Manipulating the Difficulty of C-Tests

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Abstract
We propose two novel manipulation strategies for increasing and decreasing the difficulty of C-tests automatically. This is a crucial step towards generating learner-adaptive exercises for self-directed language learning and preparing language assessment tests. To reach the desired difficulty level, we manipulate the size and the distribution of gaps based on absolute and relative gap difficulty predictions. We evaluate our approach in corpus-based experiments and in a user study with 60 participants. We find that both strategies are able to generate C-tests with the desired difficulty level.

1 Introduction
Learning languages is of utmost importance in an international society and formulated as a major political goal by institutions such as the European Council, who called for action to “teaching at least two foreign languages” (EC, 2002, p. 20). But also beyond Europe, there is a huge demand for language learning worldwide due to increasing globalization, digital communication, and migration.

Among multiple different learning activities required for effective language learning, we study one particular type of exercise in this paper: C-tests are a special type of cloze test in which the second half of every second word in a given text is replaced by a gap (Klein-Braley and Raatz, 1982). Figure 1 (a) shows an example. To provide context, the first and last sentences of the text do not contain any gaps. C-tests rely on the reduced redundancy principle (Spolsky, 1969) arguing that a language typically employs more linguistic information than theoretically necessary to communicate unambiguously. Proficient speakers intuitively understand an utterance even if the level of redundancy is reduced (e.g., when replacing a word’s suffix with a gap), whereas learners typically rely on the redundant signal to extrapolate the meaning of an utterance.

Besides general vocabulary knowledge, C-tests require orthographic, morphologic, syntactic, and semantic competencies (Chapelle, 1994) to correctly fill in all gaps, which make them a frequently used tool for language assessment (e.g., placement tests). Given that C-tests can be easily generated automatically by introducing gaps into an arbitrary text and that there is usually only a single correct answer per gap given its context, C-tests are also relevant for self-directed language learning and massive open online courses (MOOC), where large-scale personalized exercise generation is necessary.

A crucial question for such tasks is predicting and manipulating the difficulty of a C-test. For language assessment, it is important to generate C-tests with a certain target difficulty to allow for comparison across multiple assessments. For self-directed language learning and MOOCs, it is important to adapt the difficulty to the learner’s current skill level, as an exercise should be neither too easy nor too hard so as to maximize the learning effect and avoid boredom and frustration (Vygotsky, 1978). Automatic difficulty prediction of C-tests is hard, even for humans, which is why there have been many attempts to theoretically explain C-test difficulty (e.g., Sigott, 1995) and to model features used in machine learning systems for automatic difficulty prediction (e.g., Beinborn et al., 2014).

While state-of-the-art systems produce good prediction results compared to humans (Beinborn, 2016), there is yet no work on automatically manipulating the difficulty of C-tests. Instead, C-tests are generated according to a fixed scheme and manually post-edited by teachers, who might use the predictions as guidance. But this procedure is extremely time-consuming for language assessment and no option for large-scale self-directed learning.

In this paper, we propose and evaluate two strategies for automatically changing the gaps of a C-test in order to reach a given target difficulty. Our first
strategy varies the distribution of the gaps in the underlying text and our second strategy learns to decide to increase or decrease a gap in order to make the test easier or more difficult. Our approach breaks away from the previously fixed C-test creation scheme and explores new ways of motivating learners by using texts they are interested in and generating tests from them at the appropriate level of difficulty. We evaluate our strategies both automatically and in a user study with 60 participants.

2 Related Work

In language learning research, there is vast literature on cloze tests. For example, Taylor (1953) studies the relation of cloze tests and readability. In contrast to C-tests (Klein-Braley and Raatz, 1982), cloze tests remove whole words to produce a gap leading to more ambiguous solutions.

Chapelle and Abraham (1990) contrast four types of cloze tests, including fixed-ratio cloze tests replacing every $i^{th}$ word with a gap, rational cloze tests that allow selecting the words to replace according to the language trait that should be assessed, multiple-choice tests, and C-tests. Similar to our work, they conduct a user study and measure the difficulty posed by the four test types. They find that cloze tests replacing entire words with a gap are more difficult than C-tests or multiple-choice tests. In our work, we go beyond this by not only varying between gaps spanning the entire word (cloze test) or half of the word (C-test), but also changing the size of the C-test gaps. Laufer and Nation (1999) propose using C-tests to assess vocabulary knowledge. To this end, they manually construct C-tests with only a single gap, but use larger gaps than half of the word’s letters. Our work is different to these previous works, since we test varying positions and sizes for C-test gaps and, more importantly, we aim at manipulating the difficulty of a C-test automatically by learning to predict the difficulty of the gaps and how their manipulation affects the difficulty.

Previous work on automatically controlling and manipulating test difficulty has largely focused on multiple-choice tests by generating appropriate distractors (i.e., incorrect solutions). Wojatzki et al. (2016) avoid ambiguity of their generated distractors, Hill and Simha (2016) fit them to the context, and Perez and Cuadros (2017) consider multiple languages. Further work by Zesch and Melamud (2014), Beinborn (2016), and Lee and Luo (2016) employ word difficulty, lexical substitution, and the learner’s answer history to control distractor difficulty.

For C-tests, Kamimoto (1993) and Sigott (2006) study features of hand-crafted tests that influence the difficulty, and Beinborn et al. (2014) and Beinborn (2016) propose an automatic approach to estimate C-test difficulty, which we use as a starting point for our work.

Another related field of research in computer-assisted language learning is readability assessment and, subsequently, text simplification. There exists ample research on predicting the reading difficulty for various learner groups (Hancke et al., 2012; Collins-Thompson, 2014; Pilán et al., 2014). A specific line of research focuses on reducing the reading difficulty by text simplification (Chandrasekar et al., 1996). By reducing complex texts or sentences to simpler ones, more texts are made accessible for less proficient learners. This is done either on a word level by substituting difficult words with easier ones (e.g., Kilgarriff et al., 2014) or on a sentence level (Vajjala and Meurers, 2014). More recent work also explores sequence-to-sequence neural network architectures for this task (Nisioi et al., 2017). Although the reading difficulty of a text partly contributes to the overall exercise difficulty of C-tests, there are many other factors with a substantial influence (Sigott, 1995). In particular, we can generate many different C-tests from the same text and thus reading difficulty and text simplification alone are not sufficient to determine and manipulate the difficulty of C-tests.
3 Task Overview

We define a C-test $T = (u, w_1, \ldots, w_2n, v, G)$ as a tuple of left and right context $u$ and $v$ (typically one sentence) enframing $2n$ words $w_i$ where $n = |G|$ is the number of gaps in the gap set $G$. In each gap $g = (i, \ell) \in G$, the last $\ell$ characters of word $w_i$ are replaced by a blank for the learners to fill in. Klein-Braley and Raatz (1982) propose the default gap generation scheme DEF with $G = \{(2j, \lfloor \frac{|w_{2j}|}{2} \rfloor) \mid 1 \leq j \leq n\}$ in order to trim the (larger) second half of every second word. Single-letter words, numerals, and punctuation are not counted as words $w_i$ and thus never contain gaps. Figure 1 (a) shows an example C-test generated with the DEF scheme.

A major limitation of DEF is that the difficulty of a C-test is solely determined by the input text. Most tests, however, yield a medium difficulty (cf. section 6) and thus do not allow any adaptation to beginners or advanced learners unless they are manually postprocessed. In this paper, we therefore propose two strategies to manipulate the gap set $G$ in order to achieve a given target difficulty $\tau \in [0, 1]$ ranging from small values for beginners to high values for advanced learners. To estimate the difficulty $d(T) = \frac{1}{n^2} \sum_{g \in G} d(g)$ of a C-test $T$, we aggregate the predicted difficulty scores $d(g)$ of each gap. In section 4, we reproduce the system by Beinborn (2016) modeling $d(g) \approx e(g)$ as the estimated mean error rates $e(g)$ per gap across multiple learners, and we conduct additional validation experiments on a newly acquired dataset.

The core of our work is the manipulation of the gap set $G$ in order to minimize the difference $|d(T) - \tau|$ between the predicted test difficulty $d(T)$ and the requested target difficulty $\tau$. To this end, we employ our difficulty prediction system for validation and propose a new regression setup that predicts the relative change of $d(g)$ when manipulating the size $\ell$ of a gap.

Figure 2 shows our system architecture: Based on a text corpus, we generate C-tests for arbitrary texts (e.g., according to the learner’s interests). Then, we manipulate the difficulty of the generated text by employing the difficulty prediction system in order to reach the given target difficulty $\tau$ for a learner (i.e., the estimated learner proficiency) to provide neither too easy nor too hard tests.

4 C-Test Difficulty Prediction

Beinborn et al. (2014) and Beinborn (2016) report state-of-the-art results for the C-test difficulty prediction task. However, there is yet no open-source implementation of their code and there is little knowledge about the performance of newer approaches. Therefore, we (1) conduct a reproduction study of Beinborn’s (2016) system, (2) evaluate newer neural network architectures, and (3) validate the results on a newly acquired dataset.

Reproduction study. We obtain the original software and data from Beinborn (2016). This system predicts the difficulty $d(g)$ for each gap within a C-test using a support vector machine (SVM; Vapnik, 1998) with 59 hand-crafted features. The proposed features are motivated by four factors which are deemed important for assessing the gap difficulty: item dependency, candidate ambiguity, word difficulty, and text difficulty. We use the same data (819 filled C-tests), metrics, and setup as Beinborn (2016). That is, we perform leave-one-out cross validation (LOOCV) and measure the Pearson correlation $\rho$, the rooted mean squared error RMSE, and the quadratic weighted kappa $q$ as reported in the original work.

The left hand side of table 1 shows the results of our reproduced SVM compared to the original SVM results reported by Beinborn (2016). Even though we reuse the same code as in their original work, we observe small differences between our reproduction and the previously reported scores.

We were able to trace these differences back to libraries and resources which have been updated and thus changed over time. One example is Ubuntu’s system dictionary, the American English dictionary words (wamerican), on which the original system relies. We experiment with different versions of the dictionary between Ubuntu 14.04 (wamerican v.7.1.1) and 18.04 (wamerican v.2018.04.16-1) and observe differences of one or two percentage points. As a best practice, we suggest to fix the versions of all resources and avoid any system dependencies.

Neural architectures. We compare the system with deep learning methods based on multi-layer
To cope for the non-deterministic behavior of neural networks, we repeat all experiments ten times with different random weight initializations and report the averaged results (Reimers and Gurevych, 2017). While the MLP is trained similarly as our reproduced SVM, the BiLSTM receives all gaps of a C-test as sequential input. We hypothesize that this sequence regression setup is better suited to capture gaps interdependencies. As can be seen from the table, the results of the neural architectures are, however, consistently worse than the SVM results. We analyze the RMSE on the train and development sets and observe a low bias, but a high variance. Thus, we conclude that although neural architectures are able to perform well for the difficulty prediction task, they lack a sufficient amount of data to generalize.

**Experiments on new data.** To validate the results and assess the robustness of the difficulty prediction system, we have acquired a new C-test dataset from our university’s language center. 803 participants of placement tests for English courses solved five C-tests (from a pool of 53 different C-tests) with 20 gaps each. Similar to the data used by Beinborn (2016), we use the error rates \( e(g) \) for each gap as the \( d(g) \) the methods should predict.

The right-hand side of table 1 shows the performance of our SVM and the two neural methods. The results indicate that the SVM setup is well-suited for the difficulty prediction task and that it successfully generalizes to new data.

**Final model.** We train our final SVM model on all available data (i.e., the original and the new data) and publish our code source and the trained model on GitHub. Similar to Beinborn (2016), we cannot openly publish our dataset due to copyright.

### Table 1: Results of the difficulty prediction approaches.

| Model         | Original data | New data |
|---------------|---------------|----------|
|               | \( \rho \)   | RMSE     | \( q_w \) | \( \rho \) | RMSE     | \( q_w \) |
| SVM (original)| .50 .23       | .44      | –        | –        | –        | –        |
| SVM (reproduced)| .49 .24     | .47      | .50      | .21 .39  | .24 .27  |
| MLP           | .42 .25       | .31      | .41      | .22 .25  |          |          |
| BiLSTM        | .49 .24       | .35      | .39      | .24 .27  |          |          |

To validate the re-

**5 C-Test Difficulty Manipulation**

Given a C-test \( T = (u, w_1, \ldots, w_{2n}, v, G) \) and a target difficulty \( \tau \), the goal of our manipulation strategies is to find a gap set \( G \) such that \( d(T) \) approximates \( \tau \). A naïve way to achieve this goal would be to generate C-tests for all texts in a large corpus with the DEF scheme and use the one with minimal \( |d(T) - \tau| \). However, most corpora tend to yield texts of a limited difficulty range that only suit a specific learner profile (cf. section 6). Another drawback of the naïve strategy is that it is difficult to control for the topic of the underlying text and in the worst case, the necessity to search through a whole corpus for selecting a fitting C-test.

In contrast to the naïve strategy, our proposed manipulation strategies are designed to be used in real time and manipulate any given C-test within 15 seconds at an acceptable quality. Both strategies operate on a given text (e.g., on a topic a learner is interested in) and manipulate its gap set \( G \) in order to come close to the learner’s current language skill. The first strategy varies the position of the gaps and manipulate any given C-test within 15 seconds at an acceptable quality. In the worst case, the necessity to search through a whole corpus for selecting a fitting C-test.

### 5.1 Gap Selection Strategy

The default C-test generation scheme DEF creates a gap in every second word \( w_{2j} \), \( 1 \leq j \leq n \). The core idea of our first manipulation strategy SEL is to distribute the \( n \) gaps differently among the all \( 2n \) words in order to create gaps for easier or harder words than in the default generation scheme. Therefore, we use the difficulty predic-

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1. Network parameters and a description of the tuning process are provided in this paper’s appendix.
2. [https://github.com/UKPLab/acl2019-ctest-difficulty-manipulation](https://github.com/UKPLab/acl2019-ctest-difficulty-manipulation)
3. On an Intel-i5 with 4 CPUs and 16 GB RAM.
tion system to predict \( d(g) \) for any possible gap \( g \in G_{\text{FULL}} = \{ (i, \lfloor \frac{w_i}{2} \rfloor) \mid 1 \leq i \leq 2n \} \) (i.e., assuming a gap in all words rather than in every second word). Then, we alternate between adding gaps to the resulting \( G_{\text{DEL}} \) that are easier and harder than the preferred target difficulty \( \tau \), starting with those having a minimal difference \( |d(g) - \tau| \).

Algorithm 1 shows this procedure in pseudocode and figure 1 shows a C-test whose difficulty has been increased with this strategy. Note that it has selected gaps at corresponding rather than with, and soothsayers rather than the. Our proposed algorithm is optimized for runtime. An exhaustive search would require testing \( \binom{2n}{n} \) combinations if the number of gaps is constant. For \( n = 20 \), this yields 137 billion combinations. While more advanced optimization methods might find better gap selections, we show in section 6 that our strategy achieves good results.

5.2 Gap Size Strategy

Our second manipulation strategy SIZE changes the size of the gaps based on a pre-defined gap set. Increasing a gap \( g = (i, \ell) \) by one or more characters, yielding \( g' = (i, \ell + k) \), increases its difficulty (i.e., \( d(g') \geq d(g) \)), while smaller gaps make the gap easier. We identify a major challenge in estimating the effect of increasing or decreasing the gap size on the gap difficulty. Although \( d(g') \) could be estimated using the full difficulty prediction system, the search space is even larger than for the gap selection strategy, since each of the \( n \) gaps has \( w_i - 2 \) possible gap sizes to test. For \( n = 20 \) and an average word length of six, this amounts to one trillion possible combinations.

We therefore propose a new approach to predict the relative difficulty change of a gap \( g = (i, \ell) \) when increasing the gap size by one letter \( \Delta_{\text{inc}}(g) \approx d(g') - d(g) \), \( g' = (i, \ell + 1) \) and correspondingly when decreasing the gap size by one letter \( \Delta_{\text{dec}}(g) \approx d(g) - d(g') \), \( g' = (i, \ell - 1) \). The notion of relative difficulty change enables gap size manipulation in real time, since we do not have to invoke the full difficulty prediction system for all combinations. Instead, we can incrementally predict the effect of changing a single gap.

To predict \( \Delta_{\text{inc}} \) and \( \Delta_{\text{dec}} \), we train two SVMs on all gap size combinations of 120 random text from the Brown corpus (Francis, 1965) using the following features: predicted absolute gap difficulty, word length, new gap size, modified character, a binary indicator if the gap is at a th sound, and logarithmic difference of alternative solutions capturing the degree of ambiguity with varying gap size.

With a final set of only six features, our new models are able to approximate the relative difficulty change very well deviating from the original system’s prediction only by 0.06 RMSE for \( \Delta_{\text{inc}} \) and 0.13 RMSE for \( \Delta_{\text{dec}} \). The predictions of both models highly correlate with the predictions achieving a Pearson’s \( \rho \) of over 0.8. Besides achieving a much faster average runtime of 0.056 seconds for the relative model vs. 11 seconds for the full prediction of a single change, we can invoke the relative model iteratively to estimate \( d(T) \) for multiple changes of the gap size more efficiently.

The final manipulation strategy then requires just a single call of the full prediction system. If \( d(T) < \tau \), we incrementally increase the gap sizes to make \( T \) more difficult and, vice-versa, decrease the gap sizes if \( d(T) > \tau \). In each iteration, we modify the gap with the highest relative difficulty change in order to approach the given target difficulty \( \tau \) as quickly as possible. Algorithm 2 shows pseudocode for creating \( G_{\text{size}} \) with increased difficulty (i.e., \( d(T) < \tau \)) based on the default gap scheme DEF. The procedure for \( d(T) > \tau \) works analogously, but using \( \Delta_{\text{dec}} \) and decreasing the gap size. Figure 1 (c) shows a much easier version of the example C-test, in which a learner often only has to complete the last one or two letters.

6 Evaluation of the Manipulation System

To evaluate our C-test manipulation strategies, we first test their ability to cover a higher range of target difficulties than the default generation scheme and then measure how well they meet the desired target difficulty for texts from different domains. We conduct our experiments on 1,000 randomly chosen paragraphs for each of the Gutenberg (Lahiri, 2014), Reuters (Lewis et al., 2004), and Brown (Francis, 1965) corpora. We conduct our experiments on English, but our strategies can be adapted to many related languages.
Difficulty range. The black •-marked line of figure 3 shows the distribution of $d(T)$ based on our difficulty prediction system when creating a C-test with the default generation scheme DEF for all our samples of the Brown corpus. The vast majority of C-tests range between 0.15 and 0.30 with a predominant peak at 0.22.

To assess the maximal difficulty range our strategies can achieve, we generate C-tests with maximal ($\tau = 1$) and minimal target difficulty ($\tau = 0$) for both strategies $S \in \{\text{SEL, SIZE}\}$, which are also shown in figure 3 as $(S, \tau)$. Both strategies are able to clearly increase and decrease the test difficulty in the correct direction and they succeed in substantially increasing the total difficulty range beyond DEF. While SEL is able to reach lower difficulty ranges, it has bigger issues with generating very difficult tests. This is due to its limitation to the fixed gap sizes, whereas SIZE can in some cases create large gaps that are ambiguous or even unsolvable. Since SIZE is, however, limited to the 20 predefined gaps, it shows a higher variance. Especially short gaps such as is and it cannot be made more difficult. Combining the two strategies is thus a logical next step for future work, building upon our findings for both strategies. We make similar observations on the Reuters and Gutenberg corpora and provide the respective figures in the appendix.

Manipulation quality. We finally evaluate how well each strategy $S$ reaches a given target difficulty. That is, we sample a random corpus text and $\tau$, create the C-test using strategy $S$, predict the test difficulty $d(T)$ and measure its difference to $\tau$ using RMSE. Table 2 shows the results for our three corpora. Throughout all three corpora, both manipulation strategies perform well. SEL consistently outperforms SIZE, which matches our observations from the previous experiment. Mind that these results depend on the quality of the automatic difficulty predictions, which is why we conduct a user-based evaluation in the next section.

7 User-based Evaluation

Hypothesis. To evaluate the effectiveness of our manipulation strategies in a real setting, we conduct a user study and analyze the difficulty of the manipulated and unmanipulated C-tests. We investigate the following hypothesis: When increasing a test’s difficulty using strategy $S$, the participants will make more errors and judge the test harder than a default C-test and, vice versa, when decreasing a test’s difficulty using $S$, the participants will make less errors and judge the test easier.

Experimental design. We select four different English texts from the Brown corpus and shorten them to about 100 words with keeping their paragraph structure intact. None of the four texts is particularly easy to read with an average grade level above 12 and a Flesh reading ease score ranging between 25 (very difficult) to 56 (fairly difficult). In the supplementary material, we provide results of an automated readability analysis using standard metrics. From the four texts, we then generate the C-tests $T_i$, $1 \leq i \leq 4$ using the default generation scheme DEF. All tests contain exactly $n = 20$ gaps and their predicted difficulties $d(T_i)$ are in a mid range between 0.24 and 0.28. $T_1$ remains unchanged in all test conditions and is used to allow the participants to familiarize with the task. For the remaining three tests, we generate an easier variant $T_i^{S, \text{dec}}$ with target difficulty $\tau = 0.1$ and a harder variant $T_i^{S, \text{inc}}$ with $\tau = 0.5$ for both strategies $S \in \{\text{SEL, SIZE}\}$.

From these tests, we create 12 sequences of four C-tests that we give to the participants. Each participant receives $T_1$ first to familiarize with the task. Then, they receive one easy $T_i^{S, \text{dec}}$, one default $T_i$, and one hard $T_i^{S, \text{inc}}$ C-test for the same strategy $S$ based on the texts $i \in \{2, 3, 4\}$ in random order without duplicates (e.g., the sequence $T_1 T_2^{S, \text{dec}} T_3 T_4^{S, \text{inc}}$). Having finished a C-test, we ask them to judge the difficulty of this test on a
five-point Likert scale ranging from *too easy* to *too hard*. After solving the last test, we additionally collect a ranking of all four tests by their difficulty.

**Data collection.** We collect the data from our participants with a self-implemented web interface for solving C-tests. We create randomized credentials linked to a unique ID for each participant and obfuscate their order, such that we can distinguish them but cannot trace back their identity and thus avoid collecting any personal information. Additionally, we ask each participant for their consent on publishing the collected data. For experiments with a similar setup and task, we obtained the approval of the university’s ethics commission. After login, the participants receive instructions and provide a self-assessment of their English proficiency and their time spent on language learning. The participants then solve the four successive C-tests without knowing the test difficulty or the manipulation strategy applied. They are instructed to spend a maximum of five minutes per C-test to avoid time-based effects and to prevent them from consulting external resources, which would bias the results.

**Participants.** A total of 60 participants completed the study. We uniformly distributed the 12 test sequences (six per strategy), such that we have 30 easy, 30 default, and 30 hard C-test results for each manipulation strategy. No participant is native in English, 17 are taking language courses, and 57 have higher education or are currently university students. The frequency of their use of English varies, as we found a similar number of participants using English daily, weekly, monthly, and (almost) never in practice. An analysis of the questionnaire is provided in the paper’s appendix.

**Hypothesis testing.** We evaluate our hypothesis along three dimensions: (1) the actual error rate of the participants, (2) the perceived difficulty after each individual C-test (Likert feedback), and (3) the participants’ final difficulty ranking. While the latter forces the participants to provide an explicit ranking, the former allows them to rate C-tests equally difficult. We conduct significance testing at the Bonferroni-corrected $\alpha = 0.05 / 2 = 0.025$ for each dimension using one-tailed $t$-tests for the continuous error rates and one-tailed Mann–Whitney $U$ tests for the ordinal-scaled perceived difficulties and rankings. Figure 4 shows notched boxplots of our results.

To test our hypothesis, we first formulate a null hypothesis that (a) the mean error rate, (b) the median perceived difficulty (Likert feedback), and (c) the median rank of the manipulated tests equal the default tests. While the participants have an average error rate of 0.3 on default C-tests, the $T_4^{SEL, dec}$ tests are significantly easier with an average error rate of 0.15 ($t = 7.49, p < 10^{-5}$) and the $T_4^{SEL, inc}$ tests are significantly harder with an average error rate of 0.49 ($t = 7.49, p < 10^{-5}$), so we can safely reject the null hypothesis for error rates.

Table 3 shows the error rates per C-test and strategy. Both SEL and SIZE are overall able to significantly ($p < 0.025$) increase and decrease the test’s difficulty over DEF, and with the exception of $T_4^{SEL, dec}$, the effect is also statistically significant for all individual text and strategy pairs. Figure 5 shows the 30 participants per strategy on the $x$-axis and their error rates in their second to fourth C-test on the $y$-axis. C-tests, for which we increased the difficulty ($S, inc$), yield more errors than C-tests with decreased difficulty ($S, dec$) in all cases. The easier tests also yield less errors than the test with the default scheme DEF in most cases. While hard tests often have a much higher error rate than DEF, we find some exceptions, in which the participant’s error rate is close or even below the DEF error rate.

Regarding the perceived difficulty, we find that the participants judge the manipulated C-tests with lower $d(T)$ as easier on both the Likert scale ($z = 6.16, p < 10^{-5}$) and in the rankings ($z = 6.59, p < 10^{-5}$) based on the Mann-Whitney-$U$ test. The same is true for C-tests that have been manipulated to a higher difficulty level, which the participant judge harder ($z = -4.57, p < 10^{-5}$) and rank higher ($z = -3.86, p < 6 \times 10^{-5}$). We therefore reject the null hypotheses for the Likert feedback and the rankings and conclude that both strategies can effectively manipulate a C-test’s difficulty.

**Manipulation quality.** We further investigate if the strategies yield different difficulty levels. There-

|                | easy (dec) | default | hard (inc) |
|----------------|------------|---------|------------|
| $T_1$          | -          | .30     | -          |
| $T_2$          | .17*       | .34     | .44*       |
| $T_3$          | .16*       | .27     | .43*       |
| $T_4$          | .28        | .30     | .43* .45*  |
| **Average**    | .20*       | .10*    | .30 .53* .44* |

Table 3: Mean error rates $e(T)$ per text and strategy. Results marked with * deviate significantly from DEF
We furthermore investigate how well our strategies perform in creating C-tests with the given target difficulty $\tau$. Table 4 shows the RMSE for $e(T)$ and $d(T)$ as well as for $e(T)$ and $\tau$ for both strategies. As expected, our difficulty prediction system works best for C-tests generated with DEF as they use the same scheme as C-tests in the training data. Though slightly worse than for DEF, we still find very low RMSE scores for manipulated C-tests. This is especially good when considering that the system’s performance on our newly acquired dataset yields and RMSE of 0.21 (cf. section 6). Computing the RMSE with respect to our chosen target difficulties $\tau$ yields equally good results for SEL and exceptionally good results for SIZE. Figure 6 displays $d(T)$ in comparison to $e(T)$ for each individual text and strategy. With the exception of $T^\text{SEL,inc}_2$ and $T^\text{SEL,dec}_4$, all predictions are close to the optimum (i.e., the diagonal) and also close to the desired target difficulty $\tau$.

In a more detailed analysis, we find two main sources of problems demanding further investigation: First, the difficulty prediction quality when deviating from DEF and second, the increasing ambiguity in harder C-tests. However, it underestimates the $d(T) = 0.11$ for $T^\text{SEL,dec}_4$ (the same text used in figure 1), for which we found an actual error rate of 0.28. This is due to chains of four successive gaps, such as:

$$
gap \quad g$$

| $g$ | i_ | wh_ | w_ | a_ |
|-----|----|-----|----|----|
| $d(g)$ | 0.17 | 0.22 | 0.23 | 0.19 |
| $e(g)$ | 0.70 | 0.40 | 0.10 | 0.20 |

As the prediction system has been trained only on DEF-generated C-tests, it underestimates $d(g)$ for cases with limited context. It will be interesting for future work to focus on modeling gap interdependencies in C-tests deviating from DEF.

Another issue we observe is that the gap size strategy might increase the ambiguity of the C-test. In the standard scheme, there is in most cases only a single correct answer per gap. In $T^\text{SIZE,inc}_2$, however, the SIZE strategy increased the gap of the
word professional to its maximal length yielding p. One participant answered popularising for this gap, which also fits the given context. We carefully checked our dataset for other ambiguity, but only found one additional case: In $T_3$, instead of the word close, 13 participants out of 30 used clear as a modifier of correspondence, which both produce meaningful contexts. Given that this case is already ambiguous in the DEF scheme yielding the gap cl, we conclude that the issue is not severe, but that the difficulty prediction system should be improved to better capture ambiguous cases; for example, by introducing collocational features weighted by their distribution within a corpus into $\Delta_{inc}$ and $\Delta_{dec}$.

8 Conclusion

In this work, we proposed two novel strategies for automatically manipulating the difficulty of C-test exercises. Our first strategy selects which words should be turned into a gap, and the second strategy learns to increase or decrease the size of the gaps. Both strategies automatically predict the difficulty of a test to make informed decisions. To this end, we reproduced previous results, compared them to neural architectures, and tested them on a newly acquired dataset. We evaluate our difficulty manipulation pipeline in a corpus-based study and with real users. We show that both strategies can effectively manipulate the C-test difficulty, as both the participants’ error rates and their perceived difficulty yield statistically significant effects. Both strategies reach close to the desired difficulty level.

Our error analysis points out important directions for future work on detecting ambiguous gaps and modeling gap interdependencies for C-tests deviating from the default generation scheme. An important observation is that manipulating the gaps’ size and position does not only influence the C-test difficulty, but also addresses different competencies (e.g., requires more vocabulary knowledge or more grammatical knowledge). Future manipulation strategies that take the competencies into account have the potential to train particular skills and to better control the competencies required for a placement test. Another strand of research will be combining both strategies and deploying the manipulation strategies in a large scale testing platform that allows the system to adapt to an individual learner over time. A core advantage of our manipulation strategies is that we can work with any given text and thus provide C-tests that do not only have the desired difficulty, but also integrate the learner’s interest or the current topic of a language course.

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A C-Test Difficulty Manipulation

Feature description for $\Delta_{\text{inc}}$ and $\Delta_{\text{dec}}$. We provide an extended feature description for the subset of features used for our relative difficulty prediction models $\Delta_{\text{inc}}$ and $\Delta_{\text{dec}}$. Features marked with * are also used by the absolute difficulty prediction model proposed by Beinborn (2016). For a gap $g = (i, \ell)$ in word $w_i$, we define:

- the predicted absolute gap difficulty $d(g)$ for the initial C-test created with DEF obtained from our reproduced difficulty prediction system, see line 3 of algorithm 2 (PS),
- the word length $|w_i|$ (WL*),
- the new gap size $\ell \pm 1$ after modification (GL*),
- the modified character $w_i[\ell]$ when increasing or decreasing the gap (CH),
- a binary indicator if the gap is after a th sound (RG*), and
- the logarithmic difference of alternative solutions (LD*) capturing the change in the degree of ambiguity when increasing or decreasing $\ell$.

Feature ablation test. We conduct feature ablation tests to evaluate the impact of each feature on our relative difficulty prediction models $\Delta_{\text{inc}}$ and $\Delta_{\text{dec}}$. Both models were evaluated on all gap size combinations for 120 random texts from the Brown corpus (Francis, 1965) with a three-fold cross-validation. Table 5 shows the performance increase for each model after including each feature. RMSE shows the deviation and $\rho$ the correlation of our relative difficulty prediction compared to the absolute difficulty prediction. Although the increase in performance with RG is not substantial, we decided to include it as a meaningful feature which measures the impact for increasing or decreasing the gap size in words starting with th.

B Neural Network Parameters

Although obtaining state-of-the-art results in many tasks, the deep neural networks we evaluated during our preliminary experiments did perform worse than the SVM. We performed parameter tuning with 100 randomly initialized configurations for both, MLP and BiLSTM. We tune the following parameters:

- Number of hidden layers $H_l \in [1, \ldots, 5]$
- Number of hidden units $H_u \in [50, \ldots, 200]$
- Dropout rate $D_x \in [0.1, \ldots, 0.5]$

We use Adam with Nesterov Momentum (Dozat, 2016) as our optimizer and keep the batch size at 5 for both models. All models are trained for 200 epochs with an early stopping after 10 epochs with no improvement of the loss. Figure 7 shows the resulting architectures of both models after tuning. Since our goal is to output regression values, we use a linear activation function in the output layer.

In preliminary experiments, we also tuned and evaluated BiLSTMs including soft attention, however, they performed even worse than the models without any attention. Analyzing the results of the best performing attention based model showed that it had a strong bias towards predicting the mean value of the whole training set. Furthermore, similar to the other neural models, it showed a low error on the training set (low bias) and a rather high error on the development set (high variance), indicating a lack of training data.

C Evaluation of the Manipulation System

Results for additional corpora. Figure 8 and figure 9 show our results on the Gutenberg (Lahiri, 2014) and the Reuters (Lewis et al., 2004) corpora. As already discussed in the main paper, we observe very similar distributions for DEF, SEL, and SIZE across both corpora matching our descriptions for the Brown (Francis, 1965) corpus.
Figure 7: Final, tuned architectures of our BiLSTM (left) and MLP (right) models.

We further compute $\tau_{\text{max}} - \tau_{\text{min}}$ for SEL and SIZE for each text within a corpus and thus, measure the difficulty range both strategies are able to cover for a single text. As figure 10 shows, SEL achieves a larger difficulty range, whereas considerably more C-tests achieve higher difficulty levels when generated with SIZE. We again observe very similar distributions throughout the three corpora.

Figure 8: Difficulty distribution of exercises generated with DEF, SEL, and SIZE for extreme $\tau$ values on the Gutenberg corpus.

Figure 9: Difficulty distribution of exercises generated with DEF, SEL, and SIZE for extreme $\tau$ values on the Reuters corpus.

Figure 10: Error rate range ($\tau_{\text{max}} - \tau_{\text{min}}$) of exercises generated with SEL and SIZE for all three corpora.
D User-based Evaluation

Questionnaire. At the begin of our study, our participants answered a questionnaire for a self-assessment of their English proficiency described in figure 11. We partitioned our questionnaire into three sections asking about 1) our participants’ English proficiency (Q1, Q2), 2) their learning habits and goals (Q4), and 3) other languages they have been learning (Q3, Q5, Q6).

Q1: Please estimate your current language proficiency in English
A1: ○ Beginner (A1) ○ Elementary (A2) ○ Intermediate (B1) ○ Upper Intermediate (B2) ○ Advanced (C1) ○ Proficiency (C2)
Q2: I studied English for about ___ years.
Q3: Do you participate in any language learning courses (for example, at your university, evening school,...) if yes, than which ones?
A3: ○ Yes, __________. ○ No.
Q4: How often do you practice English?
A4: ○ Never ○ Monthly ○ Weekly ○ Daily
Q5: What is your native language?
A5: ____________________
Q6: Have you tried learning other languages before? If yes, than which ones?
A6: ○ Yes, __________. ○ No.

Figure 11: Self-assessment questionnaire.

Answers. As described in the main paper, 17 participants are taking in language courses (Q3). Overall, 41 participants have tried to learn a second language (Q6). The exact answers can be found in the data we provide. Note, that not all participants provided the language which they attempted to learn since this was not mandatory. Figure 12–14 shows our participants’ answers to Q1, Q2, and Q4. As can be seen, none of our participants consider themselves at the Beginner (A1) level. Furthermore, most of them are rather confident in their English proficiency and provide an estimate of either Upper Intermediate (B2) or Advanced (C1).

Figure 12: Our participants’ CEFR level self-assessment
Figure 13: The number of years our participants have been practicing English
Figure 14: The frequency our participants have been practicing English
Table 6: Automated readability analysis of the four texts used for our C-tests. Scores are based on the online tool at http://www.readabilityformulas.com.

| Readability index                      | $T_1$ | $T_2$ | $T_3$ | $T_4$ |
|----------------------------------------|-------|-------|-------|-------|
| Flesch reading ease                    | 56.1  | 24.8  | 32    | 55.6  |
| Gunning Fog                            | 9.1   | 17.7  | 18.1  | 13.1  |
| Flesch-Kincaid grade level             | 8.2   | 17.3  | 15.2  | 9.6   |
| Coleman-Liau index                     | 12    | 12    | 12    | 11    |
| SMOG index                             | 8.1   | 15.5  | 13.5  | 10.1  |
| Automated readability index            | 7.9   | 17.4  | 15.5  | 9.7   |
| Linsear Write formula                  | 6.5   | 22.3  | 18.4  | 11.2  |

C-tests. Figure 15 shows the four texts $T_1$ to $T_4$ taken from the Brown corpus and the C-tests with the default gap scheme DEF we created from them for our user study. We have shortened each text to approximately 100 words and generated $n = 20$ gaps. In figure 16, we provide the results of our manipulation strategies SEL and SIZE with decreased ($\tau = 0.1$) and increased ($\tau = 0.5$) difficulty. Note that, we only show sentences that contain gaps; the beginning and end of each text is the same as in figure 15.

Table 6 reports readability scores for multiple common automated readability formulas. A Flesch reading ease score between 50–59 indicates *fairly difficult*, 30–49 *difficult*, and 0–29 *very difficult*. A Gunning Fog score of 9.1 indicates *fairly easy to read* and scores above 12 indicates *hard to read*. The remaining readability scores corresponding to grade levels.

The study of the St. Louis area’s economic prospects prepared for the Construction Industry Joint Conference confirms and reinforces both the findings of the Metropolitan St. Louis Survey of 1957 and the easily observed picture of the Missouri-Illinois countryside. St. Louis is in the center of a relatively slow-growing mid-continent region. Its relative demography for St. Louis goods and services reflects the region’s relative lack of purchasing power. N. St. Lo. industries, of course, have a market area confined to the immediate neighborhood. But for those which do, the slow growth of the area has a retarding effect on the metropolitan core.

Your invitation to write about Serge Prokofieff to honor his 70th Anniversary for the April issue of Sovetskaya Muzyka is accepted with pleasure, because I admire the music of Prokofieff; and with sober purpose, because the development of Prokofieff personifies, in many ways, the course of music in the Union of Soviet Socialist Republics. The Se___ Prokofieff wh___ we kn___ in t___, United Sta___ of Ame___ was g___ witty, merc___ full o___ pranks a___ bonheur — a___ very cap___, as a profes___ musician. Th___ qualities ende___ him t___ both t___ musicians a___ the social-economic ha___ monde wh___ supported the concert world of the post-World War 1, era. Prokofieff’s outlook as a composer-pianist-conductor in America was, indeed, brilliant.

The superb intellectual and spiritual vitality of William James was never more evident than in his letters. Here w___ a man wi___ an enor___ gift f___ living a___ well a___ thinking. T___ both per___ and id___ he bro___ the sa___ delighted inte___ the sa___ open-minded relish f___ what w___ unique i___ each, t___ same discrim___ sensibility a___ quicksilver intell___, the same gallantry of judgment. For this latest addition to the Great Letters Series, under the general editorship of Louis Kronenberger, Miss Hardwick has made a selection which admirably displays the variety of James’s genius, not to mention the felicities of his style.

Escalation unto death The nuclear war is already being fought, except that the bombs are not being dropped on enemy targets – not yet. It i___ being fou___ moreover, i___ fairly cl___ correspondence wi___ the predi___ of t___ soothsayers o___ the th___ factories. Th___ predicted escal___ and escal___ is wh___ we a___ getting. T___ biggest nuc___ device t___ United Sta___ has expl___ measured so___ 15 megatons, although our B-52s are said to be carrying two 20-megaton bombs apiece. Some time ago, however, Mr. Khrushchev decided that when bigger bombs were made, the Soviet Union would make them.

Figure 15: Standard C-tests of our user study
The Sergi Prokofieff whom we knew in the United States of America was gay, witty, mercurial, full of pranks and bonheur – a very capable, as a professional musician. These qualities endeared him to both the musicians as the social-economic haute monde which supported.

The Sergi Prokofieff whom we knew in the United States of America was gay, witty, mercurial, full of pranks and bonheur – a very capable, as a professional musician. These qualities endeared him to both the musicians as the social-economic haute monde which supported.

(a) C-test of $T_2$ manipulated with SIZE for $\tau = 0.1$

(b) C-test of $T_2$ manipulated with SIZE for $\tau = 0.5$

(c) C-test of $T_2$ manipulated with SIZE for $\tau = 0.1$

(d) C-test of $T_2$ manipulated with SIZE for $\tau = 0.5$

Here was a man with an enormous gift for living as well as for thinking. T. both persons and ideas he brought the same delighted interest, the same discriminativeness and quicksilver intelligence, the same gallantry of judgment.

The Sergi Prokofieff whom we knew in the United States of America was gay, witty, mercurial, full of pranks and bonheur – a very capable, as a professional musician. These qualities endeared him to both the musicians as the social-economic haute monde which supported.

He was a man with an enormous gift for living as well as for thinking. T. both persons and ideas he brought the same delighted interest, the same open-minded relish for what was unique in each, the same discriminativeness and quicksilver intelligence, the same gallantry of judgment.

(i) C-test of $T_1$ manipulated with SIZE for $\tau = 0.1$

(j) C-test of $T_1$ manipulated with SIZE for $\tau = 0.5$

(k) C-test of $T_1$ manipulated with SIZE for $\tau = 0.1$

(l) C-test of $T_1$ manipulated with SIZE for $\tau = 0.5$

Figure 16: Manipulated C-tests of our user study