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RESEARCH ARTICLE

Data mining: Application of digital marketing in education

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Abstract: The excessive cost of inadequate management of stored information resources by companies means a significant loss for them, causing them to invest more than they should in technology. To overcome and avoid more significant losses, companies must counteract this type of problem. The present work's aim is to apply good data mining through digital business marketing that will allow ordering and filtering of the relevant information in the databases through RapidMiner, to supply the companies' databases with only relevant information for the normal development of their functions. For this purpose, the Knowledge Discovery Databases (KDD) methodology will be used, which will allow us to filter and search for information patterns that are hidden in order to take advantage of the historical data of investment per student in the educational sector and to establish a more accurate and efficient data prediction. As a result, it was found that over the years, the expenditure per student increases regardless of the area in which it is located, that although not in all provinces same amount is allocated, it is observed that it maintains an upward trend concerning the expenditures made, concluding that the KDD methodology allowed us to graph and showed how the expenditure allocated to the education sector has varied in the different grades of education, providing relevant information that will be useful for future related studies.

Keywords: data mining, digital marketing, KDD methodology, digital application, big data

1 Introduction

Nowadays, it has become essential to process information in a way that allows more efficient and faster decision-making at a personal and business level (Lavidas et al., 2022). As technology becomes more relevant in our lives and brings with it technological improvements such as artificial intelligence (Karakose et al., 2023), Big Data and data processing systems, this has caused marketing as it was known to be updated to be personalized for each customer. At this point, data mining also comes in, allowing companies to develop better and strategically make decisions (Bartschat et al.,2019).

Digital marketing facilitates the application of digital tools and different marketing strategies, such as mobile marketing (Lu et al., 2017). In Peru, this is one of the most used digital marketing strategies due to the increase in digital services, which also support the development of MSEs, such as Yape, Plin and similar (Romero & Ventura, 2020). Likewise, the author (Dutt et al., 2017) tells us that data mining is widely used to identify potential customers for new products through historical data on customer purchases (Mozombite-Jayo et al., 2022). It is developing a model which can be used in the form of predictive response with data mining techniques to predict probabilities that will respond to a promotion or offer, according to the author mentioned (Romero & Ventura, 2020).

Data mining is a computational process that tries to discover or follow patterns or sequences based on a set of large-scale data the company has previously obtained, in addition to that also involves new methods (Rodrigues et al., 2018), such as artificial intelligence. Autonomous learning and statistics, among others, are their way of collecting information (Lavidas et al., 2022). According to the author (Ahuja et al., 2019), companies record and accumulate too much information about their existing and potential customers, making this a significant investment in technology and the use of media in their marketing (Karakose et al., 2022), making this a review regarding the use of data mining techniques for the analysis of problems that may occur within organizations due to the inefficient use of stored information resource (Slater et al., 2016).

The KDD methodology refers to when there are large volumes of data and knowledge discovery in databases, or KDD refers to the process of identifying valid, new, potentially helpful and, for the most part, understandable patterns (Ünal, 2021).

The objective of the application of data mining to digital marketing business will be responsible for supplying the databases through RapidMiner in search of patterns of hidden or unknown information, which maintains more orderly and optimal information and, in turn, helps to understand the marketing mix, the sketch of campaigns and various business strategies, and thus make it possible to obtain the full advantage of historical data and leaving behind the ambiguity of Excel or Access tables, in order to make a more accurate and truthful business study.

2 Methodology

2.1 Methodological design

According to the author (Cheng et al.,2018), KDD is a process which aims to obtain knowledge through the data stored in information warehouses; within this process is the preparation of data, statistical analysis, the algorithm for data mining and the evaluation and interpretation of these, resulting in the discovery of new results as shown in Figure 1.

