Time Series

About the Data

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.

```
import numpy as np
import pandas as pd
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'])
)
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

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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:

```
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

```
fb.loc['2018-Q1'].equals(fb['2018-01':'2018-03'])
```

```
True
```

```
fb.first('1W')
```

```
<ipython-input-4-db06dd381446>:1: FutureWarning: first is deprecated and will be removed in a future version. Please create a mask and f
  fb.first('1W')
```

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

```
fb.last('1W')
```

```
<ipython-input-5-72731dd004c8>:1: FutureWarning: last is deprecated and will be removed in a future version. Please create a mask and fi
  fb.last('1W')
```

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

```
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()
```

```
<ipython-input-6-0de5ac54e2f0>:1: FutureWarning: The argument 'date_parser' is deprecated and will be removed in a future version. Pleas
  stock_data_per_minute = pd.read_csv(
```

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

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```
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

```
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

```
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

On average, are more shares traded within the first 30 minutes of trading or in the last 30 minutes? We can combine between_time() with Groupers and filter() from the aggregation.ipynb notebook to answer this question. For the week in question, more are traded on average around opening time than closing time:

```
shares_traded_in_first_30_min = stock_data_per_minute\
    .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
```

```
np.float64(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	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

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.index = pd.to_datetime(fb.index)
first_valid = fb.loc['2018-09'].first_valid_index()
print(first_valid)
```

```
2018-09-04 00:00:00
```

```
last_valid = fb.loc['2018-09'].last_valid_index()
print(last_valid)
```

```
2018-09-28 00:00:00
```

```
exists = fb.index.isin([pd.Timestamp('2018-09-30')])
print(exists.any())
```

```
False
```

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

	2018-09-30
open	168.33
high	168.79
low	162.56
close	164.46
volume	34265638
trading_volume	low

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()
```

	open	high	low	close	volume
date					
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()
```

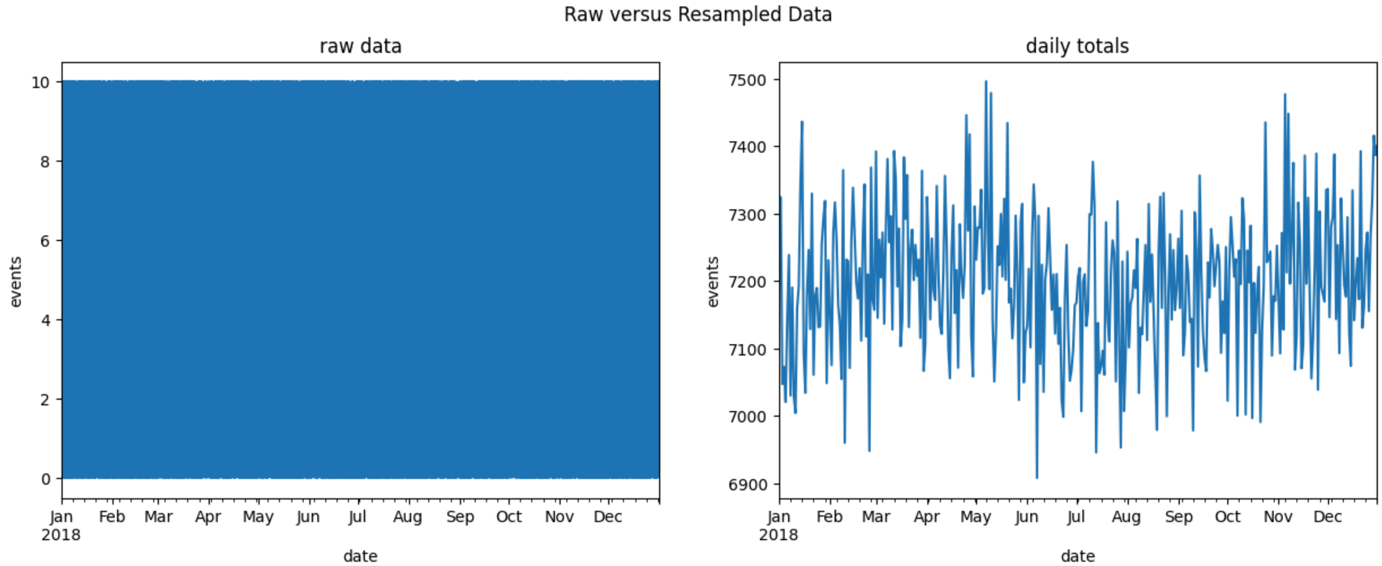
	open	high	low	close	volume
date					
2018-01-02	-7.91	-5.32	-7.3800	-5.43	4577368.0
2018-01-03	-5.32	-4.12	-5.0000	-3.61	-1108163.0
2018-01-04	-3.80	-2.59	-3.0004	-3.54	1487839.0
2018-01-05	-1.35	-0.99	-0.7000	-0.99	3044641.0
2018-01-08	-1.20	0.50	-1.0500	0.51	8406139.0

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. First, we import matplotlib for plotting:

```
import matplotlib.pyplot as plt
```

```
np.random.seed(0)
index = pd.date_range('2018-01-01', freq='min', 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

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```
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_numeric = fb.select_dtypes(include=['number'])

fb_resampled = fb_numeric.resample('QE').mean()
fb_resampled
```

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

Next steps: View recommended plots New interactive sheet

```
fb.drop(columns='trading_volume').resample('QE').apply(
    lambda x: x.loc[x.index[-1]] - x.loc[x.index[0]]
)
```

date	open	high	low	close	volume
2018-03-31	-22.53	-20.1600	-23.410	-21.63	41282390
2018-06-30	39.51	38.3997	39.844	38.93	-20984389
2018-09-30	-25.04	-28.6600	-29.660	-32.90	20304060
2018-12-31	-28.58	-31.2400	-31.310	-31.35	-1782369

```
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 New interactive sheet

```
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').ffill().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()
```

```
<ipython-input-38-fb9a9baf1cb5>:1: FutureWarning: DatetimeIndexResampler.fillna is deprecated and will be removed in a future version. U
  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()
```

```
<ipython-input-39-711fa8cf8c9d>:1: FutureWarning: 'H' is deprecated and will be removed in a future version, please use 'h' instead.
  fb.resample('6H').asfreq().assign(
<ipython-input-39-711fa8cf8c9d>:3: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a future version. Use obj.
  close=lambda x: x.close.fillna(method='ffill'), # carry forward
```

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()
```

```
Index([0], dtype='int32', name='date')
```

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

```
Index([0], dtype='int32', 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()
```

	price_x	price_y
date		
2023-10-27	150.0	170.0
2023-10-28	152.5	171.5

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

	price
date	
2023-10-27	150.0
2023-10-27	170.0
2023-10-28	152.5