

Class 9: Candy Mini-Project

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Background

In this project, we are going to look at data from a website which asked its readers to pick their favorite candies. We are going to explore this dataset and figure out some trends among the candies. By the end, I should be able to predict what candy you may like based off your favorite ones.

Importing the Candy Data

First we need to import the dataset into R. Remember we need to make sure the candy names are not supposed to be a column so we set the `row.names=1`.

```
candy_file <- "https://raw.githubusercontent.com/fivethirtyeight/data/master/candy-power-ranking.csv"
candy = read.csv(candy_file, row.names=1)
head(candy)
```

	chocolate	fruity	caramel	peanuty	almondy	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	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

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

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

[1] 38

Within the dataset, there is a variable named **winpercent**, a percentage of people who prefer this candy over another randomly chosen candy from the dataset

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

[1] 81.64291

Q3. What is your favorite candy (other than Twix) in the dataset and what is it's winpercent value?

```
candy["Reese's Peanut Butter cup", ]$winpercent
```

[1] 84.18029

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”?

The win percent value for tootsie roll snack bars is 49.653503

N.B The skim package can be helpful in quick analysis of a data set.

```
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	
peanutyalmond	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	
crispedrice-wafer	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	

skim_vari- able	n_miss- ing	com- plete_rate	mean	sd	p0	p25	p50	p75	p100	hist
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?

Yes, the `winpercent` variable appears to be on a different scale from the other columns. Its mean is 50.31676381 while the others under 1.

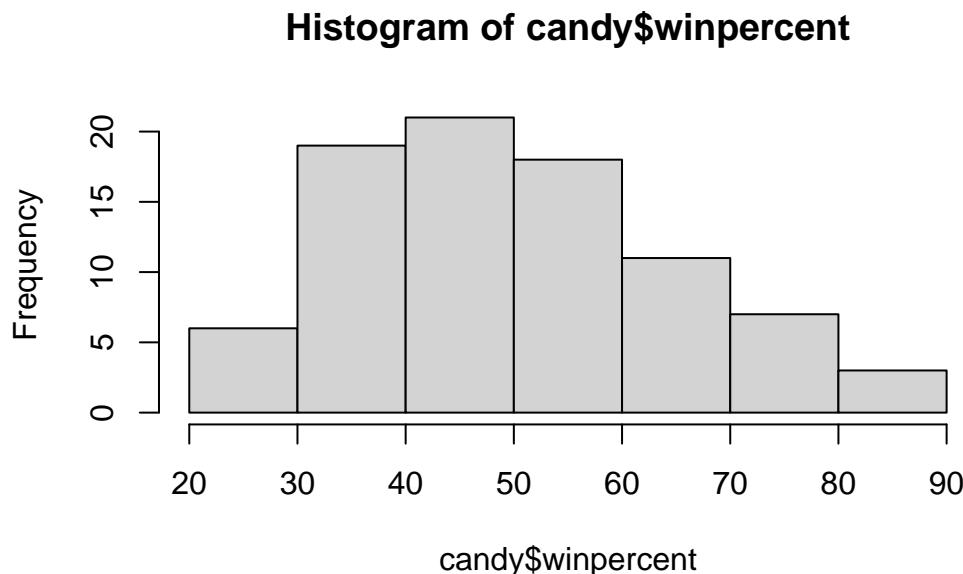
Q7. What do you think a zero and one represent for the `candy$chocolate` column?

The 0 and 1 likely represent binary, which means that the 0 or 1s are true or false. In this data set, a 1 would mean that the candy has some sort chocolate apart of it.

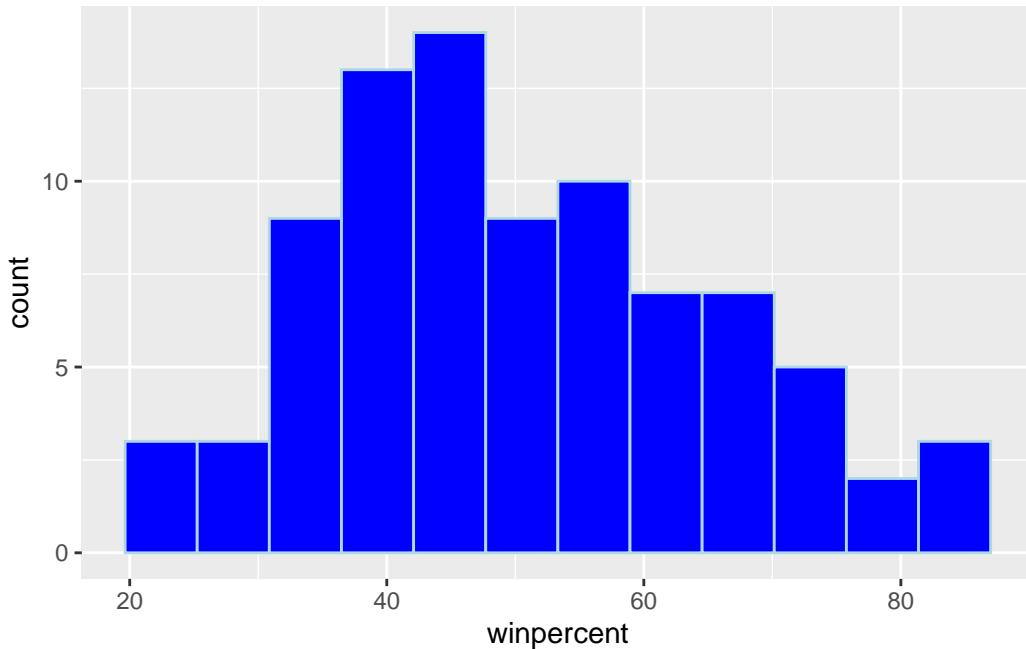
Exploratory analysis

Q8. Plot a histogram of `winpercent` values using both base R an ggplot2.

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



```
library(ggplot2)
ggplot(candy, aes(winpercent)) +
  geom_histogram(bins=12, fill="blue", col="light blue")
```



Q9. Is the distribution of winpercent values symmetrical?

The distribution of winpercent value is not symmetrical. Most of the candies fall between 35-50%. It is apparent in both histograms there is a longer tail on the right end.

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

```
mean(candy$winpercent)
```

[1] 50.31676

The center of the distribution is above 50% with a mean of 50.31676.

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

```
mean(candy$winpercent[candy$chocolate == 1])
```

[1] 60.92153

```
mean(candy$winpercent[candy$fruity == 1])
```

```
[1] 44.11974
```

On average, chocolate candy is higher ranked than fruit candy with a mean winpercent of 60.9215294 compared to the mean of fruit, 44.1197414.

Q12. Is this difference statistically significant?

```
t.test(candy$winpercent[candy$chocolate == 1],  
       candy$winpercent[candy$fruity == 1])
```

Welch Two Sample t-test

```
data: candy$winpercent[candy$chocolate == 1] and candy$winpercent[candy$fruity == 1]  
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
```

Based on the `t.test()` the difference of percents is statistically significant. The p-value of the test was 2.871e-08 which is far below the significance threshold of 0.05.

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	0
Boston Baked Beans	0	0	0	1	0	0
Chiclets	0	1	0	0	0	0
Super Bubble	0	1	0	0	0	0

Jawbusters	0	1	0	0	0	0	0
	crispedrice	wafers	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						

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

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

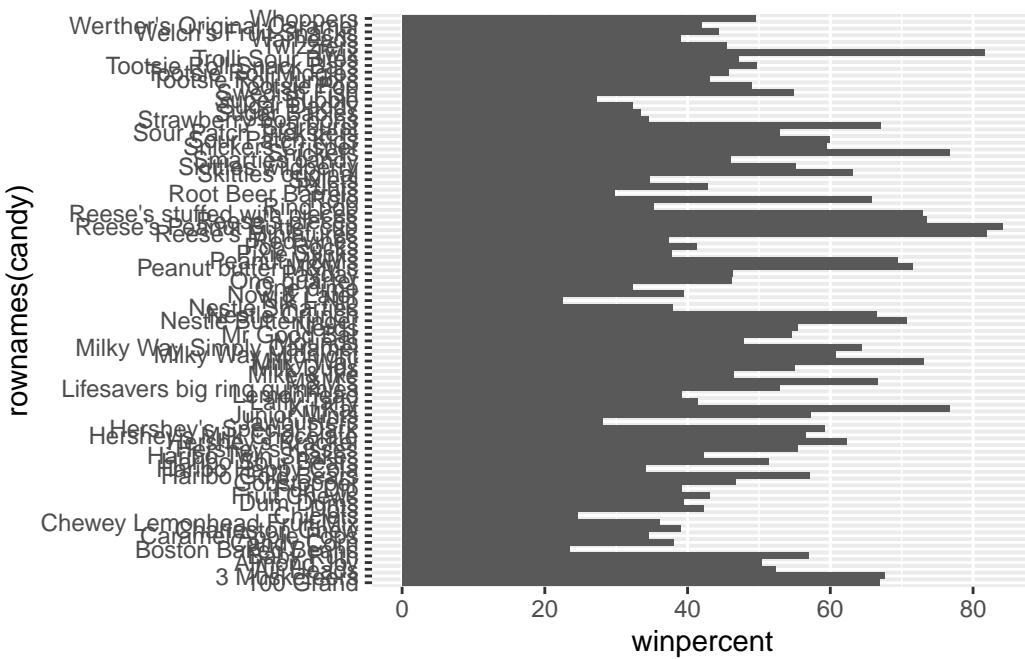
	chocolate	fruity	caramel	peanut	almond	nougat
Reese's Peanut Butter cup	1	0	0	1	0	
Reese's Miniatures	1	0	0	1	0	
Twix	1	0	1	0	0	
Kit Kat	1	0	0	0	0	
Snickers	1	0	1	1	1	
	crispedrice	wafers	hard	bar	pluribus	sugarpercent
Reese's Peanut Butter cup	0	0	0	0		0.720
Reese's Miniatures	0	0	0	0		0.034
Twix	1	0	1	0		0.546
Kit Kat	1	0	1	0		0.313
Snickers	0	0	1	0		0.546
	pricepercent	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.

```
library(ggplot2)

ggplot(candy) +
```

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

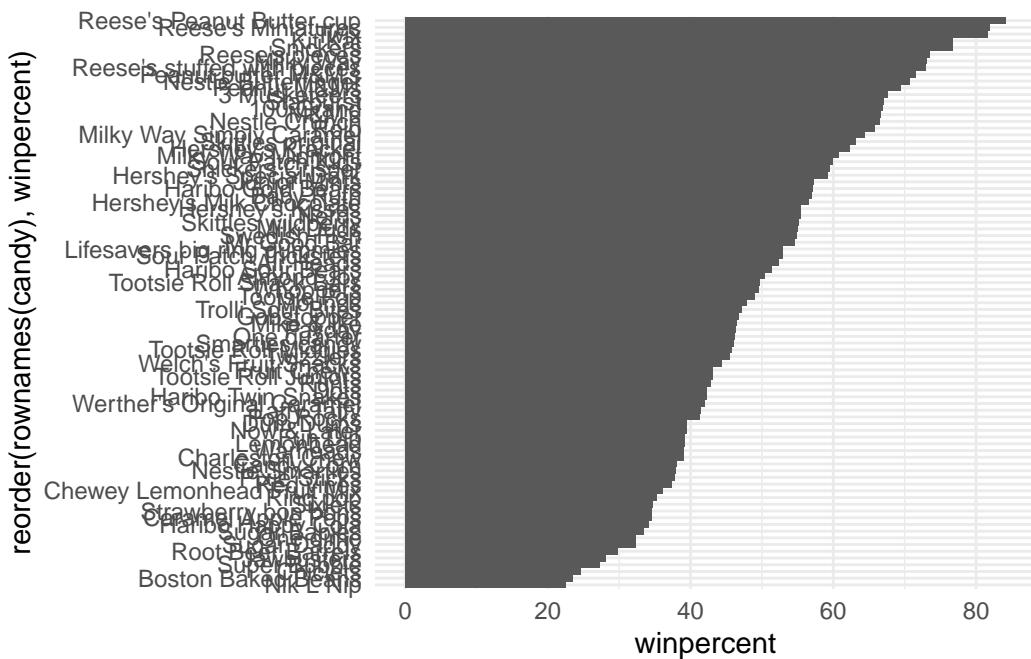


We first created our starter plot which is very very ugly. The text is all jumbled up and the bars are all over the place. Lets make it look better....

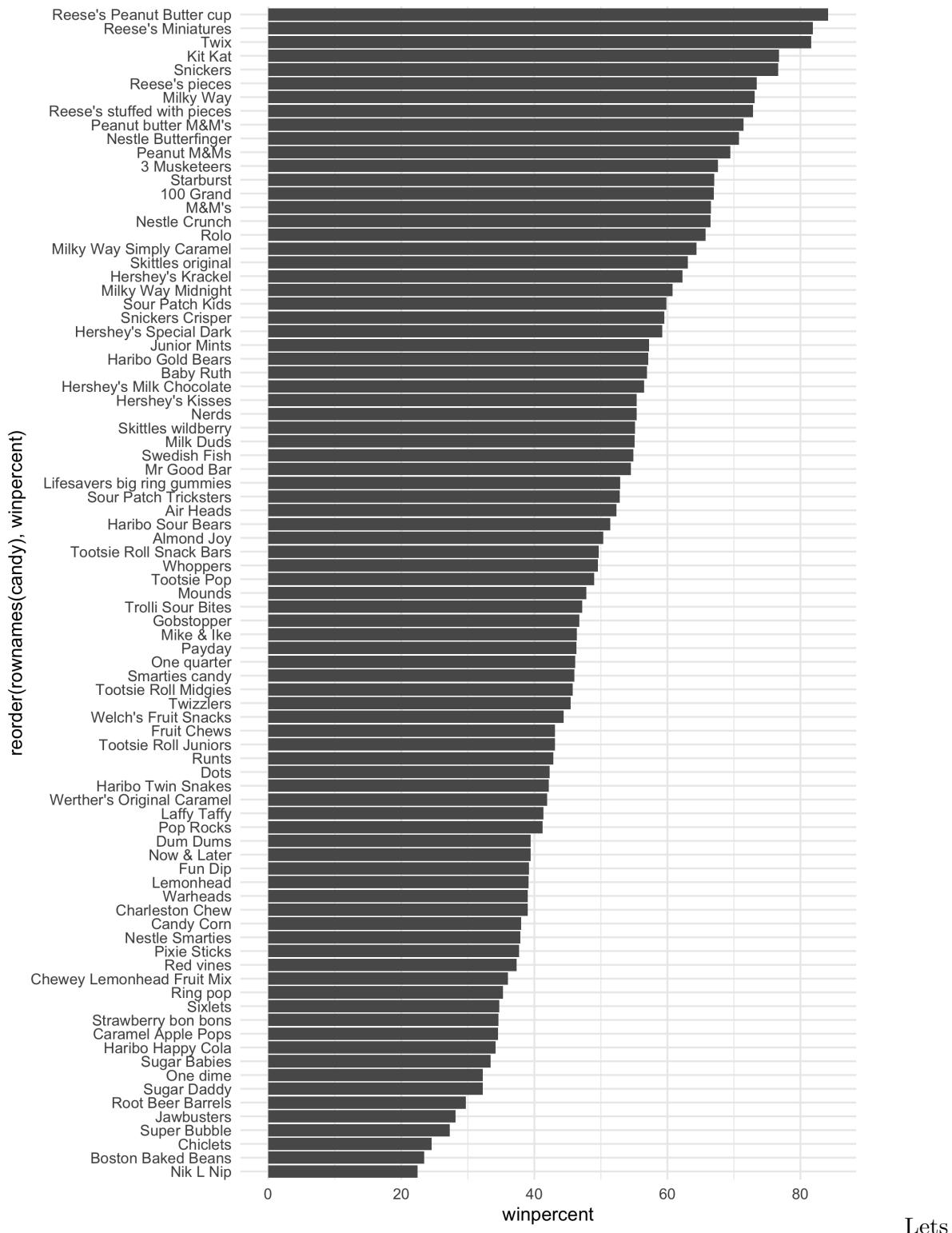
Q16. This is quite ugly, use the `reorder()` function to get the bars sorted by `winpercent`?

```
library(ggplot2)

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



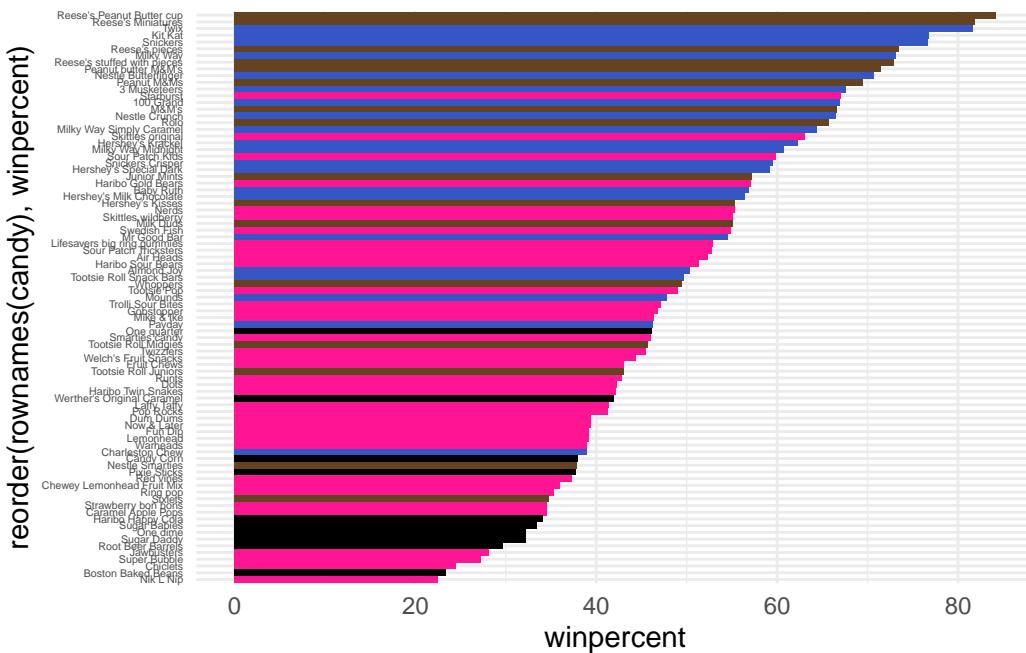
```
ggsave("barplot1.png", height=10, width=7)
```



add color to the graph to make it easier to read!

```
my_cols=rep("black", nrow(candy))
my_cols[as.logical(candy$chocolate)] = "#654321"
my_cols[as.logical(candy$bar)] = "#3556C4"
my_cols[as.logical(candy$fruity)] = "#ff1493"
```

```
ggplot(candy) +
  aes(winpercent, reorder(rownames(candy), winpercent)) +
  geom_col(fill=my_cols)+
  theme_minimal() +
  theme(axis.text.y = element_text(size = 4))
```



Q17. What is the worst ranked chocolate candy?

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

Q18. What is the best ranked fruity candy?

The best rated fruit candy is **Starburst**.

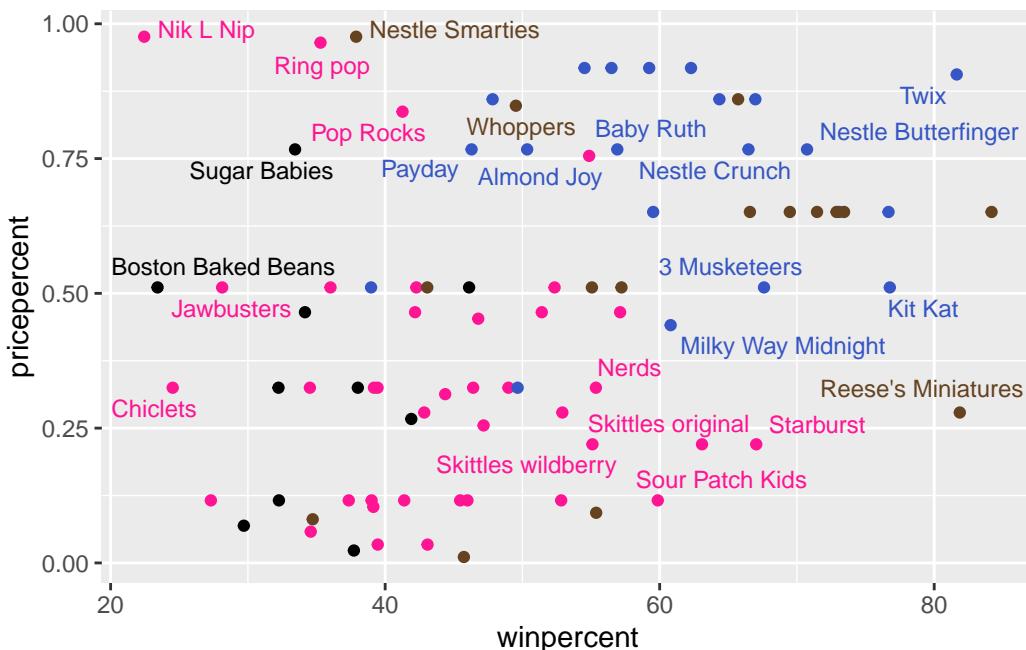
Analyzing Price Percent

Now lets look at **Price percent** aka the best candy for the least amount of money. We can do this by making a plot of winpercent vs the pricepercent variable.

```
library(ggrepel)

ggplot(candy) +
  aes(winpercent, pricepercent, label=rownames(candy)) +
  geom_point(col=my_cols) +
  geom_text_repel(col=my_cols, size=3.3, max.overlaps = 6) +
  theme_gray()
```

Warning: ggrepel: 61 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 Minis are the best candy for the cheapest price based on this graph.

