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READABILITY FORMULAS FOR THREE LEVELS OF RUSSIAN SCHOOL TEXTBOOKS

Abstract. In this work, we propose a new text complexity formula aimed at assessing the complexity of Russian school textbooks. We used the annotated Russian Academic Corpus containing over 5 million tokens as the training and validation data and employed machine learning methods in the study. The values of 4 parameters in each of the 154 texts used for the research were measured with the help of the tools from the Spacy library. Comparative analysis of the new and existing complexity formulas suggests that the differences between them are indicative and the new formulas provide more accurate results. This research advances our understanding of the interdependency between frequency and text complexity and provides a framework for effective implementation of lexical frequency patterns in discourse complexity studies. The findings can be implemented by textbooks writers and test developers to select and modify texts for specific categories of readers. Other areas of application include website design, surveys, and semantic analysis of social networks.

§1. Introduction

General concern about whether a text is appropriately comprehended and conceived by the targeted audience is essential in a number of areas. Complaints about difficulties in understanding medical records [31], military manuals equipment and tools [18], insurance and law firms contracts [9] are numerous and as such indicate that reading may result in frustration. That is why the possibility to correctly assess and modify text complexity is important in many areas, and it is of particular importance in education [27]. Text readability/complexity assessment tools are among the most sought-after instruments in education and pedagogy, hermeneutics, psycholinguistics, linguodidactics, computer modeling of human speech and thought activity [8].

Key words and phrases: Text readability formula and Russian and school textbooks.

The problems of "text complexity and comprehension" in general and "text complexity and learning" in particular have been addressed by researchers all over the world for over 80 years. For a long period in the history of complexity studies educators argued that learning is successful only if a reading text matches the reader's cognitive and linguistic abilities [2]. The idea behind it was that readers are to be exposed to texts which are neither too easy nor too hard: if a text is too easy or difficult, readers get de-motivated, as it stops being a source of information for them. This basic notion became the starting point of classifying all reading texts into three categories or levels: independent, instructional, and frustration. The independent level refers to texts that students can read successfully unassisted; frustration level refers to those texts that are too hard for students to learn from; and instructional level would be the optimum level that provides an opportunity for learning, but without too much possibility of frustration [33]. E.A. Betts argues that "Maximum development may be expected when the learner is challenged but not frustrated" [2]. The researcher also claims that the optimum reading comprehension of students is to be expected at 75-89% on recall questions about the reading text [2]. Later studies confirmed Betts' evaluations and the adjustments to these criteria are still minor [33]. Thus, pragmatic purposes determine the type of text complexity level for specific categories of readers: independent level of comprehension is probably expected in medicine, military, emergency and rescue services, self studies, while instructional level is mostly beneficial in education.

Another aspect of the same problem is evaluation of individual cognitive abilities of a reader (or "standard group" abilities for a category of readers) to understand a particular text. The evaluation procedures developed by different research schools are numerous and comprise assessment of language proficiency [24], general and topic awareness [45], reading and inference skills [16] etc.

As for text complexity estimation, it traditionally implies assessment of two types of complexities: complexity of linguistic parameters and informative complexity of the text. The latter comprises the information conveyed by the text [6] which depends on the subject matter knowledge (i.e. if the topic is familiar), inter-textuality (i.e. if references to/citations of other texts or outside ideas, theories, events, etc. are recognized), and the author's perspective (which may be similar to or different from that of the reader's) [10, 11].

Modern theories on assessment of linguistic text complexity advocate taking into account descriptive (average sentence length, average word length, etc.), morphological, lexical, syntactic and discourse parameters. As each of the clusters above has been addressed in previous work [13, 15, 19, 40, 42, 43], and the findings were consistent with the idea that the features above either add marginally to the accuracy of text complexity measurement, or significantly complicated the formula, in the current research we focus on three classical text complexity predictors: sentence length, word length and frequency. We do not assess the informative complexity of texts mentioned above assuming that it is the prerogative of textbook authors.

The study corpus comprises three level sub-corpora, i.e., Elementary school textbooks where we placed books for schoolchildren of the 2nd, 3rd, and 4th grades, Middle school subcorpus that contains textbooks from the 5th to 7th grades, and High school subcorpus in which we compiled textbooks for the 8th to 11th grades. We intentionally did not employ first grade classroom books as in Russian schools they are used to develop predominantly reading techniques not skills and as such imply lexical or syntactic rather than text-level comprehension. In this study we employ the largest available Corpus of Academic Russian [38] incorporating textbooks of nearly all school subjects, while the previous work was based on the Corpus of Social Sciences only [37]. Thus, in this study we aim to design text complexity formulas for Russian classroom texts of three academic levels (Elementary, Middle, and High) and extending our previous research that proposed a formula for assessment the complexity of Russian secondary school textbooks (grades 5-11) only [41]. The readability formula designed in previous studies, when applied to elementary school texts, tends to lose its accuracy [36].

We propose the following approach to design the formulas in question:

- compile a corpus of texts of three designated complexity levels using the grade number as the level of its complexity for convenience and following the tradition [17]
- select linguistic parameters which (and that is our Hypothesis) enable to perform discriminate analysis of complexity of the texts selected.
- measure the values of these parameters and apply machine learning methods to design a linear formula of complexity as a function of these parameters.

The structure of the rest of the paper is as follows. The "Related Work" section provides an overview of publications on automatic calibration of linguistic complexity of texts and selection of text complexity predictors. The "Materials and Methods" section describes (a) the corpus compiled and used in the study, (b) the tools, and (c) the research methodology implemented. The "Results" section offers our findings on the numerical experiments performed. Finally, in the "Conclusion" we discuss our findings, their possible applications, and research prospects.

§2. Related Work

The first formula of text complexity was proposed in [12]. This formula estimates the complexity of English texts based on two parameters: average word length (in syllables) and average sentence length (in words):

$$FKG(ASL, ASW) = 0.39ASL + 11.8ASW - 15.59,$$

where ASL is the average sentence length, ASW is the average word length. We also use these abbreviations when presenting the material below. The formula was validated in numerous studies and is now widely used, including the built-in Microsoft Word function.

In subsequent years, scientists proposed a number of formulas based on various text parameters [3, 5, 14, 26]. As mentioned above, a few of them achieve higher accuracy but substantially complicate measurement. In addition to the formula approach described above, researchers developed a parametric approach. The idea behind this approach is automatic estimation of multiple parameters which are viewed as complexity predictors, i.e., as able to affect text complexity. Provided with the values of these parameters, users are free to employ them at their discretion. At the same time, attempts to develop a text complexity typology and identify referential indices for different types of texts similar to that of genre indices [39] have also been undertaken [28].

A number of systems measuring the values of text parameters have been developed for the English language: Coh-Metrix [27], TAALES (Tool for the Automatic analysis of Lexical Sophistication) [20], TAACO (Tool for the Automatic Analysis of Cohesion) [4], TextInspector [1]. The systems differ in the number and methods of text parameter calculations. For example, Coh-Metrics measures up to 200 parameters and is equipped with the tools for graphical presentation of the results. The systems work predominantly for education. Similar studies were carried out for other languages. The list of systems worthy of attention includes ReaderBench, a multilingual system calculating values of about 200 parameters in English, French, Dutch, Romanian and Russian texts [7], and text profilers for the Russian language: RuLingva (rulingva.kpfu.ru) [13, 39], Textometr (textometr.ru [21]), and Readability (http://ru.readability.io/) created by I. Begtin back in 2014.

Recently, the paradigm has been revamped with neural networks able to profile a text and identify its complexity [7, 29, 34]. A certain disadvantage of this approach is the lack of interpretability of its assessment results, as they do not provide information on the parameters affecting its complexity.

