Time Series Forecasting in Python

Stephen CUI

November 29, 2023

Contents

Part I

Time waits for no one

Chapter 1

Understanding time series forecasting

1.1 Forecasting the historical mean

1.1.1 Implementing the historical mean baseline

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \tag{1.1}$$

A_i is the actual value at point i in time, and F_i is the forecast value at point i in time; n is simply the number of forecasts.

Chapter 2

Going on a random walk

2.1 Identifying a random walk

Definition 1 *A random walk is a series whose first difference is stationary and uncorrelated. This means that the process moves completely at random.*

2.1.1 Stationarity

A stationary time series is one whose statistical properties do not change over time. In other words, it has a constant mean, variance, and autocorrelation, and these properties are independent of time.

Augmented Dickey-Fuller (ADF) test

The augmented Dickey-Fuller (ADF) test helps us determine if a time series is stationary by testing for the presence of a unit root. If a unit root is present, the time series is not stationary. The null hypothesis states that a unit root is present, meaning that our time series is not stationary.

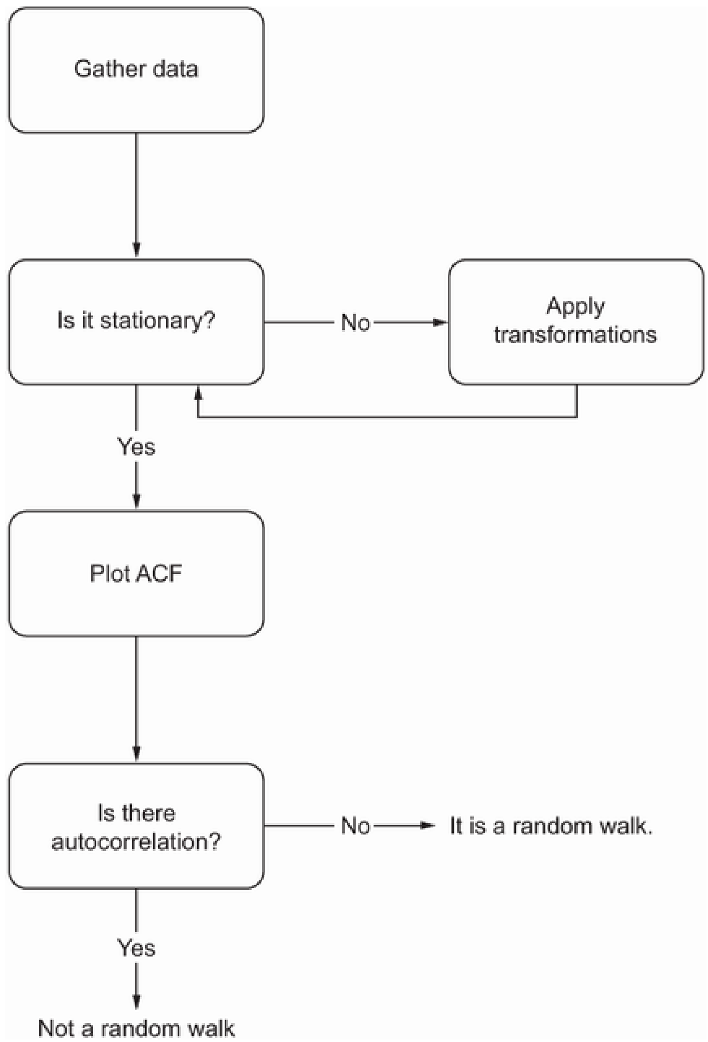

Figure 2.1: Steps to follow to identify whether time series data can be approximated as a random walk or not. The first step is naturally to gather the data. Then we test for stationarity. If it is not stationary, we apply transformations until stationarity is achieved. Then we can plot the autocorrelation function (ACF). If there is no autocorrelation, we have a random walk.

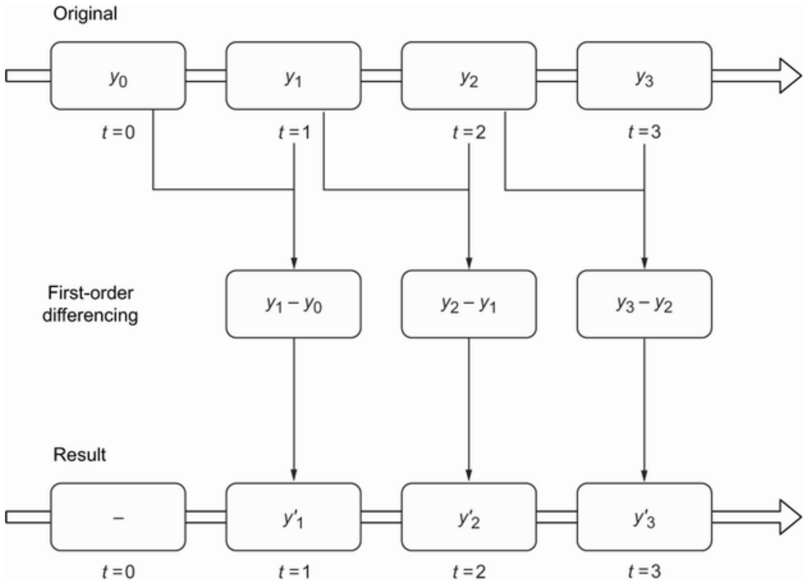

Figure 2.2: Visualizing the differencing transformation. Here, a first-order differencing is applied. Notice how we lose one data point after this transformation because the initial point in time cannot be differenced with previous values since they do not exist.

2.2 Forecasting a random walk

2.2.1 Forecasting on a long horizon

You should be convinced that forecasting a random walk on a long horizon does not make sense. Since the future value is dependent on the past value plus a random number, the randomness portion is magnified in a long horizon where many random numbers are added over the course of many timesteps.

Part II

Forecasting with statistical models

Chapter 3

3.1 Defining a moving average process

A **moving average process**, or the moving average (MA) model, states that the current value is linearly dependent on the current and past error terms. The error terms are assumed to be mutually independent and normally distributed, just like white noise.

3.2 Forecasting a moving average process

对于预测范围，移动平均模型具有特殊性。 MA(q) 模型不允许我们一次性预测未来多步。请记住，移动平均模型线性依赖于过去的误差项，并且这些项在数据集中未观察到 - 因此必须递归估计它们。这意味着对于 MA(q) 模型，我们只能预测未来的 q 步。超过该点所做的任何预测都不会包含过去的误差项，并且模型只会预测平均值。因此，对未来超过 q 步的预测没有附加值，因为预测将持平，因为仅返回平均值，这相当于基线模型。

Part III

Large-scale forecasting with deep learning

Part IV

Automating forecasting at scale