Hands-on Activity 8.1: Aggregating Data with Pandas

8.1.1 Intended Learning Outcomes

After this activity, the student should be able to:

- 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

Weather Data Collection

```
import requests
import datetime
import pandas as pd
import sqlite3
from IPython import display

class weather_data():
  def __init__(self):
    self.make_request()
    self.date()
    self.results = []
    self.response()
    self.dataframe()
    self.connection()

  def make_request(self, endpoint = 'data', payload = None):
    return requests.get(f'https://www.ncdc.noaa.gov/cdo-web/api/v2/{endpoint}',
                        headers={'token': 'uPbSRvXwGYFwftSwWzZNLZsxpPKvvaYN'},
                        params=payload)
  def date(self):
    self.current = datetime.date(2018, 1, 1)
    self.end = datetime.date(2019, 1, 1)

  def response(self):
    while self.current < self.end:
      display.clear_output(wait=True)
      display.display(f'Gathering data for {str(self.current)}')

      response = self.make_request(
          'data',
          {
              'datasetid' : 'GHCND',
              'locationid' : 'CITY:US360019',
              'startdate' : self.current,
              'enddate' : self.current,
              'units' : 'metric',
              'limit' : 1000
          }
      )

      if response.ok:
        self.results.extend(response.json()['results'])

      self.current += datetime.timedelta(days=1)

  def dataframe(self):
    self.df = pd.DataFrame(self.results)
    self.df.to_csv('/content/weather_data/nyc_weather_2018.csv', index = False)

  def connection(self):
    with sqlite3.connect('/content/weather_data/weather.db') as connection:
      self.df.to_sql('weather', connection, index = False, if_exists = 'replace')

    self.response = self.make_request('stations',{'datasetid':'GHCND',
                                        'locationid':'CITY:US360019',
                                        'limit':1000}
                            )

    self.stations = pd.DataFrame(self.response.json()['results'])[['id', 'name', 'latitude', 'longitude', 'elevation']]
    self.stations.to_csv('/content/weather_data/weather_stations.csv', index=False)

    with sqlite3.connect('/content/weather_data/weather.db') as connection:
      self.stations.to_sql('stations', connection, index=False, if_exists='replace')

weather = weather_data()
```

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

Querying and Merging

```
import pandas as pd
import sqlite3

class query_and_merge():
  def __init__(self):
    self.weather()
    self.query_weather()
    self.stationinfo()
    self.dirty_data()

    while True:
      try:
        x = input("\n0. Exit \n"\
                  "1. See the head of the weather dataframe \n"\
                  "2. See the head of the queried weather dataframe \n"\
                  "3. See the head of the station_info dataframe \n"\
                  "4. Describe unique values of station_info df \n"\
                  "5. Describe unique values of weather df \n"\
                  "6. Get info on station_info and weather dataframes \n"\
                  "7. Get sample on merged weather and station dfs \n"\
                  "8. Get sample on inner join \n"\
                  "9. Get tail on right join \n"\
                  "10. Get tail on left join \n"\
                  "11. Get sample on outer join \n"\
                  "12. Rows and columns after ij, lj, and rj \n"\
                  "13. See the head of the dirty data dataframe \n"\
                  "14. Get sample on valid stations \n"\
                  "15. Get sample on invalid stations \n"\
                  "16. See the head on the merged valid and invalid stations' dataframes \n"\
                  "17. See the head on the joined valid and invalid stations' dataframes \n"\
                  "18. See the intersection of the weather index \n"\
                  "19. See the difference of the weather index \n"\
                  "20. See the difference of the station info index \n"\
                  "21. ny_in_name == weather? \n"\
                  "22. All unique indexes of unioned weather and station_info dataframes \n"\
                  "> ")
        if x == "0":
          break
        elif x == "1":
          print(self.weather.head())
          continue
        elif x == "2":
          print(self.snow_data.head())
          continue
        elif x == "3":
          print(self.station_info.head())
          continue
        elif x == "4":
          print(self.station_info.id.describe())
          continue
        elif x == "5":
          print(self.weather.station.describe())
          continue
        elif x == "6":
          print(self.get_info('shape', self.station_info, self.weather))
          continue
        elif x == "7":
          print(self.weather.merge(self.station_info.rename(dict(id='station'), axis = 1), on = 'station').sample(5, random_state=0))
          continue
        elif x == "8":
          self.inner_join()
          print(self.inner_join.sample(5, random_state=0))
          continue
        elif x == "9":
          self.right_join()
          print(self.right_join.tail())
          continue
        elif x == "10":
          self.left_join()
          print(self.left_join.tail())
          continue
        elif x == "11":
          self.outer_join()
          print(self.outer_join.sample(4, random_state=0).append(self.outer_join[self.outer_join.station.isna()].head(2)))
          continue
        elif x == "12":
          print(self.get_info('shape', self.inner_join, self.left_join, self.right_join))
```

```
        continue
      elif x == "13":
        print(self.dirty_data.head())
        continue
      elif x == "14":
        self.valid()
        print(self.valid_station.sample(5, random_state = 0))
        continue
      elif x == "15":
        self.invalid()
        print(self.station_with_wesf.sample(5, random_state = 0))
        continue
      elif x == "16":
        print(self.valid_station.merge(self.station_with_wesf, left_index=True, right_index=True).query('WESF > 0').head())
        continue
      elif x == "17":
        print(self.valid_station.join(self.station_with_wesf, rsuffix='_?').query('WESF > 0').head())
        continue
      elif x == "18":
        self.set_index()
        print(self.weather.index.intersection(self.station_info.index))
        continue
      elif x == "19":
        print(self.weather.index.difference(self.station_info.index))
        continue
      elif x == "20":
        print(self.station_info.index.difference(self.weather.index))
        continue
      elif x == "21":
        self.symmetric_difference()
        print(self.ny_in_name.index.difference(self.weather.index).shape[0]\
        + self.weather.index.difference(self.ny_in_name.index).shape[0]\
        == self.weather.index.symmetric_difference(self.ny_in_name.index).shape[0])
        continue
      elif x == "22":
        print(self.weather.index.unique().union(self.station_info.index))
        continue

    except ValueError:
      print("Error Occured. Please try again")
      continue

def weather(self):
  self.weather = pd.read_csv('/content/query_merge/nyc_weather_2018.csv')

def query_weather(self):
  self.snow_data = self.weather.query('datatype == "SNOW" and value > 0')

def stationinfo(self):
  self.station_info = pd.read_csv('/content/query_merge/weather_stations.csv')

def inner_join(self):
  self.inner_join = self.weather.merge(self.station_info, left_on = 'station', right_on = 'id')

def left_join(self):
  self.left_join = self.station_info.merge(self.weather, left_on = 'id', right_on = 'station', how = 'left')

def right_join(self):
  self.right_join = self.weather.merge(self.station_info, left_on = 'station', right_on = 'id', how = 'right')

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

def dirty_data(self):
  self.dirty_data = pd.read_csv('/content/query_merge/dirty_data.csv', index_col='date').drop_duplicates().drop(columns='SNWD')

def valid(self):
  self.valid_station = self.dirty_data.query('station != "?"').copy().drop(columns=['WESF', 'station'])

def invalid(self):
  self.station_with_wesf = self.dirty_data.query('station == "?"').copy().drop(columns=['station', 'TOBS', 'TMIN', 'TMAX'])

def set_index(self):
  self.weather.set_index('station', inplace=True)
  self.station_info.set_index('id', inplace=True)

```

```
  def symmetric_difference(self):
    self.ny_in_name = self.station_info[self.station_info.name.str.contains('NY')]

  def station_describe(self):
    self.station_info.id.describe()

  def get_info(self, attr, *dfs):
    return list(map(lambda x: getattr(x, attr), dfs))



QueryAndMerge = query_and_merge()
```

```
0. Exit
1. See the head of the weather dataframe
2. See the head of the queried weather dataframe
3. See the head of the station_info dataframe
4. Describe unique values of station_info df
5. Describe unique values of weather df
6. Get info on station_info and weather dataframes
7. Get sample on merged weather and station dfs
8. Get sample on inner join
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10. Get tail on left join
11. Get sample on outer join
12. Rows and columns after ij, lj, and rj
13. See the head of the dirty data dataframe
14. Get sample on valid stations
15. Get sample on invalid stations
16. See the head on the merged valid and invalid stations' dataframes
17. See the head on the joined valid and invalid stations' dataframes
18. See the intersection of the weather index
19. See the difference of the weather index
20. See the difference of the station info index
21. ny_in_name == weather?
22. All unique indexes of unioned weather and station_info dataframes
> 1
  attributes datatype                 date            station  value
0       ,,N,     PRCP  2018-01-01T00:00:00  GHCND:US1CTFR0039    0.0
1       ,,N,     PRCP  2018-01-01T00:00:00  GHCND:US1NJBG0015    0.0
2       ,,N,     SNOW  2018-01-01T00:00:00  GHCND:US1NJBG0015    0.0
3       ,,N,     PRCP  2018-01-01T00:00:00  GHCND:US1NJBG0017    0.0
4       ,,N,     SNOW  2018-01-01T00:00:00  GHCND:US1NJBG0017    0.0

0. Exit
1. See the head of the weather dataframe
2. See the head of the queried weather dataframe
3. See the head of the station_info dataframe
4. Describe unique values of station_info df
5. Describe unique values of weather df
6. Get info on station_info and weather dataframes
7. Get sample on merged weather and station dfs
8. Get sample on inner join
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14. Get sample on valid stations
15. Get sample on invalid stations
16. See the head on the merged valid and invalid stations' dataframes
17. See the head on the joined valid and invalid stations' dataframes
18. See the intersection of the weather index
19. See the difference of the weather index
20. See the difference of the station info index
21. ny_in_name == weather?
22. All unique indexes of unioned weather and station_info dataframes
> 2
    attributes datatype                 date            station  value
```

Dataframe Operations

Arithmetic and Statistics

```
import numpy as np
import pandas as pd
weather = pd.read_csv('/content/Arithmetic_and_Stat/nyc_weather_2018.csv', parse_dates=['date'])
fb = pd.read_csv('/content/Arithmetic_and_Stat/fb_2018.csv', index_col='date', parse_dates=True)

x = fb.assign(abs_z_score_volume=lambda x: x.volume.sub(x.volume.mean()).div(x.volume.std()).abs())
y = fb.assign(volume_pct_change=fb.volume.pct_change(),
              pct_change_rank=lambda x: x.volume_pct_change.abs().rank(ascending=False))
print("abs_z_score_volume > 3")
print(x.query('abs_z_score_volume > 3'))
print("\n\n\npct_change_rank")
print(y.nsmallest(5, 'pct_change_rank'))
print("\n\n\n2018-01-11':'2018-01-12")
print(fb['2018-01-11':'2018-01-12'])
print("\n\n\nThroughout 2018, Facebook's stock price never had a low above $215:")
print((fb > 215).any())
print("\n\n\nFacebook's OHLC (open, high, low, and close) prices all had at least one day they were at $215 or less:")
print((fb > 215).all())
```

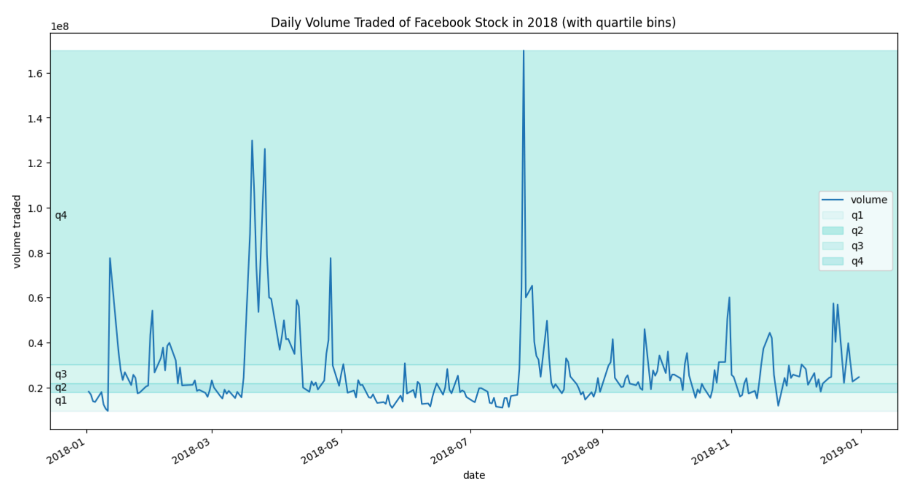
```
abs_z_score_volume > 3
              open    high     low   close     volume  abs_z_score_volume
date
2018-03-19  177.01  177.17  170.06  172.56   88140060            3.145078
2018-03-20  167.47  170.20  161.95  168.15  129851768            5.315169
2018-03-21  164.80  173.40  163.30  169.39  106598834            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



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

            pct_change_rank
date
2018-01-12              1.0
2018-03-19              2.0
2018-07-26              3.0
2018-09-21              4.0
2018-03-26              5.0



2018-01-11':'2018-01-12
              open    high     low   close    volume
date
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:
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:
open      False
high      False
low       False
close     False
volume     True
dtype: bool
```

Binning and Thresholds

```python
import matplotlib.pyplot as plt

volume_binned = pd.cut(fb.volume, bins=3, labels=['low', 'med', 'high'])
print(volume_binned.value_counts())
print("\n\n\nJuly 25th Facebook announced disappointing user growth and the stock tanked in the after hours:")
print(fb['2018-07-25':'2018-07-26'])
print("\n\n\nCambridge Analytica scandal broke on Saturday March 17th, so we look to the Monday for the numbers:")
print(fb['2018-03-16':'2018-03-20'])
```

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



July 25th Facebook announced disappointing user growth and the stock tanked in the after hours:
               open    high     low   close     volume
date
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:
              open    high     low   close     volume
date
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
```

```python
fb.plot(y='volume', figsize=(15, 8), title='Daily Volume Traded of Facebook Stock in 2018 (with quartile bins)')

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().categories.values
    ):
  plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumturquoise')
  plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

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



```python
central_park_weather = weather.query(
    'station == "GHCND:USW00094728"'
    ).pivot(index='date', columns='datatype', values='value')
central_park_weather.SNOW.clip(0, 1).value_counts()
```

```
0.0    354
1.0     11
Name: SNOW, dtype: int64
```

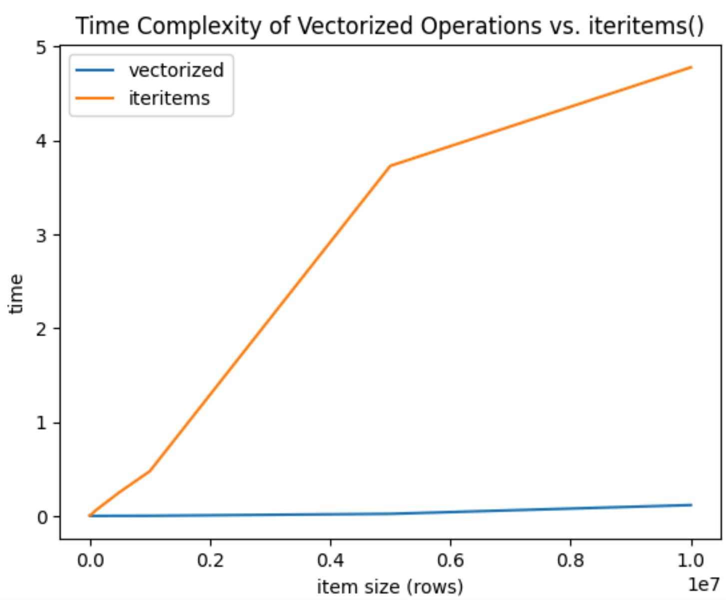
Applying Functions

```python
import numpy as np
oct_weather_z_scores = central_park_weather.loc['2018-10', ['TMIN', 'TMAX', 'PRCP']].apply(lambda x: x.sub(x.mean()).div(x.std()))
print("October 27th rained much more than the rest of the days:")
print(oct_weather_z_scores.query('PRCP > 3'))
print("\n\n\nIndeed, this day was much higher than the rest:")
print(central_park_weather.loc['2018-10', 'PRCP'].describe())
print("\n\n\n")
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))))
```

```
October 27th rained much more than the rest of the days:
datatype        TMIN      TMAX      PRCP
date
2018-10-27 -0.751019 -1.201045  3.936167



Indeed, this day was much higher than the rest:
count    31.000000
mean      2.941935
std       7.458542
min       0.000000
25%       0.000000
50%       0.000000
75%       1.150000
max      32.300000
Name: PRCP, dtype: float64




True
```

```
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.iteritems():
    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(iteritems_results, name='iteritems')]
    ).T.plot(title='Time Complexity of Vectorized Operations vs. iteritems()')

plt.xlabel('item size (rows)')
plt.ylabel('time')
plt.show()
```

```
<ipython-input-17-b1f8f4319006>:22: FutureWarning: iteritems is deprecated and will be r
  for i, v in test.iteritems():
```



Window Calculations

```python
rolling = central_park_weather['2018-10'].assign(rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum())[['PRCP', 'rolling_PRCP']]
print("Rolling Calculation of Central Park Weather for October 2018")
print(rolling.head(7).T)
print("\n\n\nPerforming Several Operations on the data in the '2018-10' column")
print(central_park_weather['2018-10'].rolling('3D').mean().head(7).iloc[:,:6])

rolling_func_per_column = central_park_weather['2018-10-01':'2018-10-07'].rolling('3D').agg(
    {'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'}).join(central_park_weather[
        ['TMAX', 'TMIN', 'AWND', 'PRCP']],lsuffix='_rolling')
print("\n\n\nDifferent Aggregation Functions per Column")
print(rolling_func_per_column.sort_index(axis=1))

isequal = central_park_weather.PRCP.expanding().sum().equals(central_park_weather.PRCP.cumsum())
print("\n\n\nIs the expanding calculation of the precipitation in central park equal to the cumulative sum of it?")
print(isequal)

expanding_agg_per_column = central_park_weather['2018-10-01':'2018-10-07'].expanding().agg({'TMAX': np.max, 'TMIN': np.min, 'AWND': np.me
    central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],lsuffix='_expanding')
print("\n\n\nExpanding Aggregations per column")
print(expanding_agg_per_column.sort_index(axis=1))

moving_average = fb.assign(close_ewma=lambda x: x.close.ewm(span=5).mean())
print("\n\n\nExponentially Weighted Moving Average")
print(moving_average.tail(10)[['close','close_ewma']])
```

```
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

datatype    TMIN_rolling
date
2018-10-01          17.2
2018-10-02          17.2
2018-10-03          17.2
2018-10-04          16.1
2018-10-05          15.6
2018-10-06          15.6
2018-10-07          15.6



Is the expanding calculation of the precipitation in central park equal to the cumulative sum of it?
False



Expanding Aggregations per column
datatype    AWND  AWND_expanding  PRCP  PRCP_expanding  TMAX  TMAX_expanding  \
date
```

Pipes

```python
1 def get_info(df):
2   return '%d rows and %d columns and max closing z-score was %d' % (*df.shape, df.close.max())
3
4 getinfo = fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
5 == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
6
7 print("Is the result of using the custom 'get_info' function the same as the get_info function using the pipe method?")
8 print(getinfo)
9
10 pipe_rolling = fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean())
11 print("\n\n\nIs the result of directly using the rolling method for the calculation of the mean the same as using pipe?")
12 print(pipe_rolling)
13
14 def window_calc(df, func, agg_dict, *args, **kwargs):
15   return df.pipe(func, *args, **kwargs).agg(agg_dict)
16
17 print("\n\n\nExpanding Median of FB using Pipe and Rolling Method (without args and kwargs)")
18 print(window_calc(fb, pd.DataFrame.expanding, np.median).head())
19
20 print("\n\n\nExponentially Weighted Moving Average (with kwargs)")
21 print(window_calc(fb, pd.DataFrame.ewm, 'mean', span=3).head())
22
23 print("\n\n\nWindow Calculation using args for the indow size")
24 print(window_calc(central_park_weather['2018-10'], pd.DataFrame.rolling,
25  {'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'},'3D').head())
```

```
Is the result of using the custom 'get_info' function the same as the get_info function using the pipe method?
True



Is the result of directly using the rolling method for the calculation of the mean the same as using pipe?
True



Expanding Median of FB using Pipe and Rolling Method (without args and kwargs)
              open     high       low    close      volume
date
2018-01-02  177.68  181.580  177.5500  181.420  18151903.0
2018-01-03  179.78  183.180  179.4400  183.045  17519233.0
2018-01-04  181.88  184.780  181.3300  184.330  16886563.0
2018-01-05  183.39  185.495  182.7148  184.500  15383729.5
2018-01-08  184.90  186.210  184.0996  184.670  16886563.0



Exponentially Weighted Moving Average (with kwargs)
                  open        high         low       close        volume
date
2018-01-02  177.680000  181.580000  177.550000  181.420000  1.815190e+07
2018-01-03  180.480000  183.713333  180.070000  183.586667  1.730834e+07
2018-01-04  183.005714  185.140000  182.372629  184.011429  1.534980e+07
2018-01-05  184.384000  186.078667  183.736560  185.525333  1.440299e+07
2018-01-08  185.837419  187.534839  185.075110  186.947097  1.625679e+07



Window Calculation using args for the indow size
datatype    TMAX  TMIN      AWND  PRCP
date
2018-10-01  24.4  17.2  0.900000   0.0
2018-10-02  25.0  17.2  0.900000  17.5
2018-10-03  25.0  17.2  0.966667  17.5
2018-10-04  25.0  16.1  0.800000  18.5
2018-10-05  24.4  15.6  1.033333   1.0
<ipython-input-30-3fcf3e16cf1b>:4: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  getinfo = fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
<ipython-input-30-3fcf3e16cf1b>:5: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
<ipython-input-30-3fcf3e16cf1b>:24: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  print(window_calc(central_park_weather['2018-10'], pd.DataFrame.rolling,
```

Aggregations

Summarizing DataFrames

```
import numpy as np
import pandas as pd
weather = pd.read_csv('/content/Aggregations/weather_by_station.csv', index_col='date', parse_dates=True)
fb = pd.read_csv('/content/Aggregations/fb_2018.csv', index_col='date', parse_dates=True).assign(
    trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
    )
pd.set_option('display.float_format', lambda x: '%.2f' % x) #All numerical outputs will be shown in 2 rounded decimal places whilst not a
print("Aggregate into a Single Series")
agg = fb.agg({
    'open': np.mean,
    'high': np.max,
    'low': np.min,
    'close': np.mean,
    'volume': np.sum
    })
print(agg)
print("\n\n\nSnowfall and Precipitation Recorded in Central Park in 2018")
print(weather.query('station == "GHCND:USW00094728"').pivot(
    columns='datatype', values='value')[['SNOW', 'PRCP']].agg('sum'))
print("\n\n\nAggregate into a Data Frame")
agg_df = fb.agg({
    'open': 'mean',
    'high': ['min', 'max'],
    'low': ['min', 'max'],
    'close': 'mean'
    })
print(agg_df)

```

```
Aggregate into a Single Series
open           171.45
high           218.62
low            123.02
close          171.51
volume   6949682394.00
dtype: float64



Snowfall and Precipitation Recorded in Central Park in 2018
datatype
SNOW   1007.00
PRCP   1665.30
dtype: float64



Aggregate into a Data Frame
       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()

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

print("Mean based on the trading volume")
print(groupby)
print("\n\n\nAggregated Values of each row of the trading volume")
print(agg_groupby)

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

print("\n\n\nGrouped Aggregation of each row of the trading volume")
print(fb_agg)

print("\n\n\nHierarchical names of the columns in the dataframe")
print(fb_agg.columns)

print("\n\n\nJoining the hierarchical names into one")
fb_agg.columns = ['_'.join(col_agg) for col_agg in fb_agg.columns]
print(fb_agg.head())

print("\n\n\nAverage Precipitation Per Day during October 2018")
print(weather['2018-10'].query('datatype == "PRCP"').groupby(
    pd.Grouper(freq='D')
    ).mean().head())

print("\n\n\nTotal Quarterly Precipitation Per Station")
print(weather.query('datatype == "PRCP"').groupby(
    ['station_name', pd.Grouper(freq='Q')]
    ).sum().unstack().sample(5, random_state=1))

print("\n\n\nTotal snowfall per New York Station (in millimeters)")
print(weather.groupby('station').filter(lambda x: 'NY' in x.name).query(
    'datatype == "SNOW"').groupby('station_name').sum().squeeze())

print("\n\n\n5 months with the most precipitation")
print(weather.query('datatype == "PRCP"').groupby(
    pd.Grouper(freq='D')
    ).mean().groupby(pd.Grouper(freq='M')).sum().value.nlargest())

print("\n\n\nThe five largest percentage of daily precipitation relative to the total precipitation in that month")
print(weather\
.query('datatype == "PRCP"')\
.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'))

print("\n\n\nStandardized Dataframe using transform")
print(fb[['open', 'high', 'low', 'close']].transform(
    lambda x: (x - x.mean()).div(x.std())
    ).head())
```

```
Mean based on the trading volume
                 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



Aggregated Values of each row of the trading volume
                  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
```

```
Grouped Aggregation of each row of the trading volume
                 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



Hierarchical names of the columns in the dataframe
MultiIndex([( 'open', 'mean'),
            ( 'high',  'min'),
            ( 'high',  'max'),
            (  'low',  'min'),
            (  'low',  'max'),
            ('close', 'mean')],
           )



Joining the hierarchical names into one
                open_mean  high_min  high_max  low_min  low_max  close_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



Average Precipitation Per Day during October 2018
            value
date
2018-10-01   0.01
2018-10-02   2.23
2018-10-03  19.69
2018-10-04   0.32
2018-10-05   0.97
```

Pivot Tables and Crosstabs

```
print("Pivot around trading volume as the column")
print(fb.pivot_table(columns='trading_volume'))
print("\n\n\nPivot around trading volume as the index")
print(fb.pivot_table(index='trading_volume'))

print("\n\n\nWeather data in the wide format")
print(weather.reset_index().pivot_table(
    index=['date', 'station', 'station_name'],
    columns='datatype',
    values='value',
    aggfunc='median'
    ).reset_index().tail())

from google.colab import drive
drive.mount('/content/drive')

print("\n\n\nFrequency Table for Trading Volume per Month")
print(pd.crosstab(
    index=fb.trading_volume,
    columns=fb.index.month,
    colnames=['month']
    ))

print("\n\n\nPercentage of the value in each row relative to the total value per month")
print(pd.crosstab(
    index=fb.trading_volume,
    columns=fb.index.month,
    colnames=['month'],
    normalize='columns'
    ))

print("\n\n\nAverage trading volume per month")
print(pd.crosstab(
    index=fb.trading_volume,
    columns=fb.index.month,
    colnames=['month'],
    values=fb.close,
    aggfunc=np.mean
    ))

print("\n\n\nNumber of times each station recorded snowfall per month")
snow_data = weather.query('datatype == "SNOW"')
print(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,
    margins_name='total observations of snow'
    ))
```

```
Pivot around trading volume as the column
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



Pivot around trading volume as the index
                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



Weather data in the wide format
datatype       date            station                         station_name  \
28740    2018-12-31  GHCND:USW00054787  FARMINGDALE REPUBLIC AIRPORT, NY US
28741    2018-12-31  GHCND:USW00094728          NY CITY CENTRAL PARK, NY US
28742    2018-12-31  GHCND:USW00094741             TETERBORO AIRPORT, NJ US
28743    2018-12-31  GHCND:USW00094745        WESTCHESTER CO AIRPORT, NY US
28744    2018-12-31  GHCND:USW00094789     JFK INTERNATIONAL AIRPORT, NY US
```

```
datatype  AWND  DAPR  MDPR    PGTM  PRCP  SNOW  SNWD  ...  WSF5  WT01  WT02  \
28740     5.00   NaN   NaN 2052.00 28.70   NaN   NaN  ... 15.70   NaN   NaN
28741      NaN   NaN   NaN     NaN 25.90  0.00  0.00  ...   NaN  1.00   NaN
28742     1.70   NaN   NaN 1954.00 29.20   NaN   NaN  ...  8.90   NaN   NaN
28743     2.70   NaN   NaN 2212.00 24.40   NaN   NaN  ... 11.20   NaN   NaN
28744     4.10   NaN   NaN     NaN 31.20  0.00  0.00  ... 12.50  1.00  1.00

datatype  WT03  WT04  WT05  WT06  WT08  WT09  WT11
28740      NaN   NaN   NaN   NaN   NaN   NaN   NaN
28741      NaN   NaN   NaN   NaN   NaN   NaN   NaN
28742      NaN   NaN   NaN   NaN   NaN   NaN   NaN
28743      NaN   NaN   NaN   NaN   NaN   NaN   NaN
28744      NaN   NaN   NaN   NaN   NaN   NaN   NaN

[5 rows x 30 columns]
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).



Frequency Table for Trading Volume per Month
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



Percentage of the value in each row relative to the total value per month
month            1    2    3    4    5    6    7    8    9    10   11   12
```

Time Series

Time-Based Selection and Filtering

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

fb = pd.read_csv('/content/Time_Series/fb_2018.csv', index_col='date', parse_dates=True).assign(
    trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
    )
print("As the index of the dataframe is the date, it does not include rows with dates under holidays or weekends")
print("Weekends (Called October 11-15):\n",fb['2018-10-11':'2018-10-15'])
print("\n\n\nHolidays (Called January 1-7):\n",fb.first('1W')) #first takes from the beginning, last takes from the end
stock_data_per_minute = pd.read_csv('/content/Time_Series/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'))
print("\n\n\nStock Data per Minute:\n", stock_data_per_minute.head())
print("\n\n\nStock Data per Day:\n", stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
    }))
print("\n\n\nData at a specific time per day (i.e. 9:30, 15:59-16:00, etc.):\n",
      "At a time\n", stock_data_per_minute.at_time('9:30'),
      "\n\n\n",
      "Between times\n",stock_data_per_minute.between_time('15:59', '16:00'))

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()

print("\n\n\nDifference between the average shares traded in the first 30 minutes to the last 30 minutes everyday: \n",
      shares_traded_in_first_30_min - shares_traded_in_last_30_min,
      "-- A positive number means that more shares are traded in the first 30 minutes, while a negative number is the opposite")

print("\n\n\nUsing Normalize to remove all specific time information:\n",
      pd.DataFrame(dict(before=stock_data_per_minute.index,
                        after=stock_data_per_minute.index.normalize())).head())
```

```
As the index of the dataframe is the date, it does not include rows with dates under holidays or weekends
Weekends (Called October 11-15):
               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



Holidays (Called January 1-7):
               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



Stock Data per Minute:
                        open    high     low   close    volume
date
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



Stock Data per Day:
               open    high     low   close      volume
date
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



Data at a specific time per day (i.e. 9:30, 15:59-16:00, etc.):
 At a time
                       open   high    low  close    volume
date
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


 Between times
                       open   high    low  close     volume
date
2019-05-20 15:59:00 182.91 182.91 182.91 182.91  134569.00
```

Shifting for Lagged Data

```
print("Using shift() to determine the previous day's closing price and change in price:\n",
      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'))

print("\n\n\nAligning the starting time to the Market Hours:\n",
      pd.date_range('2018-01-01', freq='D', periods=5) + pd.Timedelta('9 hours 30 minutes'))

print("\n\n\nFinding the valid/non-null/non-missing data in the month of September\n",
      "First:", fb['2018-09'].first_valid_index(),
      "\n Last:", fb['2018-09'].last_valid_index())

print("\n\n\nIs the market open on Feb. 30?\n",
     (fb.index == '2018-09-30').any(),
      "\n\n\nData on the last time the market was open:",
      fb.asof('2018-09-30'))
```

```
Using shift() to determine the previous day's closing price and change in price:
              open   high    low  close     volume trading_volume  prior_close  \
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

            after_hours_change_in_price  abs_change
date
2018-07-26                       -42.61       42.61
2018-04-26                        13.53       13.53
2018-01-12                        -9.71        9.71
2018-10-31                         8.78        8.78
2018-03-19                        -8.08        8.08



Aligning the starting time to the Market Hours:
 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')



Finding the valid/non-null/non-missing data in the month of September
 First: 2018-09-04 00:00:00
 Last: 2018-09-28 00:00:00



Is the market open on Feb. 30?
 False


Data on the last time the market was open: 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
<ipython-input-67-581a5bc14eac>:10: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  "First:", fb['2018-09'].first_valid_index(),
<ipython-input-67-581a5bc14eac>:11: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  "\n Last:", fb['2018-09'].last_valid_index())
```

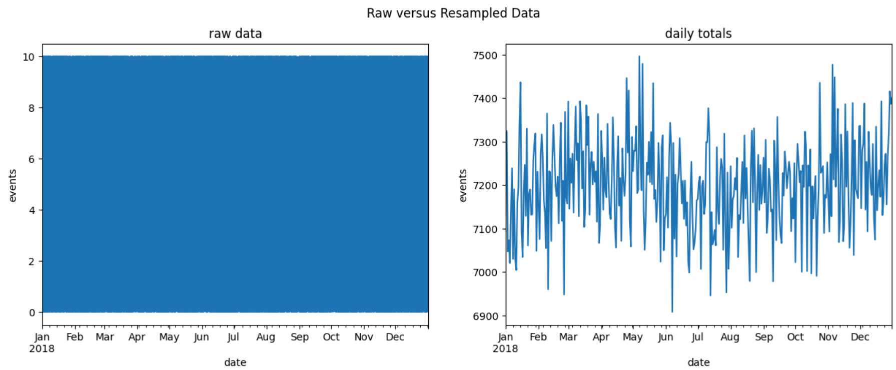
Differenced Data

```
print("Is the result of subtracting each element from its",
      "\npreceding element using the shift method equal to the\n",
      "\bresult obtained by using the diff method?\n",
 (fb.drop(columns='trading_volume') - fb.drop(columns='trading_volume').shift()
    ).equals(fb.drop(columns='trading_volume').diff()))

print("\n\n\nDaily Difference of Facebook stock\n",
      fb.drop(columns='trading_volume').diff().head(),
      "\n\nDifference between current value and the values three positions behind it\n",
      fb.drop(columns='trading_volume').diff(-3).head())

```

```
Is the result of subtracting each element from its
preceding element using the shift method equal to the
result obtained by using the diff method?
 True



Daily Difference of Facebook stock
             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

Difference between current value and the values three positions behind it
             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
```

Resampling

```
import matplotlib.pyplot as plt
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()
```




```python
print("Resampling the stock data per minute to get the daily frequency\n",
      "Head: \n", stock_data_per_minute.head(),
      "\n\nResampled: \n", stock_data_per_minute.resample('1D').agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
    }))
print("\n\n\nDownsampling to quarterly data:\n",
      fb.resample('Q').mean())
print("\n\n\nQuarterly change from start to end:\n",
      fb.drop(columns='trading_volume').resample('Q').apply(
    lambda x: x.last('1D').values - x.first('1D').values
    ))

melted_stock_data = pd.read_csv('/content/Time_Series/melted_stock_data.csv', index_col='date', parse_dates=True)
print("\n\n\nResampling Melted Stock prices:\n",
      melted_stock_data.resample('1D').ohlc()['price'],
      "\n\nPer 6 hours\n",
      fb.resample('6H').asfreq().head(),
      "\n\nHandle NaN Values using:\n",
      "\nPad(): \n", fb.resample('6H').pad().head(),
      "\n\nfillna(): \n", fb.resample('6H').fillna('nearest').head(),
      "\n\nasfreq() and assign(): \n",
      fb.resample('6H').asfreq().assign(
          volume=lambda x: x.volume.fillna(0),
          close=lambda x: x.close.fillna(method='ffill'),
          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())
```

```
Resampling the stock data per minute to get the daily frequency
 Head: 
                       open   high    low  close    volume
date
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

Resampled:
              open   high    low  close      volume
date
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



Downsampling to quarterly data:
              open   high    low  close      volume
```

```
date
2018-03-31 179.47 181.79 177.04 179.55 32926396.70
2018-06-30 180.37 182.28 178.60 180.70 24055317.75
2018-09-30 180.81 182.89 178.96 181.03 27019824.76
2018-12-31 145.27 147.62 142.72 144.87 26974331.73



Quarterly change from start to end:
 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: Q-DEC, dtype: object



Resampling Melted Stock prices:
              open   high    low  close
date
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

Per 6 hours
                       open   high    low  close      volume trading_volume
date
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
```

Merging

```python
import sqlite3

with sqlite3.connect('/content/Time_Series/stocks.db') as connection:
  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']
      )

print("Merging two data frames' prices column according to the datetime",
      "index with a 30 seconds tolerance\n",
      "\nUsing asof():\n",
      pd.merge_asof(
          fb_prices, aapl_prices,
          left_index=True, right_index=True,
          direction='nearest', tolerance=pd.Timedelta(30, unit='s')).head(),
      "\n\nUsing merge_ordered():\n",
      pd.merge_ordered(
          fb_prices.reset_index(), aapl_prices.reset_index()).set_index('date').head())

print("\n\n\nFilling NaN Values\n",
      pd.merge_ordered(fb_prices.reset_index(), aapl_prices.reset_index(),
                       fill_method='ffill').set_index('date').head())
```

```
Merging two data frames' prices column according to the datetime index with a 30 seconds tolerance

Using asof():
                         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

Using merge_ordered():
                         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 09:31:52    NaN 182.87
2019-05-20 09:32:00 182.75    NaN
2019-05-20 09:32:36    NaN 182.50



Filling NaN Values
                         FB   AAPL
date
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.

- Doing the procedure took me some effort and time, as I had to painstakingly search for the meaning and logic behind every unfamiliar method and function that I encountered in order for me to understand each and everyone of them effectively and make it worth my time and energy. In the end, after completing everything in the procedures, I left with an ample amount of knowledge and understanding behind the logic and use of every function and method in this Hands-On Activity. But, even though I understand the theory behind them, I am still experiencing a hard time making the codes themselves from scratch without aid, as it is impossible for me to remember every single one of the numerous methods and functions that I understood in the procedures. Nevertheless, the results of the procedures are perfect as according to the one that was presented in the modules 8.1 to 8.5, and I have gained a deeper understanding on what and how one should clean data.

8.1.5 Supplementary Activity

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

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.

```
import pandas as pd
import numpy as np
earthquakes = pd.read_csv('/content/Supplementary_Act/earthquakes.csv')
faang = pd.read_csv('/content/Supplementary_Act/faang.csv')

rows_with_japan = len(earthquakes.loc[earthquakes['parsed_place'].str.contains('Japan'), 'place'].value_counts())
print("Number of Earthquakes in Japan: ", rows_with_japan, "\n")

japanEarthquakes = earthquakes[(earthquakes['magType'] == 'mb') & (earthquakes['mag'] >= 4.9) & (earthquakes['place'].str.contains('Japan
num_earthquakes_in_japan = len(japanEarthquakes)
print("Number of earthquakes in Japan with a magnitude of 4.9 or greater: ",
      num_earthquakes_in_japan, "\n",
      japanEarthquakes)
```

```
Number of Earthquakes in Japan:  55

Number of earthquakes in Japan with a magnitude of 4.9 or greater:  4
       mag magType           time                         place  tsunami  \
1563  4.9      mb  1538977532250  293km ESE of Iwo Jima, Japan        0
2576  5.4      mb  1538697528010    37km E of Tomakomai, Japan        0
3072  4.9      mb  1538579732490     15km ENE of Hasaki, Japan        0
3632  4.9      mb  1538450871260    53km ESE of Hitachi, Japan        0

     parsed_place
1563        Japan
2576        Japan
3072        Japan
3632        Japan
```

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.

```
magnitude_bins = pd.cut(earthquakes.loc[earthquakes['magType'] == 'ml', 'mag'],
                        bins=np.arange(0, 11),
                        labels=[f'{i}-{i+1}' for i in range(10)])
earthqakes_per_magnitude = magnitude_bins.value_counts().sort_index()
print(earthqakes_per_magnitude)

```

```
0-1     2207
1-2     3105
2-3      862
3-4      122
4-5        2
5-6        1
6-7        0
7-8        0
8-9        0
9-10       0
Name: mag, dtype: int64
```

3

Using the faang.csv file, 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_agg_groupby = faang.groupby('ticker').resample('M').agg({
    'open': 'mean',
    'high': 'max',
    'low': 'min',
    'close': 'mean',
    'volume': 'sum'
})
print(faang_agg_groupby)
#The code above doesn't work because we first have to set the date as the index after converting it into DateTime format
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-5-58c4251796b2> in <cell line: 1>()
----> 1 faang_agg_groupby = faang.groupby('ticker').resample('M').agg({
      2     'open': 'mean',
      3     'high': 'max',
      4     'low': 'min',
      5     'close': 'mean',

2 frames

/usr/local/lib/python3.10/dist-packages/pandas/core/resample.py in _get_resampler(self,
obj, kind)
   1723             )
   1724
-> 1725         raise TypeError(
   1726             "Only valid with DatetimeIndex, "
   1727             "TimedeltaIndex or PeriodIndex, "

TypeError: Only valid with DatetimeIndex, TimedeltaIndex or PeriodIndex, but got an
instance of 'RangeIndex'
```

```
faang['date'] = pd.to_datetime(faang['date'])
faang.set_index('date', inplace=True)
faang_agg_groupby = faang.groupby('ticker').resample('M').agg({
    'open': 'mean',
    'high': 'max',
    'low': 'min',
    'close': 'mean',
    'volume': 'sum'
})
print(faang_agg_groupby)
```

```
        2018-03-31   172.421381   180.7477   162.4660   171.878919  713727447
        2018-04-30   167.332895   176.2526   158.2207   167.286924  666360147
        2018-05-31   182.635582   187.9311   162.7911   183.207418  620976206
        2018-06-30   186.605843   192.0247   178.7056   186.508652  527624365
        2018-07-31   188.065786   193.7650   181.3655   188.179724  393843881
        2018-08-31   210.460287   227.1001   195.0999   211.477743  700318837
        2018-09-30   220.611742   227.8939   213.6351   220.356353  678972040
        2018-10-31   219.489426   231.6645   204.4963   219.137822  789748068
        2018-11-30   190.828681   220.6405   169.5328   190.246652  961321947
        2018-12-31   164.537405   184.1501   145.9639   163.564732  898917007
AMZN    2018-01-31  1301.377143  1472.5800  1170.5100  1309.010952   96371290
        2018-02-28  1447.112632  1528.7000  1265.9300  1442.363158  137784020
        2018-03-31  1542.160476  1617.5400  1365.2000  1540.367619  130400151
        2018-04-30  1475.841905  1638.1000  1352.8800  1468.220476  129945743
        2018-05-31  1590.474545  1635.0000  1546.0200  1594.903636   71615299
        2018-06-30  1699.088571  1763.1000  1635.0900  1698.823810   85941510
        2018-07-31  1786.305714  1880.0500  1678.0600  1784.649048   97629820
        2018-08-31  1891.957826  2025.5700  1776.0200  1897.851304   96575676
        2018-09-30  1969.239474  2050.5000  1865.0000  1966.077895   94445693
        2018-10-31  1799.630870  2033.1900  1476.3600  1782.058261  183228552
        2018-11-30  1622.323810  1784.0000  1420.0000  1625.483810  139290208
        2018-12-31  1572.922105  1778.3400  1307.0000  1559.443158  154812304
FB      2018-01-31   184.364762   190.6600   175.8000   184.962857  495655736
        2018-02-28   180.721579   195.3200   167.1800   180.269474  516621991
        2018-03-31   173.449524   186.1000   149.0200   173.489524  996232472
        2018-04-30   164.163557   177.1000   150.5100   163.810476  751130388
        2018-05-31   181.910509   192.7200   170.2300   182.930000  401144183
        2018-06-30   194.974067   203.5500   186.4300   195.267619  387265765
        2018-07-31   199.332143   218.6200   166.5600   199.967143  652763259
        2018-08-31   177.598443   188.3000   170.2700   177.491957  549016789
        2018-09-30   164.232895   173.8900   158.8656   164.377368  500468912
        2018-10-31   154.873261   165.8800   139.0300   154.187826  622446235
        2018-11-30   141.762857   154.1300   126.8500   141.635714  518150415
        2018-12-31   137.529474   147.1900   123.0200   137.161053  558786249
GOOG    2018-01-31  1127.200952  1186.8900  1045.2300  1130.770476   28738485
        2018-02-28  1088.629474  1174.0000   992.5600  1088.206842   42384105
        2018-03-31  1096.108095  1177.0500   980.6400  1091.490476   45430049
        2018-04-30  1038.415238  1094.1600   990.3700  1035.696190   41773275
        2018-05-31  1064.021364  1110.7500  1006.2900  1069.275909   31849196
        2018-06-30  1136.396190  1186.2900  1096.0100  1137.626667   32103642
        2018-07-31  1183.464286  1273.8900  1093.8000  1187.590476   31953386
        2018-08-31  1226.156957  1256.5000  1188.2400  1225.671739   28820379
        2018-09-30  1176.878421  1212.9900  1146.9100  1175.808947   28863199
        2018-10-31  1116.082174  1209.9600   995.8300  1110.940435   48496167
        2018-11-30  1054.971429  1095.5700   996.0200  1056.162381   36735570
        2018-12-31  1042.620000  1124.6500   970.1100  1037.420526   40256461
NFLX    2018-01-31   231.269286   286.8100   195.4200   232.908095  238377533
        2018-02-28   270.873158   297.3600   236.1100   271.443684  184585819
        2018-03-31   312.712857   333.9800   275.9000   312.228095  263449491
        2018-04-30   309.129529   338.8200   271.2239   307.466190  262064417
        2018-05-31   329.779759   356.1000   305.7300   331.536818  142051114
        2018-06-30   384.557595   423.2056   352.8200   384.133333  244032001
        2018-07-31   380.969090   419.7700   328.0000   381.515238  305487432
        2018-08-31   345.409591   376.8085   310.9280   346.257826  213144082
        2018-09-30   363.326842   383.2000   335.8300   362.641579  170832156
        2018-10-31   340.025348   386.7999   271.2093   335.445652  363589920
        2018-11-30   290.643333   332.0499   250.0000   290.344762  257126498
        2018-12-31   266.309474   298.7200   231.2300   265.302368  234304628
```

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 columns.

```
earthquake_crosstab = pd.crosstab(
    earthquakes['tsunami'],
    earthquakes['magType'],
    values=earthquakes['mag'],
    aggfunc='max'
    )

print(earthquake_crosstab)
```

```
magType   mb  mb_lg    md   mh   ml  ms_20    mw  mwb  mwr  mww
tsunami
0        5.6    3.5  4.11  1.1  4.2    NaN  3.83  5.8  4.8  6.0
1        6.1    NaN   NaN  NaN  5.1    5.7  4.41  NaN  NaN  7.5
```

5

Calculate the rolling 60-day aggregations of OHLC data by ticker for the FAANG data. Use the same aggregations as exercise no. 3.

