

lab09

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Background

In this mini-project, you will explore FiveThirtyEight’s Halloween Candy dataset. FiveThirtyEight, sometimes rendered as just 538, is an American website that focuses mostly on opinion poll analysis, politics, economics, and sports blogging. They recently ran a rather large poll to determine which candy their readers like best. From their website: “While we don’t know who exactly voted, we do know this: 8,371 different IP addresses voted on about 269,000 randomly generated candy matchups”.

So what is the top ranked snack-sized Halloween candy? What made some candies more desirable than others? Was it price? Maybe it was just sugar content? Were they chocolate? Did they contain peanuts or almonds? How about crisped rice or other biscuit-esque component, like a Kit Kat or malted milk ball? Was it fruit flavored? Was it made of hard candy, like a lollipop or a strawberry bon bon? Was there nougat? What even is nougat? I know I like nougat, but I still have no real clue what the damn thing is.

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

Importing Candy Data

```
candy_file <- "candy-data.txt"

candy = read.csv(candy_file, 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?

```
#dimensions
dim(candy)
```

```
[1] 85 12
```

```
#How many different type of candy
nrow(candy)
```

```
[1] 85
```

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

```
table(sum(candy$fruity == 1))
```

38
1

Q3. What is your favorite candy?

```
candy["Hershey's Milk Chocolate", ]$winpercent
```

```
[1] 56.4905
```

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
```

Exploratory Analysis

We can use the **skimr** package to get a quick overview of a given data set. This can be useful for the first time you encounter a new data set.

```
#can also use skimr::skim()
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	
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 last column **winpercent** appears to be on a different scale to the majority of the other columns in the dataset.

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

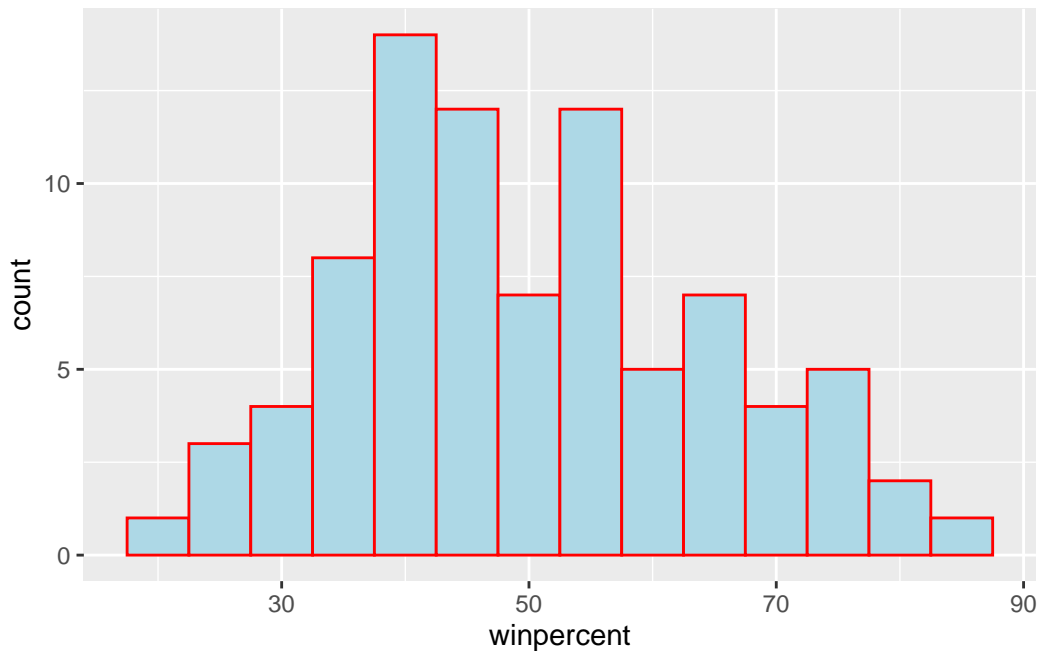
I believe the zero and one represents yes or no answers. The binomials 0 for “No” and 1 for “Yes”. Within the candy\$chocolate column it is assessing if each candy (rows) is either a chocolate or not. If it is a chocolate a 1 is inserted into the chocolate column otherwise a 0 is entered.

Hint: look at the “Variable type” print out from the skim() function. Most variables (i.e. columns) are on the zero to one scale but not all. Some columns such as chocolate are exclusively either zero or one values.

Q8. Plot a histogram of winpercent values

```
library(ggplot2)

ggplot(candy) +
  aes (winpercent) +
  geom_histogram(binwidth = 5, color = "red", fill = "lightblue")
```



Q9. Is the distribution of winpercent values symmetrical?

No, based on the histogram the distribution is not symmetrical

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

```
summary(candy$winpercent)
```

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

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

Based on the mean only **chocolate candy is preferred** as the mean is 60.92153 vs fruity candy is 44.11974.

```
choc.inds <- candy$chocolate == 1
choc.candy <- candy[choc.inds,]
choc.win <- choc.candy$winpercent
mean(choc.win)
```

```
[1] 60.92153
```

```
#Alternative: fruit.win <- candy[as.logical ( candy$fruity),]$winpercent
fruity.inds <- candy$fruity == 1
fruity.candy <- candy[fruity.inds,]
fruity.win <- fruity.candy$winpercent
mean(fruity.win)
```

```
[1] 44.11974
```

Q12. Is this difference statistically significant?

Yes, there is a significant statistical difference, chocolate is much preferred over fruity candy with a P-value of `r.ans$p.value`.

```
ans <- t.test(fruity.win, choc.win)
ans
```

Welch Two Sample t-test

```
data:  fruity.win and choc.win
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:
 -22.15795 -11.44563
sample estimates:
mean of x mean of y
 44.11974  60.92153
```

Overall Candy Rankings

There are two related functions that can help here, one is the classic `sort()` and `order()`

```
x <- c(5,10,1,4)
sort(x, decreasing = T)
```

```
[1] 10  5  4  1
```

```
order(x)
```

```
[1] 3 4 1 2
```

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

```
inds <- order(candy$winpercent)
head(candy[inds,], 5)
```

	chocolate	fruity	caramel	peanut	almond	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

	crisped	rice	wafer	hard	bar	pluribus	sugar	percent	price	percent
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

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

```
inds <- order(candy$winpercent, decreasing = T)
head(candy[inds,], 5)
```

	chocolate	fruity	caramel	peanut	almond	nougat
Reese's Peanut Butter cup	1	0	0		1	0
Reese's Miniatures	1	0	0		1	0
Twix	1	0	1		0	0
Kit Kat	1	0	0		0	0
Snickers	1	0	1		1	1

	crisped	rice	wafer	hard	bar	pluribus	sugar
Reese's Peanut Butter cup			0	0	0	0	0.720
Reese's Miniatures			0	0	0	0	0.034
Twix			1	0	1	0	0.546
Kit Kat			1	0	1	0	0.313
Snickers			0	0	1	0	0.546

	price	percent	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	

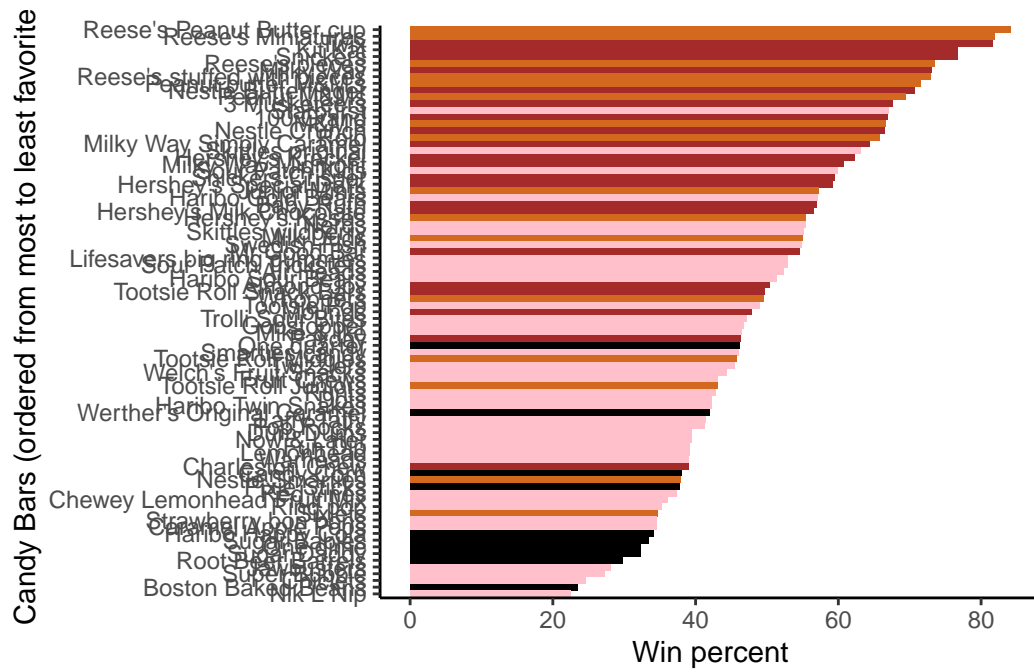
Q15. Make a first barplot of candy ranking based on winpercent values.

Here we want a custom color vector to color each bar the way we want - with chocolate and fruity candy together with it whether it is a bar or not.

```
#alternative: my_cols[2] <- "color"
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)] = "pink"
```

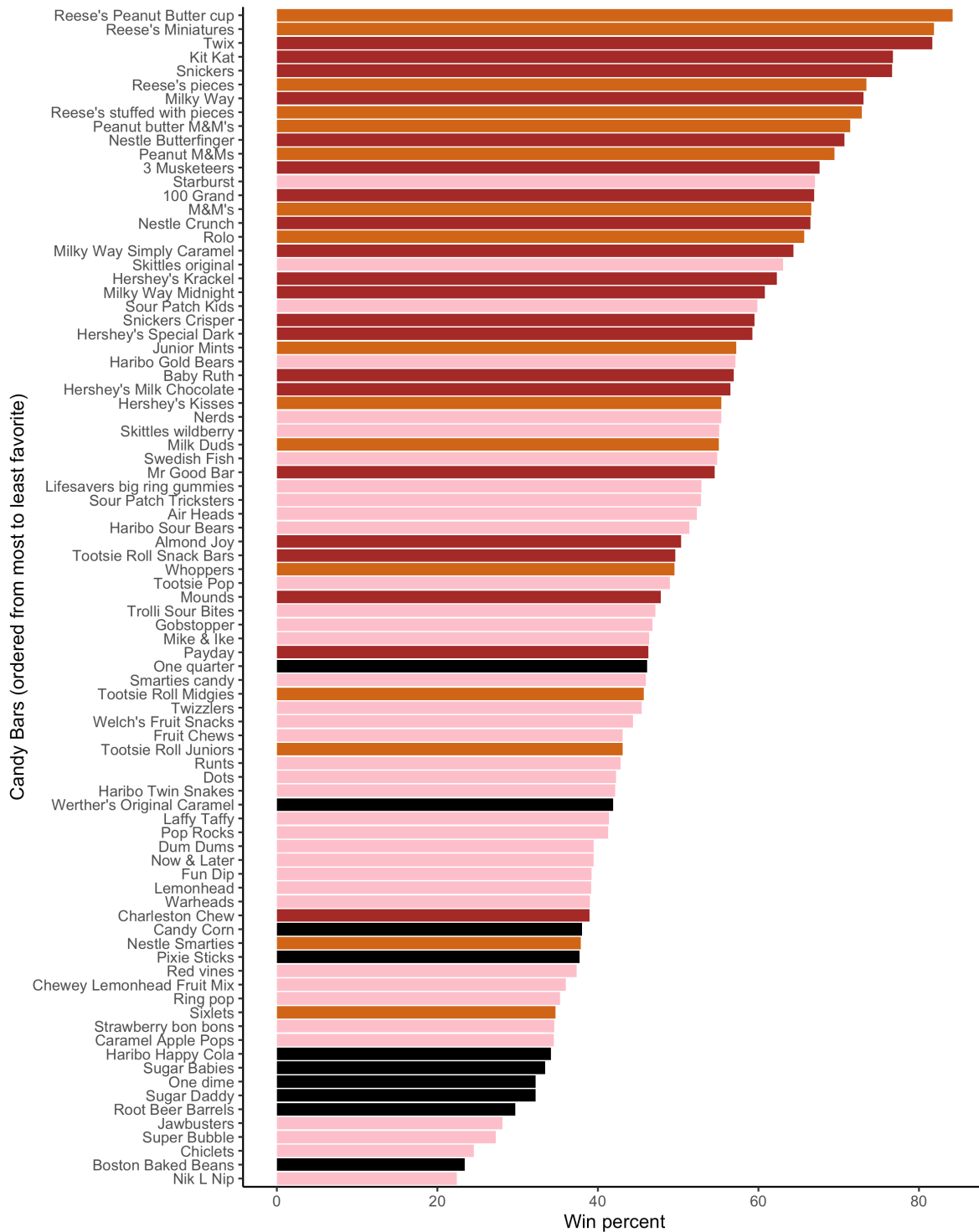
Make a bar plot and order it by winpercent values

