Importing Libraries

In [6]:
```
!pip install plotly
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import math
import plotly.express as px
import itertools
```

```
Collecting plotly
  Downloading plotly-5.14.1-py2.py3-none-any.whl (15.3 MB)
     |████████████████████████████████| 15.3 MB 10.8 MB/s eta 0:00:01
Collecting tenacity>=6.2.0
  Downloading tenacity-8.2.2-py3-none-any.whl (24 kB)
Requirement already satisfied: packaging in ./opt/anaconda3/lib/python3.
9/site-packages (from plotly) (21.0)
Requirement already satisfied: pyparsing>=2.0.2 in ./opt/anaconda3/lib/py
thon3.9/site-packages (from packaging->plotly) (3.0.4)
Installing collected packages: tenacity, plotly
Successfully installed plotly-5.14.1 tenacity-8.2.2
```

Importing the data

In [147]:
```
df = pd.read_csv("https://raw.githubusercontent.com/DrUzair/MLSD/master/Dat
```

```
/Users/ketakikolhatkar/opt/anaconda3/lib/python3.9/site-packages/IPython/
core/interactiveshell.py:3444: DtypeWarning:

Columns (73,74,76) have mixed types.Specify dtype option on import or set
low_memory=False.
```

Checking the columns - features of the data

In [9]:
```
df.columns
```

Out[9]:
```
Index(['barrels08', 'barrelsA08', 'charge120', 'charge240', 'city08',
       'city08U', 'cityA08', 'cityA08U', 'cityCD', 'cityE', 'cityUF', 'co
2',
       'co2A', 'co2TailpipeAGpm', 'co2TailpipeGpm', 'comb08', 'comb08U',
       'combA08', 'combA08U', 'combE', 'combinedCD', 'combinedUF', 'cylin
ders',
       'displ', 'drive', 'engId', 'eng_dscr', 'feScore', 'fuelCost08',
       'fuelCostA08', 'fuelType', 'fuelType1', 'ghgScore', 'ghgScoreA',
       'highway08', 'highway08U', 'highwayA08', 'highwayA08U', 'highwayC
D',
       'highwayE', 'highwayUF', 'hlv', 'hpv', 'id', 'lv2', 'lv4', 'make',
       'model', 'mpgData', 'phevBlended', 'pv2', 'pv4', 'range', 'rangeCi
ty',
       'rangeCityA', 'rangeHwy', 'rangeHwyA', 'trany', 'UCity', 'UCityA',
       'UHighway', 'UHighwayA', 'VClass', 'year', 'youSaveSpend', 'guzzle
r',
       'trans_dscr', 'tCharger', 'sCharger', 'atvType', 'fuelType2', 'ran
geA',
       'evMotor', 'mfrCode', 'c240Dscr', 'charge240b', 'c240bDscr',
       'createdOn', 'modifiedOn', 'startStop', 'phevCity', 'phevHwy',
       'phevComb'],
      dtype='object')
```

Describing the dependent feature UCity

In [10]:
```
df['UCity'].describe()
```

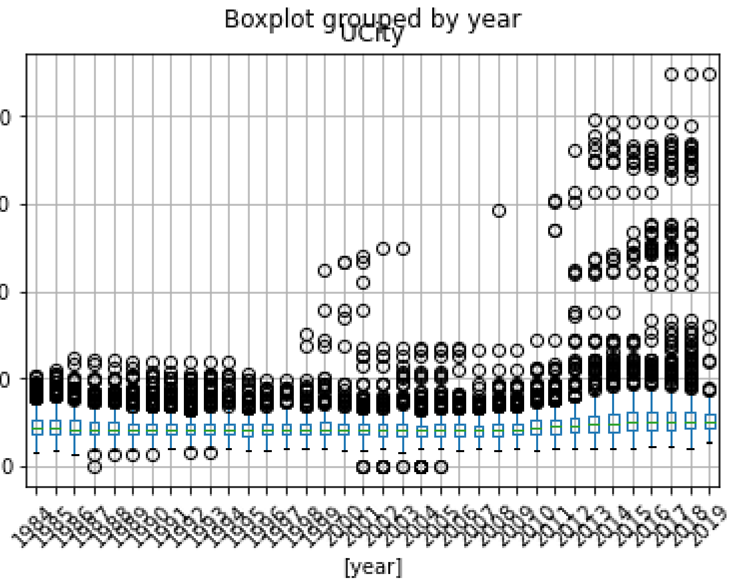
Out[10]:
```
count    40081.000000
mean        22.981798
std         10.473444
min          0.000000
25%         18.110500
50%         21.296500
75%         25.700000
max        224.800000
Name: UCity, dtype: float64
```

The Dependent Variable

Box plot of the UCity column over the years

In [11]:
```
df.boxplot(column=['UCity'], by=['year'], rot=45)
```

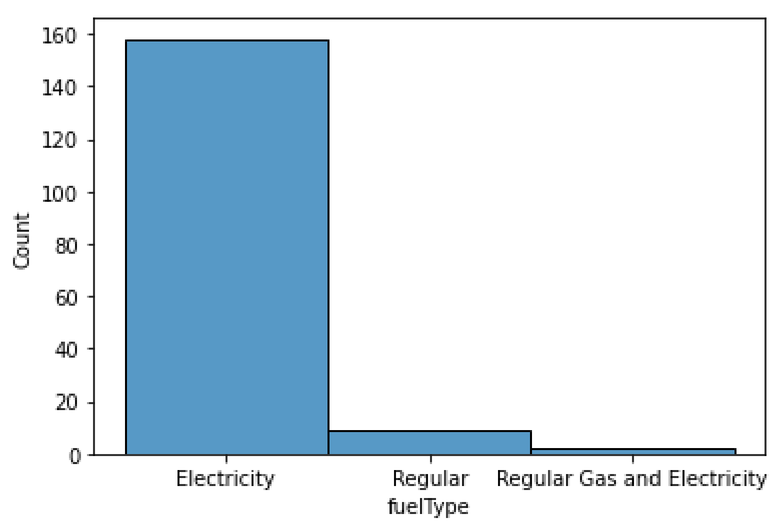
Out[11]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Distribution of fuelType by count when UCity is greater than 75

In [12]:
```
# filtering the UCity greater than 75 and plotting that against the vehicle

df1 = df[df['UCity'] > 75]
sns.histplot(data = df1, x = df1['fuelType'])
```

Out[12]: <AxesSubplot:xlabel='fuelType', ylabel='Count'>



Zero UCity vehicles

In [13]:
```
df['UCity'].value_counts()[0]
```

Out[13]: 25

Columns where the UCity value is zero

In [14]:
```
df3 = df[df['UCity'] == 0]
df3[['make', 'model', 'fuelType']]
```

Out[14]:

	make	model	fuelType
8127	Ford	F150 Dual-fuel 2WD (CNG)	Gasoline or natural gas
8128	Ford	F150 Dual-fuel 4WD (CNG)	Gasoline or natural gas
8129	Ford	F150 Dual-fuel 2WD (LPG)	Gasoline or propane
8130	Ford	F150 Dual-fuel 4WD (LPG)	Gasoline or propane
9174	Dodge	Ram Van 2500 2WD CNG	CNG
9175	Dodge	Ram Wagon 2500 2WD CNG	CNG
9183	Ford	F150 Dual-fuel 2WD (CNG)	Gasoline or natural gas
9184	Ford	F150 Dual-fuel 4WD (CNG)	Gasoline or natural gas
9185	Ford	F150 Dual-fuel 2WD (LPG)	Gasoline or propane
9186	Ford	F150 Dual-fuel 4WD (LPG)	Gasoline or propane
10282	Ford	F150 Dual-fuel 2WD (LPG)	Gasoline or propane
10283	Ford	F150 Dual-fuel 4WD (LPG)	Gasoline or propane
11584	Ford	F150 Dual-fuel 2WD (LPG)	Gasoline or propane
11585	Ford	F150 Dual-fuel 4WD (LPG)	Gasoline or propane
11586	Chevrolet	Express Cargo (Bi-fuel)	Gasoline or natural gas
11587	Chevrolet	Express Passenger (Bi-fuel)	Gasoline or natural gas
11588	GMC	Savana (cargo) (Bi-fuel)	Gasoline or natural gas
11589	GMC	Savana Passenger (Bi-fuel)	Gasoline or natural gas
11591	Chevrolet	Express Cargo (dedicated CNG)	CNG
11592	Chevrolet	Express Passenger (dedicated CNG)	CNG
11593	GMC	Savana Cargo (dedicated CNG)	CNG
11594	GMC	Savana Passenger (dedicated CNG)	CNG
12814	Dodge	Caravan/Grand Caravan 2WD	Gasoline or E85
12815	Chrysler	Voyager/Town and Country 2WD	Gasoline or E85
21505	Porsche	924 S	Regular

The Independent Variables

1. Numeric feature: atvType

In [17]:
```
df['atvType'].describe()
```

Out[17]:
```
count      3374
unique        8
top         FFV
freq       1412
Name: atvType, dtype: object
```

Checking the total number of vehicles for each type of atvType

In [18]:
```
df4 = df[['atvType']]
df4.groupby(['atvType'])['atvType'].count()
```

Out[18]:
```
atvType
Bifuel (CNG)          20
Bifuel (LPG)           8
CNG                   50
Diesel              1070
EV                   168
FFV                 1412
Hybrid               539
Plug-in Hybrid       107
Name: atvType, dtype: int64
```

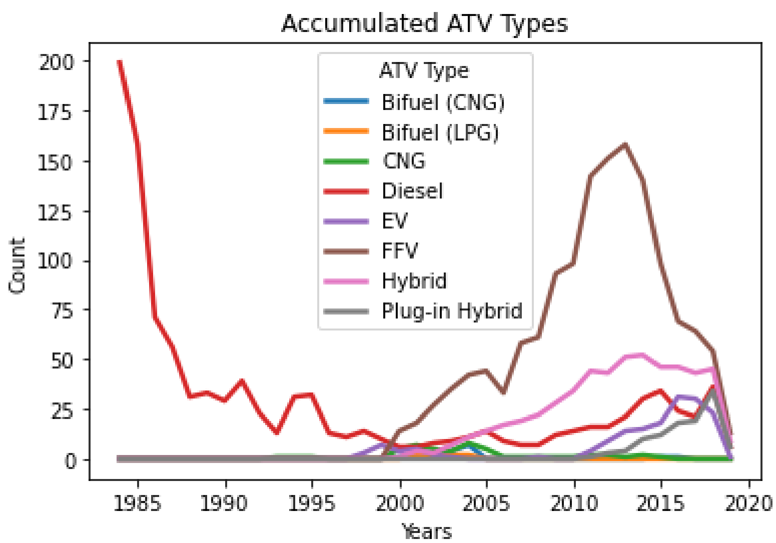
Checking the total number of Nan values is the atvType column

In [19]:
```
df4['atvType'].isna().sum()
```

Out[19]:
```
36707
```

Line Graph of the atvType over the years

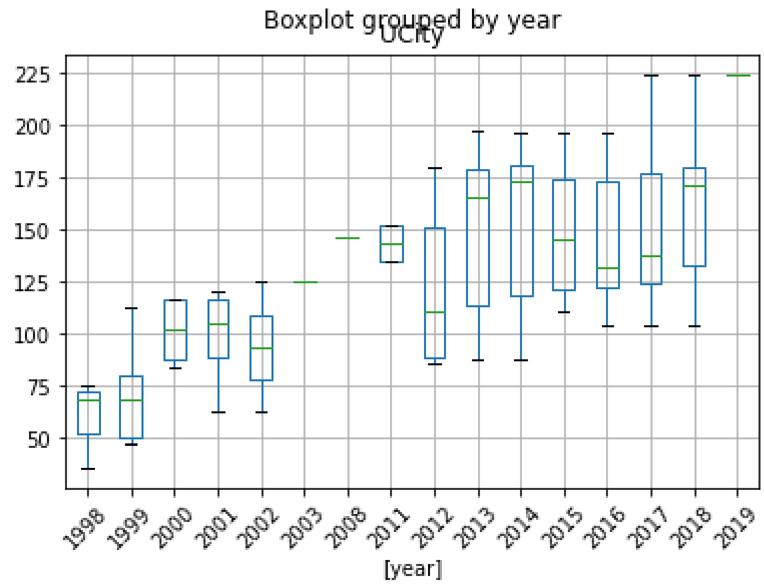
In [27]:
```
df_year_atvtype = pd.DataFrame()
df_year_atvtype['Years'] = df['year']
df_year_atvtype['atvType'] = df['atvType']
# Drop the rows where 'atvType' is NaN
df_year_atvtype_notna = df_year_atvtype.dropna(subset=['atvType'])
# Accumulate ATV types individually according to years
accumulated_types = df_year_atvtype_notna.groupby('Years')['atvType'].value
# Filter out the values that are zero
accumulated_types = accumulated_types[accumulated_types.sum(axis=1) != 0]
for column in accumulated_types.columns:
    plt.plot(accumulated_types.index, accumulated_types[column], label=colu
plt.title('Accumulated ATV Types')
plt.xlabel('Years')
plt.ylabel('Count')
plt.legend(title='ATV Type')
plt.show()
```



Box plot of EV over the years

In [28]:
```
df6 = df[['year', 'atvType', 'UCity']]
df6 = df6[df6['atvType'] == 'EV']
df6.boxplot(column=['UCity'], by=['year'], rot=45)
```

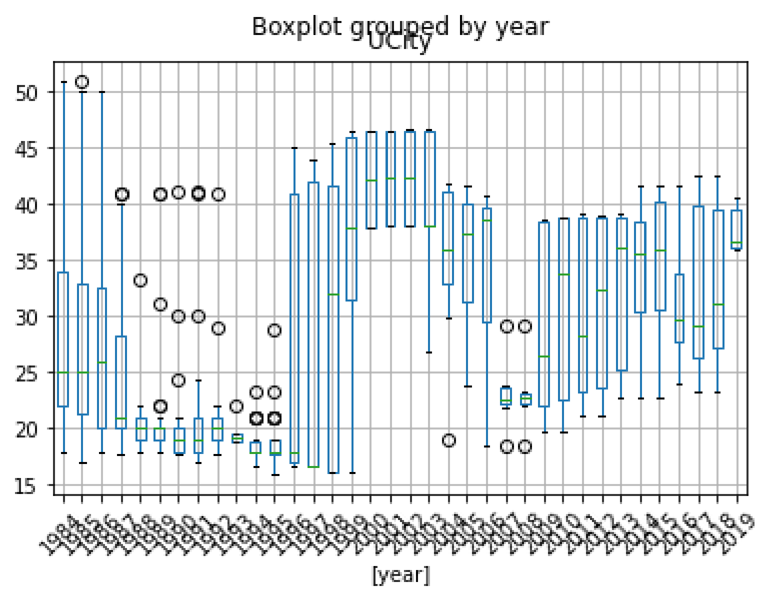
Out[28]:
```
<AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>
```



Box Plot of Diesel vehicles over the years

In [29]:
```
df7 = df[['year', 'atvType', 'UCity']]
df7 = df7[df7['atvType'] == 'Diesel']
df7.boxplot(column=['UCity'], by=['year'], rot=45)
```

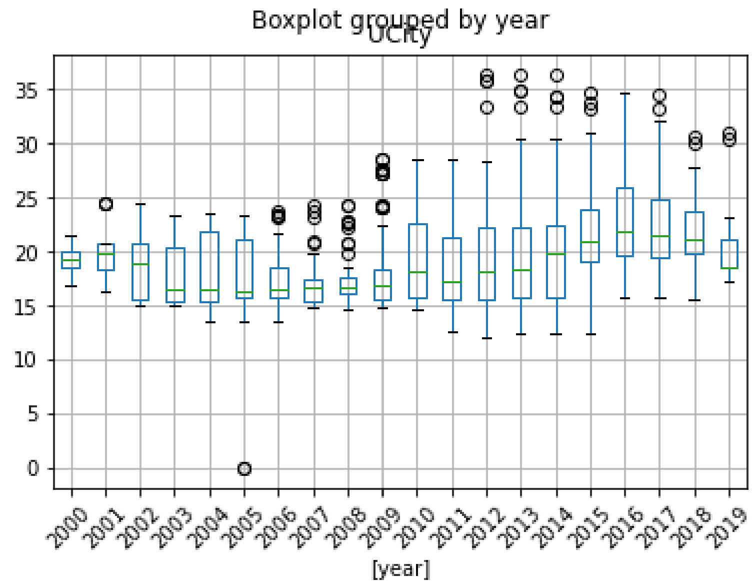
Out[29]:
```
<AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>
```



Box Plot of FFV vehicles over the years

In [30]:
```
df8 = df[['year', 'atvType', 'UCity']]
df8 = df8[df8['atvType'] == 'FFV']
df8.boxplot(column=['UCity'], by=['year'], rot=45)
```

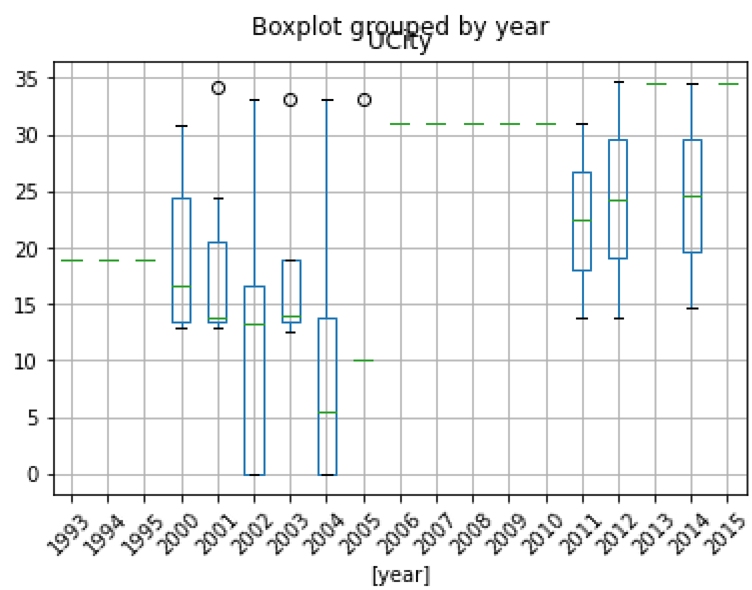
Out[30]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box Plot of CNG vehicles over the years

In [32]:
```
df10 = df[['year', 'atvType', 'UCity']]
df10 = df10[df10['atvType'] == 'CNG']
df10.boxplot(column=['UCity'], by=['year'], rot=45)
```

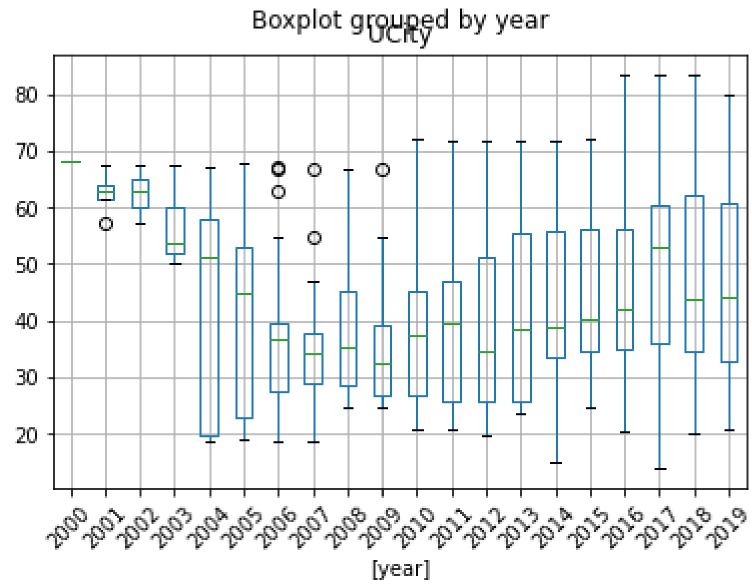
Out[32]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box Plot of Hybrid vehicles over the years

In [33]:
```
df11 = df[['year', 'atvType', 'UCity']]
df11 = df11[df11['atvType'] == 'Hybrid']
df11.boxplot(column=['UCity'], by=['year'], rot=45)
```

Out[33]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>

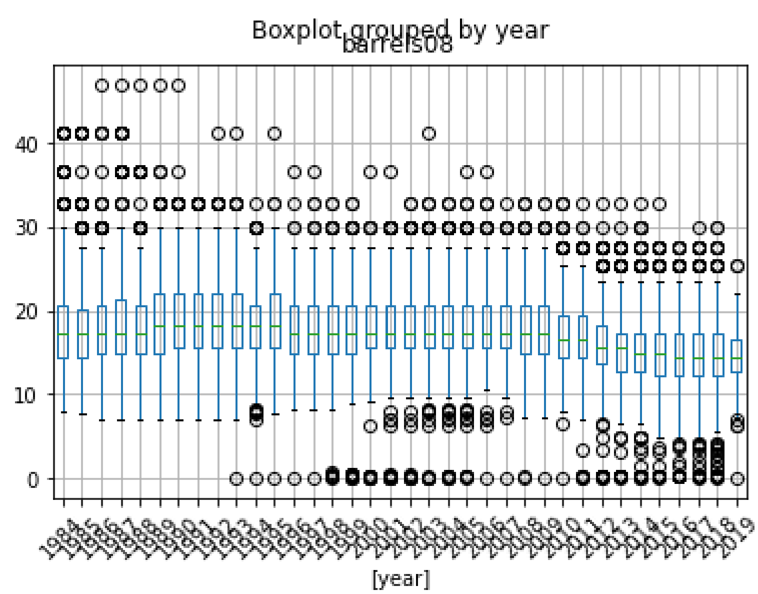


2. Numeric feature: barrelsA08

Box Plot of barrelsA08 over the years

In [34]:
```
df.boxplot(column=['barrels08'], by=['year'], rot=45)
```

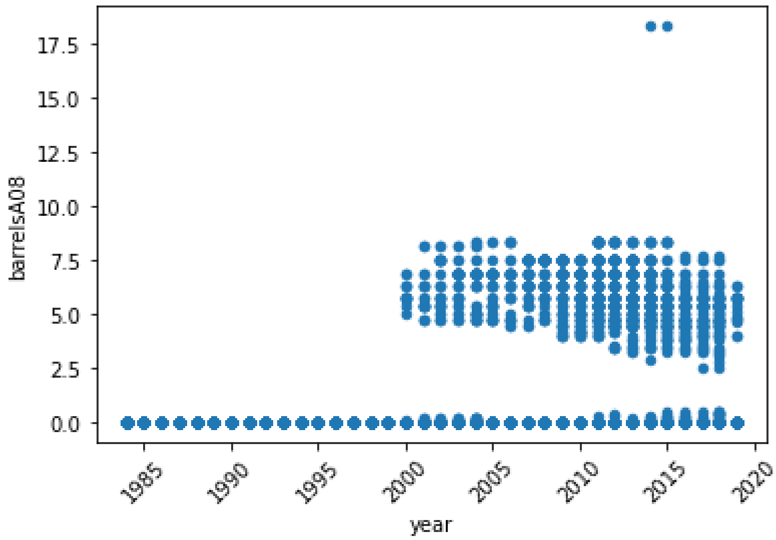
Out[34]: <AxesSubplot:title={'center':'barrels08'}, xlabel='[year]'>



Scatter Plot of barrelsA08 over the years

In [35]:
```
df.plot.scatter(x = 'year', y = 'barrelsA08', rot=45)
```

Out[35]:
```
<AxesSubplot:xlabel='year', ylabel='barrelsA08'>
```



3. Numeric feature: chargeXXXX

Describing the feature

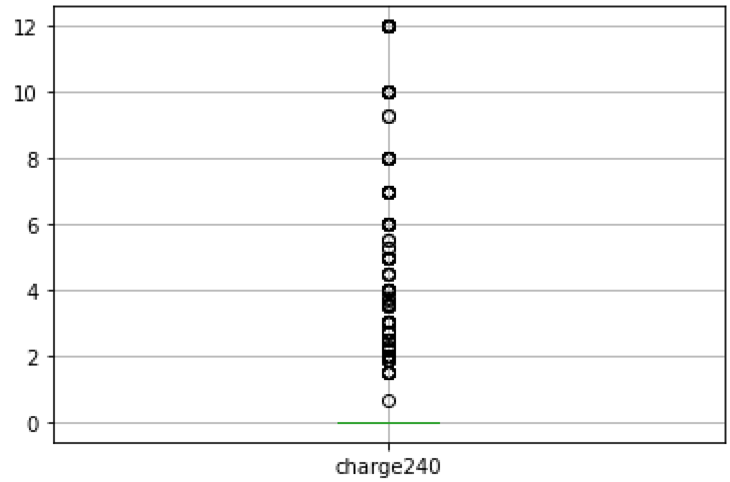
In [36]:
```
df['charge240'].describe()
```

Out[36]:
```
count    40081.000000
mean         0.036086
std          0.534894
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max         12.000000
Name: charge240, dtype: float64
```

Scatter plot of charge240

In [37]:
```
df.boxplot(column=['charge240'])
```

Out[37]: <AxesSubplot:>



All non-EVs having zero value for this charge240

In [44]:
```
df16 = df['charge240'].value_counts()
total = df16[df16.index != 0].sum()
total
```

Out[44]: 252

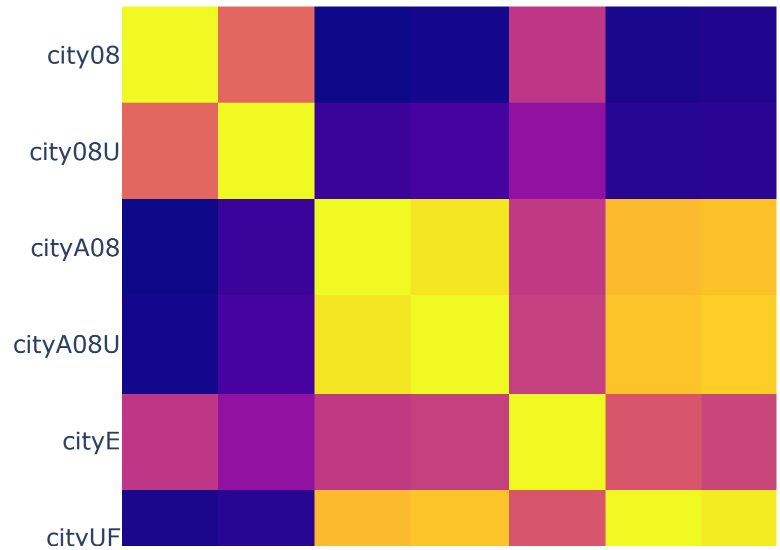
All non-EVs having zero value for this charge240b

In [45]:
```
df16 = df['charge240b'].value_counts()
total = df16[df16.index != 0].sum()
total
```

Out[45]: 62

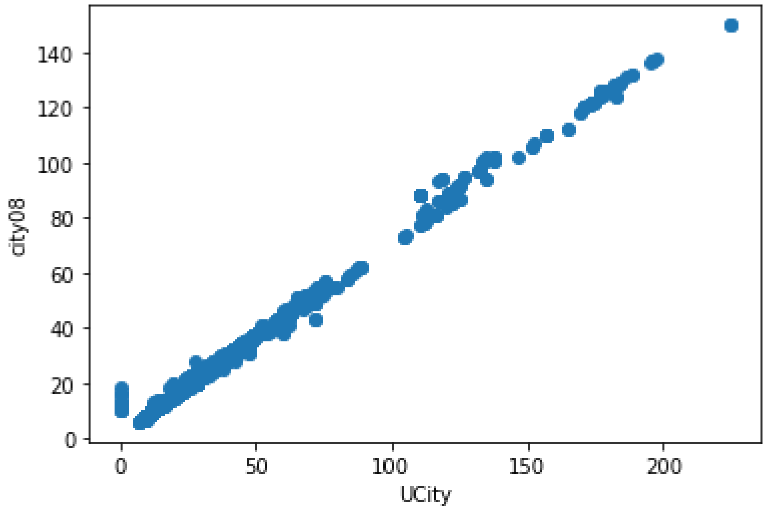
4. Numeric feature: cityXXXX

In [46]:
```
df17 = df[['city08', 'city08U', 'cityA08', 'cityA08U', 'cityE', 'cityUF', '
fig = px.imshow(df17.corr())
fig.show()
```



Scatter plot of city08 vs UCity

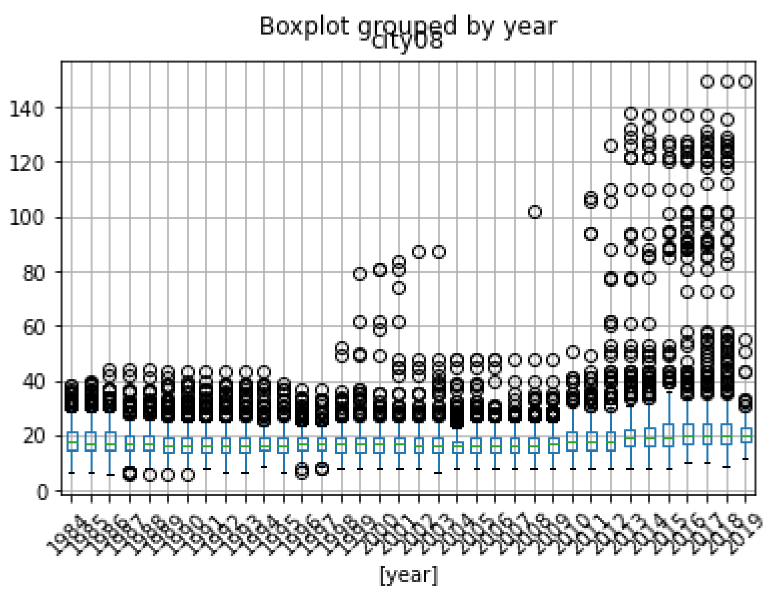
In [47]:
```
plt.scatter(df['UCity'], df['city08'])
plt.xlabel('UCity')
plt.ylabel('city08')
plt.show()
```



Box Plot of city08 every year

In [48]:
```
df.boxplot(column=['city08'], by=['year'], rot=45)
```

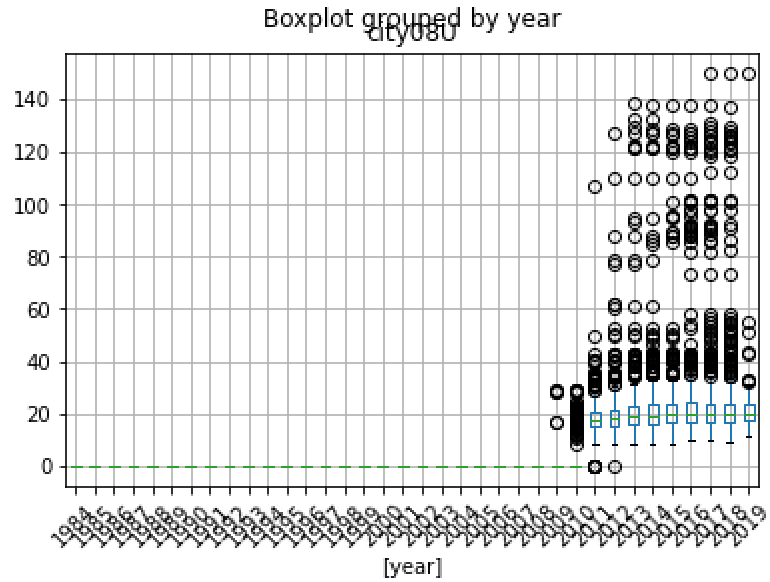
Out[48]:
```
<AxesSubplot:title={'center':'city08'}, xlabel='[year]'>
```



Box Plot of city08U per year

In [49]:
```
df.boxplot(column=['city08U'], by=['year'], rot=45)
```

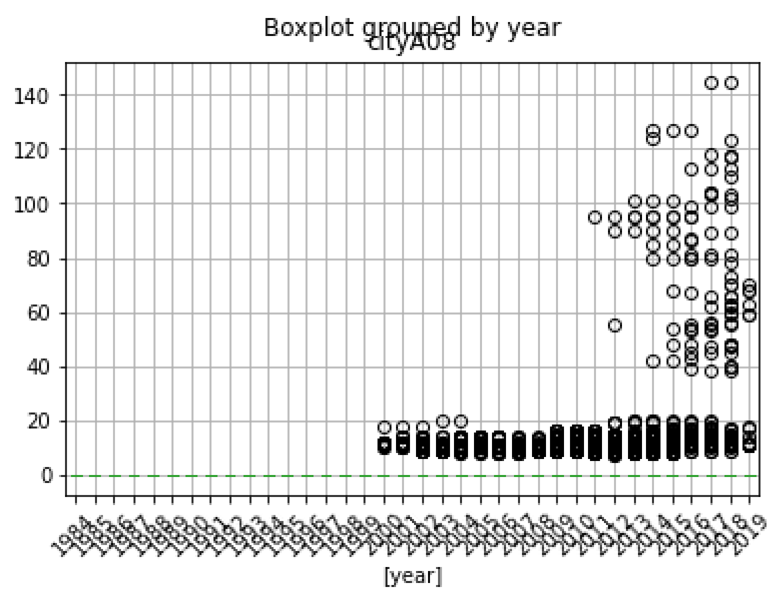
Out[49]: `<AxesSubplot:title={'center':'city08U'}, xlabel='[year]'>`



Box Plot of cityA08 per year

In [50]:
```
df.boxplot(column=['cityA08'], by=['year'], rot=45)
```

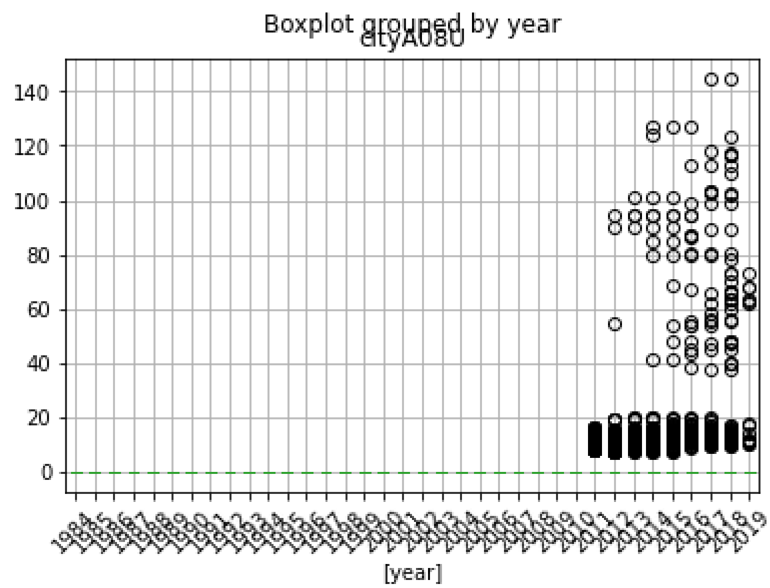
Out[50]: `<AxesSubplot:title={'center':'cityA08'}, xlabel='[year]'>`



Box Plot of cityA08U per year

In [51]:
```
df.boxplot(column=['cityA08U'], by=['year'], rot=45)
```

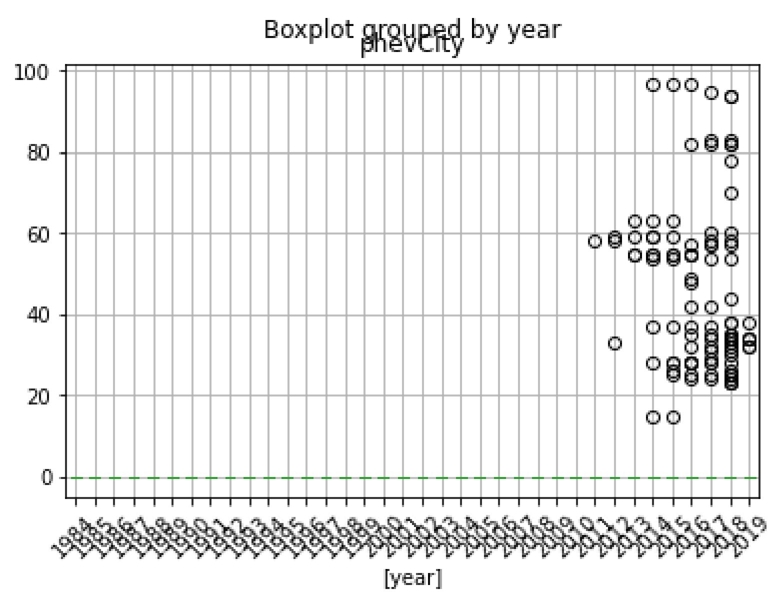
Out[51]: <AxesSubplot:title={'center':'cityA08U'}, xlabel='[year]'>



Box Plot of phevCity per year

In [52]:
```
df.boxplot(column=['phevCity'], by=['year'], rot=45)
```

Out[52]: <AxesSubplot:title={'center':'phevCity'}, xlabel='[year]'>



5. Numeric feature: co2XXXX

Vehicles that don't have co2 information

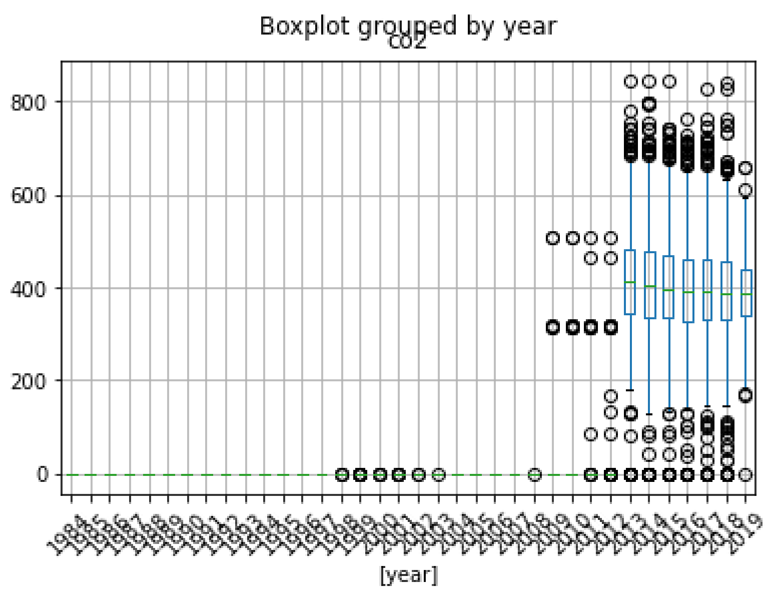
In [53]:
```
df18 = df[df['co2'] == -1]
df18.shape
```

Out[53]: (31954, 83)

Box plot of co2 against the years

In [54]:
```
df.boxplot(column=['co2'], by=['year'], rot=45)
```

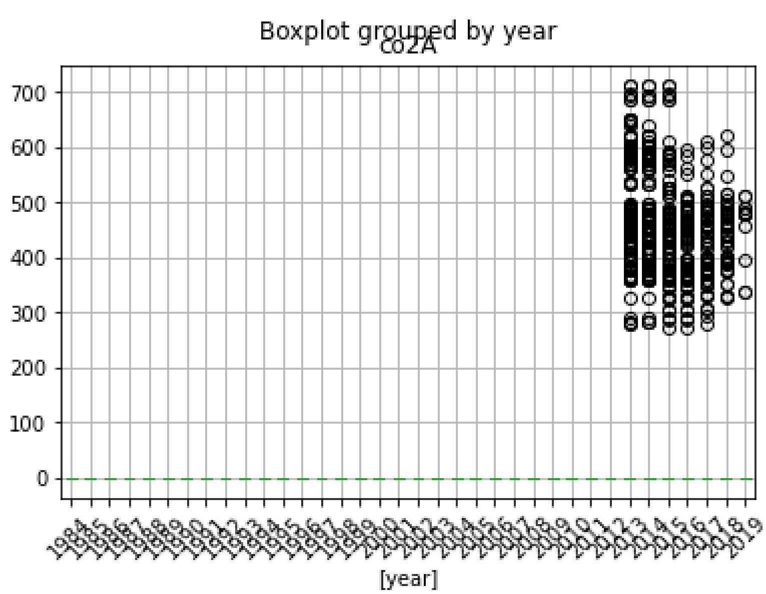
Out[54]: <AxesSubplot:title={'center':'co2'}, xlabel='[year]'>



Box plot of co2A against the years

In [55]:
```
df.boxplot(column=['co2A'], by=['year'], rot=45)
```

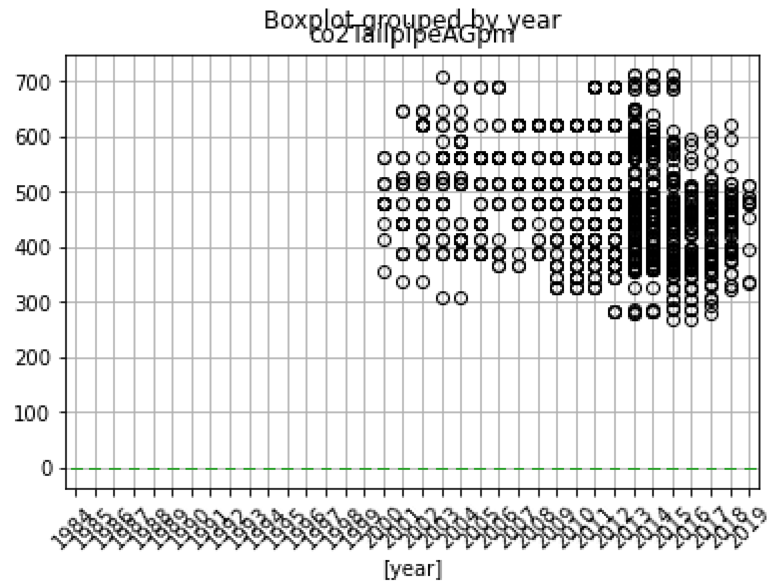
Out[55]: <AxesSubplot:title={'center':'co2A'}, xlabel='[year]'>



Box plot of co2TailpipeAGpm against the years

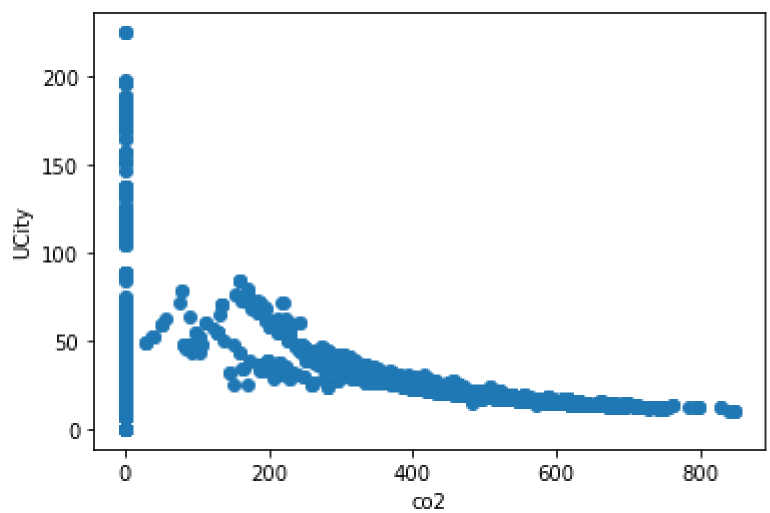
In [56]:
```
df.boxplot(column=['co2TailpipeAGpm'], by=['year'], rot=45)
```

Out[56]:
```
<AxesSubplot:title={'center':'co2TailpipeAGpm'}, xlabel='[year]'>
```



Scatter plot between co2 and UCity

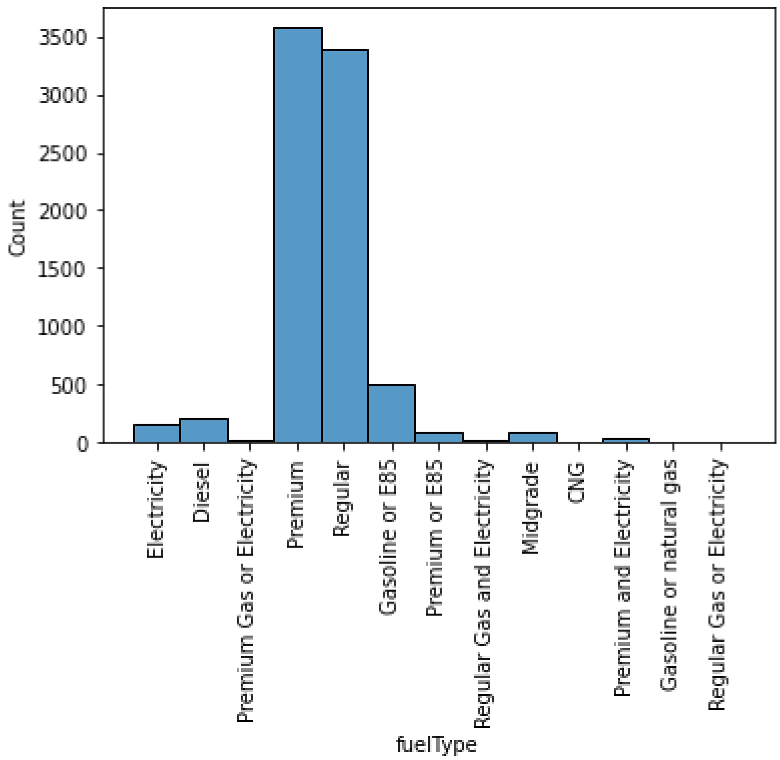
In [57]:
```
plt.scatter(df['co2'], df['UCity'])
plt.xlabel('co2')
plt.ylabel('UCity')
plt.show()
```



Histogram of vehicles with the co2 information

In [58]:
```
df19 = df[df['co2'] != -1]
df19.groupby('fuelType')['fuelType'].size()
plt.xticks(rotation=90)
sns.histplot(data = df19, x = df19['fuelType'])
```

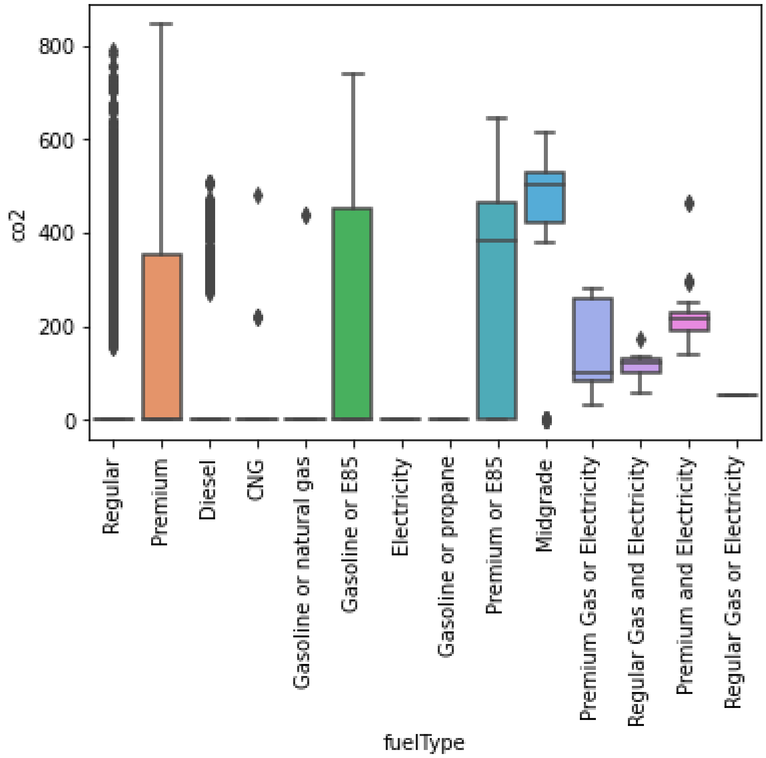
Out[58]:
```
<AxesSubplot:xlabel='fuelType', ylabel='Count'>
```



Box plots of vehicles vs the co2 emission

In [59]:
```
plt.xticks(rotation=90)
sns.boxplot(data=df, x='fuelType', y='co2')
```

Out[59]: <AxesSubplot:xlabel='fuelType', ylabel='co2'>



6. Numeric feature: cylinders

Describing the column

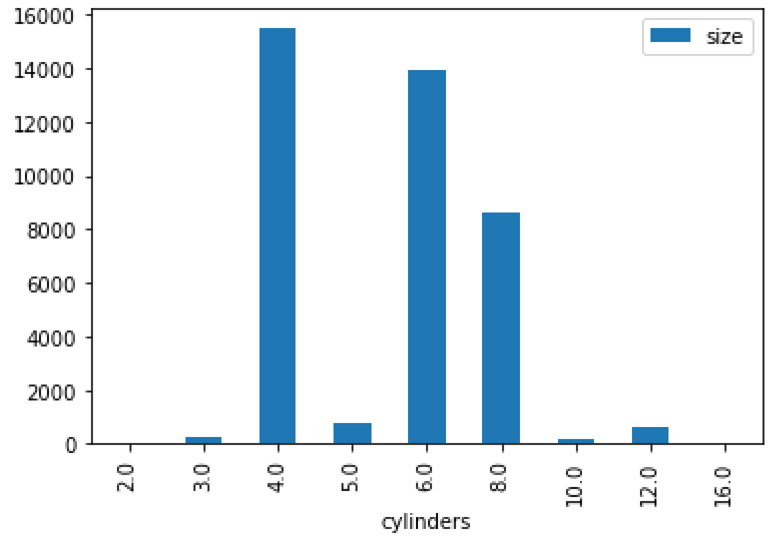
In [60]:
```
df['cylinders'].describe()
```

Out[60]:
```
count    39910.000000
mean         5.721949
std          1.754891
min          2.000000
25%          4.000000
50%          6.000000
75%          6.000000
max         16.000000
Name: cylinders, dtype: float64
```

Histogram of cylinders

In [61]:
```
df20 = df.groupby('cylinders', as_index = False)['cylinders'].size()
df20.plot(x="cylinders", y=["size"], kind="bar")
```

Out[61]: <AxesSubplot:xlabel='cylinders'>



Correlation matrix of UCity and Cylinders

In [62]:
```
df21 = df[['UCity', 'cylinders']]
df21.corr()
```

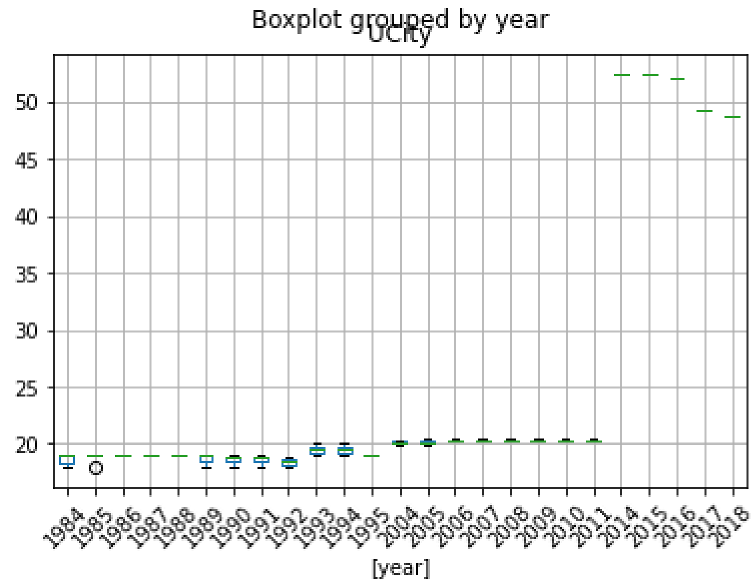
Out[62]:

	UCity	cylinders
UCity	1.000000	-0.679927
cylinders	-0.679927	1.000000

2 Cylinder Vehicles

In [63]:
```
df22 = df[df['cylinders'] == 2.0]
df22.boxplot(column=['UCity'], by=['year'], rot=45)
```

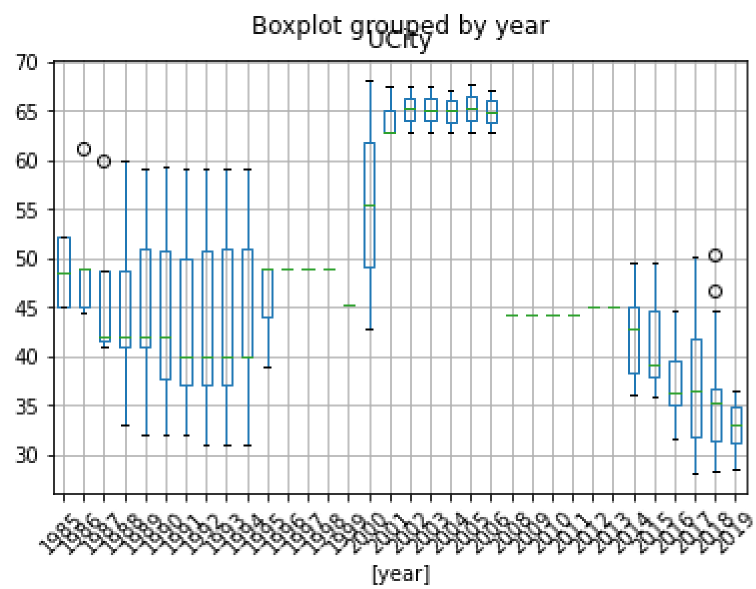
Out[63]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



3 Cylinder Vehicles

In [64]:
```
df23 = df[df['cylinders'] == 3.0]
df23.boxplot(column=['UCity'], by=['year'], rot=45)
```

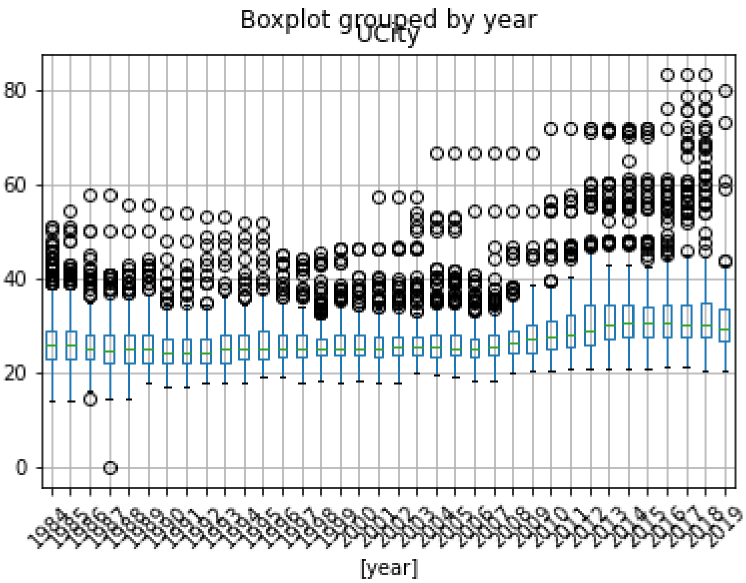
Out[64]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



4 Cylinder Vehicles

In [65]:
```
df24 = df[df['cylinders'] == 4.0]
df24.boxplot(column=['UCity'], by=['year'], rot=45)
```

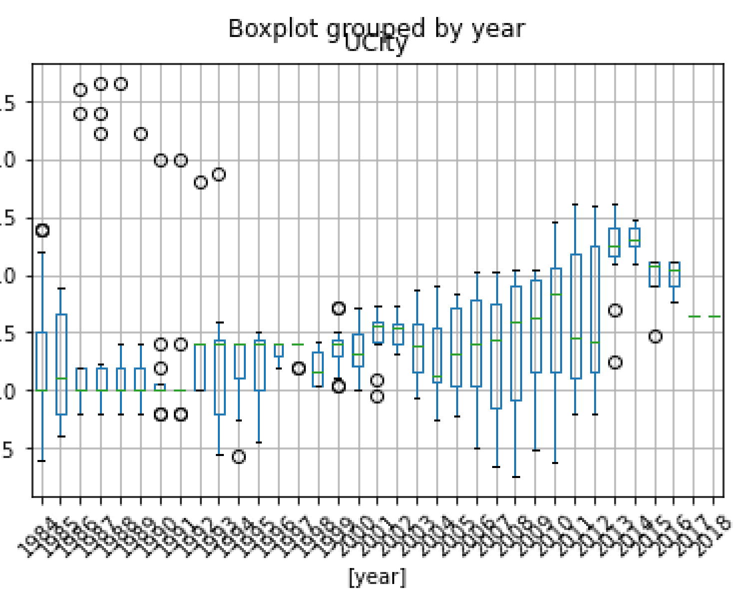
Out[65]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



5 Cylinder Vehicles

In [66]:
```
df25 = df[df['cylinders'] == 5.0]
df25.boxplot(column=['UCity'], by=['year'], rot=45)
```

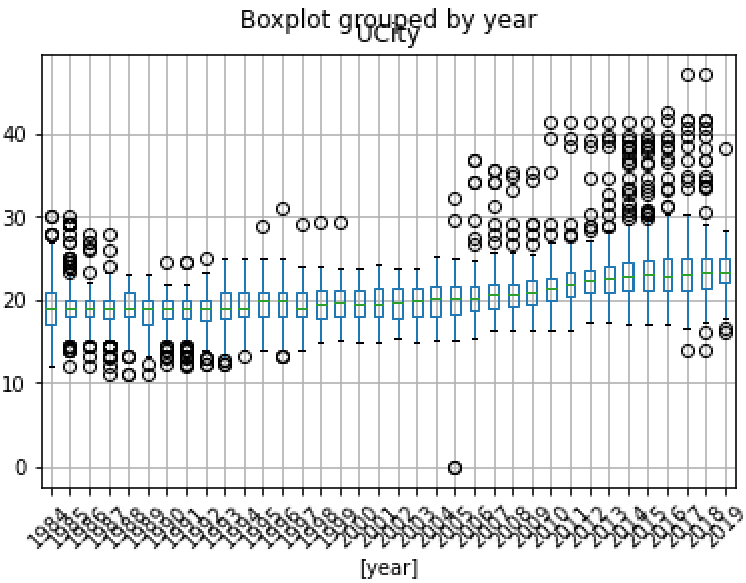
Out[66]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



6 Cylinder Vehicles

In [67]:
```
df26 = df[df['cylinders'] == 6.0]
df26.boxplot(column=['UCity'], by=['year'], rot=45)
```

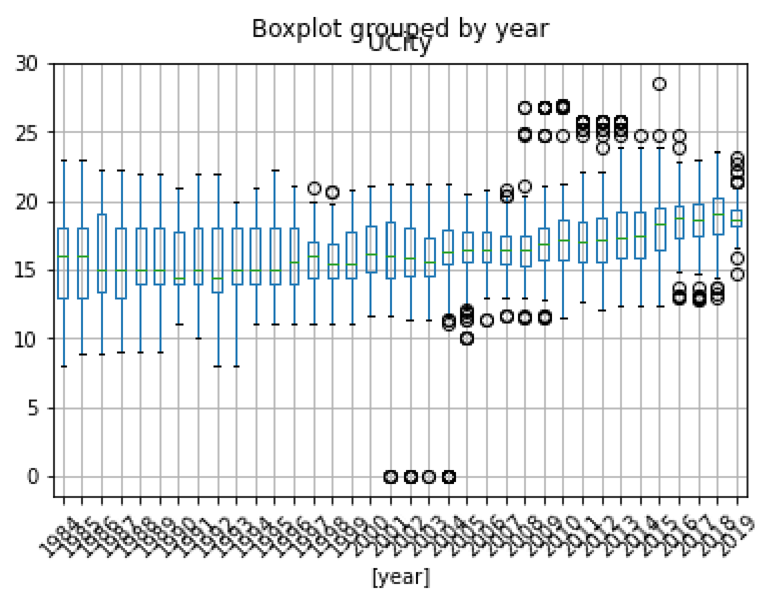
Out[67]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



8 Cylinder Vehicles

In [68]:
```
df27 = df[df['cylinders'] == 8.0]
df27.boxplot(column=['UCity'], by=['year'], rot=45)
```

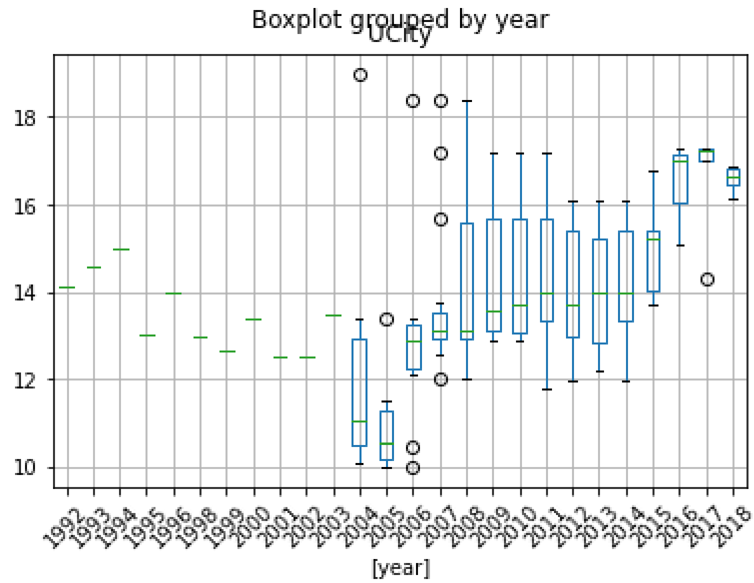
Out[68]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



10 Cylinder Vehicles

In [69]:
```python
df28 = df[df['cylinders'] == 10.0]
df28.boxplot(column=['UCity'], by=['year'], rot=45)
```

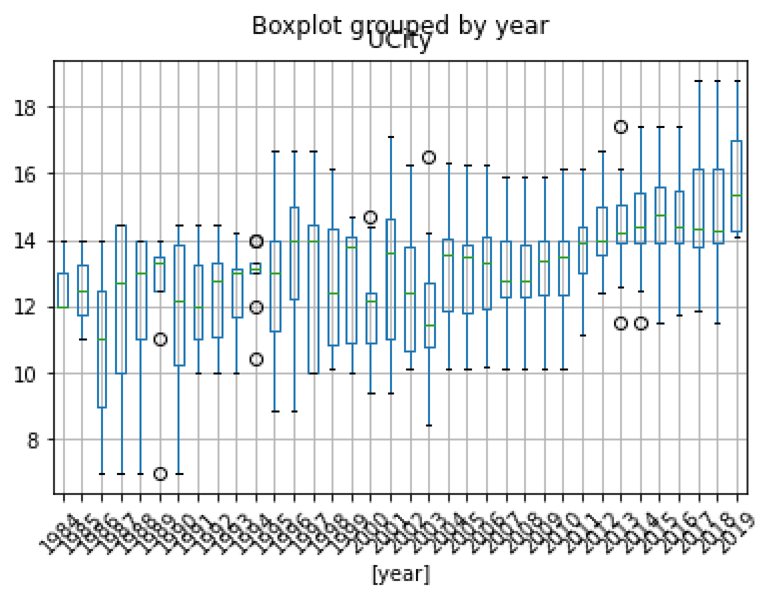
Out[69]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



12 Cylinder Vehicles

In [70]:
```python
df29 = df[df['cylinders'] == 12.0]
df29.boxplot(column=['UCity'], by=['year'], rot=45)
```

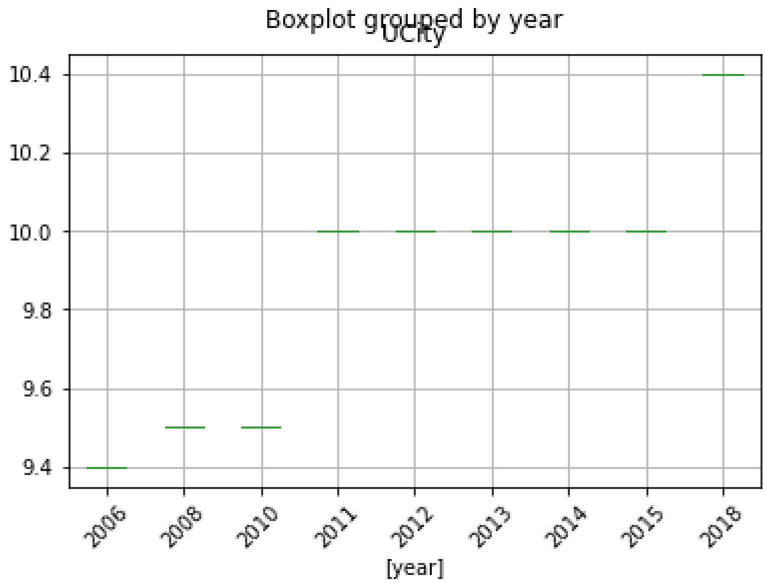
Out[70]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



16 Cylinder Vehicles

In [71]:
```
df30 = df[df['cylinders'] == 16.0]
df30.boxplot(column=['UCity'], by=['year'], rot=45)
```

Out[71]:
```
<AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>
```



7. Numeric feature: displ

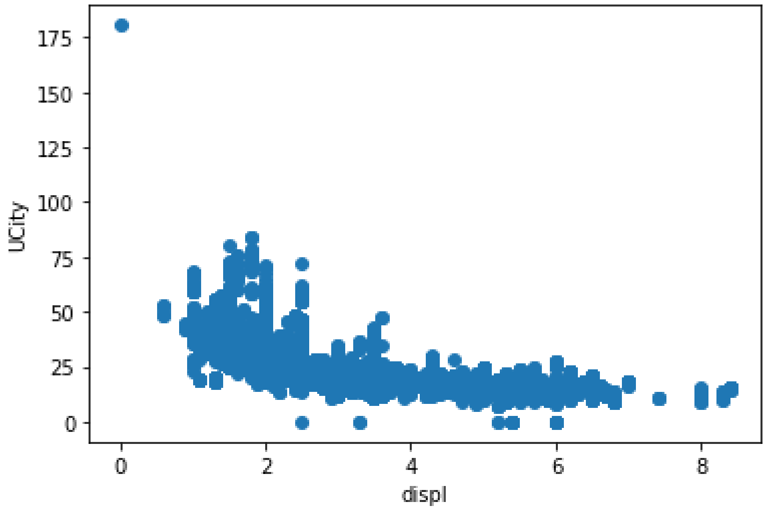
Correlation between UCity and displ

In [72]:
```
df['displ'].corr(df['UCity'])
```

Out[72]:
```
-0.7132493488120356
```

Scatter plot between displ and UCity

In [73]:
```
plt.scatter(df['displ'], df['UCity'])
plt.xlabel('displ')
plt.ylabel('UCity')
plt.show()
```



Correlation between disp_cat and UCity

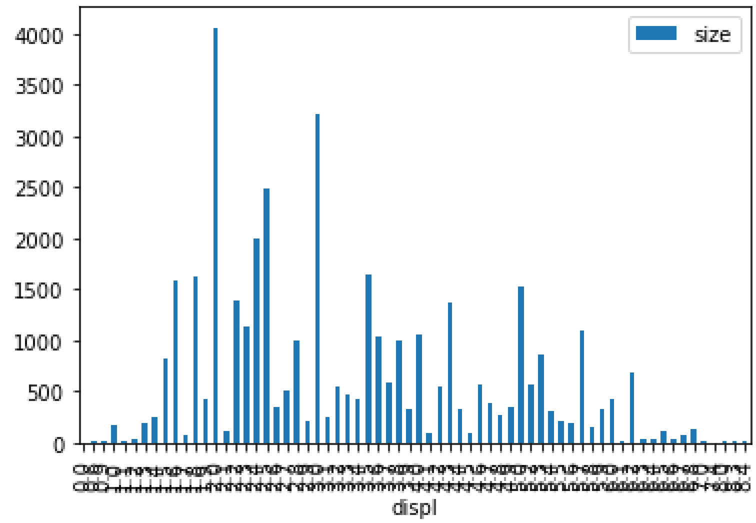
In [74]:
```
df.columns
```

Out[74]:
```
Index(['barrels08', 'barrelsA08', 'charge120', 'charge240', 'city08',
       'city08U', 'cityA08', 'cityA08U', 'cityCD', 'cityE', 'cityUF', 'co
2',
       'co2A', 'co2TailpipeAGpm', 'co2TailpipeGpm', 'comb08', 'comb08U',
       'combA08', 'combA08U', 'combE', 'combinedCD', 'combinedUF', 'cylin
ders',
       'displ', 'drive', 'engId', 'eng_dscr', 'feScore', 'fuelCost08',
       'fuelCostA08', 'fuelType', 'fuelType1', 'ghgScore', 'ghgScoreA',
       'highway08', 'highway08U', 'highwayA08', 'highwayA08U', 'highwayC
D',
       'highwayE', 'highwayUF', 'hlv', 'hpv', 'id', 'lv2', 'lv4', 'make',
       'model', 'mpgData', 'phevBlended', 'pv2', 'pv4', 'range', 'rangeCi
ty',
       'rangeCityA', 'rangeHwy', 'rangeHwyA', 'trany', 'UCity', 'UCityA',
       'UHighway', 'UHighwayA', 'VClass', 'year', 'youSaveSpend', 'guzzle
r',
       'trans_dscr', 'tCharger', 'sCharger', 'atvType', 'fuelType2', 'ran
geA',
       'evMotor', 'mfrCode', 'c240Dscr', 'charge240b', 'c240bDscr',
       'createdOn', 'modifiedOn', 'startStop', 'phevCity', 'phevHwy',
       'phevComb'],
      dtype='object')
```

Histogram of displ category to the vehicle count

In [75]:
```
df31 = df.groupby('displ', as_index = False)['fuelType'].size()
df31.plot(x="displ", y=["size"], kind="bar")
```

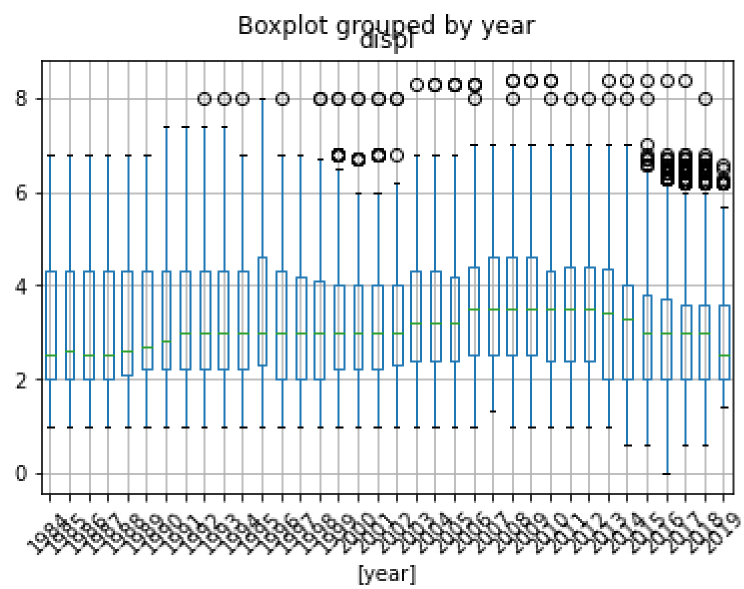
Out[75]: <AxesSubplot:xlabel='displ'>



Box plot of disp_num over the years

In [76]:
```
df.boxplot(column=['displ'], by=['year'], rot=45)
```

Out[76]: <AxesSubplot:title={'center':'displ'}, xlabel='[year]'>



8. Numeric feature: evMotor

In [77]:
```
df34 = df[(df['atvType'] == 'EV') | (df['atvType'] == 'Hybrid') | (df['atvT
df34 = df34['evMotor'].dropna()
df34.shape
```

Out[77]: (736,)

9. Numeric feature: feScore

feScore for post-2012 vehicles

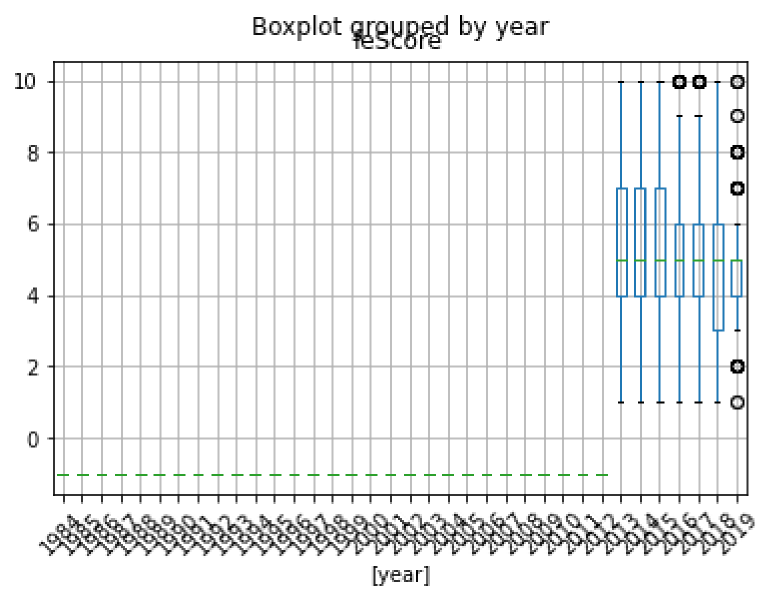
In [78]:
```
df35 = df[df['year'] >= 2012]
df35[df35['feScore'] != -1].shape
```

Out[78]:
```
(8054, 83)
```

Box Plot of feScore over the years

In [79]:
```
df.boxplot(column=['feScore'], by=['year'], rot=45)
```

Out[79]:
```
<AxesSubplot:title={'center':'feScore'}, xlabel='[year]'>
```



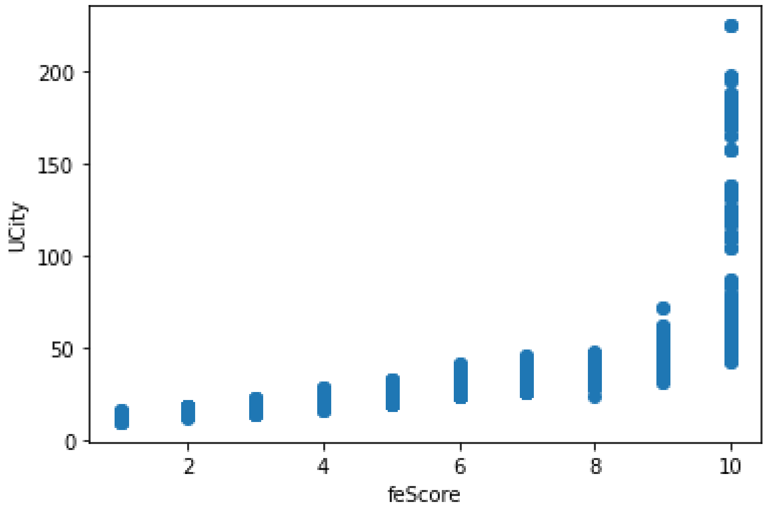
Correlation between feScore with UCity

In [80]:
```
df['feScore'].corr(df['UCity'])
```

Out[80]:
```
0.3978344569411866З
```

Scatter plot of feScore and UCity

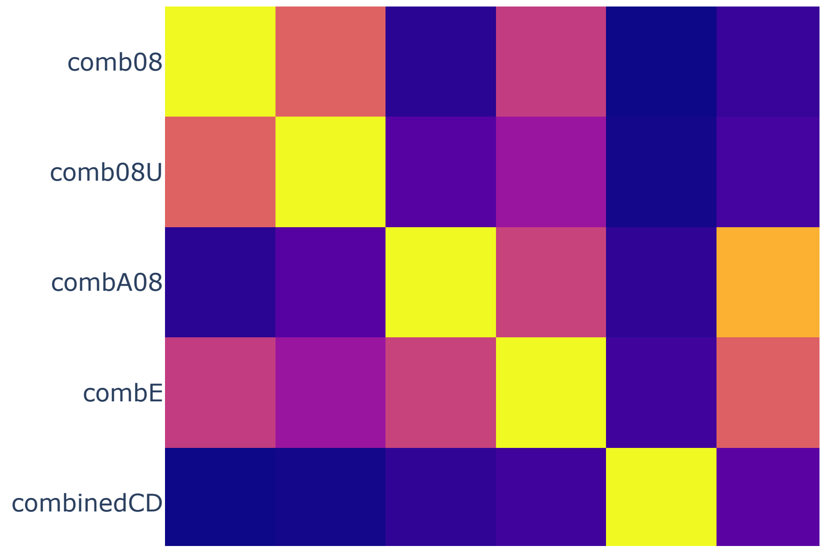
In [81]:
```
df36 = df[df['feScore'] != -1]
plt.scatter(df36['feScore'], df36['UCity'])
plt.xlabel('feScore')
plt.ylabel('UCity')
plt.show()
```



10. Numeric feature: combXXXX

Correlation matrix

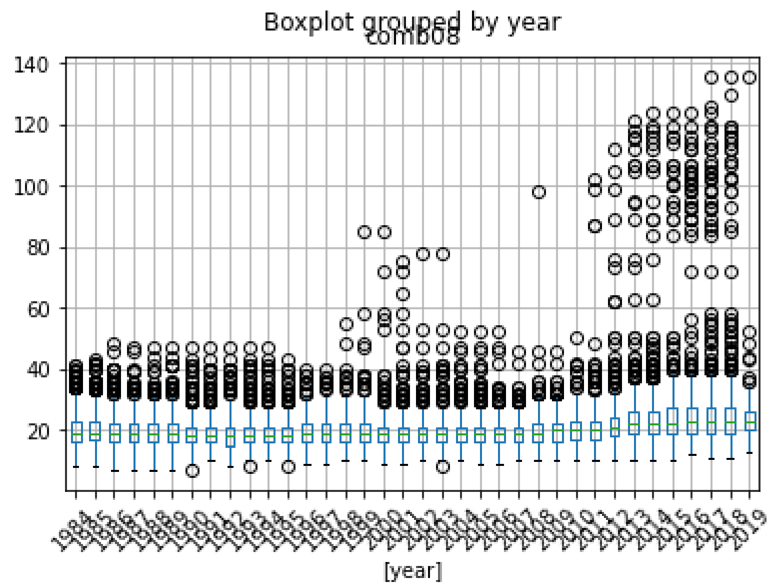
In [82]:
```
df37 = df[['comb08', 'comb08U', 'combA08', 'combE', 'combinedCD', 'combined
fig = px.imshow(df37.corr())
fig.show()
```



Box Plot for comb08 over the years

In [83]:
```
df.boxplot(column=['comb08'], by=['year'], rot=45)
```

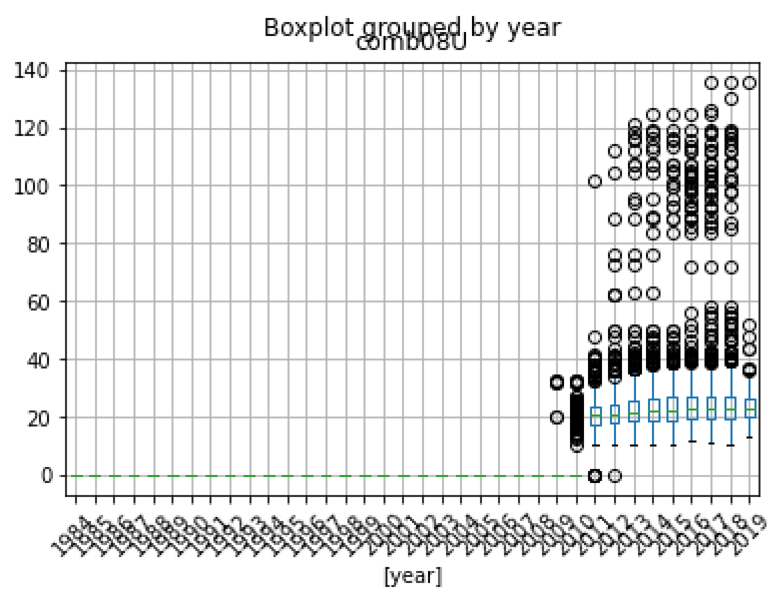
Out[83]: <AxesSubplot:title={'center':'comb08'}, xlabel='[year]'>



Box plot for comb08U over the years

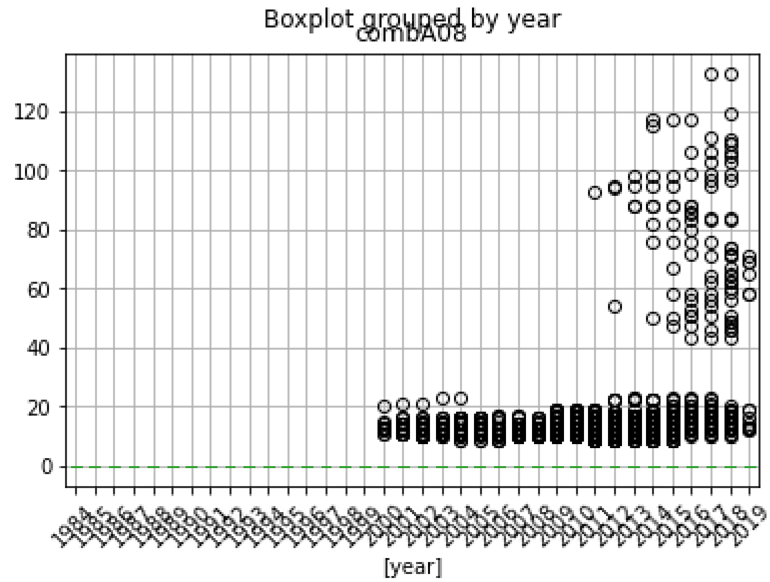
In [84]:
```
df.boxplot(column=['comb08U'], by=['year'], rot=45)
```

Out[84]: <AxesSubplot:title={'center':'comb08U'}, xlabel='[year]'>



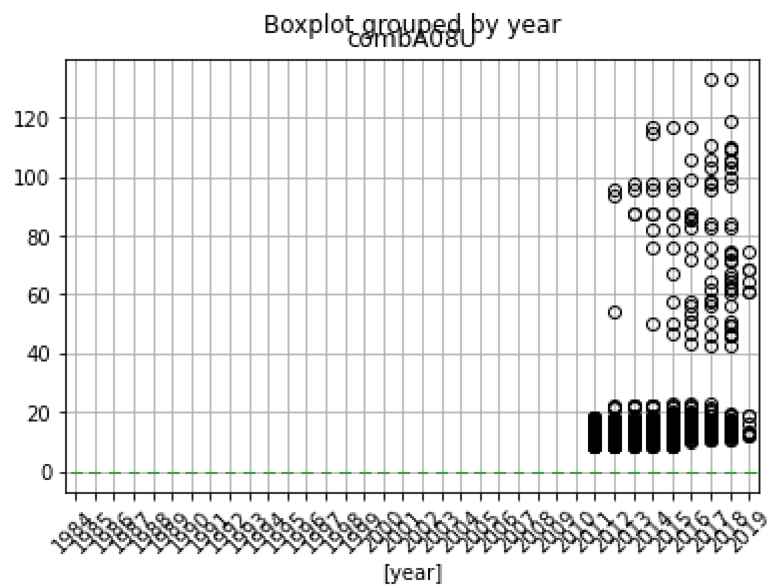
Box plot for combA08 over the years

In [85]:
```
df.boxplot(column=['combA08'], by=['year'], rot=45)
```
Out[85]:
```
<AxesSubplot:title={'center':'combA08'}, xlabel='[year]'>
```



Box plot for combA08U over the years

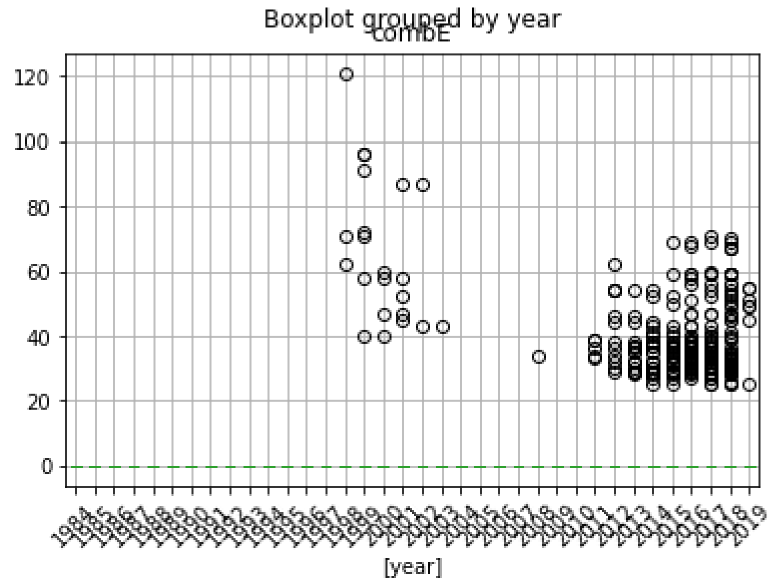
In [86]:
```
df.boxplot(column=['combA08U'], by=['year'], rot=45)
```
Out[86]:
```
<AxesSubplot:title={'center':'combA08U'}, xlabel='[year]'>
```



Box Plot for combE over the years

In [87]:
```
df.boxplot(column=['combE'], by=['year'], rot=45)
```

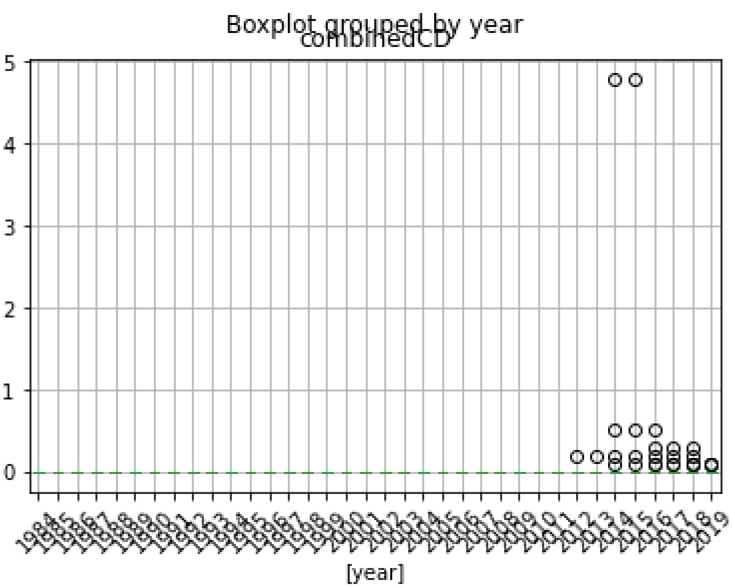
Out[87]: <AxesSubplot:title={'center':'combE'}, xlabel='[year]'>



Box Plot of combinedCD over the years

In [88]:
```
df.boxplot(column=['combinedCD'], by=['year'], rot=45)
```

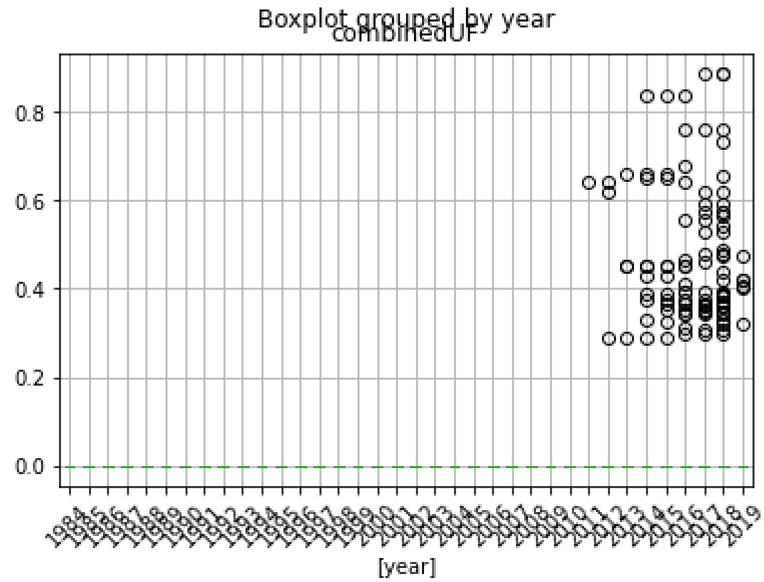
Out[88]: <AxesSubplot:title={'center':'combinedCD'}, xlabel='[year]'>



Box Plot of combinedUF over the years

In [89]:
```
df.boxplot(column=['combinedUF'], by=['year'], rot=45)
```

Out[89]:
```
<AxesSubplot:title={'center':'combinedUF'}, xlabel='[year]'>
```



11. Numeric feature: fuelCostXXXX

Describing the fuelCost08 feature

In [90]:
```
df['fuelCost08'].describe()
```

Out[90]:
```
count    40081.000000
mean      2377.809935
std        650.164538
min        500.000000
25%       1950.000000
50%       2350.000000
75%       2700.000000
max       7350.000000
Name: fuelCost08, dtype: float64
```

Describing the fuelCostA08 feature

In [91]:
```
df['fuelCostA08'].describe()
```

Out[91]:
```
count    40081.000000
mean        90.062623
std        472.905402
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max       3800.000000
Name: fuelCostA08, dtype: float64
```

In [92]:
```
df['fuelType'].unique()
```

Out[92]:
```
array(['Regular', 'Premium', 'Diesel', 'CNG', 'Gasoline or natural gas',
       'Gasoline or E85', 'Electricity', 'Gasoline or propane',
       'Premium or E85', 'Midgrade', 'Premium Gas or Electricity',
       'Regular Gas and Electricity', 'Premium and Electricity',
       'Regular Gas or Electricity'], dtype=object)
```

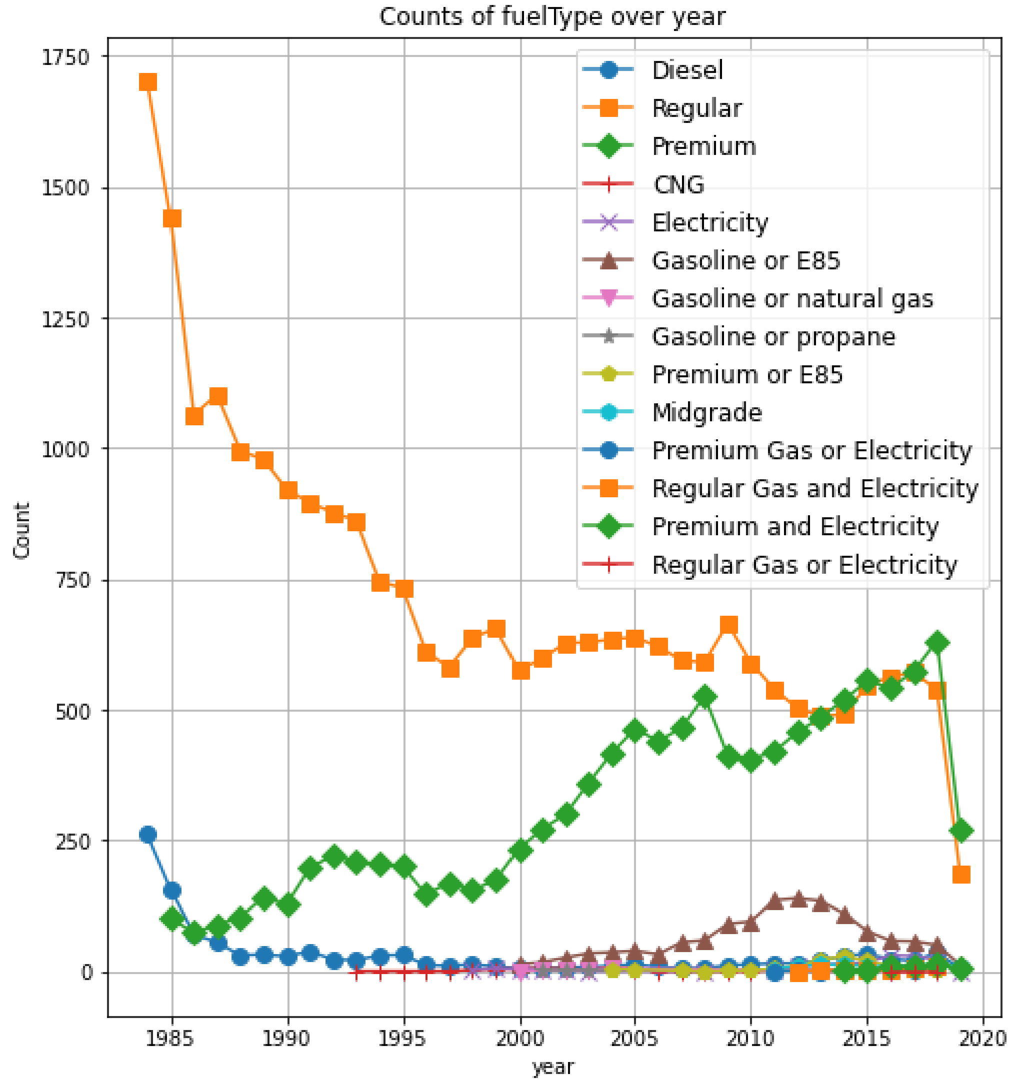
12. Numeric feature: fuelTypeX

In [93]:
```
df['fuelType'].unique()
```

Out[93]:
```
array(['Regular', 'Premium', 'Diesel', 'CNG', 'Gasoline or natural gas',
       'Gasoline or E85', 'Electricity', 'Gasoline or propane',
       'Premium or E85', 'Midgrade', 'Premium Gas or Electricity',
       'Regular Gas and Electricity', 'Premium and Electricity',
       'Regular Gas or Electricity'], dtype=object)
```

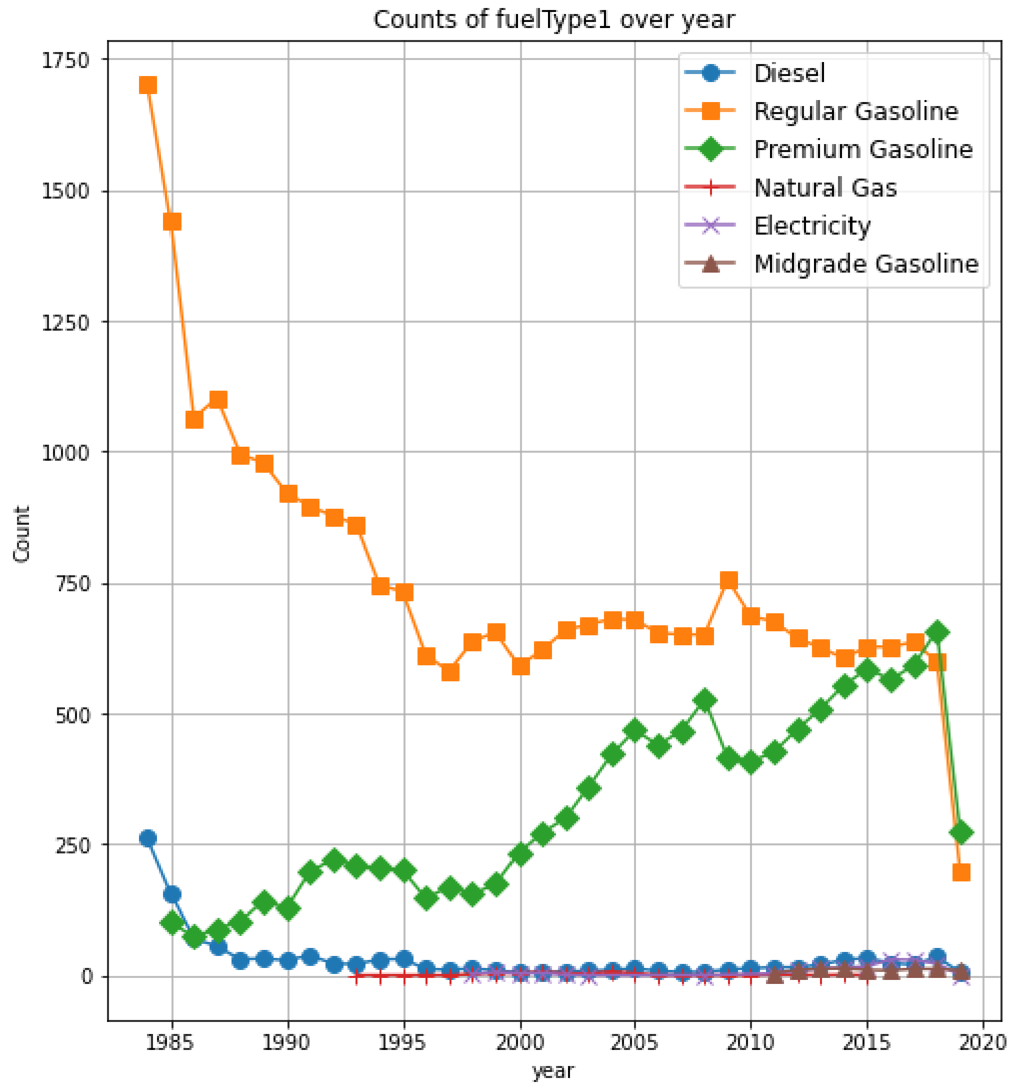
```
Line Graph of fuelType over the years
```

In [156]:
```
plot_counts_over_years(df, x_col, y_col):
df_year_fueltype = pd.DataFrame()
df_year_fueltype[x_col] = df[x_col]
df_year_fueltype[y_col] = df[y_col]
df_year_fueltype_notna = df_year_fueltype.dropna(subset=[y_col])
fueltype_counts = df_year_fueltype_notna.groupby([x_col, y_col]).size().res

# Define a list of marker symbols
marker_symbols = ['o', 's', 'D', '+', 'x', '^', 'v', '*', 'p', 'h']

# Create a dictionary mapping fuel types to marker symbols
marker_dict = {fuel_type: marker_symbols[i % len(marker_symbols)] for i, fu

plt.figure(figsize=(8,9))

for fuel_type in fueltype_counts[y_col].unique():
    fuel_type_data = fueltype_counts[fueltype_counts[y_col] == fuel_type]
    plt.plot(fuel_type_data[x_col], fuel_type_data['count'], marker=marker_

plt.title(f'Counts of {y_col} over {x_col}')
plt.xlabel(x_col)
plt.ylabel('Count')
plt.legend(loc='upper right', fontsize='large')
plt.grid(True)
plt.show()

t_counts_over_years(df, 'year', 'fuelType')
```



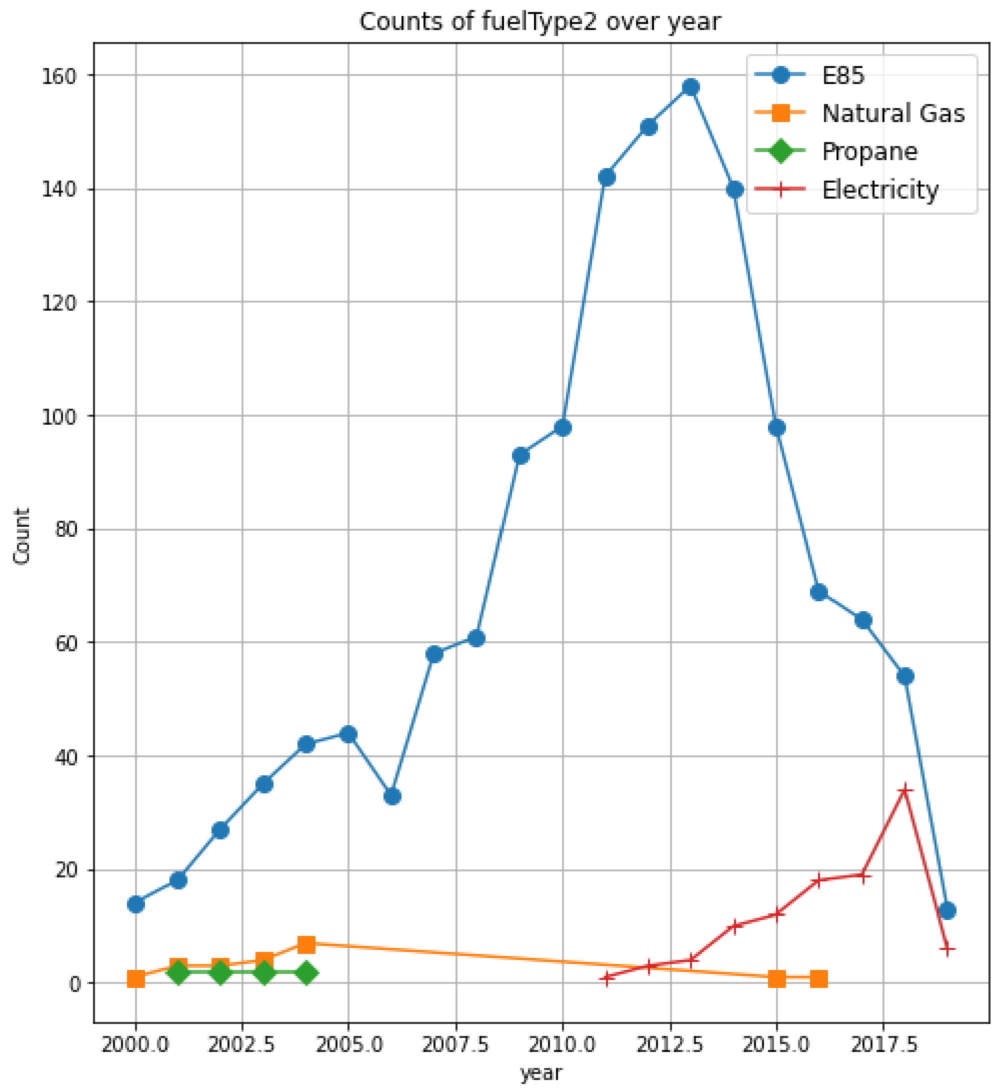

```
Line Graph of fuelType1 over the years
```

In [157]:
```
plot_counts_over_years(df, 'year', 'fuelType1')
```



Line Graph of fuelType2 over the years

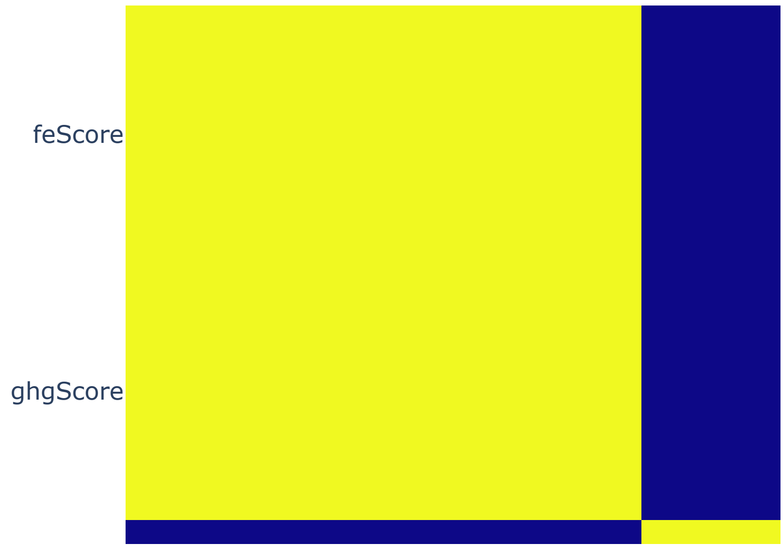
In [158]:
```
plot_counts_over_years(df, 'year', 'fuelType2')
```



13. Numeric feature: ghgScore

Correlation matrix of feScore ghgScore and UCity

In [94]:
```
df38 = df[['feScore', 'ghgScore', 'UCity']]
fig = px.imshow(df38.corr())
fig.show()
```



Vehicles with ghgScore

In [95]:
```
df39 = df.groupby('ghgScore', as_index = False)['fuelType'].size()
df39
```

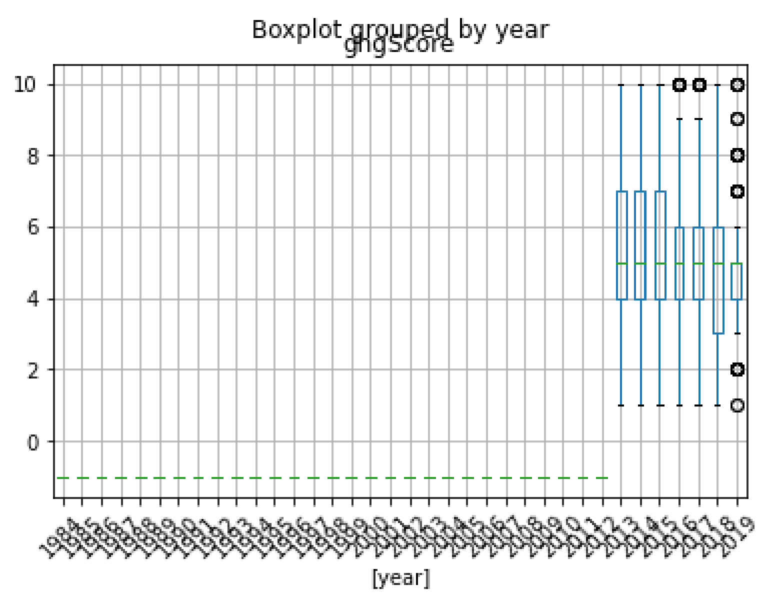
Out[95]:

	ghgScore	size
0	-1	32027
1	1	163
2	2	371
3	3	855
4	4	1570
5	5	2081
6	6	1196
7	7	962
8	8	491
9	9	116
10	10	249

Box Plot of ghgScore over the years

In [96]:
```
df.boxplot(column=['ghgScore'], by=['year'], rot=45)
```

Out[96]: <AxesSubplot:title={'center':'ghgScore'}, xlabel='[year]'>



Correlation between ghgScore and UCity

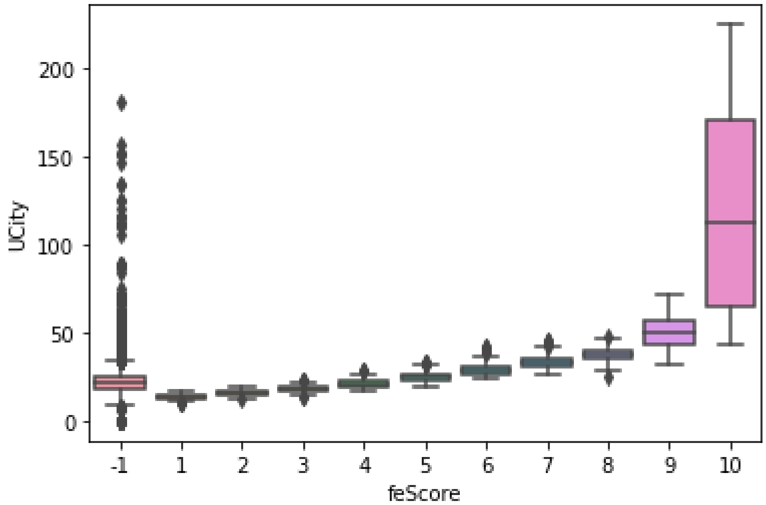
In [97]:
```
df['ghgScore'].corr(df['UCity'])
```

Out[97]: 0.3973775917099092

Box Plot of feScore vs UCity

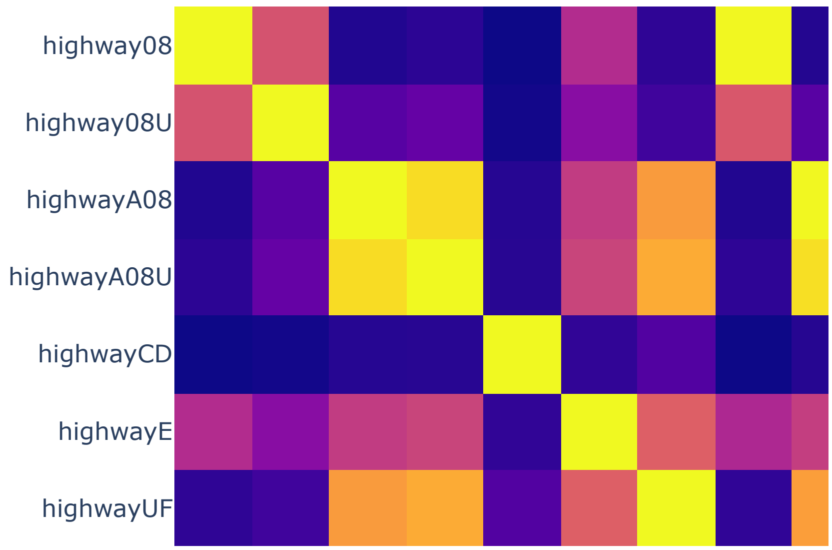
In [100]:
```
sns.boxplot(x='feScore', y='UCity', data=df)
```

Out[100]:
```
<AxesSubplot:xlabel='feScore', ylabel='UCity'>
```



14. Numeric feature: highwayXXXX

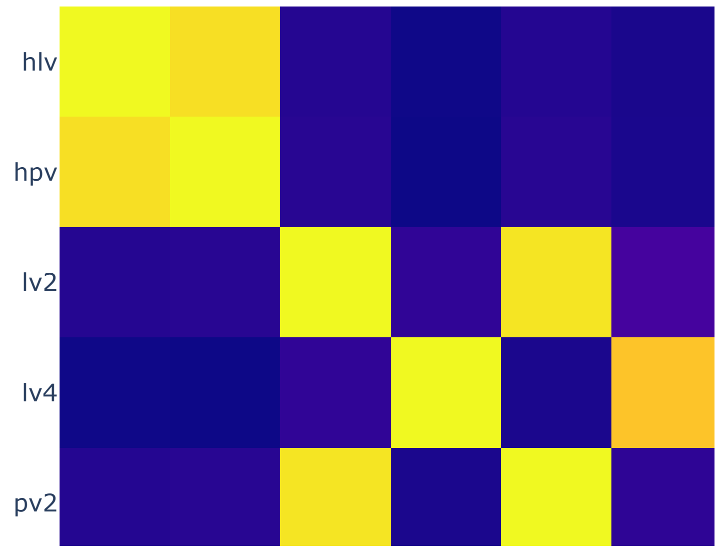
In [101]:
```
df40 = df[['highway08', 'highway08U', 'highwayA08', 'highwayA08U', 'highway
fig = px.imshow(df40.corr())
fig.show()
```



15. Numeric feature: volume hlv, hpv, lv2, lv4, pv2, pv4

Correlation matrix

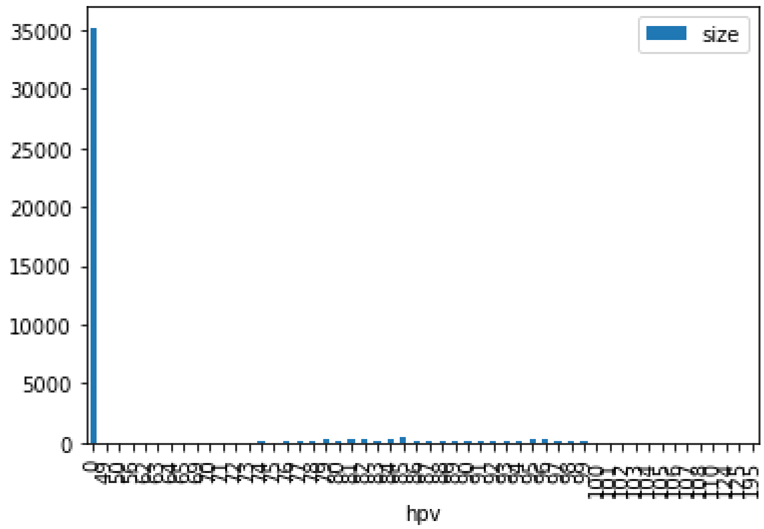
In [102]:
```
df41 = df[['hlv', 'hpv', 'lv2', 'lv4', 'pv2', 'pv4', 'UCity']]
fig = px.imshow(df41.corr())
fig.show()
```



Histogram of hpv vs its frequency

In [103]:
```
df42 = df.groupby('hpv', as_index=False)['hpv'].size()
df42.plot(x="hpv", y=["size"], kind="bar")
```

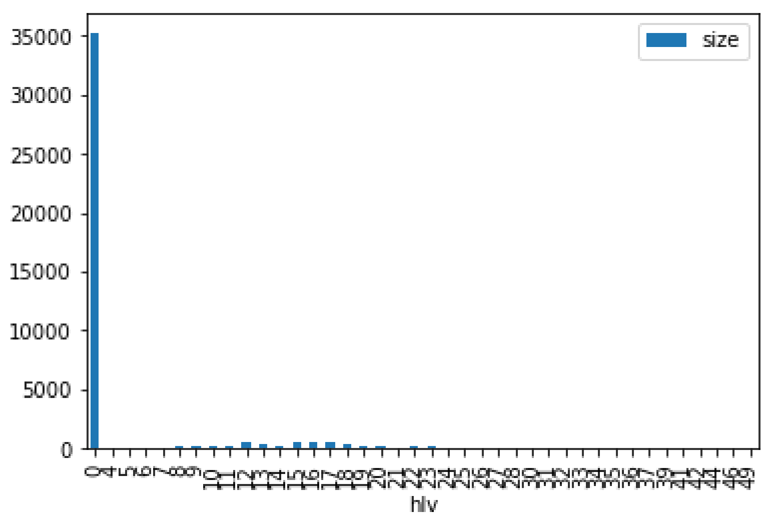
Out[103]: <AxesSubplot:xlabel='hpv'>



Histogram of hlv vs its frequency

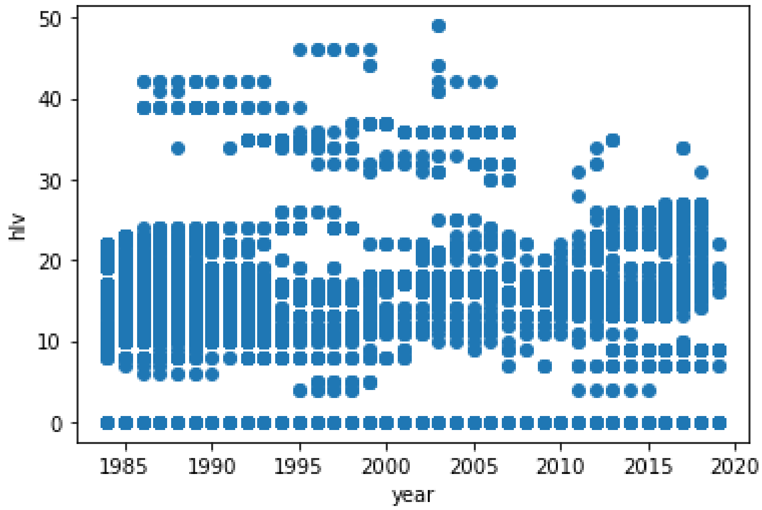
In [104]:
```
df43 = df.groupby('hlv', as_index=False)['hlv'].size()
df43.plot(x="hlv", y=["size"], kind="bar")
```

Out[104]: <AxesSubplot:xlabel='hlv'>



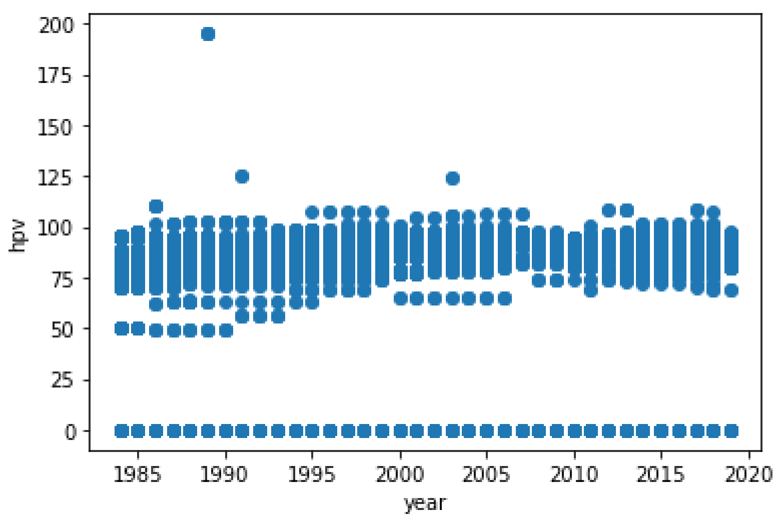
Scatter plot of hlv over the years

In [105]:
```
df44 = df[['hlv', 'year']]
plt.scatter(df44['year'], df44['hlv'])
plt.xlabel('year')
plt.ylabel('hlv')
plt.show()
```



Scatter plot of hpv over the years

In [106]:
```
df45 = df[['hpv', 'year']]
df45 = df45.dropna()
plt.scatter(df45['year'], df45['hpv'])
plt.xlabel('year')
plt.ylabel('hpv')
plt.show()
```



16. Numeric feature: range

In [107]:
```
df['range'].describe()
```

Out[107]:
```
count    40081.000000
mean         0.616377
std         11.133278
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max        335.000000
Name: range, dtype: float64
```

Correlation between range and UCity

1. List item
2. List item
3. List item

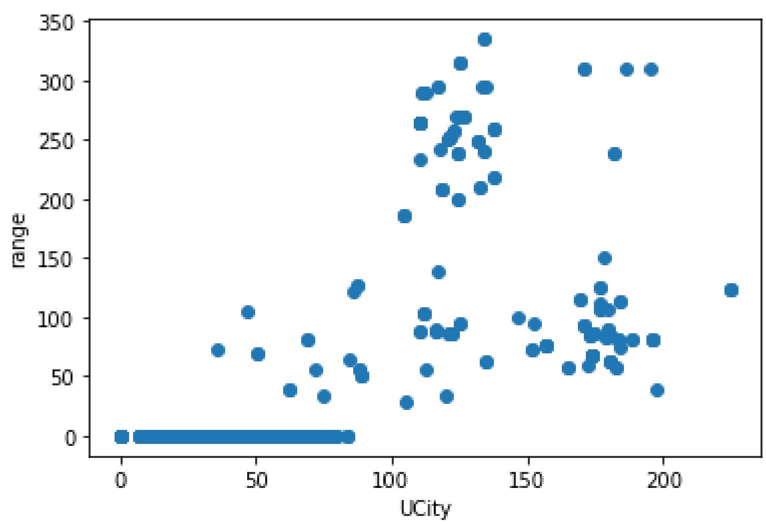
2. List item

In [108]:
```
df['range'].corr(df['UCity'])
```

Out[108]:
```
0.6013585777904684
```

Scatter plot of range and UCity

In [109]:
```
df46 = df[['range', 'UCity']]
plt.scatter(df46['UCity'], df46['range'])
plt.xlabel('UCity')
plt.ylabel('range')
plt.show()
```



Range value of EVs

In [110]:
```
df47 = df[['range', 'atvType']]
df47 = df[df['atvType'] == 'EV']
df47.shape
```

Out[110]:
```
(168, 83)
```

17. Numeric feature: rangeXXXX

Describing rangeA vehicles

In [111]:
```
df['rangeA'].describe()
```

Out[111]:
```
count     1542
unique     223
top        290
freq        74
Name: rangeA, dtype: object
```

Describing rangeCityA vehicles

In [112]:
```
df['rangeCityA'].describe()
```

Out[112]:
```
count    40081.000000
mean         0.067532
std          1.639622
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max        103.030000
Name: rangeCityA, dtype: float64
```

Describing rangeHwyA vehicles

In [113]:
```
df['rangeHwyA'].describe()
```

Out[113]:
```
count    40081.000000
mean         0.062571
std          1.479728
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max         90.550000
Name: rangeHwyA, dtype: float64
```

Correlation between range and UCity

In [114]:
```
df48 = df[['range', 'UCity']]
df48.corr()
```

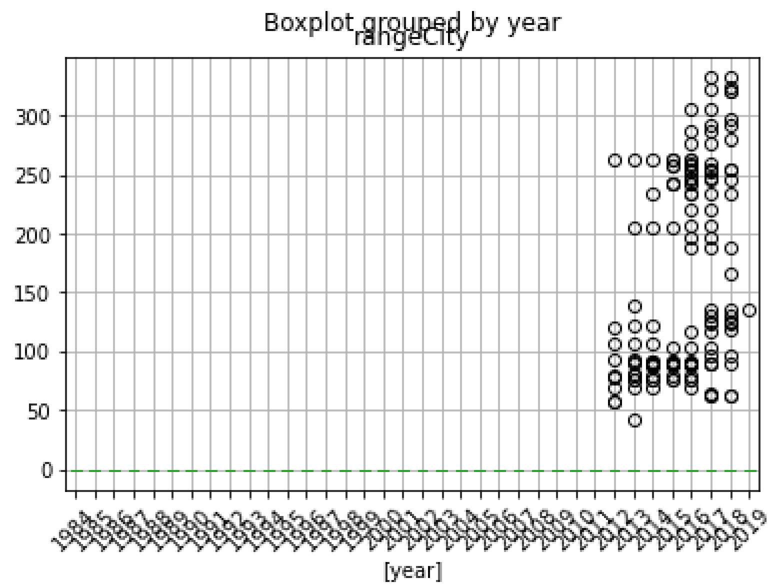
Out[114]:

	range	UCity
range	1.000000	0.601359
UCity	0.601359	1.000000

Box Plot of rangeA over the years

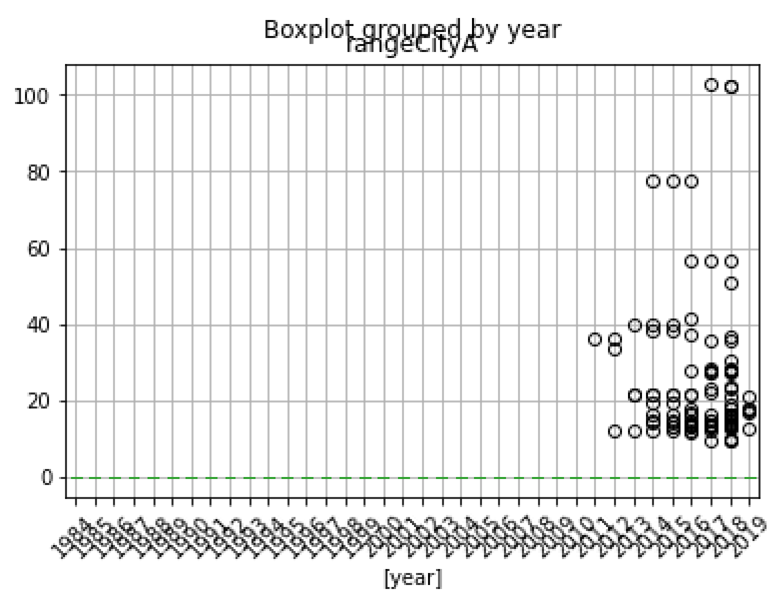
In [115]:
```
df.boxplot(column=['rangeCity'], by=['year'], rot=45)
```

Out[115]: <AxesSubplot:title={'center':'rangeCity'}, xlabel='[year]'>



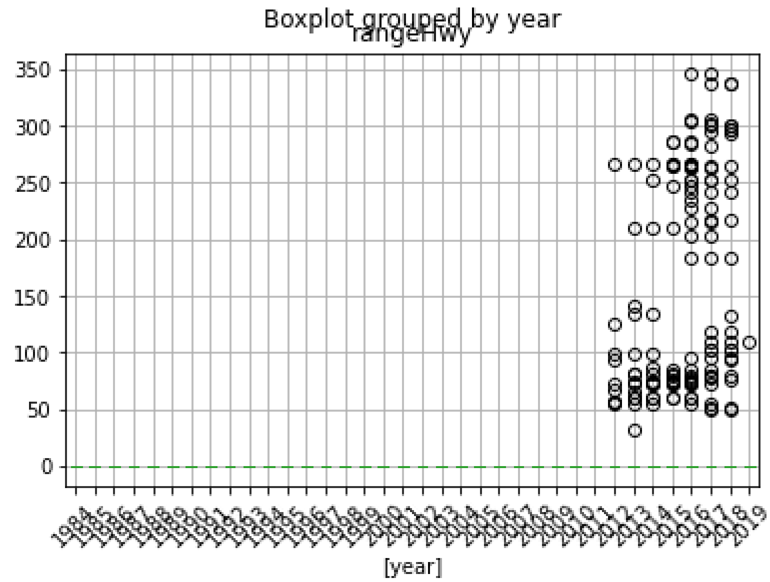
In [116]:
```
df.boxplot(column=['rangeCityA'], by=['year'], rot=45)
```

Out[116]: <AxesSubplot:title={'center':'rangeCityA'}, xlabel='[year]'>



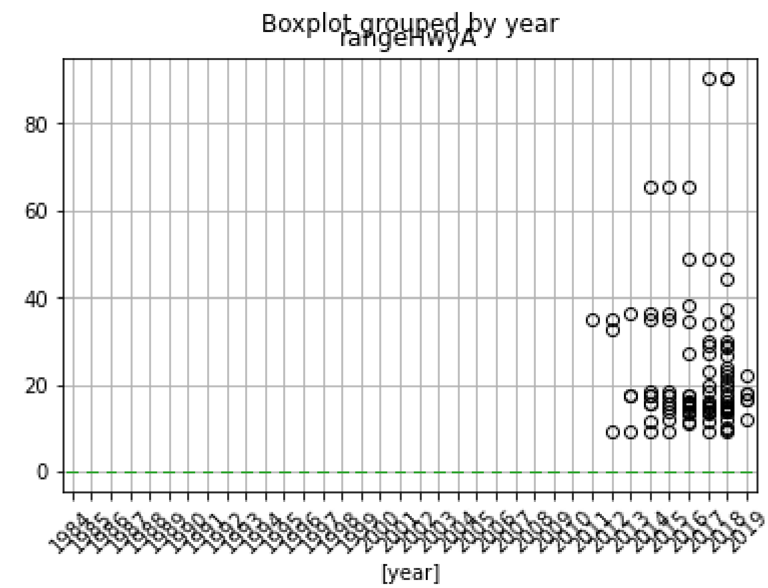
In [117]:
```
df.boxplot(column=['rangeHwy'], by=['year'], rot=45)
```

Out[117]: <AxesSubplot:title={'center':'rangeHwy'}, xlabel='[year]'>



In [118]:
```
df.boxplot(column=['rangeHwyA'], by=['year'], rot=45)
```

Out[118]: <AxesSubplot:title={'center':'rangeHwyA'}, xlabel='[year]'>



18. Numeric feature: youSaveSpend

Describing the youSaveSpend column

In [119]:
```
df['youSaveSpend'].describe()
```

Out[119]:
```
count     40081.000000
mean      -4134.565006
std        3256.499139
min      -29000.000000
25%       -5750.000000
50%       -4000.000000
75%       -2000.000000
max        5250.000000
Name: youSaveSpend, dtype: float64
```

Correlation between youSaveSpend and UCity

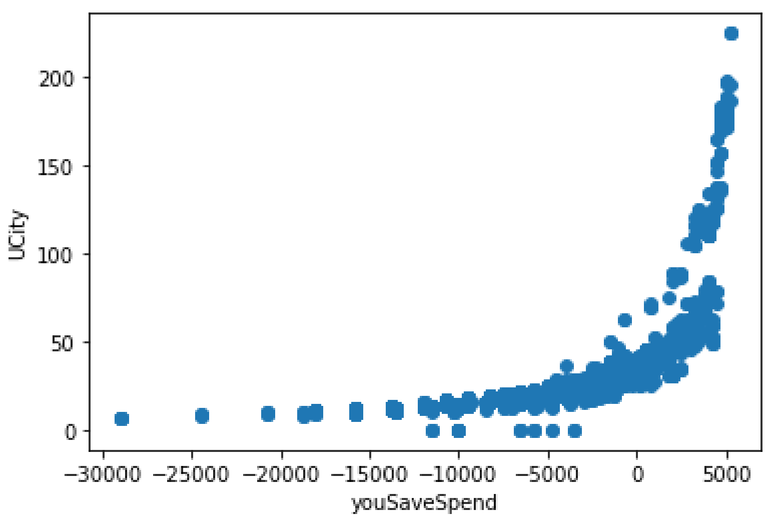
In [120]:
```
df49 = df[['youSaveSpend', 'UCity']]
df49.corr()
```

Out[120]:

	youSaveSpend	UCity
youSaveSpend	1.000000	0.658371
UCity	0.658371	1.000000

Scatter plot of youSaveSpend vs UCity

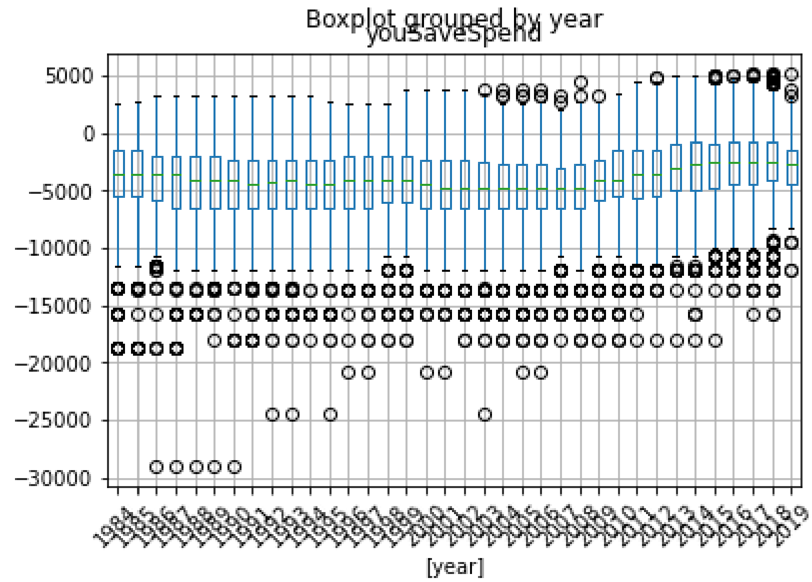
In [121]:
```
df50 = df[['youSaveSpend', 'UCity']]
plt.scatter(df50['youSaveSpend'], df50['UCity'])
plt.xlabel('youSaveSpend')
plt.ylabel('UCity')
plt.show()
```



Box Plot of youSaveSpend vs the years

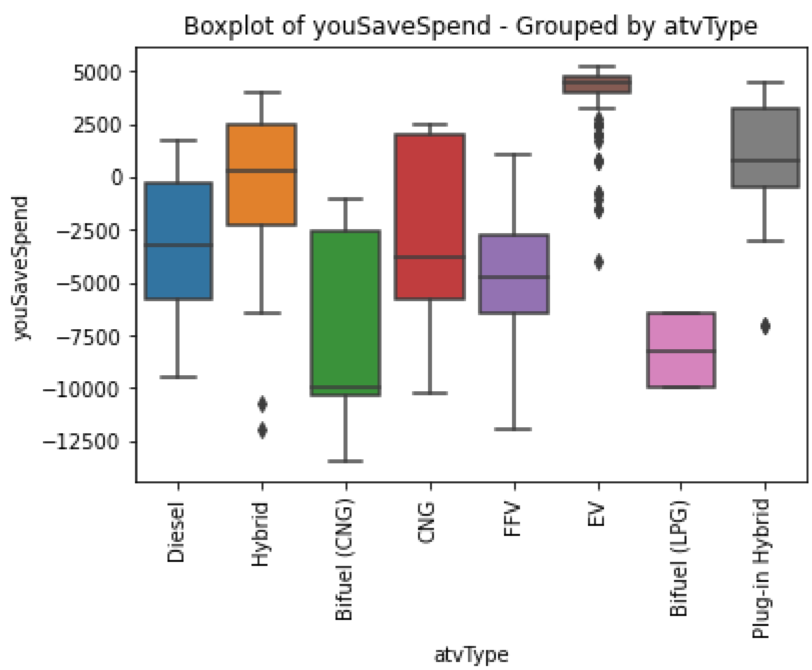
In [122]:
```
df.boxplot(column=['youSaveSpend'], by=['year'], rot=45)
```

Out[122]: <AxesSubplot:title={'center':'youSaveSpend'}, xlabel='[year]'>



Box Plot of different types of atvTypes over the years

In [151]:
```
y_col = 'youSaveSpend'
x_col = 'atvType'

df_selected = df[[x_col, y_col]].copy()
df_selected = df_selected[df_selected[y_col] != -1]  # Drop rows with y_col

sns.boxplot(x=x_col, y=y_col, data=df_selected)
plt.title(f'Boxplot of {y_col} - Grouped by {x_col}')
plt.xticks(rotation=90)
plt.show()
```



Box Plot of atvType over the years

In [123]:
```
df['atvType'].dropna().unique()
```

Out[123]:
```
array(['Diesel', 'Hybrid', 'Bifuel (CNG)', 'CNG', 'FFV', 'EV',
       'Bifuel (LPG)', 'Plug-in Hybrid'], dtype=object)
```

19. Categorical feature: drive

In [124]:
```
df51 = df.groupby('drive', as_index = False)['drive'].size()
df51
```

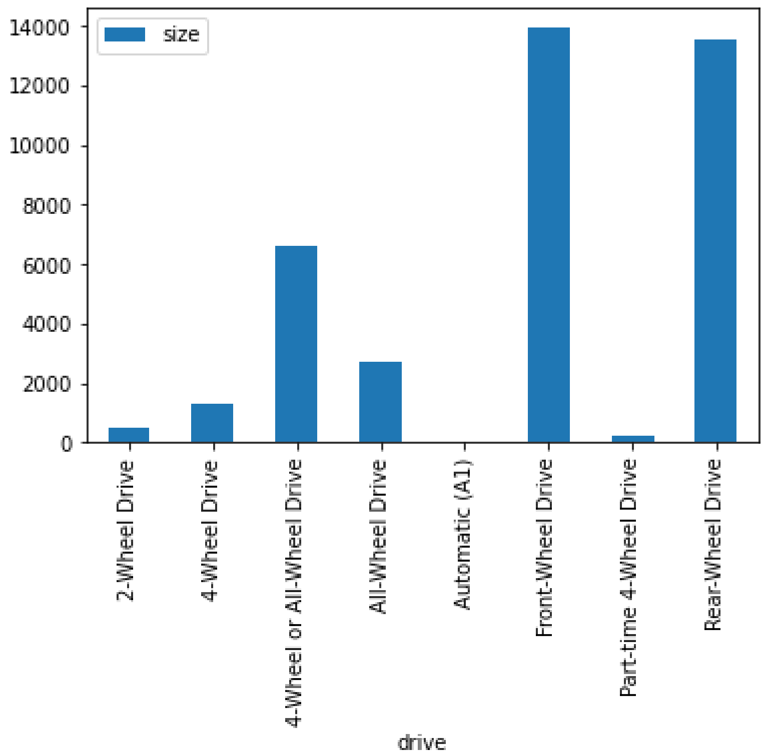
Out[124]:

	drive	size
0	2-Wheel Drive	507
1	4-Wheel Drive	1328
2	4-Wheel or All-Wheel Drive	6648
3	All-Wheel Drive	2713
4	Automatic (A1)	1
5	Front-Wheel Drive	13939
6	Part-time 4-Wheel Drive	217
7	Rear-Wheel Drive	13539

Histogram of number of drive vehicles

In [125]:
```
df51.plot(x="drive", y=["size"], kind="bar")
```

Out[125]:
```
<AxesSubplot:xlabel='drive'>
```



Correlation between UCity and drive

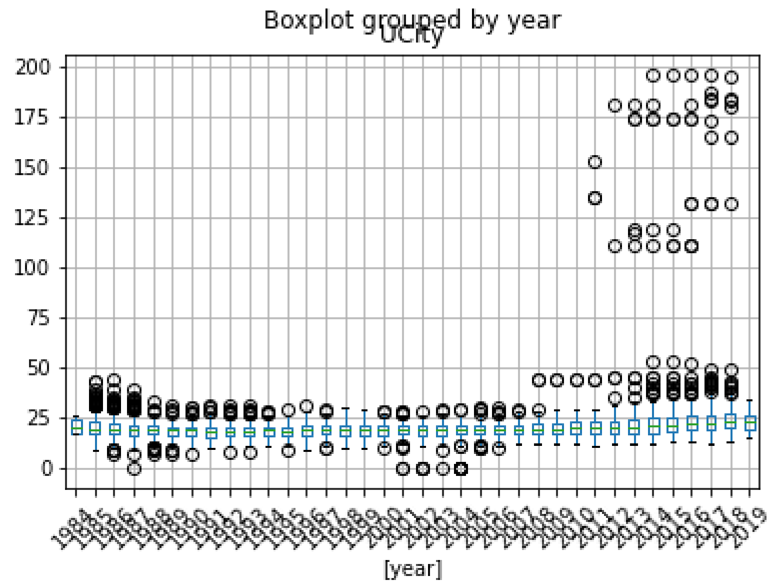
In [126]:
```
df['drive'].unique()
```

Out[126]:
```
array(['Rear-Wheel Drive', 'Front-Wheel Drive',
       '4-Wheel or All-Wheel Drive', nan, '2-Wheel Drive',
       'All-Wheel Drive', '4-Wheel Drive', 'Part-time 4-Wheel Drive',
       'Automatic (A1)'], dtype=object)
```

Box plot between Rear-Wheel drive and UCity

In [127]:
```
df52 = df[['drive', 'UCity', 'year']]
df52 = df52[df52['drive'] == 'Rear-Wheel Drive']
df52.boxplot(column=['UCity'], by=['year'], rot=45)
```

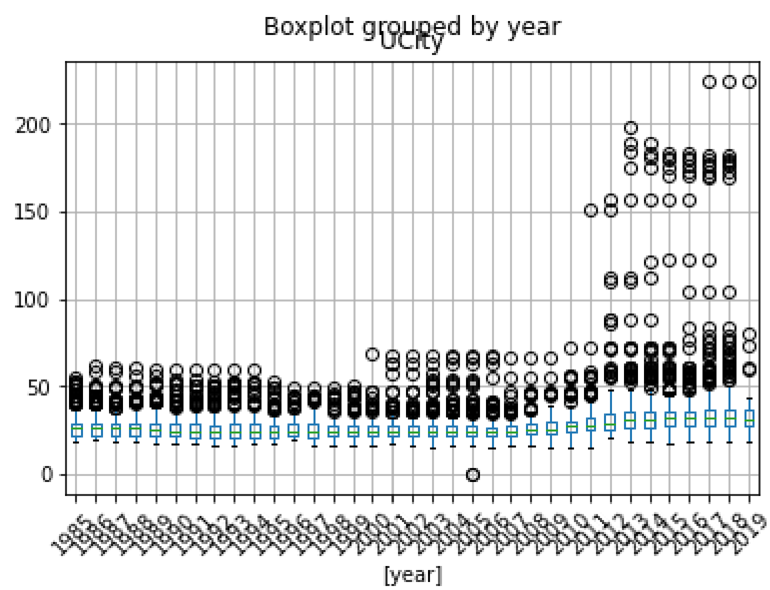
Out[127]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot between Front-Wheel drive and UCity

In [128]:
```
df53 = df[['drive', 'UCity', 'year']]
df53 = df53[df53['drive'] == 'Front-Wheel Drive']
df53.boxplot(column=['UCity'], by=['year'], rot=45)
```

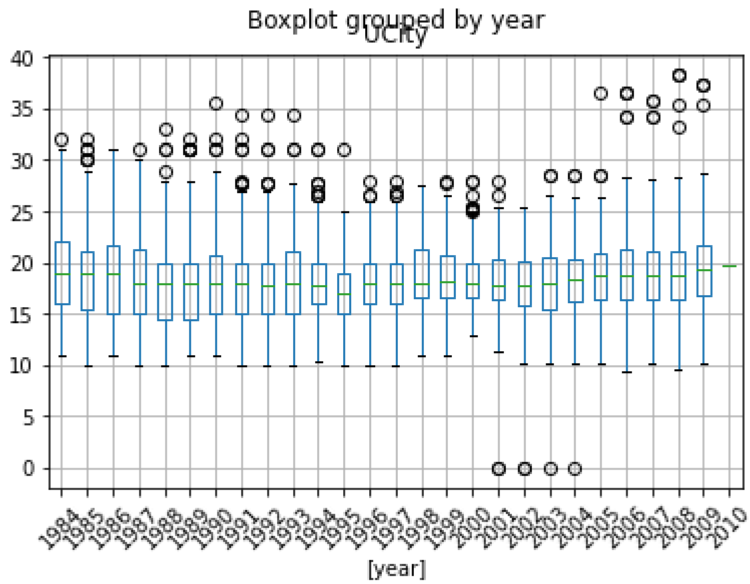
Out[128]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of 4-Wheel or All-Wheel Drive and UCity

In [129]:
```
df54 = df[['drive', 'UCity', 'year']]
df54 = df54[df54['drive'] == '4-Wheel or All-Wheel Drive']
df54.boxplot(column=['UCity'], by=['year'], rot=45)
```

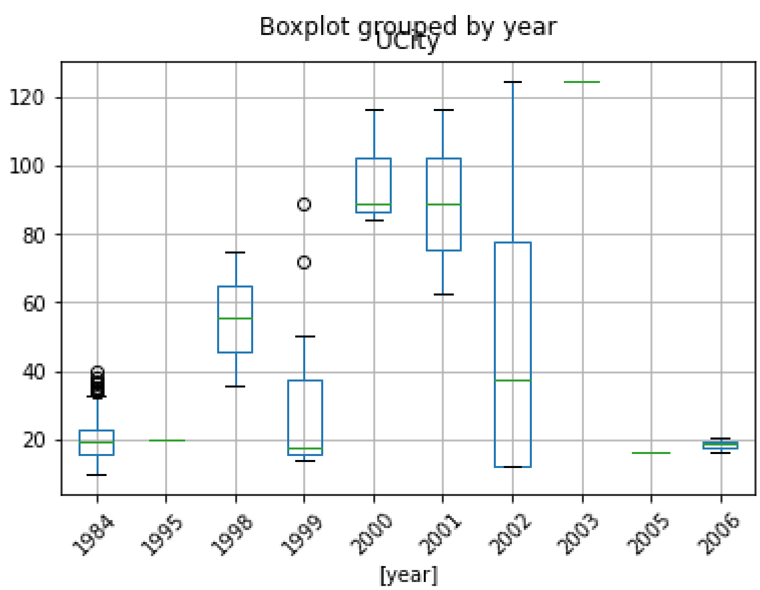
Out[129]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of 2-Wheel Drive and UCity

In [130]:
```
df55 = df[['drive', 'UCity', 'year']]
df55 = df55[df55['drive'] == '2-Wheel Drive']
df55.boxplot(column=['UCity'], by=['year'], rot=45)
```

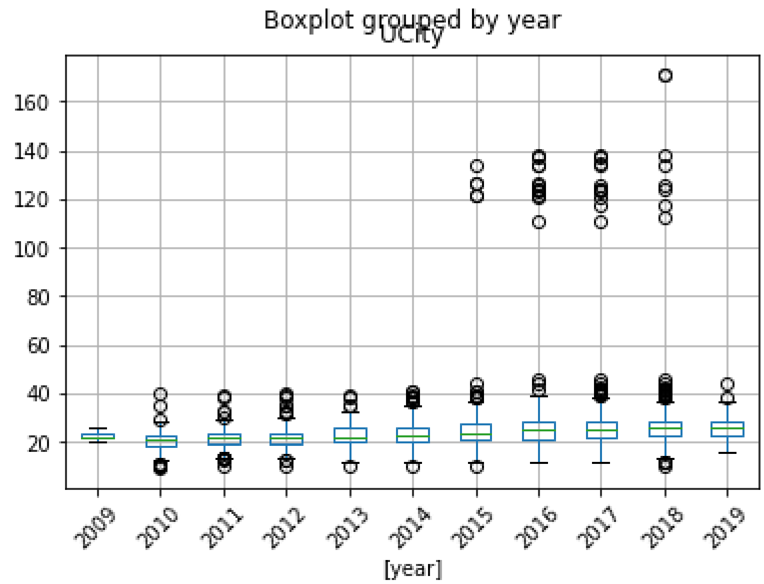
Out[130]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of All-Wheel Drive and UCity

In [131]:
```
df56 = df[['drive', 'UCity', 'year']]
df56 = df56[df56['drive'] == 'All-Wheel Drive']
df56.boxplot(column=['UCity'], by=['year'], rot=45)
```

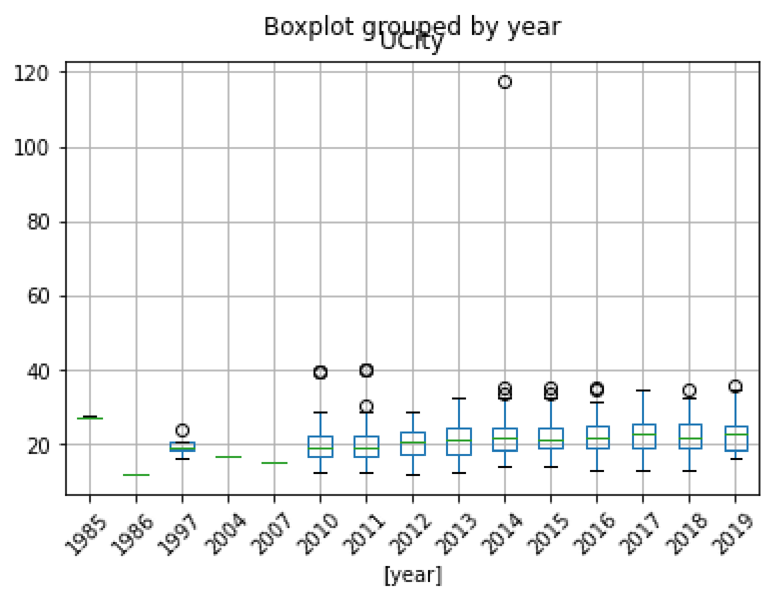
Out[131]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of 4-Wheel Drive and UCity

In [132]:
```
df57 = df[['drive', 'UCity', 'year']]
df57 = df57[df57['drive'] == '4-Wheel Drive']
df57.boxplot(column=['UCity'], by=['year'], rot=45)
```

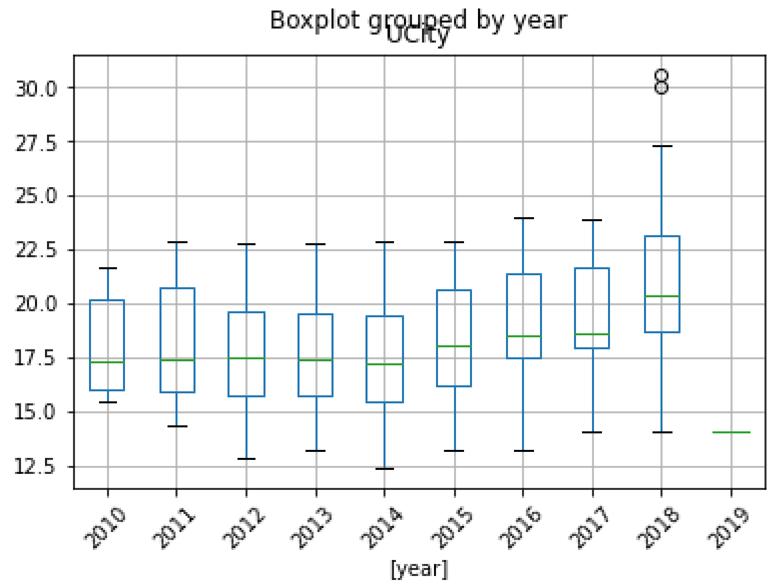
Out[132]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of Part-time 4-Wheel Drive and UCity

In [133]:
```
df58 = df[['drive', 'UCity', 'year']]
df58 = df58[df58['drive'] == 'Part-time 4-Wheel Drive']
df58.boxplot(column=['UCity'], by=['year'], rot=45)
```

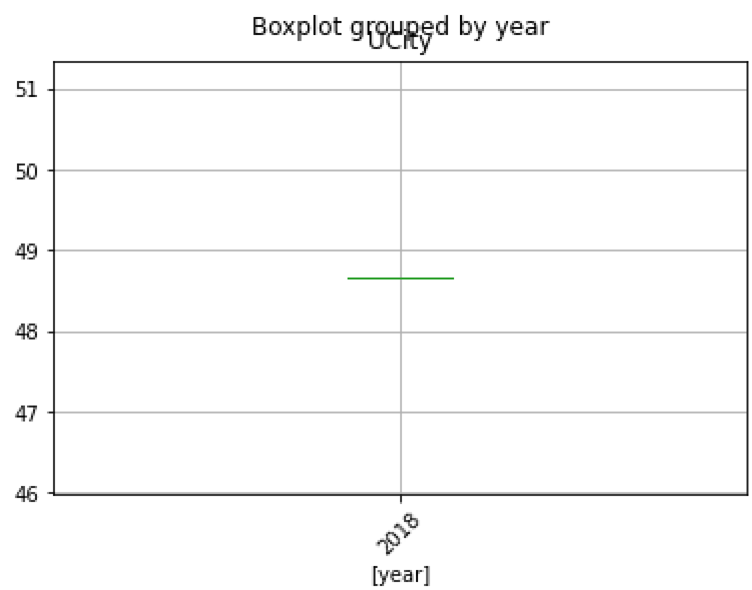
Out[133]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



Box plot of Automatic (A1) drive and UCity

In [134]:
```
df59 = df[['drive', 'UCity', 'year']]
df59 = df59[df59['drive'] == 'Automatic (A1)']
df59.boxplot(column=['UCity'], by=['year'], rot=45)
```

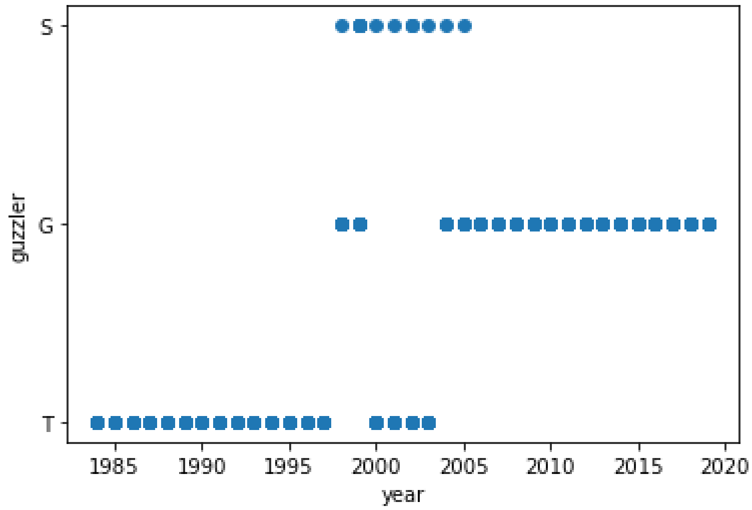
Out[134]: <AxesSubplot:title={'center':'UCity'}, xlabel='[year]'>



20. Numeric feature: guzzler

Scatter plot of guzzler across the years

In [149]:
```
df_1 = df[['year', 'guzzler']].copy().dropna()
plt.scatter(df_1['year'], df_1['guzzler'])
plt.xlabel('year')
plt.ylabel('guzzler')
plt.show()
```



21. Categorical feature: mgpData

mgpData Y vehicles

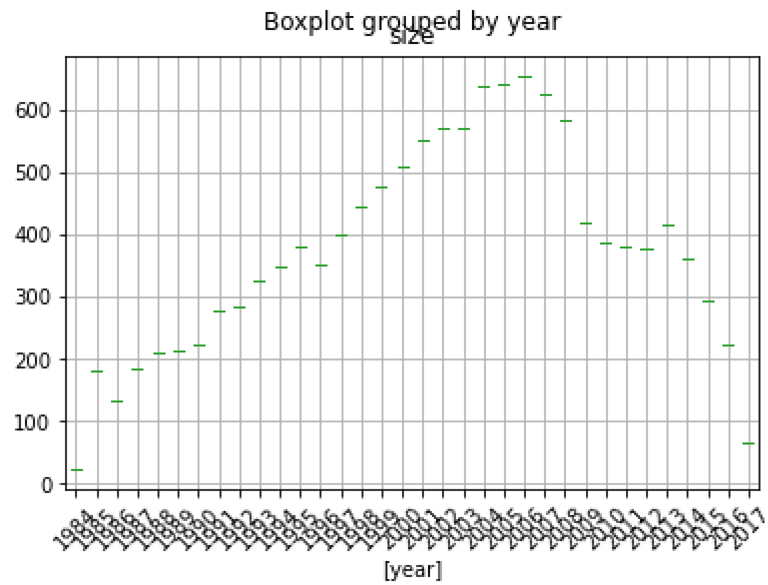
In [137]:
```
df61 = df[df['mpgData'] == 'Y']
df61.shape
```

Out[137]: (12714, 83)

Box Plot of mgpData over the years

In [138]:
```
df62 = df61.groupby('year', as_index = False)['mpgData'].size()
df62.boxplot(column=['size'], by=['year'], rot=45)
```

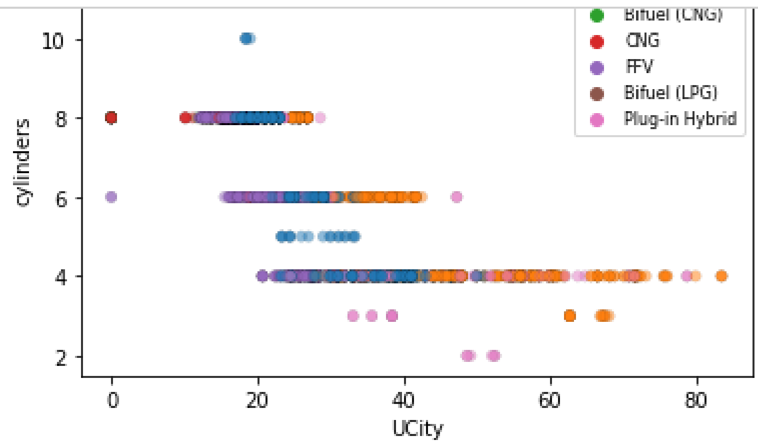
Out[138]: <AxesSubplot:title={'center':'size'}, xlabel='[year]'>



##Ans 1 b. Insights from the data

For getting new insights from the data, I have plotted the dependent feature UCity and the independent features cylinders, displ, fuelCostA08, comb08, combA08, co2 and fuelType change with respective to the different atvType. Below are the plots for each of them.

In [139]:
```
:1 = ['UCity', 'cylinders', 'displ', 'fuelCostA08', 'comb08', 'combA08', 'co
lf = df[list1 + ['atvType']].dropna()
:s = list(itertools.combinations(list1, 2))
 pair in pairs:
:int(f'{pairs[1]} vs {pairs[0]}')
:int("Correlation matrix")
:int(newdf[[pair[0], pair[1], 'atvType']].corr())


.g, ax = plt.subplots()
ıs.scatterplot(data = newdf, x = pair[0], y = pair[1], hue = 'atvType', s =
:.set_xlabel(pair[0])
:.set_ylabel(pair[1])
:.set_title(f'{pair[1]} vs {pair[0]}')
.t.legend(prop = {'size' : 8})
.t.show()
```




```
('UCity', 'displ') vs ('UCity', 'cylinders')
Correlation matrix
          UCity     displ
UCity  1.000000 -0.733715
displ -0.733715  1.000000
```

1. **cylinders vs UCity**: In this plot we can see that the Hybrid vehicles have a high UCity compared to the other atvType vehicles. Hybrid vehicles have a more running than other. We also see that the CNG vehicles operating only at 8 cylinders, while FFV, Diesel, Hybrid working at 4, 6 and 8 cylinders. Plug-in Hybrid vehicles are mostly seen working at 2, 3, 4, cylinders - but we also see some at 6, 8.
2. **displ vs UCity**: In this plot we see a clear differentiation between the UCity for Hybrid vehicles (higher UCity) while FFV vehicles with a lower UCity. Diesel vehicles lie in between with respect to the UCity value. With respect to the displ we see CNG vehicles with a higher value while Plug-in Hybrid with a lower value. Hence CNG vehicles have a higher displacement while Plug-in Hybrid are seen on the lower end.
3. **fuelCostA08 vs UCity**: In this plot we see that the FFV vehicles have a higher fuel cost compared to the rest of the atvType vehicles. Bifuel (LPG) vehicles seem to have the highest fuel cost with less number of vehicles in general. Hybrid and Diesel vehicles have the lowest fuel cost. The UCity of Diesel and FFV is on the lower side while on the higher side for Hybrid vehicles.

4. **comb08 vs UCity**: In this plot we see the comb08 value for the Hybrid vehicles is high while for Diesel it is low. This is the same distribution in terms of UCity as well. CNG, Bifuel (LPG), FFV vehicles have a low UCity and comb08 values.
5. **co2 vs UCity**: In this plot we see FFV vehicles have the most co2 value while Diesel vehicles have the least. Plug-in Hybrid vehicles have the co2 value somewhere in the middle of these two.

Ans 2.

If UCity is the dependent variable, we would have to go with the regression approach. This is because UCity column has values that are continuous and not ones with distinct category for classifying them. To make them into a categorical variable for classification we would have to bin the values at a particuar threshold for every category. These can then be classified.

For building the predictive model we would have to follow the steps:

i. Understand the scope and the requirements of the business problem - what is the final goal of this exercise, to just understand the data, predict a value or clasify into categories.

ii. Data collection and preprocessing - this step involves collecting the data from various places. For example if the project is about a particular topic, we can perform data scraping and crawling on blogs, articles on this topic to get relevant data. Data preprocessing involves data cleaning, data tramnformation, data reduction. This step helps us get the data in the format where we can work on it.

iii. Data Cleaning and Exploratory Data Analysis - data cleaning is one of the most important steps where we would have raw unprocessed data with a lot of unnecessary information. These are a few things we would look for cleaning the data - removing duplicate or irrelavent observations, fix structural errors, filter unwanted outliers, handle missing data. Exploratory Data analysis is performed for understanding the data, how one feature is changes with respect to the other, we understand correlation, presence of outliers, many insights by just looking at the plots.

iv. Validating the model - we select the model that suits best to our usecase of regression/ classification and performs well with the data. If we have a lot of missing values, a model like Random Forest would perform the best, if we want a simple classification something like logistic regression might give us good results while if our data is unlabelled, K Means algorithm would be the best. Hence according to our data and use case we choose the model that works best. We validate our model works well using evaluation metrics that suit our use case. In most cases accuracy is checked while when we false positives are important we check precision. When false negatives are important to our analysis we check the recall. We could also check the F1 score when both the quantities are important to our analysis. For regression we check the R squared value and the adjusted R squared value for the best fit of the line.

v. Model Deployment - once we have received the best performing model we deploy it to run on real time data.

vi. Monitoring and Tracking the Model - we need to monitor and track the performance of the model once deployed in case of any change in data.

Ans 3.

To know which variables we would not be considering as inputs to the model, we would have to do a bit of exploration of the correlation between features and the number of null values the features have. The exploration is done below

In [34]:
```
fig = px.imshow(df.corr())
fig.show()
```

```
<ipython-input-34-a25aa30996d6>:1: FutureWarning: The default value of nu
meric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numer
ic_only to silence this warning.
  fig = px.imshow(df.corr())
```

In [7]:
```
pd.set_option('display.max_rows', None)
count_zeros = (df == 0).astype(int).sum(axis = 0)
count_non_zeros = (df != 0 ).astype(int).sum(axis = 0)
count_df = pd.DataFrame({'Zero Counts': count_zeros, 'Non Zero Counts': cou
count_df = count_df.sort_values(by = "Zero Counts", ascending = False)
print(count_df)
pd.reset_option('display.max_rows')
```

	Zero Counts	Non Zero Counts
charge120	40081	0
highwayCD	40064	17
cityCD	40056	25
combinedCD	40054	27
charge240b	40019	62
phevBlended	40005	76
phevComb	39974	107
rangeHwyA	39974	107
phevHwy	39974	107
phevCity	39974	107
highwayUF	39974	107
cityUF	39974	107
rangeCityA	39974	107
combinedUF	39974	107
rangeCity	39940	141
rangeHwy	39940	141
range	39913	168
charge240	39829	252
cityE	39806	275
combE	39806	275
highwayE	39806	275
cityA08U	39084	997
highwayA08U	39084	997
combA08U	39084	997
co2TailpipeAGpm	38641	1440
fuelCostA08	38610	1471
UHighwayA	38580	1501
UCityA	38580	1501
combA08	38534	1547
barrelsA08	38534	1547
cityA08	38534	1547
highwayA08	38534	1547
hpv	35241	4840
hlv	35240	4841
pv2	33531	6550
lv2	33522	6559
city08U	29662	10419
highway08U	29662	10419
comb08U	29662	10419
pv4	25902	14179
lv4	25902	14179
engId	12600	27481
youSaveSpend	634	39447
co2TailpipeGpm	168	39913
co2	168	39913
UHighway	25	40056
UCity	25	40056
ghgScoreA	12	40069
displ	1	40080
mfrCode	0	40081
atvType	0	40081
trans_dscr	0	40081
tCharger	0	40081
city08	0	40081
startStop	0	40081
sCharger	0	40081

```
modifiedOn          0          40081
evMotor             0          40081
fuelType2           0          40081
rangeA              0          40081
createdOn           0          40081
c240bDscr           0          40081
c240Dscr            0          40081
guzzler             0          40081
highway08           0          40081
year                0          40081
VClass              0          40081
ghgScore            0          40081
fuelType1           0          40081
fuelType            0          40081
fuelCost08          0          40081
feScore             0          40081
eng_dscr            0          40081
id                  0          40081
make                0          40081
model               0          40081
mpgData             0          40081
drive               0          40081
cylinders           0          40081
comb08              0          40081
trany               0          40081
co2A                0          40081
barrels08           0          40081
```

As we see from the above correlation matrix, the boxes in bright yellow represent variables that are highly correlated and we want to avoid such a situation as it would lead to overfitting, bias. The features that are highly correlated and would not consider inputs to the model are:

1. one of city08 and city08U as they have a correlation of 0.9574 which is very high
2. one of phevHwy and phevComb as they have a correlation of 0.997
3. one of phevCity and phevComb as they have a correlation of 0.998
4. one of phevCity and phevHwy as they have a correlation of 0.990
5. one of phevHwy and cityUF as they have a correlation of 0.980
6. one of phevComb and cityUF as they have a correlation of 0.970
7. one of UHighwayA and highwayA08 as they have a correlation of 0.994
8. one of UCity and city08 as they have a correlation of 0.997
9. one of highwayA08U and comb08U as they have a correlation of 0.992
10. one of combE and cityE as they have a correlation of 0.998
11. one of cityUF and combinedUF as they have a correlation of 0.999
12. one of cityCD and combinedCD as they have a correlation of 0.993
13. one of cityUF and highwayUF as they have a correlation of 0.998
14. one of city08 and UCity as they have a correlation of 0.997
15. one of range and rangeHwy as they have a correlation of 0.984
16. one of highwayE and cityE as they hae a correlation of 0.992
17. charge120 as it has 40081 rows as zeros
18. highwayCD as it only has 40064 zero rows and 17 non zero rows
19. cityCD as it only has 40056 zero rows and 25 non zero rows
20. charge240b as it only has 40019 zero rows and 62 non zero rows

Ans 4.

Overfitting: this refers to an unwanted behvaiour of a Machine Learning algorithm used for predictive modeling. In this situation the training error reduces drastically but the test error is still high. The model learns the train data so well that it fails to generalize the test data. This occurs due to high variance and low bias.

How to evaluate overfitting: We need to plot of the model performance on the train and test set. It is calculated at each point during training. This plot is called the learning plot curve, showing one curve model performance on the training set and one curve for the test set for each increment of learning. The way to know overfitting can be seen on learning curve plots where model performance on the training dataset continues to improve and performance on the test or validation set improves to a point and then begins to get worse. We use a method - K-fold cross validation. The training process consists of a series of iterations. During each iteration, the steps are:

1. Keep one subset as the validation data and train the machine learning model on the remaining K-1 subsets.
2. Observe how the model performs on the validation sample.
3. Score model performance based on output data quality.

Iterations repeat until you test the model on every sample set. You then average the scores across all iterations to get the final assessment of the predictive model.

How to avoid overfitting:

1. Early stopping: this pauses the training phase before the machine learning model learns the noise of the data. Getting the timing right or the results would not be accurate.
2. Pruning: Feature selection—or pruning—identifies the most important features within the training set and eliminates irrelevant ones.
3. Regularization: Regularization is a collection of training/optimization techniques that seek to reduce overfitting. These methods try to eliminate those factors that do not impact the prediction outcomes by grading features based on importance.
4. Ensembling: Ensembling combines predictions from several separate machine learning algorithms. Some models are called weak learners because their results are often inaccurate. Ensemble methods combine all the weak learners to get more accurate results. They use multiple models to analyze sample data and pick the most accurate outcomes. The two main ensemble methods are bagging and boosting. Boosting trains different machine learning models one after another to get the final result, while bagging trains them in parallel.
5. Data augmentation: Data augmentation is a machine learning technique that changes the sample data slightly every time the model processes it. You can do this by changing the input data in small ways. When done in moderation, data augmentation makes the training sets appear unique to the model and prevents the model from learning their characteristics.

Underfitting: A model is said to be underfit when it has poor performance on the training data and results in unreliable results. Underfitting occurs due to high bias and low variance. This leads to higher training and validation errors since the model is not complex enough to classify the underlying data.

How to evaluate underfitting: We can see this by plotting the train and test errors.

How to avoid underfitting:

1. Increasing the Model Complexity: It's possible that your model is underfitting because it isn't robust enough to capture trends in the data. Using a more sophisticated model, for example by changing from a linear to a non-linear approach or by adding hidden layers to your Neural Network, may be very beneficial in this situation.
2. Reducing Regularization: By default, the algorithms you employ include regularization parameters to prevent overfitting. Thus, they sometimes hinder the algorithm from learning. Slight adjustments to their settings usually assist when trying to reduce underfit.
3. Adding Features to Training Data: As opposed to overfitting, your model may be underfitting if the training data is too limited or simple. If your model is underfitting, it may not have the characteristics required to identify key patterns and make accurate forecasts and predictions.However, underfitting can be alleviated by adding features and complexity to your data.