train_model

August 27, 2025

1 Task 1

For Task 1
- First, I will do the preprocessing in order that is specified in the Assignment Instruction. So I make make sure all the methods work properly and all the output of each steps can be seen.
- Then I will implement a preprocessing function that includes steps from above and adhere to the best practices (according to my understanding) then apply it to the original dataset

[275]:
```python
import pandas as pd
```

[276]:
```python
df = pd.read_csv("Cars.csv")
df
```

[276]:
```
                         name  year  selling_price  km_driven    fuel  \
0        Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2      Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3     Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
4        Maruti Swift VXI BSIII  2007         130000     120000  Petrol
…                             …   …              …          …     …
8123          Hyundai i20 Magna  2013         320000     110000  Petrol
8124      Hyundai Verna CRDi SX  2007         135000     119000  Diesel
8125     Maruti Swift Dzire ZDi  2009         382000     120000  Diesel
8126           Tata Indigo CR4  2013         290000      25000  Diesel
8127           Tata Indigo CR4  2013         290000      25000  Diesel

     seller_type transmission                 owner     mileage   engine  \
0     Individual       Manual           First Owner   23.4 kmpl  1248 CC
1     Individual       Manual          Second Owner  21.14 kmpl  1498 CC
2     Individual       Manual           Third Owner   17.7 kmpl  1497 CC
3     Individual       Manual           First Owner   23.0 kmpl  1396 CC
4     Individual       Manual           First Owner   16.1 kmpl  1298 CC
…              …          …                     …          …        …
8123  Individual       Manual           First Owner   18.5 kmpl  1197 CC
8124  Individual       Manual  Fourth & Above Owner   16.8 kmpl  1493 CC
8125  Individual       Manual           First Owner   19.3 kmpl  1248 CC
8126  Individual       Manual           First Owner  23.57 kmpl  1396 CC
8127  Individual       Manual           First Owner  23.57 kmpl  1396 CC
```

```
       max_power                        torque  seats
0         74 bhp                190Nm@ 2000rpm    5.0
1     103.52 bhp           250Nm@ 1500-2500rpm    5.0
2         78 bhp         12.7@ 2,700(kgm@ rpm)    5.0
3         90 bhp    22.4 kgm at 1750-2750rpm    5.0
4       88.2 bhp         11.5@ 4,500(kgm@ rpm)    5.0
…            …                             …    …
8123   82.85 bhp              113.7Nm@ 4000rpm    5.0
8124     110 bhp  24@ 1,900-2,750(kgm@ rpm)     5.0
8125    73.9 bhp                190Nm@ 2000rpm    5.0
8126      70 bhp           140Nm@ 1800-3000rpm    5.0
8127      70 bhp           140Nm@ 1800-3000rpm    5.0

[8128 rows x 13 columns]
```

1.0.1 For the feature owner, map First owner to 1, ..., Test Drive Car to 5

[277]:
```python
# Checking what are possible values and how many of them
df["owner"].value_counts()
```

[277]:
```
owner
First Owner             5289
Second Owner            2105
Third Owner              555
Fourth & Above Owner     174
Test Drive Car             5
Name: count, dtype: int64
```

[278]:
```python
# df["owner"] = df["owner"].replace(
#     {
#         "First Owner": 1,
#         "Second Owner": 2,
#         "Third Owner": 3,
#         "Fourth & Above Owner": 4,
#         "Test Drive Car": 5,
#     },
# )
```

```
C:\Users\promb\AppData\Local\Temp\ipykernel_37048\2613992967.py:1:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  df["owner"] = df["owner"].replace(
```

- The .replace() method can be used with `inplace=True` but the linter said it should not be used due to it's inconsistent behavior (https://docs.astral.sh/ruff/rules/pandas-use-of-

  inplace-argument/)
- The .replace() method shows deprecation warning about downcasting.
  - After some research, I found that by replacing column of strings with integers, pandas will try to convert data type of the column to the type of new value if possible.
  - But it will not do this in the future anymore because it can cause data loss.
  - for example: if some original value is 0001 (string), it will be converted to 7 (int), resulting in data loss.

[279]:
```python
# Now the owner column is label encoded
df["owner"].value_counts()
```

[279]:
```
owner
1    5289
2    2105
3     555
4     174
5       5
Name: count, dtype: int64
```

1.0.2 For the feature fuel, remove all rows with CNG and LPG

because CNG and LPG use a different mileage system i.e., km/kg which is different from kmfeaturepl for Diesel and Petrol

[280]:
```python
# Checking what are possible values and how many of them
df["fuel"].value_counts()
```

[280]:
```
fuel
Diesel    4402
Petrol    3631
CNG         57
LPG         38
Name: count, dtype: int64
```

To filter rows with specific value in given column, a mask that is a pandas Series of boolean values with the same indicies can be created. Then it can be used with dataframe to return only indices with True value

[281]:
```python
fuel_mask = ~df["fuel"].isin(["CNG", "LPG"])  # pd.Series[bool]
df = df[fuel_mask].copy()  # Filter
```

[282]:
```python
# Now they are gone
df["fuel"].value_counts()
```

[282]:
```
fuel
Diesel    4402
Petrol    3631
Name: count, dtype: int64
```

1.0.3 For the feature mileage, remove "kmpl" and convert the column to numerical type (e.g., float).

Hint: use df.mileage.str.split

[283]:
```
df["mileage"] = df["mileage"].str.split(" ").str[0]

# Or use .removesuffix()
# df["mileage"] = df["mileage"].str.removesuffix(" kmpl")

df["mileage"] = df["mileage"].astype(float)
df["mileage"]
```

[283]:
```
0       23.40
1       21.14
2       17.70
3       23.00
4       16.10
        …
8123    18.50
8124    16.80
8125    19.30
8126    23.57
8127    23.57
Name: mileage, Length: 8033, dtype: float64
```

1.0.4 For the feature engine, remove "CC" and convert the column to numerical type (e.g., float)

1.0.5 Do the same for max power

[284]:
```
df["engine"] = df["engine"].str.split(" ").str[0]
df["max_power"] = df["max_power"].str.split(" ").str[0]
df["engine"] = df["engine"].astype(float)
df["max_power"] = df["max_power"].astype(float)
```

[285]:
```
df[["engine", "max_power"]].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8033 entries, 0 to 8127
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   engine     7819 non-null   float64
 1   max_power  7825 non-null   float64
dtypes: float64(2)
memory usage: 188.3 KB
```

1.0.6 For the feature brand, take only the first word and remove the rest

[286]:
```
df.columns
```

[286]:
```
Index(['name', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'torque',
       'seats'],
      dtype='object')
```

[287]:
```
df = df.rename(columns={"name": "brand"})
df.columns
```

[287]:
```
Index(['brand', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'torque',
       'seats'],
      dtype='object')
```

[288]:
```
df["brand"] = df["brand"].str.split(" ").str[0]
df["brand"]
```

[288]:
```
0        Maruti
1         Skoda
2         Honda
3       Hyundai
4        Maruti
         …
8123    Hyundai
8124    Hyundai
8125     Maruti
8126       Tata
8127       Tata
Name: brand, Length: 8033, dtype: object
```

[289]:
```
df["brand"].value_counts()
```

[289]:
```
brand
Maruti           2378
Hyundai          1393
Mahindra          772
Tata              733
Toyota            488
Honda             467
Ford              397
Renault           228
Chevrolet         228
Volkswagen        186
BMW               120
Skoda             105
```

```
Nissan            81
Jaguar            71
Volvo             67
Datsun            65
Mercedes-Benz     54
Fiat              47
Audi              40
Lexus             34
Jeep              31
Mitsubishi        14
Land               6
Force              6
Isuzu              5
Ambassador         4
Kia                4
MG                 3
Daewoo             3
Ashok              1
Opel               1
Peugeot            1
Name: count, dtype: int64
```

1.0.7 Drop the feature torque, simply because Chaky's company does not understand well about it

[290]:
```
df = df.drop(columns=["torque"])
df.head()
```

[290]:
```
     brand  year  selling_price  km_driven    fuel seller_type transmission  \
0   Maruti  2014         450000     145500  Diesel  Individual       Manual
1    Skoda  2014         370000     120000  Diesel  Individual       Manual
2    Honda  2006         158000     140000  Petrol  Individual       Manual
3  Hyundai  2010         225000     127000  Diesel  Individual       Manual
4   Maruti  2007         130000     120000  Petrol  Individual       Manual

   owner  mileage  engine  max_power  seats
0      1    23.40  1248.0      74.00    5.0
1      2    21.14  1498.0     103.52    5.0
2      3    17.70  1497.0      78.00    5.0
3      1    23.00  1396.0      90.00    5.0
4      1    16.10  1298.0      88.20    5.0
```

[291]:
```
df
```

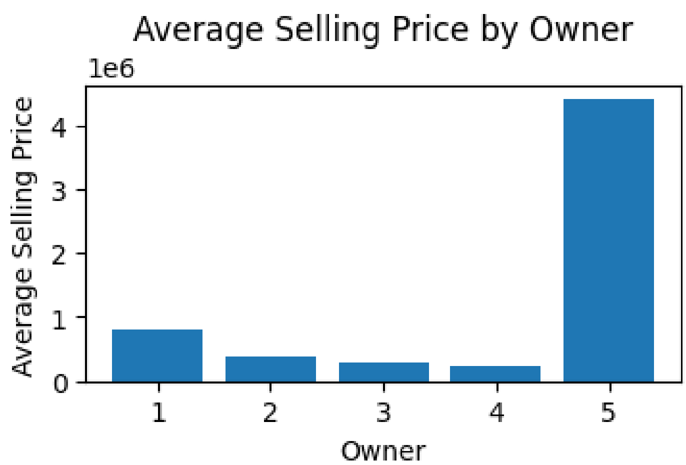
[291]:
```
           brand  year  selling_price  km_driven    fuel seller_type  \
0         Maruti  2014         450000     145500  Diesel  Individual
1          Skoda  2014         370000     120000  Diesel  Individual
```

```
2        Honda  2006         158000     140000  Petrol  Individual
3      Hyundai  2010         225000     127000  Diesel  Individual
4       Maruti  2007         130000     120000  Petrol  Individual
…          …     …               …           …       …           …
8123   Hyundai  2013         320000     110000  Petrol  Individual
8124   Hyundai  2007         135000     119000  Diesel  Individual
8125    Maruti  2009         382000     120000  Diesel  Individual
8126      Tata  2013         290000      25000  Diesel  Individual
8127      Tata  2013         290000      25000  Diesel  Individual

     transmission  owner  mileage  engine  max_power  seats
0          Manual      1    23.40  1248.0      74.00    5.0
1          Manual      2    21.14  1498.0     103.52    5.0
2          Manual      3    17.70  1497.0      78.00    5.0
3          Manual      1    23.00  1396.0      90.00    5.0
4          Manual      1    16.10  1298.0      88.20    5.0
…             …      …      …       …       …      …
8123       Manual      1    18.50  1197.0      82.85    5.0
8124       Manual      4    16.80  1493.0     110.00    5.0
8125       Manual      1    19.30  1248.0      73.90    5.0
8126       Manual      1    23.57  1396.0      70.00    5.0
8127       Manual      1    23.57  1396.0      70.00    5.0

[8033 rows x 12 columns]
```

1.0.8 You will found out that Test Drive Cars are ridiculously expensive. Since we do not want to involve this, we will simply delete all samples related to it.

[292]:
```python
import matplotlib.pyplot as plt

avg_price_by_owner = df.groupby("owner")["selling_price"].mean()
print(avg_price_by_owner)
plt.figure(figsize=(4, 2))
plt.bar(avg_price_by_owner.index, avg_price_by_owner.values)
plt.xlabel("Owner")
plt.ylabel("Average Selling Price")
plt.title("Average Selling Price by Owner")
plt.show()
```

```
owner
1    7.875987e+05
2    3.958988e+05
3    2.857358e+05
4    2.273088e+05
5    4.403800e+06
Name: selling_price, dtype: float64
```



[293]:
```
df[df["owner"] == 5]["selling_price"].mean()
```

[293]:
```
np.float64(4403800.0)
```

[294]:
```
# Remove rows with Test Drive Car
df = df[df["owner"] != 5]
```

[295]:
```
# Final Dataset
df.head()
```

[295]:
```
     brand  year  selling_price  km_driven    fuel seller_type transmission  \
0   Maruti  2014         450000     145500  Diesel  Individual       Manual
1    Skoda  2014         370000     120000  Diesel  Individual       Manual
2    Honda  2006         158000     140000  Petrol  Individual       Manual
3  Hyundai  2010         225000     127000  Diesel  Individual       Manual
4   Maruti  2007         130000     120000  Petrol  Individual       Manual

   owner  mileage  engine  max_power  seats
0      1    23.40  1248.0      74.00    5.0
1      2    21.14  1498.0     103.52    5.0
2      3    17.70  1497.0      78.00    5.0
3      1    23.00  1396.0      90.00    5.0
4      1    16.10  1298.0      88.20    5.0
```

[296]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8028 entries, 0 to 8127
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
```

```
 0   brand          8028 non-null   object
 1   year           8028 non-null   int64
 2   selling_price  8028 non-null   int64
 3   km_driven      8028 non-null   int64
 4   fuel           8028 non-null   object
 5   seller_type    8028 non-null   object
 6   transmission   8028 non-null   object
 7   owner          8028 non-null   int64
 8   mileage        7814 non-null   float64
 9   engine         7814 non-null   float64
 10  max_power      7820 non-null   float64
 11  seats          7814 non-null   float64
dtypes: float64(4), int64(4), object(4)
memory usage: 815.3+ KB
```

1.1 ========= My Preprocessing Process =========

From my understanding, preprocessing should be done before splitting, that means sometimes the testing set will have unexpected values or formats that do not follow the same pattern as training set so the preprocessing function that was already fitted to the training set cannot handle it properly.

In that case, Each column should have its own preprocessing rules to follow, some variations of data format from testing set are acceptable, but some will be treated as unknown value and they will be imputed.

In order to have imputation values, I have to do EDA first to obtain them. Also, imputation values should come from training set only, then use it to transform the testing set later

[433]:
```
def data_cleaning(input_df: pd.DataFrame) -> pd.DataFrame:
    df = input_df.copy()

    # Drop unused columns first to reduce size
    df = df.drop(columns=["torque"])

    # Drop rows that will definitely not be used
    df = df[~df["fuel"].isin(["CNG", "LPG"])]
    df = df[df["owner"] != "Test Drive Car"]

    # Remove Units
    df["mileage"] = df["mileage"].str.split(" ").str[0]
    df["engine"] = df["engine"].str.split(" ").str[0]
    df["max_power"] = df["max_power"].str.split(" ").str[0]

    # Numeric Type conversion
    df["mileage"] = df["mileage"].astype(float)
    df["engine"] = df["engine"].astype(float)
    df["max_power"] = df["max_power"].astype(float)

    # Fix Brand column
```

```
    df = df.rename(columns={"name": "brand"})
    df["brand"] = df["brand"].str.split(" ").str[0]

    return df
```

[434]:
```
# Load dataset again so it doesn't affect previous cells
df_2 = pd.read_csv("Cars.csv")
df_2
```

[434]:
```
                            name  year  selling_price  km_driven    fuel  \
0         Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1   Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2       Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3      Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
4         Maruti Swift VXI BSIII  2007         130000     120000  Petrol
…                            …     …            …         …       …
8123           Hyundai i20 Magna  2013         320000     110000  Petrol
8124       Hyundai Verna CRDi SX  2007         135000     119000  Diesel
8125      Maruti Swift Dzire ZDi  2009         382000     120000  Diesel
8126            Tata Indigo CR4  2013         290000      25000  Diesel
8127            Tata Indigo CR4  2013         290000      25000  Diesel

     seller_type transmission                 owner     mileage   engine  \
0     Individual       Manual           First Owner   23.4 kmpl  1248 CC
1     Individual       Manual          Second Owner  21.14 kmpl  1498 CC
2     Individual       Manual           Third Owner   17.7 kmpl  1497 CC
3     Individual       Manual           First Owner   23.0 kmpl  1396 CC
4     Individual       Manual           First Owner   16.1 kmpl  1298 CC
…            …          …                    …          …        …
8123  Individual       Manual           First Owner   18.5 kmpl  1197 CC
8124  Individual       Manual  Fourth & Above Owner   16.8 kmpl  1493 CC
8125  Individual       Manual           First Owner   19.3 kmpl  1248 CC
8126  Individual       Manual           First Owner  23.57 kmpl  1396 CC
8127  Individual       Manual           First Owner  23.57 kmpl  1396 CC

       max_power                    torque  seats
0         74 bhp            190Nm@ 2000rpm    5.0
1     103.52 bhp       250Nm@ 1500-2500rpm    5.0
2         78 bhp      12.7@ 2,700(kgm@ rpm)   5.0
3         90 bhp   22.4 kgm at 1750-2750rpm   5.0
4       88.2 bhp      11.5@ 4,500(kgm@ rpm)   5.0
…          …                          …     …
8123   82.85 bhp          113.7Nm@ 4000rpm    5.0
8124     110 bhp  24@ 1,900-2,750(kgm@ rpm)   5.0
8125    73.9 bhp            190Nm@ 2000rpm    5.0
8126      70 bhp       140Nm@ 1800-3000rpm    5.0
8127      70 bhp       140Nm@ 1800-3000rpm    5.0
```

```
[8128 rows x 13 columns]
```

[795]:
```
from sklearn.model_selection import train_test_split

df_train, df_test = train_test_split(df_2, test_size=0.2, random_state=42)
```

[796]:
```
print(f"Training set shape: {df_train.shape}")
print(f"Testing set shape: {df_test.shape}")
```

```
Training set shape: (6502, 13)
Testing set shape: (1626, 13)
```

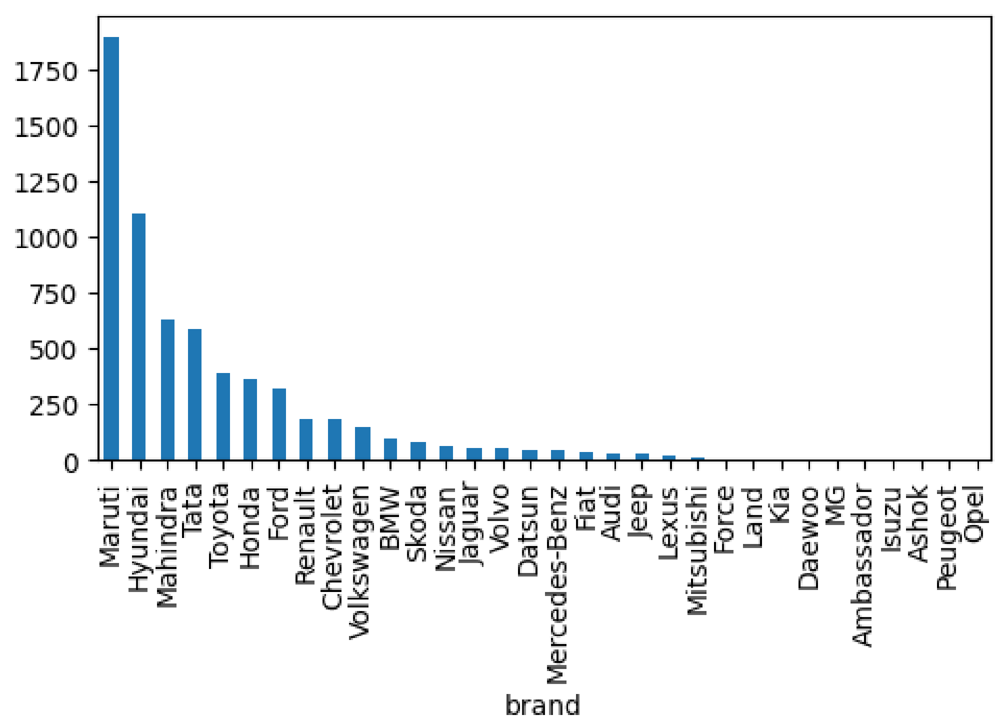
[797]:
```
df_train = data_cleaning(df_train)
df_test = data_cleaning(df_test)
```

1.2 Doing EDA to obtain imputation values from training set

[467]:
```
impute_values = {}
```

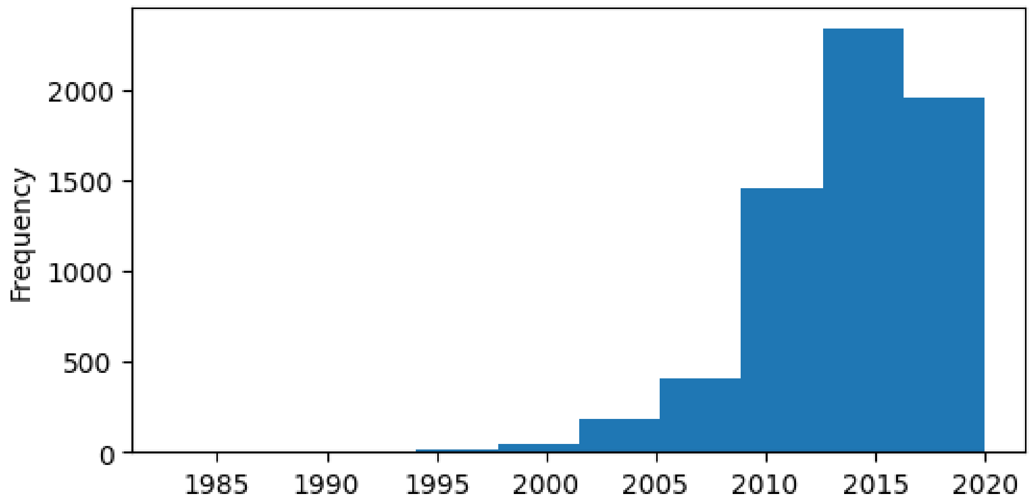
1.2.1 Brand

[468]:
```
df_train["brand"].value_counts().plot(kind="bar", figsize=(6, 3))
# Brand is a categorical variable
# So mode should be used
impute_values["brand"] = df_train["brand"].mode()[0]
```



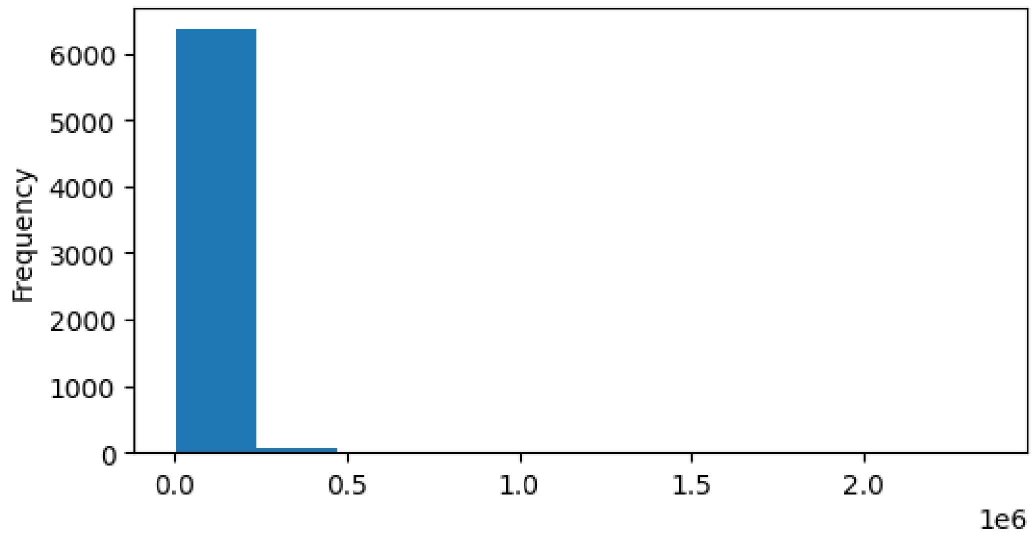
1.2.2 year

[469]:
```
df_train["year"].plot(kind="hist", figsize=(6, 3))
# Year is a continuous variable which is not in normal distribution
# Even though year looks like a discrete variable, it is actually continuous
# So median should be used
impute_values["year"] = df_train["year"].median()
```



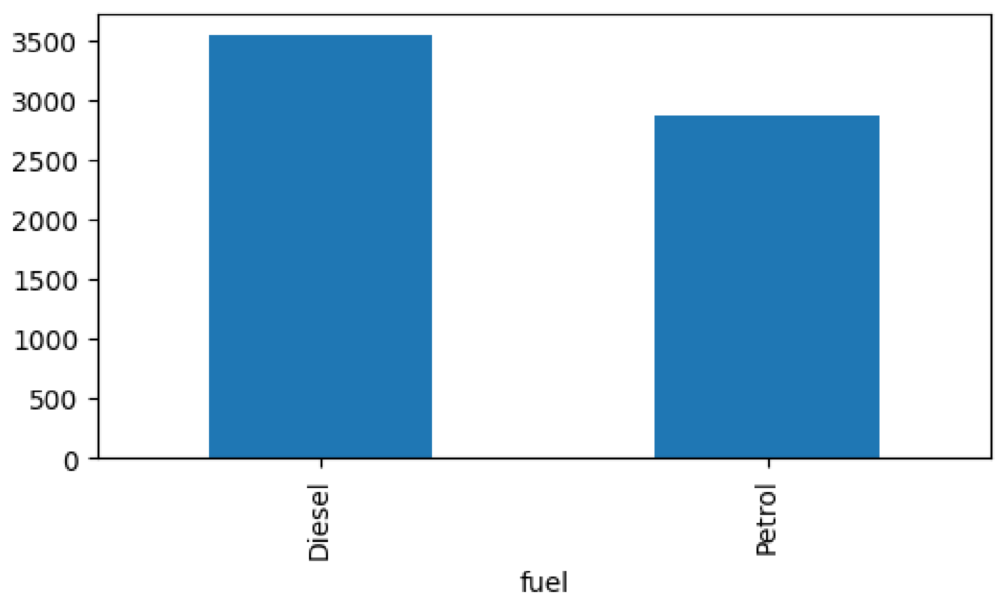
1.2.3 km_driven

[470]:
```
df_train["km_driven"].plot(kind="hist", figsize=(6, 3))
# km_driven is a continuous variable which is not in normal distribution
# It's also very skewed and has some outliers
# So median should be used
impute_values["km_driven"] = df_train["km_driven"].median()
```



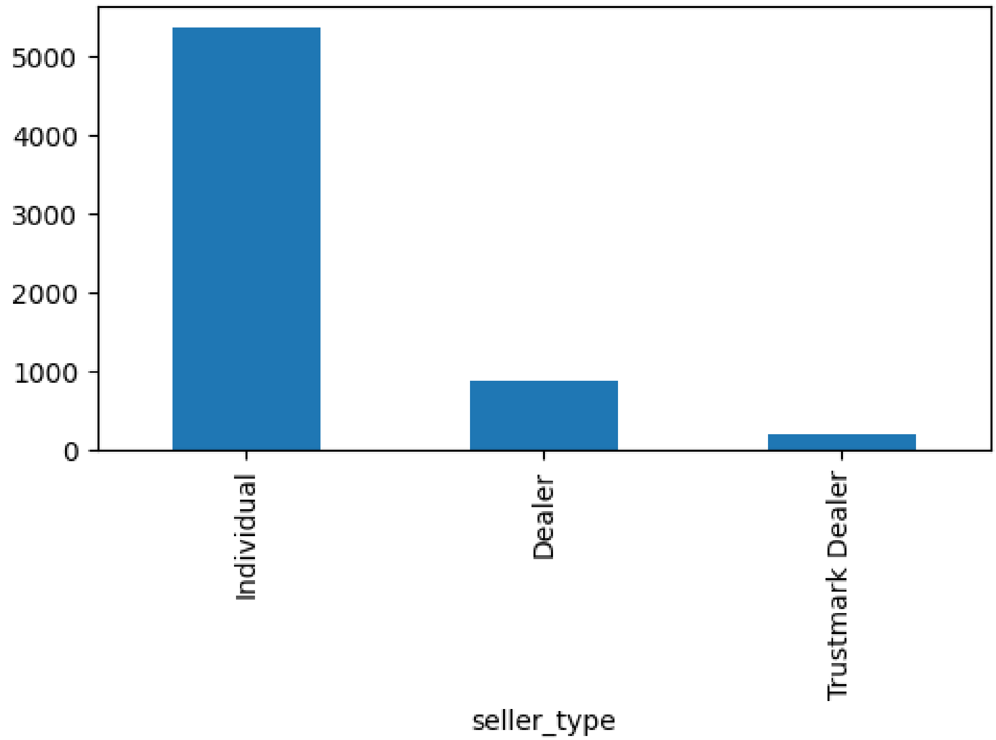
1.2.4 fuel

[471]:
```
df_train["fuel"].value_counts().plot(kind="bar", figsize=(6, 3))
# Fuel is a categorical variable
# So mode should be used
impute_values["fuel"] = df_train["fuel"].mode()[0]
```



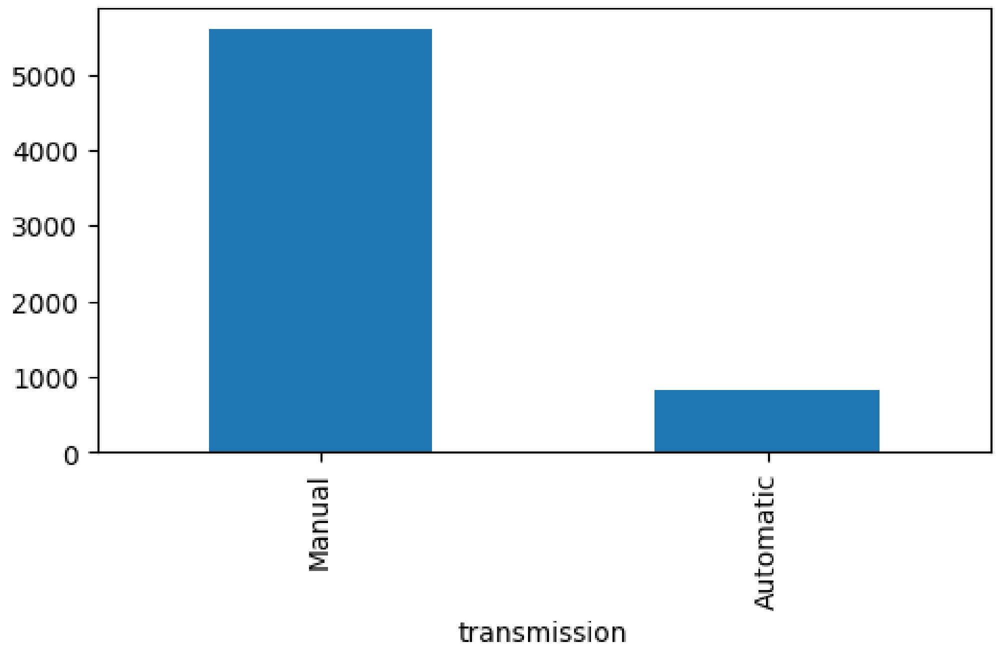
1.2.5 seller_type

[472]:
```
df_train["seller_type"].value_counts().plot(kind="bar", figsize=(6, 3))
# Seller_type is a categorical variable
# So mode should be used
impute_values["seller_type"] = df_train["seller_type"].mode()[0]
```



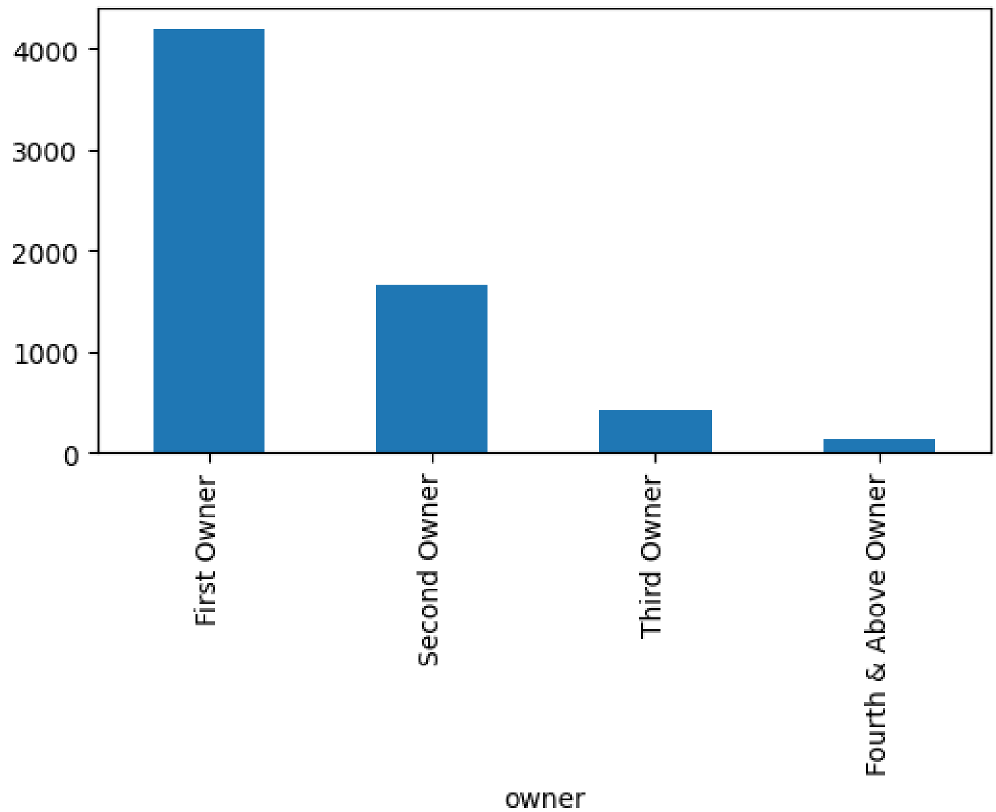
1.2.6 transmission

[473]:
```
df_train["transmission"].value_counts().plot(kind="bar", figsize=(6, 3))
# Transmission is a categorical variable
# So mode should be used
impute_values["transmission"] = df_train["transmission"].mode()[0]
```



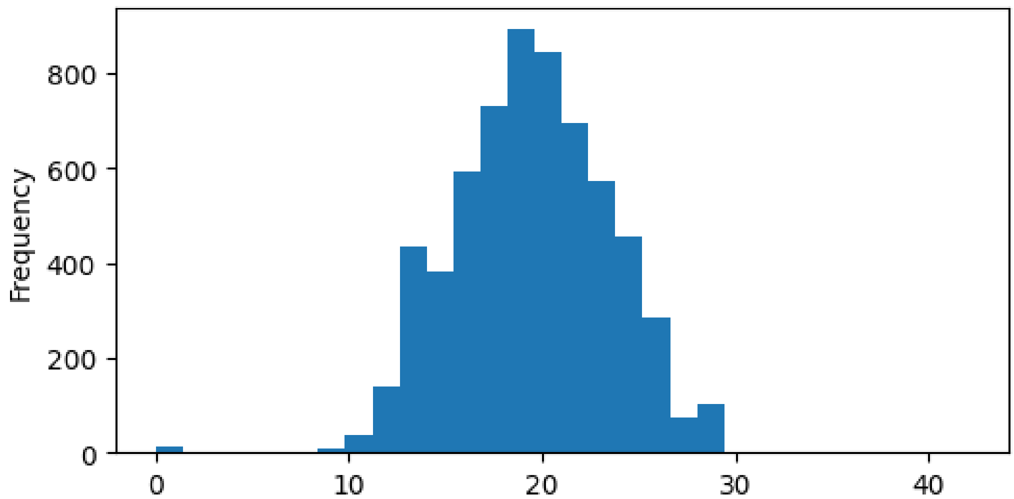
1.2.7 owner

[474]:
```
df_train["owner"].value_counts().plot(kind="bar", figsize=(6, 3))
# Owner is a categorical variable
# So mode should be used
impute_values["owner"] = df_train["owner"].mode()[0]
```



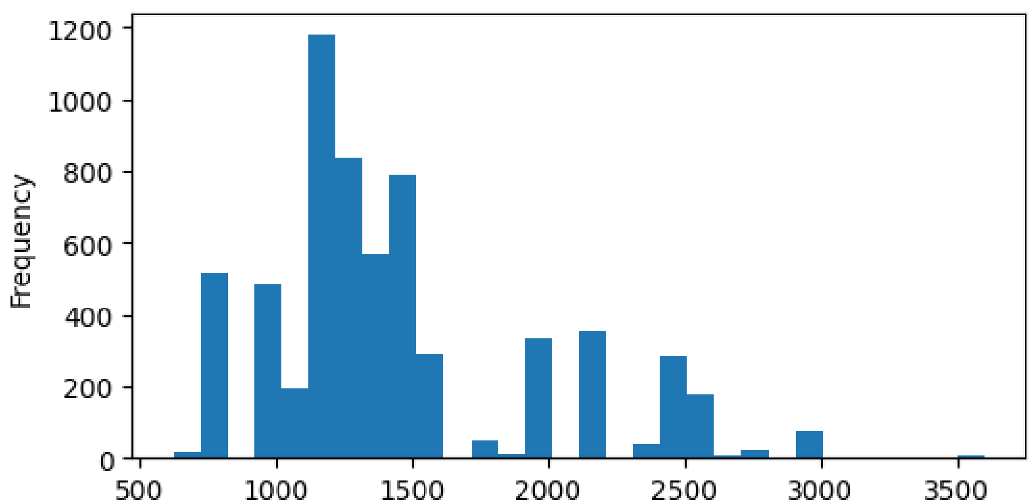
1.2.8 mileage

[475]:
```
df_train["mileage"].plot(kind="hist", figsize=(6, 3), bins=30)
# Mileage is a continuous variable which is in normal distribution
# So mean should be used
impute_values["mileage"] = df_train["mileage"].mean()
```



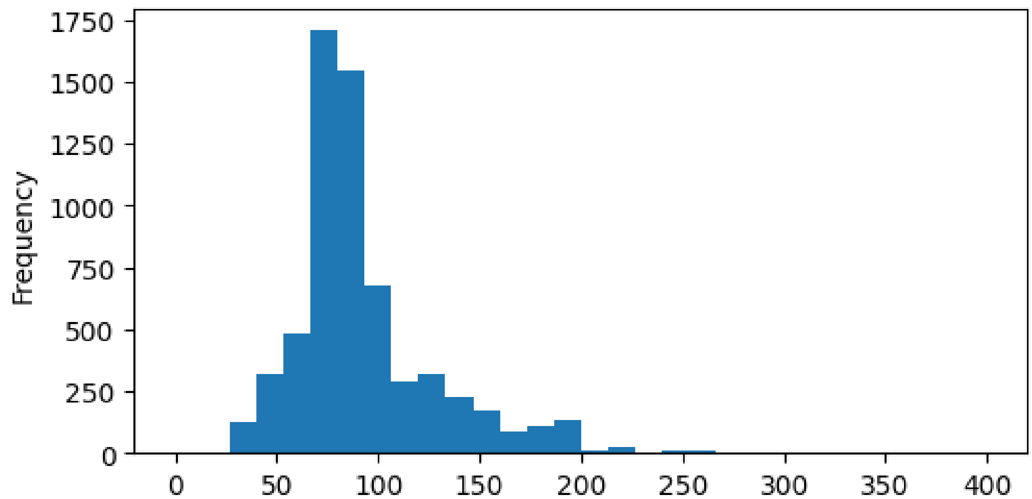
1.2.9 engine

[476]:
```
df_train["engine"].plot(kind="hist", figsize=(6, 3), bins=30)
# Engine is a continuous variable which is not in normal distribution
# So median should be used
impute_values["engine"] = df_train["engine"].median()
```



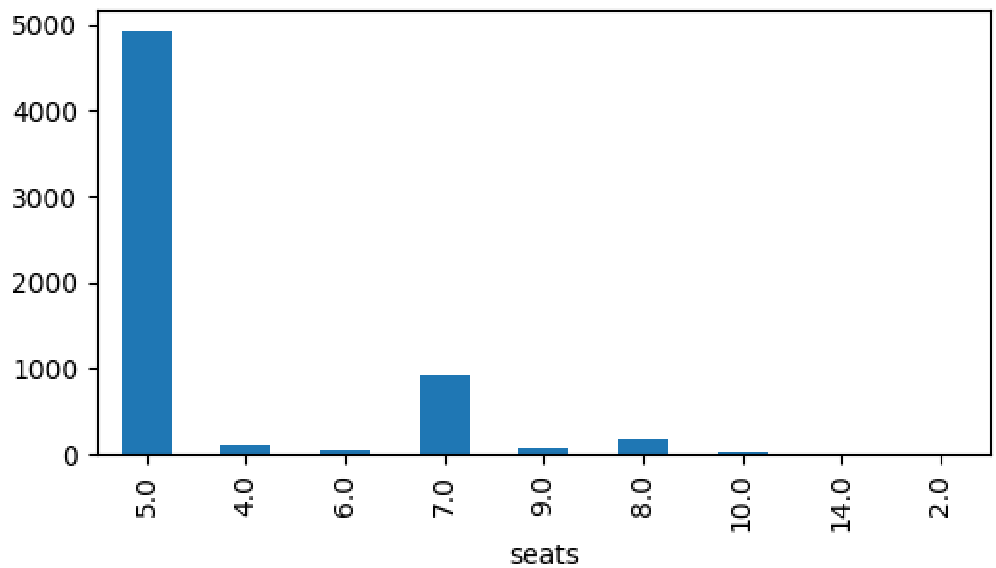
1.2.10 max_power

[477]:
```
df_train["max_power"].plot(kind="hist", figsize=(6, 3), bins=30)
# Max_power is a continuous variable which is not in normal distribution
# So median should be used
impute_values["max_power"] = df_train["max_power"].median()
```



1.2.11 seats

[478]:
```
df_train["seats"].value_counts(sort=False).plot(kind="bar", figsize=(6, 3))
# Seats is a numeric variable but it is categorical in nature
# Because no car will never be labeled as having number like 0.987 seats
# So mode should be used
impute_values["seats"] = df_train["seats"].mode()[0]
```



1.2.12 selling_price won't be imputed since it's a target variable

1.2.13 Imputation Dictionary

[479]:
```
impute_values
```

[479]:
```
{'brand': 'Maruti',
 'year': np.float64(2015.0),
 'km_driven': np.float64(60000.0),
 'fuel': 'Diesel',
 'seller_type': 'Individual',
 'transmission': 'Manual',
 'owner': 'First Owner',
 'mileage': np.float64(19.38237973469714),
 'engine': np.float64(1248.0),
 'max_power': np.float64(82.85),
 'seats': np.float64(5.0)}
```

1.3 Performing Imputation

[481]:
```
df_train.isna().sum()
```

[481]:
```
brand            0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
```

```
transmission       0
owner              0
mileage          164
engine           164
max_power        160
seats            164
dtype: int64
```

[482]:
```python
df_test.isna().sum()
```

[482]:
```
brand             0
year              0
selling_price     0
km_driven         0
fuel              0
seller_type       0
transmission      0
owner             0
mileage          50
engine           50
max_power        48
seats            50
dtype: int64
```

[798]:
```python
# Impute missing values in both train and test set
df_train["mileage"] = df_train["mileage"].fillna(impute_values["mileage"])
df_train["engine"] = df_train["engine"].fillna(impute_values["engine"])
df_train["max_power"] = df_train["max_power"].fillna(impute_values["max_power"])
df_train["seats"] = df_train["seats"].fillna(impute_values["seats"])

