Forecasting Retail Store Weekly Sales to Increase Future Sales and Account for Seasonality

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December 2022

Abstract

Forecasting future sales for retail businesses is an in-demand aspect of data analytics. Our paper will tackle forecasting retail sales, along with some of the challenges that accompany forecasting retail sales (i.e., inherent seasonality in retail sales time series data). The retail data used for this project consists of weekly sales data from 2010-2012 for 45 different retail stores, also separated by each store's departments. An exploratory data analysis was performed prior to modeling the retail sales data. Then, cleaning was done, which included steps like reformatting the Date column, combining the three data sets together, checking for and imputing missing values if necessary, and identifying and removing and/or replacing outliers. Also, during this phase, the dataset was decreased from 45 stores to 1 store. After cleaning the data, feature selection was performed to determine which external predictors would be the most useful in forecasting weekly retail sales, which we decided as Temperature. Once the EDA, cleaning, and feature selection were completed, modeling was performed using the auto.arima, ARIMA, and linear regression methods. After completing modeling, the best fit model was decided as the ARIMA model given that the majority of the 13 departments had the lowest RMSE values with the ARIMA models. Forecasts were then created for each department's ARIMA model, to observe the presence or absence of overfitting. In conclusion, to forecast retail sales, which often have very seasonal data, ARIMA modeling methods can be effective in producing accurate forecasts. This information can then be used for retail store to better prepare themselves for higher or lower sales periods.

Introduction

Forecasting retail sales is both popular and in-demand because it allows for retailers to run their businesses and determine patterns in their annual sales more efficiently. With forecasting retail sales comes the challenge that retail sales are heavily influenced by seasonal patterns (i.e., seasonality). Seasonality can be defined as a "characteristic of a time series in which the data experiences regular and predictable changes that recur…[with] predictable fluctuation or pattern" (Kenton, 2020). In order to build well performing forecasting models, features like seasonality are important to account for and address when forecasting retail sales.

Problem Statement

This paper aims to create various forecasting models to analyze retail store data. The retail stores have provided us with data from various locations and different departments. The main goal of this paper is to forecast department-specific sales for the weekly sales of the retailers provided, so the retailers can better understand what influences their weekly sales, allowing for stores to be better prepared for low or high selling periods.

Literature Review

Retail store sales are different from other types of industry sales because "shifting seasons can seriously affect the retail market" (Rubinetti, 2020). For example, coats and warm clothing sales increase during the winter season, while lighter clothing is bought during the spring and summer seasons. Given that consumer's clothing preferences often depend on factors like the season, seasonality has been shown to play an important role in retail sales forecasting. Chu & Zhang (2003) "[compared] the accuracy of various linear and nonlinear models for forecasting aggregate retail sales, … [using] seasonal dummy variables and trigonometric functions." The authors accounted for seasonality with auxiliary variables instead of the commonly used method of removing seasonality/deseasonalization. The results of this study proved that nonlinear models outperformed linear models in forecasting retail store sales, more specifically the neural network model on deseasonalized data performed the best but disproved one of the original theory's that including auxiliary variables to account for seasonality may improve forecasting results (Chu & Zhang, 2003).

Pongdatu & Putra (2018) aimed to "compare SARIMA and Holt-Winter's Exponential Smoothing methods… to generate customer transaction forecasting in Store x with high accuracy." After creating the SARIMA and Holt-Winter's Exponential Smoothing models, the authors compared the performance using mean absolute deviation (MAD). The authors concluded that "the best model with the smallest MAD value is SARIMA model… [and] that the SARIMA model is feasible to be used as a model for further [retail] forecasting" (Pongdatu & Putra, 2018).

Ramos et al. (2015), compared "state space models and ARIMA models" performance, where state space models refer to exponential smoothing methods. The authors used data of retail sales from five different women's footwear categories (i.e., boots, booties, flats, sandals, and shoes). In the end, the authors found that both "ETS and ARIMA models have the capability to forecast the trend movement and seasonal fluctuations fairly well" (Ramos et al., 2015). From the literature review we can conclude that nonlinear models (i.e., neural networks) can work well with deseasonalized retail sales data and ARIMA/SARIMA modeling may produce more accurate retail sales forecasting results compared to other modeling methods.

Methodology

Exploratory Data Analysis

Before starting the EDA process, we recognized that there was some pre-processing that needed to be done. We thought it was best to attack the preprocessing first so that we can appropriately and correctly conduct the EDA process. We noticed in the beginning when trying to attempt to perform EDA that some of the code scripts were not working in return pushing back syntax errors. Therefore, we agreed that pre-processing needed to be implemented before moving to exploring anything within the data.

The first steps in preprocessing we attempted to do is change some of the variables within the sales data to their appropriate types some of those variables are store, dept, isHoliday, as well as date. We noticed that the date column was not correctly formatted, so we made sure to reformat the Date column correctly. In addition to the sales data, we noticed that there were some negative values in the Weekly_Sales column so we removed that from the negative values from the data due to only wanting positive numbers, making the assumption that negative sales was likely a data collection error. Following making corrections to the sales data we checked for nulls and the data came back clean.

Next, we applied the same thing with the feature data set applying preprocessing to the date column as we did with the sales data. In addition to reformatting the date column we checked for missing values and noticed columns MarkDown1-5, and CPI, Unemployment had a large number of missing values. We decided to handle the missing values later on. Following checking missing data we merged the sales data with the feature data by weekly sales, calling that data “df”. Following that we factored the store data.

After performing cleaning and preprocessing to the data we decided to explore the following columns broken down below with description of the purpose:

Store - This accounts for the store number in the region.

Dept - This accounts for the unique department within a unique store.

Date - This accounts for the date of weekly sales.

Temperature - This accounts for the average temperature in the region.

Fuel Price - This accounts for the average fuel price in the region.

CPI - This accounts for the average consumer price index for the region

Unemployment - This accounts for the unemployment rate in the region.

Following choosing what columns to explore we started by creating a time series object for Weekly_Sales with the start date being “2010”, to view how each of the 13 departments Weekly_Sales change overtime. Time plots were created for all 13 of the departments. Figure 1 below displays the time plot for Department 8, where we can observe that there is a slight upwards trend in Weekly_Sales, with the clear presence of seasonality, specifically increasing before the new year. Figure 2 below is another time plot of Weekly_Sales, this time for department 10. This department has the opposite trend of what Figure 1 department 8 had. In Figure 2 we can see a very slight downward trend of sales going into the year 2013. Something to consider with this department is maybe that they are selling different types of clothing based on time of date. An example can be winter clothes not selling during this specific season, therefore there will be a downward trend in weekly sales. Note that the time plots of Weekly_Sales for the remaining departments can be viewed in the Appendix.

Figure 1

Department 8 Weekly Sales Plot

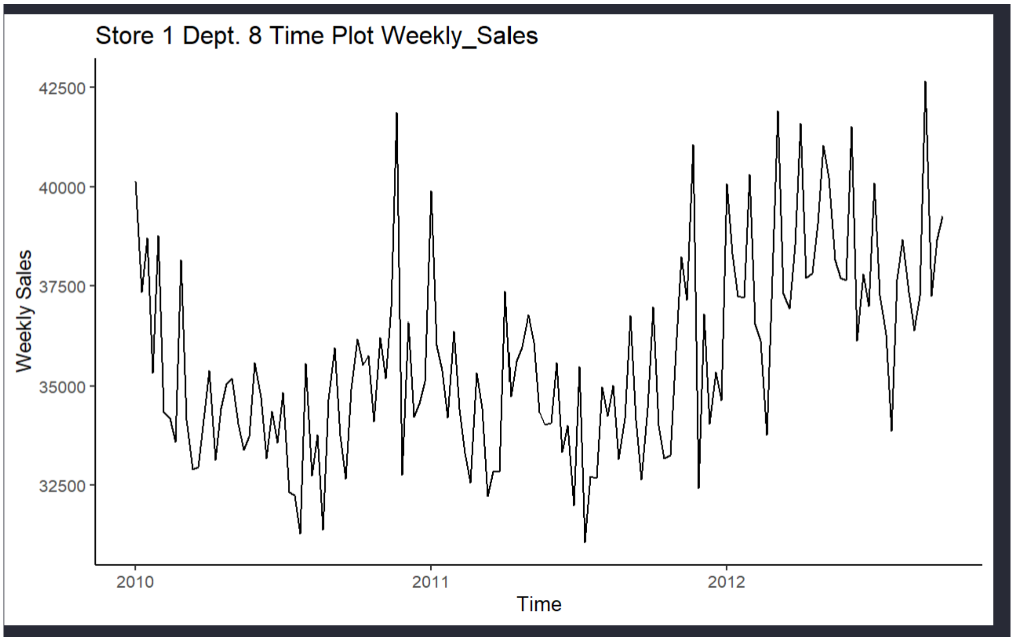
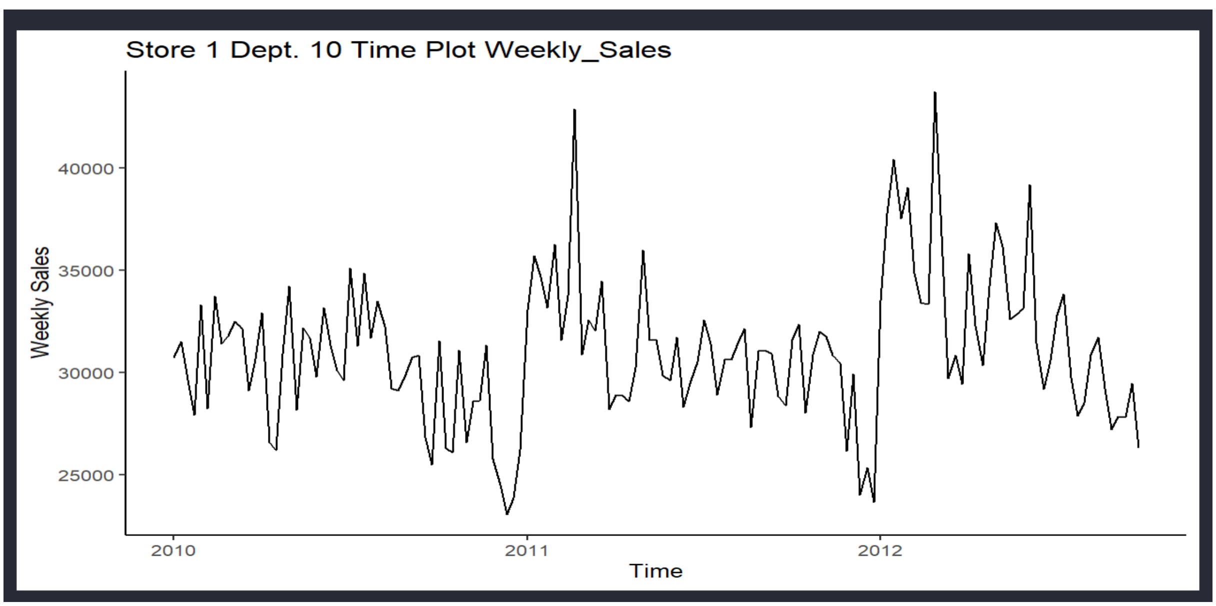


Figure 2

Department 10 Weekly Sales Plot



So far, we gathered that there is some presence of trend and/or seasonally impacting weekly sales, based on the different time plots that have been shared. Now let's take it a step further and dive into the correlation between the predictors and outcome (i.e., Weekly_Sales), done by creating scatter plots. Scatter plots were created for each department and the following predictors: CPI, Unemployment, Temperature, and Fuel Price. From the scatter plots created it can be observed that the predictor Temperature is the most correlated to Weekly_Sales compared to the other three predictors and may be the most useful in terms of forecasting Weekly_Sales. In Figure 3 we can see in one of the departments that there is an interesting trend of seasonality changing. In this figure we can observe weekly sales rise as the temperature shifts. In the beginning of the temperature (40) we can see an increase in sales which shows, in addition we can also see a decrease in sales at the tail end of the plot at 90 degrees with a slight upward push. This shows that this department has a very strong seasonality trend. In the beginning we talked about the degree weather being 40 which is fall/ winter months then the trend of sales decreases as the weather changes to being warm. This is a consistent trend around temperature across all departments. In Figure 4 we can actually see something similar as well. In terms of there being an upward trend it is, but also the price data points are not scattered off in the plane field. Instead, they're grouped in very knit spots. It is safe to say that temperature can sway forecasting sales. forecasting.

After creating both time plots and scatter plots, ACF and PACF plots were output to view the autocorrelations of the various Departments and Weekly_Sales. Note that the ACF and PACF plots can be viewed in the Appendix. The main reason for these plots is to use them to decide the parameter values (i.e., order and seasonal components) for the ARIMA models. The values of the ACF and PACF at various lags can point towards optimal forecasting parameters. Also, the ACF plot specifically shows how each value in the time series relates to the previous value, also known as autocorrelation (Shmueli & Lichtendahl Jr., 2018).

After the preliminary EDA, another cleaning step that was taken before modeling our retail store data was to identify outliers in each of the departments Weekly_Sales and handle the outlier accordingly. The tsclean function was used to identify the outliers and replace them with non-outlier values. Note that the tsclean function used quartiles and IQR to calculate values more than 1.5 standard deviations past the mean Weekly_Sales value.

Figure 3

Temperature vs Weekly Sales Plot Department 8

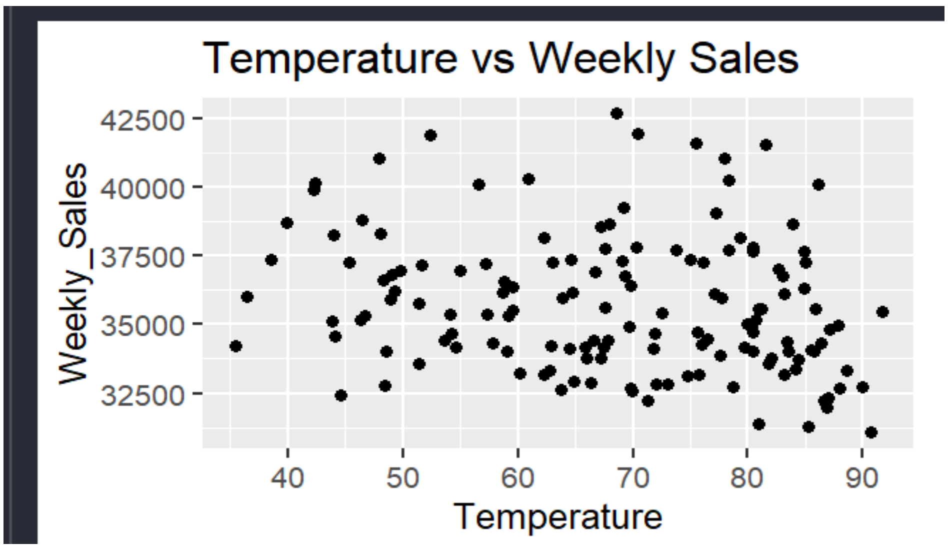
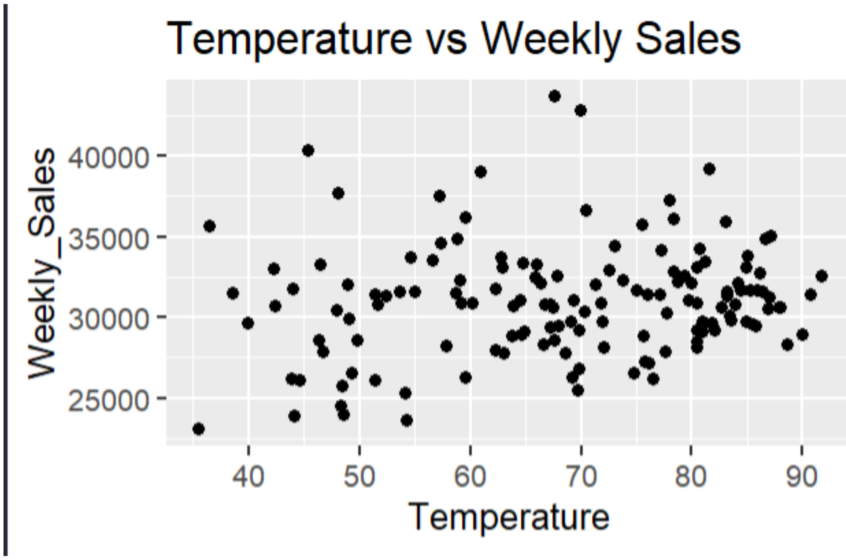


Figure 4

Temperature vs Weekly Sales Plot Department 10



Feature Selection

In terms of feature selection, we have decided to use temperature as the predictor variables since Weekly_Sales by department can differ based on temperature. We are assuming here that there is some kind of relationship between temperature and what people choose to buy at stores, seen somewhat from the scatter plots mentioned earlier. The other three possible predictors (i.e., Fuel price, CPI, and Unemployment) were deemed not very correlated to the various departments Weekly_Sales, so have not been included in the modeling process to try and combat overfitting to some degree. Also, note that the following predictors/columns were removed from the dataset due to the high presence of missing values: Markdown 1-5. IsHoliday was also removed given that we were already seeing seasonality in the data itself.

Modeling

The first step taken in the modeling phase of our project is data partitioning. Each of the 13 departments were partitioned into a training and validation period using the window function. The training period ranged from February 5, 2010, to July 27, 2012 and the validation period ranged from August 3, 2012, to October 26, 2012 (i.e., training_1.1-1.13 & validation_1.1-1.13).

Along with partitioning the various time series, the external predictors matrix for each department have also been created at this stage. As discussed earlier, temperature will be used as an external predictor for all 13 departments.

After partitioning the data into training and validation sets, we can begin to build our models. Given the research discussed in the literature review, we have opted to use both the auto.arima and ARIMA functions, and the tslm function in R to build ARIMA and linear models for the 13 departments weekly sales. With the auto.arima function, the order and seasonal components are chosen by the algorithm, whereas with the ARIMA function, we must specify the order and seasonal components. The method used to pick the various order and seasonal components for the 13 departments was the use of the ACF and PACF plots. By viewing those two plots for each department's weekly sales, which can be viewed in the exploratory data analysis, we can choose optimal values for the order and seasonal components of the ARIMA model.

The main advantage to using ARIMA models to forecast weekly sales for the 13 departments is that the ARIMA method can account for autocorrelation of the series values, whereas other method like linear modeling can account for trend and seasonality but does not have the capability to account for more complex relationships like autocorrelation (Shmueli & Lichtendahl Jr., 2018). We decided to also include linear models because of the inherent seasonality present in retail stores data, which linear models can address.

Results

Each of the 13 departments were used to create models: auto ARIMA, ARIMA, and linear model. In order to decide the best fitting model for each department, the training set RMSE value is used, with lower values indicating better fit models and higher values indicating worse fit models. Along with the RMSE, actual vs predicted values plots were also created to visually observe each model's performance on the departments.

Department 1's best fit model was the ARIMA model with a training set RMSE of 2157.25. We can observe in Figure 5 below the actual vs forecasted weekly sales for Department 1's ARIMA model and Figure 6 the actual vs forecasted weekly sales for Department 1's linear model. From Figures 5 and 6, we can see that the ARIMA model fits to the actual Department 1 weekly sales relatively well. Note that the remaining actual vs forecasted plots for each model and department can be viewed in the appendix. Department 2's best fit model was the linear model with a training set RMSE of 1548.55. Department 3's best fit model was the ARIMA model with a training set RMSE of 843.53. Department 4's best fit model was the linear model with a training set RMSE of 894.92. Department 5's best fit model was the ARIMA model with a training set RMSE of 2549.46. Department 6's best fit model was the ARIMA model with a training set RMSE of 831.02. Department 7's best fit model was the ARIMA model with a training set RMSE of 2108.84. Department 8's best fit model was the ARIMA model with a training set RMSE of 911.36. Department 9's best fit model was the ARIMA model with a training set RMSE of 1719.25. Department 10's best fit model was the ARIMA model with a training set RMSE of 1410.50. Department 11's best fit model was the linear model with a training set RMSE of 1626.42. Department 12's best fit model was the ARIMA model with a training set RMSE of 710.12. Lastly, Department 13's best fit model was the ARIMA model with a training set RMSE of 947.22. A summary of these findings can be found in Table 1 below. Given that a majority (10/13) of the department have the lowest RMSE with the ARIMA model, we have decided that the ARIMA model is our "final" model for each of the 13 departments and will be used to forecast weekly sales for the next 13 weeks, for each of the 13 departments.

Figure 5

Actual vs Forecasted Weekly Sales for Department 1 ARIMA Model

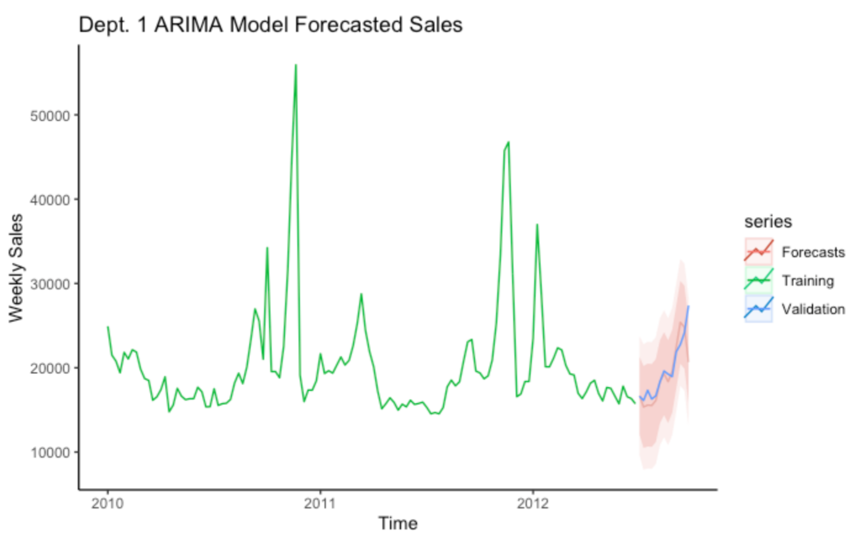


Figure 6

Actual vs Forecasted Weekly Sales for Department 1 linear Model

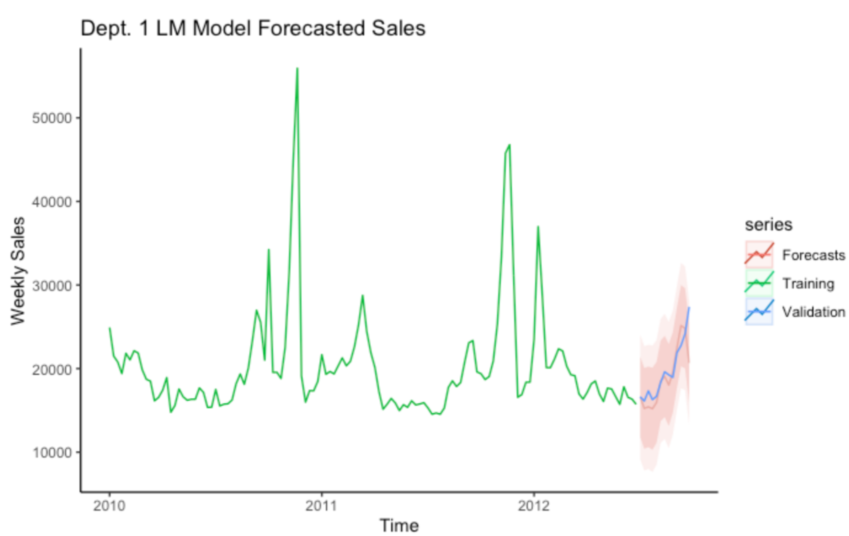


Table 1

Model training RMSE results for all 13 Departments

	Auto ARIMA Model (training set RMSE)	ARIMA Model (training set RMSE)	Linear Model (training set RMSE)
Department 1	3044.30	2157.25	2287.37
Department 2	2111.93	1644.41	1548.55
Department 3	1170.01	843.53	855.64
Department 4	1101.95	1016.04	894.92
Department 5	3621.71	2549.46	2569.96
Department 6	1138.53	831.02	927.81
Department 7	6675.15	2108.84	5097.91
Department 8	924.75	911.36	959.46
Department 9	2508.99	1719.25	1858.97
Department 10	1893.31	1410.50	1462.32
Department 11	2038.14	1840.77	1626.416
Department 12	1072.84	710.12	717.52
Department 13	1016.26	947.22	1033.43

Discussion and Limitations

After deciding upon the "final model" (i.e., ARIMA models), the 13 ARIMA models were then used to forecast the next 13 weeks of weekly sales. Using the accuracy function, validation set RMSE values are also output to view the performance of the ARIMA models on the validation sets. Table 2 below displays the validation set RMSE values for the 13 Departments. From the table, only 4 of the departments had validation set RMSE values lower than the training set RMSE values, indicating no overfitting amongst those 4 departments. But, for the other 9 departments, there appears to be some degree of overfitting given the larger RMSE value for the validation sets of those 9 departments. The overfitting is most likely due to the inclusion of the temperature predictor. Given the nature of our data, some of the departments weekly sales will be more correlated to certain departments compared to other departments. For example, coats departments, long sleeve shirts departments, and swimsuit departments are likely to be more correlated to temperature than other departments like kitchenware. So, by including temperature as an external predictor for the departments weekly sales that aren't as correlated to temperature, overfitting is likely to occur. By forecasting Weekly_Sales for the 13 departments in the store, the store can better prepare for the selling season. By looking at Figure 5 for example, we can clearly see that in the forecasted 13 weeks, there is expected to be an increase in Weekly_Sales, so the department should prepare for that by taking inventory and making necessary adjustments to the inventory to account for the expected future increase in sales.

This brings us to our first limitation of this project, which is the time constraint. If more time was had, more models would have been explored with different combinations of external predictors, that may be better related to weekly sales than temperature. Also, regional differences in Weekly_Sales could have been addressed along with the department-specific differences in Weekly_Sales. The second main limitation of this project is the data. Our data was taken from Kaggle, which is known for not having the raw data set on their site. Instead of starting from the raw data, we were most likely starting using data that had been cleaned to some extent, given that there were no missing values in our original dataset, which is pretty uncommon.

Table 2

ARIMA model validation set RMSE values

	ARIMA Model (validation set RMSE)
Department 1	2122.17
Department 2	1334.388
Department 3	5262.03
Department 4	1205.92
Department 5	2084.07
Department 6	1453.45
Department 7	4339.94
Department 8	1580.37
Department 9	1598.22
Department 10	2672.13
Department 11	2401.94
Department 12	1448.29
Department 13	1314.43

Conclusion

The main goal of this paper was to forecast weekly sales for various retail stores departments, in order to better understand how seasonality can affect weekly sales and to help stores better prepare for their expected sales per week. Many models were created to forecast future sales of one store with multiple 13 departments. We have come to the conclusion that not only is the ARIMA model the best model, but we can try to apply this method to the other stores too. Since this model was based on 13 departments' weekly sales of one store the chance this model will work for the other stores is high as well. Something to consider as well for further research is to get the location of these various stores and try to forecast future sales based on distance from each store as well as the distance between the customers and the stores as foot traffic. By forecasting weekly sales for retail stores, the stores can see which of their departments have higher sales in which periods and use that information to better prepare for those time periods.

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ADS 506 Final Project Code

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Appendix Code

Loading in Libraries

```
# cleaning the memory
rm(list = ls())
# libraries
library(ggplot2)

library(tidyr)
library(plyr)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(forecast)

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

library(lubridate)

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
library(data.table)

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:lubridate':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

#install.packages('corrplot')
library(corrplot)

## corrplot 0.91 loaded

library(chron)

##
## Attaching package: 'chron'

## The following objects are masked from 'package:lubridate':
##
##     days, hours, minutes, seconds, years

library(fpp2)

## ── Attaching packages ─────────────────────────────────────── fpp2
2.4 ──

## ✓ fma       2.4      ✓ expsmooth 2.3

##

require(gridExtra)

## Loading required package: gridExtra

##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:dplyr':
##
##     combine
```

Loading in all 3 data sets

```
Sales_df <- read.csv("/Users/clairephibbs/Desktop/ADS 506 Applied Time Series
Analysis/Final Project/sales data-set.csv")

Feature_df <- read.csv("/Users/clairephibbs/Desktop/ADS 506 Applied Time Seri
```

```
es Analysis/Final Project/Features data set.csv")

Stores_df <- read.csv("/Users/clairephibbs/Desktop/ADS 506 Applied Time Serie
s Analysis/Final Project/stores data-set.csv")
```

Sales Data

```
# change the variable into appropriate type
Sales_df <-
  Sales_df %>%
  mutate(Store = as.factor(Store),
         Dept = as.factor(Dept),
         IsHoliday = as.factor(IsHoliday),
         Date = as.Date(Date, "%d/%m/%Y"))

# removing the nenagive sales
Sales_df <- Sales_df %>%
  filter(Weekly_Sales >= 0)
```

Feature Data

```
Feature_df <-
  Feature_df %>%
  mutate(Store = as.factor(Store),
         IsHoliday = as.factor(IsHoliday),
         Date = as.Date(Date, "%d/%m/%Y"))
```

Combining Sales and Feature Data

```
df <- Sales_df %>%inner_join(Feature_df) %>%
  select(c(1:7, 13:14), Weekly_Sales)

## Joining, by = c("Store", "Date", "IsHoliday")

# attaching the data

attach(df)

# reformatting date to 2 digit years
df$Date <- as.character(df$Date, format = '%m/%d/%y')
```

Store Data

```
Stores_df <-
  Stores_df %>%
  mutate(Store = as.factor(Store))
```

Exploratory Data Analysis (EDA):

From this point forwards only working with Store 1 data.

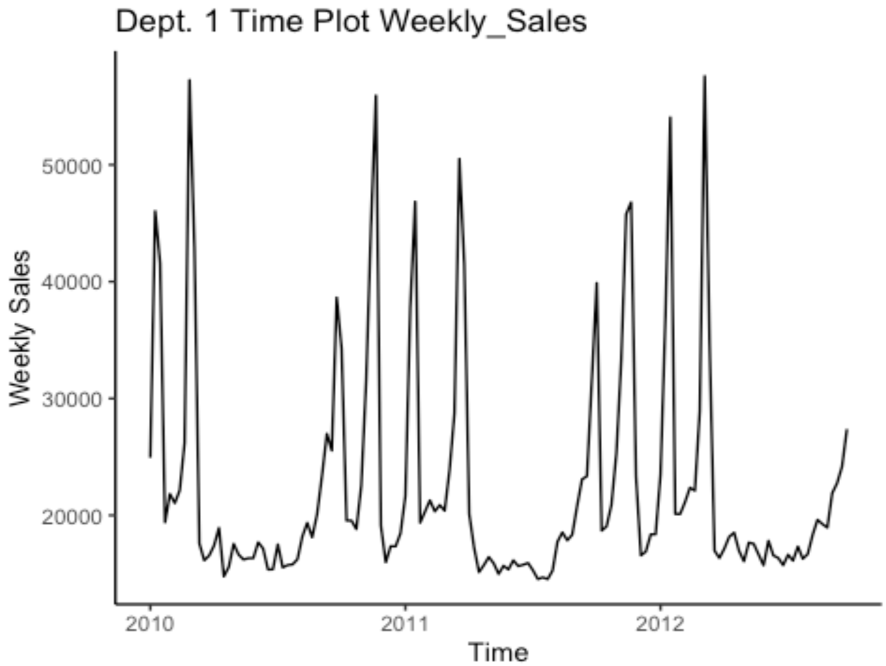
Time Series Objects for the Weekly_Sales

```
# separating departments of store 1 and creating time series objects
store_1.1 <- df[1:143, ]
```

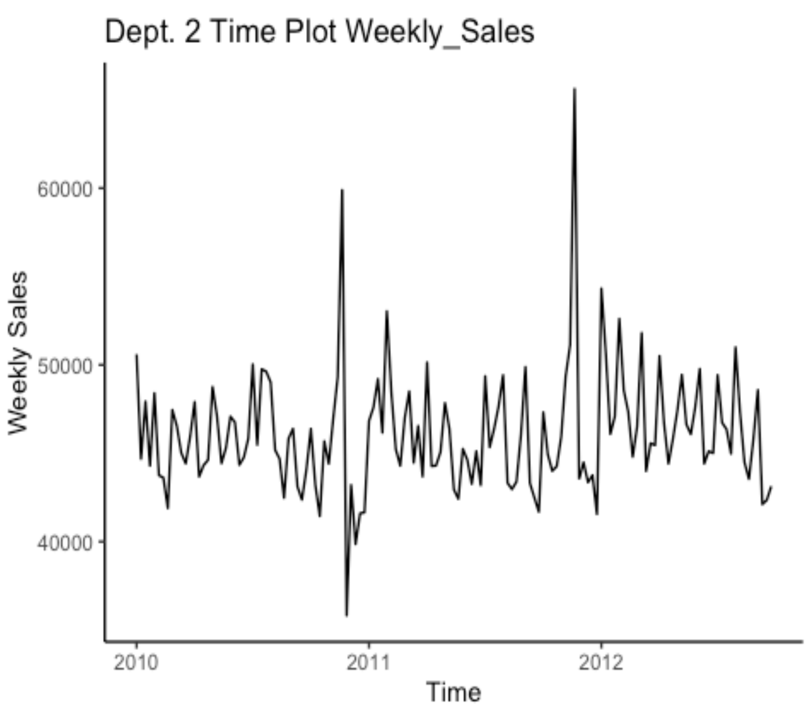
```
store_1.1_ts <- ts(store_1.1$Weekly_Sales, start = c(2010), frequency = 52)

store_1.2 <- df[144:286, ]
store_1.2_ts <- ts(store_1.2$Weekly_Sales, start = c(2010), frequency = 52)

store_1.3 <- df[287:429, ]
store_1.3_ts <- ts(store_1.3$Weekly_Sales, start = c(2010), frequency = 52)

store_1.4 <- df[430:572, ]
store_1.4_ts <- ts(store_1.4$Weekly_Sales, start = c(2010), frequency = 52)

store_1.5 <- df[573:715, ]
store_1.5_ts <- ts(store_1.5$Weekly_Sales, start = c(2010), frequency = 52)

store_1.6 <- df[715:857, ]
store_1.6_ts <- ts(store_1.6$Weekly_Sales, start = c(2010), frequency = 52)

store_1.7 <- df[858:1000, ]
store_1.7_ts <- ts(store_1.7$Weekly_Sales, start = c(2010), frequency = 52)

store_1.8 <- df[1001:1143, ]
store_1.8_ts <- ts(store_1.8$Weekly_Sales, start = c(2010), frequency = 52)

store_1.9 <- df[1144:1286, ]
store_1.9_ts <- ts(store_1.9$Weekly_Sales, start = c(2010), frequency = 52)

store_1.10 <- df[1287:1429, ]
store_1.10_ts <- ts(store_1.10$Weekly_Sales, start = c(2010), frequency = 52)

store_1.11 <- df[1430:1572, ]
store_1.11_ts <- ts(store_1.11$Weekly_Sales, start = c(2010), frequency = 52)

store_1.12 <- df[1573:1715, ]
store_1.12_ts <- ts(store_1.12$Weekly_Sales, start = c(2010), frequency = 52)

store_1.13 <- df[1716:1858, ]
store_1.13_ts <- ts(store_1.13$Weekly_Sales, start = c(2010), frequency = 52)
```

Time Plots of Store 1 Department 1-13 Weekly Sales

```
autoplot(store_1.1_ts) +
  labs(title = "Dept. 1 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```

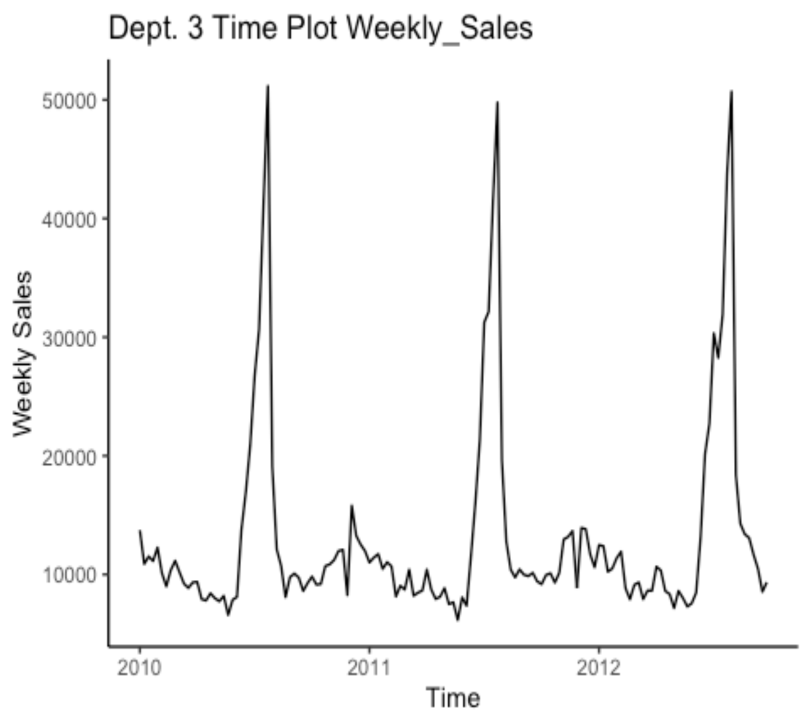



```
autoplot(store_1.2_ts) +
  labs(title = "Dept. 2 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```

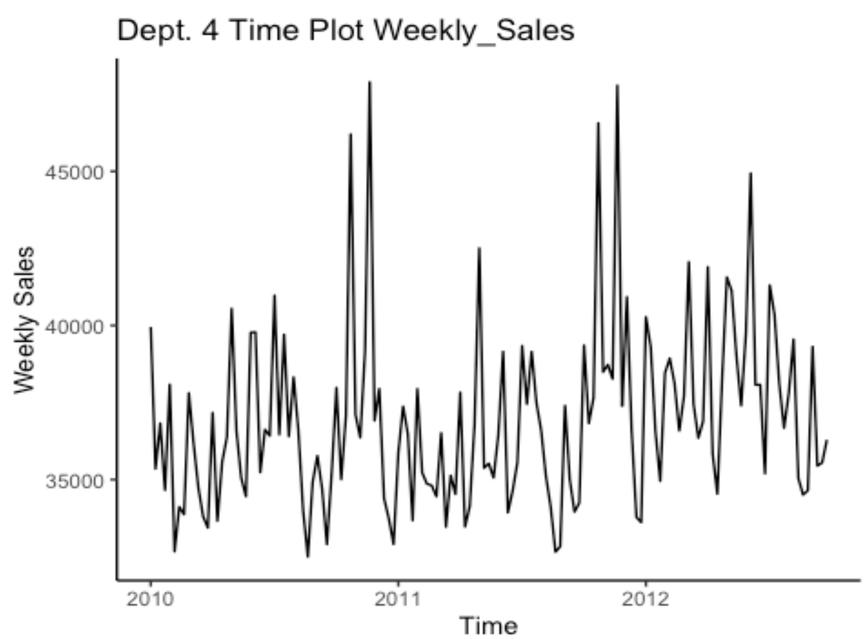



```
autoplot(store_1.3_ts) +
  labs(title = "Dept. 3 Time Plot Weekly_Sales",
```

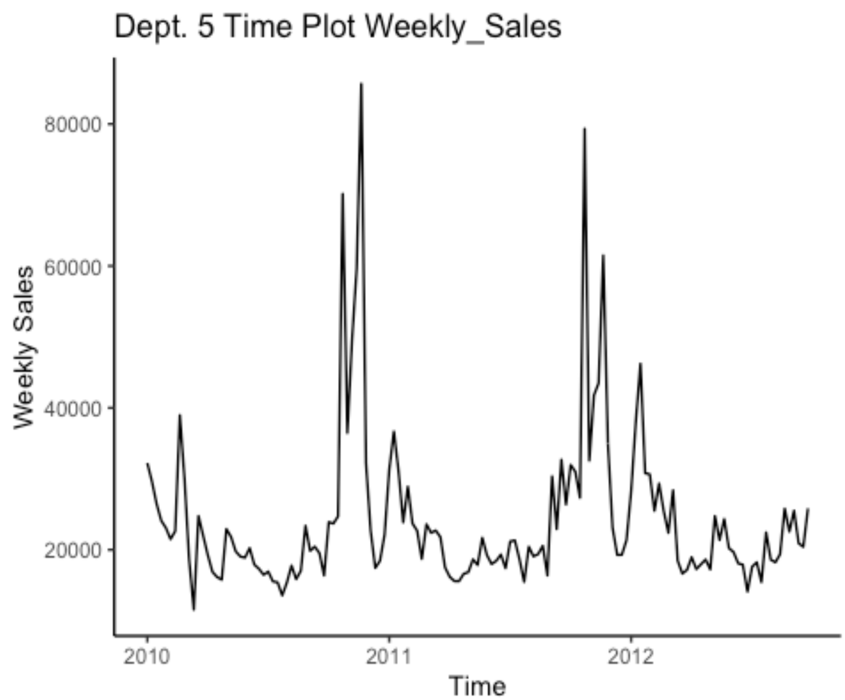
```
      x = "Time",
      y = "Weekly Sales") +
  theme_classic()
```



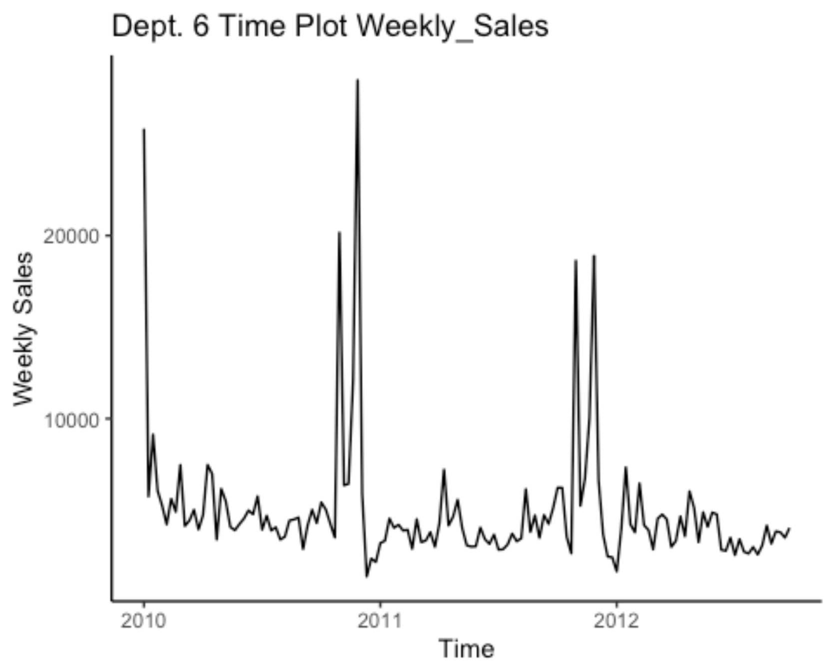

```
autoplot(store_1.4_ts) +
  labs(title = "Dept. 4 Time Plot Weekly_Sales",
      x = "Time",
      y = "Weekly Sales") +
    theme_classic()
```



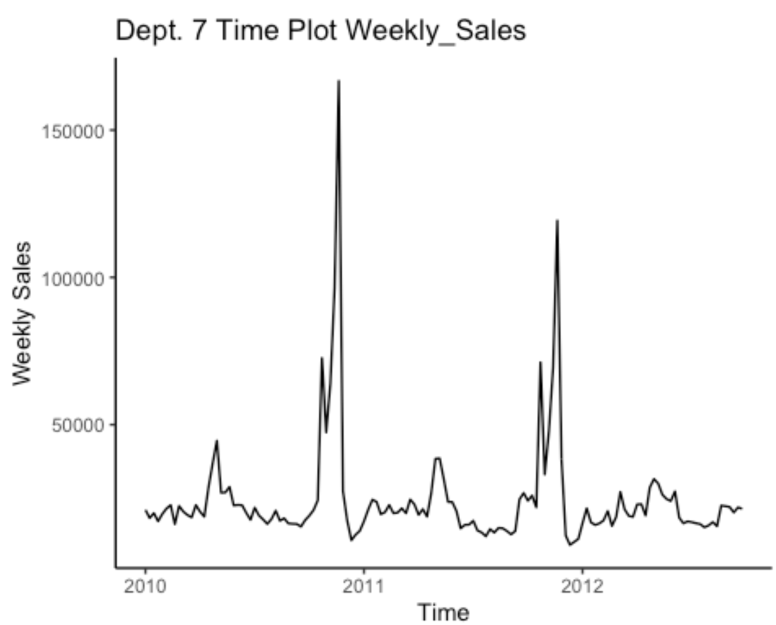
```
autoplot(store_1.5_ts) +
  labs(title = "Dept. 5 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



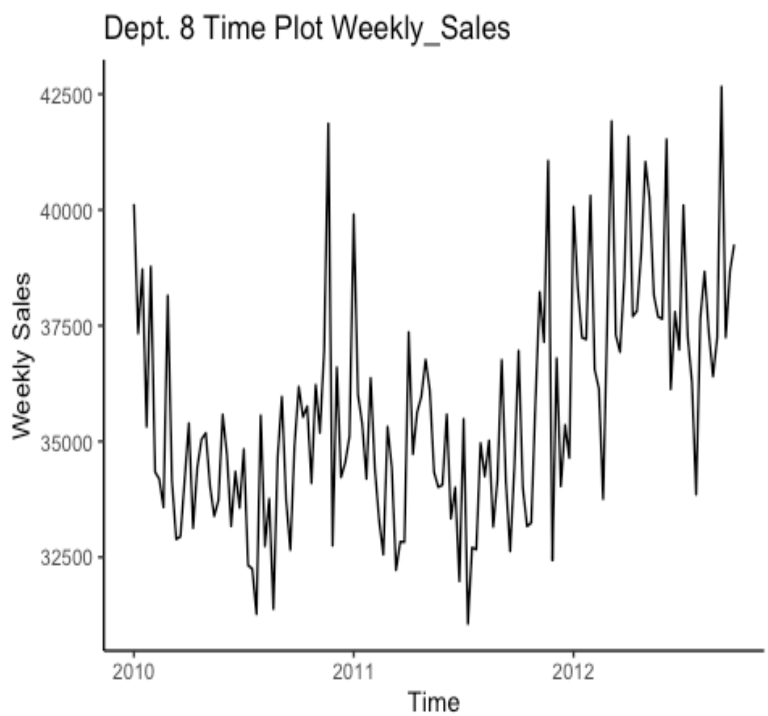

```
autoplot(store_1.6_ts) +
  labs(title = "Dept. 6 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



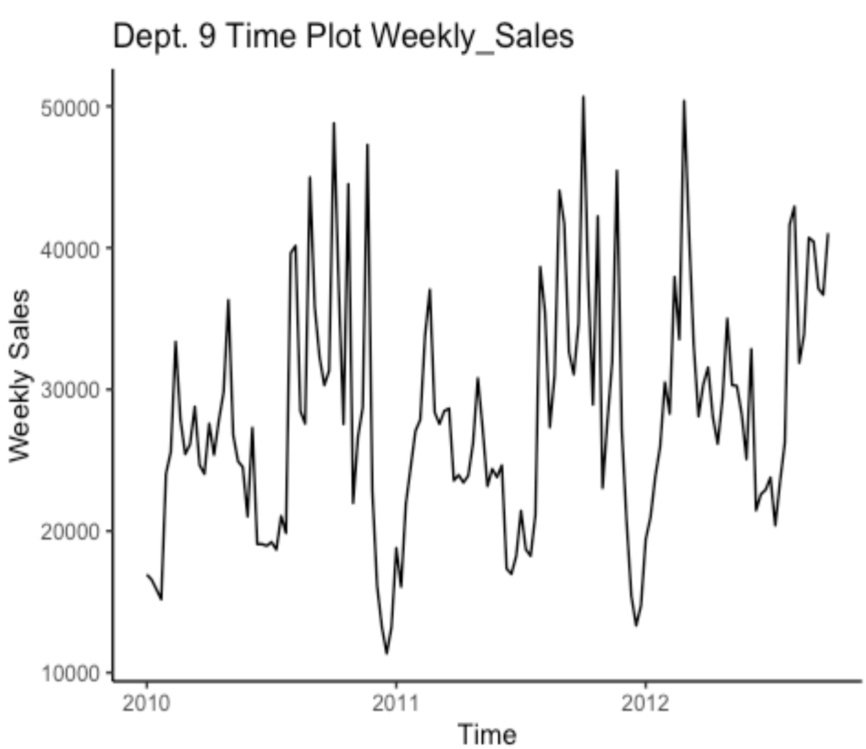

```
autoplot(store_1.7_ts) +
  labs(title = "Dept. 7 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



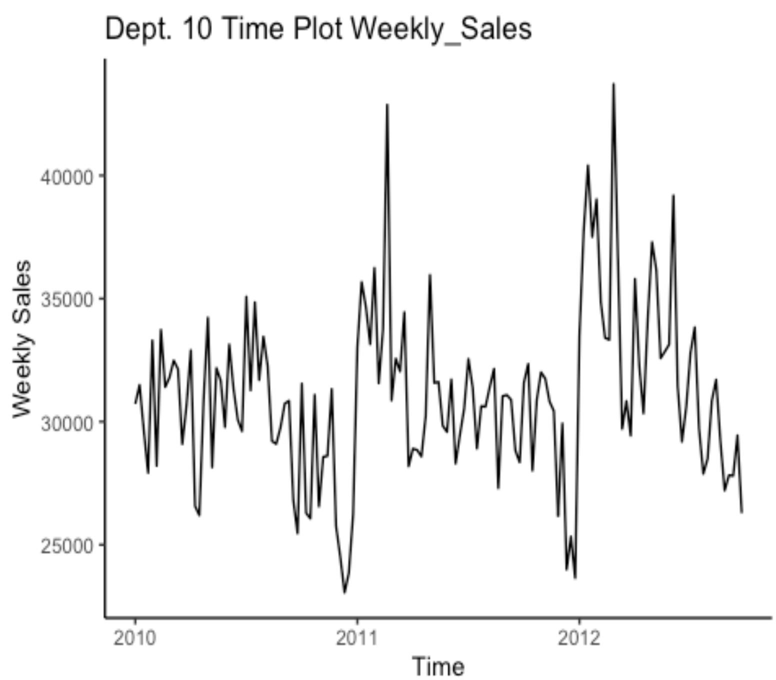

```
autoplot(store_1.8_ts) +
  labs(title = "Dept. 8 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



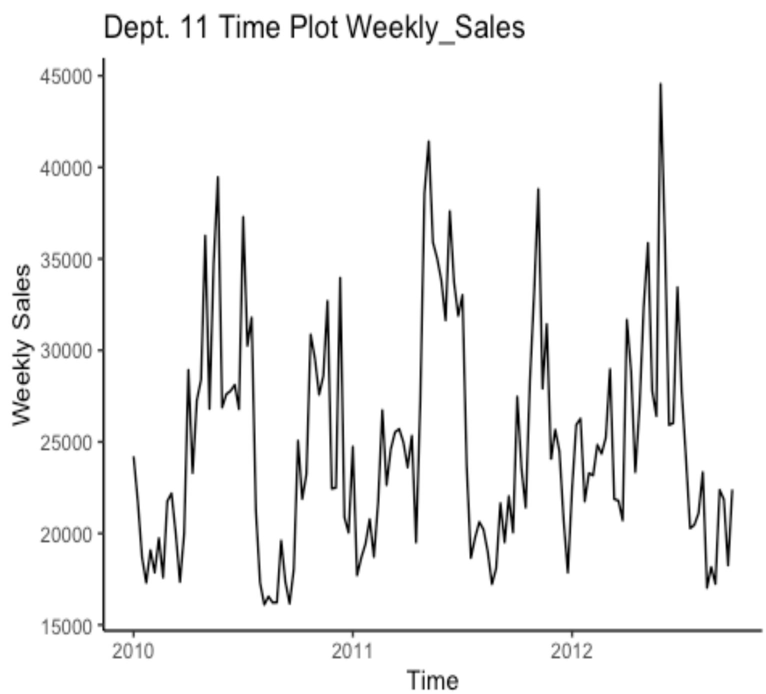

```
autoplot(store_1.9_ts) +
  labs(title = "Dept. 9 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



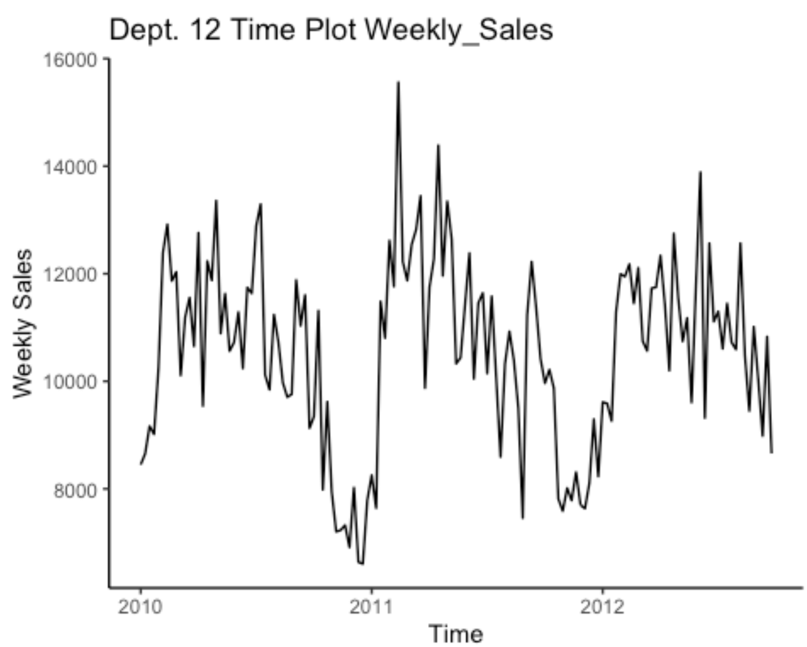
```
autoplot(store_1.10_ts) +
  labs(title = "Dept. 10 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
autoplot(store_1.11_ts) +
  labs(title = "Dept. 11 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```

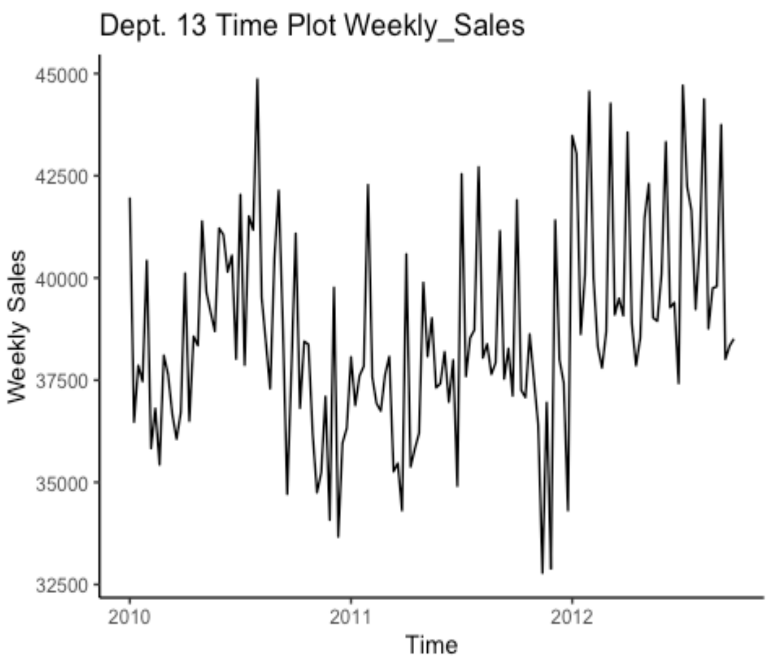



```
autoplot(store_1.12_ts) +
  labs(title = "Dept. 12 Time Plot Weekly_Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



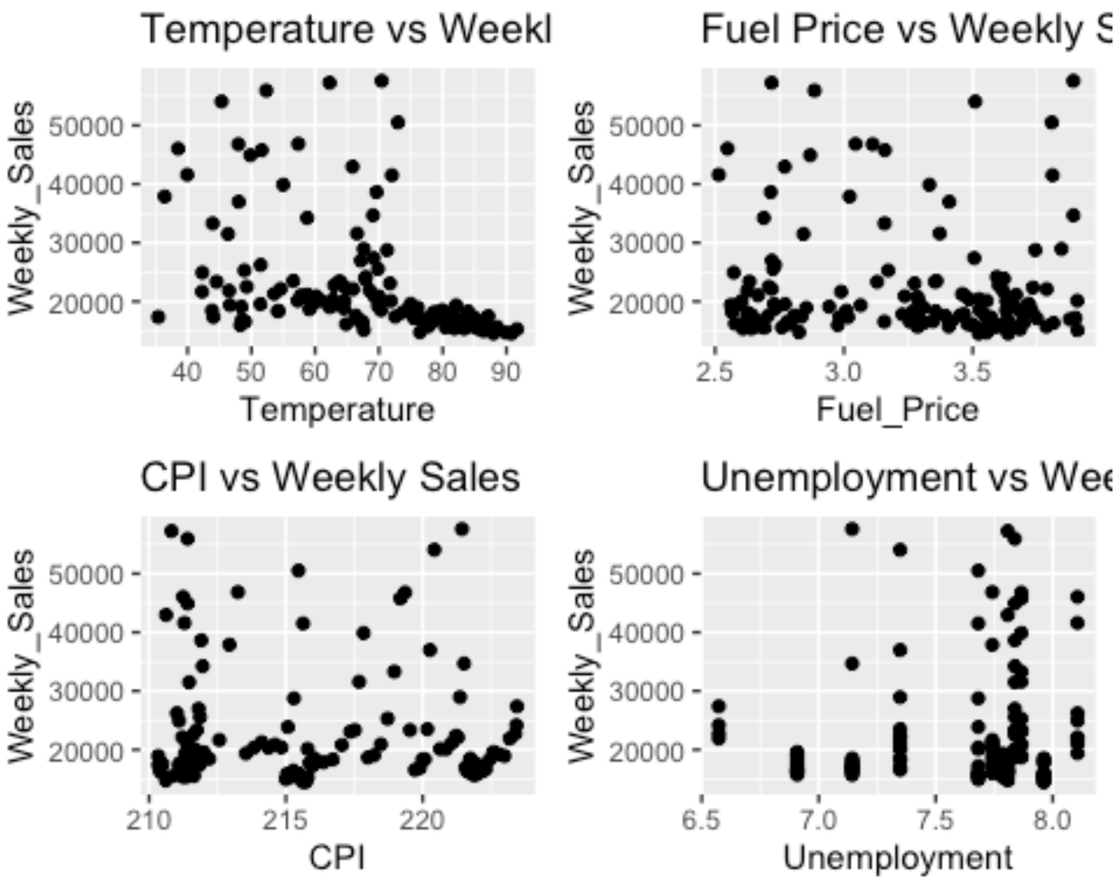

```
autoplot(store_1.13_ts) +
  labs(title = "Dept. 13 Time Plot Weekly_Sales",
       x = "Time",
```

```
       y = "Weekly Sales") +
    theme_classic()
```

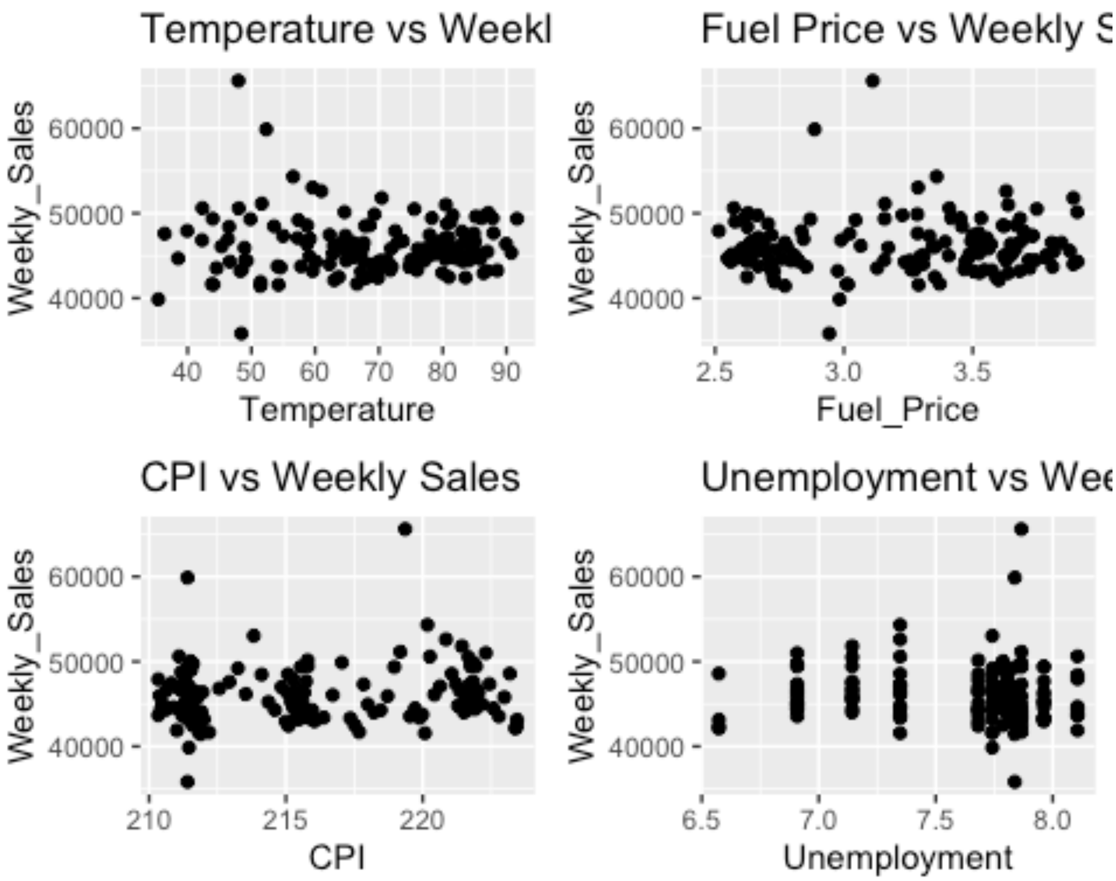


Scatter Plots of Each Departments Weekly_Sales vs. Unemployment/CPI/Temperature/Unemployment

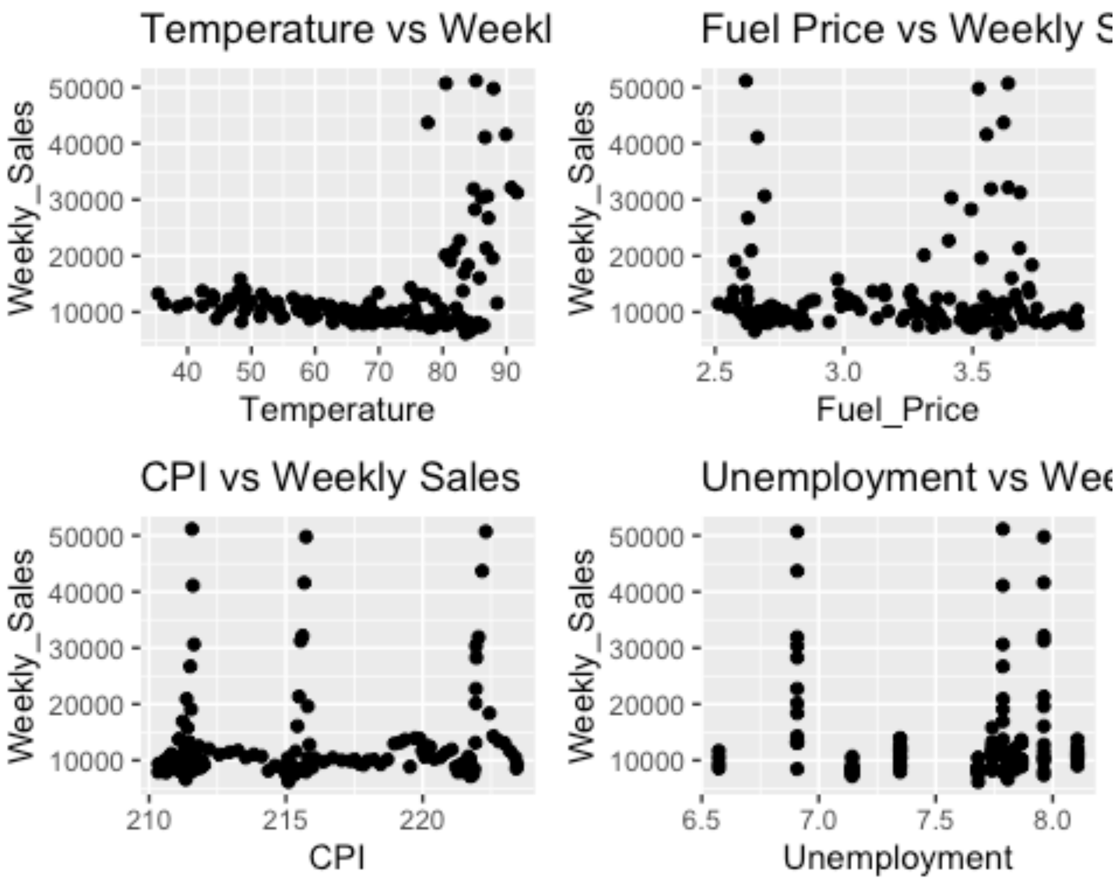
```
scatter_1.1.1 <- ggplot(store_1.1, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.1.2 <- ggplot(store_1.1, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.1.3 <- ggplot(store_1.1, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.1.4 <- ggplot(store_1.1, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.1.1, scatter_1.1.2, scatter_1.1.3, scatter_1.1.4)
```



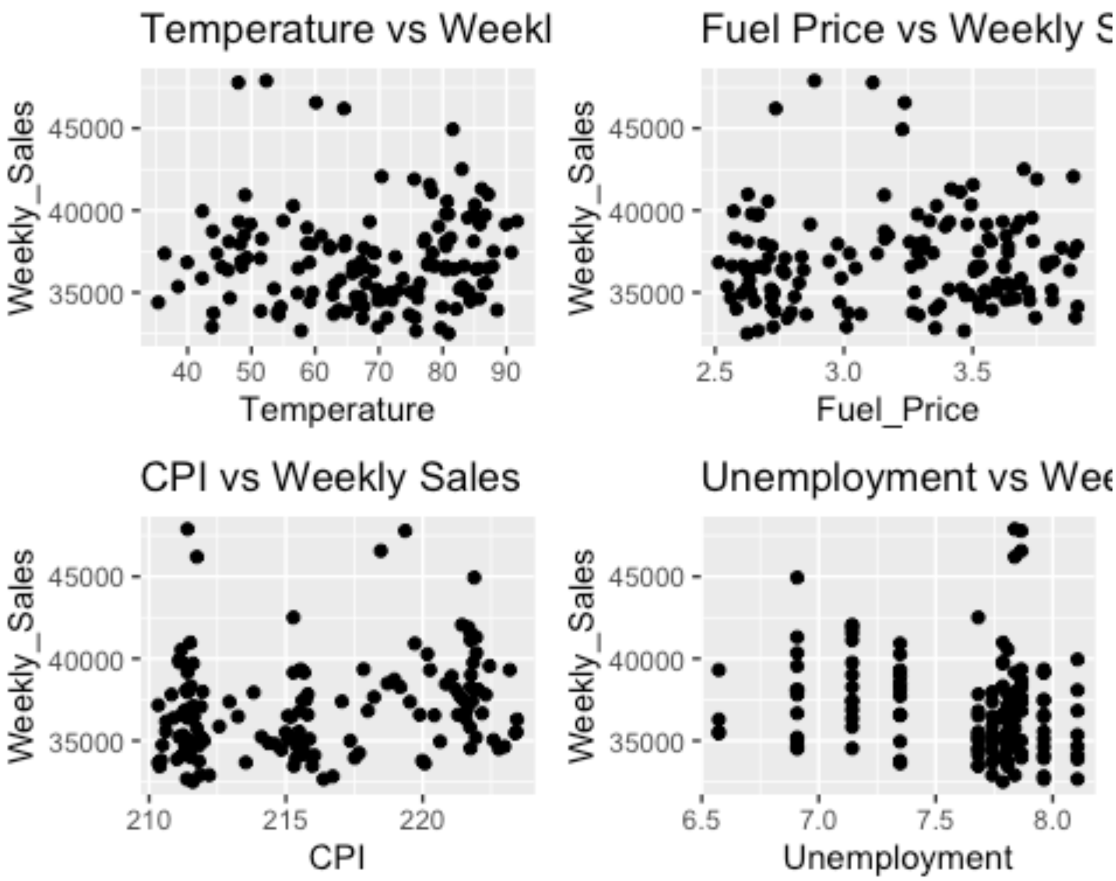

```r
scatter_1.2.1 <- ggplot(store_1.2, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.2.2 <- ggplot(store_1.2, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.2.3 <- ggplot(store_1.2, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.2.4 <- ggplot(store_1.2, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.2.1, scatter_1.2.2, scatter_1.2.3, scatter_1.2.4)
```



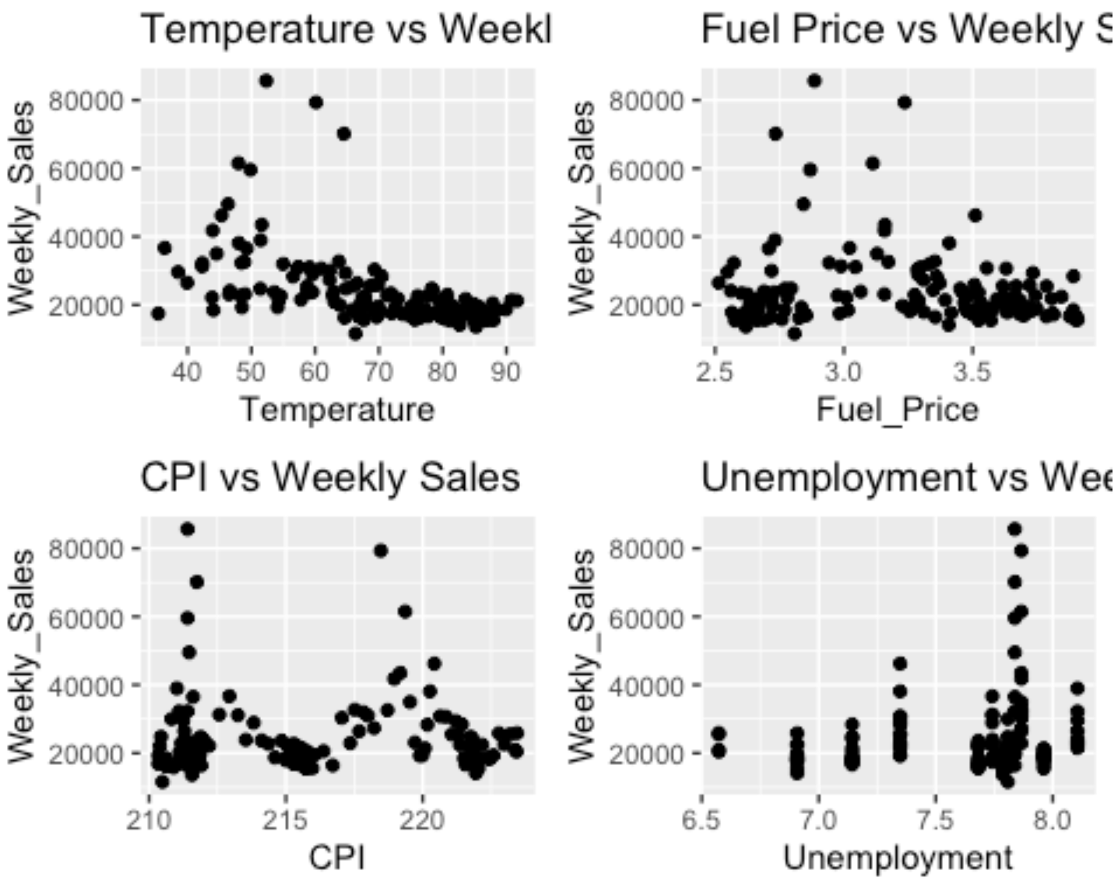

```
scatter_1.3.1 <- ggplot(store_1.3, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.3.2 <- ggplot(store_1.3, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.3.3 <- ggplot(store_1.3, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.3.4 <- ggplot(store_1.3, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.3.1, scatter_1.3.2, scatter_1.3.3, scatter_1.3.4)
```



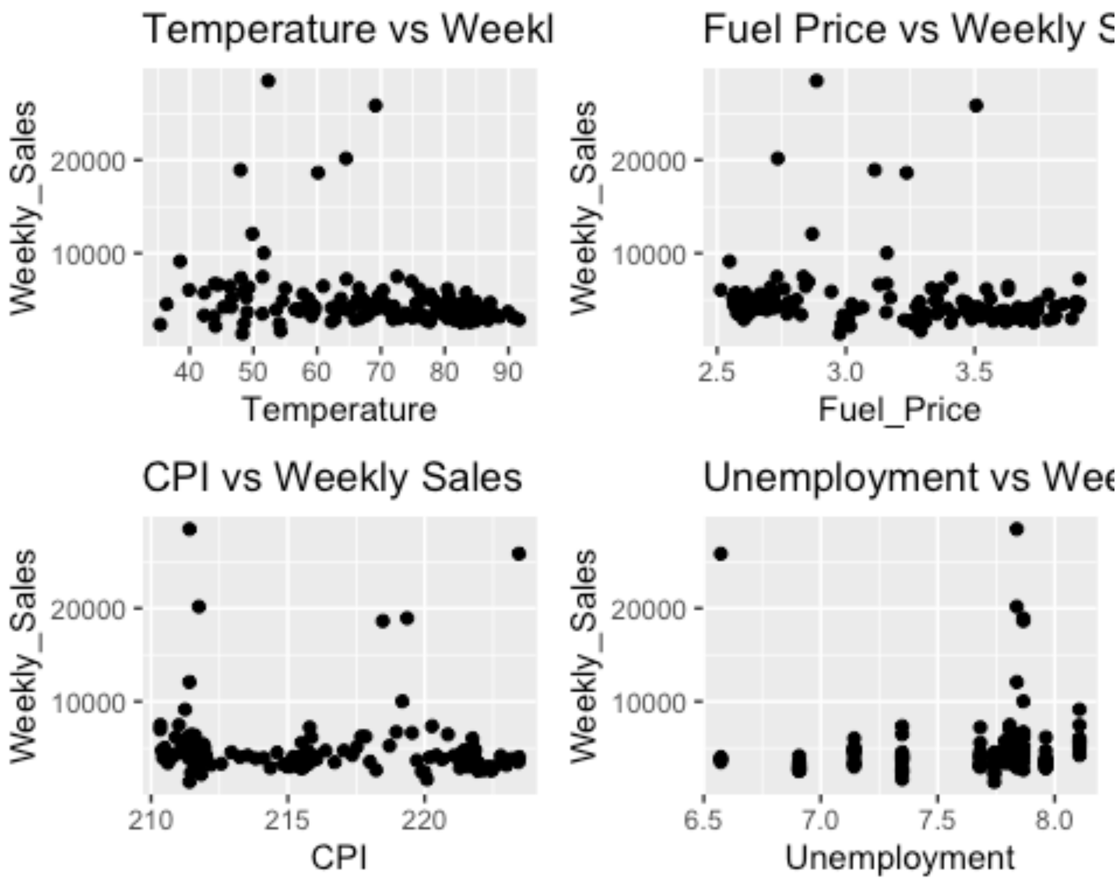

```r
scatter_1.4.1 <- ggplot(store_1.4, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.4.2 <- ggplot(store_1.4, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.4.3 <- ggplot(store_1.4, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.4.4 <- ggplot(store_1.4, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.4.1, scatter_1.4.2, scatter_1.4.3, scatter_1.4.4)
```



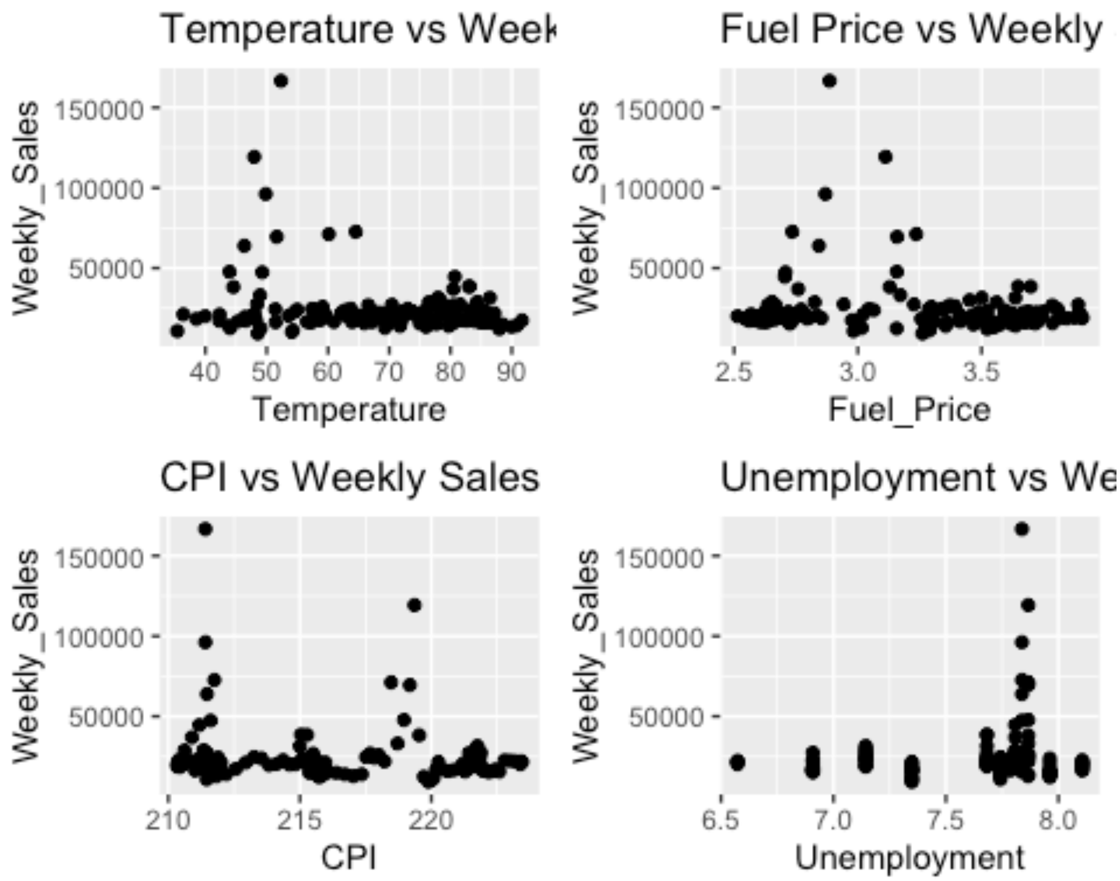

```
scatter_1.5.1 <- ggplot(store_1.5, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.5.2 <- ggplot(store_1.5, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.5.3 <- ggplot(store_1.5, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.5.4 <- ggplot(store_1.5, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.5.1, scatter_1.5.2, scatter_1.5.3, scatter_1.5.4)
```



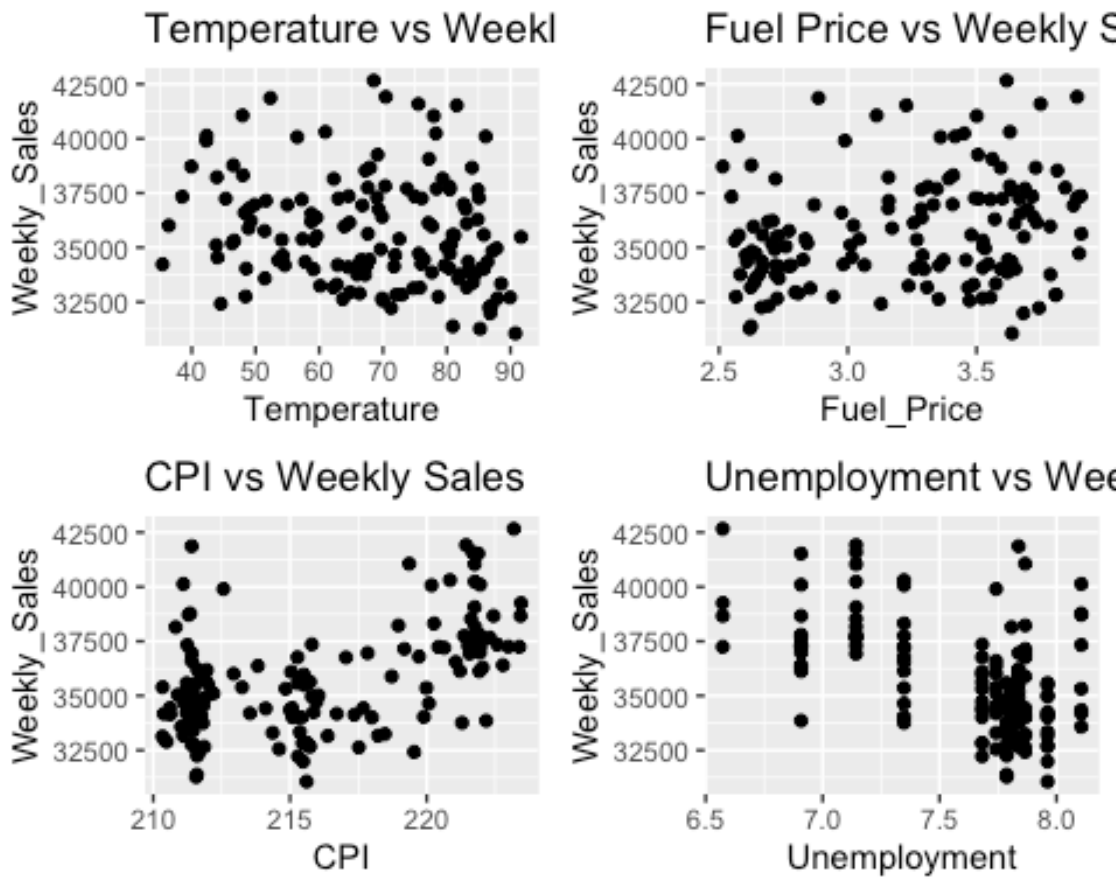

```
scatter_1.6.1 <- ggplot(store_1.6, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.6.2 <- ggplot(store_1.6, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.6.3 <- ggplot(store_1.6, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.6.4 <- ggplot(store_1.6, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.6.1, scatter_1.6.2, scatter_1.6.3, scatter_1.6.4)
```



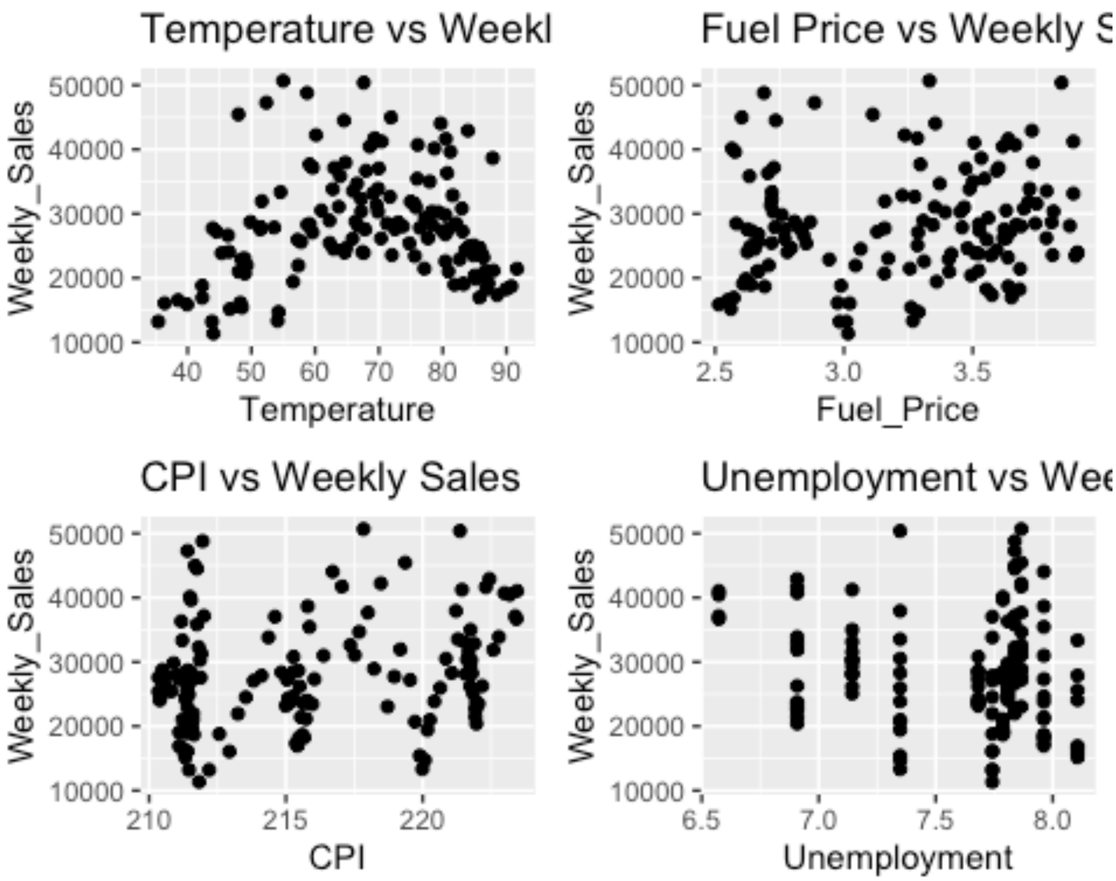

```
scatter_1.7.1 <- ggplot(store_1.7, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.7.2 <- ggplot(store_1.7, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.7.3 <- ggplot(store_1.7, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.7.4 <- ggplot(store_1.7, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.7.1, scatter_1.7.2, scatter_1.7.3, scatter_1.7.4)
```



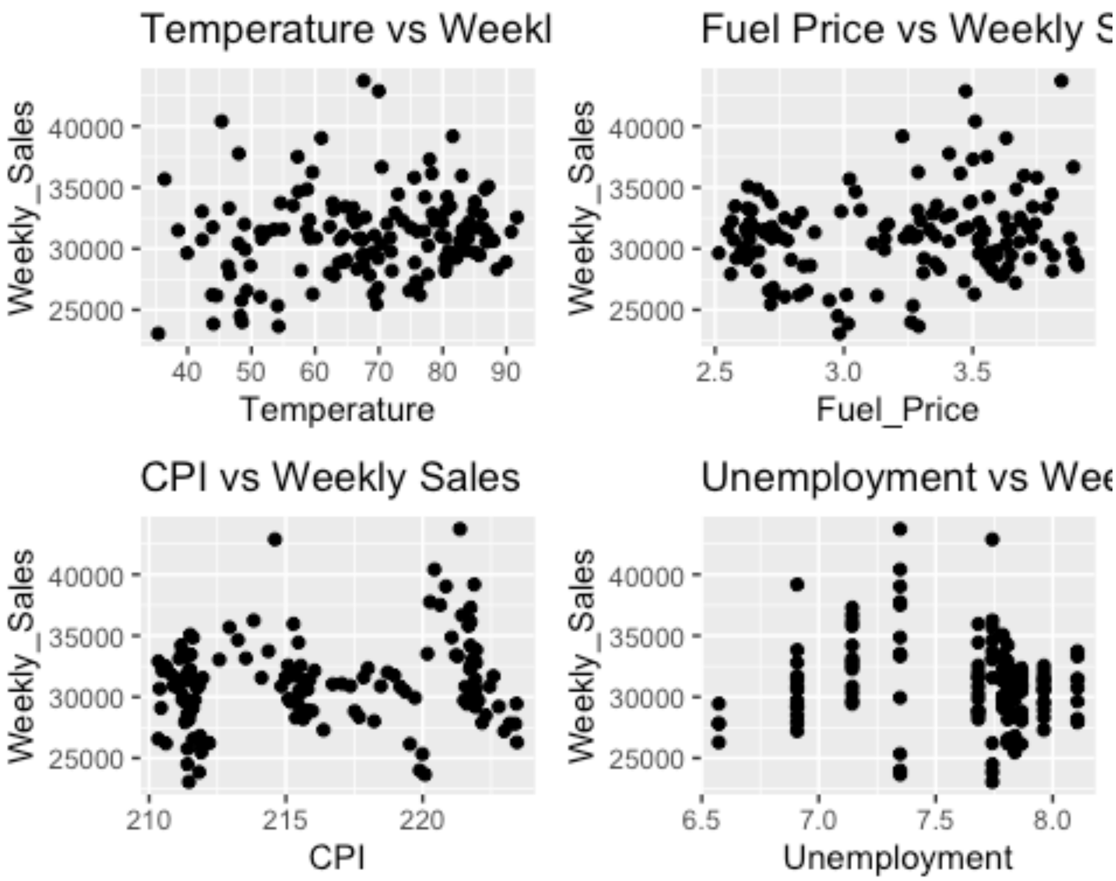

```
scatter_1.8.1 <- ggplot(store_1.8, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.8.2 <- ggplot(store_1.8, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.8.3 <- ggplot(store_1.8, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.8.4 <- ggplot(store_1.8, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.8.1, scatter_1.8.2, scatter_1.8.3, scatter_1.8.4)
```



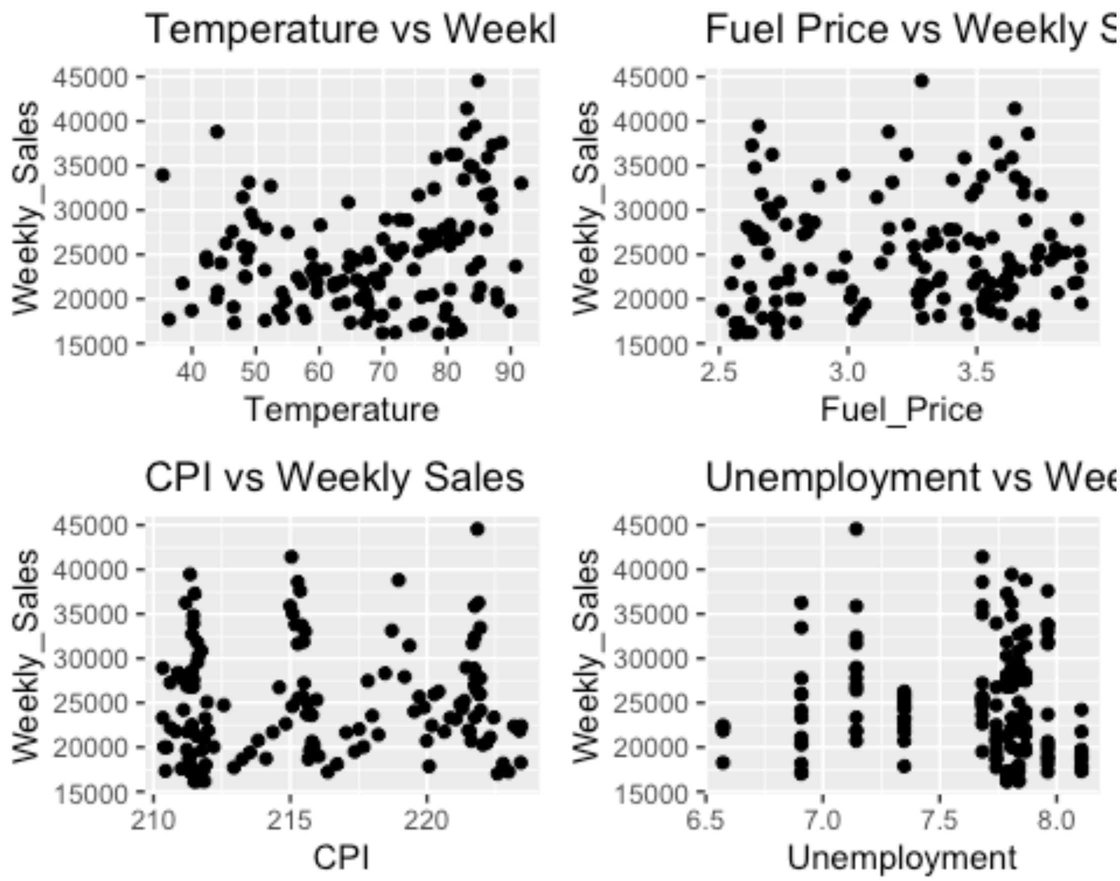

```r
scatter_1.9.1 <- ggplot(store_1.9, aes(x = Temperature, y = Weekly_Sales)) +
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.9.2 <- ggplot(store_1.9, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.9.3 <- ggplot(store_1.9, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.9.4 <- ggplot(store_1.9, aes(x = Unemployment, y = Weekly_Sales)) +
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.9.1, scatter_1.9.2, scatter_1.9.3, scatter_1.9.4)
```



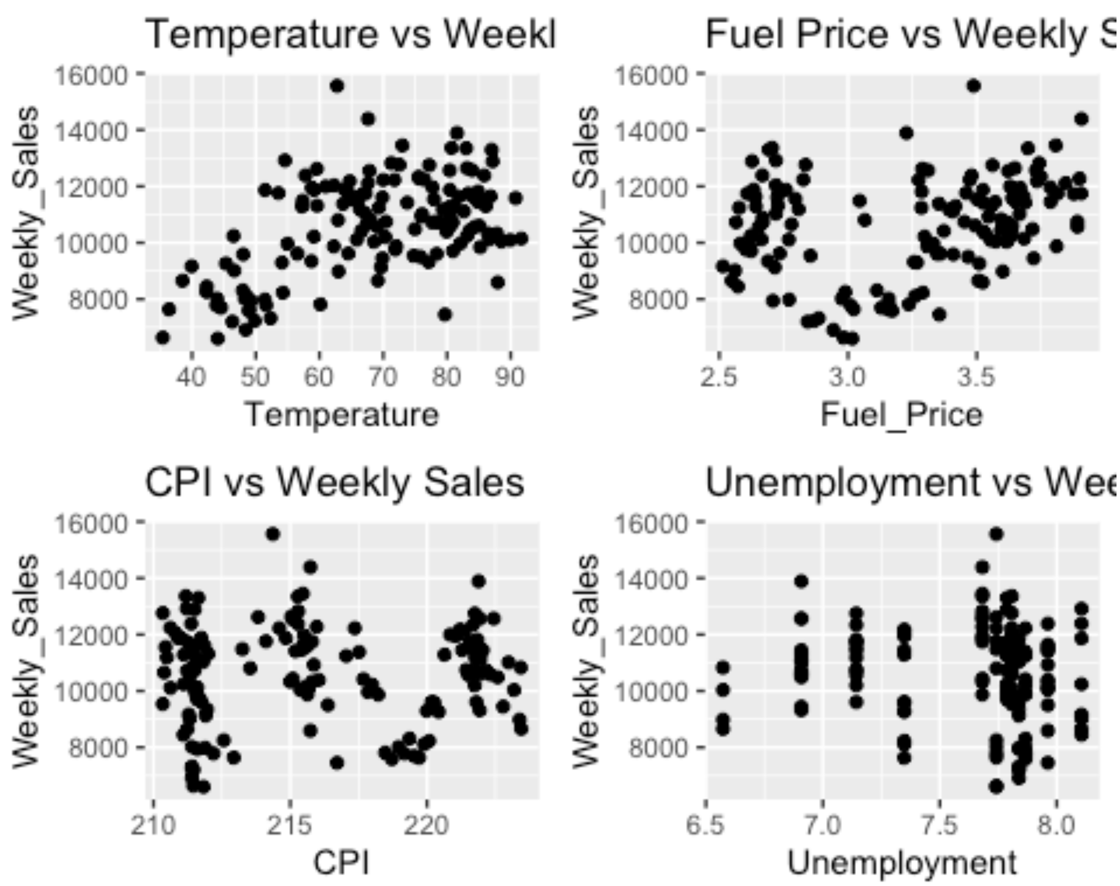

```
scatter_1.10.1 <- ggplot(store_1.10, aes(x = Temperature, y = Weekly_Sales))
+
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.10.2 <- ggplot(store_1.10, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.10.3 <- ggplot(store_1.10, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.10.4 <- ggplot(store_1.10, aes(x = Unemployment, y = Weekly_Sales))
+
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.10.1, scatter_1.10.2, scatter_1.10.3, scatter_1.10.4)
```



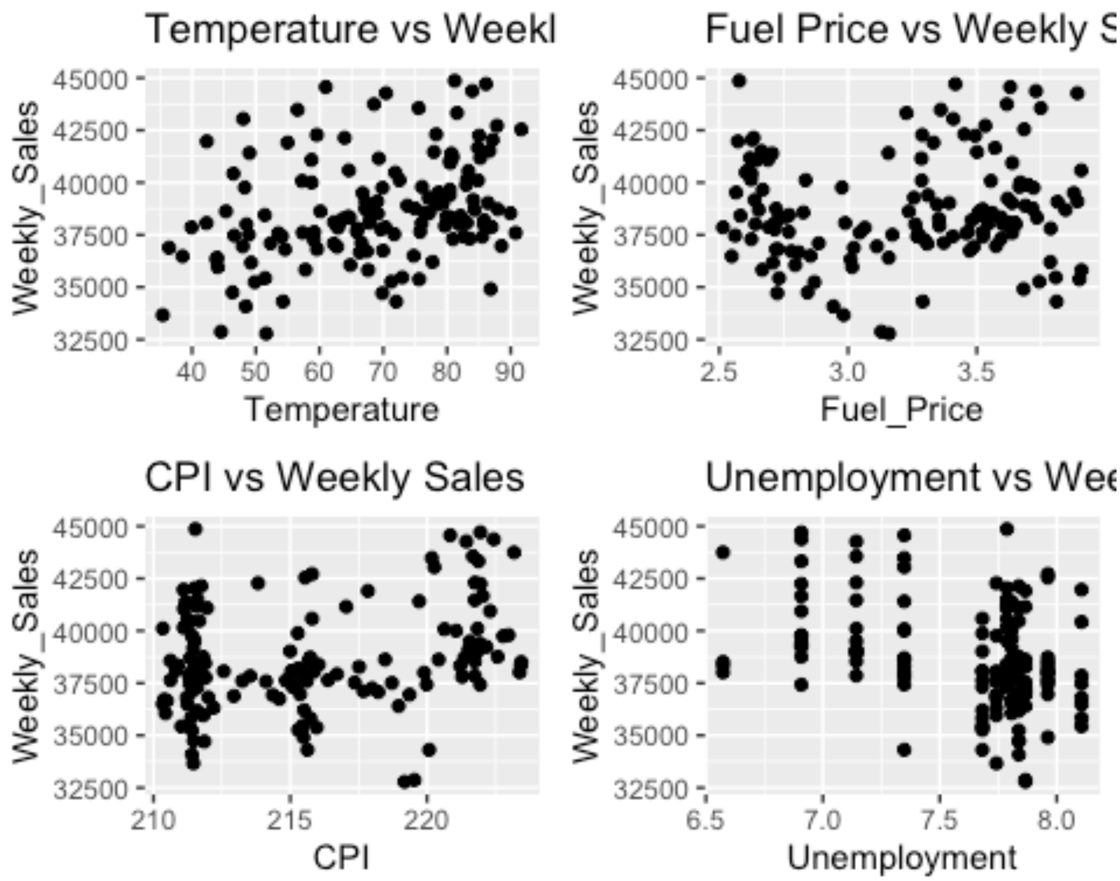

```
scatter_1.11.1 <- ggplot(store_1.11, aes(x = Temperature, y = Weekly_Sales))
+
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.11.2 <- ggplot(store_1.11, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.11.3 <- ggplot(store_1.11, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.11.4 <- ggplot(store_1.11, aes(x = Unemployment, y = Weekly_Sales))
+
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.11.1, scatter_1.11.2, scatter_1.11.3, scatter_1.11.4)
```




```
scatter_1.12.1 <- ggplot(store_1.12, aes(x = Temperature, y = Weekly_Sales))
+
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.12.2 <- ggplot(store_1.12, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.12.3 <- ggplot(store_1.12, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.12.4 <- ggplot(store_1.12, aes(x = Unemployment, y = Weekly_Sales))
+
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.12.1, scatter_1.12.2, scatter_1.12.3, scatter_1.12.4)
```

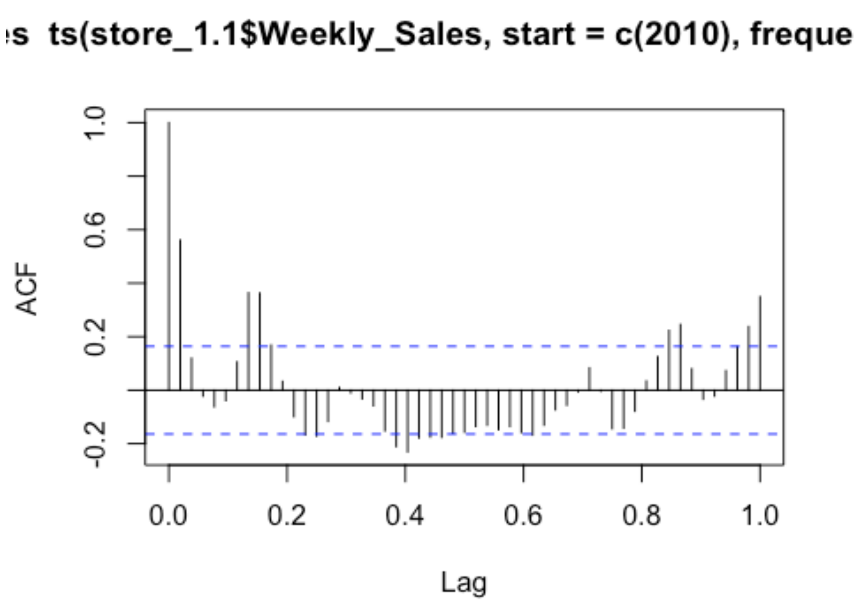



```
scatter_1.13.1 <- ggplot(store_1.13, aes(x = Temperature, y = Weekly_Sales))
+
  ggtitle("Temperature vs Weekly Sales") +
  geom_point()

scatter_1.13.2 <- ggplot(store_1.13, aes(x = Fuel_Price, y = Weekly_Sales)) +
  ggtitle("Fuel Price vs Weekly Sales") +
  geom_point()

scatter_1.13.3 <- ggplot(store_1.13, aes(x = CPI, y = Weekly_Sales)) +
  ggtitle("CPI vs Weekly Sales") +
  geom_point()

scatter_1.13.4 <- ggplot(store_1.13, aes(x = Unemployment, y = Weekly_Sales))
+
  ggtitle("Unemployment vs Weekly Sales") +
  geom_point()

grid.arrange(scatter_1.13.1, scatter_1.13.2, scatter_1.13.3, scatter_1.13.4)
```

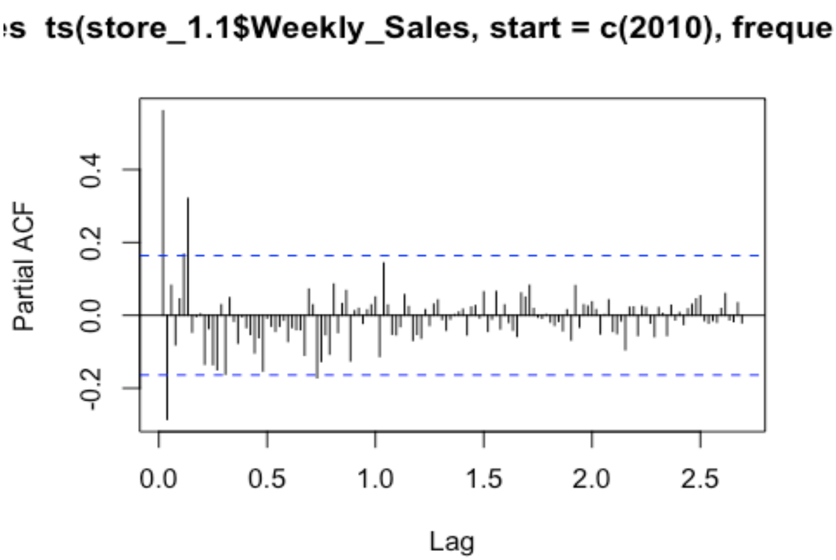


Autocorrelation Plots of Weekly_Sales

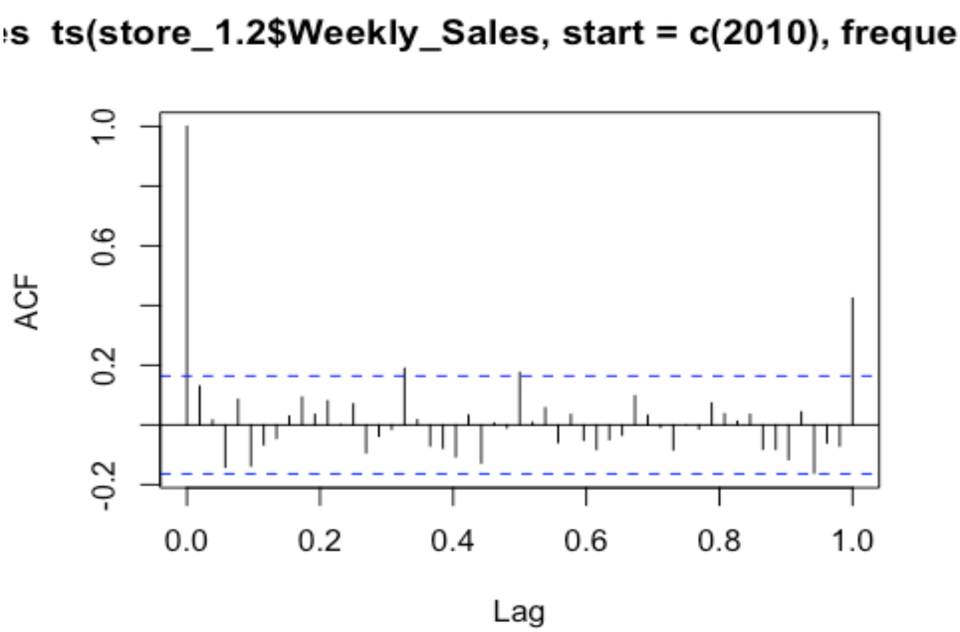
```
# department 1
acf(ts(store_1.1$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



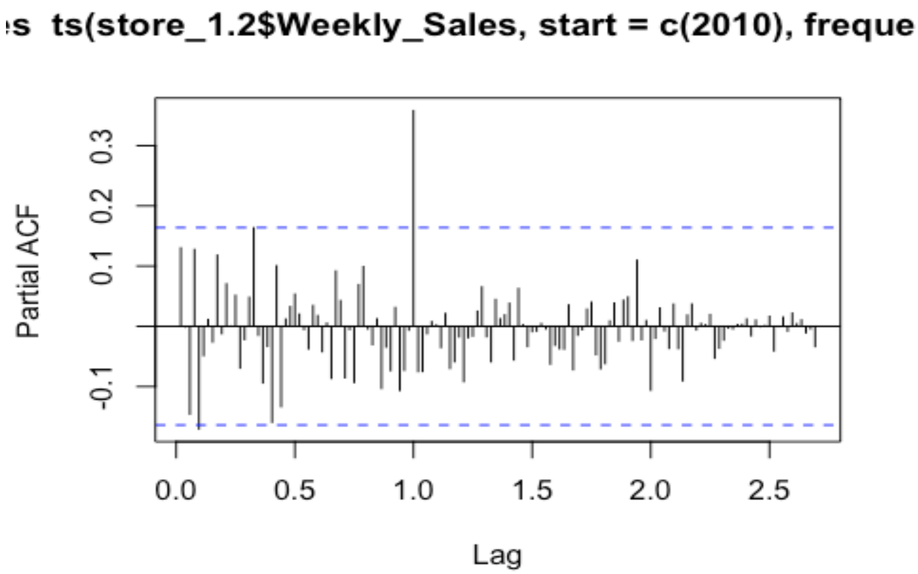
```
pacf(ts(store_1.1$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



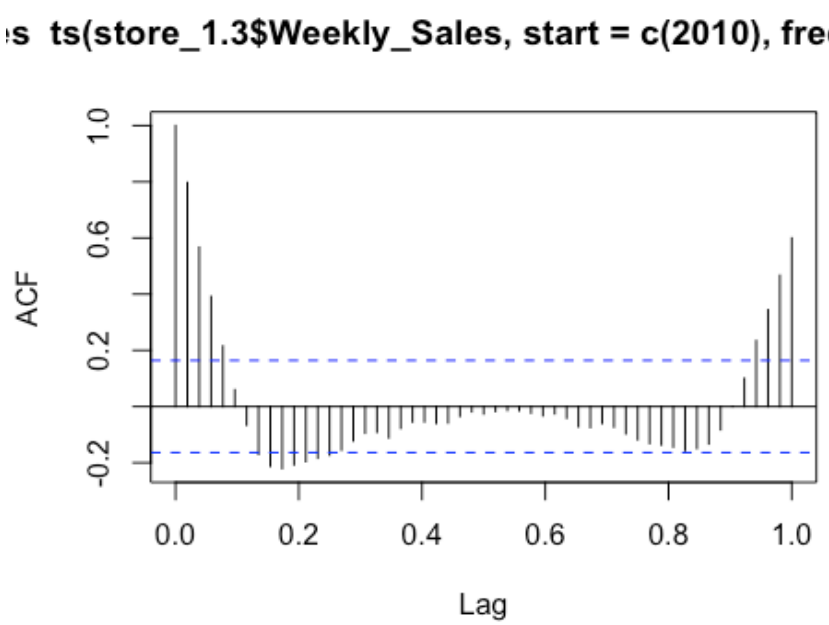

```
#department 2
acf(ts(store_1.2$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



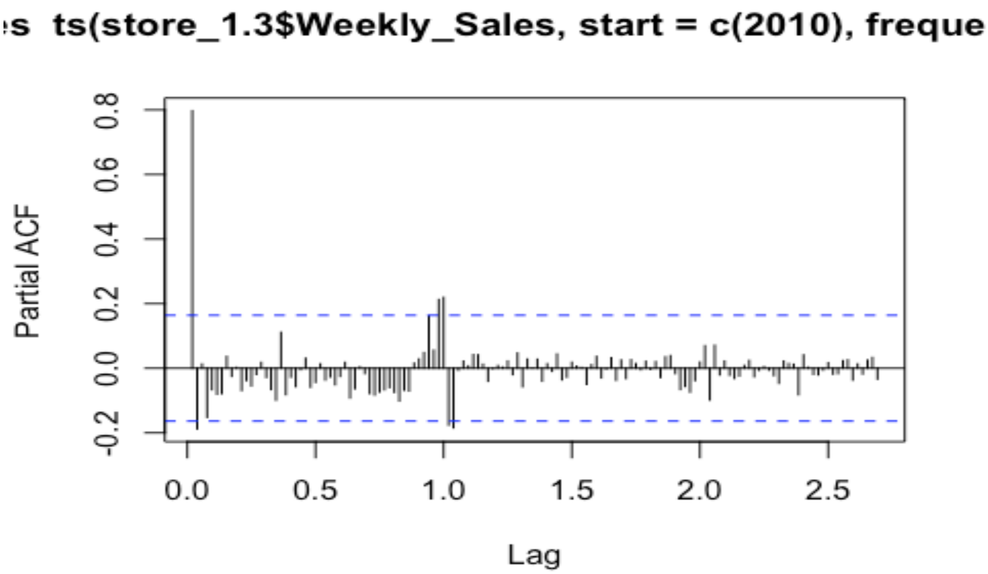

```
pacf(ts(store_1.2$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



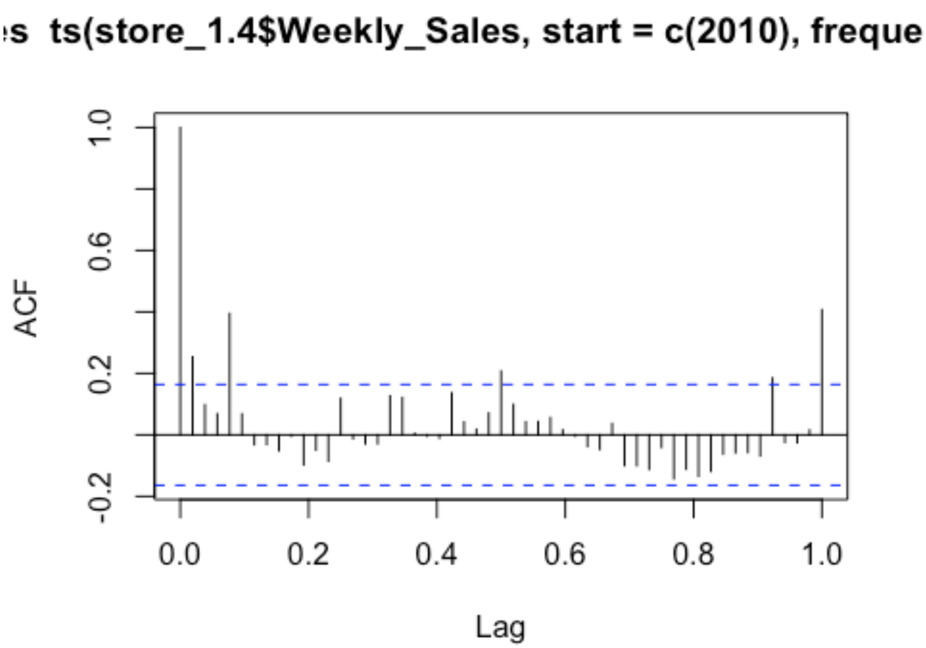

```r
# department 3
acf(ts(store_1.3$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



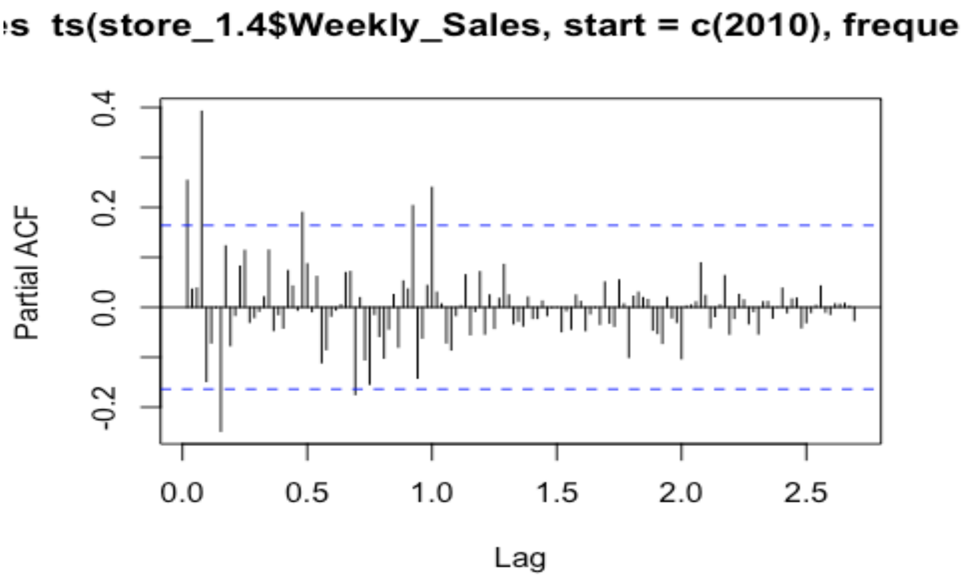

```r
pacf(ts(store_1.3$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



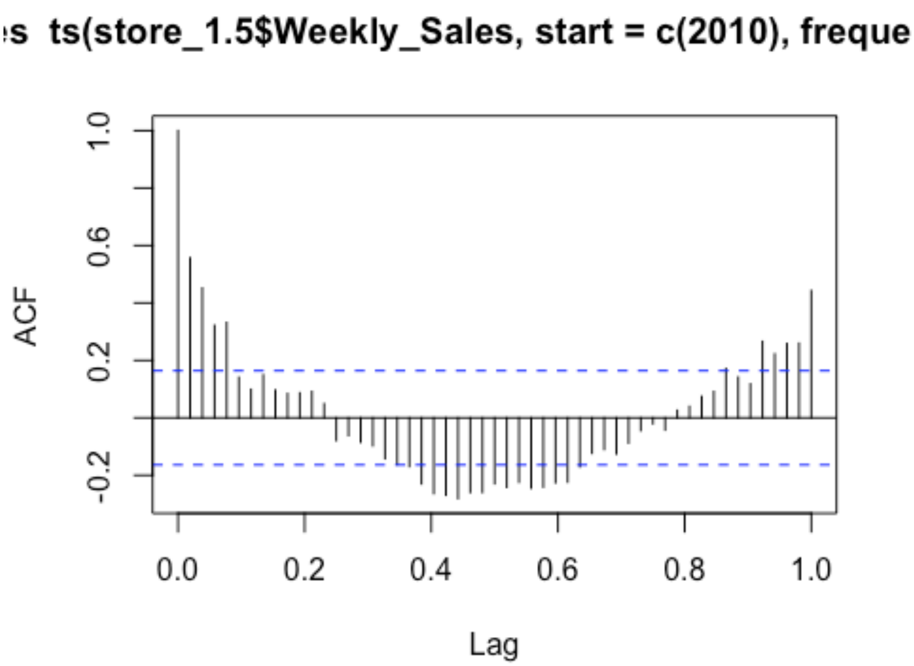

```r
# department 4
acf(ts(store_1.4$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



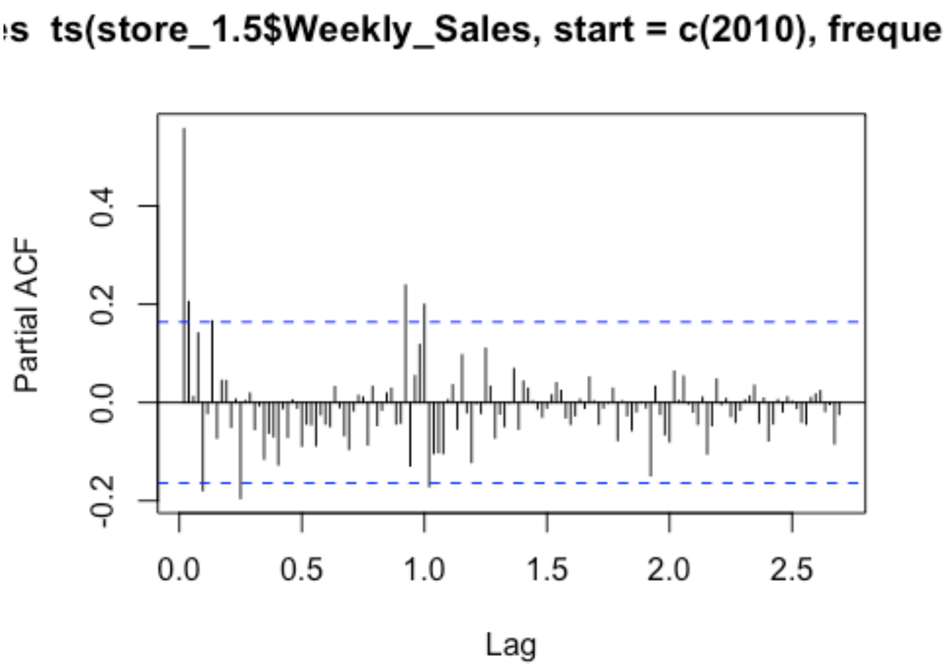

```r
pacf(ts(store_1.4$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



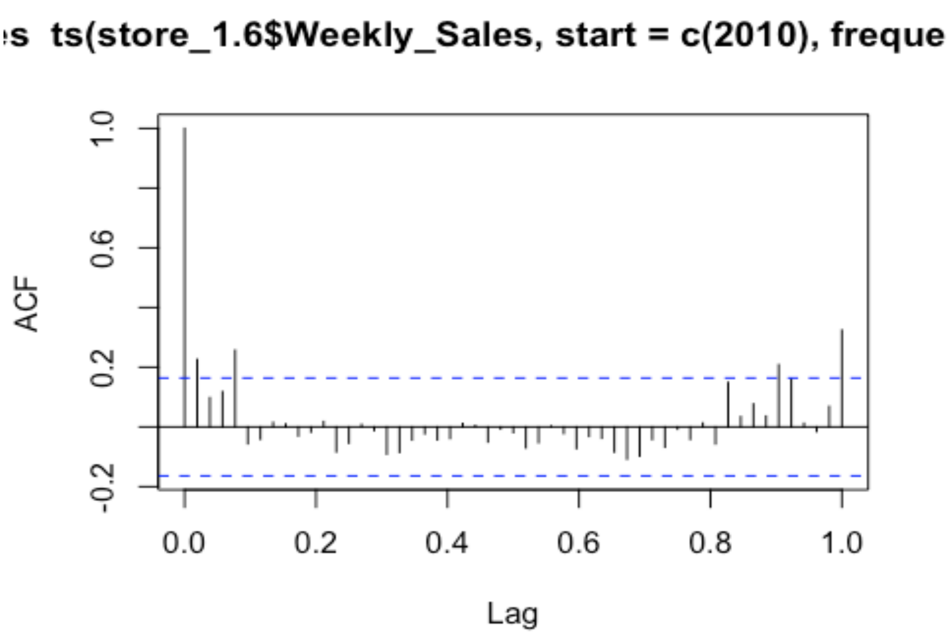

```
# department 5
acf(ts(store_1.5$Weekly_Sales, start = c(2010), frequency = 52), lag =52)
```



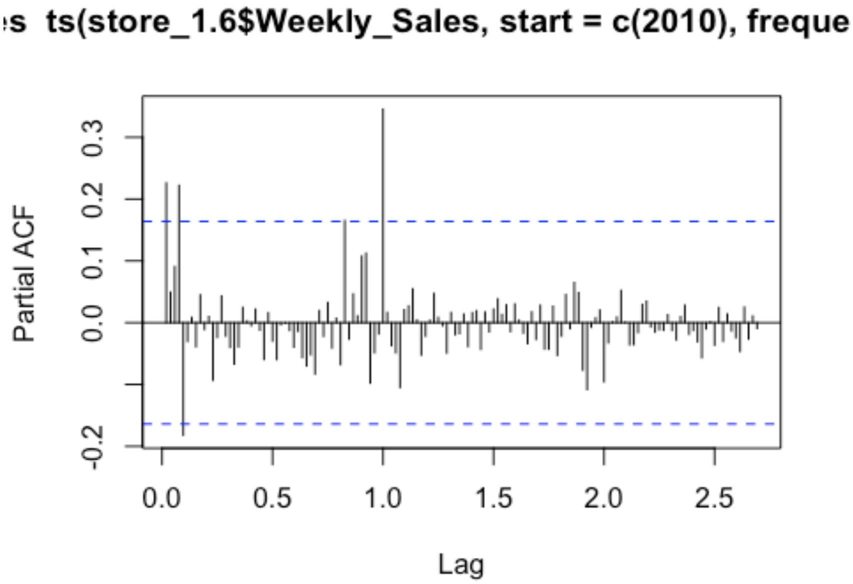

```
pacf(ts(store_1.5$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



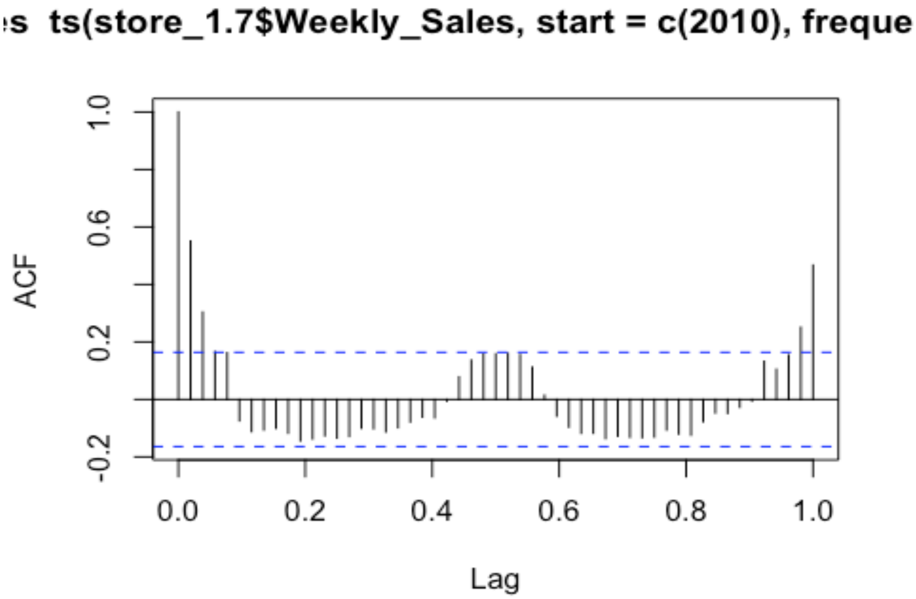

```r
# department 6
acf(ts(store_1.6$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



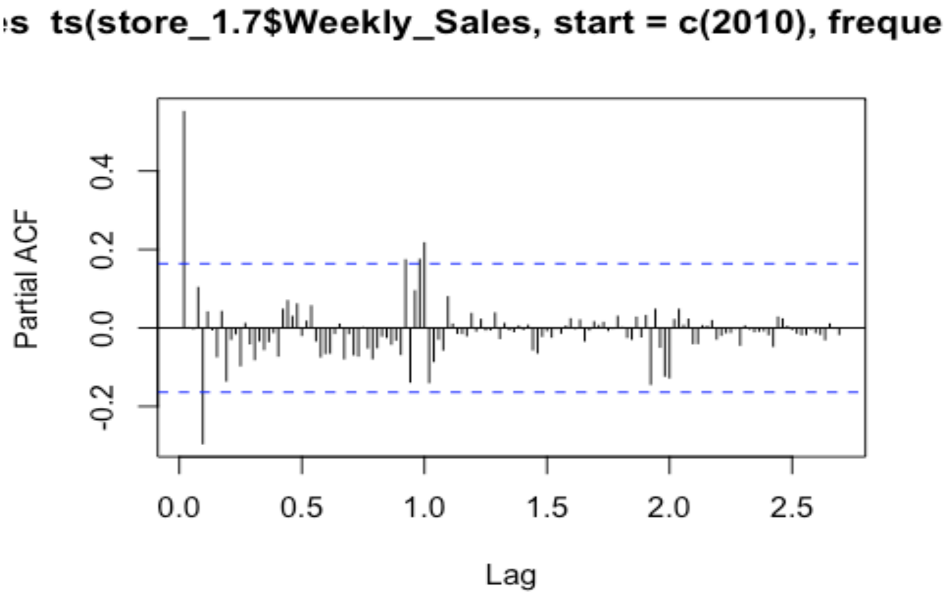