```
faang_rolling = faang.groupby('ticker').rolling('60D').agg({
    'open': 'mean',
    'high': 'max',
    'low': 'min',
    'close': 'mean',
    'volume': 'sum'
})
print(faang_rolling)
```

```
                         open      high       low       close       volume
ticker date
AAPL   2018-01-02  166.927100  169.0264  166.0442  168.987200   25555934.0
       2018-01-03  168.089600  171.2337  166.0442  168.972500   55073833.0
       2018-01-04  168.480367  171.2337  166.0442  169.229200   77508430.0
       2018-01-05  168.896475  172.0381  166.0442  169.840675  101168448.0
       2018-01-08  169.324680  172.2736  166.0442  170.080040  121736214.0
...                       ...       ...       ...         ...          ...
NFLX   2018-12-24  283.509250  332.0499  233.6800  281.931750  525657894.0
       2018-12-26  281.844500  332.0499  231.2300  280.777750  520444588.0
       2018-12-27  281.070488  332.0499  231.2300  280.162805  532679805.0
       2018-12-28  279.916341  332.0499  231.2300  279.461341  521968250.0
       2018-12-31  278.430769  332.0499  231.2300  277.451410  476309676.0

[1255 rows x 5 columns]
```

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 data.

```
faang_pivot_table = faang.pivot_table(index='ticker',
                                aggfunc='mean',
                                values=['open', 'high', 'low', 'close', 'volume'])
print(faang_pivot_table)

```

```
              close         high          low         open        volume
ticker
AAPL     186.986218   188.906858   185.135729   187.038674  3.402145e+07
AMZN    1641.726175  1662.839801  1619.840398  1644.072669  5.649563e+06
FB       171.510936   173.615298   169.303110   171.454424  2.768798e+07
GOOG    1113.225139  1125.777649  1101.001594  1113.554104  1.742645e+06
NFLX     319.290299   325.224583   313.187273   319.620533  1.147030e+07
```

7

Calculate the Z-scores for each numeric column of Netflix's data (ticker is NFLX) using apply().

```
netflixData = faang[faang['ticker'] == 'NFLX']
netflix_numeric_columns = netflixData.select_dtypes(include=[np.number])
netflix_ZScores = netflix_numeric_columns.apply(lambda x: (x - x.mean()) / x.std())
print("Z-scores for each numeric column of netflix's data:\n", netflix_ZScores)
print("\n\n\nZ-score combined with ticker:\n",
      pd.concat([netflixData.drop(columns=netflix_numeric_columns.columns), netflix_ZScores], axis=1))
```

```
Z-scores for each numeric column of netflix's data:
                 open      high       low     close    volume
date
2018-01-02 -2.500753 -2.516023 -2.410226 -2.416644 -0.088760
2018-01-03 -2.380291 -2.423180 -2.285793 -2.335286 -0.507606
2018-01-04 -2.296272 -2.406077 -2.234616 -2.323429 -0.959287
2018-01-05 -2.275014 -2.345607 -2.202087 -2.234303 -0.782331
2018-01-08 -2.218934 -2.295113 -2.143759 -2.192192 -1.038531
...              ...       ...       ...       ...       ...
2018-12-24 -1.571478 -1.518366 -1.627197 -1.745946 -0.339003
2018-12-26 -1.735063 -1.439978 -1.677339 -1.341402  0.517040
2018-12-27 -1.407286 -1.417785 -1.495805 -1.302664  0.134868
2018-12-28 -1.248762 -1.289018 -1.297285 -1.292137 -0.085164
2018-12-31 -1.203817 -1.122354 -1.088531 -1.055420  0.359444
```

```
[251 rows x 5 columns]


Z-score combined with ticker:
           ticker      open      high       low     close    volume
date
2018-01-02   NFLX -2.500753 -2.516023 -2.410226 -2.416644 -0.088760
2018-01-03   NFLX -2.380291 -2.423180 -2.285793 -2.335286 -0.507606
2018-01-04   NFLX -2.296272 -2.406077 -2.234616 -2.323429 -0.959287
2018-01-05   NFLX -2.275014 -2.345607 -2.202087 -2.234303 -0.782331
2018-01-08   NFLX -2.218934 -2.295113 -2.143759 -2.192192 -1.038531
...           ...       ...       ...       ...       ...       ...
2018-12-24   NFLX -1.571478 -1.518366 -1.627197 -1.745946 -0.339003
2018-12-26   NFLX -1.735063 -1.439978 -1.677339 -1.341402  0.517040
2018-12-27   NFLX -1.407286 -1.417785 -1.495805 -1.302664  0.134868
2018-12-28   NFLX -1.248762 -1.289018 -1.297285 -1.292137 -0.085164
2018-12-31   NFLX -1.203817 -1.122354 -1.088531 -1.055420  0.359444

[251 rows x 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

```
events_df = pd.DataFrame({
    'ticker': ['FB',
               'FB',
               'FB'],
    'date': ['2018-07-25',
             '2018-03-19',
             '2018-03-20'],
    'event': ['Disappointing user growth announced after close.',
              'Cambridge Analytica story',
              'FTC investigation']
})

events_df['date'] = pd.to_datetime(events_df['date'])
merged_data = faang.merge(events_df, how='outer', on=['date', 'ticker'])
print(merged_data)
```

```
           date ticker     open     high        low    close    volume event
0    2018-01-02     FB   177.68   181.58   177.5500   181.42  18151903   NaN
1    2018-01-03     FB   181.88   184.78   181.3300   184.67  16886563   NaN
2    2018-01-04     FB   184.90   186.21   184.0996   184.33  13880896   NaN
3    2018-01-05     FB   185.59   186.90   184.9300   186.85  13574535   NaN
4    2018-01-08     FB   187.20   188.90   186.3300   188.28  17994726   NaN
...         ...    ...      ...      ...        ...      ...       ...   ...
1250 2018-12-24   GOOG   973.90  1003.54   970.1100   976.22   1590328   NaN
1251 2018-12-26   GOOG   989.01  1040.00   983.0000  1039.46   2373270   NaN
1252 2018-12-27   GOOG  1017.15  1043.89   997.0000  1043.88   2109777   NaN
1253 2018-12-28   GOOG  1049.62  1055.56  1033.1000  1037.08   1413772   NaN
1254 2018-12-31   GOOG  1050.96  1052.70  1023.5900  1035.61   1493722   NaN

[1255 rows x 8 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.

```
faang_transformed = faang.groupby('ticker').transform(lambda x: x / x.iloc[0])
print(faang_transformed)
```

```
                open      high       low     close    volume
date
2018-01-02  1.000000  1.000000  1.000000  1.000000  1.000000
2018-01-03  1.023638  1.017623  1.021290  1.017914  0.930292
2018-01-04  1.040635  1.025498  1.036889  1.016040  0.764707
2018-01-05  1.044518  1.029298  1.041566  1.029931  0.747830
2018-01-08  1.053579  1.040313  1.049451  1.037813  0.991341
...              ...       ...       ...       ...       ...
2018-12-24  0.928993  0.940578  0.928131  0.916638  1.285047
2018-12-26  0.943406  0.974750  0.940463  0.976019  1.917695
2018-12-27  0.970248  0.978396  0.953857  0.980169  1.704782
2018-12-28  1.001221  0.989334  0.988395  0.973784  1.142383
2018-12-31  1.002499  0.986653  0.979296  0.972404  1.206986

[1255 rows x 5 columns]
```

```
1
```

Double-click (or enter) to edit