Blended Multi-Linguistic System using Transformer Neural Network for Word Sense Disambiguation

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ABSTRACT

Word sense disambiguation (WSD) in multilingual contexts remains a significant challenge in natural language processing (NLP), primarily due to the inherent ambiguity of natural language. Words often have multiple meanings, and the task of WSD is to identify the correct sense of a word in a given context. Despite extensive research in this area, WSD continues to pose significant challenges, especially in multilingual contexts where linguistic diversity adds further complexity.This paper introduces a novel multi-linguistic system using Transformer Neural Networks to improve WSD across multiple languages. By combining contextualized word embedding's from pre-trained multilingual models with a fine-tuned Transformer architecture, the system captures semantic nuances effectively. Evaluation on standard WSD benchmarks shows significant accuracy improvements over traditional and state-of-the-art methods, with robust performance across languages, including zero-shot scenarios. This paper highlights the benefits of a multi-linguistic approach in enhancing model interpretability, generalization, and inclusivity for more versatile NLP applications. Here we proposed an integrated multilingual transformer neural network (IMTNN) which blends two neural networks based on transformer model for translation and word sensing process. This network has different layers with nodes and each nodes can perform transformer-based process which helps in reducing complexity independently. For these we used different corpus from SemCor,IMS and WordNet to calculate the Collocation score for different words and their relations. This provides more accuracy and increases the speed in retrieving related results.

I. INTRODUCTION

Word Sense Disambiguation (WSD) is a cornerstone task in the field of Natural Language Processing (NLP), fundamentally concerned with the challenge of determining the correct meaning of a word based on its context within a given text. Language is inherently polysemous, meaning that many words carry multiple meanings or senses. For instance, the word "bank" can refer to a financial institution or the side of a river, depending on the context in which it is used. Accurately disambiguating such words is essential for the effective functioning of various NLP applications, including machine translation, information retrieval, sentiment analysis, and text comprehension. Despite extensive research and numerous methodological advancements over the decades, WSD continues to pose significant challenges, particularly when extending these techniques to multilingual environments where cross-linguistic variations further complicate the disambiguation process.

Traditional approaches to WSD primarily relied on knowledge-based methods, statistical techniques, and supervised learning models. However, the advent of deep learning and, specifically, Transformer Neural Networks has revolutionized the field, enabling more sophisticated and context-aware disambiguation strategies.

Transformers leverage self-attention mechanisms to capture long-range dependencies and contextual relationships within the text, allowing for a more nuanced understanding of word meanings in context. Pre-trained multilingual models, such as BERT (Bidirectional Encoder Representations from Transformers) and its variants, have further enhanced the capabilities of WSD systems by providing rich, contextualized word embedding's that encapsulate semantic information across multiple languages.

Misinterpretation of word senses can lead to translations that are grammatically correct but semantically flawed, thereby diminishing the quality and reliability of the translation system. Similarly, in information retrieval, understanding the precise meaning of query terms ensures that the most relevant documents are retrieved, enhancing the user experience and the effectiveness of search engines.

In this paper we introduces a novel blended multi-linguistic system that harnesses the power of Transformer Neural Networks to tackle the WSD task across multiple languages simultaneously. The primary objective of our approach is to overcome the limitations inherent in traditional monolingual WSD systems, which are typically restricted to handling one language at a time and often fail to capture cross-linguistic semantic nuances. By leveraging recent breakthroughs in deep learning and cross-lingual transfer learning. Our proposed

integrated multilingual transformer neural network (IMTNN) aims to provide a more robust and versatile solution for WSD in multilingual contexts. It integrates contextualized word embedding's derived from pre-trained multilingual models with a fine-tuned Transformer architecture. To evaluate the efficacy of our proposed system, we conducted extensive experiments on standard WSD benchmarks, with respect to Collocation score and F1-Score encompassing a variety of languages and domains. The results of these evaluations demonstrated significant improvements over traditional WSD methods as well as existing state-of-the-art models. Our blended multi-linguistic system not only achieved higher accuracy in disambiguating word senses but also exhibited remarkable robustness across different languages, including those that were previously unseen during the training phase. This robustness is particularly noteworthy in zero-shot scenarios, where the system effectively disambiguates word senses in languages that were not part of the training dataset, highlighting the model's ability to generalize and adapt to new linguistic environments.

