

Class 09: Halloween Mini Project

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

##Data Import

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

```
candy<- read.csv(candy_file, row.names=1)
```

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

```
dim(candy)
```

```
[1] 85 12
```

There are 85 different candy types in this dataset

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

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

```
[1] 38
```

There are 38 fruity candy types are in this dataset

What is your favorite candy?

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

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

```
[1] 81.64291
```

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

```
[1] 65.71629
```

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
```

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

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

Table 1: Data summary

Name	candy
Number of rows	85
Number of columns	12
<hr/>	
Column type frequency: numeric	12
<hr/>	
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: `candy$winpercent` is on a different scale to all others.

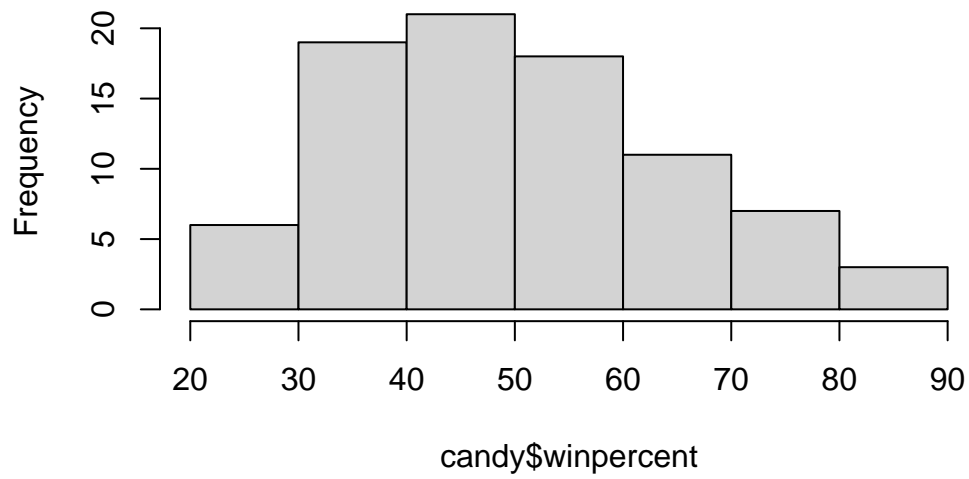
Q7. What do you think a zero and one represent for the `candy$chocolate` column?

The zero in the `candy$chocolate` column mean that that candy is not chocolate and then a 1 indicated that it is a chocolate

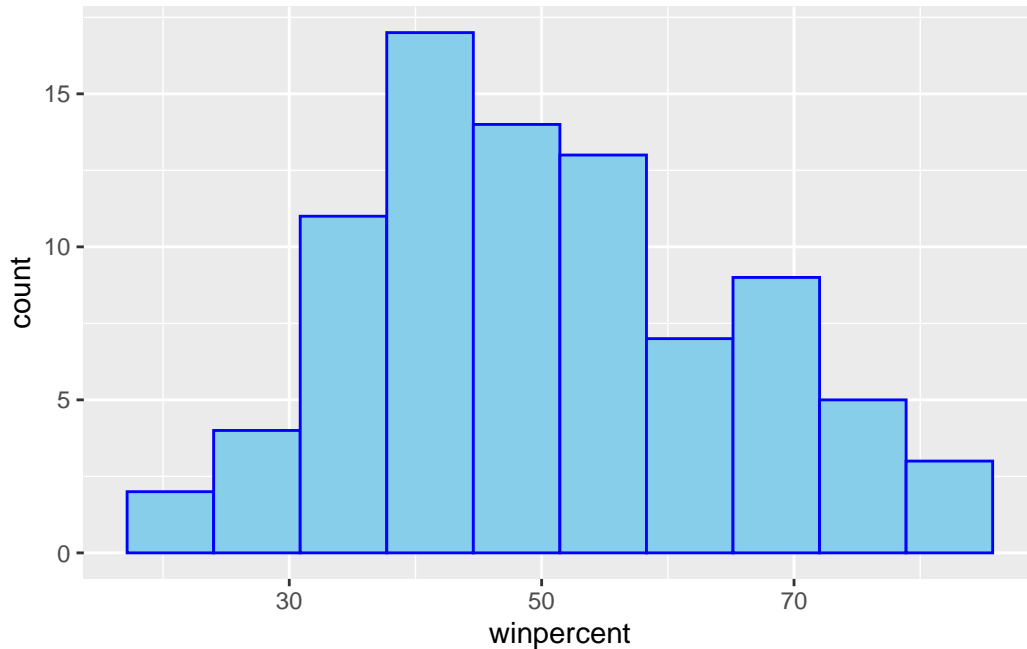
Q8. Plot a histogram of `winpercent` values

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

Histogram of candy\$winpercent



