RETAIL SPACE PLANNING

Group L

Student Id - 35493311, 35870054, 36025955, 36104313
Supervisor name: Prof. John Boylan

Word count: 3498

Table of contents

Table of figures and tables

Table of tables

Executive summary

Factors responsible for the growth of retail sales have been widely studied, however, space planning, and the impact of sales on space planning is still not discovered in depth. The report analyses which additional factors could contribute towards retail space planning for the short and long-term and how short-term planning of departmental volume could be forecast, with consideration of how other stores' seasonal patterns could help further understanding. The report highlights interesting observations within current sales volume on a departmental level and predicted values about the sales volume considering seasonal peaks. For example, FOODS 3 department sales are almost 4-8 times greater than FOODS 1 and 2, mirrored in HOUSEHOLD 1 over HOUSEHOLD 2 and HOBBIES 1 over HOBBIES 2, so should be considered within space planning. Store location, day of the week, annual season, events, month impacts the sales seen in the supermarket. If considered sales in a linear relation with the size of the items, then these would become responsible for space planning and should be considered. For long term demand forecasting, demand is affected by multifarious variables, not all of which can be forecasted accurately over 20 years. By implementing a mix of techniques to tackle both qualitative and quantitative data, via Delphi and machine learning, basic forecasts could be produced, or long-term effects on retail demand estimated, to determine the size of future stores.

Introduction

Forecasts are valuable tools used extensively to make decisions globally, in fact, forecasts produce baselines for any decision making e.g., supermarkets: if supermarket managers cannot maintain proper inventory; it could develop into customer service issues and high inventory costs. Supermarkets need forecasts for any business / strategic decisions.

This report's objective is to present the analysis of 42,840 item time series representing the hierarchical unit sales for the largest retail company in the world by revenue, Walmart. Thereby identifying challenges faced regarding retail space planning. Firstly, deciding the sizes of new outlets and secondly: space allocation in expectation of increasing demand during seasonal peaks. To formulate solutions, research on long-term forecasting was undertaken to determine the sizes of new warehouses, and forecasts for various categories were produced using the data provided, consisting of a short 6-month period and revisiting current space allocation with seasonal forecasted demand volume to address problems. Walton Mart is facing and for the former problem we would be considering briefly the forecasted volume but as we are seeing here to open a new retail market, forecasting may not turn accurate enough to draw the conclusions.

Exploratory Data Analysis

The dataset consists of 3049 scrambled, individual products from 3 product categories and 7 departments, sold in 10 stores in 3 states (California CA, Texas TX, and Wisconsin WI), the dataset has 42,840 items sales data, with 3000 item sales occurring daily. The dataset includes item level, department, product categories, and store details for 5 years from 29th Jan 2011 to 24th April 2016. Also, it contains explanatory variables e.g., price, snap events, day of the week, special events and festivals.

Preliminary analysis showed a strong presence of weekly and annual seasonality. However, at the item level, seasonality becomes less strong. The sales volume showed many items usually sold at 0 units on weekdays. There are several possible reasons behind this, such as retail product sales can vary based on seasons or temporary lack of stock or just could be because of its weekdays. Below are some observations based on the explanatory data analysis:

1. The food department recorded the highest sales across all three states.
2. California has 4 stores, it recorded maximum sales and a maximum population in comparison to TX and WI.
3. CA 3 has almost doubled the sales volume in comparison to other stores.
4. As Walmart is closed at Christmas there is no sales activity, also sales activity decreased on other festivals/holiday periods.
5. Interestingly, sales increased year to year. Highest in March, then usual trends reduced till May, lowest in June and then gradually increasing till December.
6. As discussed, sales are predominantly highest on weekends, especially for WI on Sat and for CA and TX on Sun.
7. Also at NBA sports events, sales volume increased before the event and decreased after.

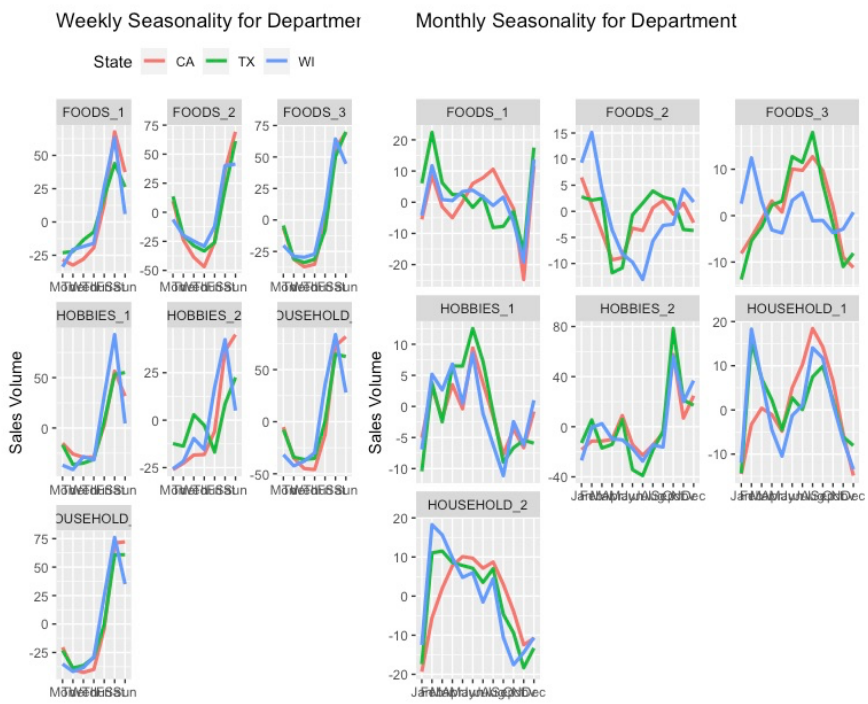

Figure 1: Seasonal plot for department

Methodology

The dataset consisted of sales volume from 10 stores across CA, TX and WI. The sales of each store were conditional to nearby stores, both competitors and Walmart's own, this impacts the sales and every function of the supermarket. The store sales help to relate sales volume to customer purchasing patterns e.g., best-sellers, regional trends, customer mindset and market trend and size. Via analysis, it allows predictions of the baseline/benchmark sales in new regional stores. Assuming predicted sales volume of departments, considering demographics, market trend, customer's preferences and sales patterns are comparable across regions, could allow benchmark sales prediction used for further analysis.

As the dataset presented has 42840 -time series based on the item level combing the aggregated levels. In the Univariate model previous months or weeks' sales volume is used to forecast while in multivariate models, the previous month's sales volume is often used alongside explanatory variables assuming causal relations/correlations. In both cases, both could be as much possible. We produce both approaches with some degree of freedom.

As shown in appendix 2 and 3 we aggregated the daily reported item-level sales within the original dataset to weekly and monthly levels on department level. When aggregating the data, we considered aggregated on mean value but not the median level, since many products sales were not observed daily, but only on weekends. Using mean values allows space allocation to be more specific and beneficial than the median at a departmental level.

