Pokemon: Gotta Catch 'Em All!

STA 210 Final Project

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Introduction and Data

As students who grew up playing Pokemon games, including Pokemon Go, Pokemon Black/White, and many others, we are interested in examining the factors that contribute to the difficulty of catching a certain species of Pokemon. It had always seemed like strong high-stat Pokemon, especially legendaries, are more difficult to catch than weak low-stat Pokemon, but there were always exceptions to this logic. After searching for data about Pokemon in relation to catch rate, we came across a data set from Kaggle called "The Complete Pokemon Dataset," with includes information about more than 800 Pokemon from all seven generations (https://www.kaggle.com/datasets/rounakbanik/pokemon?resource=download). The data set has 801 observations– each a unique Pokemon– and 41 variables that are a mix of quantitative and qualitative.

When attempting to catch a Pokemon, there are many variables that go into if the Pokemon will be caught or not. These variables include type of Poke ball used, level of the wild Pokemon, etc. All of these factors, in addition to RNG (random number generation), are factored into a specific formula to determine if a Pokemon is caught on any given attempt. Details about the formula can be found here: https://bulbapedia.bulbagarden.net/wiki/Catch_rate. Additionally, every Pokemon has its own "catch rate," which is weighted heavily in the formula. Pokemon with a higher catch rate are easier to catch. For example, Pidgey, which is a weak, unevolved Pokemon, has a catch rate of 255, (tied for the highest), meaning that Pidgey is very easy to catch. However, Mewtwo, a strong, legendary Pokemon, has a catch rate of 3, (tied for the lowest), meaning that Mewtwo is extremely difficult to catch. Please note that we use "catch rate" and "capture rate" interchangeably.

For this project, we decided to focus on the following unique variables in the data set: name, Pokedex number, generation (1 to 7), capture rate (how hard the Pokemon is to catch), percentage male, the type(s) of the Pokemon, height, weight, the number of steps per egg cycle (base egg steps), experience growth, base happiness, hp, attack, defense, special attack, special defense, speed, and whether the Pokemon is legendary or not. The original data set had 22 other variables, but in the data cleaning process, we chose to manually exclude some variables based on our knowledge of Pokemon. For classification and readability purposes, we

chose to keep the variables *name*, *pokedex_number*, and *generation*. However, we excluded the *japanese_name* variable because it is just another version of *name*. The *against_?* variables are dependent on only typing (*type1* and *type2*), and it will be more useful to just look at the typing of a Pokemon rather than how effective certain moves are against it. There are hundreds of different abilities a Pokemon can have, and very little overlap of abilities between Pokemon, so we do not need the *abilities* variable. The classification of a Pokemon is almost unique for every Pokemon (there is very little overlap), and it mainly just groups Pokemon by their evolution line, yielding *classification* unwanted. We changed the type of the *capture_rate* variable to be an integer instead of a character. Next, there was one observation, discussed later, that had two forms with different capture rates, so we mutated its catch rate to be NA. Finally, the most major change we made was adding 18 new variables to the data set. The original data set includes the variables *type1* and *type2*, but since we wanted to examine whether specific types of Pokemon have lower catch rates, we decided to add a new variable for each of the 18 types of Pokemon. This choice is discussed fully in depth in the Variable Transformation section.

In this project, we are examining the following research question: What characteristics of a Pokemon influence catch rate? Our main outcome of interest is the variable *capture_rate.* Our hypotheses are as follows: Pokemon with higher attack, defense, special attack, special defense, HP, and speed stats will have lower capture rates than Pokemon with lower stats. Larger Pokemon (in terms of height and weight) would have lower capture rates than smaller Pokemon. A Pokemon's type will not play a role in the catch rate. Finally, legendary Pokemon will have lower capture rates than non-legendary Pokemon. In the following project, we will make visualizations to explore the data, consider different types of regression models, use variable selection techniques, consider missing data, assess linear model assumptions, and select final models to examine the characteristics of Pokemon in the data set that are statistically significant in influencing capture rate.

Methodology

Type of Model

We decided a Linear Regression Model is the best model to predict the catch rate of a Pokemon.

In this data set, the catch rate of Pokemon is an integer from 3 to 255. However, there are only 33 unique catch rates among the 801 Pokemon. This visualization can be seen in the appendix. For example, 50 Pokemon have a catch rate of 60 and a whopping 250 Pokemon have a catch rate of 45. Based off of this information, it may make sense to use a multinomial regression model. Since the data are ordered, an ordinal regression model would be another good option. This would lead to a model that predicts the catch rate of a Pokemon relative to the 33 unique catch rates. However, this is a lot of outcomes for the response variable. We could simplify this ordinal regression model with some number of different "bins." For example, bin 0 could

be all Pokemon with a catch rate of 0-50, bin 1 is all Pokemon with a catch rate of 50-100, etc.

We decided against using the ordinal regression model for multiple reasons. First, 33 different outcomes for the response variable is a lot. It creates an unnecessarily complicated model. This problem can be fixed by grouping the catch rates into different "bins," as outlined above. However, this is not optimal, because we don't have a strategy for how to create the "bins." How many "bins" should we have? Should they all be of equal length? Without the proper tools, this method does not make sense for our purposes. Overall, we decided against the ordinal regression model because even though many Pokemon share a catch rate with many others, there are still Pokemon that have a unique catch rate, meaning the current catch rates of Pokemon are not the only possible catch rates. There could still be a new Pokemon introduced that has a fully unique catch rate. If we were tasked with predicting the catch rate of a new Pokemon with certain attributes, our model would no longer make sense if that Pokemon's catch rate was fully unique. We would be looking at the probability that this Pokemon has a certain catch rate, but the Pokemon wouldn't have any of the listed catch rates.

A logistic regression model also does not make sense in the context of our data because our main outcome of interest, capture rate, is a numerical predictor, and logistic regression requires the response to be categorical and binary. This leaves us with linear regression, which best fits the data we are using since our response variable is continuous. Linear regression with multiple predictors will allow us to examine the relationship between our predictors of interest and outcome while holding other variables constant. Therefore, we decided that a linear regression model would best suit our research question.

Missing Data

Many species of Pokemon do not have a gender, leading to many NA values for the *percentage_male* variable. However, there is a disproportionate amount of legendary Pokemon that do not have a gender. This is because in a Pokemon game, legendaries are unique and special; there is only one of each legendary Pokemon in the "world." Thus, in our data set, 63/70 of legendary Pokemon have an NA for *percentage_male*. This data is MAR (missing at random) since legendary status is an observed variable in the data set. Because these Pokemon are legendary, many of them have extremely low catch rates. Specifically, 53/70 legendary Pokemon have a catch rate of 3, the lowest possible catch rate. This means that our model will most likely not be able to accurately predict legendary Pokemon's catch rate, and there will be worse representation among Pokemon with lower catch rates. The best and easiest solution to this problem is to eliminate the *percentage_male* predictor from the model.

Next, we noticed that while reading the .csv file, R automatically translated the *capture_rate* variable to characters. Upon inspection, Pokemon number 774, Minior, had this listed as its catch rate: "30 (Meteorite)255 (Core)". During battle, Minior has two forms: meteor form

and core form. Interestingly, Minior has the "shields down" ability, meaning that when Minior is at half health or less, it changes from the Meteor form to the core form. However, Minior's catch rate also changes when it changes forms, from 30 (meteor form) to 255 (core form). Due to Minior's ability having a direct relation to the catch rate, we chose to exclude Minior as an observation. We decided to update Minior's catch rate to be NA, thus excluding this observation from the model. We also made *capture_rate* an integer instead of a character.

Finally, we noticed that there are 20 Pokemon with missing data for their heights and weights. Upon examining notes from the author of the data set on the website, we realized that these 20 Pokemon all have an alternate form (Alolan). The alternate forms of these Pokemon have different heights and weights than their normal form. As a result, the height and weight of these Pokemon were inputted into the data set as NA values. These values are MNAR (missing not at random), as they are related to unobserved data, which is whether the Pokemon has an alternate form or not. We also read that the data set scraped the Alolan base stats for these 20 Pokemon, so the rest of the information will be based on the alternate form of the Pokemon. We decided to exclude these 20 observations from the data set.

It is also worth nothing that Pokemon only have one type, and thus do not have a second type. This is not missing data, this is just the classification of the Pokemon.

Variable Selection

After acknowledging missing data, we must next narrow down the variables in the data set to only the important predictors for our model. As mentioned above, we manually eliminated some variables due to repetitiveness and missing data. We now run variable selection models to determine which of the following variables are best/important for predicting catch rate: *height_m*, *weight_kg*, *base_egg_steps*, *experience_growth*, *base_happiness*, *hp*, *attack*, *defense*, *sp_attack*, *sp_defense*, *speed*, and *is_legendary*. The variables *type1* and *type2* are discussed in the Variable Transformation section.

First, we considered stepwise selection methods. However, decided not to use forward selection and backward elimination methods because they often don't work well with highly correlated variables, and we suspect that some of our predictors are correlated. We next turned to LASSO, which is a regression technique that also performs variable selection. In LASSO, we are performing k-fold cross validation to choose the "best" lambda value, and then LASSO uses penalties to make coefficient estimates.

```
13 x 1 sparse Matrix of class "dgCMatrix"
                           s0
(Intercept)        .
height_m           .
weight_kg          .
base_egg_steps     .
```

```
experience_growth  .
base_happiness     .
hp                -0.5594079
attack            -0.3415237
defense           -0.4295399
sp_attack         -0.3798392
sp_defense        -0.4627282
speed             -0.4346233
is_legendary       .
```

The LASSO technique selected *hp*, *attack*, *defense*, *sp_attack*, *sp_defense*, and *speed*. LASSO shrunk the coefficients of *height_m*, *weight_kg*, *base_egg_steps*, *experience_growth*, *base_happiness*, and *is_legendary* to zero, meaning it chose to exclude them from the model.

Interaction Terms

We originally thought that there may be a connection between the size of a Pokemon and its capture rate, so we were considering using an interaction term between height and weight. This is because there is a correlation between these two quantities; tall Pokemon are usually heavier, and vice versa. However, we will not be using either of these variables in our final model, so we will not have any interaction terms.

Variable Transformation

One of the defining features of a Pokemon is its typing. There are 18 total types, and a Pokemon can have either one or two types. In the context of the data set, if a Pokemon has a type1, but an empty type2, then the Pokemon only has one type. If the Pokemon has both a type1 and type2, then it is a dual-type Pokemon (The only exception is if the Pokemon has an alternate Alolan form, which we have already decided to remove from our data set). While a Pokemon technically has a "primary" type and "secondary" type, the order of the typing is unimportant (e.g. a fire and ground Pokemon has the same typing as a ground and fire Pokemon). Because the Pokemon typing is organized this way, type1 and type2 can't be predictors themselves.

Our solution is to create 18 new variables (*is_[type]*), that has a '1' if the Pokemon is of the specified type, and '0' if the Pokemon is not. By using all 18 columns as predictors, we can successfully include a Pokemon's typing as a predictor of a Pokemon's catch rate.

However, we are seeking to find the most important factors of a Pokemon in determining its catch rate. Certain Pokemon types tend to be closely related to the factors of a Pokemon that we are already using as predictors. For example, dragon types typically have very high attack stats, and steel types typically have very high defense stats. By including the Pokemon's

type as a predictor, the overall effect of the other predictors on catch rate will most likely be understated. However, certain types may still have an effect on catch rate for reasons other than our predictors. For example, dragon types may be intended by the creators to have lower catch rates than other Pokemon for reasons other than the fact that they have slightly higher stats than the other Pokemon. Thus, this leads us to the creation of two different models.

Linear Model Assumptions

When examining the linear model assumptions, we found that independence, linearity, and constant variance are violated, but that normality is not. The actual residual plots and Q-Q plots are included in the appendix for reference. The independence assumption is violated due to the evolution lines of Pokemon. The data set includes Pokemon that are of the same evolutionary line– for example, Charmander, Charmeleon, and Charizard. Since these Pokemon are of the same evolution line, they will have similar, if not the exact same, type(s), generation, and other information. The independence assumption is violated because knowing information about Charmander would reveal information about Charmeleon and Charizard, for instance. Next, in the residual plot, we do not see symmetrically distributed observations around the horizontal axis. The observations are more spread above the axis, so we assume that the regression model is not linear in the predictors.In the same residual plot, we do not see mostly "evenly-spaced" dots. The variance of the residuals gets larger as the fitted values get larger. We can reasonably assume that there is not constant variance. Finally, from the Q-Q plot, there is some deviation the in the tails, but no clear deviation patterns. We can assume that the errors follow a normal distribution.

Results

We will have two different models. The first model only uses the predictors that were selected by the LASSO model.

```
# A tibble: 7 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)  294.       7.45       39.5  2.08e-187
2 hp            -0.598    0.0841     -7.11 2.73e- 12
3 attack        -0.345    0.0797     -4.33 1.68e-  5
4 defense       -0.470    0.0852     -5.52 4.61e-  8
5 sp_attack     -0.391    0.0776     -5.04 5.90e-  7
6 sp_defense    -0.472    0.0952     -4.96 8.67e-  7
7 speed         -0.482    0.0797     -6.05 2.30e-  9
```

The model is: $CaptureRate_i = 293.821 - 0.598hp_i - 0.345attack_i - 0.470defense_i - 0.391sp-attack_i - 0.472sp-defense_i - 0.482speed_i$

Our first model shows that the best predictors of capture rate are the six stats of a Pokemon (HP, attack, defense, sp_attack, sp_defense, speed). In general, a Pokemon with higher stats is estimated to, on average, have a lower catch rate. Specifically, HP has the greatest impact. For every 1 point increase of the base stat HP, a Pokemon is expected to, on average, have a 0.59752 decrease in catch rate, while holding the other five stats constant. This is with a very low p-value of 2.73e-12, implying a very likely correlation. Using an informal hypothesis test, each of these six predictors have a p-value lower than a significance level of 0.05, meaning that there is sufficient evidence to suggest that there is a statistically-significant relationship between capture rate and each of these predictors, holding every other predictor constant besides the one being evaluated.

The second model uses the same predictors as the first, but with the addition of the 18 type predictors.

```
# A tibble: 25 x 5
   term        estimate std.error statistic   p.value
   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
 1 (Intercept)  289.       9.42      30.7   3.68e-135
 2 hp            -0.653    0.0870    -7.50  1.78e- 13
 3 attack        -0.312    0.0856    -3.65  2.85e-  4
 4 defense       -0.384    0.0928    -4.13  3.97e-  5
 5 sp_attack     -0.323    0.0855    -3.78  1.71e-  4
 6 sp_defense    -0.490    0.0966    -5.08  4.81e-  7
 7 speed         -0.545    0.0837    -6.51  1.36e- 10
 8 is_bug        -2.11     7.45      -0.284 7.77e-  1
 9 is_dark        3.80     8.83       0.431 6.67e-  1
10 is_dragon    -19.9      9.30      -2.14  3.29e-  2
# ... with 15 more rows
```

In our second model, even with the inclusion of the *is_[type]* predictors, the stats of a Pokemon remain the best predictors. We interestingly see that *is_dragon*, *is_fire*, and *is_rock* have low p-values (and negative coefficients). This implies that there is something other than the stats of a Pokemon that causes these three types to have lower capture rates than the other types. FORMAL HYPOTHESIS TEST?

Discussion

We hypothesized that Pokemon with higher attack, defense, special attack, special defense, HP, and speed stats would have lower capture rates than Pokemon with lower stats. Our models show that this hypothesis was correct.

We hypothesized that a Pokemon's typing would not have any effect on catch rate. However, it turns out that dragon, fire, and rock Pokemon have some external reason of having a lower catch rate. We speculate that dragon types are more rare, thus the game developers want them to be more difficult to catch. However, we are unsure why fire and rock types would be harder to catch. More research can be done into specifically why these three types have lower catch rates.

We hypothesized that larger Pokemon (in terms of height and weight) would have lower capture rates than smaller Pokemon, however, the LASSO model did not choose these variables as predictors. The capture rate of a Pokemon may not depend on the height and/or weight of the Pokemon. More research can be done prove or disprove this theory.

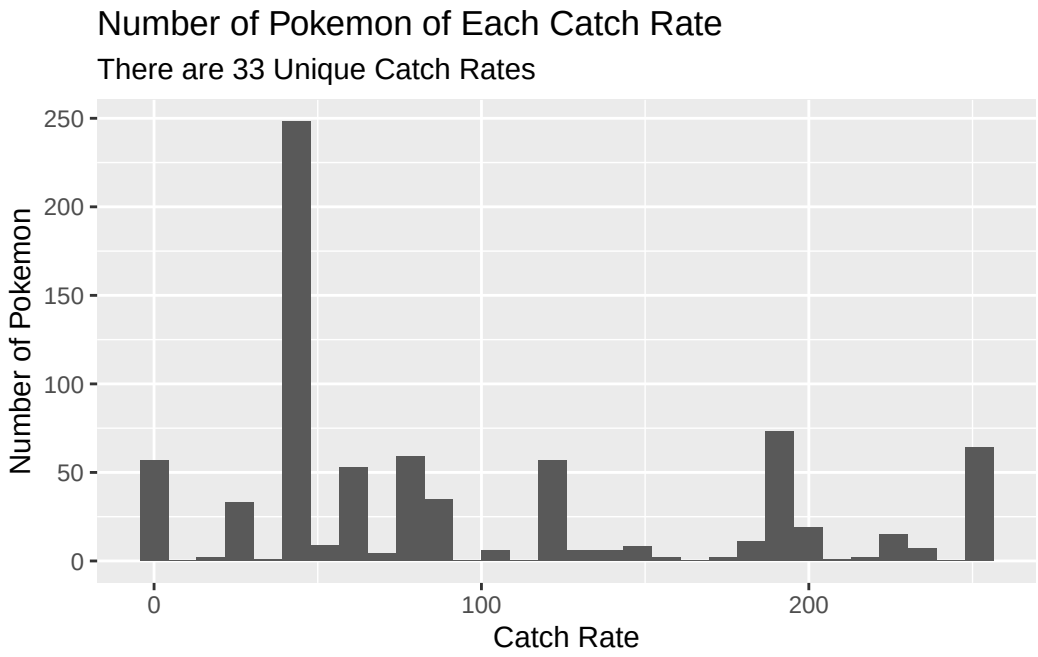
Finally, we hypothesized that legendary Pokemon would have lower capture rates than non-legendary Pokemon. We were very surprised that *is_legendary* was not chosen as a predictor by the LASSO model. Through our Pokemon experiences, we have always assumed that a legendary Pokemon was harder to catch because it was legendary. We speculate that legendary Pokemon have much higher stats in general, thus the reason they have low catch rates is due to their stats being so high, not because they are legendary. We ran a linear model that uses only *is_legendary* as a predictor, and there was a very likely correlation. More research can be conducted on specifically why *is_legendary* may not be the best predictor of catch rate.

Appendix

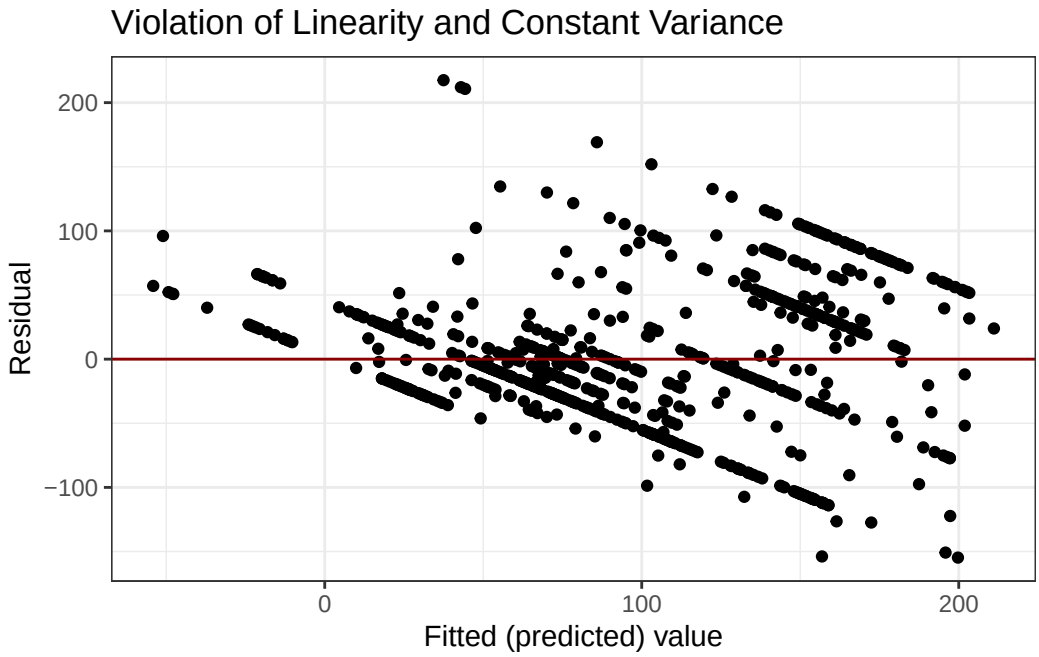
Here is a partial look at the Pokemon data set, including the transformations we completed (manually excluding some variables, adding new typing variables, changing variables types, excluding some observations, etc.).

```
         name pokedex_number generation capture_rate type1  type2 height_m
1   Bulbasaur              1          1           45 grass poison      0.7
2     Ivysaur              2          1           45 grass poison      1.0
3    Venusaur              3          1           45 grass poison      2.0
4  Charmander              4          1           45  fire             0.6
5  Charmeleon              5          1           45  fire             1.1
6   Charizard              6          1           45  fire flying      1.7
7    Squirtle              7          1           45 water             0.5
8   Wartortle              8          1           45 water             1.0
9   Blastoise              9          1           45 water             1.6
10   Caterpie             10          1          255   bug             0.3
   weight_kg base_egg_steps experience_growth base_happiness hp attack defense
1        6.9           5120           1059860             70 45     49      49
2       13.0           5120           1059860             70 60     62      63
3      100.0           5120           1059860             70 80    100     123
4        8.5           5120           1059860             70 39     52      43
```

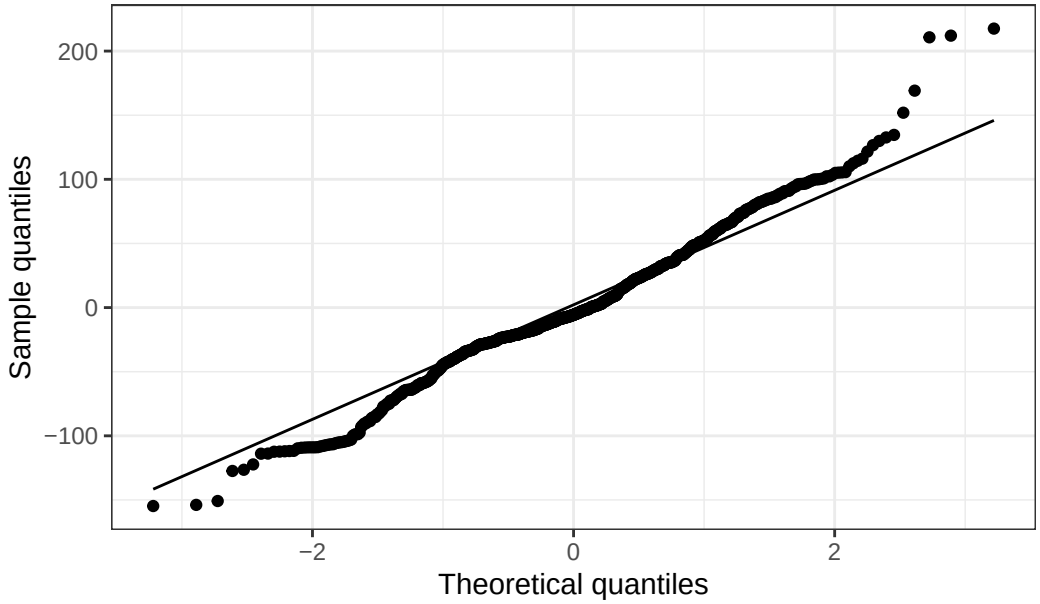
```
5       19.0           5120           1059860             70 58     64       58
6       90.5           5120           1059860             70 78    104       78
7        9.0           5120           1059860             70 44     48       65
8       22.5           5120           1059860             70 59     63       80
9       85.5           5120           1059860             70 79    103      120
10       2.9           3840           1000000             70 45     30       35
   sp_attack sp_defense speed is_legendary is_bug is_dark is_dragon is_electric
1         65         65    45            0      0       0         0           0
2         80         80    60            0      0       0         0           0
3        122        120    80            0      0       0         0           0
4         60         50    65            0      0       0         0           0
5         80         65    80            0      0       0         0           0
6        159        115   100            0      0       0         0           0
7         50         64    43            0      0       0         0           0
8         65         80    58            0      0       0         0           0
9        135        115    78            0      0       0         0           0
10        20         20    45            0      1       0         0           0
   is_fairy is_fighting is_fire is_flying is_ghost is_grass is_ground is_ice
1         0           0       0         0        0        1         0      0
2         0           0       0         0        0        1         0      0
3         0           0       0         0        0        1         0      0
4         0           0       1         0        0        0         0      0
5         0           0       1         0        0        0         0      0
6         0           0       1         1        0        0         0      0
7         0           0       0         0        0        0         0      0
8         0           0       0         0        0        0         0      0
9         0           0       0         0        0        0         0      0
10        0           0       0         0        0        0         0      0
   is_normal is_poison is_psychic is_rock is_steel is_water
1          0         1          0       0        0        0
2          0         1          0       0        0        0
3          0         1          0       0        0        0
4          0         0          0       0        0        0
5          0         0          0       0        0        0
6          0         0          0       0        0        0
7          0         0          0       0        0        1
8          0         0          0       0        0        1
9          0         0          0       0        0        1
10         0         0          0       0        0        0
```



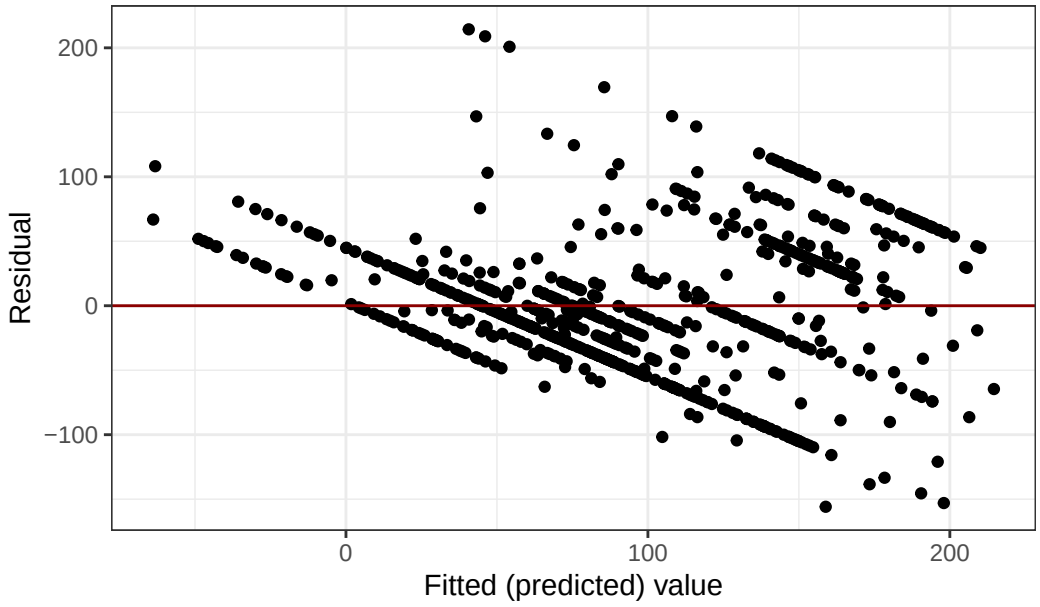
Next, here are the residual plots and the Q-Q plots for the two models.

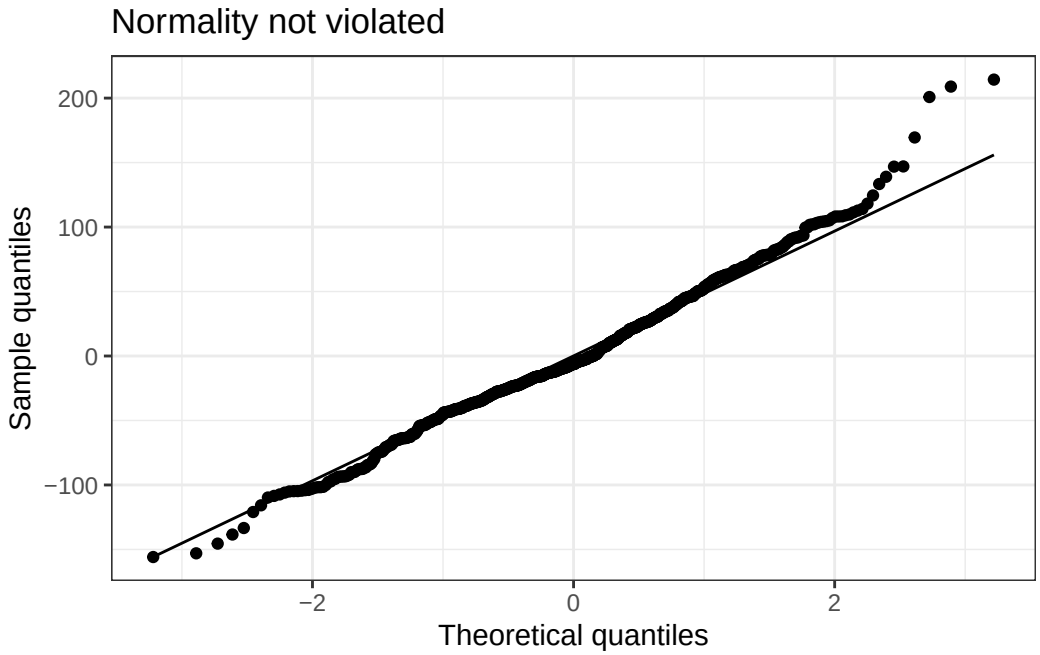


Normality not violated



Violation of Linearity and Constant Variance




Normality not violated
Sample quantiles
200
100
0
−100
−2
0
2
Theoretical quantiles