Semantic Analysis

Assignment 3

Computational Linguistics

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Introduction

To solve the problems asked in this assignment, we have made a python script which forms the ***lexicon*** of the 5-gram corpus and removes the 20 most frequent words, makes the ***bag of words*** of each word of the lexicon, computes the **tf-idf representation**, calculates the **similar words** of a given word and finds the **most similar** pair of word types.

This is done over the same script using the input arguments. These are the possible tasks that the script can do and the way to write the command:

- **Bag of words:** ./assignment3.py w5_.txt target_word **bow**
- **Representation of tf-idf**: ./assignment3.py w5_.txt target_word **tfidf**
- **Similarity:** ./assignment3.py w5_.txt target_word **similarity**
- **Max. similarity:** ./assignment3.py w5_.txt **maxSimilarity**

The script takes seconds to execute for all tasks except for the computation of the most similar pair of word types.

Lexicon

After removing the 250 most frequent words from the 5-gram corpus, we obtain the **lexicon** that we are going to use during the assignment. These are the top 20 most frequent words:

Words	Frequency
Home	33.482
Reason	33.138
News	32.772
Second	32.645
Difficult	32.014
Job	31.782
Until	31.475
Own	30.931
Pay	30.586
War	30.554
Big	30.459
Looking	30.190
White	30.155
Hands	29.849
Show	29.745
Women	29.717
Order	29.627
Beginning	29.578
Different	29.180
Ago	29.165

Another method we could have used to discard the 250 most frequent words is by using the *idf* computation of each word. The *'inverse document frequency'* is a term that measures how common a word is among a collection of documents, so the more frequent a word is, the lower is its *idf* value. Therefore, one way to determine which the 250 most frequent words are would be to calculate the idf value for each word of the lexicon and then sorting the words by their value in increasing order. The first 250 words will be the most frequent ones, so deleting them will give the requested lexicon. A script for doing this computation is provided (idf.py).

Bag of words

The bag of words of a given word is calculated by taking all the words that appear in the same 5-grams as the target word, and storing their frequency of appearance in the 5-grams. Those words will form the context of the given word.

As an example, the bag of words of ***Fireworks*** is:

Words	Frequency
July	10
Fourth	21

These are the words that appear on the same 5-grams as fireworks. This happens in these 5-grams:

- **11** fireworks on the fourth of
- **10** the fourth of july fireworks

The words in red are the ones that **don't belong** to the lexicon because they have been removed (they were on the top 250 most frequent words), and the words in green are the ones that form the ***bag of words***.

The word ***july*** appears with ***fireworks*** in one 5-gram with frequency ***10***, while the word ***fourth*** appears in two 5-grams, once with frequency ***10*** and in the other ***11***, which sums ***21***, the value that appears in the bag of words.

And this is the bag of words of ***Furnace***:

Words	Frequency
Water	6
Heater	6

These words appear in the only 5-gram where furnace appears:

- **6** the furnace and water heater

TF-IDF Representation

Using the results obtained from the bag of words in the previous point, we can compute the TF-IDF representation of words . Therefore, the values of the words in the context of a certain word will be calculated considering two weights: TF and IDF.

- **TF:** The number of times a word appears in the context (we can reuse the values from the bag of words for this computation).
- **IDF:** It is calculated based on the formula $-\log(\frac{nContextsPresent}{nContexts})$, where *nContextsPresent* is the number of times the word appears in other contexts (in other bags of words) divided by the number of contexts (which is equal to the number of words in the lexicon). According to our understanding of the handout, we consider all the contexts of all the words (included or not in the lexicon) to compute the number of contexts in which a word appears (we associate the concept of context with a document, so it would represent the number of different documents that contain the word), and the total number of contexts.

The TF-IDF representation for the words Fireworks and Furnace is the following one:

Fireworks	
Word	**Value**
July	26.5342
Fourth	46.9439

Furnace	
Word	**Value**
Water	10.5198
Heater	24.5565

Using the values of the TF-IDF representation as vectors, we can compute the similarity between two words. Therefore, each vector will have all the TF-IDF values of the words contained in the context of a given word, and also, zeros on the positions of the words that are in the other context vector and not in the current one.

For example, given the two contexts c1 = [‘hi’,’Karl’] and c2 = [‘hi’,’Charles’], with TF-IDF values of tfidf1 = [0.5,0.4] and tfidf = [0.8,0.3], we would build the vectors v1 = [0.5,0.4,0] and v2 = [0.5,0,0.3].

Once we have the vector representations of the contexts of two words, we can compute the similarity between them. As an example, the top ten similar words for the requested words in the handout are shown below.

