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# Applying Profit-driven Metrics in Predictive Models: A Case Study of the Optimization of Public Funds in Peru

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**Abstract.** Fund allocation is a crucial concern in public management, as it is an important factor for economic performance in public investment. Governments spend substantial resources to improve these investments' efficiency and effectiveness. The use of Machine Learning techniques has proven to be a relevant tool in the decision-making process. In this study we test an approach based on a profit-driven perspective, in order to assess predictive models in public resource allocation, valuing the net profit obtained by the allocation of funds for Peruvian researchers to have a specific performance measure to the fund allocation. A series of experiments were developed using data from 24 Peruvian universities. The use of a profit-driven metric allows to make better choices regarding predictive models and reaching better performance in public investment for Peruvian government. Use of Machine Learning techniques supports the correct identification and selection of researchers to optimally allocate limited resources in an emerging country and shows a novel use of predictive models in public management.

**Keywords:** Predictive analytics, machine learning, random forest; decision sciences; public management; profit-driven metrics

# 1. Introduction

The allocation of public funds for scientific research is a challenging task for agencies around the world (Woelert and McKenzie, 2018). Optimal allocation levels lead to cost-efficiency, increased savings and improved external perceptions among stakeholders (Douglas and Overmans, 2020). In the case of Peru, cost-efficiency is a major concern for the Government. Therefore, the task of assigning funds to researchers is challenging, considering the reduced amount of money that scientific research has historically received in the Peruvian annual budget (Nunez and Cornejo-Meza, 2018).

The use of analytical approaches in decision-making process can contribute to enhancing outcomes by uncovering the hidden knowledge in large datasets (Dahiya, Gautam and Gautam, 2021). Use of data mining and machine learning tools has been successful in several business tasks as improving service quality (Kowalski, Esteve and Jankin Mikhaylov, 2020) or optimizing the use of resources (Zekic-Susac, Mitrovic and Has, 2021). In Khoa et al. (2021), we can see the comparison of four machine learning algorithms in order to improve the performance of forecasting models in the US stock market. As Srinivasan, Shah and Surendra (2021) points out, the application of these techniques represents a significant opportunity to develop competitive advantages from data.

Specific examples of the application of predictive analytics in public management can be found in Psarras et al. (2020) and Kang, Croft and Bichelmeyer (2020). In both studies, model performance is assessed by statistical measures. Nevertheless, these kinds of measures are not necessarily aligned with the objective for the public agency, which is to maximize the profit or savings in the fund allocation process to assure maximal efficiency in the decision-making process. As Maldonado et al. (2020) points out, costs and benefits should be taken into account when developing a predictive model.

Churn prediction is one of the most studied problems in the field of machine learning, and is oriented to detect customers that are likely to attrite (Vafeiadis et al., 2015). This application is similar to the prediction of researchers with high or low productivity, in order to target the researchers that are most likely to have high productivity (measured in terms of patents, articles and other research output).

The prediction of high productivity researchers is a decisive task when assigning public funds for research, as far as making an accurate identification of those researchers who tend to be more productive or to produce high impact articles (Ponomarev et al., 2014) allows an optimal funding allocation, maximizing the financial performance of different public financing programs. According to Beerkens (2013), the application of research management practices had an outstanding result in the scientific productivity of Australian universities.

To the best of our knowledge, studies about profit-driven classifiers that optimize profit are insufficient in the machine learning and business analytics literatures, mostly limited to the domains of logistic regression (Stripling et al., 2018) or decision trees (Höppner et al., 2020; Liu et al., 2019). In this manner, this project aims to contribute to close the research gap by generating new evidence around the use of profit-driven approaches in predictive models for classification in public management.

Therefore, this study allows us to quantitatively assess performance in predictive models, by using a new approach centered in profit metrics rather than statistical metrics like accuracy or AUC (Hand, 2009). In this study, we propose the hypothesis that using profit metrics, when aligned to financial strategies, can improve the outcome of a predictive model making it a proper tool to support decision-making processes. From an economic perspective, this study contributes to private organizations and public agencies to validate a methodology for fund allocation based on predictive models.

Profit-driven approach is applied in the decision-making process by government agencies which have to assign resources for scientific research. The study case is based on data from researchers from 24 Peruvian universities (public and private), where the net gain (or loss) associated to each scenario of fund allocation was calculated.

The remainder of the paper is organized as follows: Section 2 describes Fund Allocation Analytics and Profit-Driven evaluation. Section 3 presents the research method and the data processing. The experimental results obtained by using a real-world dataset from Peru are presented in Section 4. Finally, the conclusions are provided in Section 5.

# 2. Literature Review

## 2.1. Fund allocation analytics

One of the main objectives for fund allocation is that these funds have a high economic and social profitability, that is, they allow for maximizing fulfillment of state goals. In the case of an agency dedicated to fund allocation for research and scientific development, the objective is that the allocated funds have high impact, measured by some indicator such as the number of scientific publications in indexed journals (Chapman et al., 2019), the number of citations per published article (Brito and Rodríguez-Navarro, 2019), or the social impact of the research results (Chernoff, 2019). The main challenge for public agencies lies in increasing their efficiency despite budget cuts (Coccia, 2008).

The use of analytical tools has been widely applied in different industries, where one of the most studied problems is predicting customer churn, finding different applications (Mitrovic et al., 2018; De Caigny, Coussement and De Bock, 2018) where the objective is to detect customers more likely to leave the service and deploy retention campaigns to maximize business profitability.

In this study, the proposed approach is centered in classifying the researchers into two groups: high and low productivity, to design differentiated strategies for both groups focused on high-productivity researchers, i.e., those who outperform in the previously presented indicators. Consequently, the decision criterion is to allocate a much higher budget to researchers classified in the high productivity category. An incorrect classification of researchers (negative false) will impact fund allocation efficiency, to the degree that all false positives will receive a reduced amount of funds, in circumstances that are highly productive researchers.

The profit of a classifier is calculated according to the benefits associated with different decisions. In this study, the goal is to achieve maximum profit instead of maximizing the accuracy of a predictive model.

## 2.2. Profit-driven evaluation

A research stream that integrates costs and benefits derived from a predictive model is profit-driven metrics (Verbeke et al., 2012), where there are better results for the organization compared with traditional metrics. In this sense, a highly accurate predictive model might not be appropriate for the context, insofar as it does not allow to optimize the gain. However, most of the studies in Business Analytics apply traditional measures, based on statistically grounded techniques (Maldonado et al., 2015)

As Verbraken et al. (2014) points out, the use of profit-based classification measures leads to better decisions in terms of monetary value as well as predictive accuracy, compared with traditional approaches. Maldonado et al. (2017) presents a profit-driven framework to assess the performance of a classifier in a credit scoring problem, showing that the proposed framework led to better performance regarding traditional metrics.

This study evaluates several classifiers based on a profit-driven point of view. In this matter, the classification is oriented to correctly identify the Peruvian scientific researchers who will have high productivity, i.e., $Y = 1$. The approach taken in this study is based on Maldonado et al. (2021), which adopts a profit-driven perspective to maximize the net savings of a student retention campaign in a Chilean university, in regard to the dropout problem.

The performance of the models used is then evaluated by considering the profit generated by all the researchers. In public management, cost-efficiency is one of the challenges that agencies need to face in order to maximize the impact of their actions. However, it is important to mention that a correct classification of a high productivity researcher does not necessarily imply that researchers will have the same performance in the future.

# 3. Research method

## 3.1. Methodology

We started our research work on a dataset of researchers from 24 Peruvian universities (public and private). Peruvian higher education system is composed by

95 universities and almost 1 million students. In terms of scientific research outcomes, Peruvian universities had steadily increased their performance. In fact, Peruvian universities have tripled their number of scientific articles published in Scopus in a period of 6 years, from 2015 to 2021. However, when assessing the allocation of public funds for research we can see that a relevant number of researchers who received some type of public funding had low productivity (measured as the number of scientific articles published in a period of time).

## 3.2. Data

Our initial dataset includes 24,254 observations, i.e., scientific researchers, and consists of 17 input variables (as shown in Table 1) including age, academic background, working status, tenure, area of knowledge (based on the Organization for Economic Cooperation and Development (OECD) classification), and university funding-type. The outcome variable Y indicates if the researcher has low or high scientific productivity.