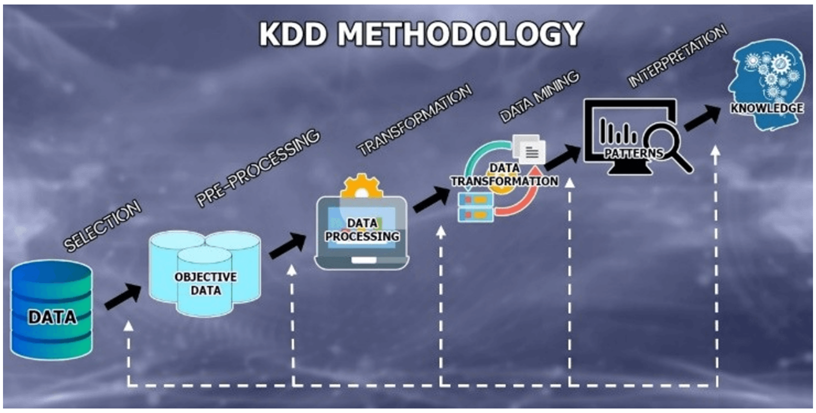


Figure 1 Phases of the methodology

Likewise, the author (Asor et al., 2021) comments that our ability to analyze and understand massive datasets is far below our ability to collect and store data, which is why new computational techniques and tools are required to support the extraction of valuable knowledge from large volumes of data (Karakose et al., 2022). Thus, data mining has succeeded in becoming a critical component to consider due to the benefits and expectations it brings to the world, and that to date, very little is known regarding the usefulness of applying knowledge discovery in transportation-related research (Asif et al., 2017). which tells us that KDD is a powerful and flexible tool for the data-driven world since it allows mastering data mining, predictive analytics and business analytics, providing unprecedented information about the data and enabling better decision-making and forecasting.

This methodology is defined as a potentially helpful discovery process (Petousi & Sifaki, 2020) since it is composed of several steps allowing its application to hypothesis validation or pattern discovery (Sunar et al., 2023). The KDD methodology is divided into phases that allow the integration and preprocessing of data, which are vital to ensure quality research and an adequate synthesis of previous concepts (Bakhshinategh et al., 2018). The importance of this methodology lies in discovering new knowledge since the time spent on it is more remarkable because it requires prior understanding and preparation to apply an appropriate data mining algorithm. Comments that the KDD is an active and essential area of research, being this a promise of significant profitability in many commercial and scientific applications, as one of its main tasks with which it counts would be that of classification, having this a very efficient method for induction in decision trees (Papadakis et al., 2021). The KDD provides an analysis of each approach's unique features, outstanding advantages and disadvantages; it also provides a global comparison of all data mining approaches presented.

2.1.1 Selection stage

After identifying the relevant and priority knowledge for the development of the KDD process during the selection stage, a set of objective data is created, from which the representative sample is selected, and the discovery work will be done.

2.1.2 Preprocessing stage

The preprocessing or cleaning stage is where the quality of the previously selected data is analyzed, applying operations such as data removal, strategies for unknown data, invalid data, duplicate data and statistics for replacement if needed. During cleaning, noisy, anonymous, and null data are ignored or replaced by default or nearest value, using statistics for preprocessing cleaning. This step is where the already selected data will be cleaned, including incomplete and unconscious data. Data without coherence should be eliminated because they could generate a preliminary analysis and give incorrect results (Konstantopoulou et al., 2022).

2.1.3 Transformation stage

After cleaning the previously selected data, we proceed to data transformation or reduction, where we look for valuable characteristics to represent the data depending on the company's objective to reduce the adequate number of variables under consideration or find representations of greater magnitude. The reduction of data can be made using a table in horizontal or vertical form; in the horizontal form, it implies the elimination of comparable data and in the vertical form, the elimination of insignificant or redundant data. Reduction techniques include aggregations, compression, histograms, segmentation, discrete ion, and sampling, among others (Fernandes et al., 2019).

2.1.4 Data mining stage

It lies in putting the goal or objective of this methodology KDD as (initial step) to an object of data mining, where the vital work of this methodology is developed. Before this, the importance of the preliminary analysis is born to give way to the hypothesis and later the selection; that is, to choose the sequence or algorithm of the DATA MINING to use for the exploration of the data patterns. This step delimits the finding of indexes of the search of interest in a form that sticks to the form in which this is represented or of a set as such (Davari et al., 2018).

2.1.5 Interpretation

Once the patterns have been identified, a re-evaluation of all the steps to identify a correct iteration can probably be performed. This step includes the visualization of these patterns and all the already-identified models (this is done to validate the algorithm's correct functionality and if it performs correctly).

2.2 Design tools

As for the design tool we will use, we have opted for "Star UML" since it will allow us to diagram our results obtained through our development tool, in addition to the fact that it also has multiple types of diagrams to work with, allowing us to have a great variety in terms of diagrams (Drayton-Brooks et al., 2020a).

2.3 Development tools

The development tool for data mining will be "RapidMiner", as it provides a visual environment which allows the preparation and mining of data and the construction of predictive models and analysis. Also, it is an easy-to-use tool which allows the connection, design and execution of data mining flows (Drayton-Brooks et al., 2020b).

3 Results and discussion

3.1 First stage

In this first stage, we searched and selected the relevant and priority information regarding our needs. In this case, we have searched for information within the "Instituto Nacional de Estadística e Informática", and we have selected the part "Public expenditures per student in regular basic education, according to educational level and department. 2008 - 2019", which we will use for the elaboration of the work as shown in Table 1.

3.2 Second stage

After selecting our relevant information, we cleaned and removed data. We were left with the expenditures made during 2015 to 2019, having remained in expenditures allocated to the education sector for the last five years. Table 2 shows the data of the highest expenditures for the period from 2015 to 2019. Table 3 shows the data on expenditures by high educational level. Table 4 shows expenditures by lowest educational level in initial education. Table 5 shows expenditures by lowest primary level in initial. Table 6 shows the data on expenditures by highest educational level in the primary. Table 7 shows expenditures by secondary education level. Table 8 shows data on expenditures by secondary education level from 2015 to 2019.

3.3 Third stage

In this stage, we will filter the data; that is to say, we will channel the excess data from the source of origin, leaving us only with accurate data to be able to carry out the transport of information to later load the data in the Database Server. Improve the already processed data by

Table 1 Government spending for the education sector, 1994-2019

Department / Educational Level	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Lima Metropolitana										
Higher Non-University	2 383	2 506	7 880	10 294	11 565	22 685	25 817	8 262	14 543	14 831
Superior University	3 414	5 905	5 905	7 016	8 743	17 532	18 243	9 540	9 843	13 299
Región Lima 1/										
Higher Non-University	2 178	3 343	5 442	6 114	4 181	2 822	3 780	5 415	4 625	4 214
Superior University	2346	3590	4282	5 381	6 553	8 619	4 862	5 259	5 929	10 763
Loreto										
Higher Non-University	2 633	3 212	2 734	2 225	2 077	2 530	2 537	2 063	4 653	3 717
Superior University	4 997	6 747	7154	9 247	10 323	9 969	8 036	7 200	7 864	10 276
Madre de Dios										
Higher Non-University	3 980	2 855	3 135	3 191	10 149	9 246	4 735	4 736	10 964	6 046
Superior University	...	7 172	8454	16 851	22 563	14 106	8 413	9 917	7 622	8 836
Moquegua										
Higher Non-University	1 839	3 873	4 307	8 110	4 912	9 078	11 489	11 097	9 574	7 966
Superior University	...	14 462	12390	12 322	21 929	15 379	20 107	20 867	27 368	35 427
Pasco										
Higher Non-University	2 038	2 807	2 399	2 648	3 334	2 953	3 801	6 814	5 318	5 873
Superior University	3 336	5 169	6879	8 665	8 533	7 283	6 988	6 164	7 350	10 090
Piura										
Higher Non-University	2 448	2 353	3 705	3 957	6 372	3 822	4 879	10 150	6 157	4 933
Superior Universitaria	3 625	5 343	6877	8 189	10 184	7 681	6 207	5 965	7 692	12 453
Puno										
Higher Non-University	1 552	2 314	2 308	3 604	2 872	2 715	3 003	3 358	4 273	5 190
Superior Universitaria	2 547	5 737	6300	8 273	8 389	8 715	8 169	7 634	7 425	9 176
San Martín										
Higher Non-University	1 867	2 441	2 234	2 990	2 475	4 431	3 048	2 900	4 462	3 622
Superior Universitaria	3 355	5 724	6686	8 255	11 538	10 186	9 164	8 964	11 659	11 044
Tacna										
Higher Non-University	2 764	5 472	9 395	6 502	4 383	4 173	3 550	16 510	3 589	7 944
Superior University	3 668	5 859	6276	7 556	6 803	7 094	9 599	9 196	8 415	9 327
Tumbes										
Higher Non-University	1 600	5 671	6 547	2 248	2 899	5 342	6 868	5 718	6 375	5 371
Superior University	6 085	8 783	11309	16 607	19 216	19 157	12 242	19 884	16 642	14 952
Ucayali										
Higher Non-University	1 632	2 634	210	1 686	4 971	3 396	3 663	8 344	7 326	5 029
Superior University	5 259	7 220	9 417	8 718	8 820	10 236	9 902	9 210	9 157	9 411

