2)   
Some distinguishable patterns appear when we plot the data. The time-series has seasonality pattern, such as temperatures are always low at the beginning of the year and high at the middle of the year. Compared to our common knowledge, Finnish weather is pretty harsh and cold, almost no sunlight during January and February, and there is a holiday called 'Midsummer Day' in June when Finns celebrate the comeback of the sun.

However, the plot above is a bit noisy, because it contains all the daily temperatures. However, looking carefully into the data points, we could see that there is only a minor temperature change between the current date and the next date.

3) We can also visualize our data using a method called time-series decomposition that allows us to decompose our time series into three distinct components: trend, seasonality, and noise.

The plot above clearly shows that the temperature is unstable, along with its obvious seasonality.

4) We are going to apply one of the most commonly used method for time-series forecasting, known as SARIMA, which stands for Seasonal Autoregressive Integrated Moving Average. SARIMA models are denoted with the notation SARIMA(p,d,q)(P,D,Q,s). These three parameters account for seasonality, trend, and noise in data:

We will use a “grid search” to iteratively explore different combinations of parameters. For each combination of parameters, we fit a new seasonal SARIMA model with the SARIMAX() function from the statsmodels module and assess its overall quality.

The AIC measures how well a model fits the data while taking into account the overall complexity of the model. A model that fits the data very well while using lots of features will be assigned a larger AIC score than a model that uses fewer features to achieve the same goodness-of-fit. Therefore, we are interested in finding the model that yields the lowest AIC value.

5)Our primary concern is to ensure that the residuals of our model are uncorrelated and normally distributed with zero-mean. If the seasonal ARIMA model does not satisfy these properties, it is a good indication that it can be further improved.

In this case, our model diagnostics suggests that the model residuals are normally distributed based on the following:

* In the top right plot, we see that the red KDE line follows closely with the N(0,1) line (where N(0,1)) is the standard notation for a normal distribution with mean 0 and standard deviation of 1). This is a good indication that the residuals are normally distributed.
* The qq-plot on the bottom left shows that the ordered distribution of residuals (blue dots) follows the linear trend of the samples taken from a standard normal distribution with N(0, 1). Again, this is a strong indication that the residuals are normally distributed.
* The residuals over time (top left plot) do not display any obvious seasonality and appear to be white noise. This is confirmed by the autocorrelation (i.e. correlogram) plot on the bottom right, which shows that the time series residuals have low correlation with lagged versions of itself.

Those observations lead us to conclude that our model produces a satisfactory fit that could help us understand our time series data and forecast future values.