

Class09: Candy Analysis Mini Project

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In today's class, we will examine some data about candy from the 538 website.

Import 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

Data exploration

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.

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

```
candy["Nerds",]$winpercent
```

```
[1] 55.35405
```

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
```

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

```
# Short cut syntax that tells R to go into package and execute the function  
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	

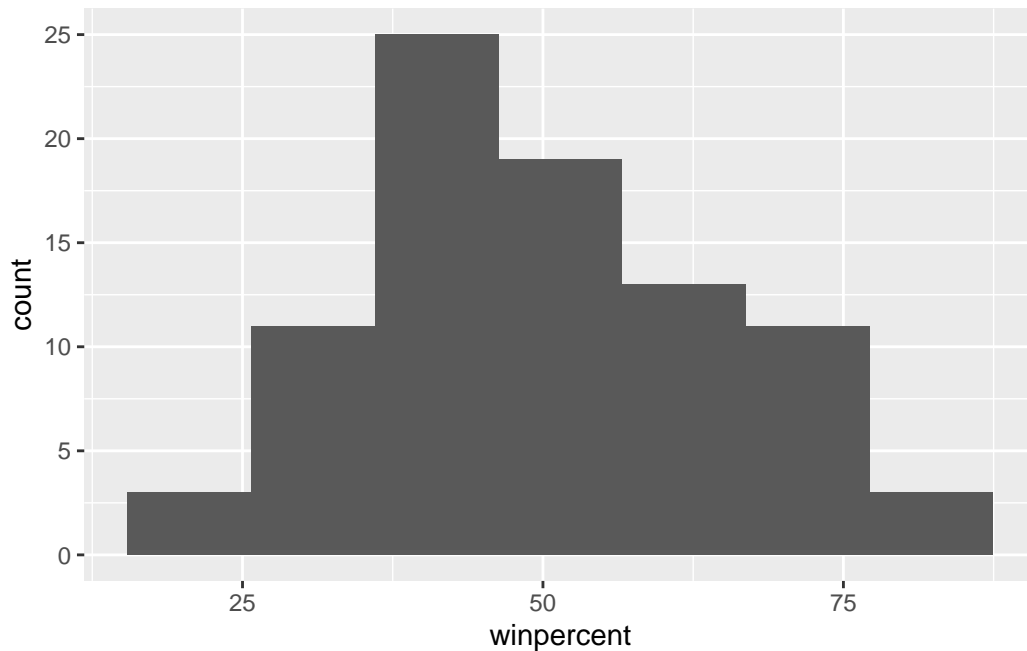
The winpercent variable is on a different scale than the other variables.

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

Zero represents that chocolate is not present, while 1 represents that chocolate is present in the candy.

Q8. Plot a histogram of winpercent values

```
library(ggplot2)
ggplot(candy) +
  aes(winpercent) +
  geom_histogram(bins=7)
```



Q9. Is the distribution of winpercent values symmetrical?

No, 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

The center is below 50%.

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

- First find all chocolate candy
- Then find their winpercent values
- Find the mean winpercent
- Then do the same for fruity candy and compare w/ the mean for chocolate candy

```
choc_winpercent <- candy$winpercent[as.logical(candy$chocolate)]
fruity_winpercent <- candy$winpercent[as.logical(candy$fruity)]
mean(choc_winpercent) > mean(fruity_winpercent)
```

```
[1] TRUE
```

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

```
[1] 60.92153
```

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

```
[1] 44.11974
```

```
mean(chocolate.win) > mean(fruity.win)
```

```
[1] TRUE
```

On average, chocolate candy is higher ranked than fruit candy (ie higher winpercent).

Q12. Is this difference statistically significant?

```
t.test(chocolate.win, fruity.win)
```

Welch Two Sample t-test

```
data: chocolate.win and fruity.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:
 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 of 2.871e-8 is less than .05.

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

```
x <- c(5,6,4)
sort(x)
```

```
[1] 4 5 6
```

```
order(x)
```

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

```
x[order(x)]
```

```
[1] 4 5 6
```

The order function returns the indices that make the input sorted.

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

```
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	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 5 least likely candy types in this set are Nik L Nip, Boston Baked Beans, Chiclets, Super Bubbles, and Jawbusters.

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

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

	chocolate	fruity	caramel	peanut	almond	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

	crisped	rice	wafer	hard	bar	pluribus	sugar	percent
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

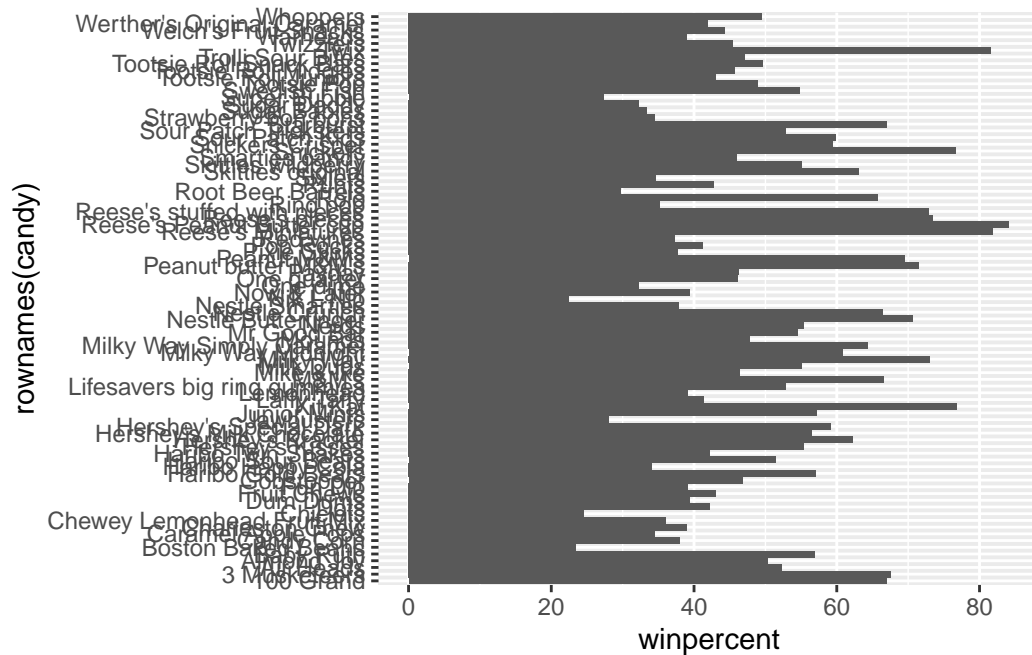
	price	percent	winpercent
Snickers	0.651	76.67	378
Kit Kat	0.511	76.76	860
Twix	0.906	81.64	291
Reese's Miniatures	0.279	81.86	626
Reese's Peanut Butter cup	0.651	84.18	029

The top 5 favorite candies 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.

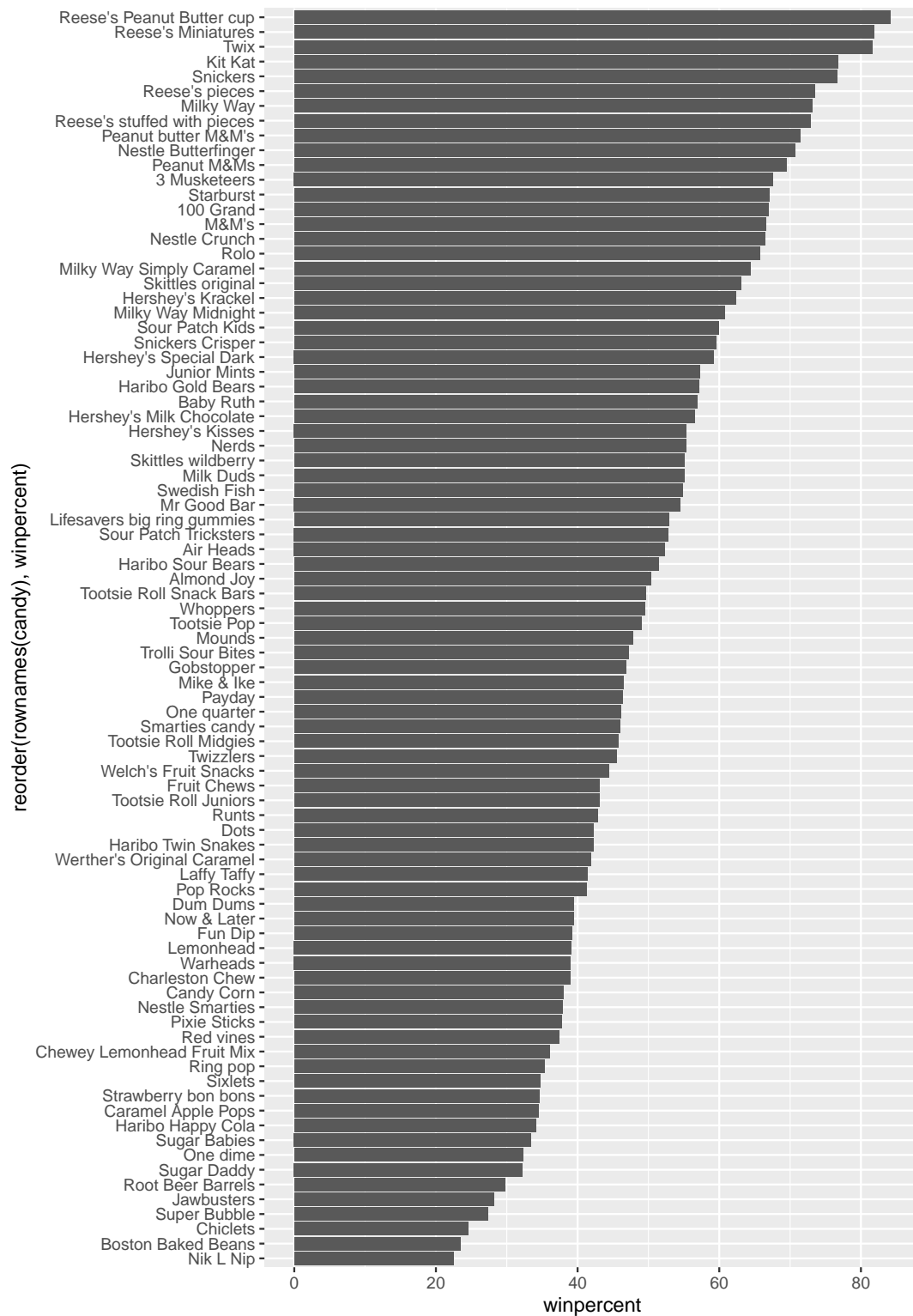
```
library(ggplot2)

ggplot(candy) +
  aes(x=winpercent, y=rownames(candy)) +
  geom_col()
```

