# **EXPERIMENT REPORT**

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| **Student Name** | Ronik Jayakumar |
| **Project Name** | MLAA Assessment 2 Experiment 5 |
| **Date** | 25/04/2024 |
| **Deliverables** | Experiment 5  Gradient Booster Classifier |

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| 1. **EXPERIMENT BACKGROUND** | |
| Provide information about the problem/project such as the scope, the overall objective, expectations. Lay down the goal of this experiment and what are the insights, answers you want to gain or level of performance you are expecting to reach. | |
| **1.a. Business Objective** | Explain clearly what is the goal of this project for the business. How will the results be used? What will be the impact of accurate or incorrect results?  We are working for a car reseller company who is planning their next marketing campaign. The goal of the described project is to build a model that can accurately predict what segment of customers are most likely to buy another car so that marketing efforts and resources can be efficiently used on the right customer category.  The results of the project will be used to identify customers who fall under a defined category based on certain business questions asked and existing data on customers. The model will be run on this data to identify customers of a certain category who are most likely to make another car purchase so that marketing efforts can be used on them.  The impact of accurate results would be correct customer segmentation and target group identification which would result in high sales turnover.  On contradiction, the impact of inaccurate results would result in wrongful customer identification which would allow marketing resources to be expelled on customers not likely to make purchase, thereby reducing profitability. |
| **1.b. Hypothesis** | Present the hypothesis you want to test, the question you want to answer or the insight you are seeking. Explain the reasons why you think it is worthwhile considering it,  The hypothesis that is being tested is to check if past trends in car maintenance can predict the correlation with a customer’s inclination to buy a second car.  The insights required relate to what are the most useful questions to put forth to customers that would help us accurately find the customer segment most inclined towards investment into a new car.  It is worthwhile considering this hypothesis and investing into this model as it would help reseller company make informed data driven decisions. A company could have hundreds of thousands of potential customers on their database. Identifying the right customer segment so that marketing efforts are rightly targeted is key.  Having an accurately working model can ensure right segments are being targeted which in turn would increase sales turnover and overall revenue. |
| **1.c. Experiment Objective** | Detail what will be the expected outcome of the experiment. If possible, estimate the goal you are expecting. List the possible scenarios resulting from this experiment.  The expected outcome of this experiment is a model that can detect, classify, and predict a certain segment of customers, based on past car related activities, on if they are likely to invest into a second car.  An estimation of the expected goal would be a model that achieves at least an 80% overall accuracy in ensuring the right customer group is identified.  The possible scenarios resulting from this experiment are as follows:   * Successful Prediction – The model identifies the right customer, and the customer makes a purchase. * Missed Opportunity – The model fails to identify a potential customer, and the customer ends up purchasing a car. * Successful Rejection – The model correctly identifies an unlikely to purchase customer. * False rejection – Model identifies a wrong customer as someone who is likely to purchase a car which results in wasted marketing efforts. |

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| 1. **EXPERIMENT DETAILS** | |
| Elaborate on the approach taken for this experiment. List the different steps/techniques used and explain the rationale for choosing them. | |
| **2.a. Data Preparation** | Describe the steps taken for preparing the data (if any). Explain the rationale why you had to perform these steps. List also the steps you decided to not execute and the reasoning behind it. Highlight any step that may potentially be important for future experiments.  Data preparation steps have been imported from experiment 1. The cleaned and prepared dataset was downloaded at the end of experiment 1 and this dataset will be used for the remaining experiments.  The steps chosen to not be executed is in changing the features chosen to go ahead with Machine Learning, one of the things kept in mind during the experimentation phase is to ensure all features remain constant throughout so an accurate reading on the differences between various models and data handling techniques affect the final output.  Steps that could be potentially important for future experiments:   * Collect and deploy more data on customers who made a purchase of a second car. The existing data has a high class imbalance between customers who did not make a purchase and the customers who did, corresponding to the 0 and 1 values in the target column. * More inclusion: Ensure more inclusion in data collection techniques to ensure representation of people from all aboriginal cultural fronts. |
| **2.b. Feature Engineering** | Describe the steps taken for generating features (if any). Explain the rationale why you had to perform these steps. List also the feature you decided to remove and the reasoning behind it. Highlight any feature that may potentially be important for future experiments  Describe the steps taken for generating features (if any). Explain the rationale why you had to perform these steps. List also the feature you decided to remove and the reasoning behind it. Highlight any feature that may potentially be important for future experiments.  Feature Engineering has been performed in the dataset.   * **Gender Column**: The column contained approximately 50% of all the values as null with the other 50% corresponding to male or female. Since a high number of rows were null, dropping them would mean getting rid of a large amount of useful data. This has been tackled using Multivariate Imputation by Chained Equations or MICE for short. The following steps were taken.   + The entire column was first encoded, followed by which the Nan class was reverted to its original form to make sure null values get predicted.   + The imputing was done into a new column gender column where all the null values were predicted.   + The values were mapped back to their base form, that is as Male and Female. * **Feature Selection**: Feature selection techniques have been performed to decide what features have the highest relation to the target column. The car\_segment and the gender\_no columns are chosen to ensure representation of people and the type of car. Along with this the following was performed:   + **Correlation Analysis:** A correlation matrix was calculated between all the columns and the target column. The correlation of each column with the target column was visualized using a heatmap.   + **ANOVA-F test**: The ANOVA test was carried out as well as a second check on the correlation analysis. Once the features with the highest influence were identified, they were isolated and a new DataFrame was created with these features along with the 2 chosen categorical features.   + **Class Imbalance:** The high class imbalance that exists in the target column has been dealt with in experiment 5 using Near Miss under sampling technique. It is an oversampling technique where the synthetic samples are generated for the minority class. This algorithm helps to overcome the overfitting problem posed by random oversampling. It focuses on the feature space to generate new instances with the help of interpolation between the positive instances that lie together. [1] |
| **2.c. Modelling** | Describe the model(s) trained for this experiment and why you choose them. List the hyperparameter tuned and the values tested and also the rationale why you choose them. List also the models you decided to not train and the reasoning behind it. Highlight any model or hyperparameter that may potentially be important for future experiments  Baseline + Main model – Gradient Boosting Classifier  It aims to balance class distribution by randomly eliminating majority class examples. When instances of two different classes are very close to each other, we remove the instances of the majority class to increase the spaces between the two classes. This helps in the classification process. To prevent problem of information loss in most under-sampling techniques, near-neighbor methods are widely used. [1]  Hyperparameters tuned:   * N\_estimators: represents the number of boosting stages or trees to be built * Learning\_rate: Controls the contribution of each tree to the model * Max\_depth: Specifies the maximum depth of each tree I the ensemble   Hyperparameters for future experimentation:   * min\_samples\_leaf: Specifies the minimum number of samples required to be at a leaf node. * max\_features: Determines the maximum number of features to consider when searching for the best split. |

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| 1. **EXPERIMENT RESULTS** | |
| Analyse in detail the results achieved from this experiment from a technical and business perspective. Not only report performance metrics results but also any interpretation on model features, incorrect results, risks identified. | |
| **3.a. Technical Performance** | Score of the relevant performance metric(s). Provide analysis on the main underperforming cases/observations and potential root causes.  The experiment results were as follows:    The main underperforming features were as follows:   * Minority class prediction before class imbalance: The minority class predictions improved after undersampling but was not up to the mark when compared with previous experiments where oversampling methods were used. * Model Optimization: More model optimization is required to ensure little to none of the class 1 target variables are missed. As we can see with this business structure, the turnover rate is low. Hence missing potential customers could prove a costly mistake to the company. |
| **3.b. Business Impact** | Interpret the results of the experiments related to the business objective set earlier. Estimate the impacts of the incorrect results for the business (some results may have more impact compared to others)   * Accuracy: The model achieves high overall accuracy of 81% on the training set, indicating its capability to correctly predict both classes (0 and 1) most of the time. However, accuracy drops slightly to 79% on the validation set and 78% on the testing set, suggesting potential overfitting or limitations in generalization. * Accuracy: The model achieves high overall accuracy of 81% on the training set, indicating its capability to correctly predict both classes (0 and 1) most of the time. However, accuracy drops slightly to 79% on the validation set and 78% on the testing set, suggesting potential overfitting or limitations in generalization. * Accuracy: The model achieves high overall accuracy of 81% on the training set, indicating its capability to correctly predict both classes (0 and 1) most of the time. However, accuracy drops slightly to 79% on the validation set and 78% on the testing set, suggesting potential overfitting or limitations in generalization. * Cost-Benefit Analysis: This can help evaluate the potential impact of deploying the classification model in real-world scenarios, considering factors such as marketing expenditures, sales revenue, and the cost of errors. * Decision Support: The classification model serves as a decision-making tool for stakeholders. The model enables targeted resource allocation and personalized marketing strategies. |
| **3.c. Encountered Issues** | List all the issues you faced during the experiments (solved and unsolved). Present solutions or workarounds for overcoming them. Highlight also the issues that may have to be dealt with in future experiments.  Problems faced during experimentation are as follows:   * Minority class sampling: The class imbalance was one of the issues faced in the experimentation phase. There exists a massive gap between the 0 and 1 target variables. * Limited features: The dataset consists of a limited number of features. This could be a positive in getting more customers to respond to surveys, but the overall number of features that the model gets to learn stays highly limited.   Future problems:   * Future problems could arise in the following ways:   + Privacy issues: Data collection on car maintenance should comply with privacy laws and regulations. Privacy, data storage, and data management could a problem. * Underrepresentation of Aboriginal culture: The aboriginal culture is a wide array of multiple nations and clans with different cultural beliefs and aspects. Ensuring proper representation and consideration into the collection, processing, and storage of data needs to align with the custodians of the land. Ensuring proper research and groundwork is done before going ahead with the project would be avid. |

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| 1. **FUTURE EXPERIMENT** | |
| Reflect on the experiment and highlight the key information/insights you gained from it that are valuable for the overall project objectives from a technical and business perspective. | |
| **4.a. Key Learning** | Reflect on the outcome of the experiment and list the new insights you gained from it. Provide rationale for pursuing more experimentation with the current approach or call out if you think it is a dead end.   * High Performance Metric: The classification report shows that the model achieves overall high accuracy, with an accuracy score of 81% on the training set and 79% and 78% on the validation and testing sets. This shows that the model can accurately predict both classes (0 and 1) with comparable accuracy and recall scores. * Precision and Recall: The model’s accuracy and precision for class 0 are standard across all sets ranging between 0.76 to 0.78. However, for class 1 (repurchasers), accuracy varies from 0.80 to 0.83, and recall ranges from 0.70 to 0.75. This suggests that the algorithm does rather well in identifying non-repurchasers but suffers significantly in categorizing repurchasers. * F1-scores: The F1-score for class 0 varies from 0.80 to 0.82, whereas for class 1, it ranges from 0.76 to 0.79 in all sets. These results suggest good ability in spotting both classes, with somewhat lower scores for class 1.   Overall Assessment: The classification report shows that the model works pretty well in discriminating between vehicle repurchasers and non-repurchasers. While there is need for improvement, notably in properly recognising repeat consumers, the model's balanced metrics indicate its potential use in real-world applications. |
| **4.b. Suggestions / Recommendations** | Given the results achieved and the overall objective of the project, list the potential next steps and experiments. For each of them assess the expected uplift or gains and rank them accordingly. If the experiment achieved the required outcome for the business, recommend the steps to deploy this solution into production.  Potential Next Steps with the experiments are as follows:   * Feature Engineering: Investing time to explore into features in the existing dataset and extra features from external sources could help add perspective to the model. * Other Sampling techniques: We have used the ADASYN links oversampling technique in this experiment. Experimenting into other sampling techniques could provide insights into the overall model performance.   Future steps to be taken with the project could be as follows:   * Privacy and Ethics: Ensure strict guidelines are established to ensure privacy and ethical concerns. The project relates to customer information. This should be done in a consensual and secure manner with proper established guidelines. * Inclusion: Ensure all groups of individuals are accounted for and represented. This includes people of aboriginal backgrounds, international immigrants, etc. * Aboriginal culture: As a company based in Australia, ensure Aboriginal culture, traditions, and customs are accounted for before deployment. This needs to be a separate sect of the company solely focused on ensuring all different nations and clans are accounted for in making decisions. This could include steps like language inclusion, cultural considerations etc.   The model worked effectively and can be considered for deployment. The steps for deployment could be as follows:   * Integration with Production Environment: Integrate the model into the production environment by working with IT and DevOps teams to install it on existing systems and infrastructure. * Privacy and Ethical laws: Ensure privacy guidelines are established with ethical and cultural considerations especially towards underrepresented classes such as aboriginals. * Monitoring and Logging: Implement real-time monitoring and recording tools to keep track of model performance and spot abnormalities or deterioration quickly. * Testing and Validation: Thoroughly test and validate the deployed model to guarantee its dependability and resilience under a variety of scenarios and edge cases. |

References:

[1] : ML | Handling Imbalanced Data with SMOTE and Near Miss Algorithm in Python – 21 march 2024 - <https://www.geeksforgeeks.org/ml-handling-imbalanced-data-with-smote-and-near-miss-algorithm-in-python/>