```
library(ggplot2)
ggplot(candy)+
  aes(winpercent)+
  geom_histogram(bins=10, color="blue", fill="skyblue")
```



Q9. Is the distribution of winpercent values symmetrical?

No

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?

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

```
[1] 66.97173 67.60294 50.34755 56.91455 38.97504 55.37545 62.28448 56.49050
[9] 59.23612 57.21925 76.76860 71.46505 66.57458 55.06407 73.09956 60.80070
[17] 64.35334 47.82975 54.52645 70.73564 66.47068 69.48379 81.86626 84.18029
[25] 73.43499 72.88790 65.71629 34.72200 37.88719 76.67378 59.52925 48.98265
[33] 43.06890 45.73675 49.65350 81.64291 49.52411
```

```
mean(choc.win)
```

```
[1] 60.92153
```

```
fruit.win<- candy[ as.logical(candy$fruity),]$winpercent  
mean(fruit.win)
```

```
[1] 44.11974
```

```
t.test(choc.win, fruit.win)
```

Welch Two Sample t-test

```
data:  choc.win and fruit.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
```

This tells us that chocolate is more liked than candy. Where it says mean of x that value is referring to chocolate, and then the mean of y is referring to candy. From there, we can see that the mean of x is larger, indicating that chocolate is more liked.

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

Yes with a P-value of 2.8713778×10^{-8} .

Q12. Is this difference statistically significant?

Yes it is statistically significant

3. 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)
```

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

```
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	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

These are the top five least liked candies

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

```
tail(candy[inds,],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	win	percent
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 top 5 candies in this dataset is snickers, Kit Kat, Twix, Reese's miniatures, and Reese's peanut butter cup.

```
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	percent
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

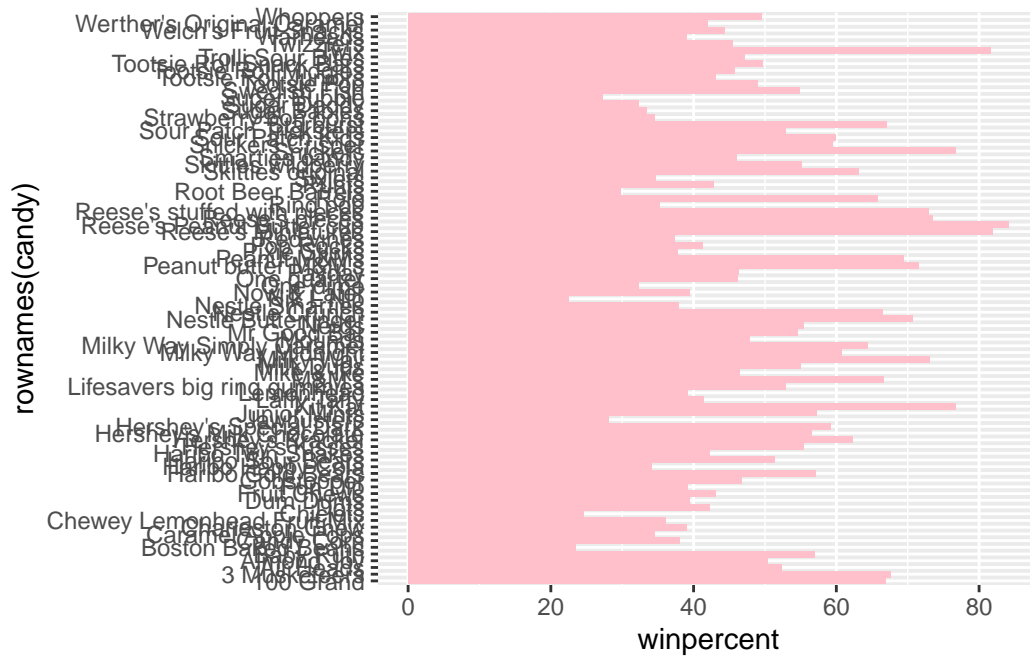
	price	percent	win	percent
Reese's Peanut Butter cup	0.651	84.18029		
Reese's Miniatures	0.279	81.86626		
Twix	0.906	81.64291		
Kit Kat	0.511	76.76860		

Snickers

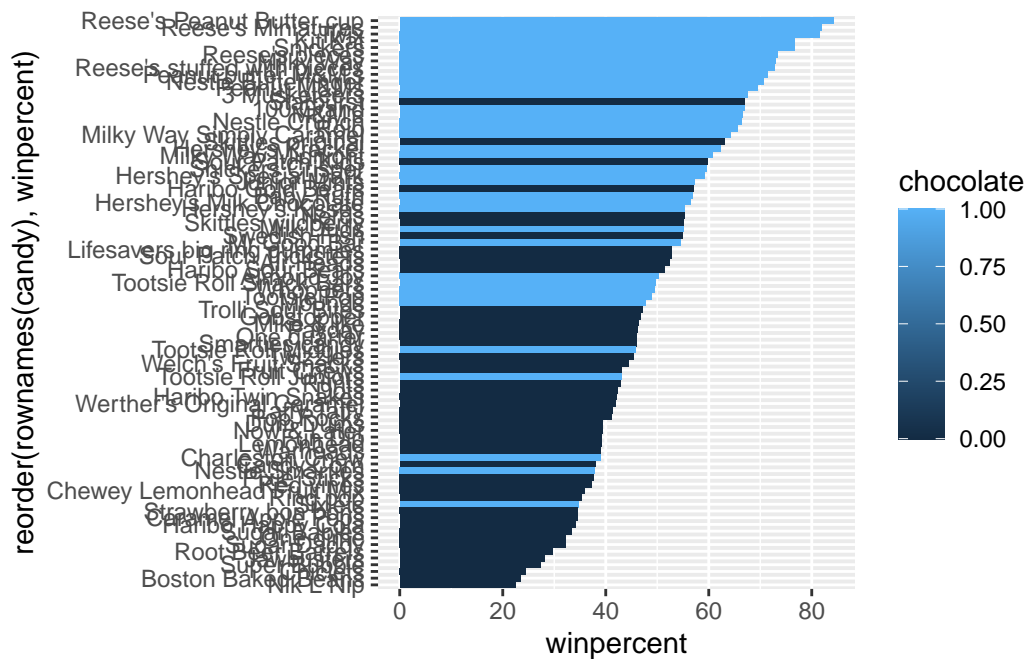
0.651 76.67378

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

```
ggplot(candy)+  
  aes(winpercent, rownames(candy))+  
  geom_col(fill="pink")
```

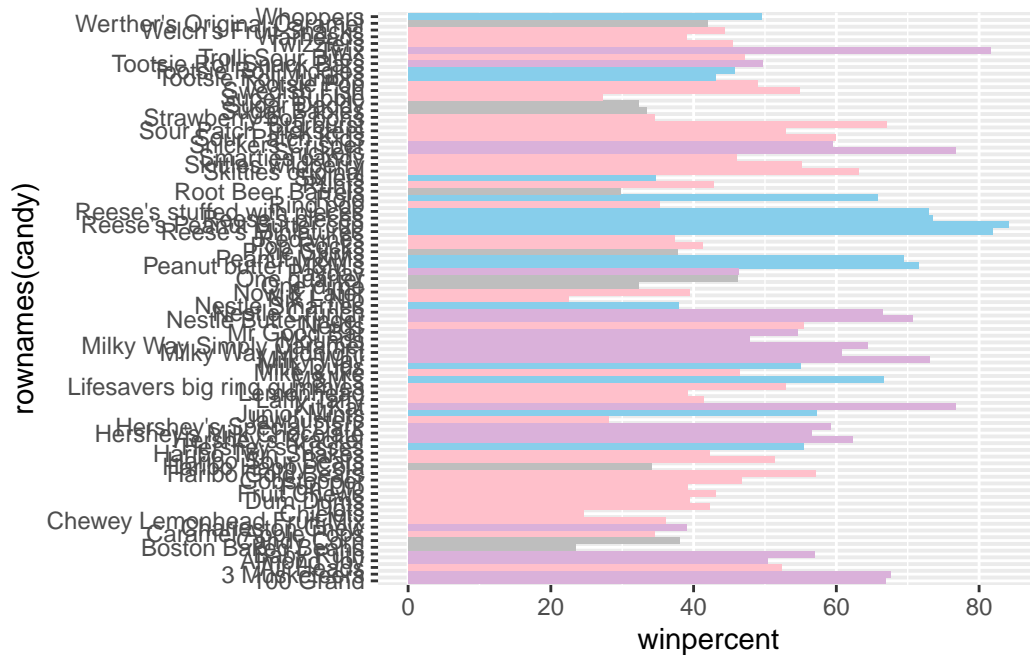


```
ggplot(candy)+  
  aes(x=winpercent, y=reorder(rownames(candy), winpercent), fill=chocolate)+  
  geom_col()
```



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

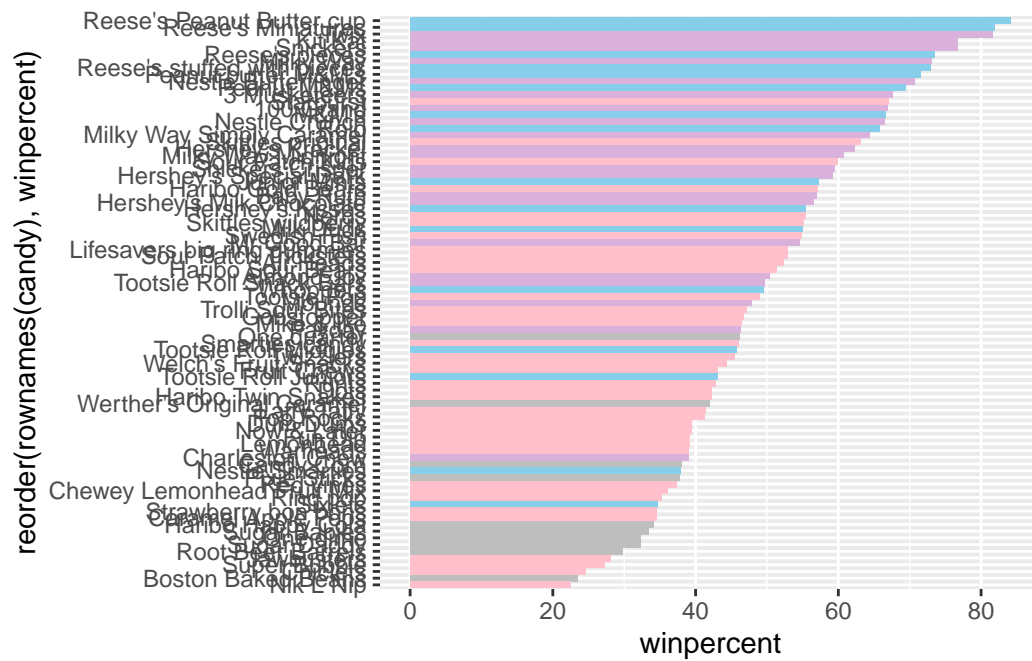
```
mycols<- rep("gray", nrow(candy))
mycols[as.logical(candy$chocolate)] <- "skyblue"
mycols[as.logical(candy$fruity)] <- "pink"
mycols[as.logical(candy$bar)] <- "#DAB1DA"
ggplot(candy)+
  aes(winpercent, rownames(candy))+
  geom_col(fill=mycols)
```



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

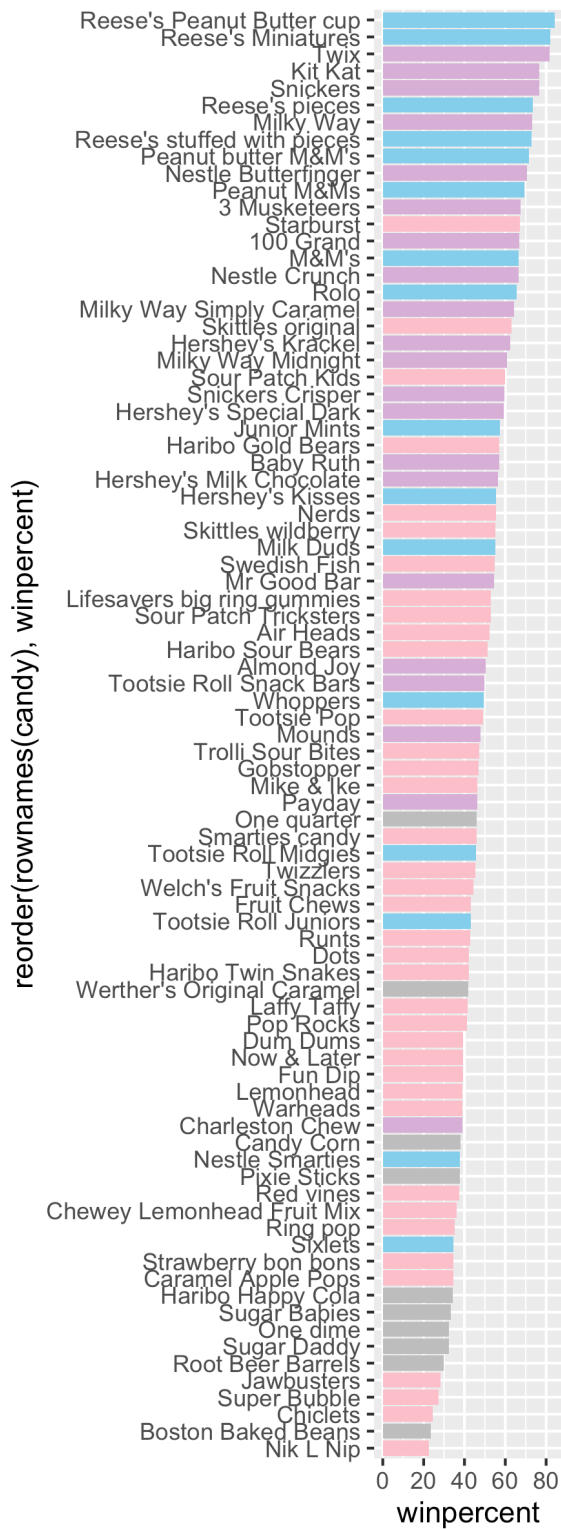
```
mycols<- rep("gray", nrow(candy))
mycols[as.logical(candy$chocolate)] <- "skyblue"
mycols[as.logical(candy$fruity)] <- "pink"
mycols[as.logical(candy$bar)] <- "#DAB1DA"

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



```
ggsave("mybarplot.png", width=3, height=8)
```

The pink represent the fruity candy and then the sky blue represents the chocolate



Q17. What is the worst ranked chocolate candy?

The worst ranked chocolate candy is Sixlet

Q18. What is the best ranked fruity candy?

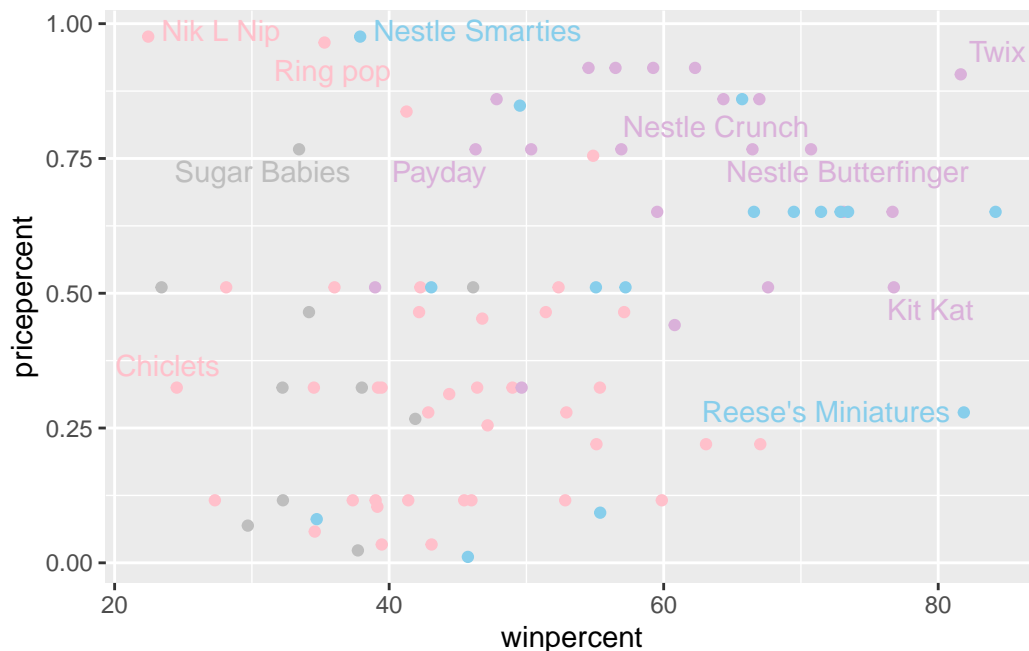
The best ranked fruity candy is Nik L Nip

4. Winpercent vs Pricepercent

```
mycols<- rep("gray", nrow(candy))
mycols[as.logical(candy$chocolate)] <- "skyblue"
mycols[as.logical(candy$fruity)] <- "pink"
mycols[as.logical(candy$bar)] <- "#DAB1DA"

library(ggrepel)
ggplot(candy) +
  aes(winpercent, pricepercent, label=rownames(candy)) +
  geom_point(col= mycols) +
  geom_text_repel(col= mycols, size=3.75, max.overlaps = 5)
```

Warning: ggrepel: 74 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

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

The top 5 most expensive candy types is Nik L Nip, Ring pop, Sugar Babies, Nestle Smarties, Pop rock

5. 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

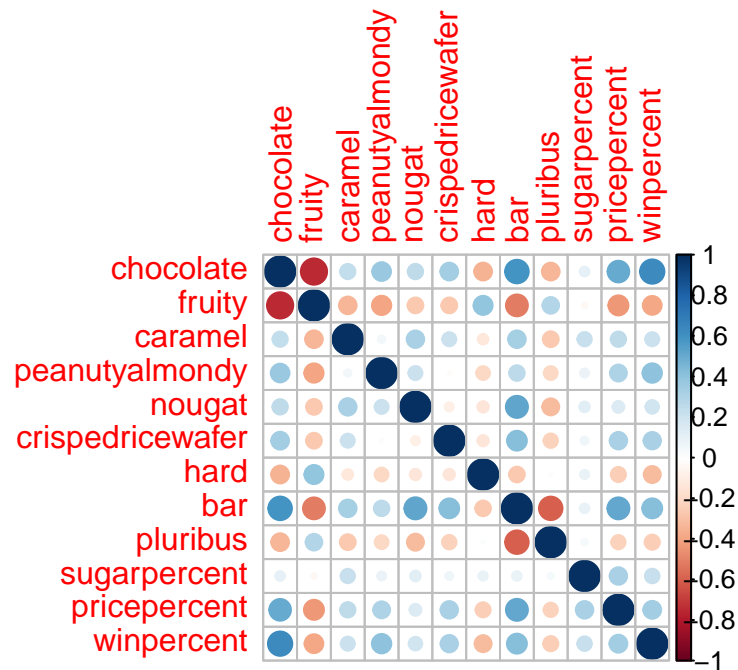
	crispedricewafer	hard	bar	pluribus
chocolate	0.34120978	-0.34417691	0.59742114	-0.33967519
fruity	-0.26936712	0.39067750	-0.51506558	0.29972522
caramel	0.21311310	-0.12235513	0.33396002	-0.26958501
peanutyalmondy	-0.01764631	-0.20555661	0.26041960	-0.20610932
nougat	-0.08974359	-0.13867505	0.52297636	-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 are negatively correlated

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

```
[1] -0.74
```

The two in the code above gives us two decimal places if we ran it without the 2 we would get a value of -1

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

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

```
[1] 0.6
```

Principle 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 other in the data set

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

Importance of components:

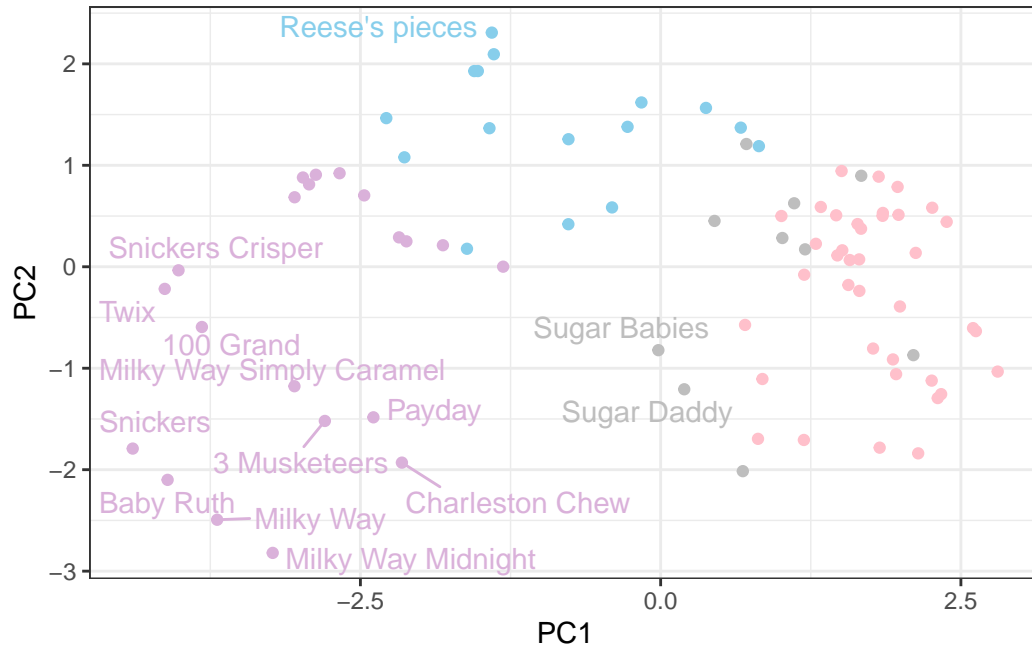
	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	2.0788	1.1378	1.1092	1.07533	0.9518	0.81923	0.81530
Proportion of Variance	0.3601	0.1079	0.1025	0.09636	0.0755	0.05593	0.05539
Cumulative Proportion	0.3601	0.4680	0.5705	0.66688	0.7424	0.79830	0.85369

	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

The first PCA captures 36% variance

```
library(ggrepel)
ggplot(pca$x)+
  aes(PC1, PC2, label=rownames(pca$x))+
  geom_point(col=mycols) +
  geom_text_repel(col= mycols, size=3.75, max.overlaps = 5)+
  theme_bw()
```

Warning: ggrepel: 71 unlabeled data points (too many overlaps). Consider increasing max.overlaps



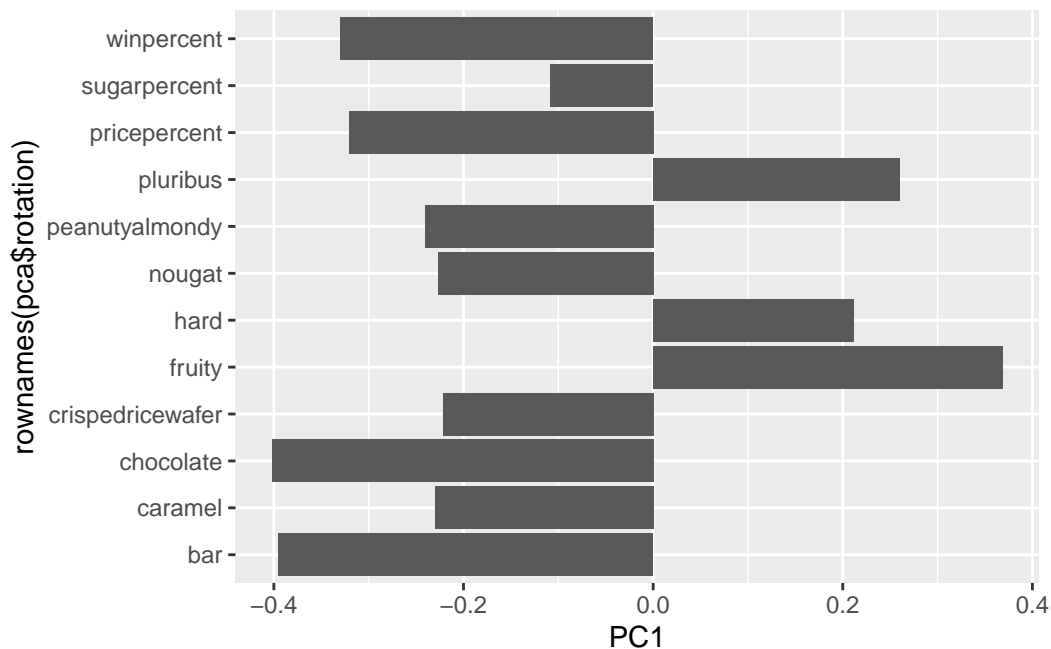
The second main PCA result is in the `pca$rotation` we can plot this to generate a so-called “loading” plot.

`pca$rotation`

	PC1	PC2	PC3	PC4	PC5
chocolate	-0.4019466	0.21404160	0.01601358	-0.016673032	0.066035846
fruity	0.3683883	-0.18304666	-0.13765612	-0.004479829	0.143535325
caramel	-0.2299709	-0.40349894	-0.13294166	-0.024889542	-0.507301501
peanutyalmondy	-0.2407155	0.22446919	0.18272802	0.466784287	0.399930245
nougat	-0.2268102	-0.47016599	0.33970244	0.299581403	-0.188852418
crispedricewafer	-0.2215182	0.09719527	-0.36485542	-0.605594730	0.034652316
hard	0.2111587	-0.43262603	-0.20295368	-0.032249660	0.574557816
bar	-0.3947433	-0.22255618	0.10696092	-0.186914549	0.077794806
pluribus	0.2600041	0.36920922	-0.26813772	0.287246604	-0.392796479
sugarpercent	-0.1083088	-0.23647379	-0.65509692	0.433896248	0.007469103
pricepercent	-0.3207361	0.05883628	-0.33048843	0.063557149	0.043358887
winpercent	-0.3298035	0.21115347	-0.13531766	0.117930997	0.168755073
	PC6	PC7	PC8	PC9	PC10
chocolate	-0.09018950	-0.08360642	-0.49084856	-0.151651568	0.107661356
fruity	-0.04266105	0.46147889	0.39805802	-0.001248306	0.362062502
caramel	-0.40346502	-0.44274741	0.26963447	0.019186442	0.229799010
peanutyalmondy	-0.09416259	-0.25710489	0.45771445	0.381068550	-0.145912362

nougat	0.09012643	0.36663902	-0.18793955	0.385278987	0.011323453
crispedricewafer	-0.09007640	0.13077042	0.13567736	0.511634999	-0.264810144
hard	-0.12767365	-0.31933477	-0.38881683	0.258154433	0.220779142
bar	0.25307332	0.24192992	-0.02982691	0.091872886	-0.003232321
pluribus	0.03184932	0.04066352	-0.28652547	0.529954405	0.199303452
sugarpercent	0.02737834	0.14721840	-0.04114076	-0.217685759	-0.488103337
pricepercent	0.62908570	-0.14308215	0.16722078	-0.048991557	0.507716043
winpercent	-0.56947283	0.40260385	-0.02936405	-0.124440117	0.358431235
	PC11	PC12			
chocolate	0.10045278	0.69784924			
fruity	0.17494902	0.50624242			
caramel	0.13515820	0.07548984			
peanutyalmondy	0.11244275	0.12972756			
nougat	-0.38954473	0.09223698			
crispedricewafer	-0.22615618	0.11727369			
hard	0.01342330	-0.10430092			
bar	0.74956878	-0.22010569			
pluribus	0.27971527	-0.06169246			
sugarpercent	0.05373286	0.04733985			
pricepercent	-0.26396582	-0.06698291			
winpercent	-0.11251626	-0.37693153			

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

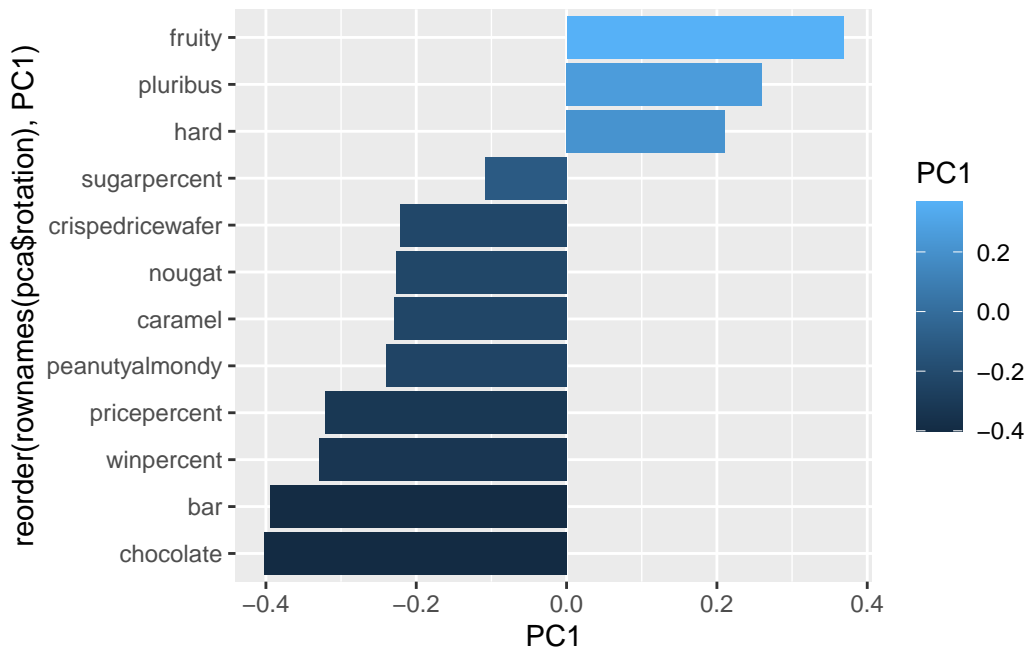


pca\$rotation

	PC1	PC2	PC3	PC4	PC5
chocolate	-0.4019466	0.21404160	0.01601358	-0.016673032	0.066035846
fruity	0.3683883	-0.18304666	-0.13765612	-0.004479829	0.143535325
caramel	-0.2299709	-0.40349894	-0.13294166	-0.024889542	-0.507301501
peanutyalmondy	-0.2407155	0.22446919	0.18272802	0.466784287	0.399930245
nougat	-0.2268102	-0.47016599	0.33970244	0.299581403	-0.188852418
crispedricewafer	-0.2215182	0.09719527	-0.36485542	-0.605594730	0.034652316
hard	0.2111587	-0.43262603	-0.20295368	-0.032249660	0.574557816
bar	-0.3947433	-0.22255618	0.10696092	-0.186914549	0.077794806
pluribus	0.2600041	0.36920922	-0.26813772	0.287246604	-0.392796479
sugarpercent	-0.1083088	-0.23647379	-0.65509692	0.433896248	0.007469103
pricepercent	-0.3207361	0.05883628	-0.33048843	0.063557149	0.043358887
winpercent	-0.3298035	0.21115347	-0.13531766	0.117930997	0.168755073
	PC6	PC7	PC8	PC9	PC10
chocolate	-0.09018950	-0.08360642	-0.49084856	-0.151651568	0.107661356
fruity	-0.04266105	0.46147889	0.39805802	-0.001248306	0.362062502
caramel	-0.40346502	-0.44274741	0.26963447	0.019186442	0.229799010
peanutyalmondy	-0.09416259	-0.25710489	0.45771445	0.381068550	-0.145912362
nougat	0.09012643	0.36663902	-0.18793955	0.385278987	0.011323453
crispedricewafer	-0.09007640	0.13077042	0.13567736	0.511634999	-0.264810144

hard	-0.12767365	-0.31933477	-0.38881683	0.258154433	0.220779142
bar	0.25307332	0.24192992	-0.02982691	0.091872886	-0.003232321
pluribus	0.03184932	0.04066352	-0.28652547	0.529954405	0.199303452
sugarpercent	0.02737834	0.14721840	-0.04114076	-0.217685759	-0.488103337
pricepercent	0.62908570	-0.14308215	0.16722078	-0.048991557	0.507716043
winpercent	-0.56947283	0.40260385	-0.02936405	-0.124440117	0.358431235
	PC11	PC12			
chocolate	0.10045278	0.69784924			
fruity	0.17494902	0.50624242			
caramel	0.13515820	0.07548984			
peanutyalmondy	0.11244275	0.12972756			
nougat	-0.38954473	0.09223698			
crispedricewafer	-0.22615618	0.11727369			
hard	0.01342330	-0.10430092			
bar	0.74956878	-0.22010569			
pluribus	0.27971527	-0.06169246			
sugarpercent	0.05373286	0.04733985			
pricepercent	-0.26396582	-0.06698291			
winpercent	-0.11251626	-0.37693153			

```
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 graph shows that fruity, pluribus, and hard are all positively correlated and the for the bars on the other side such as sugarpercent, nougat, etc are all negatively correlated