

used-car-price-preiction-2

September 15, 2024

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
pd.set_option("display.max_columns", 200)
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.model_selection import RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
```

```
[ ]: data = pd.read_csv("/content/extended_data.csv")
data.head()
```

```
[ ]:      model_year      brand      model \
0      2016      Toyota      Land Cruiser Base
1      2014      RAM      ProMaster 2500 Window Van High Roof
2      2002      Ford      Mustang GT
3      2012      BMW      428 Gran Coupe i xDrive
4      2008      Mercedes-Benz      SL-Class SL500 Roadster

      type  miles_per_gallon  premium_version      msrp  collection_car
0      SUV              13.0                1    84900.0              0
1      Van              15.0                0   35000.0              0
2      Coupe             16.0                0   26250.0              0
3      Sedan             27.0                1   45000.0              0
4  Convertible             18.0                1  100000.0              1
```

```
[ ]: data.isnull().sum()
```

```
[ ]: model_year      0
brand              0
model              0
type              0
miles_per_gallon   17
premium_version    0
```

```
msrp          17
collection_car 0
dtype: int64
```

```
[ ]: data.shape
```

```
[ ]: (28143, 8)
```

```
[ ]: data.columns
```

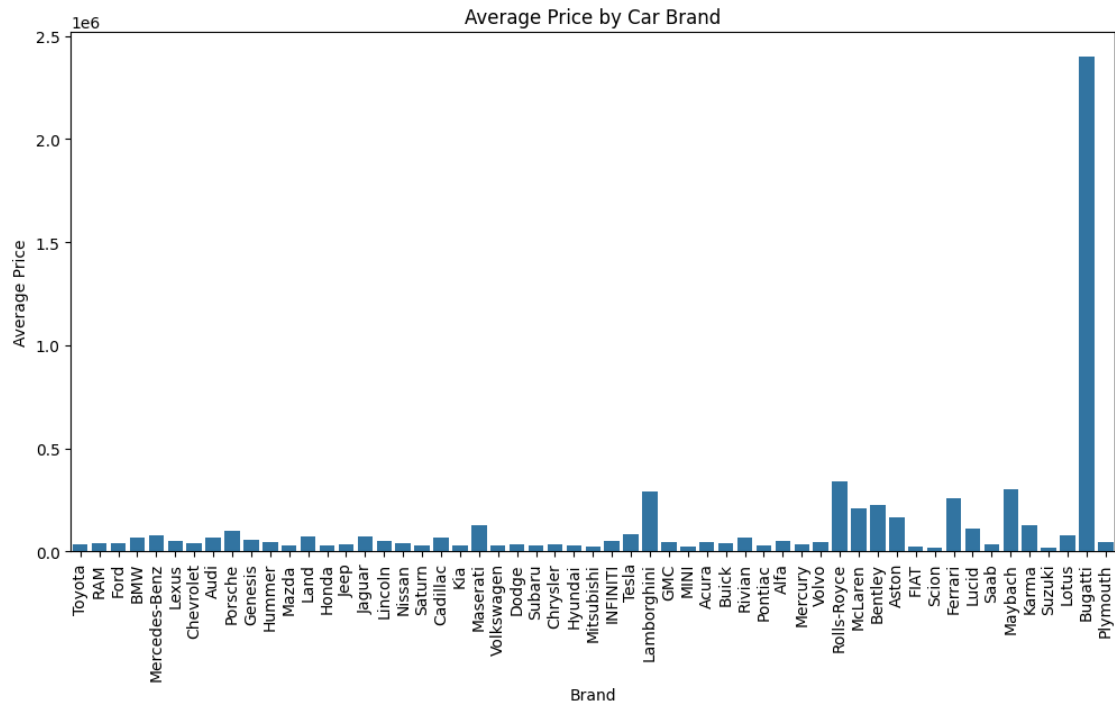
```
[ ]: Index(['model_year', 'brand', 'model', 'type', 'miles_per_gallon',
          'premium_version', 'msrp', 'collection_car'],
          dtype='object')
```

```
[ ]: data.dropna(inplace=True)
data.isnull().sum()
```

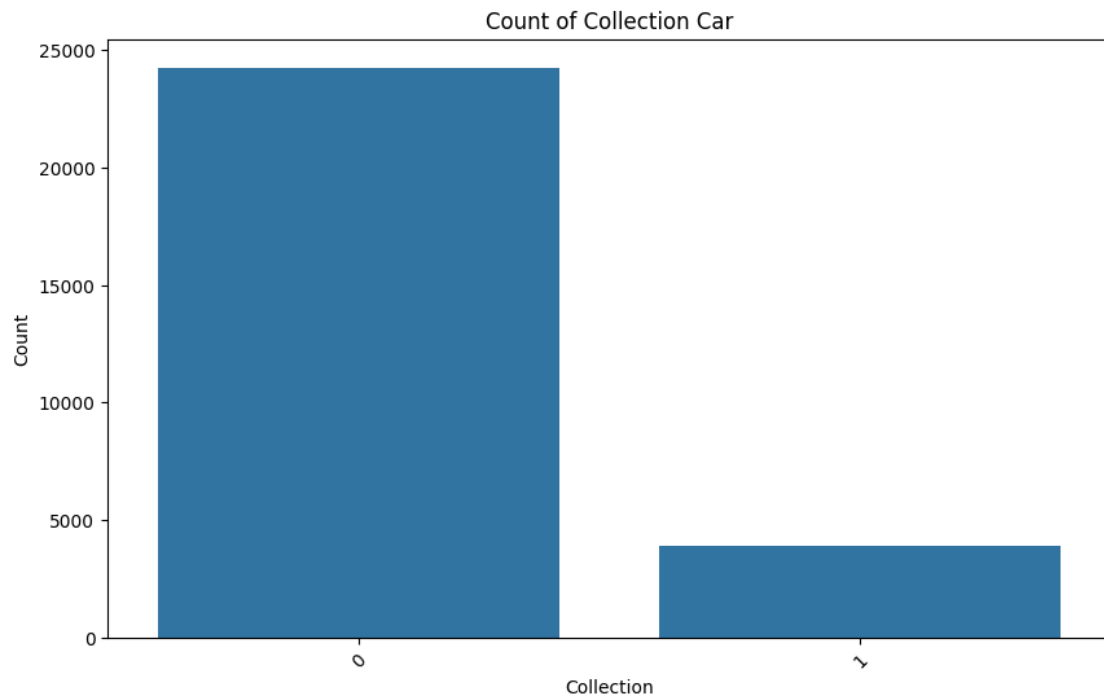
```
[ ]: model_year    0
brand            0
model            0
type             0
miles_per_gallon 0
premium_version  0
msrp             0
collection_car    0
dtype: int64
```

