Exercise 1: Data Preparation

Daily Gold Trading Volume (Exercise 1b)

Looking at the ACF plot, I noticed significant autocorrelation across multiple lags with a slow decay pattern. This suggests persistence in the data where past volume values continue to influence future volumes for some time. The PACF plot shows a strong spike at lag 1 followed by much smaller values at higher lags. This points to a potential AR(1) process - basically meaning today's trading volume is primarily influenced by yesterday's volume.

Weekly Maximum Gold Prices (Exercise 1e)

The ACF of weekly gold prices shows extremely persistent autocorrelation that barely decays as lag increases. This is classic behavior for a non-stationary series with a strong trend component, which is typical for asset prices like gold. The PACF shows its strongest spike at lag 1, but also has some smaller significant spikes at higher lags. This suggests that while last week's price is the strongest predictor, prices from several weeks ago still have some lingering influence. Gold prices clearly show the characteristics of a financial asset that follows something close to a random walk with drift. The strong persistence means we'd need to difference the series before applying most forecasting models.

Exercise 2: Model Fitting and Forecast Evaluation

Drift Method for Gold Prices

The drift method is pretty straightforward - it basically extends the average trend from the training data into the future. While it captures the general upward direction of gold prices, it has clear limitations: - It misses all the volatility that's so characteristic of gold prices - It can't account for market turning points or rapid changes in trend - It assumes the future will maintain the same average rate of change as the past Looking at the forecast graph, you can see how the drift method provides a reasonable overall direction but misses all the short-term fluctuations that matter to traders. For financial time series like gold, this method is too simple to capture the complex market dynamics, but it does provide a useful baseline.

Comparing Forecasting Methods for Daily Trading Volume

When comparing the average method (using the mean of all past observations) against the naïve method (using just the most recent observation) for forecasting gold trading volume, the naïve method performed noticeably better. This better performance of the naïve method reinforces what we saw in the ACF/PACF analysis - that gold trading volume has strong short-term memory where the most recent value is the best predictor of the next value. The series doesn't seem to revert to a long-term average but instead follows more of a random walk pattern. This finding has practical implications for traders - when estimating tomorrow's trading volume, today's volume is a much better guide than the long-term historical average.

Exercise 3: Data Preparation

Energy Consumption Patterns

The daily energy consumption data shows several interesting patterns: - Clear day-to-day variations with visible differences between weekdays and weekends - Seasonal patterns with higher consumption in winter and summer months - A gradual upward trend over the years suggesting increasing energy demand - Occasional spikes that likely correspond to extreme weather events When aggregated to monthly data, the seasonal patterns become much clearer. The winter months consistently show the highest consumption, likely due to heating needs and shorter daylight hours. Summer months show moderate increases, probably related to cooling needs, while spring and fall show the lowest consumption. The hourly pattern follows a typical daily cycle with lower consumption during night hours and peaks in the evening when both commercial activities are still ongoing and residential usage increases as people return home.

Exercise 4: Model Fitting and Forecast Evaluation

Decomposition Models for Daily Energy

I compared additive and multiplicative decomposition models for the daily energy consumption data. The key difference between these models is how they handle seasonality: - Additive model: assumes seasonal variations are consistent regardless of the overall trend level - Multiplicative model: assumes seasonal variations increase or decrease proportionally with the trend level The multiplicative model produced better forecasts with lower errors. This suggests that as overall energy consumption increases, the size of the seasonal swings increases proportionally. For example, the difference between winter and summer consumption gets larger as the overall energy usage grows over time. This makes practical sense for energy consumption - as a community grows and uses more energy overall, the absolute difference between peak and low seasons will naturally grow as well.

Holt-Winters for Monthly Energy Consumption

For the monthly data, I applied the Holt-Winters method, which handles both trend and seasonality. Again, the multiplicative version outperformed the additive version, confirming that seasonal patterns in energy consumption scale with the overall consumption level. This finding is consistent across both the daily and monthly analyses, giving us confidence that the multiplicative approach is indeed better suited for energy consumption forecasting. This insight would be valuable for energy providers planning capacity needs throughout the year.

Summary

This analysis showed that different time series require different forecasting approaches based on their underlying patterns: - For gold trading volume, the naïve method worked best, reflecting the short-term memory property of financial trading activity - For gold prices, simple methods like drift provide directional guidance but miss the volatility - For energy consumption, multiplicative models consistently outperformed additive ones, showing that seasonal variations scale with overall consumption levels Understanding these patterns helps us select more appropriate forecasting methods and provides practical insights for both financial markets and energy planning.