The prediction of sales volume could only be based on previous sales volumes of each specific department, for example, FOODS 1. Previous sales volumes would be only a single input variable but don't apply for other variables (e.g., departments) to predict sales volumes. In the univariate model, we considered the seasonal naïve model, exponential smoothing model and seasonal ARIMA model.

We should not discount the possibility of having a causal relation or correlations with department sales interdependibilty. For example, when a customer comes to purchase items from the hobby section, customers can potentially purchase food as well. To evaluate this possibility, we build the VAR model which would evaluate possible variable relationships.

Long-Term Planning Problem:

Findings:

Traditional retail forecasting techniques, to determine the possibility of expansion, include analysis of pricing, seasonality, holidays/national events, inventory management: purchasing supplies to meet demand, stock rotations (product lifecycles/discontinuation), promotional plans and advertisement campaigns (Brian Seaman, Robert Fildes). These directly affect the space, demand, and profit of departments within a business (Brian Seaman).

For space planning, pricing is proportional to consumer popularity, unstable pricing degrades the company to customer trust, too high is undesirable, both mean that sales need close monitoring to determine the popularity of products and departmental space required. This allocation determines operating costs. Modelling is traditionally static, but advancements in adapting to product life cycles and market change are desirable (Marcel Corstjens). However, this monitoring and forecasting are unstable and highly granular, so cannot be accurately forecasted past a year or two. (Brian Seaman)

Traditionally, one other key aspect of warehouse building is locations, which vary in socio-economic background, age, gender, education, surrounding area amenities (shopping centers, parks, parking), retail competition, market saturation, and customer loyalty. Then finally renting / leasing costs which will dictate the success and size of the warehouse/store (Formánek, T. & Sokol, O. (2022)).

However, there are new considerations that retailers need to account for to be able to begin to forecast current retail over longer periods, e.g., 10 to 20 years.

Changes to fundamental business models due to the introduction of e-commerce methods over the last decade, 2017 online consumerism accounted for 14.8% of sales (Robert Fildes).

In Walmart especially, omnichannel strategies with third-party sellers require monitoring online sale demand, as warehouse shipments affect brick-and-mortar demand, as demand is now split between multiple shopping channels. Today, 4 out of 7 channels are online. Negatively affecting forecasts if unaccounted (Relex Solutions, Colin Jones).

Accounting for logistics and customer relations with the company will help assess demand long-term. Customer loyalty is imperative for long-term success. Implementing surveys to gauge loyalty and maintain relationships improves the overall turbulence on long-term retail demand forecasts (Linh, L).

New working patterns, regarding trialing 4-day working weeks, societal shifts may affect in-person retail in an unforecastable manner. Due to the short-term change (REF).

From 2019 to 2020, COVID-19 highlighted the volatility of the supply chain, so strategies to enhance business regardless of external disruptions in essential (Manu Sharma). Retail sales fell by 15% in April 2020, with now 51% of shopping being done online (Ecommerce and the demographics of online shoppers, 2019). So, improvements to company systems are important to tackle deviations that cannot be forecasted long-term. (Manu Sharma).

Trends in US/UK retail decline over 100 years could help estimate the financial implications of building new stores in certain areas over the next 20 years. Brick-and-mortar stores dominate in retail parks rather than remote locations due to “day-out” experiences, but the viability of building a store needs to be considered as trends change (Conrad Kickert)

Economic changes directly affect demand, depressions/recessions equal low demand for luxury products since disposable income decreases. Leasing locations cost over 20 years also affects building (Brian Seaman).

Population growth gives initial information on demand, representative of the last decades' figures. Densely populated/bust areas produce better demand and profit expectations. Using mortality rates allows inspection of brick-and-mortar long-term target audiences e.g., ages/population of 55-74’s in the next 10-20 years, need accounting for. Most younger customers are better adapted to e-commerce, trust online shopping more, with the younger generation's online purchasing steadily increasing over the last decade (Hou, J. & Elliott, K. (2021), Lissitsa, S. & Kol, O. (2016)).

Consumer behaviors vary based on a country's culture, meaning data collection within alternative countries to the US must be acknowledged when expanding businesses (De Mooij) Retail behaviors within the UK (similar economic and cultural environment) show the highest rates of online shopping globally from 2011-2014 with departments found in Walmart encountering greater online engagement (Figure 1).

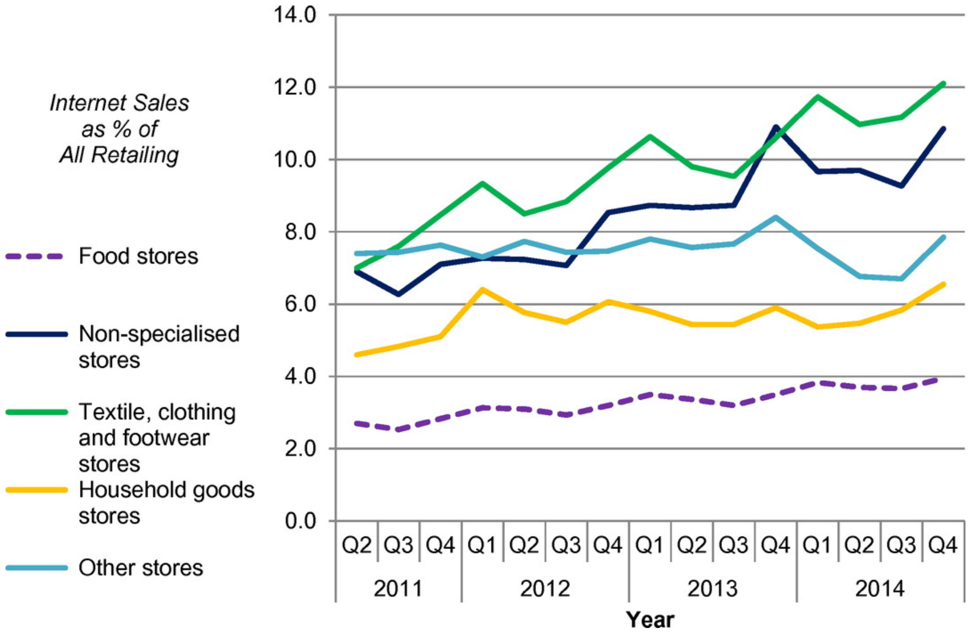

Figure 2: Online shopping sales per department 2011-2014 (Colin Jones))

Incorporating long-term effects into forecasting retail demand:

Long-term forecasts can't correctly predict all the above, forecasts must be devised via basic information and slowly built upon. The most essential information that's readily available is the US state's population growth rates. Secondly, a stabilized version of the economy over the last decade helps to determine general fluctuations in demand and the disposable income of surrounding customers. Sales data described above is aggregated both towards store and company data, meaning long-term forecasts are extremely variable per store. Walmart would face an oversaturation of graphical forecasts to produce, of which usefulness is limited to weak estimations only (Brian Seaman). Too many variables cause overfitting and uncertainty, what can be done to minimize this is to granularize long-term forecasting time series. One technique called fuzzy clustering captures essential relationships between these granules and increases the performance of long-term forecasting models. (Deloitte)

Long-term forecasting models will predominantly be trend curves, simple linear or exponential, focusing on trend projection. (Clive W.J. Granger) Regression analysis could help analyze certain relationships of more niche effects on-demand to gain a greater holistic view. Some long-term forecast methodologies Walmart could adopt consist of Expert opinion combined with The Delphi method, whereby qualitative questionnaires regarding information directly affecting new LT forecasts is obtained via experts in retail, utilized and specialized to Walmart's exact requirements (CFI). Also, Machine Learning techniques remove causal modeling and manual alterations and adapt to changes (Relex Solutions). Machine learning accesses both the quantitative and qualitative aspects of demand forecasting and can be used on a store-by-store basis once the correct data has been collected.

