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Applying Predictive Models

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Introduction

The present research, aims to explore and discover analytics science's business value in Human Resource Management beginning with its definition and ending to its application in workforce management. Moreover, a comprehensive analysis regarding algorithmic application and its ethical issues took place. Finally, an interpretation and explanation was applied to provide valuable information on existing coding development, to compare the effectiveness of four classification models; Logistic Regression, Decision Trees, Random Forests and Gaussian Naïve Bayes.

Literature Review

Business Value of Predictive Analytics in HR

Defining HR and Predictive Analytics

Living in an era, in which digitization is being increased rapidly within society, data amount, either big or small, is enormous. Data analytics strategic processes are used to make clear and useful insights within various events and industries (Tursunbayeva, et al. 2018). Espegren and Hugosson, (2023) provide valuable information regarding Bjorkman et al's (2014) practice-related framework in Human Resource Management, who provided a more comprehensive approach with the scope of making the HRM's practice innovative and understandable by setting three vital questions related to HRM's practices and practitioners; *"What, Who and How"*. Using these questions, the provided framework is creating a baseline by identifying the HRM's practices, the individuals who are related to HRM and finally the ways these practices are applied by the practitioners. Moreover, Human resource analytics is considered as a new and recent appealing function within Human Resource Management by a lot of companies and organizations. The specific function, could be defined as the data extraction, analysis and reporting to provide insights related to people's decisions and to enhance the results of organizations and individuals (Espegren and Hugosson, 2023).

Strategic Value Creation through HR Analytics

Innovation and evolvement led organizations to use the data they acquire and create an actual value through analytics. Throughout recent years, organizations were able to use a variety of tools to implement data analysis used to improve HR processes with the scope of reducing challenges and gaps related to employee retention and performance. Levenson and Pillans (2017), explore the issues and challenges of workforce analytics but also provide information on how it could be implemented successfully in a theoretical but also in a practical aspect and provide actual value through high quality analytics process. In fact, a specific and more conservative structure is presented below in order to create a strong basis in analytics.

Levenson and Pillas (2017), suggest that the prioritization of HR goals is very important to be set at the beginning in order to proceed then, with the measurement of potential optimizations in performance. That could be considered as a very reasonable structure, as the organization or the appropriate department first has to determine what data does it have and how can it use them. Moreover, it is important to mention that hypothesis testing is crucial as a second step to be implemented through analytics. By determining the project's key drivers, this could allow hypotheses to be created. However, methodology application is crucial to align business challenges with the suitable analytics techniques for data collection and analysis for insight interpretation as Levenson and Pillas (2017) support. That way, by creating business insights, the organization can propose optimizations related to workforce management to add more value on a corporate level.

On the other hand, Bottesch et al. (2025**)** provide comprehensive literature seeking to provide business value through people analytics. More specifically, Bottesch et al. (2025) support that regarding employee selection, due to the vast amount data HR is receiving, manual screening is not as feasible as it was in the past. Instead, logic-based and machine learning prescriptive models and tools can be used to offer suggestions for hiring selection. That way, these techniques can increase time efficiency but also the HR's decision-making effectiveness factors which were already established for hiring employees.

Finally, another important aspect is the employee allocation, which is the transference of an employee to a specific task or role at a specific time. Traditionally, employee allocation was implemented based on existing challenges and their prioritization was based on schedules aiming at reducing costs and fulfilling organizational requirements. Bottesch et al. (2025) suggest that by automating employee allocation based on the use of algorithms and heuristic techniques, workload efficiency would be improved.

Predictive Analytics in Employee Performance and Retention

Employee performance and retention are often linked to organizational efficiency which could create a sense of trust and employee-centric business culture towards employees, within the organization. However, the aspects affecting employees' performance and turnover might be different from the above. Employee turnover is a critical concern in business management which directly affects productivity. Jain (2025) supports that conservative points of view propose that by eliminating turnover as much as possible, it affects positively the workforce's efficiency and minimizes hiring costs.

Moreover, Jain (2025) extracted and analyzed IBM's HR dataset by applying predictive analytics techniques to predict employee turnover by analyzing both demographic variables but also workforce-related ones. This case study could be considered as an important one of presenting how predictive analytics is applied in employee performance and retention.

The predictive analysis which was applied by Jain (2025), implemented techniques such as heatmaps, histograms and pie charts for distribution, correlation and class imbalance identification. Moreover, as Jain (2025) stated, Jupyter Notebook was used, an environment to apply Python for the analysis of the dataset but also for four different predictive models.