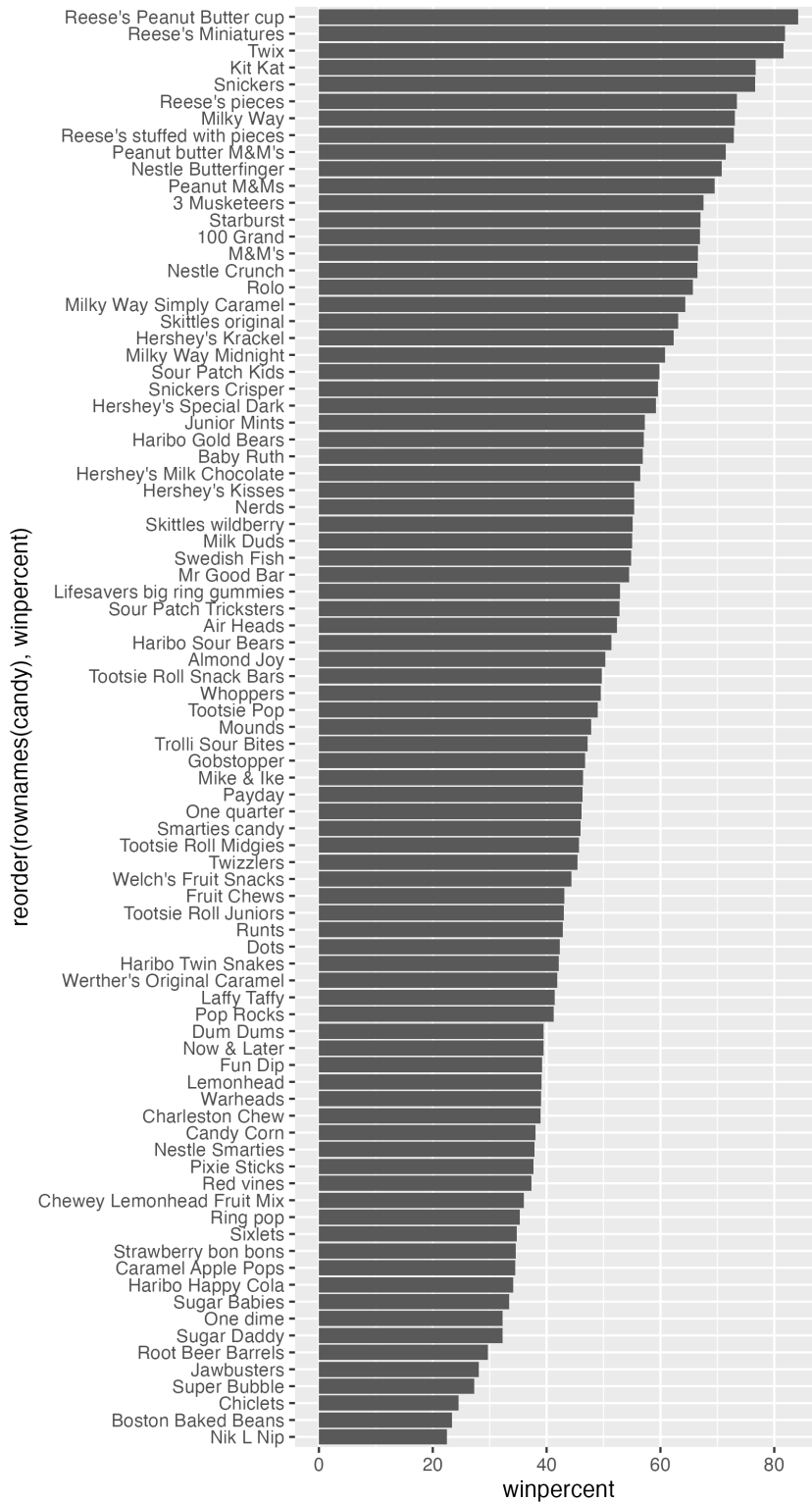
Q16. This is quite ugly, use the `reorder()` function to get the bars sorted by winpercent?

