Eric_Hirsch_622_Assignment_1

Predicting Sales Data

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Contents

Summary - We analyze sales data records and, after carefully exploring and wrangling the data, choose to predict Item Type using the Multinomial Regression and Random Forest machine learning methods. Both methods perform well on a smaller dataset, with the Random Forest algorithm giving us 87% accuracy.The smaller dataset matches the larger one closely in terms of standard deviations, means and distributions. However, RF benefits from the higher n and gives us 98% accuracy in our predictions.

1. Data Exploration

A. Summary Statistics For this exercise we will examine the 5,000 record and 50,000 record datasets from the assignment website.

The datasets contain fabricated sales orders generated by VBA for the purpose of practicing analysis. There are 14 columns, including 7 numeric columns, 5 character and two date. One of the predictors is an ID so we drop it. Here is a summary of the remaining 13 variables:

```
##     Region             Country             Item.Type          Sales.Channel
##  Length:5000        Length:5000        Length:5000        Length:5000
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
```

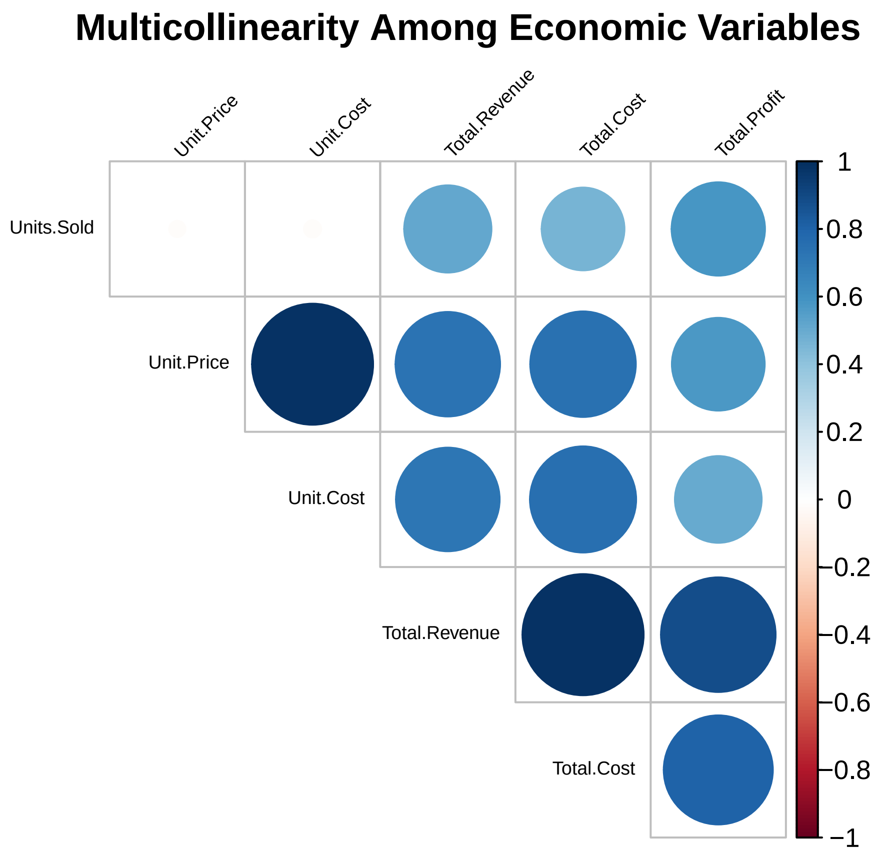
```
##  Order.Priority      Order.Date         Ship.Date           Units.Sold
##  Length:5000        Length:5000        Length:5000        Min.   :   2
##  Class :character   Class :character   Class :character   1st Qu.:2453
##  Mode  :character   Mode  :character   Mode  :character   Median :5123
##                                                            Mean   :5031
##                                                            3rd Qu.:7576
##                                                            Max.   :9999
##    Unit.Price       Unit.Cost      Total.Revenue       Total.Cost
##  Min.   :  9.33   Min.   :  6.92   Min.   :     65   Min.   :     48
##  1st Qu.: 81.73   1st Qu.: 35.84   1st Qu.: 257417   1st Qu.: 154748
##  Median :154.06   Median : 97.44   Median : 779409   Median : 468181
##  Mean   :265.75   Mean   :187.49   Mean   :1325738   Mean   : 933093
##  3rd Qu.:437.20   3rd Qu.:263.33   3rd Qu.:1839975   3rd Qu.:1189578
##  Max.   :668.27   Max.   :524.96   Max.   :6672676   Max.   :5248025
##   Total.Profit
##  Min.   :     16.9
##  1st Qu.:  85339.3
##  Median : 279095.2
##  Mean   : 392644.6
##  3rd Qu.: 565106.4
##  Max.   :1726007.5
```

```
## 'data.frame':    5000 obs. of  13 variables:
##  $ Region        : chr  "Central America and the Caribbean" "Central America and the Caribbean" "Eur
##  $ Country       : chr  "Antigua and Barbuda " "Panama" "Czech Republic" "North Korea" ...
##  $ Item.Type     : chr  "Baby Food" "Snacks" "Beverages" "Cereal" ...
##  $ Sales.Channel : chr  "Online" "Offline" "Offline" "Offline" ...
##  $ Order.Priority: chr  "M" "C" "C" "L" ...
##  $ Order.Date    : chr  "12/20/2013" "7/5/2010" "9/12/2011" "5/13/2010" ...
##  $ Ship.Date     : chr  "1/11/2014" "7/26/2010" "9/29/2011" "6/15/2010" ...
##  $ Units.Sold    : int  552 2167 4778 9016 7542 48 8258 927 8841 9817 ...
##  $ Unit.Price    : num  255.3 152.6 47.5 205.7 152.6 ...
##  $ Unit.Cost     : num  159.4 97.4 31.8 117.1 97.4 ...
##  $ Total.Revenue : num  140915 330641 226716 1854591 1150758 ...
##  $ Total.Cost    : num  88000 211152 151893 1055864 734892 ...
##  $ Total.Profit  : num  52915 119488 74823 798727 415866 ...
```

B. Multicollinearity We suspect a high degree of multicollinearity among the numeric variables, since they are components of each other - for example, total profits is made up of costs and revenues, while revenues are determined by prices and volume. We also may assume that order date and shipping date are related, and country and region will also be directly related.

The heatmap below shows the multicollinearity among the economic variables.

```
##                Units.Sold  Unit.Price   Unit.Cost Total.Revenue Total.Cost
## Units.Sold     1.00000000 -0.01749167 -0.01971201     0.5118209  0.4610137
## Unit.Price    -0.01749167  1.00000000  0.98623095     0.7350631  0.7496609
## Unit.Cost     -0.01971201  0.98623095  1.00000000     0.7226761  0.7581004
## Total.Revenue  0.51182089  0.73506309  0.72267611     1.0000000  0.9878272
## Total.Cost     0.46101374  0.74966094  0.75810043     0.9878272  1.0000000
## Total.Profit   0.58641579  0.57902433  0.50593567     0.8839900  0.8005063
##               Total.Profit
## Units.Sold       0.5864158
## Unit.Price       0.5790243
## Unit.Cost        0.5059357
## Total.Revenue    0.8839900
## Total.Cost       0.8005063
## Total.Profit     1.0000000
```



There are many different strategies we can take with the issue of multicollinearity, but because certain columns completely duplicate the information of other columns, we can't ignore it. We choose, for now, to retain a minimum of variables - Total Profit (as it summarizes most of the others), and, because the same profit may come from high revenue and high costs or low revenue and low costs, we include Unit Cost as well. (Unit cost has the lowest correlation with Total Profit of all the predictors (r=.51)).

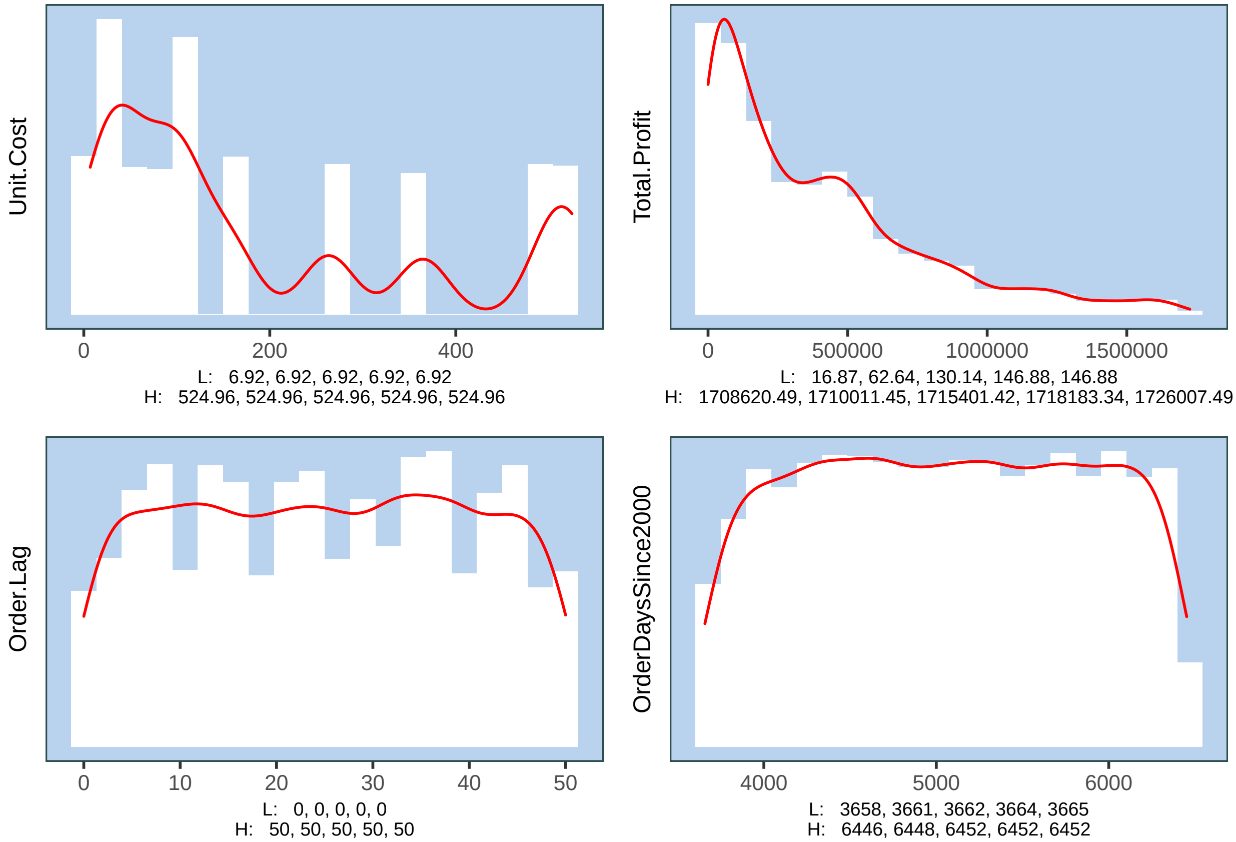
As for dates, we convert order date to an integer representing the number of days that have passed since 1/1/2000. We also create a new variable, Order.Lag, since the difference between order date and shipping date might be predictive.

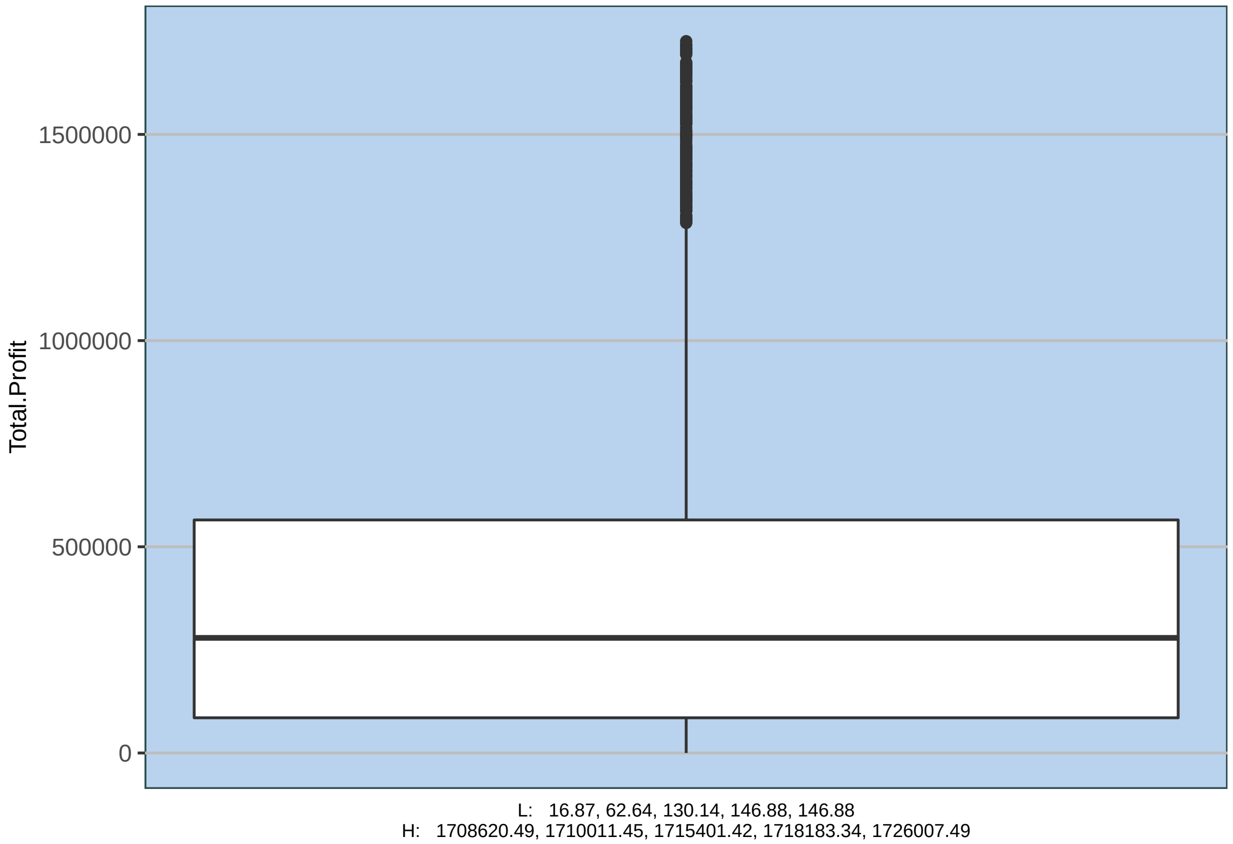
Finally, we eliminate country and retain region. This leaves us a dataframe of 8 variables.

```
##                                Region               Item.Type
##  Asia                             : 719   Beverages      : 447
##  Australia and Oceania            : 416   Fruits         : 447
##  Central America and the Caribbean: 534   Baby Food      : 445
##  Europe                           :1330   Cosmetics      : 424
##  Middle East and North Africa     : 610   Household      : 424
##  North America                    : 106   Office Supplies: 420
##  Sub-Saharan Africa               :1285   (Other)        :2393
##  Sales.Channel      Order.Priority       Unit.Cost        Total.Profit
##  Length:5000        Length:5000        Min.   :  6.92   Min.   :     16.9
##  Class :character   Class :character   1st Qu.: 35.84   1st Qu.:  85339.3
##  Mode  :character   Mode  :character   Median : 97.44   Median : 279095.2
##                                        Mean   :187.49   Mean   : 392644.6
##                                        3rd Qu.:263.33   3rd Qu.: 565106.4
##                                        Max.   :524.96   Max.   :1726007.5
##
##    Order.Lag     OrderDaysSince2000
##  Min.   : 0.00   Min.   :3658
##  1st Qu.:12.00   1st Qu.:4388
##  Median :25.00   Median :5066
##  Mean   :25.05   Mean   :5066
##  3rd Qu.:38.00   3rd Qu.:5754
##  Max.   :50.00   Max.   :6452
##
```

