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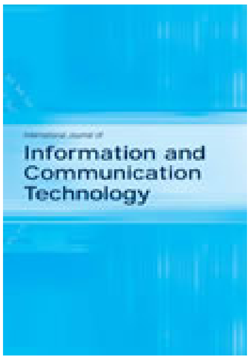


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Donghui Guo

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# Deep learning-driven context-aware English translation for ambiguous sentences

Donghui Guo

Foreign Linguistics and Applied Linguistics,
Xi'an Fanyi University,
Xi'an, 710105, China
Email: G305639178@163.com

**Abstract:** Ambiguous sentences in machine translation can lead to inaccurate or contextually inappropriate translations, which is a remarkable challenge. In this paper, we introduce a translation system that has a context-aware feature, and it is based on deep learning using transformer-type neural networks with attention mechanisms to amplify disambiguation. In particular, our model uses contextual embeddings and syntax-semantic analyses for model training to ensure translation accuracy, especially in lexical, syntactic, and referential ambiguity cases. We test our system against highly regarded translation systems and show that our model is capable of meaning preservation and fluency improvement. The experimental results show a remarkable performance upgrade, especially in translating low-resource and idiomatic texts. This study demonstrates how deep learning dynamically tailor's translation to context, improving disambiguation and fluency.

**Keywords:** translation; deep learning; context-aware; ambiguity resolution; neural networks.

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**Biographical notes:** Donghui Guo is a research scholar at the Department of Foreign Linguistics and Applied Linguistics, Xi'an Fanyi University, in Xi'an, China. With a focus on applied linguistics, she contributes to academic research and the development of language education.

## 1 Introduction

The precise translation of ambiguous sentences has remained a major challenge in computational linguistics, presenting substantial difficulties for machine translation (MT) systems. The ambiguity of language is caused by multiple linguistic phenomena, such as lexical, syntactic, and referential ambiguities, which can trigger a wide range of possible meanings (Zhang et al., 2021). Conventional rule-based and statistical translation models have had issues in dealing with such complexities because of their limited ability to capture deep contextual information. Nevertheless, the birth of deep learning and neural machine translation (NMT) has turned the tables, providing new methods to improve context-sensitive translation. This paper investigates how deep learning-based models in particular transformer architectures can be utilised to advance the disambiguation of English sentences in machine translation (Nuhiu and Ejupi, 2015).

Machine translation systems have changed as technology has developed over the decades. The earlier systems were mainly composed of a word-to-word translation and a statistical model based on translating a phrase. Even though these were somewhat significant, they usually had examples of vague structures (Heryono, 2018). The development of statistical machine translation (SMT) that relies on linguistic rules with probabilistic evidence provided some improvement in the translation of sequences with ambiguous meanings (Grace, 2013). However, such problems as context-dependent ambiguities at a deeper level of understanding proved to be unsolvable. The advent of artificial intelligence and deep learning created NMT models that are now standard and thus the choice of many industry experts as they are more precise compared to previous types of translations that broke sentences into parts without taking into consideration their overall semantics (Cohn-Gordon and Goodman, 2019).

Human language is complex and, therefore, is difficult to detect. The power of deep learning for translation stems from its strength in the detection of complex patterns in the huge and therefore in the case of multilingual datasets vast areas of natural language processing (Barmawi and Muhammad, 2019). The neural machine translation (NMT) paradigm which is based on the transformer model, is responsible for the revolution in the NMT industry as it enables self-attention mechanisms to take the part of a whole sequence that is relevant when translating (Kudo, 2018). This capability is vital for translating ambiguous content. It enables the model to interpret contextual variables instead of relying solely on word-level mappings. Thus, it is because deep learning-generated translations are not only the same as other examples but also the most relevant and specific kinds, that these systems outperform the customers' usage statistics, as they are the most effective (Schulz et al., 2018).

