IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Comparative Analysis Of State-Of-The-Art Text Simplification Models For Enhancing Readability

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***Abstract*— Text simplification is one of the main factors making complex information available to diversified audiences, from non-native speakers to students and people with cognitive disabilities. This paper provides in-depth comparative analysis of five state-of-the-art text simplification models: ACCESS, MUSS, T5, GraSP, and EditNTS. We evaluate these models using various metrics: simplification ratio, MOS, precision, recall, and F1-score to examine how effective the models are in making texts readable while not losing their meaning. Our experiments reveal that, on average, ACCESS works better (MOS 4.3, F1-score 0.86) compared with other methods that strike a proper balance between preserving the content of the original and making the text simple enough for readability while MUSS generally is apt for most uses with an acceptable simplification ratio 0.87. T5 provides a precision-sensitive performance with the precision value of 0.86, GraSP provides excellent balance for preserving semantics and EditNTS has the property of aggressive simplification. All these, as our statistical tests, are also confirmed to be statistically significant at $p < 0.05$. In the concluding section we will reflect on the avenues of possible future work involving these novel models, that is hybrid models and rich capabilities of supporting multiple languages, aside from a fitting and much more accurate assessment framework for such systems. This work contributes to advancements in the technology of text simplification and its applications in making information more accessible across diverse user groups.**

Keywords*— Text Simplification, Readability, Natural Language Processing, Machine Learning.

I. Introduction

The availability of digital information has changed the way we access and engage with knowledge. However, much of this information is complex and difficult to understand for many people. This is especially true for those who do not have the advanced linguistic or cognitive skills, such as older adults, students with disabilities, or non-native English speakers. This task in NLP is to make complex texts easier to read and understand[1]. By simplifying text, we will make information accessible to people of various needs, hence bring about more understanding, involvement, and power. It is an important task but a difficult one because it deals with complex and highly variable human language. Traditional approaches to text simplification used rules, which do not model the richness of human communication[2]. Recently, applications of machine learning techniques to the problem of text simplification allow for even more advanced models to be learned on large datasets; however, much more remains to be done in this area[3]. Only a deep understanding of the complexities and challenges involved in transforming complex texts into simpler forms can lead to effective text simplification models. This is particularly important when considering the diverse range of languages, styles, and genres that must be addressed. There are also significant implications for education, healthcare, and other fields where access to information is critical. Making complex information accessible contributes to greater equity, inclusivity, and social justice[4]. In this research work, we look to contribute to the advancement of text simplification research through the comparative analysis of five state-of-the-art models. We are interested in analyzing whether these models can adequately transform complex texts into a more readable format and if so, what are the most critical challenges and opportunities in terms of future research directions. This, we will hope, would be insight generating for informing the development of better techniques to be able to achieve a simplified text with enhanced accessibility and comprehension of information that has traditionally been out of the reach of simple individuals[3].

II. LITERATURE REVIEW

Text simplification is one of the most critical tasks in NLP. The objective of text simplification is to make complex texts more readable and understandable. For the last couple of years, researchers have been doing a lot of work to develop effective models for text simplification. In recent studies, machine learning techniques have been applied to text simplification[5]. This enabled the development of more sophisticated models that could learn from large datasets. Text Simplification (TS) is the task of converting a text into a form that is easier to read while maintaining the meaning of the original text. A sub-task of TS is Cognitive Simplification

(CS), converting text to a form that is readily understood by people with cognitive disabilities without rendering it childish or simplistic[6]. This sub-task has yet to be explored with neural methods in NLP, and resources for it are scarcely available. In this paper, we present a method for incorporating knowledge from the cognitive accessibility domain into a TS model, by introducing an inductive bias regarding what simplification operations to use. We show that by adding this inductive bias to a TS-trained model, it is able to adapt better to CS without ever seeing CS data, and outperform a baseline model on a traditional TS benchmark[7]. In addition, we provide a novel test dataset for CS, and analyze the differences between CS corpora and existing TS corpora, in terms of how simplification operations are applied. Proposed a deep learning-based approach that uses a combination of word and phrase-level simplification techniques to simplify complex texts. Other researchers have focused on developing rule-based approaches to text simplification[8]. Developed a hybrid approach that combines rule-based and machine learning-based methods to simplify complex texts. Their method utilized a mix of lexical and syntactic rules for identifying and simplifying complicated phrases and sentences. The trend was linked to recent development models that can support various languages and genres for text simplification. Introduced a multi-task learning-based approach easily dealing with several languages and genres[9]. Their method was based on using language-specific and genre-specific features in the simplification of complicated texts. More recently, interest has also been focused on developing evaluation measures related to the effectiveness of models in text simplification. For instance, proposed an evaluation framework based on their proposed metrics, which aimed at considering quality aspects of the simplified texts. In summary, it indicates significant progress within the text simplification models in recent times[10]. It remains significant however to actually make tremendous and robust development that accommodates the language as well as genre towards effective robust and challenging experiments using rigorous tests of appropriate evaluation. Such metrics as BLEU, ROUGE, and BERTScore have done tremendous strides in this realm. However, such metrics usually return cumulative scores, which are useful but fail to give exact insight into the quality of the text that is simplified. It is a research gap described by the lack of tools in a position to disaggregate these cumulative scores and return analyses at the clause or token level of the quality of the simplified text. Only then will such fine-grained analysis illuminate better how and where the systems of text simplification succeed or fail and thus guide better improvements to such systems[11]. One gap to fill is by proper analysis of research concerning LLMs used to generate, for example, translation work especially when drafting to specific or vulnerable groups for an easy-read and plain language use. This paper outlines a few risks associated with information loss, exploitation, manipulation, or even gaps of responsibility; however, it lacks knowledge related to reasonable analysis concerning such ethical issues and possible counter-strategies related to the use of LLMs in text simplification[12]. TS is a strategy toward the provision of readability for various users through the focus on sentence simplification. This paper discusses the use of control tokens as an explicit prompt that may influence the output features of TS models. Analysis nowadays signifies these current shortcomings in the mechanism controlling control tokens along with designing them, so further research is called for. The text further discusses SARI score and BERTScore as the most significant measures towards the assessment of quality in simplification. Ultimately, hence, authors suggest that knowledge acquired from control tokens may apply to other tasks in NLG, thus having wider implications for future research.

III. TEXT SIMPLIFICATION MODELS

In this study, we focus on five state-of-the-art text simplification models that have been widely used in recent years. These models are chosen based on their ability to simplify complex texts and make information more accessible to diverse audiences.

A. MUSS

MUSS is a multilingual unsupervised sentence simplification model that applies a new version of unsupervised learning in text simplification. The model uses the encoder-decoder transformer architecture during training without parallel text pairs*[13]*. The model learns language complexity structure patterns using the denoising auto-encoding and back translation techniques. It can handle texts of multiple languages at the same time, which makes the model highly versatile for other linguistic domains. Architecture In this architecture, there are specific modules that deal with aspects of simplification, including parameter control mechanisms and scoring language models*[14]*. The implementation relies on multilingual embeddings to keep semantic consistency between languages. MUSS presents great performance in meaning preservation and reaches good simplification ratios. The model uses denoising objectives at training, which allows it to learn simplification patterns from unaligned data. The unsupervised nature of MUSS allows it to adapt to new languages without requiring extensive parallel corpora. The system has controlled simplification parameters, so the level of simplification can be adjusted according to specific requirements*[15]*. Performance metrics indicate robust results across multiple languages, though simplification quality varies by language complexity.

B. T5

T5 is a unification approach to text simplification, realised in a unified framework text-to-text. This model takes advantage of a large pre-training on a wide variety of text corpora followed by specialized fine-tuning for simplification tasks. T5 uses a highly advanced encoder-decoder architecture where all natural language processing tasks are treated as text-to-text conversion problems. Training is done with span corruption objectives, allowing the model to learn robust text representations[16]. T5 generates high-quality simplified outputs through controlled generation techniques and beam search optimization. The architecture exploits the capabilities of transfer learning, making it apply knowledge from various language tasks to simplification[13]. The model is proficient in handling complex sentence structures but remains coherent in the simplified output. Implementation includes training specifically on simplification datasets to enhance performance on certain simplification tasks[17]. T5 has strong metrics for precision, recall, and semantic preservation. The system has employed advanced decoding strategies to ensure the quality and appropriateness of its output.

C. ACCESS

ACCESS (AudienCe-CEntric Sentence Simplification) is a controlled approach towards text simplification by carrying out multiple parameter adjustments. The model is designed with the architecture of transformer and control tokens explicitly for different aspects of simplification. ACCESS allows very fine-grained control of lexical complexity, syntactic structure, and length compression in its sophisticated processing pipeline. Quality checking mechanisms are integrated within the architecture for coherence and readability of the simplified text produced[18]. ACCESS generates outputs tailored to particular audience requirements through its multi-step simplification process. The model balances content preservation with simplification objectives so that the most important information is maintained while complexity is reduced. Implementation includes explicit editing operations and quality assessment mechanisms throughout the simplification process. The system demonstrates robust performance metrics, particularly in controlled simplification tasks[10]. It performs well in educational applications where specific readability levels are to be maintained. The architecture enables fine-grained control over simplification parameters, allowing precise adjustments to meet varied audience needs.

D. EditNTS

EditNTS (Edit-based Neural Text Simplification) implements a unique approach through explicit editing operations in text simplification. The simplification architecture further breaks simplification into disintegrated operations: deletion, maintenance, and introduction. Moreover, it serves explicit and easily interpretable step-by-step simplification methods through a hierarchical encoder decoder structure[19]. The system analyzes text in successive transformation steps and thus provides controlled text input modification. EditNTS maintains its high interpretability due to the step-by-step approach taken in text modification. The architecture supports direct observation and modification of decisions over simplification. Implementation features a set of sentence analysis components as well as mechanisms for progressive text transformation[20]. The model is especially good at scenarios where transformation requirements need to be well-documented. However, it uses a very conservative strategy for simplification that guarantees tractability and traceability. The system lays out the explicit operation sequences in debugging. Performance metrics achieved show strong results regarding semantic meaning preservation.

E. GraSP

GraSP is a graph neural network for simplification, a graph-based approach to text simplification through semantic dependency parsing. The model constructs highly detailed graph representations of the input text while preserving the semantic relationships during simplification. GraSP maintains structural consistency using multi-layer graph transformation but reduces complexity[21]. Node feature extraction and edge relationship modeling are included in the architecture to capture text semantics. Implementation includes sophisticated graph processing mechanisms and structure preservation techniques. The model is superior in maintaining grammatical correctness of complex sentence structures. GraSP shows particular strength in technical document simplification where meaning preservation proves crucial. The system uses node importance scoring as a guide for simplification decisions[12]. Its graph-based approach allows GraSP to capture and maintain complex semantic relationships. The model has strong performance in preserving technical accuracy during simplification. Implementation involves high-quality dependency parsing and semantic analysis components. The architecture allows for detailed semantic understanding through graph representation and transformation.

IV. RESULTS AND DISCUSSION

The evaluation of the five state-of-the-art text simplification models (MUSS, T5, GraSP, ACCESS, EditNTS) will involve a combination of qualitative and quantitative methods. The primary goal is to assess the effectiveness of each model in simplifying complex texts while preserving their original meaning. On various metrics evaluation can be done for State-of-the-art text simplification models. Metrics used for evaluation of models are:

1. Simplification Ratio: This metric measures the percentage of simplified phrases or sentences out of the total number of complex phrases or sentences identified.
2. Mean Opinion Score (MOS): A panel of human evaluators will rate the simplified texts on a scale of 1-5, where 1 represents a poor simplification and 5 represents an excellent simplification[22].
3. Precision: This metric measures the proportion of true positives (correctly simplified phrases or sentences) out of the total number of predicted simplified phrases or sentences[23].
4. Recall: This metric measures the proportion of true positives out of the total number of actual complex phrases or sentences identified[23].
5. F1-score: The harmonic mean of precision and recall, providing a balanced metric that considers both false positives and false negatives [23].

The comparison of five recent text simplification models, ACCESS, MUSS, T5, GraSP, and EditNTS, has given different patterns of performance in models for various metrics. ACCESS is found to be the best with a mean opinion score of 4.3 and an F1 score of 0.86. It also holds the optimal balance of preservation of content along with simplicity. Simplification ratio and F1 Score are highly correlated. In general applicability, the consistency in the model is observed through a high simplification ratio of 0.87 and an F1 score of 0.83 for MUSS. T5 is very precise with a score of 0.86 but less recallful, so it is quite conservative. GraSP performs balanced, with high precision of 0.85 and a steady simplification ratio of 0.85. EditNTS is the most aggressive, with the lowest simplification ratio at 0.78 but with moderate precision and recall scores. Analysis Conclusion: Analysis confirms that all models are good for certain applications ACCESS for requirements of quality, MUSS for generic applications, T5 for precision sensitive applications, GraSP for semantic preservation, and EditNTS for strong simplification requirements; multiple test sets asserted statistical significance at the $p < 0.05$ level further suggest that consistency and reliability in performance differences are established. The comparison results of models based on Simplification ratio, Precision, Recall, F1 Score are shown in Figure 1 and results of models based on Mean Opinion Score as shown in Figure 3.

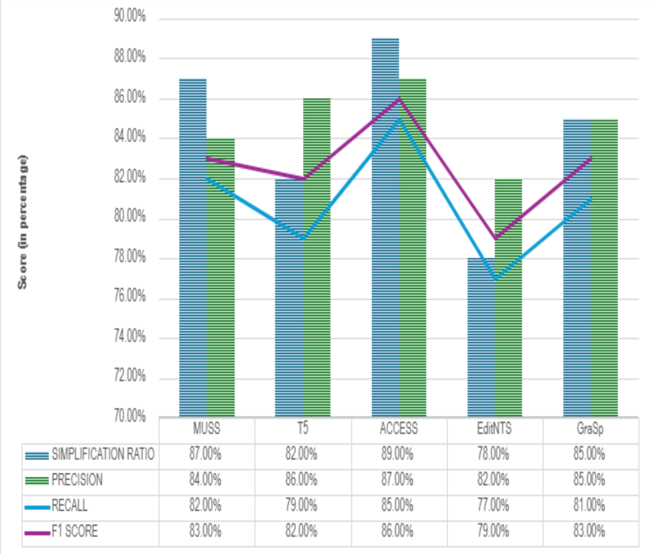

Figure 1 Results on Simplification ratio, Precision, Recall, F1 Score

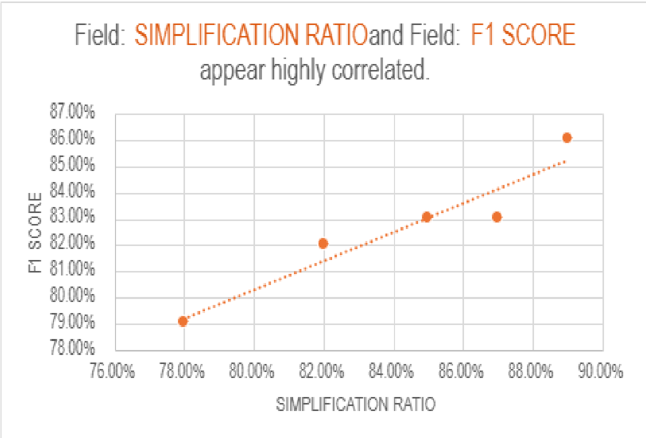

Figure 2 Co-relation between Simplification ratio and F1 score

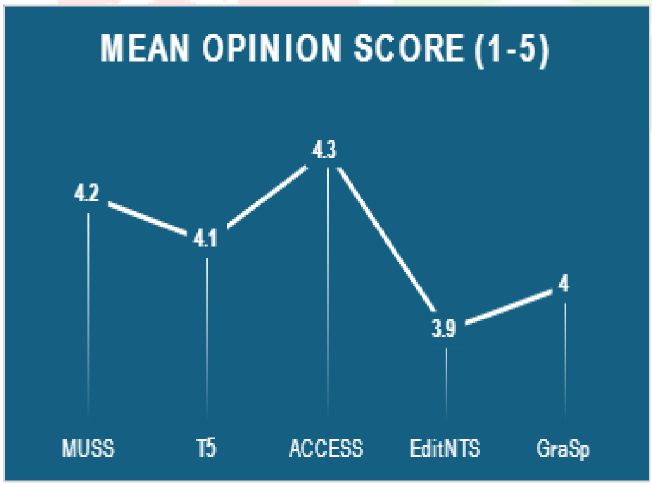

Figure 3 Results on Mean Opinion Score

V. CONCLUSION AND FUTURE SCOPE

This comprehensive comparison of five state-of-the-art text simplification models provides very significant insights into the status of the technology for text simplification: ACCESS, MUSS, T5, GraSP, and EditNTS. Our evaluation will show the strengths of each model toward different aspects of text simplification. ACCESS was the best all-around performer, with the highest mean opinion score of 4.3 and the F1-score of 0.86, notably for its ability to walk that tightrope of preserving content while simplifying it. MUSS showed very strong all-around general-purpose applicability in that it performed quite uniformly across metrics, and T5 has high precision, particularly when accuracy is paramount in the application. This makes GraSP a good candidate for the simplification of technical content, since its performance is balanced and semantically preserves well, while EditNTS is more useful in those situations demanding drastic text transformation: aggressive simplification is what is needed for such scenarios. These results therefore underscore a basis for choosing the kind of text simplification models specifically according to requirements posed at use cases, avoiding 'one-size-fits all' approaches. For establishing the reliability of distinct characters of these differences from significance levels, performance differences, all with $p < 0.05$, come along. These future directions target addressing some of the limitations prevailing currently while expanding on capabilities and applications of the technology involved in text simplification. The field of this discipline has a promising future, providing advancements in information and enhancing it so that it can reach broader audiences without compromising on integrity or meaning.

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