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Price Prediction for US Used Cars

COMS 4995 Applied Machine Learning

Group 4 - Project Deliverable 2

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1. Data exploration with insights

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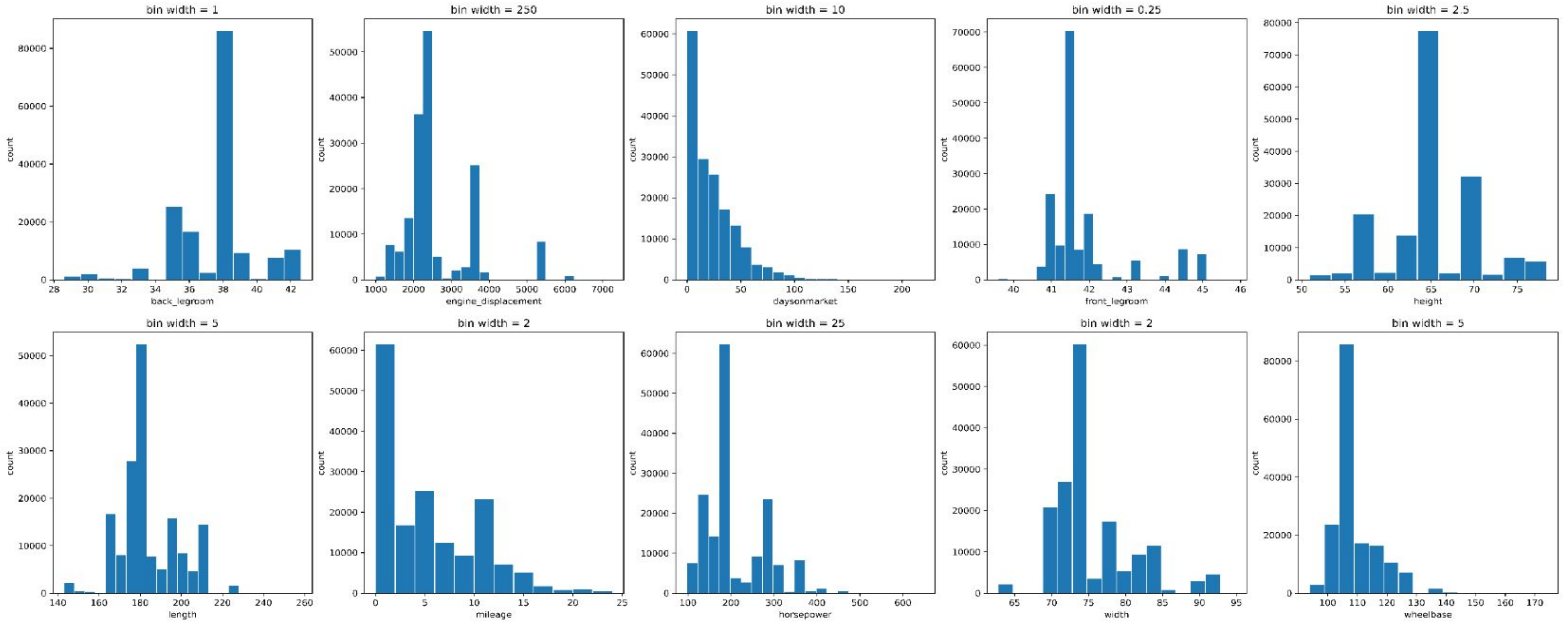
Data Overview:

- The original dataset comes from Kaggle with roughly **3 million** records. However, as mentioned in our proposal, we limit our analysis to the data from year 2021.
- The dataset contains **65** features including categorical, numerical, boolean, and textual description features and roughly **176K** records.
- The target variable is **price** to be predicted

Distribution of some of the numerical features:



Some features such as **daysonmarket**, **mileage**, and **wheelbase** are highly skewed, so we can utilize **power or log transform** to reduce the skewness

