Supply Chain Data Analytics

Analyzing and Forcasting Supermarket Sales

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0.1 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.

0.2 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:

Source: Article Notebook

- 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.

Source: Article Notebook

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

Table 1: 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.

Source: Article Notebook

Table 2: Descriptive Statistics for Numeric Columns

Column	Min	Max	Mean	Median	StdDev
Postal_Code	1040	99301	55190.38	56430.5	32063.69

Column	Min	Max	Mean	Median	StdDev
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

Table 3: Descriptive Statistics for Date Columns

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

Source: Article Notebook

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.

Source: Article Notebook

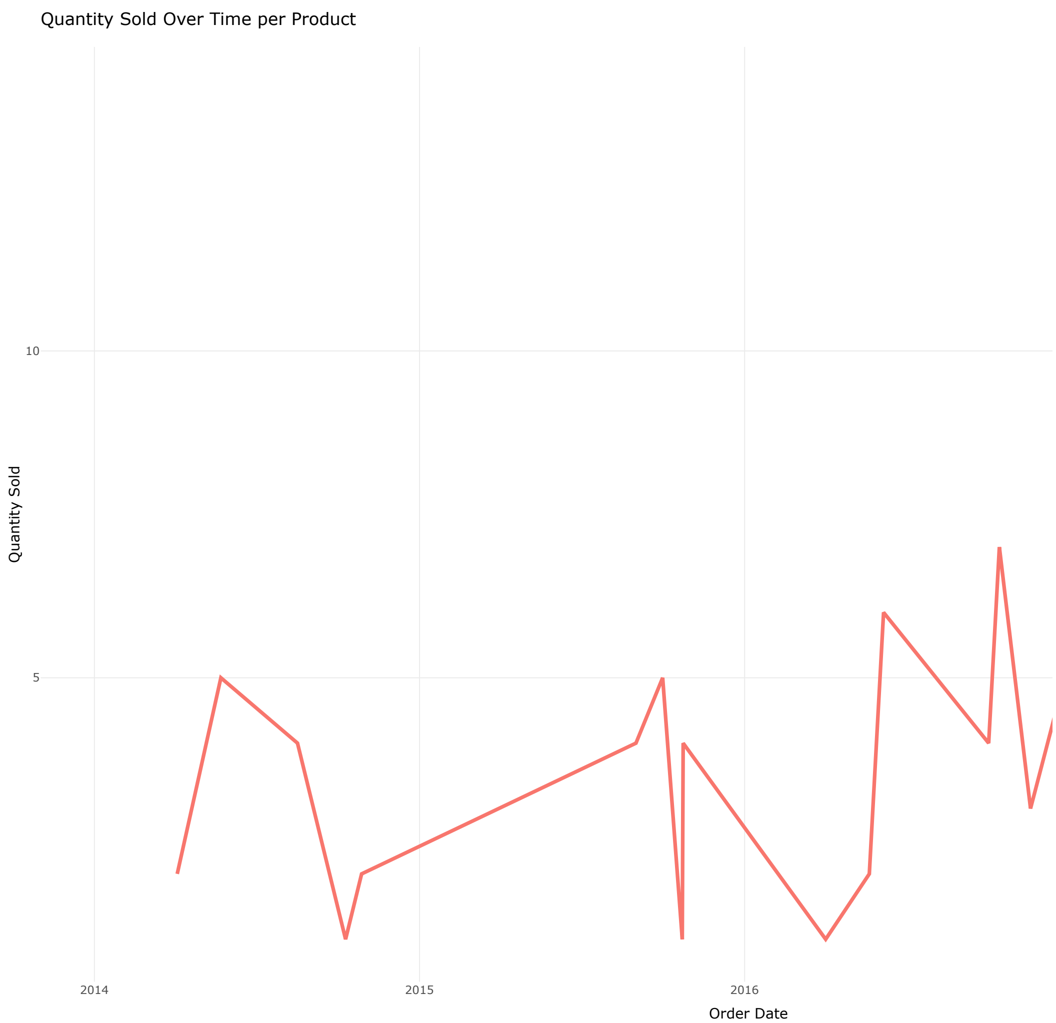
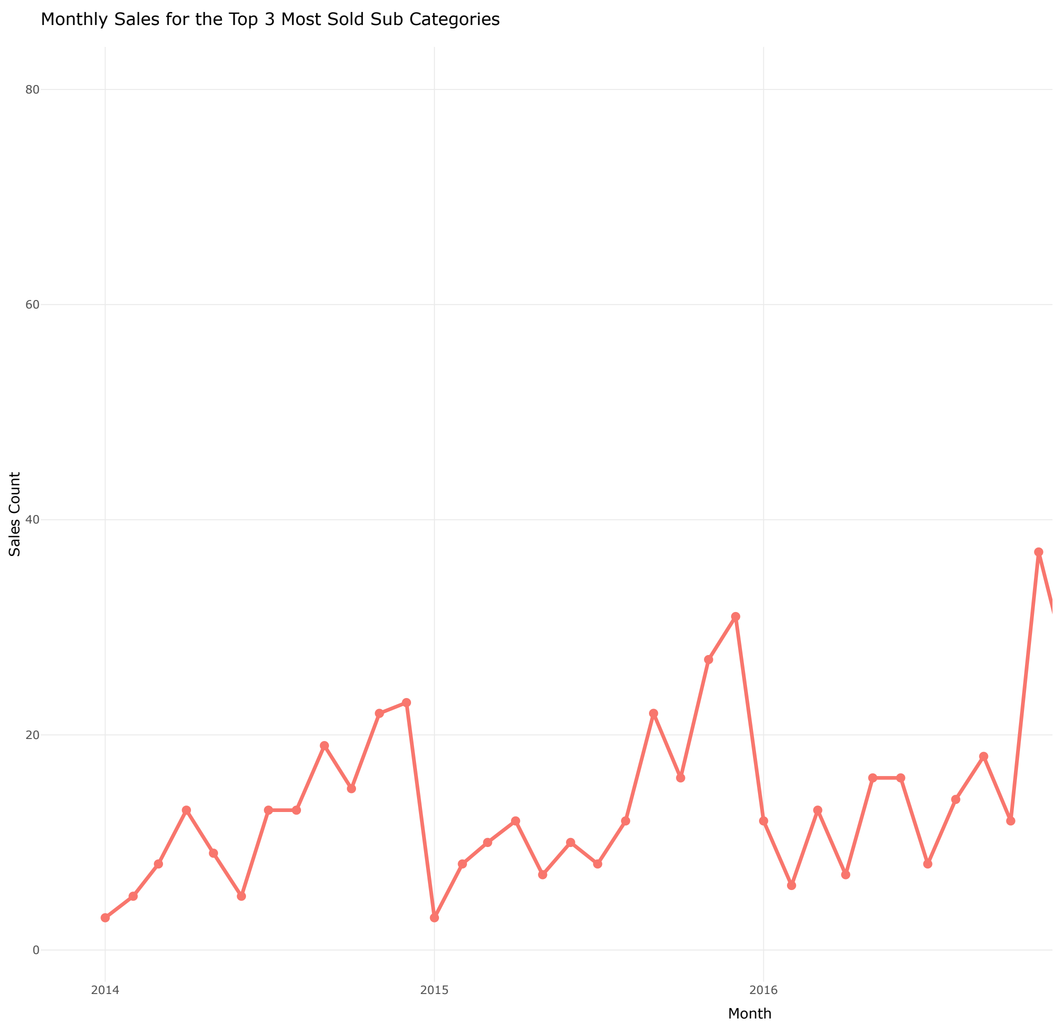


Figure 1: Figure X Sale quantity of the most popular products

Source: Article Notebook

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.