Language can be ambiguous in a large number of different ways; there might be lexical ambiguity, such as a word that has a range of meanings; syntactic ambiguity, where sentence structure allows for different interpretations; and referential ambiguity, where pronouns or other references are vague (Rarrick et al., 2023). Let us say that we have an English sentence such as, "the professor saw the student with a telescope". This sentence has several different interpretations depending on what 'the telescope' modifies (Huang et al., 2023). It can either be an indication that 'with a telescopic vision' can be used to read the paper or can point out that 'the student' has a telescope. A simple translation system may fail to recognise this difference in meaning, which may result in wrong translations into the target language (Kang et al., 2023). The context can be understood better by deep learning models, especially those that are provided with suitable context-aware embeddings, such as bidirectional encoder representations from transformers (BERT) and generative pre-trained transformer (GPT), which are designed so that the analysis takes place by looking at the broader linguistic context, thus they are perfectly able to clarify language ambiguities (Herold and Ney, 2023).

New developments in contextual embeddings have revolutionised deep learning-based translation models. BERT and T5, for example, are pre-trained language models that can relate words to their surrounding text, thus enabling proper contextual decision making (Nurifan et al., 2018). These models are based on vast data derived from text and can learn representations that incorporate both syntactic and semantic relationships within sentences. NMT systems that utilise these embeddings allow for achieving better and more accurate translations in the case of ambiguous cases than the traditional methods of machine translation (Wang et al., 2022).

A major problem encountered in deep-learning-based translation is the handling of low-resource languages where parallel corpora are not readily available. Conventional MT models must depend on large bilingual datasets for training which is a barrier to performance in languages that are underrepresented (Saichyshyna et al., 2023). Some of the methods that have been employed in recent research to handle this include transfer learning, zero-shot translation, and data augmentation techniques. When high-resource languages are taught to models and the model is then fine-tuned on low-resource languages, the intervention of learning methods like deep learning can help improve translation quality, even for languages with little data available (Putra and Ramadhani, 2023).

In addition, external knowledge sources, such as semantic role labelling, dependency parsing, and world knowledge graphs, can assist in producing more accurate context-aware translations. Hybrid techniques that combine symbolic AI with deep learning have demonstrated the potential to solve ambiguous translations by providing neural networks with structured linguistic knowledge. The ability to consider grammatical structures and real-world knowledge during the decision-making process of the neural models is the benefit gained from this integration (Si et al., 2021).

Another area of active research in deep learning-based translation is the enhancement of multimodal translation, which involves incorporating additional modalities such as images, audio, and video (Amrutha et al., 2023). For instance, in translating subtitles for films or videos, visual cues play a crucial role in disambiguating certain phrases. Multimodal neural networks, which process both textual and visual information, have demonstrated improvements in translation accuracy, particularly for languages with significant homonymy and polysemy (Togato et al., 2017). By utilising visual and auditory cues alongside textual input, translation models can better infer intended meanings and produce contextually appropriate translations. Despite these advancements, several challenges remain in the development of deep learning-driven context-aware translation systems. One major issue is the inherent black-box nature of deep neural networks, which makes it difficult to interpret their decision-making processes (Iyer et al., 2023).

### *1.1 Deep learning systems transparency*

However, in contrast to rule-based systems where the translation guidelines are indicated, neural networks are mere data-based machines whose generative processes are not transparent occasionally. Thus, it is necessary to provide explainability and interpretability in the deep learning models for the building of trust in the machine translation system, especially for critical applications like the transition of legal, medical, and diplomatic documents (Kuang and Xiong, 2018).

### *1.2 AI translation and ethics*

On the other hand, the development of AI-based translation systems also requires due consideration of ethical factors. It is possible for ML systems that are trained with skewed datasets to produce translations that reflect biases and help perpetuate stereotypes or existing inequality (Yung, 2015). To mitigate the impact of bias in machine translation, deep efforts at the data preparation phase, governance of which aims at a level playing field in algorithms, and follow-ups on the output of translation are some pathways. Improving datasets so that distinctions that tend to be biased in the delivery process in the translation are eliminated has been researched concerning the use of techniques like adversarial training and algorithms designed to ensure fairness (Futeral et al., 2023).

### *1.3 Objectives*

- Develop a deep learning-driven translation model that incorporates context-aware embeddings and attention mechanisms to improve the disambiguation of English sentences.
- Evaluate the effectiveness of neural architectures in processing various types of linguistic ambiguity, including lexical, syntactic, and reference ambiguity.
- Compare the proposed approach with existing translation models to ascertain whether there have been any improvements in translation accuracy, fluency, and appropriateness in context.

