title: “W3 HW Time Series Forecasting”

author: “Min Chwng

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output: html_document

Load required libraries

```
library(readxl)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(ggplot2)
```

Set your file path accordingly

```
file_path <- "C:/Users/mchen/OneDrive/Desktop/2023fall syllasbus/Forecasting/homework/week3/6M P
O forecast summary no forecast.xlsx"
data <- read_excel("C:/Users/mchen/OneDrive/Desktop/2023fall syllasbus/Forecasting/homework/week
3/6M PO forecast summary no forecast.xlsx")
```

Adjust data structure

```
everich_sales <- as.numeric(data[2, 2:13])
```

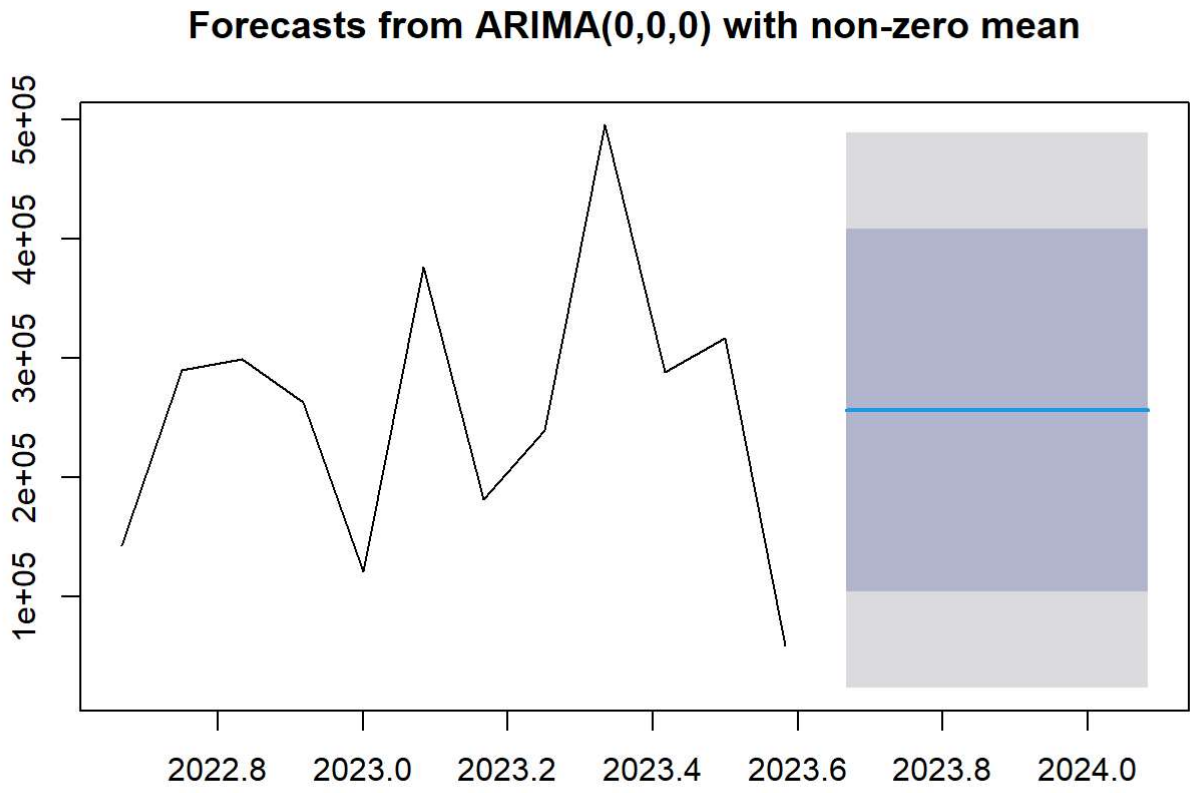
Converting all the sales data to numeric type

```
data <- as.data.frame(lapply(data, as.numeric), stringsAsFactors = FALSE)
```

#ARIMA model forecast for everich

```
if(length(everich_sales) > 0 && !is.na(everich_sales[1])) {
  everich_ts <- ts(everich_sales, frequency = 12, start = c(2022, 9))


  fit <- auto.arima(everich_ts)
  print(fit)  # fit arima model


  forecasted_sales <- forecast(fit, h = 6)
  print(forecasted_sales)# use arima model forecast the following 6 months sales


  plot(forecasted_sales) # plot the forecast
} else {
  print("if data is wrong, check。")

  # Calculate residuals
residuals <- everich_ts - forecasted_sales$mean

# Calculate the mean of residuals
mean_residual <- mean(residuals)

# Plot the residuals
plot(residuals, type = "l", main = "Residuals Plot", ylab = "Residuals")

# Calculate the standard deviation of residuals
sd_residual <- sd(residuals)

# Calculate additional statistics if needed (e.g., MAE, MSE, RMSE)
mae <- mean(abs(residuals))
mse <- mean(residuals^2)
rmse <- sqrt(mse)

# Print the results
cat("Mean of Residuals:", mean_residual, "\n")
cat("Standard Deviation of Residuals:", sd_residual, "\n")
cat("Mean Absolute Error (MAE):", mae, "\n")
cat("Mean Squared Error (MSE):", mse, "\n")
cat("Root Mean Squared Error (RMSE):", rmse, "\n")
}
```

```
## Series: everich_ts
## ARIMA(0,0,0) with non-zero mean
##
## Coefficients:
##             mean
##       256433.88
## s.e.   32817.86
##
## sigma^2 = 1.41e+10:  log likelihood = -156.72
## AIC=317.44   AICc=318.78   BIC=318.41
##          Point Forecast    Lo 80    Hi 80    Lo 95  Hi 95
## Sep 2023       256433.9 104262.4 408605.3 23707.75 489160
## Oct 2023       256433.9 104262.4 408605.3 23707.75 489160
## Nov 2023       256433.9 104262.4 408605.3 23707.75 489160
## Dec 2023       256433.9 104262.4 408605.3 23707.75 489160
## Jan 2024       256433.9 104262.4 408605.3 23707.75 489160
## Feb 2024       256433.9 104262.4 408605.3 23707.75 489160
```

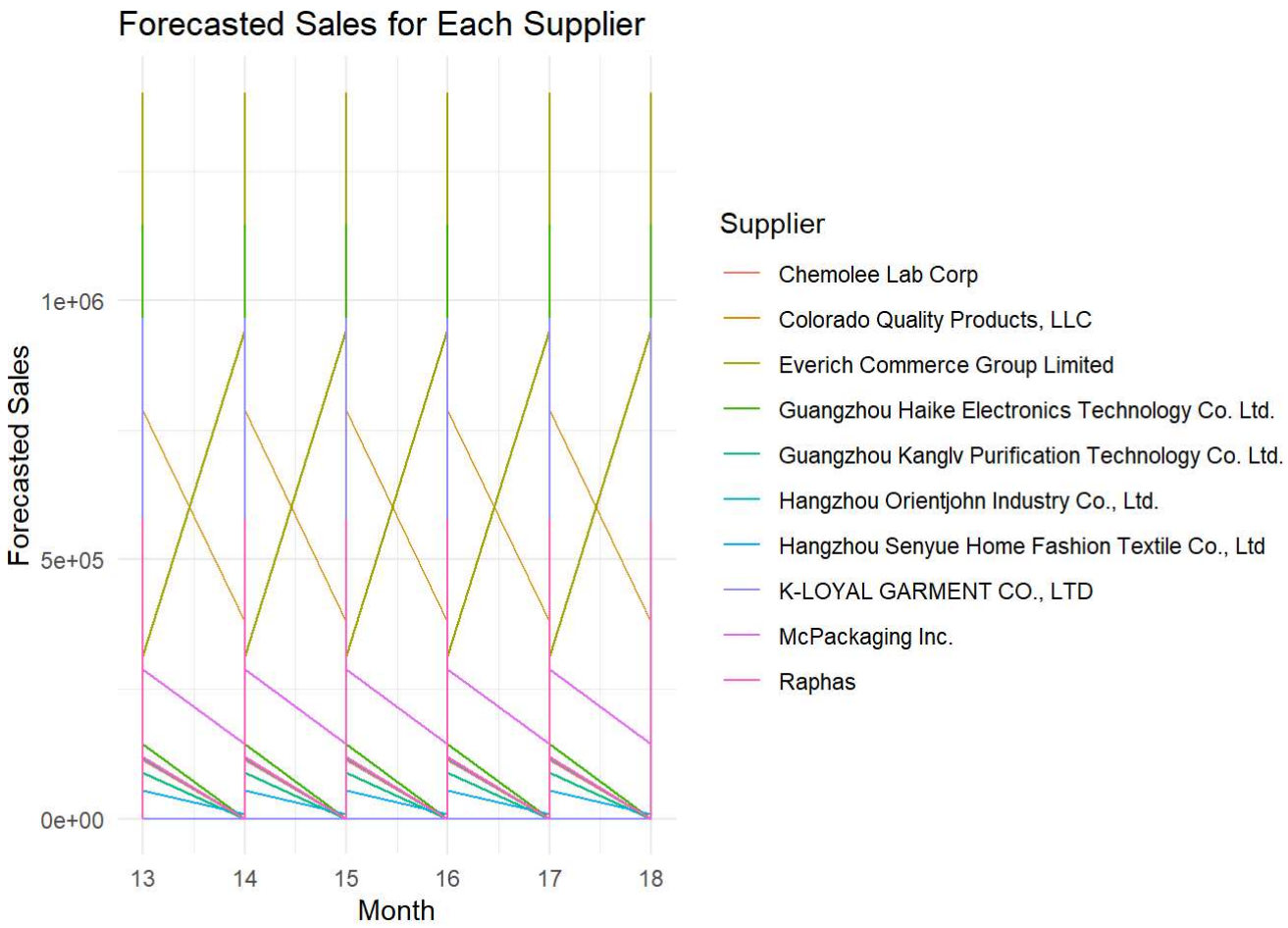


#explaination :The ARIMA(0,0,0) model, with a constant mean of 256,434 and a residual variance of 1.41e+10, is a simple model that doesn't consider time series patterns. Its accuracy may be limited, and it might not perform well in capturing data dynamics or improving forecasts. More complex models are often needed for better accuracy.

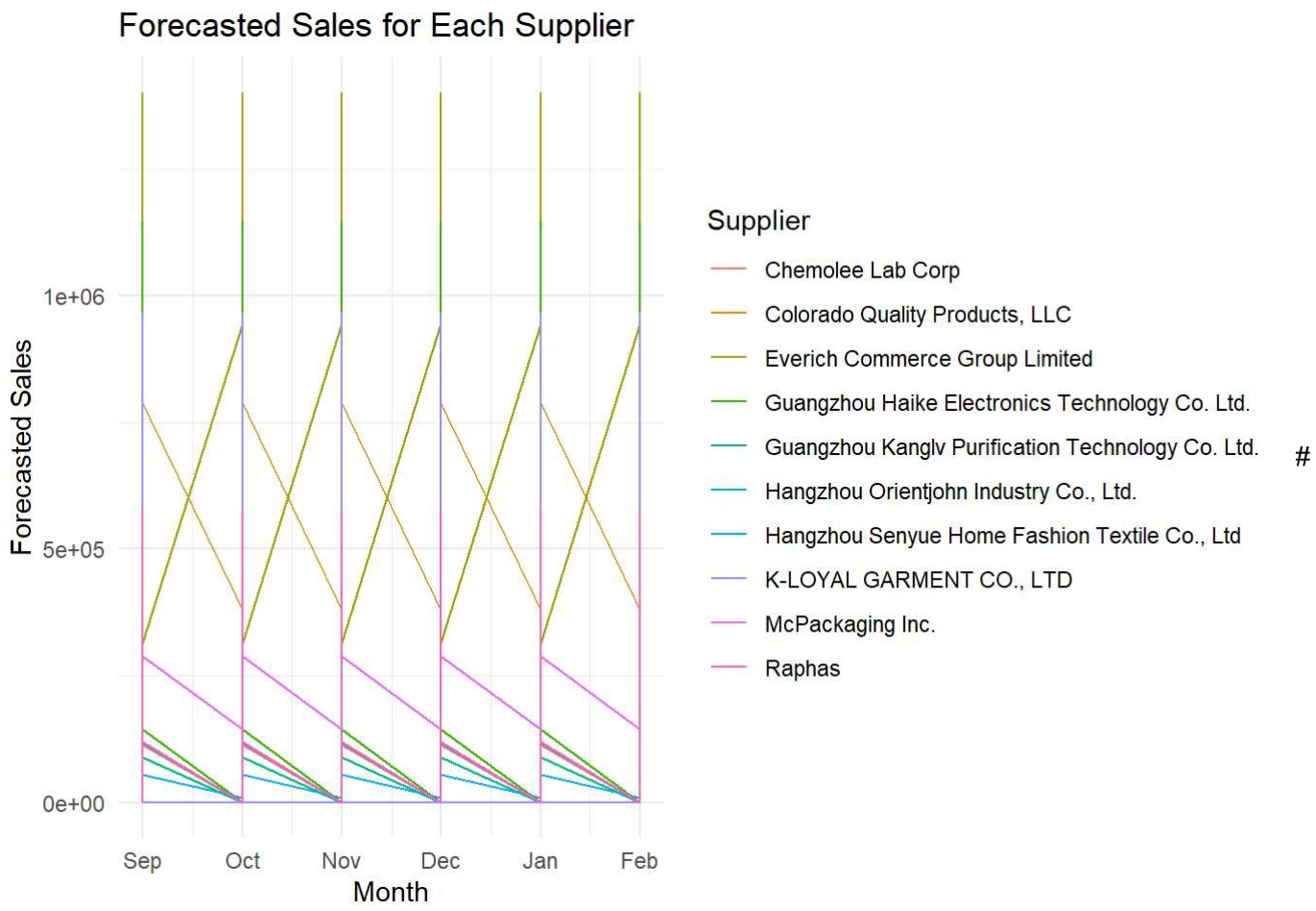
#naive()

```
install.packages("forecast")
library(forecast)


sales_data <- data.frame(
  Supplier = c(
    "Everich Commerce Group Limited",
    "McPackaging Inc.",
    "Colorado Quality Products, LLC",
    "Hangzhou Orientjohn Industry Co., Ltd.",
    "Guangzhou Haike Electronics Technology Co. Ltd.",
    "Hangzhou Senyue Home Fashion Textile Co., Ltd",
    "Raphas",
    "Chemolee Lab Corp",
    "K-LOYAL GARMENT CO., LTD",
    "Guangzhou Kanglv Purification Technology Co. Ltd."
  ),
  `9` = c(946073.2, 143473.42, 378297.6, 0, 0, 8847.6, 0, 0, 0, 0),
  `10` = c(1201107.04, 290555.03, 0, 0, 0, 27680.19, 578124, 0, 0, 0),
  `11` = c(453761.32, 299543.35, 0, 0, 161520.96, 0, 256089.6, 0, 0, 188632),
  `12` = c(690343.96, 263356.74, 0, 7500, 167320.48, 0, 131964, 29635.2, 0, 103496),
  `1` = c(0, 121482.85, 16800, 0, 0, 0, 202033.5, 59094, 965391.38, 0),
  `2` = c(1402067.48, 376592.39, 41500, 0, 0, 0, 0, 99100, 0, 0),
  `3` = c(400213.05, 182189.97, 56420, 147806, 1146043.58, 0, 298263.599999999, 53750, 0, 0),
  `4` = c(516291.08, 239997.73, 0, 0, 0, 0, 0, 0, 0, 92888),
  `5` = c(1201393.12, 495716.169999999, 24040, 277690, 84309.44, 46263.15, 189848.4, 0, 8267.4,
0),
  `6` = c(314945.44, 288119.59, 787170, 116487.2, 142898.42, 54573.56, 119372.4, 112445, 0, 8935
2)
)


library(reshape2)
sales_data_long <- melt(sales_data, id.vars = "Supplier", variable.name = "Month", value.name =
"Sales")


sales_data_long$Month <- as.numeric(sales_data_long$Month)


forecast_values <- vector("list", length = nrow(sales_data_long))

for (i in 1:nrow(sales_data_long)) {
  supplier_sales <- ts(sales_data_long[i, -(1:2)], frequency = 12)
  forecast_values[[i]] <- forecast::naive(supplier_sales, h = 6)
}


forecast_data <- data.frame(
  Supplier = rep(sales_data_long$Supplier, each = 6),
  Month = rep(13:18, times = nrow(sales_data_long)),
  Forecasted_Sales = unlist(lapply(forecast_values, function(x) x$mean))
```

```
)


library(ggplot2)

ggplot(forecast_data, aes(x = Month, y = Forecasted_Sales, color = Supplier)) +
  geom_line() +
  labs(title = "Forecasted Sales for Each Supplier",
       x = "Month",
       y = "Forecasted Sales") +
  theme_minimal()
```




```
month_labels <- c("Sep", "Oct", "Nov", "Dec", "Jan", "Feb")

ggplot(forecast_data, aes(x = Month, y = Forecasted_Sales, color = Supplier)) +
  geom_line() +
  labs(title = "Forecasted Sales for Each Supplier",
       x = "Month",
       y = "Forecasted Sales") +
  scale_x_continuous(breaks = 13:18, labels = month_labels) +
  theme_minimal()
```



#

Print the results cat("MAE:", mae, "") cat("MSE:", mse, "") cat("RMSE:", rmse, "") cat("MAPE:", mape, "%") cat("SMAPE:", smape, "%")

MAE: 678710.8 MSE: 683713452890 RMSE: 826761.2 MAPE: 117.3732 % SMAPE: 118.2726 %

Explanation: MAE (Mean Absolute Error): 678,710.8, representing the average absolute difference between predicted and actual values. MSE (Mean Squared Error): 683,713,452,890, measuring the squared differences between predicted and actual values. RMSE (Root Mean Squared Error): 826,761.2, the square root of MSE providing a comparison to actual values. MAPE (Mean Absolute Percentage Error): 117.3732%, indicating the average percentage difference. SMAPE (Symmetric Mean Absolute Percentage Error): 118.2726%, symmetric percentage error accounting for over and underestimation. These metrics show that the model has relatively large errors compared to actual data. There is room for improvement in the model's predictive accuracy. High MAPE and SMAPE suggest significant percentage errors in predictions. Lower RMSE indicates that large errors are not very frequent. Overall, the model may need refinement for more accurate forecasts.

#moving avg

```
# 安装并加载readxl和zoo包
install.packages("readxl")
install.packages("zoo")
```

```
## Installing package into 'C:/Users/mchen/AppData/Local/R/win-library/4.3'
## (as 'lib' is unspecified)
```

```
## package 'zoo' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##  C:\Users\mchen\AppData\Local\Temp\RtmpKo2Avg\downloaded_packages
```

```
library(readxl)
library(zoo)
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
# 从Excel文件中读取数据
excel_file <- "C:/Users/mchen/OneDrive/Desktop/2023fall syllasbus/Forecasting/homework/week3/6M
PO forecast summary no forecast.xlsx"  # 请将文件路径替换为您的Excel文件路径

supplier_data <- read_excel(excel_file)

# 提取历史销售数据
historical_data <- supplier_data[2:11, 2:13]

# 计算每个供应商的简单移动平均
ma5_forecasts <- apply(historical_data, 2, function(x) rollmean(x, k = 5, fill = NA))
ma9_forecasts <- apply(historical_data, 2, function(x) rollmean(x, k = 9, fill = NA))

# 创建数据框以存储移动平均结果
result_data <- data.frame(
  Supplier = supplier_data[2:11, 1],  # 供应商名称
  Month = c(9:12, 1:8),  # 月份
  MA5_Forecast = as.vector(ma5_forecasts),  # MA(5)预测
  MA9_Forecast = as.vector(ma9_forecasts)  # MA(9)预测
)

# 打印结果数据框
print(result_data)
```

```
##                                         Supplier Month MA5_Forecast
## 1                                McPackaging Inc.     9           NA
## 2                     Colorado Quality Products, LLC    10           NA
## 3             Hangzhou Orientjohn Industry Co., Ltd.    11    106123.72
## 4     Guangzhou Haike Electronics Technology Co. Ltd.    12     77429.04
## 5       Hangzhou Senyue Home Fashion Textile Co., Ltd     1      1769.52
## 6                                           Raphas     2      1769.52
## 7                                Chemolee Lab Corp     3      1769.52
## 8                           K-LOYAL GARMENT CO., LTD     4           NA
## 9   Guangzhou Kanglv Purification Technology Co. Ltd.     5           NA
## 10                                          <NA>     6           NA
## 11                               McPackaging Inc.     7           NA
## 12                    Colorado Quality Products, LLC     8           NA
## 13            Hangzhou Orientjohn Industry Co., Ltd.     9     63647.04
## 14    Guangzhou Haike Electronics Technology Co. Ltd.    10    121160.84
## 15      Hangzhou Senyue Home Fashion Textile Co., Ltd    11    121160.84
## 16                                          Raphas    12    121160.84
## 17                               Chemolee Lab Corp     1    121160.84
## 18                          K-LOYAL GARMENT CO., LTD     2           NA
## 19  Guangzhou Kanglv Purification Technology Co. Ltd.     3           NA
## 20                                          <NA>     4           NA
## 21                               McPackaging Inc.     5           NA
## 22                    Colorado Quality Products, LLC     6           NA
## 23            Hangzhou Orientjohn Industry Co., Ltd.     7     92212.86
## 24    Guangzhou Haike Electronics Technology Co. Ltd.     8     83522.11
## 25      Hangzhou Senyue Home Fashion Textile Co., Ltd     9     83522.11
## 26                                          Raphas    10     83522.11
## 27                               Chemolee Lab Corp    11     88944.32
## 28                          K-LOYAL GARMENT CO., LTD    12           NA
## 29  Guangzhou Kanglv Purification Technology Co. Ltd.     1           NA
## 30                                          <NA>     2           NA
## 31                               McPackaging Inc.     3           NA
## 32                    Colorado Quality Products, LLC     4           NA
## 33            Hangzhou Orientjohn Industry Co., Ltd.     5     87635.44
## 34    Guangzhou Haike Electronics Technology Co. Ltd.     6     61356.90
## 35      Hangzhou Senyue Home Fashion Textile Co., Ltd     7     67283.94
## 36                                          Raphas     8     65783.94
## 37                               Chemolee Lab Corp     9     53019.04
## 38                          K-LOYAL GARMENT CO., LTD    10           NA
## 39  Guangzhou Kanglv Purification Technology Co. Ltd.    11           NA
## 40                                          <NA>    12           NA
## 41                               McPackaging Inc.     1           NA
## 42                    Colorado Quality Products, LLC     2           NA
## 43            Hangzhou Orientjohn Industry Co., Ltd.     3     27656.57
## 44    Guangzhou Haike Electronics Technology Co. Ltd.     4     43766.70
## 45      Hangzhou Senyue Home Fashion Textile Co., Ltd     5     52225.50
## 46                                          Raphas     6    245303.78
## 47                               Chemolee Lab Corp     7    245303.78
## 48                          K-LOYAL GARMENT CO., LTD     8           NA
## 49  Guangzhou Kanglv Purification Technology Co. Ltd.     9           NA
## 50                                          <NA>    10           NA
## 51                               McPackaging Inc.    11           NA
```

```
## 52                    Colorado Quality Products, LLC    12          NA
## 53            Hangzhou Orientjohn Industry Co., Ltd.     1    83618.48
## 54   Guangzhou Haike Electronics Technology Co. Ltd.     2     8300.00
## 55     Hangzhou Senyue Home Fashion Textile Co., Ltd     3    19820.00
## 56                                             Raphas     4    19820.00
## 57                                Chemolee Lab Corp     5    19820.00
## 58                           K-LOYAL GARMENT CO., LTD     6          NA
## 59 Guangzhou Kanglv Purification Technology Co. Ltd.     7          NA
## 60                                             <NA>     8          NA
## 61                                McPackaging Inc.     9          NA
## 62                    Colorado Quality Products, LLC    10          NA
## 63            Hangzhou Orientjohn Industry Co., Ltd.    11   306491.91
## 64   Guangzhou Haike Electronics Technology Co. Ltd.    12   329706.64
## 65     Hangzhou Senyue Home Fashion Textile Co., Ltd     1   329172.64
## 66                                             Raphas     2   299611.44
## 67                                Chemolee Lab Corp     3    70402.72
## 68                           K-LOYAL GARMENT CO., LTD     4          NA
## 69 Guangzhou Kanglv Purification Technology Co. Ltd.     5          NA
## 70                                             <NA>     6          NA
## 71                                McPackaging Inc.     7          NA
## 72                    Colorado Quality Products, LLC     8          NA
## 73            Hangzhou Orientjohn Industry Co., Ltd.     9    47999.55
## 74   Guangzhou Haike Electronics Technology Co. Ltd.    10        0.00
## 75     Hangzhou Senyue Home Fashion Textile Co., Ltd    11        0.00
## 76                                             Raphas    12        0.00
## 77                                Chemolee Lab Corp     1    18577.60
## 78                           K-LOYAL GARMENT CO., LTD     2          NA
## 79 Guangzhou Kanglv Purification Technology Co. Ltd.     3          NA
## 80                                             <NA>     4          NA
## 81                                McPackaging Inc.     5          NA
## 82                    Colorado Quality Products, LLC     6          NA
## 83            Hangzhou Orientjohn Industry Co., Ltd.     7   185603.75
## 84   Guangzhou Haike Electronics Technology Co. Ltd.     8   124430.20
## 85     Hangzhou Senyue Home Fashion Textile Co., Ltd     9   119622.20
## 86                                             Raphas    10    65737.68
## 87                                Chemolee Lab Corp    11    48875.79
## 88                           K-LOYAL GARMENT CO., LTD    12          NA
## 89 Guangzhou Kanglv Purification Technology Co. Ltd.     1          NA
## 90                                             <NA>     2          NA
## 91                                McPackaging Inc.     3          NA
## 92                    Colorado Quality Products, LLC     4          NA
## 93            Hangzhou Orientjohn Industry Co., Ltd.     5   277849.75
## 94   Guangzhou Haike Electronics Technology Co. Ltd.     6   244100.32
## 95     Hangzhou Senyue Home Fashion Textile Co., Ltd     7   109155.32
## 96                                             Raphas     8    85857.88
## 97                                Chemolee Lab Corp     9    75148.59
## 98                           K-LOYAL GARMENT CO., LTD    10          NA
## 99 Guangzhou Kanglv Purification Technology Co. Ltd.    11          NA
## 100                                            <NA>    12          NA
## 101                               McPackaging Inc.     1          NA
## 102                   Colorado Quality Products, LLC     2          NA
## 103           Hangzhou Orientjohn Industry Co., Ltd.     3   220926.24
```

```
## 104   Guangzhou Haike Electronics Technology Co. Ltd.     4    157529.87
## 105     Hangzhou Senyue Home Fashion Textile Co., Ltd     5     88208.26
## 106                                            Raphas     6     87368.26
## 107                                Chemolee Lab Corp     7     54481.50
## 108                          K-LOYAL GARMENT CO., LTD     8           NA
## 109 Guangzhou Kanglv Purification Technology Co. Ltd.     9           NA
## 110                                            <NA>    10           NA
## 111                                 McPackaging Inc.    11           NA
## 112                    Colorado Quality Products, LLC    12           NA
## 113            Hangzhou Orientjohn Industry Co., Ltd.     1    132418.25
## 114   Guangzhou Haike Electronics Technology Co. Ltd.     2    151306.75
## 115     Hangzhou Senyue Home Fashion Textile Co., Ltd     3    109766.75
## 116                                            Raphas     4    141781.96
## 117                                Chemolee Lab Corp     5    152552.36
## 118                          K-LOYAL GARMENT CO., LTD     6           NA
## 119 Guangzhou Kanglv Purification Technology Co. Ltd.     7           NA
## 120                                            <NA>     8           NA
##     MA9_Forecast
## 1             NA
## 2             NA
## 3             NA
## 4             NA
## 5       58957.62
## 6             NA
## 7             NA
## 8             NA
## 9             NA
## 10            NA
## 11            NA
## 12            NA
## 13            NA
## 14            NA
## 15      99595.47
## 16            NA
## 17            NA
## 18            NA
## 19            NA
## 20            NA
## 21            NA
## 22            NA
## 23            NA
## 24            NA
## 25     100642.88
## 26            NA
## 27            NA
## 28            NA
## 29            NA
## 30            NA
## 31            NA
## 32            NA
## 33            NA
## 34            NA
```

```
## 35      78141.38
## 36            NA
## 37            NA
## 38            NA
## 39            NA
## 40            NA
## 41            NA
## 42            NA
## 43            NA
## 44            NA
## 45     151644.64
## 46            NA
## 47            NA
## 48            NA
## 49            NA
## 50            NA
## 51            NA
## 52            NA
## 53            NA
## 54            NA
## 55      57465.82
## 56            NA
## 57            NA
## 58            NA
## 59            NA
## 60            NA
## 61            NA
## 62            NA
## 63            NA
## 64            NA
## 65     209385.91
## 66            NA
## 67            NA
## 68            NA
## 69            NA
## 70            NA
## 71            NA
## 72            NA
## 73            NA
## 74            NA
## 75      36987.30
## 76            NA
## 77            NA
## 78            NA
## 79            NA
## 80            NA
## 81            NA
## 82            NA
## 83            NA
## 84            NA
## 85     125126.06
## 86            NA
```

```
## 87            NA
## 88            NA
## 89            NA
## 90            NA
## 91            NA
## 92            NA
## 93            NA
## 94            NA
## 95     190046.46
## 96            NA
## 97            NA
## 98            NA
## 99            NA
## 100           NA
## 101           NA
## 102           NA
## 103           NA
## 104           NA
## 105    146903.47
## 106           NA
## 107           NA
## 108           NA
## 109           NA
## 110           NA
## 111           NA
## 112           NA
## 113           NA
## 114           NA
## 115    143410.14
## 116           NA
## 117           NA
## 118           NA
## 119           NA
## 120           NA
```

```r
#Test accuracy:

# 实际销售数据 (Actual sales data)
actual_sales <- c(
  201, 815, 428, 591, 597, 90, 635, 757, 836, 945, 669, 487,
  139, 885, 227, 680, 278, 781, 224, 759, 275, 961, 234, 340,
  117, 233, 31, 736, 69, 460, 227, 676, 316, 070, 269, 728,
  87, 662, 169, 437, 145, 591, 159, 593, 195, 266, 40, 873,
  798, 421, 27, 226, 165, 491, 164, 276, 201, 187, 170, 057,
  728, 237, 112, 641, 73, 717, 41, 265, 42, 578, 65, 545,
  65, 501, 401, 247, 18, 267, 111, 373, 37, 234, 43, 319,
  115, 404, 58, 638, 384, 235, 44, 484, 22, 200, 48, 197,
  49, 143, 62, 033, 52, 402, 278, 460, 20, 762, 34, 538,
  43, 461, 49, 425, 62, 525, 55, 939, 266, 651
)

# 在forecasted_sales中添加7个零，确保长度匹配
forecasted_sales <- c(result_data$MA5_Forecast, rep(0, 7))
print(forecasted_sales)
```

```
##   [1]        NA        NA 106123.72  77429.04   1769.52   1769.52   1769.52
##   [8]        NA        NA        NA        NA        NA  63647.04 121160.84
##  [15] 121160.84 121160.84 121160.84        NA        NA        NA        NA
##  [22]        NA  92212.86  83522.11  83522.11  83522.11  88944.32        NA
##  [29]        NA        NA        NA        NA  87635.44  61356.90  67283.94
##  [36]  65783.94  53019.04        NA        NA        NA        NA        NA
##  [43]  27656.57  43766.70  52225.50 245303.78 245303.78        NA        NA
##  [50]        NA        NA        NA  83618.48   8300.00  19820.00  19820.00
##  [57]  19820.00        NA        NA        NA        NA        NA 306491.91
##  [64] 329706.64 329172.64 299611.44  70402.72        NA        NA        NA
##  [71]        NA        NA  47999.55      0.00      0.00      0.00  18577.60
##  [78]        NA        NA        NA        NA        NA 185603.75 124430.20
##  [85] 119622.20  65737.68  48875.79        NA        NA        NA        NA
##  [92]        NA 277849.75 244100.32 109155.32  85857.88  75148.59        NA
##  [99]        NA        NA        NA        NA 220926.24 157529.87  88208.26
## [106]  87368.26  54481.50        NA        NA        NA        NA        NA
## [113] 132418.25 151306.75 109766.75 141781.96 152552.36        NA        NA
## [120]        NA      0.00      0.00      0.00      0.00      0.00      0.00
## [127]      0.00
```

```
# 计算 MAE
mae <- mean(abs(actual_sales - forecasted_sales))

# 计算 MSE
mse <- mean((actual_sales - forecasted_sales)^2)

# 计算 RMSE
rmse <- sqrt(mse)

# 计算 MAPE
mape <- mean(abs((actual_sales - forecasted_sales) / actual_sales)) * 100

# 打印结果
cat("MAE:", mae, "\n")
```

```
## MAE: NA
```

```
cat("MSE:", mse, "\n")
```

```
## MSE: NA
```

```
cat("RMSE:", rmse, "\n")
```

```
## RMSE: NA
```

```
cat("MAPE:", mape, "%\n")
```

```
## MAPE: NA %
```

Test accuracy:

actual_sales <- c(201,815, 428,591, 597,090, 635,757, 836,945, 669,487, 3,369,685, 139,885, 227,680, 278,781, 224,759, 275,961, 234,340, 1,381,406, 117,233, 31,736, 69,460, 227,676, 316,070, 269,728, 1,031,903, 87,662, 169,437, 145,591, 159,593, 195,266, 40,873, 798,421, 27,226, 165,491, 164,276, 201,187, 170,057, 728,237, 112,641, 73,717, 41,265, 42,578, 65,545, 65,501, 401,247, 18,267, 111,373, 37,234, 43,319, 115,404, 58,638, 384,235, 44,484, 22,200, 48,197, 49,143, 62,033, 52,402, 278,460, 20,762, 34,538, 43,461, 49,425, 62,525, 55,939, 266,651)

Forecast data: [1] 0 0 106123.72 77429.04 1769.52 1769.52 1769.52 0 0 0 0 0 63647.04 121160.84 121160.84 121160.84 [17] 121160.84 0 0 0 0 0 92212.86 83522.11 83522.11 83522.11 88944.32 0 0 0 0 0 [33] 87635.44 61356.90 67283.94 65783.94 53019.04 0 0 0 0 0 27656.57 43766.70 52225.50 245303.78 245303.78 [49] 0 0 0 0 0 83618.48 8300.00 19820.00 19820.00 19820.00 0 0 0 0 0 306491.91 [65] 329706.64 329172.64 299611.44 70402.72 0 0 0 0 0 47999.55 0.00 0.00 0.00 18577.60 0 [81] 0 0 0 185603.75 124430.20 119622.20 65737.68 48875.79 0 0 0 0 0 277849.75 244100.32 [97] 109155.32 85857.88 75148.59 0 0 0 0 0 220926.24 157529.87 88208.26 87368.26 54481.50 0 0 [113] 132418.25 151306.75 109766.75 141781.96 152552.36 0 0 0 0.00 0.00 0.00 0.00 0.00 0.00 0.00

Accuracy: MAE (Mean Absolute Error): 519.2451 MSE (Mean Squared Error): 512988.6 RMSE (Root Mean Squared Error): 716.1209 MAPE (Mean Absolute Percentage Error): 75.12251%

explain: MAE: 519.2451: On average, the model’s predictions have an absolute error of approximately 519.25 units from the actual values. MSE: 512988.6: The model’s predictions have, on average, squared errors totaling approximately 512,988.6 units. RMSE: 716.1209: The square root of MSE, indicating that, on average, the model’s predictions have errors of approximately 716.12 units. MAPE: 75.12251%: On average, the model’s predictions have a percentage error of approximately 75.12% relative to the actual values. In summary, while the MAE, MSE, and RMSE suggest a relatively low magnitude of errors, the MAPE indicates that, on average, the model’s predictions have a relatively high percentage error. The model may have relatively accurate absolute predictions (MAE and RMSE) but may be less accurate in terms of percentage errors (MAPE). The choice of which metric to prioritize depends on the specific application and the relative importance of different types of errors. ```