Grocery Sales Forecast

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12/12/2022

Define Goal

- Apply advanced forecasting techniques to “grocery” sales.
- Demonstrate data-driven and model-based approches across product families complimentary with a “typical” grocery store chain.
- Establish, in practical terms, the feasibility of using one or more forecasting appraoches in a real-world scenario to support optimal pricing, inventory management, timely promotion, optimal staffing, and other retain grocery objectives.

- **[Descriptive Goal? (18)] [Predictive Goal? (18)]** - *Add more specifically to these types of forecasting?*
- **[Forecast Horizon? (20)] [Forecast Use? (21)]** - *Add more detail (here or below in forecasting section)?*
- **[Level of Automation? (21, 72)]** - *Address here as part of overall goal, or elsewhere?*

Get Data

Reference: [https://www.kaggle.com/competitions/store-sales-time-series-forecasting/data?select=transactions.csv (https://www.kaggle.com/competitions/store-sales-time-series-forecasting/data?select=transactions.csv)]

```
# Load dataset(s); assumes folder structure with data parallel to src
sales_df <- read.csv("../data/train.csv", header = TRUE)
sales_test_df <- read.csv("../data/test.csv", header = TRUE)
stores_df <- read.csv("../data/stores.csv", header = TRUE)
oil_df <- read.csv("../data/oil.csv", header = TRUE)
events_df <- read.csv("../data/holidays_events.csv", header = TRUE)

# Data validation and understanding, including structure, content, and statistical characteristics covered below
```

Explore & Visualize Series

Univariate Analysis and Preliminary Pre-Processing

```
# e.g., statistical characteristics (including distribution, skewness, outliers)
#   +[optionally] review sample observations
univariate(sales_df); head(sales_df, 3); #str(sales_df)
```

```
Summary Univariate Analysis for (sales_df) (3,000,888 observations)
            Type         NA% Blank%    Unique Freq       Min       Max      Mean    Median Outlier< >Outlier Skewness nZV ACF1
id          integer                  3000888                3000887            1500444    No       No               N   1.0
date        character                   1684    1                                                                   N   1.0
store_nbr   integer                       54             1        54                28    No      Yes               N   1.0
family      character                     33                                                                        N   0.8
sales       numeric             31%  379610                124717.0     357.8      11.0    No      Yes          7.4  N
onpromotion integer             79%     362                    741                        No       No         11.2  N
```

```
  id       date store_nbr     family sales onpromotion
1  0 2013-01-01         1 AUTOMOTIVE     0           0
2  1 2013-01-01         1  BABY CARE     0           0
3  2 2013-01-01         1     BEAUTY     0           0
```

```
univariate(sales_test_df); head(sales_test_df, 3); #str(sales_test_df)
```

```
Summary Univariate Analysis for (sales_test_df) (28,512 observations)
            Type         NA% Blank%    Unique Freq       Min       Max      Mean    Median Outlier< >Outlier Skewness nZV ACF1
id          integer                    28512        3000888   3029399            3015144    No       No              N   1.0
date        character                     16    1                                                                   N   1.0
store_nbr   integer                       54             1        54                 28    No      Yes              N   1.0
family      character                     33                                                                       N   0.8
onpromotion integer             55%       212                      646                     No      Yes         8.5  N
```

```
       id       date store_nbr     family onpromotion
1 3000888 2017-08-16          1 AUTOMOTIVE           0
2 3000889 2017-08-16          1  BABY CARE           0
3 3000890 2017-08-16          1     BEAUTY           2
```

```
univariate(stores_df); head(stores_df, 3); #str(stores_df)
```

```
Summary Univariate Analysis for (stores_df) (54 observations)
          Type         NA% Blank%    Unique Freq       Min       Max      Mean    Median Outlier< >Outlier Skewness nZV ACF1
store_nbr integer                       54             1        54                 28    No       No              N   0.9
city      character                     22                                                                       N   0.3
state     character                     16                                                                       N   0.4
type      character                      5                                                                       N   0.6
cluster   integer                       17             1        17                  8    No      Yes              N   0.2
```

```
  store_nbr  city     state type cluster
1         1 Quito Pichincha    D      13
2         2 Quito Pichincha    D      13
3         3 Quito Pichincha    D       8
```

```
univariate(oil_df); head(oil_df, 3); #str(oil_df)
```

```
Summary Univariate Analysis for (oil_df) (1,218 observations)
           Type         NA% Blank%    Unique Freq       Min       Max      Mean    Median Outlier< >Outlier Skewness nZV ACF1
date       character                    1218    1                                                                   N   1.0
dcoilwtico numeric       3               998           26.2     110.6      67.7      53.2    No       Yes         0.3  N   0.9
```

```
        date dcoilwtico
1 2013-01-01         NA
2 2013-01-02         93
3 2013-01-03         93
```

```
univariate(events_df); head(events_df, 3); #str(events_df)
```

```
Summary Univariate Analysis for (events_df) (350 observations)
            Type         NA% Blank%    Unique Freq       Min       Max      Mean    Median Outlier< >Outlier Skewness nZV ACF1
date        character                    312    7                                                                   N   1.0
type        character                      6                                                                       N   0.3
locale      character                      3                                                                       N   0.3
locale_name character                     24                                                                       N
description character                    103                                                                       N   0.2
transferred character                      2                                                                       Y
```

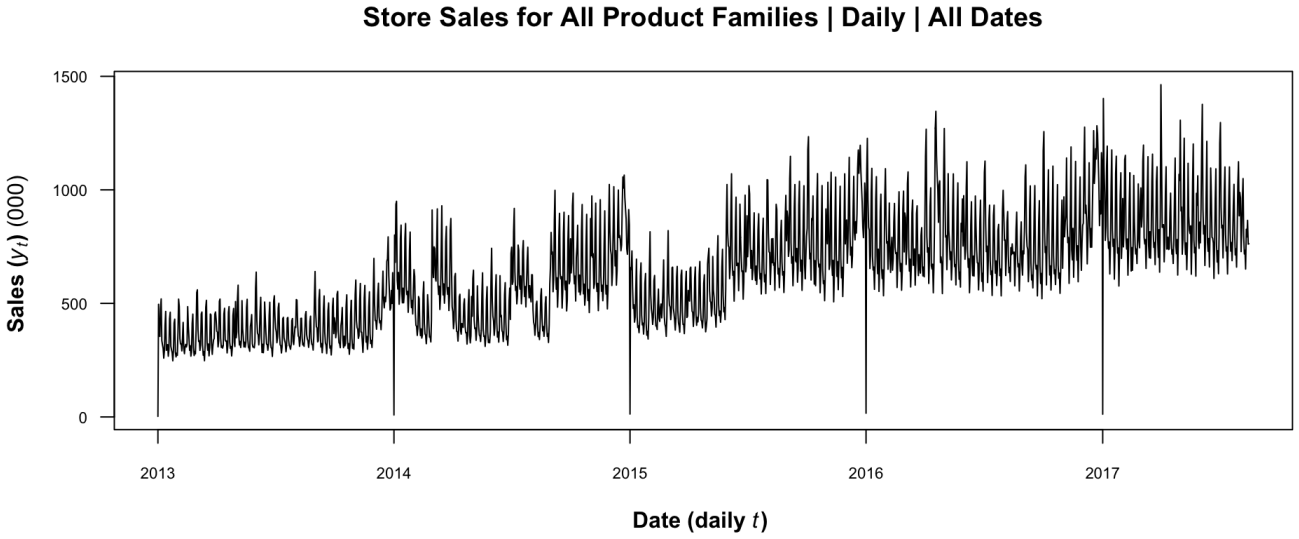
```
        date    type   locale locale_name                  description transferred
1 2012-03-02 Holiday    Local       Manta            Fundacion de Manta       False
2 2012-04-01 Holiday Regional    Cotopaxi Provincializacion de Cotopaxi       False
3 2012-04-12 Holiday    Local      Cuenca           Fundacion de Cuenca       False
```

- __[commentary on data usage - e.g., test data as provided adds no value?]

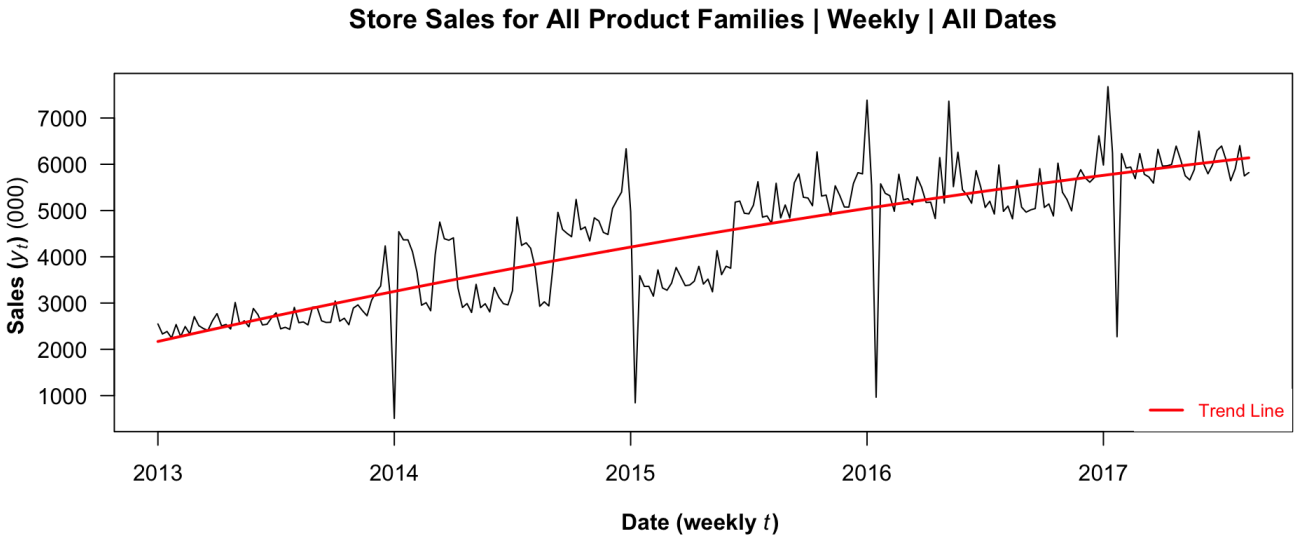
```
# Convert string mm/dd/yyyy to Date values and confirm sort
sales_df <- (sales_df %>%
               mutate(date = as.Date(date, format = "%Y-%m-%d"),) %>%
               arrange(date))
```

Series Visualization - All Product Families

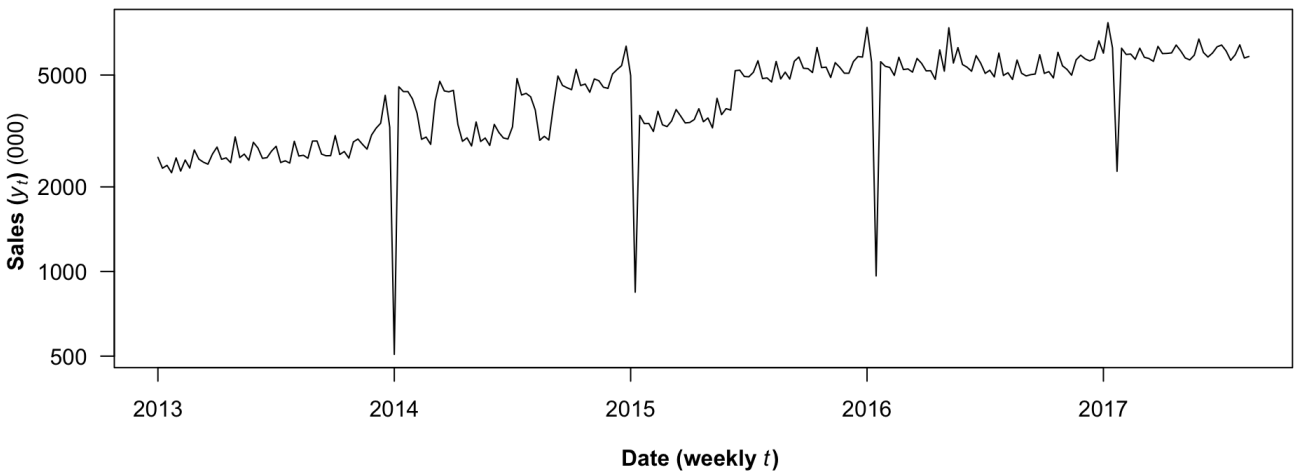
```
# Aggregate base dataframe by date (i.e., sum all product lines) and initlally plot series at
#   provided time granularity
sales_agg_df <- as.data.frame(sales_df %>%
                              group_by(date) %>%
                              summarize(sales = sum(sales / 1000.0)))
plot(x = sales_agg_df$date, y = sales_agg_df$sales, type = "l",
     main = "Store Sales for All Product Families | Daily | All Dates",
     xlab = TeX(r"(\textbf{Date (daily \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     las = 1, cex.axis = 0.7)
```



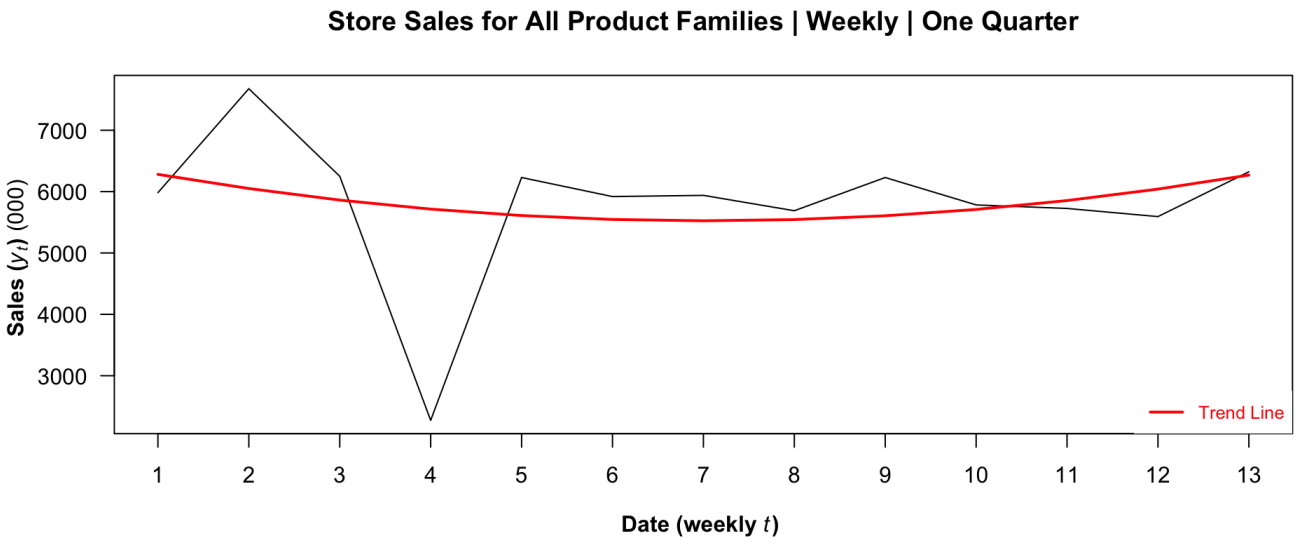

```
# Aggregate base dataframe from daily to weekly for all product families
sales_wk_df <- as.data.frame(sales_df %>%
                             mutate(year = year(date), week = week(date)) %>%
                             group_by(year, week) %>%
                             summarize(sales = sum(sales / 1000.0)))

# Create overall time series
sales_begin_year <- head(sales_wk_df$year, 1)
sales_begin_week <- head(sales_wk_df$week, 1)
sales_end_year <- tail(sales_wk_df$year, 1)
sales_end_week <- tail(sales_wk_df$week, 1)
sales_ts <- ts(sales_wk_df$sales,
               start = c(sales_begin_year, sales_begin_week),
               end = c(sales_end_year, sales_end_week), freq = 52)

# Plot overall time series with trend line
plot(sales_ts, type = "l",
     main = "Store Sales for All Product Families | Weekly | All Dates",
     xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     las = 1, cex.axis = 0.7)

sales_lm <- tslm(sales_ts ~ trend + I(trend^2))
lines(sales_lm$fitted, lwd = 2, lty = 1, col = "red")

legend("bottomright",
       legend = c("Trend Line"),
       col = c("red"),
       lwd = 2, lty = 1.2, cex = 0.8,
       box.lty = 0, text.col = "red")
```




```
# Plot overall time series w/log scale
plot(sales_ts, type = "l",
     main = "Store Sales for All Product Families | Weekly | All Dates | Log Scale",
     xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     las = 1, cex.axis = 0.7,
     log = "y")
```

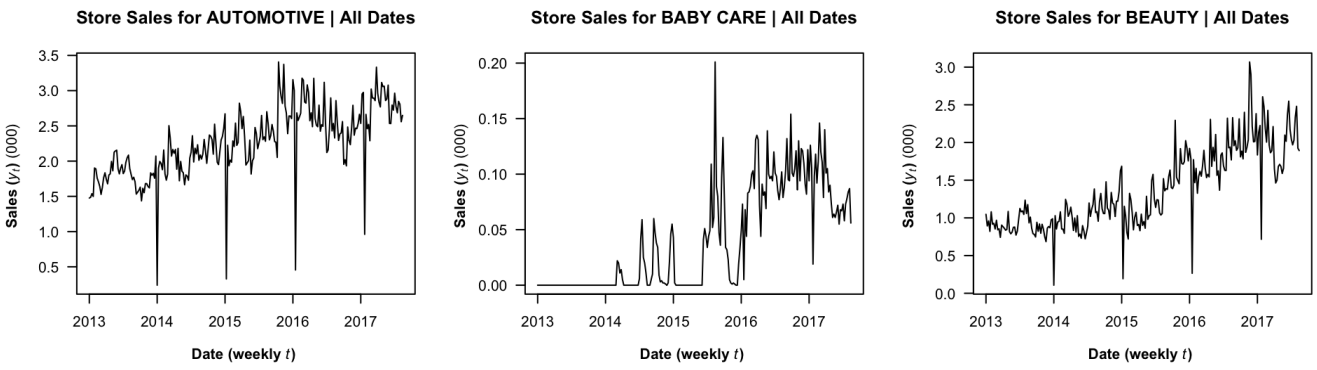


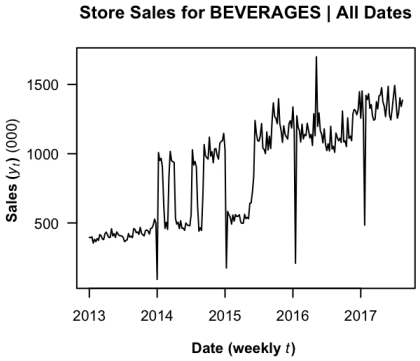

```
# Plot zoomed time series with trend line
sales_zoom_ts <- window(sales_ts, start = c(sales_end_year, 1), end = c(sales_end_year, 13))
plot(sales_zoom_ts, type = "l",
     main = "Store Sales for All Product Families | Weekly | One Quarter",
     xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     xaxt = "n",
     las = 1, cex = 0.7)

sales_zoom_lm <- tslm(sales_zoom_ts ~ trend + I(trend^2))
lines(sales_zoom_lm$fitted, lwd = 2, lty = 1, col = "red")

axis(1, at = as.numeric(time(sales_zoom_ts)), labels = seq(sales_zoom_ts))

legend("bottomright",
       legend = "Trend Line",
       col = "red",
       lwd = 2, lty = 1.2, cex = 0.8,
       box.lty = 0, text.col = "red")
```

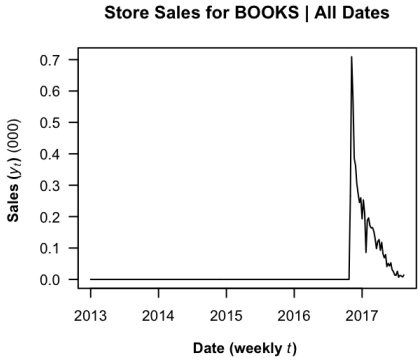


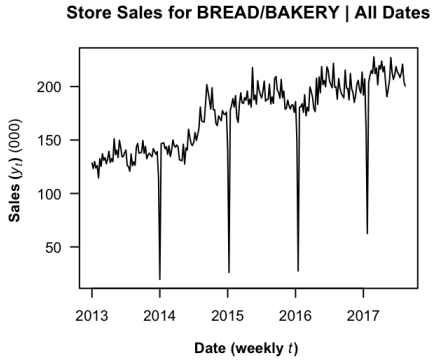
Series Visualization - Individual Product Families

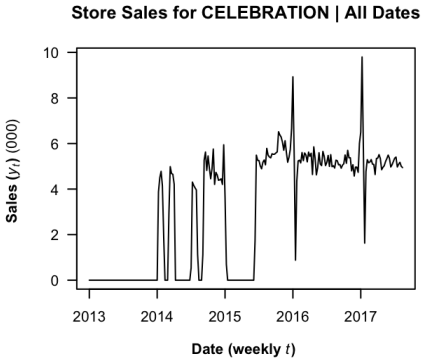
```
# Aggregate base dataframe from daily to weekly by product family
sales_wk_df <- as.data.frame(sales_df %>%
                               mutate(year = year(date), week = week(date)) %>%
                               group_by(family, year, week) %>%
                               summarize(sales = sum(sales / 1000.0)))

opar = par()
par(mfrow = c(1, 3))

for (f in unique(sales_wk_df$family)) {
  # Subset data by product family and create time series
  df <- filter(sales_wk_df, family == f)
  df_ts <- ts(df$sales,
              start = c(sales_begin_year, sales_begin_week),
              end = c(sales_end_year, sales_end_week), freq = 52)

  # Plot time series
  plot(df_ts, type = "l",
       main = paste("Store Sales for ", f, " | All Dates", sep = ""),

       height = 0.8,

       xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
       las = 1, cex.axis = 0.7)
}
```

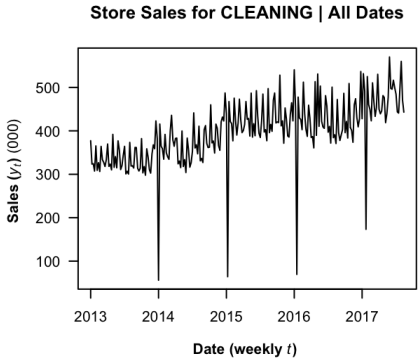


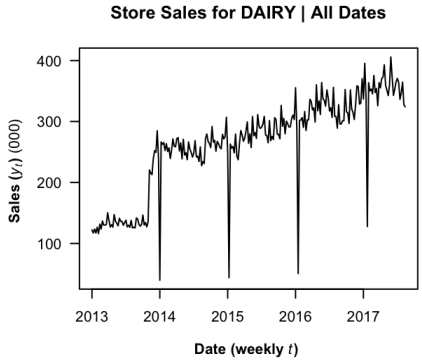

Store Sales for BEVERAGES | All Dates
Sales (y_t) (000)
1500
1000
500
2013
2014
2015
2016
2017
Date (weekly t)

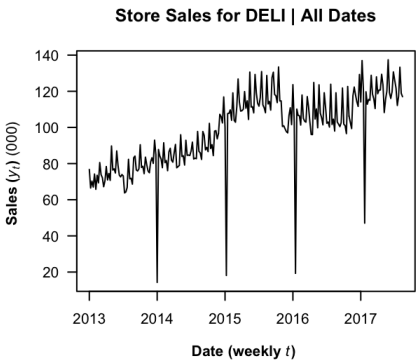

Store Sales for BOOKS | All Dates
Sales (y_t) (000)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2013
2014
2015
2016
2017
Date (weekly t)

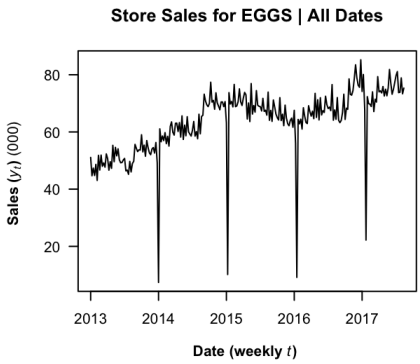

Store Sales for BREAD/BAKERY | All Dates
Sales (y_t) (000)
200
150
100
50
2013
2014
2015
2016
2017
Date (weekly t)

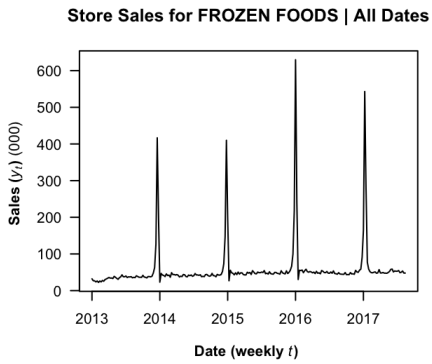

Store Sales for CELEBRATION | All Dates
Sales (y_t) (000)
10
8
6
4
2
0
2013
2014
2015
2016
2017
Date (weekly t)

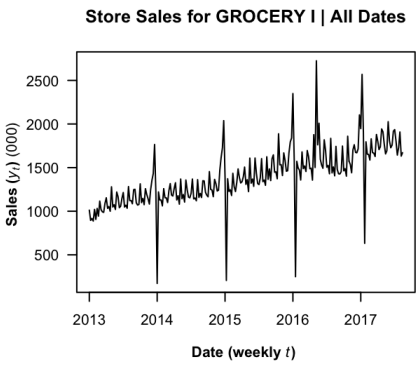

Store Sales for CLEANING | All Dates
Sales (y_t) (000)
500
400
300
200
100
2013
2014
2015
2016
2017
Date (weekly t)

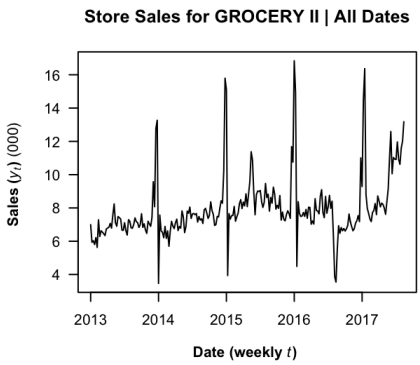

Store Sales for DAIRY | All Dates
Sales (y_t) (000)
400
300
200
100
2013
2014
2015
2016
2017
Date (weekly t)

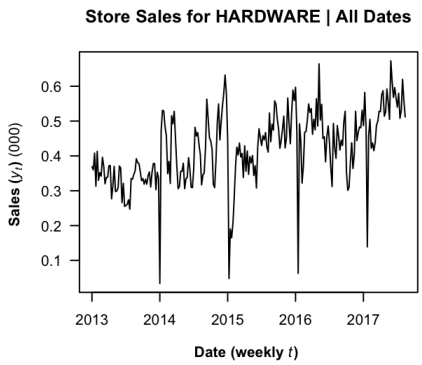

Store Sales for DELI | All Dates
Sales (y_t) (000)
140
120
100
80
60
40
20
2013
2014
2015
2016
2017
Date (weekly t)

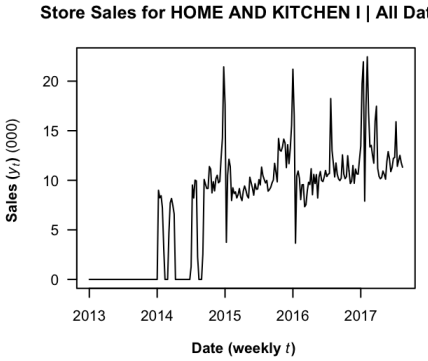

Store Sales for EGGS | All Dates
Sales (y_t) (000)
80
60
40
20
2013
2014
2015
2016
2017
Date (weekly t)

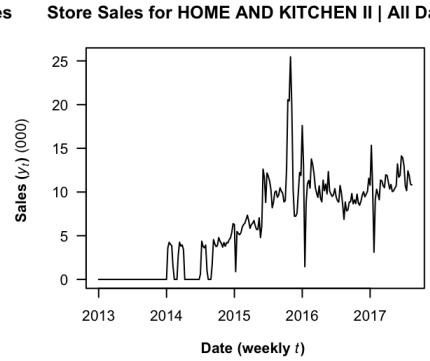

Store Sales for FROZEN FOODS | All Dates
Sales (y_t) (000)
600
500
400
300
200
100
0
2013
2014
2015
2016
2017
Date (weekly t)

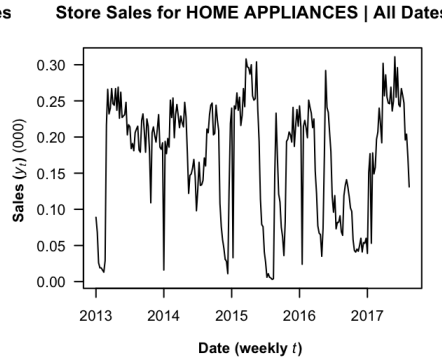

Store Sales for GROCERY I | All Dates
Sales (y_t) (000)
2500
2000
1500
1000
500
2013
2014
2015
2016
2017
Date (weekly t)

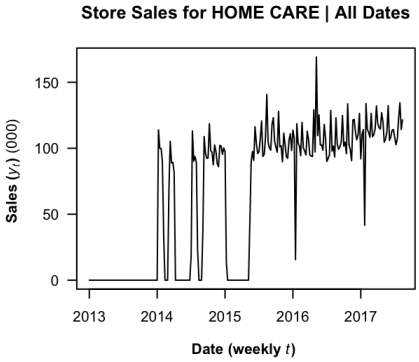

Store Sales for GROCERY II | All Dates
Sales (y_t) (000)
16
14
12
10
8
6
4
2013
2014
2015
2016
2017
Date (weekly t)

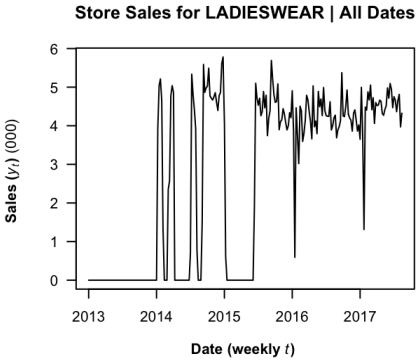

Store Sales for HARDWARE | All Dates
Sales (y_t) (000)
0.6
0.5
0.4
0.3
0.2
0.1
2013
2014
2015
2016
2017
Date (weekly t)

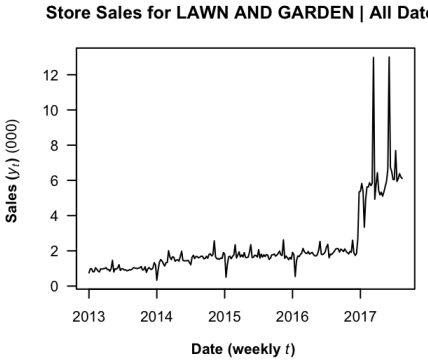

Store Sales for HOME AND KITCHEN I | All Dates
Sales (y_t) (000)
Date (weekly t)

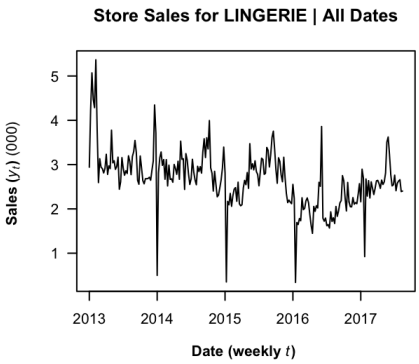

Store Sales for HOME AND KITCHEN II | All Dates
Sales (y_t) (000)
Date (weekly t)

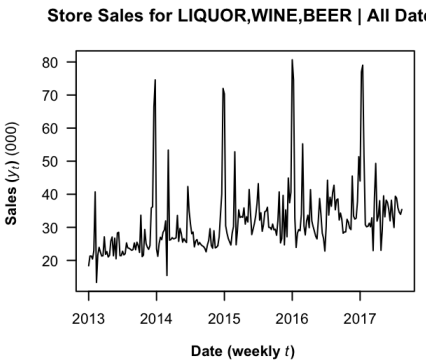

Store Sales for HOME APPLIANCES | All Dates
Sales (y_t) (000)
Date (weekly t)

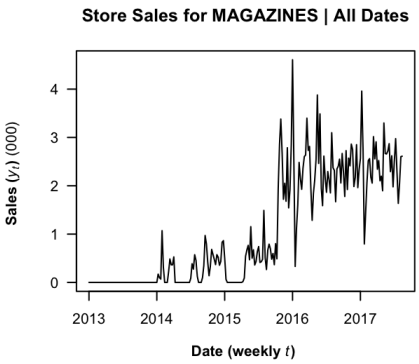

Store Sales for HOME CARE | All Dates
Sales (y_t) (000)
Date (weekly t)

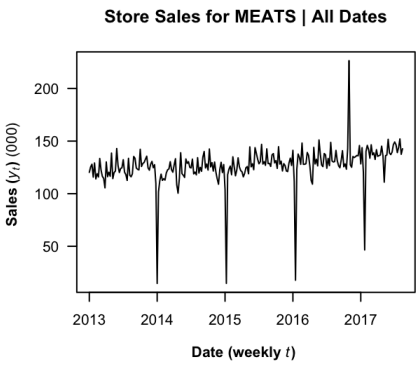

Store Sales for LADIESWEAR | All Dates
Sales (y_t) (000)
Date (weekly t)

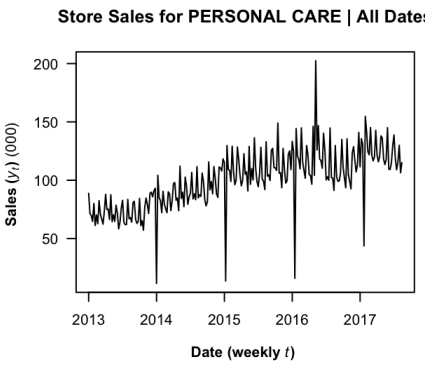

Store Sales for LAWN AND GARDEN | All Dates
Sales (y_t) (000)
Date (weekly t)

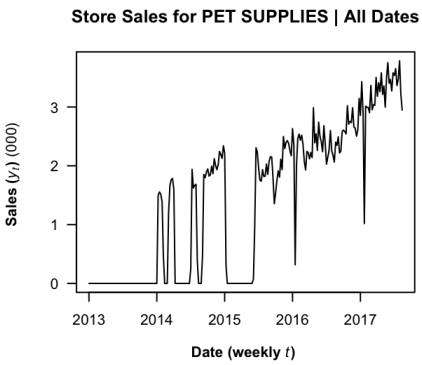

Store Sales for LINGERIE | All Dates
Sales (y_t) (000)
Date (weekly t)

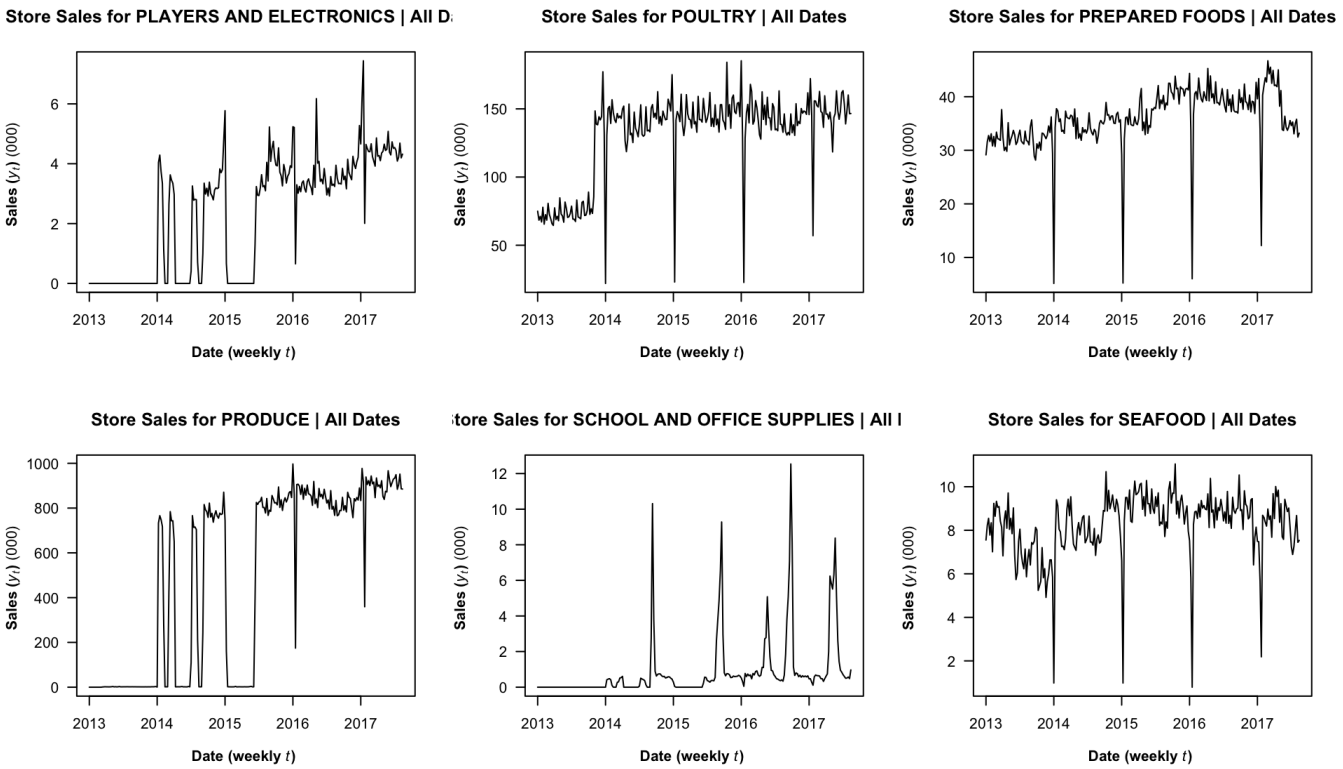

Store Sales for LIQUOR,WINE,BEER | All Dates
Sales (y_t) (000)
Date (weekly t)


Store Sales for MAGAZINES | All Dates
Sales (y_t) (000)
Date (weekly t)


Store Sales for MEATS | All Dates
Sales (y_t) (000)
Date (weekly t)


Store Sales for PERSONAL CARE | All Dates
Sales (y_t) (000)
Date (weekly t)


Store Sales for PET SUPPLIES | All Dates
Sales (y_t) (000)
Date (weekly t)




```
par(opar)
```

- **[Visualizing? (30)] [Zooming In? (30)]** - The above figures visualize the provided grocery store sales series across different frequencies, grains, and windows, with highlighted trend lines.

- **[Temporal Frequency? (26)]** - Series data is provided at a daily frequency. However, for purposes of forecasting to project goals, we are choosing to aggregate to a lower frequency of weekly?
- **[Series Granularity? (27)]** - Series grain includes store numbers and individual product families. Grocery chain sub-goals may have different requirements for this grain. For example, optimal pricing, inventory management, and timely promotion may benefit from product family detail, while optimal staffing may benefit from store number. For the purposes of this project, we are focusing on overall forecasting - i.e., aggregated above individual store and product family - knowing that patterns appear similar and project work can be taken to a new level of detail in the future?
- **[Series Granularity / Product Families]** - The above analysis highlights product families or categories that appear *adjacent* - i.e., not "core" - to the grocery business. Some of these families, e.g., books, celebration, or home appliances were introduced at different times and may be "opportunistic" or pilot families. Given this, the project is removing a subset of these types of product families in favor of basic grocery families. *(Does this also get to [domain expertise? (27)]?)*

- **[Time Series Components? (28)]** - Store sales at daily and weekly frequencies, across and within individual product families, exhibit systematic components of [average] level (by default), trend (changes from one period to the next), and seasonality, or cyclical behavior. Of course, all include non-systematic "noise."

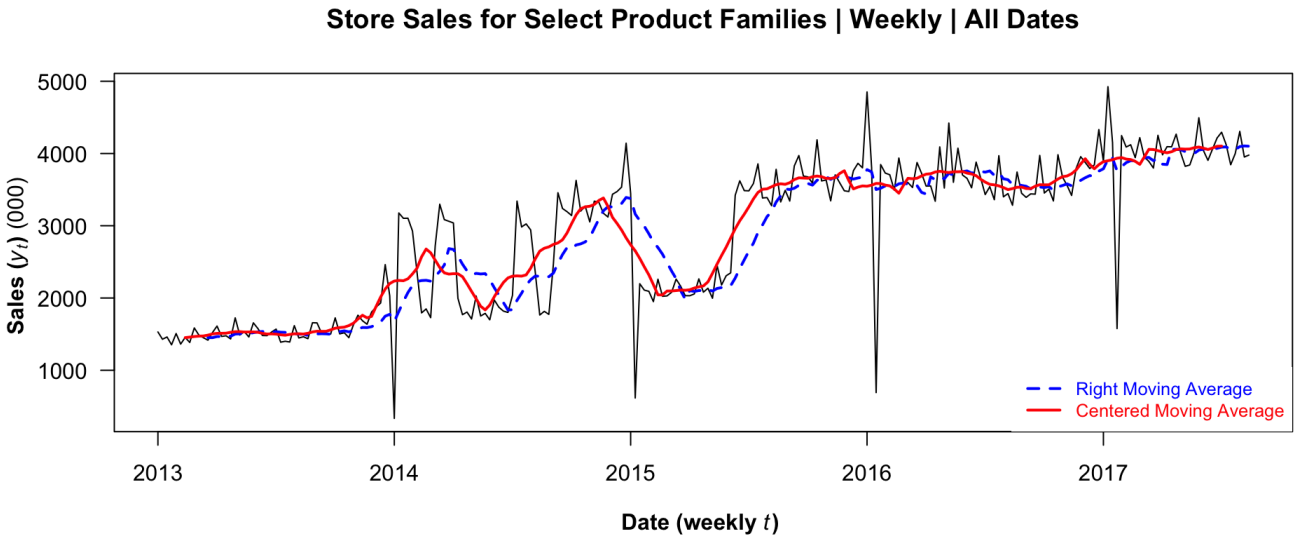
Pre-Process Data

- **[Data Qualty? (25)]** - *Not seeing major issues?*
- **[Missing Values? (39)]** - *Not seeing major issues?*
- **[Unequally Spaced Series? (40)]** - *Not seeing major issues?*
- **[Extreme Values? (40)]** - *Not seeing major issues?*

```
# Placeholder code to emove rows with NAs
#df %>%
#  na.omit()

# Placeholder code to remove rows with NAs in specific column
#df %>%
#  filter(!is.na(column_name))

# Placeholder code to reemove duplicates
#df %>%
#  distinct()

# Placeholder code to remove rows by index position
#df %>%
#  filter(!row_number() %in% c(1, 2, 4))

# Remove rows not considered "core"
keep_families <- c("BEAUTY", "BEVERAGES", "BREAD/BAKERY", "CLEANING", "DAIRY",
                   "DELI", "EGGS", "FROZEN FOODS", "GROCERY", "GROCERY II", "HARDWARE",
                   "LIQUOR,WINE,BEER", "MEATS", "PERSONAL CARE", "PET SUPPLIES", "POULTRY",
                   "PREPARED FOODS", "PRODUCE", "SEAFOOD")
remove_families <- c("AUTOMOTIVE", "BABY CARE", "BOOKS", "CELEBRATION", "HOME APPLIANCES",
                     "HOME AND KITCHEN I", "HOME AND KITCHEN II", "HOME CARE", "LADIESWEAR",
                     "LAWN AND GARDEN", "LINGERIE", "MAGAZINES", "PET SUPPLIES",
                     "PLAYERS AND ELECTRONICS", "SCHOOL AND OFFICE SUPPLIES")
sales_core_df <- (sales_df %>%
                    filter(family %in% keep_families))
```

Series Visualization - Select (“Core”) Product Families

```
# Re-aggregate base dataframe from daily to weekly for all product families
sales_wk_df <- as.data.frame(sales_core_df %>%
                               mutate(year = year(date), week = week(date)) %>%
                               group_by(year, week) %>%
                               summarize(sales = sum(sales / 1000.0)))

# Re-create overall time series
sales_begin_year <- head(sales_wk_df$year, 1)
sales_begin_week <- head(sales_wk_df$week, 1)
sales_end_year <- tail(sales_wk_df$year, 1)
sales_end_week <- tail(sales_wk_df$week, 1)
sales_ts <- ts(sales_wk_df$sales,
               start = c(sales_begin_year, sales_begin_week),
               end = c(sales_end_year, sales_end_week), freq = 52)

# Plot overall time series with moving averages
plot(sales_ts, type = "l",
     main = "Store Sales for Select Product Families | Weekly | All Dates",
     xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     las = 1, cex.axis = 0.7)

sales_l_ma <- rollmean(sales_ts, k = 12, align = "right")
sales_c_ma <- ma(sales_ts, order = 12)
lines(sales_l_ma, lwd = 2, lty = 2, col = "blue")
lines(sales_c_ma, lwd = 2, lty = 1, col = "red")

legend("bottomright",
       legend = c("Right Moving Average", "Centered Moving Average"),
       col = c("blue", "red"),
       lwd = 2, lty = c(2, 1), cex = 0.8,
       box.lty = 0, text.col = c("blue", "red"))
```



- **[Centered Moving Average Smoothing Method? (80)] [Choosing Window Width? (83)]** - The above figure provides a view of the overall time series, aggregated to weekly, for select "core grocery chain" product families. The centered and trailing moving average lines are illustrative and not intended for forecasting given trend and seasonality components. Note also that these use a window width of monthly, again, for smoothing visualizlation (series understanding) only.

Partition Series

- **[Temporal Data Partitioning? (45-46)] [Choosing the Validation Period (48)] [Fixed Partition? (65)] [choice of time span? (41)]** - Given an overall series span of over five years, the series is temporaly partitioned with a fixed validation period of one year. The balance of series data is segmented for training (with the full series span appearing relevant to future forecasts). The one year validation span was chosen based in part on the trend and seasonal natures of the grocery business, as previously highlighted in preliminary analysis, and the possibility need for a forecast horizon of up to one year.

```
# Use one year (52 weeks) as validation period (representative set of quarters, seasons)
sales_n_valid <- 52
sales_n_train <- length(sales_ts) - sales_n_valid

# Split data into training and validation periods
sales_train_ts <- window(sales_ts, start = c(sales_begin_year, 1), end = c(sales_begin_year, sales_n_train))
sales_valid_ts <- window(sales_ts, start = c(sales_begin_year, sales_n_train + 1), end = c(sales_begin_year, sales_n_train +
sales_n_valid))

# Set x axis values based on ts ranges
x_train <- sales_begin_year
x_valid <- sales_begin_year + ((sales_n_train + 1) / 52)
x_future <- x_valid + ((sales_n_valid + 1) / 52)
```

Apply Forecasting Method(s)

- **[Model-Based vs. Data-Driven (69)]** -

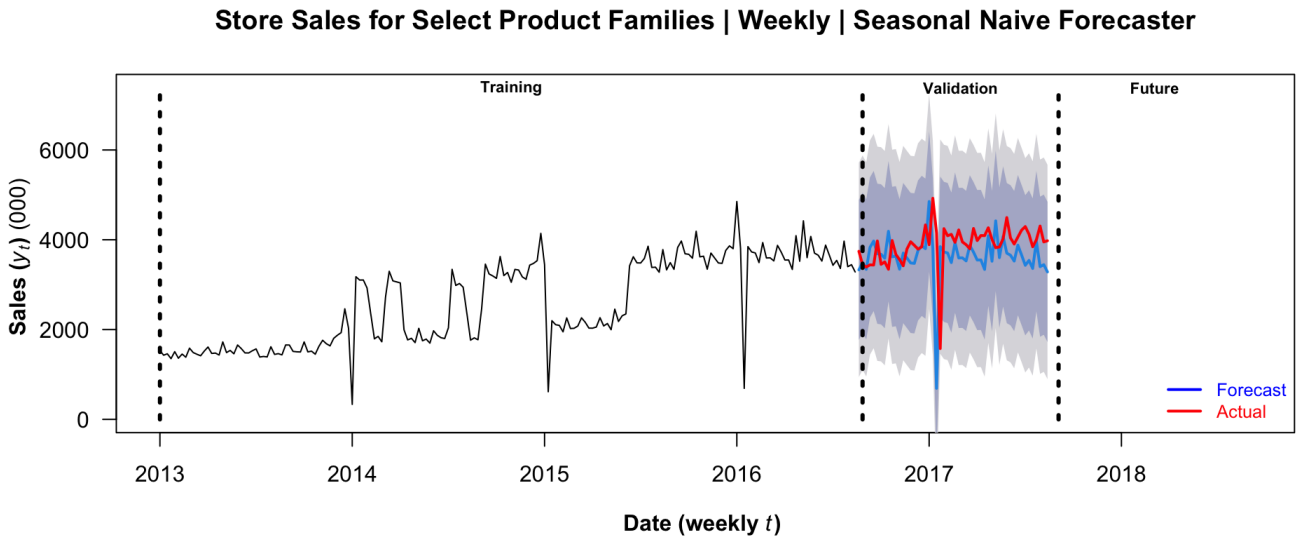
Naive Forecast Baseline

- **[Naive Forecasts (50)]** -

```
# Fit seasonal naive model
sales_snaive_pred <- snaive(sales_train_ts, h = sales_n_valid)

# Summarize seasonal naive forecast results
accuracy(sales_snaive_pred, sales_valid_ts)
```

```
                ME RMSE MAE MPE MAPE MASE ACF1 Theil's U
Training set 784 1217 996  17   38  1.0  0.5        NA
Test set     261  752 507   4   14  0.5 -0.2       0.7
```

```
# Plot seasonal naive forecaster
ymax <- max(sales_ts) * 1.5
xmax <- x_future + 1

plot(sales_snaive_pred, type = "l",
     main = "Store Sales for Select Product Families | Weekly | Seasonal Naive Forecaster",
     xlab = TeX(r"(\textbf{Date (weekly \textit{$t$})} )"), ylab = TeX(r"(\textbf{Sales (\textit{$y_t$})} (000) )"),
     las = 1, cex.axis = 0.7,
     xlim = c(x_train, xmax), ylim = c(0, ymax))

# Add additional lines
lines(sales_valid_ts, lwd = 2, col = "red")

# Add plot defintions
lines(c(x_train, x_train), c(0, ymax), lwd = 3, lty = 3)
lines(c(x_valid, x_valid), c(0, ymax), lwd = 3, lty = 3)
lines(c(x_future, x_future), c(0, ymax), lwd = 3, lty = 3)

text(x_train + ((x_valid - x_train) * 0.5), ymax, "Training", font = 2, cex = 0.7)
text(x_valid + ((x_future - x_valid) * 0.5), ymax, "Validation", font = 2, cex = 0.7)
text(x_future + 0.5, ymax, "Future", font = 2, cex = 0.7)

legend("bottomright",
       legend = c("Forecast", "Actual"),
       col = c("blue", "red"),
       lwd = 2, lty = 1, cex = 0.8,
       box.lty = 0, bg = NULL, text.col = c("blue", "red"))
```



- **[MAPE, as average deviation from forecast to actual]** -
- **[RMSE, as average "distance" from actual]** -

Data-Driven: Smoothing Methods

- **[Trailing Moving Average Smoothing Method? (81)]** -
- **[Choosing Window Width (83)]** -

- **[Differencing? (85)]** -
- **[Removing Trend? (85)]** -
- **[Removing Seasonality? (87)]** -
- **[Removing Trend and Seasonality? (87)]** -

- **[Simple Exponential Smoothing? (87)]** -
- **[Advanced Exponential Smoothing? (90)]** -

- **[Measuring Predictive Accuracy (51++)]** -

Model-Driven: Regression

- **[Regression Model with Trend? (117)]** -
- **[Regression Model with Seasonality? (125)]** -
- **[Regression Model with Trend and Seasonality? (129)]** -

- **[Measuring Predictive Accuracy (51++)]** -

Model-Driven: Regression w/Autocorrelation and External Information

---

- **[Autocorrelation? (143)]** -
- **[ARIMA Model? (147)]** -

- **[External Information (70)]** - [consider causal/correlated?]
- **[Including External Information? (154)]** -

Model-Driven: Opportunities

- **[Combining Methods and Ensembles (73)]** -

Evaluate & Compare Performance

- **[Comparing Two Models? (65)]** -
- **[Evaulating Predictability? (153)]** -

Implement Forecasts/System

- **[Joining Partitions for Forecasting (47)]** -
- **[Creating Forecasts from the Chosen Model? (132)]** -

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