Preparing Notebook

Installing and importing libraries that will be used in this notebook.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Dataset Column Descriptions

Column	Description
Model	The specific model of the car (e.g., Camry, Accord).
Type	The category of the vehicle (e.g., sedan, SUV, hatchback) that indicates its body style.
Year	The model year of the car, representing when the car was manufactured or released.
Mileage	The total distance the car has been driven, usually measured in kilometers or miles.
Transmission	The type of transmission system in the car (e.g., automatic, manual) that affects driving dynamics.
Location	The geographical area where the car is being sold or registered, which can influence its market value.
CC	The engine displacement measured in cubic centimeters (CC), indicating the size of the engine.
Variant	The specific version of the model that may include features, specifications, or design differences.
Price	The market price of the car, usually represented in a specific currency (e.g., USD, MYR).
Origin	The country where the car was manufactured or assembled, which can affect brand perception and pricing.

Load the dataset

```
df = pd.read_csv(r'C:\Users\PC\python\car_data.csv', index_col=0)
df

                                                      Model
Type  \
Title

*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA           N BOX        4D
```

```
MPV
1997 Honda CIVIC 1.6 EFI (A)                          CIVIC      4D
SEDAN
2016 Honda JAZZ 1.5 (A)                                JAZZ  4D
HATCHBACK
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION       JAZZ  4D
HATCHBACK
1997 Honda CIVIC 1.6 EFI (A)                          CIVIC      4D
SEDAN
...                                                      ...
...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!    CIVIC  4D
HATCHBACK
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION            CITY      4D
SEDAN
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER    INSIGHT  4D
HATCHBACK
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD    CIVIC      4D
SEDAN
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE         CITY      4D
SEDAN

                                                    Year      Mileage
\
Title

*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA         2019    35k - 39k

1997 Honda CIVIC 1.6 EFI (A)                        1997  300k - 349k

2016 Honda JAZZ 1.5 (A)                             2016    75k - 79k

2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION    2014  120k - 129k

1997 Honda CIVIC 1.6 EFI (A)                        1997  400k - 449k

...                                                  ...          ...

HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!  2019    25k - 29k

2019 Honda CITY 1.5 E (A) TIP TOP CONDITION         2019    85k - 89k

ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER    2011    85k - 89k

2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD  2016    60k - 64k

2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE      2015    85k - 89k


                                                   Transmission
Location  \
```

```
Title

*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA                Auto
Selangor
1997 Honda CIVIC 1.6 EFI (A)                               Auto
Terengganu
2016 Honda JAZZ 1.5 (A)                                    Auto
Selangor
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION           Auto
Selangor
1997 Honda CIVIC 1.6 EFI (A)                               Auto
Perak
...                                                         ...
...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!         Auto  Kuala
Lumpur
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION                Auto
Melaka
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER           Auto
Selangor
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD         Auto
Selangor
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE             Auto
Selangor

                                                     CC  \
Title
*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA         0.7
1997 Honda CIVIC 1.6 EFI (A)                        1.6
2016 Honda JAZZ 1.5 (A)                             1.5
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION    1.5
1997 Honda CIVIC 1.6 EFI (A)                        1.6
...                                                 ...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!  1.5
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION         1.5
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER    1.3
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD  1.5
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE      1.5


Variant  \
Title

*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA         CUSTOM GL TURBO
HONDA SENSING
1997 Honda CIVIC 1.6 EFI (A)
EFI
2016 Honda JAZZ 1.5 (A)
S
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION
```

```
S
1997 Honda CIVIC 1.6 EFI (A)
EFI
...
...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!        HATCHBACK
HONDA SENSING
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION
E
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER
(HYBRID)
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD
TC-PREMIUM
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE
S+

                                                     Price    Origin
Title
*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA          89700     JAPAN
1997 Honda CIVIC 1.6 EFI (A)                         20800  MALAYSIA
2016 Honda JAZZ 1.5 (A)                              39800  MALAYSIA
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION     36800  MALAYSIA
1997 Honda CIVIC 1.6 EFI (A)                          8500  MALAYSIA
...                                                    ...       ...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!  249888     JAPAN
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION          55000  MALAYSIA
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER     17888     JAPAN
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD   81888  MALAYSIA
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE       33999  MALAYSIA

[2072 rows x 10 columns]
```

Exploratory Data Analysis

```
#Check shape
df.shape
```

```
(2072, 10)
```

```
#Check variables type
df.dtypes
```

```
Model            object
Type             object
Year             object
Mileage          object
Transmission     object
Location         object
CC              float64
Variant          object
```

```
Price              int64
Origin            object
dtype: object
```