In the 1960s and 1970s, Russian scholars began publishing results of their studies on text complexity predictors [22, 25, 32]. Along with academic texts, they focused on scientific, journalistic, epistolary and literary texts. Numerous text complexity predictors were explored and validated, including morphological, lexical, and syntactic. G.A. Lesskis (1964) examines the syntactic complexity of literary and scientific texts and defines it as a function of average values of the following parameters: "complete" sentence length; length of a "simple independent sentence"; length of a complex sentence and length of a simple sentence in a complex sentence. In 1970, Ya.A. Mikk derives a formula of "comprehensibility" for Estonian texts:

$$X_0 = 0.131X_1 + 9.84X_2\breve{\ }4.59,$$

where X_0 is the comprehensibility index, X_1 is the average length of an independent sentence (in digits), and X_2 is the average abstractness of nouns in the text. Abstractness of the text is assessed as the ratio of abstract and concrete words in the text, and the list of abstract words is proposed to be defined in one of the two ways. The first method includes evaluating the abstractness of words on a three-point scale: a) animateness - inanimateness; b) names of phenomena perceived by senses; c) names of "thought constructions" that are not perceived by senses. The second method is based on measuring the number of words with abstract morphemes that make a text more difficult for comprehension.

In 1976, M.S. Matskovsky proposed the first Russian complexity formula:

$$X1 = 0.62X_2 + 0.123X_3 + 0.051,$$

where X_2 is the average sentence length (in words) and X_3 is the percentage of words with more than three syllables [25]. Based on the characteristics of a chemistry text, Yu.F. Shpakovsky singles out the following three text complexity predictors:

$$Y = 20.24 + 0.48X_1 + 0.58X_2 + 0.41X_3,$$

where Y is the text complexity, X_1 is the percentage of words of nine or more letters, X_2 is the percentage of all terms, X_3 is the percentage of symbols in chemical formulas [35].

Based on a comparison of parallel English and Russian texts, I.V. Oborneva adapted the Flesh-Kincaid readability formula for Russian fiction:

$$FKG\_Obor(ASL, ASW) = 0.5ASL + 8.4ASW - 15.59,$$

where FKG is the Flesh-Kincaid Grade level, ASL is the average sentence length (in words), and ASW is the average word length (in syllables) [30].

I.V.Oborneva used the free term from the English formula and customized the variables coefficients. As the average word length in Russian is noticeably longer than in English, the coefficient for ASW in the Russian formula is lower. As for the average Russian sentence length, it is, on the contrary, shorter than in English when measured in words. All the above results in the ASL coefficient increase in the Russian formula. The formula's limitation is that its application is constrained by literary texts only, which are characterized by shorter sentences than in more specialized discourse domains. Its application on texts of other types, in particular, textbooks, leads to significantly elevated results [41]. In this regard, in [41] a new formula was proposed, derived from the corpus of secondary school textbooks (Grades 5-11):

$$FKGsis(ASL, ASW) = 0.36ASL + 5.76ASW - 11.97,$$

where SIS refers to the names of the formula developers. All the formulas mentioned above were linear. Although there are no theoretical grounds for considering the dependence to be linear, the researchers chose this nature of the dependence as the simplest. The work [37] made the only known attempt to construct a non-linear formula. The resulting formula is only slightly more accurate than the linear one, but it has a very cumbersome appearance and is inconvenient for use. The most up-to-date reviews of text and language complexity studies is provided in [36, 44]

The text complexity formula designed in our previous study, FKGsis, works well on school textbooks (grades 5-11), however it is not validated on elementary textbooks. Elementary school complexity formula has still been omitted in previous research. In the current study we examine the

Table 1. Basic statistics of school books corpus.

Grade level	Number of textbooks	tokens
2	24	367,858
3	22	522,069
4	27	758,370
5	15	545,516
6	11	373,670
7	15	723,374
8	13	635,785
9	10	479,941
10	7	514,308
11	10	800,287
Total	154	5,721,178

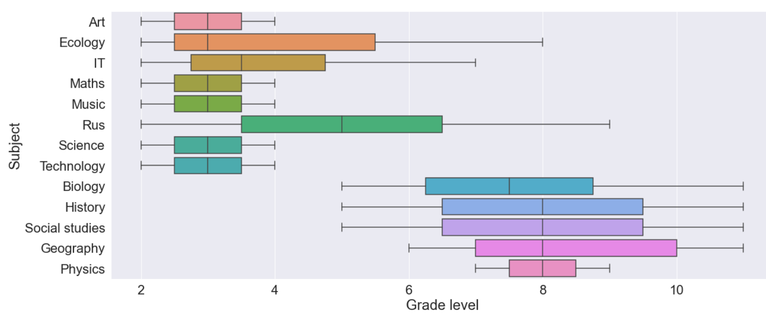

Figure 1. Distribution of grade levels and subjects.

algorithms to develop and offer the first readability formulas for this type of texts.

§3. Materials and Methods

3.1. Dataset. In the present paper we use the dataset derived from a corpus of schoolbooks (Table 1). The corpus contains full texts of 154 books and covers various subjects and grade levels from 2nd to 11th. The subjects and grades distribution is presented in Fig. 1.

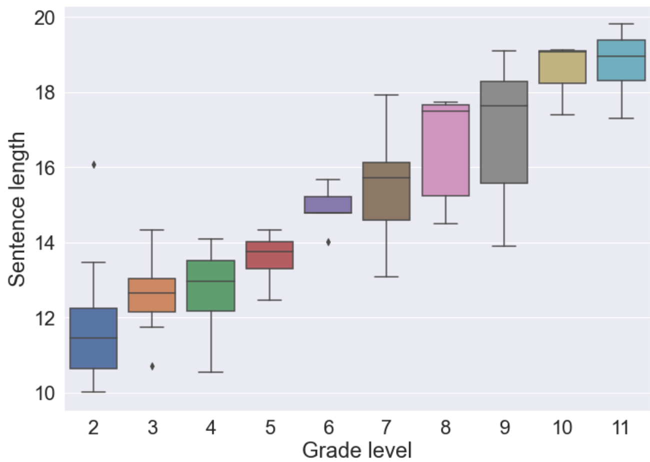

Figure 2. Distribution of average sentence length (ASL) across grade levels. The value of average sentence length varies due to different subjects and different textbook authors' styles.

To preprocess the corpus we use the tokenizer, sentence splitter and morpho-syntactical analyser from the Spacy library. Tokenization and splitting into sentences is needed for computing important features such as average sentence length in tokens (here, "tokens" include all tokens found by the tokenizer in a sentence). The average word length is calculated in characters. Corresponding features are presented in Fig. 2 and 3.

Obviously, the two parameters are very important for modeling text complexity; as can be observed from the figures, both ASL and AWS correlate with the grade level. Correlation of the ASL and AWS features with the target (grade number) are 0.823 and 0.763 respectively, which is considered as a very strong correlation. However, the correlation coefficient for different groups of grade level is significantly different as can be seen from Table 2. Therefore, the most problematic group of texts for complexity prediction are the textbooks for grades 2-4.

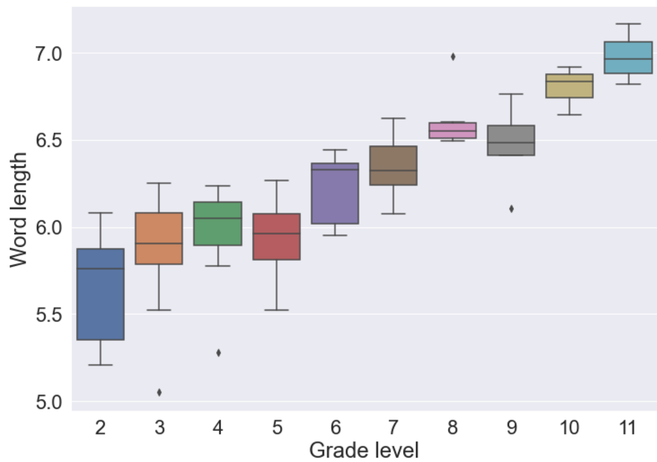

Figure 3. Distribution of average word length (AWS) across grade levels. The value of average word length varies due to different subjects and different textbook authors' styles.

Feature	2-4	5-7	8-11	2-11
ASL	0.332	0.389	0.467	0.823
AWS	0.255	0.460	0.445	0.763

Table 2. Pearson's correlation (ρ) with the grade level

Furthermore, Figure 4 also indicates that Elementary school texts do not form a solid cluster in terms of ASL and AWS thus making complexity prediction much harder (see Fig. 4).

In the next section we present linear regression models that were trained and evaluated for different groups of books to answer the following research questions:

RQ1: What are the coefficients for the readability prediction formula?

RQ2: How well does the prediction perform?

RQ3: To which extent can frequency-related features help?

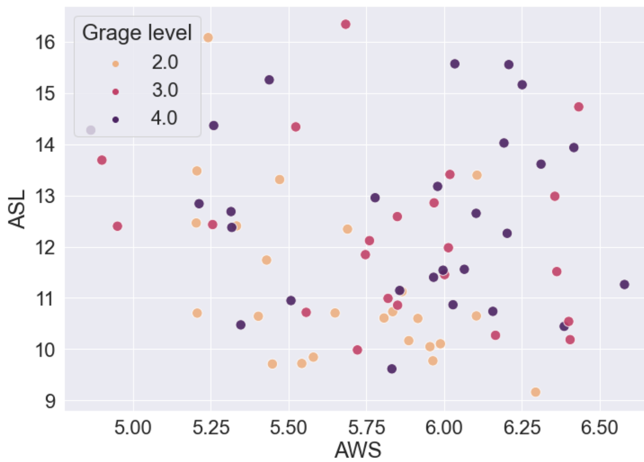

Figure 4. The scatter-plot represents distribution of average sentence length (ASL) and average word length in syllables (AWS) for 73 books from the subcorpus of the elementary school books.

§4. Results

4.1. Readability formula. A model with two parameters. We trained a linear model with two basic parameters discussed above. The formula depends on two parameters, i.e. ASL and AWS, and has the following form:

$$Grade = a_0 + a_1 * ASL + a_2 * AWS,$$

where a_0, a_1, a_2 are fitted on the train dataset (80%) and evaluated on the test dataset (20%). In our experiments, we fit the linear regression model[1] on 1,000 different random train/test splits. The coefficients of the model provided in Table 3 are aggregated mean values of a_0, a_1, a_2.

To assess the quality of the obtained formulas with the accuracy of grade levels predicted on test examples, we use the standard measures for

[1]We use the standard implementation from the sklearn library with default parameters.

Table 3. Coefficients of a linear model with two parameters: ASL and AWS.

	2-4	5-7	8-11	all (2-11)
a_0	-2.59 (±.71)	-5.29(±1.11)	-3.26(±1.69)	-17.5(±.7)
a_1	0.17(±.03)	0.20(±.05)	0.21(±.03)	0.56(±.02)
a_2	0.61(±.13)	1.34(±0.21)	1.35(±.2)	2.45(±.14)

Table 4. Performance metrics of linear regression with two parameters.

	MSE	MAE	R^2
2-4 grade	0.637	0.689	0.18
5-7 grade	0.522	0.577	0.35
8-11 grade	1.217	0.880	0.33
all (2-11)	1.572	0.987	0.80
$FKGsis$ (2-11)	5.574	1.953	-

regression: MSE, MAE, R^2. The results are shown in Table 4. Next, we compare the new formulas with our old FKG_sis formula. The values of MSE and MAE for it, provided in Table 4, indicate that the accuracy of the new formulas is much higher.

4.2. A model with three parameters. In addition to a model with two parameters, we trained a linear model with ASL, AWS, and an additional feature based on frequency. The frequency values were calculated on the corpus of elementary school books compiled of textbooks for grades 2-4. We used the corpus to develop a lexicon of Elementary school books. Then we compared two variations of the frequency-based feature. Both of them are average word frequencies in a certain text in the elementary school lexicon, although they differ in the ways they were estimated.

Frequency-based feature 1 (FREQ-1) is derived from the intersection of all elementary school vocabularies, i.e. from 2nd to 4th Grades. This list comprises 8088 words and later it was further filtered. We found it useful to filter out the words that have high values of Juilland's D coefficient that represents the variance of frequency across the range of documents. This value ranges from 0 to 100 with high values roughly corresponding to common words that appear in many documents. We experimentally found that the best value of the threshold for D is 92. Therefore, in further calculations we use only words with $D \leq 92$. For the remainder (around

Table 5. Pearson's correlation (ρ) with the grade level.

Feature	2-4	5-7	8-11	2-11
FREQ-1	-0.11	-0.05	-0.13	-0.51
FREQ-2	-0.18	-0.2	-0.36	-0.24

Table 6. Performance metrics of linear regression with three parameters.

Freq. Feature	Grade group	MSE	MAE	R^2
FREQ-1	2-4 grade	0.645	0.686	0.2
FREQ-1	5-7 grade	0.557	0.602	0.33
FREQ-1	8-11 grade	1.245	0.904	0.32
FREQ-1	all (2-11)	1.616	0.988	0.8
FREQ-2	2-4 grade	0.596	0.658	0.26
FREQ-2	5-7 grade	0.558	0.603	0.33
FREQ-2	8-11 grade	1.092	0.85	0.41
FREQ-2	all (2-11)	1.566	0.984	0.8

4000 words) we obtain a word frequency from the corpus of elementary schoolbooks.

The second variation of the word frequency (FREQ-2) was based on word frequency values from the frequency dictionary [23]. Therefore, FREQ-1 and FREQ-2 have a significantly different nature: FREQ-1 is based on a small lexicon of grades 2-4, while FREQ-2 is based on a large lexicon covering almost the entire vocabulary of textbooks for all grades. The results of experiments with both frequency features (correlation with the grade level) are presented in Table 5.

The linear regression models with three parameters have the following form:

$$Grade = b_0 + b_1 * ASL + b_2 * AWS + b_3 * FREQ\texttt{-1(2)}$$

The performance metrics for these models are presented in Table 6. The model with FREQ-2 shows marginally better results, although not significantly. Furthermore, when compared, models with 3 and 2 parameters indicate a slight improvement after the frequency parameter is added. The derived coefficients for the formula with FREQ-2 are provided in Table 7.

Table 7. Coefficients of a linear model with three parameters: ASL, AWS and FREQ-2. Parameter b_3 is relatively small comparing to others because values of feature FREQ-2 vary between 200 and 1000.

	2-4	5-7	8-11	all (2-11)
b_0	-1.21($\pm$.59)	-5.18($\pm$1.33)	1.3($\pm$2.11)	-14.46($\pm$.7)
b_1	0.2($\pm$.02)	0.17($\pm$.03)	0.23($\pm$.03)	0.58($\pm$.02)
b_2	0.56($\pm$.1)	1.35($\pm$.21)	0.88($\pm$.3)	2.15($\pm$.13)
b_3	-0.0025($\pm$0.00021)	-0.00043($\pm$.00004)	-0.0035($\pm$.00058)	-0.0026($\pm$.00041)

§5. Conclusion and future work

The present study is devoted to obtaining minimalist formulas to assess the complexity of Russian school texts. In our previous study we proposed a similar formula, but we employed a very limited collection of 14 books on one academic discipline, namely social sciences, and those were textbooks only for grades 5–11. The current work is based on a much larger and more representative collection of 154 textbooks for grades 2-11 in the majority of all subjects taught in Russian schools. The previous formula provided unsatisfactory results when applied to elementary school textbooks. As the discourse features of the three school levels of texts, namely elementary (grades 1-4), middle (5-7), and high (8-11), are so distinctly dissimilar, we hypothesize that high accuracy of complexity assessment could be achieved with a separate formula for each level.

The formulas presented in this work proved to be much more accurate than our previous formula, which was natural to expect given the large volume of the collection of training texts. In addition to the standard text complexity predictors including word length and sentence length we applied two frequency parameters derived from National and Academic Corpus of Russian language. For the purposes of this research we specifically compiled and validated the frequency list of the Russian elementary school textbooks (grades 2-4). But nonetheless, implementation of frequency parameters secured only a marginal improvement of the results.

However, we believe that frequency parameters can still be useful when based on a more representative corpus. For this purpose we plan to further improve the school frequency dictionary by increasing its volume, taking into account the vocabulary of fiction. The formulas proposed in our study are currently the best formulas for assessing the complexity of academic texts. We recommend to use the simplest formula with two variables. A general formula should be used for all grades (coefficients in the all (2-11) column), but if there is additional information about the level of the book, for whom it is intended, then separate formulas for elementary, secondary, high school can be used.

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