Exploratory data analysis

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In this notebook

In this notebook:

- We practice using `pandas` to read in and manipulate a data set
- We learn a basic "recipe" for exploratory data analysis and apply it to an example

Introduction

The first step in applying machine learning to a real problem is *finding* or *creating* an appropriate data set with which to train your model.

What makes data "good"?

What makes a good data set?

- **Size**: the more *samples* are in the data set, the more examples your machine learning model will be able to learn from, and the better it will do. Often, a simple machine learning model trained on a large data set will outperform a "fancy" model on a small data set.
- **Quality**: Are there *predictive* features in the data? Are no values (or very few values) missing, noisy, or incorrect? Is the scenario in which the data collected similar to the scenario in which your model will be used? These are examples of questions that we might ask to evaluate the quality of a data set.

One of the most important principles in machine learning is: **garbage in, garbage out**. If the data you use to train a machine learning model is problematic, or not well suited for the purpose, then even the best model will produce useless predictions.

Purpose of exploratory data analysis

Once we have identified one or more candidate data sets for a particular problem, we perform some *exploratory data analysis*. This process helps us

- detect and possibly correct mistakes in the data
- check our assumptions about the data
- identify potential relationships between features
- assess the direction and rough size of relationships between features and the target variable

Exploratory data analysis is important for understanding whether this data set is appropriate for the machine learning task at hand, and if any extra cleaning or processing steps are required before we use the data.

"Recipe" for exploratory data analysis

We will practice using a basic "recipe" for exploratory data analysis.

1. Learn about your data
2. Load data and check that it is loaded correctly
3. Visually inspect the data
4. Compute summary statistics
5. Explore the data further and look for potential issues

Every exploratory data analysis is different, as specific characteristics of the data may lead you to explore different things in depth. However, this "recipe" can be a helpful starting point.

Example: Brooklyn Bridge pedestrian data set

The Brooklyn Bridge is a bridge that connects Brooklyn and Manhattan. It supports vehicles, pedestrians, and bikers.

Support you are developing a machine learning model to predict the volume of pedestrian traffic on the Brooklyn Bridge. There is a dataset available that you think may be useful as training data: Brooklyn Bridge Automated Pedestrian Counts dataset, from the NYC Department of Transportation.

We will practice applying the "recipe" for exploratory data analysis to this data.

We will use the `pandas` library in Python, which includes many powerful utilities for managing data. You can refer to the `pandas` reference for more details on the `pandas` functions used in this notebook.

Learn about your data

The first step is to learn more about the data:

- Read about *methodology* and *data codebook*
- How many rows and columns are in the data?
- What does each variable mean? What units are data recorded in?
- What variables could be used as target variable? What variables could be used as features from which to learn?
- How was data collected? Identify sampling issues, timeliness issues, fairness issues, etc.

For the Brooklyn Bridge dataset, you can review the associated documentation on the NYC Data website:

- NYC Data Website
- Data dictionary

Load data and check that it is loaded correctly

The next step is to load the data in preparation for your exploratory data analysis.

First, we will import some useful libraries:

- In Python - libraries add powerful functionality
- You can import an entire library (`import foo`) or part (`from foo import bar`)
- You can define a nickname, which you will use to call functions of these libraries (many libraries have "conventional" nicknames)

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# set up notebook to show all outputs, not only last one
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

Now we are ready to read in our data!

Our data is in CSV format, so will use the `read_csv` function in `pandas` to read in our data.

Function documentation: pandas reference

```
pandas.read_csv(filepath_or_buffer,
    sep=',', header='infer',
    names=None,
    ...)
```

`read_csv` is for "flat" text files, where each data point is on another row, and the fields in a row are separated by some delimiter (e.g. comma). Other pandas functions exist for loading other kinds of data (read from database, Excel file, etc.)

```
url = 'https://data.cityofnewyork.us/api/views/6fi9-q3ta/rows.csv?accessType=DOWNLOAD'
df = pd.read_csv(url)
```

We will want to verify that the data was loaded correctly. For *tabular* data, we can start by looking at a few rows of data with the `head` function. (For data that is not tabular, such as image, text, or audio data, we might start by looking at a few random samples instead.)

```
df.head()
```

```
           hour_beginning          location  Pedestrians  Towards Manhattan  \
0  04/30/2019 12:00:00 AM  Brooklyn Bridge            3                  3
1  12/31/2019 10:00:00 PM  Brooklyn Bridge           10                  9
2  12/31/2019 11:00:00 PM  Brooklyn Bridge            2                  0
3  12/31/2019 09:00:00 PM  Brooklyn Bridge           12                  0
4  04/01/2019 03:00:00 AM  Brooklyn Bridge            1                  0

   Towards Brooklyn weather_summary  temperature  precipitation        lat  \
0                 0             NaN          NaN            NaN  40.708164
1                 1          cloudy         42.0         0.0005  40.708164
```

```
2                2          cloudy         42.0         0.0004  40.708164
3               12          cloudy         42.0         0.0036  40.708164
4                1     clear-night         36.0         0.0000  40.708164

        long events                             Location1
0 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
1 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
2 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
3 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
4 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
```

One thing to look for in the output above, that is easily missed: verify that column names and row names are loaded correctly, and that the first row of real data is actually data, and not column labels.

We should also check the shape of the data frame - the number of rows and columns. This, too, should be checked against our assumptions about the data from the NYC Data website.

```
df.shape
```

```
(16057, 12)
```

Check the names of the columns and their data types:

```
df.columns
df.dtypes
```

```
Index(['hour_beginning', 'location', 'Pedestrians', 'Towards Manhattan',
       'Towards Brooklyn', 'weather_summary', 'temperature', 'precipitation',
       'lat', 'long', 'events', 'Location1'],
      dtype='object')
```

```
hour_beginning        object
location              object
Pedestrians            int64
Towards Manhattan      int64
Towards Brooklyn       int64
weather_summary       object
temperature          float64
precipitation        float64
lat                  float64
long                 float64
events                object
Location1             object
dtype: object
```

We can also get a quick summary with `info()`;

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16057 entries, 0 to 16056
Data columns (total 12 columns):
hour_beginning       16057 non-null object
```

```
location             16057 non-null object
Pedestrians          16057 non-null int64
Towards Manhattan    16057 non-null int64
Towards Brooklyn     16057 non-null int64
weather_summary      16041 non-null object
temperature          16041 non-null float64
precipitation        16041 non-null float64
lat                  16057 non-null float64
long                 16057 non-null float64
events               1124 non-null object
Location1            16057 non-null object
dtypes: float64(4), int64(3), object(5)
memory usage: 1.5+ MB
```

`pandas` infers the data type of each column automatically from the contents of the data.

If the data type of a column is not what you expect it to be, this can often be a signal that the data needs cleaning. For example, if you expect a column to be numeric and it is read in as non-numeric, this indicates that there are probably some samples that include a non-numeric value in that column. (The NYC Data website indicates what type of data *should* be in each column, so you should reference that when checking this output.)

We have a date/time column that was read in as a string, so we can correct that now:

```
df['hour_beginning'] = pd.to_datetime(df['hour_beginning'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16057 entries, 0 to 16056
Data columns (total 12 columns):
hour_beginning       16057 non-null datetime64[ns]
location             16057 non-null object
Pedestrians          16057 non-null int64
Towards Manhattan    16057 non-null int64
Towards Brooklyn     16057 non-null int64
weather_summary      16041 non-null object
temperature          16041 non-null float64
precipitation        16041 non-null float64
lat                  16057 non-null float64
long                 16057 non-null float64
events               1124 non-null object
Location1            16057 non-null object
dtypes: datetime64[ns](1), float64(4), int64(3), object(4)
memory usage: 1.5+ MB
```

And once we have done that, we can order the data frame by time:

```
df = df.sort_values(by='hour_beginning')
df.head()
```

```
           hour_beginning         location  Pedestrians  Towards Manhattan  \
8846  2017-10-01 00:00:00  Brooklyn Bridge           44                 30
9473  2017-10-01 01:00:00  Brooklyn Bridge           30                 17
10098 2017-10-01 02:00:00  Brooklyn Bridge           25                 13
10733 2017-10-01 03:00:00  Brooklyn Bridge           20                 11
```

```
11527 2017-10-01 04:00:00  Brooklyn Bridge          18                10

       Towards Brooklyn      weather_summary  temperature  precipitation  \
8846                 14          clear-night         52.0         0.0001
9473                 13  partly-cloudy-night         53.0         0.0002
10098                12  partly-cloudy-night         52.0         0.0000
10733                 9  partly-cloudy-night         51.0         0.0000
11527                 8  partly-cloudy-night         51.0         0.0000

             lat       long events                               Location1
8846   40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
9473   40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
10098  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
10733  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
11527  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
```

You may notice that the `hour_beginning` variable includes the full date and time in one field. For our analysis, it would be more useful to have separate fields for the date, month, day of the week, and hour.

We can create these additional fields by assigning the desired value to them directly - then, observe the effect:

```
df['hour'] = df['hour_beginning'].dt.hour
df['month'] = df['hour_beginning'].dt.month
df['date'] = df['hour_beginning'].dt.date
df['day_name'] = df['hour_beginning'].dt.day_name()

df.head()
```

```
           hour_beginning         location  Pedestrians  Towards Manhattan  \
8846  2017-10-01 00:00:00  Brooklyn Bridge          44                30
9473  2017-10-01 01:00:00  Brooklyn Bridge          30                17
10098 2017-10-01 02:00:00  Brooklyn Bridge          25                13
10733 2017-10-01 03:00:00  Brooklyn Bridge          20                11
11527 2017-10-01 04:00:00  Brooklyn Bridge          18                10

       Towards Brooklyn      weather_summary  temperature  precipitation  \
8846                 14          clear-night         52.0         0.0001
9473                 13  partly-cloudy-night         53.0         0.0002
10098                12  partly-cloudy-night         52.0         0.0000
10733                 9  partly-cloudy-night         51.0         0.0000
11527                 8  partly-cloudy-night         51.0         0.0000

             lat       long events                               Location1  \
8846   40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
9473   40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
10098  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
10733  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)
11527  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)

       hour  month        date day_name
8846      0     10  2017-10-01   Sunday
9473      1     10  2017-10-01   Sunday
10098     2     10  2017-10-01   Sunday
```

```
10733      3      10   2017-10-01    Sunday
11527      4      10   2017-10-01    Sunday
```

For data that is recorded at regular time intervals, it is also important to know whether the data is complete, or whether there are gaps in time. We will use some helpful `pandas` functions:

- `pd.to_datetime`
- `pd.date_range`

First, we will use `date_range` to get the list of hour intervals that we expect to find in the dataset. Then, we will find the difference between this list and the actual list of hour intervals in the dataset - these are missing intervals.

```
# get beginning and end of date range
min_dt = df.hour_beginning.min()
max_dt = df.hour_beginning.max()
print(min_dt)
print(max_dt)
```

```
2017-10-01 00:00:00
2019-12-31 23:00:00
```

```
# then identify the missing hours
expected_range = pd.date_range(start = min_dt, end = max_dt, freq='H' )
missing_hours = expected_range.difference(df['hour_beginning'])
print(missing_hours)
```

```
DatetimeIndex(['2018-08-01 00:00:00', '2018-08-01 01:00:00',
               '2018-08-01 02:00:00', '2018-08-01 03:00:00',
               '2018-08-01 04:00:00', '2018-08-01 05:00:00',
               '2018-08-01 06:00:00', '2018-08-01 07:00:00',
               '2018-08-01 08:00:00', '2018-08-01 09:00:00',
               ...
               '2018-12-31 14:00:00', '2018-12-31 15:00:00',
               '2018-12-31 16:00:00', '2018-12-31 17:00:00',
               '2018-12-31 18:00:00', '2018-12-31 19:00:00',
               '2018-12-31 20:00:00', '2018-12-31 21:00:00',
               '2018-12-31 22:00:00', '2018-12-31 23:00:00'],
              dtype='datetime64[ns]', length=3672, freq=None)
```

We had the expected number of rows (the output of `shape` matched the description of the data on the NYC Data website), but the data seems to be missing samples from August 2018 through December 2018, which is worth keeping in mind if we decide to use it:

```
pd.unique(missing_hours.date)
```

```
array([datetime.date(2018, 8, 1), datetime.date(2018, 8, 2),
       datetime.date(2018, 8, 3), datetime.date(2018, 8, 4),
       datetime.date(2018, 8, 5), datetime.date(2018, 8, 6),
       datetime.date(2018, 8, 7), datetime.date(2018, 8, 8),
       datetime.date(2018, 8, 9), datetime.date(2018, 8, 10),
       datetime.date(2018, 8, 11), datetime.date(2018, 8, 12),
       datetime.date(2018, 8, 13), datetime.date(2018, 8, 14),
       datetime.date(2018, 8, 15), datetime.date(2018, 8, 16),
```

```
        datetime.date(2018, 8, 17), datetime.date(2018, 8, 18),
        datetime.date(2018, 8, 19), datetime.date(2018, 8, 20),
        datetime.date(2018, 8, 21), datetime.date(2018, 8, 22),
        datetime.date(2018, 8, 23), datetime.date(2018, 8, 24),
        datetime.date(2018, 8, 25), datetime.date(2018, 8, 26),
        datetime.date(2018, 8, 27), datetime.date(2018, 8, 28),
        datetime.date(2018, 8, 29), datetime.date(2018, 8, 30),
        datetime.date(2018, 8, 31), datetime.date(2018, 9, 1),
        datetime.date(2018, 9, 2), datetime.date(2018, 9, 3),
        datetime.date(2018, 9, 4), datetime.date(2018, 9, 5),
        datetime.date(2018, 9, 6), datetime.date(2018, 9, 7),
        datetime.date(2018, 9, 8), datetime.date(2018, 9, 9),
        datetime.date(2018, 9, 10), datetime.date(2018, 9, 11),
        datetime.date(2018, 9, 12), datetime.date(2018, 9, 13),
        datetime.date(2018, 9, 14), datetime.date(2018, 9, 15),
        datetime.date(2018, 9, 16), datetime.date(2018, 9, 17),
        datetime.date(2018, 9, 18), datetime.date(2018, 9, 19),
        datetime.date(2018, 9, 20), datetime.date(2018, 9, 21),
        datetime.date(2018, 9, 22), datetime.date(2018, 9, 23),
        datetime.date(2018, 9, 24), datetime.date(2018, 9, 25),
        datetime.date(2018, 9, 26), datetime.date(2018, 9, 27),
        datetime.date(2018, 9, 28), datetime.date(2018, 9, 29),
        datetime.date(2018, 9, 30), datetime.date(2018, 10, 1),
        datetime.date(2018, 10, 2), datetime.date(2018, 10, 3),
        datetime.date(2018, 10, 4), datetime.date(2018, 10, 5),
        datetime.date(2018, 10, 6), datetime.date(2018, 10, 7),
        datetime.date(2018, 10, 8), datetime.date(2018, 10, 9),
        datetime.date(2018, 10, 10), datetime.date(2018, 10, 11),
        datetime.date(2018, 10, 12), datetime.date(2018, 10, 13),
        datetime.date(2018, 10, 14), datetime.date(2018, 10, 15),
        datetime.date(2018, 10, 16), datetime.date(2018, 10, 17),
        datetime.date(2018, 10, 18), datetime.date(2018, 10, 19),
        datetime.date(2018, 10, 20), datetime.date(2018, 10, 21),
        datetime.date(2018, 10, 22), datetime.date(2018, 10, 23),
        datetime.date(2018, 10, 24), datetime.date(2018, 10, 25),
        datetime.date(2018, 10, 26), datetime.date(2018, 10, 27),
        datetime.date(2018, 10, 28), datetime.date(2018, 10, 29),
        datetime.date(2018, 10, 30), datetime.date(2018, 10, 31),
        datetime.date(2018, 11, 1), datetime.date(2018, 11, 2),
        datetime.date(2018, 11, 3), datetime.date(2018, 11, 4),
        datetime.date(2018, 11, 5), datetime.date(2018, 11, 6),
        datetime.date(2018, 11, 7), datetime.date(2018, 11, 8),
        datetime.date(2018, 11, 9), datetime.date(2018, 11, 10),
        datetime.date(2018, 11, 11), datetime.date(2018, 11, 12),
        datetime.date(2018, 11, 13), datetime.date(2018, 11, 14),
        datetime.date(2018, 11, 15), datetime.date(2018, 11, 16),
        datetime.date(2018, 11, 17), datetime.date(2018, 11, 18),
        datetime.date(2018, 11, 19), datetime.date(2018, 11, 20),
        datetime.date(2018, 11, 21), datetime.date(2018, 11, 22),
        datetime.date(2018, 11, 23), datetime.date(2018, 11, 24),
        datetime.date(2018, 11, 25), datetime.date(2018, 11, 26),
        datetime.date(2018, 11, 27), datetime.date(2018, 11, 28),
        datetime.date(2018, 11, 29), datetime.date(2018, 11, 30),
        datetime.date(2018, 12, 1), datetime.date(2018, 12, 2),
```

```
       datetime.date(2018, 12, 3), datetime.date(2018, 12, 4),
       datetime.date(2018, 12, 5), datetime.date(2018, 12, 6),
       datetime.date(2018, 12, 7), datetime.date(2018, 12, 8),
       datetime.date(2018, 12, 9), datetime.date(2018, 12, 10),
       datetime.date(2018, 12, 11), datetime.date(2018, 12, 12),
       datetime.date(2018, 12, 13), datetime.date(2018, 12, 14),
       datetime.date(2018, 12, 15), datetime.date(2018, 12, 16),
       datetime.date(2018, 12, 17), datetime.date(2018, 12, 18),
       datetime.date(2018, 12, 19), datetime.date(2018, 12, 20),
       datetime.date(2018, 12, 21), datetime.date(2018, 12, 22),
       datetime.date(2018, 12, 23), datetime.date(2018, 12, 24),
       datetime.date(2018, 12, 25), datetime.date(2018, 12, 26),
       datetime.date(2018, 12, 27), datetime.date(2018, 12, 28),
       datetime.date(2018, 12, 29), datetime.date(2018, 12, 30),
       datetime.date(2018, 12, 31)], dtype=object)
```

This is also a good time to look for rows that are missing data in some columns ("NA" values), that may need to be cleaned.

We can see the number of NAs in each column by summing up all the instances where the `isnull` function returns a True value:

```
df.isnull().sum()
```

```
hour_beginning          0
location                0
Pedestrians             0
Towards Manhattan       0
Towards Brooklyn        0
weather_summary        16
temperature            16
precipitation          16
lat                     0
long                    0
events              14933
Location1               0
hour                    0
month                   0
date                    0
day_name                0
dtype: int64
```

There are some rows of data that are missing weather, temperature, and precipitation data. We can see these rows with

```
df[df['temperature'].isnull()]
```

```
           hour_beginning         location  Pedestrians  Towards Manhattan  \
12271 2018-03-11 02:00:00  Brooklyn Bridge            0                  0
12796 2018-05-13 00:00:00  Brooklyn Bridge           98                 69
482   2019-01-06 00:00:00  Brooklyn Bridge            3                  3
2604  2019-01-09 00:00:00  Brooklyn Bridge            3                  3
2140  2019-01-14 00:00:00  Brooklyn Bridge            0                  0
3951  2019-01-16 00:00:00  Brooklyn Bridge            7                  2
```

```
5562  2019-02-02 00:00:00  Brooklyn Bridge           0                 0
7696  2019-03-05 00:00:00  Brooklyn Bridge           2                 0
2944  2019-03-10 02:00:00  Brooklyn Bridge           0                 0
0     2019-04-30 00:00:00  Brooklyn Bridge           3                 3
4198  2019-05-02 00:00:00  Brooklyn Bridge           3                 2
5962  2019-05-08 00:00:00  Brooklyn Bridge           3                 2
5277  2019-06-17 01:00:00  Brooklyn Bridge           0                 0
5934  2019-09-06 00:00:00  Brooklyn Bridge           2                 1
5206  2019-09-17 00:00:00  Brooklyn Bridge           2                 2
701   2019-11-03 01:00:00  Brooklyn Bridge           0                 0

       Towards Brooklyn weather_summary  temperature  precipitation  \
12271                 0             NaN          NaN            NaN
12796                29             NaN          NaN            NaN
482                   0             NaN          NaN            NaN
2604                  0             NaN          NaN            NaN
2140                  0             NaN          NaN            NaN
3951                  5             NaN          NaN            NaN
5562                  0             NaN          NaN            NaN
7696                  2             NaN          NaN            NaN
2944                  0             NaN          NaN            NaN
0                     0             NaN          NaN            NaN
4198                  1             NaN          NaN            NaN
5962                  1             NaN          NaN            NaN
5277                  0             NaN          NaN            NaN
5934                  1             NaN          NaN            NaN
5206                  0             NaN          NaN            NaN
701                   0             NaN          NaN            NaN

             lat       long                       events  \
12271  40.708164 -73.999509  Daylight Saving Time starts
12796  40.708164 -73.999509                 Mother's Day
482    40.708164 -73.999509                          NaN
2604   40.708164 -73.999509                          NaN
2140   40.708164 -73.999509                          NaN
3951   40.708164 -73.999509                          NaN
5562   40.708164 -73.999509                          NaN
7696   40.708164 -73.999509                          NaN
2944   40.708164 -73.999509  Daylight Saving Time starts
0      40.708164 -73.999509                          NaN
4198   40.708164 -73.999509                          NaN
5962   40.708164 -73.999509                          NaN
5277   40.708164 -73.999509                          NaN
5934   40.708164 -73.999509                          NaN
5206   40.708164 -73.999509                          NaN
701    40.708164 -73.999509    Daylight Saving Time ends

                                Location1  hour  month        date  \
12271  (40.7081639691088, -73.9995087014816)     2      3  2018-03-11
12796  (40.7081639691088, -73.9995087014816)     0      5  2018-05-13
482    (40.7081639691088, -73.9995087014816)     0      1  2019-01-06
2604   (40.7081639691088, -73.9995087014816)     0      1  2019-01-09
2140   (40.7081639691088, -73.9995087014816)     0      1  2019-01-14
3951   (40.7081639691088, -73.9995087014816)     0      1  2019-01-16
```

```
5562   (40.7081639691088, -73.9995087014816)     0      2  2019-02-02
7696   (40.7081639691088, -73.9995087014816)     0      3  2019-03-05
2944   (40.7081639691088, -73.9995087014816)     2      3  2019-03-10
0      (40.7081639691088, -73.9995087014816)     0      4  2019-04-30
4198   (40.7081639691088, -73.9995087014816)     0      5  2019-05-02
5962   (40.7081639691088, -73.9995087014816)     0      5  2019-05-08
5277   (40.7081639691088, -73.9995087014816)     1      6  2019-06-17
5934   (40.7081639691088, -73.9995087014816)     0      9  2019-09-06
5206   (40.7081639691088, -73.9995087014816)     0      9  2019-09-17
701    (40.7081639691088, -73.9995087014816)     1     11  2019-11-03

        day_name
12271     Sunday
12796     Sunday
482       Sunday
2604   Wednesday
2140      Monday
3951   Wednesday
5562    Saturday
7696     Tuesday
2944      Sunday
0        Tuesday
4198    Thursday
5962   Wednesday
5277      Monday
5934      Friday
5206     Tuesday
701       Sunday
```

pandas includes routines to fill in missing data using the `fillna` function (reference). We will fill these using the “forward fill” method, which caries the last valid observation forward to fill in NAs.

(Note: this makes sense only because we already sorted by date, and it’s reasonable to expect adjacent hours to have similar weather!)

```
df['temperature'] = df['temperature'].fillna(method="ffill")
df['precipitation'] = df['precipitation'].fillna(method="ffill")
df['weather_summary'] = df['weather_summary'].fillna(method="ffill")
```

Now we can count the NAs again and find that there are only missing values in the `events` column. This is the expected result, since there are many days with no event.

```
df.isnull().sum()
```

```
hour_beginning            0
location                  0
Pedestrians               0
Towards Manhattan         0
Towards Brooklyn          0
weather_summary           0
temperature               0
precipitation             0
lat                       0
long                      0
events                14933
```

```
Location1                0
hour                     0
month                    0
date                     0
day_name                 0
dtype: int64
```

Visually inspect data

Now we are ready to visually inspect the data.

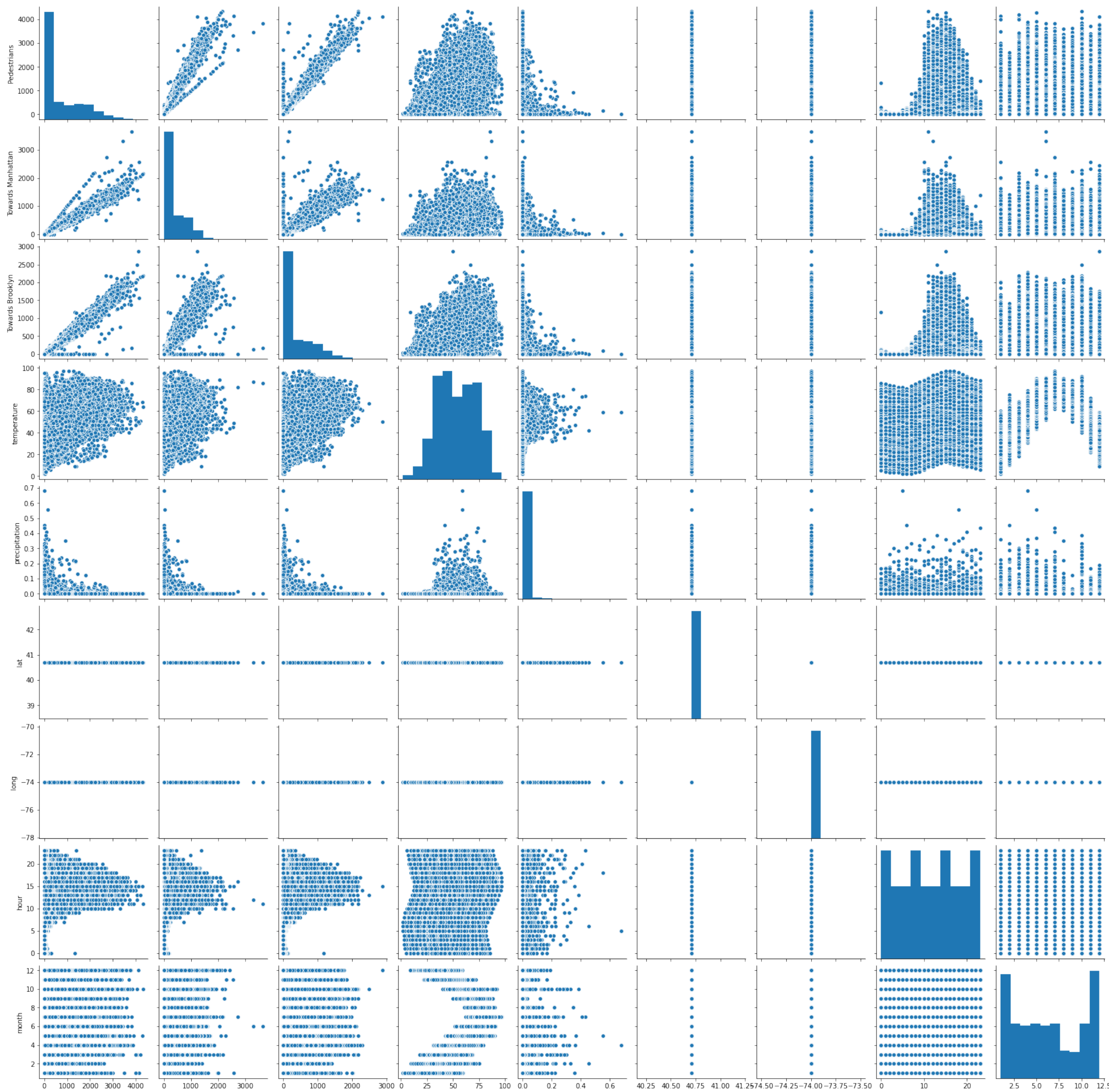
For tabular data, and especially tabular data with many numeric features, it is often useful to create a *pairplot*. A pairplot shows pairwise relationships between all numerical variables. It is a useful way to identify:

- features that are predictive - if there is any noticeable relationship between the target variable and any other variable.
- features that are correlated - if two features are highly correlated, we may be able to achieve equally good results just using one of them.

We can create a "default" pairplot with

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7feb76f6b370>
```



Here, each pane shows one numerical variable on the x-axis and another numerical variable on the y-axis, so that we can see if a relationship exists between them. The panes along the diagonal shows the empirical distribution of values for each feature in this data.

But, it is difficult to see anything useful because there is so much going on in this plot. We can improve things somewhat by:

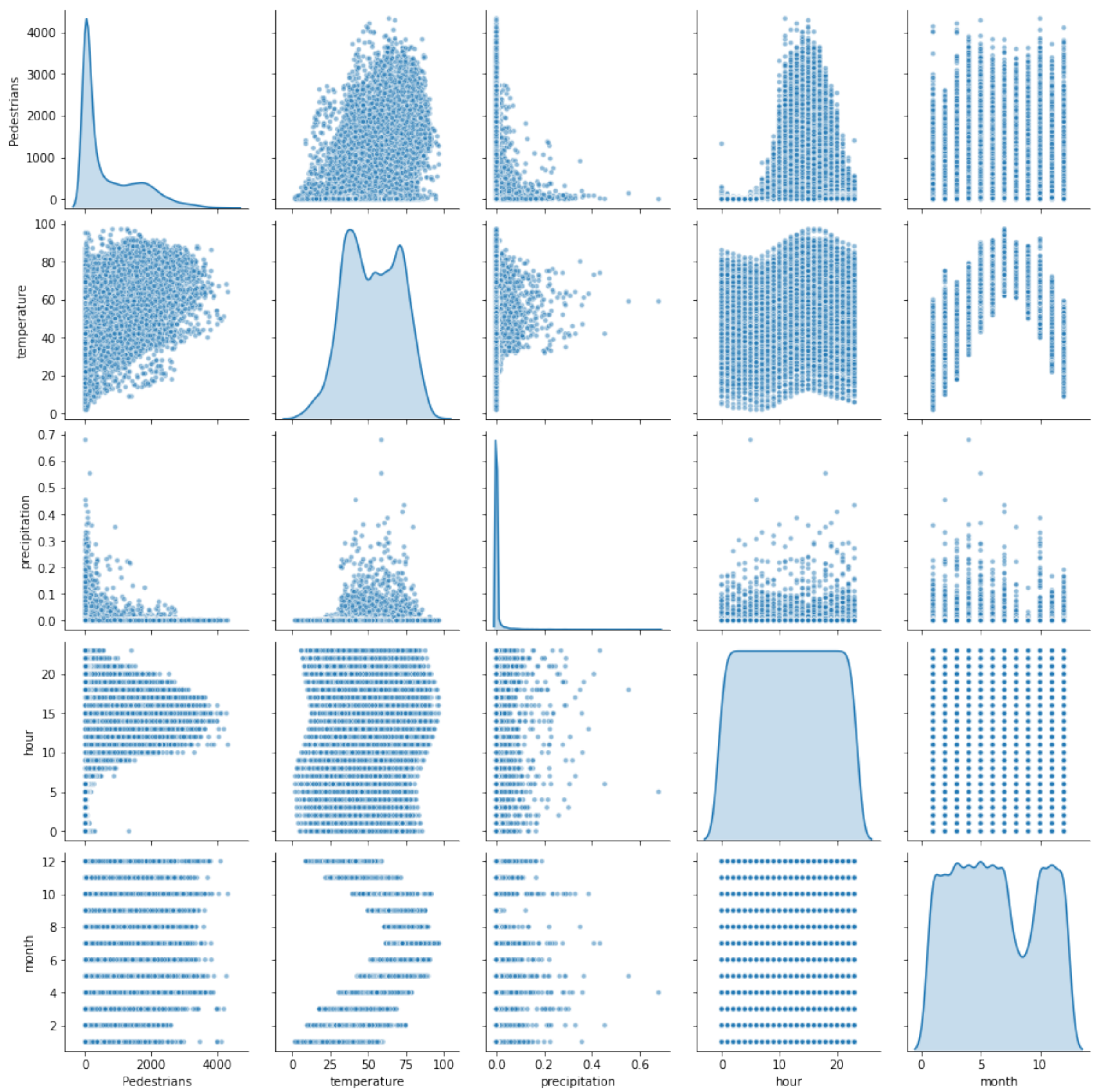
- specifying only the variables we want to include, and exluding variables that don't contain useful information, such as `lat` and `long`, and
- making the points on the plot smaller and partially transparent, to help with the overplotting.

We'll also change the histograms on the diagonal, which show the frequency of values for each variable, into a density plot which shows the same information in a more useful format.

```
sns.pairplot(df,
             vars=['Pedestrians', 'temperature', 'precipitation', 'hour', 'month'],
             diag_kind = 'kde',
```

```
            plot_kws={'alpha':0.5, 'size': 0.1})
```

```
<seaborn.axisgrid.PairGrid at 0x7feb74304040>
```



We are mainly interested in the top row of the plot, which shows how the target variable (`Pedestrians`) varies with the temperature, precipitation levels, and hour. However, it is also useful to note relationships between features. For example, there is a natural relationship between the time of data and the temperature, and between the month and the temperature.

Summary statistics

Now, we are ready to explore summary statistics. The "five number summary" - extremes (min and max), median, and quartiles -can help us gain a better understanding of the data. We can use the `describe` function in `pandas` to compute this summary.

```
df.describe()
```

```
        Pedestrians  Towards Manhattan  Towards Brooklyn   temperature  \
count  16057.000000       16057.000000      16057.000000  16057.000000
mean     687.106309         334.772436        352.286853     53.205892
std      862.244605         417.807545        456.624509     18.036476
min        0.000000           0.000000          0.000000      2.000000
25%       16.000000           9.000000          5.000000     39.000000
50%      227.000000         112.000000        111.000000     53.000000
75%     1254.000000         611.000000        632.000000     69.000000
max     4330.000000        3657.000000       2872.000000     97.000000

       precipitation           lat          long          hour         month
count   16057.000000  1.605700e+04  1.605700e+04  16057.000000  16057.000000
mean        0.004613  4.070816e+01 -7.399951e+01     11.499346      6.347076
std         0.023389  7.105649e-15  1.421130e-14      6.922682      3.544812
min         0.000000  4.070816e+01 -7.399951e+01      0.000000      1.000000
25%         0.000000  4.070816e+01 -7.399951e+01      5.000000      3.000000
50%         0.000000  4.070816e+01 -7.399951e+01     11.000000      6.000000
75%         0.000000  4.070816e+01 -7.399951e+01     17.000000     10.000000
max         0.680400  4.070816e+01 -7.399951e+01     23.000000     12.000000
```

We are especially interested in `Pedestrians`, the target variable, so we can describe that one separately:

```
df['Pedestrians'].describe()
```

```
count    16057.000000
mean       687.106309
std        862.244605
min          0.000000
25%         16.000000
50%        227.000000
75%       1254.000000
max       4330.000000
Name: Pedestrians, dtype: float64
```

For categorical variables, we can use `groupby` to get frequency and other useful summary statistics.

For example, we may be interested in the summary statistics for `Pedestrians` for different weather conditions:

```
df.groupby('weather_summary')['Pedestrians'].describe()
```

```
                      count         mean         std  min     25%     50%  \
weather_summary
clear-day            3127.0  1386.569875  861.890079  0.0  611.50  1401.0
clear-night          3755.0   102.689214  206.438992  0.0    2.00    19.0
cloudy               2383.0   540.437684  727.986539  0.0    9.00   141.0
fog                    76.0   234.473684  307.735795  0.0   15.00   110.0
partly-cloudy-day    3169.0  1422.154307  844.930127  0.0  699.00  1433.0
partly-cloudy-night  2508.0    93.880383  173.265652  0.0    3.00    23.0
rain                  920.0   256.165217  421.571020  0.0   10.00    67.5
sleet                  14.0   117.928571  157.850204  0.0    7.25    28.0
```

```
snow                    93.0   195.473118  292.630818  0.0   16.00    77.0
wind                    12.0   668.333333  682.617067  0.0    8.00   596.5

                        75%     max
weather_summary
clear-day             1982.5  4330.0
clear-night             93.5  1779.0
cloudy                 944.5  3894.0
fog                    276.5  1321.0
partly-cloudy-day     2008.0  4286.0
partly-cloudy-night     97.0  1522.0
rain                   311.0  2727.0
sleet                  254.5   404.0
snow                   258.0  1561.0
wind                  1010.0  1910.0
```

Make special note of the `count` column, which shows us the prevalence of different weather conditions in this dataset. There are some weather conditions for which we have very few examples.

Another categorical variable is `events`, which indicates whether the day is a holiday, and which holiday. Holidays have very different pedestrian traffic characteristics from other days.

```python
df.groupby('events')['Pedestrians'].describe()
```

```
                                    count         mean          std  min  \
events
Black Friday                         48.0   723.583333   952.014814  0.0
Christmas Day                        48.0   832.312500  1199.381546  0.0
Christmas Eve                        48.0   705.520833   945.112444  0.0
Cinco de Mayo                        48.0   807.750000  1047.286392  3.0
Columbus Day (regional holiday)      44.0   694.181818   854.264712  0.0
Daylight Saving Time ends            48.0   548.687500   719.950003  0.0
Daylight Saving Time starts          48.0   504.500000   708.192515  0.0
Easter Monday                        24.0   581.916667   704.003515  0.0
Easter Sunday                        48.0  1321.812500  1443.738832  0.0
Father's Day                         48.0   930.645833   836.469111  0.0
Halloween                            48.0   566.104167   789.258533  0.0
Independence Day                     48.0   749.604167   886.326983  0.0
Labor Day                            24.0   513.666667   540.116869  0.0
Martin Luther King Jr. Day           48.0   195.166667   281.788387  0.0
Memorial Day                         48.0  1314.333333  1346.292282  0.0
Mother's Day                         48.0   334.895833   430.048896  1.0
New Year's Day                       48.0   845.395833  1229.824148  2.0
New Year's Eve                       48.0   827.062500  1159.014556  0.0
Presidents' Day (regional holiday)   48.0   535.541667   622.282927  0.0
St. Patrick's Day                    48.0   747.458333   864.023344  0.0
Tax Day                              48.0   567.625000   626.338316  0.0
Thanksgiving Day                     48.0   564.708333   783.503098  0.0
Valentine's Day                      48.0   451.479167   509.012979  0.0
Veterans Day                         48.0   631.833333   803.411114  0.0
Veterans Day observed                24.0   421.083333   477.603703  2.0

                                       25%    50%      75%     max
events
```

```
Black Friday                          4.00  172.5  1515.50  2913.0
Christmas Day                         6.00   82.5  1480.75  3807.0
Christmas Eve                        10.75  113.0  1406.50  2625.0
Cinco de Mayo                        64.25  408.5   848.25  3390.0
Columbus Day (regional holiday)      28.75  332.0   878.75  2587.0
Daylight Saving Time ends            14.75  170.0   983.00  2311.0
Daylight Saving Time starts          10.00  123.5   814.25  2232.0
Easter Monday                        15.25  380.5   850.25  2242.0
Easter Sunday                        55.00  410.5  2809.50  3894.0
Father's Day                        111.75  807.5  1831.50  2128.0
Halloween                            13.75  144.0   803.00  2465.0
Independence Day                     32.00  259.0  1305.50  2727.0
Labor Day                            18.50  283.5  1080.50  1486.0
Martin Luther King Jr. Day            5.50   41.5   281.25   955.0
Memorial Day                         53.75  745.0  2752.00  3657.0
Mother's Day                         49.50  169.5   494.50  1693.0
New Year's Day                       28.25  149.0  1353.00  4141.0
New Year's Eve                        1.75  178.0  1517.00  3587.0
Presidents' Day (regional holiday)   27.00  138.5  1237.50  1648.0
St. Patrick's Day                    11.25  221.5  1557.00  2617.0
Tax Day                              16.75  284.5  1208.75  1910.0
Thanksgiving Day                      5.00  112.0  1093.50  2298.0
Valentine's Day                      17.50  193.0  1053.00  1448.0
Veterans Day                         11.75  159.0  1172.50  2265.0
Veterans Day observed                56.75  124.5   878.75  1269.0
```

It can be useful to get the total pedestrian count for the day of a holiday, rather than the summary statistics for the hour-long intervals. We can use the agg function to compute key statistics, including summing over all the samples in the group:

```
df.groupby('events').agg({'Pedestrians': 'sum'})
```

```
                                    Pedestrians
events
Black Friday                              34732
Christmas Day                             39951
Christmas Eve                             33865
Cinco de Mayo                             38772
Columbus Day (regional holiday)           30544
Daylight Saving Time ends                 26337
Daylight Saving Time starts               24216
Easter Monday                             13966
Easter Sunday                             63447
Father's Day                              44671
Halloween                                 27173
Independence Day                          35981
Labor Day                                 12328
Martin Luther King Jr. Day                 9368
Memorial Day                              63088
Mother's Day                              16075
New Year's Day                            40579
New Year's Eve                            39699
Presidents' Day (regional holiday)        25706
St. Patrick's Day                         35878
```

```
Tax Day                                   27246
Thanksgiving Day                          27106
Valentine's Day                           21671
Veterans Day                              30328
Veterans Day observed                     10106
```

Explore relationships and look for issues

Finally, let's further explore relationships between likely predictors and our target variable. We can group by `day_name`, then call the `describe` function on the `Pedestrians` column to see the effect of day of the week on traffic volume:

```
df.groupby('day_name')['Pedestrians'].describe()
```

```
            count        mean          std  min   25%    50%      75%     max
day_name
Friday     2280.0  696.521053   845.244195  0.0  17.0  243.5  1318.00  3722.0
Monday     2304.0  642.983941   777.944829  0.0  12.0  232.0  1232.00  3657.0
Saturday   2280.0  943.185965  1159.857344  0.0  22.0  241.5  1894.50  4330.0
Sunday     2305.0  753.213015   947.772750  0.0  19.0  206.0  1452.00  3894.0
Thursday   2280.0  601.263158   728.067954  0.0  16.0  214.0  1102.25  3173.0
Tuesday    2328.0  599.210911   731.047235  0.0  14.0  232.5  1122.50  4141.0
Wednesday  2280.0  574.956140   694.807586  0.0  16.0  217.0  1050.00  3807.0
```

Similarly, we can see the effect of temperature:

```
df.groupby('temperature')['Pedestrians'].describe()
```

```
             count         mean         std    min      25%     50%      75%  \
temperature
2.0            3.0    19.333333   25.929391    1.0     4.50     8.0    28.50
3.0            4.0    16.000000   32.000000    0.0     0.00     0.0    16.00
4.0            8.0    27.375000   25.767851    0.0     6.25    24.5    40.50
5.0            5.0    20.000000   41.418595    0.0     0.00     1.0     5.00
6.0           10.0    54.200000   85.590498    0.0     4.25    10.5    79.75
...            ...          ...         ...    ...      ...     ...      ...
93.0           3.0  1271.333333  707.043374  455.0  1062.00  1669.0  1679.50
94.0           4.0  1035.750000  746.532596  101.0   599.75  1202.0  1638.00
95.0           3.0   476.666667  765.789353    0.0    35.00    70.0   715.00
96.0           4.0  1161.500000  426.649349  538.0  1104.25  1301.5  1358.75
97.0           3.0  1063.666667  225.331607  828.0   957.00  1086.0  1181.50

                max
temperature
2.0            49.0
3.0            64.0
4.0            77.0
5.0            94.0
6.0           275.0
...             ...
93.0         1690.0
94.0         1638.0
95.0         1360.0
```

```
96.0         1505.0
97.0         1277.0

[96 rows x 8 columns]
```

And the effect of precipitation:

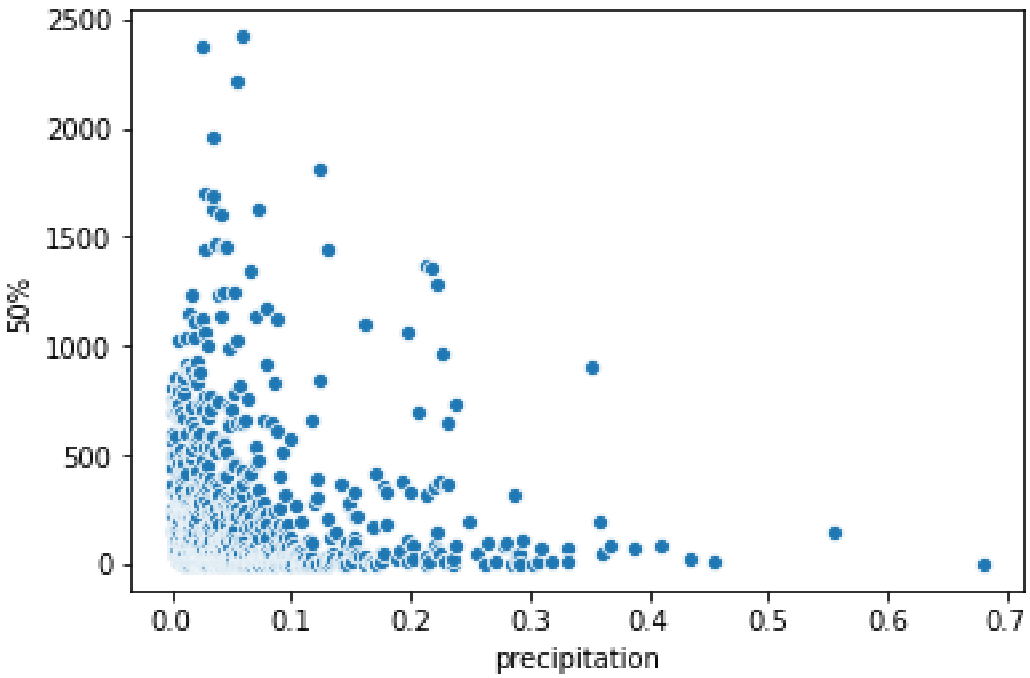
```
df.groupby('precipitation')['Pedestrians'].describe()
```

```
                 count        mean         std    min     25%    50%      75%  \
precipitation
0.0000         12338.0  731.183336  901.428828    0.0   15.00  236.0  1390.75
0.0001           226.0  548.982301  652.851843    0.0   52.25  256.0   931.00
0.0002           224.0  753.151786  849.076567    0.0   41.75  347.0  1389.50
0.0003           154.0  705.051948  733.243531    0.0   50.00  493.5  1230.00
0.0004           130.0  717.253846  766.100731    0.0   22.25  438.0  1243.00
...                ...         ...         ...    ...     ...    ...      ...
0.4090             1.0   81.000000         NaN   81.0   81.00   81.0    81.00
0.4340             1.0   18.000000         NaN   18.0   18.00   18.0    18.00
0.4543             1.0    6.000000         NaN    6.0    6.00    6.0     6.00
0.5543             1.0  141.000000         NaN  141.0  141.00  141.0   141.00
0.6804             1.0    0.000000         NaN    0.0    0.00    0.0     0.00

                  max
precipitation
0.0000         4286.0
0.0001         4330.0
0.0002         3816.0
0.0003         3485.0
0.0004         2733.0
...               ...
0.4090           81.0
0.4340           18.0
0.4543            6.0
0.5543          141.0
0.6804            0.0

[776 rows x 8 columns]
```

We can even plot it separately, by saving it in a new data frame and plotting *that* data frame:

```
df_precip = df.groupby('precipitation')['Pedestrians'].describe()
df_precip = df_precip.reset_index()
sns.scatterplot(data=df_precip, x='precipitation', y='50%')
```

```
<AxesSubplot:xlabel='precipitation', ylabel='50%'>
```



We see that certain weather conditions (very high temperature, heavy precipitation, fog) are extremely underrepresented in the dataset. This would be something to consider if, for example, we wanted to use this dataset to predict the effect of extreme weather on pedestrian traffic.