STAT 425 - Case Study #1

2024-10-22

In this case study, our objective is to identify the key qualities of a Halloween candy that make it desirable based on various attributes. We will fit a multiple regression model to explain the desirability of a Halloween candy, as measured by the percentage of votes it receives (winpercent). Key predictor variables include characteristics such as the presence of chocolate, fruity flavors, caramel, peanuts, nougat, and other ingredients. Using this model, we will estimate the desirability of at least two favorite candies and determine the attributes of the ideal Halloween candy.

The significance level that we choose for this case study is alpha = 0.05.

```r
df <- read.csv("~/Desktop/uiuc/stat425/Case Study 1/candy-data.csv")
df
```

```
##                 competitorname chocolate fruity caramel peanutyalmondy nougat
## 1                    100 Grand         1      0       1              0      0
## 2                 3 Musketeers         1      0       0              0      1
## 3                     One dime         0      0       0              0      0
## 4                  One quarter         0      0       0              0      0
## 5                    Air Heads         0      1       0              0      0
## 6                   Almond Joy         1      0       0              1      0
## 7                   Baby Ruth         1      0       1              1      1
## 8           Boston Baked Beans         0      0       0              1      0
## 9                  Candy Corn         0      0       0              0      0
## 10          Caramel Apple Pops         0      1       1              0      0
## 11             Charleston Chew         1      0       0              0      1
## 12 Chewey Lemonhead Fruit Mix         0      1       0              0      0
## 13                    Chiclets         0      1       0              0      0
## 14                        Dots         0      1       0              0      0
## 15                    Dum Dums         0      1       0              0      0
## 16                 Fruit Chews         0      1       0              0      0
## 17                     Fun Dip         0      1       0              0      0
## 18                  Gobstopper         0      1       0              0      0
## 19           Haribo Gold Bears         0      1       0              0      0
## 20           Haribo Happy Cola         0      0       0              0      0
## 21           Haribo Sour Bears         0      1       0              0      0
## 22          Haribo Twin Snakes         0      1       0              0      0
## 23             HersheyÕs Kisses         1      0       0              0      0
## 24            HersheyÕs Krackel         1      0       0              0      0
## 25     HersheyÕs Milk Chocolate         1      0       0              0      0
## 26      HersheyÕs Special Dark         1      0       0              0      0
## 27                  Jawbusters         0      1       0              0      0
## 28                Junior Mints         1      0       0              0      0
## 29                     Kit Kat         1      0       0              0      0
## 30                 Laffy Taffy         0      1       0              0      0
## 31                   Lemonhead         0      1       0              0      0
```

```
## 32 Lifesavers big ring gummies         0       1        0              0       0
## 33        Peanut butter M&MÕs         1       0        0              1       0
## 34                      M&MÕs         1       0        0              0       0
## 35                 Mike & Ike         0       1        0              0       0
## 36                  Milk Duds         1       0        1              0       0
## 37                 Milky Way          1       0        1              0       1
## 38         Milky Way Midnight         1       0        1              0       1
## 39   Milky Way Simply Caramel         1       0        1              0       0
## 40                     Mounds         1       0        0              0       0
## 41                Mr Good Bar         1       0        0              1       0
## 42                      Nerds         0       1        0              0       0
## 43        Nestle Butterfinger         1       0        0              1       0
## 44              Nestle Crunch         1       0        0              0       0
## 45                  Nik L Nip         0       1        0              0       0
## 46                Now & Later         0       1        0              0       0
## 47                     Payday         0       0        0              1       1
## 48                Peanut M&Ms         1       0        0              1       0
## 49               Pixie Sticks         0       0        0              0       0
## 50                  Pop Rocks         0       1        0              0       0
## 51                  Red vines         0       1        0              0       0
## 52         ReeseÕs Miniatures         1       0        0              1       0
## 53  ReeseÕs Peanut Butter cup         1       0        0              1       0
## 54             ReeseÕs pieces         1       0        0              1       0
## 55 ReeseÕs stuffed with pieces        1       0        0              1       0
## 56                   Ring pop         0       1        0              0       0
## 57                       Rolo         1       0        1              0       0
## 58          Root Beer Barrels         0       0        0              0       0
## 59                      Runts         0       1        0              0       0
## 60                    Sixlets         1       0        0              0       0
## 61          Skittles original         0       1        0              0       0
## 62         Skittles wildberry         0       1        0              0       0
## 63            Nestle Smarties         1       0        0              0       0
## 64             Smarties candy         0       1        0              0       0
## 65                   Snickers         1       0        1              1       1
## 66           Snickers Crisper         1       0        1              1       0
## 67            Sour Patch Kids         0       1        0              0       0
## 68       Sour Patch Tricksters        0       1        0              0       0
## 69                  Starburst         0       1        0              0       0
## 70        Strawberry bon bons         0       1        0              0       0
## 71               Sugar Babies         0       0        1              0       0
## 72                Sugar Daddy         0       0        1              0       0
## 73               Super Bubble         0       1        0              0       0
## 74               Swedish Fish         0       1        0              0       0
## 75                Tootsie Pop         1       1        0              0       0
## 76        Tootsie Roll Juniors        1       0        0              0       0
## 77        Tootsie Roll Midgies        1       0        0              0       0
## 78    Tootsie Roll Snack Bars         1       0        0              0       0
## 79          Trolli Sour Bites         0       1        0              0       0
## 80                       Twix         1       0        1              0       0
## 81                  Twizzlers         0       1        0              0       0
## 82                   Warheads         0       1        0              0       0
## 83       WelchÕs Fruit Snacks         0       1        0              0       0
## 84  WertherÕs Original Caramel        0       0        1              0       0
## 85                   Whoppers         1       0        0              0       0
```

```