```
ggplot(candy) +
  aes(winpercent, reorder(rownames(candy), winpercent)) +
  geom_col(fill = my_cols) +
  theme_classic() +
  labs(x = "Win percent", y = "Candy Bars (ordered from most to least favorite)")
```

```
ggsave("mybarplot.png", width = 8, height = 10)
```


Inserting plot png



Q17. What is the worst ranked chocolate candy?

The worst ranked chocolate candy is **Sixlets**.

Q18. What is the best ranked fruity candy?

The best ranked fruity candy is **Starburst**.

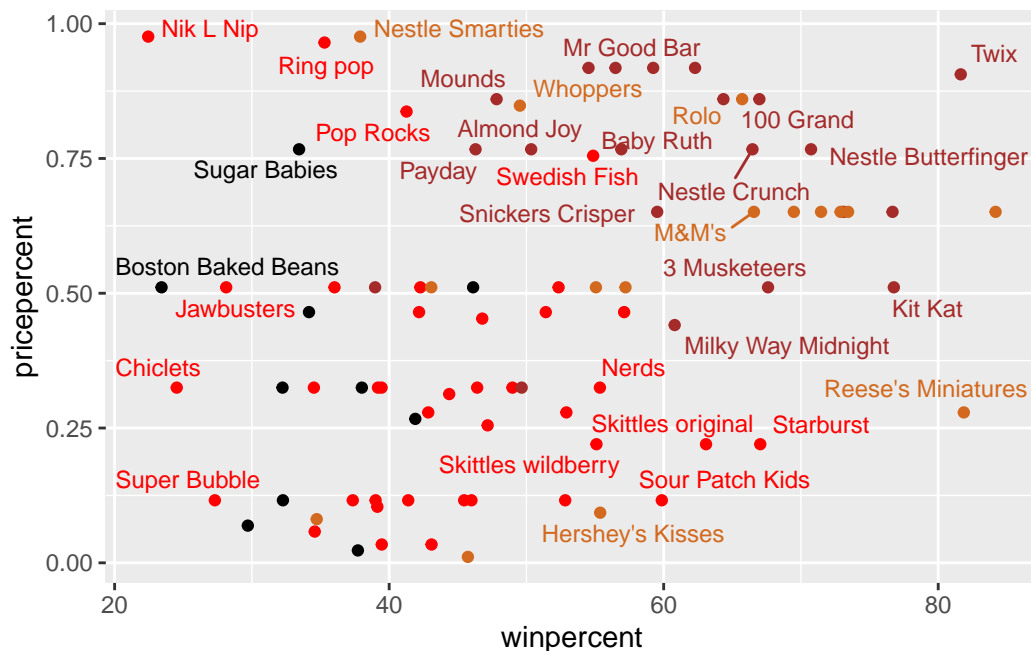
Winpercent vs Pricepercent

```
#pink is too light, lets change to red
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"

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 = 8)
```

Warning: ggrepel: 52 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?

```
inds <- order(candy$winpercent/candy$pricepercent)
head(candy[inds,], 5)
```

	chocolate	fruity	caramel	peanuty	almondy	nougat
Nik L Nip	0	1	0		0	0
Ring pop	0	1	0		0	0
Nestle Smarties	1	0	0		0	0
Sugar Babies	0	0	1		0	0
Boston Baked Beans	0	0	0		1	0

	crispedrice	wafer	hard bar	pluribus	sugarpercent	pricepercent	
Nik L Nip		0	0	0	1	0.197	0.976
Ring pop		0	1	0	0	0.732	0.965
Nestle Smarties		0	0	0	1	0.267	0.976
Sugar Babies		0	0	0	1	0.965	0.767
Boston Baked Beans		0	0	0	1	0.313	0.511

	winpercent
Nik L Nip	22.44534
Ring pop	35.29076

Nestle Smarties	37.88719
Sugar Babies	33.43755
Boston Baked Beans	23.41782

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

Top 5 most expensive candies are **Nik L Nip**, **Nestle Smarties**, **Ring Pop**, **Hershey's Krackel** and **Hershey's Milk Chocolate**. Of these five, **Nik L Nip** is also the least popular.

```
inds <- order(candy$pricepercent, decreasing = T)
head(candy[inds,], 5)
```

	chocolate	fruity	caramel	peanutyalmondy	nougat
Nik L Nip	0	1	0	0	0
Nestle Smarties	1	0	0	0	0
Ring pop	0	1	0	0	0
Hershey's Krackel	1	0	0	0	0
Hershey's Milk Chocolate	1	0	0	0	0

	crispedricewafer	hard bar	pluribus	sugarpercent	
Nik L Nip	0	0	0	1	0.197
Nestle Smarties	0	0	0	1	0.267
Ring pop	0	1	0	0	0.732
Hershey's Krackel	1	0	1	0	0.430
Hershey's Milk Chocolate	0	0	1	0	0.430

	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

Exploring the Correlation Structure

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

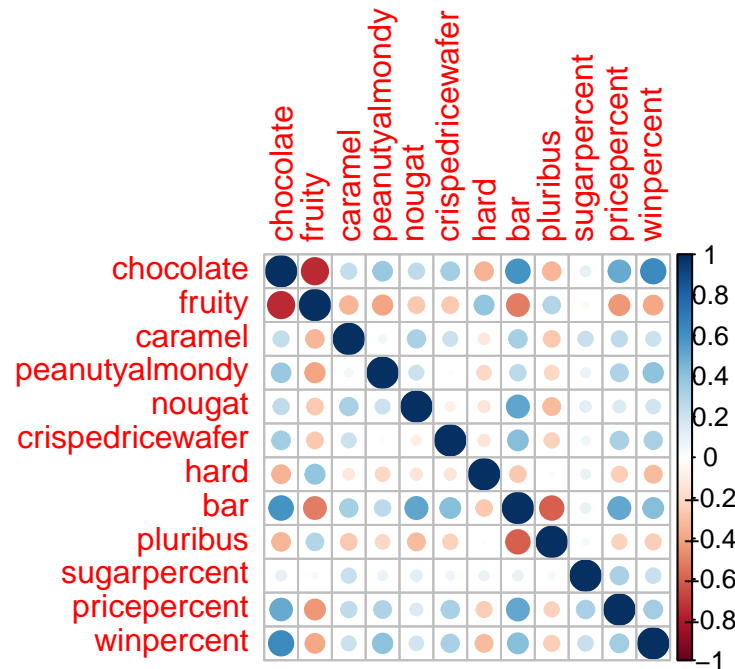
	chocolate	fruity	caramel	peanutyalmondy	nougat
--	-----------	--------	---------	----------------	--------

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		

```
library(corrplot)
```

```
corrplot 0.95 loaded
```

```
corrplot(cij)
```



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

Chocolate and Fruity have the strongest anti correlation(negatively correlated) with a correlation of -0.74.

```
round(cij["chocolate", "fruity"],2)
```

```
[1] -0.74
```

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

Chocolate and bar are the two variables most positively correlated with a correlation value of 0.6.

```
round(cij["chocolate", "bar"], 2)
```

```
[1] 0.6
```


Principal Component Analysis (PCA)

We need to be sure to scale our input `candy` data before PCA as we have the `winpercent` column on a different scale to all others in the data.

```
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

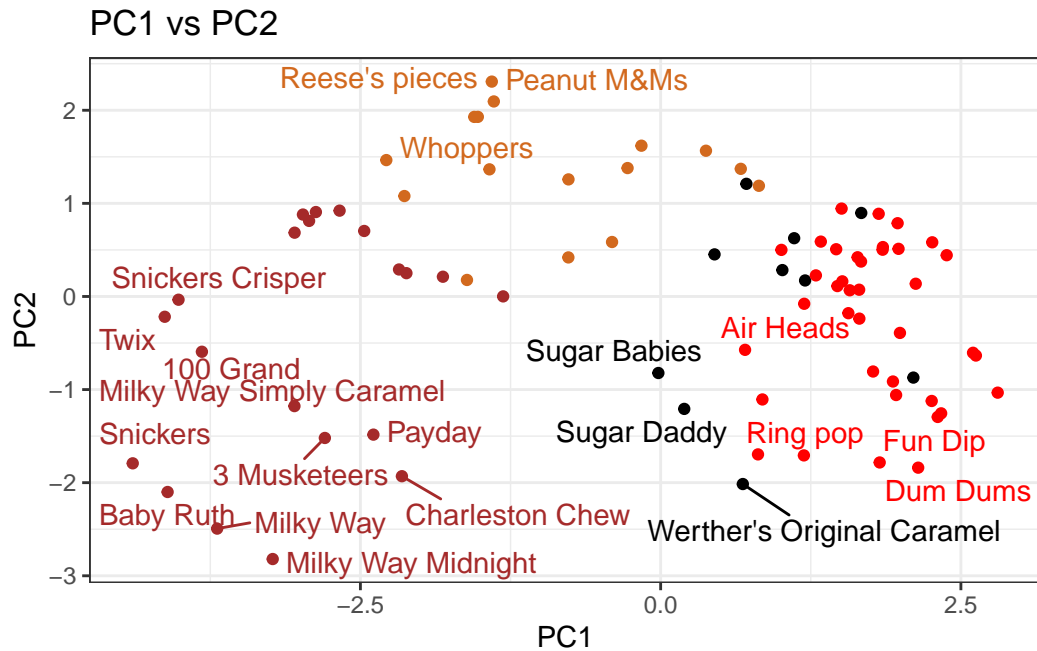
	PC8	PC9	PC10	PC11	PC12
Standard deviation	0.74530	0.67824	0.62349	0.43974	0.39760
Proportion of Variance	0.04629	0.03833	0.03239	0.01611	0.01317
Cumulative Proportion	0.89998	0.93832	0.97071	0.98683	1.00000

PCA plot

First main result figure is my “PCA plot”

```
ggplot(pca$x) +
  aes(PC1, PC2, label = rownames(pca$x)) +
  geom_point(col = my_cols) +
  geom_text_repel(max.overlaps = 7, col = my_cols) +
  theme_bw() +
  labs(title = "PC1 vs PC2")
```

Warning: ggrepel: 64 unlabeled data points (too many overlaps). Consider increasing max.overlaps

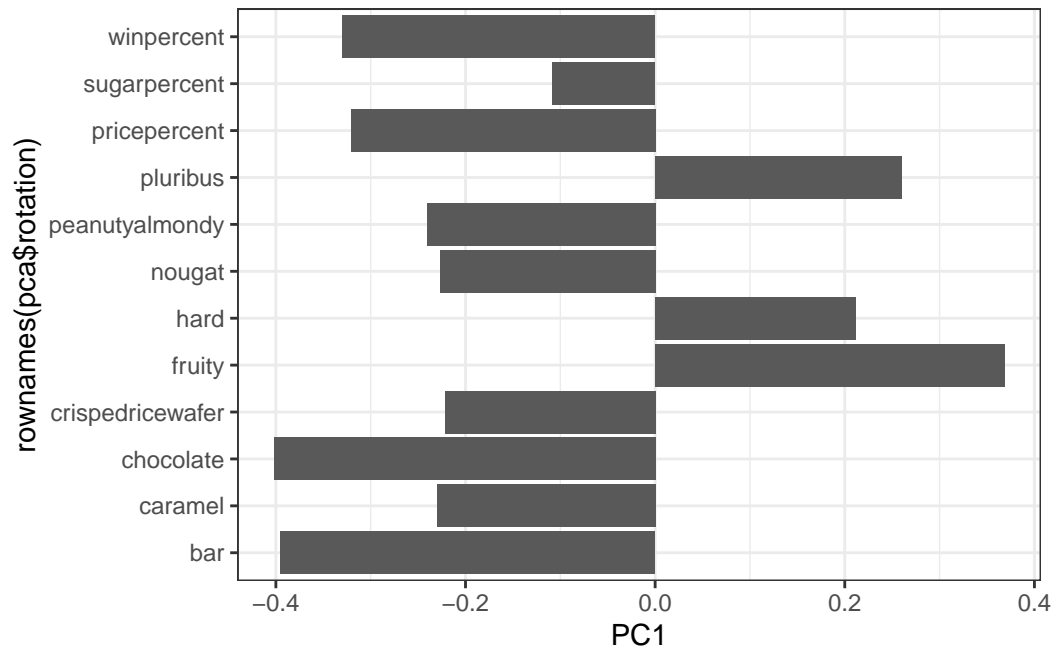


Loadings plot

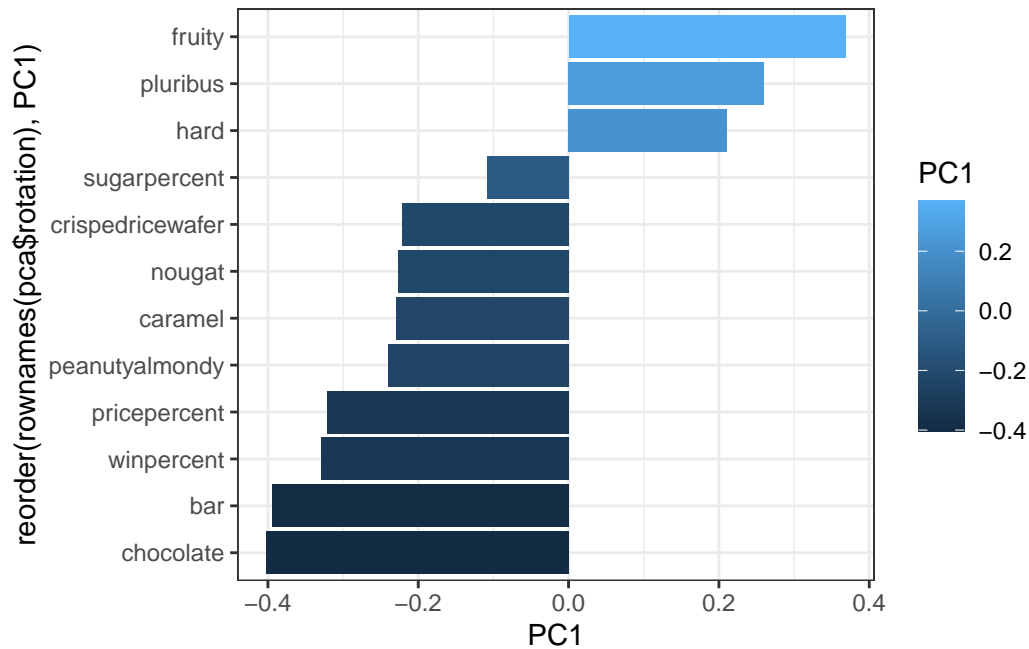
The second main PCA result is in the `pca$rotation` we can plot this to generate a so called “loadings” plot.

```
#pca$rotation

ggplot(pca$rotation) +
  aes(PC1, rownames(pca$rotation)) +
  geom_col() +
  theme_bw()
```



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



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

The original variables strongly picked up by PC1 in the positive direction are fruity, pluribus and hard, yes these variables make sense as they are contrasting the chocolate side which lines up with the other plots. The PC1 plot is separating the the fruity/hard candies from the chocolate ones, drawing a line down the middle.