Data Mining Process

Group 12
CS131 | AM09

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Google Colab Link:
https://colab.research.google.com/drive/1a0J5APMnk_F3c8o7RSpowhZCM1pJG0xI?usp=sharing

Part 1: Scraping Data

MiningProcess_Group12_Final.ipynb

Vehicle Ranking Scraper for Carbuzz.com

This site contains data about vehicles along with its ratings in certain aspects like design, reliablity, safety, which can be useful when analyzed. This can then help buyers choose their desired automobile, and manufacturers to see potential improvements to their models, enhancing consumer experience.

The group chose this site because this site offers detailed and up-to-date information on a wide range of vehicles, including specifications, reviews, and pricing, making it a valuable source for automotive data. This can then be used to provide insights into market trends, pricing dynamics, and consumer preferences, aiding in market analysis and decision-making for car manufacturers and dealers.

Colab Link: https://colab.research.google.com/drive/1a0J5APMnk_F3c8o7RSpowhZCM1pJG0xl?usp=sharing

```
[10] from bs4 import BeautifulSoup
     import requests
     import pandas as pd
     import os
     import re
     import numpy as np
```

```
[11] #type in URL, so code can be reused among different subsites.
     #Example: https://carbuzz.com/cars/best-mpg-suvs
     url = input("Enter CarbuzzRanking link: ")

     #request code from the server using the link given
     data = requests.get(url)

     #feed the request into the sooop
     soup = BeautifulSoup(data.text, 'html.parser')

     #select container for the tables
     cars = soup.find_all('div', class_='bg-block bg-car-preview-block bg-group-car-preview js-bg-block')
     #cars should be an array of the container of each cars



     #initialize lists
     car_brand = []
     car_model = []
     car_price = []
     car_mpgcity = []
```

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MiningProcess_Group12_Final.ipynb

```
[11] #initialize lists
     car_brand = []
     car_model = []
     car_price = []
     car_mpgcity = []
     car_mpghiway = []
     car_hp = []
     car_scorebuzz = []
     car_scoredesign = []
     car_scoreperformance = []
     car_scorempg = []
     car_scoreinterior = []
     car_scoreinfotainment = []
     car_scorereliability = []
     car_scoresafety = []
     car_scorevalue = []
     #get the type of car from soup
     car_type = soup.find('li', class_='breadcrumb-item active')
     car_type = car_type.text

     for car in cars: #in every car//

         #find model
         model = car.find('a', class_='bg-group-car-preview__name')

         #find container for each values, because class_='sub-model-preview-field__val' is reused
         pricecontainer = car.find('div', class_='sub-model-preview-field sub-model-preview-field_price')
         price = pricecontainer.find('div', class_='sub-model-preview-field__val')

         #repeat///
         mpgcontainer = car.find('div', class_='sub-model-preview-field sub-model-preview-field_mpg')
         mpg = mpgcontainer.find('div', class_='sub-model-preview-field__val')

         hpcontainer = car.find('div', class_='sub-model-preview-field sub-model-preview-field_horsepower')
         hp = hpcontainer.find('div', class_='sub-model-preview-field__val')

         buzzscore = car.find('span', class_='buzzscore-radial-progress__value absolute-middle')

         designratingcontainer = car.find('div', {'data-score-field-key': 'ExteriorDesign'})
         design = designratingcontainer.find('div', class_="bg-group-car-preview-score-field__value")

         performancecontainer = car.find('div', {'data-score-field-key': 'Performance'})
         performance = performancecontainer.find('div', class_="bg-group-car-preview-score-field__value")
```

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MiningProcess_Group12_Final.ipynb

File Edit View Insert Runtime Tools Help All changes saved

```python
designratingcontainer = car.find('div', {'data-score-field-key': 'ExteriorDesign'})
design = designratingcontainer.find('div', class_="bg-group-car-preview-score-field__value")

performancecontainer = car.find('div', {'data-score-field-key': 'Performance'})
performance = performancecontainer.find('div', class_="bg-group-car-preview-score-field__value")

economycontainer = car.find('div', {'data-score-field-key': 'FuelEconomy'})
economy = economycontainer.find('div', class_="bg-group-car-preview-score-field__value")

interiorcontainer = car.find('div', {'data-score-field-key': 'Interior'})
interior = interiorcontainer.find('div', class_="bg-group-car-preview-score-field__value")

infotainmentcontainer = car.find('div', {'data-score-field-key': 'Infotainment'})
infotainment = infotainmentcontainer.find('div', class_="bg-group-car-preview-score-field__value")

reliabilitycontainer = car.find('div', {'data-score-field-key': 'Reliability'})
reliability = reliabilitycontainer.find('div', class_="bg-group-car-preview-score-field__value")

safetycontainer = car.find('div', {'data-score-field-key': 'Safety'})
safety = safetycontainer.find('div', class_="bg-group-car-preview-score-field__value")

valuecontainer = car.find('div', {'data-score-field-key': 'Value'})
value = valuecontainer.find('div', class_="bg-group-car-preview-score-field__value")


#add separator for brand and model from car_model
brand = model.text.split(' ', 1)

#separate two values in mpg, set default as 0
mpgextracted = re.findall(r'\d+', mpg.text)
if not mpgextracted:
    mpgextracted = [np.nan, np.nan]

#Get the starting price, and remove $ and ,
pricemin = price.text.split(' ', 1)
pricemin_cleansed = pricemin[0].replace("$", "").replace(",", "")
if pricemin_cleansed == 'TBC':
    pricemin_cleansed = np.nan

hp_cleansed = hp.text.replace(" hp", "" ).replace(",", "")
if hp_cleansed == 'TBC':
    hp_cleansed = np.nan

#feed the acquired values into lists as text(.text)
car_brand.append(brand[0])
```

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MiningProcess_Group12_Final.ipynb

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```python
    if hp_cleansed == 'TBC':
        hp_cleansed = np.nan

    #feed the acquired values into lists as text(.text)
    car_brand.append(brand[0])
    car_model.append(model.text)
    car_price.append(pricemin_cleansed)
    car_mpgcity.append(mpgextracted[0])
    car_mpghiway.append(mpgextracted[1])
    car_hp.append(hp_cleansed)
    car_scorebuzz.append(buzzscore.text)
    car_scoredesign.append(design.text)
    car_scoreperformance.append(performance.text)
    car_scorempg.append(economy.text)
    car_scoreinterior.append(interior.text)
    car_scoreinfotainment.append(infotainment.text)
    car_scorereliability.append(reliability.text)
    car_scoresafety.append(safety.text)
    car_scorevalue.append(value.text)


#create dataframe
df = pd.DataFrame({'Brand': car_brand, 'Model': car_model, 'Price$': car_price, 'CityMPG': car_mpgcity,
                   'HiWayMPG': car_mpghiway, 'HorsePower': car_hp, 'BuzzScore': car_scorebuzz,
                   'Design': car_scoredesign, 'Performance': car_scoreperformance,
                   'Mileage': car_scorempg, 'Interior': car_scoreinterior,
                   'Infotainment': car_scoreinfotainment, 'Reliability': car_scorereliability,
                   'Safety': car_scoresafety, 'Value': car_scorevalue,
                   'Type' : car_type})


#Cleaning to replace all N/A with NaN.
df.replace('N/A', np.nan, inplace=True)


#save the file as car_type
filename = car_type + '.csv'

#save to subfolder CSVS
file_path = os.path.join('CSVS', filename)

df.to_csv(file_path)
```

```
Enter CarbuzzRanking link: https://carbuzz.com/cars/best-mpg-suvs
```

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MiningProcess_Group12_Final.ipynb

This part is for compiling all the tables(csv) saved

You can feed it as much csv files as you like.

```
[12] folder_path = 'CSVS'
     csv_files = [f for f in os.listdir(folder_path) if f.endswith('.csv')]
```

```
[13] combined_data = pd.DataFrame()

     for file in csv_files:
         file_path = os.path.join(folder_path, file)

         try:
             data = pd.read_csv(file_path)
             combined_data = pd.concat([combined_data, data], ignore_index=True)
         except Exception as e:
             print(f"Error reading file {file}: {e}")
```

```
[14] combined_data.to_csv('combined_data.csv', index=False)
```

```
[15] combined_data.shape

     (793, 17)
```

Removing the Duplicates...

Using Models as reference, we get the redundant data and remove it from the dataframe

```
[ ] #run if u already have the compiled csv

    #combined_data = pd.read_csv('clean_data.csv')
```

```
[16] duplicates = combined_data[combined_data.duplicated(subset=['Model'], keep=False)]
```


MiningProcess_Group12_Final.ipynb

Removing the Duplicates...

Using Models as reference, we get the redundant data and remove it from the dataframe

```
[ ] #run if u already have the compiled csv

    #combined_data = pd.read_csv('clean_data.csv')
```

```
[16] duplicates = combined_data[combined_data.duplicated(subset=['Model'], keep=False)]
```


```
[17] duplicates
```

	Unnamed: 0	Brand	Model	Price$	CityMPG	HiWayMPG	HorsePower	BuzzScore	Design	Performance	Mileage	Interior	Infotainment	Reliability	Safety	Value	Type
0	0	Porsche	Porsche Taycan	90900.0	78.0	81.0	429.0	9.4	10.0	10.0	9.0	9.0	9.0	10.0	10.0	8.0	Sport Sedans
1	1	Porsche	Porsche Taycan Turbo	153300.0	81.0	80.0	616.0	9.4	10.0	10.0	9.0	10.0	9.0	10.0	10.0	7.0	Sport Sedans
2	2	Honda	Honda Civic Si Sedan	28800.0	27.0	37.0	200.0	9.3	9.0	9.0	8.0	10.0	9.0	9.0	10.0	10.0	Sport Sedans
3	3	Mercedes-AMG	Mercedes-AMG CLA 45	57800.0	20.0	28.0	382.0	9.1	10.0	10.0	8.0	10.0	10.0	7.0	10.0	8.0	Sport Sedans
4	4	Audi	Audi e-tron GT	104900.0	81.0	83.0	469.0	9.1	9.0	10.0	8.0	9.0	9.0	9.0	10.0	9.0	Sport Sedans
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
788	45	Chevrolet	Chevrolet Tahoe	52600.0	15.0	20.0	355.0	8.6	8.0	8.0	7.0	9.0	10.0	10.0	9.0	8.0	SUVs With Best MPG
789	46	BMW	BMW X5	65200.0	23.0	27.0	375.0	8.6	8.0	9.0	7.0	9.0	10.0	8.0	10.0	8.0	SUVs With Best MPG
790	47	BMW	BMW X6	73900.0	23.0	26.0	375.0	8.6	8.0	9.0	8.0	9.0	10.0	8.0	10.0	7.0	SUVs With Best MPG
791	48	BMW	BMW X5 M	108900.0	13.0	18.0	600.0	8.6	9.0	10.0	6.0	9.0	10.0	8.0	9.0	8.0	SUVs With Best MPG
792	49	Toyota	Toyota Grand Highlander Hybrid	44670.0	36.0	32.0	245.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	SUVs With Best MPG

793 rows × 17 columns

```
[18] clean_data = combined_data.drop_duplicates(subset = ['Model'])
```

```
[19] print('old: ', combined_data.shape, '\nnew: ', clean_data.shape)

     old:  (793, 17)
     new:  (304, 17)
```

MiningProcess_Group12_Final.ipynb

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[19]
```
print('old: ', combined_data.shape, '\nnew: ', clean_data.shape)
```

```
old:  (793, 17)
new:  (304, 17)
```

[20]
```
clean_data.to_csv('clean_data.csv', index = False)
dframe = pd.DataFrame()
```

Mowdeling phase

since the previous steps involved cleansing, we can then proceed to visualization of data.

[21]
```
dframe = clean_data

import seaborn as sns
from scipy.stats import zscore
dframe
```

	Unnamed: 0	Brand	Model	Price$	CityMPG	HiWayMPG	HorsePower	BuzzScore	Design	Performance	Mileage	Interior	Infotainment	Reliability	Safety	Value	Type
0	0	Porsche	Porsche Taycan	90900.0	78.0	81.0	429.0	9.4	10.0	10.0	9.0	9.0	9.0	10.0	10.0	8.0	Sport Sedans
1	1	Porsche	Porsche Taycan Turbo	153300.0	81.0	80.0	616.0	9.4	10.0	10.0	9.0	10.0	9.0	10.0	10.0	7.0	Sport Sedans
2	2	Honda	Honda Civic Si Sedan	28800.0	27.0	37.0	200.0	9.3	9.0	9.0	8.0	10.0	9.0	9.0	10.0	10.0	Sport Sedans
3	3	Mercedes-AMG	Mercedes-AMG CLA 45	57800.0	20.0	28.0	382.0	9.1	10.0	10.0	8.0	10.0	10.0	7.0	10.0	8.0	Sport Sedans
4	4	Audi	Audi e-tron GT	104900.0	81.0	83.0	469.0	9.1	9.0	10.0	8.0	9.0	9.0	9.0	10.0	9.0	Sport Sedans
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
299	14	BMW	BMW 4 Series Gran Coupe	48300.0	25.0	34.0	255.0	7.8	7.0	8.0	7.0	7.0	8.0	8.0	9.0	8.0	Four-Door Coupes
300	15	Mercedes-AMG	Mercedes-AMG CLS 63	108900.0	16.0	22.0	550.0	NaN	8.0	10.0	6.0	8.0	7.0	8.0	8.0	7.0	Four-Door Coupes
301	16	BMW	BMW Alpina B6	124400.0	17.0	25.0	591.0	NaN	10.0	9.0	6.0	8.0	8.0	8.0	8.0	6.0	Four-Door Coupes
302	17	BMW	BMW M6 Gran Coupe	119900.0	14.0	20.0	560.0	NaN	10.0	10.0	6.0	8.0	8.0	8.0	8.0	6.0	Four-Door Coupes
303	18	Mercedes-AMG	Mercedes-AMG CLS 53	81550.0	21.0	26.0	429.0	NaN	9.0	9.0	8.0	9.0	10.0	8.0	9.0	6.0	Four-Door Coupes

304 rows × 17 columns

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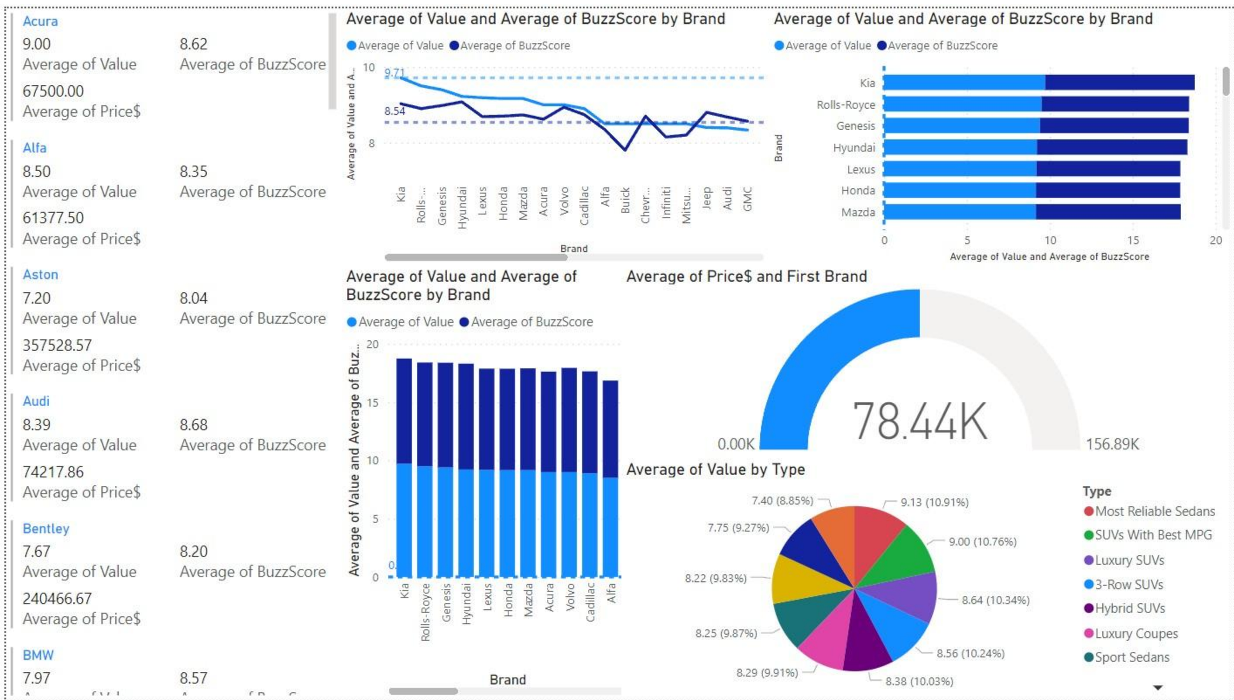
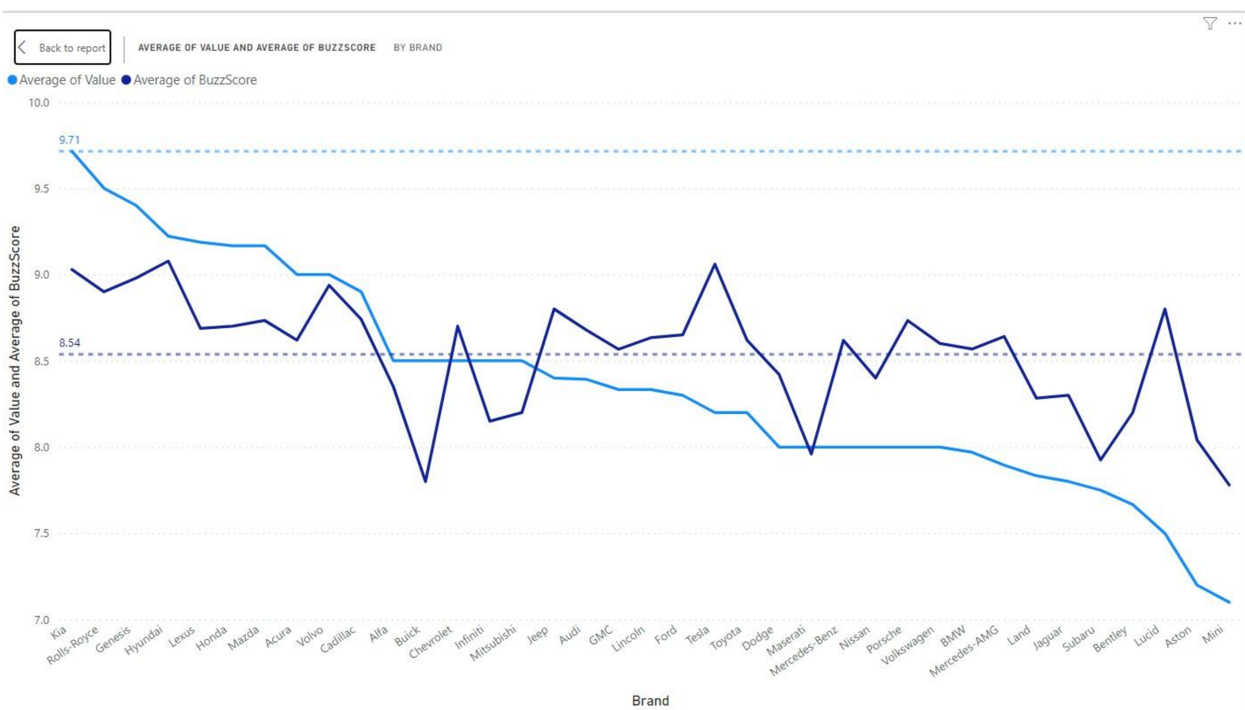
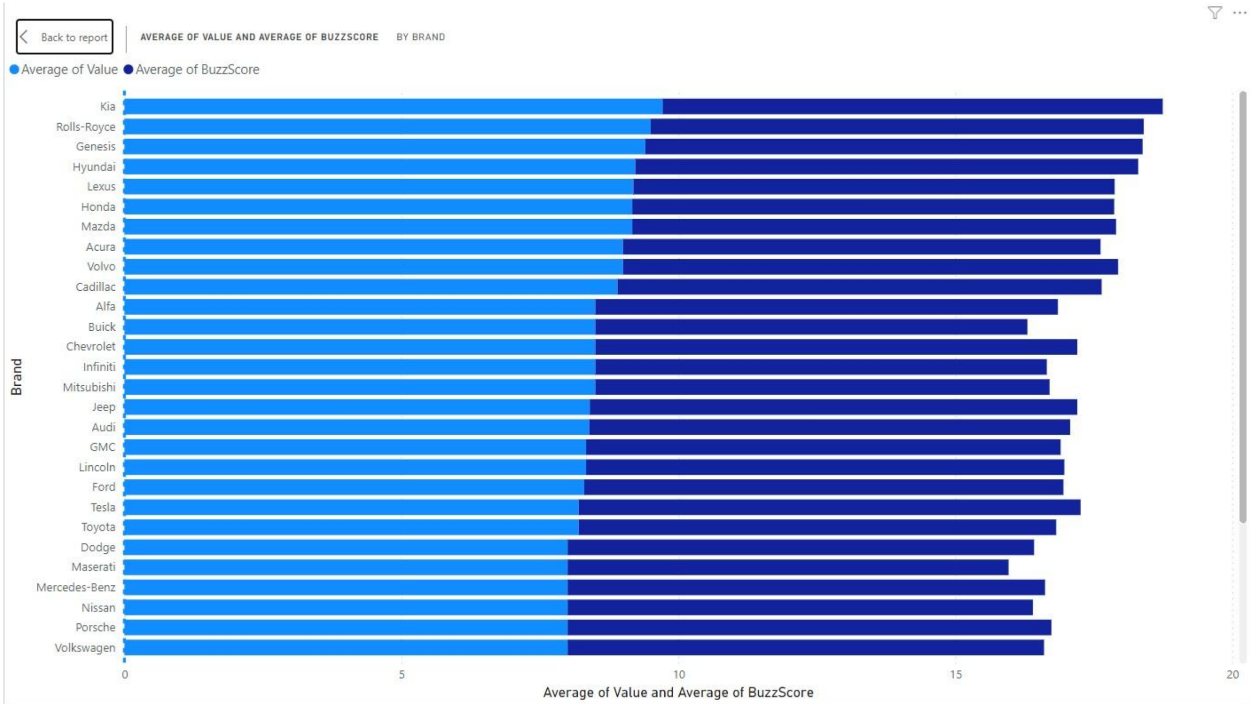
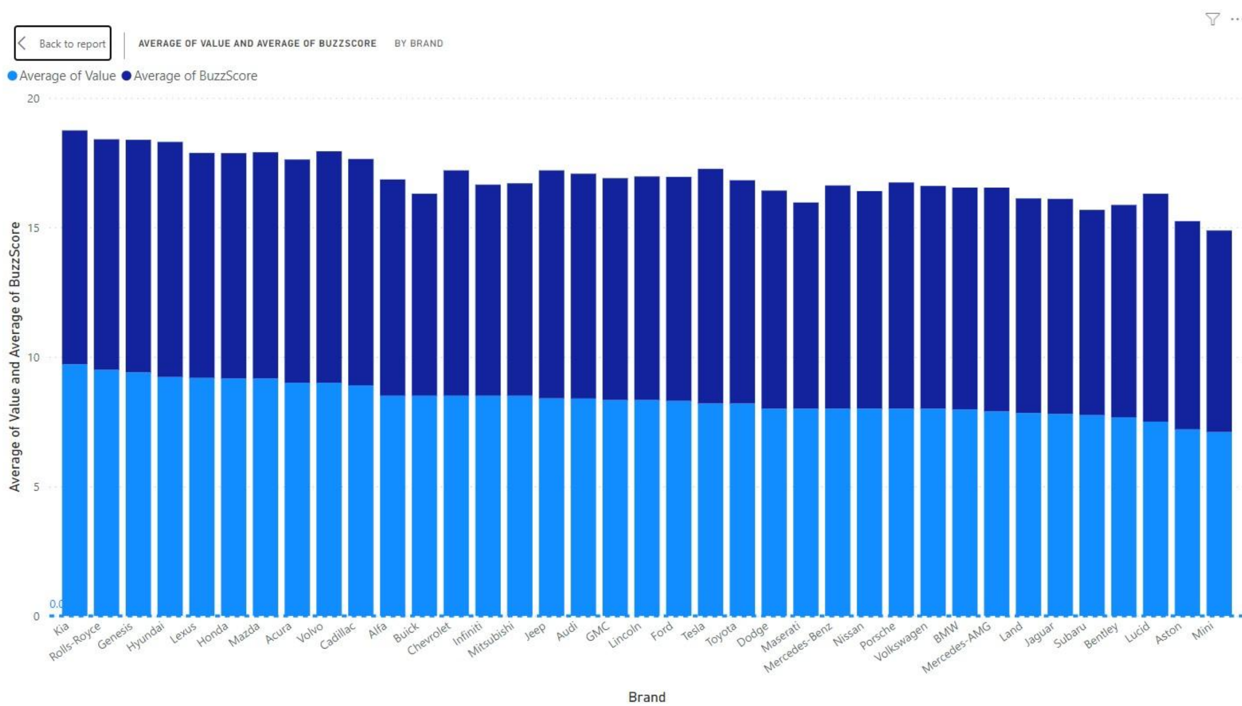
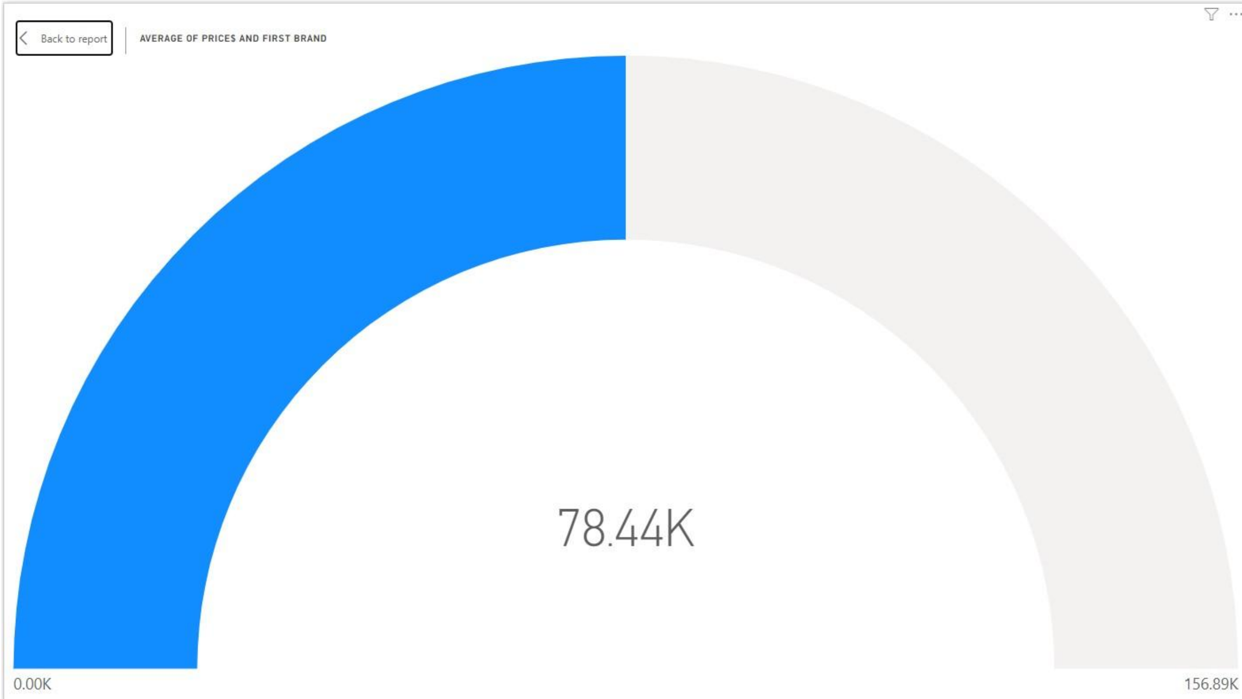
Part 2: Visualization

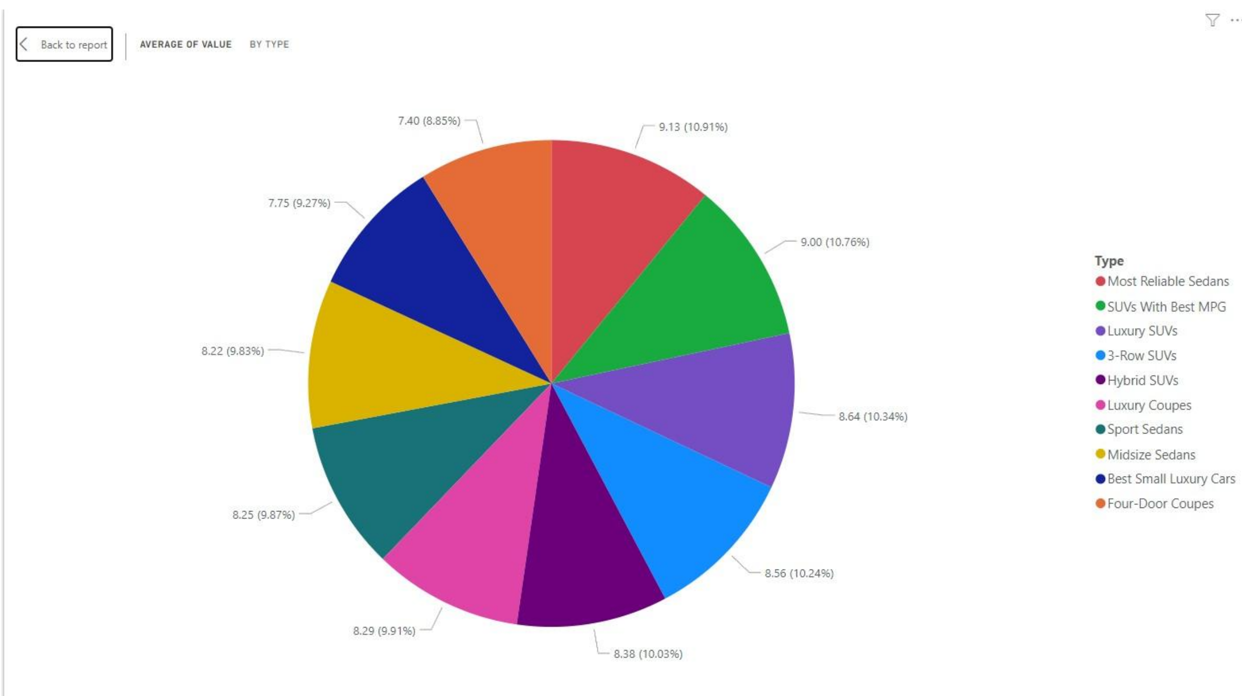




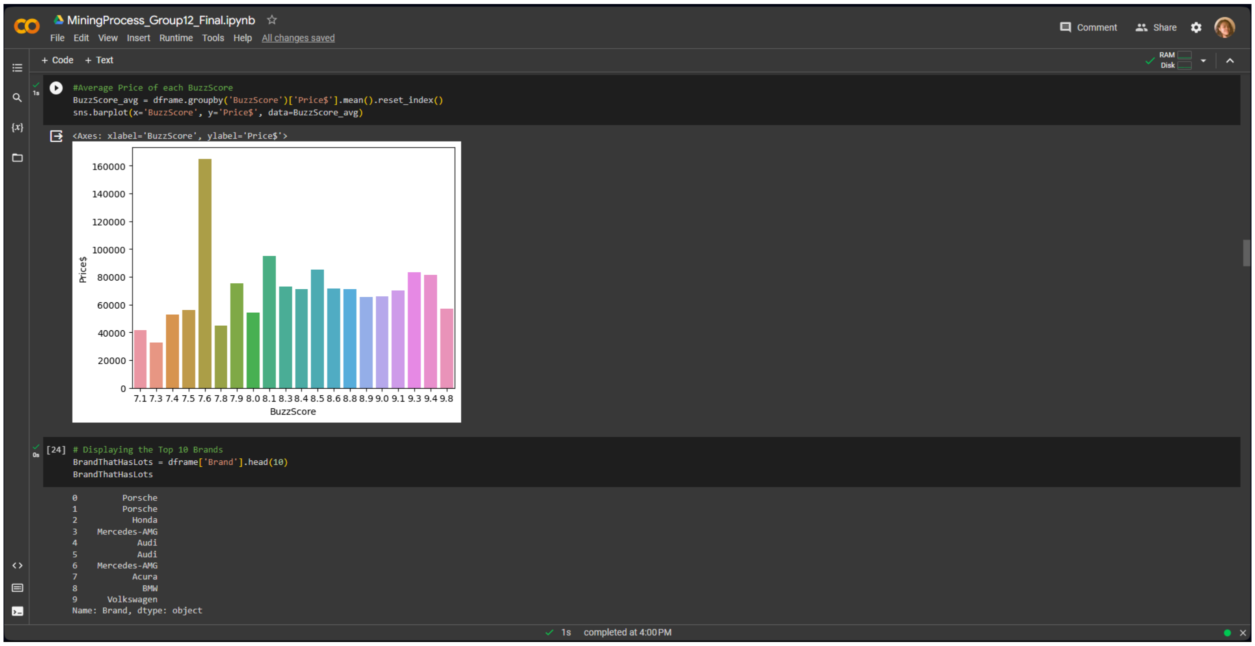

Back to report
AVERAGE OF VALUE AND AVERAGE OF BUZZSCORE BY BRAND
Average of Value
Average of BuzzScore
Brand
Kia
Rolls-Royce
Genesis
Hyundai
Lexus
Honda
Mazda
Acura
Volvo
Cadillac
Alfa
Buick
Chevrolet
Infiniti
Mitsubishi
Jeep
Audi
GMC
Lincoln
Ford
Tesla
Toyota
Dodge
Maserati
Mercedes-Benz
Nissan
Porsche
Volkswagen
0
5
10
15
20
Average of Value and Average of BuzzScore

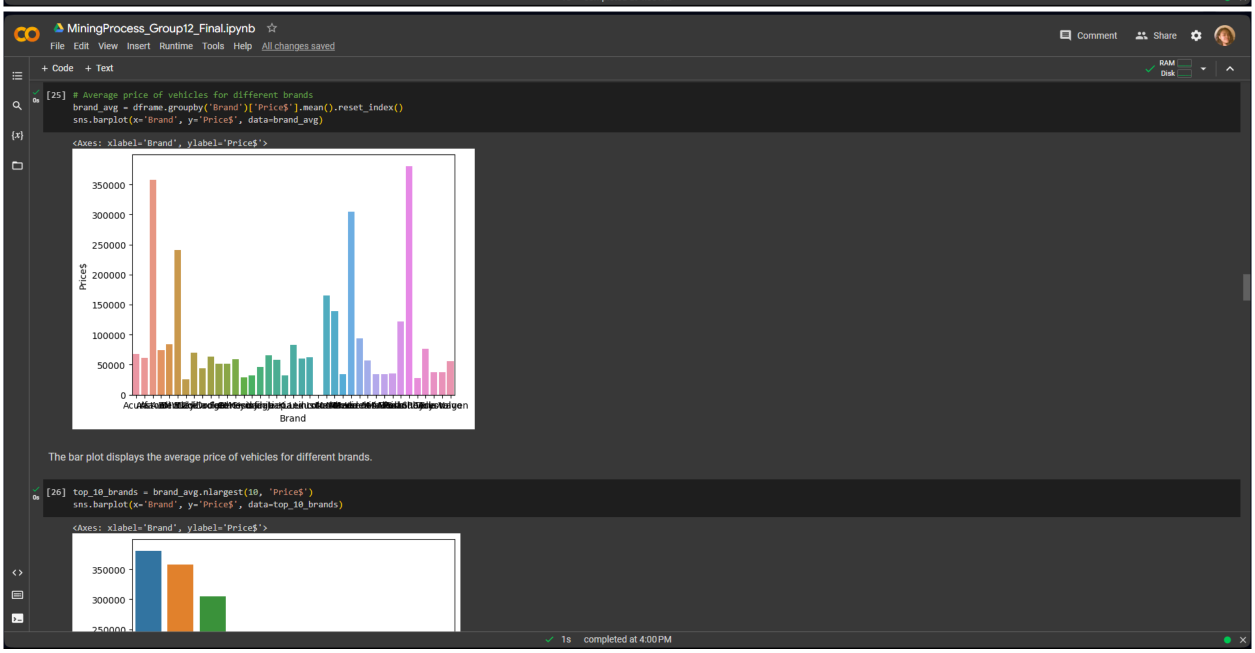

Back to report
AVERAGE OF VALUE AND AVERAGE OF BUZZSCORE BY BRAND
Average of Value
Average of BuzzScore
20
15
10
5
0
Average of Value and Average of BuzzScore
Kia
Rolls-Royce
Genesis
Hyundai
Lexus
Honda
Mazda
Acura
Volvo
Cadillac
Alfa
Buick
Chevrolet
Infiniti
Mitsubishi
Jeep
Audi
GMC
Lincoln
Ford
Tesla
Toyota
Dodge
Maserati
Mercedes-Benz
Nissan
Porsche
Volkswagen
BMW
Mercedes-AMG
Land
Jaguar
Subaru
Bentley
Lucid
Aston
Mini
Brand


Back to report
AVERAGE OF PRICES AND FIRST BRAND
78.44K
0.00K
156.89K


Back to report
AVERAGE OF VALUE BY TYPE
9.13 (10.91%)
9.00 (10.76%)
8.64 (10.34%)
8.56 (10.24%)
8.38 (10.03%)
8.29 (9.91%)
8.25 (9.87%)
8.22 (9.83%)
7.75 (9.27%)
7.40 (8.85%)
Type
Most Reliable Sedans
SUVs With Best MPG
Luxury SUVs
3-Row SUVs
Hybrid SUVs
Luxury Coupes
Sport Sedans
Midsize Sedans
Best Small Luxury Cars
Four-Door Coupes

Part 3: Modeling



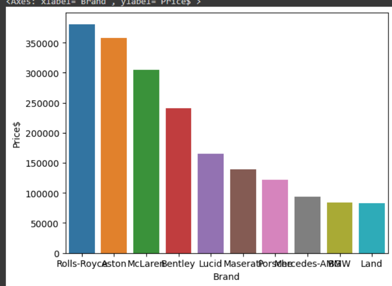


MiningProcess_Group12_Final.ipynb

The bar plot displays the average price of vehicles for different brands.

```
top_10_brands = brand_avg.nlargest(10, 'Price$')
sns.barplot(x='Brand', y='Price$', data=top_10_brands)
```

```
<Axes: xlabel='Brand', ylabel='Price$'>
```



The bar plot displays the top 10 brands with the highest average prices of vehicles.

```
[27] dframe['HorsePower'] = dframe['HorsePower'].astype(float)
     dframe['HorsePower'].dtypes
```

```
<ipython-input-27-9eae6fc31586>:1: 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
  dframe['HorsePower'] = dframe['HorsePower'].astype(float)
```

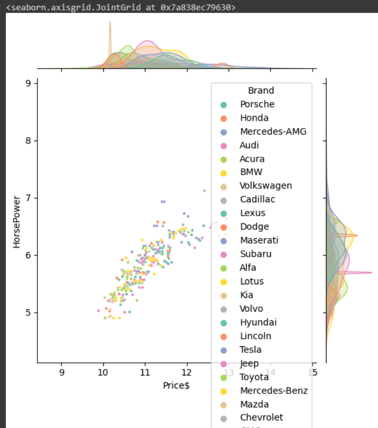
MiningProcess_Group12_Final.ipynb

```
#Normalized_HorsePower = (dframe['HorsePower'] - np.mean(dframe['HorsePower']))/np.std(dframe['HorsePower'])
#Normalized_Price = (dframe['Price$'] - np.mean(dframe['Price$']))/np.std(dframe['Price$'])

Normalized_Price = np.log(dframe['Price$'])
Normalized_Hp = np.log(dframe['HorsePower'])

sns.jointplot(data = dframe, x=Normalized_Price, y=Normalized_Hp, palette='Set2', hue = 'Brand', s=10, ratio = 5)
```

```
<seaborn.axisgrid.JointGrid at 0x7a838ec79630>
```



MiningProcess_Group12_Final.ipynb

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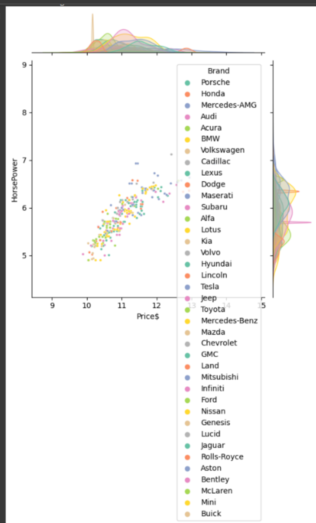

The joint plot visualizes the relationship between the logarithms of 'Price$' and 'HorsePower' for different car brands. This visualization explores how different car prices and horsepower are related to other different brands.

MiningProcess_Group12_Final.ipynb

File Edit View Insert Runtime Tools Help All changes saved

Hypothesis

After exploring the data, a hypothesis has been formed that the brand of the vehicle has more impact on the price of the vehicle than the BuzzScore or popularity.

```
[29] #feature selection
dframe
```

	Unnamed: 0	Brand	Model	Price$	CityMPG	HiWayMPG	HorsePower	BuzzScore	Design	Performance	Mileage	Interior	Infotainment	Reliability	Safety	Value	Type
0	0	Porsche	Porsche Taycan	90900.0	78.0	81.0	429.0	9.4	10.0	10.0	9.0	9.0	9.0	10.0	10.0	8.0	Sport Sedans
1	1	Porsche	Porsche Taycan Turbo	153300.0	81.0	80.0	616.0	9.4	10.0	10.0	9.0	10.0	9.0	10.0	10.0	7.0	Sport Sedans
2	2	Honda	Honda Civic Si Sedan	28800.0	27.0	37.0	200.0	9.3	9.0	9.0	8.0	10.0	9.0	9.0	10.0	10.0	Sport Sedans
3	3	Mercedes-AMG	Mercedes-AMG CLA 45	57800.0	20.0	28.0	382.0	9.1	10.0	10.0	8.0	10.0	10.0	7.0	10.0	8.0	Sport Sedans
4	4	Audi	Audi e-tron GT	104900.0	81.0	83.0	469.0	9.1	9.0	10.0	8.0	9.0	9.0	9.0	10.0	9.0	Sport Sedans
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
299	14	BMW	BMW 4 Series Gran Coupe	48300.0	25.0	34.0	255.0	7.8	7.0	8.0	7.0	7.0	8.0	8.0	9.0	8.0	Four-Door Coupes
300	15	Mercedes-AMG	Mercedes-AMG CLS 63	108900.0	16.0	22.0	550.0	NaN	8.0	10.0	6.0	8.0	7.0	8.0	8.0	7.0	Four-Door Coupes
301	16	BMW	BMW Alpina B6	124400.0	17.0	25.0	591.0	NaN	10.0	9.0	6.0	8.0	8.0	8.0	8.0	6.0	Four-Door Coupes
302	17	BMW	BMW M6 Gran Coupe	119900.0	14.0	20.0	560.0	NaN	10.0	10.0	6.0	8.0	8.0	8.0	8.0	6.0	Four-Door Coupes
303	18	Mercedes-AMG	Mercedes-AMG CLS 53	81550.0	21.0	26.0	429.0	NaN	9.0	9.0	8.0	9.0	10.0	8.0	9.0	6.0	Four-Door Coupes

304 rows × 17 columns

Preprocessing the Dataframe

In this section, we focus on data preprocessing and model preparation for building a predictive model. The data has been cleaned and preprocessed to handle missing values and encode categorical features.

```
[30] #processing numerical data

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
dframe_copy = dframe.copy()
dframe_copy = dframe_copy.dropna()
```

MiningProcess_Group12_Final.ipynb

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Preprocessing the Dataframe

In this section, we focus on data preprocessing and model preparation for building a predictive model. The data has been cleaned and preprocessed to handle missing values and encode categorical features.

[30]
```
#processing numerical data

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
dframe_copy = dframe.copy()
dframe_copy = dframe_copy.dropna()
#Scaler is used so the numerical data can be processed/normalized
scaler = StandardScaler()

#list of columns with numerical data
numericals = [ 'Price$', 'CityMPG', 'HiWayMPG', 'HorsePower', 'BuzzScore', 'Design',
           'Performance', 'Mileage', 'Interior', 'Infotainment', 'Reliability',
           'Safety', 'Value']

#Scaling all the numerical data using z = (x - u) / s(standard score)
dframe_copy[numericals] = scaler.fit_transform(dframe_copy[numericals])


#Processing categoricals (Brand and Type)

encoder = OneHotEncoder(sparse_output=False)
encoder.fit(dframe_copy)
label_encoder = LabelEncoder()

#Encoding brand
encoded_data = label_encoder.fit_transform(dframe_copy['Brand'])
dframe_copy['Encoded_Brand'] = encoded_data

encoded_data = label_encoder.fit_transform(dframe_copy['Type'])
dframe_copy['Encoded_Type'] = encoded_data

dframe_copy1 = dframe_copy
```

[31]
```
dframe_copy
```

	Unnamed: 0	Brand	Model	Price$	CityMPG	HiWayMPG	HorsePower	BuzzScore	Design	Performance	Mileage	Interior	Infotainment	Reliability	Safety	Value	Type	Encoded_Brand	Encoded_Type

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```
dframe_copy
```

	Unnamed: 0	Brand	Model	Price$	CityMPG	HiWayMPG	HorsePower	BuzzScore	Design	Performance	Mileage	Interior	Infotainment	Reliability	Safety	Value	Type	Encoded_Brand	Encoded_Type
0	0	Porsche	Porsche Taycan	0.396075	2.184459	2.498177	0.421987	1.843557	1.368975	1.446336	1.043737	0.289183	-0.004410	1.575400	1.053841	-0.404881	Sport Sedans	30	9
1	1	Porsche	Porsche Taycan Turbo	1.601846	2.316473	2.445437	1.544424	1.843557	1.368975	1.446336	1.043737	1.343590	-0.004410	1.575400	1.053841	-1.495300	Sport Sedans	30	9
2	2	Honda	Honda Civic Si Sedan	-0.803900	-0.059787	0.177583	-0.952548	1.614682	0.335704	0.532252	0.163432	1.343590	-0.004410	0.505573	1.053841	1.775957	Sport Sedans	13	9
3	3	Mercedes-AMG	Mercedes-AMG CLA 45	-0.243525	-0.367821	-0.297084	0.139877	1.156931	1.368975	1.446336	0.163432	1.343590	1.040668	-1.634083	1.053841	-0.404881	Sport Sedans	25	9
4	4	Audi	Audi e-tron GT	0.666600	2.316473	2.603659	0.662080	1.156931	0.335704	1.446336	0.163432	0.289183	-0.004410	0.505573	1.053841	0.685538	Sport Sedans	3	9
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
295	32	Subaru	Subaru Impreza Sedan	-0.977906	-0.235806	-0.138862	-1.240660	-1.589573	-2.764109	-2.210001	0.163432	-1.819630	-1.049487	1.575400	1.053841	-0.404881	Most Reliable Sedans	32	7
296	0	BMW	BMW 8 Series Gran Coupe	0.330376	-0.323816	-0.244343	-0.142233	1.614682	1.368975	0.532252	-0.716873	1.343590	1.040668	0.505573	1.053841	0.685538	Four-Door Coupes	4	2
297	6	Audi	Audi S5 Sportback	-0.282172	-0.323816	-0.191603	-0.058200	-0.216321	0.335704	-0.381833	0.163432	0.289183	-0.004410	-0.564255	-0.129857	-0.404881	Four-Door Coupes	3	2
298	8	Audi	Audi A5 Sportback	-0.498592	-0.191802	-0.033380	-0.946546	-0.445196	0.335704	-1.295917	0.163432	0.289183	-0.004410	-0.564255	-0.129857	-0.404881	Four-Door Coupes	3	2
299	14	BMW	BMW 4 Series Gran Coupe	-0.427096	-0.147797	0.019361	-0.622419	-1.818449	-1.730838	-0.381833	-0.716873	-1.819630	-1.049487	-0.564255	-0.129857	-0.404881	Four-Door Coupes	4	2

237 rows × 19 columns

[32]
```
#Splitting data BUZZSCORE VERSION
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn import utils

#selecting features(BuzzScoreonly[as individual])
feature = dframe_copy.drop(['Price$', 'Brand', 'HorsePower',
                           'Encoded_Brand', 'Encoded_Type',
                           'Type', 'Model', 'Unnamed: 0',
                           'Design' ,'Performance', 'Mileage',
                           'Interior', 'Infotainment','Reliability'
                           ,'Safety', 'CityMPG', 'HiWayMPG' ], axis=1)
#selecting target
target = dframe_copy['Price$']


#splitting data
```

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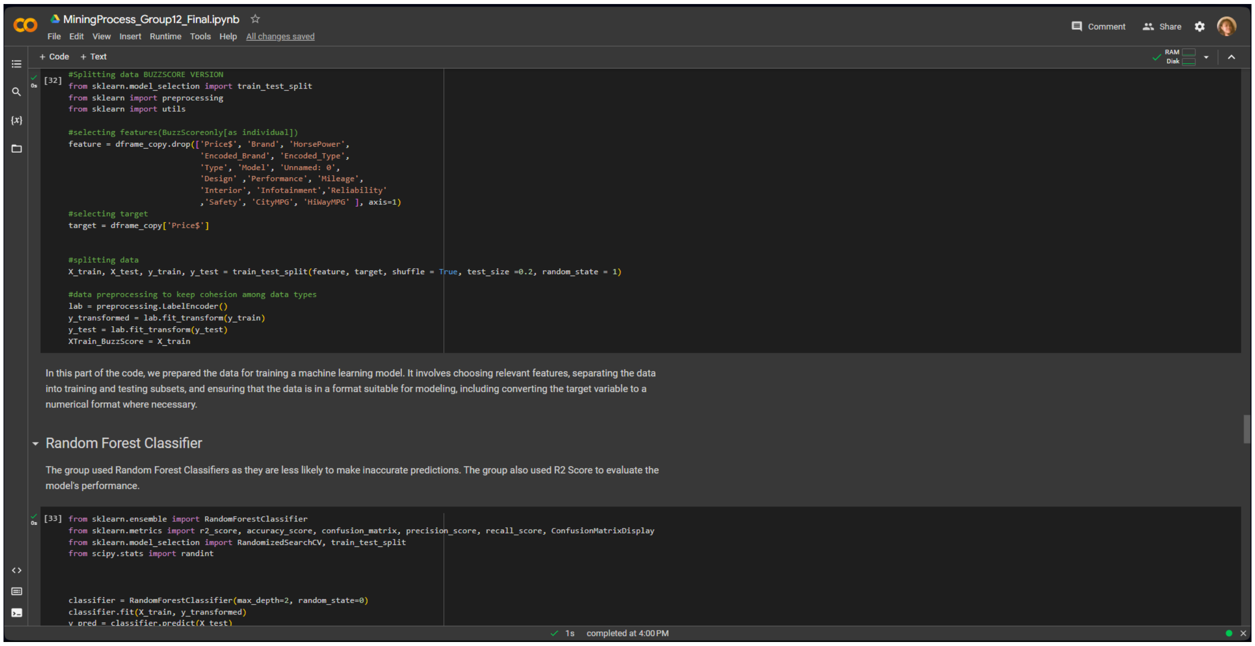

MiningProcess_Group12_Final.ipynb

```
[32] #Splitting data BUZZSCORE VERSION
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn import utils

#selecting features(BuzzScoreonly[as individual])
feature = dframe_copy.drop(['Price$', 'Brand', 'HorsePower',
                            'Encoded_Brand', 'Encoded_Type',
                            'Type', 'Model', 'Unnamed: 0',
                            'Design' ,'Performance', 'Mileage',
                            'Interior', 'Infotainment','Reliability'
                            ,'Safety', 'CityMPG', 'HiWayMPG' ], axis=1)
#selecting target
target = dframe_copy['Price$']


#splitting data
X_train, X_test, y_train, y_test = train_test_split(feature, target, shuffle = True, test_size =0.2, random_state = 1)

#data preprocessing to keep cohesion among data types
lab = preprocessing.LabelEncoder()
y_transformed = lab.fit_transform(y_train)
y_test = lab.fit_transform(y_test)
XTrain_BuzzScore = X_train
```

In this part of the code, we prepared the data for training a machine learning model. It involves choosing relevant features, separating the data into training and testing subsets, and ensuring that the data is in a format suitable for modeling, including converting the target variable to a numerical format where necessary.

Random Forest Classifier

The group used Random Forest Classifiers as they are less likely to make inaccurate predictions. The group also used R2 Score to evaluate the model's performance.

```
[33] from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import r2_score, accuracy_score, confusion_matrix, precision_score, recall_score, ConfusionMatrixDisplay
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from scipy.stats import randint



classifier = RandomForestClassifier(max_depth=2, random_state=0)
classifier.fit(X_train, y_transformed)
y_pred = classifier.predict(X_test)
```

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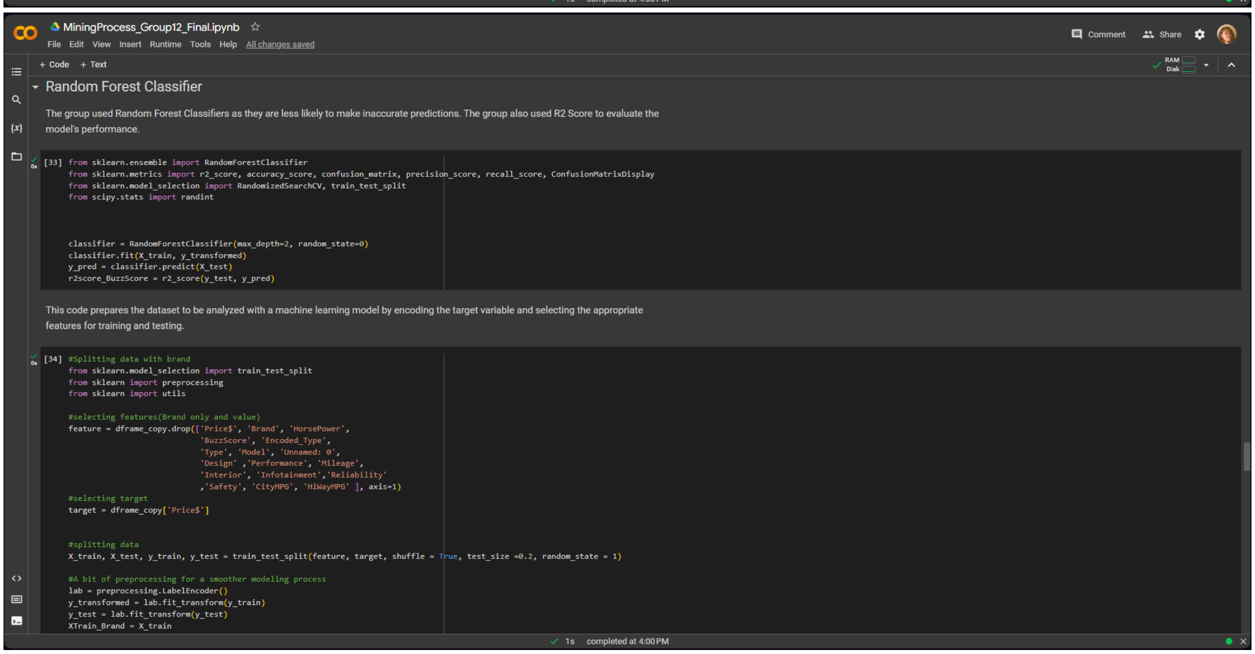

MiningProcess_Group12_Final.ipynb

Random Forest Classifier

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```
[33] from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import r2_score, accuracy_score, confusion_matrix, precision_score, recall_score, ConfusionMatrixDisplay
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from scipy.stats import randint



classifier = RandomForestClassifier(max_depth=2, random_state=0)
classifier.fit(X_train, y_transformed)
y_pred = classifier.predict(X_test)
r2score_BuzzScore = r2_score(y_test, y_pred)
```

This code prepares the dataset to be analyzed with a machine learning model by encoding the target variable and selecting the appropriate features for training and testing.

```
[34] #Splitting data with brand
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn import utils

#selecting features(Brand only and value)
feature = dframe_copy.drop(['Price$', 'Brand', 'HorsePower',
                            'BuzzScore', 'Encoded_Type',
                            'Type', 'Model', 'Unnamed: 0',
                            'Design' ,'Performance', 'Mileage',
                            'Interior', 'Infotainment','Reliability'
                            ,'Safety', 'CityMPG', 'HiWayMPG' ], axis=1)
#selecting target
target = dframe_copy['Price$']


#splitting data
X_train, X_test, y_train, y_test = train_test_split(feature, target, shuffle = True, test_size =0.2, random_state = 1)

#A bit of preprocessing for a smoother modeling process
lab = preprocessing.LabelEncoder()
y_transformed = lab.fit_transform(y_train)
y_test = lab.fit_transform(y_test)
XTrain_Brand = X_train
```

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MiningProcess_Group12_Final.ipynb

This code was used to train a Random Forest Classifier using the provided training data (X_train, y_transformed), predict on the test data (X_test), and evaluate the classifier's performance using the R2 score (r2score_Brand). The R2 score assesses how effectively the model captures the variance in the target variable based on the features, providing useful information about the Random Forest model's predictive power in this context.

```
[35] #Using Random forest,
     classifier = RandomForestClassifier(max_depth=2, random_state=0)

     #Load training data into random forest
     classifier.fit(X_train, y_transformed)
     y_pred = classifier.predict(X_test)

     #Compare predicted and test data
     r2score_Brand = r2_score(y_test, y_pred)
```

This code is required for building, training, and assessing the linear regression model's ability to predict "Design Rating" based on two features: "Value" and "Encoded_Brand."

```
[36] from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression
     from sklearn.metrics import mean_squared_error, r2_score
     import numpy as np
     import math


     # Predicting design ratings

     # Select features (X) and the target (y)
     dframe.dropna(inplace=True)
     X = dframe_copy[['Value', 'Encoded_Brand']]
     y = dframe_copy['Price$']

     # Split the 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=0)

     # Create and fit the linear regression model
     model = LinearRegression()
     model.fit(X_train, y_train)

     # Predict ratings on the test set
     y_pred = model.predict(X_test)

     # Calculate RMSE
     rmse = math.sqrt(mean_squared_error(y_test, y_pred))
```

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MiningProcess_Group12_Final.ipynb

```
     # Predicting design ratings

     # Select features (X) and the target (y)
     dframe.dropna(inplace=True)
     X = dframe_copy[['Value', 'Encoded_Brand']]
     y = dframe_copy['Price$']

     # Split the 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=0)

     # Create and fit the linear regression model
     model = LinearRegression()
     model.fit(X_train, y_train)

     # Predict ratings on the test set
     y_pred = model.predict(X_test)

     # Calculate RMSE
     rmse = math.sqrt(mean_squared_error(y_test, y_pred))
     print(f'RMSE for Design Rating: {rmse}')

     #To calculate the MSE or Mean Squared Error between y_test and y_pred
     mse = mean_squared_error(y_test, y_pred)

     #To calculate the R-Squared Score between the actual values in y_test and predicted values in y_pred
     r2_Brand = r2_score(y_test, y_pred)

     #To print the MSE and R2 Score values
     print("Mean Squared Error (MSE): ", mse)
     print("R-squared (R2) Score: ", r2_Brand)
```

```
RMSE for Design Rating: 1.0373279075450377
Mean Squared Error (MSE):  1.0760491877717662
R-squared (R2) Score:  -0.02247932860495383
<ipython-input-36-94d6a1cc0e52>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dframe.dropna(inplace=True)
```

This code calculates car design ratings based on other features in the dataset. This prediction is made using linear regression. This code determines how effectively a linear regression model predicts design ratings based on the features chosen ('Value' and 'BuzzScore'). The RMSE, MSE, and R2 scores provide information about the model's effectiveness and ability to explain design rating variance.

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MiningProcess_Group12_Final.ipynb

This code calculates car design ratings based on other features in the dataset. This prediction is made using linear regression. This code determines how effectively a linear regression model predicts design ratings based on the features chosen ('Value' and 'BuzzScore'). The RMSE, MSE, and R2 scores provide information about the model's effectiveness and ability to explain design rating variance.

```
[37] # Predicting design ratings

# Select features (X) and the target (y)
dframe.dropna(inplace=True)
X = dframe_copy[['Value', 'BuzzScore']]
y = dframe_copy['Price$']

# Split the 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=0)

# Create and fit the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict ratings on the test set
y_pred = model.predict(X_test)

# Calculate RMSE
rmse = math.sqrt(mean_squared_error(y_test, y_pred))
print(f'RMSE for Design Rating: {rmse}')

#To calculate the MSE or Mean Squared Error between y_test and y_pred
mse = mean_squared_error(y_test, y_pred)

#To calculate the R-Squared Score between the actual values in y_test and predicted values in y_pred
r2_BuzzScore = r2_score(y_test, y_pred)

#To print the MSE and R2 Score values
print("Mean Squared Error (MSE): ", mse)
print("R-squared (R2) Score: ", r2_BuzzScore)
```

```
RMSE for Design Rating: 1.0240095111990084
Mean Squared Error (MSE):  1.0485954790260323
R-squared (R2) Score:  0.0036076291336433197
<ipython-input-37-9ef3cd310168>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dframe.dropna(inplace=True)
```

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MiningProcess_Group12_Final.ipynb

```
[38] # Printing the Training Set on BuzzScore and Brand
print("Training set on BuzzScore \n", XTrain_BuzzScore,
      "\nTraining set on Brand \n ", XTrain_Brand)
```

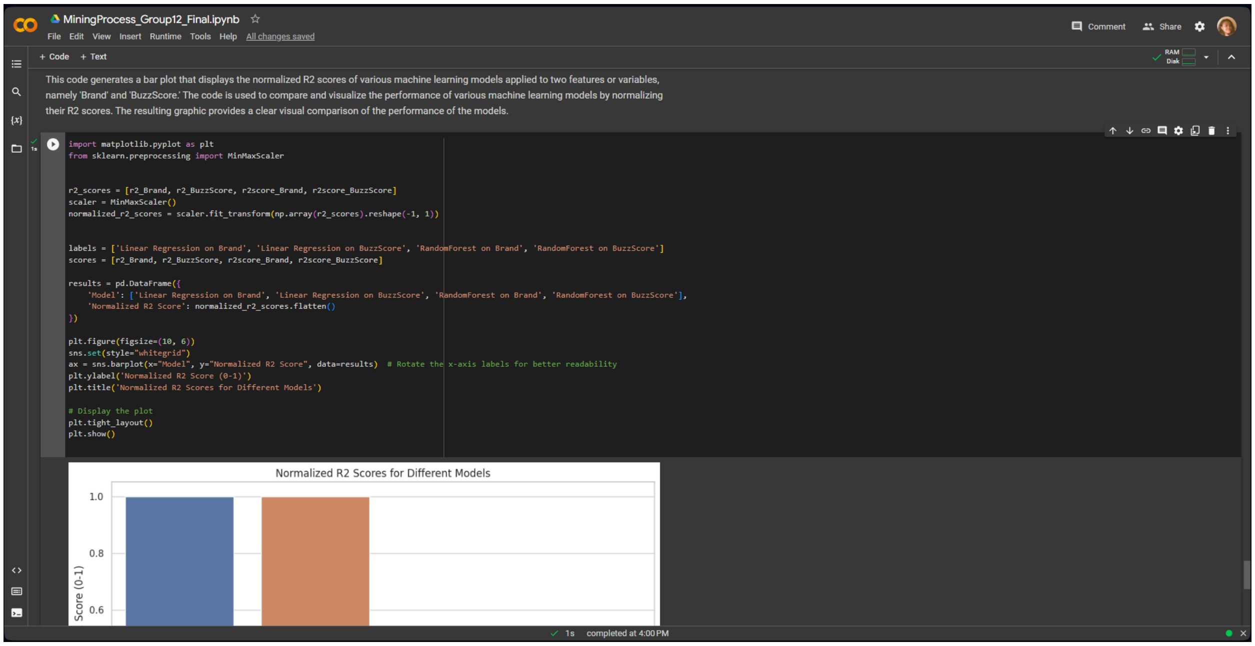
```
Training set on BuzzScore
      BuzzScore     Value
0     1.843557 -0.404881
180   1.156931  0.685538
87   -0.674072  0.685538
129  -1.131823 -1.495300
175   0.470305  0.685538
..         ...       ...
165   0.012554 -1.495300
86   -0.674072 -0.404881
168   0.928056  0.685538
298  -0.445196 -0.404881
39   -1.818449 -0.404881

[189 rows x 2 columns]
Training set on Brand
         Value  Encoded_Brand
0   -0.404881             30
180  0.685538             25
87   0.685538             11
129 -1.495300             34
175  0.685538              8
..        ...            ...
165 -1.495300              4
86  -0.404881             10
168  0.685538             24
298 -0.404881              3
39  -0.404881              1

[189 rows x 2 columns]
```

```
[39] # Printing the Linear Regression and Random Forest Classifier on both BuzzScore and Brand
print('Linear Regression on Brand: ', r2_Brand,
      '\nLinear Regression on BuzzScore: ',r2_BuzzScore,
      '\nRandomForest on Brand: ', r2score_Brand,
      '\nRandomForest on BuzzScore:', r2score_BuzzScore)
#We can plot this
```

```
Linear Regression on Brand:  -0.02247932860495383
Linear Regression on BuzzScore:  0.0036076291336433197
RandomForest on Brand:  -16.15023881893183
RandomForest on BuzzScore: -31.82142857142857
```

This code generates a bar plot that displays the normalized R2 scores of various machine learning models applied to two features or variables,

1s completed at 4:00 PM



MiningProcess_Group12_Final.ipynb

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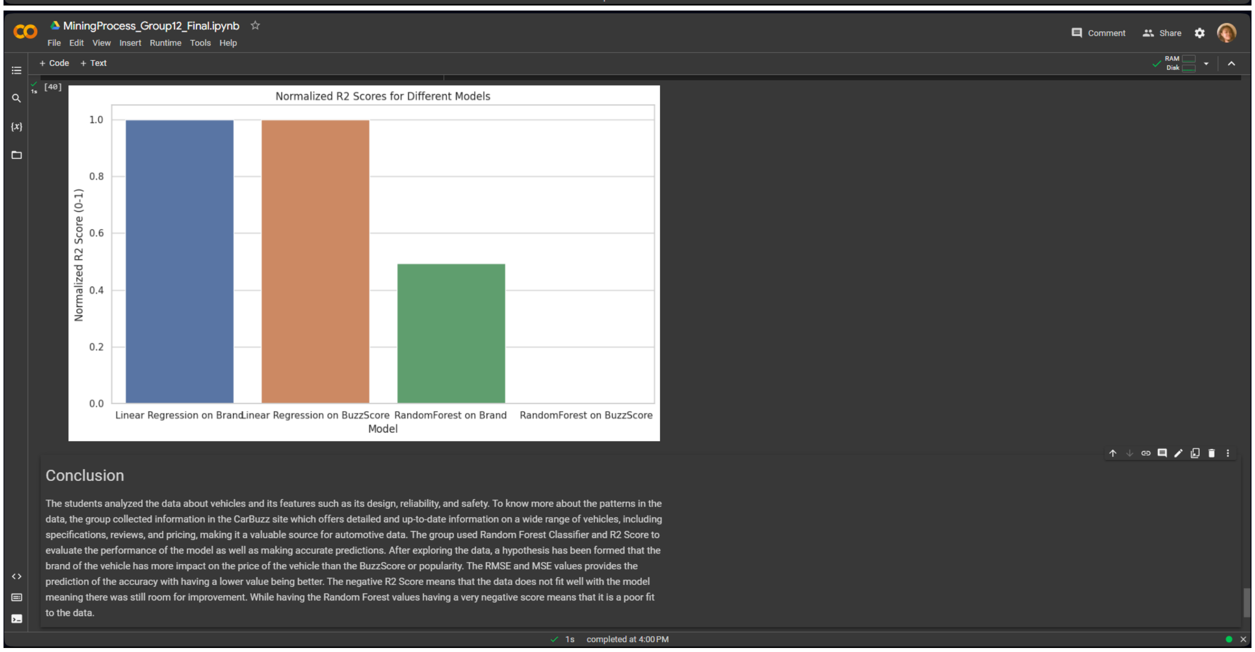
This code generates a bar plot that displays the normalized R2 scores of various machine learning models applied to two features or variables, namely 'Brand' and 'BuzzScore.' The code is used to compare and visualize the performance of various machine learning models by normalizing their R2 scores. The resulting graphic provides a clear visual comparison of the performance of the models.

```
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler


r2_scores = [r2_Brand, r2_BuzzScore, r2score_Brand, r2score_BuzzScore]
scaler = MinMaxScaler()
normalized_r2_scores = scaler.fit_transform(np.array(r2_scores).reshape(-1, 1))


labels = ['Linear Regression on Brand', 'Linear Regression on BuzzScore', 'RandomForest on Brand', 'RandomForest on BuzzScore']
scores = [r2_Brand, r2_BuzzScore, r2score_Brand, r2score_BuzzScore]

results = pd.DataFrame({
    'Model': ['Linear Regression on Brand', 'Linear Regression on BuzzScore', 'RandomForest on Brand', 'RandomForest on BuzzScore'],
    'Normalized R2 Score': normalized_r2_scores.flatten()
})

plt.figure(figsize=(10, 6))
sns.set(style="whitegrid")
ax = sns.barplot(x="Model", y="Normalized R2 Score", data=results)  # Rotate the x-axis labels for better readability
plt.ylabel('Normalized R2 Score (0-1)')
plt.title('Normalized R2 Scores for Different Models')

# Display the plot
plt.tight_layout()
plt.show()
```



MiningProcess_Group12_Final.ipynb

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Conclusion

The students analyzed the data about vehicles and its features such as its design, reliability, and safety. To know more about the patterns in the data, the group collected information in the CarBuzz site which offers detailed and up-to-date information on a wide range of vehicles, including specifications, reviews, and pricing, making it a valuable source for automotive data. The group used Random Forest Classifier and R2 Score to evaluate the performance of the model as well as making accurate predictions. After exploring the data, a hypothesis has been formed that the brand of the vehicle has more impact on the price of the vehicle than the BuzzScore or popularity. The RMSE and MSE values provides the prediction of the accuracy with having a lower value being better. The negative R2 Score means that the data does not fit well with the model meaning there was still room for improvement. While having the Random Forest values having a very negative score means that it is a poor fit to the data.

Part 4: Results Discussion

First, before the discussion of findings, it is important to explore the hypothesis we formulated after the Exploratory Data Analysis (EDA). The hypothesis suggests that *Brand* has a more significant role on the price than the *BuzzScore.* After establishing a goal, we can concentrate on working with the related to *Price$*, where the target value is *Price$.* The Test values will then be the *Brand*, and the *BuzzScore*.

After completing the modeling phase, and testing our hypothesis, we found that our hypothesis was proven wrong. Based on the results, regardless of the precision, showed that the *BuzzScore* had higher accuracy scores compared to models fed with the *Brand*. We conducted this analysis using two different machine learning algorithms, namely Random Forest Classifier, and Linear regression.

Consequently, with the results contradicting the hypothesis, we have reached the conclusion that the *BuzzScore* carries more impact than the price. This finding can enhance the credibility of *CarBuzz's analytics*, where they have their own vehicle rating system that consumers rely upon when making buying decisions. This Data Mining Process and Modeling has proven to be beneficial for the initial hypothesis, as it yielded consistent results, allowing us to draw meaningful conclusions.