Text Adaptation for Easy Read Content Generation

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Abstract

Adapting information for people with cognitive or reading difficulties is essential to foster inclusion and accessibility in society. This thesis focuses on automatic text adaptation to Easy Read (ER), including aspects of text simplification and information selection, with the goal of accelerating the work of professionals and improving access to information for vulnerable groups. Our research centres on three main aspects that are critical to achieve quality ER adaptations: resource creation, neural model adaptation and model evaluation. In this context, we address corpus alignment issues, information adaptation, as well as image and explanation integration.

Keywords

Easy Read Adaptation, Text Simplification, Resource Creation

1. Introduction

Around 25% of the population in countries like Spain experiences difficulties with reading and comprehension in their daily lives [1]. This makes information inaccessible to many, creating a communication barriers for individuals with cognitive disabilities, older adults, migrants, refugees, and people with learning difficulties, among others. Moreover, the United Nations' International Convention on the Rights of Persons with Disabilities, the Charter of Fundamental Rights of the European Union, and the Spanish Constitution all enshrine in their articles the right to access to information and culture [2, 3, 4], for everyone.

To address this issue, professionals work to adapt these texts into Easy Read,[1] a style designed to make documents easier to understand. For Spanish, experts in the field rely on the UNE 153101:2018 EX standard, which provides guidelines on creating, adapting, and verifying Easy Read documents. Additionally, the Inclusion Europe Easy Read guidelines[2] are openly available and describe the key features of an Easy Read text.

Creating or adapting a text to Easy Read involves applying various linguistic strategies to improve comprehension. Lexically, this includes avoiding difficult (e.g., "help" instead of "assist"), technical jargon or foreign words, and using quantifiers like *little* or *much* instead of large or specific numerical values. Syntactically, it involves using short sentences that convey a single idea, preferably in the second person, avoiding negations, and favouring the active voice (e.g., "You have rights. You can ask for help."). If longer sentences are necessary, they may be broken into two lines at natural pause points. Discursively, information should be well-organized: related ideas should be grouped, complex terms explained, the text structured with clear headings that reflect the content. Additionally, the text should prioritize essential content, omitting non-critical data. The challenge here lies in determining what is considered "essential", as this can vary depending on the needs and characteristics of the target audience.

Manually adapting content to Easy Read (ER) style is time-consuming, and the volume of daily information makes this process unfeasible with current resources. This PhD thesis aims to address this challenge by developing resources, models, and tools to support ER content generation, assisting professionals in the manual adaptation process. The research will notably explore the creation of quality

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[1]Also referred to as *Easy-to-read*.
[2]https://www.inclusion-europe.eu/easy-to-read-standards-guidelines/

ER resources via automated alignment, ER modelling with Large Language Models (LLMs), and the evaluation of automatically adapted ER texts.

2. Background and Related Work

2.1. Easy Read

Despite the limited research in the ER field noted by [5], there is a growing interest in leveraging natural language processing techniques for ER. This is evident in recent developments, including the creation of new ER applications [6, 7, 8, 9, 10], evaluations of LLMs for ER tasks [11, 12], and focused studies on specific aspects of automated ER adaptation, such as the incorporation of explanatory structures [13].

In terms of resources, ER data in Spanish and Basque remains scarce. For Spanish, [11] covers sports, literature, competitive examinations, and exhibitions as domains, with nearly 2,000 aligned sentences by professionals. ClearSim [10] includes 2,000 texts automatically adapted to ER using ChatGPT and validated by non-experts, along with 400 texts adapted by professionals. However, neither of these corpora is publicly available, although the raw data from the former can be requested. The only publicly available ER corpura in Spanish are IrekiaLFes [14], which consists of 35 manually aligned news documents, amounting to 705 sentences, sourced from the Basque Government's Irekia transparency portal. While ER-specific corpora remain limited, there are several publicly available datasets for general text simplification, such as Newsela [15], which does not follow ER guidelines (or does not state doing so explicitly) but can still be valuable for benchmarking and system comparison purposes.

2.2. Automatic Text Simplification

Automatic Text Simplification is described as a text-to-text task whose goal is to reduce the complexity of a text without altering its meaning, typically through various linguistic transformations. Early simplification systems relied on handcrafted rules developed by experts [16] or inferred from aligned texts [17]. These rules often involved substituting complex structures or words with simpler alternatives. As machine learning capabilities advanced, research in the field shifted toward statistical and neural models based on texts, framing the task as a monolingual machine translation problem, translating from complex to simple language, using aligned sentence pairs from parallel corpora [18].

2.2.1. Lexical Simplification

Recent lexical simplification approaches typically involve complex word identification, substitute selection, filtering and ranking; though not all of these steps are always present in a given system. LSBert [19], for example, uses a BERT model to mask complex words and predict suitable substitutes, ranking them based on the model's probabilities, word frequency in corpora, and cosine similarity with fastText static embeddings.

More recent methods employ controllable generation, where predefined parameters are included in the model's input data to guide its behaviour during inference [20]. Based on this idea, this approach has been applied in models such as T5 [21], T5-Large [22], BART [20], and most recently, mT5 [23], which achieved state-of-the-art results in Spanish, English and Portuguese using a single multilingual model. Large Language Models (LLMs) such as GPT-3 have also been explored for simplification, achieving results comparable to mT5 [24].

2.2.2. Syntactic Simplification

Before the emergence of LLMs, syntactic simplification was typically approached as a sequence-to-sequence task, with systems trained on parallel data derived from knowledge graphs [25], extracted from Wikipedia [26], or created by experts [27]. Due to challenges in generalizing to unseen data, DisSim [28] relies on a set of handcrafted rules. DSS [29] uses a syntactically annotated corpus to create rules, which are then applied in a translation-based system.

2.2.3. End-to-end Simplification

The ACCESS system [20] was the first to use input parameters, such as word character count, Levenshtein similarity, inverse frequency, and dependency tree depth; to guide the output of a Transformer model output [30]. Later, [31] tested the same approach to a pre-trained BART model and aligned large numbers of paraphrased sentence pairs from the CCNet corpus.

Other researchers have adopted this controlled generation method using the T5 model, incorporating additional parameters such as the sentence length ratio or dependency tree depth between input and output sentences [32, 33], with the latter achieving the best results.

From an unsupervised perspective, i.e. when training output data is unavailable, [34] propose using existing machine translation corpora, treating bridge language translations as simplified versions of the original sentences in the target language. [35] compute control parameters over noisy translations generated by pre-trained XLM models and attempt to recover the original sentence, incorporating penalties for length, concurrency, and complexity during output generation.

2.2.4. End-to-end Simplification with LLMs

The emergence of Large Language Models has significantly advanced the task of text simplification by addressing one of its main challenged: the scarcity of training data. Unlike earlier models, LLMs do not require large-scale annotated corpora and can perform in an unsupervised manner.

KiS model [36] uses GPT-2 in combination with a reinforcement learning algorithm that evaluates the output based on simplicity, fluency and clarity of the response. [37] assess the performance of ChatGPT in comparison to other existing models, supervised and unsupervised, finding that it achieves similar results. Similarly, [38] experiment with GPT-4, testing various prompts and instructions to optimize output quality, and report performance in par with the best supervised models.

2.2.5. Evaluation and Metrics

Given the high cost of human evaluation, various automatic metrics have been proposed to assess the quality of simplifications. Alva-Manchego et al. [39] recommended the use of metrics such as SARI [40], SAMSA [41], and BERTScore [42], as they show higher correlation with human judgements. Conversely, the use of traditional metrics such as BLEU [43] is discouraged, as it does not align well with human assessments in the context of text simplification. In addition to these metrics, readability formulas are commonly employed to estimate the linguistic complexity of simplified texts. The Flesch–Kincaid Grade Level (FKGL) [44] is one of the most widely used, along with its Spanish adaptation, the Fernández-Huerta index [45]. While these scores offer interpretable indicators of surface-level complexity, they have been criticized for their high sensitivity to small lexical or syntactic changes that may not significantly affect overall readability or simplification quality [46]. Nonetheless, they remain useful in applications aimed at producing accessible content.

3. Description of the Proposed Research and Hypotheses

This thesis aims to investigate the automatic adaptation of texts to ER, to support professional practitioners in accelerating the adaptation process and to improve access to information for vulnerable populations. The primary target languages for this research will be Basque and Spanish, with particular emphasis on Basque, where resources for text adaptation are especially scarce.

To achieve the objectives of this thesis, the development of parallel corpora (complex-adapted) is foreseen, alongside the creation of text adaptation models for various domains, including narrative, news and technical documents.

The main objectives of the thesis are:

1. **Development of methods and tools for Easy Read text adaptation.** While models for general text simplification exist, notable characteristics of the Easy Read style, such as sentence splitting

and rephrasing, or automatic sentence segmentation, are relatively less explored in end-to-end fashion. This thesis will explore methods and tools specifically designed to cover these aspects.
2. **Creation of an automatic complex-adapted text aligner.** Both Spanish and, more notably, Basque, currently lack parallel corpora for automatic text adaptation. This scarcity hinders progress in the field. An objective of this thesis is the development of components and methods to align ER texts at different levels of granularity (e.g., sentence and paragraph levels), to provide quality ER-adapted alignments and enable the creation of new corpora.
3. **Development of ER datasets in Spanish and Basque across domains.** Using the aforementioned aligner, new training datasets will be created for a variety of domains. This is essential, as the Easy Read adaptation style can vary between domains.
4. **Training and benchmarking of adapted neural models.** New neural models will be trained using both the corpora developed in this thesis and publicly available data. These models will be benchmarked against existing approaches in the literature to assess their effectiveness.
5. **Development of methods and models for the automatic generation of domain-adapted explanations of complex terms.** Easy Read texts frequently include brief explanations of complex terms, particularly when no simpler synonyms are available. This thesis explores methods and models that can identify complex terms and generate appropriate explanations in the Easy Read style, adapted to the context and domain of the text, as well as the target audience.
6. **Development of methods and models for the automatic insertion of relevant, illustrative images.** Easy Read texts are often supplemented with images that reinforce textual content and aid comprehension. Methods and models will be developed to automatically retrieve and assign suitable images to accompany the text, streamlining the adaptation process for professionals.

Based on these objectives, the following hypotheses will be tested:

1. The development of resources, methods and models tailored to Easy Read adaptation will improve the readability of texts for people with disabilities.
2. The creation of an automatic aligner tailored to ER text will improve the quality of aligned data and, consequently, the outputs of the models trained on this data.
3. Increasing the amount of training data will enhance the quality and consistency of text adaptations.
4. The inclusion of explanations for complex terms will improve the comprehensibility of adapted texts.
5. Automatically inserting relevant images will enhance the reading experience for individuals with reading difficulties.
6. The use of neural models, particularly large language models, will support the effective generation of Easy Read content.

4. Methodology and Preliminary Results

4.1. Methodology

For model training and benchmarking, various approaches will be compared, including instruction-tuned models (few-shot and zero-shot), and fine-tuned base models. These will be evaluated against existing state-of-the-art systems across multiple datasets in Spanish and Basque, where available. Evaluation will be conducted using established metrics for text adaptation, such as SARI, BLEU, and BERTScore. Given the active research in this field, additional metrics may be incorporated if they contribute meaningfully to the interpretability and robustness of the results.

To develop the automatic complex–adapted text aligner, we will contrast various methods, including embedding and lexical similarity, as well as models tuned to the specifics of ER alignment. Sequentially, regarding the training of explanation generation models, the use of task-specific architectures or the integration of explanation generation into the main simplification and adaptation models will be investigated. These models will be designed to identify complex terms and generate suitable explanations

either from a structured knowledge base or based on the surrounding context. As there are, to the best of the author's knowledge, no publicly available datasets for this task, initial experimentation will focus on few-shot and zero-shot paradigms. Dataset creation will be considered if no suitable resource is found. Following this, an image generation module will be developed to enhance Easy Read texts. This module will either use a text-to-image generation model or retrieve relevant images from a curated image bank. Both approaches will be explored to assess their feasibility and impact on comprehension.

This research will follow standard scientific procedures, including systematic reviews of state-of-the-art literature and the dissemination of findings through high-quality journals, conferences, congresses, and workshops, thereby ensuring validation by the scientific community.

4.2. Preliminary Results

Aligned with the objectives of the thesis, three topics have already been explored:

1. **Split and Rephrase.** One of the subtasks involved in syntactic and end-to-end text simplification and adaptation is Split and Rephrase, which takes a single complex sentence as input and breaks it into multiple shorter sentences while preserving the original meaning and information. We explored the capabilities of large language models for this task, demonstrating improvements over the state of the art. The study involved comparisons across different prompting strategies, domain adaptation settings, base model sizes, training data configurations, and few-shot/zero-shot approaches using instruction-tuned models. Full details can be found in [47].
2. **Text Segmentation.** Easy Read guidelines specify that each sentence should be presented on its own line. Furthermore, sentemces should be split "where people would pause when reading out loud", as recommended by the Inclusion Europe English guidelines. We introduced a novel task: automatic segmentation of sentences to conform to Easy Read principles. Two approaches were evaluated: (1) scoring-based segmentation using constituency parsers and Masked Language Model (MLM) scoring methods, and (2) generative LLM-based segmentation using in-context learning and fine-tuning. Further details are available in [48].
3. **Corpus creation.** Support for ER text generation remains limited, with few resources available for the development of automated systems. We created a novel corpus of ER news texts in Basque and Spanish, marking the first publicly accessible resource designed to support the training and evaluation of ER text adaptation models in both languages. The work outlines the methodology used to build the corpus and includes both intrinsic and extrinsic evaluations. The resource is intended to be released to the research community under a CC-BY-NC-ND 4.0 license. As of this writing, the associated publication is under review.

5. Research Topics to Discuss

As previously presented, this thesis aims to explore automatic text adaptation in Basque and Spanish, following Easy Read guidelines. While several experiments have been carried out, some key research questions and unresolved challenges remain:

- What are the optimal criteria to identify information that needs to be preserved, omitted or transformed in ER adaptation?
- How can the quality of complex-adapted alignment be evaluated accurately?
- What is the best strategy to generate domain-adapted explanations for complex terms?
- How can the hallucination problem be detected and mitigated in the generation of adapted or explanatory content?
- How can image generation or selection be guided in a way that supports text comprehension without introducing ambiguity or distraction?
- To what extent do existing evaluation metrics reflect the actual accessibility improvements brought by automated methods?

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Declaration on Generative AI

The author has not employed any Generative AI tools.

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