Class 10: Halloween Mini-Project

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In this mini project, we will be exploring FiveThirtyEight's Halloween Candy dataset, which contains the results of their poll asking Americans what is their favorite candy.

Importing Candy Data

Data will be imported from the FiveThirtyEight GitHub repo.

```
url <- "https://raw.githubusercontent.com/fivethirtyeight/data/master/candy-power-ranking/

candy <- read.csv(url, 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?

```
nrow(candy)
```

```
[1] 85
```

There are 85 candy types in this dataset.

Q2. How many fruity candy types are in the dataset?

```
sum(candy$fruity)
```

```
[1] 38
```

There are 38 fruity candy types in this dataset.

What is your favorite candy?

One of the most interesting variables in the dataset is winpercent. For a given candy, this value is the percentage of people who prefer this candy over another randomly chosen candy from the dataset (what 538 terms a "match-up"). Higher values indicate a more popular candy.

Q3. What is your favorite candy in the dataset and what is it's winpercent value?

My favorite candy in the dataset is Milky Way.

```
candy["Milky Way", ]$winpercent
```

```
[1] 73.09956
```

Milky Way's winpercent value is 73.09956%.

Q4. What is the winpercent value for "Kit Kat"?

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

```
[1] 76.7686
```

Kit Kat's winpercent value is 81.64291%.

Q5. What is the winpercent value for "Tootsie Roll Snack Bars"?

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

```
[1] 49.6535
```

Tootsie Roll Snack Bars's winpercent is 49.6535%.

Side-note: the skimr::skim() function

There is a useful `skim()` function in the skimr package that can help give you a quick overview of a given dataset. Let's install this package and try it on our candy data.

```
# install.packages("devtools")
# devtools::install_github("ropensci/skimr")

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

Table 1: 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	
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	

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
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?

Mean and standard deviation look to be on a different scale to the majority of the other columns in the data.

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

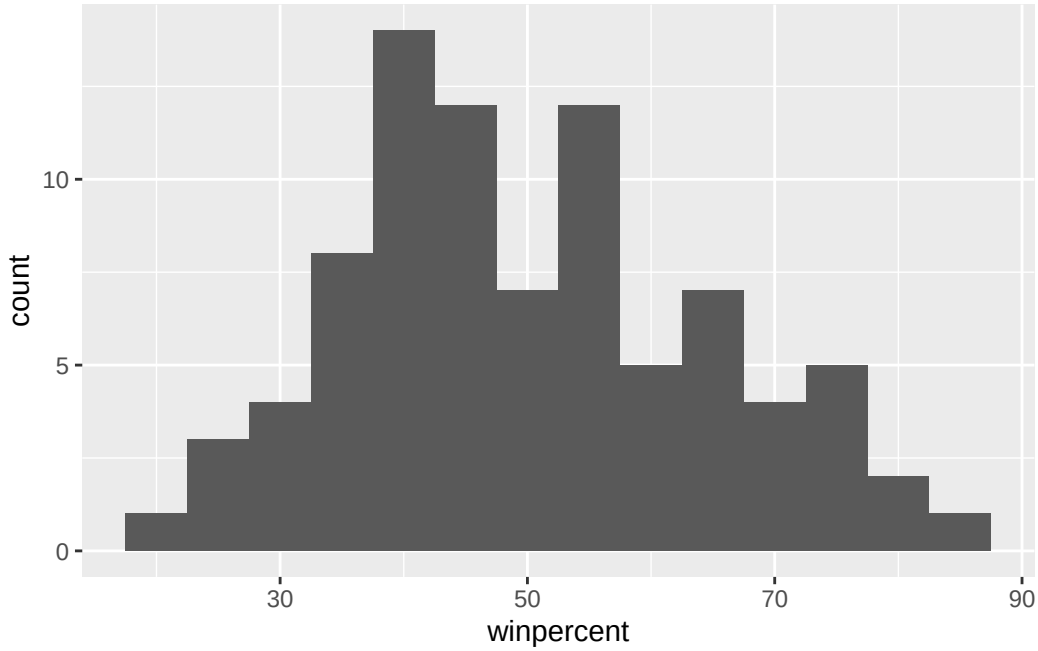
In the candy$chocolate column, a 1 represents "yes, there is chocolate in this candy" and 0 represents "no, there is no chocolate in this candy."