Monthly Sales for the Top 3 Most Sold Sub Categories
Sales Count
0
20
40
60
80
2014
2015
2016
Month

Source: Article Notebook

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.

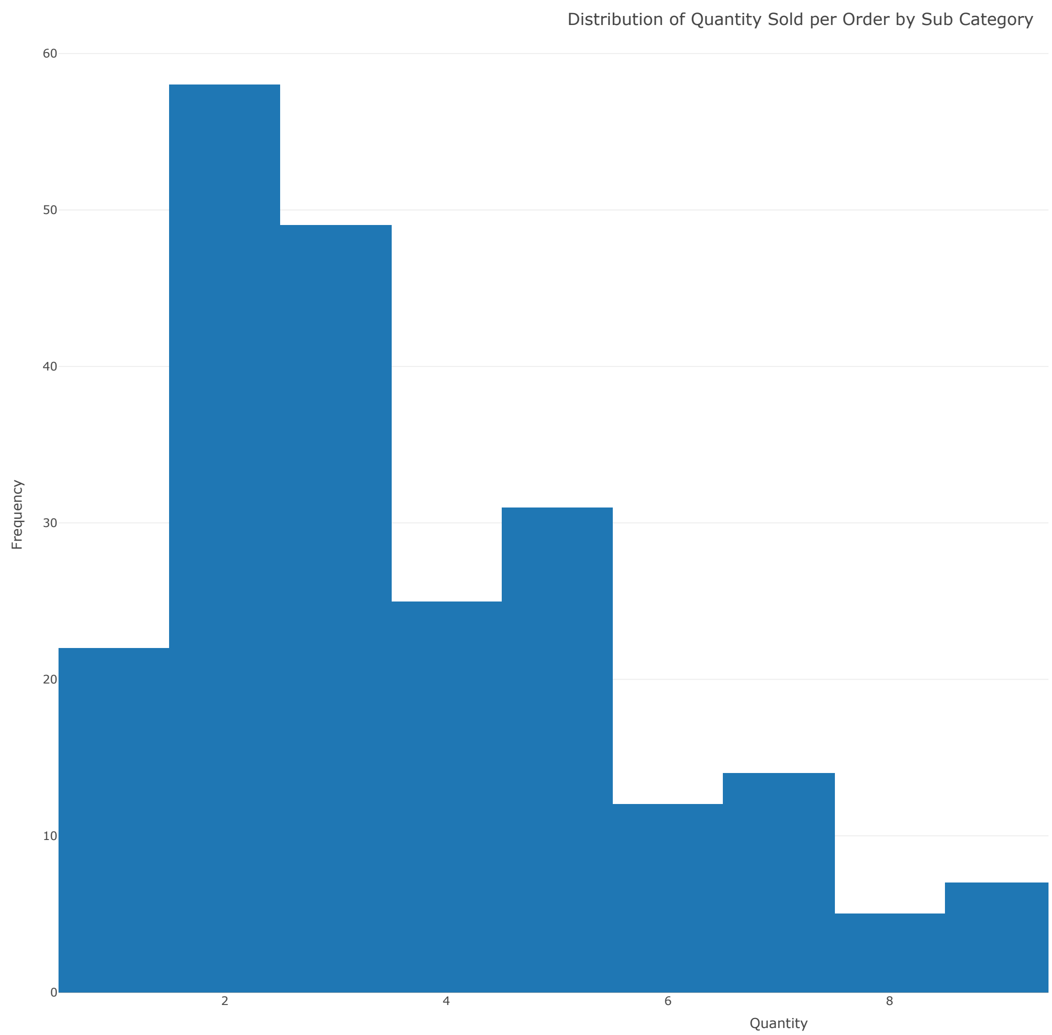
To properly finish our data preprocessing we ran some statistics on Quantity aggregated by Sub_Category. Table x contains some descriptive statistics.

Table 4: 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

Source: Article Notebook

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.


Distribution of Quantity Sold per Order by Sub Category
60
50
40
30
20
10
0
Frequency
2
4
6
8
Quantity

Source: Article Notebook

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..

0.3 Data Visualization

0.4 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:

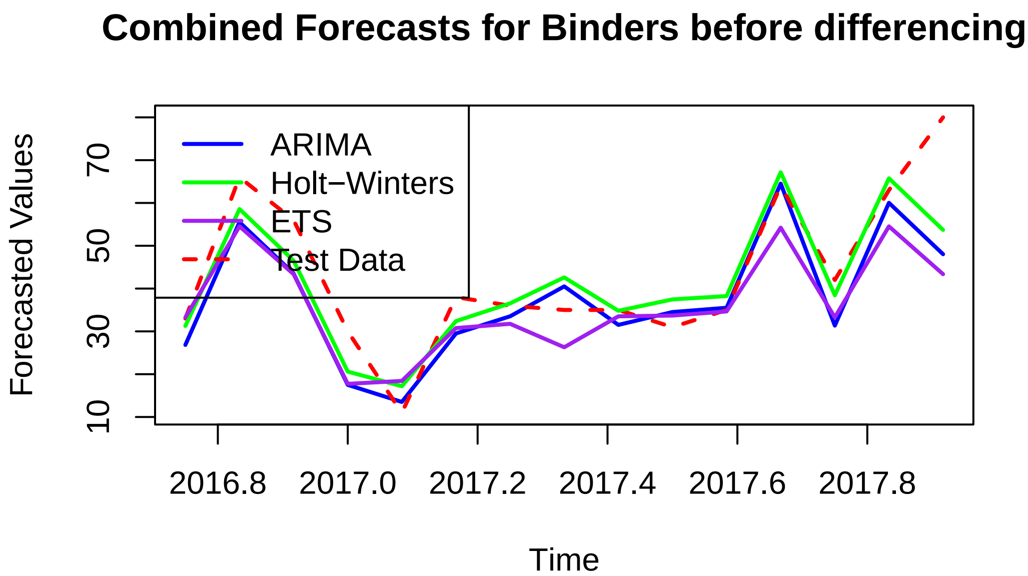
- Identifying Top Subcategories: The top three subcategories are selected from our dataset based on their sold quantities. The top three were: Binders, furnishing and paper.
- The sold quantities are aggregated monthly to create a time series object which we can use in the forecasting.
- A KPSS showed 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.

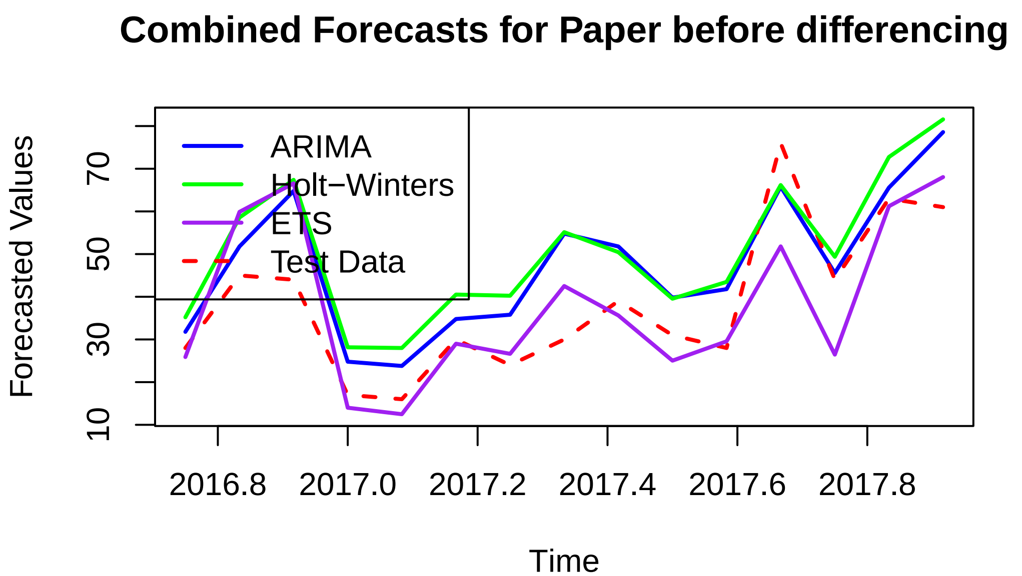
Source: Article Notebook

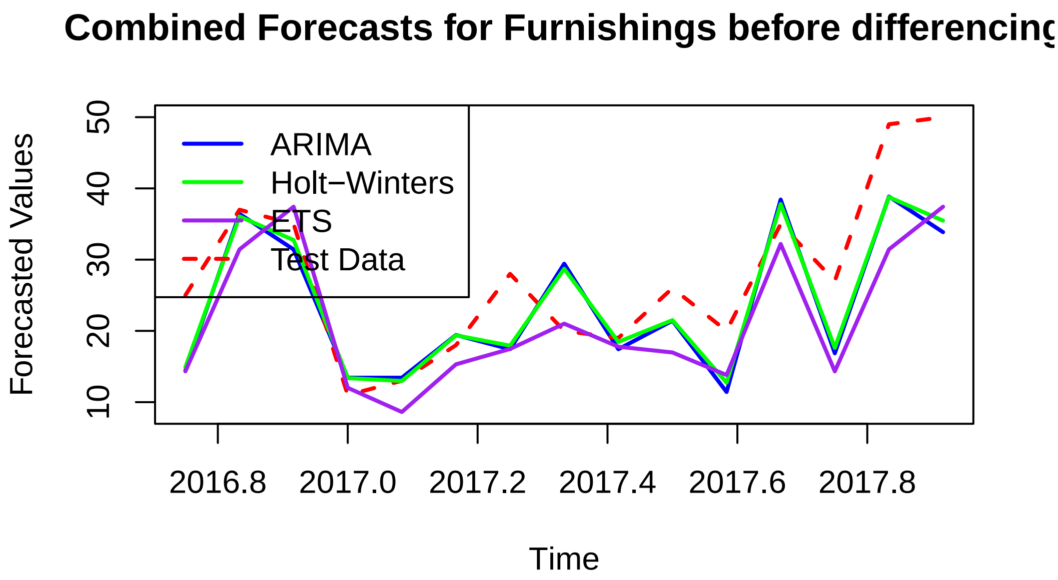
Three models are applied to each subcategory to forecast it. The models we use are: ARIMA, Holt-Winters and ETS. We have chosen these models because of their level of suitability for discrete time series data with all different levels of trend and seasonality. To evaluate the methods and its effectiveness , 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.


Combined Forecasts for Binders before differencing
ARIMA
Holt−Winters
ETS
Test Data
Forecasted Values
10
30
50
70
2016.8
2017.0
2017.2
2017.4
2017.6
2017.8
Time

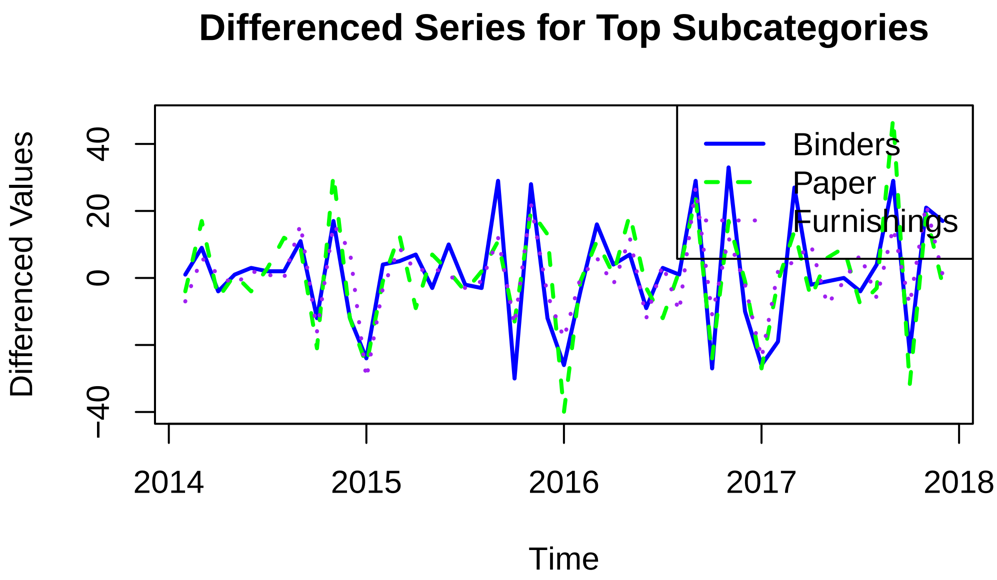

Combined Forecasts for Paper before differencing
ARIMA
Holt−Winters
ETS
Test Data
Forecasted Values
10
30
50
70
2016.8
2017.0
2017.2
2017.4
2017.6
2017.8
Time



