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 max 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:

```
import pandas as pd

df = pd.read_csv('/content/nyc_temperaturs.csv')
df.head()
```

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

Renaming Columns

We start out with the following columns:

```
df.columns
```

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

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

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

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

Type Conversion

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

```
df.dtypes
```

```
date         object
datatype     object
station      object
flags        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
```

```
<ipython-input-10-80606e5f8dec>:1: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt to set the values inp
  df.loc[:,'date'] = pd.to_datetime(df.date)
date        datetime64[ns]
datatype            object
station             object
flags               object
temp_C             float64
dtype: object
```

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

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

```
<ipython-input-11-f7d3fa946723>:1: FutureWarning: Treating datetime data as categorical rather than numeric in `.describe` is deprecated
  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=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 a datetime:

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

date	datatype	station	attributes	value
2018-10-01 00:00:00-05:00	TAVG	GHCND:USW00014732	H,,S,	21.2
2018-10-01 00:00:00-05:00	TMAX	GHCND:USW00014732	,,W,2400	25.6
2018-10-01 00:00:00-05:00	TMIN	GHCND:USW00014732	,,W,2400	18.3
2018-10-02 00:00:00-05:00	TAVG	GHCND:USW00014732	H,,S,	22.7
2018-10-02 00:00:00-05:00	TMAX	GHCND:USW00014732	,,W,2400	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()
```

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

```
<ipython-input-16-34a82283fe40>: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() :

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

```
<ipython-input-17-22abc5f95bfc>: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 = pd.read_csv('/content/nyc_temperaturs.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
```

```
date        datetime64[ns]
datatype            object
station             object
flags               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()
```

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

	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_w
0	2018-10-01	TAVG	GHCND:USW00014732	H,,S,	21.2	21	70.16	
1	2018-10-01	TMAX	GHCND:USW00014732	,,W,2400	25.6	25	78.08	
2	2018-10-01	TMIN	GHCND:USW00014732	,,W,2400	18.3	18	64.94	

Creating categories:

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

```
date            datetime64[ns]
datatype              category
station               category
flags                   object
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:

```
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)
```

	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_
19	2018-10-07	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
28	2018-10-10	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
31	2018-10-11	TMAX	GHCND:USW00014732	,,W,2400	26.7	26	80.06	
4	2018-10-02	TMAX	GHCND:USW00014732	,,W,2400	26.1	26	78.98	
10	2018-10-04	TMAX	GHCND:USW00014732	,,W,2400	26.1	26	78.98	
25	2018-10-09	TMAX	GHCND:USW00014732	,,W,2400	25.6	25	78.08	

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

	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_
28	2018-10-10	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
19	2018-10-07	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
31	2018-10-11	TMAX	GHCND:USW00014732	,,W,2400	26.7	26	80.06	
10	2018-10-04	TMAX	GHCND:USW00014732	,,W,2400	26.1	26	78.98	
4	2018-10-02	TMAX	GHCND:USW00014732	,,W,2400	26.1	26	78.98	
25	2018-10-09	TMAX	GHCND:USW00014732	,,W,2400	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')
```

	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_
19	2018-10-07	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
28	2018-10-10	TMAX	GHCND:USW00014732	,,W,2400	27.8	27	82.04	
31	2018-10-11	TMAX	GHCND:USW00014732	,,W,2400	26.7	26	80.06	

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'])
```

	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_
65	2018-10-22	TMIN	GHCND:USW00014732	,,W,2400	5.6	5	42.08	
77	2018-10-26	TMIN	GHCND:USW00014732	,,W,2400	5.6	5	42.08	
62	2018-10-21	TMIN	GHCND:USW00014732	,,W,2400	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_F_w
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	

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	date	datatype	station	flags	temp_C	temp_C_whole	temp_F	tem
0	0	2018-10-01	TAVG	GHCND:USW00014732	H,,S,	21.2	21	70.16	
1	3	2018-10-02	TAVG	GHCND:USW00014732	H,,S,	22.7	22	72.86	
2	6	2018-10-03	TAVG	GHCND:USW00014732	H,,S,	21.8	21	71.24	

Let's set the date column as our index:

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

date	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_whol
2018-10-01	TAVG	GHCND:USW00014732	H,,S,	21.2	21	70.16	7
2018-10-01	TMAX	GHCND:USW00014732	,,W,2400	25.6	25	78.08	7
2018-10-01	TMIN	GHCND:USW00014732	,,W,2400	18.3	18	64.94	6

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	datatype	station	flags	temp_C	temp_C_whole	temp_F	temp_F_whol
2018-10-11	TAVG	GHCND:USW00014732	H,,S,	23.4	23	74.12	7
2018-10-11	TMAX	GHCND:USW00014732	,,W,2400	26.7	26	80.06	8
2018-10-11	TMIN	GHCND:USW00014732	,,W,2400	21.7	21	71.06	7
2018-10-12	TAVG	GHCND:USW00014732	H,,S,	18.3	18	64.94	6

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(
    '/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
2017-01-12	2271.780029	2254.250000	2271.139893	2270.439941	3462130000	Thursday
2017-01-13	2278.679932	2271.510010	2272.739990	2274.639893	3081270000	Friday
2017-01-17	2272.080078	2262.810059	2269.139893	2267.889893	3584990000	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.

```
bitcoin = pd.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 = 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()
)
```

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
2017-01-08	942.720000	887.250000	908.170000	911.200000	158715008	Sunday
2017-01-09	3189.179990	3148.709902	3186.830088	3171.729902	3359486992	Monday
2017-01-10	3194.140020	3166.330020	3172.159971	3176.579902	3754598000	Tuesday

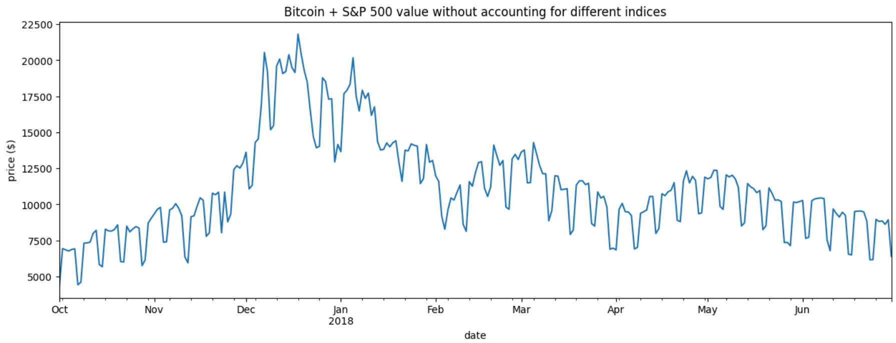
It may not be immediately obvious what is wrong with the previous data, but with a visualization we can easily see the cyclical pattern of drops on the days the stock market is closed.

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()
)
```

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()
)
```

	high	low	open	close	volume	day_of_week
date						
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-	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 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	day_of_week
date						
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
2017-01-	2276.979980	2276.979980	2276.979980	2276.979980	0.000000e+00	Saturday

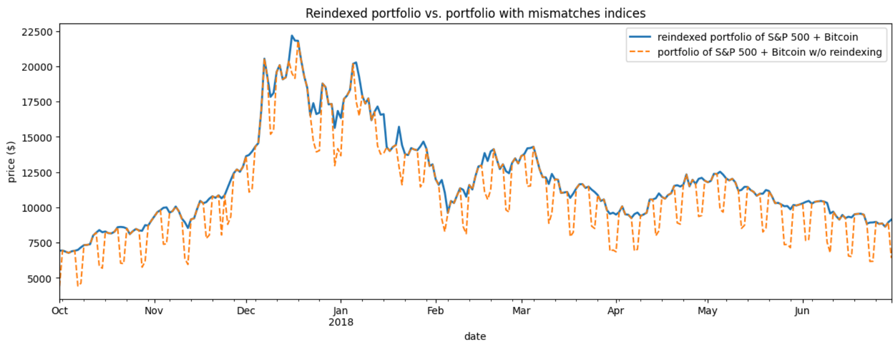
If we create visualization comparing the reindexed data to the first attempt, we see how reindexing helped maintain the asset value when the market was closed:

```
# 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
```



Double-click (or enter) to edit