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

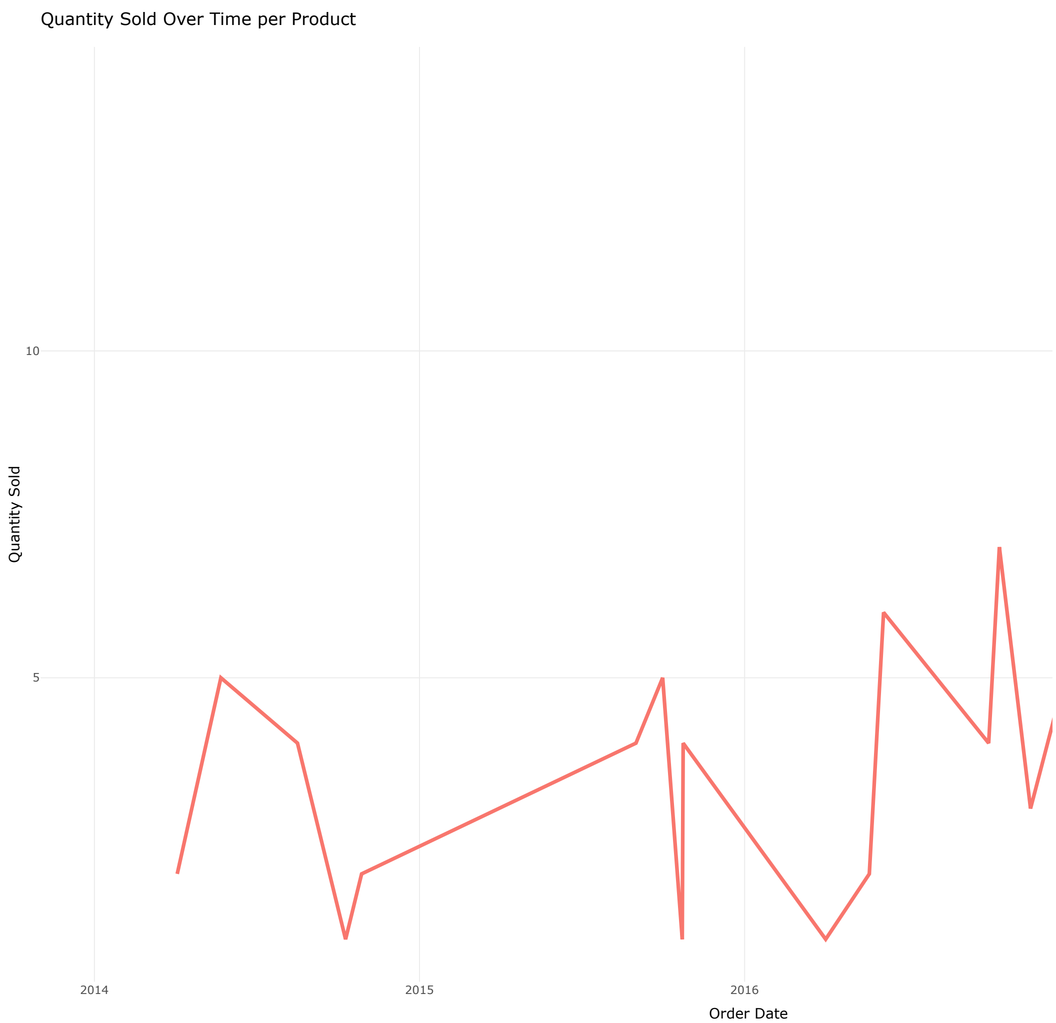
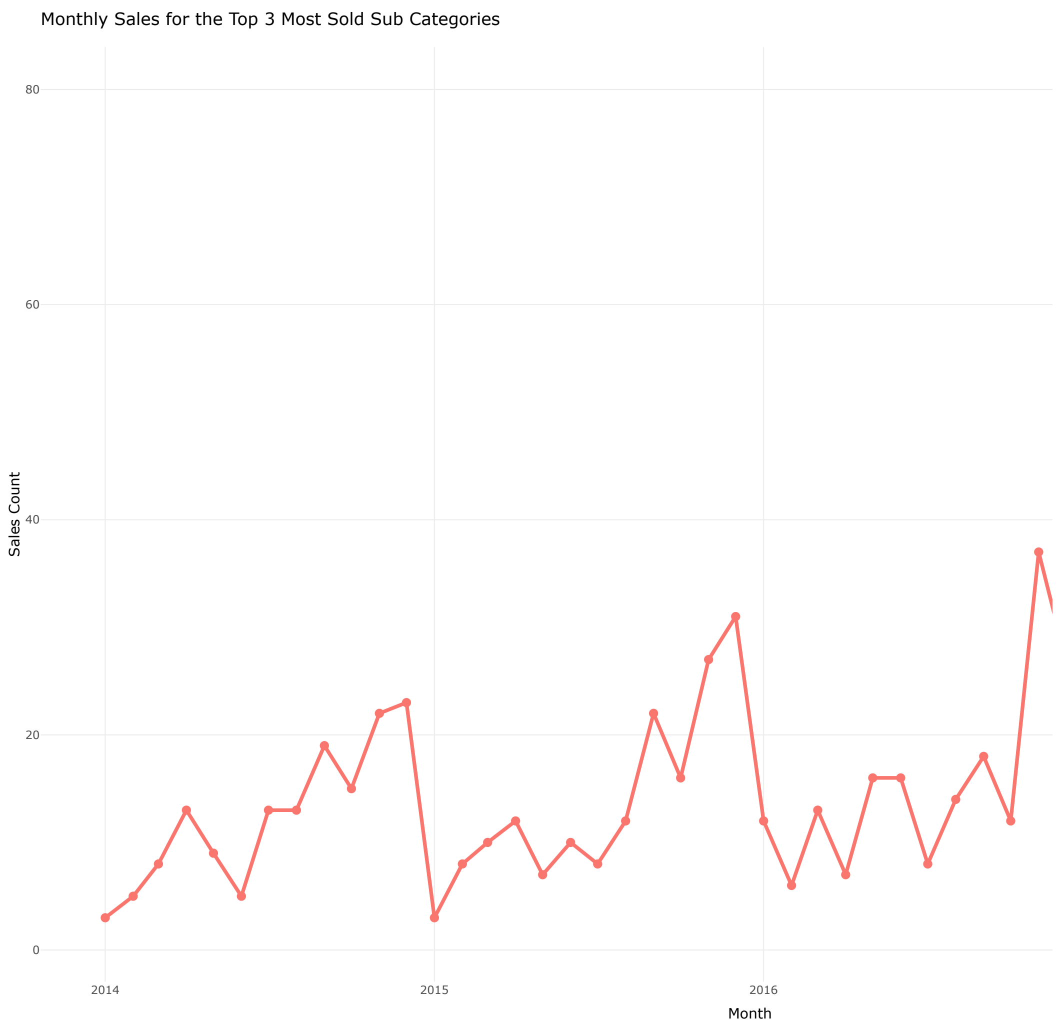


Figure 1: Figure X Sale quantity of the most popular products

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
80
60
40
20
0
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.

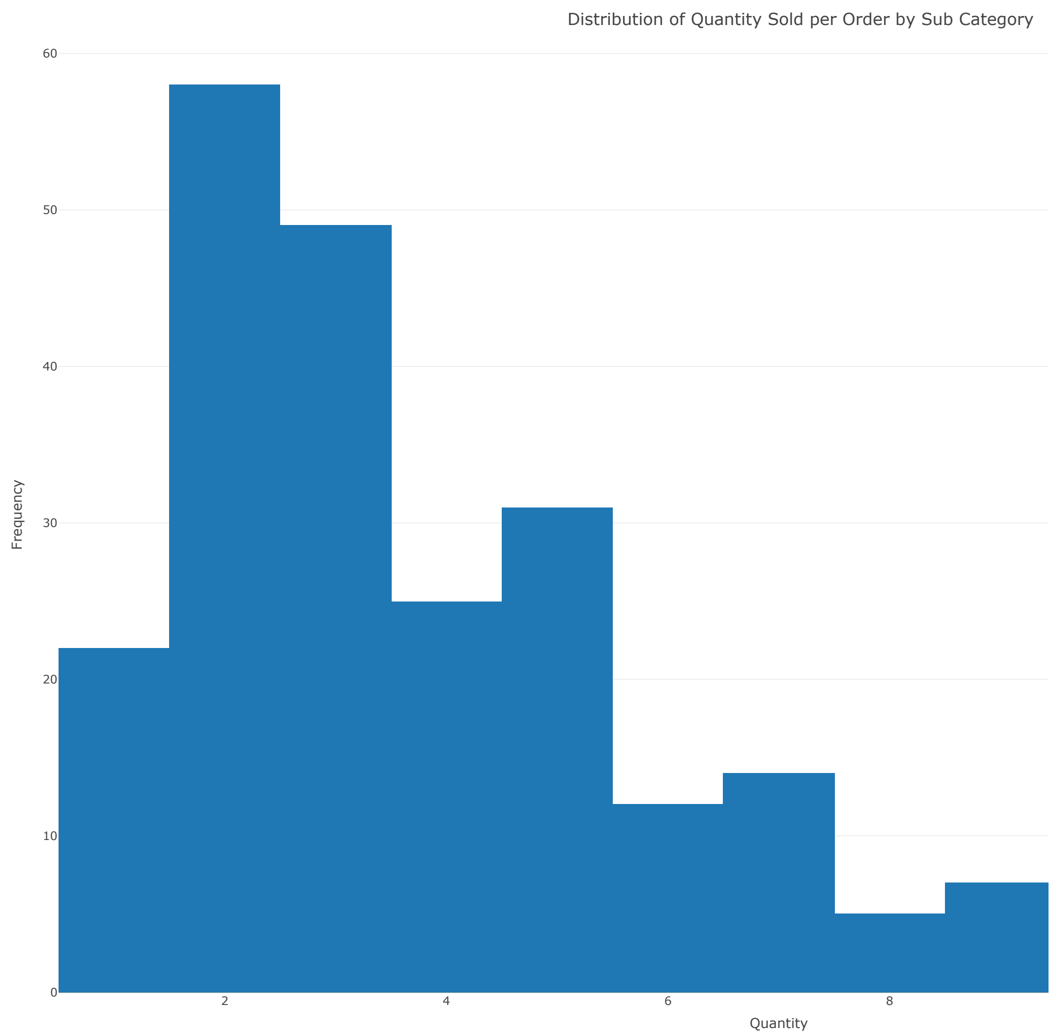
To properly finish our data preprocessing we ran some statistics on Quantity aggregated by Sub_Category. Table x contains some descriptive statistics.

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
Frequency
Quantity
0
10
20
30
40
50
60
2
4
6
8

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 Forecasting Method Evaluation

Forecasting top 3 product categories (4a)

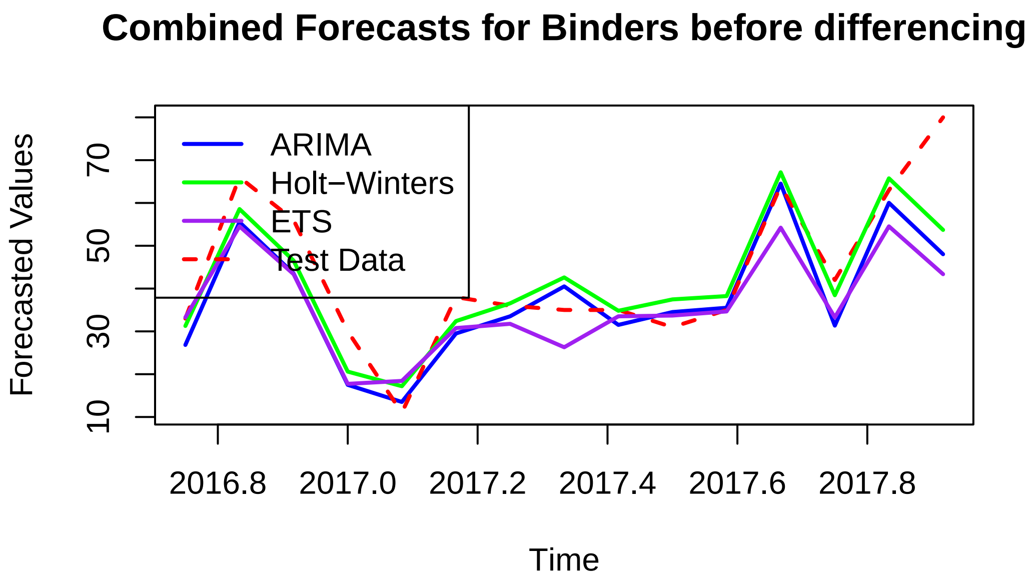
Let's forecast sold quantities for the three most sold sub-categories:

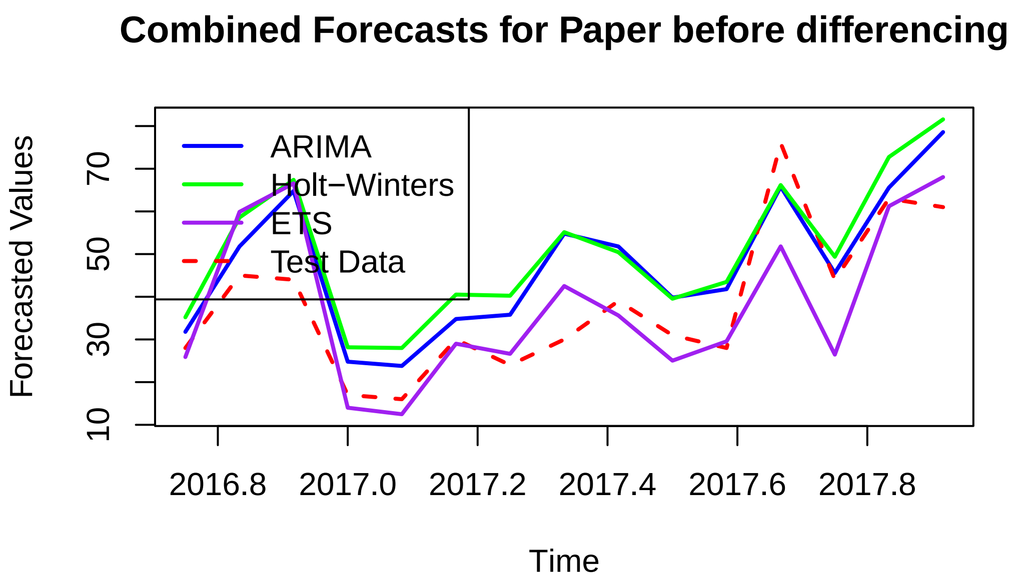
The steps taken for data preparation were:

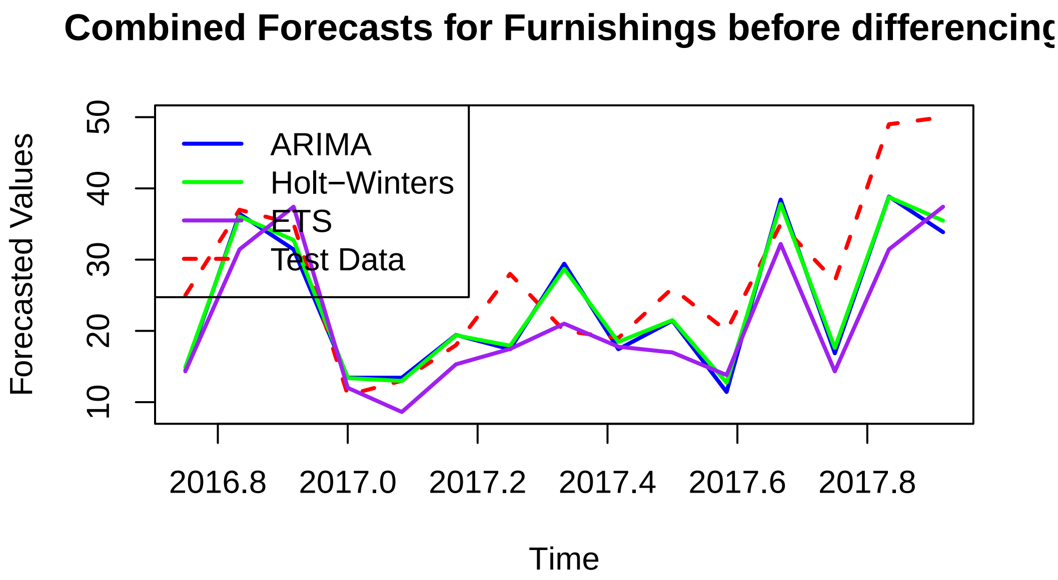
- Identifying Top Subcategories: The top three subcategories are selected from our dataset based on their sold quantities. The top three were: Binders, furnishing and paper.
- The sold quantities are aggregated monthly to create a time series object which we can use in the forecasting.
- A KPSS showed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


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


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



Source: Article Notebook

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.

Table 5: Training Set Forecast Accuracy

	Sub_Category	Method	Dataset	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
1	Binders	ARIMA	Training set	0.771	4.643	2.982	0.687	12.912	0.485	0.044
3	Binders	HoltWinters	Training set	0.867	5.215	3.790	-0.404	15.365	0.617	-0.389
5	Binders	ETS	Training set	0.743	4.713	3.656	1.359	15.417	0.595	-0.223
7	Paper	ARIMA	Training set	1.117	6.309	3.828	1.702	14.322	0.547	-0.007
9	Paper	HoltWinters	Training set	1.510	7.280	4.855	3.325	16.413	0.694	-0.027
11	Paper	ETS	Training set	0.609	6.205	4.475	-1.662	18.732	0.639	0.005
13	Furnishings	ARIMA	Training set	0.005	3.874	2.568	-6.625	20.210	0.556	-0.202
15	Furnishings	HoltWinters	Training set	0.914	4.165	3.475	7.490	24.756	0.752	-0.433
17	Furnishings	ETS	Training set	0.737	3.467	2.852	0.430	20.852	0.617	-0.209

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.

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

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.

Concerning the 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 Subcategories and forecasting (4b)

Steps Taken:

- Trend strength, random variation and seasonal strength were calculated for the subcategory using the time series we have.

Clustering:

The clustering method used is the hierarchical clustering method. To group subcategories into three different clusters based on features which are normalized. The hierarchical clustering gave the following results:

- Cluster 1: Stronger seasonality
- Cluster 2: moderate trend and seasonality
- Cluster 3: Lower trend and seasonal strength

For each different cluster we also used the models introduced in 4A (ARIMA, Holt-Winters, ETS). These results where all aggregated at the level of each cluster so we can assess mean RMSE and MAPE for each different model.

Table 6: Forecast Accuracy Results

	Sub_Category	Method	Dataset	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
2	Binders	ARIMA	Test set	5.941	10.784	7.616	10.368	17.329	1.240	0.049
4	Binders	HoltWinters	Test set	2.247	8.712	6.243	0.160	16.022	1.016	-0.002
6	Binders	ETS	Test set	7.440	12.216	8.825	10.667	20.936	1.437	0.061

	Sub_Category	Method	Dataset	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
8	Paper	ARIMA	Test set	-9.014	12.231	10.376	-30.104	31.895	1.482	0.109
10	Paper	HoltWinters	Test set	-12.037	14.481	13.347	-39.792	41.516	1.907	0.100
12	Paper	ETS	Test set	0.085	11.304	8.247	-0.085	20.476	1.178	0.342
14	Furnishings	ARIMA	Test set	3.952	7.783	6.238	10.720	22.753	1.351	-0.036
16	Furnishings	HoltWinters	Test set	3.637	7.201	5.673	9.724	20.501	1.228	0.018
18	Furnishings	ETS	Test set	6.097	8.354	6.691	20.728	23.553	1.449	0.373

Source: Article Notebook

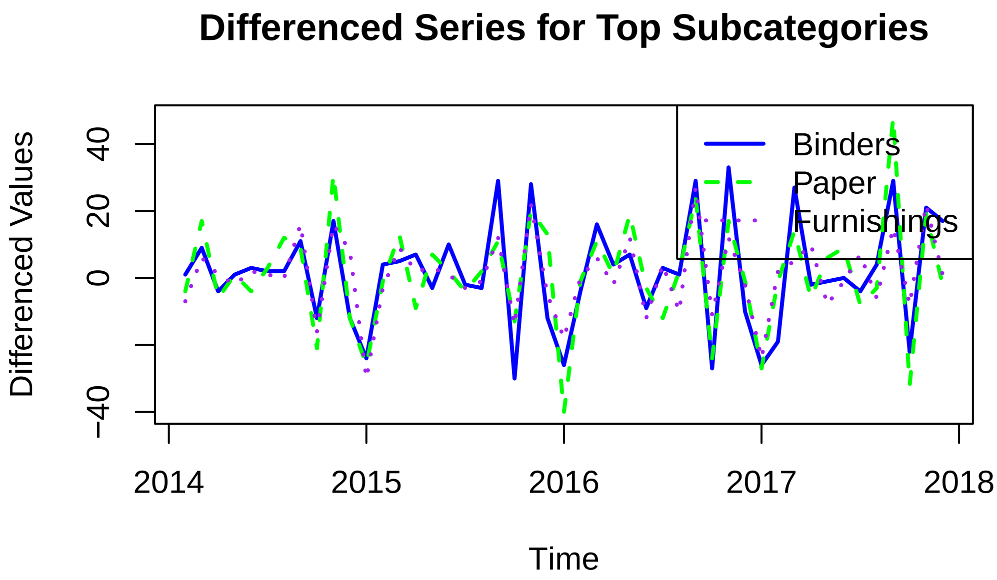
Table 7: KPSS Test Results for Top 3 Subcategories

Sub_Category	KPSS_Statistic	P_Value	Null_Hypothesis
Binders	0.785	0.01	Rejected (Non-Stationary)
Paper	0.738	0.01	Rejected (Non-Stationary)
Furnishings	0.764	0.01	Rejected (Non-Stationary)

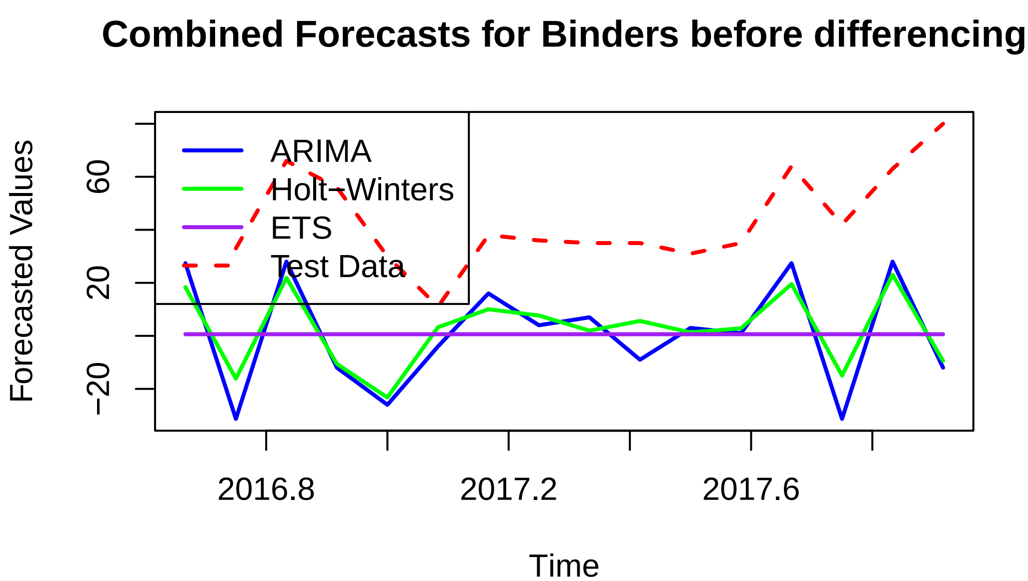
Source: Article Notebook

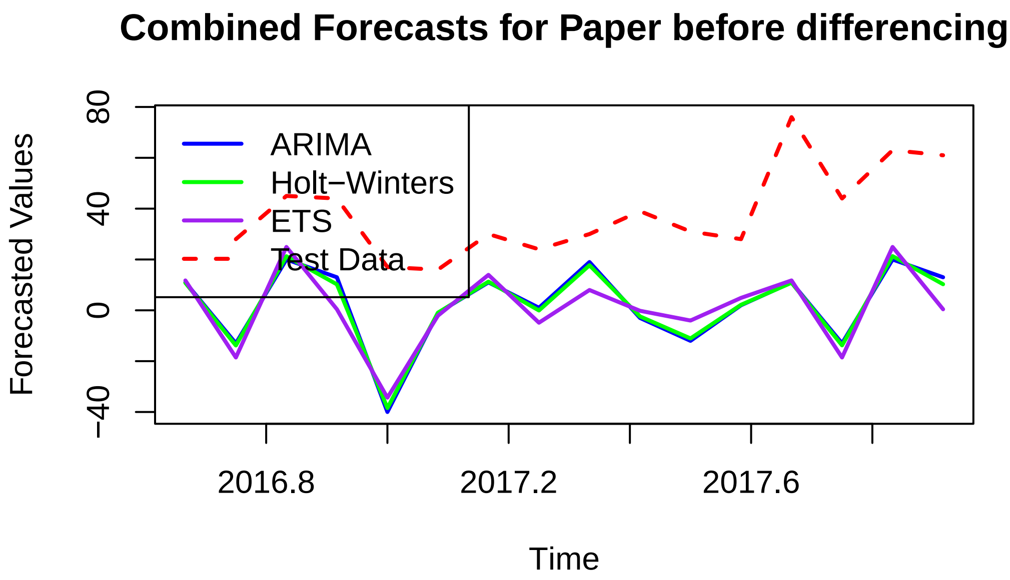
```
    KPSS Test for Level Stationarity

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
```