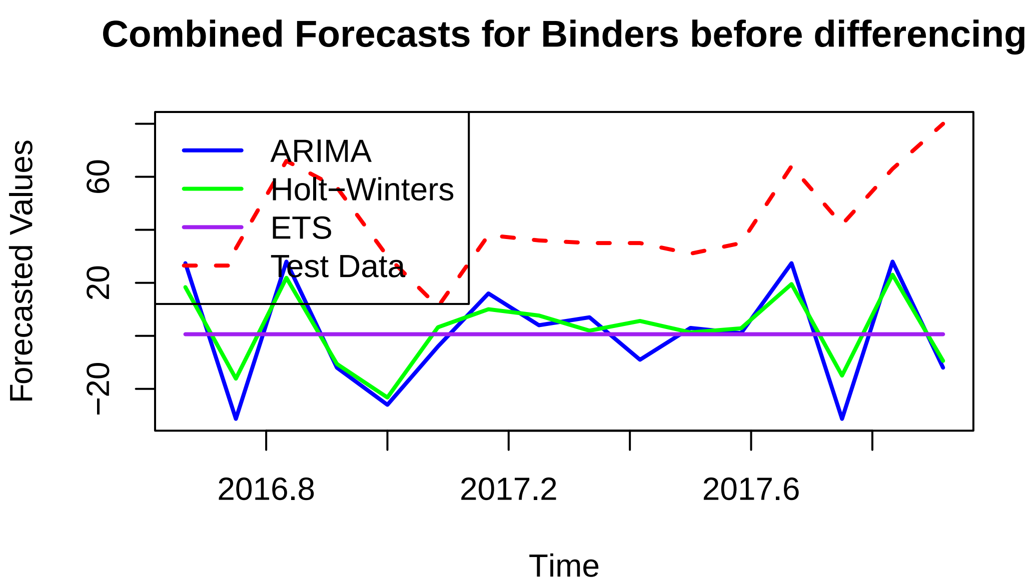
Source: Article Notebook

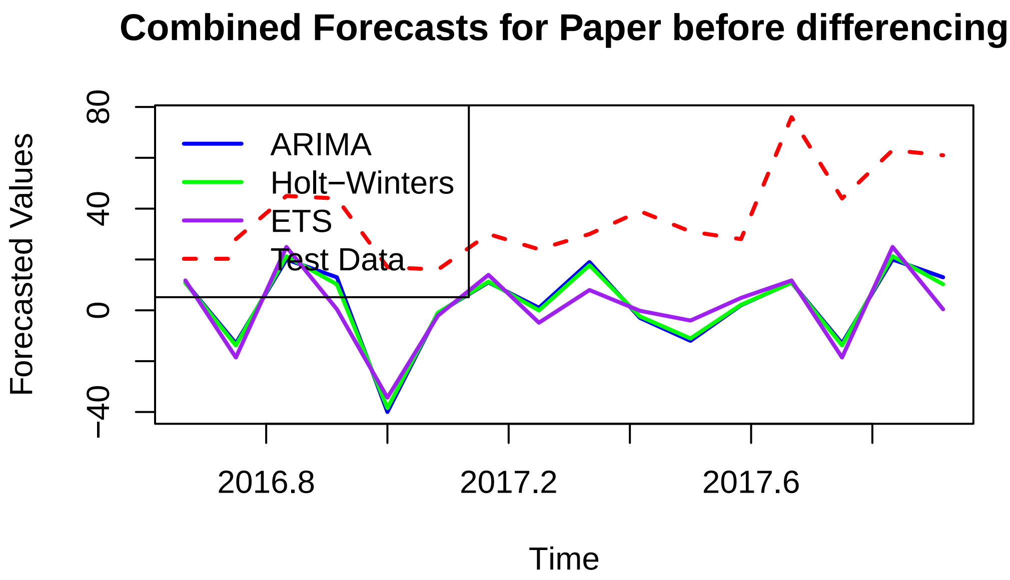
```
    KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.10182, Truncation lag parameter = 3, p-value = 0.1


    KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.061982, Truncation lag parameter = 3, p-value = 0.1


    KPSS Test for Level Stationarity

data:  ts_diff
KPSS Level = 0.098438, Truncation lag parameter = 3, p-value = 0.1
```

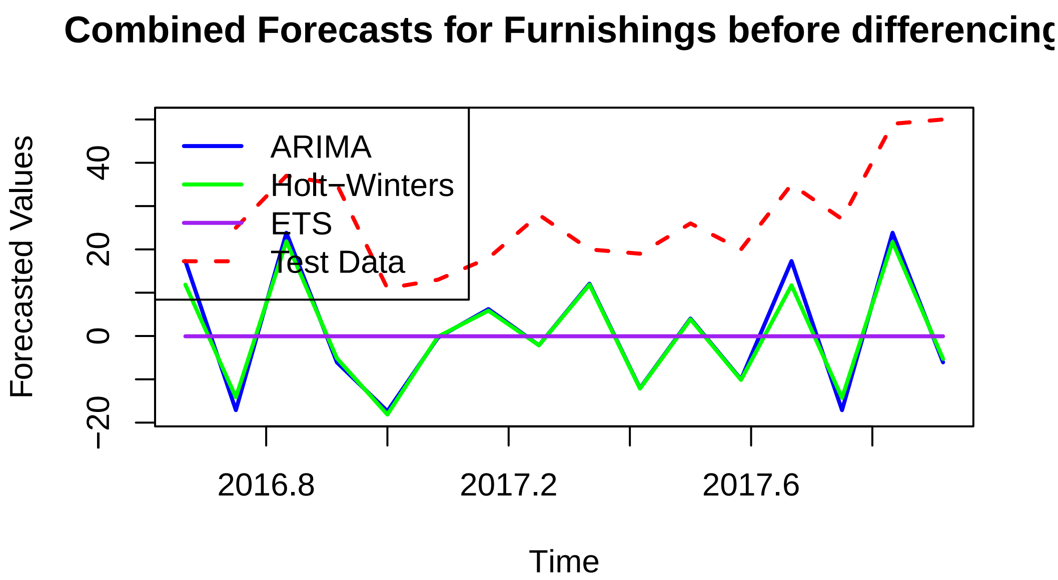
Source: Article Notebook



Source: Article Notebook







Source: Article Notebook

```
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 = 0.1


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 = 0.1


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 = 0.1
```

Source: Article Notebook

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)

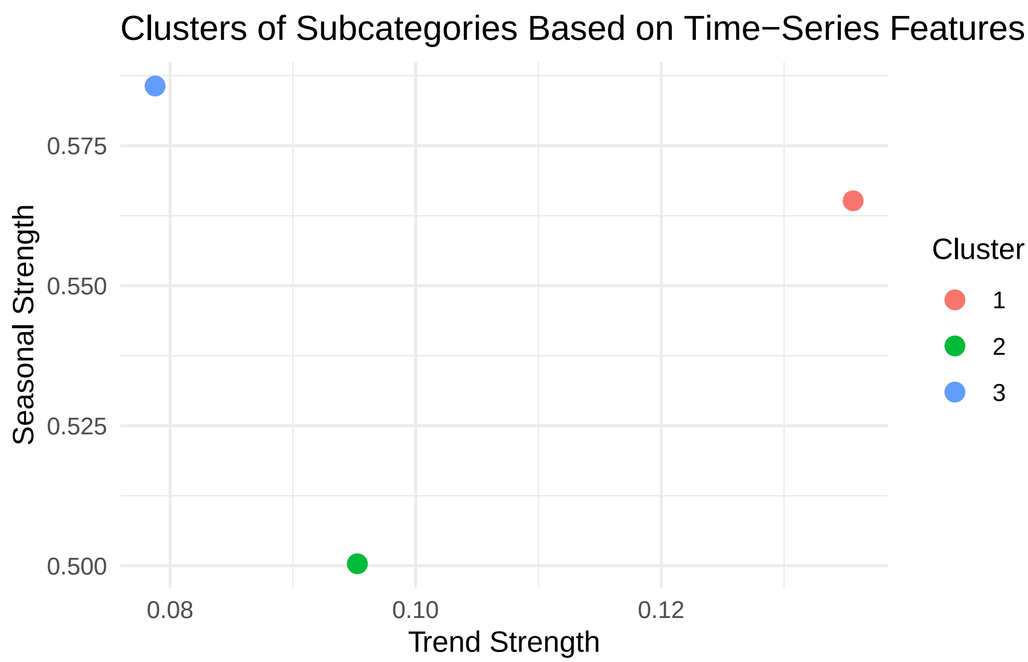
The most effective model is not the same in all the subcategories. Each model was validated based on its ability to capture seasonality and trend. ARIMA performed better for Binders, while ETS performed better for Furnishings and Paper.