# Note that impute values are from training set
df_test["mileage"] = df_test["mileage"].fillna(impute_values["mileage"])
df_test["engine"] = df_test["engine"].fillna(impute_values["engine"])
df_test["max_power"] = df_test["max_power"].fillna(impute_values["max_power"])
df_test["seats"] = df_test["seats"].fillna(impute_values["seats"])
```

[799]:
```python
df_train.isna().sum()
```

[799]:
```
brand            0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
mileage          0
```

```
engine           0
max_power        0
seats            0
dtype: int64
```

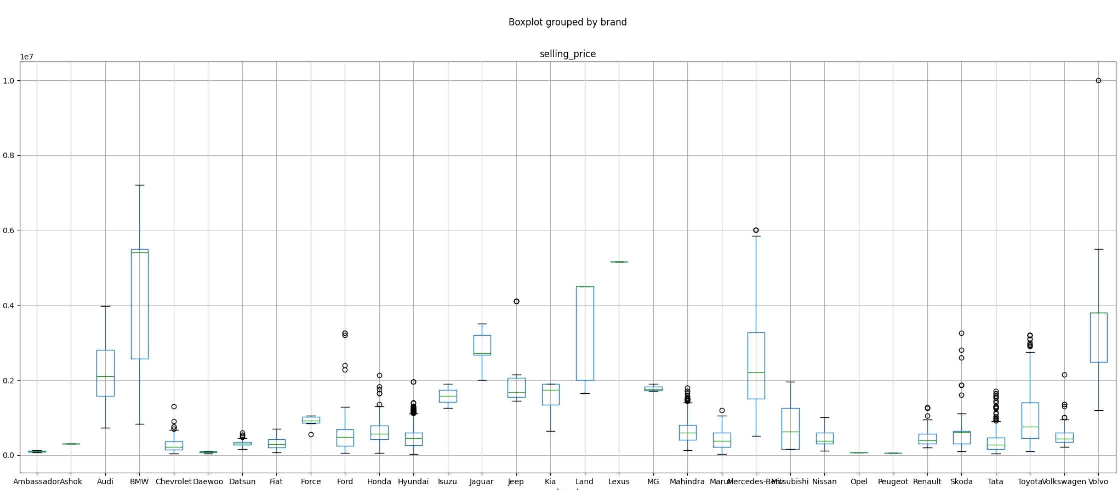
[485]:
```
df_test.isna().sum()
```

[485]:
```
brand            0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
mileage          0
engine           0
max_power        0
seats            0
dtype: int64
```

1.4 more EDA

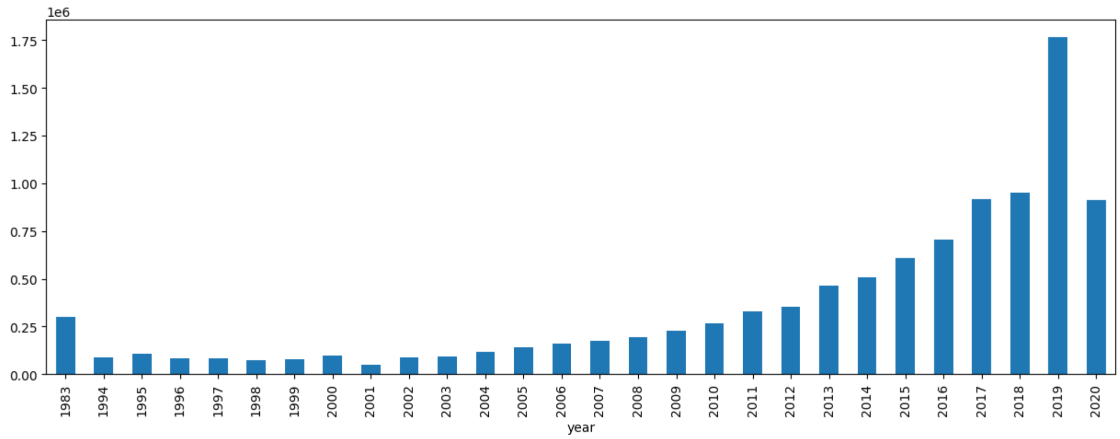
[513]:
```
df_train.boxplot(column="selling_price", by="brand", figsize=(25, 10))
# Some brands have very high an large variance prices
# like BMW, Mercedes-Benz, Volvo
# Some brands have low prices and low price variances
# like Ambassador, Daewoo, Opel
```

[513]:
```
<Axes: title={'center': 'selling_price'}, xlabel='brand'>
```

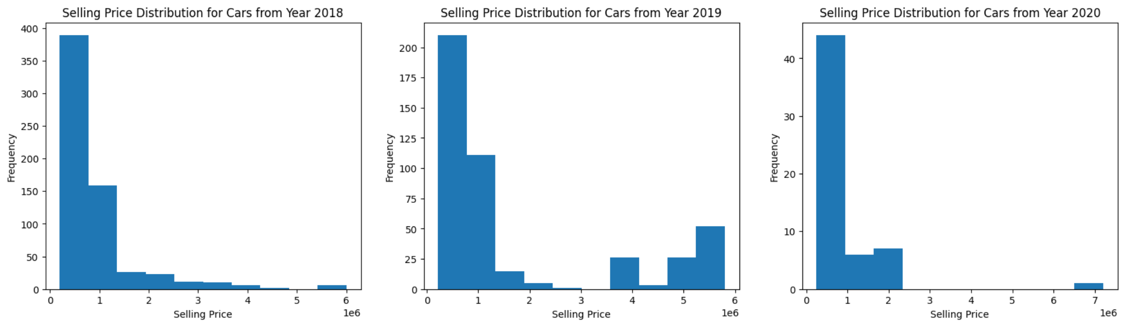


```
[523]: df_train.groupby("year")["selling_price"].mean().plot(
           kind="bar",
           figsize=(15, 5),
       )
       # There is a growing trend of average selling price per year
       # There is a spike in 2019 that should be investigated more
```

```
[523]: <Axes: xlabel='year'>
```

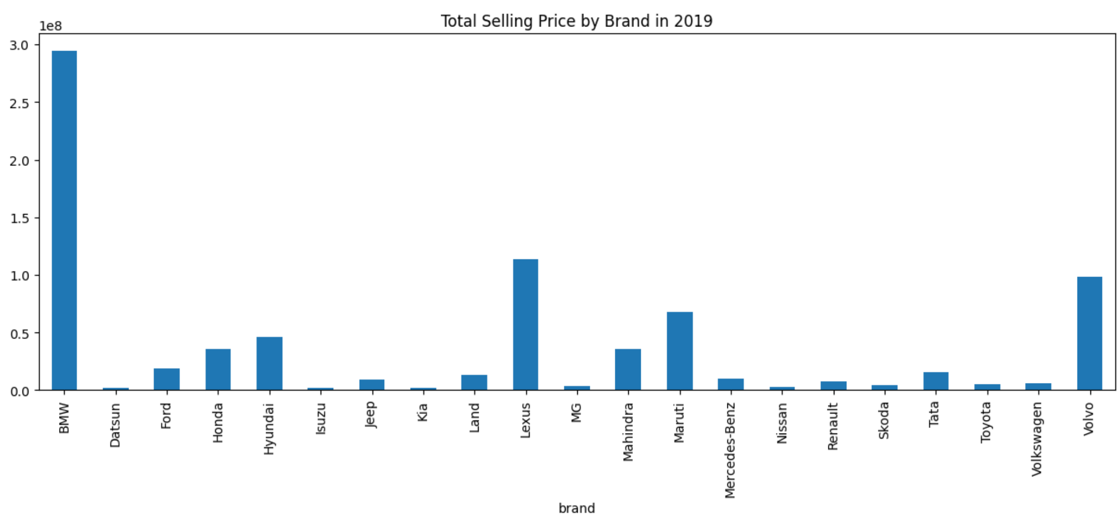



```
[538]: plt.figure(figsize=(20, 5))
       plt.subplot(1, 3, 1)
       plt.hist(df_train[df_train["year"] == 2018]["selling_price"])
       plt.xlabel("Selling Price")
       plt.ylabel("Frequency")
       plt.title("Selling Price Distribution for Cars from Year 2018")

       plt.subplot(1, 3, 2)
       plt.hist(df_train[df_train["year"] == 2019]["selling_price"])
       plt.xlabel("Selling Price")
       plt.ylabel("Frequency")
       plt.title("Selling Price Distribution for Cars from Year 2019")

       plt.subplot(1, 3, 3)
       plt.hist(df_train[df_train["year"] == 2020]["selling_price"])
       plt.xlabel("Selling Price")
       plt.ylabel("Frequency")
       plt.title("Selling Price Distribution for Cars from Year 2020")
       plt.show()

       # 2019 is clearly has more high price cars sold than neighboring years
```



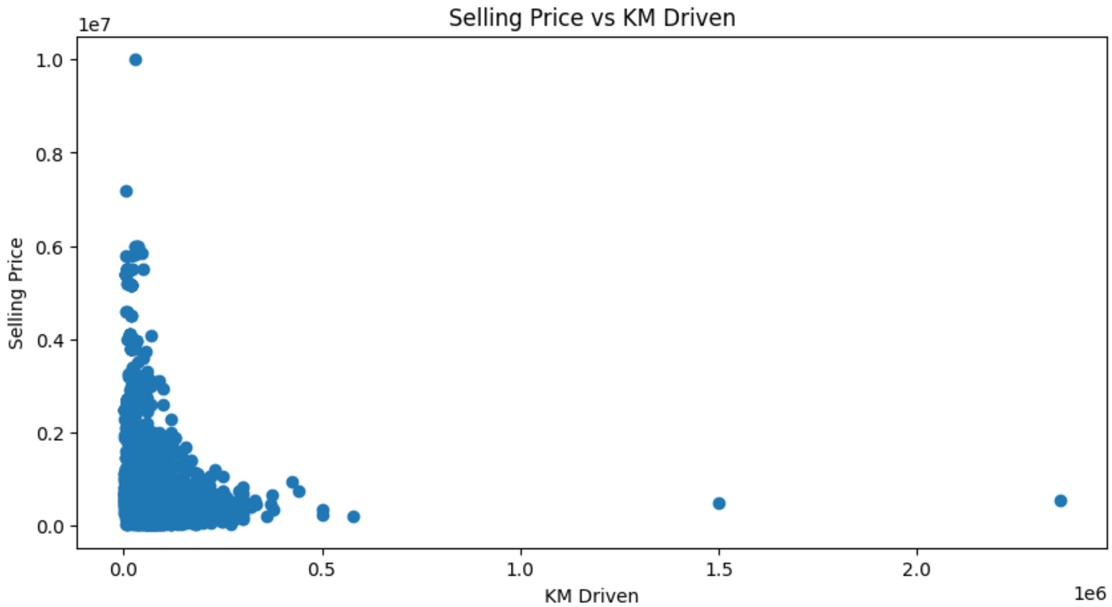

```
[547]: df_train[df_train["year"] == 2019].groupby("brand")["selling_price"].sum().plot(
           kind="bar",
           figsize=(15, 5),
           title="Total Selling Price by Brand in 2019",
       )
       # This clearly shows that in 2019, more high-end cars
       #   like BMW, Lexus, Volvo were sold
```

```
[547]: <Axes: title={'center': 'Total Selling Price by Brand in 2019'}, xlabel='brand'>
```




```
[594]: plt.figure(figsize=(10, 5))
       plt.scatter(
           df_train["km_driven"],
           df_train["selling_price"],
       )
       plt.xlabel("KM Driven")
       plt.ylabel("Selling Price")
```

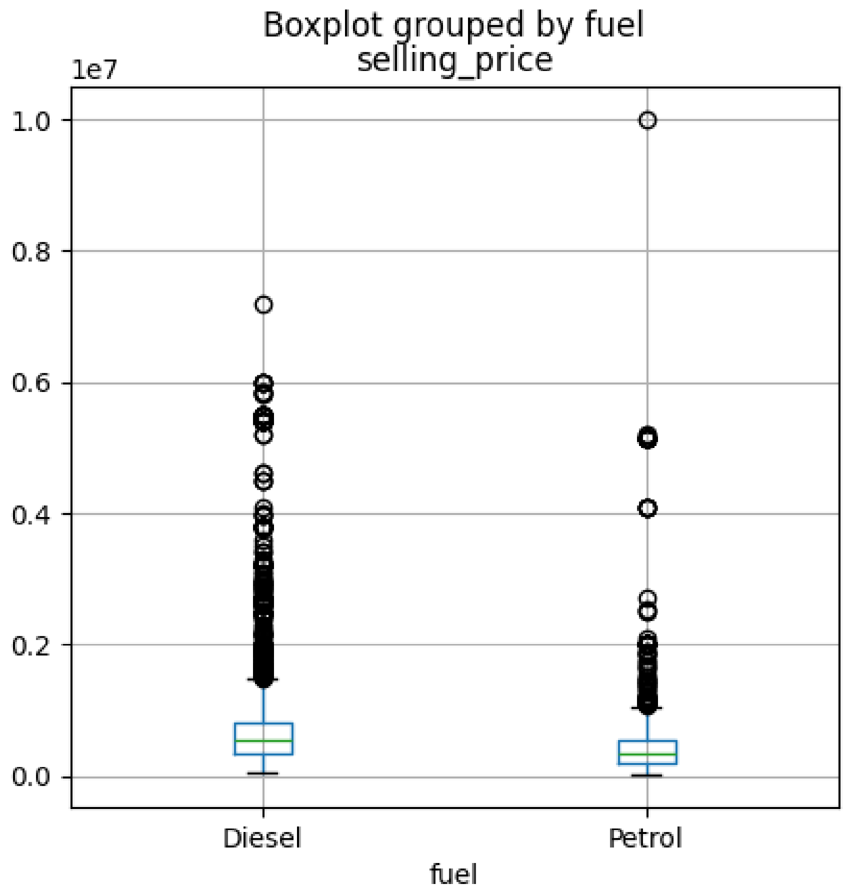
```python
plt.title("Selling Price vs KM Driven")
plt.show()
# This shows that more expensive cars tend to have lower km driven
```



[563]:

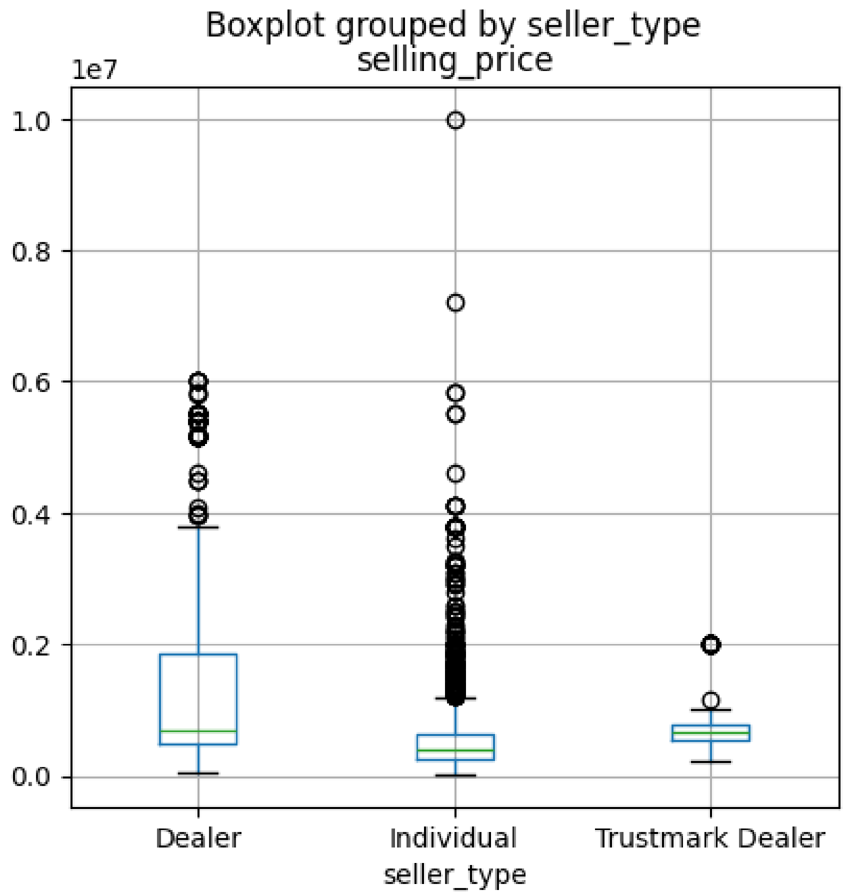
```python
df_train.boxplot(column="selling_price", by="fuel", figsize=(5, 5))
# This shows that diesel cars tend to be priced higher
```

[563]: `<Axes: title={'center': 'selling_price'}, xlabel='fuel'>`



[564]:
```
df_train.boxplot(column="selling_price", by="seller_type", figsize=(5, 5))
# This shows that individual sellers tend to price their cars inconsistently
# while dealers tend to price their cars more consistently
# But some individual sellers can also price their cars very high
```

[564]: <Axes: title={'center': 'selling_price'}, xlabel='seller_type'>

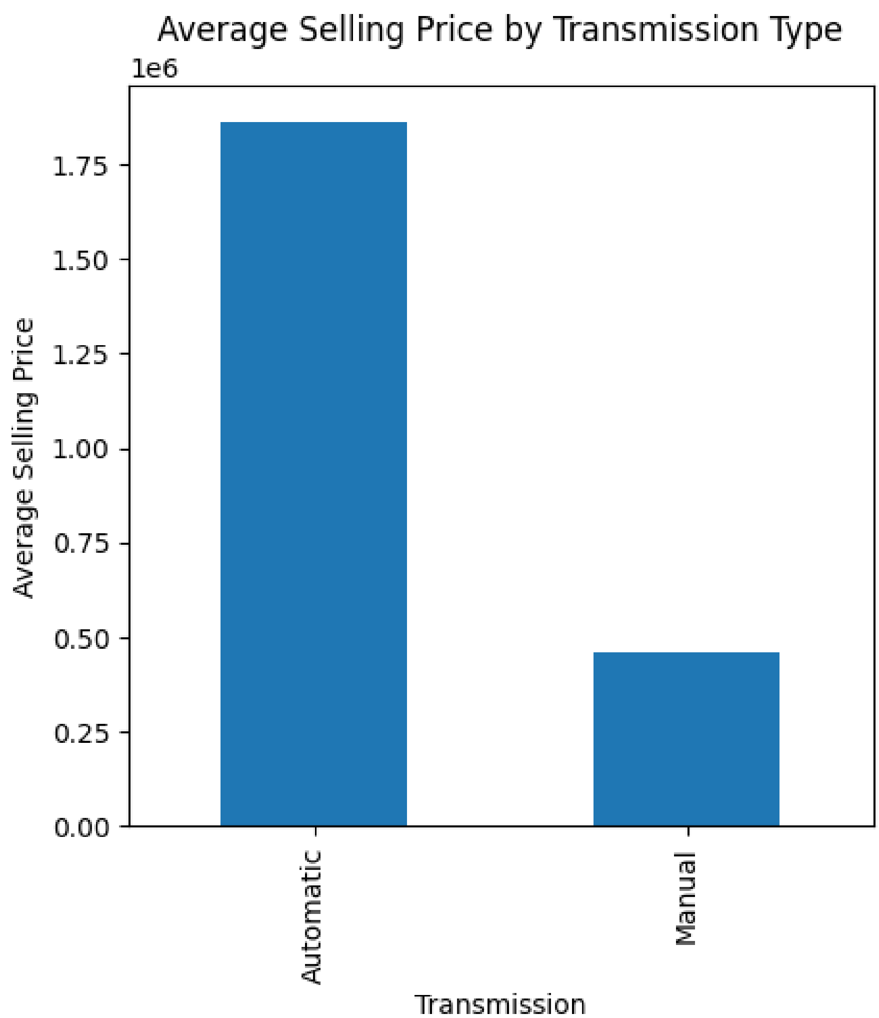


[568]:
```
df_train.columns
```

[568]:
```
Index(['brand', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'seats'],
      dtype='object')
```

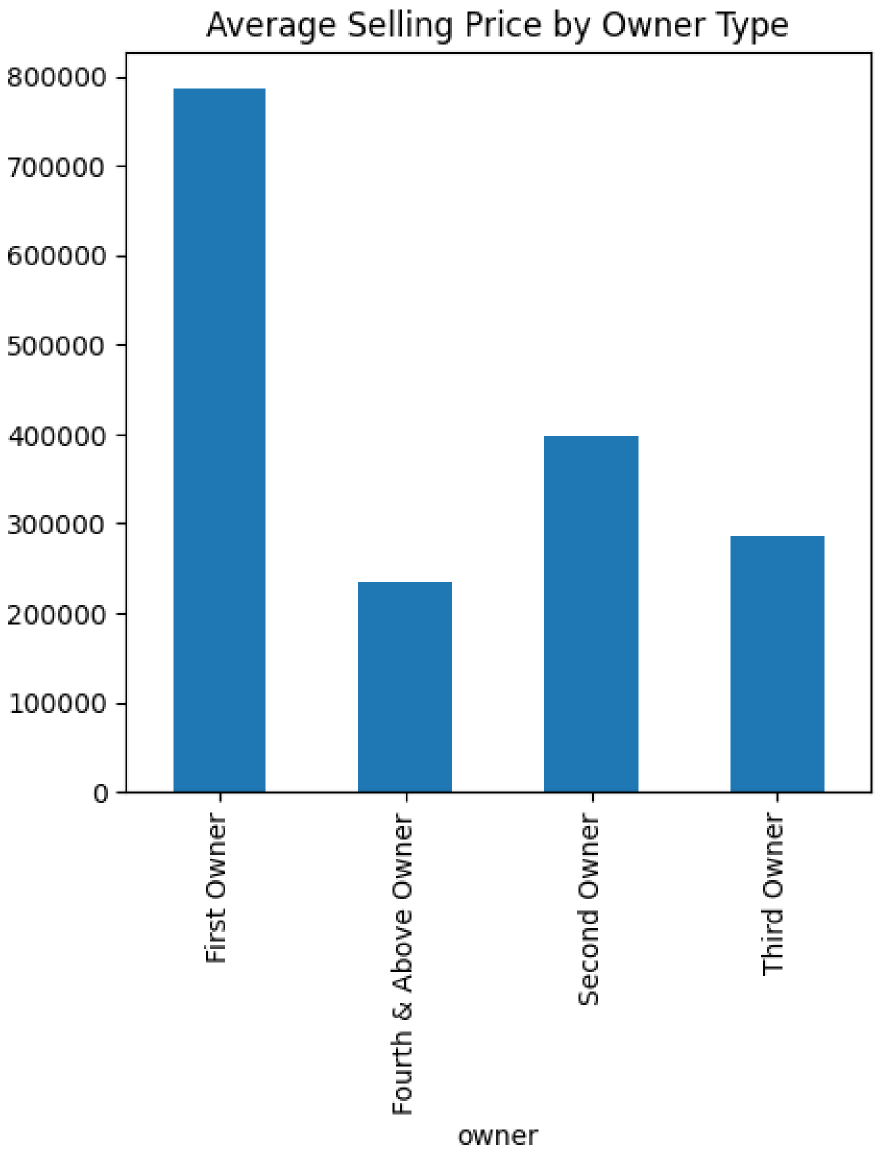
[574]:
```
df_train.groupby("transmission")["selling_price"].mean().plot(
    kind="bar",
    figsize=(5, 5),
    title="Average Selling Price by Transmission Type",
    xlabel="Transmission",
    ylabel="Average Selling Price",
)
# This shows that cars with automatic transmission tend to be priced higher
# than manual transmission cars
```

[574]:
```
<Axes: title={'center': 'Average Selling Price by Transmission Type'},
xlabel='Transmission', ylabel='Average Selling Price'>
```

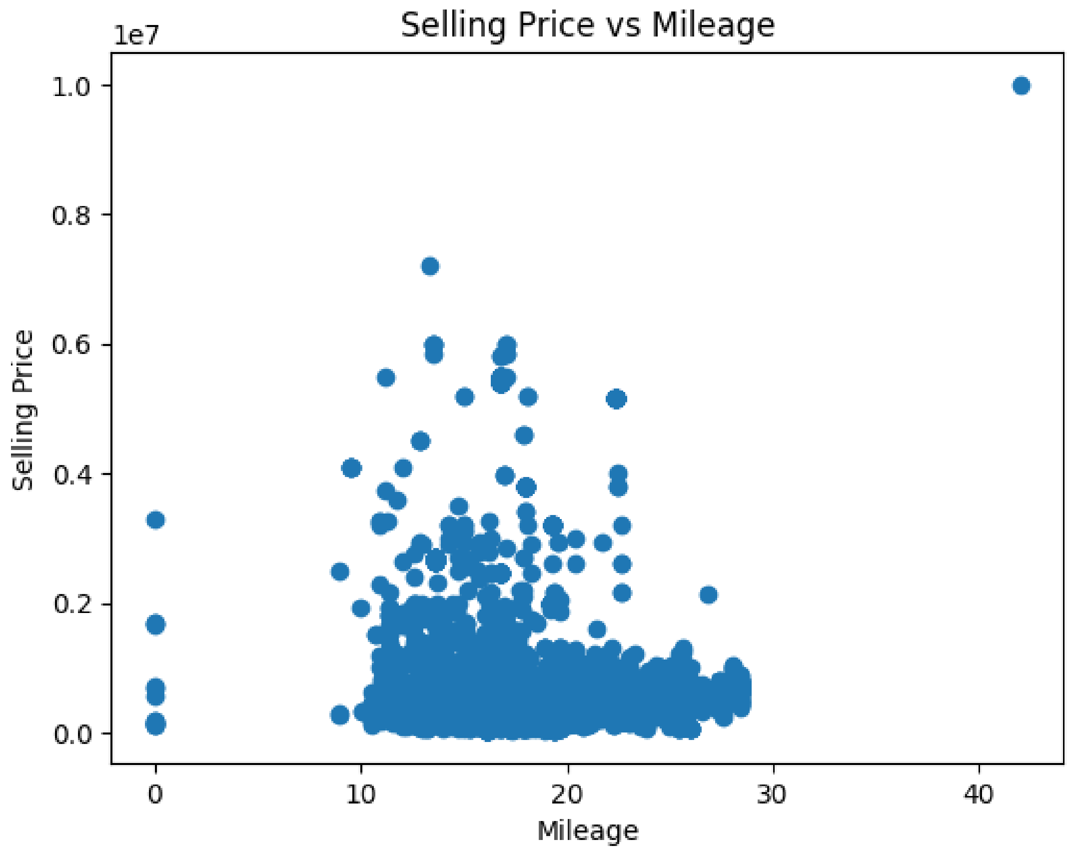


[586]:
```
df_train.groupby("owner")["selling_price"].mean().plot(
    kind="bar",
    figsize=(5, 5),
    title="Average Selling Price by Owner Type",
)
# This shows that cars tend to be priced lower as the number of owners increase
```

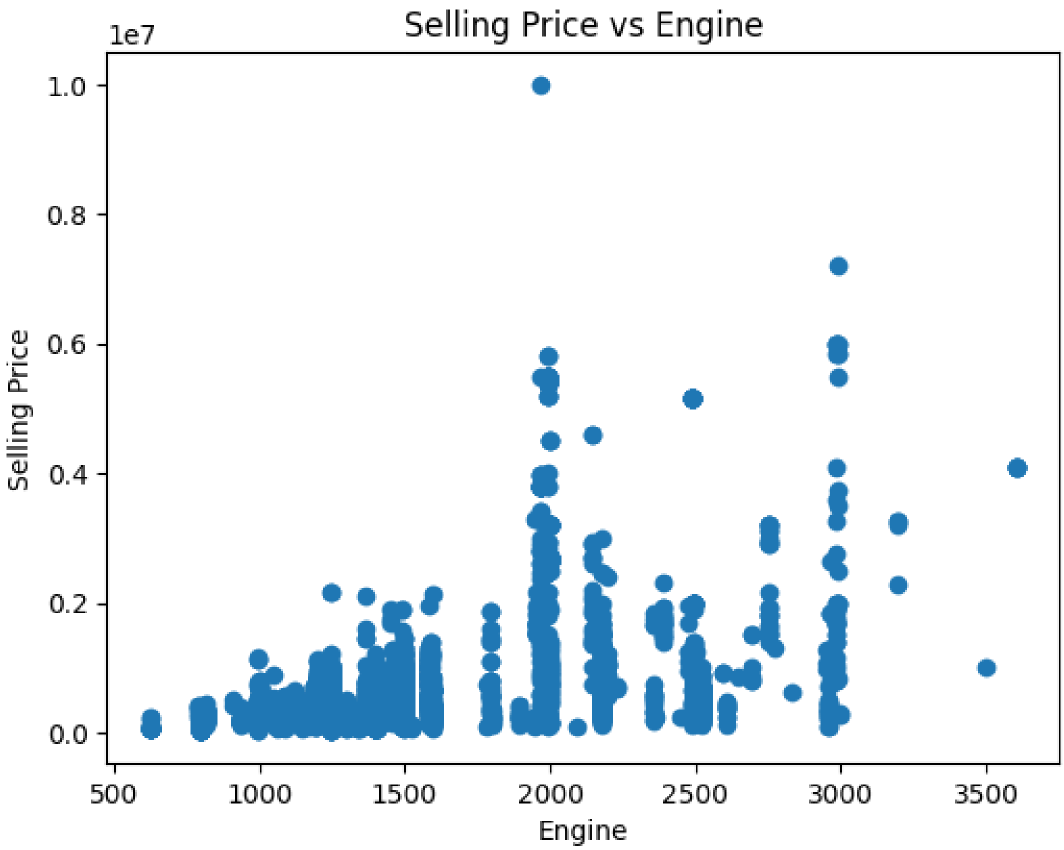
[586]: <Axes: title={'center': 'Average Selling Price by Owner Type'}, xlabel='owner'>



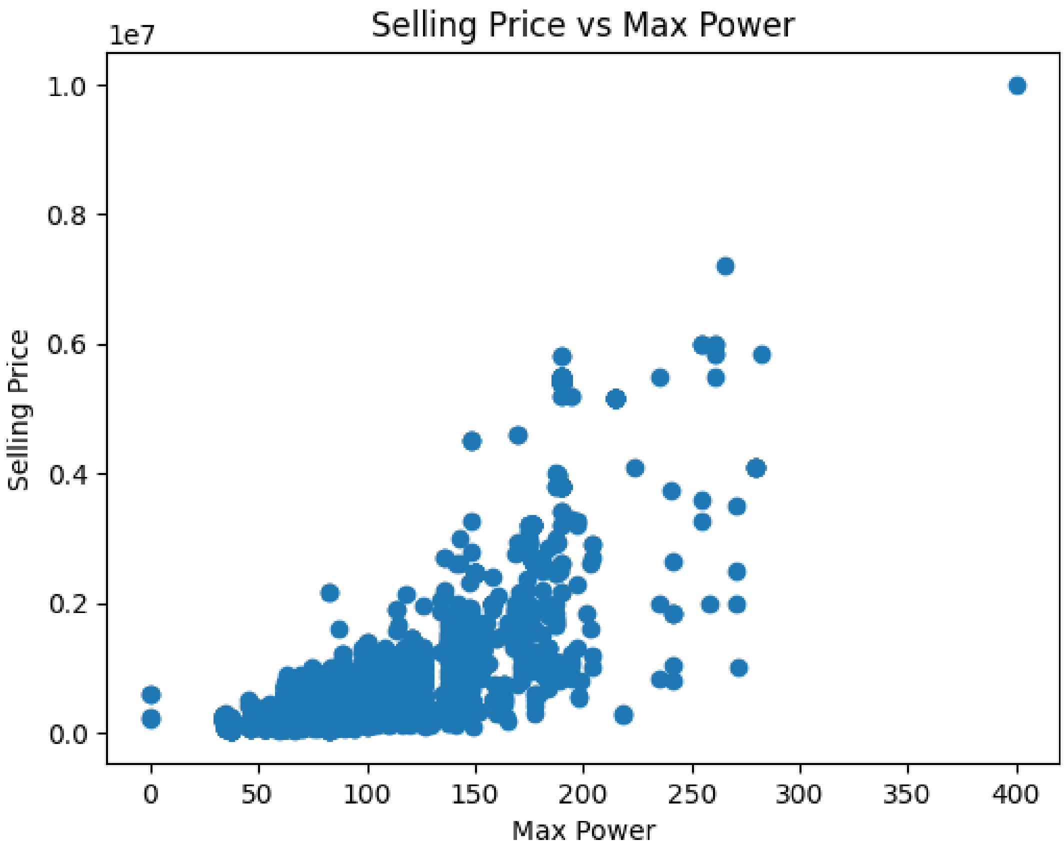
[597]:
```
plt.scatter(df_train["mileage"], df_train["selling_price"])
plt.xlabel("Mileage")
plt.ylabel("Selling Price")
plt.title("Selling Price vs Mileage")
plt.show()
# The relationship is not very clear
# but there is a slight trend that higher mileage cars tend to be priced lower
```



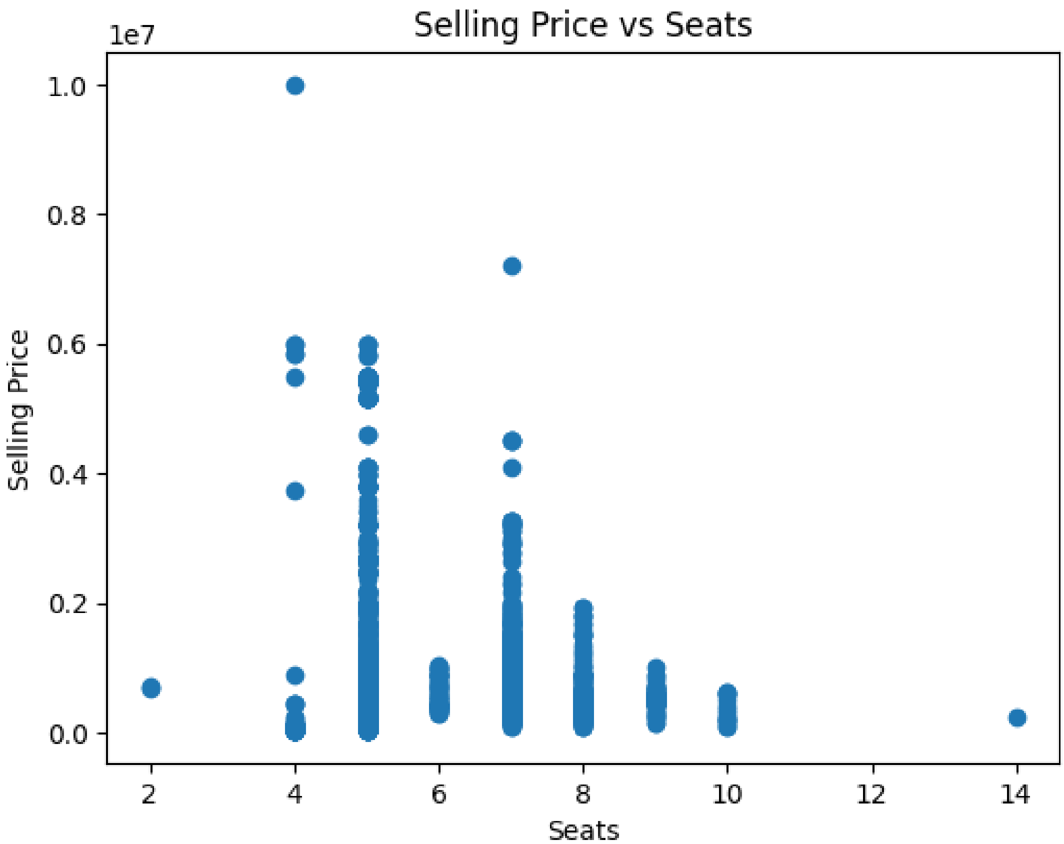
[598]:
```
plt.scatter(df_train["engine"], df_train["selling_price"])
plt.xlabel("Engine")
plt.ylabel("Selling Price")
plt.title("Selling Price vs Engine")
plt.show()
# This shows that cars with larger engines tend to be priced higher
```



[599]:
```
plt.scatter(df_train["max_power"], df_train["selling_price"])
plt.xlabel("Max Power")
plt.ylabel("Selling Price")
plt.title("Selling Price vs Max Power")
plt.show()
# This shows that cars with higher max power tend to be priced higher
```



[600]:
```
plt.scatter(df_train["seats"], df_train["selling_price"])
plt.xlabel("Seats")
plt.ylabel("Selling Price")
plt.title("Selling Price vs Seats")
plt.show()
# This shows that cars with more seats tend to be priced lower
# Which is a little bit counter-intuitive
# But I think lower seats are more luxurious cars
# And more seats are more like for utility use
```



1.5 Encoding and Scaling

[624]:
```
# cat_features = [
#     "brand",
#     "fuel",
#     "seller_type",
#     "transmission",
#     "owner",
# ]
# num_features = [
#     "year",
#     "km_driven",
#     "mileage",
#     "engine",
#     "max_power",
#     "seats",
# ]
# target = "selling_price"
```

[604]:
```python
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

[801]:
```python
# Brand has a lot of categories, so One-Hot Encoding might not be the best idea
# since it introduces a lot of dimensions, Instead, Label Encoding is used
le_brand = LabelEncoder()
df_train["brand"] = le_brand.fit_transform(df_train["brand"])
df_test["brand"] = le_brand.transform(df_test["brand"])
```

[752]:
```python
le_brand.classes_
```

[752]:
```
array(['Ambassador', 'Ashok', 'Audi', 'BMW', 'Chevrolet', 'Daewoo',
       'Datsun', 'Fiat', 'Force', 'Ford', 'Honda', 'Hyundai', 'Isuzu',
       'Jaguar', 'Jeep', 'Kia', 'Land', 'Lexus', 'MG', 'Mahindra',
       'Maruti', 'Mercedes-Benz', 'Mitsubishi', 'Nissan', 'Opel',
       'Peugeot', 'Renault', 'Skoda', 'Tata', 'Toyota', 'Volkswagen',
       'Volvo'], dtype=object)
```

[802]:
```python
# fuel has only 2 categories, so Label Encoding is used
le_fuel = LabelEncoder()
df_train["fuel"] = le_fuel.fit_transform(df_train["fuel"])
df_test["fuel"] = le_fuel.transform(df_test["fuel"])
```

[803]:
```python
# transmission has 2 categories, so Label Encoding is used
le_transmission = LabelEncoder()
df_train["transmission"] = le_transmission.
↪fit_transform(df_train["transmission"])
df_test["transmission"] = le_transmission.transform(df_test["transmission"])
```

[804]:
```python
# owner has 4 categories, but they are ordinal, so Label Encoding is used
owner_mapping = {
    "First Owner": 1,
    "Second Owner": 2,
    "Third Owner": 3,
    "Fourth & Above Owner": 4,
}
df_train["owner"] = df_train["owner"].map(owner_mapping)
df_test["owner"] = df_test["owner"].map(owner_mapping)
```

[805]:
```python
# seller_type has 3 categories, so One-Hot Encoding is used

# Use sparse_output=False to get a dense array directly
# So concatenation is easier
ohe_seller_type = OneHotEncoder(sparse_output=False, drop="first")

# Fit and transform on training set, transform on test set
seller_type_train_ohe = ohe_seller_type.fit_transform(df_train[["seller_type"]])
seller_type_test_ohe = ohe_seller_type.transform(df_test[["seller_type"]])
```

```python
# Get the new column names to create DataFrames
seller_type_ohe_cols = ohe_seller_type.get_feature_names_out(["seller_type"])
df_seller_type_train_ohe = pd.DataFrame(
    seller_type_train_ohe,
    columns=seller_type_ohe_cols,
    index=df_train.index,
)
df_seller_type_test_ohe = pd.DataFrame(
    seller_type_test_ohe,
    columns=seller_type_ohe_cols,
    index=df_test.index,
)

# Concatenate the new columns to the original DataFrame and drop the original␣
↪column
df_train = pd.concat([df_train, df_seller_type_train_ohe], axis=1)
df_test = pd.concat([df_test, df_seller_type_test_ohe], axis=1)
df_train = df_train.drop(columns=["seller_type"])
df_test = df_test.drop(columns=["seller_type"])
```

[806]:
```python
df_train.head()
```

[806]:
```
      brand  year  selling_price  km_driven  fuel  transmission  owner  \
6518     28  2019         520000       2560     1             0      1
6144     10  2013         300000      80000     1             1      2
6381     11  2011         380000     150000     0             1      4
438      20  2013         530000     120000     0             1      2
5939     20  2017         335000      25000     1             1      1

      mileage  engine  max_power  seats  seller_type_Individual  \
6518    24.00  1199.0      83.81    5.0                     1.0
6144    19.40  1198.0      86.80    5.0                     1.0
6381    23.00  1396.0      90.00    5.0                     1.0
438     23.40  1248.0      74.00    5.0                     1.0
5939    23.95   998.0      67.05    5.0                     1.0

      seller_type_Trustmark Dealer
6518                           0.0
6144                           0.0
6381                           0.0
438                            0.0
5939                           0.0
```

[616]:
```python
df_test.head()
```

[616]:
```
      brand  year  selling_price  km_driven  fuel  transmission  owner  \
1971     10  2004         198000     110000     1             1      3
4664     28  2014         500000     291977     0             1      1
5448     20  2016         425000      70000     0             1      1
3333     10  2006         150000     120000     1             1      2
2316     20  2013         525000      69000     0             1      2

      mileage  engine  max_power  seats  seller_type_Individual  \
1971     12.8  1493.0     100.00    5.0                     1.0
4664     14.0  2179.0     138.10    7.0                     1.0
5448     23.2  1248.0      73.94    5.0                     1.0
3333     16.9  1497.0     100.00    5.0                     1.0
2316     22.9  1248.0      74.00    5.0                     1.0

      seller_type_Trustmark Dealer
1971                           0.0
4664                           0.0
5448                           0.0
3333                           0.0
2316                           0.0
```

[807]:
```python
# Scale numeric features if necessary
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
num_features = [
    "year",
    "km_driven",
    "mileage",
    "engine",
    "max_power",
    "seats",
]
df_train[num_features] = scaler.fit_transform(df_train[num_features])
df_test[num_features] = scaler.transform(df_test[num_features])
```

[808]:
```python
df_train.head()
```

[808]:
```
      brand      year  selling_price  km_driven  fuel  transmission  owner  \
6518     28  1.281987         520000  -1.152821     1             0      1
6144     10 -0.199901         300000   0.169997     1             1      2
6381     11 -0.693863         380000   1.365726     0             1      4
438      20 -0.199901         530000   0.853271     0             1      2
5939     20  0.788025         335000  -0.769504     1             1      1

       mileage    engine  max_power     seats  seller_type_Individual  \
6518  1.172992 -0.521641  -0.221731 -0.430521                     1.0
```

```
6144  0.004476 -0.523645  -0.137237 -0.430521                        1.0
6381  0.918966 -0.126955  -0.046808 -0.430521                        1.0
438   1.020577 -0.423471  -0.498953 -0.430521                        1.0
5939  1.160290 -0.924342  -0.695354 -0.430521                        1.0

      seller_type_Trustmark Dealer
6518                           0.0
6144                           0.0
6381                           0.0
438                            0.0
5939                           0.0
```

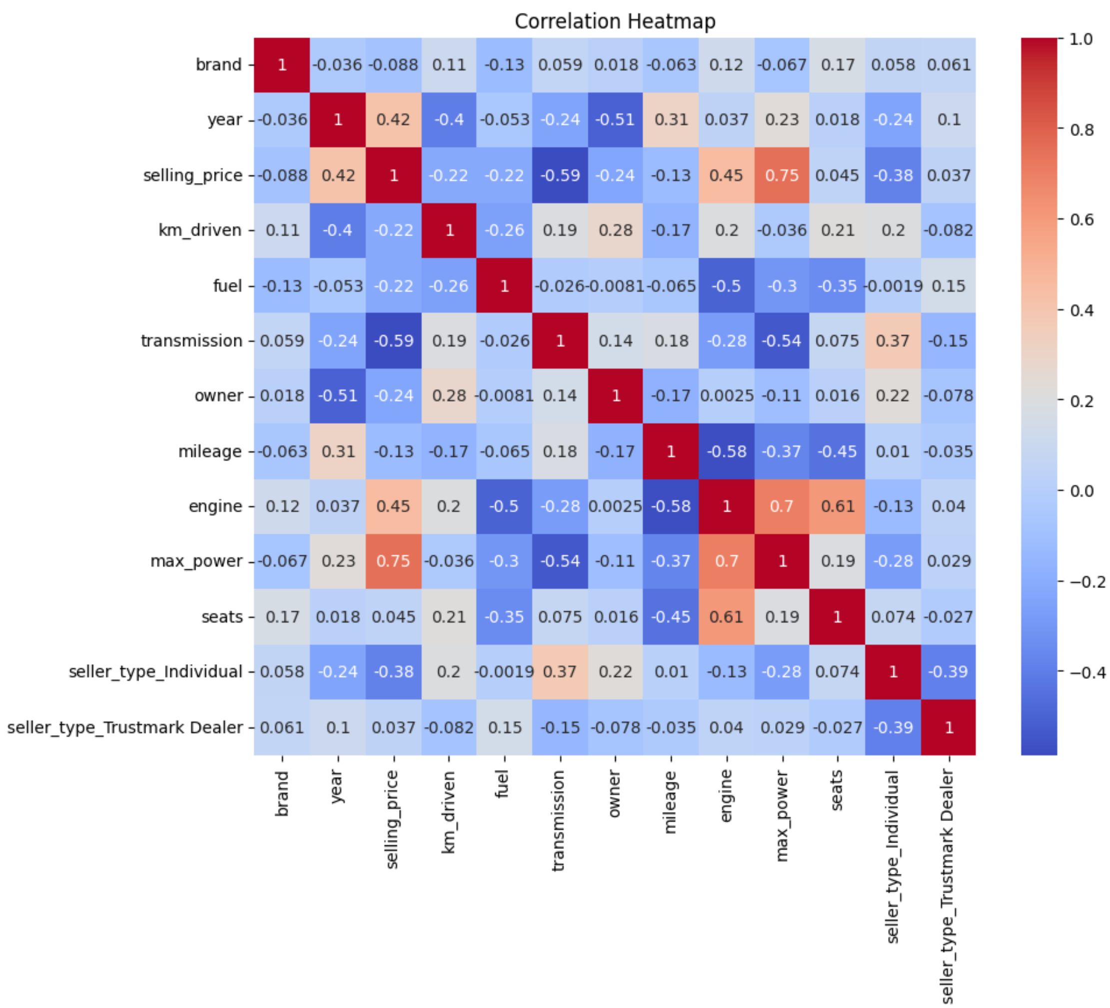
[627]:
```
df_test.head()
```

[627]:
```
      brand      year  selling_price  km_driven  fuel  transmission  owner  \
1971     10 -2.422733         198000   0.682453     1             1      3
4664     28  0.047081         500000   3.790956     0             1      1
5448     20  0.541043         425000  -0.000821     0             1      1
3333     10 -1.928770         150000   0.853271     1             1      2
2316     20 -0.199901         525000  -0.017903     0             1      2

       mileage    engine  max_power     seats  seller_type_Individual  \
1971 -1.672090  0.067383   0.235783 -0.430521                     1.0
4664 -1.367260  1.441773   1.312455  1.675668                     1.0
5448  0.969771 -0.423471  -0.500649 -0.430521                     1.0
3333 -0.630587  0.075397   0.235783 -0.430521                     1.0
2316  0.893564 -0.423471  -0.498953 -0.430521                     1.0

      seller_type_Trustmark Dealer
1971                           0.0
4664                           0.0
5448                           0.0
3333                           0.0
2316                           0.0
```

[628]:
```
print(df_train.shape)
print(df_test.shape)
```

```
(6421, 13)
(1607, 13)
```

[809]:
```
import seaborn as sns

plt.figure(figsize=(10, 8))
sns.heatmap(df_train.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



1.6 Prepare for Model Training

1.6.1 For the first training I will use all features

[632]:
```
target = "selling_price"

X_train = df_train.drop(columns=[target])
y_train = df_train[target]
X_test = df_test.drop(columns=[target])
y_test = df_test[target]
```

[633]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(6421, 12)
```

```
(6421,)
(1607, 12)
(1607,)
```

[640]:
```
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

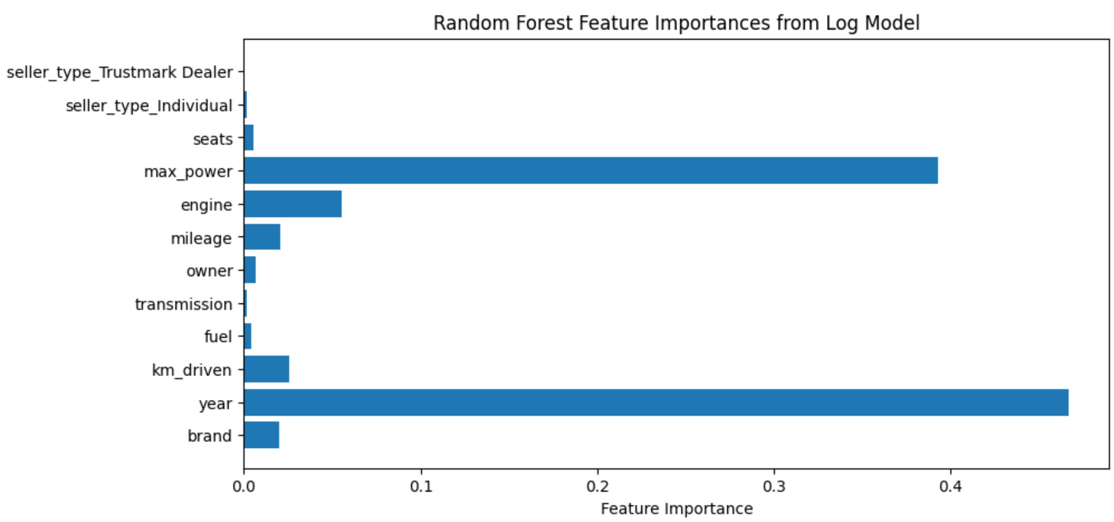
[642]:
```
# Declare two models for both algorithms to compare no log vs log transformation

lr = LinearRegression()
lr_log = LinearRegression()
rf = RandomForestRegressor(random_state=42)
rf_log = RandomForestRegressor(random_state=42)

lr.fit(X_train, y_train)
rf.fit(X_train, y_train)
lr_log.fit(X_train, np.log(y_train))  # Use log transformation to stabilize big␣
 ↪numbers
rf_log.fit(X_train, np.log(y_train))  # Use log transformation to stabilize big␣
 ↪numbers

y_pred_lr = lr.predict(X_test)
y_pred_rf = rf.predict(X_test)
y_pred_lr_log = np.exp(lr_log.predict(X_test))  # Inverse of log transformation
y_pred_rf_log = np.exp(rf_log.predict(X_test))  # Inverse of log transformation

print("Linear Regression without log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_lr))
print("R2:", r2_score(y_test, y_pred_lr))
print()
print("Linear Regression with log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_lr_log))
print("R2:", r2_score(y_test, y_pred_lr_log))
print()
print("Random Forest without log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_rf))
print("R2:", r2_score(y_test, y_pred_rf))
print()
print("Random Forest with log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_rf_log))
print("R2:", r2_score(y_test, y_pred_rf_log))

# WOW, log transformation really improved the model performance
```

```
Linear Regression without log transformation:
MSE: 196880271520.98172
```

```
R2: 0.6923800578614293

Linear Regression with log transformation:
MSE: 88821891150.21065
R2: 0.8612182683151453

Random Forest without log transformation:
MSE: 18446818737.507668
R2: 0.971177359372607

Random Forest with log transformation:
MSE: 17378746490.26027
R2: 0.9728461925185581
```

[646]:

```python
importances = rf_log.feature_importances_
features = X_train.columns

plt.figure(figsize=(10, 5))
plt.barh(features, importances)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importances from Log Model")
plt.show()
```



1.6.2 For second trainning, I will use some selected features

from feature importance these might be the best predictor

seats, max_power, engine, mileage, owner, fuel, km_driven, year, brand

[647]:
```
selected_features = [
    "seats",
    "max_power",
    "engine",
    "mileage",
    "owner",
    "fuel",
    "km_driven",
    "year",
    "brand",
]
X_train = df_train[selected_features]
y_train = df_train[target]
X_test = df_test[selected_features]
y_test = df_test[target]
```

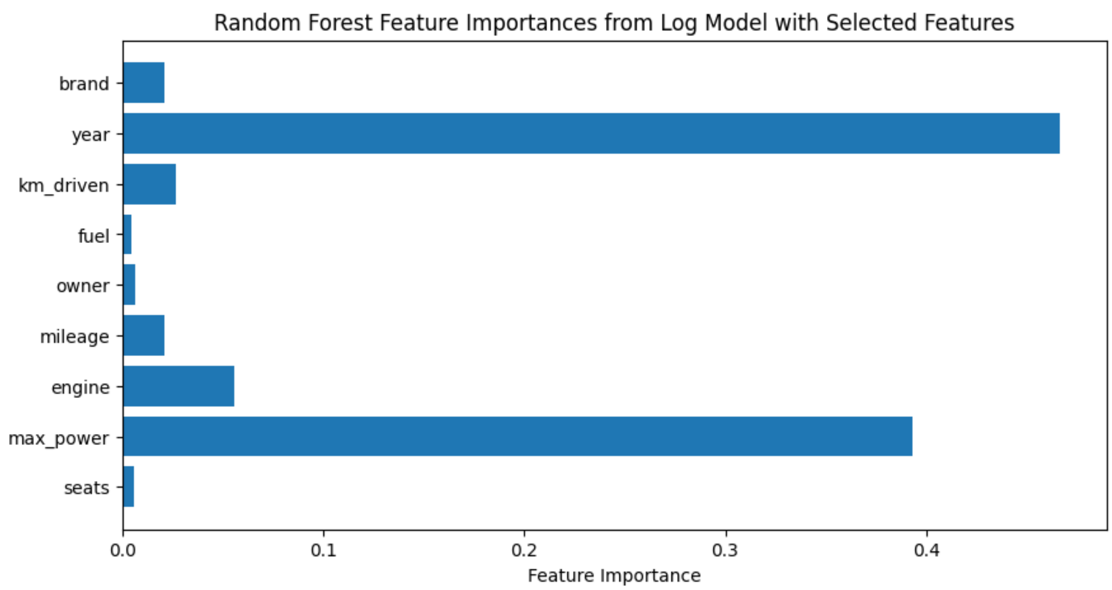
[648]:
```
# Try again with selected features

lr = LinearRegression()
lr_log = LinearRegression()
rf  = RandomForestRegressor(random_state=42)
rf_log = RandomForestRegressor(random_state=42)

lr.fit(X_train, y_train)
rf.fit(X_train, y_train)
lr_log.fit(X_train, np.log(y_train))  # Use log transformation to stabilize big␣
↪numbers
rf_log.fit(X_train, np.log(y_train))  # Use log transformation to stabilize big␣
↪numbers

y_pred_lr = lr.predict(X_test)
y_pred_rf = rf.predict(X_test)
y_pred_lr_log = np.exp(lr_log.predict(X_test))  # Inverse of log transformation
y_pred_rf_log = np.exp(rf_log.predict(X_test))  # Inverse of log transformation

print("Linear Regression without log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_lr))
print("R2:", r2_score(y_test, y_pred_lr))
print()
print("Linear Regression with log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_lr_log))
print("R2:", r2_score(y_test, y_pred_lr_log))
print()
print("Random Forest without log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_rf))
print("R2:", r2_score(y_test, y_pred_rf))
print()
```

```
print("Random Forest with log transformation:")
print("MSE:", mean_squared_error(y_test, y_pred_rf_log))
print("R2:", r2_score(y_test, y_pred_rf_log))

# Some how first 3 models performed worse than before
# But Random Forest with log transformation performed slightly better
```

```
Linear Regression without log transformation:
MSE: 218267416345.6799
R2: 0.6589632395959093

Linear Regression with log transformation:
MSE: 120787074115.41101
R2: 0.811273559999585

Random Forest without log transformation:
MSE: 18545196928.77422
R2: 0.9710236461880847

Random Forest with log transformation:
MSE: 16993161951.995321
R2: 0.9734486576230312
```

[650]:

```
importances = rf_log.feature_importances_
features = X_train.columns

plt.figure(figsize=(10, 5))
plt.barh(features, importances)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importances from Log Model with Selected␣
↪Features")
plt.show()
```



1.7 Prepare the whole pipeline from preprocessing to prediction

1. After data set loaded, it should be clean and formatted using data_cleaning function above.
2. Data splitted into train/test and pass through pipeline properly to avoid data leakage.
3. Pipeline should have multiple imputers for each features.
4. Pipeline should include model so that it can be saved and predict out of the box.

Note: For this part, I will load dataset again, clean, split, and fit it through the pipeline with all the features because the selected features above don't really improve much overall, also so i can save preprocessors and model into one file and use it to predict in the backend.

[764]:
```
import joblib
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler

df_original = pd.read_csv("Cars.csv")
```

[765]:
```
df_original.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           8128 non-null   object
 1   year           8128 non-null   int64
```

```
 2   selling_price  8128 non-null   int64
 3   km_driven      8128 non-null   int64
 4   fuel           8128 non-null   object
 5   seller_type    8128 non-null   object
 6   transmission   8128 non-null   object
 7   owner          8128 non-null   object
 8   mileage        7907 non-null   object
 9   engine         7907 non-null   object
 10  max_power      7913 non-null   object
 11  torque         7906 non-null   object
 12  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(9)
memory usage: 825.6+ KB
```

[766]:
```
df_train_final, df_test_final = train_test_split(df_original, test_size=0.2,␣
↪random_state=42)
```

[767]:
```
# This function is copied from above


def data_cleaning(input_df: pd.DataFrame) -> pd.DataFrame:
    df = input_df.copy()

    # Drop unused columns first to reduce size
    df = df.drop(columns=["torque"])

    # Drop rows that will definitely not be used
    df = df[~df["fuel"].isin(["CNG", "LPG"])]
    df = df[df["owner"] != "Test Drive Car"]

    # Remove Units
    df["mileage"] = df["mileage"].str.split(" ").str[0]
    df["engine"] = df["engine"].str.split(" ").str[0]
    df["max_power"] = df["max_power"].str.split(" ").str[0]

    # Numeric Type conversion
    df["mileage"] = df["mileage"].astype(float)
    df["engine"] = df["engine"].astype(float)
    df["max_power"] = df["max_power"].astype(float)

    # Fix Brand column
    df = df.rename(columns={"name": "brand"})
    df["brand"] = df["brand"].str.split(" ").str[0]

    return df
```

```python
# This process doesn't include fillna, encoding, scaling
df_train_final = data_cleaning(df_train_final)
df_test_final = data_cleaning(df_test_final)
```

[783]:
```python
df_train_final
```

[783]:
```
         brand  year  selling_price  km_driven    fuel seller_type  \
6518      Tata  2019         520000       2560  Petrol  Individual
6144     Honda  2013         300000      80000  Petrol  Individual
6381   Hyundai  2011         380000     150000  Diesel  Individual
438     Maruti  2013         530000     120000  Diesel  Individual
5939    Maruti  2017         335000      25000  Petrol  Individual
…          …   …              …        …       …         …
5226  Mahindra  2009         475000     120000  Diesel  Individual
5390    Maruti  2014         530000      80000  Diesel  Individual
860    Hyundai  2016         576000      35000  Petrol  Individual
7603    Maruti  2019         770000      27000  Diesel  Individual
7270    Maruti  2006         155000      70000  Petrol  Individual

     transmission                owner  mileage  engine  max_power  seats
6518    Automatic          First Owner    24.00  1199.0      83.81    5.0
6144       Manual         Second Owner    19.40  1198.0      86.80    5.0
6381       Manual  Fourth & Above Owner    23.00  1396.0      90.00    5.0
438        Manual         Second Owner    23.40  1248.0      74.00    5.0
5939       Manual          First Owner    23.95   998.0      67.05    5.0
…            …                    …       …       …        …       …
5226       Manual          First Owner    12.05  2179.0     120.00    7.0
5390       Manual         Second Owner    23.40  1248.0      74.00    5.0
860        Manual          First Owner    18.60  1197.0      81.83    5.0
7603       Manual          First Owner    28.40  1248.0      74.02    5.0
7270       Manual         Second Owner    16.10   796.0      37.00    4.0

[6421 rows x 12 columns]
```

[784]:
```python
df_train_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 6421 entries, 6518 to 7270
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   brand          6421 non-null   object
 1   year           6421 non-null   int64
 2   selling_price  6421 non-null   int64
 3   km_driven      6421 non-null   int64
 4   fuel           6421 non-null   object
 5   seller_type    6421 non-null   object
 6   transmission   6421 non-null   object
```

```
 7   owner          6421 non-null   object
 8   mileage        6257 non-null   float64
 9   engine         6257 non-null   float64
 10  max_power      6261 non-null   float64
 11  seats          6257 non-null   float64
dtypes: float64(4), int64(3), object(5)
memory usage: 652.1+ KB
```

[ ]:
```
from sklearn.impute import SimpleImputer

# Define transformers for each feature group
brand_le = (
    "brand_le",
    Pipeline(
        [
            # Pre-imputer for handling missing values before encoding
            ("pre_imputer", SimpleImputer(strategy="most_frequent")),
            ("encoder", OrdinalEncoder(handle_unknown="use_encoded_value",␣
↪unknown_value=np.nan)),
            ("post_imputer", SimpleImputer(strategy="most_frequent")),
            # Post-imputer for handling any NaN introduced by unknown␣
↪categories during encoding
            # So the pipeline is robust to unseen categories in production data
            # This won't happen if frontend limits the choices to existing␣
↪categories only
            # But it's better to be safe than sorry
        ],
    ),
    ["brand"],
)

fuel_le = (
    "fuel_le",
    Pipeline(
        [
            ("pre_imputer", SimpleImputer(strategy="most_frequent")),
            ("encoder", OrdinalEncoder(handle_unknown="use_encoded_value",␣
↪unknown_value=np.nan)),
            ("post_imputer", SimpleImputer(strategy="most_frequent")),
        ],
    ),
    ["fuel"],
)

transmission_le = (
    "transmission_le",
    Pipeline(
```

```
        [
            ("pre_imputer", SimpleImputer(strategy="most_frequent")),
            ("encoder", OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value=np.nan)),
            ("post_imputer", SimpleImputer(strategy="most_frequent")),
        ],
    ),
    ["transmission"],
)

owner_le = (
    "owner_le",
    Pipeline(
        [
            ("pre_imputer", SimpleImputer(strategy="most_frequent")),
            (
                "encoder",
                OrdinalEncoder(
                    categories=[
                        [
                            "First Owner",
                            "Second Owner",
                            "Third Owner",
                            "Fourth & Above Owner",
                        ],
                    ],
                    handle_unknown="use_encoded_value",
                    unknown_value=np.nan,
                ),
            ),
            ("post_imputer", SimpleImputer(strategy="most_frequent")),
        ],
    ),
    ["owner"],
)

seller_type_ohe = (
    "seller_type_ohe",
    Pipeline(
        [
            ("imputer", SimpleImputer(strategy="most_frequent")),
            ("encoder", OneHotEncoder(sparse_output=False, drop="first", handle_unknown="ignore")),
        ],
    ),
    ["seller_type"],
)
```

```
num_scaler = (
    "num_scaler",
    Pipeline(
        [
            (
                "imputer",
                ColumnTransformer(
                    transformers=[
                        ("year_imputer", SimpleImputer(strategy="median"),␣
 ↪["year"]),
                        ("km_imputer", SimpleImputer(strategy="median"),␣
 ↪["km_driven"]),
                        ("mileage_imputer", SimpleImputer(strategy="mean"),␣
 ↪["mileage"]),
                        ("engine_imputer", SimpleImputer(strategy="median"),␣
 ↪["engine"]),
                        ("max_power_imputer", SimpleImputer(strategy="median"),␣
 ↪["max_power"]),
                        ("seats_imputer",␣
 ↪SimpleImputer(strategy="most_frequent"), ["seats"]),
                    ],
                    remainder="passthrough",
                ),
            ),
            ("scaler", StandardScaler()),
        ],
    ),
    ["year", "km_driven", "mileage", "engine", "max_power", "seats"],
)

# Combine all transformers into the ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        brand_le,
        fuel_le,
        transmission_le,
        owner_le,
        seller_type_ohe,
        num_scaler,
    ],
    remainder="passthrough",
    verbose_feature_names_out=True,
)

# Build the pipeline
```

```
pipeline = Pipeline(
    steps=[
        ("preprocessor", preprocessor),
        ("model", RandomForestRegressor(random_state=42)),
    ],
)
```

[772]:
```
X_train_final = df_train_final.drop(columns=["selling_price"])
X_test_final = df_test_final.drop(columns=["selling_price"])
y_train_final = df_train_final["selling_price"]
y_test_final = df_test_final["selling_price"]
```

[773]:
```
print(X_train_final.shape)
print(y_train_final.shape)
print(X_test_final.shape)
print(y_test_final.shape)
```

```
(6421, 11)
(6421,)
(1607, 11)
(1607,)
```

[774]:
```
X_train_final.columns
```

[774]:
```
Index(['brand', 'year', 'km_driven', 'fuel', 'seller_type', 'transmission',
       'owner', 'mileage', 'engine', 'max_power', 'seats'],
      dtype='object')
```

[775]:
```
# Fit pipeline
pipeline.fit(X_train_final, np.log(y_train_final))
```

[775]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('brand_le',
Pipeline(steps=[('pre_imputer',
SimpleImputer(strategy='most_frequent')),
                                                                    ('encoder',
OrdinalEncoder(handle_unknown='use_encoded_value',
  unknown_value=nan)),
('post_imputer',
SimpleImputer(strategy='most_frequent'))]),
                                                  ['brand']),
                                                 ('fuel_le',
                                                  Pipeline(steps=[…
                    ['mileage']),
                   ('engine_imputer',
                    SimpleImputer(strategy='median'),
                    ['engine']),
```

```
                        ('max_power_imputer',
                         SimpleImputer(strategy='median'),
                         ['max_power']),
                        ('seats_imputer',
                         SimpleImputer(strategy='most_frequent'),
                         ['seats'])])),
                                                                    ('scaler',
StandardScaler())]),
                                                 ['year', 'km_driven',
                                                  'mileage', 'engine',
                                                  'max_power', 'seats'])])),
                ('model', RandomForestRegressor(random_state=42))])
```

[776]:

```
y_pred_final = pipeline.predict(X_test_final)
```

[ ]:

```
print(mean_squared_error(y_test_final, np.exp(y_pred_final)))
print(r2_score(y_test_final, np.exp(y_pred_final)))
```

```
17255870470.57974
0.9730381828778375
```

The performance is similar to previous best model with slight variation probably due to encoding steps which
- Manually done encoding use LabelEncoder and pd.get_dummies for One-Hot Encoding
- Pipeline encoding use OrdinalEncoder and OneHotEncoder
- LabelEncoder object can't be used in pipeline for some reason from package's design
- pd.get_dummies can't be used in pipeline because it is not a transformer class
- OrdinalEncoder is similar to LabelEncoder
- But OrdinalEncoder might give different encoding order than LabelEncoder
- However, this pipeline is much cleaner and easier to use

[794]:

```
X_test_final[:1]
```

[794]:

```
      brand  year  km_driven    fuel seller_type transmission        owner  \
1971  Honda  2004     110000  Petrol  Individual       Manual  Third Owner

      mileage  engine  max_power  seats
1971     12.8  1493.0      100.0    5.0
```

[778]:

```
# Sample 3 inferences
print("Predict:", np.exp(pipeline.predict(X_test_final[:3])))
print("Actual:", y_test_final[:3].values)
```

```
Predict: [144042.76608739 543978.14584711 426373.11498133]
Actual: [198000 500000 425000]
```

[779]:

```
# Save pipeline
joblib.dump(pipeline, "./app/backend/model/car_price_pipeline.joblib")
```

[779]: ['./app/backend/model/car_price_pipeline.joblib']

[780]:
```
# Load pipeline and predict on new sample
loaded_pipeline = joblib.load("./app/backend/model/car_price_pipeline.joblib")
```

[782]:
```
y_pred = loaded_pipeline.predict(X_test_final[:3])

print("Predict:", np.exp(y_pred))
print("Actual:", y_test_final[:3].values)
```

```
Predict: [144042.76608739 543978.14584711 426373.11498133]
Actual: [198000 500000 425000]
```

[ ]:
```
# Will be used in frontend
cat_features = ["brand", "fuel", "seller_type", "transmission", "owner"]
cat_values_dict = {col: df_train_final[col].dropna().unique().tolist() for col␣
 ↪in cat_features}
print(cat_values_dict)
```

```
{'brand': ['Tata', 'Honda', 'Hyundai', 'Maruti', 'Mahindra', 'Volkswagen',
'Toyota', 'Force', 'Skoda', 'BMW', 'Fiat', 'Ford', 'Jaguar', 'Renault', 'Jeep',
'Nissan', 'Chevrolet', 'Datsun', 'Mercedes-Benz', 'Lexus', 'Mitsubishi',
'Volvo', 'Audi', 'Ashok', 'Peugeot', 'Land', 'Ambassador', 'Isuzu', 'MG',
'Opel', 'Daewoo', 'Kia'], 'fuel': ['Petrol', 'Diesel'], 'seller_type':
['Individual', 'Dealer', 'Trustmark Dealer'], 'transmission': ['Automatic',
'Manual'], 'owner': ['First Owner', 'Second Owner', 'Fourth & Above Owner',
'Third Owner']}
```

2 Task 2: Summary

2.1 Which features are important? Which are not? Why?

According to feature importance and correlation between numerical features `year`, `engine`, and `max_power` are definitely the best 3 predictors of `selling_price` with correlation of `0.42`, `0.45`, and `0.75` respectively. Next 2 predictsors are `km_driven` and `mileage` with some small correlation of `-0.22` and `-0.13` respectively.

Next, for categorical features, even though pearson correlation cannot be used to measure the relationship between categorical and numerical features (and numerical target), some categorical features (especially features with binary values) can be converted to numerical features (0, 1) and then the correlation can mean something, this includes `fuel` and `transmission` with correlation of `-0.22` and `-0.59` respectively.

Other features are less significant, but they can still help the model to learn better. - `owner` is still quite useful since cars with more owners are usually cheaper.
- Some `brand` are expensive, but most of them are quite similar.
- `seats`, `seller_type` have some relationship with `selling_price`, but not very strong

2.2 Which algorithm performs well? Which does not? Why?

In this project, I have tried 2 algorithms: `Linear Regression` and `Random Forest Regressor`.
- `Linear Regression` with all features performs quite bad by achieving R2 of 0.69 without log transformation and 0.86 with log transformation. This is probably because the relationship between features and target is not linear so the model with "Linear" in its name cannot capture the relationship well. (1 feature is a line on 2D plane, 2 features is a plane in 3D space, 3 features is a 3D (Box?) in 4D space, and so on, but no matter how many features there are, the relationship is still linear). Another factor is the output variable `selling_price` is very large, trying to predict something that large with linear model make model unstable, so log transformation helps to reduce the scale of output variable and make the model much more stable with R2 of 0.86 (+0.17 which is a lot).
- `Random Forest Regressor` with all features performs very well by achieving R2 of 0.97 both with and without log transformation. This is probably because Random Forest is an ensemble of Decision Trees which each tree capture small part of the relationship between features and target, then combine and average them together to make a better prediction unlike `Linear Regression` with one big equation to capture everything. Also, Random Forest is somehow not affected by the scale of output variable, so log transformation does not help much.