CYO - Used Vehicle Price Predictor

A. Masmela

2023-10-18

Contents

Section 1: Project Overview:

This project aims to develop a predictive model for used vehicle prices using historical data. The model is trained and tested with historical values and evaluated with an 'out-of-time' sample from the dataset. To accomplish this, we utilize the 'Used Car Price Prediction Pakistan Dataset' obtained from Kaggle.com. This dataset, with 86,120 data points, was meticulously curated from the popular automotive marketplace website, https://www.pakwheels.com. It contains valuable insights into the world of automobiles and features eight distinct attributes.[1]

Dataset Details: (a) Make: Manufacturer (b) Model: Model of the vehicle (c) City: Location where the vehicle is sold (d) Year: Year of production (e) Mileage: Number of kilometers driven by the vehicle (f) Engine Displacement: Engine displacement in cubic centimeters (cc) (g) Battery: Capacity of the battery in kilowatt-hours (for electric vehicles) (h) Price (Rs): Price of the car in Pakistani Rupees (PKR)

To facilitate the analysis, the project converts the original prices in Pakistani Rupees into US Dollars as of September 2023, using an exchange rate of 0.0034 US dollars per Pakistani Rupee. [2]

Data Preparation: As futher detailed in section 2.1, the dataset is cleaned, and two subsets are created: a model development dataset comprising data points until the end of 2020 and an 'out-of-time' model validation dataset containing data points from 2021 to 2023. As ML algorithms are utilized in the project, the data frame was prepared, imputing missing values, and removing outliers and vehciles with small sample sizes.

Model Development: The predictive models are designed to predict vehicle prices into the future. The out-of-time data set will simulate the scenario where historical data is available until 2020, and will evaluate the model's effectiveness in predicting prices up to 2023. Predicted values are compared with actual values in section 3, assessing the model's predictive power against the 'out-of-time' data set.

In section 2.3, this project utilizes a combination of linear regression models and a suite of powerful machine learning algorithms to predict used vehicle prices. Notably, Random Forest (RF), Light Gradient Boosting Machine (LGBM), and XGBoost (XGB) are the machine learning algorithms chosen for this endeavor. [3] [4]

Model Evaluation: As described in detail in Section 3, the performance of each model is assessed using several metrics, including: (a) Root Mean Square Error (RMSE) (b) Distribution of Residuals (c) Scatter Plot of Actual vs. Predicted Values (d) Kolmogorov-Smirnov (KS) Statistic

Conclusion: The project's overarching conclusion reveals that machine learning algorithms outperform linear regression techniques in the development of this predictive model. However, it's important to note that the intrinsic characteristics of vehicles, such as the make, model, year, and engine displacement, account for only a portion of the price formation. Additional macroeconomic factors, such as inflation, inventory levels, and commerce policies, play a significant role in shaping prices in the used vehicle market.

Section 2: Methods and Techniques

In this section, we provide a comprehensive overview of the methodologies employed in our project. It is divided into three key components:

2.1. Data Cleaning and Transformation: This initial subsection deep dives into the data cleaning and transformation processes. Here, we outline the steps taken to prepare the dataset for modeling, including imputing missing values, filtering and removing outliers, and other essential preprocessing procedures.

2.2. Data Exploration: In this subsection, we conduct a thorough data exploration, where we analyze the distribution of the data by some of the most relevant features. This exploration offers insights into the dataset's characteristics and provides valuable context for our modeling decisions.

2.3. Modeling Techniques: Section 2.3 is dedicated to describing the various modeling techniques we leveraged. We detail the modeling approaches, data transformations, and other techniques used to build

and optimize our predictive models. Additionally, we share our initial observations regarding computational resources needed.

The forthcoming section (Section 3) will provide a comprehensive discussion of the predictive performance of the models, offering a robust evaluation of their effectiveness.

2.1. Data Cleaning

In addition to converting the target variable into a more universally recognizable currency, we implemented a series of meticulous data cleaning techniques:

(a) **Feature Selection**: We rigorously scrutinized the dataset to identify and retain the features with the fewest missing values. This strategic choice aimed to ensure the integrity and completeness of the dataset for our analysis.

(b) **Missing Value Imputation**: To address missing values within the "Engine Displacement" feature, we employed a straightforward yet effective imputation method, using the average value. This approach allows us to maintain the dataset's continuity and statistical robustness.

(c) **Make Filtering**: We streamlined the dataset by eliminating vehicle makes with fewer than 100 data points. This curation decision enhances the overall quality and representativeness of our dataset by focusing on brands with more significant market presence.

(d) **Outlier Removal**: To enhance the model's resilience to noise and outliers, we leveraged the z-score method with a threshold of 3 to identify and remove extreme values within the "Price" feature. This technique contributes to a more accurate and reliable model by mitigating the influence of outlier data points.

(e) **Negative Price Data Points**: We screened the dataset for data points with negative prices, recognizing that such entries are anomalous and not representative of the real-world used vehicle market. These data points were removed to maintain data integrity and model performance.

