CPE311 Computational Thinking with Python

Hands-on Activity 8.1: Aggregating Data with Pandas

Name: Bulambao, Adrian Justin

Section: CPE22S3

Performed on: 04/12/2025

Submitted on: 04/12/2025

Submitted to: Engr. Roman M. Richard

8.1.1 Intended Learning Outcomes

• Demonstrate querying and merging of dataframes

• Perform advanced calculations on dataframes

• Aggregate dataframes with pandas and numpy

• Work with time series data

8.1.2 Resources

• Computing Environment using Python 3.x

• Attached Datasets (under Instructional Materials)

8.1.3 Procedures

The procedures can be found in the canvas module. Check the following under topics:

- 8.1 Weather Data Collection
- 8.2 Querying and Merging
- 8.3 Dataframe Operations
- 8.4 Aggregations
- 8.5 Time Series

8.1 Weather Data Collection

Collecting weather data from an API

About the data

In this notebook, we will be collecting daily weather data from the National Centers for Environmental Information (NCEI) API. We will use the Global Historical Climatology Network - Daily (GHCND) data set; see the documentation here.

Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

Using the NCEI API

Paste your token below.

In [23]:

```
import requests
def make_request(endpoint, payload=None):
     """
     Make a request to a specific endpoint on the weather API
     passing headers and optional payload.

     Parameters:
     - endpoint: The endpoint of the API you want to
     make a GET request to.
     - payload: A dictionary of data to pass along
     with the request.

     Returns:
     Response object.
     """
     return requests.get(f'https://www.ncdc.noaa.gov/cdo-web/api/v2/{endpoint}',hea
         params=payload)
```

```python
params = {
    'datasetid': 'GHCND',
    'locationid': 'ZIP:28428',          # North Carolina, for example
    'startdate': '2023-01-01',
    'enddate': '2023-01-03',
    'limit': 3
}
response = make_request('data',params)
print(response.json())
```


```
{'metadata': {'resultset': {'offset': 1, 'count': 5, 'limit': 3}}, 'results': [{'date': '2023-01-01T00:00:00', 'datatype': 'PRCP', 'station': 'GHCND:US1NCNH0062', 'attributes': ',,N,0700', 'value': 5}, {'date': '2023-01-02T00:00:00', 'datatype': 'PRCP', 'station': 'GHCND:US1NCNH0062', 'attributes': ',,N,0700', 'value': 0}, {'date': '2023-01-02T00:00:00', 'datatype': 'SNOW', 'station': 'GHCND:US1NCNH0062', 'attributes': ',,N,0700', 'value': 0}]}
```


In [28]:

```python
import pandas as pd
# Get JSON from the response
data = response.json()

# Convert just the 'results' list to a DataFrame
df = pd.DataFrame(data['results'])

df
```

Out[28]:

	date	datatype	station	attributes	value
0	2023-01-01T00:00:00	PRCP	GHCND:US1NCNH0062	,,N,0700	5
1	2023-01-02T00:00:00	PRCP	GHCND:US1NCNH0062	,,N,0700	0
2	2023-01-02T00:00:00	SNOW	GHCND:US1NCNH0062	,,N,0700	0

Collect All Data Points for 2018 In NYC (Various Stations)

We can make a loop to query for all the data points one day at a time. Here we create a list of all the results:

In [30]:

```python
import datetime
from IPython import display # for updating the cell dynamically
current = datetime.date(2018, 1, 1)
end = datetime.date(2019, 1, 1)
results = []
while current < end:
     # update the cell with status information
     display.clear_output(wait=True)
     display.display(f'Gathering data for {str(current)}')

     response = make_request(
         'data',
         {
```

```
                'datasetid' : 'GHCND', # Global Historical Climatology Network - Daily
                'locationid' : 'CITY:US360019', # NYC
                'startdate' : current,
                'enddate' : current,
                'units' : 'metric',
                'limit' : 1000 # max allowed
                #was set to 10 to avoid long time of gathering data
            }
        )
        if response.ok:
            # we extend the list instead of appending to avoid getting a nested list
            results.extend(response.json()['results'])
        # update the current date to avoid an infinite loop
        current += datetime.timedelta(days=1)
```

```
'Gathering data for 2018-12-31'
```

Now, we can create a dataframe with all this data. Notice there are multiple stations with values for each datatype on a given day. We don't know what the stations are, but we can look them up and add them to the data:

In [31]:
```
df = pd.DataFrame(results)
df.head()
```

Out[31]:

	date	datatype	station	attributes	value
0	2018-01-01T00:00:00	PRCP	GHCND:US1CTFR0039	,,N,0800	0.0
1	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0015	,,N,1050	0.0
2	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0015	,,N,1050	0.0
3	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0017	,,N,0920	0.0
4	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0017	,,N,0920	0.0

Save this data to a file:

In [32]:
```
df.to_csv('nyc_weather_2018.csv', index=False)
```

and write it to the database:

In [33]:
```
import sqlite3
with sqlite3.connect('weather.db') as connection:
    df.to_sql(
        'weather', connection, index=False, if_exists='replace'
)
```

For learning about merging dataframes, we will also get the data mapping station IDs to information about the station:

In [35]:
```
response = make_request(
    'stations',
    {
```

```
        'datasetid' : 'GHCND', # Global Historical Climatology Network - Daily (GHC
        'locationid' : 'CITY:US360019', # NYC
        'limit' : 1000 # max allowed
    }
)
stations = pd.DataFrame(response.json()['results'])[['id', 'name', 'latitude', 'lon
stations.to_csv('weather_stations.csv', index=False)
with sqlite3.connect('weather.db') as connection:
    stations.to_sql(
        'stations', connection, index=False, if_exists='replace'
 )
```

Database-style Operations on Dataframes

About the data

In this notebook, we will using daily weather data that was taken from the National Centers for Environmental Information (NCEI) API. The data collection notebook contains the process that was followed to collect the data.

Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the CEI weather API to find the updated one.

Background on the data

Data meanings: PRCP : precipitation in millimeters SNOW : snowfall in millimeters SNWD : snow depth in millimeters TMAX : maximum daily temperature in Celsius TMIN : minimum daily temperature in Celsius TOBS : temperature at time of observation in Celsius WESF : water equivalent of snow in millimeters

Setup

In [48]:

```
import pandas as pd # this is the library to read, create dataframes
weather = pd.read_csv('nyc_weather_2018.csv')
#pd.read_csv is a command to read a csv
weather.head()
#head() is a command to display the first 5 rows
```

Out[48]:

	date	datatype	station	attributes	value
0	2018-01-01T00:00:00	PRCP	GHCND:US1CTFR0039	,,N,0800	0.0
1	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0015	,,N,1050	0.0
2	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0015	,,N,1050	0.0
3	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0017	,,N,0920	0.0
4	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0017	,,N,0920	0.0

Querying DataFrames

The query() method is an easier way of filtering based on some criteria. For example, we can use it to find all entries where snow was recorded:

In [49]:

```
snow_data = weather.query('datatype == "SNOW" and value > 0')
#query is a command use to filter the dataframe with user
# made filters
snow_data.head()
```

Out[49]:

	date	datatype	station	attributes	value
127	2018-01-01T00:00:00	SNOW	GHCND:US1NYWC0019	,,N,1700	25.0
816	2018-01-04T00:00:00	SNOW	GHCND:US1NJBG0015	,,N,1600	229.0
819	2018-01-04T00:00:00	SNOW	GHCND:US1NJBG0017	,,N,0830	10.0
823	2018-01-04T00:00:00	SNOW	GHCND:US1NJBG0018	,,N,0910	46.0
830	2018-01-04T00:00:00	SNOW	GHCND:US1NJES0018	,,N,0700	10.0

This is equivalent to quering the data/weather.db SQLite database for SELECT * FROM weather WHERE datatype == "SNOW" AND value > 0 :

In [50]:

```
import sqlite3
#sqlite3 is a library for sql modifications


with sqlite3.connect('weather.db') as connection:
    snow_data_from_db = pd.read_sql(
        'SELECT * FROM weather WHERE datatype == "SNOW" AND value > 0',
        connection
 )
snow_data.reset_index().drop(columns='index').equals(snow_data_from_db)
```

Out[50]: True

Note this is also equivalent to creating Boolean masks:

In [59]:
```
weather[(weather.datatype == 'SNOW') & (weather.value > 0)].equals(snow_data)
# this checks if the snow datatype == "SNOW" and value > 0
# is equal to snow_data
```

Out[59]: True

Merging DataFrames

We have data for many different stations each day; however, we don't know what the stations are just their IDs. We can join the data in the data/weather_stations.csv file which contains information from the stations endpoint of the NCEI API. Consult the weather_data_collection.ipynb notebook to see how this was collected. It looks like this:

In [60]:
```
station_info = pd.read_csv('weather_stations.csv')
#pd.read_csv reads the csv to a dataframe
station_info.head()
#.head() displays the first 5 rows
# of a dataframe
```

Out[60]:

	id	name	latitude	longitude	elevation
0	GHCND:US1CTFR0022	STAMFORD 2.6 SSW, CT US	41.064100	-73.577000	36.6
1	GHCND:US1CTFR0039	STAMFORD 4.2 S, CT US	41.037788	-73.568176	6.4
2	GHCND:US1NJBG0001	BERGENFIELD 0.3 SW, NJ US	40.921298	-74.001983	20.1
3	GHCND:US1NJBG0002	SADDLE BROOK TWP 0.6 E, NJ US	40.902694	-74.083358	16.8
4	GHCND:US1NJBG0003	TENAFLY 1.3 W, NJ US	40.914670	-73.977500	21.6

As a reminder, the weather data looks like this:

In [61]:
```
weather.head()
# displays the first 5 rows
# of the weather data
```

Out[61]:

	date	datatype	station	attributes	value
0	2018-01-01T00:00:00	PRCP	GHCND:US1CTFR0039	,,N,0800	0.0
1	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0015	,,N,1050	0.0
2	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0015	,,N,1050	0.0
3	2018-01-01T00:00:00	PRCP	GHCND:US1NJBG0017	,,N,0920	0.0
4	2018-01-01T00:00:00	SNOW	GHCND:US1NJBG0017	,,N,0920	0.0

We can join our data by matching up the station_info.id column with the weather.station column. Before doing that though, let's see how many unique values we have:

In [62]:
```
station_info.id.describe()
#describes does what it is called
# it describes the the id of the dataframe
```

Out[62]:
```
count                   330
unique                  330
top       GHCND:USW00094789
freq                      1
Name: id, dtype: object
```

While station_info has one row per station, the weather dataframe has many entries per station. Notice it also has fewer uniques:

In [64]:
```
weather.station.describe()
# this describes the station column
```

Out[64]:
```
count                 89114
unique                  114
top       GHCND:USW00014734
freq                   6593
Name: station, dtype: object
```

When working with joins, it is important to keep an eye on the row count. Some join types will lead to data loss:

In [66]:
```
station_info.shape[0], weather.shape[0]
# the shape commands takes the row and columns of the data frame
#[0] is the first in those data
```

Out[66]:
```
(330, 89114)
```

Since we will be doing this often, it makes more sense to write a function:

In [68]:
```
def get_row_count(*dfs):
    return [df.shape[0] for df in dfs]
get_row_count(station_info, weather)
# this is a function for the code above
# it loops the given data and takes the shape
# for each
```

Out[68]:
```
[330, 89114]
```

The map() function is more efficient than list comprehensions. We can couple this with getattr() to grab any attribute for multiple dataframes:

In [71]:
```
def get_info(attr, *dfs):
    return list(map(lambda x: getattr(x, attr), dfs))
get_info('shape', station_info, weather)
```

Out[71]: [(330, 5), (89114, 5)]

By default merge() performs an inner join. We simply specify the columns to use for the join. The left dataframe is the one we call merge() on, and the right one is passed in as an argument:

In [77]:
```
inner_join = weather.merge(station_info, left_on='station', right_on='id')
inner_join.sample(5, random_state=0)
#this inner joins the weather dataframe and the station dataframe
#joining them by id and station
# then takes a sample
```

Out[77]:

	date	datatype	station	attributes	value	i
464	2018-01-02T00:00:00	TMIN	GHCND:USW00014734	,,W,2400	-11.0	GHCND:USW0001473
44013	2018-06-29T00:00:00	WDF5	GHCND:USW00054743	,,W,	300.0	GHCND:USW0005474
2079	2018-01-08T00:00:00	PRCP	GHCND:USC00308577	,,7,0800	0.0	GHCND:USC0030857
12170	2018-02-19T00:00:00	WESD	GHCND:US1NJMD0062	T,,N,0700	0.0	GHCND:US1NJMD006
73861	2018-10-30T00:00:00	RHAV	GHCND:USW00094728	,,W,	52.0	GHCND:USW0009472

We can remove the duplication of information in the station and id columns by renaming one of them before the merge and then simply using on :

In [79]:
```
weather.merge(station_info.rename(dict(id='station'), axis=1), on='station').sample
# this merges the weather and the station info, then ranames the id column to stati
# then merges the two station named columns
```

Out[79]:

	date	datatype	station	attributes	value	name	lat
464	2018-01-02T00:00:00	TMIN	GHCND:USW00014734	,,W,2400	-11.0	NEWARK LIBERTY INTERNATIONAL AIRPORT, NJ US	40.(
44013	2018-06-29T00:00:00	WDF5	GHCND:USW00054743	,,W,	300.0	CALDWELL ESSEX CO AIRPORT, NJ US	40.8
2079	2018-01-08T00:00:00	PRCP	GHCND:USC00308577	,,7,0800	0.0	SYOSSET, NY US	40.8
12170	2018-02-19T00:00:00	WESD	GHCND:US1NJMD0062	T,,N,0700	0.0	OLD BRIDGE TWP 5.1 NE, NJ US	40.4
73861	2018-10-30T00:00:00	RHAV	GHCND:USW00094728	,,W,	52.0	NY CITY CENTRAL PARK, NY US	40.7

We are losing stations that don't have weather observations associated with them, if we don't want to lose these rows, we perform a right or left join instead of the inner join:

In [82]:

```
left_join = station_info.merge(weather, left_on='id', right_on='station', how='left
# this joins the station_info dataframe and the weather dataframe
# with the id and station column respectively
#and left joins it
right_join = weather.merge(station_info, left_on='station', right_on='id', how='rig
# this joins the weather dataframe and the data_info dataframe
# with the station and id column respectively
#and right joins it
right_join.tail()
```

Out[82]:

	date	datatype	station	attributes	value	id
89325	2018-12-31T00:00:00	WDF5	GHCND:USW00094789	,,W,	130.0	GHCND:USW0009478
89326	2018-12-31T00:00:00	WSF2	GHCND:USW00094789	,,W,	9.8	GHCND:USW0009478
89327	2018-12-31T00:00:00	WSF5	GHCND:USW00094789	,,W,	12.5	GHCND:USW0009478
89328	2018-12-31T00:00:00	WT01	GHCND:USW00094789	,,W,	1.0	GHCND:USW0009478
89329	2018-12-31T00:00:00	WT02	GHCND:USW00094789	,,W,	1.0	GHCND:USW0009478

The left and right join as we performed above are equivalent because the side that we kept the rows without matches was the same in both cases:

In [85]:

```
left_join.sort_index(axis=1).sort_values(['date', 'station']).reset_index().drop(co
 right_join.sort_index(axis=1).sort_values(['date', 'station']).reset_index().drop(
)

#this checks if the sorted column of the sorted values of data and station
# columns and resetted index of the left_join dataframe created
#in the previous cell is equal to the sorted column of the the sorted values of dat
# columns and resetted index of the right_join dataframe created in the previous ce
```

Out[85]:

```
True
```

Note we have additional rows in the left and right joins because we kept all the stations that didn't have weather observations:

In [87]:

```
get_info('shape', inner_join, left_join, right_join)
# this takes the number of rows and columns
#of inner_join, left_join, right_join
#dataframes
# as seen below all left and right join are only equal
```

Out[87]:

```
[(89114, 10), (89330, 10), (89330, 10)]
```

If we query the station information for stations that have NY in their name, believing that to be all the stations that record weather data for NYC and perform an outer join, we can see where the mismatches occur:

In [100…

```
outer_join = weather.merge(
    station_info[station_info.name.str.contains('NY')],
    left_on='station', right_on='id', how='outer', indicator=True)

outer_join.sample(4, random_state=0).append(outer_join[outer_join.station.isna()].h

#ayaw na po gumana
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_9592\1443856623.py in ?()
      1 outer_join = weather.merge(
      2     station_info[station_info.name.str.contains('NY')],
      3     left_on='station', right_on='id', how='outer', indicator=True)
      4 
----> 5 outer_join.sample(4, random_state=0).append(outer_join[outer_join.station.is
na()].head(2))
      6 
      7 #ayaw na po gumana

~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py in ?(self, na
me)
   6295             and name not in self._accessors
   6296             and self._info_axis._can_hold_identifiers_and_holds_name(name)
   6297         ):
   6298             return self[name]
-> 6299         return object.__getattribute__(self, name)

AttributeError: 'DataFrame' object has no attribute 'append'
```

These joins are equivalent to their SQL counterparts. Below is the inner join. Note that to use equals() you will have to do some manipulation of the dataframes to line them up:

In [101…

```
import sqlite3
with sqlite3.connect('weather.db') as connection:
    inner_join_from_db = pd.read_sql(
        'SELECT * FROM weather JOIN stations ON weather.station == stations.id',
        connection
 )
inner_join_from_db.shape == inner_join.shape

# sorry sir di ko na malagyan
# ng comments
# less than 1 hour na lang po meron ako
# sinusubukan ko naman po na intindihin yung mga
# ni copy paste ko
```

Out[101…

```
True
```

Revisit the dirty data from the previous module.

