Graph-Assisted Culturally Adaptable Idiomatic Translation for Indic languages

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Abstract

Translating multi-word expressions (MWEs) and idioms requires a deep understanding of the cultural nuances of both the source and target languages. This challenge is further amplified by the one-to-many nature of idiomatic translations, where a single source idiom can have multiple target-language equivalents depending on cultural references and contextual variations. Traditional static knowledge graphs (KGs) and prompt-based approaches struggle to capture these complex relationships, often leading to suboptimal translations. To address this, we propose an IdiomCE, an adaptive graph neural network (GNN) based methodology that learns intricate mappings between idiomatic expressions, effectively generalizing to both seen and unseen nodes during training. Our proposed method enhances translation quality even in resource-constrained settings, facilitating improved idiomatic translation in smaller models. We evaluate our approach on multiple idiomatic translation datasets using reference-less metrics, demonstrating significant improvements in translating idioms from English to various Indian languages.

1 Introduction

In linguistic terms, *idiom* is a *multi-word expression* (MWE) whose meaning cannot be derived from the literal meanings of its individual parts. Idioms have key properties such as noncompositionality, fixedness, and cultural specificity (Nunberg et al., 1994). They are integral to everyday language, enhancing expressiveness and communicative vividness. They often originate from diverse cultural, historical, and situational contexts, making them unique to specific languages or regions (Vula and Tyfekçi, 2024; Yagiz and Izadpanah, 2013).

With advancements in large language models (LLMs), neural machine translation (NMT) has significantly improved in handling complex linguistic phenomena, which led to research interest in complex linguistic tasks such as translating idioms across multiple languages (Li et al., 2023a; Rezaeimanesh et al., 2024a; Castaldo and Monti, 2024). However, despite these advancements, idiomatic translation remains a major challenge due to the inherent properties of idioms. Traditional NMT systems, both statistical and neural, struggle with noncompositionality, as they primarily process text at the word or phrase level rather than capturing an idiom's holistic meaning. This often leads to literal translations, distorting the intended meaning of the source text (Baziotis et al., 2023; Raunak et al., 2023; Dankers et al., 2022).

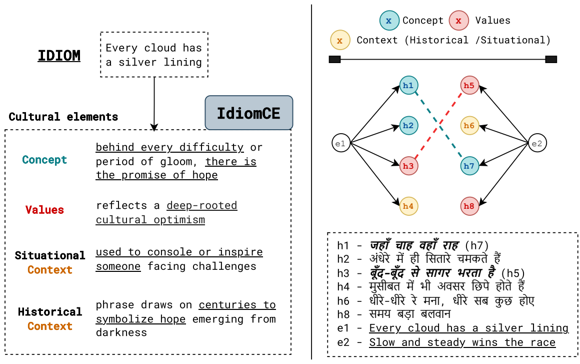

Figure 1: An example of cultural enhanced graph with different cultural elements: Concepts, Values, Context (Historical/Situational) and how we can create relationship among source and target nodes using their cultural elements.

Recent efforts to address idiomatic translation have primarily relied on (1) idiom dictionary-based substitution (Salton et al., 2014) and (2) prompting techniques, such as chain-of-thought (CoT) reasoning or explicitly providing figurative meanings in prompts (Castaldo and Monti, 2024; Li et al., 2023b; Rezaeimanesh et al., 2024b). Although these methods have shown improvements in idiomatic translation, they still fail to overcome key challenges. As shown in Figure 1, these methods often overlook cultural factors that shape idioms and influence their mappings across languages (*Challenge I*). Additionally, they fail to address the one-to-many nature of idioms, where a single source-language idiom may have multiple valid translations in the target language, with the optimal choice depending on the source sentence's context (Rezaeimanesh et al., 2024a) (*Challenge II*). Moreover, knowledge graph (KG)-based approaches are inherently constrained by the availability of idiom resources, leading to translation gaps when encountering idioms not present in the KG (Peng et al., 2023) (*Challenge III*). These challenges pose a critical research question:

How can cultural nuances be effectively integrated into many-to-many idiomatic translation to enhance model performance?

To address this challenge, one possible approach is to first analyze the cultural dependencies of idioms and identify the specific cultural elements that shape idiomatic expressions across languages. Recent studies in NLP (Liu et al., 2024) (Pawar et al., 2024) introduce a comprehensive taxonomy of cultural and sociocultural elements, highlighting the need for culturally adaptive models as well as efforts to incorporate cultural awareness. However, even with a structured understanding of these cultural elements, capturing their intricate relationships and effectively leveraging them for one-to-many idiomatic translation remains a significant challenge.

This paper introduces **IdiomCE**, an inductive graph-based approach that models the relationships between source and target idioms by leveraging complex cultural element mappings, as illustrated in Figure 1, where source is an English idiom and target are Hindi idioms. Using link prediction, our method facilitates one-to-many idiomatic translation while preserving cultural relevance across languages. Furthermore, IdiomCE is adaptable, enabling the translation of unseen idioms by leveraging the inductive capabilities of GNNs, effectively addressing the limitations of noisy and limited knowledge bases. Our key contributions are summarized as follows:

- We propose a *cultural element-based data creation* method that generates multiple target idioms for a given source idiom.
- We develop an Inductive GNN trained on this graphical data, leveraging link prediction to enable one-to-many idiomatic translation (addressing *Challenge I* and *II*).
- We design an adaptable pipeline that extends to unseen idioms using the inductive capabilities of GNNs (addressing *Challenge III*).
- Using English as a pivot language, we extend our approach to facilitate idiomatic translation across Indic languages without needing to train GNN models between all possible pairs of languages.

2 Related works and Motivation

Idiomatic Text Translation: Previous studies have explored various strategies to enhance NMT performance for idiomatic translation. (Salton et al., 2014) introduced a substitution-based method, where source-side idioms are replaced with their literal meanings before translation and reinstated post-translation to improve accuracy. (Zaninello and Birch, 2020) demonstrated that augmenting training data with idiomatic translations enhances model performance on both source and target sides. Beyond direct translation techniques, researchers have focused on learning non-compositional embeddings and automatically identifying idioms, as explored by (Weller et al., 2014), (Hashimoto and Tsuruoka, 2016), and (Tedeschi et al., 2022). More recently, prompting techniques and Chain-of-Thought (CoT) reasoning have been investigated in Large Language Models (LLMs) for idiomatic translation (Castaldo and Monti, 2024; Rezaeimanesh et al., 2024b). IdiomKB (Li et al., 2023a) further introduced a contextual approach, using figurative meanings as additional context to improve translation quality in LLMs.

Idiomatic Translation for Indic languages: Indic languages exhibit significant linguistic diversity and deeply rooted cultural nuances, making idiomatic translation a complex challenge. Despite this, research on idiomatic translation in the Indic language setting remains limited. (Shaikh, 2020) proposes Idiom Identification using grammatical rule based approach.(Modh and Saini, 2020) proposes a identification of Gujarati idioms and translation of them using contextual information. (Agrawal et al., 2018) present a multilingual parallel idiom dataset encompassing seven Indian languages and English. While these studies offer valuable contributions, the challenge of many-to-many idiomatic translation across Indic languages remains largely under-explored.

Motivation for Cultural significance in Idioms As discussed previously, most of the past studies either use a dictionary-based approach for idiom translation, which is a one-to-one mapping, or provide *figurative meaning* of the idiomatic expression for meaningful translation. Although these approaches appear to perform well, they fail to account for the cultural dependency of idioms, which is deeply embedded within them. This raises the question of how idioms can be effectively mapped from one language to another while considering this cultural dependency. Cultural dependency can be linked to various features, as discussed in (Liu et al., 2024) and (Pawar et al., 2024). Identifying these features that influence translation between languages can contribute to the development of more culturally appropriate idiomatic mappings from a source language to a target language.

Motivation for GNN

Using a static Knowledge Graph (KG) or dictionary-based approach poses several challenges, which a Graph Neural Network (GNN)-based architecture can effectively address:

Limited Generalization: KGs store only predefined idiomatic translations as edges between nodes, making them incapable of inferring translations for new idioms unless explicitly added. In contrast, GNNs learn graph patterns, enabling them to predict idiomatic translations even for unseen idioms.