Table 2 Highest expenditures by region from 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Apurímac Elementary	3813	4384	4217	4533	5181
Ayacucho Elementary	4085	3951	4911	5258	4288
Cusco Elementary	3103	3158	3464	4005	4335
Huancavelica Elementary	3936	3927	4778	4647	5449
Moquegua Elementary	4423	5358	5203	4614	4930

Table 3 Expenditures by highest educational level in initial 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Apurímac Pre-school	4629	5992	5446	5643	4950
Apurímac Elementary	3813	4384	4217	4533	5181
Apurímac Highschool	5175	4960	5048	5337	6423
Total Apurimac	13618	15336	14711	15513	16554
Ayacucho Pre-school	5856	3986	4355	4353	4442
Ayacucho Elementary	4085	3951	4911	5258	4288
Ayacucho Highschool	4547	3776	4406	5524	5987
Total Ayacucho	14488	11713	13671	15135	14717
Cusco Pre-school	3243	2473	2730	3960	4584
Cusco Elementary	3103	3158	3464	4005	4335
Cusco Highschool	3365	3458	3829	4953	5139
Total Cusco	9711	9089	10023	12918	14058
Huancavelica Pre- school	5005	5703	5758	5793	5303
Huancavelica Elementary	3936	3927	4778	4647	5449
Huancavelica Highschool	4253	4247	5905	5671	6652
Total Huancavelica	13194	13877	16441	16111	17404
Moquegua Pre-school	4088	4876	6653	5785	5257
Moquegua Elementary	4423	5358	5203	4614	4930
Moquegua Highschool	4001	4664	5744	5744	6537
Total Moquegua	12512	14898	17601	16143	16724

Table 4 Expenditures by lowest educational level in initial 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Apurímac Pre-school	4629	5992	5446	5643	4950
Cusco Pre-school	3243	2473	2730	3960	4584
Huancavelica Pre- school	5005	5703	5758	5793	5303
Madre de Dios Pre- school	3536	2499	2494	4311	5604
Moquegua Pre-school	4088	4876	6653	5785	5257

Table 5 Expenditures by lowest educational level in primary 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Callao Pre-school	2215	1894	2219	2228	2349
Ica Pre-school	1698	1790	2273	2406	2609
Lambayeque Pre- school	2254	2171	2558	2082	2061
Lima Metropolitana Pre-school	3434	3044	3223	2592	2667
Piura Pre-school	1657	1628	2103	2156	2439

Table 6 Expenditures by highest educational level in primary 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Callao Elementary	1882	1723	1815	1994	1770
Ica Elementary	2159	1958	2718	2431	2502
Lambayeque Elementary	2132	2224	2296	2064	2355
Piura Elementary	2132	2046	2585	2306	2498
Ucayali Elementary	1870	2022	2135	2045	2155

Table 7 Expenditures by secondary education level 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Apurímac High School	5175	4960	5048	5337	6423
Ayacucho High School	4547	3776	4406	5524	5987
Huancavelica High School	4253	4247	5905	5671	6652
Moquegua High School	4001	4664	5744	5744	6537
Pasco High School	4076	4596	4977	5761	5799

Table 8 Expenses by level of higher education 2015 – 2019

Educational level / Department	2015	2016	2017	2018	2019
Callao High School	2471	2656	2631	2799	2777
La Libertad High School	2781	3560	3461	3644	3602
Lambayeque High School	3040	2900	3628	3270	3696
Piura High School	2867	2724	3272	3279	3645
Ucayali High School	2646	2601	2891	3243	3496

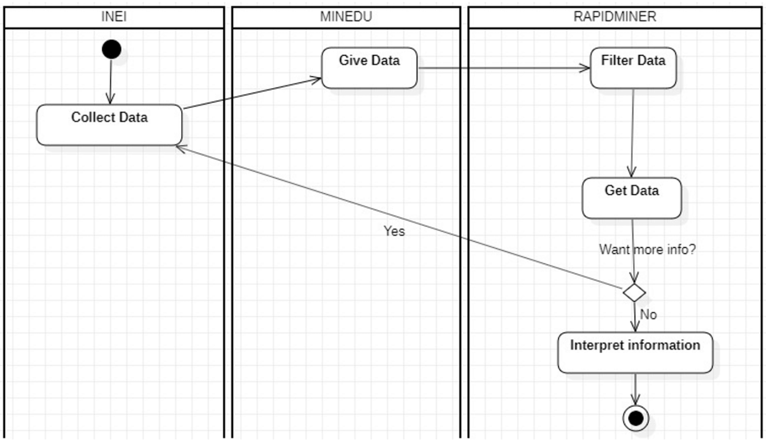


Figure 2 Data collection

performing the data reduction and the transformation of the same with the numerical transfer to interpret the information finally, as shown in Figure 2.

Figure 3 shows the stages and the data entry of the primary-level data. The choice of the data mining task by the regions, in the educational item at the national level, in this stage, we perform the classification of the data a priori. The implementation is to be able to group the cleaned data, and we implement parameters and features in our UML database through commands. Finalization of the channelling of data obtained through the INEI by regions in order to subsequently obtain the data.

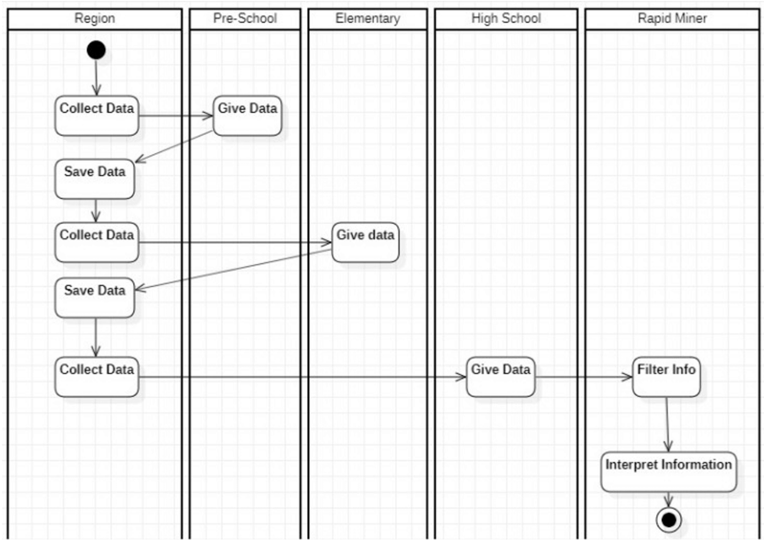


Figure 3 Data entry and education level

3.4 Fourth stage

For the adequacy of the hypotheses proposed as a result of data mining, the data obtained and the shared, linked bases will be used and provided; in this phase, the resulting data are grouped as shown in Figure 4.

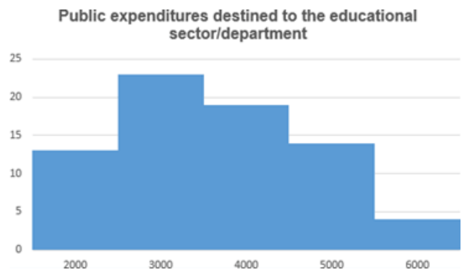


Figure 4 Histogram year 2019, public expenditures allocated to the education sector/department.

This histogram shows how public expenditures for the education sector were allocated in 2019, where it can be seen that twenty-three regions within the initial to secondary education level were allocated a total amount of approximately S/.3000 (1 Peruvian Sol is equal to 0.27 US dollar), followed by approximately S/.4000 within the education sector/department, being the most relevant in terms of money allocated. As shown in Figure 5.

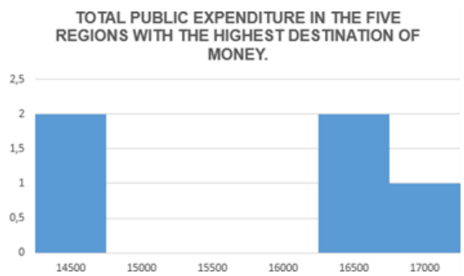


Figure 5 Histogram year 2019, total public expenditures in the five regions with the highest allocation of money.

This histogram shows the five regions with the highest rate of public expenditures, two of which have approximately S/.14,500, and the other two have approximately S/.16,500 of money destined for these regions, as shown in Figure 6.

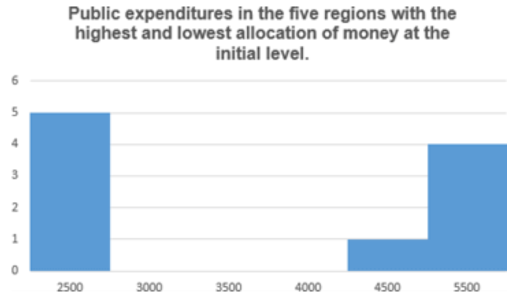


Figure 6 Histogram year 2019, public expenditures in the five regions with the highest and lowest initial level allocations.

This histogram shows the five regions with the highest rate of money allocated to the initial sector and the five with the lowest rate of money allocated, where the lowest rate has an approximate income of S/.2500 within the last five regions with the lowest rate of money allocated, while four of the five regions with the highest rate of money registered are within a radius of approximately S/.5000 to S/.5500 soles as shown in Figure 7.

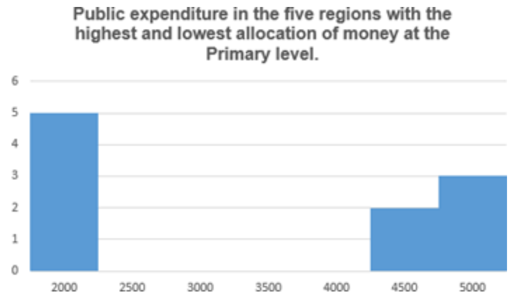


Figure 7 Histogram year 2019, public expenditures in the five regions with the highest and lowest allocation of money at the Primary level.

This histogram shows the five regions with the highest and lowest allocations in the primary education sector, among which the five lowest regions have an approximate allocation of S/.2000 to S/.2500. In contrast, three of the five with the highest allocations have an approximate allocation of S/.5000 during 2019 as shown in Figure 8.

