Time Series

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In this notebook, we will be working with 5 data sets:

(CSV) Facebook's stock price daily throughout 2018 (obtained using the stock_analysis package).

(CSV) Facebook's OHLC stock data from May 20, 2019 - May 24, 2019 per minute from Nasdaq.com.

(CSV) melted stock data for Facebook from May 20, 2019 - May 24, 2019 per minute from Nasdaq.com.

(DB) stock opening prices by the minute for Apple from May 20, 2019 - May 24, 2019 altered to have seconds in the time from Nasdaq.com.

(DB) stock opening prices by the minute for Facebook from May 20, 2019 - May 24, 2019 from Nasdaq.com.

Setup

```
import numpy as np
import pandas as pd
# The 'parse_dates' parameter is set to True to parse the dates in the 'date' column as datetime objects
fb = pd.read_csv('fb_2018.csv', index_col='date', parse_dates=True).assign(
    # This column categorizes the 'volume' column into three bins ('low', 'med', 'high') based on volume values
    trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
)
fb.head()
```

date	open	high	low	close	volume	trading_volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903	low
2018-01-03	181.88	184.78	181.3300	184.67	16886563	low
2018-01-04	184.90	186.21	184.0996	184.33	13880896	low
2018-01-05	185.59	186.90	184.9300	186.85	13574535	low
2018-01-08	187.20	188.90	186.3300	188.28	17994726	low

Next steps: View recommended plots

Time-based selection and filtering

Remember, when we have a DatetimeIndex , we can use datetime slicing. We can provide a range of dates. We only get three days back because the stock market is closed on the weekends:

```
# This selects data for the specified date range
fb['2018-10-11':'2018-10-15']
```

date	open	high	low	close	volume	trading_volume
2018-10-11	150.13	154.81	149.1600	153.35	35338901	low
2018-10-12	156.73	156.89	151.2998	153.74	25293492	low
2018-10-15	153.32	155.57	152.5500	153.52	15433521	low

```
# Checking if the two slices are equal using the equals() method
fb['2018-q1'].equals(fb['2018-01':'2018-03'])
```

```
<ipython-input-3-f01e3c270a70>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  fb['2018-q1'].equals(fb['2018-01':'2018-03'])
True
```

```
# 1W means 1 week
fb.last('1W')
```

date	open	high	low	close	volume	trading_volume
2018-12-31	134.45	134.64	129.95	131.09	24625308	low

```
# The 'date_parser' parameter is used to specify a custom function to parse dates from the CSV file
# it converts the date strings to datetime objects using the specified format
stock_data_per_minute = pd.read_csv(
    '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')
)
stock_data_per_minute.head()
```

date	open	high	low	close	volume
2019-05-20 09:30:00	181.6200	181.6200	181.6200	181.6200	159049.0
2019-05-20 09:31:00	182.6100	182.6100	182.6100	182.6100	468017.0
2019-05-20 09:32:00	182.7458	182.7458	182.7458	182.7458	97258.0
2019-05-20 09:33:00	182.9500	182.9500	182.9500	182.9500	43961.0
2019-05-20 09:34:00	183.0600	183.0600	183.0600	183.0600	79562.0

Next steps: View recommended plots

```
# Using the agg() method to perform aggregation operations on columns within each group
# The agg() method takes a dictionary where keys represent column names, and values represent aggregation functions

stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
})
```

date	open	high	low	close	volume
2019-05-20	181.62	184.1800	181.6200	182.72	10044838.0
2019-05-21	184.53	185.5800	183.9700	184.82	7198405.0
2019-05-22	184.81	186.5603	184.0120	185.32	8412433.0
2019-05-23	182.50	183.7300	179.7559	180.87	12479171.0
2019-05-24	182.33	183.5227	181.0400	181.06	7686030.0

```
# The at_time() method is used to filter rows based on the specified time
stock_data_per_minute.at_time('9:30')
```

date	open	high	low	close	volume
2019-05-20 09:30:00	181.62	181.62	181.62	181.62	159049.0
2019-05-21 09:30:00	184.53	184.53	184.53	184.53	58171.0
2019-05-22 09:30:00	184.81	184.81	184.81	184.81	41585.0
2019-05-23 09:30:00	182.50	182.50	182.50	182.50	121930.0
2019-05-24 09:30:00	182.33	182.33	182.33	182.33	52681.0

```
# The between_time() method is used to filter rows based on the time range

stock_data_per_minute.between_time('15:59', '16:00')
```

date	open	high	low	close	volume
2019-05-20 15:59:00	182.915	182.915	182.915	182.915	134569.0
2019-05-20 16:00:00	182.720	182.720	182.720	182.720	1113672.0
2019-05-21 15:59:00	184.840	184.840	184.840	184.840	61606.0
2019-05-21 16:00:00	184.820	184.820	184.820	184.820	801080.0
2019-05-22 15:59:00	185.290	185.290	185.290	185.290	96099.0
2019-05-22 16:00:00	185.320	185.320	185.320	185.320	1220993.0
2019-05-23 15:59:00	180.720	180.720	180.720	180.720	109648.0
2019-05-23 16:00:00	180.870	180.870	180.870	180.870	1329217.0
2019-05-24 15:59:00	181.070	181.070	181.070	181.070	52994.0
2019-05-24 16:00:00	181.060	181.060	181.060	181.060	764906.0

```
shares_traded_in_first_30_min = stock_data_per_minute\
    # Select rows from the DataFrame 'stock_data_per_minute' that fall within the time range 9:30 to 10:00
    .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()

shares_traded_in_first_30_min - shares_traded_in_last_30_min
```

```
18592.967741935485
```

```
pd.DataFrame(
dict(before=stock_data_per_minute.index, after=stock_data_per_minute.index.normalize())
).head()
```

	before	after
0	2019-05-20 09:30:00	2019-05-20
1	2019-05-20 09:31:00	2019-05-20
2	2019-05-20 09:32:00	2019-05-20
3	2019-05-20 09:33:00	2019-05-20
4	2019-05-20 09:34:00	2019-05-20

```
stock_data_per_minute.index.to_series().dt.normalize().head()
```

```
date
2019-05-20 09:30:00   2019-05-20
2019-05-20 09:31:00   2019-05-20
2019-05-20 09:32:00   2019-05-20
2019-05-20 09:33:00   2019-05-20
2019-05-20 09:34:00   2019-05-20
Name: date, dtype: datetime64[ns]
```

Shifting for lagged data

We can use shift() to create some lagged data. By default, the shift will be one period. For example, we can use shift() to create a new column that indicates the previous day's closing price. From this new column, we can calculate the price change due to after hours trading (after the close one day right up to the open the following day):

```
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')
```

date	open	high	low	close	volume	trading_volume	prior_close	after_hours_change_in_price	abs_change
2018-07-26	174.89	180.13	173.75	176.26	169803668	high	217.50	-42.61	42.61
2018-04-26	173.22	176.27	170.80	174.16	77556934	med	159.69	13.53	13.53
2018-01-12	178.06	181.48	177.40	179.37	77551299	med	187.77	-9.71	9.71
2018-10-31	155.00	156.40	148.96	151.79	60101251	low	146.22	8.78	8.78
2018-03-19	177.01	177.17	170.06	172.56	88140060	med	185.09	-8.08	8.08

```
pd.date_range('2018-01-01', freq='D', periods=5) + pd.Timedelta('9 hours 30 minutes')
```

```
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')
```

```
fb['2018-09'].first_valid_index()
```

```
<ipython-input-15-d8ca41528993>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  fb['2018-09'].first_valid_index()
Timestamp('2018-09-04 00:00:00')
```

```
fb['2018-09'].last_valid_index()
```

```
<ipython-input-16-ef6e024573c9>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  fb['2018-09'].last_valid_index()
Timestamp('2018-09-28 00:00:00')
```

```
fb.index.contains('2018-09-30')
```

```
fb.asof('2018-09-30')
```

```
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
```

Differenced data

Using the diff() method is a quick way to calculate the difference between the data and a lagged version of it. By default, it will yield the result of data - data.shift() :

```
(
fb.drop(columns='trading_volume')
- fb.drop(columns='trading_volume').shift()
).equals(
fb.drop(columns='trading_volume').diff()
)
```

```
True
```

```
fb.drop(columns='trading_volume').diff().head()
```

date	open	high	low	close	volume
2018-01-02	NaN	NaN	NaN	NaN	NaN
2018-01-03	4.20	3.20	3.7800	3.25	-1265340.0
2018-01-04	3.02	1.43	2.7696	-0.34	-3005667.0
2018-01-05	0.69	0.69	0.8304	2.52	-306361.0
2018-01-08	1.61	2.00	1.4000	1.43	4420191.0

```
fb.drop(columns='trading_volume').diff(-3).head()
```

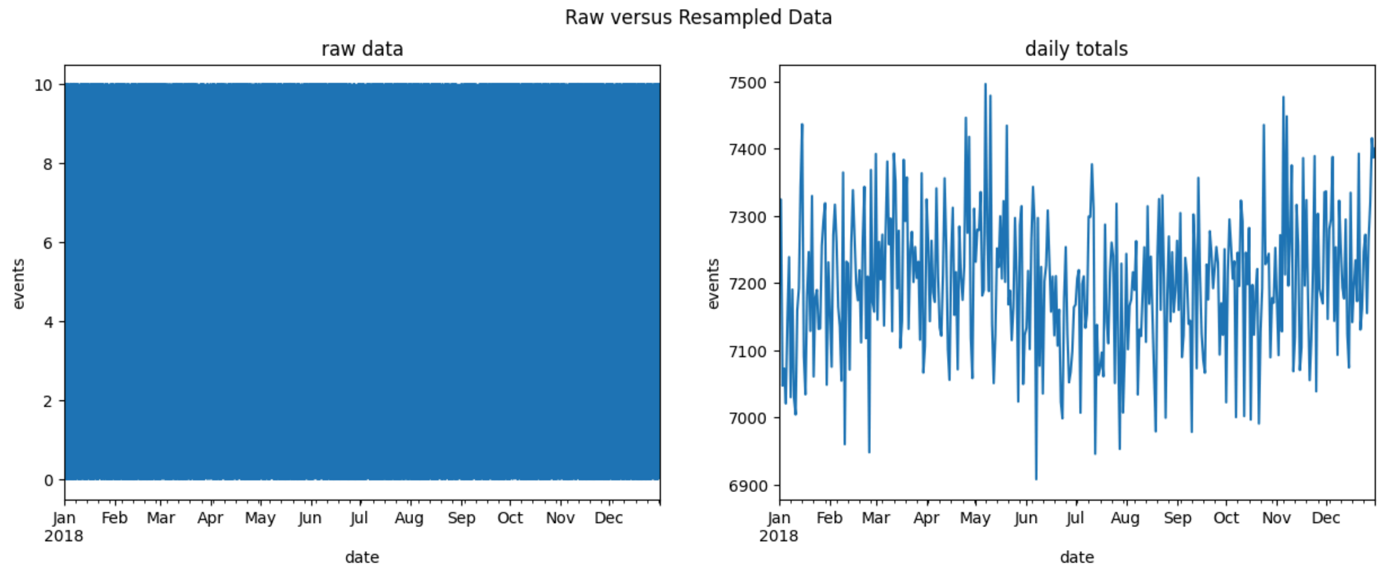
date	open	high	low	close	volume
2018-01-02	-7.91	-5.32	-7.3800	-5.43	4577368.0
2018-01-03	-5.32	-4.12	-5.0000	-3.61	-1108163.0
2018-01-04	-3.80	-2.59	-3.0004	-3.54	1487839.0
2018-01-05	-1.35	-0.99	-0.7000	-0.99	3044641.0
2018-01-08	-1.20	0.50	-1.0500	0.51	8406139.0

Resampling

Sometimes the data is at a granularity that isn't conducive to our analysis. Consider the case where we have data per minute for the full year of 2018. Let's see what happens if we try to plot this. Plotting will be covered in the next module, so don't worry too much about the code.

```
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()
```




```
stock_data_per_minute.head()
```

date	open	high	low	close	volume
2019-05-20 09:30:00	181.6200	181.6200	181.6200	181.6200	159049.0
2019-05-20 09:31:00	182.6100	182.6100	182.6100	182.6100	468017.0
2019-05-20 09:32:00	182.7458	182.7458	182.7458	182.7458	97258.0
2019-05-20 09:33:00	182.9500	182.9500	182.9500	182.9500	43961.0
2019-05-20 09:34:00	183.0600	183.0600	183.0600	183.0600	79562.0

Next steps: View recommended plots

```
stock_data_per_minute.resample('1D').agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
})
```

date	open	high	low	close	volume
2019-05-20	181.62	184.1800	181.6200	182.72	10044838.0
2019-05-21	184.53	185.5800	183.9700	184.82	7198405.0
2019-05-22	184.81	186.5603	184.0120	185.32	8412433.0
2019-05-23	182.50	183.7300	179.7559	180.87	12479171.0
2019-05-24	182.33	183.5227	181.0400	181.06	7686030.0

```
fb.resample('Q').mean()
```

```
<ipython-input-27-f6fd3d834d43>:1: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future
  fb.resample('Q').mean()
```

date	open	high	low	close	volume
2018-03-31	179.472295	181.794659	177.040428	179.551148	3.292640e+07
2018-06-30	180.373770	182.277689	178.595964	180.704688	2.405532e+07
2018-09-30	180.812130	182.890886	178.955229	181.028492	2.701982e+07
2018-12-31	145.272460	147.620121	142.718943	144.868730	2.697433e+07

```
fb.drop(columns='trading_volume').resample('Q').apply(
    lambda x: x.last('1D').values - x.first('1D').values
)
```

```
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
```

```
melted_stock_data = pd.read_csv('melted_stock_data.csv', index_col='date', parse_dates=True)
melted_stock_data.head()
```

date	price
2019-05-20 09:30:00	181.6200
2019-05-20 09:31:00	182.6100
2019-05-20 09:32:00	182.7458
2019-05-20 09:33:00	182.9500
2019-05-20 09:34:00	183.0600

Next steps: View recommended plots

```
melted_stock_data.resample('1D').ohlc()['price']
```

date	open	high	low	close
2019-05-20	181.62	184.1800	181.6200	182.72
2019-05-21	184.53	185.5800	183.9700	184.82
2019-05-22	184.81	186.5603	184.0120	185.32
2019-05-23	182.50	183.7300	179.7559	180.87
2019-05-24	182.33	183.5227	181.0400	181.06

```
fb.resample('6H').asfreq().head()
```

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.0	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
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.0	low

```
fb.resample('6H').pad().head()
```

```
<ipython-input-33-39179f05e435>:1: FutureWarning: pad is deprecated and will be removed in a future version. Use ffill instead.
  fb.resample('6H').pad().head()
```

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 06:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 12:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 18:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563	low

```
fb.resample('6H').fillna('nearest').head()
```

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 06:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 12:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-02 18:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563	low

```
fb.resample('6H').asfreq().assign(
    volume=lambda x: x.volume.fillna(0), # put 0 when market is closed
    close=lambda x: x.close.fillna(method='ffill'), # carry forward
    # take the closing price if these aren't available
    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()
```

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.0	low
2018-01-02 06:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-02 12:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-02 18:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.0	low

Merging

We saw merging examples the querying_and_merging notebook. However, they all matched based on keys. With time series, it is possible that they are so granular that we never have the same time for multiple entries. Let's work with some stock data at different granularities:

```
import sqlite3

with sqlite3.connect('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']
)
```

```
fb_prices.index.second.unique()
```

```
Int64Index([0], dtype='int64', name='date')
```

```
aapl_prices.index.second.unique()
```

```
Int64Index([ 0, 52, 36, 34, 55, 35,  7, 12, 59, 17,  5, 20, 26, 23, 54, 49, 19,
            53, 11, 22, 13, 21, 10, 46, 42, 38, 33, 18, 16,  9, 56, 39,  2, 50,
            31, 58, 48, 24, 29,  6, 47, 51, 40,  3, 15, 14, 25,  4, 43,  8, 32,
            27, 30, 45,  1, 44, 57, 41, 37, 28],
           dtype='int64', name='date')
```

```
pd.merge_asof(
    fb_prices, aapl_prices,
    left_index=True, right_index=True, # datetimes are in the index
    # merge with nearest minute
    direction='nearest', tolerance=pd.Timedelta(30, unit='s')
).head()
```

date	FB	AAPL
2019-05-20 09:30:00	181.6200	183.5200
2019-05-20 09:31:00	182.6100	NaN
2019-05-20 09:32:00	182.7458	182.8710
2019-05-20 09:33:00	182.9500	182.5000
2019-05-20 09:34:00	183.0600	182.1067

```
pd.merge_ordered(
    fb_prices.reset_index(), aapl_prices.reset_index()
).set_index('date').head()
```

date	FB	AAPL
2019-05-20 09:30:00	181.6200	183.520
2019-05-20 09:31:00	182.6100	NaN
2019-05-20 09:31:52	NaN	182.871
2019-05-20 09:32:00	182.7458	NaN