Discovering Meaningful Low-Rank Subspaces in Ancient Greek Word-Embeddings

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Abstract: State-of-the art word embeddings for Ancient Greek are developed, and a novel method for finding meaningful low-rank subspaces in embedding spaces is applied to them in order to uncover information about Greek culture that they encode. This method has general relevance beyond Ancient Greek for studying the kinds of meaning that word embeddings encode.

1 Introduction

Word embeddings have been refined extensively for English and a handful of other major modern languages, but embedding resources for most of the world's written languages are limited or non-existent. There is a rich literature on cross-lingual embedding techniques, one of the principal goals of which is to leverage the resources of languages like English to improve embeddings for NLP resource-poor languages. Though a similar approach could be taken with Ancient Greek, because of the large number of bilingual English-Greek aligned texts, I take a different approach in this paper and attempt to produce good quality embeddings from Ancient Greek text alone. I then use methods developed in the literature on bias in word embeddings to these Ancient Greek embeddings to extract interesting cultural information from them.

Given the lack of previous work on Ancient Greek in natural language processing, this is mainly an exploratory paper.[1] I propose, and evaluate as best I can, the following three hypotheses, the first about Greek word embeddings in particular, and the latter two about the meaning encoded in word embeddings in general: (1) that using lemmatized Greek results in superior word embeddings to those produced from unlemmatized text; (2) that it is possible to manually uncover many approximately low-rank, but higher than one dimensional, subspaces in the ambient embedding space, and that these subspaces are meaningful (with their approximately low-rank character being a signal of this); (3) that systematic comparison of a word's nearest neighbors can also uncover such subspaces, and in a way that is suitable for automation.

The main contributions of this paper, corresponding to the hypotheses above, are as follows. I develop and make publicly available the highest quality word embeddings for Ancient Greek yet released, and propose a simple, generally applicable method for finding meaningful low-rank subspaces given a single seed word.

2 Related Work

2.1 Ancient Greek Word Embeddings

The only previous publicly available word embeddings for Ancient Greek are those released with the shared dependency parsing task of CoNLL 2017 (6). They release embeddings for a wide range of low-resource languages. The Greek embeddings were trained on 7 million tokens of text data from the Perseus Digital library[2], using word2vec SGNS algorithm to produce 100 dimensional embeddings. These embeddings look fairly good, judging by my qualitative evaluation

[1] Most of the claims about Ancient Greek culture made in this paper are taken as starting points within the fields ancient Greek history, archaeology, and literary studies, and can be verified in any introductory handbook. The other claims I make represent consensus views, though not necessarily ones that would be included in introductory texts. What follows is a list of bibliography substantiating all claims made in this paper, starting with introductory handbooks and followed by specific subject areas that come up: introductory handbooks (16), (20); gender (8); religion (4); Athenian democratic political ideology and practice (20), (11); oligarchic political ideology and practice (19); cultural and political history of Greek city-states (12), (13); elite stereotypes against wage laborers, manual laborers, artisans (7).

[2] http://www.perseus.tufts.edu/hopper/

of them through a broad range of nearest neighbor searches and inspection of the results; their main limitation is that the quality of the nearest neighbor words returned drops off sharply after about the 10th word, and the lower ranked words include a large number of obvious noise words. This seems to be a result of the fact that they were trained on a relatively small amount of unlemmatized text data (discussed further below). Other work on Ancient Greek word embeddings includes (18) and (14), but as neither of these projects has working embeddings that are publicly available, I have not been able to evaluate them.

2.2 Embedding Bias, Stereotypes

Since 2016 with Bolukbasi et al.'s seminal paper (2), the subject of bias or stereotypes in English word embeddings has been a hot topic of research(5), (9), (22), (10).[3] The aspects of this literature relevant to the present paper are the variety of bias metrics that they develop, which I briefly survey here.

Bolukbasi et al. 2016 adopt a linear algebraic metric, identifying a "gender" subspace in the overall embedding space using PCA and then computing the gender bias of a word by the magnitude of its projection onto that subspace.[4] To identify this gender subspace they run PCA on a set of 10 vector differences between word pairs presumed to differ in meaning only in terms of gender (for example "she, he", "woman, man", "grandmother, grandfather"). The percentage of variance accounted for the principal components drops of sharply after the first principal component (accounting for about 60% of the variance), and so they take this vector to represent the "gender" direction (whose span is the one-dimensional gender subspace).

