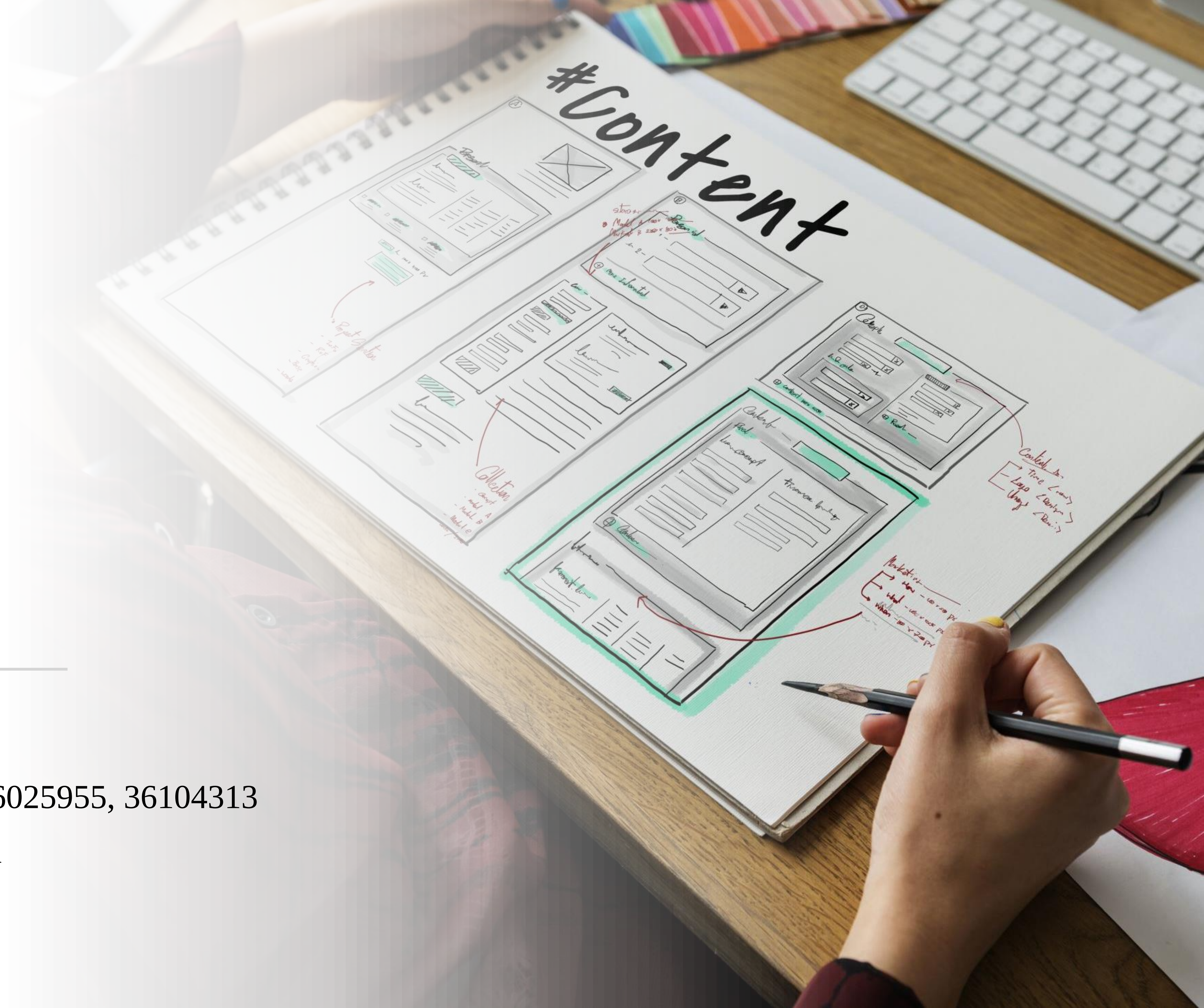


Retail Space Planning

Group L :

Student ID: 35870054, 35493311**,** 36025955, 36104313

Supervisor name: Prof. John Boylan

Objective

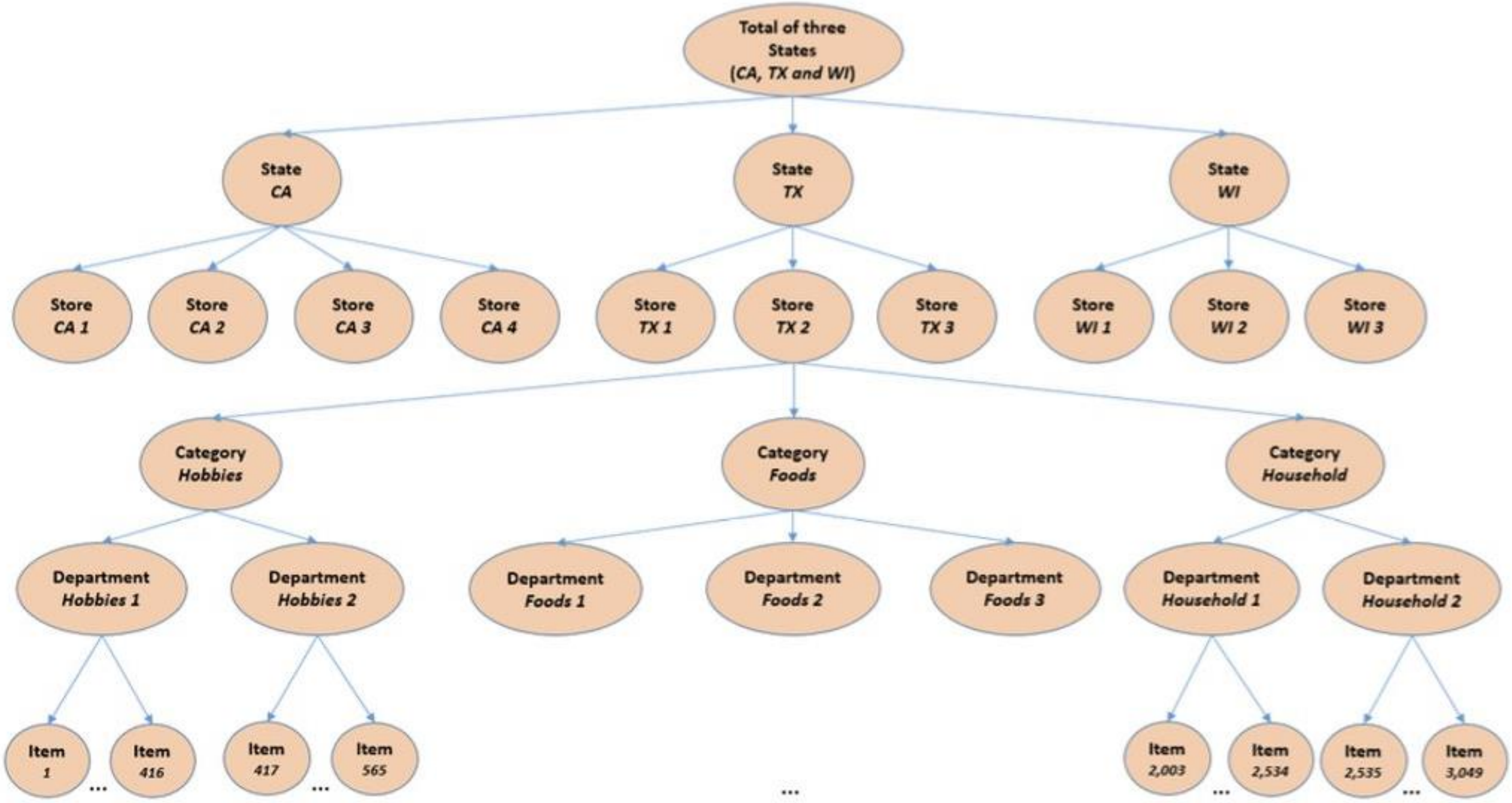
HOW LARGE THEIR NEW RETAIL OUTLETS SHOULD BE?

SHORT-TERM PLANNING WITH DEPARTMENTAL VOLUME FORECASTS THAT TAKE INTO ACCOUNT SEASONAL PATTERNS.

PROCESS TO FOLLOW TO ADDRESS THEIR LONG-TERM PLANNING PROBLEM

ADDITIONAL INFORMATION NEEDED TO ADDRESS THE LONG TERM PLANNNING

Grouped time series and hierarchical data



Methodology & Assumptions

Methodology:

Short term space planning:

- **5-year time series** for 42480 items were aggregated to a weekly and monthly level.
- Both **univariate and multivariate models** were produced.
- **Mean value** of each aggregation was calculated

Long term demand forecasting:

- **Literary analysis** on traditional retail forecasts and recent changes within retail outlined.
- **Methods** of making long term assumptions in order **to approximate demand levels**.

Initial Approach:

- Undertake **preliminary analysis**
- **Build** simple **models** from naive to VAR
- **Analyse** models using **error measures**:
  - ME, PMSE, MAE, MPE, MAPE.
- **Determine best model** for each department in each city:
  - (7 departments, in CA, TX and WI)

Models used:

- **Univariate models** included:
  - Seasonal naïve models
  - Exponential smoothening
  - ARIMA
  - Seasonal ARIMA
- **Multivariate VAR models** were used, which could evaluate inter-dependability

Exploratory Data Analysis

Strong presence of weekly and annual seasonality

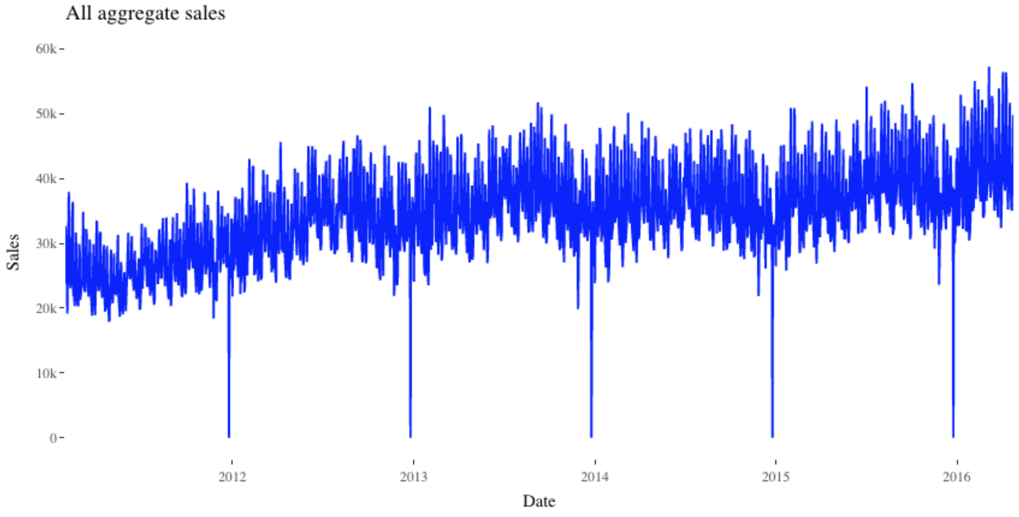
Food department recorded the highest sales across all three states

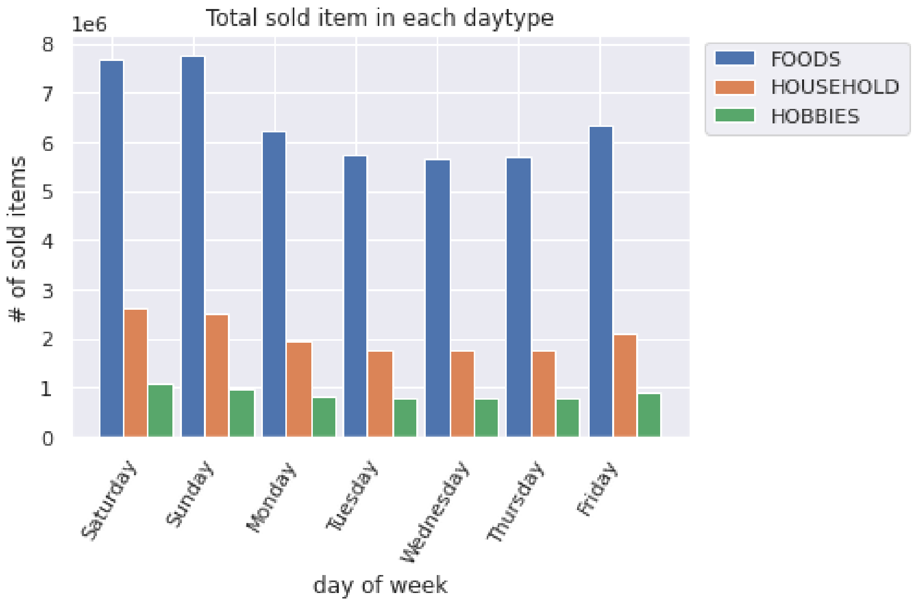
California recorded maximum sales compare to TX and WI

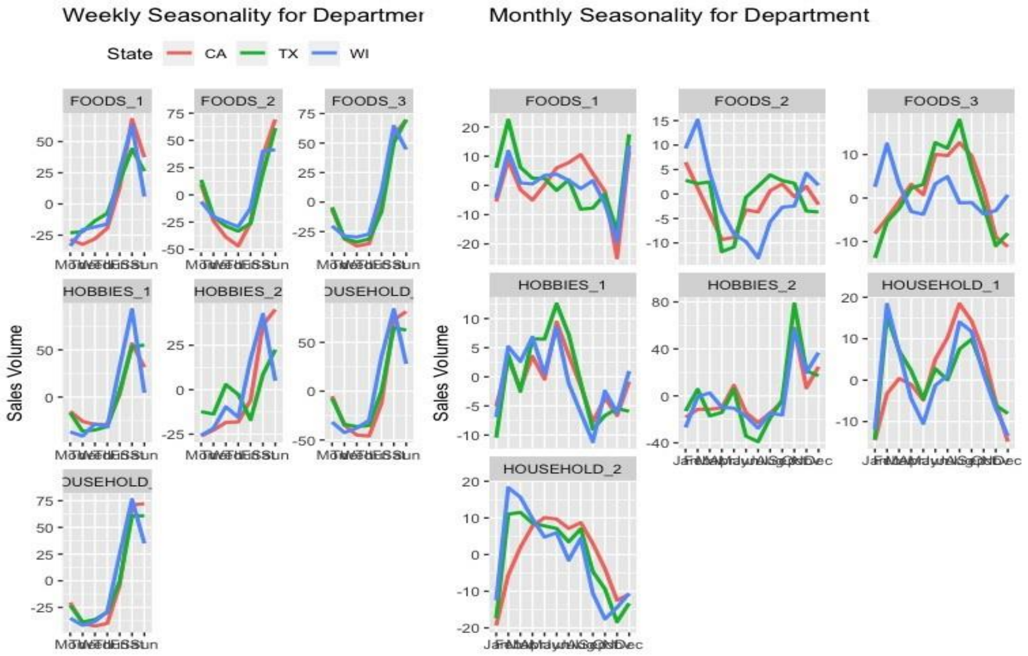
Sales was highest in March, then usual trends reduced till May, lowest in June and then gradually increasing till December.

Sales are predominantly highest on weekends

Data visualization of EDA



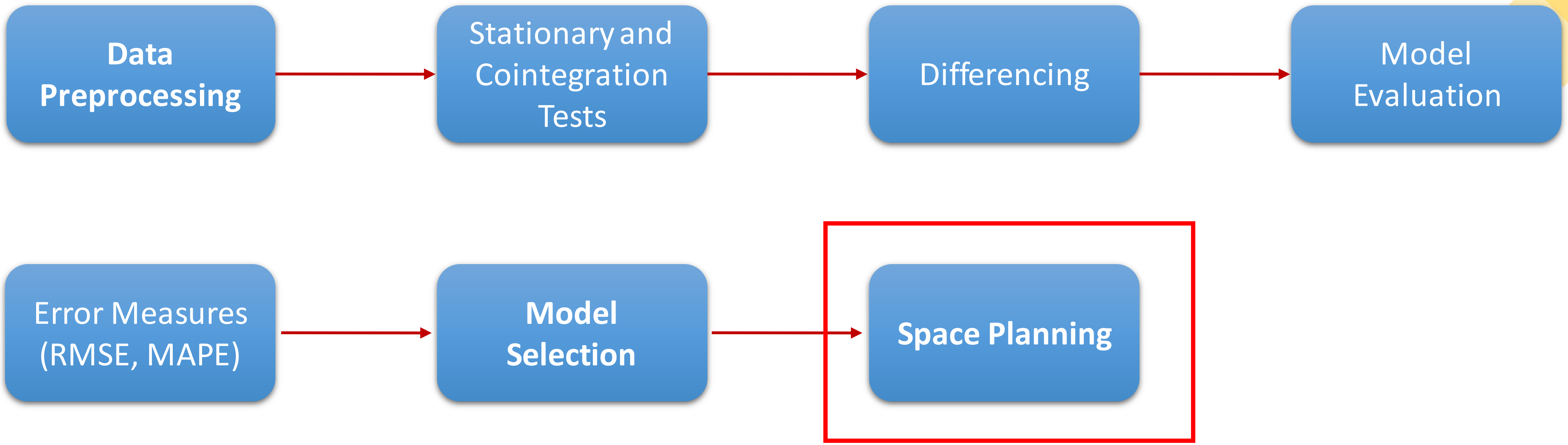




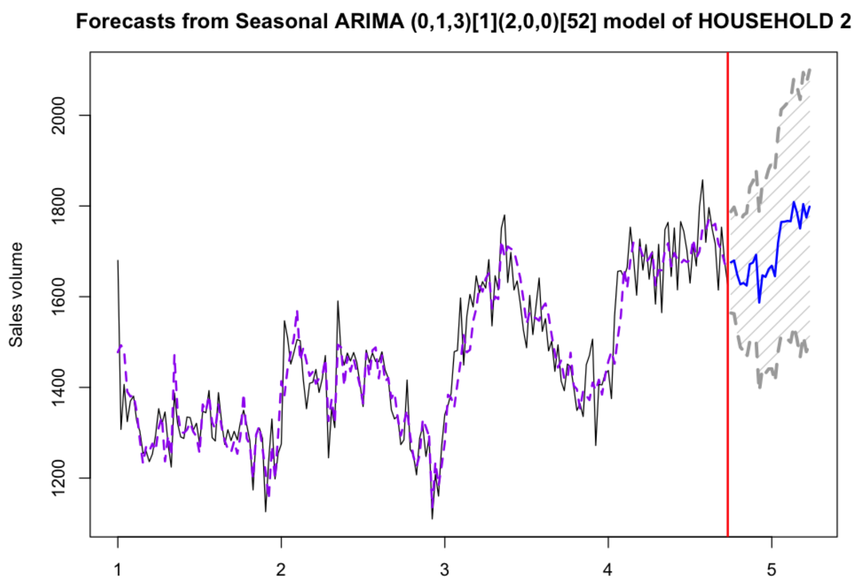
Short term forecasting

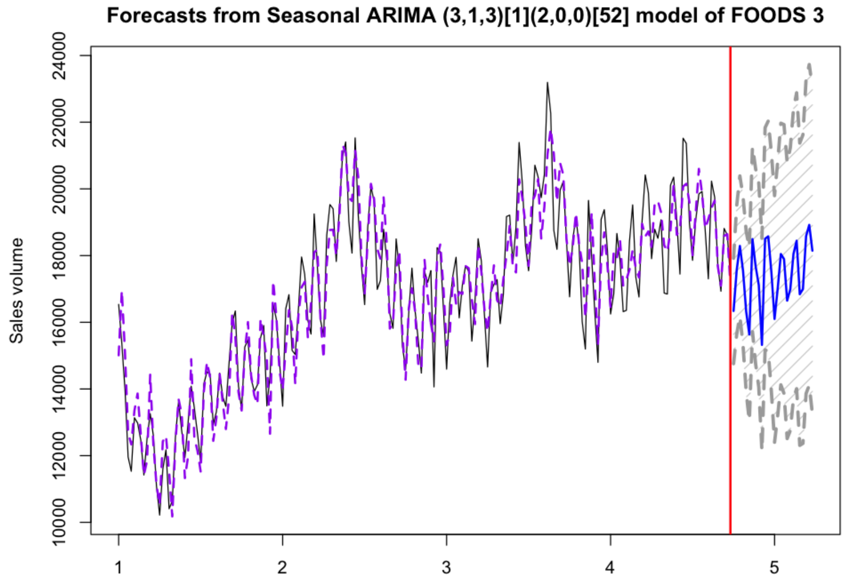
- Strong presence of weekly and annual seasonality
- Dataset aggregated on weekly and monthly frequency
- Univariate models – Seasonal Naïve, ETS and Seasonal ARIMA
- Multivariate model – VAR model
- Forecasting accuracy measured on the error scale of RMSE and MAPE
- FOODS 1, 2,3 and HOUSEHOLD 1,2 – Seasonal ARIMA
- HOBBIES 1 – Seasonal Naïve
- HOBBIES 2 – VAR Model

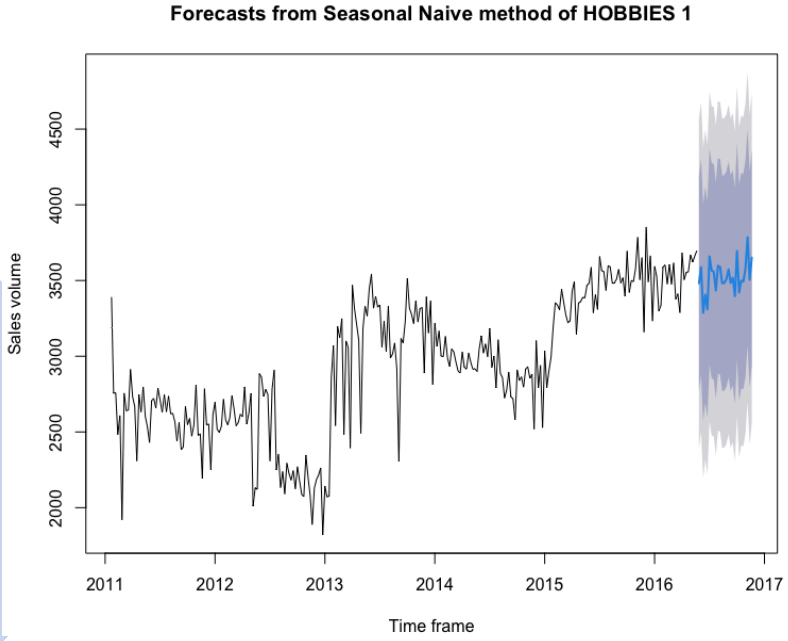
Model Building, Evaluation, Selection

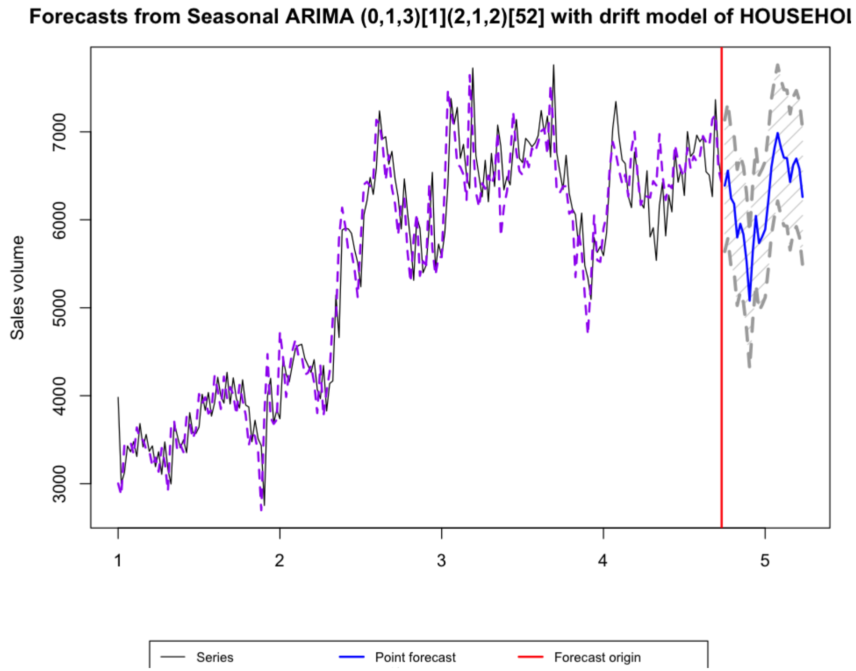


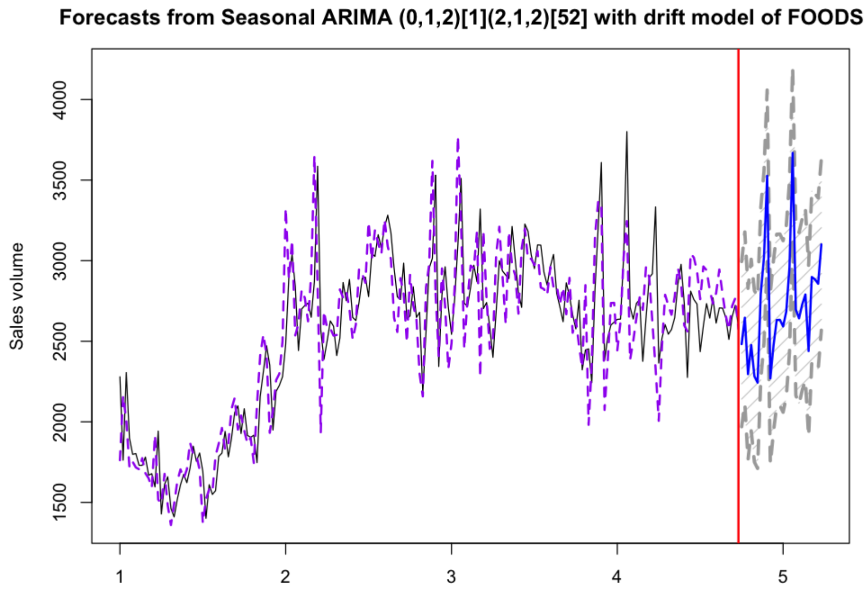
Forecasting plots – Univariate





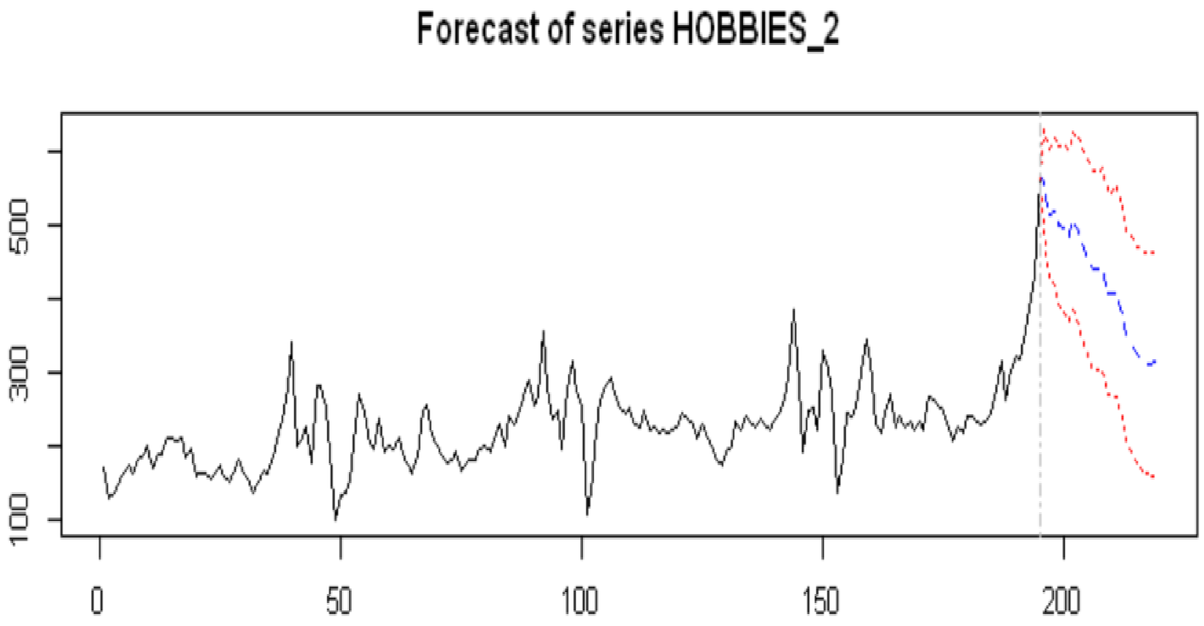






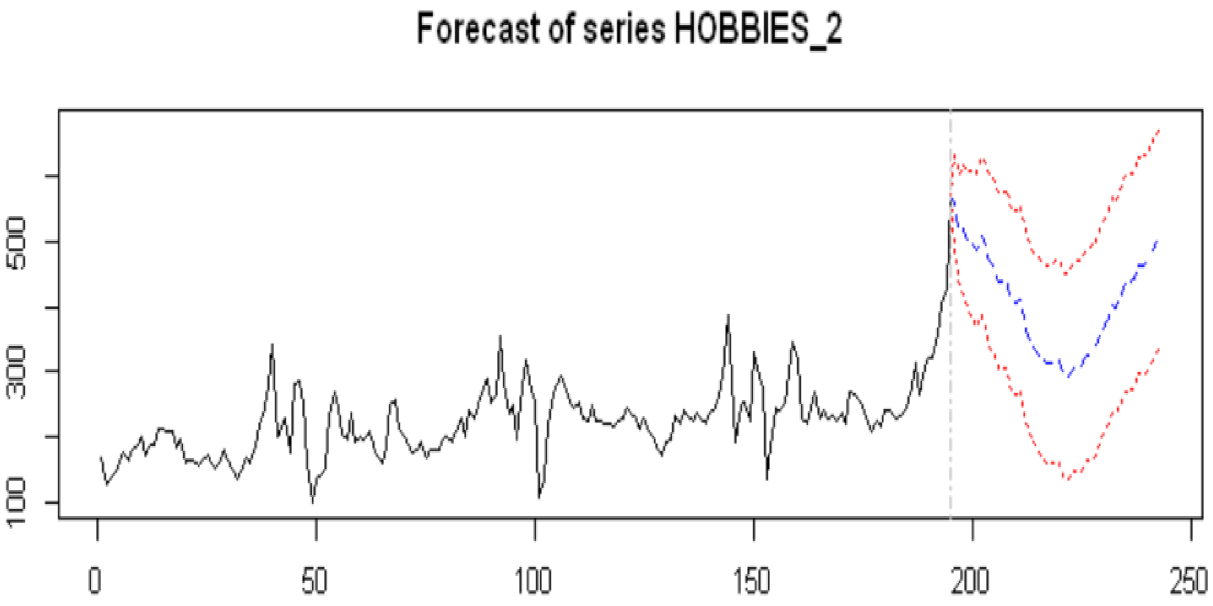
Forecasting plots – Multivariate: VAR Modelling

6 months forecasted



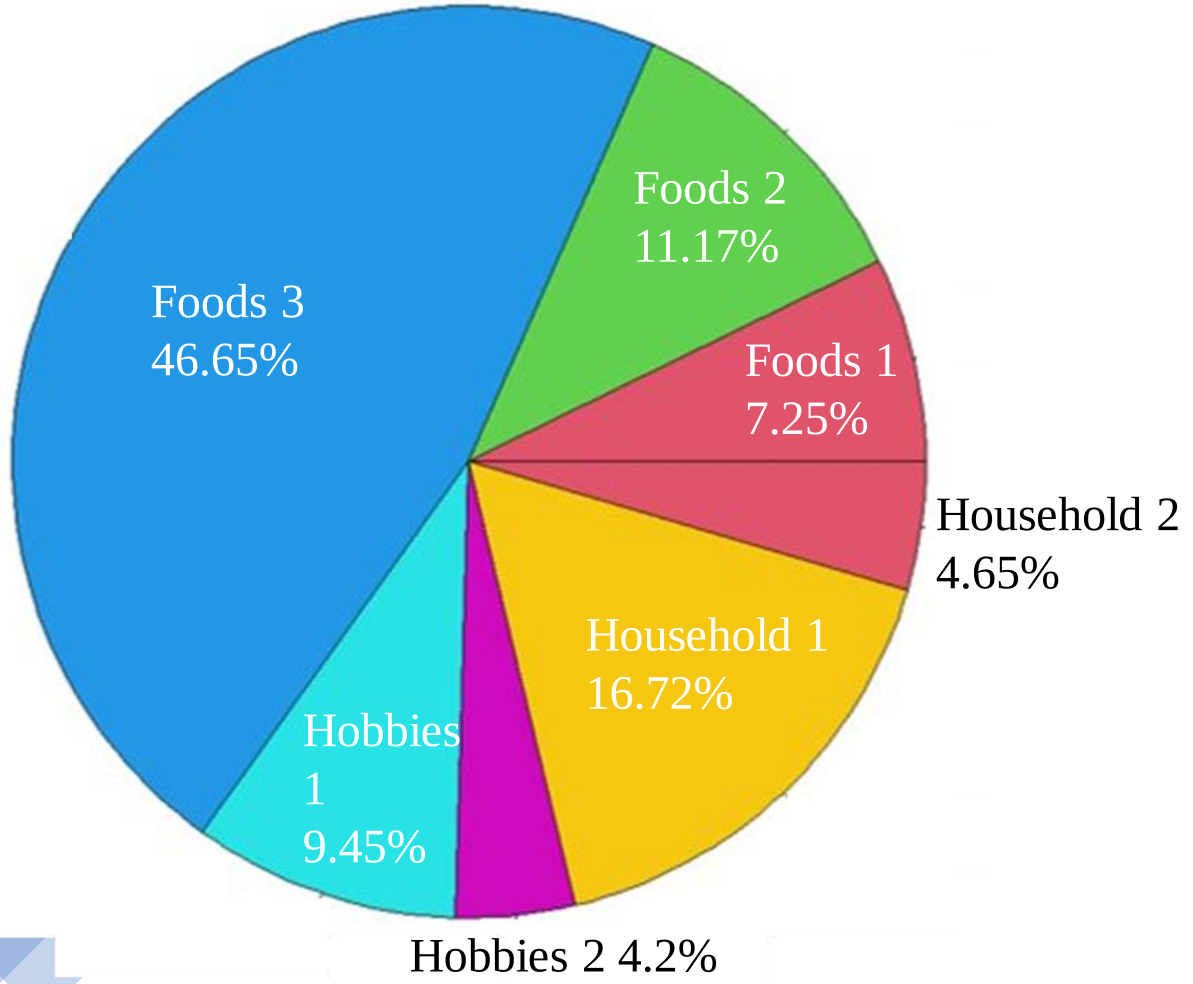
A decreasing trend, which corresponds to the test-sets trend.

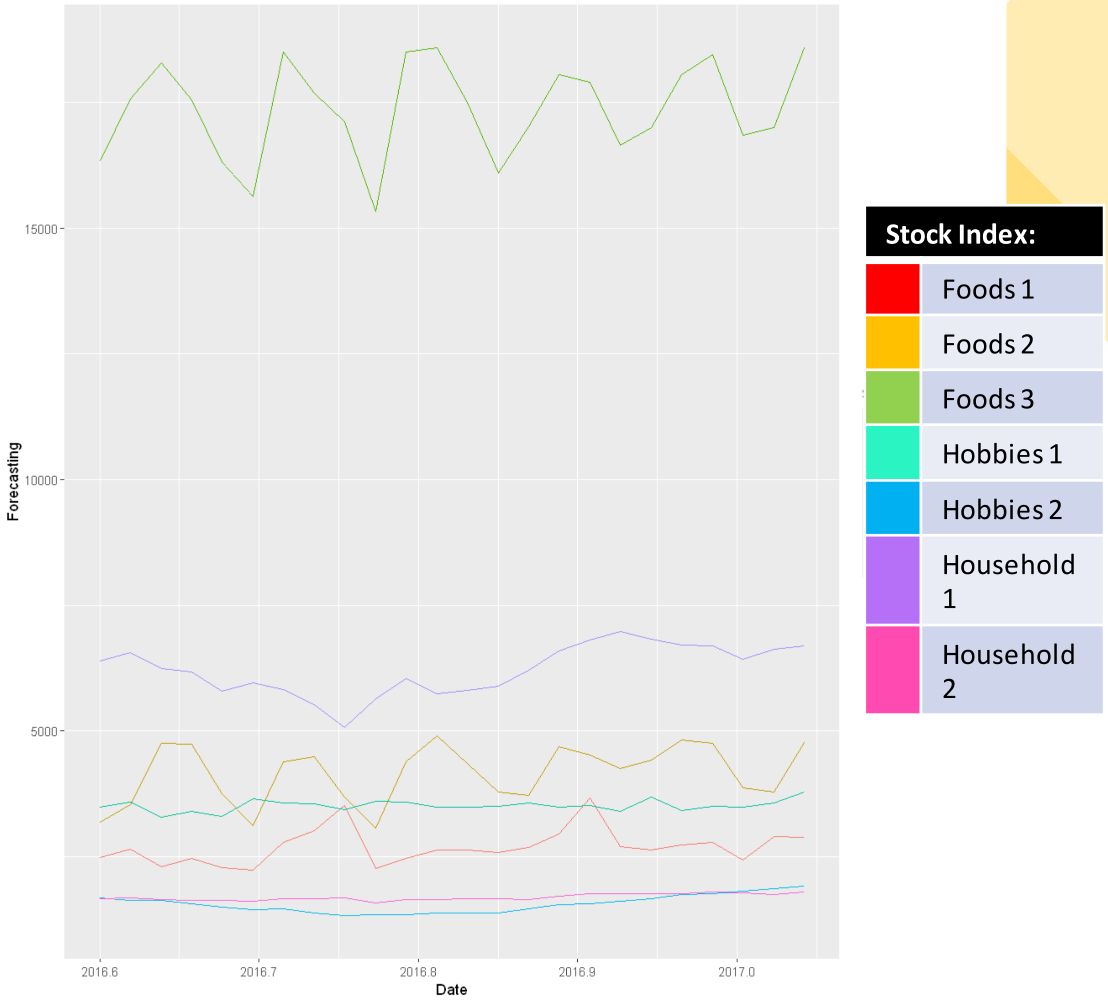
12 months forecasted



After 6 months, there is an increasing trend.

Space planning





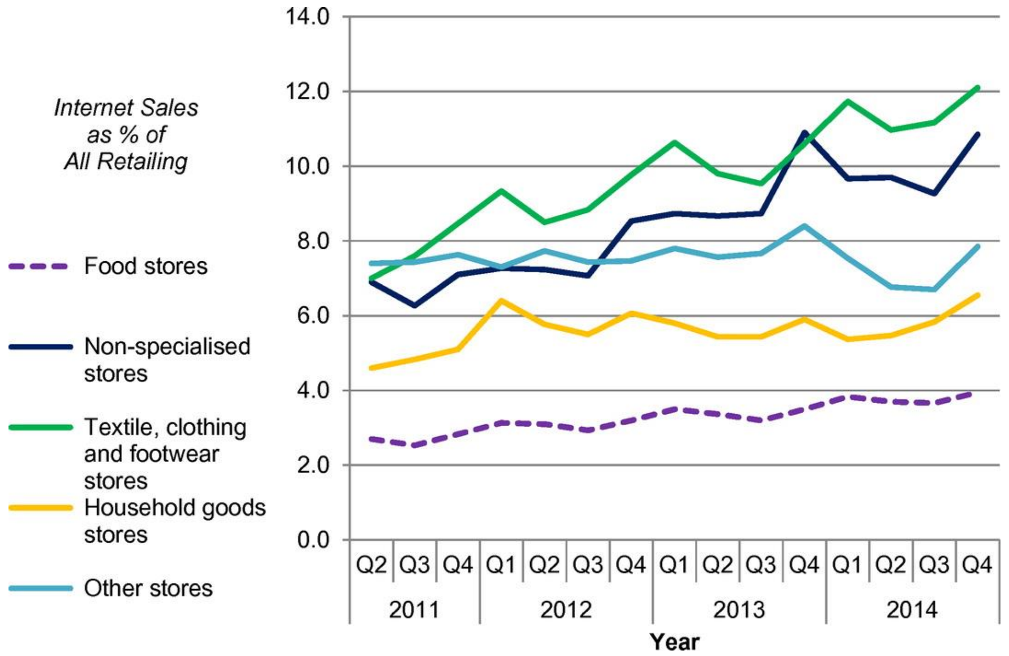
6 months ahead forecasting

Long-term retail demand forecasting

Size of new warehouses and space planning is dependent on demand for brick-and-mortar production.

Considers traditional methods and new technological advancements.

- Seasonality - promotions, advertising, holidays / national events.
- Populations – Target demographic, pop growth, mortality rates.
- Consumer popularity - questionaires and spending habits.
- Locations - surrounding amenities, economy and leasing contracts.
- E-commerce - linear increase in online sales over last decade.
- COVID 19 - Enhancing retail strategies, online and
- Economy - Changes spending habits which effect demand.



Changes in online sales over 4 years (Colin Jones)

Long-term forecasting methods

Limitations:

- Can't accurately predict all demand considerations over 20 years.
- Economic fluctuations can't be easily forecast, especially with unforecastable scenarios, e.g. covid.
- Sales data is specific to location, resulting in an oversaturation of demand forecasts.
- Too much data leads to overfitting and uncertainty.
- Forecasting Technological developments has no time frame.
- With current changes, omnichannel and e-commerce, the linear increase has to plateau at a certain point.

How to tackle information:

- Take initially basic information to build upon. E.g. population and mortality rates.
- Take stabilized version of economy as a baseline.
- Limit how much data is used in simple linear or exponential forecasts.
- Incorporate fuzzy clustering approaches to improve LT forecasts.
- For mixes of qualitative and quantitative demand effects, use machine learning.
- For qualitative Walmart should attempt the Delphi method.
- Add calculated error percentiles and variability for unforeseen effects.

Challenges

Size of the items were not present in the dataset

Information about other potential departments

Total space only 3 departments have within Walmart.

Long-term retail forecasts aren't common in literature

Best outcome for predicting long-term variables (20 years) is weaker estimations (highly theoretical)

Cannot give accurate estimations of sizes of warehouses needed long term

Conclusion and recommendations

If a linear relationship between space and size of items is assumed, then space allocation could be proportionate to individual sales volumes.

CA stores should be allocated more space if the above assumption holds true

As the FOODS 3 section accounts 4-8 times more sales than 1 and 2, same with HOBBIES 1 over the 2 and HOUSEHOLD

Space allocation should be in line with sales volume

For long-term forecasting - Delphi method are long and difficult but directly and accurately explore qualitative aspects

To implement machine learning, to add multiple LT considerations.

Combining both Delphi and machine learning procedures

Questions?

Thank You
For Listening

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