C. Distributions When we examine the distributions of the numeric variables, we find that Total profit is highly skewed, total cost is somewhat skewed, and the date variables are relatively uniform. There are many odd gaps in the cost distribution, which appears to be a series of discrete values. We may consider doing a log transformation of profit if need be. Since the data is fabricated, the uniformity of the date distributions suggests to me that these dates are just pulled randomly from a uniform distribution and won't be useful.

Not surprisingly, a boxplot shows a great number of outliers for total profits - this is consistent with the skew in the distribution.



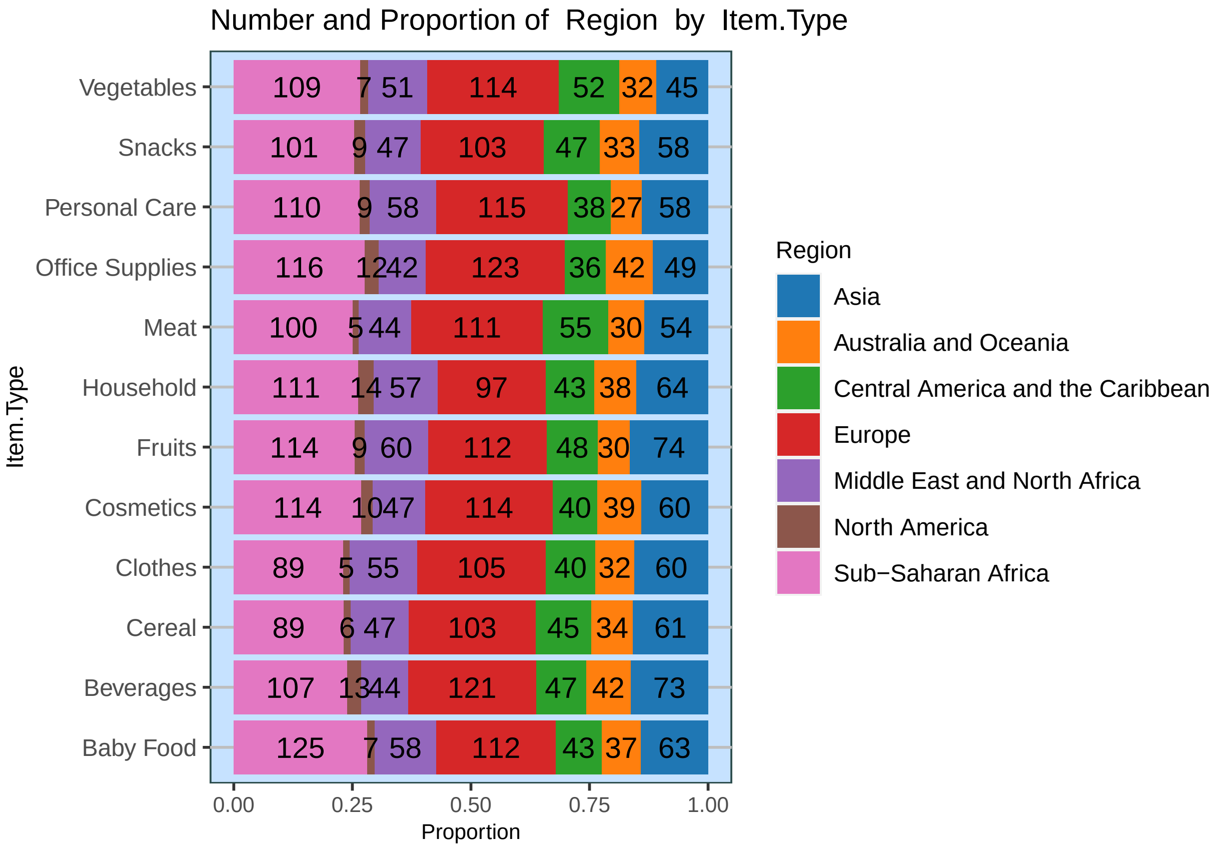


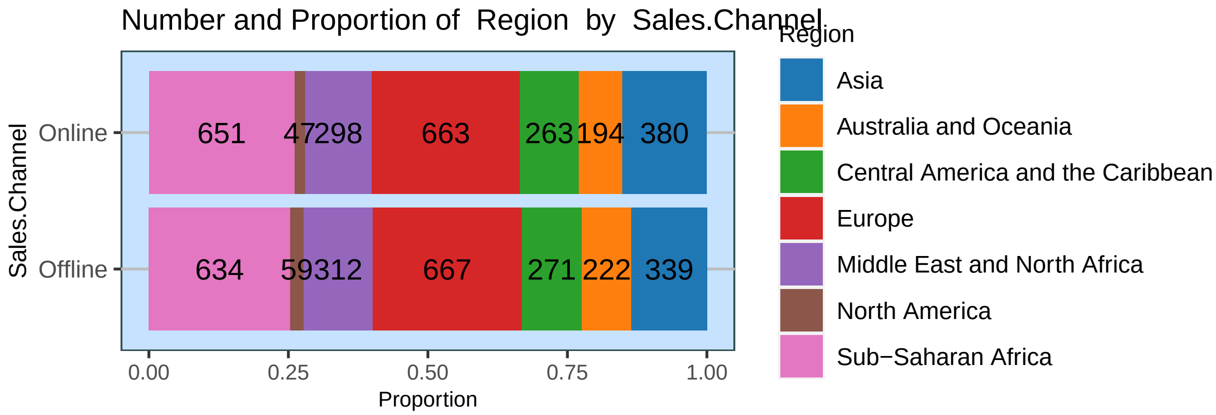
D. Relationships We can run a regression on total profit just to get an idea of some of the relationships between the numeric and categorical variables. We can see from this exploration that item types are strongly correlated with profits, as are medium priority items, but nothing else is. Unit cost could not be calculated because of singularities. We know Unit Cost is not fully correlated with Total Profit, so it must be fully correlated with another variable or in conjunction with other variables.