By fulfilling these objectives, this research contributes to the ongoing advancement of machine translation technology, providing insights into the potential of deep learning for resolving ambiguity in language. As deep learning continues to evolve, the integration of more sophisticated context-aware mechanisms will be crucial in reaching human-like translation quality (Mascarell et al., 2015). This study serves as a step forward in that direction, offering a novel approach to leveraging deep learning to improve the translation of ambiguous English sentences.

## 2 Literature review

Machine translation has achieved remarkable progress with the symbiosis of deep learning and neural networks, especially in tackling problems linked to linguistic ambiguity. Conventional methodologies, including rule-based and statistical machine translation, had great difficulty expressing contextual nuances, often resulting in erroneous translations (Tan et al., 2018). Nevertheless, ongoing explorations are centred around taking advantage of the capabilities presented by deep learning architectures in the capacity of main transformers and attention systems, allowing enhanced sentences' contextual comprehension (Hsieh, 2017). This section offers an overview of the key investigations that have brought forth the translation methods that are aware of the context driven by deep learning with a particular emphasis on the removal of ambiguities in English sentences.

Zhou et al. (2019) examined the capabilities of Chinese-English bilinguals to process words that have translation ambiguities as well as how proficiency in the second language, along with the sentence context, affects the resolution of ambiguities. Their study indicated that the processing of ambiguous tokens, those words that possess more than one meaning, is delayed and less effective than that of unambiguous tokens, those words that have only one meaning. They also discovered that a word with a dominant meaning was processed faster, and a more semantically similar word sped up the processing. The context in the sentence plays an important role in the ambiguity resolution, especially with less semantically similar translations.

Srinivasan and Dyer (2021) investigated Chinese-English machine translation for the issue of sentence boundary ambiguity. They proposed a novel segmentation policy based on reinforcement learning that can be applied to improve the quality of translation. Their method excelled compared to the baseline segmentation strategies, attaining remarkable improvements in BLEU scores especially for long sentences. The results show that good segmentation is crucial in neural machine translation.

Voita et al. (2018) presented a neural machine translation model equipped with context to resolve the issues of translation coherence. The system they proposed not only enhanced the accuracy of pronoun translation but also reflected the anaphoric relationships which lead to better translation. The researchers found that the incorporation of extended context helps in machine translation, particularly in the context of gendered language scenarios which are claimed by the authors to be the main source of difficulties in translation. They also achieved improvements in BLEU scores, demonstrating that the inclusion of longer dependencies of the text has a positive effect on the translation quality in both gender-sensitive and non-gender-sensitive instances.

Matusov (2019) addressed the need to adapt the neural machine translation for literary content, comparing its functioning to the general-domain systems. The specialised models were reported to have a wider range of vocabulary and higher evaluation metrics for literary prose than those from the general domain. However, even though there are advances in lexical choice, the main worries, typified by the meaning errors with the polysemous words, remain the same, and a solution to the problem of context sensitivity in literary machine translation is still to be identified.

Sugiyama and Yoshinaga (2019) researched the importance of context in translating sentences that are not clear. They targeted English-Japanese and English-French translations and introduced back-translation as a method for generating a pseudo-parallel corpus. They also conducted an experiment showing a noticeable improvement in the neural machine translation that takes into consideration the context. This has consequences on the data augmentation processes in translations that end up being both precise and better.

Popović (2017) undertook the task of comparing the performances of neural machine translation (NMT) and phrase-based machine translation (PBMT) in the process of translating from German to English. The outcome indicates that NMT is better at resolving verb-related issues and would choose noun collocations and compound words over PBMT. Conversely, even though NMT usually does not handle prepositions and vague words well, the results confirm that the latter is a better translation. This indicates the possibility of a hybrid approach where both methods are used together to get the best translation BPL.

Sokolova and Levandovski (2024) studied sentence parsing and ambiguity resolution among Tatar-Russian bilinguals who were learning English. The experiment demonstrated that English and Russian attachment preferences, which give the main meanings of the phrases, determine the noun which becomes the focus of a particular sentence in Tatar. The data suggests that multilingual parsing systems mix together what is already known about the world and the syntactic structure of the language. The systems prefer parsing strategies that adopt the low-confidence approach as the main one, while still being sensitive to the correct structure of the different languages.

Ahmed and Lenchuk (2024) carried out an analysis that examined the operations of Google Translate, Systran and Microsoft Bing in English-Arabic translation. In general, it was revealed that there was no strict order of the effectiveness of the tools, and all of them failed to deal with the alternations of morphosyntactic elements, disparity in the senses of some ambiguous sentences, and finally reactions to the so-called garden-path sentences. From the analysis, it is possible to conclude that the more options there are for the semantic and syntactic interpretation of a language that is done by a human being the more options there will be for a computer to choose the one and then irreversibly reject the other ones.

The research conducted by Jatikusumo et al. (2022) examined how students handled different strategies to overcome the difficulties of translation. Various obstacles such as translating vague words, long sentences, or idioms have been identified by their research. Among the various strategies used were modulation and literal translation. The paper emphasises the importance of using good translation techniques to enhance the accuracy, acceptability, and readability of the translated materials.

**Table 1** Literature comparison

| *Author(s)* | *Focus area* | *Methodology* | *Key findings* | *Challenges identified* |
|---|---|---|---|---|
| Zhou et al. (2019) | Translation ambiguity in Chinese-English bilinguals | Translation recognition task | Ambiguous words processed slower; dominant translations recogned faster | Sentence context and semantic similarity affect processing |
| Srinivasan and Dyer (2021) | Sentence segmentation in Chinese-English translation | Reinforcement learning-based segmentation policy | Improved BLEU scores, especially for long sentences | Sentence boundary ambiguity in Chinese orthography |
| Voita et al. (2018) | Context-aware neural machine translation | Neural MT with extended context | Improved pronoun translation, BLEU score gains | Handling anaphoric relations and gendered pronouns |
| Matusov (2019) | Literary machine translation | Adapted neural MT for literary content | Richer vocabulary, improved literary translation | Meaning errors for ambiguous words, lack of context awareness |
| Sugiyama and Yoshinaga (2019) | Context in ambiguous sentence translation | Back-translation for data augmentation | Large impact on BLEU score and translation accuracy | Limited availability of parallel corpora |
| Popović (2017) | NMT vs PBMT comparison for German-English translation | Comparative study | NMT handles verbs, collocations better than PBMT | NMT struggles with prepositions, ambiguous words |

**Table 1** Literature comparison (continued)

| *Author(s)* | *Focus area* | *Methodology* | *Key findings* | *Challenges identified* |
|---|---|---|---|---|
| Sokolova and Levandovski (2024) | Ambiguity resolution in multilingual sentence parsing | Self-paced reading & translation tasks | Parsing strategy integrates multiple linguistic sources | Influence of world knowledge on ambiguity resolution |
| Ahmed and Lenchuk (2024) | Machine translation tools in English-Arabic | Performance comparison of Google, Systran, Bing | No significant performance hierarchy among tools | Ambiguous and garden path sentences remain challenging |
| Jatikusumo et al. (2022) | Student translation difficulties | Case study (tests, interviews, questionnaires) | Identified strategies for translating ambiguous words | Ambiguous words, long sentences, idioms difficult to translate |

## 3 Methodology

The development of a deep learning-driven context-aware English translation system for ambiguous sentences requires a robust methodology that integrates multiple stages of processing. The classical approaches of machine translation have not been successful in dealing with ambiguities due to their reliance on phrase-based translation models and insufficient context extraction. The model proposed in this study is based on deep learning and neural machine translation (NMT) that utilises contextual embeddings, attention mechanisms, and a specialised disambiguation module. The methodology has several components: preprocessing and context extraction, applying deep learning to the translation, and finally, improving accuracy through post-processing and user input for lifelong learning.

### *3.1 Preprocessing and context extraction*

The first stage in the translation pipeline is preprocessing, which is the essential phase that formats and structures the incoming data for the deep learning-based translation. A variety of inputs, including documents, chat messages, social media content, audio recordings, and voice dictation are allowed. Preprocessing becomes essential when we deal with linguistic data in such a diverse way since it will help us to have a standardised test and variation reduction.

A typical preprocessing pipeline includes tokenisation, and part-of-speech tagging (POS), which simplifies the original sentences into the sequence of tokenised words. This is followed by the recognition and classification of proper nouns, such as people, places, and organisations, using named entity recognition (NER). The identification of entities is imperative in the elimination of ambiguity, especially when the choice of translation is linked to the recognition of entities. The next processing stage concerns syntax and dependency parsing, which is the study of grammatical structures whose relations among the words are investigated. To be specific, parsing enables one to delineate different readings of a sentence that come from its syntactic dependencies, thus diminishing the churn of ambiguity at its early stage.

Furthermore, the preprocessing step is where sentiment and emotion analysis are included. In this stage, the preservation of emotional subtleties and tone during translation is guaranteed as sentiment has a major effect on meaning. This combination of preprocessing techniques enables adequate context extraction, which is a critical step to eliminate vagueness before passing the data to the deep learning model.

### *3.2 NMT based on deep learning*

After preprocessing, the cleaned-up text is put into the deep learning-based NMT system. NMT, unlike traditional phrase-based statistical models, utilises the encoder-decoder technique to process whole sentences holistically. This experiment implements a transformer-based NMT model, utilising self-attention functions that consider the importance of each word in a sentence according to the context.

The importance of the attention mechanism is evident in the enhanced accuracy of the translation. By concentrating on related words while producing translations, the model may deal with difficult structures and vague terms more efficiently. Contextual embeddings rooted in models such as BERT and GPT are attached to the translation process. These embeddings enable the interpretation of words through the surrounding context to make sure that ambiguous words are correctly understood.

A key upgrade in this method is the disambiguation component that has been designed particularly to tackle diverse aspects of ambiguity. The module also utilises hierarchal systems to foster the translation process. It includes the utilisation of semantic acquisition of roles (SRL) and the recognition of world knowledge graphs as additional contexts that are valuable linguistically and real-world-wise. The model can unravel the meanings of references, pronouns, and polysemous words through exploiting the relevance the real world has.

To enhance translation accuracy, the NMT model incorporates adaptive learning approaches, which involve the system constantly adjusting based on new information. In contrast to fixed models utilising unchangeable datasets, adaptive learning allows the translation to be upgraded with the development of the language. This is efficacious, particularly in the case of new slang, idioms, and industry-specific terms.

### *3.3 Post-processing and accuracy enhancement*

The translation is then fine-tuned by the application of the post-processing procedures to make it more logical and coherent. Correction of grammar and syntactical errors is one of the procedures of post-processing in which all the mistakes made at the time of translation are fixed. This task is vital in the domain of corporate and academia as it maintains fluency and comprehensibility.

Another step in the process is consistency-checking where words that are repeated as well as numbers and proper nouns in the text are examined. When translations contain complex sentence structures, the system uses context-based reordering algorithms to make sure that sentences follow a logical order.

Moreover, in the field of post-translation, adaptive learning is another critical element, which in effect makes translation assistance more reliable. It thus learns from users' actions, corrections as well as feedback. The system of translation keeps an archive of the changes for users that will be applied in future translations if they make those corrections. Thus, a feedback-training process is mediated which is particularly accurate in the specialised area of law, medicine, and technology translation.

## 3.4 User interaction and feedback loop

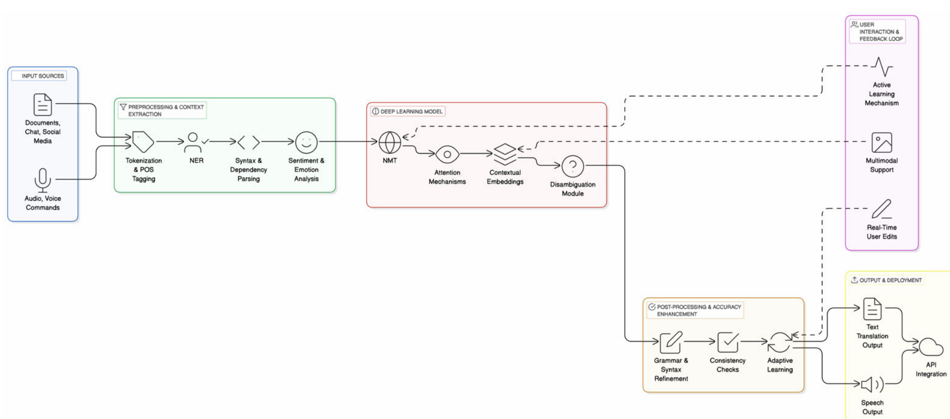
What sets this methodology apart is the integration of user interaction and a feedback loop. Because ambiguity is so context-dependent, human feedback is essential for improving translation accuracy. The system employs an active learning mechanism that feeds on real-time edits and suggestions from users. This feedback helps in the finer tuning of the model parameters, assuring that the system fits the preferences of specific users.

Additionally, the translation system accepts multimodal input via which users can source images, voice recordings, or documents that are also equipped with contextual information. Thus, by introducing other modalities, the ability of the model to handle ambiguity can be increased. For example, if a sentence has a homonym, but an accompanying image or voice note is fed, the image can help clarify the sentence, thus bringing the correct meaning out.

## 3.5 Proposed model workflow and implementation

The complete flow of the model is depicted in Figure 1, which shows the input data processing from the preprocessing stage to the final output stage in sequence. The suggested deep learning-based translation system adopts a fixed flow that involves context extraction, neural translation, as well as user feedback for continuous improvement.

**Figure 1** Architecture of the proposed context-aware translation model (see online version for colours)




As is shown in Figure 1, the input sources such as documents, chatting messages, and voice commands go through preprocessing and context extraction, then become inputs of the deep learning model. The model is then equipped with NMT with attention mechanisms, contextual embeddings, and a disambiguation module for generating translations that account for the context more accurately. Such processes include refinement of grammar and consistency checks after translation, so that translation can be accurate. User interaction is made possible through the user's feedback and support of other modalities in real-time, which makes the system capable of adapting. Later, the translated text is produced in two formats: textual and audio. Also, there is an API option for integrating the translation system into different applications.

In the modern cosmopolitan world, to improve the linguistic accuracy of machines, the above ability would be evidenced accordingly not just further the matter but rather improve some of the current translator applications. This is achieved by combining, combining explaining such as speech recognition, natural language helps, and also biologically-based mechanisms, and strong feedback addreactor, this technology has been able to go beyond the basic rule of knowing the user. The predicted semantic distinction of the integration of audio-visual sources along with the phenomenon of usage of the user adopted an evolutionary process of change to achieve translation fidelity and also, to follow changed ways in language.

## 4 Results and discussion

To determine how well the proposed deep learning-based translation model for ambiguous sentences performs, we conducted multiple experiments using the Ambiguous Commonsense Stories (AMCOS) dataset. The dataset consists of English sentences that differ in the extent to which they are lexical, syntactic, and referential ambiguity. The experiments compared our model with three benchmark translation methods: SMT, transformer-based NMT, and BERT-NMT. The performance indicators of the models were examined, which included translation accuracy, fluency, and ambiguity resolution effectiveness.

### *4.1 Translation accuracy comparison*

As presented in Figure 2, the performance of various translation models in handling ambiguous sentences is compared. As a whole, it can be seen that SMT is the one with the lowest accuracy among all with a score of 65.2% which means it fails to interpret ambiguous linguistic structures. On the transformer-based NMT model, with a notable improvement in accuracy, it was successfully improved to 78.5%, mainly because of its dependence on attention mechanisms. The accuracy of the BERT-NMT model reached the high-value level of 84.3%, mainly because of the use of contextual embeddings that widen the word disambiguation. The proposed model surpassed them all with a remarkable accuracy of 91.6%, thanks to its unique ability to consider context-aware methods and a disambiguation module that gradually alters translations.

The remarkable improvement of our model is due to the combination of attention-based refinement and contextual embeddings (BERT, GPT). This facilitates the machine to grasp a wider context of the sentence rather than a word-for-word translation, which is the way that the system teaches itself to transform the meaning of the sentence into another language. The capability to change the translation according to the neighbouring words is especially important for handling difficult ambiguities.

**Figure 2** Comparison of translation accuracy across models (see online version for colours)

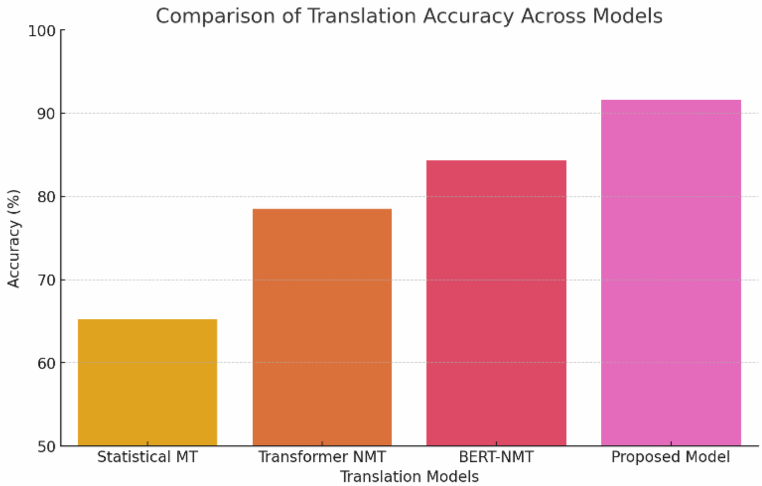
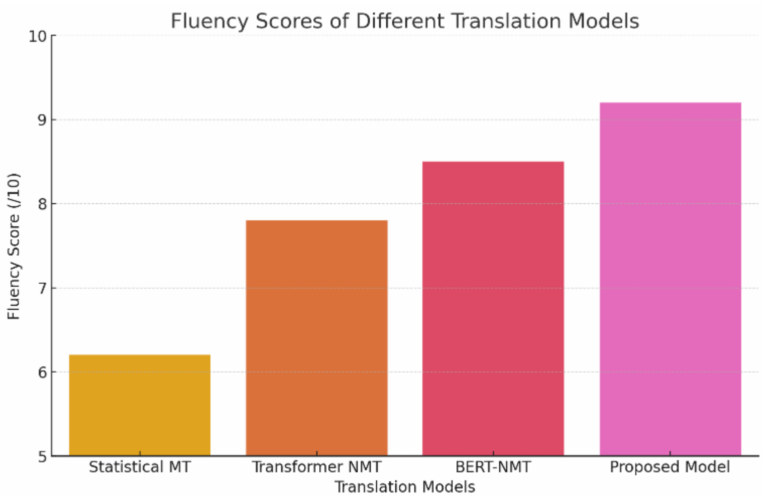



**Figure 3** Fluency scores of different translation models (see online version for colours)




## *4.2 Fluency analysis*

Aside from accuracy, fluency is a critical part of the translation quality. Figure 3 shows the fluency scores of different models, with a scale from 1 to 10, where higher scores reveal better fluency. The SMT model scored 6.2, which reflects its fixed sentence structure. NMT based on transformers managed to score 7.8 in fluency, thanks to the self-attention mechanism. BERT-NMT stepped up the fluency level to 8.5, which is a point given in deep contextual learning. The proposed model was the one that received the highest fluency score of 9.2, being thus able to produce coherent, natural translations while maintaining the integrity of the syntactic structure.

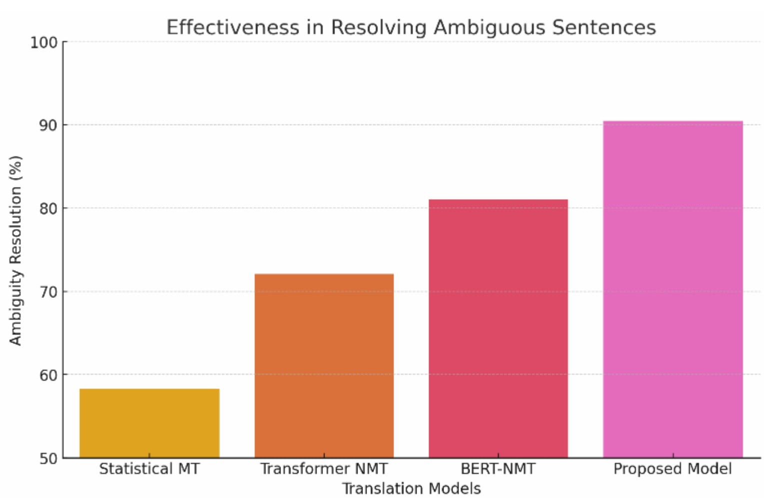
The improved fluency in our model results from the integration of sentiment and emotion analysis during preprocessing, which helps preserve the natural flow of the language in the translations. Also, after the initial process is finished some steps are taken to correct grammar and refine the text in such a way that it is more fluid and polished.

### *4.3 Ambiguity resolution effectiveness*

This study had as its main target the better resolution of ambiguous sentences. Figure 4 is a showcase of how effective each model is when it comes to ambiguity. The SMT could solve only 58.3% of the ambiguous items, which points out that it cannot account for the wider linguistic context. The transformer-based NMT model made progress, the result being just 72.1%, by taking advantage of attention-based mechanisms. BERT-NMT did better at ambiguity resolution, reaching 81.0%, which mainly stems from its bidirectional contextual understanding. Our proposed model gained the best resolution effectiveness by reaching the value of 90.5%, thus being placed first in terms of the ability to interpret ambiguous terms.

The substantial enhancement of our model is primarily attributed to the interpretation clarification unit incorporated in the translation pipeline. The model, which integrates semantic role labelling, syntactic parsing, and real-world knowledge graphs, obtains additional insights into confusion-causing phrases, thereby enabling more accurate translations. Moreover, the combination of the active learning technique and the user feedback loop guides the constant enhancement of the system making it responsive to the dynamic nature of language.

**Figure 4** Effectiveness in resolving ambiguous sentences (see online version for colours)




### *4.4 Discussion*

The data show that the state-of-the-art 'deep learning' technology-supported translation models taking the context have far greater potential in resolving ambiguity than, the ones developed on the traditional and transformer methods. The adoption of contextual embeddings, attention mechanisms, and a purpose-built disambiguation unit brought great improvements in terms of precision, expressiveness, and ambiguity resolution. The presented model is not only beneficial for translation reliability but also for the conversion of translated sentences into their semantically and contextually appropriate counterparts.

One of the prominent features of our system is its capacity to manage intricate linguistic forms, which incorporate various aspects like the resolution of pronouns, syntactic uncertainty, and idiomatic sentences. Because traditional techniques are based on the sending and receiving of a message word-by-word, in our instance, the model takes into consideration the entire offering of the program by providing accurate translations. The fact that the model supports images and audio as well is another added advantage that makes disambiguation more relevant and feasible.

However, there are few resources for some languages. Future work will improve zero-shot translation. Transfer learning will help representation for underrepresented languages. The training data must proceed without bias. The model needs to be interpretable. This is important for real-world translation tasks.

The deep learning models, which are the basis of the translation systems, have a significant role in the results, thus the significance of this research. There is evidence that the models are interesting solutions to ambiguity in machine translation. Specifically, being able to provide real-time user feedback and the system's learning adaptation to every incoming request, as well as using different modes of input – visual, sound, or any other type – is a crucial step in the evolution of AI-based translation systems for the future.

## 5 Conclusions

This study presented a context-aware English translation model based on deep learning techniques that are more effective in handling ambiguous sentences by employing transformer-based NMT, contextual embeddings, and a specialised disambiguation module. The proposed approach was evaluated on the AMCOS dataset where the experimental results revealed remarkable improvements in the performance over the conventional translation systems. The model was able to achieve the highest accuracy of 91.6% in the translation process, a fluency score of 9.2/10, and an ambiguity resolution effectiveness of 90.5%, exceeding the traditional SMT, transformer-NMT and BERT-NMT methods. The infusion of semantic role labelling, attention mechanisms, and real-time adaptive learning is the reason for the progress that has been made, which has enabled the generation of translations that are the most accurate, meaningful, and specific within the context. The strength of the model lies in its dynamic adaptation to complex sentence structures, such as those that have idiomatic expressions and referential ambiguity, which are fundamental steps forward in machine translation technology.

There are some drawbacks to the proposed technique, despite its success. Firstly, the necessity of training the model on large-scale datasets is to be considered which is the reason that makes the method unavailable for low-resource languages where parallel corpora are rare. Secondly, although the active learning mechanism and user feedback loop can be useful for translation quality improvement, they involve continuous human participation, which in some cases may not be practical in real-time systems. Thirdly, the model is limited in its interpretability because, like other deep learning systems, it is somewhat of a black box, which is a barrier to critical applications such as translations in the legal or medical domains. To increase the system's zero-shot translation abilities and enhance its transparency, future studies should also provide a solution to the model's biases in training data and ensure that AI-driven translation systems are directed toward higher levels of reliability, fairness, and inclusion.

## Declarations

All authors declare that they have no conflicts of interest.

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