Time Series

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
fb = pd.read_csv('/content/fb_2018.csv', index_col='date', parse_dates=True).assign(
    trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high']) # Assigning trading volume catego
    )
fb.head() # Displaying the first few rows of the dataframe
```

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:

```
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

We can select ranges of months and quarters:

```
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 str
  fb['2018-q1'].equals(fb['2018-01':'2018-03'])
True
```

The first() method will give us a specified length of time from the beginning of the time series. Here, we ask for a week. January 1, 2018 was a holiday—meaning the market was closed. It was also a Monday, so the week here is only four days:

```
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

The last() method will take from the end:

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

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

For the next few examples, we need datetimes, so we will read in the stock data per minute file:

```
stock_data_per_minute = pd.read_csv(
    '/content/fb_week_of_may_20_per_minute.csv', index_col='date', parse_dates=True, # Reading stock data per minute f
    date_parser=lambda x: pd.to_datetime(x, format='%Y-%m-%d %H-%M') # Parsing dates with custom format
    )
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

We can use the Grouper to roll up our data to the daily level along with first and last:

```
stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({  # Grouping stock data per minute by day
    'open': 'first',  # Getting the first value of 'open' for each day
    'high': 'max',  # Getting the maximum value of 'high' for each day
    'low': 'min',  # Getting the minimum value of 'low' for each day
    'close': 'last',  # Getting the last value of 'close' for each day
    'volume': 'sum'  # Summing up the 'volume' for each day
})
```

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 allows us to pull out all datetimes that match a certain time. Here, we can grab all the rows from the time the stock market opens (930 AM):

```
stock_data_per_minute.at_time('9:30') # Selecting rows at 9:30 AM
```

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

We can use between_time() to grab data for the last two minutes of trading daily:

```
stock_data_per_minute.between_time('15:59', '16:00')# Selecting rows between 15:59 and 16:00
```

	open	high	low	close	volume
date					
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:

```
# Calculating the average shares traded in the first 30 minutes of trading for each day
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()

# Calculating the average shares traded in the last 30 minutes of trading for each day
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()

# Calculating the difference between shares traded in the first 30 minutes and the last 30 minutes
shares_traded_in_first_30_min - shares_traded_in_last_30_min
```

```
18592.967741935485
```

In cases where time doesn't matter, we can normalize the times to midnight:

```
pd.DataFrame(
    # Creating a dictionary with 'before' and 'after' columns
    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

Note that we can also use normalize() on a Series object after accessing the dt attribute:

```
stock_data_per_minute.index.to_series().dt.normalize().head() # Normalizing the index of the dataframe to the start of t
```

```
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(  # Assigning new columns to the df
    prior_close=lambda x: x.close.shift(),  # Calculating prior close by shifting close price by one
    after_hours_change_in_price=lambda x: x.open - x.prior_close,  # Calculating after-hours change in price
    abs_change=lambda x: x.after_hours_change_in_price.abs()  # Calculating absolute change
).nlargest(5, 'abs_change')  # Selecting the 5 largest absolute changes in after-hours price
```

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

The tshift() method will shift the DatetimeIndex rather than the data. However, if the goal is to to add/subtract time we can use pd.Timedelta :

```
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')
```

When working with stock data, we only have data for the dates the market was open. We can use first_valid_index() to give us the index of the first non-null entry in our data. For September 2018, this is September 4th:

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

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

Conversely, we can use last_valid_index() to get the last entry of non-null data. For September 2018, this is September 28th:

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

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

We can use asof() to find the last non-null data before the point we are looking for, if it isn't in the index. From the previous result, we know that the market was not open on September 30th. It also isn't in the index:

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

If we ask for it, we will get the data from the index we got from fb['2018-09'].last_valid_index(), which was September 28th:

```
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():

```
(  # Starting a comparison expression
    fb.drop(columns='trading_volume')  # Dropping the 'trading_volume' column from the df
    - fb.drop(columns='trading_volume').shift()  # Subtracting the DataFrame shifted by one row
).equals(  # Checking if the expression is equal to
    fb.drop(columns='trading_volume').diff()  # Calculating the difference between consecutive elements
)
```

```
True
```

We can use this to see how Facebook stock changed day-over-day:

```
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

We can specify the number of periods, can be any positive or negative integer:

```
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.

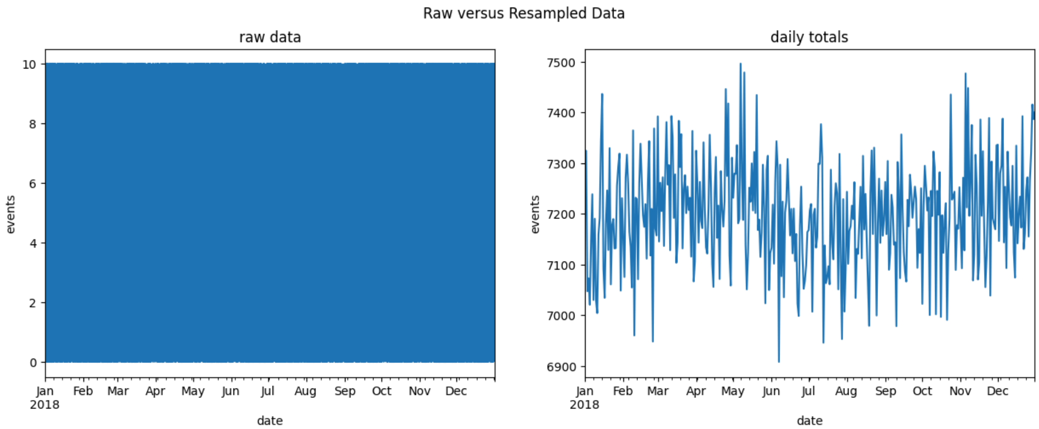
First, we import matplotlib for plotting:

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

Then we will look at the plot at the minute level and at the daily aggregated level (summed):

```
# Setting random seed for reproducibility
np.random.seed(0)

# Generating datetime index with minute frequency for one year
index = pd.date_range('2018-01-01', freq='T', periods=365*24*60)

# Creating raw DataFrame with random uniform data and datetime index
raw = pd.DataFrame(
    np.random.uniform(0, 10, size=index.shape[0]), index=index
)

# Creating subplots with 1 row and 2 columns, setting figure size
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

# Plotting raw data on the first subplot
raw.plot(legend=False, ax=axes[0], title='raw data')
```

```
# Plotting daily totals of events on the second subplot after resampling data to daily frequency
raw.resample('1D').sum().plot(legend=False, ax=axes[1], title='daily totals')

# Setting labels for x-axis and y-axis for both subplots
for ax in axes:
    ax.set_xlabel('date')
    ax.set_ylabel('events')

# Setting overall title for the figure
plt.suptitle('Raw versus Resampled Data')

# Displaying the plot
plt.show()
```



The plot on the left has so much data we can't see anything. However, when we aggregate to the daily totals, we see the data. We can alter the granularity of the data we are working with using resampling. Recall our minute-by-minute stock data:

```
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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We can resample this to get to a daily frequency:

```
stock_data_per_minute.resample('1D').agg({  # Resampling stock data per minute to daily frequency
    'open': 'first',   # Getting the first value of 'open' for each day
    'high': 'max',     # Getting the maximum value of 'high' for each day
    'low': 'min',      # Getting the minimum value of 'low' for each day
    'close': 'last',   # Getting the last value of 'close' for each day
```

```
    'volume': 'sum'    # Summing up the 'volume' for each day
})
```

	open	high	low	close	volume
date					
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

We can downsample to quarterly data:

```
fb.resample('Q').mean() # Resampling the data to quarterly frequency and calculating the mean for each quarter
```

```
<ipython-input-26-fd38d2447d6e>:1: FutureWarning: The default value of numeric_only in
  fb.resample('Q').mean() # Resampling the data to quarterly frequency and calculating
```

	open	high	low	close	volume
date					
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

We can also use apply() . Here, we show the quarterly change from start to end:

```
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
```

Consider the following melted stock data by the minute. We don't see the OHLC data directly:

```
melted_stock_data = pd.read_csv('/content/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

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We can use the ohlc() method after resampling to recover the OHLC columns:

```
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

Alternatively, we can upsample to increase the granularity. Note this will introduce NaN values:

```
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

There are many ways to handle these NaN values. We can forward-fill with pad():

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

```
<ipython-input-31-39179f05e435>:1: FutureWarning: pad is deprecated and will be removed
  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

We can specify a specific value or a method with fillna():

```
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

We can use asfreq() and assign() to specify the action per column:

```
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('/content/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']
      )
```

The Facebook prices are at the minute granularity:

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

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

However, the Apple prices have information for the second:

```
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')
```

We can perform an asof merge to try to line these up the best we can. We specify how to handle the mismatch with the direction and tolerance parameters. We will fill in with the direction of nearest and a tolerance of 30 seconds. This will place the Apple data with the minute that it is closest to, so 93152 will go with 932 and 93707 will go with 937. Since the times are on the index, we pass left_index and right_index , as we did with merges earlier this chapter:

```
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

If we don't want to lose the seconds information with the Apple data, we can use pd.merge_ordered() instead, which will interleave the two. Note this is an outer join by default (how parameter). The only catch here is that we need to reset the index in order to join on it:

```
pd.merge_ordered(
    fb_prices.reset_index(), aapl_prices.reset_index() # Resetting indices of both DataFrames before merging
    ).set_index('date').head() # Setting 'date' column as index after merging and displaying the first few rows
```

	FB	AAPL
date		
2019-05-20 09:30:00	181.6200	183.520