## How to use dates & times with pandas

MANIPULATING TIME SERIES DATA IN PYTHON



Founder & Lead Data Scientist at Applied Artificial Intelligence





#### Date & time series functionality

- At the root: data types for date & time information
  - Objects for points in time and periods
  - Attributes & methods reflect time-related details
- Sequences of dates & periods:
  - Series or DataFrame columns
  - Index: convert object into Time Series
- Many Series/DataFrame methods rely on time information in the index to provide time-series functionality

#### Basic building block: pd.Timestamp

```
import pandas as pd # assumed imported going forward
from datetime import datetime # To manually create dates
time_stamp = pd.Timestamp(datetime(2017, 1, 1))
pd.Timestamp('2017-01-01') == time_stamp
```

Timestamp is the pandas equivalent of python's Datetime and is interchangeable with it in most cases.

```
True # Understands dates as strings
```

```
time_stamp # type: pandas.tslib.Timestamp
```

If you display the timestamp, you'll notice that the time has been automatically set to midnight.

```
Timestamp('2017-01-01 00:00:00')
```



#### Basic building block: pd.Timestamp

• Timestamp object has many attributes to store time-specific information

time\_stamp.year

2017

time\_stamp.weekday\_name

'Sunday'

#### More building blocks: pd.Period & freq

```
period = pd.Period('2017-01')
period # default: month-end
Period('2017-01', 'M')
period.asfreq('D') # convert to daily
Period('2017-01-31', 'D')
period.to_timestamp().to_period('M')
Period('2017-01', 'M')
```

```
    Period object has freq
        attribute to store frequency
        info It has a method to convert between frequencies.
```

```
Convert pd.Period()to pd.Timestamp() andback
```

#### More building blocks: pd.Period & freq

```
period + 2

Period('2017-03', 'M')

pd.Timestamp('2017-01-31', 'M') + 1

Timestamp('2017-02-28 00:00:00', freq='M')
```

 Frequency info enables basic date arithmetic

#### Sequences of dates & times

• pd.DateTimeIndex : sequence of Timestamp objects with frequency info

#### Sequences of dates & times



#### Create a time series: pd.DateTimeIndex



#### Create a time series: pd.DateTimeIndex

```
np.random.random :
    Random numbers: [0,1]
     12 rows, 2 columns
data = np.random.random((size=12,2))
pd.DataFrame(data=data, index=index).info()
DatetimeIndex: 12 entries, 2017-01-31 to 2017-12-31
Freq: M
Data columns (total 2 columns):
     12 non-null float64
     12 non-null float64
dtypes: float64(2)
```



#### Frequency aliases & time info

There are many frequency aliases besides 'M' and 'D':

Period	Alias
Hour	Н
Day	D
Week	W
Month	М
Quarter	Q
Year	Α

These may be further differentiated by beginning/end of period, or business-specific definition

You can also access these pd.Timestamp() attributes:

attribute	
.second, .minute, .hour,	
.day, .month, .quarter, .year	
.weekday	
dayofweek	
.weekofyear	
.dayofyear	

### Let's practice!

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# Indexing & resampling time series

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#### Stefan Jansen

Founder & Lead Data Scientist at Applied Artificial Intelligence





#### Time series transformation

Basic time series transformations include:

- Parsing string dates and convert to datetime64
- Selecting & slicing for specific subperiods
- Setting & changing DateTimeIndex frequency
  - Upsampling vs Downsampling



#### Getting GOOG stock prices

```
google = pd.read_csv('google.csv') # import pandas as pd
google.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 504 entries, 0 to 503
Data columns (total 2 columns):
date     504 non-null object
price     504 non-null float64
dtypes: float64(1), object(1)
google.head()
```

```
date price
0 2015-01-02 524.81
1 2015-01-05 513.87
2 2015-01-06 501.96
3 2015-01-07 501.10
4 2015-01-08 502.68
```



#### Converting string dates to datetime 64

pd.to\_datetime() : Parse date string Convert to datetime 64 google.date = pd.to\_datetime(google.date) google.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 504 entries, 0 to 503 Data columns (total 2 columns): 504 non-null datetime64[ns] date 504 non-null float64 price

dtypes: datetime64[ns](1), float64(1)

#### Converting string dates to datetime 64

```
.set_index() :
    Date into index
      inplace:
     don't create copy
google.set_index('date', inplace=True)
google.info()
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 504 entries, 2015-01-02 to 2016-12-30
Data columns (total 1 columns):
        504 non-null float64
price
dtypes: float64(1)
```

#### Plotting the Google stock time series



#### Partial string indexing

Selecting/indexing using strings that parse to dates

```
google['2015'].info() # Pass string for part of date
DatetimeIndex: 252 entries, 2015-01-02 to 2015-12-31
Data columns (total 1 columns):
        252 non-null float64
price
dtypes: float64(1)
google['2015-3': '2016-2'].info() # Slice includes last month
               includes the end date
DatetimeIndex: 252 entries, 2015-03-02 to 2016-02-29
Data columns (total 1 columns):
        252 non-null float64
price
dtypes: float64(1)
memory usage: 3.9 KB
```



#### Partial string indexing

```
google.loc['2016-6-1', 'price'] # Use full date with .loc[]
```

734.15



#### .asfreq(): set frequency

```
.asfreq('D') :

    Convert DateTimeIndex to calendar day frequency

google.asfreq('D').info() # set calendar day frequency
DatetimeIndex: 729 entries, 2015-01-02 to 2016-12-30
Freq: D
Data columns (total 1 columns):
      504 non-null float64
price
dtypes: float64(1)
```

#### .asfreq(): set frequency

- Upsampling:
  - Higher frequency implies new dates => missing data

```
google.asfreq('D').head()

As a result, the DateTimeIndex now contains many dates where stock wasn't bought or sold.
```

```
price

date

2015-01-02 524.81

2015-01-03 NaN

2015-01-04 NaN

2015-01-05 513.87

2015-01-06 501.96
```

#### .asfreq(): reset frequency

#### .asfreq(): reset frequency

```
google[google.price.isnull()] # Select missing 'price' values
```

```
price

date

2015-01-19 NaN

2015-02-16 NaN

...

2016-11-24 NaN

2016-12-26 NaN
```

Business days that were not trading days

### Let's practice!

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# Lags, changes, and returns for stock price series

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#### Basic time series calculations

- Typical Time Series manipulations include:
  - Shift or lag values back or forward back in time
  - Get the difference in value for a given time period
  - Compute the percent change over any number of periods
- pandas built-in methods rely on pd.DateTimeIndex

#### Getting GOOG stock prices

Let pd.read\_csv() do the parsing for you!

```
google = pd.read_csv('google.csv', parse_dates=['date'], index_col='
google.info()
<class 'pandas.core.frame.DataFrame'>
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 504 entries, 2015-01-02 to 2016-12-30
Data columns (total 1 columns):
price     504 non-null float64
dtypes: float64(1)
```

#### Getting GOOG stock prices

```
google.head()
```

```
price

date

2015-01-02 524.81

2015-01-05 513.87

2015-01-06 501.96

2015-01-07 501.10

2015-01-08 502.68
```



#### .shift(): Moving data between past & future

- .shift():defaults to periods=1
  - 1 period into future

```
google['shifted'] = google.price.shift() # default: periods=1
google.head(3)
```

```
price shifted
date
2015-01-02 542.81 NaN
2015-01-05 513.87 542.81
2015-01-06 501.96 513.87
```

#### .shift(): Moving data between past & future

- .shift(periods=-1) :
  - lagged data
  - 1 period back in time

```
google['lagged'] = google.price.shift(periods=-1)
google[['price', 'lagged', 'shifted']].tail(3)
```

```
price lagged shifted
date
2016-12-28 785.05 782.79 791.55
2016-12-29 782.79 771.82 785.05
2016-12-30 771.82 NaN 782.79
```

#### Calculate one-period percent change

 $\bullet$   $x_t / x_{t-1}$ 

```
google['change'] = google.price.div(google.shifted)
google[['price', 'shifted', 'change']].head(3)
```

```
price shifted change

Date

2017-01-03 786.14 NaN NaN

2017-01-04 786.90 786.14 1.000967

2017-01-05 794.02 786.90 1.009048
```

#### Calculate one-period percent change

```
google['return'] = google.change.sub(1).mul(100)
google[['price', 'shifted', 'change', 'return']].head(3)
```

```
price shifted change return
date
2015-01-02 524.81 NaN NaN NaN
2015-01-05 513.87 524.81 0.98 -2.08
2015-01-06 501.96 513.87 0.98 -2.32
```

#### .diff(): built-in time-series change

- Difference in value for two adjacent periods
- $\bullet$   $x_t x_{t-1}$

```
google['diff'] = google.price.diff()
google[['price', 'diff']].head(3)
```

```
price diff
date
2015-01-02 524.81 NaN
2015-01-05 513.87 -10.94
2015-01-06 501.96 -11.91
```

#### .pct\_change(): built-in time-series % change

- Percent change for two adjacent periods
- ullet  $\frac{x_t}{x_{t-1}}$

```
google['pct_change'] = google.price.pct_change().mul(100)
google[['price', 'return', 'pct_change']].head(3)
```

```
price return pct_change

date

2015-01-02 524.81 NaN NaN

2015-01-05 513.87 -2.08 -2.08

2015-01-06 501.96 -2.32 -2.32
```

#### Looking ahead: Get multi-period returns

```
google['return_3d'] = google.price.pct_change(periods=3).mul(100)
google[['price', 'return_3d']].head()
```

```
price return_3d

date

2015-01-02 524.81 NaN

2015-01-05 513.87 NaN

2015-01-06 501.96 NaN

2015-01-07 501.10 -4.517825

2015-01-08 502.68 -2.177594
```

Percent change for two periods, 3 trading days apart

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