Visualizing Facets of Text Complexity across Registers

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Abstract

In this paper, we propose visualizing results of a corpus-based study on text complexity using radar charts. We argue that the added value of this type of visualisation is the polygonal shape that provides an intuitive grasp of text complexity similarities across the registers of a corpus. The results that we visualize come from a study where we explored whether it is possible to automatically single out different facets of text complexity across the registers of a Swedish corpus. To this end, we used factor analysis as applied in Biber’s Multi-Dimensional Analysis framework. The visualization of text complexity facets with radar charts indicates that there is correspondence between linguistic similarity and similarity of shape across registers.

Keywords: radar charts, text complexity, readability, Multi-Dimensional Analysis

1. Introduction

Data visualization refers to the graphical representation of information, data, results or findings. Graphical representations like charts, graphs, and maps, help the human brain understand and interpret trends and patterns in data. Effective data visualizations place meaning into complex information because they help disentangle complexities and unveil underlying patterns in a clear and concise way. The easiest and most common way to create a data visualization is to use bar graphs, pie charts or line graphs. These types of charts are effective and widely used. Recently, more sophisticated visualizations have been introduced, such as bullet graphs, heat maps, radial trees, radar charts or infographics.

It goes without saying that the effectiveness of the visualization depends on the purpose and on the type of data. In this paper, we ponder about the best way to “shape” the results of a corpus-based study on text complexity in order to show how different registers differ according to a number of text complexity features. The insights provided by this study may be useful to understand how to visually represent a complex notion like text complexity.

Text complexity is an important dimension of textual variation. It is crucial to pin it down because texts can be customised to different types of audiences, according to cognitive requirements (e.g. texts for the dyslectic), social or cultural background (e.g. texts for language learners) or the text complexity that is expected in certain genres or registers (e.g. academic articles vs. popularised texts). Text complexity can be analysed in several ways. The approach we used is based on factor analysis as applied in Biber’s Multi-Dimensional Analysis framework (Biber, 1988) (henceforth MDA). The corpus used in our analysis was the Swedish national corpus, called Stockholm-Umeå Corpus or SUC. Results are described in detail in Santini and Jönsson (2020), and indicate that it is indeed possible to elicit and interpret facets of text complexity using MDA, regardless some caveats due to the small size of the corpus. When we tabulated the results (see Table 1) and plotted them in a bar chart (see Figure 1), we observed that tabulation and a bar chart were useful for the identification of the text complexity similarities and dissimilarities across the registers, but their interpretation required some effort and time even for linguists. At this point we were intrigued by the following question: how can we visually shape the different facets of text complexity generated by the study in an efficient and intuitive way? In this paper, we focus on this research question and we argue that the type of visualization that seems to be the most appropriate for this type of results is the radar chart because it plots a polygon “shape” that helps emphasise similarities and dissimilarities across categories.

2. Previous Work

To our knowledge, radar charts have never been used to visualize text complexity across registers. Since there is no previous work that explores this topic, we divide this section into two separate parts, the first one focusing on text complexity, and the second one listing linguistic studies that relied on radar charts visualization.

2.1. Text Complexity

Broadly speaking, text complexity refers to the level of cognitive engagement a text provides to human understanding (Vega et al., 2013). If a text is difficult, it requires more cognitive effort than an easy-to-read text and vice versa. Text complexity is a multifarious notion, since the complexity can affect the lexicon of a text, its syntax, how the narration of the text is organised, etc. For this reason, several definitions and several standards of text complexity exist. For instance, in theoretical linguistics Dahl (2004) puts forward an interpretation of “complexity” that is not synonymous with “difficulty”. Rather, in his interpretation complexity is “an objective property of a system”, i.e. “a measure of the amount of information needed to describe or reconstruct it”. In his view, “[g]rammatical complexity is the result of historical processes often subsumed under the rubric of grammaticalization and involves what can be
called mature linguistic phenomena, that is, features that take time to develop”.

Another linguistic field where there is a persistent interest in the study of language complexity is second language (L2) research. For instance, Pallotti (2015) notes that the notion of linguistic complexity is still poorly defined and often used with different meanings. He proposes a simple, coherent view of the construct, which is defined in a purely structural way, i.e. the complexity directly arising from the number of linguistic elements and their interrelationships. More recently, Housen et al. (2019) present an overview of current theoretical and methodological practices in L2 complexity research and describe five empirical studies that investigate under-explored forms of complexity from a cross-linguistic perspective or that propose novel forms of L2 complexity measurements.

In education, one of the more comprehensive text complexity models that has been devised for teaching is the CCSS - Common Core State Standards (Hiebert, 2012). This model, mostly applied in the United States, is a three-parts model geared towards the evaluation of text complexity gradients from three points of view: qualitative, quantitative and by assessing the interaction between the reader and the task. Its benefits and drawbacks have been analysed by Fang (2016). Many other models of text complexity have been proposed for educational purposes, but none of them has gained universal status.

In recent years, the concept of text complexity has drawn the attention not only of linguists and educators, but also of consumer-oriented terminologists, of specialists dealing with writing and reading disorders and more recently also of researchers working in computational and language technology (LT). In LT, text complexity is tightly linked to corpus-based and data-driven analysis of textual difficulty, e.g. in second language acquisition (Lu, 2010) and to the development of LT applications, such as automatic readability assessment (Feng, 2010) or the automatic text simplification for those who have dyslexia (Rello et al., 2013a). Text complexity can also be seen as a sub-field of Text Simplification, which is currently a well-developed LT research area (Saggion, 2017).

Text complexity is a concept inherently tied to the notion of readability. According to Wray and Janan (2013), readability can be redefined in terms of text complexity. As pointed out by Falkenjach (2018), readability incorporates both the actual text and a specific group of readers, such as middle school students (Dale and Chall, 1949) or dyslectic people (Rello et al., 2013b), while text complexity seems to pertain to the text itself, or the text and a generalised group of readers. Readability indices are practical and robust but coarse since they cannot provide the nature of the complexity. Critics of readability indices have also pointed out some genre-based discrepancies and the bias caused by short sentences and high frequency vocabulary on the readability scores (Hiebert, 2012). It must be noted, however, that no perfect method exists to date to gauge text complexity and readability infallibly. Therefore, complexity and readability scores are useful, although they must be taken with a grain of salt.

### 3. MDA and Text Complexity

In this section, we summarise the main findings of our study on text complexity variation in the SUC. Full details can be found in Santini and Jönsson (2020). Below, we briefly describe the SUC corpus and dataset, and present MDA, together with the 3-factor solution used in the study.

#### 3.1. SUC Corpus and Dataset

The SUC (Gustafson-Capková and Hartmann, 2006) is a collection of Swedish texts and represents the Swedish language as used by native Swedish adult speakers in the 90s. The SUC includes a wide variety of texts written for several types of audiences, from academics, to newspapers’ readers, to fictions’ readers and contains subject-based text varieties (e.g. Hobby), press genres (e.g. Editorials), and mixed categories (e.g. Miscellaneous). We call them collectively “registers”, as defined in Biber and Conrad (2009). Given the composition of the SUC, we assume the presence of different levels of text complexity across SUC registers. This assumption underlies the rationale of the study, which is to identify how linguistic features co-occur in texts that have different levels of text complexity. Arguably, text complexity in children’s books is low, while specialised professionals, such as lawyers and physicians, must be able to understand very complex texts in order to practise their professions. In between easy texts for children and the domain-specific jargon used by specialises professionals, there exist texts that present different levels of textual difficulty.

From the SUC, a text complexity dataset has been extracted via SAPIS (Fahlborg and Rennes, 2016), an API Service for
| SUC Registers | Number of texts per SUC register | Mean of normalised LIX scores | Mean of normalised Dim1+ scores | Mean of normalised Dim1- scores | Mean of normalised Dim2+ scores | Mean of normalised Dim3- scores | Mean of normalised Dim3+ scores | Appositional (Information Expansion) Facet |
|---------------|---------------------------------|------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|------------------------------------------|
| a_reportage_genres | 259 | 51.82 | 27.82 | 69.47 | 28.25 | 26.81 | 85.25 | 52.23 |
| b_pedagogical_genres | 70 | 57.56 | 36.56 | 66.76 | 19.82 | 54.94 | 82.30 | 79.29 |
| c_review_genres | 127 | 52.91 | 32.11 | 68.71 | 31.07 | 32.24 | 79.29 | 52.23 |
| d_hobby_domain | 124 | 54.25 | 23.09 | 72.00 | 22.58 | 37.28 | 83.34 | 52.23 |
| e_popular_domain | 62 | 38.72 | 46.54 | 76.66 | 27.81 | 45.38 | 81.24 | 52.23 |
| f_fiction_story_genres | 27 | 44.99 | 49.44 | 19.14 | 57.36 | 23.12 | 79.29 | 52.23 |
| g_misrelated_mixed | 145 | 47.38 | 19.14 | 57.36 | 23.12 | 79.29 | 52.23 | 52.23 |
| h_scientific_writing_genres | 86 | 53.16 | 23.12 | 57.72 | 27.60 | 37.25 | 80.25 | 52.23 |
| i_imaginative_prose_genres | 130 | 50.50 | 52.55 | 57.72 | 33.58 | 35.21 | 71.20 | 52.23 |
| Total | 1040 | | | | | | | |

Table 1: Summary table of all the facets and readability level across the SUC registers.

Text Analysis and Simplification of Swedish text. The SUC dataset returned by SAPIS contains 120 linguistic features described in Falkenjazz et al. (2013). This dataset is the source dataset used in the study.

3.2. MDA

Biber (1988) describes in detail the application of factor analysis to linguistic data. Biber’s Multi-Dimensional Analysis refers to factor analysis (a bottom-up multivariate statistical method) to uncover patterns of linguistic variation across the registers collected in a corpus. The basic idea of MDA builds on the notion of “co-occurring linguistic features that have a functional underpinning” (Biber, 1988, p. 121). The co-occurrence of linguistic features across registers into factors is interpreted in terms of underlying textual dimensions.

There are three main steps in MDA, variable screening, running MDA proper, and the interpretation of the factors.

Figure 1: Summary chart of all the facets and readability levels across SUC registers.
3.2.1. Variable Screening
We started off from the SUC dataset extracted from the SUC corpus via SAPIS. The dataset contains 1,040 records and 120 features. We noticed that some of the linguistic features in the dataset were somewhat redundant. For example, both pos\_det and dep\_det refer to the number of the determiners. This redundancy is detrimental for MDA because it causes multicollinearity, a statistical phenomenon that may lead to distorted results. We ditched out multicollinear features and ended up with 45 linguistic features that are listed in the Appendix.

3.2.2. Running MDA
After having screened the variables, we carried out MDA by building a correlation matrix, checking the determinant, assessing the sample adequacy and finally determining the number of factors. The key concept of factor analysis is that multiple observed variables have similar patterns of responses because they are all associated with a latent (i.e. not directly measured) “factor”. Deciding the number of factors is not easy. Traditionally, the decision is made by looking at the scree plot. More recently, it has been shown that parallel analysis (Hayton et al., 2004) can help identify the most suitable number of factors. We then ran parallel analysis that suggested three significant factors. We extracted three factors from the correlation matrix and applied the oblique rotation called “promax”, as recommended in Biber (1988). We ditched out the loadings smaller than 0.30 (a common practice). Loadings are correlations with the unobserved factors. Normally, each of the identified factors should have at least two or three variables with high factor loadings, and each variable should load highly only on one factor.

The 3-factor solution explained 0.22 variance, which is, admittedly, a relatively small proportion of the overall variance. However, this in not uncommon with natural language data, because the linguistic data that we find in texts can be very idiosyncratic and ambiguous and this elusiveness is reflected in the factor solution.

3.2.3. Grammatical Breakdown of the Factor Solution
The results of the 3-factor solution was interpreted grammatically and functionally in terms of textual dimensions (Biber, 1988). The functional interpretation of the textual dimensions is described in Santini and Jönsson (2020). Here we list the grammatical makeup of each dimension. Since each dimension has a positive (+) and a negative side (-), that normally are mutually exclusive, we interpreted each side of each dimension as a facet characterising an aspect of text complexity (we ditched out Dim2- because its loadings were below 0.30).

**Dim1+** represents the Pronominal-Adverbial Facet. Features that tend to co-occur in Dim1+ are: pronouns, adverbs, interjections, attitude adverbials, question marks, common Swedish words, exclamation marks, negation adverbials, possessive pronouns and comparative adverbials.

**Dim1-** represents the Nominal Facet. This dimension has two loadings, both quite high, namely on prepositions and nouns, that both indicate the nominal character of the dimension.

**Dim2+** represents the Adjectival Facet. This dimension has an adjectival nature since premodifiers, postmodifier and adjectives have the highest loading on this dimension. They are all grammatical devices that elaborate and specify the exact nature of nominals and nouns.

**Dim3+** represents the Verbal Facet. The features that characterise Dim3+ are verbs, subordinators and infinitival markers and basic vocabulary.

**Dim3-** represents the Appositional Facet. The features that characterise this facet are appositions, the verb arity and commas. Appositions are “a maximally abbreviated form of postmodifier, and they include no verbs” (Biber et al., 1999). Commas are a common punctuation device to specify apposition. Verb arity indicates the number of arguments a verb may have. A high average indicates that a high amount of nominal information is glued to verbs.
3.2.4. Table and Bar Chart

We normalised the positive and negative values of the dimensions on a 0-100 scale in order to have a more accurate picture of how the text complexity facets and readability levels (Björnsson, 1968) vary across the SUC registers. Table 1 shows the SUC registers with normalised values plotted in Figure 1. The chart in Figure 1 is neat and provide interesting insights. For instance, we can observe that the readability level is rather uniform across the registers. When we map these readability values with those in Table 1, we can see that six SUC registers (the majority) have a readability level > 50 (Very difficult), two registers are between 41 and 50 (difficult). Therefore all the registers in the SUC are rather difficult with the exception of popular lore (38.7), which appears to be easier to read than other registers. We can also observe that the nominal facet is often strong when also the appositional facet is pronounced.

We realised that the interpretation of the results with this type of visualization was indeed possible but required some cognitive effort and time, even for specialised people like linguists.

4. Visualizing Text Complexity in “Shapes”

To get a more intuitive understanding of the differences and similarities across the registers, we plotted each register as a radar chart and analyzed the a polygonal shape.

We could then observe that the faceted makeup of reviews (Figure 2), scientific writing (Figure 3) and reportage (Figure 4) is very similar. These three registers have a strong nominal facet associated with a pronounced appositional facet. The pronominal-adverbial facet is very flat, and the verbal and adjectival facets are weak. These characteristics are exemplified in the excerpts shown in Tables 2, 3 and 4.

Table 2: Excerpt from a review

| Excerpt | LIX score | Text ID   | SUC Register            |
|---------|-----------|-----------|-------------------------|
| Revolution is, on top of things, a shockingly necessary enterprise. | 39.05 | c0051 | c_review_genre |

Table 3: Excerpt of scientific writing

| Excerpt | LIX score | Text ID   | SUC Register            |
|---------|-----------|-----------|-------------------------|
| On the decline of the king’s power during the period 1906-1918, see Axel Brusewitz’s seminal book “Kungamakt, herremakt, folkmakt” (1951). | 54.24 | j1007 | j_scientific_writing_genre |

Table 4: Excerpt from a reportage

| Excerpt | LIX score | Text ID   | SUC Register            |
|---------|-----------|-----------|-------------------------|
| Man in Alvarkeo arrested for threats. A 33-year-old man at the refugee camp in Alvarkeo was arrested by the Tjärp’s police on Monday evening. The man is suspected of unlawful threats and mistreatment of his wife. | 41.08 | a1006 | a_reportage_genre |

Table 5: Excerpt from a text in the Bio-Essay register

| Excerpt | LIX score | Text ID   | SUC Register            |
|---------|-----------|-----------|-------------------------|
| The hobby and miscellaneous registers (see Figures 7 and 8) are strong on the nominal-appositional facet (a similarities with the reportage, review and scientific writing registers) but they are also characterised by some prominence of the verbal facet, while the pronominal-adverbial facet and the adjectival facet are rather flat. These characteristics are exemplified in the excerpts shown in Tables and 8. | 54.24 | j1007 | j_scientific_writing_genre |

5. Discussion

We used radar charts to profile the registers of the SUC corpus with five text complexity facets and with readability levels. Figures 2-10 visually show the shape of the similarities and dissimilarities among the registers. The similarity between bio-essay and imaginative prose writing is striking and also quite intuitive if we think of the shared narration techniques that are normally used in these two registers. Similarly, the commonalities between reportage, review and academic writing is also unsurprising given the factual nature of these registers. Editorials and popular lore stick out for their dissimilarity with the other registers.

But what does a text complexity facet tell us? Essentially, a text complexity facet breaks down the linguistic nature
Table 7: Excerpt from a text of the Hobby register

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| När journaler överförs per telefax finns risk för att obehöriga kan ta del av dem, inte minst om den som faxar råkar knappa i fel nummer. | 43.09 | ba09c | b_miscellaneous_mixed |

Table 8: Excerpt from a text in the Miscellaneous register

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| Detta har förstärkt de farhågor som vuxit fram på den franska sidan av den omskrivna samarbetsaxeln för att man skall få en obunden tysk stormakt som svårhanterlig granne. | 59.07 | ba05d | b_editorial_genre |

Table 9: Excerpt from an editorial

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| Metoden gör att man på ett enkelt sätt kan minska risken för uppkomst av sprickor, förhindra tillväxt av defekter och ge skydd mot plötsliga rörbrött. | 36.53 | ba01b | l_popular_lore_domain |

Table 10: Excerpt from a text in the Popular lore register

of text complexity and show how influential that facet is with respect to other facets that have a different linguistic makeup. It is, however, the combination of text complexity facets, and not the single facet, that gives us the characterization of the texts in a register.

6. Conclusion and Future Work

In this paper, we argue that radar charts give an added value to the visualization of the results of MDA by producing “shapes” that help pin down more intuitively lin-

Table 7: Excerpt from a text of the Hobby register

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| Samtidigt vänjar han för att Tyskland kan utmålas som syndabock om man inför den europeiska rymdorganisationen Esas ministermötet i november förklarar att landet ensidigt skall dra ned på sitt engagemang. | 50.06 | ec02d | c_hobby_domain |

Table 8: Excerpt from a text in the Hobby register

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| At the same time, he warns that Germany could be painted as a scapegoat if faced with the European Space Agency ESA’s ministerial meeting in November declares that the country should unilaterally reduce its commitment. | 59.07 | ba05d | b_editorial_genre |

Table 9: Excerpt from an editorial

| Excerpt | LIX score | Text ID | SUC Register |
|---------|-----------|---------|--------------|
| The method allows you to easily reduce the risk of cracking, prevent the growth of defects and provide protection against sudden pipe failure. | 36.53 | ba01b | l_popular_lore_domain |
gon matching, which have a long tradition in geometry, to classify text complexity. What is more, the visualization of text complexity in different shapes could help people with cognitive impairments, such as people with dyslexia who have difficulties in detecting words (especially small function words) but have strong visual and spatial reasoning skills. Last but not least, shapes generated by automatic linguistic analysis could be used to as a “hallmark” of the different levels of text complexity and readability and used to guide the reader.

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Companion Website
The study described in this paper if fully reproducible. Datasets, radar charts and R code are available here: http://santini.se/registerstudies2020/

Appendix: 45 Linguistic Features

3 lexical features
Namely: ratioSweVocC, ratioSweVocD, ratioSweVocH
SweVocC: lemmas fundamental for communication.
SweVocD: lemmas for everyday use.
SweVocH: other highly frequent lemmas.
A high ratio of SweVoc words should indicate a more easy-to-read text.

20 Morphy-syntactic features
Namely: pos_JJ (adjective), pos_DT (determiner), pos_H (whPronoun), pos_RO (ordinalNum), pos_NN (noun), pos_VB (verb), pos_IE (infinitivalMarker), pos_HD (whDeterminer), pos_IN (interjection), pos_UO (foreignWord), pos_KN (coordinatingConj), pos_HA (whAdverb), pos_SN (subordinatingConj), pos_PM (properNoun), pos_PN (pronoun), pos_AB (adverb), pos_PP (preposition), pos_PS (possessivePronoun), and pos_PC (participle).

The presence of syntactic features is the most evident proof of textual complexity. The more syntactically complex a text is, the more difficult to read. These features are estimable after syntactic parsing of the text. The syntactic feature set is extracted after dependency parsing using the Maltparser (Nivre et al., 2006).

18 Syntactic features
Namely: dep_AN (apposition), dep_AT (premodifier), dep_CA (contrastiveAdverbial), dep_EF (relativeClauseCleft), dep_I? (questionMark), dep_JK (comma), dep_IP (period), dep_IQ (colon), dep_IS (semicolon), dep_IU (exclamationMark), dep_KA (comparativeAdverbial), dep_MA (attitudeAdverbial), dep_NA (negationAdverbial), dep_PT (predicativeAttribute), dep_RA (placeAdverbial), dep_TA (timeAdverbial), dep_XA (sotospeak), dep_XT (socalled).

4 Averages
Namely: avgSentenceDepth, avgVerbalArity, avgNominal-Premodifiers, avgNominalPostmodifiers
avgSentenceDepth: The average sentence depth. Sentences with deeper dependency trees could be indicative of a more complex text in the same way as phrase grammar trees has been shown to be.
Aarty indicates number of arguments of a verb. The average arity of verbs in the document, calculated as the average number of dependents per verb
avgNominalPremodifiers: The average number of nominal pre-modifiers per sentence.
avgNominalPostmodifiers: The average number of nominal post-modifiers per sentence.

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