Aggregations with pandas and numpy About the Data In this notebook, we will be working with 2 data sets:

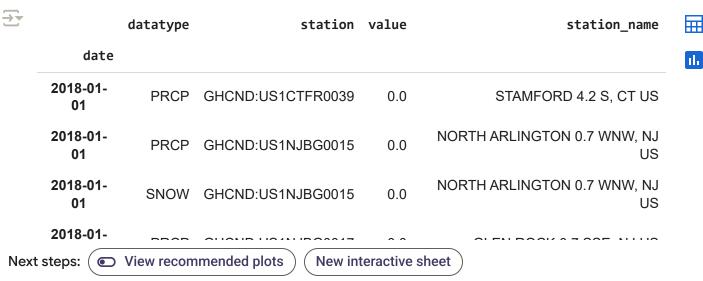
Facebook's stock price throughout 2018 (obtained using the stock_analysis package). daily weather data for NYC from the National Centers for Environmental Information (NCEI) API. Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

Background on the weather data Data meanings:

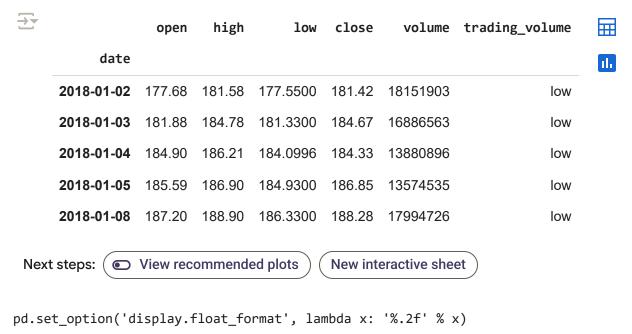
AWND : average wind speed PRCP : precipitation in millimeters SNOW : snowfall in millimeters - SNWD : snow depth in millimeters TMAX : maximum daily temperature in Celsius TMIN : minimum daily temperature in Celsius

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

weather = pd.read_csv('weather_by_station.csv', index_col='date', parse_dates=True)
weather.head()



fb = pd.read_csv('/content/fb_2018 8.3.csv', index_col='date', parse_dates=True).assign(
 trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high']))
fb.head()



Summarizing DataFrames

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

```
fb.agg({
 'open': 'mean',
 'high': 'max',
 'low': 'min',
 'close': 'mean',
 'volume': 'sum'
})
→
                           0
       open
                      171.45
       high
                      218.62
        low
                      123.02
       close
                      171.51
      volume 6949682394.00
     dtype: float64
weather.query(
 'station == "GHCND:USW00094728"'
).pivot(columns='datatype', values='value')[['SNOW', 'PRCP']].sum()
```

```
\rightarrow
                      0
      datatype
       SNOW
                 1007.00
       PRCP
                 1665.30
     dtype: float64
weather.query(
 'station == "GHCND:USW00094728"'
).pivot(columns='datatype', values='value')[['SNOW', 'PRCP']].agg('sum')
\rightarrow
                      0
      datatype
       SNOW
                 1007.00
        PRCP
                 1665.30
     dtype: float64
fb.agg({
 'open': 'mean',
 'high': ['min', 'max'],
 'low': ['min', 'max'],
 'close': 'mean'
})
→
                                              Ħ
                                     close
               open
                      high
                               low
      mean 171.45
                       NaN
                                    171.51
                               NaN
                                              M.
       min
               NaN 129.74 123.02
                                       NaN
               NaN 218.62 214.27
                                       NaN
       max
```

Using groupby()

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

```
fb.groupby('trading_volume',observed=True).mean()
```

```
\rightarrow
                         open
                                high
                                          low
                                               close
                                                             volume
                                                                       trading_volume
                                                                       ıl.
            low
                       171.36 173.46 169.31
                                               171.43
                                                        24547207.71
            med
                       175.82 179.42 172.11
                                               175.14
                                                        79072559.12
            hiah
                       167.73 170.48 161.57
                                               168.16 141924023.33
fb.groupby('trading_volume',observed=True)['close'].agg(['min', 'max', 'mean'])
\overline{\Rightarrow}
                          min
                                        mean
                                                翢
                                 max
      trading_volume
                                                 d.
            low
                       124.06 214.67 171.43
                       152.22 217.50 175.14
            med
           high
                       160.06 176.26 168.16
fb_agg = fb.groupby('trading_volume', observed = True).agg({
 'open': 'mean',
 'high': ['min', 'max'],
 'low': ['min', 'max'],
 'close': 'mean'
})
fb_agg
→
                                                                        Ħ
                               high
                       open
                                               low
                                                               close
                       mean
                               min
                                       max
                                               min
                                                       max
                                                               mean
                                                                        ılı.
      trading_volume
                       171.36 129.74 216.20 123.02 212.60
            low
                                                              171.43
                       175.82 162.85 218.62 150.75 214.27
            med
                                                               175.14
            high
                       167.73 161.10 180.13 149.02 173.75
                                                              168.16
             View recommended plots
                                            New interactive sheet
 Next steps:
fb_agg.columns
     MultiIndex([( 'open', 'mean'),
                  ( 'high',
                              'min'),
                              'max'),
                    'high',
                     'low',
                              'min'),
```

```
( 'low', 'max'),
('close', 'mean')],
```

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

4
\rightarrow \checkmark

	open_mean	high_min	high_max	low_min	low_max	close_mean	=
trading_volume							ılı
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	

161.10

Next steps: (View recommended plots

high

New interactive sheet

149.02

173.75

180.13

168.16

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

167.73

 \rightarrow

value

uate	
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

dtype: float64

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



date	2018-03-31	2018-06-30	2018-09-30	2018-12-31



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WANTAGH 1.1 NNE, NY US	279.90	216.80	472.50	277.20
STATEN ISLAND 1.4 SE, NY US	379.40	295.30	438.80	409.90
SYOSSET 2.0 SSW, NY US	323.50	263.30	355.50	459.90
STAMFORD 4.2 S, CT US	338.00	272.10	424.70	390.00
WAYNE TWP 0.8 SSW, NJ US	246.20	295.30	620.90	422.00

```
weather.groupby('station').filter(
  lambda x: 'NY' in x.name
).query('datatype == "SNOW"').groupby('station_name')['value'].sum().squeeze()
```



value

station_name

ALBERTSON 0.2 SSE, NY US	1087.00
AMITYVILLE 0.1 WSW, NY US	434.00
AMITYVILLE 0.6 NNE, NY US	1072.00
ARMONK 0.3 SE, NY US	1504.00
BROOKLYN 3.1 NW, NY US	305.00
CENTERPORT 0.9 SW, NY US	799.00
ELMSFORD 0.8 SSW, NY US	863.00
FLORAL PARK 0.4 W, NY US	1015.00
HICKSVILLE 1.3 ENE, NY US	716.00
JACKSON HEIGHTS 0.3 WSW, NY US	107.00
LOCUST VALLEY 0.3 E, NY US	0.00
LYNBROOK 0.3 NW, NY US	325.00
MASSAPEQUA 0.9 SSW, NY US	41.00
MIDDLE VILLAGE 0.5 SW, NY US	1249.00
NEW HYDE PARK 1.6 NE, NY US	0.00
NEW YORK 8.8 N, NY US	0.00
NORTH WANTAGH 0.4 WSW, NY US	471.00
PLAINEDGE 0.4 WSW, NY US	610.00
PLAINVIEW 0.4 ENE, NY US	1360.00
SADDLE ROCK 3.4 WSW, NY US	707.00
STATEN ISLAND 1.4 SE, NY US	936.00
STATEN ISLAND 4.5 SSE, NY US	89.00
SYOSSET 2.0 SSW, NY US	1039.00
VALLEY STREAM 0.6 SE, NY US	898.00
WANTAGH 0.3 ESE, NY US	1280.00
WANTAGH 1.1 NNE, NY US	940.00
WEST NYACK 1.3 WSW, NY US	1371.00

dtype: float64

dtype: float64

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

```
weather.query('datatype == "PRCP"').rename(
    columns={'value': 'prcp'}
).groupby(pd.Grouper(freq='D'))['prcp'].mean().groupby(
    pd.Grouper(freq='ME')
).transform('sum')['2018-01-28':'2018-02-03']
```

 $\overline{\Rightarrow}$

```
prcp
```

```
date

2018-01-28 69.31

2018-01-29 69.31

2018-01-30 69.31

2018-02-01 158.11

2018-02-02 158.11

2018-02-03 158.11
```

dtype: float64

```
weather \
.query('datatype == "PRCP"') \
.rename(columns={'value': 'prcp'}) \
.groupby(pd.Grouper(freq='D'))['prcp'].mean() \
.to_frame().assign(
    total_prcp_in_month=lambda x: x.groupby(pd.Grouper(freq='ME'))['prcp'].transform('sum'),
    pct_monthly_prcp=lambda x: x['prcp'].div(x.total_prcp_in_month)
) \
.nlargest(5, 'pct_monthly_prcp')
```



prcp	total_prcp_in_	_month pct _.	_monthly_prcp
------	----------------	-------------------------	---------------



2018-01-13 21.66 69.31 0.31 2018-03-02 38.77 137.46 0.28 2018-04-16 39.34 140.57 0.28	date			
2018-03-02 38.77 137.46 0.28 2018-04-16 39.34 140.57 0.28	2018-10-12	34.77	105.63	0.33
2018-04-16 39.34 140.57 0.28	2018-01-13	21.66	69.31	0.31
	2018-03-02	38.77	137.46	0.28
2018-04-17 37.30 140.57 0.27	2018-04-16	39.34	140.57	0.28
	2018-04-17	37.30	140.57	0.27

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



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

Pivot tables and crosstabs

We saw pivots in before; however, we weren't able to provide any aggregations. With pivot_table(), we get the mean by default as the aggfunc. In its simplest form, we provide a column to place along the columns:

fb.pivot_table(columns='trading_volume',observed = True)

₹	trading_volume	low	med	high	
	close	171.43	175.14	168.16	ılı
	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	

fb.pivot_table(index='trading_volume',observed = True)

→		close	close high		open	volume		
	trading_volume						ılı	
	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.reset_index().pivot_table(
index=['date', 'station', 'station_name']
columns='datatype',
```

```
values='value',
aggfunc='median'
).reset_index().tail()
```

datatype	date	statio	station_name	AWND	DAPR	MDPR	PGTM	PRCP	5
28740	2018- 12-31	GHCND:USW00054787	FARMINGDALE REPUBLIC AIRPORT, NY US	5.00	NaN	NaN	2052.00	28.70	
28741	2018- 12-31	GHCND:USW00094728	NY CITY CENTRAL PARK, NY US	NaN	NaN	NaN	NaN	25.90	
28742	2018- 12-31	GHCND:USW00094741	TETERBORO AIRPORT, NJ US	1.70	NaN	NaN	1954.00	29.20	
28743	2018- 12-31	GHCND:USW00094745	WESTCHESTER CO AIRPORT, NY US	2.70	NaN	NaN	2212.00	24.40	
	28740 28741 28742	28740 2018- 12-31 2018- 12-31 2018- 12-31 2018- 12-31 2018-	28740 2018- 12-31 GHCND:USW00054787 28741 2018- 12-31 GHCND:USW00094728 28742 2018- 12-31 GHCND:USW00094741 28743 2018- 12-31 GHCND:USW00094745	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 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,	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 5.00 NY CITY CENTRAL PARK, NY US 1.70 28742 2018- 12-31 GHCND:USW00094741 TETERBORO AIRPORT, NJ US 1.70 28743 2018- 12-31 GHCND:USW00094745 WESTCHESTER CO AIRPORT, 2.70	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 5.00 NaN NY CITY CENTRAL PARK, NaN NaN NY US 1.70 NaN 28742 2018- 12-31 GHCND:USW00094741 TETERBORO AIRPORT, NJ US 1.70 NaN 28743 2018- 12-31 GHCND:USW00094745 CO AIRPORT, 2.70 NaN	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 5.00 NaN NaN NaN NaN NaN NaN NaN NaN NaN N	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 5.00 NaN NaN 2052.00 NY CITY CENTRAL PARK, NY US 1.70 NaN NaN 1954.00 28742 2018- 12-31 GHCND:USW00094741 TETERBORO AIRPORT, NJ US 1.70 NaN NaN 1954.00 WESTCHESTER CO AIRPORT, 2.70 NaN NaN 2212.00	28740 2018- 12-31 GHCND:USW00054787 FARMINGDALE REPUBLIC AIRPORT, NY US 5.00 NaN NaN 2052.00 28.70 NY CITY US NaN NaN NaN NaN 25.90 NY US 1.70 NaN NaN 1954.00 29.20 28742 2018- 12-31 GHCND:USW00094741 TETERBORO AIRPORT, NJ US 1.70 NaN NaN 1954.00 29.20 WESTCHESTER CO AIRPORT, 2.70 NaN NaN 2212.00 24.40

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

month	1	2	3	4	5	6	7	8	9	10	11	12	
trading_volume													ılı
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	

pd.crosstab(
index=fb.trading_volume,
columns=fb.index.month,