

# Words, Zipf's Law, Miller's Monkeys

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# BASICS OF ENGLISH WORDS

## Unigram Word Count

- ▶ Same as **word frequency**, when normalized
- ▶ Just simple counting of words

## How do we define words?

- ▶ Words = Text Split by Space  
ex) English, Korean
- ▶ This definition is Non-Trivial for language without space  
ex) Chinese

**Processing Text is called  
"Tokenization" or "Text normalization"**

# TOKENIZATION

## THINGS TO CONSIDER

### Throw away Junks such as Html tags!

- ▶ But sometimes they are valuable.  
ex) navigate the document structure

### Word boundaries : White space and Punctuations

- ▶ What should we do with words like "Ph.D, isn't, e-mail"?
- ▶ Domain Dependent problem
- ▶ Manually created regular expression rules are typically used.

### Capitalization, case-folding

- ▶ Convenient to lower case every character  
Counter example : "US" vs "us"

# TOKENIZATION

## THINGS TO CONSIDER

### Stemming(Lemmatization)

- ▶ *Stem* can be *inflected* with a morphological *suffix* to produce variation.  
ex) look  $\Rightarrow$  looks, looking, looked
- ▶ Beneficial to map all inflected forms into the *stem*.
- ▶ Complex process - many exceptional cases exist.  
ex) department vs. depart

### Stemming for Korean

- ▶ 동음이의어 문제 발생  
ex) 밤(밤 울) vs. 밤(밤 야), 눈(눈 목) vs. 눈(눈 설)
- ▶ Turns into disambiguation problem.

# TOKENIZATION

## THINGS TO CONSIDER

### Stopwords(불용어)

- ▶ Most frequent words often do not carry much meaning.  
ex) the, a, of, for, in . . .
- ▶ Stopword list can vary from domains.
- ▶ For many NLP purposes, stopwords are nuisance.  
-Will regenerating stopwords for artificially created text seem more natural?
- ▶ Stopword removal is common preprocessing step.

# TOKENIZATION

## THINGS TO CONSIDER

### After Tokenization

After cleaning up text, there are two concepts.

- ▶ Word Token : Occurrence of a word
- ▶ Word Type : unique words
- ▶ ex) "The dog chases the cat"  
→ 5 Word Tokens, 4 Word Type  
There are two tokens of word type "the".

# TOKENIZATION

## THINGS TO CONSIDER

### Vocabulary

- ▶ "Vocabulary" is list of Word Types.
- ▶ Useful to have special word type "UNK" for unknown words.

### Corpus(말뭉치)

- ▶ "Corpus" is large collection of text.  
ex) several years' newspapers
- ▶ *frequency cutoff*  
Can be applied to exclude word types with small counts.  
Usually determined empirically.



# ZIPF'S LAW

## Zipf's Law

The Zipf's Law is empirically known as

$$f \times r \approx \text{constant} \quad \text{or} \quad f \propto \frac{1}{r}$$

where  $f$  is word count,  $r$  is rank of the word.

- ▶ There exists a pattern, when compute  $\text{count} \times \text{rank}$  where rank is number of word types ranked by their count.
- ▶ plot  $\log(r)$  on x-axis and  $\log(f)$  on y-axis, words roughly form a line from upper-left to lower-right.
- ▶  $f$  can be frequency (count divided by the corpus), the relation still hold.

# ZIPF'S LAW ON "MOBYDICK"

```
>moby_stem_token <- tokenize_word_stems(mobydick)
>table2 <- table(moby_stem_token)
>table21 <- sort(table2,decreasing=T)
>table22 <- as.data.frame(table21)
>table23 <-
+cbind("rank"=as.numeric(rownames(table22)),table22)

>fr <- c()
  for(i in 1:length(table23$rank)){
    fr[i] <- (table23$rank[i])*(table23$Freq[i])
  }

>table24 <- cbind("fr"=fr,table23)
>table25 <- table24[c(3,4,2,1)]
>table25
```