```
[ ]: data = data.rename(columns = {"msrp": "price"})
```

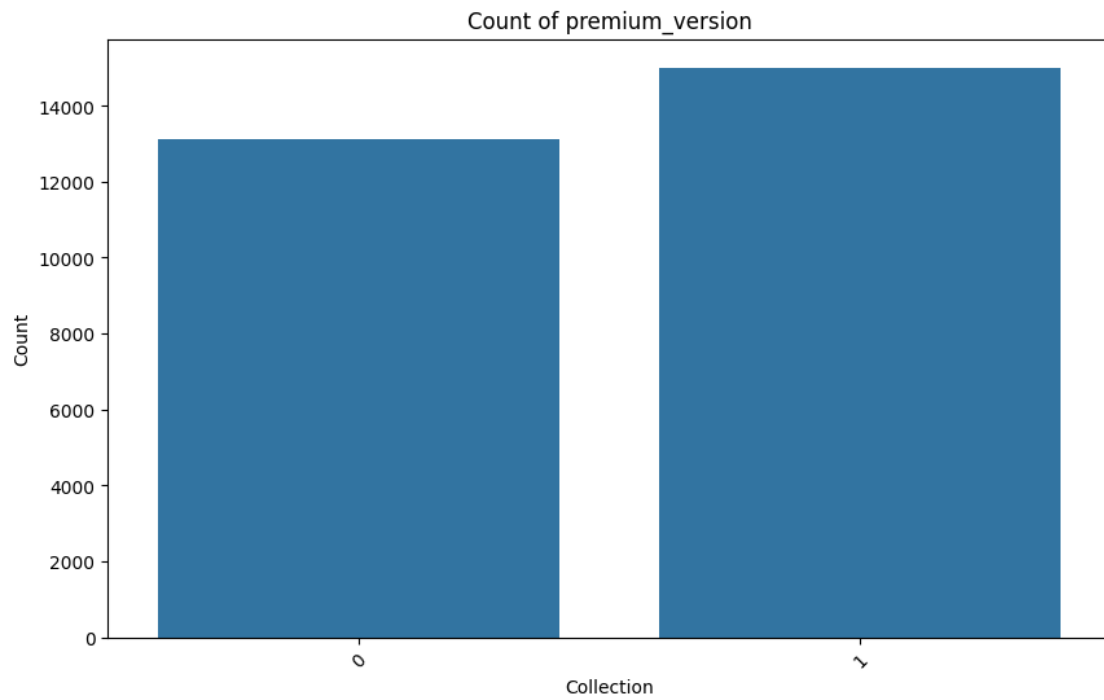
```
[ ]: plt.figure(figsize=(12, 6))
sns.barplot(x='brand', y='price', data=data[:10000], errorbar=None)
plt.title('Average Price by Car Brand')
plt.xlabel('Brand')
plt.ylabel('Average Price')
plt.xticks(rotation=90)
plt.show()
```



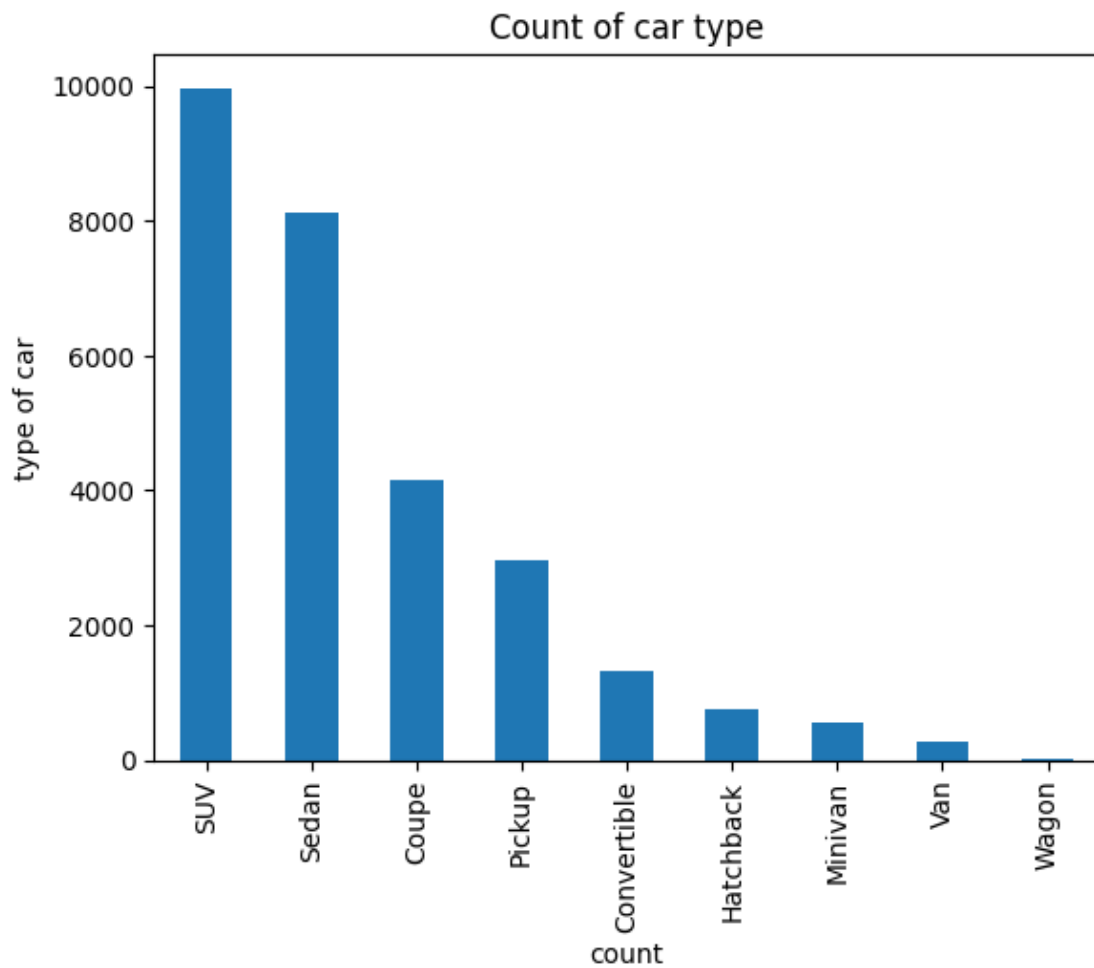
```
[ ]: plt.figure(figsize=(10, 6))
sns.countplot(x='collection_car', data=data)
plt.title('Count of Collection Car')
plt.xlabel('Collection')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



```
[ ]: plt.figure(figsize=(10, 6))
sns.countplot(x='premium_version', data=data)
plt.title('Count of premium_version')
plt.xlabel('Collection')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



