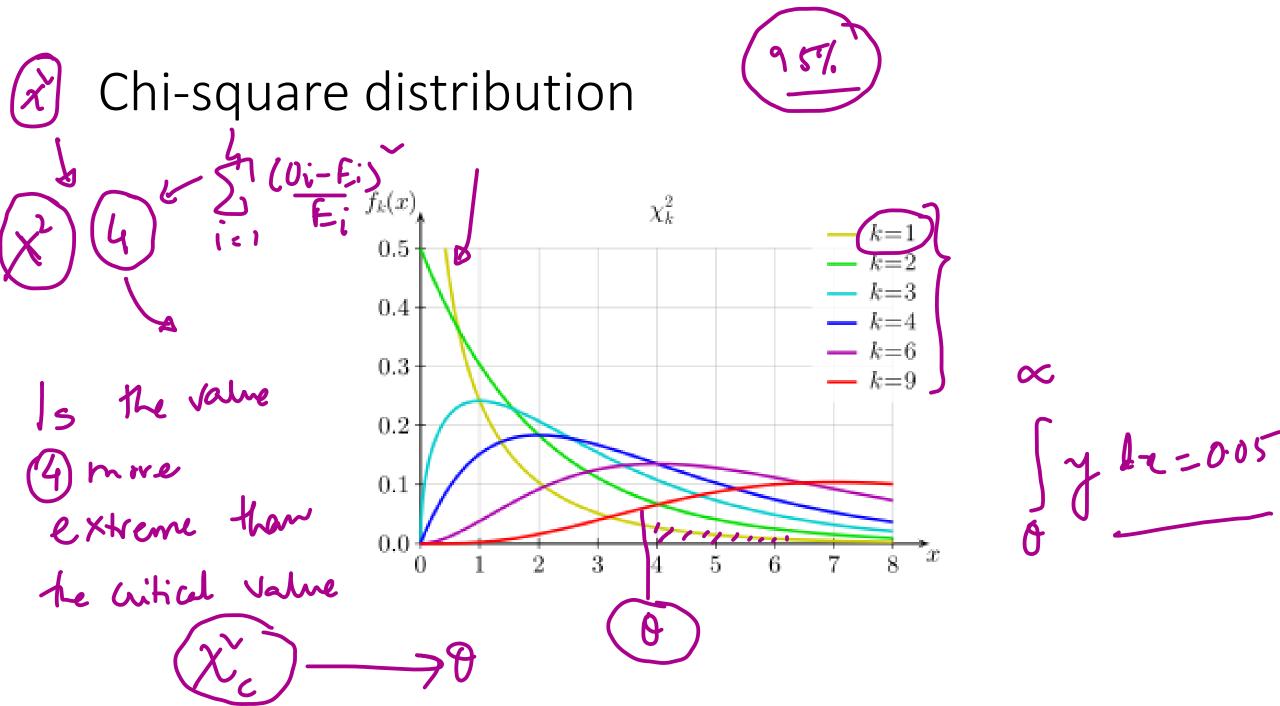
Spellcheck-2

Train and Test

Training on: Brown corpus (1 million words)

• Testing on: Wall Street Journal corpus (3/4 million words)

Confusion set	No. of	No. of	Most	Baseline
	training	test	frequent	
	cases	cases	word	
whether, weather	331	245	whether	0.922
I, me 🗸	6125	840	I	0.886
its, it's	1951	3575	its	0.863
past, passed	385	397	past	0.861
than, then	2949	1659	than	0.807
being, begin	727	449	being	0.780
effect, affect	228	162	effect	0.741
your, you're	1047	212	your	0.726
number, amount	588	429	number	0.627
council, counsel	82	83	council	0.614
rise, raise	139	301	rise	0.575
between, among	1003	730	between	0.538
led, lead	226	219	led	0.530
except, accept	232	95	except	0.442
peace, piece	310	61	peace	0.393
there, their, they're	5026	2187	there	0.306
principle, principal	184	69	principle	0.290
sight, site, cite	149	44	sight	0.114



Chi-squared (Wikipedia)

Degrees of freedom (df)						χ² valu	ue ^[13]				2.80
1	0.004	0.02	0.06	0.15	0.46	1.07	1.64	2.71	3.84	6.64	10.83
2	0.10	0.21	0.45	0.71	1.39	2.41	3.22	4.60	5.99	9.21	13.82
3	0.35	0.58	1.01	1.42	2.37	3.66	4.64	6.25	7.82	11.34	16.27
4	0.71	1.06	1.65	2.20	3.36	4.88	5.99	7.78	9.49	13.28	18.47
5	1.14	1.61	2.34	3.00	4.35	6.06	7.29	9.24	11.07	15.09	20.52
6	1.63	2.20	3.07	3.83	5.35	7.23	8.56	10.64	12.59	16.81	22.46
7	2.17	2.83	3.82	4.67	6.35	8.38	9.80	12.02	14.07	18.48	24.32
8	2.73	3.49	4.59	5.53	7.34	9.52	11.03	13.36	15.51	20.09	26.12
9	3.32	4.17	5.38	6.39	8.34	10.66	12.24	14.68	16.92	21.67	27.88
10	3.94	4.86	6.18	7.27	9.34	11.78	13.44	15.99	18.31	23.21	29.59
P value (Probability)	0.95	0.90	0.80	0.70	0.50	0.30	0.20	0.10	0.05	0.01	0.001
	Non-significant					Si	gnifica	int			

icing

desert 3

The algorithm

Training phase

- Propose all words as candidate context words.
- (2) Count occurrences of each candidate context word in the training corpus.
- (3) Prune context words that have insufficient data or are uninformative discriminators.
- (4) Store the remaining context words (and their associated statistics) for use at run time.

Run time

- (1) Initialize the probability for each word in the confusion set to its prior probability.
- (2) Go through the list of context words that was saved during training. For each context word that appears in the context of the ambiguous target word, update the probabilities.
- (3) Choose the word in the confusion set with the highest probability.

Confusion	Baseline	Cwords	Cwords	Cwords	Cwords
set		±3	± 6	±12	± 24
:					
whether	0.922	0.902	0.922	0.927	0.922
I	0.886	0.914	0.893	0.883	0.851
its	0.863	0.862	0.795	0.743	0.702
past	0.861	0.861	0.849	0.801	0.743
than	0.807	0.931	0.901	0.896	0.855
being	0.780	0.791	0.795	0.793	0.755
effect ·	0.741	0.747	0.741	0.759	0.716
your	0.726	0.816	0.783	0.774	0.736
number	0.627	0.646	0.622	0.636	0.639
council	0.614	0.639	. 0.614	0.602	0.614
rise	0.575	0.575	0.575	0.585	0.498
between	0.538	0.759	0.697	0.671	0.586
led	0.530	0.530	0.530	0.521	0.557
except	0.442	0.695	0.526	0.516	0.558
peace	0.393	0.754	0.705	0.574	0.574
there	0.306	0.726	0.623	0.557	0.466
principle	0.290	0.290	0.290	0.290	0.435
sight	0.114	0.455	0.250	0.364	0.318
Avg no. of	context words	27.9	36.9	55.9	92.9

Confusion	Baseline	Collocs	Collocs	Collocs
set		≤ 1	≤ 2	≤ 3
whether	0.922	0.939	0.931	0.931
I	0.886	0.979	0.981	0.980
its	0.863	0.943	0.945	0.950
past	0.861	0.919	0.909	0.909
than	0.807	0.966	0.965	0.966
being	0.780	0.853	0.853	0.842
effect	0.741	0.821	0.821	0.821
your	0.726	0.877	0.887	0.887
number	0.627	0.646	0.646	0.681
council	0.614	0.663	0.639	0.639
rise	0.575	0.807	0.807	0.807
between	0.538	0.699	0.730	0.733
led	0.530	0.849	0.840	0.863
except	0.442	0.800	0.789	0.789
peace	0.393	0.869	0.869	0.852
there	0.306	0.911	0.932	0.932
principle	0.290	0.841	0.812	0.812
sight	0.114	0.341	0.318	0.318
Avg no. of	collocations	33.9	263.1	985.4

corps peace united nations our heart justice state american aid international women war world piece over must great under how two for about	49 41 20 15 27 12 12 11 11 10 20 40 1 11 11	1 0 0 0 1 0 0 0 0 0 0 1 3 15 14 1
united nations our heart justice state american aid international women war world piece over must great under how : two for	20 15 27 12 12 12 11 11 10 20 40 1 1	0 0 1 0 0 0 0 0 0 0 1 3 15
nations our heart justice state american aid international women war world piece over must great under how : two for	15 27 12 12 12 11 11 11 10 20 40 1	0 1 0 0 0 0 0 0 0 1 3 15
our heart justice state american aid international women war world piece over must great under how : two for	27 12 12 12 11 11 10 20 40 1 1	1 0 0 0 0 0 0 0 1 3 15
heart justice state american aid international women war world piece over must great under how two for	12 12 11 11 11 10 20 40 1 1	0 0 0 0 0 0 0 1 3 15
justice state american aid international women war world piece over must great under how : two for	12 12 11 11 10 20 40 1 1	0 0 0 0 0 0 1 3 15
state american aid international women war world piece over must great under how two for	12 11 11 10 20 40 1 1	0 0 0 0 0 1 3 15
american aid international women war world piece over must great under how :	11 11 10 20 40 1 1	0 0 0 0 1 3 15
aid international women war world piece over must great under how :	11 11 10 20 40 1 1	0 0 0 1 3 15
international women war world piece over must great under how two for	11 10 20 40 1 1	0 0 1 3 15
women war world piece over must great under how :	10 20 40 1 1	0 1 3 15 14
war world piece over must great under how :	20 40 1 1 1	1 3 15 14
world piece over must great under how :	40 1 1 11	3 15 14
piece over must great under how :	1 1 11	15 14
over must great under how :	1 11	14
must great under how : two	11	1
great under how : two for		1
under how : two for	11	
how :		1
two for	10	1
two for	10	1
two for		
for	5	12
about	83	38
	4	9
every	4	9
little	5	10
long	6	11
one	14	23
1	179	113
so	4 1 07	14
];	9	
Total occurrences		22

peace piece

Context word

Collocation	peace	piece
corps	47	0
DET corps	32	0
ADV corps	28	0
the corps	27	0
and	22	0
_ of NS	2	60
the NS	37	1
a PREP	1	35
PREP of	1	34
a of	1	34
for	16	0
_ and NS	16	0
DET NP	32	1
NS of	2	45
corps NS	14	0
PREP CONJ	14	0
the NP	27	1
V CONJ	13	0
NS PUNC	13	0
_ of v	1	25
:		
CONJ ADJ	4	9
the NS	4	9
NS ADJ	13	26
ADV NS	12	23
PREP NS	17	31
ADV PREP	12	22
ADJ ADJ	9	14
NS	62	79
ADJ	46	54
NS NS	29	32
Total occurrences	184	126

Russel's Soundex

The alphabet was phonetically divided into categories:

Oral resonants A, E, I, O, U, Y.

Labials and labio-dentals B, F, P, V.

Gutterals and sibilants C, G, K, Q, S, X, Z.

Dental-mutes D, T/

Palatal-fricative L.

Labio-nasal M.

Den to or lingua-nasal N.

Dental fricative R.

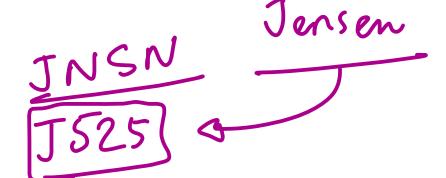
Russel also described a few additional rules to complete the indexing:

- •The initial letter of the word is always kept.
- •Two consecutive letters that had the same code are considered as a single letter (e.g. "BB" is the same as just "B")
- •If a word ended with "GH", "S" or "Z' those letters were discarded.
- •Only the first occurrence of a vowel (Group 1) is counted.

Ack: http://www.datamanagementgroup.com/Resources/Articles/Article_IntroductionToDoubleMetaphone.asp

Soundex Revised

- U.S. Government Soundex Table
 - 1. B,F,P,V
 - 2. C,G,J,K,Q,S,X,Z
 - 3. D, T
 - 4. L
 - 5. M, N
 - 6. R
- Examples
 - Johnson = J525
 - Miller = M460
 - Ricardo = R263
 - Peters = P362



Ack: http://www.datamanagementgroup.com/Resources/Articles/Article_IntroductionToDoubleMetaphone.asp

Metaphone

- Find out from:
 - http://www.lanw.com/java/phonetic/default.htm

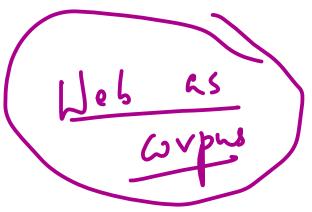
Selecting candidates for correction

The n-gram approach using inverted files

The next idea in spellcheck: Web n-grams

langrøge modeling

ceramics collection and 43
ceramics collection at 52
ceramics collection is 68
ceramics collection of 76
ceramics collection | 59
ceramics collections , 66
ceramics collections . 60
ceramics combined with 46
ceramics come from 69
ceramics comes from 660
ceramics community , 109
ceramics community . 212
ceramics community for 61
ceramics companies . 53
ceramics companies consultants 173



Two important papers

• Shane Bergsma, Dekang Lin, and Randy Goebel. 2009. Web-scale n-gram models for lexical disambiguation. In IJCAI.

W. Xu, J. Tetreault, M. Chodorow, R. Grishman, and L. Zhao. 2011.
 Exploiting syntactic and distributional information for spelling correction with webscale n-gram models. In EMNLP.