Stationary Time Series

Stationary time series are time series that look much the same in every interval of time. They are, for obvious reasons, the easiest ones to reason about. However, they rarely occur in nature. They are also not necessarily desirable. For example, you would prefer your invest portfolio to rise that to remain stationary.

Obviously, a horizontal line would be stationary. We are not requiring that much staticness. There can be wiggle but it should be wiggling around the same central point throughout and it should be about as wiggly every place you look. We will be more interested in the change of central point (local mean) than changes in wiggly-ness (variance) for the first few topics. We will deal with changing variance in the second half of the module.

Meanwhile, in this lecture, just some slightly formal definitions and some pictures. First to the defintions:

Strong Stationarity:

- ***Looking back from all points on the series gives the same probability distribution of the past***

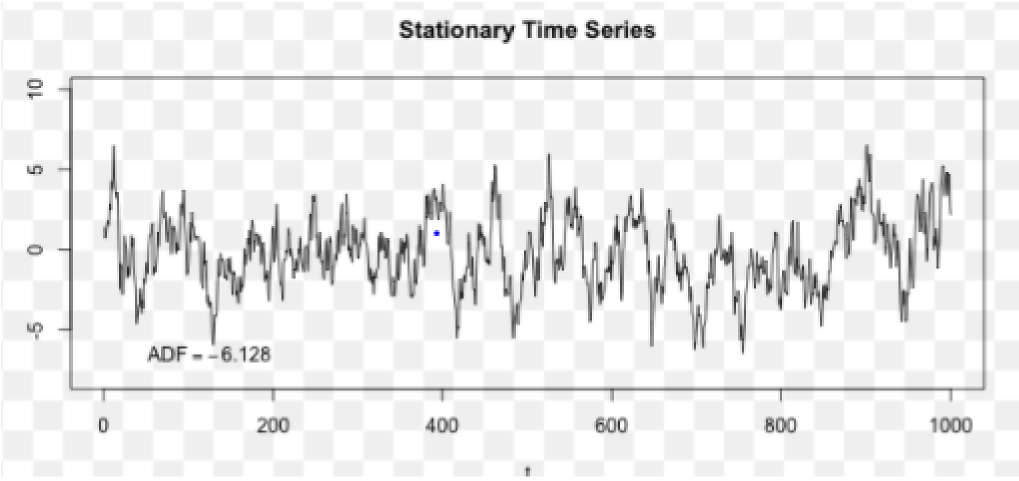
We will never be in a position to recognise this. When people in the field talk about stationarity they almost always mean:

[Weak] Stationarity

- ***The mean and variance are essentially constant***

Let's look at pictures.

From Wikimedia, a picture of a stationary series



This is a textbook version. Notice that the mean stays in the middle and the variance seems much the same in every place.

This is realworld data

Creator: Swatantra R. Kethireddy, *, Grace A. Adegoye, Paul B. Tchounwou, Francis Tuluri
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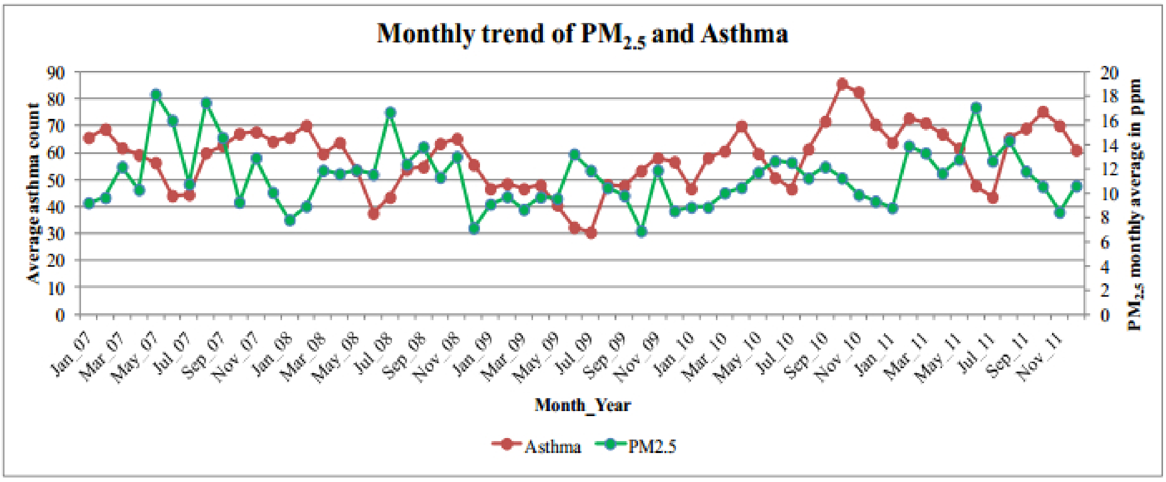


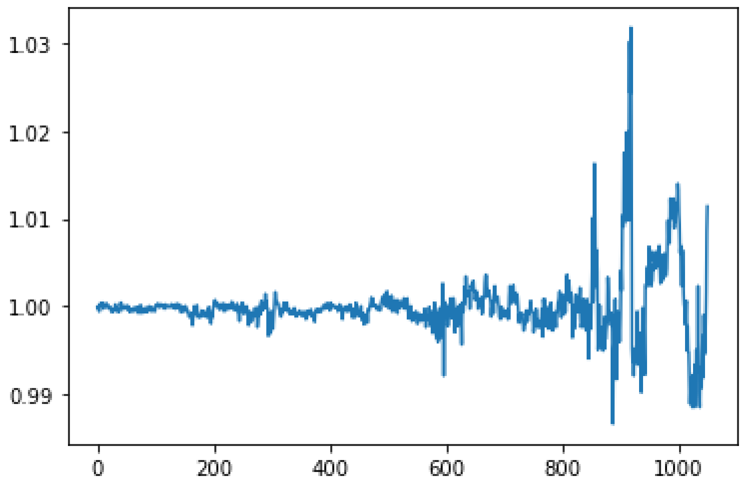
This is taken from a research paper. It is meant to show the correlation between two quantities. Notice that both graphs seem to have constant means and keep their variances more or less constant.

Here is some data I was expecting to be stationary. It is the exchange rate between two cryptocurrencies whose values are tethered to the US Dollar. USDT is called *tether*. USDC is the *Coinbase* equivalent.

In [1]:

```
import pandas as pd
Uframe = pd.read_csv('../../data/USDC-USDT.csv')
Uframe['close'].plot()
```

Out[1]: <AxesSubplot:>



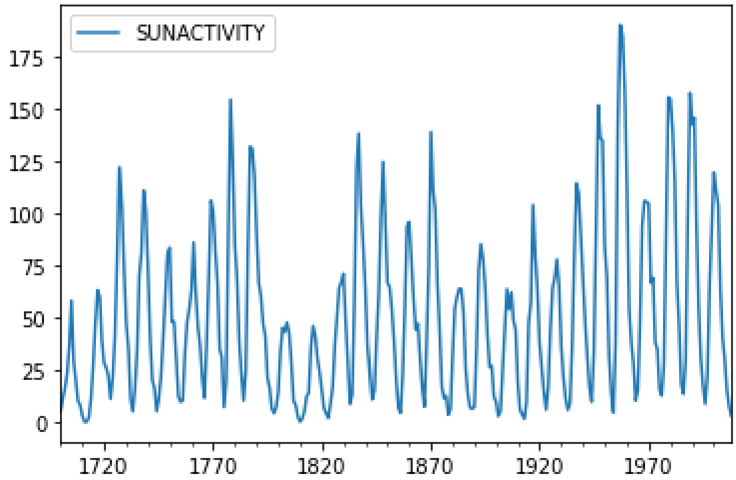
That doesn't look that stationary. The mean is fine but the variance changes the word for that is *Heteroscedasticity*. It turns out, not that surprisingly, that the sunspot data is stationary. We have seen this before.

In [2]:

```
import pandas as pd

import statsmodels.api as sm
sunspots = sm.datasets.sunspots.load_pandas().data
sunspots.index = pd.Index(sm.tsa.datetools.dates_from_range("1700", "2008"))
del sunspots["YEAR"]
sunspots.plot()
```

Out[2]: <AxesSubplot:>



The variance looks a bit variable but not much. We will learn later in the course how to check for stationarity.

What's so good about stationarity?

- Things look the same everywhere

Is stationarity a feature of much real-world data?

- Nope

What's the point?

- We are going to transform and decompose time series to get stationary data a bit in this topic and more seriously in later topics.

What are some of the things that get in the way?

Trends, Seasonal Data, variable variance, anomalies

Next up: Trends