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



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

Saving 5.5 x 10 in image

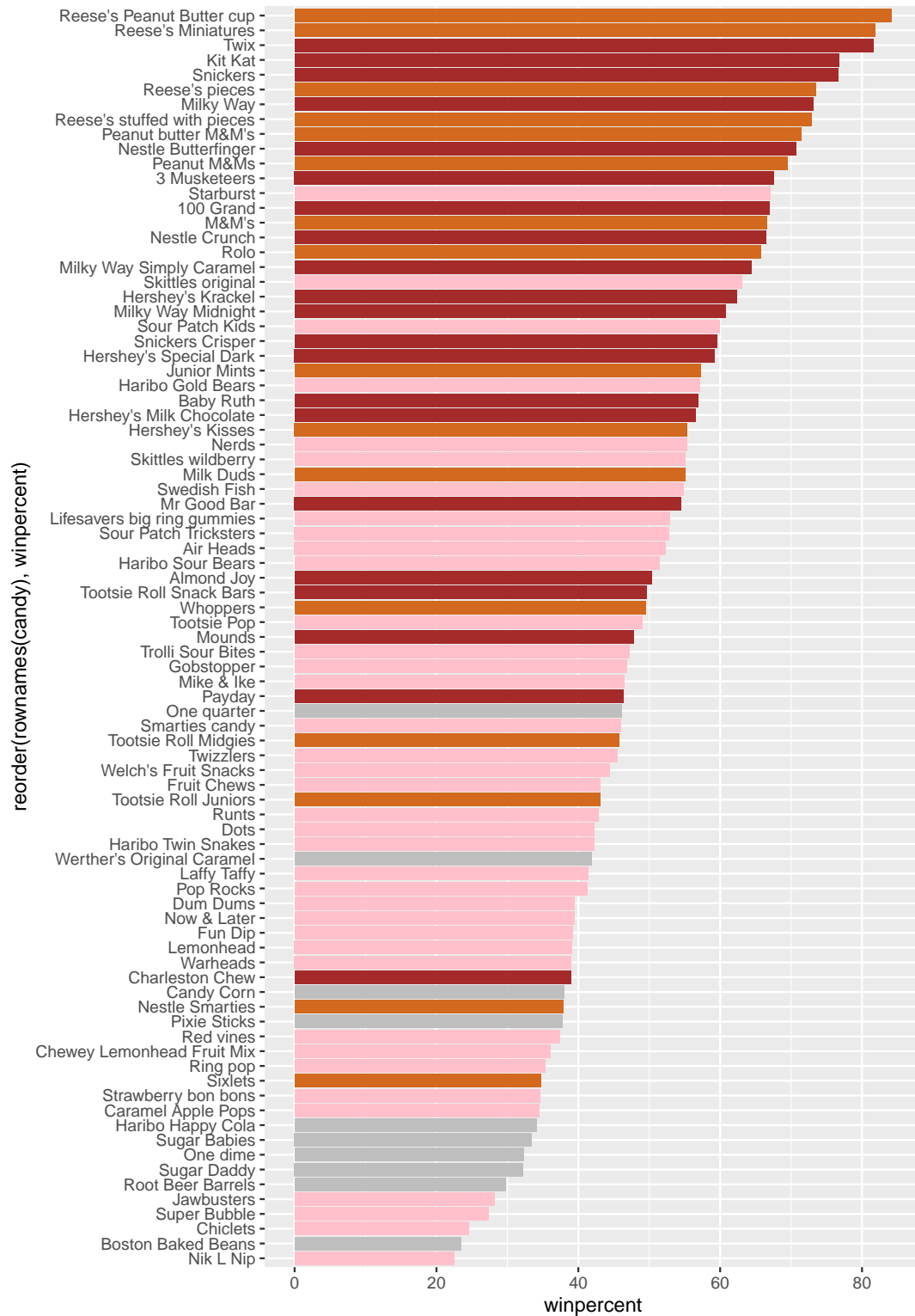


Adding my custom colors

to my bar plot

```
my_cols=rep("grey", nrow(candy))
my_cols[as.logical(candy$chocolate)] = "chocolate"
my_cols[as.logical(candy$bar)] = "brown"
my_cols[as.logical(candy$fruity)] = "pink"

ggplot(candy) +
  aes(winpercent, reorder(rownames(candy),winpercent)) +
  # `reorder(rownames(candy)), winpercent` reorders the candy row names by winpercent
  geom_col(fill=my_cols)
```



Q17. What is the worst ranked chocolate candy?

The worst ranked chocolate Sixlets.

Q18. What is the best ranked fruity candy?

The best ranked fruity candy is Starburst.

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?

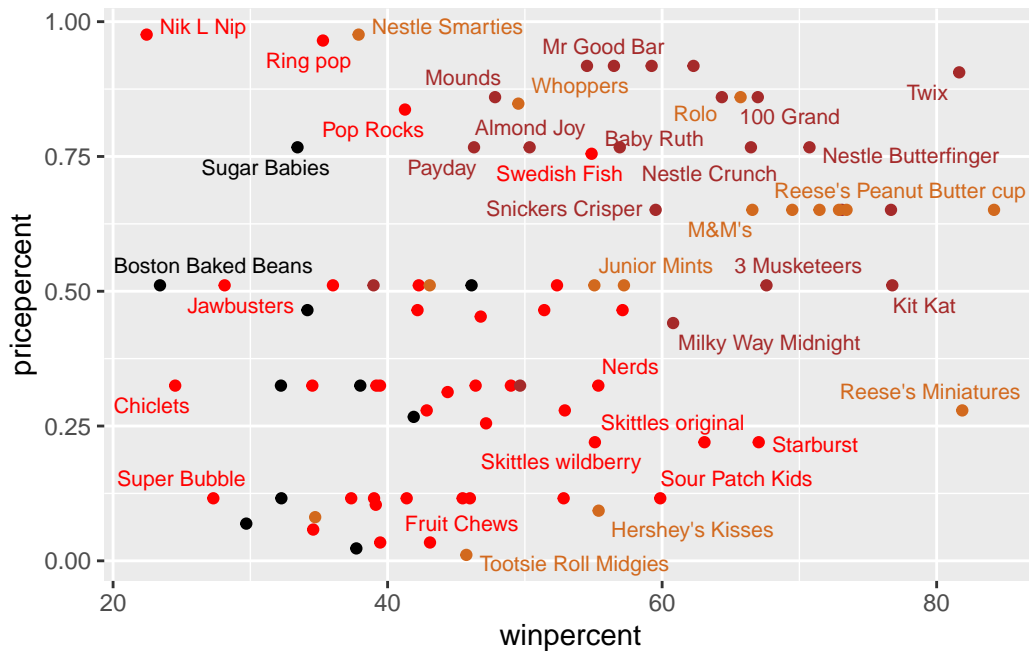
```
my_cols=rep("black", nrow(candy))
my_cols[as.logical(candy$chocolate)] = "chocolate"
my_cols[as.logical(candy$bar)] = "brown"
my_cols[as.logical(candy$fruity)] = "red"
```

We can use `ggrepel` package to do a better job of placing labels next to the data points.

```
library(ggrepel)

# How about a plot of price vs win
ggplot(candy) +
  aes(x=winpercent, y=pricepercent, label=rownames(candy)) +
  geom_point(col=my_cols) +
  geom_text_repel(col=my_cols, size=2.7, max.overlaps = 8)
```

Warning: ggrepel: 48 unlabeled data points (too many overlaps). Consider increasing max.overlaps



Reese's minatures give the most bang for your buck!

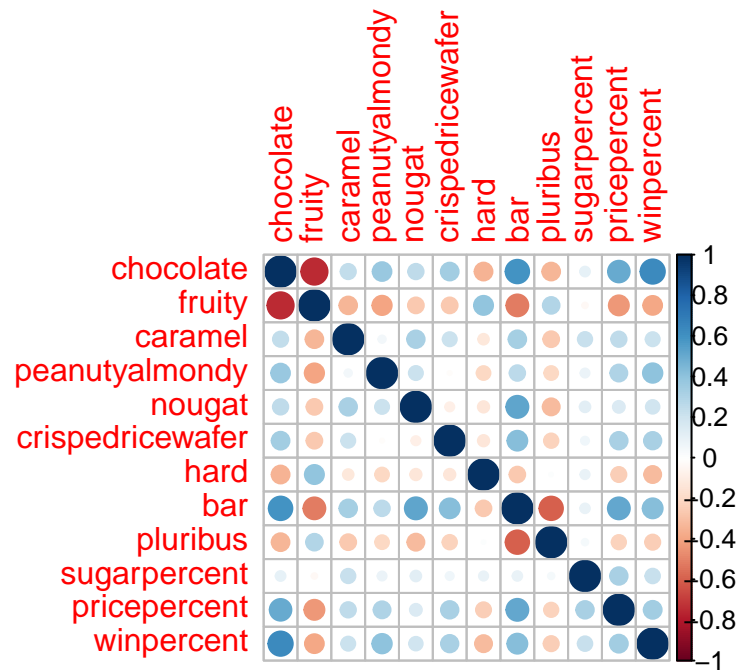
Q20. What are the top 5 most expensive candy types in the dataset and of these which is the least popular?

5 Exploring the correlation structure

```
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, and bar and pluribus are anti-correlated.

There's some redundancy in this correlation plot and PCA is better.

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

Bar and chocolate, chocolate and winpercent are the most positively correlated.

6 Principal Component Analysis

We will perform a PCA of the candy. Key question: do we need to scale the data before PCA?

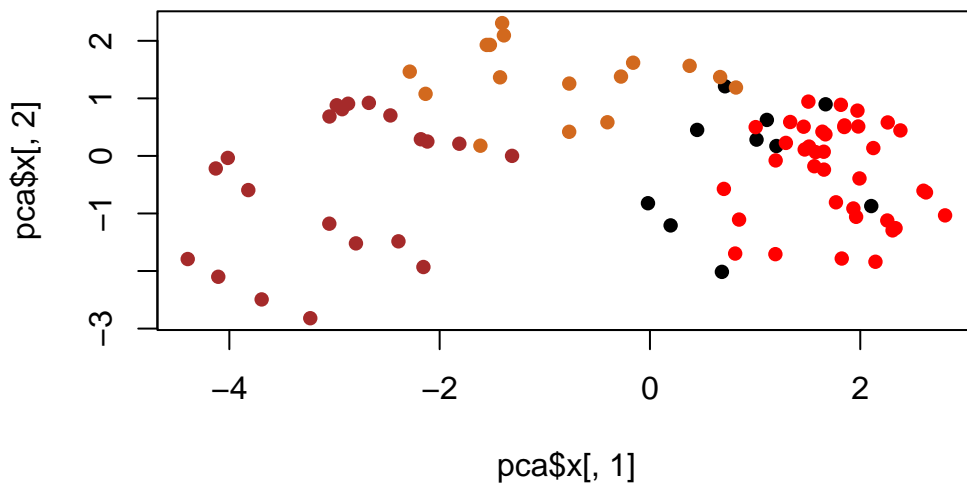
```
pca <- prcomp(candy, scale=TRUE)
summary(pca)
```

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		

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



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

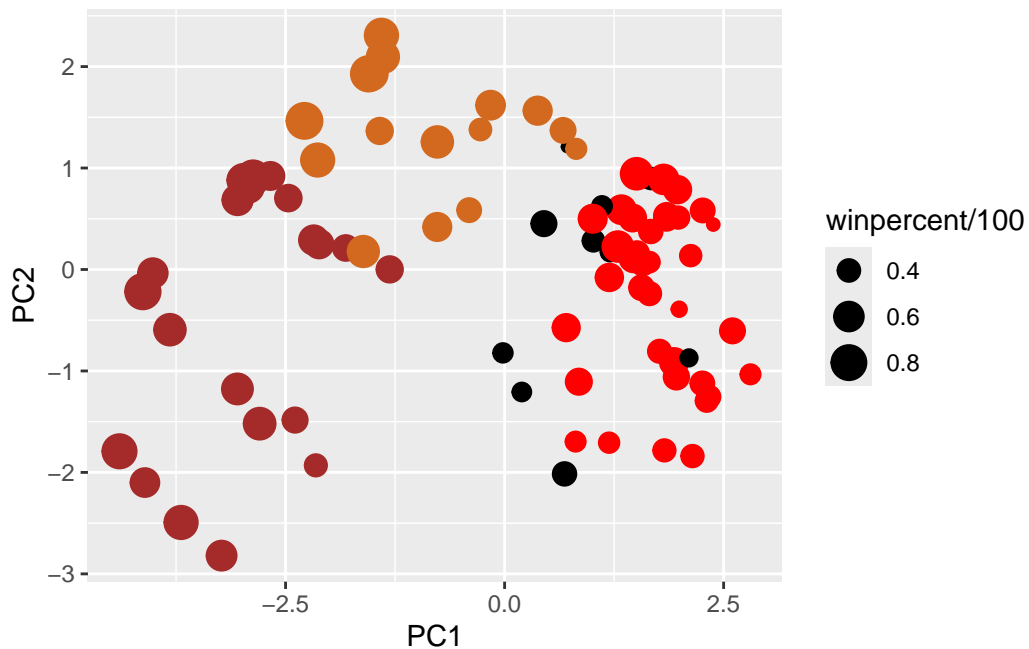
	chocolate	fruity	caramel	peanut	almond	nougat	crisp	rice	wafer
100 Grand	1	0	1		0	0			1
3 Musketeers	1	0	0		0	1			0
One dime	0	0	0		0	0			0
One quarter	0	0	0		0	0			0
Air Heads	0	1	0		0	0			0
Almond Joy	1	0	0		1	0			0
	hard bar	pluribus	sugarpercent	pricepercent	winpercent				PC1

100 Grand	0	1	0	0.732	0.860	66.97173	-3.8198617
3 Musketeers	0	1	0	0.604	0.511	67.60294	-2.7960236
One dime	0	0	0	0.011	0.116	32.26109	1.2025836
One quarter	0	0	0	0.011	0.511	46.11650	0.4486538
Air Heads	0	0	0	0.906	0.511	52.34146	0.7028992
Almond Joy	0	1	0	0.465	0.767	50.34755	-2.4683383

	PC2	PC3
100 Grand	-0.5935788	-2.1863087
3 Musketeers	-1.5196062	1.4121986
One dime	0.1718121	2.0607712
One quarter	0.4519736	1.4764928
Air Heads	-0.5731343	-0.9293893
Almond Joy	0.7035501	0.8581089

```
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)
```

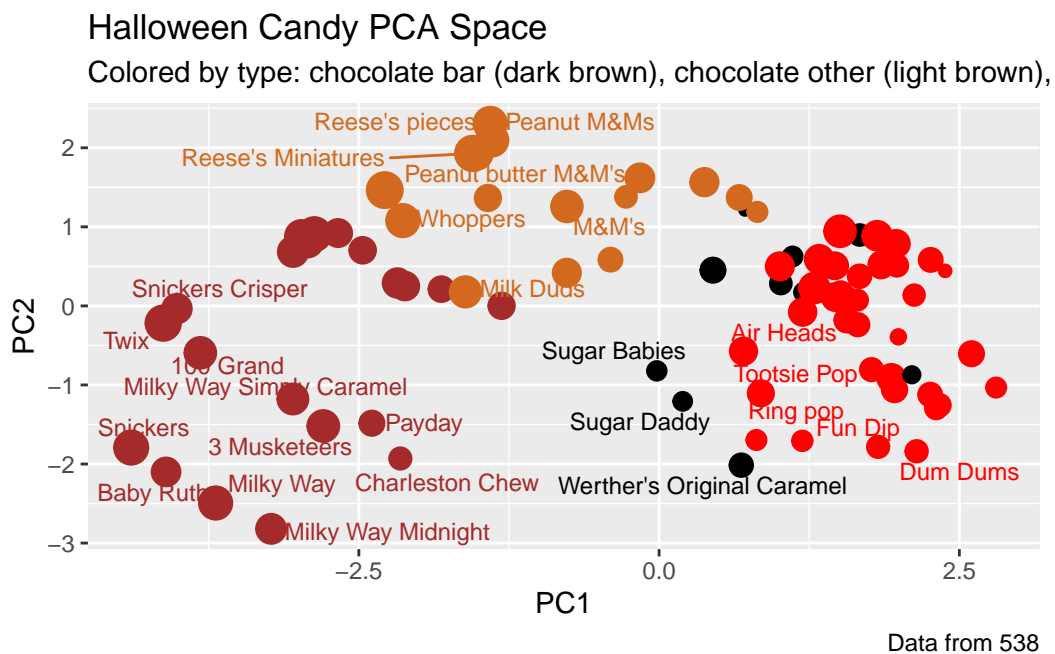
p



```
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)",
        caption="Data from 538")
```

Warning: ggrepel: 59 unlabeled data points (too many overlaps). Consider increasing max.overlaps



```
#library(plotly)
#ggplotly(p)
```

How do the original variables contribute to our PCs? For this, we look at the loadings component of our results object i.e. the `pca$rotation` object.

```
head(pca$rotation)
```

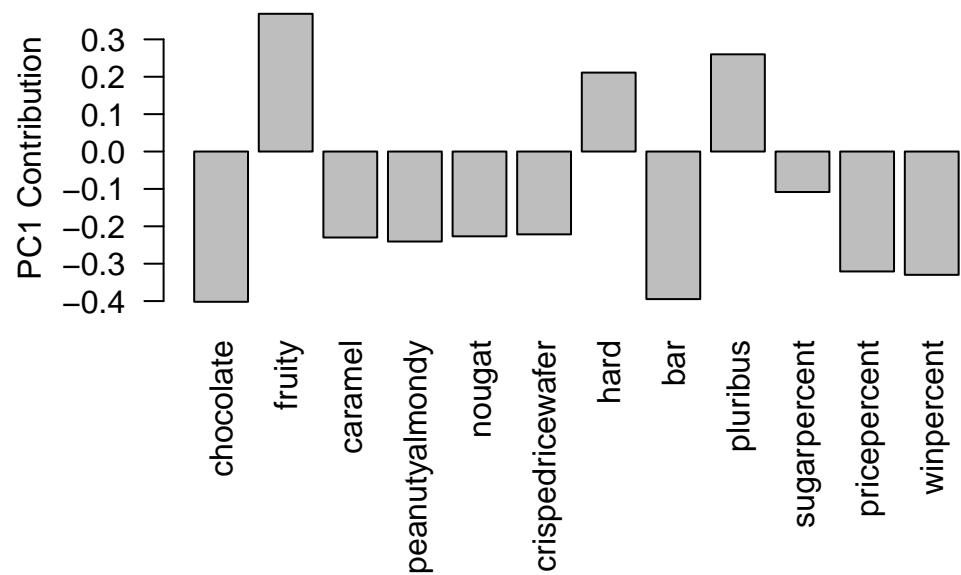
PC1 PC2 PC3 PC4 PC5

chocolate	-0.4019466	0.21404160	0.01601358	-0.016673032	0.06603585
fruity	0.3683883	-0.18304666	-0.13765612	-0.004479829	0.14353533
caramel	-0.2299709	-0.40349894	-0.13294166	-0.024889542	-0.50730150
peanutyalmondy	-0.2407155	0.22446919	0.18272802	0.466784287	0.39993025
nougat	-0.2268102	-0.47016599	0.33970244	0.299581403	-0.18885242
crispedricewafer	-0.2215182	0.09719527	-0.36485542	-0.605594730	0.03465232
	PC6	PC7	PC8	PC9	PC10
chocolate	-0.09018950	-0.08360642	-0.4908486	-0.151651568	0.10766136
fruity	-0.04266105	0.46147889	0.3980580	-0.001248306	0.36206250
caramel	-0.40346502	-0.44274741	0.2696345	0.019186442	0.22979901
peanutyalmondy	-0.09416259	-0.25710489	0.4577145	0.381068550	-0.14591236
nougat	0.09012643	0.36663902	-0.1879396	0.385278987	0.01132345
crispedricewafer	-0.09007640	0.13077042	0.1356774	0.511634999	-0.26481014
	PC11	PC12			
chocolate	0.1004528	0.69784924			
fruity	0.1749490	0.50624242			
caramel	0.1351582	0.07548984			
peanutyalmondy	0.1124428	0.12972756			
nougat	-0.3895447	0.09223698			
crispedricewafer	-0.2261562	0.11727369			

```

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

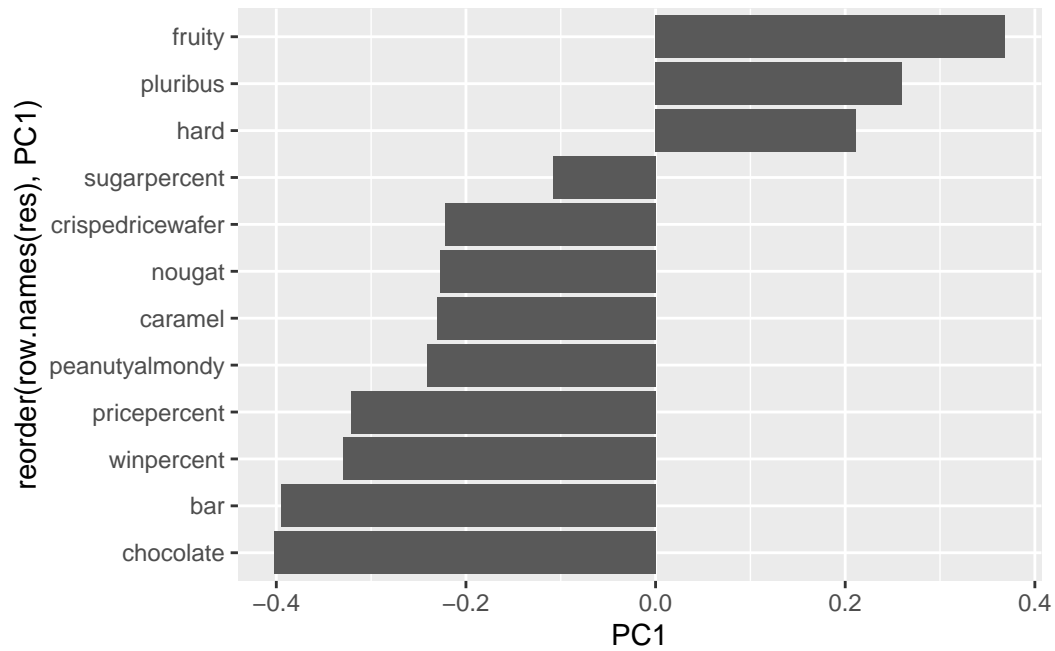
```



Make a bar plot with ggplot and order the bars by their value.

```
res <- pca$rotation

ggplot(res) +
  aes(PC1, reorder(row.names(res), PC1)) +
  geom_col()
```



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

The fruity, hard, and pluribus variables are picked up strongly by PC1 in the positive direction. This makes sense to me because based on the correlation structure in the dataset, if it is a fruity candy, then it will tend to be hard and come in a packet with multiple candies.