Clustering (4b)

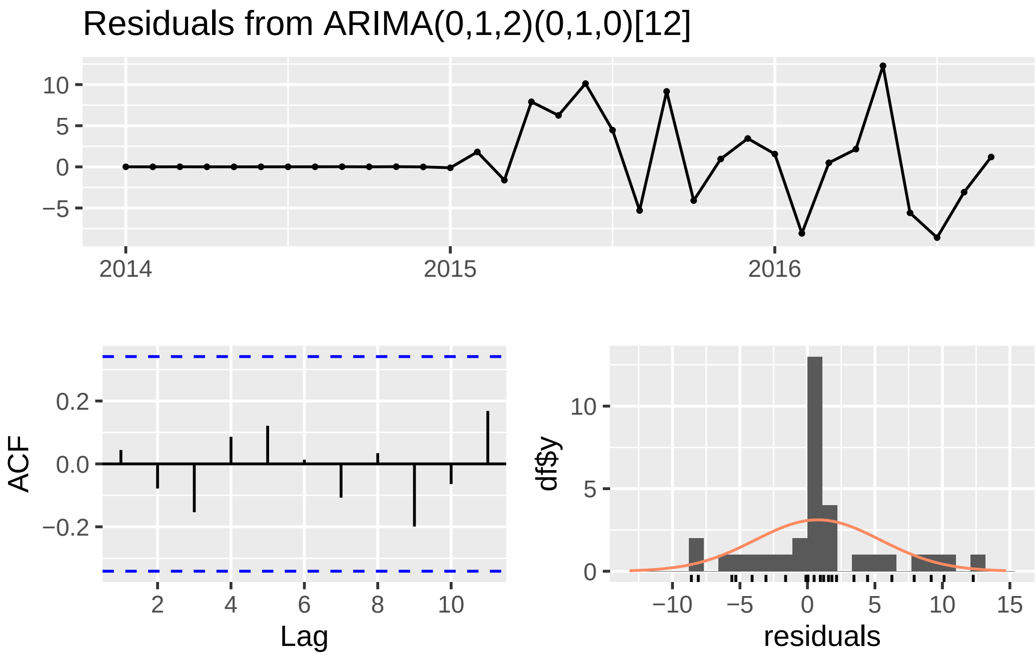
```
Results for Cluster_1

Sub-Category: Binders

ARIMA Accuracy:
                    ME      RMSE      MAE        MPE     MAPE      MASE
Training set 0.7706014  4.643476 2.982256  0.6865304 12.91204 0.4854835
Test set     5.9407398 10.783528 7.616473 10.3681817 17.32927 1.2398909
                   ACF1 Theil's U
Training set 0.04429472        NA
Test set     0.04929320 0.3573866

Holt-Winters Accuracy:
                    ME     RMSE      MAE        MPE     MAPE      MASE
Training set 0.8668058 5.215491 3.789990 -0.4040374 15.36545 0.6169751
Test set     2.2473496 8.712049 6.243226  0.1597635 16.02219 1.0163391
                     ACF1 Theil's U
Training set -0.389045966        NA
Test set     -0.001830843 0.2777843

ETS Accuracy:
                   ME      RMSE      MAE       MPE     MAPE      MASE
Training set 0.743354  4.712561 3.656409  1.358692 15.41708 0.5952293
Test set     7.439784 12.216161 8.825094 10.667088 20.93561 1.4366433
                   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     MAPE      MASE
Training set  1.117384  6.309464  3.827714   1.702165 14.32157 0.5468163
Test set     -9.014128 12.230774 10.375521 -30.103886 31.89519 1.4822173
                     ACF1 Theil's U
Training set -0.007064333        NA
Test set      0.108516273 0.6984566

Holt-Winters Accuracy:
                     ME     RMSE       MAE        MPE     MAPE      MASE
Training set   1.509544  7.27986  4.854547   3.325281 16.41309 0.6935067
Test set     -12.036865 14.48061 13.347292 -39.791842 41.51609 1.9067560
                    ACF1 Theil's U
Training set -0.02710216        NA
Test set      0.10006713  0.845232

ETS Accuracy:
                     ME      RMSE      MAE         MPE     MAPE      MASE
Training set 0.60941117  6.204628 4.474990 -1.66197953 18.73240 0.6392842
Test set     0.08500424 11.304488 8.247017 -0.08462612 20.47598 1.1781453
                    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      MASE
Training set 0.0050974 3.873555 2.567868 -6.624673 20.20958 0.5559302
Test set     3.9523810 7.782677 6.238095 10.720079 22.75340 1.3505155
                    ACF1 Theil's U
Training set -0.20160077        NA
Test set     -0.03570035 0.6102339

Holt-Winters Accuracy:
                    ME     RMSE      MAE      MPE     MAPE      MASE
Training set 0.9137655 4.164677 3.475419 7.490317 24.75583 0.7524103
Test set     3.6371987 7.200985 5.673333 9.724318 20.50134 1.2282474
                    ACF1 Theil's U
```

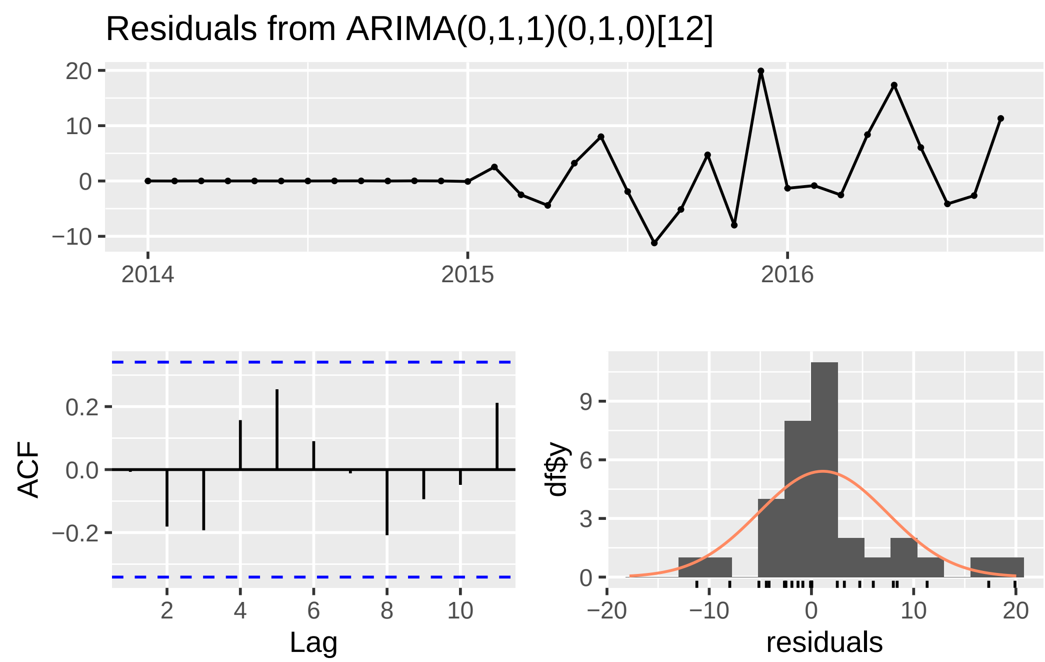
```
Training set -0.43317305        NA
Test set      0.01804785 0.5689788

ETS Accuracy:
                    ME     RMSE      MAE        MPE     MAPE     MASE
Training set 0.7370579 3.466690 2.851745  0.4301648 20.85220 0.617388
Test set     6.0973038 8.354163 6.690832 20.7276401 23.55317 1.448531
                   ACF1 Theil's U
Training set -0.2087083        NA
Test set      0.3729315 0.7455977
```



