Regional Liquor Sales in Des Moines, Iowa

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Abstract

In this project, forward stepwise selection for linear regression was applied to predict the number of Bottles Sold and the Profit Dollars incurred. The dataset used consisted of data regarding sales of liquor from different stores in different counties within the state of Iowa. Due to its large size, the dataset was subsetted to only include data pertaining to the Whiskey liquor categories by volume sold in the month of November of 2015 in Des Moines. Before outputting the models, the influential points were all removed. When the number of bottles sold was predicted, two models were rendered. In the first and third models, the only variable that showed significance was Canadian Whiskies. This variable increases the bottles sold and the profit respectively by factors of 30.67 and 27.88.

In the second model the target variable was logarithmically transformed to a more normal distribution. In this model, the variables that were highly significant were Canadian Whiskies, Scotch, and Irish. Canadian Whiskies increases the bottles sold logarithm by a factor of 0.75. Scotch and Irish will both decrease the logarithm respectively by factors of 0.6 and 0.76.

Problem

The objective of this report is to create a statistical model for the volume sold of liquor in gallons and the profit dollars in the City of Des Moines which is within the state of Iowa. This can help us make informed decisions on inventory prediction, sales, and assist wholesale distributors to plan for the predicted volume of distribution.

Introduction

In February, the Distilled Spirits Council (DISCUS), announced that spirits had an estimated retail sales of nearly $72 billion in 2015. Additionally, DISCUS credits the continuous growth of the distilled spirits industry to several key factors - continuous fascination with American Whiskeys in the United States and abroad, innovations in flavors, permutation across all spirits categories leading to consumer interest, improved regulatory and tax environment resulting in expanded market access and a relatively low number of state tax threats, and the growth of small distillers, which expanded grassroots and overall interest in the spirits category (Del Buono (2016)).

This establishes that spirit sales in the Unites States is a valuable market worth exploring for a more detailed and statistical understanding of sales and volume. We hope to more thoroughly understand what impact specific store sights may have accounting for the seasonal impact in November that might effect liquor sales. We will limit the analysis to the City of Des Moines for only whiskey sales in the month of November. In 2000 the State of Iowa reported sales at a record pace during the last half of 2000 (Boshart (2001)). The later part of the year has an increase in sales so planning to meet capacity is a suitable goal for any company. Our years of interest for this analysis will be the month of November for 2015 and 2016.

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Research Background

The main goal that has to be achieved in inventory prediction is increasing the efficiency without decreasing the service value offered to the customers. When managing the levels of inventory, it is important to maintain moderate level(s) - not too high and not too low. If the inventory level is excessive, business funds can get wasted. These funds would not be able to be used for any other purpose, thus involving an opportunity cost. The costs of shortage, handling insurance, recording and inspection would proportionately increase along with inventory volume, thus impairing profitability.

On the other hand, low level(s) of inventory may result in frequent interruptions in the production schedule resulting in under-utilization of capacity and lower sales. When making predictions about orders that should be placed, assumptions are made as follows - uncertainty always exists regardless of the method(s) used, new technologies cannot always be forecasted for which paradigms do not exist, and social policy will be formulated where the future would be affected, changing the accuracy of the forecast (David S. Walonick (1993)).

One useful method for predicting inventories is the extrapolation of trends. In this method, trends and cycles in the historical data are examined and mathematical techniques are used to extrapolate to the future. The model chosen for forecasting would depend on the historical data (David S. Walonick (1993)).

One of the most common models used in this method is decomposition, where historical data is separated into trend, seasonal, and random components. As a result, forecasts are produced using "turning point analysis". Other examples of models used are adaptive filtering, Box-Jenkins analysis, simple linear regression, curve fitting, and weighted smoothing (David S. Walonick (1993)).

According to Makridakis, "Judgmental forecasting is superior to mathematical models, although there are several forecasting applications where computer-generated models would be more feasible." When inventory levels for bulk-quantity items would need to be forecasted monthly by large manufacturing companies, generating models through computer software would be more efficient (David S. Walonick (1993)).

Forecasting the demand of a product is very essential in predicting the order quantity. As a result, a data bank is created, helping the decision makers settle targets, create plans, and demonstrate changes in the business setting.

Two different methods are utilized in the investigation of the future demand - quantitative and qualitative. In quantitative methods, mathematical consistencies in the history are searched for. Two subcategories exist in quantitative methods - time series models and correlation models. On the other hand, qualitative methods are based on the opinions that people have had about the product in the past based on their experiences, premonitions, and emotions (Kumar (2012)).

However, when the most suitable forecast model gets selected, it is not necessarily based solely on quantitative or qualitative variables. The forecast model can even combine several models (Kumar (2012)).

Methodology

Our initial data set is sufficiently large in that it includes sales by individual stores and the invoices for each store. The reason for the large size of the initial data set is due to it including every liquor transaction from 2012 to present in Iowa, so it approaches 2.68 GB. For the purposes of this analysis, to analyze a data set this large is not feasible. Therefore, we reduced the number of variables and summarized to a regional aggregate.

Additionally, we looked into the top 10 liquor categories for each year by number of bottles sold. In 2015, the top categories were American Cocktails, Blended Whiskies, Canadian Whiskies, Imported Vodka, Puerto Rico & Virgin Islands Rum, Spiced Rum, Straight Bourbon Whiskies, Tequila, Vodka 80 Proof, and Whiskey Liqueur. Interestingly straight bourbon appears to have more sales in 2015 than 2014 which coincides with the literature of strong growing whiskey sales for every whiskey segment (Anonymous (2016)). We decided to focus on whiskey do to its strong sales and growing interest in the US.

We accomplished this by looking into volume of sales by the largest `County` for Iowa which is Polk county. The City of Des Moines has the largest volume of whiskey sales in Polk county so we limited our analysis to this city.

Therefore, our final evaluation data set is the following subset of variables for largest city in Iowa of Des Moines as follows; `Vendor Name`, `Pack` (pack size of bottles sold) `Bottle Volume`, `State Bottle Cost`, `State Bottle Retail`, `Sales Dollars` (Total sales), and our dependent variables are `Volume sold in Gallons` and `Profit Dollars`.

By modeling `Bottles Sold` and `Profit Dollars` we aim to predict the volume of production needed and the possible profit dollars when producing at the predicted volume. We first began by using linear regression to model the Volume Sold in Gallons, however, the distribution was initially non-normal so we used the BoxCox method to transform our dependent variable to a more normal distribution. We then used forward selection method to determine the final form for the model of Volume Sold in Gallons. We further removed points that had unusually high influence on the model.

We then modeled our second dependent variable of `Profit Dollars`, which is the difference between the sale price and retail price, by using linear regression. After using forward selection and removing highly influence points in the second model we were able more accurately model the data set.

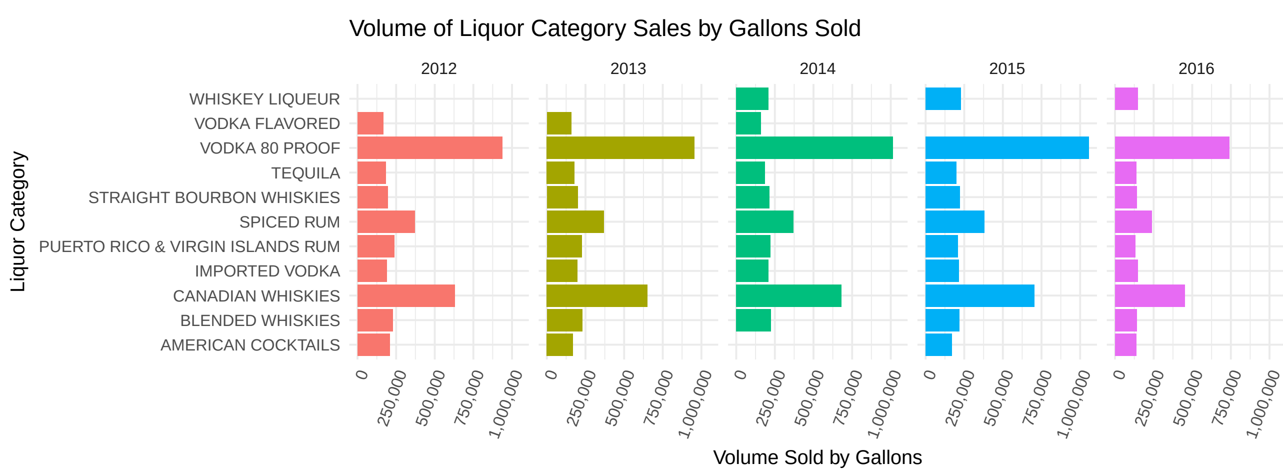
Experimentation and Results

Data Acquisition

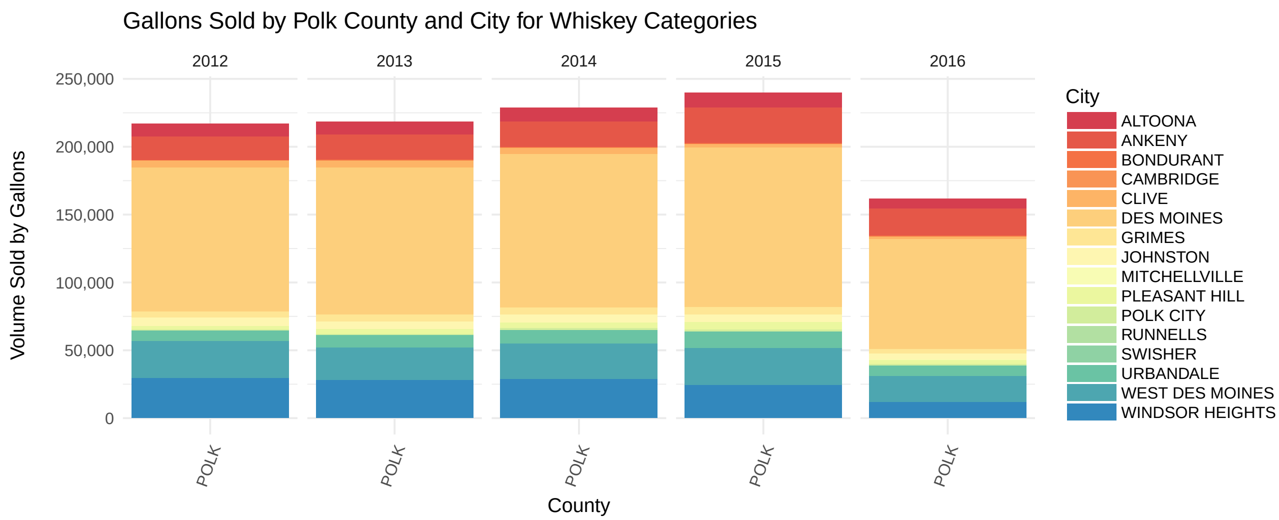
The data set contains the spirits purchase information of Iowa Class "E" liquor licensees by product and date of purchase from January 1, 2012 to current. The data set is provided by the Iowa Department of Commerce, Alcoholic Beverages Division, click here to view the data set at Data.Iowa.Gov.

As previously discussed, the data set is 2.68 GB in total size and much to large to use in a meaningful model.

We reviewed the liquor sales by gallons sold per year by Liquor Category. Initially, we viewed the top 5 Liquor Categories by volume sold but there were large disparities between years, suggesting that the top 5 change often and is likely due to changing consumer tastes. We do see a more stable set of liquor categories for the top 10 category which suggests that while tastes may change we don't see large movements in liquor categories at this level. We focused our attention on the whiskey categories.



We can further see that Des Moines accounts for a significant portion of the liquor sales in Polk County. Polk County is the most populous county in Iowa so we will limit our analysis to this city.



Model Development

Bottles Sold Model

We used forward selection method for our initial model for the Bottles Sold. However, we expect some high degrees of multicollinearity as some of our variables can be easily explained by other variables in the data set. We see a very high degree of multicollinearity in our independent variables for Bottles Sold and with good reason. If more bottles sold then certainly the volume sold by gallons would increase as would the sale dollars, we therefore removed volume sold by gallons. Below is the table highlighting the high levels of multicollinearity.

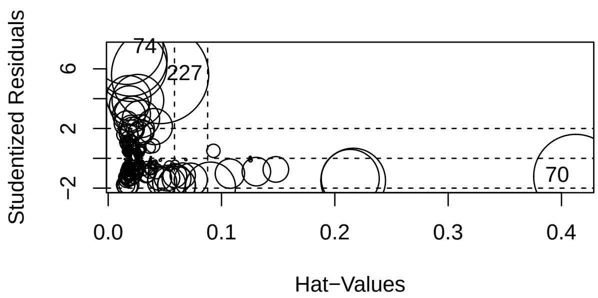
rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
Volume.Sold..Gallons.	37.245911	1	6.102943	37.245911
Category.Name	1.738855	7	1.040307	1.082239
State.Bottle.Retail	2.359291	1	1.535998	2.359291
Pack	1.248515	1	1.117370	1.248515
Sale..Dollars.	33.330891	1	5.773291	33.330891

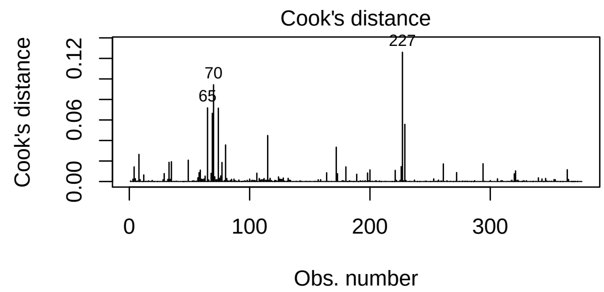
Removing Influenctial points

However, several values may have undue influence on the final form of our model. Using the `influencePlot` function from the `car` package and Cooks Distance plot, we can see which values that have the greatest impact on our model and we removed observations 65,70, and 227.

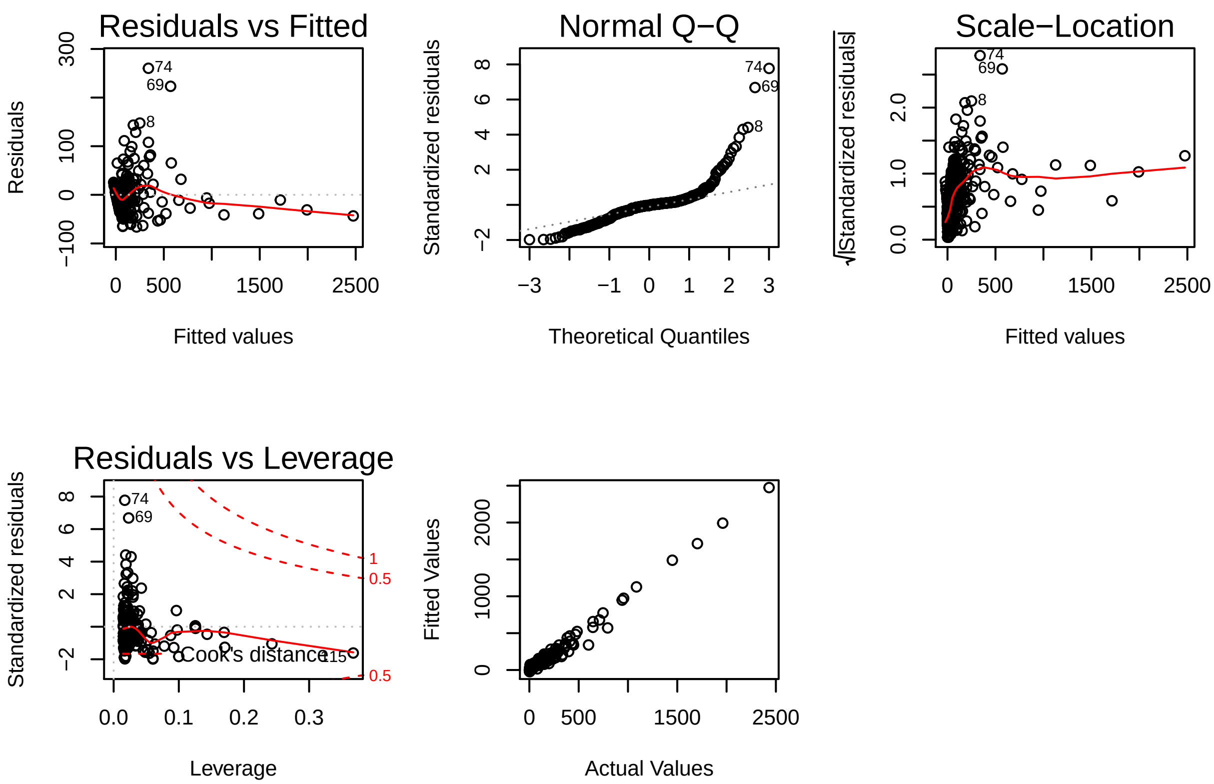
Table 2: Influential points in Bottles Sold Model

	StudRes	Hat	CookD
70	-1.216	0.4126	0.09429
74	7.415	0.01616	0.07151
227	5.591	0.04581	0.126





Below are the diagnostic plots for our Model 1, without influential points. Unfortunately, we see a non-normal distribution in residuals of the qq plot and we see a linear relationship for the fitted and actual values plot.



Our model has an extremely good Adjusted R^2 at 0.98 but we see that the distribution of the residuals is not normally distributed and the fitted values plotted to the actual values do show a clearly linear relationship. We will need to further transform the variables in order to have a more normal distribution of our residuals. We have an interesting correlation in that an increase in the Retail Price will have a .0723 increase in the number of bottles sold. The expectation would be that as retail price increases the number of bottles sold would decrease.

Bottles Sold Model with Log Transformation

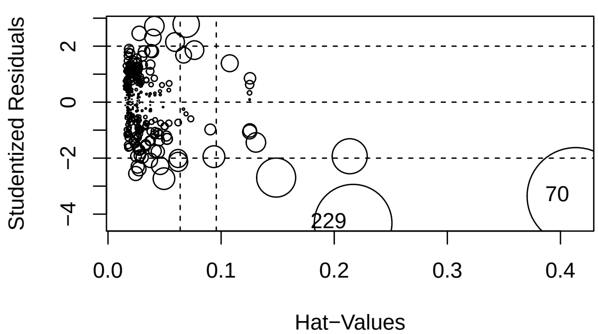
Our adjusted model uses the same selection method of forward and keeps Bottles Sold as our dependent variable. However, we use the BoxCox transformation method to transform our dependent variable. The resulting λ is 0 so our transformation is log. In using this selection method and dependent variable transformation, the final model excludes the Sales Dollars variable. Additionally, we have high multicollinearity between the Bottle Cost and the Retail variables, which is intuitive because Bottle Cost has a high impact on Retail price. We remove the Bottle Cost variable as we have more interest in the impacts Retail Price may have on our dependent variable.

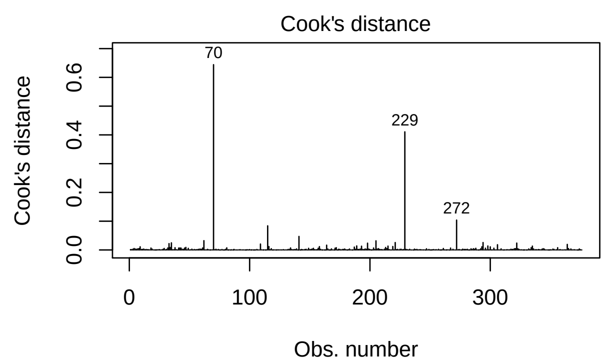
rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
State.Bottle.Cost	5.159072e+05	1	718.266832	5.159072e+05
Category.Name	2.102294e+00	7	1.054507	1.111985e+00
State.Bottle.Retail	5.158069e+05	1	718.196947	5.158069e+05
Pack	2.516499e+00	1	1.586348	2.516499e+00
Volume.Sold..Gallons.	2.231722e+00	1	1.493895	2.231722e+00
Bottle.Volume..ml.	2.332312e+00	1	1.527191	2.332312e+00

We select the values that have the greatest influence on our model and remove them to improve the model performance. The observations removed in this model is 62, 115, and 221. By excluding these values from our evaluation data set we are able to fit a more appropriate model.

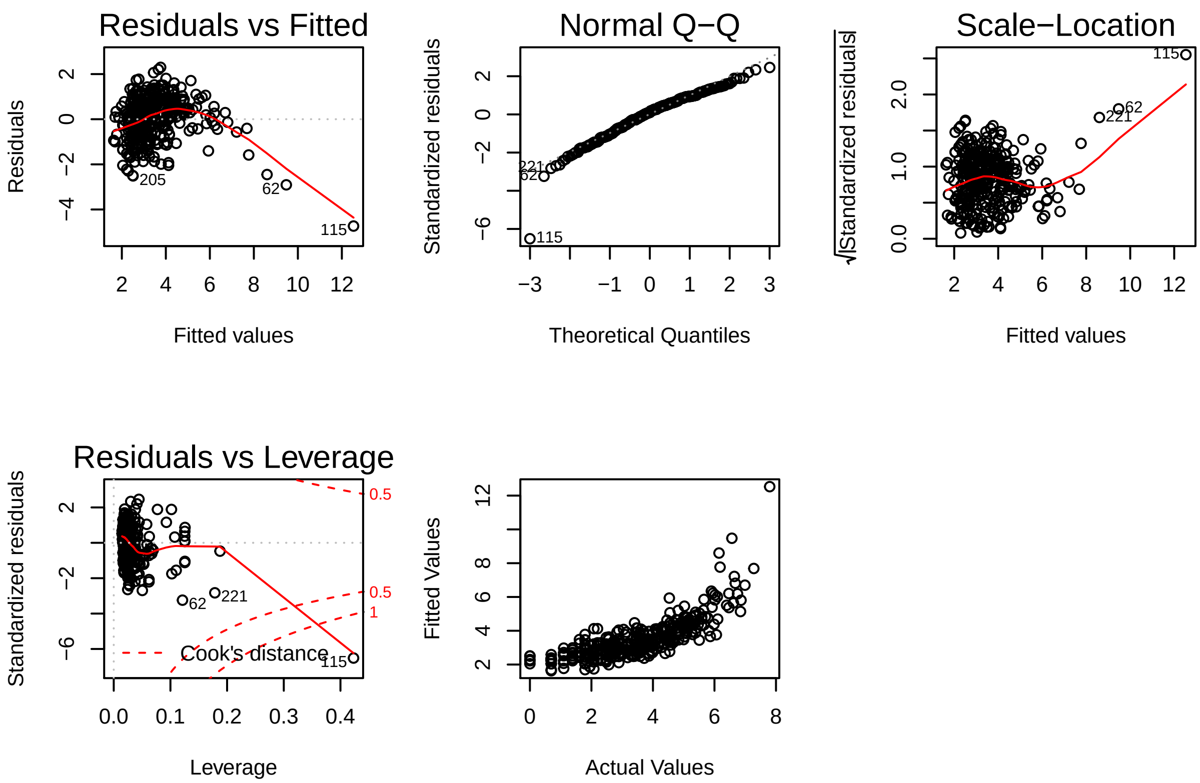
Table 4: Influential points in Log of Bottles Sold Model

	StudRes	Hat	CookD
70	-3.358	0.4135	0.6442
229	-4.322	0.2167	0.4107





We further examine our diagnostic plots for our first model with the log transformation.



The table of our detailed model is located in the Appendix and fortunately, we see a much more normal distribution of the residuals. Interestingly, our results show that one unit increase in the Retail will increase the log of bottles sold by .0032 units. We would expect a negative correlation with bottles price and bottles sold. Canadian whiskies, Irish Whiskies, and Scotch were shown to be the most significant but they do represent the majority of sales while Single Barrel Bourbon Whiskies and Straight Rye Whiskies are approaching significance. In comparison to Blended Whiskey, Canadian Whiskies will increase the log of bottles sold by 0.62, whereas, Irish Whiskies will decrease the log of bottles sold by 0.788 and Scotch will decrease the log of bottles sold by 0.71.

Also, as expected, a unit increase in the Pack will increase the log of bottles sold by 0.05 units. Another interesting finding is that a unit increase in Bottle Volume will increase log of bottles sold by .0005 units, it would suggest that larger bottles are correlated with better sales. The Adjusted Rˆ2 was improved from .588 to .631 by removing the influence points. Also, the AIC of this model is 1039.469 which is a much better AIC than 3697.202 from our previous model.

