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Project Name	*MLAA Assignment 2*
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Deliverables	*<MLAA_Assignment_2_5>* *<Experiment_Report_5>*

EXPERIMENT REPORT [E]

EXPERIMENT BACKGROUND

a. Business Objective

The overarching aim of the project is to utilise analytical and statistical methods to determine the likelihood that an existing customer of an automotive manufacturer will purchase a new vehicle. To achieve this, several experiments will be conducted using a provided historical dataset. The success of the model will empower business stakeholders to implement a cost-effective re-purchase campaign targeting existing customers who are prospective in purchasing a new or secondary vehicle.

The accuracy of the results will determine the value of the leads attained following the marketing campaign. Precise results may yield a positive return on investment by identifying these fulfilling customer leads, while incorrect results could lead to revenue loss through an unsuccessful marketing campaign, overstocking incorrect car varieties (models and segments) in anticipation of certain buyers, or granting unnecessary warranty and servicing inclusions with purchases, enacting a toll on the business, and damaging its longevity.

b. Hypothesis

Alternative hypothesis:

There is a relationship between some features in the car sales dataset and the likelihood that existing customers of an automotive manufacturer will purchase a new vehicle.

Null hypothesis:

There is no relationship between the features in the car sales dataset and the likelihood that existing customers of an automotive manufacturer will purchase a new vehicle.

The null hypothesis assumes no relationship is present between the dataset features, while the alternative hypothesis suggests that there is a relationship. By comparing the model’s performance against the null hypothesis, it determines whether the model is significantly better than random chance at predicting customer purchase behaviour.

Investigating these questions will assist with accomplishing the business goal by determining which existing customers who have purchased a second vehicle share certain features.

c. Experiment Objective

Experiment 5. will consist of an **XGBoost Classification** model. This model was selected as it is a popular choice in the industry, offering high accuracy and flexibility by combining several weaker models to construct one strong model. As the previous experiment requires a little more refinement with its recall score, it is hoped that approaching the business objective with XGBoosting will result in a finalised model suitable for deployment. As with previous experiments, the model will examine the **Target** variable (which determines if a customer has purchased more than 1 vehicle) against all other variables independently, each found in two separate data frames:

Table 1 Data frames applied for analysis and modelling.

Data Frame	Feature
cars_ALL	"*all features*" 18289 entries, 42 features
cars_NAG	"*no age-gender*" 128611 entries, 34 features

Working with two data frames facilitates a broader scope of outcome possibilities while retaining as many variables as possible without resorting to oversampling. As features such as **age_band** and **gender** offer decisive analytical data and insights into the classification of certain population groups, they will be retained where possible, however in previous experiments, have routinely been discontinued due to its data inadequacy.

For this experiment to be deemed a success, it is anticipated that precision and recall values will result in high coefficients, close to a value of 1. If a low or no depicted coefficient value is produced, it will pave the way for further experimentation with more complex algorithms.

These features will undergo further classification through evaluating model output coefficients to determine **feature importance**, where key traits about existing customers can be utilised to determine if they have purchased a second vehicle, achieving the business objective.

EXPERIMENT DETAILS

a. Data Preparation

< Data preparation method and EDA unchanged from Experiment 1. >

Data Understanding

The data frame was explored to derive foundational insights, indicating the initial seventeen features, two of which contain NaN values (**age_band** and **gender**) and four consisting of object variables (**age_band**, **gender**, **car_model** and **car_segment**) which will need to be transformed. All remaining features are full and are integer values.

Data Cleaning

In order to prepare the data for analysis and modelling, the ID column was removed to reveal 2726 duplicate entries. As duplicate entries can weigh certain outcomes and impede data accuracy and consistency, these were dropped.

Next, the NaN values were totalled: 109668 in **age_band** (85.2% of total rows) and 67455 in **gender** (52.4% of total rows) and visualised with **missingno**. As age and gender offer alternative means of classification over the dataset, aside from car-related data, it was decided to retain these features in a separate yet more condensed dataset.

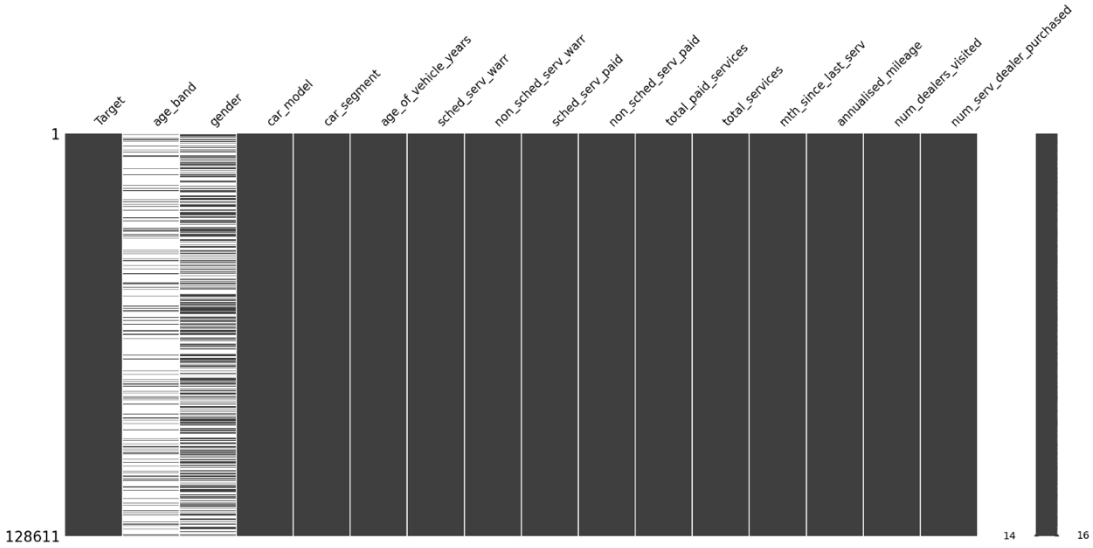


Figure 1 NaN values visualised with Missingno.

Producing Two Data Frames with All Values Converted to Integers:

cars_ALL and **cars_NAG** (see Table 1.)

For cars_ALL:

The **age_band** distribution was visualised prior to conducting **one-hot-encoding**, converting the feature into six rows with integer values of 1 and 0.

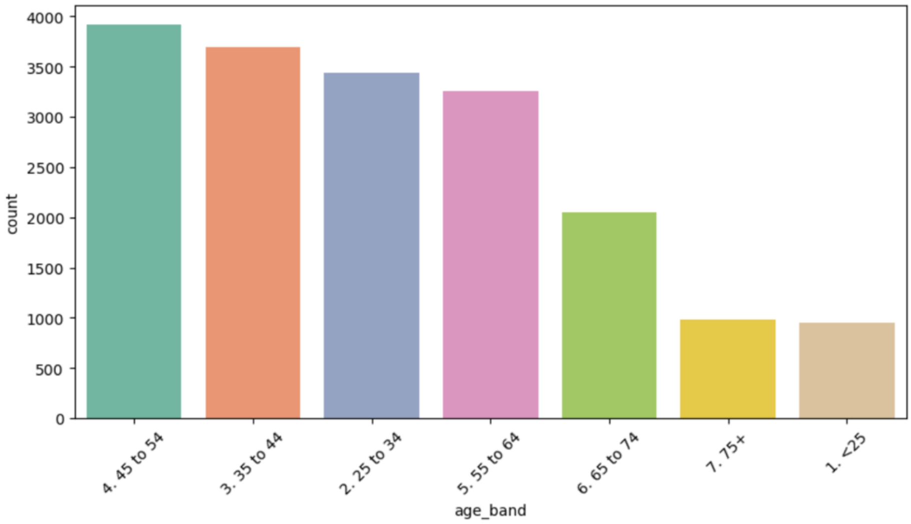


Figure 2 The age_band feature visualised.

One-hot-encoding was subsequently performed on the **gender** feature, converting the variable into two rows with integer values of 1 and 0, male and female.

For cars_ALL and cars_NAG:

The **car_segment** distribution was also visualised across both datasets prior to **one-hot-encoding**, converting the feature into four separate features with integer values of 1 and 0, Small/Medium, Large/SUV, LCV and Other

