

# Lab 10: Halloween Candy Mini-Project

AUTHOR

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## 1. Importing candy data

```
candy_data <- "candy-data.csv"
candy = read.csv(candy_data, row.names=1)
head(candy)
```

	chocolate	fruity	caramel	peanut	almond	nougat	crisped	rice	wafer
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	sugar	percent	price	percent	win	percent
100 Grand	0	1	0	0.732		0.860		66.97	173
3 Musketeers	0	1	0	0.604		0.511		67.60	294
One dime	0	0	0	0.011		0.116		32.26	109
One quarter	0	0	0	0.011		0.511		46.11	650
Air Heads	0	0	0	0.906		0.511		52.34	146
Almond Joy	0	1	0	0.465		0.767		50.34	755

Q1. How many different candy types are in this dataset?

```
nrow(candy)
```

```
[1] 85
```

There are 85 different candy types in this dataset.

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

```
table(candy[,2])
```

```
0 1
47 38
```

There are 38 fruity candy types in this dataset.

## 2. What is your favorite candy?

Q3. What is your favorite candy in the dataset and what is its winpercent value?

```
candy["Haribo Sour Bears",]$winpercent
```

[1] 51.41243

My favorite candy in the dataset is Haribo Sour Bears and its winpercent value is 51.41%.

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

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

[1] 76.7686

The winpercent value for Kit Kat is 76.76%.

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

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

[1] 49.6535

The winpercent value for Tootsie Roll Snack Bars is 49.65%.

```
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	
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	

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

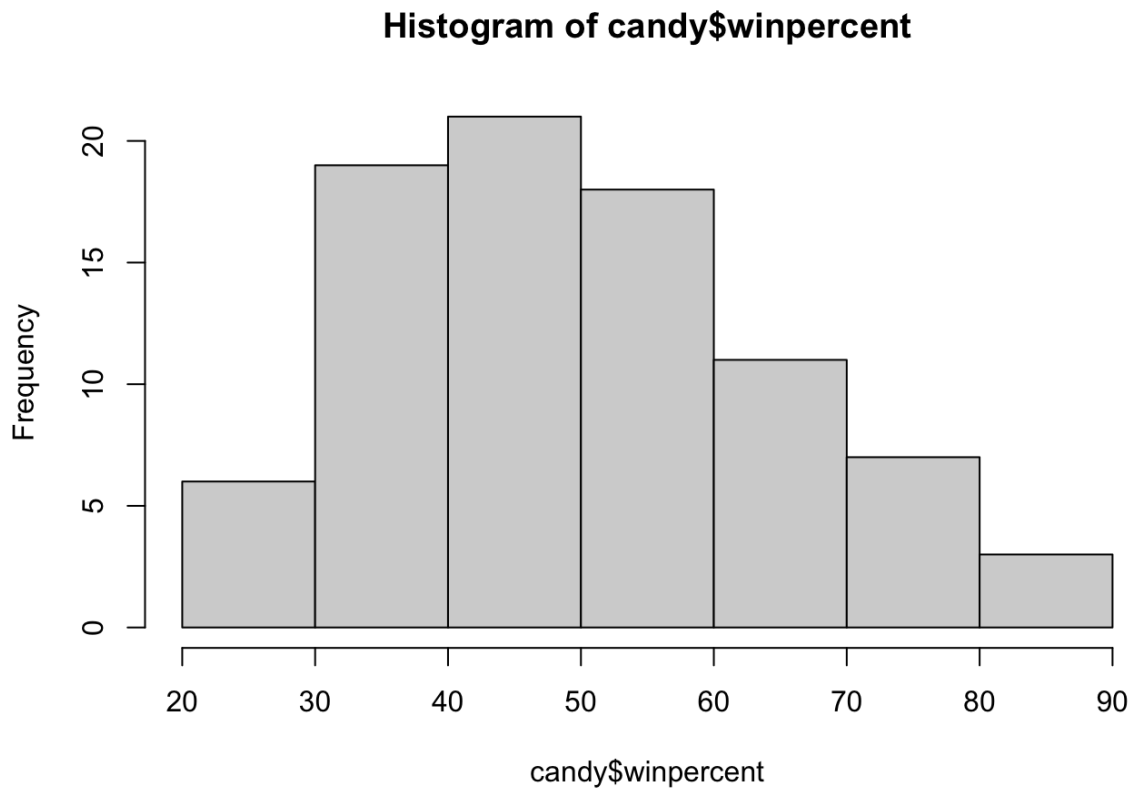
The winpercent variable appears to be on a different scale since its values are as high as (84.18) while all other variables have a maximum value of 1.

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

I think the 0 and 1 represent whether that candy has that characteristic or not (i.e if a candy contains chocolate, it would be assigned a 1 and would be assigned a 0 if it did not)

Q8. Plot a histogram of winpercent values

```
hist(candy$winpercent)
```



Q9. Is the distribution of winpercent values symmetrical?

The distribution of winpercent values is not exactly symmetrical and is shifted slightly to the left (i.e the highest frequency occurs at ~45% rather than ~50%).

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

The center of the distribution is slightly below 50%.

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

```
# Want to find what is the average of the winpercent values of candies that have a "1" value for ch  
mean_chocolate <- mean(candy$winpercent[as.logical(candy$chocolate)])  
mean_chocolate
```

```
[1] 60.92153
```

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

```
[1] 44.11974
```

On average, chocolate candy is higher ranked than fruit candy.

Q12. Is this difference statistically significant?

We can determine if this difference is statistically significant by performing a t-test.

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

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
```

The difference is statistically significant because the p-value is less than 0.05.

### 3. Overall Candy Rankings

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

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

The five least liked candies in this 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?

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

	chocolate	fruity	caramel	peanut	almondy	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

	crispedrice	wafer	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

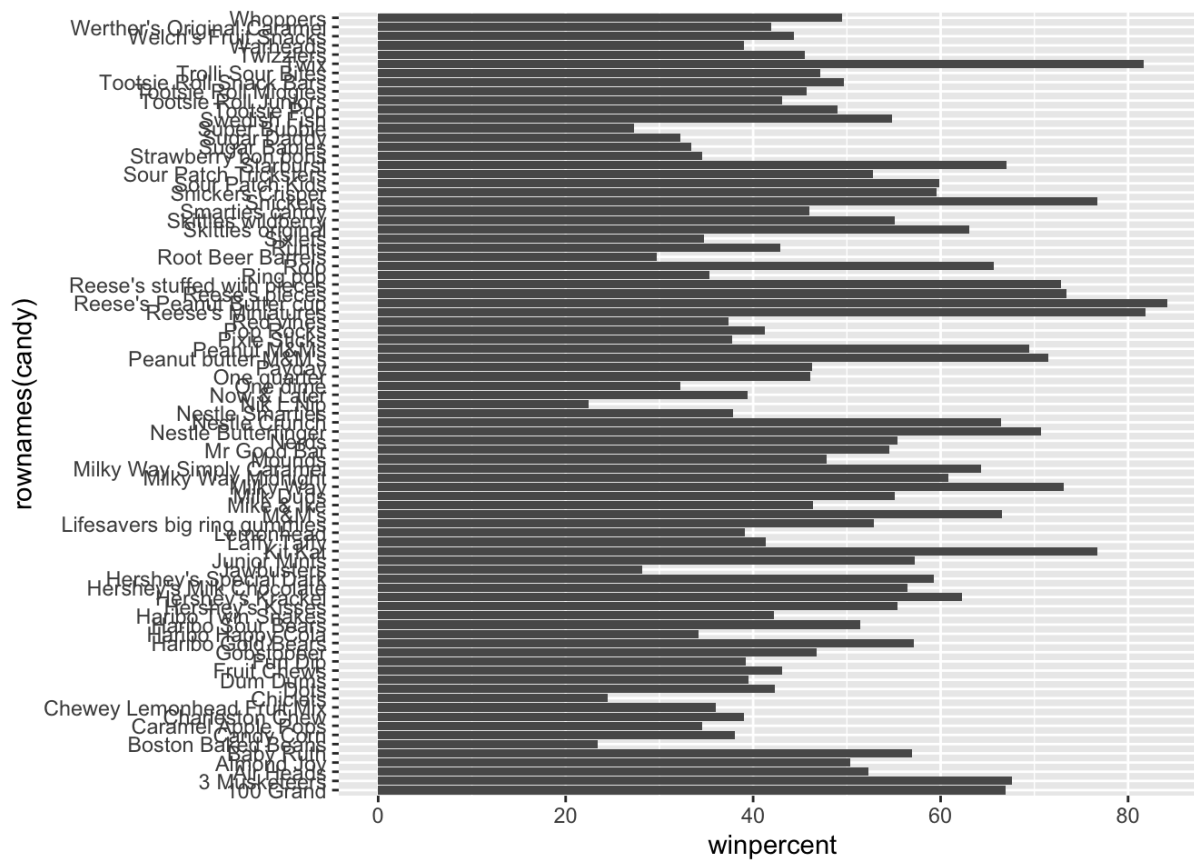
	pricepercent	winpercent
Snickers	0.651	76.67378
Kit Kat	0.511	76.76860
Twix	0.906	81.64291
Reese's Miniatures	0.279	81.86626
Reese's Peanut Butter cup	0.651	84.18029

The five most liked candies in this dataset are Snickers, Kit Kat, Twix, Reese's Miniatures, and Reese's Peanut Butter cup.

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

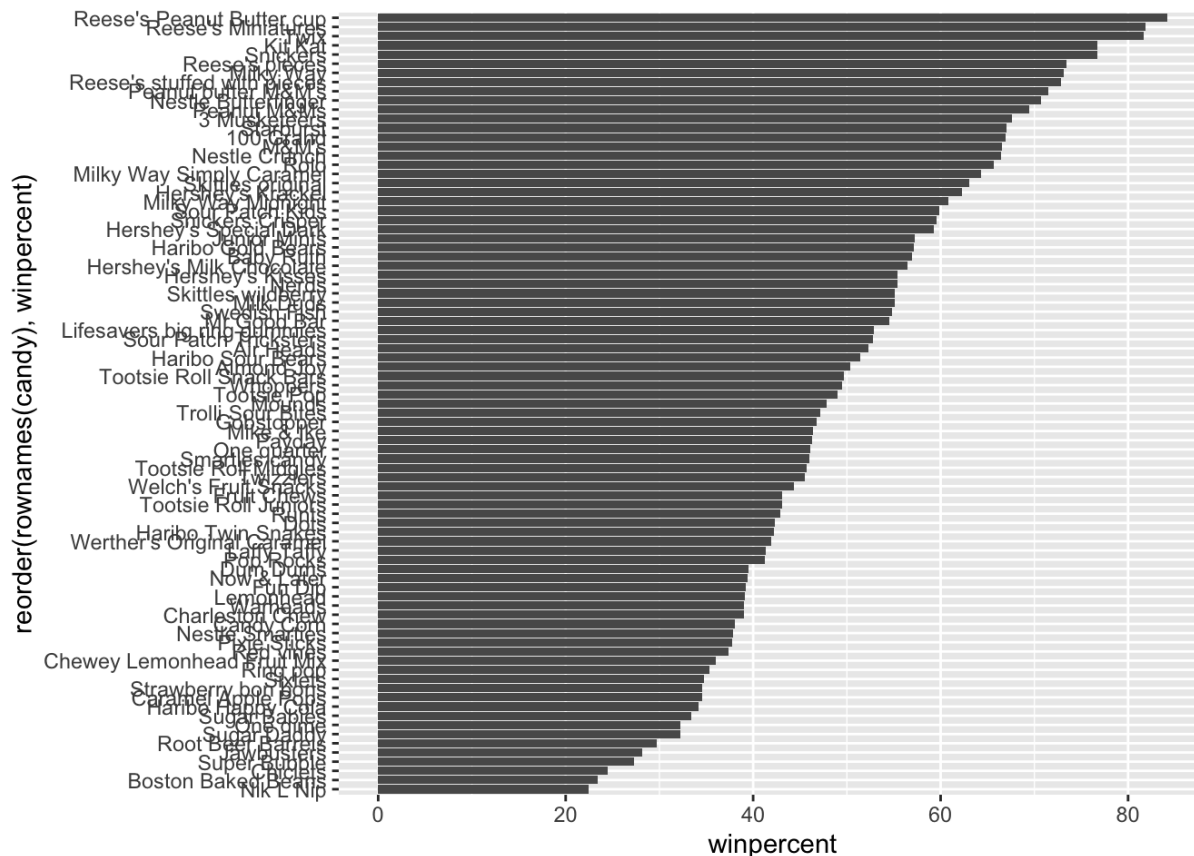
```
library(ggplot2)

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()
```

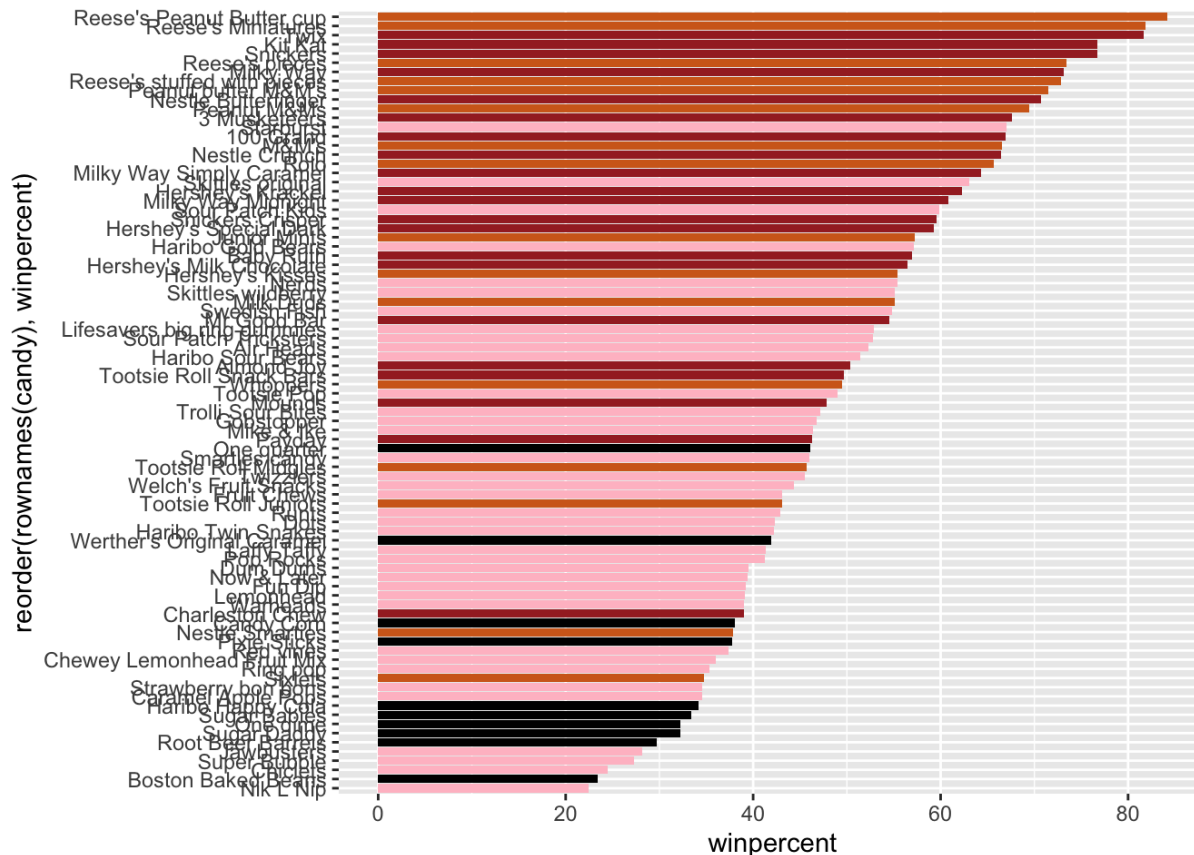


Let's setup a color vector (that signifies candy type) that we can then use for some future plots.

```
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"
```

Now let's try our barplot with these colors:

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



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.

#### 4. Taking a look at pricepercent

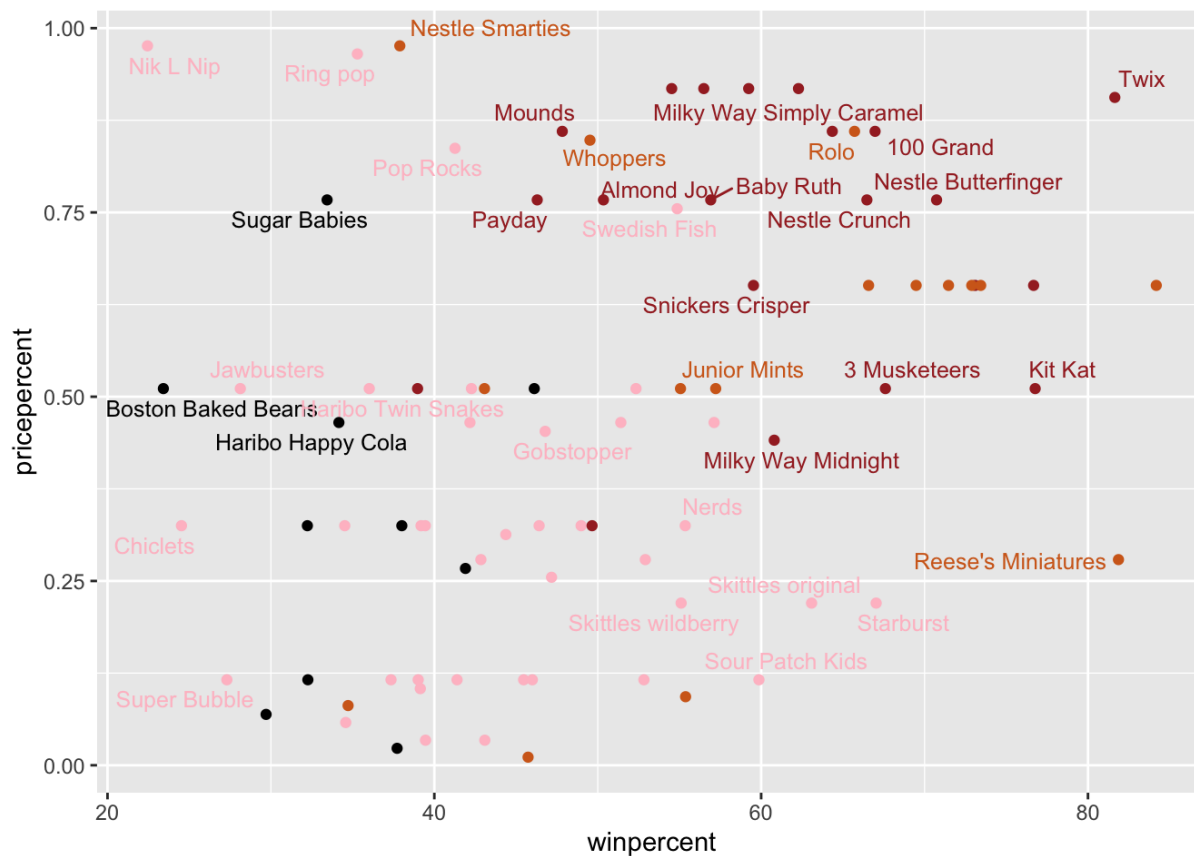
What about value for money? What is the the best candy for the least money?



```
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?

?? Reese's Miniatures have the highest ranked winpercent for the least price.

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 five most expensive candies are Nik L Nip, Neslte Smarties, Ring pop, Hershey's Krackel, and Hershey's Milk Chocolate. The least popular of these is Nik L Nip.

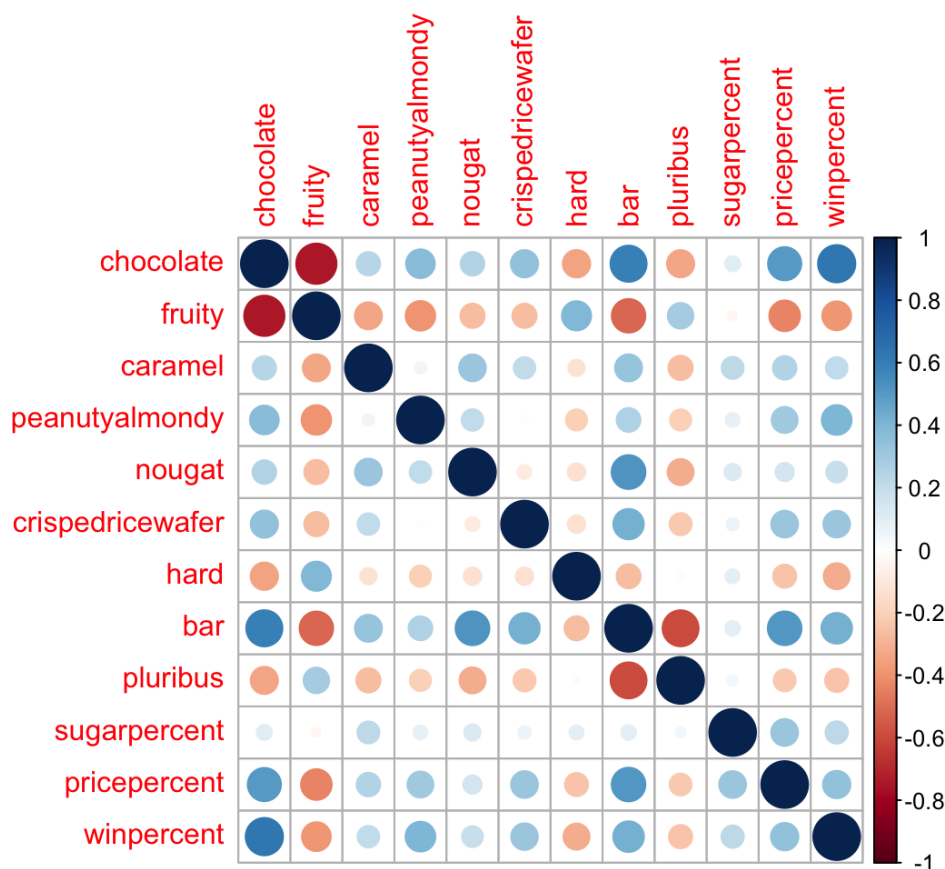
## 5. Exploring the correlation structure

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.

```
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)?

Fruity and chocolate variables are anti-correlated.

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

Chocolate and winpercent are the most positively correlated.

## 6. Principal Component Analysis

Now, we can apply PCA to our candy dataset.

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

Importance of components:

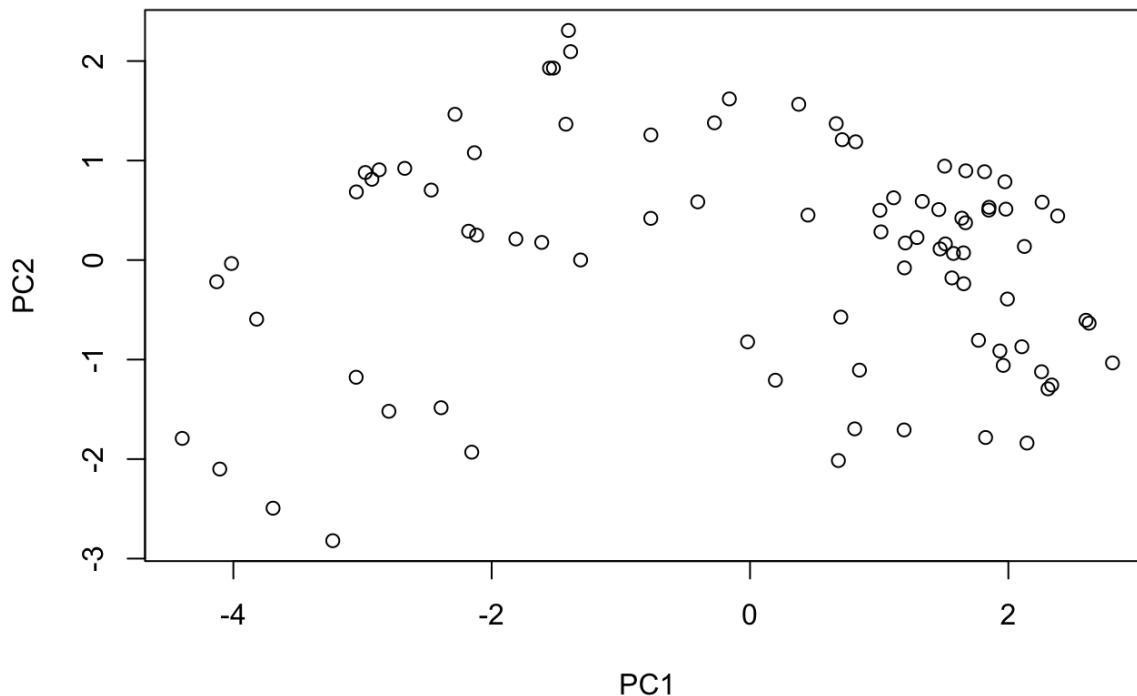
	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	2.0788	1.1378	1.1092	1.07533	0.9518	0.81923	0.81530
Proportion of Variance	0.3601	0.1079	0.1025	0.09636	0.0755	0.05593	0.05539
Cumulative Proportion	0.3601	0.4680	0.5705	0.66688	0.7424	0.79830	0.85369

	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

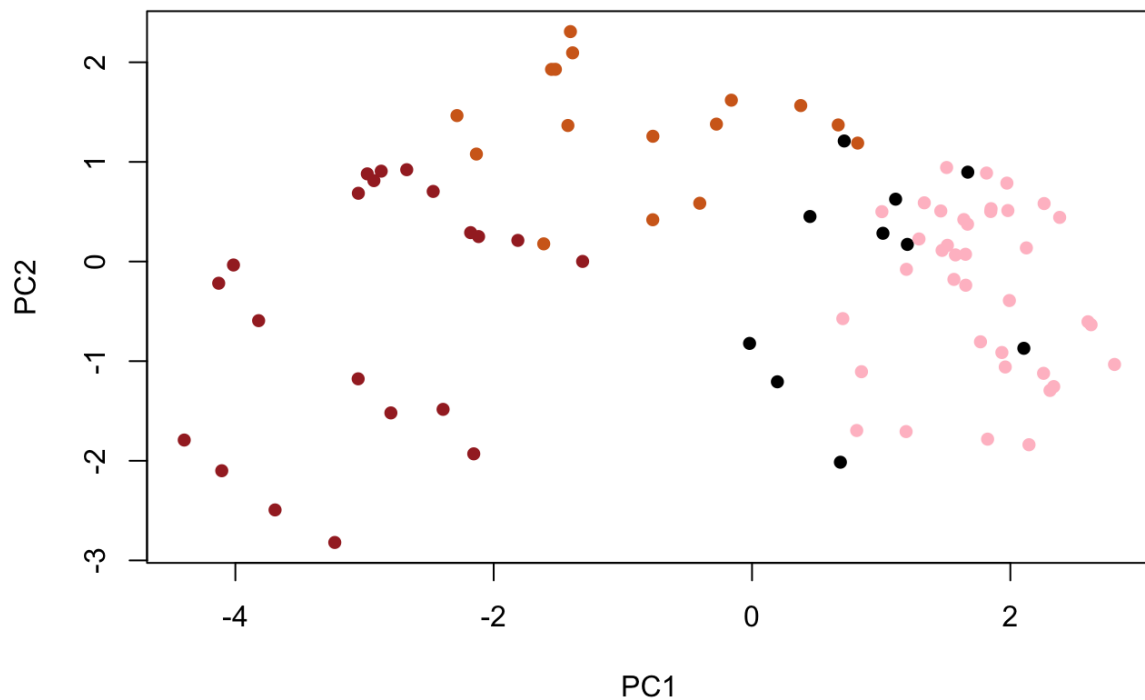
Now, we can plot PC1 vs. PC2:

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



We can change the plotting character and add some color:

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

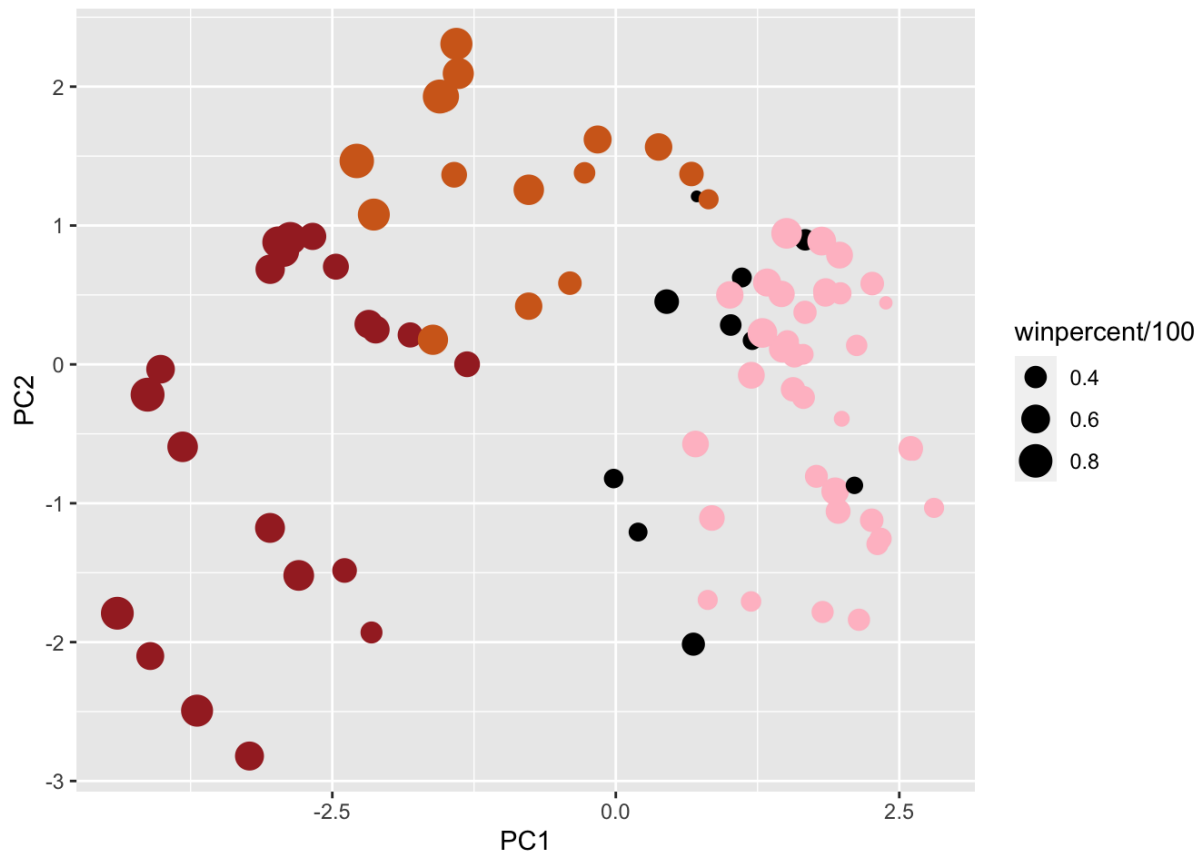


We can make a much nicer plot with the ggplot2 package but we will first need to make a new `data.frame()` with our PCA results.

```
# 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



We can also use the `ggrepel()` package to label the plot with the names of the candies in the dataset.

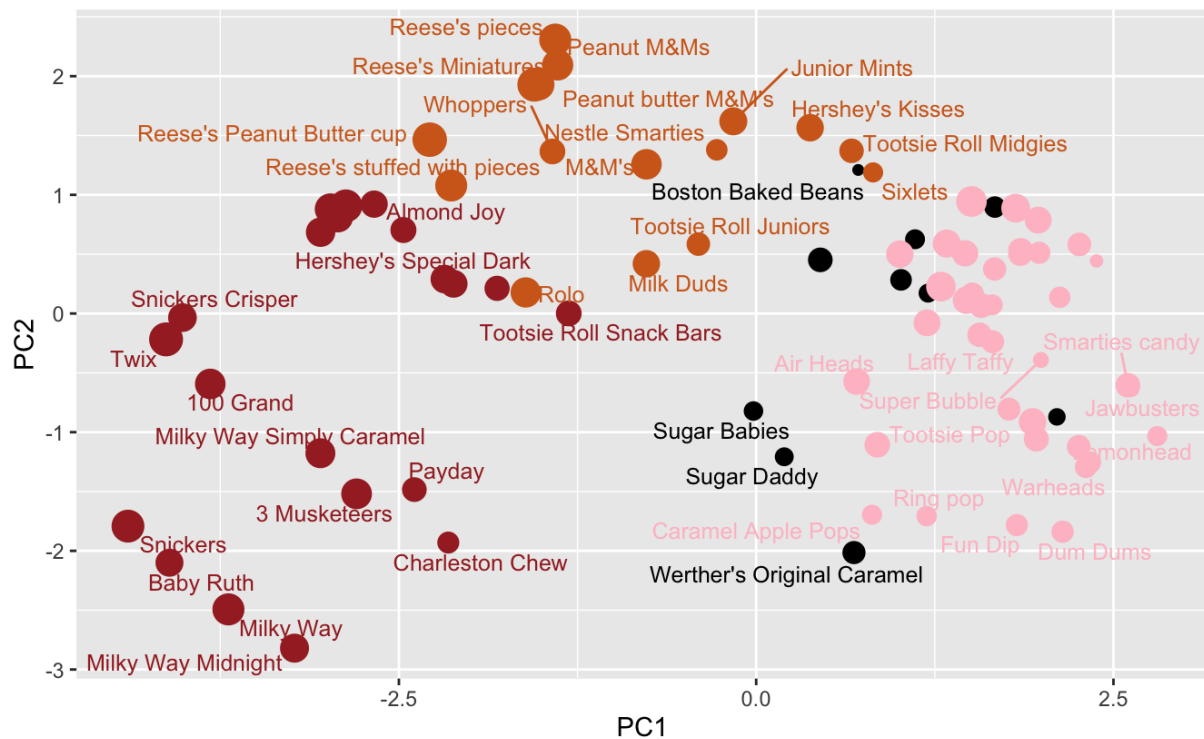
```
library(ggrepel)

p + geom_text_repel(size=3.3, col=my_cols, max.overlaps = 7) +
  theme(legend.position = "none") +
  labs(title="Halloween Candy PCA Space",
        subtitle="Colored by type: chocolate bar (dark brown), chocolate other (light brown), fruity",
        caption="Data from 538")
```

Warning: ggrepel: 39 unlabeled data points (too many overlaps). Consider increasing max.overlaps

## Halloween Candy PCA Space

Colored by type: chocolate bar (dark brown), chocolate other (light brown), fruity (red), other (black)



Data from 538

It is also helpful to use the `plotly()` function to generate an interactive plot that you can mouse over to see labels:

```
library(plotly)
```

Attaching package: 'plotly'

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

```
last_plot
```

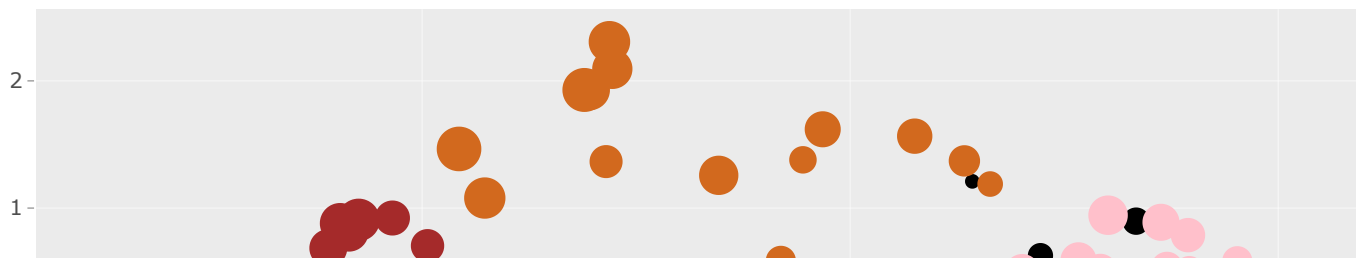
The following object is masked from 'package:stats':

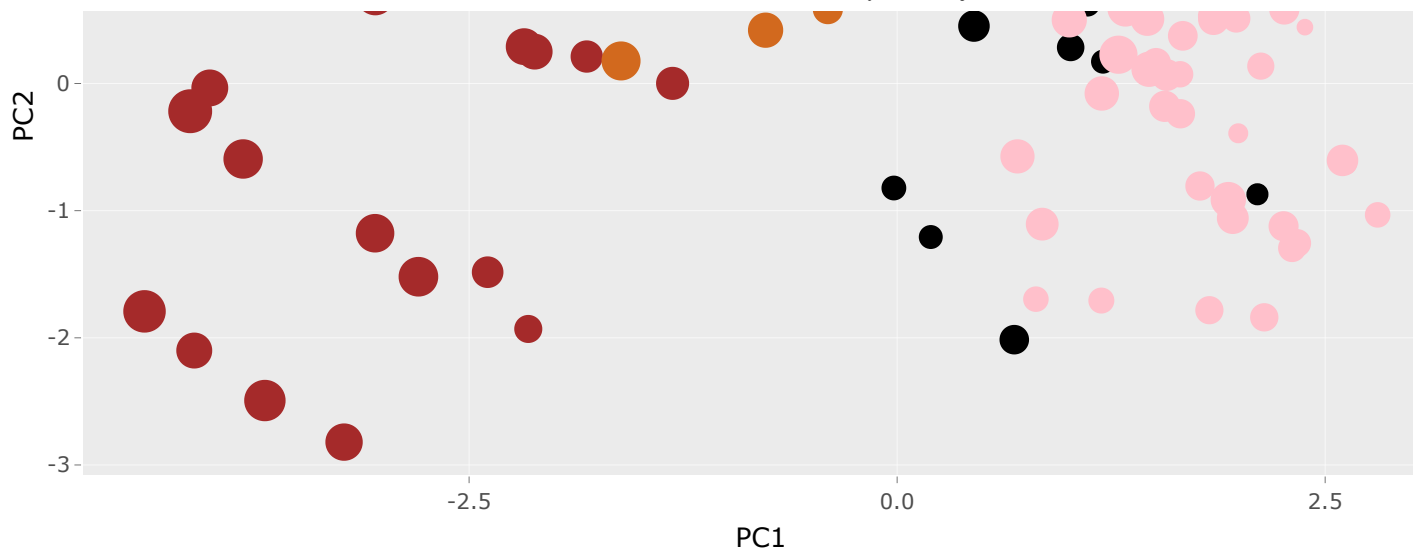
```
filter
```

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

```
layout
```

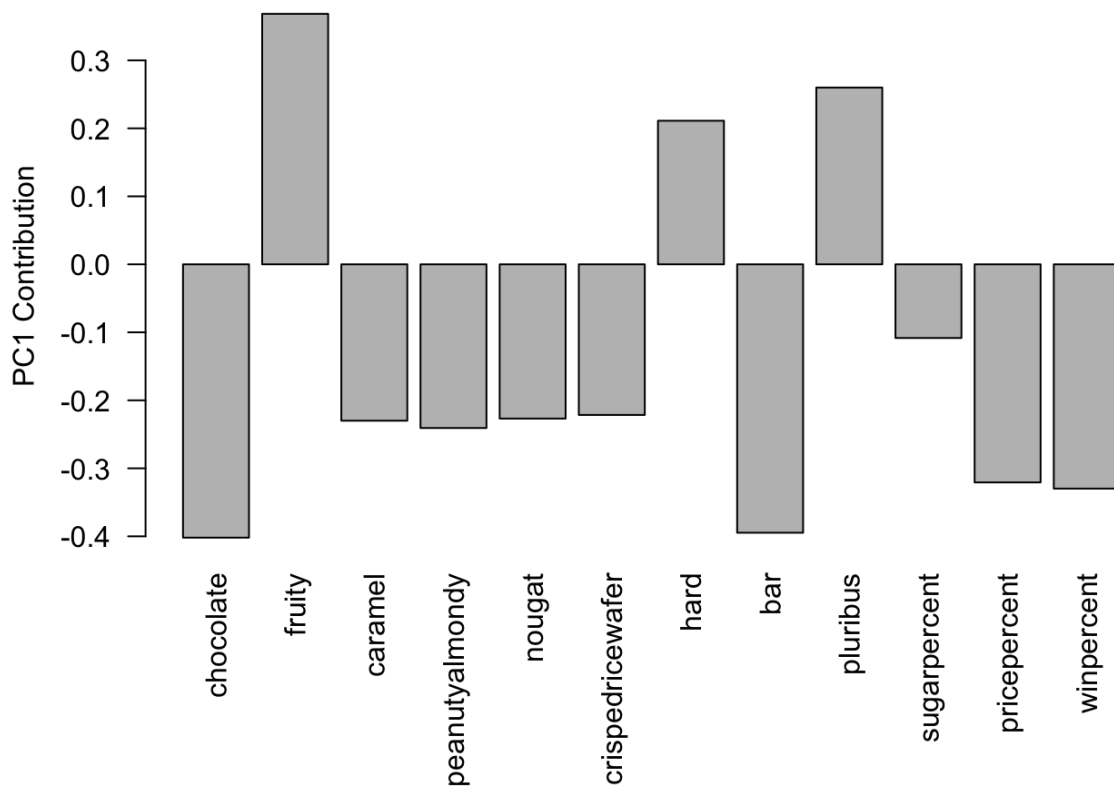
```
ggplotly(p)
```





We can wrap up by looking at the loadings of our PCA.

```
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 variables `fruity`, `hard`, and `pluribus` are associated positively with PC1.?? This signifies that these variables have a strong effect on PC1 and this makes sense when considering the types of candies that the variables represent.