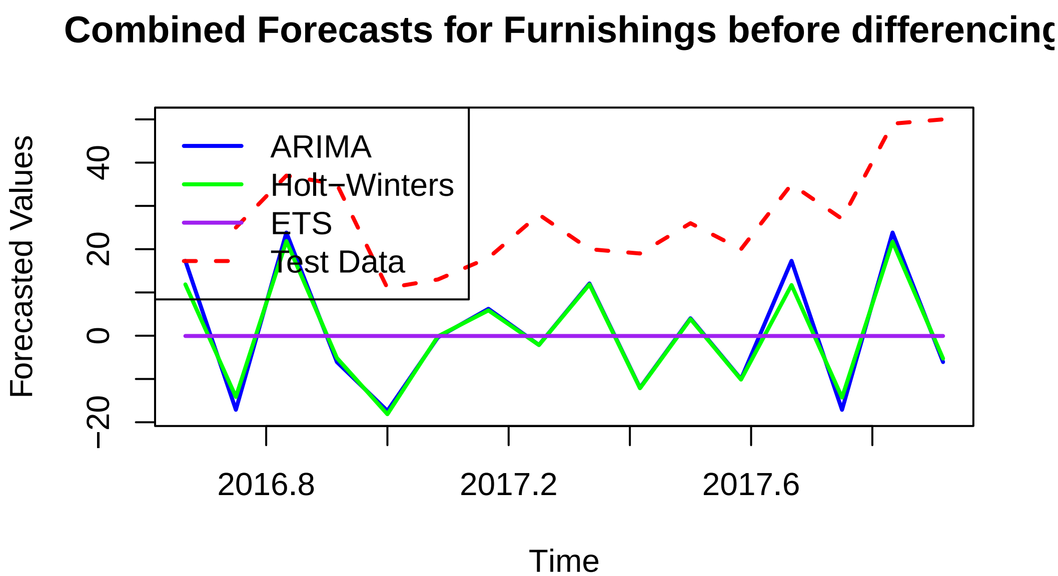
Source: Article Notebook



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

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:

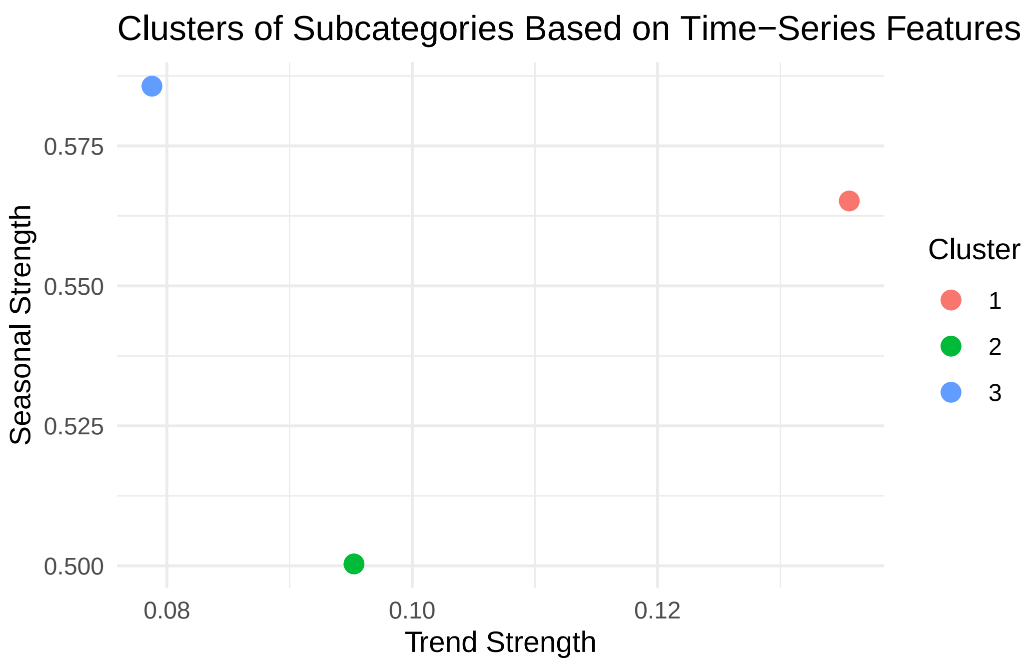
```
                    ME     RMSE      MAE       MPE     MAPE      MASE
Training set 0.0050974 3.873555 2.567868 -6.624673 20.20958 0.5559302
Test set     3.9523810 7.782677 6.238095 10.720079 22.75340 1.3505155
                    ACF1 Theil's U
Training set -0.20160077        NA
Test set     -0.03570035 0.6102339
```

Holt-Winters Accuracy:

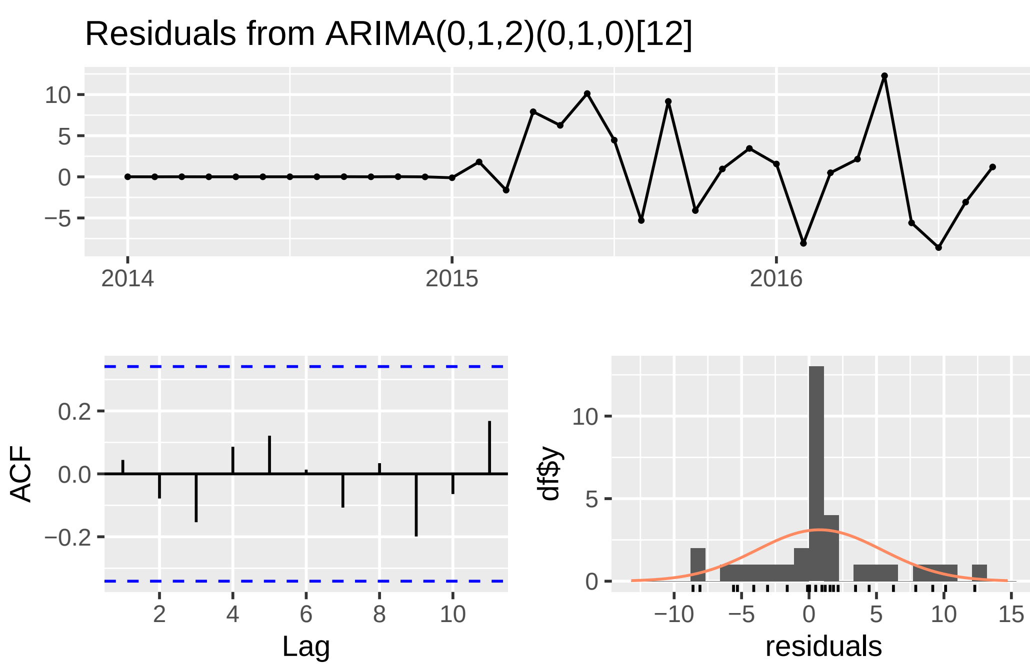
```
                    ME     RMSE      MAE      MPE     MAPE      MASE
Training set 0.9137655 4.164677 3.475419 7.490317 24.75583 0.7524103
Test set     3.6371987 7.200985 5.673333 9.724318 20.50134 1.2282474
                    ACF1 Theil's U
Training set -0.43317305        NA
Test set      0.01804785 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
```