Happy	
Word	**Value**
Happy	1.0
b.g	0.4345
Whine	0.4345
Delighted	0.4306
Glad	0.402
Appalachians	0.3978
Screams	0.3469
Clatter	0.3411
Sound	0.3061
Uncommon	0.2894

Jump	
Word	**Value**
Jump	1.0
Drawn	0.3319
Inescapable	0.3278
Foregone	0.3278
Hop	0.2909
Jumps	0.2616
Jumped	0.2584
Jumping	0.2508
Crash	0.2779
Eliptic	0.2137

Plane	
Word	**Value**
Plane	1.0
Helicopter	0.7998
Usair	0.5888
Twa	0.5429
Car	0.3272
Airplane	0.3221
Spectacular	0.3203
Killed	0.3084
Concorde	0.3012
Shootout	0.2798

Planes	
Word	**Value**
Planes	1.0
Homers	0.4641
Wreckage	0.4408
Fur	0.4408
Jetliners	0.4408
Accession	0.4408
Surplus	0.4214
Bombed	0.3922
Hardest	0.3505
Slave	0.3358

Italy	
Word	**Value**
italy	1.0
apartheid	0.573
sahara	0.5647
waziristan	0.5406
terminals	0.5406
africa	0.4826
sewanee	0.4789
carolina	0.4678
korea	0.455
sub-saharan	0.4393

Japan	
Word	**Value**
japan	1.0
taiwan	0.5183
sewanee	0.4971
iran	0.4658
north	0.459
dismantle	0.4476
africa	0.4197
six-party	0.4077
africans	0.4019
segregated	0.3982

Good	
Word	Value
superb	0.6081
perks	0.5891
admirable	0.5891
cashier	0.5891
quit	0.5876
terrific	0.5847
excellent	0.5591
landed	0.5575
pretty	0.5479
wonderful	0.5252

October	
Word	Value
october	1.0
april	0.7116
august	0.7059
december	0.6836
february	0.6119
january	0.6099
june	0.5506
teens	0.4859
afternoon	0.4338
mid	0.4212

Word ***Good*** isn't part of the lexicon after the pre-processing task (deleting the 250 most frequent words), but its context is computed anyway by taking all the words that appear in the same 5-grams as it and belong to the lexicon.

Most of the similar words have sense for us because are **synonyms**, **verbal tenses**, **derivate words** or share a relationship with their similar word (feelings, same characteristics, etc.).

This is what we have found over the similar words of the requested ones in the assignment:

- **Happy:** Words that also express feelings (glad, delighted).
- **Jump:** Synonyms (hop) and different verbal tenses (jumped, jumping).
- **Plane:** Different aircrafts with common features (helicopter, airplane, concorde).
- **Planes:** Words related with the army (bombed, wreckage).
- **Italy:** Countries, continents and regions (korea, africa, carolina).
- **Japan:** Countries and continents (taiwan, iran, africa).
- **Good:** Other similar adjectives (excellent, terrific, wonderful).
- **October:** Mostly other months (april, august, december, etc.).

