A Survey on Text Simplification

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Text Simplification (TS) aims to reduce the linguistic complexity of content to make it easier to understand. Research in TS has been of keen interest, especially as approaches to TS have shifted from manual, hand-crafted rules to automated simplification. This survey seeks to provide a comprehensive overview of TS, including a brief description of earlier approaches used, discussion of various aspects of simplification (lexical, semantic and syntactic), and latest techniques being utilized in the field. We note that the research in the field has clearly shifted towards utilizing deep learning techniques to perform TS, with a specific focus on developing solutions to combat the lack of data available for simplification. We also include a discussion of datasets and evaluations metrics commonly used, along with discussion of related fields within Natural Language Processing (NLP), like semantic similarity.

CCS Concepts: • General and reference → Surveys and overviews.

Additional Key Words and Phrases: Natural Language Processing (NLP), Text Simplification (TS), Lexical Simplification (LS), Syntactic Simplification, Machine Learning (ML), Deep Learning (DL)

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1 INTRODUCTION

Text simplification, defined narrowly, is the process of reducing the linguistic complexity of a text, while still retaining the original information and meaning. More broadly, text simplification encompasses other operations; for example, conceptual simplification to simplify content as well as form, elaborative modification, where redundancy and explicitness are used to emphasise key points, and text summarization to omit peripheral or inappropriate information [79].

TS is within the field of NLP, and within this field it is very similar to other techniques, such as machine translation, monolingual text-to-text generation, text summarization and paraphrase generation. These fields all draw on each other for techniques and resources and many techniques within TS come from these other fields [104]. TS is different from text summarization as the focus of text summarization is to reduce the length and content of input. Whilst simplified texts are typically shorter, this is not necessarily the case and simplification may result in longer output — especially when generating explanations [76]. Summarization also aims at reducing content —
removing that which may be less important or redundant. This is typically not explored within simplification, where all the content is usually kept.

As the amount of unstructured text data has exploded in recent decades, due to the advent of the Internet, so has the need, and interest, in TS research, as can be seen from Fig. 1. TS is a diverse field with a number of target audience, each with a specific focus [4]. Among the most prominent target audiences for TS are foreign language learners, for whom various approaches to simplifying text have been pursued, often focusing on lexical [2] but also sentence-level simplification [48]. TS is also of interest to dyslexics [68], and the aphasic [14], for whom particularly long words and sentences, but also certain surface forms such as specific character combinations, may pose difficulties. Application of TS for those suffering from autism focuses on reducing the amount of figurative expressions in a text or reducing syntactic complexity [29]. Reading beginners (both children and adults) are another group with very particular needs, and TS research has tried to provide this group with methods to reduce the amount of high-register language and non-frequent words [21].

![Fig. 1. Created by polling Google Scholar with the search query: ‘Text Simplification’ OR ‘Lexical Simplification’ OR ‘Syntactic Simplification’. It shows the sustained growth in TS and associated sub-fields between 2010 and 2019.](image)

1.1 Motivation and Methodology

There has been a dramatic shift in the focus on research in TS over the past decades, from traditional, statistical-based methods toward machine and deep learning techniques. Limited work has been done to summarize the efforts in TS, in terms of survey articles on the subject. The last comprehensive surveys on TS were conducted by Shardlow (2014) [76] and Siddharthan (2014) [79]. Although Paetzold conducted a comprehensive survey in 2017, their focus was limited to lexical simplification [63]. We present, to the best of our knowledge, the first comprehensive survey since 2014 that covers the field of text simplification in its entirety, including a review of latest techniques being researched and the updated resources available for the subject.

In this survey, we focus our efforts on providing a comprehensive discussion of all facets of TS, building on the works of previous surveys and including discussion of techniques and methods used by researchers since. Although we include the details of early simplification techniques, for
the sake of completeness, we focus primarily on works published since 2014, especially relating to abstractive methods of simplification, implementing latest deep learning techniques.

We include discussion of techniques and systems published only in highly reputable journals and conference publications. Although we limit our focus to TS in English, we do include references to works in other languages to highlight universally applicable techniques.

1.2 Organization of Survey

Fig. 2 shows the organization of this survey article. Section 2 provides an overview of general approaches to TS. Section 3 includes a detailed discussion of lexical simplification, followed by a discussion of novel text generation and simplification techniques in Section 4. Section 5 focuses on datasets available for TS along with discussion of related NLP techniques. Section 6 includes details of evaluation metrics used in TS, and Section 7 provides a brief discussion of direction of current and future research in the field.

Fig. 2. Organization of Survey Article

2 TEXT SIMPLIFICATION APPROACHES

Most of the early work in the field involved extractive methods of summarization – extracting the sentences from a document that conveyed the most meaning. These are easiest to implement and available readily online for free\(^1\). As research in NLP has exploded over the past decade, primarily due to availability of computing resources, the research in simplification has shifted towards abstractive approaches – actual generation of text [72]. Initially this involved sentence level simplification through lexical (word-based or phrasal-based) selection and substitution, like using the Paraphrase Database (PPDB) [1]. In recent years, text simplification has evolved to actual generation of new and novel text, thanks to the advent of neural networks, especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which allow sequence-to-sequence (seq2seq) modeling.

\(^1\)http://textsummarization.net/text-summarizer
2.1 Extractive Approach

Extractive text simplification involves simply selecting sentences from a paragraph or document that convey the most "meaning." Extractive text simplification is essentially text summarization, like using a highlighter to point out the most significant text.

The simplest of all summarization techniques is TF-IDF (Term Frequency – Inverse Document Frequency). This technique involves generating a frequency table of all the words in the corpus, usually after removing stop words (the most commonly used words in a language, like "a", "an", "the" etc.). The sentence weights are then calculated, based on word frequencies, which are normalized by sentence length, to calculate the sentences with the most "substance." We can use a threshold to retain sentences with the most "substance" or summarize a given text in a given number of sentences, by choosing the ones with the highest sentence weights.

The TF-IDF of every word $w$ in the corpus is calculated as

$$TFIDF(w) = TF(w) \times IDF(w)$$

(1)

where

$$TF(w) = \frac{Number\ of\ times\ term\ w\ appears\ in\ a\ document}{Total\ number\ of\ terms\ in\ the\ document}$$

(2)

and

$$IDF(w) = log\left(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ term\ w\ in\ it}\right)$$

(3)

The Sentence Weight (SW) for each sentence $s$ is then calculated as the sum of TFIDF of each word in that sentence, divided by the number of words.

$$SW(s) = \frac{\sum_{w \in s} TFIDF(w)}{\#\ of\ Words\ (w)\ in\ s}$$

(4)

Data preprocessing for this approach is straightforward. Since we are interested in words with most "substance," we simply convert the text to lower case, and remove the punctuations, special characters and stop words. We also use stemming or lemmatization to reduce complex words into their base linguistic form, like converting "running" to "run" and "paid" to "pay."

