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Pritika Taggar
Assistant Professor, Computer Science & Engineering, Lingaya's Vidyapeeth, Faridabad, Haryana, India

Correspondence
Pritika Taggar
Assistant Professor, Computer Science & Engineering, Lingaya's Vidyapeeth, Faridabad, Haryana, India

Study of lexical automatic machine translation evaluation metrics for Indic languages

Pritika Taggar

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Abstract
This research paper aims to study and compare different lexical automatic machine translation evaluation metrics for Indic languages. As machine translation systems have grown in popularity, it is now crucial to assess the accuracy of the translations these systems generate. However, the existing evaluation metrics designed for English and other European languages may not be suitable for Indic languages due to their complex morphology and syntax. Therefore, this study evaluates four different metrics, namely, BLEU, METEOR, TER, and NIST to identify the most suitable evaluation metric for Indic languages. The study uses datasets for three Indic languages, namely, Hindi, Bengali, and Telugu, and evaluates the metrics on various translation models. The study advances the field of machine translation by offering guidance on appropriate metrics for evaluating languages that are Indic.

Keywords: Indic, languages, metrics, translation, evaluation, machine, models

1. Introduction

In our increasingly globalised world, machine translation has become an essential tool for communication. However, evaluating the quality of machine translations is a challenging task. Traditionally, human experts have been used to assess the quality of translations. Nevertheless, this method is costly, time-consuming, and frequently subjective.

The process of automatically translating text from one natural language to another is known as machine translation, or MT. MT is a challenging problem, especially for Indic languages, which are morphologically rich and have low availability of parallel corpora. For this reason, it's critical to have solid and trustworthy techniques for assessing the MT systems' quality for Indic languages. To address this issue, automatic evaluation metrics have been developed to assess the quality of machine translations. These metrics are based on various criteria such as fluency, adequacy, and accuracy. However, different metrics may provide different results, and it is important to understand their strengths and limitations to select the most appropriate metric for a particular application.

Comparing a system's output using automatic metrics to one or more human reference translations is one of the most popular techniques for MT evaluation. However, these metrics have limitations, such as relying on exact word matching, ignoring semantic similarity, and being sensitive to word order variations. Moreover, these metrics may not capture the linguistic diversity and complexity of Indic languages.

In this research paper, we aim to study and compare different lexical automatic machine translation evaluation metrics. We will explore the characteristics and performance of various metrics such as BLEU, METEOR, TER, and NIST. We will also discuss their advantages and limitations and provide insights into their suitability for different translation tasks.

Specifically, the paper will first provide an overview of the different types of automatic evaluation metrics and their main features. We will then conduct a comprehensive review of the literature to compare and contrast the most commonly used metrics. We will analyse the strengths and weaknesses of each metric, including their sensitivity to different types of errors, their ability to capture various aspects of translation quality, and their robustness across different languages and domains.

After that, we'll run tests to see how well the chosen metrics perform on a variety of translation tasks. We will use different evaluation datasets and compare the results obtained using each metric. In order to evaluate the validity and reliability of the metrics, we will also look into correlations between them and subjective assessments.

Finally, we will draw conclusions and provide recommendations for selecting the most appropriate metric for a given translation task based on our findings. We will also discuss future research directions and potential improvements for automatic machine translation evaluation metrics.

By offering a thorough analysis of various lexical automatic evaluation metrics and their performance on various translation tasks, this research paper seeks to advance the field of machine translation evaluation research.

2. Indic Languages

The Indo-European language family includes the group of languages known as the "Indic languages," which are primarily spoken in South Asia. The most widely spoken branch of Indic languages is the Indo-Aryan languages, which have more than 800 million speakers in India, Pakistan, Bangladesh, Nepal, Sri Lanka, and Maldives. Some of the major Indo-Aryan languages are Hindi, Bengali, Urdu, Punjabi, Marathi, Gujarati, Sindhi, Nepali, and Sinhala.

