Polarity in Translation: Differences between Novice and Experts across Registers

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Abstract

Translation can obscure the subjectivity of the sources and flatten down positive and negative aspects. Thus, we perform an explorative analysis of translation in terms of sentiment properties focusing on the differences between student and professional translations of various registers. However, we do not compare translations with their sources, but analyse polarity items in two translation variants from the same text sources. We propose a multi-step analysis to investigate the distribution of polarity items and report on small experiments on a corpus of English to German translations to identify the lack of experience in translation by students. Our results show that pragmatic differences expressed in the usage of polarity words is highly dependent on the register a text belongs to. Following this, we identify registers, such as popular-scientific articles, where students translate sentiment using more and heavier polarity words.

1 Introduction

Most computational studies of translationese[1] concentrate on the analyses of lexico-grammatical, morpho-syntactic and textual language patterns ignoring semantic and pragmatic properties (Baroni and Bernardini, 2006; Volansky et al., 2015). However, multilingual computational sentiment studies show that textual sentiment, e.g. positive and negative aspects, as well as subjectivity, are altered and even vanished in translation (Mihalcea et al., 2007; Balahur and Turchi, 2014; Salameh et al., 2015; Mohammad et al., 2016). These features are linked to pragmatic competence of translators that can vary depending on their level of expertise. Moreover, pragmatic aspects and the related translation competence may also vary across textual registers as novice and professional translators have different degrees of register sensitivity as shown by Lapshinova-Koltunski (2020) and Redelinghuys (2016).

In the present paper, we analyse sentiment-related properties of English-German translations that were produced by translators of different levels of expertise. We concentrate on the distribution of positive and negative polarity items across different registers[2] translated either by students or by professionals. Although the sentiment of the source texts would bring us interesting insights, we are constrained to exclude them, as the required comparable analytical resources[3] are missing at the moment. Therefore, we concentrate on the analysis of variation in translation in terms of polarity properties. Our data contains student and professional translations of the same sources – texts belonging to various registers. We aim to identify differences in the polarity of the two translation varieties and analyse if these differences are subject to register settings. We expect that student and professional translators alter the sentiment of the originals differently, which should be reflected in the different use of the sentiment lexicon in their translations. On the one hand, as students are repetitive in their lexical choices (as shown by Kunilovskaya et al. (2018) and Redelinghuys (2016) a.o.), we might observe their overuse of certain words which follows in higher or lower sentiment of their translations. On the other hand, their lack of register sensitivity (see Bizzoni and Lapshinova-Koltunski, 2021; Redelinghuys, 2016, for details) may cause a more

[1]Linguistic characteristics of translations showing their differences from non-translated texts (Gellerstam, 1986; Baker, 1993).

[2]We understand register as contextual text variation which is reflected in distinctive distributions of linguistic patterns (Biber, 1995).

[3]This kind of analysis requires comparable polarity lists for English and German.

levelled use of sentiment lexicon in different registers.

We perform an explorative analysis of translation in terms of polarity, focusing on specific differences between professional and student translations of various registers.

2 Main Concepts and Related Work

We understand sentiment analysis as determining the polarity of a piece of text as positive or negative and measure it with the help of polarity items – negative or positive words. This approach is a type of lexicon-based sentiment analysis (Taboada et al., 2011).

As sentiment is not always similarly marked in the source and in the target, translations do not always preserve the original sentiment (Salameh et al., 2015; Mohammad et al., 2016), which was also shown for machine translation (Troiano et al., 2020). Although we measure polarity of the target texts only, we deal with translation, a product of multilingual communication. Therefore, our work is also related to multilingual sentiment analyses that have mainly addressed mapping sentiment resources from one language onto another (e.g. Mihalcea et al., 2007; Balahur and Turchi, 2014). Contrastive studies show pragmatic differences between English and German (Kranich, 2016; House, 2006) that have impact on sentiment realisation in both languages, as it was shown by Taboada et al. (2014) in the analysis of evaluative language and by Fronhofer (2020) in the analysis of emotions. The latter study points to specific language preferences in the morpho-syntactic realisation of emotions (their parts-of-speech, tenses, etc.).

Knowing about these cross-lingual contrasts, we expect translators to adapt a text's sentiment to the target language preferences. Without sufficient experience in doing so, students may fail in appropriate choices for polarity transformations or their lexico-grammatical settings. Munday (2012) shows in a study on translating attitude that students have difficulty because of the missing knowledge on lexico-grammatical features of both the source and the target language. Another study of student translations reveal their missing pragmatic competence (Pisanski Peterlin and Zlatnar Moe, 2016). Interestingly, students showed more difficulties in transferring structures that had no direct translation equivalent with similar lexico-grammatical patterning, as novice translators frequently translate word-by-word. Therefore, we should also expect variation in our data in terms of lexico-grammar, i.e. morpho-syntactic types of polarity items.

3 Methodology

In this section, we introduce the features we extract from the sentiment analysis (Section 3.1), outline the used data set (Section 3.2) and tools (Section 3.3) with our analysis methods in Section 3.4.

3.1 Features

Building upon existing studies in sentiment and translation, we formulate a number of features to analyse polarity in student and professional translations. Our aim is to find lexical differences between student and professional translators. Therefore, we don't use a classifier which would yield sentiment scores for whole texts. Instead, as the first step of our pipeline we extract sentiment words using the list SentiWS (Remus et al., 2010) containing weighted negative and positive items. We formulate the following features:

Overall polarity. 1. the total number of positive polarity words per text (`Pos`), 2. the total number of negative polarity words per text (`Neg`), 3. the sum of weights of positive polarity items (`SumWeightedPos`), 4. the sum of weights of negative polarity items (`SumWeightedNeg`).

Morpho-syntactic subtypes of polarity items. 5-7. Distribution of positive polarity nouns, adjectives and verbs (`PosN, PosV, PosA`), 8-10. Distribution of negative polarity nouns, adjectives and verbs (`NegN, NegV, NegA`), 11-13. Proportion of positive polarity nouns, adjectives and verbs calculated against the total number of nouns, verbs and adjectives, respectively (`PosNprop, PosVprop, PosAprop`), 14-16. Proportion of negative polarity nouns, adjectives and verbs calculated against the total number of nouns, verbs and adjectives, respectively (`NegNprop, NegVprop, NegAprop`).

3.2 Data

We use a dataset of German texts translated by both professional and student translators from English (PT – professional translations and ST – student translations), representing translation variants of the same original texts. These texts cover the following registers: political essays (ESSAY), fiction (FICTION), manuals (INSTR), popular-scientific articles (POPSCI), letters to shareholders (SHARE), prepared political speeches (SPEECH), and tourism leaflets (TOU). Professional translations were exported from the CroCo corpus (Hansen-Schirra et al., 2012), whereas the student translations come from the corpus VARTRA (Lapshinova-Koltunski, 2013). The main difference between the two variants in our data is the degree of expertise – professionals have a good degree of experience in translating, whereas students are trainees with little experience in translating. The whole data set contains 102 texts (51 for each translation variant) with 272,195 tokens in total (more details are given in Table 1).

	ST	**PT**
ESSAY	15,794	15,595
FICTION	12,549	11,226
INSTR	19,866	20,718
POPSCI	22,692	19,739
SHARE	24,739	24,450
SPEECH	24,303	23,373
TOU	19,687	17,464
TOTAL	139,630	132,565

Table 1: Dataset size in tokens.

3.3 Sentiment Analysis in Geist

The data is pre-processed and analysed using Geist[4] (Kliche, 2020), a web tool for converting text data in different formats[5] into formats required by applications in the Digital Humanities context, e.g. topic modeling or stylometric analyses. For the present study, the SentiWS list and the pipeline to extract the features detailed in Section 3.1 were integrated into Geist. Using the TreeTagger (Schmid, 1994), the texts are tokenised and labeled with part-of-speech tags. When one or two tokens left to a sentiment word is a negation, the polarity swaps from negative to positive or vice versa. Geist analyses each of the 102 translations separately and creates a CSV file containing the features for each document. The student translations contained in sum 139,630 Tokens (122,715 words), 8,088 of which were positive and 2,138 were negative. The texts of professional translators consist of 132,565 tokens (116,086 words), with 7,613 positive and 2,103 negative words.

[4] https://geist.uni-hildesheim.de

[5] Including PDF, RTF, Open Office or Microsoft Office formats.

3.4 Explorative and descriptive analyses

As our aim is to exploratively analyse translations and find specific differences between professionals and students, we decide for several techniques that include Correspondence Analysis (CA, Greenacre, 2007), Hierarchical Agglomerative Clustering (HC, Rokach and Maimon, 2005) and boxplots.

Correspondence Analysis. CA allows us to explore relations between features and subcorpora in our data. With the help of this explorative technique, we identify which subcorpora have similarities or differences and how these differences correlate with the selected features. For our purposes, we intend to find groupings of subcorpora based on either the experience of translators or the register a text belongs to. The feature distributions across the subcorpora are used to measure Weighted Euclidean distances, termed the χ^2 distances. The distances are represented in a two-dimensional graph. The larger the differences between the subcorpora, and also between the subcorpora and features (dots and triangles in Figure 1), the further apart they are on the graph. The dimensions are computed in such a way that any subset of *k* dimensions accounts for as much variation as possible in one dimension, the first two principal axes account for as much variation as possible in two dimensions, and so on. The length of the feature arrows indicates associations between subcorpora and features: the longer the line, the stronger is the association.

Clustering. In the next step, we perform HC on texts using the ‘strongest’ features resulting from CA. With this technique, we investigate whether texts cluster according to registers or according to the level of expertise in translation. To be consistent with the previous analysis, we use the Euclidean distance and performed Ward’s linkage to calculate the distance between new clusters on a condensed distance matrix. In each iteration, two clusters that have the smallest distance are merged together, until every text is linked into a dendrogram. The order of the initial clusters (texts we used for the analysis) represented by features that we want to analyse has little significance, the distance between clusters increases with each merging iteration and the height of each merge gives the distance between two clusters.

Boxplots. In the final step, we use boxplots to more closely observe the discovered specific dif-

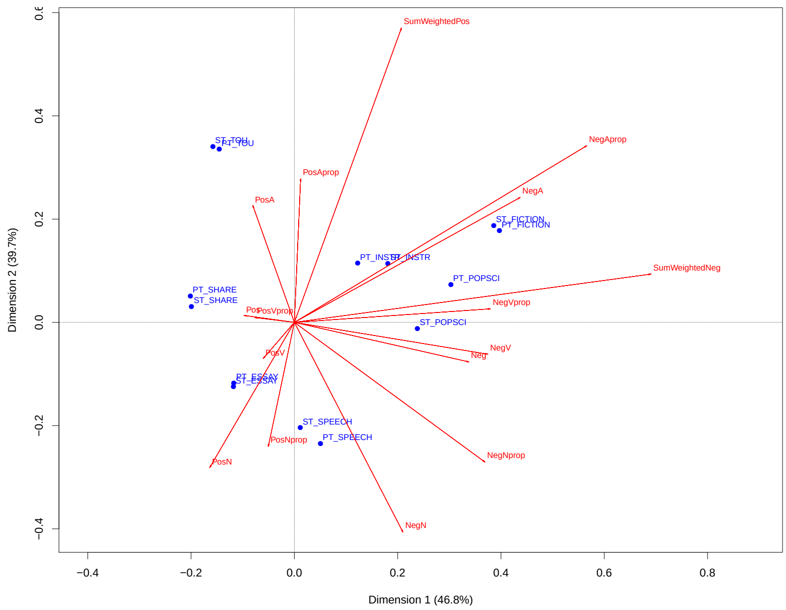

Figure 1: CA for all subcorpora with all features, dimensions 1 and 2.

ferences between professional and student translations. Boxplots are helpful to visually represent summary statistics (central tendency values and spread of data) and to compare descriptive statistics across groups.

4 Analyses

Correspondence analysis. We perform CA on the expertise and register-based subcorpora using the whole set of features defined in Section 3.1. Figure 1 presents the resulting two dimensional graph. The differences between the plotted subcorpora and features can be interpreted on both axes (dimensions 1 and 2 that explain 86,5% of the data variance). Here most student and professional subcorpora of the same registers group together. Dimension 1 (x-axis) separates translations of letters-to-shareholders (leftmost), tourism leaflets and political essays from political speeches, instructions, popular science and fiction (rightmost). Almost all negative polarity features seem to contribute to this division, as the feature arrows show positive values in the direction of the x-axis, with `SumWeightedNeg` being the most contributing feature. Interestingly, its counterpart `SumWeightedPos`, is not opposing (i.e. pointing into the opposite direction), but rather contributes most to the other breakdown in our data – the division of subcorpora observed along the y-axis (dimension 2). Here again, most of the observed groupings are register-based, except for popular science. This is the only difference between professional and student translations uncovered with CA in our data. This means that there is more variation in terms of register than experience in our data, with some text registers being more similar between each other than the others. As the features `SumWeightedNeg` and `SumWeightedPos` were found to contribute the most in determining the differences in texts, they were used for further analysis with clustering and box plots.

Clustering. We use the two features, `SumWeightedNeg` and `SumWeightedPos`, contributing most to the variation along the two dimensions discovered in the previous analysis step rather then using all of the features. This allows us to further target the differences in texts, based on the particular use of positive and negative words within different registers and translation variants. The resulting dendrograms are given in Figures 4 and 5 in Appendix, with x-axis containing texts and y-axis representing the distance.

The dendrogram based on `SumWeightedPos` visualises two major clusters, where the smaller cluster consists mostly of texts from the registers TOU, SHARE and FICTION, with student and professional translations being equally linked together. Most of the texts from other registers can be found in the second major cluster. Deeper towards the leaves of the tree, translation variants of the same text within a register are linked earlier (the distance

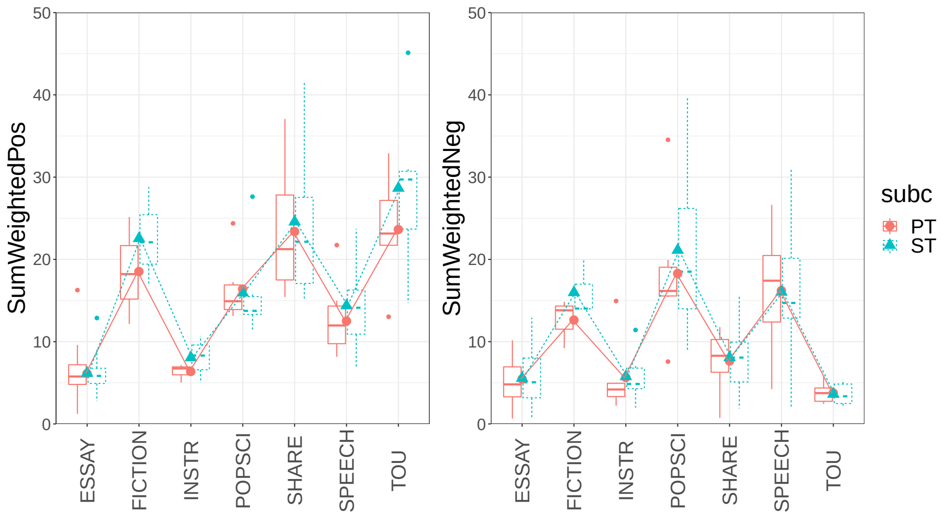

Figure 2: Polarity item weights at text level across registers in professional and student translation.

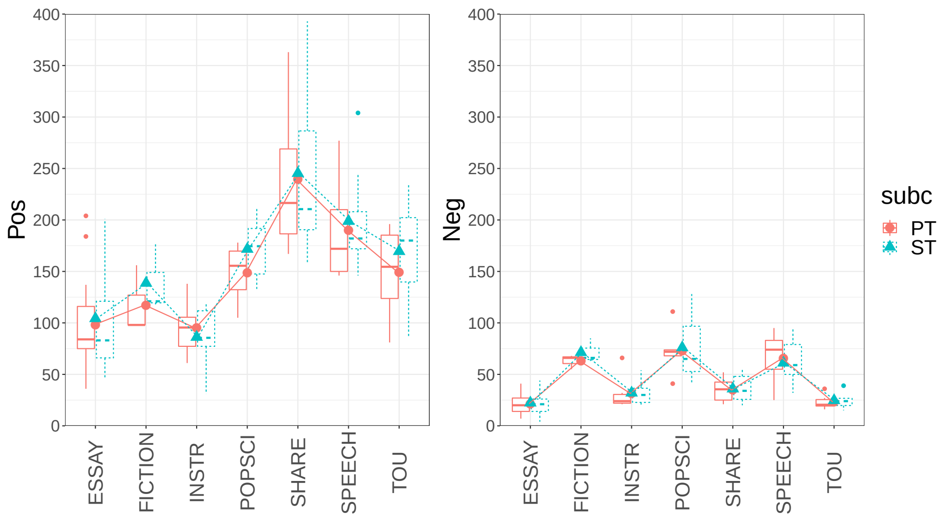

Figure 3: Polarity item distribution at text level across registers in professional and student translation.

between such clusters is smaller), which is later followed by linking of texts from the same register: most of the essay texts end up being linked together before being linked to texts from the register SPEECH and INSTR.

The dendrogram based on `SumWeightedNeg` also has two distinctive clusters, though the texts are more equally distributed across these two (in comparison to the previous dendrogram). Likewise with `SumWeightedPos`, the closest distance is found within the register, though not necessarily within the variants of translation: we can find examples like PT-ESSAY_004 and PT-ESSAY_009 being linked together earlier then the corresponding translation variant from students. Moreover, though the earliest clusters tend to belong to the same register, the registers are interwoven together as distance grows. The results of clustering confirm the observation from CA: Translation variants are highly similar in terms of sentiment features and differences are observed for groups of registers only.

Boxplots. We use boxplots (Figure 2) to directly compare student and professional translations across registers in terms of the two selected features. We observe more variation between professional and student translations when analysed across registers. As seen from the plot for `SumWeightedPos`, student translations of most registers are more positive than the professional ones, except in ESSAY and POPSCI. However, the differences do not seem to be significant in most cases, except for fictional texts and instructional manuals. The plot for `SumWeightedNeg` reveals

EO	*Using this self-administration setup and related techniques, researchers mapped the regions of the brain that mediate addictive behaviors and discovered the central role of the brain's reward circuit.*
ST	*Mithilfe dieser Selbstverabreichungsmethode und ähnlichen Methoden haben Forscher die Regionen im Gehirn lokalisiert, die das **Abhängigkeit**sverhalten steuern. Zudem hat sich herausgestellt, dass das Belohnungssystem im Gehirn eine zentrale Rolle bei der Bildung einer **Abhängigkeit** spielt.*
PT	*Mittlerweile haben Hirnforscher die am Drogenmissbrauch beteiligten Gehirnregionen kartiert. Sie kennen heute die zentrale Funktion des Belohnungssystems dabei.*

Table 2: Example illustrating the difference between student and professional translations (ST and PT), as well as the original English source (EO).

that fictional and popular science texts are more negative when translated by students. The variation of negative weights within the POPSCI texts translated by students is also remarkable pointing to heterogeneous negativity of these translations.

We also compare the overall distribution of positive and negative words in student and professional translations to discover a slightly different view (see Figure 3). Instructions translated by students contain less positive words (although being more positive). Students use more positive words in the POPSCI translations than professionals, although the overall positive polarity of both translation variants of this register remain similar. All this points to the differences in the lexicon choices by students and professionals.

A glance at the data confirms this as well: the negative polarity noun *Abhängigkeit* occurs 24 times in the student translations of POPSCI, whereas professionals use this word 5 times only. Table 2 contains an example from our corpus illustrating the observed differences in translation and showing that students (ST) are more repetitive in their lexical choices also because their translations are longer and more explicit.

5 Conclusion and Discussion

We performed explorative analysis of polarity in translations that differ with regard to the level of translators' expertise. The variation discovered in our data turned to be more register-related, than expertise-related. However, differences between student and professional translations could be observed within registers and register groupings. This points to dependency of pragmatic differences in translation on the functional text variation – the register a text belongs to.

Students use more and heavier polarity words in certain registers only. Moreover, they seem to show similar register sensitivity as professionals do, as their translations also vary in terms of polarity features, which is against our expectations.

In future, we plan to perform a more detailed analysis of distinct features. We also intend to investigate differences between the polarity vocabularies used by both groups of translators, as preliminary insights show that students tend to repeat the same words. Moreover, a cross-lingual comparison involving the sources' analysis would be an asset, which, however, requires comparable polarity lists for English and German.

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Appendix

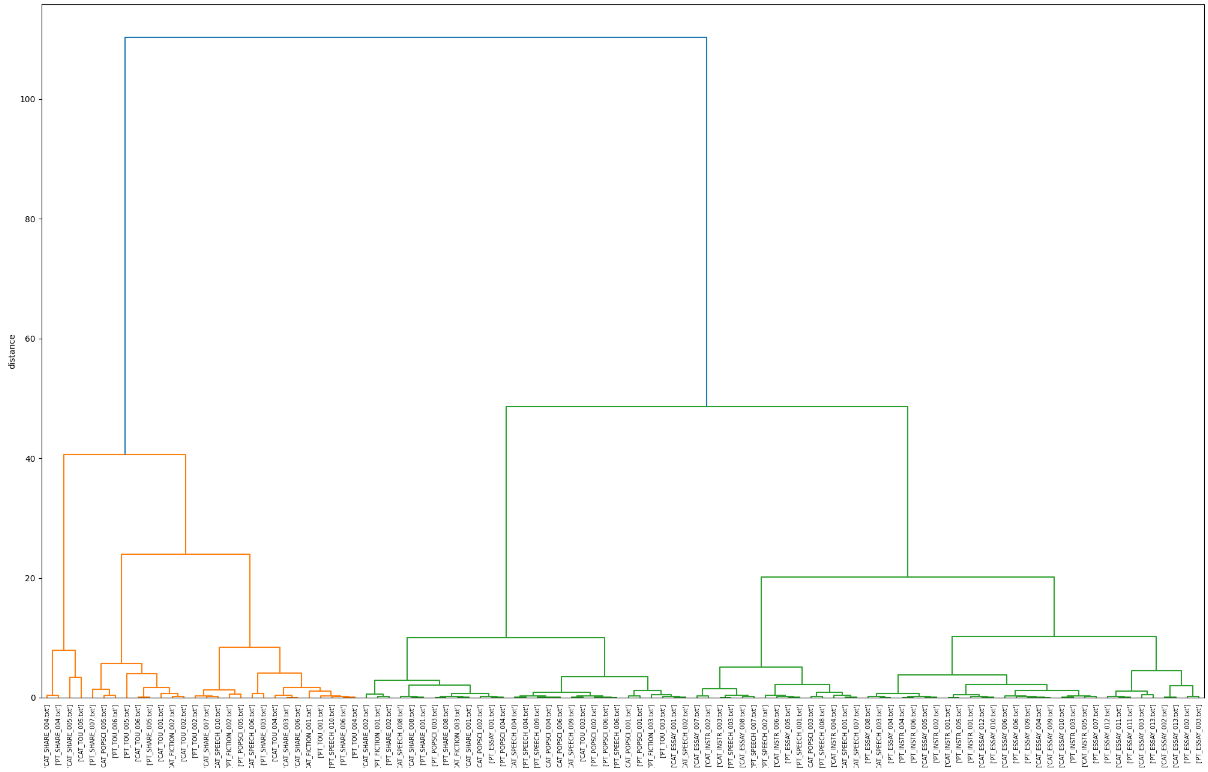

Figure 4: HC for SumWeightedPos.

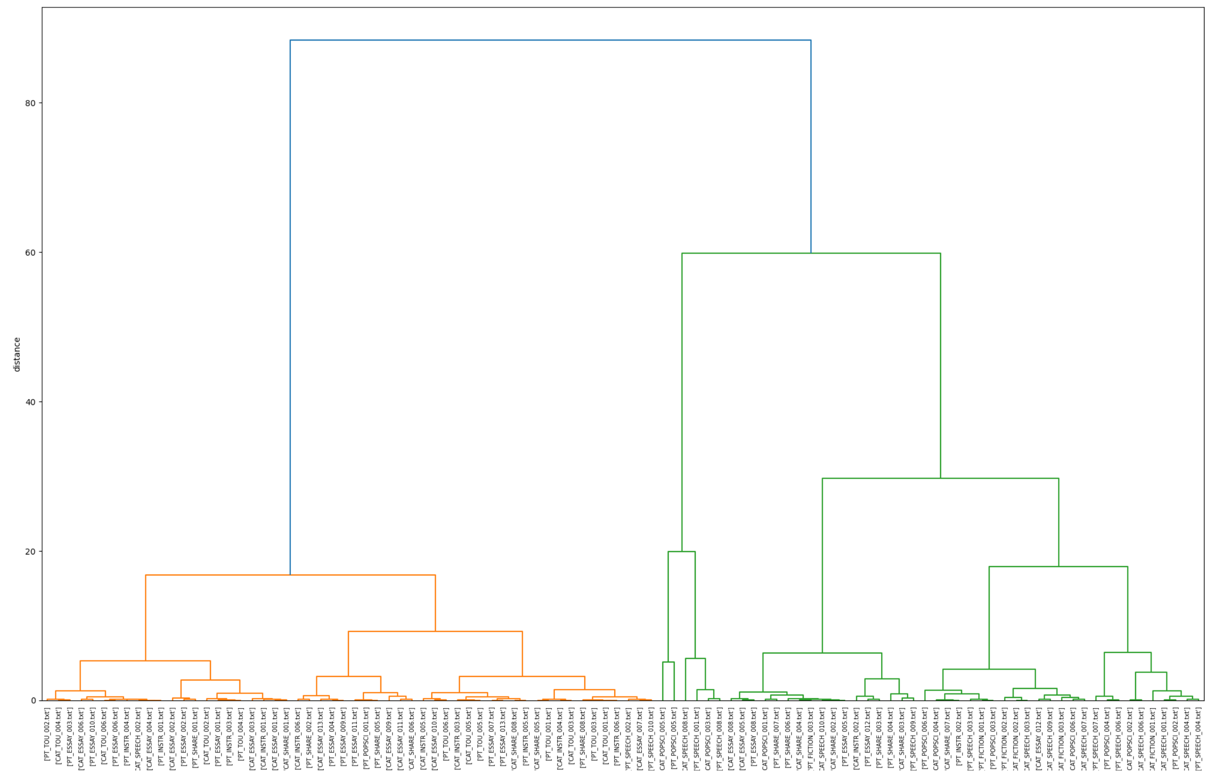

Figure 5: HC for SumWeightedNeg.