# Forecasting Weekly Sales of Perishable Goods by Purchase Channel and Location to Optimize Resources

**BAFT Team 3**

**Taylor Wu(111078507) Celine Lin(111078520)**
**Sara Tsai(111078509) Ella Yang(112078508)**

## One-page executive summary

The project focused on solving the situation that US Sales leaders in Nuqleous may struggle with fluctuating demand and ineffective perishable goods allocation due to unknown future sales under different purchase channels.

To optimize perishable goods allocation for Nuqleous, we developed several models to better understand product sales across 4 purchase channels and stores in different locations by analyzing sales trends and forecasting next month's weekly demand.

The data source we used is from Nuqleous's daily historical sales. It comprises 1.8 million records with roughly two years of data. In this project, we focused on the sales prediction of the top-selling item, SKU number 1765845, across the 4 purchase channels and among different stores in the US over the past two years.

Our data-driven forecasting solution is briefly described below.

Since our goal is to forecast the demand for the top-selling item (SKU number: 1765845), we first clean the data we needed, including combining this and last year's data, transforming daily data into weekly data, filling the gaps with no sales data, looking deep into unusual peaks, and then use reasonable ways to make the data tidy and able to run forecasting. Next, we applied 8 time-series models to each of the 4 purchase channels while considering the sale trend and seasonality at the same time. Then, we found the one with the best forecasting results under each purchase channel. Lastly, we applied those best models to forecast the weekly sales of each purchase channel for the next 4 weeks, which is our main goal of this project!

After finding the best forecasting tools and results, here are our recommendations.

Since the "In-store purchase channel" and the "Store-pickup purchase channel" have an overall decreasing trend from the forecasting plot, Nuqleous sales leaders have to be very careful if they would like to place more goods than the previous period in the future. Besides, it is necessary to evaluate these stores' sales, especially for the stores with dramatically dropped sales these years. If the ability to earn money for some physical stores were lower due to the change in customers' purchasing habits, Nuqleous can also think of gradually switching some investment to purchase channels like "store delivery channels", which had a growing sales trend these years.

In contrast, the "store delivery channel" has a clear upward total sales trend, which tells us this purchasing channel has the potential to earn more money for Nuqleous. However, the company still has to prevent ordering too many goods at a time because the overall growing trend does not promise the same increasing sales each week, instead, the sales always fluctuate.

At last, the "Online (Shipped from Store) channel" has an apparent fluctuation in sales trend and also the lowest total sales amount among the 4 purchase channels. We've found that the forecasting sales had a high correlation with the sales exactly a month (4 weeks) before that day, which can be taken into consideration when making decisions.

Overall, this project aims to assist Nuqleous in grasping the sales trend more accurately in the future in a data-driven way. This kind of tool can help when making ordering decisions and product allocation.

**Detailed Report**

### 3.1 Problem description

This project is in collaboration with Nuqleous. Founded in 2013, Nuqleous is a leading developer of intelligent technology solutions that provides retail space planning and performance analytics software to drive retailer's success. Our primary business objective is to assist Nuqleous in gaining a deeper understanding of sales trends, especially regarding the allocation of perishable goods across different purchase channels and building numbers. Due to perishable goods' short shelf life, efficient allocation is crucial. Our studies can benefit Nuqleous from meeting the demands and avoiding wasting in a data-driven way.

The main forecasting goal is to forecast weekly sales quantities for one product and predict the demand for each purchase channel in the upcoming month.

The strategy goal is to enable suppliers to proactively stock up for each purchase channel, optimizing their supply chain operations. The advantage of this goal facilitates the dynamic allocation and recruitment of manpower, including delivery drivers and clerks, as well as the efficient deployment of delivery trucks. Additionally, understanding the sales percentage across various channels provides valuable insights for the sales leader's decision-making.

### 3.2 Data description

The source of our forecasting data is from Nuqleous, and the data is from a large retailer's operational sales data. We specifically focus on one of the perishable goods' sales, with the most sales records in the data set from the 15th week of 2021 to the 12th week of 2023. We think this item is the best choice to predict, for having the least holes data in our time series and full four purchase channels. This dataset measures essential variables, including sales information, as well as details on all building numbers and dives into four purchase channels. The temporal scope of the data spans from the 15th week of 2021 to the 12th week of 2023. One thing that needs to be noted is that since the data from the 13th week of 2022 to the 14th week of 2022 are missing we create this duration of data by TSLM. To provide a comprehensive view of trends and patterns over this period. At last, we combine our daily data into weekly data. In total, our dataset comprises a substantial volume of information, with a time series length of 98 weeks.

Since the business goal is to forecast the data for next month, we plan to do the forecasting once at the end of a month. The graph below shows the time series of item 1765845, our target perishable goods in this project, in four purchase channels and the sample 10 rows per series.

### 3.3 Brief data preparation details and key charts

There are 16 attributes in our Nuqleous dataset which respectively are SKU Number, Building Nbr, Purchase Channel, Date, Day of Week, Week and Year, Store Format, State, Store Zip Code, This Year's Sales ($), Last Year's Sales ($), Sales Quantity, Average Price. Because we want to investigate the most frequent sales item in the data set, we looked into SKU numbers and found that one of the perishable goods, item 1765845, has the most records in our dataset. To forecast the demand for products of 1765845, we choose the columns of Building Nbr, Purchase Channel, Date, This Year's Sales Qty, and Last Year's Sales Qty, to get the daily demand data across different stores.

The first issue we found is, there are multiple holes in our Online purchase channel time series. After investigating the data we found that most of the time T is 0 in this Online purchase channel. So we filled the gaps in the series with 0.

Then, the next problem we met was that two unusual peaks were happening on April 1st and 2nd (Picture 1-a 1-b) We applied the center moving average to smooth the time series and remove peaks. The original temporal scope of the data spans from the 15th week of 2022 to the 12th week of 2023 and the 15th week of 2021 to the 12th week of 2022. Then we use the TSLM to forecast the missing value between the gap of two years (Picture 2-a, 2-b). Finally, since we wanted to forecast the weekly demands, we aggregated the daily data into weekly, which made the series have 365/7 seasons.

Before diving into the forecasting methods, we use the decomposition to understand which model or setting of the model is better. In our daily data, we found a strong seasonality with week. (Picture 3-a). Because the length of our time series is less than two years, which means less than two periods, we can't apply the classical decomposition to our weekly data. We try ACF and PACF to see the strong correlation between lags in different series, finding there is a strong correlation between lag 3 or 4, and lag 52, which means the seasonality might have 4 seasons (approximately 1 month) or 52 seasons (approximately 1 year) (Picture 3-b, 3-c)

### 3.4. Forecasting solution

In the forecasting method, we first partition data into the training period (2021 W15-2023 W08, 76 weeks) as well as the validation period (2023 W09 - 2023 W16, 8 weeks). We make the validation period longer to ensure that our model can have higher accuracy. We do the forecasting by using the following model. Naive, Seasonal Naive using lags, Regression with trend and seasons, Auto Arima, Auto Arima with stepwise, Neural Network. Arima with lags. We chose parameter (2,1) by examining ACF and PACF plots of the differenced series. Noticeable peaks at lags in ACF suggest the order q, while spikes in PACF suggest the order p. Moreover, the seasonal cycle we are assuming in SNAIVE, TSLM, and neural network models is all equal to 4 weeks (Picture 4).

We analyze the relative accuracy in the training period and validation period (Picture 5-a, 5-b,5-c). When we look at the graph of the fitted value, the residual values (Picture 6-a, 6-b) in the training period, and the validation period, to avoid overfitting, we decided to take the prediction intervals, fitted and predicted value plots under different models, and RMSE value into consideration to find the best model of the 4 purchase channels.

So we get our best model in these four purchase channels in time series (Picture 6-c).

The approach we employ to determine the best model involves an initial assessment based on the RMSE, followed by an examination of the corresponding graph (Picture 6-d). In cases where predictions exhibit significant inaccuracies, as indicated by an unappealing graph for the model with the minimum RMSE, such as in the case of Store delivery, we then shift to directly identifying the model that best fits from the graph (Picture 6-d).

### 3.5. Time plot of series with future forecasts, for key series.

Then we apply the roll-forward to generate the future series. Pictures 6-d, and 7-a show the results for future forecasts from the best model we select. Models are compared based on their relative accuracy in both the training and validation periods. We used 8 time-series forecasting models to train and validate our data and finally selected the best model to generate future forecasts. For “In-store” and “Store pickup” purchase channels, the best model is TSLM without specifying trend and seasonality which is autoregression. For the “Online purchase channel”, the best model is ARIMA stepwise. For the “Store delivery purchase channel”, the best model is a Neural network.

