# Principles of Data Science

## Name: Revati Jaidatta Chavare (22533031)

## Section-1 Data Understanding and exploration

*Importing required libraries..*

In [390]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%config InlineBackend.figure_format='retina'
sns.set(
    rc={ "figure.figsize": (14,6) },
    style="ticks", context="notebook", font_scale=1.2
)
```

*Loading dataset and storing it into 'advert'*

In [391]:

```
advert=pd.read_csv('adverts.csv')
```

In [392]:

```
advert.head(5)
```

Out[392]:

| | public_reference | mileage | reg_code | standard_colour | standard_make | standard_model | vehicle_condition | year_of_registration | price | body_type | cros |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 202006039777689 | 0.0 | NaN | Grey | Volvo | XC90 | NEW | NaN | 73970 | SUV | |
| **1** | 202007020778260 | 108230.0 | 61 | Blue | Jaguar | XF | USED | 2011.0 | 7000 | Saloon | |
| **2** | 202007020778474 | 7800.0 | 17 | Grey | SKODA | Yeti | USED | 2017.0 | 14000 | SUV | |
| **3** | 202007080986776 | 45000.0 | 16 | Brown | Vauxhall | Mokka | USED | 2016.0 | 7995 | Hatchback | |
| **4** | 202007161321269 | 64000.0 | 64 | Grey | Land Rover | Range Rover Sport | USED | 2015.0 | 26995 | SUV | |

In [393]:

```
advert.columns
```

Out[393]:

```
Index(['public_reference', 'mileage', 'reg_code', 'standard_colour',
       'standard_make', 'standard_model', 'vehicle_condition',
       'year_of_registration', 'price', 'body_type', 'crossover_car_and_van',
       'fuel_type'],
      dtype='object')
```

In [394]:

```
advert.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 402005 entries, 0 to 402004
Data columns (total 12 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   public_reference       402005 non-null  int64
 1   mileage                401878 non-null  float64
 2   reg_code               370148 non-null  object
 3   standard_colour        396627 non-null  object
 4   standard_make          402005 non-null  object
 5   standard_model         402005 non-null  object
 6   vehicle_condition      402005 non-null  object
 7   year_of_registration   368694 non-null  float64
 8   price                  402005 non-null  int64
 9   body_type              401168 non-null  object
 10  crossover_car_and_van  402005 non-null  bool
 11  fuel_type              401404 non-null  object
dtypes: bool(1), float64(2), int64(2), object(7)
memory usage: 34.1+ MB
```

### 1.1 Identifying missing/ null values

*Checking for null values in the raw dataset, using isna() function and sum() function to get the total number of null values in each column.*

In [395]:

```
advert.isna().sum()
```

Out[395]:

```
public_reference            0
mileage                   127
reg_code                31857
standard_colour          5378
standard_make               0
standard_model              0
vehicle_condition           0
year_of_registration    33311
price                       0
body_type                 837
crossover_car_and_van       0
fuel_type                 601
dtype: int64
```

*Here, we can see mileage, reg_code, standard_colour, year_of_registration, body_type and fuel_type contains null values.*

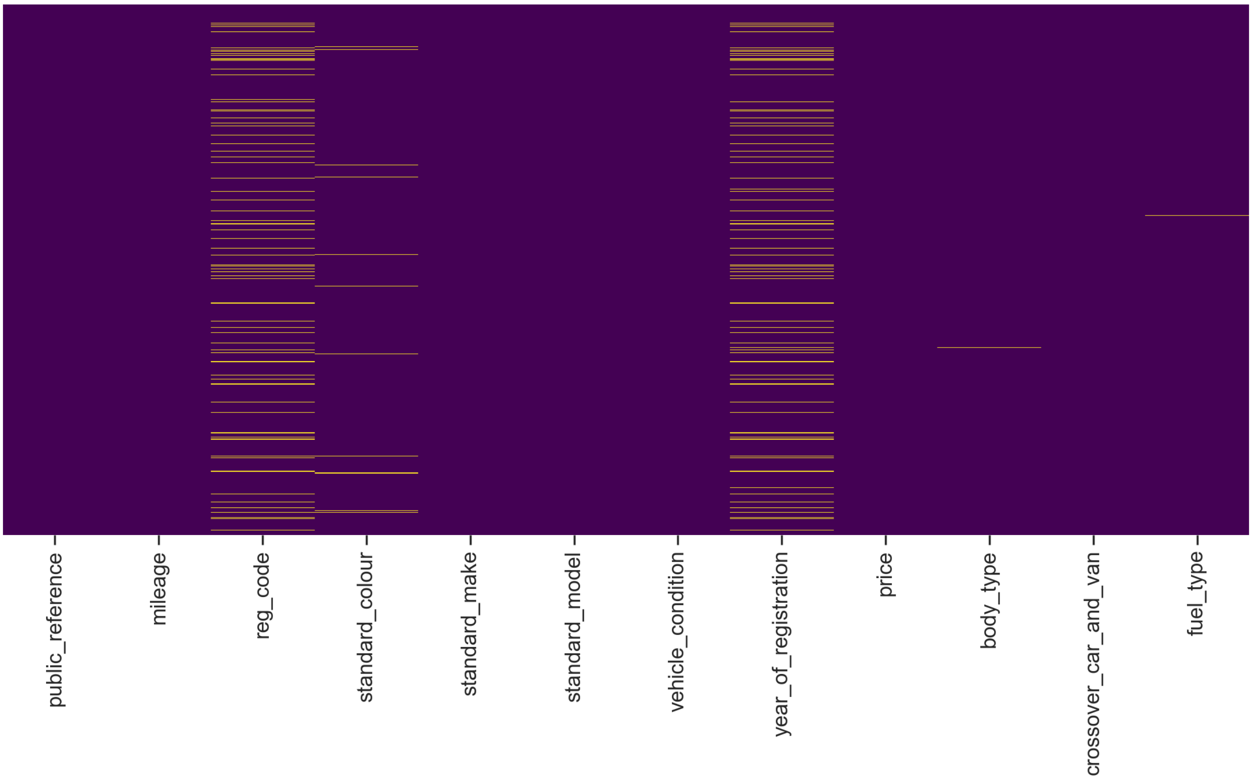
*Using heatmap to visualise null values in the dataset.*

In [396]:

```
sns.heatmap(advert.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[396]:

```
<AxesSubplot:>
```




### 1.2 Identifying outliers or noise

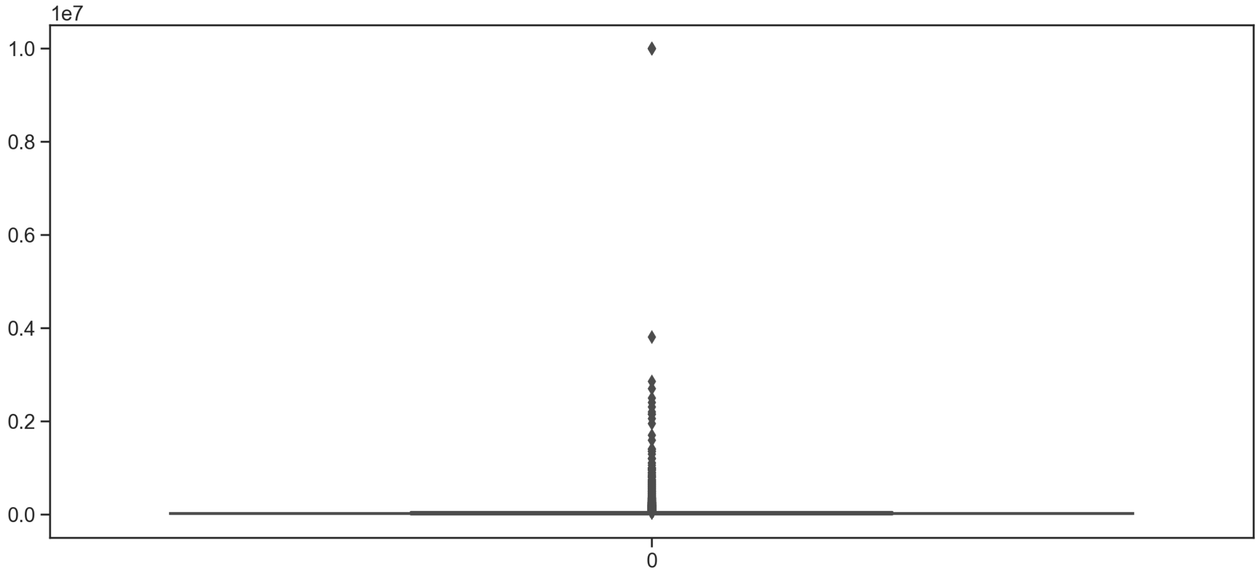
*An outlier is a distant observation in the dataset, it basically falls outside of the usual observation and can be easily spotted using boxplot or scatterplot. Here, we are looking for outliers in price, mileage and year of registration using boxplot and scatterplot respectively.*

In [397]:

```
sns.boxplot(data=advert['price'])
```

Out[397]:

```
<AxesSubplot:>
```

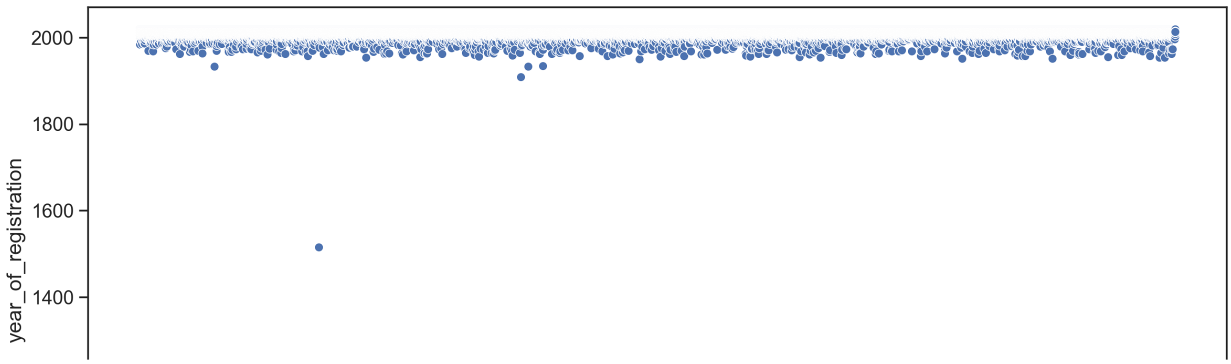



In [398]:

```
sns.scatterplot(data=advert['year_of_registration'])
```

Out[398]:

```
<AxesSubplot:ylabel='year_of_registration'>
```

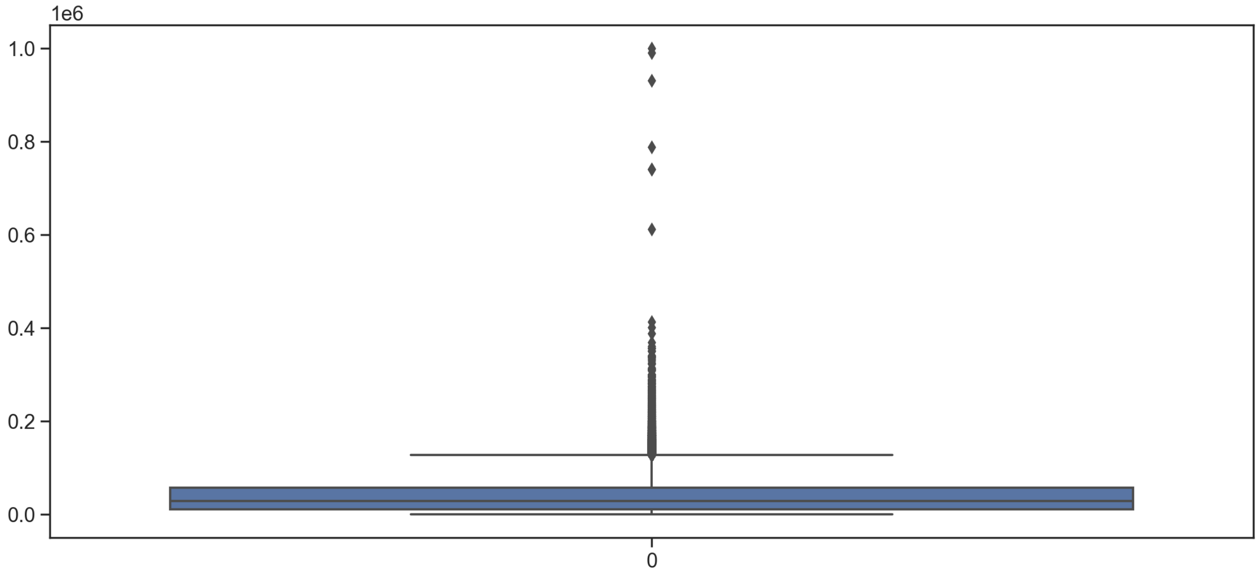


In [399]:

```
sns.boxplot(data=advert['mileage'])
```

Out[399]:

```
<AxesSubplot:>
```




*After carefully observing the plots we are now sure that there are outliers in mileage, price and year of registration and we'll have to deal with it in further steps.*

### 1.3 Identifying features

```
Features considered:

Numerical Features:
1. Mileage
2. Year of registration

Categorical Features:
1. Vehicle condition
2. Body type
3. Fuel type
```

*Many features in the dataset are not that important and we can drop those features, and work only on potential features to predict the price of a car.*

In [400]:

```
advert.columns
```

Out[400]:

```
Index(['public_reference', 'mileage', 'reg_code', 'standard_colour',
       'standard_make', 'standard_model', 'vehicle_condition',
       'year_of_registration', 'price', 'body_type', 'crossover_car_and_van',
       'fuel_type'],
      dtype='object')
```

In [401]:

```
advert.corr()['price']
```

Out[401]:

```
public_reference        -0.052344
mileage                 -0.160204
year_of_registration     0.102341
price                    1.000000
crossover_car_and_van    0.010402
Name: price, dtype: float64
```

*A quick look at the correlation between price and other numerical features in the datset. This clearly shows that year -of_registration could play a vital role in determining the price of a car, it has a significantly high correlation with price comparative to other features.*