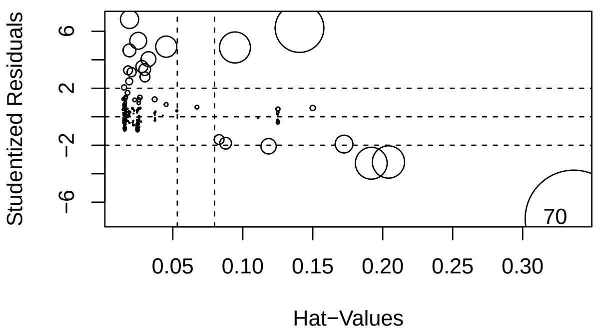
Profit Dollars Model Development

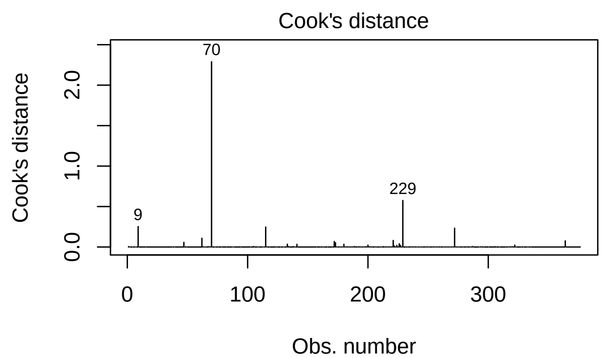
We now developed a model for the Profit Dollars for Whiskey sales in Des Moines. Profit Dollars is measured as the Retail Sale less the Cost of the liquor. We measure this value as pricing strategies are necessary in attempting to maximize profit will maintaining efficient inventory control. Using the forward selection method we find that the variables `Pack` and `Bottle Volume in ml` are not significant so they will be removed from our final model.

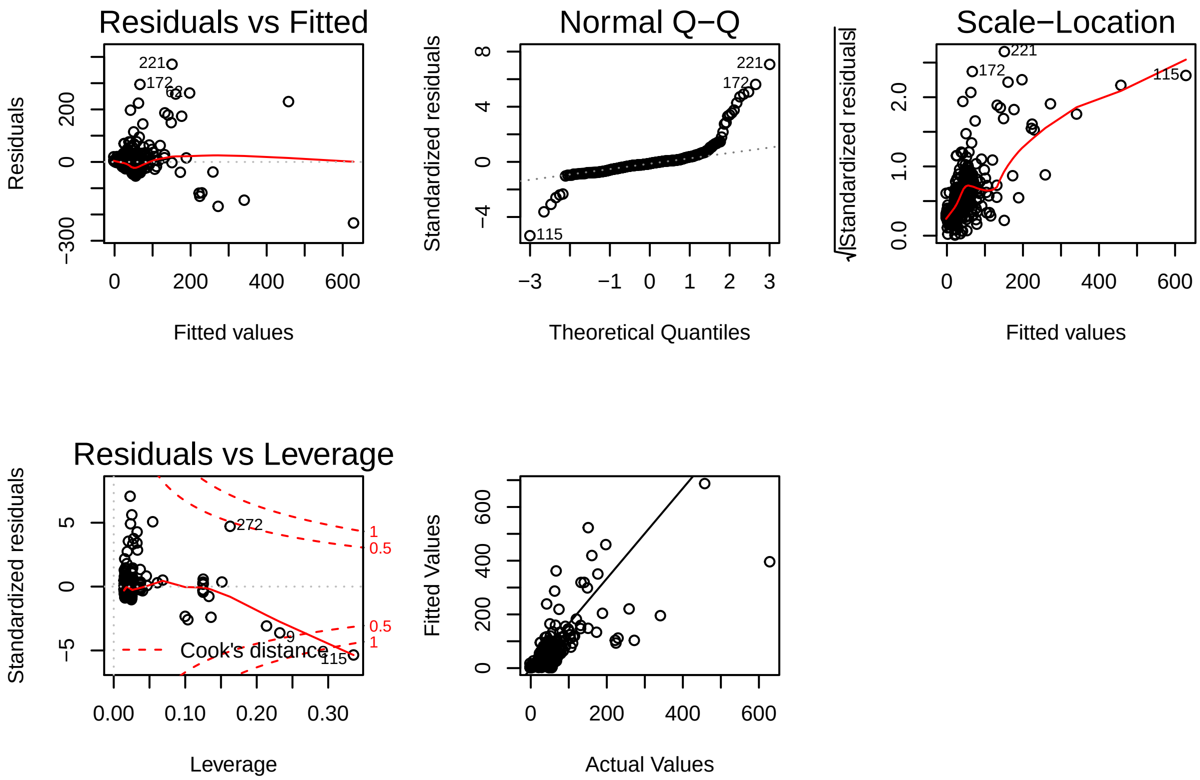
We further remove the influential points that are outliers as we did in our previous model by the observations illustrated by our influence plot and Cooks distance plot.

Table 5: Influential points in Profit Dollars Model

	StudRes	Hat	CookD
70	-7.167	0.3365	2.29







Again, we see that the distribution of the residuals is not normally distributed and the fitted values plotted to the actual values do show a clearly linear relationship. We will need to further transform the variables in order to have a more normal distribution of our residuals. In performing a Box Cox transformation on the dependent variable we find that the lambda value is close to 0 and we should therefore perform log transformation.

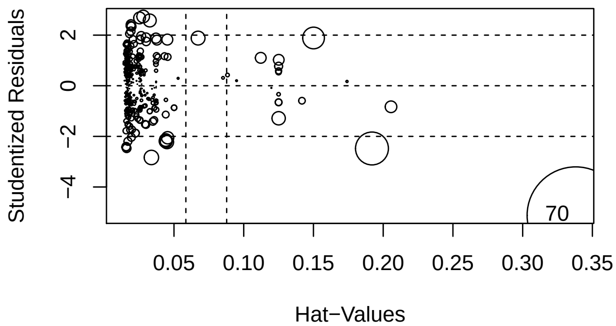
Profit Dollars Log Model

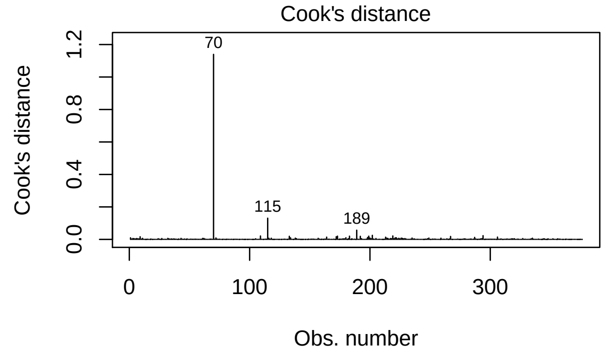
The forward selection method removed the variable Pack from our final model. Removed Pack

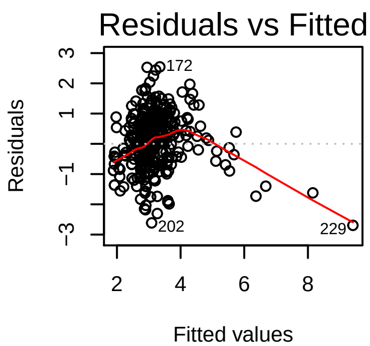
We further remove the influential points that are outliers as we did in our previous model by the observations illustrated by our influence plot and Cooks distance plot.

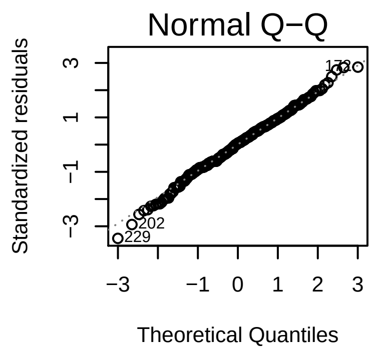
Table 6: Influential points in Log Profit Dollars Model

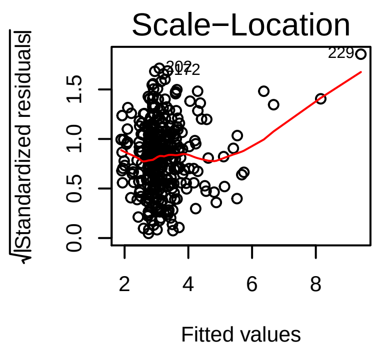
	StudRes	Hat	CookD
70	-5.123	0.338	1.14

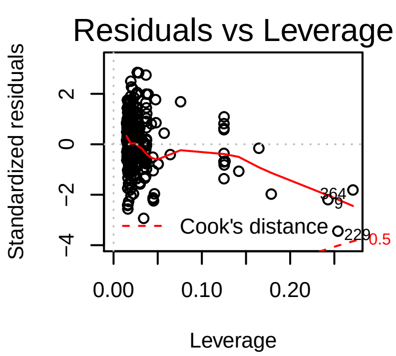


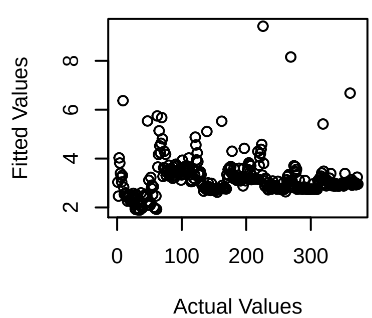












The table of our detailed model for log Profit Dollars is located in the Appendix.

Volume.Sold..Gallons=One unit of increase in volume sold in Gallons will increase the bottles sold by 1.70 units

Category.Name

CANADIAN WHISKIES is the only one that is significant.

In comparison to BLENDED WHISKIES, Canadian Whiskies will increase the bottles sold by 27.88

In comparison to BLENDED WHISKIES, IRISH Whiskies will increase the bottles sold by 21.72

In comparison to BLENDED WHISKIES, SCOTCH Whiskies will increase the bottles sold by 54.76

In comparison to BLENDED WHISKIES, SINGLE BARREL BOURBON Whiskies will increase the bottles sold by 31.54

In comparison to BLENDED WHISKIES, STRAIGHT BOURBON Whiskies will increase the bottles sold by 48.00

In comparison to BLENDED WHISKIES, STRAIGHT RYE Whiskies will increase the bottles sold by 22.16

In comparison to BLENDED WHISKIES, TENNESSEE WHISKIES will increase the bottles sold by 23.11

State..Dollars=One unit of increase in State..Dollars will decrease the bottles sold by 0.008 units

Discussion and Conclusions

In one study involving pharmaceutical distribution companies, the purpose was to propose a novel method to forecast the sales of the companies. Network-based analysis was conducted to find clique sets and group members and to use the sales data of comembers. The reason for this was the lack of sufficient historic sales records of each drug.

Three methods were used to build time series models forecasting sales - ARIMA methodology, neural network, and an advanced hybrid neural network approach. The performance of the proposed method was evaluated using a real data set provided by one of the leading pharmacy distribution companies in Iran. The results of the evaluation indicated that the proposed method can cope with the low number of past records while accurately forecasting medicine sales. An evaluation of the liquor data set using these techniques may provide greater insight as the vast number of records could produce a more accurate model.

After exploratory analysis was done on the data, it was concluded that most medicines had different and specific characteristics and sales behavior, it was impractical to make a single prediction model for all medicines, and most sales records had nonlinear relationships. This may suggest that it would be more beneficial to model liquor categories individually. However, the reason why the hybrid neural network method was carried out was due to the fact that it is not acceptable to apply a fully linear or nonlinear model on sales data. The two forecast error measures that were used to evaluate and compare model performance were mean squared error and mean absolute error. The performance of the predicted data was significantly improved when the past records of comembers were used.

http://onesearch.cuny.edu/primo_library/libweb/action/display.do?tabs=detailsTab&ct=display&fn=search&doc=TN_gale_ofa

The other study that examined prediction-based inventory optimization using data mining models, the Back propagation neural network was used for training the prediction model. The idea that gave rise to this method of inventory prediction was the idea that the demand of marketing is viewed as the foundation of inventory management. On the basis of the prediction result, a simple and concise inventory policy was established. Following this, the historic sales data was used to estimate a normal distribution of demand and to calculate the inventory cost with inventory strategy.

Two models (Back Propagation Neural Network and Support Vector Regression) were established using three input variables (historical sales data, the frequency of searching the commodity, and the click volume of the commodity page). When the back-propagation neural network method was used, there was more accuracy shown in the performance because the predicted values almost matched the actual values in the graphs. This suggests that our Naive Forecast approach could be improved through the use of theses techniques in conjunction with historical sales to create a more robust model.

http://onesearch.cuny.edu/primo_library/libweb/action/display.do?frbrVersion=2&tabs=detailsTab&ct=display&fn=search&do

In another study conducted in 2012 in Idaho, the monthly revenue generated was examined rather than the yearly revenue generated. Which is in line with our model approach for using a single month rather than a year. The continued growth was rather owed to the number of weekends a month has (five instead of four) and to the higher prices in neighboring states. In Washington, the voters approved an initiative that led the state to sell its liquor stores and add new distributor and retail fees, making prices in the neighboring states (Idaho and Oregon) look better. There were no changes made in marketing or pricing in response to the regulatory shift in Washington (**???**). Further research into the proximity of our counties to states and towns with higher prices and regulation may provide more insight into sales and volume of liquor sold. Additionally, reviewing the data by identifying months that has 5 weekends instead of four could provide further insights. A follow up study on how prices may have been impacted by pricing strategies in neighboring states and the number of weekends per month may offer further insights and improve the approach taken in this analysis.

Appendices

Supplemental tables and/or figures.

dfLiquorSales
11 Variables 376 Observations

Month

n	missing	distinct	Info	Mean	Gmd
376	0	1	0	11	0

```
Value         11
Frequency    376
Proportion     1
```

Year

n	missing	distinct	Info	Mean	Gmd
376	0	1	0	2015	0

```
Value       2015
Frequency    376
Proportion     1
```

City

n	missing	distinct	value
376	0	1	DES MOINES

```
Value       DES MOINES
Frequency          376
Proportion           1
```

Pack

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
376	0	141	0.99	13.38	6.201	6.00	6.00	9.75	12.00	16.00	21.37	24.00

```
lowest :  3.00000  4.50000  5.00000  5.25000  5.40000, highest: 30.00000 32.00000 32.57143 33.81818 36.00000
```

Bottles.Sold

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
376	0	153	0.999	116.1	173.3	3.00	5.00	9.75	32.00	96.50	247.00	444.25

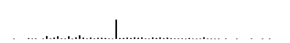
```
lowest :    1    2    3    4    5, highest: 1450 1704 1961 2431 3228
```

Sale..Dollars.

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
376	0	343	1	1891	3024	44.98	69.84	162.63	371.25	1078.08	2937.44	6963.48

```
lowest :     7.20    21.74    22.49    26.25    27.14, highest: 35818.26 38945.46 40135.98 54923.22 71157.84
```

Bottle.Volume..ml.



n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
376	0	180	0.986	803.8	345.4	375.0	435.4	573.8	750.0	953.8	1250.0	1564.3

```
lowest :  200.000  270.000  287.500  300.000  310.000, highest: 1416.667 1500.000 1550.000 1607.143 1750.000
```

State.Bottle.Cost

```
       n  missing distinct     Info     Mean      Gmd      .05      .10      .25      .50 
     376        0      319        1    101.7    127.4    7.262   10.670   18.495   47.375 
     .75      .90      .95 
 103.537  225.940  338.075 

lowest :    3.21    3.46    3.50    4.10    4.40, highest:  887.95  918.77 1045.11 1362.12 1640.44
```

State.Bottle.Retail

```
   n   missing   distinct   Info   Mean    Gmd     .05     .10     .25     .50     .75     .90     .95
 376         0        322      1  152.6  191.3   10.90   16.01   27.75   71.09  155.34  338.93  507.33

lowest :    4.82    5.19    5.25    6.15    6.60, highest: 1332.12 1378.66 1568.12 2049.35 2467.91
```

Volume.Sold..Gallons.

```
   n   missing   distinct   Info   Mean    Gmd      .05      .10      .25      .50      .75      .90      .95
 376         0        254      1   24.4  38.04   0.4225   0.7350   1.7900   5.1500  18.2400  47.0350  88.4975

lowest :   0.13   0.20   0.30   0.32   0.39, highest: 383.96 417.74 483.05 623.52 830.55
```

ProfitDollar

```
       n  missing distinct     Info     Mean      Gmd      .05      .10      .25      .50 
     376        0      317        1    50.96    63.89    3.635    5.340    9.253   23.720 
     .75      .90      .95 
  51.807  112.990  169.260 

lowest :    1.61    1.73    1.75    2.05    2.20, highest: 444.17 459.89 523.01 687.23 827.47
```

Session Info

- R version 3.3.2 (2016-10-31), `x86_64-w64-mingw32`
- Locale: `LC_COLLATE=English_United States.1252`, `LC_CTYPE=English_United States.1252`, `LC_MONETARY=English_United States.1252`, `LC_NUMERIC=C`, `LC_TIME=English_United States.1252`
- Base packages: base, datasets, graphics, grDevices, methods, stats, utils
- Other packages: car 2.1-4, data.table 1.10.0, dplyr 0.5.0, fitdistrplus 1.0-7, forecast 7.3, Formula 1.2-1, ggplot2 2.2.0, Hmisc 4.0-1, knitr 1.15.1, lattice 0.20-34, logspline 2.1.9, MASS 7.3-45, pacman 0.4.1, pander 0.6.0, purrr 0.2.2, RColorBrewer 1.1-2, readr 1.0.0, stargazer 5.2, survival 2.40-1, tibble 1.2, tidyr 0.6.0, tidyverse 1.0.0, timeDate 3012.100, zoo 1.7-13
- Loaded via a namespace (and not attached): acepack 1.4.1, assertthat 0.1, backports 1.0.4, base64 2.0, cluster 2.0.5, colorspace 1.3-1, DBI 0.5-1, digest 0.6.10, evaluate 0.10, foreign 0.8-67, fracdiff 1.4-2, grid 3.3.2, gridExtra 2.2.1, gtable 0.2.0, htmlTable 1.7, htmltools 0.3.5, latticeExtra 0.6-28, lazyeval 0.2.0, lme4 1.1-12, magrittr 1.5, Matrix 1.2-7.1, MatrixModels 0.4-1, mgcv 1.8-16, minqa 1.2.4, munsell 0.4.3, nlme 3.1-128, nloptr 1.0.4, nnet 7.3-12, openssl 0.9.5, parallel 3.3.2, pbkrtest 0.4-6, plyr 1.8.4, quadprog 1.5-5, quantreg 5.29, R6 2.2.0, Rcpp 0.12.8, rmarkdown 1.2, rpart 4.1-10, rprojroot 1.1, rticles 0.2, scales 0.4.1, SparseM 1.74, splines 3.3.2, stringi 1.1.2, stringr 1.1.0, tools 3.3.2, tseries 0.10-35, yaml 2.1.14

R statistical programming code.

Please see Final Project.rmd on GitHub for source code.

https://github.com/ChristopheHunt/DATA-621-Group-1/blob/master/Final%20Project/Final%20Project.Rmd

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Boshart, Rod. 2001. “Liquor Sales in Iowa Set Record.” *Gazette*.

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List of Tables

Table 7: Forward Selection Linear Model for Bottles Sold without Influencial Points

	Dependent variable:
	Bottles.Sold
Constant	-25.596^{***} (6.602)
Volume.Sold..Gallons.	3.771^{***} (0.045)
Category.NameCANADIAN WHISKIES	32.910^{***} (6.002)
Category.NameIRISH WHISKIES	-10.398 (6.947)
Category.NameSCOTCH WHISKIES	-12.880^{*} (7.053)
Category.NameSINGLE BARREL BOURBON WHISKIES	6.909 (13.108)
Category.NameSTRAIGHT BOURBON WHISKIES	-8.602 (6.185)
Category.NameSTRAIGHT RYE WHISKIES	10.806 (8.213)
Category.NameTENNESSEE WHISKIES	-6.136 (6.102)
State.Bottle.Retail	0.072^{***} (0.011)
Pack	2.647^{***} (0.333)
Observations	373
R^2	0.981
Adjusted R^2	0.980
Residual Std. Error	33.781 (df = 362)
F Statistic	$1{,}833.018^{***}$ (df = 10; 362) (p = 0.000)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Forward Selection Linear Model for Log of Bottles Sold with Influencial Points

	Dependent variable:
	log(Bottles.Sold)
Constant	1.845*** (0.447)
Category.NameCANADIAN WHISKIES	0.730*** (0.191)
Category.NameIRISH WHISKIES	−0.761*** (0.226)
Category.NameSCOTCH WHISKIES	−0.680*** (0.220)
Category.NameSINGLE BARREL BOURBON WHISKIES	−1.062** (0.429)
Category.NameSTRAIGHT BOURBON WHISKIES	−0.326 (0.202)
Category.NameSTRAIGHT RYE WHISKIES	−0.649** (0.286)
Category.NameTENNESSEE WHISKIES	−0.313 (0.198)
State.Bottle.Retail	0.003*** (0.0003)
Pack	0.060*** (0.014)
Volume.Sold..Gallons.	0.004*** (0.001)
Bottle.Volume..ml.	0.001** (0.0002)
Observations	376
R^2	0.583
Adjusted R^2	0.570
Residual Std. Error	1.032 (df = 364)
F Statistic	46.203*** (df = 11; 364) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9: Forward Selection Linear Model for Log of Bottles Sold without Influencial Points

	Dependent variable:
	log(Bottles.Sold)
Constant	1.863*** (0.414)
Category.NameCANADIAN WHISKIES	0.626*** (0.178)
Category.NameIRISH WHISKIES	−0.788*** (0.209)
Category.NameSCOTCH WHISKIES	−0.710*** (0.205)
Category.NameSINGLE BARREL BOURBON WHISKIES	−1.026** (0.398)
Category.NameSTRAIGHT BOURBON WHISKIES	−0.279 (0.188)
Category.NameSTRAIGHT RYE WHISKIES	−0.629** (0.265)
Category.NameTENNESSEE WHISKIES	−0.336* (0.184)
State.Bottle.Retail	0.003*** (0.0003)
Pack	0.058*** (0.013)
Volume.Sold..Gallons.	0.008*** (0.001)
Bottle.Volume..ml.	0.0005** (0.0002)
Observations	373
R^2	0.622
Adjusted R^2	0.611
Residual Std. Error	0.957 (df = 361)
F Statistic	54.043*** (df = 11; 361) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 10: Forward Selection Linear Model Profit Dollars without Influencial Points

	Dependent variable:
	ProfitDollar
Constant	−2.458 (7.447)
Volume.Sold..Gallons.	1.680*** (0.226)
Category.NameCANADIAN WHISKIES	27.875*** (9.382)
Category.NameIRISH WHISKIES	21.716* (11.499)
Category.NameSCOTCH WHISKIES	54.760*** (11.288)
Category.NameSINGLE BARREL BOURBON WHISKIES	31.538 (20.280)
Category.NameSTRAIGHT BOURBON WHISKIES	48.001*** (9.705)
Category.NameSTRAIGHT RYE WHISKIES	22.161* (12.837)
Category.NameTENNESSEE WHISKIES	23.106** (10.147)
Sale..Dollars.	−0.008*** (0.002)
Observations	374
R^2	0.528
Adjusted R^2	0.516
Residual Std. Error	53.219 (df = 364)
F Statistic	45.190*** (df = 9; 364) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 11: Forward Selection Linear Model Log Profit Dollars without Influencial Points

	Dependent variable:
	log(ProfitDollar)
Constant	1.777*** (0.196)
Volume.Sold..Gallons.	0.028*** (0.004)
Category.NameCANADIAN WHISKIES	1.171*** (0.164)
Category.NameIRISH WHISKIES	0.707*** (0.200)
Category.NameSCOTCH WHISKIES	1.133*** (0.192)
Category.NameSINGLE BARREL BOURBON WHISKIES	1.120*** (0.347)
Category.NameSTRAIGHT BOURBON WHISKIES	0.797*** (0.169)
Category.NameSTRAIGHT RYE WHISKIES	0.694*** (0.222)
Category.NameTENNESSEE WHISKIES	0.950*** (0.180)
Sale..Dollars.	−0.0002*** (0.00004)
Bottle.Volume..ml.	0.0004** (0.0002)
Observations	373
R^2	0.426
Adjusted R^2	0.410
Residual Std. Error	0.906 (df = 362)
F Statistic	26.827*** (df = 10; 362) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01