feature-engineering

November 17, 2025

0.0.1 Feature Engineering

[1]:
```
%load_ext autoreload
%autoreload 2
```

[2]:
```
from mldl_hw3.preprocessing import DataLoader
from mldl_hw3.consts import Brand
from mldl_hw3.experiment import Experiment, ExperimentConfig

from typing import Optional

from xgboost import XGBRegressor
from sklearn.pipeline import Pipeline
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.compose import TransformedTargetRegressor
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.cluster import KMeans
from category_encoders import TargetEncoder
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

[3]:
```
df_train, df_test = DataLoader("../dataset").load()
```

[4]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4428 entries, G4XLU0 to J2RCU8
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Name               4428 non-null   category
 1   Location           4428 non-null   category
 2   Year               4428 non-null   Int64
 3   Kilometers_Driven  4428 non-null   Int64
 4   Fuel_Type          4428 non-null   category
 5   Transmission       4428 non-null   category
```

```
 6   Owner_Type         4428 non-null   category
 7   Mileage            4428 non-null   float64
 8   Engine             4428 non-null   Int64
 9   Power              4336 non-null   float64
 10  Colour             4428 non-null   category
 11  Seats              4428 non-null   Int64
 12  Doors              4428 non-null   Int64
 13  New_Price          601 non-null    float64
 14  Price              4428 non-null   float64
dtypes: Int64(5), category(6), float64(4)
memory usage: 408.6+ KB
```

[5]:
```
X_train = df_train.copy()
y_train = X_train.pop("Price")
X_test = df_test.drop(columns=["Price"])
```

0.0.2 Baseline

[6]:
```
class CategoricalEncoder(TransformerMixin, BaseEstimator):
    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "CategoricalEncoder":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()

        for feature in X.select_dtypes(["category"]):
            X[feature] = X[feature].cat.codes

        return X
```

[7]:
```
def build_baseline_pipeline(**model_params) -> Pipeline:
    return Pipeline(
        [
            ("encoder", CategoricalEncoder()),
            ("model", XGBRegressor(**model_params)),
        ]
    )
```

[8]:
```
baseline_exp = Experiment(
    ExperimentConfig(name="baseline", pipeline=build_baseline_pipeline())
)

baseline_exp_result = baseline_exp.run(X_train, y_train, X_test)
```

```
[Experiment: baseline]
Cross-validating (5-folds)…
```

```
CV score: 0.1606 ± 0.0163
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/baseline.csv
Experiment complete
```

Brand extraction from `Name` Form the analysis on `preprocessing.ipynb`, we found that `Name` feature has too many cateogires. The car's name usually consists of brand and model. From common knowledge, we know that the car's brand has significant impact on forming its price. Based on this domain knowledge and to reduce category, we extract `Brand` from `Name`.

[9]:
```python
class BrandModelExtractor(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        name_col: str = "Name",
        brand_col: str = "Brand",
        model_col: str = "Model",
        brand_enum=Brand,
    ):
        self.name_col = name_col
        self.brand_col = brand_col
        self.model_col = model_col
        self.brand_enum = brand_enum

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) -> 
 ↪"BrandModelExtractor":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()

        names = X[self.name_col].str.title()
        brands = pd.Series([None] * len(names), index=names.index, dtype=object)
        models = pd.Series([None] * len(names), index=names.index, dtype=object)

        for brand in Brand:
            condition = names.str.startswith(brand.value, na=False) & brands.
 ↪isna()

            if condition.any():
                brands.loc[condition] = brand.name
                matched_names = names.loc[condition]
                residuals = matched_names.str[len(brand.value) :].str.strip()
                models.loc[condition] = residuals.where(residuals != "", None)

        brands = brands.rename("Brand").astype("category")
```

```
        models = models.rename("Model").astype("category")

        X[self.brand_col] = brands
        X[self.model_col] = models

        return X
```

[10]:
```
X_train = df_train.copy()
y_train = X_train.pop("Price")

df_train_bm = pd.DataFrame(BrandModelExtractor().fit_transform(X_train,␣
 ↪y_train))
df_train_bm
```

[10]:
```
                          Name    Location  Year  Kilometers_Driven Fuel_Type  \
ID
G4XLU0             Tata Indigo  Coimbatore  2013              59138    Diesel
CRSHOS          Toyota Corolla       Kochi  2013              81504    Diesel
FUJ4X1               Ford Ikon   Hyderabad  2007              92000    Petrol
QMVK6E             Hyundai i20     Kolkata  2012              33249    Diesel
4SWHFC              Honda City   Bangalore  2011              65000    Petrol
…                            …           …     …                  …       …
TR7SLB         Mahindra XUV500       Kochi  2016              51884    Diesel
QB41QE              Honda Jazz     Kolkata  2016              27210    Diesel
ODG8N7        Land Rover Range        Pune  2015              52000    Diesel
EV2ZBX             Maruti Alto       Delhi  2013              56000    Petrol
J2RCU8  Mercedes-Benz GL-Class   Bangalore  2014              52000    Diesel

       Transmission Owner_Type  Mileage  Engine   Power        Colour  Seats  \
ID
G4XLU0       Manual      First    17.00    1405   70.00        Others      5
CRSHOS       Manual      First    21.43    1364   87.20        Others      5
FUJ4X1       Manual      First    13.80    1299   70.00        Others      5
QMVK6E       Manual      First    21.27    1396   88.76  Black/Silver      5
4SWHFC       Manual      First    17.00    1497  118.00         White      5
…                 …          …        …       …       …             …      …
TR7SLB       Manual      First    16.00    2179  140.00         White      7
QB41QE       Manual      First    27.30    1498   98.60        Others      5
ODG8N7    Automatic      First    12.70    2179  187.70         White      5
EV2ZBX       Manual      First    24.70     796   47.30        Others      5
J2RCU8    Automatic      First    12.00    2987  224.00  Black/Silver      7

        Doors  New_Price          Brand     Model
ID
G4XLU0      4        NaN           Tata    Indigo
CRSHOS      4        NaN         Toyota   Corolla
FUJ4X1      4        NaN           Ford      Ikon
```

```
QMVK6E      4       NaN       Hyundai       I20
4SWHFC      4       NaN         Honda      City
…        …        …         …        …
TR7SLB      5       NaN      Mahindra    Xuv500
QB41QE      4       NaN         Honda      Jazz
ODG8N7      4       NaN    Land_Rover     Range
EV2ZBX      4       NaN        Maruti      Alto
J2RCU8      5       NaN Mercedes_Benz  Gl-Class

[4428 rows x 16 columns]
```

Note that `Brand` and `Model` has an hierarchical relationship.

[11]:
```python
display(
    df_train_bm[["Brand", "Model"]].groupby(["Brand", "Model"], observed=True).
 ↪count()
)
```

```
Empty DataFrame
Columns: []
Index: [(Audi, A3), (Audi, A4), (Audi, A6), (Audi, A7), (Audi, A8), (Audi, Q3),␣
 ↪(Audi, Q5), (Audi, Q7), (Audi, Rs5), (Audi, Tt), (BMW, 1), (BMW, 3), (BMW, 5),␣
 ↪(BMW, 6), (BMW, 7), (BMW, X1), (BMW, X3), (BMW, X5), (BMW, X6), (BMW, Z4),␣
 ↪(Bentley, Continental), (Chevrolet, Aveo), (Chevrolet, Beat), (Chevrolet,␣
 ↪Captiva), (Chevrolet, Cruze), (Chevrolet, Enjoy), (Chevrolet, Optra),␣
 ↪(Chevrolet, Sail), (Chevrolet, Spark), (Datsun, Go), (Datsun, Redi), (Datsun,␣
 ↪Redi-Go), (Fiat, Avventura), (Fiat, Grande), (Fiat, Linea), (Fiat, Petra),␣
 ↪(Fiat, Punto), (Fiat, Siena), (Force, One), (Ford, Aspire), (Ford, Ecosport),␣
 ↪(Ford, Endeavour), (Ford, Fiesta), (Ford, Figo), (Ford, Freestyle), (Ford,␣
 ↪Fusion), (Ford, Ikon), (Honda, Accord), (Honda, Amaze), (Honda, Br-V), (Honda,␣
 ↪Brio), (Honda, Brv), (Honda, City), (Honda, Civic), (Honda, Cr-V), (Honda,␣
 ↪Jazz), (Honda, Mobilio), (Honda, Wr-V), (Honda, Wrv), (Hyundai, Accent),␣
 ↪(Hyundai, Creta), (Hyundai, Elantra), (Hyundai, Elite), (Hyundai, Eon),␣
 ↪(Hyundai, Getz), (Hyundai, Grand), (Hyundai, I10), (Hyundai, I20), (Hyundai,␣
 ↪Santa), (Hyundai, Santro), (Hyundai, Sonata), (Hyundai, Tucson), (Hyundai,␣
 ↪Verna), (Hyundai, Xcent), (Isuzu, D-Max), (Isuzu, Mux), (Jaguar, F), (Jaguar,␣
 ↪Xe), (Jaguar, Xf), (Jaguar, Xj), (Jeep, Compass), (Lamborghini, Gallardo),␣
 ↪(Land_Rover, Discovery), (Land_Rover, Freelander), (Land_Rover, Range),␣
 ↪(Mahindra, Bolero), (Mahindra, Jeep), (Mahindra, Kuv), (Mahindra, Logan),␣
 ↪(Mahindra, Nuvosport), (Mahindra, Quanto), (Mahindra, Renault), (Mahindra,␣
 ↪Scorpio), (Mahindra, Ssangyong), (Mahindra, Thar), (Mahindra, Tuv), (Mahindra,␣
 ↪Verito), (Mahindra, Xuv300), (Mahindra, Xuv500), (Mahindra, Xylo), …]

[204 rows x 0 columns]
```

[12]:
```python
df_train_bm.Brand.unique()
```

[12]:
```
['Tata', 'Toyota', 'Ford', 'Hyundai', 'Honda', …, 'Smart', 'Isuzu', 'Volvo',
'Bentley', 'Lamborghini']
Length: 29
Categories (29, object): ['Audi', 'BMW', 'Bentley', 'Chevrolet', …, 'Tata',
'Toyota', 'Volkswagen', 'Volvo']
```

[13]:
```
df_train_bm.Brand.value_counts()
```

[13]:
```
Brand
Maruti           884
Hyundai          817
Honda            462
Toyota           309
Mercedes_Benz    239
Volkswagen       225
Ford             217
Mahindra         199
BMW              191
Audi             177
Tata             140
Skoda            117
Renault          117
Chevrolet         82
Nissan            64
Land_Rover        43
Jaguar            28
Fiat              23
Mini              21
Mitsubishi        20
Porsche           14
Volvo             14
Jeep              11
Datsun             7
Isuzu              3
Lamborghini        1
Force              1
Smart              1
Bentley            1
Name: count, dtype: int64
```

[14]:
```
df_train_bm.Model.unique()
```

[14]:
```
['Indigo', 'Corolla', 'Ikon', 'I20', 'City', …, 'Cls-Class', 'Gallardo',
'Wr-V', 'Outlander', 'Xc90']
Length: 201
Categories (201, object): ['1', '3', '5', '6', …, 'Yeti', 'Z4', 'Zen', 'Zest']
```

[15]:
```
with pd.option_context("display.max_rows", None):
    display(df_train_bm.Model.value_counts())
```

```
Model
Swift          253
City           206
I20            183
Verna          129
Grand          125
Innova         121
I10            120
Wagon          113
Alto           107
Polo           107
Xuv500          89
New             80
Amaze           80
Fortuner        77
Vento           76
3               75
Ecosport        72
Figo            71
Creta           69
Duster          65
E-Class         63
Ertiga          58
A4              55
Santro          53
Ciaz            51
Corolla         51
Etios           50
Ritz            48
5               47
Baleno          45
Brio            44
Jazz            44
Eon             44
Celerio         44
Scorpio         40
Xcent           39
A6              36
Vitara          35
Kwid            34
Superb          34
Indigo          29
Beat            29
Civic           27
Q7              27
```

Endeavour	27
Indica	27
Rapid	26
Q5	25
Fiesta	25
X1	24
Zen	24
Octavia	23
Micra	23
Range	23
Q3	22
Dzire	21
Accord	21
Laura	20
Sx4	20
Xf	20
Cr-V	19
Cooper	19
Sunny	19
Zest	19
M-Class	18
Nano	18
Terrano	18
Gla	17
Jetta	17
Ameo	17
X5	16
S	15
Xylo	15
Bolero	15
Ikon	15
Eeco	15
Pajero	15
Aveo	13
Elantra	13
Santa	13
A-Star	13
Cruze	13
Manza	12
Linea	12
Accent	12
Compass	11
Discovery	10
Mobilio	10
Freelander	10
Gl-Class	10
Gle	9
Fabia	9

Cla	9
X3	9
Spark	8
B	8
Optra	8
Tiago	8
Omni	8
Kuv	8
800	7
Cayenne	7
Ssangyong	7
Elite	7
Tuv	6
Getz	6
Camry	6
Glc	6
Safari	6
Sail	6
Pulse	5
Xj	5
6	5
Yeti	5
X6	5
Esteem	5
7	5
Passat	5
Grande	5
Scala	4
Sonata	4
S60	4
Brv	4
S-Class	4
Quanto	4
Panamera	4
Aspire	4
Ignis	4
Xc60	4
A	4
V40	4
Avventura	3
Thar	3
Tigor	3
Tucson	3
Bolt	3
Verito	3
A7	3
A3	3
Wrv	3

S-Cross	3
1	3
Redi-Go	3
Enjoy	3
Br-V	3
Fluence	3
R-Class	3
Captur	3
Qualis	3
Koleos	3
Go	3
Hexa	3
Renault	2
X-Trail	2
Logan	2
Lancer	2
A8	2
Jeep	2
Gls	2
Crosspolo	2
D-Max	2
Cayman	2
Xe	2
Xenon	2
Freestyle	2
Z4	2
Rs5	2
Tt	2
Captiva	2
Nuvosport	2
C-Class	2
Sumo	2
Fusion	1
Xc90	1
Beetle	1
Punto	1
Gallardo	1
Xuv300	1
Slc	1
F	1
Fortwo	1
S80	1
Boxster	1
Redi	1
Siena	1
Nexon	1
Slk-Class	1
Mux	1

```
Countryman       1
Platinum         1
Continental      1
Wr-V             1
Petra            1
Outlander        1
Clubman          1
One              1
Cls-Class        1
Cedia            1
Teana            1
Montero          1
Evalia           1
Name: count, dtype: int64
```

Model feature has too high cardinality, and there are non-legligible amount of categories with very small sample. Since we already have Brand, we could just drop Model. Alternatively, we could try target encoding.

0. Baseline (only Name)
1. Categorical Brand and Model added

[16]:
```python
extract_brand_model_exp = Experiment(
    ExperimentConfig(
        name="extract-brand-model",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

extract_brand_model_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: extract-brand-model]
Cross-validating (5-folds)…
CV score: 0.1905 ± 0.0190
         +0.0299  +0.0027 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/extract-brand-model.csv
Experiment complete
```

2. Drop Model

[17]:
```python
class FeatureDropper(TransformerMixin, BaseEstimator):
    def __init__(self, cols: list[str]):
        self.cols = cols

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) -> "FeatureDropper":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        return X.drop(columns=self.cols)
```

[18]:
```python
drop_model_exp = Experiment(
    ExperimentConfig(
        name="drop-model",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                ("drop_model", FeatureDropper(["Model"])),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

drop_model_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: drop-model]
Cross-validating (5-folds)…
CV score: 0.1606 ± 0.0163
         +0.0000  +0.0000 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/drop-model.csv
Experiment complete
```

3. Drop Name

[19]:
```python
drop_name_exp = Experiment(
    ExperimentConfig(
        name="drop-name",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                ("drop_name", FeatureDropper(["Name"])),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
```

```
        ),
    )
)

drop_name_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: drop-name]
Cross-validating (5-folds)…
CV score: 0.2379 ± 0.0157
         +0.0772  -0.0006 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/drop-name.csv
Experiment complete
```

4. Target encoding `Model`. (Leave `Brand` categorical)

[20]:
```
model_te_exp = Experiment(
    ExperimentConfig(
        name="model-te",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                ("target_encode", TargetEncoder(cols=["Model"])),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

model_te_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: model-te]
Cross-validating (5-folds)…
CV score: 0.1523 ± 0.0107
         -0.0083  -0.0056 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/model-te.csv
Experiment complete
```

5. Target encoding `Brand` and `Model`.

[21]:
```
brand_model_te_exp = Experiment(
    ExperimentConfig(
        name="brand-model-te",
```

```
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                ("target_encode", TargetEncoder(cols=["Brand", "Model"])),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

brand_model_te_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: brand-model-te]
Cross-validating (5-folds)…
CV score: 0.1496 ± 0.0170
         -0.0110  +0.0007 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/brand-model-te.csv
Experiment complete
```

6. Target encoding `Brand`, `Model`, and `Name`.

[22]:
```
brand_model_name_te_exp = Experiment(
    ExperimentConfig(
        name="brand-model-name-te",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name"]),
                ),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

brand_model_name_te_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: brand-model-name-te]
Cross-validating (5-folds)…
CV score: 0.1505 ± 0.0136
         -0.0101  -0.0027 compared to baseline (Negative is better)
Training on full training set…
```

```
Creating submission on test set…
Submission created: artifacts/experiment-results/brand-model-name-te.csv
Experiment complete
```

Target encoding `Brand`, `Model`, and `Name` yields the biggest gain.

Thinking deeper on the hierarchical relationship of `Brand` and `Model`, the difference of `Model` target encoded value and `Brand` target encoded value can tell how high class is the car in that brand. Test whether this helps.

[23]:
```
class ModelPremiumEncoder(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        brand_col: str = "Brand",
        model_col: str = "Model",
        premium_col: str = "Model_Premium",
    ):
        self.brand_col = brand_col
        self.model_col = model_col
        self.premium_col = premium_col

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "ModelPremiumEncoder":
        return self

    def transform(self, X: pd.DataFrame):
        X = X.copy()
        X[self.premium_col] = X[self.model_col] - X[self.brand_col]
        return X
```

[24]:
```
X_train = df_train.copy()
y_train = X_train.pop("Price")
X_test = df_test.copy().drop(columns=["Price"])

brand_model_name_mp_te_exp = Experiment(
    ExperimentConfig(
        name="model-premium",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name"]),
                ),
                ("model_premium", ModelPremiumEncoder()),
                ("category_encode", CategoricalEncoder()),
```

```
                ("model", XGBRegressor()),
            ]
        ),
    )
)

brand_model_name_mp_te_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: model-premium]
Cross-validating (5-folds)…
CV score: 0.1485 ± 0.0161
         -0.0121  -0.0002 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/model-premium.csv
Experiment complete
```

`Model_Premium` improved the performance slightly. However, the gain is marginal and standard deviation is worse than without it. I think this is not worth it and will stick with target encoded `Brand`, `Model`, and `Name`.

Location

[25]:
```
df_train.Location.value_counts()
```

[25]:
```
Location
Mumbai        586
Hyderabad     546
Coimbatore    478
Kochi         475
Pune          465
Delhi         420
Kolkata       384
Chennai       362
Jaipur        315
Bangalore     237
Ahmedabad     160
Name: count, dtype: int64
```

There is no location with significantly small datapoints.

Since location can influence car price due to regional demand, wealth, urban/rural, taxes, … target encoding could provide a valuable signal of this regional effect.

1. Categorical `Location` (Same as baseline)

[26]:
```
baseline_exp.run(X_train, y_train);
```

```
[Experiment: baseline]
Cross-validating (5-folds)…
```

```
CV score: 0.1606 ± 0.0163
Training on full training set…
Experiment complete
```

1. Target encoded `Location`

[27]:
```
X_train = df_train.copy()
y_train = X_train.pop("Price")
X_test = df_test.copy().drop(columns=["Price"])

location_te_exp = Experiment(
    ExperimentConfig(
        name="location target encoding",
        pipeline=Pipeline(
            [
                (
                    "target_encode",
                    TargetEncoder(cols=["Location"]),
                ),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

location_te_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: location target encoding]
Cross-validating (5-folds)…
CV score: 0.1559 ± 0.0162
         -0.0047  -0.0001 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/location target encoding.csv
Experiment complete
```

It does help to target encode `Location`.

Combining with the `Name` feature engineering.

[28]:
```
name_location_best_exp = Experiment(
    ExperimentConfig(
        name="name, location best feature engineering",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
```

```
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

name_location_best_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: name, location best feature engineering]
Cross-validating (5-folds)…
CV score: 0.1480 ± 0.0155
         -0.0127  -0.0008 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/name, location best feature
engineering.csv
Experiment complete
```

Combined with engineered `Name`, it further increased the performance.

- brand-model-name-te: 0.1505 ± 0.0136
- brand-model-name-location-te: 0.1480 ± 0.0155

Year

[29]:
```
df_train.Year.value_counts()
```

[29]:
```
Year
2014    571
2016    564
2015    558
2013    484
2017    443
2012    411
2011    342
2010    247
2018    216
2009    146
2008    123
2007     93
2019     75
2006     55
2005     44
```

```
2004      21
2002      12
2003      11
2001       5
2000       3
1999       2
1998       2
Name: count, dtype: Int64
```

As explored in `preprocessing.ipynb`, calculating the `Age` might be more relevant in terms of price. Assuming that current year is 2020, I should try trasnforming `Year` to `Age`.

[30]:
```
class YearToAgeTransformer(TransformerMixin, BaseEstimator):
    def __init__(
        self, year_col: str = "Year", age_col: str = "Age", current_year: int =␣
↪2020
    ):
        self.year_col = year_col
        self.age_col = age_col
        self.current_year = current_year

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "YearToAgeTransformer":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()
        X[self.age_col] = self.current_year - X[self.year_col]
        X.drop(columns=[self.year_col], inplace=True)
        return X
```

0. `Year` (Same as baseline)
1. `Year` transformed to `Age`

[31]:
```
year_to_age_transform_exp = Experiment(
    ExperimentConfig(
        name="year-to-age-transform",
        pipeline=Pipeline(
            [
                ("transform", YearToAgeTransformer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)
```

```python
year_to_age_transform_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: year-to-age-transform]
Cross-validating (5-folds)…
CV score: 0.1602 ± 0.0154
         -0.0004  -0.0009 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/year-to-age-transform.csv
Experiment complete
```

This transformation does not neccessarily add more information but makes it more interpretable and nice to work with other features.

[32]:
```python
name_location_year_exp = Experiment(
    ExperimentConfig(
        name="name-location-year-engineered",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

name_location_year_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: name-location-year-engineered]
Cross-validating (5-folds)…
CV score: 0.1479 ± 0.0159
         -0.0127  -0.0004 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/name-location-year-
engineered.csv
Experiment complete
```

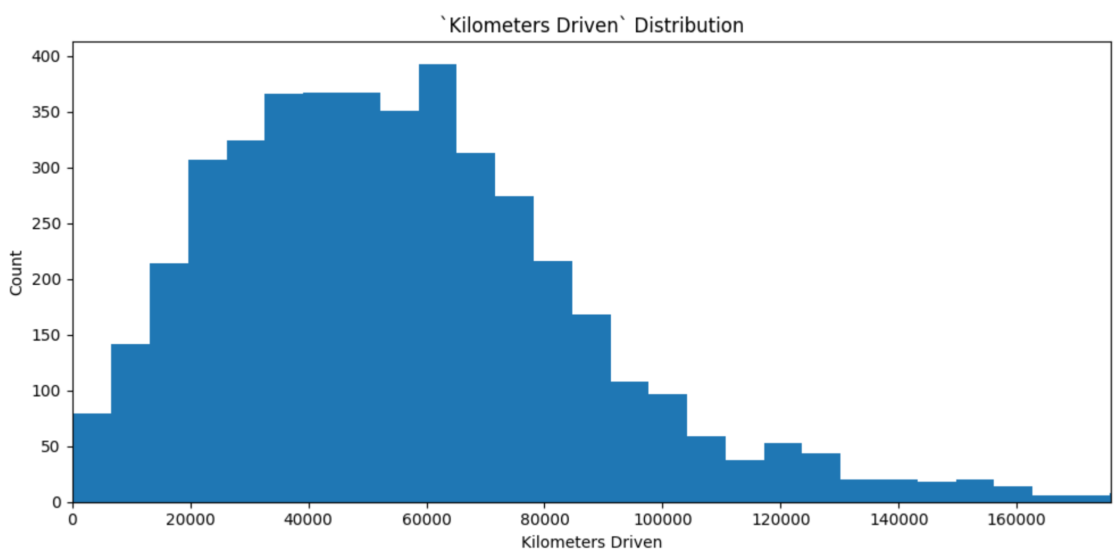
Together with the `Name` and `Location` engineered, transforming `Year` to `Age` did not help at all. It might be due to `Name` -> `Brand`, `Model`, `Name` being the dominant feature. However, I will keep this transformation since it makes the feature more interpretable while not hurting the performance. It could make this feature nicer to work with when analyzing interactions.

Kilometers Driven

[33]:
```
df_train.Kilometers_Driven
```

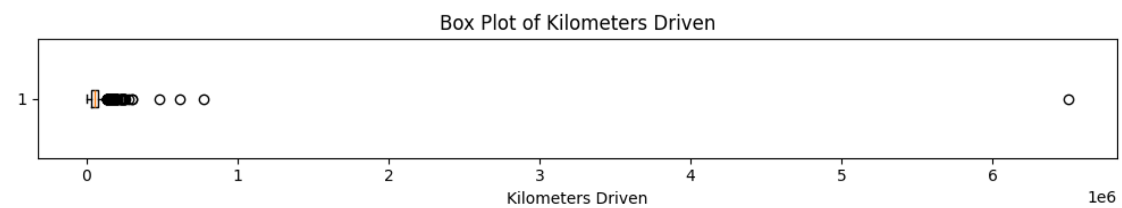
[33]:
```
ID
G4XLU0     59138
CRSHOS     81504
FUJ4X1     92000
QMVK6E     33249
4SWHFC     65000
           …
TR7SLB     51884
QB41QE     27210
ODG8N7     52000
EV2ZBX     56000
J2RCU8     52000
Name: Kilometers_Driven, Length: 4428, dtype: Int64
```

[34]:
```
plt.figure(figsize=(10, 5))
plt.hist(df_train.Kilometers_Driven, bins=1000)
limit = np.percentile(df_train.Kilometers_Driven, 99)
plt.xlim(0, limit)
plt.xlabel("Kilometers Driven")
plt.ylabel("Count")
plt.title("`Kilometers Driven` Distribution")

plt.tight_layout()
plt.show()
```



This looks like a Gamma distribution. It makes sense beacause if we model the `Kilometers_Driven` as an accumulation of daily driving(with random noise added to consistent daily driving), it will yield a Gamma distribution.

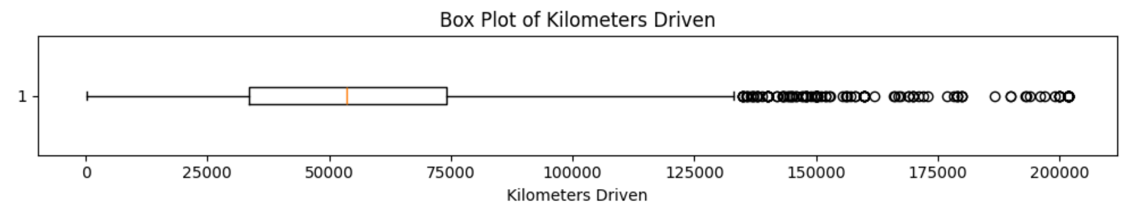
[35]:
```
plt.figure(figsize=(10, 2))
plt.boxplot(df_train["Kilometers_Driven"], vert=False)
plt.xlabel("Kilometers Driven")
plt.title("Box Plot of Kilometers Driven")
plt.tight_layout()
plt.show()
```



There are clearly some extreme impossible data points. They should be clipped.

[36]:
```
df_train.Kilometers_Driven = df_train.Kilometers_Driven.clip(
    upper=int(df_train.Kilometers_Driven.quantile(0.995))
)
df_test.Kilometers_Driven = df_test.Kilometers_Driven.clip(
    upper=int(df_test.Kilometers_Driven.quantile(0.995))
)
```

[37]:
```
plt.figure(figsize=(10, 2))
plt.boxplot(df_train["Kilometers_Driven"], vert=False)
plt.xlabel("Kilometers Driven")
plt.title("Box Plot of Kilometers Driven")
plt.tight_layout()
plt.show()
```



[38]:
```python
class KilometersDrivenClipper(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        kilometers_driven_col: str = "Kilometers_Driven",
        clipping_quantile: float = 0.995,
    ):
        self.kilometers_driven_col = kilometers_driven_col
        self.clipping_quantile = clipping_quantile

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "KilometersDrivenClipper":
        return self

    def transform(self, X: pd.DataFrame):
        X = X.copy()
        X[self.kilometers_driven_col] = X[self.kilometers_driven_col].clip(
            upper=int(X[self.kilometers_driven_col].quantile(self.
↪clipping_quantile))
        )
        return X
```

1. `Kilometers_Driven`

1. `Kilometers_Driven` Outliers clipped

[39]:
```python
kilometers_driven_outlier_clip_exp = Experiment(
    ExperimentConfig(
        name="clipping-extreme-Kilometers_Driven",
        pipeline=Pipeline(
            [
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

kilometers_driven_outlier_clip_exp.run(X_train, y_train, X_test,␣
↪baseline_exp_result);
```

```
[Experiment: clipping-extreme-Kilometers_Driven]
Cross-validating (5-folds)…
CV score: 0.1596 ± 0.0165
         -0.0010  +0.0002 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/clipping-extreme-
```

```
Kilometers_Driven.csv
Experiment complete
```

The performance increased slightly but also increased std slightly. The effect is negligible but still good to have for numerical stability.

[40]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1485 ± 0.0167
         -0.0121  +0.0004 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Fuel_Type

[41]:
```
df_train.Fuel_Type.value_counts()
```

[41]:
```
Fuel_Type
Diesel      2372
Petrol      2008
CNG           42
LPG            6
Electric       0
Name: count, dtype: int64
```

[42]:
```
df_test.Fuel_Type.value_counts()
```

[42]:
```
Fuel_Type
Diesel      790
Petrol      685
CNG          13
LPG           3
Electric      0
Name: count, dtype: int64
```

`Fuel_Type` has low cardinality but CNG, LPG, and Electric has extremely low datapoints. Grouping CNG, LPG, and Electric to Other could mitigate this problem.

[43]:
```python
class FuelTypeGrouper(TransformerMixin, BaseEstimator):
    def __init__(self, fuel_type_col: str = "Fuel_Type"):
        self.fuel_type_col = fuel_type_col

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) -> "FuelTypeGrouper":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()
        X[self.fuel_type_col] = (
            X[self.fuel_type_col]
            .astype("object")
            .replace({"CNG": "Other", "LPG": "Other", "Electric": "Other"})
            .astype("category")
        )
        return X
```

[44]:
```python
fuel_type_grouping_exp = Experiment(
    ExperimentConfig(
        name="grouping-infrequent-fuel-type",
        pipeline=Pipeline(
            [
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

fuel_type_grouping_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: grouping-infrequent-fuel-type]
Cross-validating (5-folds)…
CV score: 0.1601 ± 0.0150
         -0.0005  -0.0013 compared to baseline (Negative is better)
Training on full training set…
```

```
Creating submission on test set…
Submission created: artifacts/experiment-results/grouping-infrequent-fuel-
type.csv
Experiment complete
```

Due to low cardinality, (Petrol / Disel / Other), I do not feel the need to engineer it further (e.g. target encoding).

[45]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1489 ± 0.0151
         -0.0117  -0.0012 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Transmission

[46]:
```
df_train.Transmission.value_counts()
```

[46]:
```
Transmission
Manual       3162
Automatic    1266
Name: count, dtype: int64
```

`Transmission` has two categories and well balanced. There is no need to engineer this feature alone further.

Owner Type

[47]:
```
df_train.Owner_Type.cat.categories
```

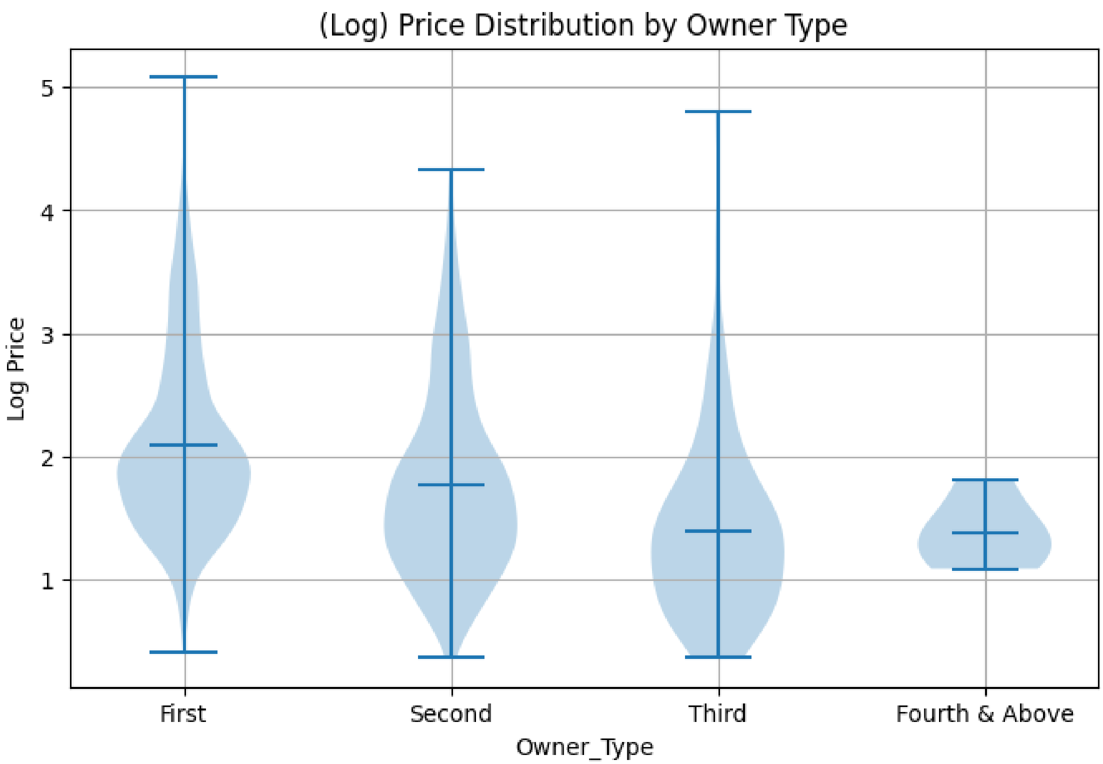
[47]:
```
Index(['First', 'Second', 'Third', 'Fourth & Above'], dtype='object')
```

[48]:
```
df_train.Owner_Type.value_counts()
```

[48]:
```
Owner_Type
First             3617
Second             715
Third               91
Fourth & Above       5
Name: count, dtype: int64
```

Based on common knowledge, `Owner_Type` might be one of the most significant predictor of `Price`.

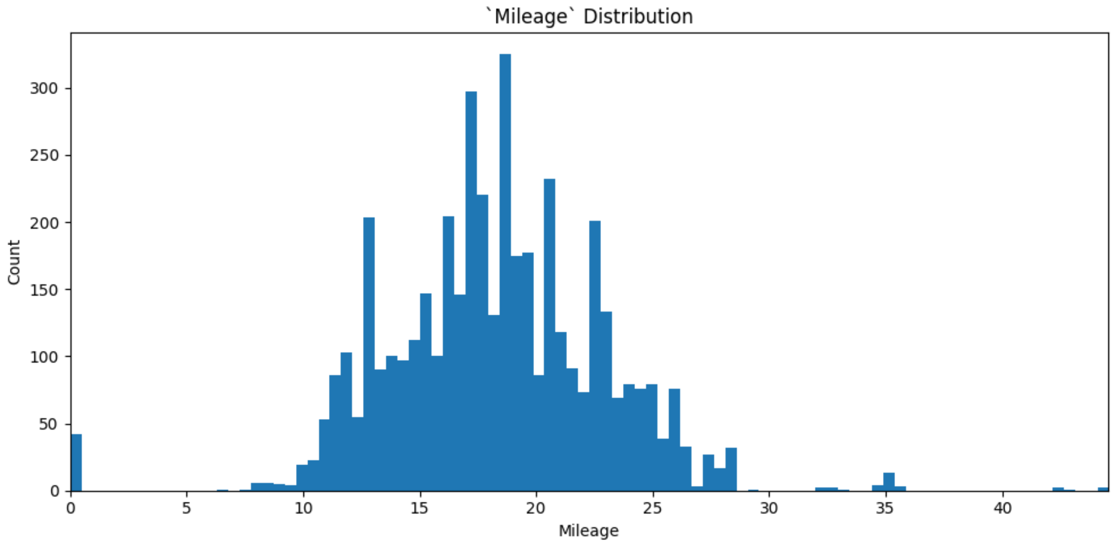
[49]:
```
categories = list(df_train.Owner_Type.cat.categories)
plt.figure(figsize=(8, 5))
plt.violinplot(
    [
        np.log1p(df_train[df_train.Owner_Type == category]["Price"])
        for category in categories
    ],
    showmeans=True,
)
plt.xticks(ticks=range(1, len(categories) + 1), labels=categories)
plt.xlabel("Owner_Type")
plt.ylabel("Log Price")
plt.title("(Log) Price Distribution by Owner Type")
plt.grid(True)
plt.show()
```



Clearly, as `Owner_Type` increases, `Price` drops monotonically. (`Owner_Type` is already encoded as ordinal category in preprocessing). It is good enough for now.

