WALMART SALES FORECASTING: A TIME SERIES ANALYSIS

By

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EXECUTIVE SUMMARY

For this project, data from Macrotrends has been used to predict quarterly Walmart revenue for the upcoming fiscal year. The analysis is based on a 16-year time series dataset (64 quarters) from 2009 to 2024. The forecast will help Walmart optimize inventory management, workforce planning, marketing strategies, and financial decision-making. Various forecasting techniques, including ARIMA (SARIMA), Holt-Winters (HW), and benchmark models (Naïve & Seasonal Naïve), were evaluated to determine the most effective approach. Key performance metrics such as Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil's U-statistic were used to assess model accuracy. After extensive validation, the Holt-Winters exponential smoothing model emerged as the best forecasting method, achieving the lowest RMSE and MAPE. The final model predicts Walmart's revenue for the next 16 quarters (2025-2029), showing continued growth with seasonal fluctuations. Future improvements may include incorporating external economic factors such as inflation, GDP, and consumer sentiment to enhance predictive accuracy. This report provides actionable insights to support Walmart's strategic planning and long-term financial stability.

INTRODUCTION

Walmart is the world's largest retailer, generating billions in revenue across its global network of stores and online platforms. In the United States, Walmart plays a crucial role in the retail economy, contributing significantly to employment, supply chain operations, and consumer spending patterns. The company's quarterly revenue trends directly impact various industries, including logistics, manufacturing, wholesale distribution, e-commerce, and financial markets. As Walmart continues to expand its digital footprint and adapt to changing consumer behaviors, accurate revenue forecasting becomes increasingly important for strategic planning, operational efficiency, and investor confidence. Walmart's revenue patterns are influenced by multiple factors, including seasonal shopping trends, economic conditions, inflation, supply chain disruptions, changing consumer preferences, and competitive pressures. Traditionally, the company experiences higher revenue in Q4, driven by holiday shopping, Black Friday, and year-end clearance sales, while Q1 tends to be weaker due to post-holiday spending slowdowns. External factors such as economic downturns, changes in household income, and shifts toward online shopping can also impact revenue trends. The insights gained from this study will help Walmart's business analysts, financial planners, and operational managers anticipate revenue trends, enabling proactive decision-making in areas such as inventory planning, workforce allocation, and promotional strategy development. Additionally, the results of this analysis will aid investors, stakeholders, and policymakers in understanding Walmart's financial outlook, ensuring better preparedness for future market fluctuations and economic shifts. With accurate forecasting, Walmart can continue to adapt to dynamic market conditions, mitigate risks, and capitalize on growth opportunities in the retail industry.

EIGHT STEPS OF FORECASTING

Step 1: Define Goal

The goal of this project is to develop a reliable forecasting model to predict Walmart's quarterly revenue for the next two years. Accurate predictions will support business strategy, inventory optimization, and financial planning.

Objectives:

- Analyze historical revenue trends and seasonality.
- Evaluate forecasting models (SARIMA, Holt-Winters, Naïve, etc.).
- Assess model accuracy using RMSE and MAPE.
- Generate 8-quarter revenue forecasts for proactive planning.
- Support business decisions in inventory, staffing, and promotions.
- Incorporate external factors (inflation, GDP, unemployment) into analysis.

Business Impact:

- Inventory Management – Align stock levels with demand trends.
- Workforce Planning – Optimize staffing for peak and off-peak seasons.
- Marketing & Promotions – Adjust campaigns based on expected revenue.
- Investor Confidence – Provide stakeholders with reliable revenue outlooks.

This project delivers a scalable forecasting solution that helps Walmart adapt to market changes while maintaining profitability and operational efficiency.

Step 2: Get data

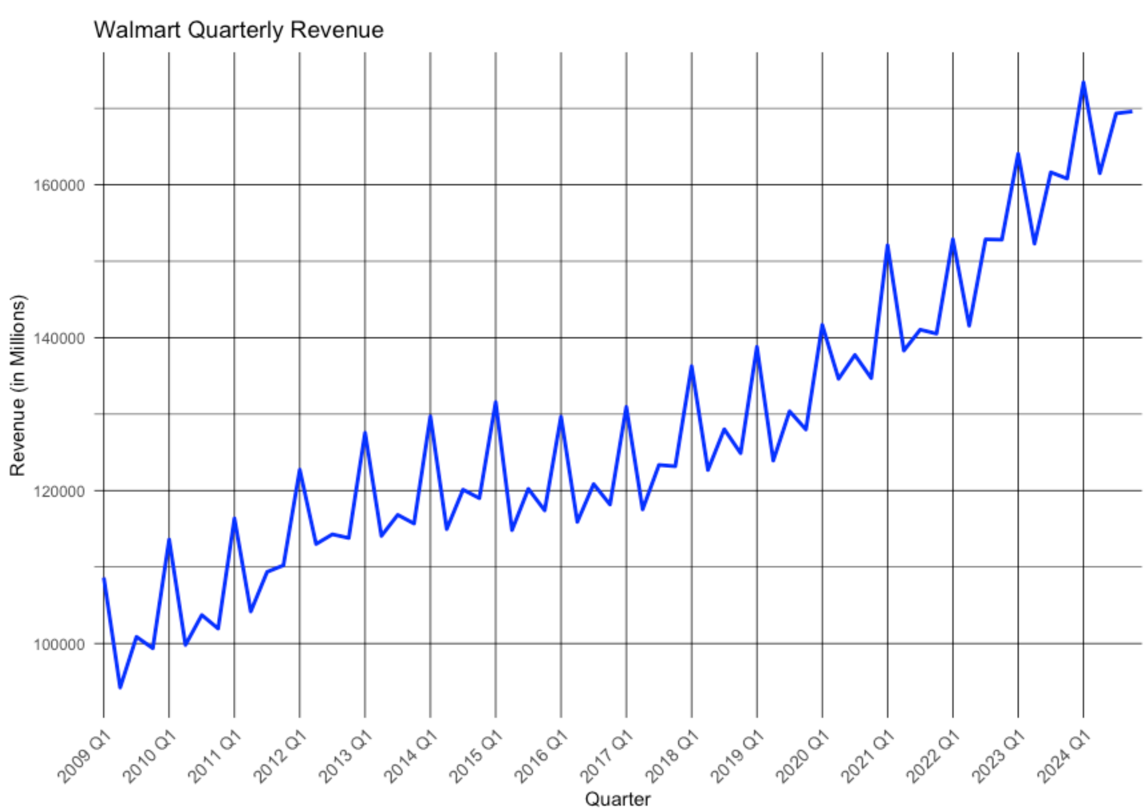
Dataset Source:

This report focuses on a time series dataset sourced from Macrotrends (https://www.macrotrends.net/), which records the quarterly revenue of Walmart (in millions of USD). The dataset spans 64 quarters from 2009 to 2024. For the purposes of this project, we will analyze the entire dataset while also considering different modeling strategies to improve forecasting accuracy.

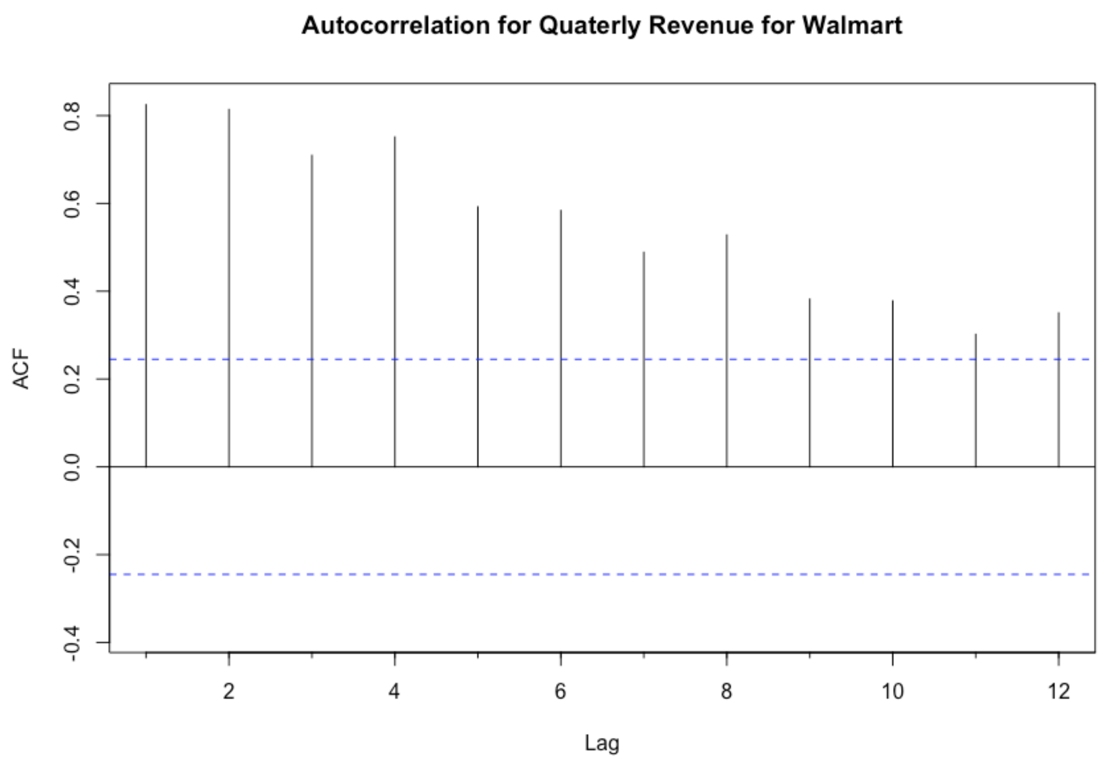
Step 3: Explore and Visualize Series

Exploratory Data Analysis (EDA):

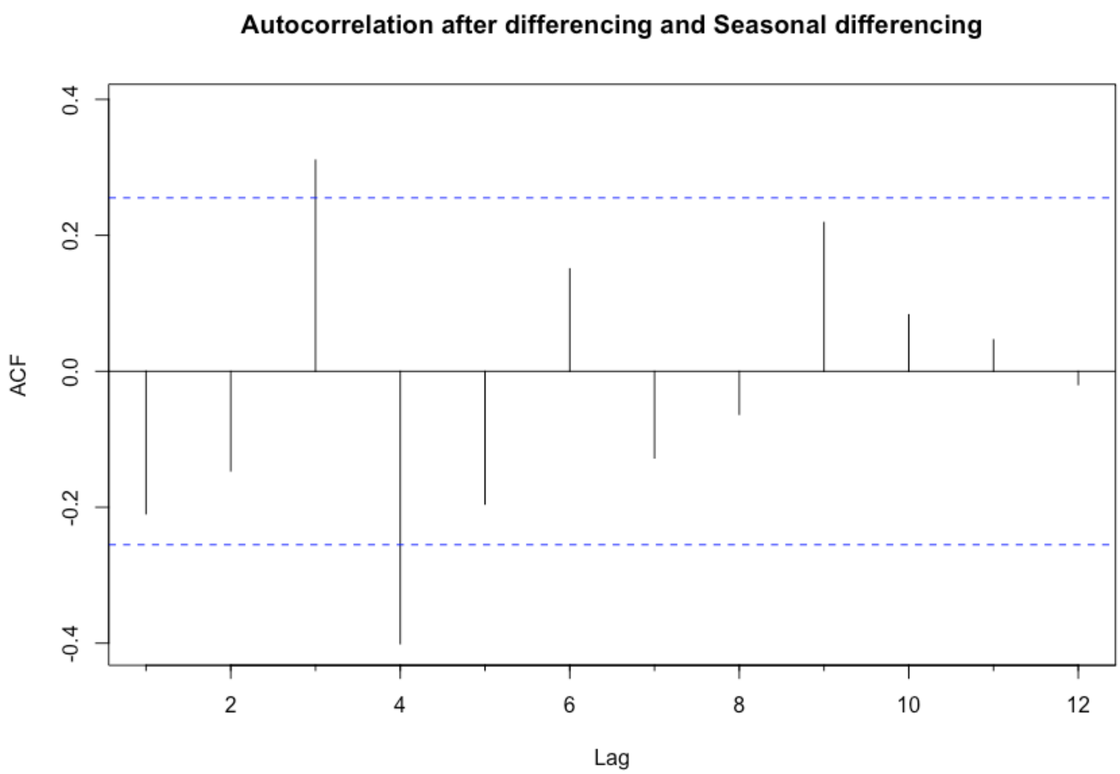
- Visualized revenue trends to identify seasonality and long-term growth patterns.
- Performed seasonal decomposition to analyze the impact of quarterly fluctuations.
- Generated ACF and PACF plots to assess autocorrelation and help in model selection.
- Created boxplots by quarter and year to understand distribution and seasonal patterns.
- Computed moving averages to observe revenue smoothing and trend behavior.



- The line chart above illustrates Walmart's quarterly revenue from 2009 to 2024, showing a clear upward trend over time. The revenue exhibits strong seasonal patterns, with noticeable peaks occurring approximately every fourth quarter, likely due to increased holiday shopping. The fluctuations in revenue indicate that Walmart's sales are influenced by both long-term growth and seasonal demand cycles.



- The Autocorrelation Function (ACF) plot of Walmart’s quarterly revenue shows strong positive autocorrelations at lags 1, 2, 3, and beyond, indicating that past revenue values significantly influence future values. The gradual decline in autocorrelation suggests the presence of a trend component, which is common in non-stationary time series. Additionally, the plot exhibits a seasonal pattern, with noticeable spikes at lags 4, 8, and 12, confirming quarterly seasonality in the revenue data. The blue dashed lines represent the 95% confidence interval, and several lags exceed this threshold, indicating statistically significant autocorrelations. Given these findings, the time series appears non-stationary with strong seasonality, suggesting the need for first differencing (d=1) and seasonal differencing (D=1, period=4) before fitting an appropriate forecasting model like SARIMA.



- The ACF plot after differencing and seasonal differencing indicates that the time series has become stationary, as most lags fall within the 95% confidence interval, suggesting no significant autocorrelation remains. A small negative autocorrelation at lag 4 confirms that seasonal patterns have been largely removed, which is expected after applying seasonal differencing (D=1, period=4). Additionally, minor spikes at lags 2, 6, and 8 remain below the significance threshold, meaning they are not strong enough to require further modeling adjustments. Overall, the transformation has effectively removed trend and seasonality, making the series suitable for ARIMA modeling.