Lack of Semantic Connectivity: KGs treat nodes independently, failing to capture relationships between idioms with similar meanings unless explicitly modeled. GNNs leverage neighborhood structures and embeddings, allowing them to infer new translations by recognizing semantic similarities.

Polysemy Handling: KGs require multiple nodes to represent idioms with multiple meanings, increasing complexity. GNNs disambiguate meanings using context, leveraging neighborhood information and learned representations to differentiate between senses based on connectivity.

3 Methodology

In this section, we first present the problem statement followed by the training and inference of our methodology, which we call **IdiomCE**.

Problem Formulation:

We address the challenge of replacing idioms in a source language with culturally aware and contextually appropriate multi-word expressions in the target language. Let $\mathcal{S}$ and $\mathcal{T}$ denote the sets of graph nodes representing source and target idioms, respectively. The combined set $\mathcal{S} \cup \mathcal{T}$ defines the node set $\mathcal{V}$ in our framework, where each node $v \in \mathcal{V}$ corresponds to an idiom.

Each Idiom v is embedded with cultural elements, reflecting its historical, situational, or value-based significance, indicating its relevance to a specific language. Our goal is to identify the most relevant set of target-language idioms $\{\bar{v} : \bar{v} \in \mathcal{T}\}$ that correspond to a given source-language idiom v. We denote this relationship with an edge $e_{v,\bar{v}}$. Let the set of all such edges be $\mathcal{E} \equiv \{e_{v,\bar{v}} : v \in \mathcal{S}, \bar{v} \in \mathcal{T}\}$ Once we construct or estimate the graph $\mathcal{G} \equiv (\mathcal{V}, \mathcal{E})$, we use it to generate translations that are both contextually and culturally relevant. Given a sentence in the source language, our approach leverages this graph $\mathcal{G}$ to produce a culturally and semantically appropriate idiomatic translation in the target language.

3.1 Training

In this section, we outline the process of constructing the initial dataset for training our IdiomCE encoder and decoder, followed by the training methodology. An overview of the entire training process is illustrated in Figure 2.

GNN Dataset Formation: We begin by extracting idioms from the collected dataset, as detailed in Section 4 (Datasets), and obtain monolingual idiom sets for each language. For each idiom, we extract three key cultural elements: *Concepts*, *Values*, and *Situational & Historical Context*. These elements are generated using the LLaMA-3.1-405B model and defined based on the Taxonomy of Culture outlined in (Liu et al., 2024). Our observations suggest that these elements are highly distinguishable and effectively capture key cultural and sociocultural dimensions essential for mapping English idioms to their counterparts in other languages. The prompt used for generating these cultural elements is provided in Appendix A.4.

To construct the **Knowledge graph (KG)**, we first convert the generated cultural elements into Embeddings (we call it cultural features) with Language-agnostic BERT Sentence Embedding (LaBSE) model (Feng et al., 2022). Once the cultural features for each idiom are generated, we compute the cosine similarity between the cultural features of English and target (Indic) language idioms to establish pairwise mappings, as illustrated in Figure 2. Moreover, to identify the most relevant idiom pairs for the KG, we focus on outliers within the cosine similarity scores, as these indicate

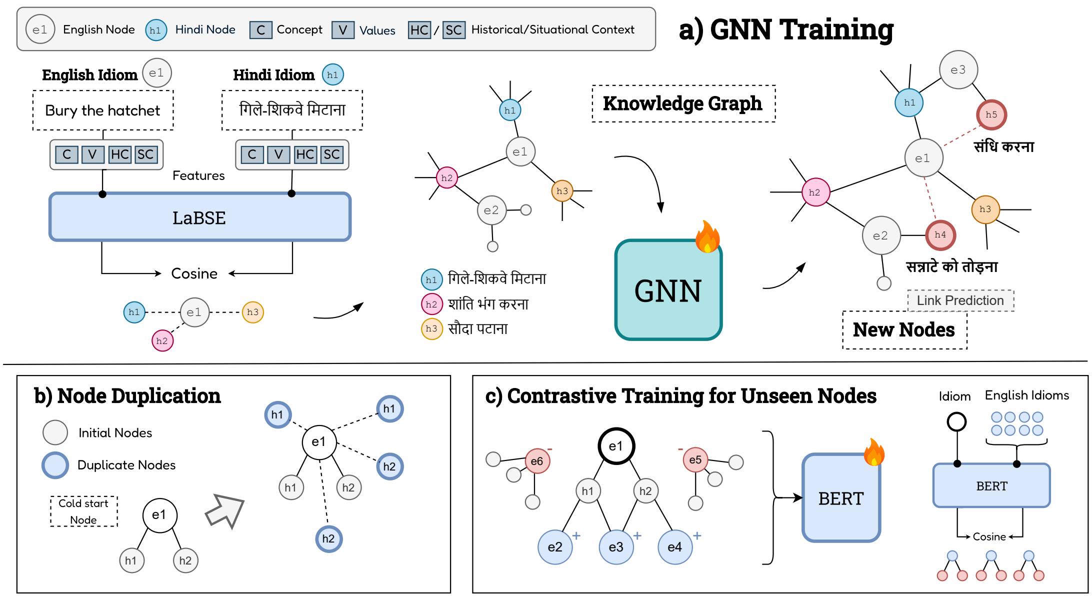

Figure 2: **Overall training process of IdiomCE**: (a) GNN training – illustrating the creation of a Knowledge Graph using source and target idioms, specifically for `en-hi`, leveraging LaBSE embeddings and training a GNN for the Link Prediction (LP) task; (b) Node Duplication – demonstrating how we address the cold start issue by duplicating target nodes; and (c) Contrastive Training – showing the training through positive and negative samples and the process of mapping unseen nodes to relevant target idioms.

strong semantic relationships. Outlier detection is performed by calibrating thresholds based on the skewness and kurtosis of the data, leveraging both the Inter-Quartile Range (IQR) and z-score. By carefully selecting thresholds in these approaches, we ensure that only high-similarity idiom pairs are connected, effectively capturing the most significant relationships. This approach, grounded in robust statistical techniques (Chandola et al., 2009), ensures that the graph reflects the most salient semantic connections.

As a result of this process, multiple KGs are constructed, each linking English idioms to idioms in a specific Indic language. Formally, each KG is represented as $\mathcal{G} \equiv (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ denotes the feature of each idiom/node and $\mathcal{E}$ represents the edges connecting source and target idioms.

3.2 IdiomCE

The proposed IdiomCE follows the widely used encoder-decoder architecture for GNN-based link prediction (Kipf and Welling, 2016) (Schlichtkrull et al., 2017) (Zhao et al., 2022) where a GNN encoder learns node representations, and a decoder predicts link existence probabilities for each node pair. Below, we provide a detailed discussion of the training process for our method.

Node Duplication Augmentation Once the above KG is constructed, we could encounter the cold start problem due to the sparsity of the dataset, which consists of only a few thousand idioms. This issue arises when certain nodes have few or no connections, leading to under-representation in the GNN during the downstream tasks (Hao et al., 2020; Zhang et al., 2023). To mitigate this, we employ a Node Duplication strategy (Guo et al., 2024), which enhances node connectivity and improves representation learning.

We provide a detailed explanation of our node duplication procedure. Let $\mathcal{S}$ and $\mathcal{T}$ represent the sets of source and target language idioms, respectively. For any node $v \in \mathcal{V} \equiv \mathcal{S} \cup \mathcal{T}$, we define its set of neighbors as:

$$\mathcal{N}_v := \{\bar{v} : e_{v,\bar{v}} \text{ or } e_{\bar{v},v} \in \mathcal{N}_v\}$$

where $\mathcal{N}_v$ consists of all nodes $\bar{v}$ connected to v by an edge. We extend the methodology of (Guo et al., 2024) by categorizing source nodes into two types:

Cold nodes ($\mathcal{T}_{cold}$): Target nodes with fewer than δ neighbors.

Warm nodes ($\mathcal{T}_{warm}$): Target nodes with at least δ neighbors. For our experiment we consider δ equals 3

For each cold node v, we duplicate its neighbors $\mathcal{N}_v$ and create new corresponding source nodes. We then insert edges from v to these duplicated source nodes, as illustrated in Figure 2. In this way, we obtain an augmented graph $\mathcal{G}'$ with these newly created nodes and edges added to the original graph. This approach differs from (Guo et al., 2024), where the authors duplicate source nodes directly based on their degree. In contrast, we duplicate source nodes based on the degree of their corresponding target nodes. This strategy enhances the sampling of under-represented cold nodes by leveraging their connections to source nodes.