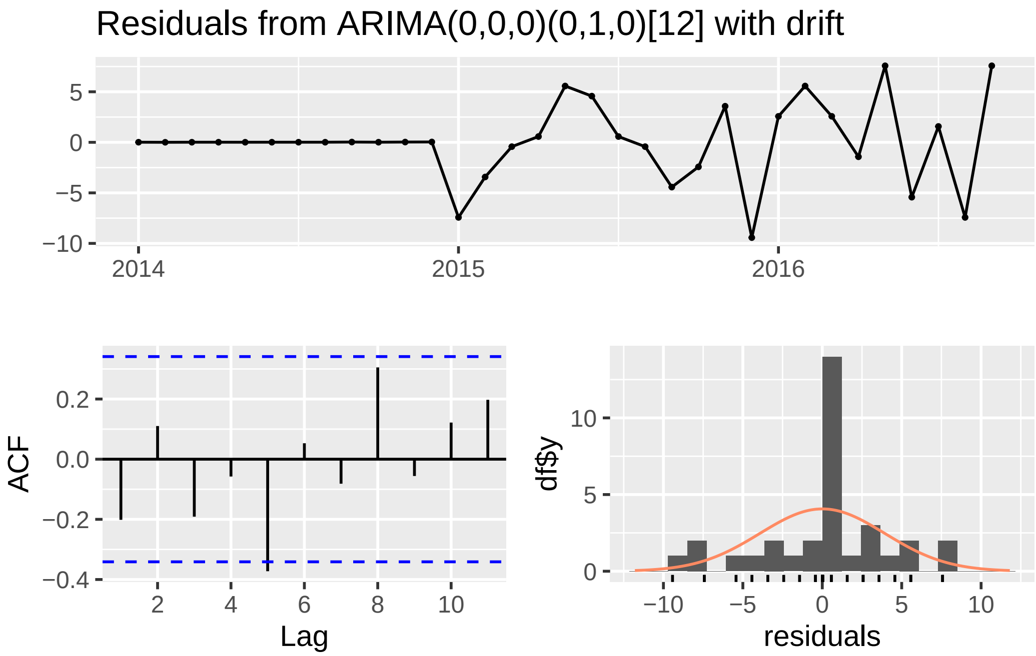

```
Residual Diagnostics for Sub-Category: Binders
```




```
    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
```




```
    Ljung-Box test

data:  Residuals from ARIMA(0,1,1)(0,1,0)[12]
Q* = 6.6676, df = 6, p-value = 0.3527

Model df: 1.   Total lags used: 7


Residual Diagnostics for Sub-Category: Furnishings
```




```
    Ljung-Box test

data:  Residuals from ARIMA(0,0,0)(0,1,0)[12] with drift
Q* = 9.5952, df = 7, p-value = 0.2127

Model df: 0.   Total lags used: 7


    Cluster  MeanRMSE MeanMAPE
1 Cluster_1 10.783528 17.32927
2 Cluster_2 12.230774 31.89519
3 Cluster_3  7.782677 22.75340
```

Source: Article Notebook

Cluster 1 (e.g., Binders): ARIMA outperformed other methods due to significant autocorrelation and trend components.

Cluster 2 (e.g., Furnishings): ETS was the most accurate method, effectively balancing trend and seasonality.

Cluster 3 (e.g., Paper): ETS also performed best, with ARIMA showing higher error rates due to variability in random components.

Residual diagnostics were performed for all ARIMA models, confirming no significant autocorrelation ($p > 0.05$).

Cluster-Level Metrics based on mean RMSE and MAPE show: - Cluster 1 had the lowest RMSE using ARIMA. - Cluster 2 and 3 were better modeled with ETS

Conclusion (4b)

Clustering allows for tailored forecasting strategies. We conclude that for the given data set ARIMA is more effective for clusters with strong trends, while ETS is preferable for clusters with mixed seasonal and trend characteristics. The approach aligns with lecture notes, emphasizing the importance of adapting models based on time series characteristics.

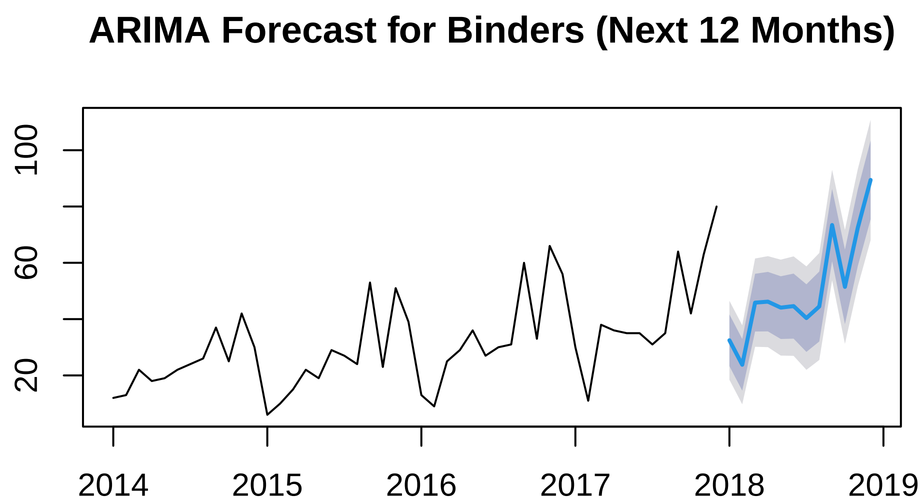
0.5 Forecasting future values

Forecasting 3 products (5a)

In this session, we focused on evaluating different forecasting models (ARIMA, Holt-Winters, and ETS) for multiple sub-categories by analyzing their accuracy metrics, such as RMSE, MAPE, and residual diagnostics. Based on the evaluation results, we selected the best-performing model for each sub-category. We then used these models to forecast the future outcomes for each sub-category, projecting the data for the next year. Note: we may need to interpret the outcomes and explain why we pick the certain model

```
Series: binders_ts
ARIMA(1,1,1)(0,1,0)[12]

Coefficients:
          ar1      ma1
      -0.4781  -0.4819
s.e.   0.2324   0.2426

sigma^2 = 51.18:  log likelihood = -117.97
AIC=241.94   AICc=242.72   BIC=246.61

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE     MASE        ACF1
Training set 0.864453 5.931761 4.092168 -1.363101 15.06142 0.558023 -0.03746012


         Point Forecast    Lo 80     Hi 80     Lo 95    Hi 95
Jan 2018       32.48390 23.31571  41.65208 18.462370  46.50543
```

