

# English Letter Frequency Counts: Mayzner Revisited or ETAOIN SRHLDCU

## Introduction

On December 17th 2012, I got a nice letter from [Mark Mayzner](#), a retired 85-year-old researcher who studied the frequency of letter combinations in English words in the early 1960s. His [1965 publication](#) has been cited in hundreds of articles. Mayzner describes his work:

*I culled a corpus of 20,000 words from a variety of sources, e.g., newspapers, magazines, books, etc. For each source selected, a starting place was chosen at random. In proceeding forward from this point, all three, four, five, six, and seven-letter words were recorded until a total of 200 words had been selected. This procedure was duplicated 100 times, each time with a different source, thus yielding a grand total of 20,000 words. This sample broke down as follows: three-letter words, 6,807 tokens, 187 types; four-letter words, 5,456 tokens, 641 types; five-letter words, 3,422 tokens, 856 types; six-letter words, 2,264 tokens, 868 types; seven-letter words, 2,051 tokens, 924 types. I then proceeded to construct tables that showed the frequency counts for three, four, five, six, and seven-letter words, but most importantly, broken down by word length and letter position, which had never been done before to my knowledge.*

and he wonders if:

*perhaps your group at Google might be interested in using the computing power that is now available to significantly expand and produce such tables as I constructed some 50 years ago, but now using the Google Corpus Data, not the tiny 20,000 word sample that I used.*

The answer is: yes indeed, I am interested! And it will be a lot easier for me than it was for Mayzner. Working 60s-style, Mayzner had to gather his collection of text sources, then go through them and select individual words, punch them on [Hollerith cards](#), and use a [card-sorting machine](#).

Here's what we can do with today's computing power (using publicly available data and the processing power of my own personal computer; I'm not relying on access to corporate computing power):

1. I consulted the [Google books Ngrams](#) raw data set, which gives word counts of the number of times each word is mentioned (broken down by year of publication) in the books that have been scanned by Google.
2. I downloaded the English Version 20120701 "1-grams" (that is, word counts) from that data set given as the files "a" to "z" (that is, <http://storage.googleapis.com/books/ngrams/books/googlebooks-eng-all-1gram-20120701-a.gz> to <http://storage.googleapis.com/books/ngrams/books/googlebooks-eng-all-1gram-20120701-z.gz>). I unzipped each file; the result is 23 GB of text (so don't try to download them on your

- phone).
- I then condensed these entries, combining the counts for all years, and for different capitalizations: "word", "Word" and "WORD" were all recorded under "WORD". I discarded any entry that used a character other than the 26 letters A-Z. I also discarded any word with fewer than 100,000 mentions. (If you want you can download the [word count file](#); note that it is 1.5 MB.)
  - I generated tables of counts, first for words, then for letters and letter sequences, keyed off of the positions and word lengths.

## Word Counts

My distillation of the Google books data gives us 97,565 distinct words, which were mentioned 743,842,922,321 times (37 million times more than in Mayzner's 20,000-mention collection). Each distinct word is called a "type" and each mention is called a "token." To no surprise, the most common word is "the". Here are the top 50 words, with their counts (in billions of mentions) and their overall percentage (looking like a Zipf distribution):

### WORD    COUNT    PERCENT    bar    graph

WORD	COUNT	PERCENT	bar	graph
the	53.10 B	7.14%		the
of	30.97 B	4.16%		of
and	22.63 B	3.04%		and
to	19.35 B	2.60%		to
in	16.89 B	2.27%		in
a	15.31 B	2.06%		a
is	8.38 B	1.13%		is
that	8.00 B	1.08%		that
for	6.55 B	0.88%		for
it	5.74 B	0.77%		it
as	5.70 B	0.77%		as
was	5.50 B	0.74%		was
with	5.18 B	0.70%		with
be	4.82 B	0.65%		be
by	4.70 B	0.63%		by
on	4.59 B	0.62%		on
not	4.52 B	0.61%		not
he	4.11 B	0.55%		he
i	3.88 B	0.52%		i
this	3.83 B	0.51%		this
are	3.70 B	0.50%		are
or	3.67 B	0.49%		or
his	3.61 B	0.49%		his
from	3.47 B	0.47%		from
at	3.41 B	0.46%		at
which	3.14 B	0.42%		which
but	2.79 B	0.38%		but
have	2.78 B	0.37%		have
an	2.73 B	0.37%		an
had	2.62 B	0.35%		had
they	2.46 B	0.33%		they
you	2.34 B	0.31%		you

were	2.27	B	0.31%	<input type="checkbox"/>	were
their	2.15	B	0.29%	<input type="checkbox"/>	their
one	2.15	B	0.29%	<input type="checkbox"/>	one
all	2.06	B	0.28%	<input type="checkbox"/>	all
we	2.06	B	0.28%	<input type="checkbox"/>	we
can	1.67	B	0.22%	<input type="checkbox"/>	can
her	1.63	B	0.22%	<input type="checkbox"/>	her
has	1.63	B	0.22%	<input type="checkbox"/>	has
there	1.62	B	0.22%	<input type="checkbox"/>	there
been	1.62	B	0.22%	<input type="checkbox"/>	been
if	1.56	B	0.21%	<input type="checkbox"/>	if
more	1.55	B	0.21%	<input type="checkbox"/>	more
when	1.52	B	0.20%	<input type="checkbox"/>	when
will	1.49	B	0.20%	<input type="checkbox"/>	will
would	1.47	B	0.20%	<input type="checkbox"/>	would
who	1.46	B	0.20%	<input type="checkbox"/>	who
so	1.45	B	0.19%	<input type="checkbox"/>	so
no	1.40	B	0.19%	<input type="checkbox"/>	no

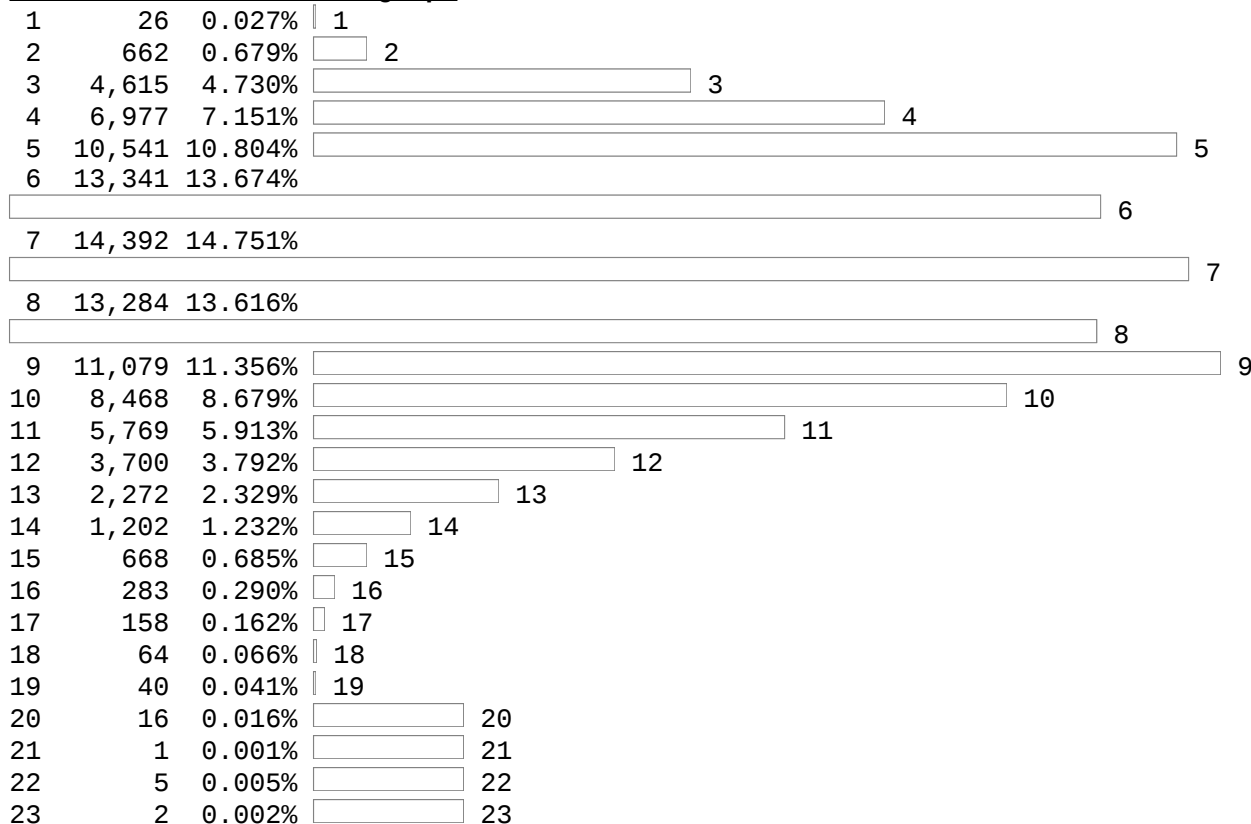
## Word Lengths

And here is the breakdown of mentions (in millions) by word length (looking like a Poisson distribution). The average is 4.79 letters per word, and 80% are between 2 and 7 letters long:

LEN	COUNT	PERCENT	bar	graph
1	22301.22 M	2.998%	<input type="checkbox"/>	1
2	131293.85 M	17.651%	<input type="checkbox"/>	2
3	152568.38 M	20.511%	<input type="checkbox"/>	3
4	109988.33 M	14.787%	<input type="checkbox"/>	4
