Cleaning Data

About the data In this notebok, we will be 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.

Setup

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

```
1 import pandas as p
2
3 df = p.read_csv('/content/nyc_temperatures.csv')
4 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:

```
1 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 the 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:

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

Those columns have been successfully renamed:

```
1 df.columns
```

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

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

```
1 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`:

```
1 df.dtypes
```

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

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

```
1 df.loc[:, 'date'] = p.to_datetime(df.date)
2 df.dtypes
```

```
<ipython-input-87-f7d341a4954e>:1: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt to set the values
  df.loc[:, 'date'] = p.to_datetime(df.date)
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:

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

```
<ipython-input-88-f7d3fa946723>:1: FutureWarning: Treating datetime data as categorical rather than numeric in `.describe` is deprec
  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:

```
1 p.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=None)
```

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 datetime:

```
1 eastern = p.read_csv(
2     '/content/nyc_temperatures.csv', index_col='date', parse_dates=True
3     ).tz_localize('EST')
4 eastern.head()
```

date	attributes	datatype	station	value
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:

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

date	attributes	datatype	station	value
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).

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

```
<ipython-input-92-34a82283fe40>:1: UserWarning: Converting to PeriodArray/Index representation will drop timezone information.
  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')
```

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

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

```
<ipython-input-93-22abc5f95bfc>:1: UserWarning: Converting to PeriodArray/Index representation will drop timezone information.
  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 = p.read_csv('/content/nyc_temperatures.csv').rename(
    columns={
        'value' : 'temp_C',
        'attributes' : 'flags'
    }
)

new_df = df.assign(
    date=p.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=p.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	temp_F	temp_
0	H,,S,	TAVG	2018-10-01	GHCND:USW00014732	21.2	21	70.16	
1	,,W,2400	TMAX	2018-10-01	GHCND:USW00014732	25.6	25	78.08	
2	,,W,2400	TMIN	2018-10-01	GHCND:USW00014732	18.3	18	64.94	
			2018-					

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           int64
temp_F               float64
temp_F_whole           int64
dtype: object
```

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

```
p.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	temp_F	temp
19	,,W,2400	TMAX	2018-10-07	GHCND:USW00014732	27.8	27	82.04	
28	,,W,2400	TMAX	2018-10-10	GHCND:USW00014732	27.8	27	82.04	
31	,,W,2400	TMAX	2018-10-11	GHCND:USW00014732	26.7	26	80.06	
4	,,W,2400	TMAX	2018-10-02	GHCND:USW00014732	26.1	26	78.98	
10	,,W,2400	TMAX	2018-10-04	GHCND:USW00014732	26.1	26	78.98	
25	,,W,2400	TMAX	2018-10-09	GHCND:USW00014732	25.6	25	78.08	
1	,,W,2400	TMAX	2018-10-01	GHCND:USW00014732	25.6	25	78.08	

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	temp_F	temp
19	,,W,2400	TMAX	2018-10-07	GHCND:USW00014732	27.8	27	82.04	
28	,,W,2400	TMAX	2018-10-10	GHCND:USW00014732	27.8	27	82.04	
31	,,W,2400	TMAX	2018-10-11	GHCND:USW00014732	26.7	26	80.06	
4	,,W,2400	TMAX	2018-10-02	GHCND:USW00014732	26.1	26	78.98	
10	,,W,2400	TMAX	2018-10-04	GHCND:USW00014732	26.1	26	78.98	

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	temp_F	temp
65	,,W,2400	TMIN	2018-10-22	GHCND:USW00014732	5.6	5	42.08	
77	,,W,2400	TMIN	2018-10-26	GHCND:USW00014732	5.6	5	42.08	
62	,,W,2400	TMIN	2018-10-21	GHCND:USW00014732	6.1	6	42.98	
74	,,W,2400	TMIN	2018-10-27	GHCND:USW00014732	6.1	6	42.98	
75	,,W,2400	TMIN	2018-10-28	GHCND:USW00014732	6.1	6	42.98	

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	temp_F	temp_
0	TAVG	2018-10-01	H,,S,	GHCND:USW00014732	21.2	21	70.16	
1	TMAX	2018-10-01	,,W,2400	GHCND:USW00014732	25.6	25	78.08	
2	TMIN	2018-10-01	,,W,2400	GHCND:USW00014732	18.3	18	64.94	
3	TAVG	2018-						

This can make selection `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	temp_F
0	0	H,,S,	TAVG	2018-10-01	GHCND:USW00014732	21.2	21	70.16
1	3	H,,S,	TAVG	2018-10-02	GHCND:USW00014732	22.7	22	72.86
2	6	H,,S,	TAVG	2018-10-03	GHCND:USW00014732	21.8	21	71.24
3	9	H,,S,	TAVG	2018-				

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

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

date	flags	datatype	station	temp_C	temp_C_whole	temp_F	temp_F_w
2018-10-01	H,,S,	TAVG	GHCND:USW00014732	21.2	21	70.16	
2018-10-01	,,W,2400	TMAX	GHCND:USW00014732	25.6	25	78.08	
2018-10-01	,,W,2400	TMIN	GHCND:USW00014732	18.3	18	64.94	
2018-							

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']
```

date	flags	datatype	station	temp_C	temp_C_whole	temp_F	temp_F_w
2018-10-11	H,,S,	TAVG	GHCND:USW00014732	23.4	23	74.12	
2018-10-11	,,W,2400	TMAX	GHCND:USW00014732	26.7	26	80.06	
2018-10-11	,,W,2400	TMIN	GHCND:USW00014732	21.7	21	71.06	
2018-10-12	H,,S,	TAVG	GHCND:USW00014732	18.3	18	64.94	

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 = p.read_csv(
    '/content/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()
)
```

date	high	low	open	close	volume	day_of_week
2017-01-03	2263.879883	2245.129883	2251.570068	2257.830078	3770530000	Tuesday
2017-01-04	2272.820068	2261.600098	2261.600098	2270.750000	3764890000	Wednesday
2017-01-05	2271.500000	2260.449951	2268.179932	2269.000000	3761820000	Thursday
2017-01-06	2282.100098	2264.060059	2271.139893	2276.979980	3339890000	Friday
2017-01-09	2275.489990	2268.899902	2273.590088	2268.899902	3217610000	Monday
2017-01-10	2279.270020	2265.270020	2269.719971	2268.899902	3638790000	Tuesday
2017-01-11	2275.320068	2260.830078	2268.600098	2275.320068	3620410000	Wednesday

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.

```
bitcoin = p.read_csv(
    '/content/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 = p.concat(
    [sp, bitcoin], sort = False
```

```
).groupby(p.Grouper(freq='D')).sum()

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

date	high	low	open	close	volume	day_of_week
2017-01-01	1003.080000	958.700000	963.660000	998.330000	147775008	Sunday
2017-01-02	1031.390000	996.700000	998.620000	1021.750000	222184992	Monday
2017-01-03	3307.959883	3266.729883	3273.170068	3301.670078	3955698000	Tuesday
2017-01-04	3432.240068	3306.000098	3306.000098	3425.480000	4109835984	Wednesday
2017-01-05	3462.600000	3170.869951	3424.909932	3282.380000	4272019008	Thursday
2017-01-06	3328.910098	3148.000059	3285.379893	3179.179980	3691766000	Friday
2017-01-07	908.590000	823.560000	903.490000	908.590000	279550016	Saturday

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.

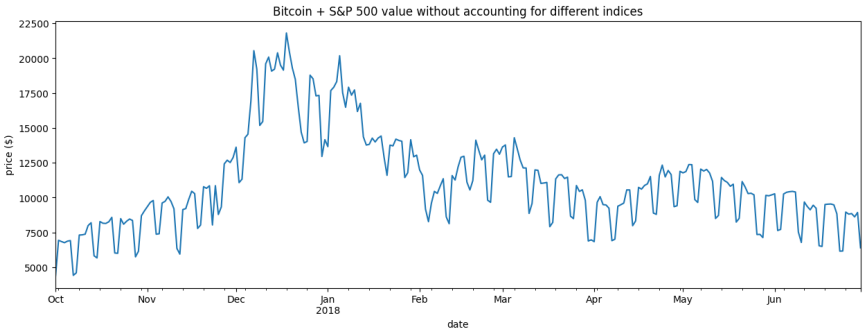
We will need to import matplotlib now:

```
import matplotlib.pyplot as pl # 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
pl.ylabel('price ($)') # label the y-axis
pl.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()
)
```

date	high	low	open	close	volume	day_of_week
2017-01-01	NaN	NaN	NaN	NaN	NaN	Sunday
2017-01-02	NaN	NaN	NaN	NaN	NaN	Monday
2017-01-03	2263.879883	2245.129883	2251.570068	2257.830078	3.770530e+09	Tuesday
2017-01-04	2272.820068	2261.600098	2261.600098	2270.750000	3.764890e+09	Wednesday
2017-01-05	2271.500000	2260.449951	2268.179932	2269.000000	3.761820e+09	Thursday
2017-01-06	2282.100098	2264.060059	2271.139893	2276.979980	3.339890e+09	Friday
2017-01-07	NaN	NaN	NaN	NaN	NaN	Saturday

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()
)
```

date	high	low	open	close	volume	day_of_week
2017-01-01	NaN	NaN	NaN	NaN	NaN	Sunday
2017-01-02	NaN	NaN	NaN	NaN	NaN	Monday
2017-01-03	2263.879883	2245.129883	2251.570068	2257.830078	3.770530e+09	Tuesday
2017-01-04	2272.820068	2261.600098	2261.600098	2270.750000	3.764890e+09	Wednesday
2017-01-05	2271.500000	2260.449951	2268.179932	2269.000000	3.761820e+09	Thursday
2017-01-06	2282.100098	2264.060059	2271.139893	2276.979980	3.339890e+09	Friday
2017-01-07	2282.100098	2264.060059	2271.139893	2276.979980	3.339890e+09	Saturday

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 ny

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 this aren't available
    open=lambda x: ny.where(x.open.isnull(), x.close, x.open),
    high=lambda x: ny.where(x.high.isnull(), x.close, x.high),
    low=lambda x: ny.where(x.low.isnull(), x.close, x.low)
)
sp_reindexed.head(10).assign(
    day_of_week = lambda x: x.index.day_name()
)
```

date	high	low	open	close	volume	day_of_week
2017-01-01	NaN	NaN	NaN	NaN	0.000000e+00	Sunday
2017-01-02	NaN	NaN	NaN	NaN	0.000000e+00	Monday
2017-01-03	2263.879883	2245.129883	2251.570068	2257.830078	3.770530e+09	Tuesday
2017-01-04	2272.820068	2261.600098	2261.600098	2270.750000	3.764890e+09	Wednesday
2017-01-05	2271.500000	2260.449951	2268.179932	2269.000000	3.761820e+09	Thursday
2017-01-06	2282.100098	2264.060059	2271.139893	2276.979980	3.339890e+09	Friday

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:

2017-01-09	2275.489990	2268.899902	2273.590088	2268.899902	3.217610e+09	Monday

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

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