Picture 8-b shows the validation period with actual values. The colors in the smaller intervals represent a 95% confidence level, while the larger intervals represent an 80% confidence level. The black line represents the actual values. The label in the bottom left corner indicates the confidence intervals for different models. From the figure, it can be observed that almost all selected models fall within the 95% confidence level, indicating that the chosen models are highly accurate.

### 3.6 Conclusions and operational recommendations

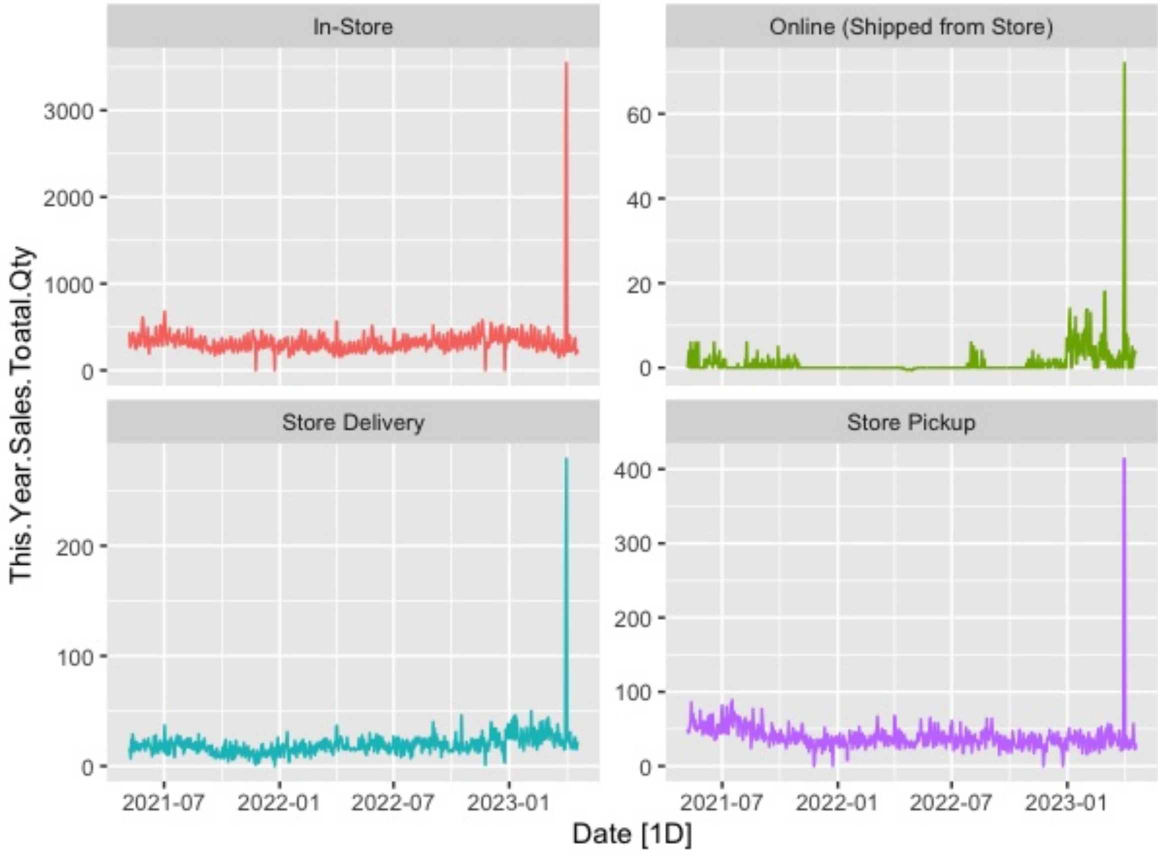
Here are some advantages and limitations of our project. For advantages, First, we use weekly updates to provide timely insights into sales trends, which fits the industry standard. Second, we select the best-performing models to ensure accurate and reliable forecasting results. Last, we consider forecast variance, contributing to a detailed understanding of data.

However, there are still some limitations in this project. Since we only have data for around two years(the 15th week of 2022 to the 12th week of 2023), some historical context will be limited. Second, we lack Specific Sales Events Information. Such as weather impacts, limits the ability to control external factors. Third, concerning markdown dollars, discounts may be embedded in the data, making it challenging for us to isolate the pure effects originating from regular prices across the four purchase channels. Last, there are some unknown reasons for missing values in Online purchase channels that also complicate analysis.

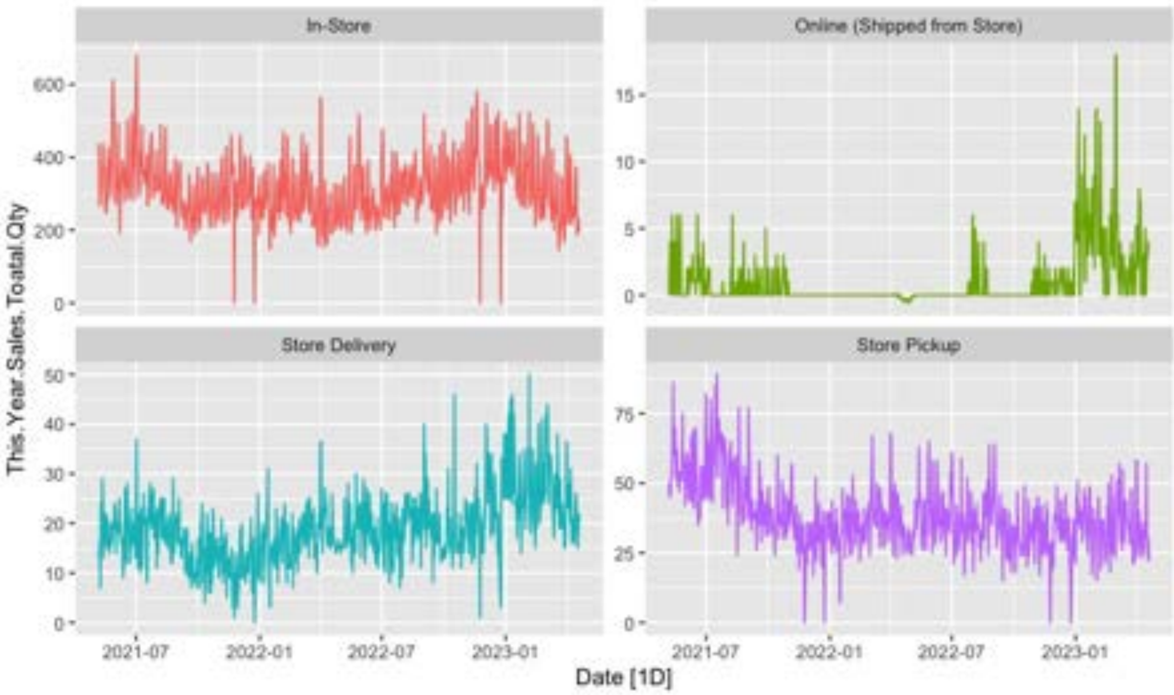
Here are our operational recommendations. First, we utilize roll-forward results to understand sales implications in specific channels for the next four weeks. Second, emphasize the dynamic nature of the data and the need for continuous monitoring in the future. Lastly, we provide specific channel-based suggestions. For the "In-Store" and "Store Pickup" channels, characterized by an overall decreasing trend in the forecasting plot, exercise caution when considering additional product placement in these low-sales stores. Consider reallocating funds to growing channels like "Store Delivery" based on sales trends. In the "Store Delivery" channel, there is a clear upward total sales trend indicating the potential to contribute more revenue, but avoid overordering due to potential sales fluctuations. In the "Online" channel, there are apparent sales fluctuations, and it has the lowest total sales among the four purchase channels. Consider the high correlation between forecasting sales and sales exactly a month (4 weeks) prior when making decisions. Since forecasting will be conducted for the next four weeks, it will be performed once every four weeks to generate data for the upcoming month.

Our project addresses Nuqleous' challenge of managing fluctuating demand and optimizing perishable goods allocation across different purchase channels. Leveraging data-driven forecasting models, we focused on identified trends in the In-store, store pickup, store delivery, and Online (Shipped from Store) channels. Overall, this data-driven approach aims to enhance Nuqleous' ability to forecast sales trends and make strategic ordering and allocation decisions in the future.

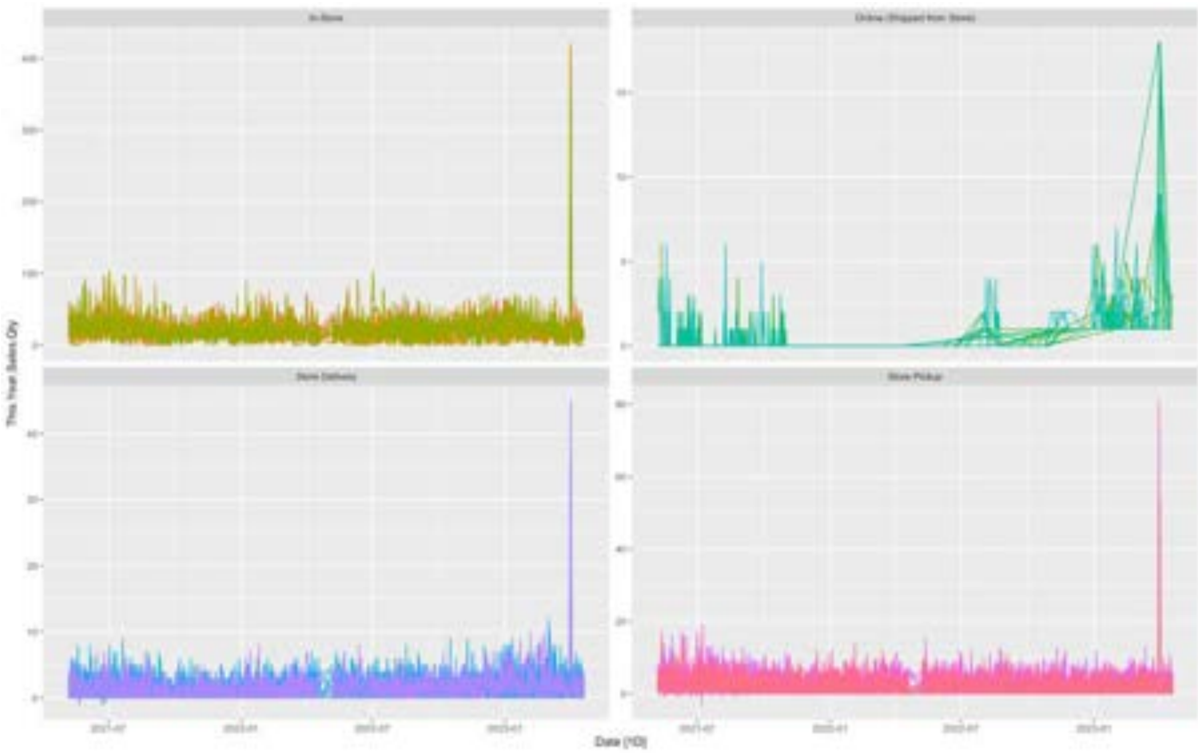
### 3.7 Appendix:



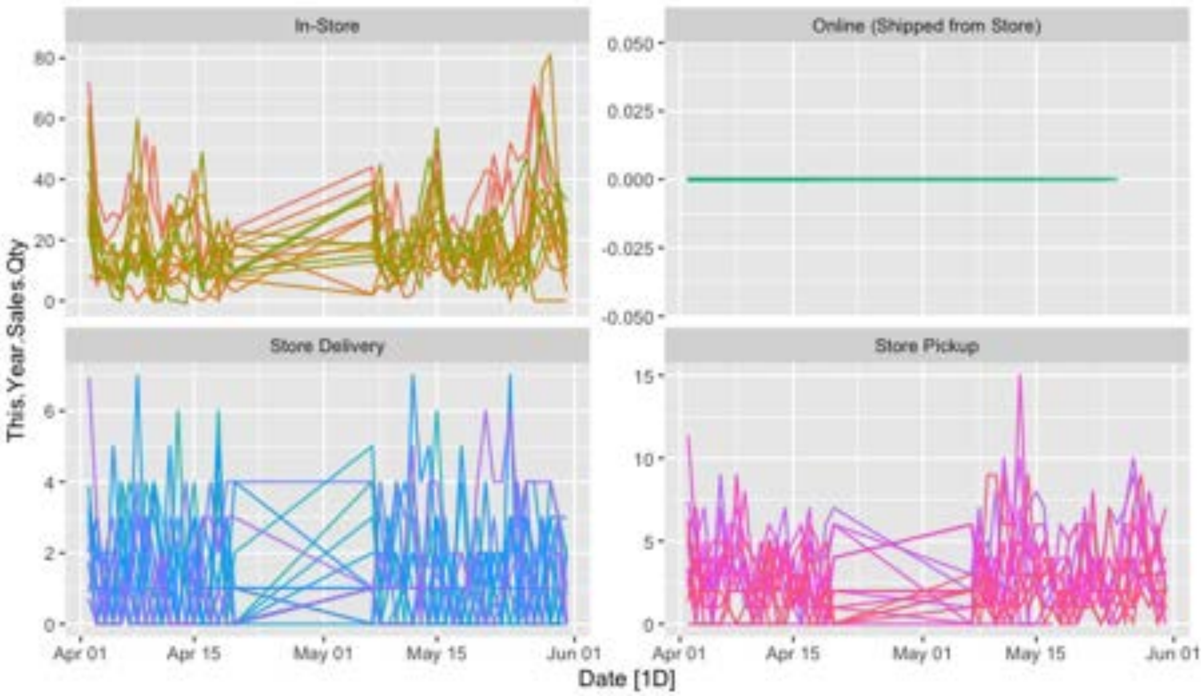

**Picture 1-a:  there are obvious peak values in 2023-04-01 and 2023-04-02**



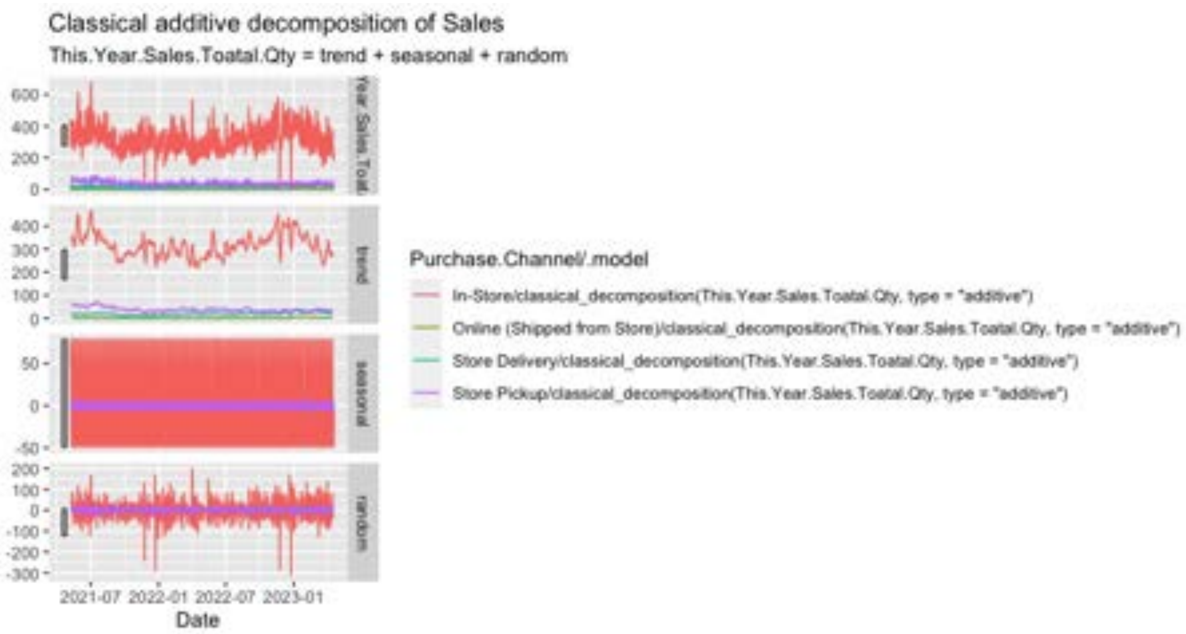

**Picture 1-b: after removing the peak, the data becomes more rational.**



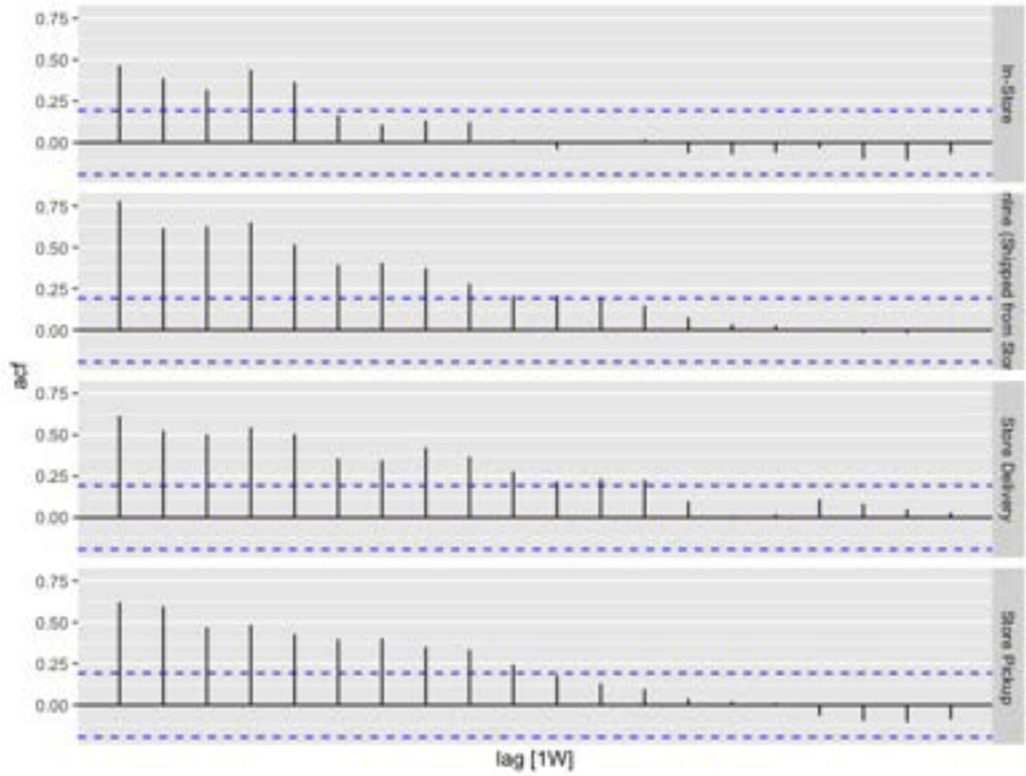
**Picture 2-a: the gap between two years of data.**



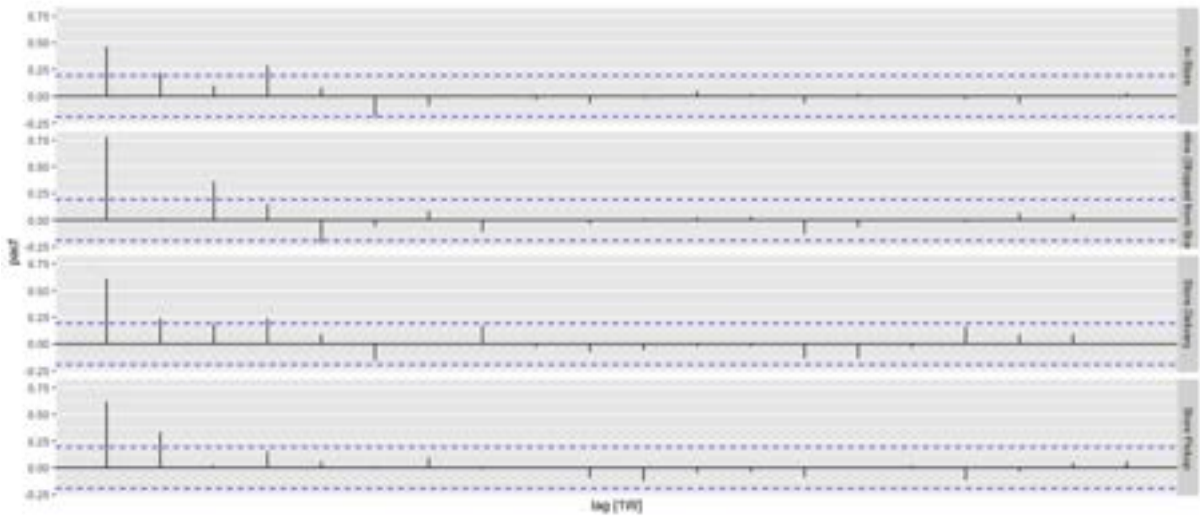

**Picture 2-b: the gap between two years of data(focus on the missing period).**




**Picture 3-a: Decomposition of daily data. There is a strong seasonality in a week, particularly evident in the In-Store series. Additionally, we observe the trend looks like the sin and cos routine. The uncertainty of residuals in the In-Store series is relatively high, suggesting a likelihood of greater variability compared to other series.**




**Picture 3-b: the ACF plot of different weekly sales data time series.**



**Picture 3-c: the PACF plot of different weekly sales data time series.**

```
model(
  naive = NAIVE(TotalSales),
```

```
  snaive = SNAIVE(TotalSales ~ lag(4)),  # lag is decided based on decomposition
result
  ets = ETS(TotalSales),
  reg = TSLM(TotalSales ~ trend() + season(4)),
  arima.stepwise = ARIMA(TotalSales), # this takes very long (~10 min)
  arima.search   = ARIMA(TotalSales, stepwise = FALSE),
  nn = NNETAR(TotalSales ~ AR(p = 4)), # neural network
  arima.lag = ARIMA(TotalSales ~ pdq(fixed = list(ar1 = 2, ma2 = 1)))
  )
```
**Picture 4: Forecasting models.**

| | Purchase.Channel | .model | .type | ME | RMSE | MAE | MPE | MAPE | MASE | RMSSE | ACF1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | In-Store | naive | Training | 1.175532e+01 | 347.152266 | 250.6551940 | -0.4823610 | 11.184329 | 0.53424186 | 0.64925517 | -0.31629549 |
| 2 | In-Store | snaive | Training | 1.018182e+01 | 457.337561 | 357.3107192 | -1.4445336 | 16.345746 | 0.76156548 | 0.85532720 | 0.38023313 |
| 3 | In-Store | ets | Training | -1.621378e+01 | 327.524670 | 231.0532686 | -3.0335848 | 11.485698 | 0.49246268 | 0.61254702 | 0.04255886 |
| 4 | In-Store | reg | Training | 0.000000e+00 | 361.068502 | 286.6332797 | -2.9456455 | 13.691664 | 0.61092489 | 0.67528175 | 0.49809310 |
| 5 | In-Store | arima.stepwise | Training | 2.632173e+01 | 309.872826 | 224.7746445 | -0.1162882 | 9.998197 | 0.47908053 | 0.57953398 | 0.11308566 |
| 6 | In-Store | arima.search | Training | 1.935783e+01 | 291.965922 | 216.1226247 | -0.1654975 | 9.753005 | 0.46063976 | 0.54604392 | 0.16086990 |
| 7 | In-Store | nn | Training | -2.703709e-02 | 39.886279 | 26.3498759 | -0.1091487 | 1.131658 | 0.05616164 | 0.07459658 | 0.05174933 |
| 8 | In-Store | arima.lag | Training | 2.365610e+01 | 310.631607 | 227.0936760 | -0.1981489 | 10.131570 | 0.48402327 | 0.58095307 | 0.15376477 |
| 9 | Online (Shipped from Store) | naive | Training | 2.446809e-01 | 5.607174 | 2.8170051 | NaN | Inf | 0.23850567 | 0.32567663 | -0.03896749 |
| 10 | Online (Shipped from Store) | snaive | Training | 1.909091e+00 | 10.237919 | 5.4582461 | NaN | Inf | 0.46213003 | 0.59464022 | 0.76931043 |
| 11 | Online (Shipped from Store) | ets | Training | 2.482192e-01 | 5.558200 | 2.8461240 | NaN | Inf | 0.24097106 | 0.32283216 | 0.05072972 |
| 12 | Online (Shipped from Store) | reg | Training | -8.227337e-16 | 9.642906 | 6.9960937 | -Inf | Inf | 0.59233405 | 0.56008061 | 0.82327531 |
| 13 | Online (Shipped from Store) | arima.stepwise | Training | 2.810517e-01 | 4.786800 | 2.6761786 | NaN | Inf | 0.22658240 | 0.27802760 | 0.01531438 |
| 14 | Online (Shipped from Store) | arima.search | Training | 2.810517e-01 | 4.786800 | 2.6761786 | NaN | Inf | 0.22658240 | 0.27802760 | 0.01531438 |
| 15 | Online (Shipped from Store) | nn | Training | 9.290145e-03 | 1.254197 | 0.6956687 | NaN | Inf | 0.05889976 | 0.07284643 | 0.13207676 |
| 16 | Online (Shipped from Store) | arima.lag | Training | 2.421684e-01 | 5.577584 | 2.7874155 | NaN | Inf | 0.23600043 | 0.32395801 | -0.03976695 |
| 17 | Store Delivery | naive | Training | 1.627660e+00 | 31.949135 | 24.4549015 | -1.7295348 | 19.436560 | 0.52260080 | 0.54465958 | -0.33712011 |
| 18 | Store Delivery | snaive | Training | 5.897727e+00 | 40.490893 | 31.2049799 | -0.9591659 | 25.090104 | 0.66684985 | 0.69027697 | 0.28897538 |
| 19 | Store Delivery | ets | Training | 1.395314e+00 | 28.174132 | 20.4540244 | -4.9109070 | 18.776372 | 0.43710213 | 0.48030441 | 0.03916883 |
| 20 | Store Delivery | reg | Training | -1.720261e-15 | 30.566567 | 24.7511328 | -6.7635188 | 22.077219 | 0.52893126 | 0.52108995 | 0.47177683 |
| 21 | Store Delivery | arima.stepwise | Training | 4.010114e+00 | 27.332715 | 20.2947667 | -0.5290728 | 16.250336 | 0.43369879 | 0.46596018 | 0.03860132 |
| 22 | Store Delivery | arima.search | Training | 4.010114e+00 | 27.332715 | 20.2947667 | -0.5290728 | 16.250336 | 0.43369879 | 0.46596018 | 0.03860132 |
| 23 | Store Delivery | nn | Training | -1.489319e-02 | 4.153865 | 2.8382007 | -0.3686360 | 2.050603 | 0.06065230 | 0.07081389 | -0.11830810 |
| 24 | Store Delivery | arima.lag | Training | 3.833598e+00 | 27.438917 | 20.3950142 | -0.6166380 | 16.255628 | 0.43584108 | 0.46777069 | 0.10147474 |
| 25 | Store Pickup | naive | Training | 9.893617e-01 | 55.222181 | 39.0262903 | -1.6538696 | 14.837999 | 0.56019906 | 0.61215881 | -0.33565729 |
| 26 | Store Pickup | snaive | Training | -8.840909e+00 | 67.247329 | 54.8360663 | -6.1183059 | 21.893542 | 0.78713894 | 0.74546213 | 0.40683172 |
| 27 | Store Pickup | ets | Training | -7.367127e+00 | 51.731319 | 37.2155925 | -6.0251875 | 15.558303 | 0.53420758 | 0.57346127 | 0.01339114 |
| 28 | Store Pickup | reg | Training | -1.795055e-15 | 55.323650 | 43.2297713 | -4.4066312 | 17.414509 | 0.62053752 | 0.61328363 | 0.46777964 |
| 29 | Store Pickup | arima.stepwise | Training | 4.753936e-02 | 47.681376 | 34.2588089 | -2.3885872 | 12.975961 | 0.49176472 | 0.52856612 | 0.14738142 |
| 30 | Store Pickup | arima.search | Training | 4.753936e-02 | 47.681376 | 34.2588089 | -2.3885872 | 12.975961 | 0.49176472 | 0.52856612 | 0.14738142 |
| 31 | Store Pickup | nn | Training | -1.293108e-02 | 5.240652 | 3.8421475 | -0.2311979 | 1.662748 | 0.05515173 | 0.05809461 | -0.20413680 |
| 32 | Store Pickup | arima.lag | Training | 3.375977e-01 | 48.920066 | 35.9518243 | -2.4246413 | 13.648724 | 0.51606694 | 0.54229748 | 0.17745480 |

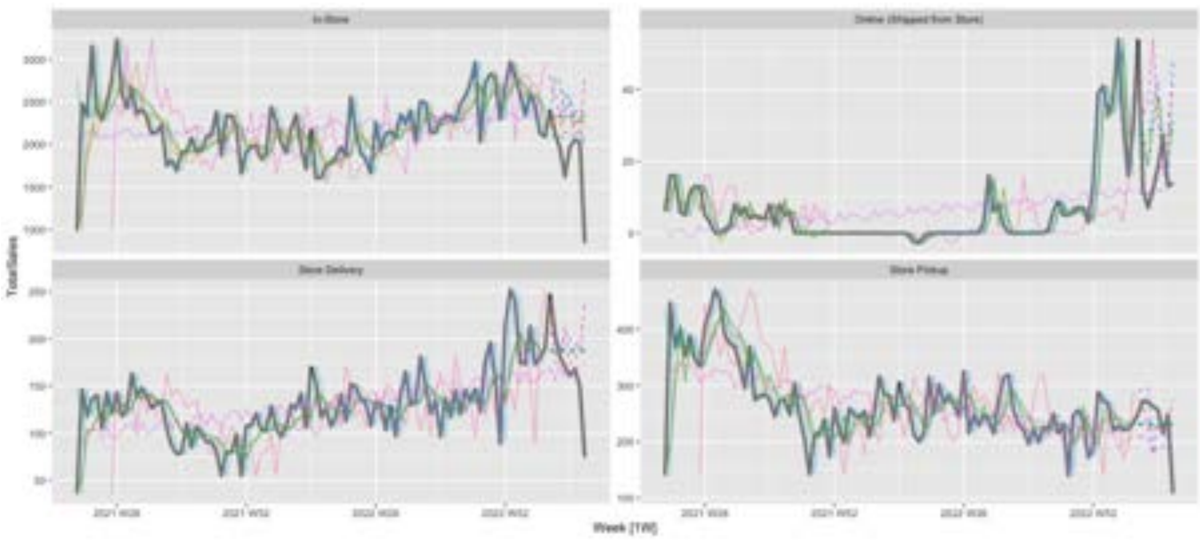
**Picture 5-a: the accuracy of each model in the training Period.**

| | .model | Purchase.Channel | .type | ME | RMSE | MAE | MPE | MAPE | MASE | RMSSE | ACF1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | arima.lag | In-Store | Test | -383.389390 | 584.05764 | 420.255752 | -32.384575 | 33.91557 | NaN | NaN | 0.003013283 |
| 2 | arima.lag | Online (Shipped from Store) | Test | -9.330645 | 16.90163 | 15.580645 | -105.868303 | 117.44238 | NaN | NaN | -0.050097708 |
| 3 | arima.lag | Store Delivery | Test | -17.605855 | 49.56726 | 37.323089 | -23.272621 | 31.60234 | NaN | NaN | 0.302682353 |
| 4 | arima.lag | Store Pickup | Test | 5.822190 | 51.36373 | 39.876821 | -6.225969 | 23.62307 | NaN | NaN | 0.052346129 |
| 5 | arima.search | In-Store | Test | -348.164710 | 545.94104 | 398.109144 | -29.870548 | 31.94465 | NaN | NaN | 0.001229629 |
| 6 | arima.search | Online (Shipped from Store) | Test | -9.281415 | 14.39062 | 13.029721 | -87.763619 | 94.89493 | NaN | NaN | -0.125070363 |
| 7 | arima.search | Store Delivery | Test | -17.674157 | 49.55831 | 37.330620 | -23.312475 | 31.61751 | NaN | NaN | 0.302978319 |
| 8 | arima.search | Store Pickup | Test | 3.925467 | 51.18192 | 39.010149 | -7.104725 | 23.44664 | NaN | NaN | 0.047196445 |
| 9 | arima.stepwise | In-Store | Test | -429.826391 | 619.20057 | 461.728704 | -35.177282 | 36.50213 | NaN | NaN | 0.008393518 |
| 10 | arima.stepwise | Online (Shipped from Store) | Test | -9.281415 | 14.39062 | 13.029721 | -87.763619 | 94.89493 | NaN | NaN | -0.125070363 |
| 11 | arima.stepwise | Store Delivery | Test | -17.674157 | 49.55831 | 37.330620 | -23.312475 | 31.61751 | NaN | NaN | 0.302978319 |
| 12 | arima.stepwise | Store Pickup | Test | 3.925467 | 51.18192 | 39.010149 | -7.104725 | 23.44664 | NaN | NaN | 0.047196445 |
| 13 | ets | In-Store | Test | -447.486499 | 627.99687 | 468.328584 | -36.138319 | 37.00185 | NaN | NaN | 0.003013283 |
| 14 | ets | Online (Shipped from Store) | Test | -7.726765 | 16.07193 | 14.377735 | -94.482507 | 106.79912 | NaN | NaN | -0.050097708 |
| 15 | ets | Store Delivery | Test | -17.638366 | 49.57881 | 37.339344 | -23.294045 | 31.61652 | NaN | NaN | 0.302682353 |
| 16 | ets | Store Pickup | Test | 4.926102 | 51.26989 | 39.428777 | -6.640534 | 23.52013 | NaN | NaN | 0.052346129 |
| 17 | naive | In-Store | Test | -211.854839 | 488.89505 | 304.354839 | -22.338930 | 26.24660 | NaN | NaN | 0.003013283 |
| 18 | naive | Online (Shipped from Store) | Test | -9.330645 | 16.90163 | 15.580645 | -105.868303 | 117.44238 | NaN | NaN | -0.050097708 |
| 19 | naive | Store Delivery | Test | -19.540323 | 50.28689 | 38.290323 | -24.547398 | 32.44620 | NaN | NaN | 0.302682353 |
| 20 | naive | Store Pickup | Test | 2.431452 | 51.09058 | 38.181452 | -7.794654 | 23.23355 | NaN | NaN | 0.052346129 |
| 21 | nn | In-Store | Test | -540.759541 | 655.58262 | 552.078746 | -38.126588 | 38.59665 | NaN | NaN | -0.129411629 |
| 22 | nn | Online (Shipped from Store) | Test | -10.934984 | 19.13430 | 16.304244 | -102.079083 | 114.59095 | NaN | NaN | -0.039342035 |
| 23 | nn | Store Delivery | Test | -28.851595 | 53.20538 | 40.407097 | -30.471982 | 35.23309 | NaN | NaN | 0.292531094 |
| 24 | nn | Store Pickup | Test | -5.939319 | 53.43111 | 42.453546 | -9.295022 | 23.46462 | NaN | NaN | -0.102923146 |
| 25 | reg | In-Store | Test | -471.680882 | 648.58654 | 486.584706 | -37.663736 | 38.28267 | NaN | NaN | 0.064254775 |
| 26 | reg | Online (Shipped from Store) | Test | 7.607577 | 16.10675 | 9.040512 | 15.083225 | 32.95037 | NaN | NaN | -0.025072403 |
| 27 | reg | Store Delivery | Test | 3.771027 | 49.09374 | 34.466075 | -9.980636 | 27.51106 | NaN | NaN | 0.340398224 |
| 28 | reg | Store Pickup | Test | 37.270786 | 63.55502 | 60.004990 | 8.350274 | 29.40046 | NaN | NaN | 0.108545278 |
| 29 | snaive | In-Store | Test | -598.479839 | 831.15985 | 598.479839 | -47.617155 | 47.61716 | NaN | NaN | -0.169982472 |
| 30 | snaive | Online (Shipped from Store) | Test | -15.580645 | 23.82200 | 21.580645 | -159.197934 | 175.40164 | NaN | NaN | 0.114833697 |
| 31 | snaive | Store Delivery | Test | -28.415323 | 63.56969 | 39.915323 | -33.624530 | 39.19449 | NaN | NaN | 0.199327684 |
| 32 | snaive | Store Pickup | Test | -6.693548 | 64.27073 | 42.056452 | -13.917125 | 27.39127 | NaN | NaN | 0.036093430 |

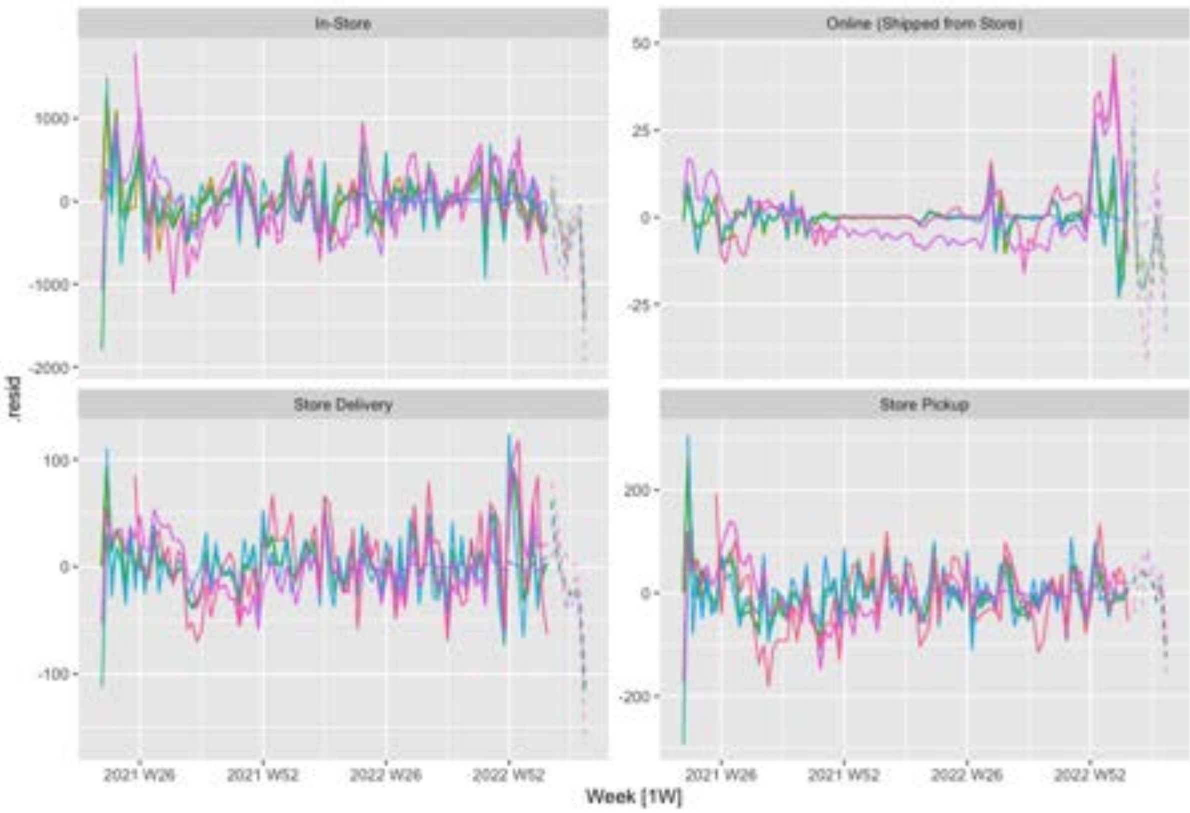
**Picture 5-b: the accuracy of each model in the validation period.**

| | Purchase.Channel | .model | sigma2 | log_lik | AIC | AICc | BIC | MSE | AMSE | MAE | r_squared | adj_r_squared | statistic | p_value | df | CV |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | In-Store | naive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 2 | In-Store | snaive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 3 | In-Store | ets | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA |
| 4 | In-Store | reg | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | [illegible] | [illegible] | [illegible] | [illegible] | 8 | [illegible] |
| 5 | In-Store | arima.stepwise | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 6 | In-Store | arima.search | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 7 | In-Store | nn | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 8 | In-Store | arima.lag | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 9 | Online (Shipped from Store) | naive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 10 | Online (Shipped from Store) | snaive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 11 | Online (Shipped from Store) | ets | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA |
| 12 | Online (Shipped from Store) | reg | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | [illegible] | [illegible] | [illegible] | [illegible] | 8 | [illegible] |
| 13 | Online (Shipped from Store) | arima.stepwise | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 14 | Online (Shipped from Store) | arima.search | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 15 | Online (Shipped from Store) | nn | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 16 | Online (Shipped from Store) | arima.lag | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 17 | Store Delivery | naive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 18 | Store Delivery | snaive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 19 | Store Delivery | ets | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA |
| 20 | Store Delivery | reg | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | [illegible] | [illegible] | [illegible] | [illegible] | 8 | [illegible] |
| 21 | Store Delivery | arima.stepwise | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 22 | Store Delivery | arima.search | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 23 | Store Delivery | nn | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 24 | Store Delivery | arima.lag | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 25 | Store Pickup | naive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 26 | Store Pickup | snaive | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 27 | Store Pickup | ets | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA |
| 28 | Store Pickup | reg | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | [illegible] | [illegible] | [illegible] | [illegible] | 8 | [illegible] |
| 29 | Store Pickup | arima.stepwise | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 30 | Store Pickup | arima.search | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 31 | Store Pickup | nn | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| 32 | Store Pickup | arima.lag | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | NA | NA | NA | NA | NA | NA | NA | NA | NA |

**Picture 5-c: the report of each model.**

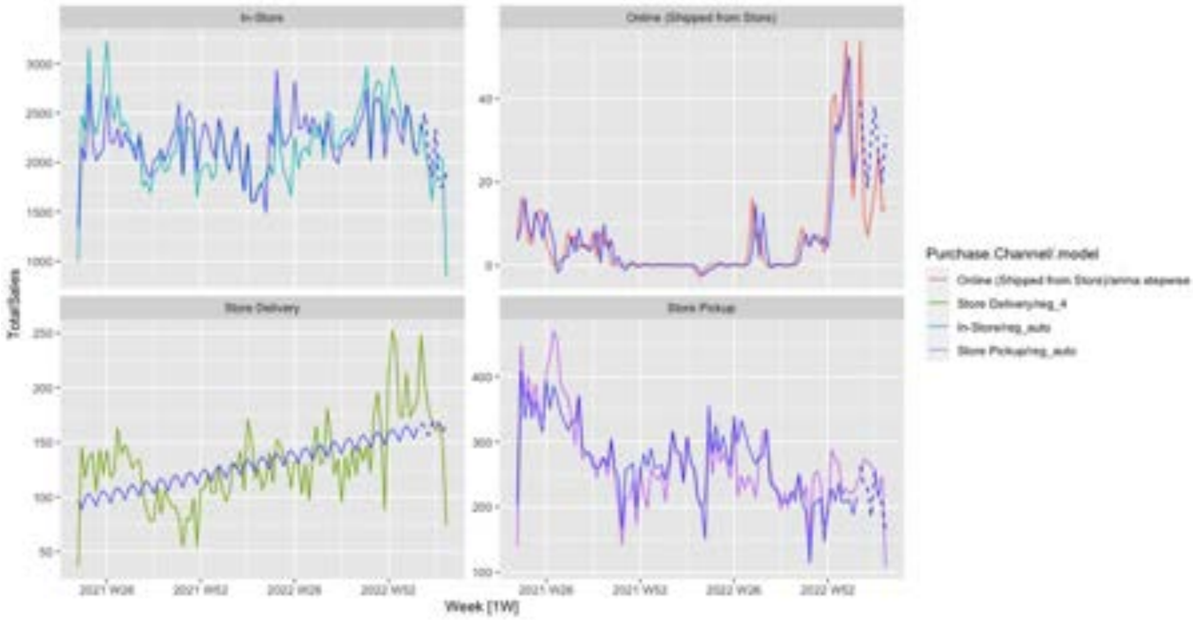



**Picture 6-a: The fitted and predicted value in both training period as well as validation periods.**

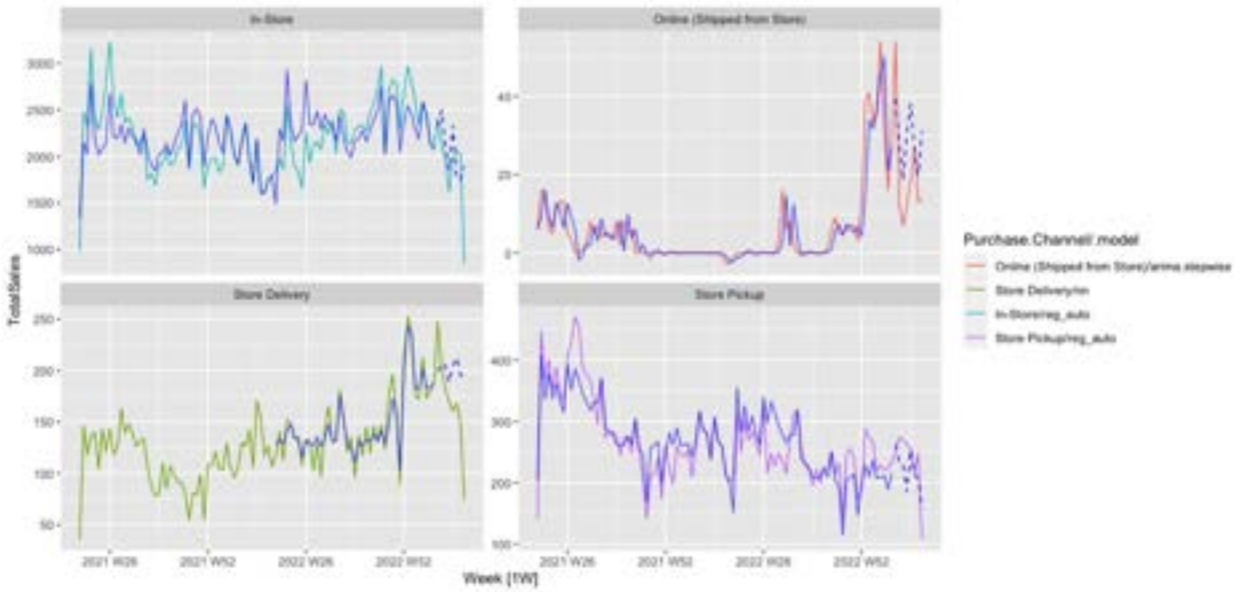



**Picture 6-b: The residuals in both training periods as well as the validation period.**

| | Purchase.Channel | .model |
|---|---|---|
| 1 | Online (Shipped from Store) | arima.stepwise |
| 2 | Store Delivery | reg_4 |
| 3 | In-Store | reg_auto |
| 4 | Store Pickup | reg_auto |



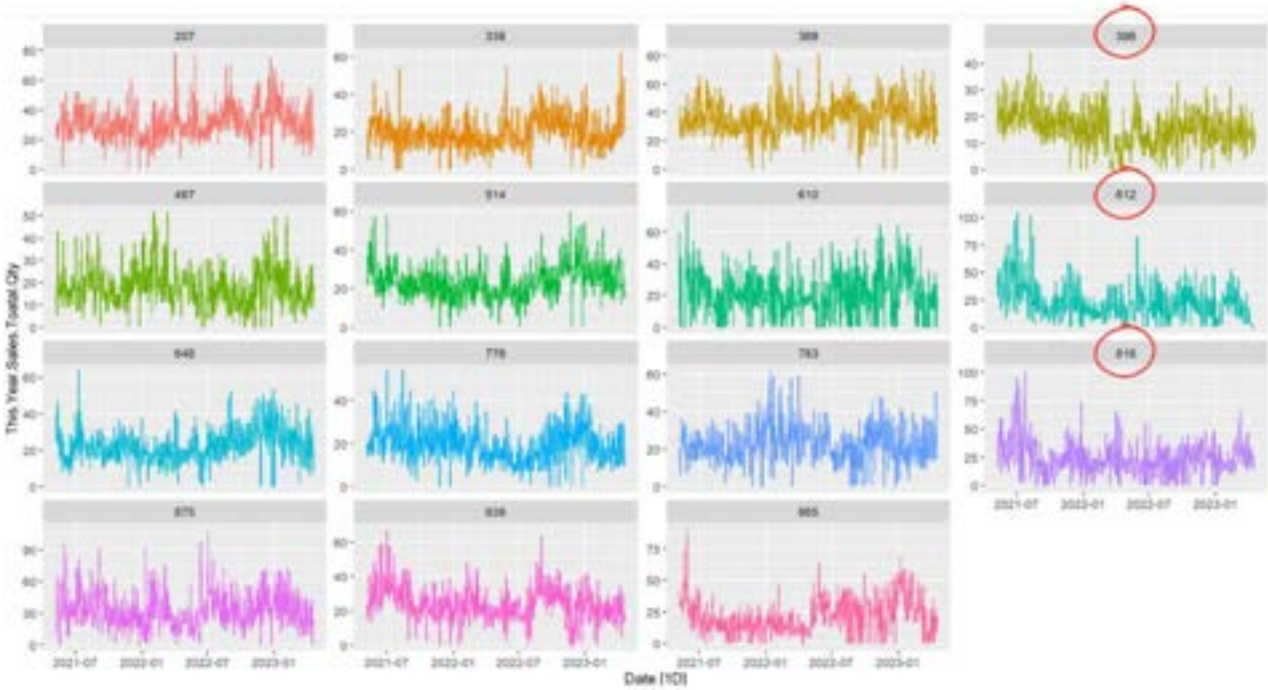

**Picture 6-c: Best model in different series(four purchase channels) using only the lowest RMSE.**



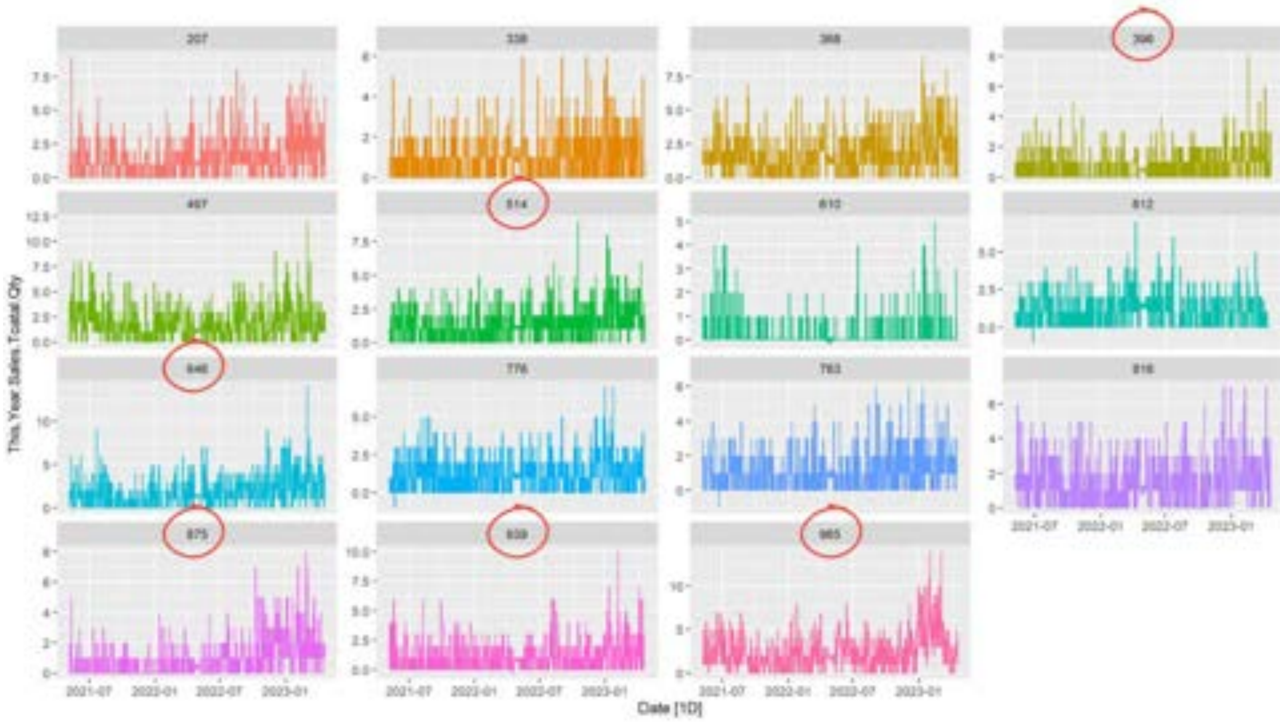

**Picture 6-d: Rechange the purchase channel of store delivery through the performance by seeing through the graph to get a better performance. According to the Picture in 6-b, we choose the NN model as the best model**

| | steps.ahead | .model | .type | MAE | RMSE | MAPE |
|---|---|---|---|---|---|---|
| 1 | 1 | arima.lag | Test | 1614.9988 | 1788.6919 | 4426.0214 |
| 2 | 1 | arima.search | Test | 1538.7378 | 1716.1209 | 4261.7237 |
| 3 | 1 | arima.stepwise | Test | 1568.8072 | 1744.6281 | 4338.7177 |
| 4 | 1 | ets | Test | 1574.4385 | 1751.6971 | 4352.5963 |
| 5 | 1 | naive | Test | 1504.2812 | 1666.5668 | 4161.3810 |
| 6 | 1 | nn | Test | 1514.9560 | 1685.9906 | 4141.5932 |
| 7 | 1 | reg | Test | 1739.5496 | 1908.0209 | 4640.4056 |
| 8 | 1 | snaive | Test | 1602.5111 | 1786.3958 | 4289.1127 |
| 9 | 2 | arima.lag | Test | 1502.7485 | 1731.3353 | 4381.0184 |
| 10 | 2 | arima.search | Test | 1404.9795 | 1635.3301 | 4175.3350 |
| 11 | 2 | arima.stepwise | Test | 1444.3296 | 1672.7701 | 4280.2825 |
| 12 | 2 | ets | Test | 1442.2504 | 1668.6855 | 4264.1317 |
| 13 | 2 | naive | Test | 1362.0625 | 1577.9607 | 4096.5677 |
| 14 | 2 | nn | Test | 1398.7409 | 1612.3414 | 4158.9900 |
| 15 | 2 | reg | Test | 1561.9020 | 1788.6684 | 4469.1789 |
| 16 | 2 | snaive | Test | 1402.8548 | 1634.3124 | 4092.7005 |
| 17 | 3 | arima.lag | Test | 1384.0914 | 1652.7426 | 3787.6441 |
| 18 | 3 | arima.search | Test | 1298.0879 | 1561.8846 | 3593.5171 |
| 19 | 3 | arima.stepwise | Test | 1345.7984 | 1613.8486 | 3717.7673 |
| 20 | 3 | ets | Test | 1343.5487 | 1609.3118 | 3702.3581 |
| 21 | 3 | naive | Test | 1256.8750 | 1507.9344 | 3440.0732 |
| 22 | 3 | nn | Test | 1298.8225 | 1559.6431 | 3627.1714 |
| 23 | 3 | reg | Test | 1432.4880 | 1701.9104 | 3861.8721 |
| 24 | 3 | snaive | Test | 1253.1673 | 1515.6179 | 3441.2909 |
| 25 | 4 | arima.lag | Test | 1220.4407 | 1535.6189 | 2758.6421 |
| 26 | 4 | arima.search | Test | 1142.0636 | 1444.5816 | 2582.0557 |
| 27 | 4 | arima.stepwise | Test | 1207.4407 | 1518.5962 | 2719.3430 |
| 28 | 4 | ets | Test | 1205.1905 | 1516.8241 | 2714.8554 |
| 29 | 4 | naive | Test | 1096.1230 | 1395.9744 | 2468.7307 |
| 30 | 4 | nn | Test | 1193.6654 | 1514.9596 | 2666.4096 |
| 31 | 4 | reg | Test | 1264.7909 | 1587.8903 | 2826.2999 |
| 32 | 4 | snaive | Test | 1098.9173 | 1396.6328 | 2472.7143 |
| 33 | 5 | arima.lag | Test | 590.9471 | 1002.4016 | 135.6830 |

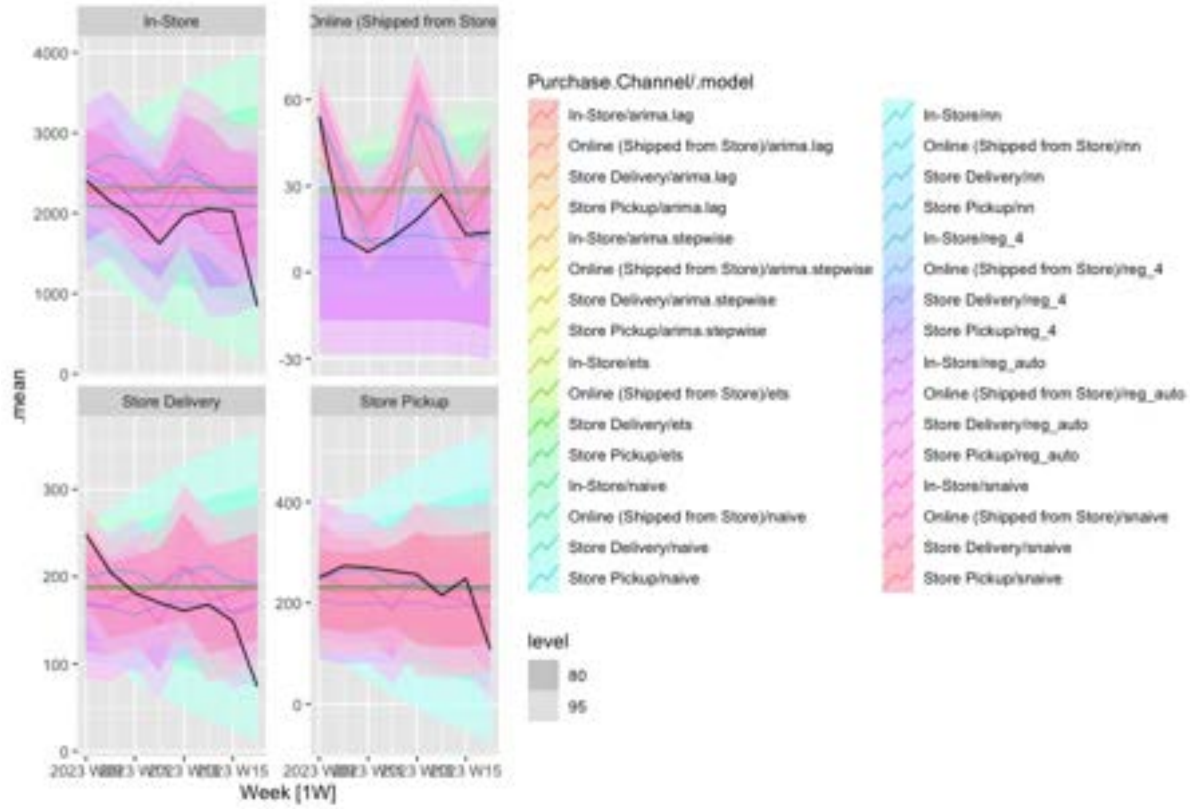
**Picture 7-a: the accuracy in each roll-forward model (Partial Result).**



**Picture 8-a: Total sales from Store pickup and In-Store channels in different stores.**



**Picture 8-b: Total sales from Store Delivery and Online (Shipped from Store) channels in different stores.**




**Picture 9-a: Confidence interval of each purchase channel. The colors within the narrower intervals signify a 95% confidence level, whereas the broader intervals indicate an 80% confidence level. The black line represents the actual values. The label in the bottom left corner denotes the confidence intervals for different models.**

**Picture 9-b: Confidence interval of each purchase channel with eight models.**