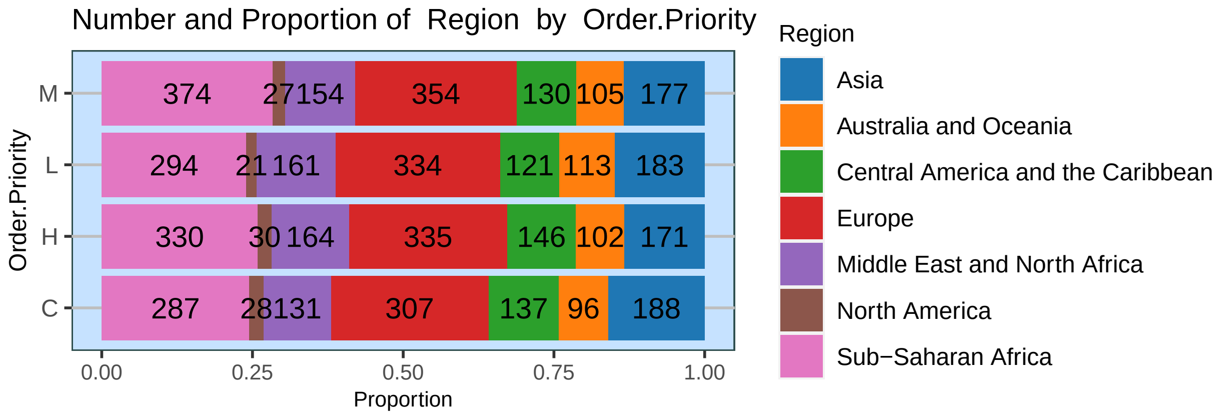
```
##
## Call:
## lm(formula = Total.Profit ~ ., data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -869368 -146888    1874  141660  847247
##
## Coefficients: (1 not defined because of singularities)
##                                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)                            4.970e+05  3.153e+04  15.762  < 2e-16
## RegionAustralia and Oceania            3.597e+03  1.687e+04   0.213   0.8312
## RegionCentral America and the Caribbean -9.154e+02  1.565e+04  -0.058   0.9534
## RegionEurope                          -1.667e+04  1.268e+04  -1.314   0.1889
## RegionMiddle East and North Africa    -1.396e+04  1.508e+04  -0.926   0.3545
## RegionNorth America                   -3.254e+04  2.850e+04  -1.142   0.2536
## RegionSub-Saharan Africa               9.604e+03  1.277e+04   0.752   0.4519
## Item.TypeBeverages                    -4.117e+05  1.834e+04 -22.452  < 2e-16
## Item.TypeCereal                       -4.083e+04  1.907e+04  -2.141   0.0323
## Item.TypeClothes                        -1.123e+05  1.904e+04  -5.896 3.98e-09
## Item.TypeCosmetics                       3.893e+05  1.857e+04  20.958  < 2e-16
## Item.TypeFruits                         -4.763e+05  1.832e+04 -25.993  < 2e-16
## Item.TypeHousehold                       3.312e+05  1.858e+04  17.826  < 2e-16
## Item.TypeMeat                           -2.166e+05  1.887e+04 -11.475  < 2e-16
## Item.TypeOffice Supplies                 1.450e+05  1.863e+04   7.784 8.49e-15
## Item.TypePersonal Care                  -3.602e+05  1.868e+04 -19.283  < 2e-16
## Item.TypeSnacks                         -2.236e+05  1.888e+04 -11.846  < 2e-16
## Item.TypeVegetables                     -1.665e+05  1.874e+04  -8.888  < 2e-16
## Sales.ChannelOnline                     -4.564e+03  7.751e+03  -0.589   0.5560
## Order.PriorityH                          1.026e+04  1.107e+04   0.927   0.3542
## Order.PriorityL                         -3.084e+03  1.119e+04  -0.276   0.7828
## Order.PriorityM                          2.292e+04  1.099e+04   2.085   0.0371
## Unit.Cost                                       NA         NA      NA       NA
## Order.Lag                                1.230e+02  2.655e+02   0.463   0.6431
## OrderDaysSince2000                      -2.448e+00  4.889e+00  -0.501   0.6165
##
## (Intercept)                             ***
## RegionAustralia and Oceania
## RegionCentral America and the Caribbean
## RegionEurope
## RegionMiddle East and North Africa
## RegionNorth America
## RegionSub-Saharan Africa
## Item.TypeBeverages                      ***
## Item.TypeCereal                         *
## Item.TypeClothes                        ***
## Item.TypeCosmetics                      ***
## Item.TypeFruits                         ***
## Item.TypeHousehold                      ***
## Item.TypeMeat                           ***
## Item.TypeOffice Supplies                ***
## Item.TypePersonal Care                  ***
## Item.TypeSnacks                         ***
## Item.TypeVegetables                     ***
## Sales.ChannelOnline
## Order.PriorityH
## Order.PriorityL
## Order.PriorityM                         *
## Unit.Cost
## Order.Lag
## OrderDaysSince2000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 273500 on 4976 degrees of freedom
## Multiple R-squared:  0.4922, Adjusted R-squared:  0.4899
## F-statistic: 209.7 on 23 and 4976 DF,  p-value: < 2.2e-16
```

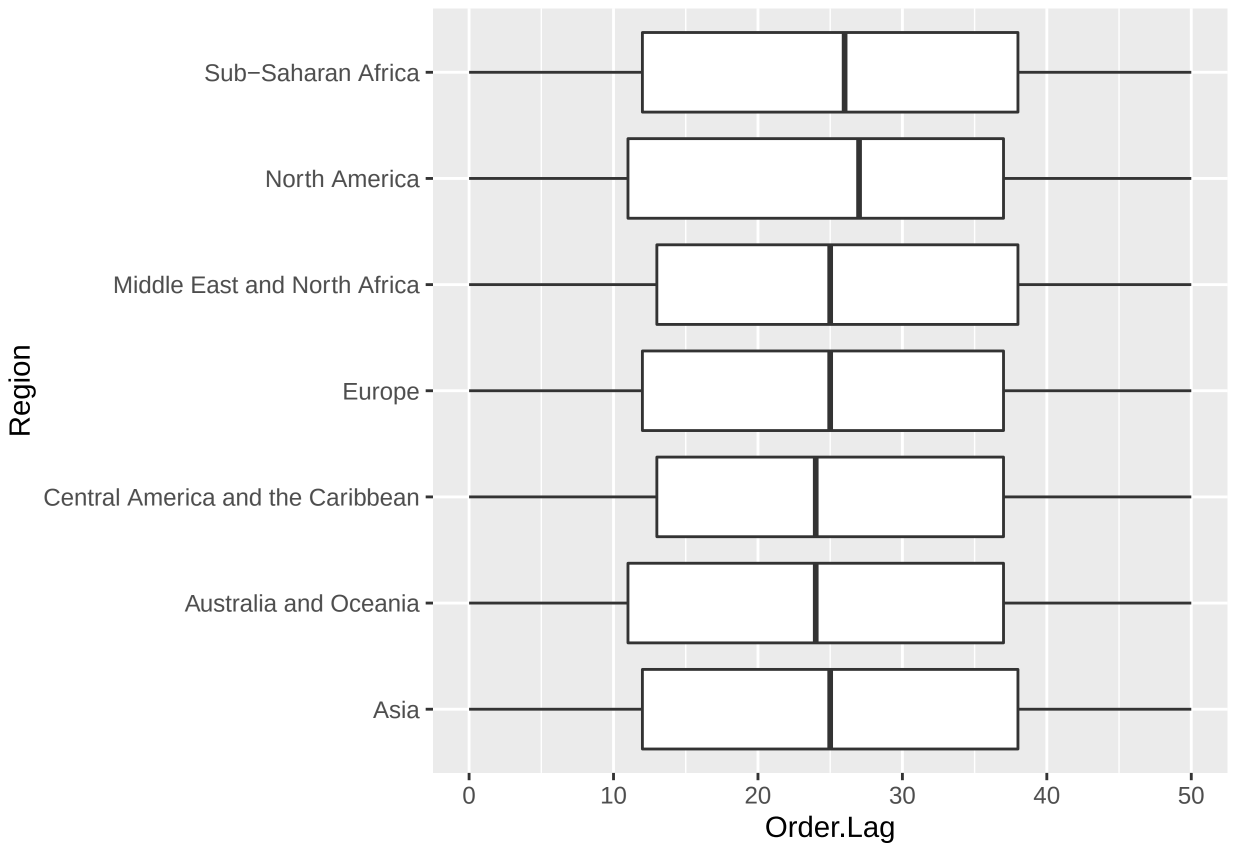
This analysis suggests that Item Type may be the most reasonable class to predict. However, region may also work, if it is correlated with some of the other variables besides profit. We can test this conjecture with some further analysis.

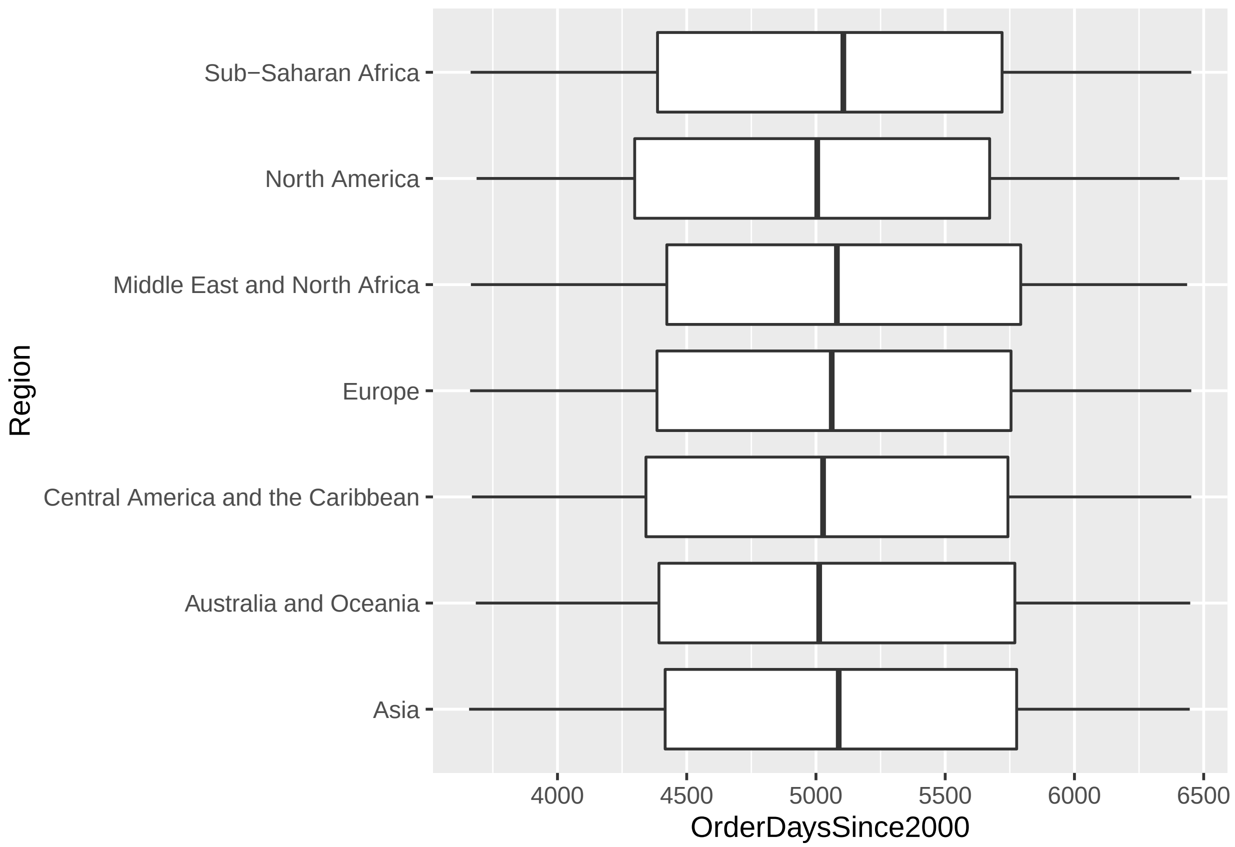
Bar charts and boxplots show relatively little relationship between region and item type, sales channel, and order priority.

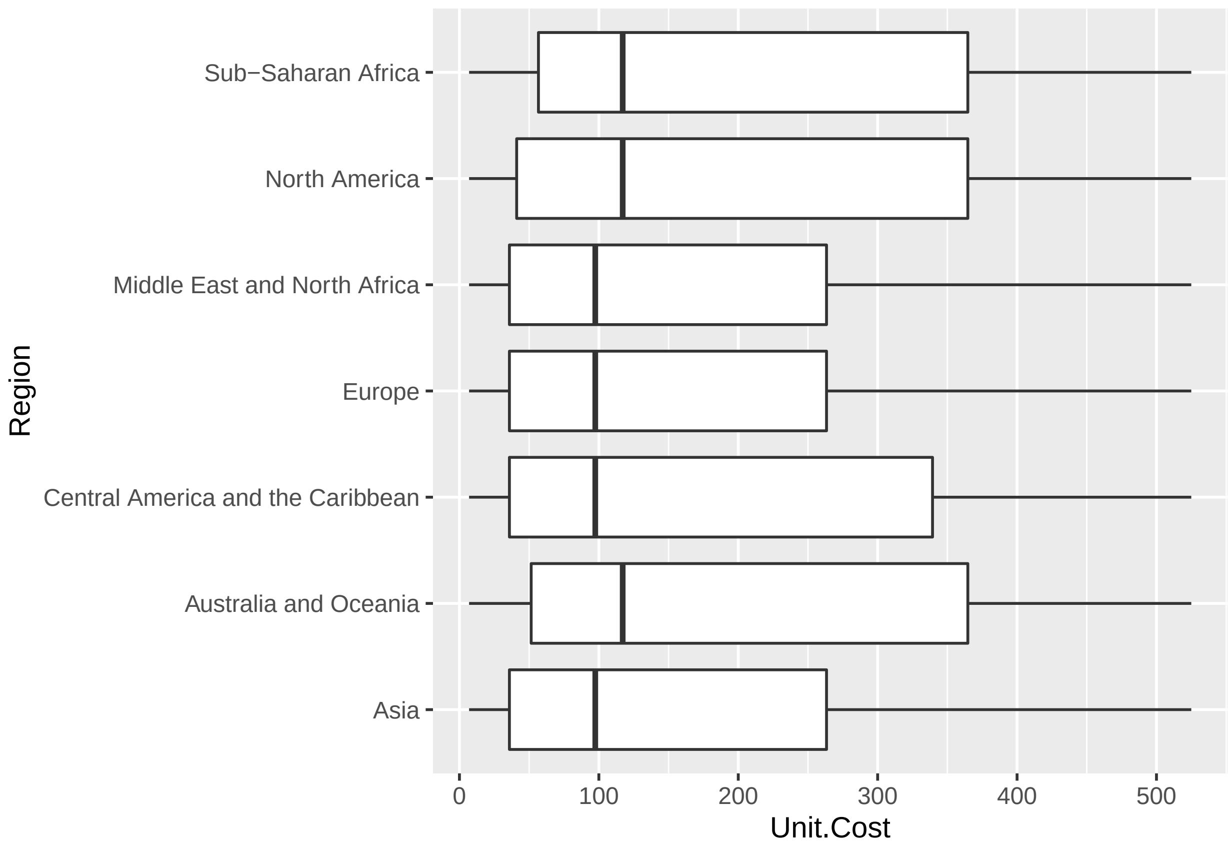

Number and Proportion of Region by Item.Type
Item.Type
Vegetables
109 7 51 114 52 32 45
Snacks
101 9 47 103 47 33 58
Personal Care
110 9 58 115 38 27 58
Office Supplies
116 12 42 123 36 42 49
Meat
100 5 44 111 55 30 54
Household
111 14 57 97 43 38 64
Fruits
114 9 60 112 48 30 74
Cosmetics
114 10 47 114 40 39 60
Clothes
89 5 55 105 40 32 60
Cereal
89 6 47 103 45 34 61
Beverages
107 13 44 121 47 42 73
Baby Food
125 7 58 112 43 37 63
0.00
0.25
0.50
0.75
1.00
Proportion
Region
Asia
Australia and Oceania
Central America and the Caribbean
Europe
Middle East and North Africa
North America
Sub−Saharan Africa


Number and Proportion of Region by Sales.Channel
Sales.Channel
Online
Offline
651
47
298
663
263
194
380
634
59
312
667
271
222
339
0.00
0.25
0.50
0.75
1.00
Proportion
Region
Asia
Australia and Oceania
Central America and the Caribbean
Europe
Middle East and North Africa
North America
Sub−Saharan Africa


Number and Proportion of Region by Order.Priority
Order.Priority
M
L
H
C
374
27
154
354
130
105
177
294
21
161
334
121
113
183
330
30
164
335
146
102
171
287
28
131
307
137
96
188
0.00
0.25
0.50
0.75
1.00
Proportion
Region
Asia
Australia and Oceania
Central America and the Caribbean
Europe
Middle East and North Africa
North America
Sub−Saharan Africa

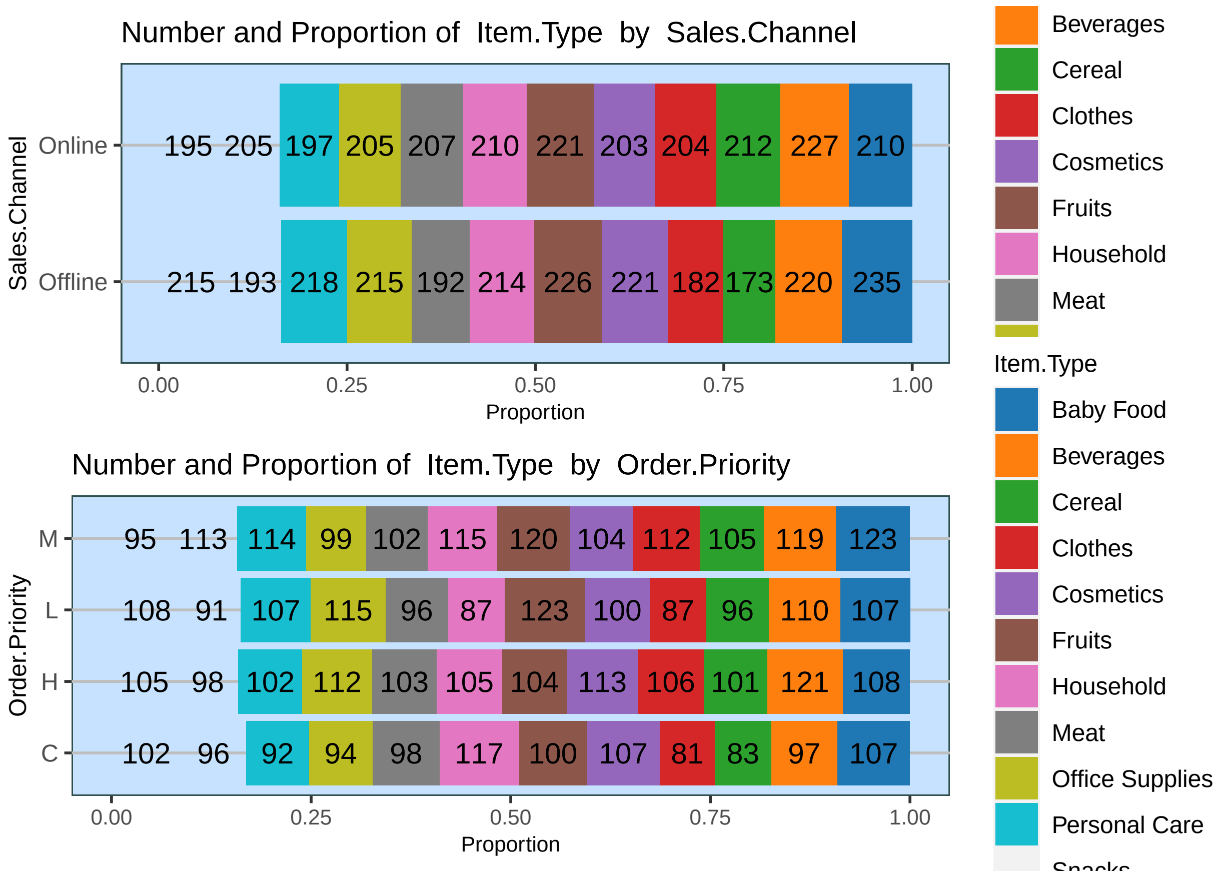

Sub−Saharan Africa
North America
Middle East and North Africa
Europe
Central America and the Caribbean
Australia and Oceania
Asia
Region
0
10
20
30
40
50
Order.Lag


Sub−Saharan Africa
North America
Middle East and North Africa
Europe
Central America and the Caribbean
Australia and Oceania
Asia
Region
4000
4500
5000
5500
6000
6500
OrderDaysSince2000



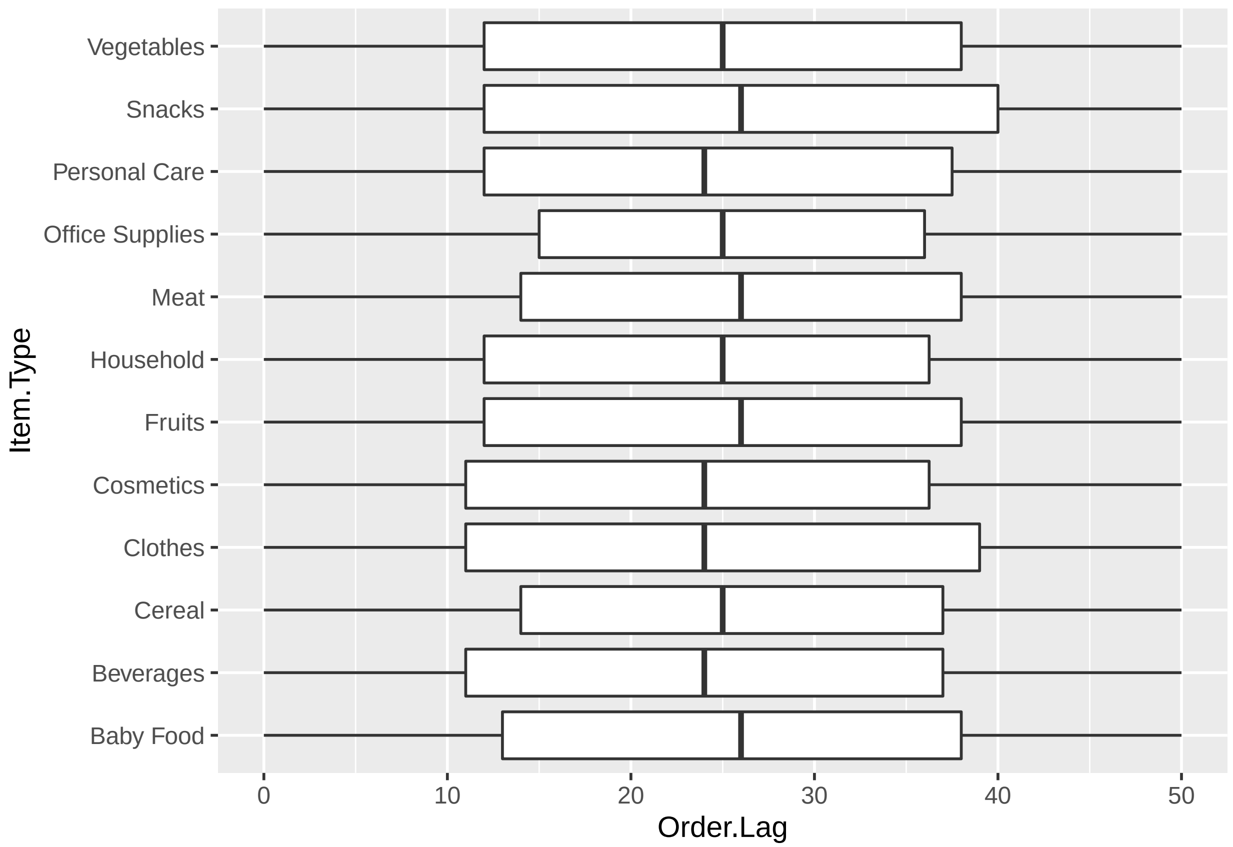
####. D. Choosing Item Type as the variable to predict

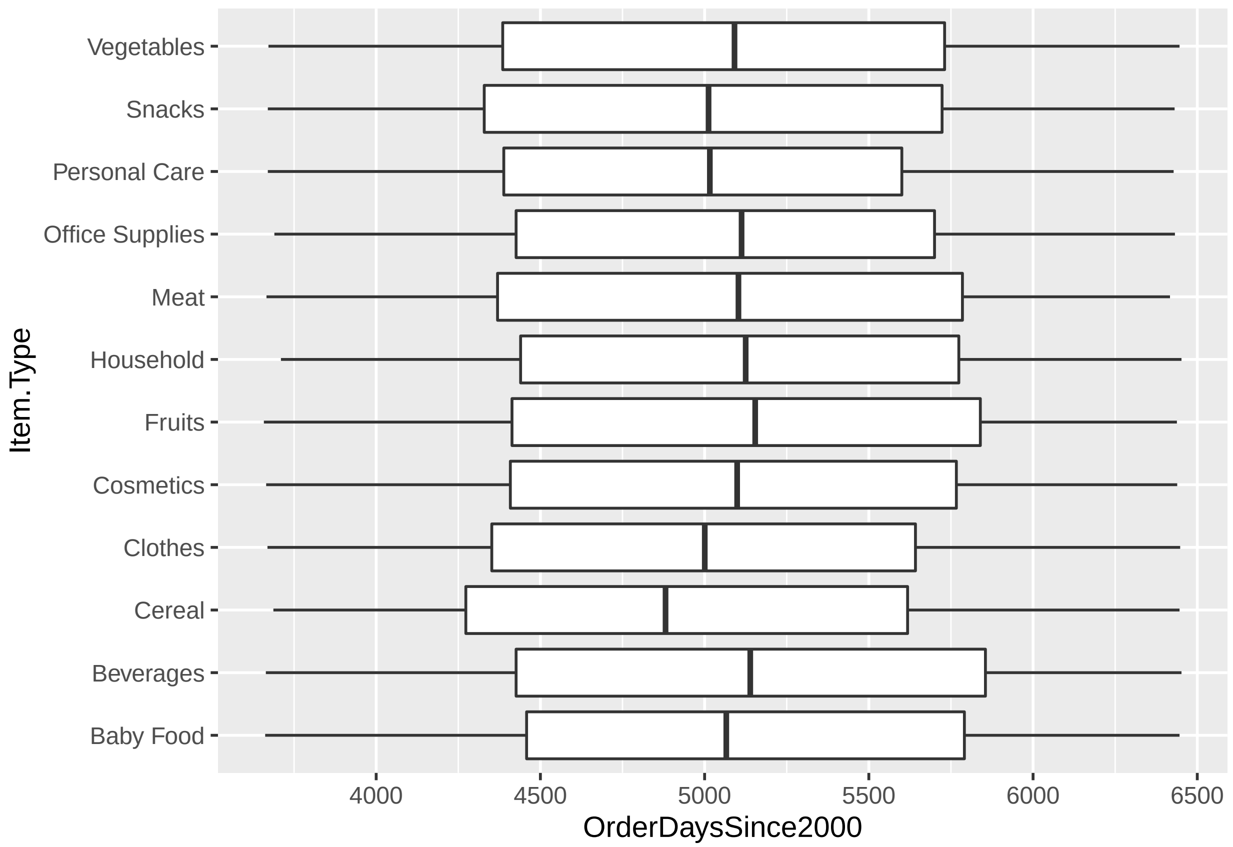
We therefore choose Item Type to predict for this analysis. As with region, we can ask, "how does it correlate with the non-economic variables?" In general, Item Type shows a similar lack of relationship to the non-economic variables as region does. But there is one major exception. Now we see the source of the singularity - each item type has one, and only one, unit price and vice versa. The two are completely correlated. Just to be sure, a regression shows an R2 of 1.

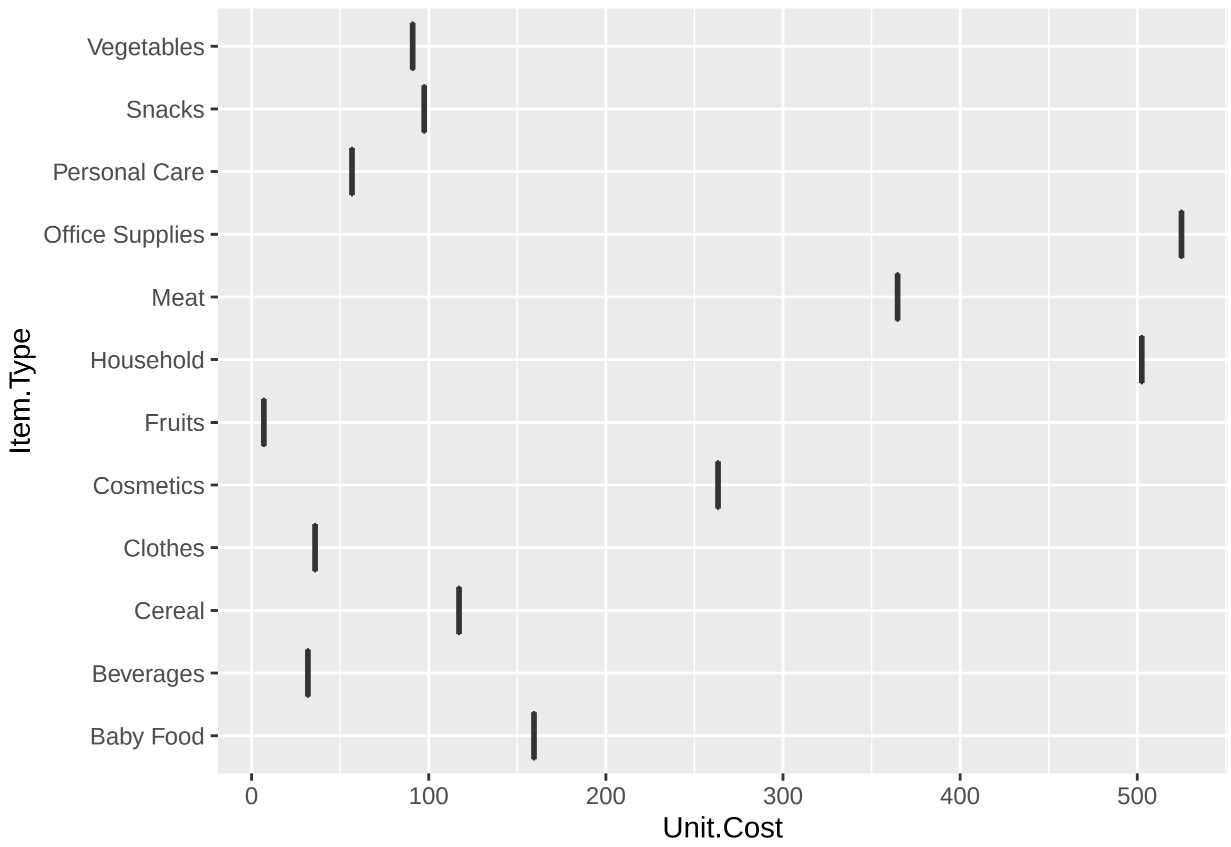


Number and Proportion of Item.Type by Sales.Channel

Number and Proportion of Item.Type by Order.Priority


Vegetables
Snacks
Personal Care
Office Supplies
Meat
Household
Fruits
Cosmetics
Clothes
Cereal
Beverages
Baby Food
Item.Type
0
10
20
30
40
50
Order.Lag


Vegetables
Snacks
Personal Care
Office Supplies
Meat
Household
Fruits
Cosmetics
Clothes
Cereal
Beverages
Baby Food
Item.Type
4000
4500
5000
5500
6000
6500
OrderDaysSince2000



```
##
## Call:
## lm(formula = Unit.Cost ~ Item.Type, data = dfx3)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -2.263e-10 -1.170e-13  0.000e+00  5.100e-14  2.305e-10
##
## Coefficients:
##                           Estimate Std. Error    t value Pr(>|t|)
## (Intercept)              1.594e+02  2.919e-13  5.461e+14   <2e-16 ***
## Item.TypeBeverages      -1.276e+02  4.124e-13 -3.095e+14   <2e-16 ***
## Item.TypeCereal         -4.231e+01  4.286e-13 -9.872e+13   <2e-16 ***
## Item.TypeClothes        -1.236e+02  4.283e-13 -2.885e+14   <2e-16 ***
## Item.TypeCosmetics       1.039e+02  4.179e-13  2.486e+14   <2e-16 ***
## Item.TypeFruits         -1.525e+02  4.124e-13 -3.698e+14   <2e-16 ***
## Item.TypeHousehold       3.431e+02  4.179e-13  8.211e+14   <2e-16 ***
## Item.TypeMeat            2.053e+02  4.245e-13  4.835e+14   <2e-16 ***
## Item.TypeOffice Supplies  3.655e+02  4.189e-13  8.726e+14   <2e-16 ***
## Item.TypePersonal Care   -1.028e+02  4.202e-13 -2.445e+14   <2e-16 ***
## Item.TypeSnacks         -6.198e+01  4.248e-13 -1.459e+14   <2e-16 ***
## Item.TypeVegetables     -6.849e+01  4.215e-13 -1.625e+14   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.158e-12 on 4988 degrees of freedom
## Multiple R-squared:      1,  Adjusted R-squared:      1
## F-statistic: 3.73e+29 on 11 and 4988 DF,  p-value: < 2.2e-16
```

With Unit Cost in the analysis, a machine learning exploration is not justified, since a lookup table in Excel would perform just as well. We will retain total profit, and add Units.Sold, which has little correlation with Unit.Cost. We remove Unit.Cost, add Units.Sold, dummify the categorical variables and scale all the predictors.

2. Models

A. Preparing the data The data needs to be partitioned into a training set and an evaluation set. We examine our classes in the training set and see that they are relatively uniform.

```
##           Item.Type   n
## 1         Baby Food 356
## 2         Beverages 358
## 3            Cereal 308
## 4           Clothes 309
## 5         Cosmetics 340
## 6            Fruits 358
## 7         Household 340
## 8              Meat 320
## 9   Office Supplies 336
## 10    Personal Care 332
## 11           Snacks 319
## 12       Vegetables 328
```

B. Selecting Models A number of factors weigh in to our decision of which models to choose. We know that we have multiple classes to predict, that total profit, a key predictor, is not normally distributed, and that, given the strong match between item type and unit cost on the one hand and total profits and unit costs on the other, classes are likely to be relatively separate. Many of our predictors are categorical so we don't expect strong linear relationships. The number of categories is small compared to the number of records, so our data is not sparse.

Random Forest (RF) and multinomial regression (MR) will likely perform well under these conditions, so this is what we choose. MR has the advantages that it may be more interpretable and, because we get probabilities instead of firm classes, it is more flexible.

We have chosen one parametric (MR) and one non-parametric method (RF). The parametric method will likely be simpler, faster and require less data. However, it may not create as good a fit with the data. The nonparametric method (RF) requires more data and will be slower, but will likely create a better fit. This will lead to more accuracy, (unless the paradigm overfits the data which is more of a concern here than with MR.)

We will use 10-fold cross validation.

Random Forest performs quite well. Mean accuracy is 88% at mtry = 14. Now we test our random forest model on the evaluation set. We see that certain classes (beverages, fruits and personal care) are predicted very well, while others (meat, snacks) perform less well. An analysis of why is beyond the scope of this exercise.

C. Making Predicions

D. Analyzing the Larger Dataset Now we examine the larger dataset and make some comparisons. Since the 5000 database is a subset of this one, we would expect many similarities. Not surprisingly, multicollinearity and distributions look the same. Unit Costs and Item Types continue to match one to one. The standard deviation of Total.Profit is slightly smaller, as is the mean. We are not adding a lot of significant information with this data set. However, the n may improve our confidence intervals.

In fact, our accuracy improves from 87 to 98%. All classes show 97% accuracy or higher. This demonstrates the benefits of increasing n.