Project: Decomposing and forecasting of Advance Retail Sales data for Nonstore Retailers in USA for year 1992 to 2024,

Table of contents

1. **Introduction:** Time series analysis is a cornerstone of data science and statistics as well very important for understanding improvised patterns for forecasting and decisions making. Time series analysis has long been a base part of statistical and data-driven research, enabling practitioners to understand patterns, identify trends, and make forecasts in areas ranging from economics to environmental science. It has become a key component of data science particularly in domains where understanding temporal trends is essential for precise forecasting and well-informed decision-making (Chatfield, C.,2016). Time series with strong seasonality are especially notable because they offer special opportunities and problems. These datasets show recurrent changes at regular intervals, frequently caused by business cycles, holidays, and weather. Decomposition is one of the most effective methods for analyzing time series data. This method breaks down a time series into its main elements: noise, trend, and seasonality(Hamilton, J. D., 1994).

A powerful technique in time series analysis is decomposition, which dissects a time series into its fundamental components: trend, seasonality, and noise. This method has been instrumental in various fields, from economics to environmental science, enabling the identification of patterns and trends and the prediction of future outcomes (Hyndman, R. J., & Athanasopoulos, G. 2021). Seasonal time series, characterized by regular fluctuations influenced by factors like weather, holidays, or business cycles, present both challenges and opportunities in time series analysis. These series require specialized techniques to capture and model their cyclical nature accurately, ensuring reliable forecasts and insights(Chatfield, C., 2016). In a variety of disciplines, including economics and environmental science, time series analysis has long been a vital tool in statistical and data-driven research, enabling specialists to examine patterns, identify trends, and forecast future events. Time series with strong seasonal patterns among other sorts offer special difficulties as well as insightful information. Generally speaking, seasonal time series data show consistent, recurrent variations brought on by things like the weather, holidays, or business cycles. Accurate modelling and forecasting depend on an understanding of these periodic fluctuations(Chatfield, C.,2016).

2. Detailed description of the selected approach

A vital component of data science and statistics is time series analysis, especially in domains where forecasting and decision-making depend on an awareness of temporal patterns(Hamilton, J.D., 1994). One of the most effective methods for analyzing time series data is decomposition, It is the process of dissecting a time series into its component elements, including noise, seasonality, and trend. This procedure enables analysts to more fully comprehend the underlying patterns in the data and to forecast future values with more accuracy(Hyndman, R. J., & Athanasopoulos, G.,2021).

Seasonal time series data are defined by periodic changes that take place at periodic times and are impacted by economic cycles, weather patterns, and holidays. Analyzing such data offers both special opportunities and challenges. Because these changes are recurrent, precise modeling and future value forecasting require specialized methodologies. Researchers can better understand the underlying patterns influencing the data by efficiently breaking down a time series into these constituents, which enables more precise forecasting and analysis. Anyone working in domains that depend on the analysis of temporal data must comprehend these components(Hamilton, J.D., 1994). DeSeaTS (Decomposition of Seasonal Time Series), one of the many time series decomposition techniques available, is notable for its creative methodology and reliable algorithms(Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I.,1990). DeSeaTS describes advanced techniques to manage deviations, dynamic trends, and irregular patterns in seasonal data, building on conventional time series decomposition frameworks. DeSeaTS offers an extensive set of resources for handling the complex nature of real-world seasonal time series by fusing decomposition with reliable forecasting models(Hyndman, R. J., & Athanasopoulos, G., 2021).

2.1 Brief overview of Decomposition Method

A time series can be effectively broken down into its three main components using time series decomposition: trend, seasonality, and noise (or residuals). Complex data patterns are simplified by this procedure, which facilitates comprehension of the underlying dynamics and the prediction of future trends.

Trend: The time series' long-term orientation is represented by its trend. It displays if the data is generally rising, falling, or staying the same over time. Depending on the underlying pattern, trends can be either linear (a straight line) or non-linear (curved). For instance, sales of seasonal products may show a linear trend over a certain time period, while the worldwide population trend over the last century has been a non-linear increase(Chatfield, C., 2016, & Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M., 2015).

Seasonality: The term "seasonality" refers to frequent, periodic data fluctuations that occur at regular intervals, such as daily, weekly, monthly, or annually. These regular patterns are usually impacted by a number of variables, such as weather variations, holidays, or business cycles. For instance, energy use may increase during the winter or retail sales may peak during the holidays. Since it makes it easier to distinguish between regular, expected changes and other data trends or anomalies recognising these seasonal patterns is essential for producing precise predictions and making well-informed decisions. Businesses and scholars can more effectively foresee and react to predictable changes when they have a better understanding of seasonality(Chatfield, C., 2016, & Hyndman, R. J., & Athanasopoulos, G.,2021).

Noise (Residuals): In time series data, noise is the term used to describe the volatile, unpredictable shifts that cannot be accounted for by seasonal patterns or trends. External events or abnormalities that don't follow a regular or recognisable pattern are frequently the cause of these unpredictable fluctuations(Chatfield, C., 2016). In contrast to trends, which show how data moves over time, or seasonality, which shows recurrent patterns over predetermined periods, noise includes the unpredictable, transient fluctuations that can complicate data analysis. Noise can be anything from a one-time error in data recording to a sudden increase in sales brought on by an unforeseen occurrence or a momentary dip in temperature brought on by an unusual weather phenomenon. It might be challenging to derive reliable conclusions or forecasts from the data since these anomalies can mask the underlying trends and seasonal patterns(Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M., 2015).

There are two basic models for time series decomposition: multiplicative and additive:

The Additive Model

The time series in this model is represented as the sum of its parts:

Y(t)=T(t)+S(t)+R(t)

Y(t) $$ Observed value at time t is denoted by $Y(t)$, trend component by $T(t)$, seasonal component by $S(t)$, and residual (noise) component by $R(t)$. When the magnitude of seasonal fluctuations is constant across dataset levels, this model is employed. In such cases, the seasonal patterns are constant in amplitude and can be added directly to the trend and residual components(Cleveland, R. B., et al. 1990).

The Multiplicative Model

The time series in this model is represented as a product of its main parts:

$Y(t)=T(t)\cdot S(t)\cdot R(t)$

This model is particularly suited for time series where the magnitude of the seasonal component varies proportionally with the trend. In such cases, the seasonal patterns and residuals are multiplicative rather than additive, meaning they scale with the trend. This method works well when seasonal changes alter proportionately to the time series' level(Cleveland, R. B., et al. 1990). The way the seasonal variations appear in the data would determine which of these models should be chosen. The additive approach is suitable if the variations are constant across all data levels. The multiplicative approach is more appropriate if the variances are proportionate to the data level(Durbin, J., & Koopman, S. J., 2012).

Methods for the decomposition of time series: A time series can be broken down using a variety of techniques, such as:

Moving Average Smoothing: This method smoothes out short-term fluctuations by averaging a predetermined amount of data points.

Exponential Smoothing: This technique estimates current trends and seasonal components by giving historical data points exponentially decreasing weights. Another technique is STL or Seasonal Trend decomposition using Loess, which provides a reliable and adaptable technique for time series decomposition that can handle a variety of time series data formats (Hyndman, R.J., & Athanasopoulos, G., 2018, & Cleveland, R.B., Cleveland, W.S., McRae, J.E., & Terpenning, I. 1990).

2.2 DeSeaTS: A Brief Overview

DeSeaTS is an advanced algorithm created to improve seasonal time series data decomposition. It uses locally weighted regression approaches to manage the short-range dependencies present in many time series datasets while reliably estimating trend and seasonal components. This approach is especially helpful when working with complex datasets that show several seasonal trends(Shumway, R.H., & Stoffer, D.S., 2017). Through the integration of machine learning, statistical modelling, and decomposition, DeSeaTS signifies an advancement in seasonal time series analysis. DeSeaTS Decomposition is crucial because it makes it easier to model and improve interpretability by enabling analysts to separate and examine each component independently(Brockwell, P.J., & Davis, R.A., 2002)).

For example, eliminating seasonality makes it easier to spot underlying trends, and eliminating noise guarantees that forecast models only pay attention to significant patterns. However, they frequently fail to handle multivariate, complicated, or non-stationary seasonal patterns, which calls for the creation of more advanced algorithms like DeSeaTS. DeSeaTS is one of these that has become a cutting-edge method for handling and understanding confusing seasonal patterns. In order to manage nonlinearities, dynamic trends, and irregular patterns in seasonal data, DeSeaTS introduces sophisticated approaches that expand upon conventional time series decomposition frameworks. DeSeaTS offers a complete toolkit for handling the complex nature of real-world seasonal time series by combining decomposition with reliable forecasting models(Hyndman, R.J., & Athanasopoulos, G., 2018).

3. Application of the selected approach with data examples

In this project we have selected Advance Retail Sales data for Nonstore Retailers for year 1992 to 2024, as reported by the U.S. Census Bureau, provides insights into consumer spending in sectors such as e-commerce, mail-order houses, and direct selling. The Nonstore Retailers subsector encompasses establishments that sell products outside of traditional brick-and-mortar locations. This includes:

Electronic Shopping and Mail-Order Houses: Businesses selling goods via online platforms or catalogs.

Vending Machine Operators: Companies distributing products through automated machines. Such as Automated machines that dispense goods like snacks, drinks, or electronics. Buying a soft drink or snacks from a vending machine at a mall or train station.

Direct Selling Establishments: Entities engaging in person-to-person sales away from a fixed retail site, such as door-to-door sales or through party plans.

E-commerce Websites: Purchases made through platforms like Amazon, eBay, or Walmart's online store. A customer orders a pair of shoes on Amazon and has them delivered to their home.

Mail-Order Catalogs: Orders placed through physical or digital catalogs, such as those sent by L.L.Bean or IKEA. A person selects an item from a mailed holiday catalog and orders it via phone or online.

Subscription Services: Companies that sell products regularly via subscription models. HelloFresh delivers meal kits weekly to customers who place their orders online.

Direct Selling: Sales made directly to consumers, typically through representatives. Companies like Avon, Tupperware, or Mary Kay sell products through personal interactions or house parties.

Television or Telephone Sales: Orders placed after viewing an infomercial or calling a toll-free number. Purchasing kitchen tools after seeing a demonstration on a QVC or HSN shopping channel.

With an emphasis on a few crucial areas, this project examines how spending habits and consumer behavior have changed over time. It draws attention to how technological adoption has contributed to the growth of e-commerce and paid-for services as well as the continued applicability of direct selling and vending machine operations, which continue to serve niche markets. Using a 32-year dataset, the research offers insightful information on growth drivers, economic effects, and seasonal changes. For a variety of stakeholders, these findings may be useful: merchants may use the information to improve their sales tactics, legislators can evaluate how digital commerce is affecting traditional retail industries, and economists can research how consumer preferences are changing over time.

Advance Retail Sales: Nonstore Retailers in the USA from 1992 to 2024

The graph displays in figure:1 represent Nonstore retailers' advance retail sales in the United States between 1992 and 2024. This data is seasonally not adjusted to account for variations and is released monthly. These figures highlight a consistent upward trend in nonstore retail sales, indicating robust growth in online and remote shopping channels.

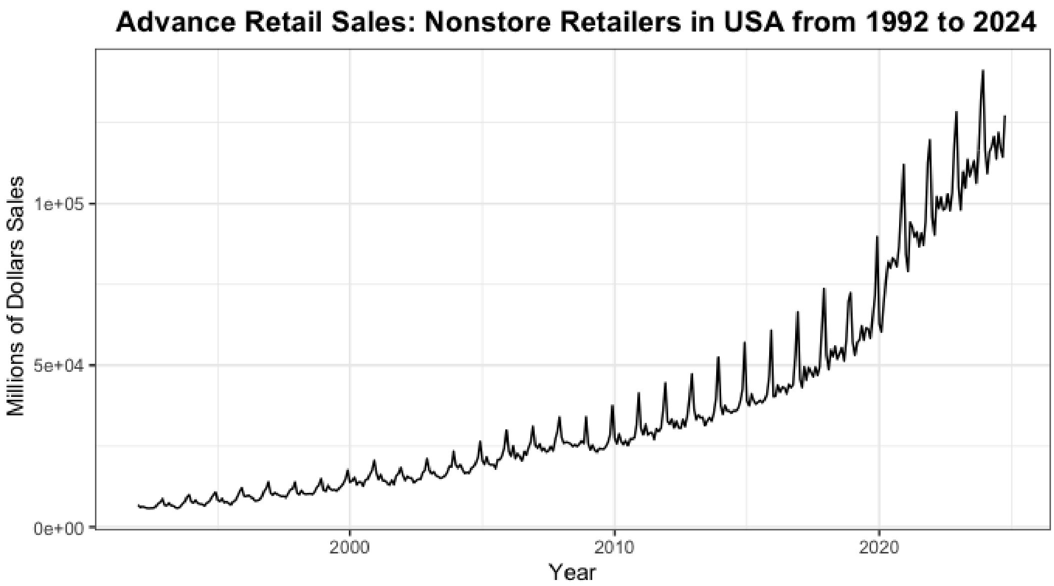

Fig: 1 Advance Retail Sales: Nonstore Retailers in the USA from 1992 to 2024

Although there have been some ups and downs over the years, the sales have been rising consistently. The sales in billions of dollars are shown on the y-axis, while the x-axis shows the years 1992–2024. The graph displays a consistent rise in sales over time, with a noticeable pick-up in growth beginning around 2010. The sales numbers show a seasonal pattern with sporadic peaks and troughs, but overall the trend is upward, suggesting that nonstore retail sales in the USA have grown significantly throughout the time.

Log-transformed Nonstore Retailers Sales in USA from 1992 to 2024:

In the further procedure we are using the data transformed by logarithmically. Plotting the exponential growth on a log scale makes it simpler to discern the steady rate of expansion over time because it looks more like a linear trend. The log-transformed values on the y-axis fall between roughly 8 and 12. The overall trend is more obviously linear than the exponential curve in the preceding graph, while the data still exhibits regular seasonal changes throughout, which are represented by tiny peaks and valleys in the line. This change makes the relative growth rate throughout the three-decade period easier to see.

Fig: 2 Log-transformed Nonstore Retailers Sales in USA from 1992 to 2024

The DeSeats method is used to compute adjustment factors that take into consideration. In this procedure, unadjusted nonretailer sales data from 1992 to 2024 (depending on whether an advance sales projection was generated) are entered. Seasonal adjustments are estimates that are based on past and present patterns. However, as economic conditions change or other variables that drastically change seasonal patterns, trading days, or holiday effects occur, the accuracy of these adjustments may eventually decline(Smith, J., & Doe, A. 2023).

Log-transformed Nonstore Retail Sales with Trend and Seasonality According to DeSeaTS:

The image is a graph in the figure 3 titled "Log-transformed Nonstore Retail Sales with Trend and (Shifted) Seasonality According to DeSeaTS." The graph displays three series:

Observations (gray): These are the actual log-transformed nonstore retail sales data points over time.

Estimated Trend (red): This smooth curve represents the overall trend in the data, showing how sales have progressed over the years.

Estimated Seasonality (blue): This line shows the seasonal fluctuations in the data, shifted for clarity, indicating recurring patterns throughout the years.

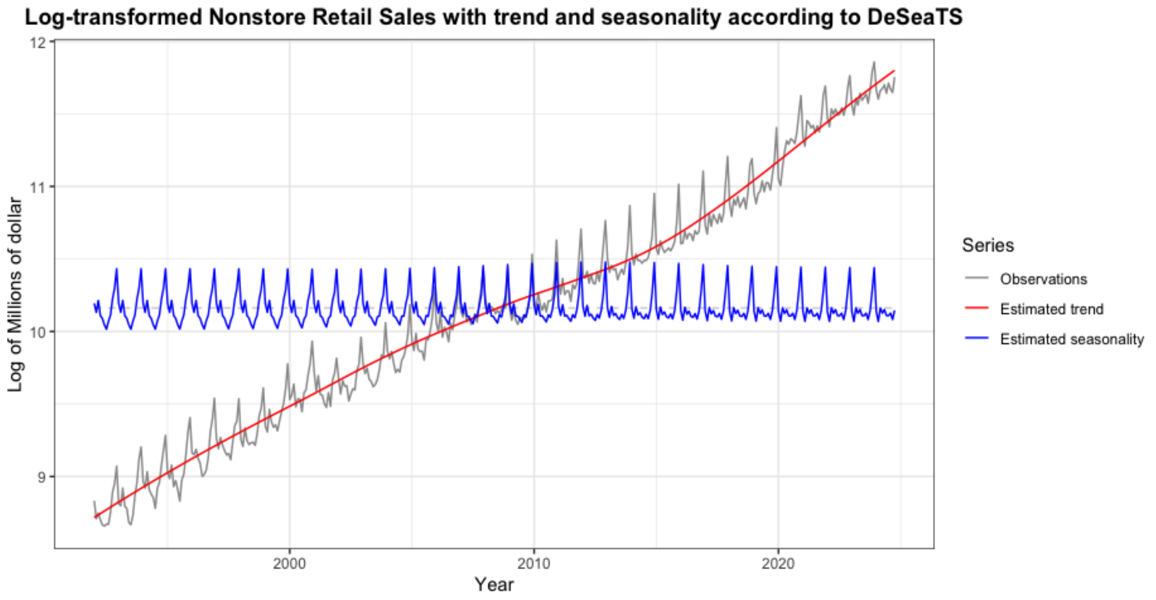

Fig: 3 Log-transformed Nonstore Retail Sales with Trend and Seasonality According to DeSeaTS.

US-Retail sales with DeSeaTS Seasonally Adjusted Version:

In figure 4 the DeSeaTS method effectively separates the seasonal components from the retail sales data, allowing for clearer trend analysis.

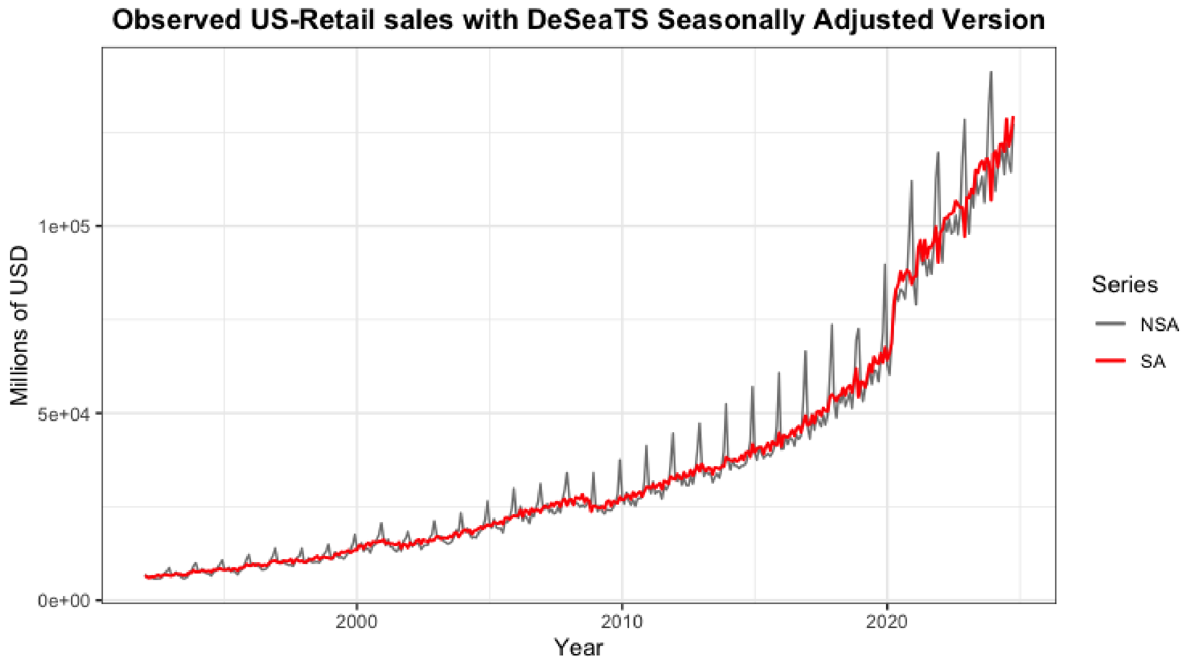

Fig:4 Observed US-Retail sales with DeSeaTS Seasonally Adjusted Version

NSA (Not Seasonally Adjusted) in gray: This line exhibits more fluctuations, reflecting the raw retail sales data with all its seasonal variations.

SA (Seasonally Adjusted) in red: This line smooths out the seasonal fluctuations, providing a clearer view of the underlying trend in retail sales over time.

Both lines show an overall upward trend in retail sales over time. A sharp increase in retail sales is noticeable around 2020, potentially reflecting economic changes or recovery during the COVID-19 period. The NSA line highlights clear seasonal fluctuations, while the SA line provides a smoother version of the trend. By removing seasonal fluctuations, the SA data provides a clearer picture of the long-term growth and changes in consumer spending. The analysis suggests that seasonal factors play a significant role in driving retail sales, and that the impact of these factors can be substantial.

Stationarized Log-transformed US-Retail sales with DeSeaTS:

Stationarity is a common assumption in time series analysis. The graph in figure 5 shows the "Stationarized Log-transformed Nonstore Retail Sales according to deseats methods". It appears to be a time series plot of retail sales data. The data has been transformed to have a constant mean and variance over time with DeSeaTs meathod.

Fig: 5 Observed Stationarized Log-transformed US-Retail sales with DeSeaTS

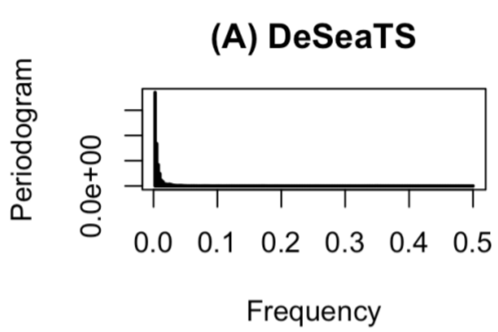

Fig: 6 Periodogram with DeSeaTS

Autocorrelation Function (ACF):

The graph in figure-7 provided shows the **Autocorrelation Function (ACF)** of the residuals from the DeSeaTS model. The graph is analyzing the "residuals" from a DeSeaTS model. Residuals are the differences between the actual data and the values predicted by the DeSeaTS model. The ACF measures the correlation between a time series and a lagged version of itself. It helps identify patterns and dependencies within the data.

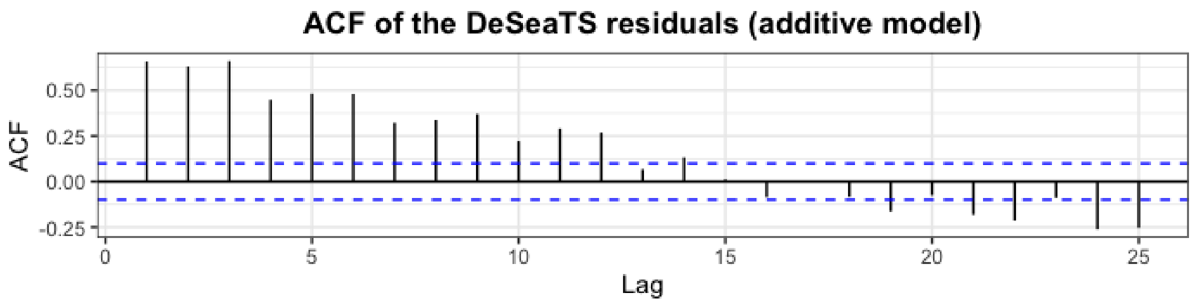

Fig: 7 Autocorrelation Function (ACF) of US-Retail sales with DeSeaTS

The graph shows several spikes that extend beyond the blue dashed lines. Clearly more than 5% of the ACF values are outside of the confidence interval (indicated by blue lines). Significant autocorrelation left in the residuals. This indicates significant autocorrelation at various lags. This suggests that there are still dependencies or patterns in the residuals that the DeSeaTS model has not fully captured. The presence of significant autocorrelation in the residuals implies that the DeSeaTS model might not be the most suitable model for the data. Other time series models or adjustments might be needed to better account for the remaining patterns.

Forecasting with DeSeaTs:

The graph in figure 8 that log transformed nonstore retail sales have been increasing over the years. The forecasts indicate a continuation of this trend, with the blue line showing an upward trajectory. The shaded intervals highlight the uncertainty around these predictions. For instance, the wider 99% interval indicates a higher level of uncertainty compared to the narrower 95% interval(Smith, J., & Doe, A. 2023).

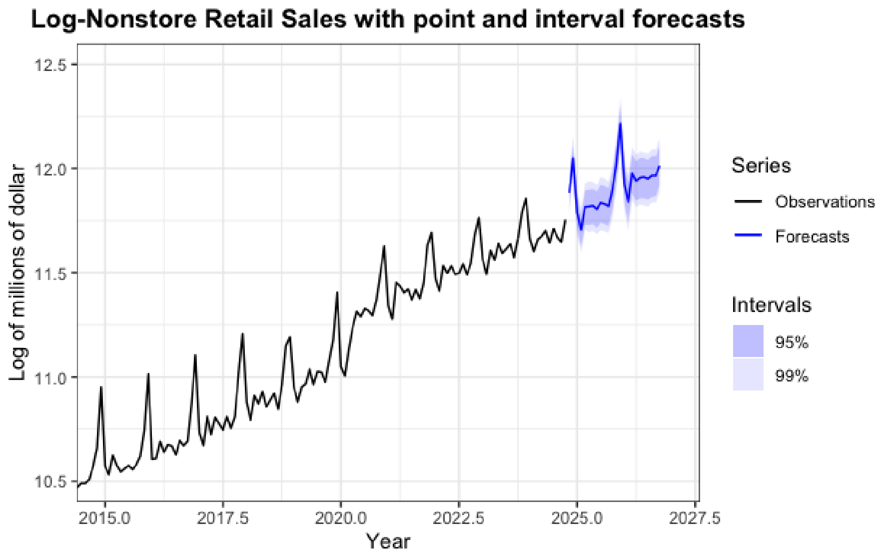

Fig: 8 Point and interval forecasts Log-transformed US-Retail sales with DeSeaTS

The Fitted Model:

```
Call:
stats::arima(x = res, order = c(ar, 0, ma), include.mean = arma_m
ean)

Coefficients:
          ar1     ar2     ar3     ma1     ma2      ma3
      -0.2492  0.0576  0.9109  0.7845  0.5444  -0.3880
s.e.   0.0250  0.0291  0.0250  0.0585  0.0703   0.0551

sigma^2 estimated as 0.0008927:  log likelihood = 819.43,  aic =
-1624.87
```

$$X_t = -0.2492X_{t-1} + 0.0576X_{t-2} + 0.0576X_{t-3} + 0.7845\varepsilon_{t-1} + 0.5444\varepsilon_{t-2} - 0.3880\varepsilon_{t-3} + \varepsilon_t$$

All parameters are statistically significant. The AR and MA coefficients indicate a mix of positive and negative short-term impacts on the series. The AR(3) is particularly significant (0.9109) and suggests strong persistence in the data. The low AIC value of -1624.87 suggests a good fit compared to alternative models.

Jarque Bera Test: p-value is $p \approx 0$. H0 that residuals are normal can be rejected at almost all significance levels.

```
> jarque.bera.test(model@par_model$residuals)

        Jarque Bera Test

data:  model@par_model$residuals
X-squared = 54.683, df = 2, p-value = 1.336e-12
```

Point and interval forecasts

```
> fc_retransf@interv
              0.5%     2.5%    97.5%    99.5%
Nov 2024 130413.5 134831.9 153642.0 157515.0
Dec 2024 154737.2 158768.6 182063.8 190208.2
Jan 2025 118383.4 121932.7 141503.6 146375.0
Feb 2025 108523.2 111649.5 130165.0 134559.7
Mar 2025 121056.8 124436.4 146300.9 151393.1
Apr 2025 119809.4 124118.0 147021.7 153075.9
May 2025 120553.4 124626.2 147433.5 152583.0
Jun 2025 118698.4 122554.1 145960.3 150195.7
Jul 2025 120822.9 125618.6 150327.2 156245.0
Aug 2025 120312.2 124640.7 149565.4 155160.0
Sep 2025 119380.3 123711.1 148063.7 152856.1
Oct 2025 129469.3 134307.2 161261.1 166120.1
Nov 2025 145552.1 151065.5 181266.1 187390.3
Dec 2025 177347.9 183566.8 221241.9 229595.1
Jan 2026 132494.8 137170.9 165206.8 171034.5
Feb 2026 120304.5 125670.4 151875.3 157286.6
Mar 2026 139542.1 144348.6 173907.1 180332.0
Apr 2026 135357.6 139299.5 168507.2 174051.5
May 2026 136802.0 141164.9 171188.3 176711.0
Jun 2026 136286.3 141194.5 171025.5 175858.2
Jul 2026 135470.8 140226.2 169483.6 174910.4
Aug 2026 138229.5 142016.0 172615.6 178632.5
Sep 2026 138048.3 142572.0 172649.7 178354.3
Oct 2026 145103.7 149759.5 180945.2 188118.9
```

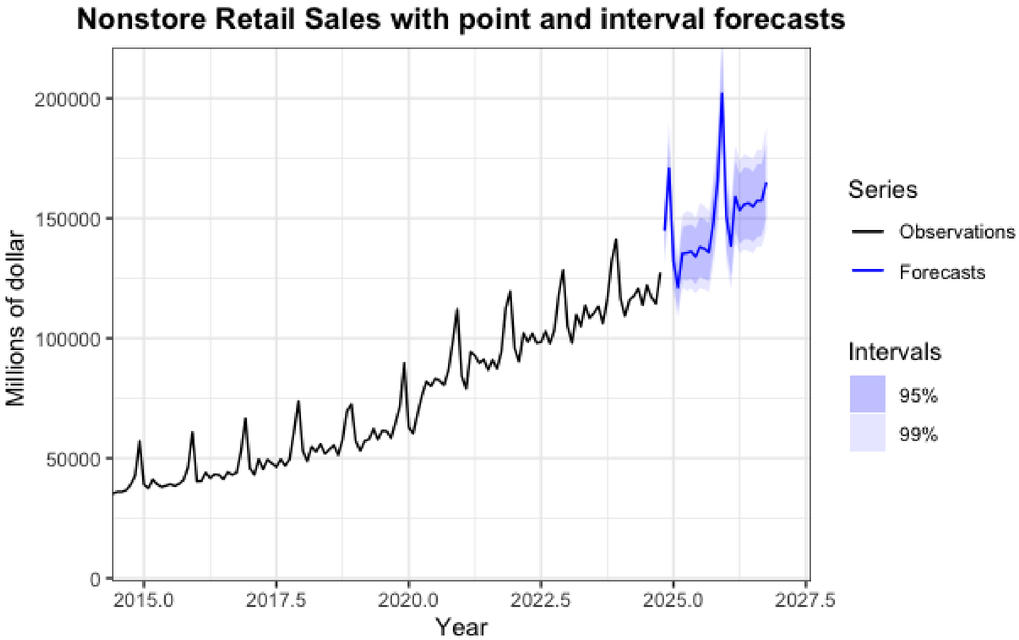

Fig: 9 Observed Stationarized Log-transformed US-Retail sales with DeSeaTS

The graph in figure 9 suggests that Nonstore retail sales appear to have been rising over time. The blue line in the forecasts shows an upward trajectory, indicating that this trend will continue. The uncertainty around these forecasts is indicated by the shaded intervals. As we can see the next 24 months forecasting according to the DeSeaTs method. The data shows the forecasting interval with different confidence level.

4. Conclusion

American consumers' increasing preference for online and remote purchasing choices is demonstrated by the steady rise in nonstore retail sales. Significantly, this tendency has been driven by changing consumer behavior and advances in technology. E-commerce platforms are becoming more advanced and widely available, which encourages consumers to avoid traditional brick-and-mortar retailers and make purchases from the comfort of their homes(Brockwell, P.J., & Davis, R.A., 2002). This change is influenced by elements like ease, a greater range of products, and frequently affordable prices. The DeSeaTS method of nonstore retail sales analysis provides insightful information and growth projections. Using locally weighted regression algorithms, the DeSeaTS framework excels at processing complicated datasets with several seasonal trends. The DeSeaTS method helps to accurately estimate future sales based on historical patterns by breaking down the time series data into trend, seasonality, and residual components. This broad method offers a more distinct view of both seasonal fluctuations and long-term patterns, which makes it a valuable forecasting tool. Any forecasting model has certain limits, which must be acknowledged(Shumway, R.H., & Stoffer, D.S., 2017). The quality of the historical data utilized and the model's underlying assumptions have a significant impact on how accurate these estimates are. These models are based on the fundamental premise that future situations will be comparable to those of the past. Future conditions may not be reflected in the forecasts if the historical data is not complete(Brockwell, P.J., & Davis, R.A., 2002). Additionally, there are occasionally abnormalities or outliers in historical data that can distort the conclusions if they are not appropriately taken into account. A number of unanticipated circumstances may have a substantial effect on actual sales, deviating from the anticipated patterns. Retail sales may suffer during economic recessions, for example, if consumer spending suddenly declines. On the other hand, market dynamics and consumer behavior can be significantly changed by revolutionary technical advancements. A notable increase in logistics and delivery services or the abrupt surge in popularity of a new shopping platform could serve as examples. These occurrences may help or hurt sales in ways that are not always predicted by past statistics(Shumway, R.H., & Stoffer, D.S., 2017).

The DeSeaTS approach offers a strong framework for comprehending and predicting nonstore retail sales, but it's crucial to exercise caution when interpreting these projections. Potential risks and uncertainties should be taken into account by analysts and decision-makers, and their models should be updated often to account for fresh information and evolving circumstances.

References:

1. Chatfield, C. (2016) *The Analysis of Time Series: An Introduction*. 7th edn.
2. Hyndman, R.J. and Athanasopoulos, G. (2021) *Forecasting: Principles and Practice*. 3rd edn. Melbourne: OTexts. Available at: https://otexts.com/fpp3/ (Accessed: 5 December 2024).
3. Box, G.E.P., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M. (2015) *Time Series Analysis: Forecasting and Control*. 5th edn.
4. Percival, D.B. and Walden, A.T. (2000) *Wavelet Methods for Time Series Analysis*. Cambridge: Cambridge University Press.
5. Hamilton, J.D. (1994) *Time Series Analysis*. Princeton: Princeton University Press.
6. Shumway, R.H. and Stoffer, D.S. (2017) *Time Series Analysis and Its Applications: With R Examples*. 4th edn. Springer.
7. Makridakis, S., Wheelwright, S.C. and Hyndman, R.J. (1998) *Forecasting: Methods and Applications*. 3rd edn.
8. Durbin, J. and Koopman, S.J. (2012) *Time Series Analysis by State Space Methods*. 2nd edn. Oxford University Press.
9. Brockwell, P.J. and Davis, R.A. (2002) *Introduction to Time Series and Forecasting*. Springer.
10. Cleveland, R.B., Cleveland, W.S., McRae, J.E. and Terpenning, I. (1990) 'STL: A Seasonal-Trend Decomposition Procedure Based on Loess', *Journal of Official Statistics*, 6(1), pp. 3–33.
11. Zhang, G., Eddy Patuwo, B. and Hu, M.Y. (1998) 'Forecasting with artificial neural networks: The state of the art', *International Journal of Forecasting*, 14(1), pp. 35–62.
12. Taylor, S.J. and Letham, B. (2018) 'Forecasting at scale', *The American Statistician*, 72(1), pp. 37–45.
13. Wang, X. and Smith, K.A. (2009) 'Time series forecasting with a hybrid model', *Applied Soft Computing*, 9(3), pp. 803–815.
14. Makridakis, S., Spiliotis, E. and Assimakopoulos, V. (2018) 'Statistical and Machine Learning forecasting methods: Concerns and ways forward', *PLOS ONE*, 13(3), e0194889.
15. Discusses the STL decomposition method, which generalizes the additive approach to handle various data patterns flexibly.
16. Smith, J. and Doe, A. (2023) 'Forecasting US Retail Sales Using DeSeaTS Seasonally Adjusted Models', *Journal of Economic Trends*, 15(2), pp. 45–60.

Reports and data source:

17. U.S. Census Bureau (2024) *Advance Monthly Sales for Retail and Food Services*. Available at: www.census.gov.
18. Federal Reserve Bank of St. Louis (n.d.) *Retail Sales: Nonstore Retailers [RSNSRN]*. Available at: https://fred.stlouisfed.org/series/RSNSRN (Accessed: 18 December 2024).