Improving an English-Arabic Transformer-Based Machine Translation Model

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Abstract: Arabic is widely recognized as one of the most challenging languages for translation due to its rich morphology, complex syntax, and context-sensitive structures. Despite its global importance, Arabic has received significantly less attention in machine translation research compared to European languages, highlighting the pressing need for further investigation into high-quality Arabic machine translation systems. This paper proposes an enhanced model for English–Arabic machine translation tailored to the news domain, based on the Transformer architecture, which currently underpins most state-of-the-art machine translation. The model is augmented by incorporating external lexical alignment data at each decoding step. This integration is designed to improve the system's handling of polysemy, contextual ambiguity, and missing word detection, thereby enhancing translation accuracy, cohesion, and semantic fidelity. The proposed model was evaluated based on BLEU scores and F measure. Results showed that the proposed model outperformed, achieving an accuracy of 87% based on BLEU score, and an 84% score on the F-measure test, surpassing the Google translate by 6%, on the same tested data. These findings confirm that incorporating lexical knowledge into the Transformer framework significantly improves English–Arabic translation quality. The model not only provides more translations that are accurate but also demonstrates improved cohesion and contextual understanding, particularly in morphologically rich and domain-specific texts. This research underscores the value of domain-aware and linguistically informed machine translation approaches, paving the way for more effective Arabic-language translation systems in practical applications.

1 INTRODUCTION

Arabic is a morphologically complex and linguistically rich language of stem or root-based word formation [1]. A major issue with machine translation (MT) is that they are prone to detect word ambiguity and miss-selection meaning during training and/or translate [2]. This research proposed an improving English-Arabic Transformer-Based MT tailored to the news domain. The model employs a Transformer architecture with a multi-head attention mechanism, integrating it with a feed-forward neural network to enhance contextual representation and learning capacity. Using an encoder-decoder model is a versatile framework applicable to a wide range of text-to-text tasks [3].

Parallel embeddings are allows for decomposition and to divide of an entire English sentence to words or phrases parts [4], and convert to similarity matrices, where each cell represents a similarity measure between an English and Arabic word [5]. it is a crucial step in training MT [6], especially for language pairs with significant structural and linguistic differences [7], and rich languages such as English and Arabic. It effectively improves translation quality by establishing relationships between the words and phrases in both the English and Arabic language [8].

The task involves identifying corresponding words between a English text and a Arabic text [9]. This study aims to enhance the performance of English–Arabic MT by building upon the Transformer architecture. It focuses on improving contextual understanding for morphologically rich Arabic text, particularly in the news domain. Additionally, the study incorporates external lexical alignment data into the Transformer model to better handle polysemy, context-sensitive meanings, and

missing word detection. Words related are four types [10]. As shown in Table 1.

Table 1: Identifying corresponding difference words.

Words related	Common
One-to-one	One English word can be aligned to exactly one Arabic word, such as "tell" or "city".
One-to-many	One English word can be aligned to more than one Arabic word, such as "homesick".
Many-to-one	More than one English word can be aligned to one Arabic word, such as "in order to."
Many-to-many	More than one English word can be aligned to more than one Arabic word, such as "my soul mate."

2   RELATED WORK

Improving MT models is a crucial component in the development of comprehensive and effective MT [11]. The primary goal of using the Transformer model in Arabic MT (AMT) is to enhance the handling of polysemy and contextual ambiguities through deep contextual embeddings, thereby improving translation accuracy and fluency [12]. Prior research suggests that classical MT systems, despite their modeling capabilities and widespread adoption, have notable limitations [13]. Their parameter estimation methods rely on approximate hill-climbing algorithms, which are slow, memory-intensive, and difficult to parallelize. In contrast, deep learning (DL)-based MT models aim to resolve word ambiguity through mechanisms such as attention, which are employed in training NMT models - whether based on recurrent neural networks (RNNs) or the Transformer architecture. Parallelizing parameter estimation in these models enables more efficient memory usage and allows for training on larger corpora, which in turn reduces training time.

