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Decision models on therapies for intensive medicine

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Abstract

Decision support models are crucial in intensive care units as they allow intensivists to make faster and better decisions. The application of optimization models in these areas becomes challenging given its complexity and multidisciplinary nature. The main objective of this study is to use the stochastic Hill Climbing optimization model in order to identify the best medication to treat the Covid Pneumonia problem, considering the top 3 medications administered as well as the cost of treatment. It should be noted that the problem to be analyzed in the optimization model was selected considering that the extracted data is from the time when Covid-19 was ravaging the intensive care units, so it will be the most interesting. The results obtained in this study denote that the n_iterations parameter was crucial in obtaining the optimal solution since all scenarios with this parameter set to a value of 1000 were able to return the optimal solution, unlike the other ones.

Keywords: Intensive Medicine; Intensive Care Units; Decision Support Systems; Optimization Techniques; Therapies

1. Introduction

Intensive Medicine (IM) is a multidisciplinary area which specifically addresses the prevention, diagnosis, and treatment of critical situations, potentially reversible, in patients who have failure of one or more vital functions. This area of medicine is present in Intensive Care Units (ICUs), where specialized technical and human resources are

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available to monitor critically ill patients 24 hours a day [1]. With the implementation of technologies in ICUs, there has been an increase in the amount of data produced, collected, and analyzed, related to the patients' condition. The trend of using Data Mining (DM) techniques in the context of ICUs has emerged, as they enable knowledge to be acquired from large volumes of data. This knowledge helps to support the decision-making process of health professionals, enabling faster and better decisions to be made, improving the delivery of health care to patients [2]. Despite the existence of some Decision Support Systems (DSS) in the ICUs, these are not sufficient, and there is a constant need to optimize processes [3].

The main objective of this paper is to use optimization algorithms that, based on a problem and the medication administered for treating it, can identify the best medication to minimize the costs associated with the treatment. Therefore, the stochastic Hill Climbing algorithm was used and 6 test scenarios were defined where various combinations were made between the number of iterations used and the probability of accepting a new solution. At the end of the study, it was possible to see that the most reliable scenarios were those that had the n_iterations parameter set to the value 1000, i.e., scenarios S4, S5 and S6.

This paper is divided into five parts, Introduction of the theme, explanation of the Background, the Study Description carried out, presentation of the Results and lastly the Conclusion.

2. Background

2.1. Intensive Medicine and Intensive Care Units

Intensive Medicine (IM) is seen as a multidisciplinary area, as it requires not only exceptional knowledge about pathophysiology and therapeutics, but also about the various technologies used in this field. It is responsible for the prevention, diagnosis, and treatment of critical situations where patients have failure of one or more vital functions, whereby the main objective of IM is to support and recover these same functions, to provide patients with the prospect of a future life with quality [4].

Given the situation of patients who are in Intensive Care Units (ICUs), it is necessary to have continuous monitoring to safeguard their lives until their vital functions recover their autonomy [5]. To this end, it is essential that ICUs provide trained and qualified human resources to manage the critical situations with the assistance of available technologies, 24 hours a day [1].

2.2. Decision Support Systems

Decision Support Systems (DSS) enhance the decision-making process by combining the knowledge of experts with the knowledge extracted from the data. They can be developed to simulate, analyze, predict or optimize situations [6].

Considering the debilitated condition of patients admitted to ICUs, it is necessary to make decisions quickly and accurately [7]. Clinical Decision Support Systems (CDSS) are a variant of DSS suitable for the practice of medicine that not only increases patient safety, but also minimizes the occurrence of medical errors [8]. Therefore, CDSS offer health professionals specific, filtered, and organized information to improve the quality of the services provided [9].

2.3. Optimization Techniques

Optimization is considered a technique to find the best values for each desired parameter, and its purpose is to obtain values that can reduce the prediction error considering the data prediction model [10]. This arises from the need for Data Mining (DM) models to be optimized over time, i.e., to be constantly trained in order to increase acuity and return more reliable solutions [11].

In the medical field, optimization has become crucial given the limited resources available and the need to make the best decision in the shortest time possible [12].