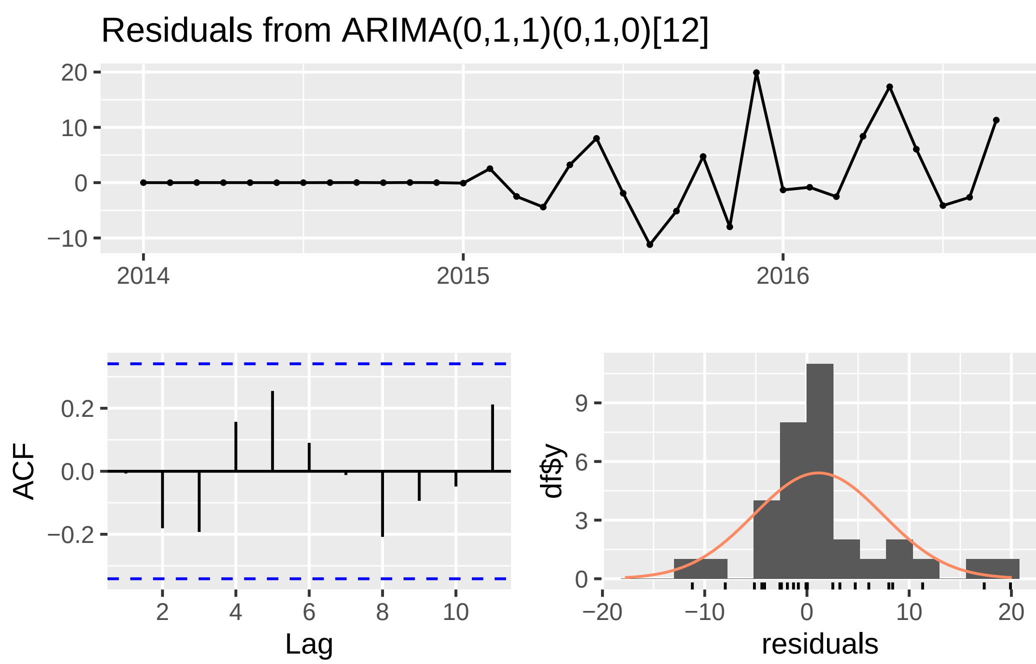



```
Residual Diagnostics for Sub-Category: Binders
```



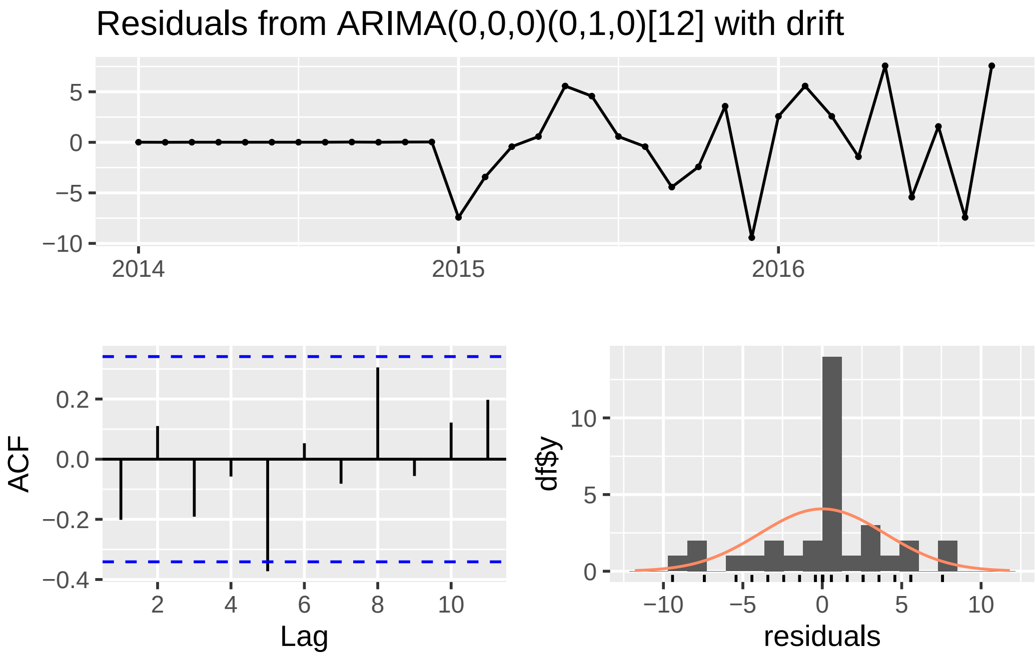
```
    Ljung-Box test

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.

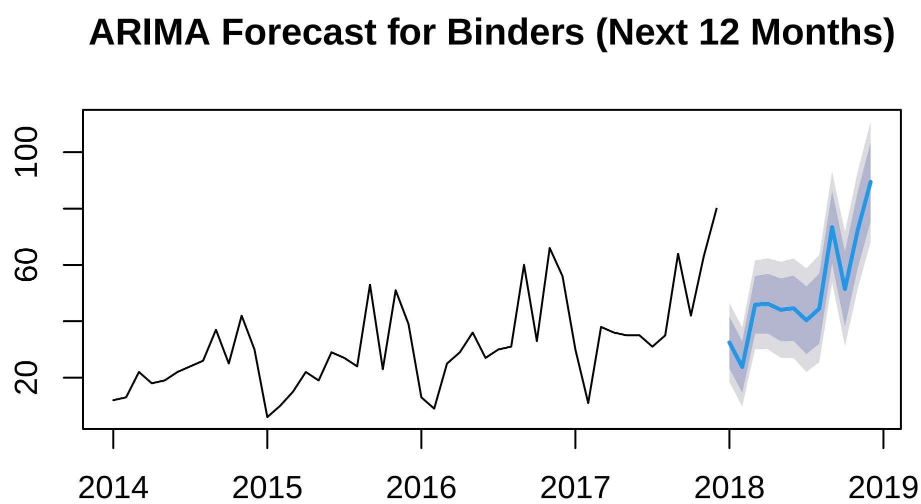
0.4 Forecasting future values

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.