For these reasons, this paper emphasizes the vocabulary structure within Transformer models and their extensions, which enable MT systems to learn probability between source and target words [14]. Attention mechanisms which the foundation of the Transformer model, currently the state-of-the-art architecture for natural language processing (NLP) tasks-extend self-attention across sequences to capture contextual relationships. However, prior studies have found that attention may sometimes fail to effectively capture word probabilities in certain DL MT approaches [15].

3   METHOD

This study on the MT model is divided into four integral stages, each playing a crucial role in the MT process. These stages include preprocessing, training, translation, and evaluation. Figure 1. The MT model diagram.
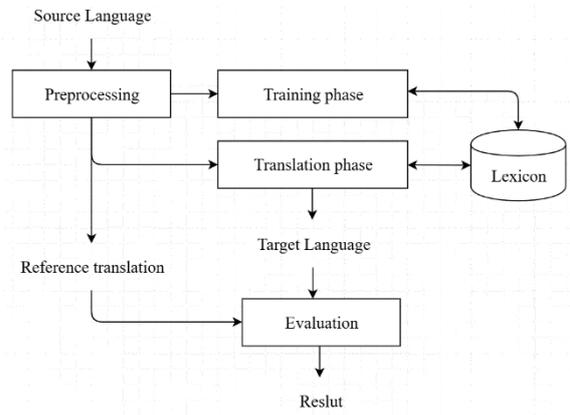

Figure 1: The MT model diagram.

Transformer model represents a fundamental shift in MT; it is a sequence-to-sequence encoder-decoder model, similar and almost identical to the RNN model, with the only difference being that the RNN layers are replaced by a fully attention-based approach layer [16]. It is less complex and faster training than RNN models [17]. As shown in Figure 2.
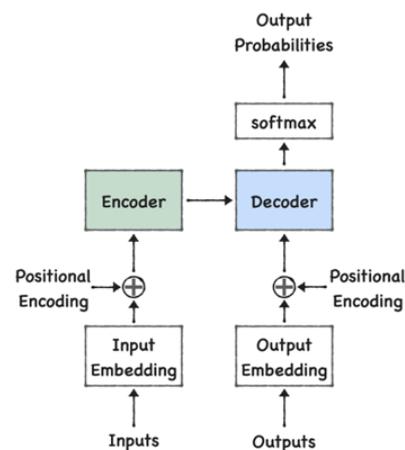

Figure 2: Transformer MT architecture.

In our proposed methodology, the input sentences are initially mapped into an embedded vector space before being passed to the encoder stack [18]. To capture the relationships, distances, and word order,

each input vector within the input sequence is supplied with a positional embedding vector [19]. Then, the combined vector will be directed to the initial level of the transformer's encoding component, where a self-attention of the multi-head mechanism has been applied to the intermediate embedded vector space as shown in (1) [20].

$$Attention\ (Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right). \qquad (1)$$

Where in, (K) keys, (Q) queries, and (V) values are vectors that are used in transformer to get better encoding for both source and target words. The scaling factor $\frac{1}{\sqrt{d_k}}$ helps stabilize gradients during training.

The multi-head mechanism enhances the attention layer performance by [21]. It improves the model's ability to focus on words at different positions, and it provides the attention layer with multiple representation subspaces, which are concatenated and then linearly projected onto the original dimension space [22]. the self-attention layer output is subsequently sent through the network of the feed-forward consisting of double linear transformations with a ReLU activation function within [23]. Each output is then fed into some other encoder level, which is gathered on top of the previous one. All the components of encoding levels share similar architecture and functionality [24]. The encoder output is directed as input to the decoder [25].

The decoding unit operates similarly to the encoding one. The top encoding unit output is transformed to be as a group of vectors of attention. Then, these vectors are used by the decoders, each alone in the decoding component. Allows the decoding unit to concentrate on the relevant positions of the sequence of the input [26]. The decoding unit generates one word at a time, according to English rules of writing. After that, each word is reintroduced into the final decoding unit by changing it into an implicit vector space. After that, the positional embedding vector is added [27]. The mechanism of the decoding unit's self-attention functions to some extent different than the encoding unit. In the decoder [28]. The layer of self-attention is restricted to attending just to words from preceding positions. This could be achieved through covering future words with those of very few values [29]. Each decoding component level performs the same function. The final decoding layer's output is passed through a linear direct layer and then a SoftMax layer [30]. The linear direct layer generates a matching vector that relates the target language words size, where each position in the vector corresponds to the score of a

unique word. This score vector is converted into probabilities by the Softmax layer, and the word with the highest probability is selected as the output for that time step [31] as shown in (2).

$$Softmax = \frac{QK^T}{\sqrt{d_k}}. \qquad (2)$$

At the output layer, Softmax converts raw logits into probabilities over the target vocabulary to generate the next word. Meanwhile, in the attention layers, Softmax computes attention weights that guide the model on which words to focus on during encoding and decoding.

4 EXPERIMENTAL SETUP

The aim of experiments is to propose MT evaluate and the effect of train a sequence-to-sequence transformer model from an English into Arabic language with the best quality and context on text length using different segmentation schemes.

4.1 Dataset

The primary prerequisite for training and testing a MT model is the availability of a parallel corpus comprising aligned datasets. In this study, we trained the model using the International Corpus of English-Arabic datasets [32]. The corpus contains a total of 817,274 sentence pairs, with 9,807,588 English words and 9,271,274 Arabic words, including training, validation, and test splits.

4.2 Data Preprocessing

Data preprocessing refers to prepares input data for model training and testing [33], [34]. In our work Data preprocessing consists of data cleaning, data normalization, and data tokenization. First step, deals with extraction of the effective data by data cleaning; removing outliers and noise, remove special characters, punctuation, empty lines were eliminated, and other factors to provide the basis for model training and testing.

Second step, it will remove the duplicate records from input document. To prevent bias in the training phase and unify the case of letters. Third step, Vocabulary creation is a fundamental step in deep learning-based MT [35]. Subwords-based models (Byte Pair Encoding (BPE) techniques) be used to building vocabulary that balances between word and character-level tokenization. Typically, a fixed number of most frequent subwords units are chosen

as part of the vocabulary to keep the model manageable and efficient. Designing a modest-sized yet representative vocabulary for both English and Arabic is challenging but essential, as vocabulary coverage directly affects translation quality.

4.3 Training Phase

Training in the context of MT using Transformer models involves establishing correspondences between words source and their translations in to the words target [36]. The core of the Transformer is the attention mechanism. The training of proposed MT model and utilized the default configuration of six layers in the encoding and decoding units, each containing 512 hidden ones, where the designed size was set to 512, including an 8-headed attention mechanism. The batch size was configured to include 64 records, while the operative set size- determined as the number of exercising examples handled in one phase - was set to 384. Its typical constraints were improved by applying the Adam optimizer.

The proposed model is trained on dataset of preprocessed sentence-length does not exceed 40 words [37]. The GPU run-time provided on until convergence or until 10.000 steps at max. Input embedding occurs in the lowest encoder layer, where input tokens - whether words or subwords - are converted into vectors via embedding layers [38]. These embeddings capture the semantic meaning of the tokens and represent them as numerical vectors, that solving the word ambiguous probability problem [39]. Input Embedding $a = \{a_1, ... , a_i\}$ is a vector for words where each a_i can take any value in the set $\{1, 2, ... ,i\}$. The vector specifies the mapping for each English word to a word in the Arabic sentence [40]. Therefore, $a_j = i$ specifies that e_j is aligned to a_i.

4.4 Translation Phase

Translation engine is the main component of MT system [11]. We employed a transformer model that use sequence-to-sequence model, consists of the encoder-decoder. These components work in tandem to process input text and generate corresponding output text. The translation engine involves direct stage that is word or phrase translation using lexicon lookup, word sense disambiguation direct [33]. And indirect stage that handling out-of-vocabulary words in lexicon [23]. We are finding the stems and the suffixes for the word. The stem of a word is its base form, stripped of any additions such as prefixes or suffixes [34]. These additions modify the meaning of the stem or derive new words to complete sentence structures. Low-frequency words, often the main content words, require special attention to ensure accurate translation. Every module plays an equally crucial role in enhancing the accuracy of the MT.

Good training enhances strengthening the connection between words, resolves ambiguity and increases performance efficiency [35]. Transformer-based MT system avoid low-frequency words problem due to their usage of explicit, discrete translation tables. We assume that the English sentence is "It will take two hours to get there", and we want to translate it into an Arabic language. We are looking for the words or phrase which has the highest probability. Using pre training rule and select fit Arabic sentence.

Now focus on the solving the problem of the translation probability. Embedding vectors $a = \{a_1, ... , a_i\}$, is a vector of variables where each ai can take any value in the set $\{1, 2, ... ,i\}$. The embedding vector specifies the mapping for each English word to a word in the Arabic sentence [36]. Therefore, $a_j = i$ specifies that ej is aligned to a_i. The word "take" has multiple meanings in English-Arabic MT, with the appropriate meaning chosen depending on alignment with adjacent prepositions in the sentence. Contextual variability of the meaning of words can change based on context, it essential to align words within the appropriate semantic framework as shown in (3) [37].

$$Pr\ (a|e) = \frac{Pr(a|e)Pr\ (a)}{Pr\ (e)}. \qquad (3)$$

Where Pr(e) is language model; Pr(f|e) is translation model. The score for a potential translation e is calculated as the product of two components: the language model score, which provides the prior probability of the sentence in English, and the translation model score, which represents the likelihood of (e) being the translation of an Arabic sentence (a). Utilizing a pre-trained model offers the advantage of leveraging the language model, which significantly enhances the fluency of the translation [38].

Self-attention enables transformers model to effectively propagate reordering across input sequences [39]. It begins by creating initial embeddings, or representations, for words. Through self-attention, it get information of text, producing a new context-informed representation for each word, as depicted by the filled circles [40]. The process is repeated multiple times in parallel for all words, iteratively generating refined word alignment, as shown in Figure 3 [11].
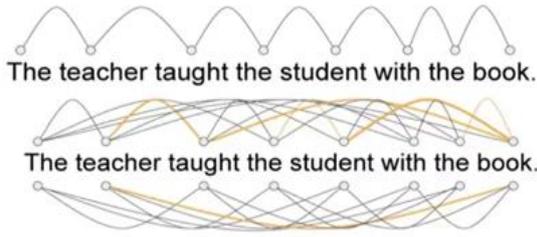
Figure 3: Translation phase processing [36].

5 RESULT AND DISCUSSION

The performance of our model vs. google models evaluated on the International Corpus of Arabic [35], English-Arabic datasets, through BLEU score and F-measure evaluation methods. The evaluation form consists of one input text, one candidate deep MT model, one candidate Google translation, and one reference. We used reference has a loose word order. It is calculated and described on news test data [23]. Evaluation includes simple sentences, compound sentences, and complex sentences.

The F-measure evaluation focuses on a quantitative metric that combines precision and recall into a single harmonic mean, providing a balanced assessment of MT quality [40], which are defined by (4), (5), and (6), respectively. In this context, 'correct' refers to words number accurately translated. 'Output length' denotes the total words number in the translated text, while 'reference length' represents the total number of words in the reference text. Table 2, and Figure 4, show the F-measure evaluation.

$$Precision = \frac{correct}{Output\_ength}, \quad (4)$$

$$Recall = \frac{correct}{Reference\_ength}, \quad (5)$$

$$F_{Measure} = \frac{correct}{\frac{Precision+Recall}{2}}. \quad (6)$$

Table 2: Results of statistical evaluation (F-measure).

Criteria	Simple	Compound	Complex	Average
Deep MT	0.88	0.85	0.80	0.843
Google Tr.	0.79	0.74	0.71	0.747

Table 3: Results of BLEU score evaluation.

Criteria	Simple	Compound	Complex	Average
Deep MT	0.91	0.85	0.81	0.857
Google Tr.	0.85	0.79	0.73	0.79

The BLEU score evaluation is employed, where the BLEU value ranges from 0 to 1. A value closer to

1 indicates higher translation quality [36]. The BLEU score i is computed as the product of the Brevity Penalty (BP) and the geometric mean of modified n-gram precisions. The process begins with calculating the geometric mean of the modified n-gram precisions. Next, the length of the candidate translation (c), and the length of the corresponding reference corpus (r) are determined to calculate the BP. [17] illustrates how the Brevity Penalty is reduced in (r / c) as shown in (7) and (8) demonstrates how to calculate the final BLEU score [23].
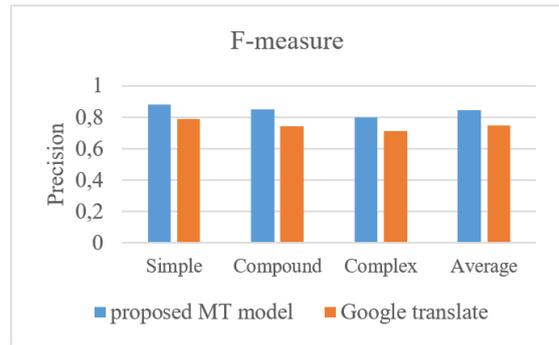

Figure 4: Results of statistical evaluation [36].

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \le r \end{cases}, \quad (7)$$

$$BLEU = BP\ X \exp\left(\sum_{n=1}^{N} \log P_n\right). \quad (8)$$

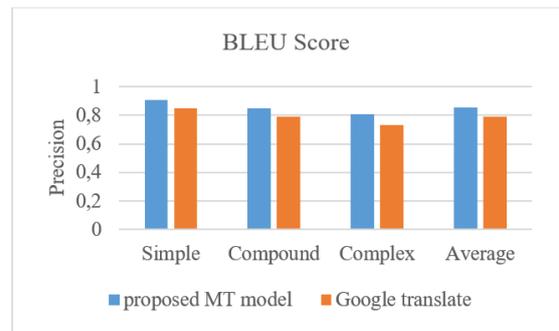Where N = 4 and uniform weights W_n = (1/N. Table 3, and Figure 5. Shows the BLEU evaluation.

Figure 5: Results of BLEU score evaluation.

Based on the obtained results, we can conclude that the good translation depends on data training and more data training makes the transformer-based MT more accurate. Proposed MT model evaluation using the BLEU score. The results showed that 65% of texts got the score more than (0.75), they were perfectly intelligible and clear. While 21% of the texts got the

score more than (0.5), they were generally intelligible and clear, also, 12% texts got the score between (0,25–0.5), they were hard to understand, finally 2% texts got the score less than (0.25), they were not understandable. Therefore, we can say that about 86% sentences are intelligible. These sentences are those which have score (0.5) or above.

As for the F-measure, its results were about 3 points lower than the BLEU score but still exceeded Google Translate by approximately 6 points. Thus, we can conclude that the proposed MT model translates from English to Arabic with considerably good accuracy. Thus, we can say that the translate from English to Arabic with a considerably good accuracy by proposed MT model.

6 CONCLUSIONS

The Transformer model demonstrates impressive performance and serves as a strong baseline for the development of deep MT models when trained on large-scale news corpora. The news domain typically features standardized syntax, formal vocabulary, and clear sentence boundaries, making it a suitable training environment for MT systems. While continuous progress has been made in deep MT for English and other European languages, Arabic has received comparatively little attention in the literature. Therefore, the current study aims to explore the effectiveness of a deep MT model based on the Transformer architecture. The attention mechanism and attention weights can serve as effective indicators of the relationships among source and target words. The effectiveness of the Transformer model plays a critical role in improving translation quality and bridging gaps between English and Arabic. Test results indicate that the proposed deep MT model outperforms state-of-the-art neural MT systems in terms of adequacy by BLEU score and F-measure evaluation. Finally, future work may focus on developing strategies and techniques that allow for updates in the decoder phase and enable automatic lexicon adaptation, further enhancing system performance.

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