3. Study Description

3.1. Methods and Tools

Although no Data Mining technique was used, the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology was chosen to guide the study. This methodology is divided into 6 phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation and Deploy. However, this chapter will only cover the phases up to Modelling.

For the development of this study, the Python programming language was used to analyze, understand, and prepare the data, as well as to build the optimization model, Hill Climbing.

3.2. Business Understanding

To solve a clinical problem, there are several therapies that can be adopted to treat a patient who is in critical condition. Therefore, the main objective of this study is to use an optimization algorithm that, based on a problem and the medication administered to treat it, can identify the best medication, minimizing the cost.

3.3. Data Understanding

For this study, two datasets were used, SOAP Data and Medication, both from the database of the Centro Hospitalar Universitário do Porto (CHUP), with data corresponding to the patients' problems and the medication administered, respectively. Both datasets contain data corresponding to the period between March 2020 and October 2021, however the SOAP dataset presented data for 47 patients whereas the Medication one contained data for only 36 patients. In tables 1 and 2 we can see the description of the SOAP and Medication dataset variables, respectively.

Table 1. SOAP Dataset

Dataset	Variable	Description
SOAP	NUM_SEQUENTIAL	Sequential number of admission
	NUM_PROCESS	Patient process number
	DATE_DAY	SOAP record day
	EPISODE	Patient's hospitalization number
	SOR	Subjective and Objective Report
	RPI	Treatment

Table 2. Medication Dataset

Dataset	Variable	Description
Medication	FMP_DATE	Day of medication administration
	NUM_SEQUENTIAL	Sequential number of admission
	FHC_NEPISODE	Patient's hospitalization number
	MED_DESIGNATION	Name of the medication administered
	ART_DESIGNATION	Detailed designation of the administered medication
	FMP_QT	Quantity of medication administered
	FMP_PRICE	Price of the quantity of medication administered

3.4. Data Preparation

To meet the purpose of this study, it was necessary to merge the two datasets, generating a final dataset. However, this merge reduced the data to only 11 patients. In addition to the merge of the datasets, it was necessary to build data that included the calculation of the duration of each treatment, the average price, and the cost. Therefore, in Table 3 we can visualize the variables that compose the final dataset as well as the distribution of numerical variables.

Table 3. Final Dataset

Variable	Description	Max	Avg	Min
PROBLEM	Name of the problem	-	-	-
MED_DESIGNATION	Name of the medication administered	-	-	-
AVERAGE_PRICE	Average price of the medication	50.22	2.61	0.01
TREATMENT_DURATION	Duration of treatment in days	15	4.4	1
COST	Cost of treatment (average price * duration of treatment)	154.80	8.58	0.02

3.5. Modeling

For the present study, the Hill Climbing optimization algorithm, stochastic version, was built using the Python programming language.

The development started by selecting only one problem from the list, in this case Covid Pneumonia since, given the pandemic situation that was experienced during the data extraction period, it was the problem that proved most interesting for analysis. Therefore, a cost function was developed where a penalty is applied considering the top 3 medications used in the treatment of Covid Pneumonia (bisacodyl, metolazone, pantoprazole) and the final cost of the solution is calculated: penalty + (price of the solution * duration of the solution). The Hill Climbing algorithm was built with two custom parameters, n_iterations and probability. In n_iterations is defined the number of iterations that the algorithm will have, and the probability corresponds to the probability of the new solution being accepted even if it is not better than the current solution, since it is a stochastic version.

Finally, given the Hill Climbing parameters, 6 test scenarios were defined, as we can see in Table 4.

Table 4. Scenarios Definition

Scenario	N_iterations	Probability
S1	100	0.1
S2	100	0.5
S3	100	0.7
S4	1000	0.1
S5	1000	0.5
S6	1000	0.7

4. Results

After the previously defined scenarios were run 10 times each, the best results were chosen and can be seen in Table 5.