```
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
```

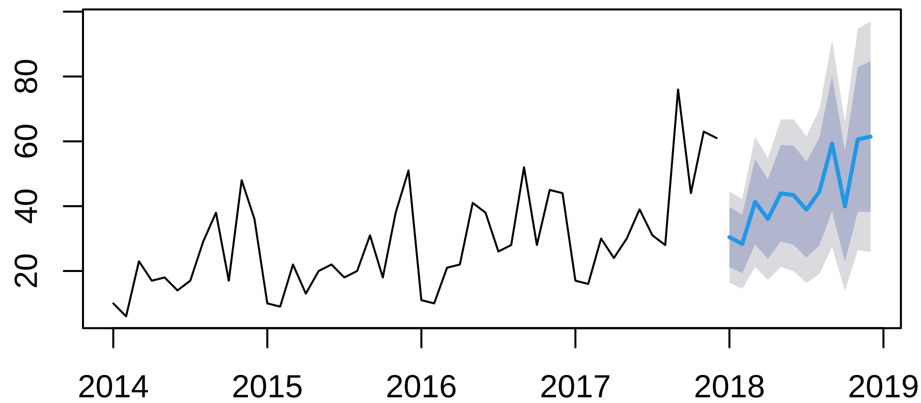
```
Mar 2018       45.85265 35.59989  56.10541 30.172412  61.53289
Apr 2018       46.20475 35.63662  56.77287 30.042185  62.36730
May 2018       44.08009 32.93968  55.22051 27.042295  61.11789
Jun 2018       44.61784 33.06359  56.17210 26.947139  62.28855
Jul 2018       40.36072 28.34867  52.37277 21.989869  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
```

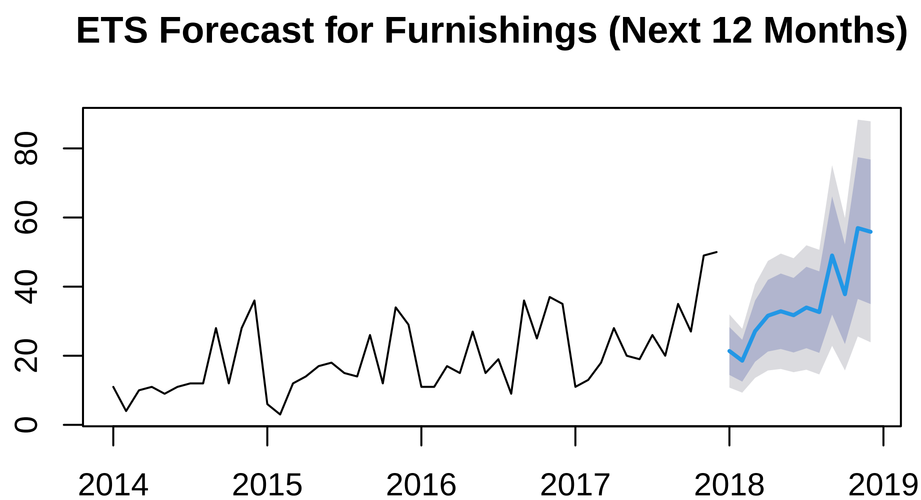
ETS Forecast for Paper (Next 12 Months)




