Class 9 | Halloween Mini-Project

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Background

Today we will take a step back to some data we can taste and explore—we will examine the correlation structure and principal components of some Halloween candy.

```
# Let's read the data into our project:
candy <- read.csv("candy-data.csv", row.names=1)
head(candy)
```

```
             chocolate fruity caramel peanutyalmondy nougat crispedricewafer
100 Grand            1      0       1              0      0                1
3 Musketeers         1      0       0              0      1                0
One dime             0      0       0              0      0                0
One quarter          0      0       0              0      0                0
Air Heads            0      1       0              0      0                0
Almond Joy           1      0       0              1      0                0
             hard bar pluribus sugarpercent pricepercent winpercent
100 Grand       0   1        0        0.732        0.860   66.97173
3 Musketeers    0   1        0        0.604        0.511   67.60294
One dime        0   0        0        0.011        0.116   32.26109
One quarter     0   0        0        0.011        0.511   46.11650
Air Heads       0   0        0        0.906        0.511   52.34146
Almond Joy      0   1        0        0.465        0.767   50.34755
```

> (Q1) How many different candy types are in this dataset?

```
# Shows that we have 85 entries.
nrow(candy)
```

```
[1] 85
```

> (Q2) How many fruity candy types are in the dataset?

```
# 38 fruity candies!
sum(candy$fruity)
```

```
[1] 38
```

What is your favorite candy?

> (Q3) What is your favorite candy in the dataset and what is it’s winpercent value?

My favorite Halloween candy are the Nestle Crunch candies. How popular is it?

```
candy["Nestle Crunch",]$winpercent
```

```
[1] 66.47068
```

> (Q4) What is the winpercent value for “Kit Kat”?

```
candy["Kit Kat",]$winpercent
```

```
[1] 76.7686
```

> (Q5) What is the winpercent value for “Tootsie Roll Snack Bars”?

```
candy["Tootsie Roll Snack Bars",]$winpercent
```

```
[1] 49.6535
```

A helpful function we can use to get a summary of a dataset is the `skim()` function from the **skimr** package, which we downloaded and can call to examine our `candy` dataset.

```
library(skimr)
skim(candy)
```

Data summary

Name	candy
Number of rows	85
Number of columns	12
________________________	
Column type frequency:	
numeric	12
________________________	
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
chocolate	0	1	0.44	0.50	0.00	0.00	0.00	1.00	1.00	▇▁▁▁▆
fruity	0	1	0.45	0.50	0.00	0.00	0.00	1.00	1.00	▇▁▁▁▆

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
caramel	0	1	0.16	0.37	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▂
peanutyalmondy	0	1	0.16	0.37	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▂
nougat	0	1	0.08	0.28	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▁
crispedricewafer	0	1	0.08	0.28	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▁
hard	0	1	0.18	0.38	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▂
bar	0	1	0.25	0.43	0.00	0.00	0.00	0.00	1.00	▇▁▁▁▂
pluribus	0	1	0.52	0.50	0.00	0.00	1.00	1.00	1.00	▇▁▁▁▇
sugarpercent	0	1	0.48	0.28	0.01	0.22	0.47	0.73	0.99	▇▇▇▇▆
pricepercent	0	1	0.47	0.29	0.01	0.26	0.47	0.65	0.98	▇▇▇▇▆
winpercent	0	1	50.32	14.71	22.45	39.14	47.83	59.86	84.18	▂▇▆▅▁

> (Q6) Is there any variable/column that looks to be on a different scale to the majority of the other columns in the dataset?

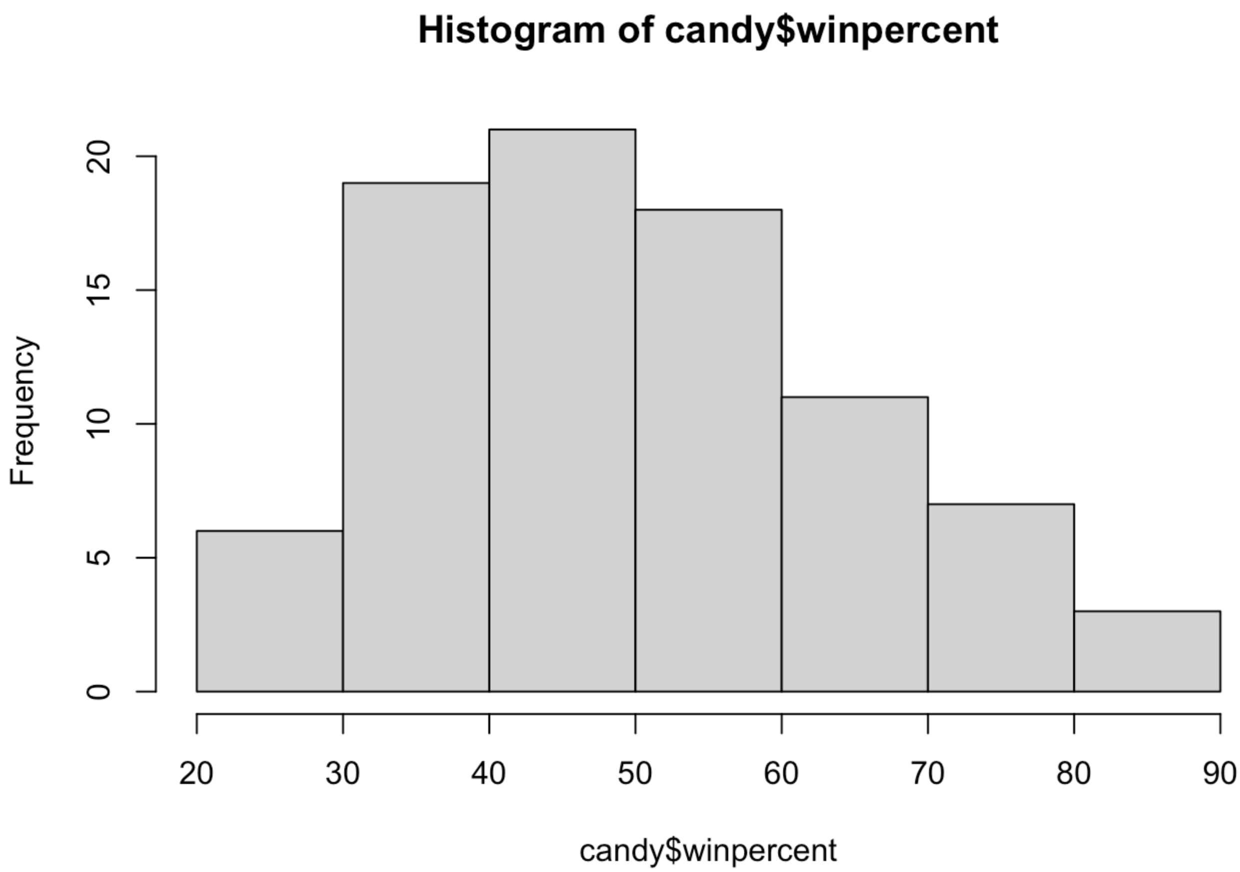
The **winpercent** column appears to be on a different scale because it is the only column without values consistently below 1.

