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 won't have a separate tutorial on `pandas` - we will learn basic `pandas` techniques as we need them.)
- 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. Set down *expectations* about the data
2. Load data and check that it is loaded correctly
3. Inspect the data to make sure it is consistent with your expectations ("sanity checks"), and clean or filter the data if needed
4. Explore relationships in the data to identify good candidate features and target variables

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.

Set down *expectations* about the data

The first step is to codify your expectations about the data *before* you look at it:

- 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 is the expected range or typical value for each column?
- What variables do you think 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 our exploratory data analysis. Then, we'll check that it is loaded correctly.

Some examples of the things we'll look for include:

- Does the `DataFrame` have the correct number of rows and columns (consistent with our expectations from the first step)?
- Is the first row of "data" in the `DataFrame` real data, or is it column labels that were misinterpreted as data? (Similarly, are the column labels actually labels, or are they the first row of data?)
- Are the data types of every column consistent with our expectations?

At this stage, we might also do some very basic manipulation of the data

- for example, compute some fields that are derived directly from other fields. (For example, suppose you have a "distance" field in miles and you wanted to convert it to meters - you could do that here!)

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)

`pandas` is a popular Python library for working with data. It is conventionally imported with the `pd` nickname.

```
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!

The main type of data structure in `pandas` is a `DataFrame`, which organizes data into a 2D table, like a spreadsheet. Unlike a `numpy` array, however, each column in a `DataFrame` can have different data types - for example, you can have a string column, an integer column, and a float column all in the same `DataFrame`.

(The other major type of data in `pandas` is a `Series`, which is like a 1D array- any individual row or column from a `DataFrame` will be a `Series`.)

You *can* create a `DataFrame` or a `Series` "by hand" - for example, try

```
pd.Series([1,2,3,99])
```

or

```
pd.DataFrame({'fruit': ['apple', 'banana', 'kiwi'], 'cost': [0.55, 0.99, 1.24]})
```

But usually, we'll read in data from a file.

Our data for this Brooklyn Bridge example is in CSV format, so will use the `read_csv` function in `pandas` to read in our data. This function accepts a URL or a path to a file, and will return our data as a `DataFrame`.

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 the first few rows of data or the last few rows of data with the `head` and `tail` functions, respectively. (For data that is not tabular, such as image, text, or audio data, we would similarly start by looking at some samples.)

```
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)
```

```
df.tail()
```

```
              hour_beginning         location  Pedestrians  \
16052  06/22/2018 04:00:00 AM  Brooklyn Bridge            7
16053  07/19/2018 06:00:00 AM  Brooklyn Bridge          192
16054  06/16/2018 04:00:00 PM  Brooklyn Bridge         2623
16055  07/24/2018 06:00:00 PM  Brooklyn Bridge         2016
16056  07/23/2018 12:00:00 AM  Brooklyn Bridge           57
```

```
       Towards Manhattan  Towards Brooklyn      weather_summary  temperature  \
16052                  4                 3  partly-cloudy-night         67.0
16053                 89               103            clear-day         65.0
16054               1161              1462            clear-day         82.0
16055               1069               947    partly-cloudy-day         80.0
16056                 20                37               cloudy         75.0

       precipitation        lat       long events  \
16052         0.0000  40.708164 -73.999509    NaN
16053         0.0000  40.708164 -73.999509    NaN
16054         0.0000  40.708164 -73.999509    NaN
16055         0.0000  40.708164 -73.999509    NaN
16056         0.0103  40.708164 -73.999509    NaN

                                  Location1
16052  (40.7081639691088, -73.9995087014816)
16053  (40.7081639691088, -73.9995087014816)
16054  (40.7081639691088, -73.9995087014816)
16055  (40.7081639691088, -73.9995087014816)
16056  (40.7081639691088, -73.9995087014816)
```

We can also get a few random rows:

```
df.sample(5)
```

```
               hour_beginning         location  Pedestrians  \
475    10/12/2019 02:00:00 PM  Brooklyn Bridge         3615
7118   11/12/2019 09:00:00 AM  Brooklyn Bridge          191
3747   05/15/2019 06:00:00 AM  Brooklyn Bridge          192
1429   07/14/2019 08:00:00 AM  Brooklyn Bridge          396
15172  07/30/2018 11:00:00 PM  Brooklyn Bridge          219

       Towards Manhattan  Towards Brooklyn    weather_summary  temperature  \
475                 1632              1983  partly-cloudy-day         64.0
7118                  93                98               rain         42.0
3747                  91               101  partly-cloudy-day         45.0
1429                 226               170          clear-day         78.0
15172                 92               127        clear-night         70.0

       precipitation        lat       long events  \
475           0.0000  40.708164 -73.999509    NaN
7118          0.0104  40.708164 -73.999509    NaN
3747          0.0000  40.708164 -73.999509    NaN
1429          0.0000  40.708164 -73.999509    NaN
15172         0.0010  40.708164 -73.999509    NaN

                                  Location1
475    (40.7081639691088, -73.9995087014816)
7118   (40.7081639691088, -73.9995087014816)
3747   (40.7081639691088, -73.9995087014816)
1429   (40.7081639691088, -73.9995087014816)
15172  (40.7081639691088, -73.9995087014816)
```

Looking at some rows can help us spot obvious problems with data loading. For example, suppose we had tried to read in the data using a tab delimiter to separate fields on the same row, instead of a comma.