Analysis

Model building

4.1 Data Preprocessing

The data is sectioned via department id column: FOODS_1, FOODS_2, FOODS_3, HOBBIES_1, HOBBIES_2, HOUSEHOLD_1, and HOUSEHOLD_2. 1941 days (approx. 5 and 1/2 years) of data is converted to 278 weeks and 65 months for further analysis. With weekly and monthly data split into 70% training and 30% test data.

4.2 Stationary and Cointegration Tests

According to output 1 in the appendix, we can see that p-value equals 0.01, which means that the series is not stationary. The p-values of remaining 6 series are all 0.01, which means that these 7 series are all not stationary.

In order to do cointegration test, we treat HOBBIES_1 as the response variable and other 6 es as explanatory variables. Then we can build a regression model and obtain residuals for this model. According to output 4, the ADF for residuals shows that the value is 3.2043, which is lower than the critical value (-3.96) on a 1% significance level. Therefore, the data are not cointegrated.

As discussed in methodology section, we would evaluate both univariate and multivariate methods to forecast the sales volume across various departments. In multivariate model, we will discuss the vector autoregressive model and in univariate model, we will start with the seasonal naïve model and then exponential smoothing and ARIMA model.

VAR Model

According to Figure3, the blue line (fitted value), fits the train data very well, and the ACF and PACF plots show no significant spikes.

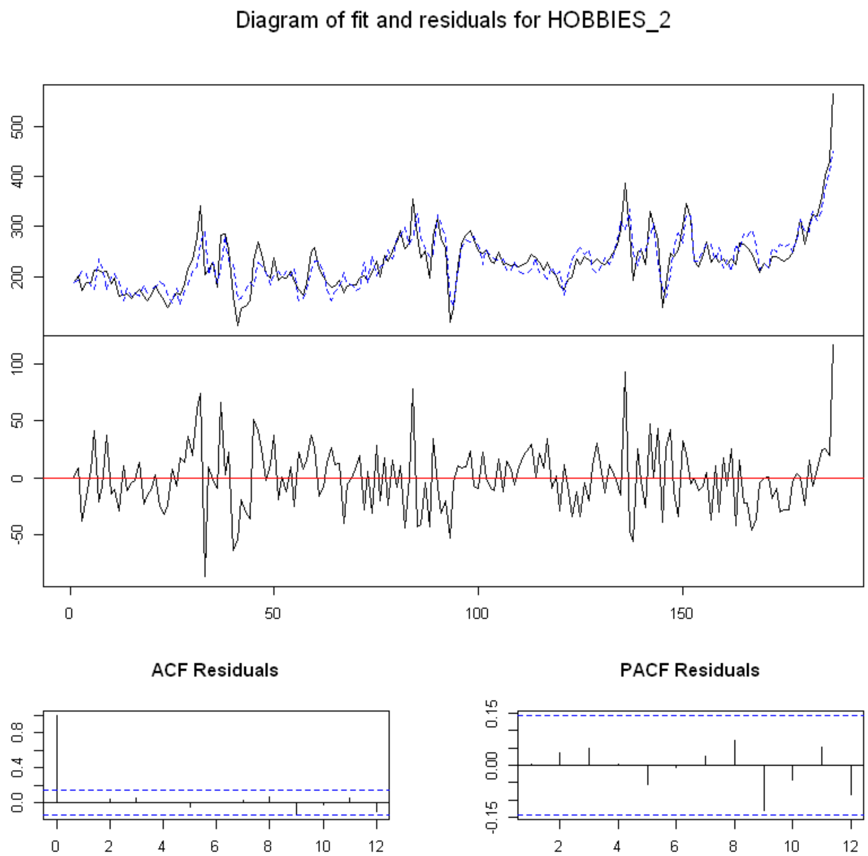

Figure 3: Forecasting HOBBIES_2 in training data

Seasonal Naïve Model

All departmental sales datasets hold strong seasonal patterns. Considering this, we started with seasonal naïve to set a benchmark for other forecasting models which we would be discussing. On a department level, both weekly and monthly aggregated datasets hold seasonal patterns, so the seasonal naïve model was applied to both weekly and monthly department data.

ETS Model

Exponential smoothing is widely used in retail sales and demand forecasting and worked well short-term. To evaluate ETS we used the "es" function (smooth package) with the "ZZZ" model to produce the optimised ETS model based on seasonal and trend patterns in departmental datasets, accuracy was checked on the test dataset.

Seasonal ARIMA Model

Along with ES, ARIMA and seasonal ARIMA (SARIMA) models worked fine for short-term retail sales and demand forecasting. To determine the appropriate ARIMA model, we used auto.ssarima (smooth package) which runs all legs and models based on ARIMA giving the recommended model based on AIC values when run in default setting.

Error measures

The summary table (Figure 4) of the forecasting models is built on the aggregated dataset for both weekly and monthly frequency for departments. Both univariate and multivariate were considered, we explored setting up different forecasting models based on individual patterns present in each department datasets. This approach gave us the liberty to utilize individual seasonal peaks/patterns for each department.

Table 1: Summary table of forecasting models result, and model selection based on error matrix