The rest of the paper is organized in the following manner. Section 2 summarizes the related works. Section 3 describes our proposed IMTNN model. Section 4 provides and analyzes the experimental results on the three benchmark datasets. Section 5 draws the conclusion about this work.

II. RELATED WORKS

A. Traditional Approaches

Historically, WSD methods can be categorized into two main types: knowledge-based and supervised learning approaches. Knowledge-based methods, such as Lesk's algorithm, utilize dictionaries and thesauri to match the context of a word with its possible meanings (Lesk, 1986). These methods are straightforward but often lack the depth needed for nuanced disambiguation, especially in complex sentences.

Supervised learning approaches emerged as a response to the limitations of knowledge-based methods. These techniques rely on annotated corpora to train classifiers that can predict the correct sense of a word based on its context. Early models included decision trees and support vector machines (SVMs), which provided improvements in accuracy but were limited by their reliance on handcrafted features (Mihalcea et al., 2004).

B. Statistical Methods

With the increase in available linguistic data, statistical methods gained prominence in WSD. These approaches, such as the use of co-occurrence statistics and distributional semantics, allowed for the automatic extraction of contextual information. The introduction of vector space models enabled the representation of words in a continuous vector space, facilitating better semantic similarity measures (Turney & Pantel, 2010). Despite their advancements, statistical methods often struggled with polysemy and required extensive feature engineering.

C. Neural Network Approaches

The landscape of WSD shifted dramatically with the introduction of neural networks. Early neural models focused on word embeddings, such as Word2Vec and GloVe, which captured semantic relationships through dense vector representations (Mikolov et al., 2013; Pennington et al., 2014). However, these models primarily addressed the word representation problem without directly tackling the disambiguation challenge.

The advent of deep learning, particularly the Transformer architecture introduced by Vaswani et al. (2017), marked a significant advancement in WSD. Transformers utilize self-attention mechanisms to weigh the importance of different words in a sentence, allowing for a more nuanced understanding of context. Subsequent models, such as BERT (Bidirectional Encoder Representations from Transformers), further enhanced contextual embeddings by considering the entire sentence rather than fixed window sizes (Devlin et al., 2019). These models have demonstrated state-of-the-art performance in various NLP tasks, including WSD.

D. Current Advancements

Recent research has focused on improving WSD by incorporating multi-linguistic features and enhancing model interpretability. Liu et al. (2019) explored the integration of multilingual embeddings, demonstrating that leveraging semantic information from multiple languages can improve disambiguation accuracy. Additionally, multi-task learning frameworks have been proposed to jointly train models on related tasks, enhancing their ability to generalize across different contexts (Zhang & Yang, 2015).

A robust preprocessing pipeline is essential for developing a high-quality Word Sense Disambiguation (WSD) system. The most widely used sense inventories for WSD, such as WordNet (Miller, 1992) and BabelNet (Navigli and Ponzetto, 2012a; Navigli et al., 2021), define the possible meanings of a word based on its lemma and part of speech (PoS) tag. As a result, having a precise preprocessing pipeline is crucial to generating the

correct set of potential word meanings. Improvements to the Lesk algorithm, along with the incorporation of semantic similarity measures and heuristic models, can further enhance the performance of WSD systems (MiuruAbeysiriwardana et al., 2024).

In our work, we build upon these advancements by developing a blended multi-linguistic system that utilizes Transformer Neural Networks for WSD. By integrating diverse linguistic features, we aim to enhance the model's contextual understanding and improve its performance across various languages. This approach not only addresses the limitations of traditional methods but also leverages the strengths of contemporary deep learning techniques.