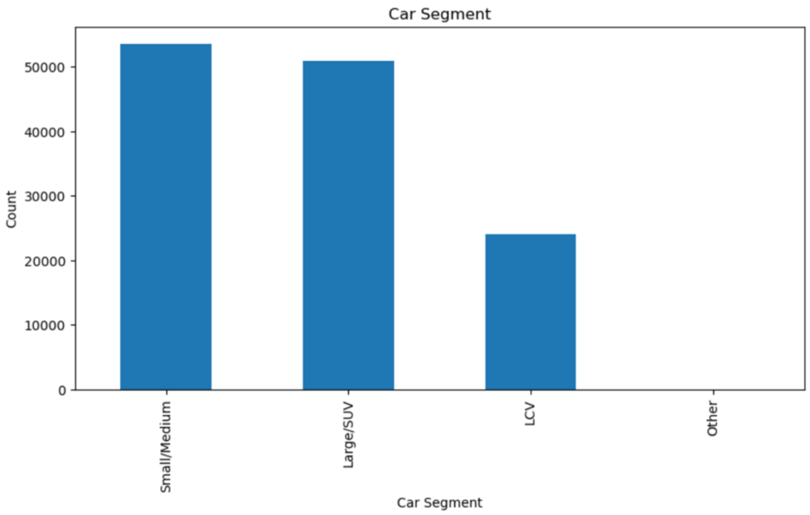


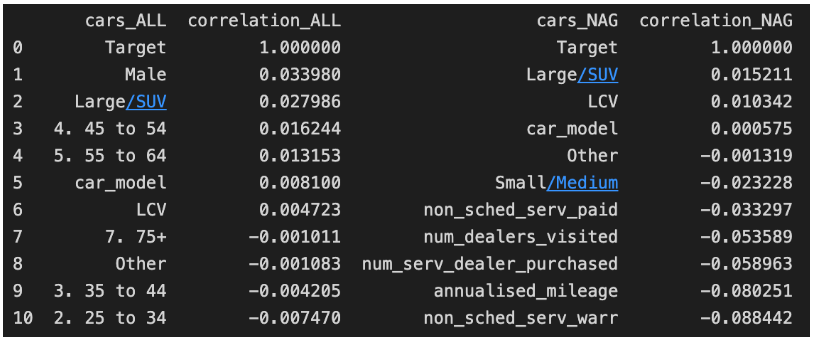
Figure 3 The car_segment feature of the cars_NAG data frame, visualised.

The **car_model** feature was the last categorical variable converted to an integer feature through **one-hot-encoding**, yielding nineteen features representing different car models with integer values of 1 and 0.

The ranges of each dataset were visualised as a final measure to ensure no outliers or abstract inputs were present.

Exploratory Data Analysis

Despite the problem residing in binary classification, linear correlations of all features against all other features of the dataset were first visualised using a heatmap, where the top 10 correlating features for each dataset were collated in a table.



```
       cars_ALL  correlation_ALL                  cars_NAG  correlation_NAG
0        Target         1.000000                    Target         1.000000
1          Male         0.033980                 Large/SUV         0.015211
2     Large/SUV         0.027986                       LCV         0.010342
3   4. 45 to 54         0.016244                 car_model         0.000575
4   5. 55 to 64         0.013153                     Other        -0.001319
5     car_model         0.008100              Small/Medium        -0.023228
6           LCV         0.004723        non_sched_serv_paid        -0.033297
7        7. 75+        -0.001011        num_dealers_visited        -0.053589
8         Other        -0.001083  num_serv_dealer_purchased        -0.058963
9   3. 35 to 44        -0.004205         annualised_mileage        -0.080251
10  2. 25 to 34        -0.007470          non_sched_serv_warr        -0.088442
```

Figure 4 The cars_ALL dataset and the cars_NAG dataset highest correlating features.

Next, the percentage of the **Target** variable class of interest (integer values of 1) was visualised with a pie graph. Indicating that only 2.7% of the 128611 entries were the population group of interest. This interpretation establishes the dataset as unbalanced.

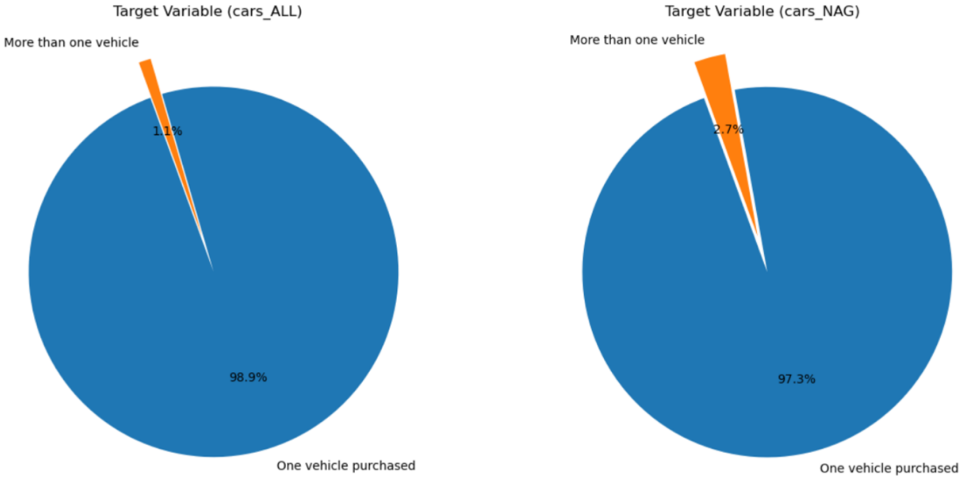


Figure 5 Pie graph visualisations of the Target variable and the class of interest.

Further visuals were subsequently constructed to gauge the perceived influence of the **gender** and **age_band** variables against other key classification features, such as the total, which share the **Target** variable and the relative **car_segment** and **car_model** choices made with their second car purchases. Overall it was interpreted that males tended to purchase a second car more than females, with the largest age brackets resting between 45 to 54. Out of these groups, the highest interest resided with Large/SUVs, models 5 and 3, among males. It is important to note that these features represent marginal percentages of the total and are not a full representation of the target cohort.