Mileage

[50]:
```
plt.figure(figsize=(10, 5))
plt.hist(df_train.Mileage, bins=100)
limit = np.percentile(df_train.Mileage, 99.9)
plt.xlim(0, limit)
plt.xlabel("Mileage")
plt.ylabel("Count")
plt.title("`Mileage` Distribution")

plt.tight_layout()
plt.show()
```




```
[51]: with pd.option_context("display.max_rows", None):
          display(df_train.Mileage.value_counts().sort_index())
```

```
Mileage
0.0000      42
6.4000       1
7.5000       1
7.8100       1
7.9400       2
8.0000       1
8.2000       2
8.4500       1
8.5000       1
8.6000       2
8.7000       2
9.0000       5
9.4300       1
9.5000       2
9.5200       1
9.7400       2
9.8000       3
9.9000       2
10.0000      5
10.1000      4
10.1300      3
10.2000      3
10.3700      2
10.4000      2
10.5000     16
```

10.8000	7
10.9000	6
10.9100	10
10.9300	5
10.9800	1
11.0000	14
11.0500	2
11.0700	1
11.1000	7
11.1800	6
11.2000	4
11.2500	2
11.3000	7
11.3300	5
11.3600	18
11.4000	4
11.4900	1
11.5000	31
11.5600	1
11.5700	6
11.6200	1
11.6800	4
11.7000	16
11.7200	2
11.7400	10
11.7900	4
11.8000	6
11.9000	3
12.0000	11
12.0500	27
12.0700	18
12.1000	2
12.1900	1
12.3000	4
12.3500	1
12.3900	5
12.4000	8
12.5000	3
12.5100	2
12.5500	26
12.6000	5
12.6200	3
12.6300	2
12.6500	2
12.7000	16
12.8000	49
12.8100	2
12.8300	2

12.8500	1
12.9000	17
12.9500	1
12.9700	1
12.9800	1
12.9900	46
13.0000	52
13.0100	7
13.0600	1
13.1000	14
13.1400	3
13.1700	1
13.2000	15
13.2200	4
13.2400	4
13.2900	1
13.3300	2
13.4000	10
13.4400	1
13.4900	2
13.5000	31
13.5300	2
13.6000	13
13.6800	15
13.7000	22
13.7300	3
13.8000	15
13.9000	4
13.9300	6
14.0000	20
14.0200	2
14.0700	1
14.1000	2
14.1600	14
14.2000	4
14.2100	12
14.2400	6
14.2800	16
14.3000	8
14.3300	1
14.3900	1
14.4000	10
14.4200	1
14.4700	1
14.4900	5
14.5300	15
14.5900	1
14.6000	2

14.6200	1
14.6600	4
14.6700	6
14.6900	6
14.7000	9
14.7400	11
14.7500	4
14.8000	13
14.8100	1
14.8400	17
14.9400	4
14.9500	4
15.0000	29
15.0400	15
15.0600	2
15.1000	46
15.1100	1
15.1500	2
15.1700	3
15.2000	5
15.2600	15
15.2900	14
15.3000	14
15.4000	15
15.4100	1
15.5000	14
15.6000	18
15.6300	4
15.6400	5
15.6800	4
15.7000	5
15.7300	15
15.7400	3
15.8000	25
15.8500	1
15.8700	2
15.9000	5
15.9600	7
15.9700	6
16.0000	63
16.0200	12
16.0500	1
16.0700	13
16.0900	7
16.1000	22
16.1200	1
16.2000	18
16.2500	2

16.3000	4
16.3600	12
16.3800	1
16.4000	5
16.4600	2
16.4700	41
16.5000	10
16.5100	1
16.5200	4
16.5500	23
16.6000	7
16.7300	6
16.7700	5
16.7800	7
16.8000	42
16.8200	4
16.9000	6
16.9300	2
16.9500	24
16.9600	5
16.9800	2
17.0000	126
17.0100	29
17.0500	15
17.0900	1
17.1000	20
17.1100	21
17.1600	1
17.1900	4
17.2000	7
17.2100	12
17.2400	1
17.3000	24
17.3200	3
17.4000	27
17.4300	2
17.4400	2
17.4500	2
17.5000	31
17.5400	2
17.5560	1
17.5700	14
17.6000	13
17.6700	3
17.6800	22
17.7000	8
17.7100	6
17.7200	2

17.8000	62
17.8400	1
17.8500	2
17.8800	3
17.9000	34
17.9200	14
17.9700	2
18.0000	53
18.0600	5
18.1000	7
18.1200	9
18.1500	4
18.1600	14
18.1900	3
18.2000	16
18.2300	1
18.2500	4
18.3000	5
18.3300	3
18.4000	5
18.4400	3
18.4800	5
18.4900	6
18.5000	43
18.5100	1
18.5300	3
18.5600	4
18.5900	2
18.6000	77
18.7000	24
18.7800	1
18.8000	2
18.8600	1
18.8800	20
18.9000	133
19.0000	30
19.0100	29
19.0800	9
19.0900	3
19.1000	27
19.1200	6
19.1500	3
19.1600	3
19.2000	7
19.2700	23
19.3000	27
19.3249	1
19.3300	5

19.3400	2
19.4000	31
19.4400	1
19.4900	1
19.5000	13
19.5900	3
19.6000	9
19.6400	8
19.6700	24
19.6900	2
19.7000	33
19.7100	3
19.7200	1
19.8100	33
19.8300	1
19.8700	14
19.9100	1
20.0000	48
20.0830	5
20.1400	19
20.3000	5
20.3400	8
20.3600	64
20.3700	3
20.3800	3
20.4000	21
20.4500	13
20.4600	4
20.5000	12
20.5100	19
20.5400	27
20.5800	3
20.6300	1
20.6400	4
20.6500	1
20.6800	6
20.7000	6
20.7300	17
20.7700	28
20.8500	7
20.8600	1
20.8900	3
20.9200	13
21.0000	1
21.0200	3
21.0300	2
21.1000	65
21.1200	5

21.1300	1
21.1400	3
21.1900	4
21.2000	1
21.2100	3
21.2700	6
21.3800	2
21.4000	29
21.4300	9
21.5000	17
21.5600	2
21.6400	11
21.6600	5
21.7000	4
21.7600	10
21.7900	1
21.8000	1
21.9000	27
22.0000	18
22.0700	26
22.1000	2
22.3000	7
22.3200	39
22.4800	11
22.5000	19
22.5400	25
22.6100	1
22.6900	19
22.7000	49
22.7400	21
22.7700	10
22.9000	36
22.9500	6
23.0000	22
23.0100	1
23.0800	12
23.1000	39
23.2000	17
23.2750	2
23.3000	2
23.4000	28
23.5000	4
23.5700	1
23.5900	27
23.6500	5
23.8000	3
23.8400	7
23.9000	7

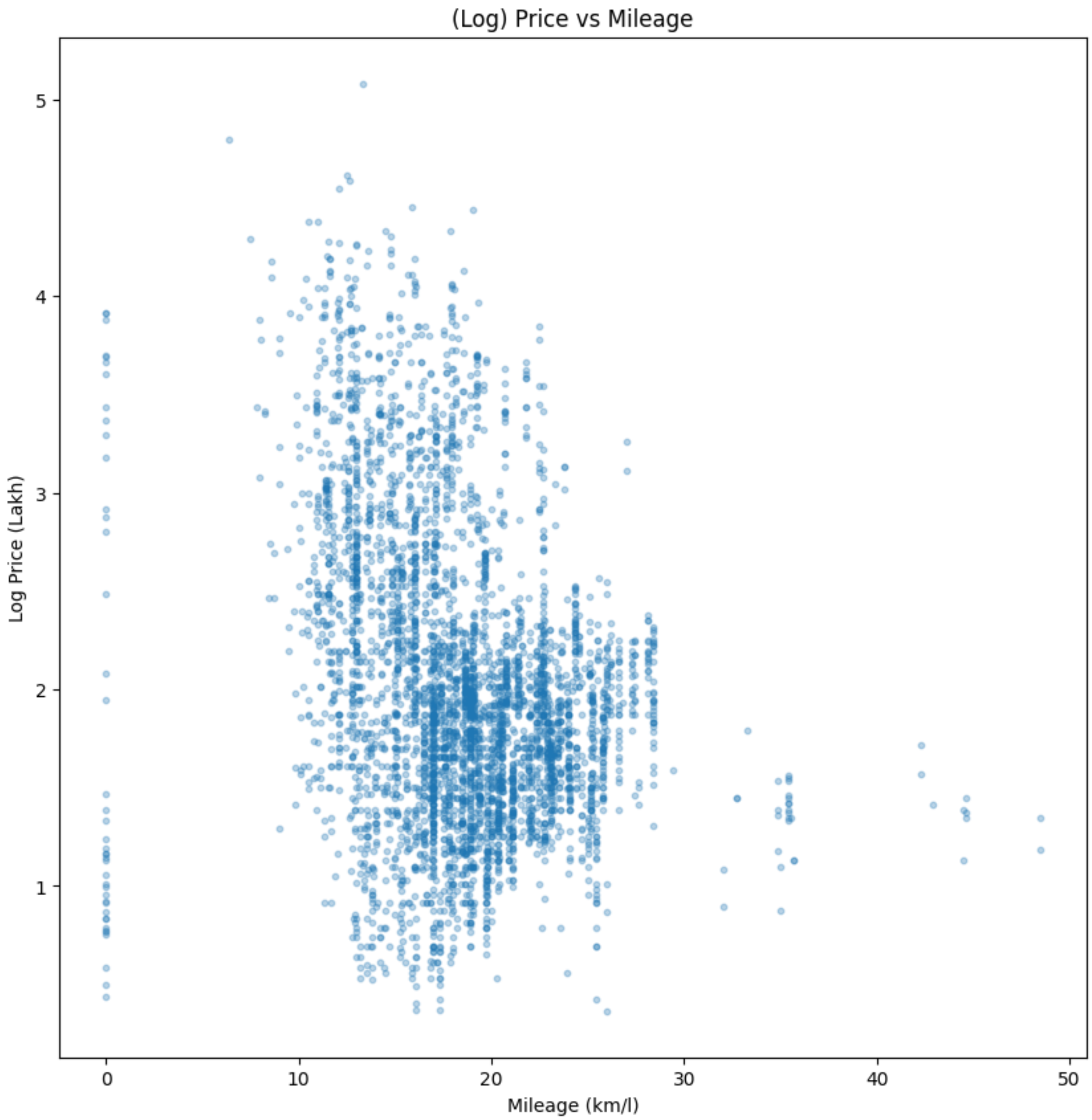
24.0000	35
24.0400	1
24.0700	23
24.2000	3
24.3000	35
24.4000	16
24.5000	3
24.5200	8
24.7000	14
24.8000	2
24.8825	1
25.0000	11
25.1000	14
25.1700	25
25.2000	26
25.3200	4
25.4000	13
25.4400	13
25.4700	7
25.6000	2
25.8000	39
25.8300	8
26.0000	25
26.1000	4
26.2100	9
26.5900	23
26.6000	1
26.8000	1
27.0300	2
27.2800	1
27.3000	13
27.3900	8
27.4000	2
27.6200	3
28.0900	17
28.4000	32
29.3930	1
32.0050	2
32.7180	2
33.2500	1
34.8460	4
34.9790	2
35.3780	11
35.5200	1
35.6839	2
42.2807	2
42.9058	1
44.4752	2

```
44.6082      3
48.4700      2
Name: count, dtype: int64
```

It is bell shaped as expected. However, the regular peaks hints that there was some bias towards round numbers.

[52]:

```
plt.figure(figsize=(10, 10))
plt.scatter(df_train.Mileage, np.log1p(df_train.Price), alpha=0.3, s=10)
plt.xlabel("Mileage (km/l)")
plt.ylabel("Log Price (Lakh)")
plt.title("(Log) Price vs Mileage")
plt.show()
```



`Mileage` alone does not show clear relationship with `Price`.

Cleaning up unrealistic outliers would stablize the model.

[53]:
```
class MileageClipper(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        mileage_col: str = "Mileage",
        clipping_quantile: float = 0.995,
    ):
        self.mileage_col = mileage_col
        self.clipping_quantile = clipping_quantile

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series] = None) ->␣
 ↪"MileageClipper":
        return self

    def transform(self, X: pd.DataFrame):
        X = X.copy()
        X[self.mileage_col] = X[self.mileage_col].clip(
            upper=int(X[self.mileage_col].quantile(self.clipping_quantile))
        )
        return X
```

[54]:
```
mileage_outlier_clip_exp = Experiment(
    ExperimentConfig(
        name="clipping-extreme-mileage",
        pipeline=Pipeline(
            [
                ("mileage_clip_outliers", MileageClipper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

mileage_outlier_clip_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: clipping-extreme-mileage]
Cross-validating (5-folds)…
CV score: 0.1578 ± 0.0153
         -0.0028  -0.0010 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/clipping-extreme-mileage.csv
Experiment complete
```

[55]:

```python
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("mileage_clip_outliers", MileageClipper()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1484 ± 0.0143
         -0.0123  -0.0020 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Engine

[56]:

```python
df_train.Engine.describe()
```

[56]:

```
count        4428.0
mean      1618.2771
std      595.245047
min           624.0
25%          1198.0
50%          1493.0
75%          1968.0
max          5998.0
Name: Engine, dtype: Float64
```

Engine feature seems reasonable enough.

Power

[57]:

```python
df_train.Power.describe()
```

[57]:
```
count    4336.000000
mean      113.171817
std        53.875993
min        34.200000
25%        75.000000
50%        94.000000
75%       138.100000
max       560.000000
Name: Power, dtype: float64
```

`Power` featrue seems reasonable enough.

However, as explored in `preprocessing.ipynb`, the percentage of missin values in `Power` was non-negligible.

[58]:
```
df_train[df_train.Power.isna()]
```

[58]:
```
                           Name   Location  Year  Kilometers_Driven Fuel_Type  \
ID
2CM572               Fiat Petra       Pune  2005             120000    Petrol
4J1SFY  Mercedes-Benz E-Class       Pune  2001             121000    Diesel
LHXSLV             Maruti Swift  Hyderabad  2014              81609    Diesel
R7UPR3              Fiat Siena     Jaipur  2001              70000    Petrol
KZI5XI             Skoda Laura       Pune  2010              85000    Petrol
…                           …        …    …                  …         …
Z3GW3N          Hyundai Santro  Hyderabad  2006              74483    Petrol
M49PV9          Hyundai Santro     Mumbai  2005             102000    Petrol
9BPQA2          Hyundai Santro       Pune  2005             100000       CNG
AOLNGH          Hyundai Santro     Jaipur  2004             200000    Petrol
MDPHOT          Hyundai Santro      Kochi  2007              58815    Petrol

       Transmission Owner_Type  Mileage  Engine  Power        Colour  Seats  \
ID
2CM572       Manual     Second    15.50    1242    NaN        Others      5
4J1SFY       Manual      First    15.00    2148    NaN         White      5
LHXSLV       Manual      First    17.80    1248    NaN        Others      5
R7UPR3       Manual      Third     0.00    1242    NaN         White      5
KZI5XI       Manual      First    17.50    1798    NaN  Black/Silver      5
…               …          …       …       …      …           …
Z3GW3N    Automatic      First     0.00     999    NaN  Black/Silver      5
M49PV9       Manual     Second    17.00    1086    NaN         White      5
9BPQA2       Manual      Third    22.61    1086    NaN         White      5
AOLNGH       Manual      First     0.00    1086    NaN  Black/Silver      5
MDPHOT       Manual      First    17.00    1086    NaN         White      5

        Doors  New_Price  Price
ID
2CM572      4        NaN   0.85
```

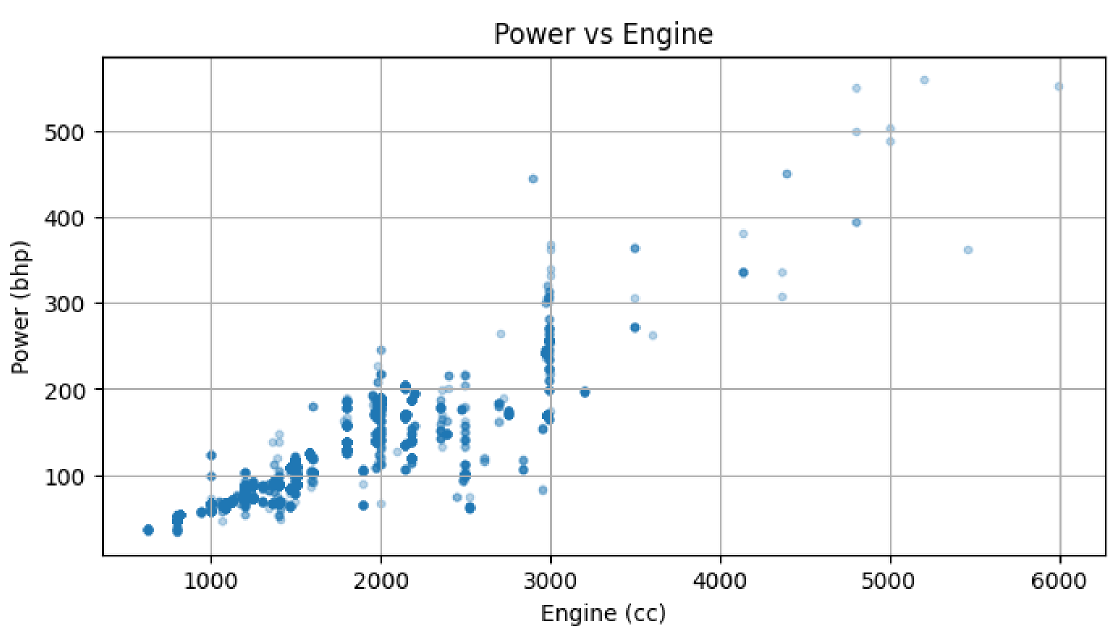
```
4J1SFY       4         NaN   5.00
LHXSLV       4         NaN   5.55
R7UPR3       4         NaN   0.55
KZI5XI       4         NaN   2.85
…       …         …    …
Z3GW3N       4         NaN   2.30
M49PV9       4         NaN   0.85
9BPQA2       4         NaN   1.20
A0LNGH       4         NaN   0.80
MDPH0T       4         NaN   1.99

[92 rows x 15 columns]
```

Power can be faithfully imputed exploiting its high relevance to Engine.

[59]:
```
print(f"Engine-Power Correlation: {df_train.Engine.corr(df_train.Power):.2f}")
```

```
Engine-Power Correlation: 0.86
```

[60]:
```
plt.figure(figsize=(8, 4))
plt.scatter(df_train["Engine"], df_train["Power"], alpha=0.3, s=10)

plt.xlabel("Engine (cc)")
plt.ylabel("Power (bhp)")
plt.title("Power vs Engine")
plt.grid(True)
plt.show()
```



[61]:
```python
class PowerImputer(TransformerMixin, BaseEstimator):
    def __init__(
        self, engine_col: str = "Engine", power_col="Power", clip_negative:␣
 ↪bool = True
    ):
        self.engine_col = engine_col
        self.power_col = power_col
        self.clip_negative = clip_negative

    def fit(self, X: pd.DataFrame, y=Optional[pd.Series]) -> "PowerImputer":
        df = X[[self.engine_col, self.power_col]].dropna()
        engines = df[self.engine_col].astype(float)
        powers = df[self.power_col].astype(float)

        # Linear regression
        cov = ((engines - engines.mean()) * (powers - powers.mean())).sum()
        var = ((engines - engines.mean()) ** 2).sum()
        self.slope = cov / var
        self.intercept = powers.mean() - self.slope * engines.mean()

        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()

        mask = X[self.power_col].isna()
        has_engine = X[self.engine_col].notna() & mask
        X.loc[has_engine, self.power_col] = (
            self.slope * X.loc[has_engine, self.engine_col] + self.intercept
        )

        if self.clip_negative:
            X[self.power_col] = X[self.power_col].clip(lower=0)

        return X
```

[62]:
```python
power_imputation_exp = Experiment(
    ExperimentConfig(
        name="power-imputation",
        pipeline=Pipeline(
            [
                ("imput_power", PowerImputer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
```

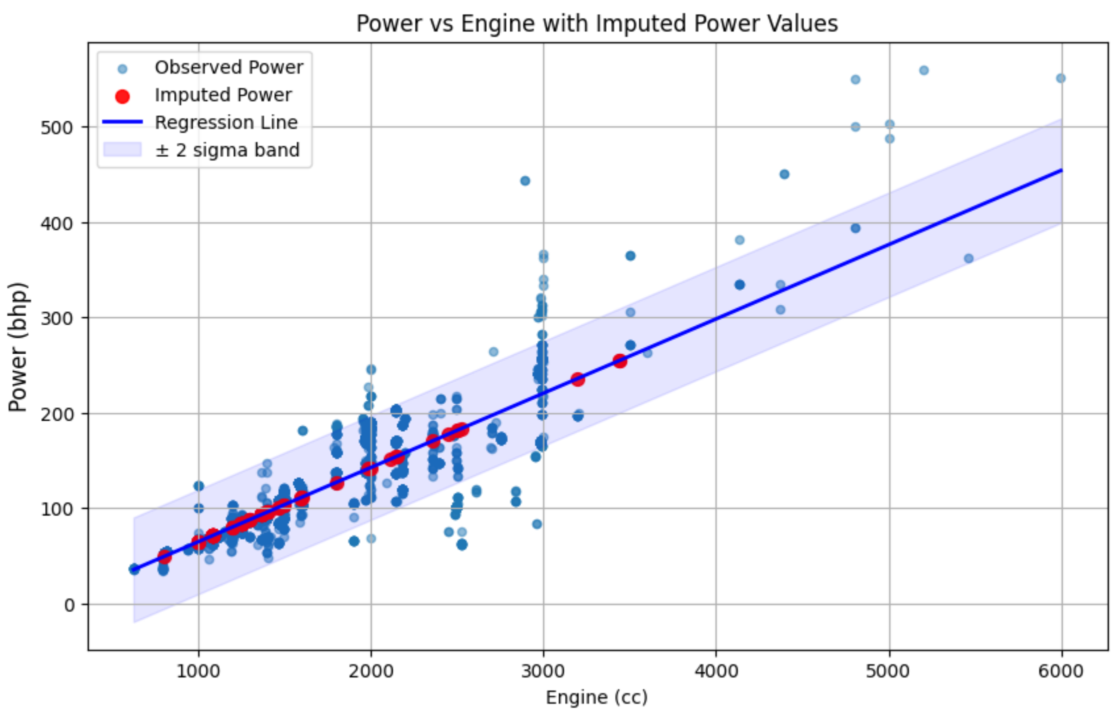
```
)

power_imputation_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: power-imputation]
Cross-validating (5-folds)…
CV score: 0.1551 ± 0.0159
         -0.0055  -0.0004 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/power-imputation.csv
Experiment complete
```

[63]:

```
imputer = PowerImputer()
imputer.fit(X_train)

slope = imputer.slope
intercept = imputer.intercept

df_plot = X_train.copy()
df_plot["imputed_Power"] = imputer.transform(X_train)[imputer.power_col]
df_plot["missing_Power"] = df_plot.Power.isna()

engine_range = np.linspace(df_plot.Engine.min(), df_plot.Engine.max(), 200)
regression_line = slope * engine_range + intercept

observed_mask = ~df_plot.missing_Power

df_observed = df_plot.loc[observed_mask]
residuals = df_observed.Power - (slope * df_observed.Engine + intercept)
sigma = residuals.std()

plt.figure(figsize=(10, 6))
plt.scatter(
    df_plot.loc[observed_mask, "Engine"],
    df_plot.loc[observed_mask, "Power"],
    s=20,
    alpha=0.5,
    label="Observed Power",
)
plt.scatter(
    df_plot.loc[df_plot.missing_Power, "Engine"],
    df_plot.loc[df_plot.missing_Power, "imputed_Power"],
    s=50,
    color="red",
    alpha=0.9,
```

```
    label="Imputed Power",
)
plt.plot(
    engine_range, regression_line, color="blue", linewidth=2, label="Regression␣
  ↪Line"
)
plt.fill_between(
    engine_range,
    regression_line - 2 * sigma,
    regression_line + 2 * sigma,
    color="blue",
    alpha=0.1,
    label="± 2 sigma band",
)

plt.xlabel("Engine (cc)", fontsize=10)
plt.ylabel("Power (bhp)", fontsize=12)
plt.title("Power vs Engine with Imputed Power Values")
plt.legend()
plt.grid(True)
plt.show()
```



Missing `Power` was effectively imputed with its highly linear correlation with `Engine`.

Combining all featrue engineering so far.

[64]:
```python
df_train.columns
```

[64]:
```
Index(['Name', 'Location', 'Year', 'Kilometers_Driven', 'Fuel_Type',
       'Transmission', 'Owner_Type', 'Mileage', 'Engine', 'Power', 'Colour',
       'Seats', 'Doors', 'New_Price', 'Price'],
      dtype='object')
```

[65]:
```python
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("mileage_clip_outliers", MileageClipper()),
                ("imput_power", PowerImputer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    ),
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1466 ± 0.0165
        -0.0140  +0.0002 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Colour

[66]:
```python
df_train.Colour.describe()
```

[66]:
```
count      4428
unique        3
top       White
freq       1539
Name: Colour, dtype: object
```

[67]:
```
df_train.Colour.value_counts()
```

[67]:
```
Colour
White           1539
Others          1519
Black/Silver    1370
Name: count, dtype: int64
```

`Colour` is already well balanced.

