Using Broad Linguistic Complexity Modeling for Cross-Lingual Readability Assessment

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Abstract

We investigate the readability classification of English and German reading materials for language learners based on a broad linguistic complexity feature set supporting the parallel analysis of both German and English. After illustrating the quality of the feature set by showing that it yields state-of-the-art classification performance for the established OneStopEnglish corpus (Vajjala and Lučić, 2018), we introduce the Spotlight corpus. This new data set contains graded reading materials produced by the same publisher for English and German, which supports an analysis comparing the linguistic characteristics of texts at different reading levels across languages. As far as we are aware, this is both the first readability corpus for German L2 learners, as well as the first corpus with comparably classified reading material for learners across multiple languages.

After discussing the first results for a readability classifier for German L2 learners, we show that the linguistic complexity analyses for the cross-language experiments identify features successfully characterizing the readability of texts for language learners across languages, as well as some language-specific characteristics of different reading levels.

1 Introduction

The language input available to language learners is a driving force for Second Language Acquisition (SLA), and reading is an important source of language input. Material that is just above the level of the learner is assumed to be best for fostering learning, which depending on the SLA tradition is characterized as i+1 input of Krashen (1981), input in the Zone of Proximal Development in socio-cultural approaches (Lantolf et al., 2015), or input reflecting second language development in usage-based SLA approaches (Ellis and Collins, 2009). Note that the focus here is not just on input that is understandable and of interest to the learner but also rich in developmentally proximal language properties.

This dependency of readability on reading purpose and individual language skills makes the identification of appropriate reading materials a major challenge for educators, especially for heterogeneous learning groups. Automatic readability assessment may facilitate the retrieval of appropriate reading materials for individual language learners. It refers to the task of identifying texts that are suitable for a given group of target readers with a specific reading purpose (Collins-Thompson, 2014). Recent approaches to automatic readability assessment also investigate the use of neural networks (Martinc et al., 2019). However, the identification of linguistic characteristics that impact the readability of texts in itself can also yield valuable insights for education, because it may inform content creators of reading materials for language learning. This also is an interesting research endeavor from a linguistic perspective and speaks against solely focusing on neural approaches. Similarly, it remains to be investigated to which extent these linguistic characteristics may generalize across languages given comparable target groups and reading purposes.

While there has been a considerable amount of work on automatic readability assessment for English, there is still insufficient research on other
languages. The lack of suitable training corpora for other languages remains as one major limiting factor (Collins-Thompson, 2014), despite some research efforts to facilitate unsupervised readability assessments (Benzahra and François, 2019; Martinc et al., 2019). For example, there has been some recent work on German readability classifiers for native speakers (Weiss and Meurers, 2018; Weiss et al., 2018; Dittrich et al., 2019). Yet, a lack of corpus resources has so far hindered the development of a readability classifier for German as a second or foreign language (L2) learners.

In this article, we introduce a novel cross-lingual feature collection for broad linguistic modeling of German and English complexity. Although neural classification approaches have been strongly represented in readability assessment, our literature review (see Section 2) shows that their success has been very much limited on the benchmark data we use for this study and fallen behind the feature-based readability classification approaches which are also providing deeper linguistic insights while requiring less computational power.\(^1\) However, while broad feature collections for language-specific complexity modeling have been proposed for English (Chen and Meurers, 2019) and German (Weiss and Meurers, 2018), they are not applicable across languages. This has so far hindered the cross-lingual study of similarities between characteristics of readability. We first validate our approach by applying it to an established readability corpus for English (Vajjala and Lučić, 2018), before using it to train two readability classifiers for labeling English and German L2 reading materials resulting in the first readability classifier of this kind for German. For this, we introduce a novel data set of English and German reading materials for beginning, intermediate, and advanced learners of English and German, the Spotlight corpus. We address the following research questions:

1. Can we train a successful readability classifier for German and for English using broad complexity modeling?
2. Can these classifiers generalize beyond their training language to cross-lingual contexts?
3. Which linguistic features are relevant for the distinction of reading levels and how do they differ between English and German?

The article is structured as follows. First, we discuss related work on readability assessment of English and German (Section 2). Then, we introduce the novel Spotlight data set (Section 3.1) as well as the OneStopEnglish corpus (Section 3.2) which we use as benchmark data set. We proceed to introduce our approach to automatic complexity assessment and the feature set (Section 4) we use throughout our machine learning experiments (Sections 5 and 6). Finally, we compare the informativeness of individual complexity features on Spotlight for the discrimination of reading levels (Section 7) before we come to the conclusion (Section 8) and outlook (Section 9).

2 Related Work

Automatic readability assessment has a long history dating back to the first readability formulas developed in the early 20th century, see DuBay (2006) for an overview. Traditional readability formulas employ few surface text characteristics such as text, sentence, and word length (Flesch, 1948; Dale and Chall, 1948). They are still widely used especially in non-linguistic studies on web accessibility (Esfahani et al., 2016; Grootens-Wiegers et al., 2015), in information retrieval systems (Miltsakaki and Troutt, 2007; Chinkina et al., 2016), and for confirming the compliance of reading materials with specific accessibility guidelines (Weiss et al., 2018; Yaneva et al., 2016), such as Easy-to-Read materials.\(^2\)

Over the last two decades, there has been a shift towards computational readability classification approaches based on machine learning techniques employing feature engineering with Natural Language Processing (NLP) methods, see Collins-Thompson (2014) and Benjamin (2012) for an overview. Among others, linguistic complexity features from SLA research (Vajjala and Meurers, 2012), word frequency measures (Chen and Meurers, 2017), and features of text cohesion (Crossley et al., 2017) from Writing Quality Assessment research (Crossley, 2020) were shown to be valuable features for readability assessment.

While most readability research focuses on English (Collins-Thompson, 2014), to a lesser degree these approaches have also been employed for other languages such as Russian (Reynolds, 2016),

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\(^1\)See Strubell et al. (2019) for a discussion of the considerable energy demands of deep learning approaches in NLP.

\(^2\)https://www.inclusion-europe.eu/easy-to-read/
French (François and Fairen, 2012), Swedish (Pilán et al., 2015), Italian (Dell’Orletta et al., 2013), or German (Vor der Brück and Hartrumpf, 2007). For German, the most recent classification approach has been proposed by Weiss and Meurers (2018) who use broad linguistic complexity modeling of German to distinguish between German media texts targeting adults and children. However, this approach only provides a rather coarse binary distinction and identifies reading materials for information retrieval (i.e., with a focus on accessibility), rather than language learning (i.e., with a focus on challenging the reader’s language competence). Given the lack of appropriate multi-level reading corpora, so far no classifiers for German L2 readers have been trained.

Recently, several neural network approaches have been proposed for readability assessment (Martinc et al., 2019; Madrazo Azpiazu and Pera, 2019). Martinc et al. (2019) investigate the performance of supervised and unsupervised neural readability classification approaches for English and Slovenian. They find that their neural approaches perform overall at the state-of-the-art level of feature-based classification approaches in both languages. For the OneStopEnglish corpus, their best classifier reaches an accuracy of 78.71% which performs at the same level as the feature-based classifier reported by Vajjala and Lučić (2018) with an accuracy of 78.12%. With this, the performance of neural approaches on OneStopEnglish does not exceed the original benchmark and lies substantially below the current state-of-the art on this data set, which is held by a feature-based classifier with an accuracy of 90.09% (Bengoetxea et al., 2020). In other words, while neural classification approaches have been very successful in several NLP tasks, they are currently not competitive with the breadth and depth of analyses supported by feature-based approaches to readability classification.

Only little research has been conducted on multilingual readability classification. While there are some neural classification approaches that are developed to be applicable across languages (Martinc et al., 2019; Madrazo Azpiazu and Pera, 2019), feature-based approaches are usually language-specific. An exception is the study by De Clercq and Hoste (2016), who compare the informativeness of lexical, semantic and syntactic features for English and Dutch readability classification. The cross-lingual applicability of multilingual models has so far not been investigated, except for a series of studies by Madrazo Azpiazu and Pera on the VikiWiki corpus, which distinguishes simplified Vikidia.org texts for 8 to 13 year old children from regular Wikipedia.org texts for Basque, Catalan, Dutch, English, French, Italian, and Spanish. On this data, Madrazo Azpiazu and Pera (2020a) investigate the transferability of the neural readability classification approach by Madrazo Azpiazu and Pera (2019). They demonstrate that training on multilingual data sets may improve readability classification results for low-resource languages in the binary classification task. Madrazo Azpiazu and Pera (2020b) follow a similar approach using a feature-based readability classification approach based on shallow features, morphological features, syntactic features, and semantic features. They report similar results as Madrazo Azpiazu and Pera (2020a). While these studies make an important first contribution to the assessment of cross-lingual readability assessment, they are clearly limited by the binary distinction of simplified texts for children and regular Wikipedia texts. The success of transfer learning for more fine-grained and practically relevant readability level distinctions remains to be empirically determined.

3 Data

3.1 Spotlight corpus

The Spotlight corpus consists of articles from the two monthly language learning magazines Spotlight4 for adult German learners of English and Deutsch perfekt5 for adult language learners of German. Both magazines are published by Spotlight Verlag, a leading European publisher for foreign language learning materials. The magazines contain reading materials for beginning, intermediate, and advanced language learners which the publisher equates with the Common European Framework of Reference (CEFR) levels A2 (level: easy), B1/B2 (level: medium) and C1 (level: advanced).

We extracted all articles from the PDF versions of the respective issues provided to us for research purposes by the publisher. The type setting of the magazines made it impossible to di-

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4 https://github.com/ionmadrazo/VikiWiki
5 https://www.spotlight-online.de
6 https://www.deutsch-perfekt.com
7 https://www.spotlight-verlag.de
rectly extract the individual articles with a PDF converter without loosing the information of their reading level. Instead, we manually identified and extracted each article using screenshots which we then converted to plain text using Google’s optical character recognition (OCR) API. This way, we extracted the English subset (henceforth Spotlight-EN) from the 110 issues of the Spotlight magazine that were published from January 2012 to December 2019 and the German subset (henceforth Spotlight-DE) from the 45 issues of the Deutsch perfekt magazine published from January 2018 to December 2019 (see corpus profiles in Table 1). The imbalance of readability levels in both data sets is due to the imbalanced distribution of reading levels in both magazines.

It is noteworthy that in both magazines, articles may vary considerably in length irrespective of their reading level. This is shown in Table 2. The table showcases that number of words – which has been and continues to be a popular surface feature for readability classification – is not sufficient to distinguish reading levels in this data set.

### 3.2 OneStopEnglish corpus

The OneStopEnglish (OSE) corpus by Vajjala and Lučić (2018) consists of overall 567 Guardian newspaper articles that were rewritten for adult English as a Second Language learners by MacMillan Education. Each Guardian article is available in an elementary (ele), intermediate (int), and advanced (adv) version resulting in a perfectly balanced corpus. The OSE corpus is a by now established reference data set for studies related to readability assessment and text simplification (Bengoetxea et al., 2020; Benzahra and François, 2019). Currently, the best results reported for OSE achieve an accuracy of 90.09% in a feature-based machine learning approach by Bengoetxea et al. (2020). Table 3 shows the corpus profile of the OSE data set. Table 4 displays the differences of article length across reading levels in OSE.

| Level  | N. docs | N. sents | N. words |
|-------|---------|----------|----------|
| Easy  | 1.030   | 13.921   | 212.267  |
| Medium| 1.528   | 60.232   | 898.695  |
| Advanced| 1.030  | 24.288   | 440.793  |
| ∑     | 3.285   | 98.441   | 1.551.755|

Table 1: Corpus profiles for Spotlight data

| Level  | N. docs | N. sents | N. words |
|-------|---------|----------|----------|
| Easy  | 763     | 16.135   | 180.178  |
| Medium| 509     | 27.107   | 338.553  |
| Advanced| 174    | 11.713   | 155.160  |
| ∑     | 1.446   | 54.955   | 673.891  |

Table 2: Article length in words in Spotlight data

| Level  | N. docs | N. sents | N. words |
|-------|---------|----------|----------|
| Ele.  | 189     | 6.033    | 105.169  |
| Int.  | 189     | 6.634    | 128.335  |
| Adv.  | 189     | 7.221    | 162.449  |
| ∑     | 567     | 19.888   | 395.953  |

Table 3: Corpus profile for OSE

| Level  | μ (±SD) | M    | Min | Max  |
|-------|---------|------|-----|------|
| Ele.  | 556(±109)| 561  | 267 | 948  |
| Int.  | 679(±117)| 691  | 315 | 1.083|
| Adv.  | 860(±171)| 857  | 357 | 1.465|

Table 4: Article length in words in OSE

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7https://cloud.google.com/vision
8https://www.onestopenglish.com

9Since the three OneStopEnglish levels (elementary, intermediate, advanced) are not explicitly aligned with the CEFR levels, used to characterize the Spotlight levels (easy=A2, medium=B, advanced=C1), we keep the labels separate throughout the article.

10The numbers reported here slightly deviate from those reported by Vajjala and Lučić (2018), due to minor differences in the automatic tokenization.
As also noted by Vajjala and Lučić (2018, p. 299), there is a general tendency of articles becoming longer with increasing reading level. However, note the standard deviation of the article length within reading levels, which is considerable despite being much lower than the variability displayed in the Spotlight data.

4 Automatic Complexity Analysis

4.1 Complexity Features

We calculate 312 features of linguistic complexity merging the feature collections proposed by us in our previous work on German (Weiss and Meurers, 2018) and English (Chen, 2018). These have been successfully used for the tasks of readability assessment (Chen and Meurers, 2018; Weiss and Meurers, 2018; Kühberger et al., 2019), second language proficiency assessment (Weiss and Meurers, 2019b, 2021), academic language proficiency (Weiss and Meurers, 2019a), and teachers’ grading objectivity (Weiss et al., 2019). While each of the feature collections contains more language-specific features than the joined feature collection proposed in this work, this is as far as we are aware the broadest collection of complexity features applicable to both, English and German, thus facilitating cross-lingual comparisons of complexity.

Our broad set of cross-lingual complexity features covers the theoretical linguistic domains of syntax, lexicon, and morphology, as well as features of discourse cohesion and psycho-linguistic features of human language use and human language processing. It also includes some surface measures from or inspired by classic readability formulas.

4.1.1 Surface Length (LEN)

We measure 21 surface text length features inspired by traditional readability formulas. They measure the raw number of sentences, syllables, letters, (unique) words including and excluding punctuation marks and numbers, and (unique) tokens. It also includes mean and standard deviations of sentence length and word length measured in letters, syllables, and words as well as the mean and standard deviation of words with more than two syllables. These categories can be applied without language-specific adjustments, except for the identification of syllables which are based on language-specific regular expressions.

4.1.2 Syntactic Complexity (SYN)

We assess several features of clausal and phrasal complexity that have been proposed in the SLA complexity literature (Wolfe-Quintero et al., 1998; Kyle, 2016) inspired by the implementations by Chen (2018) and Weiss and Meurers (2021). We measure 20 features of clausal elaborateness. This includes features measuring the length of clauses and (complex) t-units in various units (such as words, syllables, letters), as well as features of clausal coordination and subordination, such as the number of relative or dependent clauses per clause.

Furthermore, we measure 28 features of phrasal elaborateness. This includes several features focusing on the complexity of noun phrases (NPs) including the number of pre- and postnominal modifiers per complex NP, the number of (complex) NPs per clause, t-unit and sentence, and the length of NPs in words. It also entails features measuring the complexity of verb phrases (VPs) including the number of verb clusters and VPs per clause, t-unit and sentence and the length of verb clusters in words. We also measure the complexity of prepositional phrases (PPs) such as the number of (complex) PPs per clause, t-unit and sentence or the length of PPs in words. Finally, this includes measures of coordinate phrases per clause, t-unit and sentence.

While these syntactic features are identified based on language-specific TregEx (Levy and Andrew, 2006) patterns for constituency trees, we carefully designed all extraction rules to yield equivalent results across languages.

We also measure syntactic variation based on 12 measures of parse tree edit distances following Chen (2018).

4.1.3 Lexical Complexity (LEX)

We measure several complexity features assessing lexical richness, variation, and density that have been proposed in the SLA complexity literature (Wolfe-Quintero et al., 1998) inspired by the implementations by Chen (2018) and Weiss and Meurers (2021). These can be applied straightforward across languages as long as similar word categories (such as adjectives, nouns, verbs, etc.) can be identified.

This feature set includes 27 features of lexical density including POS-based lexical density features as well as 9 features of lexical diversity including lexical word, verb, noun, adjective, and
adverb variation. Finally, we assess 53 features of lexical richness including several mathematical transformations of type token ratios (TTR), parts-of-speech specific TTRs, the Uber index and HD-D (McCarthy and Jarvis, 2007).

4.1.4 Morphological Complexity (MOR)
Morphological complexity has been argued to be an important feature for readability assessment of morphologically richer languages than English, such as German (Hancke et al., 2012; Weiss and Meurers, 2018) or Basque (Gonzalez-Dios et al., 2014). However, few measures have been used in readability assessment that are applicable across languages with different morphological systems. We use the Morphological Complexity Index (MCI) proposed by Brezina and Pallotti (2019) to assess morphological complexity independent of language by measuring the variability of morphological exponents of specific parts-of-speech within a text. These morphological exponents can be identified by contrasting word forms with their stems which makes the features applicable across languages. We assess overall 40 MCI features for verbs, nouns, and adjectives based on different number of samples and sampling sizes with and without repetition.

4.1.5 Discourse Cohesion (DIS)
We assess 26 features measuring the mean overlap of word forms and lemmas of lexical words, nouns, and grammatical arguments between sentences as well as their standard deviation. Each feature is calculated locally (between neighboring sentences) and globally (across all sentences in the text). These implicit cohesion features were originally proposed in CohMetrix (McNamara et al., 2014). Unlike explicit cohesion measures, such as the number of particular connectives, they are directly applicable across languages.

4.1.6 Language Use (USE)
Word frequency features have a long tradition in both, readability and complexity research. Yet, word frequencies obtained from different frequency data bases are not necessarily comparable. We address this issue by using the SUBTLEX-US (Brysbaert et al., 2011b) and SUBTLEX-DE (Brysbaert et al., 2011a) frequency data bases. We consider both SUBTLEX frequency data bases equivalent for the purposes of our complexity analysis because they represent word frequencies from the same register and were created to be maximally comparable. To mitigate effects due to the different sizes of the underlying corpora, we only use word frequencies per million words.

Based on this, we calculate 56 word frequency features including the mean (log) frequency of all words, lexical words, and function words and their standard deviations as well as frequencies for verbs, nouns, adjectives, and adverbs.

4.1.7 Human Language Processing (HLP)
Weiss and Meurers (2018) have proposed to use features based on theories explaining human sentence processing difficulties for readability assessment. They propose features based on the Dependency Locality Theory (Gibson, 2000) using the different integration cost weight configurations proposed in Shain et al. (2016). While the psycho-linguistic theories have been formulated for English, the complexity features by Weiss and Meurers (2018) have so far not been applied for complexity modeling beyond German.

We implemented 21 features for both, English and German, based on universal dependencies to make them applicable across languages. These features calculate the average, maximal and highest adjacent discourse integration costs per finite verb across different weight configurations.

4.2 NLP Pipeline
We calculate our complexity features following a three-step procedure. First, we run a pipeline of Natural Language Processing (NLP) tools to provide linguistic annotations for the data. The annotation pipeline primarily relies on Stanford CoreNLP (Manning et al., 2014) which we use for sentence segmentation, tokenization, parts-of-speech (POS) tagging, constituency parsing, and dependency parsing for English and German. We additionally employ the Mate tools (Bohnet and Nivre, 2012) for lemmatization, because CoreNLP only provides a lemmatizer for English but not for German. We also use the OpenNLP Snowball stemmer to extract stems for English and German. For all annotations, we use the respective default models provided with the NLP tools.

Second, we count linguistic constructs using a set of extraction rules as well as word frequencies. This procedure is fully identical across languages except for syllable counts, POS-based counts, and syntactic complexity counts which we designed to be comparable across languages as described in
the previous section. For all other features we use identical extraction rules.

Third, we calculate a variety of complexity feature ratios based on these counts. This step is fully language independent.

4.3 Feature Extraction and Selection

We extracted all 312 features on OSE, Spotlight-EN and Spotlight-DE as described in the previous subsection. We then identified all features that were not variable on any of the three data sets. This way, we could exclude features that are irrelevant for the data sets while keeping the feature collections comparable across data sets. For this, we removed all features for which the most common feature value across all three data sets occurred in 95% of the data or more.

The feature removal reduced the entire feature collection to 301 features. Only human language processing features were removed through this step, including all features measuring high adjacent integration costs.

5 Establishing our Approach on OSE

5.1 Set-up

To validate the performance of our feature-based readability classification approach against an established benchmark data set, we first trained a classifier to predict reading levels on the OSE data. For this, we used the 301 complexity features from Section 4.3. All feature values were z-transformed and centered around zero. We trained a random forest (RF), an ordinal RF, a Support Vector Machine (SVM) with a radial kernel, and a SVM with a polynomial kernel in R (R Core Team, 2015) using the caret package (Kuhn, 2020). In the following, we only report the results for the SVM using a polynomial kernel, which outperformed the other algorithms. To not reduce the relatively small data set further, we train and test using 10-folds cross-validation. We compare the performance of the classifier on OSE with a) the random accuracy baseline of 33.3% and b) the state-of-the-art performance on this data set by Bengoetxea et al. (2020), reaching 90.09%. We also report the individual precision, recall and F1 score for each reading level.

5.2 Results

The OSE classifier reaches an accuracy of 92.06% with a 95% confidence interval (CI) = [89.52%, 94.15%] in 10-folds cross-validation. This significantly outperforms the random baseline of 33.33% (p-Value < 2 \cdot 10^{-16}). It also exceeds the results of Bengoetxea et al. (2020).

Table 5 displays the confusion matrix for the classification summed across all 10-folds.

| Pred\Obs. | Ele. | Int. | Adv. |
|-----------|-----|-----|-----|
| Ele.      | 179 | 9   | 4   |
| Int.      | 9   | 173 | 15  |
| Adv.      | 1   | 7   | 170 |

Table 5: Confusion matrix: OSE 10-CV

It shows that misclassifications occur predominantly at adjacent reading levels and that there does not seem to be any systematic bias. Table 6 reports precision, recall, and F1 score per level. The performance across reading levels is relatively balanced. Elementary texts have a slightly higher recall, while advanced texts have a higher precision. As expected when comparing an ordinal classification level with two adjacent levels with levels with only one adjacent level, intermediate texts receive the lowest scores for precision and recall.

6 Classifying Readability on Spotlight

6.1 Set-up

After establishing the performance of our approach against the OSE benchmark data set, we turn to our main research question, which compares feature-based readability classification across languages on Spotlight-EN for English and Spotlight-DE for German. Our classification is balanced. Elementary texts have a slightly higher recall, while advanced texts have a higher precision. As expected when comparing an ordinal classification level with two adjacent levels with levels with only one adjacent level, intermediate texts receive the lowest scores for precision and recall.

| Ele. | Int. | Adv. |
|------|-----|-----|
| Precision | 93.2 | 87.8 | 95.5 |
| Recall   | 94.7 | 91.5 | 90.0 |
| F1       | 94.0 | 89.6 | 92.6 |

Table 6: Performance for OSE 10-CV

11All R scripts, data tables, and trained models that are being reported in this and the following sections are publicly available on OSF at https://osf.io/5hbcs/

12SVM parameters: degree = 3, scale = 0.001, and C = 1.
again based on the 301 complexity features we extracted and identified following the procedure described in Section 4.3. All feature values were z-transformed and centered around zero separately for Spotlight-EN and Spotlight-DE. This way, the classifiers are learning based on the standard deviations from the data sets’ mean values rather than the raw feature values. This was supposed to mitigate language-specific differences, for example, regarding the average sentence length in German and English.

The set-up of the classification experiment is identical to the one described in Section 5.1. In the following, we only report the results for the ordinal RF which outperformed the other algorithms on both Spotlight data sets. Since this is a novel data set, we use the majority baseline as sole reference to evaluate the classifier performance in the within language condition (Section 6.2.1).

For our cross-language classification experiment (Section 6.2.2), we apply the previously trained classifiers to the respective other subset of the Spotlight data, i.e., testing on Spotlight-DE for the classifier trained on Spotlight-EN and vice versa. Unlike previous cross-linguistic readability classification approaches that used cross-lingual data to augment limited training resources, this set-up tests the generalization of our classifiers in a form of zero-shot learning. We again compare the performance of each classifier across-languages against the majority baseline on the respective testing data and the within-language classification performance.

We also report the individual precision, recall and F1 scores for each reading level throughout all classification experiments.

6.2 Results
6.2.1 Within-language Performance
Table 7 displays the results of all four classification experiments on the Spotlight data. The Spotlight-EN classifier reaches an accuracy of 74.5% in 10-folds cross-validation. This significantly outperforms the majority baseline of 46.5% (p-Value < 2.2 \times 10^{-16}).

Looking at the confusion matrix in Table 8, we see that the classification is relatively balanced, even though in proportion to their total count advanced texts are classified incorrectly more often than the other reading levels. This can also be seen in the relatively low F1 score for advanced texts displayed in the first three rows of Table 10.

The Spotlight-DE classifier reaches an accuracy of 88.0% in 10-folds cross-validation. This significantly outperforms the majority baseline of 52.8% (p-Value < 2.2 \times 10^{-16}). Table 9 shows the confusion matrix for the classification, which shows good classification results throughout all reading levels. This is mirrored in the high precision and recall scores displayed in rows four to six in Table 10.

6.2.2 Cross-language Performance
For the classification across languages, the Spotlight-EN classifier reaches an accuracy of 55.5% on Spotlight-DE. Although this performance is considerably worse than for the within-language classification, this significantly outperforms the majority baseline of 52.8% (p-Value = 0.02118) showing that the classifier somewhat generalizes beyond English even if the performance drops considerably. Looking at the confusion matrix in Table 11, one of the most common misclassifications is the labeling of easy texts as medium. The classifier overestimates the reading difficulty of many easy and medium texts. This results in a high precision but low recall for easy texts, as shown in rows seven to nine in Table 10.

The Spotlight-DE classifier reaches an accuracy of 53.4% on Spotlight-EN. Again, this is much worse than the results for the within-language classification, but significantly outperforms the majority baseline of 46.51% (p-Value = 1.284 \times 10^{-15}). This shows again that the classifier generalizes to some degree in the zero-shot learning scenario. Looking at the confusion matrix in Table 12, it can be seen that the classifier tends to underestimate the reading difficulty of advanced texts (classifying them as medium or even easy) and of medium texts (classifying them as easy). This results in a relatively high recall for easy texts and very low recall for advanced texts, as shown in the final three rows in Table 10.

6.3 Discussion
The two readability classifiers trained on Spotlight-EN and Spotlight-DE are highly successful when applied within their training language and exceed the majority baseline con-
Table 7: Overall classifier accuracy (Acc.) on Spotlight data compared against majority baseline (Maj.)

|                | Train Test Acc. | 95% CI       | Maj. Acc. | Acc. < Maj. |
|----------------|------------------|--------------|-----------|-------------|
| Spotlight-EN   | 10-folds CV      | 74.5         | [73.0, 76.0] | 46.5 | < 2.2 · 10^{-16} |
| Spotlight-DE   | 10-folds CV      | 88.0         | [86.1, 89.6] | 52.8 | < 2.2 · 10^{-16} |
| Spotlight-EN   | Spotlight-DE     | 55.5         | [52.9, 58.1] | 52.8 | 0.0218 |
| Spotlight-DE   | Spotlight-EN     | 53.4         | [51.7, 55.1] | 46.5 | 1.284 · 10^{-15} |

Table 8: Confusion matrix Spotlight-EN 10-CV

|               | Easy | Medium | Advanced |
|---------------|------|--------|----------|
| Easy          | 816  | 171    | 37       |
| Medium        | 208  | 1,210  | 268      |
| Advanced      | 6    | 147    | 422      |

Table 9: Confusion matrix Spotlight-DE 10-CV

|               | Easy | Medium | Advanced |
|---------------|------|--------|----------|
| Easy          | 727  | 83     | 1        |
| Medium        | 34   | 399    | 27       |
| Advanced      | 2    | 27     | 146      |

Table 10: Level-wise performance on Spotlight

|                            | Easy | Medium | Advanced |
|-----------------------------|------|--------|----------|
| **Spotlight-EN 10 CV**      |      |        |          |
| Precision                   | 79.7 | 71.8   | 73.4     |
| Recall                      | 79.2 | 79.2   | 58.1     |
| F1.                         | 79.5 | 75.3   | 65.0     |
| **Spotlight-DE 10 CV**      |      |        |          |
| Precision                   | 89.6 | 86.7   | 83.4     |
| Recall                      | 95.3 | 78.4   | 83.9     |
| F1.                         | 92.4 | 82.4   | 83.7     |

|                            | Easy | Medium | Advanced |
|-----------------------------|------|--------|----------|
| **Spotlight-EN on Spotlight-DE** | | | |
| Precision                   | 82.3 | 42.5   | 52.4     |
| Recall                      | 44.6 | 67.4   | 67.8     |
| F1.                         | 57.8 | 52.1   | 59.2     |

|                            | Easy | Medium | Advanced |
|-----------------------------|------|--------|----------|
| **Spotlight-DE on Spotlight-EN** | | | |
| Precision                   | 49.3 | 59.0   | 53.4     |
| Recall                      | 80.3 | 47.9   | 27.0     |
| F1.                         | 61.1 | 52.9   | 35.8     |

Table 11: Confusion matrix Spotlight-EN on Spotlight-DE

|               | Easy | Medium | Advanced |
|---------------|------|--------|----------|
| Easy          | 341  | 73     | 0        |
| Medium        | 408  | 343    | 56       |
| Advanced      | 14   | 93     | 118      |

Table 12: Confusion matrix Spotlight-DE on Spotlight-EN

|               | Easy | Medium | Advanced |
|---------------|------|--------|----------|
| Easy          | 827  | 635    | 216      |
| Medium        | 193  | 732    | 315      |
| Advanced      | 10   | 161    | 196      |

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to some extent in the zero-shot learning scenarios, despite considerable drops in performance. This result is not to be taken for granted due to the linguistic differences between English and German. These are highly promising initial results. Further research is needed to investigate to which extent this generalization also applies across other languages.

The comparison of the confusion matrices of both cross-lingual classification experiments reveals a symmetrical regularity in the misclassifications. While the German classifier underestimates the reading levels of the English texts, the English classifier tends to overestimate the readability of the German texts. Since the classifiers are trained and tested on feature z-scores centered around the mean this behavior is not immediately expected and warrants further investigation in future research.

7 Feature Informativeness on Spotlight

7.1 Set-up

To identify which of the 301 complexity features identified in Section 4.3 are most informative for the readability classification, we identify the most informative features using the correlation-based feature subset selection for machine learning approach by Hall (1999). This method identifies the subset of features that exhibits the highest correlation with the class to be predicted (in our case reading level) while minimizing the intercorrelation of features within the subset. We use the implementation provided in the WEKA toolkit version 3.9.5 (Hall et al., 2009) for feature identification. We report the percentage of features selected across each feature group before we discuss in more detail the intersection of features in both data sets.

7.2 Results

Table 13 displayed the raw number and percentage of features selected on Spotlight-EN and Spotlight-DE across feature groups and the total number of features contained in the group. We make the result summary more interpretable, we split syntactic and lexical complexity features into the individual subgroups distinguished within Sections 4.1.2 and 4.1.3. A full list of all features that are informative on either data set is displayed in Appendix A. Figure 1 shows the boxplots of all features that were selected for Spotlight-EN as well as Spotlight-DE.

On Spotlight-EN and on Spotlight-DE, up to a third of all surface length features are selected, most of which are informative on both data sets. All of the shared length features increase with reading level (see Figure 1). Also language use features seem to be central for the distinction of reading levels on both data sets. 30.4% of the features were selected for Spotlight-EN and 19.6% for Spotlight-DE. Four of the language use features are relevant for both data sets: the average word frequency and its standard deviation are decreasing with increasing reading level. The same holds for the log frequency of lexical word types. The standard deviation of the verb token frequency is increasing with higher reading levels. Lexical complexity seems to play a medium role in the distinction of reading levels. 13.5% of the lexical complexity features were selected for Spotlight-EN and 12.4% for Spotlight-DE. Especially lexical density and richness play an important role on both data sets, but there is only very little overlap between the features selected for Spotlight-EN and Spotlight-DE. Only the POS density of modifiers and proper nouns as well as the squared word TTR were selected on both feature sets. For English, the proper noun density is decreasing, while the POS density for modifiers and the squared word TTR are increasing with reading levels. For German, the squared word TTR is also increasing with reading levels, but the two POS density features exhibit a u-shaped and inverse u-shaped
Figure 1: Boxplots of features that are informative on both, Spotlight-EN and Spotlight-DE
The importance of syntactic and morphological complexity differs for Spotlight-EN and Spotlight-DE. Only 6.7% of the syntactic features were selected for Spotlight-EN, half of them features of syntactic variation. In contrast, 21.7% were selected on Spotlight-DE, all either features of clausal or phrasal complexity. Correspondingly, there is very little overlap in this domain between English an German. Only two syntactic features are informative for both data sets: the mean noun phrase length and the number of dependent clauses per t-unit, both of which are increasing with higher reading levels on both data sets. Morphological complexity features seem to play an important role for the distinction of reading levels on Spotlight-EN, but much less on Spotlight-DE. While 17.5% of the morphological complexity features were selected for Spotlight-EN, only 7.5% play a role on Spotlight-DE. Both data sets share only one feature in this domain, namely the MCI for adjectives (measured with repetition with 5 partitions of size 5), which increases with higher reading levels, though the effect is more pronounced for English.

Neither implicit discourse cohesion features nor human language processing features seem to be important features on Spotlight-DE and also on Spotlight-EN, only 8.2% of the cohesion features were identified as informative.

### 7.3 Discussion

The correlation-based feature subset selection shows that features from most feature groups contribute meaningful information for the distinction of reading levels on both data sets. Especially features of surface length, language use, and lexical complexity help to characterize reading level differences on both data sets. Morphological and syntactic complexity features seem to capture more language-specific differences. There is also a considerable overlap of features selected for both data sets. Overall 28% of the features selected for Spotlight-EN and 32% of features selected for Spotlight-DE are shared between both data sets.

Judging from the features that are shared between the feature selections for English and German, higher reading levels are characterized by the use of less frequent vocabulary, longer words, sentences, and texts, and shifts in lexical density and richness. Also the features that were selected from the domains of morphological, phrasal and syntactic complexity increase with higher reading levels. This is in line with previous findings by Weiss and Meurers (2018) regarding the readability of German media texts targeting German-native speaking adults and children. However, our results indicate that these domains play a much less pronounced role for the distinction of reading levels. Interestingly, morphological elaboration seems to be more important for English than for German.

Human language processing measures do not seem to play an important role for the distinction of reading levels in either data sets, even though these measures are motivated by psycho-linguistic studies on human sentence processing. This is again in line with previous findings reported by Weiss and Meurers (2018).

Overall, these findings explain the albeit limited cross-language generalization of both readability classifiers in the zero-shot learning experiments. While there are differences in the types of features that are informative for the identification of reading levels across languages, there is nevertheless a substantial overlap and the shared features predominantly exhibit an increase in complexity with higher reading levels. This confirms that the publisher successfully instituted a policy facilitating the creation of stratified reading materials for different levels in a way that is comparable across the different languages that we analyzed.

### 8 Conclusion

We have investigated the use of language-independent broad linguistic complexity modeling for the multi-level readability classification of English and German reading materials for language learners. Our first study designed to benchmark the performance of our methods on the established OneStopEnglish yielded new state-of-the-art results, clearly showcasing the value of broad linguistic modeling for readability assessment. Our study also shows that for certain tasks, broadly linguistically informed feature-based approaches are in fact not only competitive with neural approaches but exceeding their performance.

We then introduced a novel multi-level reading corpus for English and German on which we trained two readability classifiers that yield are highly successful within their respective training language. With this, we present the first multi-level readability classifier for German. This is highly relevant, because the much more com-
monly proposed binary classification approaches distinguishing simple and regular language are too limited to be of practical relevance for the retrieval of reading materials that are appropriate to foster foreign language learning.

We then demonstrated the generalizability of the German classifier for comparable English data and the English classifier for comparable German data. This is a novel contribution to cross-lingual readability research, not only because of the multi-level classification but also because of we propose a zero-shot cross-lingual readability classification approach unlike previous work focusing on augmenting low-resource training data. This is a central contribution to readability classification research, especially for languages other than English, given the lack of appropriate training materials for many languages.

In our final study, we compared the linguistic properties characterizing differences in reading levels in English and German. Our findings show that for both languages, texts systematically differ between reading levels in terms of the frequency and lexical complexity. Language-specific characteristics of reading levels can be found in the syntactic, discourse and morphological domains. The publisher thus successfully adapts the reading materials for different proficiency levels across a variety of linguistic domains in a systematic way. This is not a trivial insight, since previous work demonstrated that school book publishers do not always succeed in the linguistic adaptation of reading materials for different target groups (Berendes et al., 2018).

Our findings clearly demonstrate the value of feature-based classification approaches not only for the study of linguistic phenomena but also for readability classification. We demonstrate the feasibility of broad language-independent feature collections and their potential for zero-shot cross-lingual learning.

9 Outlook

As we saw in Table 7, cross-language zero-shot learning showed a promising result for training on Spotlight-DE and test on Spotlight-EN and the other way round. It is arguable that although different languages may complexify in different linguistic aspects, the general rule of more elaborate linguistic components and more varied expression usually resulting in higher complexity still applies. As a result, it is highly likely that zero-shot cross-language learning would also result in good performance, but detailed approaches need to be further designed and tested in future studies including more languages.

Another direction for future research is to see how the readability levels decided by the publisher match L2 learners’ actual perception of the texts’ difficulty. Although our models have yielded high accuracy, if the standards used to determine the levels of the texts do not actually match the learners’ perceived difficulty, the predicted results are meaningless. Vajjala and Lučić (2019) offer an interesting data set that may potentially be used to answer this question.

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Appendix A: List of Selected Features

A.1: Features selected for Spotlight-EN

**LEN** Number Of Letters, SD Token Length in Letters, Percentage of Word Types with More Than 2 Syllables Length Measures, Number of Word Types with More Than 2 Syllables, SD Sentence Length in Tokens, SD Sentence Length in Syllables, Mean Sentence Length in Syllables

**SYN** Syntactic Complexity Feature: Dependent clauses per T-unit, Clausal, Syntactic Complexity Feature: Mean Length of Noun Phrase Phrasal, SD Local Edit Distance for tokens, SD Global Edit Distance for Lemmas

**LEX** POS Density Feature: Particle, POS Density Feature: Adjective, POS Density Feature: Past Participle Verb, POS Density Feature: Coordinating Conjunction, POS Density Feature: Modifier, POS Proper Noun Density, Corrected TTR, Corrected TTR Adjectives, Squared TTR Words, Uber index (10) Adjectives, Lexical Verb Variation

**MOR** MCI-5 for Verbs (5 partitions no repetition), MCI-5 for Nouns (5 partitions no repetition), MCI-10 for Nouns (5 partitions no repetition), MCI-5 for Adjectives (2 partitions with repetition), MCI-5 for Adjectives (2 partitions no repetition), MCI-5 for Nouns (5 partitions with repetition), MCI-5 for Nouns (10 partitions no repetition)

**DIS** Global Lemma Overlap, Mean Local Noun Overlap (word form-based)

**USE** Logarithmic Word Frequency (Adj Type), Logarithmic Word Frequency (FW Type),
A.2: Features selected for Spotlight-DE

LEN  Number Of Letters, 2 Number of Word Types with More Than 2 Syllables, Mean Sentence Length in Syllables, SD Sentence Length in Tokens, SD Sentence Length in Letters

SYN  Relative Clauses per Sentence, Relative Clauses per Clause, Dependent clauses per Sentence, Dependent clauses per T-unit, Complex T-unit Ratio, Dependent clause ratio, Relative Clauses per T-Unit, Mean Length of T-unit, Verb Cluster per T-Unit, Mean Length of Noun Phrase, Postnominal Modifier per Complex Noun Phrase, Verb Phrases per Clause, Verb Phrases per T-unit

LEX  TTR Adverbs per Lexical Types, Squared TTR Nouns, Uber index (10) Verbs, Uber index (10) Nouns, Squared TTR Words, Modals per Verb, POS Modifier Density, POS To-infinitive Density, POS Possessive Pronoun Density, POS Proper Noun Density

MOR  MCI-5 for Nouns (2 partitions with repetition), MCI-5 for Nouns (5 partitions with repetition), MCI-10 for Nouns (2 partitions no repetition)

DIS  none

USE  Word Frequency (V Type), Word Frequency (SD V Type), Logarithmic Word Frequency (Adj Token), Logarithmic Word Frequency (SD V Token), Word Frequency (AW Type), Logarithmic Word Frequency (SD Adv Token), Logarithmic Word Frequency (SD LW Type), Logarithmic Word Frequency (V Type), Logarithmic Word Frequency (SD FW Token), Logarithmic Word Frequency (SD AW Token), Word Frequency (SD FW Type)