Gear

Used Car Price Analysis

Analyzing over 50,000 vehicles and building a price model

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Business Problem

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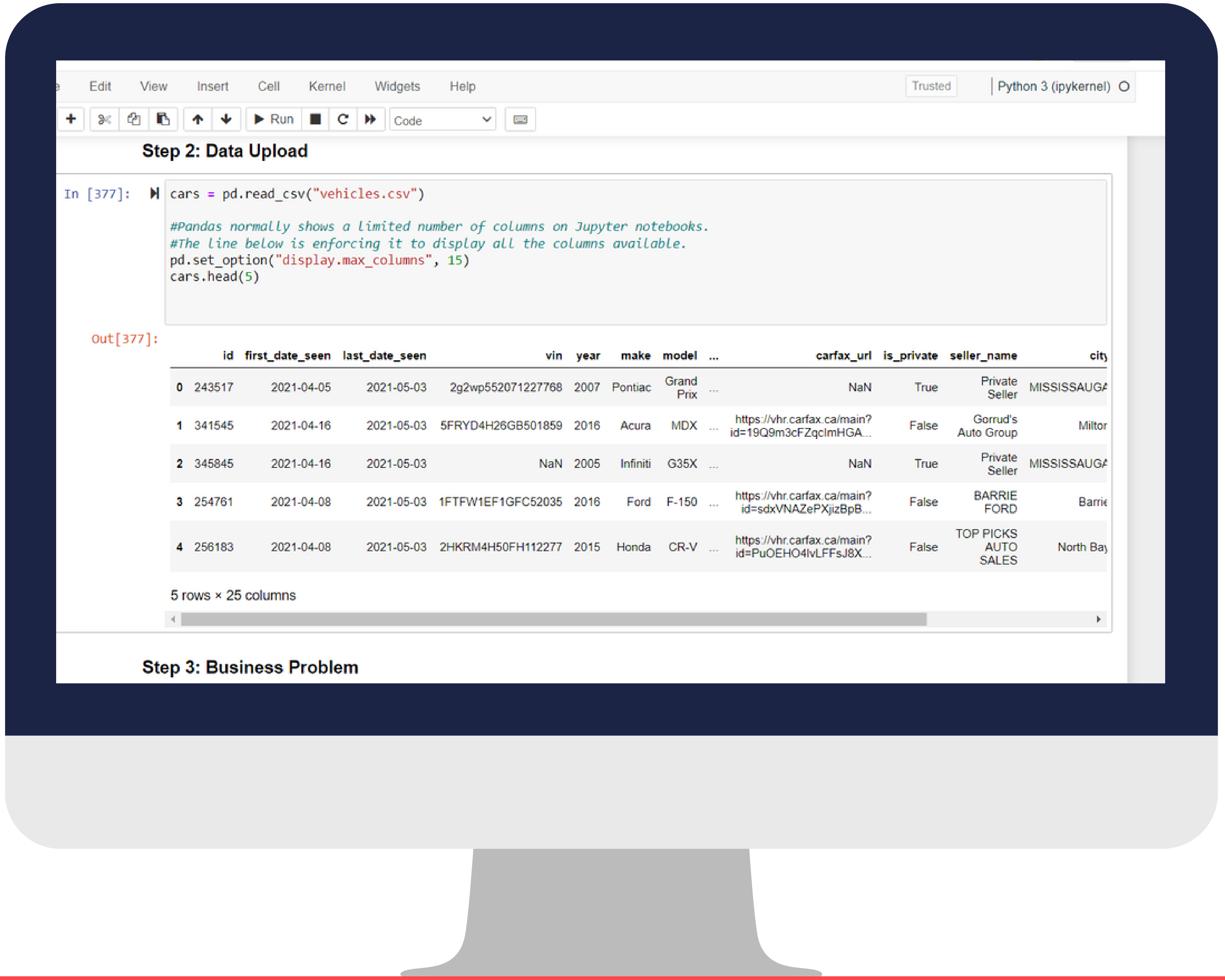
Online dealer **Gear** sits on rows of historic car data and would like to know how to get **data-driven price estimates** given that other attributes of vehicle are known.

1

Generate insights on past data

2

Leverage historic data to create predictive model



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DATASET

- Over 50,000 **unique** used car listings
- April- May, 2021
- 25 columns

Steps followed

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1. Exploratory Data Analysis (EDA)
2. Data Cleaning
3. Data Analysis
4. Modelling

EDA results

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01

NULL values

- Actual NULL values that needed treatment in columns like **bodytype**, **drivetrain**
- NULL values are the actual values like the ones in **Carfax_url** field

02

Outliers

- Actual outliers like two rare listings from a US city or vehicles with over 3,000,000 km on them
- Outliers that signals a value for analysis like extremely old cars

03

Duplicate records

- No duplicate entries except for the two US listings

04

Data entry errors

- Many new vehicles with over a million km on them signal human errors like putting an extra digit by mistake
- A 2001 Jetta with 999,999 km
- Old cars with 0 km

05

Distribution of data

- Frequency distribution on categorical fields before data points. i.e. **Color** and **make** columns had many, insignificant unique values

Data Cleaning I

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01

NULL values

- Fields like **carfax_url, vin** and **is_private** converted to boolean (1, 0)
- IMPUTATION. i.e. missing **body type** was imputed from vehicles with same model, make
- Missing values in numerical columns were filled with mean where applicable. i.e. NULLs under **mileage** field was imputed from vehicles with same **make** with same **year**

02

Data entry errors

- **Mileages** with erroneous digits are fixed. Simply divided by 10.
- **Mileage** for that 2001 Jetta with 999,999 km is rendered NULL and than filled with mean mileage of all the 2001 Jetta listings
- **City**='Richmond' converted to 'Richmond Hill' thanks to **longitude/latitude** data.

03

Distribution of data

- Captured all **color** shades under broader groups: Star White **->** White
- Tagged edge cases in fields like **color, make** under 'Other'

Data Cleaning II

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04

New fields

- Engine field had lengthy strings not feasible for transformation. **Cylinder** information was captured and stored in a new column.
- **City** field had many unique values. New field, **toronto_gta** accounts for Toronto boroughs
- Old cars built more than 30 years ago is tagged **vintage**
- **Age** column instead of **year** makes more sense for analysis purposes
- No useful info from seller name. Dropped

05

Transformations

- Many values under categorical fields required proper case cleaning for better visibility.
- **Fuel type** is cleaned to have broader categories like Elektric, Gasoline, Diesel.
- Cars with asking price < 500$ and ad **description** including 'parts' tag removed.

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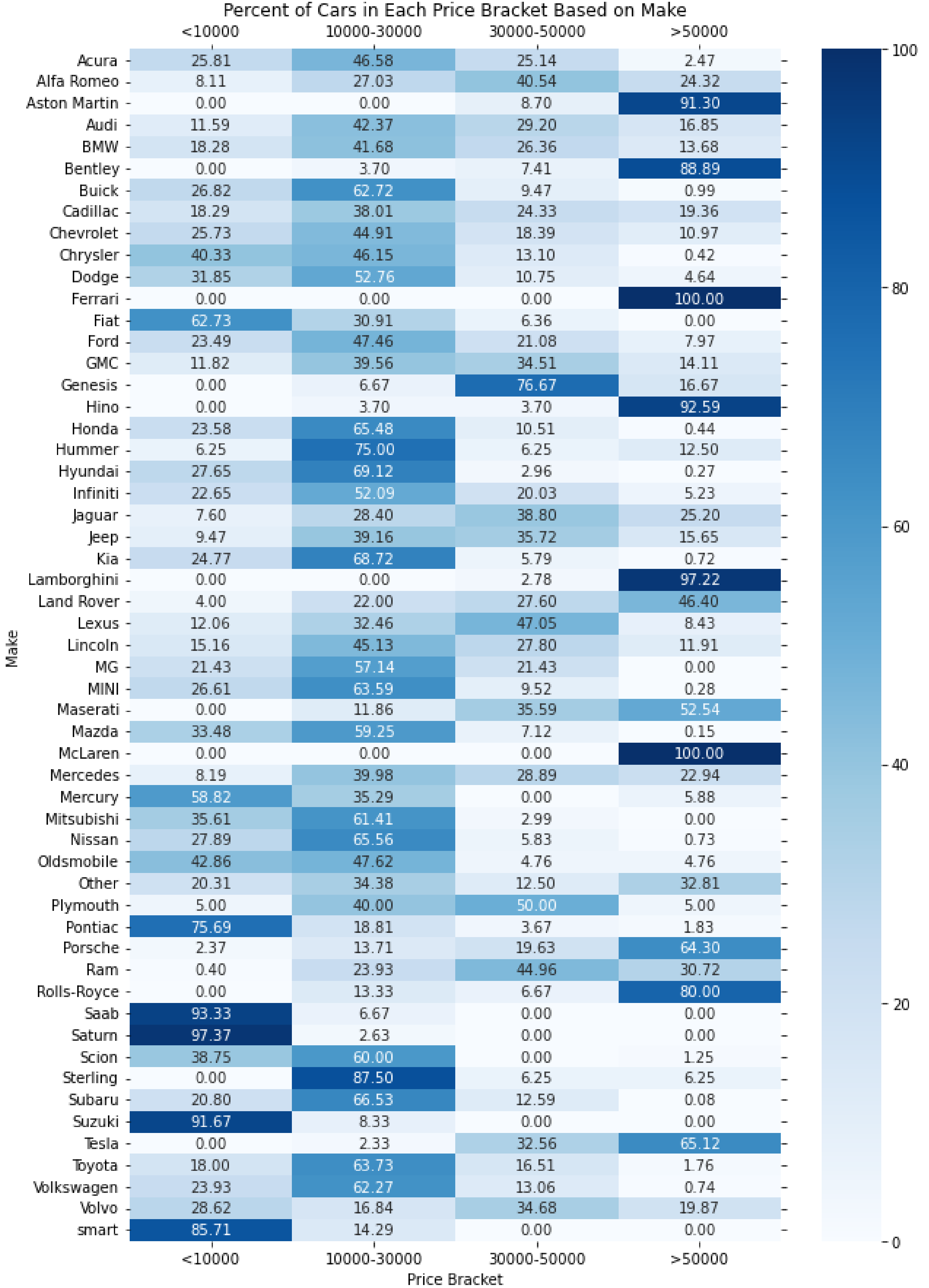
Data Analysis

Make vs Price

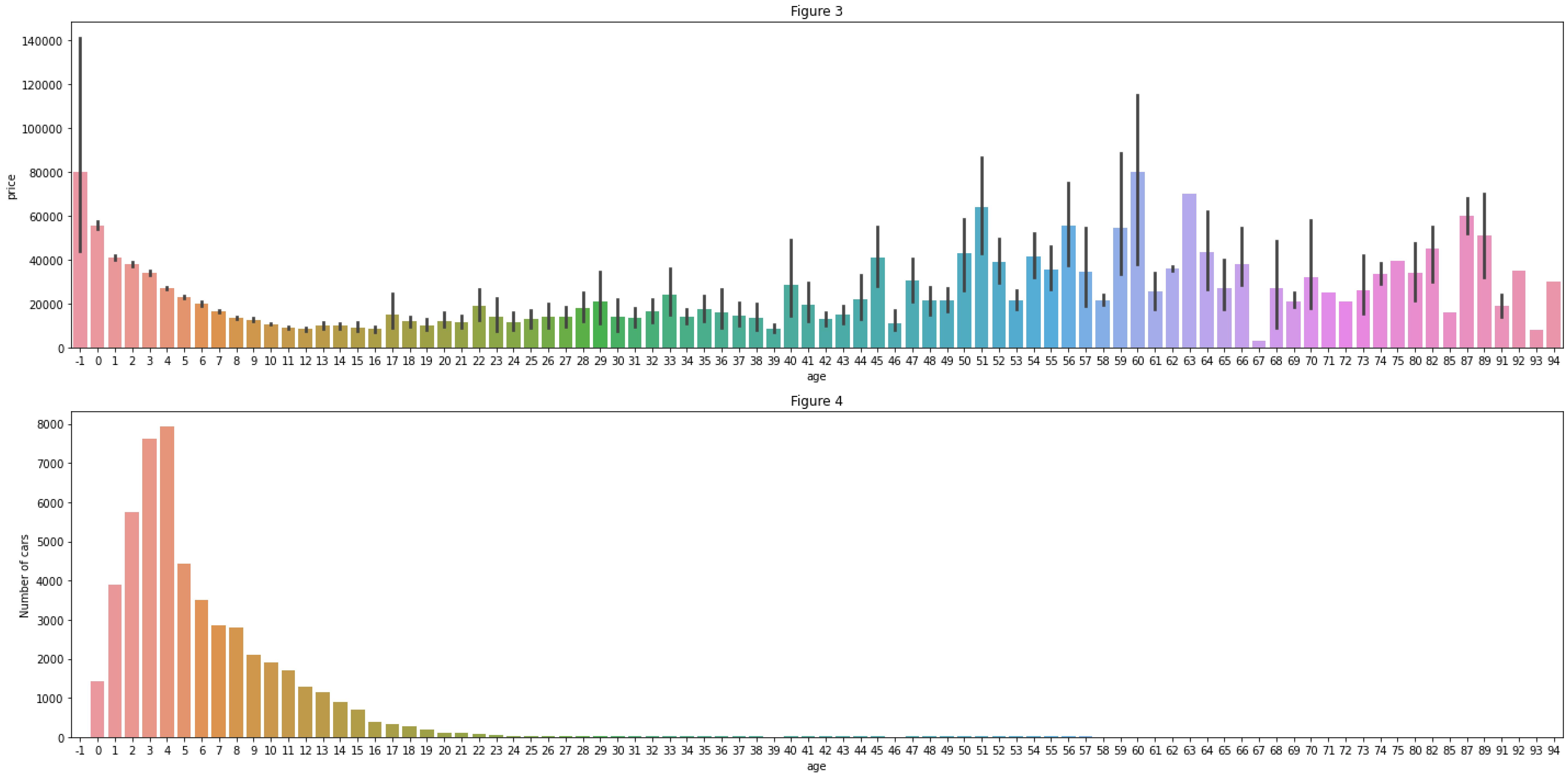
- Premium luxury vehicles such as Aston Martin, Bentley, Rolls-Royce, Ferrari, Tesla, Porsche, Maserati and Lamborghini have overwhelming majority of their cars listed upwards of **50,000$.**

- Brands like Toyota, Honda, Hyundai, Kia and Nissan have their cars mostly listed under the second tier,
 10,000$ - 30,000$.

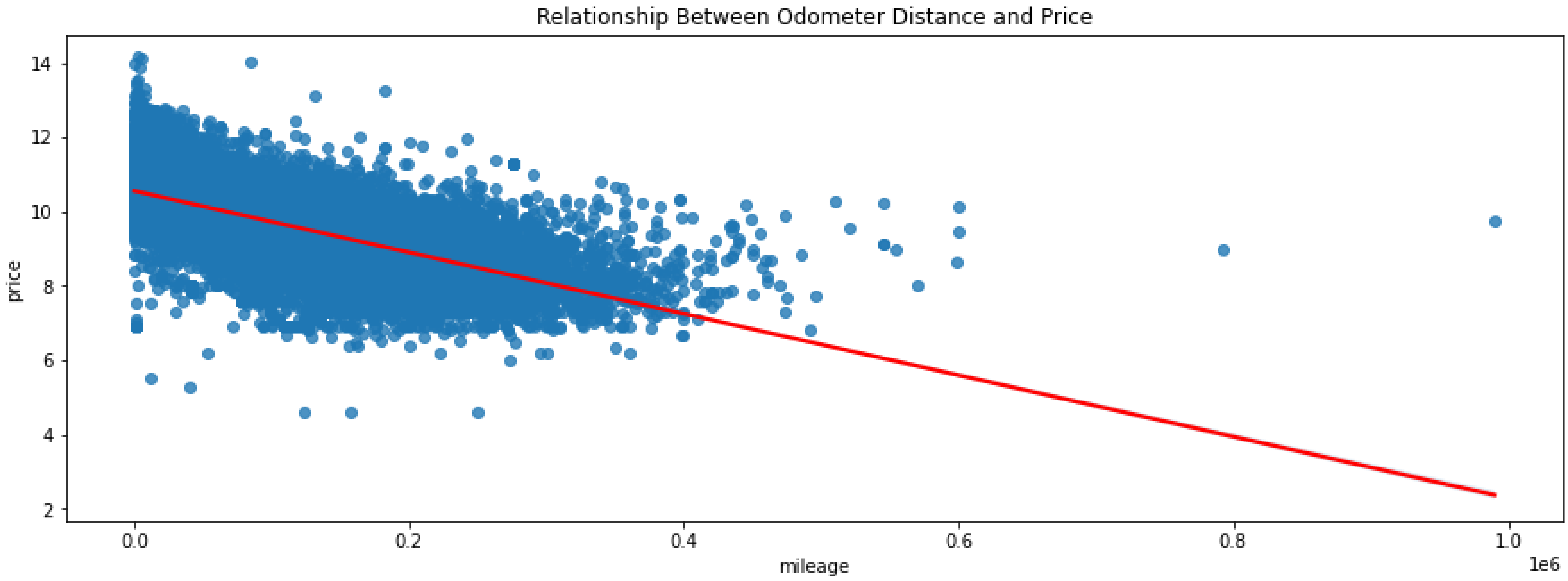
- The brands like Saturn, Saab, Suzuki, Smart and Fiat have almost all of their listings under **10,000$**. Could be due to the lower perception of brand quality in the Canadian used car market



Age vs Price



Mileage vs Price



Various fields vs Price

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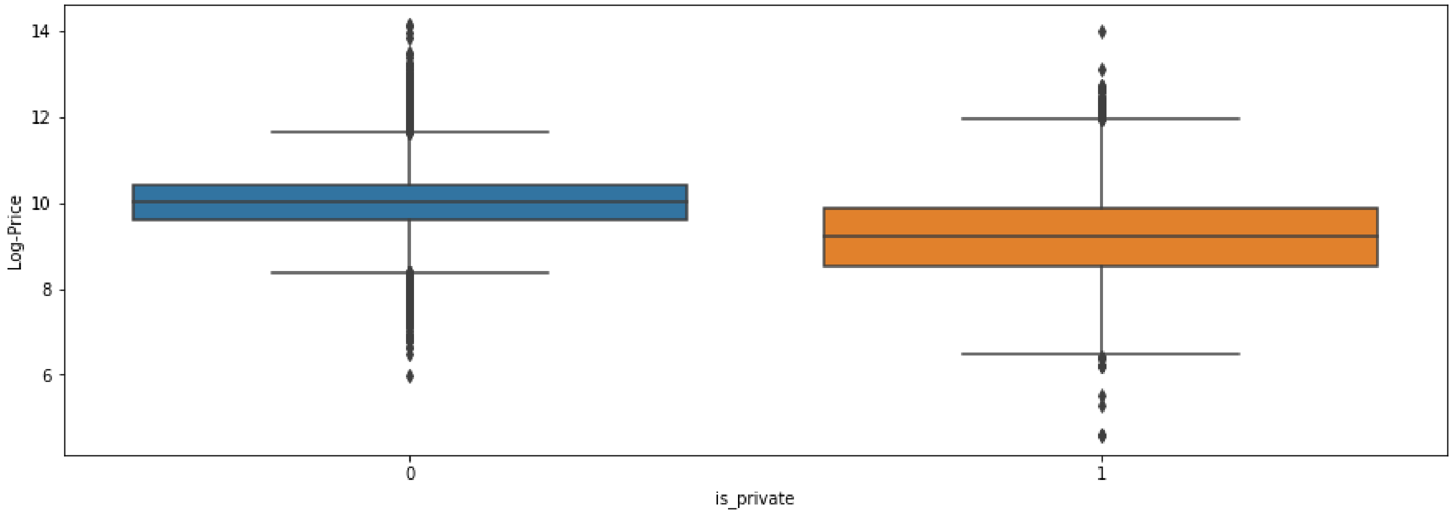

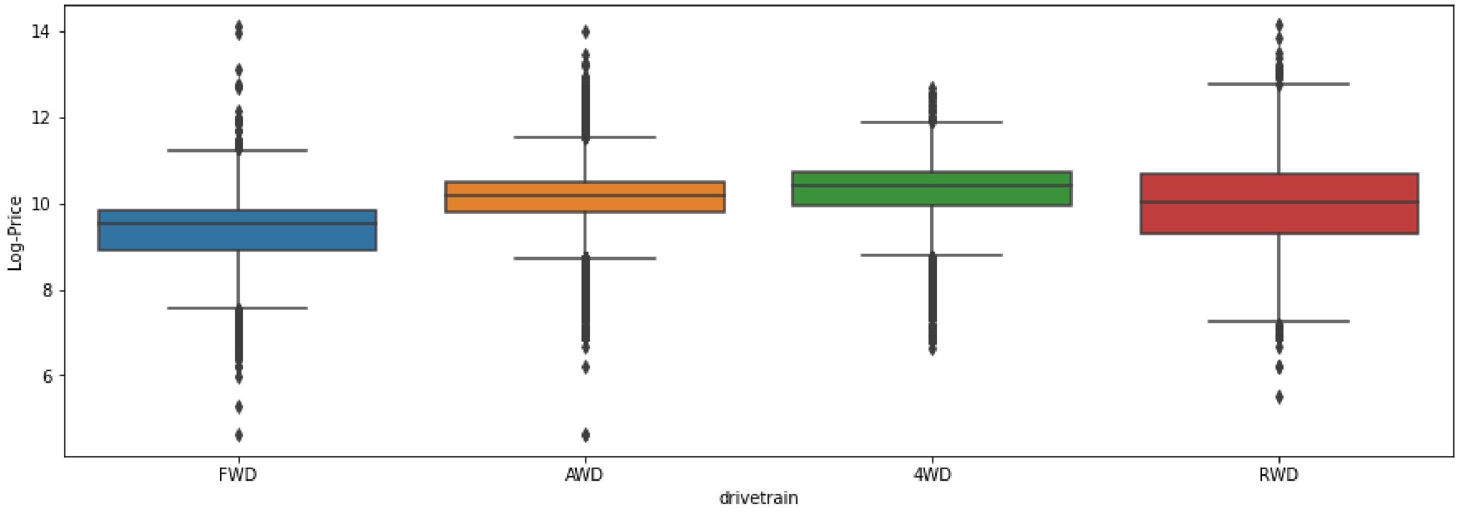

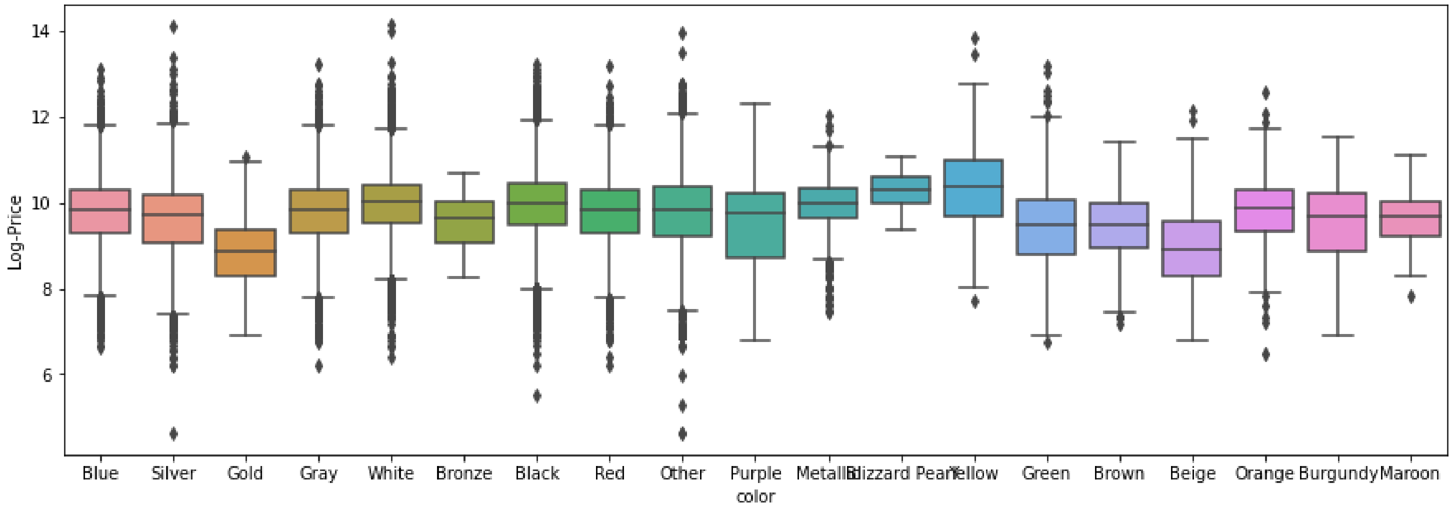

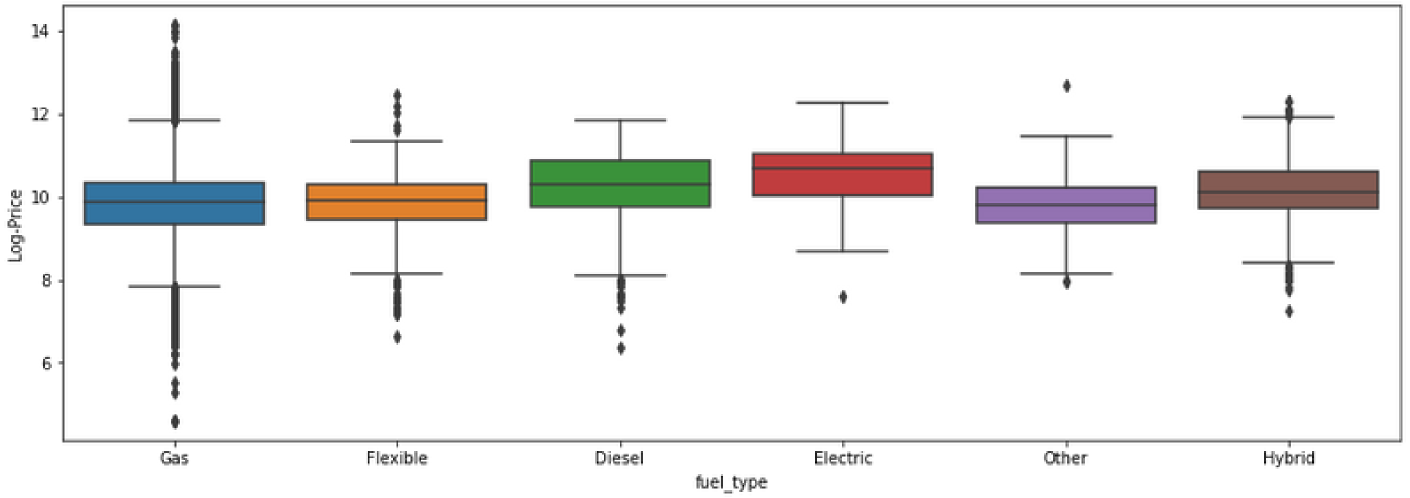

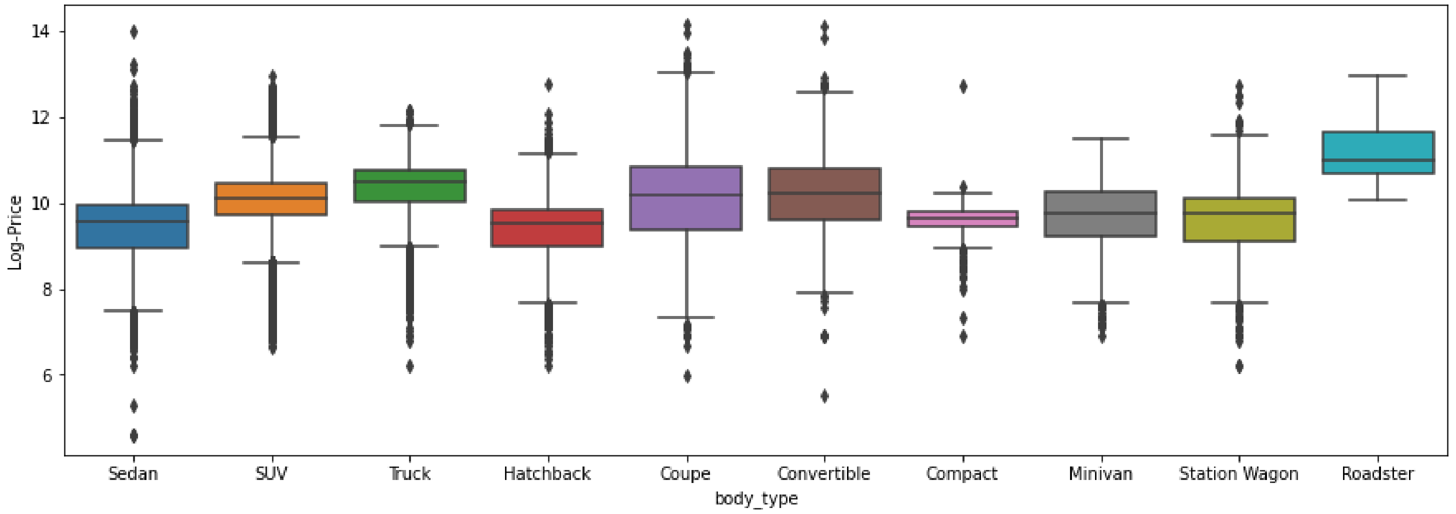

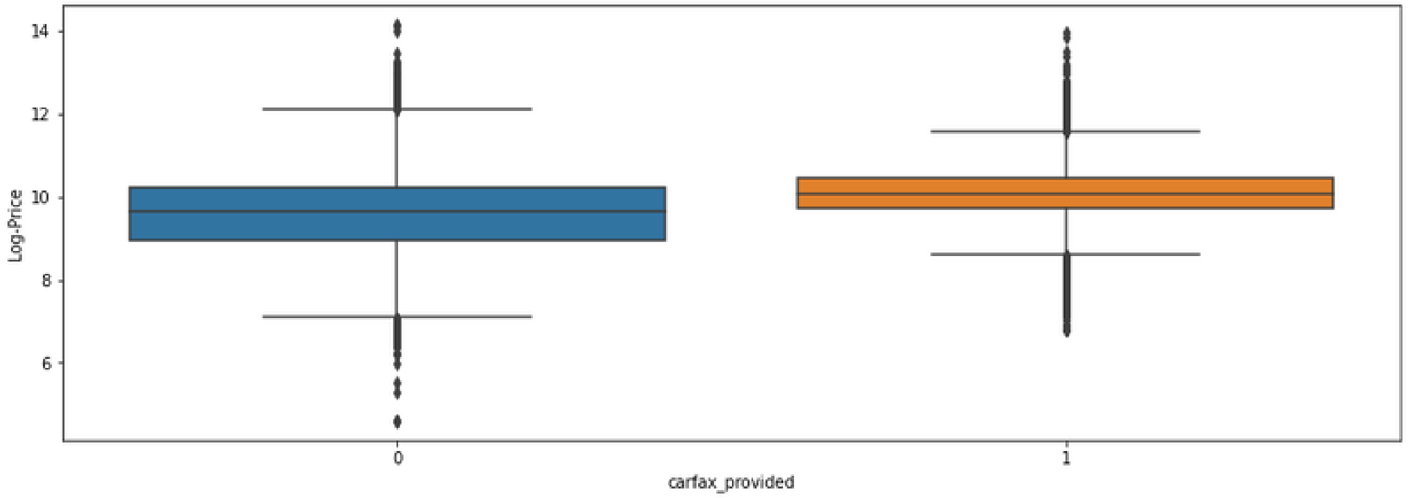

Improved description field

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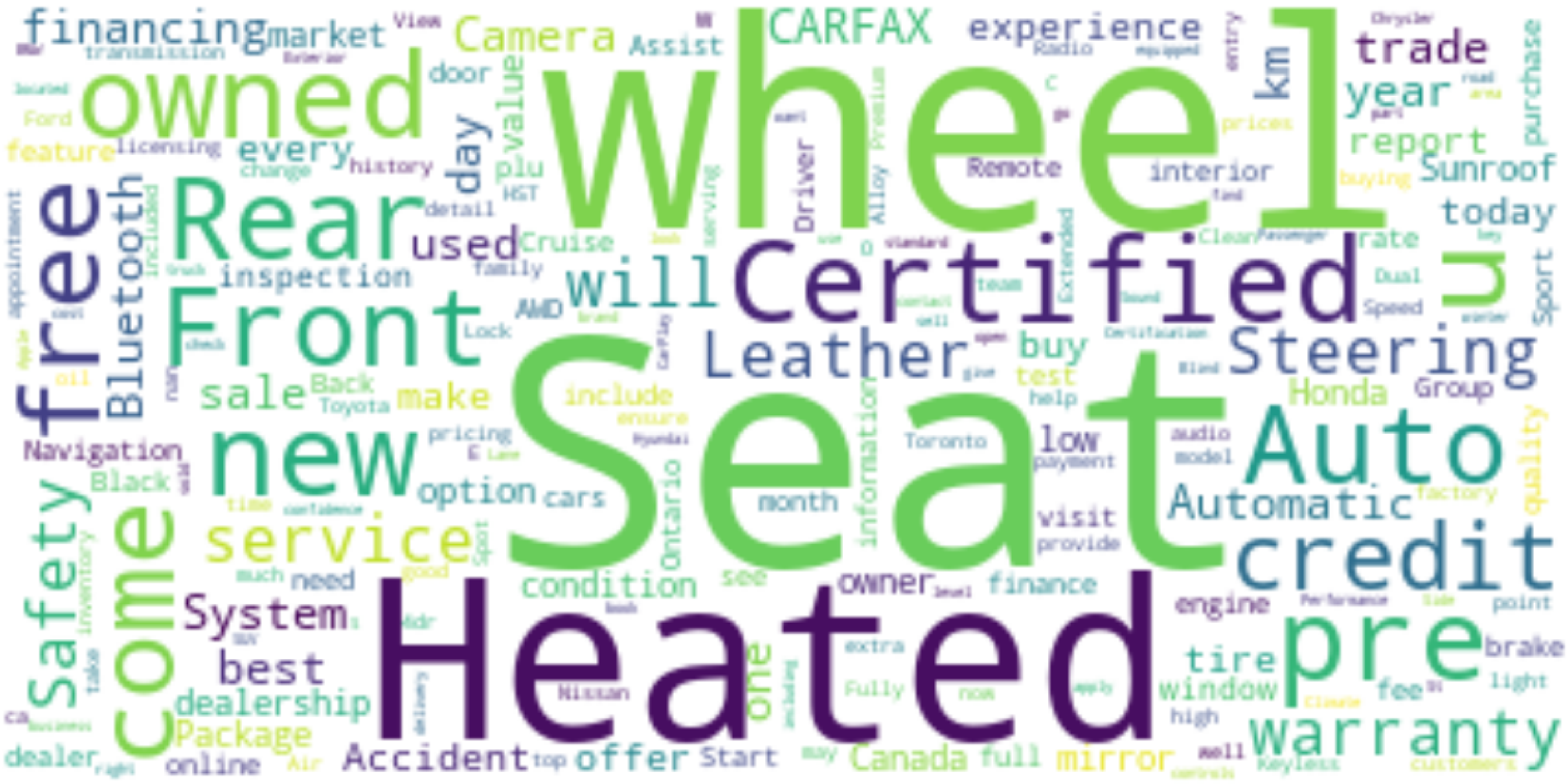
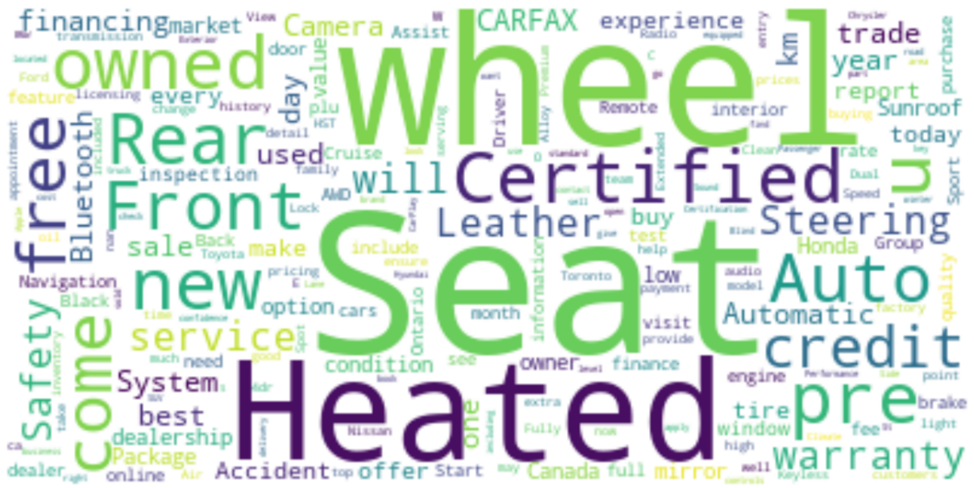
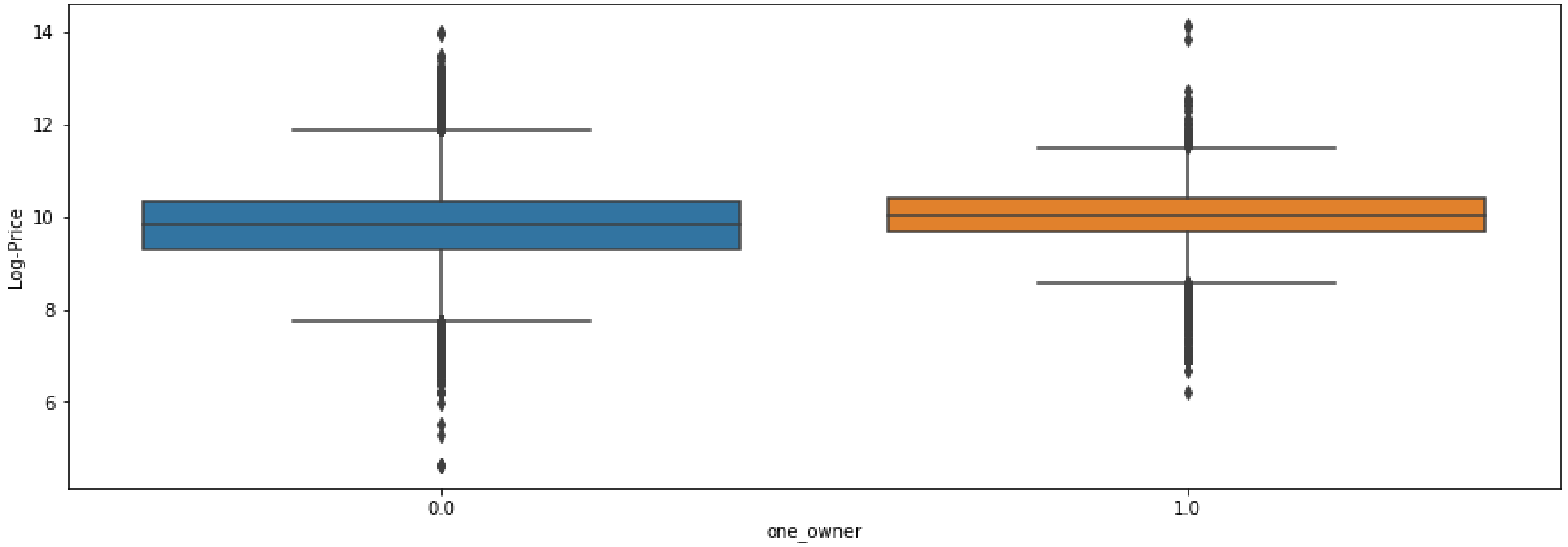
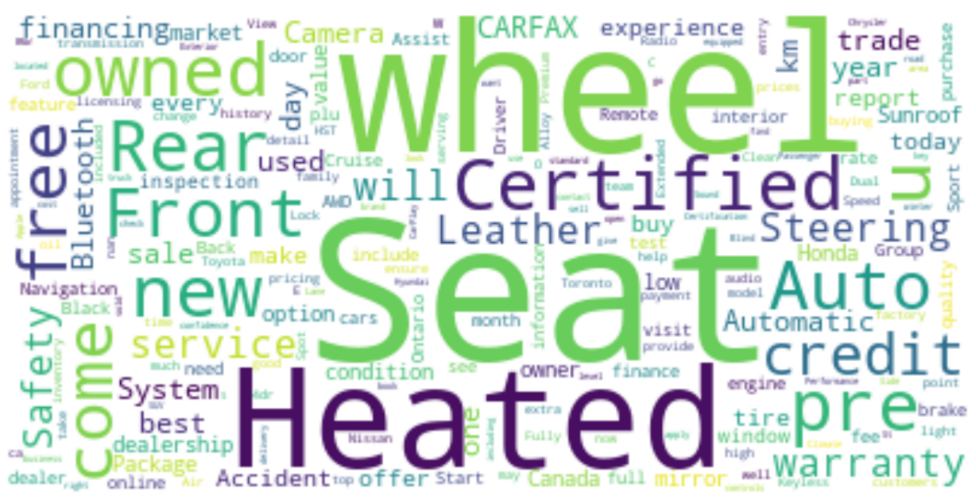


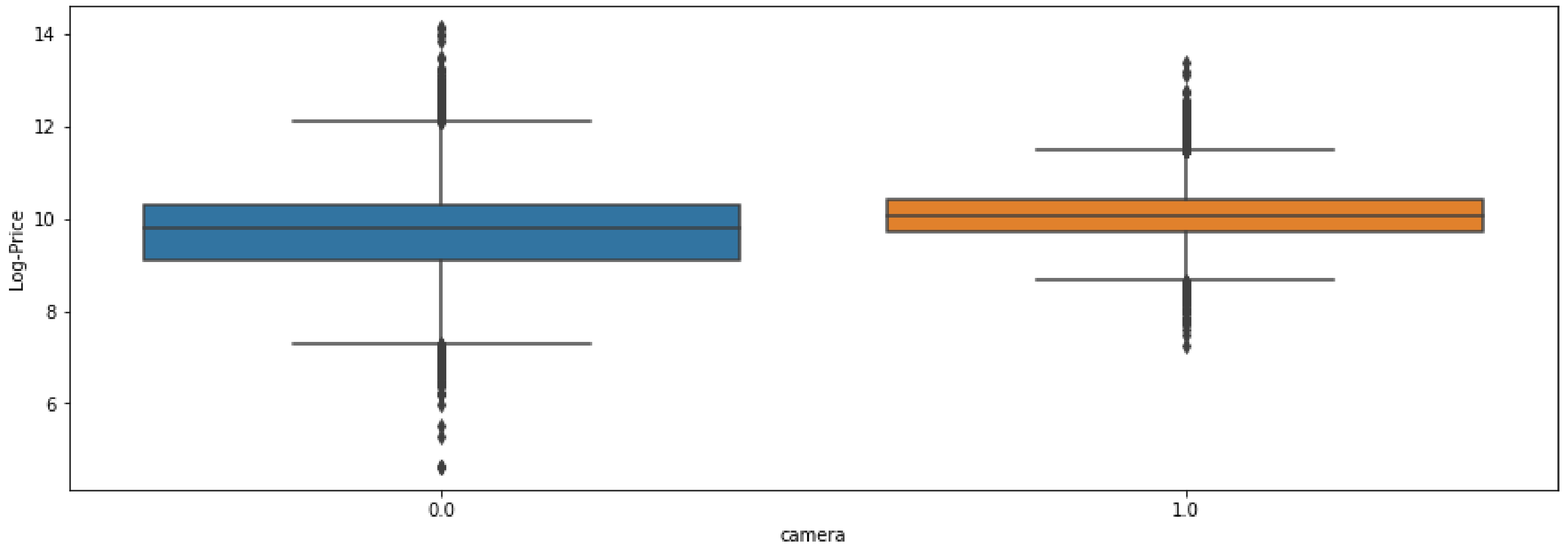
New column: One owner?



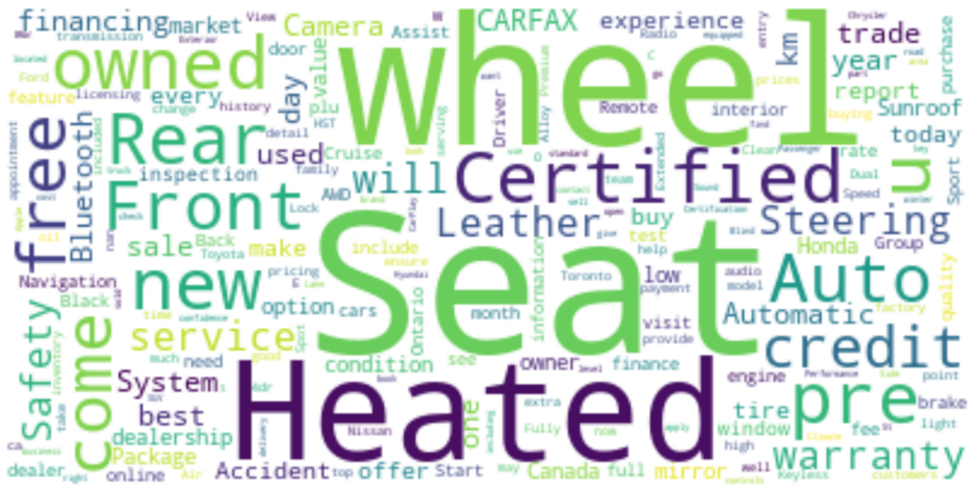


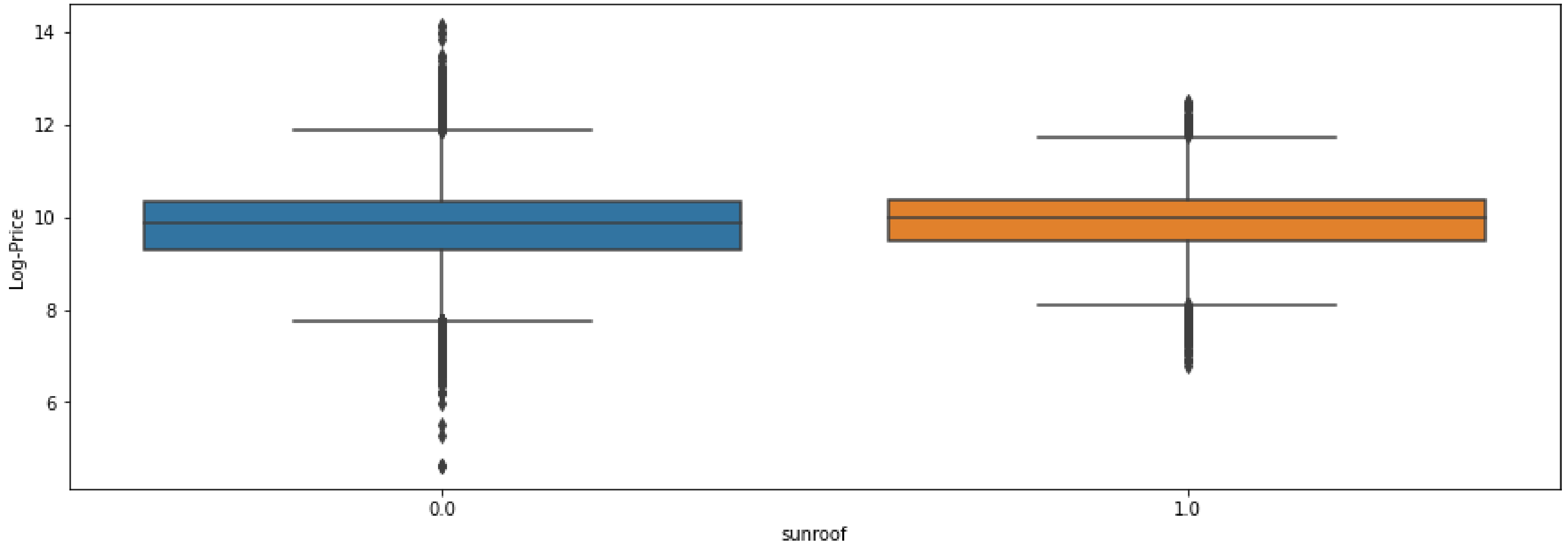
New column: Camera?



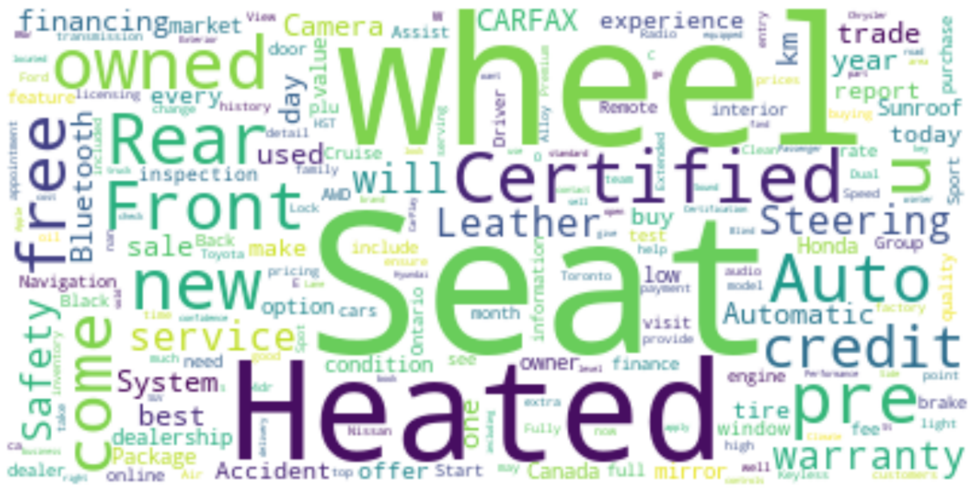


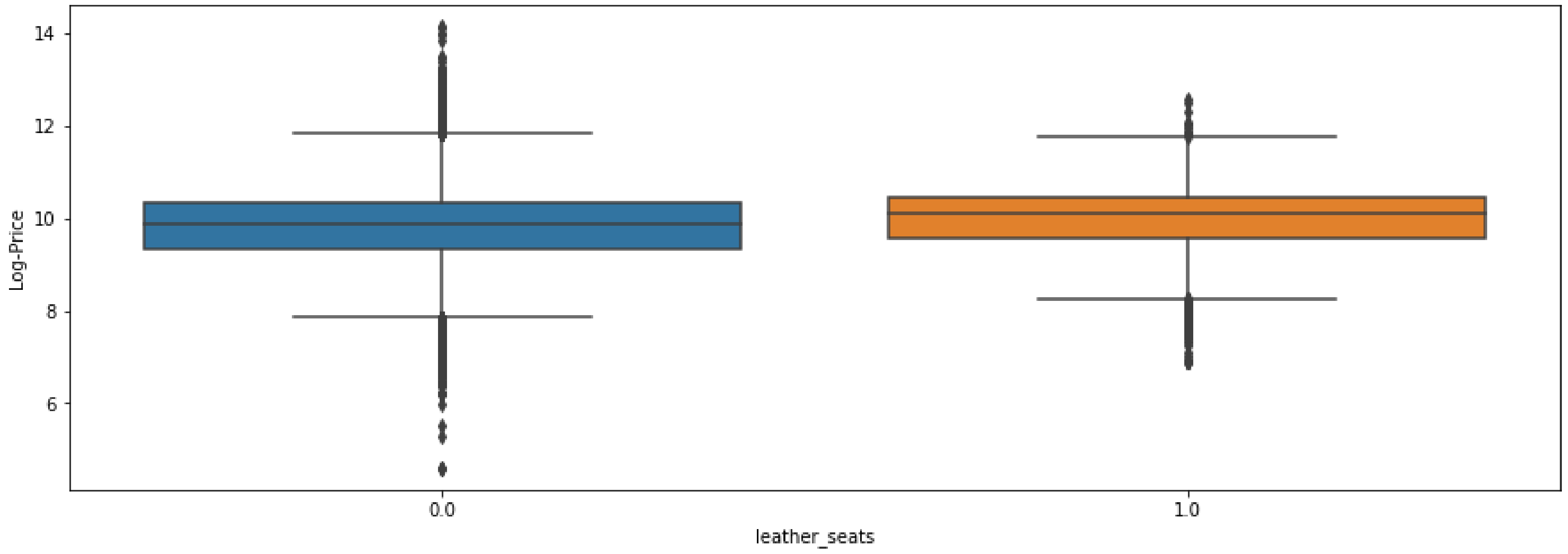
New column: Sunroof?





New column: Leather seats?





What fields are correlated?

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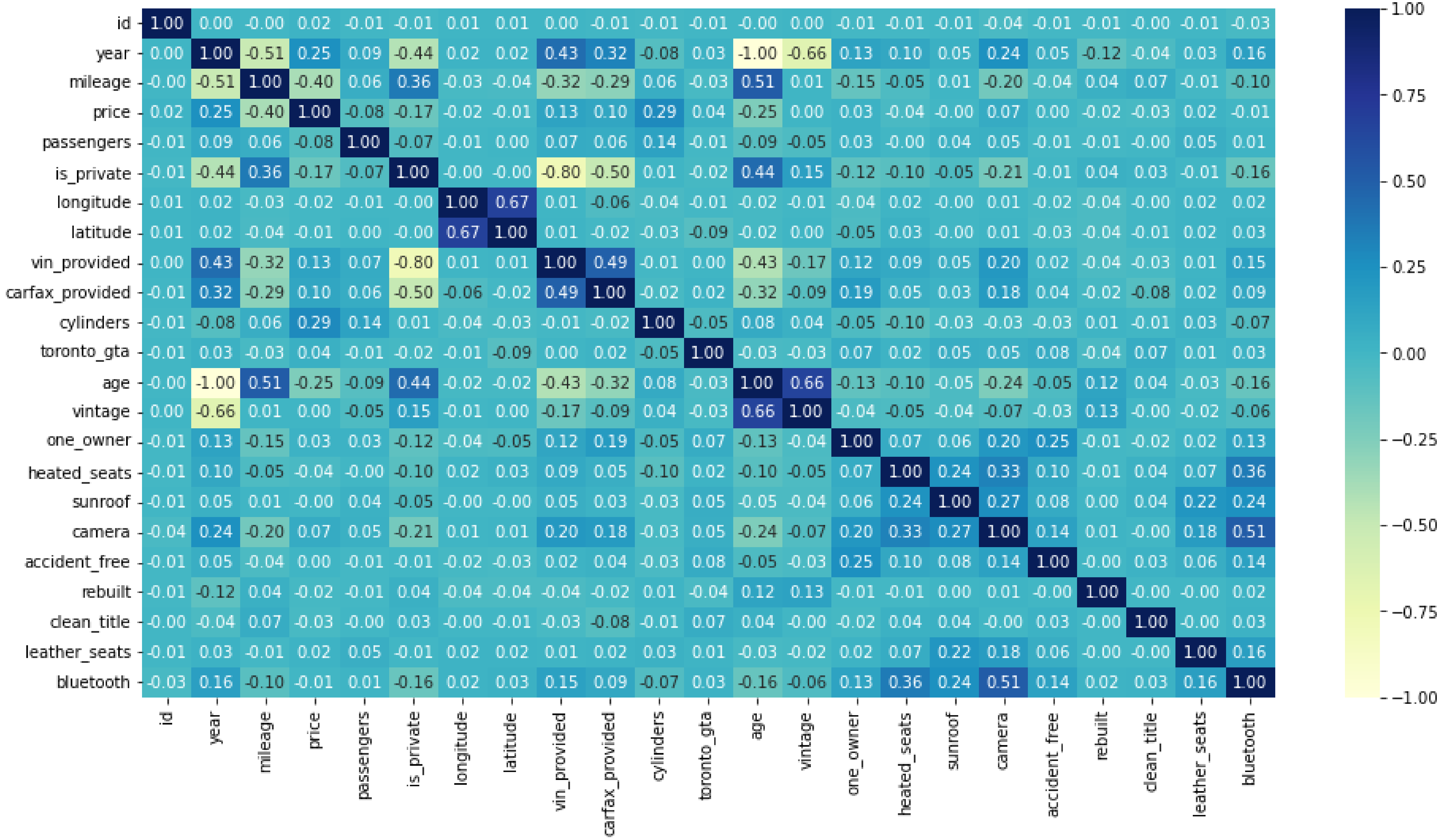

Prediction modelling

Modelling: Preprocessing

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01

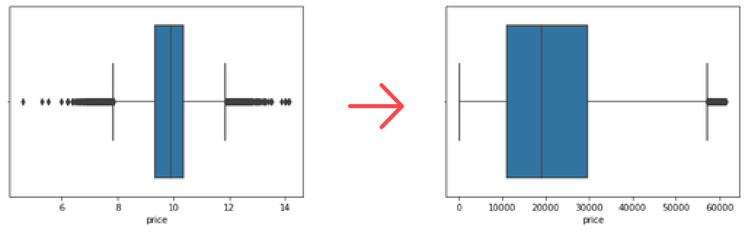
Unnecessary fields removed

- ID,
- first_date_seen
- last_date_seen
- year **(replaced by age)**
- model
- description
- longitude
- latitude
- classifications

02

Outliers removed

- Outlier removed from **price** and **mileage** fields by interquartile range filtering



03

Dummy* variables added (Total fields: 114)

- Make
- Color
- Body type
- Drive train
- Transmission
- Fuel Type

**This method assigns 1s and 0s for each class under variables in question.*

04

Variables scaled for better modelling

- When variables have different scales, it is always helpful to standardize them by subtracting the mean and then scaling to unit variance

05

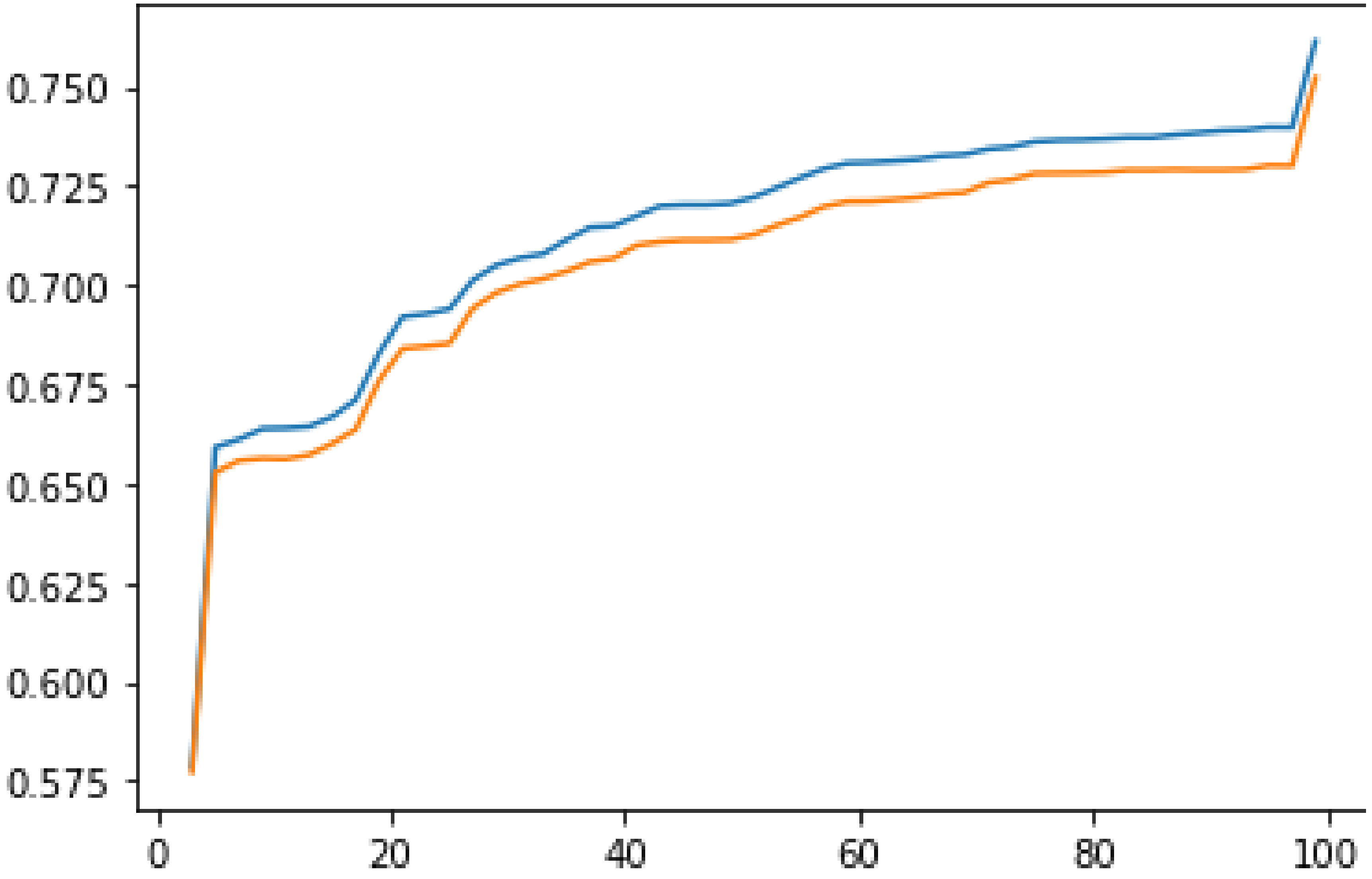
Dataset divided into test, train

- The dataset was divided into subsets, test and train by a ratio of 1/3

Modelling: Feature Selection

- **SelectKBest** from **sklearn** library is used to choose optimal number of variables

- Regression models reach an **R score** of 0.725 with around 60 variables.



Modelling: What features are important?

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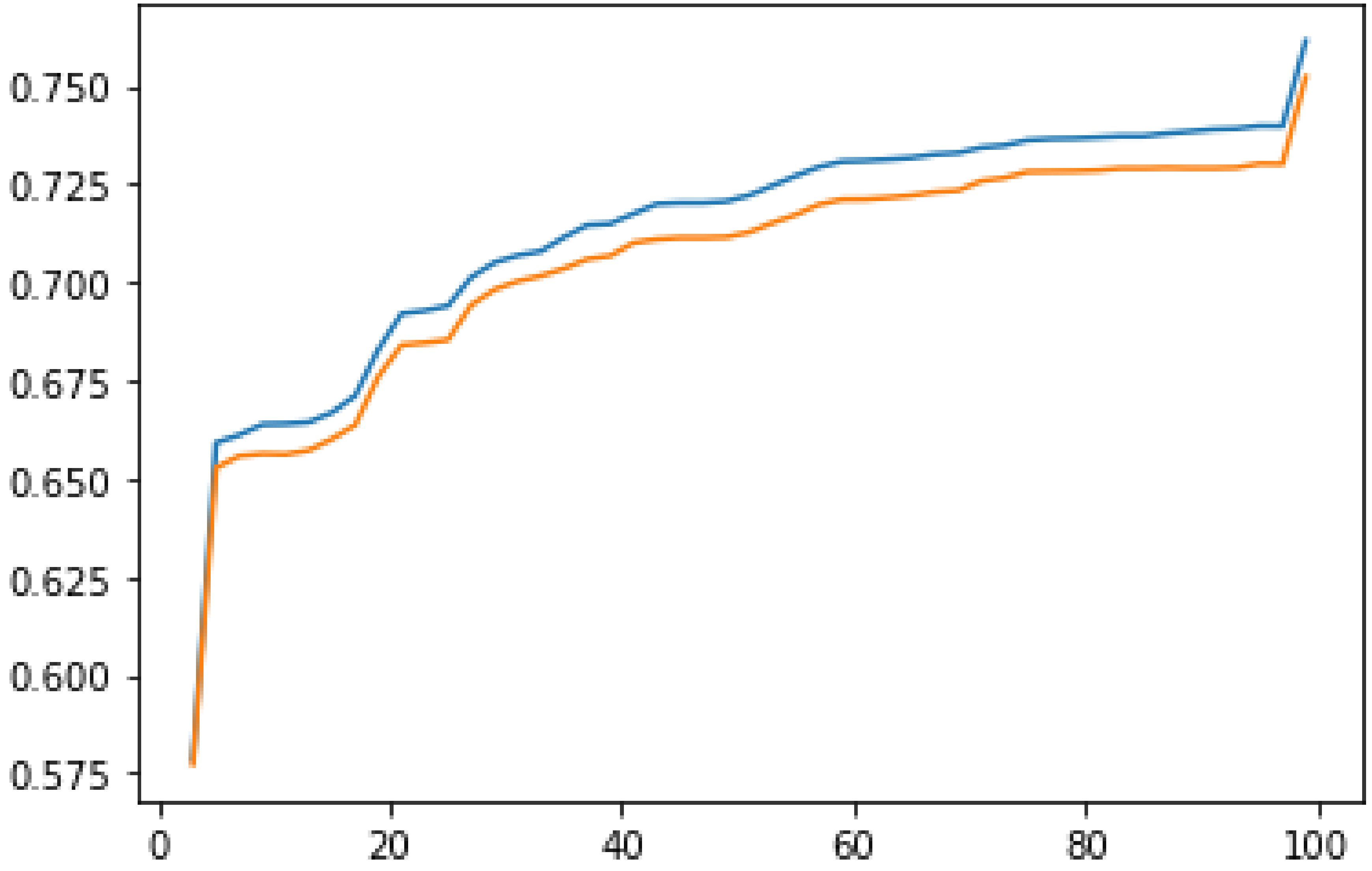
- Mileage
- Passengers
- Is_private
- Vin_provided
- Carfax_provided
- Cylinders
- Age
- One_owner
- Sunroof
- Camera
- Clean title
- Leather seats
- Bluetooth
- Make (24/56)
- Color (8/19)
- Body type
- Drive train
- Transmission
- Fuel Type

- Toronto gta
- Vintage
- Heated_seats
- Accident_free
- Rebuilt
- Make (31/56)
- Color (10)



Modelling: Fitting regression

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- With variables chosen in the earlier step, we fit all the available regression models to see that R score went even higher to 0.877

	Features	Model	Score
0	Linear	LinearRegression()	0.721019
1	Linear	Ridge()	0.721019
2	Linear	Lasso()	-0.000019
3	Linear	SVR()	0.864068
4	Linear	(DecisionTreeRegressor(max_features='auto', ra...	0.877071
5	Linear	MLPRegressor()	0.870174

Bringing all together

- An R score of .877 is a pretty good one. That means our model explains 88% of the price variation on used car prices. However, this is accomplished with a cleaned dataset. Real-life test would show performance better.

- If I had more time, I'd have
  - explored further transformations to increase performance;
  - deployed the model in a user interface with apps like Heroku;
  - been curious to have more historic data and account for COVID's impact on the used car market;
  - done some predictive analysis on Time to Sell;
  - looked for ways to get more recent data with non-expired CARFAX links;
  - explored opportunities to get broader geographical coverage
  - sought domain knowledge.

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Q&A

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