Table 1: Description of Input Variables.

| Variable Name | Type | Description |
|---|---|---|
| University Type | Qualitative | Type of University (private/public) |
| Region | Qualitative | Location of the University (Lima Region/Other Regions) |
| Surname | Qualitative | Researcher surname |
| First Name | Qualitative | Researcher first name |
| Middle Name | Qualitative | Researcher middle name |
| Age | Quantitative | Researcher age |
| Gender | Qualitative | Researcher gender |
| Years | Quantitative | Years working as researcher |
| Academic Degree | Qualitative | Highest academic degree obtained by the Researcher (PhD, Masters, etc.) |
| Area of Knowledge | Qualitative | Area of Knowledge of the Academic Degree |
| Country of Degree | Qualitative | Country where the academic degree was obtained |
| Job Status | Qualitative | Job Status (full-time, part-time) |
| Tenure | Qualitative | Hierarchy (Assistant, Associate, Full Professor, non-tenure-track) |
| Service Hours | Quantitative | University Service Hours |
| Teaching Hours | Quantitative | Teaching Hours |
| Research Hours | Quantitative | Research Hours |
| Level of Courses | Qualitative | Level of courses taught in the University |

| | | |
|---|---|---|
| | | (Undergraduate/Graduate/Doctoral Studies) |

## 3.3. Data processing

In the data processing stage, 129 cases were removed as there were incomplete features. Then 3 variables related to the identity of the researchers (name, surname, middle name) were eliminated to preserve anonymity. No imputations were performed in preprocessing. This resulted in a total of 14 features and 24,125 observations.

For the purposes of providing a deeper understanding of the dataset, we provide descriptive statistics of some of the variables involved in the model, as shown in Table 2.

Table 2: Location of University

| Region | Number of Universities | Percentage |
|---|---|---|
| Lima | 14 | 58.3% |
| Other | 10 | 41.7% |
| Total | 24 | 100% |

Table 3: Classification of researchers' productivity by type of University

| Type of University | Number of Universities | Low Productivity Researchers | High Productivity Researchers |
|---|---|---|---|
| Public | 8 | 3,800 | 4,175 |
| Private | 16 | 14,286 | 1,864 |
| Total | 24 | 18,086 | 6,039 |

Table 4: Classification of researchers' productivity by area of knowledge

| Area of Knowledge | Low Productivity Researchers | High Productivity Researchers |
|---|---|---|
| Social Sciences | 9.409 | 2,016 |
| Basic Sciences | 1,410 | 1,169 |
| Engineering and Technology | 2,419 | 1,188 |
| Humanities | 1,698 | 616 |
| Health Sciences | 2,906 | 843 |
| Agricultural Sciences | 244 | 207 |
| Total | 18,086<br>(75%) | 6,039<br>(25%) |

Five machine learning algorithms were chosen, based on cases reported in the literature regarding Higher Education Management. All the models were developed in R, using the caret package. 5-fold cross-validation was used to tune the hyperparameters. Area under the ROC curve (AUC) was the performance evaluation metric, considering that AUC is a good measure for hyperparameter tuning.

Another method used was synthetic minority oversampling technique (SMOTE) as a resampling technique considering that class imbalance is around 25%. SMOTE is a suitable approach for class-imbalance classification based on this performance. In order to train the models, the dataset is split into training and testing sets in 70% and 30%, respectively. Finally, we trained a total of 10 predictive models to report their results with and without resampling.

# 4. Results

## 4.1. Results

The results of the experiments are reported in terms of the maximum profit of the model based on the benefits and costs associated with the scientific research fund allocation. Alternatively, we present the accuracy of each model (with and without oversampling) in order to assess how resampling has an impact on predictive performance. Figure 1 shows the area under the ROC curve (AUC) for the 10 models. The bold curve represents the model with the highest maximum profit. The gray area, in comparison, displays the conjunction of curves of the models which obtained lower profits.

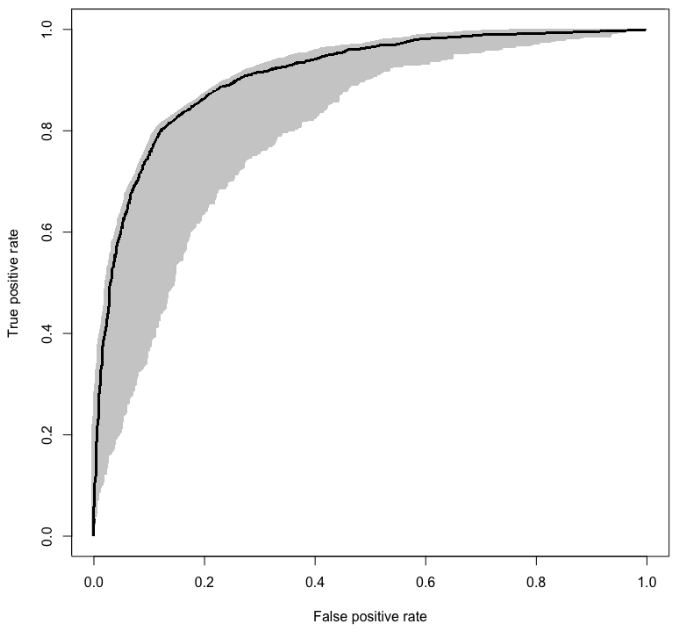


Fig. 1: Area under the ROC curve (AUC) for the 10 models

The figure shows that profit-driven approach may lead to better decision-making for the allocation of resources for researchers, by selecting the model that maximizes the financial impact of the research output, even if the selected model is not the one with the maximal accuracy.

Table 5: Performance for the classification models in terms of accuracy

| Algorithm | With Oversampling | Without Oversampling |
|---|---|---|
| Random Forest | 84.43% | 85.91% |
| Neural Networks | 85.04% | 85.01% |
| CART | 85.96% | 84.68% |
| SVM Linear | 74.95% | 84.65% |
| SVM Radial | 79.17% | 84.28% |

Table 6: Performance for the classification models in terms of maximum profit

| Algorithm | With Oversampling | Without Oversampling |
|---|---|---|
| Random Forest | $ 294,800 | $ 254,060 |
| Neural Networks | $ 243,020 | $ 212,020 |
| CART | $ 213,950 | $ 210,580 |
| SVM Linear | $ 197,280 | $ 205,660 |
| SVM Radial | $ 243,020 | $ 208,960 |

The decision derived from the predictive model is based on assigning considerable amount to those who were predicted as high productivity researchers. Using resampling methods leads to lower accuracy in three of the five algorithms selected. However, in the case of Random Forest, resampling provides better recall of true positives (Y = 1) when compared to the other algorithms. The intuition is that increasing the recall reduces losses by correctly classifying high productivity researchers. In fact, highest maximum profit ($ 294,800) is obtained when the decision is targeted to high productivity researchers, which is consistent with the fact that targeting to get high accuracy in predicting both groups does not lead to profit optimal value.

Another result worth highlighting is that with the Random Forest algorithm, oversampling to 50/50 proportion between low and high productivity researchers gives the higher profit for the model. In case of NN, CART and SVM-R, profit also increases when the proportion of positive cases is augmented by using oversampling technique.

In order to increase interpretability of the best model (Random Forest), for decision-making purposes we calculated the mean Gini coefficient decrease to measure the importance of each variable for the model. Figure 2 shows the representation of Gini coefficient valuable for the variables. We observe two variables with the highest score (*AK, Area of Knowledge* and *T, Hierarchy*) and should be prioritized when deciding which researchers receive funds.