```
[ ]: data["type"].value_counts().plot.bar()
plt.title("Count of car type")
plt.xlabel("count")
plt.ylabel("type of car")
plt.show()
```



```
[ ]: data.head()
```

```
[ ]:
  model_year    brand                                model \
0         2016    Toyota                        Land Cruiser Base
1         2014      RAM  ProMaster 2500 Window Van High Roof
2         2002    Ford                                Mustang GT
3         2012    BMW                        428 Gran Coupe i xDrive
4         2008 Mercedes-Benz                SL-Class SL500 Roadster

   type  miles_per_gallon  premium_version    price  collection_car
0    SUV              13.0                1   84900.0              0
1    Van              15.0                0  35000.0              0
2   Coupe              16.0                0  26250.0              0
3   Sedan              27.0                1  45000.0              0
4  Convertible          18.0                1 100000.0              1
```

```
[ ]: data["type"].unique()
```

```
[ ]: array(['SUV', 'Van', 'Coupe', 'Sedan', 'Convertible', 'Pickup', 'Minivan',  
          'Hatchback', 'Wagon'], dtype=object)
```

```
[ ]: data['car_age'] = 2024 - data['model_year']
```

```
[ ]: data["type"].unique()
```

```
[ ]: array(['SUV', 'Van', 'Coupe', 'Sedan', 'Convertible', 'Pickup', 'Minivan',  
          'Hatchback', 'Wagon'], dtype=object)
```

```
[ ]: #removing outliers
```

```
Q1 = data["miles_per_gallon"].quantile(0.25)  
Q3 = data["miles_per_gallon"].quantile(0.75)  
IQR = Q3 - Q1
```

```
upper_limit = Q3 + 1.5 * IQR  
lower_limit = Q1 - 1.5 * IQR
```

```
[ ]: print("UPPER LIMIT :",upper_limit)  
     print("LOWER LIMIT :",lower_limit)  
     print("IQR", IQR)
```

```
UPPER LIMIT : 34.5  
LOWER LIMIT : 6.5  
IQR 7.0
```

```
[ ]: IQR
```

```
[ ]: 7.0
```

```
[ ]: data["miles_per_gallon"].describe()
```

```
[ ]: count      28126.000000  
     mean        21.769242  
     std         13.472177  
     min         -1.000000  
     25%         17.000000  
     50%         20.000000  
     75%         24.000000  
     max         234.000000  
     Name: miles_per_gallon, dtype: float64
```

