LINGI2263 : Computational Linguistics

Group 2 : Project 3

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1 TF-IDF

For the first part of the assignment, we used the TF-IDF weighting scheme to find the most similar words to words of a given list. To do this, we first compiled the vocabulary by iterating over the 6915 definitions. Each word that was encountered was added to the vocabulary, along with how many definitions it occurred in. This allowed us to calculate the document frequency for each word (and therefore, $g_i = -log(df_i)$, the inverse document frequency or IDF).
We then did a second pass on the definitions. This time, calculated the term frequency of each word in each document. For each document, we also calculated ——d——. With these three sets of values, we could calculate the similarity between any two documents by applying the formula

$$\frac{d_1 \bullet d_2}{||d_1|| * ||d_2||}$$

It is worth noting that we don't actually have the complete d_1 and d_2 vectors, only the non-zero values. The dot-product is done as a sum of the product of term frequencies that are non-zero in both documents.

We were also asked to perform the comparison with different sized vocabularies. To do this, we sorted our vocabulary according to the IDF of each word, and removed words with the lowest values until the correct number of remaining words was reached. At the beginning, this means removing very common words that have little value for calculating the similarity, such as "a", "of", "the"...

Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	school	1.0	school	1.0	school	1.0	school	1.0
2	college	0.31126	institute	0.17327	monetary	0.24547	Ã	0.0
3	institute	0.2868	polytechnic	0.14085	pod	0.1201	Â	0.0
4	institution	0.26324	lesson	0.13468	college	0.09737	±	0.0
5	classroom	0.25206	lar	0.12211	poly	0.09162	—*	0.0
6	schoolbus	0.24714	education	0.11972	run	0.06545	,,**	0.0
7	education	0.24026	acad	0.11853	gar	0.03586	zu	0.0
8	university	0.23398	institut	0.11458	Ã	0.0	zoom	0.0
9	academy	0.21787	academy	0.10551	Â	0.0	zoological	0.0
10	junior	0.21233	college	0.10312	±	0.0	zoo	0.0
11	sekolah	0.2105	organization	0.10102	—*	0.0	zone	0.0
12	coed	0.20827	academia	0.09901	,,**	0.0	zona	0.0
13	seminary	0.19995	tradition	0.09613	zu	0.0	zombie	0.0
14	tuition	0.18183	divinity	0.09066	zoom	0.0	zoe	0.0
15	primary	0.17731	university	0.08546	zoological	0.0	ziggy	0.0
16	graduate	0.16704	monetary	0.08366	zoo	0.0	zielona	0.0
17	senior	0.1484	doctrine	0.08232	zone	0.0	zeta	0.0
18	organization	0.14168	pod	0.07685	zona	0.0	zeppelin	0.0
19	lesson	0.13977	academic	0.07592	zombie	0.0	zen	0.0
20	colegio	0.13464	alumnus	0.07035	zoe	0.0	zef	0.0

Table 1: Words most similar to "SCHOOL"

Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	book	1.0	book	1.0	book	1.0	book	1.0
2	booker	0.27659	arrive	0.19963	luck	0.29286	Ã	0.0
3	scripture	0.16318	authority	0.10306	bucket	0.17387	Â	0.0
4	yearbook	0.1601	workout	0.09804	mira	0.09648	±	0.0
5	sive	0.15158	scroll	0.0838	Ã	0.0	—*	0.0
6	page	0.14649	genesis	0.07033	Â	0.0	,,**	0.0
7	volume	0.14252	rocket	0.06596	±	0.0	zu	0.0
8	manuscript	0.13999	danger	0.06479	—*	0.0	zoom	0.0
9	record	0.13787	stamp	0.06425	,,**	0.0	zoological	0.0
10	class	0.13474	edition	0.06336	zu	0.0	zoo	0.0
11	paper	0.13241	script	0.06266	zoom	0.0	zone	0.0
12	tome	0.12552	booker	0.06256	zoological	0.0	zona	0.0
13	fo	0.1255	block	0.05923	zoo	0.0	zombie	0.0
14	writing	0.12408	bump	0.05699	zone	0.0	zoe	0.0
15	hans	0.12351	luck	0.05627	zona	0.0	ziggy	0.0
16	album	0.12313	tool	0.05164	zombie	0.0	zielona	0.0
17	read	0.12296	working	0.04908	zoe	0.0	zeta	0.0
18	handbook	0.12185	printing	0.04844	ziggy	0.0	zeppelin	0.0
19	write	0.118	tome	0.04632	zielona	0.0	zen	0.0
20	category	0.11507	fiction	0.04306	zeta	0.0	zef	0.0

Table 2: Words most similar to "BOOK"

Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	fruit	1.0	fruit	1.0	fruit	1.0	fruit	1.0
2	vegetable	0.24031	technician	0.11154	kitty	0.14292	Ã	0.0
3	mulberry	0.21794	cooking	0.09819	conception	0.10867	Â	0.0
4	grove	0.20423	inferior	0.09466	circus	0.10211	±	0.0
5	apple	0.19371	technical	0.08735	Ã	0.0	—*	0.0
6	pear	0.17097	cucumber	0.08543	Â	0.0	,,**	0.0
7	pumpkin	0.17051	salad	0.06938	±	0.0	zu	0.0
8	erik	0.16755	wally	0.06884	—*	0.0	zoom	0.0
9	berry	0.16301	ugh	0.06706	,,**	0.0	zoological	0.0
10	citrus	0.15652	molly	0.06585	zu	0.0	zoo	0.0
11	bavarian	0.15103	sissy	0.0644	zoom	0.0	zone	0.0
12	cucumber	0.1488	rosemary	0.06408	zoological	0.0	zona	0.0
13	edible	0.1448	berry	0.06317	zoo	0.0	zombie	0.0
14	jos	0.14063	style	0.06172	zone	0.0	zoe	0.0
15	pit	0.13861	nutrition	0.06027	zona	0.0	ziggy	0.0
16	sweetie	0.13861	roughly	0.05788	zombie	0.0	zielona	0.0
17	malena	0.13648	kitty	0.05579	zoe	0.0	zeta	0.0
18	championship	0.13531	flora	0.05214	ziggy	0.0	zeppelin	0.0
19	macedonia	0.12999	ladyboy	0.05173	zielona	0.0	zen	0.0
20	sweet	0.12435	feature	0.04995	zeta	0.0	zef	0.0

Table 3: Words most similar to "FRUIT"

Special characters:
* UTF-8 \xc2\xa6
** UTF-8 \xc2\x84

As we can see, for 25.000 and 10.000 vocabulary words, the results become meaningless and the first values in the dictionary are given by default. However, results for the full vocabulary are quite good. While the the similarity scores are lower for 50.000 words, the proposed words are mostly relevant and

Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	house	1.0	house	1.0	house	1.0	house	1.0
2	pr	0.65874	publication	0.13438	piss	0.1273	Ã	0.0
3	playhouse	0.33883	posh	0.11256	sunset	0.11605	Â	0.0
4	mansion	0.3003	publishing	0.10402	battery	0.11142	±	0.0
5	det	0.19648	virtual	0.1031	descendant	0.10085	—*	0.0
6	ot	0.19026	satisfaction	0.10183	fade	0.04847	,,**	0.0
7	todd	0.18531	sleepover	0.09739	casa	0.0281	zu	0.0
8	sleepover	0.17464	familial	0.09738	Ã	0.0	zoom	0.0
9	villa	0.17303	babysitter	0.0963	Â	0.0	zoological	0.0
10	notre	0.14134	guest	0.08817	±	0.0	zoo	0.0
11	puerto	0.14075	capitol	0.08478	—*	0.0	zone	0.0
12	publishing	0.13922	garage	0.08293	,,**	0.0	zona	0.0
13	speaker	0.1392	meet	0.08171	zu	0.0	zombie	0.0
14	frat	0.13526	sign	0.08089	zoom	0.0	zoe	0.0
15	home	0.13513	photo	0.07704	zoological	0.0	ziggy	0.0
16	dom	0.13344	ponce	0.06442	zoo	0.0	zielona	0.0
17	manor	0.13214	mansion	0.06164	zone	0.0	zeta	0.0
18	homestead	0.13121	moor	0.04855	zona	0.0	zeppelin	0.0
19	housing	0.1302	tanya	0.04813	zombie	0.0	zen	0.0
20	harbour	0.12646	community	0.04791	zoe	0.0		

Table 4: Words most similar to ”HOUSE”

Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	mayhem	1.0	mayhem	1.0	mayhem	1.0	mayhem	1.0
2	disorder	0.1697	unsuspecting	0.11625	unsuspecting	0.36437	Ã	0.0
3	crowd	0.14697	dart	0.07565	aftermath	0.20441	Â	0.0
4	fighting	0.08617	authority	0.07147	journalist	0.19894	±	0.0
5	chaos	0.07908	disorder	0.06073	mud	0.10568	—*	0.0
6	work	0.07287	robin	0.05557	Ã	0.0	,,**	0.0
7	unsuspecting	0.07256	peace	0.05238	Â	0.0	zu	0.0
8	pandemonium	0.07235	tower	0.05154	±	0.0	zoom	0.0
9	ring	0.07011	aftermath	0.04854	—*	0.0	zoological	0.0
10	original	0.06894	role	0.04654	,,**	0.0	zoo	0.0
11	troop	0.06616	calm	0.04615	zu	0.0	zone	0.0
12	audience	0.06452	funny	0.04526	zoom	0.0	zona	0.0
13	pull	0.06229	journalist	0.0443	zoological	0.0	zombie	0.0
14	alexia	0.06194	hood	0.04335	zoo	0.0	zoe	0.0
15	wave	0.06139	ado	0.04285	zone	0.0	ziggy	0.0
16	mantua	0.06128	pandemonium	0.04283	zona	0.0	zielona	0.0
17	joseph	0.06099	wave	0.03979	zombie	0.0	zeta	0.0
18	general	0.06065	chaos	0.0376	zoe	0.0	zeppelin	0.0
19	subdivision	0.05777	leggy	0.03677	ziggy	0.0	zen	0.0
20	dart	0.05747	fabulous	0.03503	zielona	0.0	zef	0.0

Table 5: Words most similar to ”MAYHEM”

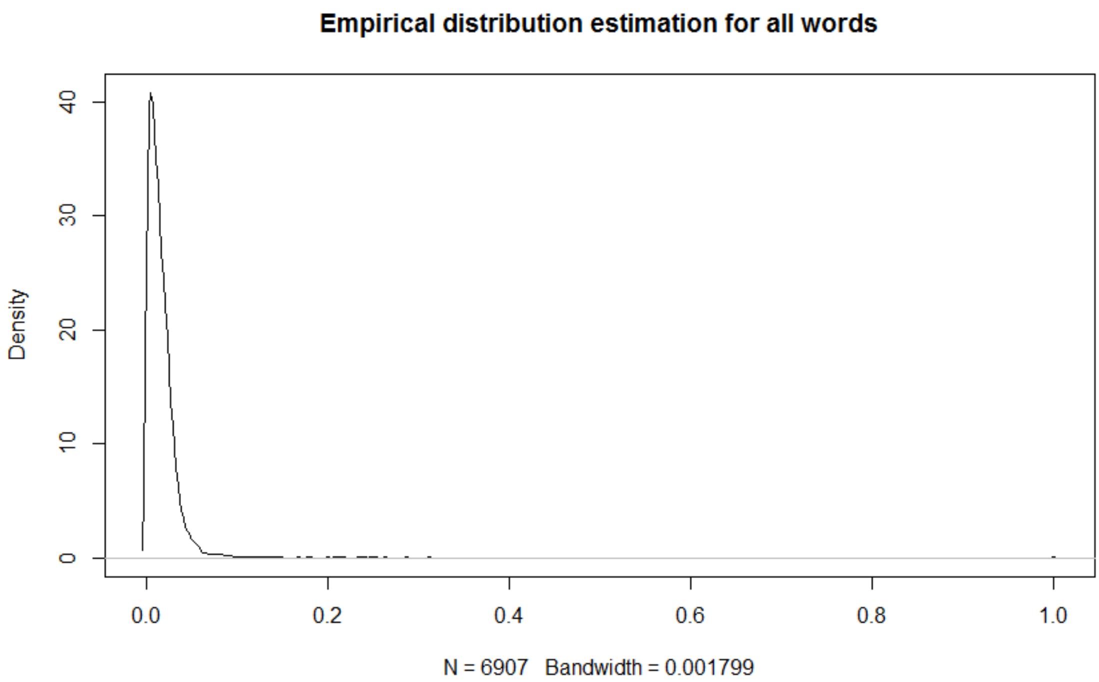
provide some information about the meaning of the original word. In some cases they even provide insight into other possible meanings of the word which the full-vocabulary list does not provide. For example, of the 20 full-vocabulary words for ”fruit”, none are related to its use for describing a homosexual man, whereas some in the 50.000 word list do.

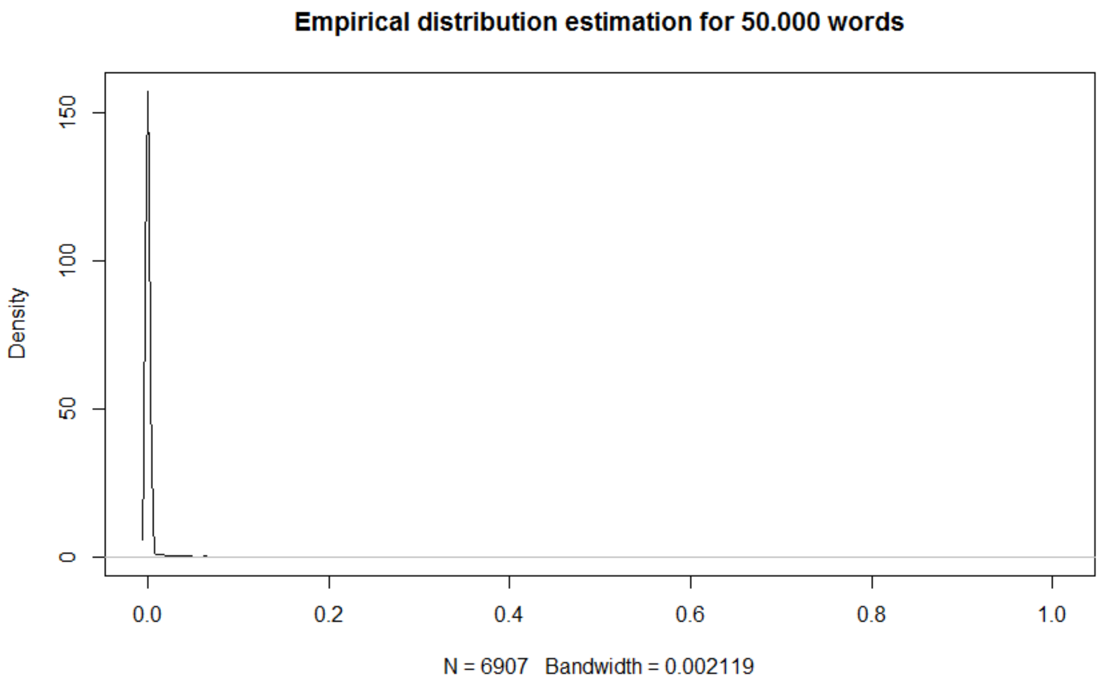
Rank	word	score	50k word	50k score	25k word	25k score	10k word	10k score
1	plane	1.0	plane	1.0	plane	1.0	plane	1.0
2	flat	0.18357	sg	0.1407	sail	0.12971	Ã	0.0
3	pla	0.17629	airplane	0.1037	spot	0.09391	Â	0.0
4	level	0.14229	smooth	0.09599	hop	0.08764	±	0.0
5	plan	0.13835	infinite	0.08568	Ã	0.0	—*	0.0
6	plain	0.13137	nara	0.08287	Â	0.0	,,**	0.0
7	airplane	0.11195	cosmic	0.0733	±	0.0	zu	0.0
8	hickory	0.10697	ranger	0.07204	—*	0.0	zoom	0.0
9	surface	0.10464	layer	0.07046	,,**	0.0	zoological	0.0
10	hop	0.10065	business	0.0669	zu	0.0	zoo	0.0
11	smooth	0.09897	range	0.06284	zoom	0.0	zone	0.0
12	circle	0.09768	perfectly	0.06224	zoological	0.0	zona	0.0
13	holly	0.09373	holly	0.05727	zoo	0.0	zombie	0.0
14	plateau	0.09244	aerodrome	0.0569	zone	0.0	zoe	0.0
15	sheet	0.08981	sandwich	0.05598	zona	0.0	ziggy	0.0
16	wood	0.08468	hank	0.05491	zombie	0.0	zielona	0.0
17	flight	0.08454	cooperative	0.05383	zoe	0.0	zeta	0.0
18	tool	0.08375	huge	0.05354	ziggy	0.0	zeppelin	0.0
19	underwater	0.08274	autumn	0.05221	zielona	0.0	zen	0.0
20	conquer	0.0825	examination	0.05004	zeta	0.0	zef	0.0

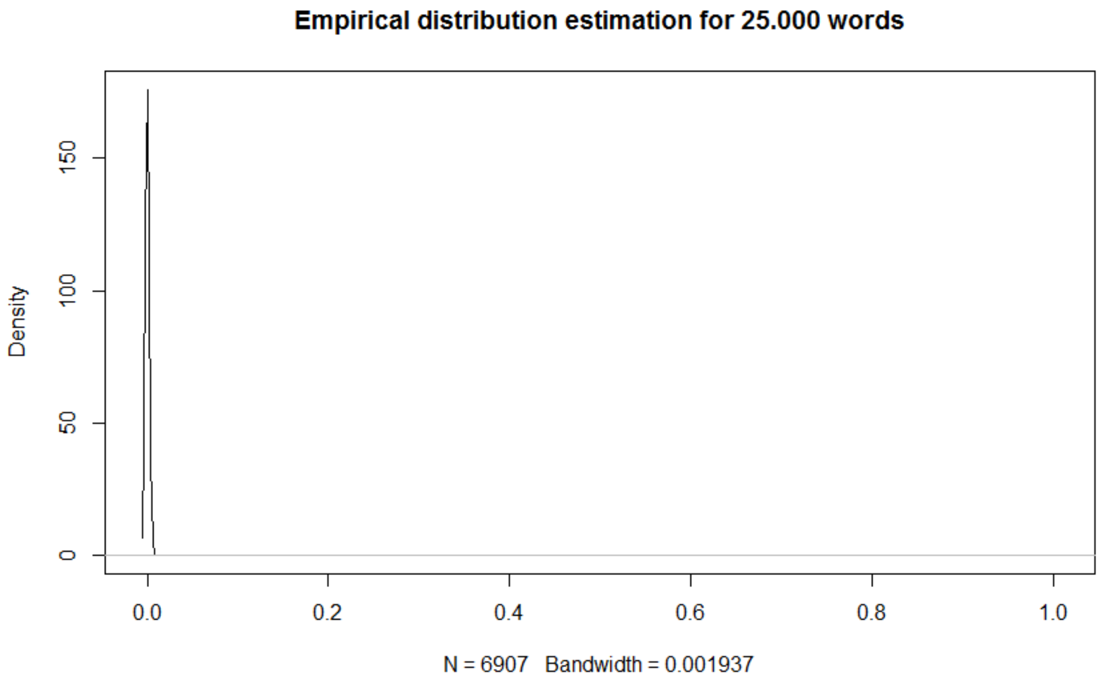
Table 6: Words most similar to "PLANE"

2 Distribution of similarity scores

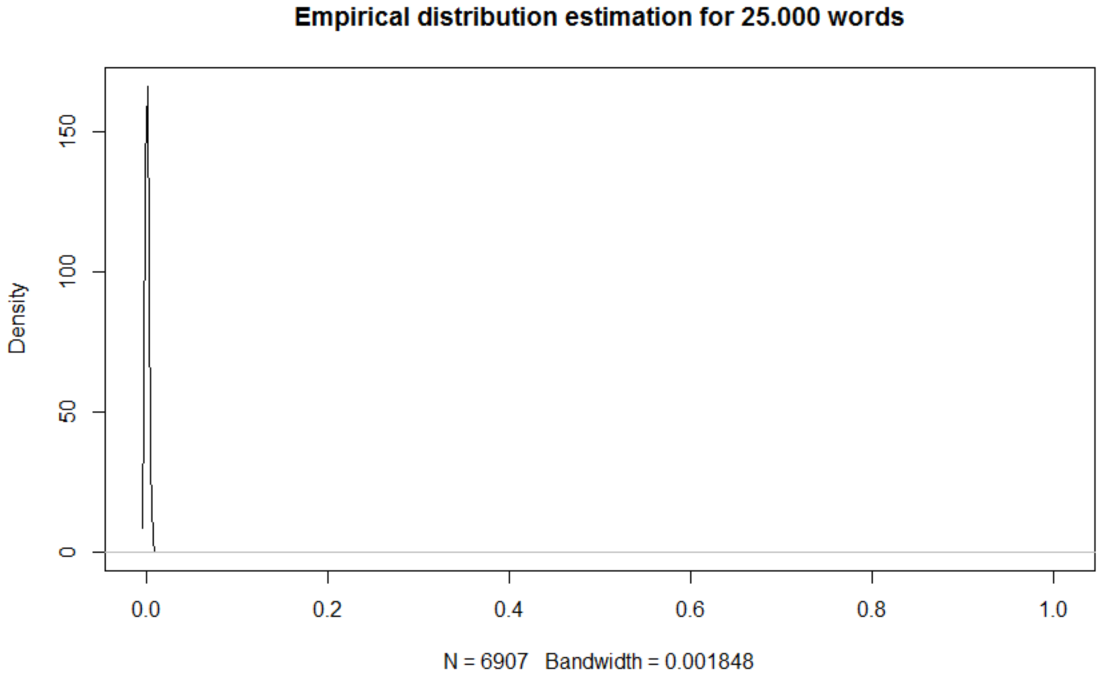
Why now attempt to observe the distribution followed by the similarity scores. To do this, we choose the word "school" and plot the similarity scores for all the defined words using the full vocabulary, and the version truncated to 50.000, 25.000 and 10.000 words. The distributions are estimated with the density() function of R. The results can be seen in the following graphs:







These distributions are an Inverse Gaussian distributions. We can see that as the vocabulary decreases, the shape factor λ decreases, giving the distribution a more and more narrow appearance (as opposed to increasing it, which makes the distribution resemble a Normal distribution).



3 The underpinnings of Log-Entropy

3.1 Why is there a '+1' in the logarithm function ?

It is simply because the logarithm function is defined on the domain of the strictly positive real: it is possible for tf_{ij} to be equal to 0 simply because of it's definition: it is possible the i^{th} document does not contain the j^{th} therm. Hence, the '+1' allows us to shift the domain of tf_{ij} from $[0, \, ||document_i||]$ to $[1, \, ||document_i|| + 1]$ on which the logarithm function is entirely defined.

3.2 What is the point to apply the logarithm function to the term frequency instead of plugging it directly in the formula ?

This allows us to diminish the relative importance of the high frequency words versus the middle ones. Indeed, the logarithm function is defined so that, compared with the linear function suggested, it keeps the middle frequencies importance while really lowering the high frequencies. This effect allows us to take into account the fact that some words tends to appear in every document while not being decisive for de description of the document (words such as "the", "a", "b", etc.). Moreover, some other words only appear a few times in the document in question while being really important for the definition/description of it; the importance of theses words is better taken into account by the logarithm function than by the linear one.

3.3 Could explain intuitively the mechanics of the global weight ? And why is there a division by log n? (Hint: What does the entropy of a distribution represents?)

First, let us remark that the global weight can easily be written as:

$$g_{ij} = 1 - \frac{-\Sigma_i \, p_{ij} \cdot \log p_{ij}}{\log n} \tag{1}$$

With this particular notation, the resemblance with formula of the entropy for the distribution p_{ij} is quite hard to miss ($\Sigma_i \; p_{ij} \cdot \log p_{ij}$). This entropy measures the uncertainty of the location of j^{th} in the i^{th} document. Now we focus on the division by the $\log n$ which is simple too: the maximum value of this entropy is actually $\log n$ meaning that we project the domain of the entropy of the distribution onto a domain bounded by 0 and 1. Then, we inverse the sense of the domain by the operation of subtraction: this allows us to define a greater weight for the terms that more certain (with less uncertainty) to be present in the document. Moreover, this also allows us to give a greater weight to the terms that a specific to this document by lowering the one of the terms that are more likely to appear in each document.