlation matrix

This program code allowed us to illustrate the plotting of the correlation matrix in the form of a heat map shown in (Figure 7).

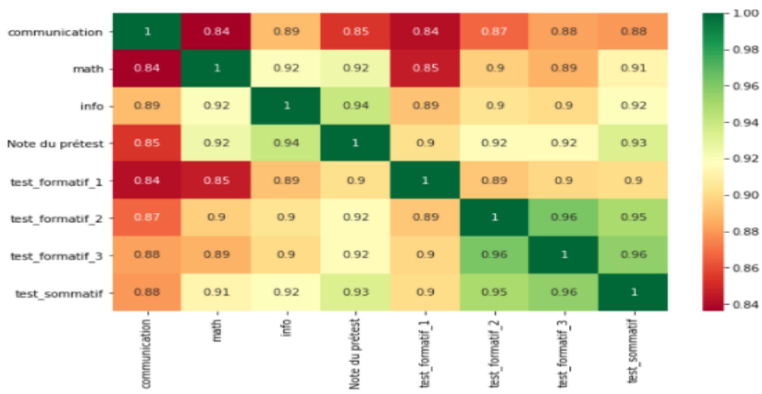

Fig. 7. Correlation matrix graph

The figure above, represents the correlation matrix (graph) with each cell filled in color according to the correlation coefficient of the pair it represents. In the next step, after obtaining the correlation matrix, we used the *describe ()* function which generates descriptive statistics by summarizing the number of distinct values, dispersion, mean, minimum and maximum and the shape of the distribution of a data set for the given series object. (Figure 8), illustrates the values obtained by the function.

```
# Display Infos About The Data
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
communication	109.0	12.798165	4.473750	2.0	10.00	14.0	16.0	20.0
Math	109.0	10.944954	3.985122	2.0	9.00	10.0	14.0	19.0
info	109.0	11.449541	3.502608	3.0	9.50	12.0	14.0	20.0
pretest	109.0	10.903670	3.533227	2.0	8.50	11.5	13.0	17.0
test_formatif_1	107.0	11.191589	3.064284	2.0	9.25	12.0	13.5	16.0
test_formatif_2	109.0	12.041284	3.209598	4.5	10.00	12.5	14.0	17.0
test_formatif_3	109.0	11.766055	3.289693	4.0	10.00	12.5	14.0	17.0
test_sommatif	109.0	12.009174	3.296309	3.5	10.00	13.0	14.0	17.0

Fig. 8. Display of data information

The analysis of the graphical correlation matrix, as well as the results obtained in (Figure 8), easily allowed us to identify the most useful parameters for grouping learners with the same prerequisites and learning levels, which are: communication, mathematics, computer science, pre-test, formative test and summative test. This function of our proposed system will give a huge solution to manage and monitor learners' learning.

Classification and grouping of learners. After identifying the parameters in the previous step, the system moves to the classification and grouping of learners. There are several ways of doing this, but in our case, we have opted to use k-means for classification and regression for prediction. Following the study and analysis of the data set, it is possible to divide the learners into three groups:

- Group A (The most advanced): these are the students who have an excellent background in mathematics, computer science and communication which allowed them to easily understand the chapters and to pass the formative tests at the end of each chapter. This group of learners, showed their seriousness and strong will and interest in following the MOOC to the end, this is what the pedagogical team noticed because they showed their commitments, especially when carrying out the activities requested by their teacher and the time, they spent connected on the platform following the courses and videos as well as their interactions in the forum.
- Group B (Average learners): already those who have an average level in mathematics, computer science and communication had average grades with the evolution of some elements.
- Group C (learners in difficulty): are those who have gaps in mathematics, computer science and communication. Those, who are close to the average were able to progress and validate some formative tests thanks, also to the remediation proposed at the end of each formative test.

In (Figure 9) and (Figure 10), the K-means application code and the results obtained are illustrated.

```
#Visualising the clusters
plt.scatter(x[y_pred == 0, 0], x[y_pred == 0, 1], s = 100, c = 'red', label = 'Class A')
plt.scatter(x[y_pred == 1, 0], x[y_pred == 1, 1], s = 100, c = 'blue', label = 'Class B')
plt.scatter(x[y_pred == 2, 0], x[y_pred == 2, 1], s = 100, c = 'green', label = 'Class C')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```

Fig. 9. The k-means application code

According to the figure above, the code produces three scatter plots, it displays the students according to their classes. Class A (advanced learners) in red, Class (B) average learners in blue and Class (C) in green (struggling learners). In (Figure 10), we have graphically visualized our dataset to observe the clusters formed.

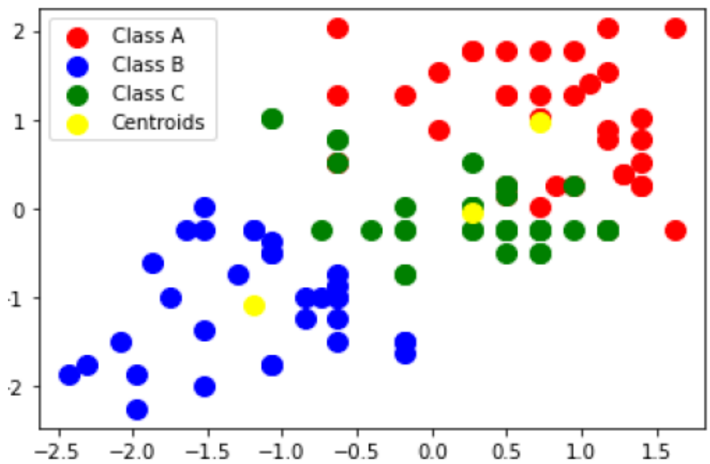

Fig. 10. Visualization of learners' classes

The figure above shows the result of the classification and grouping of the learners using the K-means algorithm, the objects are displayed as scatter plots, each cluster is presented by a color and each class of individual by a point, and the centers of the clusters are presented in yellow. Individuals with the same characteristics that belong to one of the clusters have the same colors. According to the arrangement of the points in the clouds, we can qualify the quality of the classification and clustering we have obtained, since we have a grouping of each class in a separate side from the other class, then we can say that it is a good classification and clustering.

5 Discussion

The results of the study confirm that improving learner learning in a MOOC is considered useful to improve their learning and ensure their commitment to the MOOC from start to finish. This result is consistent with the work of [19], [20].

In this regard, the results of our study provide a starting point for our university to identify the needs of students during a distance learning course in order to help them follow the MOOC from start to finish without any interruption.

The use of distance learning processes has become an obligation especially with the circumstances that the world has experienced (covid 19 and the war in Ukraine), as well as its improvement has become a necessity, in order to ensure good conditions of work for teachers and learners.

In this study, students engaged in the MOOC from start to finish because they felt truly supported during the MOOC. And according to the time the learners have been connected in the platform as well as the traces left by them in the forum, we can see that the participants have spent enough time learning and sharing their knowledge with the learners who have difficulties to help them) learn quickly and remedy its shortcomings via the notion of sharing which is very useful to help learners [21], [22].

In higher education, the integration of high-performance computer tools makes it possible to develop teachers' attitudes towards their students, in order to easily identify their needs for a better improvement of their teaching practices which influence the degree of commitment of learners and c This is what we obtained according to our study since 109 registrants committed to follow the MOOC from the beginning to the end.

On the one hand, the results obtained show that nearly 78% of the registrants were able to complete the MOOC with an improvement in learning of 68.57% for learners in group C and an improvement of 77% for learners in group B, which engenders that it is essential to consider the monitoring of learners' learning as a potential factor in the development of MOOCs.

On the other hand, this study did not encounter any difficulty in analyzing a massive amount of learner data, even though it may be difficult for most teachers [23].

Also, working according to groups of profiles with the same learning needs, levels and interests is essential to apply to future teachers [24], because it facilitates their work of monitoring and supervising learners and encourages them to better adapt courses to the characteristics of each group of profiles, to respect their learning rhythms and to eliminate any feeling of isolation, which in most cases leads to the multiplication of MOOCs by learners [25].

Our system adopted in our study has shown its performance in the analysis of numerical data but no performance has yet been reported in the analysis of qualitative data. The resolution of this ambiguity will be the prospect of our future work.

6 Conclusion

Distance learning requires the use of new computerized technologies, to improve the conditions of this type of education, as well as to facilitate the teachers' operations of monitoring and supervision of their learners. This is why in our work, we started with a case study, to reveal all the information concerning the prerequisites and the levels of the learners in order to classify them in profile groups, with the same characteristics and learning pace, in order to allow the teacher to work with each profile group according to its learning pace. Taking the tests and following, the MOOC until the end allowed us to identify a set of factors that positively influence the improvement of learners' learning.

Subsequently, we developed an approach to an intelligent system, capable of learning to classify learners into appropriate classes, according to the parameters determined in our case study. The system is equipped with the means to reveal and visualize the most useful parameters for proper user interpretation and preparation of learning data. Thanks, to our use of the K-means algorithm as a suitable method we were able to generate three adequate cluster groups and meet the result obtained in the case study. This new method, will lead to a good prediction of the factors that can improve learners' learning in a MOOC.

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