```
[ ]: data[data["miles_per_gallon"] > upper_limit]
```

```
[ ]:      model_year  brand      model      type \
160      2017      Tesla      Model S 85D      Sedan
170      2022      Tesla      Model S Long Range Plus      Sedan
191      2022      Rivian      R1S Adventure Package      SUV
253      2021      Tesla      Model Y Long Range      SUV
258      2023      Tesla      Model Y Performance      SUV
...      ...      ...      ...      ...
28085     2012      Toyota      Mirai Base      Sedan
28105     2006      Ford      Fusion Hybrid Base      Sedan
28123     2011      Tesla      Leaf SL      Sedan
28136     2010      Lexus      CT 200h Premium      Hatchback
28140     2018      Ford      Model X P100D      SUV

      miles_per_gallon  premium_version      price  collection_car  car_age
160      90.0      1      75000.0      0      7
170     120.0      1      79990.0      0      2
191      74.0      1      74900.0      0      2
253     131.0      1      53990.0      0      3
258     110.0      1      66990.0      0      1
...      ...      ...      ...      ...
28085     62.0      0      57800.0      0     12
28105     36.0      0      24995.0      0     18
28123     99.0      0      35000.0      0     13
28136     43.0      1      29900.0      0     14
28140     94.0      1     199000.0      1      6
```

[1058 rows x 9 columns]

```
[ ]: data[data["miles_per_gallon"] < lower_limit]
```

```
[ ]:      model_year  brand      model      type \
167      2007      Ford      E250 Cargo      Van
635      2019      Ford      Mustang Mach-E Premium      SUV
778      2018      Lincoln      AMG C 43 Base 4MATIC      Sedan
830      2015      Tesla      Model S P100D      Sedan
1271     2020      Rivian      R1S Adventure Package      SUV
...      ...      ...      ...      ...
27976     2009      Kia      Seltos S      SUV
27983     2023      Acura      R1S Adventure Package      SUV
27992     2009      Toyota      350Z Touring      Coupe
28051     2013      Chevrolet      Bolt EV LT      Hatchback
28106     2016      Polestar      2 Launch Edition      Sedan

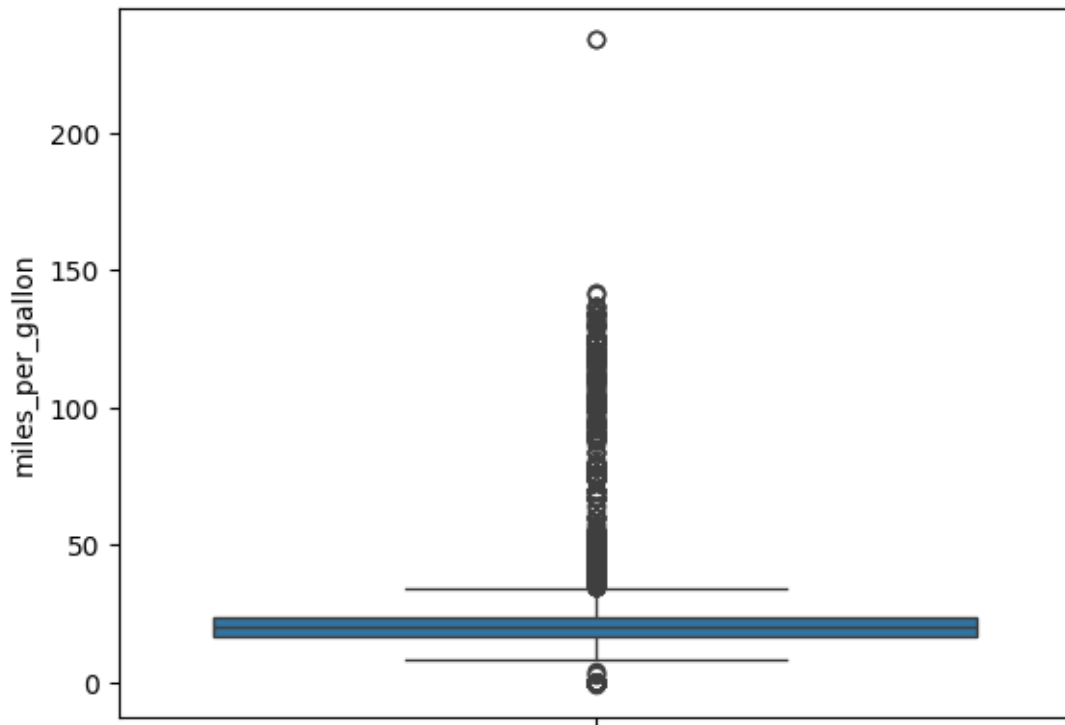
      miles_per_gallon  premium_version      price  collection_car  car_age
167      0.0      0      0.0      0     17
635      0.0      1     60000.0      0      5
778      0.0      0      0.0      0      6
```


830	0.0	1	134500.0	0	9
1271	0.0	1	70000.0	0	4
...
27976	0.0	0	0.0	0	15
27983	0.0	0	0.0	0	1
27992	0.0	0	0.0	0	15
28051	0.0	0	34995.0	0	11
28106	0.0	1	0.0	1	8

[447 rows x 9 columns]

```
[ ]: sns.boxplot(data["miles_per_gallon"])
```

```
[ ]: <Axes: ylabel='miles_per_gallon'>
```



```
[ ]: new_df_cap = data.copy()

new_df_cap['miles_per_gallon'] = np.where(
    new_df_cap['miles_per_gallon'] > upper_limit,
    upper_limit,
    np.where(
        new_df_cap['miles_per_gallon'] < lower_limit,
        lower_limit,
```

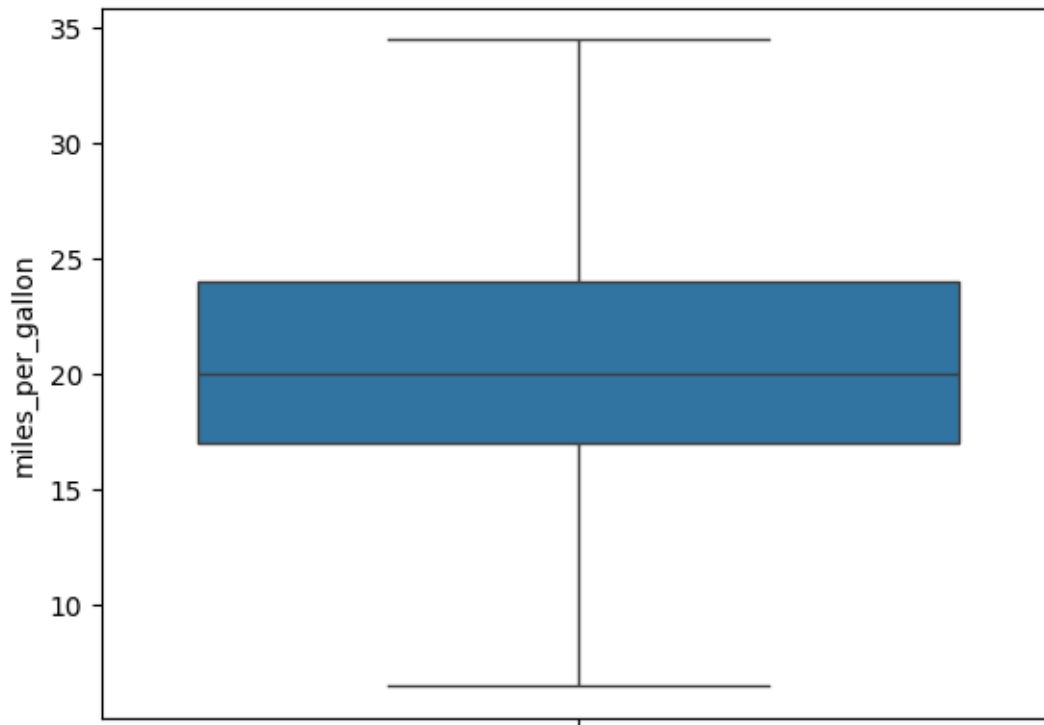
```

        new_df_cap['miles_per_gallon']
    )
)

```

```
[ ]: sns.boxplot(new_df_cap["miles_per_gallon"])
```

```
[ ]: <Axes: ylabel='miles_per_gallon'>
```



```
[ ]: final_data =
    ↪ new_df_cap[["brand", "type", "miles_per_gallon", "premium_version", "collection_car", "car_age",
final_data.head()
```

```
[ ]:
```

	brand	type	miles_per_gallon	premium_version	\
0	Toyota	SUV	13.0	1	
1	RAM	Van	15.0	0	
2	Ford	Coupe	16.0	0	
3	BMW	Sedan	27.0	1	
4	Mercedes-Benz	Convertible	18.0	1	

	collection_car	car_age	price
0	0	8	84900.0
1	0	10	35000.0
2	0	22	26250.0

```

3          0      12   45000.0
4          1      16  100000.0

```

```

[ ]: label_encoder = LabelEncoder()

final_data['brand'] = label_encoder.fit_transform(final_data['brand'])
final_data['type'] = label_encoder.fit_transform(final_data['type'])

```

```

<ipython-input-139-5cbdd1b59029>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

final_data['brand'] = label_encoder.fit_transform(final_data['brand'])
<ipython-input-139-5cbdd1b59029>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

final_data['type'] = label_encoder.fit_transform(final_data['type'])

```

```

[ ]: final_data.head()

```

```

[ ]:
   brand  type  miles_per_gallon  premium_version  collection_car  car_age  \
0     53     5             13.0                1                0        8
1     44     7             15.0                0                0       10
2     14     1             16.0                0                0       22
3      4     6             27.0                1                0       12
4     36     0             18.0                1                1       16

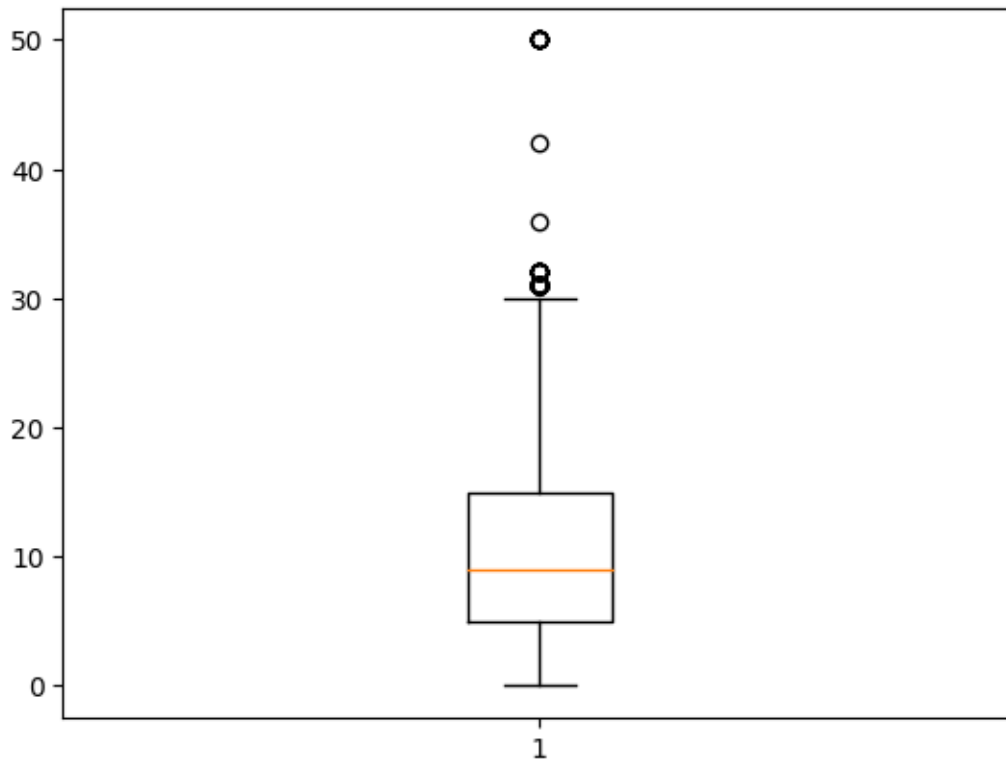
   price
0  84900.0
1  35000.0
2  26250.0
3  45000.0
4 100000.0

```