0.0.3 Seats

[68]:
```
df_train.Seats.value_counts()
```

[68]:
```
Seats
5     3736
7      503
8       83
4       69
6       21
2       12
10       2
9        2
Name: count, dtype: Int64
```

Binning could help for those rare seat counts. However, the binning should not break the ordinality.

[69]:
```
class SeatsBinner(TransformerMixin, BaseEstimator):
    def __init__(self, seats_col: str = "Seats"):
        self.seats_col = seats_col

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) -> "SeatsBinner":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()
        seats = X[self.seats_col]

        X[self.seats_col] = seats.replace(
            {
                2: 4,
                4: 4,
                # Small
                5: 5,
                # Standard
                6: 7,
                7: 7,
                8: 7,
```

```
                # Large
                9: 9,
                10: 9,
                # Van
            }
        )

        return X
```

[70]:
```
seats_binning_exp = Experiment(
    ExperimentConfig(
        name="bin-seats",
        pipeline=Pipeline(
            [
                ("bin_seats", SeatsBinner()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

seats_binning_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: bin-seats]
Cross-validating (5-folds)…
CV score: 0.1581 ± 0.0154
         -0.0025  -0.0009 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/bin-seats.csv
Experiment complete
```

Binning `Seats` had positive effect on the prediction score.

[71]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
```

```
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("mileage_clip_outliers", MileageClipper()),
                ("imput_power", PowerImputer()),
                ("bin_seats", SeatsBinner()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1479 ± 0.0159
         -0.0127  -0.0004 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Doors

[72]:
```
df_train.Doors.value_counts()
```

[72]:
```
Doors
4    3884
5     532
2      12
Name: count, dtype: Int64
```

There are very small number of cars with 2 doors. However, I think it should not be binned, since usually cars with 2 doors are very expensive sports car, and it can imply a lot, even though it has very small sample size.

[73]:
```
df_train[df_train.Doors == 2][["Name", "Engine", "Power", "Seats", "Doors"]]
```

[73]:

ID	Name	Engine	Power	Seats	Doors
UFNCV8	BMW Z4	2979	306.00	2	2
ICAVC1	Jaguar F	5000	488.10	2	2
YDPHR8	Smart Fortwo	799	NaN	2	2
RS5FNO	Audi A4	3197	NaN	2	2
X5JJRY	Porsche Boxster	2706	265.00	2	2
2OAGHR	Porsche Cayman	3436	NaN	2	2
ORNZ4O	Porsche Cayman	3436	NaN	2	2
W15E5A	Mercedes-Benz SLK-Class	3498	306.00	2	2
NF6IF1	BMW Z4	2979	306.00	2	2
RGDCTT	Mercedes-Benz SLC	2996	362.07	2	2

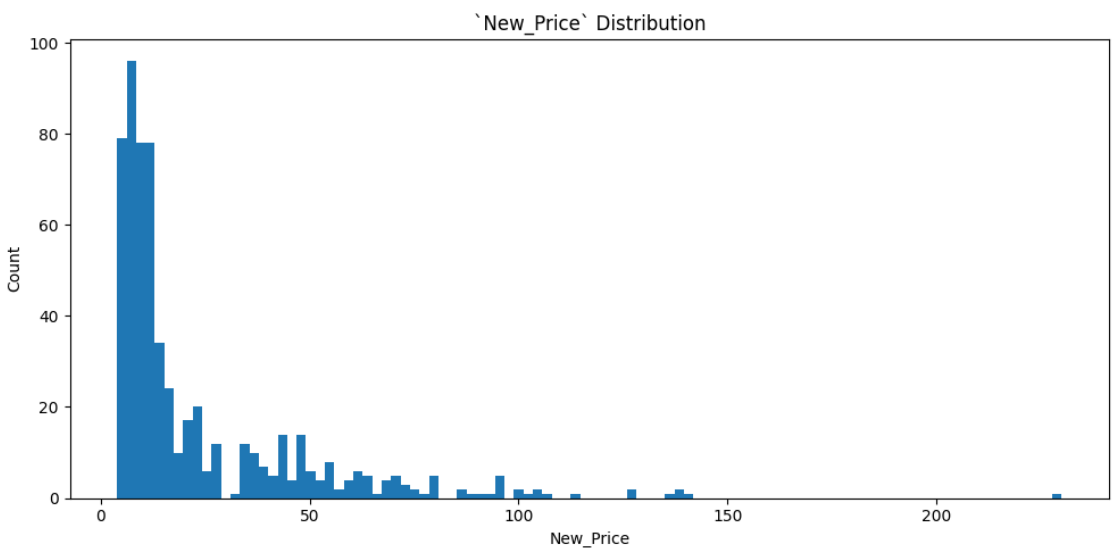
```
IJ96ZM                  Audi TT    1984  207.80      2      2
PYZN3W     Lamborghini Gallardo    5204  560.00      2      2
```

New_Price

[74]:
```
print(
    f"# of missing New_Price: {len(df_train[df_train.New_Price.isna()])} out of␣
 ↪{len(df_train)}"
)
```

```
# of missing New_Price: 3827 out of 4428
```

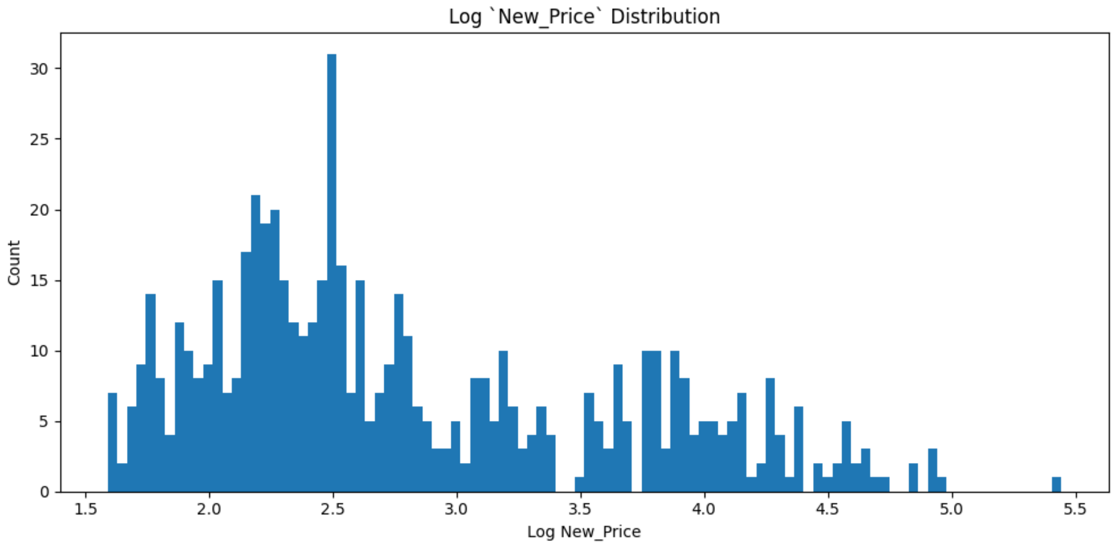
[75]:
```
observed_new_prices = df_train[df_train.New_Price.notna()].New_Price

plt.figure(figsize=(10, 5))
plt.hist(observed_new_prices, bins=100)
plt.xlabel("New_Price")
plt.ylabel("Count")
plt.title("`New_Price` Distribution")

plt.tight_layout()
plt.show()
```



Due to its high sparsity, it would be dangerous to impute naively. Instead, labeling missing New_Price might give non-trivial information from the pattern of missing New_Price. Additionally, log transformation could help the heavy skew in its distribution.

[76]:
```
observed_new_prices = df_train[df_train.New_Price.notna()].New_Price

plt.figure(figsize=(10, 5))
```

```
plt.hist(np.log1p(observed_new_prices), bins=100)
plt.xlabel("Log New_Price")
plt.ylabel("Count")
plt.title("Log `New_Price` Distribution")

plt.tight_layout()
plt.show()
```



[77]:
```
class NewPriceTransformer(TransformerMixin, BaseEstimator):
    def __init__(self, new_price_col: str = "New_Price"):
        self.new_price_col = new_price_col
        self.missing_col = "Missing_" + new_price_col

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) ->␣
 ↪"NewPriceTransformer":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()

        X[self.missing_col] = X[self.new_price_col].isna().astype(int)

        X[self.new_price_col] = X[self.new_price_col].apply(np.log1p)

        return X
```

[78]:
```
new_price_transform_exp = Experiment(
    ExperimentConfig(
```

```
        name="transform-new-price",
        pipeline=Pipeline(
            [
                ("transform_new_price", NewPriceTransformer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
)

new_price_transform_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: transform-new-price]
Cross-validating (5-folds)…
CV score: 0.1606 ± 0.0163
         +0.0000  +0.0000 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/transform-new-price.csv
Experiment complete
```

It did not yield visible gain. However, I'll keep it since this transformation can be useful in making interaction features. Should be judged later.

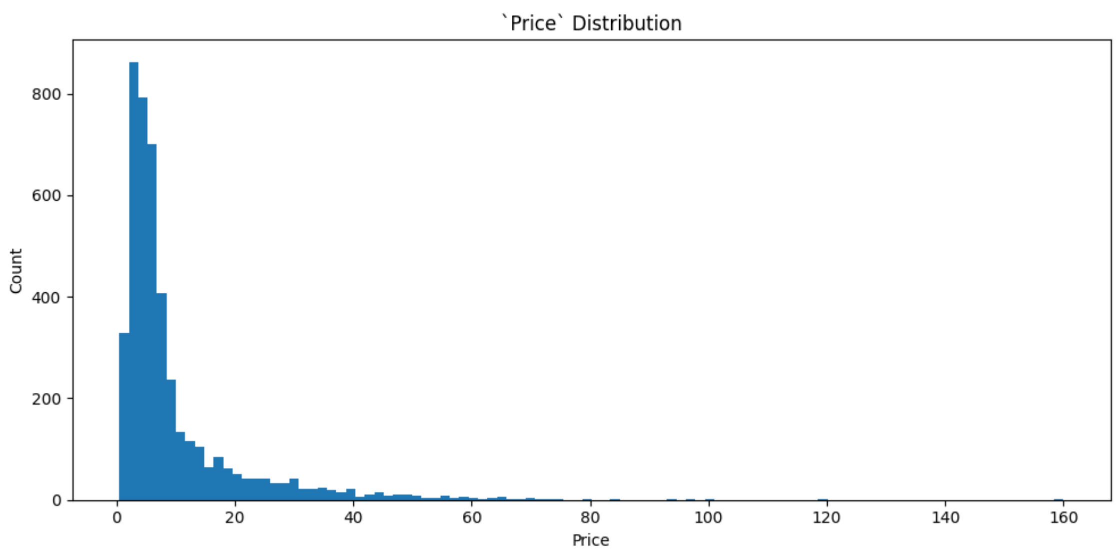
[79]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                ("extract_brand_model", BrandModelExtractor()),
                (
                    "target_encode",
                    TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
                ),
                ("transform", YearToAgeTransformer()),
                ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
                ("group_infrequent_fuel_type", FuelTypeGrouper()),
                ("mileage_clip_outliers", MileageClipper()),
                ("imput_power", PowerImputer()),
                ("bin_seats", SeatsBinner()),
                ("transform_new_price", NewPriceTransformer()),
                ("category_encode", CategoricalEncoder()),
                ("model", XGBRegressor()),
            ]
        ),
    )
```

```
)

current_best_exp.run(X_train, y_train, None, baseline_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1479 ± 0.0159
         -0.0127  -0.0004 compared to baseline (Negative is better)
Training on full training set…
Experiment complete
```

Price

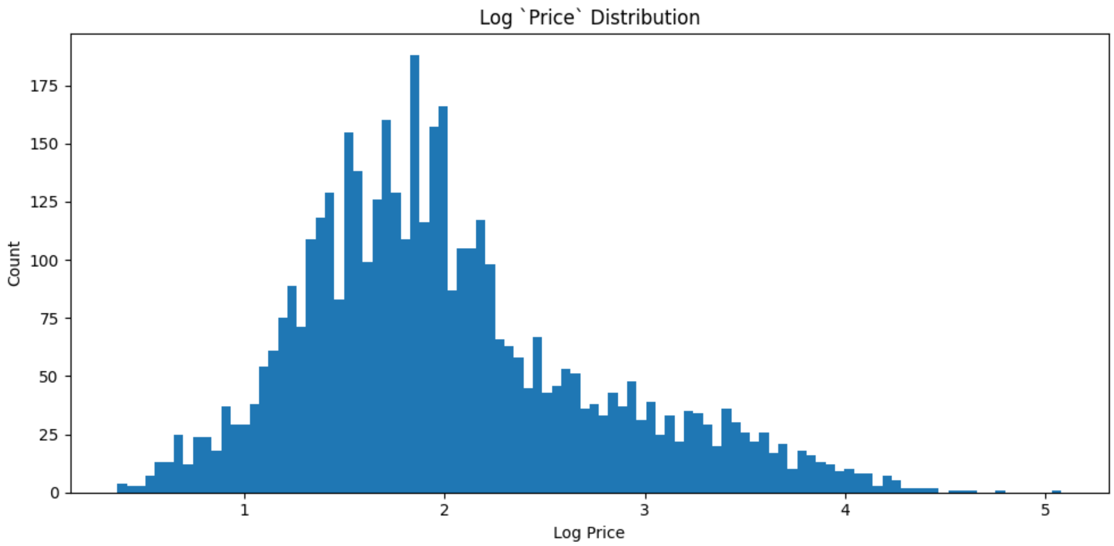
[80]:
```
plt.figure(figsize=(10, 5))
plt.hist(df_train.Price, bins=100)
plt.xlabel("Price")
plt.ylabel("Count")
plt.title("`Price` Distribution")

plt.tight_layout()
plt.show()
```



The target feature `Price` is heavily skewed. Log transformation can mediate this.

[81]:
```
plt.figure(figsize=(10, 5))
plt.hist(np.log1p(df_train.Price), bins=100)
plt.xlabel("Log Price")
plt.ylabel("Count")
plt.title("Log `Price` Distribution")
```

```
plt.tight_layout()
plt.show()
```



[82]:
```
price_transform_exp = Experiment(
    ExperimentConfig(
        name="transform-price",
        pipeline=Pipeline(
            [
                ("category_encode", CategoricalEncoder()),
                (
                    "model",
                    TransformedTargetRegressor(
                        regressor=XGBRegressor(), func=np.log1p,␣
 ↪inverse_func=np.expm1
                    ),
                ),
            ]
        ),
    )
)

price_transform_exp.run(X_train, y_train, X_test, baseline_exp_result);
```

```
[Experiment: transform-price]
Cross-validating (5-folds)…
CV score: 0.1456 ± 0.0170
         -0.0150  +0.0007 compared to baseline (Negative is better)
Training on full training set…
```

```
Creating submission on test set…
Submission created: artifacts/experiment-results/transform-price.csv
Experiment complete
```

Log transformation on `Price` was very effective.

0.0.4 Combining best transformations for each features

[83]:
```
best_single_feature_pipeline = Pipeline(
    [
        ("extract_brand_model", BrandModelExtractor()),
        (
            "target_encode",
            TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
        ),
        ("transform", YearToAgeTransformer()),
        ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
        ("group_infrequent_fuel_type", FuelTypeGrouper()),
        ("mileage_clip_outliers", MileageClipper()),
        ("imput_power", PowerImputer()),
        ("bin_seats", SeatsBinner()),
        ("transform_new_price", NewPriceTransformer()),
        ("category_encode", CategoricalEncoder()),
        (
            "model",
            TransformedTargetRegressor(
                regressor=XGBRegressor(), func=np.log1p, inverse_func=np.expm1
            ),
        ),
    ]
)
```

[84]:
```
best_feature_by_feature_exp = Experiment(
    ExperimentConfig(
        name="combine-all-feature-by-feature-engineering",
        pipeline=best_single_feature_pipeline,
    )
)

best_feature_by_feature_exp_result = best_feature_by_feature_exp.run(
    X_train, y_train, X_test, baseline_exp_result
)
```

```
[Experiment: combine-all-feature-by-feature-engineering]
Cross-validating (5-folds)…
CV score: 0.1379 ± 0.0173
```

```
        -0.0228  +0.0010 compared to baseline (Negative is better)
Training on full training set…
Creating submission on test set…
Submission created: artifacts/experiment-results/combine-all-feature-by-feature-
engineering.csv
Experiment complete
```

0.0.5 Interactions

To determine which interactions are worth investigating, I first perform residual diagnostics.

[85]:
```python
best_single_feature_pipeline.fit(X_train, y_train)

prediction_by_best_single_feature_pipeline = pd.Series(
    best_single_feature_pipeline.predict(X_train), index=y_train.index
)
residuals = y_train - prediction_by_best_single_feature_pipeline

X_train_transformed = pd.DataFrame(
    best_single_feature_pipeline[:-1].fit_transform(X_train, y_train)
)
y_train_transformed = y_train.apply(np.log10)

df_residuals = X_train_transformed.copy()
df_residuals["Residual"] = residuals
df_residuals["Prediction"] = prediction_by_best_single_feature_pipeline
df_residuals["Price"] = y_train

df_residuals
```

[85]:
```
             Name   Location  Kilometers_Driven  Fuel_Type  Transmission  \
ID
G4XLU0   4.267524  15.550690              59138          0             1
CRSHOS   7.206730  11.252232              81504          0             1
FUJ4X1   6.443593  10.093132              92000          2             1
QMVK6E   5.077432   5.460807              33249          0             1
4SWHFC   5.867476  12.628270              65000          2             1
…             …          …                  …          …             …
TR7SLB  10.542137  11.252232              51884          0             1
QB41QE   6.497267   5.460807              27210          0             1
ODG8N7  33.110594   6.749484              52000          0             0
EV2ZBX   2.542287  10.096643              56000          2             1
J2RCU8  18.250472  12.628270              52000          0             0

        Owner_Type  Mileage  Engine   Power  Colour  Seats  Doors  New_Price  \
```

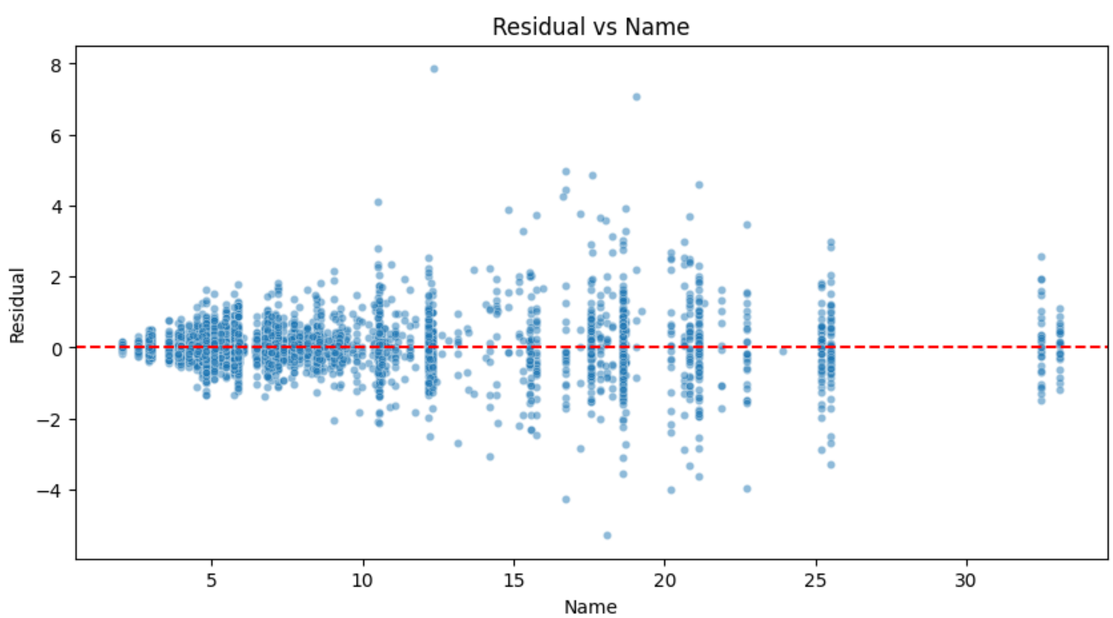
```
ID
G4XLU0            0    17.00   1405    70.00        1       5       4         NaN
CRSHOS            0    21.43   1364    87.20        1       5       4         NaN
FUJ4X1            0    13.80   1299    70.00        1       5       4         NaN
QMVK6E            0    21.27   1396    88.76        0       5       4         NaN
4SWHFC            0    17.00   1497   118.00        2       5       4         NaN
…              …      …      …       …      …      …     …       …
TR7SLB            0    16.00   2179   140.00        2       7       5         NaN
QB41QE            0    27.30   1498    98.60        1       5       4         NaN
ODG8N7            0    12.70   2179   187.70        2       5       4         NaN
EV2ZBX            0    24.70    796    47.30        1       5       4         NaN
J2RCU8            0    12.00   2987   224.00        0       7       5         NaN

            Brand      Model  Age  Missing_New_Price  Residual  Prediction  \
ID
G4XLU0   3.417323   4.267524    7                  1  0.021814    2.558186
CRSHOS  11.417767   7.206730    7                  1 -0.088608    6.618608
FUJ4X1   6.549908   6.443593   13                  1 -0.100111    1.350111
QMVK6E   5.333501   5.077432    8                  1 -0.016794    3.266794
4SWHFC   5.425303   5.867476    9                  1  0.109849    5.090151
…             …          …  …                  …         …           …
TR7SLB   8.075126  10.542137    4                  1  0.440084   12.019916
QB41QE   5.425303   6.497267    4                  1 -0.017071    5.867071
ODG8N7  37.771935  33.110594    5                  1  0.467415   39.282585
EV2ZBX   4.604672   2.542287    7                  1 -0.037402    2.137402
J2RCU8  27.104100  18.250472    6                  1  2.699703   46.300297

        Price
ID
G4XLU0   2.58
CRSHOS   6.53
FUJ4X1   1.25
QMVK6E   3.25
4SWHFC   5.20
…        …
TR7SLB  12.46
QB41QE   5.85
ODG8N7  39.75
EV2ZBX   2.10
J2RCU8  49.00