Frequency	Model	Department	ME	RMSE	MAE	MPE	MAPE	Best Model
Weekly	VAR Model	FOODS_1	-1065.099	1335.175	1136.617	-35.78802	38.05753	**Seasonal ARIMA (0,1,2)[1](2,1,2)[52] with drift** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		289.1239	452.7162	372.3632	8.929292	12.00924	
	ETS (Univariate)(MNM)		309.5619	438.0829	357.3461	9.491455	11.40316	
	Seasonal ARIMA (Univariate)(0,1,2)[1](2,1,2)[52] with drift		277.8632	**411.9655**	337.2391	8.627152	**10.89033**	
	VAR Model	FOODS_2	1268.636	1473.679	1310.04	24.35784	25.59672	**Seasonal ARIMA (3,1,3)[1](2,1,0)[52] with drift** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		1138.2255	1316.7265	1145.3924	22.214118	22.404044	
	ETS (Univariate)(ANA)		699.4228	1025.7666	819.7126	12.5932	15.813352	
	Seasonal ARIMA (Univariate)(3,1,3)[1](2,1,0)[52] with drift		409.4832	**622.9975**	489.6032	7.374663	**9.411256**	
	VAR Model	FOODS_3	5749.094	6974.572	6255.422	-33.01791	36.02059	**Seasonal ARIMA (3,1,3)[1](2,0,0)[52]** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		-762.2444	1679.254	1371.907	-4.901307	8.044527	
	ETS (Univariate)(ANM)		-434.1247	1740.896	1431.46	-3.191836	8.318593	
	Seasonal ARIMA (Univariate)(3,1,3)[1](2,0,0)[52]		-528.1551	**1468.482**	1224.894	-3.667075	**7.210612**	
	VAR Model	HOBBIES_1	1117.027	1270.35	1128.957	31.95654	32.42846	**Seasonal Naïve** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		347.0034	**489.3646**	456.0396	9.547135	**13.3976**	
	ETS (Univariate)(ANN)		547.2401	613.6693	563.952	15.593029	16.24657	
	Seasonal ARIMA (Univariate)(0,1,1)[1](2,0,0)[52]		649.3067	725.4889	668.7736	18.521156	19.2815	
	VAR Model	HOBBIES_2	**-15.94349**	**89.19532**	74.51706	-7.675719	**19.77041**	**VAR Model** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		137.97762	159.5194	138.0052	33.01384	33.01921	
	ETS (Univariate)(MAM)		-121.09773	157.8832	136.1468	-32.7876	35.80537	
	Seasonal ARIMA (Univariate)(0,1,3)[1](2,0,0)[52]		-84.56289	114.83	100.9736	-25.21353	27.95314	
	VAR Model	HOUSEHOLD_1	2736.454	3091.566	2743.45	37.6491	37.73867	**Seasonal ARIMA (0,1,3)[1](2,1,2)[52] with drift** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		1155.5731	1309.7488	1174.6093	15.032769	15.343549	
	ETS (Univariate)(ANN)		825.219	1136.1828	1015.9713	10.015388	13.347948	
	Seasonal ARIMA (Univariate)(0,1,3)[1](2,1,2)[52] with drift		680.2431	**794.3568**	716.9464	8.817588	**9.452728**	
	VAR Model	HOUSEHOLD_2	114.1519	193.3432	161.5072	6.021528	8.663891	**Seasonal ARIMA (0,1,3)[1](2,0,0)[52]** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		241.33219	272.0682	241.3563	12.917034	12.918673	
	ETS (Univariate)(ANN)		163.53129	251.8705	214.6851	7.899442	11.369976	
	Seasonal ARIMA (Univariate)(0,1,3)[1](2,0,0)[52]		60.05908	**154.86**	124.1514	2.490858	**6.701628**	
Monthly	VAR Model	FOODS_1	1074.864	1204.853	1077.772	34.83757	34.95956	**Seasonal ARIMA (0,0,3)[1](1,0,2)[12] with constant** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		283.8872	408.791	311.1001	8.821373	9.83856	
	ETS (Univariate)(ANN)		350.0529	453.1007	388.7262	10.845907	12.424471	
	Seasonal ARIMA (Univariate)(0,0,3)[1](1,0,2)[12] with constant		247.4554	**339.3833**	269.9951	7.780374	**8.647902**	
	VAR Model	FOODS_2	889.5731	1103.585	894.8955	17.02171	17.15002	**ETS (ANN)** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		1177.965	1346.172	1177.965	22.93852	22.93852	
	ETS (Univariate)(ANN)		886.77	**1093.787**	886.77	16.81183	**16.81183**	
	Seasonal ARIMA (Univariate)(0,1,0)[1](1,1,2)[12] with drift		1000.448	1218.301	1010.633	19.1578	19.4026	
	VAR Model	FOODS_3	**20.56244**	**1426.501**	1147.56	-0.4534359	**6.509281**	**VAR Model** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		-731.7819	1486.807	1301.548	-4.718927	7.58241	
	ETS (Univariate)(ANN)		-939.152	1704.911	1430.259	-6.062721	8.516411	
	Seasonal ARIMA (Univariate)(0,0,3)[1](1,0,2)[12] with constant		-407.6378	1397.314	1208.172	-2.776772	6.932151	
	VAR Model	HOBBIES_1	587.6077	680.1363	594.0033	16.88914	17.12517	**Seasonal ARIMA (0,1,0)[1](1,0,2)[12]** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		313.0274	471.0059	438.828	8.533437	12.94056	
	ETS (Univariate)(ANN)		604.2693	658.4574	604.2693	17.425218	17.42522	
	Seasonal ARIMA (Univariate)(0,1,0)[1](1,0,2)[12]		411.4378	**440.9062**	411.4378	11.961275	**11.96127**	
	VAR Model	HOBBIES_2	77.50403	114.3066	87.65539	16.68361	19.68983	**Seasonal ARIMA (0,1,1)[1](1,1,2)[12] with drift** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		147.6137	162.89579	147.6137	34.93399	34.93399	
	ETS (Univariate)(ANA)		97.88747	111.09438	97.88747	22.80879	22.80879	
	Seasonal ARIMA (Univariate)(0,1,1)[1](1,1,2)[12] with drift		55.06551	**82.22206**	61.34335	11.70604	**13.51014**	
	VAR Model	HOUSEHOLD_1	2603.132	2844.033	2603.132	34.32067	34.32067	**ETS (ANN)** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		1119.1981	1272.388	1133.263	14.5957	14.81188	
	ETS (Univariate)(ANN)		879.8566	**1117.405**	1002.344	11.03061	13.08243	
	Seasonal ARIMA (Univariate)(0,1,3)[1](1,1,2)[12]		1132.051	1201.411	1132.051	15.07539	15.07539	
	VAR Model	HOUSEHOLD_2	**-26.2903**	**104.561**	80.12679	-1.7802	4.535721	**VAR Model** is the best model based on error comparison matrix
	Seasonal Naïve (Univariate)		256.1503	282.3289	256.1503	13.758716	13.758716	
	ETS (Univariate)(ANN)		117.6551	218.5312	178.4366	5.478454	9.409137	
	Seasonal ARIMA (Univariate)(0,1,0)[1](1,0,2)[12]		155.733	231.9444	183.0518	7.679812	9.479179	

4.3 Forecasting 6 months ahead:

Table 2:6 month's ahead forecast per department

	Next 6 months forecast						
Week number	FOODS 1	FOODS 2	FOODS 3	HOBBIES 1	HOBBIES 2	HOUSEHOLD_1	HOUSEHOLD_2
Week1	2482.11	3180.05	16338.72	3481.71	1692.64	6387.56	1675.79
Week2	2645.89	3532.49	17569.84	3587.71	1628.07	6558.58	1679.95
Week3	2295.93	4749.11	18289.13	3287.00	1633.54	6246.62	1648.71
Week4	2476.30	4734.66	17548.01	3406.29	1565.08	6181.35	1627.29
Week5	2282.67	3747.63	16320.13	3309.00	1501.29	5799.39	1630.24
Week6	2243.12	3114.89	15634.01	3658.71	1443.60	5954.32	1624.49
Week7	2794.94	4389.95	18495.01	3565.43	1459.73	5833.51	1671.71
Week8	3021.18	4494.53	17675.89	3557.00	1386.11	5530.01	1675.37
Week9	3526.21	3686.69	17115.08	3434.71	1329.16	5080.63	1692.51
Week10	2269.41	3071.99	15322.95	3597.14	1350.98	5635.95	1587.03
Week11	2474.63	4382.58	18504.59	3590.00	1357.32	6043.63	1647.17
Week12	2631.65	4901.66	18577.61	3481.43	1378.66	5735.43	1643.61
Week13	2633.09	4348.73	17496.43	3484.43	1384.83	5805.14	1660.78
Week14	2591.90	3782.64	16099.98	3509.43	1390.36	5890.76	1668.35
Week15	2684.37	3718.80	17015.74	3573.71	1467.44	6214.74	1645.11
Week16	2959.14	4696.82	18046.83	3484.00	1551.14	6600.00	1719.57
Week17	3668.68	4519.44	17896.33	3518.71	1573.60	6816.29	1764.69
Week18	2696.59	4264.45	16649.01	3396.71	1619.23	6986.27	1765.43
Week19	2642.21	4422.16	16994.51	3694.29	1666.61	6826.85	1767.19
Week20	2728.71	4829.76	18050.29	3421.14	1749.72	6706.48	1766.32
Week21	2790.17	4753.78	18445.06	3499.71	1765.68	6699.92	1808.80
Week22	2439.20	3873.23	16841.64	3493.00	1815.29	6429.82	1785.68
Week23	2898.84	3786.85	16995.16	3579.14	1863.04	6623.72	1750.46
Week24	2883.99	4781.46	18581.02	3785.43	1910.06	6695.43	1804.30

We forecast based on the best fitting model for each department as discussed above and plotted the graphs as shown below:

According to Figure 4, the forecasting data for the next 6 months has a decreasing trend, which corresponds to the previous (test) decreasing trend. Within Figure 5, we see that after 6 months, there is an increasing trend.

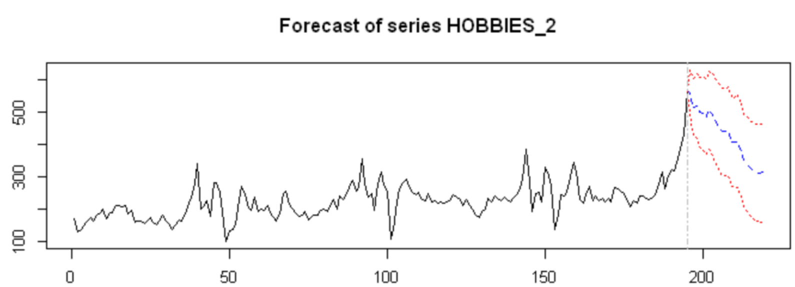

Figure 4: Forecasting 6 months ahead data for HOBBIES_2 based on the VAR model

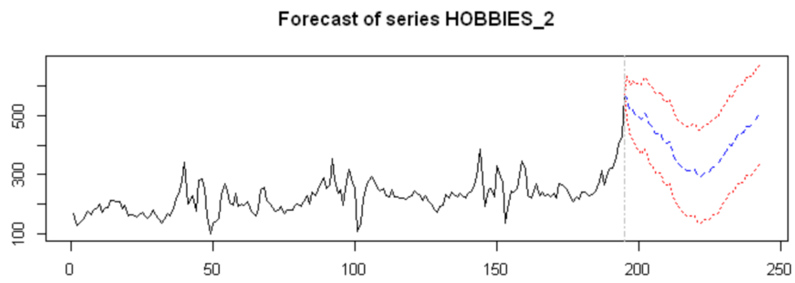

Figure 5: Forecasting 12 months ahead data for HOBBIES_2 based on the VAR model

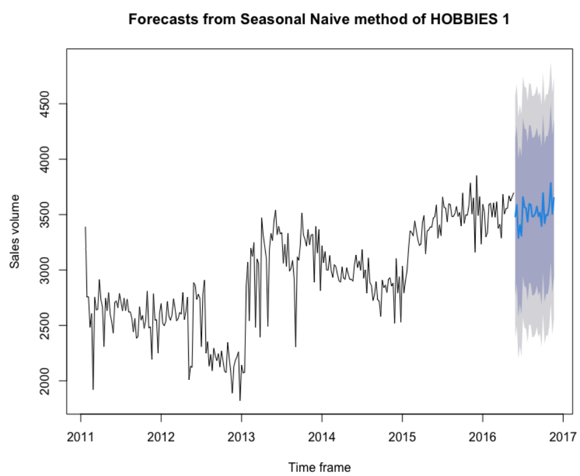

Figure 6: Forecasting 6 months ahead data for HOBBIES_1

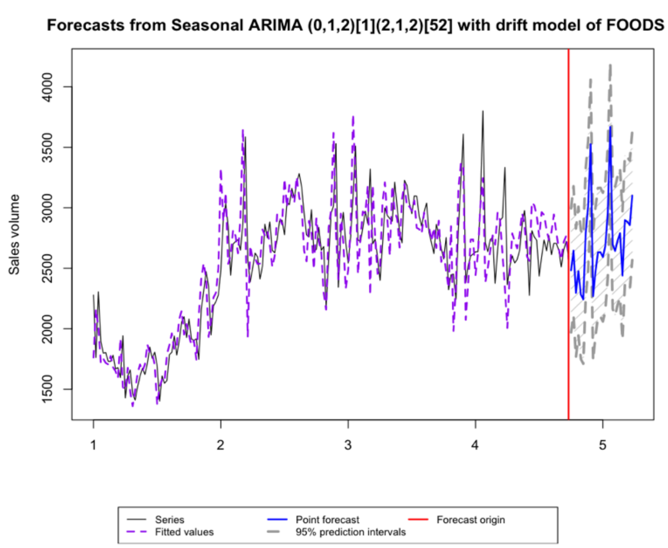

Figure 7: Forecasting 6 months ahead data for FOODS 1

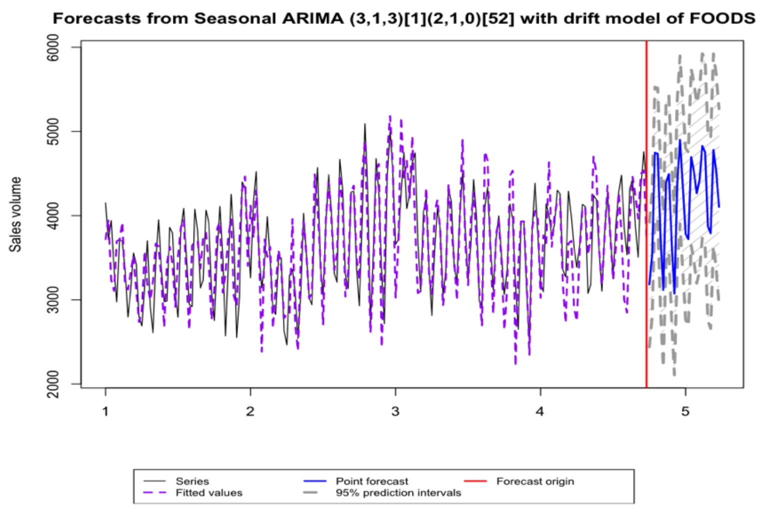

Figure 8: Forecasting 6 months ahead data for FOODS 2

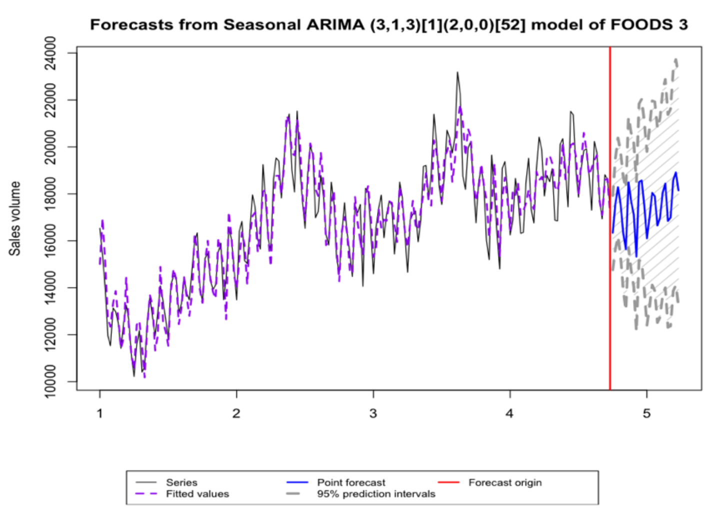

Figure 9: Forecasting 6 months ahead data for FOODS 3

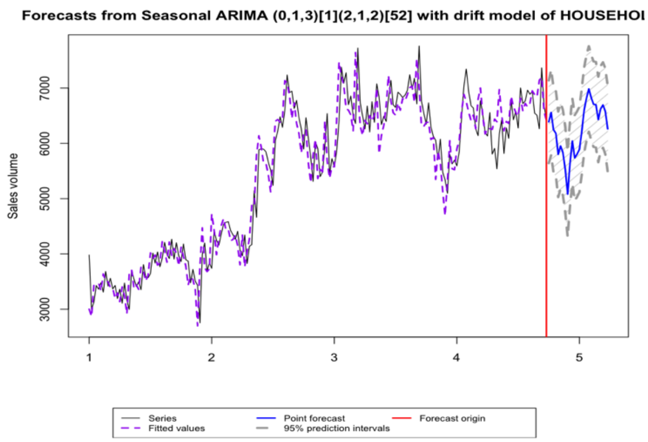

Figure 10: Forecasting 6 months ahead data for HOUSEHOLD 1

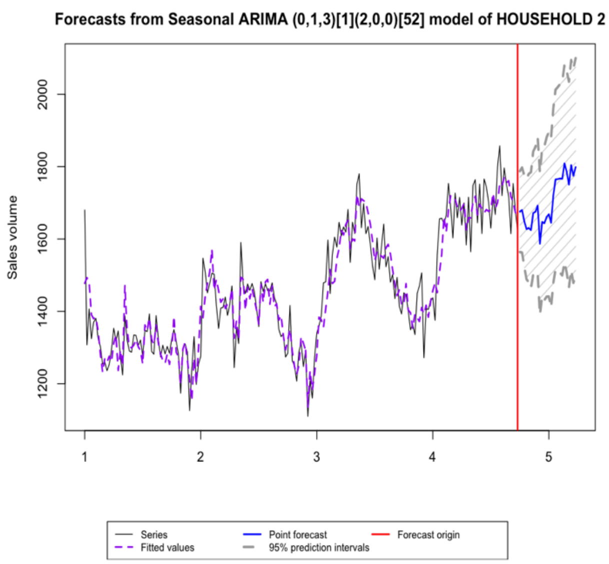

Figure 11: Forecasting 6 months ahead data for HOUSEHOLD 2

Current and forecasted sales volume over 6 months across stores would give estimations about base sale volumes expected in the following 6 months. Current supermarket size accounts for approx. 150,000 square feet to 250,000 square feet. When comparing the forecasted values with mean values for the last 5 years for 7 departments, the trendline seems stable, so average sales volume would remain similarly constant, meaning current space allocation by the department should be considered when planning the new store since the current arrangement is beneficial.

However, FOODS 1 and 2 Observed sales volumes of 2674 and 4016 over 5 years, reflected in the forecast, but FOODS 3 average sales volume is 16969, so almost 4-8 times bigger. Indicating space allocation in new stores should consider a much greater sales volume for FOODS 3 and allocate space accordingly.

Similarly, HOBBIES 1 and 2 have average sales of 2937 and 279, with forecasted sales within the same range, meaning space allocation is reasonable. HOBBIES 1 should be allocated more space than HOBBIES 2 as HOBBIES 1 since actual and forecasted sales are 10 times greater.

Similarly, HOUSEHOLD 1 and 2 have average sales of 6034 and 1567 respectively and forecasts followed within the same range, so space allocation is working, but need account for HOUSEHOLD 1 constituting 4 times more sales than HOUSEHOLD 2, so new space allocation needs this incorporated.

When analyzing sales volume per state, average sales in CA 15042, but TX and WI are 9906 and 9532. Forecasted values are 15381, 10826 and 10354. This states that, if the new store is opening in CA the space allocation should be at the higher end of 150,000 – 250,000 sq. feet and if in TX or WI, it should be average in size.

Table 3: space and size allocation criteria, assuming space allocation is proportional to sales volume. Since other variables such as current space allocation, size of the items, shelves current size, size of the products, department space etc. Isn't included within the data.

Table 3: Actual Vs Forecasting mean values per department

	FOODS 1	FOODS 2	FOODS 3	HOBBIES 1	HOBBIES 2	HOUSEHOLD_1	HOUSEHOLD_2
Actual sales daily average of 5 years	2674.00	4016.00	16969.00	2936.00	279.10	6040.00	1567.00
Forecast for next 6 months	2698.37	4156.85	17354.29	3516.49	1561.80	6220.10	1696.27

Retail space planning:

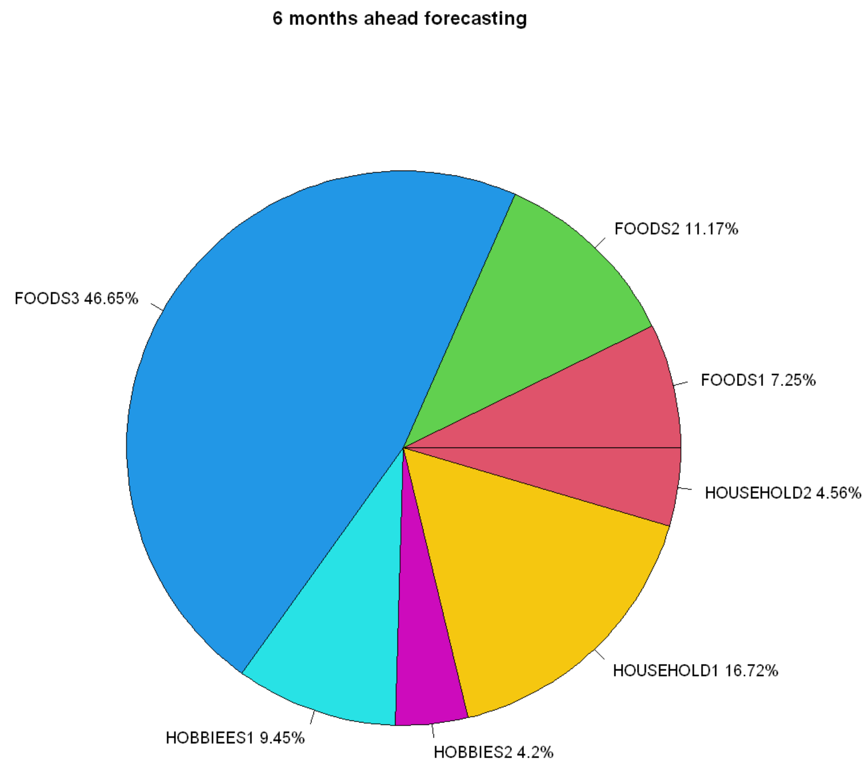

Figure 12: Pie chart of 6 months ahead forecasting

Planning benefits from departmental forecasts that have considered seasonality. Assume inventory is planned every 6 months, then new retail can plan spacing according to forecasted data. Therefore, ~46% of space is allocated to FOODS3. 16.7% and 11.2% of space are allocated to HOUSEHOLD1 and FOODS2, respectively. The HOBBIES2 need only 4.2% of spaces, which is the smallest departmental space forecasted.

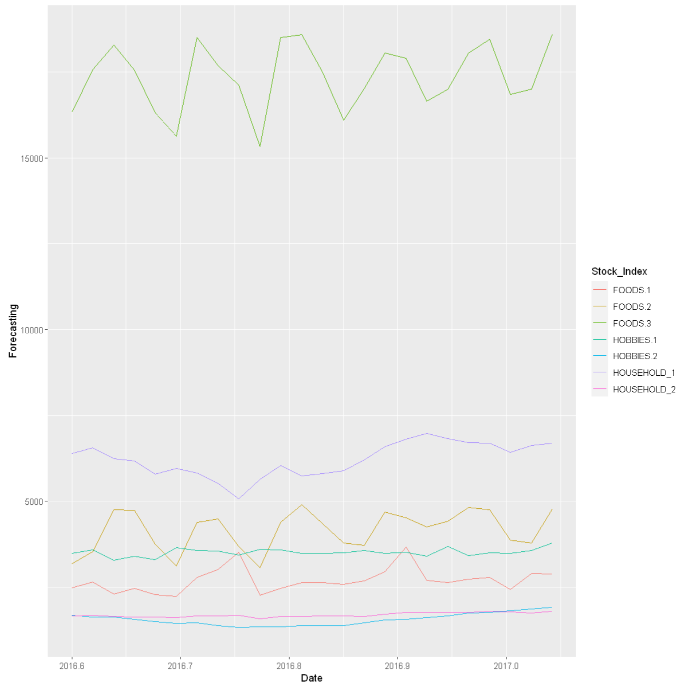

Figure 13: Line graph for 6 months ahead forecasting

According to Figure 13, we can see that FOODS1, FOODS2 and FOODS3 have strong seasonality, while HOBBIES1, HOBBIES2, and HOUSEHOLD2 does not have obvious trend and seasonality. Therefore, items with food space can vary to fill based on seasonality, whereas hobbies will remain consistent.

Discussion of results

We applied univariate and multivariate forecasting models on the departmental monthly aggregated dataset to forecast ahead of 6 months. Forecasting accuracy was under 10 % MAPE for 5 departments out of 7, and for others, it was under 15 % MAPE. The analysis suggested that sales volume predicted over the next 6 months fits the same range, follows similar trends and seasonality observed in the departmental dataset. We found HOBBIES 2 items sales have a dependency on the other departmental sales, as different forecasting model analysis concluded the best-suited model for HOBBIES 2 was the VAR model, based on RMSE and MAPE accuracy scale. For other departments, the best-suited forecasting models are univariate models -seasonal ARIMA. Forecasting models also confirmed strong seasonal patterns in departmental sales in FOOD1, FOODS2 and FOODS3. While forecasting models built were to give insight into predicting sales volume, it confirmed a trend with space planning and how sales react to seasonal peaks, which is useful when validating and determining the space needed to accommodate the sales volume in the new store.

Considering both shifts to online retail and scientific developments within society, technological advancements are forecasted based on possibilities rather than when achievements happen, meaning most technological advancement forecasts are inaccurate predictions, as it's impossible to predict time frames. (Clive W.J. Granger) Limitations within forecasting profit long-term come with constant changes of sales and large influxes of specific e-commerce data, which change space planning, demand, and turnover. Forecasts based on weekly changes are not suitable for 20 years of forecasts, due to extensive overfitting (Brian Seaman). Limitations of forecasting techniques relate to the certainty of simplicity or breaks within data. Using consistent and easily identifiable data (population, seasonality) can only give a generic guideline. The linear trend in online sales must plateau within the next 20 years but forecasting when is almost impossible, but where the breaks or dampening trend occurs, the linear model will become unsatisfactory (Clive W.J. Granger). Within Walmart, using third party selling information to dictate future product demand would help determine prices, priorities, and demand for products yearly (Brian Seaman). To improve long-term models, the addition of percentiles or variability, e.g., population growth rates, allow for the accommodation of variability over 20 years (Clive W.J. Granger).

Conclusion & recommendations

Analyzing 5-year daily sales volume on a department level and short-term predicting, we observed sales being impacted by seasonal peaks both weekly and monthly. On weekends, sales spiked from 30 to 50% more for all the departments. For multiple items, the daily sales volume was 0 on weekdays. Interestingly, sales dipped in Nov, Dec, and the summer months, with this trend being followed within forecast values. FOODS 3, HOUSEHOLD 1, HOBBIES 1 are popular departments. If a linear relationship between space and size of items is assumed, then space allocation could be proportionate to individual sales volumes. Also, CA stores have seen significant sales if compared to TX and WI for all departments, so location is a key factor that should be considered when retail space planning.

Methods for long-term forecasting e.g., Delphi are long and difficult to correctly complete, but directly and accurately explore qualitative aspects discussed for the long term, e.g., Covid, cultural changes, e-commerce, and customer relationships, proving to be a valuable tool for Walmart's LT forecast estimations. Also, alternative omnichannel research within retail has used Delphi for long term productivity (The Millenium Project, Von Briel, F. (2018)). Another possibility is to implement machine learning, to add multiple LT considerations. One issue with machine learning will be minimal judgement included in the forecasts, so combining both Delphi and machine learning procedures for 10-20 years of forecasts would provide Walmart with a good initial estimation of demand and so store size within districts of interest.

References

1. Bianchi-Aguiar, T., Hübner, A., Carravilla, M. A. & Oliveira, J. F. (2021) Retail shelf space planning problems: A comprehensive review and classification framework. *European Journal of Operational Research*, 289(1), 1-16. https://doi.org/10.1016/j.ejor.2020.06.018.
2. Botchkarev, A. (2018) Performance metrics (error measures) in machine learning regression, forecasting and prognostics: Properties and typology. *arXiv preprint arXiv:1809.03006.* Toronto, Ontario, Canada.
3. CFI, Delphi method, https://corporatefinanceinstitute.com/resources/knowledge/other/delphi-method/ (Accessed: 20/03/2022)
4. Corstjens, M. & Doyle, P. (1983) A Dynamic Model for Strategically Allocating Retail Space. *Journal of the Operational Research Society*, 34(10), 943-951. 10.1057/jors.1983.207.
5. Curhan, Ronald C. "The Relationship between Shelf Space and Unit Sales in Supermarkets." *Journal of Marketing Research*, vol. 9, no. 4, American Marketing Association, 1972, pp. 406–12, https://doi.org/10.2307/3149304.
6. Dallas Fed, https://www.dallasfed.org/-/media/documents/research/papers/2020/wp2004.pdf, (Accessed: 20/03/2022)
7. De Mooij, M. & Hofstede, G. (2002) Convergence and divergence in consumer behavior: implications for international retailing. *Journal of Retailing*, 78(1), 61-69. https://doi.org/10.1016/S0022-4359(01)00067-7.
8. Deloitte, https://www2.deloitte.com/content/dam/Deloitte/de/Documents/consumer-business/Study_Retail%20Operating%20Model%20of%20the%20Future.pdf (Accessed: 19/03/2021)
9. Ecommerce and the demographics of online shoppers, https://www.further.co.uk/blog/ecommerce-and-the-demographics-of-online-shoppers/ (Accessed: 20/03/2022)
10. Fildes, R, Ma, S and Kolassa, S. (2019) Retail forecasting: Research and practice. International Journal of Forecasting. https://doi.org/10.1016/j.ijforecast.2019.06.004
11. Fildes, R., Ma, S. & Kolassa, S. (2019) Retail forecasting: Research and practice. *International Journal of Forecasting.*
12. Formánek, T. & Sokol, O. (2022) Location effects: Geo-spatial and socio-demographic determinants of sales dynamics in brick-and-mortar retail stores. Journal of Retailing and Consumer Services, 66, 102902. https://doi.org/10.1016/j.jretconser.2021.102902.
13. Granger, C. W. J. & Jeon, Y. (2007) Long-term forecasting and evaluation. *International Journal of Forecasting*, 23(4), 539-551. https://doi.org/10.1016/j.ijforecast.2007.07.002.
14. Hyndman R., Koehler A.B., Ord J.K., Snyder R.D.Forecasting with exponential smoothing: the state space approach Springer Science & Business Media (2008), 10.1007/978-3-540-71918-2 URL https://robjhyndman.com/expsmooth/
15. Hyndman, R.J., & Athanasopoulos, G. (2021) Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on 28 November 2021.

16. Jones, C. & Livingstone, N. (2018) The ‘online high street’ or the high street online? The implications for the urban retail hierarchy. The International Review of Retail, Distribution and Consumer Research, 28(1), 47-63. 10.1080/09593969.2017.1393441.
17. Kaggle, https://www.kaggle.com/c/m5-forecasting-accuracy/overview, Accessed (10/03/2022)
18. Kickert, C., Vom Hofe, R., Haas, T., Zhang, W. & Mahato, B. (2020) Spatial dynamics of long-term urban retail decline in three transatlantic cities. *Cities*, 107, 102918. https://doi.org/10.1016/j.cities.2020.102918.
19. Linh, L. & Vo, D. (2014) International Journal of Economics, Commerce and Management FACTORS AFFECTING A LONG-TERM RELATIONSHIP BETWEEN A RETAILER AND A SUPPLIER A CASE STUDY FROM VIETNAM. 2, 1-13.
20. Relex solutions. Available at: https://www.relexsolutions.com/resources/demand-forecasting/ [Accessed 15/03/2022].
21. Science Direct, https://www.sciencedirect.com/science/article/pii/S0378437108001040, Accessed (07/03/2022)
22. Seaman, B. (2018) Considerations of a retail forecasting practitioner. *International Journal of Forecasting*, 34(4), 822-829. https://doi.org/10.1016/j.ijforecast.2018.03.001.
23. Sharma, M., Luthra, S., Joshi, S. & Kumar, A. (2021) Accelerating retail supply chain performance against pandemic disruption: adopting resilient strategies to mitigate the long-term effects. *Journal of Enterprise Information Management*, 34(6), 1844-1873. 10.1108/JEIM-07-2020-0286. Appendices
24. The Fulfillment Lab, https://www.thefulfillmentlab.com/blog/demand-forecasting, (Accessed:20/03/2022)
25. The Millenium Project, The Delphi Method, https://millennium-project.org/wp-content/uploads/2020/02/04-Delphi.pdf, (Accessed: 20/03/2022)
26. Von Briel, F. (2018) The future of omnichannel retail: A four-stage Delphi study. *Technological Forecasting and Social Change*, 132, 217-229. https://doi.org/10.1016/j.techfore.2018.02.004.

Appendix

1.Output-1 Stationary test for FOODS_1

```
Warning message in adf.test(total_2[, 1]):
"p-value smaller than printed p-value"

	Augmented Dickey-Fuller Test

data:  total_2[, 1]
Dickey-Fuller = -5.8637, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

2. First few observations of the weekly aggregated dataset for 7 departments

```
> head(weekly_mean)
              FOODS_1  FOODS_2  FOODS_3 HOBBIES_1 HOBBIES_2 HOUSEHOLD_1 HOUSEHOLD_2
2011-01-30 2279.500 4151.500 16537.00  3391.000  169.5000    3981.500    1680.000
2011-02-06 1762.000 3718.571 15355.29  2757.429  130.2857    3002.000    1307.286
2011-02-13 2305.857 3940.143 14002.57  2755.857  138.0000    3124.571    1406.571
2011-02-20 1897.857 3376.143 11960.43  2480.857  149.1429    3429.429    1324.429
2011-02-27 1798.286 2974.429 11531.00  2608.429  161.8571    3362.429    1370.000
2011-03-06 1803.143 3713.286 13138.86  1920.857  176.0000    3479.000    1380.714
```

3. First few observations of the monthly aggregated dataset for 7 departments

```
> head(monthly_mean)
              FOODS_1  FOODS_2  FOODS_3 HOBBIES_1 HOBBIES_2 HOUSEHOLD_1 HOUSEHOLD_2
2011-01-31 2072.000 3825.667 15139.00  3093.000  174.6667    3596.667    1486.667
2011-02-28 1934.107 3497.107 13149.14  2618.429  144.5000    3241.893    1356.786
2011-03-31 1726.677 3283.613 12245.00  2520.645  179.0645    3395.613    1280.581
2011-04-30 1689.267 3185.167 12111.17  2681.833  191.4667    3434.233    1297.300
2011-05-31 1527.677 3080.290 11255.03  2616.000  203.7742    3222.742    1306.161
2011-06-30 1613.933 3378.333 12536.43  2648.433  168.9000    3467.300    1299.333
```

4. Output-4 KPSS test for differenced data

```
kpss.test(data.frame(diff_data)$FOODS_1)

Warning message in kpss.test(data.frame(diff_data)$FOODS_1):
"p-value greater than printed p-value"

        KPSS Test for Level Stationarity

data:  data.frame(diff_data)$FOODS_1
KPSS Level = 0.040666, Truncation lag parameter = 4, p-value = 0.1
```