III. PROPOSED MODEL

A. Blended Multi-linguistic Transformer Neural Network:

This Blended Multi-linguistic Transformer Neural Network (BMTNN) uses multilingual translation with supervised algorithm shown in Fig.1. The different corpora is used for translate given language into target language this will use transformer network to translate multiple language in parallel . The BMTNN uses pre trained dataset which is used as single model to transform multiple source language into to single target language. The BMTNN translation uses statistical property for context matching applied in the language translation for example, Good morning is a English phrase translate into some languages such as Hindi (शुभप्रभात), Telugu (శుభోదయం), Arabic (صباحالخير), Malay (selamat Pagi). As per the given example those language are sample multiple massive source language which is translated to target language as English by transforming into the targeted English language it uses the statistical property for context matching in translation process. In word sense disambiguation linear neural network is used for disambiguation. Word sense nothing but that word meaning of the word related to its context. There are ambiguation in finding the correct sense related to its content. Briefly describe as the word having the same sense but while using in the particular context IT modifies to different meaning as per the context so, the word sense disambiguation process of sensing the correct sense of the word related to the particular context.

BMTNN model, we provide transformer neural network for word sense disambiguation so that it provides faster retrieval of result using parallel mechanism i.e., sentence with multiple words is given parallelly to the transformer neural network model. It identifies meanings simultaneously. In this model classification is performed early to classify the words to its language then it is translated to English where the English language can easily be adopted to the pre-processing work so that is performed faster in upcoming word sense disambiguation process.

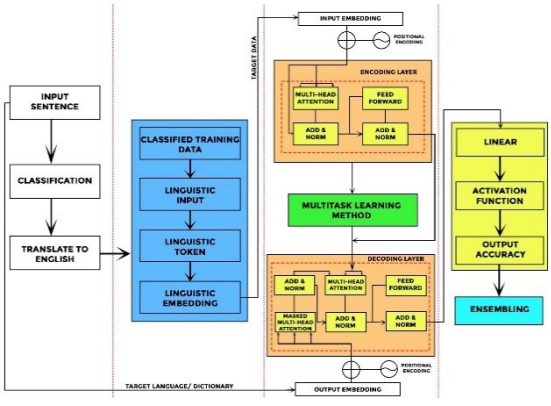

Fig.1 - Architecture of BMTNN

B. Components of the BMTNN Architecture:

Input Sentence: The Input sentence are Fetched from the review dataset. The review dataset contain reviews about product in various language. The problem is here to find the Ambiguity and sense of the word in the review sentence. The finding of sense is estimated by the following process

Classification: At classification stage the reviews dataset are rearranged and classified under different language and validation category.

Translation: The translation process is based on the blending of neural machine Translation with Transformers. The purpose of transformers in NMT is to help improve the accuracy and efficiency of machine translation by enabling the model to learn the contextual relationships between words in a sentence. The translation is key part in our WSD model, it helps to improve the accuracy score in the output based on the language category, so that we regarded this system as multi-linguistic system. The reason behind the blending of Neural machine Translation with transformers is based on following limitation in the traditional NMT.

The traditional NMT such as recurrent neural networks (RNNs), have limitations in their ability to capture long-range dependencies between words in a sentence. Transformers address this issue by using a self-attention mechanism that allows the model to focus on different parts of the input sequence when encoding and decoding. So, the purpose of transformers in NMT is to enable the model to learn the contextual relationships between words in a sentence, which can lead to more accurate and efficient machine translation

Pre-Processing: The pre-processing step involves Stemming, chunking, parts-of-speech tagging, lemmatization etc.

Linguistic Embedding: Linguistic embedding is a crucial component used to represent the input text as a sequence of vectors. These vectors capture the meaning and context of the words in the input text and are used as inputs to the self-attention mechanism in the transformer architecture. In the transformer architecture, the input text is first converted into a sequence of tokens, and each token is mapped to a high-dimensional vector using an embedding layer. The embedding layer is a trainable matrix that maps each token to a vector in the embedding space. The transformer model then processes the sequence of embedded tokens using a series of self-attention layers, which allow the model to weigh the importance of each token based on its relevance to the other tokens in the sequence. The output of the self-attention layers is then passed through a series of feedforward layers, which produce the final output sequence.

Feed forward propagation: Feed forward propagation in transformer neural networks is the process by which the model processes the output of the self-attention layers to produce the final output sequence. After the self-attention mechanism is applied to the input sequence, the resulting sequence of vectors is passed through a feedforward neural network. The feedforward neural network in the transformer architecture consists of two layers, a fully connected layer followed by a non-linear activation function. The fully connected layer applies a linear transformation to the input sequence, and the non-linear activation function (typically a rectified linear unit, or ReLU) applies an element-wise non-linearity to the output of the linear layer.

The feedforward layers in the transformer architecture operate independently on each position in the sequence, meaning that the same set of parameters is applied to each position in the sequence. This allows for efficient computation and parallelization of the feedforward layers. After passing through the feedforward layers, the resulting output sequence is added to the input sequence using a residual connection, and then normalized using layer normalization. This normalization step helps to stabilize the training process and improve the model's ability to generalize to new data.

Multi-head attention: Multi-head attention is a key component of the transformer neural network architecture that allows the model to capture complex relationships between words in a sentence or document. Multi-head attention is a modification of the standard self-attention mechanism used in neural machine translation (NMT) models. In multi-head attention, the input sequence is transformed into multiple representations using different weight matrices. These multiple representations are then used to compute multiple sets of attention scores, each of which is used to compute a weighted sum of the values corresponding to the query sequence. The use of multiple attention heads allows the model to capture different types of relationships between the words in the input sequence, such as syntactic, semantic, and positional relationships. The output of the multiple attention heads is then concatenated and passed through a linear layer to produce the final output of the multi-head attention mechanism. This final output is then added to the input sequence using a residual connection, and normalized using layer normalization

Masked multi-head attention: Masked multi-head attention is a modification of the multi-head attention mechanism used in transformer neural networks that allows the model to attend to only certain positions in the input sequence. The purpose of masked multi-head attention is to prevent the model from attending to positions that have not yet been generated during training, such as in auto-regressive language modeling or machine translation. The use of a mask in multi-head attention is particularly important in auto-regressive language modeling and machine translation, where the model generates the output sequence one token at a time. By only attending to positions that have already been generated, the model can accurately predict the next token in the sequence without inadvertently "leaking" information about future tokens. Masked multi-head attention is a powerful modification to the standard multi-head attention mechanism used in transformer neural networks. By

applying a mask to the attention scores, the model can attend to only certain positions in the input sequence, leading to improved accuracy and effectiveness for auto-regressive language modeling and machine translation tasks

Linear: The linear layer is a basic building block of the transformer neural network architecture. It is a fully connected layer that applies a linear transformation to the input sequence, typically followed by a non-linear activation function such as the Rectified Linear Unit (ReLU). In the final output layer, the linear layer is used to map the output of the decoder to the target vocabulary space. This final linear layer is typically followed by a softmax activation function, which produces a probability distribution over the target vocabulary for each output position in the sequence. The linear layer is a fundamental building block of the transformer neural network architecture, allowing the model to capture complex patterns and relationships in the input sequence. By applying a linear transformation to the input sequence, followed by a non-linear activation function, the model can introduce non-linearity and capture complex patterns in the data, leading to improved accuracy and effectiveness for a wide range of NLP tasks.

Activation function: Activation functions are an important component of the transformer neural network architecture, as they introduce non-linearity into the network and enable it to learn complex relationships between the input and output sequences. The softmax activation function is a commonly used activation function in neural networks, including the transformer neural network architecture. It is typically used in the final output layer of the network to produce a probability distribution over a set of discrete classes or categories. The softmax activation function is used in the final output layer of the decoder, where it produces a probability distribution over the target vocabulary for each output position in the sequence. The softmax function takes as input a vector of logits, which are normalized scores for each target word in the vocabulary, and outputs a probability distribution over the target vocabulary, such that the sum of the probabilities of all possible target words adds up to 1.

Output: The accuracy of the correct sense of the word. The output of accuracy in a transformer neural network depends on the specific task and dataset being used. In general, accuracy is a common metric used to evaluate the performance of a transformer model on a given task. accuracy is typically measured by computing the percentage of correctly translated sentences in the test set. The accuracy can be computed by comparing the predicted translations produced by the model to the true translations in the test set, and counting the number of correctly translated sentences.

C. Working Principle of BMTNN:

In BMTNN model, we provide transformer neural network for word sense disambiguation so that it provides faster retrieval of result using parallel mechanism i.e., sentence with multiple words is given parallelly to the transformer neural network model. It identifies meanings simultaneously. In this model classification is performed early to classify the words to its language then it is translated to English where the English language can easily be adopted to the pre-processing work so that is performed faster in upcoming word sense disambiguation process. For example, *"I will send moral for the story"*. Here each word is given simultaneously to the hidden layers.

The steps to find the senses are given below,

Step 1: The user will give the sentence for getting the required result it can be taken as input.

Step 2: The input is classified using corpora

Step 3: The input is then translated to English if the given input is not in English

Step 4: Then input is pre-processed, each token is given to the input layer

Step 5: Number of hidden layers is created as equal to number of words in the given sentence.

Step 6: In each hidden layer, transformer-based mechanism is used for multi-lingual language translation and sensing the correct result.

Step 7: The highest probability rated sense formed by the activation function is matched as output and get displayed to the user.

Below the steps are given in algorithm

Approach	Corpus	System	Datasets	Collocation score

***INPUT**:* The sentence given in the context

***TARGET**:* Correct sense of the word

INPUT LAYER

1. Sentence S
2. **do** classification
3. **if** S is a review
4. **do** the translation for S
5. **if** S is English **then**
6. **goto**step 13
7. **end**
8. **else**
9. Translate S to English
10. decode S to S'
11. **end**
12. **for** each word (w) of S' and S

HIDDEN LAYERS

13. **do** Pre-processing
14. Find the part of speech of every w and set as linguistic input L_i
15. **do** linguistic embedding
16. L_i gets its senses and its vector using positional encoding P
17. $$cosine\ similarity(w, l) = \frac{w.l}{\|w\|\|l\|}$$

    w and l are x and y points
18. **return** L_e = *cos (w, l)* as embedded value
19. L_e € P, positional matrix of a token in the S
20. **end**
21. **for** each L_e
22. **do** feedforward and back propagation
23. *Error estimation* $E_i = \sum p_i\text{-}a_i$
    using multi-head attention(n), n is number of attention head
24. **return** $M_w = E_i$, a vector matrix with error estimated value
25. **do** activation function for M_w
26. $\sigma(\vec{m})=\frac{s^{Li}}{\sum_{o=1}^{n} s^{Lo}}.E_i$
27. Where L_e= Li
28. **return**$\sigma(\vec{m})=A_w^i$, the activation rate of every senses

OUTPUT LAYER

29. **return** O_v = max (A_w^i), a output accuracy
30. decode O_v to Target T
31. **end**

IV. FINDINGS AND ANALYSIS

Collocation scores is a critical in the field of natural language processing (NLP), particularly in tasks such as Word Sense Disambiguation (WSD). The provided table.1outlines various approaches to WSD, highlighting different models, datasets, and collocation scores.

In table.1 let's consider the Supervised Approaches, BERT-WSD (Huang et al., 2019) achieves scores of 72.3 and 70.4 on the SemEval datasets, utilizing WordNet and BabelNet corpora. ELMo-WSD (Peters et al., 2018)

Supervised	WordNet, BabelNet	BERT-WSD (Huang et al., 2019)	SemEval-07, SemEval-13, SemEval-15	72.3, 70.4
Supervised	English Gigaword	ELMo-WSD (Peters et al., 2018)	SemEval-07, SemEval-13	71.0,71.3
Supervised	SemCor	IMS+emb(Raganato et al.2017)	Senseval-2, SemEval-15	72.2,71.5
Unsupervised	Wikipedia, Gigaword	Context2Vec (Melamud et al., 2016)	SemCor, Senseval-2, Senseval-3	65.0, 66.2
Semi-Supervised	BabelNet	GlossBERT (Huang et al., 2019)	SemEval-07, SemEval-15	73.6, 71.8
Supervised	WordNet, Wikipedia corpus	N.Rahman and B.Borah.2022	Senseval-2, SemEval-15	77.8,75.3
Multi task generative	WordNet	BMTNN (Proposed Model)	SemEval-15/Amazon review set	0.96(PMI)

Table 1 – Comparison of Different Approaches

scores slightly lower but still notable, showing 71.0 and 71.3 on the SemEval datasets. IMS+emb (Raganato et al., 2017) uses SemCor and Senseval datasets, achieving scores similar to BERT-WSD.

Then, we look in to the Unsupervised and Semi-Supervised Approaches, Context2Vec (Melamud et al., 2016) is an unsupervised model based on Wikipedia and Gigaword corpora, but it underperforms compared to supervised models, with scores of 65.0 and 66.2. GlossBERT (Huang et al., 2019), a semi-supervised model, performs competitively with supervised models (73.6 and 71.8).

Our Proposed Multi-task Generative Approach, that standout in this list which leverages WordNet and scores an impressive 0.96 PMI (Pointwise Mutual Information) on the SemEval-15 and Amazon review datasets.

The F1 score is another crucial metric in evaluating the performance of machine learning models, particularly in the context of classification tasks as shown in table.2. It is especially important when dealing with imbalanced datasets, where one class may significantly outnumber another. The F1 score combines precision and recall into a single metric, making it easier to compare different models effectively. In this detailed analysis, we will explore the F1 scores of various transformer models and discuss their implications in natural language processing (NLP) tasks.

The F1 score is calculated using the formula:

$$\boldsymbol{F1 = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}}$$

This formula emphasizes the balance between precision (the accuracy of positive predictions) and recall (the model's ability to find all relevant instances).

A high F1 score indicates that a model has a good balance of precision and recall, which is especially critical in tasks like sentiment analysis, fraud detection, and other classification problems. It emphasizes the promise of multi-task generative models, The key differentiator in this approach is that it seems to combine multiple tasks into a unified framework, which might include not only WSD but also other generative tasks

The F1 score serves as a key performance indicator, particularly in scenarios where the cost of false positives and false negatives is significant. For example, in sentiment analysis, misclassifying a negative review as positive can lead to poor customer experiences. Similarly, in medical diagnosis, failing to identify a disease (low

recall) can have serious consequences, while incorrectly labelling a healthy individual (low precision) can lead to unnecessary anxiety and interventions.

Performance Evaluation:

From the performance scores, it's evident as shown in table.3 that:

- Supervised methods still perform better on most traditional benchmarks, especially when trained on large, annotated datasets like WordNet and SemCor.
- The multi-task generative approach stands out in terms of Pointwise Mutual Information (PMI), which indicates a strong ability to predict the co-occurrence of words with their correct senses, making it valuable for tasks involving real-world datasets, such as Amazon reviews.

To evaluate the performance of translation and word-sense disambiguation (WSD) outputs, various standardized scoring systems are employed. Each metric provides insight into different aspects of the systems' performance. Translation evaluation measures how well a system converts text from one language to another, while WSD evaluates how accurately a system can determine the intended meaning of a word in context when that word has multiple possible meanings. In this detailed exploration, we will focus on several key metrics that assess both translation and WSD outputs: BLEU, ROUGE, METEOR, BERT Score, Accuracy, F1 Score, and Perplexity.

The BLEU score for translation output is 0.85, which is quite high, indicating that the system generates translations that closely align with human references. For WSD, the BLEU score is lower at 0.73, reflecting the inherent difficulty in disambiguating word meanings and generating translations that fit contextually. A high BLEU score in translation suggests the model can accurately reproduce sentences that match human intuition.

Table.3– Performance Metrics for Translation and WSD

Metric	Translation Output Result (minimum viable score)	WSD Output Result (minimum viable score)
BLEU	**0.85**	**0.73**
ROUGE	**0.76**	**0.85**
METEOR	**0.64**	**0.75**
BERT Score	**0.93**	**0.93**
Accuracy	**87%**	**87%**
F1 Score	**0.96**	**0.96**
Perplexity	**95**	**95**

However, BLEU might not capture subtle errors related to meaning or fluency, particularly for WSD tasks. The discrepancy between the translation and WSD BLEU scores could point to challenges in dealing with polysemy—words with multiple meanings—where more contextual understanding is required.

The ROUGE score for translation output in the document is 0.76, while for WSD output, it is 0.85. This indicates that the WSD output retains more relevant content from the reference when compared to the translation output. The relatively high ROUGE score for WSD suggests that even though the system might struggle with disambiguating word meanings (as indicated by the BLEU score), it still manages to capture significant contextual elements from the reference translations. ROUGE complements BLEU by focusing on recall rather than precision. A higher ROUGE score for WSD might indicate that, although the system's word choices may not be perfect (leading to a lower BLEU score), it effectively captures the context or gist of the text. This is particularly important for WSD, where capturing the meaning in context is crucial.

The METEOR scores are 0.64 for translation output and 0.75 for WSD output. These scores suggest that while both systems convey meaning reasonably well, the WSD system performs better in terms of using correct word meanings and placing them in appropriate contexts. The higher METEOR score for WSD reflects that the system might struggle less with choosing the right sense of a word in context, even if the wordings vary slightly from the reference. METEOR is generally more sensitive to word choice and semantics, which is crucial for WSD tasks that require more nuanced understanding of language.

Both translation and WSD outputs have the same BERT Score of 0.93, indicating that both systems are highly effective in capturing the semantic content of the reference translations. A high BERT Score suggests that even when the exact wording or phrase structure of the output differs from the reference, the system still conveys the

correct meaning. This is particularly important for WSD, where capturing the intended meaning of ambiguous words in context is the primary goal.

Accuracy is simply the number of correct outputs divided by the total number of predictions made. This metric is easy to interpret but may oversimplify performance, especially in tasks where partial correctness or gradations of meaning are important. It reports an accuracy of 87% for both translation and WSD outputs. This means that in both tasks, 87% of the time, the systems are producing correct or acceptable translations/disambiguations according to the references. While an accuracy of 87% is solid, it's important to note that this metric alone doesn't capture nuances such as fluency, semantic accuracy, or partial correctness. For WSD, a high accuracy score suggests the system is frequently choosing the correct sense of the word in context.

Perplexity is the exponentiation of the entropy of a distribution. Lower perplexity means the model is more confident in its predictions, while higher perplexity suggests greater uncertainty. Both translation and WSD outputs have a perplexity of 95. This suggests that while the systems are reasonably confident in their predictions, there is still room for improvement in reducing uncertainty. Perplexity is an important indicator of how uncertain the system is about its outputs. In WSD, high perplexity might indicate difficulties in disambiguating certain words, especially those with multiple closely related meanings.

The performance of translation and WSD systems can be effectively measured using a range of standardized metrics. Each metric offers a different perspective: BLEU focuses on n-gram precision, ROUGE emphasizes recall, METEOR incorporates synonym and stemming matches, BERT Score captures semantic similarity, while Accuracy, F1 Score, and Perplexity provide broader insights into the overall correctness and confidence of the system.

For translation, high BLEU, ROUGE, and BERT Scores indicate that the system performs well in generating coherent and accurate translations, but metrics like Perplexity and METEOR suggest that there are areas of uncertainty or room for improvement in terms of handling more complex or ambiguous text. For WSD, the relatively lower BLEU score points to the difficulty of choosing the right sense of words, but strong performance in BERT Score, ROUGE, and METEOR indicates that the system still captures much of the correct meaning in context.

Ultimately, combining these metrics allows a more nuanced understanding of the strengths and weaknesses of both translation and WSD systems. No single metric can fully capture the complexities of language tasks, but together they provide a comprehensive framework for performance evaluation.

IV. CONCLUSION

The BMTNN model combines transformer neural networks with contextualized word embeddings from pre-trained multilingual models to disambiguate word meanings across different languages. This system addresses the complexity of multilingual word sense disambiguation by leveraging cross-lingual transfer learning and improving the accuracy of disambiguation in languages not seen during training, including in zero-shot scenarios. The proposed approach significantly improves upon traditional WSD methods and state-of-the-art techniques by offering better generalization, interpretability, and robustness.Future research should focus on optimizing computational efficiency, expanding language coverage, enhancing real-time capabilities, and improving model interpretability.

The success of the BMTNN relies heavily on large annotated corpora like WordNet and BabelNet. For many languages, especially low-resource languages, such large annotated datasets may not exist, limiting the model's applicability in these cases. The model's performance in these languages could be improved by exploring unsupervised or semi-supervised learning techniques that rely on less annotation.

Pre-trained multilingual models often inherit biases present in the datasets used to train them. As a result, the BMTNN might exhibit biases when dealing with certain languages or dialects, potentially leading to inaccurate disambiguation in specific cultural or linguistic contexts. Efforts to mitigate bias through fairness-aware model design or more diverse training data could be explored in future work.

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