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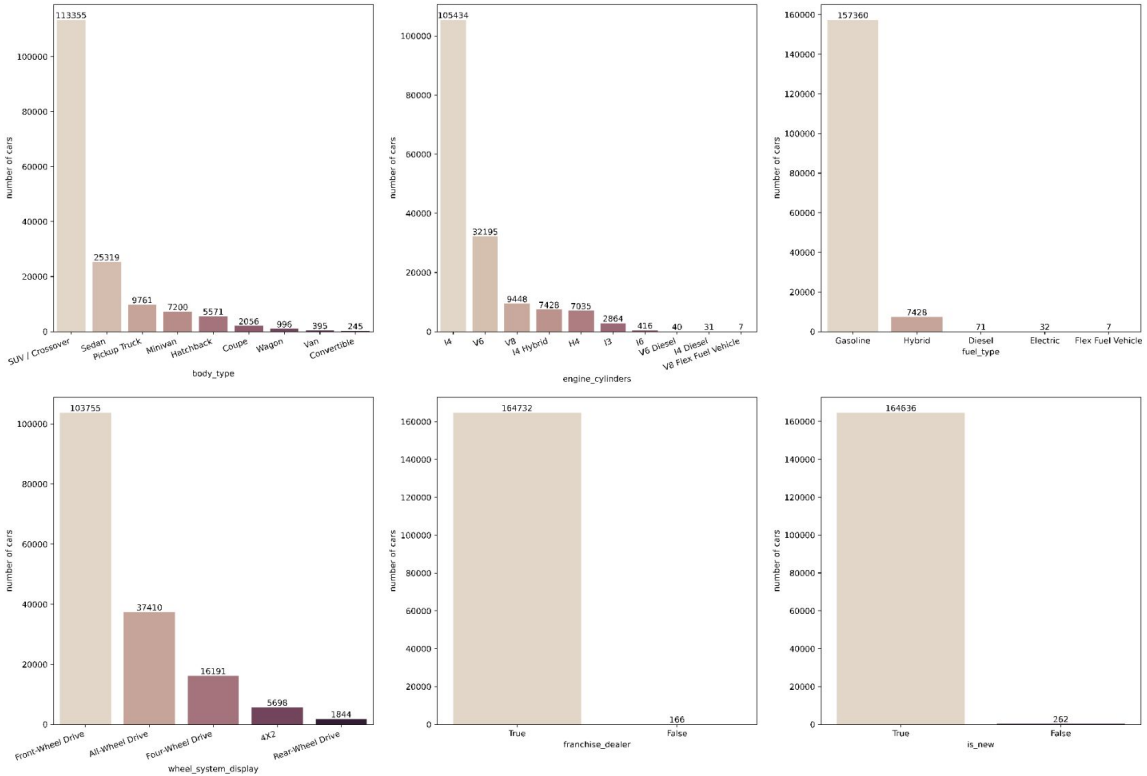
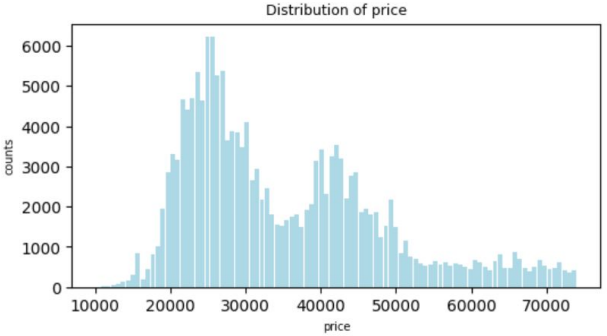
Distribution of some categorical and boolean features:



- From the distributions of some of the categorical and boolean features, we notice that there is **imbalance** in the feature values.

Distribution of target variable: price



- The distribution of price is slightly skewed, with more cars being in the range of **$20000-$45000**. There are two peaks in this distribution, which suggests a bimodal distribution.

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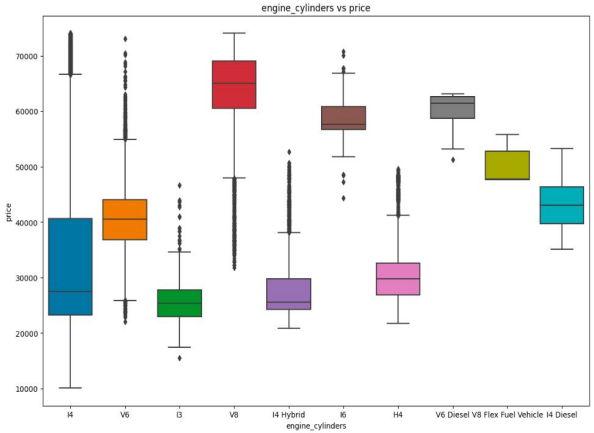
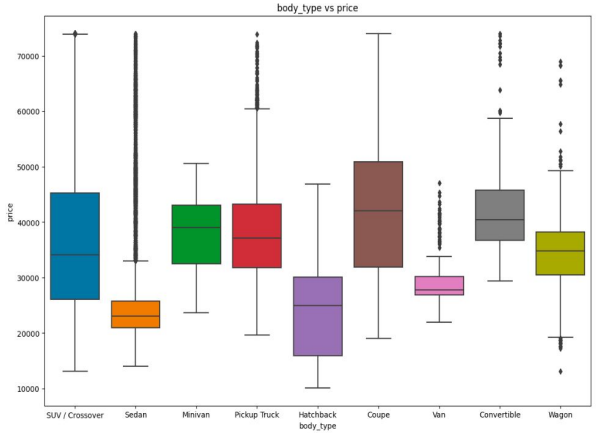
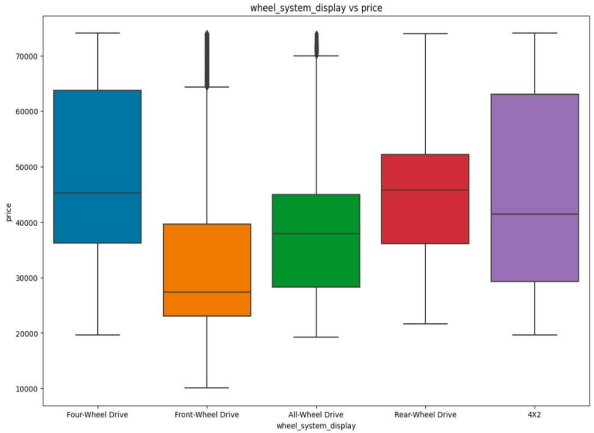
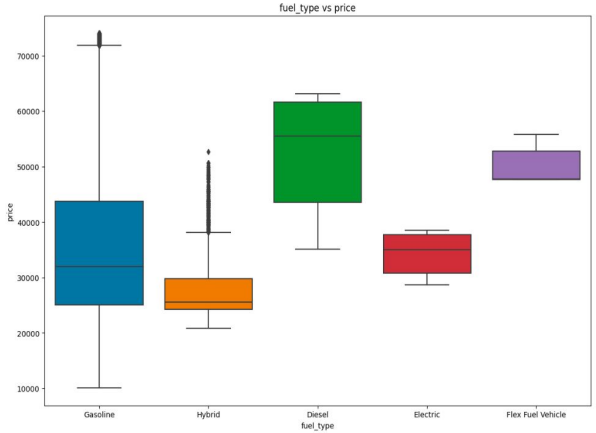
Categorical features vs price:

- Several types of engine cylinders have noticeable outliers in the car price values
- The price values of **Sedan** cars have significant number of outliers
- **Front-wheel Drive** has a lower median car price compared to other wheel system displays.
- The median car prices of **Diesel** and **Flex Fuel** type are noticeably higher than other fuel types









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Data processing and categorical data encoding:

- **9** categorical features with more than **10** unique values are encoded using Target encoding
- **engine_cylinders**, **fuel_type** features are encoded using Ordinal encoding and importance is assigned based on the usually observed sale prices of the cars with those different feature values
- **body_type**, **wheel_system_display** features are One Hot encoded
- **major_options** is a list of major features and is encoded as the length of list indicating the more the number of features the higher the importance
- **franchise_dealer**, **is_new** are boolean features and True is encoded as 1 and False as 0

- Some of the numerical features have metric representations like **gal, in, etc** and they are removed to make the values fully numeric

transmission_display	trim_name	wheel_system_display
Automatic	Altitude 4WD	Four-Wheel Drive
Automatic	Altitude 4WD	Four-Wheel Drive
Automatic	Altitude 4WD	Four-Wheel Drive
Automatic	Altitude 4WD	Four-Wheel Drive
Automatic	Altitude 4WD	Four-Wheel Drive

wheelbase	width
103.8 in	80 in
103.8 in	80 in
103.8 in	80 in
103.8 in	80 in
103.8 in	80 in

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Correlation matrix:

- **franchise_make** and **make_name** are highly correlated, so **make_name** feature is dropped (0.98)
- Similarly, **length** and **wheelbase** are highly correlated, so **wheelbase** feature is dropped (0.93)

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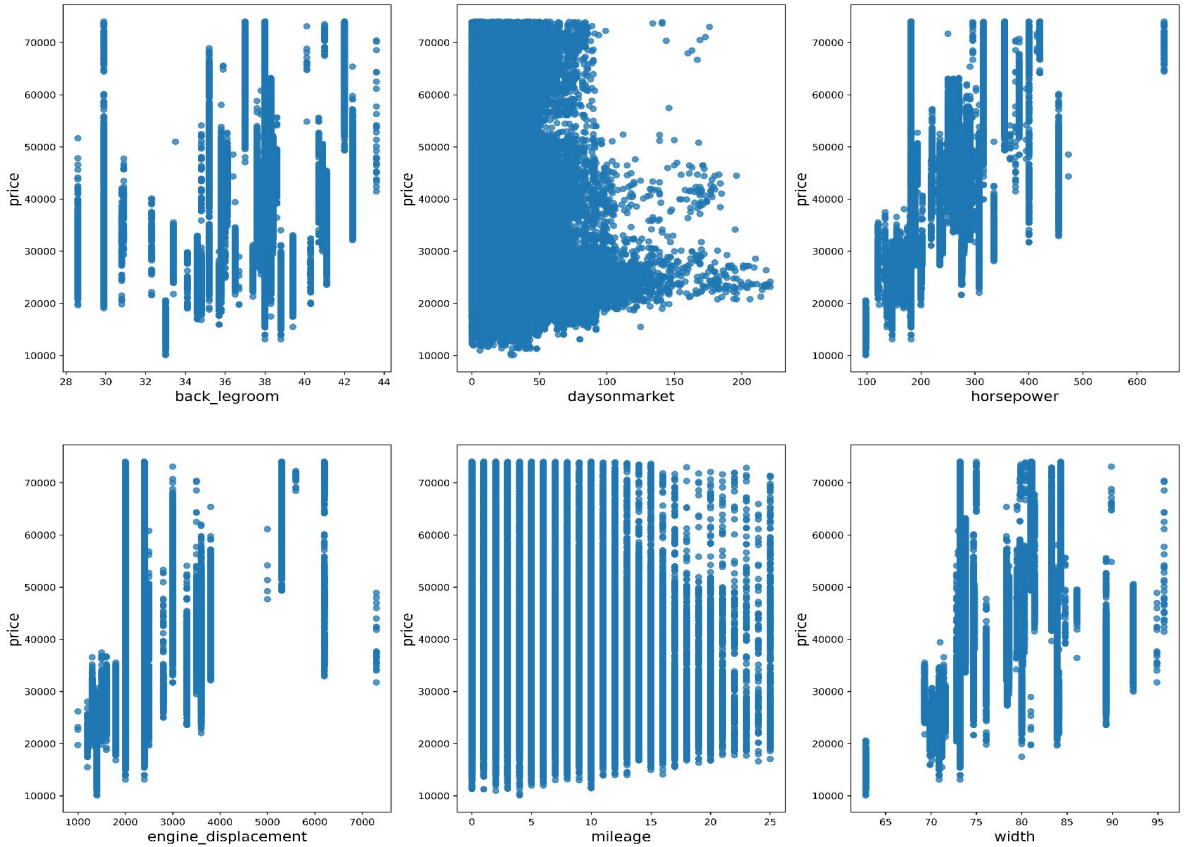
Scatter plots of some of the numerical features vs price:



- Some of the numerical features are **not a linear function** of the price, so the linear regression model may not be suitable for this data

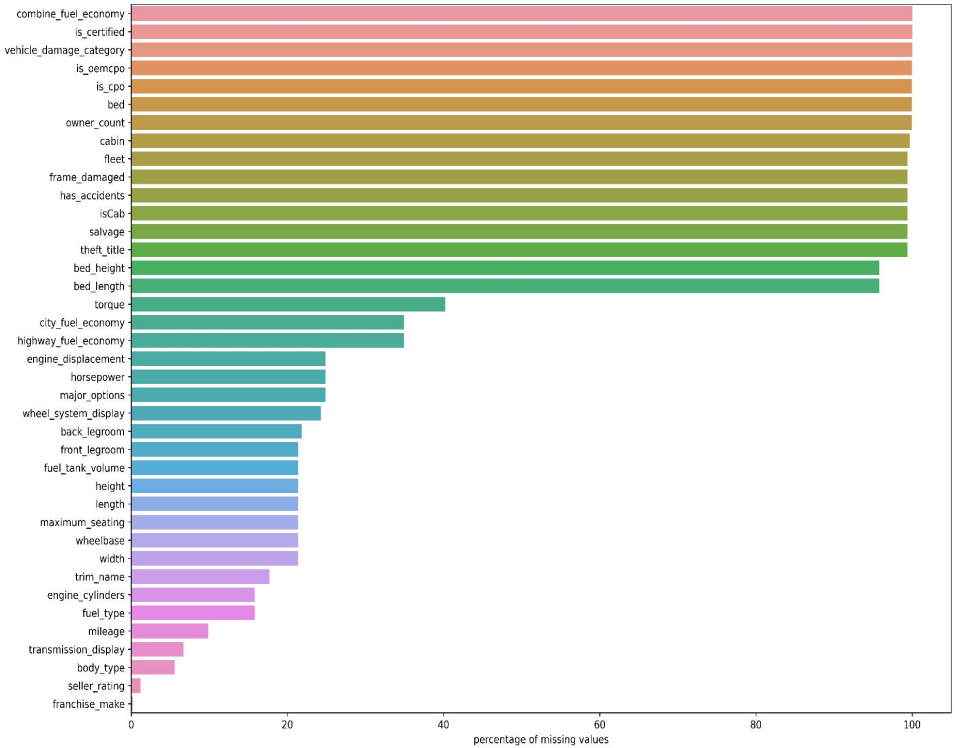
2. Cleaning and Sampling

Relevant features:

- Out of the **65** features, the **49** features which provide relevant information are considered and the rest are dropped. We also dropped textual features such as description since language processing is not our goal.

Missing values:

- All the rows in the dataset have some feature value missing. So we cannot just **drop the rows**.
- **Features** with more than **30%** values missing are dropped. In other words **19** out of the **49** features are dropped.
- **savings_amount** feature has only one unique value after outlier handling, so it is also dropped.
- All the categorical missing values are imputed using **mode** of the feature.
- Some of the numerical missing values are imputed using **median** of the features.
- **mileage** has several rows with value **0**, so the missing information is filled with **0**.
- **major_options** missing values are considered as lack of any major options, so the missing information is filled with **0**.



2. Cleaning and Sampling

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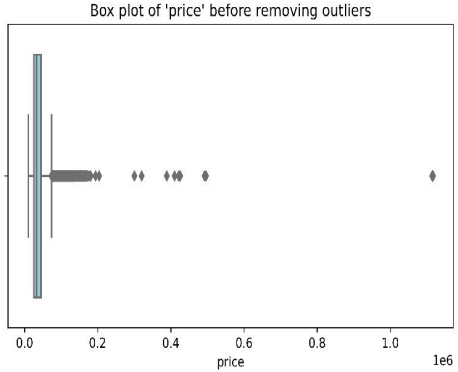
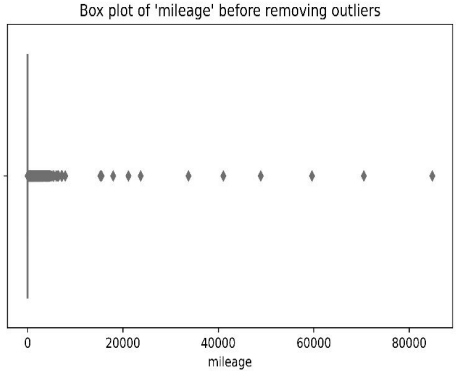
Outliers removal:

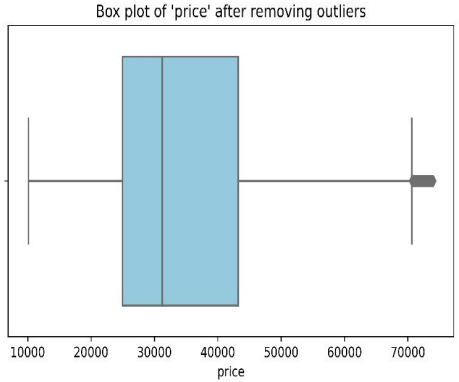
- Outliers are present in the target variable **price**, feature **mileage** as observed from the box plots, so removing this noise will improve the performance of models
- We used Interquartile Range to identify and remove the rows with **price**, **mileage** values outside the range
- Roughly **12K** records are removed (**6.6%** of the **176K** records)

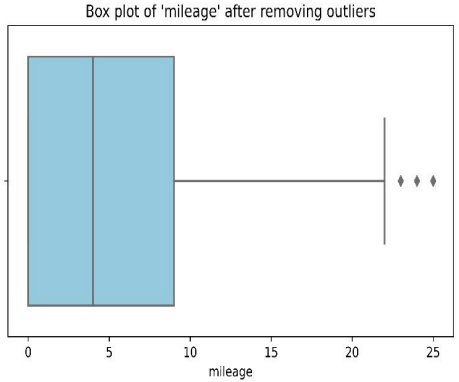




Data sampling:

- Since this is a regression task there is no relevancy of class imbalance, so we do not require any **data sampling**.





Data splitting:

- Since we do not need to worry about class imbalance we use **random splitting** to split the dataset.
- We split the dataset into training (60%), validation (20%), and test (20%) sets.
- The validation set will be used for finding the optimal hyperparameters

3. Machine learning techniques proposed

Models Choice:

- Linear Regression (baseline)
- Lasso, Ridge, and Elastic-Net
- Decision trees and Ensemble Methods (including Bagging and Gradient Boosting)
- Deep Learning Model: TabNet

Model Performance Evaluation:

- AUROC
- RMSE

Hyperparameter Tuning:

- Grid Search
- Random Search
- Hyperband