04b_data_pandas

November 23, 2022

1 Doing More with Data: `pandas`

1.1 Introduction to Python

Data Sciences Institute, University of Toronto

Instructor: Kaylie Lau | TA: Salaar Liaqat

November - December 2022

2 Contents:

1. Setup
2. Intro to `pandas`
3. Getting data
4. Profiling and initial data exploration: changing data types, descriptive statistics
5. Wrangling and plotting: concatenating, merging, adding and removing columns, filtering and selecting, null values, grouping and aggregating, plotting
6. Writing to file
7. More wrangling: reshaping, applying functions

2.1 Data

This module uses four datasets: bike thefts, TTC subway delays and subway delay reason codes, and neighbourhood profiles. All four are available in the course repo, and originally come from Toronto Open Data.

The specific file names are: - bicycle-thefts - 4326.csv - ttc-subway-delay-data-2021.xlsx - ttc-subway-delay-codes.xlsx - neighbourhood-profiles-2016-140-model.csv

3 `pandas`

3.1 What is `pandas`?

`pandas` is a package for data analysis and manipulation. (The name is a reference to panel data, not the animal.) It gives us data frames, which represent data in a table of columns and rows, and functions to manipulate and plot them. `pandas` also provides a slew of functions for reading and writing data to a variety of sources, including files, SQL databases, and compressed binary formats.

[ ]:
```
import numpy as np
# pd is the conventional alias for pandas
import pandas as pd

# display all columns
pd.set_option("display.max_columns", None)
```

3.2 DataFrames

Columns are labeled with their names. Rows also have a label, or *index*. If row labels are not specified, `pandas` uses numbers as the default. Each column is a *Series*, or one-dimensional array, where values share a data type. Unlike `numpy` arrays, DataFrames can have columns of different data types. However, like arrays and lists, **DataFrames are mutable** -- this means that if more than one variable refers to the same DataFrame, updating one updates them all!

3.3 Getting data

We can create a DataFrame manually with `DataFrame()` constructor. If a dictionary is passed to `DataFrame()`, the keys become column names, and the values become the rows. Calling just `DataFrame()` creates an empty DataFrame to which data can be added later.

[ ]:
```
trees = pd.DataFrame({
    'name': ['sugar maple', 'black oak', 'white ash', 'douglas fir'],
    'avg_lifespan': [300, 100, 260, 450],
    'quantity': [53, 207, 178, 93]
})
trees
```

[ ]:
```
          name  avg_lifespan  quantity
0  sugar maple           300        53
1    black oak           100       207
2    white ash           260       178
3  douglas fir           450        93
```

We can create an individual column with `Series()`. The `name` argument corresponds to a column name.

[ ]:
```
tree_types = pd.Series(['deciduous', 'deciduous', 'deciduous', 'evergreen'],
                       name='foliage')
tree_types
```

[ ]:
```
0    deciduous
1    deciduous
2    deciduous
```

```
3    evergreen
Name: foliage, dtype: object
```

3.3.1 Data from csv

Of course, we're more likely to load data into a DataFrame than to create DataFrames manually. `pandas` has read functions for different file formats. To read data from a csv or other delimited file, we use `pd.read_csv()`, then pass in the local file path or the URL of the csv to read. `pandas` will infer the data type of each column based on the values in the first chunk of the file loaded.

[ ]:
```
thefts = pd.read_csv('/content/data/bicycle-thefts - 4326.csv')
```

3.4 Profiling and initial data cleaning

We got our data, but now we need to understand what's in it. We can start to understand the DataFrame by checking out its `dtypes` and `shape` attributes, which give column data types and row by column dimensions, respectively. Note that `object` is `pandas`' way of saying values are represented as string data.

[ ]:
```
thefts.shape
```

[ ]:
```
(25569, 33)
```

[ ]:
```
thefts.dtypes
```

[ ]:
```
_id                          int64
OBJECTID                     int64
event_unique_id             object
Primary_Offence             object
Occurrence_Date             object
Occurrence_Year              int64
Occurrence_Month            object
Occurrence_DayOfWeek        object
Occurrence_DayOfMonth        int64
Occurrence_DayOfYear         int64
Occurrence_Hour              int64
Report_Date                 object
Report_Year                  int64
Report_Month                object
Report_DayOfWeek            object
Report_DayOfMonth            int64
Report_DayOfYear             int64
Report_Hour                  int64
Division                    object
City                        object
```

```
Hood_ID                    object
NeighbourhoodName          object
Location_Type              object
Premises_Type              object
Bike_Make                  object
Bike_Model                 object
Bike_Type                  object
Bike_Speed                  int64
Bike_Colour                object
Cost_of_Bike              float64
Status                     object
ObjectId2                   int64
geometry                   object
dtype: object
```

3.4.1 head()s and tail()s

To check out the first few rows, we can call the DataFrame `head()` method. Similarly, we can see the last few rows with the `tail()` method. Five rows are shown by default, but we can change that by passing an integer as an argument.

[ ]:
```
thefts.head()
```

[ ]:
```
   _id  OBJECTID event_unique_id        Primary_Offence      Occurrence_Date  \
0    1     17744  GO-20179016397            THEFT UNDER  2017-10-03T00:00:00
1    2     17759  GO-20172033056  THEFT UNDER - BICYCLE  2017-11-08T00:00:00
2    3     17906  GO-20189030822  THEFT UNDER - BICYCLE  2018-09-14T00:00:00
3    4     17962   GO-2015804467            THEFT UNDER  2015-05-07T00:00:00
4    5     17963  GO-20159002781            THEFT UNDER  2015-05-16T00:00:00

   Occurrence_Year Occurrence_Month Occurrence_DayOfWeek  \
0             2017          October              Tuesday
1             2017         November            Wednesday
2             2018        September               Friday
3             2015              May             Thursday
4             2015              May             Saturday

   Occurrence_DayOfMonth  Occurrence_DayOfYear  Occurrence_Hour  \
0                      3                   276               14
1                      8                   312                3
2                     14                   257                9
3                      7                   127               18
4                     16                   136               12

           Report_Date  Report_Year Report_Month Report_DayOfWeek  \
0  2017-10-03T00:00:00         2017      October          Tuesday
```

```
1  2017-11-08T00:00:00         2017     November        Wednesday
2  2018-09-17T00:00:00         2018    September           Monday
3  2015-05-14T00:00:00         2015          May         Thursday
4  2015-05-16T00:00:00         2015          May         Saturday

   Report_DayOfMonth  Report_DayOfYear  Report_Hour Division     City Hood_ID  \
0                  3               276           18      D22  Toronto      15
1                  8               312           22      D22  Toronto      15
2                 17               260           16      D22  Toronto      15
3                 14               134           14      D22  Toronto      15
4                 16               136           15      D22  Toronto      15

     NeighbourhoodName                                      Location_Type  \
0  Kingsway South (15)  Streets, Roads, Highways (Bicycle Path, Privat…
1  Kingsway South (15)  Single Home, House (Attach Garage, Cottage, Mo…
2  Kingsway South (15)                                 Ttc Subway Station
3  Kingsway South (15)                                 Ttc Subway Station
4  Kingsway South (15)                                 Ttc Subway Station

  Premises_Type     Bike_Make  Bike_Model Bike_Type  Bike_Speed Bike_Colour  \
0       Outside            GI    ESCAPE 2        OT           7         BLK
1         House  UNKNOWN MAKE         NaN        TO           1         BLK
2       Transit            OT  CROSSTRAIL        MT          24         BLK
3       Transit            GT         NaN        TO          10      BLKDGR
4       Transit            GI         NaN        MT           6         RED

   Cost_of_Bike     Status  ObjectId2  \
0         700.0     STOLEN          1
1        1100.0  RECOVERED          2
2         904.0     STOLEN          3
3         400.0     STOLEN          4
4         600.0     STOLEN          5

                                            geometry
0  {'type': 'Point', 'coordinates': (-79.50655965…
1  {'type': 'Point', 'coordinates': (-79.50484874…
2  {'type': 'Point', 'coordinates': (-79.51170915…
3  {'type': 'Point', 'coordinates': (-79.51170915…
4  {'type': 'Point', 'coordinates': (-79.51132657…
```

[ ]:
```
# last 3
thefts.tail(3)
```

[ ]:
```
         _id  OBJECTID event_unique_id        Primary_Offence  \
25566  25567     11462   GO-20169005434            THEFT UNDER
25567  25568     11695   GO-20161170896            THEFT UNDER
25568  25569     11883   GO-20169007653  THEFT UNDER - BICYCLE
```

```
         Occurrence_Date  Occurrence_Year Occurrence_Month  \
25566  2016-06-04T00:00:00             2016             June
25567  2016-07-04T00:00:00             2016             July
25568  2016-07-22T00:00:00             2016             July

      Occurrence_DayOfWeek  Occurrence_DayOfMonth  Occurrence_DayOfYear  \
25566             Saturday                      4                   156
25567               Monday                      4                   186
25568               Friday                     22                   204

       Occurrence_Hour          Report_Date  Report_Year Report_Month  \
25566               22  2016-06-07T00:00:00         2016         June
25567               20  2016-07-04T00:00:00         2016         July
25568                9  2016-07-23T00:00:00         2016         July

      Report_DayOfWeek  Report_DayOfMonth  Report_DayOfYear  Report_Hour  \
25566          Tuesday                  7               159           16
25567           Monday                  4               186           20
25568         Saturday                 23               205           11

      Division     City Hood_ID NeighbourhoodName  \
25566      D42  Toronto     132     Malvern (132)
25567      D42  Toronto     132     Malvern (132)
25568      D42  Toronto     132     Malvern (132)

                                           Location_Type Premises_Type  \
25566                   Apartment (Rooming House, Condo)     Apartment
25567  Other Commercial / Corporate Places (For Profi…    Commercial
25568  Parking Lots (Apt., Commercial Or Non-Commercial)       Outside

          Bike_Make       Bike_Model Bike_Type  Bike_Speed Bike_Colour  \
25566            SC           ANTRIM        MT          24         WHI
25567  UNKNOWN MAKE              NaN        SC           1         NaN
25568            SU  ASCENT MOUNTAIN        MT          21         ONG

       Cost_of_Bike  Status  ObjectId2  \
25566         700.0  STOLEN      25567
25567        3000.0  STOLEN      25568
25568         200.0  STOLEN      25569

                                                geometry
25566  {'type': 'Point', 'coordinates': (-79.2360175,…
25567  {'type': 'Point', 'coordinates': (-79.20060719…
25568  {'type': 'Point', 'coordinates': (-79.23734742…
```

3.4.2 Renaming columns

Most, but not all, of the bike theft columns follow the same naming convention. For convenience's sake, though, let's convert the column names to all lowercase. We can do this with the DataFrame `rename()` method. `rename()` accepts either a dictionary with current column names as the keys and new names as the values, or the name of a function to transform names. Let's write a function.

```
[ ]: # notice that we do not add () to the function name
     thefts = thefts.rename(columns=str.lower)
```

Let's also rename `cost_of_bike` so it follows the pattern of the other bike attribute columns.

```
[ ]: thefts = thefts.rename(columns={'cost_of_bike':'bike_cost'})

     # view column names
     print(list(thefts))
```

```
['_id', 'objectid', 'event_unique_id', 'primary_offence', 'occurrence_date',
'occurrence_year', 'occurrence_month', 'occurrence_dayofweek',
'occurrence_dayofmonth', 'occurrence_dayofyear', 'occurrence_hour',
'report_date', 'report_year', 'report_month', 'report_dayofweek',
'report_dayofmonth', 'report_dayofyear', 'report_hour', 'division', 'city',
'hood_id', 'neighbourhoodname', 'location_type', 'premises_type', 'bike_make',
'bike_model', 'bike_type', 'bike_speed', 'bike_colour', 'bike_cost', 'status',
'objectid2', 'geometry']
```

3.4.3 Profiling columns

It can be useful to focus on a subset of columns, particularly to understand value sets. To select a single column in a DataFrame, we can supply the name of the column in square brackets, just like we did when accessing values in a dictionary. `pandas` will return the column as a Series. To get unique values, we can use the `unique()` Series method. If we want to count how many times each value appears, we can use the `value_counts()` method.

```
[ ]: thefts['status']
```

```
[ ]: 0           STOLEN
     1        RECOVERED
     2           STOLEN
     3           STOLEN
     4           STOLEN
                …
     25564       STOLEN
     25565       STOLEN
     25566       STOLEN
     25567       STOLEN
     25568       STOLEN
```

```
Name: status, Length: 25569, dtype: object
```

```
[ ]: thefts['status'].unique()
```

```
[ ]: array(['STOLEN', 'RECOVERED', 'UNKNOWN'], dtype=object)
```

```
[ ]: thefts['status'].value_counts()
```

```
[ ]: STOLEN       24807
     UNKNOWN        454
     RECOVERED      308
     Name: status, dtype: int64
```

We can summarize numeric Series much like we did with `numpy` functions.

```
[ ]: thefts['bike_cost'].median()
```

```
[ ]: 600.0
```

```
[ ]: thefts['bike_cost'].quantile(0.9)
```

```
[ ]: 2000.0
```

3.4.4 `info()`

We can get an overview of the DataFrame by profiling it with the `info()` method.

`info()` prints a lot of information about a DataFrame, including: * the `shape` as the number of rows and columns * column names and their `dtype` * the number of non-null values in each column * how big the DataFrame is in terms of memory usage

The bicycle theft data looks quite complete, though some records are missing bike descriptors like bike_make, bike_model, bike_colour, and bike_cost.

Most of the column dtypes make sense. We'll want to convert the dates to proper dates. We may also want to convert string columns with limited value sets, like status, to categorical data.

```
[ ]: thefts.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25569 entries, 0 to 25568
Data columns (total 33 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   _id                    25569 non-null  int64
 1   objectid               25569 non-null  int64
 2   event_unique_id        25569 non-null  object
 3   primary_offence        25569 non-null  object
 4   occurrence_date        25569 non-null  object
 5   occurrence_year        25569 non-null  int64
 6   occurrence_month       25569 non-null  object
 7   occurrence_dayofweek   25569 non-null  object
 8   occurrence_dayofmonth  25569 non-null  int64
 9   occurrence_dayofyear   25569 non-null  int64
 10  occurrence_hour        25569 non-null  int64
 11  report_date            25569 non-null  object
 12  report_year            25569 non-null  int64
 13  report_month           25569 non-null  object
 14  report_dayofweek       25569 non-null  object
 15  report_dayofmonth      25569 non-null  int64
 16  report_dayofyear       25569 non-null  int64
 17  report_hour            25569 non-null  int64
 18  division               25569 non-null  object
 19  city                   25569 non-null  object
 20  hood_id                25569 non-null  object
 21  neighbourhoodname      25569 non-null  object
 22  location_type          25569 non-null  object
 23  premises_type          25569 non-null  object
 24  bike_make              25448 non-null  object
 25  bike_model             15923 non-null  object
 26  bike_type              25569 non-null  object
 27  bike_speed             25569 non-null  int64
 28  bike_colour            23508 non-null  object
 29  bike_cost              23825 non-null  float64
 30  status                 25569 non-null  object
 31  objectid2              25569 non-null  int64
 32  geometry               25569 non-null  object
dtypes: float64(1), int64(12), object(20)
memory usage: 6.4+ MB
```

3.4.5 Changing data types

Before exploring the bike theft data further, let's fix the date and categorical columns. To convert a column to datetime, we use the `pd.to_datetime()` function, passing in the column to convert, and reassign the output back to the column we're converting.

`pandas` knows how to convert the dates in the bike thefts data, but for less common formats, it is necessary to use the `format` keyword argument to specify how dates should be parsed. `format` strings use `strftime` codes. See https://strftime.org/ for a cheat sheet.

```
[ ]: thefts['occurrence_date'] = pd.to_datetime(thefts['occurrence_date'],
                                               format='%Y-%m-%d')
     thefts['occurrence_date']
```

```
[ ]: 0        2017-10-03
     1        2017-11-08
     2        2018-09-14
     3        2015-05-07
     4        2015-05-16
                 …
     25564    2015-04-01
     25565    2016-05-16
     25566    2016-06-04
     25567    2016-07-04
     25568    2016-07-22
     Name: occurrence_date, Length: 25569, dtype: datetime64[ns]
```

```
[ ]: # convert report_date without the format argument
     thefts['report_date'] = pd.to_datetime(thefts['report_date'])
     thefts['report_date']
```

```
[ ]: 0        2017-10-03
     1        2017-11-08
     2        2018-09-17
     3        2015-05-14
     4        2015-05-16
                 …
     25564    2015-04-01
     25565    2016-05-16
     25566    2016-06-07
     25567    2016-07-04
     25568    2016-07-23
     Name: report_date, Length: 25569, dtype: datetime64[ns]
```

All other data type conversions can be done with the `astype()` method. If we were converting to a number, `pd.to_numeric()` provides an easy way to convert without having to pick a specific numeric data type.

```
[ ]: thefts['status'] = thefts['status'].astype('category')
     thefts['status']
```

```
[ ]: 0           STOLEN
     1        RECOVERED
     2           STOLEN
     3           STOLEN
     4           STOLEN
                …
     25564       STOLEN
     25565       STOLEN
     25566       STOLEN
     25567       STOLEN
```

```
25568       STOLEN
Name: status, Length: 25569, dtype: category
Categories (3, object): ['RECOVERED', 'STOLEN', 'UNKNOWN']
```

We can select and convert multiple columns at once by passing a list of columns in the square brackets., then using `.astype()`.

```
[ ]: thefts[['location_type', 'premises_type']] =␣
      ↪thefts[['location_type','premises_type']].astype('category')

     # check data types
     thefts[['location_type', 'premises_type']].dtypes
```

```
[ ]: location_type    category
     premises_type    category
     dtype: object
```

3.4.6 describe()

To get a sense of the values in a DataFrame, we can use the `describe()` method. `describe()` summarizes only numeric columns by default. Passing the `include='all'` argument will produce summary statistics for other columns as well.

```
[ ]: thefts.describe(include='all',
                     datetime_is_numeric=True)  # silence warning about upcoming␣
      ↪pandas change
```

```
[ ]:                  _id      objectid event_unique_id primary_offence  \
     count   25569.000000  25569.000000           25569           25569
     unique           NaN           NaN           22771              66
     top              NaN           NaN   GO-20201550944    THEFT UNDER
     freq             NaN           NaN              14           11904
     mean    12785.000000  12909.173218             NaN             NaN
     min         1.000000      1.000000             NaN             NaN
     25%      6393.000000   6456.000000             NaN             NaN
     50%     12785.000000  12918.000000             NaN             NaN
     75%     19177.000000  19360.000000             NaN             NaN
     max     25569.000000  25806.000000             NaN             NaN
     std      7381.278853   7448.318562             NaN             NaN

                           occurrence_date  occurrence_year occurrence_month  \
     count                           25569     25569.000000            25569
     unique                            NaN              NaN               12
     top                               NaN              NaN             July
     freq                              NaN              NaN             4002
     mean    2017-09-04 03:39:28.321013504      2017.124174              NaN
```

```
min              2009-09-01 00:00:00      2009.000000              NaN
25%              2016-01-06 00:00:00      2016.000000              NaN
50%              2017-09-05 00:00:00      2017.000000              NaN
75%              2019-06-20 00:00:00      2019.000000              NaN
max              2020-12-30 00:00:00      2020.000000              NaN
std                              NaN         1.960127              NaN

       occurrence_dayofweek  occurrence_dayofmonth  occurrence_dayofyear  \
count                 25569           25569.000000          25569.000000
unique                    7                    NaN                   NaN
top                  Friday                    NaN                   NaN
freq                   3924                    NaN                   NaN
mean                    NaN              15.616684            202.227698
min                     NaN               1.000000              1.000000
25%                     NaN               8.000000            153.000000
50%                     NaN              16.000000            205.000000
75%                     NaN              23.000000            259.000000
max                     NaN              31.000000            366.000000
std                     NaN               8.592886             76.821431

        occurrence_hour                    report_date   report_year  \
count      25569.000000                          25569  25569.000000
unique              NaN                            NaN           NaN
top                 NaN                            NaN           NaN
freq                NaN                            NaN           NaN
mean          13.274395  2017-09-12 12:02:37.127771904   2017.143572
min            0.000000            2014-01-01 00:00:00   2014.000000
25%            9.000000            2016-01-22 00:00:00   2016.000000
50%           14.000000            2017-09-12 00:00:00   2017.000000
75%           19.000000            2019-06-26 00:00:00   2019.000000
max           23.000000            2020-12-31 00:00:00   2020.000000
std            6.530181                            NaN      1.955024

       report_month report_dayofweek  report_dayofmonth  report_dayofyear  \
count         25569            25569       25569.000000      25569.000000
unique           12                7                NaN               NaN
top            July           Monday                NaN               NaN
freq           3988             4318                NaN               NaN
mean            NaN              NaN          15.924870        203.493723
min             NaN              NaN           1.000000          1.000000
25%             NaN              NaN           9.000000        154.000000
50%             NaN              NaN          16.000000        206.000000
75%             NaN              NaN          23.000000        260.000000
max             NaN              NaN          31.000000        366.000000
std             NaN              NaN           8.549584         77.115977

         report_hour division     city hood_id  \
count   25569.000000    25569    25569   25569
unique           NaN       18        2     141
top              NaN      D14  Toronto      77
freq             NaN     4580    25560    2576
mean       14.224139      NaN      NaN     NaN
min         0.000000      NaN      NaN     NaN
25%        11.000000      NaN      NaN     NaN
50%        14.000000      NaN      NaN     NaN
75%        18.000000      NaN      NaN     NaN
max        23.000000      NaN      NaN     NaN
std         5.052944      NaN      NaN     NaN

                            neighbourhoodname  \
count                                   25569
unique                                    141
top     Waterfront Communities-The Island (77)
freq                                     2576
mean                                      NaN
min                                       NaN
25%                                       NaN
50%                                       NaN
75%                                       NaN
max                                       NaN
std                                       NaN

                           location_type premises_type bike_make bike_model  \
count                              25569         25569     25448      15923
unique                                42             7       820       8097
top     Apartment (Rooming House, Condo)       Outside        OT    UNKNOWN
freq                                5887          7960      4991        304
mean                                 NaN           NaN       NaN        NaN
min                                  NaN           NaN       NaN        NaN
25%                                  NaN           NaN       NaN        NaN
50%                                  NaN           NaN       NaN        NaN
75%                                  NaN           NaN       NaN        NaN
max                                  NaN           NaN       NaN        NaN
std                                  NaN           NaN       NaN        NaN

       bike_type    bike_speed bike_colour     bike_cost  status  \
count      25569  25569.000000       23508  23825.000000   25569
unique        13           NaN         252           NaN       3
top           MT           NaN         BLK           NaN  STOLEN
freq        8245           NaN        7422           NaN   24807
mean         NaN     14.164144         NaN    949.542371     NaN
min          NaN      0.000000         NaN      0.000000     NaN
25%          NaN      6.000000         NaN    350.000000     NaN
50%          NaN     15.000000         NaN    600.000000     NaN
```

```
75%           NaN     21.000000         NaN    1000.000000     NaN
max           NaN     99.000000         NaN  120000.000000     NaN
std           NaN     10.559215         NaN    1675.880345     NaN

          objectid2                                             geometry
count   25569.000000                                               25569
unique           NaN                                                5816
top              NaN  {'type': 'Point', 'coordinates': (-79.38372586…
freq             NaN                                                 167
mean    12785.000000                                                 NaN
min         1.000000                                                 NaN
25%      6393.000000                                                 NaN
50%     12785.000000                                                 NaN
75%     19177.000000                                                 NaN
max     25569.000000                                                 NaN
std      7381.278853                                                 NaN
```

3.5 Wrangling and Plotting

3.5.1 Combining datasets: concatenation

Just as `pandas` has `read_csv()` for flat files, there is a `read_excel()` function to load Excel files.

The TTC publishes subway delay data as a multi-sheet Excel workbook, with a month's worth of data per sheet. `read_excel()` loads just the first sheet in an Excel file by default. To load all sheets, pass in the keyword argument `sheet_name=None`. The result is a dictionary, where each key is the sheet name and each value is a DataFrame with the contents of the sheet.

[ ]:
```
delays = pd.read_excel('/content/data/ttc-subway-delay-data-2021.xlsx',␣
 ↪sheet_name=None)
```

[ ]:
```
type(delays)
```

[ ]:
```
dict
```

To combine them all, we create an empty DataFrame, then loop through the dictionary items and use `pd.concat()` to append data. `concat()` takes a list of DataFrames to combine. Since we did not specify an index, row labels are numbers: the first row of each sheet has an index of 0, and so on. To reset row labels so that they are sequential again, we set `ignore_index=True`.

[ ]:
```
# create an empty DataFrame
all_delays = pd.DataFrame()

for sheet_name, values in delays.items():
    # print the number of rows
    print(f'Adding {values.shape[0]} rows from {sheet_name}')
    # add each sheet to all_delays
    all_delays = pd.concat([all_delays, values],
                           axis=0,  # concatenate rows
                           ignore_index=True)  # reset row labels

all_delays.shape
```

```
Adding 1216 rows from January21
Adding 1245 rows from Feb 21
Adding 1167 rows from March '21
Adding 1170 rows from April '21
Adding 1168 rows from May '21
Adding 1265 rows from June 21
Adding 1244 rows from July 21
Adding 1273 rows from August 21
Adding 1433 rows from Sept 21
Adding 1560 rows from Oct 21
Adding 1771 rows from Nov 21
Adding 1858 rows from December21
```

```
[ ]: (16370, 10)
```

```
[ ]: all_delays.head()
```

```
[ ]:         Date   Time     Day                Station   Code  Min Delay  Min Gap  \
     0 2021-01-01  00:33  Friday          BLOOR STATION  MUPAA          0        0
     1 2021-01-01  00:39  Friday      SHERBOURNE STATION   EUCO          5        9
     2 2021-01-01  01:07  Friday      KENNEDY BD STATION   EUCD          5        9
     3 2021-01-01  01:41  Friday        ST CLAIR STATION   MUIS          0        0
     4 2021-01-01  02:04  Friday  SHEPPARD WEST STATION   MUIS          0        0

       Bound Line  Vehicle
     0     N   YU     6046
     1     E   BD     5250
     2     E   BD     5249
     3   NaN   YU        0
     4   NaN   YU        0
```

The TTC delays data includes a reason code for the delay. Code definitions, however, are in a separate Excel file, `ttc-subway-delay-codes.xlsx`. This file has been modified slightly to make it easier to work with. Codes are split between two tabs, so we will load both to a DataFrame, `delay_reasons`.

```
[ ]: dr = pd.read_excel('/content/data/ttc-subway-delay-codes.xlsx', sheet_name=None)

     delay_reasons = pd.DataFrame()
     for sheet_name, values in dr.items():
         delay_reasons = pd.concat([delay_reasons, values],
                                  axis=0,
                                  ignore_index=True)

     delay_reasons
```

```
[ ]:     RMENU CODE                     CODE DESCRIPTION SUB OR SRT
     0         EUAC                   Air Conditioning        SUB
     1         EUAL                Alternating Current        SUB
     2        EUATC                 ATC RC&S Equipment        SUB
     3         EUBK                             Brakes        SUB
     4         EUBO                               Body        SUB
     ..         …                                  …         …
     195      TRNOA   No Operator Immediately Available        SUB
     196        TRO     Transportation Department - Other        SRT
     197      TRSET  Train Controls Improperly Shut Down        SRT
     198       TRST                       Storm Trains        SRT
     199       TRTC      Transit Control Related Problems        SRT

     [200 rows x 3 columns]
```

We will rename the columns in both `all_delays` and `delay_reasons` so that we replace spaces with underscores as well as convert all letters to lowercase.

```
[ ]: def clean_names(string):
         return string.lower().replace(' ', '_')

     delay_reasons = delay_reasons.rename(columns=clean_names)
     all_delays = all_delays.rename(columns=clean_names)
     print(list(delay_reasons))
     print(list(all_delays))
```

```
['rmenu_code', 'code_description', 'sub_or_srt']
['date', 'time', 'day', 'station', 'code', 'min_delay', 'min_gap', 'bound',
'line', 'vehicle']
```

3.6 Combining datasets: merging

Ideally, the delays data would include code descriptions. We can get descriptions into `all_delays` by *merging* in `delay_reasons`. Merging is analagous to joining in SQL databases. To merge two DataFrames, we pass them as arguments to the `pd.merge()`. Then, we specify `how` to merge the two DataFrames and what column names to merge `on`.

Let's review the `all_delays` and `delay_reasons` DataFrames. `code` is equivalent to `rmenu_code`. If we pass in `all_delays` as the first DataFrame, then it will be the left frame, and `delay_reasons` the right one. We want to keep all the delay records, even if there isn't a matching code in `delay_reasons`, so we will perform a left join.

```
[ ]: all_delays.head(2)
[ ]:          date   time     day             station   code  min_delay  min_gap  \
     0 2021-01-01  00:33  Friday       BLOOR STATION  MUPAA          0        0
     1 2021-01-01  00:39  Friday  SHERBOURNE STATION   EUCO          5        9

       bound line  vehicle
     0     N   YU     6046
     1     E   BD     5250
```

```
[ ]: delay_reasons.head(2)
```

```
[ ]:   rmenu_code     code_description sub_or_srt
     0       EUAC     Air Conditioning        SUB
     1       EUAL  Alternating Current        SUB
```

```
[ ]: delays_w_reasons = pd.merge(all_delays,
                                  delay_reasons,
                                  how='left',
                                  left_on='code',
                                  right_on='rmenu_code')
     delays_w_reasons.head(3)
```

```
[ ]:          date   time     day             station   code  min_delay  min_gap  \
     0 2021-01-01  00:33  Friday       BLOOR STATION  MUPAA          0        0
     1 2021-01-01  00:39  Friday  SHERBOURNE STATION   EUCO          5        9
     2 2021-01-01  01:07  Friday   KENNEDY BD STATION   EUCD          5        9

       bound line  vehicle rmenu_code  \
     0     N   YU     6046      MUPAA
     1     E   BD     5250       EUCO
     2     E   BD     5249       EUCD

                                        code_description sub_or_srt
     0  Passenger Assistance Alarm Activated - No Trou…        SUB
     1                                          Couplers        SUB
     2         Consequential Delay (2nd Delay Same Fault)        SUB
```

3.7 drop()

The resulting DataFrame has both our join columns, which is redundant. We can drop one with the `drop()` DataFrame method, passing in the column name(s) we want to drop in the `columns` keyword argument.

```
[ ]: delays_w_reasons = delays_w_reasons.drop(columns='rmenu_code')
     delays_w_reasons.head(3)
```

```
[ ]:         date   time     day             station   code  min_delay  min_gap  \
     0 2021-01-01  00:33  Friday       BLOOR STATION  MUPAA          0        0
     1 2021-01-01  00:39  Friday  SHERBOURNE STATION   EUCO          5        9
     2 2021-01-01  01:07  Friday  KENNEDY BD STATION   EUCD          5        9

       bound line  vehicle                                   code_description  \
     0     N   YU     6046  Passenger Assistance Alarm Activated - No Trou…
     1     E   BD     5250                                           Couplers
     2     E   BD     5249         Consequential Delay (2nd Delay Same Fault)

       sub_or_srt
     0        SUB
     1        SUB
     2        SUB
```

3.8 Creating new columns

Adding a column to a DataFrame looks like adding a key-value pair to a dictionary. At its simplest, we can assign a single value to repeat down a column.

```
[ ]: delays_w_reasons['year'] = 2021
     delays_w_reasons['year'].unique()
```

```
[ ]: array([2021])
```

We can also write an expression and store the resulting values in a new column.

```
[ ]: delays_w_reasons['hour_delay'] = round(delays_w_reasons['min_delay'] / 60, 2)
     delays_w_reasons[['min_delay', 'hour_delay']].head()
```

```
[ ]:    min_delay  hour_delay
     0          0        0.00
     1          5        0.08
     2          5        0.08
     3          0        0.00
     4          0        0.00
```

It is also possible to extract parts of a datetime column with the `dt` accessor.

```
[ ]: delays_w_reasons['month'] = delays_w_reasons['date'].dt.month
     delays_w_reasons['month']
```

```
[ ]: 0         1
     1         1
     2         1
     3         1
     4         1
```

```
         ..
16365    12
16366    12
16367    12
16368    12
16369    12
Name: month, Length: 16370, dtype: int64
```

It is possible to create a new integer column, `hour`, that contains the hour in which a delay occurred. Below we highlight two methods.

```
[ ]: # two ways to extract hour
     # convert to time, then access hour
     delays_w_reasons['hour'] = pd.to_datetime(delays_w_reasons['time'], format='%H:
      ↪%M').dt.hour

     # split and take first part
     delays_w_reasons['hour'] = delays_w_reasons['time'].str.split(':',␣
      ↪expand=True)[0]
     delays_w_reasons['hour'] = delays_w_reasons['hour'].astype(int)
```

3.9 Filtering and selecting data

Let's take another look at the TTC subway delay data. There are only 4 subway lines in Toronto, but `describe()` reported 17 unique values.

```
[ ]: delays_w_reasons['line'].unique()
```

```
[ ]: array(['YU', 'BD', 'SHP', 'SRT', 'YU/BD', nan, 'YONGE/UNIVERSITY/BLOOR',
            'YU / BD', 'YUS', '999', 'SHEP', '36 FINCH WEST', 'YUS & BD',
            'YU & BD LINES', '35 JANE', '52', '41 KEELE', 'YUS/BD'],
           dtype=object)
```

Looks like some of the line values should be updated (YU/BD variants) and others should be dropped (e.g., 36 FINCH WEST, NaNs). Luckily there don't seem to be too many affected records, though the NaNs are not shown.

```
[ ]: delays_w_reasons['line'].value_counts()
```

```
[ ]: YU                          8880
     BD                          5734
     SHP                          657
     SRT                          656
     YU/BD                        346
     YUS                           18
     YU / BD                       17
     YU & BD LINES                  1
```

```
41 KEELE                    1
52                          1
35 JANE                     1
999                         1
YUS & BD                    1
36 FINCH WEST               1
SHEP                        1
YONGE/UNIVERSITY/BLOOR      1
YUS/BD                      1
Name: line, dtype: int64
```

3.9.1 .loc[] and isna()

To find the records with no line, we can use `.loc[]`, which lets us access rows and columns with either a boolean array or row/column labels.

In this case, the boolean array is the product of the `isna()` Series method.

[ ]:
```
# access rows of data where line is NA
delays_w_reasons.loc[delays_w_reasons['line'].isna()]
```

[ ]:
```
            date   time        day                station   code  min_delay  \
495   2021-01-13  15:22  Wednesday      FINCH WEST STATION  MUSAN          3
513   2021-01-13  22:08  Wednesday   EGLINTON WEST STATION  PUMEL          0
1044  2021-01-27  22:00  Wednesday  YONGE-UNIVERSITY AND B    MUO          0
1045  2021-01-27  23:00  Wednesday           FINCH STATION    MUO          0
1362  2021-02-04  01:45   Thursday        LAWRENCE STATION   TUSC          0
1679  2021-02-11  01:12   Thursday      GREENWOOD CARHOUSE   MUIE          0
2179  2021-02-22  08:27     Monday      BICHMOUNT DIVISION   MUIE          0
2204  2021-02-22  22:33     Monday           BLOOR STATION   SUAP          4
2206  2021-02-22  23:36     Monday        EGLINTON STATION    MUO          0
3039  2021-03-17  05:15  Wednesday         INGLIS BUILDING  PUMEL          0
3330  2021-03-24  19:13  Wednesday         INGLIS BUILDING  PUMEL          0
3407  2021-03-26  09:03     Friday  WILSON YARD (SOUTH TAI   PUTO          0
3557  2021-03-30  00:36    Tuesday         INGLIS BUILDING  PUMEL          0
3944  2021-04-08  23:45   Thursday         DAVISVILLE YARD   MUIE          0
4097  2021-04-13  10:57    Tuesday         SPADINA STATION   SUAE          0
4119  2021-04-13  22:00    Tuesday  YONGE-UNIVERSITY AND B    MUO          0
4336  2021-04-19  23:00     Monday  SHEPPARD WEST TO LAWRE    MUO          0
4748  2021-04-29  22:00   Thursday  YONGE UNIVERSITY SPADI    MUO          0
5312  2021-05-15  05:05   Saturday      SPADINA BD STATION  MUNCA          0
5448  2021-05-18  20:15    Tuesday      VAUGHAN MC STATION   MUWR          0
5484  2021-05-19  18:11  Wednesday    QUEEN'S QUAY STATION  PUMEL          0
5642  2021-05-23  23:19     Sunday       ST ANDREW STATION   SUDP          0
5685  2021-05-25  00:19    Tuesday      DUNDA WEST STATION    SUO          0
6042  2021-06-02  22:28  Wednesday          WARDEN STATION  MUIRS          0
6046  2021-06-02  00:56  Wednesday             BAY STATION    SUO          0
```

```
6540  2021-06-14  22:43     Monday        YONGE BD STATION   MUIS           0
6560  2021-06-15  07:15    Tuesday  SUBWAY OPERATIONS BUIL  PUMEL           0
7137  2021-06-28  01:03     Monday          COXWELL STATION  MUNCA           0
7766  2021-07-14  03:51  Wednesday  TRANSIT CONTROL CENTRE   PUSO           0
8889  2021-08-11  07:46  Wednesday          TRANSIT CONTROL   MUIE           0
9628  2021-08-29  15:49     Sunday        YORKDALE STATION  SUPOL           0
9629  2021-08-29  16:13     Sunday      YORK MILLS STATION    MUO           0
9780  2021-09-01  20:35  Wednesday   MAIN STREET AND UNION    MUO           0
9789  2021-09-01  22:14  Wednesday  UNION AND KENNEDY STAT    MUO           0
10336 2021-09-13  17:20     Monday         MCBRIEN BUILDING    SUO           0
10951 2021-09-26  15:50     Sunday           WILSON STATION  PUOPO           0
11223 2021-10-01  00:33     Friday        WELLESLEY STATION   SUDP           0
12533 2021-10-28  14:18   Thursday   VICTORIA PARK STATION   MUIS           0
12826 2021-11-02  12:22    Tuesday           GREENWOOD SHOP   MUIE           0
13007 2021-11-05  08:59     Friday            BLOOR STATION  MUIRS           0
13080 2021-11-06  18:41   Saturday       KENNEDY BD STATION    MUO           0
13273 2021-11-10  16:25  Wednesday      SUMMERHILL STATION    TUS           3
13402 2021-11-12  20:42     Friday       CLOSURES BUILDING   MUIE           0
13410 2021-11-12  00:02     Friday          TRANSIT CONTROL    MUO           0
14177 2021-11-25  21:14   Thursday          WILSON CARHOUSE   MUIE           0
14371 2021-11-29  05:10     Monday              GO PROTOCOL    MUO           0
14935 2021-12-08  06:00  Wednesday  TORONTO TRANSIT COMMIS    MUO           0
14952 2021-12-08  13:58  Wednesday          KIPLING STATION   MUIS           0
14967 2021-12-08  17:14  Wednesday     QUEEN'S PARK STATION    MUO           0
15581 2021-12-19  00:42     Sunday          WILSON CARHOUSE    MUO           0
15623 2021-12-20  16:23     Monday  YONGE-SHEPPARD (LINE 4  MUIRS           0
16332 2021-12-31  14:34     Friday              GO PROTOCOL    MUO           0

       min_gap bound line  vehicle  \
495          6     S  NaN     5751
513          0   NaN  NaN        0
1044         0   NaN  NaN        0
1045         0   NaN  NaN        0
1362         0     S  NaN     5596
1679         0   NaN  NaN        0
2179         0   NaN  NaN        0
2204         9     N  NaN     6006
2206         0   NaN  NaN        0
3039         0   NaN  NaN        0
3330         0   NaN  NaN        0
3407         0   NaN  NaN        0
3557         0   NaN  NaN        0
3944         0   NaN  NaN        0
4097         0   NaN  NaN        0
4119         0   NaN  NaN        0
4336         0   NaN  NaN        0
4748         0   NaN  NaN        0
```

```
5312          0  NaN  NaN        0
5448          0  NaN  NaN        0
5484          0  NaN  NaN        0
5642          0  NaN  NaN        0
5685          0    E  NaN        0
6042          0  NaN  NaN        0
6046          0  NaN  NaN        0
6540          0  NaN  NaN        0
6560          0  NaN  NaN        0
7137          0  NaN  NaN        0
7766          0  NaN  NaN        0
8889          0  NaN  NaN        0
9628          0  NaN  NaN        0
9629          0  NaN  NaN        0
9780          0  NaN  NaN        0
9789          0  NaN  NaN        0
10336         0  NaN  NaN        0
10951         0    N  NaN     5471
11223         0  NaN  NaN        0
12533         0  NaN  NaN        0
12826         0  NaN  NaN        0
13007         0    S  NaN        0
13080         0  NaN  NaN        0
13273         6    N  NaN     6501
13402         0  NaN  NaN        0
13410         0  NaN  NaN        0
14177         0  NaN  NaN        0
14371         0  NaN  NaN        0
14935         0  NaN  NaN        0
14952         0  NaN  NaN        0
14967         0  NaN  NaN        0
15581         0  NaN  NaN        0
15623         0  NaN  NaN        0
16332         0  NaN  NaN        0

                                 code_description sub_or_srt  year  \
495                             Unsanitary Vehicle        SUB  2021
513                   Escalator/Elevator Incident        SUB  2021
1044                          Miscellaneous Other        SUB  2021
1045                          Miscellaneous Other        SUB  2021
1362                         Operator Overspeeding        SUB  2021
1679                             Injured Employee        SUB  2021
2179                             Injured Employee        SUB  2021
2204                    Assault / Patron Involved        SUB  2021
2206                          Miscellaneous Other        SUB  2021
3039                  Escalator/Elevator Incident        SUB  2021
3330                  Escalator/Elevator Incident        SUB  2021
```

```
3407                                             T&S Other        SUB  2021
3557                            Escalator/Elevator Incident        SUB  2021
3944                                     Injured Employee        SUB  2021
4097                             Assault / Employee Involved        SUB  2021
4119                                  Miscellaneous Other        SUB  2021
4336                                  Miscellaneous Other        SUB  2021
4748                                  Miscellaneous Other        SUB  2021
5312                                                  NaN        NaN  2021
5448                                         Work Refusal        SUB  2021
5484                            Escalator/Elevator Incident        SUB  2021
5642                                     Disorderly Patron        SUB  2021
5685                                       Passenger Other        SUB  2021
6042   Injured or ill Customer (In Station) - Medical…       SUB  2021
6046                                       Passenger Other        SUB  2021
6540   Injured or ill Customer (In Station) - Transpo…       SUB  2021
6560                            Escalator/Elevator Incident        SUB  2021
7137                                                  NaN        NaN  2021
7766                              S/E/C Department Other        SUB  2021
8889                                     Injured Employee        SUB  2021
9628                        Held By Polce - Non-TTC Related        SUB  2021
9629                                  Miscellaneous Other        SUB  2021
9780                                  Miscellaneous Other        SUB  2021
9789                                  Miscellaneous Other        SUB  2021
10336                                      Passenger Other        SUB  2021
10951                      OPTO (COMMS) Train Door Monitoring        SUB  2021
11223                                    Disorderly Patron        SUB  2021
12533  Injured or ill Customer (In Station) - Transpo…       SUB  2021
12826                                    Injured Employee        SUB  2021
13007  Injured or ill Customer (In Station) - Medical…       SUB  2021
13080                                 Miscellaneous Other        SUB  2021
13273                       Crew Unable to Maintain Schedule        SUB  2021
13402                                    Injured Employee        SUB  2021
13410                                 Miscellaneous Other        SUB  2021
14177                                    Injured Employee        SUB  2021
14371                                 Miscellaneous Other        SUB  2021
14935                                 Miscellaneous Other        SUB  2021
14952  Injured or ill Customer (In Station) - Transpo…       SUB  2021
14967                                 Miscellaneous Other        SUB  2021
15581                                 Miscellaneous Other        SUB  2021
15623  Injured or ill Customer (In Station) - Medical…       SUB  2021
16332                                 Miscellaneous Other        SUB  2021

       hour_delay  month  hour
495          0.05      1    15
513          0.00      1    22
1044         0.00      1    22
1045         0.00      1    23
```

1362	0.00	2	1
1679	0.00	2	1
2179	0.00	2	8
2204	0.07	2	22
2206	0.00	2	23
3039	0.00	3	5
3330	0.00	3	19
3407	0.00	3	9
3557	0.00	3	0
3944	0.00	4	23
4097	0.00	4	10
4119	0.00	4	22
4336	0.00	4	23
4748	0.00	4	22
5312	0.00	5	5
5448	0.00	5	20
5484	0.00	5	18
5642	0.00	5	23
5685	0.00	5	0
6042	0.00	6	22
6046	0.00	6	0
6540	0.00	6	22
6560	0.00	6	7
7137	0.00	6	1
7766	0.00	7	3
8889	0.00	8	7
9628	0.00	8	15
9629	0.00	8	16
9780	0.00	9	20
9789	0.00	9	22
10336	0.00	9	17
10951	0.00	9	15
11223	0.00	10	0
12533	0.00	10	14
12826	0.00	11	12
13007	0.00	11	8
13080	0.00	11	18
13273	0.05	11	16
13402	0.00	11	20
13410	0.00	11	0
14177	0.00	11	21
14371	0.00	11	5
14935	0.00	12	6
14952	0.00	12	13
14967	0.00	12	17
15581	0.00	12	0
15623	0.00	12	16

```
16332        0.00     12    14
```

`.loc[]` also lets us access data by label, with row conditions first and column conditions second.

```
[ ]: (delays_w_reasons.loc[delays_w_reasons['line'].isna(),  # filter rows
                          ['time', 'station', 'line']]  # get columns
                         .head())  # first 5 lines to save space
```

```
[ ]:        time                station line
     495   15:22      FINCH WEST STATION  NaN
     513   22:08    EGLINTON WEST STATION  NaN
     1044  22:00  YONGE-UNIVERSITY AND B  NaN
     1045  23:00           FINCH STATION  NaN
     1362  01:45        LAWRENCE STATION  NaN
```

3.9.2 query()

Alternatively, we can use the DataFrame `query()` method, which takes a filter condition as a string, and returns a DataFrame of records that met the condition. `query()` is slower than `loc[]`, but it can be easier to read.

```
[ ]: delays_w_reasons['line'].unique()
```

```
[ ]: array(['YU', 'BD', 'SHP', 'SRT', 'YU/BD', nan, 'YONGE/UNIVERSITY/BLOOR',
            'YU / BD', 'YUS', '999', 'SHEP', '36 FINCH WEST', 'YUS & BD',
            'YU & BD LINES', '35 JANE', '52', '41 KEELE', 'YUS/BD'],
           dtype=object)
```

```
[ ]: delays_w_reasons['line'].isna()
```

```
[ ]: 0        False
     1        False
     2        False
     3        False
     4        False
              …
     16365    False
     16366    False
     16367    False
     16368    False
     16369    False
     Name: line, Length: 16370, dtype: bool
```

```
[ ]: # slower than .loc, but can be easier to read
     delays_w_reasons.query('line.isna()', engine='python').head()
```

```
[ ]:            date   time        day                station   code  min_delay  \
     495   2021-01-13  15:22  Wednesday     FINCH WEST STATION  MUSAN          3
     513   2021-01-13  22:08  Wednesday  EGLINTON WEST STATION  PUMEL          0
     1044  2021-01-27  22:00  Wednesday  YONGE-UNIVERSITY AND B    MUO          0
     1045  2021-01-27  23:00  Wednesday          FINCH STATION    MUO          0
     1362  2021-02-04  01:45   Thursday       LAWRENCE STATION   TUSC          0

           min_gap bound line  vehicle             code_description sub_or_srt  \
     495         6     S  NaN     5751          Unsanitary Vehicle        SUB
     513         0   NaN  NaN        0  Escalator/Elevator Incident        SUB
     1044        0   NaN  NaN        0         Miscellaneous Other        SUB
     1045        0   NaN  NaN        0         Miscellaneous Other        SUB
     1362        0     S  NaN     5596        Operator Overspeeding        SUB

           year  hour_delay  month  hour
     495   2021        0.05      1    15
     513   2021        0.00      1    22
     1044  2021        0.00      1    22
     1045  2021        0.00      1    23
     1362  2021        0.00      2     1
```

3.9.3 dropna()

In this case, the number of records without lines is relatively small. Most do not have delay durations. Some appear to be at rail yards, i.e. not on a rail line. For our analysis, we may drop them with the `dropna()` DataFrame method. We can drop rows missing lines by passing a `subset`.

```
[ ]: delays_w_reasons = delays_w_reasons.dropna(subset=['line'])
```

3.9.4 Filtering data with .loc[] and isin()

We can use `.loc[]` to create a delays DataFrame without the invalid lines. To to this, we first create a list of values to exclude, then pass the list to the Series `isin()` method. Finally, we negate the expression, and assign the output back to `delays_w_reasons`.

Note: The negation operator here is `~`, not `!`. The `and` and `or` operators are different as well: `&` and `|` respectively.

```
[ ]: # set up filter list
     filter_list = ['999', '36 FINCH WEST', '35 JANE', '52', '41 KEELE']
```

```
[ ]: # filter out records with invalid lines
     delays_w_reasons = delays_w_reasons.loc[~delays_w_reasons['line'].
      ↪isin(filter_list)]
     delays_w_reasons['line'].unique()
```

```
[ ]: array(['YU', 'BD', 'SHP', 'SRT', 'YU/BD', 'YONGE/UNIVERSITY/BLOOR',
            'YU / BD', 'YUS', 'SHEP', 'YUS & BD', 'YU & BD LINES', 'YUS/BD'],
           dtype=object)
```

3.9.5 Replacing values with `str.replace()`

To standardize the YU/BD values, we can replace the less common ones. One way to do this is by selecting the line Series and using `str.replace()`, like below for ”YUS”.

```
[ ]: delays_w_reasons['line'] = (delays_w_reasons['line']
                                .str.replace('YUS', 'YU'))
     delays_w_reasons['line'].unique()
```

```
[ ]: array(['YU', 'BD', 'SHP', 'SRT', 'YU/BD', 'YONGE/UNIVERSITY/BLOOR',
            'YU / BD', 'SHEP', 'YU & BD', 'YU & BD LINES'], dtype=object)
```

Another is to assign ”YU/BD” to values selected by `.loc[]`

```
[ ]: yubd_list = ['YONGE/UNIVERSITY/BLOOR',
                  'YU / BD',
                  'YU & BD',
                  'YU & BD LINES']

     # check the .loc[] selection
     delays_w_reasons.loc[delays_w_reasons['line'].isin(yubd_list), 'line']
```

```
[ ]: 590      YONGE/UNIVERSITY/BLOOR
     852                     YU / BD
     1137                    YU / BD
     1628                    YU / BD
     1672                    YU / BD
     1700                    YU / BD
     6725                    YU / BD
     7469                    YU / BD
     8034                    YU & BD
     8301                    YU / BD
     8341                    YU / BD
     8463                    YU / BD
     9164                    YU / BD
     9541              YU & BD LINES
     9839                    YU / BD
     10792                   YU / BD
     11119                   YU / BD
     11299                   YU / BD
     12128                   YU / BD
     15574                   YU / BD
     Name: line, dtype: object
```

```
[ ]: delays_w_reasons.loc[delays_w_reasons['line'].isin(yubd_list), 'line'] = 'YU/BD'
     delays_w_reasons['line'].unique()
```

```
[ ]: array(['YU', 'BD', 'SHP', 'SRT', 'YU/BD', 'SHEP'], dtype=object)
```

3.10 Grouping

A core workflow in pandas is *split-apply-combine*: * **splitting** data into groups * **applying** a function to each group, such as calculating group sums, standardizing data, or filtering out some groups * **combining** the results into a data structure

This workflow starts by grouping data by calling the `groupby()` method. We'll pass in a column name or list of names to group by.

```
[ ]: line_groups = delays_w_reasons.groupby('line')
```

`groupby()` returns a grouped DataFrame that we can use to calculate groupwise statistics. The grouping column values become indexes, or row labels. **Note that this grouped DataFrame still references the original, so mutating one affects the other.**

```
[ ]: # how many hours of delays did each line have in 2021?
     line_groups['hour_delay'].sum()
```

```
[ ]: line
     BD       329.47
     SHEP       0.00
     SHP       28.43
     SRT       57.82
     YU       477.50
     YU/BD      0.00
     Name: hour_delay, dtype: float64
```

We can group by more than one column by passing a list into `groupby()`. Data is grouped in the order of column names.

```
[ ]: # group by line first, then reason code description
     line_code_groups = delays_w_reasons.groupby(['line', 'code_description'])
```

3.10.1 Chaining methods and `unstack()`ing

We can *chain* methods together for convenience and code readability. Here, we calculate the `size()` of each group, then `unstack()` the resulting Series by the first part of the row label, line. The `tail()` method is added to the end so that the output takes less screen space.

```
[ ]: # view the number of delays by reason and line
     line_code_groups.size().unstack(0).tail()
```

```
[ ]: line                          BD  SHEP  SHP  SRT    YU  YU/BD
     code_description
     Work Refusal                 4.0   NaN  1.0  NaN  12.0    NaN
     Work Vehicle                 3.0   NaN  NaN  NaN   7.0    NaN
     Work Zone Problems - Signals 4.0   NaN  4.0  NaN   5.0    NaN
     Work Zone Problems - Track  12.0   NaN  NaN  NaN  29.0    NaN
     Yard/Carhouse Related Problems 17.0   NaN  NaN  NaN  15.0    NaN
```

3.10.2 agg()regating

So far, we have applied one function at a time. The `agg()` DataFrame method lets us apply multiple functions on different columns at once.

`agg()`'s argument syntax is a little unusual. It follows this pattern:

```
DataFrame.agg(agg_colname=('column_to_aggregate', 'aggregation_function_name'),
              agg_colname2=('col_to_agg2', 'agg_func_name'))
```

```
[ ]: delay_summary = (delays_w_reasons
                       .groupby('date')
                       .agg(delay_count=('station', 'count'),
                            total_delay_min=('min_delay', 'sum'),
                            mean_delay_min=('min_delay', 'mean')))

     delay_summary.head()
```

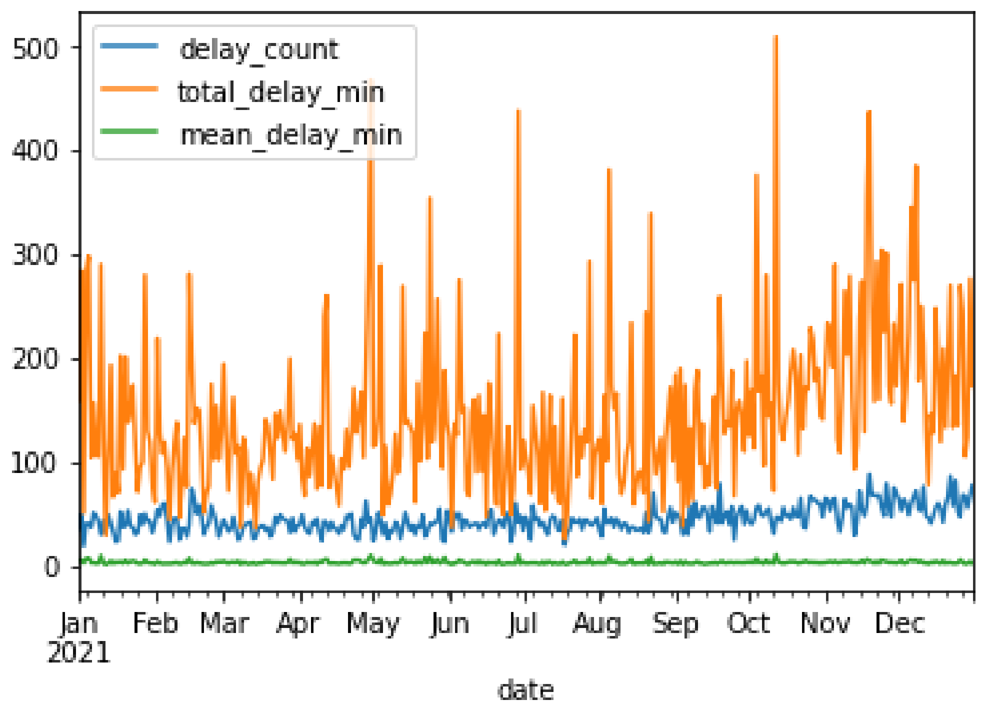
```
[ ]:             delay_count  total_delay_min  mean_delay_min
     date
     2021-01-01           36              159        4.416667
     2021-01-02           49              284        5.795918
     2021-01-03           19               51        2.684211
     2021-01-04           41              284        6.926829
     2021-01-05           40              298        7.450000
```

3.11 Plotting

The summary table we just generated can be easily plotted within `pandas`. Since the index contains dates, `pandas` automatically knows to plot values as time series data, with the dates in the x-axis -- we just have to call the `plot()` method.

```
[ ]: delay_summary.plot()
```

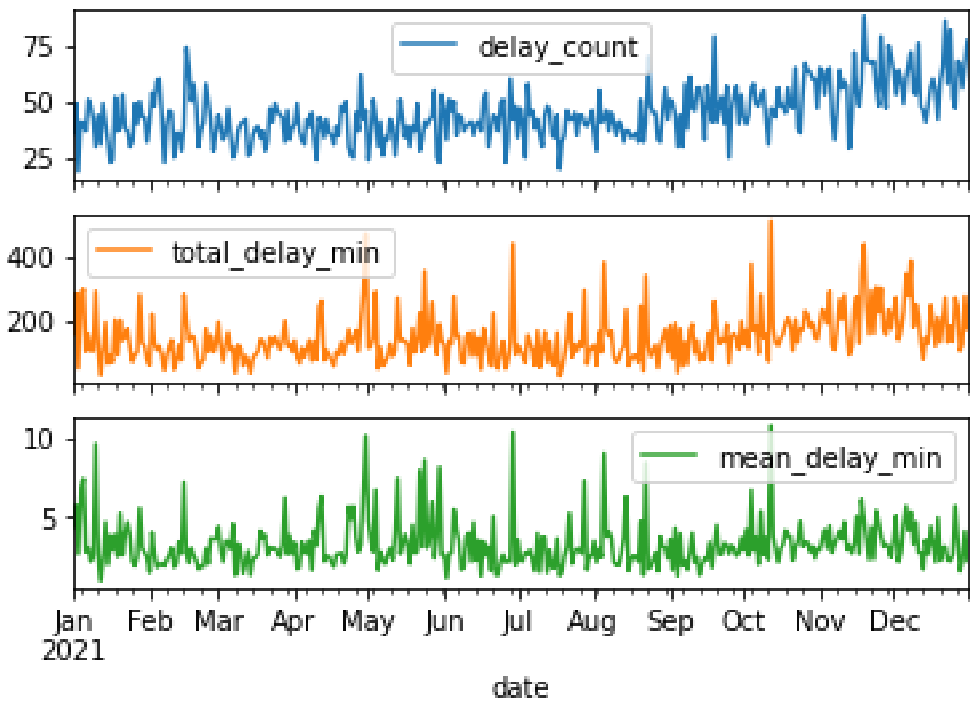
```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3fcb623d0>
```



To create a separate plot for each column, we can specify `subplots=True`

```
[ ]: delay_summary.plot(subplots=True)
```

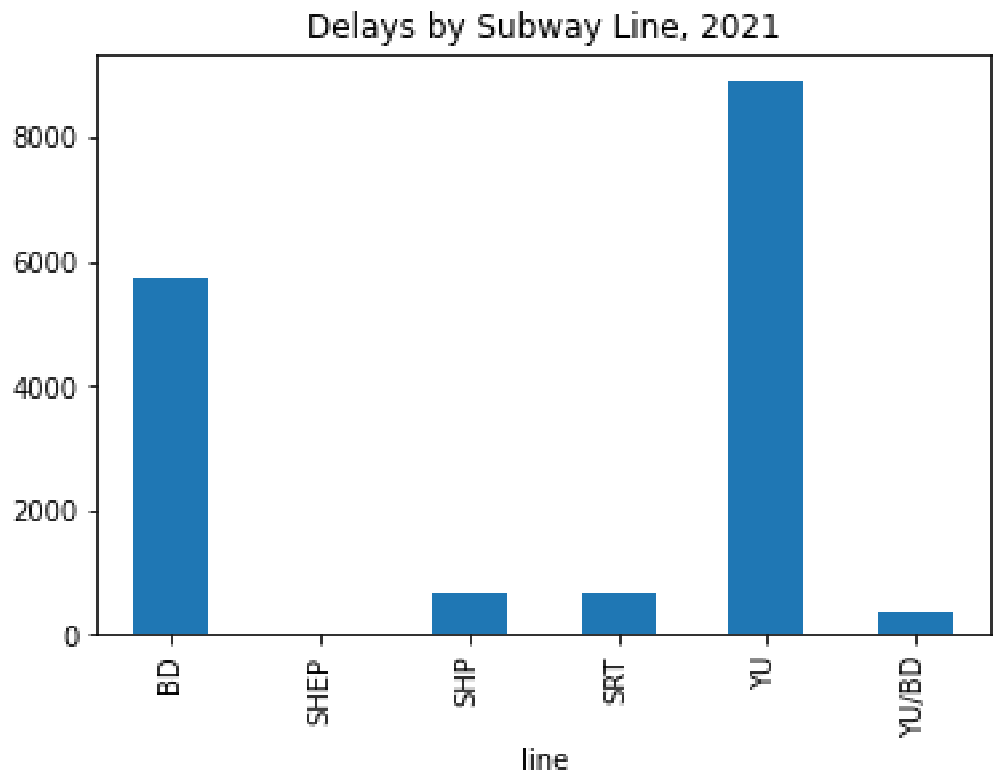
```
[ ]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x7fe3fca515d0>,
            <matplotlib.axes._subplots.AxesSubplot object at 0x7fe3fc52db50>,
            <matplotlib.axes._subplots.AxesSubplot object at 0x7fe3fca1bf90>],
           dtype=object)
```



We can plot other aggregations too. Below, we use `line_groups` and calculate the size of each group, i.e., the number of delays reported on each line. Then we plot the data, telling `pandas` that the plot `kind` should be a bar graph, with TTC lines should in the `x`-axis. We also pass in a title.

```
[ ]: (line_groups
      .size()
      .plot(x='line',
            kind='bar',
            title='Delays by Subway Line, 2021'))
```

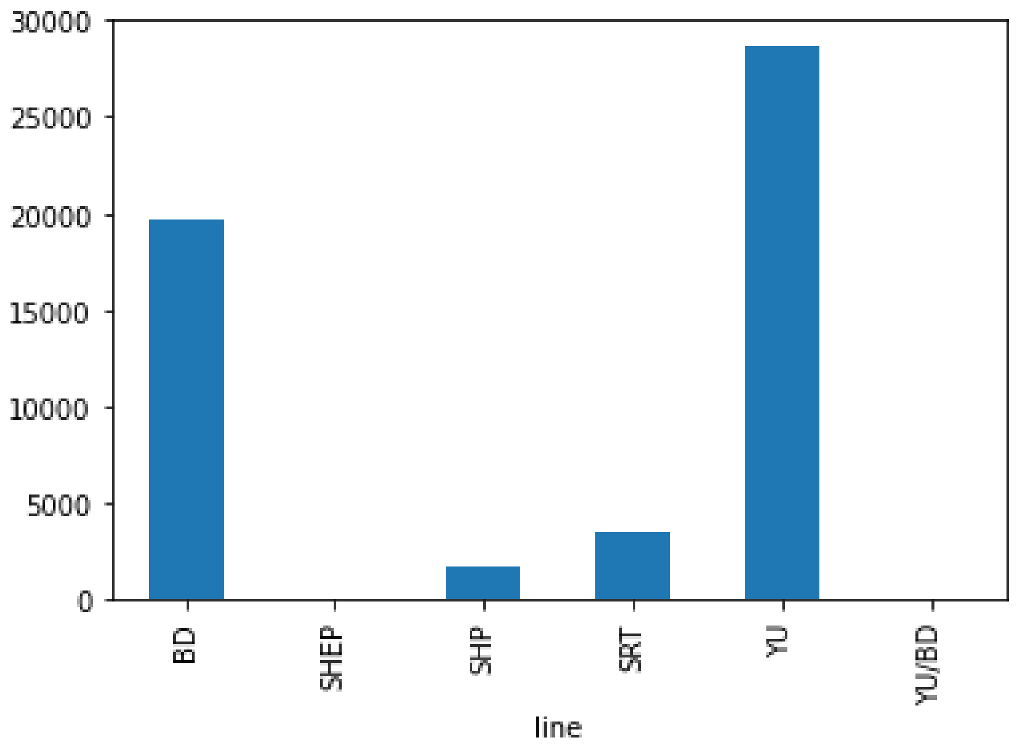
```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3fc287ed0>
```



It is possible to sum up and plot the total delay time, in hours, by line.

```
[ ]: (delays_w_reasons
      .groupby('line')['min_delay']
      .sum()
      .plot(x='line', kind='bar'))
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3fc198350>
```



4 Writing to file

4.1 Exporting DataFrames

DataFrames have `to_[file format]()` methods, analagous to `pandas` read functions. The counterpart to `pd.read_csv()`, for instance, is `DataFrame.to_csv()`. The export methods generally take a file path to save to as their first argument. Additional arguments vary a bit by export format, but `index` is a common useful one. It takes a boolean of whether to write the index to file -- set it to `False` if the index is the numbered default.

Two additional useful parameters in `DataFrame.to_csv()` and `DataFrame.to_excel()` are `na_rep`, which takes a string to use for null values, and `columns`, which lets us write out a subset of columns.

```
[ ]: # write delays_w_reasons to an Excel file
     delays_w_reasons.to_excel('/content/data/ttc_subway_delays_w_reasons.xlsx',␣
      ↪index=False)
```

5 More wrangling

5.1 Neighbourhood Profiles

The bike theft data includes neighbourhood identifiers. These neighbourhoods are designated by City of Toronto, which publishes neighbourhood demographic profiles. Let's get this data to start investigating if neighbourhoods with more bike theft reports simply have higher populations. In the process, we will reinforce what we learned so far. We will also learn about two last ways to reshape data: `melt()`, which rearranges data from a wide format to a long format; and `pivot()`, which reorganizes data based on index and column values.

5.2 Getting data

Let's load the neighbourhood data and explore it.

```
[ ]: profiles = pd.read_csv('/content/data/neighbourhood-profiles-2016-140-model.
     ↪csv')
```

```
[ ]: profiles.shape
```

```
[ ]: (2383, 146)
```

The neighbourhood profiles are in an unusual format. Neighbourhood names are in the columns, while attribute fields are rows, and there are thousands of attributes.

```
[ ]: profiles.head()
```

```
[ ]:    _id                 Category                        Topic  \
     0    1  Neighbourhood Information  Neighbourhood Information
     1    2  Neighbourhood Information  Neighbourhood Information
     2    3                 Population   Population and dwellings
     3    4                 Population   Population and dwellings
     4    5                 Population   Population and dwellings

                           Data Source               Characteristic  \
     0                 City of Toronto         Neighbourhood Number
     1                 City of Toronto         TSNS2020 Designation
     2  Census Profile 98-316-X2016001             Population, 2016
     3  Census Profile 98-316-X2016001             Population, 2011
     4  Census Profile 98-316-X2016001  Population Change 2011-2016

       City of Toronto Agincourt North Agincourt South-Malvern West  \
     0             NaN             129                          128
     1             NaN  No Designation               No Designation
     2       2,731,571          29,113                       23,757
     3       2,615,060          30,279                       21,988
     4           4.50%          -3.90%                        8.00%
```

```
        Alderwood           Annex Banbury-Don Mills  Bathurst Manor  \
0              20              95                42              34
1  No Designation  No Designation    No Designation  No Designation
2          12,054          30,526            27,695          15,873
3          11,904          29,177            26,918          15,434
4           1.30%           4.60%             2.90%           2.80%

  Bay Street Corridor Bayview Village Bayview Woods-Steeles  \
0                  76              52                    49
1      No Designation  No Designation        No Designation
2              25,797          21,396                13,154
3              19,348          17,671                13,530
4              33.30%          21.10%                -2.80%

  Bedford Park-Nortown Beechborough-Greenbrook         Bendale  \
0                   39                     112             127
1       No Designation                     NIA  No Designation
2               23,236                   6,577          29,960
3               23,185                   6,488          27,876
4                0.20%                   1.40%           7.50%

  Birchcliffe-Cliffside Black Creek     Blake-Jones Briar Hill-Belgravia  \
0                   122          24              69                  108
1        No Designation         NIA  No Designation       No Designation
2                22,291      21,737           7,727               14,257
3                21,856      22,057           7,763               14,302
4                 2.00%      -1.50%          -0.50%               -0.30%

  Bridle Path-Sunnybrook-York Mills Broadview North Brookhaven-Amesbury  \
0                                41              57                  30
1                    No Designation  No Designation      No Designation
2                             9,266          11,499              17,757
3                             8,713          11,563              17,787
4                             6.30%          -0.60%              -0.20%

  Cabbagetown-South St. James Town Caledonia-Fairbank       Casa Loma  \
0                               71                109              96
1                   No Designation     No Designation  No Designation
2                           11,669              9,955          10,968
3                           12,053              9,851          10,487
4                           -3.20%              1.10%           4.60%

  Centennial Scarborough Church-Yonge Corridor Clairlea-Birchmount  \
0                    133                    75                 120
1         No Designation        No Designation      No Designation
2                 13,362                31,340              26,984
```

```
3                 13,093                28,349              24,770
4                  2.10%                10.60%               8.90%

     Clanton Park      Cliffcrest Corso Italia-Davenport        Danforth  \
0              33             123                     92              66
1  No Designation  No Designation         No Designation  No Designation
2          16,472          15,935                 14,133           9,666
3          14,612          15,703                 13,743           9,444
4          12.70%           1.50%                  2.80%           2.40%

  Danforth East York Don Valley Village             Dorset Park  \
0                 59                 47                     126
1     No Designation     No Designation  Emerging Neighbourhood
2             17,180             27,051                  25,003
3             16,712             26,739                  24,363
4              2.80%              1.20%                   2.60%

  Dovercourt-Wallace Emerson-Junction Downsview-Roding-CFB  Dufferin Grove  \
0                                  93                   26              83
1                      No Designation                  NIA  No Designation
2                              36,625               35,052          11,785
3                              34,631               34,659          11,449
4                               5.80%                1.10%           2.90%

  East End-Danforth Edenbridge-Humber Valley Eglinton East Elms-Old Rexdale  \
0                62                        9           138                5
1    No Designation           No Designation           NIA              NIA
2            21,381                   15,535        22,776            9,456
3            20,839                   14,943        22,829            9,550
4             2.60%                    4.00%        -0.20%           -1.00%

      Englemount-Lawrence Eringate-Centennial-West Deane Etobicoke West Mall  \
0                      32                             11                  13
1  Emerging Neighbourhood                 No Designation      No Designation
2                  22,372                         18,588              11,848
3                  22,086                         18,810              10,927
4                   1.30%                         -1.20%               8.40%

  Flemingdon Park Forest Hill North Forest Hill South Glenfield-Jane Heights  \
0              44               102               101                     25
1             NIA    No Designation    No Designation                    NIA
2          21,933            12,806            10,732                 30,491
3          22,168            12,474            10,926                 31,390
4          -1.10%             2.70%            -1.80%                 -2.90%

  Greenwood-Coxwell       Guildwood      Henry Farm High Park North  \
0                65             140              53              88
```

```
1    No Designation  No Designation  No Designation  No Designation
2            14,417           9,917          15,723          22,162
3            14,083           9,816          11,333          21,292
4             2.40%           1.00%          38.70%           4.10%

  High Park-Swansea  Highland Creek Hillcrest Village  \
0                87             134                48
1    No Designation  No Designation    No Designation
2            23,925          12,494            16,934
3            21,740          13,097            17,656
4            10.10%          -4.60%            -4.10%

  Humber Heights-Westmount Humber Summit Humbermede Humewood-Cedarvale  \
0                        8            21         22                106
1   Emerging Neighbourhood           NIA        NIA     No Designation
2                   10,948        12,416     15,545             14,365
3                   10,583        12,525     15,853             14,108
4                    3.40%        -0.90%     -1.90%              1.80%

  Ionview Islington-City Centre West   Junction Area Keelesdale-Eglinton West  \
0     125                         14              90                      110
1     NIA             No Designation  No Designation                      NIA
2  13,641                     43,965          14,366                   11,058
3  13,091                     38,084          14,027                   10,638
4   4.20%                     15.40%           2.40%                    3.90%

  Kennedy Park Kensington-Chinatown Kingsview Village-The Westway  \
0          124                   78                             6
1          NIA       No Designation                           NIA
2       17,123               17,945                        22,000
3       17,058               18,495                        21,723
4        0.40%               -3.00%                         1.30%

   Kingsway South Lambton Baby Point             L'Amoreaux Lansing-Westgate  \
0              15                114                    117               38
1  No Designation     No Designation  Emerging Neighbourhood   No Designation
2           9,271              7,985                  43,993           16,164
3           9,170              7,921                  44,919           14,642
4           1.10%              0.80%                  -2.10%           10.40%

  Lawrence Park North Lawrence Park South Leaside-Bennington Little Portugal  \
0                 105                 103                 56              84
1      No Designation      No Designation     No Designation  No Designation
2              14,607              15,179             16,828          15,559
3              14,541              15,070             17,011          12,050
4               0.50%               0.70%             -1.10%          29.10%
```

```
      Long Branch                 Malvern      Maple Leaf   Markland Wood  \
0              19                     132              29              12
1  No Designation  Emerging Neighbourhood  No Designation  No Designation
2          10,084                  43,794          10,111          10,554
3           9,632                  45,086          10,197          10,436
4           4.70%                  -2.90%          -0.80%           1.10%

         Milliken Mimico (includes Humber Bay Shores) Morningside  \
0             130                                  17         135
1  No Designation                      No Designation         NIA
2          26,572                              33,964      17,455
3          27,167                              26,541      17,587
4          -2.20%                              28.00%      -0.80%

        Moss Park Mount Dennis Mount Olive-Silverstone-Jamestown  \
0              73          115                                 2
1  No Designation          NIA                               NIA
2          20,506       13,593                            32,954
3          16,306       13,145                            32,788
4          25.80%        3.40%                             0.50%

  Mount Pleasant East Mount Pleasant West     New Toronto Newtonbrook East  \
0                  99                 104              18               50
1      No Designation      No Designation  No Designation   No Designation
2              16,775              29,658          11,463           16,097
3              15,982              28,593          10,900           16,423
4               5.00%               3.70%           5.20%           -2.00%

  Newtonbrook West         Niagara North Riverdale North St. James Town  \
0               36              82              68                   74
1   No Designation  No Designation  No Designation       No Designation
2           23,831          31,180          11,916               18,615
3           23,052          21,274          12,191               17,832
4            3.40%          46.60%          -2.30%                4.40%

  Oakridge Oakwood Village O'Connor-Parkview   Old East York  \
0      121             107                54              58
1      NIA  No Designation    No Designation  No Designation
2   13,845          21,210            18,675           9,233
3   13,497          21,073            18,316           9,118
4    2.60%           0.70%             2.00%           1.30%

  Palmerston-Little Italy Parkwoods-Donalda Pelmo Park-Humberlea  \
0                      80                45                   23
1          No Designation    No Designation       No Designation
2                  13,826            34,805               10,722
3                  13,746            34,617                8,710
```

```
4                  0.60%             0.50%               23.10%

  Playter Estates-Danforth   Pleasant View Princess-Rosethorn Regent Park  \
0                       67              46                 10          72
1           No Designation  No Designation     No Designation         NIA
2                    7,804          15,818             11,051      10,803
3                    7,653          16,144             11,197      10,007
4                    2.00%          -2.00%             -1.30%       8.00%

  Rexdale-Kipling Rockcliffe-Smythe    Roncesvalles Rosedale-Moore Park  \
0               4               111              86                  98
1  No Designation               NIA  No Designation      No Designation
2          10,529            22,246          14,974              20,923
3          10,488            22,267          15,050              20,631
4           0.40%            -0.10%          -0.50%               1.40%

            Rouge Runnymede-Bloor West Village  Rustic Scarborough Village  \
0             131                           89      28                 139
1  No Designation               No Designation     NIA                 NIA
2          46,496                       10,070   9,941              16,724
3          45,912                        9,632   9,951              16,609
4           1.30%                        4.50%  -0.10%               0.70%

  South Parkdale South Riverdale St.Andrew-Windfields                  Steeles  \
0             85              70                   40                      116
1            NIA  No Designation       No Designation  Emerging Neighbourhood
2         21,849          27,876               17,812                   24,623
3         21,251          25,642               17,958                   25,017
4          2.80%           8.70%               -0.80%                   -1.60%

  Stonegate-Queensway Tam O'Shanter-Sullivan Taylor-Massey     The Beaches  \
0                  16                    118            61              63
1      No Designation         No Designation           NIA  No Designation
2              25,051                 27,446        15,683          21,567
3              24,691                 27,398        15,594          21,130
4               1.50%                  0.20%         0.60%           2.10%

  Thistletown-Beaumond Heights Thorncliffe Park Trinity-Bellwoods  \
0                            3               55                81
1                          NIA              NIA    No Designation
2                       10,360           21,108            16,556
3                       10,138           19,225            16,802
4                        2.20%            9.80%            -1.50%

       University Victoria Village Waterfront Communities-The Island  \
0              79               43                                77
1  No Designation              NIA                    No Designation
```

```
2          7,607            17,510                            65,913
3          7,782            17,182                            43,361
4         -2.20%             1.90%                            52.00%

  West Hill West Humber-Clairville     Westminster-Branson  Weston  \
0       136                      1                       35     113
1       NIA         No Designation  Emerging Neighbourhood     NIA
2    27,392                 33,312                  26,274  17,992
3    26,547                 34,100                  25,446  18,170
4     3.20%                 -2.30%                   3.30%  -1.00%

  Weston-Pelham Park Wexford/Maryvale Willowdale East Willowdale West  \
0                 91              119              51              37
1                NIA   No Designation  No Designation  No Designation
2             11,098           27,917          50,434          16,936
3             12,010           27,018          45,041          15,004
4             -7.60%            3.30%          12.00%          12.90%

  Willowridge-Martingrove-Richview  Woburn Woodbine Corridor Woodbine-Lumsden  \
0                                7     137                64               60
1                   No Designation     NIA    No Designation   No Designation
2                           22,156  53,485            12,541            7,865
3                           21,343  53,350            11,703            7,826
4                            3.80%   0.30%             7.20%            0.50%

         Wychwood  Yonge-Eglinton  Yonge-St.Clair York University Heights  \
0              94             100              97                      27
1  No Designation  No Designation  No Designation                     NIA
2          14,349          11,817          12,528                  27,593
3          13,986          10,578          11,652                  27,713
4           2.60%          11.70%           7.50%                  -0.40%

        Yorkdale-Glen Park
0                       31
1  Emerging Neighbourhood
2                   14,804
3                   14,687
4                    0.80%
```

Because of the layout and formatting characters, all of the numeric values have been read in as text data. It also looks like the characteristics are not unique.

[ ]:
```
profiles.dtypes.value_counts()
```

[ ]:
```
object    145
int64       1
dtype: int64
```

```
[ ]: len(profiles['Characteristic'].unique())
```

```
[ ]: 1651
```

5.3 Removing extra whitespace

The characteristic values contain extra whitespace. Let's remove the whitespace up with `str.strip()`.

```
[ ]: # the whitespace is easier to see in a list than a Series
     list(profiles['Characteristic'][95:100])
```

```
[ ]: ['    Female parent',
      '    Male parent',
      'Couple census families in private households',
      '  Couples with children',
      '    1 child']
```

```
[ ]: profiles['Characteristic'] = profiles['Characteristic'].str.strip()

     # get the first 10 characteristics
     list(profiles['Characteristic'][95:100])
```

```
[ ]: ['Female parent',
      'Male parent',
      'Couple census families in private households',
      'Couples with children',
      '1 child']
```

5.4 Subsetting data

1651 characteristics is still a lot. Let's check out the categories to understand the areas covered.

```
[ ]: profiles['Category'].unique()
```

```
[ ]: array(['Neighbourhood Information', 'Population',
            'Families, households and marital status', 'Language', 'Income',
            'Immigration and citizenship', 'Visible minority', 'Ethnic origin',
            'Aboriginal peoples', 'Education', 'Housing', 'Language of work',
            'Labour', 'Journey to work', 'Mobility'], dtype=object)
```

”Journey to work” sounds relevant. We can use `.loc[]` to get the rows in that category, then select the Topic column and get its unique values.

```
[ ]: profiles.loc[profiles['Category'] == 'Journey to work']['Topic'].unique()
[ ]: array(['Commuting destination', 'Main mode of commuting',
            'Commuting duration', 'Time leaving for work'], dtype=object)
```

The "Population and dwellings" topic we saw in the DataFrame head looked promising as well. Let's check out the Characteristics in that topic.

```
[ ]: profiles.loc[profiles['Topic'] == 'Population and dwellings']['Characteristic'].
      ↪unique()
```

```
[ ]: array(['Population, 2016', 'Population, 2011',
            'Population Change 2011-2016', 'Total private dwellings',
            'Private dwellings occupied by usual residents',
            'Population density per square kilometre',
            'Land area in square kilometres'], dtype=object)
```

Now that we know what topics we're interested in, let's create a subset DataFrame limited to them. We'll use the `copy()` DataFrame method to leave the original data untouched.

```
[ ]: topics = ['Neighbourhood Information', 'Population and dwellings', 'Main mode␣
      ↪of commuting']

     # make sure it's an independent copy
     profiles_subset = profiles.copy()

     # get just the topics we're interested in
     profiles_subset = profiles_subset.loc[profiles['Topic'].isin(topics)]
     profiles_subset.shape
```

```
[ ]: (16, 146)
```

5.5 Reshaping data with `melt()`

Now we're ready to reshape our data. We can `drop()` the ID, data source, and category columns now.

To `melt()` a DataFrame, we specify `id_vars` -- the columns to keep as identifiers. All other columns are 'melted' into a new `variable` column. The values at DataFrame[id_vars, variable_col] move into a `value` column. We can change the names of the variable and value columns with the `var_name` and `value_name` arguments.

The `pandas` documentation provides an illustrative example.

Let's `melt()` the profiles subset. We'll keep `Topic` and `Characteristic` as our `id_vars`. This will melt the neighbourhood names into the `variable` column, which we'll rename `Neighbourhood`.

```
[ ]: profiles_melt = (profiles_subset
                      .drop(columns=['_id', 'Data Source', 'Category'])
                      .melt(id_vars=['Topic', 'Characteristic'],
                           var_name='Neighbourhood'))
profiles_melt.head()
```

[ ]:
```
                       Topic              Characteristic    Neighbourhood  \
0  Neighbourhood Information         Neighbourhood Number  City of Toronto
1  Neighbourhood Information         TSNS2020 Designation  City of Toronto
2   Population and dwellings             Population, 2016  City of Toronto
3   Population and dwellings             Population, 2011  City of Toronto
4   Population and dwellings  Population Change 2011-2016  City of Toronto

       value
0        NaN
1        NaN
2  2,731,571
3  2,615,060
4      4.50%
```

5.6 Reshaping data with pivot()

The profile data is looking much closer to what we want! The next step is to make the Topic/Characteristic the column header, `pivot()`ing the values. To do this, we specify the column(s) to use as the `index`, or row labels; the column(s) whose values we should use as `column` names, and which column our `values` come from.

Pivoting on two columns creates a multi-level column header, so we then drop the top `Topic` level with `droplevel()`. Finally, we `reset_index()` to make neighbourhood names a regular column.

[ ]:
```
neighbourhoods = (profiles_melt.pivot(index='Neighbourhood',
                                      columns=['Topic', 'Characteristic'],
                                      values='value')
                               .droplevel(0, axis=1) # remove topic col header
                               .reset_index()) # make Neighbourhood a regular␣
 ↪column
neighbourhoods.head()
```

[ ]:
```
Characteristic                  Neighbourhood Neighbourhood Number  \
0                             Agincourt North                  129
1                Agincourt South-Malvern West                  128
2                                   Alderwood                   20
3                                       Annex                   95
4                           Banbury-Don Mills                   42

Characteristic TSNS2020 Designation Population, 2016 Population, 2011  \
0                    No Designation           29,113           30,279
1                    No Designation           23,757           21,988
2                    No Designation           12,054           11,904
3                    No Designation           30,526           29,177
```

```
4                   No Designation          27,695          26,918

Characteristic Population Change 2011-2016 Total private dwellings  \
0                                 -3.90%                    9,371
1                                  8.00%                    8,535
2                                  1.30%                    4,732
3                                  4.60%                   18,109
4                                  2.90%                   12,473

Characteristic Private dwellings occupied by usual residents  \
0                                                   9,120
1                                                   8,136
2                                                   4,616
3                                                  15,934
4                                                  12,124

Characteristic Population density per square kilometre  \
0                                                3,929
1                                                3,034
2                                                2,435
3                                               10,863
4                                                2,775

Characteristic Land area in square kilometres  \
0                                         7.41
1                                         7.83
2                                         4.95
3                                         2.81
4                                         9.98

Characteristic Total - Main mode of commuting for the employed labour force aged
15 years and over in private households with a usual place of work or no fixed
workplace address - 25% sample data  \
0                                                     11,820
1                                                     10,160
2                                                      6,045
3                                                     14,910
4                                                     11,395

Characteristic Car, truck, van - as a driver Car, truck, van - as a passenger  \
0                                      7,155                              930
1                                      6,135                              665
2                                      4,090                              355
3                                      3,290                              290
4                                      7,150                              500

Characteristic Public transit Walked Bicycle Other method
```

```
0                        3,350    265      70            45
1                        2,985    280      35            65
2                        1,285    195      65            65
3                        6,200  3,200   1,675           225
4                        2,945    615      65           140
```

5.7 Renaming all columns

Much better! These column names could be shorter, though. Let's rename them to be easier to work with. We could use the `rename()` DataFrame method, passing in a dictionary of old and new names. Since there isn't an easy renaming function, and some of the current names are very long, we will instead reassign a list of new names to the `columns` attribute of our DataFrame.

```
[ ]: # rename all columns
neighbourhoods.columns = ['neighbourhood',
                          'n_id',
                          'designation',
                          'pop_2016',
                          'pop_2011',
                          'pop_change',
                          'private_dwellings',
                          'occupied_dwllings',
                          'pop_dens',
                          'area',
                          'total_commuters',
                          'drive',
                          'car_passenger',
                          'transit',
                          'walk',
                          'bike',
                          'other']
neighbourhoods.columns
```

```
[ ]: Index(['neighbourhood', 'n_id', 'designation', 'pop_2016', 'pop_2011',
        'pop_change', 'private_dwellings', 'occupied_dwllings', 'pop_dens',
        'area', 'total_commuters', 'drive', 'car_passenger', 'transit', 'walk',
        'bike', 'other'],
       dtype='object')
```

5.8 Replacing values in multiple columns

All of the values in our neighbourhood data are text right now. Part of the problem is that numbers contain characters like commas and percentage signs. We can remove these from everywhere in our data with the DataFrame `replace()` method, which takes a string to look for and a replacement string. Normally, `replace()` looks for a perfect, full-string match. Since we're only looking for a substring match, we set `regex=True`.

```
[ ]: # for those comfortable with regex, ',|%' and '[,%]' also work
     neighbourhoods = (neighbourhoods.replace(',', '', regex=True)
                                     .replace('%', '', regex=True))
     neighbourhoods.head(2)
```

```
[ ]:                    neighbourhood n_id     designation pop_2016 pop_2011  \
     0                Agincourt North  129  No Designation    29113    30279
     1  Agincourt South-Malvern West  128  No Designation    23757    21988

       pop_change private_dwellings occupied_dwllings pop_dens  area  \
     0      -3.90              9371              9120     3929  7.41
     1       8.00              8535              8136     3034  7.83

       total_commuters drive car_passenger transit walk bike other
     0           11820  7155           930    3350  265   70    45
     1           10160  6135           665    2985  280   35    65
```

5.9 apply()ing a function to multiple columns

Now the numbers look like numbers, but they are still strings. We can convert them with `pd.to_numeric()`, which takes a Series and returns it as the most appropriate numeric data type. Doing this for columns one-by-one would be tedious. Instead, we can use the `apply()` DataFrame method to run a function on every column in a DataFrame. `apply()` takes the name of the function to apply and any arguments needed to run that function. We only want to convert from `pop_2016` onwards, so we'll use `.loc[]` to select the correct columns.

```
[ ]: # select all rows, columns from pop_2016 to end
     neighbourhoods.loc[:, 'pop_2016':] = neighbourhoods.loc[:, 'pop_2016':].
      ↪apply(pd.to_numeric)
     neighbourhoods.head()
```

```
[ ]:                    neighbourhood n_id     designation pop_2016 pop_2011  \
     0                Agincourt North  129  No Designation  29113.0  30279.0
     1  Agincourt South-Malvern West  128  No Designation  23757.0  21988.0
     2                      Alderwood   20  No Designation  12054.0  11904.0
     3                          Annex   95  No Designation  30526.0  29177.0
     4              Banbury-Don Mills   42  No Designation  27695.0  26918.0

       pop_change private_dwellings occupied_dwllings pop_dens  area  \
     0       -3.9            9371.0            9120.0   3929.0  7.41
     1        8.0            8535.0            8136.0   3034.0  7.83
     2        1.3            4732.0            4616.0   2435.0  4.95
     3        4.6           18109.0           15934.0  10863.0  2.81
     4        2.9           12473.0           12124.0   2775.0  9.98

       total_commuters   drive car_passenger transit    walk    bike   other
```

```
0        11820.0  7155.0        930.0  3350.0   265.0    70.0   45.0
1        10160.0  6135.0        665.0  2985.0   280.0    35.0   65.0
2         6045.0  4090.0        355.0  1285.0   195.0    65.0   65.0
3        14910.0  3290.0        290.0  6200.0  3200.0  1675.0  225.0
4        11395.0  7150.0        500.0  2945.0   615.0    65.0  140.0
```

[ ]:
```
# confirm dtypes
neighbourhoods.dtypes
```

[ ]:
```
neighbourhood         object
n_id                  object
designation           object
pop_2016              object
pop_2011              object
pop_change            object
private_dwellings     object
occupied_dwllings     object
pop_dens              object
area                  object
total_commuters       object
drive                 object
car_passenger         object
transit               object
walk                  object
bike                  object
other                 object
dtype: object
```

5.10 Calculating more columns

Let's fix the population change column and calculate the percentage of commuters who bike.

[ ]:
```
neighbourhoods['pop_change'] = neighbourhoods['pop_change'] / 100
neighbourhoods['pct_bike'] = neighbourhoods['bike'] /␣
 ↪neighbourhoods['total_commuters']
neighbourhoods.head()
```

[ ]:
```
                  neighbourhood n_id     designation pop_2016 pop_2011  \
0               Agincourt North  129  No Designation  29113.0  30279.0
1  Agincourt South-Malvern West  128  No Designation  23757.0  21988.0
2                     Alderwood   20  No Designation  12054.0  11904.0
3                         Annex   95  No Designation  30526.0  29177.0
4             Banbury-Don Mills   42  No Designation  27695.0  26918.0

  pop_change private_dwellings occupied_dwllings pop_dens  area  \
0     -0.039            9371.0            9120.0   3929.0  7.41
```

```
1      0.08             8535.0            8136.0   3034.0  7.83
2     0.013             4732.0            4616.0   2435.0  4.95
3     0.046            18109.0           15934.0  10863.0  2.81
4     0.029            12473.0           12124.0   2775.0  9.98

  total_commuters   drive car_passenger transit    walk    bike  other  \
0         11820.0  7155.0         930.0  3350.0   265.0    70.0   45.0
1         10160.0  6135.0         665.0  2985.0   280.0    35.0   65.0
2          6045.0  4090.0         355.0  1285.0   195.0    65.0   65.0
3         14910.0  3290.0         290.0  6200.0  3200.0  1675.0  225.0
4         11395.0  7150.0         500.0  2945.0   615.0    65.0  140.0

   pct_bike
0  0.005922
1  0.003445
2  0.010753
3  0.112341
4  0.005704
```

5.11 merge()ing

The profile are now ready to merge into the bike thefts data!

[ ]:
```
thefts_demo = pd.merge(thefts,
                       neighbourhoods,
                       how='left',
                       left_on='hood_id',
                       right_on='n_id')
thefts_demo.head()
```

[ ]:
```
   _id  objectid event_unique_id        primary_offence occurrence_date  \
0    1     17744  GO-20179016397            THEFT UNDER      2017-10-03
1    2     17759  GO-20172033056  THEFT UNDER - BICYCLE      2017-11-08
2    3     17906  GO-20189030822  THEFT UNDER - BICYCLE      2018-09-14
3    4     17962   GO-2015804467            THEFT UNDER      2015-05-07
4    5     17963  GO-20159002781            THEFT UNDER      2015-05-16

   occurrence_year occurrence_month occurrence_dayofweek  \
0             2017          October              Tuesday
1             2017         November            Wednesday
2             2018        September               Friday
3             2015              May             Thursday
4             2015              May             Saturday

   occurrence_dayofmonth  occurrence_dayofyear  occurrence_hour report_date  \
0                      3                   276               14  2017-10-03
```

```
1                   8                   312                 3  2017-11-08
2                  14                   257                 9  2018-09-17
3                   7                   127                18  2015-05-14
4                  16                   136                12  2015-05-16

   report_year report_month report_dayofweek  report_dayofmonth  \
0         2017      October          Tuesday                  3
1         2017     November        Wednesday                  8
2         2018    September           Monday                 17
3         2015          May         Thursday                 14
4         2015          May         Saturday                 16

   report_dayofyear  report_hour division     city hood_id  \
0               276           18      D22  Toronto      15
1               312           22      D22  Toronto      15
2               260           16      D22  Toronto      15
3               134           14      D22  Toronto      15
4               136           15      D22  Toronto      15

     neighbourhoodname                                      location_type  \
0  Kingsway South (15)  Streets, Roads, Highways (Bicycle Path, Privat…
1  Kingsway South (15)  Single Home, House (Attach Garage, Cottage, Mo…
2  Kingsway South (15)                                 Ttc Subway Station
3  Kingsway South (15)                                 Ttc Subway Station
4  Kingsway South (15)                                 Ttc Subway Station

  premises_type     bike_make  bike_model bike_type  bike_speed bike_colour  \
0       Outside            GI    ESCAPE 2        OT           7         BLK
1         House  UNKNOWN MAKE         NaN        TO           1         BLK
2       Transit            OT  CROSSTRAIL        MT          24         BLK
3       Transit            GT         NaN        TO          10      BLKDGR
4       Transit            GI         NaN        MT           6         RED

   bike_cost     status  objectid2  \
0      700.0     STOLEN          1
1     1100.0  RECOVERED          2
2      904.0     STOLEN          3
3      400.0     STOLEN          4
4      600.0     STOLEN          5

                                            geometry   neighbourhood n_id  \
0  {'type': 'Point', 'coordinates': (-79.50655965…  Kingsway South   15
1  {'type': 'Point', 'coordinates': (-79.50484874…  Kingsway South   15
2  {'type': 'Point', 'coordinates': (-79.51170915…  Kingsway South   15
3  {'type': 'Point', 'coordinates': (-79.51170915…  Kingsway South   15
4  {'type': 'Point', 'coordinates': (-79.51132657…  Kingsway South   15
     designation pop_2016 pop_2011 pop_change private_dwellings  \
0  No Designation   9271.0   9170.0      0.011            3710.0
1  No Designation   9271.0   9170.0      0.011            3710.0
2  No Designation   9271.0   9170.0      0.011            3710.0
3  No Designation   9271.0   9170.0      0.011            3710.0
4  No Designation   9271.0   9170.0      0.011            3710.0

  occupied_dwllings pop_dens  area total_commuters   drive car_passenger  \
0            3584.0   3593.0  2.58          3735.0  2210.0         120.0
1            3584.0   3593.0  2.58          3735.0  2210.0         120.0
2            3584.0   3593.0  2.58          3735.0  2210.0         120.0
3            3584.0   3593.0  2.58          3735.0  2210.0         120.0
4            3584.0   3593.0  2.58          3735.0  2210.0         120.0

  transit   walk  bike other  pct_bike
0  1185.0  115.0  30.0  50.0  0.008032
1  1185.0  115.0  30.0  50.0  0.008032
2  1185.0  115.0  30.0  50.0  0.008032
3  1185.0  115.0  30.0  50.0  0.008032
4  1185.0  115.0  30.0  50.0  0.008032
```

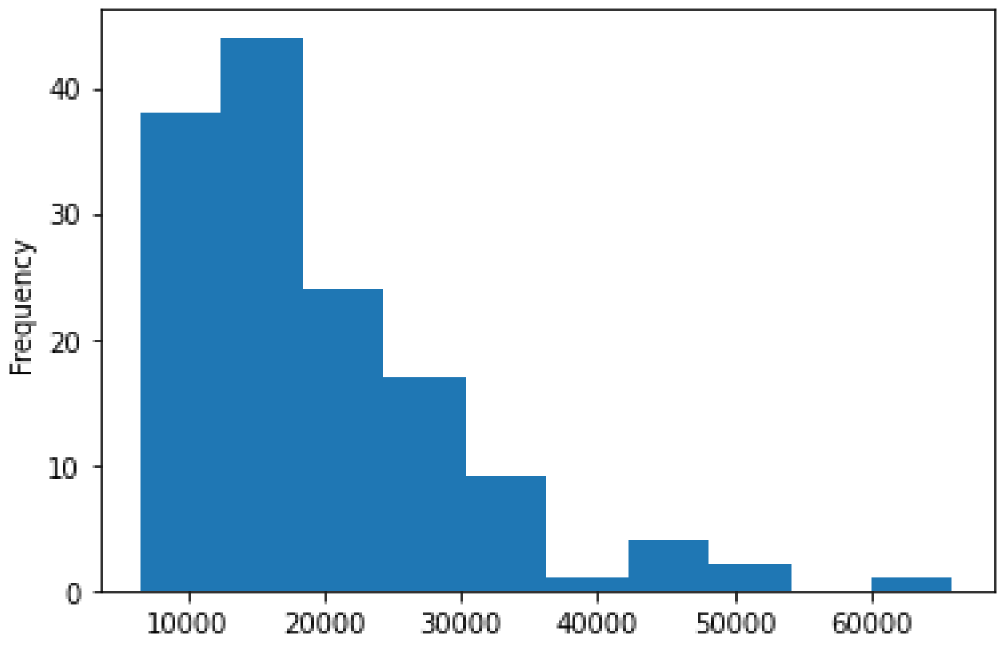
5.12 Grouping and plotting

With the datasets joned, we can aggregate and plot the data. We can start using statistical methods, like `corr()` to check for relationships between variables as well.

```
[ ]: thefts_2016_grouped = (thefts_demo
                            .query('occurrence_year == 2016')
                            .groupby(['neighbourhood']))
```

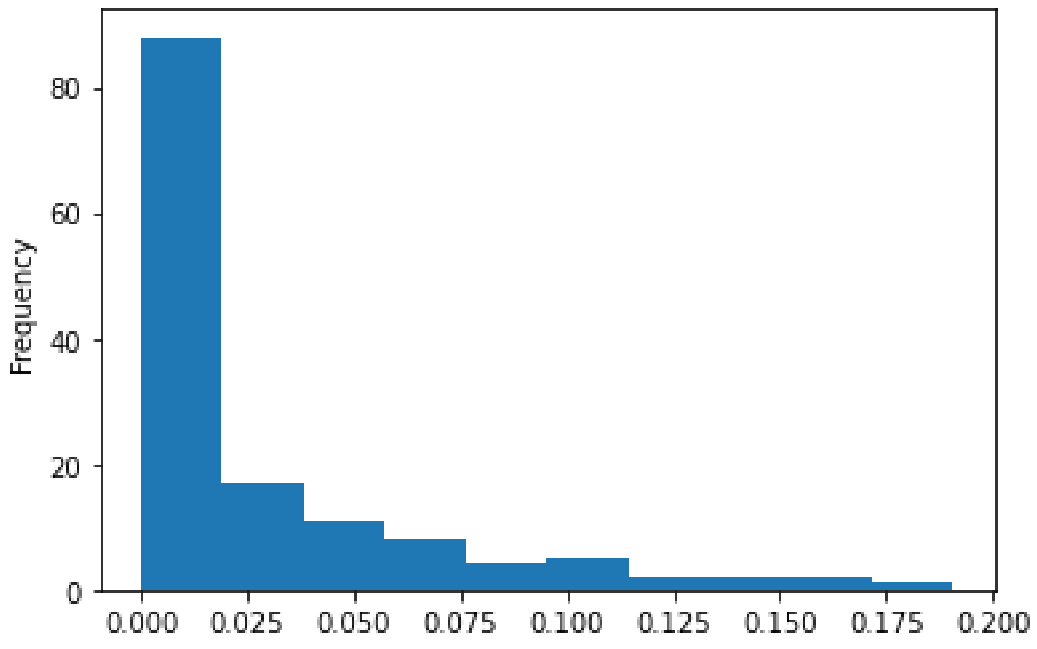
```
[ ]: # neighbourhood populations are skewed
     neighbourhoods.query('neighbourhood != "City of Toronto"')['pop_2016'].
      ↪plot(kind='hist')
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3f7e297d0>
```



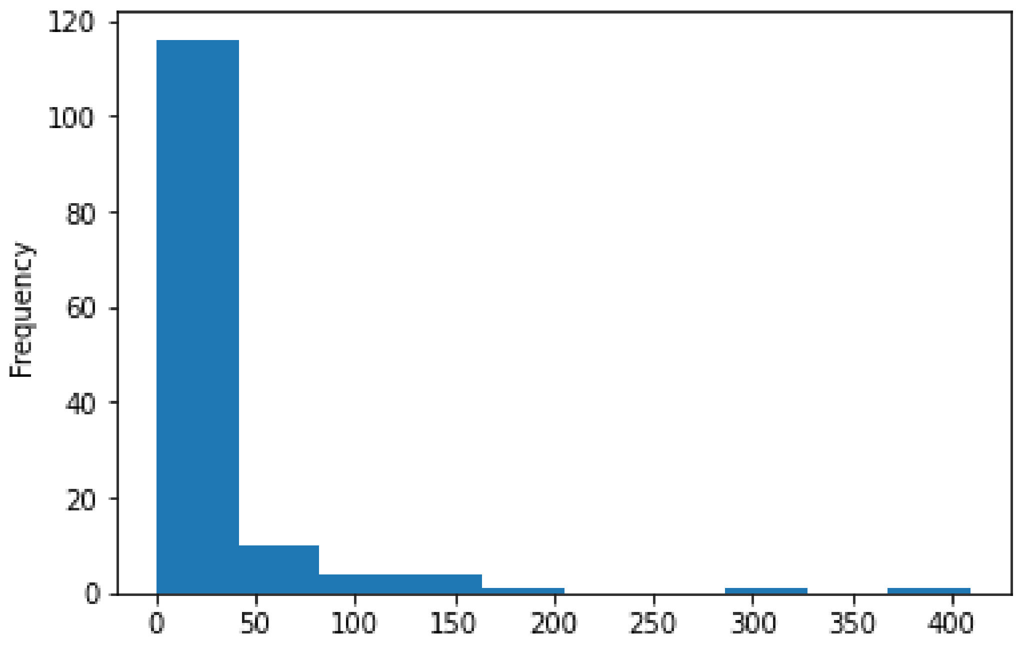
```
[ ]: # so are the % of commuters who bike to work
     neighbourhoods.query('neighbourhood != "City of Toronto"')['pct_bike'].
      ↪plot(kind='hist')
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3f7b61e50>
```



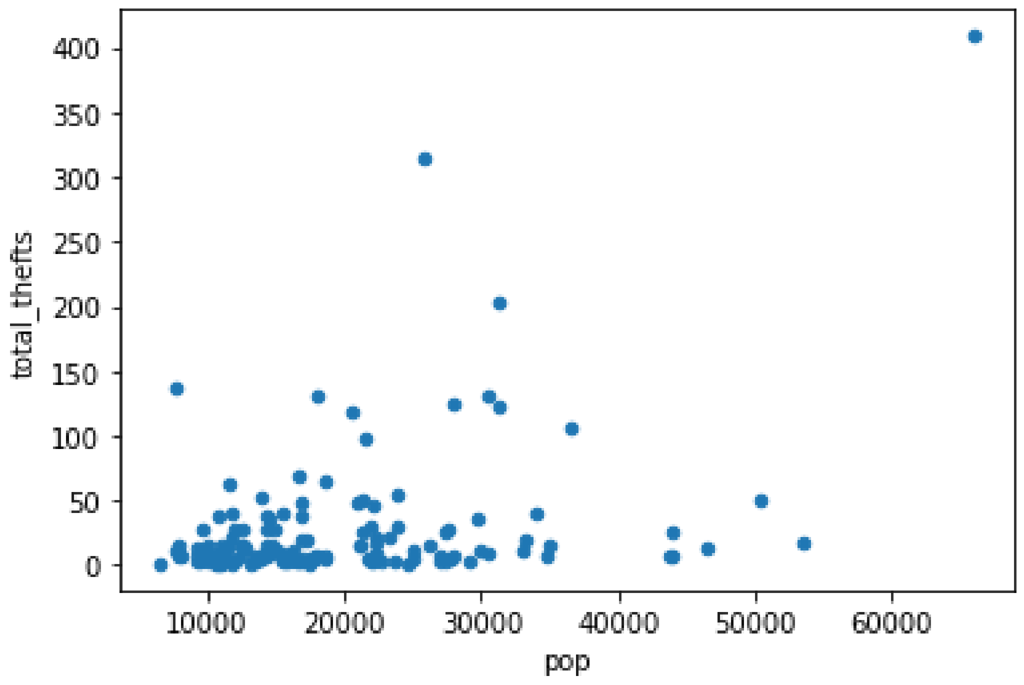
```
[ ]: # as are thefts
     thefts_2016_grouped.size().plot(kind='hist')
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3f7b5bc90>
```



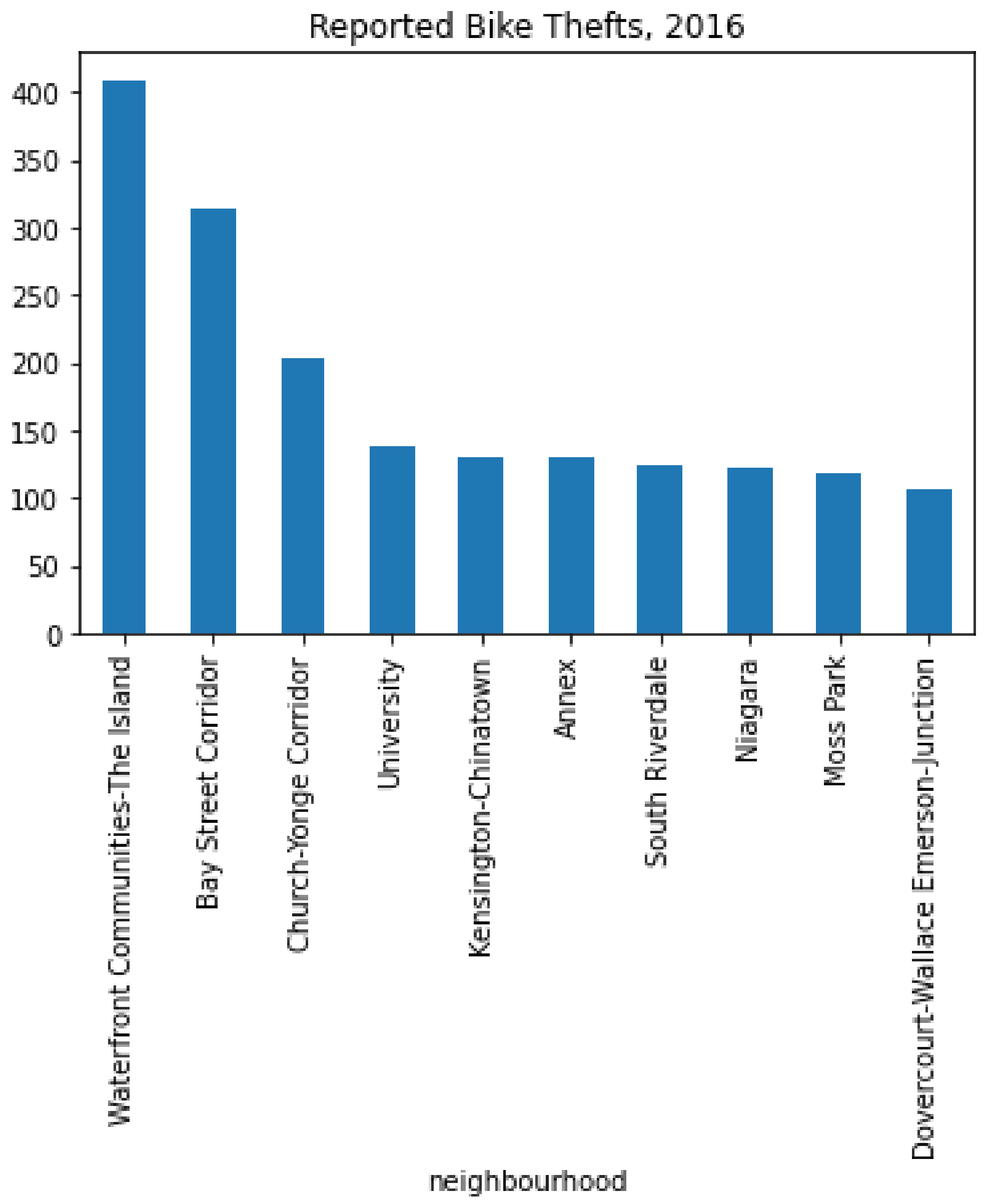
```
[ ]: # thefts counts vs population
     (thefts_2016_grouped
      .agg(total_thefts=('_id', 'count'),
           pop=('pop_2016', 'median'),
           pct_bike=('pct_bike', 'mean'))
      .reset_index()
      .plot(kind='scatter', y='total_thefts', x='pop'))
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3f7a3bcd0>
```



```
[ ]: (thefts_2016_grouped
      .size()
      .sort_values(ascending=False)
      .head(10)
      .plot(kind='bar', title='Reported Bike Thefts, 2016'))
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe3f79c4b90>
```



```
[ ]: # a quick correlation check
     (thefts_2016_grouped
      .agg(total_thefts=('_id', 'count'),
           pop=('pop_2016', 'median'),
           dens=('pop_dens', 'median'),
           pct_bike=('pct_bike', 'mean'))
      .corr('spearman'))
```

```
[ ]:               total_thefts       pop      dens  pct_bike
     total_thefts      1.000000  0.267761  0.485556  0.651319
```

```
pop              0.267761  1.000000  0.020082 -0.222565
dens             0.485556  0.020082  1.000000  0.605242
pct_bike         0.651319 -0.222565  0.605242  1.000000
```

[ ]:
```
thefts_demo.to_csv('/content/data/bike_thefts_joined.csv', index=False)
neighbourhoods.to_csv('/content/data/neighbourhoods.csv', index=False)
```

6 References

6.0.1 Programming

- pandas development team. *API reference.* https://pandas.pydata.org/pandas-docs/stable/reference/index.html
- pandas development team. *User guide.* https://pandas.pydata.org/pandas-docs/stable/user_guide/index.html
- *Python strftime cheatsheet.* https://strftime.org/

6.0.2 Data Sources

- Open Data Toronto. *Neighbourhood Profiles.* https://open.toronto.ca/dataset/neighbourhood-profiles/
- Open Data Toronto. *TTC Subway Delay Data.* https://open.toronto.ca/dataset/ttc-subway-delay-data/
- Open Data Toronto. *Bicyle Thefts.* https://open.toronto.ca/dataset/bicycle-thefts/