Aggregations with pandas and numpy

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

Setup

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

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

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

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

```
pd.set_option('display.float_format', lambda x: '%.2f' % x) # convert to proper float format
```

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({ #.agg() aggregates columns depending on the numpy functions
   'open': np.mean,
   'high': np.max,
   'low': np.min,
   'close': np.mean,
   'volume': np.sum
})
```

```
open            171.45
high            218.62
low             123.02
```

```
close           171.51
volume   6949682394.00
dtype: float64
```

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

```
weather.query( # get individual  of snow and prcp column
    'station == "GHCND:USW00094728"'
).pivot(columns='datatype', values='value')[['SNOW', 'PRCP']].sum()
```

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

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

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

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

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

```
fb.agg({ # use agg() to perform certain functions on specific columns
    'open': 'mean',
    'high': ['min', 'max'],
    'low': ['min', 'max'],
    'close': 'mean'
})
```

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

Using groupby()

Often we won't want to aggregate on the entire dataframe, but on groups within it. For this purpose, we can run trading_volume column, we will get a row for each of the values it takes on

```
fb.groupby('trading_volume').mean() # create trading volume group with mean
```

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

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

```
fb.groupby('trading_volume')['close'].agg(['min', 'max', 'mean']) # aggregations are still an option for groupby()
```

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

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

```
fb_agg = fb.groupby('trading_volume').agg({ # this format changes the hierarchical index
 'open': 'mean',
 'high': ['min', 'max'],
 'low': ['min', 'max'],
 'close': 'mean'
 })
fb_agg
```

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

The hierarchical index in the columns looks like this:

```
fb_agg.columns

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

```
fb_agg.columns = ['_'.join(col_agg) for col_agg in fb_agg.columns]
fb_agg.head() # insert '_' in the middle of the two-word columns
```

	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

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

```
weather['2018-10'].query('datatype == "PRCP"').groupby(
  pd.Grouper(freq='D') # Grouper() allows us to adjust datetimes by frequency
).mean().head()
```

```
<ipython-input-16-20d0a919e057>:1: FutureWarning: Indexing a DataFrame with a datetimeli
  weather['2018-10'].query('datatype == "PRCP"').groupby(
<ipython-input-16-20d0a919e057>:3: FutureWarning: The default value of numeric_only in D
  ).mean().head()
```

	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

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

```
weather.query('datatype == "PRCP"').groupby(
 ['station_name', pd.Grouper(freq='Q')] # in this case, Quarterly total is used
).sum().unstack().sample(5, random_state=1) # follow it with unstack() to see the values per quarter
```

```
<ipython-input-69-2c39d805d7ac>:3: FutureWarning: The default value of numeric_only in D
  ).sum().unstack().sample(5, random_state=1)
```

	value			
date	**2018-03-31**	**2018-06-30**	**2018-09-30**	**2018-12-31**
station_name				
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

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

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

```
<ipython-input-18-3ff96a93d3ec>:3: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future v
  ).query('datatype == "SNOW"').groupby('station_name').sum().squeeze() # aggregate and make a series (squeeze)
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
Name: value, dtype: float64
```

Let's see which months have the most precipitation. First, we need to group by day and average the precipitation across the stations. Then we can group by month and sum the resulting precipitation. We use nlargest() to give the 5 months with the most precipitation:

```
weather.query('datatype == "PRCP"').groupby(
  pd.Grouper(freq='D') # use Grouper to see what days to get the average precipitation across stations
).mean().groupby(pd.Grouper(freq='M')).sum().value.nlargest() # group by month and total to sum up the top 5 months with nlargest()
```

```
<ipython-input-19-e21798636da3>:3: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future
  ).mean().groupby(pd.Grouper(freq='M')).sum().value.nlargest()
date
2018-11-30   210.59
2018-09-30   193.09
2018-08-31   192.45
2018-07-31   160.98
2018-02-28   158.11
Name: value, 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(
   dict(value='prcp'), axis=1 # rename it to lowercase
).groupby(pd.Grouper(freq='D')).mean().groupby(  # use Grouper to see what days to get the average precipitation across stations
   pd.Grouper(freq='M') #
).transform(np.sum)['2018-01-28':'2018-02-03'] # outputs the average precipitation per day
```

```
<ipython-input-20-665e9bd4e783>:3: FutureWarning: The default value of numeric_only in D
  ).groupby(pd.Grouper(freq='D')).mean().groupby(
```

	prcp
date	
2018-01-28	69.31
2018-01-29	69.31
2018-01-30	69.31
2018-01-31	69.31
2018-02-01	158.11
2018-02-02	158.11
2018-02-03	158.11

Notice how we have the same value repeated for each day in the month it belongs to. This will allow us to calculate the percentage of the monthly precipitation that occurred each day and then pull out the largest values:

```
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( # get total precipitation per month
                pd.Grouper(freq='M')
        ).transform(np.sum),
        pct_monthly_prcp=lambda x: x.prcp.div( # divide all the precipitation values by their total prcp to get pctg of monthly prcp
            x.total_prcp_in_month
        )
    ).nlargest(5, 'pct_monthly_prcp') # largest percentage for monthly precipitations
```

```
<ipython-input-70-9f4e38c3d7d4>:4: FutureWarning: The default value of numeric_only in D
  .groupby(pd.Grouper(freq='D')).mean()\
```

date	prcp	total_prcp_in_month	pct_monthly_prcp
2018-10-12	34.77	105.63	0.33
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
2018-04-17	37.30	140.57	0.27

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

z score formula = (x - mean) / std

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

date	open	high	low	close
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') #pivot_table for getting columns of trading_volume
```

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

By placing the trading volume in the index, we get the aggregation from the first example in the group by section above:

```
fb.pivot_table(index='trading_volume') #pivot_table using trading_volume as index
```

trading_volume	close	high	low	open	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

With pivot(), we also weren't able to handle multi-level indices or indices with repeated values. For this reason we haven't been able to put the weather data in the wide format. The pivot_table() method solves this issue:

```
weather.reset_index().pivot_table( # pivot table uesd three indices
  index=['date', 'station', 'station_name'],
  columns='datatype', # use datatype as columnn
  values='value', # get their values
  aggfunc='median' # get all their medians
).reset_index().tail()
```

datatype	date	station	station_name	AWND	DAPR	MDPR	PGTM	PRCP	SN
28740	2018-12-31	GHCND:USW00054787	FARMINGDALE REPUBLIC AIRPORT, NY US	5.00	NaN	NaN	2052.00	28.70	Na
28741	2018-12-31	GHCND:USW00094728	NY CITY CENTRAL PARK, NY US	NaN	NaN	NaN	NaN	25.90	0.
28742	2018-12-31	GHCND:USW00094741	TETERBORO AIRPORT, NJ US	1.70	NaN	NaN	1954.00	29.20	Na
28743	2018-12-31	GHCND:USW00094745	WESTCHESTER CO AIRPORT, NY US	2.70	NaN	NaN	2212.00	24.40	Na
			JFK						

We can use the pd.crosstab() function to create a frequency table. For example, if we want to see how many low-, medium-, and high-volume trading days Facebook stock had each month, we can use crosstab:

```
pd.crosstab( #crosstab() allows the dataframe be in a different format
  index=fb.trading_volume, # use trading_volume as the index
  columns=fb.index.month,
  colnames=['month'] # name the columns index 'month' built in in crosstab
)
```

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

We can normalize with the row or column totals with the normalize parameter. This shows percentage of the total :

```
pd.crosstab(
    index=fb.trading_volume,
    columns=fb.index.month,
    colnames=['month'],
    normalize='columns' # this yields the percentage of the total
)
```

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

If we want to perform a calculation other than counting the frequency, we can pass the column to run the calculation on to values and the

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

month	1	2	3	4	5	6	7	8	9	1
trading_volume										
low	185.24	180.27	177.07	163.29	182.93	195.27	201.92	177.49	164.38	154.1
med	179.37	NaN	164.76	174.16	NaN	NaN	194.28	NaN	NaN	Na
high	NaN	NaN	164.11	NaN	NaN	NaN	176.26	NaN	NaN	Na

We can also get row and column subtotals with the margins parameter. Let's count the number of times each station recorded snow per month and include the subtotals:

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

month	1	2	3	4	5	6	7	8	9	10	11	12	total observations of snow
station_name													
ALBERTSON 0.2 SSE, NY US	3.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	9
AMITYVILLE 0.1 WSW, NY US	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
AMITYVILLE 0.6 NNE, NY US	3.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8
ARMONK 0.3 SE, NY US	6.00	4.00	6.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	3.00	23
BLOOMINGDALE 0.7 SSE, NJ US	2.00	1.00	3.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	8
...	...	...	...	...	...	...	...	...	...	...	...	...	...
WESTFIELD 0.6 NE, NJ US	3.00	0.00	4.00	1.00	0.00	NaN	0.00	0.00	0.00	NaN	1.00	NaN	9
WOODBRIDGE TWP 1.1 ESE, NJ US	4.00	1.00	3.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	11
WOODBRIDGE TWP 1.1 NNE, NJ US	2.00	1.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	7
WOODBRIDGE TWP 3.0 NNW, NJ US	NaN	0.00	0.00	NaN	NaN	0.00	NaN	NaN	NaN	0.00	0.00	NaN	0
total observations of snow	190.00	97.00	237.00	81.00	0.00	0.00	0.00	0.00	0.00	0.00	49.00	13.00	667

99 rows × 13 columns