TBD

Zaid and Zoe

```
library(tidyverse)
library(tidymodels)
library(stringr)
library(stringi)
library(leaps)
library(MASS)
library(glmnet)
library(caret)
library(Matrix)
pass <- read.csv("data/pass.csv")
```

```
uniqchars <- function(x) unique(strsplit(x, "")[[1]])

pass_more <- pass |>
  mutate(true_val = ifelse(time_unit == "years", 31536000*value,
                           ifelse(time_unit == "months", 2592000*value,
                                  ifelse(time_unit == "days", 86400*value,
                                         ifelse(time_unit == "hours", 3600*value,
                                                ifelse(time_unit =="minutes", 60*value,val
         true_val = jitter(true_val),
         pass_length = nchar(password),
         font_size = NULL,
         value = NULL,
         time_unit = NULL,
         rank_alt = NULL,
         num_digits = str_count(password, "[0-9]"),
         num_letters = str_count(password, "[a-z]"),
         num_vowels = str_count(password, "[a,e,i,o,u]"),
         num_unique = sapply(strsplit(password, ""), function(x) length(unique(x)))) |>
  filter(!is.na(rank)) |>
```

```
  filter(strength < 11)

nrow(pass_more)
```

```
[1] 485
```

```
#this is just to organize categories for EDA

pass_ordered <- pass_more

pass_ordered$category <- with(pass_ordered,
                              reorder(category, strength, median, na.rm=T))
```

Introduction

Research Question and Motivation

In our increasingly technology-oriented world, data security is a pressing and essential topic. As cybercriminals' hacking tools have improved, data leaks at major companies across industries such as Yahoo, Facebook, LinkedIn, Mariott International, Adobe, Bank of America, British Airways, and CVS have compromised billions of users' personal information. In 2022, IBM found that the average data breach in the U.S. cost companies an average of $9.44 million in lost business, crisis management efforts, and ransom payments. Data breaches can also allow hackers to access users' personal information such as names, addresses, credit card details, and Social Security numbers, which can be used for financial fraud or identity theft. One critical aspect of data security is password strength, which can reduce the risk of cybercriminals guessing users' passwords and acesssing personal information. Given our interset in datasecurity and the topcality of password strength as a key facet of this subject area, we wanted to explore password data for our project.

Our research question is: What characteristics yield strong passwords? We measure password strength in two ways: "strength" (which is calculated by an algorithm based on the password's length and complexity and is comparative to the generally bad passwords in the dataset) and the time the password takes to crack by online guessing. We decide which passwords are the strongest overall by looking at the characteristics that appear to impact both measures of password strength.

do we want to look at true_val or offline crack sec

External research: https://www.keepersecurity.com/blog/2022/09/14/why-is-password-security-important/ https://www.bleepingcomputer.com/news/security/the-benefits-of-making-password-strength-more-transparent/ https://www.ibm.com/downloads/cas/3R8N1DZJ

Data source: https://github.com/rfordatascience/tidytuesday/tree/master/data/2020/2020-01-14 https://docs.google.com/spreadsheets/d/1cz7TDhm0ebVpySqbTvrHrD3WpxeyE4hLZtifWSnoNTQ/edit#

