Wordle

January 16, 2022

1 Wordle Analysis

The first thing to do is load the required libraries! I am using pandas for my datasets, seaborn for my plotting, string for its useful alphabet string and matplotlib for managing my seaborn plots.

```
[1]: %matplotlib inline
import string
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

We will now load the dataset words.txt from this source. I then filter this dataset: -len(word) == 5 only 5 letter words - word.isalpha() only words made of pure text (no hypens) -word[0].upper() != word[0] to remove any proper nouns

You may ask why I didn't choose to use the words-alpha.txt, the issue with this document is that it is all in lower case, so I have no idea which words are proper nouns!

```
with open("words.txt", "r", encoding="utf-8") as f:
    words = [
        word.upper()
        for word in f.read().splitlines()
        if len(word) == 5 and word.isalpha() and word[0].upper() != word[0]
    ]
    num_words = len(words)

# letter = (pd.DataFrame.from_records(letter_count[0]))
```

We will then create an empty DataFrame which will be used to count how often each letter falls in each position of a letter! For example, the word "pilot", has one "P" in the column count1, one "I" in the column count1 etc...

	count0	count1	count2	count3	count4
Α	0	0	0	0	0
В	0	0	0	0	0
С	0	0	0	0	0
D	0	0	0	0	0
Ε	0	0	0	0	0
F	0	0	0	0	0
G	0	0	0	0	0
Н	0	0	0	0	0
Ι	0	0	0	0	0
J	0	0	0	0	0
K	0	0	0	0	0
L	0	0	0	0	0
M	0	0	0	0	0
N	0	0	0	0	0
0	0	0	0	0	0
Р	0	0	0	0	0
Q	0	0	0	0	0
R	0	0	0	0	0
S	0	0	0	0	0
T	0	0	0	0	0
U	0	0	0	0	0
V	0	0	0	0	0
W	0	0	0	0	0
X	0	0	0	0	0
Y	0	0	0	0	0
Z	0	0	0	0	0

For every word, do the same as we did for the word "pilot".

```
[4]: for word in words:
    for idx, letter in enumerate(word):
        letter_count.at[letter, f"count{idx}"] += 1

print(letter_count)
```

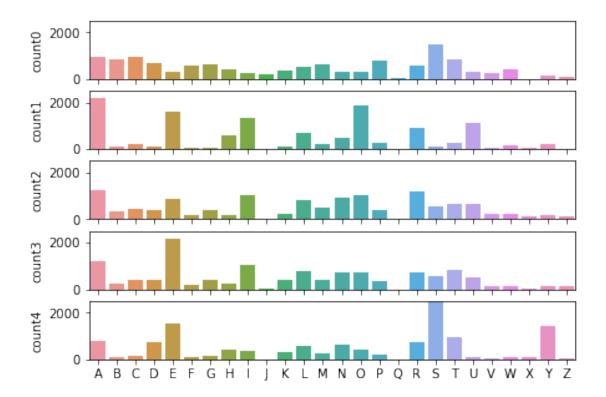
	count0	count1	count2	count3	count4
A	928	2183	1221	1217	808
В	868	94	353	236	85
С	946	223	441	406	172
D	669	110	403	404	761
Ε	335	1600	874	2141	1525
F	599	38	170	195	90
G	616	84	367	402	168
Η	438	606	159	242	390
Ι	250	1336	1030	1038	338
J	193	15	40	26	2
K	366	89	257	425	293

```
L
                710
                         803
                                   761
                                            589
       516
Μ
       618
                194
                         510
                                   388
                                            245
N
                499
                         935
                                   715
       326
                                            619
0
       289
               1889
                        1016
                                   742
                                            399
Ρ
                         376
                                   374
       790
                249
                                            199
                                     2
Q
        71
                 18
                           21
                                               4
R
       582
                899
                        1196
                                   702
                                            711
S
      1509
                          555
                                   586
                                           2813
                128
Τ
       829
                271
                          644
                                   836
                                            953
U
       294
               1144
                         661
                                   521
                                            122
٧
       244
                 71
                          233
                                   163
                                             19
W
       407
                154
                         241
                                   146
                                             93
Х
                 70
                                    15
                                             85
        17
                          114
Y
                227
                          185
       134
                                   127
                                           1406
Ζ
        93
                 26
                          122
                                   117
                                             38
```

Create a plot showing the frequency of each letter in the dataset (by position)