> (Q7) What do you think a zero and one represent for the candy$chocolate column?

Each “zero” represents a “No/FALSE”, while each “one” represents a “Yes/TRUE”, such as in binary code.

> (Q8) Plot a histogram of winpercent values.

```
# Let's just generate a simple histogram here
hist(candy$winpercent)
```



> (Q9) Is the distribution of winpercent values symmetrical?

No, the distribution is swayed to the left, closer to lower `candy$winpercent` values.

> (Q10) Is the center of the distribution above or below 50%?

As alluded to in **Q8**, the center of the distribution is below 50%.

> (Q11) On average is chocolate candy higher or lower ranked than fruit candy?

Let's check the values for each:

```
# Here is the mean value for chocolate candy:
mean(candy$winpercent[as.logical(candy$chocolate)])
```

```
[1] 60.92153
```

```
# And here is the mean for fruity candy:
mean(candy$winpercent[as.logical(candy$fruity)])
```

```
[1] 44.11974
```

We can see that chocolate candy has **~16%** higher `winpercent` values than fruity candy.

> (Q12) Is this difference statistically significant?

```
# We can use a T-test to find the p-value and significance:
t.test(x=candy$winpercent[as.logical(candy$chocolate)],y=candy$winpercent[as.logical(cand
```

```

	Welch Two Sample t-test

data:  candy$winpercent[as.logical(candy$chocolate)] and
candy$winpercent[as.logical(candy$fruity)]
t = 6.2582, df = 68.882, p-value = 2.871e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 11.44563 22.15795
sample estimates:
mean of x mean of y 
 60.92153  44.11974 
```

We get a very small p-value of **2.871e-08**, which indicates a very statistically significant difference between the `winpercent` of chocolate and fruity candies.

Overall Candy Rankings

We can make this easier by ordering the data by `winpercent`, which would allow us to see the most/least liked candies.

> (Q13) What are the five least liked candy types in this set?

There are two related functions that can help here, one is the classic `sort()` function and the `order()` function. But, here let's play with the `dplyr` package.

```
# Let's experiment with the dplyr package!
library(dplyr)
```

```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':
```

```
    intersect, setdiff, setequal, union
```

```
candy %>% arrange(winpercent) %>% head(5)
```

```
                   chocolate fruity caramel peanutyalmondy nougat
Nik L Nip                  0      1       0              0      0
Boston Baked Beans         0      0       0              1      0
Chiclets                   0      1       0              0      0
Super Bubble               0      1       0              0      0
Jawbusters                 0      1       0              0      0
                   crispedricewafer hard bar pluribus sugarpercent pricepercent
Nik L Nip                         0    0   0        1        0.197        0.976
Boston Baked Beans                0    0   0        1        0.313        0.511
Chiclets                          0    0   0        1        0.046        0.325
Super Bubble                      0    0   0        0        0.162        0.116
Jawbusters                        0    1   0        1        0.093        0.511
                   winpercent
Nik L Nip            22.44534
Boston Baked Beans   23.41782
Chiclets             24.52499
Super Bubble         27.30386
Jawbusters           28.12744
```

The 5 least liked candies in the dataset are “Nik L Nip”, “Boston Baked Beans”, “Chiclets”, “Super Bubble”, and “Jawbusters”.

> (Q14) What are the top 5 all time favorite candy types out of this set?

To solve this in a similar manner, we can use the `tail()` function.

```
# Let's experiment with the dplyr package!
library(dplyr)
candy %>% arrange(winpercent) %>% tail(5)
```

```
                          chocolate fruity caramel peanutyalmondy nougat
Snickers                          1      0       1              1      1
Kit Kat                           1      0       0              0      0
Twix                              1      0       1              0      0
Reese's Miniatures                1      0       0              1      0
Reese's Peanut Butter cup         1      0       0              1      0
                          crispedricewafer hard bar pluribus sugarpercent
Snickers                                 0    0   1        0        0.546
Kit Kat                                  1    0   1        0        0.313
Twix                                     1    0   1        0        0.546
Reese's Miniatures                       0    0   0        0        0.034
Reese's Peanut Butter cup                0    0   0        0        0.720
                          pricepercent winpercent
Snickers                         0.651   76.67378
Kit Kat                          0.511   76.76860
```

```
Twix                          0.906   81.64291
Reese's Miniatures            0.279   81.86626
Reese's Peanut Butter cup     0.651   84.18029
```

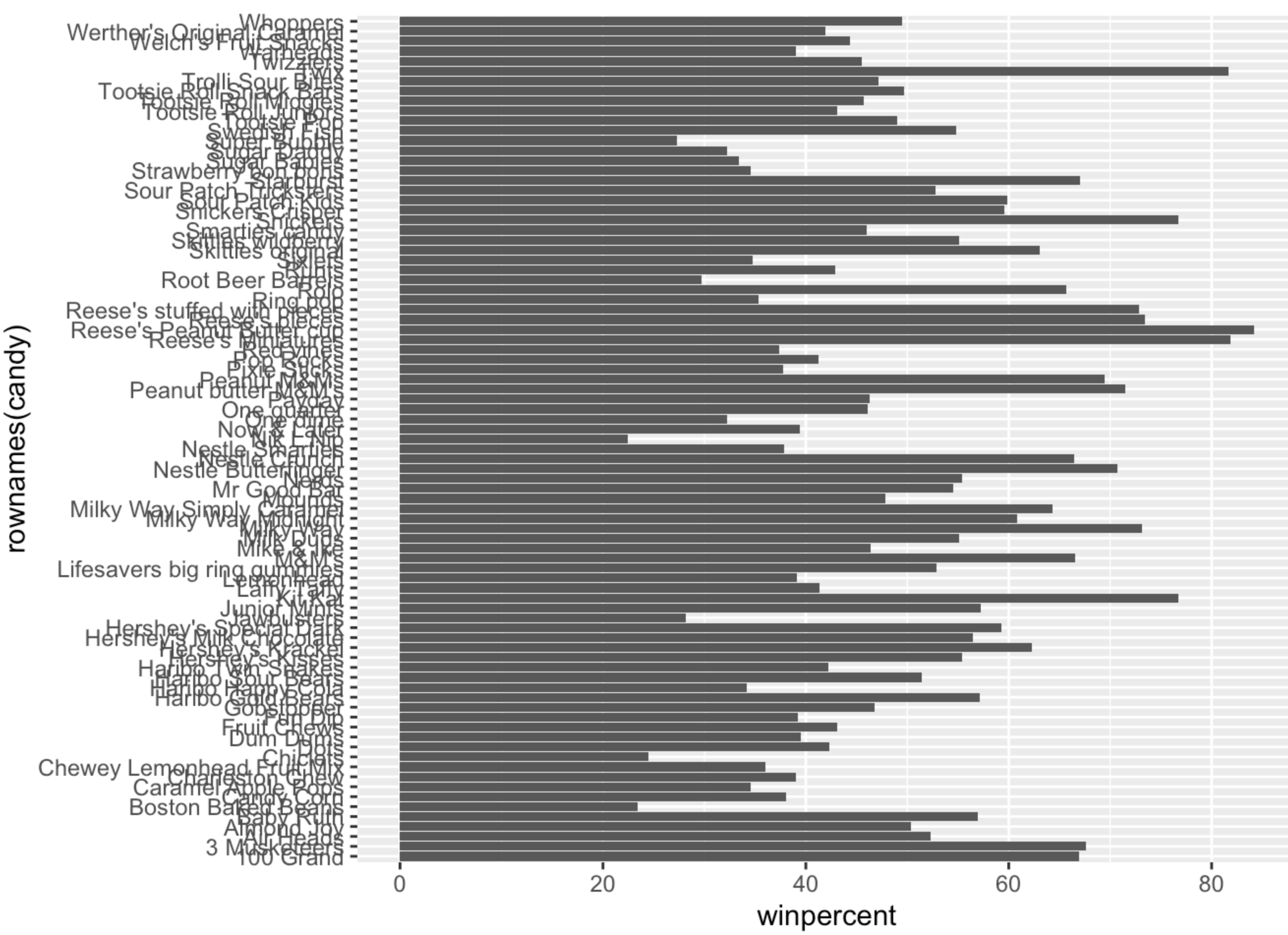
According to the data, the 5 most liked candies are “Reese’s Peanut Butter Cups”, “Reese’s Miniatures”, “Twix”, “Kit Kat”, and “Snickers”.

Making a Barplot

Let’s make an intricate barplot to analyze the overall rankings of the candy. We will start simple and build from there.

> (Q15) Make a first barplot of candy ranking based on winpercent values.

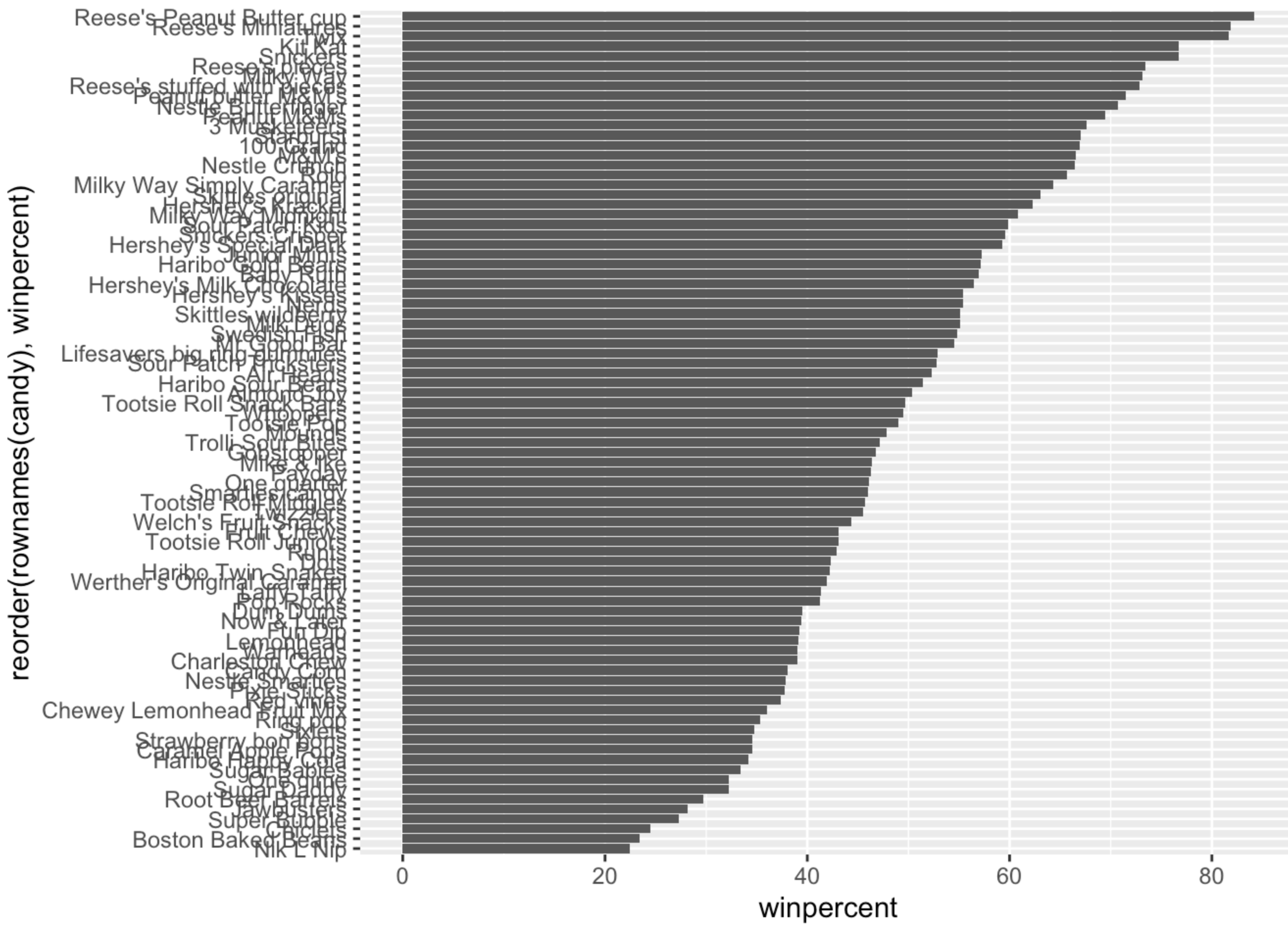
```r
library(ggplot2)
ggplot(candy) +
  aes(winpercent, rownames(candy)) +
  geom_col()
```



> (Q16) This is quite ugly, use the reorder() function to get the bars sorted by `winpercent`.

We can use the `reorder()` function within the `aes()` part of creating a **ggplot** by giving it a variable to sort by.

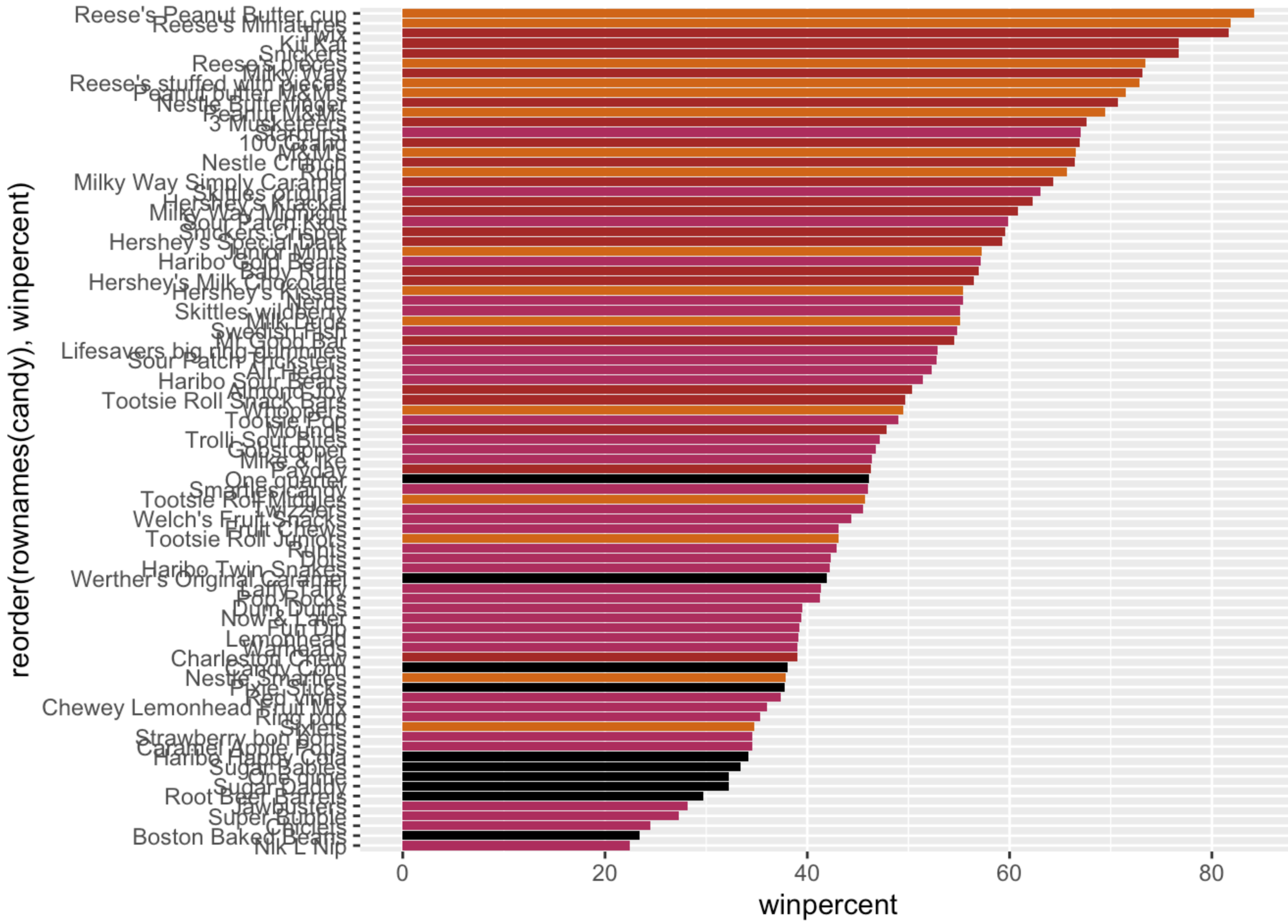
```r
ggplot(candy) +
  aes(winpercent, reorder(rownames(candy), winpercent)) +
  geom_col()
```



I can make it even prettier by adding colors to the bars. Let's color by candy type *(the code is borrowed from the Class Lab worksheet)*, and reprint the barplot.

```r
# Here we define our color categories,
my_cols=rep("black", nrow(candy))
my_cols[as.logical(candy$chocolate)] = "chocolate"
my_cols[as.logical(candy$bar)] = "brown"
my_cols[as.logical(candy$fruity)] = "maroon"

# And here we reprint our barplot.
ggplot(candy) +
  aes(winpercent, reorder(rownames(candy),winpercent)) +
  geom_col(fill=my_cols)
```




```
# Why not save it?
ggsave("my_ugly_barplot.png", width=6, height=9)
```

Using our new colored plot…

> (Q17) What is the worst ranked chocolate candy?

The lowest ranked chocolate candy is “Sixlets”.

> (Q18) What is the best ranked fruity candy?

The highest ranked fruity candy is “Starburst”.

Taking a look at `pricepercent`

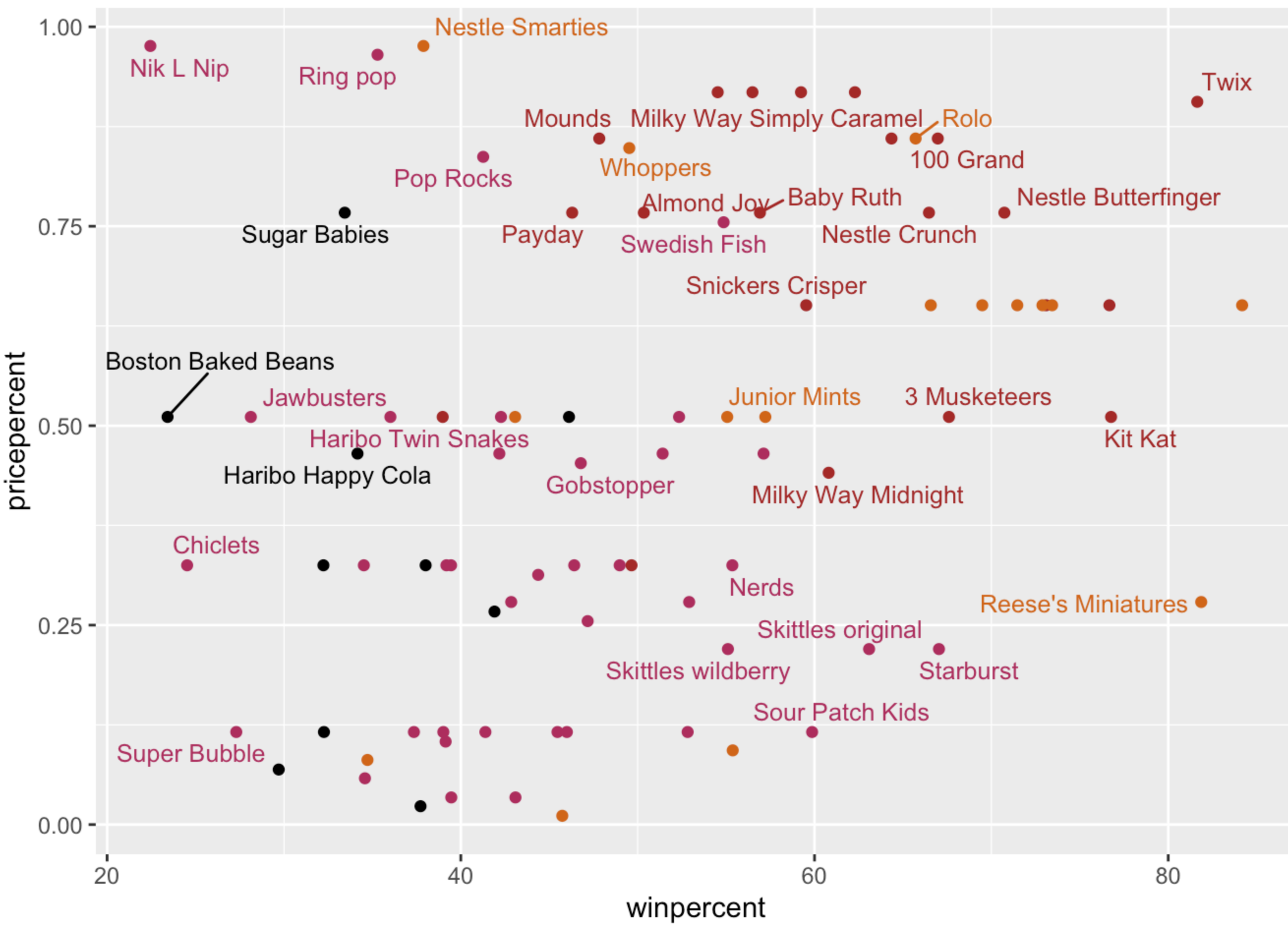
Let’s compare `pricepercent` and `winpercent` to see which candy will give us the greatest bang for our buck. We want lower `pricepercent` and higher `winpercent`.

```
library(ggrepel)

# How about a plot of price vs win?
```

```
ggplot(candy) +
  aes(winpercent, pricepercent, label=rownames(candy)) +
  geom_point(col=my_cols) +
  geom_text_repel(col=my_cols, size=3.3, max.overlaps = 5)
```

```
Warning: ggrepel: 50 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```



> (Q19) Which candy type is the highest ranked in terms of winpercent for the least money - i.e. offers the most bang for your buck?

```
ord <- order(candy$winpercent, decreasing = TRUE)
head(candy[ord,c(11,12)], n=5)
```

```
                          pricepercent winpercent
Reese's Peanut Butter cup        0.651   84.18029
Reese's Miniatures               0.279   81.86626
Twix                             0.906   81.64291
Kit Kat                          0.511   76.76860
Snickers                         0.651   76.67378
```

We can see that the best candies with regards to both `pricepercent` and `winpercent` are **Reese's Miniatures**.

> (Q20) What are the top 5 most expensive candy types in the dataset and of these which is the least popular?

```
ord <- order(candy$pricepercent, decreasing = TRUE)
head(candy[ord,c(11,12)], n=5)
```

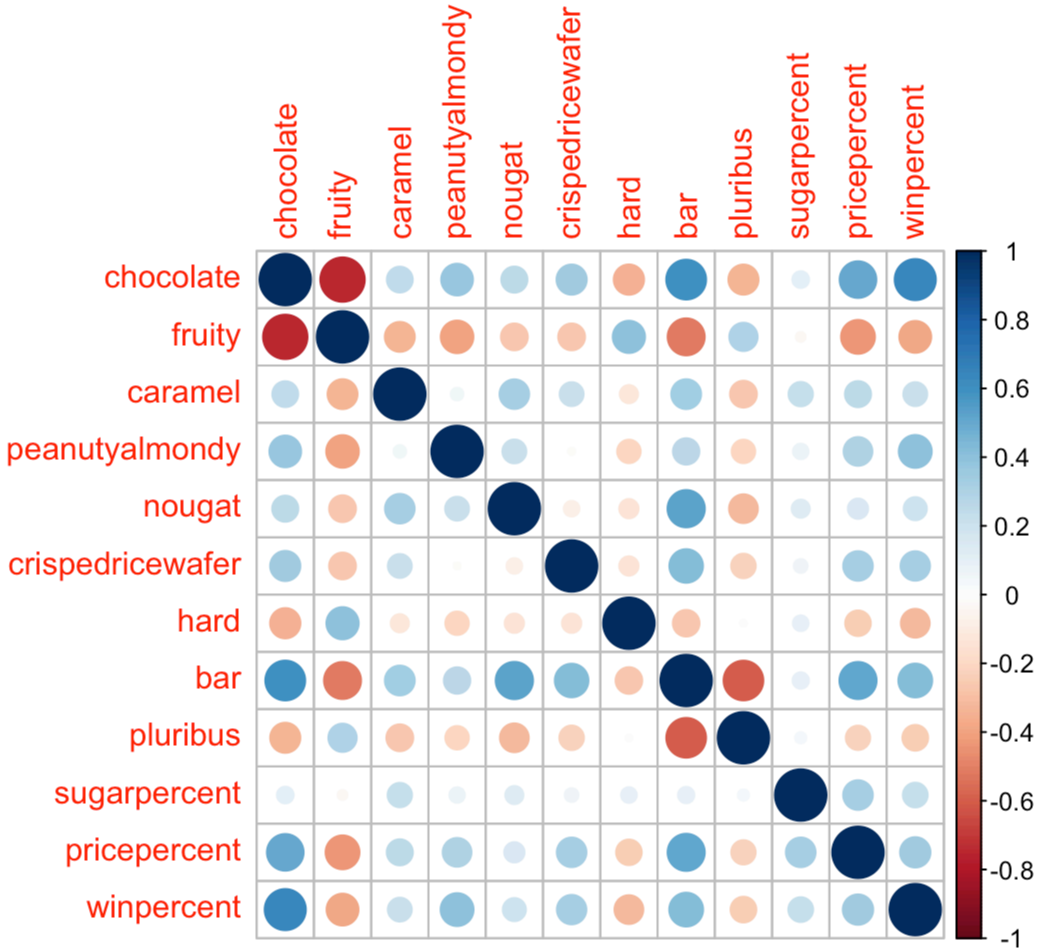
```
                         pricepercent winpercent
Nik L Nip                       0.976   22.44534
Nestle Smarties                 0.976   37.88719
Ring pop                        0.965   35.29076
Hershey's Krackel               0.918   62.28448
Hershey's Milk Chocolate        0.918   56.49050
```

The top 5 most expensive candy types are **Nik L Nip, Nestle Smarties, Ring Pops, Hershey's Krackel, and Hershey's Milk Chocolate**. Out of these 5, the least popular is **Nik L Nip**, which is also the most expensive! Not a great choice...

Exploring the Correlation Structure

Let's check the correlation between different candy characteristics to see what we can find.

```
# We have to download the `corrplot` library first
c <- cor(candy)
corrplot::corrplot(c)
```



> (Q22) Examining this plot what two variables are anti-correlated (i.e. have minus values)?

The strongest anti-correlation on this plot is between **chocolate** and **fruity**, with a **-0.74** correlation.

> (Q23) Similarly, what two variables are most positively correlated?

Outside of the 1.00 correlation between the same variable, the greatest positive correlation is between **chocolate** and **winpercent**, with a **+0.64** correlation.

Principal Component Analysis

We need to be sure to scale our data, because we recall that `winpercent` is on a different scale than the rest of the data.

```
# Our first two PCAs only account for 47%...
pca <- prcomp(candy, scale=T)
summary(pca)
```

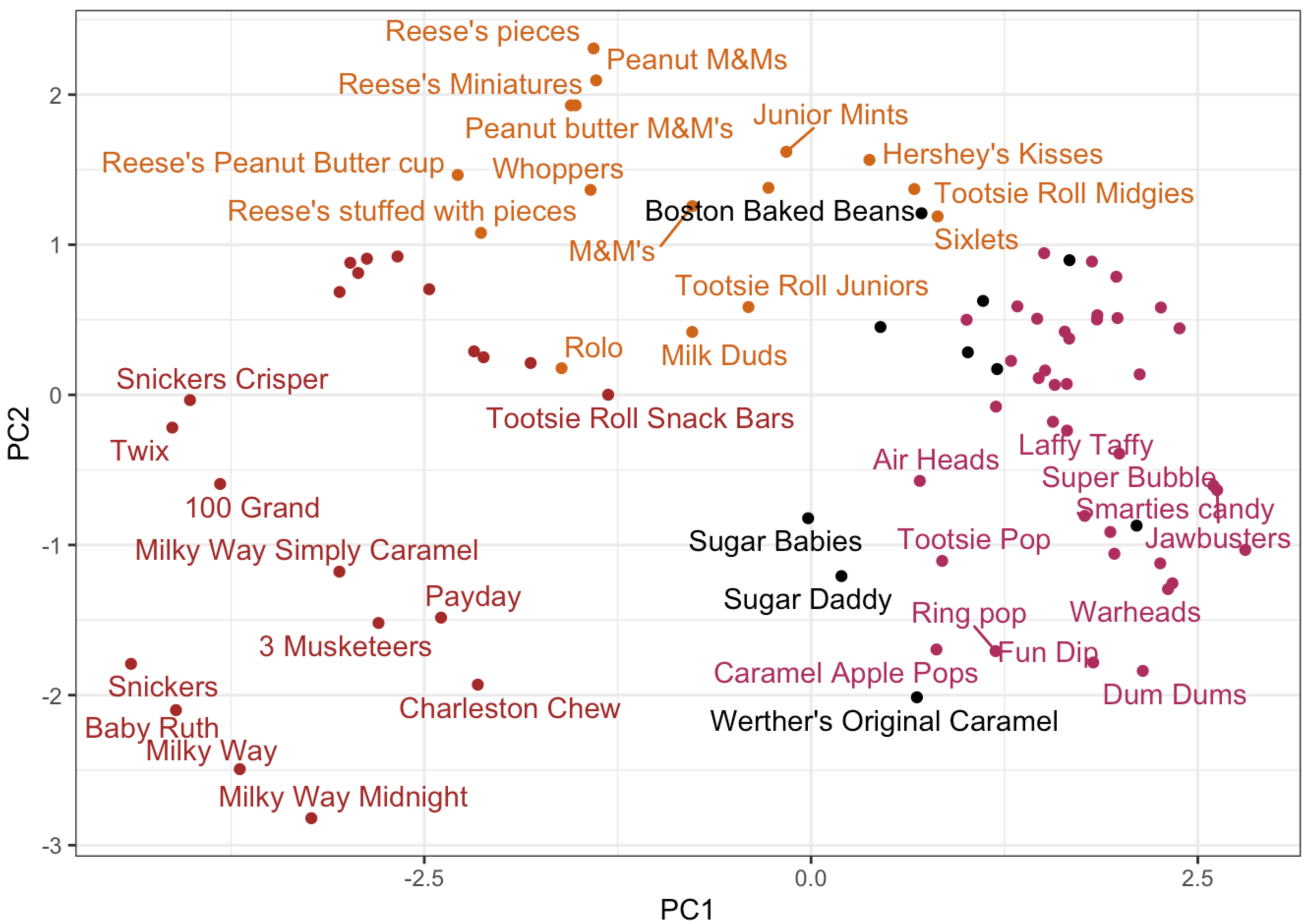
```
Importance of components:
                          PC1    PC2    PC3     PC4    PC5     PC6     PC7
Standard deviation     2.0788 1.1378 1.1092 1.07533 0.9518 0.81923 0.81530
```

```
Proportion of Variance 0.3601 0.1079 0.1025 0.09636 0.0755 0.05593 0.05539
Cumulative Proportion  0.3601 0.4680 0.5705 0.66688 0.7424 0.79830 0.85369
                           PC8     PC9    PC10    PC11    PC12
Standard deviation     0.74530 0.67824 0.62349 0.43974 0.39760
Proportion of Variance 0.04629 0.03833 0.03239 0.01611 0.01317
Cumulative Proportion  0.89998 0.93832 0.97071 0.98683 1.00000
```

First, lets make a "PCA plot":

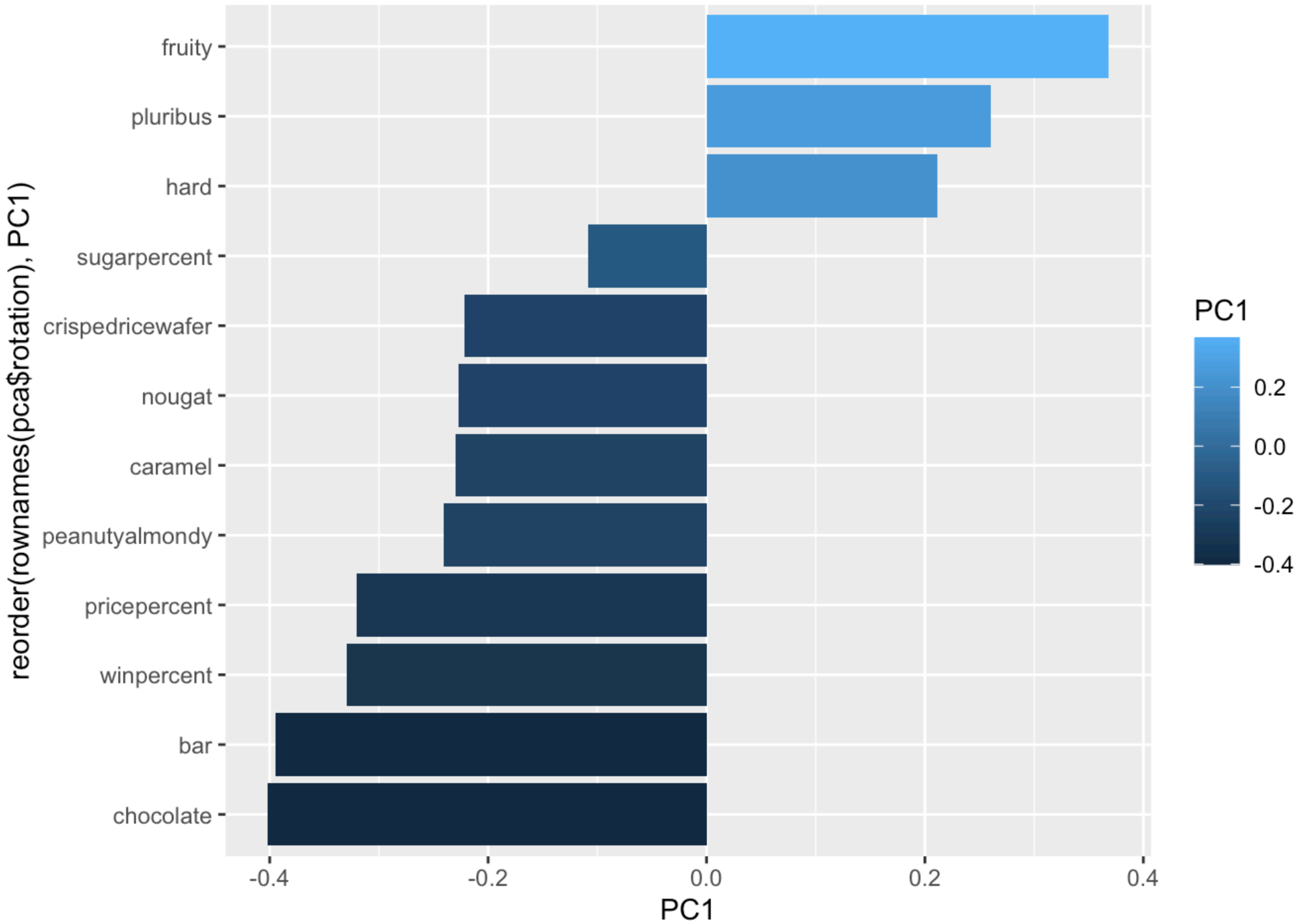
```
ggplot(pca$x) +
  aes(PC1, PC2, label=rownames(pca$x)) +
  geom_point(col=my_cols) +
  geom_text_repel(max.overlaps = 6, col=my_cols) +
  theme_bw()
```

```
Warning: ggrepel: 43 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```



The second main PCA result is in the `pca$rotation` object; we can plot this to generate a so-called "loadings" plot.

```
ggplot(pca$rotation) +
  aes(PC1, reorder(rownames(pca$rotation), PC1), fill=PC1) +
  geom_col()
```



> (Q24) What original variables are picked up strongly by PC1 in the positive direction? Do these make sense to you?

The strongest positively correlated variables with PC1 are **fruity, pluribus, and hard**. This makes sense, because many fruity candies come in packs with more than one candy, and are often also hard candies.