By meticulously implementing these data preprocessing steps, we optimized the dataset for our analysis, ensuring that our predictive model is built on a solid foundation of clean, complete, and representative data.

2.2. Data Exploration

After cleaning the data, we conducted a comprehensive data exploration, discovering the following insights:

1. **Distribution by Make:** Notably, Toyota, Suzuki, and Honda emerge as the dominant vehicle manufacturers, each contributing around 200,000 data points to the dataset.
2. **Distribution by Model:** The dataset prominently features the Corolla, Civic, and City as the most prevalent car models, with an impressive presence of nearly 15,000, 10,000, and 6,000 vehicles, respectively.
3. **Distribution by City and Average Price by City:** Among the cities, Lahore, Karachi, and Islamabad emerged as the major hubs for car sales, each hosting over 10,000 transactions. While analyzing the average prices by city, we found that prices are relatively consistent across all urban centers.
4. **Distribution of Cars by Year:** A noteworthy trend is the substantial increase in the number of used vehicles over time, with fewer observations in the early '80s and a peak of 6,000 vehicles per model year in the 2020s. Interestingly, economic contractions and high unemployment rates seem to have left their mark, with years like 2008 and 2020 displaying particularly low observations.

5. **Distribution of Cars by Mileage:** It's evident that vehicles typically have mileage ranging from 25,000 to 50,000 kilometers, with more recent models exhibiting lower mileage, as expected. However, outliers at the high end of the distribution reveal mileage exceeding 50,000 and even 100,000 kilometers, even in models as recent as 2019.

6. **Distribution of Cars by Engine Displacement vs. Year:** Across model years, engine power remains relatively stable, with engine capacities consistently below 5,000 cc for all models. While there are rare outliers reaching 10,000 and 15,000 cc, most vehicles adhere to this range.

7. **Distribution of Price:** As anticipated, newer vehicles have higher prices. Nonetheless, vehicles from recent years exhibit surprisingly low prices, often just a few hundred dollars. This phenomenon could be attributed to total loss vehicles, repossessed vehicles, or those with significant wear and tear. The majority of vehicles fall below the $30,000 price range, resulting in a modest overall average price of approximately $8,000. Nonetheless, there are a few exceptional outliers since 2010 and 2015, surpassing $60,000 and $90,000 in used prices.

8. **Average Price per Year:** The average price trend exhibits an upward trajectory since the '80s. However, a noteworthy surge occurs after the economic recovery following the 2008 Financial Crisis. Average prices experienced a substantial rise, increasing from around $7,000 in 2012 to approximately $17,000 in 2019. The world pandemic caused a temporary dip in average prices, but as consumer purchasing power rebounded, average prices soared, nearing almost $23,000 by the close of 2023.

2.3. Model Development

2.3.1. Benchmark Model

Following our data exploration, we established a simple benchmark model to serve as a baseline for evaluating the subsequent models. This uncomplicated benchmark assumes that all vehicles possess the average vehicle price, approximately $10,000. While this is a somewhat simplistic assumption, it provides a fundamental point of reference against which all models in our analysis should demonstrate superior performance.

The results of this benchmark, alongside those of each developed model, will be discussed in detail in section 3.

2.3.2. Linear Regression Model

Our initial modeling approach involved the use of traditional linear regression. In constructing this linear regression model, we specifically focused on numerical variables as linear models are effective for handling numerical variables because they rely on linear relationships between input features and the target variable.

In these models, predictions are made by calculating a weighted sum of numerical features, allowing for a quantification of the impact of variables on particuar changes on the target variable. However, linear models tend to have challenges with non-numerical data, such as categorical variables, as they lack a direct numerical relationship.

Our initial step consisted of constructing a correlation matrix among these numerical variables. The correlation matrix revealed significant insights, most notably, a robust positive correlation between engine displacement and price (0.49). Furthermore, we observed a slightly less substantial correlation between the year and price (0.34). Notably, these two features, engine displacement and year, displayed weak correlations with each other, indicating their independence and their potential to contribute distinct value to the model. Lastly, mileage exhibited a modest negative correlation with price (-0.12) by itself and displayed a negative correlation with the year (-0.26). Mileage can be valuable in distinguishing vehicles with similar engine displacement and model year, serving as a relevant additional variable in the model.

X	Price_Us	year	mileage	Engine_displacement
Price_Us	1.0000000	0.3444260	-0.1282792	0.4932434
year	0.3444260	1.0000000	-0.2683262	-0.1381026
mileage	-0.1282792	-0.2683262	1.0000000	0.0773300
Engine_displacement	0.4932434	-0.1381026	0.0773300	1.0000000

2.3.3. Linear Regression Model: Corolla Cars Only

In our initial linear regression model, we did not include specific car models as factors. However, upon segmenting the data to focus solely on the most prevalent vehicle model, the Corolla, we observed a noteworthy shift in the correlation dynamics, with substantially strengthened relationships. The correlation between the year and price exhibited the highest correlation coefficient of 0.79, underlining a robust positive relationship, while a negative correlation of -0.37 was observed between mileage and price. Notably, year and mileage displayed a relatively strong correlation with each other, as older vehicles tend to accumulate more mileage. Furthermore, due to the inherent similarity in engine displacement among Corolla models, the correlation between price and engine displacement exhibited a weaker relationship, with a correlation coefficient of 0.14.

X	Price_Us	year	mileage	Engine_displacement
Price_Us	1.0000000	0.7934767	-0.3715621	0.1494276
year	0.7934767	1.0000000	-0.2861786	-0.0173860
mileage	-0.3715621	-0.2861786	1.0000000	0.0084351
Engine_displacement	0.1494276	-0.0173860	0.0084351	1.0000000

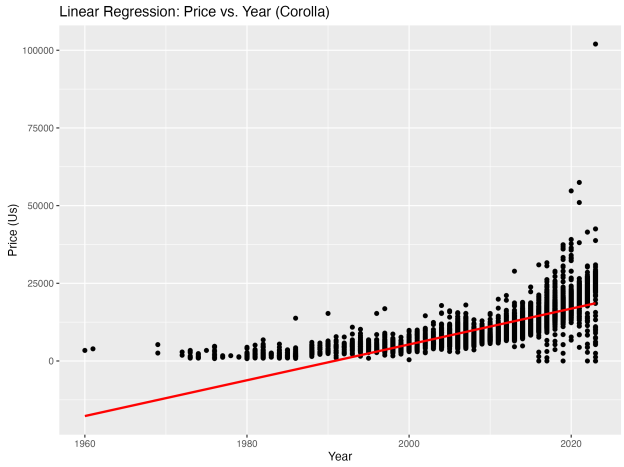


Figure 1: Linear Regression: Corolla Price vs. Year

2.3.4. Machine Learning model: kNN

Later in the project, we incorporated machine learning algorithms. Our initial choice was k-Nearest Neighbors (kNN), a versatile algorithm primarily known as a classification algorithm, where it assigns a class label to a new data point based on the majority class among its k-nearest neighbors in the training dataset. However, kNN can also be used for regression tasks, where it predicts continuous variables. [footnote]

In the context of this project, we leveraged it for predictive modeling. To prepare the data for kNN, we carried out several critical transformations. Firstly, we addressed missing values by imputing them with the

respective feature's average values. Moreover, we applied label encoding to text-based features, converting them into integers, which enabled kNN to use them as predictors. This preprocessing step was particularly essential for categorical variables, ensuring the algorithm's compatibility. Additionally, in our kNN model, we opted for a k-value of five, indicating the number of nearest neighbors considered for predictions.

2.3.5. Machine Learning model: Random Forest

Later in the project, we harnessed more robust algorithms tailored for regression scenarios. We initiated this phase with Random Forest (RF), an ensemble learning method renowned for its adaptability in handling both classification and regression tasks. RF, as a collection of decision trees, excels at capturing complex patterns in the data. [reference] One notable advantage of RF is its compatibility with categorical variables, making it suitable for our specific use case, where "make" and "model" were vital predictors. In our data preparation process, apart from addressing missing values through imputation, we employed a practical strategy for handling categorical features. Specifically, we grouped categories with low frequencies, which strengthened the robustness of the RF algorithm and enhanced its ability to make accurate predictions.

2.3.6. Machine Learning model: LightGBM

Furthermore, we integrated the Light GBM (LGBM) algorithm into our machine learning model. LGBM is a powerful gradient boosting framework that boasts exceptional speed and efficiency, making it well-suited for a range of machine learning applications [reference]. In preparation for LGBM, we converted our data frames into matrices, a requisite step that not only optimizes computational and memory efficiency but also facilitates parallel processing, as matrices can be effortlessly distributed for parallel computation.

LGBM provides numerous adjustable parameters for various use-cases. One of these parameters enables us to define the model as a regression model, thus distinguishing it from classification tasks, such as those typically associated with k-Nearest Neighbors (kNN). To ensure an equitable comparison with our other models, we employed the Root Mean Square Error (RMSE) as our evaluation metric, a choice that accentuates the model's performance by penalizing the influence of outliers. Our strategic selection of a learning rate of 0.1 served to mitigate overshooting issues, a common concern in gradient boosting models. Maintaining a relatively shallow depth of six levels further guarded against overfitting, ensuring the model's generalizability. Lastly, we opted for one hundred boosting rounds, permitting the algorithm to iteratively correct errors from preceding trees. Although a high number of boosting rounds can extend the training time, it's important to note that the impact on training time was relatively minimal due to the dataset's manageable size, consisting of approximately 86,000 observations. This parameter configuration empowered LGBM to deliver robust and efficient regression predictions.

2.3.7. Machine Learning model: Xgboost

Lastly, we incorporated XGBoost, a highly efficient gradient boosting algorithm known for its speed and accuracy. [reference] Both Light GBM and XGBoost demonstrated remarkable efficiency, requiring minimal computational time due to the dataset's manageable size of approximately 86,000 observations. As detailed in section 5, our machine-learning-based regression models produced impressive results.

In addition to the data transformations performed for Light GBM, which involved converting data frames into matrices and handling categorical variables, we followed a similar preprocessing approach for XGBoost. However, in the case of XGBoost, we retained the target variable within the data frame, eliminating the need for extensive feature reordering prior to algorithm execution. Given the regression task at hand, we specified the objective as "reg:squarederror," instructing the model to minimize the squared error loss during training. Leveraging the dataset's manageable scale, we comfortably set the number of boosting rounds to five hundred without demanding a significant computational power. To safeguard against overfitting, we constrained the depth of each tree to six levels. Lastly, we opted for a relatively low learning rate for the boosting rounds, ensuring that the model learned progressively and effectively.

Section 3: Results of Model Performance

To assess the performance of each model, we employed four evaluation methodologies: Root Mean Square Error (RMSE), the Distribution of Residuals, a graphical representation through Scatter Plots illustrating the differences between actual and predicted prices, and the Kolmogorov-Smirnov (KS) statistic to compare the cumulative distribution functions (CDFs) of actual and predicted prices.

3.1. RMSE

In the context of RMSE evaluation, the benchmark model, which simply averages all observations' prices, yielded an RMSE of USD$11,304.45. Consequently, our models were expected to achieve lower RMSE values to demonstrate their superior performance.

Both linear regression models exhibited promising results, with an RMSE of USD$8,492.50 when considering all models and USD$4,852.83 when focusing on one of the top-selling models, the Corolla. Encouraged by the performance of the segmented linear regression model, we sought to create a simplified segmentation strategy based on the correlation between the model year and price. However, instead of running three separate models for each segment, we incorporated the clusters as an additional feature to evaluate if it enhanced the linear model's performance. Unfortunately, the RMSE of this new model remained similar to that of the initial linear model, resulting in an RMSE of USD$8,391.56. Aside from the unsatisfactory outcomes, this code displayed instability, leading us to exclude it from our R script.

Subsequently, as we transitioned into machine learning algorithms, we began with a demonstration using k-Nearest Neighbors (kNN), an algorithm not inherently designed for continuous variable prediction. As anticipated, the RMSE of this model failed to surpass the benchmark, registering an RMSE of USD$14,892.31. However, we later shifted to machine learning algorithms explicitly designed for regression tasks. Our first choice was the Random Forest (RF) algorithm, which allowed us to incorporate more predictive categorical variables, such as the vehicle model. The RF model delivered an RMSE of USD$5,206.83. Despite its effectiveness, it demanded more computational resources, which was noteworthy even with our relatively small dataset.

The Light GBM model provided a comparable RMSE of USD$6,299.64 while consuming significantly less computational time. Finally, the XGBoost model demonstrated remarkable predictive power, achieving a similarly low RMSE of USD$5,462.64, all while executing five hundred boosting rounds with remarkable efficiency. It's essential to emphasize that this efficient performance was feasible due to our dataset's modest size, allowing for relatively low computational time.

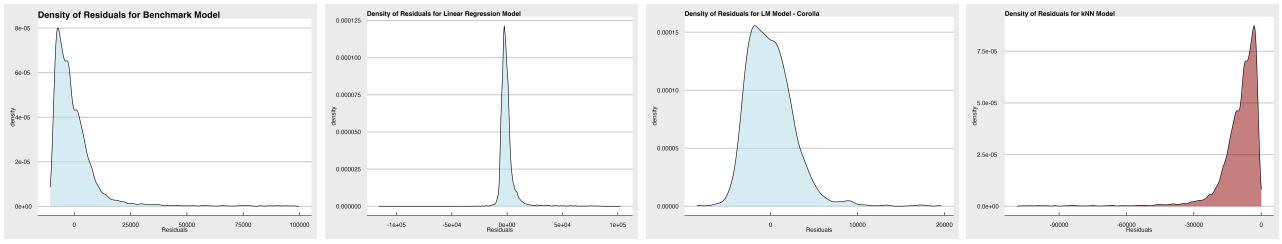
3.2. Distribution of Residuals

The distribution of residuals is a critical aspect, representing the disparity between actual and predicted values. In an accurate model, one expects the residuals to form a tight normal distribution centered around zero. The subsequent plots illustrate the distribution of residuals for each model.

In the benchmark model, the distribution of residuals does not conform to a normal distribution and exhibits a significant right skew, indicating substantial underprediction in higher-priced instances.

The distribution of residuals in the first linear regression model is predominantly centered around zero, although it features thin tails on both ends and a slight skew towards positive residuals. A similar slight skew towards positive residuals is observed in the linear regression model focused solely on Corolla vehicles. The tighter distribution around zero in the latter model might be a reflection of the generally lower prices associated with this particular car model.

Conversely, the distribution of residuals in the k-Nearest Neighbors (kNN) model, which is not well-suited for this type of prediction, displays a pronounced skew towards negative residuals, signifying substantial

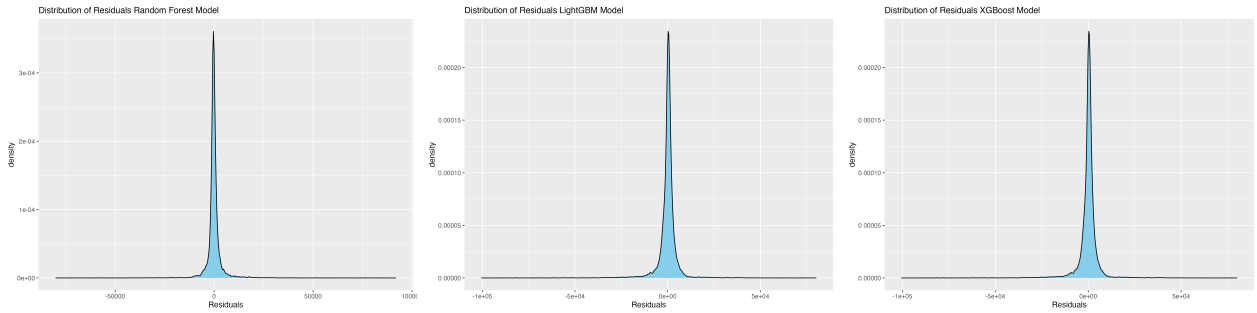


(a) Benchmark (b) Linear Regression (c) LM - Corolla (d) kNN

Figure 2: Density of Residuals

underprediction of prices. Furthermore, this distribution does not conform to the normal distribution, underscoring that the kNN algorithm and approach are inappropriate for this use case.

In contrast, the appropriate machine learning algorithms for this use-case, namely Random Forest (RF), Light GBM (LGBM), and XGBoost (XGB), all yield tight, normal distributions centered around zero with similarly proportioned tails on both ends, highlighting their superior performance for this task.



(a) Random Forest (b) Light GBM (c) Xgboost

Figure 3: Density of Residuals

3.3. Scatter plot of Actuals vs Predicted prices

The scatter plot illustrating Actual vs. Predicted prices provides an intuitive visualization of the disparity between predictions and actual values. In the case of the benchmark model, which simply averages all observations, the scatter plot appears as a flat line across the actual values.

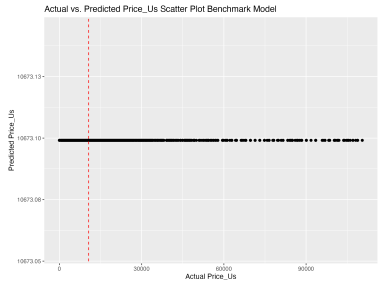
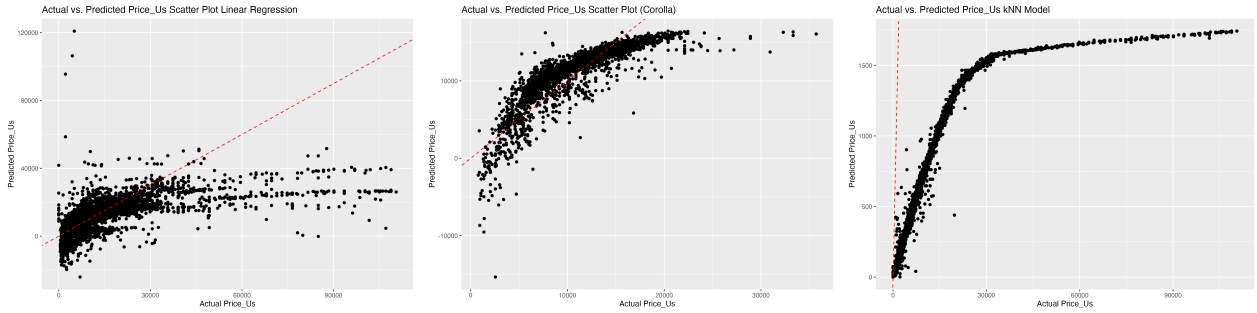


Figure 4: Scatter Plot Predicted vs. Actuals: Benchmark

As illustrated below, the linear regression model encompassing all car models exhibits data points falling along the diagonal line for lower prices, i.e, less than USD$30,000. However, it tends to underpredict higher

prices, which all are predicted below USD$50,000. When filtering for Corolla car models, the regression model shows improved performance, yet it continue predicting some prices as negative.

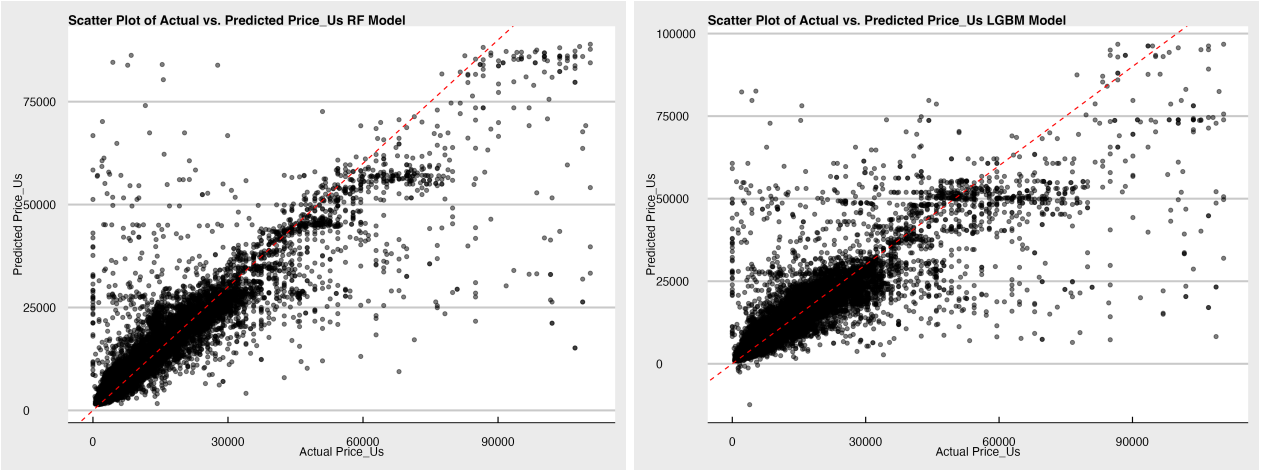


(a) Linear Regression (b) LM - Corolla (c) kNN

Figure 5: Scatter Plot Predicted vs. Actuals

The initial machine learning model, kNN, designed for classification rather than continuous variables, displays the weakest performance, consistently underpredicting prices by a substantial magnitude. This underprediction grows exponentially as prices exceed USD$30,000.

On the other hand, both the Random Forest (RF) and Light GBM (LGBM) models yield satisfactory scatter distributions of predicted vs. actual values, with data points clustered around the diagonal. RF appears to outperform LGBM, with predictions evenly distributed on both sides of the diagonal. LGBM tends to exhibit more underpredictions in the high-end price range. However, the enhanced performance of RF may not offset the additional computational time required for model training.



(a) Random Forest (b) Light GBM

Figure 6: Scatter Plot Predicted vs. Actuals

Lastly, in the Xgboost model, we color-coded overpredictions in blue and underpredictions in green for clarity. This model's performance is deemed satisfactory. The color-coding aids in understanding the model's predictive power. Ultimately, each observation represents either a gain or loss for the asset owner. The Xgboost model exhibits a similar distribution around the diagonal for accurate values, displaying good predictive ability for vehicles priced up to USD$60,000. Similar to the LGBM model, the Xgboost model tends to underpredict vehicles with high prices.

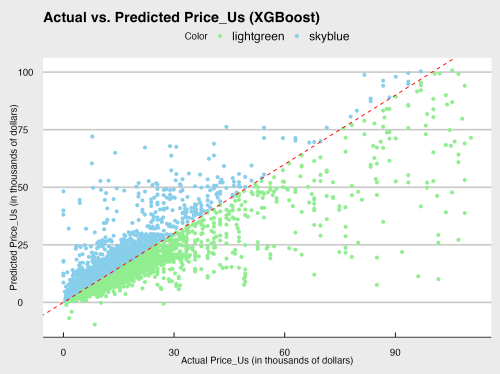


Figure 7: Scatter Plot Predicted vs. Actuals: Xgboost

3.4. KS statistics and CDF plot

The KS (Kolmogorov-Smirnov) statistic is a measure used to evaluate the goodness-of-fit between two distributions, in this case, the predicted and actual prices. It quantifies the maximum vertical distance between the cumulative distribution functions (CDFs) of these two distributions, providing valuable insights into the model's performance. [5] [6] [7]

The cumulative distribution function (CDF) of a dataset is a mathematical function that describes the probability that a random outcome variable takes on a value less than or equal to a specific value. In the context of our analysis, the CDF of actual prices shows how the prices are distributed in the dataset, and the CDF of predicted prices shows how the model's predictions are distributed. The KS statistic calculates the maximum vertical distance between these two CDFs, helping us understand how closely the model's predictions match the actual price distribution.

The purpose of the KS statistic is to assess how well a model's predictions align with the actual data distribution. A lower KS value indicates a better fit, suggesting that the model's predicted values closely resemble the actual values.

To visualize this statistic, we created CDF plots that display the predicted prices' cumulative distribution alongside the actual prices' CDF. In an ideal scenario, a well-fitting model would have its CDF distribution closely following the CDF distribution of actual prices.

The benchmark model's CDF shows imperfections, with predicted values, i.e., average price, forming a vertical line noticeably distant from the CDF distribution of actual prices, resulting in a KS of 0.54.

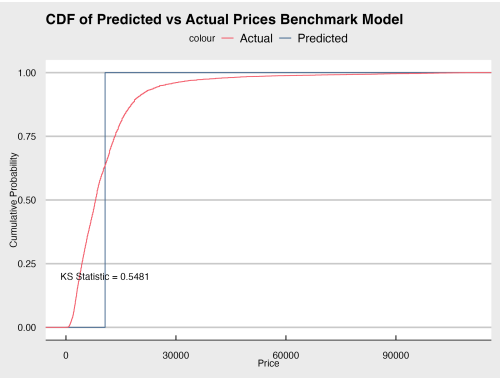
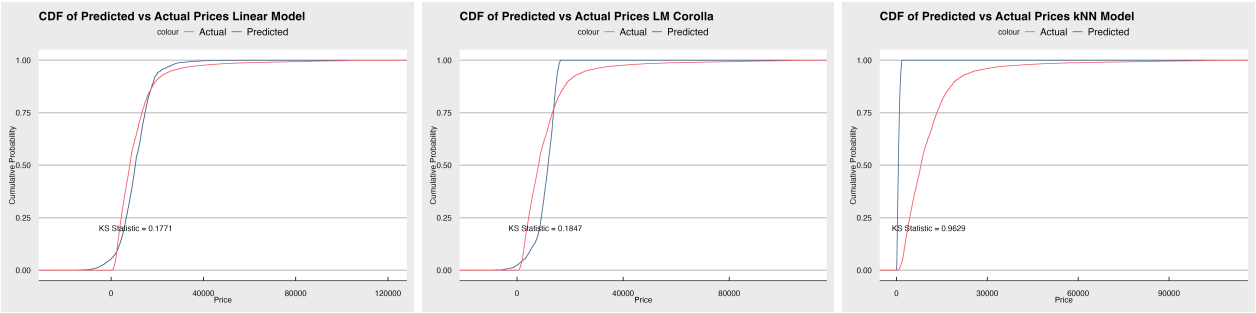


Figure 8: KS (Kolmogorov-Smirnov) statistic: Benchmark

The linear regression model significantly improves this fit, achieving a KS of 0.17, as evident in the closely

matched CDF distributions of predicted and actual prices. This improvement is also observed in the linear model specifically for Corolla car models, with a similar KS value of 0.18.

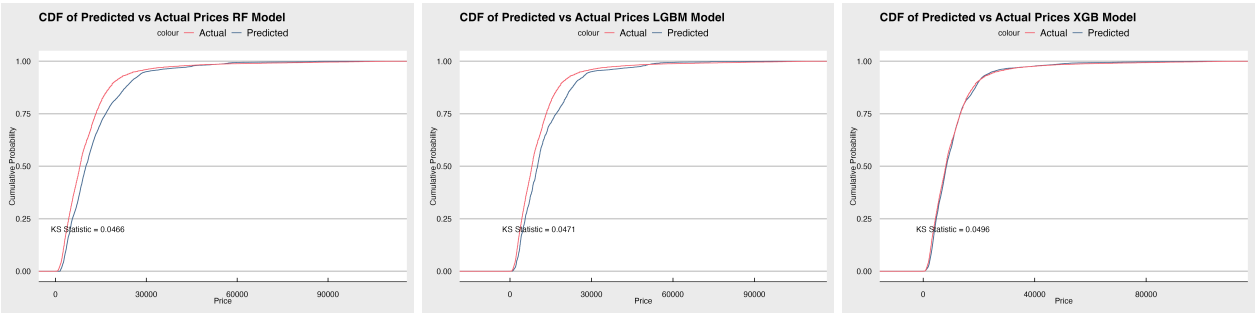


(a) Linear Model (b) LM - Corolla (c) kNN

Figure 9: KS (Kolmogorov-Smirnov) statistic

As expected, the kNN model exhibits the worst KS at 0.96, clearly illustrated by the considerable discrepancy between CDF distributions.

In contrast, machine learning algorithms designed for regression and continuous variable prediction, such as RF, LGBM, and Xgboost, deliver superior KS values of 0.04. Their CDF distributions nearly overlap the CDF distribution of actual prices, with Xgboost's distribution being almost identical, indicating their strong predictive power.



(a) Random Forest (b) Light GBM (c) Xgboost

Figure 10: KS (Kolmogorov-Smirnov) statistic

3.5. Xgboost model validation

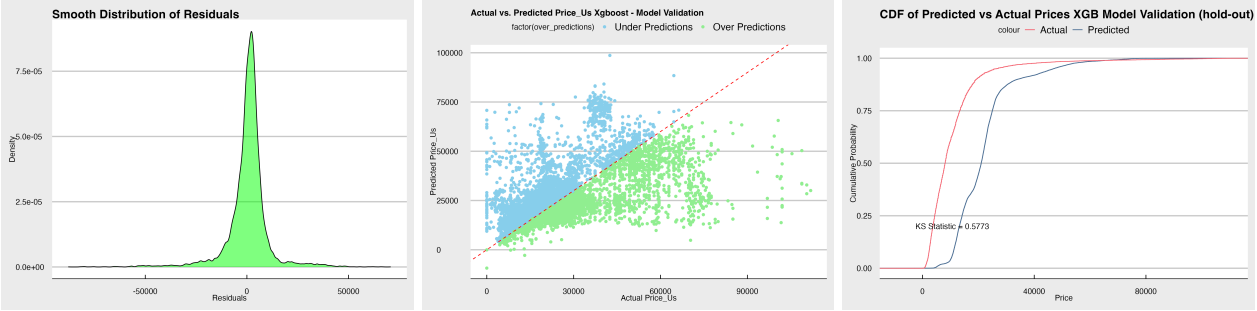
Based on the comprehensive analysis conducted above, we selected the Xgboost model for validation against an out-of-time sample. As previously described, Xgboost demonstrated optimal computational efficiency, with tightly distributed residuals, a low RMSE, and a satisfactory scatter plot showing predicted prices closely aligned with actual values. The model also exhibited a superior KS statistic, indicating a near-identical cumulative distribution function (CDF) of predicted values compared to the CDF of actual prices.

It's important to note that the out-of-time test sample comprised vehicle prices from 2021 onwards. As highlighted in the data exploration section, vehicle prices saw a significant increase during this period due to supply chain constraints and overall inflation.

When the Xgboost model was applied to the out-of-time test data, the RMSE increased substantially. While the distribution of residuals maintained its normal distribution, it exhibited a slightly broader spread compared to the training phase. The scatter plot of predicted versus actual prices maintained a symmetric

distribution around the expected diagonal, although the points deviated further from this line. Additionally, the KS statistic increased to 0.57, and the CDF distribution shifted to the right.

These observations suggest that there are external factors influencing car prices that were not considered in the model's training phase. Elements such as inventory levels, production dynamics, and customer purchasing power can impact vehicle prices beyond the model's scope.



(a) Density of Residuals (b) Scatter Plot Actuals vs. Predicted (c) KS (Kolmogorov-Smirnov) statistic

Figure 11: Model Validation: Out-Of-Time

Section 4: Conclusion and Future Work

We explored seven distinct approaches for predicting car prices, with machine learning algorithms exhibiting remarkable superior performance, surpassing conventional models like linear regression. Nevertheless, harnessing the potential of machine learning algorithms requires more extensive data preprocessing efforts. We learned that not all machine learning algorithms yielded favorable results. Specifically, algorithms unsuited for continuous variable prediction, such as kNN, demonstrated poor performance, even falling behind a basic benchmark of simple average prices. Among the machine learning algorithms, Random Forest (RF) incurred a higher computational effort, while Light GBM and Xgboost showcased comparable performance with efficient computational demands.

These algorithms have applications extending beyond car price prediction, finding utility in forecasting the values of assets like real estate and commercial equipment. Moreover, they can be adapted for predicting stock prices and commodity values within financial markets.

Nevertheless, it is vital to recognize their limitations, including the presence of exogenous factors and factors subject to significant shifts due to unforeseen macroeconomic conditions. Exploring these macroeconomic factors would be an exciting direction for future endeavors as a data scientist.

Section 5: References

[1] Muhammad Awais Tayyab. Used Car Price Prediction - Pakistan Dataset. URL: https://www.kaggle.com/datasets/muhammadawaistayyab/used-car-price-prediction-pakistan/data

[2] Pakistani Rupee to US dollar 2023 exchange rate. URL: https://www.google.com/search?client=safari&rls=en&q=exchange+rate+pak+rupee+to+us+dollar&ie=UTF-8&oe=UTF-8

[3] Analytics Vidhya. (2023). A Complete Guide to K-Nearest Neighbors (Updated 2023). URL: https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/

[4] Analytics Vidhya. (2021). Gradient Boosting Algorithm: A Complete Guide for Beginners. URL: https://www.analyticsvidhya.com/blog/2021/09/gradient-boosting-algorithm-a-complete-guide-for-beginners/

[5] Arize. Kolmogorov Smirnov Test: When and Where To Use It. URL: https://arize.com/blog-course/kolmogorov-smirnov-test/

[6] Rafael A. Irizarry. (2019). Advanced Data Science: Statistics and Prediction Algorithms Through Case Studies. Section 1 Distributions. URL: http://rafalab.dfci.harvard.edu/dsbook-part-2/summaries/distributions.html

[7] Rafael A. Irizarry. (2023). Introduction to Data Science: Data Analysis and Prediction Algorithms with R. Chapter 13 Probability. URL: http://rafalab.dfci.harvard.edu/dsbook/probability.html