

THE PRICE IS RIGHT

A car pricing exercise by Agata Gramatyka

INTRODUCTION

- Selling or buying a car is one of the largest transactions most people make in their lives
- Over 70% of all cars sold in France are second-hand
- → In 2016 alone, 5.6 million of them exchanged hands
- Finding the right price can be tricky, despite some guidance from websites like Argus
- → Being able to determine the true value is also important for insurers
- Machine Learning can help determine the price in a more accurate and transparent way

THE DATASET

- → 371,500 car sale ads scraped from German ebay in 2016
- Available from Kaggle (https://www.kaggle.com/orgesleka/used-cars-database)
- → Good level of detail across 13 columns of data including:
 - > Car make and model
 - > Month and year of registration
 - Mileage
 - > Brake horsepower
 - > Transmission
 - Body and fuel type
 - > Presence of unrepaired damage
 - > Sale price

Missing values: count by variable

name	0
seller	0
price	13320
vehicleType	37869
yearOfRegistration	0
gearbox	20209
powerPS	0
model	20484
kilometer	0
monthOfRegistration	0
fuelType	33386
brand	0
notRepairedDamage	72060

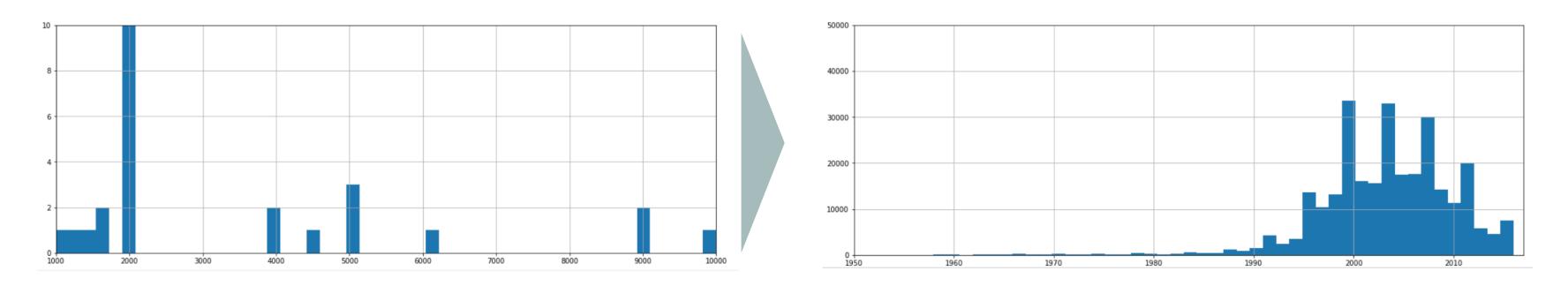
- Missing values: employed techniques
 - 1. Price/Unrepaired Damage: remove all concerned rows
 - 2. Gearbox/Fuel/Body type: impute from most common kind by model
 - 3. Model: extract from the ad title if possible, remove otherwise

A name	
Golf_3_1.6	
A5_Sportback_2.7_Tdi	
Jeep_Grand_Cherokee_ "Overland"	
GOLF_4_1_43T�RER	
Skoda_Fabia_1.4_TDI_ PD_Classic	
BMW_316ie36_Limou sineBastlerfahrze ugExport	

Outliers: extreme or unrealistic values

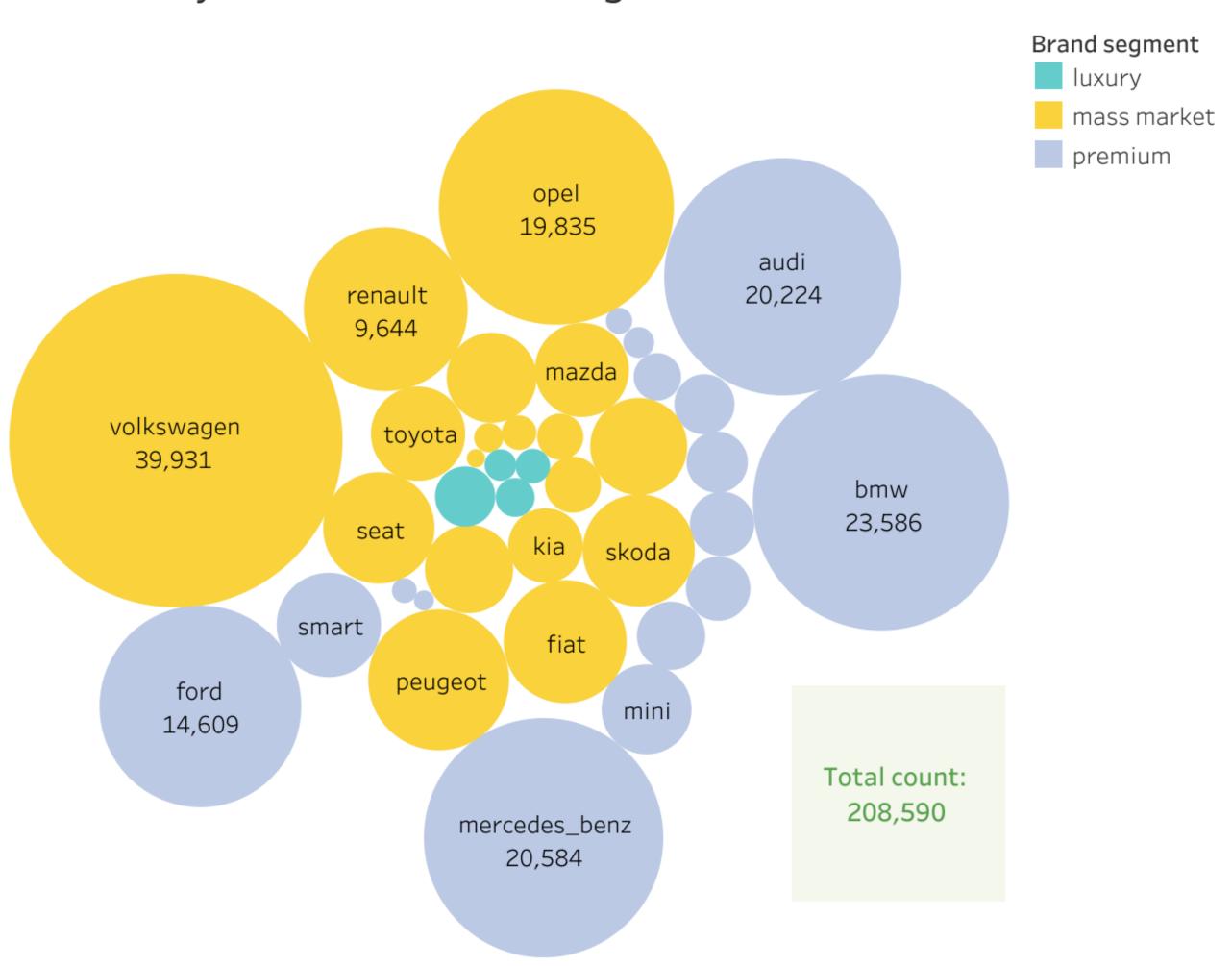
	price	yearOfRegistration	powerPS	kilometer	monthOfRegistration
count	3.715280e+05	371528.000000	371528.000000	371528.000000	371528.000000
mean	1.729514e+04	2004.577997	115.549477	125618.688228	5.734445
std	3.587954e+06	92.866598	192.139578	40112.337051	3.712412
min	0.000000e+00	1000.000000	0.000000	5000.000000	0.000000
25%	1.150000e+03	1999.000000	70.000000	125000.000000	3.000000
50%	2.950000e+03	2003.000000	105.000000	150000.000000	6.000000
75%	7.200000e+03	2008.000000	150.000000	150000.000000	9.000000
max	2.147484e+09	9999.000000	20000.000000	150000.000000	12.000000

- Outliers: employed techniques
 - 1. Year of registration: remove where <1950 and >2016 (further narrowed down to 2000-2016)

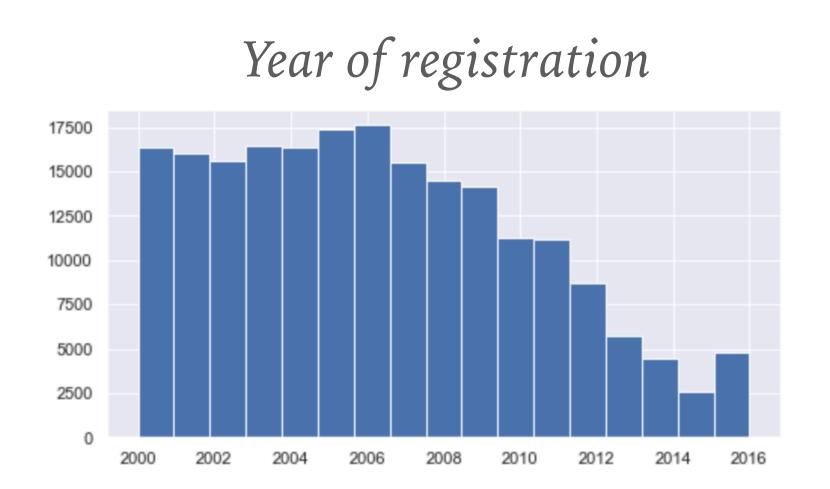


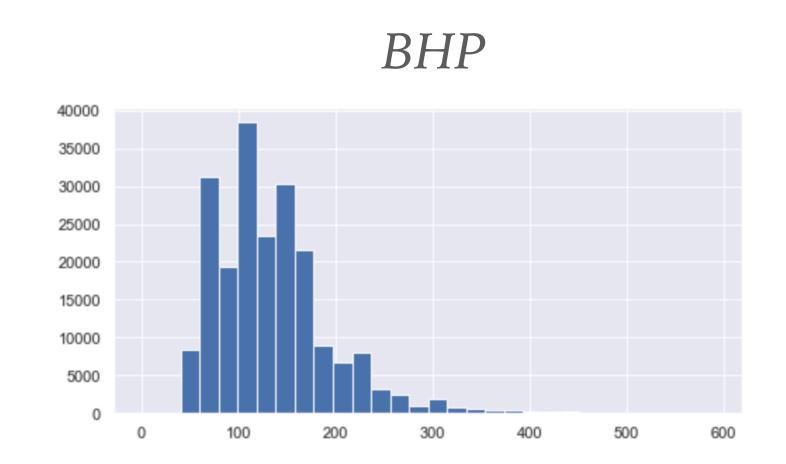
- 2. Price: remove where <100€ and >100,000€
- 3. BHP: replace all zero and >600 observations with a mean for the given model
 - Size of dataset brought down to 208,590 records

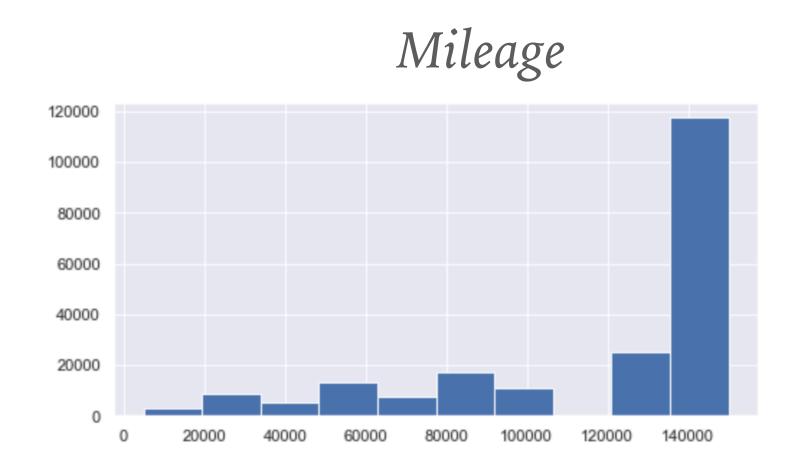
Dataset by brand and market segment

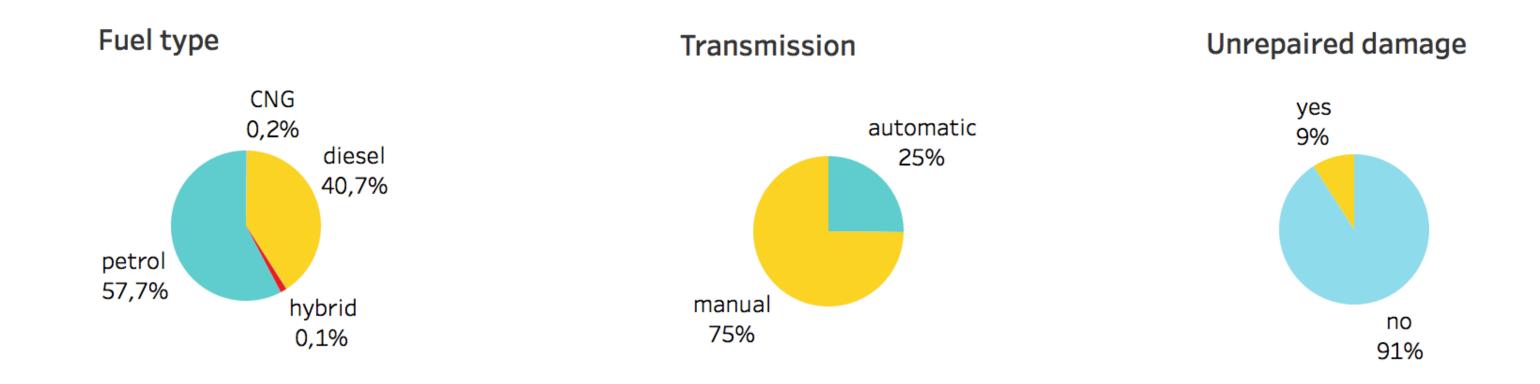


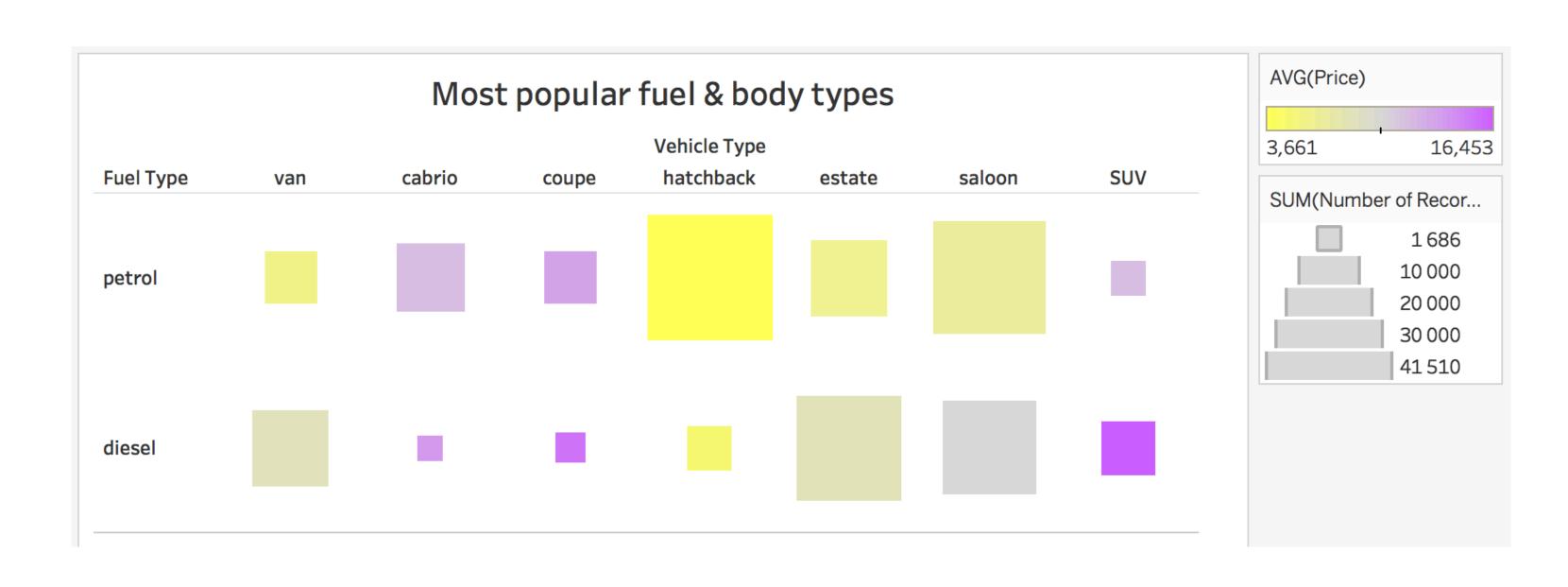


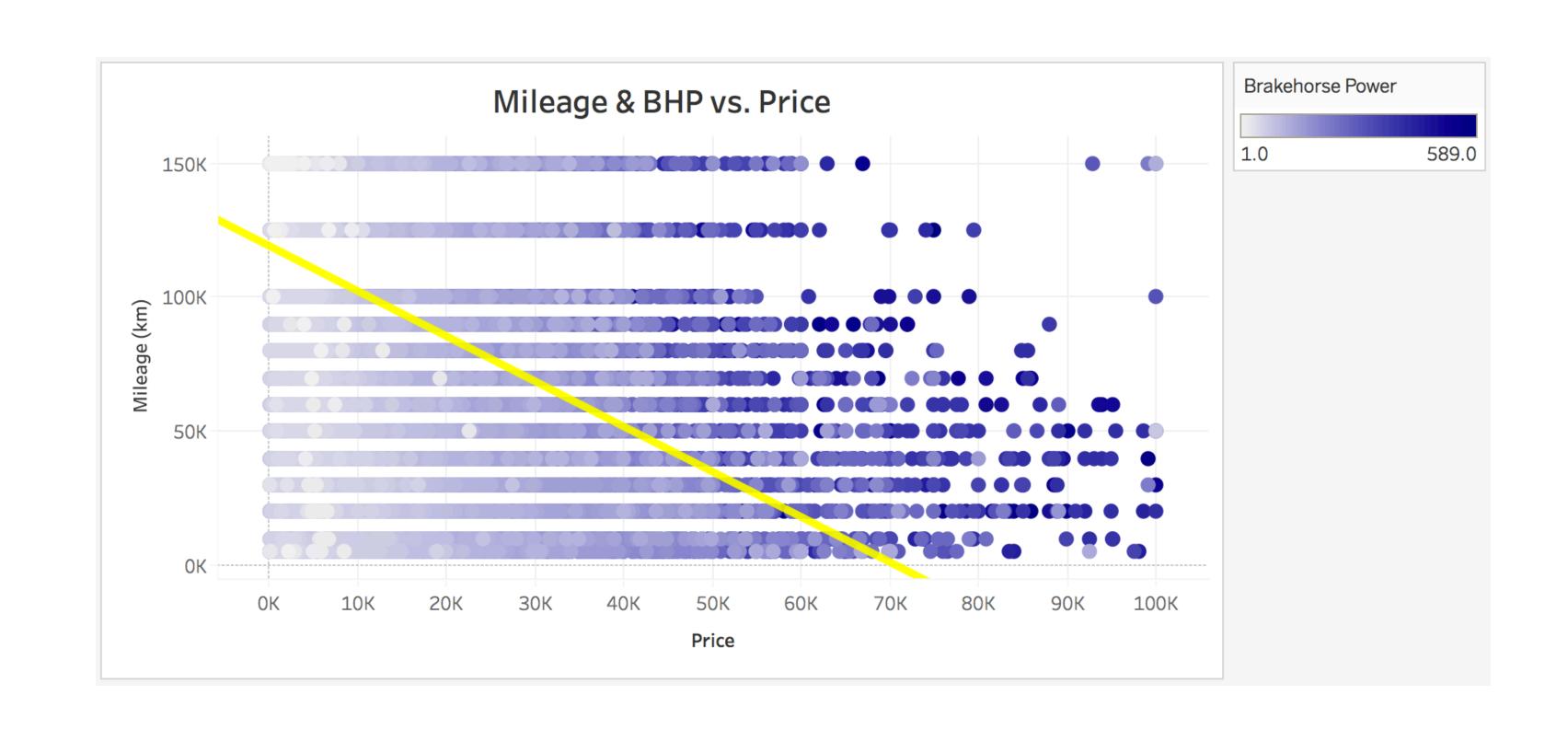


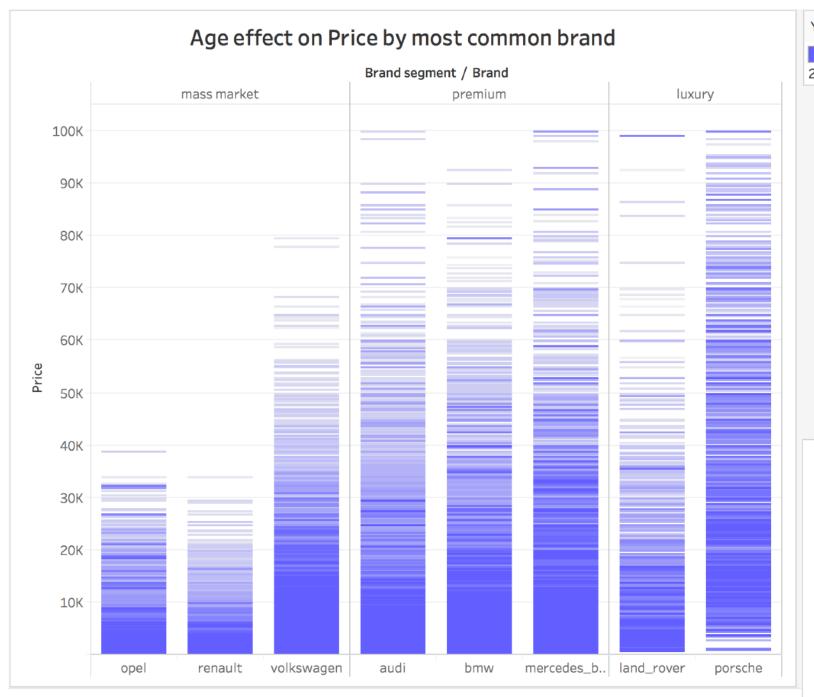


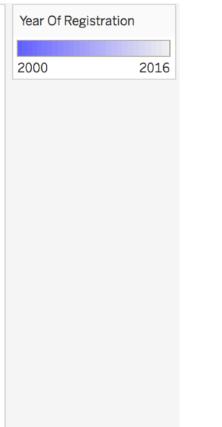


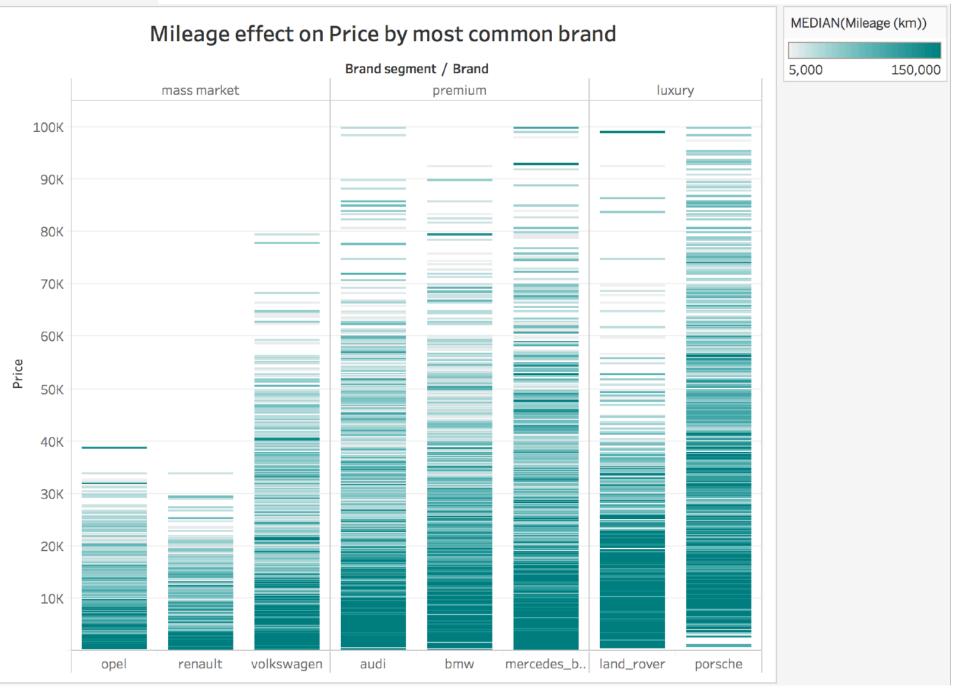




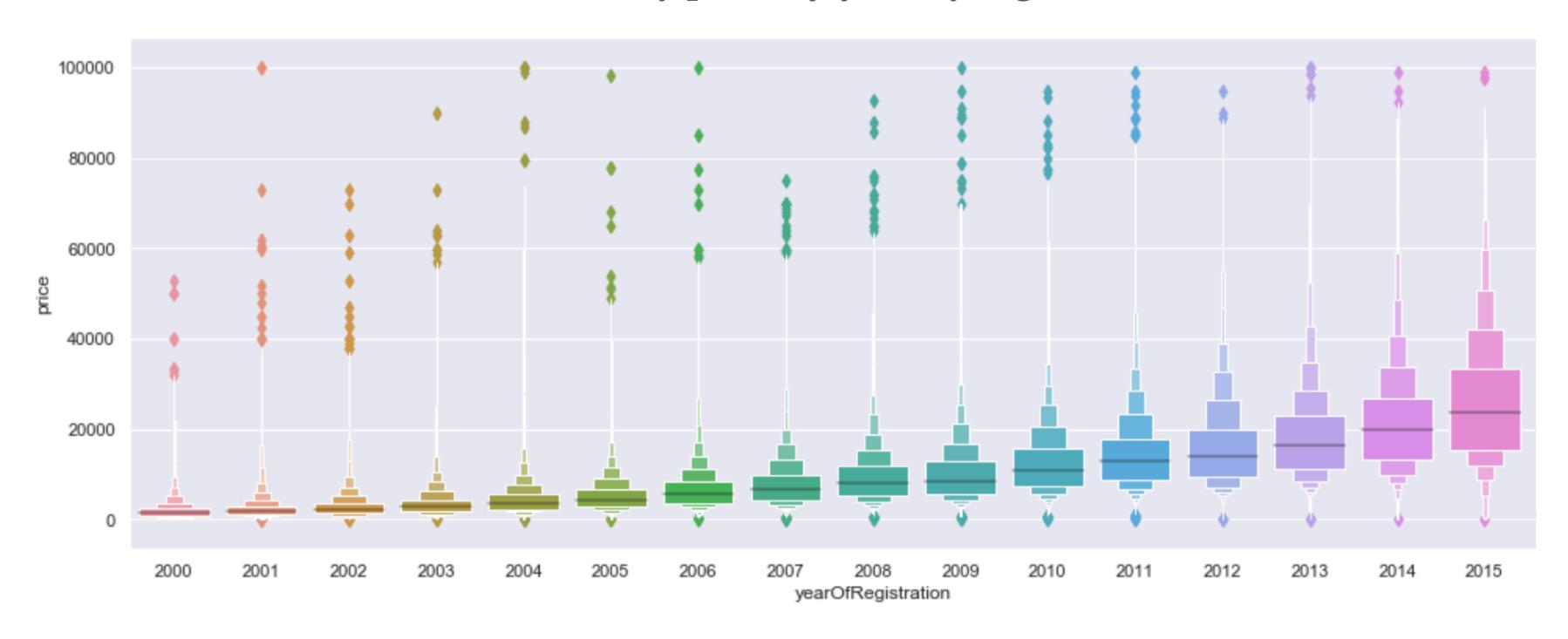




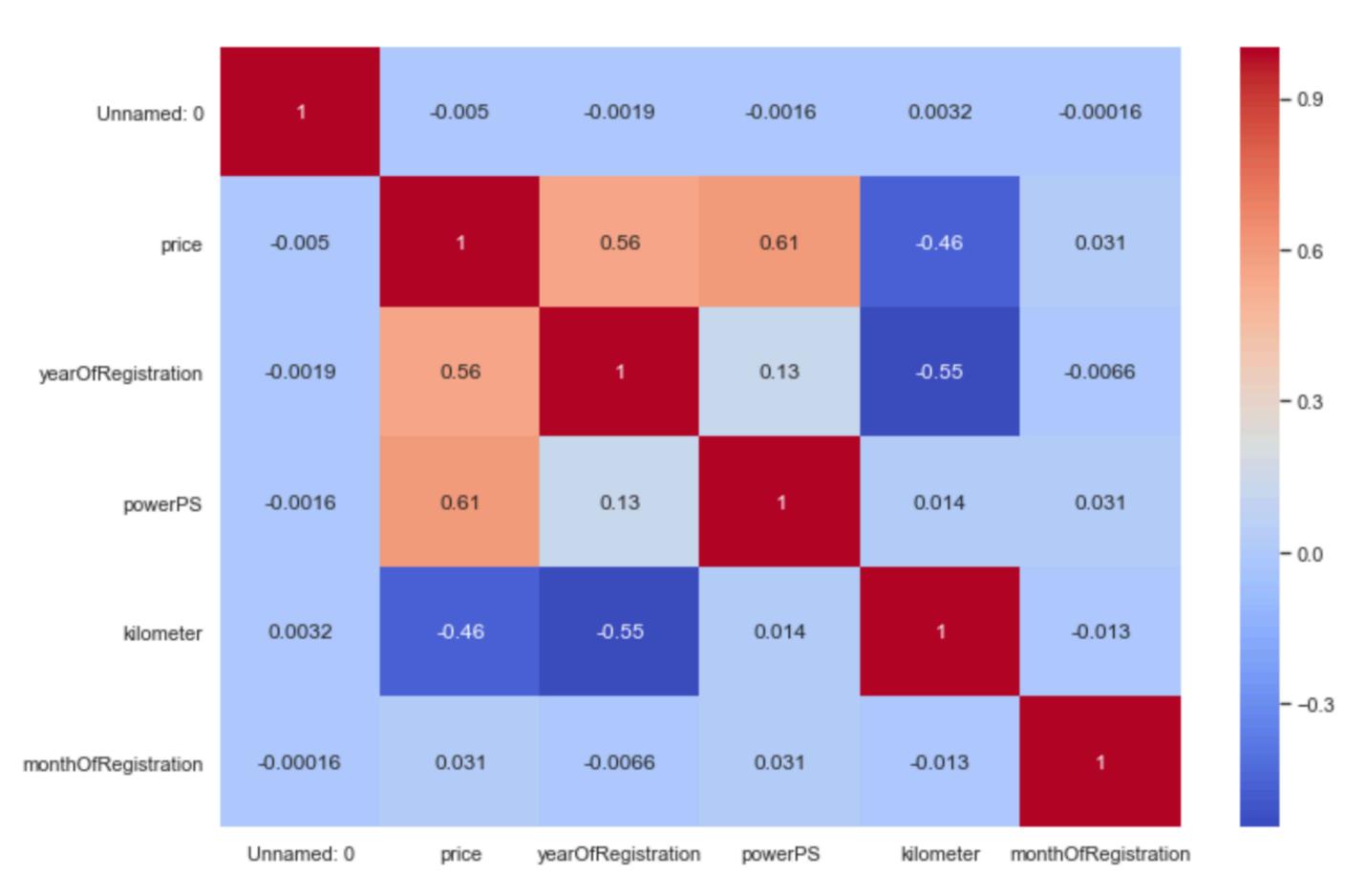




Distribution of price by year of registration



Correlations between variables



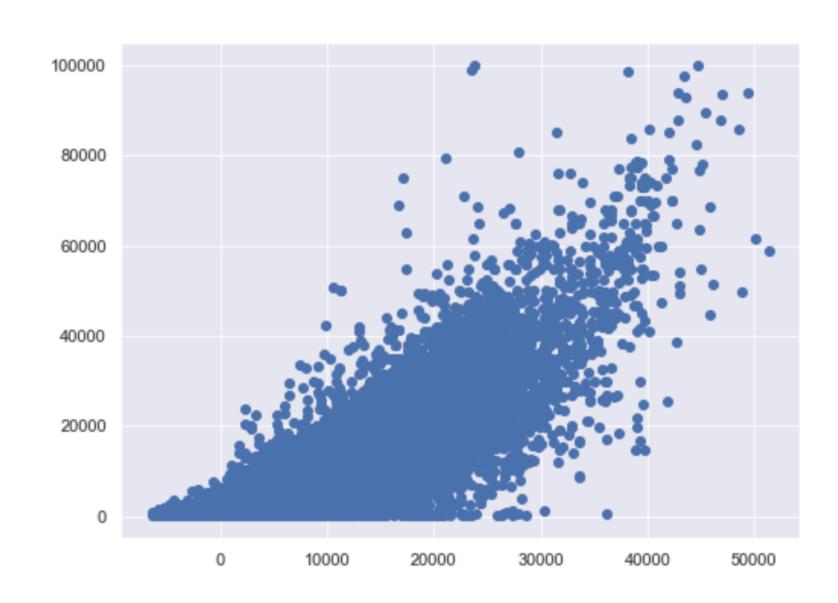
STEP 3: MODELLING

- → The applied Multiple Linear Regression model takes into account all key variables
- The brands were split into three market segments: mass market, premium and luxury
- → The R-squared is 0.70 which indicates good fit
- → The weight of the respective coefficients confirms the trends and influences observed through visual analysis of the dataset

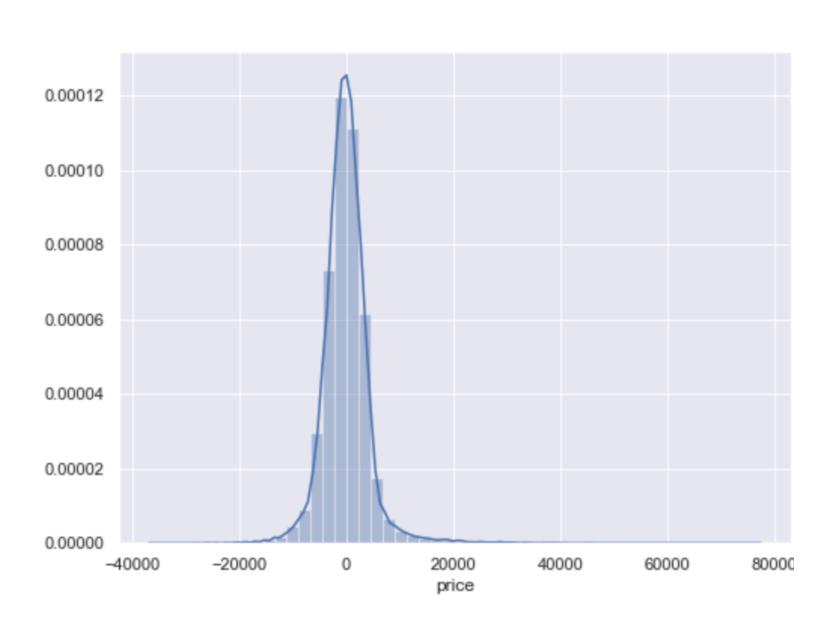
Independent variable	Coefficient		
Intercept	11428		
brake horsepower	64		
mileage (km)	-0,06		
Age (years)	-578		
unrepaired damage	-2063		
<u>Brand segment</u>			
luxury	8396		
premium	568		
mass market	0		
<u>Body type</u>			
cabriolet	1774		
coupe	1179		
SUV	783		
van	493		
hatchback	290		
saloon	-463		
estate	-829		
<u>Transmission</u>			
automatic	0		
manual	-784		
<u>Fuel type</u>			
hybrid	2202		
diesel	1990		
petrol	0		
elektro	-706		
lpg	-1118		

STEP 3: MODELLING

Predicted vs. observed price



Error distribution



STEP 3: MODELLING

→ Now let's sell your car!



THANK YOU