

# How Do Password Characteristics Affect Password Strength?

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## 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 such as Yahoo, Facebook, LinkedIn, Marriott 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 accessing personal information. Given our interest in data security and the topicality of password strength as a key aspect of this subject area, we wanted to explore password data for our project.

Our research question is: How do various password characteristics affect password strength? 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 (a brute force attack that guesses all possible combinations).

### Data Description

Variable Name	Type	Description
rank	numeric	Popularity in their database of released passwords
password	character	Actual text of password
category	categorical	Classification of type of password
true_val	double	Time to crack by online guessing standardized to seconds
true_val_strength	double	true_val made numeric where 11 is most crack time, 1 is lowest
offline_crack_sec	double	Time to crack offline in seconds
rank_alt	numeric	Secondary popularity rank in database of released passwords
font_size	numeric	Arbitrary font size Knowledge Is Beautiful used in graphic
strength	numeric	Quality of password where 10 is highest, 1 is lowest
pass_length	numeric	Length of the password

Variable Name	Type	Description
num_digits	numeric	Number of digits in the password
num_letters	numeric	Number of letters in the password
num_unique	numeric	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. Therefore, the **strength** variable indicates password strength in relation to these generally weak passwords.

In the cleaning process, we removed the last seven observations, as all their values were “NA.” We also removed observations that had a strength recorded over ten as those may have been miscalculations or strengths that were not standardized to values 1 through 10. From there, we were left with 485 observations. Additionally, 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). Based on **true\_val**, we made a new variable called **true\_val\_strength** for use in ordinal regression. This variable translated **true\_val** values to numbers 1-11, since **true\_val** values were not actually continuous but rather discrete values (2.17 years, 0.00321 days, etc.). Translating these times to 1-11 also allowed us to better visualize our data, since there was a large gap between observations—some took only seconds to crack, while others took years. Finally, we added four new variables: **pass\_length**, **num\_digits**, **num\_letters**, and **num\_unique**. We added these variables because we believe that password length and composition could impact strength.

## Exploratory Data Analysis

Given our prior knowledge of what makes passwords stronger, we chose to focus our exploratory data analysis on the predictors password length and number of unique characters, along with their relationships with other variables in the dataset.

### Summary Statistics:

	Variable	Mean	Median	Sd	Min	Max
1	<b>strength</b>	6.6	7	2.3	0	10
2	<b>true_val_strength</b>	8.6	9	2.1	1	11
3	<b>pass_length</b>	6.2	6	1.1	4	9
4	<b>num_digits</b>	0.46	0	1.6	0	9
5	<b>num_letters</b>	5.7	6	1.9	0	8
6	<b>num_unique</b>	5.2	5	1.5	1	9

From the table, the average number of digits in a password are 0.464, the average number of letters is 5.718, the average number of unique characters is 5.192, and the average password length is 6.181. In general, this indicates that the most popular passwords in the data leaks used all unique letters and rarely used numbers. In terms of our predictors, the average strength was 6.6, and the average **true\_val\_strength** was 8.6, representing an online crack time (OCT) of about two and a half days. This indicates that the compared to generally weak passwords, the average password in this dataset had a higher-than-average “strength” by both measures. In other words, the distribution of our data under **strength** and **true\_val\_strength** are left-skewed. An explanation of why we focused on these variables can be found in the methodology section.

## Plots:

Longer Passwords are Typically Stronger

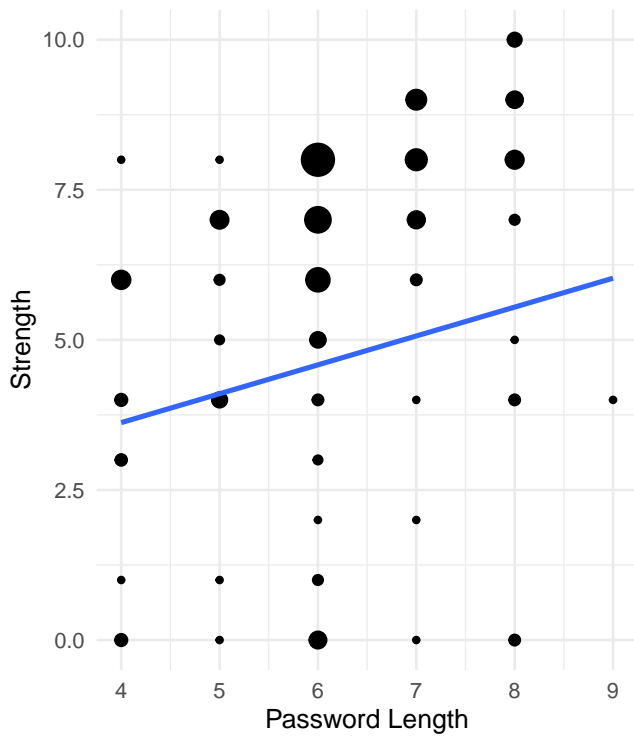


Figure 1

Longer Passwords Typically Take Longer crack time represented by numbers 1–10

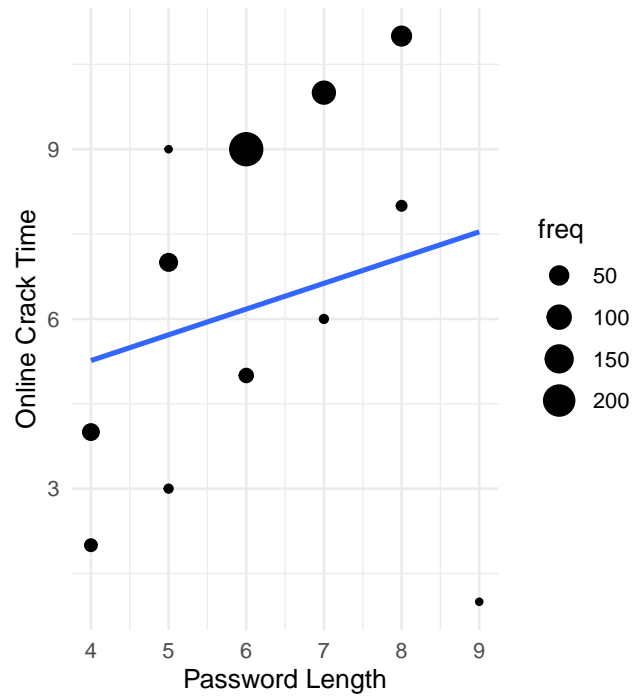


Figure 3

Unique Characters Tend To Increase Strength Grouped by Category

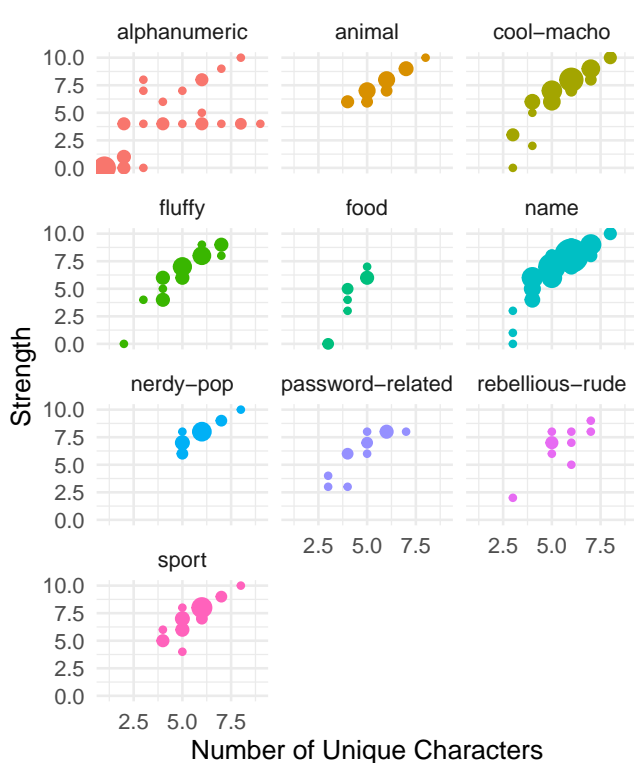


Figure 2

Unique Characters Tend to Increase Time Grouped by Category

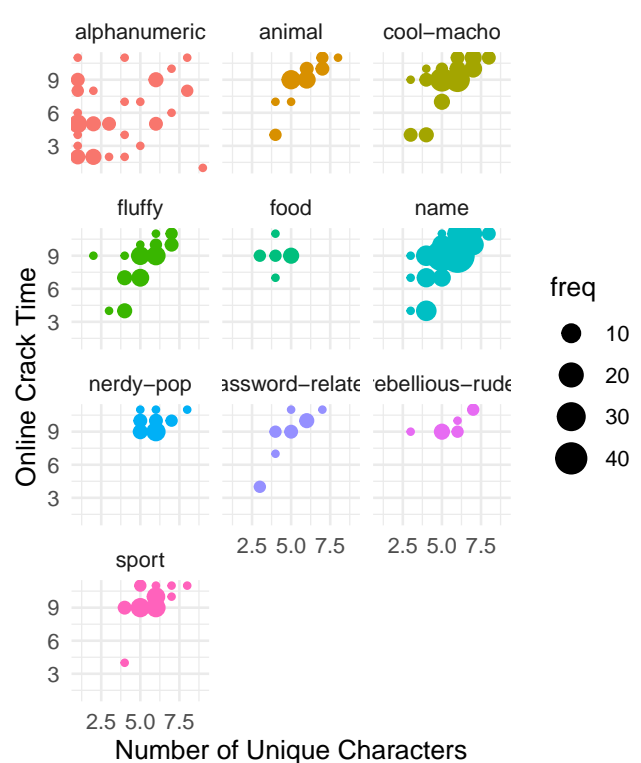


Figure 4

Figure 1 demonstrates that there appears to be a positive relationship between password length and the strength variable. We can also see this from the data themselves based on how the size of the points change as strength increases. For passwords of length 6-8, most passwords have strengths of above 5. The large size of several points show that most passwords in this dataset have length 6. Figure 2 demonstrates that the number of unique characters appears to have a positive relationship with password strength. This relationship holds for all categories, except simple-alphanumeric. The horizontal line in this plot shows that some passwords with varying numbers of unique terms have the same password strength. Additionally, the size of the points in the plot demonstrates that some categories of passwords were more popular in our data.

Figure 3 shows a positive relationship between password length and OCT (`true_val_strength`), as demonstrated by the positive slope of the line of best fit. In general, longer passwords take longer to crack, and the majority of passwords with OCT categories of 9 or above are 6 characters or longer. It appears that there should be a stronger positive relationship between password length and OCT, but the outlier at length 9 may have reduced the slope of our line of best fit. Figure 4 demonstrates that there appears to be a positive relationship between number of unique characters and OCT. Trends change by category, with passwords in the food, nerdy-pop, and sport categories being clustered around high OCTs and not having any clear pattern, while passwords in the alphanumeric category are consistent with the general trend of a positive relationship. Several passwords with 2 or less unique characters also have high OCTs, demonstrated by the vertical line at the left of the plot, and one point with 9 unique characters has a very low OCT.

## Methodology

In terms of our predictors, we focused on `pass_length`, `num_digits`, `num_letters`, and `num_unique` variables. Based on our research and prior knowledge, we believed it was reasonable to focus on these as the most important predictors of strength. Longer passwords with more varied compositions are typically harder to guess as that increases the options for what the password might look like. Category may also be an indicator of strength as passwords that fall into certain categories may be more common and easier to crack. We excluded `offline_crack_sec` because it is merely transformation of `online_crack_sec`. The `rank` and `rank_alt` variables because these were merely an ID/numbering variable. We excluded the password variable, since the actual password cannot be used as a predictor. We did not use `num_letters` in our model because the ordinal model could not handle it. This should not affect our analysis, since the number of letters can be derived from the number of digits as no passwords had special characters. We considered an interaction variable for category with the number of digits and unique characters, but ended up not going through with it since the interpretation would be hard to understand, and a test model came out insignificant on this term anyway.

In our analysis, we run two ordinal regressions, one on strength, and one on OCT. The strength variable is an ordered number 1-10, in order of increasing password strength, making an ordinal model the best fit. The strength variable meets the ordinal assumption of proportional odds, since it is reasonable to assume that one-unit changes in each predictor have the same conditional relationship with being in each strength category. For example, the strength variable is calculated in part based on the number of unique characters, and each one-unit increase in the number of unique characters has the same conditional relationship with being in each strength category. Ordinal regression is also a good fit for the `true_val_strength` variable, which is ordered 1-11 in increasing order of time to crack the password. The variable also meets the proportional odds assumption, as it is reasonable to assume that one-unit changes in each predictor have the same conditional relationship with being in each `true_val_strength` category, by similar reasoning as the strength variable.

We also did logistic regressions for both these response variables, where they each had a threshold of a value of 8 or above for being considered “strong”. This allows us to bolster our ordinal models to see if the predictor variables they pick are similar. In terms of the linearity assumption, we would show that our continuous variables are roughly linearly related to the log odds of the response. Given the limited values of our continuous variables, and limited observations, it was not possible to create plots as the `num_groups` parameter would have

to be set to two, which would make the plot irrelevant, so we assume linearity. Additionally, for independence the observations shouldn't be related to each other because people chose their passwords based on what they wanted and not what other people have said. There are no groupings so it is hard to see how one observation would inform us about another.

Ordinal Model for Strength and True Val Strength Respectively:

	sum1[Start:End]		
	Coefficients:		
	Value	Std. Error	t value
categoryanimal	-0.5422	0.7617	-0.7119
categorycool-macho	-0.8514	0.7015	-1.2137
categoryfluffy	-0.8548	0.7243	-1.1802
categoryfood	-3.0098	0.9140	-3.2929
categoryname	-0.6723	0.6809	-0.9873
categorynerdy-pop	-0.2455	0.7982	-0.3076
categorypassword-related	-0.7074	0.8632	-0.8195
categoryrebellious-rude	-1.5309	0.9026	-1.6960
categorysport	-0.8894	0.7473	-1.1901
pass_length	-0.3116	0.1418	-2.1972
num_digits	-1.1207	0.2267	-4.9428
num_unique	3.6946	0.2155	17.1474

	sum2[Start:End]		
	Coefficients:		
	Value	Std. Error	t value
categoryanimal	-2.1008	1.7570	-1.1956
categorycool-macho	-2.2598	1.3952	-1.6197
categoryfluffy	-2.1499	1.4265	-1.5071
categoryfood	-1.3163	3.5464	-0.3712
categoryname	-2.0787	1.2922	-1.6087
categorynerdy-pop	-0.8051	3.3502	-0.2403
categorypassword-related	-2.5701	1.9118	-1.3443
categoryrebellious-rude	3.1858	1.8991	1.6776
categorysport	-1.7996	2.0268	-0.8879
pass_length	12.2155	1.1713	10.4294
num_digits	-4.0217	0.4257	-9.4473
num_unique	-0.1844	0.1566	-1.1776

Logistic Model for Strength and True Value Strength Respectively

# A tibble: 13 x 5				
term	estimate	std.error	statistic	p.value
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
1 (Intercept)	-24.9	2.88	-8.67	4.34e-18
2 categoryanimal	-0.586	1.55	-0.378	7.05e- 1
3 categorycool-macho	0.147	1.47	0.0999	9.20e- 1
4 categoryfluffy	0.330	1.54	0.215	8.30e- 1
5 categoryfood	-13.5	983.	-0.0138	9.89e- 1
6 categoryname	0.483	1.43	0.337	7.36e- 1
7 categorynerdy-pop	1.56	1.63	0.951	3.41e- 1
8 categorypassword-related	2.04	1.79	1.14	2.56e- 1
9 categoryrebellious-rude	-1.20	1.79	-0.674	5.00e- 1
10 categorysport	0.466	1.54	0.303	7.62e- 1
11 pass_length	-0.301	0.291	-1.03	3.01e- 1
12 num_digits	-1.76	0.295	-5.96	2.57e- 9
13 num_unique	4.77	0.459	10.4	2.21e-25

```
# A tibble: 13 x 5
  term                estimate std.error statistic    p.value
  <chr>              <dbl>    <dbl>    <dbl>    <dbl>
1 (Intercept)        -52.0      9.59     -5.42  0.0000000587
2 categoryanimal      -1.11      4.57     -0.243  0.808
3 categorycool-macho  -0.950     3.83     -0.248  0.804
4 categoryfluffy      -1.86      3.72     -0.499  0.618
5 categoryfood        -1.48      5.96     -0.248  0.804
6 categoryname        -1.35      3.26     -0.414  0.679
7 categorynerdy-pop   13.7     4963.      0.00276  0.998
8 categorypassword-related -1.72      6.53     -0.264  0.792
9 categoryrebellious-rude 21.3     5643.      0.00378  0.997
10 categorysport       4.40      48.2      0.0913  0.927
11 pass_length        10.4       1.96      5.30  0.000000115
12 num_digits         -3.31      0.779     -4.25  0.0000210
13 num_unique         -0.592     0.502     -1.18  0.238
```

Figure 1: Predictions for Strength

	0	1
Not Strong	252	8
Strong	15	210

Figure 2: Predictions for True Strength

	0	1
Not Strong	103	2
Strong	1	379

Figure 3: AUC for ROC of Strength

.metric	.estimator	.estimate
roc_auc	binary	0.9772103

Figure 4: AUC for ROC of True Strength

.metric	.estimator	.estimate
roc_auc	binary	0.9961892

## Results

### Ordinal Models

To reiterate, the main models in our analysis are the ordinal ones, and thus, they are our final models. The logistic models are only present to bolster our findings. Depending on one's definition of strength, they can look at either of the two equations. If the definition involves mostly computerized, brute forced look, then the second one may be more applicable. If it involves a more holistic look at all the factors that hackers could use to steal passwords, the first model is a good fit.

First Ordinal Model:

$$\text{logit}(\text{strength}) = -0.5422 * \text{categoryAnimal}_i + -0.8514 * \text{categoryCoolMacho}_i + -0.8548 * \text{categoryFluffy}_i + -3.0098 * \text{categoryFood}_i + -0.6723 * \text{categoryName}_i + -0.2455 * \text{categoryNerdyPop}_i + -0.7074 * \text{categoryPasswordRelated}_i + -1.5309 * \text{categoryRebelliousRude}_i + -0.8894 * \text{categorySport}_i + -0.3116 * \text{passLength} + -1.1207 * \text{numDigits} + 3.6946 * \text{numUnique}$$

Second Ordinal Model:

$$\text{logit}(\text{trueValueStrength}) = -2.1008 * \text{categoryAnimal}_i + -2.2598 * \text{categoryCoolMacho}_i + -2.1499 * \text{categoryFluffy}_i + -1.3163 * \text{categoryFood}_i + -2.0787 * \text{categoryName}_i + -0.8051 * \text{categoryNerdyPop}_i + -2.5701 * \text{categoryPasswordRelated}_i + 3.1858 * \text{categoryRebelliousRude}_i + -1.7996 * \text{categorySport}_i + 12.2155 * \text{passLength} + -4.0217 * \text{numDigits} + -0.1844 * \text{numUnique}$$

Our first ordinal model shows the relationship between the predictors category, password length, number of digits, and number of unique characters and the log-odds of being in the next-highest strength category. The predictors with the greatest impact on strength, as indicated by the magnitude of their slopes, are number of unique characters and being categorized as food-related. The number of digits also had a relatively high slope magnitude, and password length had a small slope magnitude. It may seem strange that `num_digits` and `password_length` have negative slopes. However, this is because our model controls for the number of unique characters: a unique additional digit or character (which would make the password longer) is predicted to increase the odds of being in the next-highest strength category, but if the additional digit or character is not unique, it is predicted to decrease those odds. The high-magnitude t-values associated with the number of digits, being in the food category, and especially the number of unique characters (t value of 17.147) suggest that these predictors have a meaningful relationship with password strength and are important to include in a model predicting strength.

In terms of what the key coefficients from our model mean in context, the slope for `categoryfood` indicates that while controlling for all other predictors, our model predicts being in the food category to decrease a password's odds of being in the next-highest strength category (1 to 2, or 2 to 3, for example) by a multiplicative factor of 0.049. The slope for `num_unique` indicates that while controlling for all other predictors, as the number of unique characters in the password increases by 1, our model predicts the odds of being in the next-highest strength category to increase by 40.23 times.

Our second ordinal model shows the relationship between the same predictors and `true_val_strength`, which again represents an OCT, represented by values 1-10. The predictors with the largest impact on strength, as indicated by the magnitude of their slopes are password length, number of digits, and being in the rebellious-rude category. The low magnitude slope for the number of unique characters makes sense in this model because if the computer is guessing every possible character every time, then uniqueness does not matter. The high-magnitude t-values associated with the number of digits (t value of -9.447) and password length (10.429) indicate that these predictors have a meaningful relationship with OCT.

In terms of what the key coefficients from our model mean in context, the slope for `categoryrebellious-rude` indicates that while controlling for all other predictors, our model predicts being in the rebellious-rude category to increase a password's odds of being in the next-highest strength category by 24.19 times. The slope for `pass_length` means that while controlling for all other predictors, as the password length increases by 1 character or digit, our model predicts the odds of being in the next-highest strength category to increase by 201,894.4 times.

## Logistic Regressions

We conduct a hypothesis test with  $\alpha = 0.05$ . Our null hypothesis is that there exists no relationship between strength and the differential odds any of the other variables in the model. Our alternative hypothesis will say that such a relationship does exist. Based on our strength model output, our significant predictors (i.e. the predictors with p-values less than 0.05) are `num_digits` and `num_unique`. They had p-values of  $2.57e^{-9}$  and  $2.21e^{-25}$  respectively with z-statistics of -5.96 and 10.4. The z-statistics have a standard normal distribution under  $H_0$ . This means that we have enough evidence to reject  $H_0$  and conclude that these two variables may have a relationship with the log\_odds of a password being classified as high or low-strength.

Our null and alternative hypotheses for our OCT model are the same, except with `true_val_strength` as our outcome variable. Based on our model output for OCT, our significant predictors are `num_digits` and `pass_length`. They had p values of 0.0000210 and 0.000000115 respectively with z statistics of -4.25 and 5.3. The z-statistics have a standard normal distribution under  $H_0$ . This means that we have enough evidence to reject  $H_0$  and conclude that these two variables may have a relationship with the log\_odds of a password being classified as high or low-strength (strength here meaning OCT).

Our AUC for the strength logistic regression is 0.977. In content, the AUC means that the probability of a randomly selected “strong” password having a higher predicted probability of being classified as strong than that of a “weak” password is 0.977, which is very close to 1. This means our model is a very good fit for our data. Our model also appears to be a good fit based on its high positive predictive value, which is 0.933, and the negative predicted value of 0.969.

Our AUC for the true\_val logistic regression is 0.996. In content, the AUC means that the probability of a randomly selected “strong” password (here, referring to crack time category) having a higher predicted probability of being classified as strong than that of a “weak” password is 0.996. Our model also appears to be a good fit based on its high positive predictive value, which is 0.997, and the negative predicted value of 0.981.

## Discussion

### Conclusions

Our two ordinal models suggest that to increase the traditional, numeric measure of password strength, it may be most helpful to have more unique characters. Additionally, it may be helpful to not have a food-related password, as these passwords may be more easily guessed. To increase the time it takes to crack the password online, it appears most important to have a longer password, regardless of its composition. This makes sense based on the mechanism of online guessing, which is guessing all possible combinations.

The conclusions from our two ordinal models are supported by our findings for our logistic regressions, which also help clarify how we should interpret some of our predictors. Like our ordinal regression for strength, our logistic regression for strength shows that the number of unique characters appears to be associated with the odds of being classified as a strong password, given its positive slope and low p-value. The logistic regression finds the number of digits to be a significant predictor of being classified as a strong password, a conclusion that was not as easy to draw from the ordinal regression given the lack of p-values. Finally, our logistic regression clarifies that although being in the food category has a large magnitude slope, it is ultimately not a significant predictor of being classified as a strong password. In comparison to our ordinal regression for online crack time, our logistic regression finds password length to be a significant predictor of the odds being classified as strong, using the definition of online crack time. It also finds number of digits to be a significant predictor of the odds of being classified as strong, which is more difficult to see from the ordinal regression.

Thus, it appears that different characteristics improve password strength depending on how password strength is defined. Those hoping to increase their password strength against people or programs that based their guesses in part off of common passwords should increase the number of unique characters and digits in their passwords. Those hoping to defend against brute-force computer programs should focus on increasing their password length and number of digits. Overall, best practices for strong passwords appear to having a long password with numbers and as many unique characters as possible.

### Limitations and Future Research

To reiterate, this data holds the 500 most common passwords from a data leak, and so since they are the most common, most are relatively simple and not strong to begin with. As such, a high value for the strength variable means only that the password was good compared to others in the dataset. Therefore, our data are not representative of all passwords in data breaches, or all passwords overall. In fact, most passwords nowadays are forced to be inherently strong with a minimum character, digit, and special character limit, and most of these leaked passwords did not follow these rules. To improve upon this analysis (although this may not be totally ethical), it would help to have a more representative sample of passwords from a data breach



(as opposed to just the most popular ones) or a more representative sample of passwords overall. Future work could use these kinds of more representative samples, or larger samples so we could determine whether the linearity assumption was met. We assumed linearity to conduct our analysis, and we believe it is a reasonable assumption, but this may not have been accurate and may limit the validity of our model. Future work could also explore which characteristics of passwords make them stronger against other hacking techniques, such as more advanced AI algorithms. Given that data security is becoming a more pressing issue with technological advances, the avenues for future research remain both vast and topical.

## Sources

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/blob/master/data/2020/2020-01-14/readme.md>