```
df_bad  = pd.read_csv(url, sep='\t')
df_bad.head()
```

```
  hour_beginning,location,Pedestrians,Towards Manhattan,Towards
      Brooklyn,weather_summary,temperature,precipitation,lat,long,events,Location1
0  04/30/2019 12:00:00 AM,Brooklyn Bridge,3,3,0,,...
1  12/31/2019 10:00:00 PM,Brooklyn Bridge,10,9,1,...
2  12/31/2019 11:00:00 PM,Brooklyn Bridge,2,0,2,c...
3  12/31/2019 09:00:00 PM,Brooklyn Bridge,12,0,12...
4  04/01/2019 03:00:00 AM,Brooklyn Bridge,1,0,1,c...
```

This "bad" version of the `DataFrame` has only a single column (because it believes tabs are used to separate fields in the same row, when actually commas are used). The variable names are combined together into one long column name. By looking at the first few rows of data, we can spot this obvious error.

Here is another example of a "bad" `DataFrame`. Suppose we tell `read_csv` that the data file itself does not have a header row at the top, with column names in it; instead, we supply column names ourselves.

```
col_names = ["hour_beginning", "location", "Pedestrians", "Towards Manhattan",
    "Towards Brooklyn", "weather_summary", "temperature", "precipitation",
    "lat", "long", "events", "Location1"]
df_bad  = pd.read_csv(url, header=None, names=col_names)
df_bad.head()
```

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

   Towards Brooklyn  weather_summary  temperature  precipitation  \
0  Towards Brooklyn  weather_summary  temperature  precipitation
1                 0              NaN          NaN            NaN
2                 1           cloudy           42         0.0005
3                 2           cloudy           42         0.0004
4                12           cloudy           42         0.0036

                lat                long  events  \
0               lat                long  events
1  40.7081639691088  -73.9995087014816     NaN
2  40.7081639691088  -73.9995087014816     NaN
3  40.7081639691088  -73.9995087014816     NaN
4  40.7081639691088  -73.9995087014816     NaN

                               Location1
0                              Location1
1  (40.7081639691088, -73.9995087014816)
2  (40.7081639691088, -73.9995087014816)
3  (40.7081639691088, -73.9995087014816)
4  (40.7081639691088, -73.9995087014816)
```

In this example, the first row in the file *is* actually a column header, and we mistakenly read it in as data. (A similar problem can occur in reverse - if we told `read_csv` that the first row *is* a header when it is not, then our "column labels" would actually be the first row of data.)

We should always check the shape of the data frame - the number of rows and columns. This, too, should be checked against our assumptions about the data (in this case, what we know 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
```

The main data types we'll see most often are `int64` (integer), `float64` (numeric), `bool` (True or False), or `object` (which includes string).

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 (`hour_beginning`) that was read in as a string. Let's take a closer look at that. We can get one column of data either using a notation like a dictionary, as in

```
df['hour_beginning']
```

or using class attribute-like notation, as in

```
df.hour_beginning
```

(either one returns exactly the same thing!) (Note that if the column name includes spaces, you can only use the notation with the brackets, since it encloses the column name in quotes.)

`pandas` includes a `to_datetime` function to convert this string to a "native" date/time format, so we can use 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
```

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:

```python
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  \
0 2019-04-30 00:00:00  Brooklyn Bridge            3                  3
1 2019-12-31 22:00:00  Brooklyn Bridge           10                  9
2 2019-12-31 23:00:00  Brooklyn Bridge            2                  0
3 2019-12-31 21:00:00  Brooklyn Bridge           12                  0
4 2019-04-01 03:00:00  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  hour  month  \
0 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     0      4
1 -73.999509    NaN  (40.7081639691088, -73.9995087014816)    22     12
2 -73.999509    NaN  (40.7081639691088, -73.9995087014816)    23     12
3 -73.999509    NaN  (40.7081639691088, -73.9995087014816)    21     12
4 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     3      4

         date day_name
0  2019-04-30  Tuesday
1  2019-12-31  Tuesday
2  2019-12-31  Tuesday
3  2019-12-31  Tuesday
4  2019-04-01   Monday
```

Inspect (and possibly clean/filter) the data

Now we are ready to inspect the data.

Some examples of the things we'll look for include:

- Are there missing values? There may be rows *in* the data where some or all fields are missing (which can be denoted as None, NaN, or even 0 or -1 - which can be misleading when 0 or -1 are also valid values for that field.) There may also be rows *not in* the data, that we expect *should be* in the data.
- For numeric fields: Is the min and max of each field consistent with our expectation? Is the median consistent with our expectation?
- For non-numeric fields: Are the number of unique values in each field consistent with our expectations? Are the values of the factor levels (where these can reasonably be assessed) described consistently throughout the data?
- Are the relationships *between* variables consistent with our expectations? (We can evaluate this visually, and also by looking at summary statistics.)
- If the data is a time series, is the trend of each variable over time consistent with our expectations?