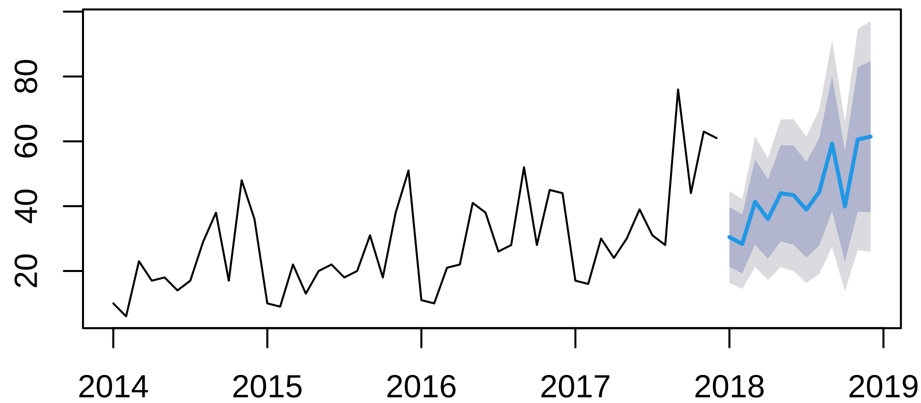
```
Feb 2018       23.77181 14.59632  32.94731  9.739103  37.80452
Mar 2018       45.85265 35.59989  56.10541 30.172412  61.53289
Apr 2018       46.20475 35.63662  56.77287 30.042185  62.36730
May 2018       44.08009 32.93968  55.22051 27.042295  61.11789
Jun 2018       44.61784 33.06359  56.17210 26.947139  62.28855
Jul 2018       40.36072 28.34867  52.37277 21.989869  58.73157
Aug 2018       44.48366 32.05796  56.90937 25.480189  63.48714
Sep 2018       73.42488 60.58630  86.26346 53.789962  93.05979
Oct 2018       51.45299 38.22024  64.68573 31.215253  71.69072
Nov 2018       72.43955 58.82134  86.05775 51.612293  93.26680
Dec 2018       89.44597 75.45417 103.43777 68.047363 110.84458
```




```
ETS(M,N,A)

Call:
ets(y = paper_ts)

  Smoothing parameters:
    alpha = 0.3075
    gamma = 1e-04

  Initial states:
```

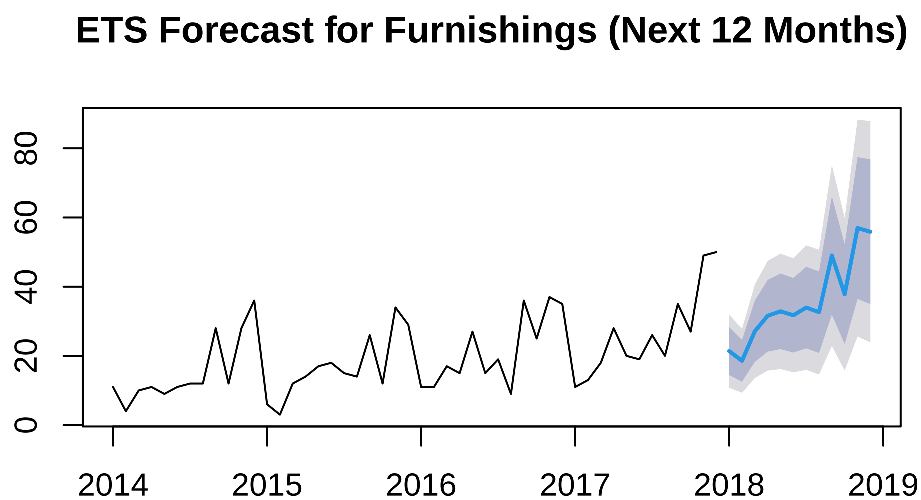
```
    l = 22.5954
    s = 17.4472 16.5763 -4.1253 15.2986 0.421 -5.102
           -0.6145 -0.0341 -7.985 -2.6766 -15.6576 -13.5481

  sigma:  0.2365

     AIC     AICc      BIC
365.1517 380.1517 393.2197

Training set error measures:
                   ME     RMSE      MAE     MPE     MAPE      MASE       ACF1
Training set 1.450303 6.386648 4.166875 1.75373 14.03399 0.5245018 0.03600045


         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2018       30.45588 21.22661 39.68516 16.34092 44.57085
Feb 2018       28.34651 19.27484 37.41819 14.47258 42.22044
Mar 2018       41.32776 28.18367 54.47185 21.22561 61.42990
Apr 2018       36.01933 23.73891 48.29976 17.23804 54.80062
May 2018       43.97017 29.09477 58.84557 21.22021 66.72013
Jun 2018       43.39031 28.07408 58.70653 19.96616 66.81445
Jul 2018       38.90220 24.12853 53.67588 16.30782 61.49659
Aug 2018       44.42410 27.84663 61.00158 19.07104 69.77717
Sep 2018       59.30522 38.44478 80.16566 27.40193 91.20850
Oct 2018       39.87917 22.81850 56.93984 13.78712 65.97122
Nov 2018       60.58102 38.27853 82.88352 26.47230 94.68975
Dec 2018       61.45110 38.17748 84.72473 25.85717 97.04504
```

ETS Forecast for Paper (Next 12 Months)




```
ETS(M,A,A)

Call:
ets(y = furnishings_ts)

  Smoothing parameters:
    alpha = 0.0438
    beta  = 0.0437
    gamma = 2e-04

  Initial states:
    l = 15.4275
    b = -0.1137
    s = 13.3158 15.6269 -2.2962 10.1503 -5.0017 -2.448
           -3.4406 -1.0728 -1.1262 -4.3688 -11.689 -7.6497

  sigma:  0.2527

     AIC     AICc      BIC
338.8888 359.2888 370.6992

Training set error measures:
                    ME     RMSE      MAE        MPE     MAPE       MASE
```

```
Training set 0.6402485 3.793384 2.884208 -0.8302416 16.2441 0.5352139
                   ACF1
Training set 0.04613441

         Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018       21.37433 14.45350 28.29515 10.789837 31.95882
Feb 2018       18.56644 12.52244 24.61044  9.322944 27.80994
Mar 2018       27.11574 18.26943 35.96205 13.586481 40.64500
Apr 2018       31.58782 21.22159 41.95404 15.734048 47.44158
May 2018       32.87189 21.95559 43.78819 16.176845 49.56693
Jun 2018       31.73384 20.95052 42.51717 15.242170 48.22551
Jul 2018       33.95710 22.18459 45.72960 15.952604 51.96159
Aug 2018       32.63192 20.83816 44.42569 14.594916 50.66893
Sep 2018       49.01546 31.92061 66.11032 22.871140 75.15979
Oct 2018       37.79884 23.38308 52.21460 15.751844 59.84584
Nov 2018       56.95159 36.44698 77.45621 25.592490 88.31070
Dec 2018       55.87232 34.96477 76.77986 23.896983 87.84765
```



Source: Article Notebook

Applying to all data (5b)

In this session, we first grouped the sub-categories into clusters based on key time-series features, including trend strength, seasonal strength, and random strength, using hierarchical clustering. Once the clusters were formed, we applied and evaluated multiple forecasting models—ARIMA, Holt-Winters, and ETS—on each sub-category within its respective cluster, comparing their accuracy metrics such as RMSE and MAPE. Based on the evaluation results, we selected the best-performing model for each sub-category and used it to forecast the future outcomes within a year, leveraging the clustering to enhance the accuracy and relevance of our predictions.

