Hands-on Activity 8.1 Aggregating Pandas DataFrames

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8.1.4 Data Analysis

Provide some comments here about the results of the procedures.

8.1.5 Supplementary Activity

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
```

```
eq = pd.read_csv('/content/earthquakes.csv')
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

9332 rows × 6 columns

```
Japan = eq.query('parsed_place == "Japan" and magType == "mb" and mag > 4.8')
Japan
# filtering earthquakes data for events with magnitude greater than 4.8 recorded in Japan
```

	mag	magType	time	place	tsunami	parsed_place
1563	4.9	mb	1538977532250	293km ESE of Iwo Jima, Japan	0	Japan
2576	5.4	mb	1538697528010	37km E of Tomakomai, Japan	0	Japan
3072	4.9	mb	1538579732490	15km ENE of Hasaki, Japan	0	Japan
3632	4.9	mb	1538450871260	53km ESE of Hitachi, Japan	0	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.

```
eq.query("magType == 'ml'").assign(mag_bin=lambda x: pd.cut(x.mag, np.arange(0, 10))).mag_bin.value_counts()
# querying earthquakes data for events with magnitude type 'ml', then binning magnitude values and counting occurrences
```

```
(1, 2]    3105
(0, 1]    2207
(2, 3]     862
(3, 4]     122
(4, 5]       2
(5, 6]       1
(6, 7]       0
(7, 8]       0
(8, 9]       0
Name: mag_bin, 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

```
fd = pd.read_csv('/content/faang.csv', index_col='date', parse_dates=True)
monthly_data = fd.groupby("ticker").resample("M").agg({
    "open": "mean",
    "high": "max",
    "low": "min",
    "close": "mean",
    "volume": "sum"
})
monthly_data
# group data by ticker and resampling to monthly frequency, then aggregate
```

		open	high	low	close	volume
ticker	**date**					
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
	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.

```
pd.crosstab(eq.tsunami, eq.magType, values=eq.mag, aggfunc='max')
#create crosstabulation with tsunami and magtype with max value
```

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

```
day60_data = fd.groupby('ticker').rolling('60D').agg({
    "open": "mean",
    "high": "max",
    "low": "min",
    "close": "mean",
    "volume": "sum"
})
day60_data
#calculate the statistics in 60 days for each ticker from faang data
```

		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 × 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.

```
fd.pivot_table(index='ticker')
```

	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()

```
fd.loc['2018-Q4'].query("ticker == 'NFLX'").drop(columns='ticker').apply(
    lambda x: x.sub(x.mean()).div(x.std())).head()
```

	open	high	low	close	volume
date					
2018-10-01	1.928718	2.093688	2.258109	2.243683	-1.132050
2018-10-02	2.149499	2.112240	2.210572	2.126546	-1.074925
2018-10-03	1.998084	1.954397	2.238959	2.124089	-1.693794
2018-10-04	1.929494	1.819677	1.847834	1.758207	-0.980000
2018-10-05	1.512521	1.485701	1.377868	1.422360	-0.010635

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

```
event = pd.DataFrame({ #create data frame for events related to FB
    'ticker': 'FB',
    'date': pd.to_datetime(['2018-07-25', '2018-03-19', '2018-03-20']),
    'event': [
         'Disappointing user growth announced after close.',
         'Cambridge Analytica story',
         'FTC investigation']}).set_index(['date', 'ticker'])

fd.reset_index().set_index(['date', 'ticker']).join(event, how='outer').sample(10, random_state=0)
#joining events df with faang data using outer
```

		open	high	low	close	volume	event
date	ticker						
2018-01-03	AAPL	169.2521	171.2337	168.6929	168.9578	29517899	NaN
2018-05-23	NFLX	329.0400	345.0000	328.0900	344.7200	10049147	NaN
2018-01-17	FB	179.2600	179.3200	175.8000	177.6000	27992376	NaN
2018-10-17	AMZN	1842.7900	1845.0000	1807.0000	1831.7300	5295177	NaN
2018-02-26	AMZN	1509.2000	1522.8400	1507.0000	1521.9500	4954988	NaN
2018-01-05	GOOG	1094.0000	1104.2500	1092.0000	1102.2300	1279123	NaN
2018-04-04	FB	152.0250	155.5600	150.5100	155.1000	49885584	NaN
2018-05-30	AMZN	1618.1000	1626.0000	1612.9300	1624.8900	2907357	NaN
2018-04-17	NFLX	329.6600	338.6200	323.7700	336.0600	33866456	NaN
2018-06-15	AMZN	1714.0000	1720.8700	1708.5200	1715.9700	4777646	NaN

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.

```
fd = fd.reset_index().set_index(['ticker', 'date']) #resetting and setting index for faang data
faang_index = (fd / fd.groupby(level='ticker').transform('first')) #calculate faang by each first prioce
faang_index.groupby(level='ticker').agg('head', 3) #group by selecting the first 3 row
```

		open	high	low	close	volume
ticker	date					
FB	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
AAPL	2018-01-02	1.000000	1.000000	1.000000	1.000000	1.000000
	2018-01-03	1.013928	1.013059	1.015952	0.999826	1.155031
	2018-01-04	1.013987	1.006791	1.016661	1.004470	0.877863
AMZN	2018-01-02	1.000000	1.000000	1.000000	1.000000	1.000000
	2018-01-03	1.013908	1.013017	1.015199	1.012775	1.153758
	2018-01-04	1.028157	1.021739	1.029175	1.017309	1.121579
NFLX	2018-01-02	1.000000	1.000000	1.000000	1.000000	1.000000
	2018-01-03	1.030342	1.022613	1.031112	1.019794	0.783392
	2018-01-04	1.051504	1.026779	1.043909	1.022679	0.549802
GOOG	2018-01-02	1.000000	1.000000	1.000000	1.000000	1.000000
	2018-01-03	1.015234	1.018136	1.017202	1.016413	1.155633
	2018-01-04	1.037831	1.024959	1.037092	1.020094	0.811760