# ZIPF'S LAW ON "MOBYDICK"

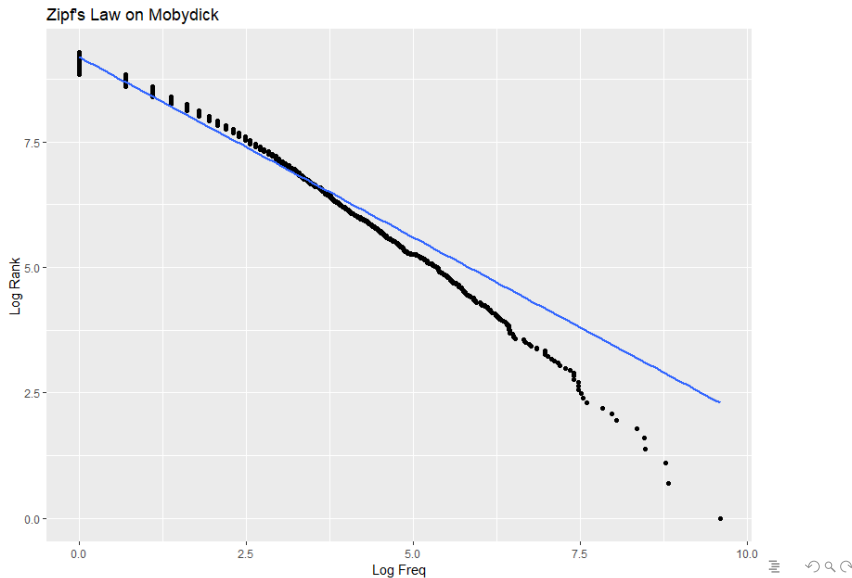
```
> table25
```

	moby_stem_token	Freq	rank	fr
1	the	14620	1	14620
2	of	6736	2	13472
3	and	6502	3	19506
4	a	4778	4	19112
5	to	4709	5	23545
6	in	4231	6	25386
7	that	3099	7	21693
8	it	2916	8	23328
9	his	2530	9	22770
10	i	1989	10	19890
11	he	1878	11	20658
12	but	1823	12	21876
13	with	1770	13	23010

# ZIPF'S LAW ON "MOBYDICK"

```
>moby_df <- table25 %>%  
  mutate(log_rank = log(rank), log_f = log(Freq))  
  
>moby_lm <- lm(log_rank~log_f, data = moby_df)  
>summary(moby_lm)  
  
>ggplot(moby_df, aes(x='log_f', y=log_rank)) +  
  geom_point() +  
  stat_smooth(method="lm", se=TRUE) +  
  labs(x="Log Freq", y="Log Rank",  
       title="Zipf's Law on Mobydick")
```

# ZIPF'S LAW ON "MOBYDICK"



# ZIPF'S LAW

- ▶ See [Zipf's Law R Example](#) for more practice.

# ZIPF'S LAW

## Zipf's Law generalized by Mandelbrot

The Zipf's Law generalized by Mandelbrot is

$$f = P(r + \rho)^{-B}$$

where  $f$  is word count,  $r$  is rank of the word.

- ▶ Adding more parameters to Zipf's Law.
- ▶ With more parameters, the Law become more flexible.
- ▶ See Miller's Monkey for more detail.

# MILLER'S MONKEYS

## Imagine,

Promise a Monkey some stock options and ask it to type tirelessly on a computer keyboard.

What do we get?

What frequency and rank relation do monkey word possess?

## Assumption for Simplification

- ▶ Keyboard has 27 keys : a to z, and white space.
- ▶ Monkey hit each key with equal probability.
- ▶ Let a sequence of letters separated by white space "Word".



# MILLER'S MONKEYS

## Probability of monkey word with length $i$

$$P(i) = (1/27)^i(1/27) = (1/27)^{i+1}$$

- ▶ Longer the word, lower its probability and expected count
- ▶ Rank all monkey words by its probability, then

**The rank  $r_i$  of a word with length  $i$  satisfies**

$$\sum_{j=1}^{i-1} 26^j < r_i \leq \sum_{j=1}^i 26^j$$

# MILLER'S MONKEYS

## Deriving 'Fractional length' $i'$

$$i' = \frac{\log(\frac{25}{26}r + 1)}{\log 26}$$

proof)

Let us consider the word with rank

$$r = \sum_{j=1}^i 26^j = \frac{26}{25}(26^i - 1)$$

$$\frac{25}{26}r = 26^i - 1 \quad \Rightarrow \quad 26^i = \frac{25}{26}r + 1 \quad \Rightarrow$$

$$i \times \log 26 = \log \frac{25}{26}r + 1 \quad \Rightarrow \quad i = \frac{\log(\frac{25}{26}r + 1)}{\log 26}$$

# MILLER'S MONKEYS

## Word frequency with 'Fractional length' $i'$

$$\begin{aligned}
 p(i') &= (1/27)^{i'+1} \\
 &= (1/27)^{\frac{\log(\frac{25}{26}r+1)}{\log 26} + 1} \\
 &= (1/27)(1/27)^{\frac{\log(\frac{25}{26}r+1)}{\log 26}} \\
 &= (1/27)\left(\frac{25}{26}r + 1\right)^{\frac{\log(\frac{1}{27})}{\log 26}} \quad \text{using the fact } a^{\log b} = b^{\log a} \\
 &= (1/27)\left(\frac{25}{26}r + 1\right)^{-\frac{\log 27}{\log 26}} \\
 &\approx 0.04(r + 1.04)^{-1.01}
 \end{aligned}$$

# MILLER'S MONKEYS

## Word frequency with 'Fractional length' $i'$

$$\therefore p(i') \approx 0.04(r + 1.04)^{-1.01}$$

Recall Zipf's Law generalized by Mandelbrot

$$f = P(r + \rho)^{-B}$$

$P(i')$  fits Mandelbrot's Law, and is fairly close to Zipf's Law.

Zipf's law may not reflect some deep knowledge of Language.  
It still points to an important observation that

**"Almost all words are rare!"**

# REFERENCE

Just reorganization of

- ▶ CS838-1 Advanced NLP class material by Xiaojin Zhu
- ▶ [Introduction to the tokenizers Package](#)
- ▶ [Opensource Shakespeare](#)
- ▶ [NLTK 자연어 처리 패키지](#)