

Supply Chain Data Analytics

Analyzing and Forecasting Supermarket Sales

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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.

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.

please visit

https://sjbrou.github.io/Supply_Chain_Data_Analysis/
for an interactive version with better
visualizations!

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-2016-138688
Order_Date	2016-11-08	2016-06-12
Ship_Date	2016-11-11	2016-06-16
Ship_Mode	Second Class	Second Class
Customer_ID	CG-12520	DV-13045
CustomerName	Claire Gute	Darrin Van Huff
Segment	Consumer	Corporate
City	Henderson	Los Angeles
State	Kentucky	California
Postal_Code	42420	90036
Region	South	West
Product_ID	FUR-BO-10001798	OFF-LA-10000240
Category	Furniture	Office Supplies

Sub_Category	Books	Chairs	Labels
Product Line	Hon 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
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](#)

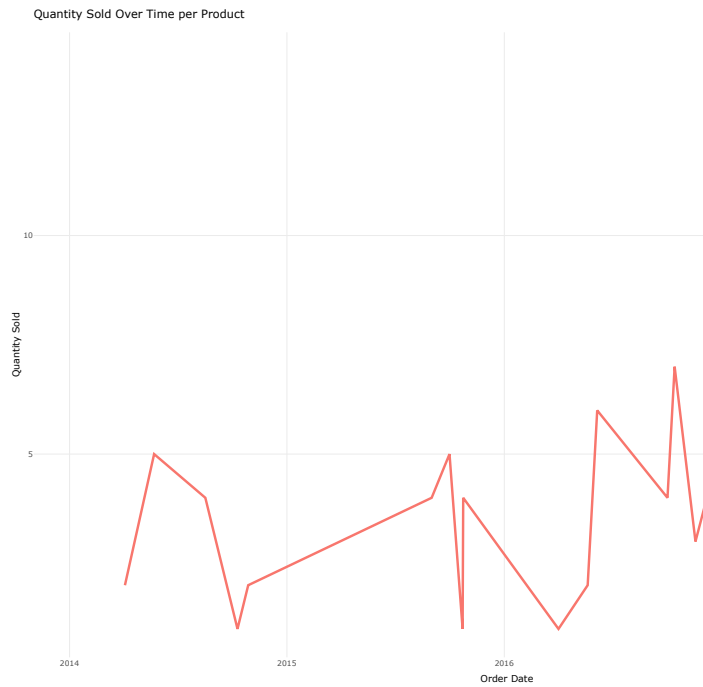
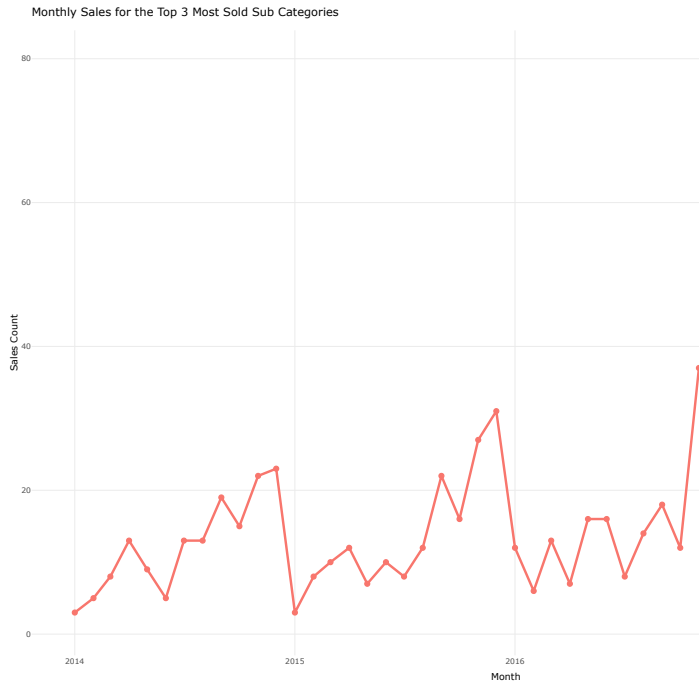


Figure 1: Figure X Sale quantity of the most popular products

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.



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.