```

[ ]: plt.boxplot(final_data["car_age"])
plt.show()

```



```
[ ]: Q1 = final_data["car_age"].quantile(0.25)
      Q3 = final_data["car_age"].quantile(0.75)
      IQR = Q3 - Q1

      upper_limit = Q3 + 1.5 * IQR
      lower_limit = Q1 - 1.5 * IQR

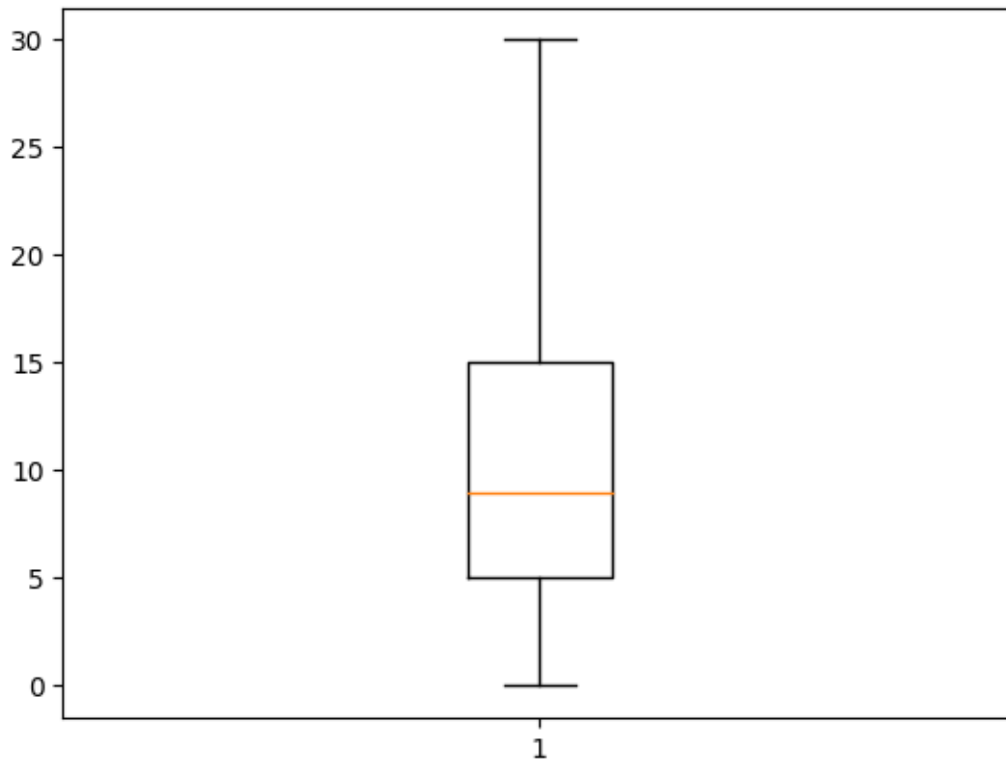
      final_data['car_age'] = np.where(
          final_data['car_age'] > upper_limit,
          upper_limit,
          np.where(
              final_data['car_age'] < lower_limit,
              lower_limit,
              final_data['car_age']
          )
      )
```

<ipython-input-142-a877fec76e8c>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

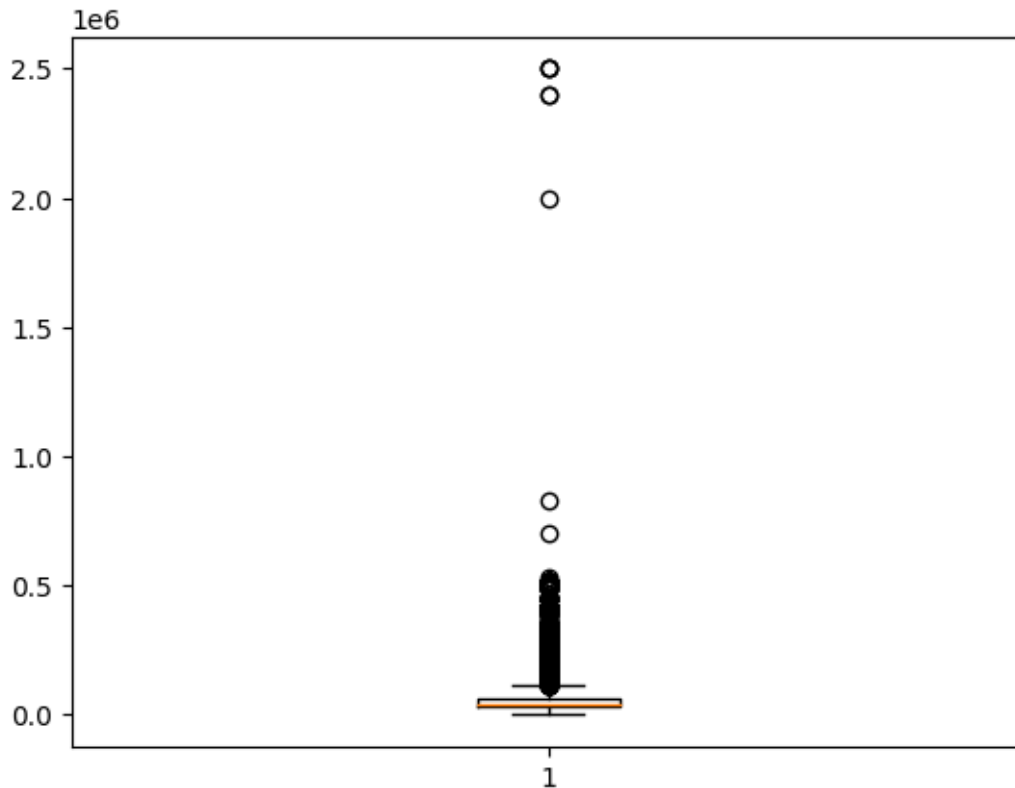
See the caveats in the documentation: <https://pandas.pydata.org/pandas->

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
final_data['car_age'] = np.where(
```

```
[ ]: plt.boxplot(final_data["car_age"])
plt.show()
```



```
[ ]: plt.boxplot(final_data["price"])
plt.show()
```



```
[ ]: X = final_data.iloc[:, :-1]
     y = final_data.iloc[:, -1]
```

```
[ ]: from sklearn.ensemble import ExtraTreesRegressor

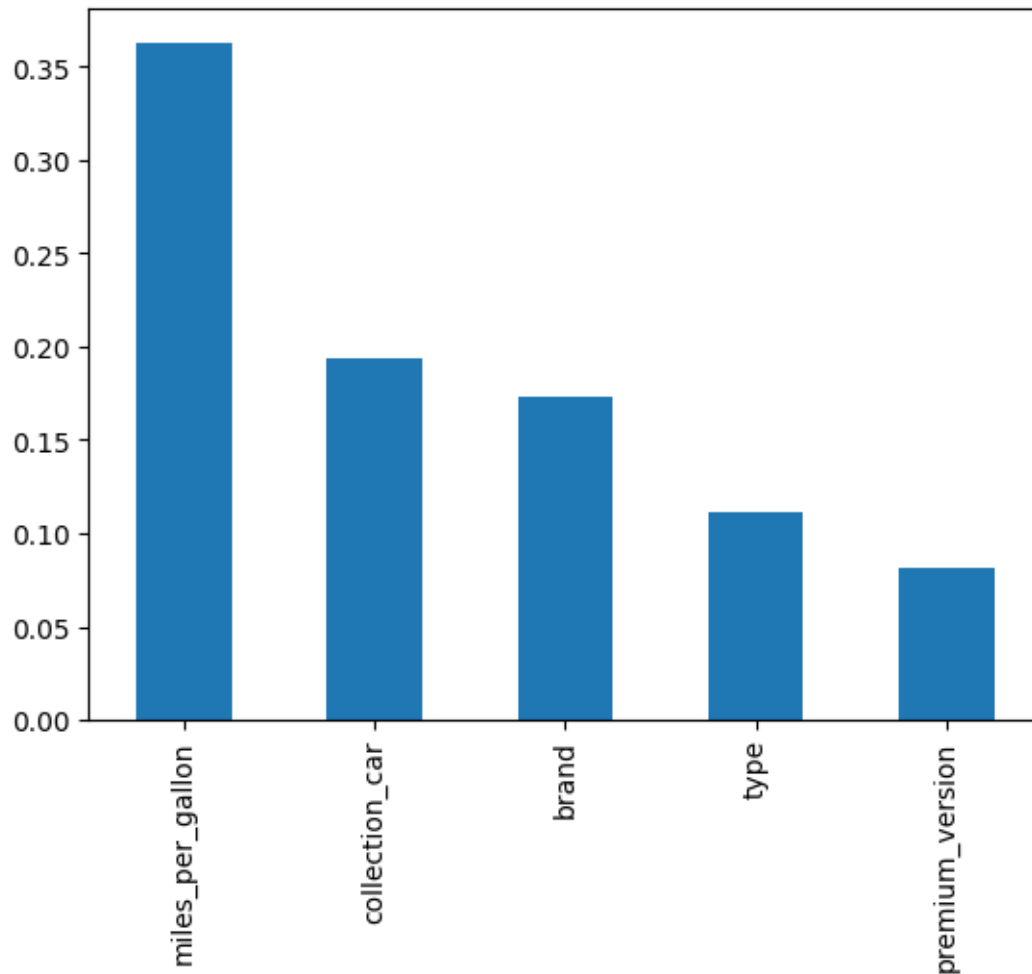
     e_tree_reg = ExtraTreesRegressor()
     e_tree_reg.fit(X, y)
```

```
[ ]: ExtraTreesRegressor()
```

```
[ ]: print(e_tree_reg.feature_importances_)
```

```
[0.17356152 0.11162471 0.36279878 0.08095634 0.19336636 0.07769229]
```

```
[ ]: #Identify important features in our data
     f_imp = pd.Series(e_tree_reg.feature_importances_, index=X.columns)
     f_imp.nlargest(5).plot(kind="bar")
     plt.show()
```



```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,  
↳ random_state=42)
```

```
model = RandomForestRegressor()
```