For example, if we have the following text to simplify:

"Peter and Elizabeth took a taxi to attend the night party in the city. While in the party, Elizabeth collapsed and was rushed to the hospital. Since she was diagnosed with a brain injury, the doctor told Peter to stay besides her until she gets well. Therefore, Peter stayed with her at the hospital for 3 days without leaving."

Table 1. Sentence Weights (SWs) for extractive simplification example

| Sentence | SW |
|----------|----|
| Peter and Elizabeth took a taxi to attend the night party in the city. | 1.8571 |
| While in the party, Elizabeth collapsed and was rushed to the hospital. | 2.1428 |
| Since she was diagnosed with a brain injury, the doctor told Peter to stay besides her until she gets well. | 1.6923 |
| Therefore, Peter stayed with her at the hospital for 3 days without leaving. | 1.9 |

The extractive approach involves creating a frequency distribution of all the words, after preprocessing, and calculates Sentence Weights (SWs) for each sentence, as shown in Table 1. We can
summarize the original text by either selecting N number of sentences with the highest SW or by selecting all sentences above a certain threshold SW.

2.2 Abstractive Approach
Abstractive text simplification involves generation of new and novel text, which is lexically and/or syntactically simpler than the original. Abstractive approaches have mostly focused on lexical or phrasal substitutions for sentence-level simplification [63]. This process focuses solely on simplifying the vocabulary of a text, instead of additional simplification tasks of grammatical or syntactic simplification [76].

By contrast, truly abstractive simplification approaches involve sentence splitting, and text deletion and addition. The most common approach has been seq2seq modeling, using tree-based approaches, RNNs, and LSTMs. The pipeline for these approaches, although much more universal, is also fairly involved. The data preprocessing for seq2seq modeling involves cleaning the input and target text, possibly removing punctuations and special characters, and assembling a common words dictionary. Both input and target sentences are then vectorized into numerical form for the model, with a uniform length vector, either by truncation or padding. Once the model has been trained, any new test instance is first vectorized, converted to uniform length, then simplified by the model, before being converted back from numerical form to text form. Abstractive approaches to TS can be categorized broadly as lexical simplification or novel text generation.

3 ABSTRACTIVE APPROACH - LEXICAL SIMPLIFICATION
Lexical Simplification (LS), first introduced in the work of Devlin and Tait (1998) [25], is a form of abstractive TS that aims to replace complex words, which may challenge certain audience, by simpler alternatives [60]. The performance of a substitution technique, like LS, depends heavily on the database being referenced and the criteria for selecting a suitable word or phrase.

The most commonly used resource for LS is PPDB [1], a collection of lexical, phrasal and syntactic pairings with over 40 variables describing each relationship. Although a fairly comprehensive resource, PPDB contains lexical, semantic and syntactic substitutions that are not always simplified versions. Pavlick et al (2016) released a condensed version of the PPDB -Simple PPDB- by training a supervised model on the large original database, and extracting paraphrase rules that produced actual simplifications [66]. The motivation behind their approach seeked to retain the meaning of a word or phrase, while producing a simplified output, measuring their simplification performance with criteria like length in characters, length in syllables, Google Ngram frequency, and Simple/Regular English Wikipedia Ratio [66].

3.1 The Lexical Simplification Pipeline
Most LS systems employ a multi step pipeline, as illustrated in Fig. 4, starting with Complex Word Identification, and followed by Substitution Generation, Substitution Selection and finally Substitution Ranking [4]. An example of the steps involved in the pipeline is illustrated in Fig. 3.

3.1.1 Complex Word Identification (CWI).
Commonly performed before any other step in the LS pipeline, CWI involves determining which words to simplify, given a target audience, to ensure that the LS system doesn’t make any unnecessary substitutions [60]. Early LS systems, like that by Devlin and Tait (1998) [25] didn’t perform CWI, and assumed that all words were valid candidates for simpler substitution. However, using this "simplify everything" approach, they reported that in their system, 16.60% of all simplified content had their grammatical structure changed, and over 44% had their meaning modified significantly. Shardlow (2014) noted that not using any CWI led to modifications that were not necessary and
made the original content ungrammatical or incoherent [76]. They demonstrated that a realistic LS system, without a valid CWI, leads to changes that make the content more obscure and often less meaningful.

Several other strategies have been proposed for the task of CWI in recent research, which could be broadly categorized as follows:

a. **Threshold-based approaches** use a simplicity metric $M$ for any word $w$ such that $M(w) < t$, for some threshold $t$, which confidently allows for a word to be classified as complex or
simple. Word frequency has been a very popular metric used for threshold-based CWI - simplifying words that appear the least frequently in a large corpus [63]. Leroy et al. (2013), when simplifying text in the medical domain, chose to simplify only those words in their text that belonged to the 5,000 least frequent words in the Google IT corpus [47]. Human evaluators of their technique reported significant reduction in the perceived reading difficulty from the original complex text. Shardlow (2013) used a dedicated CW corpus [75] for learning the best threshold for complex-simple word separation, using the word frequencies from the SUBTLEX corpus [13] as a metric [74]. Wrobel (2016) achieved the highest F-score in the in the CWI task at SemEval 2016, also learning the complex word threshold, but over Simple Wikipedia [98].

Although easy to implement and intuitive to understand, threshold-based approaches have been shown to be too simple to be effective alone. Bott et al. (2012) found that, after performing manual simplification on a sample dataset, less than 70% of the words being simplified were shorter in length than their complex counterparts [11]. Shardlow (2014) confirmed the limitations of the threshold-based approaches in their analysis, using Kucera-Francis coefficient as a metric of complex word identification [77]. They found a mistake was made in CWI over 65% of the time, and 99 out of 119 mistakes were caused by a simple word being mistakenly identified as complex, and unnecessarily being replaced.

b Lexicon-based approaches to CWI tackle the limitations of threshold-based approaches by using a domain-specific lexicon to identify complex words. Manually created lexicons can be very useful, when available, as proved by the works of Deleger and Zweigenbaum (2009), who present a method for creating a lexicon of complex words and phrases in the medical domain [23]. Elhadad and Sutaria (2007) [28] use the Unified Medical Language System (UMLS) lexicon [9], a database of technical medical terms, to identify complex words and expressions very effectively, and Elhadad (2006) [27] use UMLS with cross referencing the Brown corpus, proceeding on the assumption that words and phrases appearing across-domain are not complex.

The effectiveness of the lexicon-based CWI is no where more apparent than in the use of FACILITA [97], a tool designed to simplify web pages, that is part of the PorSimples project [3]. FACILITA uses words extracted from childrens’ books for CWI, and has proven to be effective in helping low-literacy readers in digesting complex content, like news articles. However, the limitations of lexicon-based approach for CWI are self-evident, as manually producing domain-specific lexicons is usually prohibitively expensive [63]. Also, which words to include in the lexicon of complex words is a challenge as different target audience would consider different words complex or simple.

c Implicit CWI doesn’t perform the identification of complex words as an initial step in the simplification pipeline, but in conjunction with other steps, by allowing all words to be substituted, and then discarding the substitutions which replace simpler words with complex alternatives. Biran et al. (2011) [7] and Bott et al. (2012) [11] both use metrics like word length and frequency, in addition to other measures, to decide whether to discard a substitution if it is more complex than the source. Horn et al. (2014) add the word itself to a possible list of substitutions and discard the substitutions if the word itself is considered the most simplified variant [35].

