

# WordleBot

## Research Computing Coursework

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18th January 2023

### Abstract

This project investigates the use of information theory in order to solve the game Wordle using WordleBot. The bot maximises the entropy of the next guess in order to give the highest expected information. The starting word “salet” is found to average the fewest number of guesses when compared to other common starters such as “crane” or “audio”. This is consistent with literature that finds “salet” is statistically the best starting word, despite not being a possible final Wordle answer itself. During the development of the WordleBot, the cut-off point at which it should stop guessing from the larger set of guess words and only choose words from the remaining small set of possible words is considered. It is found that the optimum cut-off point when using the word “salet” is when there are five possible words remaining. This yields a minimum average number of guesses of 3.448, which is only 0.027 off the best possible bot performance. It is found having an earlier cut-off point leads to a larger standard deviation of total guesses, regardless of starting word. Profile testing finds these games can be completed on average in 1.2 seconds at 0.34 seconds per guess when starting with “salet”, due to the precomputation of every best second guesses. It is concluded that it would be possible to improve accuracy marginally by planning two steps ahead, however, this would come at a cost to execution time.

## 1 Background and Motivation

In October 2021 Josh Wardle released the game *Wordle*. The game was simple but soon captured the attention of hundreds of thousands of players who would attempt to find the word of the day. The popularity of the game led to it being purchased by New York Time’s for an undisclosed seven figure fee in January 2022. At the peak of its powers, Wordle’s dedicated players would regularly debate what the best starting word to achieve the lowest average number of guesses. This problem naturally caught the attention of statisticians and data scientists who attempted to find the formula for the perfect game.

The laws that govern Wordle are relatively simple. There is a five letter word the player needs to find in the fewest number of guesses. After each five letter guess, each letter tile will turn a colour depending on whether it is present in the true word. A grey tile means the letter is not present in the true word at all, yellow tile means the letter is present but not in this position and green tile means the letter is in the correct position. Double and triple letter rules are slightly more complex, where only one of the double guess letters will have a colour if it appears once in the true word. The same rule applies if triple guess letters appear once or twice in the true word. The first occurrences of the correct letter are normally given the coloured

tile, unless there is a green tile later on in the letter. After you know these rules you are able to simulate the outcomes of the Wordle tiles, just like the website, for any pair of words.

Being able to simulate a game of Wordle is useful, however, since there are over 158,000 five letter words in the English language, it would still be difficult to computationally find the formula for the perfect game. Furthermore, a thorough statistical analysis would require an understanding of how common words are in the English language. How much more likely is the word “hello” to be used than the word “ouija”? Luckily this does not actually need to be considered as the official Wordle word lists were conveniently found in the source code. The first list uncovered is a list of 12,947 five letter words that Wordle will accept as a guess. The other list is a subset of 2,309 of these words that are used as possible true words. Interestingly Wordle moves one place down this list each day meaning each possible answer word has the same probability of being today’s word. You could even cross words out of this list if you know words that occurred the days before, however, out of fairness most ignore this.

Given that the word lists are known and it is possible to deterministically predict the outcome of any Wordle game, what is the best way to play the perfect game? The secret to this is picking the guess which provides the most information on what the true word might be. This is a concept of information theory.

In the context of Wordle, the new information is not given by the guess word, it is given by the tile pattern that it produces. Information theory defines a single bit of information  $I$  as a tile pattern  $x_i$  that can reduce the number of possible remaining Wordle answers by a half, given guess word  $g$ . The conditional probability of getting a pattern given a guess word is defined as (Brillouin 2013)

$$p(x_i|g) = \left(\frac{1}{2}\right)^I \quad (1)$$

This equation can be rearranged to make information the subject

$$I = -\log_2(p(x_i|g)) \quad (2)$$

This tells us that the pattern combinations that are least likely provide the most information. It is true, however, that when selecting a potential guess word  $g$  it is not possible to know for sure what tile pattern it will produce since the true Wordle word of the day is unknown. For this reason, the expected information  $E[I]$  must be considered across all  $N$  unique tile patterns a guess can yield

$$H = E[I] = -\sum_i^N p(x_i|g) \log_2(p(x_i|g)) \quad (3)$$

This expected information is equal to entropy. It is this quantity that needs to be maximised in order to pick the best next guess.

It is possible to take Eq.(3) further and include the expected information of the best next guess in the calculation of the expected information for the current guess. In other words, it is possible to plan multiple steps ahead when determining your guess. To consider every future step when choosing the first guess is incredibly computationally expensive as it requires simulating every possible game of Wordle. This does not only mean simulating every Wordle answer, but also simulating every guess word at every step before a single move has been made. Despite the computational complexity of this problem, it has been implemented. Bertsimas and Paskov (2022) showed that the optimal starting word is “salet”. They use optimal classification trees to showcase their policy which yields an average of 3.421 guesses to solve Wordle. This is to date the best performance on Wordle achieved using a set of algorithmic rules and it is unlikely to be beaten.

Some might argue that it is best to take a machine learning approach that would not require the same level of statistical computation or rigor. Bhambri et al. (2022) used reinforcement

learning algorithms that learnt the optimal policy by repeatedly playing Wordle games and learning from it. Although this did not require the same high levels of computation as analytical solutions, the approximations meant on the reinforcement learning solution had a higher average of 3.508 guesses.

This project will take a light-weight analytical approach where the WordleBot will maximise information based on the next guess without planning ahead. The objective of the project is to minimise the average number of guesses needed to solve the game. Special attention will be focused on the optimal point to stop guessing from the guess list and guess words from the remaining possible answers. The project will also aim to make guesses quickly in real-time, so that the bot can be used to solve a live game of Wordle. The report will first outline on methodology used, then it will look at the development of prototypes and will finally comment on the accuracy and efficiency of the best implementation.

## 2 Method

The model will make decisions by only calculating the expected information gain for the next guess word using Eq. (3). In practice this is done considering every possible Wordle pattern where each of the 12,947 allowed guess words are used to guess the 2,309 possible Wordle answers. This relies on simulating the tile outcomes for nearly 30 million different guess and true word pairs. The results of these tile outcome patterns are stored in a compressed three dimensional array that can be accessed quickly by the WordleBot. To calculate the expected information gain by picking each guess word, the probability of each unique pattern given a guess word is calculated. This involves counting the number of possible true words that would give a certain unique pattern given a guess word and dividing it by the total number of possible words remaining. The probabilities of each pattern are converted into the expected information of a guess using Eq. (3). This process can be repeated for each guess quickly by considering a two-dimensional guess slice of the three dimensional precomputed tile patterns array.

Since it has been statistically proven that the first guess word that provides the highest expected information gain is “salet”, the WordleBot always start with this guess word by default unless instructed otherwise. The WordleBot will then wait for the tile pattern response for this starter word, given interactively by the user or simulated if the true word is known. Once the pattern is given the bot will remove potential answer words that are not capable of producing this tile pattern given the first guess word. Since these impossible words are also removed from the tile patterns array, the next computation of the expected information gain of each guess word is different. The WordleBot will then pick the guess word that maximises the expected information gain. This process is repeated until there are only a few possible words remaining. Since “salet” is the default first guess word it is useful to precompute the best second guess word corresponding to each possible pattern the first guess can produce. This increases time-efficiency of the bot as it is only calculates the expected information of each guess once the possible word list is substantially reduced.

After the possible word list has been substantially reduced there comes a point where the algorithm should only make a guess from this small list and not from the list of 12,947 allowed guesses. It obvious to swap to this list when there are at least two words remaining since one guess will eliminate the other. It could also be argued that if there are three possible words remaining the next guess could be chosen carefully based on expected information so that if it is wrong, it could eliminate another possible answer as well as itself. This logic can be applied to when there are four or five possible words remaining, but it not obvious where the best cut-off point is to guess only from the smaller list. This cut-off point is investigate during the development of WordleBot.

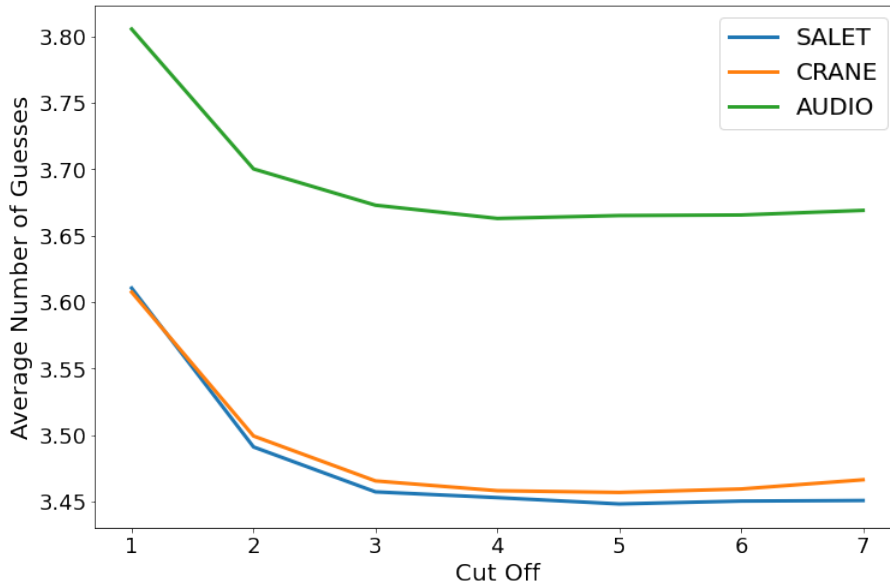


Figure 1: The average number of total guesses WordleBot takes to solve Wordle as a function of the cut-off parameter for three different starter words.

### 3 Development

The first stage of development involved implementing an algorithm that would accurately predict what tiles a guess word would produce for a given true word. This was non-trivial as it relied on getting the tiles correct for guess words that have duplicates or even triplicates of a letter that only appears once or twice in the true word. This meant that the algorithm had to cycle through each guess letter at least twice as it is not possible to know whether a tile should be yellow or grey before reading the full word. After dealing with these tricky cases, unit tests were constructed so it could test whether the right tiles were being produced for all the sensitive words.

The next step was to test the simplest version of the algorithm that would iteratively reduce word list by maximising entropy until there was only one word remaining. The performance of the first WordleBot prototype took an average of 3.611 guesses to solve each possible answer. At this point it was also simple to trial different starter words. “crane” and “audio” are fan favourite starter words for Wordle. “Audio” yielded an average performance of 3.806 guesses, which was considerably worse than “salet”. Interestingly, for this prototype, “crane” took the lowest number of guesses with an average of 3.608. This is likely because it is possible to guess the answer in one guess since the word “crane” is itself on the possible answers list. All three starter words would take a maximum of six guesses to solve Wordle. The prototype results were encouraging as it showed that the algorithm performed well without a cut-off strategy.

The final version of the WordleBot had a cut-off feature, this controlled the point at which the algorithm would guess from only the remaining possible words. As described in Section 2, the best cut-off point is not trivial, so a hyperparameter is added that describes the maximum number of remaining words the bot will take a guess from. Figure 2 shows the effect that varying this hyperparameter has on the average number of guesses for the three tested starter words. It can be seen that three words benefit from the cut-off process. It is found that “salet” and “audio” have the smallest average guesses when the cut off is at five remaining words. “Crane” has the lowest average when the cut-off is 6 words. The averages gradually increase if the cut-off point is increased beyond the optimal list lengths. These tests told us that the optimal WordleBot would start with the word “salet” and have a cut-off point at 5 remaining words,

that had an average of 3.448. The average is only 0.027 more guesses away from those solutions that analytically pre-planned all future steps with an exhaustive search.

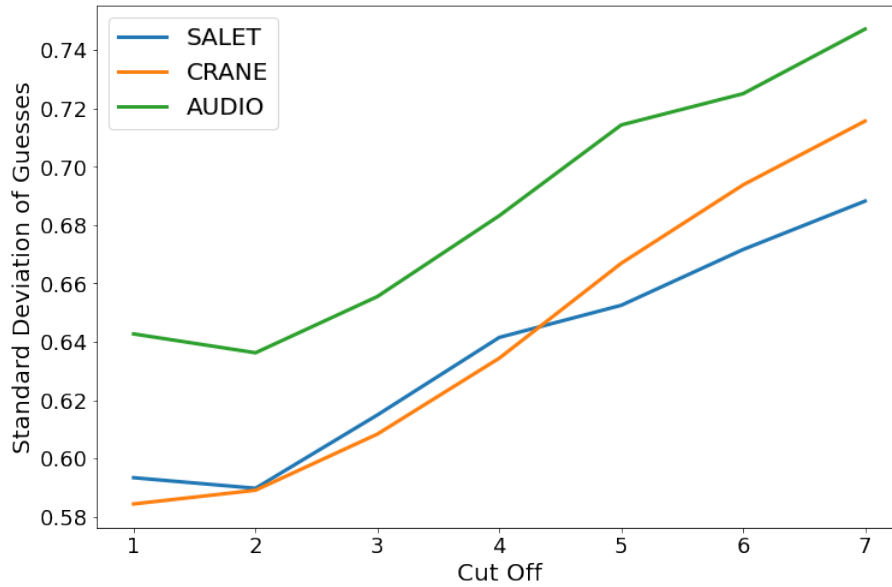


Figure 2: The standard deviation of the number of total guesses WordleBot takes to solve Wordle as a function of the cut-off parameter for three different starter words.

Figure 2 shows how the standard deviation of the total number of guesses varied as a function of the cut-off point. It can be seen that increasing the cut off point increases the spread of total guesses. This is a predictable effect as choosing from the possible word list can will occasionally result in the true word being found sooner, but can also result in the true word taking longer to find, particularly if the final few words only differ by one letter. Figure 3 shows that bots with the starting word “salet” take a maximum of six guesses up to the cut-off point of five. The “audio” and “crane” bots will only tolerate cut-offs with much smaller list sizes before the maximum number of guesses increases. This again demonstrates the optimal WordleBot has a cut-off at point at five and starts with “salet”.

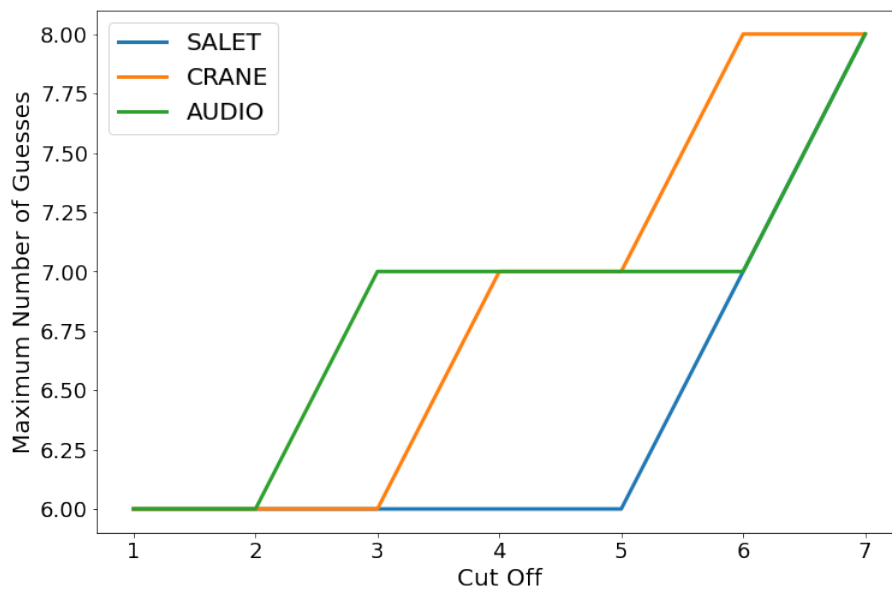


Figure 3: The maximum number of total guesses WordleBot takes to solve Wordle as a function of the cut-off parameter for three different starter words.

## 4 Final Results

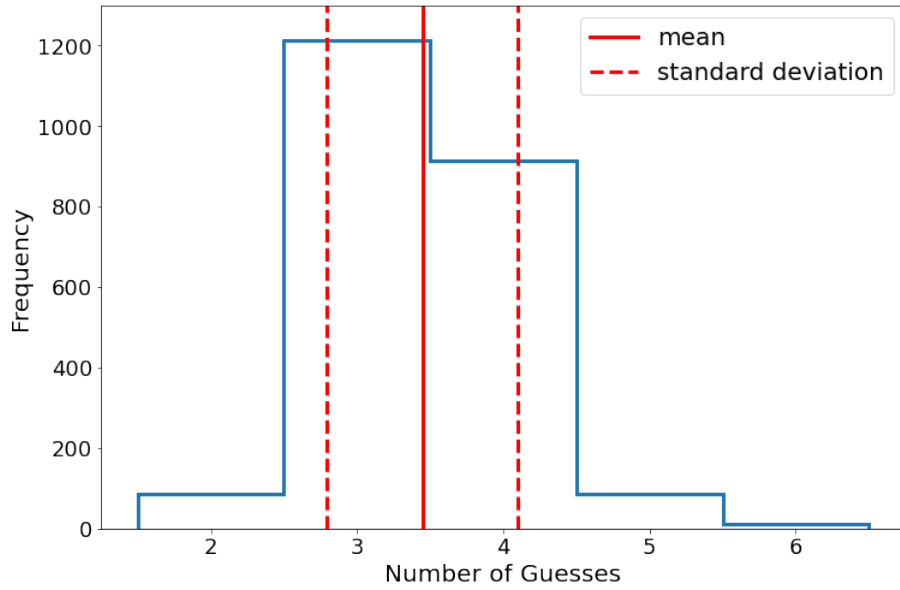


Figure 4: The distribution of total number of guesses for the optimal WordleBot when applied to all possible answers.

The performance of the optimal WordleBot, that started with “salet” and began guessing possible answers when only five were left, was analysed in greater detail in Figure 4. The average number of guesses was  $3.448 \pm 0.652$ . The bot most commonly solved Wordle in only three guesses with 1213 being solved this quickly. The bot guessed 85 words within two guesses. Examples of these include “asset”, “pulse” and “smart”. The algorithm took a maximum number of six attempts to solve twelve of the possible answers. These words include “punch”, “wight” and “woody”. All of these words are similar to other words by one letter and start with letters lower down in the alphabet. This suggests it would be beneficial investigating the effects of the possible word list being in alphabetical order, perhaps using a random ordering may have improved results.

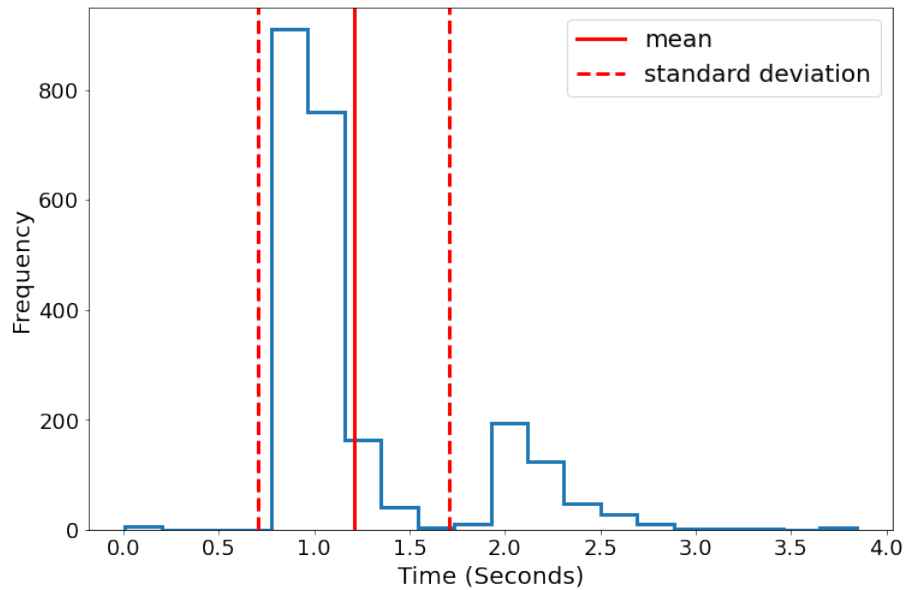


Figure 5: The distribution of total time elapsed to solve every possible Wordle using WordleBot.

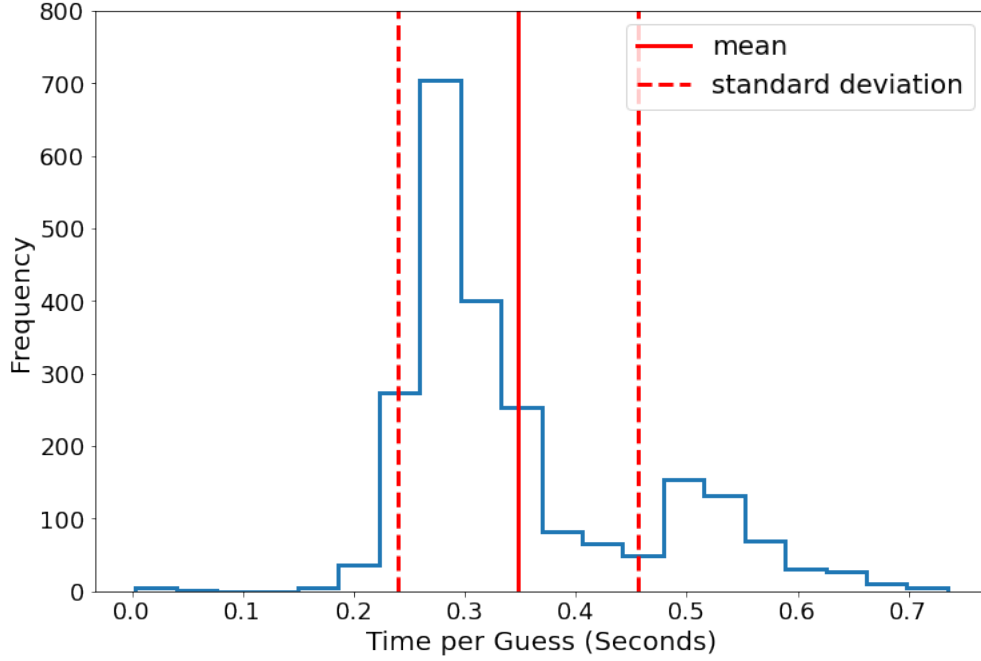


Figure 6: The distribution of total time per guess to solve every possible Wordle using Wordle-Bot.

Figure 5 shows the total time taken to solve each every possible Wordle word with Wordle-Bot. The average total time taken was  $1.2 \pm 0.5$  seconds. Factors that led to the fast performance included precomputation of patterns and best second words, the use of *cython* and minimising the number of iterative loops. The fastest word to solve was the word “allay” taking only 0.006 seconds in two moves, down to its distinctive double letters and being earlier in the alphabet. The word “rover” was the slowest to solve, taking a total of 3.84 seconds in six moves, due to being both late in the alphabet and similar to other words such as “cover”, “hover”, “lover” and “mover”. The average time taken per guess was  $0.3 \pm 0.1$  second which fits the brief. Figure 6 shows the distribution of time taken per guess. The two peaks in the plot are consistent with words solved within three or four guesses. Each guess WordleBot makes gets faster due to there being fewer possible words remaining. No WordleBot guess takes longer than 1.3 seconds using the guess word “salet”, which comes from true words that yield five grey tiles.

## 5 Conclusions

After investigating the best starter word for WordleBot was found to be “salet” that yielded a lowest average and maximum number of guesses compared to other words. It was also found that the best time to take a guess from the remaining possible words was when there are five words remaining. This strategy decreased the average total number of guesses but did increase the standard deviation. The project could be extended further to study the marginal gains of planning future steps ahead of time and the effects of the alphabetical ordering of the true word list. In conclusion, the brief of the project has been met by creating a wordle solver that can solve all possible words taking on average  $3.448 \pm 0.652$  guesses and  $0.3 \pm 0.1$  seconds per move.

## References

Bertsimas D., Paskov A., 2022, An Exact and Interpretable Solution to Wordle.

Bhambri S. et al., 2022, *Reinforcement Learning Methods for Wordle: A POMDP/Adaptive Control Approach*, arXiv preprint arXiv:2211.10298.

Brillouin L., 2013, *Science and Information Theory*, Academic Press, Inc., New York.