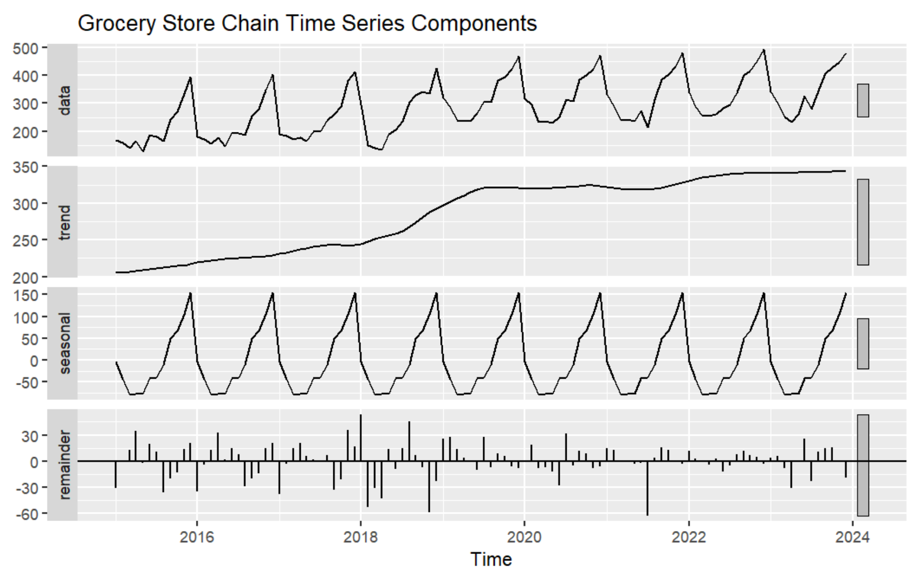
# Case Study #1: Sales Forecasting

**1. Identify time series components and plot the data.**

**a. Create time series data set sales.ts in R using the ts() function.**
We have used sales.ts to create a dataset from January 2015 until December 2023 with a frequency of 12 for monthly data.

We also used the autoplot() function to visualize the time series data:

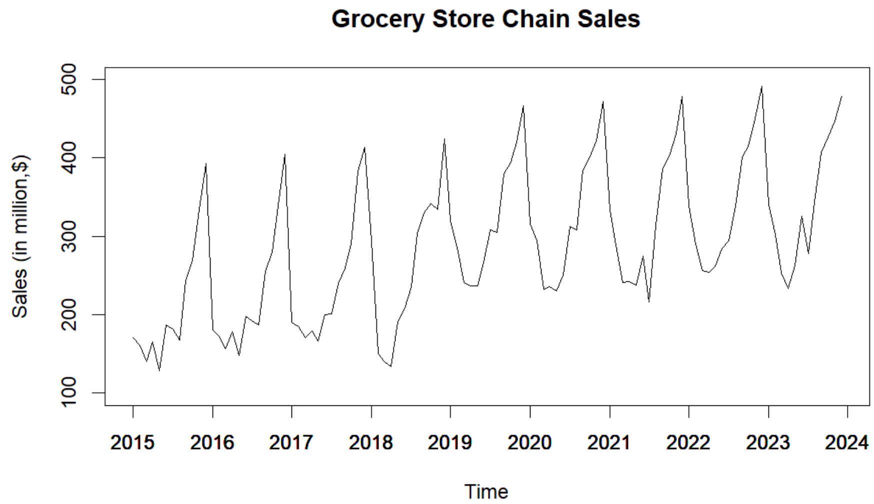
```
> #1(a)Creating time series data set sales.ts in R using the ts() function.
> sales.ts <-ts(Case1.data$Sales,
+               start = c(2015, 1), end = c(2023, 12), freq = 12)
> sales.ts
       Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep   Oct   Nov   Dec
2015 169.9 160.2 140.1 164.8 128.6 187.2 181.7 167.1 243.2 269.1 333.9 392.5
2016 180.5 172.4 156.1 178.3 147.3 197.1 192.6 186.7 255.2 279.8 347.6 404.4
2017 189.5 184.8 170.4 179.4 165.6 199.4 200.4 240.3 259.7 289.5 382.7 413.8
2018 294.3 149.5 140.1 133.3 191.4 207.0 236.0 303.6 329.9 341.6 334.5 424.5
2019 320.1 285.4 240.7 236.9 236.3 265.4 307.8 304.7 380.2 394.5 420.2 467.0
2020 316.3 294.1 232.2 235.1 229.9 250.8 312.4 308.1 384.7 400.3 421.9 472.0
2021 333.5 289.0 240.6 242.1 237.3 274.2 215.5 314.1 385.9 402.7 430.6 478.8
2022 338.8 290.3 255.7 253.9 262.1 284.0 294.2 338.6 401.4 414.4 450.1 491.5
2023 340.8 302.2 253.1 233.2 262.3 325.6 278.2 343.8 406.5 426.2 447.4 478.9
>
```




**b. Employ the plot() function to create a data plot of the historical data, provide it in your report, and explain what data patterns can be visualized in this plot.**

We used plot() function to create a data plot of the historical data. We observe an upward linear trend with mostly additive seasonality, except the sales were at the lowest in the initial months of 2018.

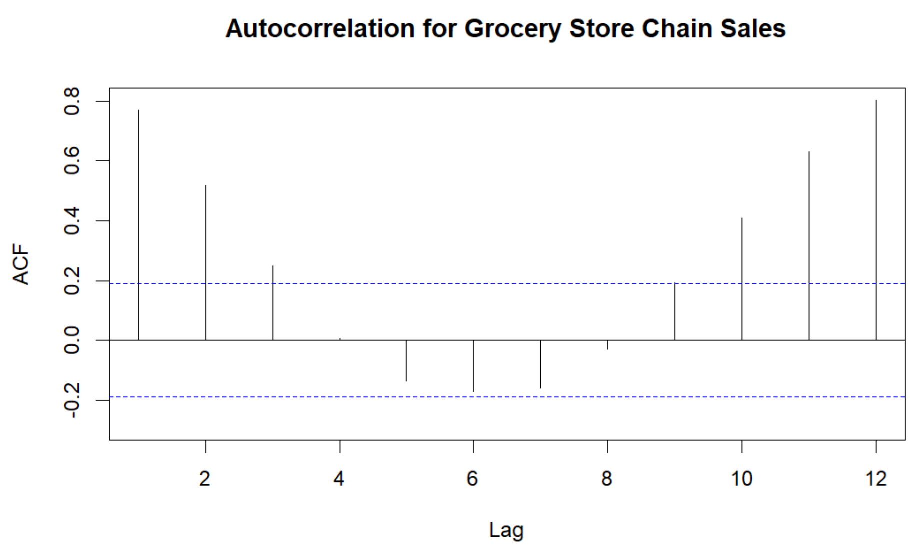
It is also observed that the sales are typically lower at the beginning of each year, and gradually increase through the months, with the highest during the months of October-December. This can be potentially due to the Holidays season and sales/discounts.




**c. Apply the Acf() function to identify possible time series components. Provide in the report the autocorrelation chart and explain time series components existing in the historical data.**

We observe positive autocorrelation for lags 1, 2, 3, 9, 10, 11, and 12. The positive correlation for lags 1 and 12 is the highest; it is negative for lags 5, 6, 7, and 8, and zero for 4.

We can assume that there's an upward trend, a level component, as well as seasonality in the given dataset.



```
+                main = "Au
> data.frame(Lag, ACF)
   Lag    ACF
1    0  1.000
2    1  0.770
3    2  0.518
4    3  0.248
5    4  0.005
6    5 -0.136
7    6 -0.170
8    7 -0.158
9    8 -0.028
10   9  0.192
11  10  0.410
12  11  0.630
13  12  0.801
> 
```

**2. Use trailing MA for forecasting time series.**

**a. Develop data partition with the validation partition of 24 monthly periods (2 years) and training partition of 84 monthly periods (7 years). Provide the data partition's R code in your report.**

We have used the following code to develop the data partition:

```
nValid <- 24
nTrain <- length(sales.ts) - nValid
nTrain
train.ts <- window(sales.ts, start = c(2015, 1), end = c(2015, nTrain))
valid.ts <- window(sales.ts, start = c(2015, nTrain + 1),
                   end = c(2015, nTrain + nValid))
```

**b. Use the rollmean() function to develop 3 trailing MAs with the window width of 4, 6, and 12 for the training partition. Present the R code for these MAs in your report.**

We have used the following code to develop the trailing MAs:

```
#2(b)
# Using rollmean() to create trailing moving average with window widths
#of k = 4, 6, and 12.
ma.trailing_4 <- rollmean(train.ts, k = 4, align = "right")
ma.trailing_6 <- rollmean(train.ts, k = 6, align = "right")
ma.trailing_12 <- rollmean(train.ts, k = 12, align = "right")
```

**c. Use the forecast() function to create a trailing MA forecast for each window width from question 2b in the validation period, and present one of them, e.g., with window width of 4, in your report.**

We created the trailing MA forecast for k = 4, 6, and 12. The same for the window width of 4 is as follows:

```
> ma.trail_4.pred
         Point Forecast     Lo 0     Hi 0
Jan 2022       415.7363 415.7363 415.7363
Feb 2022       390.1537 390.1537 390.1537
Mar 2022       345.4365 345.4365 345.4365
Apr 2022       287.1568 287.1568 287.1568
May 2022       269.7001 269.7001 269.7001
Jun 2022       269.0454 269.0454 269.0454
Jul 2022       284.8164 284.8164 284.8164
Aug 2022       302.3676 302.3676 302.3676
Sep 2022       334.1653 334.1653 334.1653
Oct 2022       360.0781 360.0781 360.0781
Nov 2022       393.9507 393.9507 393.9507
Dec 2022       437.6319 437.6319 437.6319
Jan 2023       428.8682 428.8682 428.8682
Feb 2023       403.2856 403.2856 403.2856
Mar 2023       358.5684 358.5684 358.5684
Apr 2023       300.2887 300.2887 300.2887
May 2023       282.8319 282.8319 282.8319
Jun 2023       282.1773 282.1773 282.1773
Jul 2023       297.9482 297.9482 297.9482
Aug 2023       315.4995 315.4995 315.4995
Sep 2023       347.2972 347.2972 347.2972
Oct 2023       373.2100 373.2100 373.2100
Nov 2023       407.0826 407.0826 407.0826
Dec 2023       450.7638 450.7638 450.7638
>
```

**d. Apply the accuracy() function to compare accuracy of the three trailing MA forecasts in the validation period. Present the accuracy measures in your report, compare MAPE and RMSE of these forecasts, and identify the best trailing MA forecast.**

The accuracy measures have been given below. Comparing the MAPE and RMSE of the 3 forecasts with windows width of 4, 6, and 12, we notice that the most accurate forecast comes out to be the trailing MA forecast with window width of 4, with the lowest MAPE and RMSE of 16.198% and 59.89, respectively.

```
> round(accuracy(ma.trail_4.pred$mean, valid.ts), 3)
             ME  RMSE    MAE    MPE   MAPE  ACF1 Theil's U
Test set -6.869 59.89 52.245 -4.873 16.198 0.714     1.273
> round(accuracy(ma.trail_6.pred$mean, valid.ts), 3)
            ME   RMSE    MAE    MPE   MAPE  ACF1 Theil's U
Test set 7.812 77.742 71.217 -2.136 21.529 0.779     1.728
> round(accuracy(ma.trail_12.pred$mean, valid.ts), 3)
             ME  RMSE    MAE   MPE   MAPE  ACF1 Theil's U
Test set 20.257 80.55 66.439 1.116 18.847 0.737     1.609
```

**3. Apply the two-level forecast with regression and trailing MA for residuals.**

**a. Develop using the tslm() function a regression model with linear trend and seasonality. Present the model summary in your report. Present and briefly explain the model equation in your report. Using this model, forecast monthly sales in the validation period with the forecast() function. Present the forecast in your report.**

We have developed a regression model with linear trend and seasonality. The regression model includes a trend as well as 11 seasonal variables from February until December.

```
Call:
tslm(formula = train.ts ~ trend + season)

Residuals:
    Min      1Q  Median      3Q     Max 
-84.176 -13.857   0.967  17.228  51.108 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 191.4617    11.6113  16.489  < 2e-16 ***
trend         1.7910     0.1276  14.036  < 2e-16 ***
season2     -40.1767    15.0027  -2.678  0.00920 ** 
season3     -72.7106    15.0044  -4.846 7.16e-06 ***
season4     -67.4016    15.0071  -4.491 2.68e-05 ***
season5     -73.9783    15.0109  -4.928 5.24e-06 ***
season6     -40.8121    15.0157  -2.718  0.00825 ** 
season7     -33.2746    15.0217  -2.215  0.02996 *  
season8      -9.6084    15.0288  -0.639  0.52466    
season9      47.7720    15.0369   3.177  0.00220 ** 
season10     65.7953    15.0461   4.373 4.12e-05 ***
season11    105.9900    15.0564   7.040 9.94e-10 ***
season12    158.7133    15.0677  10.533 3.71e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.07 on 71 degrees of freedom
Multiple R-squared:  0.9216,	Adjusted R-squared:  0.9083 
F-statistic: 69.55 on 12 and 71 DF,  p-value: < 2.2e-16
```


```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.07 on 71 degrees of freedom
Multiple R-squared:  0.9216,	Adjusted R-squared:  0.9083 
F-statistic: 69.55 on 12 and 71 DF,  p-value: < 2.2e-16
```


We have also forecasted monthly sales in the validation period with the forecast() function:

```
> trend.seas.pred
         Point Forecast     Lo 0     Hi 0
Jan 2022       343.6964 343.6964 343.6964
Feb 2022       305.3107 305.3107 305.3107
Mar 2022       274.5679 274.5679 274.5679
Apr 2022       281.6679 281.6679 281.6679
May 2022       276.8821 276.8821 276.8821
Jun 2022       311.8393 311.8393 311.8393
Jul 2022       321.1679 321.1679 321.1679
Aug 2022       346.6250 346.6250 346.6250
Sep 2022       405.7964 405.7964 405.7964
Oct 2022       425.6107 425.6107 425.6107
Nov 2022       467.5964 467.5964 467.5964
Dec 2022       522.1107 522.1107 522.1107
Jan 2023       365.1884 365.1884 365.1884
Feb 2023       326.8027 326.8027 326.8027
Mar 2023       296.0598 296.0598 296.0598
Apr 2023       303.1598 303.1598 303.1598
May 2023       298.3741 298.3741 298.3741
Jun 2023       333.3313 333.3313 333.3313
Jul 2023       342.6598 342.6598 342.6598
Aug 2023       368.1170 368.1170 368.1170
Sep 2023       427.2884 427.2884 427.2884
Oct 2023       447.1027 447.1027 447.1027
Nov 2023       489.0884 489.0884 489.0884
Dec 2023       543.6027 543.6027 543.6027
```

**b. Identify regression residuals in the training period, apply a trailing MA (window width of 3) for these residuals using the rollmean() function, and identify trailing MA forecasts of these residuals in the validation period (use the forecast() function). Provide the trailing MA forecast for residuals in the validation period in your report.**

The trailing MA forecast for residuals is as follows:

```
> #Residuals forecast for validation period.
> ma.trail.res.pred <- forecast(ma.trail.res, h = nValid, level = 0)
> ma.trail.res.pred
         Point Forecast      Lo 0      Hi 0
Jan 2022      -12.91321 -12.91321 -12.91321
Feb 2022      -12.91321 -12.91321 -12.91321
Mar 2022      -12.91321 -12.91321 -12.91321
Apr 2022      -12.91321 -12.91321 -12.91321
May 2022      -12.91321 -12.91321 -12.91321
Jun 2022      -12.91321 -12.91321 -12.91321
Jul 2022      -12.91321 -12.91321 -12.91321
Aug 2022      -12.91321 -12.91321 -12.91321
Sep 2022      -12.91321 -12.91321 -12.91321
Oct 2022      -12.91321 -12.91321 -12.91321
Nov 2022      -12.91321 -12.91321 -12.91321
Dec 2022      -12.91321 -12.91321 -12.91321
Jan 2023      -12.91321 -12.91321 -12.91321
Feb 2023      -12.91321 -12.91321 -12.91321
Mar 2023      -12.91321 -12.91321 -12.91321
Apr 2023      -12.91321 -12.91321 -12.91321
May 2023      -12.91321 -12.91321 -12.91321
Jun 2023      -12.91321 -12.91321 -12.91321
Jul 2023      -12.91321 -12.91321 -12.91321
Aug 2023      -12.91321 -12.91321 -12.91321
Sep 2023      -12.91321 -12.91321 -12.91321
Oct 2023      -12.91321 -12.91321 -12.91321
Nov 2023      -12.91321 -12.91321 -12.91321
Dec 2023      -12.91321 -12.91321 -12.91321
```

**c. Develop a two-level forecast for the validation period by combining the regression forecast and trailing MA forecast for residuals. Present in your report a table that contains validation data, regression forecast, trailing MA forecast for residuals, and two-level (combined) forecast in the validation period. Apply the accuracy() function to compare accuracy of the regression model with linear trend and seasonality and the two-level (combined) model with the regression and trailing MA for residuals. Present the accuracy measures in your report, compare MAPE and RMSE of these forecasts, and identify the best forecasting model for the validation period.**

We have represented validation data, regression forecast, MA forecast for residuals, and two-level combined  forecast in the validation period. We also calculated the accuracy measures, from which we can derive that out of the two forecasting models in the validation period, the two-level model is more accurate with MAPE and RMSE as 5.313% and 22.907, respectively.

```
> #Developing two-level forecast for validation period
> #by combining regression forecast and trailing MA forecast for residuals
> fst.2level <- trend.seas.pred$mean + ma.trail.res.pred$mean
> fst.2level
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep
2022 330.7832 292.3975 261.6546 268.7546 263.9689 298.9261 308.2546 333.7118 392.8832
2023 352.2752 313.8895 283.1466 290.2466 285.4609 320.4180 329.7466 355.2038 414.3752
          Oct      Nov      Dec
2022 412.6975 454.6832 509.1975
2023 434.1895 476.1752 530.6895
```

```
> valid.df
   Sales Regression.Fst MA.Residuals.Fst Combined.Fst
1  338.8       343.6964        -12.91321     330.7832
2  290.3       305.3107        -12.91321     292.3975
3  255.7       274.5679        -12.91321     261.6546
4  253.9       281.6679        -12.91321     268.7546
5  262.1       276.8821        -12.91321     263.9689
6  284.0       311.8393        -12.91321     298.9261
7  294.2       321.1679        -12.91321     308.2546
8  338.6       346.6250        -12.91321     333.7118
9  401.4       405.7964        -12.91321     392.8832
10 414.4       425.6107        -12.91321     412.6975
11 450.1       467.5964        -12.91321     454.6832
12 491.5       522.1107        -12.91321     509.1975
13 340.8       365.1884        -12.91321     352.2752
14 302.2       326.8027        -12.91321     313.8895
15 253.1       296.0598        -12.91321     283.1466
16 233.2       303.1598        -12.91321     290.2466
17 262.3       298.3741        -12.91321     285.4609
18 325.6       333.3313        -12.91321     320.4180
19 278.2       342.6598        -12.91321     329.7466
20 343.8       368.1170        -12.91321     355.2038
21 406.5       427.2884        -12.91321     414.3752
22 426.2       447.1027        -12.91321     434.1895
23 447.4       489.0884        -12.91321     476.1752
24 478.9       543.6027        -12.91321     530.6895
```

```
> round(accuracy(trend.seas.pred$mean, valid.ts), 3)
              ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -27.102 32.526 27.102 -8.638 8.638 0.231     0.763
> round(accuracy(fst.2level, valid.ts), 3)
              ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -14.189 22.907 16.548 -4.651 5.313 0.231     0.538
```

**d. For the entire data set, identify the regression model with linear trend and seasonality and trailing MA with the window width of 3 for the regression residuals. Use these models to forecast the 12 months of 2024 and develop a two-level forecast for the 12 future months as a combination of the specified forecasts. Present in your report a table that contains the regression forecast, trailing MA forecast for residuals, and two-level (combined) forecast in the 12 months of 2024.**