Specia (2010) [81] and Zhu et al. (2010) [104] achieved promising results when using machine translation for CWI, using a model trained on aligned parallel corpora, which may contain useful simplifications. Wubben et al. (2012) complement a typical phrase-based translation model by adding a re-ranking step that uses the Levenshtein distance as a metric [99]. The work of Xu et al. (2016) goes a step further and adapts a typical statistical translation model by
crafting two new objective functions that better suit TS, and by incorporating pre-produced paraphrase databases during training, to compensate for the lack of large complex-to-simple parallel corpora [101]. These implicit approaches avoid the problem of trying to decide which words are inherently complex enough for simplification, and instead focus on the question of whether or not simpler substitutions can be found for a given word. Although it is difficult to compare their performance to that of more traditional CWI methods, these approaches can be a very suitable alternative, especially in cases where one can assume with reasonable confidence that the training data used captures the needs of the addressed audience [63].

**Machine learning-assisted** - Machine learning can also be employed for the task of CWI, given there is data available to train a model on. If we have sentences, for example, with words labelled as complex or simple, then we can train a binary classifier for CWI. If we have some sort of a complexity quantifier as a label, we can even train a regression model to learn and predict the degree of complexity of words. The applicability and effectiveness of machine learning techniques can be gauged by the performance of systems submitted for the CWI task of SemEval 2016. The majority of the 42 systems submitted used some machine learning technique [63], some using standard support vector machines (SVMs), decision trees and neural networks [46] [70] [5], while others employing more complex ensembles of various machine learning techniques and feature sets [18] [52] [32]. Many of the machine learning approaches used at SemEval 2016 were quite minimalistic. The UWB [44] system used only one feature for CWI, the number of documents in Wikipedia in which a word appears, and ranked in the top five performers. The LTG [49] systems, which also achieved some of the highest scores in the task, trained their model using only word length and n-gram probabilities from a language model [63]. The highest performing system for CWI, however, was the Performance-Oriented Soft Voting ensemble method of Paetzold and Specia (2016) [59], which combined different types of lexicon-based, threshold-based, and machine learning approaches.

### 3.1.2 Substitution Generation (SG)

The goal of SG is to generate possible candidates for replacement of complex words. An ideal SG strategy would lead to finding all possible simplification candidates for a complex word, regardless of context, and the Substitution Selection step would then decide which candidate is ideal. This aims to maximise the recall of candidate substitutions for complex words, and consequently should lead to better simplifications. The biggest challenge of SG is to not create too many superfluous candidates for substitution that can confuse the models employed in subsequent steps. Existing SG approaches fall under one of two categories:

**a Linguistic Database Querying** - Although it would be ideal to search manually and professionally created linguistic databases for possible substitutions, such resources are expensive and time consuming to construct. Early LS systems generated substitutions by extracting synonyms, hypernyms and paraphrases from thesauri [25] [11] [21], such as WordNet. However, Shardlow (2014) showed that using only WordNet synonyms can limit the potential of LS, since WordNet does not cover all complex words in the English vocabulary, nor does it contain all candidates which can replace a complex word [77]. This limitation can be rectified by combining multiple linguistic databases for SG. Leroy et al. (2013) used the relations provided by WordNet, along with the ones provided by UMLS (Unified Medical Language
System) and Wiktionary\(^2\) [47]. Chen et al. (2012) also used UMLS to replace complex medical expressions with simpler equivalent terms to improve the performance of statistical machine translation systems [16]. Elhadad (2006) used the “define” function of Google’s search engine to gather multiple dictionary definitions of medical expressions, with promising results [27].

b Automatic Substitution Generation - Extracting substitutions automatically for aligned complex-simple corpora can be less expensive and a more viable solution to SG. A popular resource for employing this strategy has been the Simple English Wikipedia (SEW), which contains a subset of the articles from the original English Wikipedia edited by volunteers such that more readers can understand them [63].

Yatskar et al. (2010) extracted paraphrases of complex terms from Simple Wikipedia edits marked with the "simplification" label, and have shown to produce many useful paraphrases [102]. Biran et al. (2011) consider every pair of distinct words in the Wikipedia and Simple Wikipedia to be a possible simplification pair, and filter any pairs which are morphological variants of each other or that are not registered as either synonyms or hypernyms in WordNet [7].

Feblowitz and Kauchak (2013) use a tree transduction model to extract lexical and syntactic simplifications from a corpus of parallel sentences taken from Regular Wikipedia and Simple Wikipedia [68]. Tree transduction models attempt to learn tree-to-tree rewritings from parallel data, and are often able to capture complex transformations such as word re-orderings, as well as lexical replacements. Their adapted model has been shown to capture many reliable paraphrases [63]. Paetzold and Specia (2013) [56] and Horn et al. (2014) [35] used generators instead of thesauri to generate substitutions from aligned parallel sentences from Regular and Simple English Wikipedia. Although easier to produce automatically, parallel corpora can be limited in their coverage of complex words, and therefore, have limited applicability in LS systems [60].

Work by Glavas and Stajner (2015) aims to address these limitations by using word embedding models, selecting words for substitution with the highest cosine similarity with the source complex word [33]. However, this approach introduces the problem of word sense ambiguity. Paetzold and Specia (2016) attempt to solve this problem by suggesting a context-aware SG scheme, where the training corpus is tagged with part-of-speech (POS) tags [61]. They also use the stem or lemma or the word to ensure that a substitution is both valid (based on POS tag), and not just a morphological variant of the original (given the stem or lemma).

Associating the querying of linguistic databases with an automatic approach may be the ideal solution for SG, as showed by the promising results of De Belder and Moens (2010) [21]. They intersected the synonyms extracted from WordNet, with a set of related words learned through a latent-variable language model, and found that the resulting reduced set had fewer spurious substitution candidates.

3.1.3 Substitution Selection (SS).
The aim of SS is to choose which of candidates produced during SG would fit the context of the sentence being simplified, with respect to grammatical construction and meaning [63]. This is a critical step of any LS system as it should prevent alternations that would make a sentence incomprehensible. Early LS systems did not perform SS, considering all possible substitutions. Shardlow (2014) demonstrated the impact of not performing SS on the performance of an LS system. In their experiments, they found that absence of a SS strategy led to drastic change in the meaning
of the sentence being simplified over 29% of the time [77]. Several SS strategies have been proposed and adapted over the past decade:

a **Explicit sense labelling** treats SS as a word sense disambiguation (WSD) task, using classification methods to select the sense label for an ambiguous word, and choosing valid candidates with same label, usually found from linguistic databases like WordNet [63]. Thomas and Anderson (2012) compare several WSD strategies, during SG and SS, using synset codes from WordNet as sense labels [92]. Nunes et al. (2013) use explicit sense labelling for SS in their LS system, using synonyms from WordNet related to the meaning of the complex word, determined by human readers [55]. Although promising, the limitations for explicit sense labelling arise primarily from the need for manually created sense/synonym databases, which are expensive to produce. Also, the nature of WSD prevents complex words to be substituted with potentially simpler multi-word phrases [63].

b **Implicit sense labelling** tries to overcome to limitations of explicit sense labelling by automating the learning of sense classes of complex words, rather than searching from a sense database. De Belder and Moens (2010) utilize this approach by selecting substitutions that are grouped together by a latent variable language model, trained over a large corpus [21]. Latent variable language models work by automatically learning "latent" classes, which are group of words that appear in similar context, and can be interpreted as "sense" classes because of their strong relationship to synonymy. The drawback of this approach is primarily due to the complexity of algorithms used to generate the models [63].

c **Part-of-Speech (POS) tags** have been used instead of sense labels for appropriate substitution selection, especially in the absence of WSD resources. Paetzold and Specia (2013) use a tree transduction approach to replace complex words and phrases with automatically learned substitutes, but in conjunction with other more abstract filtering methods [56]. POS tagging alone is not sufficient for highly ambiguous words, such as "pitch", which has 23 meanings in WordNet, and can be a both noun or verb [63].

d **Semantic similarity filtering** tries to select substitutions based on a similarity metric, calculated between the sentence with the original complex word and its possible simpler substitute, in context. Biran et al. (2011) show promising results when using a 10-token window to calculate similarity in context, and discarding substitutions with similarity values below a given threshold [7]. Paetzold and Specia (2015) apply a similar filtering approach, but use a word embedding model instead of co-occurrence model to calculate similarity [57]. Paetzold and Specia (2016) introduced an unsupervised boundary ranking approach to consider various features in deciding the best substitute for a complex word, and reported the highest F-scores when compared to other approaches [61].

### Substitution Ranking (SR)

The last step of any LS pipeline involves ranking and deciding which of the substitutes generated produce the simplest output, in the given context, based on some quantitative measure. Several strategies have been proposed for the task for SR:

a Frequency-based approaches, although simple, have shown to be some of the most popular and effective, building on the intuition that the more commonly a word occurs, the more familiar it is to readers [63]. One of the earliest and most widely used frequency-based approaches is Kucera-Francis [69], a metric based on word frequency computed from the Brown corpus. This approach has been replaced recently by use of frequency measures from very large corpora, such as Microsoft N-gram Services platform[^3] and Google 1T Corpus [63].

[^3]: Microsoft Web Language Model API. https://azure.microsoft.com/engb/services/cognitive-services/web-language-model.
b An alternative to frequency-based approaches is calculating a metric for simplicity that combines multiple features. Biran et al. (2011) consider a combination of word frequency and length as their simplicity metric [7]. Sinha (2012) combine word length, its number of senses in WordNet, along with frequency of occurrence in several corpora to determine simplicity [80]. Kajiwara et al. (2013) used a hybrid SS and SR approach to capture meaning and grammatical preservation, representing simplicity as the weighted sum of five metrics that consider various relations between substitution candidate and the sentence to be simplified [93]. Glavas and Stajner (2015) use a similar approach, but combining various simplicity metrics automatically, rather than hand-crafting them [33].

c Due to recent success of machine learning, it has been applied to the SR step in LS systems as well. Jauhar and Specia (2012) uses an SVM ranker, along with the combination of various ranking functions to order candidates by simplicity [36]. Paetzold and Specia (2015) introduce a different supervised approach named Boundary Ranking, combining n-gram frequency calculation from subtitles [57]. Most recently, Paetzold and Specia (2017) use a multi-layer perception that receives a set of features for a pair of candidates as input, and produces as output the simplicity difference between them [63].

3.2 Discussion of LS Systems

Although the LS pipeline has been well defined for some time now, with each component having its own approaches and challenges, there are a few aspects of LS systems as a whole.

Frequent words in the English language have shown to have a clear impact on the readability of the text [68], and several LS systems have attempted to improve simplification systems by improving the frequency metric being used [76]. Although Simple English Wikipedia has proven better than Regular English Wikipedia for frequency counting [40], and N-grams have shown to provide better context for frequency counts, one of the most effective source so far has proven to be the use of a very large dataset – Google Web IT [76].

There are several challenges that are open research problems for LS systems. For example, word sense ambiguity occurs when a word has several meanings and it is difficult to determine which one is correct, in the given context [76]. Not taking the correct meaning of a word could have disastrous consequences in a LS system, as wrong words produce completely different substitutions. Early systems [25] did not take this into account, often selecting synonyms at the expense of maintaining textual cohesion. This challenge has been tackled usually by incorporating a word sense disambiguation algorithm at some point in the LS pipeline, such as the Words Language Model (WLM) [24], which is applied to lexical simplification during the Substitution Generation step of the pipeline [76].

Also, phrasal substitution in an LS system is a bit more complex than word substitution, requiring knowledge of how words cluster into phrases, and how these phrases can be simplified into a single word, which may convey the same sentiment, or another phrase, which may be simpler in terms of language used. Several techniques have been suggested for phrasal substitutions, like comparing revision histories of Simple English Wikipedia [102] or by comparing technical documents with simplified counterparts [28].

The most effective technique remains large look-up databases, like the PPDB, which offer two distinct advantages. First, it allows for pre-defined, more readable phrases to be substituted, allowing rudimentary syntactic simplification to be carried out. Secondly, it helps provide a defense against the issue that arises when simplifying a single word in a complex phrase, which can be detrimental to the understanding of that phrase. Rather than a word-level simplification, the whole phrase actually needs to be simplified, to provide the most accurate meaning [76].

Kriz et al. (2018) [45] implement a classifier that takes into account both lexical and contextual features, and extracts candidate substitutes for the identified complex words from SimplePPDB [50]. They select the substitutes that best fit each context using a word embedding-based lexical substitution model, and their results show that they are able to detect complex words with higher accuracy than other commonly used methods, and propose good simplification substitutes in context.

4 ABSTRACTIVE APPROACH - NOVEL TEXT GENERATION

Latest techniques in TS are extensively data driven, taking advantage of complex data structures and recently developed neural techniques. Bingel and Sogaard (2016) present a structured approach to TS, using conditional random fields over top-down traversals of dependency graphs that jointly predicts possible compressions and paraphrases [6]. Other AI-inspired approaches to TS include deep reinforcement learning [103], pointer generator networks [72], memory-augmented networks [94], LSTM encoder/decoder models [95], neural machine translation (NMT) methods [17] [88], and other deep learning methods [86] [53] [64]. Stajnet and Nisioi (2019) provide a detailed evaluation of neural seq2seq models for in-domain and cross-domain TS [85]. There has also been an effort to move towards unsupervised TS, as can be seen from the works of Qiang and Wu (2019) [67] and Surya et al. (2019) [90]. The following sections outline various types of simplification techniques used to generate novel text.

4.1 Syntactic Simplification

As opposed to LS, which aims to reduce the complexity of a text by simplifying the vocabulary, syntactic simplification seeks to identify grammatically complex text, and rewrite it so that it is easier to comprehend. This may involve splitting long sentences into shorter, more digestible chunks, changing passive voice usage to active, and resolving ambiguities and anaphora [76].

The seminal work in syntactic simplification was a system for the automatic creation of rewrite rules for simplifying text [15], which took annotated corpora and learned rules for domain specific sentence simplification. Although this original system was designed to be a pre-processing step for other natural language applications, later works focused on applying this syntactic simplification as an assistive technology [14] [42]. Later works in syntactic simplification focused on improvements to the discourse structure (ensuring that clauses of sentences appeared in the correct order) [78], and on applying syntactic simplification as a tool for Named Entity Recognition (NER), especially in the medical domain [37].

Syntactic simplification is typically done in three phases:

1. The text is first analyzed to identify its structure and create a parse tree. This may be done at varying levels of granularity, but has been shown to work best at a rather coarse level, where words and phrases are grouped together into 'super-tags,' which represent a chunk of the underlying sentence [76]. These super-tags can be joined together with conventional grammar rules to provide a structured version of the text. During this phase, the complexity of a sentence is determined to decide whether it will require simplification. This may be done by automatically matching rules, but has also been done using a Support Vector Machine (SVM) binary classifier [76].

2. In the transformation phase, the parse tree is modified according to a set of rewrite rules, which perform the simplification operations, such as sentence splitting [25], clause rearrangement [78] and clause dropping [83]. Although automated techniques for applying these rules exist [15], most syntactic simplification systems use hand written rewrite rules, as it eliminates the need for annotated corpora and usually leads to improved accuracy [76].
After transformation, a regeneration phase may also be carried out, during which further modifications are made to the text to improve cohesion, relevance and readability.

Syntactic simplification was considered an essential component of TS systems, and was implemented in PSET [25] and PorSimples [3], two systems considered ubiquitous in assistive technologies. The strengths of syntactic simplification lie in its high accuracy and applicability to other NLP tasks [76]. However, creation and validation of the rewrite rules is a difficult process, and recent advances in deep learning techniques have led to the automation of discovery and application of syntactic simplification.

4.2 Statistical Machine Translation (SMT)
Automated machine translation is an established technique in NLP [88], and involves automatic conversion of the lexicon and syntax of one language to that of another, resulting in translated text. This has been applied very successfully to TS by converting the problem of simplification to a case of monolingual text-to-text generation [76]. We consider our translation task as that of converting from the source language of complex English to the target of simple English. Recent research in machine translation has focused on phrase based statistical techniques, which learn valid translations from large aligned bilingual corpora, and are then able to apply these to novel texts. This task is made easier when the source and target languages are very similar, so few changes are necessary. And it is this type of machine translation that has been applied to TS [76].

Work to perform TS by SMT has been performed for English [20] [104] [99], Brazilian and Portuguese [81], and has been proposed for German [41], Chinese [16] and Swedish [87], among others. Practically, systems often use and modify a standard SMT tool, such as Moses [43], which has been applied to the TS task for English [20]. Moses was augmented with a phrase deletion module which removed unnecessary parts of the complex source text, with promising results [76].

Word embeddings have recently been used as a viable approach to TS [54]. Qiang and Wu focus on the problem on unsupervised simplification without using parallel simple and complex sentences, by using phrase-tables assembled from word embeddings and word frequencies, from complex and simple corpora [67]. Nisioi et al. (2017) proposed a neural sequence-to-sequence model, adapting the available OpenNMT architecture to fit the task of simplification [54].

The performance of seq2seq modeling for SMT relies heavily on the dataset being used to train the model. For example, if the input contains too long of sentences, or simplifications that are structurally unsimilar to the input, this approach is unable to track and align different parts of the sentences. Also, this technique doesn’t take into account punctuations and sentence splitting, making it unable to understand the underlying context.

4.3 Latest Deep Learning Techniques
Deep learning algorithms had been applied to SMT successfully earlier in this decade, as evident by work of Cho et al. (2014), who proposed an RNN Encoder–Decoder for the task of translating from English to French [17]. They showed that their approach of scoring phrase pairs with an RNN Encoder–Decoder improves the translation performance, and that their model learns a continuous space representation of a phrase that preserves both the semantic and syntactic structure of the phrase [17].

Wang et al. (2016) proposed using an RNN-based NMT model for the task of TS [96]. However, they cited the lack of any aligned complex-simple sentence pairs to allow for the development of such a model, and focused their efforts of applying NMT to LS only. Wang et al. (2016) also proposed using an LSTM Encoder-Decoder model to learn operation rules such as reversing, sorting,
and replacing from sequence pairs, which are similar to simplification rules that change sentence structure, substitute words, and remove words [95].

Around the same time, Bingel and Sogaard (2016) proposed an approach to sentence simplification that used linear-chain conditional random fields over dependency graphs to jointly predict compression and paraphrasing of entire syntactic units, with the goal of deleting or paraphrasing entire subtrees in dependency graphs, as a strategy to avoid ungrammatical output [6]. They made innovative use of a three-fold parallel monolingual corpus that features headlines and compressions to learn paraphrases and deletions, respectively, demonstrating that their approach leads to readability figures that are comparable to previous state-of-the-art approaches to the more basic sentence compression task, based on human evaluation [6].

There were two significant issues with early seq2seq models:

i Reproduce inaccurate output: While the encoder/decoder in seq2seq models is able to learn from the source text, its performance depends heavily on word embedding (location of the word in the source relative to other words). For infrequent words, the model is unable to place the word in the correct location in the output. Nisioi et al. (2017) propose ways of dealing with this issue by adding a pointer to the source text, while the decoder is producing simplified output [54]. This has shown promising results in maintaining an accurate context of newly generated simplified text.

ii Repetitions in output: This problem occurs noticeably and frequently in simple seq2seq models. The challenge occurs because the common words, or stop words (“a”, “and”, “the”, “it”), are much more prevalent in text than non stop words. This leads to the model “learning” to predict those words more commonly, leading to their repetition. It has been proposed to add a penalty term for repetition by keeping a “coverage” vector, which monitors the “attention” and “context” vector, and adds a loss when there is overlap between “coverage” and “attention” [72].

Graph-based approached to TS have been proposed to resolve these isues [34] [31]. See et al. (2017) proposed a novel architecture that augmented the standard seq2seq model by using a hybrid pointer-generator network that could copy words from the source text and by using coverage to keep track of what has been summarized [72]. Their network could be viewed as a balance between extractive and abstractive approaches, and improved accuracy and handling of out-of-vocabulary words, while retaining the ability to generate new words [72].

Zhang and Lapata (2017) developed a reinforcement learning-based TS model, which could jointly model simplicity, grammaticality, and semantic fidelity, with a lexical simplification component that further boosts performance [103]. They found that reinforcement learning offers a great means to inject prior knowledge to the simplification task, achieving good results across multiple datasets based on BLEU and SARI metrics [103]. Nisioi et al. (2017) proposed a neural seq2seq model for automated TS, trained on aligned complex-simple sentence pairs from Regular and Simple English Wikipedia [54]. They showed, through extensive human testing and based on evaluation metrics, that their neural text simplification (NTS) system achieved almost perfect grammatical and meaning preservation of output sentences, while producing higher levels of simplification [54].

Neural Machine Translation (NMT) techniques have dominated the text simplification field over the past few years, by generally producing better outputs (better preservation of grammatical structure and meaning). However, there still exist challenges with these approaches, such as too many name entities present in the source text [86].

Sulem et al. (2018) proposed a simplification system combining semantic structures and NMT, showing that it outperforms existing lexical and structural systems, based on BLEU and SARI metric, addressing the over-conservatism of MT-based systems for TS, which often fail to modify the source
in any way [88]. Vu et al. (2018) go beyond the conventional LSTM/GRU-based seq2seq models, and propose to use a memory-augmented RNN architecture called Neural Semantic Encoders (NSE) [94]. Their results from both automatic and human evaluation on different datasets show that their model is capable of significantly reducing the reading difficulty of the input, while performing well in terms of grammaticality and meaning preservation [94].

One of the advancements attempted in text simplification lately has been to simplify text to a particular reading level. Previous attempts at achieving this goal have focused on training a simplification model with the grade level tag, extracted from the Newselela corpus. Although a good start, this technique still tends to output words too complex for a given grade level [53]. Nishihara et al. (2019) proposed a solution by adding a weight to the training loss of their model for complex words that appear often at a particular grade level [53].

Because lack of data to train on remains one of the major problems for TS, most of the recent advancements in, and focus of, research has been to solve this problem. Aprosio et al. (2019) exploit large amounts of heterogeneous data to automatically select simple sentences, which are then used to create synthetic simplification pairs [64]. Inspired by the MT field, where synthetic parallel pairs generated from monolingual data have shown to produce significant improvements to neural models, their techniques yield performance improvements over a baseline seq2seq configuration [64].

In addition to creating synthetic data, developing unsupervised techniques for TS has also been of keen interest. Qiang and Wu (2019) propose a novel phrase-based unsupervised TS system by leveraging a careful initialization of phrase tables and two language models, from regular Wikipedia, without requiring any parallel sentence pairs [67]. They populate the phrase tables using Wikipedia as a massive information source, acquiring word embeddings, which capture semantic properties of words, and word frequencies, which reflect the level of difficulty, outperforming even some supervised models based on BLEU and SARI [67].

Surya et al. (2019) propose an unsupervised NTS model for TS, using unlabelled data from regular and simple Wikipedia [90]. Their proposed framework, composed of a shared encoder and a pair of attentional-decoders, assisted by discrimination-based losses and denoising, is able to perform TS at both lexical and syntactic levels, competitive to existing supervised methods [90].

5 DATASETS

The quality of any supervised learning system depends first and foremost on the quality of data available for training [100]. Since the research in text simplification is still in its stages of infancy, there are only a few data sources available for use.

5.1 Datasets for Lexical Simplification

The most useful LS datasets are those annotated manually, and each instance of which contain a sentence, a target complex word, and a set of suitable substitutions provided and ranked by humans with respect to their simplicity [63]. Currently available datasets include:

- **SemEval 2012** [82] - Contains 2,010 instances of simplicity rankings, and considered a classic dataset for LS that has been widely used in benchmarks, as it stands out for reliably capturing the concept of simplicity as perceived by non-native speakers of English.
- **LSeval** [22] - Consists of 430 instances of simplicity rankings produced by 46 Amazon Mechanical "turkers" and 9 Ph.D students. The intensive annotation process used in the creation

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4https://www.cs.york.ac.uk/semeval-2012/task1
5http://www.mturk.com
of this dataset ensured that complex words are actually simplified. However, LSeval uses the same base data as the SemEval 2012.

- LexMTurk\(^6\) [35] - Contains 500 instances of sentences from Wikipedia with target complex words and simpler substitutions suggested by 50 English speaking turkers each. Since each of its instance is annotated by 50 turkers, LexMTurk offers a very high coverage of gold simplifications.

- BenchLS\(^7\) [58] - Contains 929 instances, and is a compilation of the LSeval and LexMTurk datasets, automatically corrected for spelling and inflection errors. Since it combines two other datasets, BenchLS offers the largest range of distinct target complex words amongst the LS datasets for English.

- NNSeval\(^8\) [60] - Is a filtered version of BenchLS, consisting of 239 instances. NNSeval captures the needs of non-native English speakers more accurately than the other datasets because it was created from BenchLS by discarding:
  i) any instances of which the target word was not deemed complex by a non-native English speaker
  ii) any candidates that were deemed complex by a non-native English speaker

5.2 Datasets for Novel Text Generation

The seq2seq modeling for novel text generation requires datasets consisting of complex and simple aligned sentences. This necessity has been partially fulfilled by Newsela and Simple English Wikipedia [64].

- Simple English Wikipedia (SEW) - Widely used as it is publicly available and because of the popularity of regular English Wikipedia. SEW includes simplified versions of articles in regular English Wikipedia, and datasets are available with aligning “equivalent” sentences from the two to allow seq2seq model training. However, since there is only one aligned sentence per source, SARI cannot be used for evaluation. The release of Simple English Wikipedia has shifted the focus of text simplification from a rule-based approach to a purely data-driven one [86].

- Wikipedia-Simple Wikipedia\(^9\) [40] - Created by Kauchak (2013), this dataset consists of 167,689 aligned sentences from 60,000 aligned articles.

- PWKP\(^10\) [104] - Created by Zhu et al. (2010), this dataset consists of 108,016 aligned sentences from 65,133 aligned articles in Wikipedia and Simple Wikipedia.

- SS Corpus\(^11\) [39] - Kajiwara and Komachi (2016) created this dataset, which contains 492,993 aligned sentences, also extracted from regular and Simple English Wikipedia.

- WikiSmall - Paetzold and Specia (2016) [62] created a consolidated and standardized sentence pairing from SEW to create WikiSmall, which has been used widely to evaluate simplification systems’ performances (again only using BLEU, not SARI).

- Turk Corpus - Xu et al. created the Turk Corpus along with their SARI metric [100] in 2016. This dataset was created using Amazon Mechanical Turk, providing 8 simplified reference sentences for each input, allowing the SARI statistic to be calculated.

- Newsela - This dataset, also created by Xu et al. contains news articles with 4 simplified versions for each, produced manually by professional editors. Corpus level simplification is

\(^6\)http://www.cs.pomona.edu/~dkauchak/simplification/lex.mturk.14
\(^7\)http://ghpaetzold.github.io/data/BenchLS.zip
\(^8\)http://ghpaetzold.github.io/data/NNSeval.zip
\(^9\)http://www.cs.pomona.edu/~dkauchak/simplification/data.v2
\(^10\)https://www.ukp.tu-darmstadt.de/data/sentence-simplification
\(^11\)https://github.com/tmu-nlp/sscorpus
available, however, it has to be processed for sentence-level simplification. Newsela contains parallel simple-complex news articles with 11 grade levels [53].

5.3 Need for Dataset Extraction/Compilation

Most of the current simplification datasets consist of lexically simpler sentences, as opposed to syntactically simpler [12]. The most commonly used data sources for supervised learning in text simplification are the Newsela Corpus and the Simple English Wikipedia (SEW). Both of these sources, however, contain mostly document level simplifications, and occasionally paragraph-level simplifications. For most Statistical Machine Translation (SMT) and Neural Machine Translation (NMT) models, we require sets of complex and simplified sentences. To fulfill the data requirement for simplification models, it is necessary to extract simplified versions of sentences from the SEW and Newsela corpora. This requires understanding of related NLP fields, like semantic similarity, and adoption of tools, like MASSAligner [62].

Kajiwara and Komachi (2016) propose an unsupervised method that automatically builds the monolingual parallel corpus for TS using sentence similarity based on word embeddings [39]. For any sentence pair comprising a complex sentence and its simple counterpart, they employ a many-to-one method of aligning each word in the complex sentence with the most similar word in the simple sentence, and compute sentence similarity by averaging these word similarities, reporting excellent performance in construction of a monolingual parallel corpus construction for TS in English.

Scarton et al. (2018) extract complex-simple sentence pairs from the Newsela corpus and explore the data in different ways [71]. They show how traditional readability metrics capture surprisingly well the different complexity levels and build machine learning models to classify sentences into complex vs. simple and to predict complexity levels that outperform their respective baselines.

Satjner et al. (2019) propose an alignment tool called Customized Alignment for Text Simplification (CATS), which is able to provide paragraph or sentence level alignment of parallel text, while also providing three different sentence (or paragraph) similarity measures which can be further used to filter retrieved sentence/paragraph pairs for customised modeling of text simplification operations [84]. Their method has the added advantage of being applicable to any language.

5.4 Techniques for Data Compilation/extraction

Before delving into data extraction from a large document-level aligned complex/simple corpus, it is necessary to establish a quantitative measure of successful extraction, as was the goal in the shared task of on quality assessment for text simplification (QATS)12, where two tasks were addressed [38]. One was to estimate a real-value quality score for given sentence pair, while the other was to classify given sentence pair into one of the three classes (good, ok, and bad).

Kajiwara and Fujita (2017) examine the usefulness of semantic features based on word alignments for estimating the quality of text simplification [38]. They introduce seven types of alignment-based features computed on the basis of word embeddings and paraphrase lexicons and achieve state-of-the-art performance on the QATS dataset.

5.4.1 Semantic Similarity: Text similarity is assessing the similarity between two words, sentences or expression, based on the likelihood of their meaning. There are two predominant methods used for calculating the similarity between expressions, Corpus-based or Distributional Semantic models (DSMs) and Knowledge-based models. Knowledge-based methods use word senses, parts of speech and taxonomic information to calculate the similarity between expressions, whereas the Corpus-based methods determine similarity based on the assumption that similar words occur in similar

12http://qats2016.github.io/shared.html
documents. The major drawback of Corpus-based methods is that they ignore the sentence structure and the difference in word meaning based on the context, while the knowledge-based approach is restricted by the availability of human-crafted dictionaries. Recent researchers have worked on hybrid models combining the above methods to generate similar sentence pairs with better performance than the traditional methods [30]. A clear understanding between ‘text-relatedness’ and ‘text-similarity’ is an integral part of text extraction based on similarity. Work by Bollegala et al. (2007) [10] and Cilibrasi (2007) [19] uses web search engine results for calculation word relatedness, where words with opposite meanings also have a high similarity score.

Models based on neural networks have also been developed for semantic similarity calculation between text. Recurrent Neural Networks, especially Long Short-Term Memory (LSTM) networks, have been proven to be naturally suitable for classification of variable-length inputs like sentences [8] [51]. The Tree-LTSM model proposed by Tai et al. (2015) uses variations of LSTM Neural Network models for calculating the similarity of text [91].

Models like Word2Vec, Sent2Vec, Doc2Vec, Glove are used to convert words or sentences to vectors (word vectors/word embeddings) and the similarity (cosine) between these vectors are considered as the semantic similarity of the words. The Word2Vec algorithm builds a distributed semantic representation of words. The two approaches include a bag of words and a skip grams model. The bag of words model involves predicting the context words using a center word, while the skip-gram model involves predicting the word using the context words. The Sent2Vec and Doc2Vec are extensions of Word2Vec where the model calculates the mathematical average of the word vector representations of all the words in the sentence or documents. The major challenges faced with neural network-based methods are, in addition to not being able to capture multiple senses of words, word embeddings also fail to capture the meanings of phrases and multi-word expressions, which can be a function of the meaning of their constituent words, or have an entirely new meaning on its own.

5.4.2 Vicinity-driven Aligner model: MASSAligner, proposed by Paetzold and Specia (2016), is available as an open-source Python library, which allows aligned paragraphs or sentences to be extracted from a document based on a similarity threshold specified [62]. The steps involved in sentence pairs extraction from document-level or paragraph-level aligned documents include:

i) Measuring semantic similarity: The model calculates the semantic similarity between sentence pairs using the TF-IDF model. The model converts documents to a bag of words, forms word vectors based on the normalized term frequency (frequency of a term / total number of terms), and finally calculates the cosine similarity between word vectors. The model returns a similarity matrix containing the similarity between all the sentences.

ii) Aligning sentences based on similarity: The model follows a vicinity driven approach to extract the sentences that are similar, based on a threshold value provided as a hyperparameter. The aligner then traverses through the similarity matrix to establish an alignment path that searches for the best pair of similar sentences. Given a coordinate \([i,j]\) in a matrix, there are three vicinities taken into consideration:

\[
V_1 = [i, j + 1], [i + 1, j], [i + 1, j + 1],
\]

(5)

\[
V_2 = [i + 1, j + 2], [i + 2, j + 1],
\]

(6)

and \(V_3\) as all remaining \([x,y]\) where \(x>i\) and \(y>j\). The initial point begins at the coordinate that is closest to the first point \((0,0)\) and has a similarity greater than 0.2 (hyperparameter set by default). The algorithm searches the three vicinities to find the coordinates having the highest similarity.
5.4.3 **Creation of Synthetic Data:** One proposed solution for the problem of lack of data is to generate synthetic pairs of sentences, by starting with a simple sentence, and generating the complex version of it [64].