Data Description

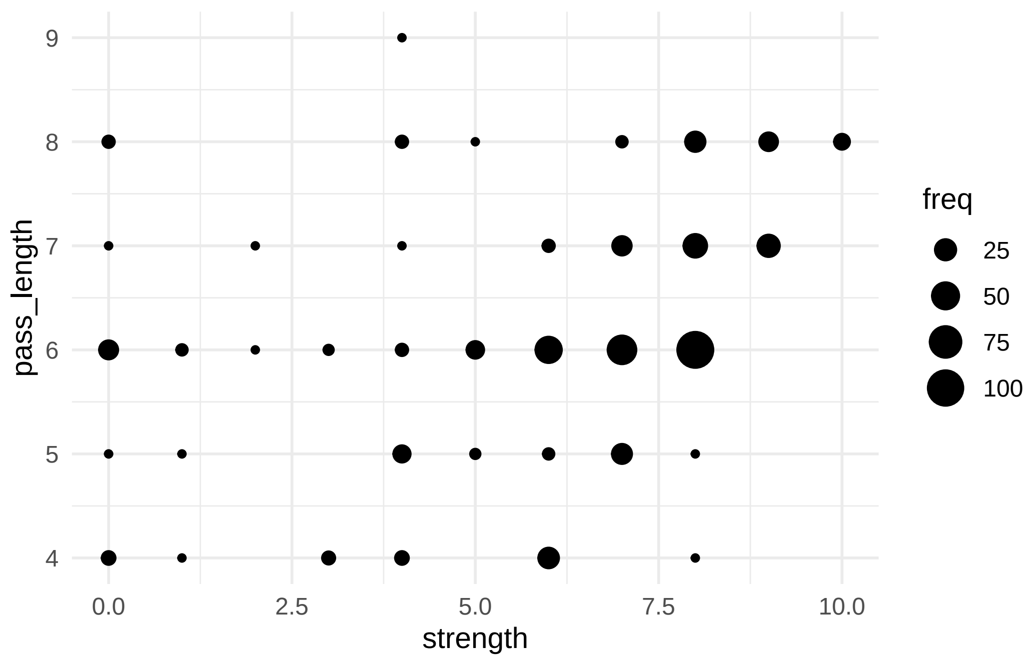
Variable Name	Type	Description
rank	double	Popularity in their database of released passwords
password	character	Actual text of password
category	character	Classification of type of password
true_val	double	Time to crack by online guessing standardized to seconds
offline_crack_sec	double	Time to crack offline in seconds
strength	double	Quality of password where 10 is highest, 1 is lowest
pass_length	double	Length of the password
num_digits	double	Number of digits in the password
num_letters	double	Number of letters in the password
num_vowels	double	Number of vowels in the password
num_unique	double	Number of unique characters (letters or numbers in the password)

Our data come from Tidy Tuesday, originally sourced from Information is Beautiful, a design company that distills data into visualizations and infographics. Information is Beautiful acquired its data on passwords by deep-mining 20 separate data breaches in 2017, including breaches of Facebook, Sony, and Yahoo. The data only includes the 500 most popular passwords, which also tended to be low-strength.

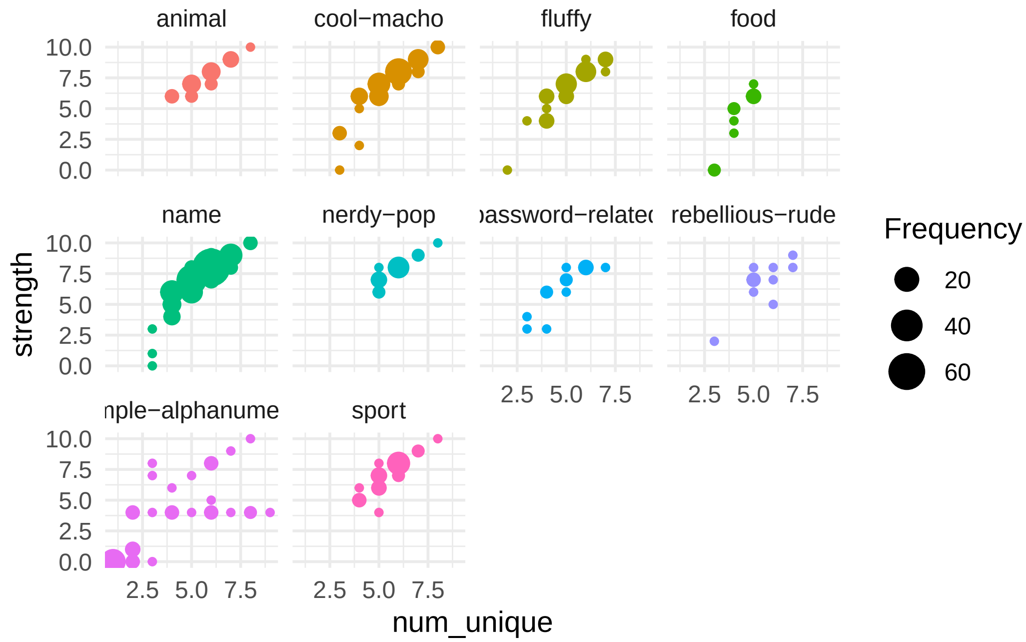
In the cleaning process, we removed the last seven observations, as all their values were "NA." We also removed several variables that appeared in the original dataset. First, we removed the variables that had a strength recorded over ten as those may have been miscalculations or strengths that were not standardized to values 1 through 10. Second, we removed the `rank_alt` variable because we wanted to focus on the passwords' first ranks of popularity, as opposed to their secondary ranks, because their first ranks were a clearer indicator of how common they were. Third, also removed the font_size variable, as the font sizes were chosen arbitrarily to display passwords in a graphic on the Knowledge is Beautiful webiste. Fourth and finally, we combined the `value` and `time_unit` variables into one time standardized to seconds called `true_val`. Previously, `value` referred to the time to crack by online guessing, and time unit was the time unit to match with that value (seconds, minutes, hours, days, months, or years). We added noise to our new `true_val` variable because the time to crack by online guessing only included discrete values (2.17 years, 0.00321 days, etc.). From there, we were left with 485 observations. Additionally, we added five new variables: pass_length, num_digits, num_letters, num_vowels, and num_unique. We added these variables because we believe that the length of the password, as well as its composition could impact password strength.

Exploratory Data Analysis

```
#this one needs to be a basic eda what vars do u think

pass_more %>%
  group_by(strength, pass_length) %>%
  summarize(freq=n()) |>
  ggplot(aes(x = strength, y=pass_length, size = freq)) +
  geom_point() +
  theme_minimal() +
  scale_fill_viridis_d()
```

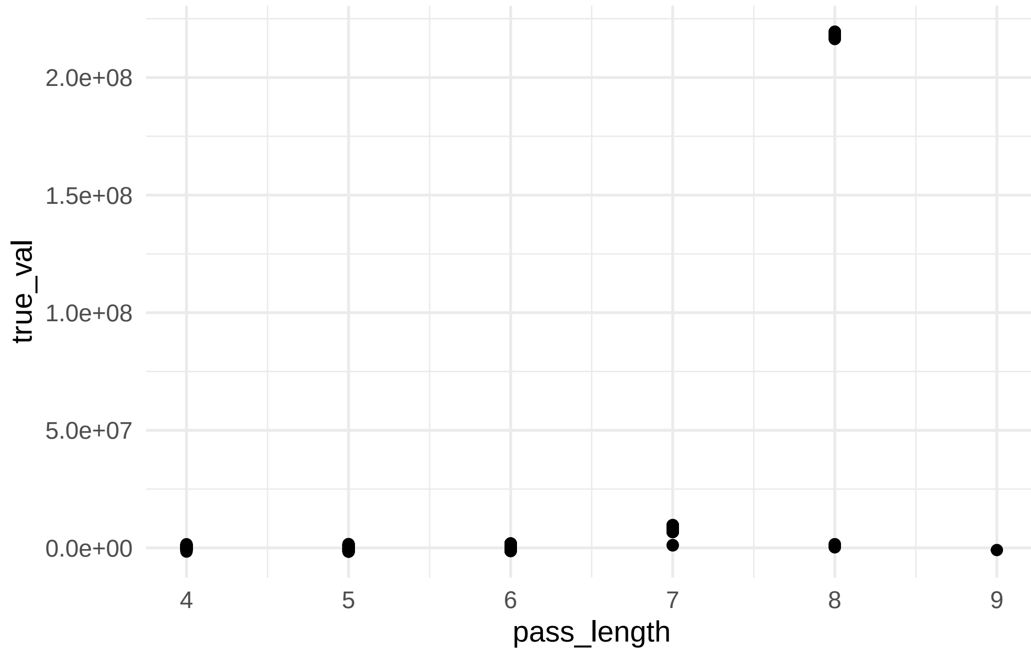


```r
# pass_ordered |>
#   ggplot(aes(x = strength, y = category, fill = category)) +
#   geom_boxplot() +
#   theme_minimal() +
#   scale_fill_viridis_d() +
#   labs(x = "Strength", y = "Category")

pass_more %>%
  group_by(num_unique, strength, category) %>%
  summarize(freq=n()) |>
  ggplot(aes(x = num_unique, y = strength, color = category, size = freq)) +
  facet_wrap(~category) +
  geom_point() +
  theme_minimal() +
  scale_fill_viridis_d() +
  guides(size=guide_legend("Frequency"), color = "none")
```




```r
# okay i chose one to do (the one above) what do you think the below thing should use

pass_more |>
  group_by(pass_length, true_val) |>
```

```
ggplot(aes(x = pass_length, y = true_val))+
geom_point() +
theme_minimal() +
scale_fill_viridis_d()
```




```
# we need summary statistics too according to directions : will add that tmr
```

Preliminary findings: strength - most common strength is 8, but again, note that this is in relation to the generally bad passwords in the dataset.

The explanatory data analysis helps the reader better understand the observations in the data along with interesting and relevant relationships between the variables. It incorporates appropriate visualizations and summary statistics.

Methodology

```
y1 <- pass_more$strength
x1 <- model.matrix(strength ~ . - password - true_val - offline_crack_sec - rank,
               data = pass_more)
```

```r
y2 <- pass_more$true_val
x2 <- model.matrix(true_val ~ . - password - offline_crack_sec - strength - rank,
            data = pass_more)

m_lasso_strength <- cv.glmnet(x1, y1, alpha = 1)
best_lambda <- m_lasso_strength$lambda.min
best_lambda
```

```
[1] 0.02345198
```

```r
m_best <- glmnet(x1, y1, alpha = 1, lambda = best_lambda)
m_best$beta
```

```
15 x 1 sparse Matrix of class "dgCMatrix"
                                     s0
(Intercept)                   .
categorycool-macho            .
categoryfluffy                .
categoryfood                 -1.17744127
categoryname                  0.04378974
categorynerdy-pop             0.15385968
categorypassword-related      .
categoryrebellious-rude      -0.21682159
categorysimple-alphanumeric -0.38005274
categorysport                 .
pass_length                  -0.09581339
num_digits                   -0.30570217
num_letters                   .
num_vowels                    .
num_unique                    1.20915166
```

```r
m_lasso_strength <- cv.glmnet(x2, y2, alpha = 1)
best_lambda <- m_lasso_strength$lambda.min
best_lambda
```

```
[1] 1080209
```

```r
m_best <- glmnet(x2, y2, alpha = 1, lambda = best_lambda)
m_best$beta
```

```
15 x 1 sparse Matrix of class "dgCMatrix"
                                   s0
(Intercept)                         .
categorycool-macho            2012322
categoryfluffy                1832250
categoryfood                        .
categoryname                        .
categorynerdy-pop            -9534308
categorypassword-related            .
categoryrebellious-rude             .
categorysimple-alphanumeric  30085235
categorysport                -3896478
pass_length                  34973706
num_digits                          .
num_letters                   9576635
num_vowels                          .
num_unique                   -2738214
```

Based on prior knowledge / research, the variables we think will be important to include are pass_length, num_digits, and num_unique - *do we think category is important?* - since online cracking is partially done by guessing common passwords…

to-dos - LASSO for online crack sec (and offline if we decide to do that) - hypothesis test for idk yet - should we plug in our LASSO variables into a regression (e.g. ordinal for password strength?, OLS for crack time?) or should we just use the LASSO coefficients themselves - would it be too much to see whether these strong passwords are the most common?

Results

Discussion