Findings of the specific case study analysis showed that among the four different applied predictive models (DT, SVM, LR and CNN), CNN model was the one with the highest accuracy and precision on predicting employees' turnover, which based on Jain's (2025) discussion, provides valuable evidence that predictive analytics could contribute with high efficiency within workforce analytics.

From Technical Capability to Organizational Practice

Pivoting towards organizational practice, the technical capability and efficiency of analytics in HRM, it is important to be explored and discussed in a practical view. This was shown through the research by McCartney and Fu (2024), which was structured in two phases. Phase 1 focused on associating analytical skills with professionals' performance in people analytics while phase 2, refers to the collection of data from 50 people analytics employees by using interviews (McCartney and Fu, 2024). The aim of this research is to link the relationship between storytelling skills' importance with job performance.

McCartney and Fu's (2024) literature explores the practical skill set of people analytics employees, from which, authors emphasize in analytical skills, which adds value by using methods through statistics and testing techniques to provide insights in business challenges and gaps. Moreover, technical skills but also, visualization and programming means such as PowerBI, Tableau, R and Python play a vital role in manipulating and using data for exploratory analyses but also in creating and designing reports, dashboards and developing predictive models through trend analyses (McCartney and Fu, 2024). Furthermore, storytelling could not be considered as a standalone skill. McCartney and Fu, (2024) claim that storytelling is related to the creation, promotion, and interpretation data into stories, whose aspect and criticality in business decision-making is very important, as storytelling allows the identification of trends, existing problems but also is able to provide predictive outcomes through patterns.

Finally, the research provided clear results regarding organizations that are constantly developing people analytics (McCartney and Fu, 2024). The findings showed that people analytics professionals, view analytical skills as a major tool but with the combination of storytelling, which results to higher job performance (McCartney and Fu, 2024). The above show that HR departments recognize people analytics' value that is added through practice and that the importance of the specific expertise within organizational environments is very high in terms of decision-making.

Limitations and Structural Barriers

The science of analytics within HRM, provided a respectable value in terms of workforce management and people analytics. However, barriers and limitations exist which concern its utilization. Angrave et al. (2016) conceptualize these barriers by confirming the HR professionals' skeptical standpoint regarding the metrics' measurement of people. Moreover, the authors discuss the generic HR responsibilities that has, which could act as a negative factor in using the existing data efficiently to get insights to business challenges. However, it is also stated that this is not an HR's issue but it is the main issue of analytics expertise in general.

Furthermore, on its technical aspect, consultancy companies provide software programs to organizations related to talent acquisition processes which can extract and provide applicants' data to HR. These HRIS called systems (Angrave et al. 2016), could be considered as means to meet specific strategic goals. However, training of staff and software's customization is needed, to meet the organization's culture and processes for the creation of reports and dashboards to be developed. These software programs create some limitations in terms of insights-creation and reporting. Angrave et al. (2016) explore the programs' efficiency related to the above mentioned limitation and discover that the limitation focuses on the availability of analysis for more important questions, which shows that the HRIS systems' providers are focusing on selling the product instead of providing actual problem-solving solutions. This aspect can be confirmed also by Heuvel and Bondarouk (2017), whose research showed that one of the upcoming challenges in HR analytics would be the IT infrastructure integration related to multi-source data. This could provide insights and could be the solution of providing answers to big questions through the use of software programs as was mentioned by Angrave et al. (2016).

Ethical Issues & Explainability of Classification Models

Algorithmic Decision-Making and Ethical Risk

Within the modern society, people are constantly surrounded by digitized environments and operations consisted of algorithms. In business context, professionals are exposed to data, which should be interpreted using specific algorithms and to formulate a strategy on how they should be used. However, due to the use of algorithms in important processes, a concern is raised regarding the ethical risks that exist.

Mittelstadt et al. (2016) raise concerns and trigger a debate on ethical aspects related to algorithms. Specifically, algorithms such as recommendation systems, profiling and classification algorithms are implemented in people's daily life, but also data mining algorithms for behavioral analysis in various platforms (Mittelstadt et al. 2016). However, the identification of algorithms' effect in an ethical way is difficult. Mittelstadt et al. (2016) investigated the complexity of algorithms' ethical impact and examined 6 areas on the same subject from which, the current project will focus on "Inconclusive evidence and Inscrutable evidence" (Mittelstadt et al. 2016).

Inconclusive evidence could be considered as uncertain outcomes drawn through data processing by using machine learning means. Despite the fact that statistical methods could be used to provide significant correlations, these could not be considered as effective and even if it was to be applied in a respectable amount of data, again the correlations and causal knowledge would be uncertain and unclear (Mittelstadt et al. 2016).

As Mittelstadt et al. (2016) support, inscrutable evidence is provided as conclusion by processed data. While machine learning algorithms' capabilities are limited in terms of data and outcomes' accessibility and explainability, it provides a knowledge gap regarding how data are used, which negatively affects practical challenges.

Finally, the above showcase a concern related to transparency as algorithms' capabilities on accessibility and explainability is weak. Turilli and Floridi (2009) describe transparency as "the availability of information, the conditions of accessibility and how the information . . . may pragmatically or epistemically support the user's decision-making process" (p. 6 cited in Mittelstadt et al., 2016). That can be confirmed by Mittelstadt et al. (2016) as the authors support that the data processing in commercial related context could be affected in a negative way by transparency. Thus, this relationship between data processing by machine learning algorithms and transparency could provide a disturbance between knowledge and decision-making.

Bias, Fairness and Discrimination

Another important topic to be discussed related to ethical concerns is bias, fairness and discrimination of classification models and machine learning in data analysis Obermeyer et al. (2019) showcases a predictive algorithmic analysis related to patients' population affected by illnesses. This analysis identified racial biases on black population's sickness significance than White patients. Fianlly, it was found that the bias came from the algorithmic prediction of health care costs than the illness itself which drew the conclusion that the healthcare system spends more money for white patients than black patients.

Moreover, Mehrabi et al. (2019) conducted a survey which investigated applications that showed biases in different ways, and sources that could affect AI applications. An example which was presented by the authors was the non-balanced dataset selection of IJB-A and Adience which included mostly light-skinned subjects. This brought a discriminatory bias towards dark skin groups who are not strongly included within the data.

Finally, the above cases showed that machine learning algorithms could be considered as an uncertain-result oriented mean, if the used data contain imbalanced demographic variables and due to their nature of lacking accessibility and further interpretation.

Trade-offs in Fairness and Accuracy

Artificial Intelligence (AI) is evolving constantly within the organizational context nowadays, and through that, decision-making is affected a lot. As data is integrating with Artificial Intelligence and analyzed by automated learning models, it is reasonable, a demand for higher analysis accuracy and consistency to be exhibited. AI algorithms are proved to be less fair and consistent, and as mentioned previously, algorithms generate biases and unfairness through the data process (Pessach and Shmueli, 2020). Authors are setting a path of algorithmic bias measurement, by addressing a variety of measures like "Disparate impact, Demographic Parity and Equal opportunity".

The fairness measurements can be used to measure trade-offs, but also Pessach and Shmueli, (2020) point out that by seeking high level of fairness it could create an accuracy consensus. Moreover, the authors suggest 3 types of processes on how the fairness could be increased in machine learning algorithms. Pre-process mechanisms involves the training data to be modified before their import in machine learning algorithm, which allows the data groups to be more similar and then to eliminate potential biases (Pessach and Shmueli, 2020). Furthermore, In-process mechanisms are means of increasing fairness which includes the process of modification of machine learning algorithms to monitor fairness's level during training process (Pessach and Shmueli, 2020). Finally, the last type is the Post-process mechanism in which Pessach and Shmueli, (2020) defines it as "… mechanisms perform post processing of the output scores of the classifier to make decisions fairer" (p. 8 cited in Pessach and Shmueli, 2020).

Finally, mechanisms' selection could be used with any classification algorithm but they would affect negatively the results' explainability (Pessach and Shmueli, 2020). The aforementioned usage of methods depends on the expected fairness level the user wants but also on the test time's attributes.

Explainability and the Black-Box Problem

By exploring the algorithms' functionality and trade-offs regarding fairness and accuracy, it is important that black-box models' case to be discussed. Black-box models could be identified as decision-making support applications which were designed and developed in a way that they encrypt their internal logic to the individual that uses those (Guidotti et al. 2018). Discussing further about black-box models, this structure provides a variety of usage providing solutions to different challenges. However, these models are bringing various problems to the surface in terms of explanation and interpretation.

Moreover, it is important to mention that black-box models can provide a more transparent result (Guidotti et al. 2018). On the other hand, Lipton (2017) provides a discussion about black-box design classification models and focuses on linear models comparing them to deep neural networks regarding their interpretability. Furthermore, it is again confirmed by Lipton, (2017) that using black-box algorithms for predictive goals, it might generate biases but is linked to new methods as a negative affection by the author.

Finally, it is important to mention that based on Lipton's (2017) discussion, post-hoc notions must be used with caution as they might product distracting explanations through algorithms' optimizations. Therefore, this misleading process could generate various demographic types of discrimination, which can be confirmed and linked with Obermeyer et al. (2019) and Mehrabi et al. (2019) cases.

Accountability, Transparency and Regulation

Another topic that is worthy to be discussed is the algorithmic accountability and the regulations that exist around them. The accountability towards algorithms is related to the quality of data and the data value chain as Kemper and Kolkman (2019) support. Authors confirm that transparency is affected by the extended development of data analytics techniques and functionalities. The authors also provided a comprehensive path for transparency by discussing the importance of policies creation to dictate the proper use and creation of algorithms.

On the other hand, Wachter et al. (2017), explore EU General Data Protection Regulation's (GDPR) lack of policies regarding the transparency and accountability of automated algorithms through the discussion of the called "right to explanation" act on automated decision-making systems.

Finally, an actual observation can be derived. While Kemper and Kolkman (2019) explore and discuss comprehensively the functionality of automated algorithms and their criteria related to accountability and transparency, Wachter et al. (2017) connects with the first mentioned authors, by exploring and discussing the regulative and legislative environment of GDPR and European Law around automated algorithmic decision-making systems. Therefore, the connection between the 2 contexts brings a versatile discussion and provides a clearer point of view on policies and the accountability of automated algorithms.

Interpretation and explanation of classification outcomes

This chapter focuses on an exploratory data analysis, implemented within a financial-related dataset. The dataset offered an inclusive view related to loan applications together with financial and demographic attributes, which play an important role in loan approval or rejection. The aim of this chapter is to interpret and explain the used classification models but also to discuss the outcome and therefore, to provide a clear view behind the Python coding process was used for this purpose.

The “loan_data.csv”, dataset was used and analyzed within the “Jupyter Notebook” functionality in Anaconda application. For this analysis Python programming language was used regarding the dataset’s preparation and classification models’ implementation. Finally, the exploratory data analysis, was developed using the following classification models.

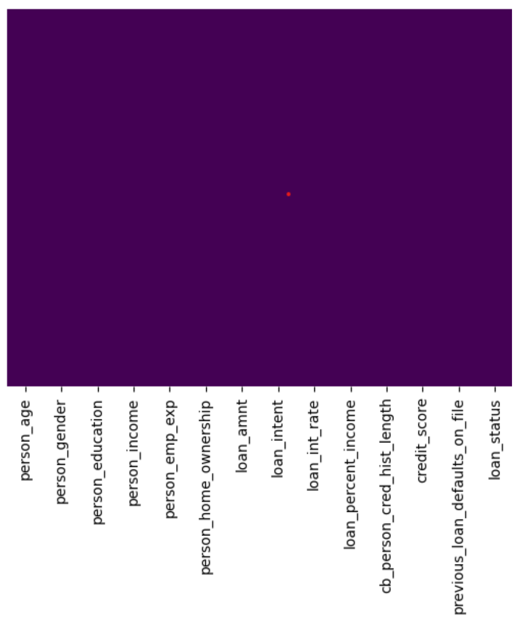
1. Logistic Regression
2. Decision Trees
3. Random Forests
4. Gaussian Naïve Bayes classifier

Logistic Regression

Beginning with Logistic Regression classification model, the specific model's purpose is the probability of loan approval estimation as a predictors' function by modeling the logarithm of the odds ratio (Norton and Dowd, 2018). The first steps were the preparation of the "Notebook" feature to read the ".csv" dataset's format and to integrate numerical Python as Nympy.

Furthermore, "import matplotlib.pyplot as plt" allows Jupyter Notebook to use a Python library for data visualization, as "import seaborn as sns" allows it for statistical graphics development and creation. Finally, "%matplotlib inline" commands data visualization streamline workflows within Jupyter Notebook.

Moreover, a heatmap was created to identify potential missing values and to detect missing data patterns. The below heatmap produced for the "loan_data" dataset, shows that there is no any missing value or missing data patterns. In addition, "df.dropna(inplace=True)" focuses on removing potential Null values' rows. In the used dataset, there was no any row with missing value, and by using the command "df.isnull().sum()", that could be confirmed.

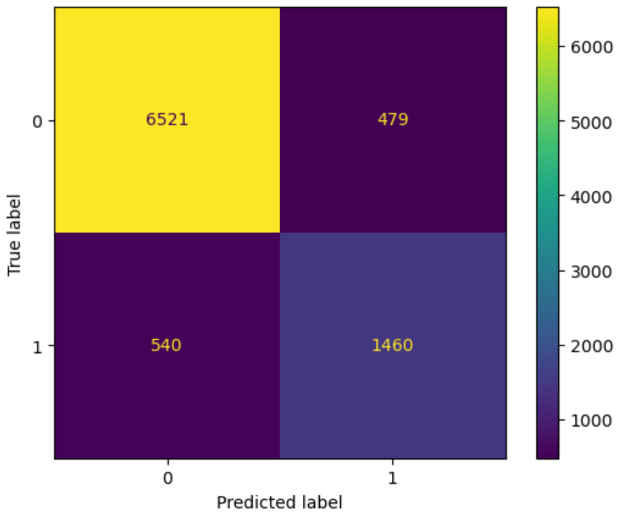


Furthermore, X and y variables had to be defined, in which X independent variables were defined as "features" and "loan_status" as y. Within X definition, categorical variables were included which can be considered as a barrier for proceeding to predictions and confusion matrix creation. Therefore, encoding process was applied. The encoding required defining the X as X_encoded, to convert categorical variables' columns that had to be encoded.

The train test split function's purpose was to randomly divide arrays or matrices into separate groups for training and testing data. Moreover, importing linear model in Logistic Regression classifier from the scikit-learn library command was applied. The logmodel command was used because Logistic Regression gave warnings at first, due to feature scaling differences and high number of features from one-hot encoding. The case was fixed by standardizing the numeric predictors and increasing the iteration limit.

Moreover, by using train and test split function for X, y and X_encoded, the dataset was split into two parts: 1st part: Training set and 2nd part: Test set. Within the first part, data were used to train the model by defining "X_train and y_train" and lastly data were reserved for evaluation by defining "X_test and y_test". *"Test_size=0.2"* parameter dictates the 20% of the data to be held out for testing. Furthermore, *"random_state=42"* parameter ensures that the results are reproducible and finally *"stratify=y"* preserves the class distribution of loan_status. Finally, Logistic Regression model was trained on X and y variables. During training, the model learns how the independent variables (X) relate to the chance that loan status equals 1.

After training the model, the next step was to apply predictions. Firstly, prediction of outcomes on unseen data was implemented. Secondly, confusion matrix on y_test and predictions was used to evaluate how well the classification model is performing by comparing its predictions to the true outcome. Furthermore, confusion matrix visualization tool and classification report were applied. Confusion matrix's prediction on y_test, predicted that 6521 loan applications were actually rejected and were correctly predicted as rejected, 479 loan applications were rejected but the model approved them, 540 applications were approved but the model rejected them and 1460 applications were approved and were correctly predicted as approved. This shows that there are bad loans that the model would approve, which represents financial risk.



Confusion Matrix Visualization

A classification report on y_test prediction was applied to summarize how effectively the classification model works for each class, using multiple evaluation metrics by comparing the actual loan outcomes (y_test) with the predicted loan outcomes (predictions). The below table was produced by using the classification report, for each class 0 and 1, but also for the overall model, which provided information on how efficient the model's performance is, regarding loan rejections and loan approvals in a separate view. Finally, the below table shows for Class 0, 7,000 cases of loan rejections and for Class 1, 2,000 cases of loan approvals, while the total observations were 9,000.

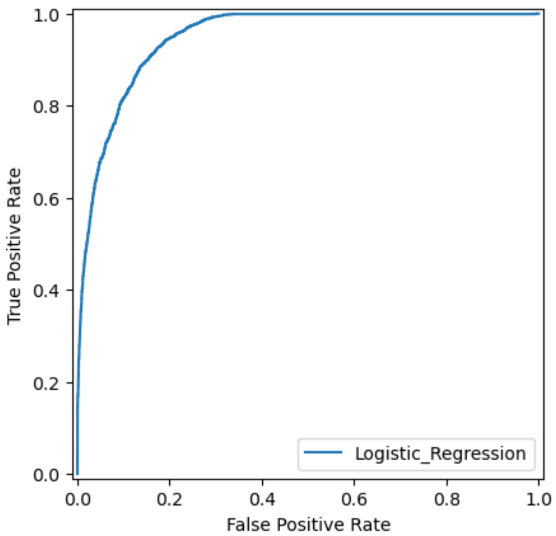
	Precision	**Recall**	**F1-score**	**Support**
Loan Status 0	0.92	0.93	0.93	7000
Loan Status 1	0.75	0.73	0.74	2000
Accuracy	-		0.89	9000
Macro avg.	0.84	0.83	0.83	9000
Weighted avg.	0.89	0.89	0.89	9000

Classification Report Visualization

ROC Curve

Moreover, ROC (Receiver Operating Characteristic) Curve was input to import evaluation tools used to assess how effectively the two classes (0 and 1) were separated by a classification model. Specifically, "Roc curve" is used to compute ROC points, while "Roc Curve Display" is focused on Roc curve visualization and "Roc auc score" to quantify overall separation ability. In addition, y_score was input to acquire a continuous score from the trained Logistic Regression model that shows how likely each loan application is to be approved or rejected. This score, is needed in this classification model for performance model evaluation across possible thresholds. Finally, the relation of y_score to the dataset reflects on the combination of financial, credit and demographic variables and how these influence the model's decision.

Proceeding to "fpr" and "tpr" (False Positive Rate and True Positive Rate), this process focuses on the needed values' calculation for ROC curve development, while "pos_label" feature guarantees that the approved loan class (1) is recognized as positive outcome and finally the plotting of the ROC curve by using the already calculated fpr and tpr values through the usage of "RocCurveDisplay". Below, the ROC curve graph is displayed.



ROC curve – Logistic Regression Rate graph

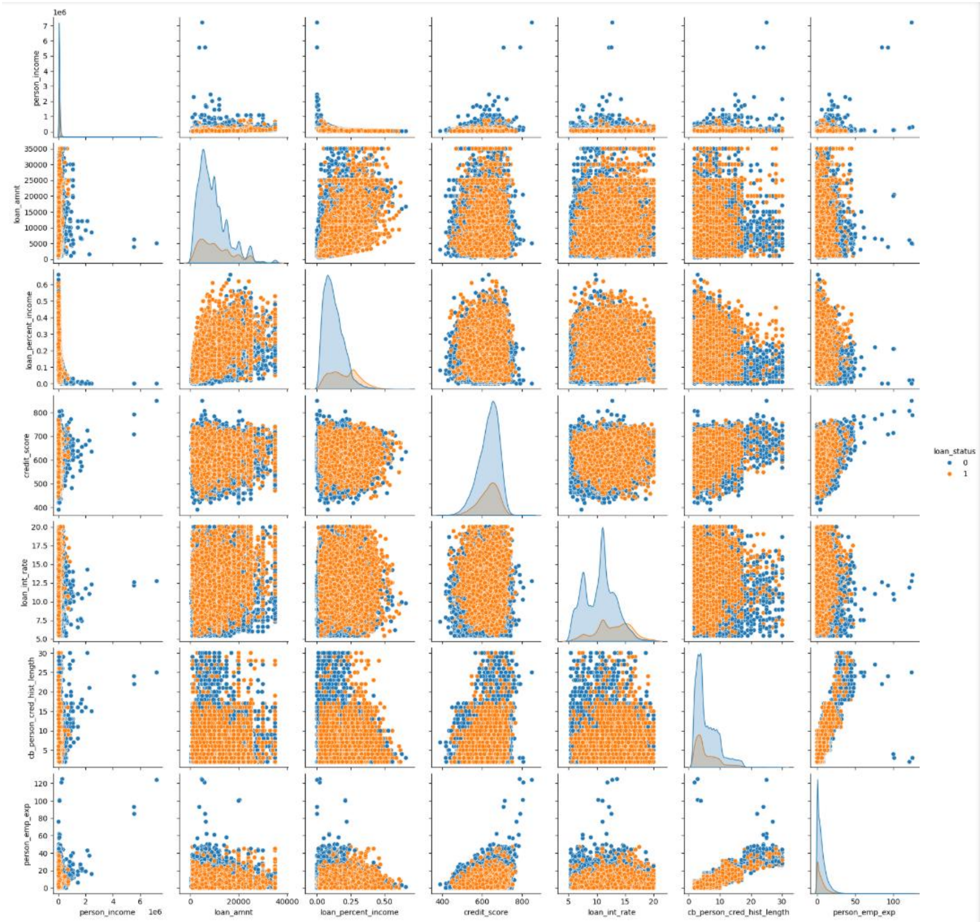
The graph presented the X-axis of "False Positive Rate"; the amount of loan applications there were actually rejected but they were predicted as approved, while the Y-axis represented the "True Positive Rate"; the amount of loan application that were actually approved and correctly predicted as approved. The curve was generated using y_test; the loan outcome (loan_status) and the model scores (y_score). The model was trained using financial, credit, employment and demographic variables. The curve shows a top-left corner which could indicate separation between approved and rejected loans in the dataset. Finally, the ROC curve shows that Logistic Regression model can show the difference between approved and rejected loan applications.

Completing the Logistic Regression process, the roc auc score was calculated by using the y_test (loan outcome) and y_score (scored produced by the model). The AUC (Area Under the ROC Curve) result ranges from 0 to 1, approximately at 0.95, which indicates that the model's effectiveness is high with regard to ranking loan applications.

Decision Trees

In this subsection the decision trees process will be interpreted and explained, to explore how variables are related, to highlight key predictors and how different situations can lead to different results. Also, they are especially helpful in the exploratory data analysis because they show which variables are important and present results as clear if-then rules.

The variables that were included within the scatter plots and histograms had to be selected to apply the Decision Trees model. Financial variables were selected within the sns pairplot including the dependent variable loan_status and then the dependent variable was set as "hue" to show the data points based on loan approval or rejection. The selected key variables are present below. The pairplot shows the difference between approved and rejected loans.



Pairplot: Scatter plots and Histograms

- **Person_income:** The distribution is strongly right-skewed, with most applicants concentrated at lower income levels and a few very high-income outliers.
- **Loan_amnt:** Loan amounts cluster at lower and mid-range values. Approved and rejected loans appear across similar ranges.
- **Loan_percent income:** The distribution is skewed towards lower values.
- **Credit_score:** Credit scores form an almost bell-shaped distribution at the histogram.
- **Loan_int_rate:** Interest rates span a moderate range with noticeable overlap between classes.
- **Cb_person_cred_hist_length:** Credit history length is skewed toward shorter histories.

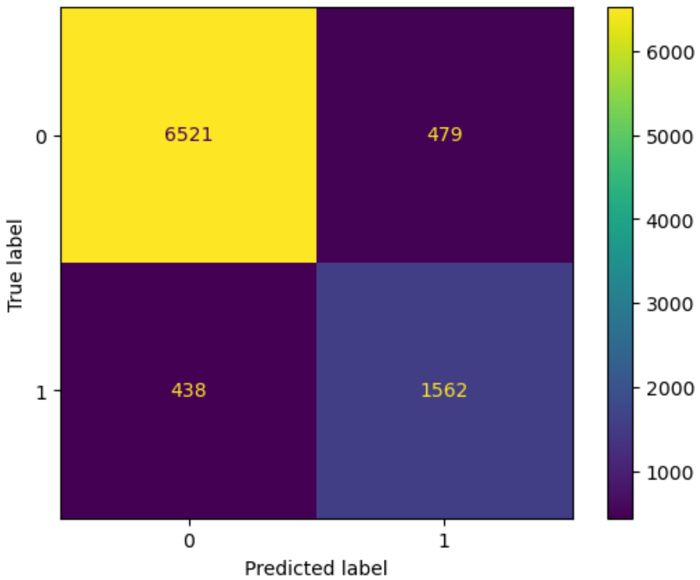
- **Person_emp_exp:** Employment experience is concentrated at lower values with some long-tenure outliers.

The pairplot supports the model approach by showing that several variables together affect loan decisions. The plot also shows why probabilistic models and ensemble methods are a good fit, and why is needed performance evaluation to be applied.

Moreover, data was split into training and testing subsets following the same procedure as Logistic Regression, to predict the loan approval outcome (loan_status).

The process continued by defining again X predictors and y target as it was applied in the previous model. The data was split into 80% training data and 20% testing data in order to build the model using the training data and the test set to be reserved for unseen data performance evaluation, while random state secures reproducibility as stated before. Furthermore, a fixed random state was set within the Decision Tree model. The model was trained using the training data which learnt decision rules with relation to the predictors and the loan approval outcome. Moreover, predictions were generated using X_test from which the model predicts loan rejection as 0 and loan approval as 1.

The evaluation using a confusion matrix took place in which a comparison between actual loan outcome (y_test) and predicted loan outcome (predictions) was applied and then the visualization was implemented. The classification report which was applied produced a standard evaluation metrics' summary for each class.



Decision Trees Confusion Matrix Display

	Precision	Recall	F1-Score	Support
0	0.94	0.93	0.93	7000
1	0.77	0.78	0.77	2000
Accuracy			0.90	9000
Macro avg.	0.85	0.86	0.85	9000
Weighted avg.	0.90	0.90	0.90	9000

Classification Report on y_test and predictions

The Decision Trees confusion matrix's prediction on y_test, showcases similar results with the Logistic Regression's one, but with a small difference on applications which were approved but the model rejected them and applications which were approved and were correctly predicted as approved.

The classification Report on y_test and predictions summarizes the Decision Trees classifier's performance when predicting loan_status. The test contains the same rejected and approved loan samples as Logistic Regression 9. Class 0 (loan rejected), shows 2% better precision than Logistic Regression and Class 1 (loan approved), shows the same percentage but is less effective when comparing approved loans to rejected ones as some loans were misclassified. Finally, the Macro avg. indicates that the performance between approved and rejected loans is differentiated, while weighted avg. is matching overall accuracy because rejected loans are more than approved ones within the dataset.

Random Forests

Random Forests are used for classification, regression and feature evaluation, especially when working with complex datasets that need strong predictive results.

Firstly, the creation of a Random Forest was applied with 100 decision trees from which, each tree was trained on a different subset of the training data. Morover, the final prediction was based on the combined output of all trees. The next step was the model to be trained by using the training dataset, which assists the model to learn patterns linking the predictors to loan_status. By generating predictions, the model produced predicted loan outcome defining 0 for “rejected” and 1 for “approved” by applying the trained model to unseen loan applications. Afterwards, confusion matrix was input to compare actual loan outcomes with the model's predictions. The results showed that 6,824 loans were correctly rejected, 1,530 loans were correctly approved, 176 rejected loans were incorrectly approved and lastly 470 approved loans were incorrectly rejected, which shows that the model made relatively few incorrect approvals.

The final step of the Random Forests' process was the classification report generation, to identify the precision of predicted loan rejections and approvals, but also the accuracy of classified loans. The results showed that the Random Forest predicted correctly loan rejections with precision at 94% and with recall at 97% which means that the actual rejections were identified correctly. Moreover, regarding to Class 1 (loan approved), the predictions of approved loans showed that were correct with precision at 90% and that most approved loan were identified despite the fact that some were missed with recall being at 77%. Finally, by analyzing the overall performance, the accuracy was at 93% which represents the 93% of all loans that were correctly classified and that the weighted average reflected the imbalance that the class had within the dataset.

Gaussian Naive Bayes Classifier

The Gaussian Naïve Bayes classifier serves as mean for classification models and it's suitable for dataset with numerical predictors and relatively simple patters. It also serves in situations which require fast training and prediction but also when a baseline or reference model is needed.

For the Gaussian Naïve Bayes model application it was important also to prepare Notebook to import and initialize the model. That way the model assumes that each predictor follows a normal Gaussian distribution and also that each other predictors are independent. The model's training was essential by using the training data because that way it could learn the distribution of each predictor for rejected and approved loans which set to be used to assign class labels to new observations. Moreover, by generating predictions, the model was able to predict loan outcome for the test dataset. Its output indicated that the model, across the test set, predicted mostly loan rejections (0). Afterwards, the model's accuracy generation was applied which presented that the model classified about 80% of the loan applications in the test set, correctly. This value reflects overall correctness. Finally, the confusion matrix input showed that 6,735 rejected loans were correctly predicted as rejected, 502 approved loans were correctly predicted as approved, 265 rejected loans were incorrectly predicted as approved and 1,498 approved loans were incorrectly predicted as rejected. This indicated that the Gaussian model performs much better at identifying rejections.

Summarizing, for the given dataset “loan_data.csv”, four models were applied; Logistic Regression, Decision Trees, Random Forests and Gaussian Naïve Bayes Classifier. All four models were trained and tested on the same feature set, which allows a fair comparison to be applied. By conducting a model by model comparison, Logistic Regression showed strong overall discrimination which can be view by the high ROC-AUC=0.95. Moreover, it performs effectively at ranking loan applications by approval likelihood and it’s more conservative in final class decisions depending on threshold. Regarding to Decision Trees achieved good overall accuracy around 90% and provides clear and rule-based decisions. It handled non-linear patterns better than Logistic Regression. Random Forests achieved the highest overall accuracy being around 93%. It provided strong precision and recall for both classes and fewer incorrect approvals and better balance between classes, as it has most consistent performance across evaluation metrics. Finally, Gaussian Naïve Bayes classifier showed the lowest overall accuracy around 80%, having strong bias toward predicting loan rejections. Many approved loans were misclassified as rejected.

Conclusion

This study has examined the business value of analytics within the field of Resource Management, beginning with a conceptual understanding of HR analytics and extending its practical application in workforce management. By conducting a comprehensive analysis, it pointed how predictive analytics could assist on data-driven decision-making with HR. Furthermore, the study examined the use of algorithmic functions and ethical issues such as transparency, fairness and accountability. Finally, an interpretation was conducted on comparing four classification models; Logistic Regression, Decision Trees, Random Forests and Gaussian Naïve Bayes.

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