Techniques involved in supplementing the limited available data include:

i. **Over-sampling:** Multiplying the dataset up to five (5) or ten (10) times could maximize the availability and use of the few "gold" stand simplified sentences [64].

ii. **Simple-to-simple synthetic pair creation:** The simplest possible sentences are extracted from a large monolingual corpus, using heuristical techniques, and then replicated to form simplified versions. These sentences, when added to a complex-simple sentence pairs training set allows for better word embeddings, and created a bias in the system towards simpler sentences [64].

iii. **Simple-to-complex synthetic pair creation:** OpenNMT is a python library that is utilized to create a "complexifier system." The limited ideal simplified sentences are first used to train the system, inspired by works in MT [73] and in keyword-to-question [26]. The simple sentences extracted earlier are passed through the "complexifier" system to create synthetic simple-to-complex sentence pairs [64].

5.4.4 **Other Data Collecting Strategies:** Brunato et al. (2016) [12] have proposed a three step process for acquiring simplified sentence pairs:

i. In the first step, an unsupervised technique is developed to first collect a large number of lexically similar, but structurally different sentences. The resulting sentences are then ranked according to a similarity metric, designed to look for lexically-equial sentences, having gone through structural change.

ii. In the second step, the list of top sentence pairs is manually revised to develop a classifier to detect lexically and syntactically correct sentence pairs.

iii. In the last step, an automatic readability assessment tool is used to order the sentences obtained, in terms of lexical complexity.

6 **EVALUATION METRICS**

Paetzold and Special focus on benchmarking LS systems, both as a whole and on the individual component level [58]. LS systems are benchmarked based on annotated datasets, with statistics like accuracy, precision, recall, and f1-score.

6.1 **Evaluating Novel Text Generation**

Due to the subjective nature of TS, especially when simplifying sentences through seq2seq modeling, it has been suggested that the best approach to evaluation is by a human being, to be judged in terms of grammaticality (or fluency), meaning preservation (or adequacy) and simplicity, using Likert scales (1-3 or 1-5). However, in a quest towards unsupervised learning, a number of metrics have been developed to evaluate the quality of simplification.

- **BLEU** - Introduced by Zhu et al. as an evaluation for machine translation in 2002 [65]. Although the metric correlates with human evaluation, it is not well suited to gauge lexical or structural complexity.

- **SARI** - Developed by Xu et al. in 2016, SARI is currently the main metric used for simplification model [101]. Although a lexical simplicity metric, SARI measures the “fit” of added, deleted, and retained words by comparing the output to several simplified reference sentences. Again, although showing a high correlation with human evaluators, this metric requires several simplified reference sentences to be compared against, which may not be always available.

- **Readability Indices** - Used in the U.S. to assign a grade level to any text corpus, as a measure of simplicity. Commonly used readability indices include Flesch Reading Ease, Flesch Kincaid...
Grade (based on words, sentences and syllables), Coleman Liau (relies on characters per word), Automated Readability Index (based on characters, words and sentences), Linsear Write Formula (based on “easy” and “hard” words per sentence), and Gunning FOG (based on regular and complex words per sentence). However, these metrics are computed using techniques similar to extractive evaluation, weighing words and syllables and their diversity of use. Some of the flaws in these metrics include giving higher weight to short sentences, and not being able to recognize grammatically incorrect or non-sensible outputs.

- SAMSA - A new metric proposed by Sulem et al. that can evaluate simplification, including sentence splitting, not just summarization, like SARI [89]. Due to its recent release, this metric is not currently widely used.

7 DISCUSSION AND CONCLUSION

Having started with simple statistical approached to simplification, like extractive simplification resembling summarization, TS has come a long way since. Most of the current approaches to TS are abstractive, either involving LS or novel text generation. LS tries to simplify words and phrases through a pipeline, starting with identifying complex words, then generating, selecting and ranking possible substitutions to simplify the content. LS is often performed through training and testing on annotated corpora, using evaluation metrics like accuracy, precision, recall and f1-score.

Novel text generation attempts to perform simplification through syntactic simplification, statistical machine translation and seq2seq modeling, utilizing deep learning techniques. Trained on corpora consisting of pairs of complex and simple sentences, the models produced through these techniques are capable of simplifying any text. One of the main challenges in such abstractive techniques is the subjective nature of language, and development of metrics able to measure relative and absolute levels of simplification of text. Although several such metrics have been proposed, like BLEU and SARI, this area remains one of active research.

Interest in TS research has been increasing dramatically in the recent years and decades, thanks to availability of more economical computing resources and advances in software support. That said, TS is still in relative infancy, both as a field itself and as a part of NLP. This results in challenges like unavailability of extensive high quality data sources necessary for automated TS, especially using AI or deep learning techniques. The linguistic part of TS research brings other challenges to the field, like imprecision in our ability of measure simplification, and the subjective nature of language itself. However, with focus and interest in the field at an all-time high, we expect continuous advances in the field, and hope that this paper can provide a foundation to anyone seeking to familiarize themselves with TS research.

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# List of Relevant Abbreviations

Table 2 contains a list of all abbreviations referenced in this article, along with their descriptions.

| Abbreviation | Description                                              |
|--------------|----------------------------------------------------------|
| CATS         | Customized Alignment for Text Simplification             |
| CRA          | Canada Revenue Agency                                    |
| CWI          | Complex Word Identification                              |
| DL           | Deep Learning                                            |
| DSM          | Distributional Semantic Model                            |
| GRU          | Gated Recurrent Unit                                     |
| LS           | Lexical Simplification                                   |
| LSTM         | Long Short-Term Memory network                           |
| ML           | Machine Learning                                         |
| NER          | Named Entity Recognition                                 |
| NLP          | Natural Language Processing                              |
| NMT          | Neural Machine Translation                               |
| NSE          | Neural Semantic Encoder                                  |
| NTS          | Neural Text Simplification                               |
| POS          | Part-of-speech                                           |
| PPDB         | Paraphrase Database                                      |
| QATS         | Quality Assessment for Text Simplification               |
| RNN          | Recurrent Neural Network                                 |
| seq2seq      | Sequence-to-sequence                                     |
| SEW          | Simple English Wikipedia                                 |
| SG           | Substitution Generation                                  |
| SMT          | Statistical Machine Translation                          |
| SR           | Substitution Ranking                                     |
| SS           | Substitution Selection                                   |
| SVM          | Support Vector Machine                                   |
| SW           | Sentence Weight                                          |
| TF-IDF       | Term Frequency - Inverse Document Frequency              |
| TS           | Text Simplification                                      |
| UMLS         | Unified Medical Language System                          |
| WLM          | Words Language Model                                     |
| WSD          | Word Sense Disambiguation                                |