Practical No. 1

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1 Part 1

a)

In Figure 1 we can see that all occupations are clustered together, which is pleasing. However, we can see that 'literatura' is so close to occupations that it could be mistaken as one.

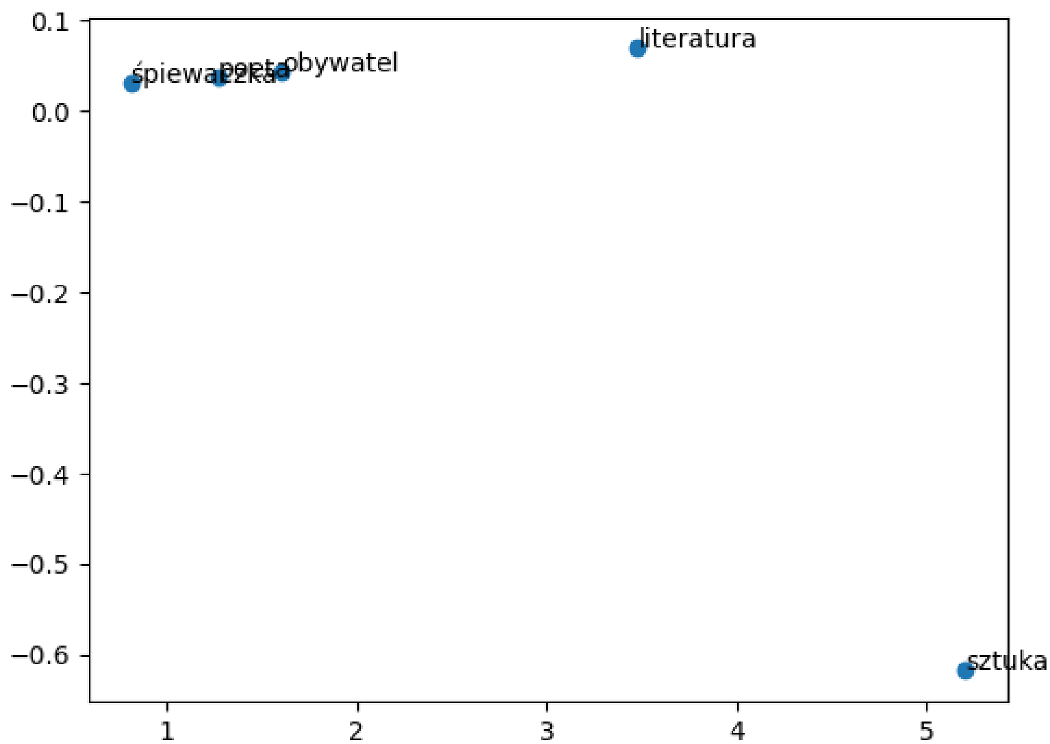

Figure 1: Normalized Polish corpus vector space

b)

In Figure 2 there's a similar situation: occupations are well clustered, while 'sztuka' is correctly distanced. Problem with 'literatura' has lessened, but I think it should be closer to 'sztuka' compared to the occupations still.

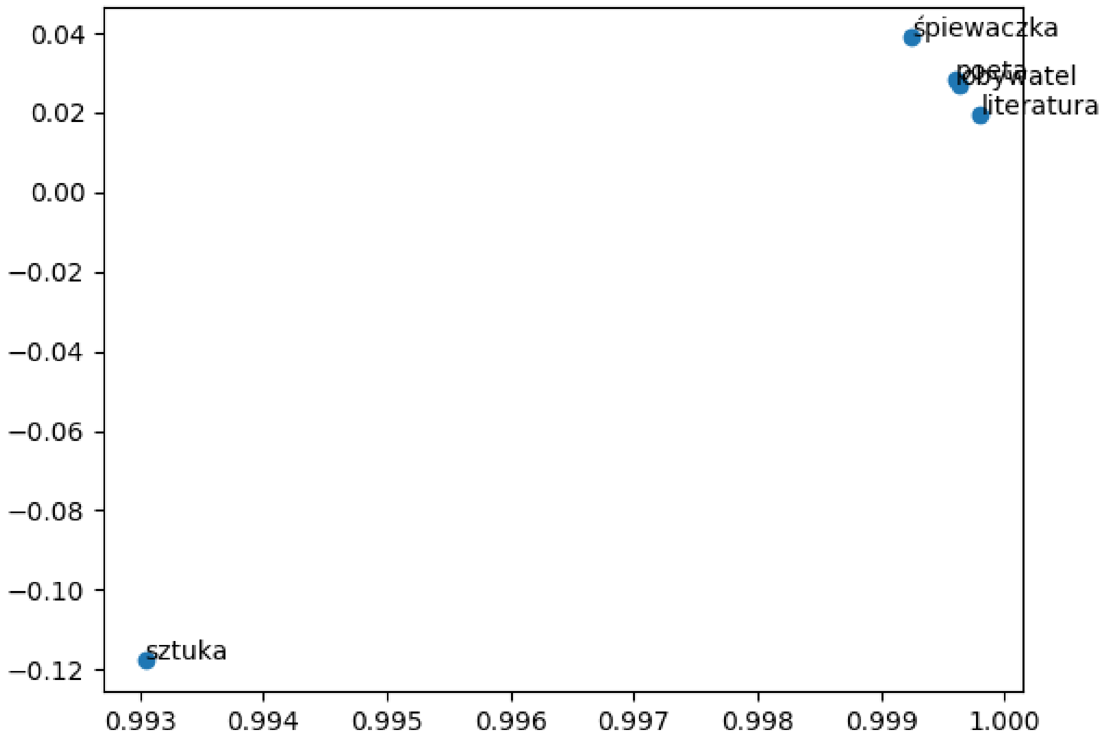

Figure 2: Unnormalized Polish corpus vector space

2 Prediction-Based Word Vectors in Polish Corpus

a) Reducing dimensionality of Word2Vec Word Embeddings

Figure 3 shows that, after reducing dimensionality, most of sample words are quite spaced out, we see new relations such as 'sztuka' close to 'artystyczny', however words denoting occupations ('poeta' and 'śpiewaczka') are quite far away.

b) Polysemous words

Example of a polysemous word I found was 'guzik': in most similar words, it had both 'przycisk', alluding to a keyboard or a panel, and 'pasek', which is much closer to its meaning in tayloring.

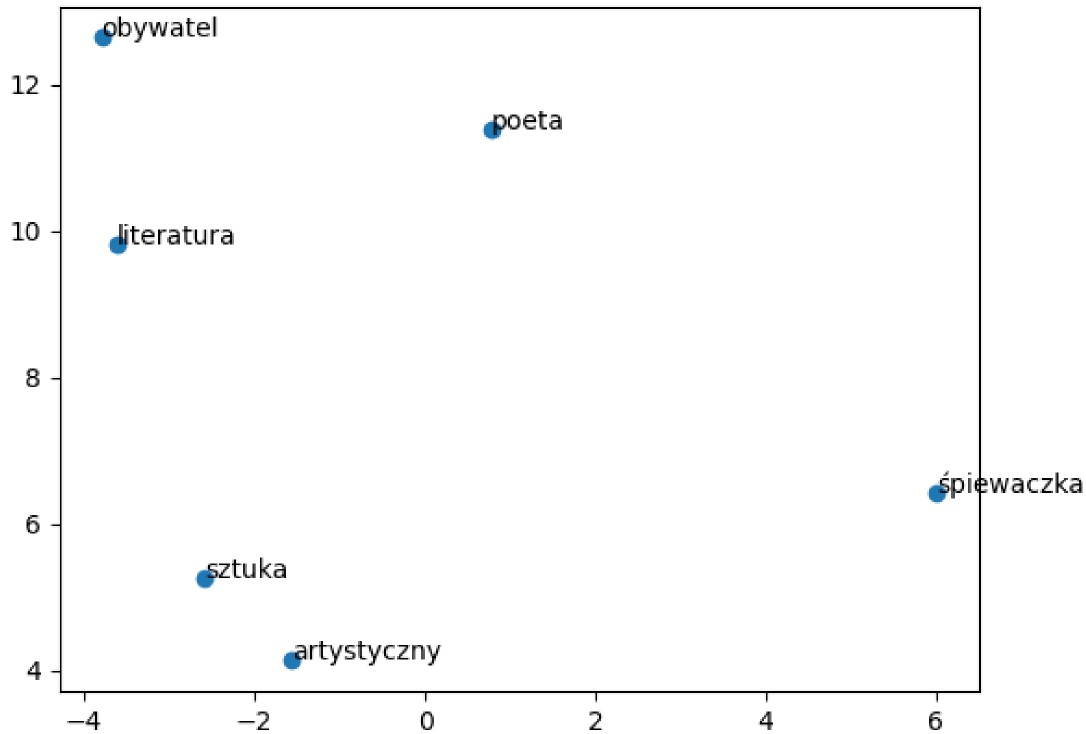

Figure 3: Polish corpus vector space with reduced dimensionality

c) Synonyms and Antonyms

An example of antonyms that are closer than synonyms is ’czysty’, ’szlachetny’ and ’brudny’. I believe that word ’czysty’ is much more frequently associated with physical state of cleanliness, while ideas of noblity are quite archaic.

d) Finding Analogies

An analogy I found was ’pociag’:’dworzec’ :: ’samolot’:’lotnisko’.
I think that similarity lays in that trains stop on railway stations and planes stop on airports.

e) Incorrect Analogies

An analogy I found was ’człowiek’:’dom’ :: ’pies’:’kurnik’.
Dogs are not housed in chicken coops. Clearly, ’buda’ would be much more appropriate.

f) Guided Analysis of Bias in Word Vectors

In the top 10 most similar results, we find 'agent' and 'wiceprezes', which suggests that words representing women are further away from words representing leadership roles.

g) Independent Analysis of Bias in Word Vectors

In the same vein as the example in subsection f, most analogous word to fit in 'mężczyzna':'garaż' :: 'kobieta':'X', according to the model, is 'pralnia', which reveales some unsettlingly sexist relations in the data.

h) The source of bias in word vectors

The model in this example is assinging each word a point, but there are some words which don't have such singular meaning – for example, some words are for both genders. In such situations, model has to compromise and choose the value that is more frequent, which often reveales bias of how the word is used on the original corpus. Additionally, Polish corpus seems to be more limited in volume in comparison to the English one.

3 Prediction-Based Word Vectors in English Corpus

b) Polysemous words

Example of a polysemous word I found was 'free': in most similar words, it had both 'restricted', alluding to freedom, and 'nominal fee', which is much closer to its meaning as a price.

c) Synonyms and Antonyms

An example of antonyms that are closer than synonyms is 'smart', 'wise' and 'dull'. I believe that word 'smart' is much more frequently associated with being sharp and exciting and its meaning corresponding to intelligence is used less often.

d) Finding Analogies

An analogy I found was 'plane':'airport' :: 'ship':'docks'.
I think that similarity lays in that planes stop on airports and ships stop in docks.

e) Incorrect Analogies

An analogy I found was 'human':'apartment' :: 'dog':'chinatown'.
This is just a stereotype.

f) Guided Analysis of Bias in Word Vectors

In the top 10 most similar results, we find 'receptionist' and 'coworker', which suggests that words representing women are further away from words representing leadership roles.

g) Independent Analysis of Bias in Word Vectors

In the same vein as the example in subsection f, most analogous word to fit in 'man':'blue' :: 'woman':'X', according to the model, is 'pink'. I do not think this is offensive, but it does show that model learned some stereotypes.

h) The source of bias in word vectors

The model in this example is assinging each word a point, but there are some words which don't have such singular meaning – for example, some words are for both genders. In such situations, model has to compromise and choose the value that is more frequent, which often reveales bias of how the word is used on the original corpus.