```
[5]: f, axs = plt.subplots(5, 1, figsize=(7, 5), sharex=True)
    for ax in axs:
        ax.set(ylim=(0, 2500))
    sns.barplot(x=letter_count.index, y=letter_count.count0, ax=axs[0])
    sns.barplot(x=letter_count.index, y=letter_count.count1, ax=axs[1])
    sns.barplot(x=letter_count.index, y=letter_count.count2, ax=axs[2])
    sns.barplot(x=letter_count.index, y=letter_count.count3, ax=axs[3])
    sns.barplot(x=letter_count.index, y=letter_count.count4, ax=axs[4])

plt.show()
```



This here creates a scoring system for every 5 letter word! It's easiest to explaing this with an example! Let's take the word "hello"

Let's refer to our previous table: - the letter "h" in the column count0 scores: 438 (because it occurs 438 times in the dataset! - "e", count1: 1600 - "l", count2: 803 - "l", count3: 761 - "o", count4: 399

So the total score of "hello" is: 4001

```
Word Score
9610 SANES 9581
10534 SORES 9548
9584 SALES 9449
```

```
9650 SATES 9290
10508 SONES 9287
```

The issue with this method, is that it gives high scores to words with repeated letters. Clearly, repeated letters do appear, but what if the letter had no "s", "SANES", "SORES", "SALES", "SATES", "SONES" all have these repeated letters (because that is the most common occurance).

So, what if we look at the total occurance of all the letters?

```
[7]: letter_count["sum"] = letter_count.sum(axis=1)
print(letter_count["sum"].to_dict())
```

```
{'A': 6357, 'B': 1636, 'C': 2188, 'D': 2347, 'E': 6475, 'F': 1092, 'G': 1637, 'H': 1835, 'I': 3992, 'J': 276, 'K': 1430, 'L': 3379, 'M': 1955, 'N': 3094, 'O': 4335, 'P': 1988, 'Q': 116, 'R': 4090, 'S': 5591, 'T': 3533, 'U': 2742, 'V': 730, 'W': 1041, 'X': 301, 'Y': 2079, 'Z': 396}
```

And then take the top 5 most common letters:

```
[8]: highest_frequency = sorted(letter_count["sum"].to_dict().items(), key=lambda

item: item[1])[-5:]

high_freq_1 = ([group[0] for group in highest_frequency])
```

And then we can see which words conform to only these unique 5 letters:

```
[9]: [word for word in word_scoring["Word"] if sorted(list(word)) ==

sorted(high_freq_1)]
```

```
[9]: ['AROSE', 'SEORA']
```

There are some issues with this: - Not all the words in the dataset are allowed on wordle! For example, "SEORA" is not acceptable! This will cause skewness in our analysis! - It's still not a perfect solution, but what if we were to combine our knowledge from the "per position" scoring and the "per letter" scoring, and analyse it that way?

```
[12]: # word_scoring.rename({"Score": "CountScore", "Word": "Word"})
word_scoring["LetterScore"] = np.nan
word_scoring
```

```
[12]:
               Word Score
                           LetterScore
      0
             AAHED 6172
                                    NaN
      1
              AALII 5290
                                    NaN
      2
             AARGH 5099
                                    NaN
      3
             ABACA 3457
                                    NaN
             ABACI 2987
                                    NaN
                . . .
                      . . .
      12922
             ZORRO 4279
                                    NaN
      12923
             ZOWIE 4786
                                    NaN
      12924
             ZUCCO
                    2483
                                    {\tt NaN}
      12925
             ZUDDA 2852
                                    NaN
```

35963.0

35720.0

35695.0

35630.0

35601.0

35601.0

35594.0

35526.0

35518.0

35458.0

9644

9818

3663

6432

10159

9794

9035

774

652

10534

SASSE 6358

SEERS 7498

ESSES 5972

SORES 9548

LASES 8208

AREAS 6731

SISES 8354

SEATS 7979

RARES 8915

ATEES 7027

29605.0

28222.0

29723.0

26082.0

27393.0

28870.0

27240.0

27547.0

26603.0

28431.0

708	ARSES	7336	28104.0	35440.0
9544	SADES	9049	26361.0	35410.0
9790	SEALS	7904	27393.0	35297.0

The problem we see here is that "AROSE" doesn't even appear on this list!

This is probably because my statistical analysis is not good enough! The problem is that "S" is disproportionately outwaying the other letters because a lot of these words are 4 letter plurals (so 5 with an "S" at the end)

I hope this information could help someone do their own analysis of this dataset, it would be interesting to see what the best word is! Perhaps making a simulation of the game would give different results?

[]: