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Forecasting with Moving Averages: Advanced Models for Seasonal and Trend Data

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Abstract

The simple moving average (SMA) is a cornerstone of time series forecasting, prized for its simplicity and interpretability. However, its standard formulation is notoriously inadequate for data characterized by significant seasonality and trends, often resulting in lagged and inaccurate forecasts. This research addresses this critical limitation by developing and evaluating a suite of advanced moving average-based models specifically designed to decompose and capture these complex components.

We propose a hybrid framework that integrates classical decomposition techniques with adaptive moving average filters. The methodology involves: (1) applying seasonal differencing or seasonal adjustment to isolate the trend-cycle, (2) utilizing double or triple moving averages to project the underlying trend, and (3) incorporating seasonal indices to reinstate periodic fluctuations. The performance of these advanced models—including Holt-Winters-inspired moving average adaptations—is rigorously tested against the standard SMA and more complex benchmarks like SARIMA and ETS models.

Using a diverse set of synthetic and real-world datasets with known seasonal and trend patterns, our empirical analysis demonstrates that the proposed advanced moving average models achieve a substantial reduction in forecast error compared to the simple moving average. While not universally superior to sophisticated statistical models, they offer a compelling trade-off, providing a significant boost in accuracy with only a marginal increase in computational complexity. The findings indicate that these enhanced techniques are a highly viable and accessible forecasting tool for practitioners in business and economics, bridging the gap between simplistic and statistically complex methods.

Keywords: Time Series Forecasting, Moving Averages, Seasonality, Trend Analysis, Forecasting Models, Business Forecasting, Decomposition Methods.

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Introduction

Time series forecasting is an indispensable tool across a myriad of domains, from inventory management and supply chain optimization in business to resource planning in public policy and signal processing in engineering. The ability to accurately predict future values based on historical data empowers decision-makers to allocate resources efficiently, mitigate risks, and capitalize on emerging opportunities. Among the vast arsenal of forecasting techniques, the Simple Moving Average (SMA) stands as one of the most fundamental and widely adopted methods. Its appeal lies in its intrinsic simplicity, computational efficiency, and ease of interpretation, making it an accessible starting point for analysts and a robust baseline for more complex models.

Despite its widespread use, the conventional SMA suffers from a well-documented and critical shortcoming: its inherent lag and poor performance when applied to time series data exhibiting structural components beyond random noise. Specifically, the SMA is designed for stationary data and performs inadequately in the presence of trends and seasonality. A trend represents a persistent, long-term upward or downward movement in the data, while seasonality refers to periodic, repeating fluctuations driven by factors such as weather, holidays, or cultural cycles. When these components are present, the SMA consistently produces forecasts that are biased and lag behind the actual data, leading to suboptimal and often costly decisions. For instance, using a simple average to forecast seasonal product demand can result in significant overstocking or stockouts.

This gap between the simplicity of the SMA and the complexity of real-world data forms the core motivation for this research. While sophisticated models like ARIMA (Auto Regressive Integrated Moving Average), Exponential Smoothing State Space (ETS) models, and machine learning approaches exist to handle seasonality and trends, they often present a steep learning curve and require significant statistical expertise. There exists a clear need for a middle ground—forecasting methods that retain the intuitive appeal and computational simplicity of moving averages while being adaptively enhanced to capture trend and seasonal patterns effectively.

Review of Literature

The foundation of effective time series forecasting lies in the principle of decomposition, a concept formalized by Cleveland et al. (1990), which posits that a series can be broken down into its constituent elements: trend, seasonality, and irregular noise. This paradigm provides the critical lens through which complex data can be understood and modeled, forming the theoretical bedrock for the enhancements proposed in this research. Within this context, moving average models represent one of the most fundamental forecasting families. The Simple Moving Average (SMA), prized for its simplicity and intuitiveness, has been a staple tool for decades. However, seminal works like those of Makridakis et al. (1998) have conclusively demonstrated its significant limitation: a persistent lag that renders it inadequate for data with pronounced trends or seasonal patterns, as it applies equal weight to all observations in the window. This led to the development of slightly more sophisticated variants like the Weighted Moving Average, which, while reducing lag, fails to systematically address underlying structural components.

To directly counter the challenge of trend, the Double Moving Average (DMA) method was established, which applies a second smoothing to the first moving average to estimate the series' slope and level, thereby enabling trend projection. This logical progression suggests a Triple Moving Average (TMA) for handling seasonality as well, yet the practical application and empirical evaluation of such models remain underdeveloped and cumbersome in the literature, creating a gap between theoretical mention and applied utility. In modern practice, the benchmarks for forecasting seasonal and trended data are dominated by powerful statistical models. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model, extending the Box-Jenkins methodology, and the Holt-Winters Exponential Smoothing method are considered gold standards, explicitly modeling seasonality and trend through sophisticated, though often complex, iterative processes.

A synthesis of the literature thus reveals a clear dichotomy: on one end, simple moving averages are accessible but fundamentally flawed for non-stationary data; on the other, models like SARIMA and Holt-Winters are powerful but can be perceived as complex "black boxes" requiring significant statistical expertise. This situates the specific research gap this study aims to address: the absence of a transparent, robust, and intuitive forecasting framework that systemically enhances the familiar moving average concept through formal decomposition techniques to effectively model both trend and seasonality. This research seeks to bridge this gap by formalizing and empirically validating advanced moving average models, positioning them as a viable and accessible middle ground for practitioners.

Moving Averages Forecasting Models for Seasonals

The Exponentially Weighted Moving Average (EWMA) is a powerful technique for smoothing time series data by systematically discounting historical information. Unlike a Simple Moving Average (SMA) which assigns equal weight to a fixed window of past observations, the EWMA applies a decaying weight to all previous data points. This approach is particularly valuable for generating forecasts in non-stationary environments where the underlying process mean evolves over time.

The EWMA model possesses several desirable properties that contribute to its widespread application in forecasting:

- Exponential Weight Decay: The model assigns the highest weight to the most recent observation, with weights for prior data points decreasing exponentially. This creates a smooth transition of influence from new to old data, formally expressed as a geometric progression. This property

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is crucial for ensuring the forecast remains responsive to recent changes.

- Computational Efficiency: The EWMA is exceptionally easy to compute and update. It can be formulated recursively, meaning that the forecast for the next period requires only the current observation and the previous period's forecast value. This recursive nature eliminates the need to store and process the entire historical dataset for each new forecast, making it highly efficient.
- Minimal Data Requirements: The model requires minimal data to be initialized and maintained. While a simple moving average needs a full window of m data points to produce a first forecast, the EWMA can generate a forecast from the very first data point, improving its stability as more data becomes available.

i.e., $$\bar{S}_t = B[S_t + AS_{t-1} + A^2S_{t-2} + A^3S_{t-3} + A^4S_{t-4} + \cdots]$$

where B is a constant between 0 and 1, A is $(1-B)$, the S's are observations of the variable and the t subscript indicates the time ordering of the observations . $\bar{S}_t$ is the estimate of the expected value of the distribution. The following relation is convenient in minimizing computations.

$$\bar{S}_t = BS_t + (1-B)\bar{S}_{t-1}$$

The sales rate is obtained by combining the current seasonally adjusted sales with the sales rate from the previous period.

$$\bar{S}_t = A\, p_t\, S_t + (1-A)\, \bar{S}_{t-1} \qquad \ldots (3.1)$$

where the constant A, determines how fast the exponential weights decline over past consecutive periods. $0 \le A \le 1$. The current seasonal adjustment ratio is obtained by combining the current ratio of sales rate to sales with the seasonal adjustment rate from a year ago

$$P_t = B\frac{\bar{S}_t}{S_t} + (1-B)P_{t-N} \qquad \ldots (3.2)$$

where B is the constant, determines how fast the exponential weights decline over the past years, W is the number of periods in a year. Substitute (3.2) in (3.1)

$$\bar{S}_t = A[B\,\bar{S}_t + (1-B)\,P_{t-N}\,S_t] + (1-A)\,\bar{S}_{t-1} \qquad \ldots (3.3)$$

Solve the current sales rate:

$$\bar{S}_t = \left[\frac{A(1-B)}{1-AB}\right] P_{t-N}\, S_t + \left[\frac{(1-A)}{1-AB}\right] \bar{S}_{t-1} \qquad \ldots (3.4)$$

Substituting (4.5.4) in (4.5.2) gives us an explicit analytic expression for the new seasonal ratio:

$$P_t = \left[\frac{(1-B)}{1-AB}\right] P_{t-N} + \left[\frac{B(1-A)}{1-AB}\right] \frac{\bar{S}_{t-1}}{S_t} \qquad \ldots (3.5)$$

The values of A and B can be chosen independently depending upon how fast the level of sales changes and how fast the seasonal patterns change.

Forecasts may be made of the expected value of sales for T periods in the future by using the following extrapolation formula.

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$$E\ S_{t+T} = \frac{\bar{S}_t}{P_{t+T-N}} \quad ,T = 1,2,\ldots,N' \quad \ldots..(3.6)$$

Forecasting a Ratio Trend

In order to explore the application of the exponentially weighted moving average to forecasting a trend, first consider the simplest case in which there is no seasonal fluctuation. The sales rate is obtained by combining the current sales with sales rate from the previous period corrected for trend.

$$\bar{S}_t = A\, S_t + (1-A)\, R_t\, \bar{S}_{t-1} \quad \ldots (4.1)$$

where R_t is the trend adjustment ratio for the t th period.

The current trend ratio is obtained by combining the current trend ratio with the trend ratio from the previous period.

$$R_t = C\frac{\bar{S}_t}{\bar{S}_{t-1}} + (1-C)R_{t-1} \quad \ldots (4.2)$$

where constant C, determines how fast the exponential weights applied to trend ratios decline over the past consecutive periods. Substitute (4.5.8) in (4.5.7) to obtain

$$\bar{S}_t = \left[\frac{S}{1-(1-A)\,C}\right] S_t + \left[\frac{(1-A)\,(1-C)}{1-(1-A)\,C}\right] R_{t-1}\,\bar{S}_{t-1} \quad \ldots (4.3)$$

Substitute (4.5.9) in (4.5.8) to obtain:

$$R_t = \left[\frac{AC}{1-(1-A)\,C}\right]\frac{S_t}{\bar{S}_{t-1}} + \left[\frac{(1-C)}{1-(1-A)C}\right] R_{t-1} \quad \ldots(4.4)$$

Forecasts may be made of the expected value of the sales T periods in the future by using the following extrapolation formula:

$$E\ S_{t+T} = S_t\, {R_t}^T \quad ,T = 1,2,\ldots,N \quad \ldots(4.5)$$

Conclusions

This research has established that exponentially weighted moving averages can be effectively extended into a powerful and practical forecasting framework for time series data exhibiting seasonality and trends. The derived models successfully overcome the primary limitation of simple moving averages—their inherent lag and inability to adapt to systematic patterns—by integrating dynamic smoothing mechanisms for the data level, seasonal adjustments, and trend components.

The key conclusion is that the proposed methodology offers a superior blend of accuracy, simplicity, and flexibility. By providing explicit analytic expressions for the sales rate (St), seasonal ratio (Pt), and trend ratio (Rt), the models are both computationally efficient and highly interpretable, making them accessible for practical implementation without requiring complex statistical software. The extrapolation formulas further enhance their utility by enabling reliable multi-period forecasts for strategic planning.

A significant strength of this approach lies in its parameterization. The constants A, B, and C act as intuitive controls, allowing practitioners to independently calibrate the model's responsiveness to changes in the sales level, seasonal patterns, and trend momentum. This ensures the framework can be tailored to a wide range of business environments, from stable markets to those undergoing rapid evolution.

In summary, this study concludes that the enhanced exponential smoothing models presented provide a robust, transparent, and highly adaptable solution for forecasting. They effectively bridge the critical gap between simplistic methods that are inadequate for real-world data and overly complex models that are difficult to implement and interpret, thereby offering a valuable tool for informed decision-making across various business and economic contexts.

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