Hands On Activty 8.1 Aggregating Data with Pandas

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Section: CPE22S3

Course: Computational thinking with Python

Course Code: CPE311

8.1 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 Rersources

- 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

8.1.4 Data Analysis

Provide some comments here about the results of the procedures.

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

```
eq = pd.read_csv('data/earthquakes.csv') #reading the csv file
eq
```

	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

Next steps: View recommended plots

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.

pandas.DataFrame.loc

property `DataFrame.loc`

Access a group of rows and columns by label(s) or a boolean array.

`.loc[]` is primarily label based, but may also be used with a boolean array.

```
eq.loc[(eq['magType'] == 'mb') & (eq['mag'] >= 4.9)] #using .loc to select specific values
```

	mag	magType	time	place	tsunami	parsed_place
227	5.2	mb	1539389603790	15km WSW of Pisco, Peru	0	Peru
229	4.9	mb	1539389546300	193km N of Qulansiyah, Yemen	0	Yemen
248	4.9	mb	1539382925190	151km S of Severo-Kuril'sk, Russia	0	Russia
258	5.1	mb	1539380306940	236km NNW of Kuril'sk, Russia	0	Russia
391	5.1	mb	1539337221080	Pacific-Antarctic Ridge	0	Pacific-Antarctic Ridge
...	...	...	...	...	...	...
9154	4.9	mb	1537268270010	Southwest Indian Ridge	0	Southwest Indian Ridge
9175	5.2	mb	1537262729590	126km N of Dili, East Timor	1	East Timor

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.

```
eq['bins'] = pd.cut(eq.mag, bins = 2, labels = ['0-1', '1-2'])
eq
```

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

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

```
import pandas as pd
import numpy as np

faang = pd.read_csv('data/faang.csv') #reading the faang csv
faang['date'] = pd.to_datetime(faang['date']) #chaing the data type of the date column
faang
```

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

1255 rows × 7 columns

Next steps: View recommended plots

pandas.DataFrame.groupby

`DataFrame.groupby(by=None, axis=_NoDefault.no_default, level=None, as_index=True, sort=True, group_keys=True, observed=_NoDefault.no_default, dropna=True)` [source]

Group DataFrame using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

pandas.DataFrame.resample

`DataFrame.resample(rule, axis=_NoDefault.no_default, closed=None, label=None, convention=_NoDefault.no_default, kind=_NoDefault.no_default, on=None, level=None, origin='start_day', offset=None, group_keys=False)` [source]

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. The object must have a datetime-like index (*DatetimeIndex*, *PeriodIndex*, or *TimedeltaIndex*), or the caller must pass the label of a datetime-like series/index to the `on`/`level` keyword parameter.

pandas.DataFrame.agg

DataFrame.agg(*func=None*, *axis=0*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

```
aggre = { #dictionary for the aggregation
    'open' : 'mean',
    'high' : 'max',
    'low' : 'min',
    'close' : 'mean',
    'volume' : 'sum'
}
faang.groupby('ticker').resample('M', on = 'date').agg(aggre)

#using the groupby() for grouping the rows
#using resample() to select the frequency
#using the agg() for the aggregations
```

ticker	date	open	high	low	close	volume
AAPL	**2018-01-31**	170.714690	176.6782	161.5708	170.699271	659679440
	2018-02-28	164.562753	177.9059	147.9865	164.921884	927894473
	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

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.

pandas.crosstab

`pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name='All', dropna=True, normalize=False)` [source]

Compute a simple cross tabulation of two (or more) factors.

By default, computes a frequency table of the factors unless an array of values and an aggregation function are passed.

```
eq4  = pd.crosstab(
    index = eq['tsunami'], #setting the tsunami as index
    columns = eq['magType'], # setting the magType as the columns
    values=eq['mag'], # setting the values with accordance to mag column
    aggfunc='max' # function for the max value for each magType
)
eq4
```

magType tsunami	mb	mb_lg	md	mh	ml	ms_20	mw	mwb	mwr	mww
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

Next steps: View recommended plots

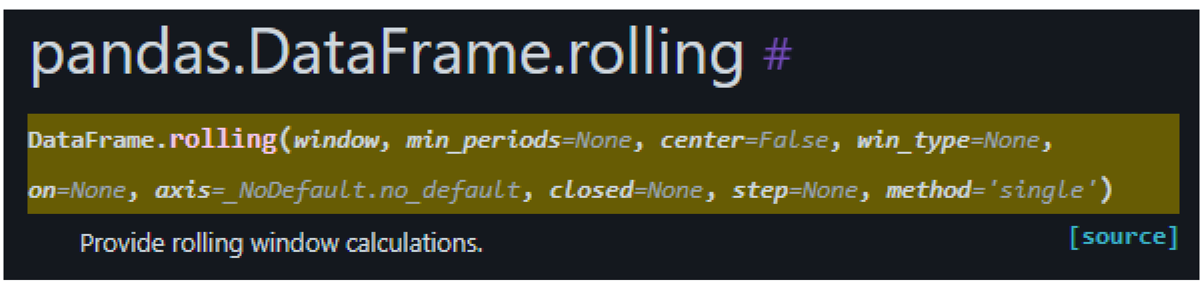
We can also set the magType as the index and tsunami as the columns, we will have the same values but the table will look different

```
eq4_1  = pd.crosstab(
    index = eq['magType'], #setting the magType as index
    columns = eq['tsunami'], # setting the tsunami as the columns
    values=eq['mag'],
    aggfunc='max'
)
eq4_1
```

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

Next steps: View recommended plots

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




```
faang6_1 = faang.set_index('date')
faang6_1 = faang6_1.sort_index()
faang6_1 = faang6_1.groupby('ticker').rolling('60D').agg(aggre)
faang6_1
```

ticker	date	open	high	low	close	volume
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 × 5 columns

Next steps: View recommended plots

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

pandas.DataFrame.pivot

`DataFrame.pivot(*, columns, index=_NoDefault.no_default, values=_NoDefault.no_default)` [source]

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a "pivot" table) based on column values. Uses unique values from specified *index* / *columns* to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the User Guide for more on reshaping.

```
faang = pd.pivot_table(faang, index='ticker', values=['open', 'high', 'low', 'close', 'volu
faang
```

ticker	close	high	low	open	volume
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

Next steps: View recommended plots

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

pandas.DataFrame.apply

DataFrame.apply(*func*, *axis=0*, *raw=False*, *result_type=None*, *args=()*, *by_row='compat'*, *engine='python'*, *engine_kwargs=None*, ***kwargs*) [source]

Apply a function along an axis of the DataFrame.

Objects passed to the function are Series objects whose index is either the DataFrame's index (`axis=0`) or the DataFrame's columns (`axis=1`). By default (`result_type=None`), the final return type is inferred from the return type of the applied function. Otherwise, it depends on the *result_type* argument.

```
faang_nflx = faang.loc[faang['ticker'] == 'NFLX']# creating a new dataframe for ticker netf
faang= faang_nflx[['open', 'high', 'low', 'close'] #accessing each column
                  ].apply(lambda x: x.sub(x.mean()).div(x.std())) #formula for the z score

faang['ticker'] = 'NFLX' #adding the NFLX
faang = faang.set_index('ticker') # setting it as the index
faang
```

	open	high	low	close
ticker				
NFLX	-2.500753	-2.516023	-2.410226	-2.416644
NFLX	-2.380291	-2.423180	-2.285793	-2.335286
NFLX	-2.296272	-2.406077	-2.234616	-2.323429
NFLX	-2.275014	-2.345607	-2.202087	-2.234303
NFLX	-2.218934	-2.295113	-2.143759	-2.192192
...	...	...	...	...
NFLX	-1.571478	-1.518366	-1.627197	-1.745946
NFLX	-1.735063	-1.439978	-1.677339	-1.341402
NFLX	-1.407286	-1.417785	-1.495805	-1.302664
NFLX	-1.248762	-1.289018	-1.297285	-1.292137
NFLX	-1.203817	-1.122354	-1.088531	-1.055420

251 rows × 4 columns

Next steps: View recommended plots

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8. 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