nti-data-visualization

September 8, 2024

[3]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

1 1- Data Gathering

1.1 a- Loading Data

[5]:
```python
df = pd.read_csv('fuel-econ.csv')
```

1.2 b- Data Preview

[6]:
```python
df.head()
```

[6]:
```
      id        make           model  year           VClass  \
0  32204      Nissan            GT-R  2013  Subcompact Cars
1  32205  Volkswagen              CC  2013     Compact Cars
2  32206  Volkswagen              CC  2013     Compact Cars
3  32207  Volkswagen      CC 4motion  2013     Compact Cars
4  32208   Chevrolet  Malibu eAssist  2013     Midsize Cars

               drive              trans          fuelType  cylinders  displ  \
0    All-Wheel Drive   Automatic (AM6)  Premium Gasoline          6    3.8
1  Front-Wheel Drive  Automatic (AM-S6)  Premium Gasoline          4    2.0
2  Front-Wheel Drive     Automatic (S6)  Premium Gasoline          6    3.6
3    All-Wheel Drive     Automatic (S6)  Premium Gasoline          6    3.6
4  Front-Wheel Drive     Automatic (S6)  Regular Gasoline          4    2.4

   pv2  pv4     city    UCity  highway  UHighway     comb  co2  feScore  \
0   79    0  16.4596  20.2988  22.5568   30.1798  18.7389  471        4
1   94    0  21.8706  26.9770  31.0367   42.4936  25.2227  349        6
2   94    0  17.4935  21.2000  26.5716   35.1000  20.6716  429        5
3   94    0  16.9415  20.5000  25.2190   33.5000  19.8774  446        5
4    0   95  24.7726  31.9796  35.5340   51.8816  28.6813  310        8

   ghgScore
```

```
0         4
1         6
2         5
3         5
4         8
```

[7]:
```python
df.tail()
```

[7]:
```
         id     make              model  year         VClass              drive  \
3924  39882   Toyota        Prius Prime  2018  Midsize Cars  Front-Wheel Drive
3925  39898  Hyundai      Sonata Hybrid  2018  Midsize Cars  Front-Wheel Drive
3926  39899  Hyundai   Sonata Hybrid SE  2018  Midsize Cars  Front-Wheel Drive
3927  39900    Lexus             LS 500  2018  Midsize Cars   Rear-Wheel Drive
3928  39901    Lexus         LS 500 AWD  2018  Midsize Cars    All-Wheel Drive

                                trans          fuelType  cylinders  displ  \
3924  Automatic (variable gear ratios)  Regular Gasoline          4    1.8
3925                   Automatic (AM6)  Regular Gasoline          4    2.0
3926                   Automatic (AM6)  Regular Gasoline          4    2.0
3927                   Automatic (S10)  Premium Gasoline          6    3.4
3928                   Automatic (S10)  Premium Gasoline          6    3.4

      pv2  pv4     city    UCity  highway  UHighway     comb  co2  feScore  \
3924    0    0  55.2206  78.8197  53.0000   73.6525  54.4329   78       10
3925    0  106  39.0000  55.9000  44.3066   64.0000  41.0000  217        9
3926    0  106  40.0000  56.0000  46.0000   64.0000  42.0000  212        9
3927   99    0  19.2200  24.2000  30.2863   43.4000  23.0021  387        5
3928   99    0  18.0431  22.6000  27.0000   39.3000  21.3945  417        4

      ghgScore
3924        10
3925         9
3926         9
3927         5
3928         4
```

- Tidy Issue in **pv2, pv4** columns

2 2- Inspect Data

[8]:
```python
df.shape
```

[8]:
```
(3929, 20)
```

[9]:
```python
df.describe()
```

[9]:

```
                 id         year    cylinders        displ          pv2  \
count   3929.000000  3929.000000  3929.000000  3929.000000  3929.000000
mean   36006.724357  2015.500891     5.468313     2.950573    23.660982
std     2189.349923     1.694775     1.878319     1.305901    37.724901
min    32204.000000  2013.000000     2.000000     0.600000     0.000000
25%    34087.000000  2014.000000     4.000000     2.000000     0.000000
50%    36020.000000  2015.000000     5.000000     2.500000     0.000000
75%    37935.000000  2017.000000     6.000000     3.600000    70.000000
max    39901.000000  2018.000000    12.000000     7.000000   102.000000

               pv4         city        UCity      highway     UHighway  \
count  3929.000000  3929.000000  3929.000000  3929.000000  3929.000000
mean     59.239247    21.830462    28.044011    29.973842    42.850295
std      48.667549     6.246273     9.087195     5.747571     9.100423
min       0.000000    10.540200    12.900000    16.559400    21.800000
25%       0.000000    17.746900    22.200000    25.754200    36.000000
50%      91.000000    20.823200    26.400000    29.633800    42.200000
75%     100.000000    24.981400    32.264800    33.773100    48.900000
max     127.000000    57.808800    83.559800    59.416900    79.100000

              comb          co2      feScore     ghgScore
count  3929.000000  3929.000000  3929.000000  3929.000000
mean     24.791339   376.564266     5.668872     5.659201
std       6.003246    92.338892     1.755860     1.754589
min      12.821700    29.000000     1.000000     1.000000
25%      20.658100   315.000000     5.000000     5.000000
50%      24.000000   369.000000     5.000000     5.000000
75%      28.227100   429.000000     7.000000     7.000000
max      57.782400   692.000000    10.000000    10.000000
```

[10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3929 entries, 0 to 3928
Data columns (total 20 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   id         3929 non-null   int64
 1   make       3929 non-null   object
 2   model      3929 non-null   object
 3   year       3929 non-null   int64
 4   VClass     3929 non-null   object
 5   drive      3929 non-null   object
 6   trans      3929 non-null   object
 7   fuelType   3929 non-null   object
 8   cylinders  3929 non-null   int64
 9   displ      3929 non-null   float64
```

```
 10  pv2        3929 non-null   int64
 11  pv4        3929 non-null   int64
 12  city       3929 non-null   float64
 13  UCity      3929 non-null   float64
 14  highway    3929 non-null   float64
 15  UHighway   3929 non-null   float64
 16  comb       3929 non-null   float64
 17  co2        3929 non-null   int64
 18  feScore    3929 non-null   int64
 19  ghgScore   3929 non-null   int64
dtypes: float64(6), int64(8), object(6)
memory usage: 614.0+ KB
```

- Tidy Issue **year** column should be data

3 3- Data Backup

[11]:
```
# take a backup of my original DataFarme
df_backup = df.copy
```

4 4- Quality Issues

- i- Missing Data
- ii- Dublicate Data
- iii- Inconsisted Data Types
- ix- Inconsistant Data

4.1 3-i Missing values

[13]:
```
# check missing Values
df.isna().sum()
```

[13]:
```
id           0
make         0
model        0
year         0
VClass       0
drive        0
trans        0
fuelType     0
cylinders    0
displ        0
pv2          0
pv4          0
city         0
UCity        0
```

```
highway      0
UHighway     0
comb         0
co2          0
feScore      0
ghgScore     0
dtype: int64
```

- No Missing Values

4.2 3-ii Dublicated Data

[15]:
```python
# check Dublicate
df.duplicated().sum()
```

[15]:
```
0
```

- No Dublicated Rows

4.3 3-iii Inconsistant Data Type

[16]:
```python
# check Data Type foreach column
df.dtypes
```

[16]:
```
id              int64
make           object
model          object
year            int64
VClass         object
drive          object
trans          object
fuelType       object
cylinders       int64
displ         float64
pv2             int64
pv4             int64
city          float64
UCity         float64
highway       float64
UHighway      float64
comb          float64
co2             int64
feScore         int64
ghgScore        int64
dtype: object
```

4.3.1 iii-a Define

- **year** column Should be 'date'

4.3.2 iii-b Code

[17]:
```
# convert 'year' column Datatype to be 'date'
df['year'] = pd.to_datetime(df['year'], format='%Y')
```

4.3.3 iii-c Test

[18]:
```
df.dtypes
```

[18]:
```
id                    int64
make                 object
model                object
year         datetime64[ns]
VClass               object
drive                object
trans                object
fuelType             object
cylinders             int64
displ               float64
pv2                   int64
pv4                   int64
city                float64
UCity               float64
highway             float64
UHighway            float64
comb                float64
co2                   int64
feScore               int64
ghgScore              int64
dtype: object
```

4.4 3-iv- Inconsistant Values

- Has No Inconsistant Values

5 5- Tidiness Issues

- i- Each variable forms a column
- ii- Each observation forms a row
- iii- Each type of observational unit forms a table

5.0.1 i-a Define

- **pv2, pv4** Values forms Columns

5.0.2 i-b Code

[19]:
```
# using melt function to handle two columns
#   - assing pv2 and pv4 Values to a column ['efficiency_value'] variable
#   - assing the values of pv2 and pv4 columns to ['pv_value'] column

df_2 = df.melt(
    id_vars=['id', 'make', 'model', 'year', 'VClass', 'drive', 'trans',
             'fuelType', 'cylinders', 'displ', 'city', 'UCity', 'highway',
             'UHighway', 'co2', 'feScore', 'ghgScore'],
    value_vars=['pv2', 'pv4'],
    var_name='efficiency_value',
    value_name='pv_value'
)
```

5.0.3 i-c Test

[20]:
```
df_2.head(2)
```

[20]:
```
      id        make model        year            VClass             drive  \
0  32204      Nissan  GT-R  2013-01-01  Subcompact Cars    All-Wheel Drive
1  32205  Volkswagen    CC  2013-01-01     Compact Cars  Front-Wheel Drive

               trans          fuelType  cylinders  displ     city    UCity  \
0    Automatic (AM6)  Premium Gasoline          6    3.8  16.4596  20.2988
1  Automatic (AM-S6)  Premium Gasoline          4    2.0  21.8706  26.9770

   highway  UHighway  co2  feScore  ghgScore efficiency_value  pv_value
0  22.5568   30.1798  471        4         4              pv2        79
1  31.0367   42.4936  349        6         6              pv2        94
```

- ii- Each observation forms a row
    - Not an Issues
- iii- Each type of observational unit forms a table
    - Not an Issues

6 6- Export as CSV file

[ ]:
```
df_2.to_csv('fuel-econ-v2.csv', index=False)
```

7 7- Visualization

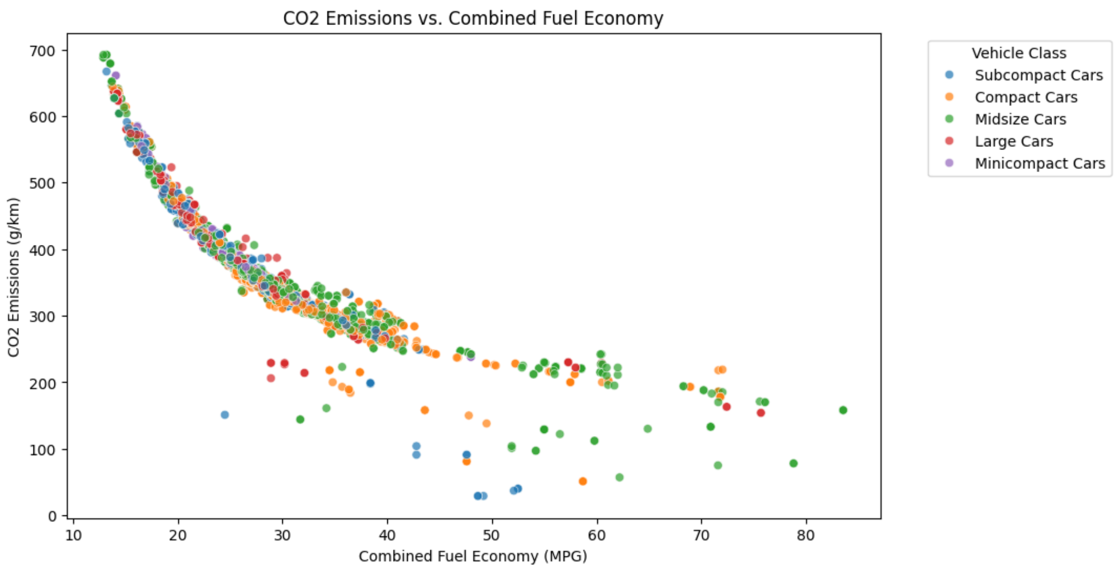
- i- Efficiency vs. Emissions
- ii- Engine Displacement vs. Fuel Economy.
- iii- Vehicle Class Comparison
- ix- Manufacturers' Performance

- x- Correlation Between Features

7.1 i- Efficiency vs. Emissions

- Understanding how fuel efficiency metrics (e.g., city, highway, combined MPG) correlate with CO2 emissions across different vehicle classes

[21]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='UCity', y='co2', hue='VClass', alpha=0.7)
plt.title('CO2 Emissions vs. Combined Fuel Economy')
plt.xlabel('Combined Fuel Economy (MPG)')
plt.ylabel('CO2 Emissions (g/km)')

plt.legend(title='Vehicle Class', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

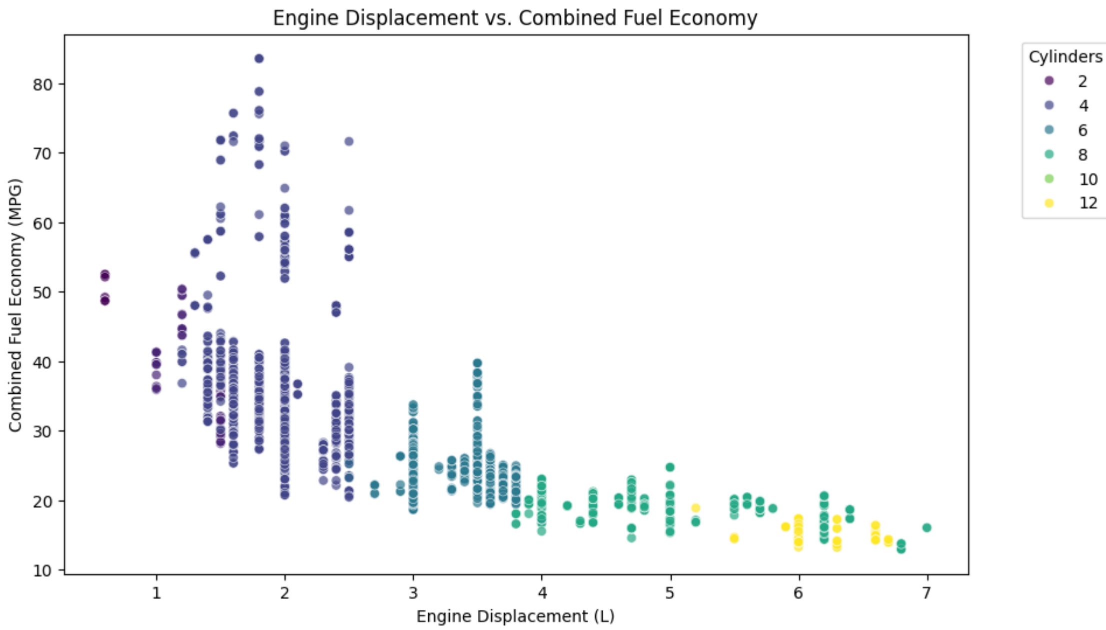


7.2 ii- Engine Displacement vs. Fuel Economy.

- Analyzing how engine displacement and the number of cylinders affect fuel economy and emissions

[22]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='displ', y='UCity', hue='cylinders',␣
↪palette='viridis', alpha=0.7)
plt.title('Engine Displacement vs. Combined Fuel Economy')
plt.xlabel('Engine Displacement (L)')
plt.ylabel('Combined Fuel Economy (MPG)')

plt.legend(title='Cylinders', bbox_to_anchor=(1.05, 1), loc='upper left')
```

```
plt.show()
```

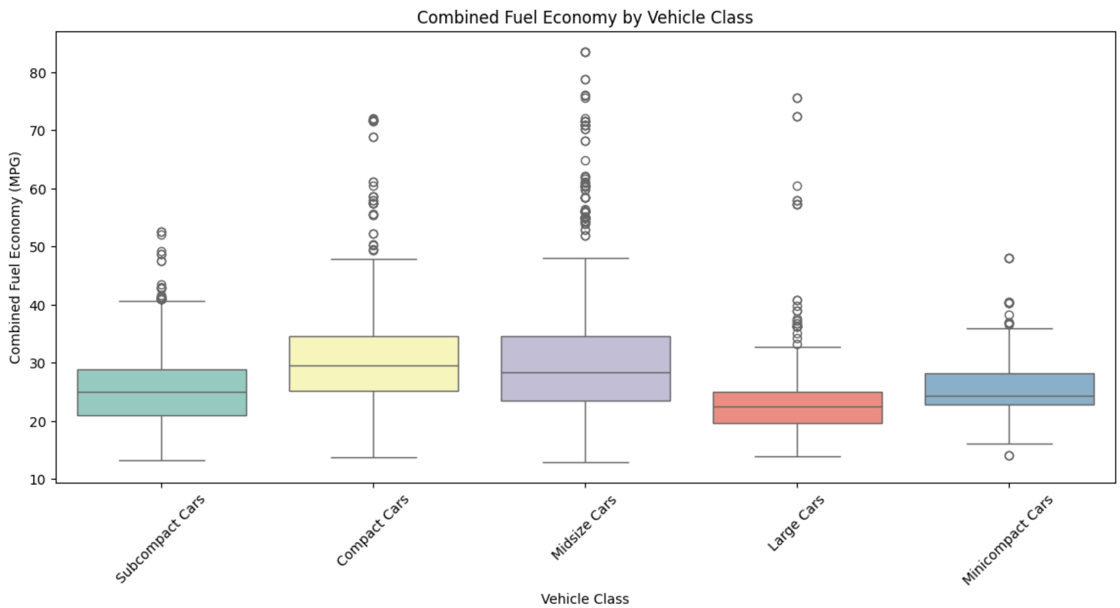


7.3 iii- Combined Fuel Economy by Vehicle Class

- Identifying which vehicle classes tend to be more fuel-efficient or emit less CO2

[23]:
```
plt.figure(figsize=(14, 6))
sns.boxplot(data=df, x='VClass', y='UCity', palette='Set3')
plt.title('Combined Fuel Economy by Vehicle Class')
plt.xlabel('Vehicle Class')
plt.ylabel('Combined Fuel Economy (MPG)')

plt.xticks(rotation=45)
plt.show()
```

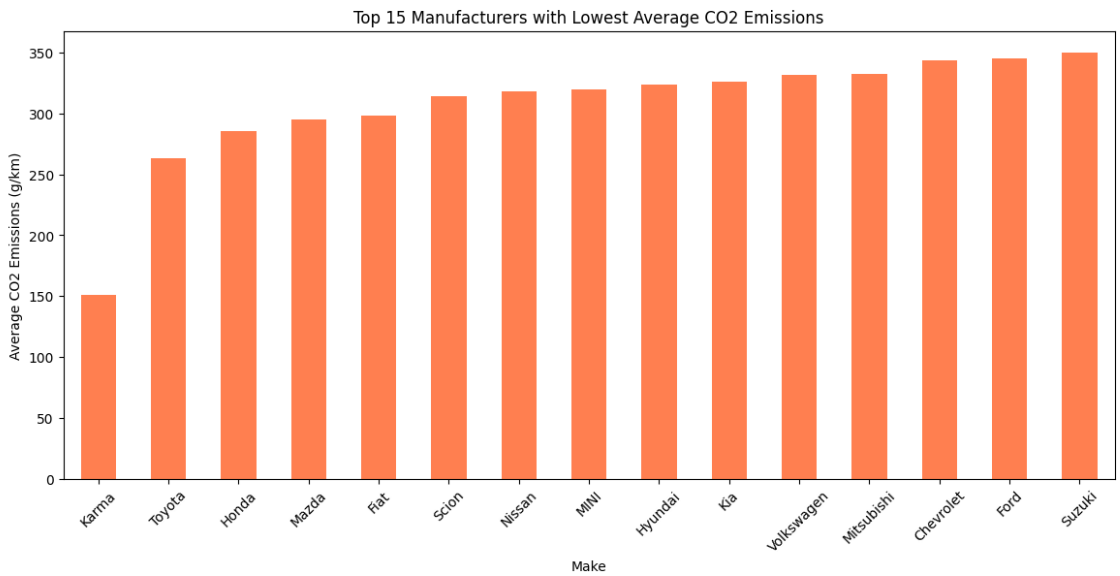
```
<ipython-input-23-565b49f661ae>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='VClass', y='UCity', palette='Set3')
```



7.4 iv- Manufacturers' Performance:

- Comparing fuel economy and emissions across different manufacturers to see if some consistently perform better or worse.

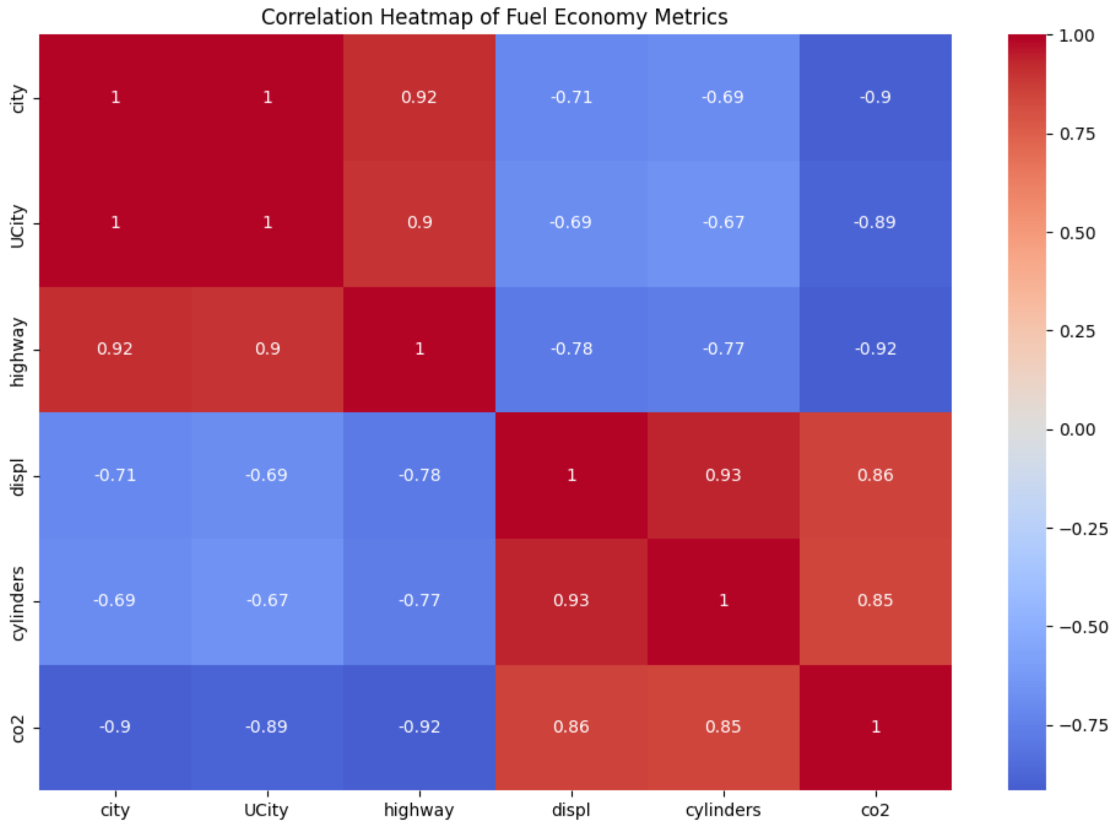
[24]:
```
# Average CO2 emissions by make
avg_co2_by_make = df.groupby('make')['co2'].mean().sort_values()

plt.figure(figsize=(14, 6))
avg_co2_by_make.head(15).plot(kind='bar', color='coral')
plt.title('Top 15 Manufacturers with Lowest Average CO2 Emissions')
plt.xlabel('Make')
plt.ylabel('Average CO2 Emissions (g/km)')
plt.xticks(rotation=45)
plt.show()
```



7.5 v- Correlation Between Features

- Identifying the relationships between numeric variables like CO2, combined MPG, engine size, and cylinders.

[25]:
```
plt.figure(figsize=(12, 8))
corr = df[['city', 'UCity', 'highway', 'displ', 'cylinders', 'co2']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap of Fuel Economy Metrics')
plt.show()
```


Correlation Heatmap of Fuel Economy Metrics
city
UCity
highway
displ
cylinders
co2
1
1
0.92
-0.71
-0.69
-0.9
1
1
0.9
-0.69
-0.67
-0.89
0.92
0.9
1
-0.78
-0.77
-0.92
-0.71
-0.69
-0.78
1
0.93
0.86
-0.69
-0.67
-0.77
0.93
1
0.85
-0.9
-0.89
-0.92
0.86
0.85
1
city
UCity
highway
displ
cylinders
co2
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75