Realizing mileage and year is not in numerical type, then i have to make changes to that.

```
# Function to convert mileage ranges and '<' values to numeric
def convert_mileage_range(mileage):
    if isinstance(mileage, str):
        if mileage.startswith('<'):
            return int(mileage.replace('<', '').replace('k',
'').strip()) * 1000 - 1  # Just below 4000
        elif ' - ' in mileage:  # Check if the string contains a range
            low, high = mileage.replace('k', '').split(' - ')
            return (int(low) + int(high)) / 2 * 1000  # Convert to
actual numbers
        else:
            # Handle cases that don't match expected formats (if
needed)
            return None  # or some default value, depending on your
needs
    return mileage

# Apply the conversion
df['Mileage'] = df['Mileage'].apply(convert_mileage_range)

# Convert the column to numeric
df['Mileage'] = pd.to_numeric(df['Mileage'])

print(df['Mileage'])

Title
*2019 Honda N BOX 660 CUSTOM GL TURBO HONDA             37000.0
1997 Honda CIVIC 1.6 EFI (A)                           324500.0
2016 Honda JAZZ 1.5 (A)                                 77000.0
2014 Honda JAZZ 1.5 ONE OWNER CAR KING CONDITION       124500.0
1997 Honda CIVIC 1.6 EFI (A)                           424500.0
                                                          ...
HONDA CIVIC TYPE R GT 316HP mileage 27000km ONLY!!      27000.0
2019 Honda CITY 1.5 E (A) TIP TOP CONDITION             87000.0
ORI2011 Honda INSIGHT 1.3 HYBRID MUGEN ONE OWNER        87000.0
2017 Honda CIVIC 1.5 TC-PREMIUM(A)F/SERVICE RECORD      62000.0
2015 Honda CITY 1.5 S+ (A) ANDROID LOW MILEAGE          87000.0
Name: Mileage, Length: 2072, dtype: float64

# Change year from object to int
def clean_year(year):
    if isinstance(year, str):
        if 'or older' in year:
            # Extract the numeric part
```

```
            return int(year.split()[0])  # Return just the year part
        else:
            try:
                return int(year)  # Convert to int if it's a valid
year
            except ValueError:
                return None  # Return None for invalid entries
    return year  # Return as is if not a string

# Apply the cleaning function
df['Year'] = df['Year'].apply(clean_year)

# Convert to integer type
df['Year'] = df['Year'].astype(int)

#Check dataset description
df.describe()
```

	Year	Mileage	CC	Price
count	2072.000000	2071.000000	2072.000000	2072.000000
mean	2016.665541	81533.269918	1.674373	70240.799710
std	4.538755	44718.469299	0.276008	49362.441397
min	1995.000000	3999.000000	0.700000	2500.000000
25%	2015.000000	57000.000000	1.500000	41700.000000
50%	2017.000000	82000.000000	1.500000	58800.000000
75%	2019.000000	104500.000000	1.800000	83999.000000
max	2024.000000	424500.000000	3.000000	341700.000000

Correlation Analysis

```
# Select only the numeric columns from the DataFrame
df_numeric = df.select_dtypes(include=['float64', 'int64'])

# Calculate the correlation matrix
corr = df_numeric.corr()

# Display the correlation matrix
print(corr)
```

```
             Year   Mileage        CC     Price
Year     1.000000 -0.725908 -0.256806  0.597478
Mileage -0.725908  1.000000  0.186329 -0.575426
CC      -0.256806  0.186329  1.000000  0.080316
Price    0.597478 -0.575426  0.080316  1.000000
```

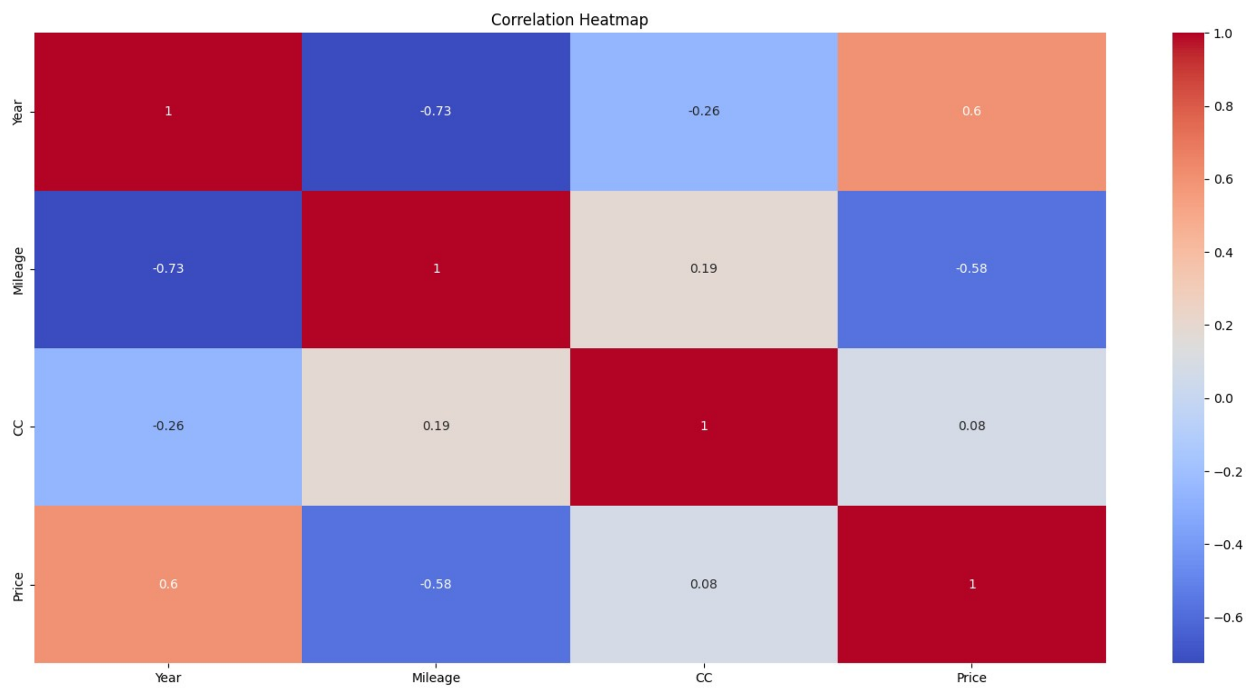
Correlation Analysis Summary

The correlation matrix provides insights into the relationships between the variables: Year, Mileage and Price.

- **Year vs. Mileage (-0.726)**
  - **Negative correlation**: As the **Year** of the car increases , the **Mileage** tends to be lower. Newer cars typically have less mileage.
- **Year vs. Price (0.597)**
  - **Positive correlation**: Newer cars (higher **Year**) tend to have a higher **Price**. This is logical, as newer cars are generally more expensive.
- **Mileage vs. Price (-0.575)**
  - **Negative correlation**: As **Mileage** increases, the **Price** tends to decrease. Cars with higher mileage are typically cheaper due to wear and tear.