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 5 most expensive candy types in the data set are Nik L Nip, Nestle Smarties, Ring pop, Hershey's Krackel, and Hershey Milk Chocolate. The least popular out of these 5 are the Nik L Nip which also happens to be tied for the worst price percent

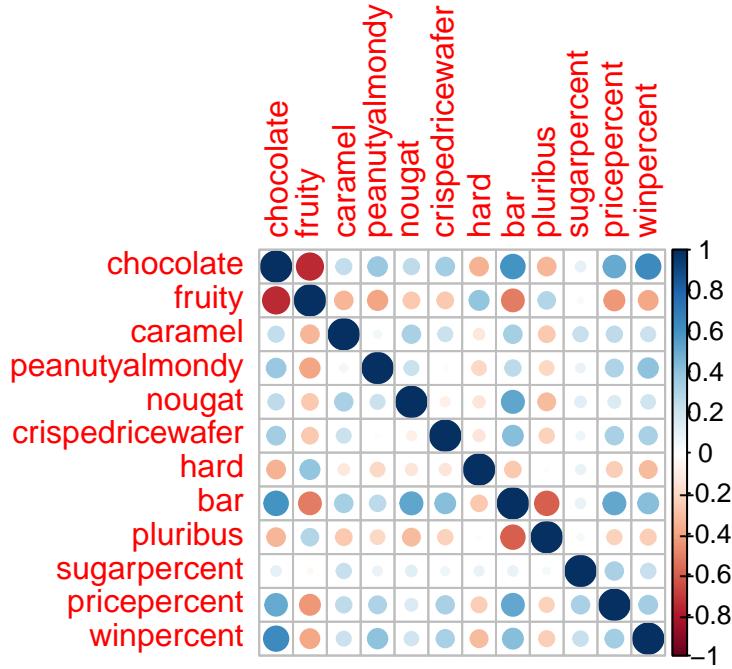
Exploring the correlation structure

Now that we have identified general trends and have a bit of a better understanding of the data, lets see how they interact with each other. Lets use the **corrplot** package to do this.

```
library(corrplot)
```

```
corrplot 0.95 loaded
```

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



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

The most anti-correlated variables that I can see are: pluribus (several in a package) + bar, fruity + bar, and fruity + chocolate just to name a few. You can see that fruity things tend to have a lower win percent however is associated with being less expensive

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

The most positively correlated are chocolate + bar, nougat + bar, wafer + bar, fruity + hard. You can also see that chocolate tends to get chosen more than fruity but is more expensive.

Principal Component Analysis

We can now apply PCA using the `prcomp()` function to our candy dataset. We need to make sure to set the `scale=TRUE` argument as we identified `winpercent` as a different scale earlier.

```
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

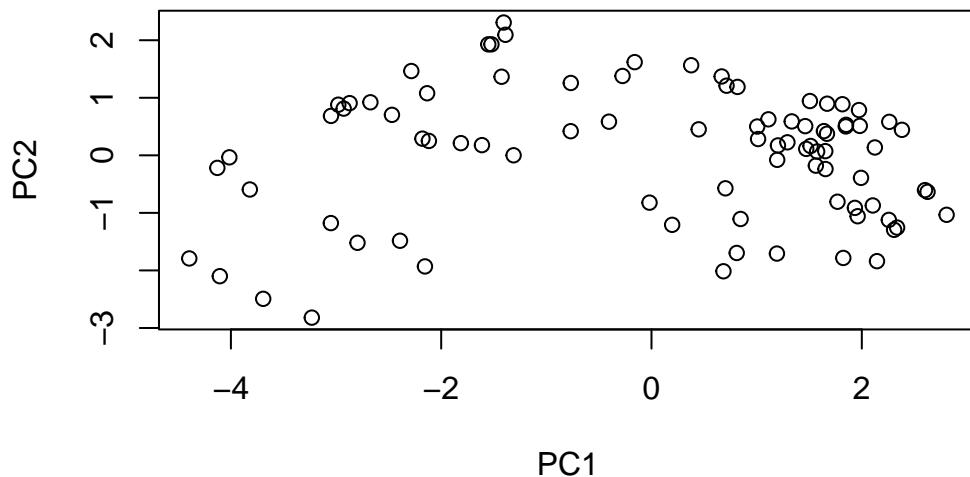
```

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

```

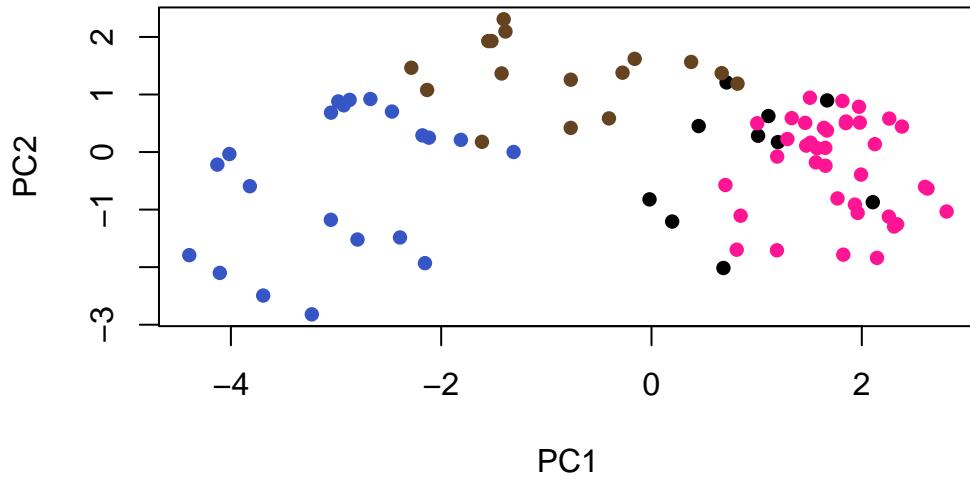
Lets now plot our main PCA score plot of PC1 vs PC2.

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



We can make it look a little better than that righttt...

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

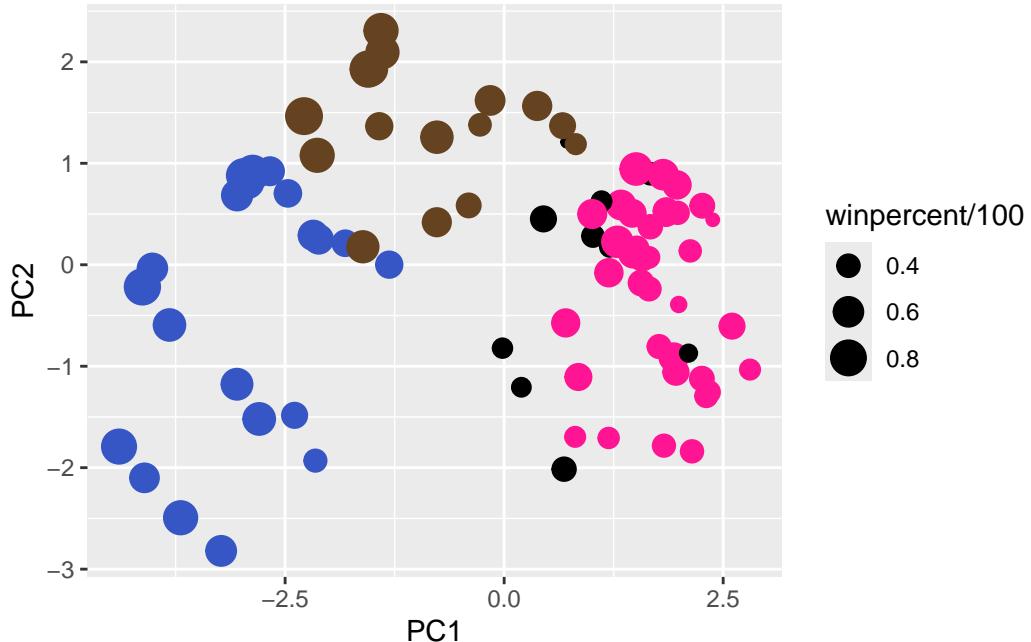


We can do even better than that come on now...

```
my_data <- cbind(candy, pca$x[,1:3])
```

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

```
p
```



We can use `ggrepel` package along with the `ggrepel::geom_text_repel()` function to create some labels and put some sense to the dots.

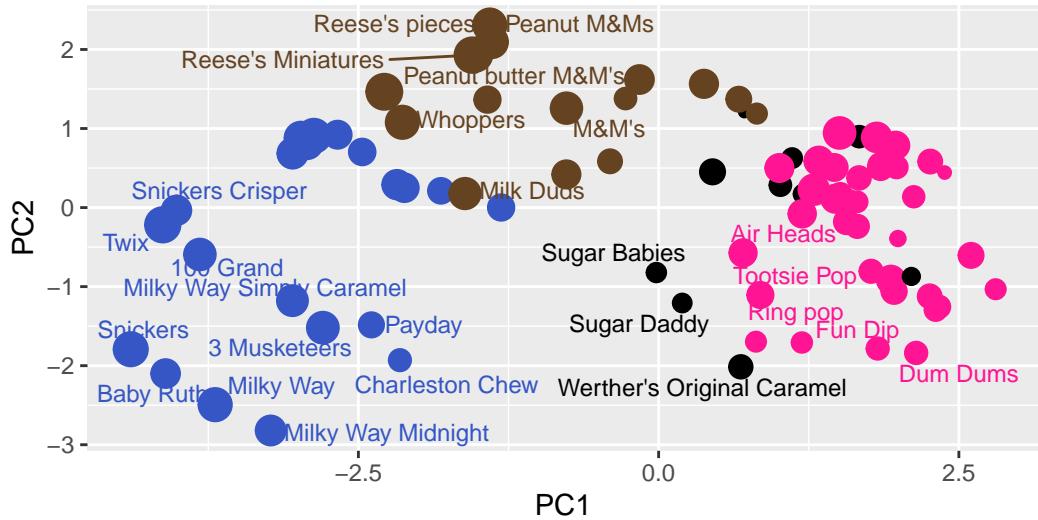
```
library(ggrepel)

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 (blue), chocolate other (dark brown), fruity",
       caption="Data from 538")
```

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

Halloween Candy PCA Space

Colored by type: chocolate bar (blue), chocolate other (dark brown), fruity (pink)

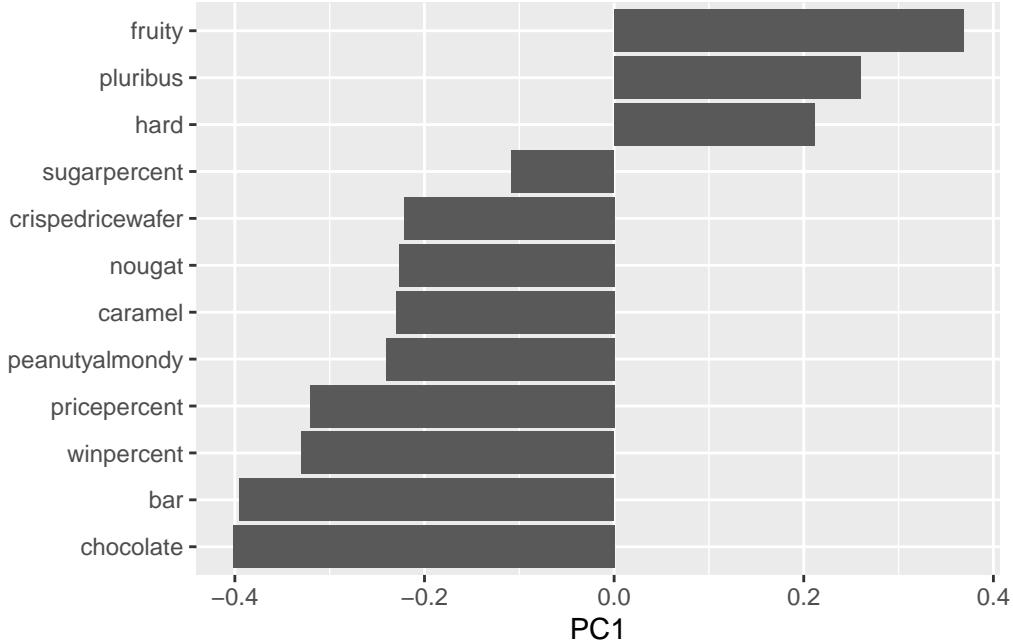


Data from 538

You can also make an interactive plot with **plotly**

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

ggplot(pca$rotation) +
  aes(PC1, reorder(rownames(pca$rotation), PC1)) +
  geom_col() +
  labs(y = "")
```



Q24. Complete the code to generate the loadings plot above. What original variables are picked up strongly by PC1 in the positive direction? Do these make sense to you? Where did you see this relationship highlighted previously?

In the positive direction, we can see the variables with the largest PC1 loading are fruity, multi-piece, and hard. This captures a broad type of candy which are the opposite of chocolate, bar-style, rich candies. This was highlighted in the correlation matrix. In simple terms PC1 is essentially a fruity / hard / pluribus vs chocolate bar axis.

Q25. Based on your exploratory analysis, correlation findings, and PCA results, what combination of characteristics appears to make a “winning” candy? How do these different analyses (visualization, correlation, PCA) support or complement each other in reaching this conclusion?

Based on my data, the best characteristics to make a winning candy are chocolate-based, bar, with something like nuts or caramel inside. You would want to stay away from fruity, hard candies while making the prices moderately expensive. You want to for sure stay away from fruity chocolate things and to make sure that if you are making chocolate bars, it isn't pluribus. The visualizations showed me that chocolate tend to cluster towards the higher win percents and fruity candy to be on the lower end. The correlation analyses showed that there was a strong negative correlation between fruity and chocolate while positively associating chocolate, caramel, nuts, and bars together. The PC1 results separated fruity/hard/pluribus candies from chocolate/bar candies displaying the preference patterns. Together we can apply them together in order to reinforce our conclusion from different perspectives and improving confidence.