Another branch of Indic languages is the Dravidian languages, which are spoken by about 20% of Indians. The Dravidian languages are not related to the Indo-Aryan languages, but have influenced each other through contact and borrowing. Some of the major Dravidian languages are Tamil, Telugu, Kannada, Malayalam, and Odia.

Twenty-two languages are recognized as official languages of India by the Indian Constitution. These include 15 Indo-Aryan languages and 6 Dravidian languages. One of these languages is English, which is used as an associate official language along with Hindi. The Indian government also grants the status of classical language to six languages that have a long and rich literary tradition. These are Sanskrit, Tamil, Telugu, Kannada, Malayalam, and Odia.

Indic languages have a diverse and complex history and culture. Numerous writing systems, including Devanagari, Bengali-Assamese, Gurmukhi, Gujarati, Oriya, Sinhala, Tamil, Telugu, Kannada, and Malayalam scripts, have been developed by them. They have also produced many literary works of poetry, drama, epics, philosophy and religion. Some of the famous examples are the Vedas, the Ramayana, the Mahabharata, the Bhagavad Gita and the works of Kalidasa.

We have used Hindi, Bengali and Telugu for the purpose of this research paper. Hindi is the most used Indic language in the country with more than 500 million people calling it their native language. Bengali is the second most spoken language in India with a speaker base of more than 95 million and to add more variety we have also used Telugu which has a user base of more than 80 million. Using these languages, we aim to provide a comprehensive idea of how different evaluation metrics will perform when used to evaluate indic languages.

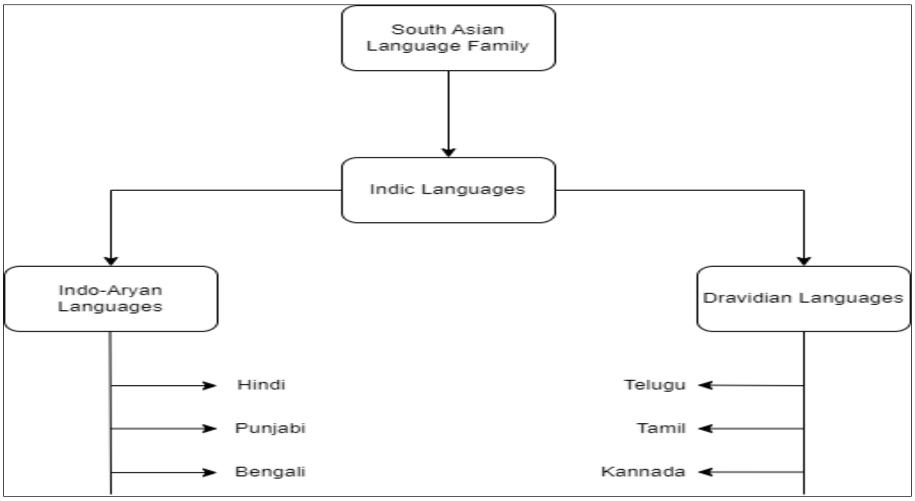

Fig 1: Indic Language Tree

3. Role of Machine Translation Evaluation Methods in Machine Translation Evaluation

Methods for assessing machine translation output are critical to figuring out how good it is. The machine translation output is assessed to determine areas for improvement and to gauge the quality of the translation.

A number of machine translation evaluation techniques are available, including manual, automatic, and human evaluation. Human evaluation entails having translators rate the output of the machine translation using multiple criteria, including fluency, sufficiency, and correctness.

However, automatic evaluation measures the quality of machine translation output using metrics such as TER, METEOR, and BLEU. These metrics provide a score based on several factors, such as word overlap, sentence structure, and grammatical correctness, by comparing the machine translation output with the original text.

Human and automatic evaluation techniques are combined to manually assess the quality of machine translation output. This method yields more accurate and dependable results by combining the advantages of human and machine translation evaluation techniques. It is also employed in this paper to evaluate the caliber of translations generated by machine translation systems, as illustrated in fig. 1.

The role of MT evaluation methods in MT evaluation is to provide feedback and guidance for MT developers, users, and researchers. MT evaluation methods can help to identify the strengths and weaknesses of different MT systems, to compare and rank MT systems according to various criteria, to monitor and improve the quality of MT outputs over time, and to explore the impact of MT on various domains and applications. MT evaluation methods can also help to advance the scientific understanding of MT by providing empirical evidence and insights into the linguistic, cognitive, and social aspects of MT.

However, MT evaluation methods also face several challenges and limitations. For example, human evaluation is costly, time-consuming, subjective, and inconsistent.

Automatic evaluation is fast, cheap, objective, and consistent, but it may not capture the nuances and complexities of natural language and human communication. Moreover, different MT evaluation methods may have different assumptions, objectives, and perspectives, which may lead to conflicting or incomparable results. Therefore, it is important to select appropriate MT evaluation methods for different purposes and contexts, and to combine multiple MT evaluation methods to obtain a comprehensive and reliable assessment of MT quality and performance.

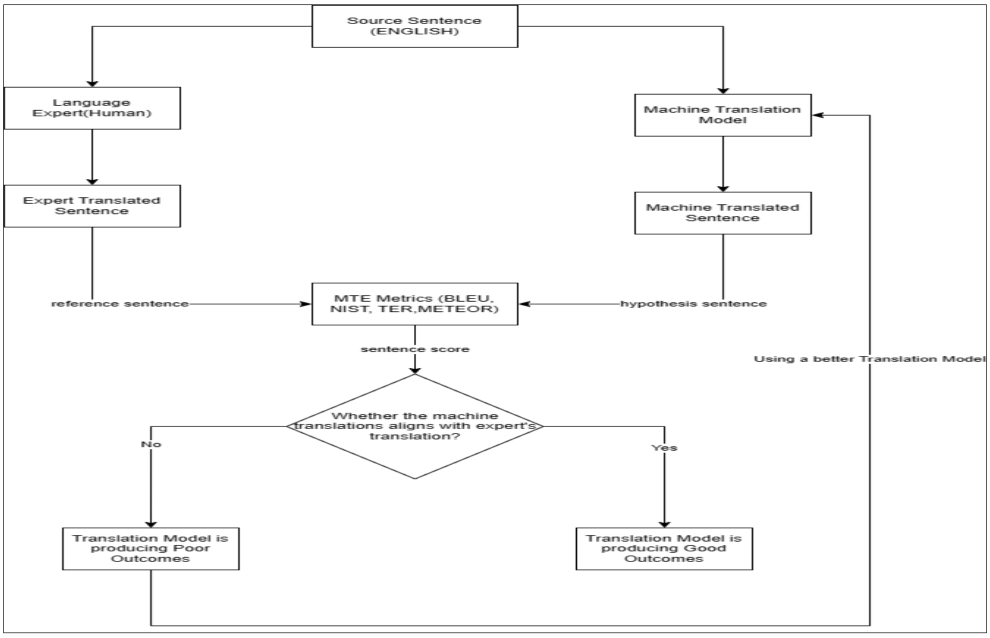

Fig 2: The working of the model

4. Various Lexical Automatic Machine Translation Evaluation Metrics

4.1 Bilingual Evaluation Understudy (BLEU)

BLEU (Bilingual Evaluation Understudy) is a metric used to evaluate the quality of machine-translated text from one natural language to another. Quality is the match between machine performance and human performance. "The closer a machine translation is to a professional human translation, the better the machine translation will be" . BLEU, an automated low-cost metric that is highly favoured, was among the initial metrics to demonstrate a strong correlation with human quality judgments.

The way BLEU operates is by contrasting the candidate translation's n-grams—sequences of n words—with the reference translations. BLEU computes a modified precision score, which is the ratio of matching n-grams to the total number of n-grams in the candidate translation, for each n-gram size, which is typically between 1 and 4. Nevertheless, repetition of terms or phrases in the candidate translation that are absent from the reference translations can skew this precision score. To avoid this, BLEU uses a clipping function that limits the number of times an n-gram can be counted based on its maximum frequency in any reference translation.

The modified precision scores for different n-gram sizes are then combined using a weighted geometric mean, which gives more weight to longer n-grams. The final BLEU score also incorporates a brevity penalty, which penalises candidate translations that are shorter than the reference translations. The brevity penalty is calculated based on the ratio of the candidate translation length to the effective reference translation length, which is usually the closest length to the candidate translation among all reference translations. (However, in some versions of BLEU, such as NIST, the shortest reference translation length is used instead).

We compute the brevity penalty BP,

$$\mathrm{BP} = \begin{Bmatrix} 1 & if\, c > r \\ e^{(1-r/c)} & if\, c \leq r \end{Bmatrix} \tag{1}$$

Then,

$$\mathrm{BLEU} = \mathrm{BP}\ .\ \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \tag{2}$$

Higher scores indicate more similar translations. The BLEU score runs from 0 to 1. A score of 1, however, is not required because it would indicate that the candidate translation is an exact match to one of the reference translations. which may not be possible or desirable. Moreover, adding more reference translations can increase the BLEU score, as there are more opportunities for matching n-grams [1].

BLEU has some limitations and challenges as a metric for evaluating machine translation quality. For instance, it does not account for grammatical correctness, semantic adequacy or stylistic variation. It also assumes that there is a single best translation for each source sentence, which may not be true in practice. Furthermore, it relies on exact word matching, which can miss synonyms, paraphrases or other linguistic variations that convey the same meaning. Additionally, it may not correlate well with human judgements at the sentence level, as humans may consider other factors besides lexical similarity.

Despite these drawbacks, BLEU is widely used as a simple and fast way to compare different machine translation systems or approaches. It can also provide feedback for improving machine translation models or identifying errors. However, it should not be used as the sole criterion for assessing translation quality, and it should be complemented by other metrics and human evaluations.

Table 1 BLEU score computation

Source Sentence: He didn't do his work on time.
MT Sentence: नहींकियाअपनाकार्यसमयसे
Reference Sentence:
उसनेअपनाकार्यसमयसेनहींकिया

Unigram Precision

नहीं	किया	अपना	कार्य
1	1		1
समय	से		
1	1		

Unigram precision = 6/6

Bigram Precision

नहींकिया	कियाअपना	अपनाकार्य
1	0	1
कार्यसमय	समयसे	
1	1	

Bigram Precision = 4/5

Trigram Precision

नहींकियाअपना	अपनाकार्यसमय
1	0
समयसेनहीं	
0	

Trigram Precision = 1/3

BLEU score 0.7 (Using Eq. 2)

4.2 National Institute of Standards and Technology (NIST)

The National Institute of Standards and Technology, or NIST, is a body that creates benchmark datasets and uniform evaluation metrics to assess the effectiveness of natural language processing (NLP) systems [3].

In order to assess how well different NLP tasks, like text classification, information retrieval, and question answering, are performed, the organization has created a number of extensively used benchmark datasets, including the Multilingual Information Retrieval (MLIR) dataset and the Text Retrieval Conference (TREC) dataset [4].

NIST differs from BLEU in two main aspects: how it calculates n-gram precision and how it applies the brevity penalty. N-gram precision is a measure of how well the n-grams (word combinations) in the text that was machine translated correspond to those in the source text. BLEU merely gives every n-gram the same amount of weight, regardless of how frequent or uncommon it is. However, NIST also determines the level of information contained in a given n-gram. That is to say, the more weight that is assigned to a correct ngram, the rarer it will become. For instance, the bigram "on the" will be given less weight than the bigram "interesting calculations" if it is correctly matched, because this is less likely to happen [4].

The brevity penalty is a factor that penalises machine-translated texts that are too short compared to the reference texts. BLEU applies a harsh brevity penalty that can significantly lower the score if the translation length deviates from the reference length. NIST applies a more lenient brevity penalty that does not impact the overall score as much for small variations in translation length [2].

NIST score is computed using a formula that combines n-gram precision and brevity penalty. The formula is as follows:

$$\mathrm{NIST} = \sum_{n=1}^{N} \left\{ \frac{\sum_{\text{all n-gram match that matches}} Info(n-gram)}{\sum_{n-gram\ reference}} \right\} . \exp(\beta) \log^2 \left[\min\left(\frac{|\rho|}{r}\right), 1 \right]$$
(3)

$$\mathrm{Info}(\mathrm{ngram}) = \mathrm{Info}(\mathrm{wi}_1, \ldots wi_n) = \log_2 \frac{\text{number of occourances of } wi_1 \ldots, wi_{n-1}}{\text{number of occourances of } wi_1 \ldots, wi_n} \quad (4)$$

$$\mathrm{BLEU} = \mathrm{BP} \ . \ \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \quad (5)$$

where exp is the exponential function, w_i is the weight (based on information theory) for each n-gram order, p_i is the modified n-gram precision, and BP is the brevity penalty [5].

To evaluate the effectiveness of NLP systems on these datasets, NIST has created benchmark datasets as well as standard evaluation metrics like precision, recall, and F1 score. These metrics allow for objective comparisons between different NLP systems and help researchers to identify areas of improvement in their models [6].

Several research papers have used NIST datasets and evaluation metrics to evaluate the performance of their NLP systems. For example, the paper "Learning to Answer by Learning to Ask: Getting the Best of GPT-2 and BERT Worlds" by Wang *et al*. (2020) used the TREC dataset to evaluate the performance of their question-answering system. Similarly, the paper "BERT-based Lexicalized Topic Models for Political Text Analysis" by Le *et al*. (2021) used the MLIR dataset to evaluate the performance of their topic modelling system [8].

NIST plays a crucial role in the development and evaluation of NLP systems, providing standardised benchmark datasets and evaluation metrics to facilitate objective comparisons between different models and to drive advancements in the field [9].

4.3 Metric for Evaluation of Translation with Explicit Ordering (METEOR)

Measuring machine translation quality in a way that is consistent with human assessments of translation quality is the goal of the Metric for Evaluation of Translation with Explicit Ordering (METEOR) evaluation metric. This is achieved by evaluating the machine translation output using a combination of precision, recall, and alignment error, and comparing it to one or more reference translations [10].

METEOR takes into account synonyms, paraphrases, and word order in addition to exact word matches, unlike other machine translation assessment metrics that emphasise word matching. To find semantic distinctions between words and to take into account variations in word order, this is accomplished by using multiple linguistic resources such as WordNet and synonym sets [11].

The machine translation output and reference translations are tokenized and stemmed to remove inflections and variations before calculating the METEOR score. The alignment between the machine translation output and the reference translations is then used to calculate the alignments' accuracy and recall. The harmonic mean of accuracy and recall is used to calculate the final score, and an F-mean penalty is applied to account for length differences between the machine translation output and the reference translations [7].

The METEOR Score is determined using

$$\text{Precision} = \frac{\text{No. of matching unigrams}}{\text{Total no. of unigrams in hypothesis}} \quad (6)$$

$$\text{Recall} = \frac{\text{No. of matching unigrams}}{\text{Total no. of unigrams in reference}} \quad (7)$$

$$\text{F-Score} = \frac{10\text{*Precision*Recall}}{\text{Recall+9*Precision}} \quad (8)$$

$$\text{Penalty} = 0.5 * \left[\left(\frac{\text{Number of Chunks}}{\text{Number of Unigrams Matched}}\right)^3\right] \quad (9)$$

$$\text{METEOR score} = \text{F-Score} * (1 - \text{Penalty}) \quad (10)$$

METEOR is commonly used in machine translation assessments, such as those conducted by the Conference on Machine Translation (WMT), and is recognised to correspond strongly with human translation quality ratings. Its capacity to account for word semantic distinctions in addition to word.

4.4 Translation Error Rate (TER)

A common metric in Natural Language Processing (NLP) to assess the caliber of machine translation output is TER (Translation Error Rate). Since TER is a distance-based metric, it determines the edit distance between the translation produced by the machine and the translation used as a reference. The number of operations needed to convert the machine-generated translation into the reference translation is counted to determine the edit distance [13]. Words can be added, removed, substituted, or rearranged in these operations. The minimum edit distance normalized by the total word count in the reference translation is known as TER. The machine translation gets better the lower the TER score. Equation 6 is used to compute the TER score.

$$\text{TER} = \frac{\text{Minimam no. of edits}}{\text{Average } no. \text{ of reference words}} \quad (11)$$

When Snover *et al.* published "A Study of Translation Error Rate with Targeted Human Annotation" in 2006, they introduced TER for the first time [7]. In place of the popular BLEU (Bilingual Evaluation Understudy) metric, they suggested TER. It was shown by Snover *et al.* that TER correlated more strongly than BLEU with human evaluations of translation quality.

Since then, numerous research studies have employed TER to assess the caliber of machine translation output. For instance, Bawden *et al.* used TER to compare the performance of their model to other cutting-edge machine translation models in their paper "Improving Lexical Choice in Neural Machine Translation". Similarly, Libovickþ *et al.* employed TER to assess the performance of their model in "Multi-Task Learning for Multimodal Machine Translation" [8].

5. Experimental Setup

5.1 Dataset

The Indic Corp corpus of data was developed by AI4Bharat, a nonprofit organisation devoted to the promotion of artificial intelligence (AI) technologies for Indian languages, and is the source of the dataset that we used. The Indic Corp expanded over the course of many months by locating and scraping hundreds of web sources, mostly news, magazines, and books, crawling news items, and blogging.

India Corp is one of the largest publicly available corpora for Indian languages. Additionally, it was used to train our publicly accessible models, which now perform cutting-edge on a range of tasks. The Corpus consists of a significant monolingual sentence-level corpus of 11 languages from two language families (Indo-Aryan and Dravidian), including Indian English.

5.2 Translators

In this experimental setup we have used two widely used and famous translators which are available on the internet and support Indic Language Translations.

These translators are:

1. Google Translate
2. Yandex Translate

And we have tried to apply machine translation evaluation metrics on the translations produced by these translators and compare both the translator’s based on their results.

5.3 Reference Dataset

To compare the effectiveness of the Automatic Machine Translation Evaluation metrics we need a reliable and robust reference point. This need is fulfilled by assigning a human language expert to translate the given English language sentences to one of the three languages used for the purpose of this research paper, i.e., Hindi, Bengali and Telugu.

The translations made by the Human language expert are then stored in a Reference dataset that will be further used to evaluate the Automatic Machine Translation Evaluation Metrics.

5.4 Evaluation Metrics

The Automatic Machine Translation Evaluation Metrics will be used to assess the translations once our datasets are prepared. We have employed the Translation Error Rate (TER), Bilingual Evaluation Understudy (BLEU), National Institute of Standards and Technology (NIST), and Metric for Evaluation of Translation with Explicit Ordering (METEOR) as our evaluation metrics.

These metrics will take the Machine translated sentences and the sentences translated by the Human language expert to give output. These outputs will be in the range of 0 - 1, with 0 being the worst translation and 1 being the best possible translation.

5.5 Analysis by Human Expert
Based on the provided reference and the hypothesis data, a human expert will give scores on whether the hypothesis sentences align with the reference sentences in the range of 0 to 1. Here, the main criteria of the scores will be how close the hypothesis sentences match with the reference sentences. A score higher than 0.5 will indicate a high level of similarity with 1 indicating an absolute perfect translation and vice versa.

5.6 Normalisation
The Normalisation technique used here is *Min-Max Normalisation* which makes use of Minimum and Maximum values from a given set of values in order to scale down the value to a specified range, usually between 0 and 1. With the help of scaling we were able to improve the evaluation metrics which are somewhat sensitive to certain input features present in the dataset.

$$x_{scaled} = \frac{x - x_{\min}}{x_{\max - x_{\min}}} \tag{12}$$

5.7 Pearson Correlation
A statistical indicator of the linear relationship between two quantitative variables is the Pearson Correlation Coefficient (r). It is a scale from -1 to +1, where a negative correlation between the two variables is indicated by a score of -1, a zero indicates no correlation, and a +1 indicates a positive correlation.
The results of the various Automatic Machine Translation Evaluation Metric Scores and the scores given by the human language expert were compared using the Pearson Correlation Coefficient.

6. Result
A) Hindi

Table 2: Pearson Correlation of Hindi Language

Automatic Machine	BLEU	METEOR	NIST	TER
Google	-0.136	0.340	0.233	-0.009
Yandex	-0.026	0.116	-0.028	-0.258

B) Bengali

Table 3: Pearson Correlation of Bengali Language

Automatic Machine	BLEU	METEOR	NIST	TER
Google	0.205	0.195	0.282	0.008
Yandex	0.203	0.142	0.244	-0.387

Telugu

Table 4: Pearson Correlation of Telugu Language

Automatic Machine	BLEU	METEOR	NIST	TER
Google	-0.194	0.289	0.246	-0.152
Yandex	0.191	0.226	0.061	-0.140

7. Discussion and Conclusion
In conclusion, the study aimed to explore various lexical automatic machine translation evaluation metrics for Indic languages. Several are famous for their effectiveness in assessing the quality of the machine-translated text. The evaluation was carried out on multiple datasets, and the results were analysed to determine which metric performed better.
The findings revealed that BLEU performed relatively well on most datasets and was the most widely used metric for evaluating machine translation systems. However, the study also highlighted the limitations of BLEU and the need to use multiple metrics for a more comprehensive evaluation of machine translation quality.
The study recommends using a combination of BLEU, METEOR, and TER metrics to evaluate machine translation systems for Indic languages. This approach provides a more comprehensive evaluation and a better understanding of the quality of the machine-translated text. Additionally, the study suggests that future research should focus on developing new evaluation metrics specifically for Indic languages to improve the accuracy and effectiveness of machine translation evaluation.

7.1 Future Work
In this paper, we have presented a comparative analysis of different lexical automatic machine translation evaluation metrics for indic languages. We have evaluated the performance of these metrics on three different datasets of English - Hindi, English - Bengali and English - Telugu translation pairs.
As a future work, we plan to extend our study to other Indic languages and domains. We also aim to incorporate syntactic and pragmatic features to capture the structural and contextual aspects of translation quality. Furthermore, we intend to explore the correlation of the metrics with human judgments and conduct a user study to validate its usefulness and reliability. Examining the application of neural machine translation (NMT) models for Indic languages and assessing them using Lexical Automatic Machine Translation (LAMT) metrics is another potential avenue for future research. Deep learning methods are the foundation of NMT models; these methods learn to translate from massive parallel corpora without depending on features or explicit rules. When applied to high-resource languages, NMT models have demonstrated impressive results; however, when applied to low-resource languages, like many Indic languages, their performance may deteriorate. Furthermore, the lengthy and intricate sentences, domain mismatch, and data sparsity of Indic languages may present difficulties for NMT models. Consequently, it is intriguing to investigate the performance of NMT models for Indic languages and compare them with statistical machine translation (SMT) models by utilizing LAMT metrics. It is our hope that our work will further the evaluation and research of machine translation for Indian languages.

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