

Cars 4 You: Expediting Car Evaluations with ML

Group Project Machine Learning 2024/2025



GROUP 12 - HANDOUT

Project members:

- Ricardo Isidro - 20250374
- Rodrigo Santos - 20250387
- Rodrigo Texeira - 20250393

Overall structure of our project pipeline:

1. Data Import & Exploration

Training and **test** datasets are imported using pandas. Exploratory Data Analysis (EDA) includes **descriptive statistics**, **correlation heatmaps**, and **distribution plots** to identify **trends**, **missing values**, and **outliers**.

2. Preprocessing & Data Cleaning.

- **Dropped Columns:** `hasDamage` was removed due to a single value (**0**), providing no predictive information.
- **Text Standardization:** All categorical columns (**Brand**, **model**, etc.) were converted to lower-case to consolidate unique values and fix typos using `fix_typos()`.

2.1 Outlier Handling: **Negative**, **unrealistic**, and **outlier numeric values** were set to ***Nan*** using boxplot analysis. Outliers were removed only for **Linear Regression**, since **Random Forest** is **robust** to them.

- `mileage < 0`
- `tax` not in range [0, 400]
- `mpg` not in range [0, 150]
- `engineSize` not in range [1, 6]
- `paintQuality% > 100`
- `year` not in range [1990, 2020]
- `previousOwners` not in range [0,4]

The **Linear Regression** model is extremely sensitive to outliers. Therefore, removal and clipping were crucial:

- ❖ **Unrealistic Values** (e.g., `mileage < 0`, `paintQuality% > 100`, `mpg>150`): These were removed to prevent distortion of the regression coefficients, ensuring the model learns valid and logical relationships.
- ❖ **Extreme Outliers (Interval Clipping):** The removal of very rare/extreme values (e.g., tax, mpg, year, engineSize) was performed because these points would have **high leverage**, pulling the regression line and violating the assumption of **linearity** in the main sample.
- ❖ **Percentile Clipping (tax, engineSize):** Limiting to the 1st/99th percentile **before** logarithmic transformation to **stabilize the model**, reducing the extreme variance introduced by milder outliers.
- ❖ **Log-Transformation (np.log1p):** Applied to the target (price) and skewed variables (mileage, mpg and tax), this is essential for Linear Regression because it:
 - **Normalizes distributions**, bringing them closer to the symmetry required for the assumption of **normal residuals** (model error).
 - **Linearizes relationships** (e.g., log(price) vs. log(mileage)).
 - **Reduces Heteroscedasticity** (disproportionate errors at high price values).

2.2.1 Categorical Missing Values

Theil's U (Asymmetric Uncertainty) was used to guide the selection of auxiliary variables, ensuring contextual imputations:

- ❖ **Contextual Imputation (Brand, model):** A custom helper function (`fill_NaN_with_categorical`) was used to fill NaNs with the group mode from the most correlated group. For example, **Brand** was inferred based on the combination of **model**, **transmission**, and **fuelType**, preserving feature dependency.
- ❖ **Simple Imputation (transmission, fuelType):** NaNs were filled using the global mode of the respective column.

2.2.1 Numerical Missing Values

The Correlation Ratio R² scores were used to identify the best predictors for numerical variables:

- ❖ **Mixed and Contextual Imputation (year, mileage, tax, engineSize):** A mixed-method function

(fill_NaN_with_mixed) was used, which fills the NaN with the mode within a group defined by one categorical variable (model) and one highly correlated, discretized (*binned*) numerical variable. This highly granular approach maintains the data dependency structure.

- ❖ **Robust Median Imputation (*paintQuality%*, *previousOwners*):** The median was used to fill NaNs. The median is a robust statistic that minimizes the impact of imputation on skewed distributions or those with residual outliers.
-

3. Feature Engineering

- **Categorical Encoding:**
 - **One-Hot Encoding** applied to ***Brand***, ***transmission***, and ***fuelType*** to convert nominal categories into binary indicator variables.
 - **K-Fold Target Encoding** was applied to the ***Brand*** and ***model*** variables due to the **high cardinality** of the ***model*** feature. This approach allows the model to effectively capture price-related information (average price patterns by Brand and model) while **reducing overfitting** through cross-validation.
 - **Min-Max normalization** applied to numerical features to standardize scales between 0 and 1. It offers stability to the model and is ideal when the data distribution is already well-behaved (without outliers).

4. Feature Selection Strategy

Feature relevance was evaluated using both statistical and model-driven methods:

- **Pearson Correlation:** Used to evaluate linear relationships between numerical variables and the target (price), as well as to identify and remove multicollinear predictors that could distort regression coefficients.
- **Recursive Feature Elimination (RFE):** Performed using both Linear Regression and Random Forest models to iteratively rank and select the most informative subset of predictors based on their contribution to model performance.
- **LassoCV:** Applied to penalize less relevant predictors through L1 regularization, automatically setting weak feature coefficients to zero and improving model generalization.

Final retained features (used in both models): ***year***, ***engineSize***, ***tax***, ***mpg***, ***mileage***, ***Brand***, ***model***, and ***transmission***.

5. Model Training and Evaluation

- The task was formulated as a supervised regression problem.
- Linear Regression served as a baseline model for interpretability and benchmarking.
- Random Forest Regressor was employed as the final model to capture nonlinear dependencies and feature interactions.
- Evaluation Metrics:
 - **R² Score:** Measures the proportion of variance explained by the model.
 - **Mean Absolute Error (MAE):** Represents the average prediction error.
 - **Root Mean Squared Error (RMSE):** Highlights larger deviations more heavily.

Pipeline overview table

Stage	Techniques Used
Exploration	Descriptive statistics, histograms, correlation matrix, missing value analysis
Preprocessing	Outlier filtering (IQR & quantile clipping), missing value imputation (median or inferred), typo correction, data type adjustments
Feature Engineering	<i>One-Hot Encoding</i> and K-Fold target encoding (for categorical variables), log transformation for skewed numeric variables, Min-Max normalization
Feature Selection	Pearson correlation, Recursive Feature Elimination (RFE), LassoCV
Modeling	Linear Regression (baseline) and Random Forest Regressor (final model) using 70/30 train-validation split
Evaluation	R ² , MAE, RMSE — Random Forest achieved better generalization and lower error

- Results: The Random Forest Regressor consistently outperformed Linear Regression across all metrics, demonstrating better predictive accuracy, robustness, and generalization to unseen data.