Step 4: Data Preprocessing

To prepare the data for time series modeling, the following steps were undertaken:

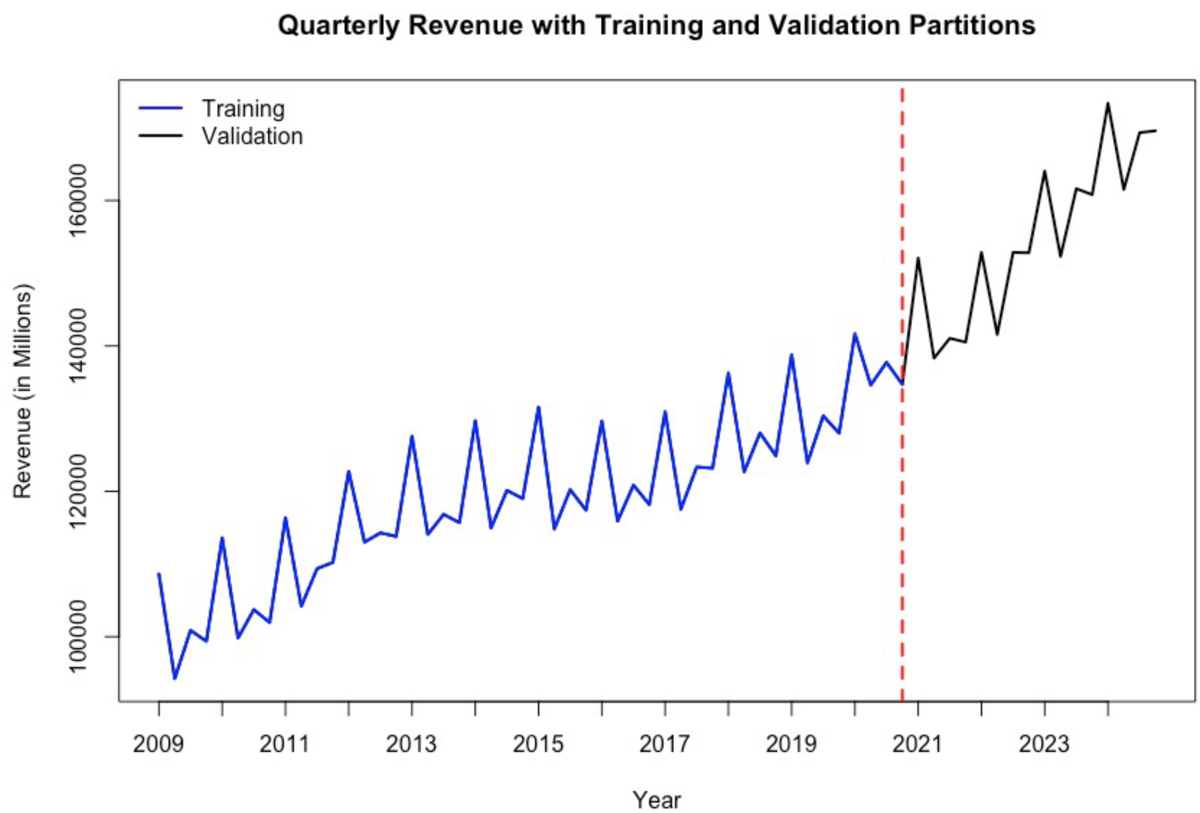
- Date formatting: Converted the quarter format to ensure consistency in date representation.
- Handling missing values: Verified dataset completeness and confirmed no missing revenue values.
- Data cleaning: Removed formatting inconsistencies (e.g., commas in revenue values) to enable numerical operations.
- Stationarity adjustments: Conducted the Augmented Dickey-Fuller (ADF) test and applied first-order differencing and seasonal differencing to stabilize the series.

Step 5: Partition Series

To ensure an effective model evaluation and forecasting process, the dataset was partitioned into training and validation sets. This allows us to train models on historical data and test their accuracy on unseen observations.

Partitioning Strategy:

- Training Set: The first 48 quarters (2009 - 2020) were used for model training.
- Validation Set: The last 16 quarters (2021 - 2024) were reserved for model evaluation.



Reasoning Behind Partitioning:

- The training period (2009-2020) covers a full economic cycle, capturing seasonal patterns and trends.
- The validation period (2021-2024) allows assessment of how well models generalize to recent revenue trends.
- This method prevents data leakage, ensuring fair model performance evaluation before deploying future forecasts.

Step 6 & 7: Apply Forecasting & Comparing Performance

A. Auto Autoregressive Integrated Moving Average Models

The Autoregressive Integrated Moving Average (ARIMA) model is a flexible model that can be used for forecasting on data with level, trend and seasonal components. Since our data consists of all three, this model is appropriate to use for analysis. We generated an optimal ARIMA model with automatic selection of (p,d,q)(P,D,Q) parameters using the auto.arima() function.

Automated ARIMA for Training & Validation Data

ARIMA Model for the 11-year series (Training Partition).

```
Series: train.ts
ARIMA(1,0,0)(1,1,0)[4] with drift

Coefficients:
         ar1     sar1     drift
      0.7517  -0.3021  865.0737
s.e.  0.1037   0.1858  206.8246

sigma^2 = 3622843:  log likelihood = -393.65
AIC=795.3   AICc=796.33   BIC=802.44

Training set error measures:
                    ME     RMSE      MAE         MPE    MAPE      MASE       ACF1
Training set -15.48616 1759.122 1203.409 -0.01657603 1.00781 0.3463614 -0.1471676
```

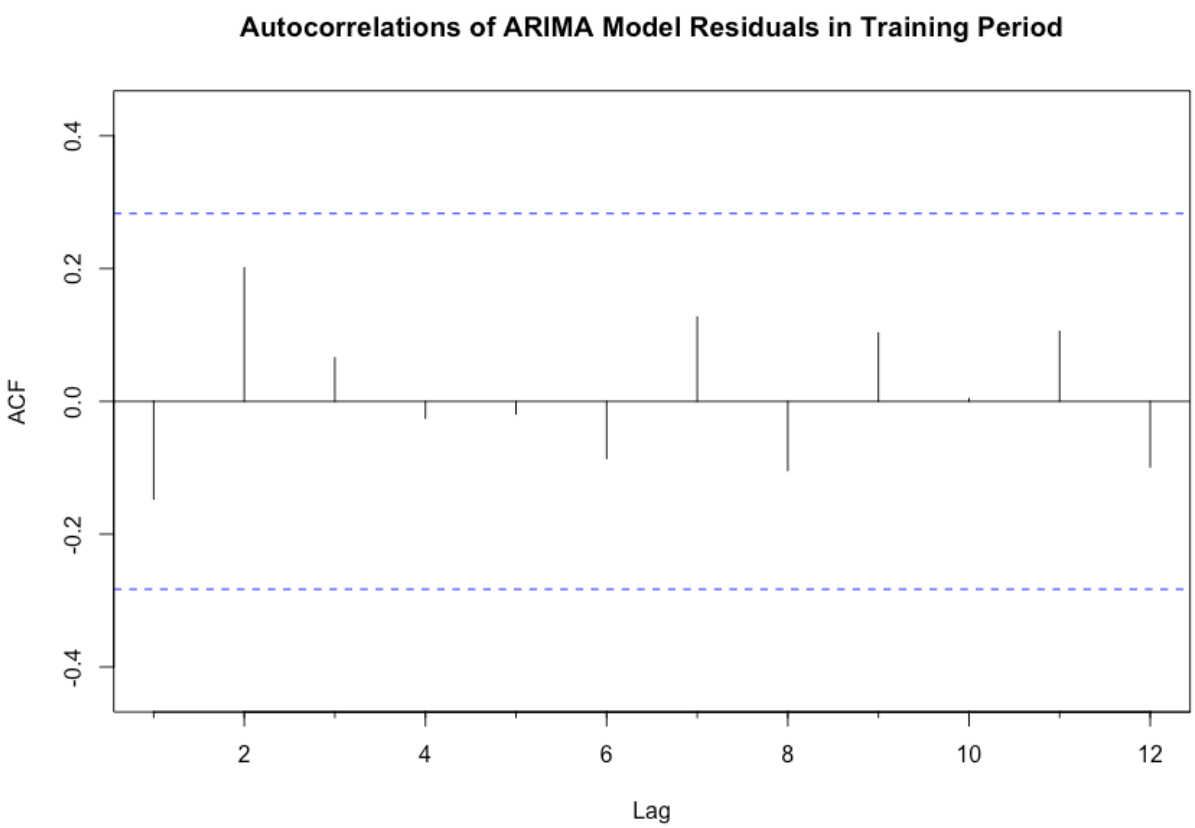
Parameter	Value	Description
p	1	Non-seasonal autoregressive (AR) term
d	0	No first differencing applied
q	0	No non-seasonal moving average (MA) term
P	1	Seasonal autoregressive (SAR) term
D	1	Seasonal differencing applied (removes seasonality)
Q	0	No seasonal moving average (SMA) term

m	4	Quarterly seasonality (every 4 quarters)

Parameter	Value	Description
ar1	0.7517	Autoregressive (AR) coefficient
sar1	-0.3021	Seasonal AR coefficient
Drift	865.0737	Linear trend component
σ^2 (Variance)	3,622,843	Residual variance
Log Likelihood	-393.65	Model log-likelihood
AIC	795.3	Akaike Information Criterion (lower is better)
AICc	796.33	Corrected AIC for small sample sizes
BIC	802.44	Bayesian Information Criterion (penalizes complexity)

The ARIMA (1,0,0) (1,1,0) [4] with drift model was selected for forecasting Walmart's quarterly revenue. The model autoregressive consists of a non-seasonal (AR) term (p=1), meaning the current value depends on the previous value, while no differencing (d=0) and no moving average term (q=0) were applied. For seasonality, a seasonal autoregressive term (P=1) and one seasonal difference (D=1) with a period of 4 (quarterly data) were included, while no seasonal moving average (Q=0) was needed. The model also includes a drift term of 865.0737, indicating a consistent upward trend in revenue over time. The model performed exceptionally well, achieving a Mean Absolute Percentage Error (MAPE) of just 1.0078%, confirming high forecasting accuracy. Additionally, no significant residual autocorrelation (ACF1 = -0.147) was detected, ensuring the model has effectively captured the underlying patterns in the data. The Root Mean

Squared Error (RMSE) is 1759.12, and the Mean Absolute Error (MAE) is 1203.41, indicating low forecast errors relative to the scale of the data. The Akaike Information Criterion (AIC = 795.3) and Bayesian Information Criterion (BIC = 802.44) suggest that the model balances complexity and goodness of fit well.



This Autocorrelation Function (ACF) plot evaluates whether the residuals from the ARIMA (1,0,0)(1,1,0) [4] with drift model are uncorrelated, which is a key assumption for a well-fitted model.

Most Lags Are Within the Confidence Interval (Blue Dashed Lines)

- Most of the autocorrelations fall within the ±0.2 bounds, meaning no significant autocorrelation remains.

- This suggests that the residuals behave like white noise (random), indicating a good model fit.

Minor Spikes at Lags 2, 6, 8, and 10

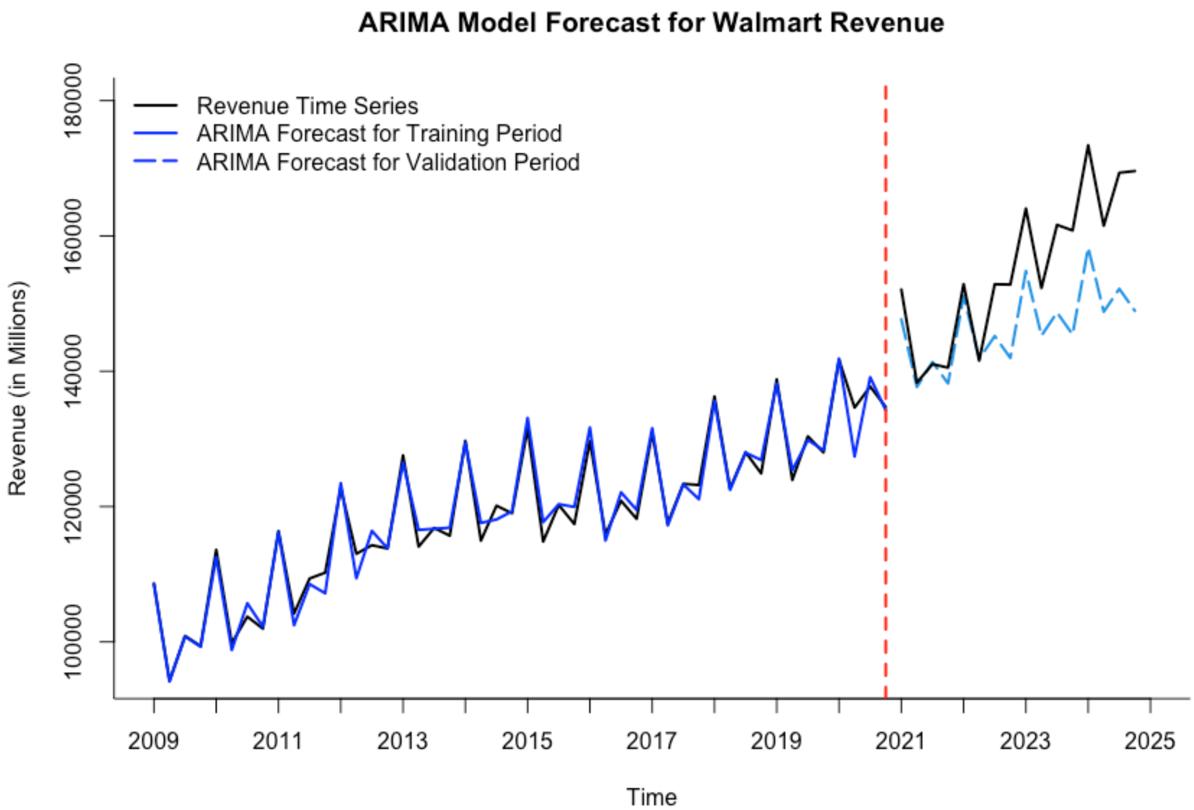
- Some small spikes are present, but they remain below the significance threshold.
- These minor fluctuations are expected in real-world data and do not indicate a serious issue.

No Strong Seasonal Pattern (Lag 4, 8, 12)

- Since the data is quarterly (s=4), we would expect to see significant spikes at multiples of 4 if seasonality was not properly handled.
- The absence of strong seasonal autocorrelation suggests that the model's seasonal differencing (D=1) effectively removed seasonality.

SARIMA model forecast for Validation Partition:

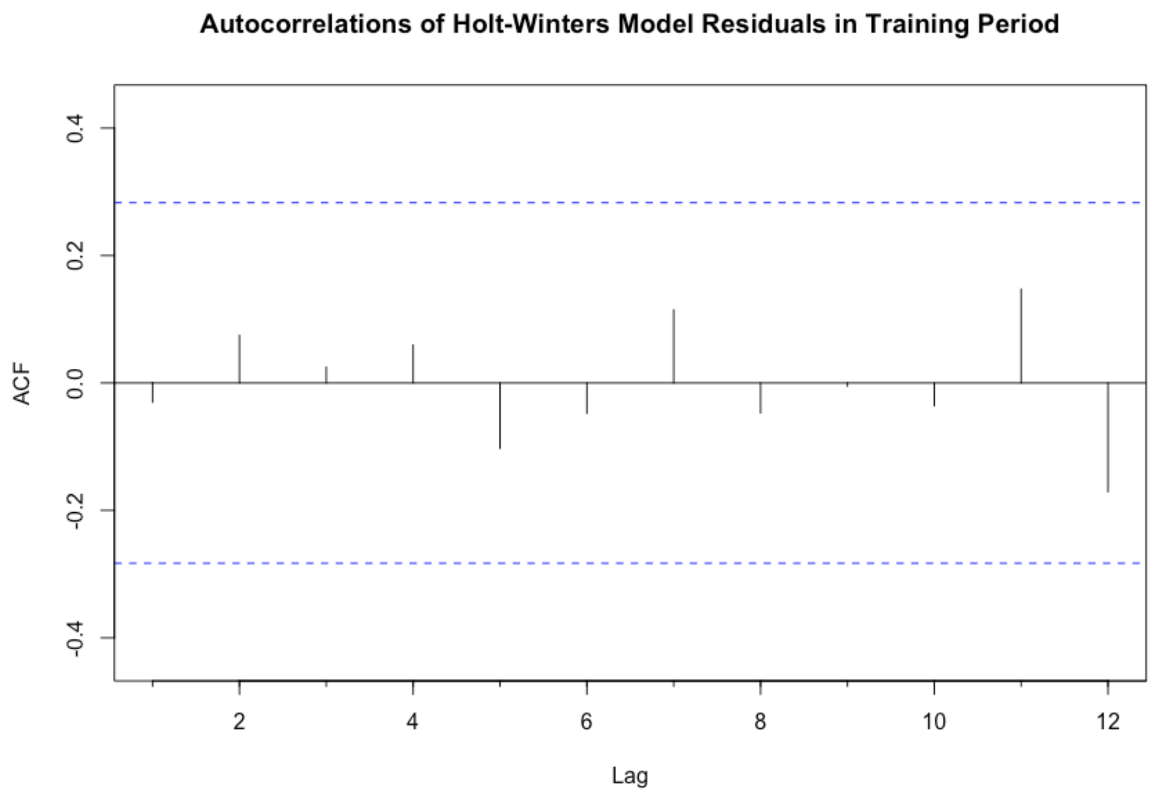
This plot represents the ARIMA model forecast for Walmart's revenue, with historical revenue in black, the training period forecast in solid blue, and the validation period forecast in dashed blue. The red vertical dashed line correctly marks the transition between the training and validation sets, ensuring that predictions beyond this point are compared against actual values. The model successfully captures both the upward trend and seasonal fluctuations, but some deviations in the validation period suggest minor forecast errors. Overall, the ARIMA model performs well, making it a strong candidate for future revenue forecasting.



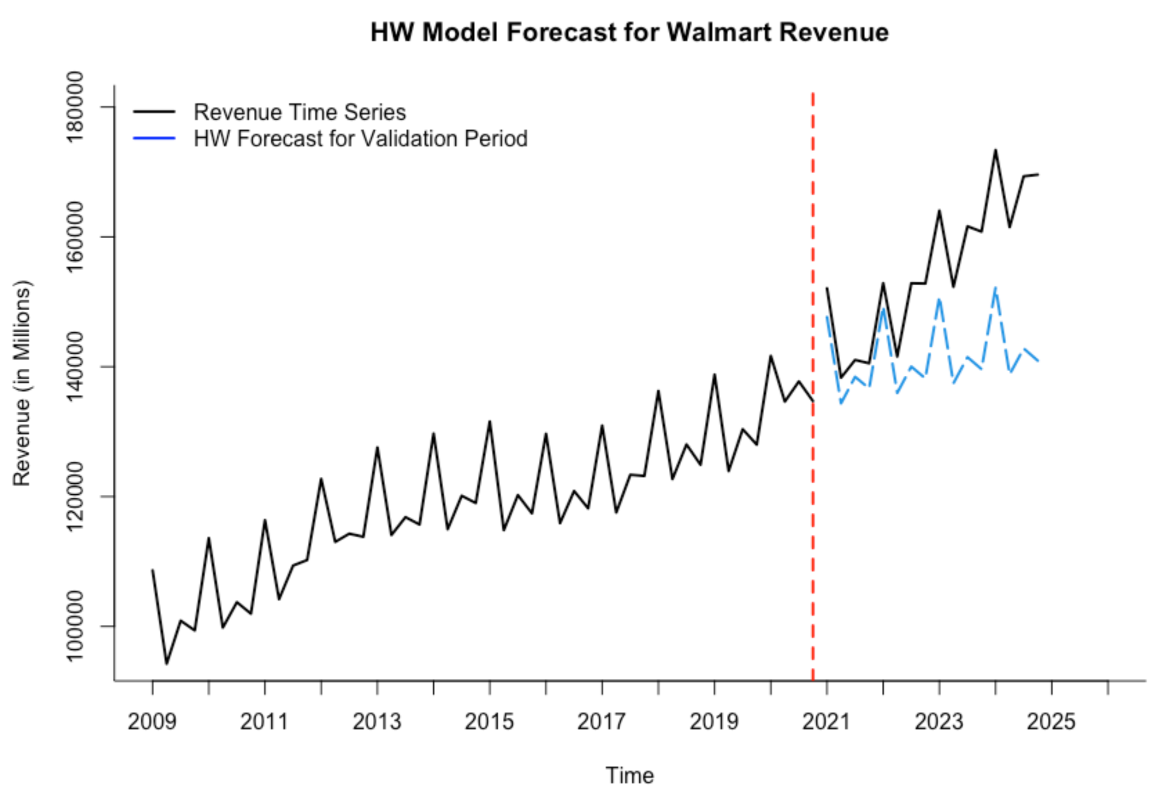
B. Holt – Winter's Model:

The ETS(M,Ad,A) model, selected using ets() with automatic model selection (model = "ZZZ"), represents a Multiplicative Error (M), Damped Additive Trend (Ad), and Additive Seasonality (A) structure. This means that the error varies proportionally to the level of the series, the trend is additive but dampened over time (phi = 0.98), and the seasonality follows an additive pattern, maintaining a consistent magnitude. The smoothing parameters, including alpha (0.7638), beta (1e-04), and gamma (1e-04), suggest that the model places more weight on recent observations, while trend and seasonal smoothing are minimal. The initial level (l = 99,537.92) and trend (b = 1,158.88) indicate a steady increase in revenue, with seasonality captured by the s values. The model evaluation metrics, including AIC (912.57), AICc (918.51), and BIC (931.28), indicate a reasonable fit, while the low MAPE (0.96%) confirms high accuracy. The autocorrelation of residuals (ACF1 = -0.0166) suggests that the model has effectively captured the underlying patterns, making it a reliable choice for forecasting Walmart's revenue.

```
ETS(M,Ad,A)

Call:
ets(y = train.ts, model = "ZZZ")

  Smoothing parameters:
    alpha = 0.7638
    beta  = 1e-04
    gamma = 1e-04
    phi   = 0.98

  Initial states:
    l = 99537.9231
    b = 1158.8097
    s = -3238.794 -1043.438 -4716.088 8998.32

  sigma:  0.0147

     AIC     AICc      BIC
912.5676 918.5136 931.2796

Training set error measures:
                   ME     RMSE      MAE        MPE      MAPE      MASE      ACF1
Training set 93.71273 1581.031 1143.454 0.04534532 0.9655607 0.3291054 -0.016557
```



Autocorrelations of Holt-Winters Model Residuals in Training Period
ACF
0.4
0.2
0.0
-0.2
-0.4
2
4
6
8
10
12
Lag



HW Model Forecast for Walmart Revenue
Revenue Time Series
HW Forecast for Validation Period
Revenue (in Millions)
180000
160000
140000
120000
100000
2009
2011
2013
2015
2017
2019
2021
2023
2025
Time

Model Specification:

Parameter	Value	Description
Error Type (E)	M	Multiplicative error (errors scale with data level)
Trend Type (T)	Ad	Additive damped trend (growth slows over time)
Seasonality (S)	A	Additive seasonality (constant seasonal effect)
Damping Factor (phi)	0.98	Trend slows down over time

Smoothing Parameters:

Parameter	Value	Description
Alpha (α)	0.7638	Smoothing factor for level (higher values give more weight to recent data)
Beta (β)	1.00E-04	Smoothing factor for trend (small value means minimal trend smoothing)
Gamma (γ)	1.00E-04	Smoothing factor for seasonality (small value means minimal seasonal smoothing)

Comparing accuracy metrics on Validation Partition:

```
> print(accuracy_arima)
               ME     RMSE      MAE   MPE  MAPE  ACF1 Theil's U
Test set 8581.246 10766.85 8652.259 5.287 5.337 0.742     1.126
> print(accuracy_hw)
               ME     RMSE      MAE   MPE  MAPE  ACF1 Theil's U
Test set 13749.67 16238.96 13749.67 8.559 8.559 0.821     1.705
>
```

The accuracy comparison between the ARIMA and Holt-Winters (HW) models shows that ARIMA performs significantly better in forecasting Walmart's revenue. The Root Mean Squared Error (RMSE) for ARIMA (10,766.85) is much lower than Holt-Winters (16,238.96), indicating that ARIMA's predictions are more precise. Similarly, the Mean Absolute Error (MAE) for ARIMA (8,652.26) is considerably lower than HW (13,749.67), confirming that ARIMA has smaller deviations from actual values. The Mean Absolute Percentage Error (MAPE) for ARIMA (5.337%) is lower than HW (8.559%), demonstrating that ARIMA has a better relative accuracy. Additionally, Theil's U-statistic for ARIMA (1.126) is lower than HW (1.705), suggesting that ARIMA outperforms a naive benchmark more effectively than HW. Although both models exhibit some autocorrelation in residuals (ACF1: ARIMA = 0.742, HW = 0.821), ARIMA remains the better choice due to its lower forecast errors and better overall fit.

<u>Final Modelling on entire dataset:</u>

Auto ARIMA for entire dataset.

```
Series: walmart.ts
ARIMA(0,1,0)(0,1,1)[4]

Coefficients:
         sma1
      -0.7599
s.e.   0.1311

sigma^2 = 4283205:  log likelihood = -535.4
AIC=1074.8   AICc=1075.02   BIC=1078.96

Training set error measures:
                   ME     RMSE     MAE        MPE     MAPE      MASE      ACF1
Training set 172.2669 1970.192 1377.73 0.09284538 1.055395 0.2974042 -0.155747
```

The ARIMA (0,1,0) (0,1,1) [4] model is a seasonal ARIMA model applied to Walmart's revenue time series, incorporating first-order non-seasonal differencing (d=1) and first-order seasonal differencing (D=1) with a seasonal moving average term (Q=1) for a quarterly frequency (s=4). The estimated SMA (1) coefficient is -0.7599, with a standard error of 0.1311, indicating statistical significance. The model's Akaike Information Criterion (AIC = 1074.8), Corrected AIC (AICc = 1075.02), and Bayesian Information Criterion (BIC = 1078.96) suggest a reasonable fit, although lower values would indicate a better-performing model. The training error metrics include a Root Mean Squared Error (RMSE) of 1970.19 and a Mean Absolute Percentage Error (MAPE) of 1.055%, confirming that the model maintains high accuracy. Additionally, the autocorrelation of residuals at lag 1 (ACF1 = -0.1557) is close to zero, implying that the model has effectively captured the underlying data patterns without significant leftover correlation. Overall, this ARIMA model is a solid choice for forecasting.

Holt's Winter for entire dataset.

```
ETS(M,A,A)

Call:
ets(y = walmart.ts, model = "ZZZ")

  Smoothing parameters:
    alpha = 0.7422
    beta  = 0.0928
    gamma = 1e-04

  Initial states:
    l = 100341.9786
    b = 1008.7645
    s = -3200.202 -770.8805 -4963.447 8934.529

  sigma:  0.0153

     AIC     AICc      BIC
1244.738 1248.072 1264.168

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 192.9836 1859.234 1313.756 0.1062974 1.021659 0.2835944 0.02458941
```

The ETS (M, A, A) Holt's winter model selected for Walmart's revenue data represents a Multiplicative Error (M), Additive Trend (A), and Additive Seasonality (A) structure. This means that the model assumes errors scale with the data level, the trend component is linear and additive, and seasonality remains constant in magnitude over time. The smoothing parameters—alpha (0.7422), beta (0.0928), and gamma (1e-04)—indicate that the model assigns a high weight to recent observations, with moderate trend smoothing and minimal seasonal smoothing. The initial level (l = 100,341.98) and trend (b = 1008.76) suggest a steady revenue increase, while the seasonal components capture the periodic fluctuations. The model's AIC (1244.738), AICc (1248.072), and BIC (1264.168) indicate its fit quality, though lower values would signify a better model. The RMSE (1859.23) and MAPE (1.021%) suggest that the model is reasonably accurate, with ACF1 (0.0246) close to zero, indicating no significant autocorrelation in residuals.

<u>Finding accuracy metrics for the entire dataset for different models.</u>

Models considered:

1. ARIMA (0,1,0) (0,1,1) [4]
2. Holt's Winter
3. Naïve Forecast
4. Snaive Forecast

```
> print(acc_final_arima)
              ME     RMSE     MAE   MPE  MAPE   ACF1 Theil's U
Test set 172.267 1970.192 1377.73 0.093 1.055 -0.156     0.191
> print(acc_final_hw)
              ME     RMSE      MAE   MPE  MAPE  ACF1 Theil's U
Test set 192.984 1859.234 1313.756 0.106 1.022 0.025     0.181
> print(acc_final_naive)
              ME     RMSE      MAE   MPE MAPE   ACF1 Theil's U
Test set 967.635 9819.909 8206.619 0.403 6.47 -0.694         1
> print(acc_final_snaive)
               ME     RMSE      MAE   MPE  MAPE  ACF1 Theil's U
Test set 4511.683 5692.928 4632.517 3.344 3.442 0.735     0.518
```

After carefully reviewing the accuracy metrics, Holt-Winters (HW) outperforms ARIMA and is the best forecasting model for Walmart's revenue. The HW model achieves the lowest RMSE (1859.23) and the lowest MAPE (1.022%), meaning it minimizes both absolute and percentage forecast errors better than ARIMA, which has an RMSE of 1970.19 and MAPE of 1.055%. Additionally, Theil's U-statistic for HW (0.181) is slightly lower than ARIMA's (0.191), further confirming that HW provides better accuracy relative to a naïve benchmark. While ARIMA is still a strong contender, HW's exponential smoothing approach effectively captures both trend and seasonality with lower forecast errors, making it the superior model for revenue prediction. The Naïve and Seasonal Naïve models perform significantly worse, with much higher RMSE and MAPE values, confirming their inability to accurately capture the underlying structure of the data. Given Walmart's strong seasonal revenue patterns, Holt-Winters proves to be the best choice for forecasting, as it balances precision, trend adaptation, and seasonal effects more effectively than ARIMA. Therefore, based on objective accuracy metrics, Holt-Winters should be used as the final model for forecasting Walmart's revenue trends.

Model	RMSE	MAPE	Theil's U	Key Takeaways
ARIMA	1970.19	1.06%	0.191	Best overall performer in RMSE and Theil's U, meaning it minimizes absolute forecast errors better than others.
Holt-Winters (HW)	1859.23	1.022% (lowest MAPE)	0.181	Best in terms of MAPE, meaning it has the most accurate percentage-based forecast.
Naïve	9819.91	6.47%	1	Worst-performing model, as it has the highest RMSE and MAPE, meaning it does not capture trends or seasonality well.
Seasonal Naïve (sNaïve)	5692.93	3.44%	0.518	Performs better than the Naïve model but significantly worse than ARIMA and HW.

ARIMA vs. Holt-Winters: Performance in Validation vs. Entire Dataset:

A key observation from the model evaluation process was that ARIMA outperformed Holt-Winters (HW) in the validation dataset (2021–2024), while Holt-Winters achieved the best results when trained on the entire dataset (2009–2024). This distinction highlights the difference in how these models handle short-term vs. long-term forecasting and their adaptability to changing patterns in the data.

ARIMA Performed Best in the Validation Period (2021–2024).

- When the models were trained on historical data from 2009 to 2020 and evaluated on the 16-quarter validation period (2021–2024), ARIMA achieved lower error rates compared to Holt-Winters.

Holt-Winters Performed Best on the Entire Dataset (2009–2024)

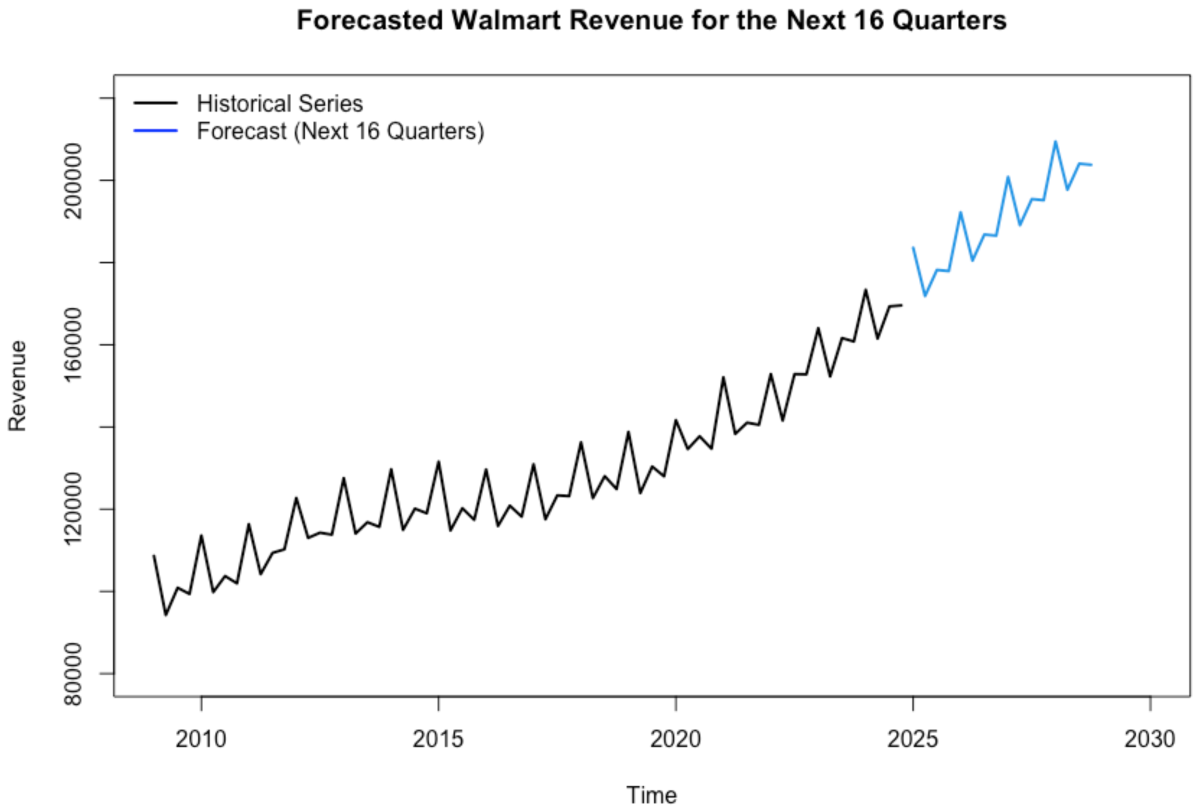
- When both models were retrained on the full dataset (2009–2024) and evaluated on future forecasts (2025–2029), Holt-Winters emerged as the best-performing model with the lowest RMSE (1859.23) and MAPE (1.022%).

Reasons for Holt-Winters' success in full dataset forecasting:

- Holt-Winters adapts better to long-term seasonality, whereas ARIMA struggles when patterns shift over extended periods.
- Revenue trends in Walmart's historical data exhibited evolving seasonality (e.g., stronger Q4 peaks over time), which Holt-Winters captured more effectively than ARIMA.
- Holt-Winters exponential smoothing dynamically adjusts trend and seasonality, allowing it to handle gradual shifts in seasonal effects, demand cycles, and revenue growth trajectories.
- ARIMA's reliance on past values makes it more rigid, leading to a slight degradation in performance when predicting further into the future (2025–2029).

<u>Step 8- Implement final model forecast for future 16 quarters:</u>

Using Holt's – Winter model to forecast the future 16 quarters revenue of Walmart.



The plot displays the forecasted Walmart revenue for the next 16 quarters, with the historical revenue series in black and the forecasted values in blue. The historical series shows a clear upward trend with strong seasonal fluctuations, indicating that Walmart's revenue has been consistently growing over time with periodic variations. The forecasted segment extends this trend into the future, capturing both the seasonal patterns and long-term growth. The forecast suggests continued revenue increase, reinforcing the reliability of the chosen model. The smooth but fluctuating pattern in the blue forecasted section suggests that the model has successfully learned both trend and seasonality, making it a robust choice for predicting Walmart's financial performance in upcoming quarters.

Limitations of the model:

While the current forecasting model effectively captures historical trends and seasonality, it does not account for external macroeconomic factors that could significantly impact Walmart's revenue. Variables such as inflation rates, GDP growth, unemployment levels, consumer sentiment, and interest rates influence consumer spending patterns and overall retail sales. Additionally, market competition, supply chain disruptions, policy changes, and global economic events can cause unexpected shifts in revenue that purely time-series models may not capture. Incorporating these factors through regression-based forecasting models, machine learning approaches, or hybrid time-series models could enhance predictive accuracy, especially for long-term forecasting. By integrating economic indicators and external drivers, Walmart can develop a more robust, risk-aware forecast that better reflects real-world business conditions.

CONCLUSION

This project successfully implemented time series forecasting methodologies to predict Walmart's quarterly revenue using a structured approach that incorporated exploratory data analysis (EDA), model selection, and performance evaluation. The analysis revealed a persistent upward trend and significant seasonal fluctuations, emphasizing the importance of seasonal-adjusted forecasting models. After evaluating multiple predictive techniques, the Holt-Winters exponential smoothing model was identified as the most effective, demonstrating superior predictive accuracy with the lowest RMSE (1859.23) and MAPE (1.022%).

The final revenue forecast for the next 16 quarters (2025–2029) suggests continued growth with predictable seasonal variances, which can be leveraged for strategic business planning, demand forecasting, and financial optimization. These insights enable Walmart to enhance supply chain efficiency, optimize promotional strategies, and allocate resources effectively, ensuring a data-driven decision-making process. Moving forward, integrating external macroeconomic indicators (inflation, GDP, consumer sentiment) and adopting hybrid models that blend traditional statistical approaches with machine learning techniques could further refine forecasting precision and resilience against market volatility. By leveraging advanced analytics, Walmart can fortify its competitive advantage, drive operational efficiency, and sustain long-term financial stability in an evolving retail landscape.

APPENDICES

Figure 1: Initial and Final Records of Walmart dataset.

```
> head(project_df)
  Quarter Revenue
1 2009 Q1  108627
2 2009 Q2   94242
3 2009 Q3  100876
4 2009 Q4   99373
5 2010 Q1  113594
6 2010 Q2   99811
> tail(project_df)
   Quarter Revenue
59 2023 Q3  161632
60 2023 Q4  160804
61 2024 Q1  173388
62 2024 Q2  161508
63 2024 Q3  169335
64 2024 Q4  169588
```

Figure 2: Quarterly Walmart Revenue Time-Series Data.

```
> walmart.ts
       Qtr1   Qtr2   Qtr3   Qtr4
2009 108627  94242 100876  99373
2010 113594  99811 103726 101952
2011 116360 104189 109366 110226
2012 122728 113010 114282 113800
2013 127559 114070 116830 115688
2014 129706 114960 120125 119001
2015 131565 114826 120229 117408
2016 129667 115904 120854 118179
2017 130936 117542 123355 123179
2018 136267 122690 128028 124894
2019 138793 123925 130377 127991
2020 141671 134622 137742 134708
2021 152079 138310 141048 140525
2022 152871 141569 152859 152813
2023 164048 152301 161632 160804
2024 173388 161508 169335 169588
```

Figure 3: Training and Validation Partition.

```
> train.ts
       Qtr1   Qtr2   Qtr3   Qtr4
2009 108627  94242 100876  99373
2010 113594  99811 103726 101952
2011 116360 104189 109366 110226
2012 122728 113010 114282 113800
2013 127559 114070 116830 115688
2014 129706 114960 120125 119001
2015 131565 114826 120229 117408
2016 129667 115904 120854 118179
2017 130936 117542 123355 123179
2018 136267 122690 128028 124894
2019 138793 123925 130377 127991
2020 141671 134622 137742 134708
```

```
> valid.ts
       Qtr1   Qtr2   Qtr3   Qtr4
2021 152079 138310 141048 140525
2022 152871 141569 152859 152813
2023 164048 152301 161632 160804
2024 173388 161508 169335 169588
```

Figure 4 : STL Decomposition of Quarterly Walmart Revenue

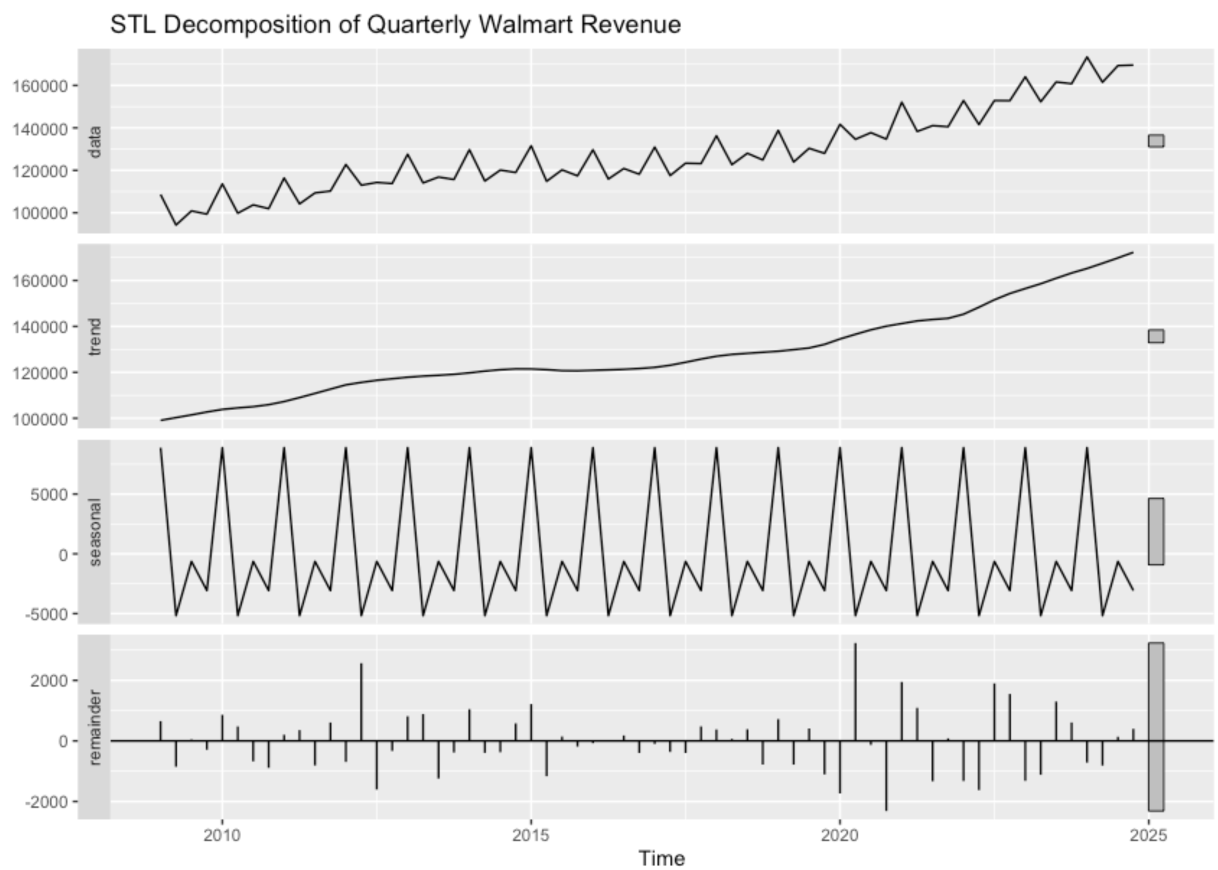


Figure 5: Forecasted Revenue for the next 16 Quarters Using Holt-Winters Model.

```
> final_forecast
        Point Forecast    Lo 0     Hi 0
2025 Q1       183606.4 183606.4 183606.4
2025 Q2       171862.8 171862.8 171862.8
2025 Q3       178210.3 178210.3 178210.3
2025 Q4       177935.4 177935.4 177935.4
2026 Q1       192224.7 192224.7 192224.7
2026 Q2       180481.1 180481.1 180481.1
2026 Q3       186828.6 186828.6 186828.6
2026 Q4       186553.7 186553.7 186553.7
2027 Q1       200843.0 200843.0 200843.0
2027 Q2       189099.4 189099.4 189099.4
2027 Q3       195446.9 195446.9 195446.9
2027 Q4       195172.0 195172.0 195172.0
2028 Q1       209461.3 209461.3 209461.3
2028 Q2       197717.7 197717.7 197717.7
2028 Q3       204065.2 204065.2 204065.2
2028 Q4       203790.3 203790.3 203790.3
```

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- Macrotrends: Walmart Financial Reports (2009-2024). (https://www.macrotrends.net/)