Jessica Duong
Data Immersion Achievement
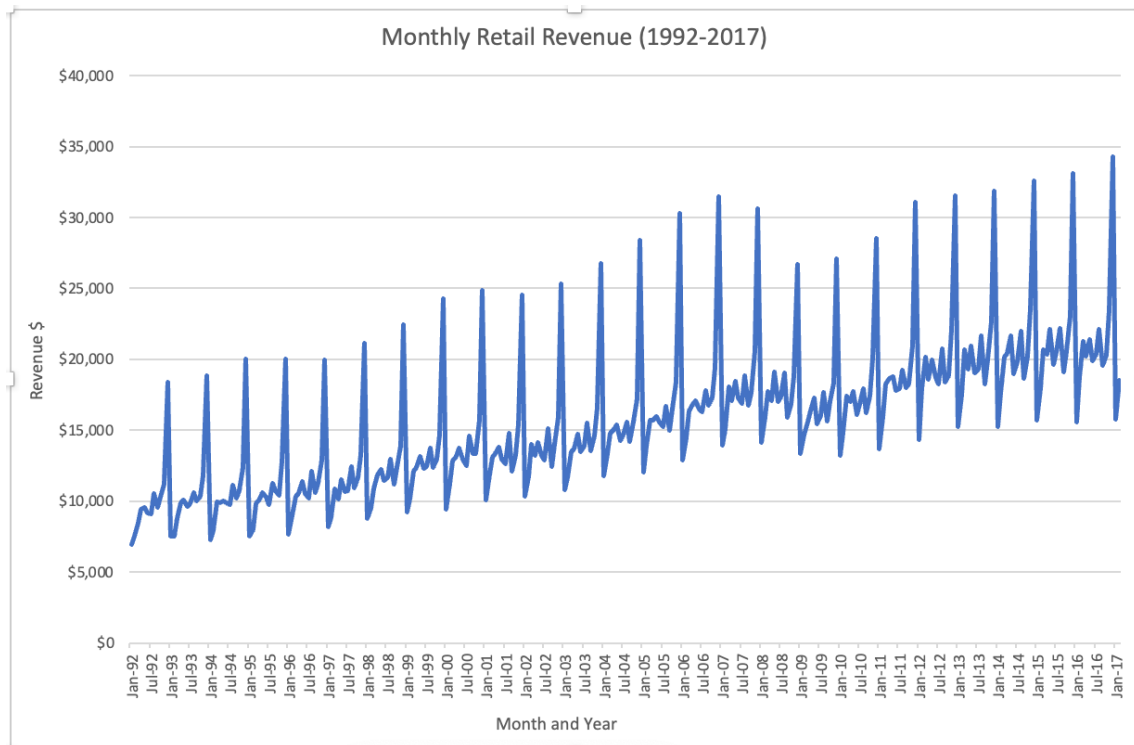Data Ethics & Applied Analytics

Time Series Analysis Forecasting

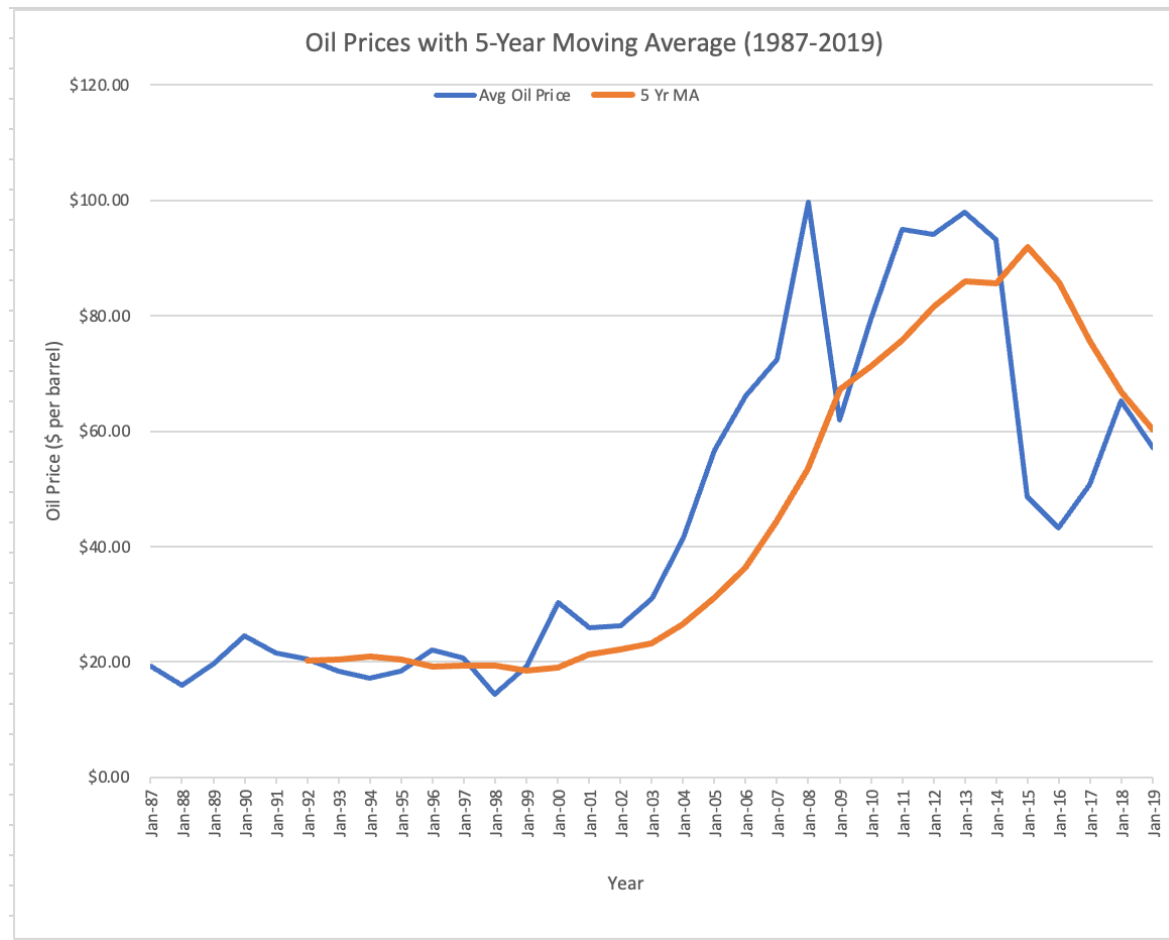## Time Series Analysis: Retail Sales

Steps 1 & 2:

The time series displays a strong upward trend combined with clear seasonality, indicating that the data is non-stationary. Revenue steadily increases over time, showing long-term growth in the retail business. In addition, there are consistent, repeating spikes at regular annual intervals, which demonstrates seasonality that is likely tied to recurring high-demand periods such as holidays or peak shopping seasons. Because both the mean level and the variance change over time, the series does not meet the definition of stationarity and therefore reflects both trend and seasonal components.

Based on this time series, the client should plan inventory, staffing, and marketing spend around the predictable annual revenue spikes, as these peaks occur consistently each year and represent critical high-revenue periods. The long-term upward trend also indicates sustained business growth, suggesting that the client should gradually scale operations, storage capacity, and supplier contracts to support increasing demand. Because both growth and seasonality are predictable, the client can use forecasting models to proactively manage inventory levels, avoid stockouts during peak periods, and reduce excess inventory during lower-demand months.

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Moving Average Analysis: Oil Prices

Steps 3 & 4:

The oil price time series shows a clear non-stationary upward trend from the late 1980s through the early 2010s, followed by a sharp decline and partial recovery. Prices are highly volatile, with large year-to-year fluctuations caused by market shocks and changes in global demand.

The five-year average smooths these fluctuations and reveals the underlying long-term trend. It highlights a steady rise into the early 2020s, a peak around 2013-2014, and a gradual decline afterward. By reducing short-term volatility, the moving average makes it easier to identify long-term patterns and supports more stable and reliable forecasting.

Stationarity & Forecasting

Non-stationary time series have changing means, trends, and variance over time, which can distort forecasting models and reduce prediction accuracy. Many forecasting models assume that the underlying statistical properties of the data remain stable. By converting a non-stationary time series into a stationary one, such as by removing trends or seasonality, the data becomes more predictable and consistent, allowing models to better detect true patterns rather than reacting to temporary fluctuations. This improves forecast reliability and model performance.

Additional Forecasting Models

Arima Model:

The ARIMA (Autoregressive Integrated Moving Average) model is a traditional forecasting method that predicts future values by looking at patterns in past data. It works best when data follows a consistent trend over time and can be adjusted to remove long-term growth or decline. ARIMA is commonly used in finance and business planning to forecast short-term trends such as demand, pricing, or revenue because it is reliable when historical patterns remain stable.

Facebook Prophet:

Facebook Prophet is a forecasting tool developed by Meta (Facebook) to make time-series predictions easier for business users. It automatically detects trends, seasonal patterns, and the impact of holidays, making it useful for sales and revenue forecasting. Prophet handles missing data and sudden changes more easily than other traditional models, which is why it's popular for real-world business forecasting.

Sources

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