For many of these "sanity checks", we will need some *domain knowledge*. It's hard to have reasonable expectations about the values in the data if you do not understand the topic that the data relates to.

Check whether data is complete Let us start by checking whether the data is complete. First, we'll check whether there are any rows in the data where some or all fields are missing.

We can see the number of missing values 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
```

(Note that this only tells us about missing values that are explicitly denoted as such - for example, explicit `NaN` values. If a missing value is coded as something else - like a 0 or -1 - we wouldn't know unless we noticed an unusually high frequency of 0 or -1 values.)

We notice that the majority of rows are missing a value in the `events` field, which is used to mark dates that are holidays or other special events. This is reasonable, since most dates do not have any remarkable events.

Let's look at the rows that *do* have a value in the `events` field. To filter a dataframe, we'll use the `.loc[]` operator. This accepts either an index (for example, we can do `df.loc[0]` to see the first record in the dataframe), an array of indices (for example, `df.loc[[0,1,2]]`), or an array of boolean values the length of the entire dataframe. That's what we'll use here.

```
df.loc[df['events'].notnull()]
```

```
           hour_beginning         location  Pedestrians  Towards Manhattan  \
5     2019-12-25 14:00:00  Brooklyn Bridge         3171               1685
65    2019-10-31 00:00:00  Brooklyn Bridge           13                 11
76    2019-03-17 23:00:00  Brooklyn Bridge            1                  0
78    2019-02-18 16:00:00  Brooklyn Bridge         1439                622
89    2019-09-02 01:00:00  Brooklyn Bridge            0                  0
...                   ...              ...          ...                ...
15962 2018-07-04 16:00:00  Brooklyn Bridge         2726               2726
15990 2018-07-04 12:00:00  Brooklyn Bridge         2010               1073
15997 2018-06-17 23:00:00  Brooklyn Bridge          353                168
16017 2018-06-17 03:00:00  Brooklyn Bridge           16                 11
```

```
16024 2018-06-17 14:00:00  Brooklyn Bridge        2038              897

       Towards Brooklyn      weather_summary  temperature  precipitation  \
5                  1486            clear-day         44.0         0.0000
65                    2               cloudy         61.0         0.0000
76                    1          clear-night         37.0         0.0000
78                  817    partly-cloudy-day         40.0         0.0002
89                    0  partly-cloudy-night         69.0         0.0000
...                 ...                  ...          ...            ...
15962                 0    partly-cloudy-day         82.0         0.0133
15990               937    partly-cloudy-day         84.0         0.0000
15997               185          clear-night         74.0         0.0000
16017                 5          clear-night         66.0         0.0000
16024              1141            clear-day         86.0         0.0000

             lat       long                              events  \
5      40.708164 -73.999509                       Christmas Day
65     40.708164 -73.999509                           Halloween
76     40.708164 -73.999509                   St. Patrick's Day
78     40.708164 -73.999509  Presidents' Day (regional holiday)
89     40.708164 -73.999509                           Labor Day
...          ...        ...                                 ...
15962  40.708164 -73.999509                    Independence Day
15990  40.708164 -73.999509                    Independence Day
15997  40.708164 -73.999509                        Father's Day
16017  40.708164 -73.999509                        Father's Day
16024  40.708164 -73.999509                        Father's Day

                                  Location1  hour  month        date  \
5      (40.7081639691088, -73.9995087014816)    14     12  2019-12-25
65     (40.7081639691088, -73.9995087014816)     0     10  2019-10-31
76     (40.7081639691088, -73.9995087014816)    23      3  2019-03-17
78     (40.7081639691088, -73.9995087014816)    16      2  2019-02-18
89     (40.7081639691088, -73.9995087014816)     1      9  2019-09-02
...                                      ...   ...    ...         ...
15962  (40.7081639691088, -73.9995087014816)    16      7  2018-07-04
15990  (40.7081639691088, -73.9995087014816)    12      7  2018-07-04
15997  (40.7081639691088, -73.9995087014816)    23      6  2018-06-17
16017  (40.7081639691088, -73.9995087014816)     3      6  2018-06-17
16024  (40.7081639691088, -73.9995087014816)    14      6  2018-06-17

        day_name
5      Wednesday
65      Thursday
76        Sunday
78        Monday
89        Monday
...          ...
15962  Wednesday
15990  Wednesday
15997     Sunday
16017     Sunday
16024     Sunday
```

```
[1124 rows x 16 columns]
```

We also notice a small number of rows missing weather information. It's not clear why these are missing. Let's take a closer look at some of those rows, by *filtering* the dataframe to only rows that meet a specific condition - in this case, that the `temperature` field is missing.

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