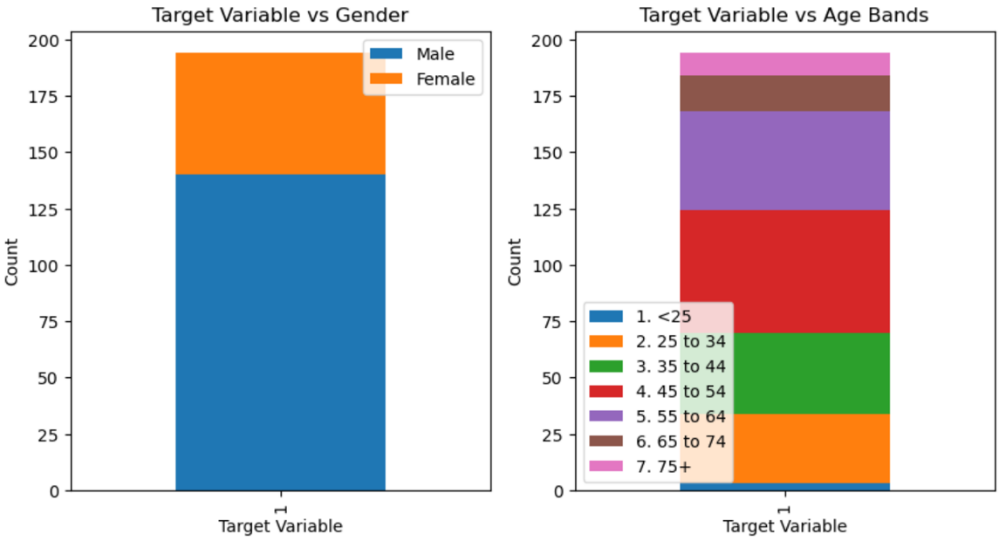


Figure 6 A segmented bar graph illustrating the male and female cohorts, beside the age band cohorts, with a Target value of 1.

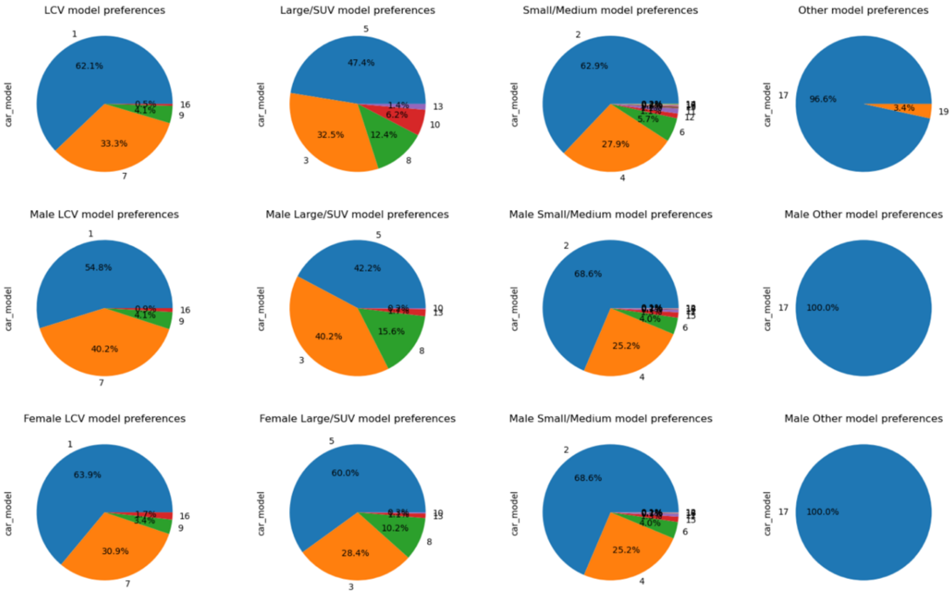


Figure 7 A series of pie charts illustrating the popularity of car models against the variety of car segments. The first row covers the overall majority, while the second and third rows cover the male and female preferences.

The final key exploratory analysis involved charting the frequencies of the **Target** variable with a value of 1 against **total_services**, **annualised_mileage**, **age_of_vehicle_years**, and **non_sched_serv_war**. The value was to visualise whether specific features of a customer's existing had an influence on their decision to purchase a new one. A key insight derived from this is that recurring customers typically engage with 2 to 3 total services (deciles), with slightly more non-scheduled services.

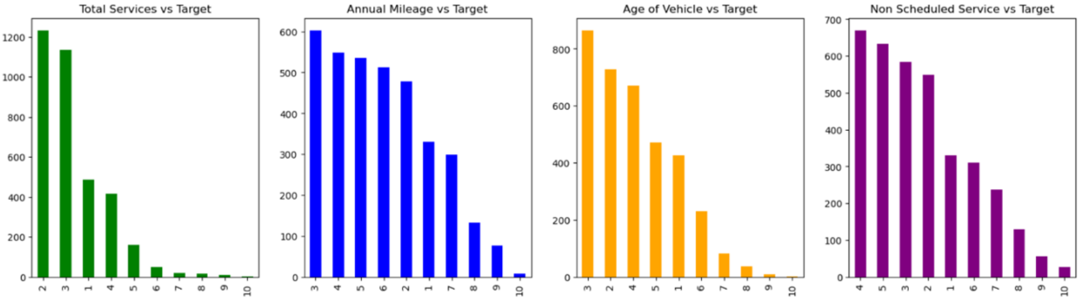


Figure 8 Four bar graphs illustrating total_services, annualised_mileage, age_of_vehicle_years, and non_sched_serv_war in deciles, against the target variable with a value of 1.

b. Feature Engineering

Once the final XGBoost model is tuned for its most suited hyperparameters, three further features will be engineered based on the results of the Random Forest model and whether they align with the significant features seen in the subsequent XGBoost.

The features to be engineered will be:

The **total services**, divided by the **annualised mileage** – to determine how much driving takes place on average between each service. This feature was constructed to discern whether customers may seek to replace a vehicle if it requires regular servicing or not.

cars_NAG['total_services_per_mile']
= cars_NAG['total_services'] / cars_NAG['annualised_mileage']

The **total services**, divided by the **age of the vehicle** – to determine how frequent servicing may be, as the age of the vehicle increases. This feature may help discern whether customers seek to replace a vehicle if they are more often servicing their vehicle due to its age.

cars_NAG['total_services_per_year']
= cars_NAG['total_services'] / cars_NAG['age_of_vehicle_years']

The **month since a customer's last service**, divided by their **total services** – to determine a customer's overall servicing total and whether this has changed in the latest month.

cars_NAG['mth_since_last_service_per_serv']
= cars_NAG['mth_since_last_serv'] / cars_NAG['total_services']

c. Modelling

Selecting a performance metric

As the business objective still resides with a binary classification problem, **Precision** remains the key performance metric to determine the model's success. Precision examines the proportion of true positives among the total positive predictions. By applying precision, a reduction in predicting the wrong customer is achieved. As precision metrics may share output similarity across models, an additional metric, **Recall**, will also be evaluated. Recall examines the proportion of true positives among all actual positive outcomes, meaning higher recall results in more lost opportunities for the marketing campaign.

Moving forward, a **precision-recall curve** will be constructed with each model to act as a visual depiction of the model's performance. In a successful model, the concavity of the curve determines the overall accuracy of results. In addition, an F1 and accuracy score will be shown alongside a confusion matrix. While excessive with verifying the accuracy, these steps feel important, as publishing incorrect data may enact a toll on the business. The variation in reporting performance metrics facilitates a deeper understanding of the model's predictive capability and how it compares with future experiments

Establishing the model:

All models across all experiments, will be constructed through a Python function. This helps establish consistency across all metrics within the dataset and throughout the transformation of the data prior to and during machine learning. The subsequent model selected for this stage of the experiment is intended to expand upon Experiment 1's insights and tangent away from a simple model.

XGBoosting Classification

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y_i}^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t)$$

Complexity: Complex

< The completed function marginally differs from Experiments 2, 3 and 4.>

Prior to constructing the function, both data frames (cars_ALL and cars_NAG) were first split at a **random_state** of 100 into a training and testing set with embedded stratification (operating under the conventional **80% training / 20% testing** approach).

A function for the support vector machine was then defined as **ML_results**, where subsequent iterations of the function could interchange the **dataset**, **feature**, **target,** and **model** variables. The model variable, in this case, is **XGBClassifier()**. The function would first normalise the data first through **StandardScaler()**, which subtracts the mean from each data point and divides it by the standard deviation. The following enables data points with different units of measurement to be compared against one another and is essential prior to running a multivariate model. The output variables from this process will produce **X_train_s** and **X_test_s**.

The function then instantiates and fits the model to the training data (**.fit**) and creates predictions on the training and test data (**.predict**).

To gauge the model's performance, the function will print a confusion matrix, followed by the accuracy score of both training and testing sets, followed by an F1 score of both training and testing sets (**confusion_matrix, accuracy_score, f1_score).**

The last aspect of the function is establishing a Boolean with .**predict_proba** to plot a precision-recall curve (**.precision_recall_curve**). The precision results extracted to construct the curve will also be embedded in a Pandas data frame displayed below, presenting all precision scores of **0.75** or **greater**.

No baseline metric (for assessing null accuracy) was applied to compare performance against naïve predictions and determine whether the model is adding value. This was selected, as the majority of the data in the **Target** cohort is negative, making the null accuracy equal to the proportion of negative samples.

Hyperparameter tuning:

Hyperparameter tuning comprises determining the most fitting set of hyperparameters for a model. These parameters are not learned from the data and are required to be set by the user prior to training a model. Like previous experiments, a grid approach (**.GridSearchCV**) will be applied to a hyperparameter dictionary (**hyperparmeters_dict**). The dictionary will be embedded into a different function with the same functionality as **ML_results**, although renamed to **ML_results_cv**. Should hyperparameters need to be tuned, the function **ML_results_cv** will be applied in conjunction with separate hyperparameter dictionaries. The corresponding dictionaries used are present in the results section of this report.

These finalised functions were first applied to the **cars_ALL** and **cars_NAG** data frames where appropriate, defining the **dataset, feature**, **Target** and **model** with each iteration.

EXPERIMENT RESULTS

a. Technical Performance

Evaluation of precision

In general, a high precision score indicates the model has a low rate of false positives, while a high recall score indicates that the model has a low rate of false negatives. To meet the business objective, successful model outcomes should aim to achieve both precision and recall scores close to 1.

Technical evaluation

As with previous experiments, the first XGBoost classification model was performed on the cars_ALL dataset without prior hyperparameter tuning, resulting in a strong precision and recall, however performing less precise than the Random Forest classification. The **precision** score of 0.86 means that out of all the instances predicted as positive, 86% were positive, while the remaining 14% were false positives. While the precision is strong, there is room for improvement.

With a **recall** score of 0.8, it describes that out of all the instances that were actually positive, 80% were correctly identified by the model, which is the highest recall score achieved in any model. The model, like the Random Forest, is still a strong predictive tool, however, is marginally less precise.

The precision-recall curve shape, while roughly concave, remains jagged and uniform, indicating "noise" may be apparent within the features or an overall lack of data to represent the entire population and predict properly.

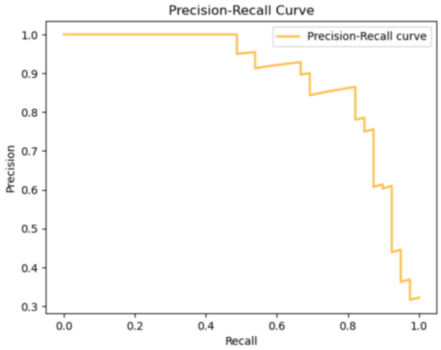
From a business perspective, the model would be considered adequate to accurately meet the business objective in forecasting the features that relate to the target class of prospective buyers, however, the Random Forest classification remains most precise.

Performance Metrics for XGBoosting Classification 1.
Dataset: cars_ALL

Confusion Matrix Training Set	
14476	0
0	155
Confusion Matrix Testing Set	
3614	5
8	31

Training Set	
Precision	1.0
Recall	1.0
Testing Set	
Precision	0.861
Recall	0.795

Accuracy Training Set	1.0
Accuracy Testing Set	1.0
F1 Score Training Set	1.0
F1 Score Testing Set	1.0



The second XGBoost classification model was performed on the cars_NAG dataset without hyperparameter tuning, resulting in a very strong precision and recall ratio, making it the best-performing model currently. The **precision** score of 0.94 represents that out of all the instances predicted as positive, 94% were actually positive, while the remaining 6% were mostly false positives.

The strong **recall** score of 0.84 means that out of all the instances that were actually positive, only 84% were correctly identified by the model, while the remaining 16% were mostly false negatives. With such an improvement in the recall score, the model is a strong predictive tool for classifying the cars_ALL dataset. The key distinction between this model, and the previous best, is a trade-off of **0.02 precision** for **0.1 recall**.

The precision-recall curve is clearly uniform, like the Random Forest classification curve and indicates a strong concavity in models with strong prediction capacities. Where minor bumps are apparent, this may indicate noise with some features and possibly allude to the need to tune hyperparameters.

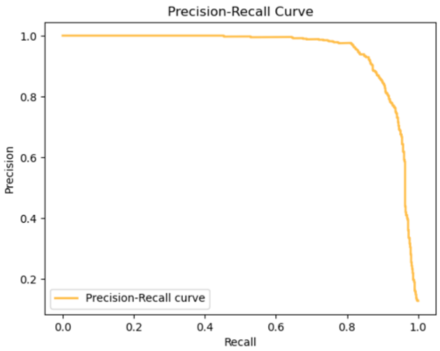
From a business perspective, the model in its current form is a strong tool that may provide insights about future customers and accurately meet the business objective in forecasting the features that may relate to the target class of prospective buyers.

Performance Metrics for XGBoosting Classification 2.
Dataset: cars_NAG

Confusion Matrix Training Set	
100034	36
238	2579
Confusion Matrix Testing Set	
24983	36
116	588

Training Set	
Precision	0.986
Recall	0.916
Testing Set	
Precision	0.942
Recall	0.835

Accuracy Training Set	1.0
Accuracy Testing Set	0.99
F1 Score Training Set	1.0
F1 Score Testing Set	0.99



The final XGBoost classification model was also performed on the cars_NAG dataset, following iterations and tweaked hyperparameters. The hyperparameters tweaked were varying combinations primarily of **max_depth** (depth of each decision tree)**, min_child_weight** (minimum weights of each child node), **subsample** (training instances in each decision tree), **colsample_bytree** (fraction of each feature used in each decision tree) and **learning_rate** (stepsize of each iteration during boosting). Each hyperparameter selected overall, helps reduce overfitting.

The decision to discontinue the use of the cars_ALL dataset was selected, like the previous experiments, as its precision-recall curve continued to lack uniformity, meaning the dataset is likely inadequate. This discontinued use, however, does not rule out **gender** and **age_band** as valuable features for future modelling. The most successful of these hyperparameter combinations are listed below. The impact of tuning hyperparameters resulted in a fractionally stronger precision and a higher recall, making it better than the previous iteration.

The **precision** score of 0.95 represents that out of all the instances predicted as positive, 95% were actually positive, while the remaining 5% were mostly false positives. The strong **recall** score of 0.81 means that out of all the instances that were actually positive, only 81% were correctly identified by the model, while the remaining 19% were mostly false negatives. With high precision and recall scores, the model is a strong predictive tool when classifying the cars_ALL dataset.

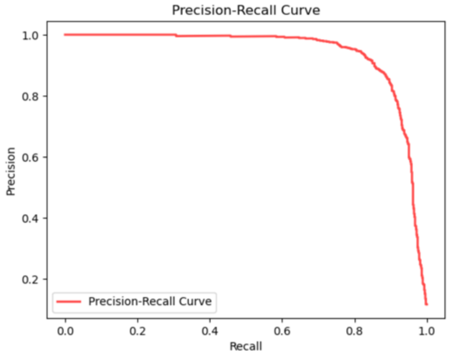
The precision-recall curve is uniform and bears a strong concavity. Only one minor indent is apparent, accounting for the marginal loss in precision. From a business perspective, a model is a strong tool that may provide insights about future customers and accurately meet the business objective in forecasting the features that may relate to the target class of prospective buyers.

Performance Metrics for XGBoosting Classification 3.
Dataset: cars_NAG
Hyperparameters tuned: ‘max_depth’ (5)
‘min_child_weight’ (1)
‘subsample’ (0.8)
‘colsample_bytree (0.8)
‘learning_rate’ (0.2)

Confusion Matrix Training Set	
99962	109
422	2395
Confusion Matrix Testing Set	
24986	33
131	573

Training Set	
Precision	0.961
Recall	0.851
Testing Set	
Precision	0.948
Recall	0.808

Accuracy Training Set	0.99
Accuracy Testing Set	0.99
F1 Score Training Set	0.99
F1 Score Testing Set	0.99



Feature Significance

By utilising the **feature_importances_** tool, the significance of each feature could be charted and sorted by frequency. When examining the cars_NAG dataset features, the emphasised features share similarities to experiment 4 and the Random Forest Classification.

The feature significances of XGBoosting appear to weigh higher value over the **sched_serv_warr, mth_since_last_serv, total_services** and **annualised_mileage** features as key indicators if an existing customer is likely to make a repurchase. As Experiment 5 incorporated feature engineering, a separate graph displaying the significance of these constructed features was also generated, indicating **total_services_per_mile**, as the most significant of these.

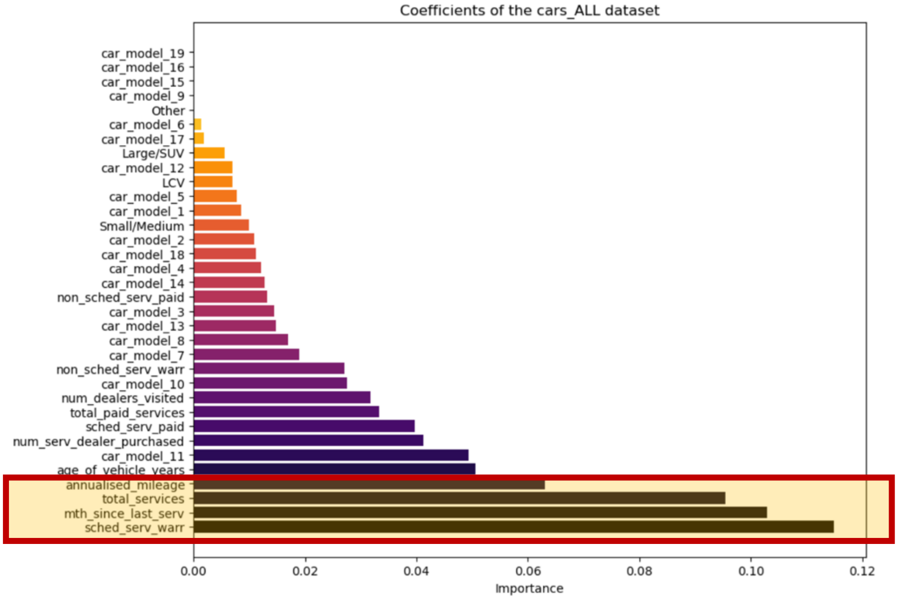


Figure 8 Feature Importance of the cars_NAG dataset following XGBoosting modelling.