We have developed the regression model with linear trend and seasonality and trailing MA with the window width of 3 for the regression residuals. We then used it to develop models to forecast the 12 months of 2024 and developed a two-level forecast for the 12 future months as a combination of the specified forecasts. The output is as follows:

```
> #Creating a table with regression forecast, trailing MA for residuals,
> #total forecast for future 12 periods.
> future12.df <- data.frame(tot.trend.seas.pred$mean, tot.ma.trail.res.pred$mean,
+                           tot.fst.2level)
> future12.df
   tot.trend.seas.pred.mean tot.ma.trail.res.pred.mean tot.fst.2level
1                  366.8021                  -22.21898       344.5831
2                  327.2688                  -22.21898       305.0498
3                  294.0576                  -22.21898       271.8387
4                  297.1688                  -22.21898       274.9498
5                  297.5910                  -22.21898       275.3720
6                  334.2465                  -22.21898       312.0275
7                  337.3688                  -22.21898       315.1498
8                  369.3910                  -22.21898       347.1720
9                  429.3576                  -22.21898       407.1387
10                 448.4021                  -22.21898       426.1831
11                 487.3799                  -22.21898       465.1609
12                 537.8799                  -22.21898       515.6609
```

**e. Develop a seasonal naïve forecast for the entire historical data set and apply the accuracy() function to compare accuracy of the three forecasting models: seasonal naïve forecast, regression model with linear trend and seasonality, and two-level (combined) model with the regression and trailing MA for residuals. Present the accuracy measures in your report, compare MAPE and RMSE of these forecasts, and identify the best forecasting model for forecasting monthly sales in 2024.**

The accuracy measures are as follows. The two-level model is more accurate with MAPE and RMSE as 5.227% and 17.232, respectively.

```
> # 3(e)
> #Developing a seasonal naïve forecast for the entire historical data set
> #and applying accuracy() to compare accuracy of the three forecasting models.
> round(accuracy(tot.trend.seas.pred$fitted, sales.ts), 3)
         ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set  0 25.193 18.941 -1.133 7.752 0.405     0.525
> round(accuracy(tot.trend.seas.pred$fitted+tot.ma.trail.res, sales.ts), 3)
             ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -0.198 17.232 12.659 -0.559 5.227 0.048     0.356
> round(accuracy((snaive(sales.ts))$fitted, sales.ts), 3)
             ME   RMSE    MAE   MPE MAPE  ACF1 Theil's U
Test set 16.249 36.324 23.574 5.273  8.9 0.357     0.645
```

**4.**
**Use advanced exponential smoothing methods.**

**a. For the training partition(from question 2a), use the ets() function to develop a Holt-Winter's (HW) model with automated selection of error, trend, and seasonality options, and automated selection of smoothing parameters for the training partition.**

**Present the model summary (output) and explain the model in your report. Use the model to forecast monthly sales for the validation period using the forecast() function, and present this forecast in your report.**

The Holt-Winters (HW) model with the automated selection of the model options and automated selection of the smoothing parameters for the training period has been made and the summary is as follows.
This HW model has the (A, A, A) options, i.e., additive error, additive trend, and additive seasonality. The optimal value for exponential smoothing constant (alpha) is 0.1951, beta is 0.0001, and gamma is the same 0.0001.

```
ETS(A,A,A)

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

  Smoothing parameters:
    alpha = 0.1951
    beta  = 1e-04
    gamma = 1e-04

  Initial states:
    l = 201.4349
    b = 1.569
    s = 157.8048 103.5611 60.5357 42.4259 -13.9408 -25.3492
           -46.1451 -78.2233 -72.2383 -78.0027 -43.2154 -7.2129

  sigma:  27.9821

     AIC     AICc      BIC
948.1414 957.4142 989.4653
```

```
         Point Forecast     Lo 0     Hi 0
Jan 2022       323.1783 323.1783 323.1783
Feb 2022       288.7394 288.7394 288.7394
Mar 2022       255.5209 255.5209 255.5209
Apr 2022       262.8517 262.8517 262.8517
May 2022       258.4331 258.4331 258.4331
Jun 2022       292.0789 292.0789 292.0789
Jul 2022       314.4322 314.4322 314.4322
Aug 2022       327.4177 327.4177 327.4177
Sep 2022       385.3516 385.3516 385.3516
Oct 2022       405.0276 405.0276 405.0276
Nov 2022       449.6175 449.6175 449.6175
Dec 2022       505.4270 505.4270 505.4270
Jan 2023       341.9785 341.9785 341.9785
Feb 2023       307.5396 307.5396 307.5396
Mar 2023       274.3210 274.3210 274.3210
Apr 2023       281.6519 281.6519 281.6519
May 2023       277.2332 277.2332 277.2332
Jun 2023       310.8791 310.8791 310.8791
Jul 2023       333.2323 333.2323 333.2323
Aug 2023       346.2178 346.2178 346.2178
Sep 2023       404.1517 404.1517 404.1517
Oct 2023       423.8278 423.8278 423.8278
Nov 2023       468.4177 468.4177 468.4177
Dec 2023       524.2271 524.2271 524.2271
>
```

**b. To make a forecast in the 12 months of 2024, use the entire data set (no partitioning) to develop the HW model using the ets() function for the model with the automated selection of error, trend, and seasonality options, and automated selection of smoothing parameters. Present the model summary (output) and explain this model in your report. Use the model to forecast monthly sales in the 12 months of 2024 using the forecast() function, and present the forecast in your report.**

We developed a forecast using ets() function with the automated selections mentioned. This HW model has the (A, A, A) options, i.e., additive error, additive trend, and additive seasonality. The optimal value for exponential smoothing constant (alpha) is 0.2017, beta is 0.0001, and gamma is the same 0.0001.

Also, the summary is as follows:

```
> # 4(b)
> #Making a forecast in the 12 months of 2024
> HW.ZZZ <- ets(sales.ts, model = "ZZZ")
> HW.ZZZ
ETS(A,A,A)

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

  Smoothing parameters:
    alpha = 0.2017
    beta  = 1e-04
    gamma = 1e-04

  Initial states:
    l = 202.496
    b = 1.3772
    s = 156.7496 105.029 65.6201 47.3008 -11.9245 -38.2964
           -43.5536 -77.6554 -77.1076 -80.0095 -42.8196 -3.3328

  sigma:  25.1588
```

```
     AIC     AICc      BIC
1218.998 1225.798 1264.594
> #Using forecast() function to make predictions using the model for 12 months
> HW.ZZZ.pred <- forecast(HW.ZZZ, h = 12 , level = 0)
> HW.ZZZ.pred
         Point Forecast     Lo 0     Hi 0
Jan 2024       345.1928 345.1928 345.1928
Feb 2024       307.0794 307.0794 307.0794
Mar 2024       271.2673 271.2673 271.2673
Apr 2024       275.5425 275.5425 275.5425
May 2024       276.3692 276.3692 276.3692
Jun 2024       311.8473 311.8473 311.8473
Jul 2024       318.4755 318.4755 318.4755
Aug 2024       346.2273 346.2273 346.2273
Sep 2024       406.8265 406.8265 406.8265
Oct 2024       426.5198 426.5198 426.5198
Nov 2024       467.3017 467.3017 467.3017
Dec 2024       520.3950 520.3950 520.3950
> 
```

**c. Apply the accuracy() function to compare the two models: seasonal naïve forecast (applied in question 3e) and the HW model developed in question 4b. Present the**

**accuracy measures in your report, compare MAPE and RMSE of these forecasts, and identify the best forecasting model.**

The MAPE and RMSE in the HW are better than those for the seasonal naïve forecast. We can conclude that the HW is more accurate than the others.

```
> # 4(c)
> #Applying the accuracy() function to compare the two models
> round(accuracy(snaive(sales.ts)$fitted, sales.ts), 3)
             ME   RMSE    MAE   MPE MAPE  ACF1 Theil's U
Test set 16.249 36.324 23.574 5.273  8.9 0.357     0.645
> round(accuracy(HW.ZZZ.pred$fitted, sales.ts), 3)
             ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -0.209 23.221 17.423 -0.739 7.242 0.154     0.492
```

**d. Compare the best forecasts identified in questions 3e and 4c. Explain what your final choice of the forecasting model in this case will be.**

As we can see from the accuracy measures, the HW model (the bottom one)  is better with MAPE and RMSE as 5.313% and 22.907, respectively.

```
> round(accuracy(HW.ZZZ.pred$fitted, sales.ts), 3)
             ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -0.209 23.221 17.423 -0.739 7.242 0.154     0.492
```

```
> round(accuracy(fst.2level, valid.ts), 3)
              ME   RMSE    MAE    MPE  MAPE  ACF1 Theil's U
Test set -14.189 22.907 16.548 -4.651 5.313 0.231     0.538
```