```
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
```

```
acc = r2_score(y_test, y_pred)
```

```
print(f"Accuracy Score: {acc}")
```

```
0.7853381823327864
```

```
[ ]: def data_preprocessing(data, upper_limit, lower_limit):  
    data.dropna(inplace=True)
```

```

data = data.rename(columns={"msrp": "suggested_price"})

data['car_age'] = 2024 - data['model_year']

new_df_cap = data.copy()

new_df_cap['miles_per_gallon'] = np.where(
    new_df_cap['miles_per_gallon'] > upper_limit,
    upper_limit,
    np.where(
        new_df_cap['miles_per_gallon'] < lower_limit,
        lower_limit,
        new_df_cap['miles_per_gallon']
    )
)

final_data = new_df_cap[["brand", "type", "miles_per_gallon",
↪ "premium_version", "collection_car", "car_age", "suggested_price"]]

label_encoder = LabelEncoder()
final_data['brand'] = label_encoder.fit_transform(final_data['brand'].
↪ values)
final_data['type'] = label_encoder.fit_transform(final_data['type'].values)

return final_data

def model_selection(final_data, threshold=0.3):
    X = final_data.iloc[:, :-1].values
    y = final_data.iloc[:, -1].values

    X_train, X_test, y_train, y_test = train_test_split(X, y,
↪ test_size=threshold, random_state=42)
    sc = StandardScaler()
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)
    return X_train, X_test, y_train, y_test

def model_prediction(X_train, X_test, y_train, y_test):
    rf = RandomForestRegressor()

    n_estimators = [int(x) for x in np.linspace(start=100, stop=1200, num=12)]
    max_features = ['auto', 'sqrt']
    max_depth = [int(x) for x in np.linspace(start=5, stop=30, num=6)]
    min_samples_split = [2, 5, 10, 15, 100]
    min_samples_leaf = [1, 2, 5, 10]