A good place to start any exploratory analysis is with a histogram. We can use either `hist()` or `ggplot()` with `geom_hist()`.

Plots

Q8. Plot a histogram of winpercent values

```
# hist(candy$winpercent)

library(ggplot2)

ggplot(candy, aes(winpercent)) +
  geom_histogram(binwidth=5)
```



Q9. Is the distribution of winpercent values symmetrical?

No, the distribution of winpercent values is not symmetrical.

Q10. Is the center of the distribution above or below 50%?

The center of distribution is below 50%.

Q11. On average is chocolate candy higher or lower ranked than fruit candy?

```
mean(candy$winpercent[as.logical(candy$chocolate)])
```

```
[1] 60.92153
```

```
mean(candy$winpercent[as.logical(candy$fruity)])
```

```
[1] 44.11974
```

On average, chocolate candy is higher ranked than fruity candy (61% vs 44%).

Q12. Is this difference statistically significant?

```
t.test(candy$winpercent[as.logical(candy$chocolate)], candy$winpercent[as.logical(candy$fr
```

```
    Welch Two Sample t-test

data:  candy$winpercent[as.logical(candy$chocolate)] and candy$winpercent[as.logical(candy$fi
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
```

The p-value is 2.871e-08, which is smaller than 0.05. This indicates that the difference is statistically significant.

Overall Candy Rankings

Let's use the base R `order()` function together with `head()` to sort the whole dataset by winpercent, or you can use the function `arrange()` with `head()` if using the dplyr package.

```
# head(candy[order(candy$winpercent),], n=5)

# install.packages("dplyr")
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
```

```
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
```

Q13. What are the five least liked candy types in this set?

The five least liked candy types in this set are: Nik L Nip, Boston Baked Beans, Chiclets, Super Bubble, and Jawbusters.

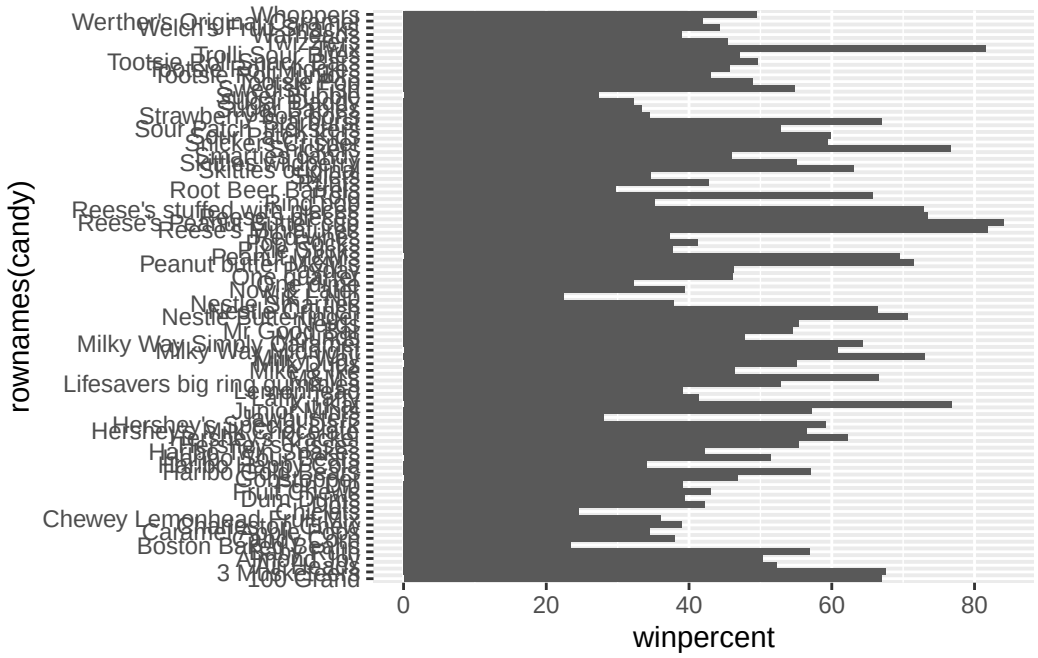
Q14. What are the top 5 all time favorite candy types out of this set?

The top 5 all time favorite candy types out of this set are Snickers, Kit Kat, Twix, Reese's Miniatures, and Reese's Peanut Butter cup.

To examine more of the dataset in this vain, we can make a barplot to visualize the overall rankings. We will use an iterative approach to building a useful visualization by getting a rough starting plot and then refining and adding useful details in a stepwise process.

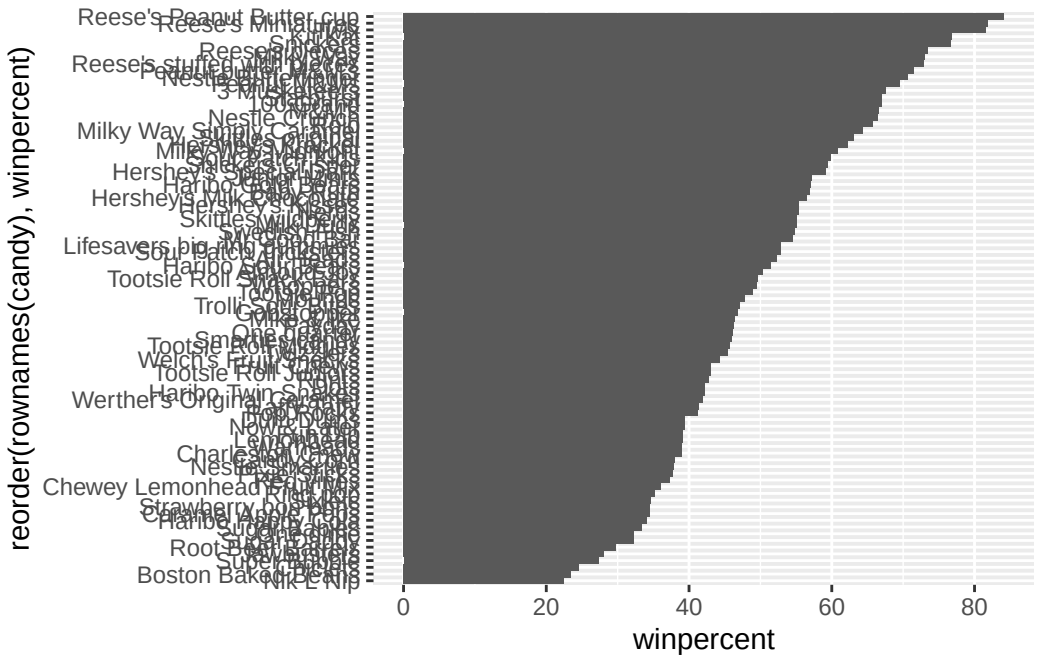
Q15. Make a first barplot of candy ranking based on winpercent values.

```
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.

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



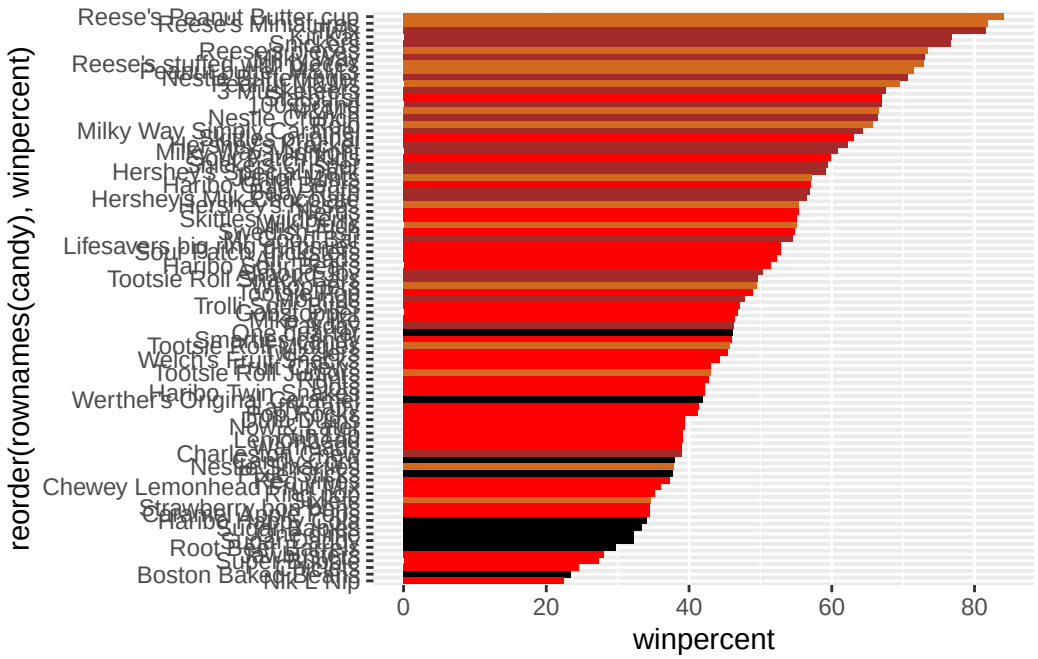
Time to add some useful color

Let's setup a color vector (that signifies candy type) that we can then use for some future plots. We start by making a vector of all black values (one for each candy). Then we overwrite chocolate (for chocolate candy), brown (for candy bars) and red (for fruity candy) values.

```
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)] = "red"
```

Now, let's make a new bar plot using these new colors.

```
ggplot(candy) +
  aes(winpercent, reorder(rownames(candy),winpercent)) +
  geom_col(fill=my_cols)
```



Q17. What is the worst ranked chocolate candy?

The worse ranked chocolate candy is Sixlets.

Q18. What is the best ranked fruity candy?

The best ranked fruity candy is Starburst.

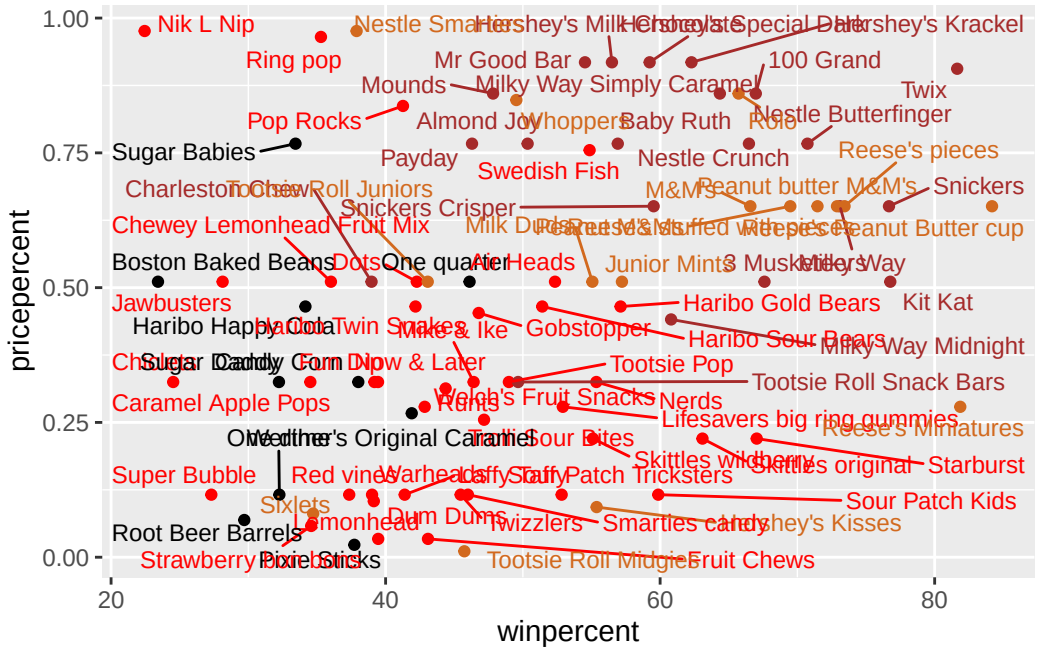
Taking a look at pricepercent

What is the the best candy for the least money? One way to get at this would be to make a plot of winpercent vs the pricepercent variable. The pricepercent variable records the percentile rank of the candy's price against all the other candies in the dataset. Lower vales are less expensive and high values more expensive.

To this plot, we will add text labels so we can more easily identify a given candy. There is a regular `geom_label()` that comes with ggplot2. However, as there are quite a few candies in our dataset, lots of these labels will be overlapping and hard to read. To help with this, we can use the `geom_text_repel()` function from the ggrepel package.

```
# install.packages("ggrepel")
```

```
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 = 25)
```



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?

Reese's Miniatures are the highest ranked in terms of winpercent for the least money. When looking at overall types, more fruity candy types have the highest rank in terms of winpercent for the least money.

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 in the dataset are: Nik L Nip, Nestle Smarties, Ring pop, Hershey's Krackel, and Hershey's Milk Chocolate.

Of these 5, the candy type that is the least popular is Nik L Nip.

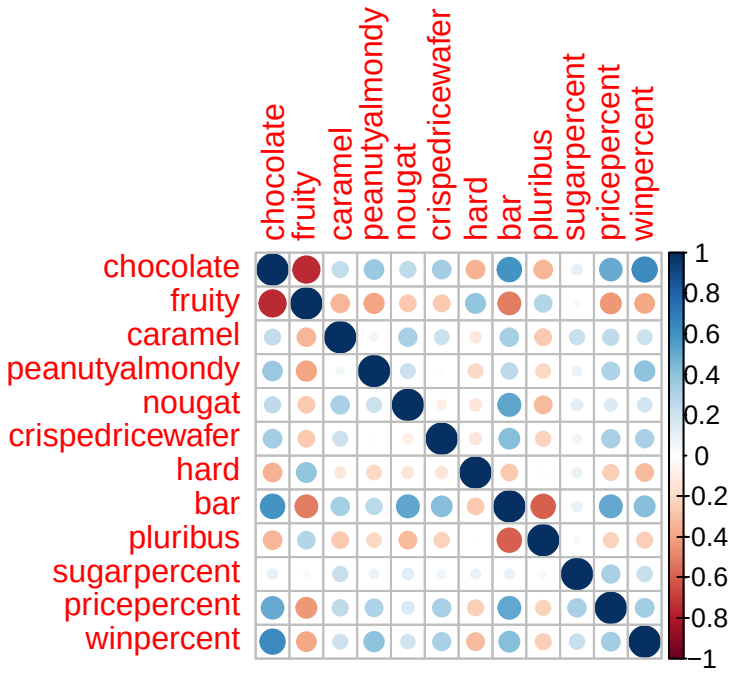
Exploring the correlation structure

Now that we've explored the dataset a little, we'll see how the variables interact with one another. We'll use correlation and view the results with the corrplot package to plot a correlation matrix.

```
# install.packages("corrplot")
library(corrplot)
```

```
corrplot 0.92 loaded
```

```
cij <- cor(candy)
corrplot(cij)
```



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

The two variables that are anti-correlated are chocolate and fruity (and pluribus and bar).

Q23. Similarly, what two variables are most positively correlated?

Two variables that are most positively correlated are chocolate and bar (and chocolate and winpercent).

Principal Component Analysis

Let's apply PCA using the `prcom()` function to our candy dataset, remembering to set the scale=TRUE argument.

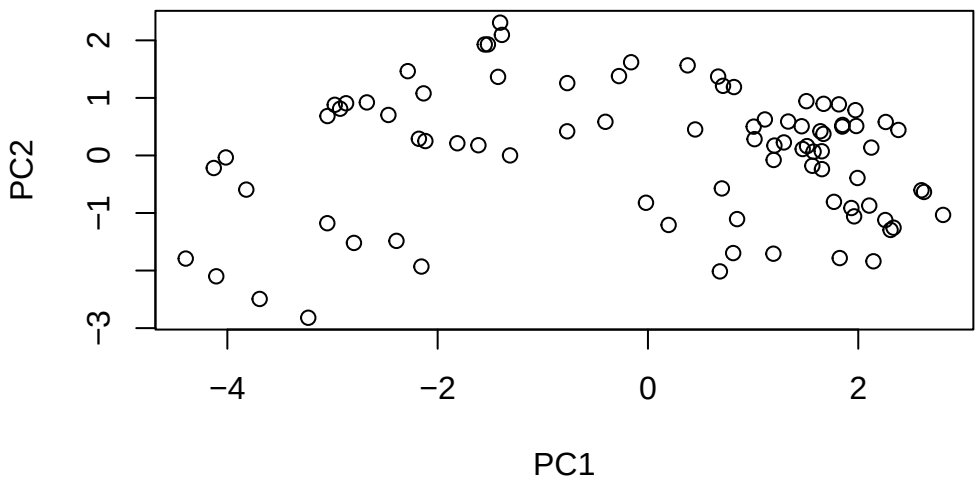
```
pca <- prcomp(candy, scale=TRUE)

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
```

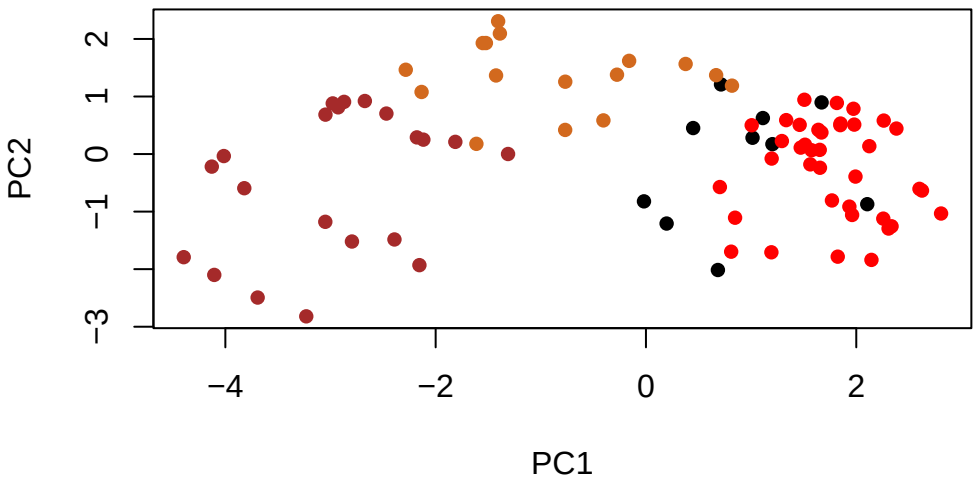
Let's plot our main PCA score plot of PC1 vs PC2.

```
plot(pca$x[,1:2])
```



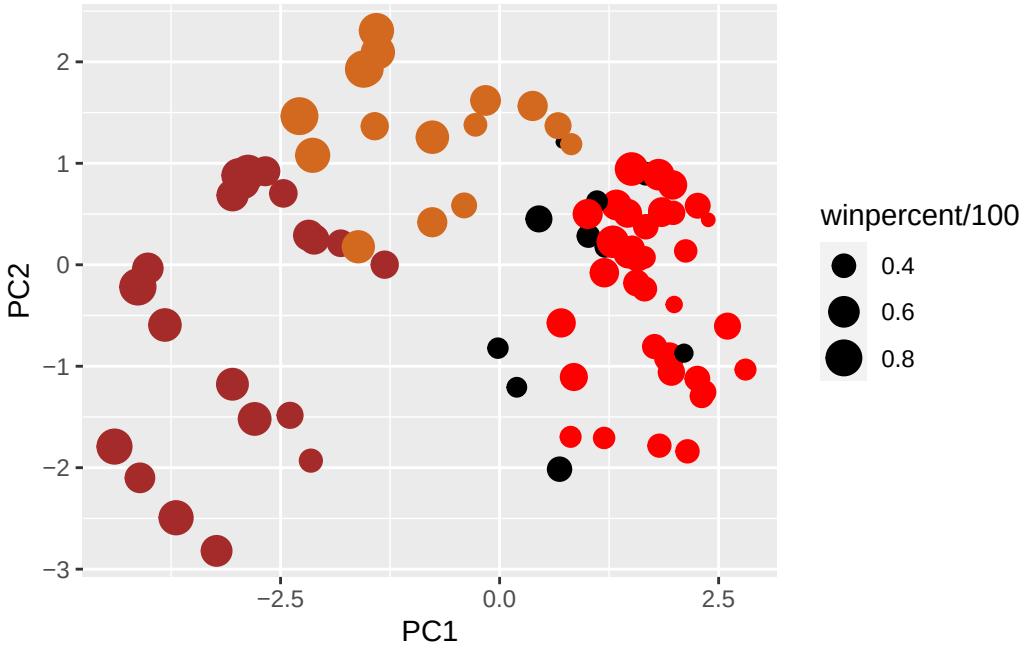
Let's add color.

```
plot(pca$x[,1:2], col=my_cols, pch=16)
```



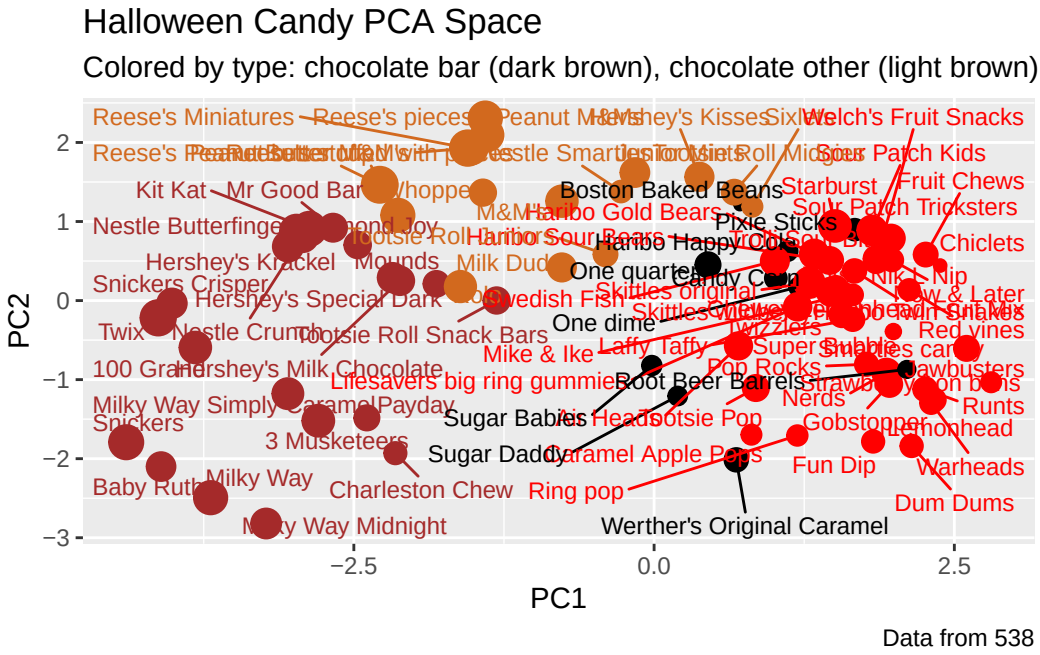
If we want to make a nicer plot, we can use the ggplot2 package. Before doing so, we must create a new data.frame that includes a separate column for each aesthetic along with out PCA results and candy data.

```
# Make a new data-frame with our PCA results and candy data
my_data <- cbind(candy, pca$x[,1:3])

p <- ggplot(my_data) +
        aes(x=PC1, y=PC2,
            size=winpercent/100,
            text=rownames(my_data),
            label=rownames(my_data)) +
        geom_point(col=my_cols)

p
```



Again, we can use the ggrepel package and the function `ggrepel::geom_text_repel()` to label up the plot with non-overlapping candy names. We will also add a title and subtitle like so:

```
library(ggrepel)

p + geom_text_repel(size=3.3, col=my_cols, max.overlaps = 37)  +
  theme(legend.position = "none") +
  labs(title="Halloween Candy PCA Space",
       subtitle="Colored by type: chocolate bar (dark brown), chocolate other (light brown
       caption="Data from 538")
```

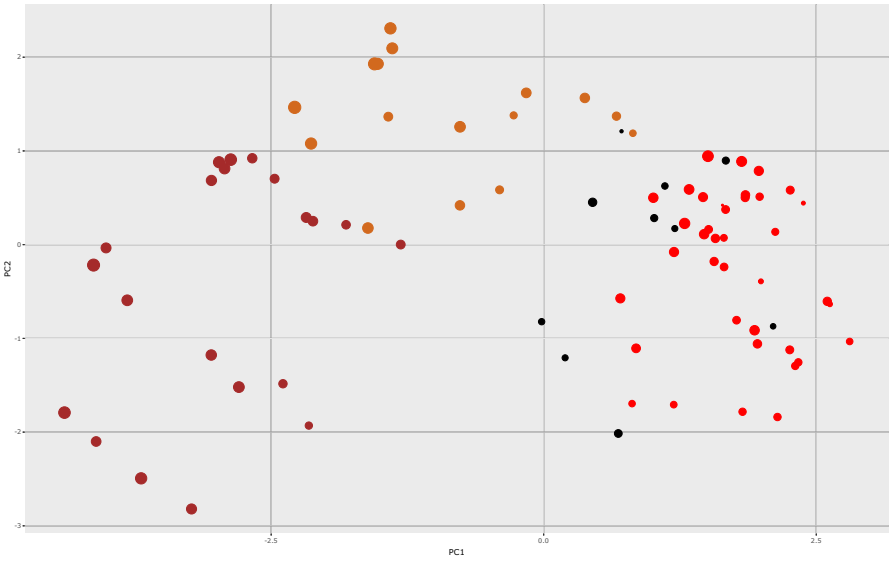


If you want to see more candy labels, you can change the max.overlaps value to allow more overlapping labels or pass the ggplot object p to plotly, like so, to generate an interactive plot that you can move your mouse over to see labels:

```
# install.packages("plotly")
library(plotly)
```

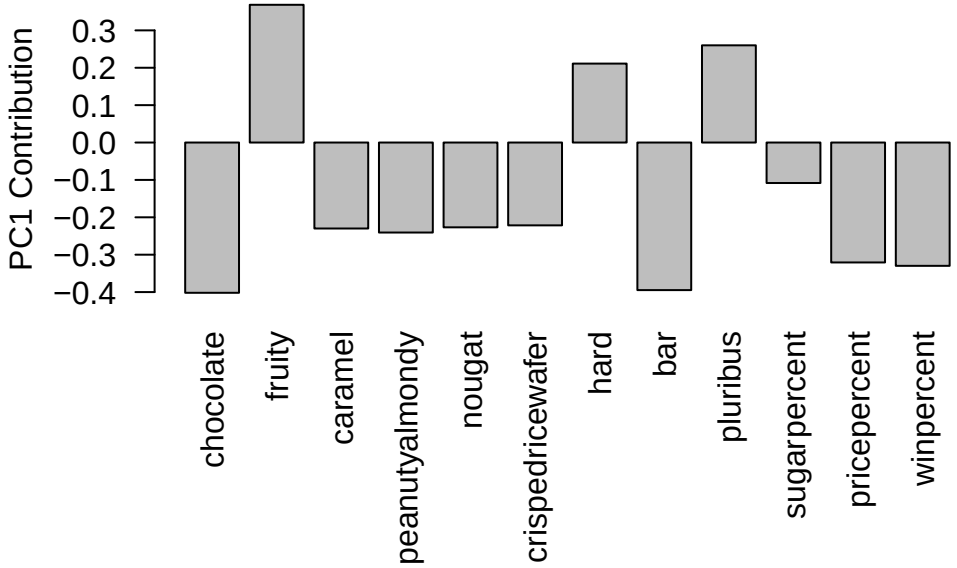
```
Attaching package: 'plotly'

The following object is masked from 'package:ggplot2':

    last_plot

The following object is masked from 'package:stats':

    filter

The following object is masked from 'package:graphics':

    layout
```

```
ggplotly(p)
```



Let's finish by taking a quick look at our PCA loadings. Do these make sense to you? Notice the opposite effects of chocolate and fruity and the similar effects of chocolate and bar (i.e. we already know they are correlated).

```
par(mar=c(8,4,2,2))
barplot(pca$rotation[,1], las=2, ylab="PC1 Contribution")
```



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

The original variables that are picked up strongly by PC1 in the positive direction are fruity, hard, and pluribus. This does make sense since these 3 variables had more negative correlation (or less positive correlation) with the other variables in the dataset.