5	79589.32 M	10.700%	<input type="checkbox"/>	5
6	62391.21 M	8.388%	<input type="checkbox"/>	6
7	59052.66 M	7.939%	<input type="checkbox"/>	7
8	44207.29 M	5.943%	<input type="checkbox"/>	8
9	33006.93 M	4.437%	<input type="checkbox"/>	9
10	22883.84 M	3.076%	<input type="checkbox"/>	10
11	13098.06 M	1.761%	<input type="checkbox"/>	11
12	7124.15 M	0.958%	<input type="checkbox"/>	12
13	3850.58 M	0.518%	<input type="checkbox"/>	13
14	1653.08 M	0.222%	<input type="checkbox"/>	14
15	565.24 M	0.076%	<input type="checkbox"/>	15
16	151.22 M	0.020%	<input type="checkbox"/>	16
17	72.81 M	0.010%	<input type="checkbox"/>	17
18	28.62 M	0.004%	<input type="checkbox"/>	18
19	8.51 M	0.001%	<input type="checkbox"/>	19
20	6.35 M	0.001%	<input type="checkbox"/>	20
21	0.13 M	0.000%	<input type="checkbox"/>	21
22	0.81 M	0.000%	<input type="checkbox"/>	22
23	0.32 M	0.000%	<input type="checkbox"/>	23

Here is the distribution for distinct words (that is, counting each word only once regardless of how many times it is mentioned). Now the average is 7.60 letters long, and 80% are between 4 and 10 letters long:

**LEN COUNT PERCENT bar graph**



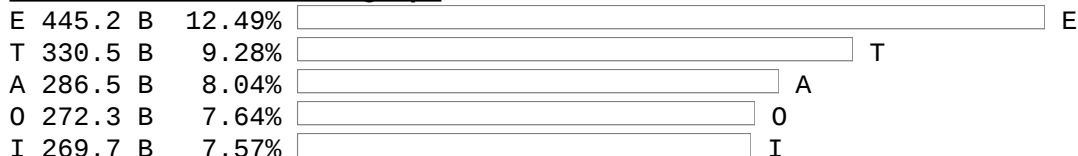
Here are the 24 words with length of 20 or more (that are mentioned at least 100,000 times each in the book corpus):