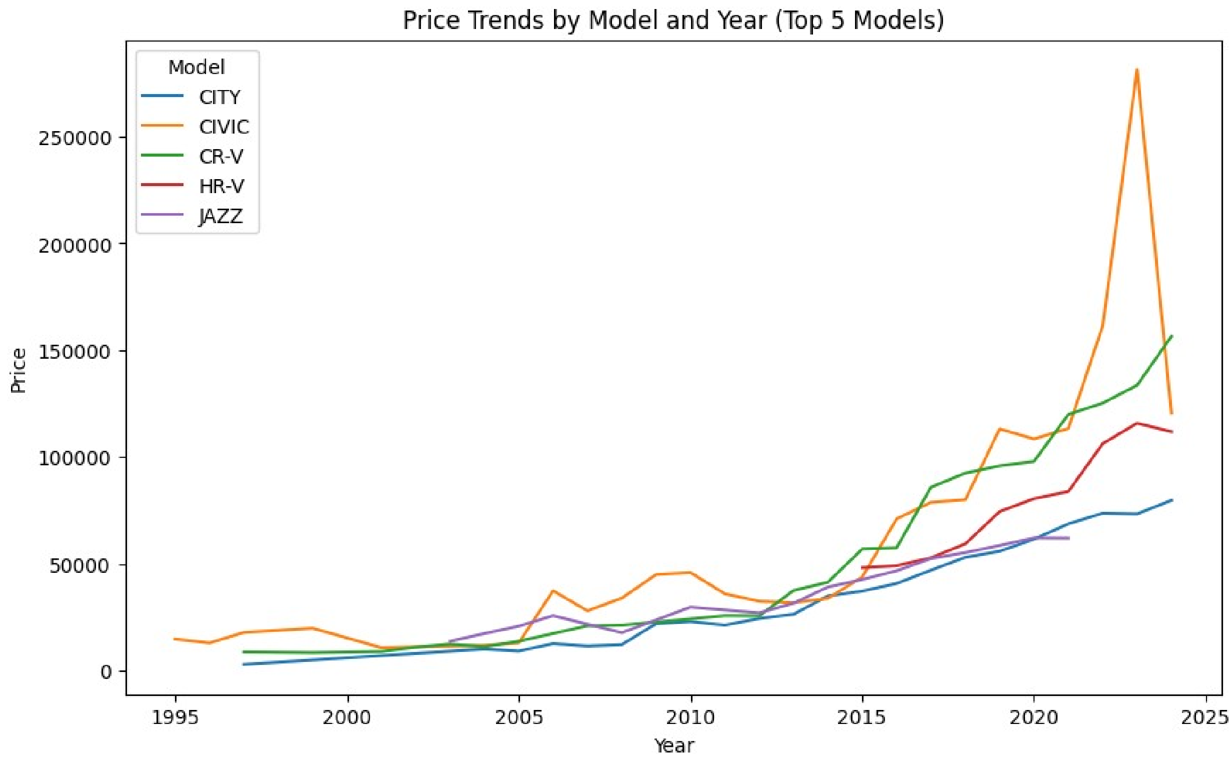
Heatmap correlation between variables.

```
matrix = df_numeric.corr()
plt.figure(figsize=(19,9))
sns.heatmap(matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



Price Trends by Model and Year (Top 5 Models)

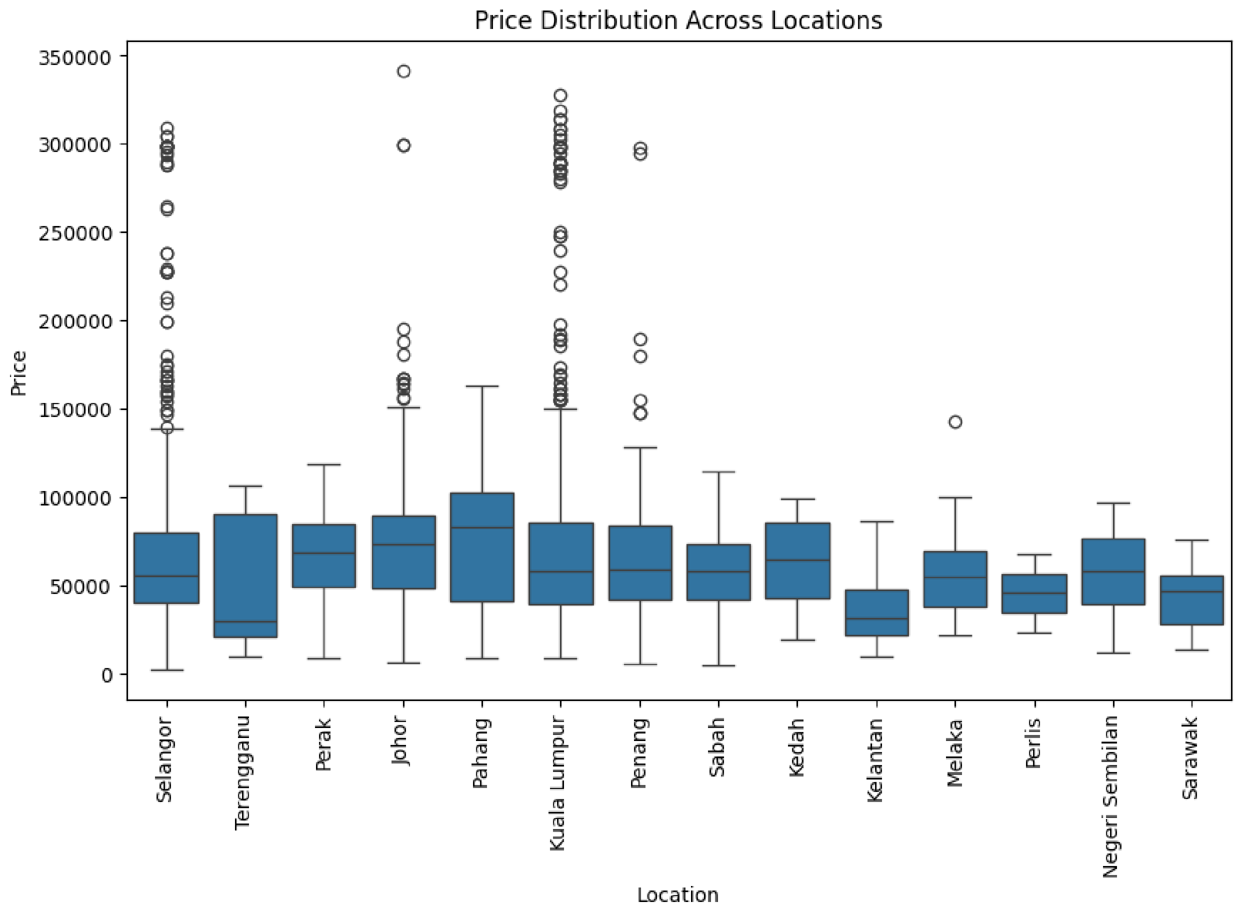
```
top_5_models = df['Model'].value_counts().nlargest(5).index
filtered_price_trend =
price_trend[price_trend['Model'].isin(top_5_models)]
plt.figure(figsize=(10,6))
sns.lineplot(data=filtered_price_trend, x='Year', y='Price',
hue='Model')
plt.title('Price Trends by Model and Year (Top 5 Models)')
plt.show()
```



This plot shows an overall increasing trend in prices across all Honda models. Notably, there is a significant spike in the price of the **Civic** line, which can be attributed to the recent launch of the **Honda Civic Type R** model in 2023.

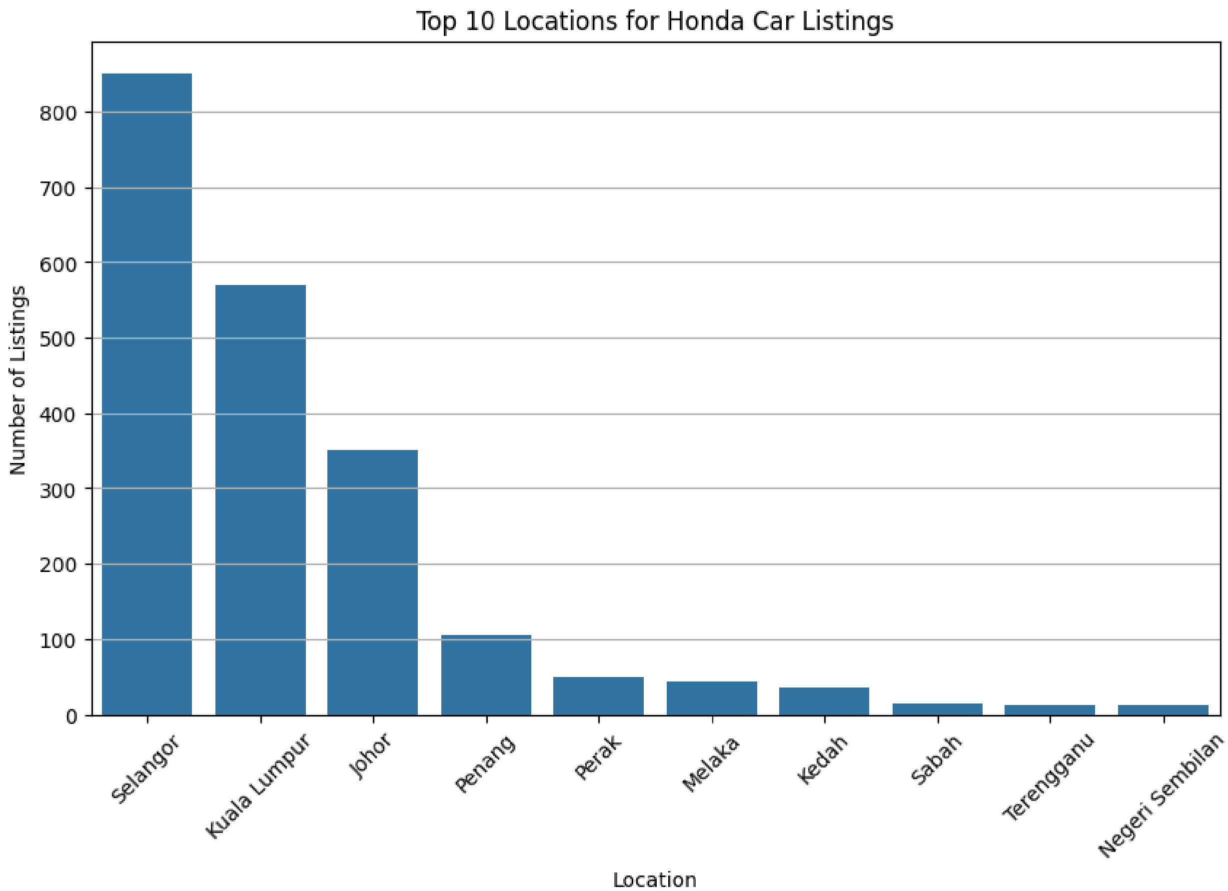
Price Distribution Across Location Boxplot

```
plt.figure(figsize=(10,6))
sns.boxplot(x='Location', y='Price', data=df)
plt.title('Price Distribution Across Locations')
plt.xticks(rotation=90)
plt.show()
```



Top 10 Locations for Honda Car Listing Bar PLot

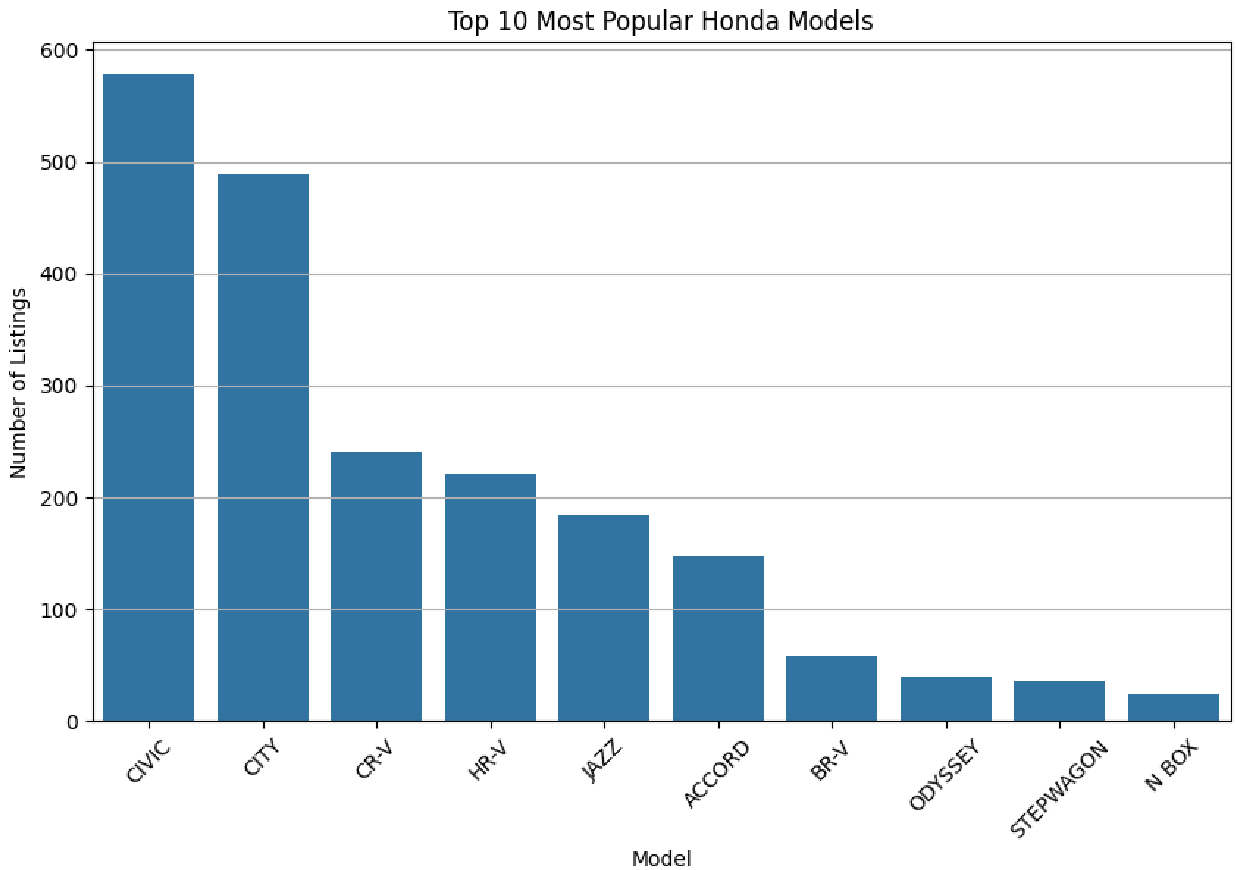
```
popular_locations = df['Location'].value_counts().head(10)
plt.figure(figsize=(10, 6))
sns.barplot(x=popular_locations.index, y=popular_locations.values)
plt.title('Top 10 Locations for Honda Car Listings')
plt.xticks(rotation=45)
plt.ylabel('Number of Listings')
plt.xlabel('Location')
plt.grid(axis='y')  # Optional: Adds a grid for better readability
plt.show()
```



The bar plot illustrates the top 10 locations where Honda cars are listed for sale, with **Selangor** showing the highest demand in the Honda market, followed closely by **Kuala Lumpur**.

Top 10 Most Popular Honda Models

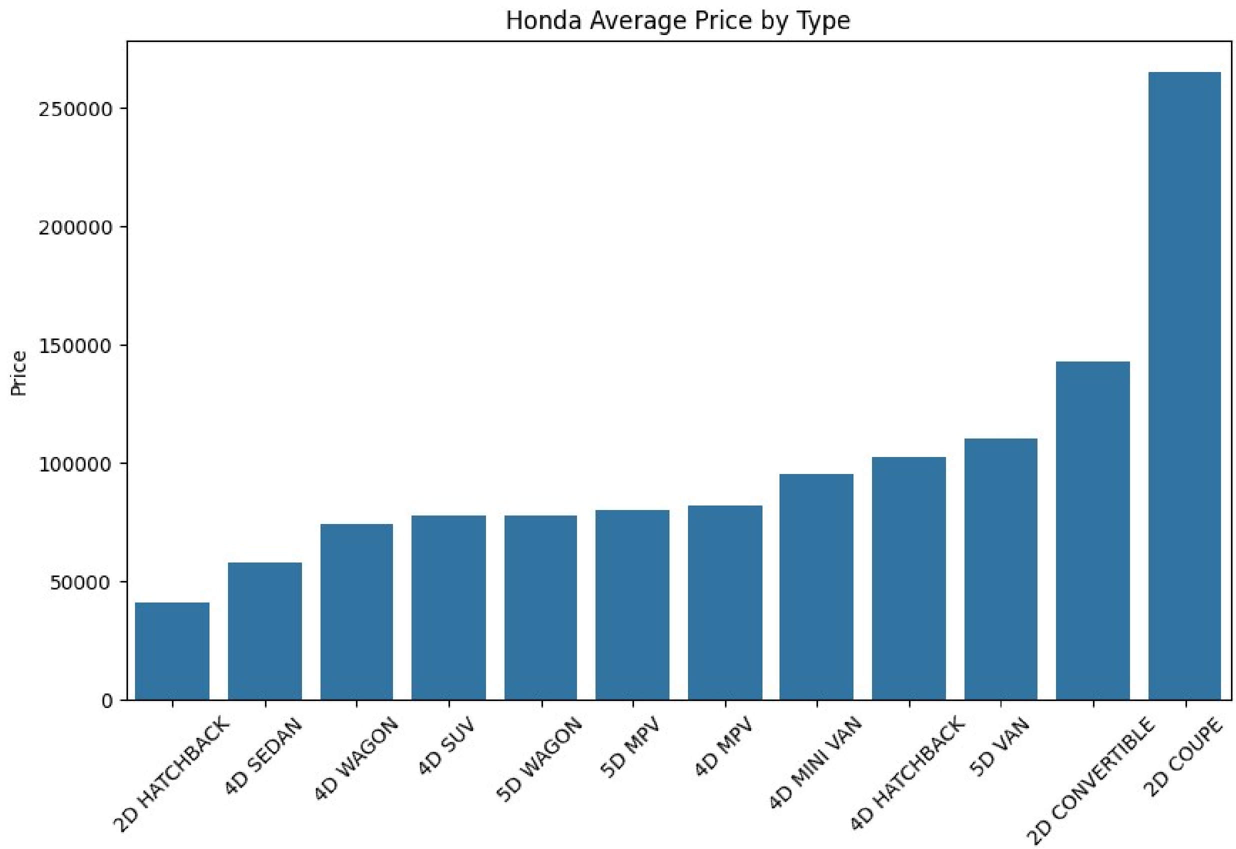
```
popular_models = df['Model'].value_counts().head(10)
plt.figure(figsize=(10, 6))
sns.barplot(x=popular_models.index, y=popular_models.values)
plt.title('Top 10 Most Popular Honda Models')
plt.xticks(rotation=45)
plt.ylabel('Number of Listings')
plt.xlabel('Model')
plt.grid(axis='y')  # Optional: Adds a grid for better readability
plt.show()
```



Honda Average Price by Type

```
year_price = df.groupby('Type')['Price'].mean().sort_values()

plt.figure(figsize=(10,6))
plt.title("Honda Average Price by Type")
sns.barplot(x=year_price.index, y=year_price.values)
plt.ylabel('Price')
plt.xlabel('Type')
plt.xticks(rotation=45)
plt.show()
```

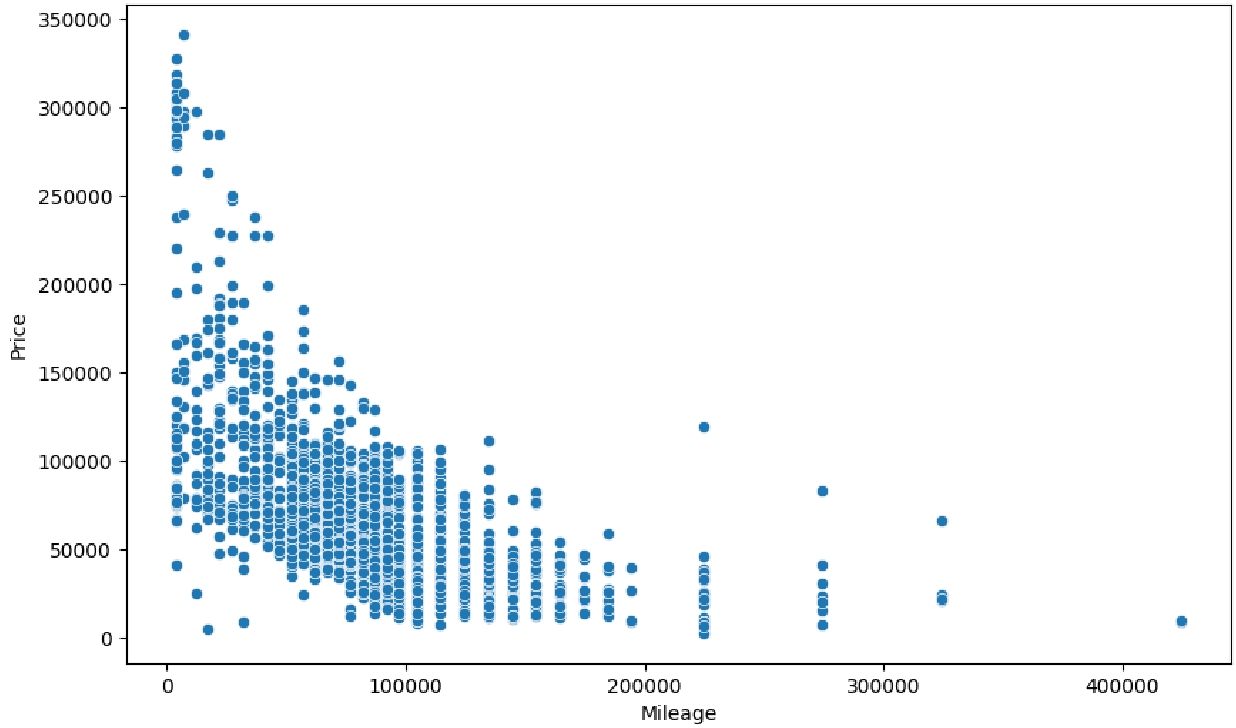


Overall, the data suggests that consumer preferences for Honda cars vary by type, with 2 Doors Coupe generally commanding higher average prices, while hatchbacks remain more affordable.

Scatter Plot Price VS Mileage

```
df_numeric = df_numeric.reset_index(drop=True)
plt.figure(figsize=(10,6))
sns.scatterplot(x=df_numeric['Mileage'], y=df_numeric['Price'])
```

```
<Axes: xlabel='Mileage', ylabel='Price'>
```



Most of the data points cluster at lower mileage levels with higher prices, suggesting that newer, low-mileage Honda cars are priced significantly higher than those with extensive use. A few outliers are visible, where certain cars with higher mileage still maintain relatively high prices. These could represent well-maintained vehicles or popular models that retain value better.

Overall, the analysis highlights the inverse relationship between price and mileage for Honda cars, with lower mileage typically commanding higher prices.

Machine Learning Algorithm - Random Forest Regressor

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Convert categorical variables to numeric
df['Model'] = df['Model'].astype('category').cat.codes
df['Location'] = df['Location'].astype('category').cat.codes

# Drop unwanted column
df = df.drop(['Type', 'Transmission','Variant','Origin'], axis=1)

# Features and target
X = df[['Year', 'Mileage', 'Model', 'Location']]  # Example features
y = df['Price']  # Target variable (car price)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
```

```
test_size=0.2, random_state=42)

# Create random forest regressor model
model = RandomForestRegressor(n_estimators=100,random_state=42)
model.fit(X_train,y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model using Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)  # Root Mean Squared Error (RMSE)
print(f'Root Mean Squared Error: {rmse}')
```

```
Root Mean Squared Error: 11140.222771935132
```

- **Root Mean Squared Error (RMSE)**:
  The RMSE of the model is **11,140.22**, which means that, on average, the model's predictions deviate from the actual car prices by approximately 11,140 units.
- **Percentage Error**:
  Given that the mean car price in the dataset is **70,000**, the percentage error can be calculated as:

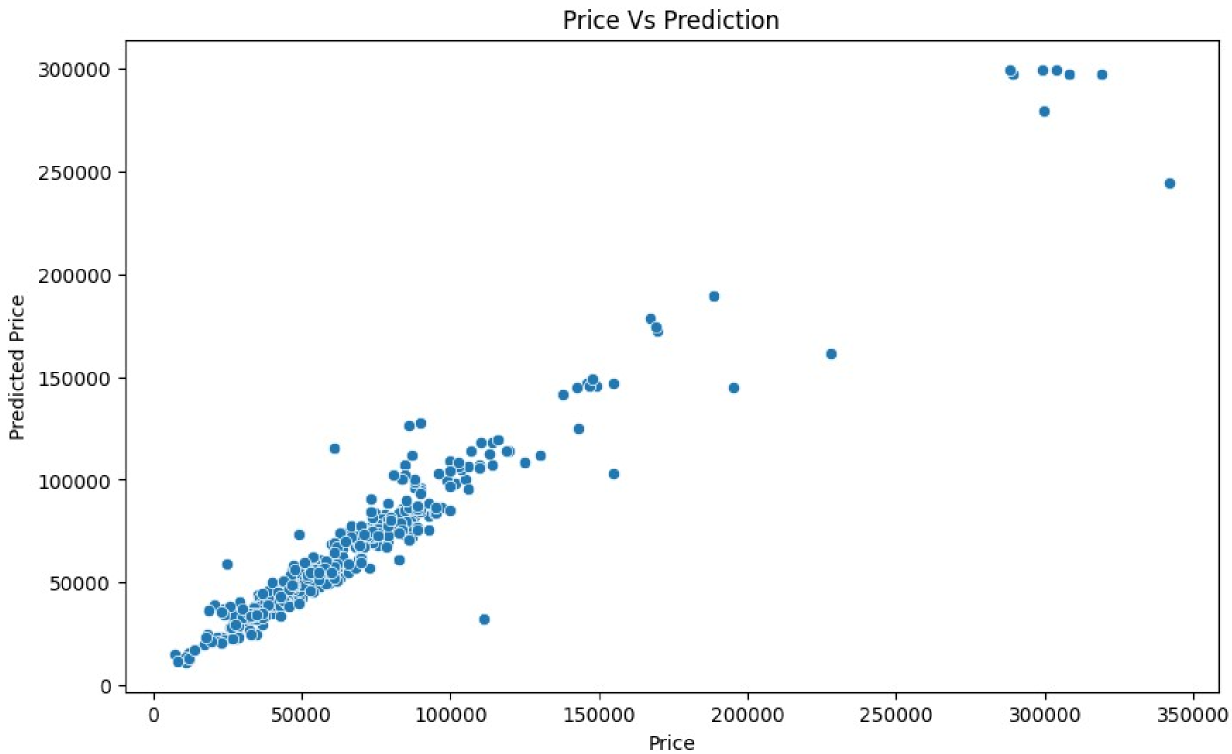
  Percentage Error = (RMSE / Mean Price) * 100 = (11,140.22 / 70,000) * 100 ≈ 15.92%

  This means that the model's average prediction error is **15.92%** of the mean price.

While this is a decent result, futher improvement could be made by adding more data into dataset.

```
plt.figure(figsize=(10,6))
sns.scatterplot(x=y_test, y=y_pred)
plt.title('Price Vs Prediction')
plt.xlabel('Price')
plt.ylabel('Predicted Price')
```

```
Text(0, 0.5, 'Predicted Price')
```




```
plt.figure(figsize=(10, 6))
sns.regplot(x=y_test, y=y_pred, scatter_kws={'alpha':0.5},
line_kws={'color': 'red'})
plt.title('Price Vs Prediction')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.grid(True)
plt.show()
```

The scatterplot of prices versus predictions shows a mostly straight line, with a small amount of spread. As they are close to diagonal line (where actual = predicted), it indicates better model's performance.