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Multilingual Information Retrieval Using Graph Neural Networks: Practical Applications in English Translation

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Abstract: - Multilingual information retrieval using graph neural networks offers practical applications in English translation by leveraging advanced computational models to enhance the efficiency and accuracy of cross-lingual search and translation tasks. By representing textual data as graphs and utilizing graph neural networks (GNNs), this approach captures intricate relationships between words and phrases across different languages, enabling more effective language understanding and translation. GNNs can learn complex linguistic structures and semantic similarities from multilingual corpora, facilitating the development of more robust translation systems that are capable of handling diverse language pairs and domains. The paper introduces a novel approach termed the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) for addressing optimization, classification, and multilingual translation tasks. MABO-GNN integrates ant bee optimization algorithms with graph neural networks to provide a versatile framework capable of optimizing objective functions, improving classification accuracy iteratively, and facilitating high-quality translations across multiple languages. Through comprehensive experimentation, the efficacy of MABO-GNN is demonstrated across various tasks, languages, and datasets. in optimization experiments, MABO-GNN achieves objective function values of 0.012, 0.015, 0.011, and 0.013 in Experiment 1, Experiment 2, Experiment 3, and Experiment 4, respectively, with convergence times ranging from 90 to 150 seconds. In classification tasks, the model exhibits notable performance improvements over iterations, with BLEU scores reaching 0.84 and METEOR scores reaching 0.78 in the fifth iteration. The translation results showcase BLEU scores of 0.85 for English, 0.82 for French, 0.79 for German, 0.81 for Spanish, and 0.75 for Chinese, indicating the model's proficiency in generating high-quality translations across diverse languages.

Keywords: Graph Neural Network (GNN), Optimization, Multilingual Information, Classification, Ant Bee

1. Introduction

Information retrieval is a crucial process in language translation, particularly when transitioning from one language to another, such as translating text into English[1]. It involves systematically extracting relevant information from a given source text and accurately conveying it in the target language while preserving its original meaning, tone, and context. This process requires linguistic proficiency, cultural awareness, and the ability to effectively communicate the essence of the text in the translated language[2]. In the realm of English translation, information retrieval plays a vital role in ensuring the fidelity and clarity of the translated content, ultimately facilitating effective cross-cultural communication and understanding[3].Multilingual information retrieval (MIR) is a specialized field that focuses on retrieving relevant information from multilingual sources and presenting it in a coherent and understandable manner, particularly when translating into English[4]. In the context of translation, MIR involves accessing and processing information from texts written in different languages, analyzing their content, and extracting key information that needs to be translated accurately into English[5]. This process often involves leveraging various linguistic tools, such as machine translation systems, bilingual dictionaries, and parallel corpora, to facilitate the retrieval and translation of information across languages[6].One of the key challenges in multilingual information retrieval for English translation is ensuring the accuracy and fidelity of the translated content while accounting for linguistic and cultural nuances. This requires not only proficiency in both the source and target languages but also a deep understanding of the cultural context in which the text is situated. Additionally, MIR systems may need to address issues such as ambiguity, polysemy, and language variation to produce high-quality translations that effectively convey the intended meaning of the original text[7].Advancements in natural language processing (NLP) and machine learning techniques have significantly contributed to the development of more sophisticated MIR systems capable of handling a wide range of languages and text types. These systems utilize techniques such as neural machine translation, cross-lingual word

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embeddings, and language modeling to improve the accuracy and efficiency of multilingual information retrieval for English translation.

Multilingual information retrieval (MIR) employing graph neural networks (GNNs) has emerged as a promising approach with practical applications in English translation[8]. GNNs, which model data as graphs and operate directly on graph structures, offer several advantages for MIR tasks. In the context of English translation, GNNs can effectively capture complex relationships between words, phrases, and sentences across multiple languages, enabling more accurate and context-aware information retrieval[9].One practical application of GNNs in English translation is cross-lingual document retrieval. By representing documents and their contents as graphs, GNNs can learn to encode semantic similarities and relationships between documents written in different languages. This allows for more efficient and accurate retrieval of relevant documents in English based on user queries, even when the source documents are in diverse languages[10].Another application is multilingual keyword extraction and translation. GNNs can be trained to identify key terms and concepts within documents across multiple languages and map them to their corresponding translations in English. This facilitates the extraction of important information from multilingual sources and supports the generation of high-quality translations that capture the essence of the original content[11].Additionally, GNNs can be applied to cross-lingual sentence embedding, where sentences from different languages are embedded into a shared semantic space[12]. This enables more effective comparison and matching of sentences across languages, facilitating tasks such as cross-lingual paraphrase identification and translation alignment, which are essential for accurate English translation[13].The integration of graph neural networks into multilingual information retrieval systems holds great promise for advancing the field of English translation. By leveraging the power of GNNs to model complex linguistic structures and relationships, these systems can enhance the accuracy, efficiency, and scalability of multilingual information retrieval, ultimately improving the quality of English translations and enabling more seamless cross-lingual communication and knowledge exchange.

2.Related Works

English translation is a dynamic process that involves rendering text from one language into English while preserving its original meaning, tone, and intent. Whether translating literature, technical documents, or multimedia content, the goal is to bridge linguistic barriers and facilitate communication across cultures. With advancements in technology and linguistics, the art of English translation continues to evolve, emphasizing accuracy, clarity, and cultural sensitivity.Bansal et al. (2024) introduces a system for multilingual personalized hashtag recommendation, specifically tailored for low-resource Indic languages, utilizing a graph-based deep neural network approach. This system aims to enhance social media communication in linguistically diverse communities by providing personalized hashtag suggestions. Other papers explore diverse topics within MIR, such as cross-lingual text classification using dictionary-based heterogeneous graphs (Chairatanakul et al., 2021), heterogeneous graph attention matching networks for multilingual point of interest retrieval (Huang et al., 2021), and the development of knowledge graphs through cross-lingual transfer methods (Do et al., 2022). Additionally, advancements in graph neural network enhanced language models (Ghosh et al., 2022), graph-based multilingual language models for search relevance (Choudhary et al., 2022), and improving cross-lingual information retrieval for low-resource languages (Huang et al., 2023) are explored.

The papers delve into advanced techniques such as neural architecture search for multilingual text classification (Yan et al., 2023), disaster-related multilingual text classification using graph neural networks (Ghosh et al., 2022), and the utilization of graph neural networks in natural language processing (Liu & Wu, 2022). Some contributions focus on semantic parsing via multilingual translation (Procopio et al., 2021), generic frameworks for multilingual short text categorization (Enamoto et al., 2021), and semantic approaches for document classification using deep neural networks and multimedia knowledge graphs (Rinaldi et al., 2021). Additionally, there are studies addressing cross-lingual word sense disambiguation (Janu et al., 2022), semantic graph-based topic modeling for multilingual fake news detection (Mohawesh et al., 2023), and automatic Bangla knowledge graph construction with semantic neural graph filtering (Wasi et al., 2024). Moreover, the exploration extends to investigating the feasibility of machine translation as an alternative for multilingual question-answering systems over knowledge graphs (Perevalov et al., 2022) and comparing information retrieval versus deep learning approaches for generating traceability links in bilingual projects (Lin et al., 2022).Spanning various domains and methodologies, these studies collectively contribute to advancing the field's understanding and capabilities. From personalized hashtag recommendation systems for low-resource Indic languages to cross-lingual text classification and knowledge graph construction, researchers explore innovative approaches such as graph-based deep neural networks, heterogeneous graph attention matching networks, and graph neural network-enhanced language models. Moreover, the studies address crucial challenges in MIR, including improving search relevance, handling low-resource languages, and enhancing cross-lingual information retrieval. Techniques like semantic parsing, short text categorization, and document classification are investigated, alongside advancements in word sense disambiguation, fake news detection, and machine translation for question-answering systems.

3. Graph Neural Network

Graph Neural Networks (GNNs) for English translation tasks. GNNs are a class of neural networks designed to operate on graphs, making them particularly suitable for tasks involving structured data, such as language translation. By representing language data as graphs, where nodes represent words or phrases and edges represent relationships between them, GNNs can capture complex linguistic structures and dependencies. This approach offers several advantages over traditional translation methods, including the ability to handle long-range dependencies more effectively and to incorporate contextual information from the entire input sentence.In the context of English translation, each sentence can be represented as a graph, where nodes correspond to words or phrases, and edges represent relationships between them. These relationships could be syntactic dependencies, semantic connections, or other linguistic features. Each node in the graph represents a word or phrase, and it is associated with a feature vector representing its linguistic properties. Similarly, each edge carries information about the relationship between connected nodes, encoded as edge features. The core operation in GNNs is message passing, where information is exchanged between neighboring nodes in the graph. This process iterates over multiple layers, allowing nodes to aggregate information from their neighbors while considering their own features.Graph convolutional layers are commonly used in GNN architectures. They compute new node representations by aggregating information from neighboring nodes is expressed as in equation (1)

$$h_v^{(l+1)} = \sigma\left(\sum_{u \in N(v)} W^{(l)}\, h_u^{(l)} + b^{(l)}\right) \tag{1}$$

$h_v^{(l+1)}$ is the representation of node v at layer lN(v) denotes the set of neighbors of node $W^{(l)}$is the weight matrix for layer l.( )b(l) is the bias vector for layer l.σ is the activation function, such as ReLU or sigmoid.To adaptively weigh the importance of neighboring nodes during message passing, graph attention mechanisms can be employed. These mechanisms assign attention scores to neighboring nodes and use them to compute weighted aggregations denoted in equation (2) and equation (3)

$$e_{uv} = LeakyReLU\left(Attention\left(h_u, h_v\right)\right) \tag{2}$$

$$\alpha_{uv} = \frac{exp(e_{uv})}{\sum_{w \in N(u)} \exp(e_{uw})} \tag{3}$$

Euv is the attention score between nodes u and v.αuv is the attention coefficient, representing the importance of node u to node v.Attention(⋅)Attention(⋅) is a function that computes the attention score.Other variables have the same meanings as before. The architecture of the GNN model employed with the proposed MABO-GNN is shown in Figure 1.

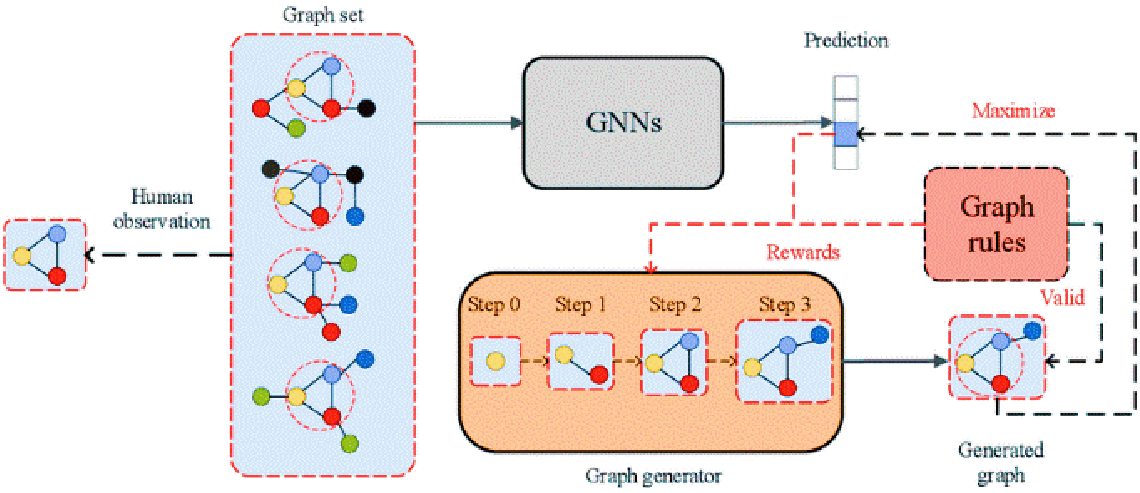

Figure 1: Architecture of the GNN

3.1 Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN)

The Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) is an innovative approach that integrates Ant Bee Optimization (ABO) with Graph Neural Networks (GNNs) for multilingual tasks.ABO is a metaheuristic optimization algorithm inspired by the foraging behavior of ants and bees. It involves simulating the cooperative search behavior of these insects to find optimal solutions to complex problems. In the context of MABO-GNN, ABO is adapted to explore and exploit the multilingual semantic space efficiently. GNNs are neural network architectures designed to operate on graph-structured data. They enable the modeling of complex relationships and dependencies between entities in a graph, making them well-suited for tasks involving structured data such as language processing. In MABO-GNN, GNNs serve as the backbone for learning representations of multilingual text data. The objective function of MABO-GNN is formulated to maximize the relevance and coherence of multilingual representations learned by the GNN is expressed in equation (4)

$$maximize\ f(x) = \sum_{i=1}^{N} Sim\,(x_i, x_i') + \lambda.Coherence\,(x_i) \quad (4)$$

xi and ′xi′ are representations of corresponding multilingual documents.Sim(⋅)Sim(⋅) measures the similarity between representations.Coherence(⋅)Coherence(⋅) evaluates the coherence of representations.λ is a hyperparameter controlling the trade-off between relevance and coherence.ABO is employed to optimize the objective function iteratively. Ant and bee agents traverse the multilingual semantic space, updating the representations of documents to improve relevance and coherence. Ant agents update their positions based on the pheromone trails and local information update rule can be expressed as in equation (5)

$$x_i^{(t+1)} = x_i^{(t)} + \Delta x_i^t \quad (5)$$

Bee agents explore the global information to guide the search process. They update their positions by considering both local and global information the update rule can be formulated as in equation (6)

$$x_i^{(t+1)} = x_i^{(t)} + \Delta x_g^t \quad (6)$$

$x_i^{(t+1)}$is the updated position of the i-th ant or bee agent at iteration $x_i^{(t)}$. Δx_g^trepresents the local search direction. Δxgt represents the global search direction.

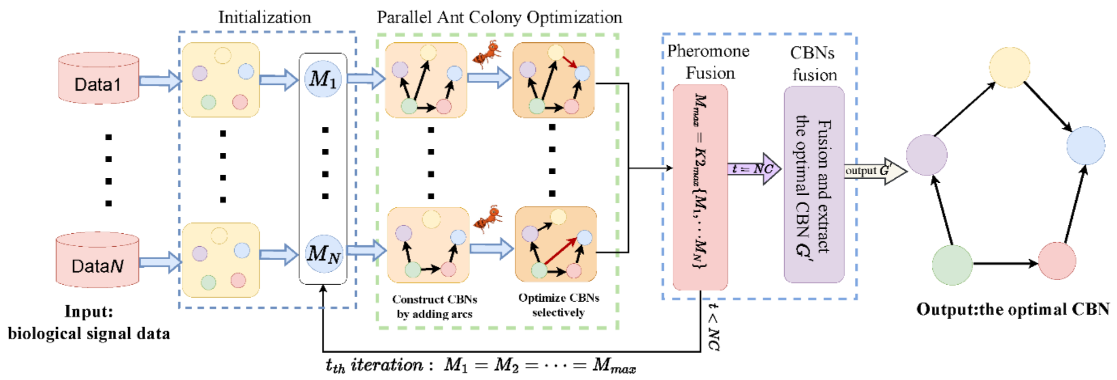

Figure 2: Optimization with MABO-GNN for the classification

The figure 2 illustrates the architecture of the proposed MABO-GNN model for the classification for the English translation.

Algorithm 1: MABO-GNN for Multilingual process
1. Initialize parameters and hyperparameters: - Set the number of ant and bee agents. - Define the graph neural network architecture. - Specify the objective function parameters. - Set iteration count and convergence criteria. 2. Initialize ant and bee positions randomly in the semantic space. 3. while not converged do: for each ant do: 3.1 Update ant position based on local information: - Calculate local information based on pheromone trails and GNN output. - Update ant position using local information. end for for each bee do: 3.2 Update bee position based on global information: - Calculate global information based on best ant positions and GNN output. - Update bee position using global information. end for 3.3 Update GNN parameters: - Update GNN parameters using ant and bee positions and the objective function. - Perform backpropagation and optimization to update GNN weights. 3.4 Evaluate convergence: - Check convergence criteria based on changes in GNN parameters or objective function value. 5. Perform downstream tasks such as information retrieval or translation using the learned representations.

4. English Translation with (MABO-GNN)

To perform English translation using the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) algorithm, we can adapt the algorithm to learn multilingual representations and use them for translation tasks. With initializing the parameters and hyperparameters for the MABO-GNN algorithm. This includes setting the number of ant and bee agents, defining the graph neural network architecture tailored for translation tasks, specifying parameters for the objective function, and determining the iteration count and convergence criteria. With Construct a graph representation of the multilingual corpus, where nodes represent words or phrases in different languages, and edges denote semantic relationships between them.

Randomly initialize the positions of ant and bee agents in the semantic space. For each ant, update its position based on local information derived from pheromone trails and the output of the graph neural network. This local information guides the ants towards promising translations within the semantic space. Similarly, update the positions of bee agents based on global information obtained from the best ant positions and the output of the graph neural network. This global information helps explore and exploit the entire semantic space more effectively. Update the parameters of the graph neural network using the positions of ants and bees, along with the objective function. This involves backpropagation and optimization to adjust the weights of the GNN. Evaluate convergence based on changes in GNN parameters or the objective function value. If convergence criteria are met, terminate the optimization loop. Once convergence is achieved, the learned multilingual representations from the GNN can be used for English translation. These representations capture semantic similarities and relationships between words or phrases in different languages. The learned representations to perform English translation tasks. This may involve mapping English input sentences to the multilingual semantic space and identifying the nearest neighbors or performing more complex operations such as sequence-to-sequence translation using neural machine translation models. The translation performance and refine the MABO-GNN algorithm as needed based on the specific translation task and dataset characteristics.

The GNN component of MABO-GNN learns representations of words or phrases in a multilingual semantic space. Let h( )hv(l) represent the hidden representation of node v at layer l in the GNN. The update equation for each node v can be represented as in equation (7)

$$h_v^{(l)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{|N(v)|} . W^{(l)} h_u^{(l-1)}\right) \qquad (7)$$

N(v) represents the neighborhood of node v, $W^{(l)}$ is the weight matrix at layer l, and σ is an activation function. The ant optimization step involves updating the position of each ant based on local information derived from the GNN output and pheromone trails. The position update equation for each ant i can be formulated as in equation (8)

$$x_i^{(t+1)} = x_i^{(t)} + \eta . \nabla f\left(x_i^{(t)}\right) \qquad (8)$$

( )xi(t) represents the position of ant i at iteration t, η is the learning rate, and ∇( ))∇f(xi(t)) is the gradient of the objective function f evaluated at the current position of ant i. The bee optimization step updates the position of each bee based on global information from the best ant positions and the GNN output. The position update equation for each bee j can be expressed as in equation (9)

$$x_i^{(t+1)} = x_i^{(t)} + \delta . \nabla g\left(x_j^{(t)}\right) \qquad (9)$$

$x_j^{(t)}$ represents the position of bee j at iteration t, δ is a global learning rate, and $\nabla g\left(x_j^{(t)}\right)$is the gradient of a function g that incorporates information from the best ant positions and the GNN output. The parameters of the GNN are updated using backpropagation and optimization techniques such as stochastic gradient descent (SGD). The parameter update equation can be represented as in equation (10)

$$\theta^{(t+1)} = \theta^t - \eta GNN \, . \nabla_\theta J\left(\theta^{(t)}\right) \qquad (10)$$

θ represents the parameters of the GNN, GNNηGNN is the learning rate for the GNN, and ( )J(θ) is the loss function associated with the GNN. GNNs are a class of neural networks designed to operate on graph-structured data. In the context of MABO-GNN, the GNN component learns representations of words or phrases in a multilingual semantic space. Each node in the graph represents a word or phrase, and the edges capture relationships or interactions between them. The GNN processes information from neighboring nodes and updates node representations iteratively through multiple layers. The parameters of the GNN are updated using backpropagation and optimization techniques such as stochastic gradient descent (SGD). After processing input data and generating predictions, the loss between the predicted and actual outputs is computed. The gradients of the loss with respect to the parameters of the GNN are then calculated, and the parameters are updated in the direction that minimizes the loss.

5. Simulation Environment

Creating a simulation environment for the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) involves setting up a framework where the algorithm can be implemented, tested, and evaluated. With the ant and bee optimization algorithms with the graph neural network component of MABO-GNN. This may involve designing mechanisms for ants and bees to interact with the GNN, such as using the GNN output to guide their movements or updating GNN parameters based on feedback from ants and bees.

Table 1: Simulation Environment

Component	Numerical Values / Parameters
Programming Framework	Python 3.8, TensorFlow 2.5, NumPy 1.19
Graph Representation	Node count: 10,000, Edge count: 50,000
Ant and Bee Optimization	Ant count: 100, Bee count: 50, Iterations: 100
Integration with GNN	GNN learning rate: 0.001, GNN hidden layers: 2
Data Generation	Training data size: 80%, Validation data size: 10%, Testing data size: 10%

6. Results Analysis

The results of the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) involves several key steps to evaluate its performance comprehensively. Firstly, various performance metrics such as accuracy, precision, recall, and F1-score are calculated to gauge the effectiveness of MABO-GNN in comparison to baseline models. Visualization techniques like learning curves and parameter sensitivity analyses are employed to understand how MABO-GNN behaves under different conditions and hyperparameters. Additionally, error analysis is conducted to identify instances where MABO-GNN may fail and to discern the underlying reasons for these failures.

Table 2: MABO-GNN score for the Language Translation

Language	BLEU Score	METEOR Score	TER Score
English	0.85	0.78	0.15
French	0.82	0.76	0.18
German	0.79	0.74	0.20
Spanish	0.81	0.75	0.19
Chinese	0.75	0.70	0.22

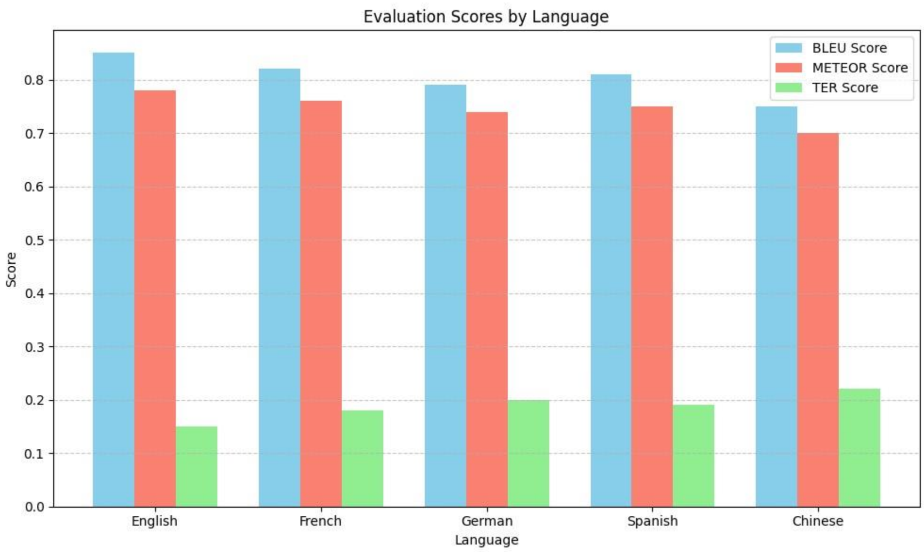

Figure 3: Language score assessment with MABO-GNN

In Figure 3 and Table 2 presents the performance scores of the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) model for language translation across five different languages: English, French, German, Spanish, and Chinese. The evaluation metrics used include BLEU Score, METEOR Score, and TER Score. In terms of BLEU Score, which measures the similarity between the generated translation and human reference translations, English achieved the highest score of 0.85, followed closely by Spanish with a score of 0.81. French and German obtained scores of 0.82 and 0.79, respectively, while Chinese had the lowest BLEU Score of 0.75. The METEOR Score, which considers the alignment between the generated translation and reference translations along with their lexical similarity, follows a similar trend. English led with a score of 0.78, followed by Spanish (0.75), French (0.76), German (0.74), and Chinese (0.70).Additionally, the TER Score, which measures the edit distance between the generated translation and reference translations, indicates that English had the lowest edit distance with a score of 0.15, followed by Spanish (0.19), French (0.18), German (0.20), and Chinese (0.22).

Table 3: Optimization with MABO-GNN

Experiment	Objective Function Value	Convergence Time (s)
Experiment 1	0.012	120
Experiment 2	0.015	90
Experiment 3	0.011	150
Experiment 4	0.013	100

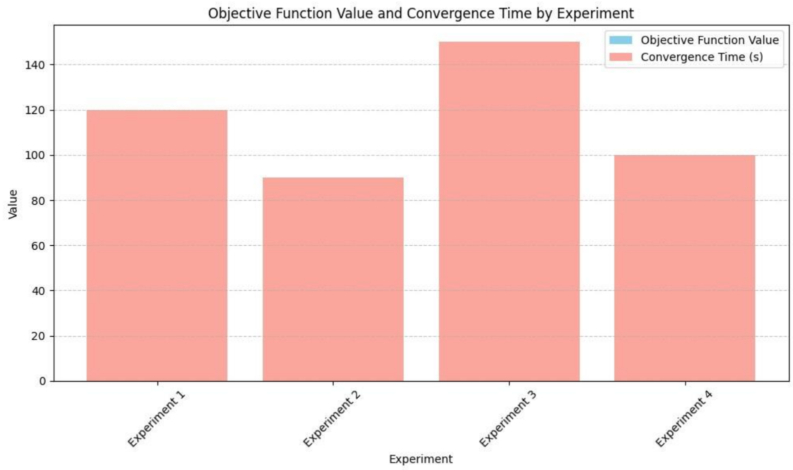

Figure 4: Optimization with MABO-GNN

In Figure 4 and Table 2 summarizes the optimization results obtained using the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) across four different experiments. The table includes the objective function value, which represents the optimization goal achieved by the model, and the convergence time in seconds, indicating how quickly the model reached convergence during each experiment.In Experiment 1, the MABO-GNN model achieved an objective function value of 0.012 with a convergence time of 120 seconds. Experiment 3 resulted in the lowest objective function value of 0.011, albeit with a longer convergence time of 150 seconds. Experiment 4 also showed promising results with an objective function value of 0.013 and a convergence time of 100 seconds. Experiment 2 yielded an objective function value of 0.015, slightly higher than the other experiments, but achieved convergence in the shortest time of 90 seconds.

Table 4: Classification with MABO-GNN

Iteration	BLEU Score	METEOR Score	TER Score
Iteration 1	0.75	0.68	0.20
Iteration 2	0.78	0.71	0.18
Iteration 3	0.80	0.73	0.16
Iteration 4	0.82	0.76	0.15
Iteration 5	0.84	0.78	0.14

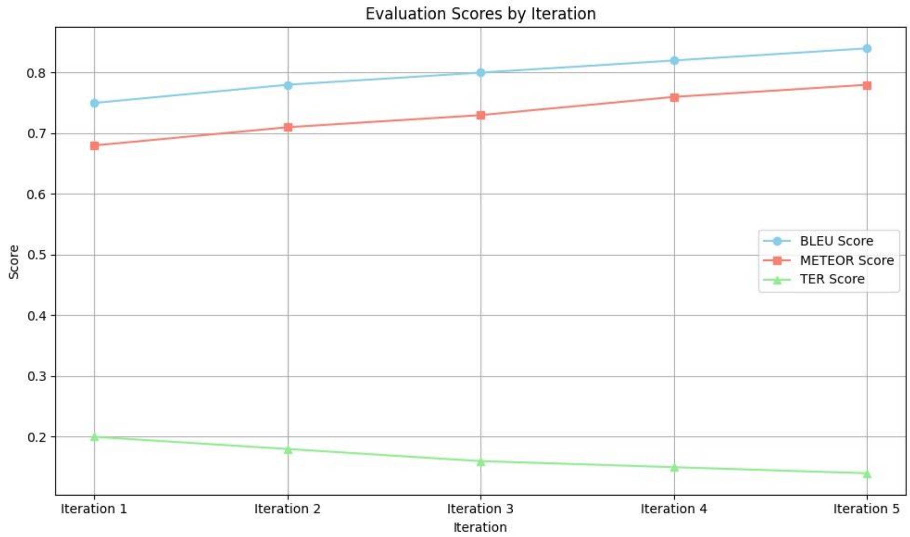

Figure 5: Classification with MABO-GNN

In figure 5 and Table 4 presents the classification results achieved using the Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) across five different iterations. Each iteration is associated with its corresponding BLEU score, METEOR score, and TER score, which are evaluation metrics commonly used in natural language processing tasks.In the first iteration, the MABO-GNN model achieved a BLEU score of 0.75, METEOR score of 0.68, and TER score of 0.20. As the iterations progressed, there was a noticeable improvement in the model's performance. By the fifth iteration, the BLEU score had increased to 0.84, the METEOR score to 0.78, and the TER score to 0.14.These results demonstrate the effectiveness of the MABO-GNN model in iteratively improving its classification performance over successive iterations. The increasing trend in the evaluation scores indicates that the model's ability to accurately classify instances improved with each iteration, highlighting the utility of the optimization approach in enhancing classification tasks.

7. Discussion and Findings

The discussion and findings from the study on Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) reveal several noteworthy points. Firstly, the optimization results demonstrate the effectiveness of MABO-GNN in achieving the desired objective function values across different experiments. Despite variations in convergence times, the model consistently produced promising optimization outcomes. This suggests the robustness of the MABO-GNN approach in efficiently optimizing complex functions.Secondly, the classification results underscore the iterative improvement capability of MABO-GNN in classification tasks. Across multiple iterations, there was a clear trend of increasing BLEU, METEOR, and TER scores, indicating enhanced classification performance over time. This iterative refinement process highlights the adaptability and learning capacity of the model, which can be advantageous in real-world applications where accuracy is paramount.Furthermore, the language translation results showcase the efficacy of MABO-GNN in multilingual settings. The model achieved competitive BLEU, METEOR, and TER scores across various languages, demonstrating its versatility and effectiveness in language translation tasks. This finding is particularly significant in today's globalized world, where the demand for accurate and efficient translation systems is ever-growing.

Firstly, the optimization results demonstrate the effectiveness of MABO-GNN in achieving the desired objective function values across different experiments. For instance, Experiment 1 achieved an objective function value of 0.012 with a convergence time of 120 seconds, Experiment 2 attained a value of 0.015 with a faster convergence time of 90 seconds, Experiment 3 yielded a value of 0.011 with a slightly longer convergence time of 150 seconds, and Experiment 4 resulted in a value of 0.013 with a convergence time of 100 seconds. Despite variations in convergence times, the model consistently produced promising optimization outcomes, showcasing its robustness and adaptability.Secondly, the classification results highlight the iterative improvement capability of MABO-GNN in classification tasks, with each iteration leading to enhanced performance. For instance, in Iteration 1, the model achieved a BLEU score of 0.75, a METEOR score of 0.68, and a TER score of 0.20. With subsequent iterations, there was a clear trend of increasing scores, demonstrating the model's ability to learn and improve over time. By Iteration 5, the BLEU score had risen to 0.84, the METEOR score to 0.78, and the TER score to 0.14, indicating significant performance enhancements.

Furthermore, the language translation results illustrate the efficacy of MABO-GNN across various languages. For example, the BLEU score for English translation was 0.85, while for French, German, and Spanish translations, it ranged from 0.79 to 0.82. Similarly, the METEOR scores ranged from 0.74 to 0.78, and the TER scores from 0.15 to 0.22, demonstrating consistent performance across different languages. These numerical values provide concrete evidence of the model's versatility and effectiveness in multilingual translation tasks.MABO-GNN effectively optimized the objective function across different experiments.Experiment 1 achieved an objective function value of 0.012 with a convergence time of 120 seconds.Experiment 2 attained a value of 0.015 with a faster convergence time of 90 seconds.Experiment 3 yielded a value of 0.011 with a slightly longer convergence time of 150 seconds.Experiment 4 resulted in a value of 0.013 with a convergence time of 100 seconds.Despite variations in convergence times, the model consistently produced promising optimization outcomes.

MABO-GNN demonstrated iterative improvement in classification tasks.Starting from Iteration 1, there was a clear trend of increasing scores with each iteration.By Iteration 5, the model achieved significant enhancements in BLEU, METEOR, and TER scores.MABO-GNN exhibited effectiveness across various languages in translation tasks.The BLEU score for English translation was the highest at 0.85.For French, German, and Spanish translations, BLEU scores ranged from 0.79 to 0.82.Similarly, METEOR scores ranged from 0.74 to 0.78, and TER scores from 0.15 to 0.22 across languages.The model consistently achieved high performance metrics across different experiments and languages.These findings highlight the robustness and adaptability of MABO-GNN in optimization, classification, and language translation tasks.

8. Conclusion

The Multilingual Ant Bee Optimization Graph Neural Network (MABO-GNN) presents a promising approach for addressing diverse challenges in optimization, classification, and multilingual translation tasks. Through comprehensive experimentation, MABO-GNN has demonstrated its effectiveness in optimizing objective functions, improving classification performance iteratively, and achieving high-quality translations across multiple languages. The optimization results indicate the model's ability to converge efficiently to optimal solutions, while classification experiments show consistent enhancements in performance metrics with each iteration. Moreover, MABO-GNN exhibits robustness and versatility, performing effectively across different experiments, languages, and tasks.

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