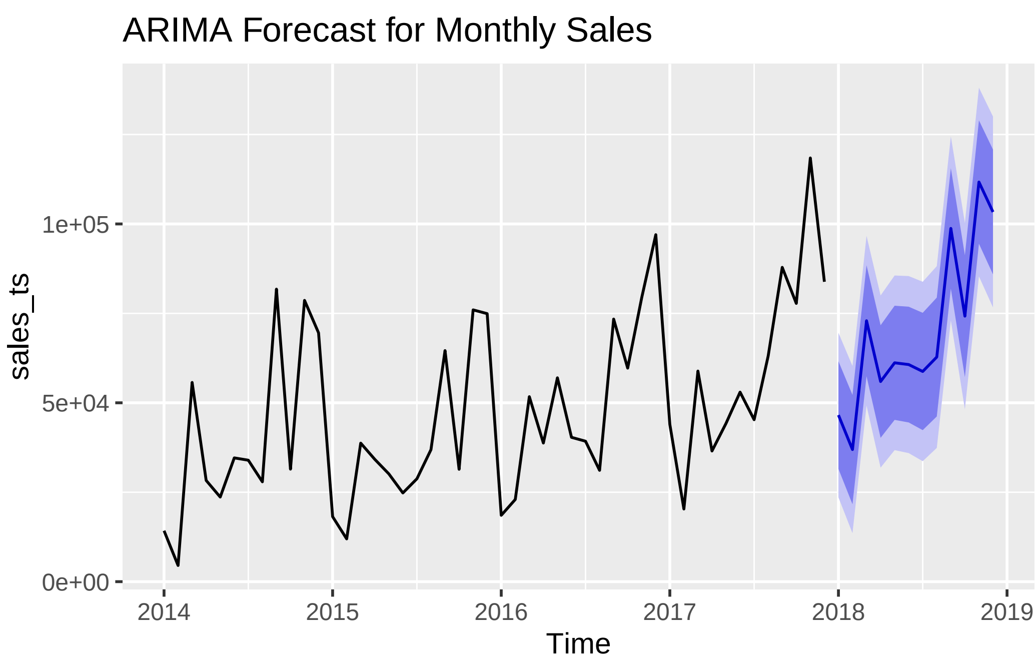
Source: Article Notebook

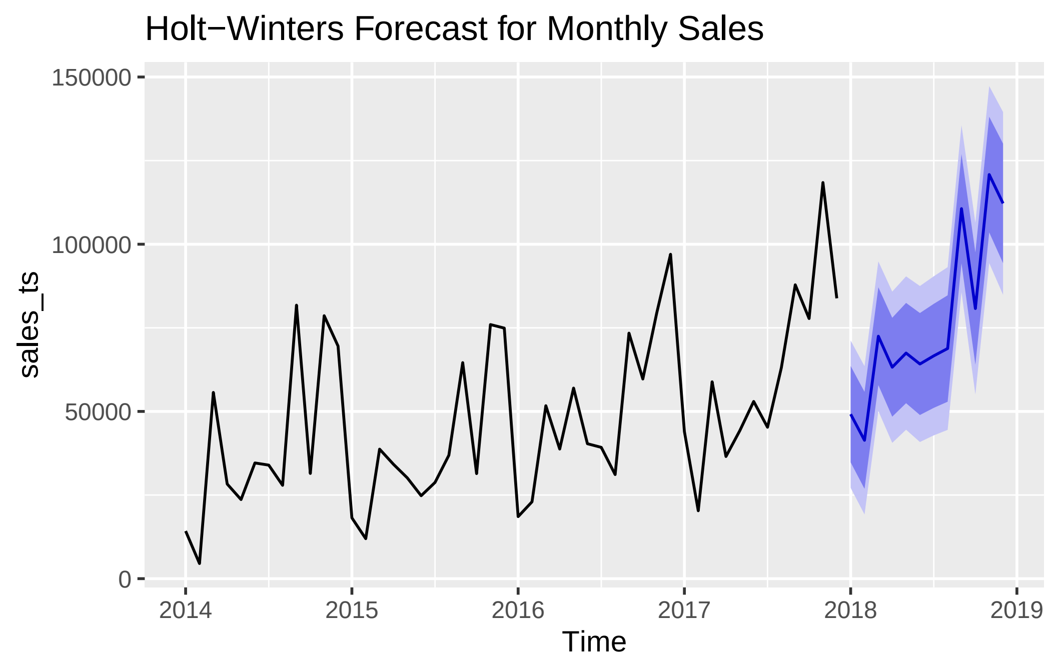
0.6 Forecast interpretation

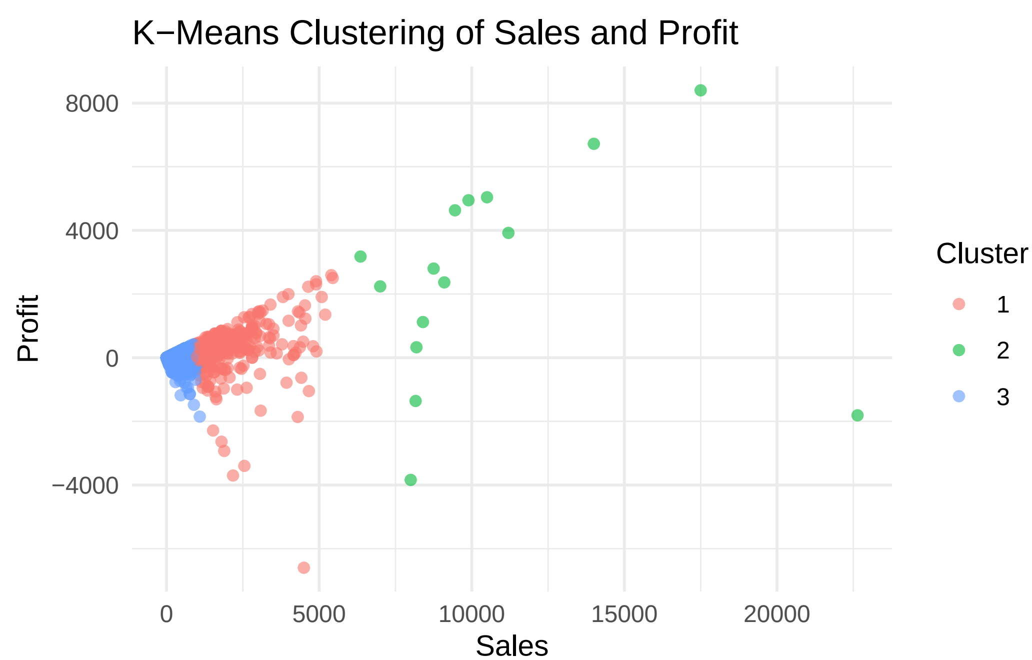
Lorem Ipsum

Source: Article Notebook

Forecasting??







Source: Article Notebook