Caliskan et al. 2017 put forth a more statistically oriented measure of bias, using a permutation test of the differential similarity/association between target words and attribute words (their underlying vector similarity metric is cosine similarity). Its flexibility allows them to apply it to a wider range of domains than just gender (including racial stereotypes and, for validation, the association between flowers and pleasantness). Their work raises the question of whether Bolukbasie et al.'s linear algebraic approach of finding subspaces in embeddings could be applied to the associations that Caliskan et al. uncover (e.g. in English embeddings are there "ethnicity" subspaces, a "pleasantness" subspace, etc.). I explore this idea for Ancient Greek in the present paper.

Garg et al. 2018 use a Euclidean distance based metric of strength of association/stereotype that they call relative norm distance (RND). They define it as:

$$\text{RND(M)}= \sum_{v_m \in M} \|v_m - v_1\|_2 - \|v_m - v_2\|_2$$

Here M is a set of target words (such as stereotypically male occupations "programmer", "doctor", etc.) and v_1 and v_2 are two group vectors representing two groups of people (like "males" vs. "females"), where each group vector is obtained by averaging the vectors of a list of words representative of that group.

3 The Ancient Greek Embeddings

3.1 Data

The dataset I use consists of 25.5 million tokens in 1.4 million sentences, released in 2017 by Giuseppe Celano of the Perseus Project.[5] 21.5 million of the tokens are lemmatized with high confidence (agreement by two high-precision Ancient Greek lemmatizers, Morpheus and PerseusUnderPhilologic). The remaining words are not assigned a lemma either because the lemmatizers did not contain the relevant word form or because they disagreed. Though this is a small dataset by current standards, its quality is high. The lemmatization, sentence tokenization, and related tasks draw on the work of over a century of careful scholarship on Ancient Greek, and have been extensively refined by hand (something that many Classical scholars find it worthwhile to do). Furthermore, the Perseus Online Library, which most readers of Ancient Greek use regularly, has a crowd-sourcing annotation mechanism where users can vote on the most likely lemmatization of a given form that they have encountered and asked Perseus to parse. I do not know

[3] An earlier paper that investigates biased language from a natural language processing perspective is (17), but they do not deal specifically with word embeddings.

[4] All of the bibliography on bias in embeddings cited in this paper assumes a binary conception of gender. This is a serious oversimplification when it comes to contemporary societies–in fact, a major bias itself, baked into the framing of the issue of "bias" in embeddings. For studying Ancient Greek culture, on the other hand, the assumption is not problematic, since Ancient Greek culture had a resolutely binary conception of gender (regardless of underlying social reality).

[5] Available at https://github.com/gcelano/LemmatizedAncientGreekXML.

the details, but I believe these human annotations are taken into account in the final lemmatized texts released by the Perseus project (e.g. using significant inter-annotator disagreement as an indicator for a form that an expert should inspect and lemmatize by hand).

3.2 Model

The most effective embedding model and parameters were word2vec SGNS with 300 dimensions, a window size of 10, and a negative sampling rate of 10 (10 negative examples for every 1 positive). I also tried SGNS with dimensions 100, 200 and window sizes 5, 20; SVD embeddings with dimensions 100, 200, 3000 and window sizes 5 and 10; and FastText with dimension 300, window size of 10. FastText[6] (1) embeddings failed in an interesting way due how they incorporate subword information, combined with the morphological characteristics of Ancient Greek. The embeddings tended to group together words with similar morphological suffixes rather than similar lexical meanings. I suspect this is because Ancient Greek has a much richer system of inflectional morphology than English, and also a few extremely productive derivational endings. For instance, a search for the nearest neighbors of *politikos* 'political' would return other nominals ending in the *-ikos* suffix, which is a productive suffix for deriving adjectives from nouns, rather than words that are semantically related to *politikos* (e.g. *polites* 'citizen', *politeia* 'constitution').