```
           hour_beginning        location  Pedestrians  Towards Manhattan  \
0     2019-04-30 00:00:00  Brooklyn Bridge            3                  3
482   2019-01-06 00:00:00  Brooklyn Bridge            3                  3
701   2019-11-03 01:00:00  Brooklyn Bridge            0                  0
2140  2019-01-14 00:00:00  Brooklyn Bridge            0                  0
2604  2019-01-09 00:00:00  Brooklyn Bridge            3                  3
2944  2019-03-10 02:00:00  Brooklyn Bridge            0                  0
3951  2019-01-16 00:00:00  Brooklyn Bridge            7                  2
4198  2019-05-02 00:00:00  Brooklyn Bridge            3                  2
5206  2019-09-17 00:00:00  Brooklyn Bridge            2                  2
5277  2019-06-17 01:00:00  Brooklyn Bridge            0                  0
5562  2019-02-02 00:00:00  Brooklyn Bridge            0                  0
5934  2019-09-06 00:00:00  Brooklyn Bridge            2                  1
5962  2019-05-08 00:00:00  Brooklyn Bridge            3                  2
7696  2019-03-05 00:00:00  Brooklyn Bridge            2                  0
12271 2018-03-11 02:00:00  Brooklyn Bridge            0                  0
12796 2018-05-13 00:00:00  Brooklyn Bridge           98                 69

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

             lat       long                      events  \
0      40.708164 -73.999509                         NaN
482    40.708164 -73.999509                         NaN
701    40.708164 -73.999509    Daylight Saving Time ends
2140   40.708164 -73.999509                         NaN
2604   40.708164 -73.999509                         NaN
2944   40.708164 -73.999509  Daylight Saving Time starts
3951   40.708164 -73.999509                         NaN
4198   40.708164 -73.999509                         NaN
5206   40.708164 -73.999509                         NaN
```

```
5277   40.708164 -73.999509                          NaN
5562   40.708164 -73.999509                          NaN
5934   40.708164 -73.999509                          NaN
5962   40.708164 -73.999509                          NaN
7696   40.708164 -73.999509                          NaN
12271  40.708164 -73.999509  Daylight Saving Time starts
12796  40.708164 -73.999509                 Mother's Day

                                    Location1  hour  month        date  \
0      (40.7081639691088, -73.9995087014816)     0      4  2019-04-30
482    (40.7081639691088, -73.9995087014816)     0      1  2019-01-06
701    (40.7081639691088, -73.9995087014816)     1     11  2019-11-03
2140   (40.7081639691088, -73.9995087014816)     0      1  2019-01-14
2604   (40.7081639691088, -73.9995087014816)     0      1  2019-01-09
2944   (40.7081639691088, -73.9995087014816)     2      3  2019-03-10
3951   (40.7081639691088, -73.9995087014816)     0      1  2019-01-16
4198   (40.7081639691088, -73.9995087014816)     0      5  2019-05-02
5206   (40.7081639691088, -73.9995087014816)     0      9  2019-09-17
5277   (40.7081639691088, -73.9995087014816)     1      6  2019-06-17
5562   (40.7081639691088, -73.9995087014816)     0      2  2019-02-02
5934   (40.7081639691088, -73.9995087014816)     0      9  2019-09-06
5962   (40.7081639691088, -73.9995087014816)     0      5  2019-05-08
7696   (40.7081639691088, -73.9995087014816)     0      3  2019-03-05
12271  (40.7081639691088, -73.9995087014816)     2      3  2018-03-11
12796  (40.7081639691088, -73.9995087014816)     0      5  2018-05-13

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

We can see that for these particular instances, all of the weather information is missing. There's no obvious reason or pattern. We'll deal with these soon, when we try to clean/filter the data.

Before we do that, though, let's check for the *other* kind of missing data: rows that are missing completely, that we expect *should* be present.

In this example, the data is a time series, and we expect that there is exactly one row of data for every single hour over the time period in which this data was collected.

Let's see if the data is complete, or if there are gaps in time.

First, we will use `pd.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
```

```
expected_range = pd.date_range(start = min_dt, end = max_dt, freq='H' )
expected_range
```

```
DatetimeIndex(['2017-10-01 00:00:00', '2017-10-01 01:00:00',
               '2017-10-01 02:00:00', '2017-10-01 03:00:00',
               '2017-10-01 04:00:00', '2017-10-01 05:00:00',
               '2017-10-01 06:00:00', '2017-10-01 07:00:00',
               '2017-10-01 08:00:00', '2017-10-01 09:00:00',
               ...
               '2019-12-31 14:00:00', '2019-12-31 15:00:00',
               '2019-12-31 16:00:00', '2019-12-31 17:00:00',
               '2019-12-31 18:00:00', '2019-12-31 19:00:00',
               '2019-12-31 20:00:00', '2019-12-31 21:00:00',
               '2019-12-31 22:00:00', '2019-12-31 23:00:00'],
              dtype='datetime64[ns]', length=19728, freq='H')
```

```
# then identify the missing hours
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)
```

Let's also check if any hour appears more than once in the data. We can use `pandas`'s `value_counts` function to find out how many times each unique value appears in the data:

```
df['hour_beginning'].value_counts()
```

```
2019-11-03 01:00:00    2
2019-05-04 01:00:00    1
2019-09-21 04:00:00    1
2018-06-18 19:00:00    1
2018-02-22 01:00:00    1
                      ..
2017-12-24 21:00:00    1
2018-06-06 11:00:00    1
2017-10-22 09:00:00    1
2019-02-19 03:00:00    1
2019-02-21 22:00:00    1
Name: hour_beginning, Length: 16056, dtype: int64
```

It looks like at least one hour appears twice in the data, which is unexpected! Let's use filtering again to find out all of the instances where that occurs:

```
hour_counts = df['hour_beginning'].value_counts()
hour_counts.loc[hour_counts > 1]
```

```
2019-11-03 01:00:00    2
Name: hour_beginning, dtype: int64
```

It seems to happen exactly once. Let's filter the dataframe to find the rows corresponding to the duplicate day.

Here's a useful clue - we can see that this hour appears twice because the clock is shifted for Daylight Savings time. (It's not clear why there is no duplicate hour for that same event in 2017. Perhaps only one of those hours is recorded.)

```
df.loc[df['hour_beginning']=="2019-11-03 01:00:00"]
```

```
          hour_beginning         location  Pedestrians  Towards Manhattan  \
701  2019-11-03 01:00:00  Brooklyn Bridge            0                  0
3019 2019-11-03 01:00:00  Brooklyn Bridge            1                  0

      Towards Brooklyn weather_summary  temperature  precipitation        lat  \
701                  0             NaN          NaN            NaN  40.708164
3019                 1     clear-night         44.0            0.0  40.708164

           long                    events  \
701  -73.999509  Daylight Saving Time ends
3019 -73.999509  Daylight Saving Time ends

                                 Location1  hour  month        date day_name
701   (40.7081639691088, -73.9995087014816)     1     11  2019-11-03   Sunday
3019  (40.7081639691088, -73.9995087014816)     1     11  2019-11-03   Sunday
```

Handle missing values Now that we have evaluated the "completeness" of our data, we have to decide what to do about missing values.

Some machine learning models cannot tolerate data with missing values. Depending on what *type* of data is missing and *why* it is missing, we can

- drop rows with missing values from the dataset
- fill in ("impute") the missing values with some value: a 0, the mode of that column, the median of that column, or forward/back fill data from the nearest row that is not missing

For this data, let's try the forward/back fill method. This makes some sense because the data has a logical order in time, and the missing value - weather - changes relatively slowly with respect to time. We can expect that the weather at any given hour is probably similar to the weather in the previous (or next) hour.

For this to work, we'll first have to sort the data by time. (Note that the data was not sorted originally.)

```
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)

       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
```

We can also "reset" the index now, so that if we ask for `df.loc[0]` we'll get the first row in time, and so on.

```
df.reset_index(drop=True, inplace=True)
df.head()
```

```
       hour_beginning         location  Pedestrians  Towards Manhattan  \
0 2017-10-01 00:00:00  Brooklyn Bridge           44                 30
1 2017-10-01 01:00:00  Brooklyn Bridge           30                 17
2 2017-10-01 02:00:00  Brooklyn Bridge           25                 13
3 2017-10-01 03:00:00  Brooklyn Bridge           20                 11
4 2017-10-01 04:00:00  Brooklyn Bridge           18                 10

   Towards Brooklyn      weather_summary  temperature  precipitation  \
0                14          clear-night         52.0         0.0001
1                13  partly-cloudy-night         53.0         0.0002
2                12  partly-cloudy-night         52.0         0.0000
3                 9  partly-cloudy-night         51.0         0.0000
4                 8  partly-cloudy-night         51.0         0.0000

         lat       long events                              Location1  hour  \
0  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     0
1  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     1
2  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     2
3  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     3
4  40.708164 -73.999509    NaN  (40.7081639691088, -73.9995087014816)     4

   month        date day_name
0     10  2017-10-01   Sunday
1     10  2017-10-01   Sunday
2     10  2017-10-01   Sunday
3     10  2017-10-01   Sunday
4     10  2017-10-01   Sunday
```

Now we can fill in missing data using the `fillna` function (reference). We will fill the missing weather data using the "forward fill" method, which caries the last valid observation forward to fill in NAs.

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

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

Having imputed missing vaules in the weather-related columns, we can count the NAs again and find that there are only missing values in the `events` column.

```python
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
```

Validating expectations Now that we have some idea of the completeness of the data, let's look at whether the data values are consistent with our expectations.

To start, let's look at summary statistics. The "five number summary" - extremes (min and max), median, and quartiles -can help us gain a better understanding of numeric fields in the data, and see whether they have reasonable values. We can use the `describe` function in `pandas` to compute this summary.

```python
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 can only compute those summary statistics for numerical variables. For categorical variables, we can use `value_counts()` to get frequency of each value.

For example, let's see how often each `weather` condition occurs, and whether it is reasonable for NYC:

```
df.weather_summary.value_counts()
```

```
clear-night            3755
partly-cloudy-day      3169
clear-day              3127
partly-cloudy-night    2508
cloudy                 2383
rain                    920
snow                     93
fog                      76
sleet                    14
wind                     12
Name: weather_summary, dtype: int64
```

It's also useful to verify expected relationships.

For example, we expect to see precipitation when the weather is rainy. We can use `groupby` in `pandas` to capture the effect between a categorical variable (`weather_summary`) and a numerical one, `precipitation`:

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

```
                      count      mean       std     min       25%     50%  \
weather_summary
clear-day            3127.0  0.000235  0.001193  0.0000  0.000000  0.0000
clear-night          3755.0  0.000055  0.000455  0.0000  0.000000  0.0000
cloudy               2383.0  0.001705  0.005100  0.0000  0.000000  0.0000
fog                    76.0  0.003432  0.005740  0.0000  0.000000  0.0009
partly-cloudy-day    3169.0  0.000839  0.002985  0.0000  0.000000  0.0000
partly-cloudy-night  2508.0  0.000904  0.003619  0.0000  0.000000  0.0000
rain                  920.0  0.065898  0.071727  0.0006  0.025500  0.0433
sleet                  14.0  0.061729  0.066759  0.0089  0.029025  0.0399
snow                   93.0  0.025419  0.030711  0.0013  0.011500  0.0168
wind                   12.0  0.002450  0.006447  0.0000  0.000000  0.0000

                          75%     max
weather_summary
clear-day            0.000000  0.0241
clear-night          0.000000  0.0157
cloudy               0.000500  0.1090
fog                  0.003650  0.0246
partly-cloudy-day    0.000000  0.0480
partly-cloudy-night  0.000000  0.1000
rain                 0.080150  0.6804
sleet                0.056975  0.2284
snow                 0.026700  0.2029
wind                 0.001075  0.0225
```

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.

Similarly, we can validate our expectation of hotter weather in the summer months:

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

```
        count       mean        std   min   25%   50%    75%   max
month
1      1488.0  31.140457  11.459811   2.0  24.0  31.0  39.00  60.0
2      1344.0  37.706101   9.723386  10.0  31.0  37.0  43.00  75.0
3      1488.0  39.809140   7.925757  18.0  34.0  39.0  45.00  69.0
4      1440.0  50.865278   9.304510  31.0  43.0  51.0  57.25  79.0
5      1488.0  63.358199   9.183699  43.0  56.0  63.0  69.00  90.0
6      1440.0  71.056250   7.499476  52.0  66.0  71.0  76.00  91.0
7      1488.0  77.695565   6.300003  62.0  73.0  77.0  82.00  97.0
8       744.0  74.668011   5.929941  61.0  71.0  74.0  79.00  90.0
9       720.0  69.451389   6.882513  50.0  64.0  69.0  74.00  88.0
10     1488.0  60.635753   8.061906  40.0  55.0  60.0  66.00  92.0
11     1441.0  44.060375   8.779543  22.0  38.0  44.0  50.00  72.0
12     1488.0  35.851478   9.679955   9.0  31.0  36.0  42.00  59.0
```

as well as during the middle of the day:

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

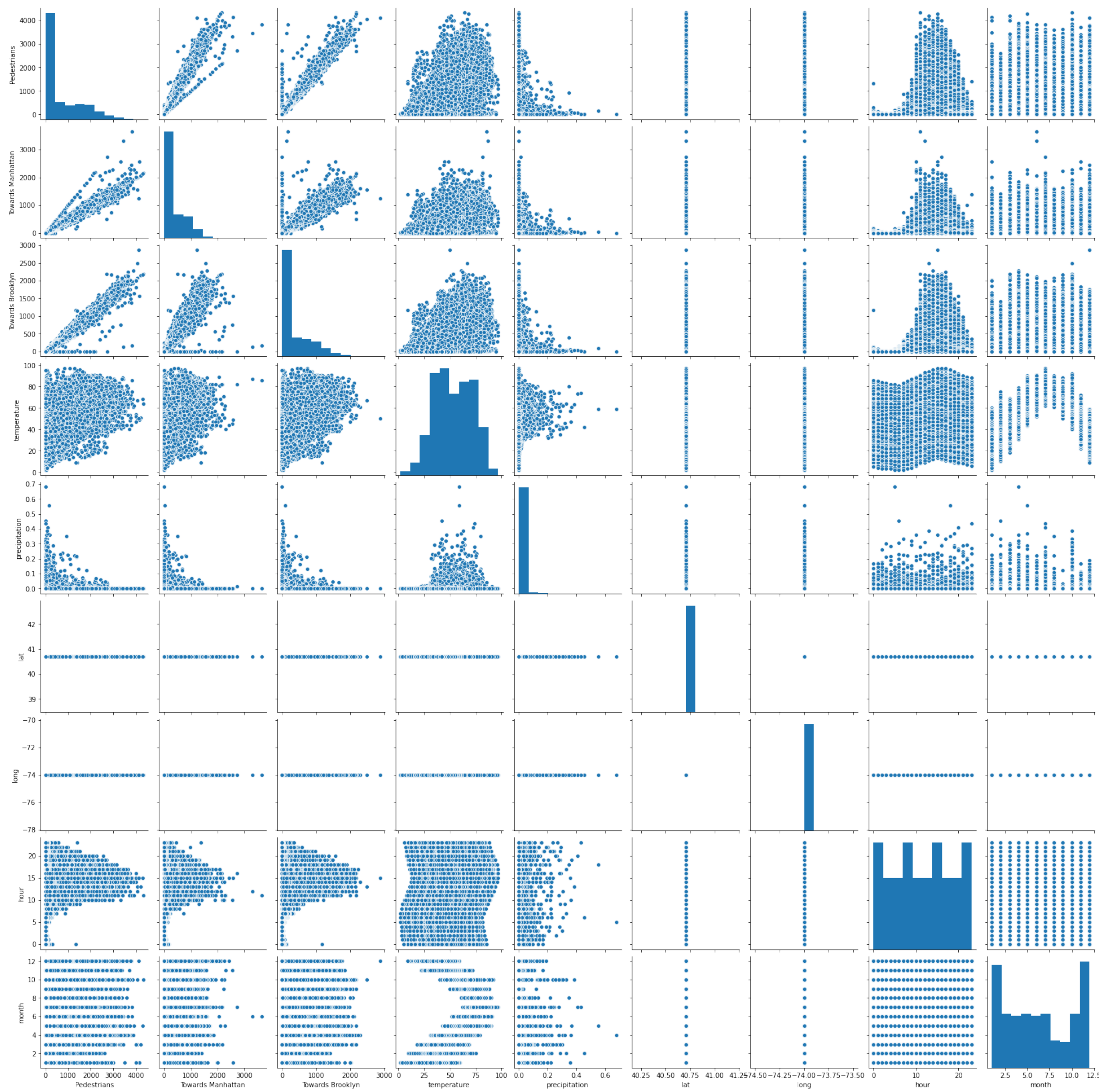
```
      count       mean        std   min   25%   50%   75%   max
hour
0     669.0  51.230194  17.075762   5.0  37.0  52.0  67.0  86.0
1     670.0  50.617910  16.990729   4.0  37.0  51.0  66.0  85.0
2     669.0  50.067265  16.900022   3.0  36.0  50.0  65.0  84.0
3     669.0  49.538117  16.860571   3.0  36.0  50.0  64.0  83.0
4     669.0  49.049327  16.771776   3.0  35.0  50.0  64.0  82.0
5     669.0  48.606876  16.708742   2.0  35.0  49.0  63.0  82.0
6     669.0  48.330344  16.668034   2.0  35.0  49.0  63.0  81.0
7     669.0  48.627803  16.997460   2.0  34.0  49.0  64.0  83.0
8     669.0  49.760837  17.303981   3.0  36.0  50.0  65.0  85.0
9     669.0  51.493274  17.603382   4.0  37.0  52.0  67.0  87.0
10    669.0  53.303438  17.913858   6.0  39.0  53.0  70.0  89.0
11    669.0  54.992526  18.165035   8.0  40.0  55.0  71.0  91.0
12    669.0  56.437967  18.364844   9.0  42.0  56.0  72.0  93.0
13    669.0  57.584454  18.519309  11.0  43.0  57.0  73.0  94.0
14    669.0  58.324365  18.557751  12.0  43.0  57.0  75.0  96.0
15    669.0  58.636771  18.656152  13.0  44.0  57.0  75.0  97.0
16    669.0  58.428999  18.752959  12.0  43.0  57.0  75.0  97.0
17    669.0  57.690583  18.871808  11.0  42.0  57.0  74.0  97.0
18    669.0  56.642750  18.711952  10.0  42.0  56.0  73.0  96.0
19    669.0  55.464873  18.389841   9.0  41.0  55.0  72.0  94.0
20    669.0  54.391629  17.987495   8.0  40.0  54.0  70.0  92.0
21    669.0  53.346786  17.462087   8.0  39.0  53.0  69.0  90.0
22    669.0  52.524664  17.305845   7.0  38.0  53.0  69.0  89.0
23    669.0  51.853513  17.193755   6.0  38.0  52.0  68.0  88.0
```

Create a pairplot For tabular data with multiple 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 variables that have a relationship.