##    crispedricewafer hard bar pluribus sugarpercent pricepercent winpercent
## 1                 1    0   1        0        0.732        0.860   66.97173
## 2                 0    0   1        0        0.604        0.511   67.60294
## 3                 0    0   0        0        0.011        0.116   32.26109
## 4                 0    0   0        0        0.011        0.511   46.11650
## 5                 0    0   0        0        0.906        0.511   52.34146
## 6                 0    0   1        0        0.465        0.767   50.34755
## 7                 0    0   1        0        0.604        0.767   56.91455
## 8                 0    0   0        1        0.313        0.511   23.41782
## 9                 0    0   0        1        0.906        0.325   38.01096
## 10                0    0   0        0        0.604        0.325   34.51768
## 11                0    0   1        0        0.604        0.511   38.97504
## 12                0    0   0        1        0.732        0.511   36.01763
## 13                0    0   0        1        0.046        0.325   24.52499
## 14                0    0   0        1        0.732        0.511   42.27208
## 15                0    1   0        0        0.732        0.034   39.46056
## 16                0    0   0        1        0.127        0.034   43.08892
## 17                0    1   0        0        0.732        0.325   39.18550
## 18                0    1   0        1        0.906        0.453   46.78335
## 19                0    0   0        1        0.465        0.465   57.11974
## 20                0    0   0        1        0.465        0.465   34.15896
## 21                0    0   0        1        0.465        0.465   51.41243
## 22                0    0   0        1        0.465        0.465   42.17877
## 23                0    0   0        1        0.127        0.093   55.37545
## 24                1    0   1        0        0.430        0.918   62.28448
## 25                0    0   1        0        0.430        0.918   56.49050
## 26                0    0   1        0        0.430        0.918   59.23612
## 27                0    1   0        1        0.093        0.511   28.12744
## 28                0    0   0        1        0.197        0.511   57.21925
## 29                1    0   1        0        0.313        0.511   76.76860
## 30                0    0   0        0        0.220        0.116   41.38956
## 31                0    1   0        0        0.046        0.104   39.14106
## 32                0    0   0        0        0.267        0.279   52.91139
## 33                0    0   0        1        0.825        0.651   71.46505
## 34                0    0   0        1        0.825        0.651   66.57458
## 35                0    0   0        1        0.872        0.325   46.41172
## 36                0    0   0        1        0.302        0.511   55.06407
## 37                0    0   1        0        0.604        0.651   73.09956
## 38                0    0   1        0        0.732        0.441   60.80070
## 39                0    0   1        0        0.965        0.860   64.35334
## 40                0    0   1        0        0.313        0.860   47.82975
## 41                0    0   1        0        0.313        0.918   54.52645
## 42                0    1   0        1        0.848        0.325   55.35405
## 43                0    0   1        0        0.604        0.767   70.73564
## 44                1    0   1        0        0.313        0.767   66.47068
## 45                0    0   0        1        0.197        0.976   22.44534
## 46                0    0   0        1        0.220        0.325   39.44680
## 47                0    0   1        0        0.465        0.767   46.29660
## 48                0    0   0        1        0.593        0.651   69.48379
## 49                0    0   0        1        0.093        0.023   37.72234
## 50                0    1   0        1        0.604        0.837   41.26551
## 51                0    0   0        1        0.581        0.116   37.34852
## 52                0    0   0        0        0.034        0.279   81.86626
## 53                0    0   0        0        0.720        0.651   84.18029
```

```
## 54                    0    0   0         1         0.406         0.651    73.43499
## 55                    0    0   0         0         0.988         0.651    72.88790
## 56                    0    1   0         0         0.732         0.965    35.29076
## 57                    0    0   0         1         0.860         0.860    65.71629
## 58                    0    1   0         1         0.732         0.069    29.70369
## 59                    0    1   0         1         0.872         0.279    42.84914
## 60                    0    0   0         1         0.220         0.081    34.72200
## 61                    0    0   0         1         0.941         0.220    63.08514
## 62                    0    0   0         1         0.941         0.220    55.10370
## 63                    0    0   0         1         0.267         0.976    37.88719
## 64                    0    1   0         1         0.267         0.116    45.99583
## 65                    0    0   1         0         0.546         0.651    76.67378
## 66                    1    0   1         0         0.604         0.651    59.52925
## 67                    0    0   0         1         0.069         0.116    59.86400
## 68                    0    0   0         1         0.069         0.116    52.82595
## 69                    0    0   0         1         0.151         0.220    67.03763
## 70                    0    1   0         1         0.569         0.058    34.57899
## 71                    0    0   0         1         0.965         0.767    33.43755
## 72                    0    0   0         0         0.418         0.325    32.23100
## 73                    0    0   0         0         0.162         0.116    27.30386
## 74                    0    0   0         1         0.604         0.755    54.86111
## 75                    0    1   0         0         0.604         0.325    48.98265
## 76                    0    0   0         0         0.313         0.511    43.06890
## 77                    0    0   0         1         0.174         0.011    45.73675
## 78                    0    0   1         0         0.465         0.325    49.65350
## 79                    0    0   0         1         0.313         0.255    47.17323
## 80                    1    0   1         0         0.546         0.906    81.64291
## 81                    0    0   0         0         0.220         0.116    45.46628
## 82                    0    1   0         0         0.093         0.116    39.01190
## 83                    0    0   0         1         0.313         0.313    44.37552
## 84                    0    1   0         0         0.186         0.267    41.90431
## 85                    1    0   0         1         0.872         0.848    49.52411
```

```
unique(df$competitorname)
```

```
##  [1] "100 Grand"                   "3 Musketeers"
##  [3] "One dime"                    "One quarter"
##  [5] "Air Heads"                   "Almond Joy"
##  [7] "Baby Ruth"                   "Boston Baked Beans"
##  [9] "Candy Corn"                  "Caramel Apple Pops"
## [11] "Charleston Chew"             "Chewey Lemonhead Fruit Mix"
## [13] "Chiclets"                    "Dots"
## [15] "Dum Dums"                    "Fruit Chews"
## [17] "Fun Dip"                     "Gobstopper"
## [19] "Haribo Gold Bears"           "Haribo Happy Cola"
## [21] "Haribo Sour Bears"           "Haribo Twin Snakes"
## [23] "HersheyÕs Kisses"            "HersheyÕs Krackel"
## [25] "HersheyÕs Milk Chocolate"    "HersheyÕs Special Dark"
## [27] "Jawbusters"                  "Junior Mints"
## [29] "Kit Kat"                     "Laffy Taffy"
## [31] "Lemonhead"                   "Lifesavers big ring gummies"
## [33] "Peanut butter M&MÕs"         "M&MÕs"
## [35] "Mike & Ike"                  "Milk Duds"
## [37] "Milky Way"                   "Milky Way Midnight"
```

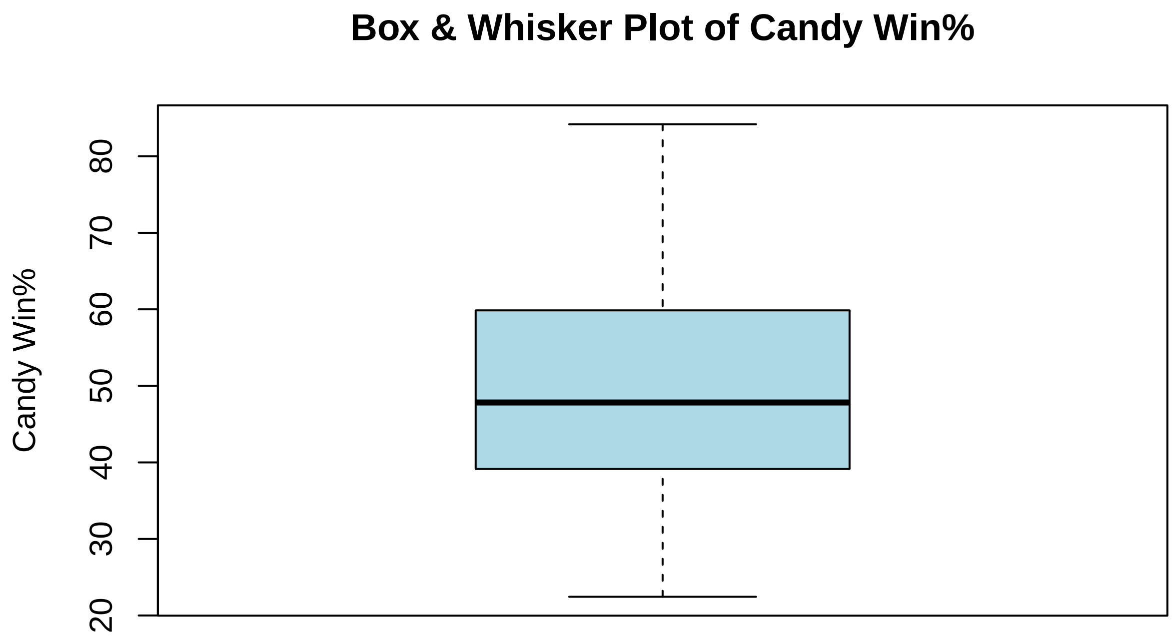
```
## [39] "Milky Way Simply Caramel"    "Mounds"
## [41] "Mr Good Bar"                 "Nerds"
## [43] "Nestle Butterfinger"         "Nestle Crunch"
## [45] "Nik L Nip"                   "Now & Later"
## [47] "Payday"                      "Peanut M&Ms"
## [49] "Pixie Sticks"                "Pop Rocks"
## [51] "Red vines"                   "ReeseÕs Miniatures"
## [53] "ReeseÕs Peanut Butter cup"   "ReeseÕs pieces"
## [55] "ReeseÕs stuffed with pieces" "Ring pop"
## [57] "Rolo"                        "Root Beer Barrels"
## [59] "Runts"                       "Sixlets"
## [61] "Skittles original"           "Skittles wildberry"
## [63] "Nestle Smarties"             "Smarties candy"
## [65] "Snickers"                    "Snickers Crisper"
## [67] "Sour Patch Kids"             "Sour Patch Tricksters"
## [69] "Starburst"                   "Strawberry bon bons"
## [71] "Sugar Babies"                "Sugar Daddy"
## [73] "Super Bubble"                "Swedish Fish"
## [75] "Tootsie Pop"                 "Tootsie Roll Juniors"
## [77] "Tootsie Roll Midgies"        "Tootsie Roll Snack Bars"
## [79] "Trolli Sour Bites"           "Twix"
## [81] "Twizzlers"                   "Warheads"
## [83] "WelchÕs Fruit Snacks"        "WertherÕs Original Caramel"
## [85] "Whoppers"
```

We have chosen to display the five-number summary alongside a box and whisker plot to analyze the distribution and variance of the winpercent variable. This provides a clearer understanding of the range and spread of the data, which will be useful as we proceed with the multiple linear regression (MLR) model.

```r
print(summary(df$winpercent))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   22.45   39.14   47.83   50.32   59.86   84.18
```

```r
boxplot(df$winpercent, main = "Box & Whisker Plot of Candy Win%",
        ylab = "Candy Win%", col = "lightblue", na.rm = TRUE)
```

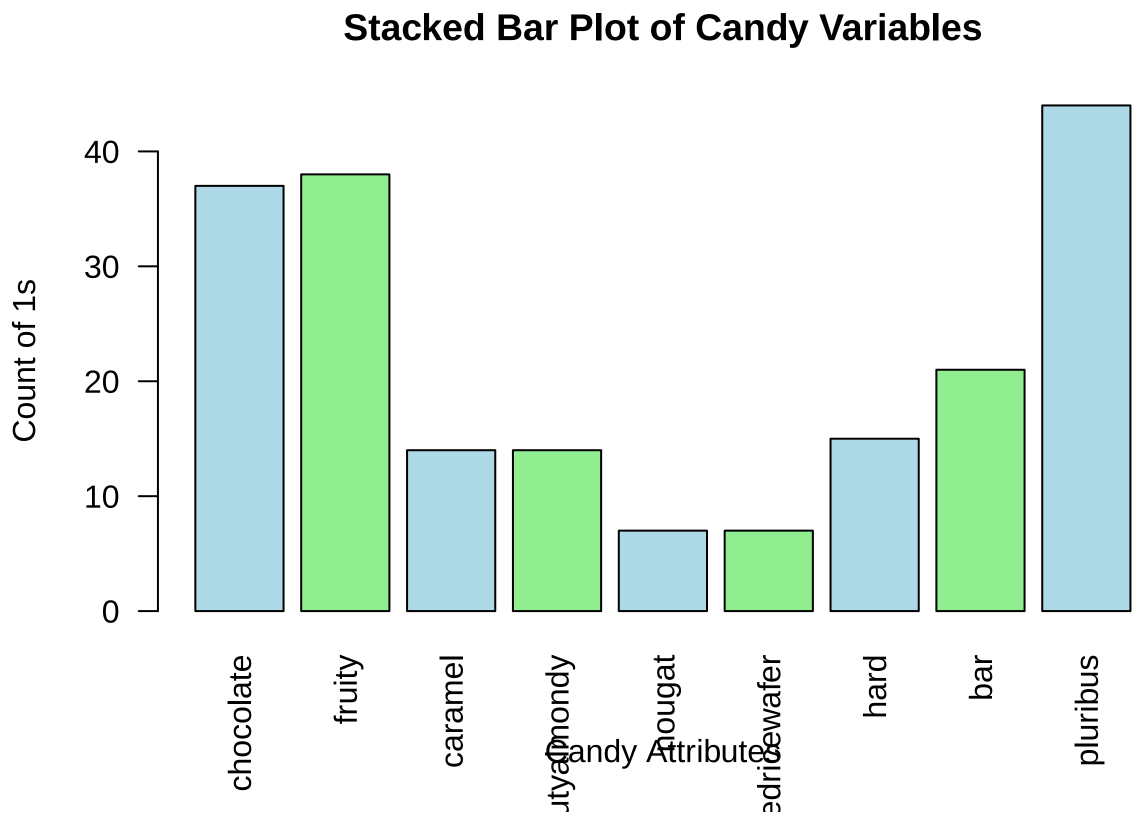


We created this model to visualize the frequency of each candy attribute, which helps in understanding the distribution of key variables. By examining the count of each attribute (chocolate, fruity, caramel, etc.), we can determine which attributes are more common in candies, giving us an idea of the factors that may influence the win percentage. This stacked bar plot serves as a useful descriptive statistic visualization, allowing us to compare the prevalence of different variables side by side. Additionally, it highlights potential predictors of win percentage in the MLR model, guiding us toward identifying which variables might have a stronger effect on candy success.

```
selected_columns <- df[, c("chocolate", "fruity", "caramel", "peanutyalmondy", "nougat", "crispedricewa


binary_counts <- colSums(selected_columns)

barplot(binary_counts,
        main = "Stacked Bar Plot of Candy Variables",
        ylab = "Count of 1s",
        xlab = "Candy Attributes",
        col = c("lightblue", "lightgreen"),
        las = 2,
        beside = TRUE)
```



The correlation matrix is a valuable tool in regression analysis because it helps us identify relationships between independent variables and the dependent variable, as well as correlations between independent variables themselves. In the context of an MLR (Multiple Linear Regression) model, it is important to understand the relationships between variables to avoid multicollinearity, which occurs when independent variables are highly correlated with one another. Multicollinearity can make it difficult to interpret the coefficients of the regression model and may inflate standard errors. By reviewing this correlation matrix, we can also identify which predictors have strong correlations with the dependent variable (winpercent in this case) and prioritize those in our model, thereby improving model performance and interpretability.

```
binary_vars <- df[, c("chocolate", "fruity", "caramel", "peanutyalmondy", "nougat", "crispedricewafer",

cor_matrix <- cor(binary_vars)
cor_matrix
```

```
##                   chocolate      fruity     caramel peanutyalmondy      nougat
## chocolate         1.0000000 -0.74172106  0.24987535     0.37782357  0.25489183
## fruity           -0.7417211  1.00000000 -0.33548538    -0.39928014 -0.26936712
## caramel           0.2498753 -0.33548538  1.00000000     0.05935614  0.32849280
## peanutyalmondy    0.3778236 -0.39928014  0.05935614     1.00000000  0.21311310
## nougat            0.2548918 -0.26936712  0.32849280     0.21311310  1.00000000
## crispedricewafer  0.3412098 -0.26936712  0.21311310    -0.01764631 -0.08974359
## hard             -0.3441769  0.39067750 -0.12235513    -0.20555661 -0.13867505
## bar               0.5974211 -0.51506558  0.33396002     0.26041960  0.52297636
## pluribus         -0.3396752  0.29972522 -0.26958501    -0.20610932 -0.31033884
## sugarpercent      0.1041691 -0.03439296  0.22193335     0.08788927  0.12308135
## pricepercent      0.5046754 -0.43096853  0.25432709     0.30915323  0.15319643
```

```
## winpercent        0.6365167 -0.38093814  0.21341630     0.40619220  0.19937530
##                  crispedricewafer        hard         bar    pluribus
## chocolate              0.34120978 -0.34417691  0.59742114 -0.33967519
## fruity                -0.26936712  0.39067750 -0.51506558  0.29972522
## caramel                0.21311310 -0.12235513  0.33396002 -0.26958501
## peanutyalmondy        -0.01764631 -0.20555661  0.26041960 -0.20610932
## nougat                -0.08974359 -0.13867505  0.52297636 -0.31033884
## crispedricewafer       1.00000000 -0.13867505  0.42375093 -0.22469338
## hard                  -0.13867505  1.00000000 -0.26516504  0.01453172
## bar                    0.42375093 -0.26516504  1.00000000 -0.59340892
## pluribus              -0.22469338  0.01453172 -0.59340892  1.00000000
## sugarpercent           0.06994969  0.09180975  0.09998516  0.04552282
## pricepercent           0.32826539 -0.24436534  0.51840654 -0.22079363
## winpercent             0.32467965 -0.31038158  0.42992933 -0.24744787
##                  sugarpercent pricepercent winpercent
## chocolate          0.10416906    0.5046754  0.6365167
## fruity            -0.03439296   -0.4309685 -0.3809381
## caramel            0.22193335    0.2543271  0.2134163
## peanutyalmondy     0.08788927    0.3091532  0.4061922
## nougat             0.12308135    0.1531964  0.1993753
## crispedricewafer   0.06994969    0.3282654  0.3246797
## hard               0.09180975   -0.2443653 -0.3103816
## bar                0.09998516    0.5184065  0.4299293
## pluribus           0.04552282   -0.2207936 -0.2474479
## sugarpercent       1.00000000    0.3297064  0.2291507
## pricepercent       0.32970639    1.0000000  0.3453254
## winpercent         0.22915066    0.3453254  1.0000000
```

```r
df_clean <- df[, -which(names(df) == "competitorname")]
full_model <- lm(winpercent ~ ., data = df_clean)

summary(full_model)
```

```
##
## Call:
## lm(formula = winpercent ~ ., data = df_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.2244  -6.6247   0.1986   6.8420  23.8680
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       34.5340     4.3199   7.994 1.44e-11 ***
## chocolate         19.7481     3.8987   5.065 2.96e-06 ***
## fruity             9.4223     3.7630   2.504  0.01452 *
## caramel            2.2245     3.6574   0.608  0.54493
## peanutyalmondy    10.0707     3.6158   2.785  0.00681 **
## nougat             0.8043     5.7164   0.141  0.88849
## crispedricewafer   8.9190     5.2679   1.693  0.09470 .
## hard              -6.1653     3.4551  -1.784  0.07852 .
## bar                0.4415     5.0611   0.087  0.93072
## pluribus          -0.8545     3.0401  -0.281  0.77945
## sugarpercent       9.0868     4.6595   1.950  0.05500 .
```

```
## pricepercent      -5.9284     5.5132  -1.075  0.28578
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.7 on 73 degrees of freedom
## Multiple R-squared:  0.5402, Adjusted R-squared:  0.4709
## F-statistic: 7.797 on 11 and 73 DF,  p-value: 9.504e-09
```

In the full model, we include all potential predictor variables from the dataset to assess their relationships with the response variable, winpercent. This model is necessary as it allows us to observe the statistical significance of each variable, measured by their p-values, which indicate whether or not each predictor is contributing meaningful information to explain variations in winpercent.

From the model output, we can see which variables have significant p-values (below a threshold, typically 0.05) and which do not. In this case, chocolate, fruity, and peanutyalmondy are statistically significant with p-values well below 0.05. Other variables like nougat, bar, pluribus, and others have much higher p-values, meaning they are not significant predictors in this model.

Once we identify the statistically insignificant variables, we can exclude them from the model, creating a reduced model that only includes the significant variables. This process of variable selection is important because it simplifies the model, making it more interpretable, reduces multicollinearity, and improves generalizability by focusing only on the predictors that have a meaningful relationship with the response variable.

```r
reduced_model <- lm(winpercent ~ chocolate + fruity + peanutyalmondy, data = df_clean)

summary(reduced_model)
```

```
##
## Call:
## lm(formula = winpercent ~ chocolate + fruity + peanutyalmondy,
##     data = df_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.0497  -7.3084  -0.4523   7.9446  23.8712
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      35.788      3.237  11.057  < 2e-16 ***
## chocolate        21.983      3.599   6.108 3.34e-08 ***
## fruity            7.753      3.625   2.139   0.0354 *
## peanutyalmondy    9.066      3.520   2.576   0.0118 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.94 on 81 degrees of freedom
## Multiple R-squared:  0.4673, Adjusted R-squared:  0.4475
## F-statistic: 23.68 on 3 and 81 DF,  p-value: 4.209e-11
```

```r
candy_row_nums <- which(df$competitorname %in% c("ReeseÕs Peanut Butter cup", "Snickers", "Almond Joy",

actual_values <- df$winpercent[candy_row_nums]
```

```r
predictions <- predict(reduced_model, newdata = df[candy_row_nums,])

residual_error <- abs(actual_values - predictions)
```

```r
results <- data.frame(
  Candy = df$competitorname[candy_row_nums],
  Predicted = round(predictions,2),
  Actual = round(actual_values,2),
  Residual = round(residual_error,2)
)

print(results)
```

```
##                        Candy Predicted Actual Residual
## 6                 Almond Joy     66.84  50.35    16.49
## 9                 Candy Corn     35.79  38.01     2.22
## 53 ReeseÕs Peanut Butter cup     66.84  84.18    17.34
## 65                  Snickers     66.84  76.67     9.84
```

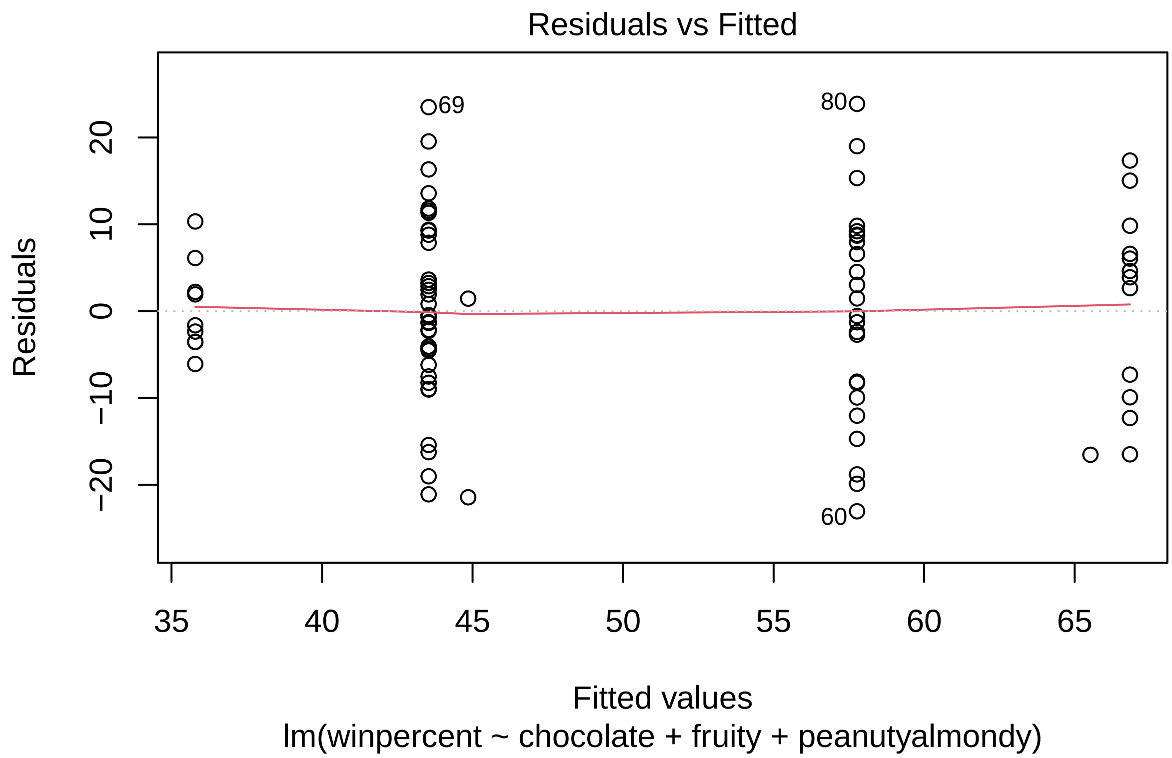
The predictions for the win percentages of Reese's Peanut Butter Cup, Snickers, and Almond Joy were all around 66.84%, with Candy Corn having a prediction of 35.78%. However, the actual win percentages varied for each candy:

Reese's Peanut Butter Cup had an actual win percentage of 84.18%. Snickers had an actual win percentage of 76.67%. Almond Joy had an actual win percentage of 50.35%. Candy Corn had an actual win percentage of 38.01%. The residuals, which represent the difference between the actual values and the predicted values, are as follows:

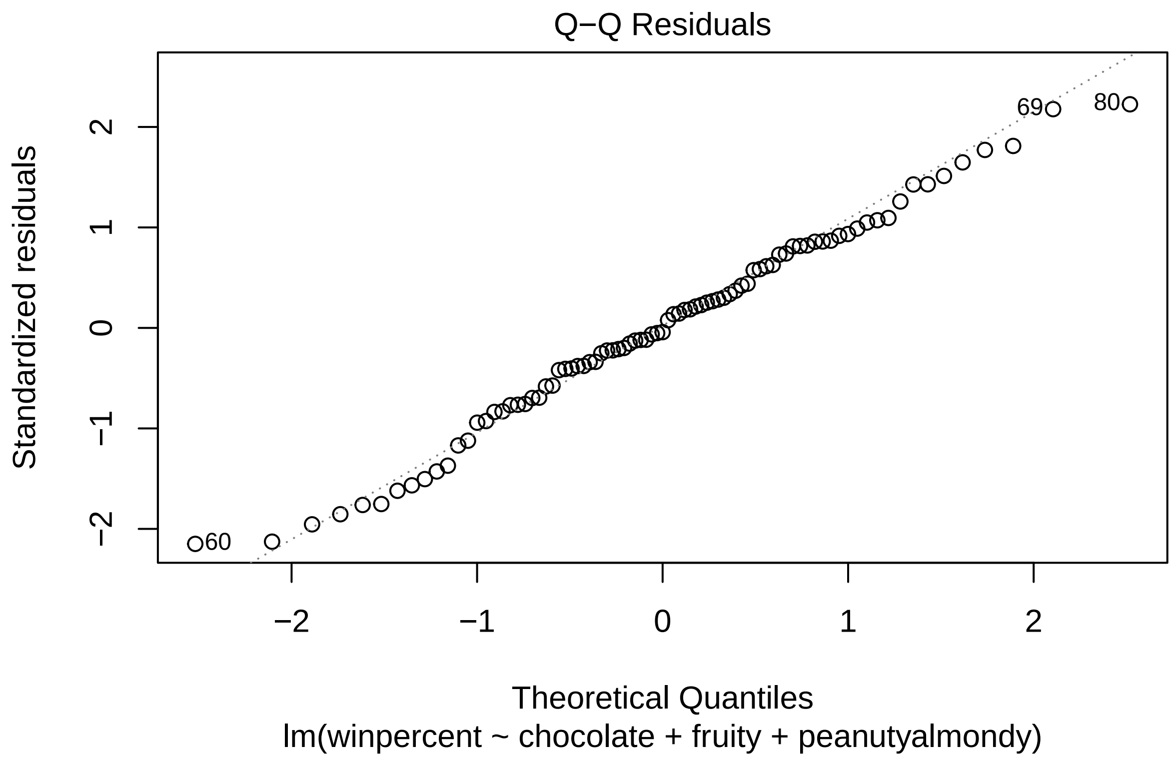
Reese's Peanut Butter Cup: 17.34 Snickers: 9.84 Almond Joy: 17.34 Candy Corn: 2.22

These residuals indicate that the model under-predicted the win percentages for all candies, particularly for Reese's Peanut Butter Cup and Almond Joy, where the predicted values were considerably lower than the actual values. Candy Corn had the smallest residual error, meaning the model's prediction was closer to its actual value.

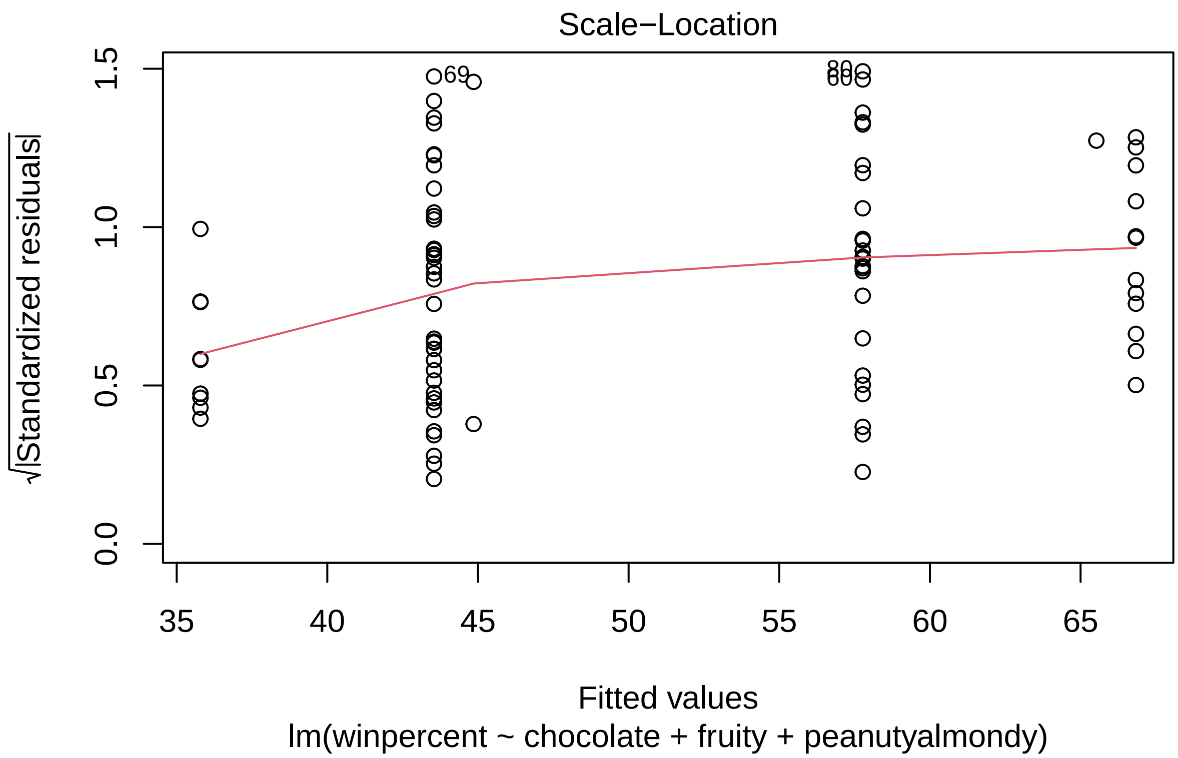
```r
plot(reduced_model, which = 1)
```



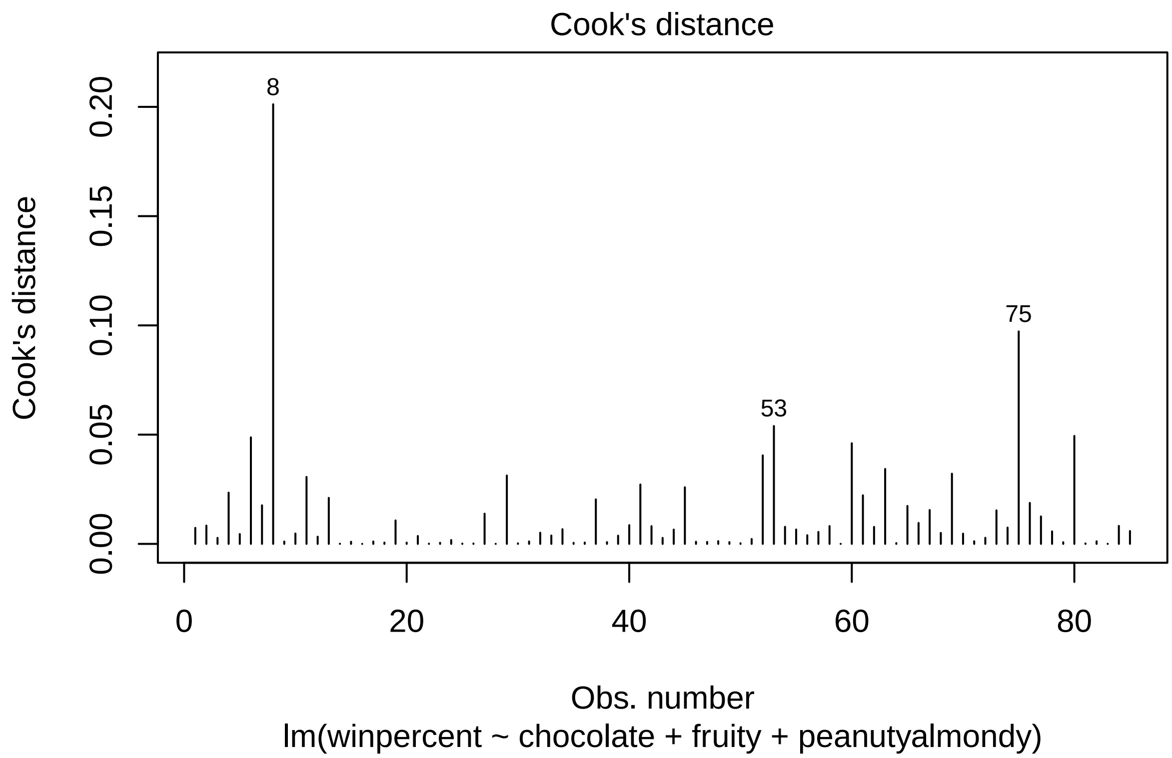

```r
plot(reduced_model, which = 2)
```




```r
plot(reduced_model, which = 3)
```




```r
plot(reduced_model, which = 4)
```




```r
vif(reduced_model)
```

```
##      chocolate         fruity peanutyalmondy
##       2.262878       2.307766       1.211022
```

The VIF values in the output assess the level of multicollinearity in the reduced model. Specifically:

Chocolate: 2.262878 Fruity: 2.307766 Peanutyalmondy: 1.211022

In our model, we calculated the Variance Inflation Factor (VIF) for the variables chocolate, fruity, and peanutyalmondy. The VIF values we found are all below 5, which is the generally accepted threshold for multicollinearity. This means that while there may be some correlation between these variables and others in the model, it is low enough that it doesn't pose a problem.

Because the VIF values are low (with values of around 2 for chocolate and fruity, and 1.2 for peanutyalmondy), we can confidently say that multicollinearity is not a concern in our model. In other words, the variables are relatively independent of each other, which means they won't cause inflated standard errors or distort the results. This allows us to trust the estimates of the regression coefficients for these variables without worrying that they're being affected by strong correlations with other predictors.

Ho: B_chocolate = B_fruity = B_peanutyalmondy = 0 Ha: B_chocolate != B_fruity != B_peanutyalmondy != 0

Conclusion: Since the p-values for chocolate (3.34e-08), fruity (0.0354), and peanutyalmondy (0.0118) are all less than the significance level of 0.05, we reject the null hypothesis. This means that all three predictors are significantly related to the winpercent of candy.

Interpretation of the p-value: The p-values for each variable indicate the probability of observing the data, or something more extreme, assuming the null hypothesis is true. For chocolate, the p-value is extremely small (3.34e-08), indicating very strong evidence against the null hypothesis and suggesting that chocolate has a significant positive effect on the winpercent. The p-values for fruity (0.0354) and peanutyalmondy (0.0118) are also below the 0.05 threshold, indicating that these variables also significantly impact the winpercent, though with slightly less strength than chocolate. Therefore, at the 5% significance level, we conclude that these predictors have a statistically significant effect on the winpercent.