IdiomCE Encoder: As discussed in the previous section, once our augmented $\mathcal{G}'$ is created, we convert $\mathcal{G}'$ into the GNN training format by creating a feature vector of each idiom node with a BERT based embedding model, i.e., LaBSE (Feng et al., 2022). We then construct an initial bi-directional adjacency matrix of edge indices required for training. To ensure generalization across potentially unseen idioms, we employ an inductive GNN for training, specifically SAGEConv (Hamilton et al., 2018). In SAGEConv, each node updates its representation by aggregating the features of its neighbors. The aggregation is done using a permutation invariant function. In our case, we use the mean aggregator, which computes the average of the feature vectors of a node's neighbors. This ensures that the order of neighbors does not affect the result. For a given node v, let $\mathcal{N}(v)$ represent the set of neighbors and h_u denote the features vectors of node u. The mean aggregator is defined as:

$$\mathbf{h}_{\mathcal{N}(v)} = \frac{1}{|\mathcal{N}(v)|} \sum_{u \in \mathcal{N}(v)} \mathbf{h}_u. \tag{1}$$

Next, the node's updated representation is computed by concatenating its own feature vector $\mathbf{h}_v$ with the aggregated neighbor features and then applying a learnable linear transformation followed by a non-linear activation function as given below:

$$\mathbf{h}'_v = \sigma\left(\mathbf{W} \cdot \mathrm{CONCAT}\big(\mathbf{h}_v, \mathbf{h}_{\mathcal{N}(v)}\big)\right), \tag{2}$$

IdiomCE Decoder: We perform the task of link prediction by pairing our IdiomCE encoder with a Multi-Layer Perceptron (MLP) model as a decoder. Given a source node i with GNN embeddings h_i and target node j with GNN embeddings h_j from the Encoder, we first concatenate their embeddings, then pass it through the MLP layer.

$$z_{ij} = [h_i \,\|\, h_j]$$
$$\widehat{y}_{ij} = \mathrm{MLP}(z_{ij})$$

Once we obtain the prediction from the MLP layer, we then backpropagate using BCE loss and jointly train the GNN and MLP layer for the Link prediction task defined by the loss function given below:

$$\mathcal{L} = -\frac{1}{N} \sum_{(i,j)\in\mathcal{D}} [y_{ij} \log \widehat{y}_{ij} + (1 - y_{ij}) \log (1 - \widehat{y}_{ij})] \tag{3}$$

3.3 Dealing with Unseen nodes

One of the key properties of inductive GNNs is their ability to generalize to unseen nodes, such as idioms absent from the training set. To incorporate an unseen idiom into a trained GNN, it must be connected to relevant neighbors, allowing the model to compute meaningful node embeddings through message passing. A naïve approach is to add edges by randomly selecting target nodes from the initial dataset. However, this often results in dispersed and suboptimal embeddings due to the lack of semantic coherence in the connections. Therefore, to generate high-quality embeddings for an unseen idiom, it is essential to establish connections with semantically relevant neighbors that closely align with its ideal (gold) translation. Given the one-to-many nature of idioms where a single target idiom may correspond to multiple source idioms conveying the same figurative meaning, it is crucial to connect the unseen node to the most similar target idiom neighbors.

To achieve this, we propose training a BERT-based encoder (denoted as $\mathcal{B}_{CL}(\cdot)$) in a contrastive learning setting (Cohan et al., 2020; Ostendorff et al., 2022). The training process leverages a triplet framework designed to align with the graphical structure of our GNN, i.e., $\langle$*anchor* a, *positive* p, *negative* n $\rangle$ where a denotes the source node representing the idiom in the source language, p denotes the source language nodes that are connected to the anchor (i.e., first-hop neighbors in our KG), and n represents nodes that are disconnected (no path exists) to the anchor, ensuring that they do not share semantic similarity. This triplet construction is used in a contrastive loss $\mathcal{L}_t$ that minimizes the distance between the anchor and its positive examples while maximizing the distance to the negative examples. Formally, if h_a, h_p, and h_n are representations of anchor, positive and negative examples, respectively, then with margin α,

$$\mathcal{L}_{\sqcup} = \sum_{(a,p,n)\in\mathcal{D}} \max(0, \|h_a - h_p\| - \|h_a - h_n\| + \alpha)$$