```r
pacf(ts(store_1.6$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



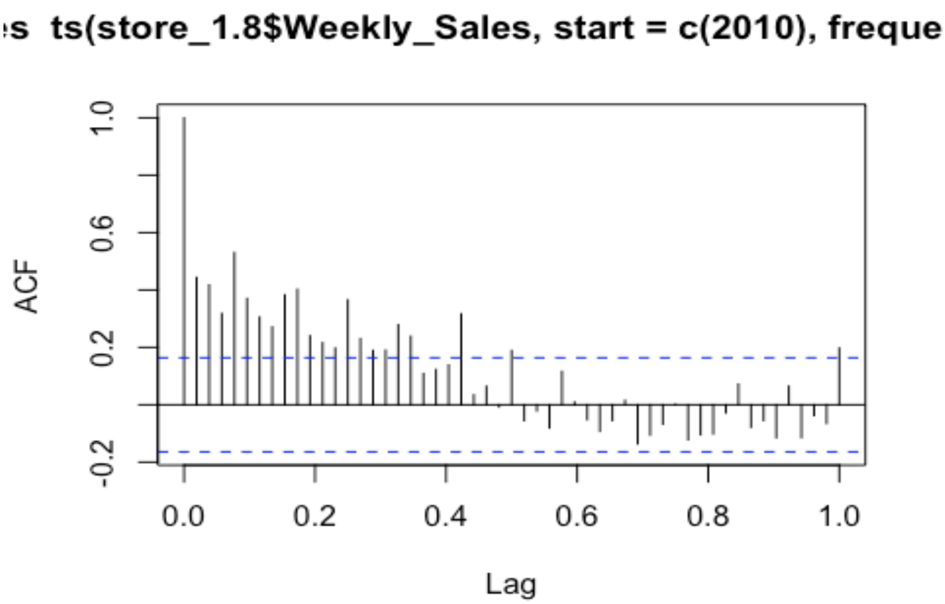

```r
# department 7
acf(ts(store_1.7$Weekly_Sales, start = c(2010), frequency = 52), lag =52)
```



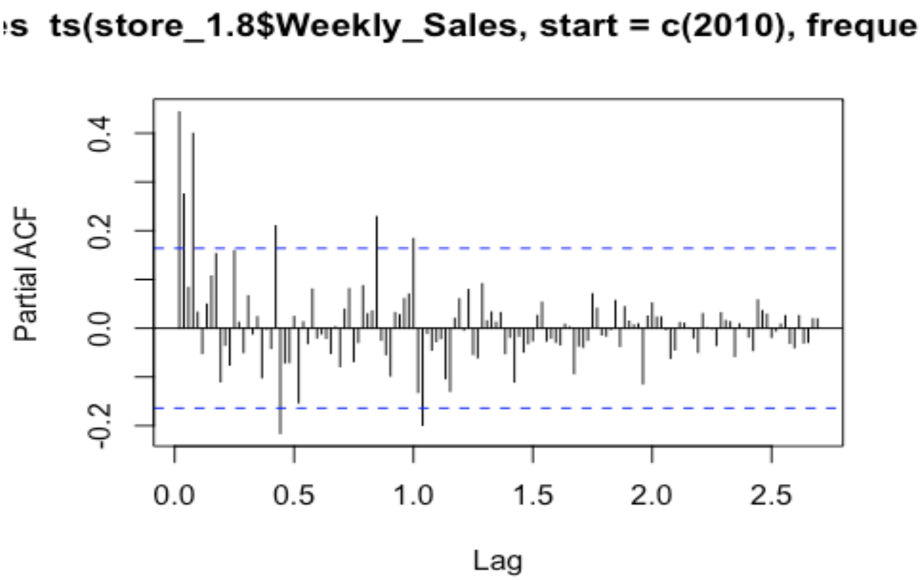

```r
pacf(ts(store_1.7$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



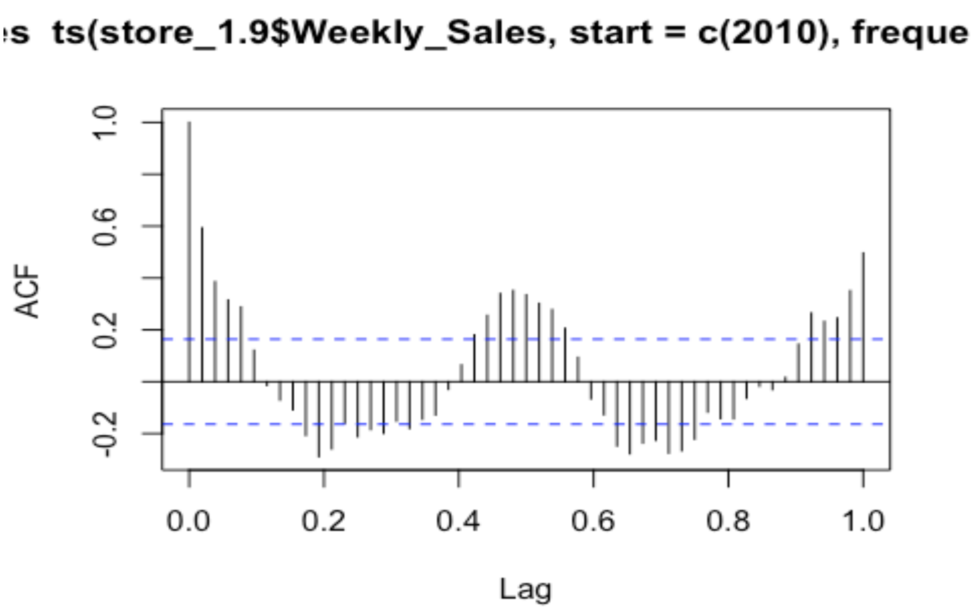

```r
# department 8
acf(ts(store_1.8$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



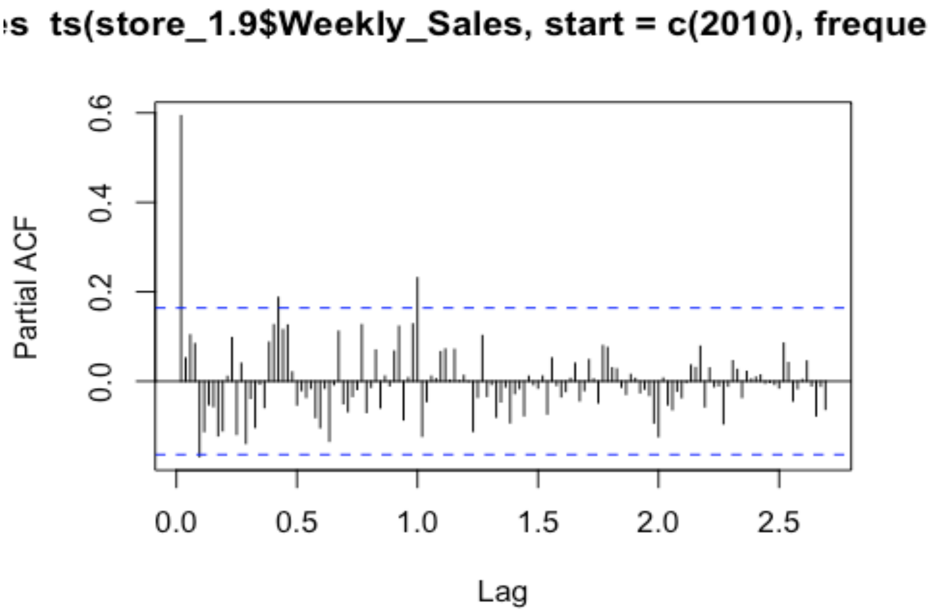

```r
pacf(ts(store_1.8$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



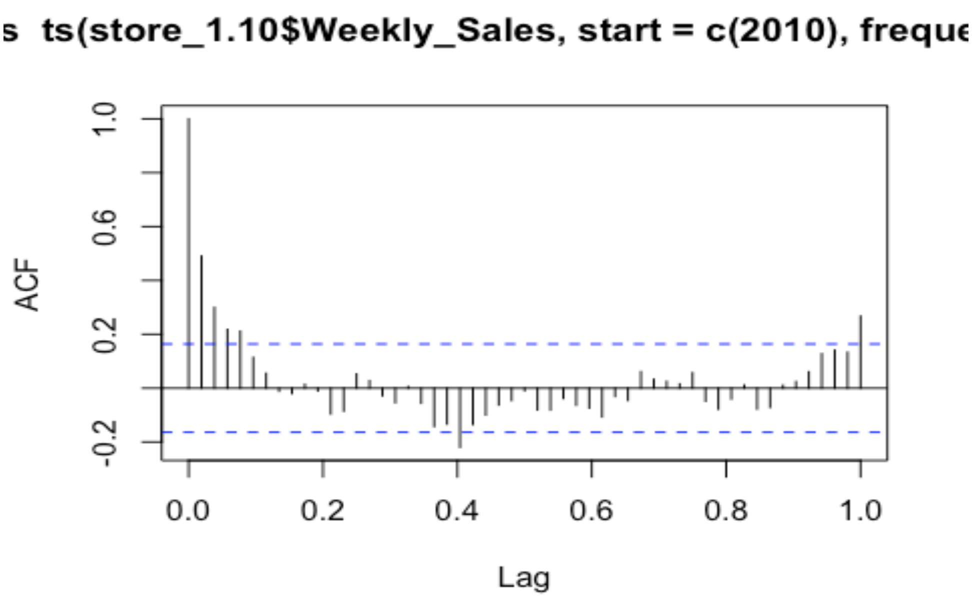

```
# department 9
acf(ts(store_1.9$Weekly_Sales, start = c(2010), frequency = 52), lag =52)
```



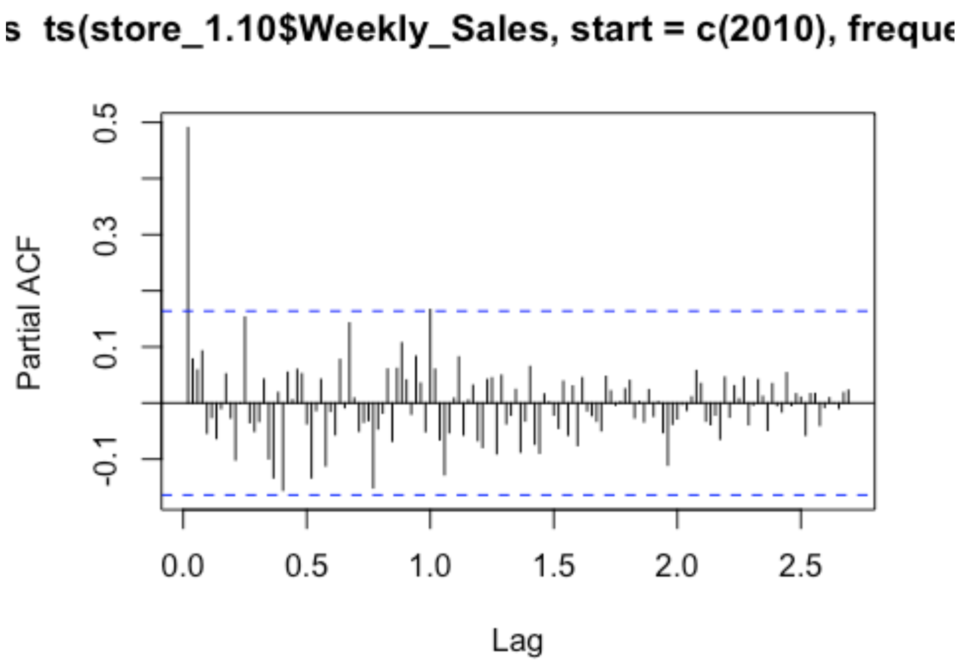

```
pacf(ts(store_1.9$Weekly_Sales, start = c(2010), frequency = 52), lag.max = 1
40)
```



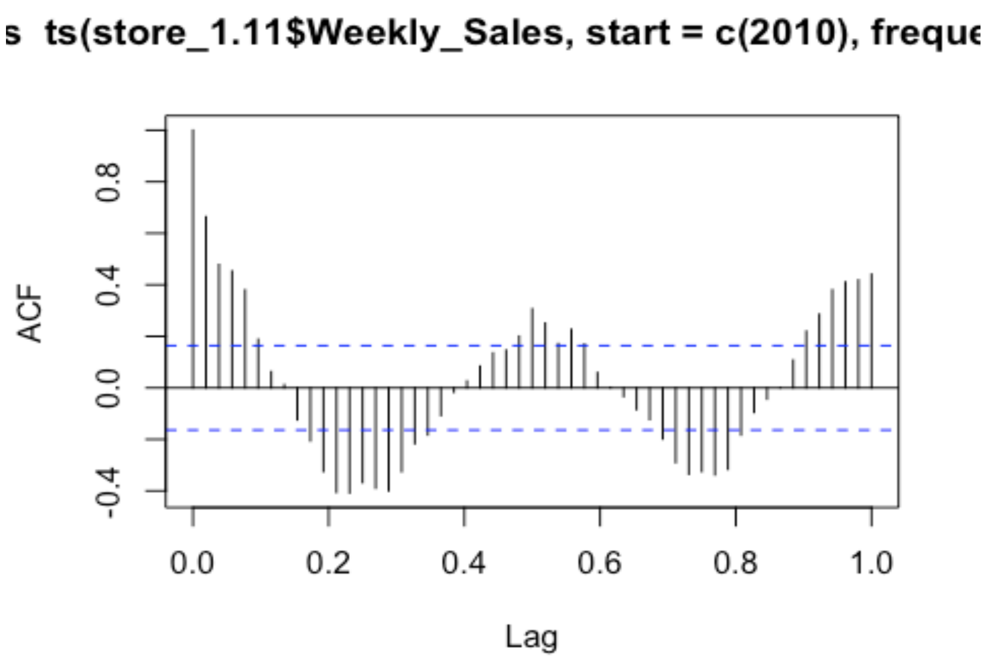

```r
# department 10
acf(ts(store_1.10$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```




```r
pacf(ts(store_1.10$Weekly_Sales, start = c(2010), frequency = 52), lag.max =
140)
```

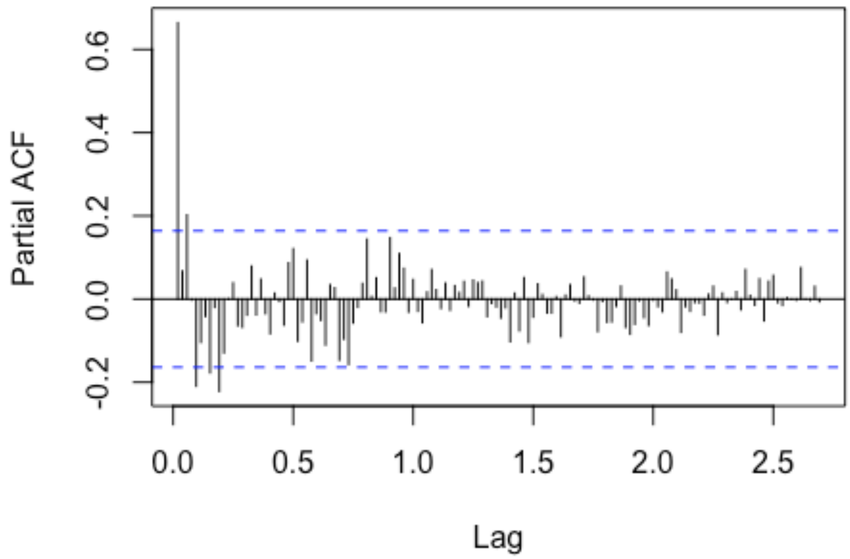



```r
# department 11
acf(ts(store_1.11$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```



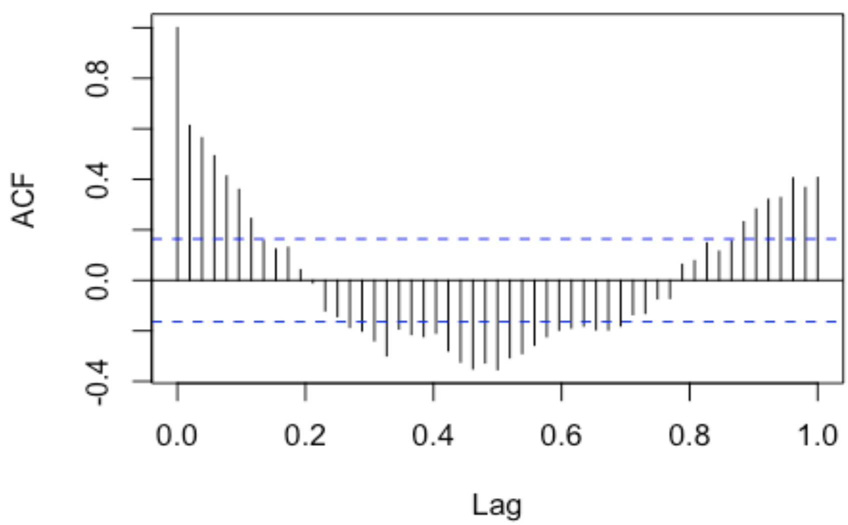

```r
pacf(ts(store_1.11$Weekly_Sales, start = c(2010), frequency = 52), lag.max =
140)
```

s ts(store_1.11$Weekly_Sales, start = c(2010), freque

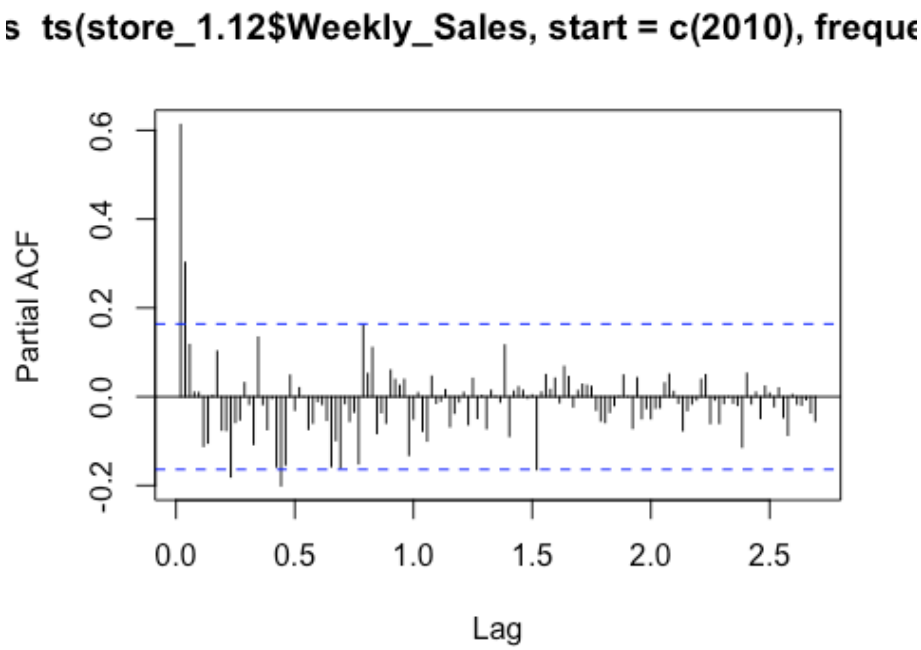



```r
# department 12
acf(ts(store_1.12$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```

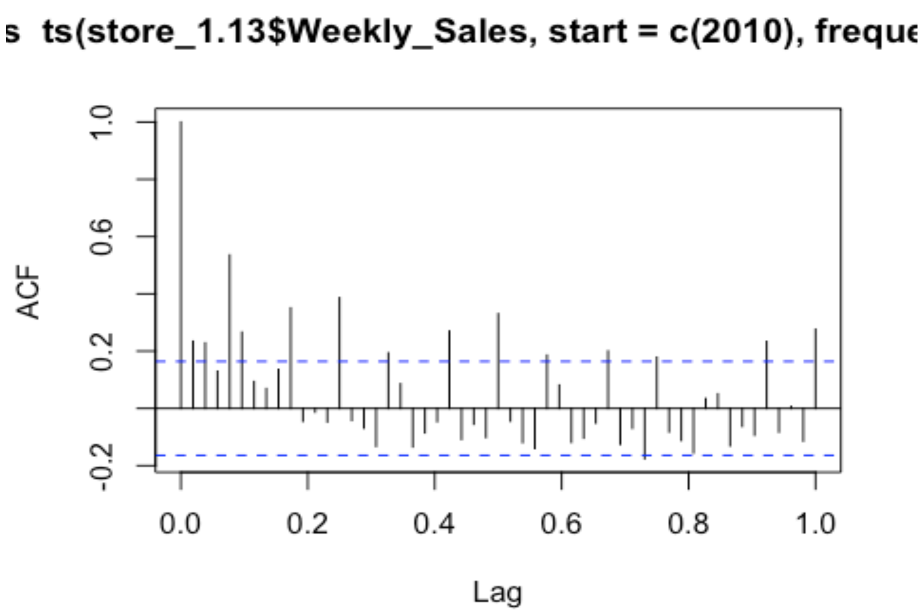
s ts(store_1.12$Weekly_Sales, start = c(2010), freque




```r
pacf(ts(store_1.12$Weekly_Sales, start = c(2010), frequency = 52), lag.max =
140)
```

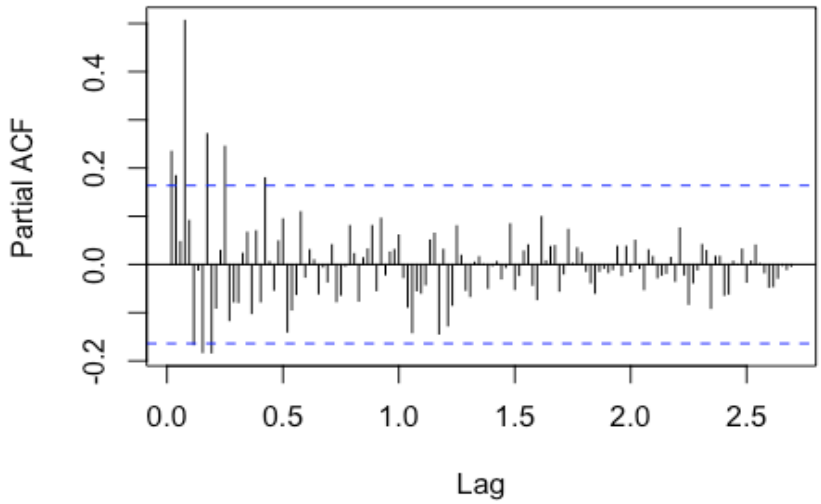



```r
# department 13
acf(ts(store_1.13$Weekly_Sales, start = c(2010), frequency = 52), lag = 52)
```




```r
pacf(ts(store_1.13$Weekly_Sales, start = c(2010), frequency = 52), lag.max =
140)
```

s ts(store_1.13$Weekly_Sales, start = c(2010), freque



Data Cleaning:

Identifying and replacing outliers

```
# using tsclean function, which identifies and replaced outliers
store_1.1_clean <- tsclean(store_1.1_ts)
store_1.2_clean <- tsclean(store_1.2_ts)
store_1.3_clean <- tsclean(store_1.3_ts)
store_1.4_clean <- tsclean(store_1.4_ts)
store_1.5_clean <- tsclean(store_1.5_ts)
store_1.6_clean <- tsclean(store_1.6_ts)
store_1.7_clean <- tsclean(store_1.7_ts)
store_1.8_clean <- tsclean(store_1.8_ts)
store_1.9_clean <- tsclean(store_1.9_ts)
store_1.10_clean <- tsclean(store_1.10_ts)
store_1.11_clean <- tsclean(store_1.11_ts)
store_1.12_clean <- tsclean(store_1.12_ts)
store_1.13_clean <- tsclean(store_1.13_ts)
```

Modeling:

Partitioning Data

```
# store 1 dept 1
training_1.1 <- window(store_1.1_clean, end = c(2012, 26))
validation_1.1 <- window(store_1.1_clean, start = c(2012, 27))

predictors_1.1 <- as.matrix(store_1.1["Temperature"][1:130,])

# store 1 dept 2
training_1.2 <- window(store_1.2_clean, end = c(2012, 26))
```

```r
validation_1.2 <- window(store_1.2_clean, start = c(2012, 27))

predictors_1.2 <- as.matrix(store_1.2["Temperature"][1:130,])

# store 1 dept 3
training_1.3 <- window(store_1.3_clean, end = c(2012, 26))
validation_1.3 <- window(store_1.3_clean, start = c(2012, 27))

predictors_1.3 <- as.matrix(store_1.3["Temperature"][1:130,])

# store 1 dept 4
training_1.4 <- window(store_1.4_clean, end = c(2012, 26))
validation_1.4 <- window(store_1.4_clean, start = c(2012, 27))

predictors_1.4 <- as.matrix(store_1.4["Temperature"][1:130,])

 # store 1 dept 5
training_1.5 <- window(store_1.5_clean, end = c(2012, 26))
validation_1.5 <- window(store_1.5_clean, start = c(2012, 27))

predictors_1.5 <- as.matrix(store_1.5["Temperature"][1:130,])

# store 1 dept 6
training_1.6 <- window(store_1.6_clean, end = c(2012, 26))
validation_1.6 <- window(store_1.6_clean, start = c(2012, 27))

predictors_1.6 <- as.matrix(store_1.6["Temperature"][1:130,])

# store 1 dept 7
training_1.7 <- window(store_1.7_clean, end = c(2012, 26))
validation_1.7 <- window(store_1.7_clean, start = c(2012, 27))

predictors_1.7 <- as.matrix(store_1.7["Temperature"][1:130,])

# store 1 dept 8
training_1.8 <- window(store_1.8_clean, end = c(2012, 26))
validation_1.8 <- window(store_1.8_clean, start = c(2012, 27))

predictors_1.8 <- as.matrix(store_1.8["Temperature"][1:130,])

# store 1 dept 9
training_1.9 <- window(store_1.9_clean, end = c(2012, 26))
validation_1.9 <- window(store_1.9_clean, start = c(2012, 27))

predictors_1.9 <- as.matrix(store_1.9["Temperature"][1:130,])

# store 1 dept 10
training_1.10 <- window(store_1.10_clean, end = c(2012, 26))
```

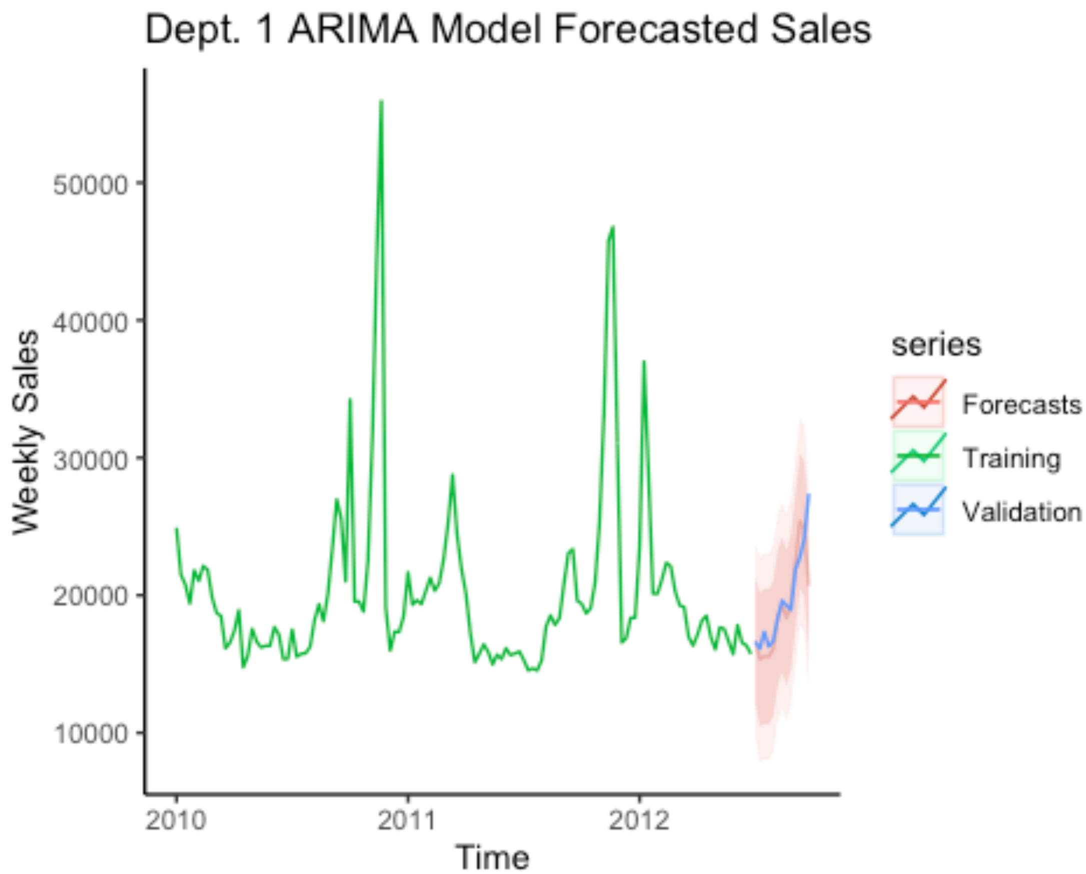
```
validation_1.10 <- window(store_1.10_clean, start = c(2012, 27))

predictors_1.10 <- as.matrix(store_1.10["Temperature"][1:130,])

# store 1 dept 11
training_1.11 <- window(store_1.11_clean, end = c(2012, 26))
validation_1.11 <- window(store_1.11_clean, start = c(2012, 27))

predictors_1.11 <- as.matrix(store_1.11["Temperature"][1:130,])

# store 1 dept 12
training_1.12 <- window(store_1.12_clean, end = c(2012, 26))
validation_1.12 <- window(store_1.12_clean, start = c(2012, 27))

predictors_1.12 <- as.matrix(store_1.12["Temperature"][1:130,])

# store 1 dept 13
training_1.13 <- window(store_1.13_clean, end = c(2012, 26))
validation_1.13 <- window(store_1.13_clean, start = c(2012, 27))

predictors_1.13 <- as.matrix(store_1.13["Temperature"][1:130,])
```

Department 1 Models:

```
AutoArima_1.1 <- auto.arima(training_1.1, xreg = predictors_1.1)
summary(AutoArima_1.1)

## Series: training_1.1
## Regression with ARIMA(1,0,0)(0,1,0)[52] errors
##
## Coefficients:
##          ar1     xreg
##       0.4198   7.6841
## s.e.  0.1023  70.5586
##
## sigma^2 = 15852734:  log likelihood = -756.34
## AIC=1518.67   AICc=1519   BIC=1525.74
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 27.52535 3044.298 1340.801 -0.5772076 6.070496 0.5054659
##                    ACF1
## Training set -0.0297231

# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.1 <- Arima(training_1.1, xreg = predictors_1.1, order = c(0, 1, 3), s
easonal = c(0, 1, 1))
summary(arima_1.1)

## Series: training_1.1
## Regression with ARIMA(0,1,3)(0,1,1)[52] errors
```

```
##
## Coefficients:
##          ma1      ma2      ma3     sma1     xreg
##       -0.682  -0.1859  -0.1321  -0.9992  -0.1983
## s.e.   0.126   0.1570   0.1110   0.6437  76.6634
##
## sigma^2 = 8402521:  log likelihood = -745.56
## AIC=1503.12   AICc=1504.32   BIC=1517.19
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 21.15138 2157.245 954.3406 -0.5351687 4.337541 0.3597749
##                    ACF1
## Training set 0.01322383
```

```
# prediction on the arima
new.predictors_1.1 <- as.matrix(store_1.1["Temperature"][131:143,])
forecast.arima.sales_1.1 <- forecast(arima_1.1, xreg = new.predictors_1.1)

# plot of forecasted values
autoplot(training_1.1, series = "Training") +
  autolayer(forecast.arima.sales_1.1, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.1, series = "Validation") +
  labs(title = "Dept. 1 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.1 <- store_1.1[1:130, 6]
linear_1.1 <- tslm(training_1.1 ~ trend + season + temp_1.1)
summary(linear_1.1)

##
## Call:
## tslm(formula = training_1.1 ~ trend + season + temp_1.1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7472.5  -923.2  -149.6   743.6 10600.4
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 21569.828   3822.259   5.643 2.73e-07 ***
## trend           4.177      7.414   0.563  0.57486
## season2      2767.099   2484.286   1.114  0.26886
## season3      -298.131   2442.879  -0.122  0.90319
## season4     -4035.299   2522.459  -1.600  0.11380
## season5     -2916.729   2523.637  -1.156  0.25140
## season6     -2556.742   2543.324  -1.005  0.31795
## season7     -2236.600   2640.554  -0.847  0.39964
```

```
## season8     -2297.040   2692.077  -0.853  0.39620
## season9     -3009.648   2709.301  -1.111  0.27013
## season10    -3025.775   2889.464  -1.047  0.29834
## season11    -2004.092   2922.450  -0.686  0.49495
## season12    -4932.793   2893.754  -1.705  0.09235 .
## season13    -5876.320   2920.762  -2.012  0.04777 *
## season14    -5987.215   3004.315  -1.993  0.04987 *
## season15    -6244.059   3176.984  -1.965  0.05302 .
## season16    -8105.091   3026.936  -2.678  0.00908 **
## season17    -8390.852   3358.453  -2.498  0.01463 *
## season18    -7874.205   3465.387  -2.272  0.02590 *
## season19    -7837.702   3468.078  -2.260  0.02669 *
## season20    -8409.296   3610.211  -2.329  0.02250 *
## season21    -8409.806   3544.694  -2.373  0.02020 *
## season22    -8878.636   3634.651  -2.443  0.01690 *
## season23    -7430.336   3570.596  -2.081  0.04080 *
## season24    -8207.939   3586.248  -2.289  0.02487 *
## season25    -8852.632   3598.520  -2.460  0.01616 *
## season26    -9023.249   3629.807  -2.486  0.01512 *
## season27    -8383.836   4167.171  -2.012  0.04778 *
## season28    -9734.313   4136.279  -2.353  0.02119 *
## season29    -9542.306   4102.249  -2.326  0.02268 *
## season30    -9538.439   4007.161  -2.380  0.01980 *
## season31    -8879.376   3894.627  -2.280  0.02542 *
## season32    -6432.042   3533.167  -1.820  0.07262 .
## season33    -5585.336   3711.366  -1.505  0.13649
## season34    -6454.529   3579.533  -1.803  0.07532 .
## season35    -5147.264   3457.600  -1.489  0.14071
## season36    -1967.422   3086.353  -0.637  0.52574
## season37      868.415   3189.152   0.272  0.78613
## season38      373.312   3090.523   0.121  0.90417
## season39    -3808.036   3136.767  -1.214  0.22851
## season40     3061.973   2821.545   1.085  0.28126
## season41    -4718.474   2873.096  -1.642  0.10466
## season42    -4455.624   2820.498  -1.580  0.11832
## season43    -4080.003   2947.711  -1.384  0.17037
## season44      399.048   2736.163   0.146  0.88443
## season45     9023.771   2739.765   3.294  0.00150 **
## season46    21773.015   2744.464   7.933 1.48e-11 ***
## season47    27805.645   2741.263  10.143 8.89e-16 ***
## season48     1666.743   2736.311   0.609  0.54426
## season49    -7236.324   2736.449  -2.644  0.00994 **
## season50    -6165.837   2768.465  -2.227  0.02890 *
## season51    -5681.928   2738.220  -2.075  0.04137 *
## season52    -5118.715   2738.519  -1.869  0.06545 .
## temp_1.1       33.495     74.303   0.451  0.65343
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2992 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.8763, Adjusted R-squared:   0.79
## F-statistic: 10.16 on 53 and 76 DF,  p-value: < 2.2e-16
```

```
# calculating RMSE
sqrt(mean(linear_1.1$residuals^2))
```

```
## [1] 2287.37
```

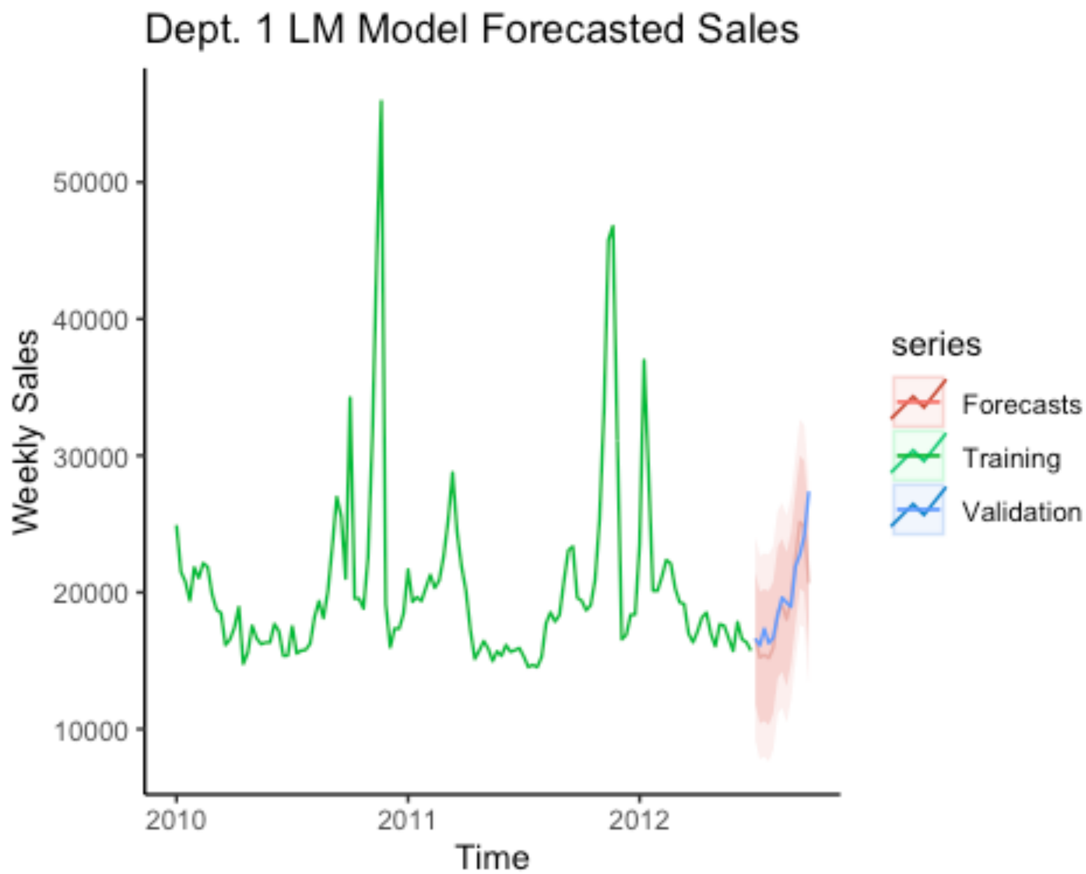
```
# forecasting
temp.new_1.1 <- store_1.1[131:143, 6]
forecast.lm.sales_1.1 <- forecast(linear_1.1, temp.new_1.1, h = 13)
```

```
## Warning in forecast.lm(linear_1.1, temp.new_1.1, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.
```

```
forecast.lm.sales_1.1
```

```
##          Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
## 2012.500       16617.41 11798.29 21436.54  9193.071 24041.76
## 2012.519       15235.61 10410.67 20060.54  7802.313 22668.90
## 2012.538       15425.09 10604.40 20245.79  7998.326 22851.86
## 2012.558       15192.31 10285.23 20099.39  7632.464 22752.16
## 2012.577       15950.34 11123.09 20777.59  8513.484 23387.20
## 2012.596       18518.08 13707.58 23328.58 11107.018 25929.14
## 2012.615       19067.84 14212.97 23922.71 11588.433 26547.25
## 2012.635       18032.00 13133.69 22930.32 10485.658 25578.35
## 2012.654       19551.45 14757.21 24345.68 12165.448 26937.45
## 2012.673       22483.25 17692.18 27274.32 15102.133 29864.37
## 2012.692       25137.03 20275.56 29998.50 17647.451 32626.61
## 2012.712       24812.91 20021.05 29604.78 17430.565 32195.26
## 2012.731       20675.60 15883.49 25467.71 13292.870 28058.33
```

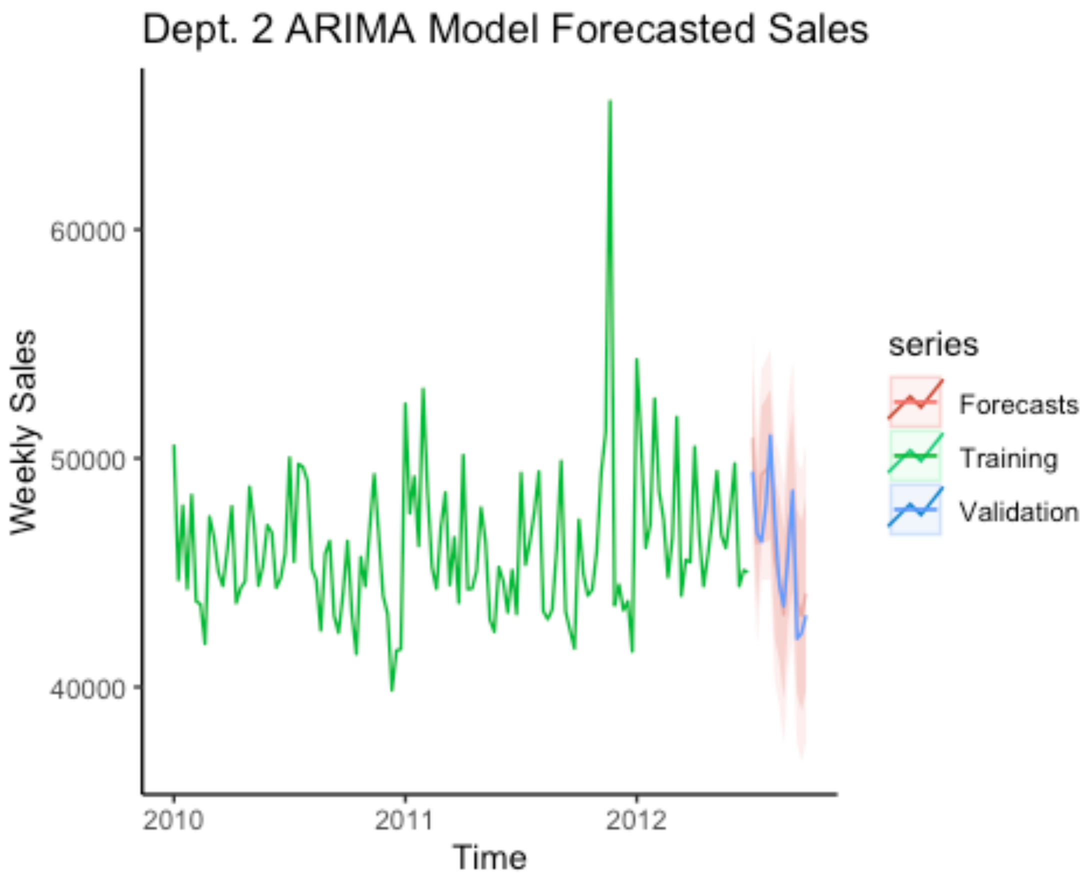
```
# plot of forecasted values
autoplot(training_1.1, series = "Training") +
  autolayer(forecast.lm.sales_1.1, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.1, series = "Validation") +
  labs(title = "Dept. 1 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 2 Models:

```
# Auto ARIMA model
AutoArima_1.2 <- auto.arima(training_1.2, xreg = predictors_1.2)
summary(AutoArima_1.2)

## Series: training_1.2
## Regression with ARIMA(1,0,1)(0,1,0)[52] errors
##
## Coefficients:
##          ar1      ma1     xreg
##       0.9108  -0.7351  17.0723
## s.e.  0.0798   0.1174  48.1717
##
## sigma^2 = 7731094:  log likelihood = -727.88
## AIC=1463.75   AICc=1464.3   BIC=1473.18
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 224.2849 2111.93 1020.085 0.3279628 2.111287 0.5438332 -0.099
5141
```

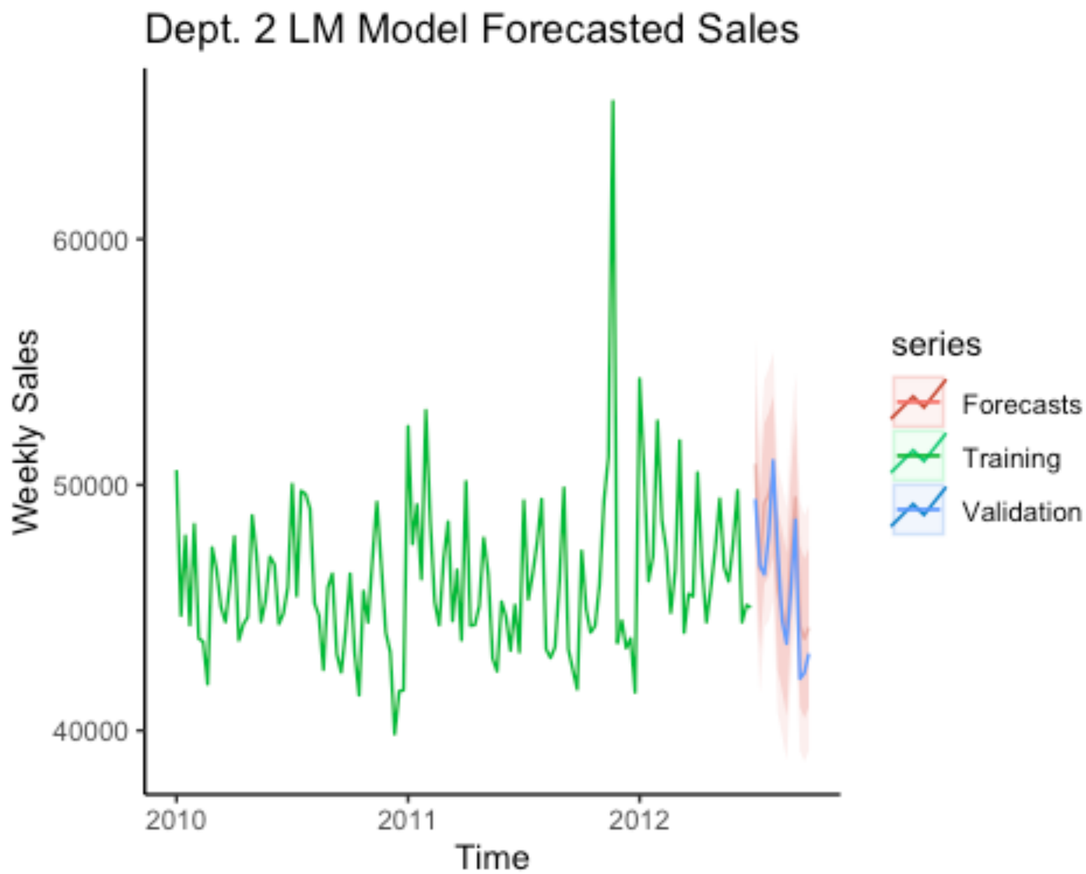
```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.2 <- Arima(training_1.2, xreg = predictors_1.2, order = c(4, 1, 0), s
easonal = c(1, 1, 1))
summary(arima_1.2)

## Series: training_1.2
## Regression with ARIMA(4,1,0)(1,1,1)[52] errors
##
## Coefficients:
##           ar1      ar2      ar3      ar4      sar1      sma1     xreg
##       -0.8705  -0.6119  -0.3698  -0.1716   -0.7336    0.0423  25.5466
## s.e.   0.1159   0.1542   0.1661   0.1183  378.7502  771.4222  59.4157
##
## sigma^2 = 5021841:  log likelihood = -718.54
## AIC=1453.08   AICc=1455.2   BIC=1471.83
##
## Training set error measures:
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set -61.27756 1644.405 851.6671 -0.2511672 1.787644 0.4540452
##                     ACF1
## Training set -0.04005042

# prediction on the arima
new.predictors_1.2 <- as.matrix(store_1.2["Temperature"][131:143,])
forecast.arima.sales_1.2 <- forecast(arima_1.2, xreg = new.predictors_1.2)
forecast.arima.sales_1.2

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       50894.45 48021.25 53767.65 46500.27 55288.63
## 2012.519       46311.92 43414.75 49209.09 41881.08 50742.76
## 2012.538       49283.15 46279.84 52286.45 44689.99 53876.31
## 2012.558       49483.43 46349.86 52617.00 44691.05 54275.81
## 2012.577       49735.91 46452.64 53019.19 44714.58 54757.25
## 2012.596       45569.36 42101.47 49037.24 40265.69 50873.03
## 2012.615       44724.58 41157.54 48291.61 39269.27 50179.88
## 2012.635       43170.47 39479.83 46861.12 37526.12 48814.82
## 2012.654       46638.69 42826.09 50451.28 40807.82 52469.55
## 2012.673       48172.38 44240.66 52104.10 42159.33 54185.43
## 2012.692       43732.72 39685.93 47779.51 37543.69 49921.74
## 2012.712       43098.29 38944.87 47251.71 36746.18 49450.39
## 2012.731       44099.77 39838.30 48361.24 37582.42 50617.13

# plot of forecasted values
autoplot(training_1.2, series = "Training") +
  autolayer(forecast.arima.sales_1.2, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.2, series = "Validation") +
  labs(title = "Dept. 2 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.2 <- store_1.2[1:130, 6]
linear_1.2 <- tslm(training_1.2 ~ trend + season + temp_1.2)
summary(linear_1.2)

##
## Call:
## tslm(formula = training_1.2 ~ trend + season + temp_1.2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9111.1  -663.8    79.7   745.8  9111.1
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    49974.56    2587.67  19.313  < 2e-16 ***
## trend             16.33       5.02   3.253 0.001707 **
## season2        -4627.50    1681.86  -2.751 0.007415 **
## season3        -4747.56    1653.83  -2.871 0.005304 **
## season4        -6930.13    1707.70  -4.058 0.000119 ***
## season5        -1448.14    1708.50  -0.848 0.399319
## season6        -5919.43    1721.83  -3.438 0.000954 ***
## season7        -7603.63    1787.65  -4.253 5.93e-05 ***
```

```
## season8      -9413.59    1822.54  -5.165 1.87e-06 ***
## season9      -6119.28    1834.19  -3.336 0.001316 **
## season10     -4344.38    1956.16  -2.221 0.029339 *
## season11     -8848.15    1978.50  -4.472 2.67e-05 ***
## season12     -7826.53    1959.07  -3.995 0.000148 ***
## season13     -8337.92    1977.35  -4.217 6.77e-05 ***
## season14     -3944.50    2033.92  -1.939 0.056169 .
## season15     -8716.31    2150.82  -4.053 0.000121 ***
## season16     -9166.86    2049.23  -4.473 2.66e-05 ***
## season17     -8595.20    2273.67  -3.780 0.000310 ***
## season18     -5843.93    2346.07  -2.491 0.014922 *
## season19     -6239.74    2347.89  -2.658 0.009589 **
## season20     -9309.12    2444.11  -3.809 0.000281 ***
## season21     -9356.86    2399.76  -3.899 0.000207 ***
## season22     -7375.48    2460.66  -2.997 0.003678 **
## season23     -6955.10    2417.29  -2.877 0.005205 **
## season24    -10027.00    2427.89  -4.130 9.23e-05 ***
## season25     -9060.70    2436.20  -3.719 0.000380 ***
## season26     -9414.54    2457.38  -3.831 0.000261 ***
## season27     -4179.39    2821.17  -1.481 0.142625
## season28     -8464.83    2800.26  -3.023 0.003412 **
## season29     -5797.45    2777.22  -2.088 0.040194 *
## season30     -5186.81    2712.84  -1.912 0.059653 .
## season31     -4557.19    2636.66  -1.728 0.087979 .
## season32     -9298.15    2391.95  -3.887 0.000215 ***
## season33     -9865.79    2512.59  -3.927 0.000188 ***
## season34    -10680.56    2423.34  -4.407 3.39e-05 ***
## season35     -7606.46    2340.79  -3.250 0.001723 **
## season36     -5114.41    2089.46  -2.448 0.016684 *
## season37    -10152.68    2159.05  -4.702 1.13e-05 ***
## season38    -10857.20    2092.28  -5.189 1.70e-06 ***
## season39    -10466.05    2123.59  -4.928 4.73e-06 ***
## season40     -6134.95    1910.18  -3.212 0.001935 **
## season41     -9018.20    1945.08  -4.636 1.45e-05 ***
## season42    -10293.60    1909.48  -5.391 7.62e-07 ***
## season43     -8246.38    1995.60  -4.132 9.15e-05 ***
## season44     -7617.41    1852.38  -4.112 9.82e-05 ***
## season45     -4509.26    1854.82  -2.431 0.017409 *
## season46     -2652.14    1858.00  -1.427 0.157555
## season47      3285.18    1855.83   1.770 0.080705 .
## season48     -8996.40    1852.48  -4.856 6.25e-06 ***
## season49     -9008.51    1852.58  -4.863 6.10e-06 ***
## season50    -11034.82    1874.25  -5.888 9.99e-08 ***
## season51    -10222.56    1853.77  -5.514 4.62e-07 ***
## season52    -11309.46    1853.98  -6.100 4.11e-08 ***
## temp_1.2        33.95      50.30   0.675 0.501785
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2025 on 76 degrees of freedom
```

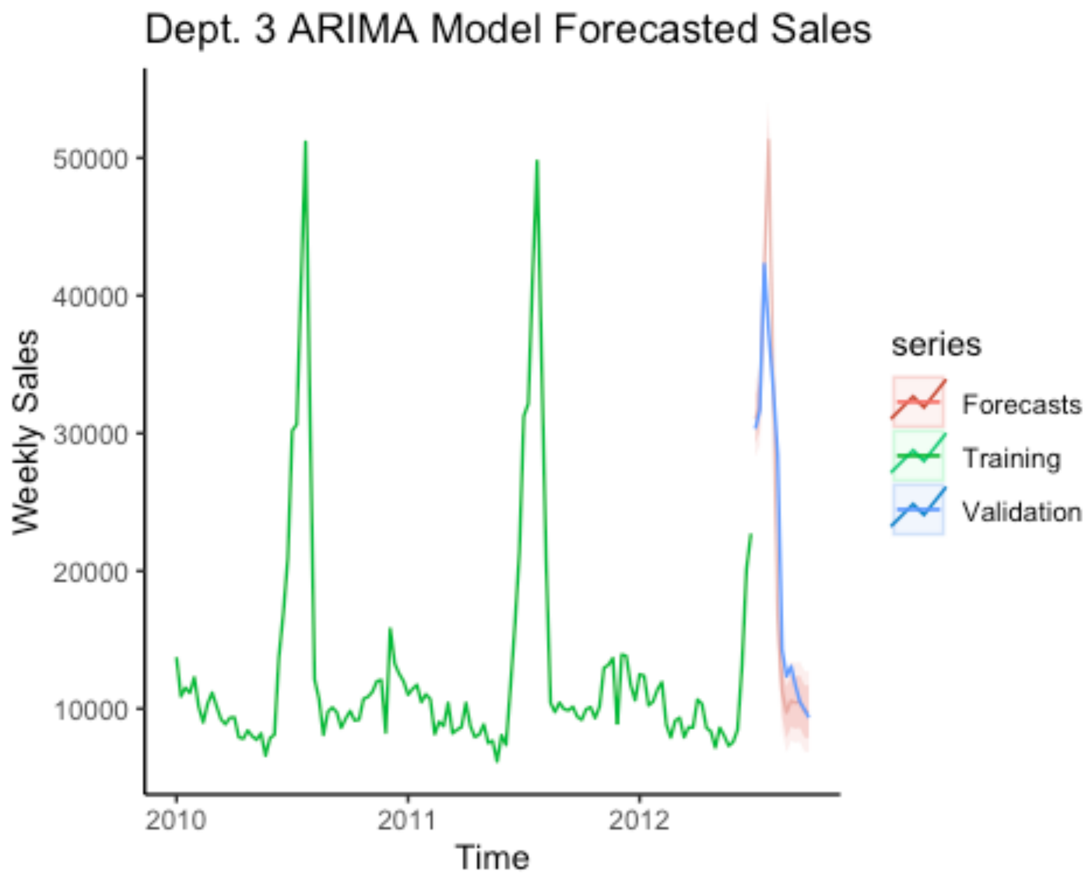
```
## Multiple R-squared:  0.7667, Adjusted R-squared:  0.6041
## F-statistic: 4.713 on 53 and 76 DF,  p-value: 5.202e-10

# calculating RMSE
sqrt(mean(linear_1.2$residuals^2))

## [1] 1548.548

# forecasting
temp.new_1.2 <- store_1.2[131:143, 6]
forecast.lm.sales_1.2 <- forecast(linear_1.2, temp.new_1.2, h = 13)

## Warning in forecast.lm(linear_1.2, temp.new_1.2, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.2

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       50857.34 47594.79 54119.88 45831.06 55883.61
## 2012.519       46552.24 43285.76 49818.72 41519.90 51584.57
## 2012.538       49229.15 45965.54 52492.76 44201.23 54257.07
## 2012.558       49612.02 46289.93 52934.11 44494.01 54730.03
## 2012.577       50354.04 47086.00 53622.09 45319.30 55388.79
## 2012.596       45747.21 42490.50 49003.92 40729.93 50764.50
## 2012.615       44890.69 41603.95 48177.44 39827.14 49954.25
## 2012.635       43919.10 40602.95 47235.26 38810.23 49027.97
## 2012.654       47220.36 43974.66 50466.05 42220.04 52220.68
## 2012.673       49473.10 46229.55 52716.65 44476.09 54470.11
## 2012.692       44262.39 40971.18 47553.60 39191.95 49332.83
## 2012.712       43743.26 40499.18 46987.35 38745.42 48741.11
## 2012.731       44191.14 40946.88 47435.40 39193.04 49189.24

# plot of forecasted values
autoplot(training_1.2, series = "Training") +
  autolayer(forecast.lm.sales_1.2, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.2, series = "Validation") +
  labs(title = "Dept. 2 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 3 Models:

```
# Auto ARIMA model
AutoArima_1.3 <- auto.arima(training_1.3, xreg = predictors_1.3)
summary(AutoArima_1.3)

## Series: training_1.3
## Regression with ARIMA(0,1,2)(0,1,0)[52] errors
##
## Coefficients:
##           ma1      ma2      xreg
##       -0.6785  -0.2514  -12.5049
## s.e.   0.1276   0.1345   29.4822
##
## sigma^2 = 2404864:  log likelihood = -674.33
## AIC=1356.66   AICc=1357.22   BIC=1366.04
##
## Training set error measures:
##                   ME     RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 149.289 1170.01 612.0587 0.4733439 5.184392 0.5780193 -0.0269
8826
```

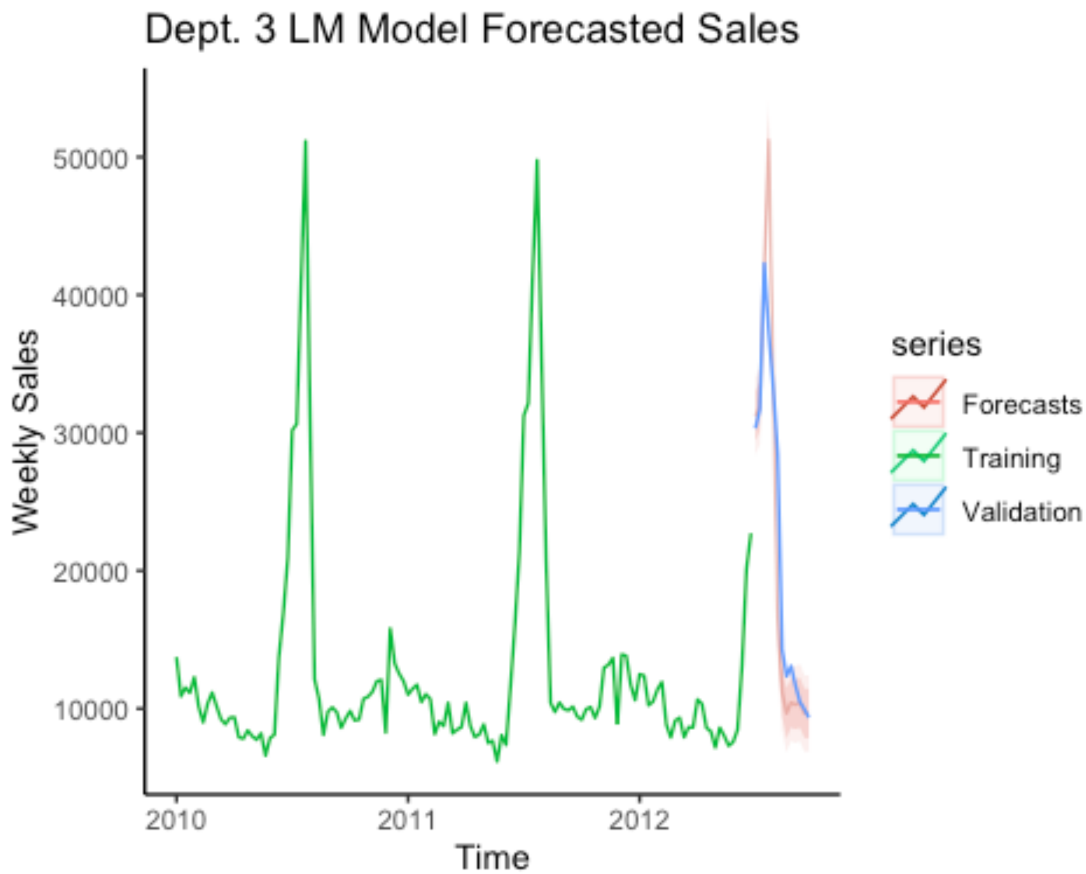
```
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.3 <- Arima(training_1.3, xreg = predictors_1.3, order = c(0, 1, 3), s
easonal = c(0, 1, 1))
summary(arima_1.3)

## Series: training_1.3
## Regression with ARIMA(0,1,3)(0,1,1)[52] errors
##
## Coefficients:
##           ma1      ma2     ma3     sma1      xreg
##       -0.7139  -0.3030  0.1025  -0.9968  -38.8556
## s.e.   0.1171   0.1334  0.1131   0.8625   31.8638
##
## sigma^2 = 1284735:  log likelihood = -672.07
## AIC=1356.15   AICc=1357.35   BIC=1370.21
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE    MAPE      MASE
ACF1
## Training set 88.35297 843.5314 458.2682 0.09653082 3.90974 0.4327819 0.010
85711

# prediction on the arima
new.predictors_1.3 <- as.matrix(store_1.3["Temperature"][131:143,])
forecast.arima.sales_1.3 <- forecast(arima_1.3, xreg = new.predictors_1.3)
forecast.arima.sales_1.3

##          Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
## 2012.500      31034.176 29257.494 32810.86 28316.976 33751.38
## 2012.519      31974.470 30126.314 33822.63 29147.960 34800.98
## 2012.538      41954.948 40106.676 43803.22 39128.259 44781.64
## 2012.558      51282.888 49428.374 53137.40 48446.654 54119.12
## 2012.577      33677.978 31817.244 35538.71 30832.230 36523.73
## 2012.596      16686.518 14819.584 18553.45 13831.288 19541.75
## 2012.615      11271.535  9398.422 13144.65  8406.856 14136.22
## 2012.635       9725.615  7846.343 11604.89  6851.516 12599.71
## 2012.654      10562.334  8676.923 12447.75  7678.847 13445.82
## 2012.673      10423.491  8531.961 12315.02  7530.646 13316.34
## 2012.692      10522.976  8625.347 12420.60  7620.803 13425.15
## 2012.712       9798.161  7894.453 11701.87  6886.691 12709.63
## 2012.731       9779.762  7869.993 11689.53  6859.023 12700.50

# plot of forecasted values
autoplot(training_1.3, series = "Training") +
  autolayer(forecast.arima.sales_1.3, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.3, series = "Validation") +
  labs(title = "Dept. 3 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.3 <- store_1.3[1:130, 6]
linear_1.3 <- tslm(training_1.3 ~ trend + season + temp_1.3)
summary(linear_1.3)

##
## Call:
## tslm(formula = training_1.3 ~ trend + season + temp_1.3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4164.1  -472.2    -9.6   460.7  4164.1
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 14388.083   1429.794  10.063 1.26e-15 ***
## trend           4.349      2.774   1.568  0.12103
## season2     -1133.453    929.298  -1.220  0.22636
## season3     -1236.296    913.809  -1.353  0.18010
## season4     -1321.177    943.577  -1.400  0.16553
## season5      -457.909    944.018  -0.485  0.62903
## season6     -1068.569    951.382  -1.123  0.26490
## season7     -3133.615    987.753  -3.172  0.00218 **
```

```
## season8     -2612.164   1007.027  -2.594  0.01138 *
## season9     -2025.140   1013.469  -1.998  0.04927 *
## season10    -1490.011   1080.863  -1.379  0.17208
## season11    -2976.271   1093.202  -2.723  0.00803 **
## season12    -2807.136   1082.468  -2.593  0.01140 *
## season13    -2565.086   1092.571  -2.348  0.02149 *
## season14    -1200.904   1123.825  -1.069  0.28864
## season15    -2177.171   1188.416  -1.832  0.07087 .
## season16    -3211.965   1132.287  -2.837  0.00584 **
## season17    -2716.416   1256.298  -2.162  0.03375 *
## season18    -2905.476   1296.299  -2.241  0.02792 *
## season19    -2961.376   1297.305  -2.283  0.02524 *
## season20    -2837.211   1350.473  -2.101  0.03897 *
## season21    -4169.770   1325.965  -3.145  0.00237 **
## season22    -2946.253   1359.615  -2.167  0.03337 *
## season23    -2855.757   1335.654  -2.138  0.03572 *
## season24     1988.656   1341.510   1.482  0.14237
## season25     6886.377   1346.100   5.116 2.28e-06 ***
## season26    10855.544   1357.804   7.995 1.13e-11 ***
## season27    20292.262   1558.815  13.018  < 2e-16 ***
## season28    20939.220   1547.260  13.533  < 2e-16 ***
## season29    30865.227   1534.530  20.114  < 2e-16 ***
## season30    39895.758   1498.960  26.616  < 2e-16 ***
## season31    22379.807   1456.865  15.362  < 2e-16 ***
## season32     5461.171   1321.653   4.132 9.16e-05 ***
## season33     -277.896   1388.312  -0.200  0.84188
## season34    -2047.662   1338.997  -1.529  0.13035
## season35     -994.723   1293.386  -0.769  0.44423
## season36    -1504.155   1154.514  -1.303  0.19656
## season37    -1602.247   1192.968  -1.343  0.18324
## season38    -2159.402   1156.073  -1.868  0.06563 .
## season39    -2125.308   1173.372  -1.811  0.07405 .
## season40    -2501.849   1055.457  -2.370  0.02031 *
## season41    -2342.982   1074.740  -2.180  0.03235 *
## season42    -2365.928   1055.065  -2.242  0.02785 *
## season43    -1753.443   1102.652  -1.590  0.11594
## season44    -1889.080   1023.518  -1.846  0.06883 .
## season45     -493.135   1024.865  -0.481  0.63178
## season46      261.103   1026.623   0.254  0.79993
## season47      519.765   1025.426   0.507  0.61371
## season48    -3972.790   1023.573  -3.881  0.00022 ***
## season49     2433.476   1023.625   2.377  0.01996 *
## season50      798.234   1035.601   0.771  0.44322
## season51     -304.411   1024.287  -0.297  0.76713
## season52    -1129.421   1024.399  -1.103  0.27371
## temp_1.3      -46.888     27.794  -1.687  0.09571 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1119 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.9886, Adjusted R-squared:  0.9806
## F-statistic:   124 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.3$residuals^2))

## [1] 855.6376

# forecasting
temp.new_1.3 <- store_1.3[131:143, 6]
forecast.lm.sales_1.3 <- forecast(linear_1.3, temp.new_1.3, h = 13)

## Warning in forecast.lm(linear_1.3, temp.new_1.3, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.3

##          Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
## 2012.500      31212.527 29409.835 33015.22 28435.300 33989.75
## 2012.519      31913.535 30108.670 33718.40 29132.959 34694.11
## 2012.538      41853.268 40049.987 43656.55 39075.134 44631.40
## 2012.558      51225.275 49389.681 53060.87 48397.360 54053.19
## 2012.577      33580.979 31775.248 35386.71 30799.071 36362.89
## 2012.596      16503.990 14704.523 18303.46 13731.731 19276.25
## 2012.615      11190.796  9374.734 13006.86  8392.970 13988.62
## 2012.635       9664.508  7832.193 11496.82  6841.643 12487.37
## 2012.654      10430.621  8637.239 12224.00  7667.737 13193.51
## 2012.673      10278.605  8486.409 12070.80  7517.548 13039.66
## 2012.692      10445.560  8627.027 12264.09  7643.929 13247.19
## 2012.712       9659.252  7866.757 11451.75  6897.734 12420.77
## 2012.731       9641.897  7849.309 11434.49  6880.236 12403.56

# plot of forecasted values
autoplot(training_1.3, series = "Training") +
  autolayer(forecast.lm.sales_1.3, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.3, series = "Validation") +
  labs(title = "Dept. 3 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



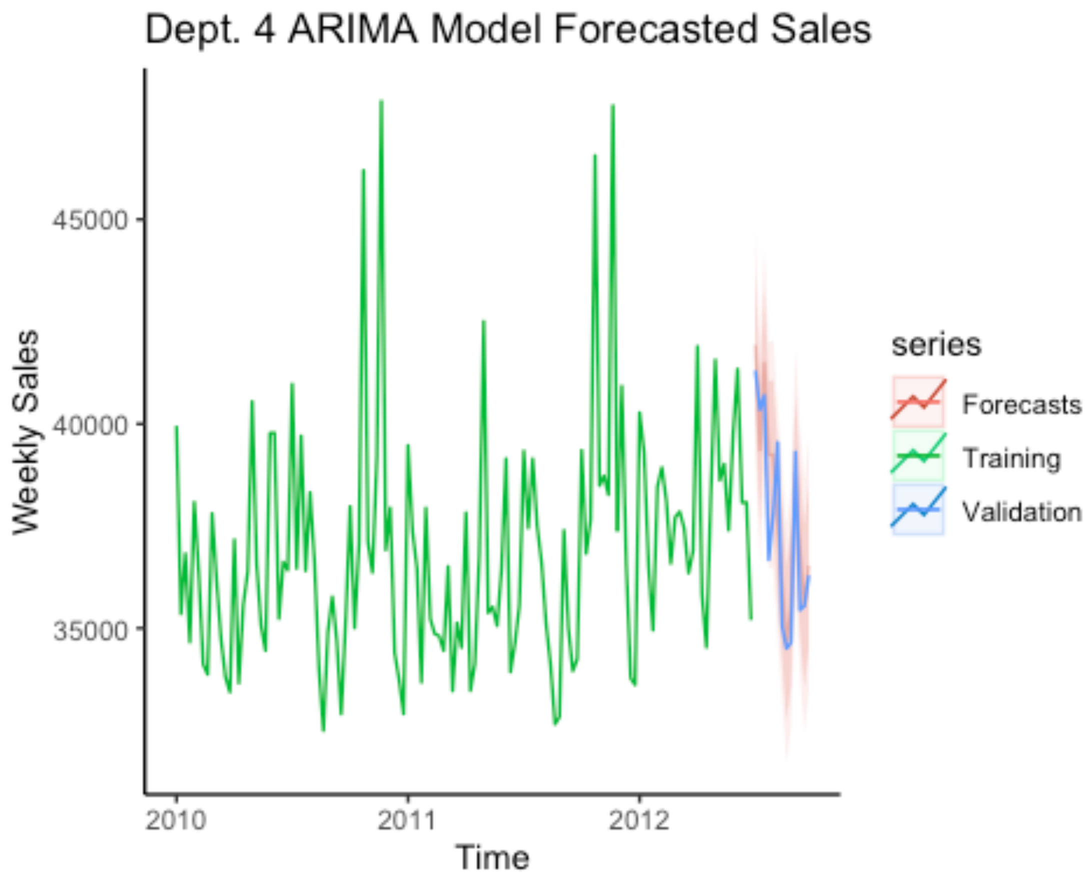
Department 4 Models:

```
# Auto ARIMA model
AutoArima_1.4 <- auto.arima(training_1.4, xreg = predictors_1.4)
summary(AutoArima_1.4)

## Series: training_1.4
## Regression with ARIMA(0,1,1)(0,1,0)[52] errors
##
## Coefficients:
##           ma1     xreg
##       -0.8408  13.6148
## s.e.   0.0543  25.3298
##
## sigma^2 = 2104781:  log likelihood = -669.39
## AIC=1344.78   AICc=1345.11   BIC=1351.81
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 110.4931 1101.951 700.5318 0.2553229 1.897304 0.4728834 -0.07
66048
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.4 <- Arima(training_1.4, xreg = predictors_1.4, order = c(1, 1, 3), s
easonal = c(0, 1, 1))
summary(arima_1.4)
```

```
## Series: training_1.4
## Regression with ARIMA(1,1,3)(0,1,1)[52] errors
##
## Coefficients:
##          ar1      ma1     ma2     ma3     sma1     xreg
##       0.6045  -1.4955  0.4865  0.0802  -0.4037  -6.5806
## s.e.  1.1541   1.1686  1.1787  0.2237   0.3027  30.8903
##
## sigma^2 = 1890203:  log likelihood = -667.46
## AIC=1348.93   AICc=1350.55   BIC=1365.33
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE    MAPE      MASE
ACF1
## Training set 76.57734 1016.042 641.7766 0.1695963 1.73829 0.4332216 -0.015
4414
```

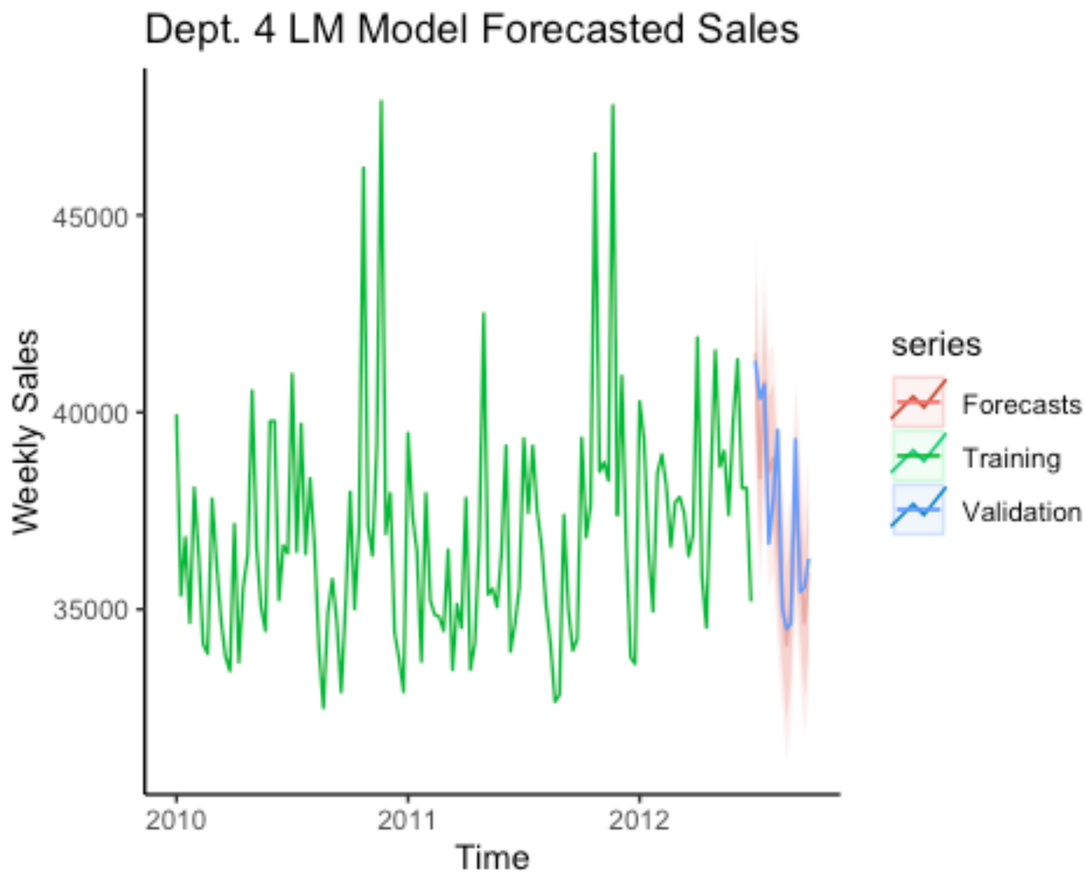
```r
# prediction on the arima
new.predictors_1.4 <- as.matrix(store_1.4["Temperature"][131:143,])
forecast.arima.sales_1.4 <- forecast(arima_1.4, xreg = new.predictors_1.4)

# plot of forecasted values
autoplot(training_1.4, series = "Training") +
  autolayer(forecast.arima.sales_1.4, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.4, series = "Validation") +
  labs(title = "Dept. 4 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.4 <- store_1.4[1:130, 6]
linear_1.4 <- tslm(training_1.4 ~ trend + season + temp_1.4)
summary(linear_1.4)

##
## Call:
## tslm(formula = training_1.4 ~ trend + season + temp_1.4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2326.1  -601.8     0.0   551.0  2237.4
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 40489.861   1495.434  27.076  < 2e-16 ***
## trend          16.119      2.901   5.557 3.89e-07 ***
## season2     -2760.029    971.961  -2.840 0.005792 **
## season3     -3299.123    955.760  -3.452 0.000913 ***
## season4     -5256.556    986.895  -5.326 9.87e-07 ***
## season5     -1537.037    987.356  -1.557 0.123692
## season6     -2844.817    995.059  -2.859 0.005483 **
## season7     -3876.691   1033.100  -3.752 0.000340 ***
```

```
## season8     -4450.499   1053.258  -4.225 6.56e-05 ***
## season9     -2879.837   1059.996  -2.717 0.008157 **
## season10    -2554.240   1130.484  -2.259 0.026723 *
## season11    -4173.172   1143.389  -3.650 0.000479 ***
## season12    -4332.760   1132.162  -3.827 0.000264 ***
## season13    -4470.455   1142.729  -3.912 0.000198 ***
## season14     -413.912   1175.418  -0.352 0.725708
## season15    -4953.967   1242.974  -3.986 0.000153 ***
## season16    -4645.005   1184.269  -3.922 0.000191 ***
## season17    -2047.820   1313.973  -1.558 0.123271
## season18     2393.859   1355.810   1.766 0.081474 .
## season19    -2303.328   1356.863  -1.698 0.093686 .
## season20    -2560.992   1412.471  -1.813 0.073760 .
## season21    -3508.654   1386.838  -2.530 0.013477 *
## season22     -450.944   1422.033  -0.317 0.752028
## season23      927.442   1396.972   0.664 0.508767
## season24    -3423.996   1403.096  -2.440 0.017004 *
## season25    -2734.077   1407.897  -1.942 0.055848 .
## season26    -3452.663   1420.138  -2.431 0.017404 *
## season27     1555.223   1630.378   0.954 0.343157
## season28    -1677.688   1618.292  -1.037 0.303162
## season29      759.930   1604.978   0.473 0.637226
## season30    -1786.083   1567.775  -1.139 0.258178
## season31    -1360.134   1523.747  -0.893 0.374876
## season32    -3196.986   1382.328  -2.313 0.023444 *
## season33    -4901.509   1452.048  -3.376 0.001163 **
## season34    -6476.398   1400.469  -4.624 1.51e-05 ***
## season35    -5276.291   1352.763  -3.900 0.000206 ***
## season36    -2860.148   1207.515  -2.369 0.020396 *
## season37    -4527.577   1247.735  -3.629 0.000514 ***
## season38    -6044.145   1209.147  -4.999 3.60e-06 ***
## season39    -4723.322   1227.240  -3.849 0.000246 ***
## season40    -1141.590   1103.911  -1.034 0.304354
## season41    -3831.430   1124.080  -3.409 0.001048 **
## season42    -2474.849   1103.501  -2.243 0.027829 *
## season43     6692.880   1153.273   5.803 1.42e-07 ***
## season44    -2312.054   1070.506  -2.160 0.033943 *
## season45    -2702.945   1071.915  -2.522 0.013776 *
## season46    -1383.474   1073.753  -1.288 0.201499
## season47     7711.445   1072.501   7.190 3.84e-10 ***
## season48    -3113.878   1070.564  -2.909 0.004757 **
## season49     -769.766   1070.618  -0.719 0.474350
## season50    -4939.298   1083.144  -4.560 1.92e-05 ***
## season51    -6467.549   1071.310  -6.037 5.36e-08 ***
## season52    -6982.584   1071.428  -6.517 7.03e-09 ***
## temp_1.4      -30.680     29.070  -1.055 0.294605
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1170 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.9016, Adjusted R-squared:  0.8329
## F-statistic: 13.13 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.4$residuals^2))

## [1] 894.9186

# forecasting
temp.new_1.4 <- store_1.4[131:143, 6]
forecast.lm.sales_1.4 <- forecast(linear_1.4, temp.new_1.4, h = 13)

## Warning in forecast.lm(linear_1.4, temp.new_1.4, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.4

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       41514.88 39629.43 43400.33 38610.16 44419.61
## 2012.519       38330.61 36442.88 40218.33 35422.38 41238.84
## 2012.538       40790.48 38904.42 42676.55 37884.81 43696.16
## 2012.558       38481.18 36561.31 40401.04 35523.44 41438.92
## 2012.577       38836.42 36947.79 40725.05 35926.80 41746.04
## 2012.596       36909.23 35027.15 38791.31 34009.70 39808.76
## 2012.615       35496.64 33597.20 37396.07 32570.37 38422.91
## 2012.635       34094.33 32177.90 36010.77 31141.88 37046.79
## 2012.654       35120.04 33244.33 36995.75 32230.31 38009.76
## 2012.673       37783.32 35908.85 39657.79 34895.51 40671.13
## 2012.692       36302.59 34400.57 38204.61 33372.34 39232.84
## 2012.712       34649.36 32774.57 36524.14 31761.06 37537.65
## 2012.731       35949.79 34074.91 37824.67 33061.34 38838.23

# plot of forecasted values
autoplot(training_1.4, series = "Training") +
  autolayer(forecast.lm.sales_1.4, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.4, series = "Validation") +
  labs(title = "Dept. 4 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



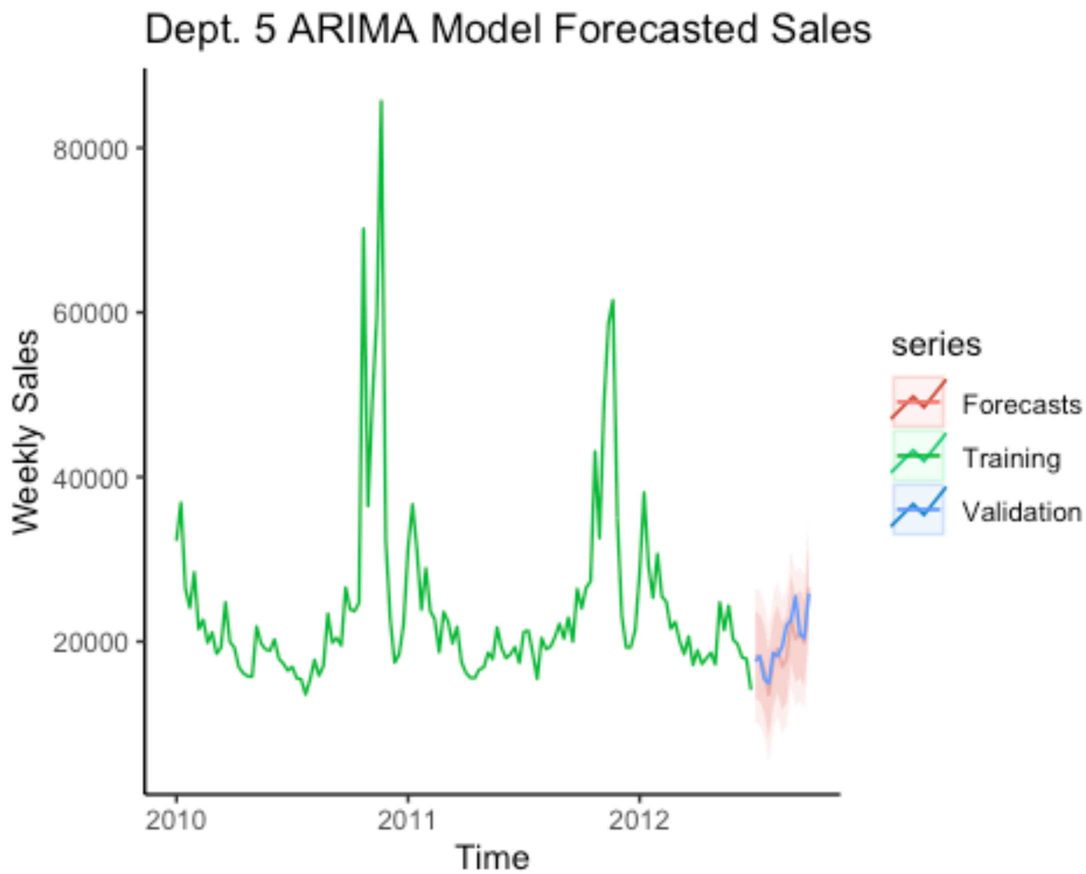
Department 5 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.5 <- auto.arima(training_1.5, xreg = predictors_1.5)
summary(AutoArima_1.5)

## Series: training_1.5
## Regression with ARIMA(0,0,0)(0,1,0)[52] errors
##
## Coefficients:
##          xreg
##       92.8756
## s.e.  77.8587
##
## sigma^2 = 22145163:  log likelihood = -769.79
## AIC=1543.57   AICc=1543.73   BIC=1548.28
##
## Training set error measures:
##                     ME     RMSE     MAE       MPE     MAPE      MASE
ACF1
## Training set -26.78433 3621.705 1518.52 0.8008909 6.045876 0.6010607 0.118
2823
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.5 <- Arima(training_1.5, xreg = predictors_1.5, order = c(0, 0, 1), s
easonal = c(0, 1, 1))
summary(arima_1.5)
```

```
## Series: training_1.5
## Regression with ARIMA(0,0,1)(0,1,1)[52] errors
##
## Coefficients:
##          ma1     sma1      xreg
##       0.1317  -0.9999  108.6980
## s.e.  0.1146   0.3988   84.0944
##
## sigma^2 = 11266209:  log likelihood = -765.7
## AIC=1539.4   AICc=1539.95   BIC=1548.83
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -30.72939 2549.458 1047.808 0.4313792 4.128701 0.4147436
##                      ACF1
## Training set 0.0007677673
```

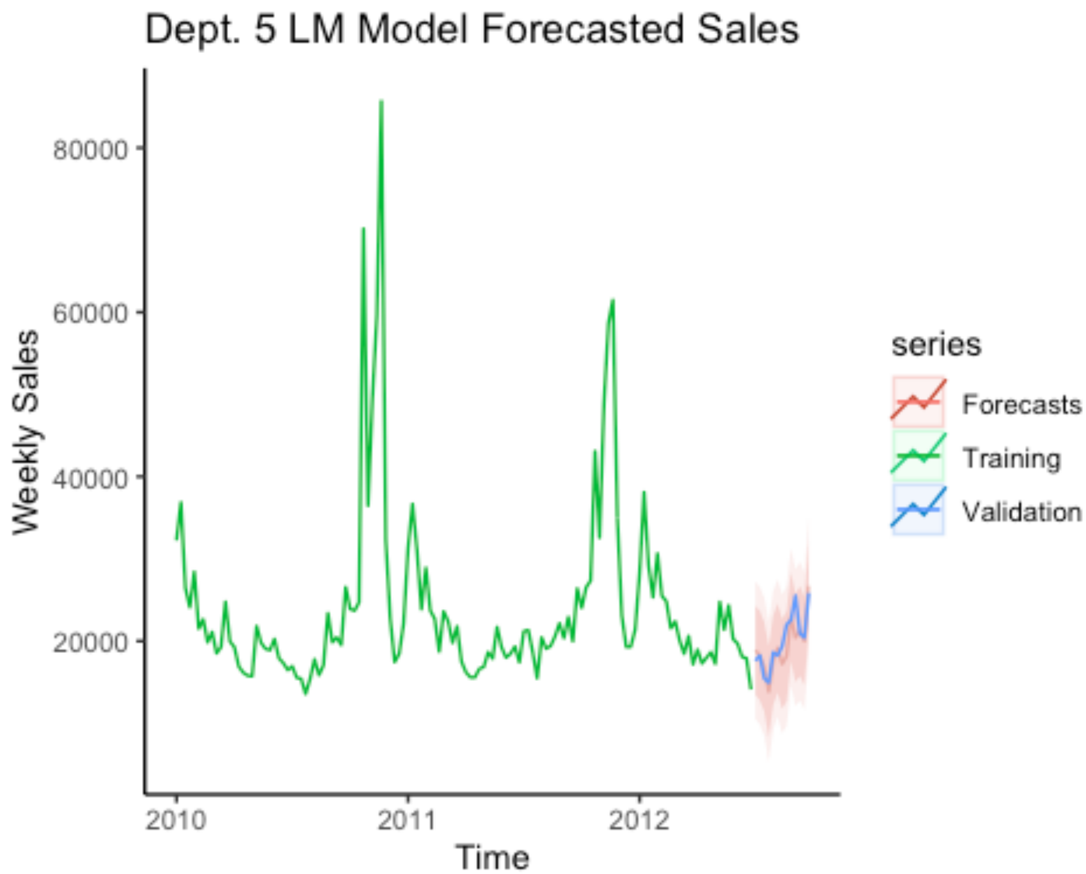
```r
# prediction on the arima
new.predictors_1.5 <- as.matrix(store_1.5["Temperature"][131:143,])
forecast.arima.sales_1.5 <- forecast(arima_1.5, xreg = new.predictors_1.5)

# plot of forecasted values
autoplot(training_1.5, series = "Training") +
  autolayer(forecast.arima.sales_1.5, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.5, series = "Validation") +
  labs(title = "Dept. 5 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.5 <- store_1.5[1:130, 6]
linear_1.5 <- tslm(training_1.5 ~ trend + season + temp_1.5)
summary(linear_1.5)

##
## Call:
## tslm(formula = training_1.5 ~ trend + season + temp_1.5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13377.0   -886.6     15.5    891.0  13377.0
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    26252.056   4294.479   6.113 3.90e-08 ***
## trend              1.668      8.331   0.200 0.841829
## season2         7152.190   2791.206   2.562 0.012373 *
## season3        -1734.540   2744.683  -0.632 0.529307
## season4        -6949.676   2834.095  -2.452 0.016494 *
## season5        -2074.345   2835.419  -0.732 0.466673
## season6        -7924.841   2857.537  -2.773 0.006977 **
## season7        -8470.602   2966.780  -2.855 0.005543 **
```

```
## season8     -11974.589   3024.669  -3.959 0.000168 ***
## season9      -9704.905   3044.020  -3.188 0.002079 **
## season10    -12214.135   3246.441  -3.762 0.000329 ***
## season11    -13435.850   3283.503  -4.092 0.000106 ***
## season12    -10156.241   3251.261  -3.124 0.002527 **
## season13    -14397.020   3281.607  -4.387 3.65e-05 ***
## season14    -14654.494   3375.481  -4.341 4.31e-05 ***
## season15    -16553.780   3569.483  -4.638 1.44e-05 ***
## season16    -16282.540   3400.898  -4.788 8.14e-06 ***
## season17    -16472.916   3773.372  -4.366 3.95e-05 ***
## season18    -17064.564   3893.516  -4.383 3.71e-05 ***
## season19    -11940.486   3896.540  -3.064 0.003018 **
## season20    -14251.722   4056.233  -3.514 0.000748 ***
## season21    -12122.320   3982.622  -3.044 0.003208 **
## season22    -14517.873   4083.692  -3.555 0.000654 ***
## season23    -14560.970   4011.724  -3.630 0.000512 ***
## season24    -15747.692   4029.310  -3.908 0.000200 ***
## season25    -15742.118   4043.098  -3.894 0.000211 ***
## season26    -17983.213   4078.250  -4.410 3.36e-05 ***
## season27    -15391.881   4682.002  -3.287 0.001532 **
## season28    -15967.968   4647.293  -3.436 0.000960 ***
## season29    -17321.395   4609.059  -3.758 0.000334 ***
## season30    -19672.159   4502.224  -4.369 3.89e-05 ***
## season31    -16098.718   4375.787  -3.679 0.000435 ***
## season32    -14935.385   3969.670  -3.762 0.000329 ***
## season33    -16072.463   4169.885  -3.854 0.000241 ***
## season34    -14656.951   4021.764  -3.644 0.000488 ***
## season35    -10457.387   3884.768  -2.692 0.008735 **
## season36    -12288.445   3467.656  -3.544 0.000679 ***
## season37    -10974.505   3583.155  -3.063 0.003032 **
## season38    -12664.328   3472.340  -3.647 0.000483 ***
## season39     -6062.292   3524.298  -1.720 0.089476 .
## season40     -7547.394   3170.132  -2.381 0.019781 *
## season41     -6624.157   3228.052  -2.052 0.043608 *
## season42     -5490.243   3168.955  -1.733 0.087239 .
## season43     24608.153   3311.885   7.430 1.35e-10 ***
## season44      3702.409   3074.201   1.204 0.232192
## season45     18760.013   3078.248   6.094 4.21e-08 ***
## season46     28153.801   3083.527   9.130 7.52e-14 ***
## season47     42659.560   3079.931  13.851  < 2e-16 ***
## season48      3040.620   3074.367   0.989 0.325790
## season49     -7884.525   3074.523  -2.564 0.012305 *
## season50    -11820.242   3110.494  -3.800 0.000290 ***
## season51    -11961.807   3076.512  -3.888 0.000215 ***
## season52     -9081.440   3076.849  -2.952 0.004203 **
## temp_1.5        90.668     83.483   1.086 0.280878
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3361 on 76 degrees of freedom
```

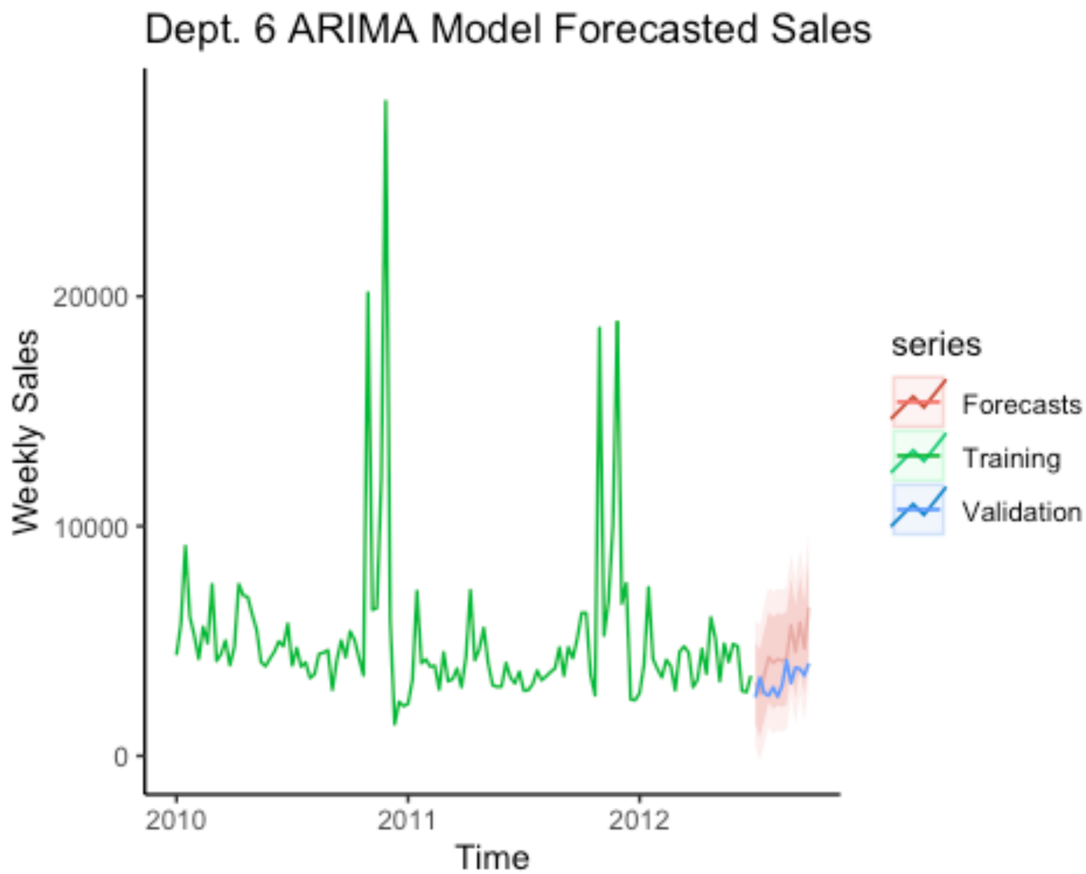
```
## Multiple R-squared:  0.9443, Adjusted R-squared:  0.9054
## F-statistic: 24.29 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.5$residuals^2))

## [1] 2569.963

# forecasting
temp.new_1.5 <- store_1.5[131:143, 6]
forecast.lm.sales_1.5 <- forecast(linear_1.5, temp.new_1.5, h = 13)

## Warning in forecast.lm(linear_1.5, temp.new_1.5, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.5

##          Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
## 2012.500       18886.15 13471.65 24300.65 10544.574 27227.73
## 2012.519       18215.63 12794.60 23636.66  9863.987 26567.26
## 2012.538       16845.73 11429.46 22262.00  8501.428 25190.04
## 2012.558       13844.73  8331.41 19358.05  5350.908 22338.56
## 2012.577       17676.43 12252.81 23100.06  9320.793 26032.07
## 2012.596       19156.05 13751.24 24560.87 10829.396 27482.71
## 2012.615       17205.53 11750.87 22660.19  8802.083 25608.98
## 2012.635       18160.30 12656.83 23663.78  9681.650 26638.96
## 2012.654       22924.59 17538.05 28311.13 14626.087 31223.09
## 2012.673       20412.46 15029.49 25795.44 12119.452 28705.48
## 2012.692       21223.96 15761.88 26686.04 12809.077 29638.84
## 2012.712       19987.33 14603.46 25371.20 11692.936 28281.73
## 2012.731       26698.93 21314.78 32083.08 18404.104 34993.76

# plot of forecasted values
autoplot(training_1.5, series = "Training") +
  autolayer(forecast.lm.sales_1.5, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.5, series = "Validation") +
  labs(title = "Dept. 5 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 6 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.6 <- auto.arima(training_1.6, xreg = predictors_1.6)
summary(AutoArima_1.6)

## Series: training_1.6
## Regression with ARIMA(2,1,2)(0,1,0)[52] errors
##
## Coefficients:
##           ar1      ar2      ma1      ma2     xreg
##       -0.1649  -0.2878  -0.4236  -0.4366  11.5603
## s.e.   0.2015   0.1322   0.1967   0.1858  22.3813
##
## sigma^2 = 2340461:  log likelihood = -672.34
## AIC=1356.69   AICc=1357.89   BIC=1370.75
##
## Training set error measures:
##                     ME     RMSE      MAE      MPE     MAPE      MASE
ACF1
## Training set 154.5196 1138.532 570.3112 4.633932 12.25336 0.4759583 -0.025
36936
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.6 <- Arima(training_1.6, xreg = predictors_1.6, order = c(2, 1, 3), s
easonal = c(0, 1, 1))
summary(arima_1.6)

## Series: training_1.6
## Regression with ARIMA(2,1,3)(0,1,1)[52] errors
##
## Coefficients:
##           ar1      ar2      ma1      ma2      ma3    sma1     xreg
##       -0.2377  -0.3328  -0.3276  -0.4555  -0.0637  0.9899   9.2830
## s.e.   0.6075   0.2364   0.6452   0.2001   0.4410  0.7164  17.9185
##
## sigma^2 = 1282534:  log likelihood = -670.8
## AIC=1357.61   AICc=1359.73   BIC=1376.36
##
## Training set error measures:
##                     ME     RMSE      MAE     MPE     MAPE      MASE
ACF1
## Training set 103.5397 831.0205 429.7156 3.21585 9.327156 0.3586229 -0.0221
7434

# prediction on the arima
new.predictors_1.6 <- as.matrix(store_1.6["Temperature"][131:143,])
forecast.arima.sales_1.6 <- forecast(arima_1.6, xreg = new.predictors_1.6)

# plot of forecasted values
autoplot(training_1.6, series = "Training") +
  autolayer(forecast.arima.sales_1.6, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.6, series = "Validation") +
  labs(title = "Dept. 6 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.6 <- store_1.6[1:130, 6]
linear_1.6 <- tslm(training_1.6 ~ trend + season + temp_1.6)
summary(linear_1.6)

##
## Call:
## tslm(formula = training_1.6 ~ trend + season + temp_1.6)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4502.1  -434.2   -30.6   458.9  4502.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4084.306   1668.058   2.449 0.016649 *
## trend         -11.342      2.955  -3.838 0.000255 ***
## season2      1177.418   1019.618   1.155 0.251805
## season3      4681.709   1071.806   4.368 3.91e-05 ***
## season4      1623.899   1016.792   1.597 0.114398
## season5      1324.663    990.877   1.337 0.185257
## season6       766.134    990.904   0.773 0.441822
## season7      1520.571    991.199   1.534 0.129164
```

```
## season8       880.449    999.768   0.881 0.381282    
## season9      1947.059   1007.274   1.933 0.056961 .  
## season10      991.549   1010.139   0.982 0.329413    
## season11     1238.483   1045.680   1.184 0.239953    
## season12     1516.970   1053.202   1.440 0.153878    
## season13      394.030   1046.827   0.376 0.707665    
## season14     1217.848   1053.021   1.157 0.251088    
## season15     3573.898   1072.876   3.331 0.001337 ** 
## season16     2066.149   1117.268   1.849 0.068305 .  
## season17     3013.239   1078.666   2.793 0.006595 ** 
## season18     2828.987   1167.820   2.422 0.017798 *  
## season19     1482.525   1198.973   1.236 0.220082    
## season20     1259.080   1199.903   1.049 0.297357    
## season21      935.381   1242.570   0.753 0.453908    
## season22     1317.493   1222.948   1.077 0.284750    
## season23     1751.058   1250.304   1.401 0.165431    
## season24     1042.447   1231.028   0.847 0.399759    
## season25      881.630   1235.904   0.713 0.477815    
## season26     1633.229   1239.773   1.317 0.191676    
## season27      436.707   1359.654   0.321 0.748948    
## season28      876.009   1444.856   0.606 0.546125    
## season29      606.625   1435.231   0.423 0.673731    
## season30     1001.662   1424.666   0.703 0.484151    
## season31      452.658   1395.233   0.324 0.746502    
## season32      615.921   1360.959   0.453 0.652152    
## season33     1116.495   1256.136   0.889 0.376897    
## season34     1258.417   1306.767   0.963 0.338601    
## season35     1763.110   1269.214   1.389 0.168849    
## season36      281.012   1235.858   0.227 0.820737    
## season37     1502.683   1146.407   1.311 0.193881    
## season38     1717.305   1168.824   1.469 0.145890    
## season39     1776.921   1147.433   1.549 0.125631    
## season40     2920.902   1157.316   2.524 0.013694 *  
## season41     2665.274   1108.697   2.404 0.018655 *  
## season42      950.399   1112.280   0.854 0.395536    
## season43      132.072   1108.885   0.119 0.905507    
## season44    16500.650   1121.984  14.707  < 2e-16 ***
## season45     2830.276   1125.874   2.514 0.014058 *  
## season46     3595.009   1150.073   3.126 0.002511 ** 
## season47     8114.825   1119.375   7.249 2.97e-10 ***
## season48    20786.495   1121.918  18.528  < 2e-16 ***
## season49     3314.327   1141.595   2.903 0.004832 ** 
## season50     1529.941   1129.396   1.355 0.179541    
## season51     -537.147   1177.946  -0.456 0.649688    
## season52     -593.571   1127.795  -0.526 0.600205    
## temp_1.6       -6.326     27.581  -0.229 0.819219    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 1213 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.9258, Adjusted R-squared:  0.8741
## F-statistic: 17.89 on 53 and 76 DF,  p-value: < 2.2e-16
```

```
# calculating RMSE
sqrt(mean(linear_1.6$residuals^2))
```

```
## [1] 927.8138
```

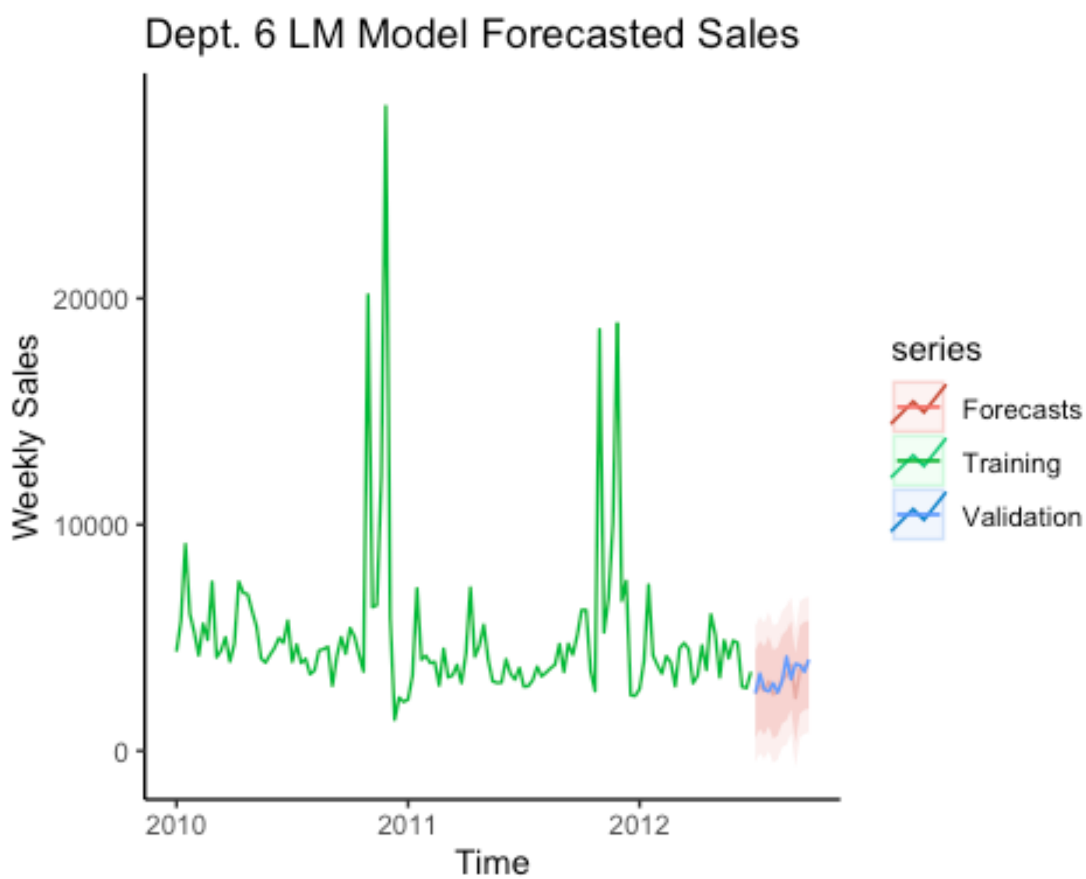
```
# forecasting
temp.new_1.6 <- store_1.6[131:143, 6]
forecast.lm.sales_1.6 <- forecast(linear_1.6, temp.new_1.6, h = 13)
```

```
## Warning in forecast.lm(linear_1.6, temp.new_1.6, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.
```

```
forecast.lm.sales_1.6
```

```
##          Point Forecast     Lo 80    Hi 80       Lo 95    Hi 95
## 2012.500       2512.370  565.3117 4459.428 -487.267859 5512.008
## 2012.519       2918.507  967.0393 4869.975  -87.924223 5924.939
## 2012.538       2645.752  691.7229 4599.780 -364.624900 5656.128
## 2012.558       3074.927 1082.5071 5067.346    5.405221 6144.448
## 2012.577       2496.680  533.5769 4459.784 -527.676685 5521.038
## 2012.596       2626.652  681.6377 4571.666 -369.836839 5623.141
## 2012.615       3172.750 1223.9955 5121.505  170.498744 6175.002
## 2012.635       3335.591 1339.0003 5332.182  259.643543 6411.538
## 2012.654       3789.660 1841.1283 5738.192  787.752069 6791.568
## 2012.673       2343.852  374.5865 4313.116 -689.997973 5377.701
## 2012.692       3589.351 1636.7594 5541.943  581.188362 6597.514
## 2012.712       3761.130 1814.4667 5707.793  762.100723 6760.159
## 2012.731       3801.877 1858.3611 5745.392  807.696780 6796.056
```

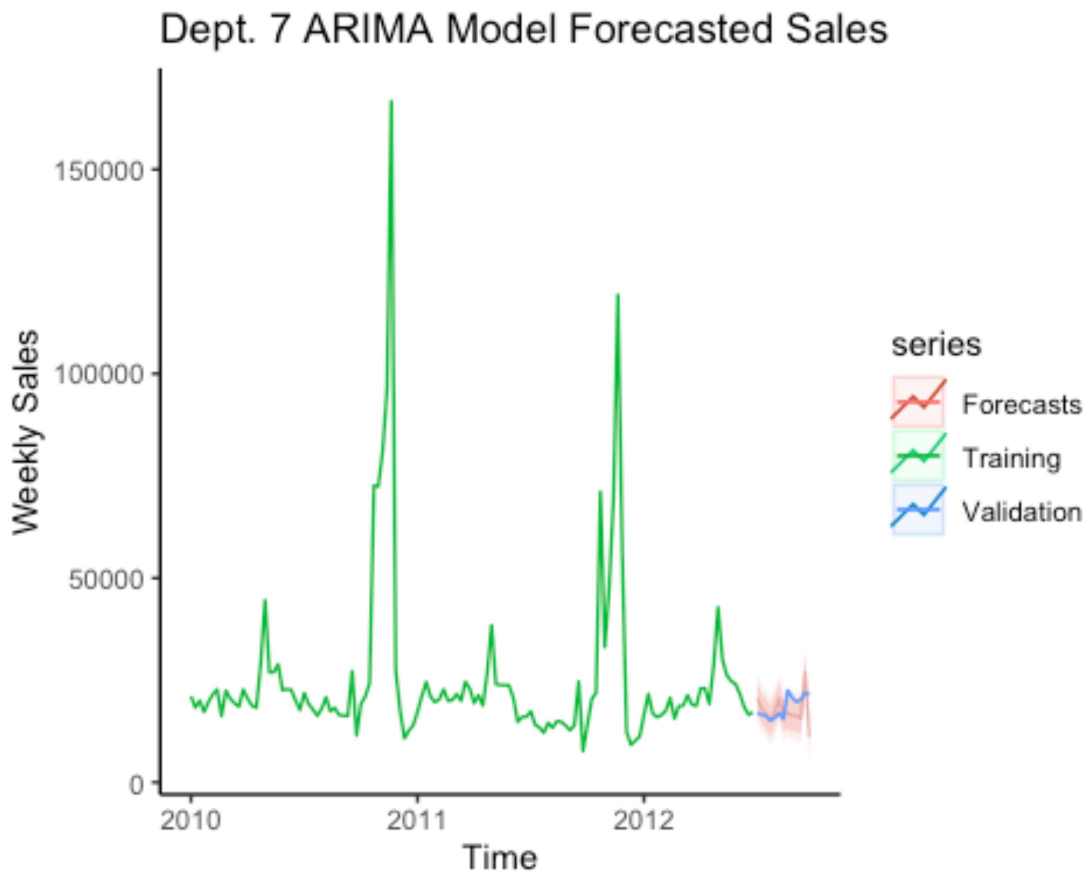
```
# plot of forecasted values
autoplot(training_1.6, series = "Training") +
  autolayer(forecast.lm.sales_1.6, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.6, series = "Validation") +
  labs(title = "Dept. 6 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 7 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.7 <- auto.arima(training_1.7, xreg = predictors_1.7)
summary(AutoArima_1.7)

## Series: training_1.7
## Regression with ARIMA(2,0,0)(0,1,0)[52] errors
##
## Coefficients:
##          ar1     ar2    drift      xreg
##       0.2126  0.2275  -55.677  151.4137
## s.e.  0.1091  0.1092   33.258  150.4872
##
## sigma^2 = 78277001:  log likelihood = -817.57
## AIC=1645.14   AICc=1645.98   BIC=1656.93
##
## Training set error measures:
##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.01804208 6675.154 2347.383 0.03687121 8.484803 0.4725356
##                      ACF1
## Training set -0.004579969
```

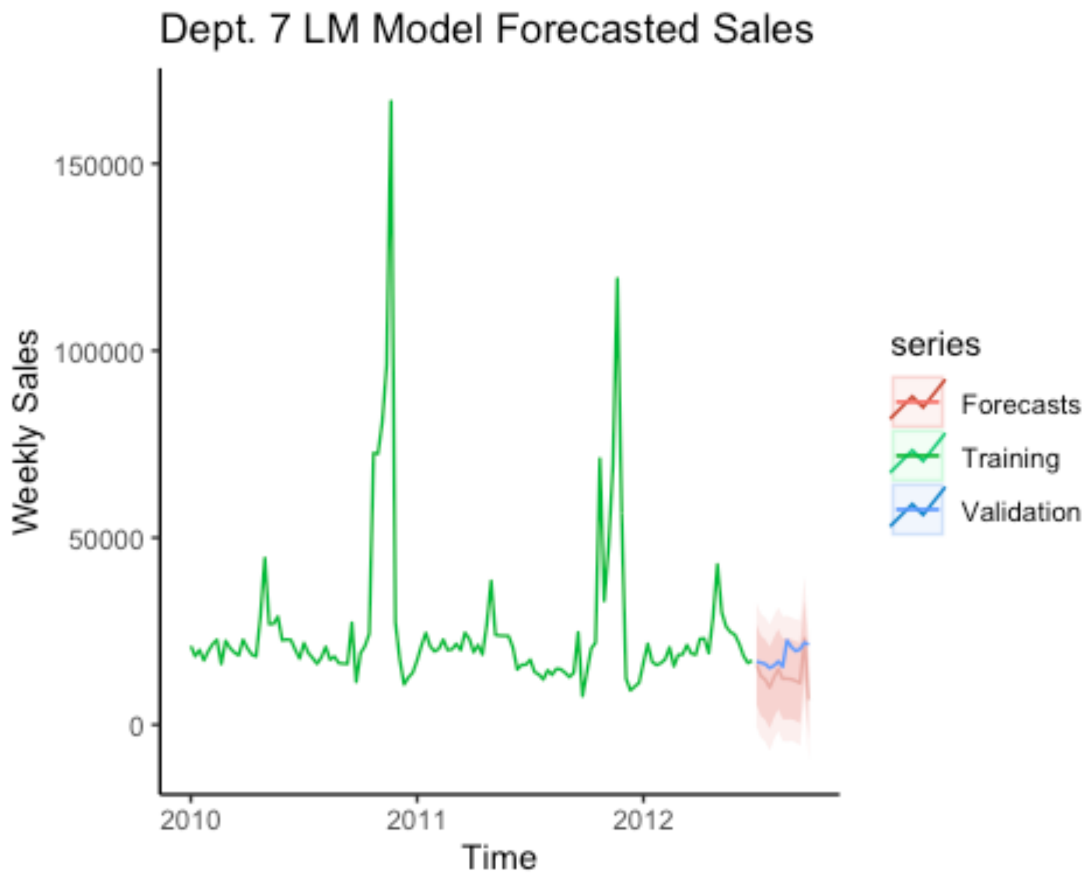
```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.7 <- Arima(training_1.7, xreg = predictors_1.7, order = c(2, 0, 1), s
easonal = c(1, 1, 0))
summary(arima_1.7)

## Series: training_1.7
## Regression with ARIMA(2,0,1)(1,1,0)[52] errors
##
## Coefficients:
##          ar1      ar2      ma1      sar1      xreg
##       0.8775  -0.0048  -0.6554  -0.9662   71.5952
## s.e.  0.0322   0.0310   0.1343   0.0034  116.6786
##
## sigma^2 = 7919706:  log likelihood = -798.2
## AIC=1608.41   AICc=1609.59   BIC=1622.55
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -269.0521 2108.843 956.0441 -1.274203 3.859567 0.1924547
##                     ACF1
## Training set -0.0304153

# prediction on the arima
new.predictors_1.7 <- as.matrix(store_1.7["Temperature"][131:143,])
forecast.arima.sales_1.7 <- forecast(arima_1.7, xreg = new.predictors_1.7)

# plot of forecasted values
autoplot(training_1.7, series = "Training") +
  autolayer(forecast.arima.sales_1.7, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.7, series = "Validation") +
  labs(title = "Dept. 7 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.7 <- store_1.7[1:130, 6]
linear_1.7 <- tslm(training_1.7 ~ trend + season + temp_1.7)
summary(linear_1.7)

##
## Call:
## tslm(formula = training_1.7 ~ trend + season + temp_1.7)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -22380.5  -1266.3     -7.6   1316.6  22380.5
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    14089.38    8518.75   1.654 0.102268
## trend            -39.42      16.52  -2.386 0.019543 *
## season2         2924.06    5536.78   0.528 0.598958
## season3         2180.79    5444.50   0.401 0.689875
## season4        -1264.63    5621.86  -0.225 0.822622
## season5         -710.95    5624.49  -0.126 0.899747
## season6          389.27    5668.36   0.069 0.945429
## season7         2167.93    5885.06   0.368 0.713615
```

```
## season8      -2798.45    5999.89  -0.466 0.642251
## season9        303.67    6038.28   0.050 0.960023
## season10      -436.34    6439.81  -0.068 0.946157
## season11      -625.68    6513.33  -0.096 0.923724
## season12        42.74    6449.37   0.007 0.994730
## season13       710.98    6509.57   0.109 0.913315
## season14       -36.94    6695.78  -0.006 0.995613
## season15      -394.75    7080.62  -0.056 0.955686
## season16     -2224.55    6746.20  -0.330 0.742497
## season17      6287.15    7485.06   0.840 0.403565
## season18     19851.95    7723.38   2.570 0.012115 *
## season19      4913.17    7729.38   0.636 0.526915
## season20      3293.69    8046.16   0.409 0.683435
## season21      3631.54    7900.14   0.460 0.647058
## season22      1090.79    8100.63   0.135 0.893240
## season23      -473.51    7957.87  -0.060 0.952708
## season24     -3555.66    7992.75  -0.445 0.657685
## season25     -4662.45    8020.10  -0.581 0.562728
## season26     -5241.60    8089.83  -0.648 0.518987
## season27     -4345.23    9287.47  -0.468 0.641224
## season28     -7217.76    9218.62  -0.783 0.436087
## season29     -8115.64    9142.77  -0.888 0.377526
## season30     -9253.14    8930.85  -1.036 0.303447
## season31     -6864.30    8680.04  -0.791 0.431513
## season32     -5052.57    7874.45  -0.642 0.523036
## season33     -6430.48    8271.60  -0.777 0.439326
## season34     -5676.36    7977.78  -0.712 0.478940
## season35     -6628.84    7706.03  -0.860 0.392376
## season36     -6003.12    6878.62  -0.873 0.385564
## season37     -5799.67    7107.74  -0.816 0.417070
## season38      5444.27    6887.92   0.790 0.431748
## season39    -11058.81    6990.98  -1.582 0.117833
## season40     -2500.82    6288.44  -0.398 0.691977
## season41      1303.27    6403.33   0.204 0.839265
## season42      4121.94    6286.11   0.656 0.513983
## season43     52185.33    6569.63   7.943 1.41e-11 ***
## season44     34873.79    6098.15   5.719 2.01e-07 ***
## season45     47073.83    6106.18   7.709 3.96e-11 ***
## season46     64816.17    6116.65  10.597  < 2e-16 ***
## season47    125079.87    6109.51  20.473  < 2e-16 ***
## season48     24532.85    6098.48   4.023 0.000135 ***
## season49     -2692.92    6098.79  -0.442 0.660068
## season50     -6723.14    6170.14  -1.090 0.279321
## season51     -6195.77    6102.73  -1.015 0.313210
## season52     -4983.03    6103.40  -0.816 0.416803
## temp_1.7       133.78     165.60   0.808 0.421696
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6667 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.9378, Adjusted R-squared:  0.8944
## F-statistic: 21.62 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.7$residuals^2))

## [1] 5097.913

# forecasting
temp.new_1.7 <- store_1.7[131:143, 6]
forecast.lm.sales_1.7 <- forecast(linear_1.7, temp.new_1.7, h = 13)

## Warning in forecast.lm(linear_1.7, temp.new_1.7, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.7

##          Point Forecast      Lo 80    Hi 80      Lo 95    Hi 95
## 2012.500      16099.828  5359.3380 26840.32  -446.9703 32646.63
## 2012.519      13046.075  2292.6335 23799.52 -3520.6764 29612.83
## 2012.538      12082.016  1338.0161 22826.02 -4470.1895 28634.22
## 2012.558       9943.207  -993.3099 20879.72 -6905.5904 26792.00
## 2012.577      12671.224  1912.6315 23429.82 -3903.4630 29245.91
## 2012.596      14907.752  4186.4772 25629.03 -1609.4436 31424.95
## 2012.615      12287.732  1467.5790 23107.89 -4381.7953 28957.26
## 2012.635      12320.148  1403.1627 23237.13 -4498.5589 29138.85
## 2012.654      12159.028  1474.0067 22844.05 -4302.3150 28620.37
## 2012.673      11737.954  1059.9975 22415.91 -4712.5050 28188.41
## 2012.692      11158.168   323.3000 21993.04 -5534.0292 27850.37
## 2012.712      23028.913 12349.1776 33708.65  6575.7133 39482.11
## 2012.731       6645.611 -4034.6792 17325.90 -9808.4433 23099.66

# plot of forecasted values
autoplot(training_1.7, series = "Training") +
  autolayer(forecast.lm.sales_1.7, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.7, series = "Validation") +
  labs(title = "Dept. 7 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



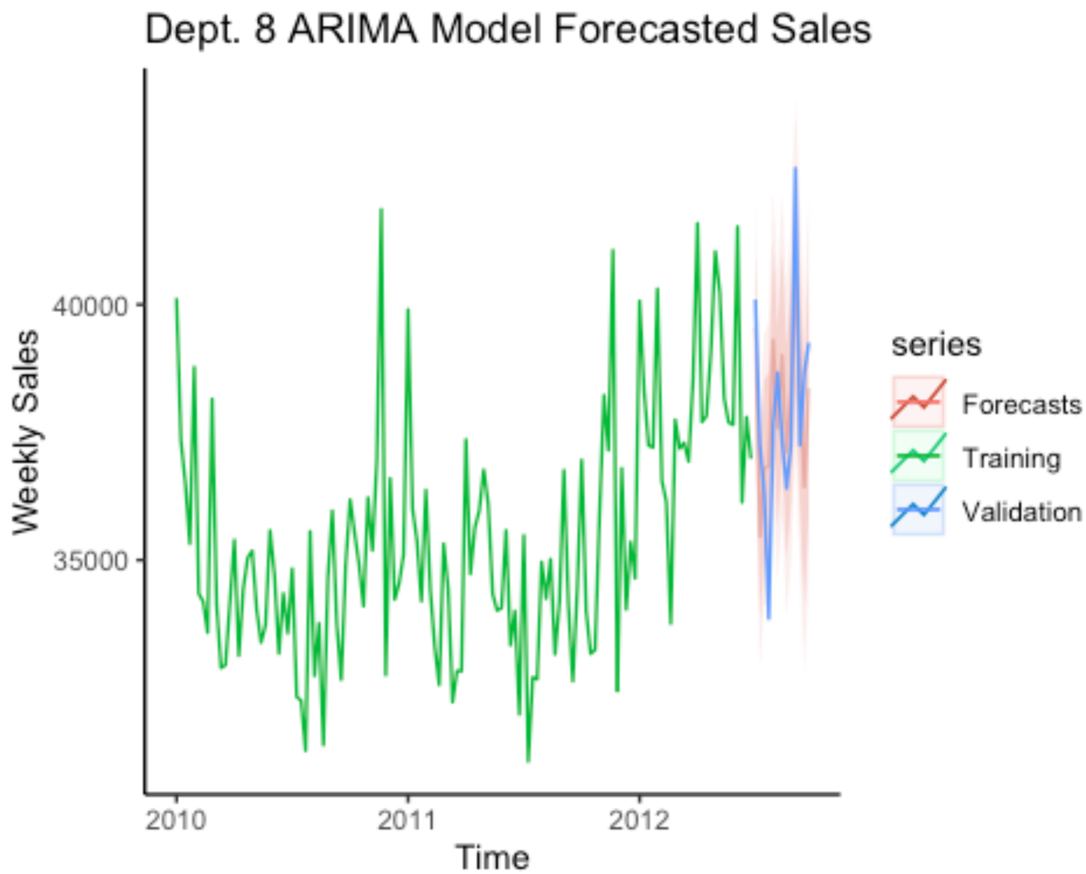
Department 8 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.8 <- auto.arima(training_1.8, xreg = predictors_1.8)
summary(AutoArima_1.8)

## Series: training_1.8
## Regression with ARIMA(0,1,1)(0,1,0)[52] errors
##
## Coefficients:
##           ma1      xreg
##       -0.6632  -45.7139
## s.e.   0.0869   21.2363
##
## sigma^2 = 1482269:  log likelihood = -655.56
## AIC=1317.12   AICc=1317.44   BIC=1324.15
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
## Training set 100.6768 924.7459 570.1565 0.2413113 1.587832 0.3226816
##                     ACF1
## Training set -0.01309687
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.8 <- Arima(training_1.8, xreg = predictors_1.8, order = c(1, 1, 1), s
easonal = c(0, 1, 1))
summary(arima_1.8)
```

```
## Series: training_1.8
## Regression with ARIMA(1,1,1)(0,1,1)[52] errors
##
## Coefficients:
##          ar1      ma1     sma1      xreg
##       0.0185  -0.6666  -0.1735  -46.9825
## s.e.  0.1677   0.1203   0.2143   22.3972
##
## sigma^2 = 1479111:  log likelihood = -655.21
## AIC=1320.42   AICc=1321.26   BIC=1332.14
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
## Training set 100.0455 911.3604 569.2195 0.2388208 1.582977 0.3221513
##                     ACF1
## Training set -0.01536931
```

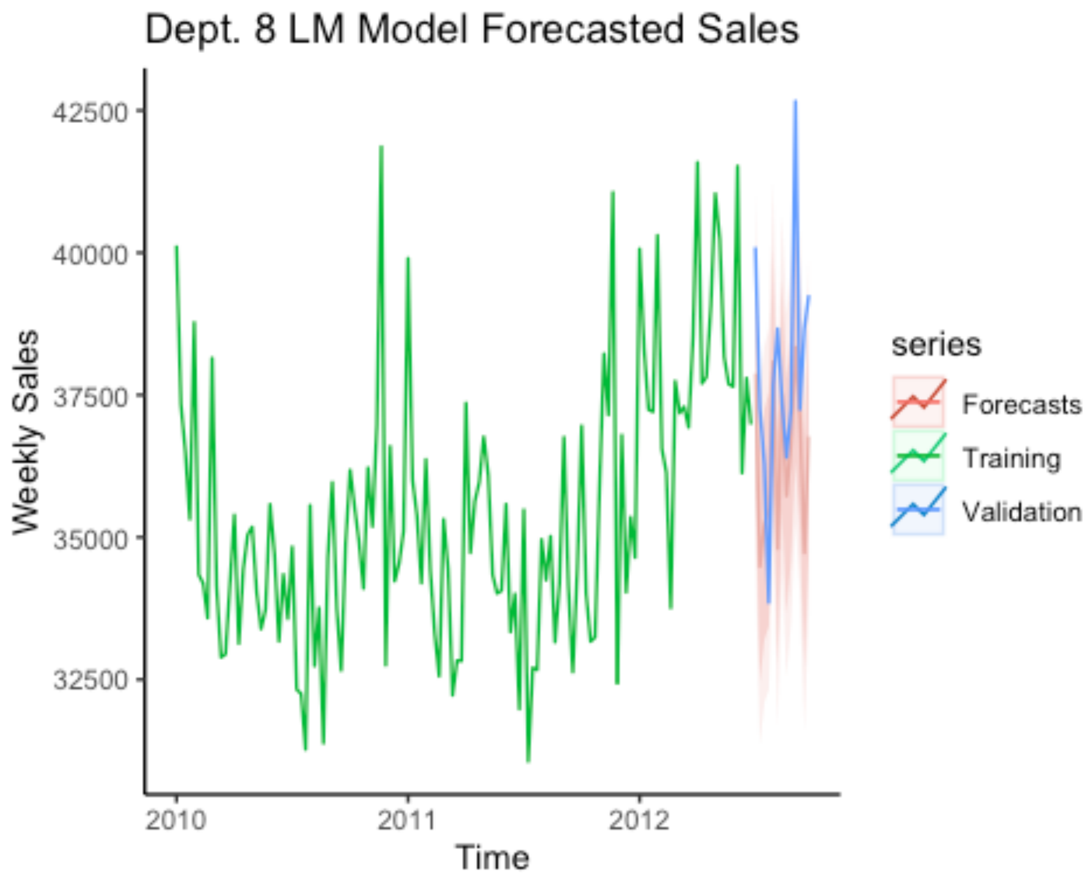
```r
# prediction on the arima
new.predictors_1.8 <- as.matrix(store_1.8["Temperature"][131:143,])
forecast.arima.sales_1.8 <- forecast(arima_1.8, xreg = new.predictors_1.8)

# plot of forecasted values
autoplot(training_1.8, series = "Training") +
  autolayer(forecast.arima.sales_1.8, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.8, series = "Validation") +
  labs(title = "Dept. 8 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```r
# linear model
temp_1.8 <- store_1.8[1:130, 6]
linear_1.8 <- tslm(training_1.8 ~ trend + season + temp_1.8)
summary(linear_1.8)

##
## Call:
## tslm(formula = training_1.8 ~ trend + season + temp_1.8)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2300.10  -621.60    54.33   598.13  2635.06
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 45194.55    1603.29  28.189  < 2e-16 ***
## trend          28.86       3.11   9.278 3.92e-14 ***
## season2     -3704.73    1042.06  -3.555 0.000654 ***
## season3     -3642.91    1024.69  -3.555 0.000654 ***
## season4     -3331.85    1058.07  -3.149 0.002342 **
## season5      -436.86    1058.57  -0.413 0.680995
## season6     -3700.53    1066.82  -3.469 0.000865 ***
## season7     -3722.11    1107.61  -3.360 0.001220 **
```

```
## season8     -4745.26    1129.22  -4.202 7.13e-05 ***
## season9      -921.12    1136.44  -0.811 0.420169    
## season10    -2050.99    1212.02  -1.692 0.094701 .  
## season11    -3079.56    1225.85  -2.512 0.014119 *  
## season12    -3106.78    1213.82  -2.560 0.012468 *  
## season13    -2097.61    1225.14  -1.712 0.090950 .  
## season14     1098.35    1260.19   0.872 0.386187    
## season15    -1313.48    1332.62  -0.986 0.327437    
## season16    -1029.70    1269.68  -0.811 0.419903    
## season17      667.18    1408.74   0.474 0.637144    
## season18     1902.80    1453.59   1.309 0.194468    
## season19     1012.36    1454.72   0.696 0.488608    
## season20     -131.07    1514.34  -0.087 0.931254    
## season21     -478.78    1486.86  -0.322 0.748331    
## season22      347.94    1524.59   0.228 0.820092    
## season23     1667.61    1497.72   1.113 0.269034    
## season24    -1380.59    1504.29  -0.918 0.361642    
## season25     -202.47    1509.44  -0.134 0.893648    
## season26    -1354.26    1522.56  -0.889 0.376563    
## season27     1149.12    1747.96   0.657 0.512906    
## season28    -2419.53    1735.01  -1.395 0.167219    
## season29    -1746.70    1720.73  -1.015 0.313282    
## season30    -2526.01    1680.85  -1.503 0.137029    
## season31      443.35    1633.64   0.271 0.786829    
## season32    -2376.76    1482.02  -1.604 0.112923    
## season33     -984.00    1556.77  -0.632 0.529231    
## season34    -3511.45    1501.47  -2.339 0.021983 *  
## season35    -1760.70    1450.33  -1.214 0.228506    
## season36    -1146.35    1294.60  -0.885 0.378691    
## season37    -3194.90    1337.72  -2.388 0.019409 *  
## season38    -4898.41    1296.35  -3.779 0.000312 ***
## season39    -2711.29    1315.75  -2.061 0.042759 *  
## season40    -2442.02    1183.53  -2.063 0.042495 *  
## season41    -3920.80    1205.15  -3.253 0.001703 ** 
## season42    -5031.94    1183.09  -4.253 5.94e-05 ***
## season43    -4650.04    1236.45  -3.761 0.000331 ***
## season44    -4178.61    1147.71  -3.641 0.000494 ***
## season45    -4118.02    1149.22  -3.583 0.000596 ***
## season46    -3002.01    1151.19  -2.608 0.010967 *  
## season47     1293.31    1149.85   1.125 0.264229    
## season48    -8132.86    1147.77  -7.086 6.05e-10 ***
## season49    -3743.49    1147.83  -3.261 0.001661 ** 
## season50    -7288.73    1161.26  -6.277 1.95e-08 ***
## season51    -5485.81    1148.58  -4.776 8.50e-06 ***
## season52    -5593.19    1148.70  -4.869 5.95e-06 ***
## temp_1.8     -142.21      31.17  -4.563 1.90e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1255 on 76 degrees of freedom
```

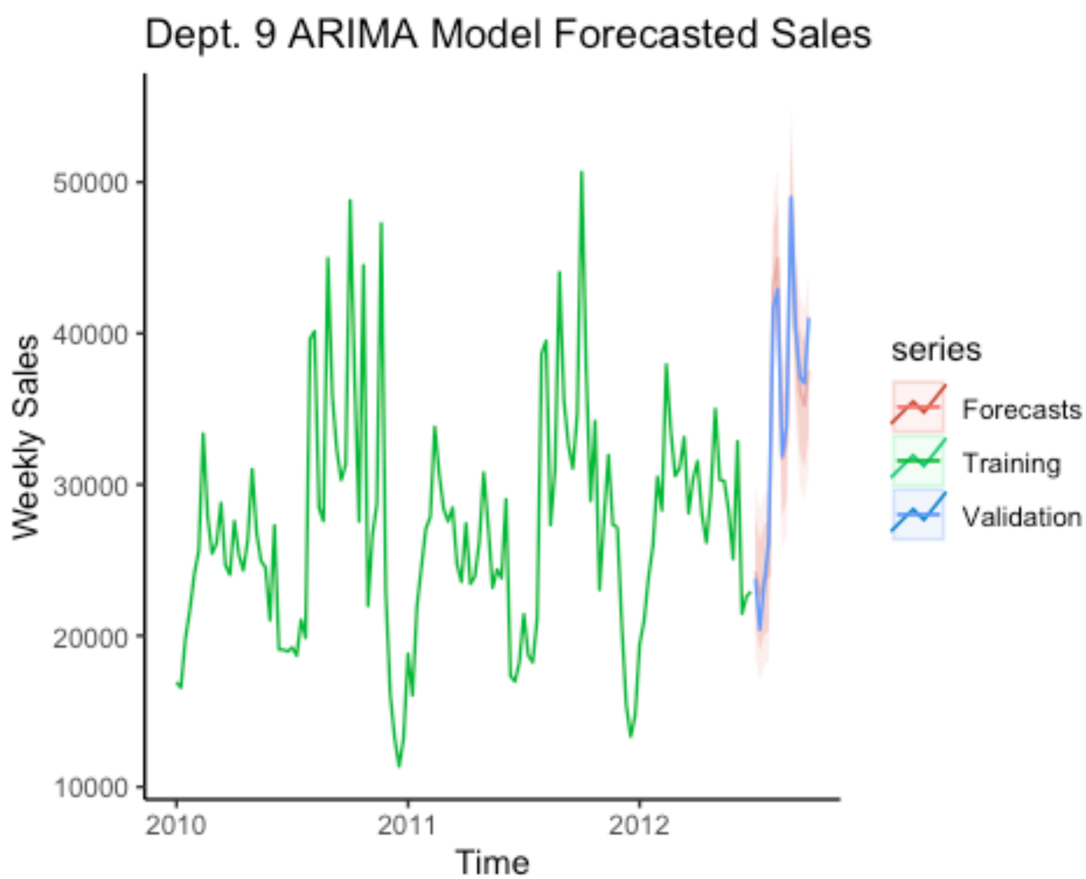
```r
## Multiple R-squared:  0.8318, Adjusted R-squared:  0.7146
## F-statistic: 7.094 on 53 and 76 DF,  p-value: 1.526e-14

# calculating RMSE
sqrt(mean(linear_1.8$residuals^2))

## [1] 959.4617

# forecasting
temp.new_1.8 <- store_1.8[131:143, 6]
forecast.lm.sales_1.8 <- forecast(linear_1.8, temp.new_1.8, h = 13)

## Warning in forecast.lm(linear_1.8, temp.new_1.8, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.8

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       37878.22 35856.78 39899.65 34764.00 40992.44
## 2012.519       34489.16 32465.29 36513.03 31371.19 37607.14
## 2012.538       35219.29 33197.20 37241.38 32104.05 38334.52
## 2012.558       35491.32 33433.00 37549.65 32320.26 38662.38
## 2012.577       38087.09 36062.25 40111.93 34967.62 41206.55
## 2012.596       34802.37 32784.55 36820.18 31693.72 37911.01
## 2012.615       37502.44 35466.01 39538.87 34365.12 40639.76
## 2012.635       35729.12 33674.47 37783.77 32563.73 38894.52
## 2012.654       36625.61 34614.61 38636.60 33527.47 39723.74
## 2012.673       38339.65 36329.99 40349.32 35243.57 41435.74
## 2012.692       37110.64 35071.45 39149.84 33969.06 40252.23
## 2012.712       34727.78 32717.78 36737.78 31631.18 37824.38
## 2012.731       36774.53 34764.43 38784.63 33677.77 39871.30

# plot of forecasted values
autoplot(training_1.8, series = "Training") +
  autolayer(forecast.lm.sales_1.8, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.8, series = "Validation") +
  labs(title = "Dept. 8 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 9 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.9 <- auto.arima(training_1.9, xreg = predictors_1.9)
summary(AutoArima_1.9)

## Series: training_1.9
## Regression with ARIMA(0,1,2)(0,1,0)[52] errors
##
## Coefficients:
##           ma1     ma2     xreg
##       -1.0764  0.2246  61.8295
## s.e.   0.1409  0.1443  53.6981
##
## sigma^2 = 11058829:  log likelihood = -732.94
## AIC=1473.88   AICc=1474.44   BIC=1483.26
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 168.8795 2508.989 1180.516 0.7077426 4.671497 0.4613915 0.027
93121
```

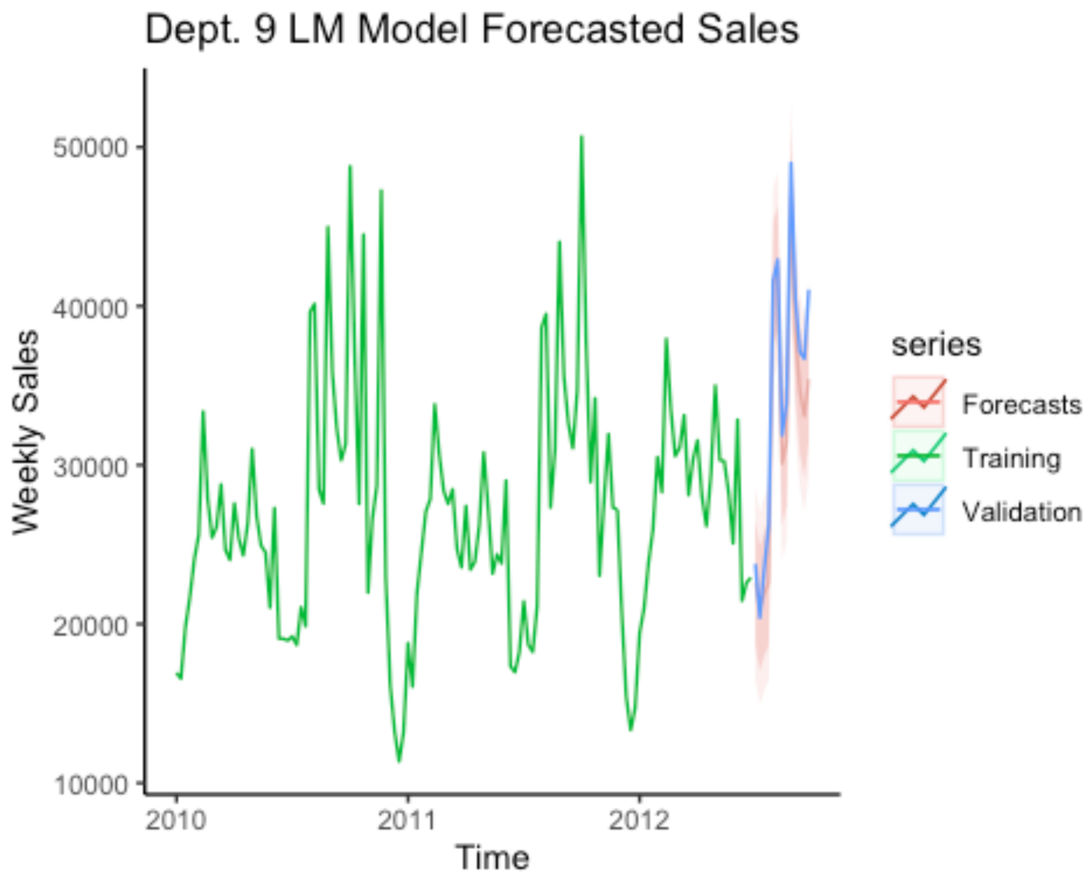
```
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.9 <- Arima(training_1.9, xreg = predictors_1.9, order = c(0, 1, 4), s
easonal = c(0, 1, 1))
summary(arima_1.9)

## Series: training_1.9
## Regression with ARIMA(0,1,4)(0,1,1)[52] errors
##
## Coefficients:
##            ma1     ma2     ma3     ma4     sma1      xreg
##        -1.0311  0.0685  0.0985  0.0415  -0.9998  103.8517
## s.e.    0.1324  0.1609  0.1596  0.1300   0.3516   58.4138
##
## sigma^2 = 5412065:  log likelihood = -726.94
## AIC=1467.88   AICc=1469.51   BIC=1484.29
##
## Training set error measures:
##                    ME    RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 95.69437 1719.25 780.5302 0.4228348 3.092106 0.3050615 -0.023
48425

# prediction on the arima
new.predictors_1.9 <- as.matrix(store_1.9["Temperature"][131:143,])
forecast.arima.sales_1.9 <- forecast(arima_1.9, xreg = new.predictors_1.9)

# plot of forecasted values
autoplot(training_1.9, series = "Training") +
  autolayer(forecast.arima.sales_1.9, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.9, series = "Validation") +
  labs(title = "Dept. 9 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.9 <- store_1.9[1:130, 6]
linear_1.9 <- tslm(training_1.9 ~ trend + season + temp_1.9)
summary(linear_1.9)

##
## Call:
## tslm(formula = training_1.9 ~ trend + season + temp_1.9)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10700.7   -798.1    183.8    786.4  10700.7
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 15462.445   3106.385   4.978 3.91e-06 ***
## trend          30.412      6.026   5.047 2.98e-06 ***
## season2      -376.184   2019.002  -0.186 0.852689
## season3      3409.244   1985.349   1.717 0.090015 .
## season4      5338.135   2050.025   2.604 0.011079 *
## season5      8467.089   2050.983   4.128 9.28e-05 ***
## season6      8445.275   2066.982   4.086 0.000108 ***
## season7     16095.232   2146.002   7.500 9.91e-11 ***
```

```
## season8     11673.255   2187.875   5.335 9.51e-07 ***
## season9      9054.041   2201.873   4.112 9.83e-05 ***
## season10     9010.102   2348.293   3.837 0.000256 ***
## season11    10832.643   2375.102   4.561 1.92e-05 ***
## season12     6524.248   2351.780   2.774 0.006960 **
## season13     6627.323   2373.730   2.792 0.006623 **
## season14     9410.471   2441.633   3.854 0.000241 ***
## season15     6033.755   2581.964   2.337 0.022081 *
## season16     5275.828   2460.018   2.145 0.035178 *
## season17     7541.158   2729.445   2.763 0.007182 **
## season18    12433.061   2816.351   4.415 3.30e-05 ***
## season19     8243.079   2818.538   2.925 0.004544 **
## season20     6145.443   2934.051   2.095 0.039546 *
## season21     5744.411   2880.805   1.994 0.049736 *
## season22     3258.543   2953.913   1.103 0.273453
## season23     9676.900   2901.856   3.335 0.001322 **
## season24     -785.588   2914.576  -0.270 0.788246
## season25     -574.715   2924.550  -0.197 0.844732
## season26     -128.758   2949.977  -0.044 0.965300
## season27      757.804   3386.697   0.224 0.823545
## season28     -886.793   3361.591  -0.264 0.792647
## season29       56.452   3333.934   0.017 0.986535
## season30      920.468   3256.656   0.283 0.778219
## season31    19595.397   3165.199   6.191 2.81e-08 ***
## season32    20441.449   2871.436   7.119 5.24e-10 ***
## season33     8391.734   3016.261   2.782 0.006807 **
## season34     9814.350   2909.118   3.374 0.001170 **
## season35    25079.505   2810.023   8.925 1.86e-13 ***
## season36    16511.082   2508.307   6.583 5.31e-09 ***
## season37    13147.554   2591.853   5.073 2.70e-06 ***
## season38    11411.613   2511.696   4.543 2.05e-05 ***
## season39    13666.659   2549.279   5.361 8.59e-07 ***
## season40    30679.916   2293.095  13.379  < 2e-16 ***
## season41    18263.563   2334.991   7.822 2.41e-11 ***
## season42     9131.959   2292.244   3.984 0.000154 ***
## season43    20051.901   2395.632   8.370 2.15e-12 ***
## season44     3550.855   2223.704   1.597 0.114456
## season45     8302.005   2226.632   3.729 0.000369 ***
## season46    11265.821   2230.450   5.051 2.94e-06 ***
## season47    18223.912   2227.849   8.180 4.98e-12 ***
## season48     6029.357   2223.824   2.711 0.008284 **
## season49     -681.076   2223.937  -0.306 0.760253
## season50    -4628.210   2249.957  -2.057 0.043116 *
## season51    -6828.265   2225.376  -3.068 0.002982 **
## season52    -5231.000   2225.619  -2.350 0.021351 *
## temp_1.9       27.884     60.387   0.462 0.645570
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2431 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.9378, Adjusted R-squared:  0.8943
## F-statistic:  21.6 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.9$residuals^2))

## [1] 1858.967

# forecasting
temp.new_1.9 <- store_1.9[131:143, 6]
forecast.lm.sales_1.9 <- forecast(linear_1.9, temp.new_1.9, h = 13)

## Warning in forecast.lm(linear_1.9, temp.new_1.9, h = 13): newdata column n
ames
## not specified, defaulting to first variable required.

forecast.lm.sales_1.9

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       22605.31 18688.76 26521.86 16571.48 28639.14
## 2012.519       20961.57 17040.30 24882.84 14920.46 27002.67
## 2012.538       21929.65 18011.82 25847.47 15893.85 27965.45
## 2012.558       22623.59 18635.56 26611.62 16479.63 28767.54
## 2012.577       41407.84 37484.69 45330.99 35363.84 47451.84
## 2012.596       42381.06 38471.52 46290.60 36358.03 48404.10
## 2012.615       30111.08 26165.48 34056.68 24032.50 36189.66
## 2012.635       31421.90 27440.99 35402.80 25288.92 37554.88
## 2012.654       46890.63 42994.31 50786.94 40887.96 52893.29
## 2012.673       38142.65 34248.90 42036.39 32143.95 44141.35
## 2012.692       34654.49 30703.53 38605.45 28567.64 40741.34
## 2012.712       33087.83 29193.44 36982.22 27088.13 39087.53
## 2012.731       35406.47 31511.87 39301.06 29406.46 41406.48

# plot of forecasted values
autoplot(training_1.9, series = "Training") +
  autolayer(forecast.lm.sales_1.9, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.9, series = "Validation") +
  labs(title = "Dept. 9 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



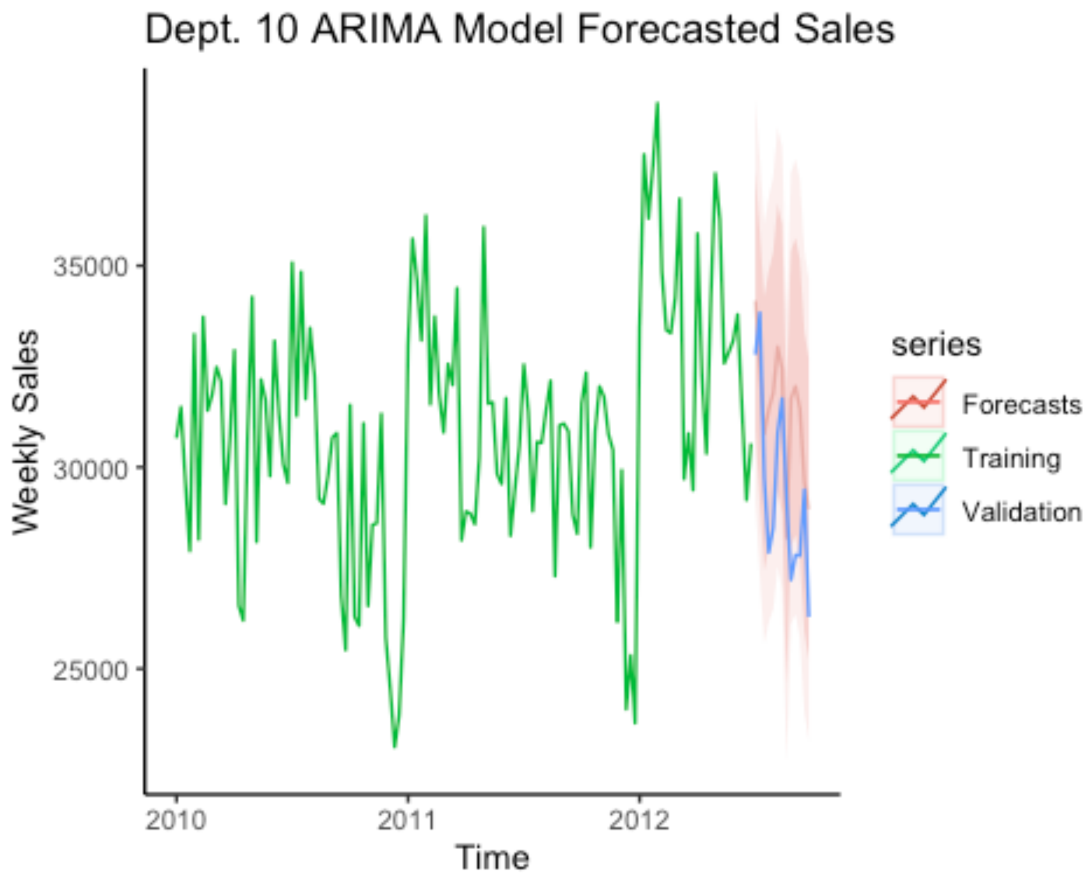
Department 10 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.10 <- auto.arima(training_1.10, xreg = predictors_1.10)
summary(AutoArima_1.10)

## Series: training_1.10
## Regression with ARIMA(1,0,1)(0,1,0)[52] errors
##
## Coefficients:
##          ar1      ma1     xreg
##       0.9217  -0.6960  61.8860
## s.e.  0.0825   0.1521  44.2999
##
## sigma^2 = 6213341:  log likelihood = -719.44
## AIC=1446.89   AICc=1447.43   BIC=1456.31
##
## Training set error measures:
##                      ME     RMSE      MAE      MPE     MAPE      MASE
ACF1
## Training set 191.0152 1893.309 1214.645 0.413074 3.881143 0.5353974 0.0435
4789
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.10 <- Arima(training_1.10, xreg = predictors_1.10, order = c(1, 0, 4)
, seasonal = c(0, 1, 2))
summary(arima_1.10)
```

```
## Series: training_1.10
## Regression with ARIMA(1,0,4)(0,1,2)[52] errors
##
## Coefficients:
##          ar1      ma1      ma2     ma3     ma4     sma1    sma2     xreg
##       0.9329  -0.6562  -0.1107  0.0534  0.0195  -0.1529  0.8665  50.4281
## s.e.  0.2122   0.2350   0.1692  0.1884  0.2155   0.3619  3.4224  47.7553
##
## sigma^2 = 3694778:  log likelihood = -718.56
## AIC=1455.12   AICc=1457.77   BIC=1476.33
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE     MASE
## Training set 130.8027 1410.495 908.4041 0.2734734 2.898582 0.400411
##                      ACF1
## Training set -0.006280305
```

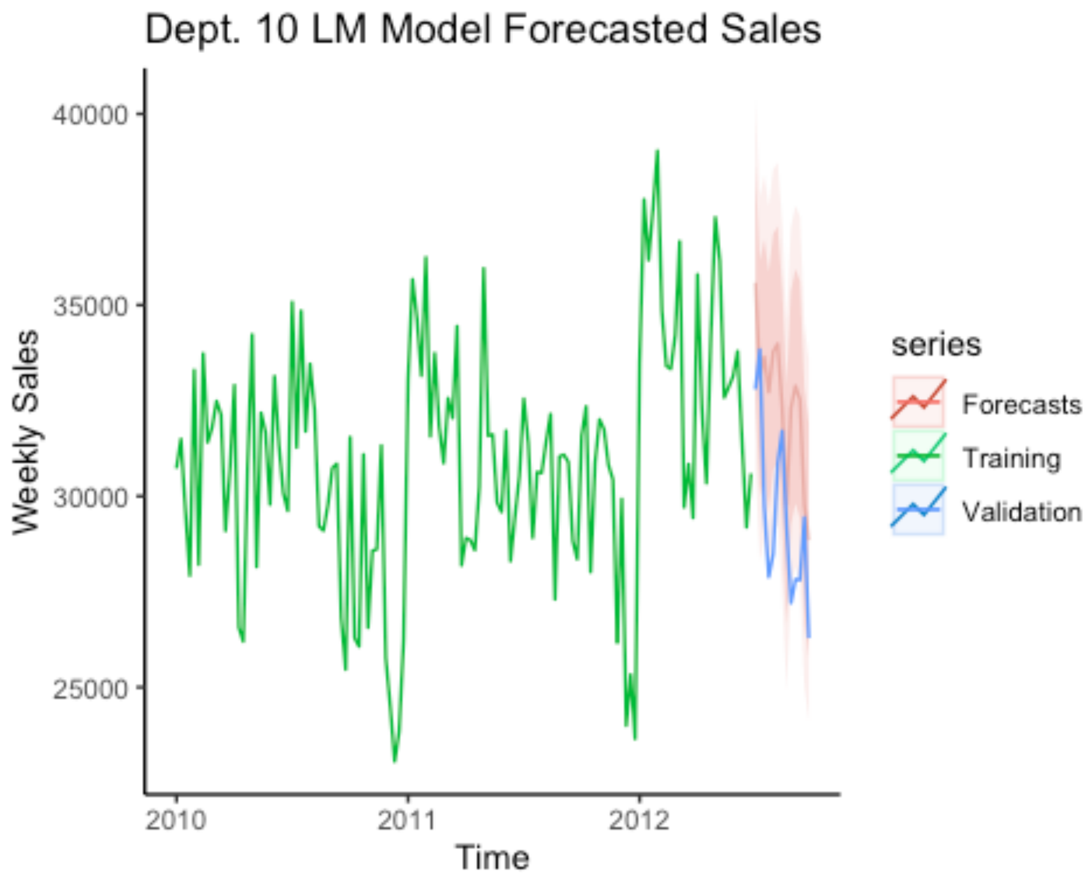
```r
# prediction on the arima
new.predictors_1.10 <- as.matrix(store_1.10["Temperature"][131:143,])
forecast.arima.sales_1.10 <- forecast(arima_1.10, xreg = new.predictors_1.10)

# plot of forecasted values
autoplot(training_1.10, series = "Training") +
  autolayer(forecast.arima.sales_1.10, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.10, series = "Validation") +
  labs(title = "Dept. 10 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.10 <- store_1.10[1:130, 6]
linear_1.10 <- tslm(training_1.10 ~ trend + season + temp_1.10)
summary(linear_1.10)

##
## Call:
## tslm(formula = training_1.10 ~ trend + season + temp_1.10)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3665.5 -1000.0    32.3   974.1  3665.5
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 29344.57    2443.58  12.009  < 2e-16 ***
## trend          24.34       4.74   5.136 2.10e-06 ***
## season2      2756.98    1588.21   1.736 0.086633 .
## season3       992.70    1561.74   0.636 0.526920
## season4        32.83    1612.61   0.020 0.983809
## season5      3339.90    1613.37   2.070 0.041836 *
## season6     -1374.39    1625.95  -0.845 0.400607
## season7       531.75    1688.11   0.315 0.753627
```

```
## season8     -1005.98    1721.05  -0.585 0.560606
## season9      -942.09    1732.06  -0.544 0.588094
## season10      458.42    1847.24   0.248 0.804676
## season11    -2208.44    1868.33  -1.182 0.240875
## season12    -2042.89    1849.98  -1.104 0.272957
## season13    -4122.96    1867.25  -2.208 0.030257 *
## season14    -1118.00    1920.66  -0.582 0.562229
## season15    -4593.91    2031.05  -2.262 0.026566 *
## season16    -5349.07    1935.13  -2.764 0.007156 **
## season17    -2236.41    2147.07  -1.042 0.300894
## season18     1709.11    2215.43   0.771 0.442827
## season19    -2184.37    2217.15  -0.985 0.327644
## season20    -2148.38    2308.02  -0.931 0.354888
## season21    -2800.39    2266.13  -1.236 0.220354
## season22    -3505.71    2323.64  -1.509 0.135518
## season23    -1437.66    2282.69  -0.630 0.530707
## season24    -3998.04    2292.70  -1.744 0.085235 .
## season25    -4814.06    2300.54  -2.093 0.039725 *
## season26    -4192.70    2320.54  -1.807 0.074756 .
## season27     -228.64    2664.08  -0.086 0.931833
## season28    -2718.50    2644.33  -1.028 0.307188
## season29    -2169.42    2622.58  -0.827 0.410708
## season30    -2846.07    2561.79  -1.111 0.270083
## season31    -1921.17    2489.84  -0.772 0.442743
## season32    -1867.73    2258.76  -0.827 0.410892
## season33    -3188.34    2372.68  -1.344 0.183021
## season34    -5593.10    2288.40  -2.444 0.016839 *
## season35    -3317.26    2210.45  -1.501 0.137572
## season36    -2484.03    1973.11  -1.259 0.211906
## season37    -2657.24    2038.83  -1.303 0.196403
## season38    -5630.80    1975.78  -2.850 0.005626 **
## season39    -6615.57    2005.34  -3.299 0.001478 **
## season40    -1551.89    1803.82  -0.860 0.392309
## season41    -3920.25    1836.78  -2.134 0.036042 *
## season42    -6125.63    1803.15  -3.397 0.001086 **
## season43    -2415.53    1884.48  -1.282 0.203809
## season44    -3637.11    1749.23  -2.079 0.040967 *
## season45    -2634.48    1751.54  -1.504 0.136702
## season46    -3317.88    1754.54  -1.891 0.062432 .
## season47    -2152.74    1752.50  -1.228 0.223092
## season48    -6961.81    1749.33  -3.980 0.000156 ***
## season49    -5810.18    1749.42  -3.321 0.001379 **
## season50    -9266.90    1769.89  -5.236 1.42e-06 ***
## season51    -8497.07    1750.55  -4.854 6.31e-06 ***
## season52    -8175.82    1750.74  -4.670 1.27e-05 ***
## temp_1.10      38.11      47.50   0.802 0.424904
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1913 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.7765, Adjusted R-squared:  0.6206
## F-statistic: 4.982 on 53 and 76 DF,  p-value: 1.4e-10

# calculating RMSE
sqrt(mean(linear_1.10$residuals^2))

## [1] 1462.321

# forecasting
temp.new_1.10 <- store_1.10[131:143, 6]
forecast.lm.sales_1.10 <- forecast(linear_1.10, temp.new_1.10, h = 13)

## Warning in forecast.lm(linear_1.10, temp.new_1.10, h = 13): newdata column
names
## not specified, defaulting to first variable required.

forecast.lm.sales_1.10

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       35586.54 32505.66 38667.41 30840.14 40332.94
## 2012.519       33080.62 29996.03 36165.22 28328.50 37832.75
## 2012.538       33646.43 30564.54 36728.31 28898.48 38394.38
## 2012.558       32720.11 29583.01 35857.22 27887.09 37553.14
## 2012.577       33777.21 30691.14 36863.28 29022.81 38531.61
## 2012.596       33987.23 30911.87 37062.60 29249.32 38725.14
## 2012.615       32348.36 29244.63 35452.09 27566.76 37129.96
## 2012.635       29773.59 26642.09 32905.09 24949.19 34597.98
## 2012.654       32310.43 29245.47 35375.40 27588.55 37032.32
## 2012.673       32881.05 29818.11 35943.99 28162.29 37599.82
## 2012.692       32520.30 29412.35 35628.25 27732.19 37308.41
## 2012.712       29760.86 26697.42 32824.31 25041.31 34480.42
## 2012.731       28845.79 25782.18 31909.39 24125.99 33565.58

# plot of forecasted values
autoplot(training_1.10, series = "Training") +
  autolayer(forecast.lm.sales_1.10, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.10, series = "Validation") +
  labs(title = "Dept. 10 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



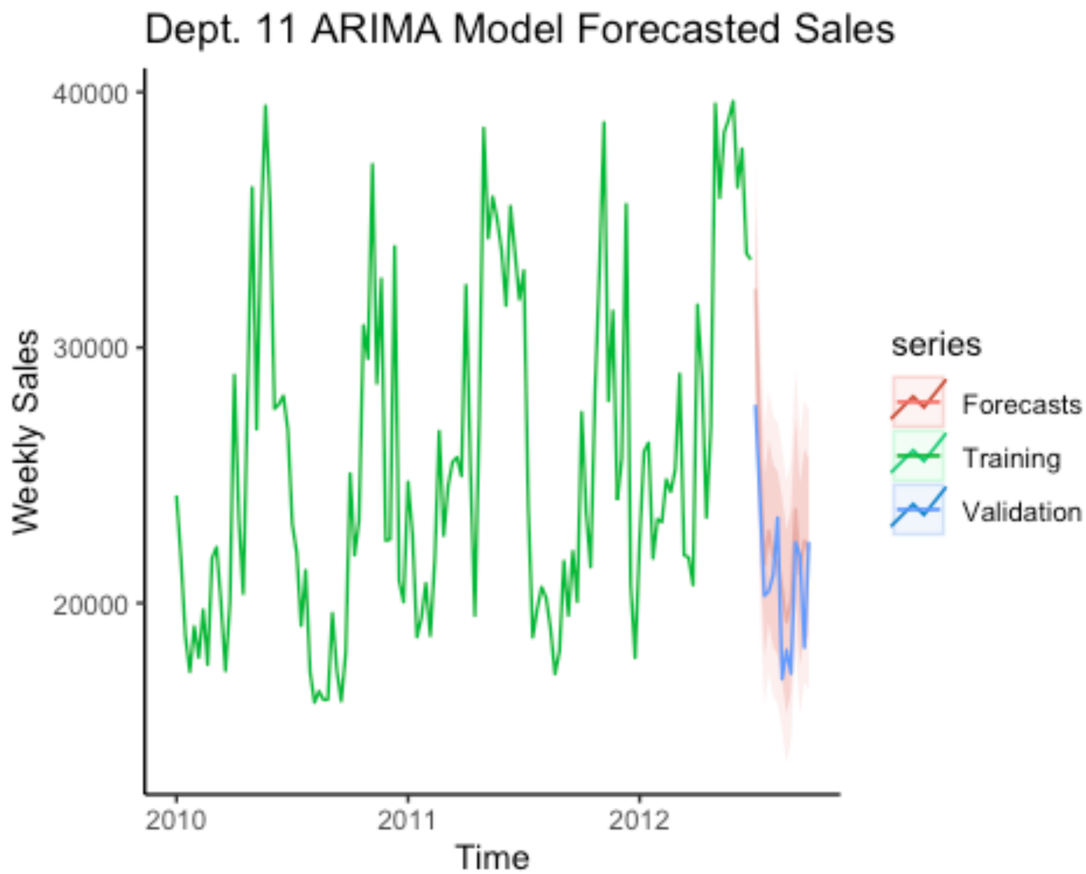
Department 11 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.11 <- auto.arima(training_1.11, xreg = predictors_1.11)
summary(AutoArima_1.11)

## Series: training_1.11
## Regression with ARIMA(0,0,1)(0,1,0)[52] errors
##
## Coefficients:
##          ma1    drift     xreg
##       0.5171  36.4454  55.6796
## s.e.  0.0842   8.7526  46.4534
##
## sigma^2 = 7200287:  log likelihood = -725.1
## AIC=1458.19   AICc=1458.74   BIC=1467.62
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
ACF1
## Training set 12.50009 2038.139 1276.635 -0.3792063 4.934208 0.4369941 0.03
83231
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.11 <- Arima(training_1.11, xreg = predictors_1.11, order = c(0, 1, 2)
, seasonal = c(1, 1, 0))
summary(arima_1.11)
```

```
## Series: training_1.11
## Regression with ARIMA(0,1,2)(1,1,0)[52] errors
##
## Coefficients:
##           ma1      ma2     sar1     xreg
##       -0.5053  -0.4947  -0.4191  41.2856
## s.e.   0.1068   0.0927   0.1521  50.0273
##
## sigma^2 = 6034169:  log likelihood = -715.35
## AIC=1440.7   AICc=1441.54   BIC=1452.41
##
## Training set error measures:
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set -5.165186 1840.766 1141.668 -0.4183546 4.404359 0.3907944
##                    ACF1
## Training set 0.02744617
```

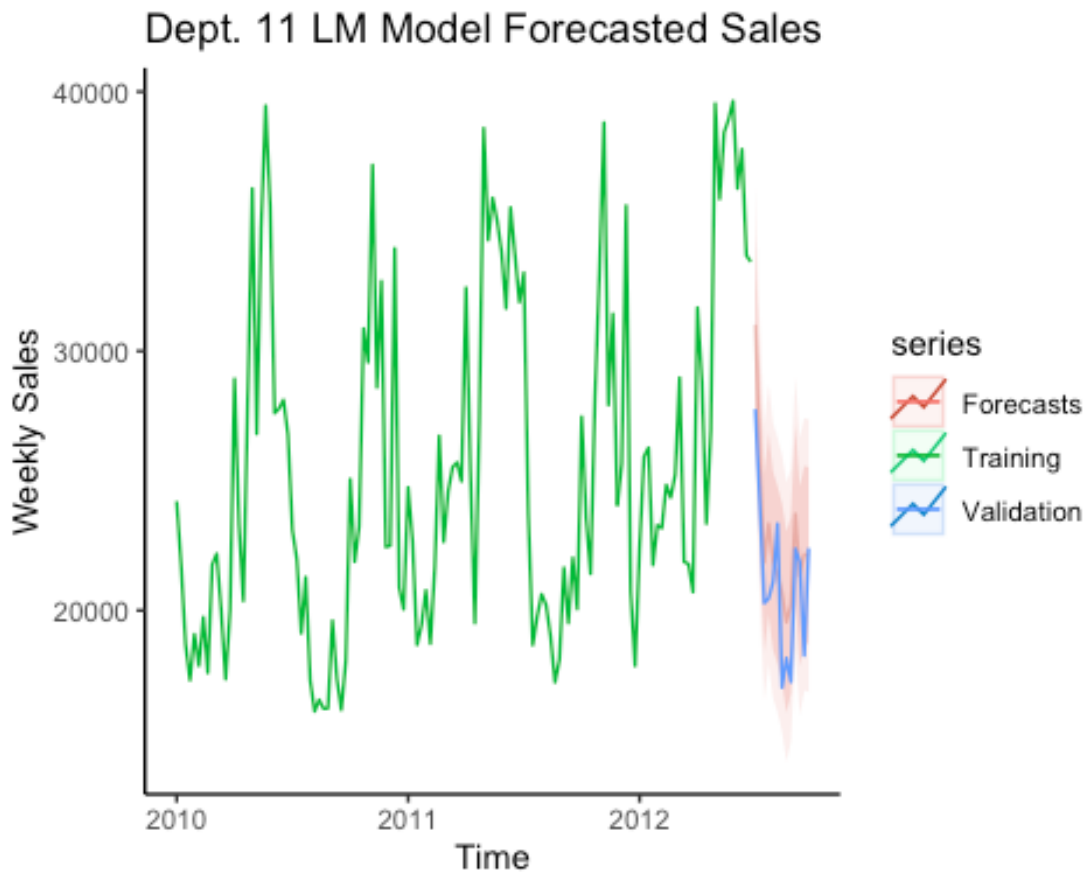
```r
# prediction on the arima
new.predictors_1.11 <- as.matrix(store_1.11["Temperature"][131:143,])
forecast.arima.sales_1.11 <- forecast(arima_1.11, xreg = new.predictors_1.11)

# plot of forecasted values
autoplot(training_1.11, series = "Training") +
  autolayer(forecast.arima.sales_1.11, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.11, series = "Validation") +
  labs(title = "Dept. 11 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.11 <- store_1.11[1:130, 6]
linear_1.11 <- tslm(training_1.11 ~ trend + season + temp_1.11)
summary(linear_1.11)

##
## Call:
## tslm(formula = training_1.11 ~ trend + season + temp_1.11)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3897.2  -669.7   -19.3  1051.8  3971.9
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 20574.852   2717.786   7.570 7.28e-11 ***
## trend          38.956      5.272   7.389 1.61e-10 ***
## season2      -231.512   1766.431  -0.131 0.896072
## season3     -2668.732   1736.989  -1.536 0.128590
## season4     -4628.569   1793.574  -2.581 0.011789 *
## season5     -3113.653   1794.412  -1.735 0.086760 .
## season6     -4309.624   1808.410  -2.383 0.019666 *
## season7     -2275.575   1877.545  -1.212 0.229269
```

```
## season8     -1554.662   1914.180  -0.812 0.419224
## season9     -1286.429   1926.426  -0.668 0.506297
## season10      589.294   2054.530   0.287 0.775025
## season11    -2256.350   2077.984  -1.086 0.280984
## season12    -3128.916   2057.580  -1.521 0.132490
## season13    -2902.844   2076.784  -1.398 0.166252
## season14     6126.514   2136.193   2.868 0.005344 **
## season15      805.606   2258.969   0.357 0.722360
## season16    -3904.021   2152.278  -1.814 0.073640 .
## season17     2317.642   2388.001   0.971 0.334858
## season18    12854.327   2464.035   5.217 1.53e-06 ***
## season19     6994.227   2465.949   2.836 0.005846 **
## season20    10957.494   2567.011   4.269 5.62e-05 ***
## season21    12371.052   2520.426   4.908 5.12e-06 ***
## season22    10842.355   2584.389   4.195 7.31e-05 ***
## season23     6312.552   2538.843   2.486 0.015099 *
## season24     8126.969   2549.973   3.187 0.002086 **
## season25     6226.136   2558.698   2.433 0.017311 *
## season26     5035.189   2580.945   1.951 0.054754 .
## season27     3223.528   2963.033   1.088 0.280071
## season28    -2025.787   2941.067  -0.689 0.493051
## season29    -5996.931   2916.870  -2.056 0.043222 *
## season30    -4357.757   2849.259  -1.529 0.130308
## season31    -5906.005   2769.243  -2.133 0.036177 *
## season32    -6575.308   2512.229  -2.617 0.010689 *
## season33    -7085.924   2638.936  -2.685 0.008897 **
## season34    -8114.638   2545.197  -3.188 0.002079 **
## season35    -7651.499   2458.498  -3.112 0.002616 **
## season36    -4000.025   2194.526  -1.823 0.072278 .
## season37    -6297.231   2267.621  -2.777 0.006905 **
## season38    -5610.229   2197.491  -2.553 0.012684 *
## season39    -5734.587   2230.373  -2.571 0.012090 *
## season40     1724.473   2006.237   0.860 0.392737
## season41    -1931.370   2042.892  -0.945 0.347446
## season42    -2291.093   2005.492  -1.142 0.256870
## season43     4797.366   2095.946   2.289 0.024865 *
## season44     6839.857   1945.526   3.516 0.000743 ***
## season45    13541.862   1948.088   6.951 1.08e-09 ***
## season46     3632.327   1951.429   1.861 0.066559 .
## season47     7416.024   1949.153   3.805 0.000285 ***
## season48    -1362.396   1945.631  -0.700 0.485920
## season49     -609.294   1945.730  -0.313 0.755029
## season50    10217.644   1968.495   5.191 1.69e-06 ***
## season51    -3982.432   1946.989  -2.045 0.044273 *
## season52    -5866.907   1947.202  -3.013 0.003513 **
## temp_1.11      24.555     52.832   0.465 0.643431
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2127 on 76 degrees of freedom
```

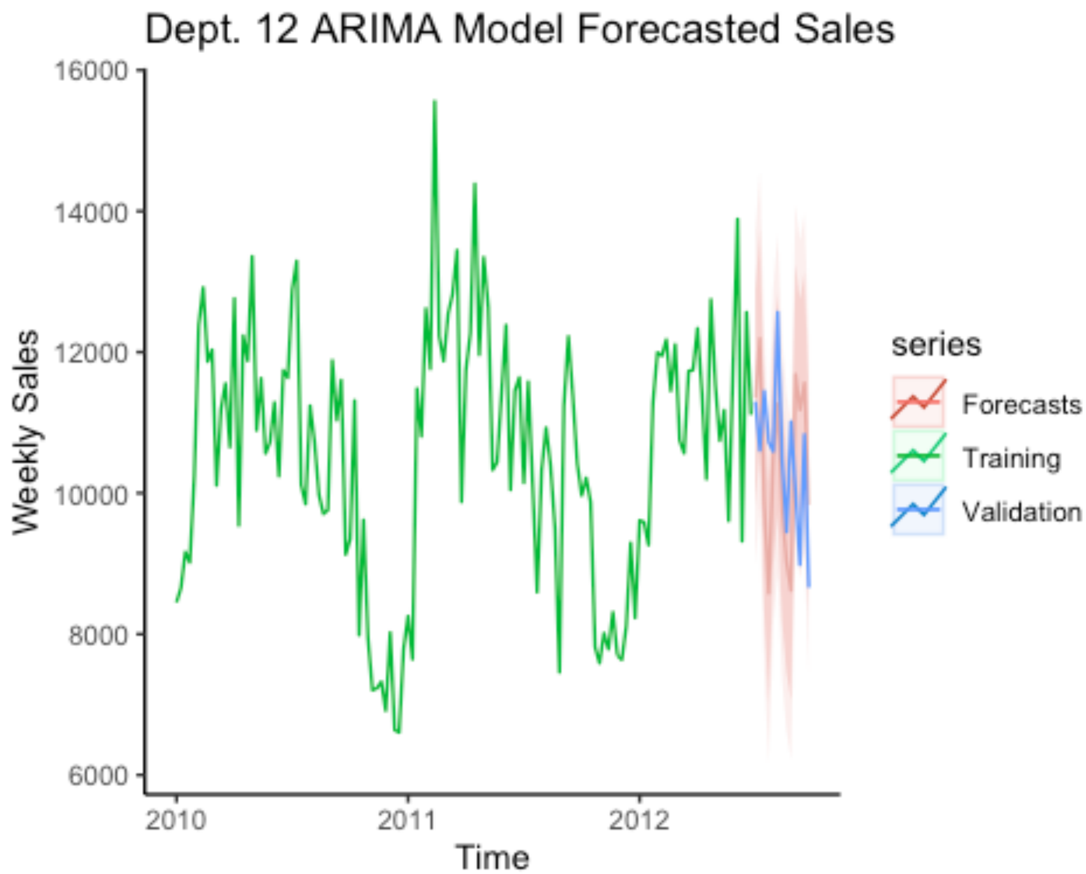
```
## Multiple R-squared:  0.9381, Adjusted R-squared:  0.895
## F-statistic: 21.75 on 53 and 76 DF,  p-value: < 2.2e-16

# calculating RMSE
sqrt(mean(linear_1.11$residuals^2))

## [1] 1626.416

# forecasting
temp.new_1.11 <- store_1.11[131:143, 6]
forecast.lm.sales_1.11 <- forecast(linear_1.11, temp.new_1.11, h = 13)

## Warning in forecast.lm(linear_1.11, temp.new_1.11, h = 13): newdata column
names
## not specified, defaulting to first variable required.

forecast.lm.sales_1.11

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       31016.01 27589.42 34442.61 25737.00 36295.03
## 2012.519       25779.63 22348.90 29210.36 20494.24 31065.01
## 2012.538       21842.53 18414.81 25270.25 16561.79 27123.27
## 2012.558       23344.11 19854.97 26833.25 17968.75 28719.48
## 2012.577       21904.31 18471.94 25336.68 16616.39 27192.23
## 2012.596       21359.17 17938.70 24779.64 16089.59 26628.74
## 2012.615       20666.76 17214.75 24118.78 15348.59 25984.94
## 2012.635       19551.78 16068.87 23034.68 14186.01 24917.54
## 2012.654       20206.35 16797.45 23615.26 14954.60 25458.11
## 2012.673       23711.89 20305.24 27118.54 18463.61 28960.17
## 2012.692       21317.12 17860.41 24773.83 15991.71 26642.52
## 2012.712       22165.36 18758.14 25572.57 16916.20 27414.51
## 2012.731       22109.17 18701.78 25516.57 16859.74 27358.60

# plot of forecasted values
autoplot(training_1.11, series = "Training") +
  autolayer(forecast.lm.sales_1.11, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.11, series = "Validation") +
  labs(title = "Dept. 11 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Department 12 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.12 <- auto.arima(training_1.12, xreg = predictors_1.12)
summary(AutoArima_1.12)

## Series: training_1.12
## Regression with ARIMA(0,0,0)(0,1,0)[52] errors
##
## Coefficients:
##          xreg
##       71.7328
## s.e.  23.0638
##
## sigma^2 = 1943222:  log likelihood = -674.89
## AIC=1353.78   AICc=1353.94   BIC=1358.49
##
## Training set error measures:
##                     ME    RMSE      MAE       MPE    MAPE      MASE      A
CF1
## Training set -17.67594 1072.84 653.7614 -0.510745 6.12837 0.5566233 0.1362
223
```

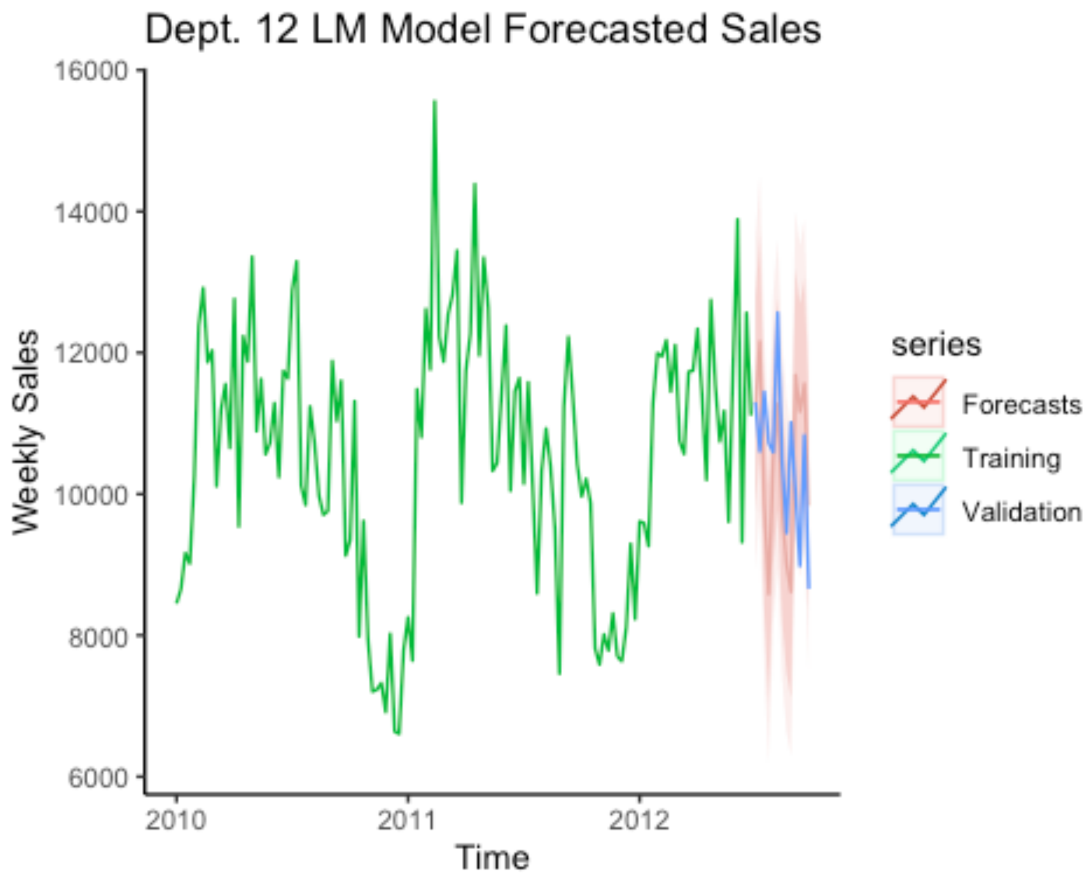
```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.12 <- Arima(training_1.12, xreg = predictors_1.12, order = c(0, 1, 5)
, seasonal = c(0, 1, 1))
summary(arima_1.12)

## Series: training_1.12
## Regression with ARIMA(0,1,5)(0,1,1)[52] errors
##
## Coefficients:
##           ma1      ma2    ma3      ma4      ma5     sma1     xreg
##       -0.9117  -0.0068  0.005  -0.0501  -0.0363  -0.9999  67.6375
## s.e.   0.1355   0.1561  0.172   0.1543   0.1050   0.4438  25.8786
##
## sigma^2 = 936497:  log likelihood = -660.11
## AIC=1336.22   AICc=1338.34   BIC=1354.97
##
## Training set error measures:
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set -50.57084 710.1182 443.4773 -0.7057122 4.156725 0.3775839
##                      ACF1
## Training set -0.009835111

# prediction on the arima
new.predictors_1.12 <- as.matrix(store_1.12["Temperature"][131:143,])
forecast.arima.sales_1.12 <- forecast(arima_1.12, xreg = new.predictors_1.12)

# plot of forecasted values
autoplot(training_1.12, series = "Training") +
  autolayer(forecast.arima.sales_1.12, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.12, series = "Validation") +
  labs(title = "Dept. 12 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.12 <- store_1.12[1:130, 6]
linear_1.12 <- tslm(training_1.12 ~ trend + season + temp_1.12)
summary(linear_1.12)

##
## Call:
## tslm(formula = training_1.12 ~ trend + season + temp_1.12)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1987.66  -464.56   -75.79   443.51  2379.71
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5513.7328  1198.9988   4.599 1.67e-05 ***
## trend          -0.1605     2.3258  -0.069  0.94516
## season2       277.3182   779.2919   0.356  0.72293
## season3      1164.8640   766.3029   1.520  0.13263
## season4      1002.5695   791.2663   1.267  0.20901
## season5      2245.9813   791.6359   2.837  0.00583 **
## season6      2589.4748   797.8113   3.246  0.00174 **
## season7      3832.9632   828.3115   4.627 1.49e-05 ***
```

```
## season8      2004.6691   844.4737   2.374  0.02013 *
## season9      2124.6466   849.8765   2.500  0.01458 *
## season10      904.2687   906.3916   0.998  0.32161
## season11     1237.6258   916.7390   1.350  0.18101
## season12     2005.1012   907.7373   2.209  0.03019 *
## season13      470.3921   916.2095   0.513  0.60915
## season14     1855.2833   942.4189   1.969  0.05264 .
## season15      385.3047   996.5833   0.387  0.70011
## season16     1808.0128   949.5150   1.904  0.06068 .
## season17     1243.9865  1053.5082   1.181  0.24136
## season18     1653.2617  1087.0519   1.521  0.13244
## season19      323.9361  1087.8962   0.298  0.76670
## season20     -241.4492  1132.4816  -0.213  0.83174
## season21    -1001.5520  1111.9299  -0.901  0.37058
## season22       -2.8070  1140.1481  -0.002  0.99804
## season23     1279.9053  1120.0549   1.143  0.25674
## season24    -1393.3360  1124.9649  -1.239  0.21932
## season25      643.1910  1128.8143   0.570  0.57050
## season26      142.6065  1138.6287   0.125  0.90066
## season27     -197.3568  1307.1935  -0.151  0.88039
## season28      760.0332  1297.5030   0.586  0.55977
## season29    -1529.8750  1286.8282  -1.189  0.23819
## season30    -2298.8330  1257.0002  -1.829  0.07135 .
## season31     -591.7979  1221.6998  -0.484  0.62949
## season32      -49.7228  1108.3137  -0.045  0.96433
## season33     -948.0659  1164.2128  -0.814  0.41799
## season34    -1343.1296  1122.8582  -1.196  0.23535
## season35    -2158.7568  1084.6094  -1.990  0.05015 .
## season36     1431.6594   968.1535   1.479  0.14334
## season37     1300.3564  1000.4004   1.300  0.19759
## season38     1350.8967   969.4615   1.393  0.16755
## season39     -459.7473   983.9677  -0.467  0.64167
## season40      203.5106   885.0863   0.230  0.81876
## season41     1139.9345   901.2572   1.265  0.20980
## season42     -521.1550   884.7578  -0.589  0.55758
## season43    -1113.1410   924.6631  -1.204  0.23239
## season44    -1146.2220   858.3028  -1.335  0.18571
## season45    -1027.1378   859.4329  -1.195  0.23575
## season46    -1517.1807   860.9067  -1.762  0.08204 .
## season47    -1166.4817   859.9027  -1.357  0.17895
## season48    -1424.4537   858.3492  -1.660  0.10113
## season49    -1050.6835   858.3927  -1.224  0.22473
## season50    -1040.8167   868.4358  -1.198  0.23445
## season51     -958.8417   858.9480  -1.116  0.26781
## season52     -898.9028   859.0421  -1.046  0.29869
## temp_1.12      69.4466    23.3079   2.980  0.00387 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 938.4 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.8399, Adjusted R-squared:  0.7283
## F-statistic: 7.525 on 53 and 76 DF,  p-value: 2.975e-15

# calculating RMSE
sqrt(mean(linear_1.12$residuals^2))

## [1] 717.5218

# forecasting
temp.new_1.12 <- store_1.12[131:143, 6]
forecast.lm.sales_1.12 <- forecast(linear_1.12, temp.new_1.12, h = 13)

## Warning in forecast.lm(linear_1.12, temp.new_1.12, h = 13): newdata column
names
## not specified, defaulting to first variable required.

forecast.lm.sales_1.12

##          Point Forecast     Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500      11275.398  9763.694 12787.10 8946.467 13604.33
## 2012.519      12159.014 10645.487 13672.54 9827.275 14490.75
## 2012.538       9855.056  8342.858 11367.25 7525.364 12184.75
## 2012.558       8586.616  7047.322 10125.91 6215.180 10958.05
## 2012.577      10490.025  8975.773 12004.28 8157.169 12822.88
## 2012.596      11272.919  9763.920 12781.92 8948.155 13597.68
## 2012.615       9750.091  8227.174 11273.01 7403.886 12096.30
## 2012.635       9000.688  7464.143 10537.23 6633.487 11367.89
## 2012.654       8616.164  7112.268 10120.06 6299.261 10933.07
## 2012.673      11683.487 10180.585 13186.39 9368.116 13998.86
## 2012.692      11165.900  9640.913 12690.89 8816.505 13515.30
## 2012.712      11562.124 10058.971 13065.28 9246.367 13877.88
## 2012.731       9833.961  8330.730 11337.19 7518.084 12149.84

# plot of forecasted values
autoplot(training_1.12, series = "Training") +
  autolayer(forecast.lm.sales_1.12, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.12, series = "Validation") +
  labs(title = "Dept. 12 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



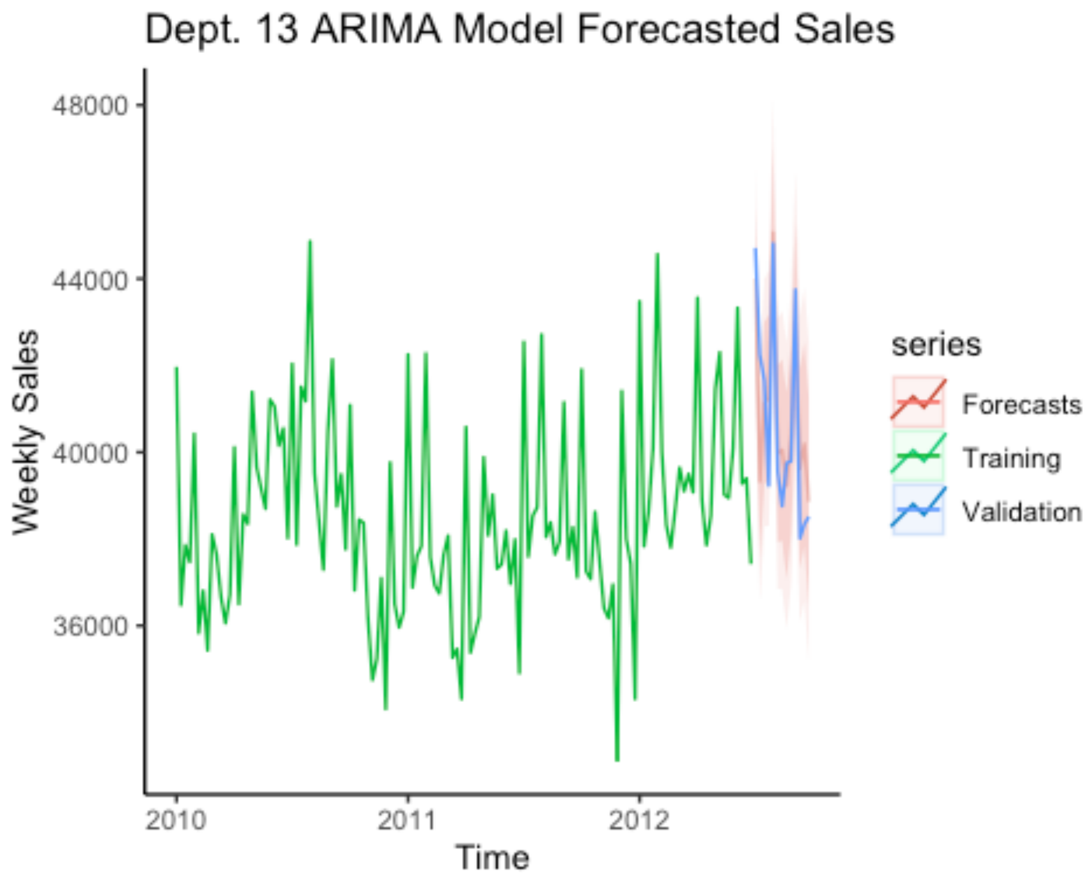
Department 13 Models:

```
# Auto ARIMA model
#predictors.diff_1.1 <- diff(predictors_1.1)
#training.diff_1.1 <- diff(training_1.1)
AutoArima_1.13 <- auto.arima(training_1.13, xreg = predictors_1.13)
summary(AutoArima_1.13)

## Series: training_1.13
## Regression with ARIMA(0,1,1)(0,1,0)[52] errors
##
## Coefficients:
##           ma1      xreg
##       -0.6861  -23.3267
## s.e.   0.0837   22.7037
##
## sigma^2 = 1790171:  log likelihood = -662.86
## AIC=1331.71   AICc=1332.04   BIC=1338.74
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 46.28885 1016.263 629.6389 0.05937672 1.637053 0.3773887
##                    ACF1
## Training set 0.09415731
```

```r
# ARIMA model parameters decided by the ACF and PACF plots above
arima_1.13 <- Arima(training_1.13, xreg = predictors_1.13, order = c(0, 1, 3)
, seasonal = c(0, 1, 1))
summary(arima_1.13)
```

```
## Series: training_1.13
## Regression with ARIMA(0,1,3)(0,1,1)[52] errors
##
## Coefficients:
##           ma1      ma2      ma3     sma1      xreg
##       -0.5709  -0.1185  -0.0213  -0.3703  -17.7384
## s.e.   0.1330   0.1048   0.1264   0.2927   26.2842
##
## sigma^2 = 1619980:  log likelihood = -660.97
## AIC=1333.93   AICc=1335.13   BIC=1348
##
## Training set error measures:
##                    ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 23.52022 947.2167 584.8002 0.001047953 1.517771 0.3505135
##                     ACF1
## Training set -0.01214954
```

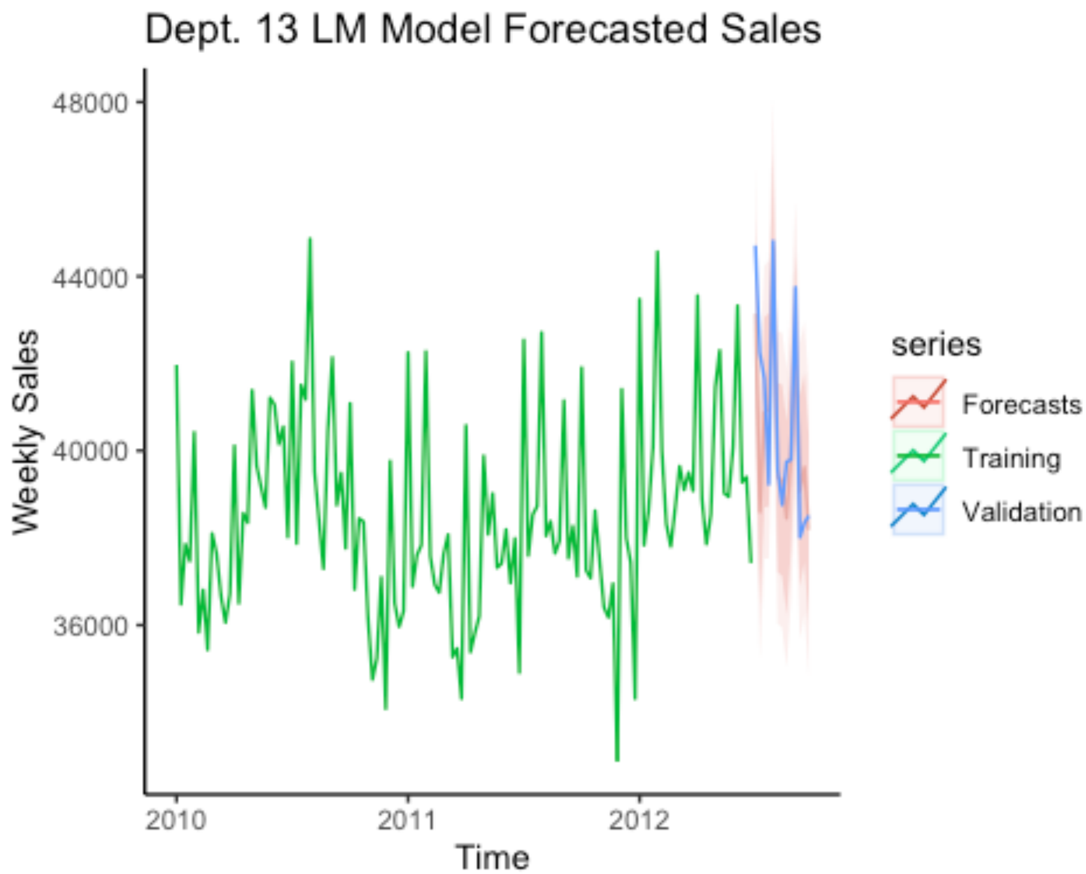
```r
# prediction on the arima
new.predictors_1.13 <- as.matrix(store_1.13["Temperature"][131:143,])
forecast.arima.sales_1.13 <- forecast(arima_1.13, xreg = new.predictors_1.13)

# plot of forecasted values
autoplot(training_1.13, series = "Training") +
  autolayer(forecast.arima.sales_1.13, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.13, series = "Validation") +
  labs(title = "Dept. 13 ARIMA Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```




```
# linear model
temp_1.13 <- store_1.13[1:130, 6]
linear_1.13 <- tslm(training_1.13 ~ trend + season + temp_1.13)
summary(linear_1.13)

##
## Call:
## tslm(formula = training_1.13 ~ trend + season + temp_1.13)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2585.58  -647.14    -3.98   651.85  2080.10
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43220.842   1726.882  25.028  < 2e-16 ***
## trend           9.868      3.350   2.946 0.004273 **
## season2     -5664.703   1122.391  -5.047 2.98e-06 ***
## season3     -4545.931   1103.683  -4.119 9.60e-05 ***
## season4     -3920.997   1139.637  -3.441 0.000946 ***
## season5        31.800   1140.170   0.028 0.977823
## season6     -4570.428   1149.064  -3.978 0.000158 ***
## season7     -4931.227   1192.992  -4.133 9.11e-05 ***
```

```
## season8     -5591.046   1216.270  -4.597 1.68e-05 ***
## season9     -4102.502   1224.052  -3.352 0.001254 **
## season10    -3676.859   1305.449  -2.817 0.006182 **
## season11    -5110.465   1320.352  -3.871 0.000228 ***
## season12    -5138.814   1307.387  -3.931 0.000185 ***
## season13    -5436.648   1319.589  -4.120 9.56e-05 ***
## season14     -679.696   1357.338  -0.501 0.617989
## season15    -5087.925   1435.349  -3.545 0.000676 ***
## season16    -4689.307   1367.558  -3.429 0.000982 ***
## season17    -4241.486   1517.336  -2.795 0.006561 **
## season18     -984.480   1565.648  -0.629 0.531365
## season19    -1890.670   1566.864  -1.207 0.231306
## season20    -2777.701   1631.080  -1.703 0.092658 .
## season21    -3567.832   1601.479  -2.228 0.028850 *
## season22    -2279.020   1642.121  -1.388 0.169238
## season23    -1035.127   1613.182  -0.642 0.523019
## season24    -3098.587   1620.253  -1.912 0.059592 .
## season25    -2586.704   1625.798  -1.591 0.115753
## season26    -5110.666   1639.933  -3.116 0.002584 **
## season27      783.087   1882.712   0.416 0.678629
## season28    -3798.715   1868.755  -2.033 0.045571 *
## season29    -1533.103   1853.380  -0.827 0.410717
## season30    -1655.704   1810.420  -0.915 0.363325
## season31     2119.543   1759.578   1.205 0.232105
## season32    -3072.519   1596.271  -1.925 0.057996 .
## season33    -3376.671   1676.781  -2.014 0.047572 *
## season34    -4382.848   1617.219  -2.710 0.008310 **
## season35    -2725.554   1562.131  -1.745 0.085068 .
## season36     -520.809   1394.403  -0.373 0.709816
## season37    -3964.370   1440.847  -2.751 0.007415 **
## season38    -3300.528   1396.287  -2.364 0.020645 *
## season39    -4718.959   1417.179  -3.330 0.001343 **
## season40     -953.068   1274.763  -0.748 0.456982
## season41    -5360.415   1298.054  -4.130 9.24e-05 ***
## season42    -4708.155   1274.290  -3.695 0.000413 ***
## season43    -3843.738   1331.765  -2.886 0.005073 **
## season44    -5844.155   1236.188  -4.728 1.02e-05 ***
## season45    -7215.589   1237.816  -5.829 1.27e-07 ***
## season46    -6955.697   1239.938  -5.610 3.14e-07 ***
## season47    -5661.582   1238.492  -4.571 1.84e-05 ***
## season48    -9311.341   1236.255  -7.532 8.62e-11 ***
## season49    -2156.179   1236.317  -1.744 0.085197 .
## season50    -5671.390   1250.782  -4.534 2.12e-05 ***
## season51    -6055.188   1237.117  -4.895 5.40e-06 ***
## season52    -7446.657   1237.253  -6.019 5.78e-08 ***
## temp_1.13     -25.017     33.570  -0.745 0.458443
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1352 on 76 degrees of freedom
```

```
## Multiple R-squared:  0.7918, Adjusted R-squared:  0.6466
## F-statistic: 5.454 on 53 and 76 DF,  p-value: 1.519e-11

# calculating RMSE
sqrt(mean(linear_1.13$residuals^2))

## [1] 1033.425

# forecasting
temp.new_1.13 <- store_1.13[131:143, 6]
forecast.lm.sales_1.13 <- forecast(linear_1.13, temp.new_1.13, h = 13)

## Warning in forecast.lm(linear_1.13, temp.new_1.13, h = 13): newdata column
names
## not specified, defaulting to first variable required.

forecast.lm.sales_1.13

##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2012.500       43142.50 40965.24 45319.76 39788.21 46496.79
## 2012.519       38597.08 36417.20 40776.97 35238.75 41955.42
## 2012.538       40877.57 38699.59 43055.54 37522.18 44232.95
## 2012.558       40944.70 38727.70 43161.70 37529.19 44360.21
## 2012.577       44659.02 42478.09 46839.95 41299.08 48018.96
## 2012.596       39390.02 37216.65 41563.39 36041.73 42738.31
## 2012.615       39320.63 37127.22 41514.05 35941.47 42699.80
## 2012.635       38451.91 36238.87 40664.95 35042.50 41861.32
## 2012.654       39963.72 37797.70 42129.74 36626.75 43300.69
## 2012.673       42366.71 40202.12 44531.29 39031.95 45701.47
## 2012.692       39072.11 36875.71 41268.50 35688.34 42455.87
## 2012.712       39621.23 37456.29 41786.18 36285.92 42956.55
## 2012.731       38182.90 36017.84 40347.96 34847.41 41518.39

# plot of forecasted values
autoplot(training_1.13, series = "Training") +
  autolayer(forecast.lm.sales_1.13, alpha = 0.3, series = "Forecasts") +
  autolayer(validation_1.13, series = "Validation") +
  labs(title = "Dept. 13 LM Model Forecasted Sales",
       x = "Time",
       y = "Weekly Sales") +
    theme_classic()
```



Model Forecasts

```
accuracy(forecast.arima.sales_1.1, validation_1.1)

##                     ME     RMSE       MAE        MPE     MAPE      MASE
## Training set  21.15138 2157.245  954.3406 -0.5351687 4.337541 0.3597749
## Test set     558.06393 2122.165 1251.7916  2.5564757 5.699299 0.4719103
##                    ACF1 Theil's U
## Training set 0.01322383        NA
## Test set     0.02455164  1.243851

accuracy(forecast.arima.sales_1.2, validation_1.2)

##                      ME     RMSE       MAE        MPE     MAPE      MASE
## Training set  -61.27756 1644.405  851.6671 -0.2511672 1.787644 0.4540452
## Test set     -469.15896 1334.388 1119.6226 -1.0674250 2.420985 0.5968991
##                     ACF1 Theil's U
## Training set -0.04005042        NA
## Test set      0.05387770 0.4754589

accuracy(forecast.arima.sales_1.3, validation_1.3)

##                     ME      RMSE       MAE        MPE     MAPE      MASE
## Training set  88.35297  843.5314  458.2682 0.09653082  3.90974 0.4327819
## Test set     448.60214 5262.0309 2887.2858 5.32342144 12.53876 2.7267109
```

```
##                     ACF1 Theil's U
## Training set 0.01085711        NA
## Test set     0.12916644 0.8517941
```

```
accuracy(forecast.arima.sales_1.4, validation_1.4)
```

```
##                       ME     RMSE      MAE        MPE     MAPE      MASE
## Training set   76.57734 1016.042 641.7766  0.1695963 1.738290 0.4332216
## Test set     -440.71691 1205.924 974.7109 -1.2515450 2.595574 0.6579639
##                     ACF1 Theil's U
## Training set -0.0154414        NA
## Test set     -0.2373537 0.4716432
```

```
accuracy(forecast.arima.sales_1.5, validation_1.5)
```

```
##                      ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -30.72939 2549.458 1047.808 0.4313792 4.128701 0.4147436
## Test set     851.81988 2084.068 1450.688 3.8005975 7.062688 0.5742117
##                        ACF1 Theil's U
## Training set  0.0007677673        NA
## Test set     -0.1758945840 0.7742576
```

```
accuracy(forecast.arima.sales_1.6, validation_1.6)
```

```
##                       ME      RMSE       MAE       MPE      MAPE      MASE
## Training set   103.5397  831.0205  429.7156   3.21585  9.327156 0.3586229
## Test set     -1160.9442 1453.4501 1269.2482 -36.75868 39.932352 1.0592623
##                      ACF1 Theil's U
## Training set -0.02217434        NA
## Test set     -0.10321541  2.220785
```

```
accuracy(forecast.arima.sales_1.7, validation_1.7)
```

```
##                      ME     RMSE       MAE       MPE      MAPE      MASE
## Training set -269.0521 2108.843  956.0441 -1.274203  3.859567 0.1924547
## Test set      925.6704 4339.935 3455.9492  3.327876 17.480362 0.6956934
##                      ACF1 Theil's U
## Training set -0.03041530        NA
## Test set     -0.05752251  1.575108
```

```
accuracy(forecast.arima.sales_1.8, validation_1.8)
```

```
##                      ME      RMSE       MAE        MPE     MAPE      MASE
## Training set 100.04547  911.3604  569.2195  0.2388208 1.582977 0.3221513
## Test set     -79.80077 1580.3739 1411.7828 -0.3752218 3.755754 0.7990023
##                      ACF1 Theil's U
## Training set -0.01536931        NA
## Test set     -0.01578996 0.5987785
```

```
accuracy(forecast.arima.sales_1.9, validation_1.9)
```

```
##                      ME     RMSE       MAE       MPE     MAPE      MASE
## Training set  95.69437 1719.250  780.5302 0.4228348 3.092106 0.3050615
## Test set     232.38088 1598.221 1227.9743 0.4060347 3.831337 0.4799400
##                     ACF1 Theil's U
## Training set -0.02348425        NA
## Test set      0.21578220 0.2244506
```

```
accuracy(forecast.arima.sales_1.10, validation_1.10)
```

```
##                       ME     RMSE       MAE        MPE     MAPE     MASE
## Training set   130.8027 1410.495  908.4041  0.2734734 2.898582 0.400411
## Test set     -1928.5263 2672.129 2284.7815 -6.8979737 8.019320 1.007098
##                      ACF1 Theil's U
## Training set -0.006280305        NA
## Test set      0.159955092  1.434442
```

```
accuracy(forecast.arima.sales_1.11, validation_1.11)
```

```
##                        ME     RMSE      MAE        MPE     MAPE      MASE
## Training set    -5.165186 1840.766 1141.668 -0.4183546 4.404359 0.3907944
## Test set     -1572.854944 2401.973 2007.578 -7.9275753 9.831922 0.6871968
##                     ACF1 Theil's U
## Training set  0.02744617        NA
## Test set     -0.39902106 0.6359822
```

```
accuracy(forecast.arima.sales_1.12, validation_1.12)
```

```
##                     ME      RMSE       MAE        MPE      MAPE      MASE
## Training set -50.57084  710.1182  443.4773 -0.7057122  4.156725 0.3775839
## Test set      98.97203 1448.2936 1236.1143  0.1292516 11.919343 1.0524482
##                      ACF1 Theil's U
## Training set -0.009835111        NA
## Test set      0.200639904  1.079634
```

```
accuracy(forecast.arima.sales_1.13, validation_1.13)
```

```
##                       ME      RMSE       MAE          MPE     MAPE      MAS
E
## Training set   23.52022  947.2167  584.8002  0.001047953 1.517771 0.350513
5
## Test set     -224.85128 1314.4269 1055.2115 -0.667298855 2.624314 0.632465
5
##                     ACF1 Theil's U
## Training set -0.01214954        NA
## Test set      0.18182869 0.4253533
```