Table 5. Results

Scenario	Solution	Solution Cost
S1	bisacodyl	1.82
S2	amlodipine	464.42
S3	furosemide	464.62
S4	bisacodyl	1.82
S5	bisacodyl	1.82
S6	bisacodyl	1.82

Based on the results presented above we can conclude that those which proved most reliable in finding the optimal solution were S4, S5 and S6, and they have in common the fact that they are set to run 1000 iterations.

Regarding scenarios S1, S2 and S3, only scenario S1 succeeds in obtaining bisacodyl as the optimal solution.

5. Conclusion

Once the study described in this article was completed, it was possible to draw some conclusions from the results obtained as well as what can be done in the future.

Given the stochastic Hill Climbing algorithm, it was found that the n_iterations parameter set to a value of 1000 was crucial in obtaining an optimal solution, i.e., the bisacodyl medication that is in the top 1 medication used to treat the Covid Pneumonia problem and has the lowest cost.

In the future it would be interesting to use other optimization algorithms to solve this same problem and analyze which one gets better results.

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References

[1] R. H. Sampieri, “Avaliação da Situação Nacional das Unidades de Cuidados Intensivos,” p. 634, 2016.

[2] A. Braga, F. Portela, M. F. Santos, A. Abelha, J. Machado, Á. Silva, and others,“Data mining to predict the use of vasopressors in intensive medicine patients,” *J. Teknol.*, vol. 78, no. 6–7, pp. 1–6, 2016, doi: 10.11113/jt.v78.9075.

[3] F. Portela, M. F. Santos, Á. Silva, F. Rua, A. Abelha, and J. Machado, “Adoption of Pervasive Intelligent Information Systems in Intensive Medicine,” *Procedia Technol.*, vol. 9, pp. 1022–1032, 2013, doi: 10.1016/j.protcy.2013.12.114.

[4] M. Gramacho, *Cuidados intensivos.*, vol. 18, no. 1. 1971.

[5] H. Blockeel, M. Bruynooghe, and G. Van Den Berghe, “Mining data from intensive care patients,” vol. 21, pp. 243–256, 2007, doi: 10.1016/j.aei.2006.12.002.

[6] R. Rupnik and M. Kukar, “Decision Support System to support decision processes with Data Mining,” *J. Inf. Organ. Sci.*, vol. 31, no. 1, pp. 217–232, 2007.

[7] F. Portela, M. F. Santos, J. Machado, A. Abelha, Á. Silva, and F. Rua, “An intelligent approach for open clinical laboratory results in Intensive Care medicine,” *IEEE Int. Conf. Ind. Eng. Eng. Manag.*, pp. 1092–1096, 2014, doi: 10.1109/IEEM.2013.6962579.

[8] A. Braga, F. Portela, M. F. Santos, J. Machado, A. Abelha, Á. Silva, and others , “Step Towards a Patient Timeline in Intensive Care

Units," *Procedia Comput. Sci.*, vol. 64, pp. 618–625, 2015, doi: 10.1016/j.procs.2015.08.575.

[9] A. Naharro-Abellán, B. Lobo-Valbuena, and F. Gordo, "Clinical Decision Support Systems: Future or Present in ICU?," *ICU Manag. Pract.*, vol. 19, no. 4, p. 2868508, 2020.

[10] J. Ferreira, F. Portela, J. Machado, and M. F. Santos, "Adaptive business intelligence in healthcare - A platform for optimising surgeries," *Adv. Intell. Syst. Comput.*, vol. 932, pp. 611–620, 2019, doi: 10.1007/978-3-030-16187-3_59.

[11] M. F. Santos, F. Portela, M. Vilas-Boas, J. Machado, A. Abelha, J. Neves, and others, "Information architecture for intelligent decision support in intensive medicine," *WSEAS Trans. Comput.*, vol. 8, no. 5, pp. 810–819, 2009.

[12] P. Oliveira, F. Portela, M. F. Santos, J. Machado, A. Abelha, Á. Silva, and others, "Optimization techniques to detect early ventilation extubation in intensive care units," *Adv. Intell. Syst. Comput.*, vol. 445, pp. 599–608, 2016, doi: 10.1007/978-3-319-31307-8_62.