EDA IN PYTHON 2024

April 7, 2024

[14]:
```
#Importing relevant packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[15]:
```
#Importing the data
EV = pd.read_csv(r'C:\\Users\\Brian Motee\\Desktop\\dataset\\Electric_Vehicle.
 ↪csv')
#Inspecting the first 5 rows of the dataset
EV.head()
```

[15]:

	VIN (1-10)	County	City	State	Postal Code	Model Year
0	5UXKT0C59G	Yakima	Zillah	WA	98953.0	2016
1	5YJ3E1EA2J	Snohomish	Edmonds	WA	98020.0	2018
2	1G1RE6E4XE	Kitsap	Port Orchard	WA	98367.0	2014
3	2C4RC1L76M	Skagit	Bow	WA	98232.0	2021
4	5YJ3E1EA2J	Thurston	Olympia	WA	98513.0	2018

	Make	Model	Electric Vehicle Type
0	BMW	X5	Plug-in Hybrid Electric Vehicle (PHEV)
1	TESLA	MODEL 3	Battery Electric Vehicle (BEV)
2	CHEVROLET	VOLT	Plug-in Hybrid Electric Vehicle (PHEV)
3	CHRYSLER	PACIFICA	Plug-in Hybrid Electric Vehicle (PHEV)
4	TESLA	MODEL 3	Battery Electric Vehicle (BEV)

	Clean Alternative Fuel Vehicle (CAFV) Eligibility	Electric Range
0	Not eligible due to low battery range	14.0
1	Clean Alternative Fuel Vehicle Eligible	215.0
2	Clean Alternative Fuel Vehicle Eligible	38.0
3	Clean Alternative Fuel Vehicle Eligible	32.0
4	Clean Alternative Fuel Vehicle Eligible	215.0

	Base MSRP	Legislative District	DOL Vehicle ID
0	0.0	15.0	206822717
1	0.0	21.0	137721636
2	0.0	26.0	197718468
3	0.0	40.0	256274308

```
4        0.0                    2.0       259176578

                  Vehicle Location        Electric Utility  2020 Census Tract
0     POINT (-120.26317 46.40556)              PACIFICORP       5.307700e+10
1     POINT (-122.37507 47.80807)  PUGET SOUND ENERGY INC       5.306105e+10
2   POINT (-122.6847073 47.50524)  PUGET SOUND ENERGY INC       5.303509e+10
3  POINT (-122.440636 48.5613885)  PUGET SOUND ENERGY INC       5.305795e+10
4    POINT (-122.817545 46.98876)  PUGET SOUND ENERGY INC       5.306701e+10
```

[16]:
```
#Inpecting the data structure
EV.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 173533 entries, 0 to 173532
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype
---  ------                                             --------------   -----
 0   VIN (1-10)                                         173533 non-null  object
 1   County                                             173528 non-null  object
 2   City                                               173528 non-null  object
 3   State                                              173533 non-null  object
 4   Postal Code                                        173528 non-null  float64
 5   Model Year                                         173533 non-null  int64
 6   Make                                               173533 non-null  object
 7   Model                                              173533 non-null  object
 8   Electric Vehicle Type                              173533 non-null  object
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  173533 non-null  object
 10  Electric Range                                     173532 non-null  float64
 11  Base MSRP                                          173532 non-null  float64
 12  Legislative District                               173157 non-null  float64
 13  DOL Vehicle ID                                     173533 non-null  int64
 14  Vehicle Location                                   173523 non-null  object
 15  Electric Utility                                   173528 non-null  object
 16  2020 Census Tract                                  173528 non-null  float64
dtypes: float64(5), int64(2), object(10)
memory usage: 22.5+ MB
```

[17]:
```
#Renaming Variables
EV.rename(columns={'VIN (1-10)':'Vin','Postal Code':'Postal_Code','Model Year':
 ↪'Model_Year','Electric Vehicle Type':'Electric_Vehicle_Type','Clean␣
 ↪Alternative Fuel Vehicle (CAFV) Eligibility':
 ↪'Clean_Alternative_Fuel_Vehicle_Eligibility','Electric Range':
 ↪'Electric_Range','Base MSRP':'Base_MSRP','Legislative District':
 ↪'Legislative_District','DOL Vehicle ID':'DOL_Vehicle_ID','Vehicle Location':
 ↪'Vehicle_Location','Electric Utility':'Electric_Utility','2020 Census Tract':
 ↪'2020_Census_Tract'}, inplace=True)
```

[18]:
```
#Inspecting if changes reflect
EV.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 173533 entries, 0 to 173532
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype
---  ------                                             --------------   -----
 0   Vin                                                173533 non-null  object
 1   County                                             173528 non-null  object
 2   City                                               173528 non-null  object
 3   State                                              173533 non-null  object
 4   Postal_Code                                        173528 non-null  float64
 5   Model_Year                                         173533 non-null  int64
 6   Make                                               173533 non-null  object
 7   Model                                              173533 non-null  object
 8   Electric_Vehicle_Type                              173533 non-null  object
 9   Clean_Alternative_Fuel_Vehicle_Eligibility         173533 non-null  object
 10  Electric_Range                                     173532 non-null  float64
 11  Base_MSRP                                          173532 non-null  float64
 12  Legislative_District                               173157 non-null  float64
 13  DOL_Vehicle_ID                                     173533 non-null  int64
 14  Vehicle_Location                                   173523 non-null  object
 15  Electric_Utility                                   173528 non-null  object
 16  2020_Census_Tract                                  173528 non-null  float64
dtypes: float64(5), int64(2), object(10)
memory usage: 22.5+ MB
```

[19]:
```
#Changing Data types
EV = EV.astype({'Vin':'string','County':'string','City':'string','State':
 ↪'string','Make':'string','Model':'string','Electric_Vehicle_Type':
 ↪'string','Electric_Utility':'string'})
#Inspecting the new data types
EV.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 173533 entries, 0 to 173532
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype
---  ------                                             --------------   -----
 0   Vin                                                173533 non-null  string
 1   County                                             173528 non-null  string
 2   City                                               173528 non-null  string
 3   State                                              173533 non-null  string
 4   Postal_Code                                        173528 non-null  float64
 5   Model_Year                                         173533 non-null  int64
 6   Make                                               173533 non-null  string
 7   Model                                              173533 non-null  string
```

