M5 Forecasting - Exploratory Data Analysis

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4/14/2020

Abstract

The M5 Forecasting data is a set of datasets provided by Walmart to Kaggle for a competition in forecasting the quantity of sales a month out. The link for the competition page, where the datasets can be found is here:

https://www.kaggle.com/c/m5-forecasting-accuracy

Walmart captured the sales of their retail goods from Jan 2011 to June 2016. The variables that have been tracked are: time, state, department, category, item, cost of item, quantity of items purchased, holiday, holiday type, acceptance of SNAP food stamps. This data is set up in a hierarchical fashion so that we can look at the information in many ways. We can look at it from the:

- Item Level: 3,490 cases
- Department Level: 7 cases
- Category Level: 3 cases
- Store Level: 10 cases
- State Level: 3 cases

The dataset comes from three separate files containing the sales information, the price information, and the calendar information. There are 1941 days, or cases, in this data set.

The two variables we will be interested in will be the quantity of items sold and the price of items. Some of the questions we are interested in answering are as follows:

- How does time effect the variables? (i.e. seasonality, weekly, holiday)
- Is there a difference between sales by the different location?
- How about the 3 different categories and their prices in each state?

Import the Data

The first step in doing our analysis will be importing the data and trying to get an understanding of how it is set up.

Train Data

The train data is of size (30490, 1919) with the following names. This data set is set up where the variables are id, item_id, dept_id, cat_id, store_id, state_id, d_1, d_2, …., d_1913. The id variable is just a combination of the other 5 id's.

Here is a quick look at the top 5 rows for some of the columns.

item_id	dept_id	cat_id	store_id	state_id	d_1	d_1909	d_1910	d_1911	d_1912	d_1913
HOBBIES_1_001	HOBBIES_1	HOBBIES	CA_1	CA	0	1	3	0	1	1
HOBBIES_1_002	HOBBIES_1	HOBBIES	CA_1	CA	0	1	0	0	0	0
HOBBIES_1_003	HOBBIES_1	HOBBIES	CA_1	CA	0	1	0	1	1	1
HOBBIES_1_004	HOBBIES_1	HOBBIES	CA_1	CA	0	0	1	3	7	2
HOBBIES_1_005	HOBBIES_1	HOBBIES	CA_1	CA	0	1	2	2	2	4

Looking at the unique values in the qualitative columns of the dataframe, shown in the table below, gives an idea of what this dataframe is telling us. There are 3049 items spread out through 10 stores in 3 different states. A lot of these items are repeated through the different stores. In each store there are 3 categories with 7 departments.

	item_id	dept_id	cat_id	store_id	state_id
unique	3049	7	3	10	3

The table below is the distribution of 3 random days for all the items through all of the stores and categories. With the Median value being 0, you can see that a lot of these values are zero. This is because they will not always sell all of the items every day, or some may have been discontinued. The amount of zeros doesn't pose much of a threat since we are aggregating over different variables and time.

	d_193	d_1171	d_158
Mean	0.8597245	1.511414	0.872286
Std.Dev	3.6145279	4.492225	3.591203
Min	0.0000000	0.000000	0.000000
Median	0.0000000	0.000000	0.000000
Max	106.0000000	136.000000	91.000000

Price Data

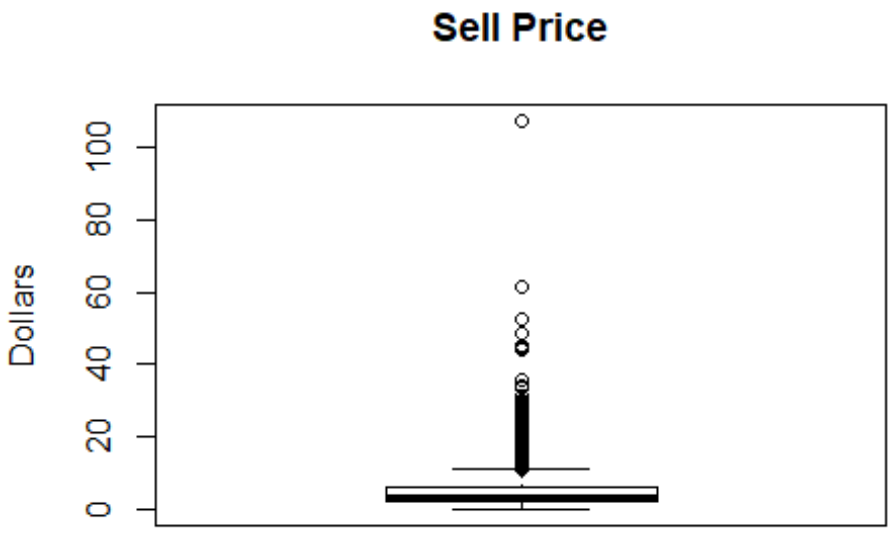
The prices data frame has a size of (6841121, 4) with the following variables; store_id, item_id, wm_yr_wk, sell_price. There are a couple of rows that tie this data frame to the train data frame, which are store_id, item_id.

Here is a quick look at the head of the dataframe.

store_id	item_id	wm_yr_wk	sell_price
CA_1	HOBBIES_1_001	11325	9.58
CA_1	HOBBIES_1_001	11326	9.58
CA_1	HOBBIES_1_001	11327	8.26
CA_1	HOBBIES_1_001	11328	8.26
CA_1	HOBBIES_1_001	11329	8.26
CA_1	HOBBIES_1_001	11330	8.26

The only new real interesting variable we get from this dataframe is the "sell_price" variable, which we can use to calculate revenue later. The sell price is given as a weekly average of the price for that item at that store. The stats and box-plot of this value are shown below.

	sell_price
Mean	4.410952
Std.Dev	3.408814
Min	0.010000
Median	3.470000
Max	107.320000



Looking at the box plot, we can see that a lot of the item prices are pretty low with a select few of them reaching over 40 dollars.

Calendar Data

The calendar data frame has a size of (1969, 14) with the following variables; date, wm_yr_wk, weekday, wday, month, year, d, event_name_1, event_type_1, event_name_2, event_type_2, snap_CA, snap_TX, snap_WI.

The column d is the column name that ties this dataset back to the train dataset and represents d_0001, d0002, … , d1913.

By looking at the first and last values in the data frame, we can see that the time frame from 2011-01-29 to 2016-06-19. This data set also gives data on whether there is an event and what that event type is. It also gives information on whether that day is a SNAP day or not in either of the three states. The number of events and event types are displayed in the table below. The unique descriptor also includes regular days without any events.

	event_name_1	event_type_1	event_name_2	event_type_2	snap_CA	snap_TX	snap_WI
count	162	162	0	0	650	650	650
unique	31	5	1	1	2	2	2

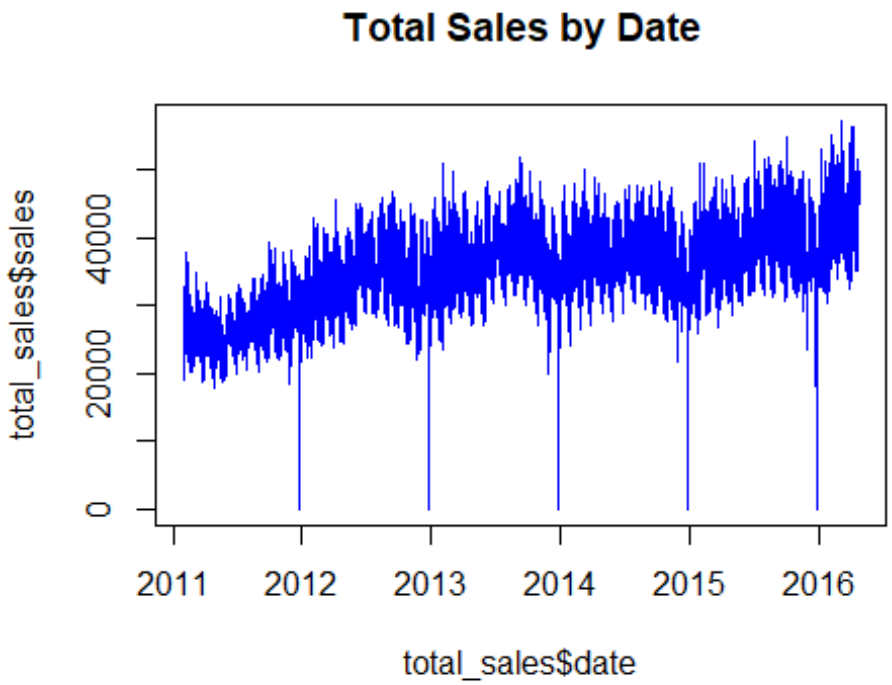
There are not a lot of events throughout the year that this keeps track of, just 30 unique events in all of the 5 plus years. Each state only has a total of 650 SNAP days because they are required to have so many in 1 year.

The “wm_yr_wk” column tracks the number of weeks in a year but it does it in a tricky way. It start the 1st week on the first day of data collection, and starts it count there. So week 52 of the first year will actually be around 2012-01-30. This can be seen with the following table, which looks at the 1st 5 values of the first year and the second year.

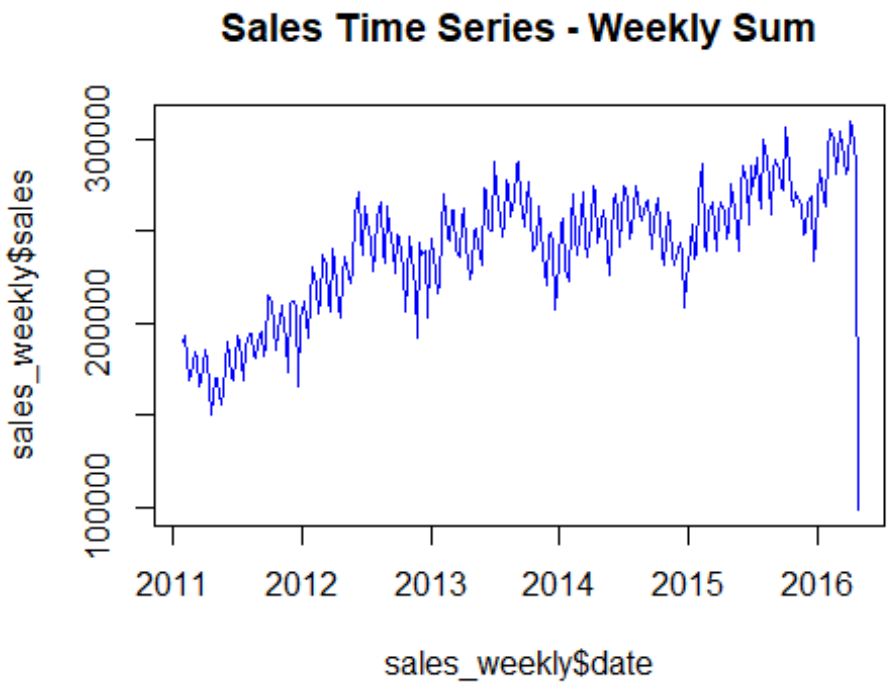
date	wm_yr_wk
2011-01-29	11101
2011-01-30	11101
2011-01-31	11101
2011-02-01	11101
2011-02-02	11101
2012-01-30	11201
2012-01-31	11201
2012-02-01	11201
2012-02-02	11201
2012-02-03	11201

Exploratory Analysis

By aggregating all of the sales and pivoting the training table we can see the amount sales for each day in all 10 of the stores. The following time series chart shows how the total sales change per day.



Seasonality in quantity of sales over the years can be seen. The drops at the end of every year are Christmas where the stores are closed for part of the day. We can also look at this weekly instead of daily to reduce the noise by summing up the total sales in a week, which is displayed below.

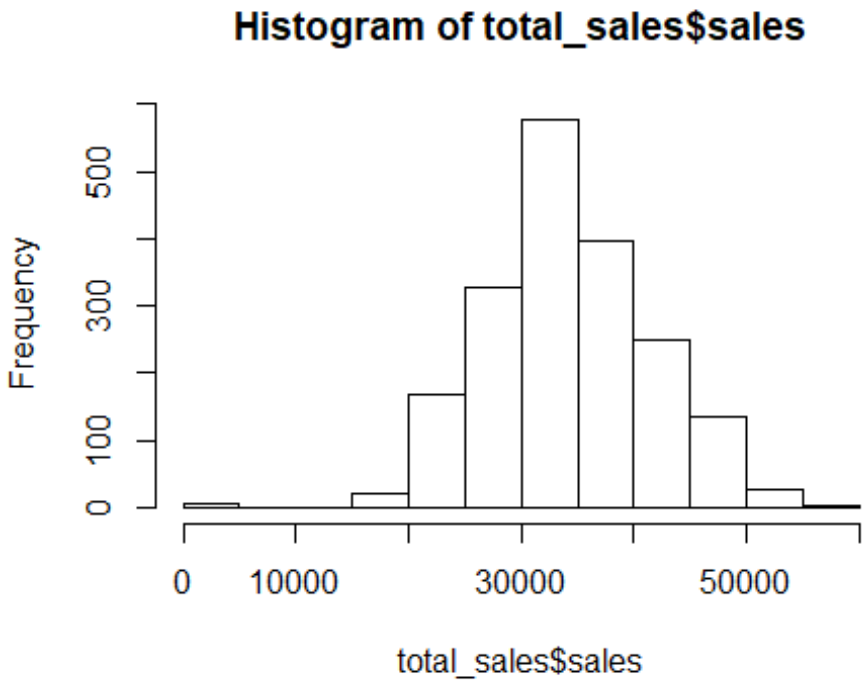


One thing we can dive deeper into is how the sales correlates to different aspects of times, such as year, month, week, week day. The following is the correlation between sales and those factors.

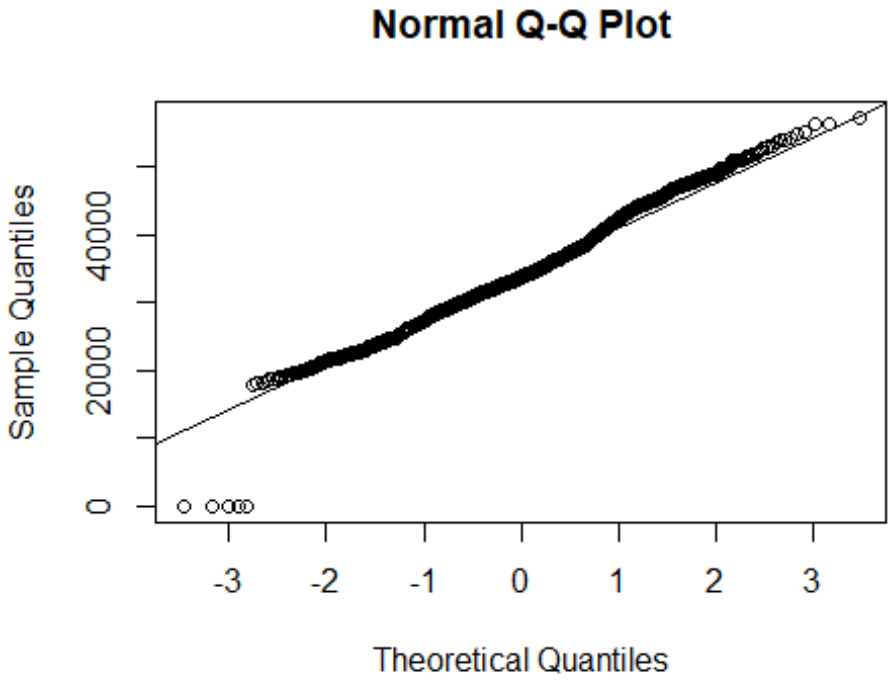
	r
sales	1.0000000
year	0.5311059
month	-0.0037429
week	-0.0348703
wday	-0.4544096

The two factors that correlate the most with sales are year and weekday, and even those are not great. Month and week number in the year have pretty much no correlation.

The following is a dive into the distribution of the sales data and determining whether to use parametric or non-parametric analysis. It can be seen in the histogram below that the data has good shape with some potential outliers.



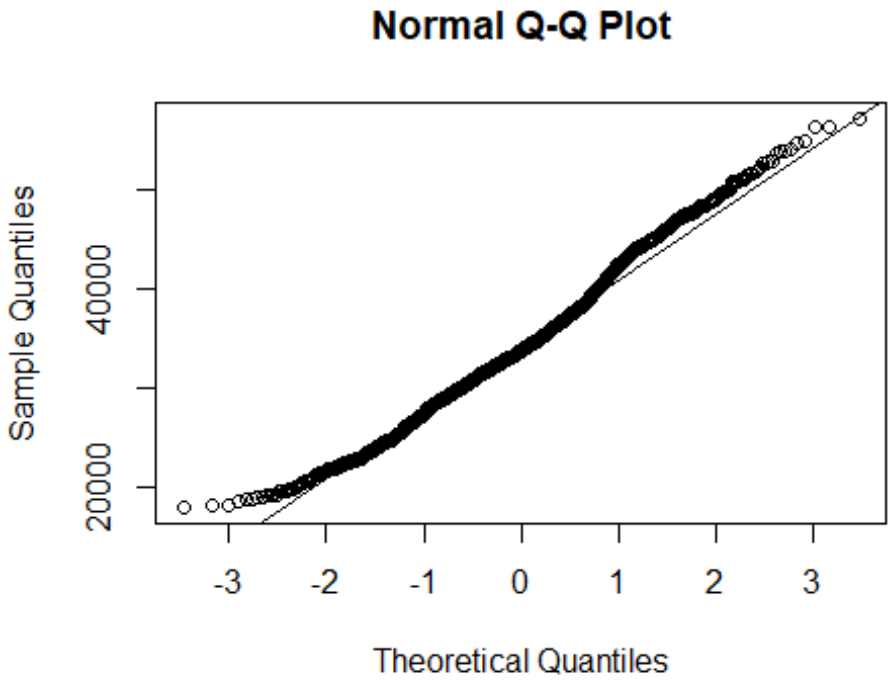
Looking at the Normal Q-Q Plot below, it can definitely be seen that there are some outliers in the data. Outside of that the data appears normal.



Doing a Shapiro-Wilks to do a quick check on the normality of the sales data gives us the results below.

```
##  Shapiro-Wilk normality test
##
## data:  total_sales$sales
## W = 0.98562, p-value = 6.226e-13
```

It can be seen from the test that the data is not normal at all. But lets try and remove the outliers and recheck the assumptions for parametric models. The outliers that need to be removed fall on Christmas days, where there are significantly less sales on this event than on any other day. The Q-Q Plot for sales without the outliers is below, followed by the Shapiro-Wilk normality test.

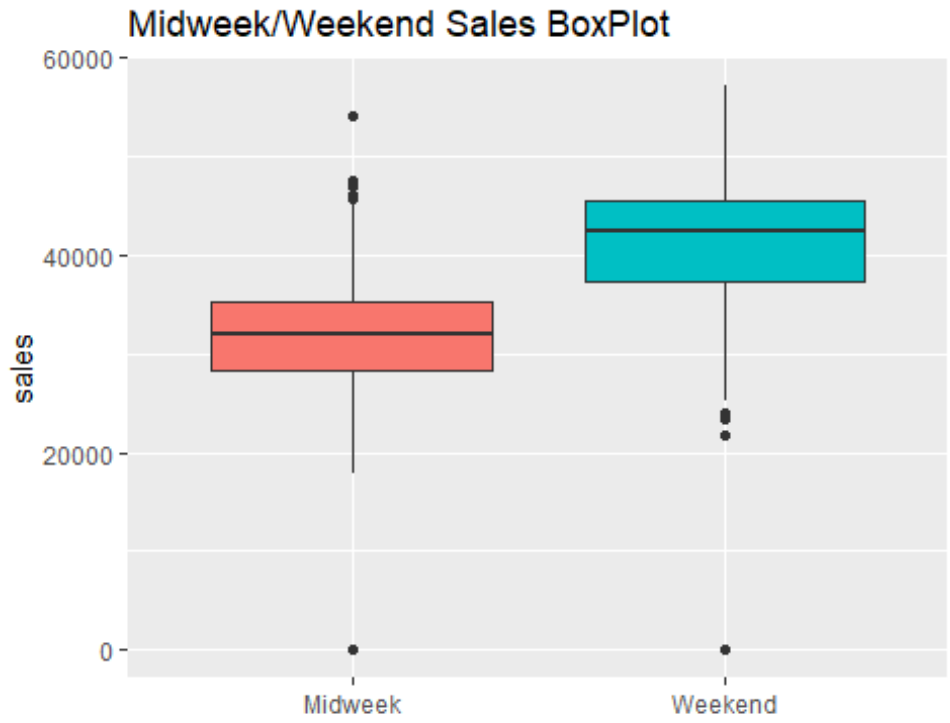



```
##  Shapiro-Wilk normality test
##
## data:  X$sales
## W = 0.98945, p-value = 1.424e-10
```

It can be seen that the data, even with the removed outliers, is not normal by the p-value being so small. This means statistical analysis on the sales part of the data will have to use non-parametric methods.

Comparison of Midweek Sales vs. Weekend Sales

The following is a box plot for midweek and weekend sales. It appears that there are more sales on Saturday and Sunday compared to the 5 other days.



One of our questions of interest was if weekend sales differed from weekday sales. Leading us to the following hypothesis:

H_0: $\mu_{midweek} = \mu_{weekend}$

H_a: $\mu_{midweek} \neq \mu_{weekend}$

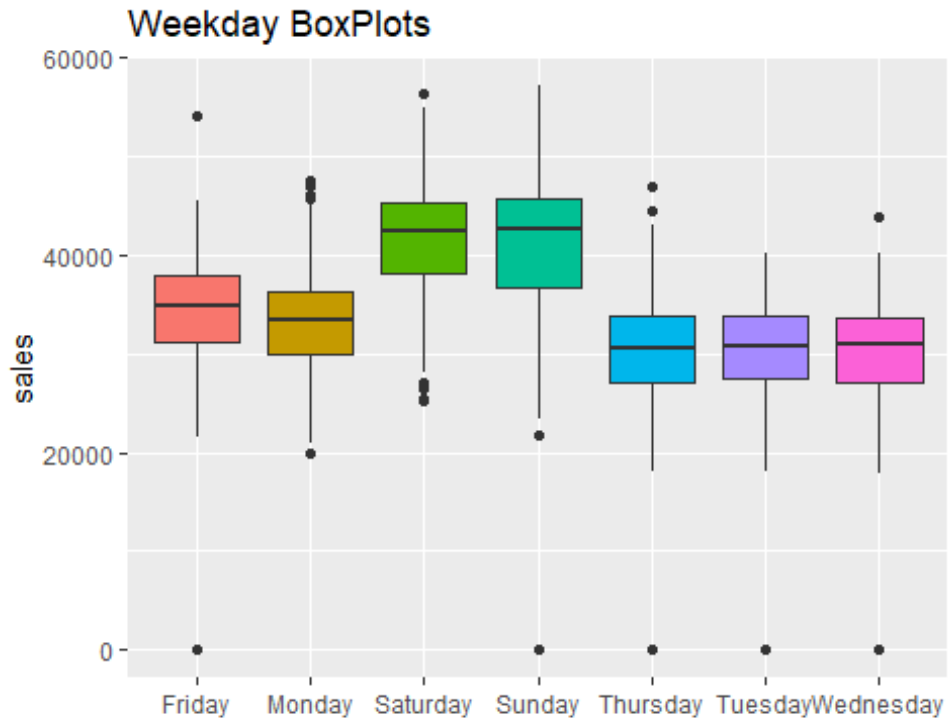
The p-value is <.05 so we reject the null hypothesis and claim that there is a difference in sales between midweek days and the weekend.

```
##  Kruskal-Wallis rank sum test
##
## data:  total_sales$sales and total_sales$weekend
## Kruskal-Wallis chi-squared = 652.91, df = 1, p-value < 2.2e-16
```

The results from this test shows that we have enough evidence to support our claim that there is a difference between the sales on the weekend and midweek. This leads us to exploring which days have the least amount of sales and which days have the most.

Comparison of Sales and Weekday

The following plot is a box plot of the days in the week and sales. By looking at this plot, it appears that there are less sales between Tuesday, Wednesday, and Thursday than in the other days of the week. It also appears that the most shopping is done on Saturday and Sunday.



This proposes the following hypothesis:

$H_0: \mu_{Mon} = \mu_{Tue} = \mu_{Wed} = \mu_{Thu} = \mu_{Fri} = \mu_{Sat} = \mu_{Sun}$
$H_a: \mu_i \neq \mu_i \ \ where\ i, j = Mon, Tue, Wed, Thu, Fri, Sat, Sun\ and\ i \neq j$

The below table is the descriptive stats for the days in the week. Just by looking at the descriptive stats, it appears that there is some difference between the day of the week means.

	Mean	Std_Dev	Count	Median
Friday	34225.99	5602.040	273	34775
Monday	32852.97	5223.532	273	33444
Saturday	41546.89	6120.411	274	42437
Sunday	41130.02	6997.728	274	42586
Thursday	30205.01	5342.799	273	30658
Tuesday	30368.78	5088.428	273	30710
Wednesday	30010.02	5164.106	273	30911

Looking at the Kruskal-Wallis test for the days of the week, we can see that there is enough evidence to reject the null hypothesis and know there is a difference for at least one of the days of the week.

```
##  Kruskal-Wallis rank sum test
##
```

```
## data:  X$sales and X$weekday
## Kruskal-Wallis chi-squared = 756.21, df = 6, p-value < 2.2e-16
```

The Wilcox test was applied to look at the relationship between the individual weekdays and their respective significance levels. The table below has been created and shows the p-value for the Wilcox test between the row and column days. Since multiple tests were completed, the p-value has been adjusted vie the Bonferroni method.

	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday
Sunday	1.000000e+00	NA	NA	NA	NA	NA
Monday	7.599074e-45	7.587249e-41	NA	NA	NA	NA
Tuesday	8.269229e-61	1.168020e-56	1.925761e-07	NA	NA	NA
Wednesday	3.011778e-62	3.347556e-58	1.634494e-09	1.000000e+00	NA	NA
Thursday	3.103323e-60	2.332928e-56	1.782153e-08	1.000000e+00	1.00000e+00	NA
Friday	5.983331e-37	4.963647e-32	1.895647e-03	2.099749e-16	3.17094e-19	9.235386e-18

From this table, you can see that Saturday and Sunday are significantly different from every other day in the week, but are practically equal against each other. It also looks like the sales on Tuesday, Wednesday, and Thursday are not different from each other, but those three days are different from all of the others. Using this table and the above plots, a conclusion can be made that if a crowd is desired, shop on Saturday and Sunday. If the goal is to avoid the crowd, as much as possible, then shop on Tuesday, Wednesday and Thursday.

Comparison of Sales and Event Type

Next, the different types of events are looked at and compared between each other to see if there is any specific event that stands out from a normal day. Below is a list of the descriptive statistics for the average sales per day for following types of events. It appears that the event type 'National' may have the largest difference in mean sales per day.

Event Type	Mean	Std_Dev	Count	Median
Cultural	34234.74	7380.082	35	35089
National	29458.51	12117.064	51	32656
nothing	34489.21	7133.702	1759	33714
Religious	33760.69	7069.625	52	33760
Sporting	35796.06	6651.927	16	34998

The following hypothesis can be stated:

$H_o: \mu_{nothing} = \mu_i \; where \; i = Cultural, National, Religious, Sporting$

$H_a: \mu_{nothing} \neq \mu_i \; where \; i = Cultural, National, Religious, Sporting$

The following is the Krusdal-Wallis.

```
##
##  Kruskal-Wallis rank sum test
##
## data:  sales.events$sales and sales.events$event_type_1
## Kruskal-Wallis chi-squared = 7.1705, df = 4, p-value = 0.1271
```

According to this test, there is not enough evidence to reject the null hypothesis that the sales on events is different from the sales on a day with no event. Below is a table of p-values using the Wilcox test for the p-values. Looking at this table, it appears that National is significantly different from a day with no events. This table was created without an adjustment.

	nothing	Sporting	Cultural	National
Sporting	0.32868284	NA	NA	NA
Cultural	0.78395647	0.6511688	NA	NA
National	0.01580517	0.0628413	0.06362522	NA
Religious	0.62357013	0.2503907	0.57663456	0.1251287

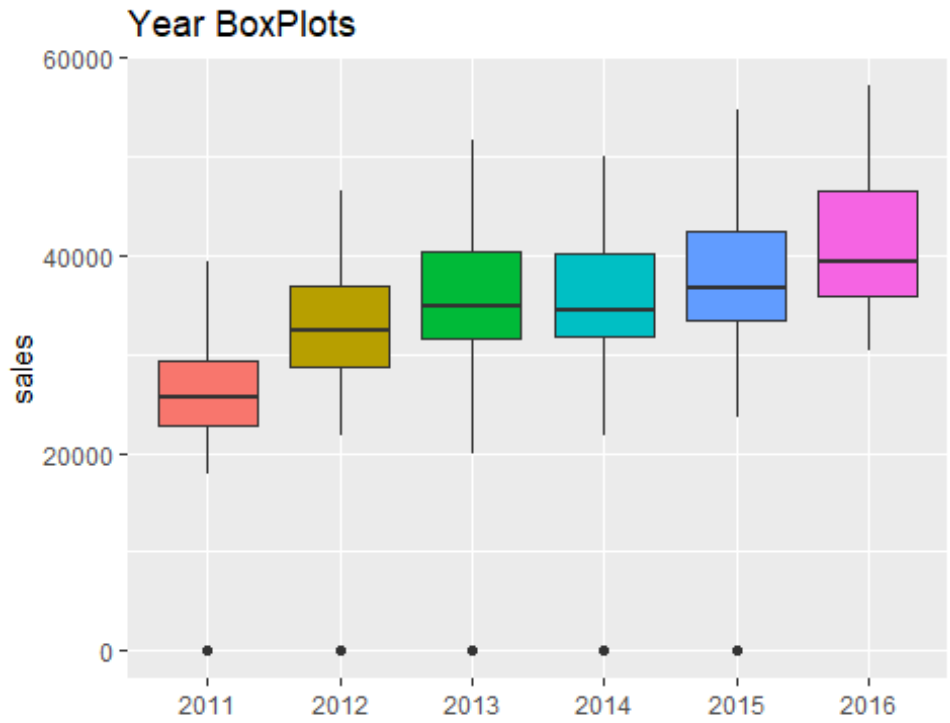
The following table was created with an adjustment and the significance has been lost between the National events and days with no events.

	nothing	Sporting	Cultural	National
Sporting	1.0000000	NA	NA	NA
Cultural	1.0000000	1.0000000	NA	NA
National	0.1580517	0.5655717	0.5655717	NA
Religious	1.0000000	1.0000000	1.0000000	0.8759012

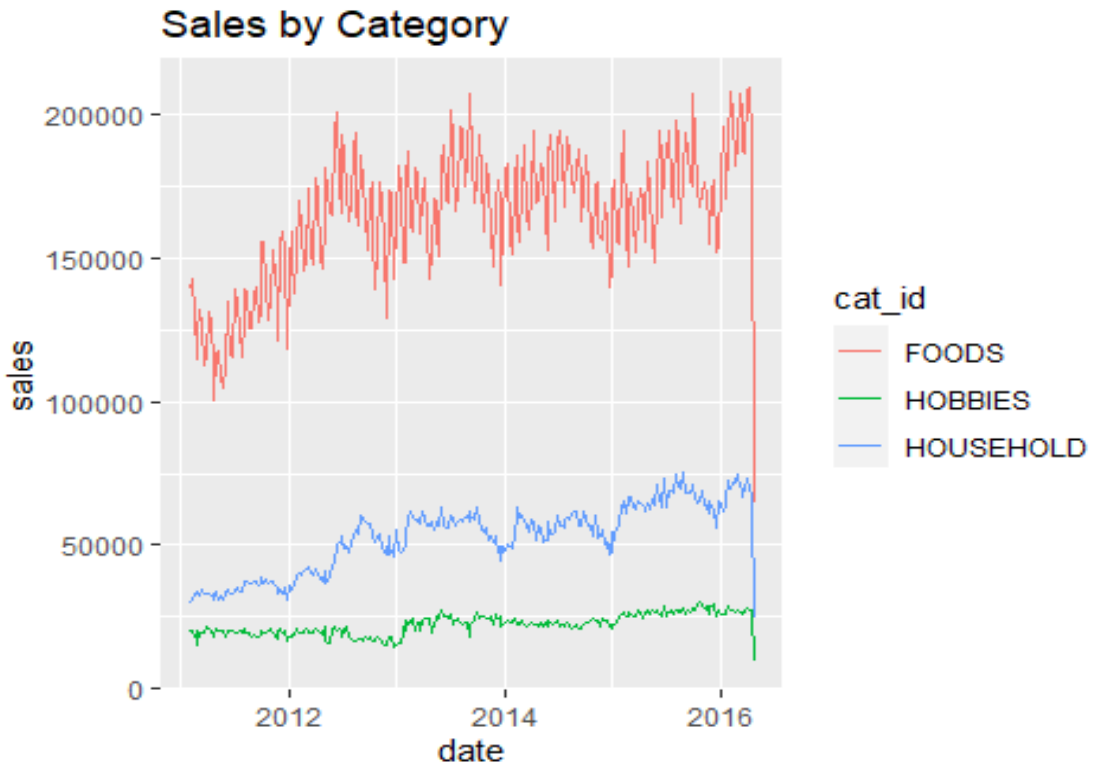
In conclusion, there is not enough evidence to support a claim that any events have a significantly different sales than a day with no events.

Look at Sales and Year

This next chart shows the box plots of the sales through each year.

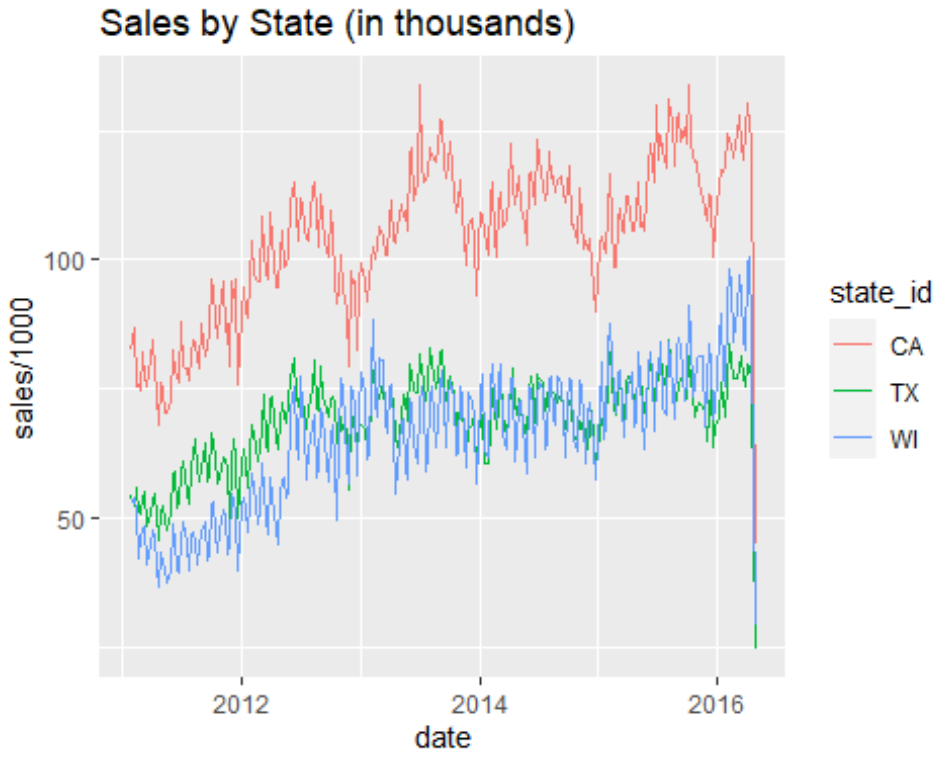


This appears to show that there is a steady increase in sales as the years progress. The next graph shows a time series of sales by each category: food, household, and hobbies.



Comparison of States

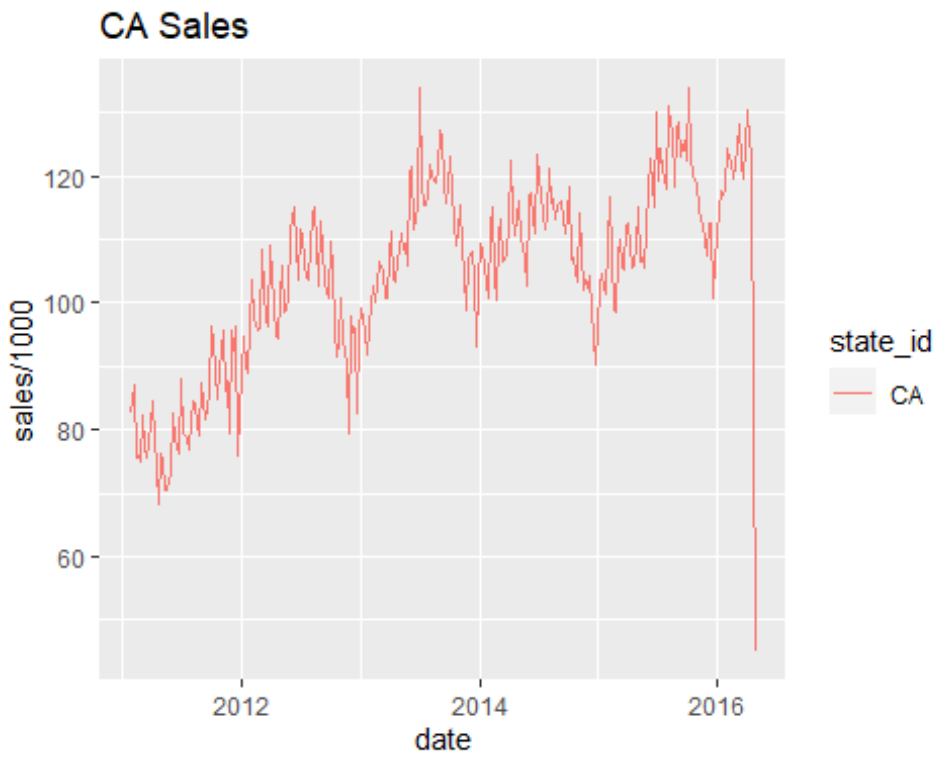
The next graph shows a time series of sales by each category: California, Texas, and Wisconsin.



Looking at the graph, it almost appears that every state has its own rate for increase in sales per time. It appears that CA and WI may be similar but TX seems to be less steep than the other two. We will also like to compare the rates of sales increase in each step by looking at the following.

$H_0: \beta_{1,CA} = \beta_{1,TX} = \beta_{1,WI}$
$H_a: \beta_{1,i} \neq \beta_{1,j} \ \ where \ \ i,j = CA, TX, WI \ \ and \ \ i \neq j$

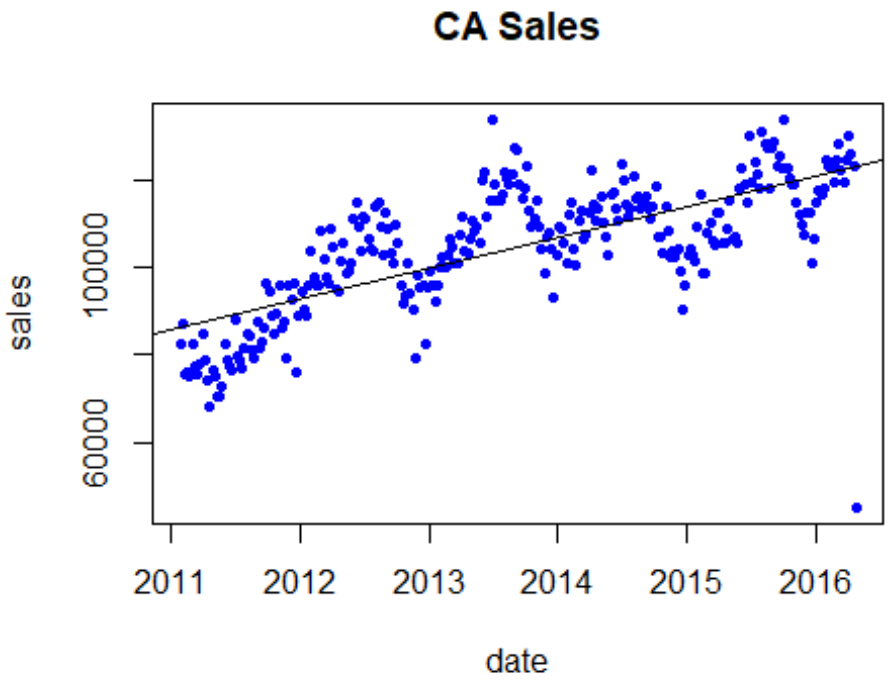
The following is a look at weekly sales by state. First is CA.



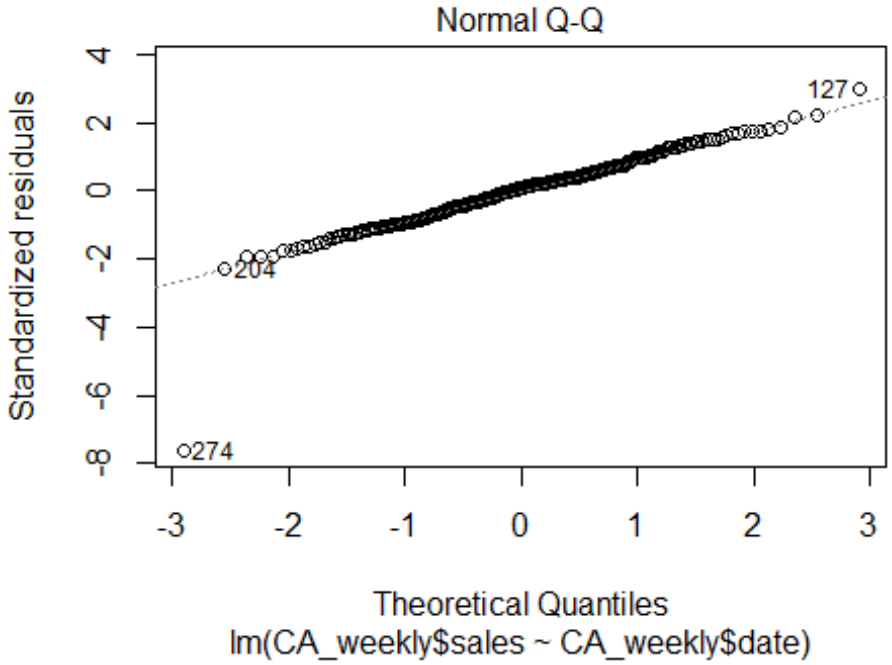
A linear regression gives us our β_0 and $\beta 1$ coefficients, as displayed in the following table.

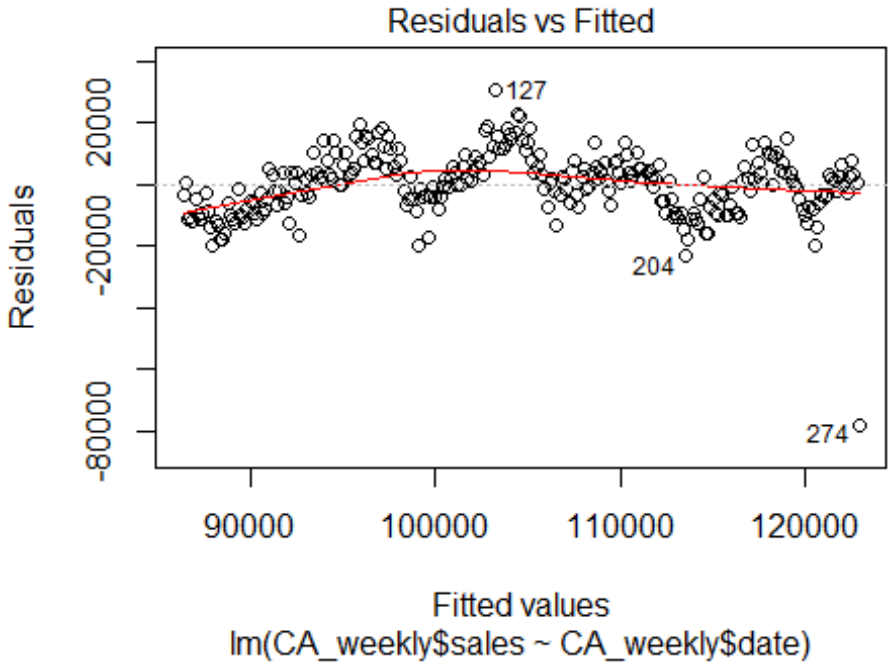
```
##
## Call:
## lm(formula = CA_weekly$sales ~ CA_weekly$date, data = CA_weekly)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -77919  -6363    876   5937  30469
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2.007e+05  1.796e+04  -11.18   <2e-16 ***
## CA_weekly$date  1.914e+01  1.125e+00   17.01   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10310 on 272 degrees of freedom
## Multiple R-squared:  0.5155, Adjusted R-squared:  0.5137
## F-statistic: 289.4 on 1 and 272 DF,  p-value: < 2.2e-16
```

We can also see our fitted line with the following chart. It is obvious from this plot that Sales data follows a cyclical/seasonal pattern.

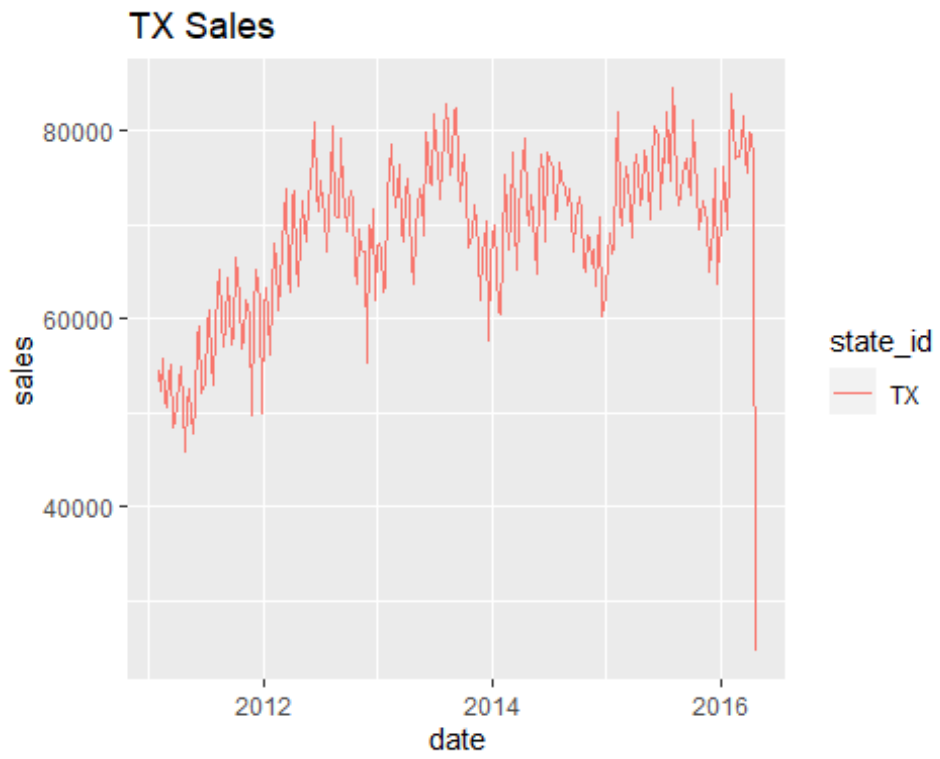


The following two plots shows that CA sales are normally distributed with a fairly equal variance. Index 274 seems to be a bit of an outlier, corresponds to the week of May 23, 2016, the final week in the analysis.





Next is a look at weekly sales in Texas.

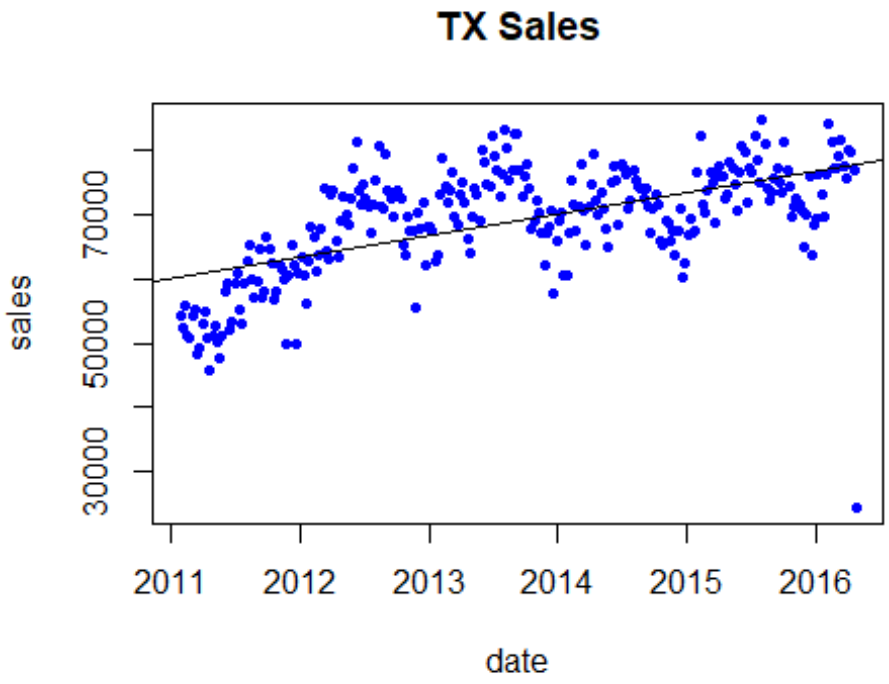


The following is the linear model table for Texas.

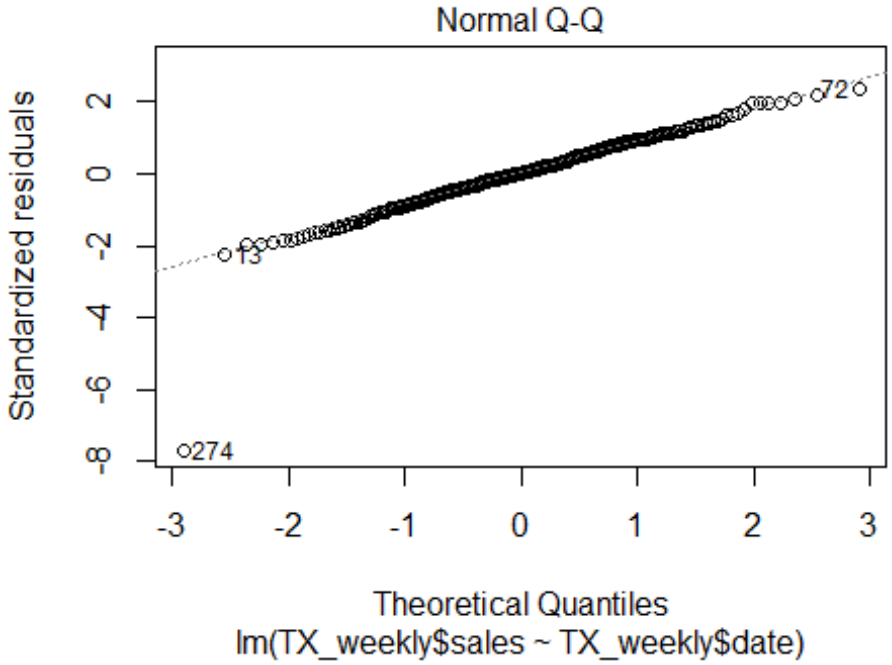
```
##
## Call:
## lm(formula = TX_weekly$sales ~ TX_weekly$date, data = TX_weekly)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -53013  -3732     69   4466  16196
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -7.443e+04  1.210e+04  -6.153 2.71e-09 ***
## TX_weekly$date  8.986e+00  7.576e-01  11.862  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6943 on 272 degrees of freedom
## Multiple R-squared:  0.3409, Adjusted R-squared:  0.3385
## F-statistic: 140.7 on 1 and 272 DF,  p-value: < 2.2e-16
```

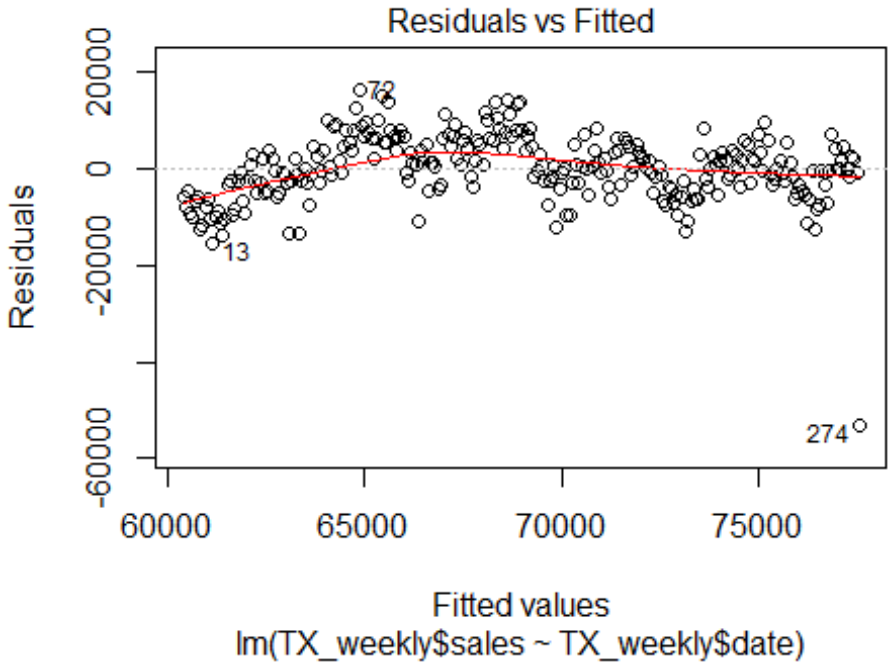
Texas' slope is 8.986286 and California's slope is 19.1362012.

The following is the plot of the fitted line. Again, a seasonal sales pattern is obvious in the plot.

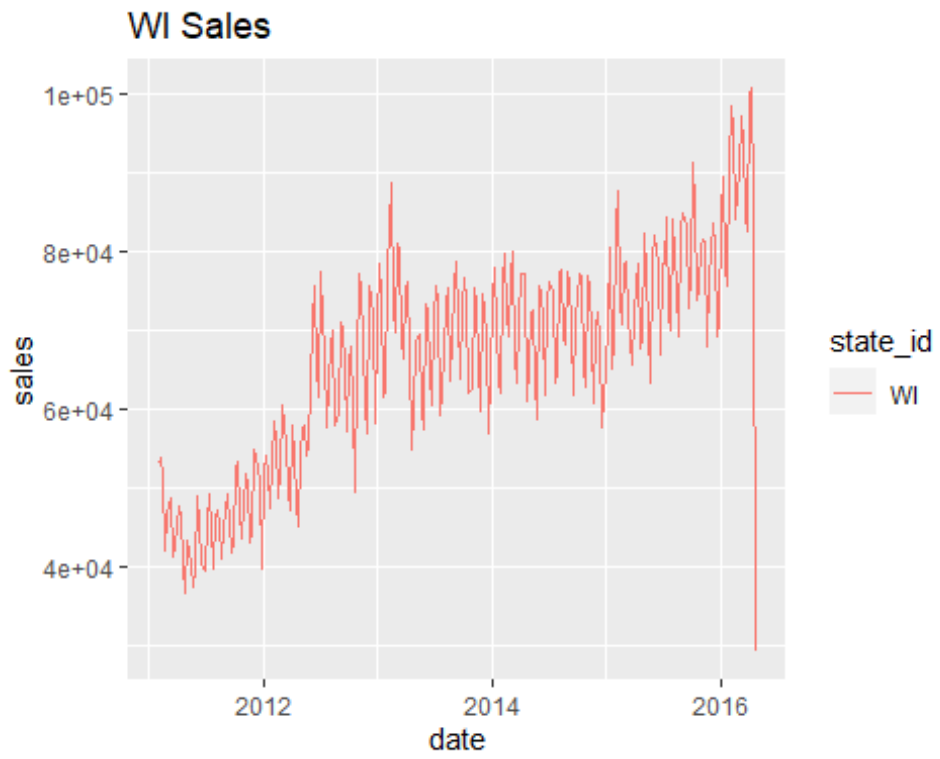


The following two plots shows that TX sales are normally distributed with a fairly equal variance. As with California, Index 274 corresponds to the week of May 23, 2016, the final week in the analysis.





The following is a look at Wisconsin's weekly sales.

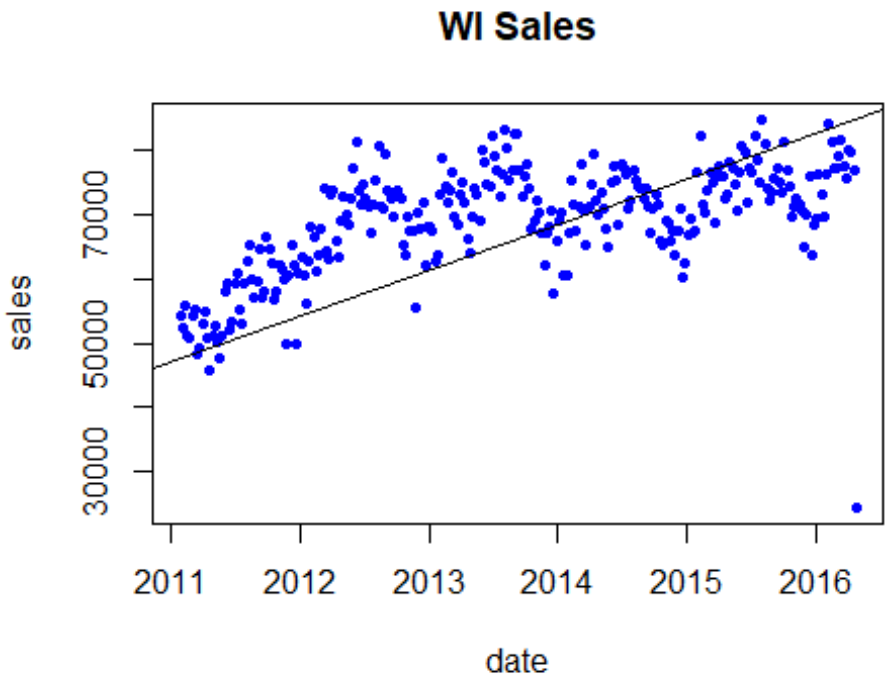


The following is the linear model table for Wisconsin.

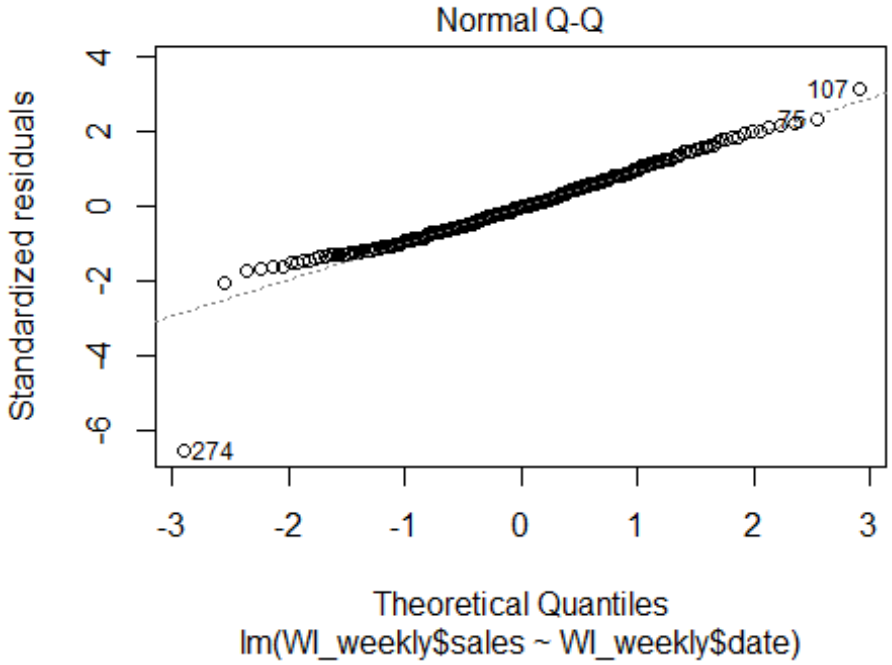
```
##
## Call:
## lm(formula = WI_weekly$sales ~ WI_weekly$date, data = WI_weekly)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -55450  -5777   -285   5433  26518
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2.429e+05  1.489e+04  -16.31   <2e-16 ***
## WI_weekly$date  1.936e+01  9.327e-01   20.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8548 on 272 degrees of freedom
## Multiple R-squared:  0.6131, Adjusted R-squared:  0.6117
## F-statistic:   431 on 1 and 272 DF,  p-value: < 2.2e-16
```

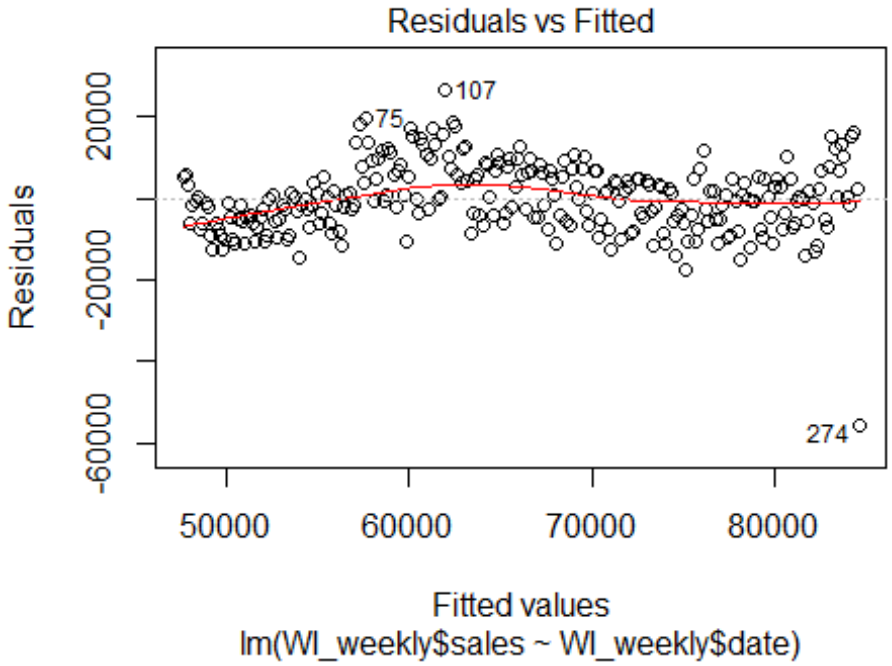
Texas' slope is 8.986286, California's slope is 19.1362012, and Wisconsin's slope is 19.3650254.

The following is plot of the fitted line.



The following two plots shows that WI sales are normally distributed with a fairly equal variance.





The next step will be doing the Hypothesis test on the difference in the β_1 coefficients for each of these states.

The null hypothesis is that the β_1 coefficients between the 3 states are equal.

H_0: $\beta_{1\ California} = \beta_{1\ Texas} = \beta_{1\ Wisconsin}$

H_a: At least one β_1 is different.

From the linear regression, the 95% confidence interval for California's β_1 coefficient is (21.35, 16.92)

```
##                          2.5 %        97.5 %
## (Intercept)    -236093.69411 -165365.87862
## CA_weekly$date      16.92154      21.35086
```

The 95% confidence interval for Texas' β_1 coefficient is (10.48, 7.49)

```
##                          2.5 %       97.5 %
## (Intercept)    -98248.701163 -50617.63879
## TX_weekly$date      7.494842     10.47773
```

The 95% confidence interval for Wisconsin's β1 coefficient is (21.20, 17.53)

```
##                          2.5 %        97.5 %
## (Intercept)    -272224.43024 -213580.06296
## WI_weekly$date      17.52873      21.20132
```

Therefore, the decision is to reject the null hypothesis and conclude that at least one β_1 coefficient is different than the others. In this particular case, Texas' β1 coefficient differs from the other two states since its confidence interval does not overlap with the other two.

Comparison of Category Price by State

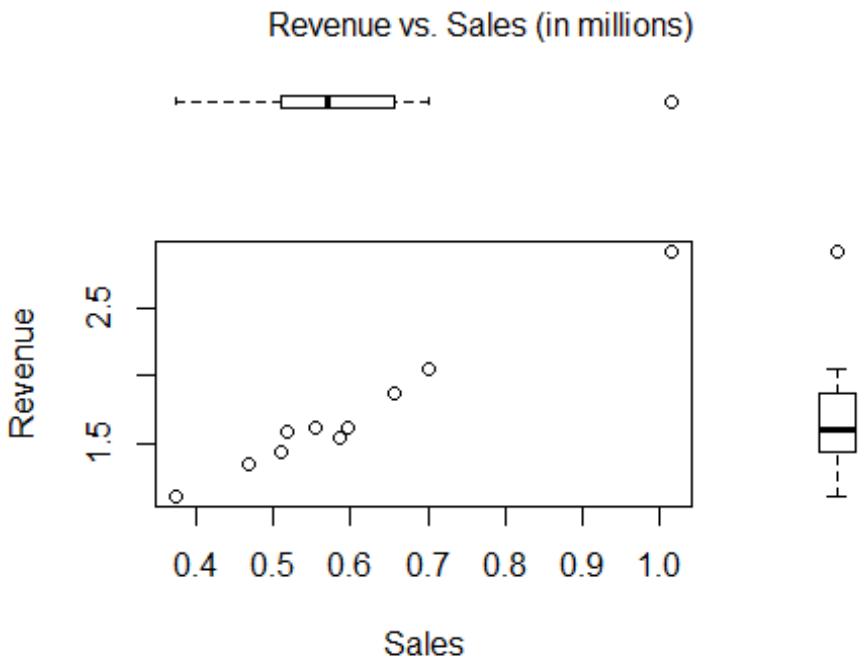
The next thing we want to look at is the sales, revenue, and average price of the ten stores compares to each other.

The following table shows the average yearly sales and revenue for each store.

store_id	sales	revenue
CA_1	699837.8	2047296
CA_2	516861.4	1582677
CA_3	1017107.3	2918975

CA_4	373061.5	1109741
TX_1	508662.9	1429924
TX_2	655853.1	1865294
TX_3	553575.5	1617884
WI_1	468096.5	1342658
WI_2	594910.2	1608249
WI_3	584343.8	1538810

The following graph show the scatter plot with box plots of this data. Our next steps will be to do a multivariate analysis of the data and see if we find anything significant.



This next table shows the basic descriptive statics for sales and revenue for all of the stores. Each store sells on average about 597,231 items brining in about 1.7 million dollars over these 10 stores.

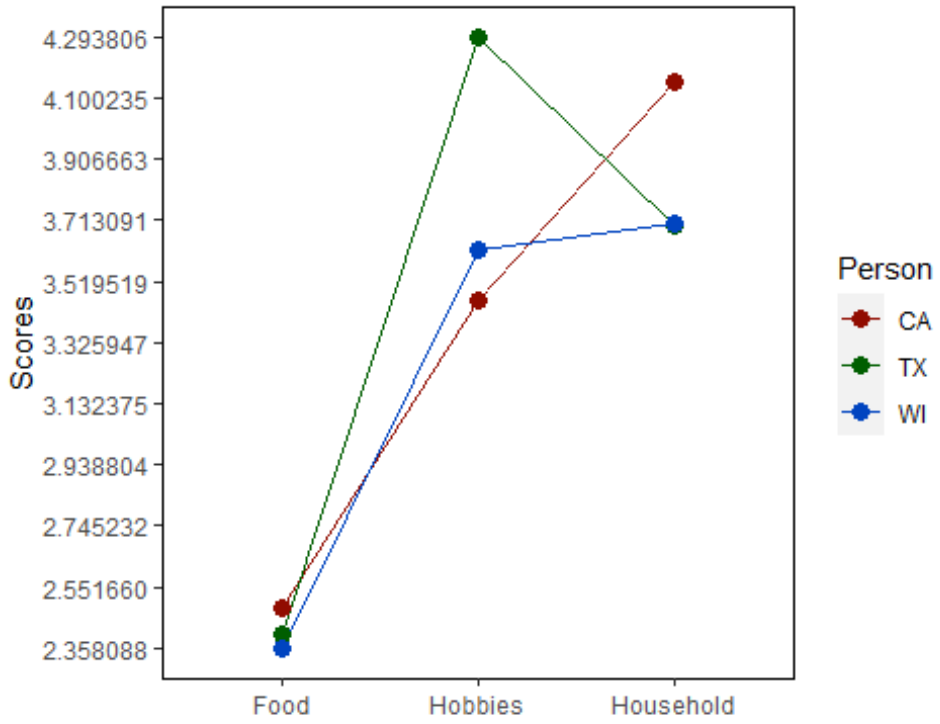
	sales	**revenue**
Mean	597231.0	1706150.6
Std.Dev	174346.2	498598.7
Min	373061.5	1109740.6
Median	568959.6	1595462.9
Max	1017107.3	2918974.5

That is interesting, but what about how much each state compares for each of three categories Food, Hobbies, and Household? The following table is the descriptive statistics for each category in each store.

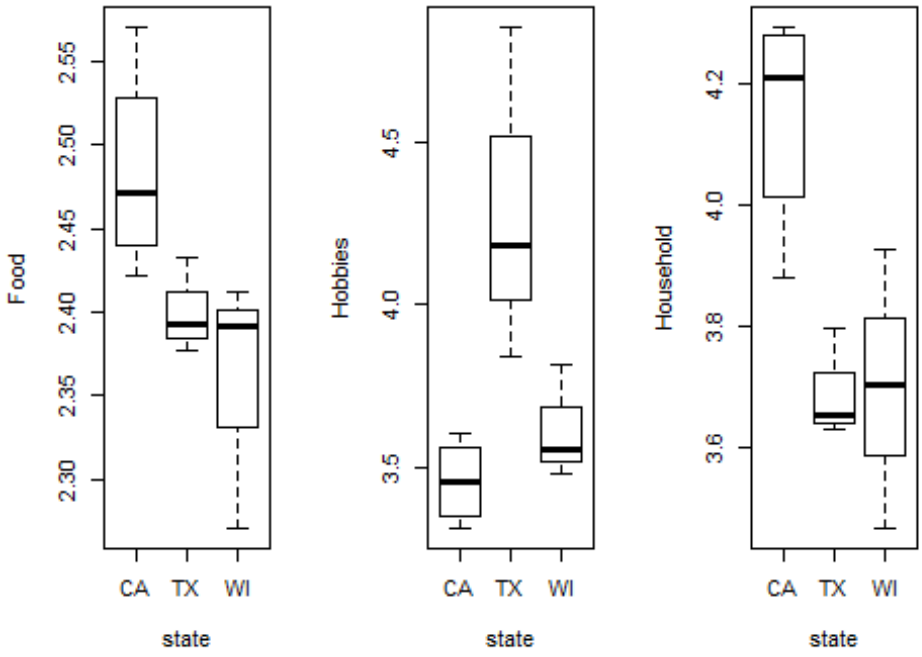
	sales	revenue	avg_price
Mean	199077.00	568716.9	3.3520975
Std.Dev	171107.05	380413.8	0.7372562
Min	33655.82	128554.6	2.2707652
Median	127481.73	461423.7	3.5398370
Max	683253.64	1654610.9	4.8520368

In each category, (Food, Hobbies, and Household), sells on average 199077 items and brings on average 57000 dollars for each store.

The following plot is the profile plot of the average sales price in each category per state. It appears according to this that Hobbies are priced higher in Texas than in the other states. It also appears that California prices higher its Household items than the other states. All states have a similar price for food.

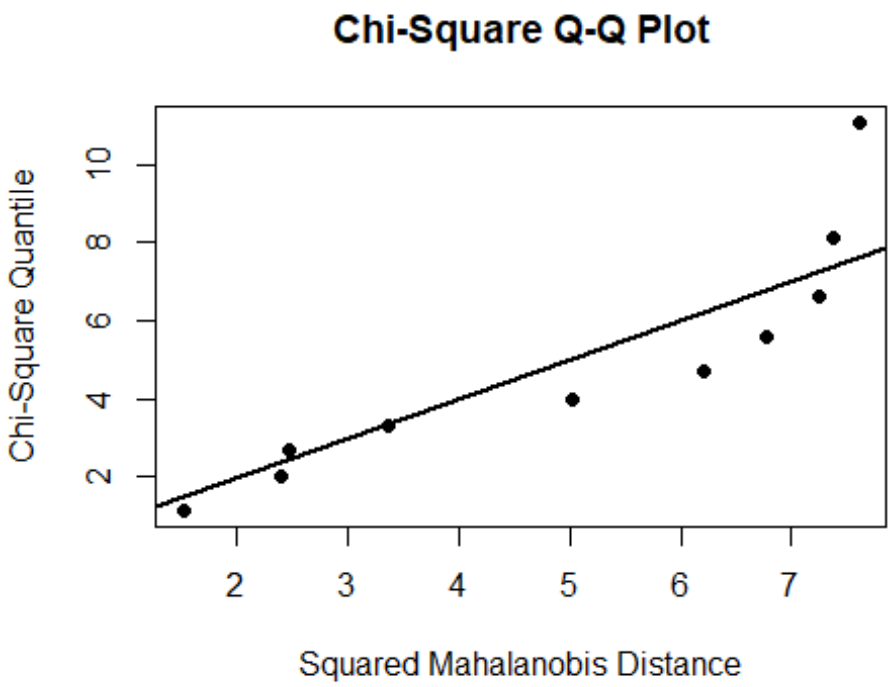


Below are 3 box plots, one for each category, showing the average price for item in each state and how they compare.



According to these plots, there may be a significant difference between the category costs for each state.

The multivariate normal test was applied to determine whether the data had a normal distribution. The below plot is a Q-Q plot of the $X^2$and the distances. The data appears to follow the distribution quite well, until the end.



Looking at the results from the MVN test, it is shown that the assumption of normality is true.

```
## $multivariateNormality
##               Test          Statistic           p value Result
## 1 Mardia Skewness   42.8050821440668 0.171113756339515    YES
## 2 Mardia Kurtosis -0.940084372658701 0.347174284063481    YES
## 3             MVN               <NA>              <NA>    YES
##
## $univariateNormality
##           Test  Variable Statistic   p value Normality
## 1 Shapiro-Wilk   sales      0.8709    0.1023    YES
## 2 Shapiro-Wilk  revenue     0.8436    0.0487    NO
## 3 Shapiro-Wilk   Food       0.9520    0.6925    YES
## 4 Shapiro-Wilk  Hobbies     0.8270    0.0308    NO
## 5 Shapiro-Wilk Household    0.9367    0.5166    YES
##
## $Descriptives
##            n         Mean      Std.Dev       Median          Min
Max
## sales     10 5.972310e+05 1.743462e+05 5.689596e+05 3.730615e+05 1.017107e
+06
## revenue   10 1.706151e+06 4.985987e+05 1.595463e+06 1.109741e+06 2.918975e
+06
## Food      10 2.421212e+00 7.771637e-02 2.417037e+00 2.270765e+00 2.570264e
+00
## Hobbies   10 3.757124e+00 4.616413e-01 3.579253e+00 3.313599e+00 4.852037e
```

```
+00
## Household 10 3.877956e+00 2.826975e-01 3.839093e+00 3.468583e+00 4.293026e
+00
##                    25th         75th       Skew   Kurtosis
## sales     5.107125e+05 6.406174e+05 1.14324583  0.6920951
## revenue   1.457145e+06 1.803442e+06 1.24103067  0.7681932
## Food      2.391436e+00 2.451135e+00 0.02047398 -0.1726584
## Hobbies   3.493317e+00 3.838218e+00 1.23035986  0.3869497
## Household 3.666367e+00 4.095470e+00 0.23155700 -1.5211614
```

The following Bartlett's test are to test the assumption of equal variance. Since some of the states had only 3 stores and the number of variables are equal to 3, average price and 3 categories, the Bartlett test were implied instead of the BoxM Test. Looking at the test values, it appears that there is not enough evidence to support the rejection of equal variance for these categories.

```
##  Bartlett test of homogeneity of variances
##
## data:  Food by state
## Bartlett's K-squared = 1.408, df = 2, p-value = 0.4946
```

```
##  Bartlett test of homogeneity of variances
##
## data:  Hobbies by state
## Bartlett's K-squared = 4.2441, df = 2, p-value = 0.1198
```

```
##  Bartlett test of homogeneity of variances
##
## data:  Household by state
## Bartlett's K-squared = 1.2964, df = 2, p-value = 0.523

## The following object is masked _by_ .GlobalEnv:
##
##     state
```

The following shows the results from a MANOVA test, using Pillai's Trace is displayed below. According to this method, there is enough evidence to support a statistical difference between the state's prices in each category with a $p < 0.05$.

```
##           Df Pillai approx F num Df den Df Pr(>F)
## state      2 1.2559   3.3757      6     12 0.0346 *
## Residuals  7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Using the Wilks method, there is still some evidence to support significance between the state's prices in each category, but it not as much significance as Pillai's Trace. This p value greater than .05 but less than .10.

```
##           Df   Wilks approx F num Df den Df  Pr(>F)
## state      2 0.12001   3.1445      6     10 0.05326 .
## Residuals  7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

To dig a little deeper, lets look at the individual ANOVA test and their respective p-values which are in the table below. If a significance level of .10 is used, then it can be seen that there is a difference in the states cost for the two categories Hobbies and Household. Food has no evidence to support any difference among the states.

Category	Adjust P-Value
Food	0.209
Hobbies	0.064
Household	0.055

Conclusion

After analyzing the Walmart sales data, we were able to make several conclusions about the questions we set out to answer. Overall, there is enough evidence to conclude that the day of the week affects the amount of sales. The average sales on weekends are higher than on weekdays, with Tuesday, Wednesday, and Thursday having the lowest weekly sales. From the coefficient analysis, it is shown that although all three state's sales increased in time, Texas had the slowest increase in sales over the years of analysis. It was found that categorical cost of goods differed between states, with California selling Food and Household items at higher prices, and Texas selling Hobby items at higher prices. Surprisingly, it was found that Sporting events, National Events, Religious Holidays, and other Cultural events have no effect on weekly sales.

References

[1] *https://www.kaggle.com/headsortails/back-to-predict-the-future-interactive-m5-eda*

[2] *Applied Multivariate Statistical Analysis, Sixth Edition*

[3] *Dr. Poliak lecture notes, Spring 2020*