Wordle Difficulty Analysis

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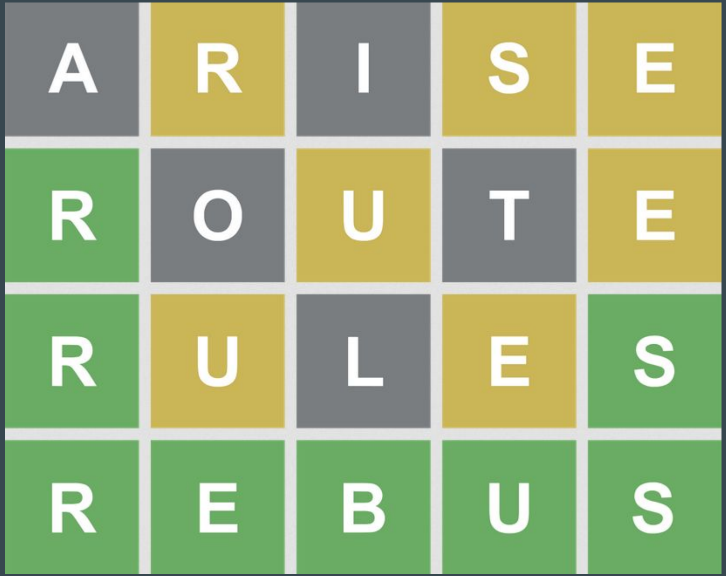
Background

https://en.wikipedia.org/wiki/File:Wordle_196_example.svg



- Wordle is a word puzzle game where the player has six tries to guess the five-letter answer word
- Each letter in the guessed word will be assigned one of three colors:
  - Gray: not in answer
  - Yellow: in answer, incorrect position
  - Green: in answer, correct position
- Wordle was originally created by Josh Wardle, and is now owned by the New York Times: https://www.nytimes.com/games/wordle/index.html

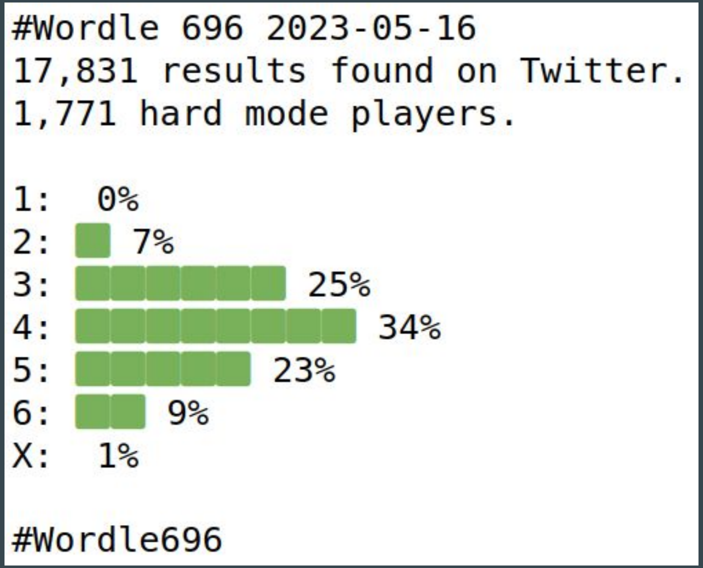
Project Overview

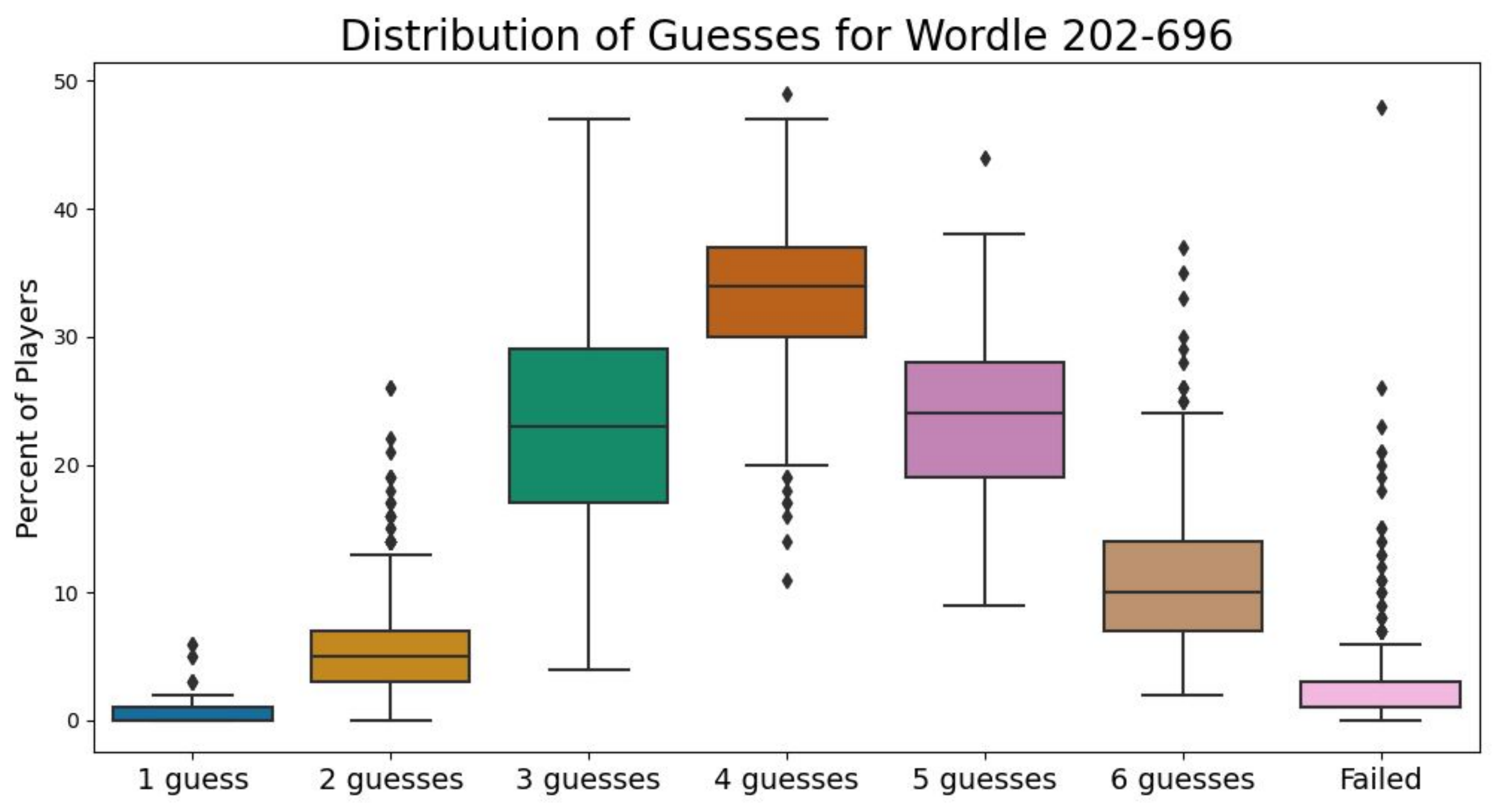
- The goal of this project was to use machine learning to predict the difficulty of solving a Wordle puzzle given the answer word
- We will use the average player score (i.e., the average number of required guesses) as a measure of difficulty
    - Higher average score → greater difficulty