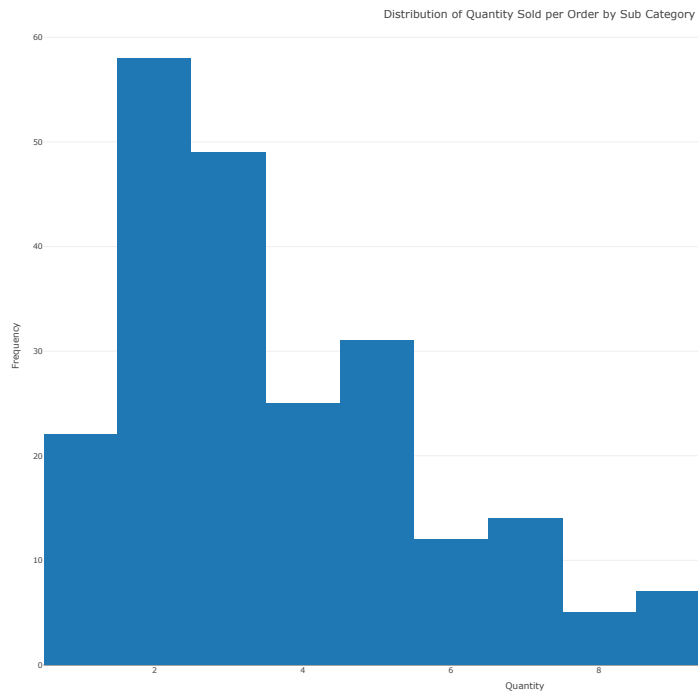
To properly finish our data preprocessing we ran some statistics on Quantity aggregated by Sub_Category. Table x contains some descriptive statistics.

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.



Source: [Article Notebook](#)

The histograms show that the quantities are 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..

Forecasting Method Evaluation

Forecasting top 3 product categories (4a)

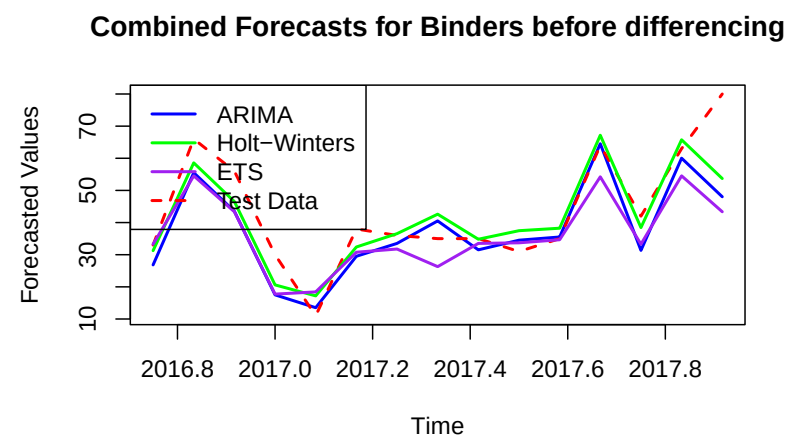
Let's forecast sold quantities for the three most sold sub-categories:

The steps taken for data preparation were:

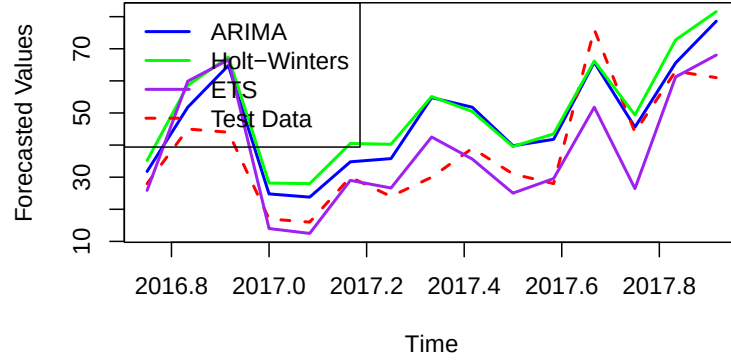
- Identifying Top Subcategories: The top three subcategories are selected from our dataset based on their sold quantities. The top three were: Binders, furnishing and paper.
- The sold quantities are aggregated monthly to create a time series object which we can use in the forecasting.
- A KPSS showed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

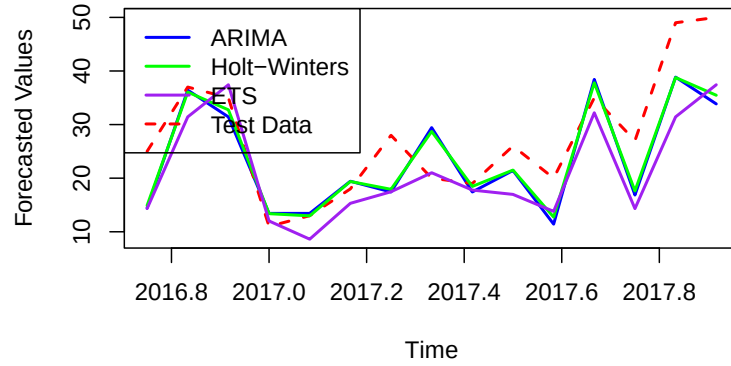
Three models are applied to each subcategory to forecast it. The models we use are: ARIMA, Holt-Winters and ETS. We have chosen these models because of their level of suitability for discrete time series data with all different levels of trend and seasonality. To evaluate the methods and its effectiveness,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



Combined Forecasts for Paper before differencing



Combined Forecasts for Furnishings before differencing



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	T
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	

	Sub_Category	Method	Dataset	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	T
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 were 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	T
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	
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

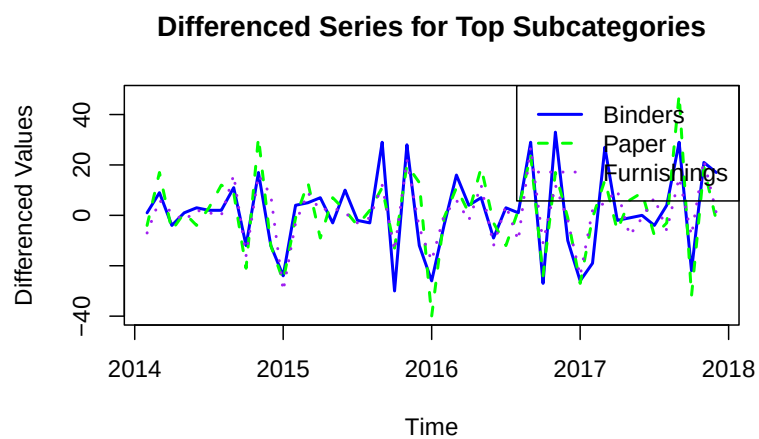
KPSS Level = 0.061982, Truncation lag parameter = 3, p-value = 0.1

KPSS Test for Level Stationarity

data: ts_diff

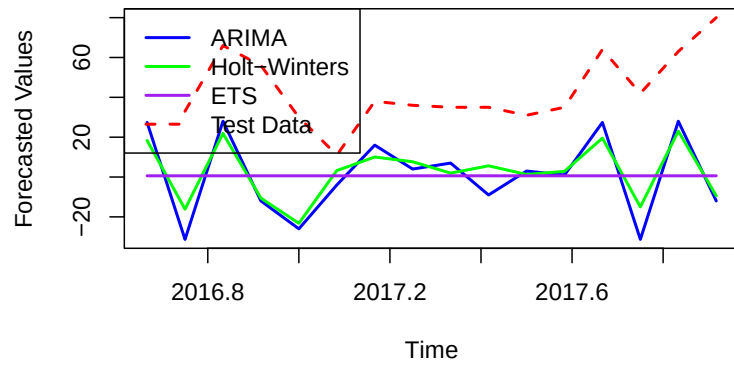
KPSS Level = 0.098438, Truncation lag parameter = 3, p-value = 0.1

Source: [Article Notebook](#)

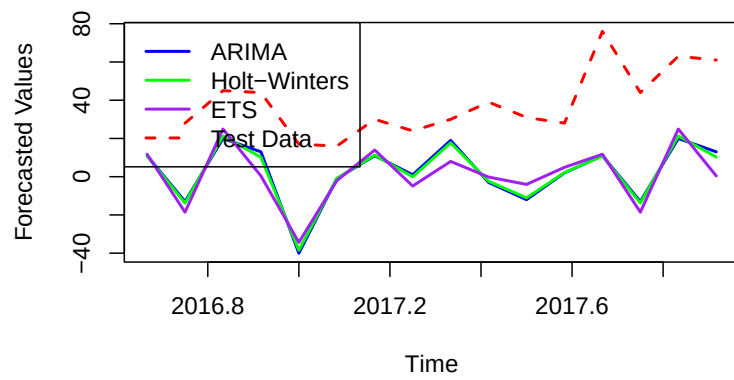


Source: [Article Notebook](#)

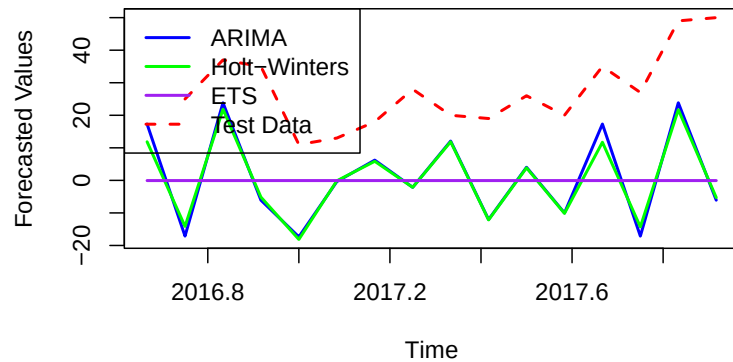
Combined Forecasts for Binders before differencing



Combined Forecasts for Paper before differencing



Combined Forecasts for Furnishings before differencing



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:

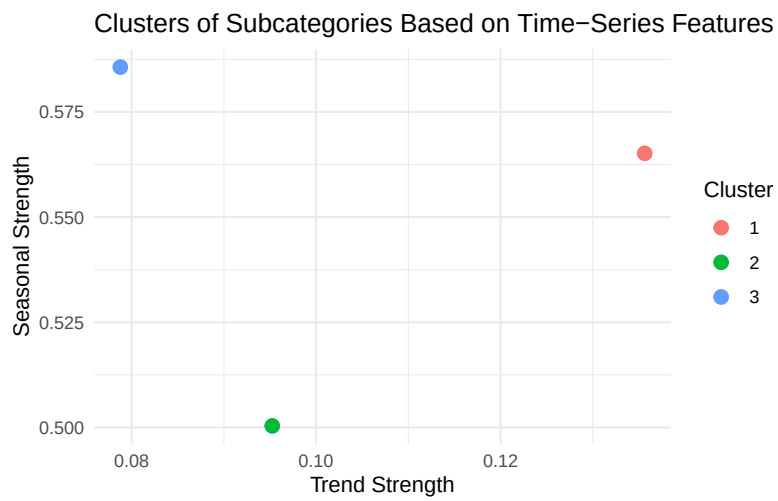
	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.9137655	4.164677	3.475419	7.490317	24.75583	0.7524103
Test set	3.6371987	7.200985	5.673333	9.724318	20.50134	1.2282474
ACF1 Theil's U						

Training set	-0.43317305	NA
Test set	0.01804785	0.5689788

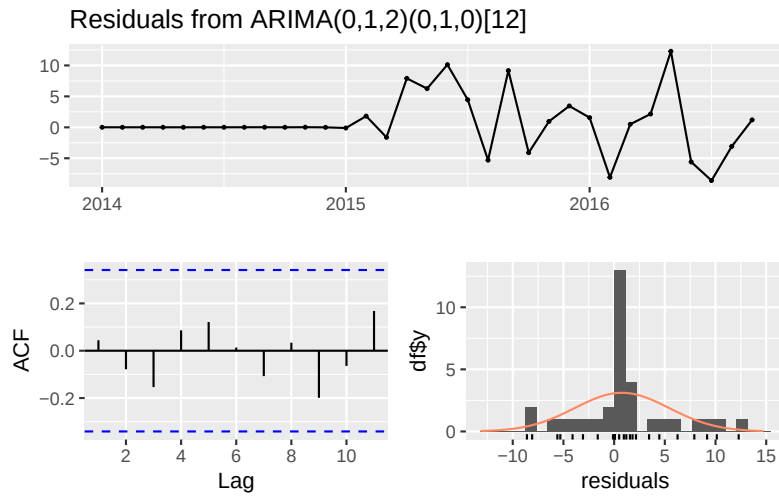
ETS Accuracy:

	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

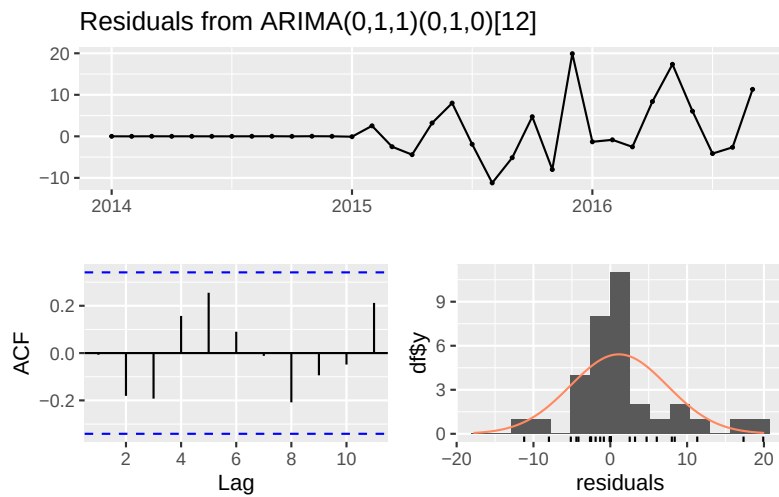


Ljung-Box test

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

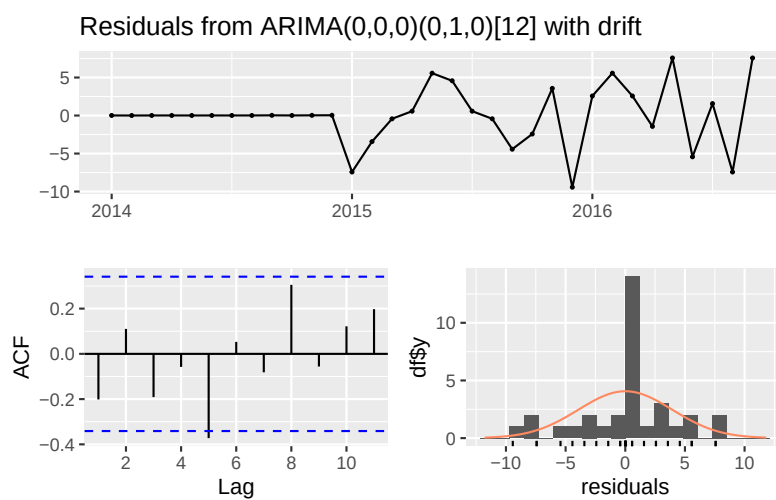


Ljung-Box test

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.

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

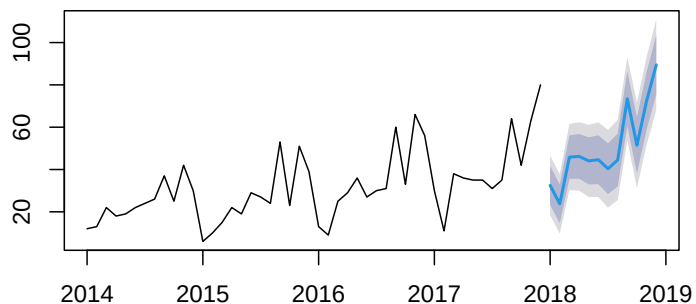
sigma^2 = 51.18: log likelihood = -117.97
 AIC=241.94 AICc=242.72 BIC=246.61

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

ARIMA Forecast for Binders (Next 12 Months)



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

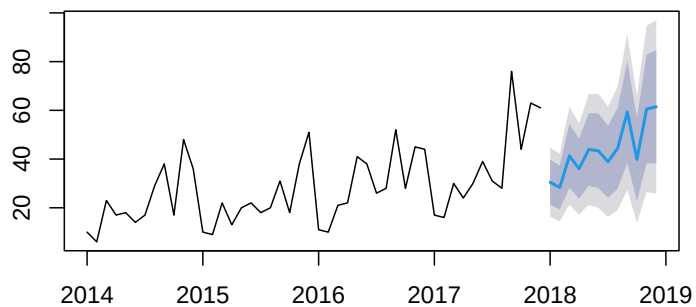
Training set error measures:

	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

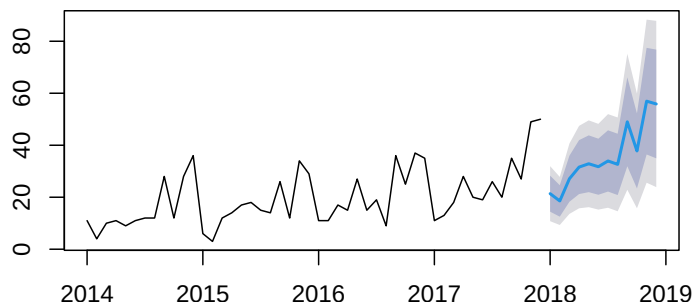
AIC AICc BIC
 338.8888 359.2888 370.6992

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

ETS Forecast for Furnishings (Next 12 Months)



Source: [Article Notebook](#)

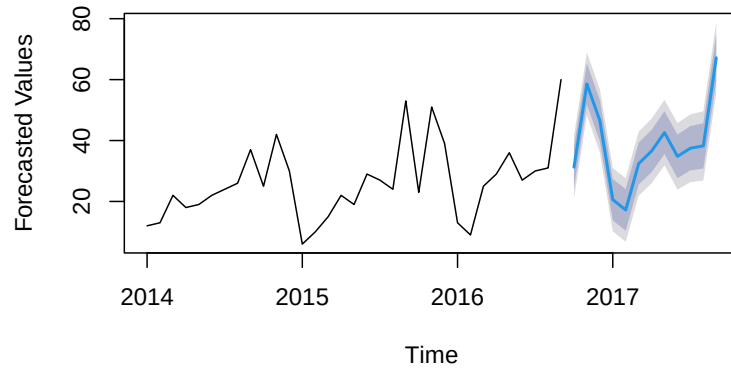
Applying to all data (5b)

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

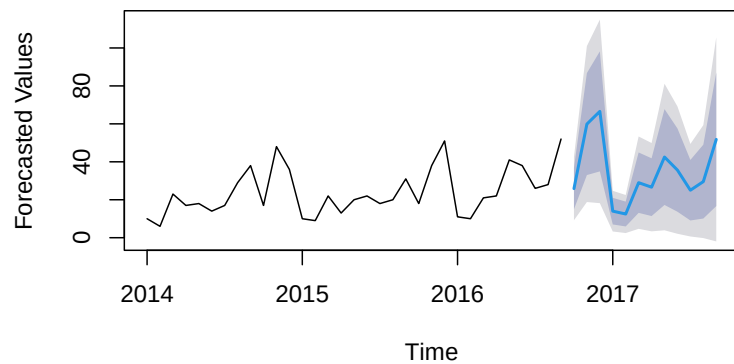
Jun 2017	34.81156	27.66868	41.95444	23.887472	45.73565
Jul 2017	37.46761	30.19266	44.74256	26.341532	48.59368
Aug 2017	38.24466	30.81304	45.67627	26.878978	49.61034
Sep 2017	67.16755	59.55368	74.78141	55.523142	78.81195

Holt-Winters Forecast for Binders (Next 12 Months)



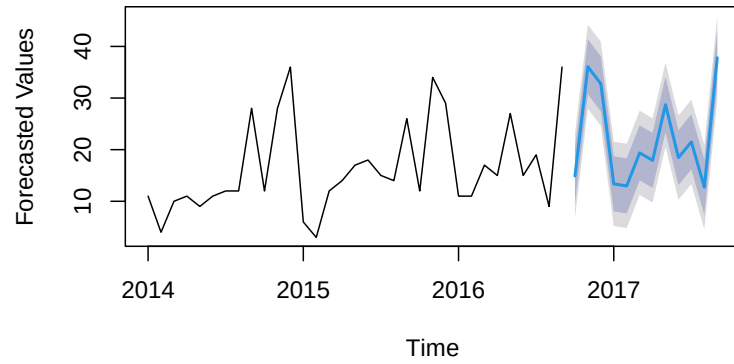
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Oct 2016	25.88021	14.987312	36.77312	9.2209588	42.53947
Nov 2016	59.89171	33.023650	86.75978	18.8005561	100.98287
Dec 2016	66.56848	34.945434	98.19153	18.2052047	114.93176
Jan 2017	14.00226	6.995420	21.00910	3.2862229	24.71830
Feb 2017	12.48362	5.931497	19.03574	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

ETS Forecast for Paper (Next 12 Months)



	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

Holt-Winters Forecast for Furnishings (Next 12 Months)



Source: [Article Notebook](#)

Forecast interpretation

Source: [Article Notebook](#)

Source: [Article Notebook](#)