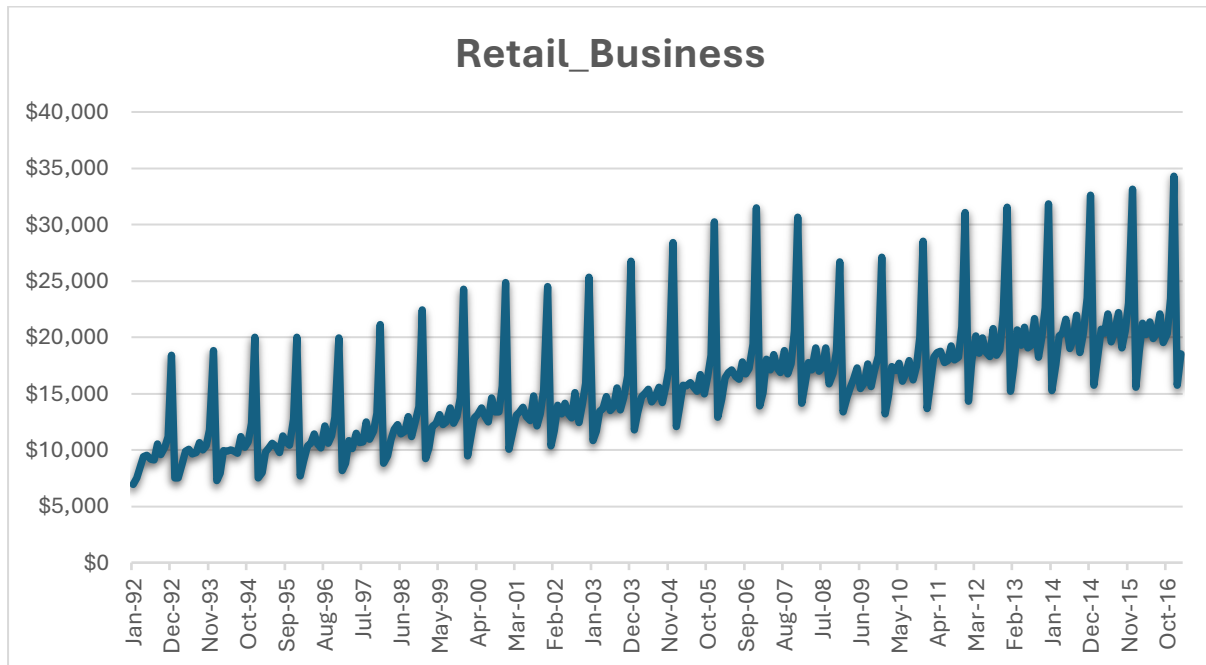# Exercise 5.6 Time Series Analysis & Forecasting
Submitted by Balachandar Kaliappan

Step 1: Create a time series using the instructions provided in the Exercise.

Step 2: Observe the pattern of the line in your time series and answer the following questions

What characteristics does the pattern display?

    The line chart illustrates the trend of seasonal sales for a specific product. Sales gradually increased from January to August, peaking in December. There is a consistent dip in June, July, and September nearly every year. The pattern is non-stationary, as the sales figures over the years remain similar despite this trend.

What advice might you give your client based on this time series?

    The client should increase inventory in November and December, as there are more sales during those months. If sales dip in January, the company can find ways to increase them, or, alternatively, reduce the number of promotions to cut costs.

Step 3: Create a simple moving average chart using the instructions in the Exercise.

Simple Moving Average & 5 year Moving Average - Oil Price
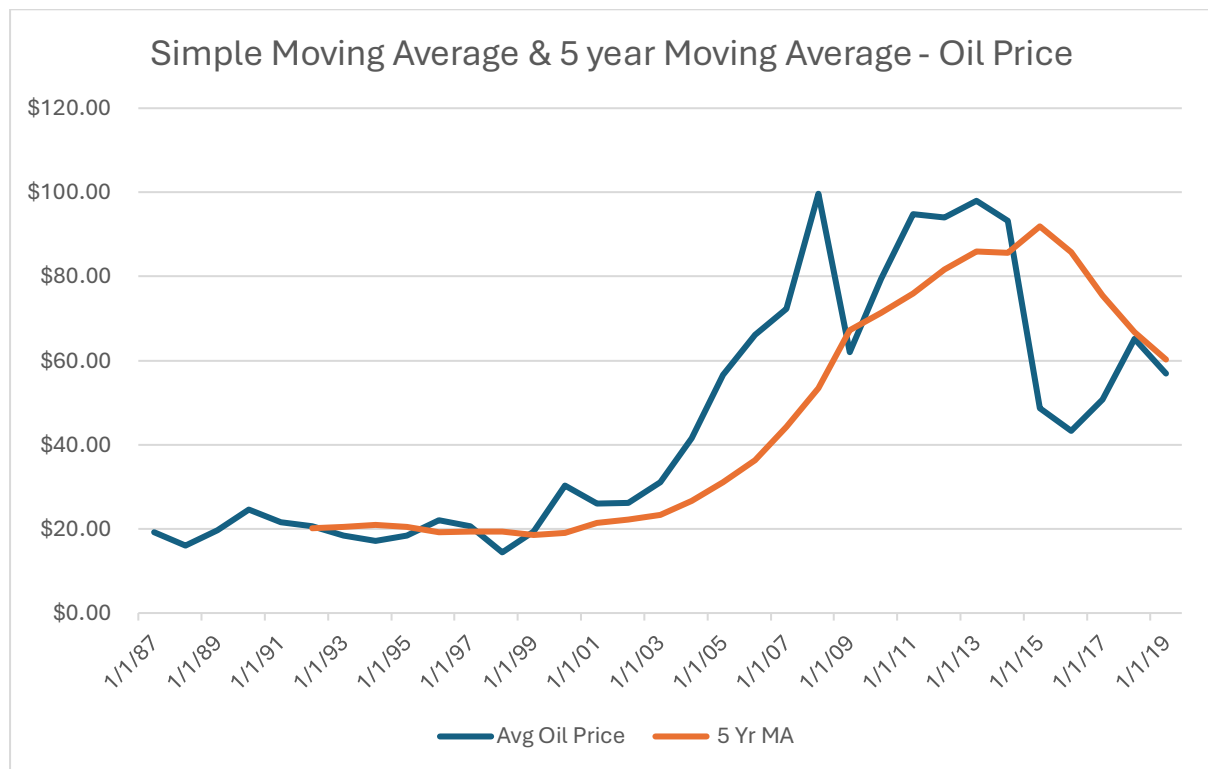
Step 4: Observe the pattern/trend of the oil price line in relation to the five-year moving average line and answer the following questions:

Is there a certain characteristic to the pattern and trend? Make sure to provide a short explanation for your answer.

The trend of oil prices shows significant fluctuations when we examine the simple moving average chart. However, the 5-year moving average trend line presents a smoother view, indicating an increase in oil prices until 2015, followed by a subsequent dip.

Explain how the moving average affects oil price volatility and how it makes forecasting easier.

Considering only the simple moving average values, we see that the oil price is highly volatile due to significant economic events. However, the 5-year moving average indicates that there was a steady increase in oil prices until 2015. Predicting oil prices using simple moving average methods would be quite challenging. Nevertheless, employing the 5-year moving average method or a weighted average method will provide a clearer direction for accurately predicting future oil prices.

Step 5: Briefly explain why you might convert a non-stationary time series into a stationary time series before applying a forecasting model.

Since there is significant variance in the non-stationary data, transforming it into stationary data with a consistent mean and variance will enable us to develop an effective forecasting model. By converting non-stationary data to stationary data, we enhance the reliability of the forecasting model.

Step 6: *Do some research on the ARIMA model and one other model not covered in this Exercise; Facebook Prophet is one example that's become popular in recent years.*

ARIMA model:

Source: https://medium.com/@wainaina.pierre/the-complete-guide-to-time-series-forecasting-models-ef9c8cd40037

The ARIMA model stands for Autoregressive Integrated Moving Average Method. This model is particularly suitable for data exhibiting trends or seasonality. The ARIMA model incorporates differencing to address non-stationary data. In this context, differencing involves transforming non-stationary data into stationary by applying transformations. For instance, subtracting previous values from current values makes the means more consistent over time, thus eliminating the non-stationary characteristics of the data.

Exponential smoothing method:

Source: https://www.cybrosys.com/blog/what-are-the-different-types-of-time-series-forecasting-methods

The exponential smoothing method assigns different weights to past data, placing greater emphasis on more recent data. This approach captures trends and seasonality within the data. In exponential smoothing methods, the weights of the data decrease exponentially as they move further back in time. This is significantly different from the weighted average method, where weights are allocated based on balancing.

Facebook Prophet method:

Source: https://facebook.github.io/prophet/

The Prophet method is highly suitable for daily datasets, as it incorporates key events in a year (such as holidays, weekdays, weekends, and special events) to make the forecast robust. This method also allows the data analyst to run forecasting models with missing data and outliers.