```



```

random_grid = {
    "n_estimators": n_estimators,
    "max_features": max_features,
    "max_depth": max_depth,
    "min_samples_split": min_samples_split,
    "min_samples_leaf": min_samples_leaf
}

rf_random = RandomizedSearchCV(estimator=rf,
    ↪param_distributions=random_grid,
                                scoring="neg_mean_squared_error", n_iter=10,
    ↪cv=5, verbose=2, random_state=42)

rf_random.fit(X_train, y_train)

best_rf = rf_random.best_estimator_

y_pred = best_rf.predict(X_test)

accuracy = r2_score(y_test, y_pred)

return accuracy, y_pred

if __name__ == "__main__":
    data = pd.read_csv("extended_data.csv")

    Q1 = data["miles_per_gallon"].quantile(0.75)
    Q3 = data["miles_per_gallon"].quantile(0.25)

    IQR = Q3-Q1

    upper_limit = Q3 + 1.5 * IQR
    lower_limit = Q1 - 1.5 * IQR

    data = data_preprocessing(data, upper_limit, lower_limit)

    X_train1, X_test1, y_train1, y_test1 = model_selection(data)

    accuracy, y_pred = model_prediction(X_train1, X_test1, y_train1, y_test1)

    print(accuracy)

```

<ipython-input-151-96a751c7f009>:23: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: <https://pandas.pydata.org/pandas->

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
    final_data['brand'] = label_encoder.fit_transform(final_data['brand'].values)
<ipython-input-151-96a751c7f009>:24: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
    final_data['type'] = label_encoder.fit_transform(final_data['type'].values)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5,
min_samples_split=5, n_estimators=900; total time= 6.4s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5,
min_samples_split=5, n_estimators=900; total time= 5.2s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5,
min_samples_split=5, n_estimators=900; total time= 6.3s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5,
min_samples_split=5, n_estimators=900; total time= 5.3s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5,
min_samples_split=5, n_estimators=900; total time= 6.3s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=1100; total time= 9.2s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=1100; total time= 10.2s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=1100; total time= 9.9s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=1100; total time= 9.3s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=1100; total time= 11.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=100, n_estimators=300; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=100, n_estimators=300; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=100, n_estimators=300; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=100, n_estimators=300; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=100, n_estimators=300; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=5, n_estimators=400; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=5, n_estimators=400; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
min_samples_split=5, n_estimators=400; total time= 0.0s
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5,
```



```

min_samples_split=10, n_estimators=700; total time= 2.7s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=700; total time= 2.7s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=10, n_estimators=700; total time= 3.3s
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1,
min_samples_split=15, n_estimators=700; total time= 0.0s
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1,
min_samples_split=15, n_estimators=700; total time= 0.0s
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1,
min_samples_split=15, n_estimators=700; total time= 0.0s
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1,
min_samples_split=15, n_estimators=700; total time= 0.0s
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1,
min_samples_split=15, n_estimators=700; total time= 0.0s

/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py:425: FitFailedWarning:
20 fits failed out of a total of 50.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
-----
20 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1145, in
wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 638, in
_validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/utils/_param_validation.py", line 96, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of RandomForestRegressor must be an int in the range [1, inf), a float
in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto'
instead.

warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:979:

```

```
UserWarning: One or more of the test scores are non-finite: [-2.33552584e+09
-2.12914880e+09          nan          nan
          nan -2.08839383e+09 -2.67947501e+09 -2.00869776e+09
-2.67034990e+09          nan]
warnings.warn(
```

Accuracy: 0.6212086746532638

Thank you