Time Series Analysis with Pandas

In this lesson, we will learn about the powerful time series tools in the pandas library.

Originally developed for financial time series such as daily stock market prices, the robust and flexible data structures in pandas can be applied to time series data in any domain, including business, science, engineering, public health, and many others. With these tools you can easily organize, transform, analyze, and visualize your data at any level of granularity — examining details during specific time periods of interest, and zooming out to explore variations on different time scales, such as monthly or annual aggregations, recurring patterns, and long-term trends.

In the broadest definition, a **time series** is any data set where the values are measured at different points in time. Many time series are uniformly spaced at a specific frequency, for example, hourly weather measurements, daily counts of web site visits, or monthly sales totals. Time series can also be irregularly spaced and sporadic, for example, timestamped data in a computer system's event log or a history of 911 emergency calls. Pandas time series tools apply equally well to either type of time series.

This lesson will focus mainly on the data wrangling and visualization aspects of time series analysis. Working with a time series of energy data, we'll see how techniques such as time-based indexing, resampling, and rolling windows can help us explore variations in electricity demand and renewable energy supply over time. We'll be covering the following topics:

- The data set: Open Power Systems Data
- Time series data structures
- Time-based indexing
- Visualizing time series data
- Seasonality
- Frequencies
- Resampling
- Rolling windows

- Trends

We'll be using Python 3.6, pandas, matplotlib, and seaborn. To get the most out of this lesson, you'll want to be familiar with the basics of pandas and matplotlib.

The data set: Open Power Systems Data

In this lesson, we'll be working with daily time series of Open Power System Data (OPSD) for Germany, which has been rapidly expanding its renewable energy production in recent years. The data set includes country-wide totals of electricity consumption, wind power production, and solar power production for 2006-2017. You can download the data here.

Electricity production and consumption are reported as daily totals in gigawatt-hours (GWh). The columns of the data file are:

- `Date` — The date (*yyyy-mm-dd* format)
- `Consumption` — Electricity consumption in GWh
- `Wind` — Wind power production in GWh
- `Solar` — Solar power production in GWh
- `Wind+Solar` — Sum of wind and solar power production in GWh

We will explore how electricity consumption and production in Germany have varied over time, using pandas time series tools to answer questions such as:

- When is electricity consumption typically highest and lowest?
- How do wind and solar power production vary with seasons of the year?
- What are the long-term trends in electricity consumption, solar power, and wind power?
- How do wind and solar power production compare with electricity consumption, and how has this ratio changed over time?

Time series data structures

Before we dive into the OPSD data, let's briefly introduce the main pandas data structures for working with dates and times. In pandas, a single point in time is represented as a **Timestamp**. We can use the `to_datetime()` function to create Timestamps from strings in a wide variety of date/time formats. Let's import pandas and convert a few dates and times to Timestamps.

```
import pandas as pd
pd.to_datetime('2018-01-15 3:45pm')

Timestamp('2018-01-15 15:45:00')

pd.to_datetime('7/8/1952')

Timestamp('1952-07-08 00:00:00')
```

As we can see, `to_datetime()` automatically infers a date/time format based on the input. In the example above, the ambiguous date `'7/8/1952'` is assumed to be *month/day/year* and is interpreted as July 8, 1952. Alternatively, we can use the `dayfirst` parameter to tell pandas to interpret the date as August 7, 1952.

```
pd.to_datetime('7/8/1952, dayfirst=True)
```

```
Timestamp('1952-08-07 00:00:00')
```

If we supply a list or array of strings as input to `to_datetime()`, it returns a sequence of date/time values in a **DatetimeIndex** object, which is the core data structure that powers much of pandas time series functionality.

```
pd.to_datetime(['2018-01-05', '7/8/1952', 'Oct 10, 1995'])
```

```
DatetimeIndex(['2018-01-05', '1952-07-08', '1995-10-10'],
dtype='datetime64[ns]', freq=None)
```

If we're dealing with a sequence of strings all in the same date/time format, we can explicitly specify it with the `format` parameter. For very large data sets, this can greatly speed up the performance of `to_datetime()` compared to the default behavior, where the format is inferred separately for each individual string. Any of the format codes from the `strftime()` and `strptime()` functions in Python's built-in datetime module can be used. The example below uses the format codes `%m` (numeric month), `%d` (day of month), and `%y` (2-digit year) to specify the format.

```
pd.to_datetime(['2/25/10', '8/6/17', '12/15/12'], format='%m/%d/%y')
```

```
DatetimeIndex(['2010-02-25', '2017-08-06', '2012-12-15'],
dtype='datetime64[ns]', freq=None)
```

In addition to Timestamp and DatetimeIndex objects representing individual points in time, pandas also includes data structures representing durations (e.g., 125 seconds) and periods (e.g., the month of November 2018). For more about these data structures, there is a nice summary here. In this lesson we will use DatetimeIndexes, the most common data structure for pandas time series.

Creating a time series DataFrame

To work with time series data in pandas, we use a DatetimeIndex as the index for our DataFrame (or Series). Let's see how to do this with our OPSD data set. First, we use the `read_csv()` function to read the data into a DataFrame, and then display its shape.

```
df = pd.read_csv('power.csv')
df.shape
```

```
(4383, 5)
```

The DataFrame has 4383 rows, covering the period from January 1, 2006 through December 31, 2017. To see what the data looks like, let's use the `head()` and `tail()` methods to display the first three and last three rows.

```
df.head(3)
```

	Date	Consumption	Wind	Solar	Wind+Solar
0	2006-01-01	1069.184	NaN	NaN	NaN
1	2006-01-02	1380.521	NaN	NaN	NaN

	Date	Consumption	Wind	Solar	Wind+Solar
2	2006-01-03	1442.533	NaN	NaN	NaN

```
df.tail(3)
```

	Date	Consumption	Wind	Solar	Wind+Solar
4380	2017-12-29	1295.08753	584.277	29.854	614.131
4381	2017-12-30	1215.44897	721.247	7.467	728.714
4382	2017-12-31	1107.11488	721.176	19.980	741.156

Next, let's check out the data types of each column.

```
df.dtypes

Date datetime64[ns]
Consumption float64
Wind float64
Solar float64
Wind+Solar float64
dtype: object
```

Now that the `Date` column is the correct data type, let's set it as the DataFrame's index.

```
df = df.set_index('Date')
df.head(3)
```

	Consumption	Wind	Solar	Wind+Solar
Date				
2006-01-01	1069.184	NaN	NaN	NaN
2006-01-02	1380.521	NaN	NaN	NaN
2006-01-03	1442.533	NaN	NaN	NaN

```
df.index

DatetimeIndex(['2006-01-01', '2006-01-02', '2006-01-03', '2006-01-04',
'2006-01-05', '2006-01-06', '2006-01-07', '2006-01-08',
'2006-01-09', '2006-01-10',
...
'2017-12-22', '2017-12-23', '2017-12-24', '2017-12-25',
'2017-12-26', '2017-12-27', '2017-12-28', '2017-12-29',
'2017-12-30', '2017-12-31'],
dtype='datetime64[ns]', name='Date', length=4383, freq=None)
```

Alternatively, we can consolidate the above steps into a single line, using the `index_col` and `parse_dates` parameters of the `read_csv()` function. This is often a useful shortcut.

```
df = pd.read_csv('opsd_germany_daily.csv', index_col=0, parse_dates=True)
```

Now that our DataFrame's index is a DatetimeIndex, we can use all of pandas' powerful time-based indexing to wrangle and analyze our data, as we shall see in the following sections.

Another useful aspect of the DatetimeIndex is that the [individual date/time components] are all available as attributes such as `year`, `month`, `day`, and so on. Let's add a few more columns to `df`, containing the year, month, and weekday name.

```
# Add columns with year, month, and weekday name
df['Year'] = df.index.year
```

```
df['Month'] = df.index.month
df['Weekday Name'] = df.index.weekday_name
# Display a random sampling of 5 rows
df.sample(5, random_state=0)
```

	Consumption	Wind	Solar	Wind+Solar	Year	Month	Weekday Name
Date							
2008-08-23	1152.011	NaN	NaN	NaN	2008	8	Saturday
2013-08-08	1291.984	79.666	93.371	173.037	2013	8	Thursday
2009-08-27	1281.057	NaN	NaN	NaN	2009	8	Thursday
2015-10-02	1391.050	81.229	160.641	241.870	2015	10	Friday
2009-06-02	1201.522	NaN	NaN	NaN	2009	6	Tuesday

Time-based indexing

One of the most powerful and convenient features of pandas time series is **time-based indexing** — using dates and times to intuitively organize and access our data. With time-based indexing, we can use date/time formatted strings to select data in our DataFrame with the `loc` accessor. The indexing works similar to standard label-based indexing with `loc`, but with a few additional features.

For example, we can select data for a single day using a string such as `'2017-08-10'`.

```
df.loc['2017-08-10']
```

```
Consumption 1351.49
Wind 100.274
Solar 71.16
Wind+Solar 171.434
Year 2017
Month 8
Weekday Name Thursday
Name: 2017-08-10 00:00:00, dtype: object
```

We can also select a slice of days, such as `'2014-01-20':'2014-01-22'`. As with regular label-based indexing with `loc`, the slice is inclusive of both endpoints.

```
df.loc['2014-01-20':'2014-01-22']
```

	Consumption	Wind	Solar	Wind+Solar	Year	Month	Weekday Name
Date							
2014-01-20	1590.687	78.647	6.371	85.018	2014	1	Monday
2014-01-21	1624.806	15.643	5.835	21.478	2014	1	Tuesday
2014-01-22	1625.155	60.259	11.992	72.251	2014	1	Wednesday

Another very handy feature of pandas time series is **partial-string indexing**, where we can select all date/times which partially match a given string. For example, we can select the entire year 2006 with `df.loc['2006']`, or the entire month of February 2012 with `df.loc['2012-02']`.

```
df.loc['2012-02']
```

	Consumption	Wind	Solar	Wind+Solar	Year	Month	Weekday Name
Date							
2012-02-01	1511.866	199.607	43.502	243.109	2012	2	Wednesday

	Consumption	Wind	Solar	Wind+Solar	Year	Month	Weekday Name
Date							
2012-02-02	1563.407	73.469	44.675	118.144	2012	2	Thursday
2012-02-03	1563.631	36.352	46.510	82.862	2012	2	Friday
2012-02-04	1372.614	20.551	45.225	65.776	2012	2	Saturday
2012-02-05	1279.432	55.522	54.572	110.094	2012	2	Sunday
2012-02-06	1574.766	34.896	55.389	90.285	2012	2	Monday
2012-02-07	1615.078	100.312	19.867	120.179	2012	2	Tuesday
2012-02-08	1613.774	93.763	36.930	130.693	2012	2	Wednesday
2012-02-09	1591.532	132.219	19.042	151.261	2012	2	Thursday
2012-02-10	1581.287	52.122	34.873	86.995	2012	2	Friday
2012-02-11	1377.404	32.375	44.629	77.004	2012	2	Saturday
2012-02-12	1264.254	62.659	45.176	107.835	2012	2	Sunday
2012-02-13	1561.987	25.984	11.287	37.271	2012	2	Monday
2012-02-14	1550.366	146.495	9.610	156.105	2012	2	Tuesday
2012-02-15	1476.037	413.367	18.877	432.244	2012	2	Wednesday
2012-02-16	1504.119	130.247	38.176	168.423	2012	2	Thursday
2012-02-17	1438.857	196.515	17.328	213.843	2012	2	Friday
2012-02-18	1236.069	237.889	26.248	264.137	2012	2	Saturday
2012-02-19	1107.431	272.655	30.382	303.037	2012	2	Sunday
2012-02-20	1401.873	160.315	53.794	214.109	2012	2	Monday
2012-02-21	1434.533	281.909	57.984	339.893	2012	2	Tuesday
2012-02-22	1453.507	287.635	74.904	362.539	2012	2	Wednesday
2012-02-23	1427.402	353.510	18.927	372.437	2012	2	Thursday
2012-02-24	1373.800	382.777	29.281	412.058	2012	2	Friday
2012-02-25	1133.184	302.102	42.667	344.769	2012	2	Saturday
2012-02-26	1086.743	95.234	37.214	132.448	2012	2	Sunday
2012-02-27	1436.095	86.956	43.099	130.055	2012	2	Monday
2012-02-28	1408.211	231.923	16.190	248.113	2012	2	Tuesday
2012-02-29	1434.062	77.024	30.360	107.384	2012	2	Wednesday

Visualizing time series data

With pandas and matplotlib, we can easily visualize our time series data. In this section, we'll cover a few examples and some useful customizations for our time series plots. First, let's import matplotlib.

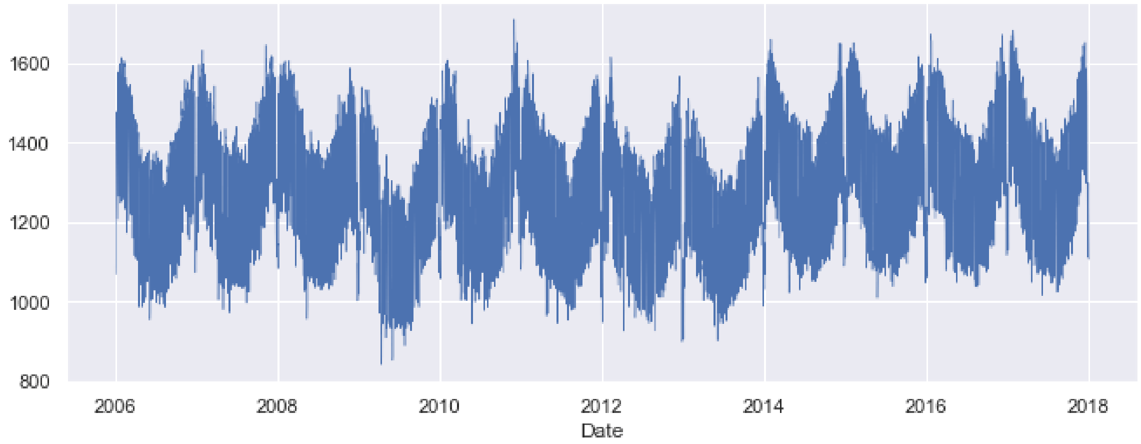
```
import matplotlib.pyplot as plt
# Display figures inline in Jupyter notebook
```

We'll use seaborn styling for our plots, and let's adjust the default figure size to an appropriate shape for time series plots.

```
import seaborn as sns
# Use seaborn style defaults and set the default figure size
sns.set(rc={'figure.figsize':(11, 4)})
```

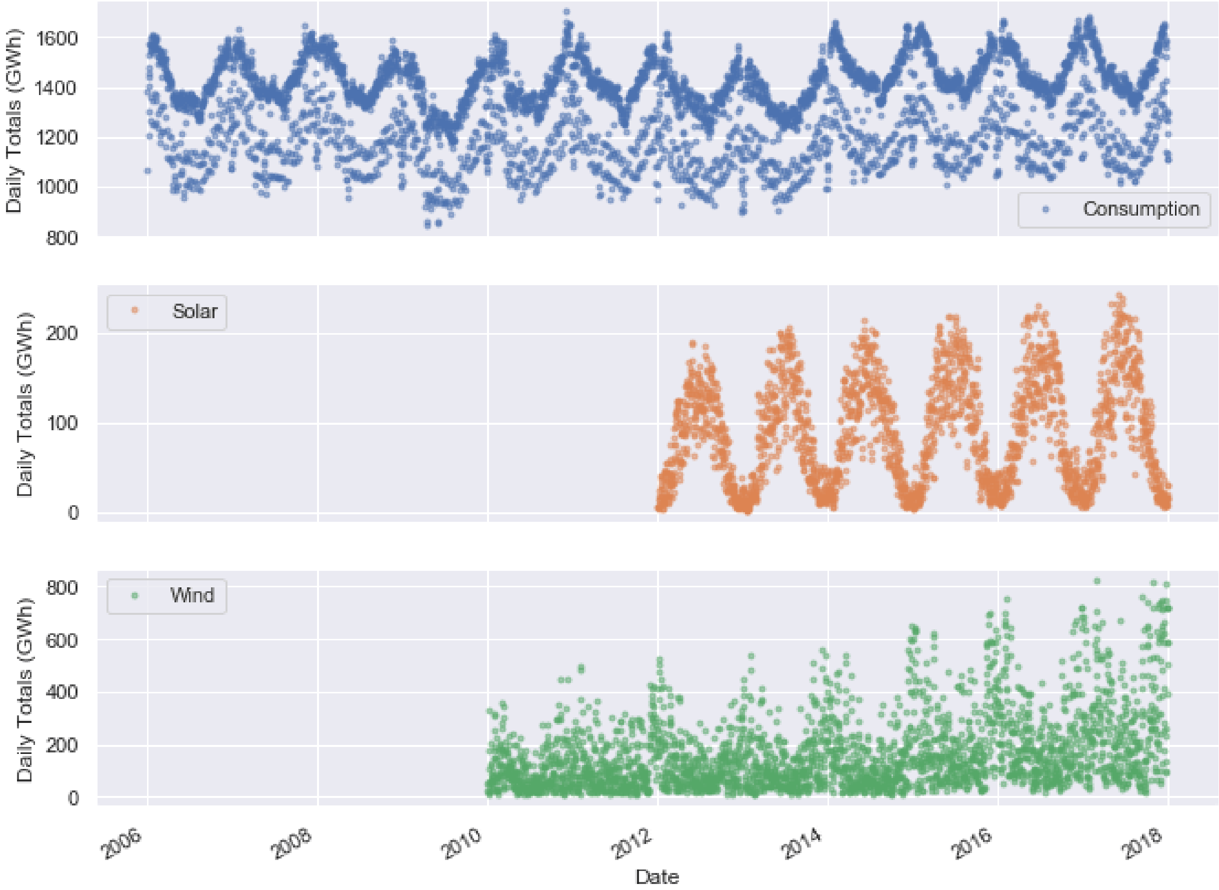
Let’s create a line plot of the full time series of Germany’s daily electricity consumption, using the DataFrame’s `plot()` method.

```
df['Consumption'].plot(linewidth=0.5);
```



We can see that the `plot()` method has chosen pretty good tick locations (every two years) and labels (the years) for the x-axis, which is helpful. However, with so many data points, the line plot is crowded and hard to read. Let’s plot the data as dots instead, and also look at the `Solar` and `Wind` time series.

```
cols_plot = ['Consumption', 'Solar', 'Wind']
axes = df[cols_plot].plot(marker='.', alpha=0.5, linestyle='None', figsize=(11,
9), subplots=True)
for ax in axes:
    ax.set_ylabel('Daily Totals (GWh)')
```



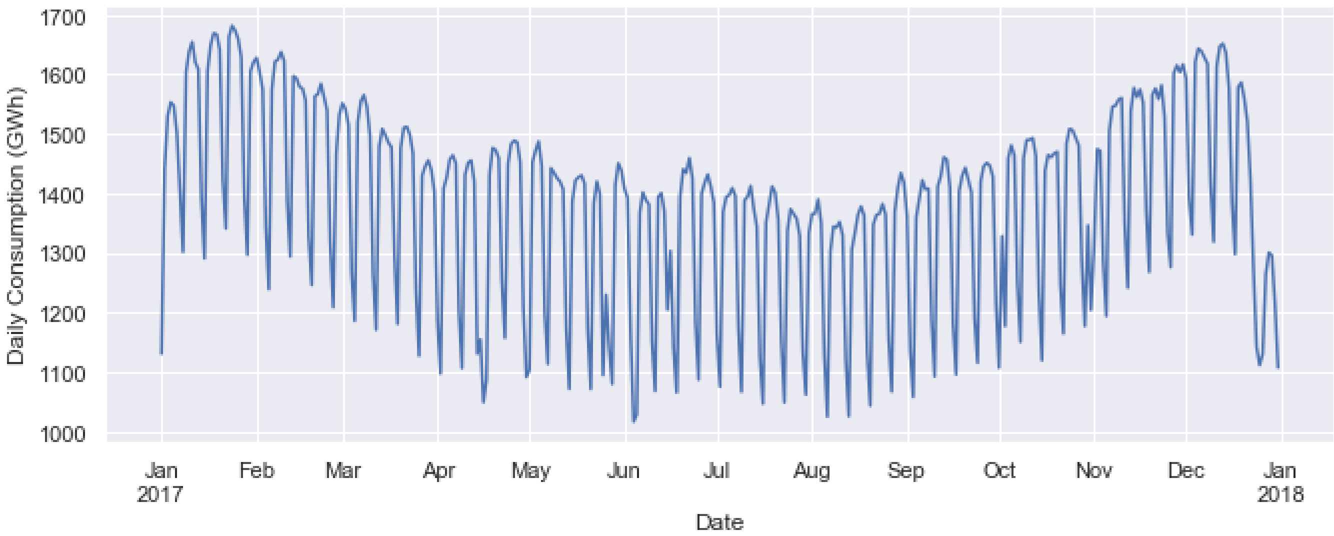
We can already see some interesting patterns emerge:

- Electricity consumption is highest in winter, presumably due to electric heating and increased lighting usage, and lowest in summer.
- Electricity consumption appears to split into two clusters — one with oscillations centered roughly around 1400 GWh, and another with fewer and more scattered data points, centered roughly around 1150 GWh. We might guess that these clusters correspond with weekdays and weekends, and we will investigate this further shortly.
- Solar power production is highest in summer, when sunlight is most abundant, and lowest in winter.
- Wind power production is highest in winter, presumably due to stronger winds and more frequent storms, and lowest in summer.
- There appears to be a strong increasing trend in wind power production over the years.

All three time series clearly exhibit periodicity—often referred to as **seasonality** in time series analysis—in which a pattern repeats again and again at regular time intervals. The `Consumption`, `Solar`, and `Wind` time series oscillate between high and low values on a yearly time scale, corresponding with the seasonal changes in weather over the year. However, seasonality in general does not have to correspond with the meteorological seasons. For example, retail sales data often exhibits yearly seasonality with increased sales in November and December, leading up to the holidays.

Seasonality can also occur on other time scales. The plot above suggests there may be some weekly seasonality in Germany's electricity consumption, corresponding with weekdays and weekends. Let's plot the time series in a single year to investigate further.

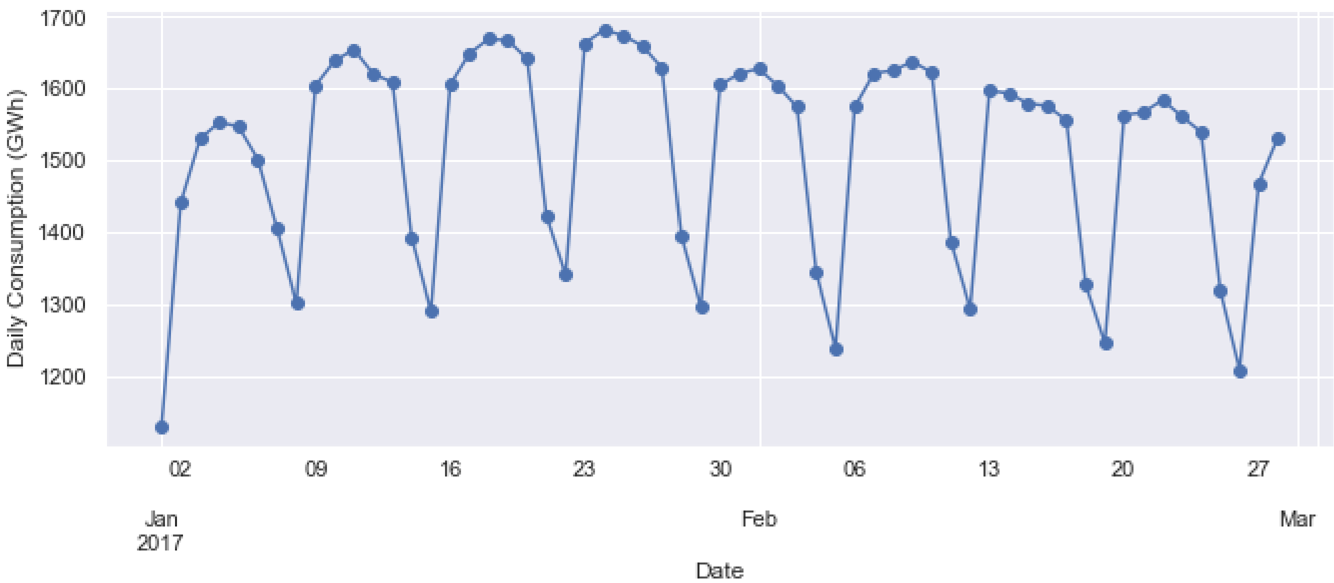
```
ax = df.loc['2017', 'Consumption'].plot()
ax.set_ylabel('Daily Consumption (GWh)');
```



Now we can clearly see the weekly oscillations. Another interesting feature that becomes apparent at this level of granularity is the drastic decrease in electricity consumption in early January and late December, during the holidays.

Let's zoom in further and look at just January and February.

```
ax = df.loc['2017-01':'2017-02', 'Consumption'].plot(marker='o', linestyle='-')
ax.set_ylabel('Daily Consumption (GWh)');
```



As we suspected, consumption is highest on weekdays and lowest on weekends.

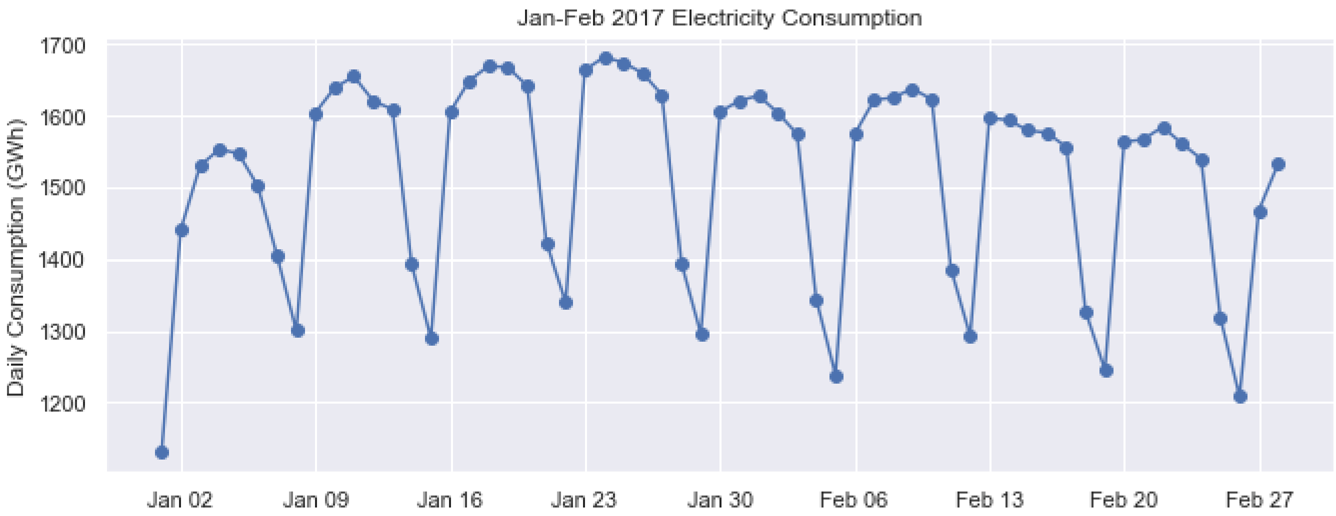
Customizing time series plots

To better visualize the weekly seasonality in electricity consumption in the plot above, it would be nice to have vertical gridlines on a weekly time scale (instead of on the first day of each month). We can customize our plot with matplotlib.dates, so let's import that module.

```
import matplotlib.dates as mdates
```

Because date/time ticks are handled a bit differently in matplotlib.dates compared with the DataFrame's `plot()` method, let's create the plot directly in matplotlib. Then we use `mdates.WeekdayLocator()` and `mdates.MONDAY` to set the x-axis ticks to the first Monday of each week. We also use `mdates.DateFormatter()` to improve the formatting of the tick labels, using the format codes we saw earlier.

```
fig, ax = plt.subplots()
ax.plot(df.loc['2017-01':'2017-02', 'Consumption'], marker='o', linestyle='-')
ax.set_ylabel('Daily Consumption (GWh)')
ax.set_title('Jan-Feb 2017 Electricity Consumption')
# Set x-axis major ticks to weekly interval, on Mondays
ax.xaxis.set_major_locator(mdates.WeekdayLocator(byweekday=mdates.MONDAY))
# Format x-tick labels as 3-letter month name and day number
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b %d'));
```



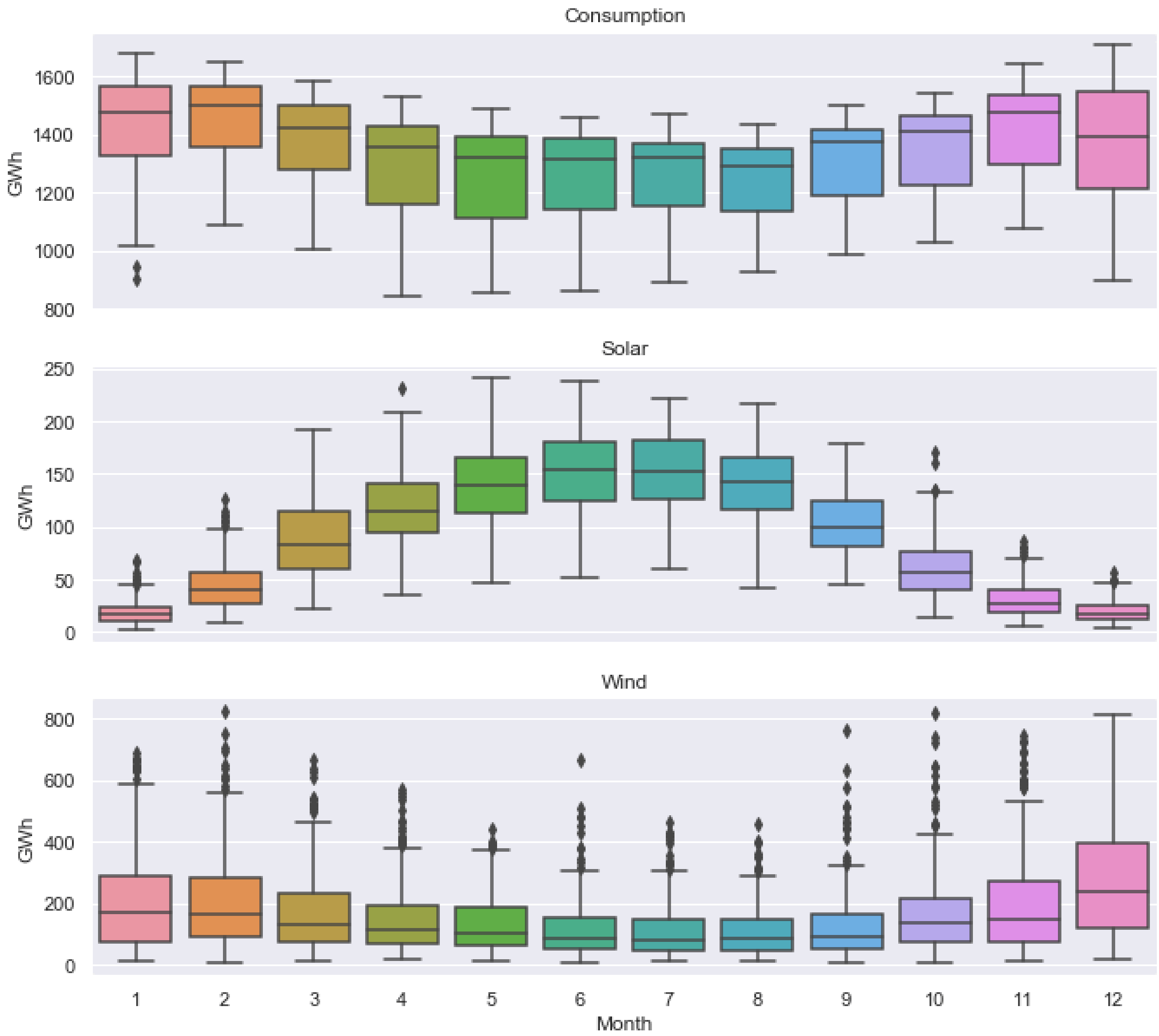
Now we have vertical gridlines and nicely formatted tick labels on each Monday, so we can easily tell which days are weekdays and weekends.

There are many other ways to visualize time series, depending on what patterns you're trying to explore — scatter plots, heatmaps, histograms, and so on. We'll see other visualization examples in the following sections, including visualizations of time series data that has been transformed in some way, such as aggregated or smoothed data.

Seasonality

Next, let's further explore the seasonality of our data with box plots, using seaborn's `boxplot()` function to group the data by different time periods and display the distributions for each group. We'll first group the data by month, to visualize yearly seasonality.

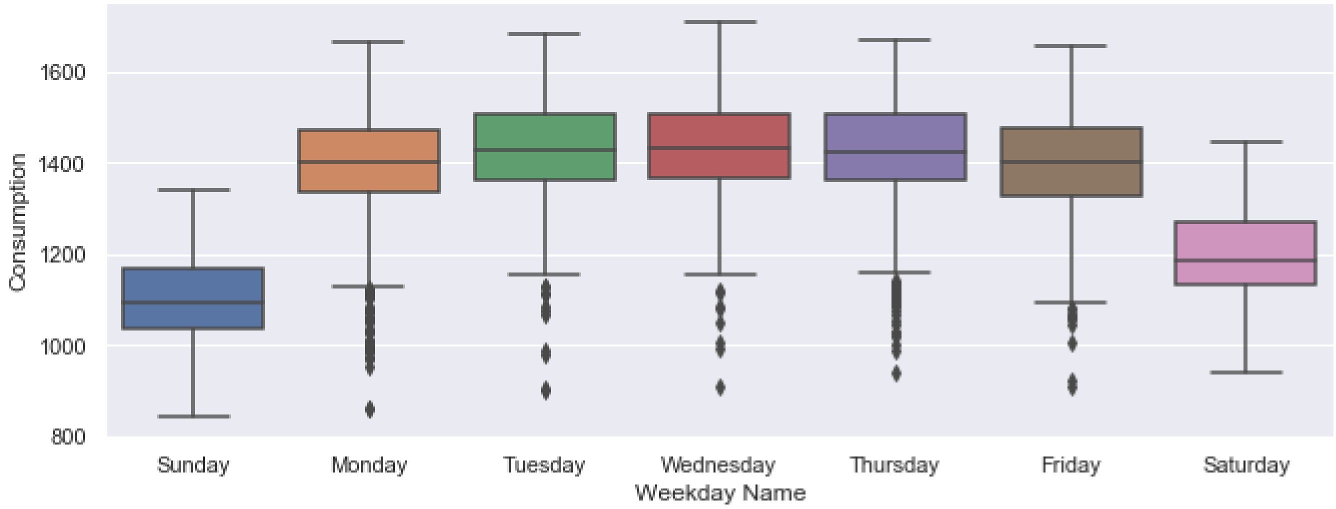
```
fig, axes = plt.subplots(3, 1, figsize=(11, 10), sharex=True)
for name, ax in zip(['Consumption', 'Solar', 'Wind'], axes):
sns.boxplot(data=df, x='Month', y=name, ax=ax)
ax.set_ylabel('GWh')
ax.set_title(name)
# Remove the automatic x-axis label from all but the bottom subplot
if ax != axes[-1]:
    ax.set_xlabel('')
```



These box plots confirm the yearly seasonality that we saw in earlier plots and provide some additional insights:
* Although electricity consumption is generally higher in winter and lower in summer, the median and lower two quartiles are lower in December and January compared to November and February, likely due to businesses being closed over the holidays. We saw this in the time series for the year 2017, and the box plot confirms that this is consistent pattern throughout the years.
* While solar and wind power production both exhibit a yearly seasonality, the wind power distributions have many more outliers, reflecting the effects of occasional extreme wind speeds associated with storms and other transient weather conditions.

Next, let's group the electricity consumption time series by day of the week, to explore weekly seasonality.

```
sns.boxplot(data=df, x='Weekday Name', y='Consumption');
```



As expected, electricity consumption is significantly higher on weekdays than on weekends. The low outliers on weekdays are presumably during holidays.

.