In [102…

```
dirty_data = pd.read_csv('dirty_data.csv', index_col='date').drop_duplicates().drop
dirty_data.head()
```

Out[102...

date	station	PRCP	SNOW	TMAX	TMIN	TOBS	WESF	inclement_w
2018-01-01T00:00:00	?	0.0	0.0	5505.0	-40.0	NaN	NaN	
2018-01-02T00:00:00	GHCND:USC00280907	0.0	0.0	-8.3	-16.1	-12.2	NaN	
2018-01-03T00:00:00	GHCND:USC00280907	0.0	0.0	-4.4	-13.9	-13.3	NaN	
2018-01-04T00:00:00	?	20.6	229.0	5505.0	-40.0	NaN	19.3	
2018-01-05T00:00:00	?	0.3	NaN	5505.0	-40.0	NaN	NaN	

We need to create two dataframes for the join. We will drop some unecessary columns as well for easier viewing:

In [103...

```
valid_station = dirty_data.query('station != "?"').copy().drop(columns=['WESF', 'st
station_with_wesf = dirty_data.query('station == "?"').copy().drop(columns=['statio
```

In [104...

```
valid_station.merge(
    station_with_wesf, left_index=True, right_index=True
).query('WESF > 0').head()
```

Out[104...

date	PRCP_x	SNOW_x	TMAX	TMIN	TOBS	inclement_weather_x	PRCP_y	SNOW
2018-01-30T00:00:00	0.0	0.0	6.7	-1.7	-0.6	False	1.5	1
2018-03-08T00:00:00	48.8	NaN	1.1	-0.6	1.1	False	28.4	N
2018-03-13T00:00:00	4.1	51.0	5.6	-3.9	0.0	True	3.0	1
2018-03-21T00:00:00	0.0	0.0	2.8	-2.8	0.6	False	6.6	11
2018-04-02T00:00:00	9.1	127.0	12.8	-1.1	-1.1	True	14.0	15

The columns that existed in both dataframes, but didn't form part of the join got suffixes added to their names: _x for columns from the left dataframe and _y for columns from the right dataframe. We can customize this with the suffixes argument:

In [105…

```
valid_station.merge(station_with_wesf, left_index=True, right_index=True, suffixes=
).query('WESF > 0').head()
```

Out[105…

date	PRCP	SNOW	TMAX	TMIN	TOBS	inclement_weather	PRCP_?	SNOW_?	W
2018-01-30T00:00:00	0.0	0.0	6.7	-1.7	-0.6	False	1.5	13.0	
2018-03-08T00:00:00	48.8	NaN	1.1	-0.6	1.1	False	28.4	NaN	
2018-03-13T00:00:00	4.1	51.0	5.6	-3.9	0.0	True	3.0	13.0	
2018-03-21T00:00:00	0.0	0.0	2.8	-2.8	0.6	False	6.6	114.0	
2018-04-02T00:00:00	9.1	127.0	12.8	-1.1	-1.1	True	14.0	152.0	

Since we are joining on the index, an easier way is to use the join() method instead of merge() . Note that the suffix parameter is now lsuffix for the left dataframe's suffix and rsuffix for the right one's:

In [106…

```
valid_station.join(station_with_wesf, rsuffix='_?').query('WESF > 0').head()
```

Out[106…

date	PRCP	SNOW	TMAX	TMIN	TOBS	inclement_weather	PRCP_?	SNOW_?	W
2018-01-30T00:00:00	0.0	0.0	6.7	-1.7	-0.6	False	1.5	13.0	
2018-03-08T00:00:00	48.8	NaN	1.1	-0.6	1.1	False	28.4	NaN	
2018-03-13T00:00:00	4.1	51.0	5.6	-3.9	0.0	True	3.0	13.0	
2018-03-21T00:00:00	0.0	0.0	2.8	-2.8	0.6	False	6.6	114.0	
2018-04-02T00:00:00	9.1	127.0	12.8	-1.1	-1.1	True	14.0	152.0	

Joins can be very resource-intensive, so it's a good idea to figure out what type of join you need using set operations before trying the join itself. The pandas set operations are performed on the index, so whichever columns we will be joining on will need to be the index. Let's go back to the weather and station_info dataframes and set the station ID columns as the index:

In [107…
```
weather.set_index('station', inplace=True)
station_info.set_index('id', inplace=True)
```

In [108…
```
weather.index.intersection(station_info.index)
```

Out[108…
```
Index(['GHCND:US1CTFR0039', 'GHCND:US1NJBG0015', 'GHCND:US1NJBG0017',
       'GHCND:US1NJBG0018', 'GHCND:US1NJBG0023', 'GHCND:US1NJBG0030',
       'GHCND:US1NJBG0039', 'GHCND:US1NJBG0044', 'GHCND:US1NJES0018',
       'GHCND:US1NJES0024',
       ...
       'GHCND:USC00284987', 'GHCND:US1NJES0031', 'GHCND:US1NJES0029',
       'GHCND:US1NJMD0086', 'GHCND:US1NJMS0097', 'GHCND:US1NJMN0081',
       'GHCND:US1NJMD0088', 'GHCND:US1NJES0033', 'GHCND:US1NJES0040',
       'GHCND:US1NYQN0029'],
      dtype='object', length=114)
```

The set difference will tell us what we lose from each side. When performing an inner join, we lose nothing from the weather dataframe:

In [109…
```
weather.index.difference(station_info.index)
```

Out[109…
```
Index([], dtype='object')
```

We lose 153 stations from the station_info dataframe, however:

In [110…
```
station_info.index.difference(weather.index)
```

Out[110…
```
Index(['GHCND:US1CTFR0022', 'GHCND:US1NJBG0001', 'GHCND:US1NJBG0002',
       'GHCND:US1NJBG0005', 'GHCND:US1NJBG0006', 'GHCND:US1NJBG0008',
       'GHCND:US1NJBG0011', 'GHCND:US1NJBG0012', 'GHCND:US1NJBG0013',
       'GHCND:US1NJBG0020',
       ...
       'GHCND:USC00308749', 'GHCND:USC00308946', 'GHCND:USC00309117',
       'GHCND:USC00309270', 'GHCND:USC00309400', 'GHCND:USC00309466',
       'GHCND:USC00309576', 'GHCND:USC00309580', 'GHCND:USW00014708',
       'GHCND:USW00014786'],
      dtype='object', length=216)
```

The symmetric difference will tell us what gets lost from both sides. It is the combination of the set difference in both directions:

In [111…
```
ny_in_name = station_info[station_info.name.str.contains('NY')]
ny_in_name.index.difference(weather.index).shape[0]\
+ weather.index.difference(ny_in_name.index).shape[0]\
== weather.index.symmetric_difference(ny_in_name.index).shape[0]
```

Out[111…
```
True
```

The union will show us everything that will be present after a full outer join. Note that since these are sets (which don't allow duplicates by definition), we must pass unique entries for union:

In [112…
```
weather.index.unique().union(station_info.index)
```

Out[112…
```
Index(['GHCND:US1CTFR0022', 'GHCND:US1CTFR0039', 'GHCND:US1NJBG0001',
       'GHCND:US1NJBG0002', 'GHCND:US1NJBG0003', 'GHCND:US1NJBG0005',
       'GHCND:US1NJBG0006', 'GHCND:US1NJBG0008', 'GHCND:US1NJBG0010',
       'GHCND:US1NJBG0011',
       ...
       'GHCND:USW00014708', 'GHCND:USW00014732', 'GHCND:USW00014734',
       'GHCND:USW00014786', 'GHCND:USW00054743', 'GHCND:USW00054787',
       'GHCND:USW00094728', 'GHCND:USW00094741', 'GHCND:USW00094745',
       'GHCND:USW00094789'],
      dtype='object', length=330)
```

Note that the symmetric difference is actually the union of the set differences:

In [113…
```
ny_in_name = station_info[station_info.name.str.contains('NY')]
ny_in_name.index.difference(weather.index).union(weather.index.difference(ny_in_nam
 weather.index.symmetric_difference(ny_in_name.index)
)
```

Out[113…
```
True
```

DataFrame Operation

About the Data

In this notebook, we will be working with 2 data sets:

Facebook's stock price throughout 2018 (obtained using the stock_analysis package).

daily weather data for NYC from the National Centers for Environmental Information (NCEI) API. Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

Background on the weather data

Data meanings: AWND : average wind speed PRCP : precipitation in millimeters SNOW : snowfall in millimeters SNWD : snow depth in millimeters TMAX : maximum daily temperature in Celsius TMIN : minimum daily temperature in Celsius

Setup

In [114…

```
import numpy as np
import pandas as pd
weather = pd.read_csv('nyc_weather_2018.csv', parse_dates=['date'])
weather.head()
```

Out[114…

	date	datatype	station	attributes	value
0	2018-01-01	PRCP	GHCND:US1CTFR0039	,,N,0800	0.0
1	2018-01-01	PRCP	GHCND:US1NJBG0015	,,N,1050	0.0
2	2018-01-01	SNOW	GHCND:US1NJBG0015	,,N,1050	0.0
3	2018-01-01	PRCP	GHCND:US1NJBG0017	,,N,0920	0.0
4	2018-01-01	SNOW	GHCND:US1NJBG0017	,,N,0920	0.0

In [116…

```
fb = pd.read_csv('fb_2018.csv', index_col='date', parse_dates=True)
fb.head()
```

Out[116…

	open	high	low	close	volume
date					
2018-01-02	177.68	181.58	177.5500	181.42	18151903
2018-01-03	181.88	184.78	181.3300	184.67	16886563
2018-01-04	184.90	186.21	184.0996	184.33	13880896
2018-01-05	185.59	186.90	184.9300	186.85	13574535
2018-01-08	187.20	188.90	186.3300	188.28	17994726

Arithmetic and statistics

We already saw that we can use mathematical operators like + and / with dataframes directly. However, we can also use methods, which allow us to specify the axis to perform the calculation over. By default this is per column. Let's find the z-scores for the volume traded and look at the days where this was more than 3 standard deviations from the mean:

In [117…

```
fb.assign(
    abs_z_score_volume=lambda x: x.volume.sub(x.volume.mean()).div(x.volume.std()).
).query('abs_z_score_volume > 3')
```

Out[117…

date	open	high	low	close	volume	abs_z_score_volume
2018-03-19	177.01	177.17	170.06	172.56	88140060	3.145078
2018-03-20	167.47	170.20	161.95	168.15	129851768	5.315169
2018-03-21	164.80	173.40	163.30	169.39	106598834	4.105413
2018-03-26	160.82	161.10	149.02	160.06	126116634	5.120845
2018-07-26	174.89	180.13	173.75	176.26	169803668	7.393705

We can use rank() and pct_change() to see which days had the largest change in volume traded from the day before:

In [118…

```
fb.assign(
 volume_pct_change=fb.volume.pct_change(),
 pct_change_rank=lambda x: x.volume_pct_change.abs().rank(
 ascending=False
 )
).nsmallest(5, 'pct_change_rank')
```

Out[118…

date	open	high	low	close	volume	volume_pct_change	pct_change_rank
2018-01-12	178.06	181.48	177.40	179.37	77551299	7.087876	1.0
2018-03-19	177.01	177.17	170.06	172.56	88140060	2.611789	2.0
2018-07-26	174.89	180.13	173.75	176.26	169803668	1.628841	3.0
2018-09-21	166.64	167.25	162.81	162.93	45994800	1.428956	4.0
2018-03-26	160.82	161.10	149.02	160.06	126116634	1.352496	5.0

January 12th was when the news that Facebook changed its news feed product to focus more on content from a users' friends over the brands they follow. Given that Facebook's advertising is a key component of its business (nearly 89% in 2017), many shares were sold and the price dropped in panic:

In [119…

```
fb['2018-01-11':'2018-01-12']
```

Out[119...

date	open	high	low	close	volume
2018-01-11	188.40	188.40	187.38	187.77	9588587
2018-01-12	178.06	181.48	177.40	179.37	77551299

Throughout 2018, Facebook's stock price never had a low above $215:

In [120...

```
(fb > 215).any()
```

Out[120...

```
open       True
high       True
low       False
close      True
volume     True
dtype: bool
```

Facebook's OHLC (open, high, low, and close) prices all had at least one day they were at $215 or less:

In [121...

```
(fb > 215).all()
```

Out[121...

```
open      False
high      False
low       False
close     False
volume     True
dtype: bool
```

Binning and thresholds

When working with the volume traded, we may be interested in ranges of volume rather than the exact values. No two days have the same volume traded:

In [122...

```
(fb.volume.value_counts() > 1).sum()
```

Out[122...

```
np.int64(0)
```

We can use pd.cut() to create 3 bins of even an even range in volume traded and name them. Then we can work with low, medium, and high volume traded categories:

In [123...

```
volume_binned = pd.cut(fb.volume, bins=3, labels=['low', 'med', 'high'])
volume_binned.value_counts()
```

Out[123...

```
volume
low     240
med       8
high      3
Name: count, dtype: int64
```

In [125…

```
fb[volume_binned == 'high'].sort_values('volume', ascending=False)
```

Out[125…

date	open	high	low	close	volume
2018-07-26	174.89	180.13	173.75	176.26	169803668
2018-03-20	167.47	170.20	161.95	168.15	129851768
2018-03-26	160.82	161.10	149.02	160.06	126116634

July 25th Facebook announced disappointing user growth and the stock tanked in the after hours:

In [126…

```
fb['2018-07-25':'2018-07-26']
```

Out[126…

date	open	high	low	close	volume
2018-07-25	215.715	218.62	214.27	217.50	64592585
2018-07-26	174.890	180.13	173.75	176.26	169803668

Cambridge Analytica scandal broke on Saturday March 17th, so we look to the Monday for the numbers:

In [127…

```
fb['2018-03-16':'2018-03-20']
```

Out[127…

date	open	high	low	close	volume
2018-03-16	184.49	185.33	183.41	185.09	24403438
2018-03-19	177.01	177.17	170.06	172.56	88140060
2018-03-20	167.47	170.20	161.95	168.15	129851768

Since most days have similar volume, but a few are very large, we have very wide bins. Most of the data is in the low bin.

Note: visualizations will be covered in chapters 5 and 6

In [130…

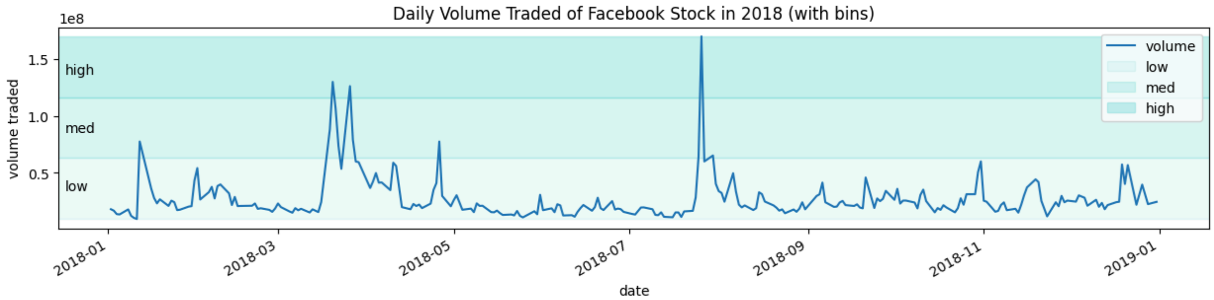
```
import matplotlib.pyplot as plt
```

In [131…

```
fb.plot(y='volume', figsize=(15, 3), title='Daily Volume Traded of Facebook Stock i
for bin_name, alpha, bounds in zip(
 ['low', 'med', 'high'], [0.1, 0.2, 0.3], pd.cut(fb.volume, bins=3).unique().catego
):
 plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumt
```

```
 plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

plt.ylabel('volume traded')
plt.legend()
plt.show()
```



If we split using quantiles, the bins will have roughly the same number of observations. For this, we use qcut() . We will make 4 quartiles:

In [132…

```
volume_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
volume_qbinned.value_counts()
```

Out[132…

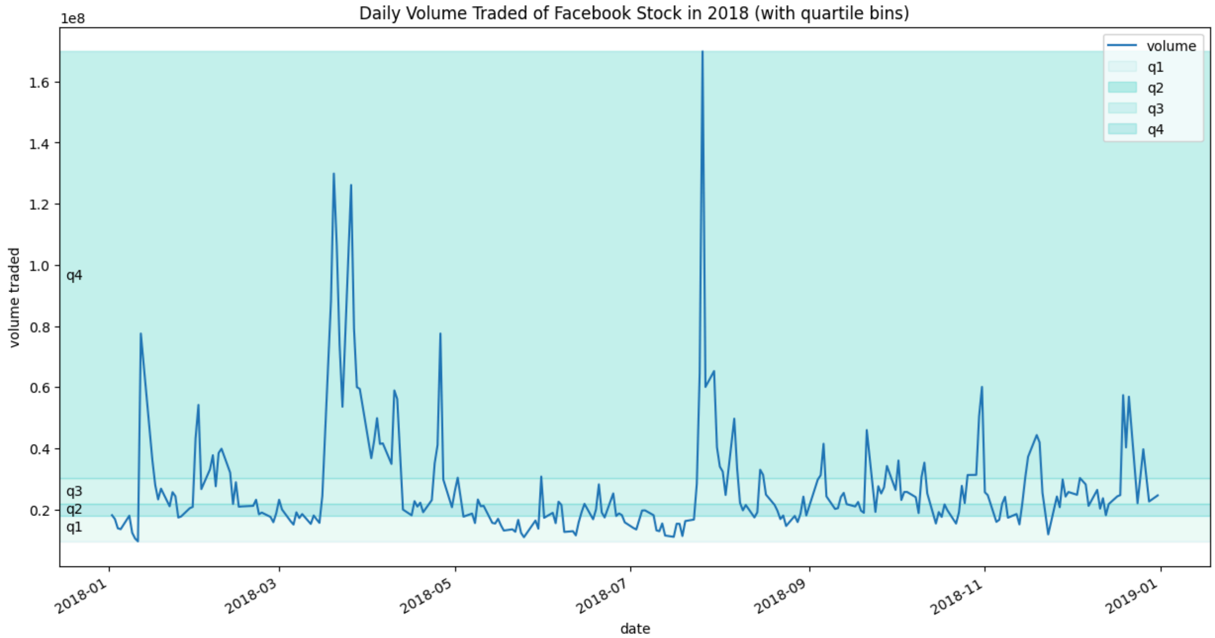
```
volume
q1    63
q2    63
q4    63
q3    62
Name: count, dtype: int64
```

Notice the bins don't cover ranges of the same size anymore:

In [133…

```
fb.plot(y='volume', figsize=(15, 8), title='Daily Volume Traded of Facebook Stock i
for bin_name, alpha, bounds in zip(
 ['q1', 'q2', 'q3', 'q4'], [0.1, 0.35, 0.2, 0.3], pd.qcut(fb.volume, q=4).unique().
):
 plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumt
 plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

plt.ylabel('volume traded')
plt.legend()
plt.show()
```



Sometimes we don't want to make bins, but rather cap values at a threshold. Before we look at an example, let's pivot our weather data for the Central Park station:

In [138…

```
central_park_weather = weather.query(
 'station == "GHCND:USW00094728"'
).pivot(index='date', columns='datatype', values='value')

central_park_weather.head()
```

Out[138…

datatype date	ADPT	ASLP	ASTP	AWBT	AWND	PRCP	RHAV	RHMN	RHMX	SNOW
2018-01-01	-194.0	10278.0	10224.0	-122.0	3.5	0.0	48.0	34.0	60.0	0.0
2018-01-02	-156.0	10278.0	10227.0	-94.0	3.6	0.0	52.0	42.0	62.0	0.0
2018-01-03	-161.0	10237.0	10196.0	-78.0	1.4	0.0	42.0	28.0	51.0	0.0
2018-01-04	-94.0	9990.0	9925.0	-61.0	5.6	19.3	70.0	39.0	92.0	249.0
2018-01-05	-206.0	10098.0	10030.0	-128.0	5.8	0.0	43.0	33.0	56.0	0.0

5 rows × 22 columns

Say we don't care how much snow their was, just that it snowed in Central Park. However, we don't want to make a Boolean column since we need to preserve the data type of float. We can use clip() to replace values above a upper threshold with the threshold and replace values below a lower threshold with the lower threshold. This means we can use clip(0, 1) to change all the snow values of one or more to 1, which easily shows us the days snow was recorded in Central Park. Preserving the data type will save some work later on if we are building a model:

In [139…
```
central_park_weather.SNOW.clip(0, 1).value_counts()
```

Out[139…
```
SNOW
0.0    343
1.0     10
Name: count, dtype: int64
```

Note: the clip() method can also be called on the dataframe itself.

Applying Functions

We can use the apply() method to run the same operation on all columns (or rows) of the dataframe. Let's calculate the z-scores of the TMIN, TMAX, and PRCP observations in Central Park in October 2018:

In [140…
```
oct_weather_z_scores = central_park_weather.loc[
 '2018-10', ['TMIN', 'TMAX', 'PRCP']
].apply(lambda x: x.sub(x.mean()).div(x.std()))
oct_weather_z_scores.describe().T
```

Out[140…

datatype	count	mean	std	min	25%	50%	75%	max
TMIN	30.0	1.110223e-16	1.0	-1.307499	-0.717650	-0.440074	1.056235	1.884625
TMAX	30.0	2.581269e-16	1.0	-1.276439	-0.863456	-0.151720	0.990573	1.658374
PRCP	30.0	4.070818e-17	1.0	-0.401814	-0.401814	-0.401814	-0.239899	3.867458

October 27th rained much more than the rest of the days:

In [141…
```
oct_weather_z_scores.query('PRCP > 3')
```

Out[141…

date	TMIN	TMAX	PRCP
2018-10-27	-0.71765	-1.170996	3.867458

Indeed, this day was much higher than the rest:

In [142…

```
central_park_weather.loc['2018-10', 'PRCP'].describe()
```

Out[142…

```
count    30.000000
mean      3.040000
std       7.565694
min       0.000000
25%       0.000000
50%       0.000000
75%       1.225000
max      32.300000
Name: PRCP, dtype: float64
```

When the function we want to apply isn't vectorized, we can:

```
        use np.vectorize() to vectorize it (similar to how map() works)
    and then use it with apply()
        use applymap() and pass it the non-vectorized function directly
```

Say we wanted to count the digits of the whole numbers for the Facebook data. len() is not vectorized:

In [145…

```
import numpy as np
fb.apply(lambda x: np.vectorize(lambda y: len(str(np.ceil(y))))(x)
).astype('int64').equals(fb.applymap(lambda x: len(str(np.ceil(x)))))
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\290225260.py:3: FutureWarn
ing: DataFrame.applymap has been deprecated. Use DataFrame.map instead.
  ).astype('int64').equals(fb.applymap(lambda x: len(str(np.ceil(x)))))
```

Out[145…

```
True
```

A simple operation of addition to each element in a series grows linearly in time complexity when using iteritems() , but stays near 0 when using vectorized operations. iteritems() and related methods should only be used if there is no vectorized solution:

In [155…

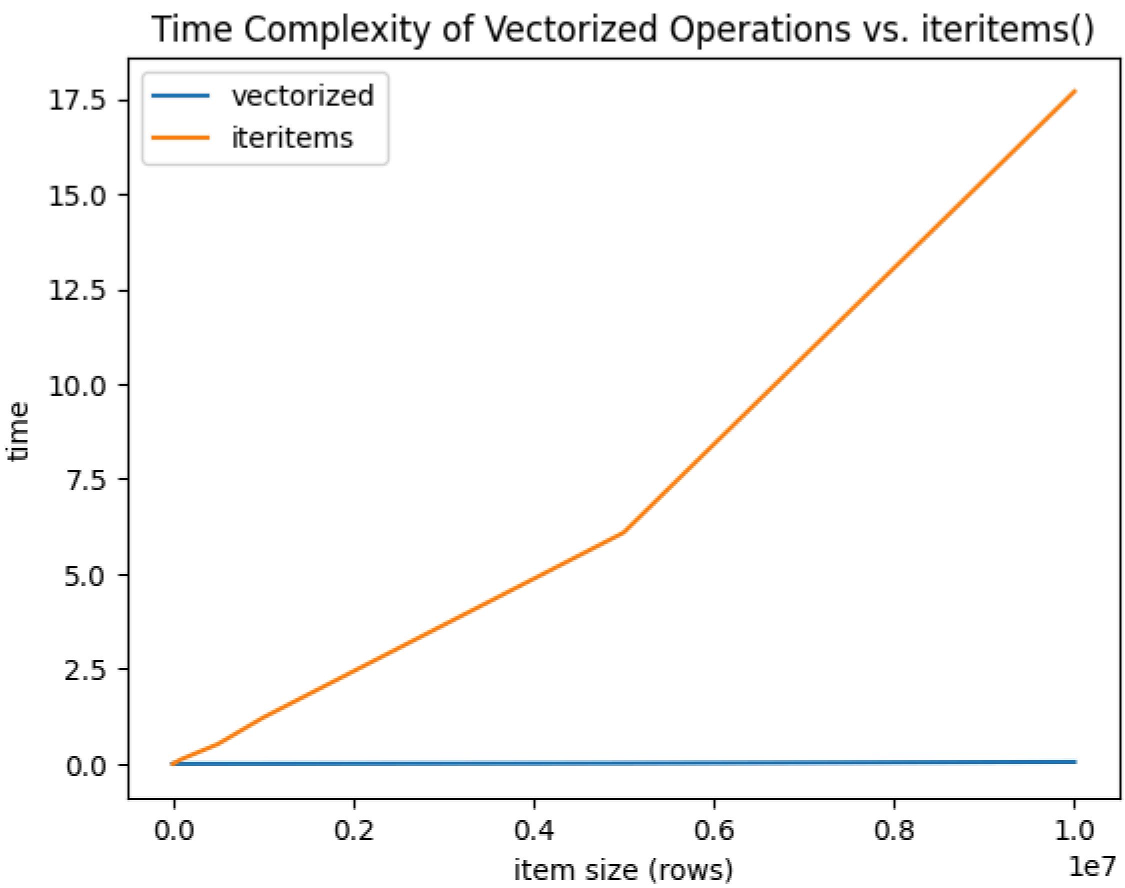
```
import time
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
np.random.seed(0)
vectorized_results = {}
iteritems_results = {}
for size in [10, 100, 1000, 10000, 100000, 500000, 1000000, 5000000, 10000000]:
    test = pd.Series(np.random.uniform(size=size))

    start = time.time()
    x = test + 10
    end = time.time()
    vectorized_results[size] = end - start

    start = time.time()
    x = []
    for i, v in test.items():  # <--- fixed line
```

```python
        x.append(v + 10)
    x = pd.Series(x)
    end = time.time()
    iteritems_results[size] = end - start


pd.DataFrame( [pd.Series(vectorized_results, name='vectorized'), pd.Series(iteritem
).T.plot(title='Time Complexity of Vectorized Operations vs. iteritems()')
plt.xlabel('item size (rows)')
plt.ylabel('time')
plt.show()
```



Window Calculations

Consult the understanding windows calculation notebook for interactive visualizations to help understand window calculations. The rolling() method allows us to perform rolling window calculations. We simply specify the window size (3 days here) and follow it with a call to an aggregation function (sum here):

In [159…

```python
central_park_weather.loc['2018-10'].assign(
    rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum()
)[['PRCP', 'rolling_PRCP']].head(7).T
```

Out[159…

date	2018-10-02	2018-10-03	2018-10-04	2018-10-05	2018-10-06	2018-10-07	2018-10-08
datatype							
PRCP	17.5	0.0	1.0	0.0	0.0	0.0	0.0
rolling_PRCP	17.5	17.5	18.5	1.0	1.0	0.0	0.0

In [160…

```
central_park_weather.loc['2018-10'].rolling('3D').mean().head(7).iloc[:,:6]
```

Out[160…

datatype	ADPT	ASLP	ASTP	AWBT	AWND	PRCP
date						
2018-10-02	189.000000	10196.000000	10152.000000	200.000000	0.900000	17.500000
2018-10-03	172.500000	10184.500000	10138.500000	186.000000	1.000000	8.750000
2018-10-04	176.000000	10175.000000	10128.333333	187.000000	0.800000	6.166667
2018-10-05	155.666667	10177.333333	10128.333333	170.333333	1.033333	0.333333
2018-10-06	157.333333	10194.333333	10145.333333	170.333333	0.833333	0.333333
2018-10-07	163.000000	10217.000000	10165.666667	177.666667	1.066667	0.000000
2018-10-08	177.666667	10245.333333	10193.000000	188.666667	1.133333	0.000000

We can use different aggregation functions per column if we use agg() instead. We pass in a dictionary mapping the column to the aggregation to perform on it:

In [162…

```
central_park_weather.loc['2018-10-01':'2018-10-07'].rolling('3D').agg(
 {'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'}
).join( # join with original data for comparison
 central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
 lsuffix='_rolling'
).sort_index(axis=1) # sort columns so rolling calcs are next to originals
```

Out[162...

datatype date	AWND	AWND_rolling	PRCP	PRCP_rolling	TMAX	TMAX_rolling	TMIN	TMIN_
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	18.3	
2018-10-03	1.1	1.000000	0.0	17.5	23.3	25.0	17.2	
2018-10-04	0.4	0.800000	1.0	18.5	24.4	25.0	16.1	
2018-10-05	1.6	1.033333	0.0	1.0	21.7	24.4	15.6	
2018-10-06	0.5	0.833333	0.0	1.0	20.0	24.4	17.2	
2018-10-07	1.1	1.066667	0.0	0.0	26.1	26.1	19.4	

Rolling calculations (rolling()) use a sliding window. Expanding calculations (expanding()) however grow in size. These are equivalent to cumulative aggregations like cumsum() ; however, we can specify the minimum number of periods required to start calculating (default is 1):

In [163...

```
central_park_weather.PRCP.expanding().sum().equals(central_park_weather.PRCP.cumsum
```

Out[163...

```
False
```

Separate expanding aggregations per column. Note that agg() will accept numpy functions too:

In [164...

```
central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
 {'TMAX': np.max, 'TMIN': np.min, 'AWND': np.mean, 'PRCP': np.sum}
).join(
 central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
 lsuffix='_expanding'
).sort_index(axis=1)
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3438569374.py:1: FutureWar
ning: The provided callable <function max at 0x00000187192896C0> is currently using
Expanding.max. In a future version of pandas, the provided callable will be used dir
ectly. To keep current behavior pass the string "max" instead.
  central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3438569374.py:1: FutureWar
ning: The provided callable <function min at 0x0000018719289800> is currently using
Expanding.min. In a future version of pandas, the provided callable will be used dir
ectly. To keep current behavior pass the string "min" instead.
  central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3438569374.py:1: FutureWar
ning: The provided callable <function mean at 0x000001871928A0C0> is currently using
Expanding.mean. In a future version of pandas, the provided callable will be used di
rectly. To keep current behavior pass the string "mean" instead.
  central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3438569374.py:1: FutureWar
ning: The provided callable <function sum at 0x0000018719288CC0> is currently using
Expanding.sum. In a future version of pandas, the provided callable will be used dir
ectly. To keep current behavior pass the string "sum" instead.
  central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
```

Out[164…

datatype	AWND	AWND_expanding	PRCP	PRCP_expanding	TMAX	TMAX_expanding	TI
date							
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	
2018-10-03	1.1	1.000000	0.0	17.5	23.3	25.0	
2018-10-04	0.4	0.800000	1.0	18.5	24.4	25.0	
2018-10-05	1.6	1.000000	0.0	18.5	21.7	25.0	
2018-10-06	0.5	0.900000	0.0	18.5	20.0	25.0	
2018-10-07	1.1	0.933333	0.0	18.5	26.1	26.1	

We can calculate the exponentially weighted moving average as follows. Note that span here is the periods to use:

In [165…

```
fb.assign(
 close_ewma=lambda x: x.close.ewm(span=5).mean()
).tail(10)[['close', 'close_ewma']]
```

Out[165...

date	close	close_ewma
2018-12-17	140.19	142.235433
2018-12-18	143.66	142.710289
2018-12-19	133.24	139.553526
2018-12-20	133.40	137.502350
2018-12-21	124.95	133.318234
2018-12-24	124.06	130.232156
2018-12-26	134.18	131.548104
2018-12-27	134.52	132.538736
2018-12-28	133.20	132.759157
2018-12-31	131.09	132.202772

Consult the understanding_window_calculations.ipynb notebook for interactive visualizations to help understand window calculations.

Pipes

Pipes all use to apply any function that accepts our data as the first argument and pass in any additional arguments. This makes it easy to chain steps together regardless of if they are methods or functions:

We can pass any function that will accept the caller of pipe() as the first argument:

In [168...

```
def get_info(df):
 return '%d rows and %d columns and max closing z-score was %d' % (*df.shape, df.cl
fb.loc['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
 == get_info(fb.loc['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
```

Out[168... True

For example, passing pd.DataFrame.rolling to pipe() is equivalent to calling rolling() directly on the dataframe, except we have more flexiblity to change this:

In [169...

```
fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean())
```

Out[169... True

The pipe takes the function passed in and calls it with the object that called pipe() as the first argument. Positional and keyword arguments are passed down:

In [170...

```
pd.DataFrame.rolling(fb, '20D').mean().equals(fb.rolling('20D').mean())
```

Out[170… True

We can use a pipe to make a function that we can use for all our window calculation needs:

In [175…
```
from window_calc import window_calc
window_calc??

def window_calc(df, func, agg_dict, *args, **kwargs):
    """
    Run a window calculation of your choice on a DataFrame.

    Parameters:
    - df: The DataFrame to run the calculation on.
    - func: The window calculation method that takes df
      as the first argument.
    - agg_dict: Information to pass to `agg()`, could be a
      dictionary mapping the columns to the aggregation
      function to use, a string name for the function,
      or the function itself.
    - args: Positional arguments to pass to `func`.
    - kwargs: Keyword arguments to pass to `func`.

    Returns:
    - A new DataFrame object.
    """
    return df.pipe(func, *args, **kwargs).agg(agg_dict)
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[175], line 1
----> 1 from window_calc import window_calc
      2 get_ipython().run_line_magic('pinfo2', 'window_calc')
      4 def window_calc(df, func, agg_dict, *args, **kwargs):

ModuleNotFoundError: No module named 'window_calc'
```

We can use the same interface to calculate various window calculations now. Let's find the expanding median for the Facebook data:

can't install window_calc

can't proceed anymore

In [ ]:

In [ ]:

Aggregations with pandas and numpy

About the Data

In this notebook, we will be working with 2 data sets:

```
Facebook's stock price throughout 2018 (obtained using the
stock_analysis package).

daily weather data for NYC from the National Centers for
Environmental Information (NCEI) API.
```

Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

Background on the weather data

Data meanings:

```
AWND : average wind speed

PRCP : precipitation in millimeters

SNOW : snowfall in millimeters

SNWD : snow depth in millimeters

TMAX : maximum daily temperature in Celsius

TMIN : minimum daily temperature in Celsius
```

Setup

In [178…

```
import numpy as np
import pandas as pd
weather = pd.read_csv('weather_by_station.csv', index_col='date', parse_dates=True)
weather.head()
```

Out[178...

date	datatype	station	value	station_name
2018-01-01	PRCP	GHCND:US1CTFR0039	0.0	STAMFORD 4.2 S, CT US
2018-01-01	PRCP	GHCND:US1NJBG0015	0.0	NORTH ARLINGTON 0.7 WNW, NJ US
2018-01-01	SNOW	GHCND:US1NJBG0015	0.0	NORTH ARLINGTON 0.7 WNW, NJ US
2018-01-01	PRCP	GHCND:US1NJBG0017	0.0	GLEN ROCK 0.7 SSE, NJ US
2018-01-01	SNOW	GHCND:US1NJBG0017	0.0	GLEN ROCK 0.7 SSE, NJ US

In [180...

```
fb = pd.read_csv('fb_2018.csv', index_col='date', parse_dates=True).assign(
 trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
)
fb.head()
```

Out[180...

date	open	high	low	close	volume	trading_volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903	low
2018-01-03	181.88	184.78	181.3300	184.67	16886563	low
2018-01-04	184.90	186.21	184.0996	184.33	13880896	low
2018-01-05	185.59	186.90	184.9300	186.85	13574535	low
2018-01-08	187.20	188.90	186.3300	188.28	17994726	low

Before we dive into any calculations, let's make sure pandas won't put things in scientific notation. We will modify how floats are formatted for displaying. The format we will apply is .2f , which will provide the float with 2 digits after the decimal point:

In [181...

```
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

Summarizing DataFrames

We learned about agg() in the dataframe operations notebook when we learned about window calculations; however, we can call this on the dataframe directly to aggregate its contents into a single series:

In [182...

```
fb.agg({
 'open': np.mean,
 'high': np.max,
 'low': np.min,
 'close': np.mean,
 'volume': np.sum
})
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\1226741615.py:1: FutureWar
ning: The provided callable <function mean at 0x000001871928A0C0> is currently using
Series.mean. In a future version of pandas, the provided callable will be used direc
tly. To keep current behavior pass the string "mean" instead.
  fb.agg({
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\1226741615.py:1: FutureWar
ning: The provided callable <function max at 0x00000187192896C0> is currently using
Series.max. In a future version of pandas, the provided callable will be used direct
ly. To keep current behavior pass the string "max" instead.
  fb.agg({
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\1226741615.py:1: FutureWar
ning: The provided callable <function min at 0x0000018719289800> is currently using
Series.min. In a future version of pandas, the provided callable will be used direct
ly. To keep current behavior pass the string "min" instead.
  fb.agg({
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\1226741615.py:1: FutureWar
ning: The provided callable <function sum at 0x0000018719288CC0> is currently using
Series.sum. In a future version of pandas, the provided callable will be used direct
ly. To keep current behavior pass the string "sum" instead.
  fb.agg({
```

Out[182…

```
open             171.45
high             218.62
low              123.02
close            171.51
volume   6949682394.00
dtype: float64
```

We can use this to find the total snowfall and precipitation recorded in Central Park in 2018:

In [183…

```
weather.query(
 'station == "GHCND:USW00094728"'
).pivot(columns='datatype', values='value')[['SNOW', 'PRCP']].sum()
```

Out[183…

```
datatype
SNOW    1007.00
PRCP    1665.30
dtype: float64
```

This is equivalent to passing 'sum' to agg() :

In [184…

```
weather.query(
 'station == "GHCND:USW00094728"'
).pivot(columns='datatype', values='value')[['SNOW', 'PRCP']].agg('sum')
```

Out[184…

```
datatype
SNOW    1007.00
PRCP    1665.30
dtype: float64
```

Note that we aren't limited to providing a single aggregation per column. We can pass a list, and we will get a dataframe back instead of a series. nan values are placed where we don't have a calculation result to display:

In [185…

```
fb.agg({
 'open': 'mean',
 'high': ['min', 'max'],
 'low': ['min', 'max'],
'close': 'mean'
})
```

Out[185…

	open	high	low	close
mean	171.45	NaN	NaN	171.51
min	NaN	129.74	123.02	NaN
max	NaN	218.62	214.27	NaN

Using groupby()

Often we won't want to aggregate on the entire dataframe, but on groups within it. For this purpose, we can run groupby() before the aggregation. If we group by the trading_volume column, we will get a row for each of the values it takes on:

In [186…

```
fb.groupby('trading_volume').mean()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\46027550.py:1: FutureWarni
ng: The default of observed=False is deprecated and will be changed to True in a fut
ure version of pandas. Pass observed=False to retain current behavior or observed=Tr
ue to adopt the future default and silence this warning.
  fb.groupby('trading_volume').mean()
```

Out[186…

	open	high	low	close	volume
trading_volume					
low	171.36	173.46	169.31	171.43	24547207.71
med	175.82	179.42	172.11	175.14	79072559.12
high	167.73	170.48	161.57	168.16	141924023.33

After we run the groupby() , we can still select columns for aggregation:

In [187…

```
fb.groupby('trading_volume')['close'].agg(['min', 'max', 'mean'])
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3607524933.py:1: FutureWar
ning: The default of observed=False is deprecated and will be changed to True in a f
uture version of pandas. Pass observed=False to retain current behavior or observed=
True to adopt the future default and silence this warning.
  fb.groupby('trading_volume')['close'].agg(['min', 'max', 'mean'])
```

Out[187…

	min	max	mean
trading_volume			
low	124.06	214.67	171.43
med	152.22	217.50	175.14
high	160.06	176.26	168.16

We can still provide a dictionary specifying the aggregations to perform, but passing a list for a column will result in a hierarchical index for the columns:

In [188…

```
fb_agg = fb.groupby('trading_volume').agg({
 'open': 'mean',
 'high': ['min', 'max'],
 'low': ['min', 'max'],
 'close': 'mean'
})
fb_agg
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3643718693.py:1: FutureWar
ning: The default of observed=False is deprecated and will be changed to True in a f
uture version of pandas. Pass observed=False to retain current behavior or observed=
True to adopt the future default and silence this warning.
  fb_agg = fb.groupby('trading_volume').agg({
```

Out[188…

	open	high		low		close
	mean	**min**	**max**	**min**	**max**	**mean**
trading_volume						
low	171.36	129.74	216.20	123.02	212.60	171.43
med	175.82	162.85	218.62	150.75	214.27	175.14
high	167.73	161.10	180.13	149.02	173.75	168.16

The hierarchical index in the columns looks like this:

In [189…

```
fb_agg.columns
```

Out[189…

```
MultiIndex([( 'open', 'mean'),
            ( 'high',  'min'),
            ( 'high',  'max'),
            (  'low',  'min'),
            (  'low',  'max'),
            ('close', 'mean')],
           )
```

Using a list comprehension, we can join the levels (in a tuple) with an _ at each iteration:

In [190…

```
fb_agg.columns = ['_'.join(col_agg) for col_agg in fb_agg.columns]
fb_agg.head()
```

Out[190…

trading_volume	open_mean	high_min	high_max	low_min	low_max	close_mean
low	171.36	129.74	216.20	123.02	212.60	171.43
med	175.82	162.85	218.62	150.75	214.27	175.14
high	167.73	161.10	180.13	149.02	173.75	168.16

We can group on datetimes despite them being in the index if we use a Grouper :

In [192…

```
weather.loc['2018-10'].query('datatype == "PRCP"').groupby(
 pd.Grouper(freq='D')
).mean().head()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1942, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1941 try:
-> 1942     res_values = self._grouper.agg_series(ser, alt, preserve_dtype=True)
   1943 except Exception as err:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:864,
in BaseGrouper.agg_series(self, obj, func, preserve_dtype)
    862     preserve_dtype = True
--> 864 result = self._aggregate_series_pure_python(obj, func)
    866 npvalues = lib.maybe_convert_objects(result, try_float=False)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:885,
in BaseGrouper._aggregate_series_pure_python(self, obj, func)
    884 for i, group in enumerate(splitter):
--> 885     res = func(group)
    886     res = extract_result(res)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2454, in GroupBy.mean.<locals>.<lambda>(x)
   2451 else:
   2452     result = self._cython_agg_general(
   2453         "mean",
-> 2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6549, in
Series.mean(self, axis, skipna, numeric_only, **kwargs)
   6541 @doc(make_doc("mean", ndim=1))
   6542 def mean(
   6543     self,
   (...)
   6547     **kwargs,
   6548 ):
-> 6549     return NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12420, i
n NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)
  12413 def mean(
  12414     self,
  12415     axis: Axis | None = 0,
   (...)
  12418     **kwargs,
  12419 ) -> Series | float:
> 12420     return self._stat_function(
  12421         "mean", nanops.nanmean, axis, skipna, numeric_only, **kwargs
  12422     )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12377, i
n NDFrame._stat_function(self, name, func, axis, skipna, numeric_only, **kwargs)
  12375 validate_bool_kwarg(skipna, "skipna", none_allowed=False)
> 12377 return self._reduce(
```

```
  12378     func, name=name, axis=axis, skipna=skipna, numeric_only=numeric_only
  12379 )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6457, in
Series._reduce(self, op, name, axis, skipna, numeric_only, filter_type, **kwds)
   6453     raise TypeError(
   6454         f"Series.{name} does not allow {kwd_name}={numeric_only} "
   6455         "with non-numeric dtypes."
   6456     )
-> 6457 return op(delegate, skipna=skipna, **kwds)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:147, in b
ottleneck_switch.__call__.<locals>.f(values, axis, skipna, **kwds)
    146 else:
--> 147     result = alt(values, axis=axis, skipna=skipna, **kwds)
    149 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:404, in _
datetimelike_compat.<locals>.new_func(values, axis, skipna, mask, **kwargs)
    402     mask = isna(values)
--> 404 result = func(values, axis=axis, skipna=skipna, mask=mask, **kwargs)
    406 if datetimelike:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:720, in n
anmean(values, axis, skipna, mask)
    719 the_sum = values.sum(axis, dtype=dtype_sum)
--> 720 the_sum = _ensure_numeric(the_sum)
    722 if axis is not None and getattr(the_sum, "ndim", False):

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:1701, in
_ensure_numeric(x)
   1699 if isinstance(x, str):
   1700     # GH#44008, GH#36703 avoid casting e.g. strings to numeric
-> 1701     raise TypeError(f"Could not convert string '{x}' to numeric")
   1702 try:

TypeError: Could not convert string 'PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCP' to numeric

The above exception was the direct cause of the following exception:

TypeError                                 Traceback (most recent call last)
Cell In[192], line 3
      1 weather.loc['2018-10'].query('datatype == "PRCP"').groupby(
      2  pd.Grouper(freq='D')
----> 3 ).mean().head()

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2452, in GroupBy.mean(self, numeric_only, engine, engine_kwargs)
   2445     return self._numba_agg_general(
   2446         grouped_mean,
   2447         executor.float_dtype_mapping,
   2448         engine_kwargs,
```

```
   2449         min_periods=0,
   2450     )
   2451 else:
-> 2452     result = self._cython_agg_general(
   2453         "mean",
   2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1998, in GroupBy._cython_agg_general(self, how, alt, numeric_only, min_count, **kwar
gs)
   1995     result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996     return result
-> 1998 new_mgr = data.grouped_reduce(array_func)
   1999 res = self._wrap_agged_manager(new_mgr)
   2000 if how in ["idxmin", "idxmax"]:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\managers.
py:1469, in BlockManager.grouped_reduce(self, func)
   1465 if blk.is_object:
   1466     # split on object-dtype blocks bc some columns may raise
   1467     #  while others do not.
   1468     for sb in blk._split():
-> 1469         applied = sb.apply(func)
   1470         result_blocks = extend_blocks(applied, result_blocks)
   1471 else:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\blocks.p
y:393, in Block.apply(self, func, **kwargs)
    387 @final
    388 def apply(self, func, **kwargs) -> list[Block]:
    389     """
    390     apply the function to my values; return a block if we are not
    391     one
    392     """
--> 393     result = func(self.values, **kwargs)
    395     result = maybe_coerce_values(result)
    396     return self._split_op_result(result)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1995, in GroupBy._cython_agg_general.<locals>.array_func(values)
   1992     return result
   1994 assert alt is not None
-> 1995 result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1946, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1944     msg = f"agg function failed [how->{how},dtype->{ser.dtype}]"
   1945     # preserve the kind of exception that raised
-> 1946     raise type(err)(msg) from err
   1948 if ser.dtype == object:
   1949     res_values = res_values.astype(object, copy=False)
```

```
TypeError: agg function failed [how->mean,dtype->object]
```

This Grouper can be one of many group by values. Here, we find the quarterly total precipitation per station:

In [193…

```
weather.query('datatype == "PRCP"').groupby(
 ['station_name', pd.Grouper(freq='Q')]
).sum().unstack().sample(5, random_state=1)
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\24788615.py:2: FutureWarni
ng: 'Q' is deprecated and will be removed in a future version, please use 'QE' inste
ad.
  ['station_name', pd.Grouper(freq='Q')]
```

Out[193…

date		2018-03-31
station_name		
WANTAGH 1.1 NNE, NY US	PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPR...	PRCPPRCPPRCPPRCP
STATEN ISLAND 1.4 SE, NY US	PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPR...	PRCPPRCPPRCPPRCP
SYOSSET 2.0 SSW, NY US	PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPR...	PRCPPRCPPRCPPRCP
STAMFORD 4.2 S, CT US	PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPR...	PRCPPRCPPRCPPRCP
WAYNE TWP 0.8 SSW, NJ US	PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCP	PRCPPRCPPRCPPRCP

Note that we can use filter() to exclude some groups from aggregation. Here, we only keep groups with 'NY' in the group's name attribute, which is the station ID in this case:

In [194…

```
weather.groupby('station').filter( # station IDs with NY in them
 lambda x: 'NY' in x.name
).query('datatype == "SNOW"').groupby('station_name').sum().squeeze() # aggregate a
```

Out[194…

	datatype	
station_name		
ALBERTSON 0.2 SSE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
AMITYVILLE 0.1 WSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH
AMITYVILLE 0.6 NNE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH
ARMONK 0.3 SE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHCN
BROOKLYN 3.1 NW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
CENTERPORT 0.9 SW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH
ELMSFORD 0.8 SSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOW	GHCN
FLORAL PARK 0.4 W, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
HICKSVILLE 1.3 ENE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
JACKSON HEIGHTS 0.3 WSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
LOCUST VALLEY 0.3 E, NY US	SNOWSNOWSNOW	GHC
LYNBROOK 0.3 NW, NY US	SNOWSNOWSNOWSNOWSNOWSNOW	GHC
MASSAPEQUA 0.9 SSW, NY US	SNOWSNOW	
MIDDLE VILLAGE 0.5 SW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHC
NEW HYDE PARK 1.6 NE,	SNOW	

	datatype	
station_name		
NY US		
NEW YORK 8.8 N, NY US	SNOWSNOWSNOWSNOWSNOW	GH(
NORTH WANTAGH 0.4 WSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
PLAINEDGE 0.4 WSW, NY US	SNOWSNOWSNOWSNOW	GH(
PLAINVIEW 0.4 ENE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
SADDLE ROCK 3.4 WSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GHCI
STATEN ISLAND 1.4 SE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH
STATEN ISLAND 4.5 SSE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH
SYOSSET 2.0 SSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
VALLEY STREAM 0.6 SE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
WANTAGH 0.3 ESE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
WANTAGH 1.1 NNE, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH(
WEST NYACK 1.3 WSW, NY US	SNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSNOWSN...	GH

In [195…

```
weather.query('datatype == "PRCP"').groupby(
 pd.Grouper(freq='D')
).mean().groupby(pd.Grouper(freq='M')).sum().value.nlargest()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1942, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1941 try:
-> 1942     res_values = self._grouper.agg_series(ser, alt, preserve_dtype=True)
   1943 except Exception as err:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:864,
in BaseGrouper.agg_series(self, obj, func, preserve_dtype)
    862     preserve_dtype = True
--> 864 result = self._aggregate_series_pure_python(obj, func)
    866 npvalues = lib.maybe_convert_objects(result, try_float=False)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:885,
in BaseGrouper._aggregate_series_pure_python(self, obj, func)
    884 for i, group in enumerate(splitter):
--> 885     res = func(group)
    886     res = extract_result(res)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2454, in GroupBy.mean.<locals>.<lambda>(x)
   2451 else:
   2452     result = self._cython_agg_general(
   2453         "mean",
-> 2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6549, in
Series.mean(self, axis, skipna, numeric_only, **kwargs)
   6541 @doc(make_doc("mean", ndim=1))
   6542 def mean(
   6543     self,
   (...)
   6547     **kwargs,
   6548 ):
-> 6549     return NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12420, i
n NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)
  12413 def mean(
  12414     self,
  12415     axis: Axis | None = 0,
   (...)
  12418     **kwargs,
  12419 ) -> Series | float:
> 12420     return self._stat_function(
  12421         "mean", nanops.nanmean, axis, skipna, numeric_only, **kwargs
  12422     )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12377, i
n NDFrame._stat_function(self, name, func, axis, skipna, numeric_only, **kwargs)
  12375 validate_bool_kwarg(skipna, "skipna", none_allowed=False)
> 12377 return self._reduce(
```

```
  12378     func, name=name, axis=axis, skipna=skipna, numeric_only=numeric_only
  12379 )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6457, in
Series._reduce(self, op, name, axis, skipna, numeric_only, filter_type, **kwds)
   6453     raise TypeError(
   6454         f"Series.{name} does not allow {kwd_name}={numeric_only} "
   6455         "with non-numeric dtypes."
   6456     )
-> 6457 return op(delegate, skipna=skipna, **kwds)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:147, in b
ottleneck_switch.__call__.<locals>.f(values, axis, skipna, **kwds)
    146 else:
--> 147     result = alt(values, axis=axis, skipna=skipna, **kwds)
    149 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:404, in _
datetimelike_compat.<locals>.new_func(values, axis, skipna, mask, **kwargs)
    402     mask = isna(values)
--> 404 result = func(values, axis=axis, skipna=skipna, mask=mask, **kwargs)
    406 if datetimelike:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:720, in n
anmean(values, axis, skipna, mask)
    719 the_sum = values.sum(axis, dtype=dtype_sum)
--> 720 the_sum = _ensure_numeric(the_sum)
    722 if axis is not None and getattr(the_sum, "ndim", False):

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:1701, in
_ensure_numeric(x)
   1699 if isinstance(x, str):
   1700     # GH#44008, GH#36703 avoid casting e.g. strings to numeric
-> 1701     raise TypeError(f"Could not convert string '{x}' to numeric")
   1702 try:

TypeError: Could not convert string 'PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCP' to numeri
c

The above exception was the direct cause of the following exception:

TypeError                                 Traceback (most recent call last)
Cell In[195], line 3
      1 weather.query('datatype == "PRCP"').groupby(
      2  pd.Grouper(freq='D')
----> 3 ).mean().groupby(pd.Grouper(freq='M')).sum().value.nlargest()

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2452, in GroupBy.mean(self, numeric_only, engine, engine_kwargs)
   2445     return self._numba_agg_general(
   2446         grouped_mean,
   2447         executor.float_dtype_mapping,
   2448         engine_kwargs,
```

```
   2449         min_periods=0,
   2450     )
   2451 else:
-> 2452     result = self._cython_agg_general(
   2453         "mean",
   2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1998, in GroupBy._cython_agg_general(self, how, alt, numeric_only, min_count, **kwar
gs)
   1995     result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996     return result
-> 1998 new_mgr = data.grouped_reduce(array_func)
   1999 res = self._wrap_agged_manager(new_mgr)
   2000 if how in ["idxmin", "idxmax"]:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\managers.
py:1469, in BlockManager.grouped_reduce(self, func)
   1465 if blk.is_object:
   1466     # split on object-dtype blocks bc some columns may raise
   1467     #  while others do not.
   1468     for sb in blk._split():
-> 1469         applied = sb.apply(func)
   1470         result_blocks = extend_blocks(applied, result_blocks)
   1471 else:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\blocks.p
y:393, in Block.apply(self, func, **kwargs)
    387 @final
    388 def apply(self, func, **kwargs) -> list[Block]:
    389     """
    390     apply the function to my values; return a block if we are not
    391     one
    392     """
--> 393     result = func(self.values, **kwargs)
    395     result = maybe_coerce_values(result)
    396     return self._split_op_result(result)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1995, in GroupBy._cython_agg_general.<locals>.array_func(values)
   1992     return result
   1994 assert alt is not None
-> 1995 result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1946, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1944     msg = f"agg function failed [how->{how},dtype->{ser.dtype}]"
   1945     # preserve the kind of exception that raised
-> 1946     raise type(err)(msg) from err
   1948 if ser.dtype == object:
   1949     res_values = res_values.astype(object, copy=False)
```

```
TypeError: agg function failed [how->mean,dtype->object]
```

Perhaps the previous result was surprising. The saying goes "April showers bring May flowers"; yet April wasn't in the top 5 (neither was May for that matter). Snow will count towards precipitation, but that doesn't explain why summer months are higher than April. Let's look for days that accounted for a large percentage of the precipitation in a given month. In order to do so, we need to calculate the average daily precipitation across stations and then find the total per month. This will be the denominator. However, in order to divide the daily values by the total for their month, we will need a Series of equal dimensions. This means we will need to use transform() :

In [196…

```
weather.query('datatype == "PRCP"').rename(
 dict(value='prcp'), axis=1
).groupby(pd.Grouper(freq='D')).mean().groupby(
 pd.Grouper(freq='M')
).transform(np.sum)['2018-01-28':'2018-02-03']
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1942, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1941 try:
-> 1942     res_values = self._grouper.agg_series(ser, alt, preserve_dtype=True)
   1943 except Exception as err:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:864,
in BaseGrouper.agg_series(self, obj, func, preserve_dtype)
    862     preserve_dtype = True
--> 864 result = self._aggregate_series_pure_python(obj, func)
    866 npvalues = lib.maybe_convert_objects(result, try_float=False)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\ops.py:885,
in BaseGrouper._aggregate_series_pure_python(self, obj, func)
    884 for i, group in enumerate(splitter):
--> 885     res = func(group)
    886     res = extract_result(res)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2454, in GroupBy.mean.<locals>.<lambda>(x)
   2451 else:
   2452     result = self._cython_agg_general(
   2453         "mean",
-> 2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6549, in
Series.mean(self, axis, skipna, numeric_only, **kwargs)
   6541 @doc(make_doc("mean", ndim=1))
   6542 def mean(
   6543     self,
   (...)
   6547     **kwargs,
   6548 ):
-> 6549     return NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12420, i
n NDFrame.mean(self, axis, skipna, numeric_only, **kwargs)
  12413 def mean(
  12414     self,
  12415     axis: Axis | None = 0,
   (...)
  12418     **kwargs,
  12419 ) -> Series | float:
> 12420     return self._stat_function(
  12421         "mean", nanops.nanmean, axis, skipna, numeric_only, **kwargs
  12422     )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\generic.py:12377, i
n NDFrame._stat_function(self, name, func, axis, skipna, numeric_only, **kwargs)
  12375 validate_bool_kwarg(skipna, "skipna", none_allowed=False)
> 12377 return self._reduce(
```

```
  12378     func, name=name, axis=axis, skipna=skipna, numeric_only=numeric_only
  12379 )

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\series.py:6457, in
Series._reduce(self, op, name, axis, skipna, numeric_only, filter_type, **kwds)
   6453     raise TypeError(
   6454         f"Series.{name} does not allow {kwd_name}={numeric_only} "
   6455         "with non-numeric dtypes."
   6456     )
-> 6457 return op(delegate, skipna=skipna, **kwds)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:147, in b
ottleneck_switch.__call__.<locals>.f(values, axis, skipna, **kwds)
    146 else:
--> 147     result = alt(values, axis=axis, skipna=skipna, **kwds)
    149 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:404, in _
datetimelike_compat.<locals>.new_func(values, axis, skipna, mask, **kwargs)
    402     mask = isna(values)
--> 404 result = func(values, axis=axis, skipna=skipna, mask=mask, **kwargs)
    406 if datetimelike:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:720, in n
anmean(values, axis, skipna, mask)
    719 the_sum = values.sum(axis, dtype=dtype_sum)
--> 720 the_sum = _ensure_numeric(the_sum)
    722 if axis is not None and getattr(the_sum, "ndim", False):

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\nanops.py:1701, in
_ensure_numeric(x)
   1699 if isinstance(x, str):
   1700     # GH#44008, GH#36703 avoid casting e.g. strings to numeric
-> 1701     raise TypeError(f"Could not convert string '{x}' to numeric")
   1702 try:

TypeError: Could not convert string 'PRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRC
PPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCPPRCP' to numeri
c

The above exception was the direct cause of the following exception:

TypeError                                 Traceback (most recent call last)
Cell In[196], line 3
      1 weather.query('datatype == "PRCP"').rename(
      2  dict(value='prcp'), axis=1
----> 3 ).groupby(pd.Grouper(freq='D')).mean().groupby(
      4  pd.Grouper(freq='M')
      5 ).transform(np.sum)['2018-01-28':'2018-02-03']

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
2452, in GroupBy.mean(self, numeric_only, engine, engine_kwargs)
   2445     return self._numba_agg_general(
   2446         grouped_mean,
```

```
   2447         executor.float_dtype_mapping,
   2448         engine_kwargs,
   2449         min_periods=0,
   2450     )
   2451 else:
-> 2452     result = self._cython_agg_general(
   2453         "mean",
   2454         alt=lambda x: Series(x, copy=False).mean(numeric_only=numeric_only),
   2455         numeric_only=numeric_only,
   2456     )
   2457     return result.__finalize__(self.obj, method="groupby")

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1998, in GroupBy._cython_agg_general(self, how, alt, numeric_only, min_count, **kwar
gs)
   1995     result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996     return result
-> 1998 new_mgr = data.grouped_reduce(array_func)
   1999 res = self._wrap_agged_manager(new_mgr)
   2000 if how in ["idxmin", "idxmax"]:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\managers.
py:1469, in BlockManager.grouped_reduce(self, func)
   1465 if blk.is_object:
   1466     # split on object-dtype blocks bc some columns may raise
   1467     #  while others do not.
   1468     for sb in blk._split():
-> 1469         applied = sb.apply(func)
   1470         result_blocks = extend_blocks(applied, result_blocks)
   1471 else:

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\internals\blocks.p
y:393, in Block.apply(self, func, **kwargs)
    387 @final
    388 def apply(self, func, **kwargs) -> list[Block]:
    389     """
    390     apply the function to my values; return a block if we are not
    391     one
    392     """
--> 393     result = func(self.values, **kwargs)
    395     result = maybe_coerce_values(result)
    396     return self._split_op_result(result)

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1995, in GroupBy._cython_agg_general.<locals>.array_func(values)
   1992     return result
   1994 assert alt is not None
-> 1995 result = self._agg_py_fallback(how, values, ndim=data.ndim, alt=alt)
   1996 return result

File ~\.conda\envs\CPE311_BULAMBAO\Lib\site-packages\pandas\core\groupby\groupby.py:
1946, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)
   1944     msg = f"agg function failed [how->{how},dtype->{ser.dtype}]"
   1945     # preserve the kind of exception that raised
-> 1946     raise type(err)(msg) from err
   1948 if ser.dtype == object:
```

```
   1949     res_values = res_values.astype(object, copy=False)

TypeError: agg function failed [how->mean,dtype->object]
```

In [201…

```
.rename(dict(value='prcp'), axis=1)\
 .groupby(pd.Grouper(freq='D')).mean()\
 .assign(
 total_prcp_in_month=lambda x: x.groupby(
 pd.Grouper(freq='M')
 ).transform(np.sum),
 pct_monthly_prcp=lambda x: x.prcp.div(
 x.total_prcp_in_month
 )
 ).nlargest(5, 'pct_monthly_prcp')
# didn't work
```

```
  Cell In[201], line 1
    .rename(dict(value='prcp'), axis=1)\
    ^
SyntaxError: invalid syntax
```

transform() can be used on dataframes as well. We can use it to easily standardize the data:

In [202…

```
fb[['open', 'high', 'low', 'close']].transform(
 lambda x: (x - x.mean()).div(x.std())
).head()
```

Out[202…

	open	high	low	close
date				
2018-01-02	0.32	0.41	0.41	0.50
2018-01-03	0.53	0.57	0.60	0.66
2018-01-04	0.68	0.65	0.74	0.64
2018-01-05	0.72	0.68	0.78	0.77
2018-01-08	0.80	0.79	0.85	0.84

Pivot tables and crosstabs

In [203…

```
fb.pivot_table(columns='trading_volume')
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3311801863.py:1: FutureWar
ning: The default value of observed=False is deprecated and will change to observed=
True in a future version of pandas. Specify observed=False to silence this warning a
nd retain the current behavior
  fb.pivot_table(columns='trading_volume')
```

Out[203…

trading_volume	low	med	high
close	171.43	175.14	168.16
high	173.46	179.42	170.48
low	169.31	172.11	161.57
open	171.36	175.82	167.73
volume	24547207.71	79072559.12	141924023.33

In [204…

```
fb.pivot_table(index='trading_volume')
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\1557930399.py:1: FutureWar
ning: The default value of observed=False is deprecated and will change to observed=
True in a future version of pandas. Specify observed=False to silence this warning a
nd retain the current behavior
  fb.pivot_table(index='trading_volume')
```

Out[204…

	close	high	low	open	volume
trading_volume					
low	171.43	173.46	169.31	171.36	24547207.71
med	175.14	179.42	172.11	175.82	79072559.12
high	168.16	170.48	161.57	167.73	141924023.33

In [207…

```
weather.reset_index().pivot_table(
 index=['date', 'station', 'station_name'],
 columns='datatype',
 values='value',
 aggfunc='median'
).reset_index().tail()
```

Out[207…

datatype	date	station	station_name	AWND	DAPR	MDPR	PGTM	PI
28740	2018-12-31	GHCND:USW00054787	FARMINGDALE REPUBLIC AIRPORT, NY US	5.00	NaN	NaN	2052.00	28
28741	2018-12-31	GHCND:USW00094728	NY CITY CENTRAL PARK, NY US	NaN	NaN	NaN	NaN	25
28742	2018-12-31	GHCND:USW00094741	TETERBORO AIRPORT, NJ US	1.70	NaN	NaN	1954.00	29
28743	2018-12-31	GHCND:USW00094745	WESTCHESTER CO AIRPORT, NY US	2.70	NaN	NaN	2212.00	24
28744	2018-12-31	GHCND:USW00094789	JFK INTERNATIONAL AIRPORT, NY US	4.10	NaN	NaN	NaN	31

5 rows × 30 columns

In [208…

```
pd.crosstab(
 index=fb.trading_volume,
 columns=fb.index.month,
 colnames=['month'] # name the columns index
)
```

Out[208…

month	1	2	3	4	5	6	7	8	9	10	11	12
trading_volume												
low	20	19	15	20	22	21	18	23	19	23	21	19
med	1	0	4	1	0	0	2	0	0	0	0	0
high	0	0	2	0	0	0	1	0	0	0	0	0

In [209…

```
pd.crosstab(
 index=fb.trading_volume,
 columns=fb.index.month,
 colnames=['month'],
 normalize='columns'
)
```

Out[209…

month	1	2	3	4	5	6	7	8	9	10	11	12
trading_volume												
low	0.95	1.00	0.71	0.95	1.00	1.00	0.86	1.00	1.00	1.00	1.00	1.00
med	0.05	0.00	0.19	0.05	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00
high	0.00	0.00	0.10	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00

In [210…

```
pd.crosstab(
 index=fb.trading_volume,
 columns=fb.index.month,
 colnames=['month'],
 values=fb.close,
 aggfunc=np.mean
)
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\853386191.py:1: FutureWarn
ing: The provided callable <function mean at 0x000001871928A0C0> is currently using
DataFrameGroupBy.mean. In a future version of pandas, the provided callable will be
used directly. To keep current behavior pass the string "mean" instead.
  pd.crosstab(
```

Out[210…

month	1	2	3	4	5	6	7	8	9	
trading_volume										
low	185.24	180.27	177.07	163.29	182.93	195.27	201.92	177.49	164.38	154.
med	179.37	NaN	164.76	174.16	NaN	NaN	194.28	NaN	NaN	Na
high	NaN	NaN	164.11	NaN	NaN	NaN	176.26	NaN	NaN	Na

In [211…

```
snow_data = weather.query('datatype == "SNOW"')
pd.crosstab(
 index=snow_data.station_name,
 columns=snow_data.index.month,
 colnames=['month'],
values=snow_data.value,
 aggfunc=lambda x: (x > 0).sum(),
 margins=True, # show row and column subtotals
 margins_name='total observations of snow' # name the subtotals
)
```

Out[211…

month	1	2	3	4	5	6	7	8	9	10	11
station_name											
ALBERTSON 0.2 SSE, NY US	3.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
AMITYVILLE 0.1 WSW, NY US	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AMITYVILLE 0.6 NNE, NY US	3.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARMONK 0.3 SE, NY US	6.00	4.00	6.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BLOOMINGDALE 0.7 SSE, NJ US	2.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
...	...	...	...	...	...	...	...	...	...	...	...
WESTFIELD 0.6 NE, NJ US	3.00	0.00	4.00	1.00	0.00	NaN	0.00	0.00	0.00	NaN	1.00
WOODBRIDGE TWP 1.1 ESE, NJ US	4.00	1.00	3.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
WOODBRIDGE TWP 1.1 NNE, NJ US	2.00	1.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
WOODBRIDGE TWP 3.0 NNW, NJ US	NaN	0.00	0.00	NaN	NaN	0.00	NaN	NaN	NaN	0.00	0.00
total observations of snow	190.00	97.00	237.00	81.00	0.00	0.00	0.00	0.00	0.00	0.00	49.00

99 rows × 13 columns

In [ ]:

Time Series

About the Data

In this notebook, we will be working with 5 data sets:

```
(CSV) Facebook's stock price daily throughout 2018 (obtained using
the stock_analysis package).

(CSV) Facebook's OHLC stock data from May 20, 2019 - May 24, 2019
per minute from Nasdaq.com.

(CSV) melted stock data for Facebook from May 20, 2019 - May 24,
2019 per minute from Nasdaq.com.

(DB) stock opening prices by the minute for Apple from May 20, 2019
- May 24, 2019 altered to have seconds in the time from Nasdaq.com.

(DB) stock opening prices by the minute for Facebook from May 20,
2019 - May 24, 2019 from Nasdaq.com.
```

Setup

In [213…

```
import numpy as np
import pandas as pd
fb = pd.read_csv('fb_2018.csv', index_col='date', parse_dates=True).assign(
 trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
)
fb.head()
```

Out[213…

	open	high	low	close	volume	trading_volume
date						
2018-01-02	177.68	181.58	177.55	181.42	18151903	low
2018-01-03	181.88	184.78	181.33	184.67	16886563	low
2018-01-04	184.90	186.21	184.10	184.33	13880896	low
2018-01-05	185.59	186.90	184.93	186.85	13574535	low
2018-01-08	187.20	188.90	186.33	188.28	17994726	low

Time-based selection and filtering

In [214…

```
fb.loc['2018-10-11':'2018-10-15']
```

Out[214…

	open	high	low	close	volume	trading_volume
date						
2018-10-11	150.13	154.81	149.16	153.35	35338901	low
2018-10-12	156.73	156.89	151.30	153.74	25293492	low
2018-10-15	153.32	155.57	152.55	153.52	15433521	low

In [215…

```python
fb.loc['2018-q1'].equals(fb.loc['2018-01':'2018-03'])
```

Out[215…

```
True
```

In [216…

```python
fb.first('1W')
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2655357208.py:1: FutureWar
ning: first is deprecated and will be removed in a future version. Please create a m
ask and filter using `.loc` instead
  fb.first('1W')
```

Out[216…

	open	high	low	close	volume	trading_volume
date						
2018-01-02	177.68	181.58	177.55	181.42	18151903	low
2018-01-03	181.88	184.78	181.33	184.67	16886563	low
2018-01-04	184.90	186.21	184.10	184.33	13880896	low
2018-01-05	185.59	186.90	184.93	186.85	13574535	low

In [217…

```python
fb.last('1W')
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2477606097.py:1: FutureWar
ning: last is deprecated and will be removed in a future version. Please create a ma
sk and filter using `.loc` instead
  fb.last('1W')
```

Out[217…

	open	high	low	close	volume	trading_volume
date						
2018-12-31	134.45	134.64	129.95	131.09	24625308	low

In [219…

```python
stock_data_per_minute = pd.read_csv(
 'fb_week_of_may_20_per_minute.csv', index_col='date', parse_dates=True,
 date_parser=lambda x: pd.to_datetime(x, format='%Y-%m-%d %H-%M')
)
stock_data_per_minute.head()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3716198482.py:1: FutureWar
ning: The argument 'date_parser' is deprecated and will be removed in a future versi
on. Please use 'date_format' instead, or read your data in as 'object' dtype and the
n call 'to_datetime'.
  stock_data_per_minute = pd.read_csv(
```

Out[219…

date	open	high	low	close	volume
2019-05-20 09:30:00	181.62	181.62	181.62	181.62	159049.00
2019-05-20 09:31:00	182.61	182.61	182.61	182.61	468017.00
2019-05-20 09:32:00	182.75	182.75	182.75	182.75	97258.00
2019-05-20 09:33:00	182.95	182.95	182.95	182.95	43961.00
2019-05-20 09:34:00	183.06	183.06	183.06	183.06	79562.00

In [220…

```
stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({
 'open': 'first',
 'high': 'max',
 'low': 'min',
 'close': 'last',
 'volume': 'sum'
})
```

Out[220…

date	open	high	low	close	volume
2019-05-20	181.62	184.18	181.62	182.72	10044838.00
2019-05-21	184.53	185.58	183.97	184.82	7198405.00
2019-05-22	184.81	186.56	184.01	185.32	8412433.00
2019-05-23	182.50	183.73	179.76	180.87	12479171.00
2019-05-24	182.33	183.52	181.04	181.06	7686030.00

In [221…

```
stock_data_per_minute.at_time('9:30')
```

Out[221…

date	open	high	low	close	volume
2019-05-20 09:30:00	181.62	181.62	181.62	181.62	159049.00
2019-05-21 09:30:00	184.53	184.53	184.53	184.53	58171.00
2019-05-22 09:30:00	184.81	184.81	184.81	184.81	41585.00
2019-05-23 09:30:00	182.50	182.50	182.50	182.50	121930.00
2019-05-24 09:30:00	182.33	182.33	182.33	182.33	52681.00

In [222…

```
stock_data_per_minute.between_time('15:59', '16:00')
```

Out[222...

date	open	high	low	close	volume
2019-05-20 15:59:00	182.91	182.91	182.91	182.91	134569.00
2019-05-20 16:00:00	182.72	182.72	182.72	182.72	1113672.00
2019-05-21 15:59:00	184.84	184.84	184.84	184.84	61606.00
2019-05-21 16:00:00	184.82	184.82	184.82	184.82	801080.00
2019-05-22 15:59:00	185.29	185.29	185.29	185.29	96099.00
2019-05-22 16:00:00	185.32	185.32	185.32	185.32	1220993.00
2019-05-23 15:59:00	180.72	180.72	180.72	180.72	109648.00
2019-05-23 16:00:00	180.87	180.87	180.87	180.87	1329217.00
2019-05-24 15:59:00	181.07	181.07	181.07	181.07	52994.00
2019-05-24 16:00:00	181.06	181.06	181.06	181.06	764906.00

In [223...

```
shares_traded_in_first_30_min = stock_data_per_minute\
 .between_time('9:30', '10:00')\
 .groupby(pd.Grouper(freq='1D'))\
 .filter(lambda x: (x.volume > 0).all())\
 .volume.mean()
shares_traded_in_last_30_min = stock_data_per_minute\
 .between_time('15:30', '16:00')\
 .groupby(pd.Grouper(freq='1D'))\
 .filter(lambda x: (x.volume > 0).all())\
 .volume.mean()
shares_traded_in_first_30_min - shares_traded_in_last_30_min
```

Out[223...

```
np.float64(18592.967741935485)
```

In [224...

```
pd.DataFrame(
 dict(before=stock_data_per_minute.index, after=stock_data_per_minute.index.normali
).head()
```

Out[224...

	before	after
0	2019-05-20 09:30:00	2019-05-20
1	2019-05-20 09:31:00	2019-05-20
2	2019-05-20 09:32:00	2019-05-20
3	2019-05-20 09:33:00	2019-05-20
4	2019-05-20 09:34:00	2019-05-20

In [225...

```
stock_data_per_minute.index.to_series().dt.normalize().head()
```

Out[225…

```
date
2019-05-20 09:30:00   2019-05-20
2019-05-20 09:31:00   2019-05-20
2019-05-20 09:32:00   2019-05-20
2019-05-20 09:33:00   2019-05-20
2019-05-20 09:34:00   2019-05-20
Name: date, dtype: datetime64[ns]
```

Shifting for lagged data

We can use shift() to create some lagged data. By default, the shift will be one period. For example, we can use shift() to create a new column that indicates the previous day's closing price. From this new column, we can calculate the price change due to after hours trading (after the close one day right up to the open the following day):

In [226…

```
fb.assign(
 prior_close=lambda x: x.close.shift(),
 after_hours_change_in_price=lambda x: x.open - x.prior_close,
 abs_change=lambda x: x.after_hours_change_in_price.abs()
).nlargest(5, 'abs_change')
```

Out[226…

	open	high	low	close	volume	trading_volume	prior_close	after_hours_
date								
2018-07-26	174.89	180.13	173.75	176.26	169803668	high	217.50	
2018-04-26	173.22	176.27	170.80	174.16	77556934	med	159.69	
2018-01-12	178.06	181.48	177.40	179.37	77551299	med	187.77	
2018-10-31	155.00	156.40	148.96	151.79	60101251	low	146.22	
2018-03-19	177.01	177.17	170.06	172.56	88140060	med	185.09	

In [227…

```
pd.date_range('2018-01-01', freq='D', periods=5) + pd.Timedelta('9 hours 30 minutes
```

Out[227…

```
DatetimeIndex(['2018-01-01 09:30:00', '2018-01-02 09:30:00',
               '2018-01-03 09:30:00', '2018-01-04 09:30:00',
               '2018-01-05 09:30:00'],
              dtype='datetime64[ns]', freq='D')
```

In [228…

```
fb.loc['2018-09'].first_valid_index()
```

Out[228…

```
Timestamp('2018-09-04 00:00:00')
```

In [229…
```
fb.loc['2018-09'].last_valid_index()
```
Out[229…
```
Timestamp('2018-09-28 00:00:00')
```
In [230…
```
fb.index.contains('2018-09-30')
```
```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[230], line 1
----> 1 fb.index.contains('2018-09-30')

AttributeError: 'DatetimeIndex' object has no attribute 'contains'
```
In [231…
```
fb.asof('2018-09-30')
```
Out[231…
```
open                  168.33
high                  168.79
low                   162.56
close                 164.46
volume              34265638
trading_volume           low
Name: 2018-09-30 00:00:00, dtype: object
```
In [232…
```
(
 fb.drop(columns='trading_volume')
 - fb.drop(columns='trading_volume').shift()
).equals(
 fb.drop(columns='trading_volume').diff()
)
```
Out[232…
```
True
```
In [233…
```
fb.drop(columns='trading_volume').diff().head()
```
Out[233…

	open	high	low	close	volume
date					
2018-01-02	NaN	NaN	NaN	NaN	NaN
2018-01-03	4.20	3.20	3.78	3.25	-1265340.00
2018-01-04	3.02	1.43	2.77	-0.34	-3005667.00
2018-01-05	0.69	0.69	0.83	2.52	-306361.00
2018-01-08	1.61	2.00	1.40	1.43	4420191.00

In [234…
```
fb.drop(columns='trading_volume').diff(-3).head()
```

Out[234...

	open	high	low	close	volume
date					
2018-01-02	-7.91	-5.32	-7.38	-5.43	4577368.00
2018-01-03	-5.32	-4.12	-5.00	-3.61	-1108163.00
2018-01-04	-3.80	-2.59	-3.00	-3.54	1487839.00
2018-01-05	-1.35	-0.99	-0.70	-0.99	3044641.00
2018-01-08	-1.20	0.50	-1.05	0.51	8406139.00

In [235...

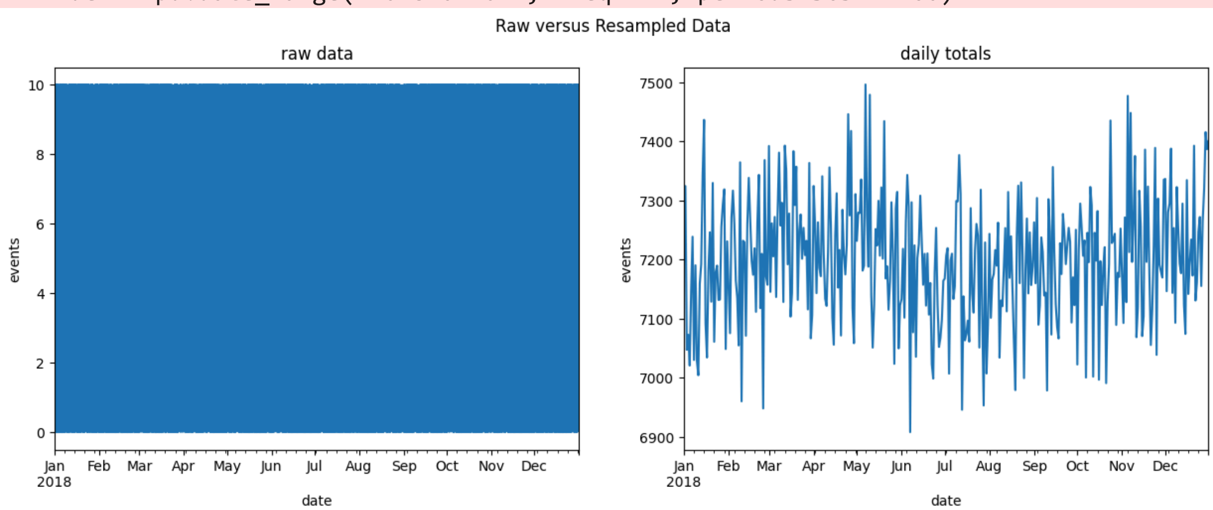
```
import matplotlib.pyplot as plt
```

In [236...

```
np.random.seed(0)
index = pd.date_range('2018-01-01', freq='T', periods=365*24*60)
raw = pd.DataFrame(
 np.random.uniform(0, 10, size=index.shape[0]), index=index
)
fig, axes = plt.subplots(1, 2, figsize=(15, 5))
raw.plot(legend=False, ax=axes[0], title='raw data')
raw.resample('1D').sum().plot(legend=False, ax=axes[1], title='daily totals')
for ax in axes:
 ax.set_xlabel('date')
 ax.set_ylabel('events')

plt.suptitle('Raw versus Resampled Data')
plt.show()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\188799855.py:2: FutureWarn
ing: 'T' is deprecated and will be removed in a future version, please use 'min' ins
tead.
  index = pd.date_range('2018-01-01', freq='T', periods=365*24*60)
```



In [237...

```
stock_data_per_minute.head()
```

Out[237…

date	open	high	low	close	volume
2019-05-20 09:30:00	181.62	181.62	181.62	181.62	159049.00
2019-05-20 09:31:00	182.61	182.61	182.61	182.61	468017.00
2019-05-20 09:32:00	182.75	182.75	182.75	182.75	97258.00
2019-05-20 09:33:00	182.95	182.95	182.95	182.95	43961.00
2019-05-20 09:34:00	183.06	183.06	183.06	183.06	79562.00

In [238…

```
stock_data_per_minute.resample('1D').agg({
 'open': 'first',
 'high': 'max',
 'low': 'min',
 'close': 'last',
 'volume': 'sum'
})
```

Out[238…

date	open	high	low	close	volume
2019-05-20	181.62	184.18	181.62	182.72	10044838.00
2019-05-21	184.53	185.58	183.97	184.82	7198405.00
2019-05-22	184.81	186.56	184.01	185.32	8412433.00
2019-05-23	182.50	183.73	179.76	180.87	12479171.00
2019-05-24	182.33	183.52	181.04	181.06	7686030.00

In [ ]:

```
fb.resample('Q').mean()
```

In [240…

```
fb.drop(columns='trading_volume').resample('Q').apply(
 lambda x: x.last('1D').values - x.first('1D').values
)
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2934583360.py:1: FutureWar
ning: 'Q' is deprecated and will be removed in a future version, please use 'QE' ins
tead.
  fb.drop(columns='trading_volume').resample('Q').apply(
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2934583360.py:2: FutureWar
ning: last is deprecated and will be removed in a future version. Please create a ma
sk and filter using `.loc` instead
  lambda x: x.last('1D').values - x.first('1D').values
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2934583360.py:2: FutureWar
ning: first is deprecated and will be removed in a future version. Please create a m
ask and filter using `.loc` instead
  lambda x: x.last('1D').values - x.first('1D').values
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2934583360.py:2: FutureWar
ning: last is deprecated and will be removed in a future version. Please create a ma
sk and filter using `.loc` instead
  lambda x: x.last('1D').values - x.first('1D').values
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2934583360.py:2: FutureWar
ning: first is deprecated and will be removed in a future version. Please create a m
ask and filter using `.loc` instead
  lambda x: x.last('1D').values - x.first('1D').values
```

Out[240…

```
date
2018-03-31    [[-22.53, -20.160000000000025, -23.41000000000...
2018-06-30    [[39.50999999999999, 38.399700000000024, 39.84...
2018-09-30    [[-25.039999999999992, -28.659999999999997, -2...
2018-12-31    [[-28.580000000000013, -31.24000000000001, -31...
Freq: QE-DEC, dtype: object
```

In [242…

```
melted_stock_data = pd.read_csv('melted_stock_data.csv', index_col='date', parse_da
melted_stock_data.head()
```

Out[242…

	price
date	
2019-05-20 09:30:00	181.62
2019-05-20 09:31:00	182.61
2019-05-20 09:32:00	182.75
2019-05-20 09:33:00	182.95
2019-05-20 09:34:00	183.06

In [243…

```
melted_stock_data.resample('1D').ohlc()['price']
```

Out[243...

date	open	high	low	close
2019-05-20	181.62	184.18	181.62	182.72
2019-05-21	184.53	185.58	183.97	184.82
2019-05-22	184.81	186.56	184.01	185.32
2019-05-23	182.50	183.73	179.76	180.87
2019-05-24	182.33	183.52	181.04	181.06

In [244...

```
fb.resample('6H').asfreq().head()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2962105639.py:1: FutureWar
ning: 'H' is deprecated and will be removed in a future version, please use 'h' inst
ead.
  fb.resample('6H').asfreq().head()
```

Out[244...

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.00	low
2018-01-02 06:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-02 12:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-02 18:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.00	low

In [ ]:

```
fb.resample('6H').pad().head()
```

In [246...

```
fb.resample('6H').fillna('nearest').head()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3498320007.py:1: FutureWar
ning: 'H' is deprecated and will be removed in a future version, please use 'h' inst
ead.
  fb.resample('6H').fillna('nearest').head()
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3498320007.py:1: FutureWar
ning: DatetimeIndexResampler.fillna is deprecated and will be removed in a future ve
rsion. Use obj.ffill(), obj.bfill(), or obj.nearest() instead.
  fb.resample('6H').fillna('nearest').head()
```

Out[246...

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 06:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 12:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-02 18:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563	low

In [247...

```
fb.resample('6H').asfreq().assign(
 volume=lambda x: x.volume.fillna(0), # put 0 when market is closed
 close=lambda x: x.close.fillna(method='ffill'), # carry forward
 # take the closing price if these aren't available
 open=lambda x: np.where(x.open.isnull(), x.close, x.open),
 high=lambda x: np.where(x.high.isnull(), x.close, x.high),
 low=lambda x: np.where(x.low.isnull(), x.close, x.low)
).head()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2081602865.py:1: FutureWar
ning: 'H' is deprecated and will be removed in a future version, please use 'h' inst
ead.
  fb.resample('6H').asfreq().assign(
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2081602865.py:3: FutureWar
ning: Series.fillna with 'method' is deprecated and will raise in a future version.
Use obj.ffill() or obj.bfill() instead.
  close=lambda x: x.close.fillna(method='ffill'), # carry forward
```

Out[247...

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.00	low
2018-01-02 06:00:00	181.42	181.42	181.42	181.42	0.00	NaN
2018-01-02 12:00:00	181.42	181.42	181.42	181.42	0.00	NaN
2018-01-02 18:00:00	181.42	181.42	181.42	181.42	0.00	NaN
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.00	low

Merging

We saw merging examples the querying_and_merging notebook. However, they all matched based on keys. With time series, it is possible that they are so granular that we never have the same time for multiple entries. Let's work with some stock data at different granularities

In [249...

```
import sqlite3
with sqlite3.connect('stocks.db') as connection:
```

```python
fb_prices = pd.read_sql(
'SELECT * FROM fb_prices', connection,
index_col='date', parse_dates=['date']
)
aapl_prices = pd.read_sql(
'SELECT * FROM aapl_prices', connection,
index_col='date', parse_dates=['date']
)
```

In [250…

```python
fb_prices.index.second.unique()
```

Out[250…

```
Index([0], dtype='int32', name='date')
```

In [251…

```python
aapl_prices.index.second.unique()
```

Out[251…

```
Index([ 0, 52, 36, 34, 55, 35,  7, 12, 59, 17,  5, 20, 26, 23, 54, 49, 19, 53,
       11, 22, 13, 21, 10, 46, 42, 38, 33, 18, 16,  9, 56, 39,  2, 50, 31, 58,
       48, 24, 29,  6, 47, 51, 40,  3, 15, 14, 25,  4, 43,  8, 32, 27, 30, 45,
        1, 44, 57, 41, 37, 28],
      dtype='int32', name='date')
```

In [252…

```python
pd.merge_asof(
 fb_prices, aapl_prices,
 left_index=True, right_index=True, # datetimes are in the index
 # merge with nearest minute
 direction='nearest', tolerance=pd.Timedelta(30, unit='s')
).head()
```

Out[252…

	FB	AAPL
date		
2019-05-20 09:30:00	181.62	183.52
2019-05-20 09:31:00	182.61	NaN
2019-05-20 09:32:00	182.75	182.87
2019-05-20 09:33:00	182.95	182.50
2019-05-20 09:34:00	183.06	182.11

In [253…

```python
pd.merge_ordered(
 fb_prices.reset_index(), aapl_prices.reset_index(),
 fill_method='ffill'
).set_index('date').head()
```

Out[253…

date	FB	AAPL
2019-05-20 09:30:00	181.62	183.52
2019-05-20 09:31:00	182.61	183.52
2019-05-20 09:31:52	182.61	182.87
2019-05-20 09:32:00	182.75	182.87
2019-05-20 09:32:36	182.75	182.50

8.1.4 Data Analysis

Provide some comments here about the results of the procedures.

8.1.5 Supplementary Activity

Using the CSV files provided and what we have learned so far in this module complete the following exercises:

In [281…

```
import pandas as pd
import numpy as np
```

In [311…

```
earthquake = pd.read_csv('earthquakes.csv')
#this reads the earthquakes.csv
# using the read_csv() command
#from pandas library
earthquake
```

Out[311…

	mag	magType	time	place	tsunami	parsed_place
0	1.35	ml	1539475168010	9km NE of Aguanga, CA	0	California
1	1.29	ml	1539475129610	9km NE of Aguanga, CA	0	California
2	3.42	ml	1539475062610	8km NE of Aguanga, CA	0	California
3	0.44	ml	1539474978070	9km NE of Aguanga, CA	0	California
4	2.16	md	1539474716050	10km NW of Avenal, CA	0	California
...	...	...	...	...	...	...
9327	0.62	md	1537230228060	9km ENE of Mammoth Lakes, CA	0	California
9328	1.00	ml	1537230135130	3km W of Julian, CA	0	California
9329	2.40	md	1537229908180	35km NNE of Hatillo, Puerto Rico	0	Puerto Rico
9330	1.10	ml	1537229545350	9km NE of Aguanga, CA	0	California
9331	0.66	ml	1537228864470	9km NE of Aguanga, CA	0	California

9332 rows × 6 columns

In [313…

```
#1. With the earthquakes.csv file, select all the earthquakes in Japan
#with a magType of mb and a magnitude of 4.9 or greater.
# placing the dataframe with with the column call the column
# placing >, <, >=, <=  or == can be used to
#filter out the column with specific entries using &
# to add another filter to be used
earthquake[(earthquake['mag'] >= 4.9) & (earthquake['magType'] == 'mb')]
```

Out[313…

	mag	magType	time	place	tsunami	parsed_place
227	5.20	mb	1539389603790	15km WSW of Pisco, Peru	0	Peru
229	4.90	mb	1539389546300	193km N of Qulansiyah, Yemen	0	Yemen
248	4.90	mb	1539382925190	151km S of Severo-Kuril'sk, Russia	0	Russia
258	5.10	mb	1539380306940	236km NNW of Kuril'sk, Russia	0	Russia
391	5.10	mb	1539337221080	Pacific-Antarctic Ridge	0	Pacific-Antarctic Ridge
...	...	...	...	...	...	...
9154	4.90	mb	1537268270010	Southwest Indian Ridge	0	Southwest Indian Ridge
9175	5.20	mb	1537262729590	126km N of Dili, East Timor	1	East Timor
9176	5.20	mb	1537262656830	90km S of Raoul Island, New Zealand	0	New Zealand
9213	5.10	mb	1537255481060	South of Tonga	0	Tonga
9304	5.10	mb	1537236235470	34km NW of Finschhafen, Papua New Guinea	1	Papua New Guinea

122 rows × 6 columns

In [298…

```
# 2. Create bins for each full number of magnitude
#(for example, the first bin is 0-1, the second is 1-2, and so on)
#with a magType of ml and count how many are in each bin.

bin_range = [x for x in range(int(earthquake['mag'].min()),int(earthquake['mag'].ma
bin_range
bin_text = [str(x) for x in bin_range]


earthquake['quake bins'] = pd.cut(earthquake['mag'],bin_range, bin_text)

earthquake.head()
```

Out[298...

	mag	magType	time	place	tsunami	parsed_place	quake bins
0	1.35	ml	1539475168010	9km NE of Aguanga, CA	0	California	(1, 2]
1	1.29	ml	1539475129610	9km NE of Aguanga, CA	0	California	(1, 2]
2	3.42	ml	1539475062610	8km NE of Aguanga, CA	0	California	(3, 4]
3	0.44	ml	1539474978070	9km NE of Aguanga, CA	0	California	(0, 1]
4	2.16	md	1539474716050	10km NW of Avenal, CA	0	California	(2, 3]

In [299...

```
earthquake.groupby(['quake bins'])['mag'].count()
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\3740247262.py:1: FutureWar
ning: The default of observed=False is deprecated and will be changed to True in a f
uture version of pandas. Pass observed=False to retain current behavior or observed=
True to adopt the future default and silence this warning.
  earthquake.groupby(['quake bins'])['mag'].count()
```

Out[299...

```
quake bins
(-1, 0]     525
(0, 1]     2941
(1, 2]     3802
(2, 3]     1157
(3, 4]      233
(4, 5]      534
(5, 6]      117
(6, 7]        7
(7, 8]        1
Name: mag, dtype: int64
```

In [314...

```
#3. Using the faang.csv file,
faang = pd.read_csv('faang.csv') # reading the csv file
# turning the date column entries to a
# datetime format using pd.to_datetime()
faang['date'] = pd.to_datetime(faang['date'])
# setting the index to the date colum
faang.set_index('date', inplace = True)
faang.head()
```

Out[314...

date	ticker	open	high	low	close	volume
2018-01-02	FB	177.68	181.58	177.55	181.42	18151903
2018-01-03	FB	181.88	184.78	181.33	184.67	16886563
2018-01-04	FB	184.90	186.21	184.10	184.33	13880896
2018-01-05	FB	185.59	186.90	184.93	186.85	13574535
2018-01-08	FB	187.20	188.90	186.33	188.28	17994726

In [315...

```
#group by the ticker and resample to monthly frequency.
#Make the following aggregations:
#Mean of the opening price
#Maximum of the high price
#Minimum of the low price
#Mean of the closing price
#Sum of the volume traded
faang.groupby(['ticker']).resample('ME').agg({
    'open':'mean',
    'high':'max',
    'low': 'min',
    'close':'mean',
    'volume':'sum'
    })
#groupby is used to group each entry by what is inside the parenthesis
# the agg() is used to take a specific value
```

Out[315…

ticker	date	open	high	low	close	volume
AAPL	2018-01-31	170.71	176.68	161.57	170.70	659679440
	2018-02-28	164.56	177.91	147.99	164.92	927894473
	2018-03-31	172.42	180.75	162.47	171.88	713727447
	2018-04-30	167.33	176.25	158.22	167.29	666360147
	2018-05-31	182.64	187.93	162.79	183.21	620976206
	2018-06-30	186.61	192.02	178.71	186.51	527624365
	2018-07-31	188.07	193.76	181.37	188.18	393843881
	2018-08-31	210.46	227.10	195.10	211.48	700318837
	2018-09-30	220.61	227.89	213.64	220.36	678972040
	2018-10-31	219.49	231.66	204.50	219.14	789748068
	2018-11-30	190.83	220.64	169.53	190.25	961321947
	2018-12-31	164.54	184.15	145.96	163.56	898917007
AMZN	2018-01-31	1301.38	1472.58	1170.51	1309.01	96371290
	2018-02-28	1447.11	1528.70	1265.93	1442.36	137784020
	2018-03-31	1542.16	1617.54	1365.20	1540.37	130400151
	2018-04-30	1475.84	1638.10	1352.88	1468.22	129945743
	2018-05-31	1590.47	1635.00	1546.02	1594.90	71615299
	2018-06-30	1699.09	1763.10	1635.09	1698.82	85941510
	2018-07-31	1786.31	1880.05	1678.06	1784.65	97629820
	2018-08-31	1891.96	2025.57	1776.02	1897.85	96575676
	2018-09-30	1969.24	2050.50	1865.00	1966.08	94445693
	2018-10-31	1799.63	2033.19	1476.36	1782.06	183228552
	2018-11-30	1622.32	1784.00	1420.00	1625.48	139290208
	2018-12-31	1572.92	1778.34	1307.00	1559.44	154812304
FB	2018-01-31	184.36	190.66	175.80	184.96	495655736
	2018-02-28	180.72	195.32	167.18	180.27	516621991
	2018-03-31	173.45	186.10	149.02	173.49	996232472
	2018-04-30	164.16	177.10	150.51	163.81	751130388
	2018-05-31	181.91	192.72	170.23	182.93	401144183

ticker	date	open	high	low	close	volume
	2018-06-30	194.97	203.55	186.43	195.27	387265765
	2018-07-31	199.33	218.62	166.56	199.97	652763259
	2018-08-31	177.60	188.30	170.27	177.49	549016789
	2018-09-30	164.23	173.89	158.87	164.38	500468912
	2018-10-31	154.87	165.88	139.03	154.19	622446235
	2018-11-30	141.76	154.13	126.85	141.64	518150415
	2018-12-31	137.53	147.19	123.02	137.16	558786249
GOOG	**2018-01-31**	1127.20	1186.89	1045.23	1130.77	28738485
	2018-02-28	1088.63	1174.00	992.56	1088.21	42384105
	2018-03-31	1096.11	1177.05	980.64	1091.49	45430049
	2018-04-30	1038.42	1094.16	990.37	1035.70	41773275
	2018-05-31	1064.02	1110.75	1006.29	1069.28	31849196
	2018-06-30	1136.40	1186.29	1096.01	1137.63	32103642
	2018-07-31	1183.46	1273.89	1093.80	1187.59	31953386
	2018-08-31	1226.16	1256.50	1188.24	1225.67	28820379
	2018-09-30	1176.88	1212.99	1146.91	1175.81	28863199
	2018-10-31	1116.08	1209.96	995.83	1110.94	48496167
	2018-11-30	1054.97	1095.57	996.02	1056.16	36735570
	2018-12-31	1042.62	1124.65	970.11	1037.42	40256461
NFLX	**2018-01-31**	231.27	286.81	195.42	232.91	238377533
	2018-02-28	270.87	297.36	236.11	271.44	184585819
	2018-03-31	312.71	333.98	275.90	312.23	263449491
	2018-04-30	309.13	338.82	271.22	307.47	262064417
	2018-05-31	329.78	356.10	305.73	331.54	142051114
	2018-06-30	384.56	423.21	352.82	384.13	244032001
	2018-07-31	380.97	419.77	328.00	381.52	305487432
	2018-08-31	345.41	376.81	310.93	346.26	213144082
	2018-09-30	363.33	383.20	335.83	362.64	170832156
	2018-10-31	340.03	386.80	271.21	335.45	363589920

ticker	date	open	high	low	close	volume
	2018-11-30	290.64	332.05	250.00	290.34	257126498
	2018-12-31	266.31	298.72	231.23	265.30	234304628

In [316…

```
# 4. Build a crosstab with the earthquake
#data between the tsunami column and the magType column.
#Rather than showing the frequency count, show the maximum
#magnitude that was observed for each combination. Put the magType along the column

cross_tabs = pd.crosstab(earthquake['tsunami'],earthquake['magType'],values = earth
cross_tabs
```

Out[316…

	max									
magType	**mb**	**mb_lg**	**md**	**mh**	**ml**	**ms_20**	**mw**	**mwb**	**mwr**	**mww**
tsunami										
0	5.60	3.50	4.11	1.10	4.20	NaN	3.83	5.80	4.80	6.00
1	6.10	NaN	NaN	NaN	5.10	5.70	4.41	NaN	NaN	7.50

In [317…

```
#5. Calculate the rolling 60-day aggregations of OHLC data by ticker for
#the FAANG data. Use the same aggregations as exercise no. 3.
roll = faang.groupby(['ticker']).rolling('60D').agg({
    'open':'mean',
    'high':'max',
    'low': 'min',
    'close':'mean',
    'volume':'sum'

})
roll
```

Out[317...

ticker	date	open	high	low	close	volume
AAPL	**2018-01-02**	166.93	169.03	166.04	168.99	25555934.00
	2018-01-03	168.09	171.23	166.04	168.97	55073833.00
	2018-01-04	168.48	171.23	166.04	169.23	77508430.00
	2018-01-05	168.90	172.04	166.04	169.84	101168448.00
	2018-01-08	169.32	172.27	166.04	170.08	121736214.00
...	**...**	...	...	...	...	...
NFLX	**2018-12-24**	283.51	332.05	233.68	281.93	525657894.00
	2018-12-26	281.84	332.05	231.23	280.78	520444588.00
	2018-12-27	281.07	332.05	231.23	280.16	532679805.00
	2018-12-28	279.92	332.05	231.23	279.46	521968250.00
	2018-12-31	278.43	332.05	231.23	277.45	476309676.00

1255 rows × 5 columns

In [318...

```
#6. Create a pivot table of the FAANG data that compares the stocks.
#Put the ticker in the rows and show the averages of the OHLC and volume traded dat
pivot_table = faang.pivot_table(index = faang['ticker'],
values = faang[['open','high','low','close','volume']], aggfunc = ['mean'])
pivot_table
```

Out[318...

	mean				
	close	**high**	**low**	**open**	**volume**
ticker					
AAPL	186.99	188.91	185.14	187.04	34021449.63
AMZN	1641.73	1662.84	1619.84	1644.07	5649562.81
FB	171.51	173.62	169.30	171.45	27687977.67
GOOG	1113.23	1125.78	1101.00	1113.55	1742645.08
NFLX	319.29	325.22	313.19	319.62	11470299.17

In [319...

```
#7. Calculate the Z-scores for each numeric column
# of Netflix's data (ticker is NFLX) using apply().
NTFLX = faang.query('ticker == "NFLX"')
columns = ['open','high','low','close','volume']

NTFLX[columns] = NTFLX[columns].apply(lambda x: (x - x.mean())/x.std())
```

```
NTFLX
```

```
C:\Users\Arnel Bulambao\AppData\Local\Temp\ipykernel_9592\2097626456.py:6: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  NTFLX[columns] = NTFLX[columns].apply(lambda x: (x - x.mean())/x.std())
```

Out[319…

	ticker	open	high	low	close	volume
date						
2018-01-02	NFLX	-2.50	-2.52	-2.41	-2.42	-0.09
2018-01-03	NFLX	-2.38	-2.42	-2.29	-2.34	-0.51
2018-01-04	NFLX	-2.30	-2.41	-2.23	-2.32	-0.96
2018-01-05	NFLX	-2.28	-2.35	-2.20	-2.23	-0.78
2018-01-08	NFLX	-2.22	-2.30	-2.14	-2.19	-1.04
...	...	...	...	...	...	...
2018-12-24	NFLX	-1.57	-1.52	-1.63	-1.75	-0.34
2018-12-26	NFLX	-1.74	-1.44	-1.68	-1.34	0.52
2018-12-27	NFLX	-1.41	-1.42	-1.50	-1.30	0.13
2018-12-28	NFLX	-1.25	-1.29	-1.30	-1.29	-0.09
2018-12-31	NFLX	-1.20	-1.12	-1.09	-1.06	0.36

251 rows × 6 columns

8. Add event descriptions:

   • Create a dataframe with the following three columns: ticker, date, and event. The columns should have the following values:

   - `ticker: 'FB'`
   - `date: ['2018-07-25', '2018-03-19', '2018-03-20']`
   - `event: ['Disappointing user growth announced after close.', 'Cambridge Analytica story', 'FTC investigation']`

   • Set the index to ['date', 'ticker']

   • Merge this data with the FAANG data using an outer join

In [326...

```
faang_n = {
    'ticker':'FB',
    'date':['2018-07-25', '2018-03-19', '2018-03-20'],
    'event':['Disappointing user growth announced after close.', 'Cambridge Analyti
}

# Now we successsfully created a new dataframe
faang_n = pd.DataFrame(faang_n)
# since the are no datatypes after creating dataframe we must set it first before t

faang_n['date'] = pd.to_datetime(faang_n['date'])
# we set index of date and ticker into the new faang
faang_n.set_index(['date','ticker'], inplace = True)
```

In [321...

```
merge_df = faang.merge(faang_n, on = ['date','ticker'], how = 'outer')
merge_df = merge_df.sort_index()
```

In [322...

```
merge_df
```

Out[322...

	ticker	open	high	low	close	volume	event
date							
2018-01-02	AAPL	166.93	169.03	166.04	168.99	25555934	NaN
2018-01-02	AMZN	1172.00	1190.00	1170.51	1189.01	2694494	NaN
2018-01-02	FB	177.68	181.58	177.55	181.42	18151903	NaN
2018-01-02	GOOG	1048.34	1066.94	1045.23	1065.00	1237564	NaN
2018-01-02	NFLX	196.10	201.65	195.42	201.07	10966889	NaN
...	...	...	...	...	...	...	...
2018-12-31	AAPL	157.85	158.68	155.81	157.07	35003466	NaN
2018-12-31	AMZN	1510.80	1520.76	1487.00	1501.97	6954507	NaN
2018-12-31	FB	134.45	134.64	129.95	131.09	24625308	NaN
2018-12-31	GOOG	1050.96	1052.70	1023.59	1035.61	1493722	NaN
2018-12-31	NFLX	260.16	270.10	260.00	267.66	13508920	NaN

1255 rows × 7 columns

9. Use the transform() method on the FAANG data to represent all the values in terms of the first date in the data. To do so, divide all the values for each ticker by the values for the first date in the data for that ticker. This is referred to as an index, and the data for the first date is the base (https://ec.europa.eu/eurostat/statistics-explained/ index.php/ Beginners:Statisticalconcept-Indexandbaseyear). When data is in this format, we can easily see growth over time. Hint: transform() can take a function name.

In [323…

```
m_copy = merge_df.copy()
```

In [325…

```
columns = ['open','high','low','close','volume']
# this are the columns that need to be outputted
#using groupby to group the datas by ticker
#and using the columns made as the coulmns of datas that are needed to be taken
m_copy.groupby(['ticker'])[columns].transform(lambda x: x/x.iloc[0])
```

Out[325…

	open	high	low	close	volume
date					
2018-01-02	1.00	1.00	1.00	1.00	1.00
2018-01-02	1.00	1.00	1.00	1.00	1.00
2018-01-02	1.00	1.00	1.00	1.00	1.00
2018-01-02	1.00	1.00	1.00	1.00	1.00
2018-01-02	1.00	1.00	1.00	1.00	1.00
...	...	...	...	...	...
2018-12-31	0.95	0.94	0.94	0.93	1.37
2018-12-31	1.29	1.28	1.27	1.26	2.58
2018-12-31	0.76	0.74	0.73	0.72	1.36
2018-12-31	1.00	0.99	0.98	0.97	1.21
2018-12-31	1.33	1.34	1.33	1.33	1.23

1255 rows × 5 columns

In [ ]: