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An Overview of Text Translation and Text Simplification Tasks

Dhawal Khem*[1], Shailesh Panchal[2], Chetan Bhatt[3]

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Abstract—In NLP text translation and text simplification can be defined as text conversion processes. In text translation a source language text is getting converted into a target language text, and in text simplification a complex input text is converted into a simplified output text. Both of these processes are not easy and straightforward. They require language expertise and certain domain knowledge. With increase in cultural globalization and social media usage, these services are becoming essential. They help to improve the interaction between entities by reducing the communication gaps between them. Automation of these tasks have gained the interest of so many research persons. Many approaches, tools and techniques have been invented so far. Every approach has its own limitations and challenges. All techniques at core face a common challenge known as ambiguity problem. The ambiguity can be defined as a decision level confusion, where the decision is to select a correct appropriate replacement text for the current input text among the available candidate texts. The ambiguity resolution is an open problem, which is an unsolved problem keeping human intelligence a far ahead milestone to be achieved by artificial intelligence.

This paper aims to correlate the text translation and text simplification tasks by overviewing their various approaches, their internal processes, and their evaluation mechanism. We are trying here to bring the similarities of these tasks to make it easy to learn, and understand.

Keywords-*Text Translation, Text Transformation, Text Simplification, Natural Language Processing*

1. Introduction

In current globalization time, people are traveling to distant locations, interacting with each other on social media, exploring information about different regions, religions and matters; foreign language becomes a barrier to access information. Historically humans have served as the intermediate translator for many years. As the text translation and text simplification remained essential services to improve the communication between entities [1]–[3]. An assumption here is, the better the communication the better clarity can be maintained; this may help to reduce the chances of miscommunication, and misinterpretation, and avoid the situation of lack of information or unawareness. In short, with better communication, understanding differences can be reduced.

Ph.D Scholar, Computer Engineering,
Gujarat Technology University, GTU,
Ahmedabad(Gujarat), India
e-mail: khemdhawal@gmail.com
ORCID ID : 0000-0002-8064-5954
Professor, PG-Cyber security,
Graduate School of Engineering & Technology (GSET)
Ahmedabad(Gujarat), India
e-mail: sdpanchal@gtu.edu.in
Professor, Instrumentation and Control Engineering,
MCA College Maninagar, K. K. Shastri Educational Campus,
Khokhra Road, Ahmedabad(Gujarat), India
e-mail: chetan_bhatt@yahoo.com

For the above-discussed thought several research have been done so far to automate the text translation and text simplification processes. Also various tools and techniques have been developed as well. Every approach has its way of text translation and text simplification and has its limitations and challenges. There are existing surveys done by research scholars on these topics. But we did not find any one which is talking about both together, or showing similarities between text translation and text simplification processes. With this thought of providing a useful article for those who are beginners or learners, who are interested to learn both of these NLP areas; they can find here an overview of text translation and simplification processes for a quick and easy understanding.

We are discussing here the basics of machine translation and text simplification approaches, the challenges involved in these processes, and the quality measurement benchmarks used to do a comparative study. We also bring here the typical limitations and challenges involved during these processes, which deep dive into the unsolved open problem called the ambiguity resolution. Here section II covers text translation and its approaches, challenges, and performance evaluation, section III talks about text simplification and its approaches, challenges, and performance evaluation, and section IV covers the typical limitations and challenges for both text translation and simplification processes, and section V sums up into the conclusion.

2. Text Translation(TT)

Converting a source language text into a target-language text is known as text translation. It requires a certain level of expertise in both the source and target language, and world knowledge to identify the context of the communication. Historically a human has served as the translator for many years. In the current time of globalization, the massive span of human-to-human interaction through social media, tourism, and international events, automating text translation known as machine translation has become a promising area of research [1], [2], [4]–[6].

A. How Translator Works

As defined earlier, the translation process takes the source language (SL) statement as input and produces the target language(TL) statement as output. Figure 1 shows the Vauquois Triangle which describes the insights of the translation process. The translation process passes through the Analysis(A) phase, the Transfer(T) phase, and the Generate(G) phase.

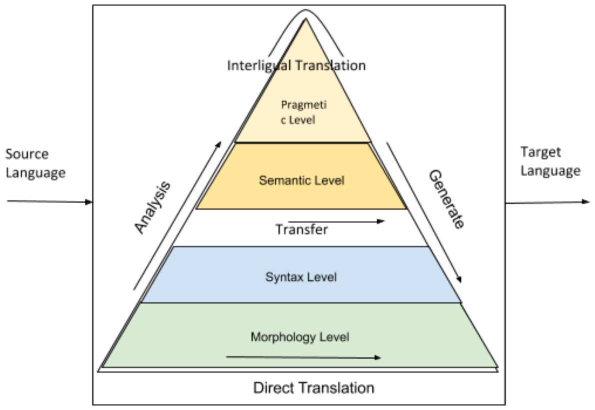

Fig. 1 Vauquois Triangle

1) *Analysis Phase (Heading 3):*

In this phase the source text is statistically analyzed before going to the next transfer phase. There are various analysis levels as shown in Figure 1. From bottom to top the analysis level goes from simple to complex level. The higher the analysis is, the more the source language approaches the interlingua state, an universal language behaving as an intermedial language among any other language. To define in simple terms, the morphological analysis is at word level, the syntactic analysis is at sentence grammatical structure level, the semantic analysis is at meaning level, and pragmatic analysis is at the context level (i.e. world knowledge level). At all these levels the analysis phase has to deal with their corresponding ambiguities, that is to identify the correct choice among the available options. The higher the analysis phase becomes the more time it takes, and the deeper level of information can be derived. The common steps that are performed during the analysis phase are:

*(1) Tokenization**:*** The input text is chopped into pieces, which are known as tokens. This task identifies the known words, clauses, or phrases from the input text.

(2) Stemming: The inflectional and derivational endings such as prefixes and suffixes from a word are removed or substituted in this process.

(3) Lemmatization: This also tries to remove the inflectional and derivational endings from a word, but this returns a dictionary form of a word, known as lemma.

(4) POS Tagging: This task identifies the parts of speech of words, such as noun, verb, adjective, pronoun, etc.

(5) Information Extraction: This process extracts information from unstructured or semi-structured text. It finds entities as well as classifies and stores the entities in a database. The Named Entity Recognition is a sub-task of information extraction that seeks to locate and classify named entities mentioned in unstructured text into predefined categories such as person names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages, etc.

(6) Dependency Resolution: This task identifies the dependency relationship between the words. This helps to find the root word and the grammatical structure of the input text.

2) *Transfer Phase*

The second phase of the ATG process is the transfer phase. This phase converts the input text to the corresponding target text with the help of the collected information from the analysis phase. The higher the analysis is, the smaller and more straightforward the transfer phase becomes.

3) *Generation Phase*

It is the last phase of the ATG process. In this phase, the final target output is generated after the morphological adjustments to the target text collected from the transfer phase.

It is believed that to achieve a high-quality translation between any languages means to have an interlingual universal language, which can represent every possible term of every existing language. But a language itself is an infinite set of strings, thus having an interlingual universal language itself becomes an imagination to have it. Here, there exists a trade between domain, speed, and accuracy. All three of these can not be achieved together. But any two of these can be achieved [7]. Thus, various machine translation approaches as per their requirement trade-off use different levels of ATG phases. And each variation in ATG deals with a different set of issues and challenges.

B. Machine Translation Approaches

Machine Translation systems can be classified according to their core methodologies: 1) Rule-Based Approach, 2) Corpus-Based Approach, and 3) Hybrid Approach.

1) *Rule-based Machine Translation (RbMT)*

Rule-based machine translation is based on linguistic information retrieved from both source and target languages. This linguistic information is retrieved from bilingual dictionaries and language grammar. Such information is categorized into morphological, syntactic, semantic, and pragmatic knowledge of both the source and target languages.

Based on the depth of source language analysis and the extent to which RbMT attempts to reach a language-independent interlingual representation of the meaning (context), the RbMT is divided into three sub approaches, 1) Direct Machine Translation (DMT), 2) Interlingual Machine Translation, and 3) Transfer-Based Machine Translation [7]. These sub-approaches are shown in Table 1.

TABLE I. RBMT APPROACH

Type	Description	Challenges
Direct MT	It is a bilingual uni-directional word-by-word dictionary-based translation approach. It does a little syntactic and semantic analysis with simple grammatical adjustments. LMT(logic-based machine translation) is an experimental English-to-German MT system developed in the framework of logic programming [3].	Mistranslations at the lexical level. Inappropriate syntax structures. Weak at finding linguistic grammatical relationships between the core parts of the sentence
Interlingual MT	It uses interlingual language for translation purposes. First, the source language is transformed into an interlingual language and then the target language is generated from the interlingua. An example translator for this approach is Calliope-Aero [4].	Defining interlingua language. Creating interlingua translation by extracting meaning from the source text.
Transfer Based MT	It depends upon both the source language and the target language. It uses all the ATG phases. In the Analysis(A) phase the syntactic representation of the source language sentence is produced. In the Transfer(T) phase, the result of the Analysis stage is converted into equivalent Target-Language(TL) representation. In the Generation(G) phase, the TL morphological analyzer converts the TL representation into the final TL text.	Defining rules at every step of translation Building reusable modules of analysis and synthesis. Keeping transfer modules as simple as possible.

Issues with RbMT Systems:

- Rules conflict occurs when in certain situations more than one rule becomes applicable. Therefore, rules have to be ordered carefully.
- First come first serve. The first rule that appears will get executed first. So It may be possible that a more appropriate rule is ordered later, so it may never apply.
- Rule-based systems are high precision and low recall; means when they apply they almost get it right (high precision), but it is not often that they apply (low recall).

2) *Corpus-based Machine Translation(CBMT)*

CBMT is a nonmanual data-driven approach. It uses a large amount of bilingual raw data in a parallel corpus to acquire translation knowledge. This raw data contains source language text and their corresponding target language translations. The CBMT translator uses the corpus data for its training and testing to learn the linguistic characteristics of both source and target languages.

The CBMT approach is further classified into two sub approaches Statistical Machine Translation(SMT) and Example-Based Machine Translation (EBMT) [5], explained in Table 2.

TABLE II. CBMT APPROACH

Type	Description	Challenges
Statistical MT	It works based on statistical model extraction from parallel aligned bilingual text corpora. In which every word in the target language has a translation probability from the source language words. The words with the highest probability give the best translation. Google Translate [8], Microsoft Translator [9], Systran [10], etc., are examples of the SMT approach.	Corpus creation can be costly for users with limited resources. The results are unexpected. Superficial fluency can be deceiving. It does not work well between languages with significantly different word orders (e.g. Indo Aryan and European languages).
Example Based MT	It uses a bilingual corpus with parallel example texts, which have a point-to-point mapping between source language sentences and target language translations. There are four tasks performed in EBMT: example acquisition, example base and management, example application, and synthesis.	It requires analysis and generation modules to produce the dependency trees needed for the examples database and analyze the sentence. Computational efficiency especially for large databases.

Issues with CBMT Systems :

- Handling divergence in reordering.
- Handling ambiguities, i.e. a single sentence in the source language can have multiple translations in the target language and vice versa.
- Miss translation may happen due to statistical anomalies in training sets.
- Lack of bilingual corpora may result in bad quality or inappropriate translation.
- Idioms may not translate idiomatically.
- Word order differs in languages.

3) *Hybrid Machine Translation (HMT)*

It is a combination of both rules (RbMT) and statistics(SMT). This can be used in different ways. In one way, translations are performed by RbMT and later adjustments or corrections are achieved by using statistical information. In another way, translations are performed using the SMT system, and the RbMT approach performs the pre & post-processes. It requires language dictionaries and grammar rules, as well as the language translation parallel corpus. Various translators such as PROMPT [11], SYSTRAN [10], and Omniscient Technologies use this approach.

Issues with HMT Systems

- It requires analysis (pre-processing) and generation (post-processing) modules to produce the dependency trees needed for the example database and analyze the sentence.
- Computational time grows, especially for large databases

C. *TT Performance Evaluators*

The translation quality of MT systems is evaluated by manual techniques as well as by automated evaluators.

1) *Manual MT Evaluation Techniques:*

In such evaluation, human evaluators are required, who are linguistic experts. So the evaluation is slow and costly with good quality. Here are the criteria of human evaluation.

a) *Adequacy(A):* It is to measure how faithfully the meaning of a sentence is transferred from the source language to the target language. The evaluation is done using relative probability. (i.e. A = P (f / e), where f is a source language statement, and e is the target language statement)

b) *Fluency(F):* It is to measure the native speaker's acceptability of translated sentences. It requires correct word choice, correct word order, and registration.

2) *Automated MT Evaluation Techniques*

The automated evaluation system helps to evaluate the quality of translation. The evaluator requires the reference translations provided by the human translators, and the actual translation given by the machine translator. The better the correlation between the actual translation and the human judgment, the better the evaluation metric score. The greater the reference translations, the higher the confidence in the result of translation.

TABLE III. Confusion Matrix

		Predicted Output	
		Negative(N)	***Positive(P)***
Actual Output	***Negative(N)***	True Negative (TN)	False Positive (FP)
	Positive(P)	False Negative (FN)	True Positive (TP)

Table 4 shows the confusion matrix to calculate the corresponding performance evaluation metrics [11]. The actual output indicates the expected outcomes, which were given along with the input sentences in the corpus. The predicted results are those that the MT model predicts during its execution. The Positive(P) refers to the number of confirmed positive cases in the data. The Negative(N) refers to the actual negative cases in the data. The True Positive (TP) is the correct acceptance. The True Negative (TN) is the correct rejection. The False Positive (FP) indicates the number of outputs that were expected negative but predicted positive. The False Negative (FN) indicates the number of outputs that were expected positive but predicted negative. The automated MT evaluators based on the confusion matrix are listed below.

Precision(P) = TP / (TP + FP)

Precision indicates how many selected items are relevant.

Recall(R) = TP / (TP + FN)

Recall indicates how many relevant items are selected.

F1 score(F) = 2PR / (P + R)

F1 score is a harmonic mean of Precision and Recall.

Accuracy(A) = (TP + TN) / (TP + TN + FP + FN)

Accuracy is the ratio of exact answers to all answers.

Specificity(S) = (TN / (TN + FP)

Specificity shows how many selected items are irrelevant.

There are other algorithms used as well for the MT performance evaluation, such as BLEU (Bilingual Evaluation Understudy) [12], NIST (National Institute of Standards and Technology), METEOR (Metric for Evaluation of Translation with Explicit Ordering), etc. for evaluating the quality of text which has been machine-translated from one natural language to another [13]. These evaluators take the predicted output text and compare it with the list of references. They give the n-gram similarity scores, where the n-gram is the number of continuous words to be compared. The higher the score is, the better the quality of translation it indicates.

Below in Table 5, the Gujarati to English language Text Translation samples with their BLEU and NIST scores are shown. The corresponding BLEU and NIST graphs are shown in Figure #,#.

TABLE IV. TEXT TRANSLATION SCORES

Text Translation		**Scores**	
Input (Gujarati)	***Output (English)***	***BLEU***	***NIST***
જનનીની જોડ સખી નહિ જડે રે લોલ (Jananini Jod Sakhi Nahi Jade Re Lol)	The genital mutilation will not tighten	0.28	0.1
મિત્ર માઁ સમાન અન્ય કોઈ નહિ મળે (Mitra Maa Saman Anya Koi Nahi Made)	I will not find anyone else like my friend	0.3	0.95
મિત્ર માતા સમાન અન્ય કોઈ નહિ મળે) (Mitra Mata Saman Anya Koi Nahi Made)	No one else can be the same as a friend mother	0.37	3.73
મિત્ર, માતા સમાન અન્ય કોઈ નહિ મળે (Mitra, Mata Saman Anya Koi Nahi Made)	Friend, no one else can be found equal to mother.	0.41	4.09

3. Text Simplification(TS)

Text simplification is converting the input text so that the readability and understandability of text improve. Here the language used for the input text and the output text remains the same. In the simplification process, it may be possible that either the text gets reduced or gets increased. So the text summarization task can be considered one aspect of text simplification itself. In most cases in text simplification, the input text length increases. These building tools suggest authors to improve their content readability and understandability. Text simplification can be a useful pre-processing tool for many NLP applications, such as machine translation, text summarization, and information retrieval. With Wordnet, text simplification can further be helpful to build encyclopedias like simplified Wikipedia, Bhagwadgomandal, Gujarati Wordnet, etc. Also, it helps to improve the quality of translators and information retrieval systems [14].

D. Text Simplification Approaches

There are three approaches to text simplification, 1) Lexical Level Simplification, 2) Syntactic Level Simplification, and 3) Discourse Level Simplification.

1) Lexical Level Simplification

It involves replacing difficult words with simpler synonyms. It requires Wordnet to find a replacement. The Wordnet is an electronic semantic lexicon for language. Practical Implication of English Texts-PSET(PSET), Help Aphasic People Process Information(HAPPI), and ETS's ATA v.1.0 are software examples of lexical text simplification [15].

Challenge:

- Identifying difficult words.
- Replacing difficult words with simpler synonyms.

2) Syntactic Level Simplification

It is used to identify simplifiable complex constructs. It requires deep analysis of the input text and sophisticated methods for knowledge representation. Reference [16] has mentioned the work of Chandrasekhar [17]; Siddharthan [18]; Applications of syntactic level simplification [19].

3) Discourse Level Simplification

It is similar to syntactic level simplification, it is also used to identify simplifiable complex constructs which require deep analysis of the input text and sophisticated methods for knowledge representation. The difference is the length of sentences. The discourse level simplification sentences are complete and larger in text.

E. TS Performance Evaluators:

Table V shows the manual evaluation criteria, and Table VI explains the automated evaluation measures for text simplification.

4) *Manual TT Evaluation Techniques*

a) *Correctness:* This is a manual verification approach to check if the simplified text is grammatically correct or not. i.e. Yes/No.

b) *Preservation of meaning:* It is to rank the preservation of meaning in the output simplified text. i.e. 0, 1, 2, 3

c) *Coherence:* The degree of semantic relatedness between sentences. This is measured manually with ranking. i.e. 0, 1, 2, 3

5) *Automated TT Evaluation Techniques*

a) *Readability:* This indicates how easy it is to read. This is being calculated using the FLESCH formula [20], [21], and LIX formula. Below are the readability score evaluating formulas. These are divided into two categories based on the level.

- **Pre-school Level Formula:**
  Flesch Reading Ease(RE)=206.835 - 1.015 (ASL) - 84.6(ASW)
  Automated Readability = 4.17 (Characters/Words) + 0.5 (words/sentences) - 21.43

- **Grade Level Formula:**
  Flesch-Kincaid Readability (FKRA) = (0.39 x ASL) + (11.8 x ASW) - 15.59
  Gunning Fog = 0.4 (ASL + PHW)
  SMOG Readability = 3 + Square Root of Polysyllabic Count
  Coleman–Liau (CLI) = 0.0588 x L - 0.296 x S - 15.8
  Linsear Write Formula = if((A=(1 * No. simplewords + 3*No. difficult words)/No.sentences) > 20, A/2, (A-2)/2)

where the Average Sentence Length(ASL): The number of words divided by the number of sentences. The average number of syllables per word(ASW): The number of syllables divided by the number of words. Percentage of Hard Words (PHW): The ratio of hard words and total words. L is the average number of letters per 100 words. S is the average number of sentences per 100 words. The higher the score is, the higher the grade level.

Table 6, shows the Text simplification sample of the Gujarati language. Table 7 shows the readability scores of sentences given in Table 6.

TABLE V. Text Simplification

		Performance Evaluation Scores
	Stmts	***Input (Gujarati)***
Text Transformation	***OS***	જનનીની જોડ સખી નહિ જડે રે લોલ (Jananini Jod Sakhi Nahi Jade Re Lol)
	SS1	મિત્ર માઁ સમાન અન્ય કોઈ નહિ મળે (Mitra Maa Saman Anya Koi Nahi Made)
	SS2	મિત્ર માતા સમાન અન્ય કોઈ નહિ મળે (Mitra Mata Saman Anya Koi Nahi Made)
	SS3	મિત્ર, માતા સમાન અન્ય કોઈ નહિ મળે (Mitra, Mata Saman Anya Koi Nahi Made)

OS: Original Sentence, SS: Simplified Sentence

TABLE VI. Text Readability Score

	Readability Scores						
Stmts	***1***	***2***	***3***	***4***	***5***	***6***	***7***
OS	10.32	-4.23	15.55	2.8	3	-15.8	2.5
SS1	36.53	-3.04	11.39	14.23	4.41	-15.8	10.5
SS2	23.43	-2.44	13.47	14.23	4.41	-15.8	10.5
SS3	32.99	-3.36	12.39	13.2	4.41	-15.8	12

b) *Understandability:* This is to measure how easy the text is at the understanding level. It is being measured using the CLOZE test in which words are deleted from the passage as per certain criteria, and that is being given to the reader, who enters the missing word into the passage as per its understanding.

4. Common Limitation and Challenges of both MT and TS

From our machine translations and text simplification study from various available online resources, we found the following common limitations and challenges shown in Table 7 to the best of our knowledge.

TABLE VII. MT & TS LIMITATIONS AND CHALLENGES

	Limitation	**Challenges**
Machine Translation	Availability of good and cost-effective linguistic resources like dictionaries, corpus, set of rules, etc.	Ambiguity Resolution Giving both higher precision and higher recall. Designing Language translation rules from every aspect and arranging them in a non-overlapping hierarchical order. Quality assurance
Text Transformation	Availability of good and cost-effective linguistic resources like dictionaries, wordnet, simple Wikipedia, etc.	Complex word identification, Ambiguity Resolution improving readability, and understandability

The corpus development for automated MT and TS requires significant efforts and funding. The availability of good and cost-effective linguistic resources creates bottlenecks in training these MT and TS models. Due to this resource constraint languages like Gujarati are at the initial level in NLP compared to other languages like English. The ambiguity of deciding which text to be selected for replacement during the text translation or the text simplification process, is a common challenge, which is yet to be resolved. No matter how rich and better the corpus is created, it is impractical to accept that it can cover every aspect of both languages having one-to-one correspondence in all real-life communication scenarios. A language is considered as an infinite set of strings so the parallel corpus will become the infinite set of strings as well. And that shows that solving ambiguity entirely is not feasible.

5. Conclusions

With globalization, to overcome the language barrier, text translation and text simplification processes become essential. The translation and simplification processes are categorized into manual, non-manual, and semi-manual or hybrid approaches based on human involvement. Each of these approaches has its limitations and challenges. At the core, all these approaches try to resolve the ambiguity problem and decide what text is to be selected and replaced. The ATG processes of the Vauquois triangle describe the overall flow of these process executions. The better the analysis phase the smaller and more manageable the transfer and generation phase become.

The quality of the translation and simplification process and the output are judged based on various evaluation scores. Again this scoring is manual as well as automated. The confusion metrics help evaluate the translation and simplification model quality by classifying the actual and predicted outcomes into four categories, true positive, true negative, false positive, and false negative. Based on the confusion metrics, the evaluation scores like precision, recall, and F1 score are calculated. The quality of generated output is measured manually based on the rating of adequacy and fluency; while non manually measured by the BLEU, NIST, and other scores. The quality of simplification is decided based on the text readability and understandability scores. The better the evaluation score is, the better the quality of output is assumed. Finally, the availability of good cost-effective linguistic resources raises the limitation to the development of a good translator and transformer, and ambiguity resolution remains an open unsolved problem.

References

[1] D. V. Sindhu and B. M. Sagar, “Study on machine translation approaches for Indian languages and their challenges,” 2016 Int. Conf. Electr. Electron. Commun. Comput. Optim. Tech. ICEECCOT 2016, pp. 262–267, 2017, doi: 10.1109/ICEECCOT.2016.7955227.

[2] N. J. Khan, W. Anwar, and N. Durrani, “Machine Translation Approaches and Survey for Indian Languages,” 2017, [Online]. Available: http://arxiv.org/abs/1701.04290

[3] M. D. Okpor, “Machine Translation Approaches: Issues and Challenges,” IJCSI Int. J. Comput. Sci. Issues, vol. 11, no. 5, pp. 159–165, 2014.

[4] C. Boitet, “The French National MT-Project: Technical organization and translation results of CALLIOPE-AERO,” Comput. Transl., vol. 1, no. 4, pp. 239–267, 1986, doi: 10.1007/BF00936424.

[5] J. C. Modh, “A STUDY OF MACHINE TRANSLATION APPROACHES FOR GUJARATI LANGUAGE,” Int. J. Adv. Res. Comput. Sci., vol. 9, no. 1, pp. 285–288, Feb. 2018, doi: 10.26483/ijarcs.v9i1.5266.

[6] Z. B. Vaishnav and P. S. Sajja, “Knowledge-Based Approach for Word Sense Disambiguation Using Genetic Algorithm for Gujarati,” in Information and Communication Technology for Intelligent Systems, vol. 106, S. C. Satapathy and A. Joshi, Eds. Singapore: Springer Singapore, 2019, pp. 485–494. doi: 10.1007/978-981-13-1742-2_48.

[7] A. Hautli-Janisz, “Pushpak Bhattacharyya: Machine translation,” Mach. Transl., vol. 29, no. 3–4, pp. 285–289, Dec. 2015, doi: 10.1007/s10590-015-9170-7.

[8] Wikipedia contributors, “Google Translate --- {Wikipedia}{,} The Free Encyclopedia.” 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Google_Translate&oldid=1027169496

[9] Wikipedia contributors, “Microsoft Translator --- {Wikipedia}{,} The Free Encyclopedia.” 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Microsoft_Translator&oldid=1027580776

[10] Wikipedia contributors, “SYSTRAN --- {Wikipedia}{,} The Free Encyclopedia.” 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=PROMT&oldid=1007876553

[11] H. Dalianis and H. Dalianis, “Evaluation Metrics and Evaluation,” Clin. Text Min., no. 1967, pp. 45–53, 2018, doi: 10.1007/978-3-319-78503-5_6.

[12] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “BLEU,” in Proceedings of the 40th Annual Meeting on Association for Computational Linguistics - ACL ’02, Morristown, NJ, USA, 2001, p. 311. doi: 10.3115/1073083.1073135.

[13] W. contributors, “Evaluation of machine translation {\textemdash} Wikipedia, The Free Encyclopedia.” 2020.

[14] P. Panchal, N. Panchal, and H. Samani, “Development of Gujarati WordNet for Family of Words,” Int. Res. J. Comput. Sci., vol. 1, no. 4, p. 5, 2014.

[15] J. Carroll, G. Minnen, Y. Canning, S. Devlin, and J. Tait, “Practical simplification of English Newspaper Text to Assist Aphasic Readers,” AAAI-98 Workshop Integrating Artif. Intell. Assist. Technol., pp. 7–10, 1998.

[16] L. Feng, “Text simplification: A survey,” City Univ. N. Y. Tech Rep, 2008, [Online]. Available: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Text+Simplification+:+A+Survey#0%5Cnhttp://scholar.google.com/scholar?hl=en%7B&%7DbtnG=Search%7B

&%7Dq=intitle:Text+Simplification+:+A+Survey%7B%2 3%7D0

[17] R. Chandrasekar, C. Doran, and B. Srinivas, “Motivations and methods for text simplification,” in Proceedings of the 16th conference on Computational linguistics -, Morristown, NJ, USA, 1996, vol. 2, p. 1041. doi: 10.3115/993268.993361.

[18] A. Siddharthan, “A survey of research on text simplification,” ITL - Int. J. Appl. Linguist., vol. 165, no. 2, pp. 259–298, 2014, doi: 10.1075/itl.165.2.06sid.

[19] F. I.-S. Applications, B. B. Klebanov, K. Knight, and D. Marcu, “Text Simplification,” in On the Move to Meaningful Internet Systems, Lecture Notes in Computer Science, 2004, pp. 735–747.

[20] W. Contributors, “Flesch{\textendash}Kincaid readability tests,” Flesch-Kincaid readability tests. Wikipedia, The Free Encyclopedia. 2020. Accessed: Jun. 01, 2020. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Flesch-Kincaid_readability_tests&oldid=961213915

[21] M. Solnyshkina, R. Zamaletdinov, L. A. Gorodetskaya, and A. I. Gabitov, “Evaluating Text Complexity and Flesch-Kincaid Grade Level,” J. Soc. Stud. Educ. Res., vol. 8, pp. 238–248, Nov. 2017.

[22] Wikipedia contributors (2021c) Promt - Wikipedia, the free encyclopedia. URL https://en.wikipedia.org/w/index.php?title=PROMT&oldid=1007876553, [Online; accessed 9-June-2021