3.3 Evaluation

Since there do not exist any word-relatedness or similarity test sets for Ancient Greek, there is no established way to evaluate and compare embeddings. In this paper I have relied mainly on extensive qualitative evaluation through inspecting the results of top 50 nearest neighbor searches for a broad range of words. As an attempt at a more quantitative metric when comparing my own embeddings with the CoNLL embeddings, I prepared several lists of words which I thought, on a conservative/high-confidence estimate, should be among the top 50 nearest neighbors of a number of target words, before looking at the CoNLL embeddings or starting to make any embeddings of my own. In training my own embeddings, I did extensive nearest neighbor searches, but not on any of the target test words. Since it would be unreasonable to try to guess what all of the nearest neighbors should be, but I could think of certain key words which are strongly associated with the target word in Ancient Greek, I decided to calculate recall on the top 50 nearest neighbors returned for each target word as the relevant evaluation metric. The results are presented below. A representative example of one evaluation list, for the target word *demokratia* 'democracy' is included in the appendix. It needs to be emphasized that this is a very error-prone evaluation, since a non-native speaker's introspective guess as to what words should be near one another in Ancient Greek embeddings rests on shaky ground (and is very laborious). For now, qualitative evaluation by extensive inspection of nearest neighbor searches seems to give a better sense of the quality of Ancient Greek embeddings. The most significant general difference between the CoNLL embeddings and the embeddings I develop here is that, whereas both tend to produce good results for the top 10 nearest neighbors, the quality of CoNLL results below the top 10 decline rapidly into noise words, whereas my embeddings show relevant results well past the top 50 nearest neighbors. Many of the noise words in the CoNLL embeddings are inflected forms of tokens that "belong" (from a lemmatized perspective) somewhere else in the embedding space.

target word	**CoNLL**	**new**
demokratia 'democracy'	0.36	0.77
dikaios 'just'	0.45	0.68
philosophia 'philosophy'	0.22	0.63
mache 'battle'	0.36	0.63
aoidos 'song'	0.41	0.77

Table 1: Recall on top 50 nearest neighbors task for CoNLL embeddings and this paper's new embeddings. All test lists consisted of 22 words. See Table 2 for an example test list for the word *demokratia* 'democracy'.

4 Finding Cultural Information in Word Embeddings

I first implement two baseline method from the literature on gender bias in word embeddings for measuring the differential association of groups of target words (like occupations) with groups of definitionally gendered terms (like 'she, her, woman' vs. 'he, him, man'). I then generalize these methods to discover cultural information beyond gen-

[6] https://github.com/facebookresearch/fastText

test neighbor word for *demokratia*	CoNLL	new
aristokratia ‘aristocracy’	+	+
oligarkhia ‘oligarchy’	+	+
turannis ‘tyrant/tyranny’	+	+
monarkhia ‘monarch’	-	+
psephisma ‘vote (noun)’	+	+
psephizo ‘vote (verb)’	+	+
ekklesia ‘assembly’	-	-
ekklesiazo ‘participate in the assembly’	-	-
politeuma ‘constitution’	-	+
politeia ‘constitution’	+	+
politeuo ‘participate in political life’	-	+
eleutheria ‘freedom’	+	+
polites ‘citizen’	-	+
bouleutes ‘council member’	-	+
politikos ‘political’	+	-
dikasterion ‘lawcourt’	-	+
Athenaios ‘Athenian’	-	+
Perikles ‘Pericles’	-	+
Kleisthenes ‘Cleisthenes’	-	+
Solon ‘Solon’	-	+
nomos ‘law’	-	-
nomothetes ‘lawgiver/lawmaker’	-	-

Table 2: Example test set of 22 words, for target word *demokratia* ‘democracy’. “+” indicates that the Greek word was found among the top 50 nearest neighbors of *demokratia* in the embedding space, “–” that it was not. The embeddings

der associations in Greek embeddings, using hand selected lists of terms. Finally, I present a simple method for automating the discovery of meaningful low-rank subspaces pertaining to a single seed word, which is a step toward eliminating the need to intuit ahead of time the pairs of contrasting words that will be related to one another by an interesting low-rank subspace in the ambient embedding space.