[4428 rows x 20 columns]
```

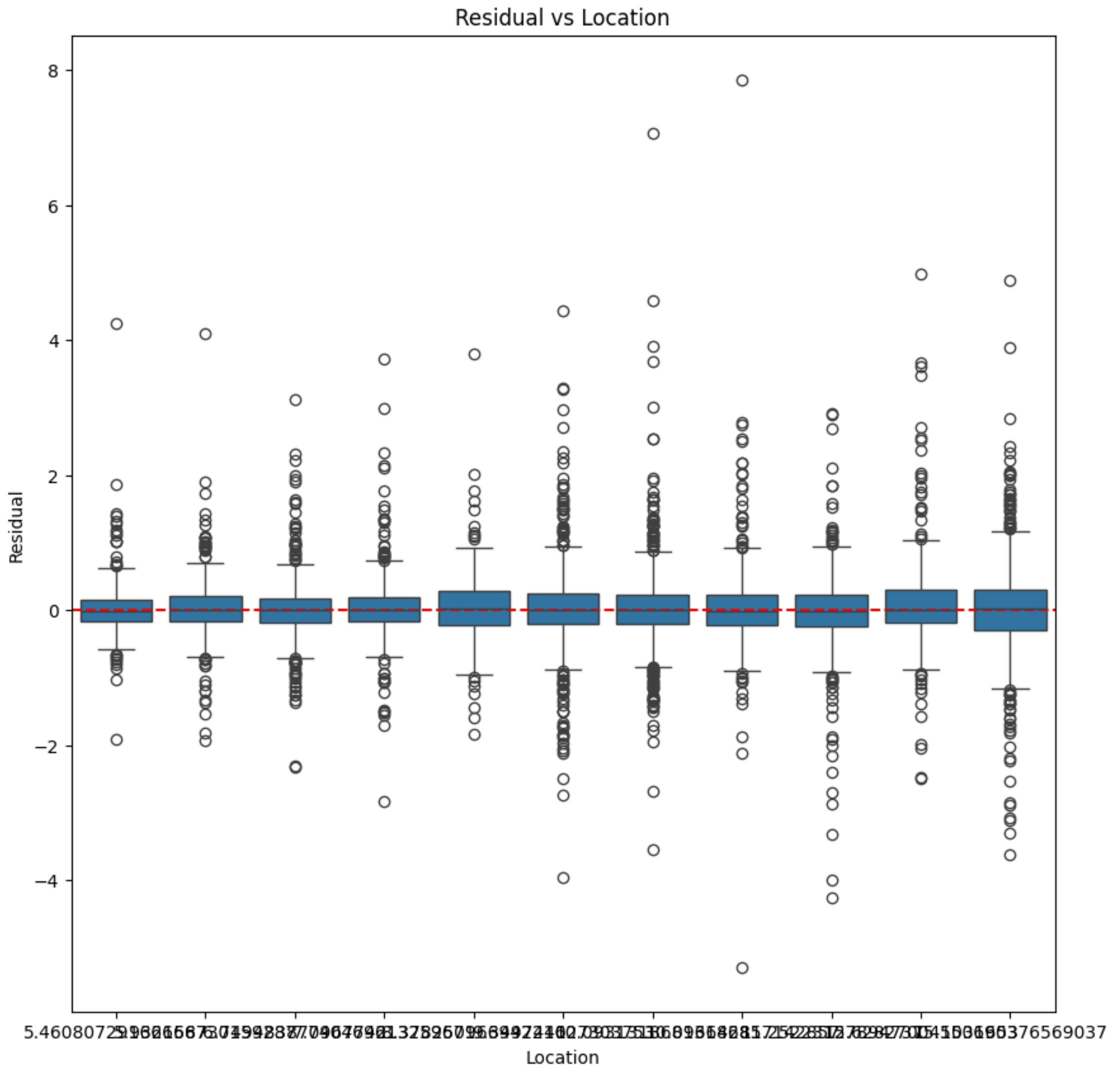
[86]:

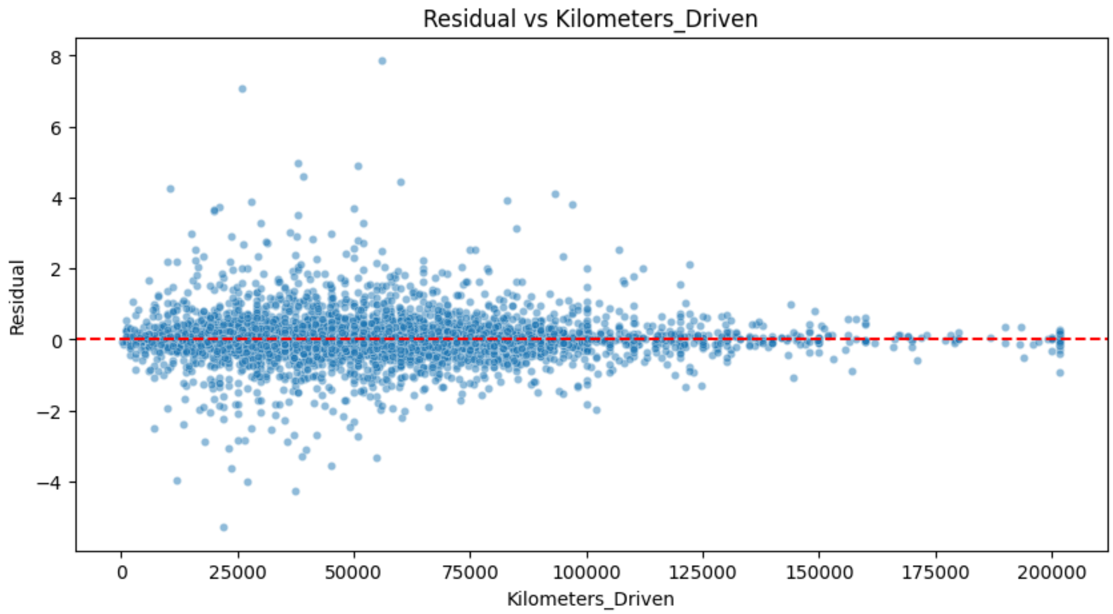
```python
def residual_plot(feature, bins=False):
    plt.figure(figsize=(10, 10 if bins else 5))
    x = df_residuals[feature][df_residuals[feature].notna()]
    if bins:
```

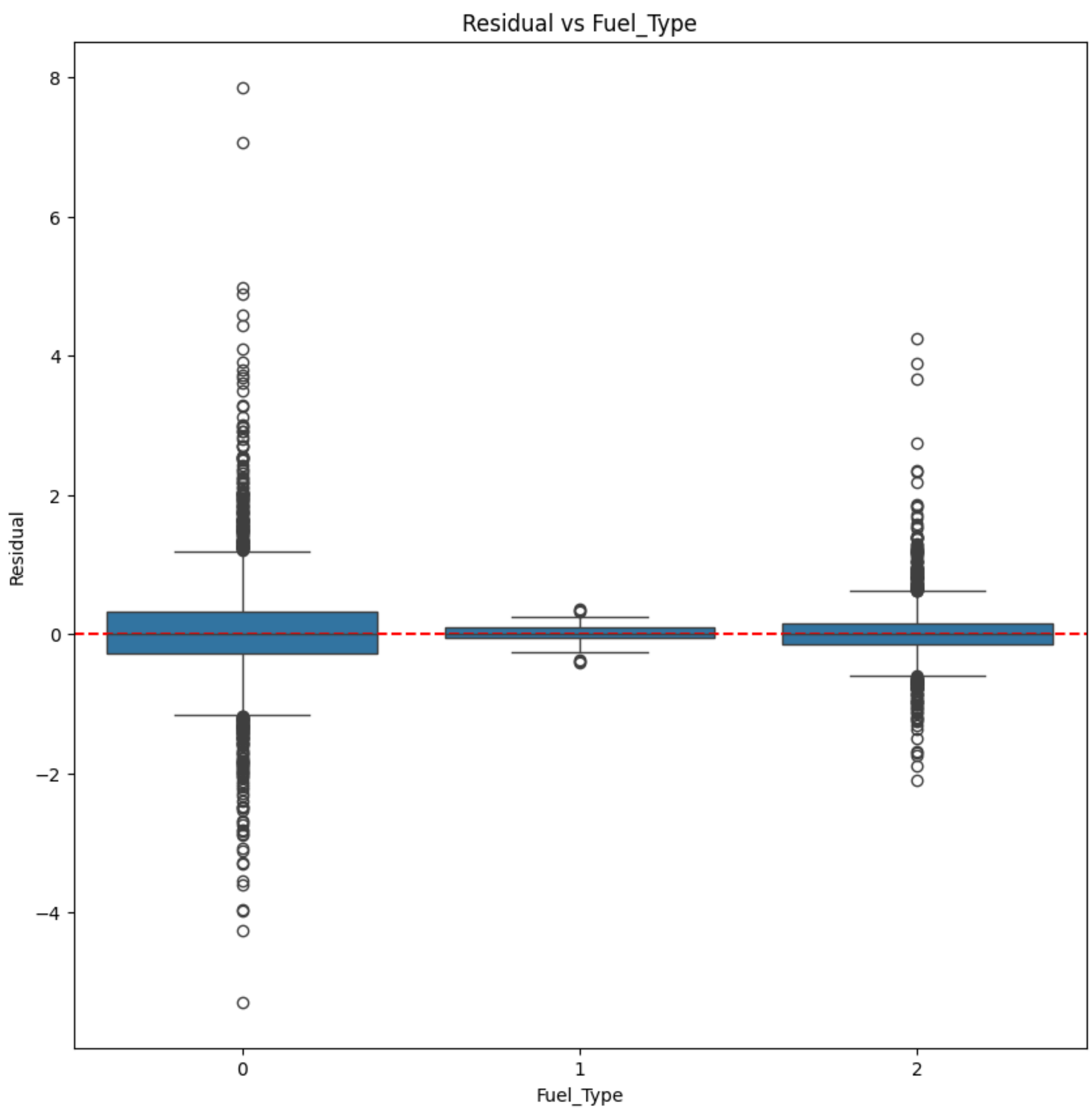
```
        sns.boxplot(x=x, y=df_residuals["Residual"])
    else:
        sns.scatterplot(
            x=x,
            y=df_residuals["Residual"],
            alpha=0.5,
            s=20,
        )
    plt.axhline(0, color="red", linestyle="--")
    plt.title(f"Residual vs {feature}")
    plt.show()
```

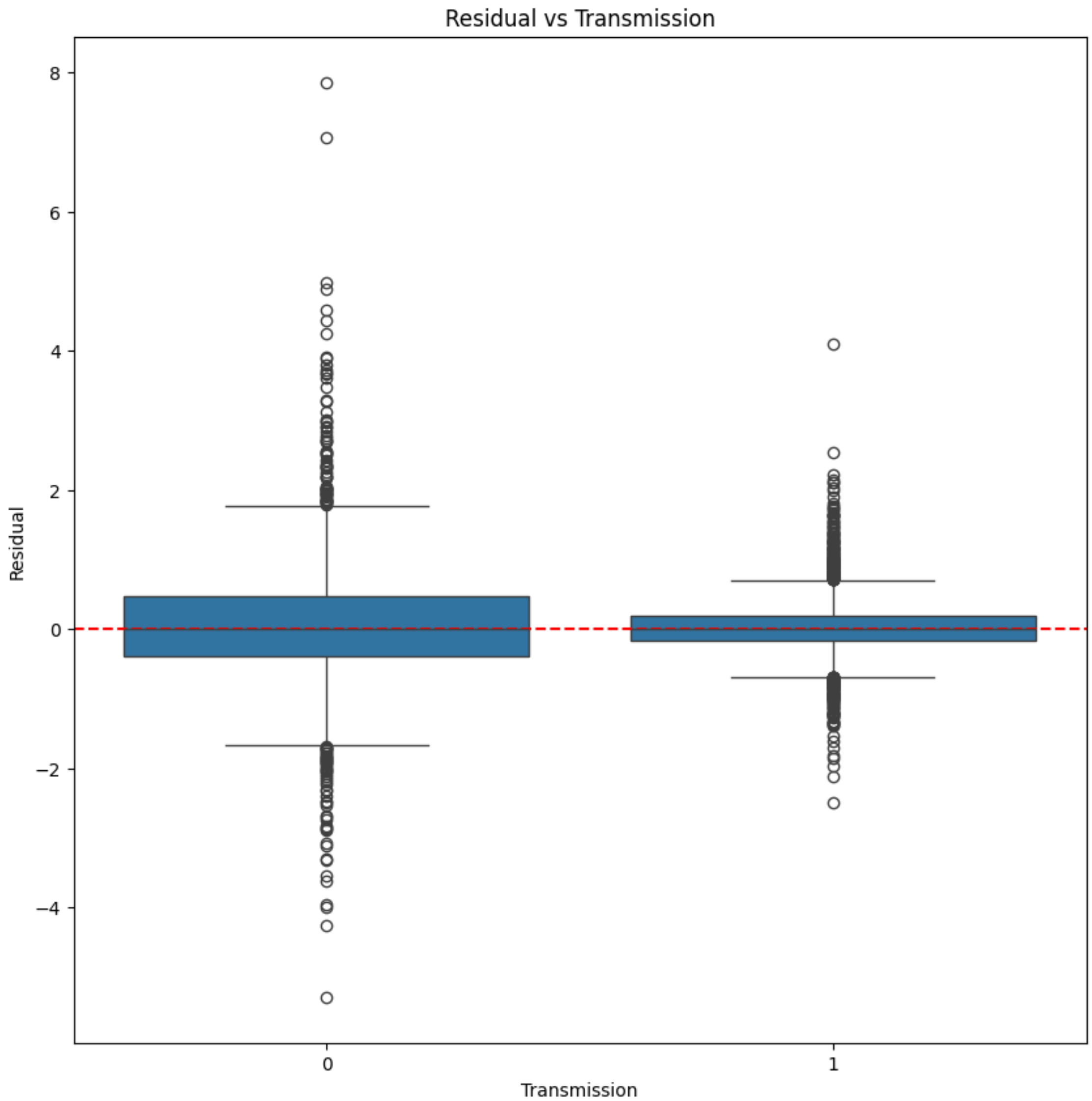
[87]:
```
for feature in df_residuals.drop(columns=["Residual", "Price", "Prediction"]).
 ↪columns:
    use_box_plot = (
        True
        if len(df_residuals[feature].unique()) < 15
        or df_residuals[feature].dtype.name == "category"
        else False
    )
    residual_plot(feature, bins=use_box_plot)
```



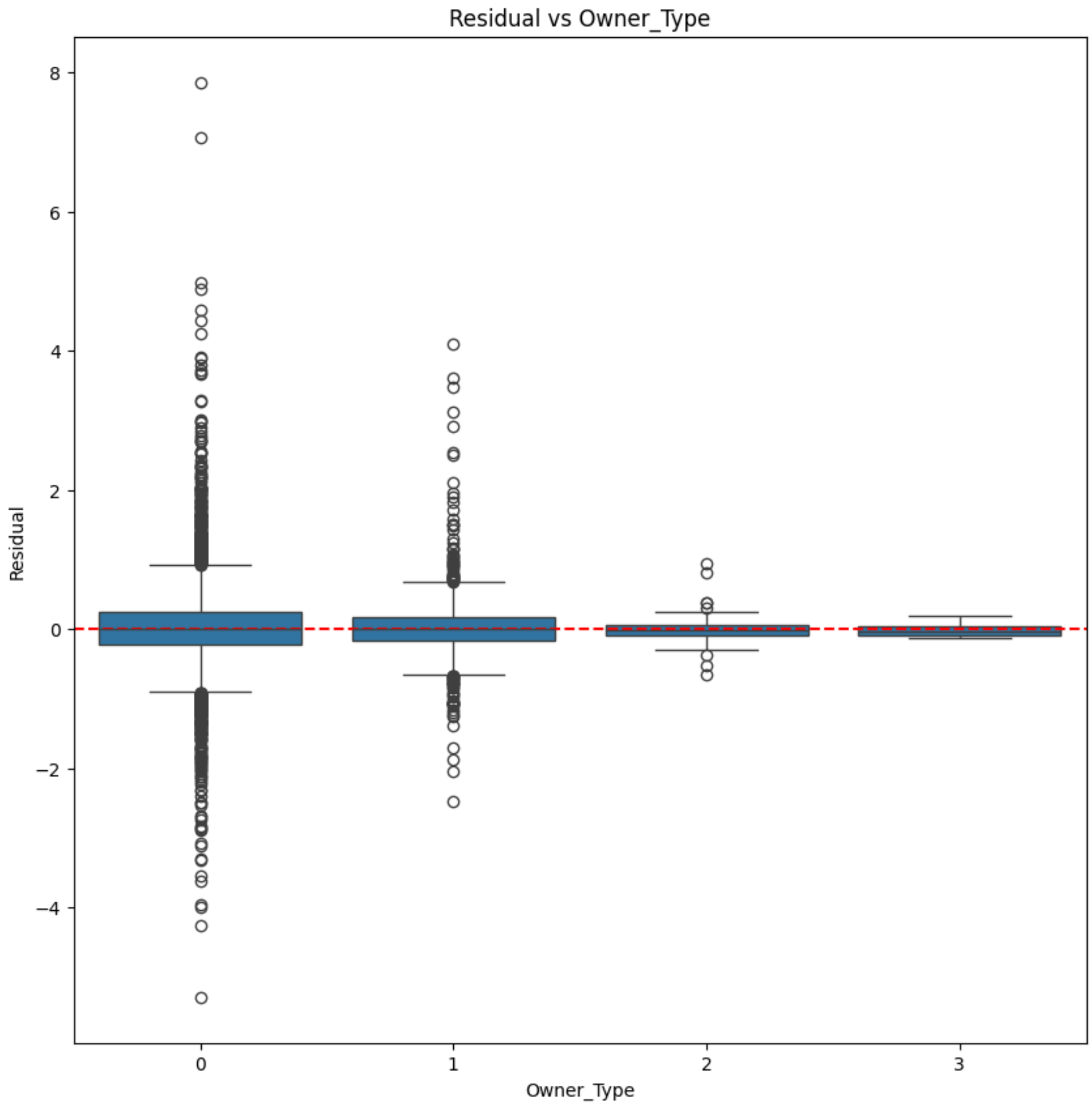

Residual vs Location
Residual
Location
8
6
4
2
0
−2
−4

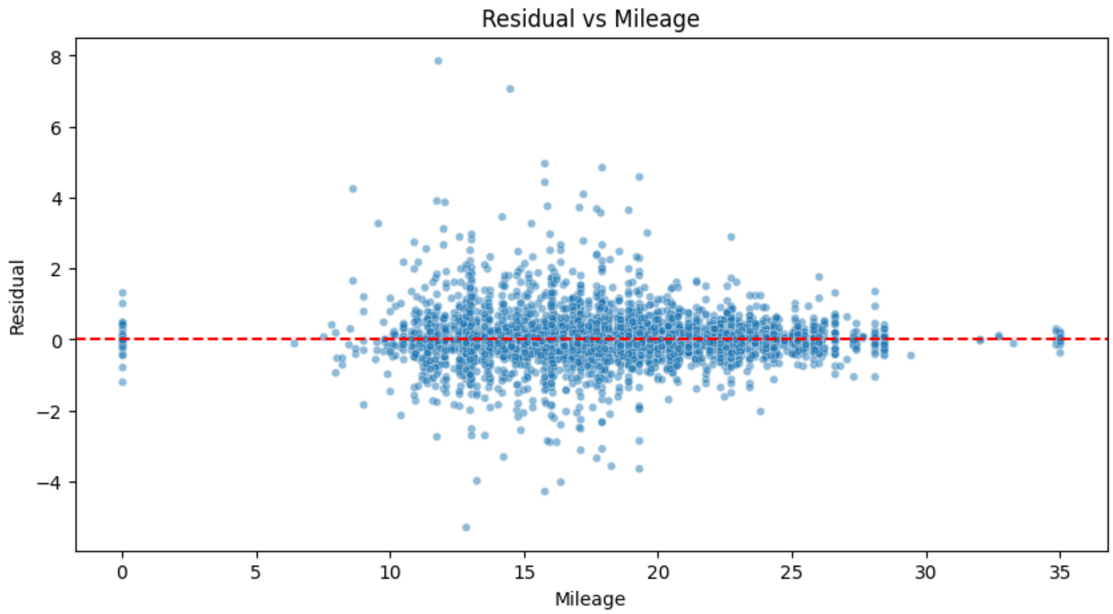

Residual vs Kilometers_Driven
Residual
8
6
4
2
0
−2
−4
0
25000
50000
75000
100000
125000
150000
175000
200000
Kilometers_Driven


Residual vs Fuel_Type
Residual
8
6
4
2
0
−2
−4
0
1
2
Fuel_Type

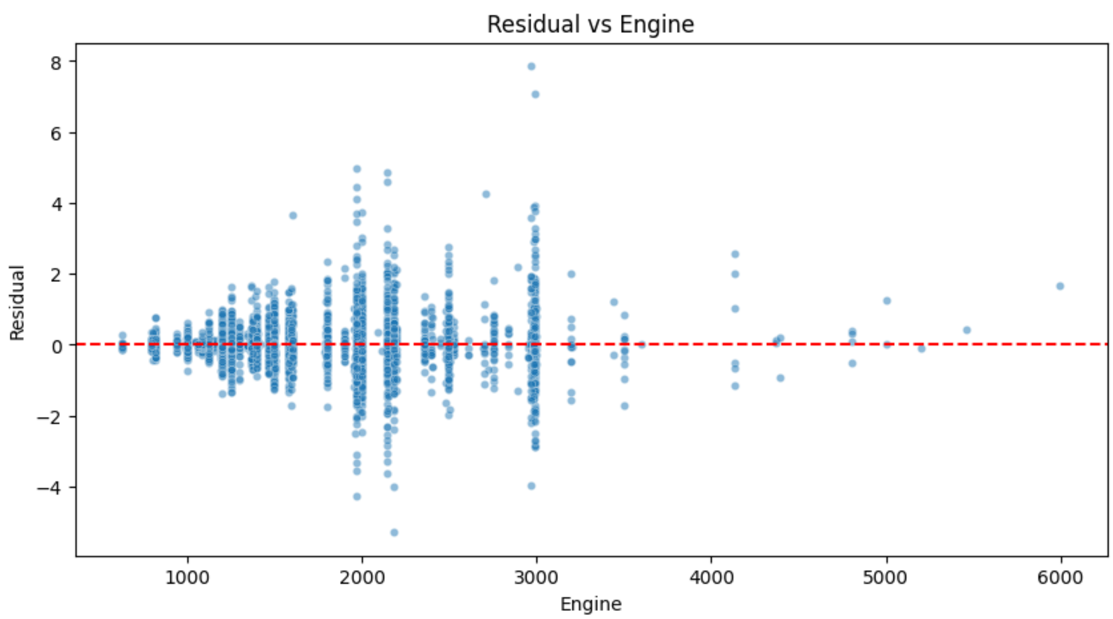


Residual vs Transmission
8
6
4
2
0
−2
−4
Residual
0
1
Transmission

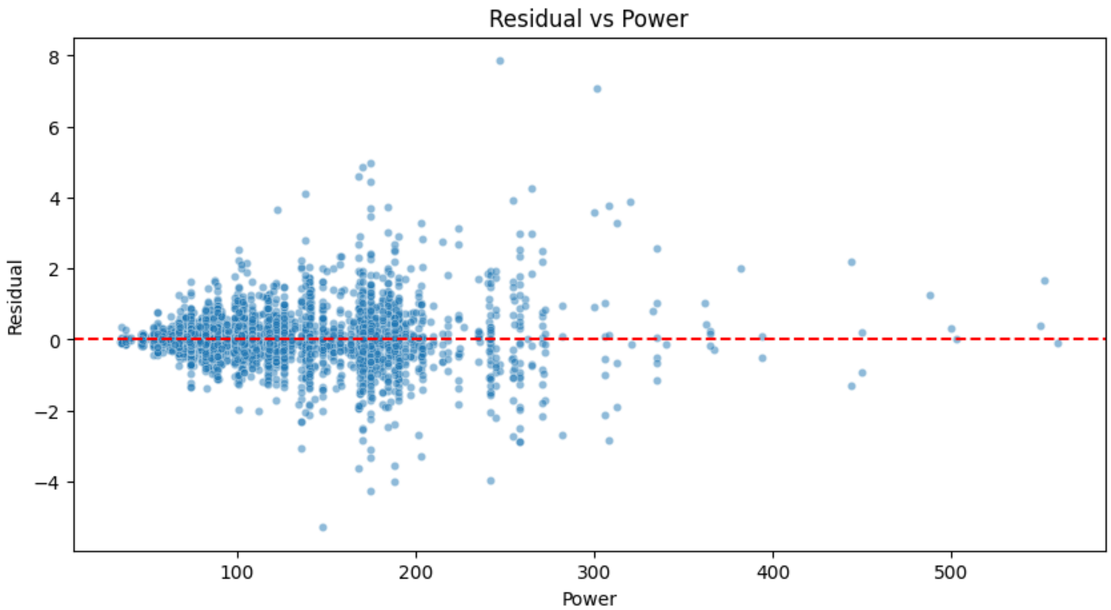

Residual vs Owner_Type
Residual
Owner_Type
8
6
4
2
0
−2
−4
0
1
2
3



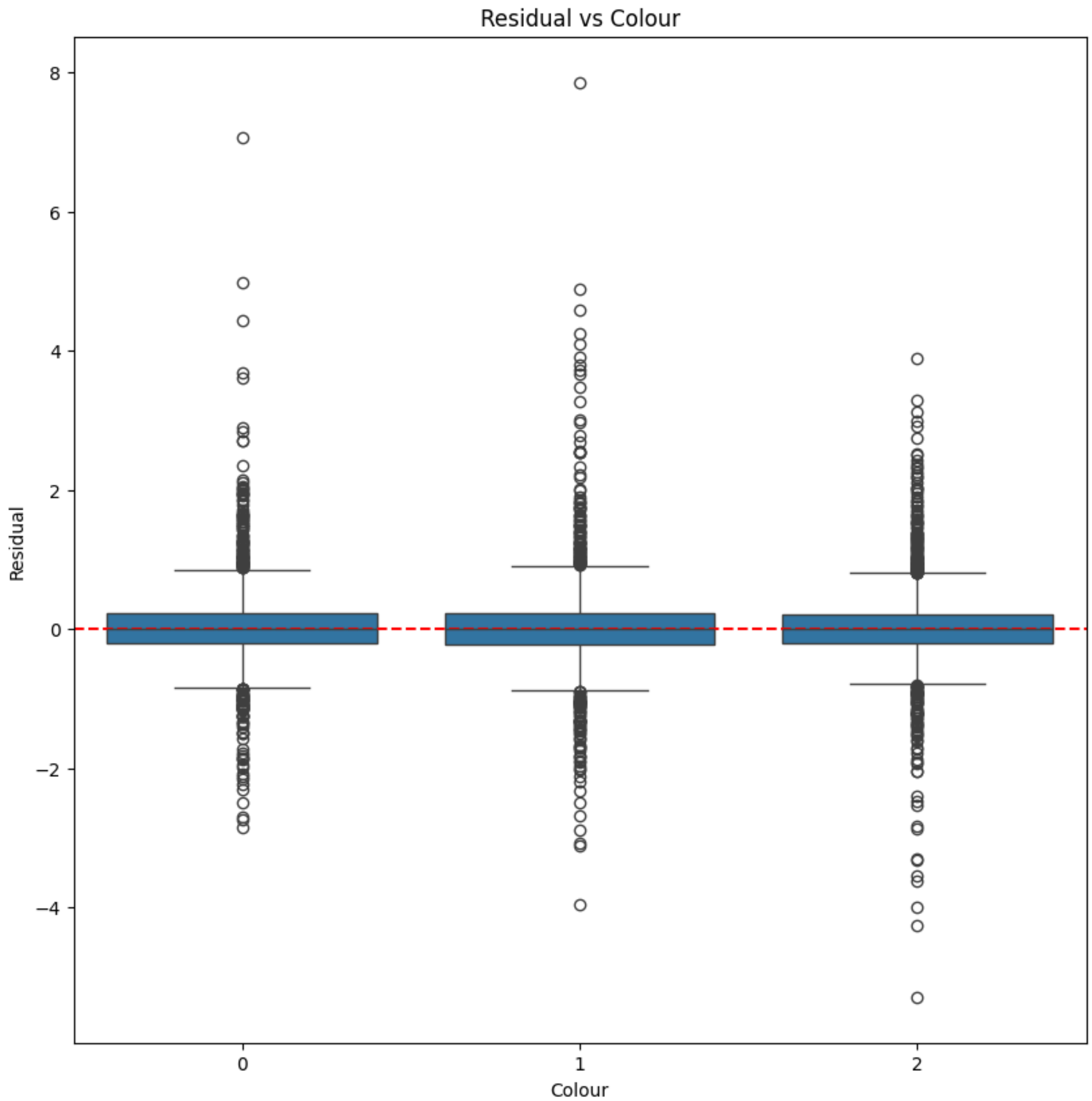
Residual vs Mileage
Residual
Mileage
8
6
4
2
0
−2
−4
0
5
10
15
20
25
30
35

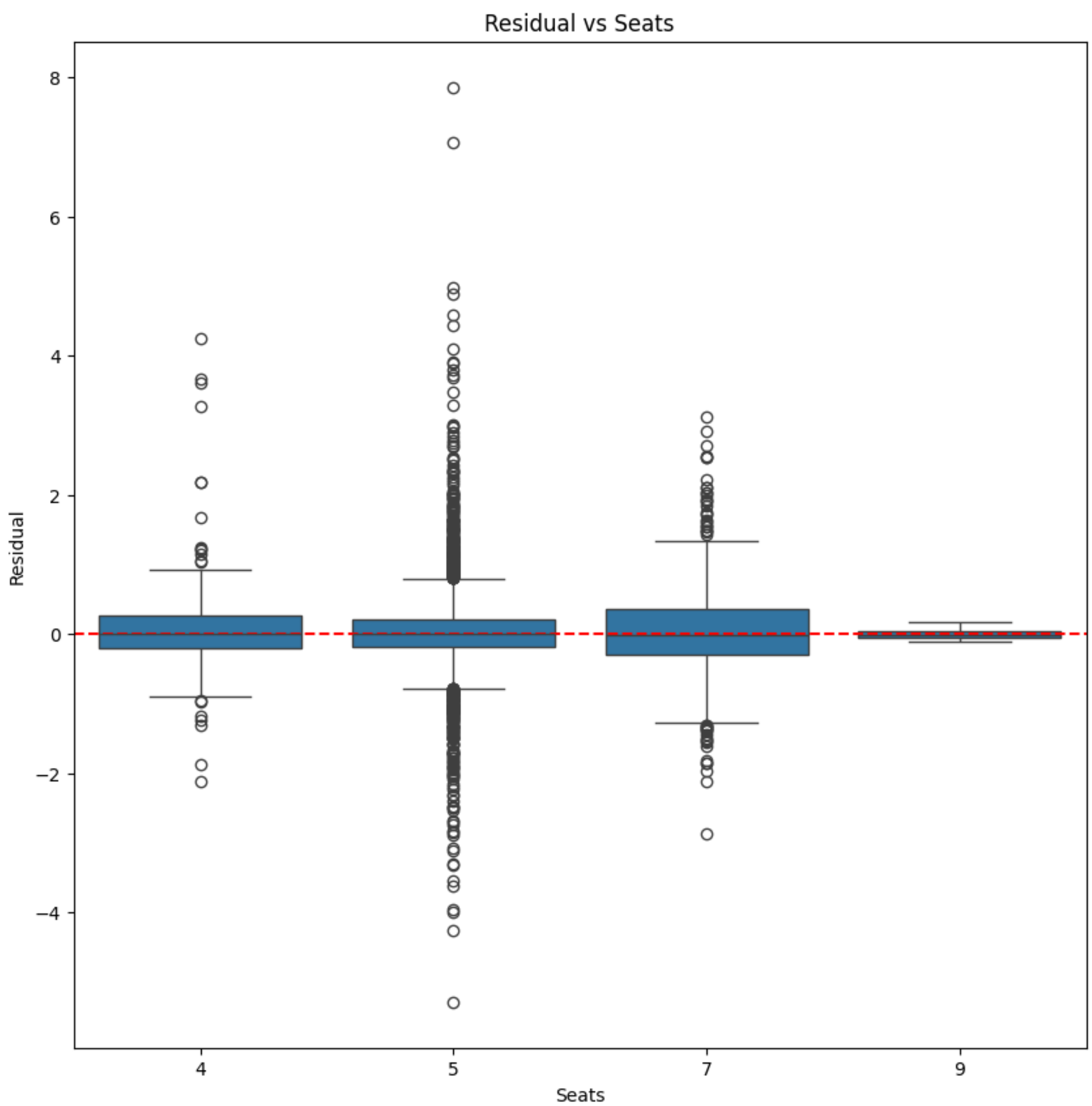


Residual vs Engine
Residual
Engine
8
6
4
2
0
−2
−4
1000
2000
3000
4000
5000
6000

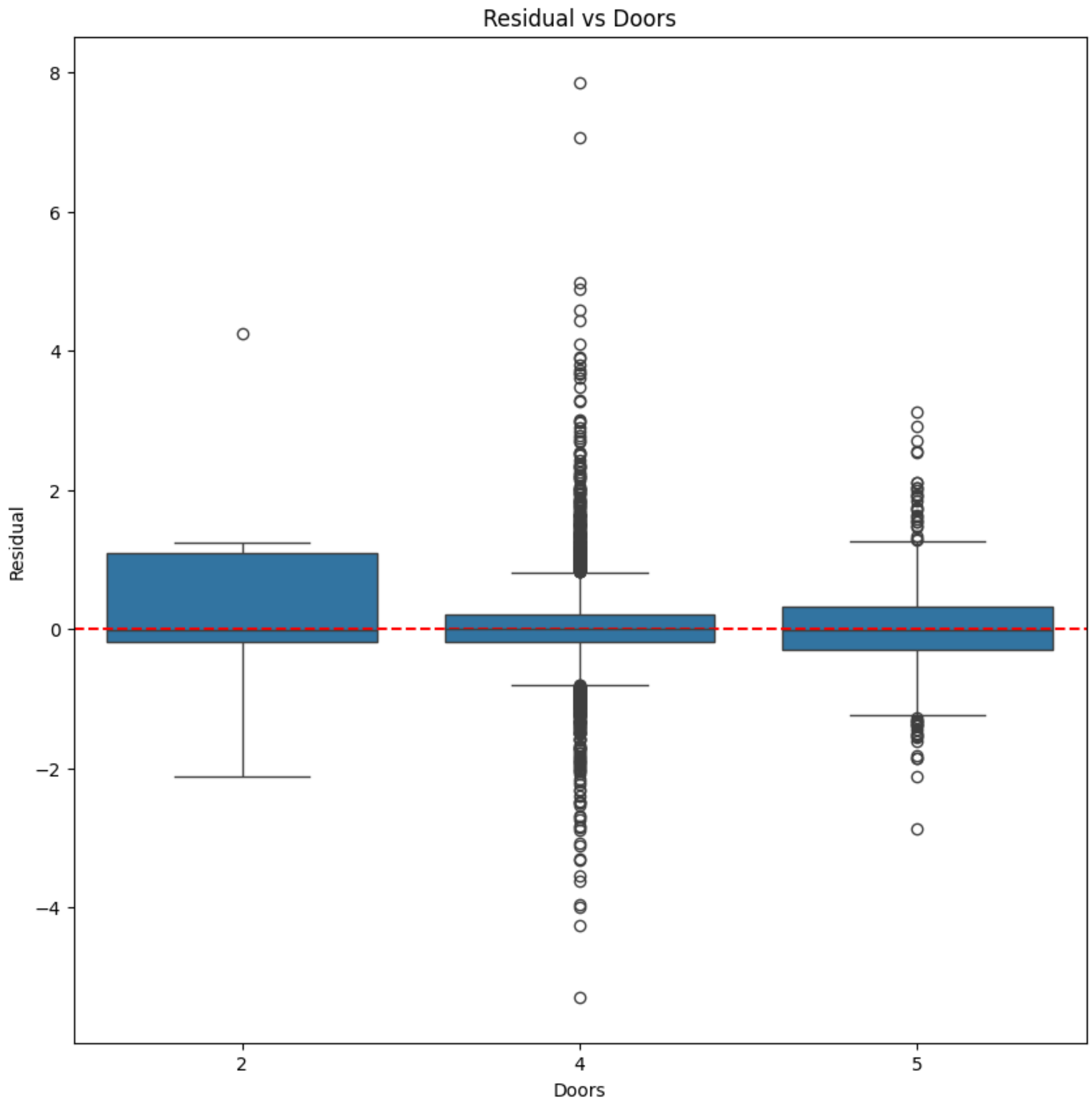


Residual vs Power
8
6
4
2
0
−2
−4
Residual
100
200
300
400
500
Power

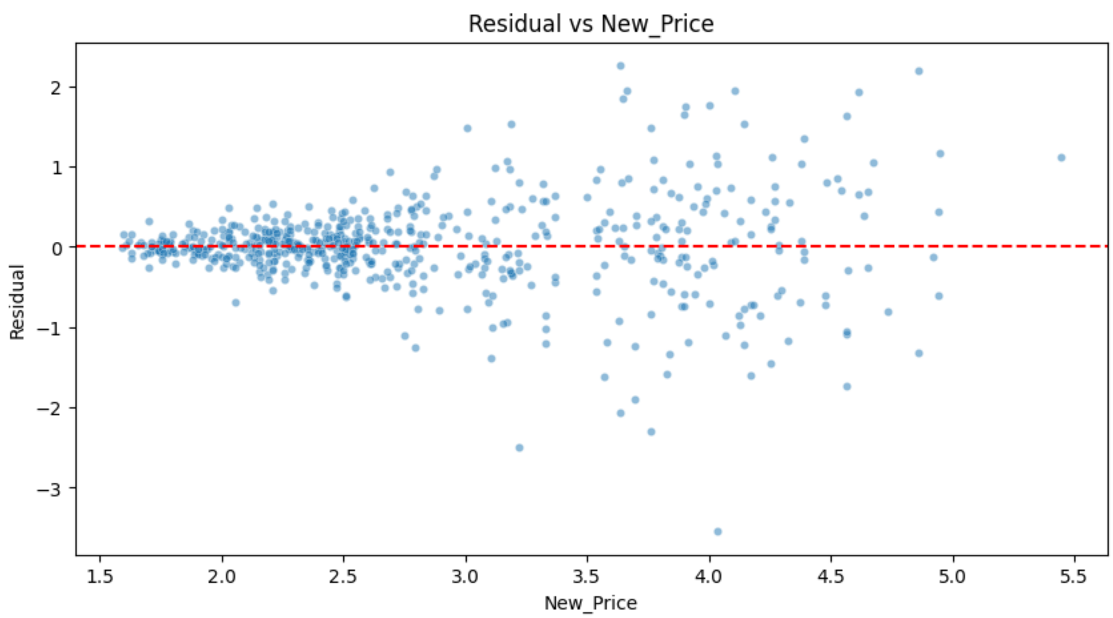

Residual vs Colour
8
6
4
2
0
−2
−4
Residual
0
1
2
Colour

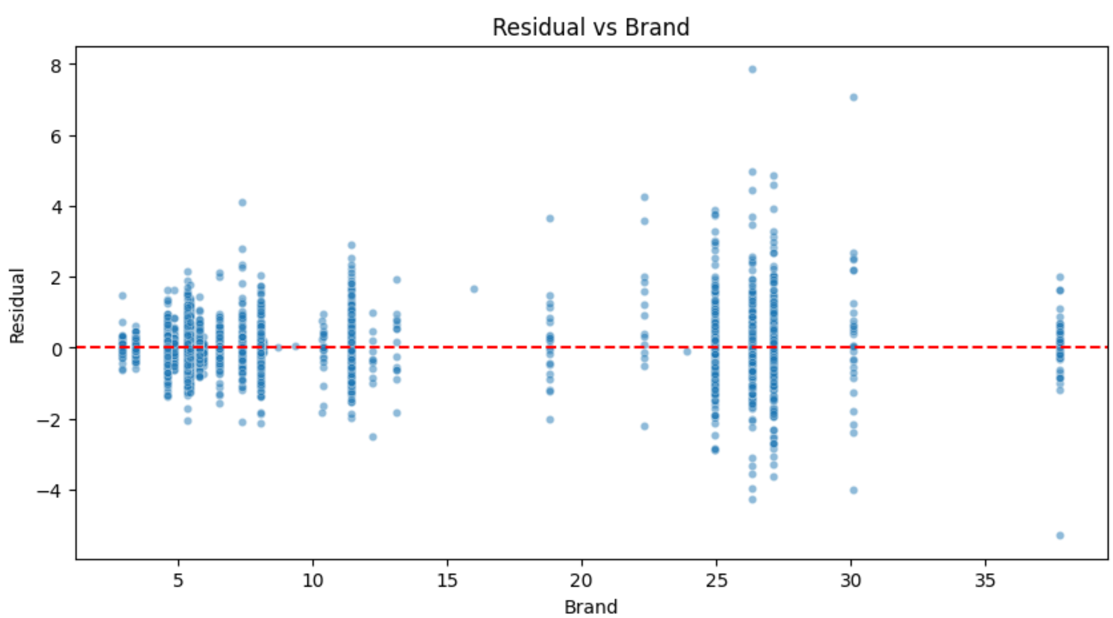


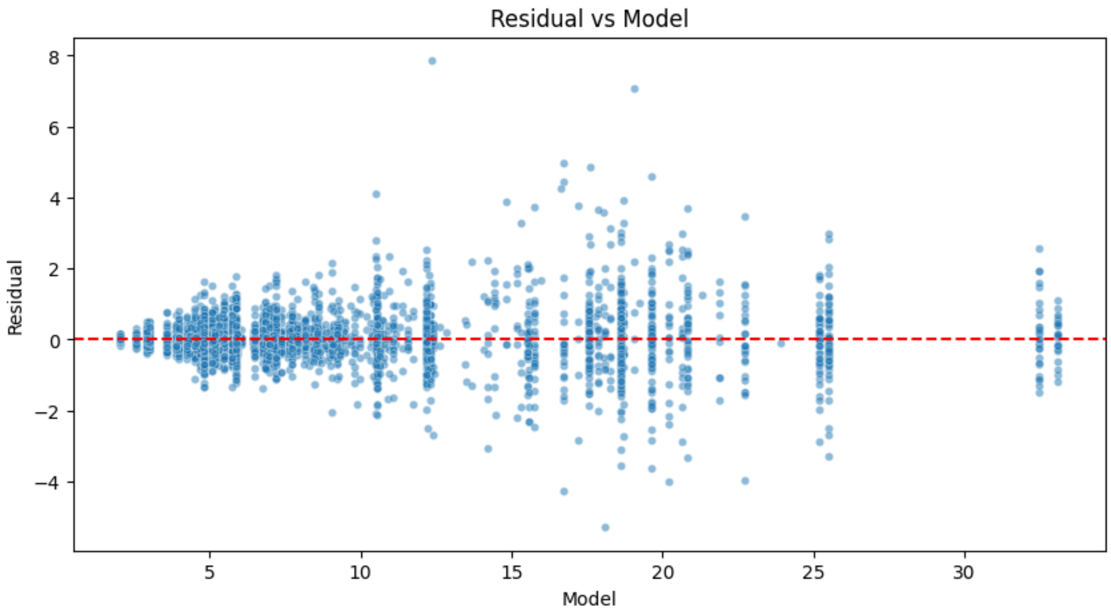
Residual vs Seats
Residual
Seats
8
6
4
2
0
−2
−4
4
5
7
9

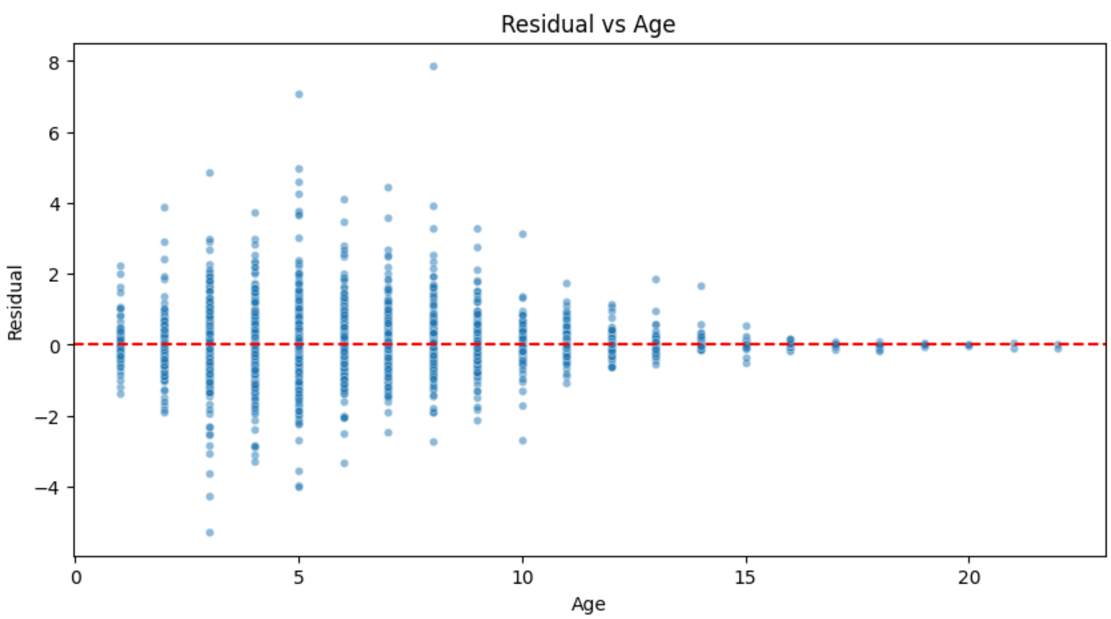


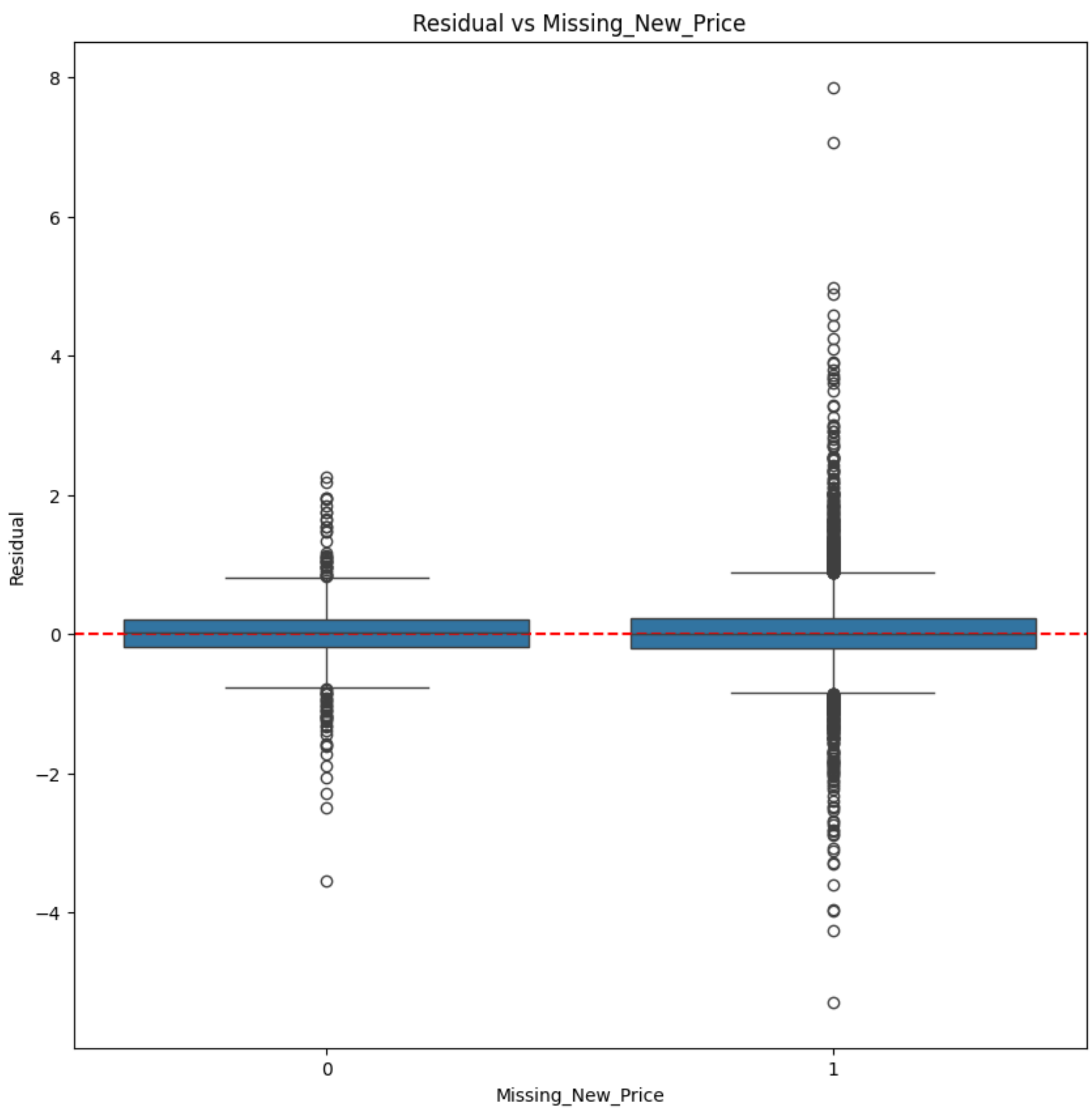
Residual vs Doors
Residual
Doors
8
6
4
2
0
−2
−4
2
4
5


Residual vs New_Price
Residual
New_Price
2
1
0
−1
−2
−3
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5


Residual vs Brand
Residual
Brand
8
6
4
2
0
−2
−4
5
10
15
20
25
30
35

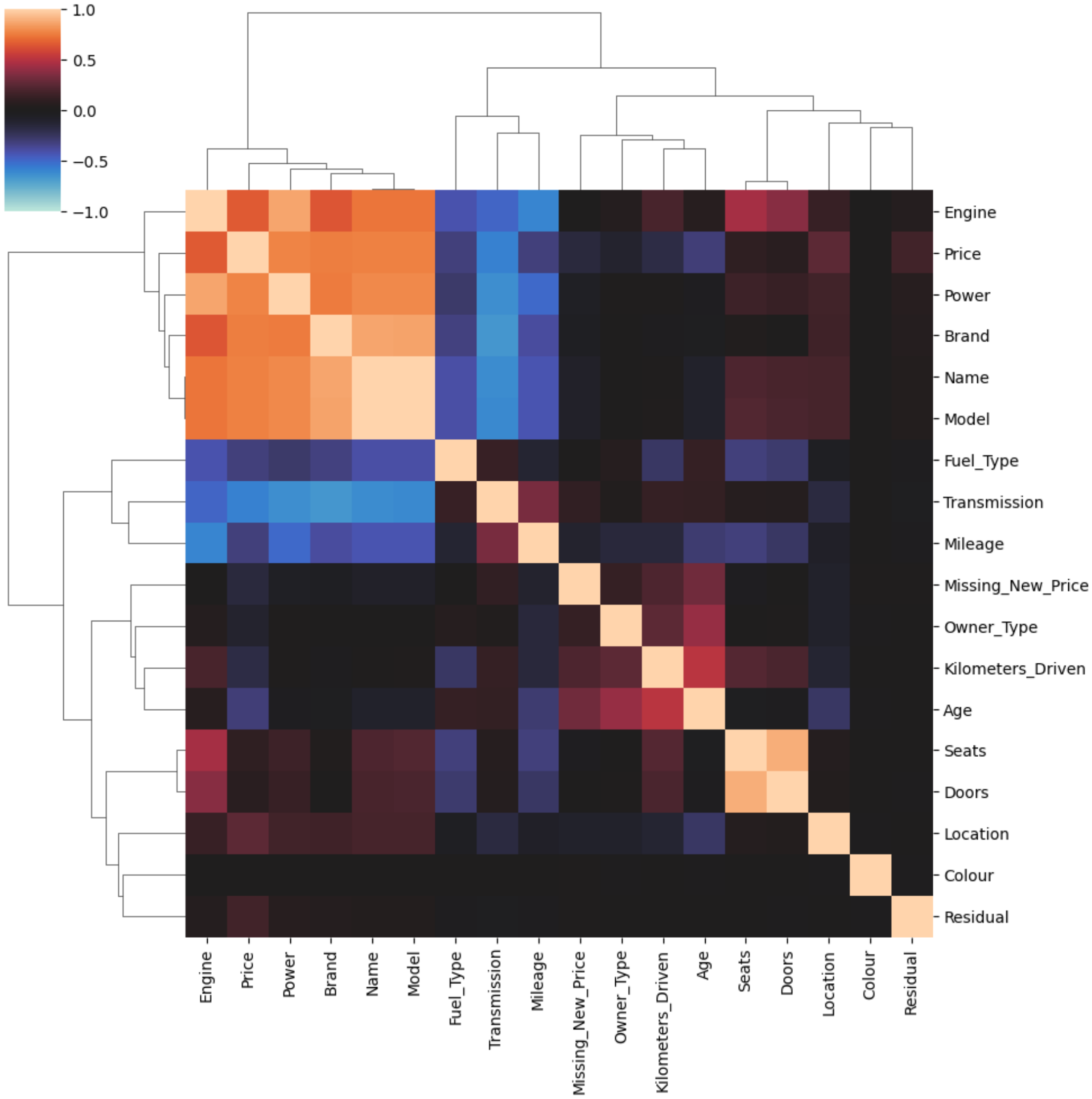

Residual vs Model
8
6
4
2
0
−2
−4
Residual
5
10
15
20
25
30
Model


Residual vs Age
8
6
4
2
0
−2
−4
Residual
0
5
10
15
20
Age



[88]:
```
def plot_correlation(df, method="pearson", annot=True, **kwargs):
    sns.clustermap(
        df.corr(method, numeric_only=True),
        vmin=-1.0,
        vmax=1.0,
        cmap="icefire",
        method="complete",
        annot=annot,
        **kwargs,
    )
```

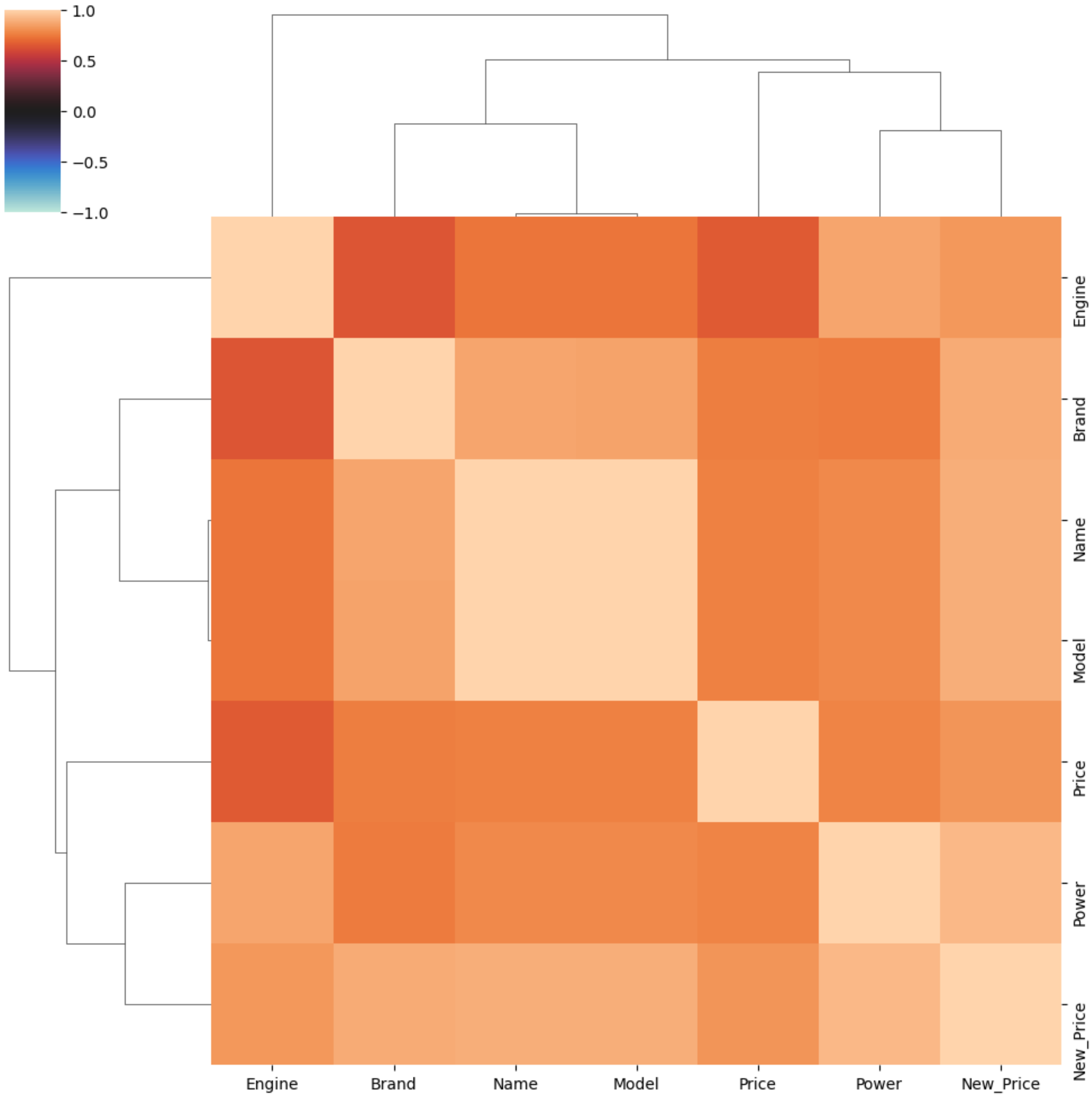
```
plot_correlation(df_residuals.drop(columns=["New_Price", "Prediction"]),␣
↪annot=False)
```



There is highly correlated block.

```
[89]: plot_correlation(
          df_residuals.drop(
              columns=[
                  "Prediction",
                  "Transmission",
                  "Mileage",
                  "Location",
                  "Fuel_Type",
```

```
                "Seats",
                "Doors",
                "Missing_New_Price",
                "Owner_Type",
                "Kilometers_Driven",
                "Age",
                "Colour",
                "Residual",
            ]
        ),
        annot=False,
)
```



Brand × Engine The residual correlation matrix strongly suggests correlation between `Brand` and `Engine`. This is plausible since the `Engine` given a `Brand` can give a strong signal on its tier within the `Brand`.

[90]:
```
class BrandEngineInteraction(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        brand_col: str = "Brand",
        engine_col: str = "Engine",
        brand_engine_col: str = "Brand-Engine",
    ):
        self.brand_col = brand_col
        self.engine_col = engine_col
        self.brand_engine_col = brand_engine_col

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) ->␣
 ↪"BrandEngineInteraction":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()
        X[self.brand_engine_col] = X[self.brand_col] * X[self.engine_col]
        return X
```

[91]:
```
brand_engine_interaction_exp = Experiment(
    ExperimentConfig(
        name="brand_engine_interaction",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("brand_engine_interaction", BrandEngineInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

brand_engine_interaction_exp.run(
    X_train, y_train, None, best_feature_by_feature_exp_result
);
```

```
[Experiment: brand_engine_interaction]
Cross-validating (5-folds)…
CV score: 0.1382 ± 0.0161
         +0.0004  -0.0012 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

It decreased the performance. This could be due to XGBoost already capturing such interaction implicitly, and the introduction of this interaction featrue did not bring meaningfully more information.

`Brand` × `Power` Similarly, `Brand` and `Power` shows strong correlation and this is plausible with the same reason as why `Brand` and `Engine` interaction is meaningful.

[92]:
```
class BrandPowerInteraction(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        brand_col: str = "Brand",
        power_col: str = "Power",
        brand_power_col: str = "Brand-Pwer",
    ):
        self.brand_col = brand_col
        self.power_col = power_col
        self.brand_power_col = brand_power_col

    def fit(self, X: pd.DataFrame, y: Optional[pd.Series]) ->␣
 ↪"BrandPowerInteraction":
        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        X = X.copy()
        X[self.brand_power_col] = X[self.brand_col] * X[self.power_col]
        return X
```

[93]:
```
brand_power_interaction_exp = Experiment(
    ExperimentConfig(
        name="brand_power_interaction",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("brand_power_interaction", BrandPowerInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

brand_power_interaction_exp.run(
    X_train, y_train, None, best_feature_by_feature_exp_result
);
```

```
[Experiment: brand_power_interaction]
Cross-validating (5-folds)…
```

```
CV score: 0.1371 ± 0.0115
        -0.0008  -0.0058 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

It improved the performance.

Age × **New_Price** `Age` and `New_Price` can can represent depreciation. One of the most strongest model agnostic signal in predicting used-car price can be starting from `New_Price` and monotonically decreasing as it `Age`s.

[94]:
```python
class AgeNewPriceInteraction(BaseEstimator, TransformerMixin):
    def __init__(
        self,
        age_col="Age",
        new_price_col="New_Price",
        out_col="Age-NewPrice",
    ):
        self.age_col = age_col
        self.new_price_col = new_price_col
        self.out_col = out_col

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X = X.copy()
        X[self.out_col] = X[self.new_price_col] * X[self.age_col]
        return X
```

[95]:
```python
age_new_price_interaction_exp = Experiment(
    ExperimentConfig(
        name="age_new_price_interaction",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("age_new_price_interaction", AgeNewPriceInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

age_new_price_interaction_exp.run(
    X_train, y_train, None, best_feature_by_feature_exp_result
);
```

```
[Experiment: age_new_price_interaction]
Cross-validating (5-folds)…
CV score: 0.1368 ± 0.0159
         -0.0010  -0.0014 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

It slightly increased the performance and stability.

[96]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("brand_power_interaction", BrandPowerInteraction()),
                ("age_new_price_interaction", AgeNewPriceInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None,␣
 ↪best_feature_by_feature_exp_result);
```

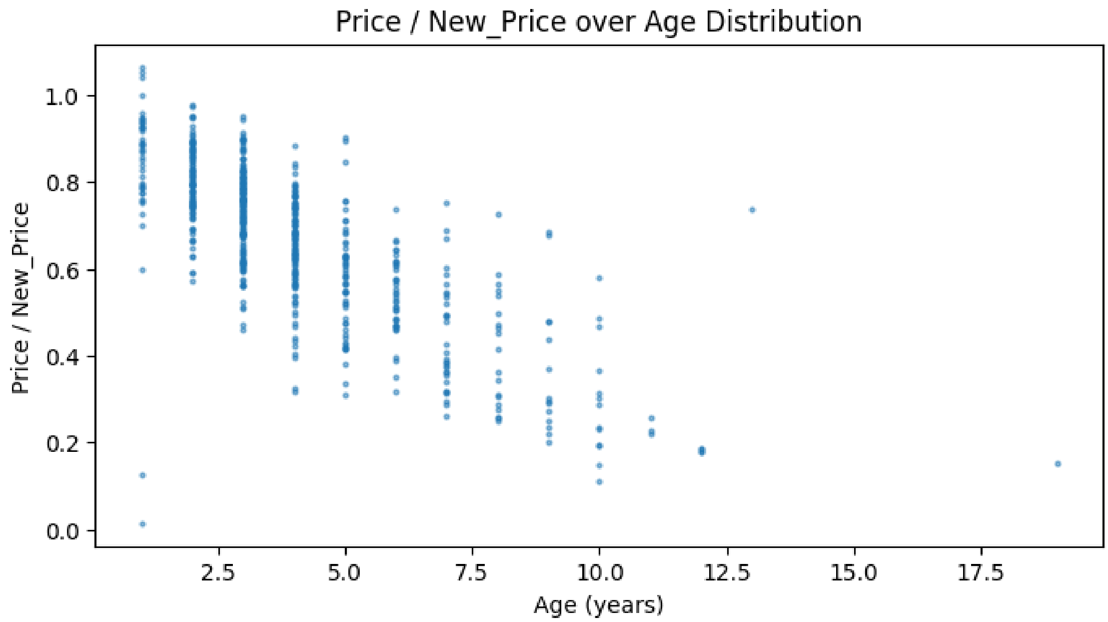
```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1380 ± 0.0105
         +0.0002  -0.0068 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

I'll try more directly modeling depreciation.

The ratio of `Price` to `New_Price` could tell the normalized amount of depreciation. Assuming constant rate of price drop per year.

[97]:
```
X_train_intersection = X_train.dropna(subset=["New_Price"])
y_train_intersection = y_train.loc[X_train_intersection.index]
current_year = 2020

ages = current_year - X_train_intersection.Year
prices_over_new_price = y_train_intersection / X_train_intersection.New_Price
```

```
plt.figure(figsize=(8, 4))
plt.scatter(ages, prices_over_new_price, s=4, alpha=0.5)


plt.xlabel("Age (years)")
plt.ylabel("Price / New_Price")
plt.title("Price / New_Price over Age Distribution")
plt.show()
```



Model × Power

[98]:
```
class ModelPowerInteraction(BaseEstimator, TransformerMixin):
    def __init__(
        self,
        model_col="Model",
        power_col="Power",
        model_power_col="Model-Power",
    ):
        self.model_col = model_col
        self.power_col = power_col
        self.model_power_col = model_power_col

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X = X.copy()
```

```
        X[self.model_power_col] = X[self.model_col] * X[self.power_col]
        return X
```

[99]:
```
model_power_interaction_exp = Experiment(
    ExperimentConfig(
        name="model_power_interaction",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("model_power_interaction", ModelPowerInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

model_power_interaction_exp.run(
    X_train, y_train, None, best_feature_by_feature_exp_result
);
```

```
[Experiment: model_power_interaction]
Cross-validating (5-folds)…
CV score: 0.1360 ± 0.0141
         -0.0018  -0.0032 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

[100]:
```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("brand_power_interaction", BrandPowerInteraction()),
                ("model_power_interaction", ModelPowerInteraction()),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

current_best_exp.run(X_train, y_train, None,␣
 ↪best_feature_by_feature_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
```

```
CV score: 0.1372 ± 0.0116
         -0.0007  -0.0057 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

Ontology Approach

[101]:
```python
df_train.columns
```

[101]:
```
Index(['Name', 'Location', 'Year', 'Kilometers_Driven', 'Fuel_Type',
       'Transmission', 'Owner_Type', 'Mileage', 'Engine', 'Power', 'Colour',
       'Seats', 'Doors', 'New_Price', 'Price'],
      dtype='object')
```

Purely data-driven approach is failing. Attempting to build a strongly domain-knowledge based ontology of features.

[102]:
```python
used_car_price_ontology = {
    "Car_Spec": {
        "Power": ["Engine", "Power", "Fuel_Type", "Transmission"],
        "Form": ["Seats", "Doors", "Colour"],
        "Positioning": ["Brand", "Model", "Name", "New_Price"],
    },
    "Condition": {"Wear": ["Age", "Kilometers_Driven"], "Ownership":␣
 ↪["Owner_Type"]},
    "Market": ["Location"],
}
```

The `Car_Spec` will determine the car's `BaseValue`, the `Condition` will determine the car's `Depreciation`, and the `Market` will determine the `MarketInfluence`.

[103]:
```python
class BaseValueIndexTransformer(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        brand_col="Brand",
        model_col="Model",
        fuel_col="Fuel_Type",
        trans_col="Transmission",
        engine_col="Engine",
        power_col="Power",
        seats_col="Seats",
        doors_col="Doors",
        name_col="Name",
        new_price_col="New_Price",
        n_segments=3,
    ):
        self.brand_col = brand_col
```

```python
        self.model_col = model_col
        self.fuel_col = fuel_col
        self.trans_col = trans_col
        self.engine_col = engine_col
        self.power_col = power_col
        self.seats_col = seats_col
        self.doors_col = doors_col
        self.name_col = name_col
        self.new_price_col = new_price_col
        self.n_segments = n_segments

    def _spec_features(self, df: pd.DataFrame) -> pd.DataFrame:
        out = pd.DataFrame(index=df.index)

        out["LogEngine"] = np.log1p(df[self.engine_col])
        out["LogPower"] = np.log1p(df[self.power_col])
        out["PowerDensity"] = df[self.power_col] / df[self.engine_col]

        out[self.seats_col] = df[self.seats_col]
        out[self.doors_col] = df[self.doors_col]

        return out

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "BaseValueIndexTransformer":
        df = X.copy()

        mask = df[self.new_price_col].notna()
        df_known = df.loc[mask].copy()

        num_df = self._spec_features(df_known)

        cat_df = df_known[
            [self.brand_col, self.model_col, self.fuel_col, self.trans_col]
        ]

        self.ohe_ = OneHotEncoder(handle_unknown="ignore", sparse_output=False)
        cat_arr = self.ohe_.fit_transform(cat_df)

        num_arr = num_df.fillna(0).values
        X_spec = np.hstack([cat_arr, num_arr])

        self.kmeans_ = KMeans(n_clusters=self.n_segments, random_state=42)
        segments = self.kmeans_.fit_predict(X_spec)
        df_known["Segment"] = segments
```

```
        self.num_features_ = num_df.columns.tolist()

        X_reg = np.hstack([X_spec, segments.reshape(-1, 1)])
        y_reg = df_known[self.new_price_col]

        self.reg_ = LinearRegression()
        self.reg_.fit(X_reg, y_reg)

        self.base_mean_ = y_reg.mean()

        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        df = X.copy()

        num_df = self._spec_features(df)

        cat_df = df[[self.brand_col, self.model_col, self.fuel_col, self.
↪trans_col]]
        cat_arr = self.ohe_.transform(cat_df)

        num_arr = num_df.fillna(0).values

        X_spec = np.hstack([cat_arr, num_arr])

        segments = self.kmeans_.predict(X_spec)
        df["Segment"] = segments

        X_reg = np.hstack([X_spec, segments.reshape(-1, 1)])

        estimated_np = self.reg_.predict(X_reg)

        df["BaseValueIndex"] = estimated_np / self.base_mean_

        return df
```

[104]:
```
class WearIndexTransformer(TransformerMixin, BaseEstimator):
    def __init__(
        self,
        age_col="Age",
        km_col="Kilometers_Driven",
        engine_col="Engine",
        owner_col="Owner_Type",
    ):
        self.age_col = age_col
        self.km_col = km_col
        self.engine_col = engine_col
```

```python
        self.owner_col = owner_col

    def _build_wear_features(self, df: pd.DataFrame) -> pd.DataFrame:
        out = pd.DataFrame(index=df.index)

        age = df[self.age_col].fillna(0)
        km = df[self.km_col].fillna(0)

        engine = df[self.engine_col].fillna(df[self.engine_col].median())

        out["Age_scaled"] = age
        out["KM_per_Year"] = km / (age + 1)
        out["WearFactor"] = km / (engine + 1)

        return out

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "WearIndexTransformer":
        df = X.copy()

        wear_df = self._build_wear_features(df)

        owner_vals = df[self.owner_col].astype("category").cat.codes
        wear_df["OwnerEncoded"] = owner_vals

        self.scaler_ = StandardScaler()
        wear_scaled = self.scaler_.fit_transform(wear_df)

        self.reg_ = LinearRegression()
        self.reg_.fit(wear_scaled, np.arange(len(wear_scaled)))

        self.w_ = self.reg_.coef_

        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        df = X.copy()

        wear_df = self._build_wear_features(df)
        owner_vals = df[self.owner_col].astype("category").cat.codes
        wear_df["OwnerEncoded"] = owner_vals

        wear_scaled = self.scaler_.transform(wear_df)

        wear_score = wear_scaled @ self.w_
```

```python
        wear_index = (wear_score - wear_score.min()) / (
            wear_score.max() - wear_score.min()
        )

        df["WearIndex"] = wear_index

        return df
```

[105]:
```python
class MarketIndexTransformer(TransformerMixin, BaseEstimator):
    def __init__(self, location_col="Location"):
        self.location_col = location_col

    def fit(
        self, X: pd.DataFrame, y: Optional[pd.Series] = None
    ) -> "MarketIndexTransformer":
        df = X.copy()
        df["Price"] = y

        loc_means = df.groupby(self.location_col)["Price"].mean()

        df["LocMean"] = df[self.location_col].map(loc_means)

        self.ohe_ = OneHotEncoder(handle_unknown="ignore", sparse_output=False)
        loc_ohe = self.ohe_.fit_transform(df[[self.location_col]])

        self.reg_ = LinearRegression()
        self.reg_.fit(loc_ohe, df["LocMean"])

        self.global_mean_ = df["Price"].mean()

        return self

    def transform(self, X: pd.DataFrame) -> pd.DataFrame:
        df = X.copy()

        loc_ohe = self.ohe_.transform(df[[self.location_col]])

        loc_score = self.reg_.predict(loc_ohe)

        df["MarketIndex"] = loc_score / self.global_mean_

        return df
```

[106]:
```python
class OntologyFeatureBuilder(BaseEstimator, TransformerMixin):
    def __init__(
        self,
        base_transformer,
```

```
        wear_transformer,
        market_transformer,
        add_interactions=True,
        add_composite=True,
    ):
        self.base_transformer = base_transformer
        self.wear_transformer = wear_transformer
        self.market_transformer = market_transformer
        self.add_interactions = add_interactions
        self.add_composite = add_composite

    def fit(self, X, y):
        self.base_transformer.fit(X)

        self.wear_transformer.fit(X)

        self.market_transformer.fit(X, y)

        return self

    def transform(self, X):
        df = X.copy()

        df = self.base_transformer.transform(df)
        df = self.wear_transformer.transform(df)
        df = self.market_transformer.transform(df)

        base = df["BaseValueIndex"]
        wear = df["WearIndex"]
        market = df["MarketIndex"]

        if self.add_interactions:
            df["Base_x_Wear"] = base * wear
            df["Base_x_Market"] = base * market
            df["Wear_x_Market"] = wear * market

        if self.add_composite:
            df["CompositeValue"] = base * wear * market

        return df
```

[107]:
```
ontology_transformer = OntologyFeatureBuilder(
    base_transformer=BaseValueIndexTransformer(),
    wear_transformer=WearIndexTransformer(),
    market_transformer=MarketIndexTransformer(),
    add_interactions=True,
    add_composite=True,
```

```
)
```

[108]:

```
ontology_exp = Experiment(
    ExperimentConfig(
        name="ontology-based-engineering",
        pipeline=Pipeline(
            [
                *best_single_feature_pipeline.steps[:-2],
                ("ontology", ontology_transformer),
                *best_single_feature_pipeline.steps[-2:],
            ]
        ),
    )
)

ontology_exp.run(X_train, y_train, None, best_feature_by_feature_exp_result);
```

```
[Experiment: ontology-based-engineering]
Cross-validating (5-folds)…
CV score: 0.1475 ± 0.0179
         +0.0096  +0.0005 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```

Final Feature Engineering Pipeline

[109]:

```
def final_pipeline_builder(model_config=dict()) -> Pipeline:
    return Pipeline(
        [
            ("extract_brand_model", BrandModelExtractor()),
            (
                "target_encode",
                TargetEncoder(cols=["Brand", "Model", "Name", "Location"]),
            ),
            ("transform", YearToAgeTransformer()),
            ("Kilometers_Driven_clip_outliers", KilometersDrivenClipper()),
            ("group_infrequent_fuel_type", FuelTypeGrouper()),
            ("mileage_clip_outliers", MileageClipper()),
            ("input_power", PowerImputer()),
            ("bin_seats", SeatsBinner()),
            ("transform_new_price", NewPriceTransformer()),
            ("brand_power_interaction", BrandPowerInteraction()),
            ("model_power_interaction", ModelPowerInteraction()),
            ("category_encode", CategoricalEncoder()),
            (
```

```
                "model",
                TransformedTargetRegressor(
                    regressor=XGBRegressor(**model_config),
                    func=np.log1p,
                    inverse_func=np.expm1,
                ),
            ),
        ]
    )
```

[110]:

```
current_best_exp = Experiment(
    ExperimentConfig(
        name="current-best",
        pipeline=final_pipeline_builder(),
    )
)

current_best_exp.run(X_train, y_train, None,␣
 ↪best_feature_by_feature_exp_result);
```

```
[Experiment: current-best]
Cross-validating (5-folds)…
CV score: 0.1372 ± 0.0116
         -0.0007  -0.0057 compared to combine-all-feature-by-feature-engineering
(Negative is better)
Training on full training set…
Experiment complete
```