We can create a "default" pairplot with

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

```
<seaborn.axisgrid.PairGrid at 0x7f0900fc4700>
```



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:

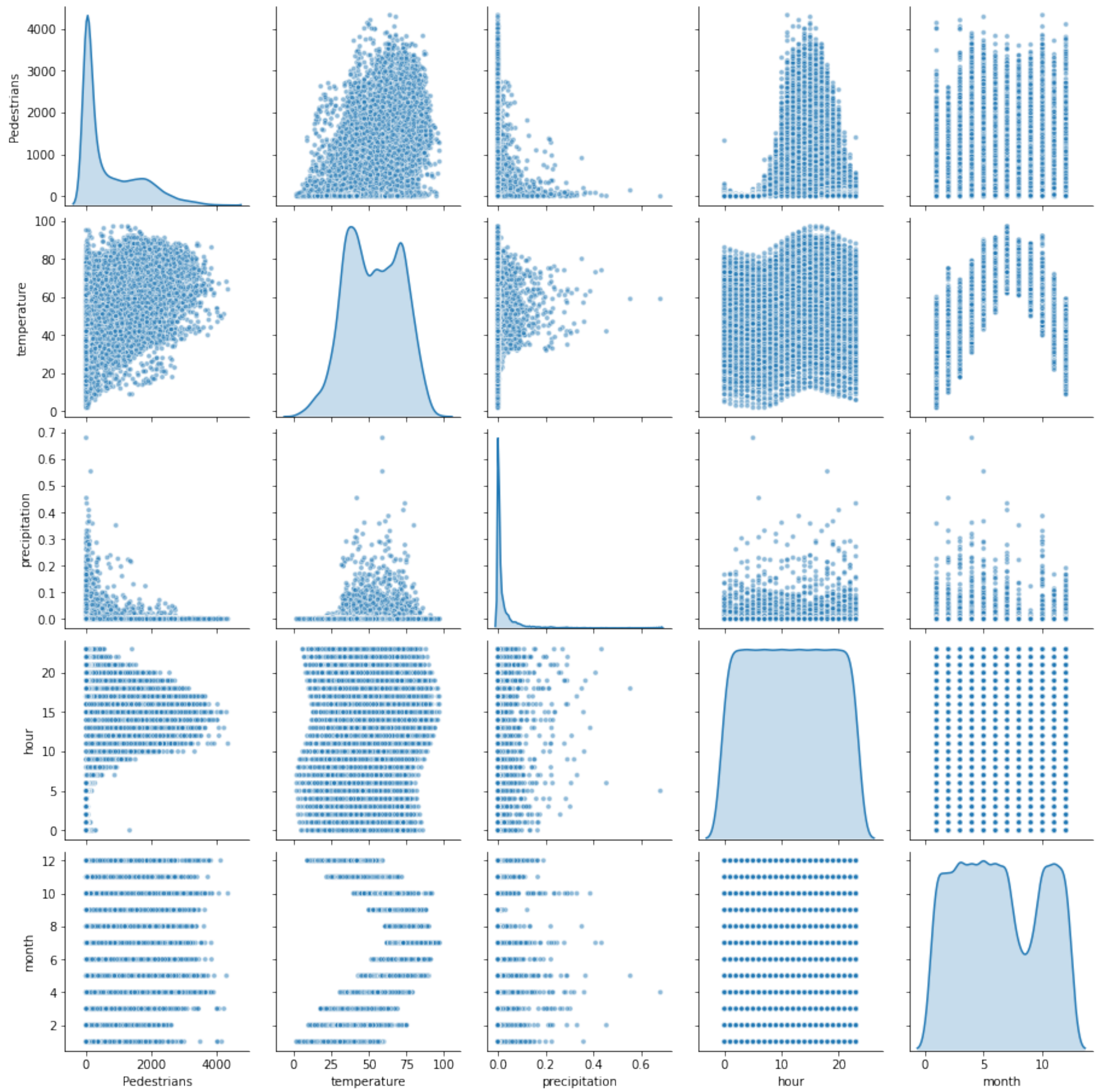
- specifying only the variables we want to include, and exluding variables that don't contain useful information, such as `lat` and `long`, and

- 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 0x7f08f63580a0>
```



This plot validates the relationship between `temperature` and `hour`, and between `temperature` and `month`. However, we can also use this plot to identify useful features - features that appear to be related to the `target` variable.

Explore relationships and identify target variable and features

Finally, since our goal is to train a machine learning model, we want to identify:

- an appropriate target variable - something on which to train our model. (Either a direct target variable, or a proxy.)
- features that are predictive - if there is any noticeable relationship between the target variable and any other variable, this is likely to be a useful feature.
- features that are correlated with one another - if two features are highly correlated, this presents some difficulty to certain types of models, so we'll want to know about it.

The `Pedestrians` variable is the obvious target variable for this learning problem: it's exactly the quantity we want to predict.

To identify potential predictive features among the numeric variables in the data, we can use the pairplot. Look at the row of the pairplot in which `Pedestrians` is on the vertical axis, and each of the other variables in turn is on the horizontal axis. Which of these seem to show a relationship? (Note: the relationship does not necessarily need to be a linear relationship.)

We will also want to evaluate the categorical variables. For example, to look for a relationship between day of the week and pedestrian volume, we can group by `day_name`, then call the `describe` function on the `Pedestrians` column:

```
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 weather:

```
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
```

And the effect of various holidays:

```
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
```

Now armed with information about these relationships, we can identify good candidate features for a machine learning model.