In [459]:

```
Total_no_of_cars=advert.groupby(['standard_make','standard_model']).size().reset_index().rename(columns={0:'Total number of cars'})
```

In [460]:

```
Total_no_of_cars
```

Out[460]:

| | standard_make | standard_model | Total number of cars |
|---|---|---|---|
| **0** | AC | Cobra | 3 |
| **1** | AK | Cobra | 1 |
| **2** | Abarth | 124 Spider | 61 |
| **3** | Abarth | 500 | 109 |
| **4** | Abarth | 500C | 27 |
| **...** | ... | ... | ... |
| **1212** | Westfield | Se | 1 |
| **1213** | Westfield | Sei | 1 |
| **1214** | Westfield | Sport | 1 |
| **1215** | Wolseley | 6/110 | 1 |

*Using group_by() function, here we got the total number of cars of each standard_make and standard_model in the dataset.*

## Section-2 Data processing

### 2.1 Handling missing/ null values

*As mentioned earlier, we can drop some features and work on potential fetaures. So, here we are dropping public_reference, reg_code, standard_colour,standard_make,standard_model and crossover_car_and_van. Features we are dealing with:*

1. Mileage
2. Vehicle condition
3. Year of registration
4. Body type
5. Fuel type

   We are working on to predict the price of a car, so price is our target and all above mentioned fetaures are predictors.

In [410]:

```
t=advert.drop(columns=['public_reference','reg_code','standard_colour','standard_make','standard_model','crossover_car_and_van'], axis=1)
```

In [411]:

```
sample_advert.isna().sum()
```

Out[411]:

```
mileage                  127
vehicle_condition          0
year_of_registration   33311
price                      0
body_type                837
fuel_type                601
dtype: int64
```

*Above code shows the sum of null values in our potential features, so now we'll deal with the missing values in those features. Data is important and we can't afford loosing any of it. However we are not using drop() function neither to drop a column nor a row.*

1. For Mileage, year of registration and price we are replacing the null values with the mean of the entire column using fillna() and mean() function.

In [412]:

```
sample_advert['mileage']=sample_advert['mileage'].fillna(sample_advert.mileage.mean())
```

In [413]:

```
sample_advert['year_of_registration']=sample_advert['year_of_registration'].fillna(sample_advert.year_of_registration.mean()).astype(int)
```

In [414]:

```
sample_advert['price']=sample_advert['price'].fillna(sample_advert.price.mean())
```

2. To deal with missing values in body_type and fuel_type, we have replaced the null values with the maximum number of onservations in that columns. For eg. In case of body_type, maximum number of body_type is 'Hatchback', so we have replaced it with 'Hatchback'.

In [415]:

```
sample_advert['body_type'].value_counts()
```

Out[415]:

```
Hatchback          167315
SUV                115872
Saloon              36641
Estate              24692
Coupe               23258
Convertible         16038
MPV                 16026
Pickup                620
Combi Van             214
Limousine             159
Minibus               149
Camper                 77
Panel Van              61
Window Van             41
Chassis Cab             3
Car Derived Van         2
Name: body_type, dtype: int64
```

In [416]:

```
sample_advert['body_type']=sample_advert['body_type'].fillna("Hatchback")
```

In [417]:

```
sample_advert['fuel_type'].value_counts()
```

Out[417]:

```
Petrol                    216929
Diesel                    158120
Petrol Hybrid              13602
Petrol Plug-in Hybrid       6160
Electric                    4783
Diesel Hybrid               1403
Bi Fuel                      221
Diesel Plug-in Hybrid        185
Natural Gas                    1
Name: fuel_type, dtype: int64
```

In [418]:

```
sample_advert['fuel_type']=sample_advert['fuel_type'].fillna("Petrol")
```

In [419]:

```
sample_advert.isna().sum()
```

Out[419]:

```
mileage                 0
vehicle_condition       0
year_of_registration    0
price                   0
body_type               0
fuel_type               0
dtype: int64
```

*Now, as we can see all the missing values are removed.*

### 2.2 Handling outliers

*To deal with the outliers, we can use two techniques Z-score and Interquantile range (IQR).*

IQR= Q3-Q1 It is basically the first quartile subtracted from the third quartile and measures the dispersion similar to standard deviation.

*Here we are dealing with the outliers in year_of_registration.*

In [420]:

```
sample_advert['year_of_registration'].describe()
```

Out[420]:

```
count    402005.000000
mean       2015.005691
std           7.625632
min         999.000000
25%        2014.000000
50%        2016.000000
75%        2018.000000
max        2020.000000
Name: year_of_registration, dtype: float64
```

In [421]:

```
upper_boundary=sample_advert['year_of_registration'].mean()+3*sample_advert['year_of_registration'].std()
lower_boundary=sample_advert['year_of_registration'].mean()-3*sample_advert['year_of_registration'].std()
print(lower_boundary),print(upper_boundary),print(sample_advert['year_of_registration'].mean())
```

```
1992.1287952316097
2037.8825877113886
2015.0056914714992
```

Out[421]:

```
(None, None, None)
```

In [422]:

```
IQR=sample_advert.year_of_registration.quantile(0.75)-sample_advert.year_of_registration.quantile(0.25)
```

In [423]:

```
lower_bridge=sample_advert['year_of_registration'].quantile(0.25)-(IQR*1.5)
upper_bridge=sample_advert['year_of_registration'].quantile(0.75)+(IQR*1.5)
print(lower_bridge),print(upper_bridge)
```

```
2008.0
2024.0
```

Out[423]:

```
(None, None)
```

*After using the IQR technique, now we got the minimum and maximum year_of_registration. We can only work on those years.*

In [424]:

```
sample_advert=sample_advert.query("year_of_registration >2007 and year_of_registration<2024")
```

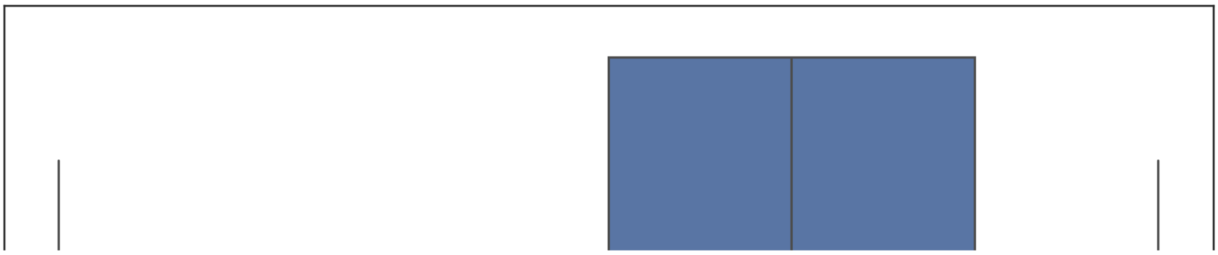
In [426]:

```
sns.boxplot(sample_advert['year_of_registration'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a ke
yword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without
an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[426]:

```
<AxesSubplot:xlabel='year_of_registration'>
```



*The outliers in year_of_registration is removed as seen in the boxplot above.*

In [427]:

```
sample_advert['price'].describe()
```

Out[427]:

```
count    3.786670e+05
mean     1.790488e+04
std      4.693150e+04
min      2.500000e+02
25%      8.000000e+03
50%      1.300000e+04
75%      2.069500e+04
max      9.999999e+06
Name: price, dtype: float64
```

In [428]:

```
upper_boundary=sample_advert['price'].mean()+3*sample_advert['price'].std()
lower_boundary=sample_advert['price'].mean()-3*sample_advert['price'].std()
print(lower_boundary),print(upper_boundary),print(sample_advert['price'].mean())
```

```
-122889.60707963898
158699.36707456858
17904.87999746479
```

Out[428]:

```
(None, None, None)
```

In [429]:

```
IQR=sample_advert.price.quantile(0.75)-sample_advert.price.quantile(0.25)
```

In [430]:

```
lower_bridge=sample_advert['price'].quantile(0.25)-(IQR*1.5)
upper_bridge=sample_advert['price'].quantile(0.75)+(IQR*1.5)
print(lower_bridge),print(upper_bridge)
```

```
-11042.5
39737.5
```

Out[430]:

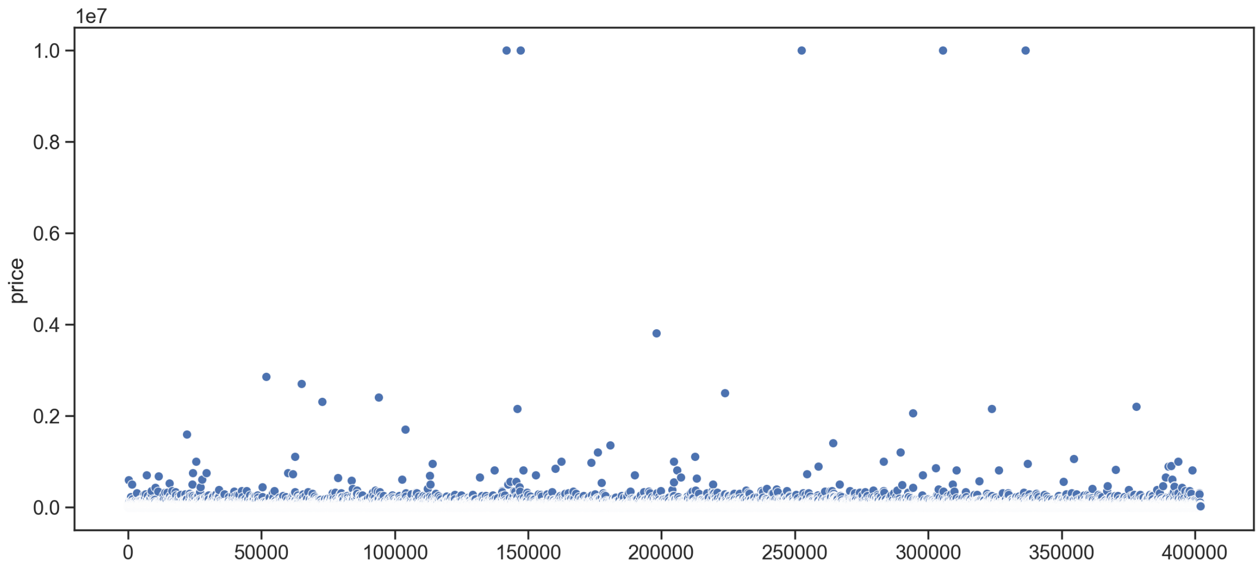
```
(None, None)
```

In [432]:

```
sns.scatterplot(data=sample_advert['price'])
```

Out[432]:

```
<AxesSubplot:ylabel='price'>
```




### 2.3 Feature engineering

In this part, we will be working on converting the categorical data to numeric, to check the correlation between all the features (predictors).

1. Firstly we will scale the data, where it gives structure to data and standardize the range of features of an input data set.

In [433]:

```
from sklearn.preprocessing import StandardScaler
```

In [434]:

```
Scaler=StandardScaler()
```

In [436]:

```
Scaler.fit_transform(sample_advert[['mileage','year_of_registration']])
```

Out[436]:

```
array([[-1.08346843, -0.25340458],
       [ 2.31985881, -1.6303757 ],
       [-0.83819491,  0.43508098],
       ...,
       [ 0.57558678, -1.28613292],
       [-0.76115388, -0.25340458],
       [-0.64323392, -0.59764736]])
```

In [463]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, OrdinalEncoder
oe=OrdinalEncoder()
```

*We are using Ordinal Encoding for vehicle_condition, body_type and fuel_type*

In [464]:

```
sample_advert.vehicle_condition=oe.fit_transform(sample_advert[["vehicle_condition"]]).astype(int)
```

In [465]:

```
sample_advert.body_type=oe.fit_transform(sample_advert[["body_type"]]).astype(int)
```

In [466]:

```
sample_advert.fuel_type=oe.fit_transform(sample_advert[["fuel_type"]]).astype(int)
```

After scaling the data and converting categorical values to numerical we have the dataset as below:

In [441]:

```
sample_advert.head()
```

Out[441]:

| | mileage | vehicle_condition | year_of_registration | price | body_type | fuel_type |
|---|---|---|---|---|---|---|
| **0** | 0.0 | 0 | 2015 | 73970 | 13 | 7 |
| **1** | 108230.0 | 1 | 2011 | 7000 | 14 | 1 |
| **2** | 7800.0 | 1 | 2017 | 14000 | 13 | 5 |
| **3** | 45000.0 | 1 | 2016 | 7995 | 7 | 1 |
| **4** | 64000.0 | 1 | 2015 | 26995 | 13 | 1 |

In [442]:

```
sample_advert.corr()['price']
```

Out[442]:

```
mileage                -0.152224
vehicle_condition      -0.095481
year_of_registration    0.118914
price                   1.000000
body_type               0.043248
fuel_type               0.018249
Name: price, dtype: float64
```

Now again, checking the correlation between all the features (predictors) and price (target). Year_of_registration, body_type and fuel type shows positive and correlation, while mileage shows the least.

## Section-3 Analysis

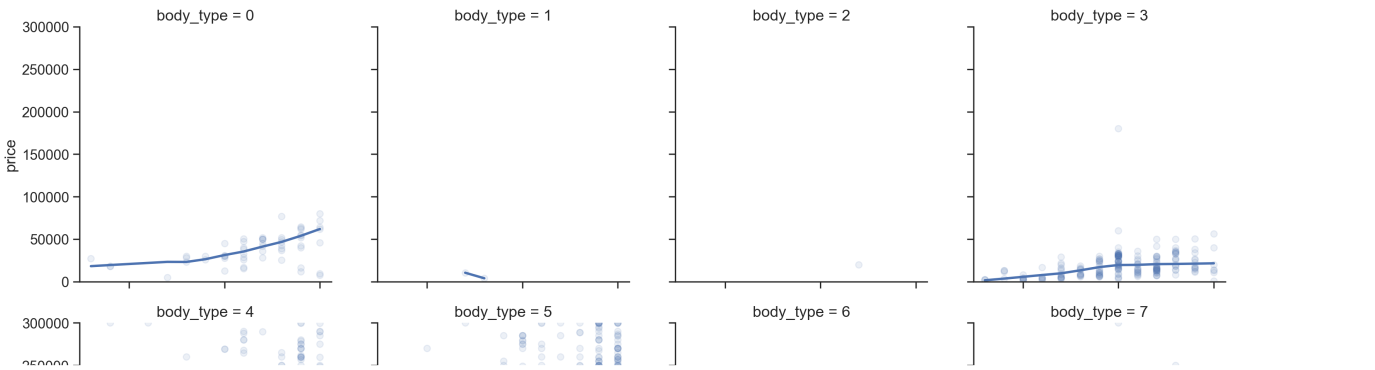
### 1.1 Quantitative - Quantitative analysis

In [469]:

```
sns.lmplot(
    data=sample_advert, x='year_of_registration', y='price',col='body_type', col_wrap=4,
    scatter_kws=dict(alpha=0.1), height=4, lowess=True).set(ylim=(0,300000))
```

Out[469]:

```
<seaborn.axisgrid.FacetGrid at 0x216e4f8d670>
```




Observations:

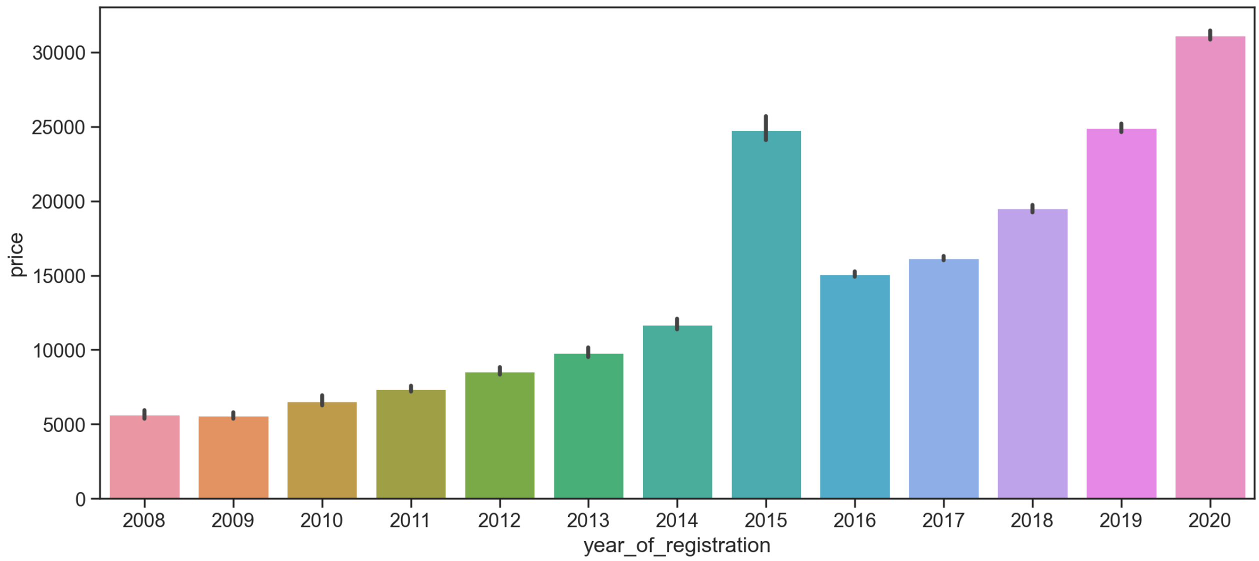
1. Respective to body_type the price of a car increases/ decreases along with the year_of_registration.
2. Body type 8 has a huge spike in the price in the year between 2018-19.
3. On the other hand, body type 3 has a fall in the price has the year increased.

In [447]:

```
sns.barplot(data=sample_advert, x='year_of_registration',y='price')
```

Out[447]:

```
<AxesSubplot:xlabel='year_of_registration', ylabel='price'>
```




Observations:

1. Price increases as year of registration increases.
2. Spike in price in year 2015.

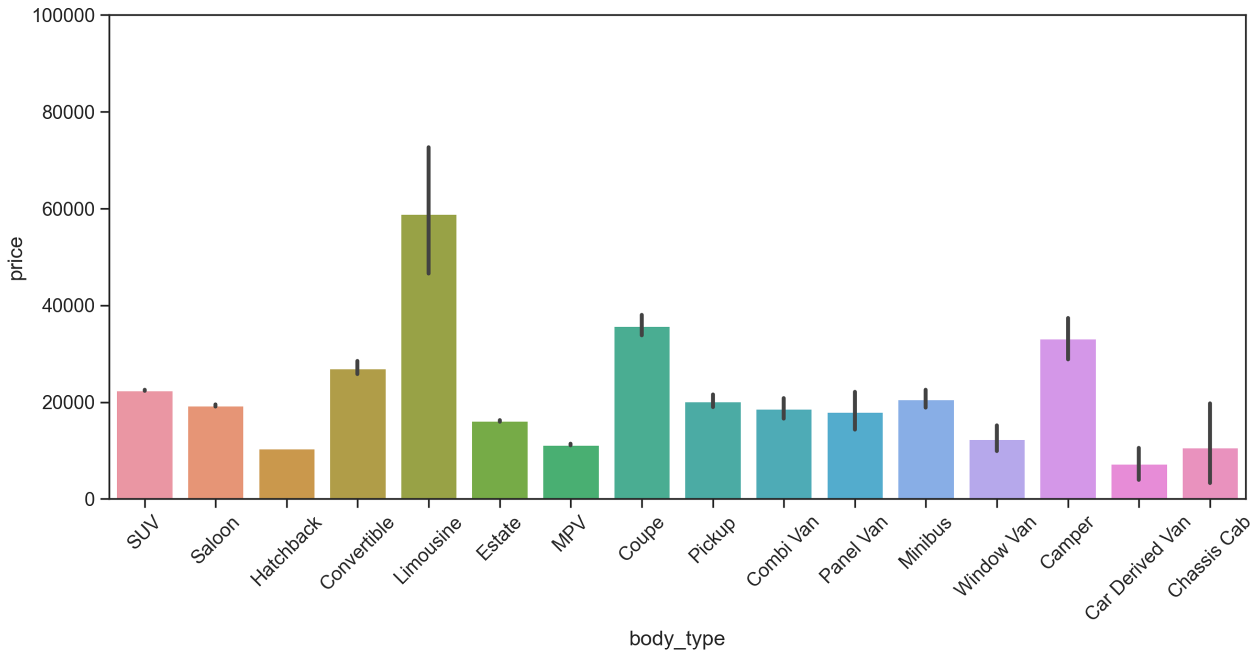
### 3.2 Quantitative-Categorical analysis

In [352]:

```
price_bodytype=sns.barplot(data=advert, x='body_type',y='price').set(ylim=(0,100000))
price_bodytype
plt.xticks(rotation=45)
```

Out[352]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
 [Text(0, 0, 'SUV'),
  Text(1, 0, 'Saloon'),
  Text(2, 0, 'Hatchback'),
  Text(3, 0, 'Convertible'),
  Text(4, 0, 'Limousine'),
  Text(5, 0, 'Estate'),
  Text(6, 0, 'MPV'),
  Text(7, 0, 'Coupe'),
  Text(8, 0, 'Pickup'),
  Text(9, 0, 'Combi Van'),
  Text(10, 0, 'Panel Van'),
  Text(11, 0, 'Minibus'),
  Text(12, 0, 'Window Van'),
  Text(13, 0, 'Camper'),
  Text(14, 0, 'Car Derived Van'),
  Text(15, 0, 'Chassis Cab')])
```



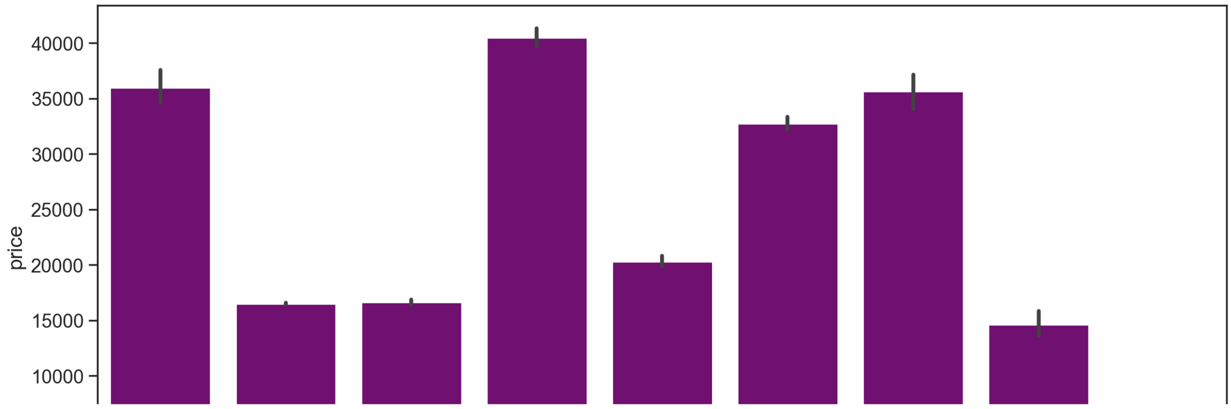

Observations:

1. Limousine is the most expensive body type, camper takes the second spot.
2. Car Derived Van is the cheapest car.

In [353]:

```
price_fueltype=sns.barplot(data=advert, x='fuel_type',y='price',color='purple')
price_fueltype
plt.xticks(rotation=45)
```

```
 Text(8, 0, 'Natural Gas')])
```




Observations:

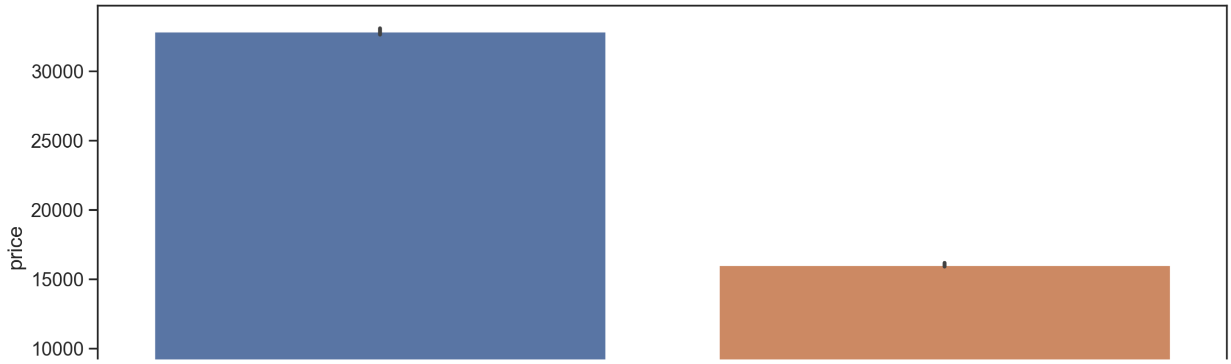
1. Diesel Hybrid is the most expensive, petrol plug-in hybrid and diesel plug-in hybrid are the second most expensive.
2. Natural Gas is the cheapest fuel_type.

In [354]:

```
sns.barplot(x = 'vehicle_condition', y = 'price', data = advert)
```

Out[354]:

```
<AxesSubplot:xlabel='vehicle_condition', ylabel='price'>
```




Observations:

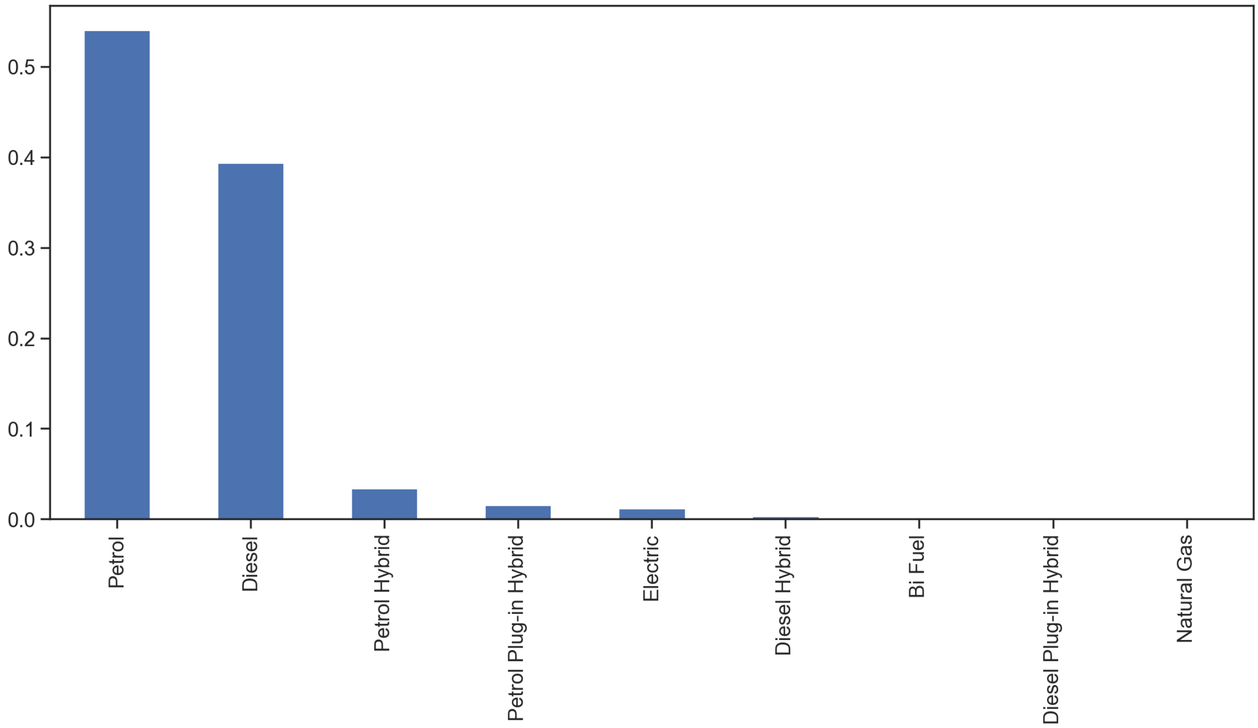
1. New cars are more expensive than used cars.

In [309]:

```
advert['fuel_type'].value_counts(normalize=True).plot.bar()
```

Out[309]:

```
<AxesSubplot:>
```

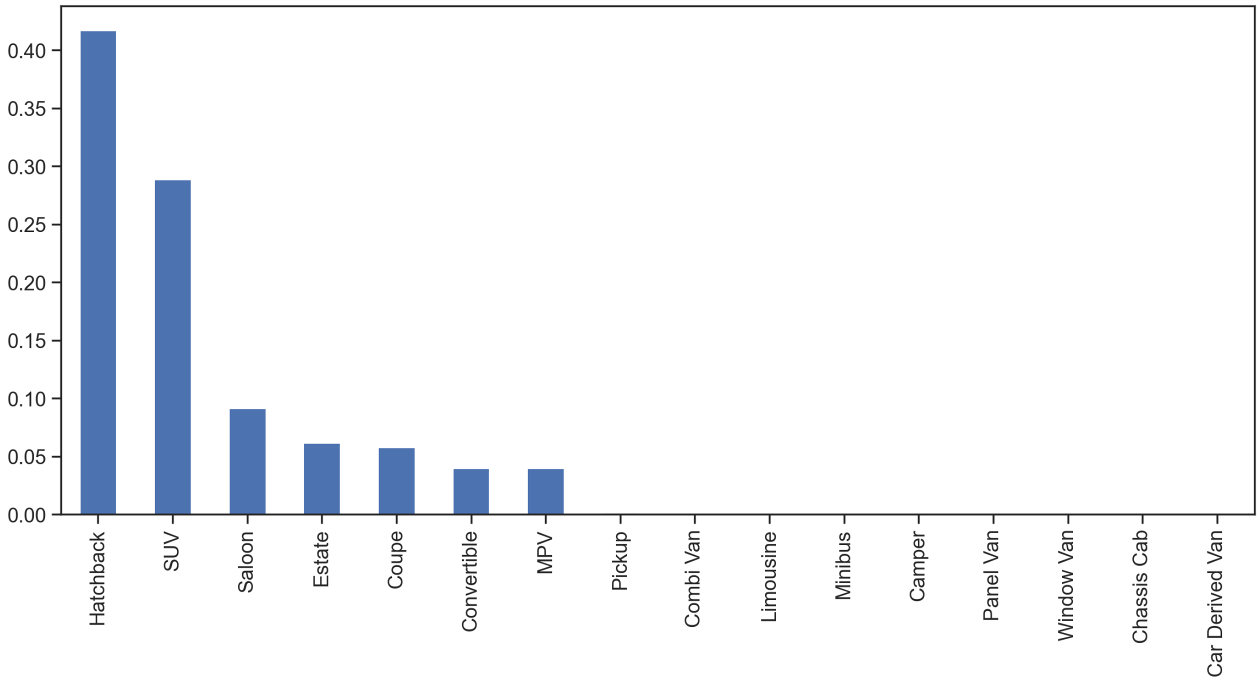



In [310]:

```
advert['body_type'].value_counts(normalize=True).plot.bar()
```

Out[310]:

```
<AxesSubplot:>
```



### 3.3 Categorical-Categorical analysis

In [474]:

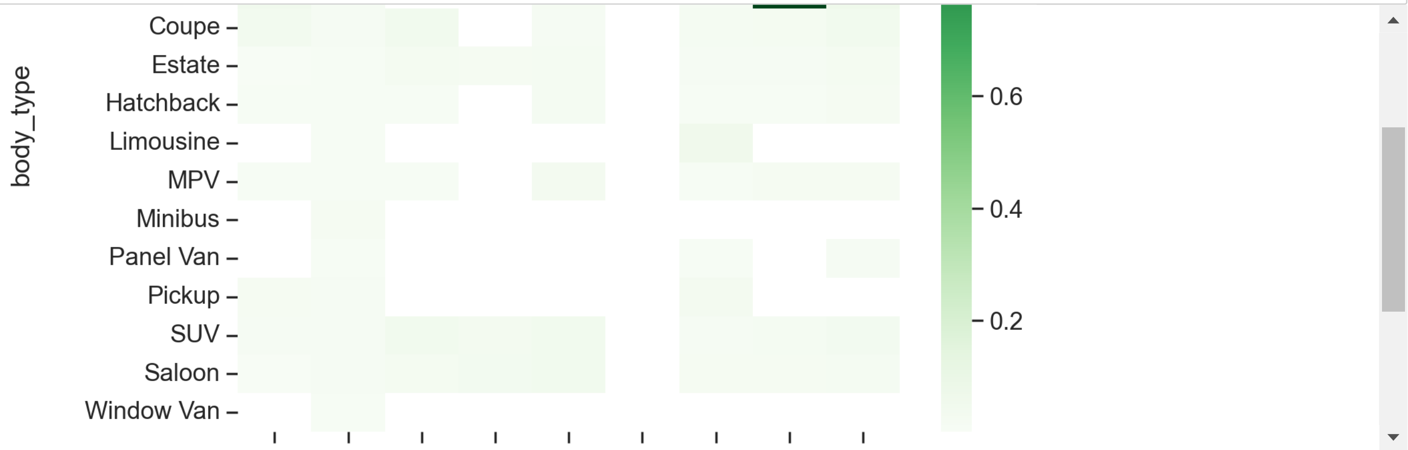
```
rnd = advert.groupby(['body_type', 'fuel_type'])['price'].median().unstack()
rnd.head(10)
```

Out[474]:

| fuel_type<br>body_type | Bi Fuel | Diesel | Diesel Hybrid | Diesel Plug-in Hybrid | Electric | Natural Gas | Petrol | Petrol Hybrid | Petrol Plug-in Hybrid |
|---|---|---|---|---|---|---|---|---|---|
| **Camper** | 9497.5 | 39497.5 | NaN | NaN | NaN | NaN | 13750.0 | NaN | NaN |
| **Car Derived Van** | NaN | 7245.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **Chassis Cab** | NaN | 8750.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **Combi Van** | NaN | 14995.0 | NaN | NaN | 30933.5 | 3795.0 | 15995.0 | NaN | NaN |
| **Convertible** | 57000.0 | 14295.0 | NaN | NaN | 18944.0 | NaN | 14990.0 | 1099950.0 | 69147.0 |
| **Coupe** | 41995.0 | 14995.0 | 47565.0 | NaN | 14495.0 | NaN | 22995.0 | 27295.0 | 48500.0 |
| **Estate** | 3790.0 | 11950.0 | 31221.0 | 19500.0 | 25216.5 | NaN | 15990.0 | 14799.5 | 27997.0 |
| **Hatchback** | 11519.5 | 9495.0 | 8297.0 | NaN | 23990.0 | NaN | 8495.0 | 13295.0 | 21495.0 |
| **Limousine** | NaN | 8497.0 | NaN | NaN | NaN | NaN | 59995.0 | NaN | NaN |
| **MPV** | 5750.0 | 9995.0 | 10550.0 | NaN | 32475.0 | NaN | 9000.0 | 19397.5 | 20995.0 |

In [475]:

```
plt.subplots(figsize=(8,6))
sns.heatmap(
    data=rnd, cmap='Greens'
);
```




Observations:

1. Convertible with Petrol hybrid is most expensive.

In [313]:

```
avg_price=advert.groupby(['body_type','vehicle_condition'])['price'].mean()
```

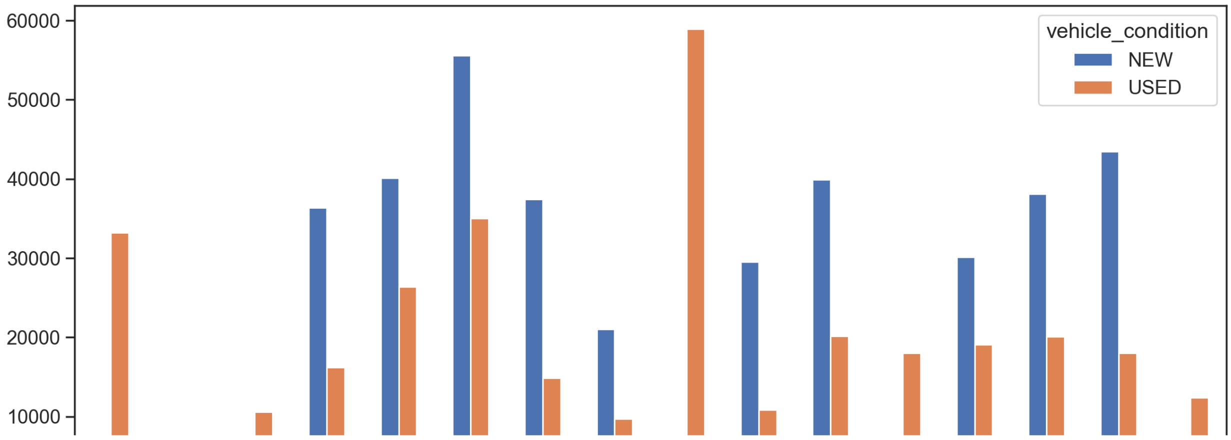
In [314]:

```
avg_price
```

```
                 USED            26387.292081
Coupe            NEW             55624.437666
                 USED            35041.950898
Estate           NEW             37462.720141
                 USED            14866.036989
Hatchback        NEW             20993.277737
                 USED             9709.684775
Limousine        USED            58953.911950
MPV              NEW             29510.039039
                 USED            10828.357803
Minibus          NEW             39935.000000
                 USED            20179.931507
Panel Van        USED            18028.868852
Pickup           NEW             30135.935484
                 USED            19080.241935
SUV              NEW             38125.806350
                 USED            20118.343669
Saloon           NEW             43461.319194
                 USED            18014.629809
Window Van       USED            12402.853659
```

In [316]:

```
(advert
 .groupby(['body_type', 'vehicle_condition'])
 ['price']
 .mean()
 .unstack()
 .plot.bar()
);
```




Observations:

1. We do not have New cars in Camper,Car derived van, Chassis cab,Panel van,Limousine and window van.
2. Limousine (Used) the most expensive car.
3. Coupe (New) the most expensive car.

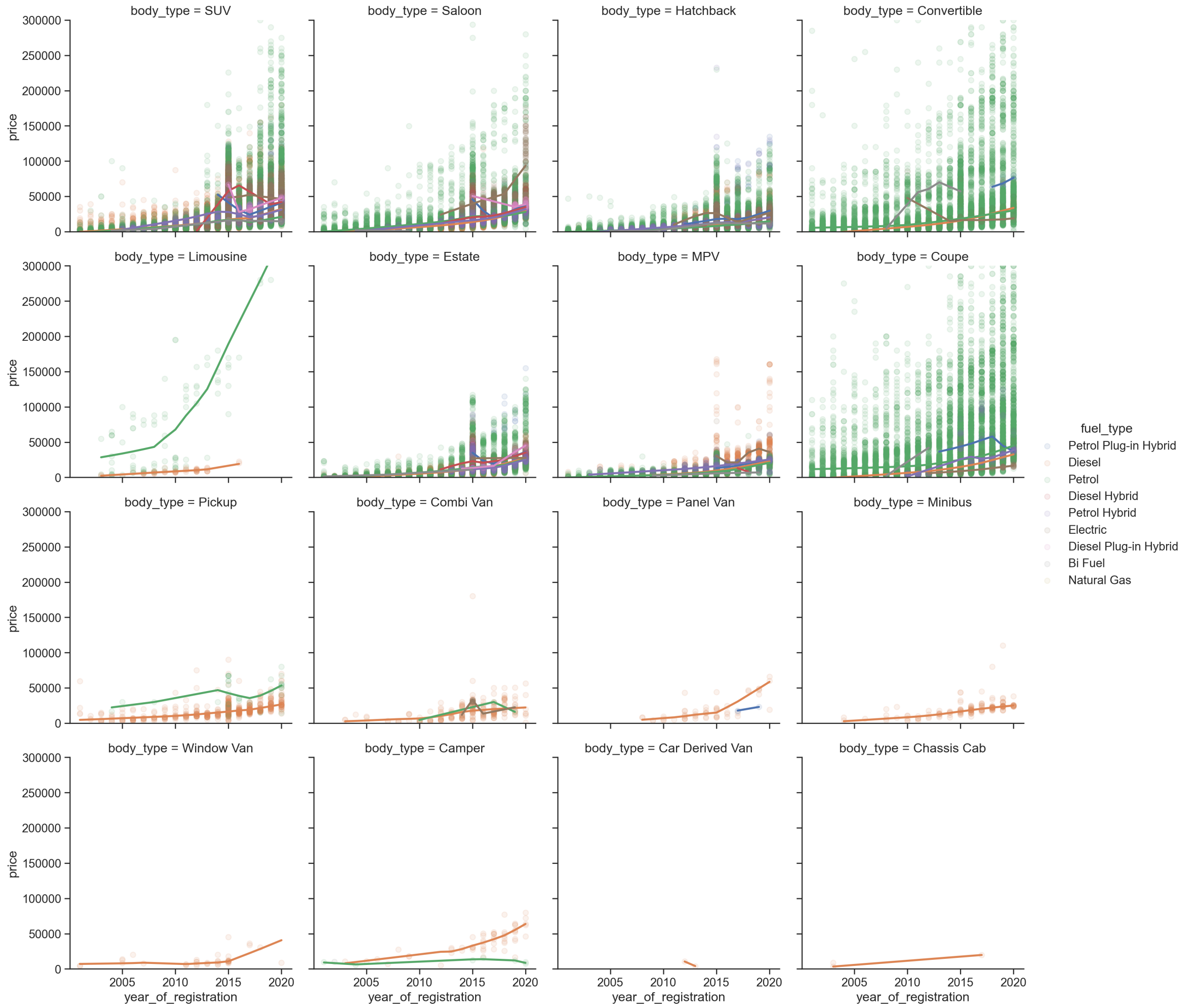
In [318]:

```
sns.lmplot(
    data=advert, x='year_of_registration', y='price',hue='fuel_type', col='body_type', col_wrap=4,
    scatter_kws=dict(alpha=0.1), height=4, lowess=True).set(ylim=(0,300000))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\nonparametric\smoothers_lowess.py:227: RuntimeWarning: invalid value
encountered in true_divide
  res, _ = _lowess(y, x, x, np.ones_like(x),
```

Out[318]:

```
<seaborn.axisgrid.FacetGrid at 0x2164cb80730>
```




In [ ]:

In [ ]: