Cleaning Data

About the data

In this notebook, we will using daily temperature data from the National Centers for Environmental Information (NCEI) API. We will use the Global Historical Climatology Network - Daily (GHCND) data set; see the documentation here.

This data was collected for the LaGuardia Airport station in New York City for October 2018. It contains:

- the daily minimum temperature (`TMIN`)
- the daily maximum temperature (`TMAX`)
- the daily average temperature (`TAVG`)

Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

In addition, we will be using S&P 500 stock market data for the S&P 500 and data for bitcoin for 2017 through 2018. Both were obtained using the `stock_analysis` package we will build in chapter 7.

Setup

We need to import `pandas` and read in our data to get started:

```
import pandas as pd

df = pd.read_csv('data/nyc_temperatures.csv')
df.head()
```

```
  attributes datatype                 date            station  value
0      H,,S,     TAVG  2018-10-01T00:00:00  GHCND:USW00014732   21.2
1   ,,W,2400     TMAX  2018-10-01T00:00:00  GHCND:USW00014732   25.6
2   ,,W,2400     TMIN  2018-10-01T00:00:00  GHCND:USW00014732   18.3
3      H,,S,     TAVG  2018-10-02T00:00:00  GHCND:USW00014732   22.7
4   ,,W,2400     TMAX  2018-10-02T00:00:00  GHCND:USW00014732   26.1
```

Renaming Columns

We start out with the following columns:

```
df.columns
```

```
Index(['attributes', 'datatype', 'date', 'station', 'value'],
dtype='object')
```

We want to rename the `value` column to indicate it contains the temperature in Celsius and the `attributes` column to say `flags` since each value in the comma-delimited string is a different flag about the data collection. For this task, we use the `rename()` method and pass in a dictionary mapping the column names to their new names. We pass `inplace=True` to change our original dataframe instead of getting a new one back:

```
df.rename(
    columns={
        'value' : 'temp_C',
        'attributes' : 'flags'
    }, inplace=True
)
```

Those columns have been successfully renamed:

```
df.columns
```

```
Index(['flags', 'datatype', 'date', 'station', 'temp_C'],
dtype='object')
```

We can also perform string operations on the column names with `rename()`:

```
df.rename(str.upper, axis='columns').columns
```

```
Index(['FLAGS', 'DATATYPE', 'DATE', 'STATION', 'TEMP_C'],
dtype='object')
```

Type Conversion

The `date` column is not currently being stored as a `datetime`:

```
df.dtypes
```

```
flags         object
datatype      object
date          object
station       object
temp_C       float64
dtype: object
```

Let's perform the conversion with `pd.to_datetime()`:

```
df.loc[:,'date'] = pd.to_datetime(df.date)
df.dtypes
```

```
flags               object
datatype            object
date        datetime64[ns]
station             object
temp_C             float64
dtype: object
```

Now we get useful information when we use `describe()` on this column:

```
df.date.describe()
```

```
count                        93
unique                       31
top       2018-10-01 00:00:00
freq                          3
first     2018-10-01 00:00:00
last      2018-10-31 00:00:00
Name: date, dtype: object
```

We can use `tz_localize()` on a `DatetimeIndex`/`PeriodIndex` to convert to a desired timezone:

```
pd.date_range(start='2018-10-25', periods=2,
freq='D').tz_localize('EST')
```

```
DatetimeIndex(['2018-10-25 00:00:00-05:00', '2018-10-26 00:00:00-
05:00'], dtype='datetime64[ns, EST]', freq='D')
```

This also works with a `Series`/`DataFrame` with one of the aforementioned as its `Index`. Let's read in the CSV again for this example and set the `date` column to be the index and stored as a datetime:

```
eastern = pd.read_csv(
    'data/nyc_temperatures.csv', index_col='date', parse_dates=True
).tz_localize('EST')
eastern.head()
```

```
                          attributes datatype            station
value
date

2018-10-01 00:00:00-05:00      H,,S,     TAVG  GHCND:USW00014732
21.2
2018-10-01 00:00:00-05:00   ,,W,2400     TMAX  GHCND:USW00014732
25.6
2018-10-01 00:00:00-05:00   ,,W,2400     TMIN  GHCND:USW00014732
18.3
2018-10-02 00:00:00-05:00      H,,S,     TAVG  GHCND:USW00014732
22.7
```

```
2018-10-02 00:00:00-05:00    ,,W,2400     TMAX   GHCND:USW00014732
26.1
```

We can use `tz.convert()` to convert to another timezone from there. If we convert the Eastern datetimes to UTC, they will now be at 5 AM, since `pandas` will use the offsets to convert:

```
eastern.tz_convert('UTC').head()
```

```
                          attributes datatype            station
value
date

2018-10-01 05:00:00+00:00      H,,S,     TAVG   GHCND:USW00014732
21.2
2018-10-01 05:00:00+00:00   ,,W,2400     TMAX   GHCND:USW00014732
25.6
2018-10-01 05:00:00+00:00   ,,W,2400     TMIN   GHCND:USW00014732
18.3
2018-10-02 05:00:00+00:00      H,,S,     TAVG   GHCND:USW00014732
22.7
2018-10-02 05:00:00+00:00   ,,W,2400     TMAX   GHCND:USW00014732
26.1
```

We can change the period of the index as well. We could change the period to be monthly to make it easier to aggregate later. (Aggregation will be discussed in chapter 4).

```
eastern.to_period('M').index
```

```
PeriodIndex(['2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
```

```
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10', '2018-10', '2018-10',
'2018-10',
             '2018-10', '2018-10', '2018-10'],
            dtype='period[M]', name='date', freq='M')
```

We now get a `PeriodIndex` which we can change back into a `DatetimeIndex` with `pd.to_timestamp()`:

```
eastern.to_period('M').to_timestamp().index

DatetimeIndex(['2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01', '2018-10-01', '2018-10-01', '2018-10-01',
               '2018-10-01'],
              dtype='datetime64[ns]', name='date', freq=None)
```

We can use the `assign()` method for working with multiple columns at once (or creating new ones). Since our `date` column has already been converted, we need to read in the data again:

```
df = pd.read_csv('data/nyc_temperatures.csv').rename(
    columns={
```

```
        'value' : 'temp_C',
        'attributes' : 'flags'
    }
)

new_df = df.assign(
    date=pd.to_datetime(df.date),
    temp_F=(df.temp_C * 9/5) + 32
)
new_df.dtypes
```

```
flags                 object
datatype              object
date          datetime64[ns]
station               object
temp_C               float64
temp_F               float64
dtype: object
```

The `date` column now has datetimes and the `temp_F` column was added:

```
new_df.head()
```

```
      flags datatype       date            station  temp_C  temp_F
0     H,,S,     TAVG 2018-10-01  GHCND:USW00014732    21.2   70.16
1  ,,W,2400     TMAX 2018-10-01  GHCND:USW00014732    25.6   78.08
2  ,,W,2400     TMIN 2018-10-01  GHCND:USW00014732    18.3   64.94
3     H,,S,     TAVG 2018-10-02  GHCND:USW00014732    22.7   72.86
4  ,,W,2400     TMAX 2018-10-02  GHCND:USW00014732    26.1   78.98
```

We can also use `astype()` to perform conversions. Let's create columns of the integer portion of the temperatures in Celsius and Fahrenheit:

```
df = df.assign(
    date=pd.to_datetime(df.date),
    temp_C_whole=df.temp_C.astype('int'),
    temp_F=(df.temp_C * 9/5) + 32,
    temp_F_whole=lambda x: x.temp_F.astype('int')
)

df.head()
```

```
      flags datatype       date            station  temp_C
temp_C_whole  \
0     H,,S,     TAVG 2018-10-01  GHCND:USW00014732    21.2
21
1  ,,W,2400     TMAX 2018-10-01  GHCND:USW00014732    25.6
25
2  ,,W,2400     TMIN 2018-10-01  GHCND:USW00014732    18.3
```

```
18
3     H,,S,     TAVG 2018-10-02  GHCND:USW00014732    22.7
22
4   ,,W,2400    TMAX 2018-10-02  GHCND:USW00014732    26.1
26

   temp_F  temp_F_whole
0   70.16            70
1   78.08            78
2   64.94            64
3   72.86            72
4   78.98            78
```

Creating categories:

```
df_with_categories = df.assign(
    station=df.station.astype('category'),
    datatype=df.datatype.astype('category')
)
df_with_categories.dtypes
```

```
flags                   object
datatype              category
date            datetime64[ns]
station               category
temp_C                 float64
temp_C_whole             int32
temp_F                 float64
temp_F_whole             int32
dtype: object
```

Our categories have no order, but this is something `pandas` supports:

```
pd.Categorical(
    ['med', 'med', 'low', 'high'],
    categories=['low', 'med', 'high'],
    ordered=True
)
```

```
[med, med, low, high]
Categories (3, object): [low < med < high]
```

Reordering, reindexing, and sorting

Say we want to find the hottest days in the temperature data; we can sort our values by the `temp_C` column with the largest on top to find this:

```
df.sort_values(by='temp_C', ascending=False).head(10)
```

```
       flags datatype       date            station  temp_C
temp_C_whole  \
19  ,,W,2400     TMAX 2018-10-07  GHCND:USW00014732    27.8
27
28  ,,W,2400     TMAX 2018-10-10  GHCND:USW00014732    27.8
27
31  ,,W,2400     TMAX 2018-10-11  GHCND:USW00014732    26.7
26
4   ,,W,2400     TMAX 2018-10-02  GHCND:USW00014732    26.1
26
10  ,,W,2400     TMAX 2018-10-04  GHCND:USW00014732    26.1
26
25  ,,W,2400     TMAX 2018-10-09  GHCND:USW00014732    25.6
25
1   ,,W,2400     TMAX 2018-10-01  GHCND:USW00014732    25.6
25
7   ,,W,2400     TMAX 2018-10-03  GHCND:USW00014732    25.0
25
27     H,,S,     TAVG 2018-10-10  GHCND:USW00014732    23.8
23
30     H,,S,     TAVG 2018-10-11  GHCND:USW00014732    23.4
23

    temp_F  temp_F_whole
19   82.04            82
28   82.04            82
31   80.06            80
4    78.98            78
10   78.98            78
25   78.08            78
1    78.08            78
7    77.00            77
27   74.84            74
30   74.12            74
```

```
df.sort_values(by=['temp_C', 'date'], ascending=False).head(10)
```

```
       flags datatype       date            station  temp_C
temp_C_whole  \
28  ,,W,2400     TMAX 2018-10-10  GHCND:USW00014732    27.8
27
19  ,,W,2400     TMAX 2018-10-07  GHCND:USW00014732    27.8
27
31  ,,W,2400     TMAX 2018-10-11  GHCND:USW00014732    26.7
26
10  ,,W,2400     TMAX 2018-10-04  GHCND:USW00014732    26.1
26
4   ,,W,2400     TMAX 2018-10-02  GHCND:USW00014732    26.1
26
25  ,,W,2400     TMAX 2018-10-09  GHCND:USW00014732    25.6
```

```
25
1   ,,W,2400     TMAX 2018-10-01  GHCND:USW00014732    25.6
25
7   ,,W,2400     TMAX 2018-10-03  GHCND:USW00014732    25.0
25
27    H,,S,      TAVG 2018-10-10  GHCND:USW00014732    23.8
23
30    H,,S,      TAVG 2018-10-11  GHCND:USW00014732    23.4
23

    temp_F  temp_F_whole
28   82.04            82
19   82.04            82
31   80.06            80
10   78.98            78
4    78.98            78
25   78.08            78
1    78.08            78
7    77.00            77
27   74.84            74
30   74.12            74
```

When just looking for the n-largest values, rather than wanting to sort all the data, we can use `nlargest()`:

```
df.nlargest(n=5, columns='temp_C')

       flags datatype       date            station  temp_C
temp_C_whole  \
19  ,,W,2400     TMAX 2018-10-07  GHCND:USW00014732    27.8
27
28  ,,W,2400     TMAX 2018-10-10  GHCND:USW00014732    27.8
27
31  ,,W,2400     TMAX 2018-10-11  GHCND:USW00014732    26.7
26
4   ,,W,2400     TMAX 2018-10-02  GHCND:USW00014732    26.1
26
10  ,,W,2400     TMAX 2018-10-04  GHCND:USW00014732    26.1
26

    temp_F  temp_F_whole
19   82.04            82
28   82.04            82
31   80.06            80
4    78.98            78
10   78.98            78
```

We use `nsmallest()` for the n-smallest values. Note that these can also take a list of columns; however, it won't work with the `date` column.

```
df.nsmallest(n=5, columns=['temp_C', 'date'])
```

```
       flags datatype       date            station  temp_C
temp_C_whole  \
53  ,,W,2400     TMIN 2018-10-18  GHCND:USW00014732     6.7
6
62  ,,W,2400     TMIN 2018-10-21  GHCND:USW00014732     6.1
6
65  ,,W,2400     TMIN 2018-10-22  GHCND:USW00014732     5.6
5
74  ,,W,2400     TMIN 2018-10-25  GHCND:USW00014732     6.1
6
77  ,,W,2400     TMIN 2018-10-26  GHCND:USW00014732     5.6
5

    temp_F  temp_F_whole
53   44.06            44
62   42.98            42
65   42.08            42
74   42.98            42
77   42.08            42
```

The `sample()` method will give us rows (or columns with `axis=1`) at random. We can provide the `random_state` to make this reproducible. The index after we do this is jumbled:

```
df.sample(5, random_state=0).index
```

```
Int64Index([2, 30, 55, 16, 13], dtype='int64')
```

We can use `sort_index()` to order it again:

```
df.sample(5, random_state=0).sort_index().index
```

```
Int64Index([2, 13, 16, 30, 55], dtype='int64')
```

The `sort_index()` method can also sort columns alphabetically:

```
df.sort_index(axis=1).head()
```

```
  datatype       date     flags            station  temp_C
temp_C_whole  \
0     TAVG 2018-10-01     H,,S,  GHCND:USW00014732    21.2
21
1     TMAX 2018-10-01  ,,W,2400  GHCND:USW00014732    25.6
25
2     TMIN 2018-10-01  ,,W,2400  GHCND:USW00014732    18.3
18
3     TAVG 2018-10-02     H,,S,  GHCND:USW00014732    22.7
22
```

```
4     TMAX 2018-10-02  ,,W,2400  GHCND:USW00014732    26.1
26

   temp_F  temp_F_whole
0   70.16            70
1   78.08            78
2   64.94            64
3   72.86            72
4   78.98            78
```

This can make selection with `loc` easier for many columns:

```
df.sort_index(axis=1).head().loc[:,'temp_C':'temp_F_whole']

   temp_C  temp_C_whole  temp_F  temp_F_whole
0    21.2            21   70.16            70
1    25.6            25   78.08            78
2    18.3            18   64.94            64
3    22.7            22   72.86            72
4    26.1            26   78.98            78
```

We must sort the index to compare two dataframes. If the index is different, but the data is the same, they will be marked not-equal:

```
df.equals(df.sort_values(by='temp_C'))

False
```

Sorting the index solves this issue:

```
df.equals(df.sort_values(by='temp_C').sort_index())

True
```

We can also use `reset_index()` to get a fresh index and move our current index into a column for safe keeping. This is especially useful if we had data, such as the date, in the index that we don't want to lose:

```
df[df.datatype == 'TAVG'].head().reset_index()

   index  flags datatype       date            station  temp_C
temp_C_whole  \
0      0  H,,S,     TAVG 2018-10-01  GHCND:USW00014732    21.2
21
1      3  H,,S,     TAVG 2018-10-02  GHCND:USW00014732    22.7
22
2      6  H,,S,     TAVG 2018-10-03  GHCND:USW00014732    21.8
21
3      9  H,,S,     TAVG 2018-10-04  GHCND:USW00014732    21.3
```

```
21
4     12  H,,S,     TAVG 2018-10-05  GHCND:USW00014732    20.3
20

   temp_F  temp_F_whole
0   70.16            70
1   72.86            72
2   71.24            71
3   70.34            70
4   68.54            68
```

Let's set the `date` column as our index:

```
df.set_index('date', inplace=True)
df.head()

                flags datatype            station  temp_C  temp_C_whole
\
date

2018-10-01     H,,S,     TAVG  GHCND:USW00014732    21.2            21

2018-10-01  ,,W,2400     TMAX  GHCND:USW00014732    25.6            25

2018-10-01  ,,W,2400     TMIN  GHCND:USW00014732    18.3            18

2018-10-02     H,,S,     TAVG  GHCND:USW00014732    22.7            22

2018-10-02  ,,W,2400     TMAX  GHCND:USW00014732    26.1            26


             temp_F  temp_F_whole
date
2018-10-01   70.16            70
2018-10-01   78.08            78
2018-10-01   64.94            64
2018-10-02   72.86            72
2018-10-02   78.98            78
```

Now that we have a `DatetimeIndex`, we can do datetime slicing. As long as we provide a date format that pandas understands, we can grab the data. To select all of 2018, we simply use `df['2018']`, for the third quarter of 2018 we can use `['2018-Q3']`, grabbing October is as simple as using `df['2018-10']`; these can also be combined to build ranges. Let's grab October 11, 2018 through October 12, 2018 (inclusive of both endpoints):

```
df['2018-10-11':'2018-10-12']

                flags datatype            station  temp_C  temp_C_whole
\
date
```

```
2018-10-11     H,,S,     TAVG  GHCND:USW00014732    23.4             23
2018-10-11  ,,W,2400     TMAX  GHCND:USW00014732    26.7             26
2018-10-11  ,,W,2400     TMIN  GHCND:USW00014732    21.7             21
2018-10-12     H,,S,     TAVG  GHCND:USW00014732    18.3             18
2018-10-12  ,,W,2400     TMAX  GHCND:USW00014732    22.2             22
2018-10-12  ,,W,2400     TMIN  GHCND:USW00014732    12.2             12


            temp_F  temp_F_whole
date
2018-10-11   74.12            74
2018-10-11   80.06            80
2018-10-11   71.06            71
2018-10-12   64.94            64
2018-10-12   71.96            71
2018-10-12   53.96            53
```

Reindexing allows us to conform our axis to contain a given set of labels. Let's turn to the S&P 500 stock data in the `data/sp500.csv` file to see an example of this. Notice we only have data for trading days (weekdays, excluding holidays):

```
sp = pd.read_csv(
    'data/sp500.csv', index_col='date', parse_dates=True
).drop(columns=['adj_close'])

sp.head(10).assign(
    day_of_week=lambda x: x.index.day_name()
)
```

```
                  high          low         open        close
volume  \
date

2017-01-03  2263.879883  2245.129883  2251.570068  2257.830078
3770530000
2017-01-04  2272.820068  2261.600098  2261.600098  2270.750000
3764890000
2017-01-05  2271.500000  2260.449951  2268.179932  2269.000000
3761820000
2017-01-06  2282.100098  2264.060059  2271.139893  2276.979980
3339890000
2017-01-09  2275.489990  2268.899902  2273.590088  2268.899902
3217610000
2017-01-10  2279.270020  2265.270020  2269.719971  2268.899902
```

```
3638790000
2017-01-11  2275.320068  2260.830078  2268.600098  2275.320068
3620410000
2017-01-12  2271.780029  2254.250000  2271.139893  2270.439941
3462130000
2017-01-13  2278.679932  2271.510010  2272.739990  2274.639893
3081270000
2017-01-17  2272.080078  2262.810059  2269.139893  2267.889893
3584990000

            day_of_week
date
2017-01-03     Tuesday
2017-01-04   Wednesday
2017-01-05    Thursday
2017-01-06      Friday
2017-01-09      Monday
2017-01-10     Tuesday
2017-01-11   Wednesday
2017-01-12    Thursday
2017-01-13      Friday
2017-01-17     Tuesday
```

If we want to look at the value of a portfolio (group of assets) that trade on different days, we need to handle the mismatch in the index. Bitcoin, for example, trades daily. If we sum up all the data we have for each day (aggregations will be covered in chapter 4, so don't fixate on this part), we get the following:

```
bitcoin = pd.read_csv(
    'data/bitcoin.csv', index_col='date', parse_dates=True
).drop(columns=['market_cap'])

# every day's closing price = S&P 500 close + Bitcoin close (same for
other metrics)
portfolio = pd.concat(
    [sp, bitcoin], sort=False
).groupby(pd.Grouper(freq='D')).sum()

portfolio.head(10).assign(
    day_of_week=lambda x: x.index.day_name()
)

                   high          low         open        close
volume  \
date

2017-01-01  1003.080000   958.700000   963.660000   998.330000
147775008
2017-01-02  1031.390000   996.700000   998.620000  1021.750000
```

```
222184992
2017-01-03  3307.959883  3266.729883  3273.170068  3301.670078
3955698000
2017-01-04  3432.240068  3306.000098  3306.000098  3425.480000
4109835984
2017-01-05  3462.600000  3170.869951  3424.909932  3282.380000
4272019008
2017-01-06  3328.910098  3148.000059  3285.379893  3179.179980
3691766000
2017-01-07   908.590000   823.560000   903.490000   908.590000
279550016
2017-01-08   942.720000   887.250000   908.170000   911.200000
158715008
2017-01-09  3189.179990  3148.709902  3186.830088  3171.729902
3359486992
2017-01-10  3194.140020  3166.330020  3172.159971  3176.579902
3754598000

            day_of_week
date
2017-01-01      Sunday
2017-01-02      Monday
2017-01-03     Tuesday
2017-01-04   Wednesday
2017-01-05    Thursday
2017-01-06      Friday
2017-01-07    Saturday
2017-01-08      Sunday
2017-01-09      Monday
2017-01-10     Tuesday
```

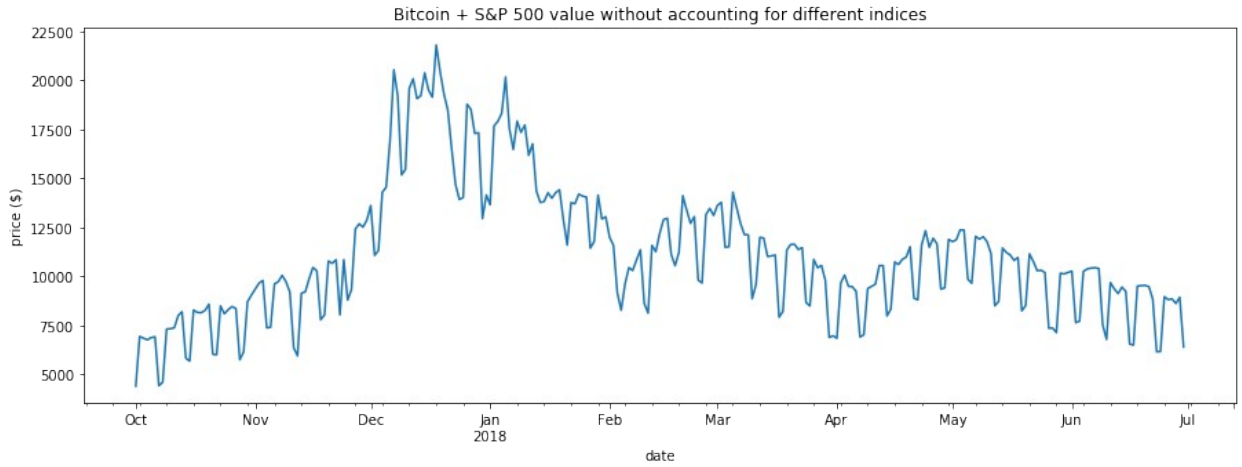
It may not be immediately obvious what is wrong with the previous data, but with a visualization we can easily see the cyclical pattern of drops on the days the stock market is closed. (Don't worry about the plotting code too much, we will cover it in depth in chapters 5 and 6).

We will need to import `matplotlib` now:

```
import matplotlib.pyplot as plt # we use this module for plotting
```

Now we can see why we need to reindex:

```
portfolio['2017-Q4':'2018-Q2'].plot(
    y='close', figsize=(15, 5), legend=False,
    title='Bitcoin + S&P 500 value without accounting for different
indices'
) # plot the closing price from Q4 2017 through Q2 2018
plt.ylabel('price ($)') # label the y-axis
plt.show() # show the plot
```



We need to align the index of the S&P 500 to match bitcoin in order to fix this. We will use the `reindex()` method, but by default we get `NaN` for the values that we don't have data for:

```
sp.reindex(bitcoin.index).head(10).assign(
    day_of_week=lambda x: x.index.day_name()
)
```

```
                  high          low         open        close
volume  \
date

2017-01-01          NaN          NaN          NaN          NaN
NaN
2017-01-02          NaN          NaN          NaN          NaN
NaN
2017-01-03  2263.879883  2245.129883  2251.570068  2257.830078
3.770530e+09
2017-01-04  2272.820068  2261.600098  2261.600098  2270.750000
3.764890e+09
2017-01-05  2271.500000  2260.449951  2268.179932  2269.000000
3.761820e+09
2017-01-06  2282.100098  2264.060059  2271.139893  2276.979980
3.339890e+09
2017-01-07          NaN          NaN          NaN          NaN
NaN
2017-01-08          NaN          NaN          NaN          NaN
NaN
2017-01-09  2275.489990  2268.899902  2273.590088  2268.899902
3.217610e+09
2017-01-10  2279.270020  2265.270020  2269.719971  2268.899902
3.638790e+09

           day_of_week
date
2017-01-01      Sunday
```

```
2017-01-02      Monday
2017-01-03     Tuesday
2017-01-04   Wednesday
2017-01-05    Thursday
2017-01-06      Friday
2017-01-07    Saturday
2017-01-08      Sunday
2017-01-09      Monday
2017-01-10     Tuesday
```

So now we have rows for every day of the year, but all the weekends and holidays have `NaN` values. To address this, we can specify how to handle missing values with the `method` argument. In this case, we want to forward fill, which will put the weekend and holiday values as the value they had for the Friday (or end of trading week) before:

```
sp.reindex(
    bitcoin.index, method='ffill'
).head(10).assign(
    day_of_week=lambda x: x.index.day_name()
)
```

```
                    high          low         open        close
volume  \
date

2017-01-01          NaN          NaN          NaN          NaN
NaN
2017-01-02          NaN          NaN          NaN          NaN
NaN
2017-01-03  2263.879883  2245.129883  2251.570068  2257.830078
3.770530e+09
2017-01-04  2272.820068  2261.600098  2261.600098  2270.750000
3.764890e+09
2017-01-05  2271.500000  2260.449951  2268.179932  2269.000000
3.761820e+09
2017-01-06  2282.100098  2264.060059  2271.139893  2276.979980
3.339890e+09
2017-01-07  2282.100098  2264.060059  2271.139893  2276.979980
3.339890e+09
2017-01-08  2282.100098  2264.060059  2271.139893  2276.979980
3.339890e+09
2017-01-09  2275.489990  2268.899902  2273.590088  2268.899902
3.217610e+09
2017-01-10  2279.270020  2265.270020  2269.719971  2268.899902
3.638790e+09

           day_of_week
date
2017-01-01      Sunday
```

```
2017-01-02      Monday
2017-01-03     Tuesday
2017-01-04   Wednesday
2017-01-05    Thursday
2017-01-06      Friday
2017-01-07    Saturday
2017-01-08      Sunday
2017-01-09      Monday
2017-01-10     Tuesday
```

This isn't perfect though. We probably want 0 for the volume traded and to put the closing price for the open, high, low, and close on the days the market is closed:

```
import numpy as np

sp_reindexed = sp.reindex(
    bitcoin.index
).assign(
    volume=lambda x: x.volume.fillna(0), # put 0 when market is closed
    close=lambda x: x.close.fillna(method='ffill'), # carry this
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)
)
sp_reindexed.head(10).assign(
    day_of_week=lambda x: x.index.day_name()
)
```

```
                    high          low         open        close
volume  \
date

2017-01-01          NaN          NaN          NaN          NaN
0.000000e+00
2017-01-02          NaN          NaN          NaN          NaN
0.000000e+00
2017-01-03  2263.879883  2245.129883  2251.570068  2257.830078
3.770530e+09
2017-01-04  2272.820068  2261.600098  2261.600098  2270.750000
3.764890e+09
2017-01-05  2271.500000  2260.449951  2268.179932  2269.000000
3.761820e+09
2017-01-06  2282.100098  2264.060059  2271.139893  2276.979980
3.339890e+09
2017-01-07  2276.979980  2276.979980  2276.979980  2276.979980
0.000000e+00
2017-01-08  2276.979980  2276.979980  2276.979980  2276.979980
```

```
0.000000e+00
2017-01-09  2275.489990  2268.899902  2273.590088  2268.899902
3.217610e+09
2017-01-10  2279.270020  2265.270020  2269.719971  2268.899902
3.638790e+09

           day_of_week
date
2017-01-01      Sunday
2017-01-02      Monday
2017-01-03     Tuesday
2017-01-04   Wednesday
2017-01-05    Thursday
2017-01-06      Friday
2017-01-07    Saturday
2017-01-08      Sunday
2017-01-09      Monday
2017-01-10     Tuesday
```

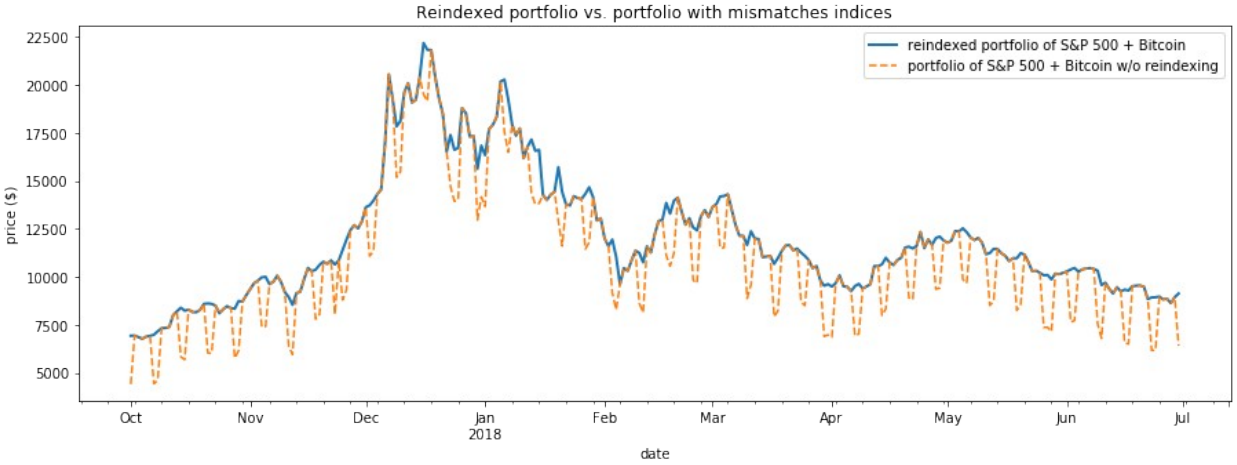
If we create visualization comparing the reindexed data to the first attempt, we see how reindexing helped maintain the asset value when the market was closed:

```
# every day's closing price = S&P 500 close adjusted for market
closure + Bitcoin close (same for other metrics)
fixed_portfolio = pd.concat([sp_reindexed, bitcoin],
sort=False).groupby(pd.Grouper(freq='D')).sum()

ax = fixed_portfolio['2017-Q4':'2018-Q2'].plot(
    y='close', label='reindexed portfolio of S&P 500 + Bitcoin',
figsize=(15, 5), linewidth=2,
    title='Reindexed portfolio vs. portfolio with mismatches indices'
) # plot the reindexed portfolio's closing price from Q4 2017 through
Q2 2018

portfolio['2017-Q4':'2018-Q2'].plot(
    y='close', ax=ax, linestyle='--', label='portfolio of S&P 500 +
Bitcoin w/o reindexing'
).set_ylabel('price ($)') # add line for original portfolio for
comparison and label y-axis

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


Reindexed portfolio vs. portfolio with mismatches indices
reindexed portfolio of S&P 500 + Bitcoin
portfolio of S&P 500 + Bitcoin w/o reindexing
price ($)
22500
20000
17500
15000
12500
10000
7500
5000
Oct
Nov
Dec
Jan
2018
Feb
Mar
Apr
May
Jun
Jul
date