```
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

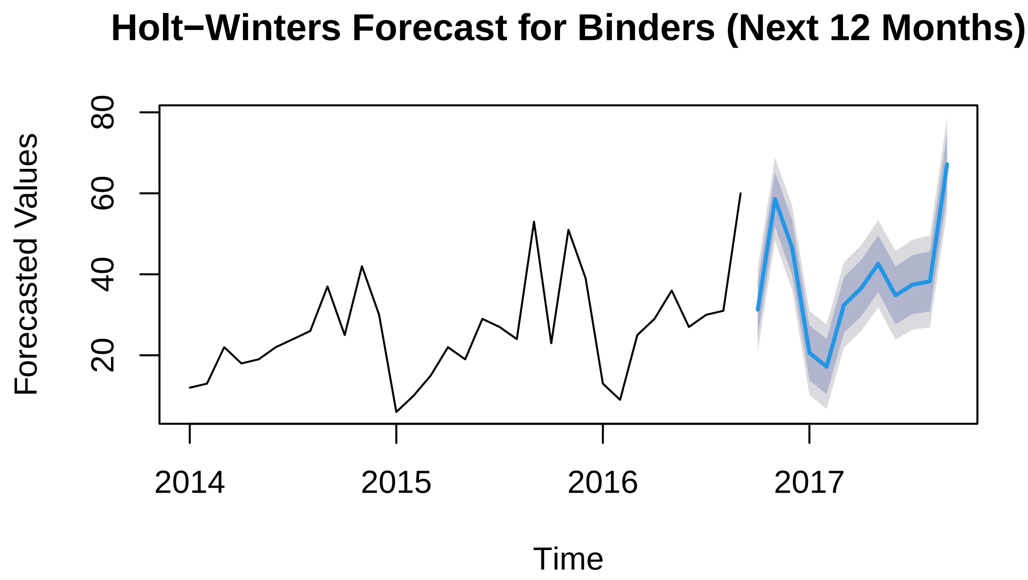


Source: Article Notebook

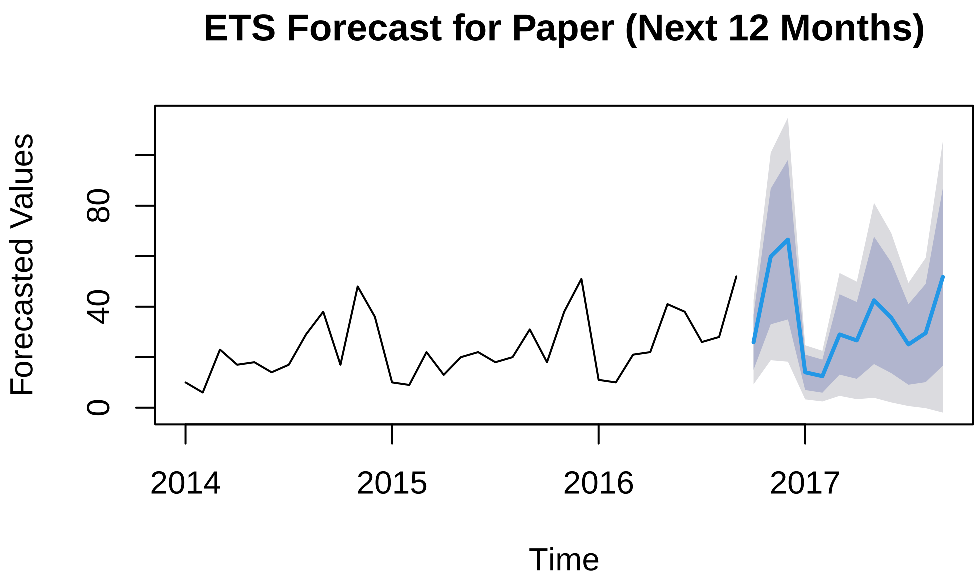
Applying to all data (5b)

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.

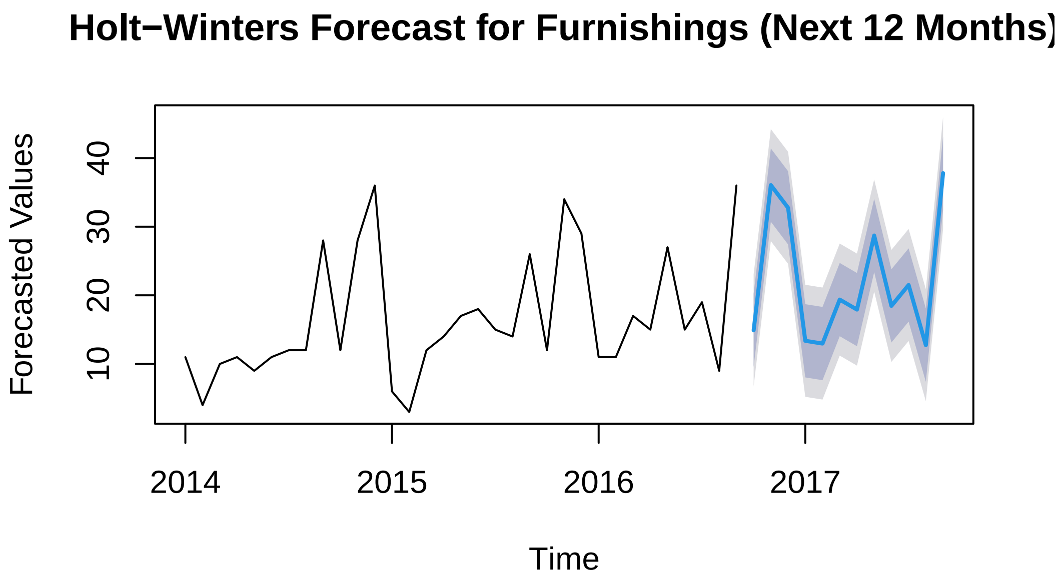
```
         Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
Oct 2016       31.26733 24.51360 38.02106 20.938398 41.59627
Nov 2016       58.57211 51.81274 65.33147 48.234553 68.90966
Dec 2016       46.52209 39.75006 53.29412 36.165163 56.87901
Jan 2017       20.60516 13.81068 27.39965 10.213895 30.99643
Feb 2017       17.19081 10.36138 24.02023  6.746097 27.63551
Mar 2017       32.40031 25.52088 39.27975 21.879129 42.92150
Apr 2017       36.54419 29.59727 43.49111 25.919798 47.16858
May 2017       42.60581 35.57173 49.63990 31.848113 53.36351
Jun 2017       34.81156 27.66868 41.95444 23.887472 45.73565
Jul 2017       37.46761 30.19266 44.74256 26.341532 48.59368
Aug 2017       38.24466 30.81304 45.67627 26.878978 49.61034
Sep 2017       67.16755 59.55368 74.78141 55.523142 78.81195
```



	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Oct 2016	25.88021	14.987312	36.77312	9.2209588	42.53947
Nov 2016	59.89171	33.023650	86.75978	18.8005561	100.98287
Dec 2016	66.56848	34.945434	98.19153	18.2052047	114.93176
Jan 2017	14.00226	6.995420	21.00910	3.2862229	24.71830
Feb 2017	12.48362	5.931497	19.03574	2.4630129	22.50422
Mar 2017	29.00633	13.095755	44.91690	4.6732073	53.33945
Apr 2017	26.62997	11.410973	41.84896	3.3545236	49.90541
May 2017	42.52022	17.268520	67.77192	3.9010776	81.13936
Jun 2017	35.62513	13.690064	57.56019	2.0783432	69.17191
Jul 2017	25.03347	9.084935	40.98201	0.6422896	49.42466
Aug 2017	29.56385	10.109840	49.01785	-0.1884895	59.31618
Sep 2017	51.80976	16.651800	86.96771	-1.9596973	105.57921



	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Oct 2016	14.89552	9.559730	20.23131	6.735134	23.05590
Nov 2016	36.06019	30.724406	41.39598	27.899811	44.22058
Dec 2016	32.74939	27.413606	38.08518	24.589010	40.90978
Jan 2017	13.37457	8.038784	18.71036	5.214189	21.53496
Feb 2017	12.97277	7.636978	18.30855	4.812382	21.13315
Mar 2017	19.37898	14.043187	24.71476	11.218592	27.53936
Apr 2017	17.92073	12.584940	23.25652	9.760344	26.08111
May 2017	28.71390	23.378112	34.04969	20.553516	36.87428
Jun 2017	18.46131	13.125525	23.79710	10.300929	26.62170
Jul 2017	21.50610	16.170317	26.84189	13.345721	29.66649
Aug 2017	12.73905	7.403259	18.07484	4.578664	20.89943
Sep 2017	37.80356	32.467775	43.13935	29.643179	45.96395



Source: Article Notebook

0.5 Forecast interpretation

Source: Article Notebook

Source: Article Notebook