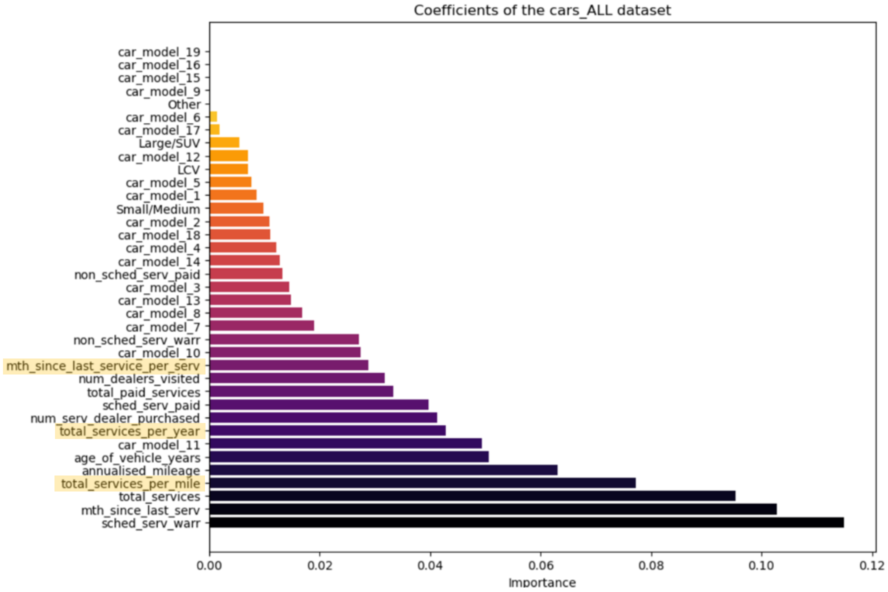


Figure 9 Feature Importance of the cars_NAG dataset, with included engineered features, following XGBoosting modelling.

b. Business Impact

As the final **XGBoosting** classification model (following hyperparameter tweaking) bears marginally stronger predictability (an increased ratio of precision to recall) capacity than the Random Forest model, when searching for relationships between the **Target** variable and features of the cars_NAG dataset, it is deemed a successful experiment outcome. The model can aid in evaluating existing customers to procure leads for marketing with a 95% success rate; however, it won't have the capacity to discern all due to a 81% recall score.

As the results are verified to be accurate through the **confusion matrix** (95% accuracy to discern a True Positive), **F1_score** (0.99) and **accuracy_score** (0.99), providing business advice on these results should imply a predominately accurate predictive capacity. In the event the results are not accurate, a loss of capital would be at stake through funding an unsuccessful marketing campaign, in addition to overstocking specific models in anticipation of leads that commit to a purchase.

c. Encountered Issues

Existing issues from previous experiments were likewise encountered within this experiment.

The application of both data frames

As with all previous experiments, the use of the cars_ALL data frame was ultimately discontinued during this experiment prior to hyperparameter tuning. The resulting precision-recall curve continued to remain jagged and lack uniformity.

Applying feature engineering

Considering valuable features to undergo tweaking and integration in the dataset proved challenging, especially considering each significant feature was reduced to deciles. Despite establishing presumably valuable features to transform, based on the Random Forest Classification results, no significant impact on the project outcome was noticed.

FUTURE EXPERIMENT

a. Key Learning

Exploratory Data Analysis

< Data Insights from EDA remain unchanged from Experiment 1. >

XGBoosting Classification

- The **XGBoosting** tools proved to be a powerful and adaptable model to integrate. The prediction metrics extracted from the model have demonstrated strong applications within the cars_NAG dataset and the capacity to predict future customers who are likely to purchase a new car.
- While the performance metrics aren't entirely optimised (81% recall on testing data), they're strong enough to gauge the model's prediction capacity.
- The implementation and application of hyperparameter tuning with this model is comprehensive and complex. While effort was invested into entirely understanding the ranges and parameters for XGBoosting, practice is required to completely optimise the approach for future integration into a workflow.
- The significant features evaluated from this model are **sched_serv_warr, mth_since_last_serv, total_services** and **annualised_mileage** (Figure 9). This means a customer's service history, in combination with other features, is a strong indicator that they'll likely repurchase another vehicle
- The most significant engineered feature is **total_services_per_mile**, meaning the number of services relative to the amount of driving a customer can achieve out of their vehicle is a strong indicator for determining the likelihood of repurchasing another vehicle.

b. Suggestions / Recommendations

Given that the testing process has endured 5 experimental iterations, yielding three probable models worth integrating to accurately meet the business objective (SVC, Random Forest and XGBoosting), it is suggested XGBoosting be applied to this circumstance, as it possesses the highest precision, in conjunction with the best precision-recall ratio.

Deployment

The finalised model has the capacity to make relatively accurate predictions, with a 95% accuracy at detecting a true positive. Unless the business owner is interested in investing further resources to increase this accuracy fractionally, it is suggested that deployment is suitable.