```
 8   Electric_Vehicle_Type                          173533 non-null  string
 9   Clean_Alternative_Fuel_Vehicle_Eligibility     173533 non-null  object
 10  Electric_Range                                 173532 non-null  float64
 11  Base_MSRP                                      173532 non-null  float64
 12  Legislative_District                           173157 non-null  float64
 13  DOL_Vehicle_ID                                 173533 non-null  int64
 14  Vehicle_Location                               173523 non-null  object
 15  Electric_Utility                               173528 non-null  string
 16  2020_Census_Tract                              173528 non-null  float64
dtypes: float64(5), int64(2), object(2), string(8)
memory usage: 22.5+ MB
```

[20]:
```
#Inspecting the electric range variable
EV.Electric_Range.unique()
```

[20]:
```
array([ 14., 215.,  38.,  32.,  23., 239., 220., 153.,  19., 107.,  33.,
       291., 249.,  73.,  72., 238.,   0.,  21., 208.,  84.,  26., 259.,
       150.,  75., 210.,  25.,  82., 151., 270., 204.,  30., 293., 125.,
        35.,  87., 200.,  22., 308., 266., 234.,  47.,  83.,  81.,  97.,
        13., 149.,  53.,  37., 322.,  10., 330.,  58.,  18., 203.,   6.,
       289., 100.,  42.,  16.,  17.,  76.,  62.,  20., 126.,  93.,  29.,
        15., 233.,  39., 258.,  28., 111.,  27.,   8., 170., 192., 218.,
       110.,  68.,  24.,  34., 222.,  41.,  12., 124., 114., 265.,  11.,
       337.,  40.,  48.,  31., 103., 245.,  74.,  59.,   9.,  56.,  57.,
        36.,  95.,  51.,  nan])
```

Electric_Range is the distance a vehicle can travel purely on electric charge. It is evident that the variable has zeros(0) and missing data.This is my main variable, I want it to be complete hence I will drop the zeros.

[22]:
```
#Filtering out rows in the Electric_Range variable with values equal to 0
EV = EV[EV['Electric_Range']!=0]
#inspecting missing values per variable
EV.isna().sum()
```

[22]:
```
Vin                                            0
County                                         5
City                                           5
State                                          0
Postal_Code                                    5
Model_Year                                     0
Make                                           0
Model                                          0
Electric_Vehicle_Type                          0
Clean_Alternative_Fuel_Vehicle_Eligibility     0
Electric_Range                                 1
Base_MSRP                                      1
Legislative_District                         226
```

```
DOL_Vehicle_ID                     0
Vehicle_Location                   9
Electric_Utility                   5
2020_Census_Tract                  5
dtype: int64
```

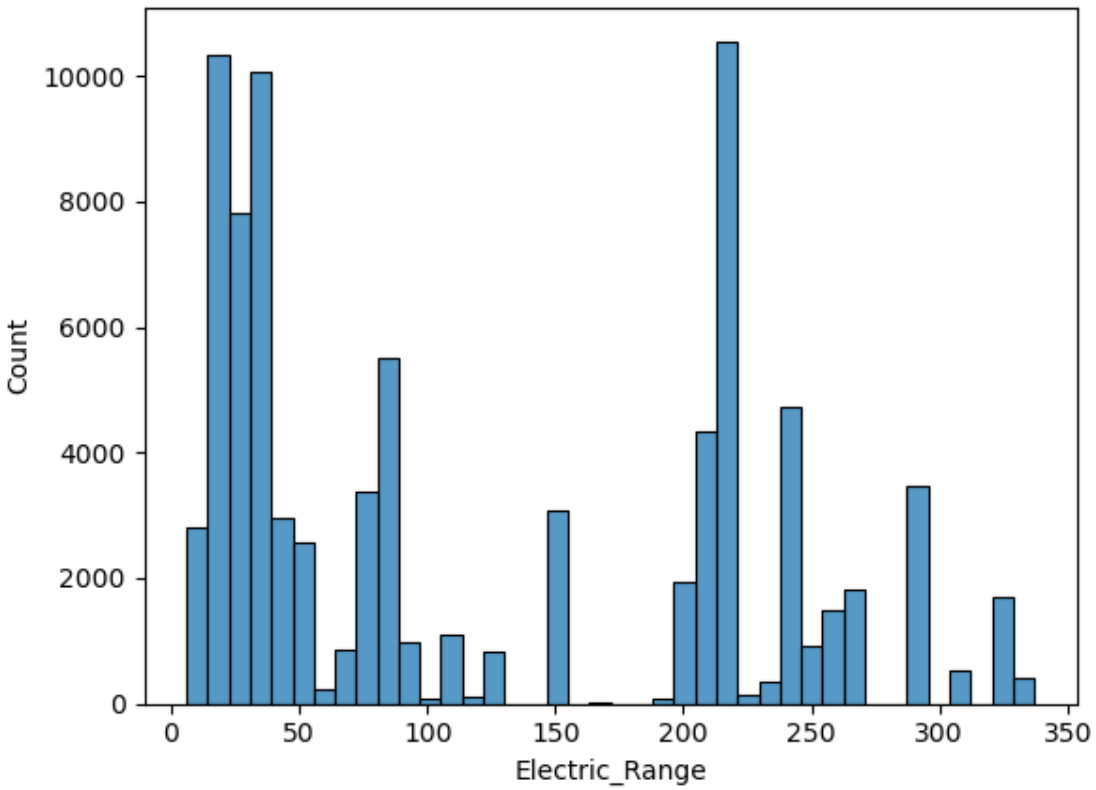
1 UNIVARIATE STATISTICS

[23]:
```
#Display measures of central tendancy for Electric_Range
print('The average electric range is ' + str(EV.Electric_Range.mean()))
print('The median electric range is ' + str(EV.Electric_Range.median()))
print('The mode electric range is ' + str(EV.Electric_Range.mode()))
```

```
The average electric range is 122.4639563533967
The median electric range is 84.0
The mode electric range is 0    215.0
Name: Electric_Range, dtype: float64
```

The difference between the mean and the median is too big, suggesting the variable Electric_Range has outliers and possibly skewed.I will visualize the data to confirm my suspicion.

[24]:
```
#Checking the distribution of Electric_Range using a histogram
sns.histplot(x='Electric_Range',data=EV)
plt.show()
plt.clf()
```




```
<Figure size 640x480 with 0 Axes>
```

That means I cannot rely on the mean When I am analyzing the data as the mean is affected by the presence of outliers. Therefore to evaluate the spread of data, I will use interquartile range instead of standard deviation

[25]:
```
#Describing the variability of Electric_Range
EV.Electric_Range.quantile(0.75)-EV.Electric_Range.quantile(0.25)
```

[25]:
```
183.0
```

An interquartile range of 183.0 means that the middle 50% of the data values in the dataset span a range of 183.0 units. This suggests that the spread of the data values within this middle 50% is relatively large.

2 # Categorical variable

[26]:
```
#Getting the top 10 Electric Vehicles manufacturers
EV.Make.value_counts(normalize=True).head(10)
```

[26]:
```
Make
TESLA        0.300431
```

```
NISSAN        0.127395
CHEVROLET     0.109573
TOYOTA        0.068074
BMW           0.065481
JEEP          0.050956
FORD          0.045946
KIA           0.044737
CHRYSLER      0.034706
VOLVO         0.031291
Name: proportion, dtype: Float64
```

30% of the electric vehicles in this dataset are from manufactured by Tesla, followed by Nissan 13% and Chevrolet 11%.

[27]:
```
#Proportion of Electric vehicles by electric vehicle type
EV.Electric_Vehicle_Type.value_counts(normalize=True)
```

[27]:
```
Electric_Vehicle_Type
Battery Electric Vehicle (BEV)            0.555138
Plug-in Hybrid Electric Vehicle (PHEV)    0.444862
Name: proportion, dtype: Float64
```

More than half the Electric Vehicles(56%) are Battery Electric Vehicle(BEV).

3 BIVARIATE STATISTICS.

Electric_Range describes how far a vehicle can travel purely on electric charge. I will examine the association between top two manufacturers and evaluate Electric Range, and also the association between Electric_Vehicle_Type and Electric_Range

[30]:
```
#Getting data for Tesla and Nissan
Tesla_EV = EV.Electric_Range[EV.Make=='TESLA']
Nissan_EV = EV.Electric_Range[EV.Make=='NISSAN']
Chevrolet_EV = EV.Electric_Range[EV.Make=='CHEVROLET']
Toyota_EV = EV.Electric_Range[EV.Make=='TOYOTA']
BMW_EV = EV.Electric_Range[EV.Make=='BMW']
Jeep_EV = EV.Electric_Range[EV.Make=='JEEP']
Ford_EV = EV.Electric_Range[EV.Make=='FORD']
Kia_EV = EV.Electric_Range[EV.Make=='KIA']
Chrysler_EV = EV.Electric_Range[EV.Make=='CHRYSLER']
Volvo_EV = EV.Electric_Range[EV.Make=='VOLVO']
#Getting the means for Tesla and Nissan
Mean_Tesla = np.mean(Tesla_EV)
Mean_Nissan = np.mean(Nissan_EV)
mean_Chevrolet = np.mean(Chevrolet_EV)
mean_Toyota = np.mean(Toyota_EV)
mean_BMW = np.mean(BMW_EV)
mean_Jeep = np.mean(Jeep_EV)
```

```
mean_Ford = np.mean(Ford_EV)
mean_Kia = np.mean(Kia_EV)
mean_chrysler = np.mean(Chrysler_EV)
mean_Volvo = np.mean(Volvo_EV)
#Printing the means
print("This is Tesla's average Electric Range: " + str(Mean_Tesla))
print("This is Nissan's average Electric Range: " + str(Mean_Nissan))
print("This is Chevrolet's average Electric Range: " + str(mean_Chevrolet))
print("This is Toyota's average Electric Range: " + str(mean_Toyota))
print("This is BMW's average Electric Range: " + str(mean_BMW))
print("This is Jeep's average Electric Range: " + str(mean_Jeep))
print("This is Ford's average Electric Range: " + str(mean_Ford))
print("This is Kia's average Electric Range: " + str(mean_Kia))
print("This is Chrysler's average Electric Range: " + str(mean_chrysler))
print("This is Volvo's average Electric Range: " + str(mean_Volvo))
```

```
This is Tesla's average Electric Range: 240.81777708349605
This is Nissan's average Electric Range: 104.23586295818751
This is Chevrolet's average Electric Range: 136.74590427240605
This is Toyota's average Electric Range: 29.017580144777664
This is BMW's average Electric Range: 46.92886579466045
This is Jeep's average Electric Range: 22.380612479852637
This is Ford's average Electric Range: 25.31996935648621
This is Kia's average Electric Range: 87.08943089430895
This is Chrysler's average Electric Range: 32.21399594320487
This is Volvo's average Electric Range: 24.388076490438696
```

4 ## Interpretation

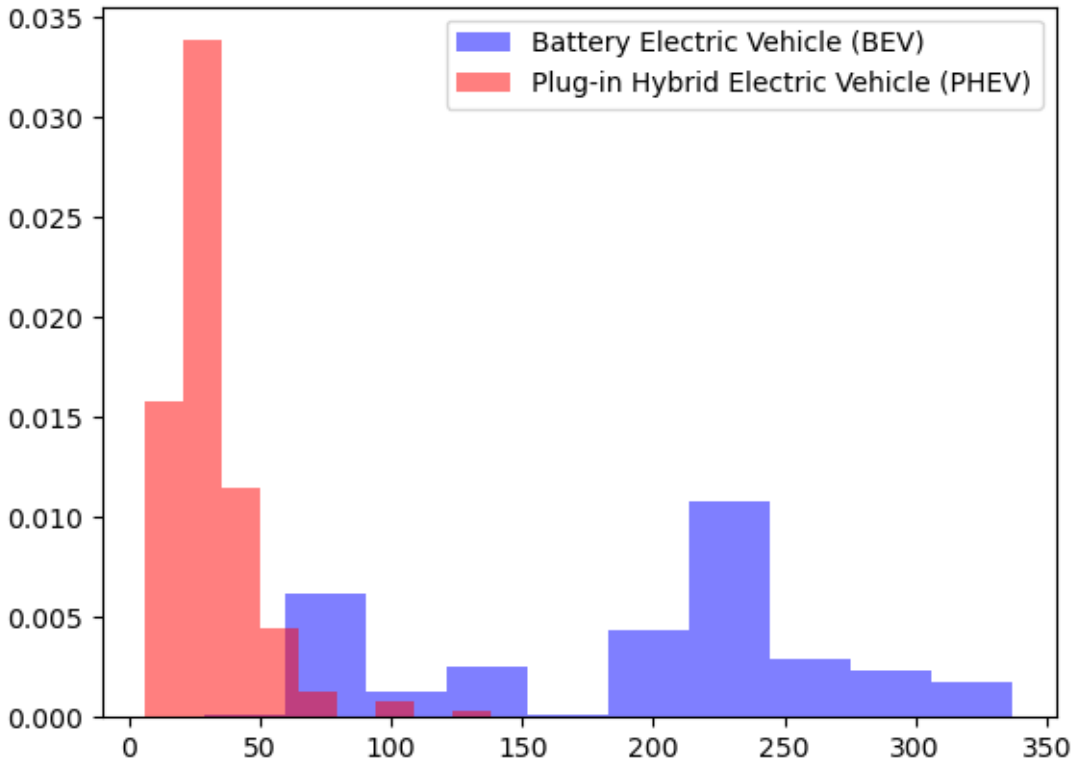
The huge difference in the means suggest there is an association between electric ranges and the manufacturers as it varies depending on the manufacturer. for instance Tesla has more than twice electric range of Nissan

[33]:
```
#Evaluating the association between Electric vehicle type and electric range
BEV = EV.Electric_Range[EV.Electric_Vehicle_Type =='Battery Electric Vehicle␣
 ↪(BEV)']
PHEV = EV.Electric_Range[EV.Electric_Vehicle_Type =='Plug-in Hybrid Electric␣
 ↪Vehicle (PHEV)']
#Getting the means
BEV_Mean = np.mean(BEV)
PHEV_Mean = np.mean(PHEV)
#Printing the means
print("The average BEV Electric range is " + str(BEV_Mean))
print("The average PHEV Electric range is " + str(PHEV_Mean))
```

```
The average BEV Electric range is 195.93080418471942
The average PHEV Electric range is 30.78298826322036
```

The BEV electric vehicle travels more than 6 times further than the PHEV electric vehicle

[35]:
```
#Illustrating the associations with an overlapping histogram
plt.hist(BEV, color='blue',label='Battery Electric Vehicle␣
 ↪(BEV)',density=True,alpha=0.5)
plt.hist(PHEV, color='red',label='Plug-in Hybrid Electric Vehicle␣
 ↪(PHEV)',density=True,alpha=0.5)
plt.legend()
plt.show()
```



The overlapping histogram suggests that there is a strong association between the electric vehicle type and Electric Range

[ ]: