Supply Chain Data Analytics

Analyzing and Forcasting Supermarket Sales

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1 Data selection

We analyze, forecast and interpret the Superstore sales provided by Tableau using different statistical and machine learning methods.

The dataset provided contains information about products, sales and profits of a fictitious US company. The dataset contains about 10,000 rows with 1,850 unique product names and 17 product subcategories, covering four consecutive years on a daily basis.

We describe our work in the PDF version. However, we would like to recommend reading our quarto manuscript *here* as it contains the **relevant** R code in the Article Notebook.

2 Data Pre-processing

The superstore data set we selected is of high quality: At first glance (which needs to be verified during the visualization), the data appears to have been recorded regularly and without interruptions. There is no sign of a sudden structural change. Since the data are consumer products, it should contain both trends and seasonality. Nevertheless, we have included hypothetical steps to demonstrate our understanding of the data preprocessing procedure. In detail, we did:

- Remove whitespaces from column names
- Remove the `Row_ID` column as it can be inferred by it’s index
- Remove all columns with a single unique value, as storing these would be redundant
- Ensure machine-readable date formats in `yyyy-mm-dd` as these usually differ per locale.
- Ensure proper decimal separators
- Calculate the number of missing values (both NA and empty string “”) per column.

After these steps (and transposing the table for better document formatting), the data looks as follows:

First 3 Rows of the Data (Transposed)

Order_ID	CA-2016-152156	CA-2016-152156	CA-2016-138688
Order_Date	2016-11-08	2016-11-08	2016-06-12
Ship_Date	2016-11-11	2016-11-11	2016-06-16
Ship_Mode	Second Class	Second Class	Second Class
Customer_ID	CG-12520	CG-12520	DV-13045
Customer_Name	Claire Gute	Claire Gute	Darrin Van Huff
Segment	Consumer	Consumer	Corporate
City	Henderson	Henderson	Los Angeles
State	Kentucky	Kentucky	California
Postal_Code	42420	42420	90036
Region	South	South	West
Product_ID	FUR-BO-10001798	FUR-CH-10000454	OFF-LA-10000240
Category	Furniture	Furniture	Office Supplies
Sub_Category	Bookcases	Chairs	Labels
Product_Name	Bush Somerset Collection Bookcase	Hon Deluxe Fabric Upholstered Stacking Chairs, Rounded Back	Self-Adhesive Address Labels for Typewriters by Universal
Sales	261.96	731.94	14.62
Quantity	2	3	2
Discount	0	0	0
Profit	41.9136	219.5820	6.8714

Source: Article Notebook

We did not find any missing values, confirming the quality of the data set. There is some more processing to do, for instance the removal of outliers. However, by doing so we impose our own assumptions on the data. Let’s start by evaluating the descriptive statistics of our data and check if further processing is required.

Descriptive Statistics for Numeric Columns

Column	Min	Max	Mean	Median	StdDev
Postal_Code	1040	99301	55190.38	56430.5	32063.69
Sales	0.444	22638.48	229.858	54.49	623.2451
Quantity	1	14	3.789574	3	2.22511
Discount	0	0.8	0.1562027	0.2	0.206452
Profit	-6599.978	8399.976	28.6569	8.6665	234.2601

Descriptive Statistics for Date Columns

Column	Earliest	Latest
Order_Date	2014-01-03	2017-12-30
Ship_Date	2014-01-07	2018-01-05

We inspect the orders with the lowest and highest Sales amount (in USD). The most expensive orders were professional printers, cameras and teleconferencing units with high unit prices. The orders with the lowest sales amount were often binders and had a high Discount rate.

Interestingly there are orders with a negative profit. They typically have high Discount rates and often concern the same item, such as the “Cubify CubeX 3D Printer Triple Head Print”. The orders with a negative Profit were often part of a larger order (for instance CA-2016-108196), and placed by customers with multiple orders. We suspect these negative Profit’s to be caused by items of lower quality that receive discounts, general discount codes, or volume discounts. However, due to the high discounts especially on orders with negative profit, we assume these to be valid orders.

** Some negative profit products **

In figure x we plotted the quantities of the most sold products. Unfortunately, the sold quantities of individual products were too low to determine any meaningful trends.

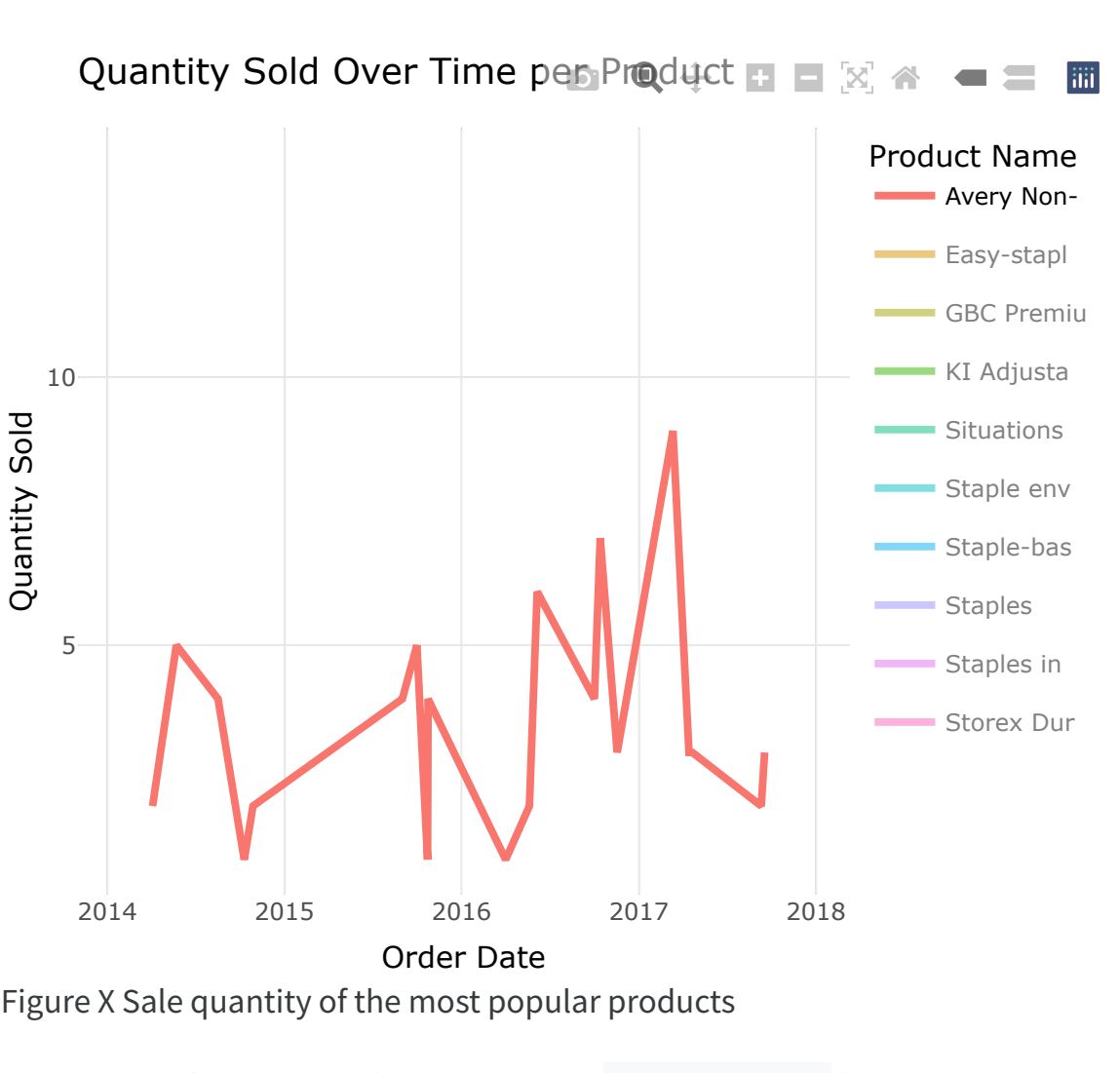
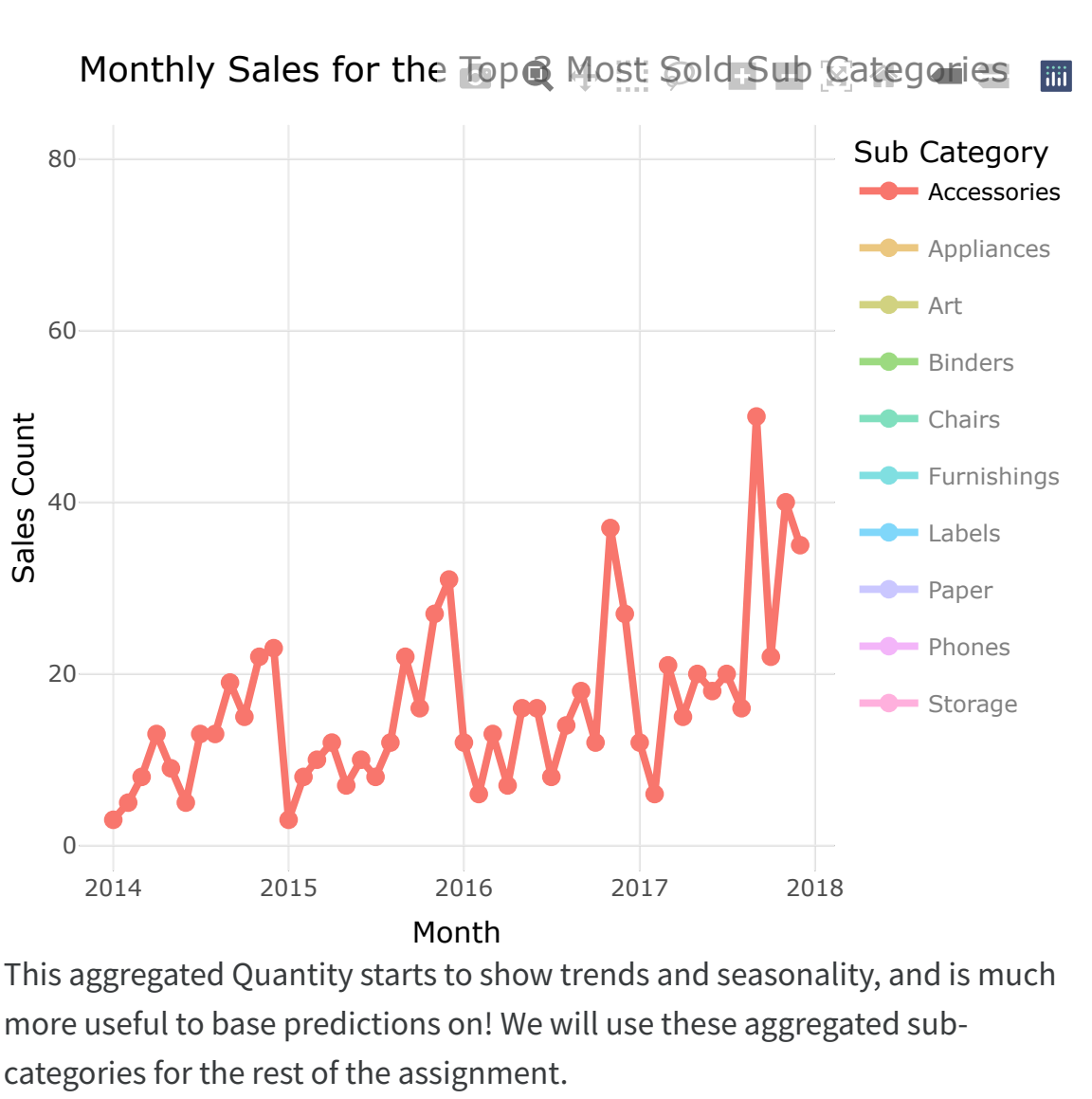


Figure X Sale quantity of the most popular products

Our proposed workaround is to aggregate `Product_Name` by `Sub_Category`, and treat it as a single product for the rest of the assignment, which we plotted in figure X.



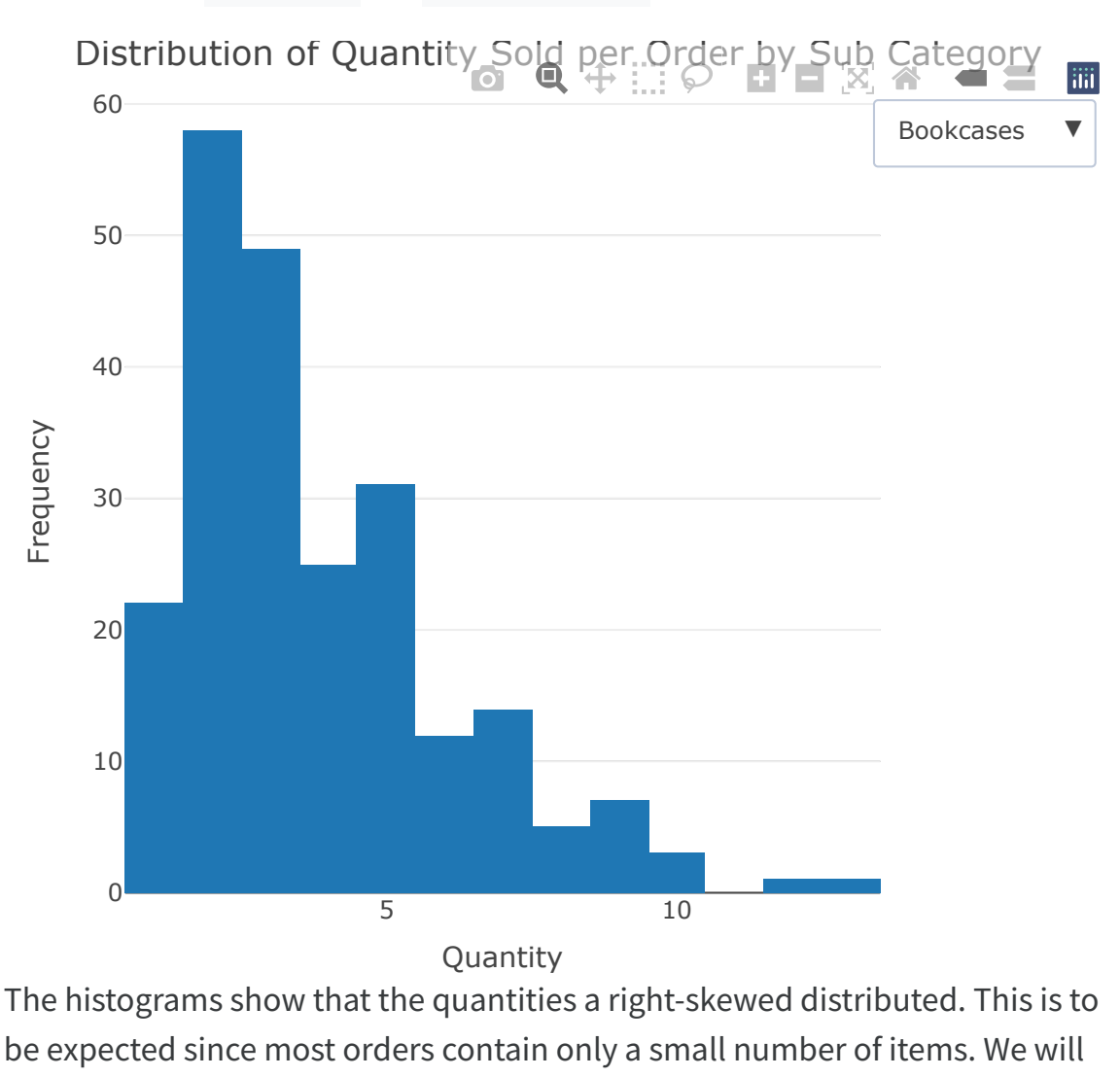
This aggregated Quantity starts to show trends and seasonality, and is much more useful to base predictions on! We will use these aggregated sub-categories for the rest of the assignment.

To properly finish our data preprocessing we ran some statistics on Quantity aggregated by Sub_Category. Table x contains some descriptive statistics.

Statistics for Sub_Category quantity

Sub_Category	Min	Mean	Max	Sd	CI_lower	CI_upper
Accessories	1	3.84	14	2.28	3.68	4.00
Appliances	1	3.71	14	2.12	3.52	3.90
Art	1	3.77	14	2.13	3.62	3.92
Binders	1	3.92	14	2.29	3.80	4.04
Bookcases	1	3.81	13	2.28	3.51	4.11
Chairs	1	3.82	14	2.28	3.64	4.00
Copiers	1	3.44	9	1.83	3.01	3.87
Envelopes	1	3.57	9	2.05	3.32	3.82
Fasteners	1	4.21	14	2.41	3.89	4.53
Furnishings	1	3.72	14	2.16	3.58	3.86
Labels	1	3.85	14	2.35	3.61	4.09
Machines	1	3.83	11	2.17	3.43	4.23
Paper	1	3.78	14	2.23	3.66	3.90
Phones	1	3.70	14	2.19	3.56	3.84
Storage	1	3.73	14	2.19	3.58	3.88
Supplies	1	3.41	10	1.84	3.15	3.67
Tables	1	3.89	13	2.45	3.62	4.16

The statistics for `Quantity` aggregated by `Sub_Category` looks valid. We can visualize it as histogram and check for anomalies. Figure y contains histograms of `Quantity` per `Sub_Category`.



The histograms show that the quantities a right-skewed distributed. This is to be expected since most orders contain only a small number of items. We will not remove the outliers with large quantities since they appear valid..

3 Data Visualization

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4 Forecasting Method Evaluation

Forecasting top 3 product categories (4a)

Let’s forecast sold quantities for the three most sold sub-categories:

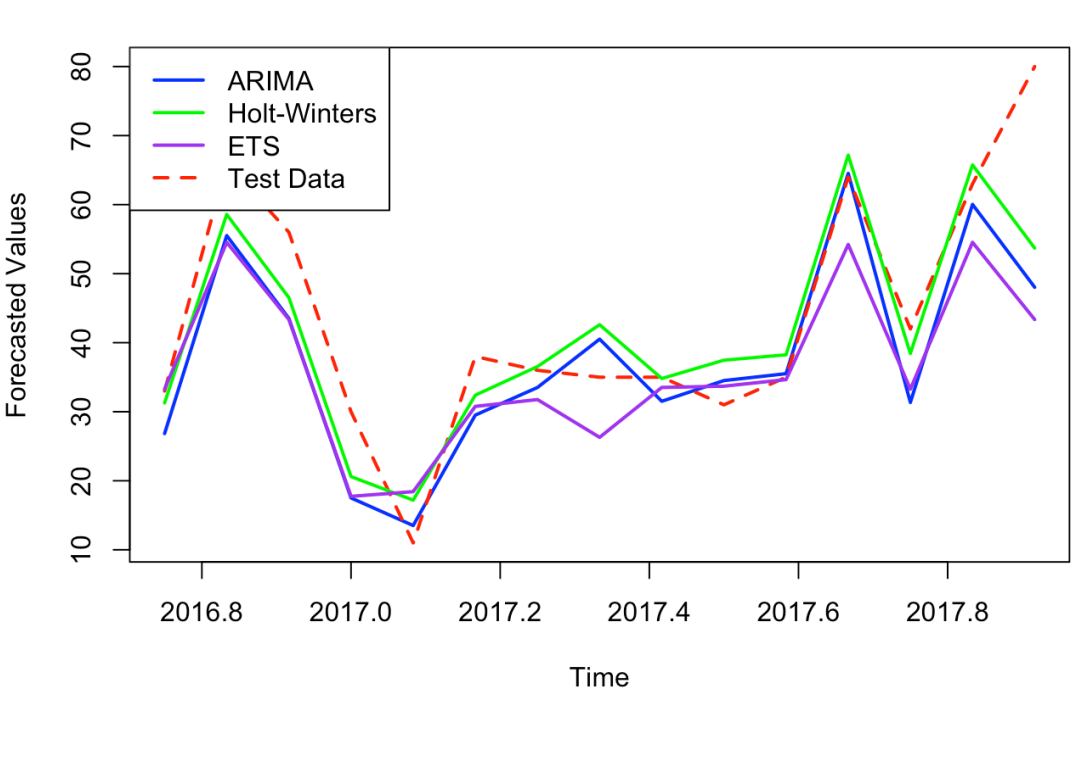
The steps taken for data preparation were:

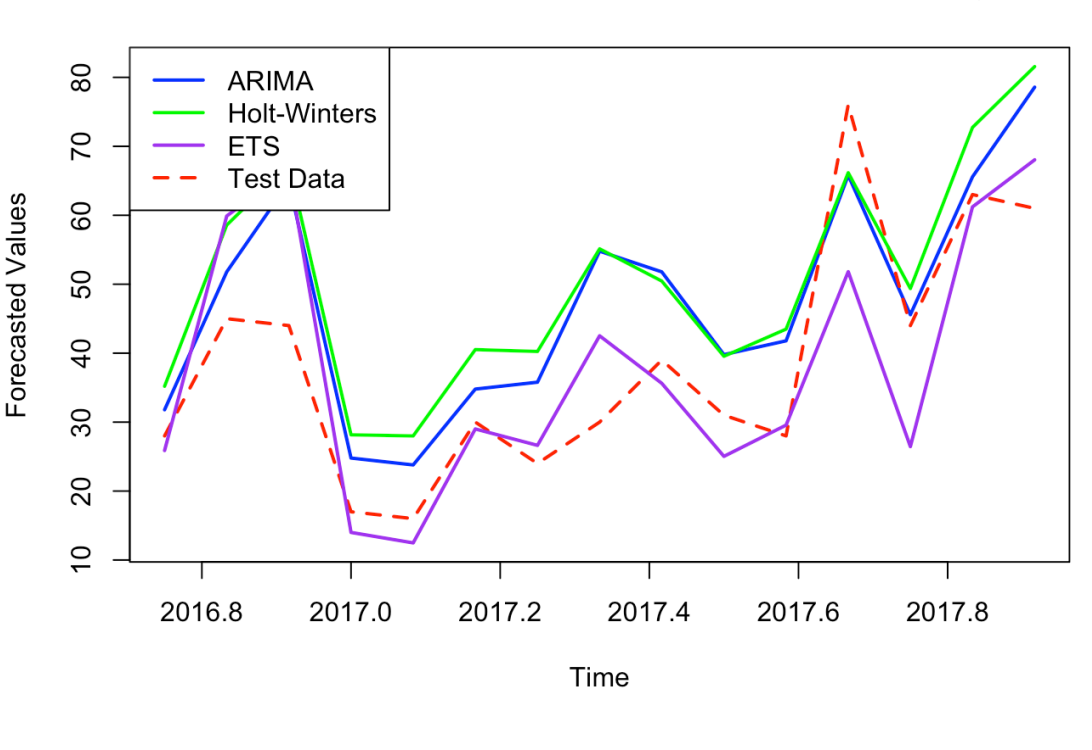
- Identifying Top Subcategories: The top three subcategories are selected from our dataset based on their sold quantities. The top three were: Binders, furnishing and paper.
- The sold quantities are aggregated monthly to create a time series object which we can use in the forecasting.
- A KPSS showed that the data is non stationary. First-order differencing is applied to transform the data from non-stationary to stationary. The KPSS results in a p-value >0.05 showing the stationarity.

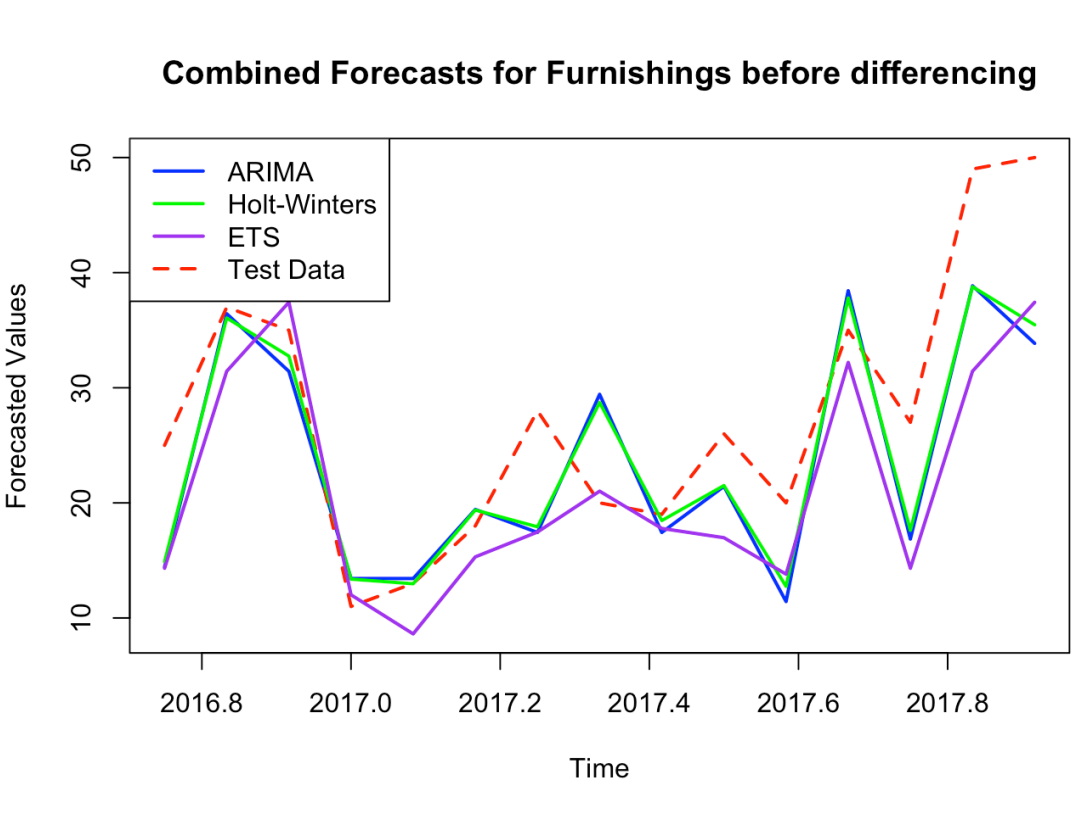
Three models are applied to each subcategory to forecast it. The models we use are: ARIMA, Holt-Winters and ETS. We have chosen these models because of their level of suitability for discrete time series data with all different levels of trend and seasonality. To evaluate the methods and its effectiveness , the data is split into a training set (70%) and testing set (30%).

To assess the results, we use the following performance metrics: ME, RMSE, MAE and MAPE. They are calculated for the training and testing phases of the forecast.

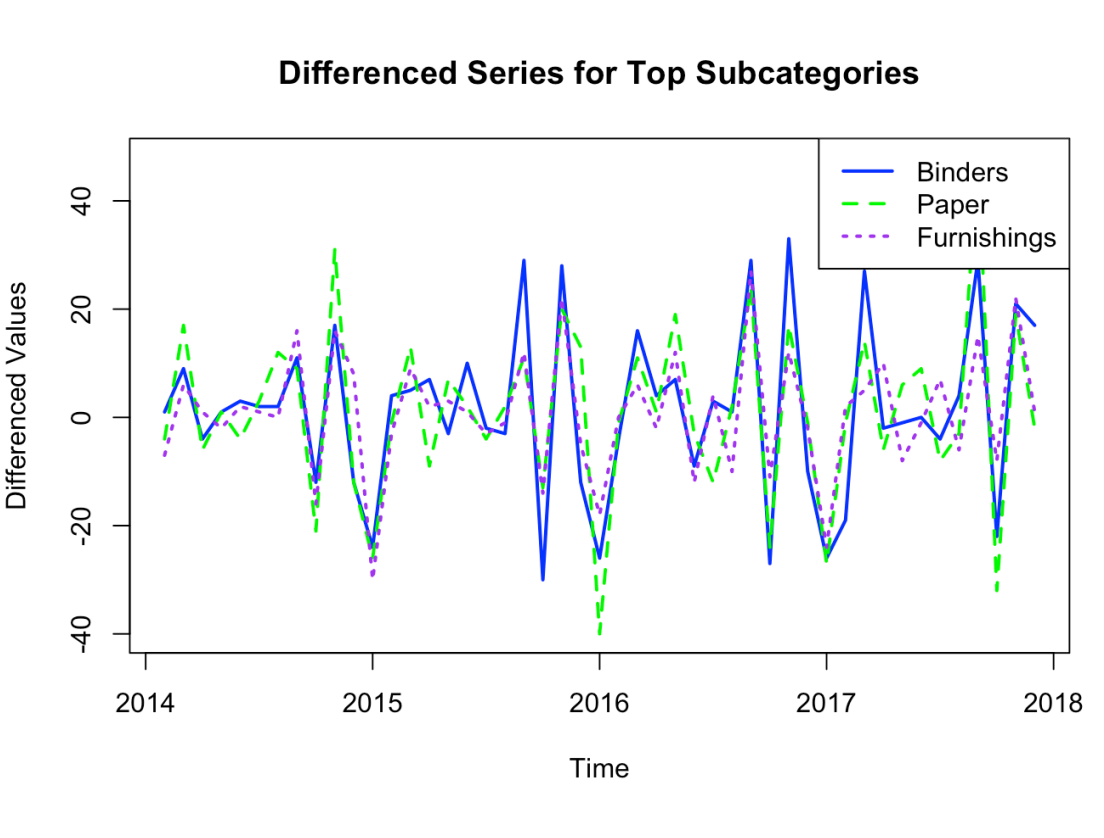
As we can see on the forecasting results ARIMA performed well for binders. We can state this because of the lowest RMSE if you compare it to the other models.

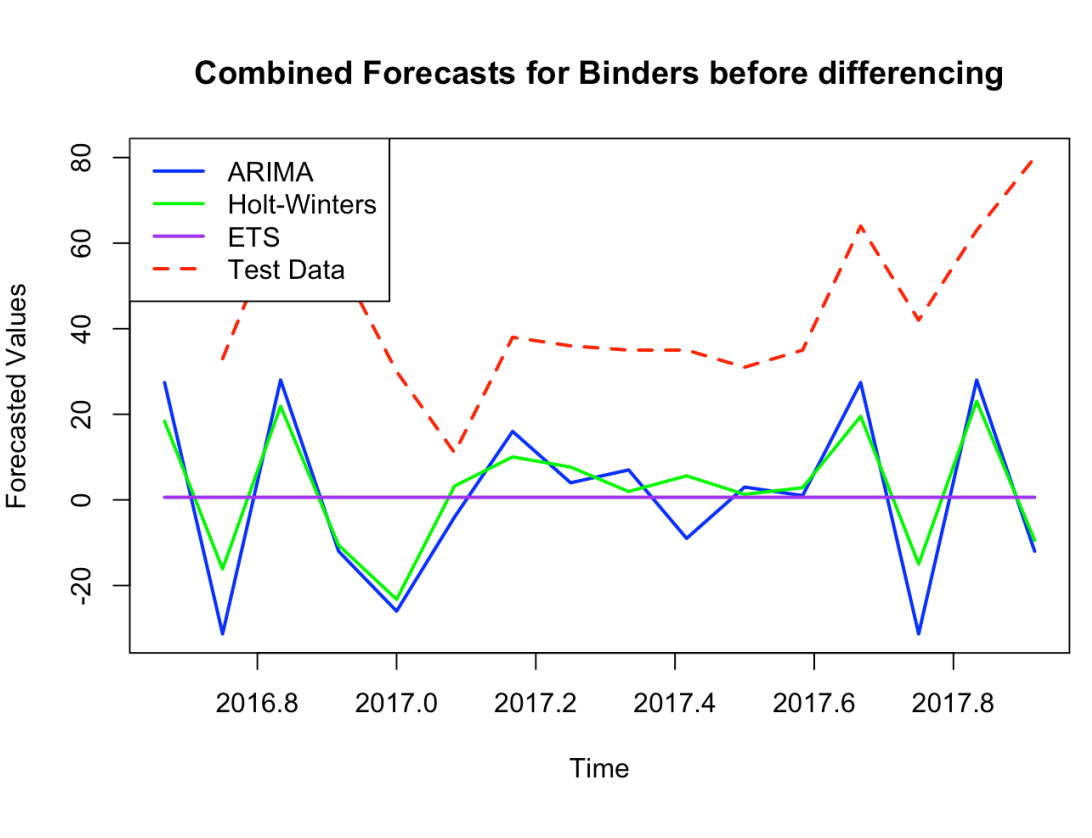


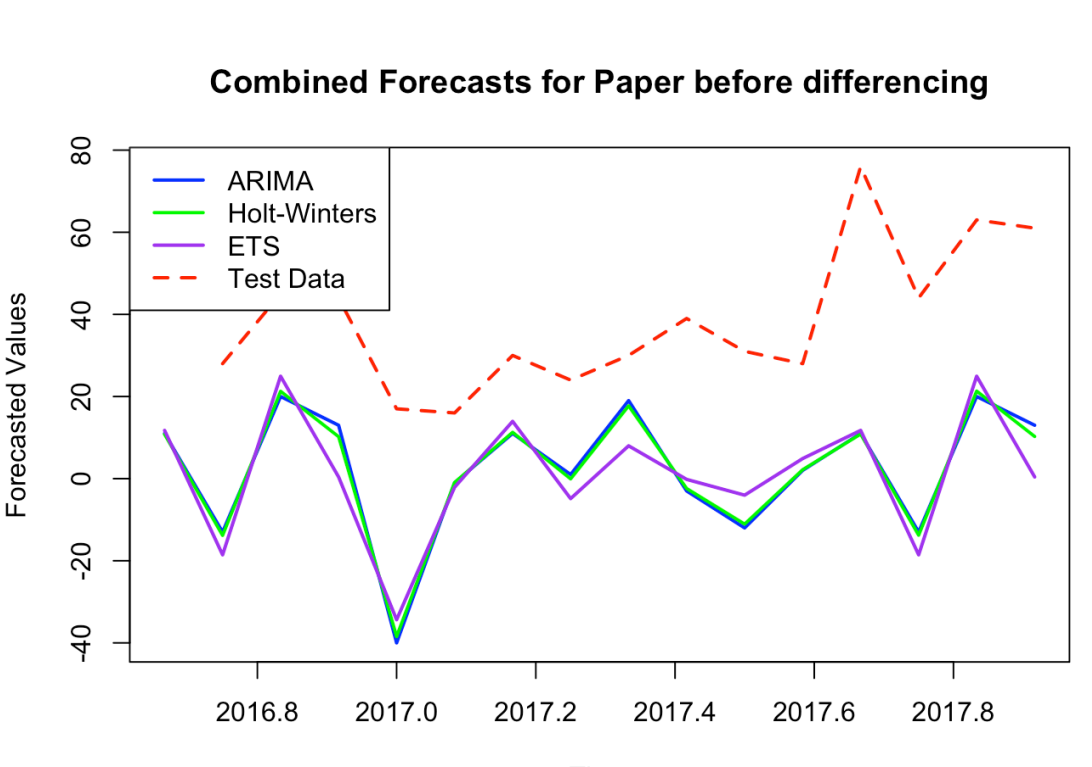


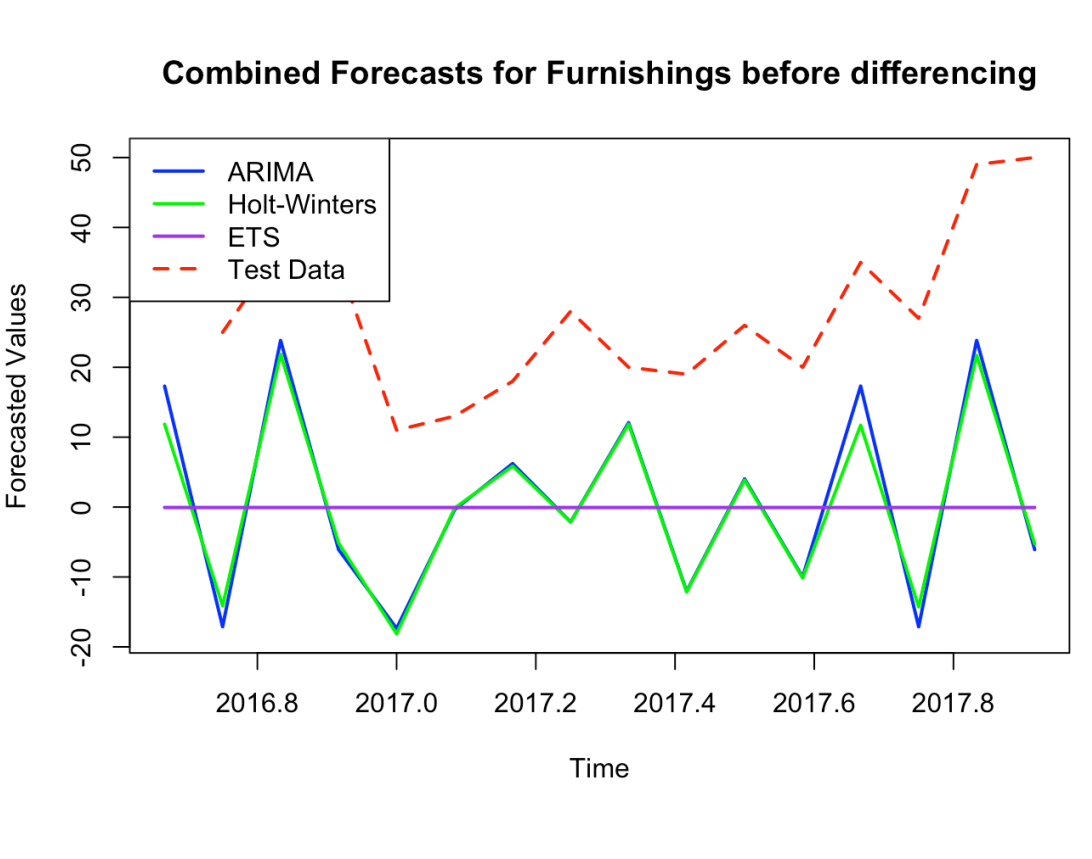


```
	KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.10182, Truncation lag parameter = 3, p-value =


	KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.061982, Truncation lag parameter = 3, p-value


	KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.098438, Truncation lag parameter = 3, p-value
```









```
KPSS Test for Differenced Sub-Category: Binders

	KPSS Test for Level Stationarity

data:  ts_current
KPSS Level = 0.10182, Truncation lag parameter = 3, p-value =


KPSS Test for Differenced Sub-Category: Paper

	KPSS Test for Level Stationarity

data:  ts_current
KPSS Level = 0.061982, Truncation lag parameter = 3, p-value


KPSS Test for Differenced Sub-Category: Furnishings

	KPSS Test for Level Stationarity

data:  ts_current
KPSS Level = 0.098438, Truncation lag parameter = 3, p-value
```

As we can see on the forecasting results ARIMA performed well for binders. We can state this because of the lowest RMSE. - ARIMA Binders: - Forecasting results Binders:

For the subcategory furnishings we can see that the ETS forecasting method is the most stable across the training and testing phase. - ETS furnishings - Forecasting results Furnishings:

For the last subcategory and product paper the ETS model is again the most consistent, comparing the statistics for training and test set. The high variability in the test data leads to larger forecasting errors in all the 3 models.

- ETS Furnishings:
- Forecasting results:

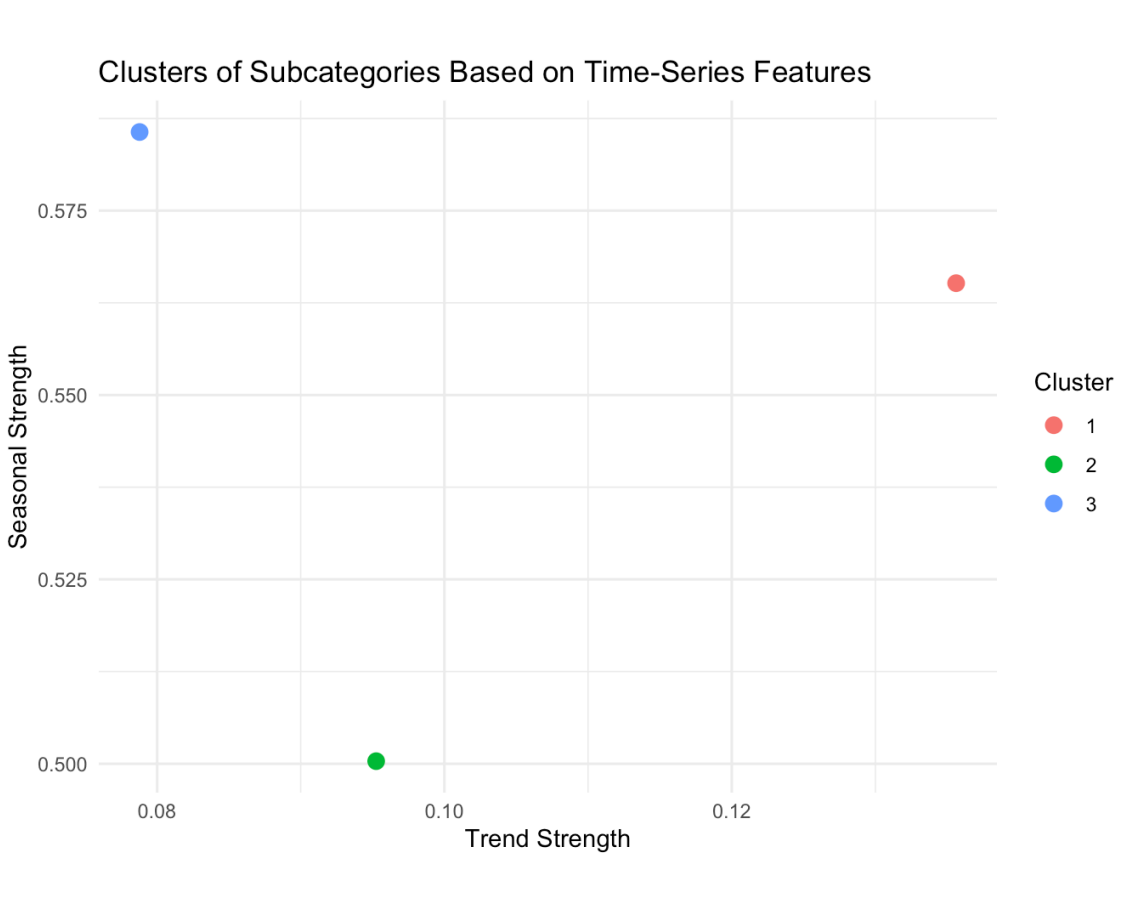
Residual Diagnostics: - The checks show no real autocorrelation for ARIMA models. Which indicates a good fitting forecast.

Conclusion (4a)

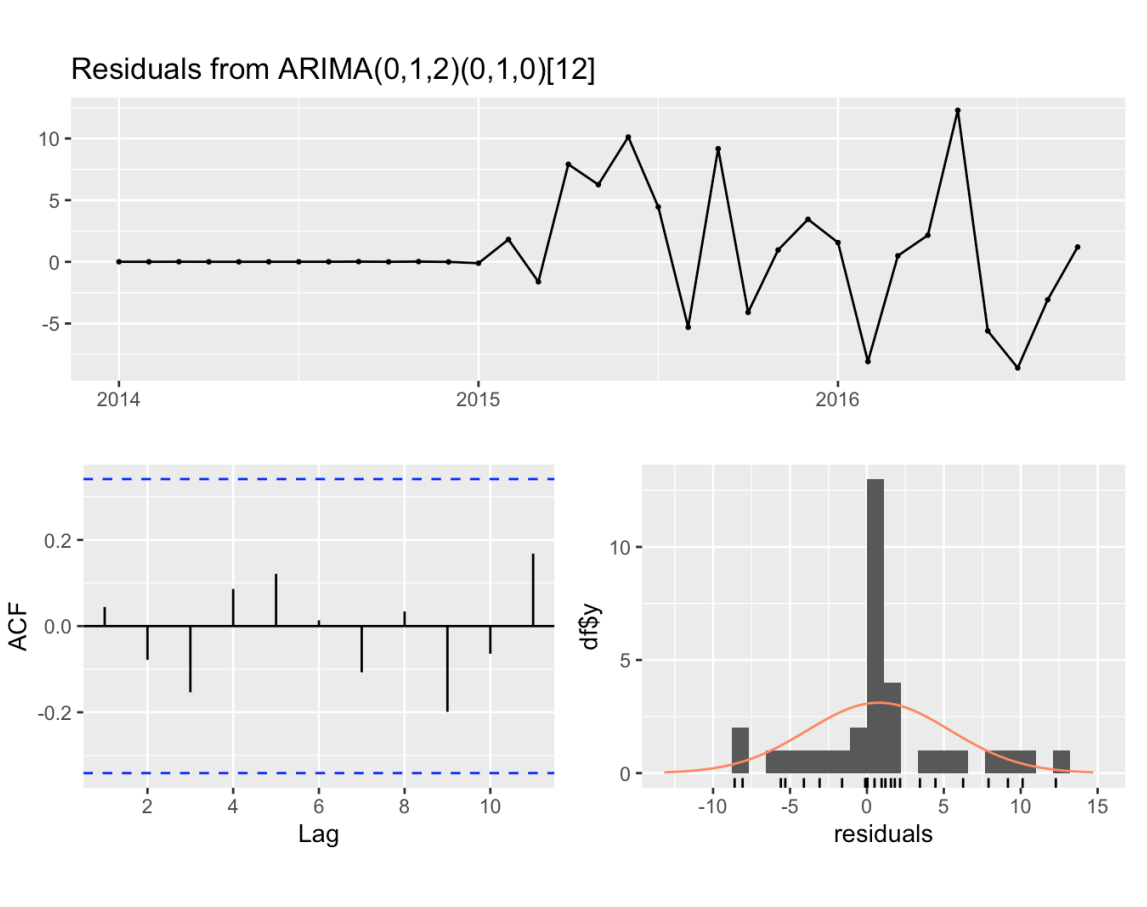
The most effective model is not the same in all the subcategories. Each model was validated based on its ability to capture seasonality and trend. ARIMA performed better for Binders, while ETS performed better for Furnishings and Paper.

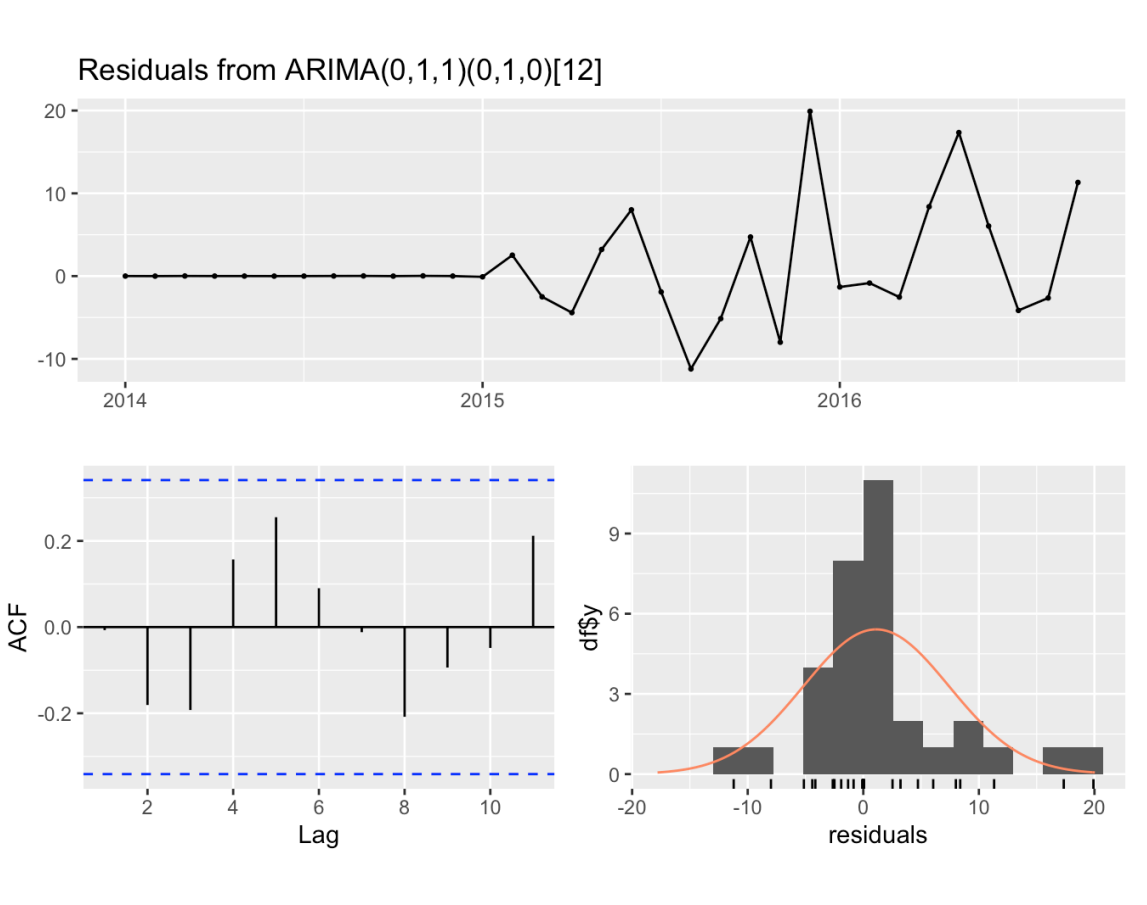
Clustering (4b)

```
Results for Cluster_1

Sub-Category: Binders

ARIMA Accuracy:
                    ME      RMSE      MAE        MPE     MAPE
Training set 0.7706014  4.643476 2.982256  0.6865304 12.91204
Test set     5.9407398 10.783528 7.616473 10.3681817 17.32927
                   ACF1 Theil's U
Training set 0.04429472        NA
Test set     0.04929320 0.3573866

Holt-Winters Accuracy:
                    ME     RMSE      MAE        MPE     MAPE
Training set 0.8668058 5.215491 3.789990 -0.4040374 15.36545
Test set     2.2473496 8.712049 6.243226  0.1597635 16.02219
                     ACF1 Theil's U
Training set -0.389045966        NA
Test set     -0.001830843 0.2777843

ETS Accuracy:
                   ME      RMSE      MAE       MPE     MAPE
Training set 0.743354  4.712561 3.656409  1.358692 15.41708 0
Test set     7.439784 12.216161 8.825094 10.667088 20.93561 1
                   ACF1 Theil's U
Training set -0.2225537        NA
Test set      0.0608554 0.3767484


Results for Cluster_2

Sub-Category: Paper

ARIMA Accuracy:
                    ME      RMSE       MAE        MPE     MAP
Training set  1.117384  6.309464  3.827714   1.702165 14.3215
Test set     -9.014128 12.230774 10.375521 -30.103886 31.8951
                     ACF1 Theil's U
Training set -0.007064333        NA
Test set      0.108516273 0.6984566

Holt-Winters Accuracy:
                     ME     RMSE       MAE        MPE     MAP
Training set   1.509544  7.27986  4.854547   3.325281 16.4130
Test set     -12.036865 14.48061 13.347292 -39.791842 41.5160
                    ACF1 Theil's U
Training set -0.02710216        NA
Test set      0.10006713  0.845232

ETS Accuracy:
                     ME      RMSE      MAE         MPE     MA
Training set 0.60941117  6.204628 4.474990 -1.66197953 18.732
Test set     0.08500424 11.304488 8.247017 -0.08462612 20.475
                    ACF1 Theil's U
Training set 0.005205508        NA
Test set     0.341519997  0.582549


Results for Cluster_3

Sub-Category: Furnishings

ARIMA Accuracy:
                    ME     RMSE      MAE       MPE     MAPE
Training set 0.0050974 3.873555 2.567868 -6.624673 20.20958 0
Test set     3.9523810 7.782677 6.238095 10.720079 22.75340 1
                    ACF1 Theil's U
Training set -0.20160077        NA
Test set     -0.03570035 0.6102339

Holt-Winters Accuracy:
                    ME     RMSE      MAE      MPE     MAPE
Training set 0.9137655 4.164677 3.475419 7.490317 24.75583 0.
Test set     3.6371987 7.200985 5.673333 9.724318 20.50134 1.
                    ACF1 Theil's U
Training set -0.43317305        NA
Test set      0.01804785 0.5689788

ETS Accuracy:
                    ME     RMSE      MAE        MPE     MAPE
Training set 0.7370579 3.466690 2.851745  0.4301648 20.85220
Test set     6.0973038 8.354163 6.690832 20.7276401 23.55317
                   ACF1 Theil's U
Training set -0.2087083        NA
Test set      0.3729315 0.7455977
```



```
Residual Diagnostics for Sub-Category: Binders
```



```
	Ljung-Box test

data:  Residuals from ARIMA(0,1,2)(0,1,0)[12]
Q* = 2.6295, df = 5, p-value = 0.7569

Model df: 2.   Total lags used: 7


Residual Diagnostics for Sub-Category: Paper
```