4.1 Baselines for Gender Associations

The first baseline I implement is Garg et al.’s (9) method for measuring the associations between groups of words. It is a simple but effective Euclidean distance-based metric of strength of association/stereotype that they call relative norm distance. They define relative norm distance (RND) as

RND(M)= $\sum_{v_m \in M} \|v_m - v_1\|_2 - \|v_m - v_2\|_2$

Here M is a set of target words (such as stereotypically male occupations “programmer”, “doctor”, etc.) and v_1 and v_2 are two group vectors representing two groups of people (like “males” vs. “females”), where each group vector is obtained by averaging the vectors of a list of words representative of that group.

The relative norm distance proved an effective measure for a variety of cultural associations in Greek. Here are three representative examples, measuring the association between the target words in parenthesis with averaged representative group vectors for male and female (first stereotypically ‘female’ target words (for an Ancient Greek), stereotypically male target words, and then three neutral verbs).

RND(*paidopoiia* ‘baby-making/raising’, *brephos* ‘baby’, *numphios* ‘maidenly’, *eueides* ‘pretty’, *histos* ‘loom’) = -1.024061381816864

RND(*polites* ‘citizen’, *eugenes* ‘noble’, *phronimos* ‘intelligent’, *arete* ‘courage/virtue’, *mache* ‘battle’, *andreios* ‘courageous’) = 0.8998430967330933

RND(*tithemi* ‘put’, *didomi* ‘give’, *phero* ‘bring’) = -0.03630650043487549

Ancient Greek culture was deeply sexist and patriarchal, and we see that the word embeddings accurately reflect this fact (weaving was something most women spent much of their lives doing, hence the strong association between *histos* 'loom' and women). As a control, we see that the third RND calculation, with neutral target words, shows no particular association with male or female genders.

The second baseline I implement is Bolukbasi et al.'s (2) method for discovering the gender subspace within English embeddings (specifically the word2vec Google news embeddings).

I replicated Bolukbasi et al.'s results on the Google news embeddings as well as on the GLoVE Wikipedia/Gigaword 5 300 dimensional embeddings, finding the same drop-off in explained variance after the first principal component. I then constructed an analogous experiment for ancient Greek, using pairs of words that contrast primarily in terms of gender alone. The drop off after the first principal component is likewise steep, though there is still a fair amount of meaning in the second principal component. I believe that this is because the word pairs I use contrast systematically in other dimensions besides gender (notably age, which probably corresponds to the second principal component), and are otherwise noisier because they are gendered nouns rather than pronouns. Bolukbasi et al. use gendered pronoun forms for several of their contrasting pairs, which intuitively seem likely to give the cleanest possible signal of gender. This was not possible with the lemmatized Greek data I used, since all pronominal forms in the data were mapped to their lemmas; since gender is conveyed by inflectional morphology in Greek, this lemmatization undoes pronominal gender distinctions. Still, when we compare the principal components of the Greek gendered words with the principal components of random pairs of contrasting Greek words (fig. 1 middle), and even more with random vectors filled with samples from a standard normal distribution (fig. 1 right), we see that there is a fairly strong signal which likely corresponds to gender.

4.2 Generalizing Low-rank Subspace Discovery

To begin evaluating my hypothesis that it is possible to find other approximately low-rank, meaningful subspaces in word embeddings, I attempted to apply Bolukbasi et al.'s method for discovering the gender subspace to other similarly polar concepts in Ancient Greek culture (here I use 'polar' in the loose sense of defining some sort of spectrum along which things can be contrasted). This required selecting the right pairs of contrasting words, which is a difficult, error-prone task given that I am not a native speaker of Ancient Greek. Even so, the results were surprisingly strong. Figure 2 shows what I interpret as the 'political polarity' subspace, where the respective poles are 'democracy' and 'oligarchy'. That there should be such a meaning direction in Ancient Greek word embeddings aligns very well with the historical reality of political life in ancient Greek city-states, in which there was widespread, ongoing conflict between factions of citizens who sympathized with oligarchic states and constitutions, and factions who sympathized with democratic ones. Other low-rank subspaces discovered manually in this way ('wealth-class polarity', 'political life vs. work/labor') are documented in the appendix following the bibliography.

It is worth pointing out that two of these subspaces are very "Ancient Greek", culturally speaking: the 'democracy vs. oligarchy' subspace and the 'political life vs. work/labor'. For contemporary American embeddings, there is an anologouse political polarity subspace (as I verified in the GLoVE embeddings), but its poles are defined by 'liberal' and 'conservative'–a very different space than that defined by 'democracy' and 'oligarchy'. I was unable to find anything analogous in English embeddings to the 'political life vs. work/labor' subspace. This makes intuitive sense, because of two relevant cultural differences between the contemporary U.S. and Ancient Greece. First, for Ancient Greeks living in city-states, participating in political life was generally seen as one of the highest and most desirable forms of activity that an adult man could (and was expected to) engage in (it was only ever the privilege of men). This contrasts sharply with the (understandable) cynicism and apathy characteristic of our own political culture. Second, there was a strong prejudice among many Ancient Greeks against manual labor. The historical reasons for this are complex, but the main one is that Ancient Greece was a slave society. Working with ones hands, and many other kinds of economically productive tasks, were considered "slavish" in virtue of the fact that slaves were most often the ones doing them. So, in An-

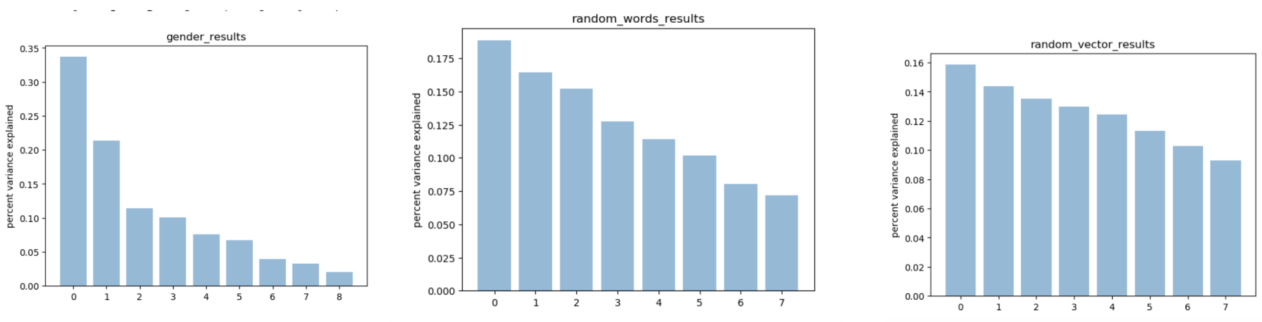

Figure 1: Shows percentage of variance explained by each principal component returned by PCA on 9 difference vectors. The left plot shows difference vectors for 9 pairs of gender contrasting words. The middle plot shows difference vectors between pairs formed from 18 randomly selected words. The right plot shows difference vectors between pairs of randomly generated 300 dimensional vectors (each coordinate sampled from a standard normal distribution)

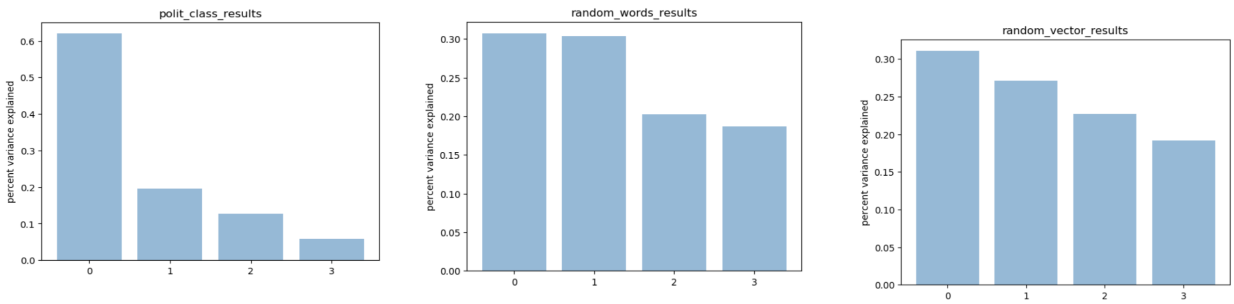

Figure 2: Same as figure 1, except with left plot showing the PCA results for difference vectors between four pairs of politically contrasting words. The middle plot and left plot show, respectively, the results for randomly selected words, and randomly generated vectors.

cient Greece political life was elevated above and contrasted with the life of work, and it therefore makes sense that there would be a subspace corresponding to this in Greek word embeddings.

4.3 Automating Low-Rank Subspace Discovery

My method for automatically discovering low-rank subspaces starts from the observations that antonyms are usually near one another in word embedding spaces. This is a well-known and well-understood fact, since antonyms are identical in meaning except in the one or two dimensions where they contrast. More generally, we can expect that pairs of words that we would not stricly call antonyms, but whose meaning is identical in all but a few dimensions of their meaning, will end up close to one another in word embedding spaces. If this is right, then it should be possible to discover low-rank subspaces representing polarities by systematically comparing the nearest neighbors of words (at least words that participate in some kind of prominent semantic contrast relationship with other words). The method I developed tests this idea systematically. Given a seed word w it collects the N nearest neighbors (where N is odd) of w in the embeddings space, and then computes the PCA of all possible pairings of these N words plus the seed word. The method returns a list of these PCA results, ranked by the strength (percent variance explained) of the first principal component.

I applied the method to 80 Greek seed words, which were selected based on the hunch that they could participate in a significant polarity in Ancient Greek culture. This returned many interesting results, a representative example of which is the word *sophron*. This a central ethical concept in Ancient Greek culture that means 'prudent, temperate, self-controlled'. The highest ranked word-pairings show a similar drop-off of variance explained after the first principal component (an example is figure 3), indicating that they mark out a meaningful low-rank subspace. The lowest ranked pairings of the same nearby words show no significant drop off after the first principal component (figure 4), indicating that their difference vectors do not define a meaningful subspace. Inspecting the word pairs and bringing in knowledge of Ancient Greek culture, we can hypothesize, with a fairly high degree of confidence, that the contrast here is between 'temperateness, self-control, moderation' and 'wildness, lack of self control, outrageous behavior', which were two important poles defining the Ancient Greek moral universe. To further interpret the top-ranked subspaces and evaluate the hypothesis about what polarity they're capturing, we can project some informative words onto their top two principal components. Three such projections are displayed in figure 5 in the appendix.

5 Limitations and future work

There are at least two major limitations of this method for automatically discovering low-rank subspaces. The first is that it is computationally inefficient in my naive implementation. It scales exponentially in the number of nearest neighbors searched, and searching more than 22 was unfeasible on my laptop. It would be straightforward to optimize this algorithm more (pruning off unpromising word-pairings), but it is unlikely to be able to scale to large numbers of neighbors. The second limitation is that it is limited to discovering low-rank subspaces that are "topically localized" in the sense it is only going to find polarities that are reflected in words that are very near one another in the embedding space. But more abstract polarities, like that of gender, are encoded much more broadly throughout different regions of an embedding space, in a wide variety of topically different words. One interesting direction for future research would be to apply the same basic approach to pairs of words drawn one each from meaningful clusters over the whole embedding space, where the clusters could either be generated by an unsupervised method like k-means, or hand selected for a specific purpose or research question. Another direction for future research, which I began to pursue during this project, is developing methods for measuring the "distance" between higher than one dimensional subspaces. The linear algebraic concept of the principal angles between two subspaces[7] of the same dimension allows for a multi-dimensional distance metric between them that is analogous to 1-dimensional cosine similarity for individual word vectors. My initial experiments with this metric, on subspaces of approximate rank 2, 3, and 4 discovered by the method outlined above, seem promising, but I have not yet

[7] Wikipedia has a good basic overview https://en.wikipedia.org/wiki/Angles_between_flats

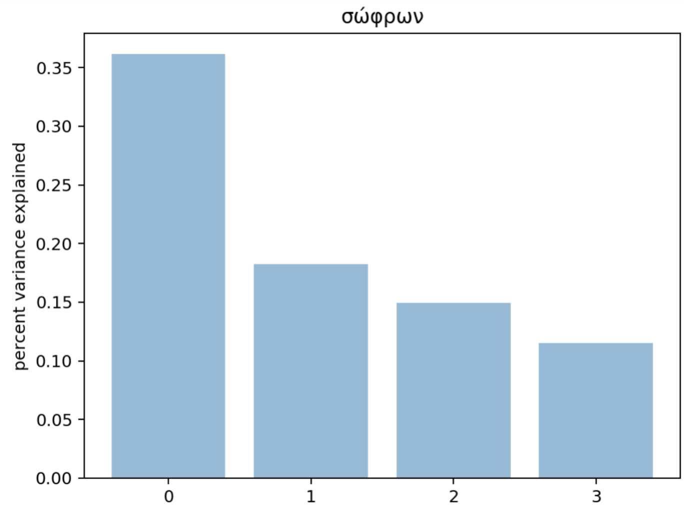

Figure 3: Shows percentage of variance explained by the highest ranking top 4 principal components returned by PCA on 7 difference vectors formed from pairings of the 14 words nearest to *sofron* 'temperate, self-controlled' (including *sofron* itself among them). Here "highest ranking" means that this pairing of the 14 words and their associated difference vectors resulted in the highest percentage of variance explained by the first principal component. The last three principal components are excluded for space.

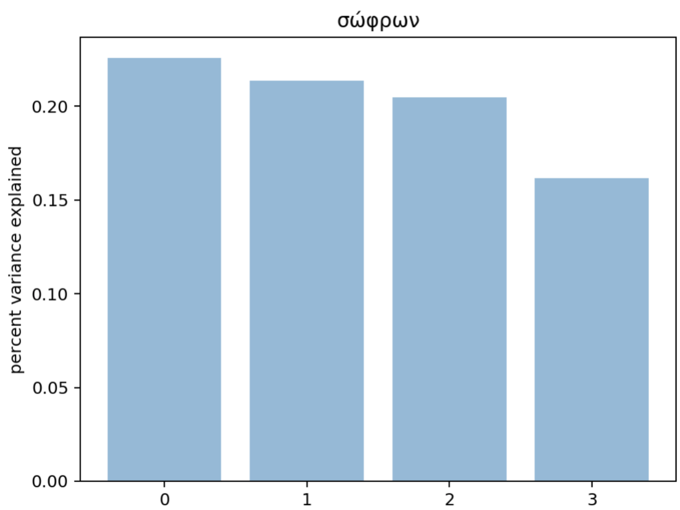

Figure 4: Same as figure 3, except shows the top 4 principal components of the lowest ranking pairing of the same 14 nearest neighbors of *sofron*. The slow tapering off of variance explained shows that the difference vectors between this pairing of *sofron*'s nearest neighbors did not lie in an approximately low-rank subspace, and therefore don't collectively represent a meaningful polarity.

been able to develop a framework for interpreting the results.

6 Code and Data

Code for training embeddings on the Perseus Lemmatized Ancient Greek XML files and visualizing clusters of nearest neighbor words can be found at https://github.com/nickdgardner/notebooks/tree/main/greek-word-embeddings.

The Perseus XML files used in the code can be found here: https://github.com/gcelano/LemmatizedAncientGreekXML.

7 Acknowledgments

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8 Authorship

This paper was written for the class CS224U: Natural Language Understanding, Spring 2019. I am the sole author.

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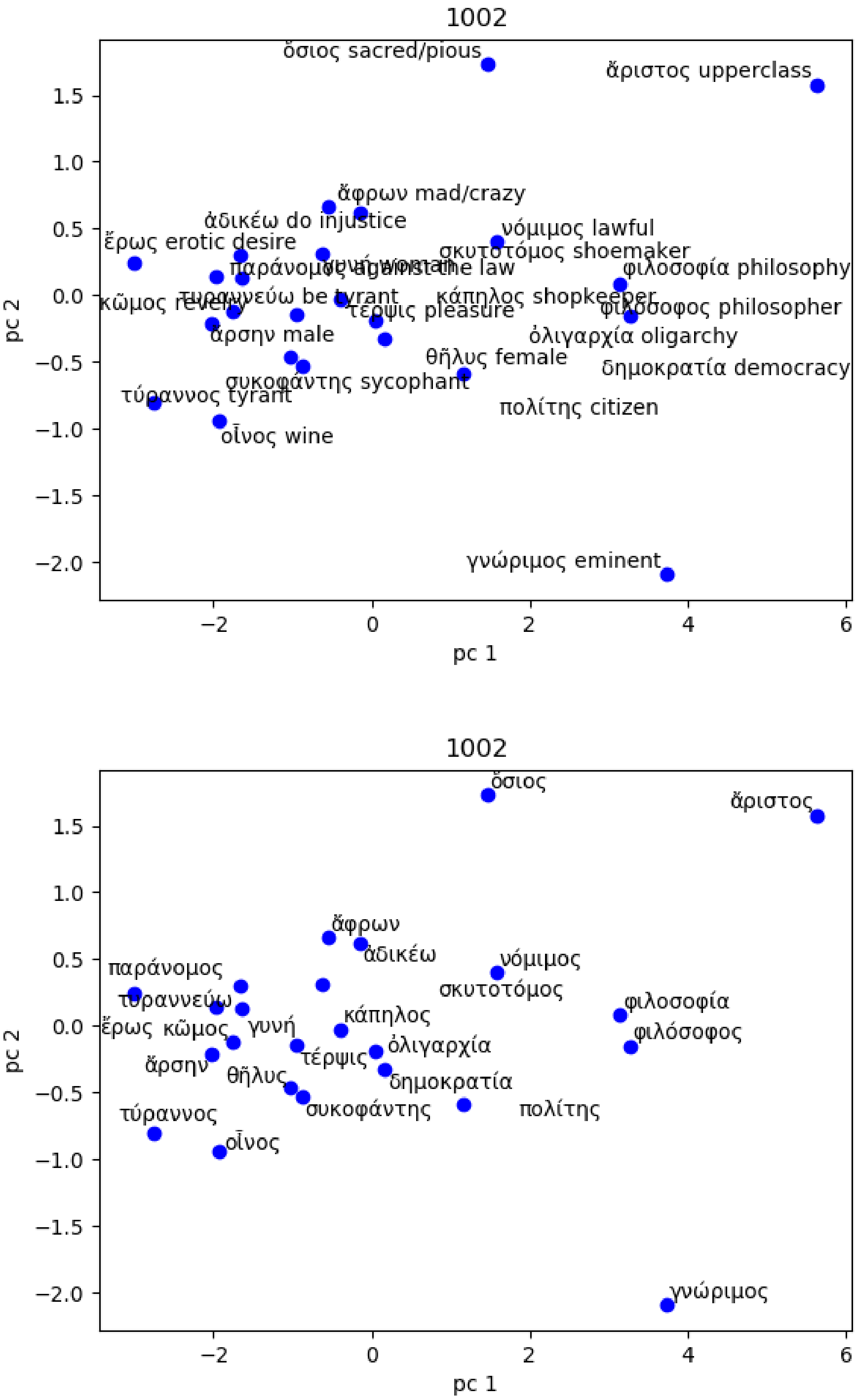

Figure 5: A set of informative words projected onto the top two principal components of a subspace surrounding *sofron* ‘temperate, self-controlled’ (the two plots are the same data twice, above with English glosses and below without, for clarity). This plot and others show a remarkable fidelity to Greek elite culture and many of its distinctive stereotypes–too many to thoroughly discuss. Some notable points. The ‘tyrant’ close to ‘wine’, and their proximity to ‘be a tyrant’, ‘against the law’, and ‘erotic desire’–all very much traits that were bundled together in Greek perceptions of tyrants. On the other end of PC1, are some “respectable” elitists of the ancient Greek world: ‘philosopher’ ‘eminent person’, ‘elite’. Most of our Greek texts were produced by people who considered themselves of this status, so the texts often reflect their view of the world. They are near ‘lawful’, and separated from the ‘shoe-maker’ (whose label should be assigned to the unlabelled point straight to its left and below ‘mad/crazy’ and ‘do injustice’) and the ‘shopkeeper’ (often reviled in surviving elite texts).