Predicting the Relative Difficulty of Single Sentences With and Without Surrounding Context

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Abstract

The problem of accurately predicting relative reading difficulty across a set of sentences arises in a number of important natural language applications, such as finding and curating effective usage examples for intelligent language tutoring systems. Yet while significant research has explored document- and passage-level reading difficulty, the special challenges involved in assessing aspects of readability for single sentences have received much less attention, particularly when considering the role of surrounding passages. We introduce and evaluate a novel approach for estimating the relative reading difficulty of a set of sentences, with and without surrounding context. Using different sets of lexical and grammatical features, we explore models for predicting pairwise relative difficulty using logistic regression, and examine rankings generated by aggregating pairwise difficulty labels using a Bayesian rating system to form a final ranking. We also compare rankings derived for sentences assessed with and without context, and find that contextual features can help predict differences in relative difficulty judgments across these two conditions.

1 Introduction

The reading difficulty, or readability, of a text is an estimate of linguistic complexity and is typically based on lexical and syntactic features, such as text length, word frequency, and grammatical complexity (Collins-Thompson and Callan, 2004; Schwarm and Ostendorf, 2005; Kidwell et al., 2011; Kanungo and Orr, 2009). Such estimates are often expressed as age- or grade-level measures and are useful for a range of educational and research applications. For example, instructors often wish to select stories or books that are appropriately matched to student grade level.

Many measures have been designed to calculate readability at the document level (e.g., for web pages, articles, or books) (Collins-Thompson and Callan, 2004; Schwarm and Ostendorf, 2005), as well as the paragraph or passage level (Kidwell et al., 2011; Kanungo and Orr, 2009). However, much less work has attempted to characterize the readability of single sentences (Pilán et al., 2014). This problem is challenging because single sentences provide much less data than is typically required for reliable estimates, particularly for measures that rely on aggregate statistics.

The absence of reliable single-sentence estimates points to a substantive gap in natural language processing (NLP) research. Single sentences are used in a variety of experimental and NLP applications: for example, in studies of reading comprehension. Because readability estimates have been shown to predict a substantial portion of variance in comprehension of different texts, it would be extremely useful to have measures of single-sentence readability. Thus, one aim of the current study was to estimate the relative readability of single sentences with a high degree of accuracy. To our knowledge, general-purpose methods for computing such estimates have not been developed.

The second aim is to compare the readability of single sentences in isolation with the readability of these same sentences embedded in a larger discourse (e.g., paragraph, passage, or document). When a single sentence is extracted from a text, it is likely to
contain linguistic elements, such as anaphores (e.g., "he" or "the man"), which are semantically or syntactically dependent on surrounding context. Not surprisingly, sentences that contain these elements are more effortful to comprehend: an anaphoric noun phrase, or NP (e.g., "he"), automatically triggers the need to resolve reference, typically by understanding the link between the anaphore and a full NP from a previous sentence (e.g., "John" or "The man that I introduced you to at the party last night" (Perfetti and Frishkoff, 2008). In general, studies have shown a link between reading comprehension and the presence of such cross-sentence relationships in the text (McNamara, 2001; Liederholm et al., 2000; Voss and Silfies, 1996). This implies that the very notion of readability at the sentence level may depend on discourse (cohesion and coherence), as well as word- and sentence-level features. Therefore, it is important to compare readability estimates for single sentences that occur in isolation versus those that occur within a larger discourse context, particularly if the target sentence contains multiple anaphores or other features related to discourse coherence or cohesion.

To address these aims, the present study first conducted two crowdsourcing experiments. In the first, ‘sentence-only’ experiment, workers were asked to judge which of two ‘target’ sentences they thought was more difficult. In the second, ‘discourse-embedded’ experiment, another group of workers was presented with the same target sentences that were used in the first experiment. However, in the second experiment, target sentences were embedded in their original discourse contexts.

Next, we analyzed these judgments of relative readability for each condition (sentence-only versus discourse-embedded) by developing models for predicting pairwise relative difficulty of sentences. These models used a rich representation of target sentences based on a combination of lexical, syntactic, and discourse features. Significant differences were found in readability judgments for sentences with and without their surrounding context. This demonstrates that discourse-level features (i.e., features related to coherence and cohesion) can affect the readability of single sentences.

2 Related Work

Recent approaches to predicting readability have used a variety of linguistic features. The Lexile Framework (Stenner, 1996) uses word frequency estimates as a measure of lexical difficulty, and sentence length as a grammatical feature. Methods based on statistical machine learning, such as the reading difficulty measures developed by Collins-Thompson and Callan (Collins-Thompson and Callan, 2004) and (Schwarm and Ostendorf, 2005) used a feature set based on language models. Later work (Heilman et al., 2008) added grammatical features by parsing the sentences in a text, and creating subtrees of one- to three-level depth, using each as a feature that would correspond to the grade level. These features allow direct analysis of the sentence structure itself, instead of using proxy features, such as sentence length. However, the sentences are attributed a level according to the context of the entire document, not the individual sentence. The linguistic features proposed in these works capture specific components of language that correspond to difficulty, and while their application was to document-level difficulty, our work here investigates their effectiveness for characterizing aspects of difficulty at the sentence level.

Methods of calculating the difficulty of smaller portions of text have been proposed. While these works did not model sentence-level difficulty, they deal with the problems inherent in measuring shorter pieces of text. For example, a model was proposed to predict short web summaries in Kanungo and Orr (2009). In (Kidwell et al., 2011), Age of Acquisition measures were used to predict the grade levels of passages. Age of Acquisition measures allow the lexical component of difficulty to be represented in higher-level features. Some methods have explored the classification of specific aspects of sentences. For example, (Pilán et al., 2014) classified individual sentences that would be understood by second-language learners.

Other approaches have considered the relationship of reading difficulty to structures within the whole text. These relationships can include the number of coreferences present in a text. Coh-Metrix (Graesser et al., 2011) measures text cohesiveness, accounting for both the reading difficulty of the text and other lexical and syntactic measures as well as
a measure of prior knowledge needed for comprehension, and the genre of the text. Coh-Metrix uses co-reference detection as a factor in the cohesiveness of a document. They do not, however, use these measures at a more granular, sentence level. These factors account for the difficulty of constructing the mental representation of the text. TextEvaluator (Sheehan et al., 2013; Sheehan et al., 2014) is designed to help educators select materials for instruction. The tool includes several components in its evaluation of text, including narrativity, style, and cohesion, beyond traditional difficulty and is again at the whole document level. This approach illustrates that the difficulty of a text relies on the relationships within it. This motivates the need to consider context when measuring difficulty.

Generating reading difficulty rankings of longer texts from pairwise preferences has been performed in other contexts. Chen et al. (2013) proposed a model to predict passage ranking based on pairwise comparisons made by workers. In a study by De Clercq et al. 2014, pairwise judgments of whole passages were obtained from crowdworkers, and found to given comparable results in aggregate to those obtained from experts. A pairwise ranking of text readability was created in Pitler and Nenkova 2008. For their work, readability was defined by subjective questions asked to the reader after finishing the article, such as "How well-written is this article?". There also has been research into predicting the result of a pairwise decision. In the Machine Translation field, the pairwise prediction of the best translation between two sentence options is often used. Unlike pairwise prediction of difficulty, there is a reference sentence, or set of reference sentences. For example, in Song and Cohn (2011), a pairwise prediction model was built using n-gram precision and recall, as well as function, content, and word counts. Unlike these previous MT studies, we focus on characterizing and predicting the relative readability of sentences.

3 Data Collection and Processing

We now describe methods used to create our dataset of sentences, to collect pairwise assessments of difficulty, and to aggregate these pairwise preferences into a complete ranking.

3.1 Data Set

The study sentences were drawn from a corpus combining the American National Corpus (Reppen et al., 2005), the New York Times Corpus (Sandhaus, 2008), and the North American News Text Corpus (McClosky et al., 2008). The domain of these corpora is largely news text, but also includes other topics, such as travel guides and other non-fiction. In total, this database contains 60,663,803 sentences that served as initial candidates. From that, sentences were filtered out that were judged inappropriate for middle school and elementary readers, since that is the target demographic for instruction. This was done using a series of filters. Sentences were filtered that didn’t include one of the 70 target words that one of the authors selected for a study on teaching vocabulary to 8-14 year-old students. Other sentences were removed based on length, keeping only sentences between 6 and 20 words. Some sentences were removed due to the presence of one or more rare words. Finally, sentences from documents with high school reading levels (9th grade or higher), determined by using a lexical or a grammatical readability model, were excluded. The data set gathered by (removed for blind review) was obtained in order to add to the amount of lower level reading material in the collected corpora.

With these sentences, two crowdsourced tasks were prepared to gather pairwise assessments of sentence reading difficulty. In one task, the sentences were presented alone, outside of their original passage context. In the other task, the same sentences were presented within their original passage context. The objective was to generate two sets of pairwise comparisons of the readability of a sentence. In total, 120 sentence pairs were used for the first task and 120 passage pairs were used for the second. Each sentence was compared to five others, which created 300 comparisons in each task. The five sentences matched to each sentence were selected to ensure that a variety of document level pairs would be created. Within each type of pair, a random pair was selected.

There were several constraints when generating pairs for comparison. To allow for sentences to be taken from documents with a range of reading levels, sentences were selected evenly from documents at each reading level. From the twelve standard U.S.
grade levels used in readability, each document was considered to be part of a bin consisting of two grade levels, such as grades 1 and 2, for example. Sentences were selected evenly from those bins.

Each sentence needed sufficient context to ensure that there would be equivalent context for each item that would be compared, so only passages of sufficient size were included. A document that contains 75 words would have been excluded, as it did not provide enough context. Contexts that had at least two sentences before and after the sentence in question were strongly preferred. Each selected sentence was paired with one sentence from each of the other grade level bins. For example, a sentence from grade 1 would be paired with one sentence each from grade 3-4, 5-6, 7-8, 9-10, and 11-12. Finally, each pair of sentences was presented in AB and BA order. For each pair, there were seven worker decisions.

3.2 Crowdsourcing

Both of these tasks were carried out on the Crowdflower platform. The workers were first given instructions for each task, which included a description of the general purpose of the task. In the sentence-only task, workers were asked to select which of the two sentences was more difficult. In the sentence-within-passage task, workers were similarly asked to decide which underlined sentence was more difficult. The instructions requested that the workers make their judgment only on the sentence, not on the whole context. In both tasks, there was an option for “I don’t know or can’t decide”. The workers were asked to make their decision based on the vocabulary and grammatical structure of the sentences. Finally, examples for each task were provided with explanations for each answer. The full instructions for both tasks are in the supplementary materials.

For each task, at least 40 gold standard questions were created from pairs of sentences that were judged to be sufficiently distinct from one another so that they could easily be answered correctly. For the sentence-in-passage task, several gold standard questions were written to verify that the instructions were being followed, since it was possible that a worker might judge the sentences based on the quality of the passage alone. These gold examples consisted of an easier sentence in a difficult passage compared with a difficult sentence within an easy passage. For each task, the worker saw three questions, including one gold standard question. A worker needed to maintain an 85% accuracy rating on gold standard questions to continue, and needed to spend at least 25 seconds per page.

A weighted disagreement rate was calculated for each worker. If a workers response to a question differed from the most frequent answer to that question, the percentage of agreement was counted against the worker. If a worker, for the sentence-only task, had a disagreement rate (the weighted disagreement penalty divided by the total questions they answered) of 15% or higher, their contribution was removed from the data set (or 17% or higher for the sentence in passage task). This resulted in the removal of 5.7% and 4.5% of pairwise judgments, respectively.

For each question, there was an optional text form to allow workers to submit feedback. The sentence-only task paid 11 cents per page, and the sentence-in-passage task paid 22 cents per page.

3.3 Ranking Generation

Each task resulted in 4,200 pairwise preference judgments, excluding gold-standard answers. To aggregate these pairwise preferences into an overall ranking of sentences, we use a simple, publicly available approach evaluated by Chen et al. as being competitive with their own Crowd-BT aggregation method: the Microsoft Trueskill algorithm (Herbrich et al., 2007). Trueskill is a Bayesian skill rating system that generalized the well-known Elo rating system, in that it generates a ranking from pairwise decisions. As Trueskills ranking algorithm depends on the order in which the samples are processed, we report the ranking as an average of 50 runs.

The judgments were not aggregated for each comparison. Instead, each of the judgments was treated individually. This allows Trueskill to consider the degree of agreement between workers, since a sentence judgment that has high agreement reflects a larger difference in ranking than one that has lower agreement. Each sentence was considered a player, and the winner between two, A or B, was the sentence considered most difficult. If a worker chose "I don’t know or can’t tell”, it was considered a draw. The prediction resulting in "I don’t know or can’t tell” is rare; 2.2% of decisions in the sentence only task resulted in a draw, and 2.0% for sentences
within passages. After processing each of the judgments, a rating can be built of sentences, ranked from least difficult to most difficult.

We can compare the rankings for the sentence only task and the sentence within passage task, to see if context made a difference. The differences are measured in terms of correlation, and the individual differences between sentences.

4 Modeling Pairwise Relative Difficulty

Our first step in exploring relative difficulty ordering for a set of sentences was to develop a model that could accurately predict relative difficulty for a single pair of sentences, corresponding to the pairwise judgements of relative difficulty we gathered from the crowd. We did this for both the sentence-only and the sentence-in-passage tasks. In predicting a pairwise judgment for the sentence-only task, the model uses only the sentence texts. In the model for the sentence-in-passage task, the Stanford Deterministic Coreference Resolution System (Raghunathan et al., 2010) is used to find coreference chains within the passage. From these coreference chains, sentences with references to and from the target sentence can be identified. If any additional sentences are found, these are used in a separate feature set that is included in the model; for all possible features, they are calculated for the target sentence, and separately for the additional sentence set.

Prior to training the final model, feature selection was performed using five-fold stratified cross validation. Training data was used to fit a Random Forest Classifier, and based on the resulting classifier, the most important variables were selected using sklearn’s feature importance method. We implemented our models using (Pedregosa et al., 2011) in Python. The resulting features were used to train a Logistic Regression model. We chose Logistic Regression as it less likely to overfit a small data set, and the role of each feature is interpretable from the resulting parameter weights. The features selected for each iteration of cross validation were recorded, and any features that were selected 60% or more of the time were selected for the final model. Since a given feature has a value for sentence A and B, if a feature was selected for only Sentence A or B, the feature for the other sentence was also added. We used the NLTK library (Bird et al., 2009) to tokenize the sentence for feature processing.

At the sentence level, the familiarity or difficulty of the words is an important factor to consider in any judgment on difficulty. The grammatical structure of a sentence is important to consider as well: if the sentence uses a more familiar structure, it is likely to be considered less difficult than a sentence with more unusual structure. We thus identified two groups of potential features: lexical and grammatical, described below.

4.1 Lexical Features

For lexical features, based partly on the work of (Song and Cohn 2011) we included the percentage of content words, the total number of words and the total number of characters as features. We included the percentage of words in the text found in the Revised Dale-Chall word list (dal) to capture the presence of more difficult words in the sentence.

Because sentences that contain rarer sequences of words are likely to be more difficult, and the likelihood of the sentence based on a large corpus should reflect this, we included the ngram likelihood of each sentence, over each of 1-5 ngrams, as a feature. The Microsoft WebLM service (Wang et al., 2010) was used to calculate the ngram likelihood.

In the field of psycholinguistics, Age of Acquisition (AoA) refers to the age at which a word is first learned by a child. A database of 51,715 words collected by (Kuperman et al., 2012) provides a rich resource for use in reading difficulty measures. With this dataset, we computed several additional features: the average, maximum, and standard deviation of the aggregated AoA for all words in a sentence that were present in the database. Since the data set also includes the number of syllables in each word, and as (Kincaid et al., 1975) proposes that words with more syllables are more difficult, we also included the average and maximum syllable count as potential features.

4.2 Syntactic Features

We parsed each sentence in the data set using the BLLIP Parser (Charniak and Johnson, 2005), which includes a pre-trained model built on the Wall Street Journal Corpus. This provided both a syntactic tree and part of speech tags for the sentence. As Part of Speech tagging is often used as a high-level linguistic feature, we computed percentages for each PoS
Table 1: Accuracy of pairwise relative difficulty prediction model on held-out data. With coref indicates coreference features were used. Arrow indicates which immediately adjacent accuracy result is used for p-value comparison, e.g. Model B sentence-only is compared to model C sentence-only, and model B passage, no coref is compared to model B passage, with coref.

| Feature Combination       | Sentence Only | In Passage, With Coref | In Passage, No Coref |
|---------------------------|---------------|------------------------|---------------------|
|                           | Acc.          | p-value                | Acc.                | p-value            |
| Oracle (A)                | 93.59%        | —                      | 89.87%              | —                  |
| All Features (B)          | 90.18%        | 0.002 ↓                | 84.74%              | 0.234 ↓           |
| AoA + Parse Likelihood (C)| 86.78%        | 0.014 ↓                | 83.33%              | 0.689 ↓           |
| AoA (D)                   | 83.25%        | 0.001 ↓                | 82.82%              | 0.001 ↓           |
| Stratified Random (Baseline) | 48.43%        | —                      | 50.00%              | —                  |

tag present, since the percentages might vary between difficult sentences and easier sentences. The percentage for each Part of Speech tag is defined as the number of times a certain tag occurred, divided by the total tags. The diversity of part of speech tags was used since this might vary between difficult and easier sentences.

Using the syntactic tree provided by the parser, we obtained the likelihood of the parse, and the likelihood produced by the re-ranker, as syntactic features. If a sentence parse has a comparatively high likelihood, it is likely to be a more common structure and thus more likely to be easier to read. The length and height of the parse were also included as features, since each of these could reflect the difficulty of the parse. Including the entire parse of the sentence would create too much sparsity since syntactic parses vary highly from sentence to sentence. Therefore, as was done in (Heilman et al., 2008), subtrees of depth one to three were created from the syntactic parse, and were added as features. This creates a smaller feature set, and one that can potentially model specific grammatical structures that are associated with a specific level of difficulty.

5 Pairwise Difficulty Prediction Results

The accuracy of the logistic regression models trained with different feature sets, for each task, is shown in Table 1. The accuracy is computed on a held-out test set that was not used in training cross-validation, with the pairwise judgments randomly separated into training (80% of data) and test (20% of data) sets. The test set contains 60 aggregate pairs, all of which are sentences (24 in total) that were not present in the training data. The test sets for the sentence-in-passage and sentence-only task contain the same sentence pairs, but the individual judgements are different. The sentence-in-passage test dataset contained 780 individual judgments, and the sentence-only set contained 764.

For comparison, an oracle is included that represents the accuracy a model would achieve if it made the optimal prediction for each aggregate pair. For example, for some pair A and B, if 10 workers selected A as the more difficult sentence, and 4 workers selected B, the oracle’s prediction for that pair would be that A is more difficult. The judgments of the four workers that selected B would be counted as inaccurate, since the feature set is the same for the judgments with A and the judgments with B. Therefore, the oracle represents the highest accuracy a model can achieve, consistent with the provided labels, using the features provided.

Examining the results in Table 1 we find the best performing configuration, Model B, used all features as candidates. The exact number of features selected varied depending on the task. However, the simplest model, the Age of Acquisition model (D) consisting of the average, standard deviation, and maximum AoA features (sentence-only: 6 features, sentence-in-passage: 12 features) performed surprisingly well, achieving over 80% accuracy on all tasks, showing that most of the relative difficulty signal at the sentence level can be captured with a few lexical difficulty features. The Age of Acquisition + Parse Likelihood model (C) consists of all Age of Acquisition features, plus the likelihood of the parse (sentence-only: 10 features, sentence-in-passage: 20 features).

To assess the contribution of different features to the model prediction, the logistic regression feature coefficients for Model B are shown in Table 2. These

1The p-value for each accuracy measurement compares its significance, using a two-sided z-score test, to the neighboring model in the direction of the arrow. For example, the sentence-only Model B is compared to sentence-only Model A.
represent the average absolute logistic regression coefficients, run over five iterations of five-fold cross validation on the training set. The Syn features are syntactic subtrees with Penn Treebank-style tags; for example, (NP \rightarrow PRP) represents a noun phrase consisting of a personal pronoun. POS are part of speech percentages for a given type. However, POS diversity is the type-token percentage of part of speech tags. Syll Avg is the average number of syllables in the sentence. Word % not in AoA represents the percentage of words not present in the Age of Acquisition dataset. Finally, 4-gram Lang. Model is the likelihood of the sentence from a four-gram language model.

These prediction results show that relative reading difficulty can be predicted for sentence pairs with relatively high accuracy, even with fairly simple feature sets. In particular, the results for AoA model D, which uses a small number of targeted features, are competitive with the best model B that relies on a much larger feature set. A larger feature set resulted in significantly improved results in the Sentence-In-Passage task, but not in the Sentence-Only task. The addition of coreference features did not significantly change the accuracy of the Sentence-In-Passage task. Of the logistic regression feature coefficients, one of the strongest was a coreference feature, but the remaining were features only based on the sentence.

6 Ranking Results

Using the pairwise aggregation method described in Section 3.3, we ranked sentences by relative difficulty for both the sentence-only and sentence-in-passage tasks. By observing how the overall rank ordering of sentences changes across these conditions, we can identify differences in how workers judged the relative difficulty of sentences with and without context.

6.1 Rank Differences

We report differences in ranking in terms of average and standard deviation of the absolute difference in rank index of each sentence across the two rankings, along with Pearson’s coefficient and Spearman’s rank order coefficients. The results for the comparison between the rankings for each task are shown in Table 3.

In comparing the crowd-generated rankings for the sentence-only and sentence-in-passage task, the results show a statistically significant aggregate difference in how the crowd ranks sentence difficulty with and without the surrounding passage. While the correlation between the two rankings is high, and the average normalized change in rank position is 7.7%, multiple sentences exhibited a large change in ranking. For example, the sentence ‘As a result, the police had little incentive to make concessions.’ was ranked significantly easier when presented out of context than when presented in context (rank change: -30 positions). For that example, the surrounding passage explained the rather complex political environment referred to indirectly in that sentence.

6.2 Feature Correlation with Rank Differences

To examine why sentences may be ranked as more or less difficult, depending on the context, we examined the correlation between a sentence’s change in rank (Sentence-Only Ranking minus the Sentence-in-Passage ranking) and the normalized difference in feature values between the sentence representation
Table 5: Sentence-Only and Sentence-In-Passage Ranking Correlation with Individual Features. Gold indicates only gold-standard questions were used to build ranking. All correlations have \( p < 0.0001 \) except those with an asterisk *, which have \( p < 0.001 \).

| Feature          | Sentence | Sentence (Gold) | Sentence-In-Passage | Sentence-In-Passage (Gold) |
|------------------|----------|-----------------|---------------------|---------------------------|
|                  | Pearson  | Spearman        | Pearson             | Spearman                  |
| AoA Avg          | 0.6971   | 0.7151          | 0.7366              | 0.7598                    |
| AoA Std Dev      | 0.6366   | 0.6396          | 0.7074              | 0.7385                    |
| AoA Max          | 0.7084   | 0.6814          | 0.8036              | 0.7877                    |
| Parser L.        | -0.4942  | -0.5297         | -0.4065*            | 0.4920                    |
| Reranker L.      | -0.4923  | -0.5280         | -0.4574*            | -0.4751                   |

and the remaining context representation. We found that percentage change in parser and reranker likelihoods had the most significant correlation (-0.33) with ranking change, as shown in Table 4.

To interpret this result, note that the parser and reranker likelihood represent the probability the parser and reranker models assign to the syntactic parse produced by the sentence. In other words, they are a measure of how likely it is that the sentence structure occurs, based on the model’s training data. If the difficulty of the sentence-in-passage is ranked higher than the sentence alone, this correlates with the target sentence having a syntactic structure with higher likelihood than the average of the surrounding sentence structures. This means that if a sentence that has a frequently-seen syntactic structure is in a passage with sentences that have less common structures, the sentence within the passage is more likely to be judged as more difficult. The reverse is also true: if a sentence that has a more unusual syntactic structure is in a passage with sentences with more familiar structures, the sentence without context is more likely to be ranking as more difficult.

We also examined the rank correlation of crowd-generated rankings with rankings produced by sorting sentences based on the value individual features. For this analysis, in addition to the full rankings, a ranking produced only by the gold standard examples, denoted Sentence(Gold), was constructed and included in the comparison. The gold standard questions consist of examples constructed by the authors to have a clear relative difficulty result. The rank correlations are shown in Table 5 for both tasks; all correlations are have \( p < 0.0001 \), except those with an asterisk, which have \( p < 0.001 \).

The evidence for what causes discrepancies in relative difficulty assessment between the sentence-only and sentence-in-passage conditions requires further exploration. While the correlation between the percentage change in probability of the parse and the difference in ranking is significant, it is not large. It does indicate that despite being explicitly told to only consider the sentence, the properties of the surrounding passage can indeed influence the perceived relative difficulty of the sentence.

7 Conclusion

Using a rich sentence representation based on lexical and syntactic features leveraged from previous work on document-level readability, we introduced and evaluated several models for predicting the relative reading difficulty of single sentences, with and without surrounding context. We found that while the best prediction performance was obtained by using all feature classes, simpler representations based on lexical features such as Age of Acquisition norms were surprisingly effective. The accuracy achieved by the best prediction model came within 5% of the oracle accuracy for both tasks.

Many of the features identified had a high correlation with the rankings produced by the crowd. This indicates that these features can be used to build a model of sentence difficulty. With the rankings built from crowdsourced judgments on sentence difficulty, small but significant differences were found in how sentences are ranked with and without the surrounding passages. This result shows that properties of the context of a sentence can change the perceived difficulty of a sentence.

We envision several next steps for this research. We plan to increase the number of sentences in our data set, so that additional more fine-grained features might be considered. For example, weights for lexical features could be more accurately estimated with more data. Our use of the crowd-based labels directly was intended to reduce noise in the ranking analysis, but we also intend to use the pairwise predictions produced by the logistic model as the in-
put to the aggregation model, so that rankings can be obtained for previously unseen sentences in operational settings. Another goal is to obtain absolute difficulty labels for sentences by calibrating ordinal ranges based on the relative ranking. Finally, we are interested in exploring further the effect of context on sentence difficulty.

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**Appendix**

### 7.1 Instructions for the sentence-only task

Our work concerns helping teachers find texts that are at just the right reading difficulty level for their students. In order to help us , the purpose of this task is to determine the relative reading difficulty of sentences, by comparing a pair of sentences. In each question, there are two sentences, labelled Sentence A and Sentence B. Please read both sentences, and then select the one, in your opinion, that would be more challenging to read and understand compared to the other.

For each sentence, consider which has more difficult vocabulary, that would likely be understood only by a more advanced reader. For example, the verb in I changed the settings is less difficult to understand than I readjusted the settings. Also, consider the complexity of the grammatical structure of each sentence. For example, The man is eating a sandwich has a less complex grammatical structure than A sandwich is being eaten by the man.

**Example 1:**

Sentence A: Each community has many different people who do different things.

Sentence B: Between him and Darcy there was a very steady friendship, in spite of great opposition of character.

All of the words in Sentence A would likely be understood by an elementary school student. In Sentence B, words such as steady and spite are more advanced words and are likely to be understood by more advanced readers. The structure of Sentence B is more advanced, as such phrases as in spite of great opposition of character are rarer than phrases in Sentence A. Therefore, Sentence B is more difficult than Sentence A.

**Example 2:**

Sentence A: But some photos and films appear to be authentic.

Sentence B: Its buildings were designed before cars became the standard mode of travel.

In Sentence A, the word authentic is more advanced, but the remainder of the words are likely to be understood by most readers. In Sentence B, mode would be considered an advanced word. Therefore, we can judge the difficulty of the vocabulary to be similar. However, the structure of Sentence B is more complex than in Sentence A. Therefore, Sentence B is more difficult than Sentence A.
Example 3:
Sentence A: North Korea frees American helicopter pilot Hall held for 13 days, allowing him to return home to Florida for New Year’s Day and keeping alive its nuclear deal with United States.
Sentence B: Whether or no, the mender of roads ran, on the sultry morning, as if for his life, down the hill, knee-high in dust, and never stopped till he got to the fountain.

In Sentence A, the words nuclear and the name North Korea are advanced. In Sentence B, the words mender and sultry are advanced, and more advanced than the words in Sentence A. While both sentences have difficult grammatical structures, Sentence B has a high number of commas, which in this case denotes a high number of clauses, which makes it more difficult than Sentence A. Therefore, Sentence B is more difficult than Sentence A. Note that although Sentence A is longer than Sentence B, Sentence B is more difficult.

Example 4:
Sentence A: Numerous experts agree that this picture may be unique.
Sentence B: Most kids backpacks can easily hold school necessities. Is one pack better than another or are they pretty much equal behind the brand name and the price tag? To find out, we bought a half-dozen moderately priced packs plus a messenger bag. They were all reported to be popular. We then asked 18 middle-school boys and girls to check them out. We ran lab tests for durability, water-resistance, and other practical stuff to generate the ratings below. The kids didn’t favor one backpack over another. But they quickly made it clear that they preferred a traditional backpack to the messenger bags single-strap design.

In Sentence A, the words experts and numerous are advanced. In Sentence B, there are no words that would be considered advanced. Therefore, Sentence A is more difficult than Sentence B. Note that Sentence A is more difficult despite being the shorter of the two sentences.

7.2 Instructions for the sentence in passage task
Our work concerns helping teachers find texts that are at just the right reading difficulty level for their students. In order to help us, the purpose of this task is to determine the relative reading difficulty of sentences, by comparing a pair of sentences. In each question, there are two underlined sentences, labelled Sentence A and Sentence B, within two passages. Please read the entirety of both passages. Then, select the underlined sentence that, in your opinion, would be more challenging to read and understand compared to the other underlined sentence. Please make your comparison based only on the text of the sentences.

For each sentence, consider which has more difficult vocabulary, that would likely be understood only by a more advanced reader. For example, the verb in I changed the settings is less difficult to understand than I readjusted the settings. Also, consider the complexity of the grammatical structure of each sentence in the passages. For example, The man is eating a sandwich has a less complex grammatical structure than A sandwich is being eaten by the man.

Example 1:
Sentence A: It all started when Miss Fritz, our fourth grade science teacher, was showing a video about the solar system and different planets. Halfway through the video, I noticed a sparkling metal disc, about the size of a quarter, lying on the floor. I kept trying to pay attention to the video, but found myself reaching over to grasp the shiny disk that was next to my desk. As soon as I touched the metal disk, something strange happened. I wasn’t in the classroom anymore. I was hovering in the air, way above the school. I could see the whole town, or rather the rooftops of the whole town. I was a little nervous, but also pretty excited. What was happening? How could I be floating?
Sentence B: Most kids backpacks can easily hold school necessities. Is one pack better than another or are they pretty much equal behind the brand name and the price tag? To find out, we bought a half-dozen moderately priced packs plus a messenger bag. They were all reported to be popular. We then asked 18 middle-school boys and girls to check them out. We ran lab tests for durability, water-resistance, and other practical stuff to generate the ratings below. The kids didn’t favor one backpack over another. But they quickly made it clear that they preferred a traditional backpack to the messenger bags single-strap design.

In Sentence A, words such as attention and grasp are more difficult words. The structure of Sentence A is also complex, containing three clauses. In Sentence B, the words are less difficult, and the sentence structure is relatively simple. Therefore, Sentence A is more difficult than Sentence B. Note that the passage of Sentence B contains many other difficult words, such as durability, and is a more difficult passage to read. Despite this, Sentence A is more difficult than Sentence B when comparing the contents of only the selected sentences.

Example 2:
Sentence A: In 1815 an English banker named Nathan Rothschild made his fortune by relying on
messages sent to him by carrier pigeons. English troops were fighting Napoleons forces in France, and the English were believed to be losing. A financial panic gripped London. Government bonds were offered at low prices. Few people noticed that Rothschild was snapping up these bonds when everyone else was desperately trying to sell them. He knew something others didn’t. A few days later, London learned the truth; the Duke of Wellington had defeated Napoleon at the battle of Waterloo. The value of the bonds soared, and Rothschild became fabulously wealthy . . . all because his pigeons had brought him news of the victory before anyone else knew of it.

Sentence B: Some pet birds, such as parrots, can be great talkers. Among the large parrots, the best talkers are African greys and Amazons. The most popular smaller parrots are the budgies, otherwise known as parakeets. One should remember that just because a certain kind of bird can talk does not mean it will talk. Each bird has a different personality. Some birds never learn to talk. Some may learn only a few words or sounds. Others seem to learn a large vocabulary easily, soaking up new words like some sort of feathered sponge. Although each bird is different, younger birds are more likely to learn to talk than older birds. Also, male birds are usually better talkers than females. However, if you teach a bird to whistle before it learns to talk, it may never learn to talk. This might be because whistling is easier for the bird.

In Sentence A, all of the words are at an average level, and the sentence structure is of average complexity. In Sentence B, there are more difficult words, such as vocabulary, and the sentence structure is more complex than that of Sentence A. Therefore, Sentence B is more difficult than Sentence A. Note that some of the topics in Sentence A, financial matters and the Napoleonic wars, which would be considered more advanced do not influence the fact that Sentence B is more difficult.

Example 3:

Sentence A: He spent months at his easel, often painting into the night, the only light coming from flickering gas lamps. I have always held that the grandest, most beautiful or wonderful in nature would, in capable hands, make the grandest, most beautiful or wonderful pictures, the artist later wrote. If I fail to prove this, I fail to prove myself worthy of the name painter. Thomas Moran proved himself more than worthy. His Grand Canyon of the Yellowstone, a monumental seven-by-12-foot oil painting, is one of the finest landscapes in 19th-century American art. While Moran worked in his studio, Hayden knocked on Congressional doors. With expedition photos and Morans vivid field sketches in hand, Hayden had an arsenal of visual ammunition to push forward the park legislation.

Sentence B: The choices in Connecticut and Massachusetts were easy to make, but how did other states choose their trees? The people in Maine and Minnesota picked conifer trees because the trees are used for lumber and shipbuilding, important industries in the two states. Maine chose the white pine, and Minnesota chose the red pine. The people of Alaska named the Sitka spruce as their official state tree. It provided a lightweight wood that served many purposes. Hawaii is the only state that chose a tree that was not originally from its own state. The people of Hawaii chose the candlenut tree, which originally came from southeastern Asia. The paste of candlenut kernels was once used to make candles. That is why it is called the candlenut tree. Virginia chose the flowering dogwood as its tree. The flowering dogwood blooms in the spring and grows throughout the state.

In Sentence A, worthy is an advanced word, and the construction of the sentence is more advanced. In Sentence B, all words would likely be understood by a lower-level reader, and despite the fact that it is longer than Sentence A, the structure is more common than Sentence B. Therefore, Sentence A is more difficult than Sentence B.

Example 4:

Sentence A: On the other hand, seeing a movie in a theater is an experience all its own. For one thing, you can see the movie on a wide screen as the filmmaker intended. A good film must be changed in some way to make it smaller in order to be viewed on a television screen. One way is known as the pan-and-scan method, which involves removing some of the details in the picture, and this results in an image that is not complete. The other way, called letterboxing, keeps the image the way it is on the big screen, with one annoying exception: because the big-screen version is wide, the same picture on a television screen must be long and narrow, with black strips above and below it.
Sentence B: Like all good farmers, Okonkwo had begun to sow with the first rains. He had sown four hundred seeds when the rains and the heat returned. He watched the sky all day for signs of rain clouds and lay awake all night. Ready at dawn, he returned to his farm to the sight of withering tendrils. He had tried to protect them from the smoldering earth by making rings of sisal leaves around them. But by the end of the day the sisal rings were burned dry and gray. He changed them everyday, and prayed that the rain might fall in the night. But the drought continued for eight market weeks and the yams were killed.

In Sentence A, there are no difficult words. In Sentence B, there are several difficult words, such as withering and tendrils. Sentence A has a relatively simple structure, while Sentence B is more complex, as it has an embedded infinitive. Therefore, Sentence B is more difficult than Sentence A. Note that this is the case despite Sentence A being longer than Sentence B.