    - If a player failed to guess the word after 6 guesses, they will be assigned a score of 7

Data

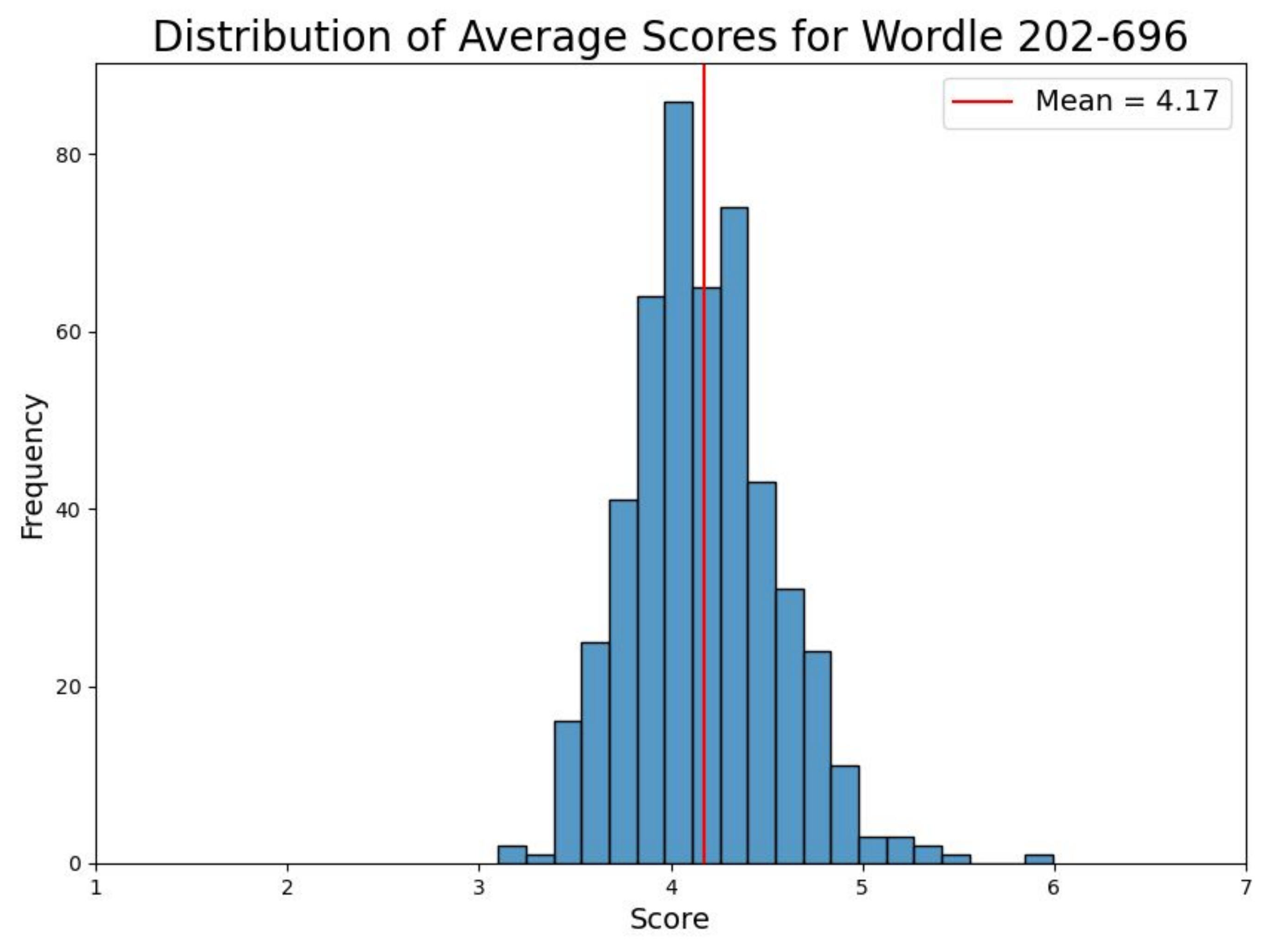
- Player score data was obtained from https://twitter.com/WordleStats, which is a Twitter account that aggregates scores from player tweets
- For this project, we will use data from Wordle 202-696 (except for Wordle 591 and 608, which are missing from the Twitter account)

Example tweet:





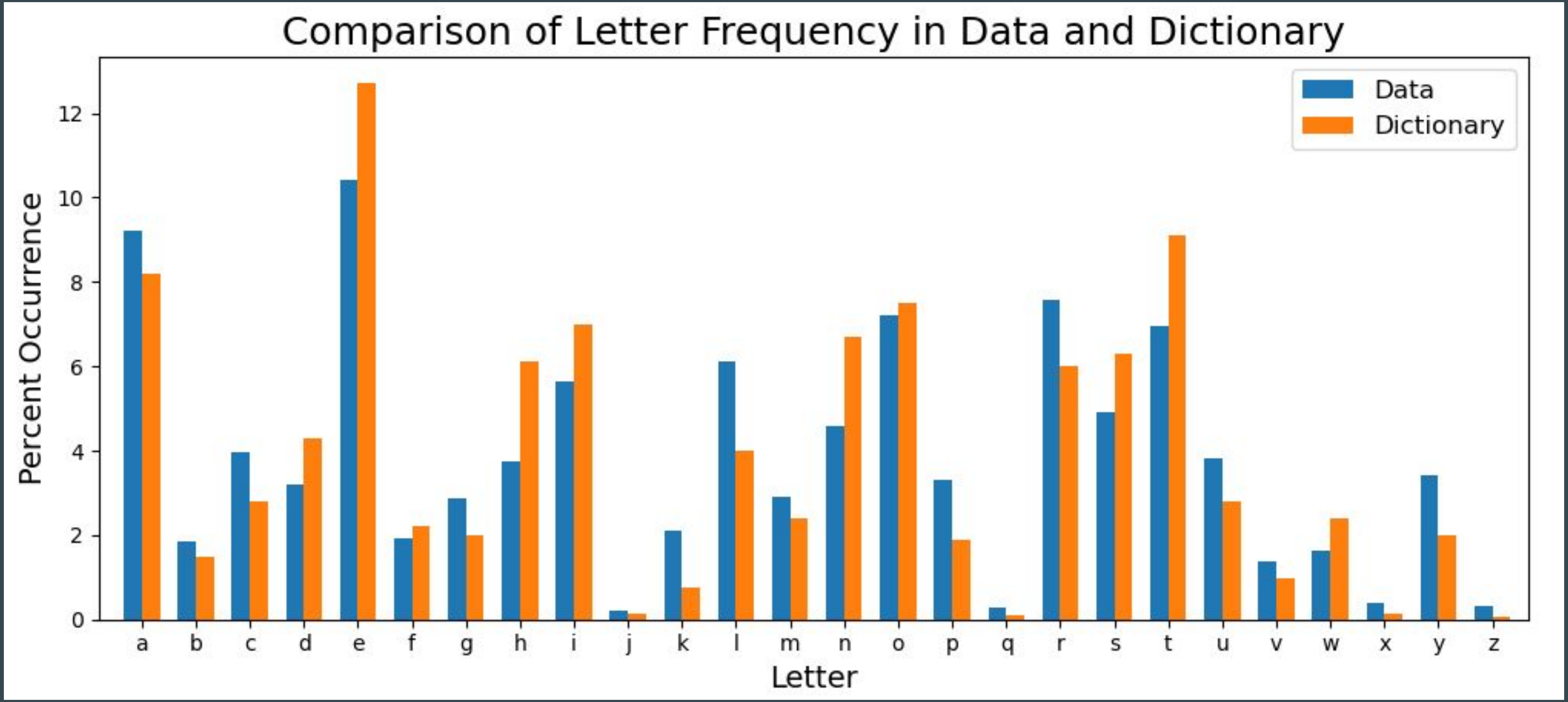
Distribution of Guesses for Wordle 202-696
Percent of Players
0
10
20
30
40
50
1 guess
2 guesses
3 guesses
4 guesses
5 guesses
6 guesses
Failed



Distribution of Average Scores for Wordle 202-696
Mean = 4.17
Frequency
Score
0
20
40
60
80
1
2
3
4
5
6
7

Other Data

- The answer words for each Wordle puzzle were obtained from https://wordfinder.yourdictionary.com/wordle/answers/
- Data on word frequency in the English language was obtained from https://github.com/IlyaSemenov/wikipedia-word-frequency/tree/master, which is a project maintained by Ilya Semenov to count word frequencies on Wikipedia articles
- Data on letter frequency in the dictionary was obtained from https://en.wikipedia.org/wiki/Letter_frequency

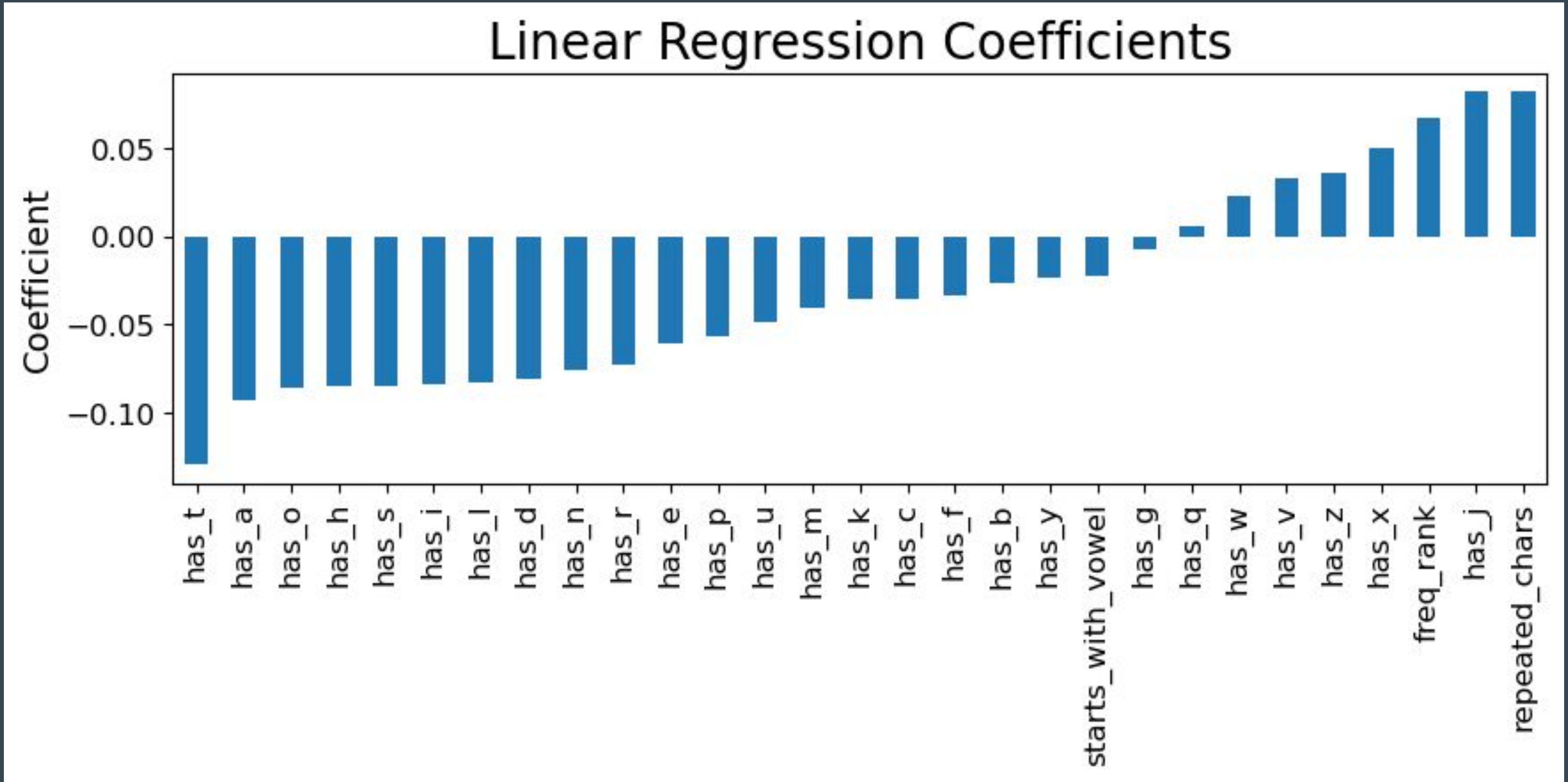

Comparison of Letter Frequency in Data and Dictionary
Data
Dictionary
Percent Occurrence
0
2
4
6
8
10
12
a b c d e f g h i j k l m n o p q r s t u v w x y z
Letter

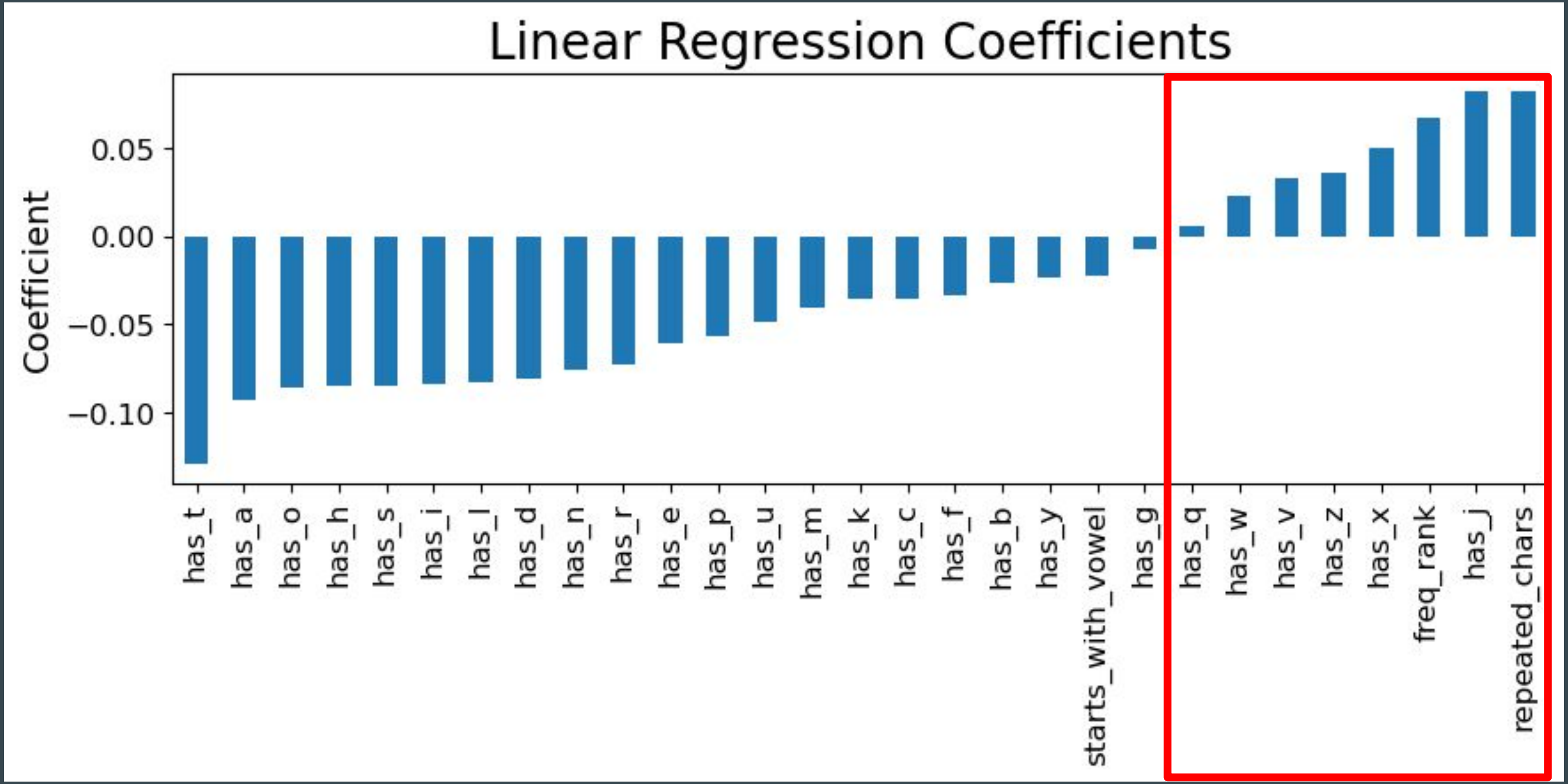
Building a Model

- Target variable: average score (possible values between 1 and 7)
- Features:
  - English language frequency ranking for the answer word
  - For each letter of the alphabet, a boolean for whether the answer word contains the letter
  - A boolean for whether the answer word contains any letter multiple times
  - A boolean for whether the answer word starts with a vowel
- Features were standardized (transformed so that the mean is 0 and the standard deviation is 1) using StandardScaler prior to model fitting

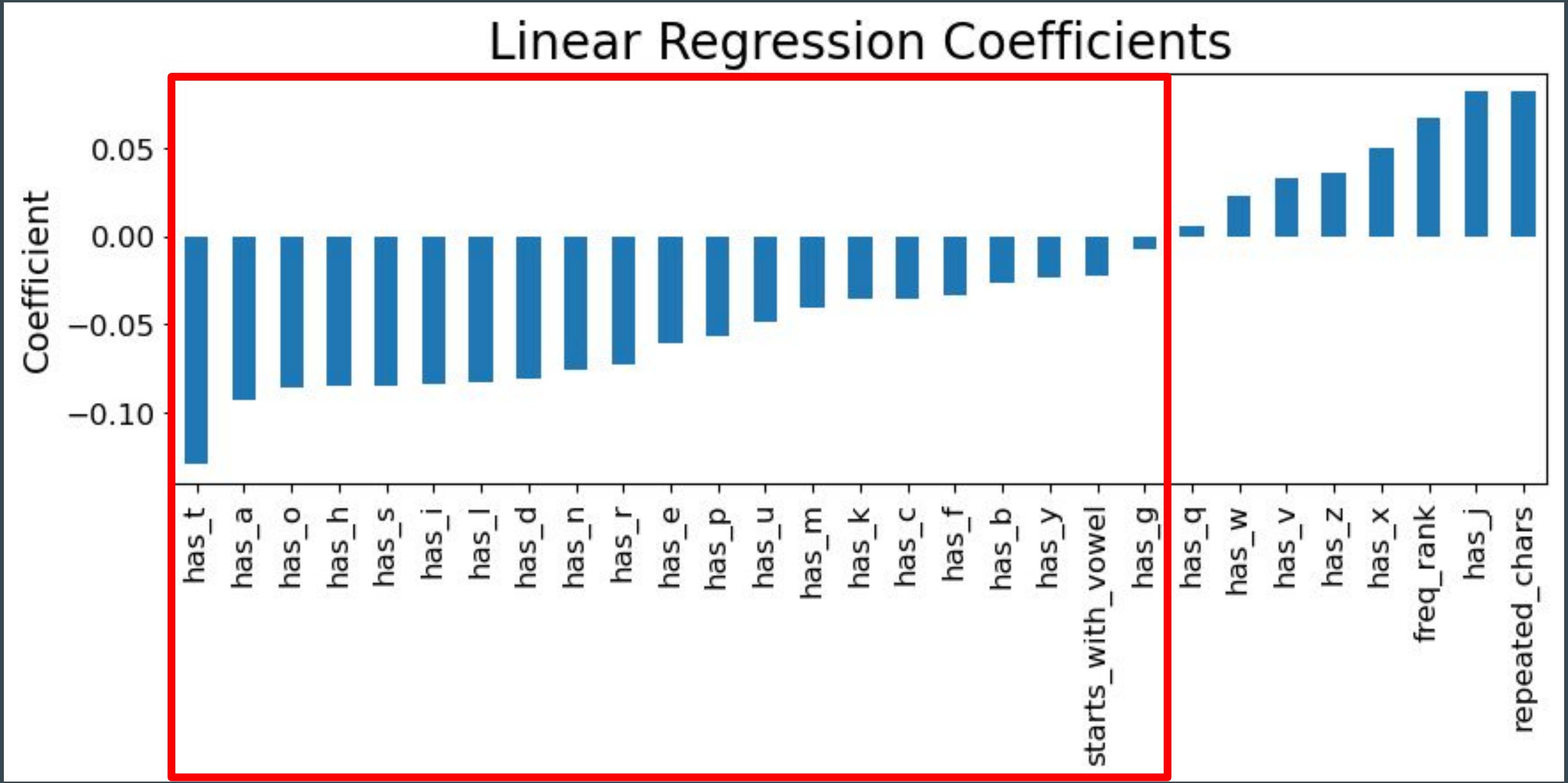
Initial Model: Linear Regression

- The data was fit to a linear regression model using ordinary least squares
  - For the training data, R^2 was 0.506
  - For the test data, R^2 was 0.373
- Since the R^2 value is significantly lower for the test data, this model is overfitting the data
- We can still gain insight by looking at the regression coefficients

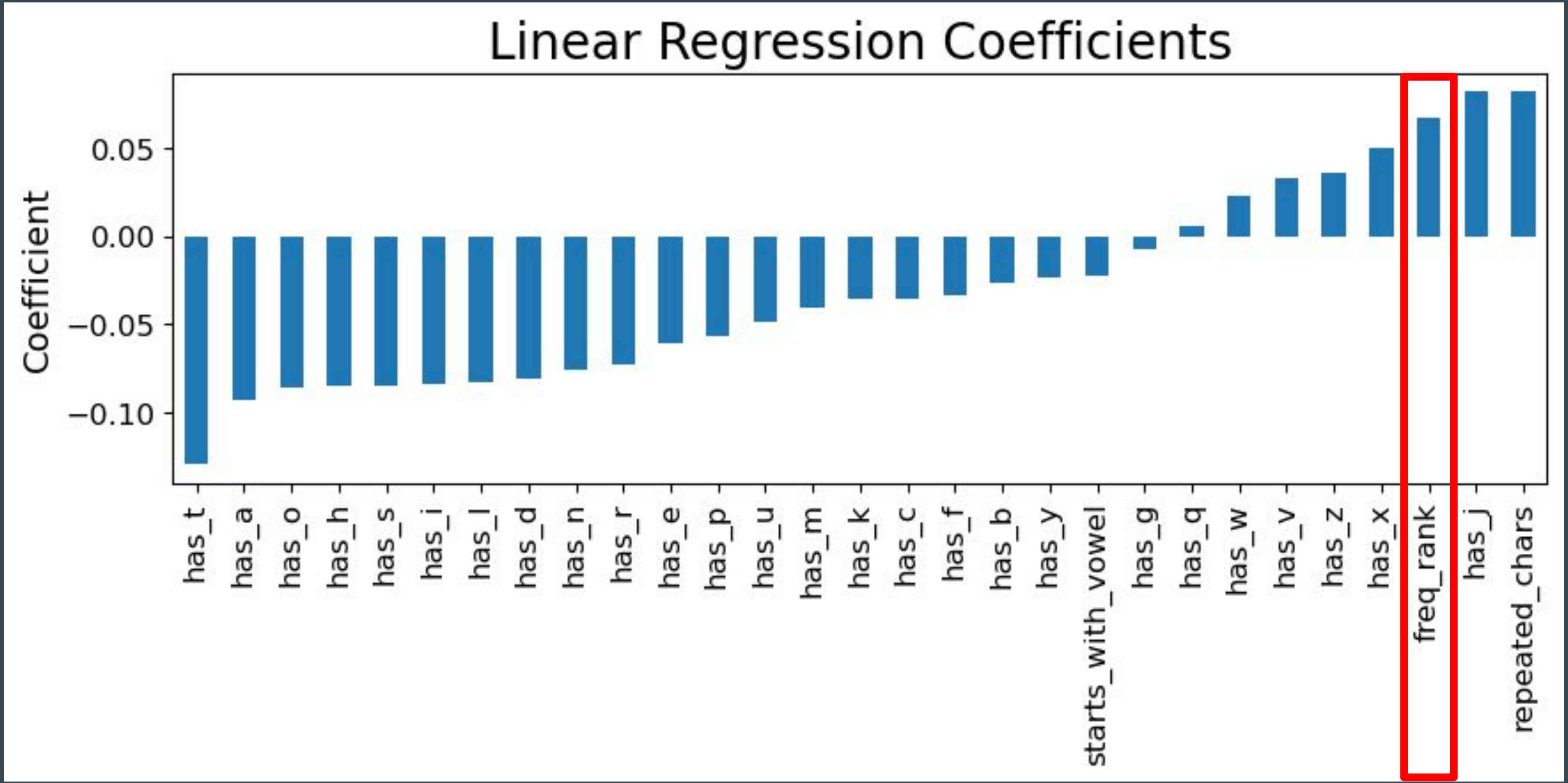

Linear Regression Coefficients
Coefficient
0.05
0.00
−0.05
−0.10
has_t
has_a
has_o
has_h
has_s
has_i
has_l
has_d
has_n
has_r
has_e
has_p
has_u
has_m
has_k
has_c
has_f
has_b
has_y
starts_with_vowel
has_g
has_q
has_w
has_v
has_z
has_x
freq_rank
has_j
repeated_chars



- If a feature has a *positive* coefficient, the puzzle is more difficult when the feature is true and less difficult when the feature is false

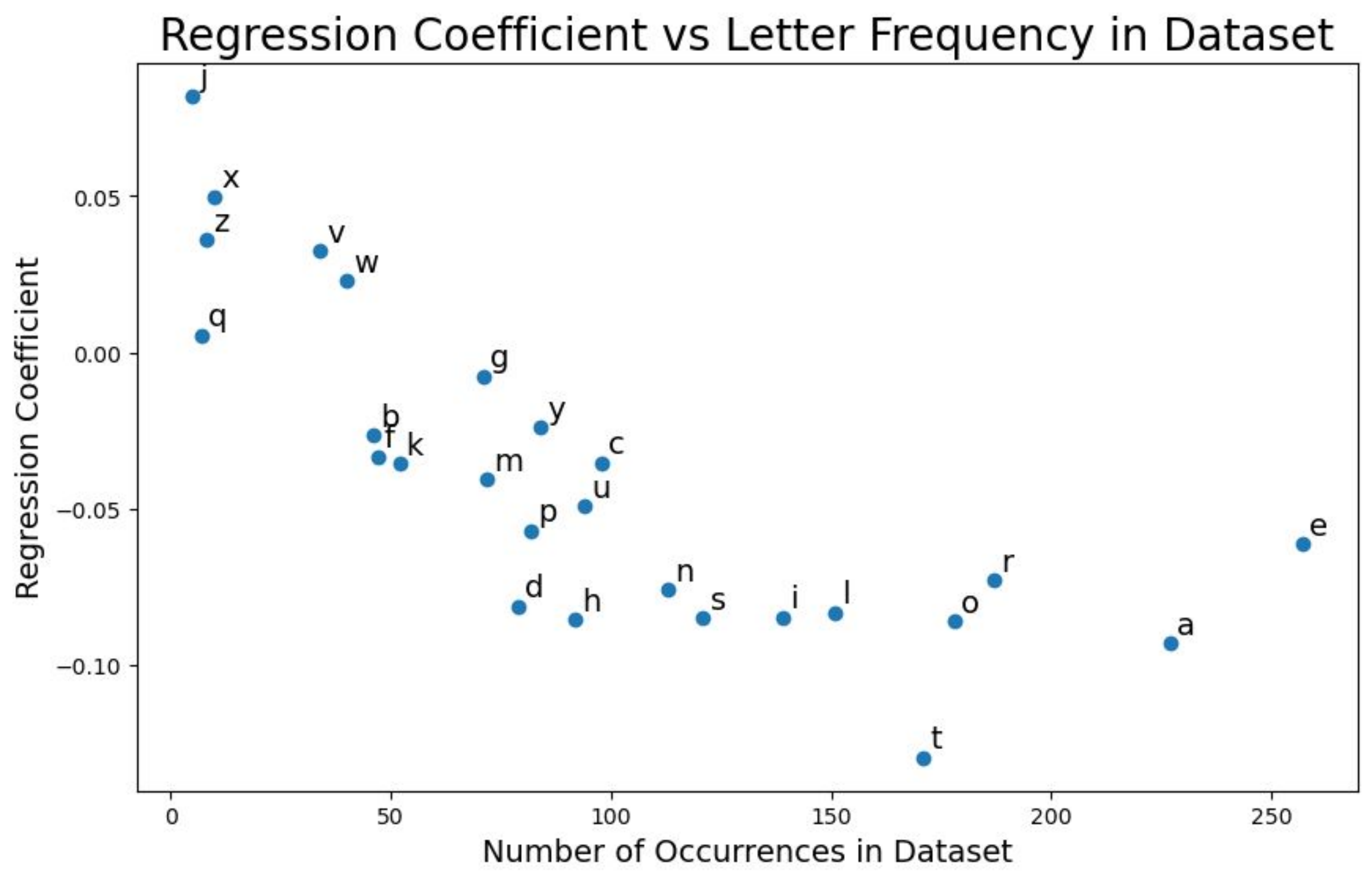


- If a feature has a *negative* coefficient, the puzzle is less difficult when the feature is true and more difficult when the feature is false



- For the frequency ranking, a higher ranking (less common word) results in a more difficult puzzle

More common letters tend to have more negative coefficients (easier to guess):



Improving the Model

- To correct for overfitting, the following improvements were tested:
  - L1 (Lasso) regularization
  - L2 (Ridge) regularization
  - Bagging ensemble model
- In each case, the model was cross-validated using GridSearchCV to find the optimal hyperparameter values

Improving the Model

- Both lasso and ridge regularization did not significantly improve the model
- The bagging ensemble model was slightly less overfit compared to the original linear regression model

Model	Training R^2	Test R^2
Basic Linear Regression	0.506	0.373
Lasso Regularization	0.485	0.328
Ridge Regularization	0.495	0.370
Bagging Ensemble Method	0.491	0.380

Conclusions

- We have developed a machine learning model to predict the difficulty of a Wordle puzzle given the answer word
- The original linear regression model was overfit
- Regularization did not significantly improve the overfitting
- Using a bagging ensemble model resulted in a slight improvement to the overfitting

Future Work

- Try using different features, such as:
  - The part of speech of the answer word
  - Bigrams (does having certain *pairs* of letters affect the difficulty?)
  - The *number of occurrences* of a given letter in the answer word rather than a boolean for whether the letter is present
- Use automated feature selection methods to find a more predictive combination of features
- Use a categorical target variable (e.g., is the average score greater than 4?)
- Try other machine learning models (e.g., decision tree, k-nearest neighbors)