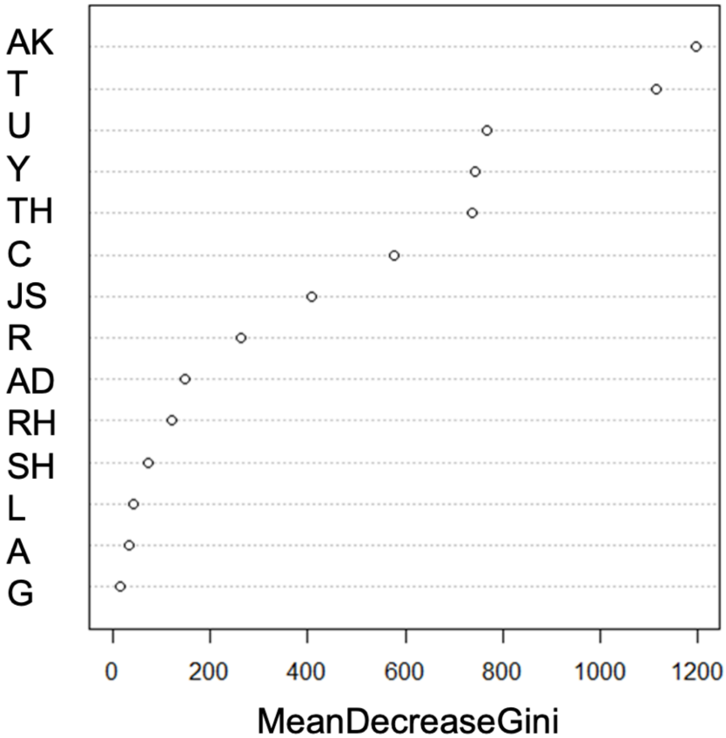


Fig. 2: Mean gini coefficient decrease

The first variable (*AK*) describes the area of knowledge of the researcher, and the subareas of Social Sciences, Engineering and Technology and Basic Sciences are the ones with more researchers in high productivity class (Y = 1) in absolute terms. In case of the variable *T*, the model clearly shows that in Peruvian universities, associate and assistant professors can be more productive than full professors or lecturers. Another variable with an interesting pattern is *TH*, which indicates that researchers with approximately 10 weekly hours of teaching (leaving 30 hours or more per week for research purposes) are more likely to be high productivity researchers.

This finding is important in terms that provide a clear insight by defining a threshold in researchers' teaching workload. When analyzing the patterns related to explain the presence of more productive researchers, the study allowed to discover which researchers can lead to higher impact (in terms of scientific output), bringing the Peruvian Government should clear insights to assign public funds in the future.

## 4.2. Discussion

From the analytical point of view, it's important to highlight that even the accuracy of the models can reach levels of 85%, the performance of the models can improve in the future by adding more data. Considering that only 24 of 95 universities were included in the models, there is enough space to get better outcomes in future analysis, leading to better decisions in public management related to higher education. The findings of the study can be applied in tasks like research administration, human resources management and higher education management. The analytical approach of this project can shed light to public and private organizations by providing a case study based on the application of profit-driven metrics in predictive models.

In relation to the performance of the selected algorithms, it is important to emphasize that traditional metrics as accuracy, recall and precision may depend on the characteristics of the dataset. In this sense, the fact that Random Forest provides the better results in this experiment provides evidence that in certain conditions, algorithms can perform better or worse. For example, in Ahuja and Sharma (2021) the best classifier is Support Vector Machine (SVM), having accuracy, precision, recall with values higher than 99%, leaving Random Forest in third place (after SVM and XGBoost algorithms) of 12 selected algorithms in this study. In other hand, Ho, Cheong and Weldon (2021) used several algorithms as Neural Networks, Random Forest, Multiple Linear Regression, K-Nearest Neighbors, among others. However, results are poor in terms of accuracy and recall, having values lower than 80% in the aforementioned algorithms. Results are mixed in terms of accuracy and recall in this experiment for the three algorithms.

Regarding the management perspective, the proposed approach (based on machine learning techniques) confirms that an intensive use of data for the decision-making process may lead to an optimal use of financial resources, by the allocation of funds to high productivity researchers. In fact, when comparing the profit generated by the two most accurate algorithms (RF and CART) we may see a difference of 27.4% of the profit (with oversampling) and 17.1% of the profit (without oversampling) in favor of Random Forest, which is one of the most versatile algorithms for predictive analytics in educational management, as shown in Fernandez-Garcia et al. (2021) regarding the prediction of university dropouts at different stages. The characteristics of Random Forest algorithm are more suitable for datasets composed by qualitative and quantitative variables, which leads to better performance in this context, as shown in Brohi et al. (2019).

One limitation of this study is related to the size of the sample used for the experiments, considering that the dataset of the project is composed of only 24 universities, while Peru has 95 universities.

Finally, this paper contributes to the literature in machine learning and business analytics by generating new evidence about the use of profit-driven approaches in predictive models for classification in public management.

# 5. Conclusions

The accuracy of a classification algorithm is probably the most used measures to assess the performance of the predictive model. However, this approach may not necessarily be the most suitable to evaluate the economic impact of the decision taken to allocate public funds for scientific research. In public management, it is very important to maximize the benefits obtained by the adequate allocation of funds.

In this project, we presented a case study of the use of profit-driven metrics in the allocation of public funds for scientific research in Peru, in which we could show that the best model in terms of profit (Random Forest with oversampling) is not the most accurate one. Our findings suggest that in this type of problem (predicting productivity of scientific researchers), recall is a better measure than accuracy. Results show that resampling does not always lead to an increase in profit.

Future research should consider larger datasets to assess the impact of profit-driven approach in the whole Peruvian system. Further work on profit-driven metrics in predictive models are necessary to validate the conclusions that can be drawn from this study.

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