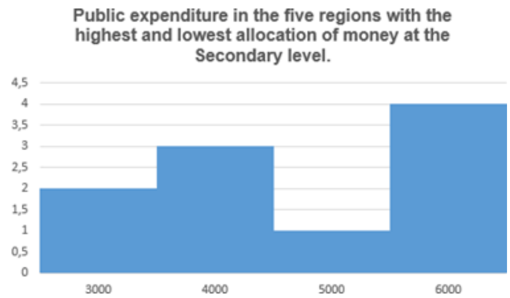
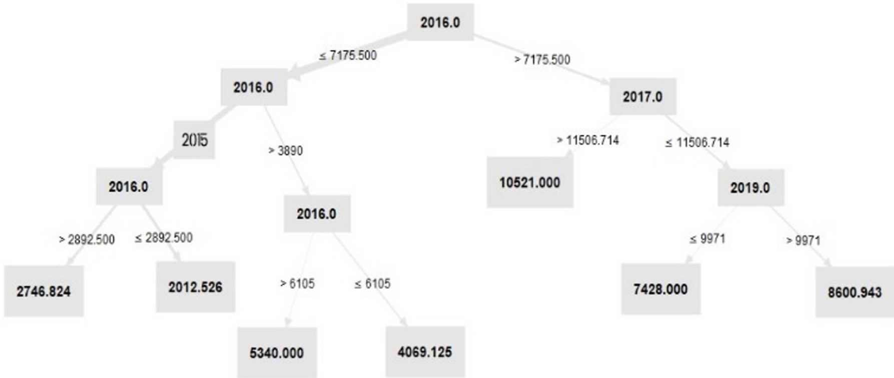


Figure 8 Histogram year 2019, public expenditures in the five regions with the highest and lowest allocation of money at the Secondary level.

This histogram shows how the money allocated to the secondary education sector in the regions with the lowest allocation, two out of five regions have approximately S/.3000, while in the regions with the highest allocation, four out of five regions have an approximate amount more than S/.6000.

3.5 Fifth stage

The current graphical representation indicates the probability of increasing public spending per student in basic education. When evaluating the efficiency in the investment of public spending in regular education by educational level, region and year, the unit of analysis was the region and the year. The unit of analysis was the region and the transcendence in years. The achievements studied and modelled were: corresponding to the last five years reported by the INEI, resulting in a minimum predictability of S/ 7428 per student investment in the public sector for the coming year, as well as a maximum investment of S/ 10521 nuevos soles per student, at the national level according to data provided by the INEI and the use of the standardized predictive software Rapidminer as shown in Figure 9.



Note: Public Spending per Student in Regular Basic Education, By Levvel of Eucation and Department. 2008 – 2019

Figure 9 Decision tree

The indicators of public expenditure investment in the education sector are expressed in monetary terms; according to the new Suns' table, the expenditure per student is expressed as the educational level increases yearly. Therefore, the current educational policies and context should reduce the inequalities and differences in the current regular basic education between different educational levels, regions and poverty levels.

4 Conclusion

In recent years the KDD methodology in data mining has experienced more accurate and precise information, resulting from all the information processed by this methodology. In the beginning, the accuracy of the information mining was focused on generating knowledge from thematic data. The study of spatial data had to be done almost manually. The application of techniques allows us to perform algorithms specifically designed for particular data and its application (Papadopoulou et al., 2022). For the first case, the design of data channelling was implemented through the KDD methodology since its transformation was performed through the massive data download of the INEI and its visualization through the data design with the UML software, and for the second one was developed in the casuistry of the discovery system the application of the base in the KDD methodology through the RAPIDMINER software, where the information has transformed the information and its conclusions. The results demonstrate an efficient performance when working with massive data sets and the software's responses depending on the downloaded information's size.

In contrast, the results graphs facilitate the final interpretation and possible conclusions (Mohammed, 2022). In the educational aspect at the national level, there was a radical change in terms of projected investment and actual investment (Dahal et al., 2022), since by the latest events developed globally in the years 2018 and the current context, you can visualize the rise in the cost of investment per student in the public education sector and with this same, develop possible cost adequacy or plan funding as the results of these cases (Aguayo et al., 2022). The current work demonstrated that it is feasible to adapt and channel information within data mining, developed in the first instance, which can be applied in other fields of research and not only in education as developed in this work is why it should be to the context of geographic data, depending on the research topic to be performed, adaptation and the results generated by the RAPIDMINER (applied on quantitative data) were transformed to show them graphically and conceptually using a friendly software.

Conflicts of interest

The authors declare that they have no conflict of interest.

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