- |                         |                      |
|-------------------------|----------------------|
| electroencephalographic | radiopharmaceuticals |
| polytetrafluoroethylene | electroencephalogram |
| forschungsgemeinschaft  | keratoconjunctivitis |
| deinstitutionalization  | counterrevolutionary |
| counterrevolutionaries  | immunohistochemistry |
| dehydroepiandrosterone  | internationalisation |
| electroencephalography  | hypercholesterolemia |
| immuno-electrophoresis  | phosphatidylinositol |
| institutionalisation    | compartmentalization |
| acetylcholinesterase    | electrophysiological |
| internationalization    | electrocardiographic |
| institutionalization    | uncharacteristically |

**Letter Counts**

Enough of words; let's get back to Mayzner's request and look at letter counts. There were 3,563,505,777,820 letters mentioned. Here they are in frequency order:

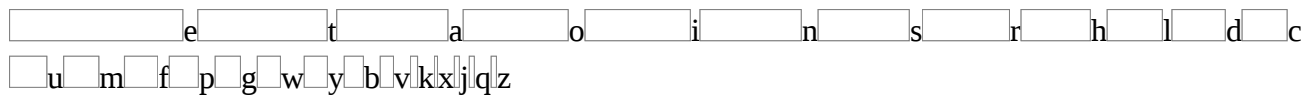
**LET COUNT PERCENT bar graph**



N	257.8	B	7.23%		N
S	232.1	B	6.51%		S
R	223.8	B	6.28%		R
H	180.1	B	5.05%		H
L	145.0	B	4.07%		L
D	136.0	B	3.82%		D
C	119.2	B	3.34%		C
U	97.3	B	2.73%		U
M	89.5	B	2.51%		M
F	85.6	B	2.40%		F
P	76.1	B	2.14%		P
G	66.6	B	1.87%		G
W	59.7	B	1.68%		W
Y	59.3	B	1.66%		Y
B	52.9	B	1.48%		B
V	37.5	B	1.05%		V
K	19.3	B	0.54%		K
X	8.4	B	0.23%		X
J	5.7	B	0.16%		J
Q	4.3	B	0.12%		Q
Z	3.2	B	0.09%		Z

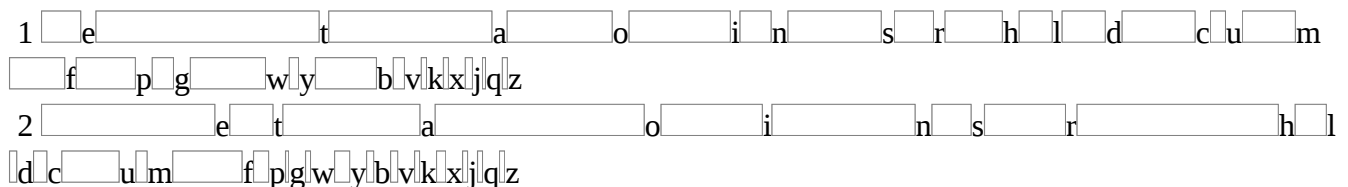
Note there is a standard order of frequency used by typesetters, ETAOIN SHRDLU, that is slightly violated here: L, R, and C have all moved up one rank, giving us the less mnemonic ETAOIN SRHLDCU.

In the colored-bar chart below (inspired by the Wikipedia article on [Letter Frequency](#)), the frequency of each letter is proportional to the length of the color bar. If you hover the mouse over each color bar, you can see the exact percentages and counts. (This is the same information as in the table above, presented in a different way.)



## Letter Counts by Position Within Word

Now we show the letter frequencies by position within word. That is, the frequencies for just the first letter in each word, just the second letter, and so on. We also show frequencies for positions relative to the end of the word: "-1" means the last letter, "-2" means the second to last, and so on. We can see that the frequencies vary quite a bit; for example, "e" is uncommon as the first letter (4 times less frequent than elsewhere); similarly "n" is 3 times less common as the first letter than it is overall. The letter "e" makes a comeback as the most common last letter (and also very common at 3rd and 5th letter places). The most common first letter is "t" and the most common second letter is "o".



3 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

4 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

5 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

6 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

7 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

-7 e t a o i n s r h l d c u  
m f p g w y b v k x j q z

-6 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

-5 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

-4 e t a o i n s r h l d c u  
m f p g w y b v k x j q z

-3 e t a o i n s r h l d c  
u m f p g w y b v k x j q z













-2 e t a o i n s r h  
l d c u m f p g w y b v k x j q z

-1 e t a o i n s r h l d c  
u m f p g w y b v k x j q z

## Two-Letter Sequence (Bigram) Counts

Now we turn to sequences of letters: consecutive letters anywhere within a word. In the list below are the 50 most frequent two-letter sequences (which are called "bigrams"):

### **BI**   **COUNT**   **PERCENT**   **bar graph**

TH	100.3	B (3.56%)		TH
HE	86.7	B (3.07%)		HE
IN	68.6	B (2.43%)		IN
ER	57.8	B (2.05%)		ER
AN	56.0	B (1.99%)		AN
RE	52.3	B (1.85%)		RE
ON	49.6	B (1.76%)		ON
AT	41.9	B (1.49%)		AT
EN	41.0	B (1.45%)		EN
ND	38.1	B (1.35%)		ND
TI	37.9	B (1.34%)		TI
ES	37.8	B (1.34%)		ES

OR	36.0	B	(1.28%)		OR
TE	34.0	B	(1.20%)		TE
OF	33.1	B	(1.17%)		OF
ED	32.9	B	(1.17%)		ED
IS	31.8	B	(1.13%)		IS
IT	31.7	B	(1.12%)		IT
AL	30.7	B	(1.09%)		AL
AR	30.3	B	(1.07%)		AR
ST	29.7	B	(1.05%)		ST
TO	29.4	B	(1.04%)		TO
NT	29.4	B	(1.04%)		NT
NG	26.9	B	(0.95%)		NG
SE	26.3	B	(0.93%)		SE
HA	26.1	B	(0.93%)		HA
AS	24.6	B	(0.87%)		AS
OU	24.5	B	(0.87%)		OU
IO	23.5	B	(0.83%)		IO
LE	23.4	B	(0.83%)		LE
VE	23.3	B	(0.83%)		VE
CO	22.4	B	(0.79%)		CO
ME	22.4	B	(0.79%)		ME
DE	21.6	B	(0.76%)		DE
HI	21.5	B	(0.76%)		HI
RI	20.5	B	(0.73%)		RI
RO	20.5	B	(0.73%)		RO
IC	19.7	B	(0.70%)		IC
NE	19.5	B	(0.69%)		NE
EA	19.4	B	(0.69%)		EA
RA	19.3	B	(0.69%)		RA
CE	18.4	B	(0.65%)		CE
LI	17.6	B	(0.62%)		LI
CH	16.9	B	(0.60%)		CH
LL	16.3	B	(0.58%)		LL
BE	16.2	B	(0.58%)		BE
MA	15.9	B	(0.57%)		MA
SI	15.5	B	(0.55%)		SI
OM	15.4	B	(0.55%)		OM
UR	15.3	B	(0.54%)		UR

Below is a table of all  $26 \times 26 = 676$  bigrams; in each cell the orange bar is proportional to the frequency, and if you hover you can see the exact counts and percentage. There are only seven bigrams that do not occur among the 2.8 trillion mentions: JQ, QG, QK, QY, QZ, WQ, and WZ. If you look closely you see they are shown as deleted.

AA	BA	CA	DA	EA
AB	BB	CB	DB	EB
AC	BC	CC	DC	EC
AD	BD	CD	DD	ED
AE	BE	CE	DE	EE
AF	BF	CF	DF	EF





l	nd	ter	from	inter	tation	develop	importan
important	d	ti	hat	ould	ional	should	america
articul	ar	cular	tha	ting	ratio	resent	however
particula	u	or	ere	hich	would	genera	eration
represent	m	te	ate	whic	tiona	dition	nationa
individua	f	of	his	ctio	these	ationa	conside
ndividual	p	ed	con	ence	state	produc	onsider
relations	g	is	res	have	natio	throug	ference
political	w	it	ver	othe	thing	hrough	positio
informati	y	al	all	ight	under	etween	osition
nformatio	b	ar	ons	sion	ssion	betwee	ization
universit	v	st	nce	ever	ectio	differ	fferent
following	k	to	men	ical	catio	icatio	without
experienc	x	nt	ith	they	latio	people	ernment
stitution	j	ng	ted	inte	about	iffere	vernmen
xperience	q	se	ers	ough	count	fferen	overnme
education	z	ha	pro	ance	ments	struct	governm
roduction	as	thi	were	rough	action	ulation	mportant
niversity	ou	wit	tive	ative	person	another	rticular
therefore	io	are	over	prese	eneral	importa	particul
nstitutio	le	ess	ding	feren	system	interes	epresent
ification	ve	not	pres	hough	relati	ninterest	represen
establish	co	ive	nter	ution	ctions	elation	increase
understan	me	was	comp	roduc	ecause	rmation	individu
nderstand	de	ect	able	resen	becaus	mportan	ndividua
difficult	hi	rea	heir	thoug	before	product	dividual
structure	ri	com	thei	press	ession	formati	elations
knowledge	ro	eve	ally	first	develo	communi	nformati
struction	ic	per	ated	after	evelop	lations	politica
something	ne	int	ring	cause	uction	ormatio	olitical

necessary	ea	est	ture	where	change	certain	universi
hemselves	ra	sta	cont	tatio	follow	increas	function
themselve	ce	cti	ents	could	positi	relatio	informat
plication	li	ica	cons	efore	govern	special	niversit
anization	ch	ist	rati	contr	sition	process	iversity
according	ll	ear	thin	hould	merica	against	lication
differenc	be	ain	part	shoul	direct	problem	experien
operation	ma	one	form	tical	bility	nstitut	structur
ifference	si	our	ning	gener	effect	politic	determin
rganizati	om	iti	ecti	esent	americ	ination	ollowing
organizat	ur	rat	some	great	public	univers	followin
ganizatio							

## N-gram Counts by Word Length and Position within Word

Finally we are ready to break out the results by n-gram length, by position within word (as we did for letter counts), and also by word length. You will be able to get counts for, say, the number of times the bigram "he" appears in positions 2 through 3 of 4-letter words, for example. This is the kind of tables provided by Mayzner, but with 37 million times more data (and with a few more columns). The tables are large, so we present them in separate files; for each n-gram length from n=1 to n=9, we offer a Google Fusion Table file; you can browse the table online, or download it (with the "File > Download" menu item). We also offer all the files rolled up into a .zip file, or in a fusion table folder:

N	
1	
2	
3	
4	
5	
6	
7	
8	
9	
*	

## N-gram column notation

Each column is given a name of the form "*wordlength / start : end*". For example, "4/2:3" means that the column counts the number of ngrams that occur in 4 letter words (such as "then"), and only in position 2 through 3 (such as the "he" in "then"). We aggregate counts with a notation involving a "\*": the notation "\*2:3" refers to the second through third position within words of any length; "4/\*" refers to any start positions in words of length 4; and "\*/\*" means any start position within words of any length. Finally, we also aggregate counts for positions near the ends of words: the notation "\*/-3:-2" means the third-to-last through second-to-last position in words of any length (for example, this would be the bigram "he" for the words "hen", "then", "lexicographer", and "greatgrandfather").

## Closing Thoughts

Technology has certainly changed. Here's where you would typically see a comparison saying that if you punched the 743 billion words one to a card and stacked them up, then assuming 100 cards per inch, the stack would be 100,000 miles high; nearly halfway to the moon. But that's silly, because the stack would topple over long before then. If I had 743 billion cards, what I would do is stack them up in a big building, like, say, the [Vehicle Assembly Building](#) (VAB) at Kennedy Space Center, which has a capacity of 3.6 million cubic meters. The cards [work out](#) to only 2.9 million cubic meters; easy peasy; room to spare. And an IBM model 84 card sorter could blast through these at a rate of 2000 cards per minute, which means it would only take 700 years per pass (but you'd need multiple passes to get the whole job done).

Aren't you glad I'm providing these tables online, rather than on cards? If you use these tables to do some interesting analysis, leave a comment to let us know. Enjoy!

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*[Peter Norvig](#)*

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