# Exploratory Data Analysis

**Exploratory Data Analysis (EDA)**: This is the process of sifting through the data and trying to make sense of the individual columns and the relationships between them.

We are going to use a dataset from www.fueleconomy.gov that provides information about makes and models of cars from 1984 through 2018. Using EDA we will explore many of the columns and relationships found in this data.

## Summary statistics

Summary statistics include the mean, quartiles, and standard deviation. The `.describe` method will calculate these measures on all of the numeric columns in a DataFrame.

### How to do it...

1. Load the dataset:

```
>>> import pandas as pd
>>> import numpy as np
>>> fueleco = pd.read_csv("data/vehicles.csv.zip")
>>> fueleco
       barrels08  barrelsA08  ...  phevHwy  phevComb
0      15.695714         0.0  ...        0         0
1      29.964545         0.0  ...        0         0
2      12.207778         0.0  ...        0         0
3       29.964545         0.0  ...        0         0
4       17.347895         0.0  ...        0         0
...          ...         ...  ...      ...       ...
39096  14.982273         0.0  ...        0         0
39097  14.330870         0.0  ...        0         0
39098  15.695714         0.0  ...        0         0
39099  15.695714         0.0  ...        0         0
39100  18.311667         0.0  ...        0         0
```

2. Call individual summary statistics methods such as `.mean`, `.std`, and `.quantile`:

```
>>> fueleco.mean()
barrels08         17.442712
barrelsA08         0.219276
charge120          0.000000
```

```
charge240           0.029630
city08             18.077799
                      ...
youSaveSpend    -3459.572645
charge240b          0.005869
phevCity            0.094703
phevHwy             0.094269
phevComb            0.094141
Length: 60, dtype: float64


>>> fueleco.std()
barrels08           4.580230
barrelsA08          1.143837
charge120           0.000000
charge240           0.487408
city08              6.970672
                      ...
youSaveSpend     3010.284617
charge240b          0.165399
phevCity            2.279478
phevHwy             2.191115
phevComb            2.226500
Length: 60, dtype: float64


>>> fueleco.quantile(
...     [0, 0.25, 0.5, 0.75, 1]
... )
      barrels08  barrelsA08  ...  phevHwy  phevComb
0.00   0.060000    0.000000  ...      0.0       0.0
0.25  14.330870    0.000000  ...      0.0       0.0
0.50  17.347895    0.000000  ...      0.0       0.0
0.75  20.115000    0.000000  ...      0.0       0.0
1.0 47.087143   18.311667  ...     81.0      88.0
```

3. Call the `.describe` method:

```
>>> fueleco.describe()
         barrels08   barrelsA08  ...      phevHwy     phevComb
count  39101.00...  39101.00...  ...  39101.00...  39101.00...
mean     17.442712     0.219276  ...     0.094269     0.094141
std       4.580230     1.143837  ...     2.191115     2.226500
min       0.060000     0.000000  ...     0.000000     0.000000
25%      14.330870     0.000000  ...     0.000000     0.000000
50%      17.347895     0.000000  ...     0.000000     0.000000
75%      20.115000     0.000000  ...     0.000000     0.000000
max      47.087143    18.311667  ...    81.000000    88.000000
```

4. To get summary statistics on the object columns, use the `.include` parameter:

```
>>> fueleco.describe(include=object)
              drive eng_dscr  ...   modifiedOn startStop
count         37912    23431  ...        39101      7405
unique            7      545  ...           68         2
top        Front-Wh...    (FFS)  ...  Tue Jan ...         N
```

```
freq          13653    8827  ...          29438      5176
```

### How it works...

By default, `.describe` will calculate summary statistics on the numeric columns. You can pass the `include` parameter to tell the method to include non-numeric data types. Note that this will show the count of unique values, the most frequent value (top), and its frequency counts for the object columns.

### There's more...

One tip that often makes more data appear on the screen is transposing a DataFrame. I find that this is useful for the output of the `.describe` method:

```
>>> fueleco.describe().T
               count         mean  ...       75%          max
barrels08    39101.0    17.442712  ...    20.115    47.087143
barrelsA08   39101.0     0.219276  ...     0.000    18.311667
charge120    39101.0     0.000000  ...     0.000     0.000000
charge240    39101.0     0.029630  ...     0.000    12.000000
city08       39101.0    18.077799  ...    20.000   150.000000
...              ...          ...  ...       ...          ...
youSaveSpend 39101.0 -3459.572645  ... -1500.000  5250.000000
charge240b   39101.0     0.005869  ...     0.000     7.000000
phevCity     39101.0     0.094703  ...     0.000    97.000000
phevHwy      39101.0     0.094269  ...     0.000    81.000000
phevComb     39101.0     0.094141  ...     0.000    88.000000
```

## Column types

You can glean information about the data in pandas simply by looking at the types of the columns. In this recipe, we will explore the column types.

### How to do it...

Inspect the `.dtypes` attribute:

```
>>> fueleco.dtypes
barrels08      float64
barrelsA08     float64
charge120      float64
charge240      float64
city08           int64
```

```
                  ...
modifiedOn      object
startStop       object
phevCity         int64
phevHwy          int64
phevComb         int64
Length: 83, dtype: object
```

Summarize the types of columns:

```
>>> fueleco.dtypes.value_counts()
float64    32
int64      27
object     23
bool        1
2. dtype: int64
```

## How it works...

When you read a CSV file in pandas, it has to infer the types of the columns. The process looks something like this:

- If all of the values in a column look like whole numeric values, convert them to integers and give the column the type `int64`
- If the values are float-like, give them the type `float64`
- If the values are numeric, float-like, or integer-like, but missing values, assign them to the type `float64` because the value typically used for missing values, `np.nan`, is a floating-point type
- If the values have `false` or `true` in them, assign them to Booleans
- Otherwise, leave the column as strings and give it the `object` type (these can be missing values with the `float64` type)

Note that if you use the `parse_dates`, parameter, it is possible that some of the columns were converted to datetimes.

By just looking at the output of `.dtypes` I can divine more about the data than just the data types. I can see if something is a string or missing values. Object types may be strings or categorical data, but they could also be numeric-like values that need to be nudged a little so that they are numeric. I typically leave integer columns alone. I tend to treat them as continuous values. If the values are float values, this indicates that the column could be:

- All floating-point values with no missing values
- Floating-point values with missing values
- Integer values that were missing some values and hence converted to floats

## There's more...

When pandas converts columns to floats or integers, it uses the 64-bit versions of those types. If you know that your integers fail into a certain range (or you are willing to sacrifice some precision on floats), you can save some memory by converting these columns to columns that use less memory.

```
>>> fueleco.select_dtypes("int64").describe().T
                count         mean  ...     75%     max
city08        39101.0    18.077799  ...    20.0   150.0
cityA08       39101.0     0.569883  ...     0.0   145.0
co2           39101.0    72.538989  ...    -1.0   847.0
co2A          39101.0     5.543950  ...    -1.0   713.0
comb08        39101.0    20.323828  ...    23.0   136.0
...               ...          ...  ...     ...     ...
year          39101.0  2000.635406  ...  2010.0  2018.0
youSaveSpend  39101.0 -3459.572645  ... -1500.0  5250.0
phevCity      39101.0     0.094703  ...     0.0    97.0
phevHwy       39101.0     0.094269  ...     0.0    81.0
phevComb      39101.0     0.094141  ...     0.0    88.0
```

We can see that the `city08` and `comb08` columns don't go above 150. The `iinfo` function in NumPy will show us the limits for integer types. We can see that we would not want to use an `int8` for this column, but we can use an `int16`. By converting to that type, the column will use 25% of the memory:

```
>>> np.iinfo(np.int8)
iinfo(min=-128, max=127, dtype=int8)

>>> np.iinfo(np.int16)
iinfo(min=-32768, max=32767, dtype=int16)

>>> fueleco[["city08", "comb08"]].info(memory_usage="deep")
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   city08  39101 non-null  int64
 1   comb08  39101 non-null  int64
dtypes: int64(2)
memory usage: 611.1 KB
>>> (
...     fueleco[["city08", "comb08"]]
...     .assign(
...         city08=fueleco.city08.astype(np.int16),
...         comb08=fueleco.comb08.astype(np.int16),
...     )
...     .info(memory_usage="deep")
... )
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
```

```
---  ------  --------------  -----
 0   city08  39101 non-null  int16
 1   comb08  39101 non-null  int16
dtypes: int16(2)
memory usage: 152.9 KB
```

Note that there is an analogous `finfo` function in NumPy for retrieving float information.

An option for conserving memory for string columns is to convert them to categories. If each value for a string column is unique, this will slow down pandas and use more memory, but if you have low cardinality, you can save a lot of memory. The `make` column has low cardinality, but the `model` column has a higher cardinality, and there is less memory saving for that column.

Below, we will show pulling out just these two columns. But instead of getting a Series, we will index with a list with just that column name in it. This will gives us back a DataFrame with a single column. We will update the column type to categorical and look at the memory usage. Remember to pass in `memory_usage='deep'` to get the memory usage for object columns:

```
>>> fueleco.make.nunique()
134

>>> fueleco.model.nunique()
3816

>>> fueleco[["make"]].info(memory_usage="deep")
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   make    39101 non-null  object
dtypes: object(1)
memory usage: 2.4 MB

>>> (
...     fueleco[["make"]]
...     .assign(make=fueleco.make.astype("category"))
...     .info(memory_usage="deep")
... )
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   make    39101 non-null  category
dtypes: category(1)
memory usage: 90.4 KB
>>> fueleco[["model"]].info(memory_usage="deep")
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   model   39101 non-null  object
```

```
dtypes: object(1)
memory usage: 2.5 MB

>>> (
...     fueleco[["model"]]
...     .assign(model=fueleco.model.astype("category"))
...     .info(memory_usage="deep")
... )
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39101 entries, 0 to 39100
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   model   39101 non-null  category
dtypes: category(1)
memory usage: 496.7 KB
```

## Categorical data

We can broadly classify data into dates, continuous values, and categorical values. In this section, we will explore quantifying and visualizing categorical data.

### How to do it...

1. Pick out the columns with data types that are `object`:

```
>>> fueleco.select_dtypes(object).columns
Index(['drive', 'eng_dscr', 'fuelType', 'fuelType1', 'make', 'model',
       'mpgData', 'trany', 'VClass', 'guzzler', 'trans_dscr', 'tCharger',
       'sCharger', 'atvType', 'fuelType2', 'rangeA', 'evMotor', 'mfrCode',
       'c240Dscr', 'c240bDscr', 'createdOn', 'modifiedOn', 'startStop'],
      dtype='object')
```

2. Use `.nunique` to determine the cardinality:

```
>>> fueleco.drive.nunique()
7
```

3. Use `.sample` to see some of the values:

```
>>> fueleco.drive.sample(5, random_state=42)
4217      4-Wheel ...
1736      4-Wheel ...
36029     Rear-Whe...
37631     Front-Wh...
1668      Rear-Whe...
Name: drive, dtype: object
```

4. Determine the number and percent of missing values:

```
>>> fueleco.drive.isna().sum()
1189
>>> fueleco.drive.isna().mean() * 100
3.0408429451932175
```

5. Use the `.value_counts` method to summarize a column:

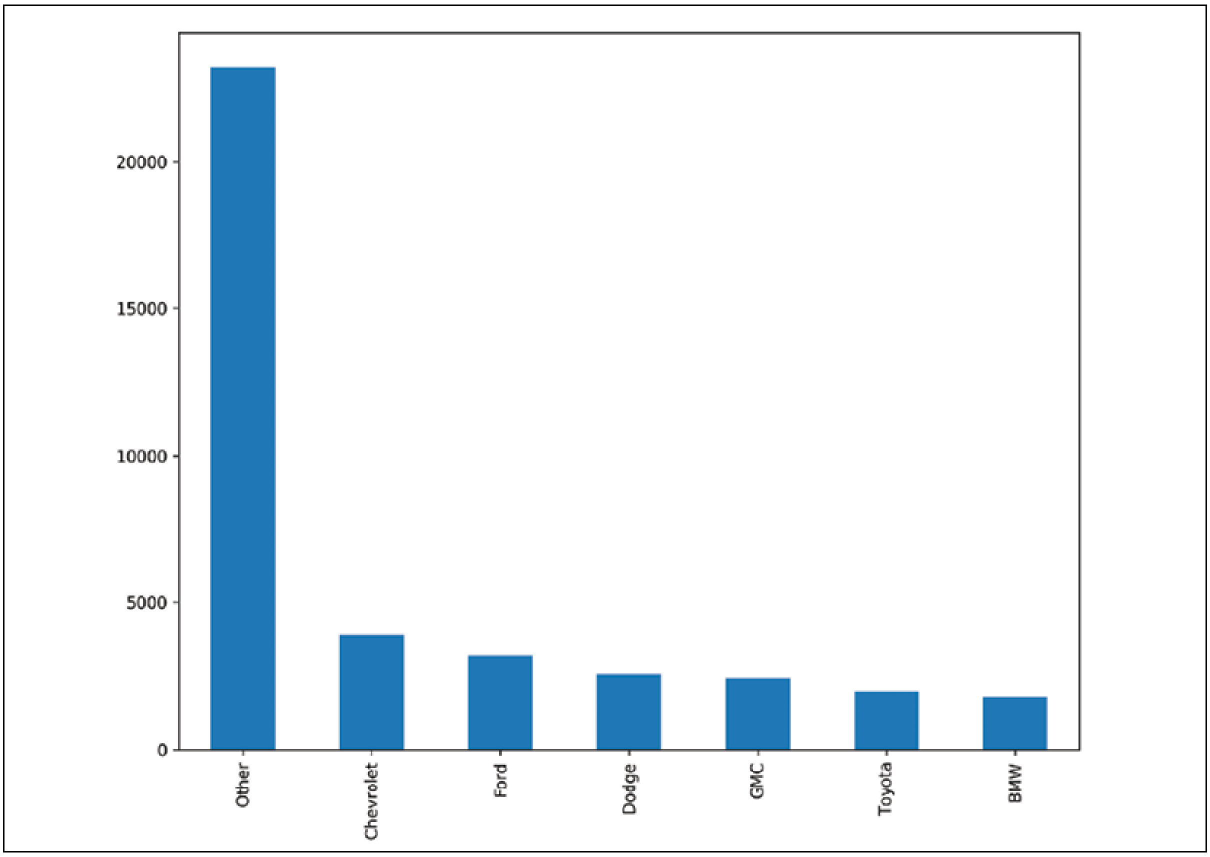
```
>>> fueleco.drive.value_counts()
Front-Wheel Drive             13653
Rear-Wheel Drive              13284
4-Wheel or All-Wheel Drive     6648
All-Wheel Drive                2401
4-Wheel Drive                  1221
2-Wheel Drive                   507
Part-time 4-Wheel Drive         198
Name: drive, dtype: int64
```

6. If there are too many values in the summary, you might want to look at the top 6 and collapse the remaining values:

```
>>> top_n = fueleco.make.value_counts().index[:6]
>>> (
...     fueleco.assign(
...         make=fueleco.make.where(
...             fueleco.make.isin(top_n), "Other"
...         )
...     ).make.value_counts()
... )
Other         23211
Chevrolet      3900
Ford           3208
Dodge          2557
GMC            2442
Toyota         1976
BMW            1807
Name: make, dtype: int64
```

7. Use pandas to plot the counts and visualize them:

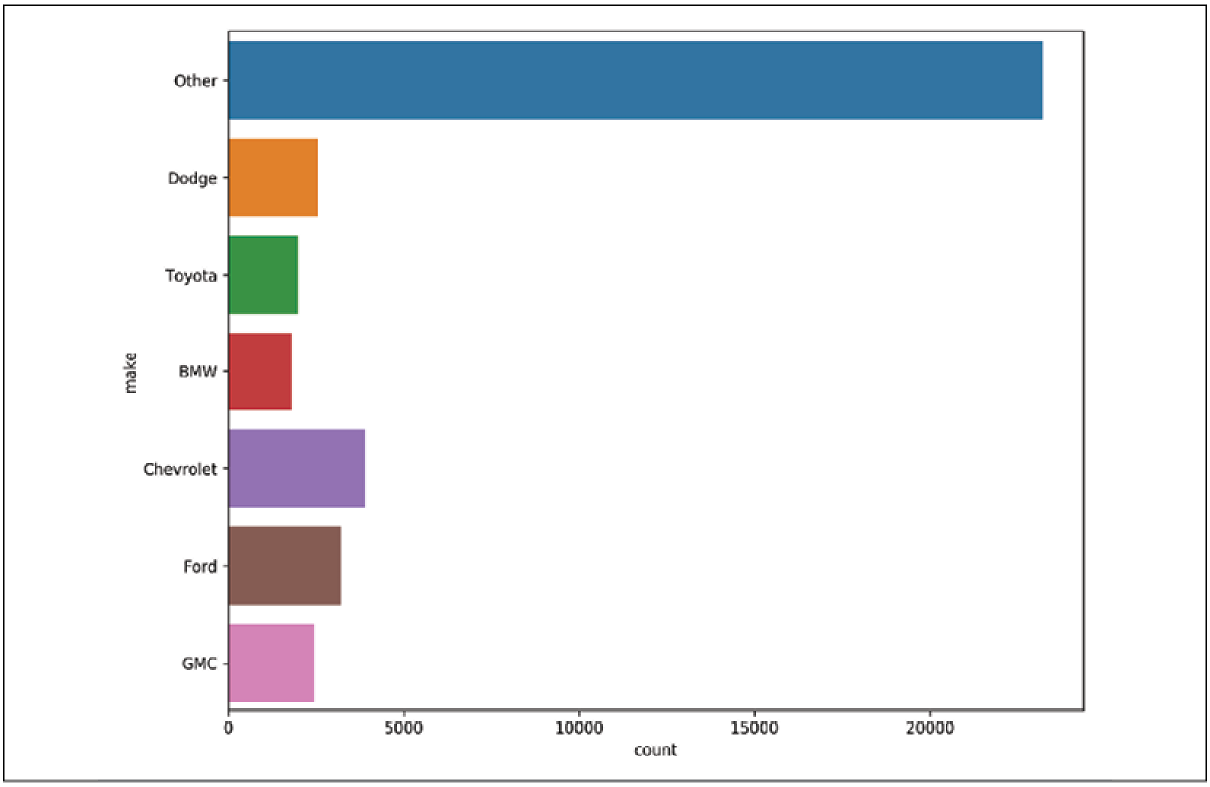
```
>>> import matplotlib.pyplot as plt
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> top_n = fueleco.make.value_counts().index[:6]
>>> (
...     fueleco.assign(
...         make=fueleco.make.where(
...             fueleco.make.isin(top_n), "Other"
...         )
...     )
...     .make.value_counts()
...     .plot.bar(ax=ax)
... )
>>> fig.savefig("c5-catpan.png", dpi=300)
```




pandas categorical

8. Use `seaborn` to plot the counts and visualize them:

```
>>> import seaborn as sns
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> top_n = fueleco.make.value_counts().index[:6]
>>> sns.countplot(
...     y="make",
...     data=(
...         fueleco.assign(
...             make=fueleco.make.where(
...                 fueleco.make.isin(top_n), "Other"
...             )
...         )
...     ),
... )
>>> fig.savefig("c5-catsns.png", dpi=300)
```



Seaborn categorical

## How it works...

When we are examining a categorical variable, we want to know how many unique values there are. If this is a large value, the column might not be categorical, but either free text or a numeric column that pandas didn't know how to store as numeric because it came across a non-valid number.

The `.sample` method lets us look at a few of the values. With most columns, it is important to determine how many are missing. It looks like there are over 1,000 rows, or about 3% of the values, that are missing. Typically, we need to talk to an SME to determine why these values are missing and whether we need to impute them or drop them.
Here is some code to look at the rows where the *drive* is missing:

```
>>> fueleco[fueleco.drive.isna()]
       barrels08  barrelsA08  ...  phevHwy  phevComb
7138    0.240000         0.0  ...        0         0
8144    0.312000         0.0  ...        0         0
8147    0.270000         0.0  ...        0         0
18215  15.695714         0.0  ...        0         0
18216  14.982273         0.0  ...        0         0
...          ...         ...  ...      ...       ...
23023   0.240000         0.0  ...        0         0
23024   0.546000         0.0  ...        0         0
23026   0.426000         0.0  ...        0         0
23031   0.426000         0.0  ...        0         0
23034   0.204000         0.0  ...        0         0
```

The smart method for inspecting categorical columns is the `.value_counts` method. By default, it does not show missing values, but you can use the `dropna` parameter to fix that:

```
>>> fueleco.drive.value_counts(dropna=False)
Front-Wheel Drive             13653
Rear-Wheel Drive              13284
4-Wheel or All-Wheel Drive     6648
All-Wheel Drive                2401
4-Wheel Drive                  1221
NaN                            1189
2-Wheel Drive                   507
Part-time 4-Wheel Drive         198
Name: drive, dtype: int64
```

Finally, you can visualize this output using pandas or seaborn. A bar plot is an appropriate plot to do this. However, if this is a higher cardinality column, you might have too many bars for an effective plot. You can limit the number of columns as we do in *step 6*, or use the `order` parameter for `countplot` to limit them with seaborn.

## There's more...

Some columns report `object` data types, but they are not really categorical. In this dataset, the `rangeA` column has an `object` data type. However, if we use my favorite categorical method, `.value_counts`, to examine it, we see that it is not really categorical, but a numeric column posing as a category.
This is because, as seen in the output of `.value_counts`, there are slashes (`/`) and dashes (`-`) in some of the entries and pandas did not know how to convert those values to numbers, so it left the whole column as a string column.

```
>>> fueleco.rangeA.value_counts()
290        74
270        56
280        53
310        41
277        38
           ..
328         1
250/370     1
362/537     1
310/370     1
340-350     1
Name: rangeA, Length: 216, dtype: int64
```

Another way to find offending characters is to use the `.str.extract` method with a regular expression:

```
>>> (
...     fueleco.rangeA.str.extract(r"([^0-9.])")
```

```
...     .dropna()
...     .apply(lambda row: "".join(row), axis=1)
...     .value_counts()
... )
/    280
-     71
Name: rangeA, dtype: int64
```

This is actually a column that has two types: float and string. The data type is reported as `object` because that type can hold heterogenous typed columns. The missing values are stored as NaN and the non-missing values are strings:

```
>>> set(fueleco.rangeA.apply(type))
{<class 'str'>, <class 'float'>}
```

Here is the count of missing values:

```
>>> fueleco.rangeA.isna().sum()
37616
```

According to the `fueleconomy.gov` website, the `rangeA` value represents the range for the second fuel type of dual fuel vehicles (E85, electricity, CNG, and LPG). Using pandas, we can replace the missing values with zero, replace dashes with slashes, then split and take the mean value of each row (in the case of a dash/slash):

```
>>> (
...     fueleco.rangeA.fillna("0")
...     .str.replace("-", "/")
...     .str.split("/", expand=True)
...     .astype(float)
...     .mean(axis=1)
... )
0        0.0
1        0.0
2        0.0
3        0.0
4        0.0
        ...
39096    0.0
39097    0.0
39098    0.0
39099    0.0
39100    0.0
Length: 39101, dtype: float64
```

We can also treat numeric columns as categories by binning them. There are two powerful functions in pandas to aid binning, `cut` and `qcut`. We can use `cut` to cut into equal-width bins, or bin widths that we specify. For the `rangeA` column, most of the values were empty and we replaced them with 0, so 10 equal-width bins look like this:

```
>>> (
...     fueleco.rangeA.fillna("0")
...     .str.replace("-", "/")
...     .str.split("/", expand=True)
...     .astype(float)
```

```
...     .mean(axis=1)
...     .pipe(lambda ser_: pd.cut(ser_, 10))
...     .value_counts()
... )
(-0.45, 44.95]     37688
(269.7, 314.65]      559
(314.65, 359.6]      352
(359.6, 404.55]      205
(224.75, 269.7]      181
(404.55, 449.5]       82
(89.9, 134.85]        12
(179.8, 224.75]        9
(44.95, 89.9]          8
(134.85, 179.8]        5
dtype: int64
```

Alternatively, `qcut` (quantile cut) will cut the entries into bins with the same size. Because the `rangeA` column is heavily skewed, and most of the entries are 0, we can't quantize 0 into multiple bins, so it fails. But it does (somewhat) work with `city08`. I say somewhat because the values for `city08` are whole numbers and so they don't evenly bin into 10 buckets, but the sizes are close:

```
>>> (
...     fueleco.rangeA.fillna("0")
...     .str.replace("-", "/")
...     .str.split("/", expand=True)
...     .astype(float)
...     .mean(axis=1)
...     .pipe(lambda ser_: pd.qcut(ser_, 10))
...     .value_counts()
... )
Traceback (most recent call last):
  ...
ValueError: Bin edges must be unique: array([  0. ,   0. ,   0. ,   0. ,   0. ,
0. ,   0. ,   0. ,   0. ,
         0. , 449.5]).
>>> (
...     fueleco.city08.pipe(
...         lambda ser: pd.qcut(ser, q=10)
...     ).value_counts()
... )
(5.999, 13.0]    5939
(19.0, 21.0]     4477
(14.0, 15.0]     4381
(17.0, 18.0]     3912
(16.0, 17.0]     3881
(15.0, 16.0]     3855
(21.0, 24.0]     3676
(24.0, 150.0]    3235
(13.0, 14.0]     2898
(18.0, 19.0]     2847
Name: city08, dtype: int64
```

## Continuous data

The broad definition of continuous data is data that is stored as a number, either an integer or a float. There is some gray area between categorical and continuous data. For example, the grade level could be represented as a number (ignoring Kindergarten, or using 0 to represent it). A grade column, in this case, could be both categorical and continuous, so the techniques in this section and the previous section could both apply to it.

We will examine a continuous column from the fuel economy dataset in this section. The `city08` column lists the miles per gallon that are expected when driving a car at the lower speeds found in a city.

## How to do it...

Pick out the columns that are numeric (typically `int64` or `float64`):

```
>>> fueleco.select_dtypes("number")
       barrels08  barrelsA08  ...  phevHwy  phevComb
0      15.695714         0.0  ...        0         0
1      29.964545         0.0  ...        0         0
2      12.207778         0.0  ...        0         0
3      29.964545         0.0  ...        0         0
4      17.347895         0.0  ...        0         0
...          ...         ...  ...      ...       ...
39096  14.982273         0.0  ...        0         0
39097  14.330870         0.0  ...        0         0
39098  15.695714         0.0  ...        0         0
39099  15.695714         0.0  ...        0         0
39100  18.311667         0.0  ...        0         0
```

Use `.sample` to see some of the values:

```
>>> fueleco.city08.sample(5, random_state=42)
4217     11
1736     21
36029    16
37631    16
1668     17
Name: city08, dtype: int64
```

Determine the number and percent of missing values:

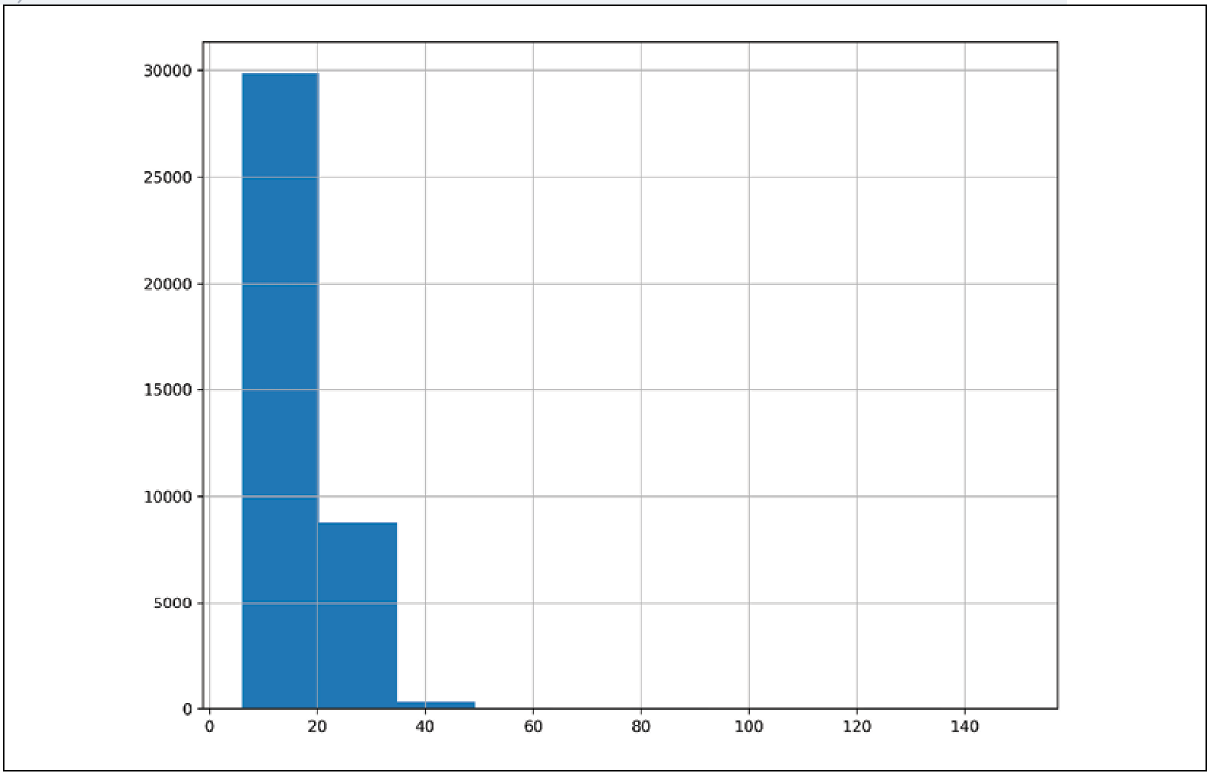
```
>>> fueleco.city08.isna().sum()
0
>>> fueleco.city08.isna().mean() * 100
0.0
```

Get the summary statistics:

```
>>> fueleco.city08.describe()
count    39101.000000
mean        18.077799
std          6.970672
min          6.000000
25%         15.000000
50%         17.000000
75%         20.000000
max        150.000000
Name: city08, dtype: float64
```

Use pandas to plot a histogram:

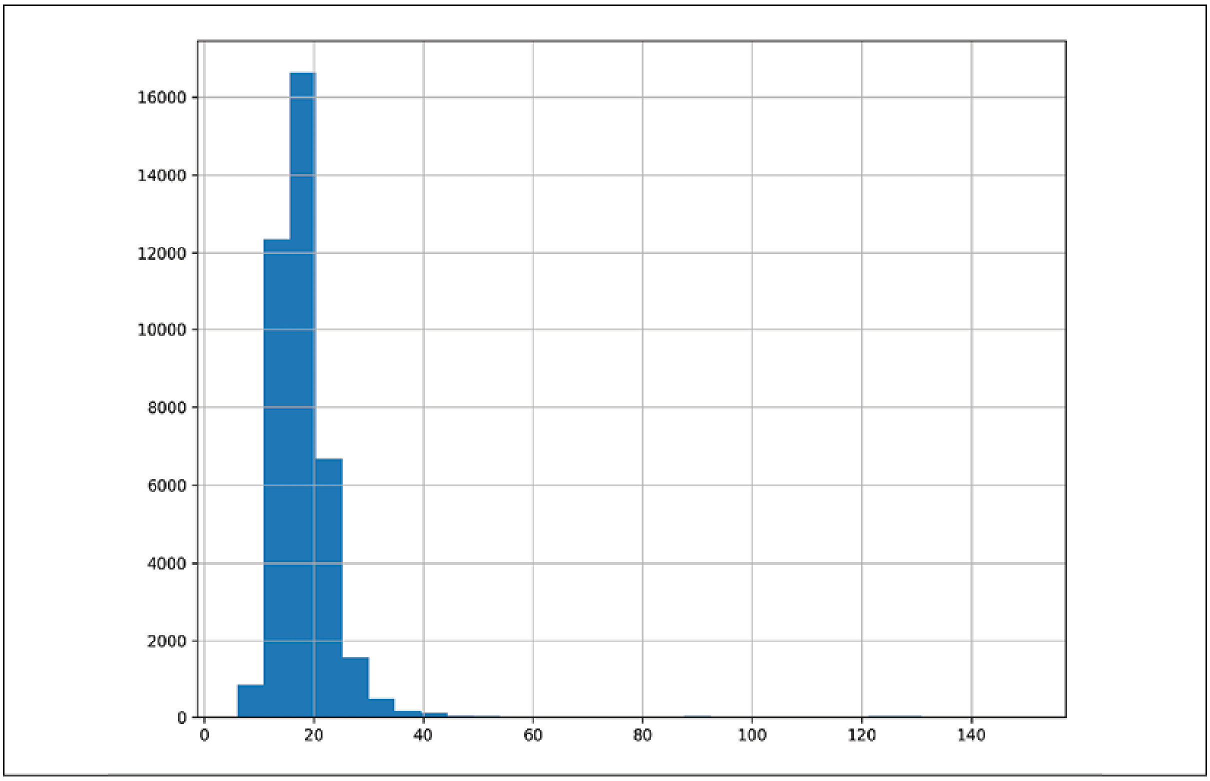
```
>>> import matplotlib.pyplot as plt
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> fueleco.city08.hist(ax=ax)
>>> fig.savefig(
...     "c5-conthistpan.png", dpi=300
... )
```




pandas histogram

This plot looks very skewed, so we will increase the number of bins in the histogram to see if the skew is hiding behaviors (as skew makes bins wider):

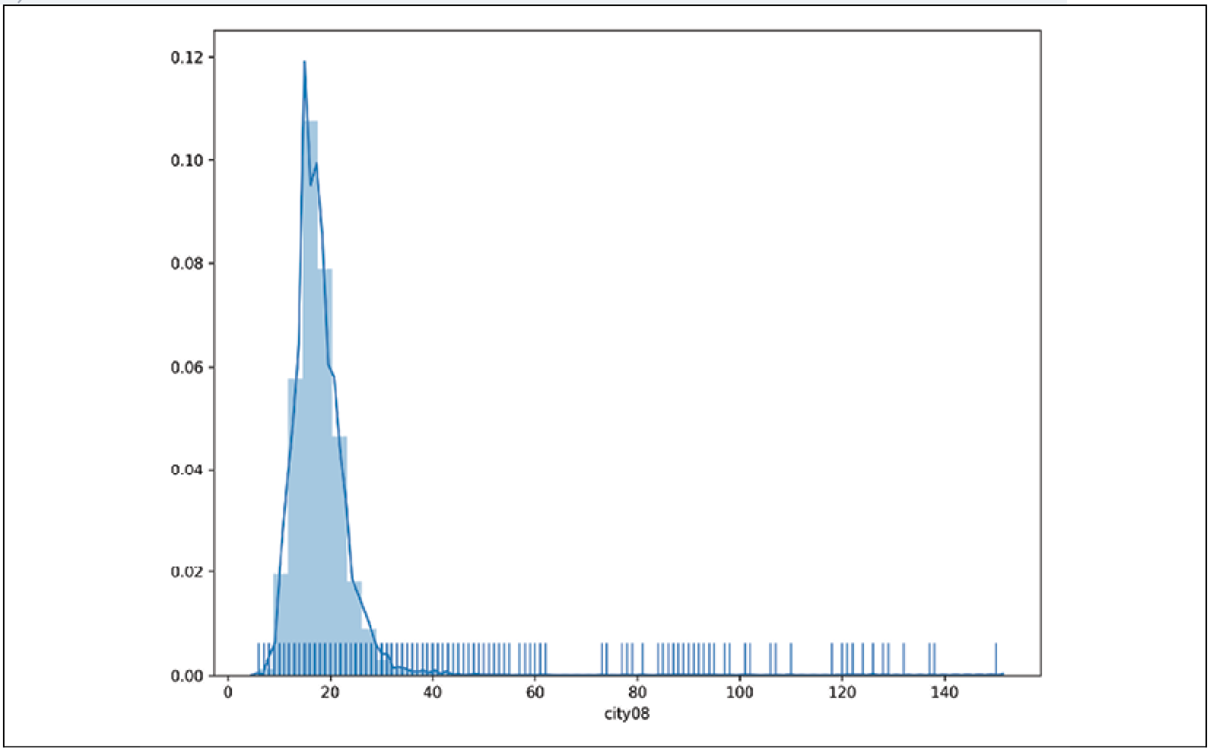
```
>>> import matplotlib.pyplot as plt
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> fueleco.city08.hist(ax=ax, bins=30)
>>> fig.savefig(
...     "c5-conthistpanbins.png", dpi=300
... )
```




pandas histogram

Use seaborn to create a distribution plot, which includes a histogram, a **kernel density estimation** (**KDE**), and a rug plot:

```
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> sns.distplot(fueleco.city08, rug=True, ax=ax)
>>> fig.savefig(
...     "c5-conthistsns.png", dpi=300
... )
```




Seaborn histogram

## How it works...

It is good to get a feel for how numbers behave. Looking at a sample of the data will let you know what some of the values are. We also want to know whether values are missing. Recall that pandas will ignore missing values when we perform operations on columns.

The summary statistics provided by `.describe` are very useful. This is probably my favorite method for inspecting continuous values. I like to make sure I check the minimum and maximum values to make sure that they make sense. It would be strange if there was a negative value as a minimum for the miles per gallon column. The quartiles also give us an indication of how skewed the data is. Because the quartiles are reliable indicators of the tendencies of the data, they are not affected by outliers.
Another thing to be aware of is infinite values, either positive or negative. This column does not have infinite values, but these can cause some math operations or plots to fail. If you have infinite values, you need to determine how to handle them. Clipping and removing them are common options that are easy with pandas.

Take advantage of plots because, as the cliché goes, a picture tells a thousand words.

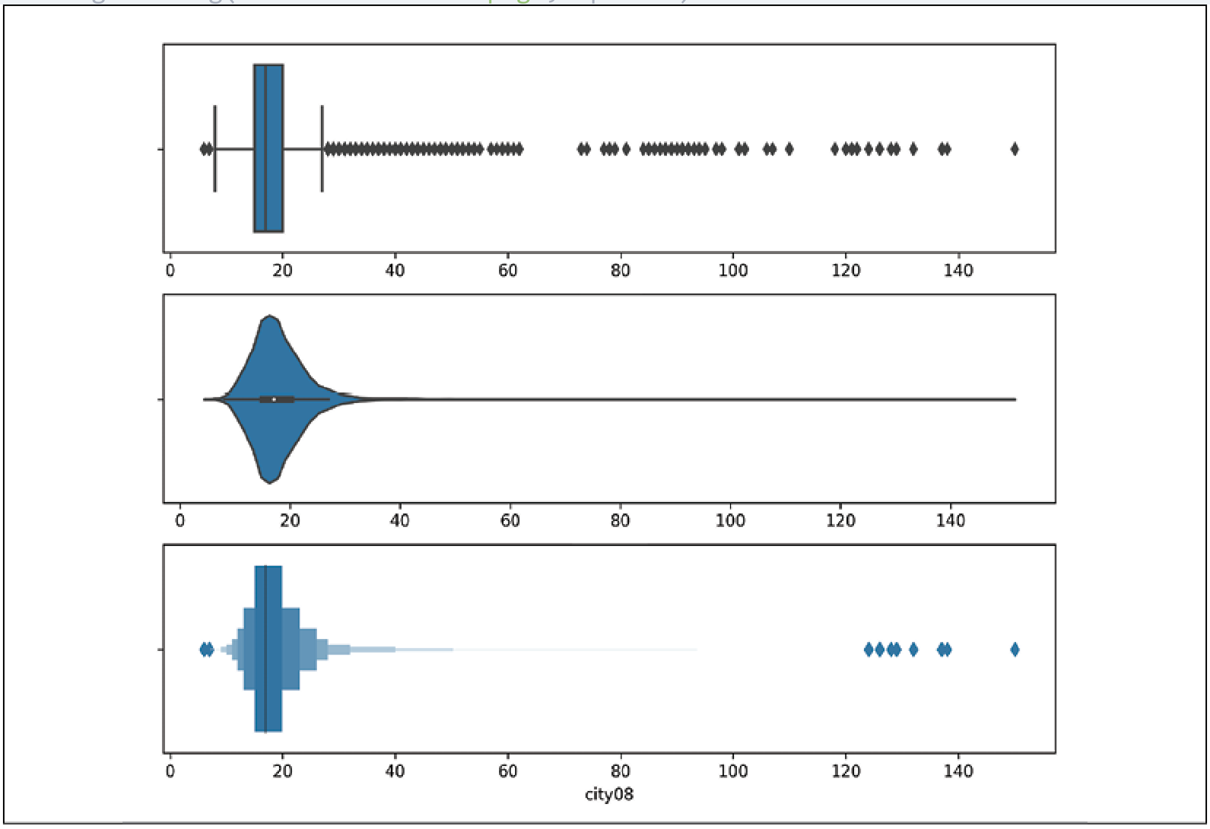
## There's more...

The seaborn library has many options for summarizing continuous data. In addition to the `distplot` function, there are functions for creating box plots, boxen plots, and violin plots.
A boxen plot is an enhanced box plot. The R folks created a plot called a *letter value* plot, and when the seaborn author replicated it, the name was changed to boxen. The median value is the black line. It steps half of the way from the median 50 to 0 and 100. So the tallest block shows the range from 25-75 quantiles. The next box on the low end goes from 25 to half of that value (or 12.5), so the 12.5-25 quantile. This pattern repeats, so the next box is the 6.25-12.5 quantile, and so on.

A violin plot is basically a histogram that has a copy flipped over on the other side. If you have a bi-model histogram, it tends to look like a violin, hence the name:

```
>>> fig, axs = plt.subplots(nrows=3, figsize=(10, 8))
>>> sns.boxplot(fueleco.city08, ax=axs[0])
```

```
>>> sns.violinplot(fueleco.city08, ax=axs[1])
>>> sns.boxenplot(fueleco.city08, ax=axs[2])
>>> fig.savefig("c5-contothersns.png", dpi=300)
```




A boxplot, violin plot, and boxen plot created with seaborn

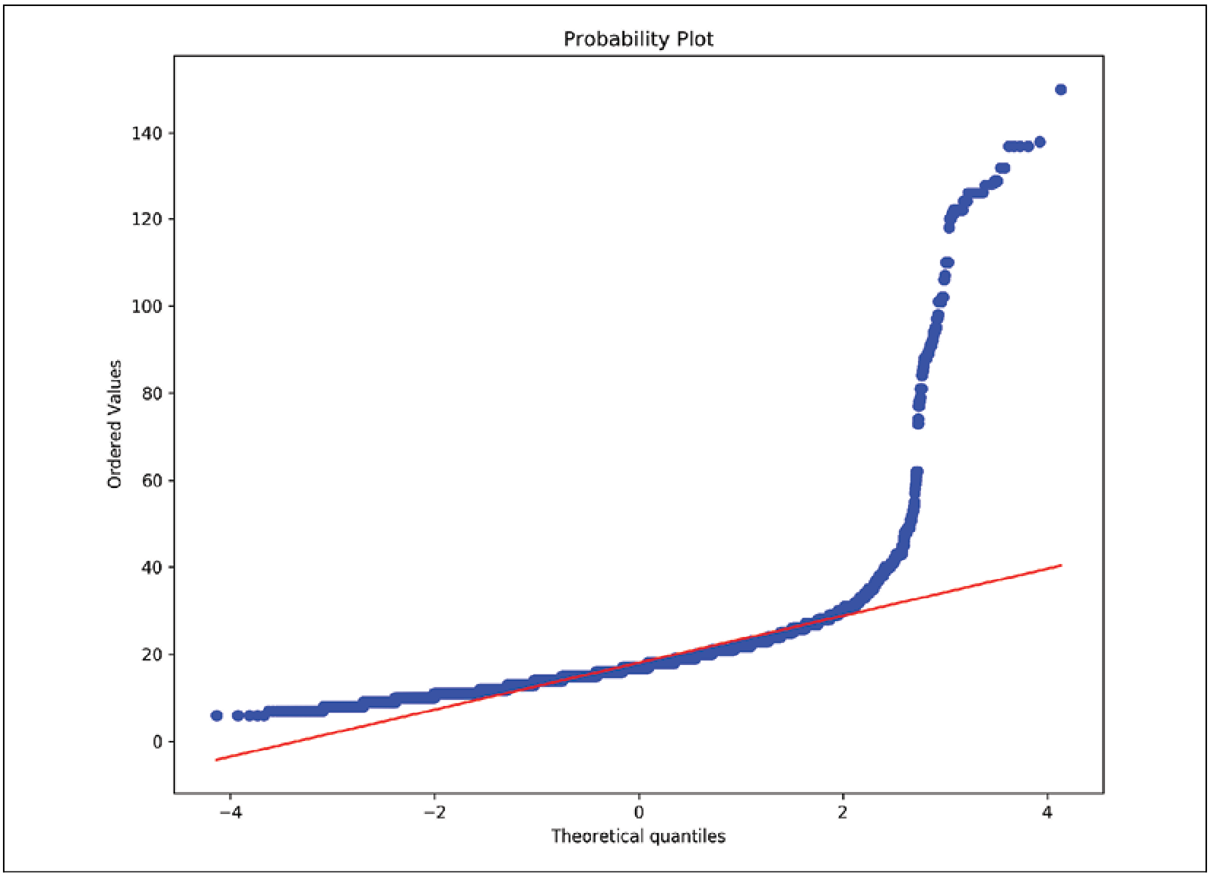
If you are concerned with whether the data is normal, you can quantify this with numbers and visualizations using the SciPy library.

The Kolmogorov-Smirnov test can evaluate whether a distribution is normal. It provides us with a p-value. If this value is significant (< 0.05), then the data is not normal:

```
>>> from scipy import stats
>>> stats.kstest(fueleco.city08, cdf="norm")
KstestResult(statistic=0.9999999990134123, pvalue=0.0)
```

We can plot a probability plot to see whether the values are normal. If the samples track the line, then the data is normal:

```
>>> from scipy import stats
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> stats.probplot(fueleco.city08, plot=ax)
>>> fig.savefig("c5-conprob.png", dpi=300)
```



A probability plot shows us if the values track the normal line

## Comparing continuous values across categories

The previous sections discussed looking at a single column. This section will show how to compare continuous variables in different categories. We will look at mileage numbers in different brands: Ford, Honda, Tesla, and BMW.

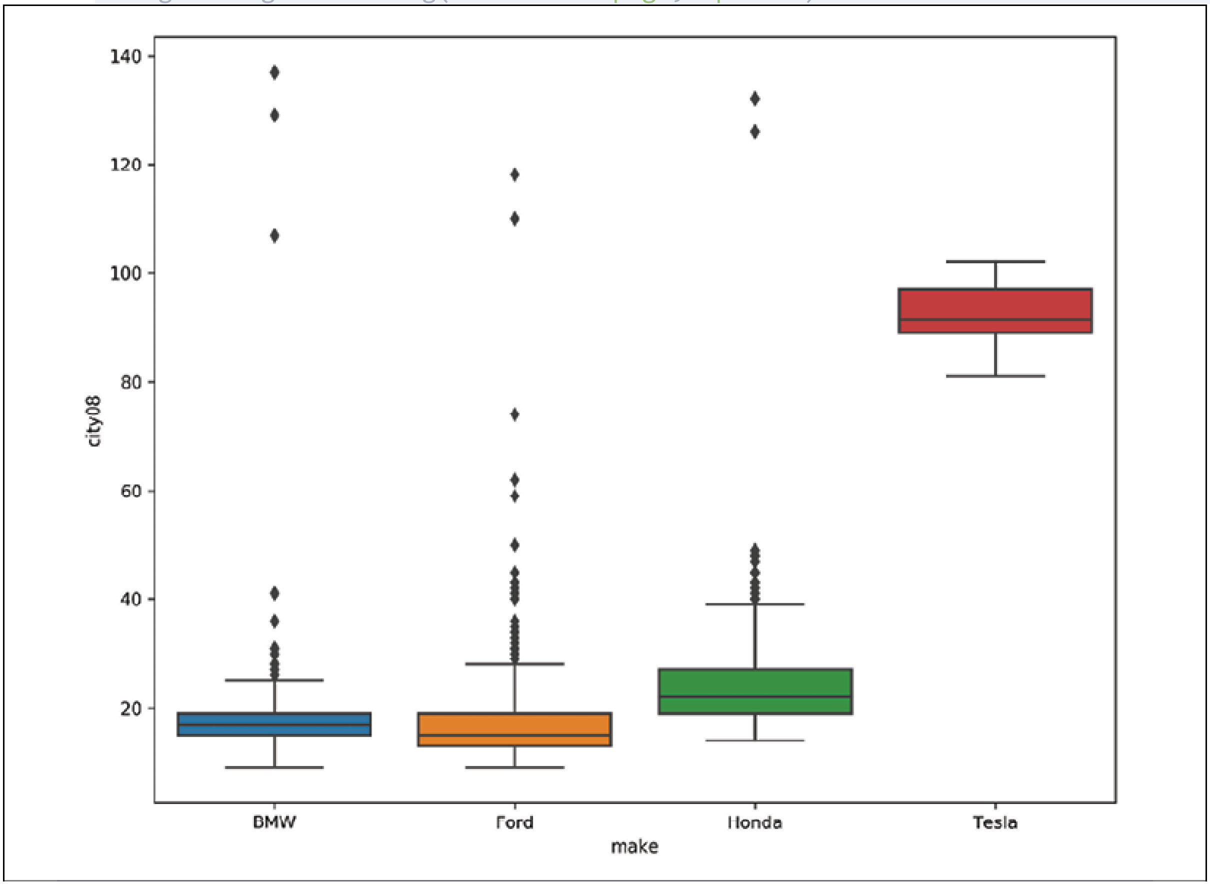
### How to do it...

Make a mask for the brands we want and then use a group by operation to look at the mean and standard deviation for the `city08` column for each group of cars:

```
>>> mask = fueleco.make.isin(
...     ["Ford", "Honda", "Tesla", "BMW"]
... )
>>> fueleco[mask].groupby("make").city08.agg(
...     ["mean", "std"]
... )
            mean       std
make
BMW    17.817377  7.372907
Ford   16.853803  6.701029
Honda  24.372973  9.154064
Tesla  92.826087  5.538970
```

Visualize the `city08` values for each make with seaborn:

```
>>> g = sns.catplot(
...     x="make", y="city08", data=fueleco[mask], kind="box"
... )
>>> g.ax.figure.savefig("c5-catbox.png", dpi=300)
```




Box plots for each make

## How it works...

If the summary statistics change for the different makes, that is a strong indicator that the makes have different characteristics. The central tendency (mean or median) and the variance (or standard deviation) are good measures to compare. We can see that Honda gets better city mileage than both BMW and Ford but has more variance, while Tesla is better than all of them and has the tightest variance.

Using a visualization library like seaborn lets us quickly see the differences in the categories. The difference between the four car makes is drastic, but you can see that there are outliers for the non-Tesla makes that appear to have better mileage than Tesla.

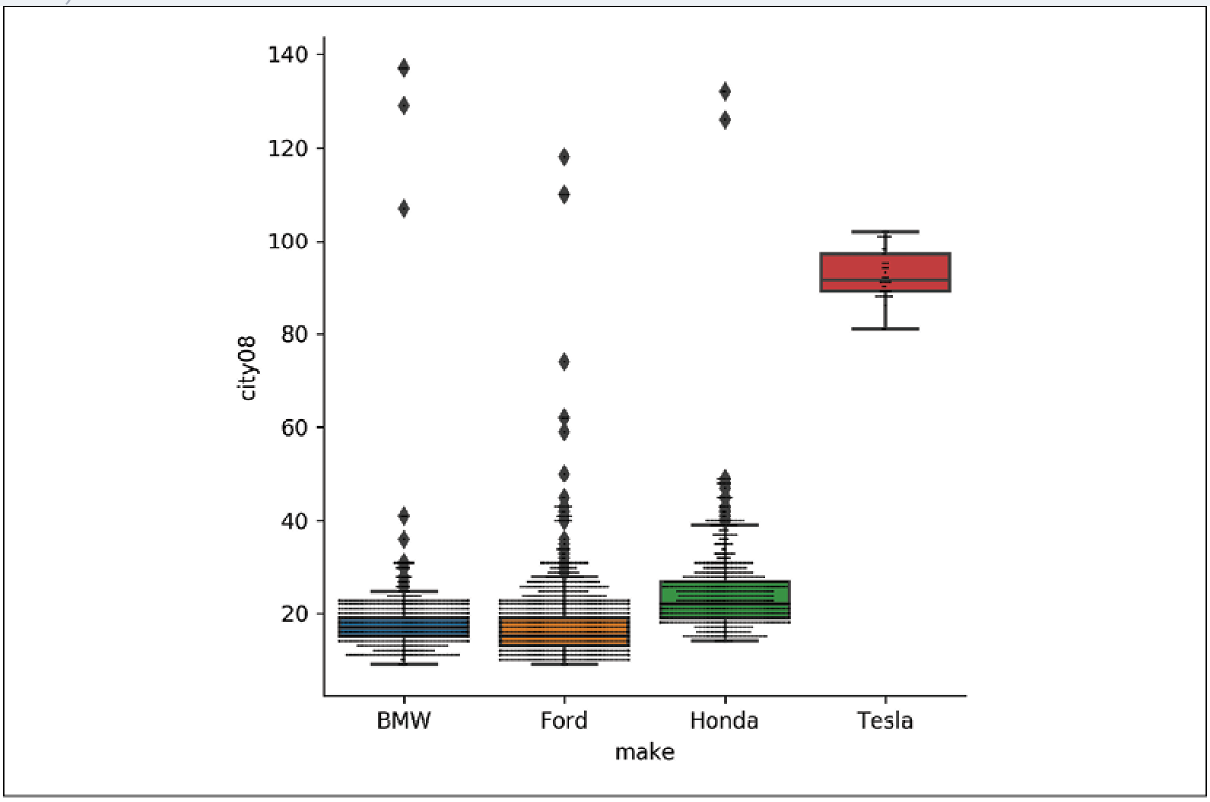
## There's more...

One drawback of a boxplot is that while it indicates the spread of the data, it does not reveal how many samples are in each make. You might naively think that each boxplot has the same number of samples. We can quantify that this is not the case with pandas:

```
>>> mask = fueleco.make.isin(
...     ["Ford", "Honda", "Tesla", "BMW"]
... )
>>> (fueleco[mask].groupby("make").city08.count())
make
BMW      1807
Ford     3208
Honda     925
Tesla      46
Name: city08, dtype: int64
```

Another option is to do a swarm plot on top of the box plots:

```
>>> g = sns.catplot(
...     x="make", y="city08", data=fueleco[mask], kind="box"
... )
>>> sns.swarmplot(
...     x="make",
...     y="city08",
...     data=fueleco[mask],
...     color="k",
...     size=1,
...     ax=g.ax,
... )
>>> g.ax.figure.savefig(
...     "c5-catbox2.png", dpi=300
... )
```

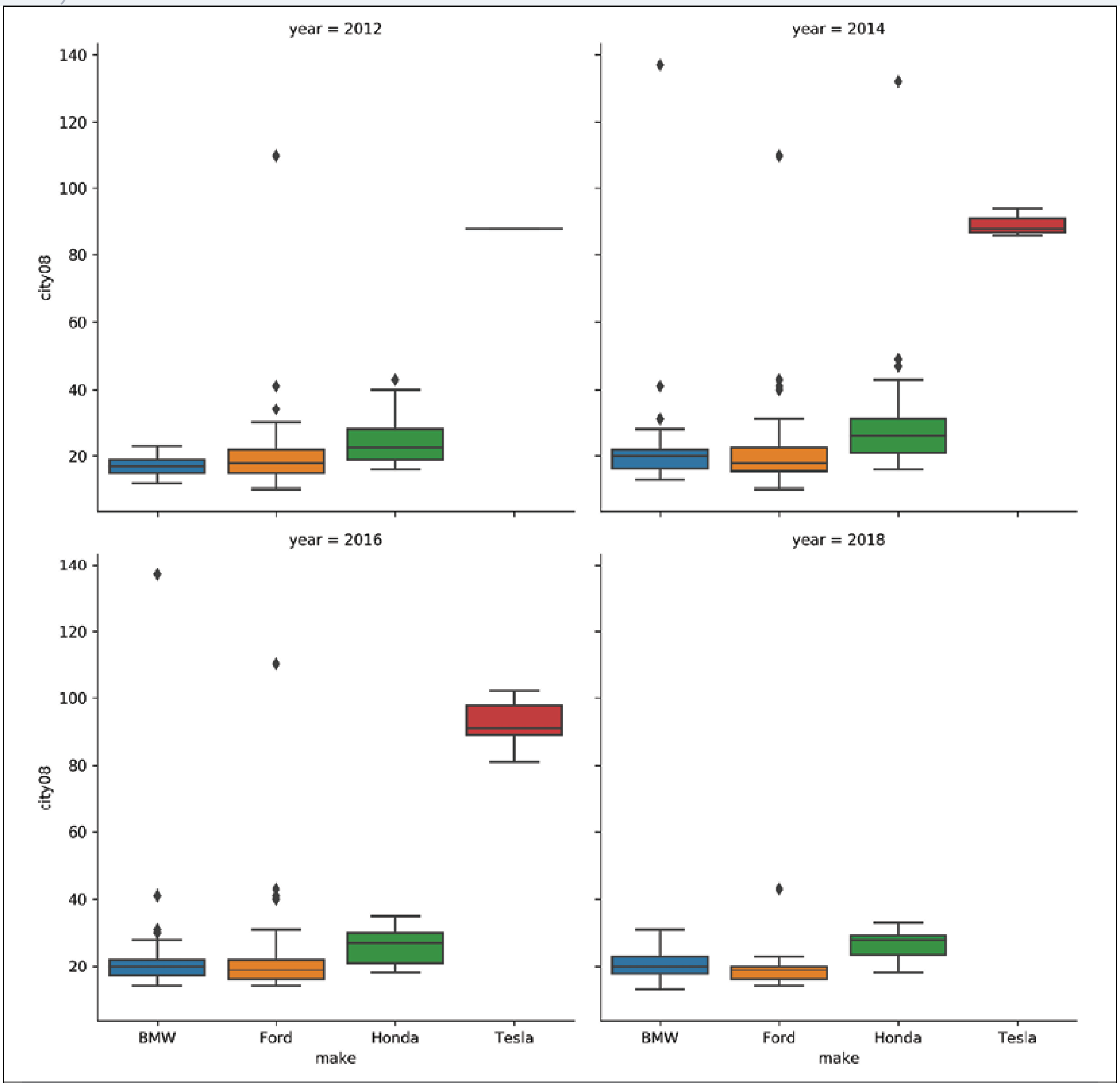


A seaborn boxplot with a swarm plot layered on top

Additionally, the `catplot` function has many more tricks up its sleeves. We are showing two dimensions right now, city mileage and make. We can add more dimensions to the plot.

You can facet the grid by another feature. You can break each of these new plots into its own graph by using the `col` parameter:

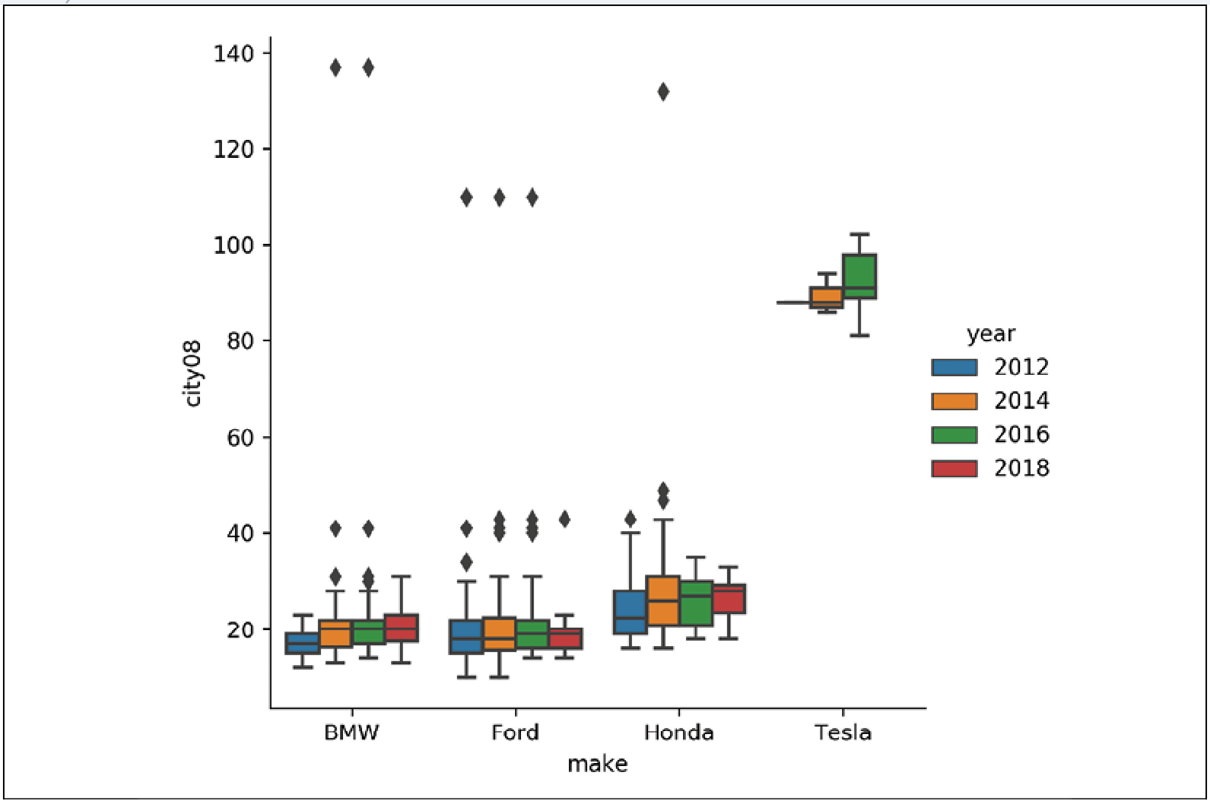
```
>>> g = sns.catplot(
...     x="make",
...     y="city08",
...     data=fueleco[mask],
...     kind="box",
...     col="year",
...     col_order=[2012, 2014, 2016, 2018],
...     col_wrap=2,
... )
>>> g.axes[0].figure.savefig(
...     "c5-catboxcol.png", dpi=300
... )
```



A seaborn boxplot with hues for makes and faceted by year

Alternatively, you can embed the new dimension in the same plot by using the `hue` parameter:

```
>>> g = sns.catplot(
...     x="make",
...     y="city08",
...     data=fueleco[mask],
...     kind="box",
...     hue="year",
...     hue_order=[2012, 2014, 2016, 2018],
... )
>>> g.ax.figure.savefig(
...     "c5-catboxhue.png", dpi=300
... )
```




A seaborn boxplot for every make colored by year

If you are in Jupyter, you can style the output of the `groupby` call to highlight the values at the extremes. Use the `.style.background_gradient` method to do this:

```
>>> mask = fueleco.make.isin(
...     ["Ford", "Honda", "Tesla", "BMW"]
... )
>>> (
...     fueleco[mask]
...     .groupby("make")
...     .city08.agg(["mean", "std"])
...     .style.background_gradient(cmap="RdBu", axis=0)
... )
```

Out[58]:

| | mean | std |
|---|---|---|
| **make** | | |
| **BMW** | 17.8174 | 7.37291 |
| **Ford** | 16.8538 | 6.70103 |
| **Honda** | 24.373 | 9.15406 |
| **Tesla** | 92.8261 | 5.53897 |

Using the pandas style functionality to highlight minimum and maximum values from the mean and standard deviation

## Comparing two continuous columns

Evaluating how two continuous columns relate to one another is the essence of regression. But it goes beyond that. If you have two columns with a high correlation to one another, often, you may drop one of them as a redundant column. In this section, we will look at EDA for pairs of continuous columns.

### How to do it...

Look at the covariance of the two numbers if they are on the same scale:

```
>>> fueleco.city08.cov(fueleco.highway08)
46.33326023673625
>>> fueleco.city08.cov(fueleco.comb08)
47.41994667819079
>>> fueleco.city08.cov(fueleco.cylinders)
-5.931560263764761
```

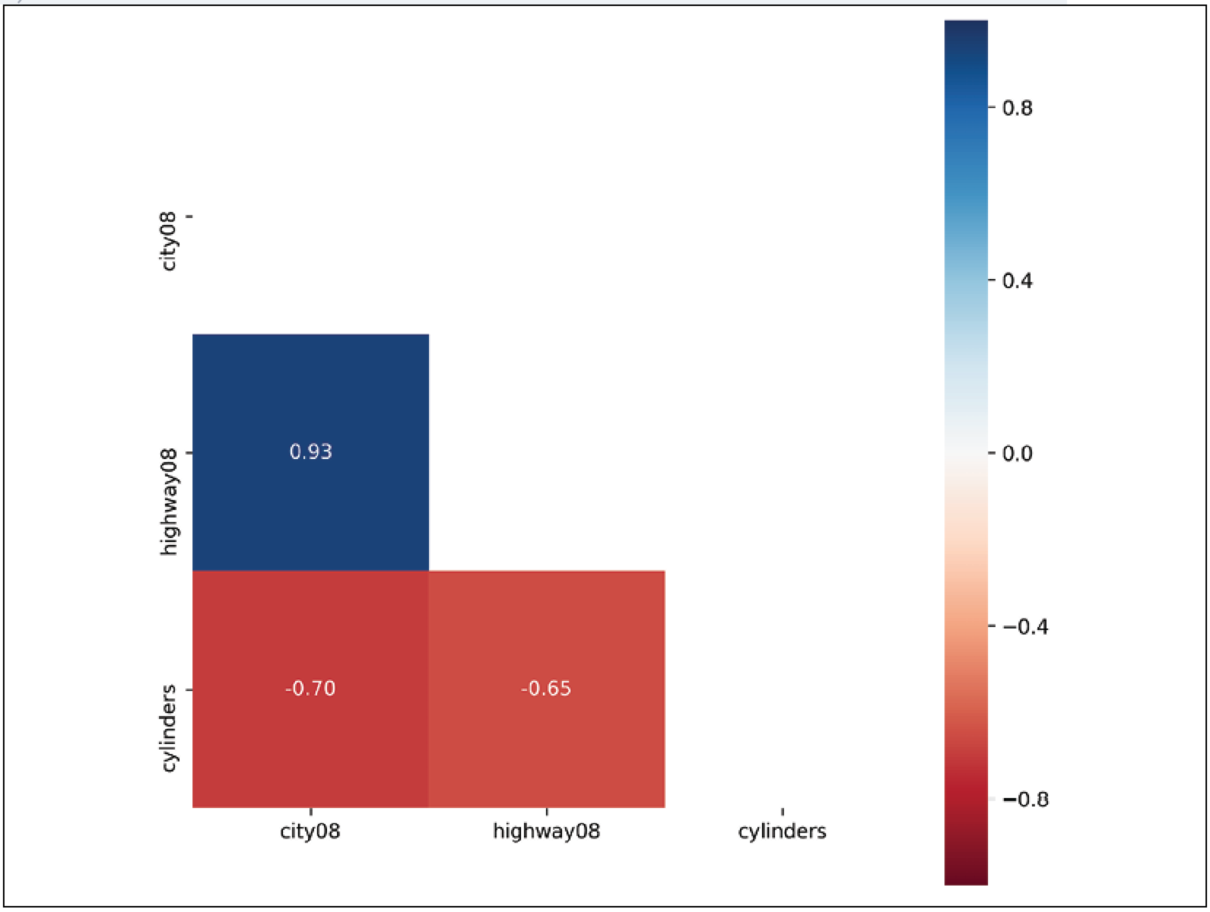
Look at the Pearson correlation between the two numbers:

```
>>> fueleco.city08.corr(fueleco.highway08)
0.932494506228495
>>> fueleco.city08.corr(fueleco.cylinders)
-0.701654842382788
```

Visualize the correlations in a heatmap:

```
>>> import seaborn as sns
>>> fig, ax = plt.subplots(figsize=(8, 8))
>>> corr = fueleco[
...     ["city08", "highway08", "cylinders"]
... ].corr()
>>> mask = np.zeros_like(corr, dtype=np.bool)
>>> mask[np.triu_indices_from(mask)] = True
>>> sns.heatmap(
...     corr,
...     mask=mask,
...     fmt=".2f",
...     annot=True,
...     ax=ax,
...     cmap="RdBu",
...     vmin=-1,
```

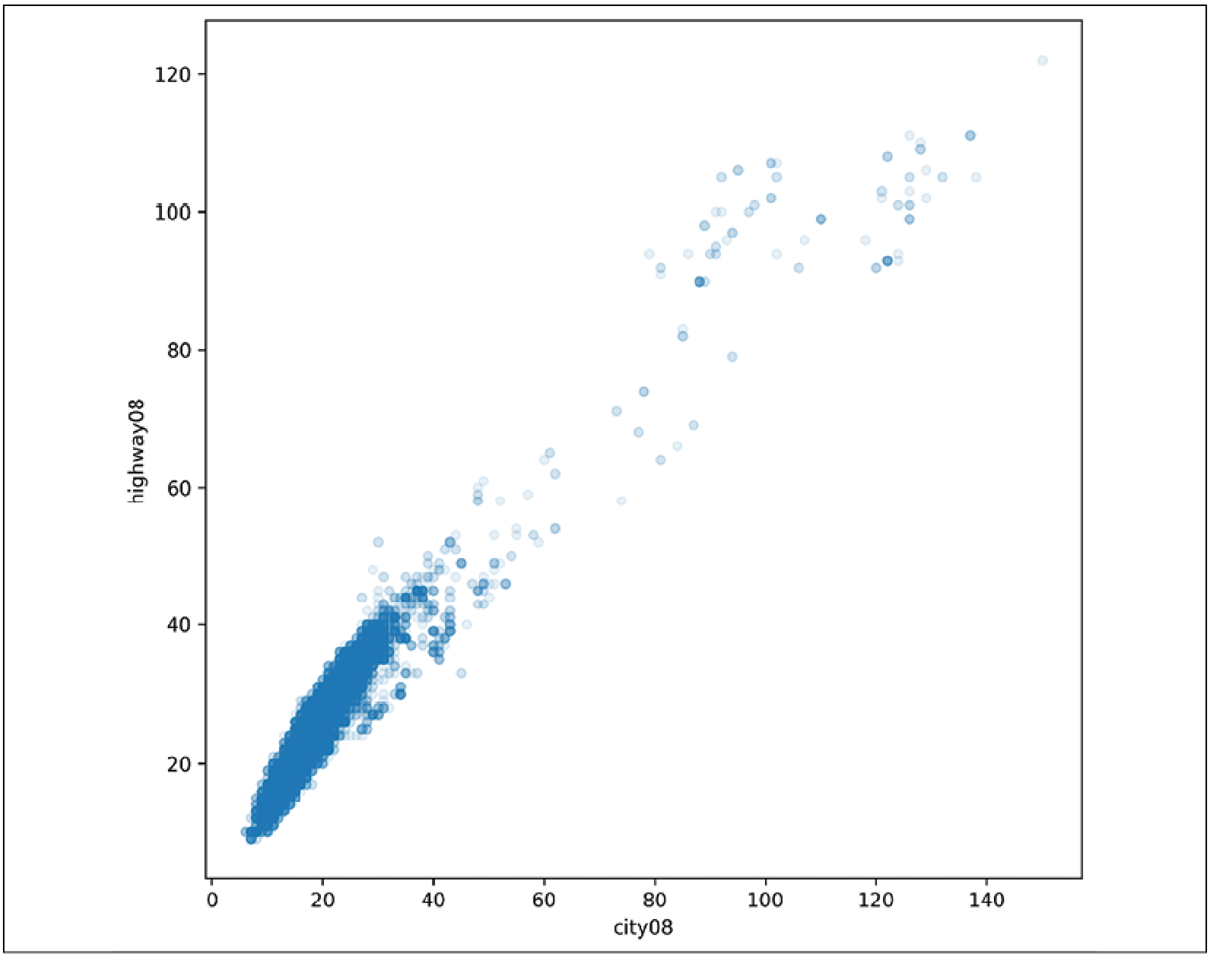
```
...     vmax=1,
...     square=True,
... )
>>> fig.savefig(
...     "c5-heatmap.png", dpi=300, bbox_inches="tight"
... )
```




A seaborn heatmap

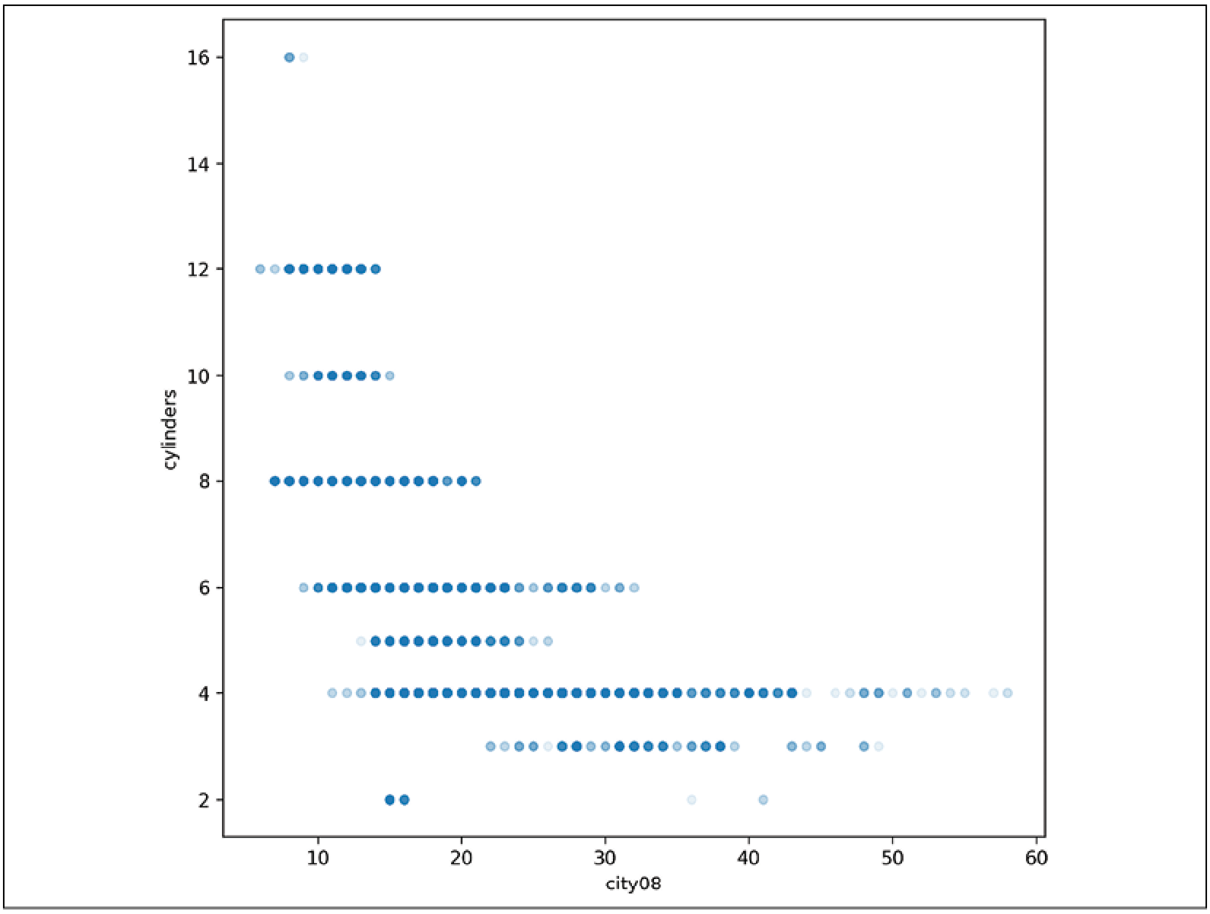
Use pandas to scatter plot the relationships:

```
>>> fig, ax = plt.subplots(figsize=(8, 8))
>>> fueleco.plot.scatter(
...     x="city08", y="highway08", alpha=0.1, ax=ax
... )
>>> fig.savefig(
...     "c5-scatpan.png", dpi=300, bbox_inches="tight"
... )
```



A pandas scatter plot to view the relationships between city and highway mileage

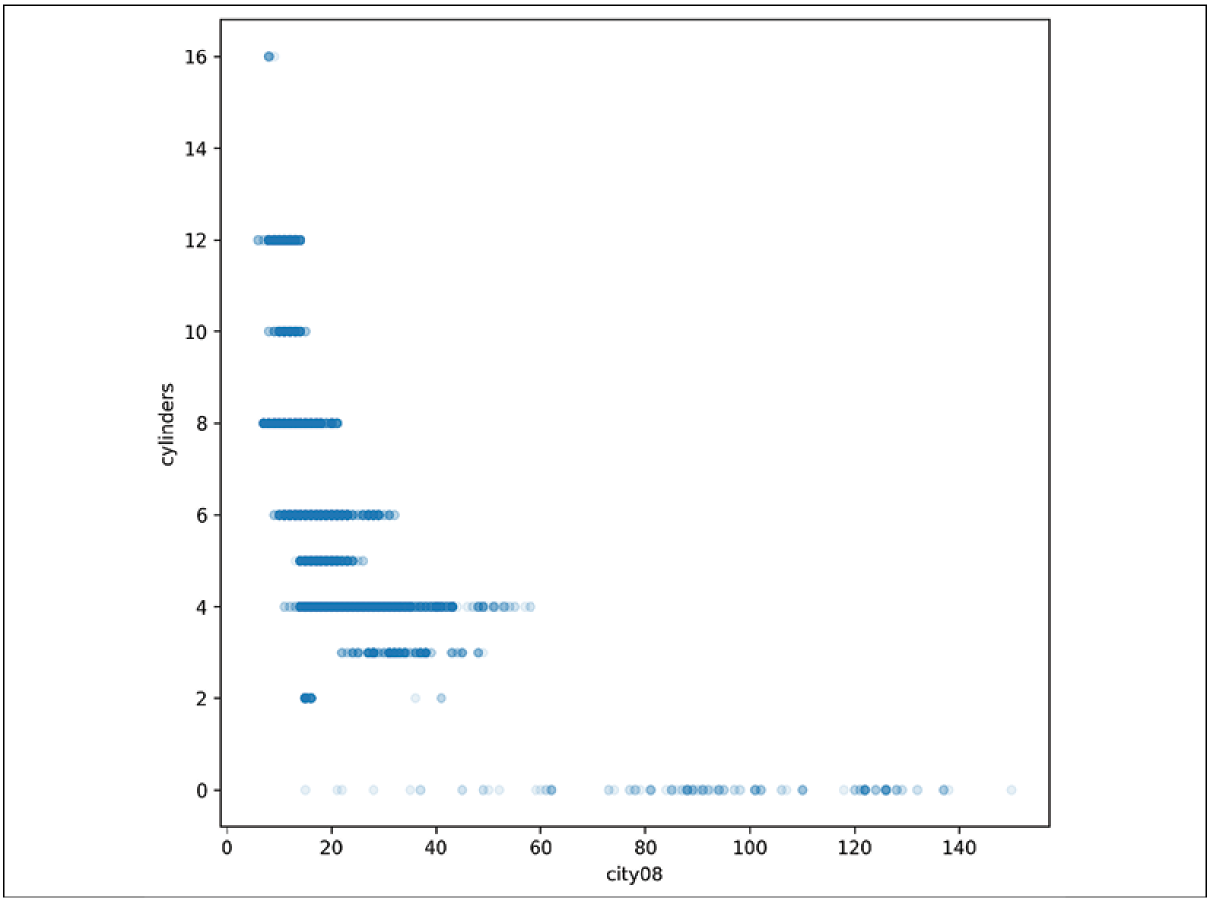
```
>>> fig, ax = plt.subplots(figsize=(8, 8))
>>> fueleco.plot.scatter(
...     x="city08", y="cylinders", alpha=0.1, ax=ax
... )
>>> fig.savefig(
...     "c5-scatpan-cyl.png", dpi=300, bbox_inches="tight"
... )
```




Another pandas scatter to view the relationship between mileage and cylinders

Fill in some missing values. From the cylinder plot, we can see that some of the high-end values for mileage are missing. This is because these cars tend to be electric and not have cylinders. We will fix that by filling those values in with 0:

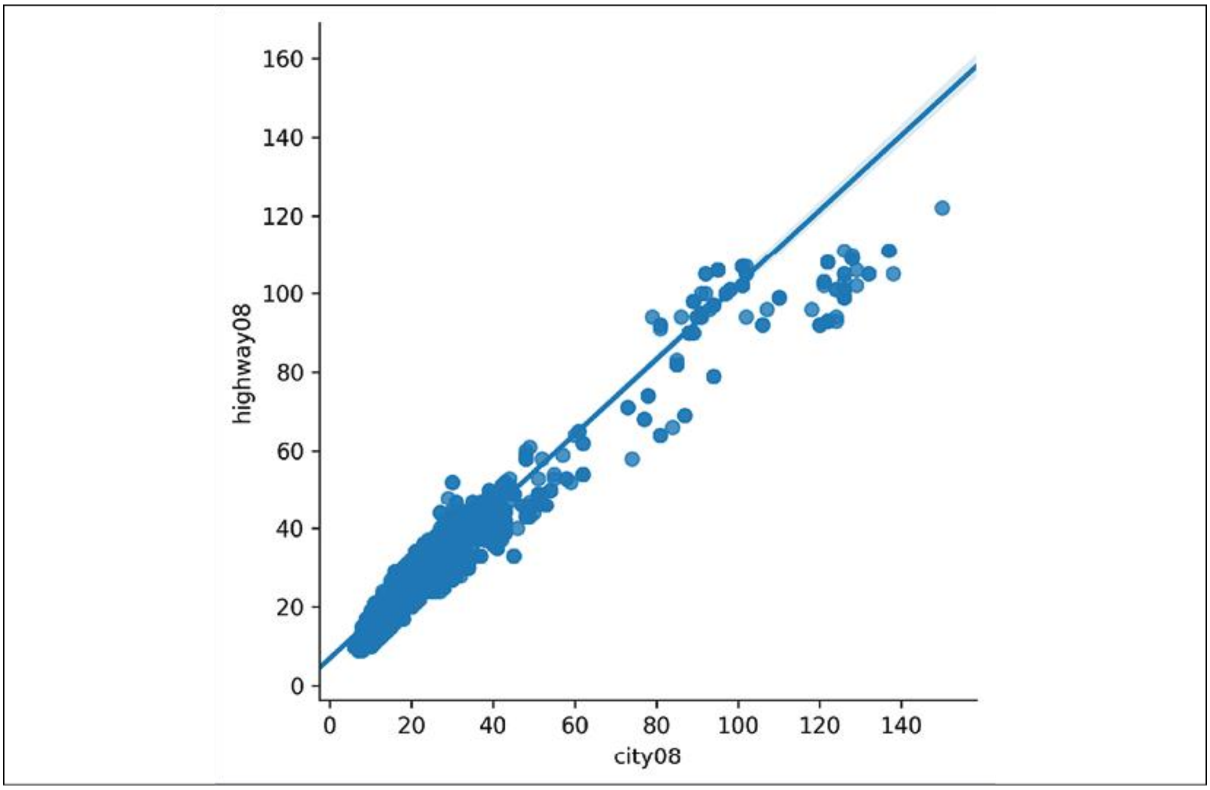
```
>>> fueleco.cylinders.isna().sum()
145
>>> fig, ax = plt.subplots(figsize=(8, 8))
>>> (
...     fueleco.assign(
...         cylinders=fueleco.cylinders.fillna(0)
...     ).plot.scatter(
...         x="city08", y="cylinders", alpha=0.1, ax=ax
...     )
... )
>>> fig.savefig(
...     "c5-scatpan-cyl0.png", dpi=300, bbox_inches="tight"
... )
```




Another pandas scatter to view the relationship between mileage and cylinders, with missing numbers for cylinders filled in with 0

Use seaborn to add a regression line to the relationships:

```
>>> res = sns.lmplot(
...     x="city08", y="highway08", data=fueleco
... )
>>> res.fig.savefig(
...     "c5-lmplot.png", dpi=300, bbox_inches="tight"
... )
```




A seaborn scatter plot with a regression line

## How it works...

Pearson correlation tells us how one value impacts another. It is between -1 and 1. In this case, we can see that there is a strong correlation between city mileage and highway mileage. As you get better city mileage, you tend to get better highway mileage.

Covariance lets us know how these values vary together. Covariance is useful for comparing multiple continuous columns that have similar correlations. For example, correlation is scale-invariant, but covariance is not. If we compare `city08` to two times `highway08`, they have the same correlation, but the covariance changes.

```
>>> fueleco.city08.corr(fueleco.highway08 * 2)
0.932494506228495
>>> fueleco.city08.cov(fueleco.highway08 * 2)
92.6665204734725
```

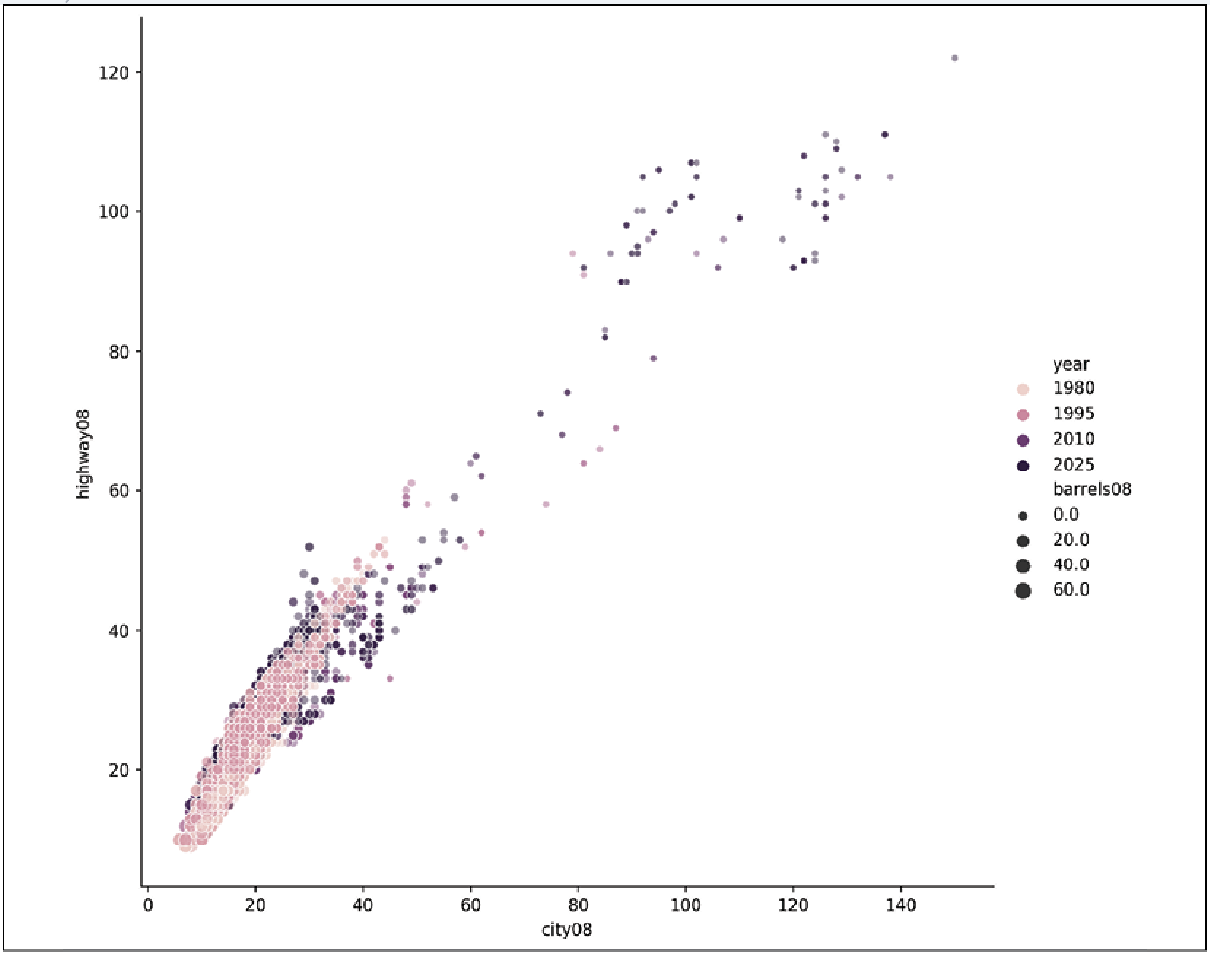
A heatmap is a great way to look at correlations in aggregate. We can look for the most blue and most red cells to find the strongest correlations. Make sure you set the `vmin` and `vmax` parameters to -1 and 1, respectively, so that the coloring is correct.

Scatter plots are another way to visualize the relationships between continuous variables. It lets us see the trends that pop out. One tip that I like to give students is to make sure you set the `alpha` parameter to a value less than or equal to .5. This makes the points transparent and tells a different story than scatter plots with markers that are completely opaque.

## There's more...

If we have more variables that we want to compare, we can use seaborn to add more dimensions to a scatter plot. Using the `relplot` function, we can color the dots by year and size them by the number of barrels the vehicle consumes. We have gone from two dimensions to four!

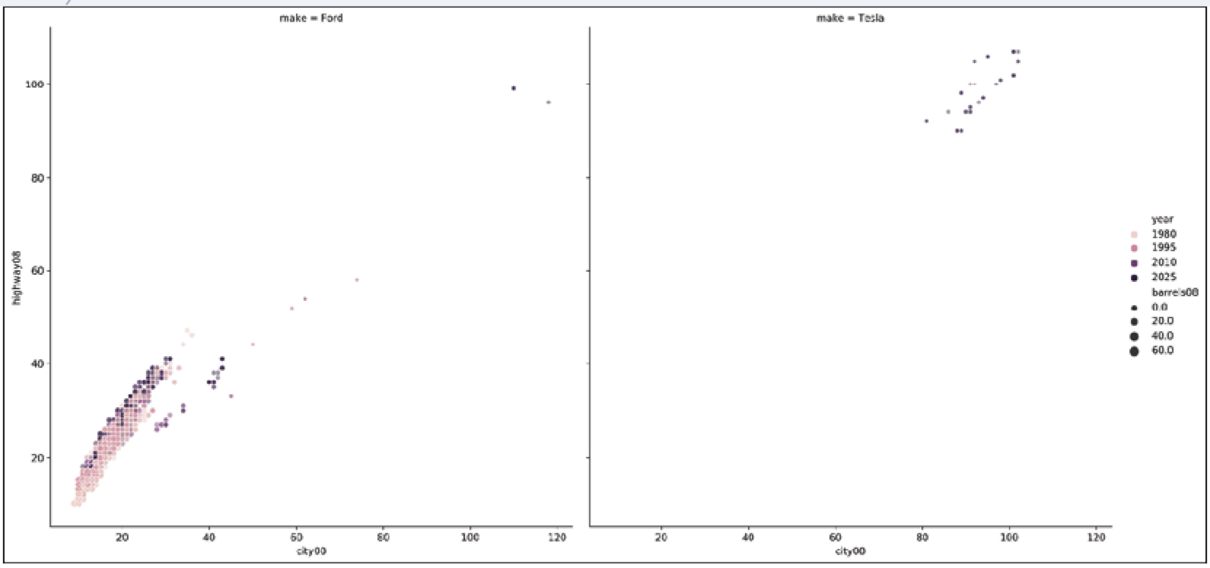
```
>>> res = sns.relplot(
...     x="city08",
...     y="highway08",
...     data=fueleco.assign(
...         cylinders=fueleco.cylinders.fillna(0)
...     ),
...     hue="year",
...     size="barrels08",
...     alpha=0.5,
...     height=8,
... )
>>> res.fig.savefig(
...     "c5-relplot2.png", dpi=300, bbox_inches="tight"
... )
```




A seaborn scatter plot showing the mileage relationships colored by year and sized by the number of barrels of gas a car uses

Note that we can also add in categorical dimensions as well for `hue`. We can also facet by column for categorical values:

```
>>> res = sns.relplot(
...     x="city08",
...     y="highway08",
...     data=fueleco.assign(
...         cylinders=fueleco.cylinders.fillna(0)
...     ),
...     hue="year",
...     size="barrels08",
...     alpha=0.5,
...     height=8,
...     col="make",
...     col_order=["Ford", "Tesla"],
... )
>>> res.fig.savefig(
...     "c5-relplot3.png", dpi=300, bbox_inches="tight"
... )
```




A seaborn scatter plot showing the mileage relationships colored by year, sized by the number of barrels of gas a car uses, and faceted by make

Pearson correlation is intended to show the strength of a linear relationship. If the two continuous columns do not have a linear relationship, another option is to use *Spearman correlation*. This number also varies from -1 to 1. It measures whether the relationship is monotonic (and doesn't presume that it is linear). It uses the rank of each number rather than the number. If you are not sure whether there is a linear relationship between your columns, this is a better metric to use.

```
>>> fueleco.city08.corr(
...     fueleco.barrels08, method="spearman"
... )
-0.9743658646193255
```

## Comparing categorical values with categorical values

In this section, we will focus on dealing with multiple categorical values. One thing to keep in mind is that continuous columns can be converted into categorical columns by binning the values.

In this section, we will look at makes and vehicle class.

### How to do it...

Lower the cardinality. Limit the `VClass` column to six values, in a simple class column, `SClass`. Only use Ford, Tesla, BMW, and Toyota:

```
>>> def generalize(ser, match_name, default):
...     seen = None
...     for match, name in match_name:
...         mask = ser.str.contains(match)
...         if seen is None:
...             seen = mask
...         else:
...             seen |= mask
...         ser = ser.where(~mask, name)
...     ser = ser.where(seen, default)
...     return ser
>>> makes = ["Ford", "Tesla", "BMW", "Toyota"]
>>> data = fueleco[fueleco.make.isin(makes)].assign(
...     SClass=lambda df_: generalize(
...         df_.VClass,
...         [
...             ("Seaters", "Car"),
...             ("Car", "Car"),
...             ("Utility", "SUV"),
...             ("Truck", "Truck"),
...             ("Van", "Van"),
...             ("van", "Van"),
...             ("Wagon", "Wagon"),
...         ],
...         "other",
...     )
... )
```

Summarize the counts of vehicle classes for each make:

```
>>> data.groupby(["make", "SClass"]).size().unstack()
SClass     Car    SUV  ...  Wagon  other
make                   ...
BMW     1557.0  158.0  ...   92.0    NaN
Ford    1075.0  372.0  ...  155.0  234.0
Tesla     36.0   10.0  ...    NaN    NaN
Toyota   773.0  376.0  ...  132.0  123.0
```

Use the `crosstab` function instead of the chain of pandas commands:

```
>>> pd.crosstab(data.make, data.SClass)
SClass   Car  SUV  ...  Wagon  other
make                ...
BMW     1557  158  ...     92      0
```

```
Ford     1075  372  ...    155    234
Tesla      36   10  ...      0      0
Toyota    773  376  ...    132    123
```

Add more dimensions:

```
>>> pd.crosstab(
...     [data.year, data.make], [data.SClass, data.VClass]
... )
SClass                 Car              ...                          other
VClass       Compact Cars  Large Cars   ... Special Purpose Vehicle 4WD
year make                               ...
1984 BMW                6           0   ...                  0
     Ford              33           3   ...                 21
     Toyota            13           0   ...                  3
1985 BMW                7           0   ...                  0
     Ford              31           2   ...                  9
...                   ...         ...   ...                ...
2017 Tesla              0           8   ...                  0
     Toyota             3           0   ...                  0
2018 BMW               37          12   ...                  0
     Ford               0           0   ...                  0
     Toyota             4           0   ...                  0
```

Use Cramér's V measure (https://stackoverflow.com/questions/46498455/categorical-features-correlation/46498792#46498792) to indicate the categorical correlation:

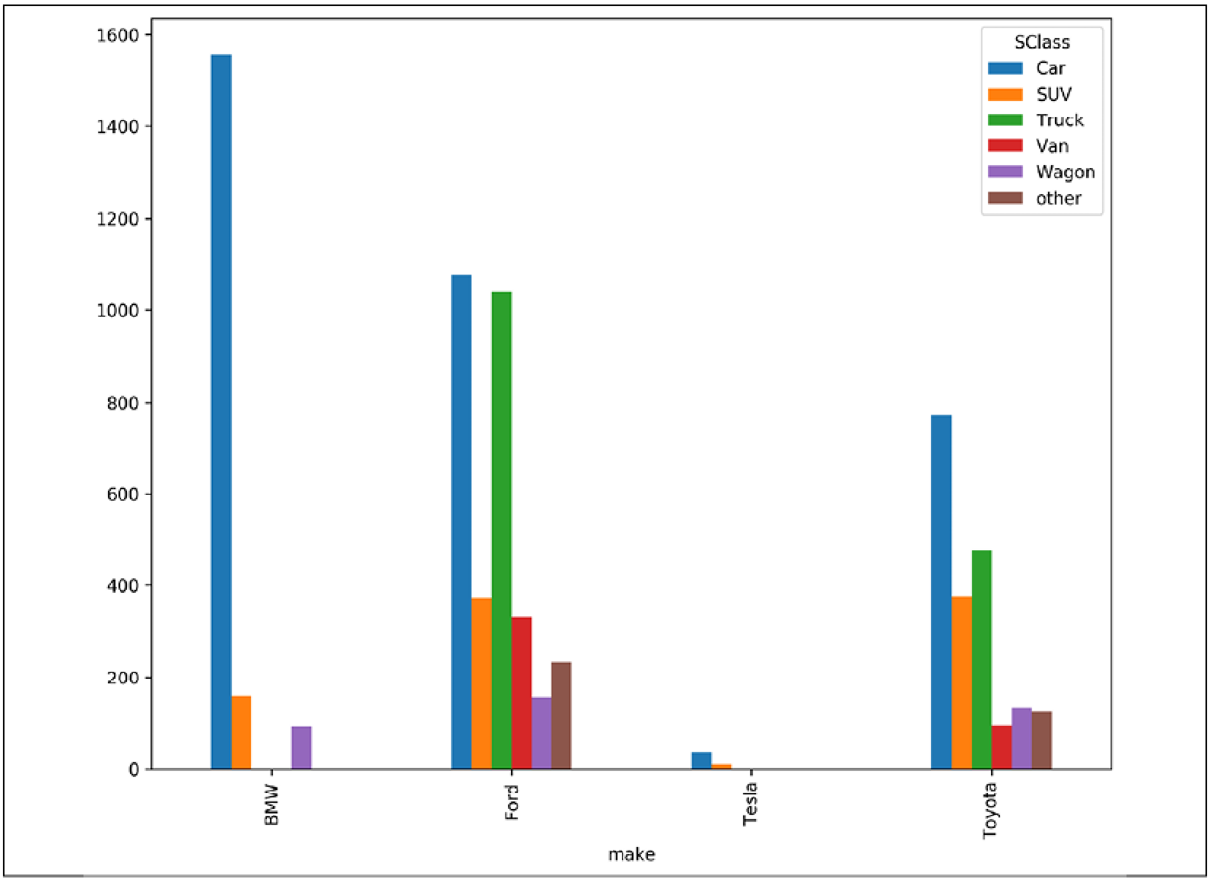
```
>>> import scipy.stats as ss
>>> import numpy as np
>>> def cramers_v(x, y):
...     confusion_matrix = pd.crosstab(x, y)
...     chi2 = ss.chi2_contingency(confusion_matrix)[0]
...     n = confusion_matrix.sum().sum()
...     phi2 = chi2 / n
...     r, k = confusion_matrix.shape
...     phi2corr = max(
...         0, phi2 - ((k - 1) * (r - 1)) / (n - 1)
...     )
...     rcorr = r - ((r - 1) ** 2) / (n - 1)
...     kcorr = k - ((k - 1) ** 2) / (n - 1)
...     return np.sqrt(
...         phi2corr / min((kcorr - 1), (rcorr - 1))
...     )
>>> cramers_v(data.make, data.SClass)
0.2859720982171866
```

The `.corr` method accepts a callable as well, so an alternative way to invoke this is the following:

```
>>> data.make.corr(data.SClass, cramers_v)
0.2859720982171866
```

Visualize the cross tabulation as a bar plot:

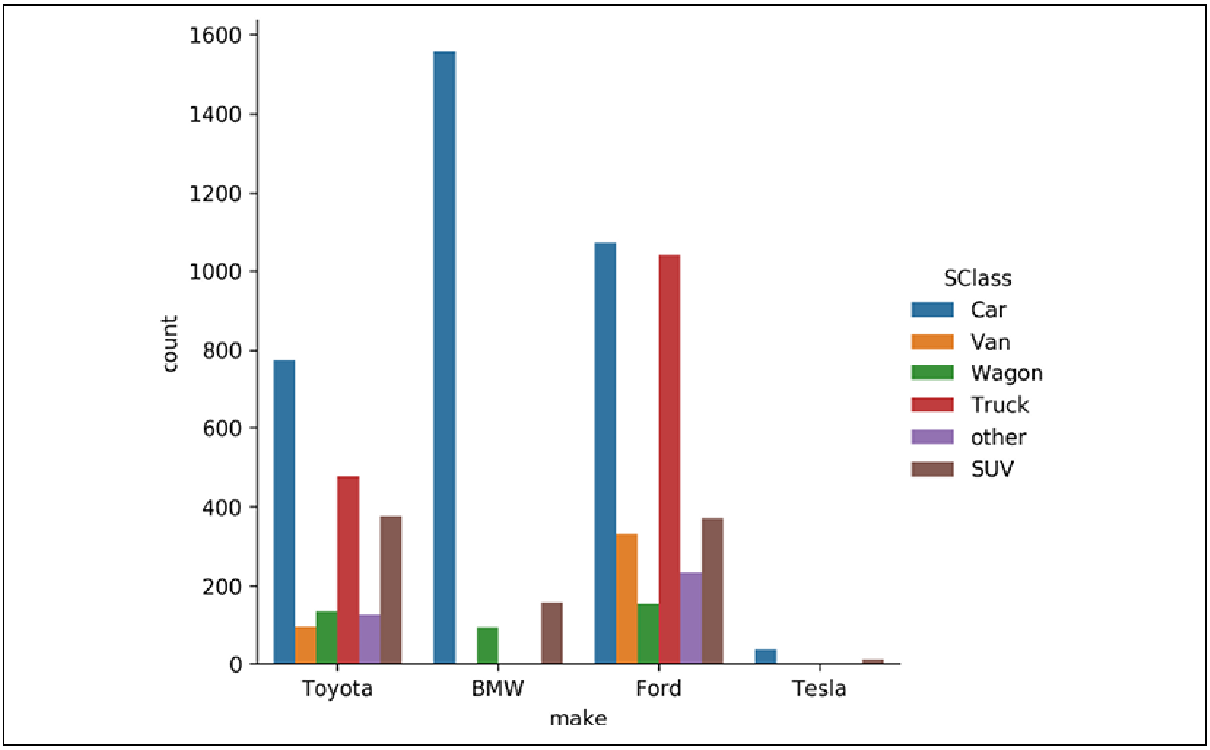
```
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> (
...     data.pipe(
...         lambda df_: pd.crosstab(df_.make, df_.SClass)
...     ).plot.bar(ax=ax)
... )
>>> fig.savefig("c5-bar.png", dpi=300, bbox_inches="tight")
```




A pandas bar plot

Visualize the cross tabulation as a bar chart using seaborn:

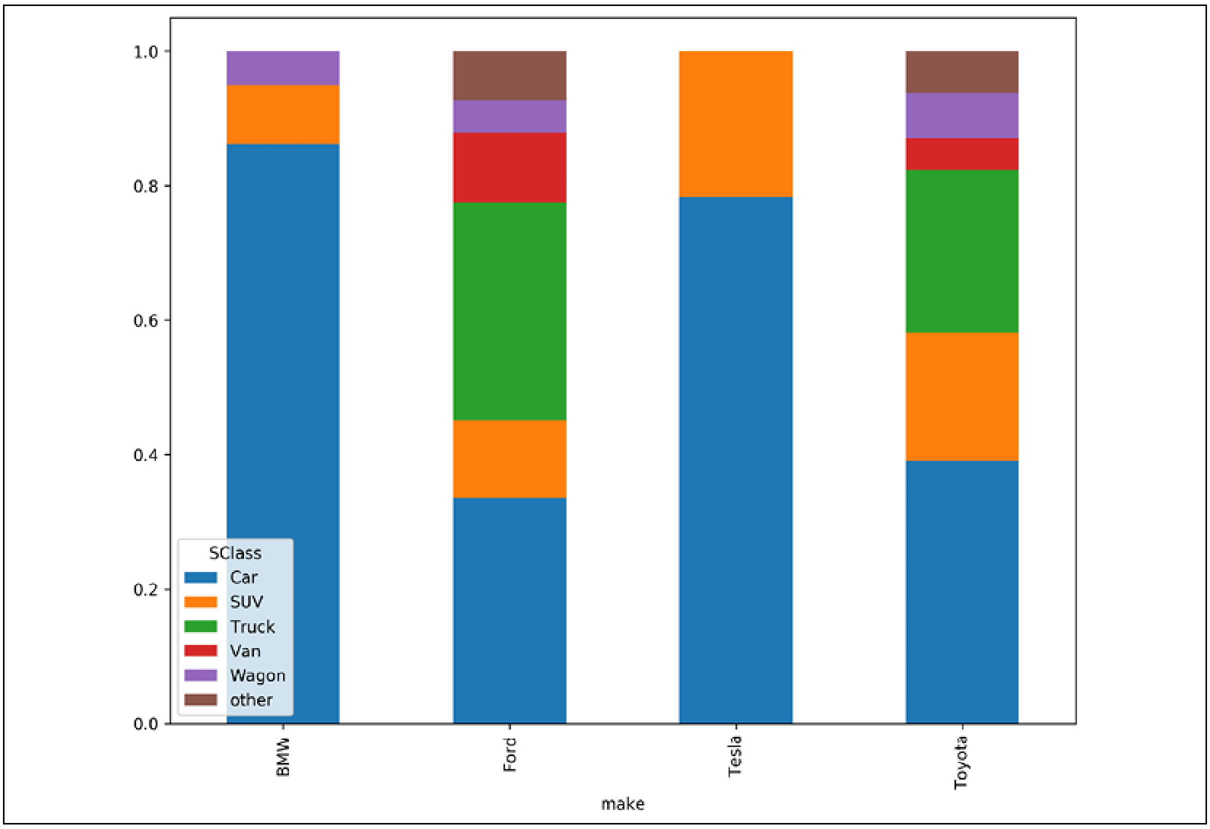
```
>>> res = sns.catplot(
...     kind="count", x="make", hue="SClass", data=data
... )
>>> res.fig.savefig(
...     "c5-barsns.png", dpi=300, bbox_inches="tight"
... )
```



A seaborn bar plot

Visualize the relative sizes of the groups by normalizing the cross tabulation and making a stacked bar chart:

```
>>> fig, ax = plt.subplots(figsize=(10, 8))
>>> (
...     data.pipe(
...         lambda df_: pd.crosstab(df_.make, df_.SClass)
...     )
...     .pipe(lambda df_: df_.div(df_.sum(axis=1), axis=0))
...     .plot.bar(stacked=True, ax=ax)
... )
>>> fig.savefig(
...     "c5-barstacked.png", dpi=300, bbox_inches="tight"
... )
```




pandas bar plot

## How it works...

We reduced the cardinality of the `VClass` column by using the `generalize` function that we created. We did this because bar plots need spacing; they need to breathe. We typically will limit the number of bars to fewer than 30. The `generalize` function is useful for cleaning up data, and you might want to refer back to it in your own data analyses.

We can summarize the counts of categorical columns by creating a cross-tabulation. You can build this up using group by semantics and unstacking the result, or take advantage of the built-in function in pandas, `crosstab`. Note that `crosstab` fills in missing numbers with 0 and converts the types to integers. This is because the `.unstack` method potentially creates sparsity (missing values), and integers (the `int64` type) don't support missing values, so the types are converted to floats.

You can add arbitrary depths to the index or columns to create hierarchies in the cross-tabulation.

There exists a number, Cramér's V, for quantifying the relationship between two categorical columns. It ranges from 0 to 1. If it is 0, the values do not hold their value relative to the other column. If it is 1, the values change with respect to each other.

For example, if we compare the `make` column to the `trany` column, this value comes out larger:

```
>>> cramers_v(data.make, data.trany)
0.6335899102918267
```

What that tells us is that as the `make` changes from Ford to Toyota, the `trany` column should change as well. Compare this to the value for the `make` versus the `model`. Here, the value is very close to 1. Intuitively, that should make sense, as model could be derived from make.

```
>>> cramers_v(data.make, data.model)
0.9542350243671587
```

Finally, we can use various bar plots to view the counts or the relative sizes of the counts. Note that if you use seaborn, you can add multiple dimensions by setting `hue` or `col`.

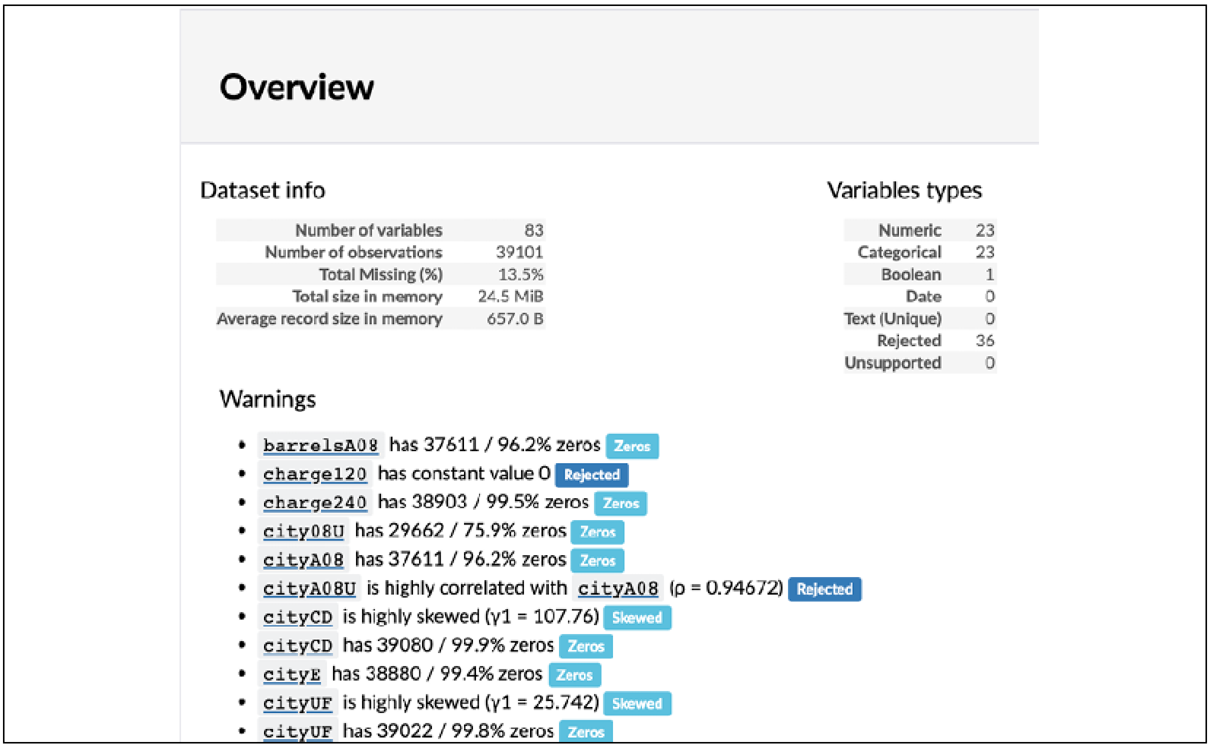
## Using the pandas profiling library

There is a third-party library, pandas Profiling (https://pandas-profiling.github.io/pandas-profiling/docs/), that creates reports for each column. These reports are similar to the output of the `.describe` method, but include plots and other descriptive statistics.
In this section, we will use the pandas Profiling library on the fuel economy data. Use `pip install pandas-profiling` to install the library.

### How to do it...

Run the `profile_report` function to create an HTML report:

```
>>> import pandas_profiling as pp
>>> pp.ProfileReport(fueleco)
```



## Overview

Dataset info

| | |
|---|---|
| Number of variables | 83 |
| Number of observations | 39101 |
| Total Missing (%) | 13.5% |
| Total size in memory | 24.5 MiB |
| Average record size in memory | 657.0 B |

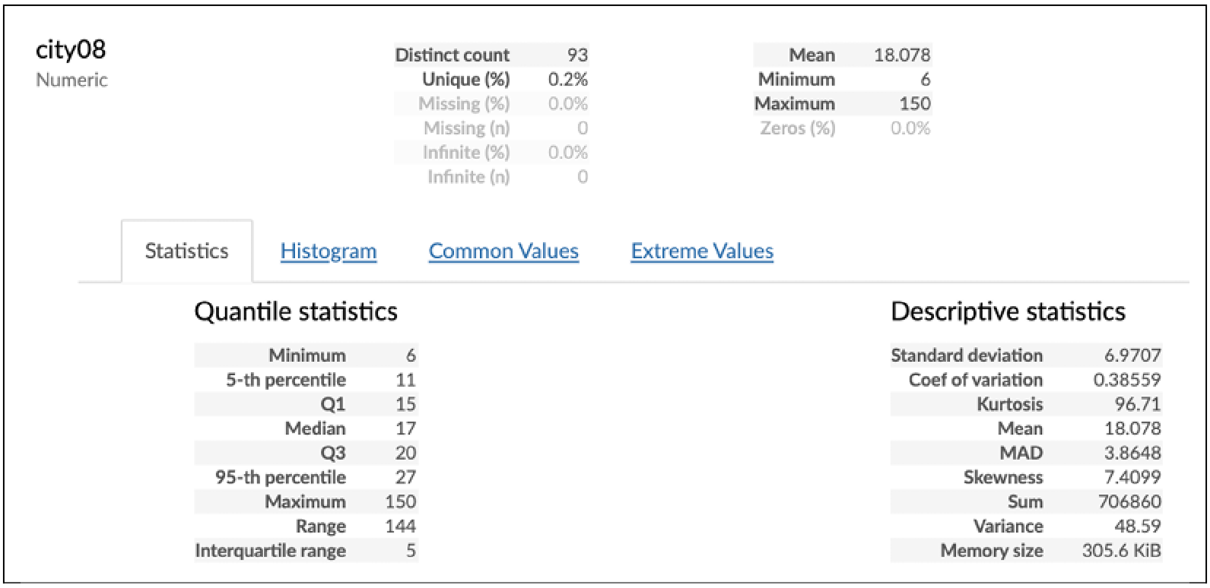
Variables types

| | |
|---|---|
| Numeric | 23 |
| Categorical | 23 |
| Boolean | 1 |
| Date | 0 |
| Text (Unique) | 0 |
| Rejected | 36 |
| Unsupported | 0 |

Warnings

- `barrelsA08` has 37611 / 96.2% zeros Zeros
- `charge120` has constant value 0 Rejected
- `charge240` has 38903 / 99.5% zeros Zeros
- `city08U` has 29662 / 75.9% zeros Zeros
- `cityA08` has 37611 / 96.2% zeros Zeros
- `cityA08U` is highly correlated with `cityA08` (ρ = 0.94672) Rejected
- `cityCD` is highly skewed (γ1 = 107.76) Skewed
- `cityCD` has 39080 / 99.9% zeros Zeros
- `cityE` has 38880 / 99.4% zeros Zeros
- `cityUF` is highly skewed (γ1 = 25.742) Skewed
- `cityUF` has 39022 / 99.8% zeros Zeros

pandas profiling summary



city08
Numeric

| | |
|---|---|
| Distinct count | 93 |
| Unique (%) | 0.2% |
| Missing (%) | 0.0% |
| Missing (n) | 0 |
| Infinite (%) | 0.0% |
| Infinite (n) | 0 |

| | |
|---|---|
| Mean | 18.078 |
| Minimum | 6 |
| Maximum | 150 |
| Zeros (%) | 0.0% |

Statistics Histogram Common Values Extreme Values

Quantile statistics

| | |
|---|---|
| Minimum | 6 |
| 5-th percentile | 11 |
| Q1 | 15 |
| Median | 17 |
| Q3 | 20 |
| 95-th percentile | 27 |
| Maximum | 150 |
| Range | 144 |
| Interquartile range | 5 |

Descriptive statistics

| | |
|---|---|
| Standard deviation | 6.9707 |
| Coef of variation | 0.38559 |
| Kurtosis | 96.71 |
| Mean | 18.078 |
| MAD | 3.8648 |
| Skewness | 7.4099 |
| Sum | 706860 |
| Variance | 48.59 |
| Memory size | 305.6 KiB |

pandas profiling details

## How it works...

The pandas Profiling library generates an HTML report. If you are using Jupyter, it will create it inline. If you want to save this report to a file (or if you are not using Jupyter), you can use the `.to_file` method:

```
>>> report = pp.ProfileReport(fueleco)
>>> report.to_file("fuel.html")
```

This is a great library for EDA. Just make sure that you go through the process of understanding the data. Because this can overwhelm you with the sheer amount of output, it can be tempting to skim over it, rather than to dig into it.