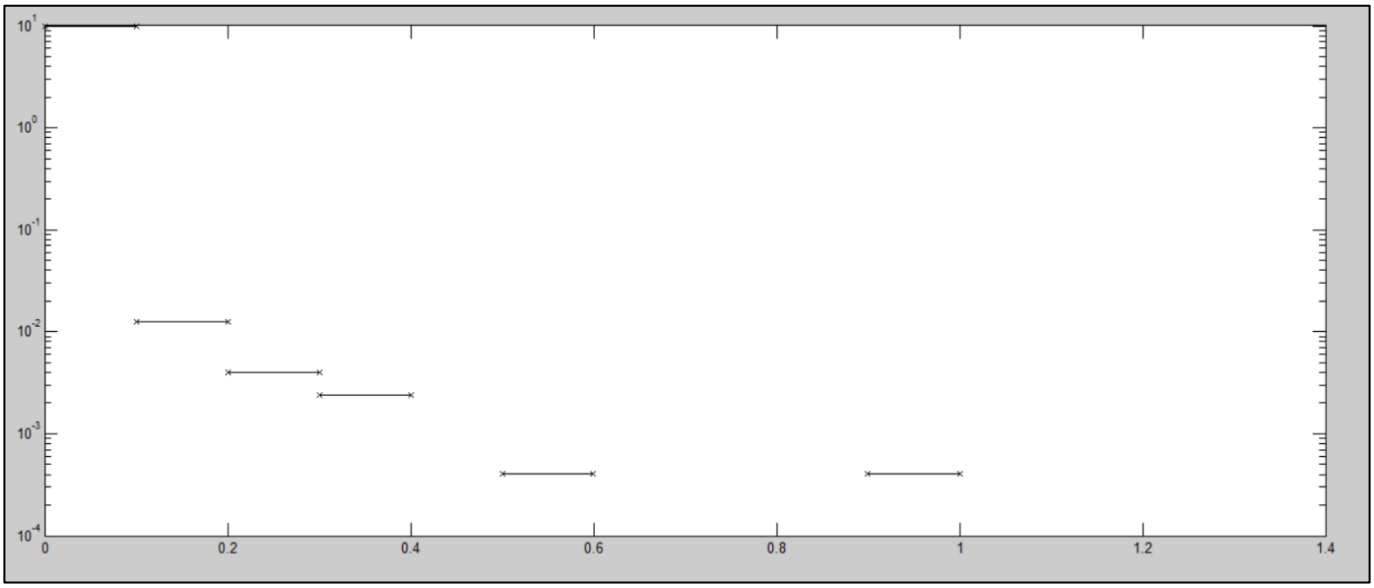
Bonus task

Due to time constraints when computing the two most similar words, we weren't able to obtain the final value in time (the script didn't finish executing in time), but the code to compute it is in *assignment.py*.

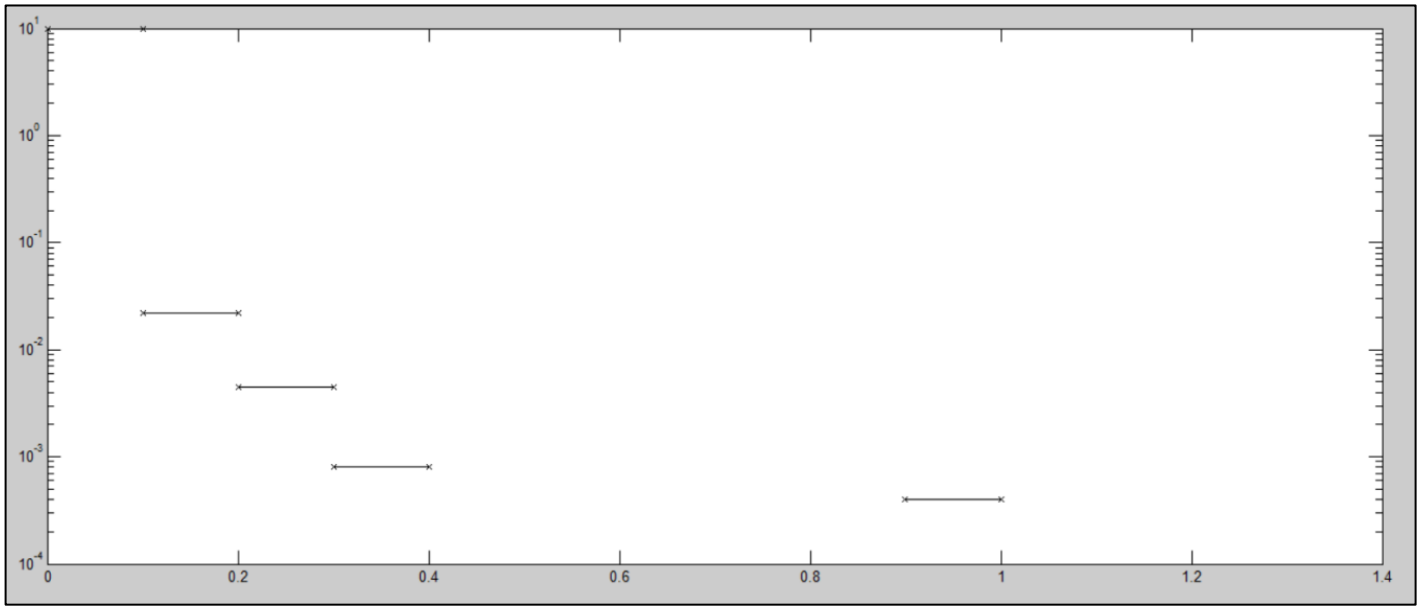
Distribution of similarity scores

The empirical distribution of similarity scores between the whole lexicon and the terms *Christmas* and *Gift* are shown below.

For ***Christmas***:



For ***Gift***:



The Y axis represents the cumulative probability of the values in the X axis.

As can be seen, the probability distribution in both graphs shows that the most common case is that of words that are not similar to the given words. Therefore, only a few words from the whole lexicon will be more similar to the requested ones (being the same word the one that has the lowest value in the Y axis and the highest one in the X axis).