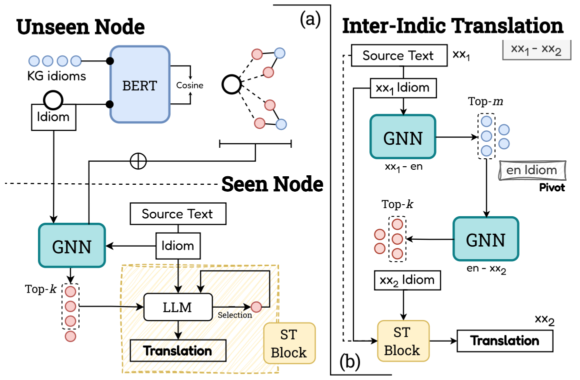

Figure 3: Inference strategy: (a) Unseen & Seen Node Translation – a BERT-trained GNN adapts to unseen nodes, with the Selection and Translation (ST) block selecting idioms via an LLM before translation; (b) Inter-Indic Translation – using English as a pivot between xx_1 and xx_2.

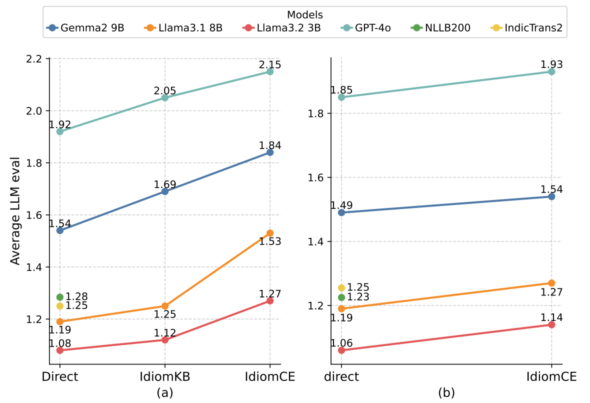

Figure 4: Performance comparison on average LLM score of Models on seen nodes (idiom) (a) and unseen nodes (b) across en-xx direction

3.4 Inference

From the trained bi-directional GNNs on English and specific Indic languages, we explore idiomatic translation through three approaches, as illustrated in Figure 3: seen nodes, unseen nodes and inter-indic. The *seen nodes*, refer to idioms for which GNN has prior knowledge, including their relationships with other idioms. On the other hand, *unseen nodes* pertain to idioms for which the GNN has no prior information nor any established connections to other idioms. Lastly, *inter-indic* translation where english idioms are treated as pivot, more explanation in section 3.4.3. We assume idiom detection is a well-explored problem, enabling us to focus directly on the translation task without treating idiom identification as an intermediate step. We also presume that the idiom in the source sentence is provided for retrieval through IdiomCE.

3.4.1 Seen Nodes

To infer with *seen nodes*, we first retrieve top-k target idioms using the trained GNN by link prediction by providing source idiom as input. Next, we refine the selection by filtering out the most contextually relevant target idiom based on the source sentence. This is achieved by passing the retrieved idioms into a selection prompt as context in an LLM. Finally, once the most relevant target idiom is identified, we perform LLM-based inference by passing the source text, source idiom, and the selected target idiom into a translation prompt. The details of both prompts are provided in Appendix A.2 and A.3.

3.4.2 Unseen Nodes

For unseen nodes, completely isolated idioms would yield no meaningful results. To address this, we make the following assumption about the training dataset $\mathcal{D}$.

Assumption: For any unseen node u, $\exists v \in \mathcal{D}$ such that $\cos(\mathcal{B}_{CL}(u), \mathcal{B}_{CL}(v)) \geqslant \tau$, where $\tau \in [0, 1]$. For our experiments, we choose τ to be 0.75.

To infer on unseen nodes, we first retrieve the most similar idioms in the source language using cosine similarity based on embeddings from the trained contrastive embedding model $\mathcal{B}_{CL}$. After selecting the top M source language idioms, we randomly select five target-language idioms linked to these source idioms and connect them to the unseen idiom, incorporating them into our graphical data. Once integrated, we perform link prediction on the unseen node to retrieve the most suitable target idiom.

3.4.3 Inter Indic Languages translation

We train the IdiomCE encoder bidirectionally between English and individual Indic languages. In addition to direct translation from $\mathcal{S}$ to $\mathcal{T}$, we propose leveraging trained GNNs for indirect translation. Let $\mathcal{A}_1$, $\mathcal{A}_2$ and $\mathcal{A}_3$ be nodes in languages A_1, A_2 and A_3 respectively. Let $\mathcal{G}_{12} : \mathcal{A}_1 \to \mathcal{A}_2$ and $\mathcal{G}_{23} : \mathcal{A}_2 \to \mathcal{A}_3$ be GNNs trained between the respective languages. To generate a translation from A_1 to A_3, we use A_2 as the *pivot* language, shown in Figure 3.

4 Experimental set up

Datasets: The initial knowledge graph (KG) construction is based on the dataset from Agrawal et al.

(2018) (Agrawal et al., 2018), which provides mappings of idioms between English (en) and seven Indian languages. For our study, we utilize four Indic languages: Tamil (ta), Telugu (te), Bengali (bn), and Hindi (hi). Additionally, we incorporate a parallel idiomatic sentence dataset from Thakre et al. (2018) (Thakre et al., 2018). Beyond these existing resources, we also web-scraped to collect idioms in various Indic languages. For evaluation, we sample 400 sentences from the MAGPIE dataset (Haagsma et al., 2020) to assess translation effectiveness from English to Indic languages. To analyze performance under different conditions, we conduct experiments in two setups: (1) Seen Idioms, where idioms present in the training data are tested, and (2) Unseen Idioms, where idioms not encountered during training are evaluated. For the Inter-Indic language setting, we curate a dataset of 200 idiomatic sentences per Indic language from the Samanantar dataset (Ramesh et al., 2023), ensuring coverage across multiple language pairs.

Evaluation Metrics: Most automatic evaluation metrics, like BLEU (Papineni et al., 2002; Post, 2018) and ChrF (Popović, 2015), rely on reference matching but struggle with one-to-many translation, especially idioms, where n-gram matches fall short. They also fail to distinguish literal from figurative translations. While CometKiwi (Rei et al., 2022) improves on traditional metrics by being reference-less and semantic-focused, it still struggles to reward high-quality idiomatic translations. Hence, for our evaluation, we adopt the GPT-4o-based evaluation method proposed by (Li et al., 2023a) as our primary metric, as it is an LLM-based approach specifically designed for assessing idiomatic translations we call it here LLM-eval and use WMT22-CometKiwi-DA as a supplementary evaluation metric.

Models: We test the effectiveness of our approach by using base LLMs of varying sizes like Gemma2 9B (Team et al., 2024), Llama-3.1 8B, Llama-3.2 3B (Grattafiori et al., 2024) and GPT-4o mini (OpenAI et al., 2024) in our methodology. We also evaluate our method by comparing them with translations generated from traditional NMT systems like NLLB 3.3B (Team et al., 2022) and IndicTrans2 (Gala et al., 2023). In our experiments `Direct` represents either directly prompting the LLM to translate the given source sentence, or passing the sentence through the NMT model for generating translation prompt can we referred from Appendix A.1. Specific training details and performanceof GNN and MLP layer with other experimental parameters are added in Table 4 in Appendix.

5 Results

Results on Mixed Dataset: This dataset contains a mix of idioms, both seen and unseen during training. We conducted experiments on English-to-Hindi, Bengali, Tamil, and Telugu translation directions. The results in Table 1 show: 1) IdiomCE, our approach that retrieves target idioms based on English idioms, outperforms the direct prompting method, highlighting the effectiveness of our retrieval-based training for idiomatic translation. 2) Among smaller models, Gemma2 9B achieves the best performance, even with direct prompting, demonstrating its strong capabilities in idiomatic translation. 3) With IdiomCE, very small models like Llama 3.2 3B perform comparably to the Directly Prompted larger Llama 3.1 8B variant. 4) Even for larger models like GPT-4o, IdiomCE improves performance, proving its effectiveness across different model sizes. 5) Foundational models like NLLB and IndicTrans2 struggle with idiomatic translation, showing low scores in LLM-eval. On average, IdiomCE improves LLM-eval scores by 18.51% for en-hi, 14.71% for en-bn, 6.45% for en-ta, and 10.33% for en-te. We have also provided example translation in Appendix B.

Results on Seen and Unseen Dataset: In Figure 4, we have shown on average LLM evaluation for different models on various methods across languages. Notably, results for the IdiomKB baseline are shown only for the seen dataset, as IdiomKB supports only idioms present in the training set. On average, the Gemma2 9B model demonstrates the best performance among open-source LLMs on both seen and unseen datasets. Compared to IdiomKB and Direct Method, our approach, IdiomCE outperform them by 14.28% and 21.78%, respectively, across open-source LLMs for seen dataset. Similarly, for unseen dataset, IdiomCE achieves 5.67% improvement over direct method. Even with GPT-4o results, our approach shows significant improvements for both seen and unseen datasets. Further details on language-specific performance can be found in the Appendix in Table 5 and 6

Results on Inter-Indic Languages: Table 2 presents the average performance across Indic languages. Our findings indicate: 1)Using English as a pivot to retrieve idioms for translation between

Model	Methods	`en-hi`		`en-bn`		`en-ta`		`en-te`	
		LLM-eval	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**
NLLB-200	`Direct`	1.3	0.70	1.43	0.769	1.18	0.691	1.1	0.643
Indictrans2	`Direct`	1.247	0.74	1.275	0.77	1.243	0.769	1.24	0.747
LLama-3.2-3B	`IdiomCE`	1.34	0.59	1.2	0.6	1.105	0.51	1.18	0.51
	`Direct`	1.12	0.62	1.05	0.6	1.04	0.52	1.07	0.52
Gemma2-9b-it	`IdiomCE`	**1.88**	0.68	**1.7**	0.68	**1.63**	0.67	**1.56**	0.62
	`Direct`	1.6	**0.73**	1.44	**0.71**	1.56	**0.71**	1.46	**0.67**
LLama-3.1-8B	`IdiomCE`	1.655	0.63	1.40	0.63	1.25	0.57	1.3	0.54
	`Direct`	1.27	0.68	1.23	0.67	1.16	0.62	1.12	0.59
GPT-4o	`IdiomCE`	2.39	0.70	2.25	0.69	1.87	0.67	1.83	0.66
	`Direct`	2.14	0.73	1.99	0.764	1.741	0.72	1.67	0.71

Table 1: Performance Metrics of Various Models on Mixed Dataset; COMET range [0,1]

Model	Methods	`hi-xx`		`bn-xx`		`ta-xx`		`te-xx`	
		LLM-eval	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**
NLLB-200	`Direct`	1.85	0.79	1.70	0.78	1.84	0.77	1.81	0.78
Indictrans2	`Direct`	**1.92**	0.81	1.78	0.81	**2.01**	0.77	1.97	0.77
LLama-3.2-3B	`IdiomCE`	1.263	0.5663	1.23	0.5867	1.2567	0.53867	1.273	0.5493
	`Direct`	1.1867	0.589	1.17	0.6163	1.253	0.572	1.1867	0.609
Gemma2-9b-it	`IdiomCE`	**1.8233**	0.7283	**1.783**	0.727	**1.9867**	0.7267	**2.02**	0.724
	`Direct`	1.4833	**0.75**	1.49	**0.775**	1.563	**0.755**	1.5467	**0.773**
LLama-3.1-8B	`IdiomCE`	1.42	0.616	1.46	0.6404	1.533	0.5993	1.493	0.626
	`Direct`	1.34	0.6533	1.367	0.688	1.25	0.6393	1.25	0.677

Table 2: Performance Metrics of Various Models For Inter-Indic languages; COMET range [0,1]

Hits @k	Without NodeDup	With NodeDup
Hits@5	81.33 $\pm$ 2.36	**85.28** $\pm$ 2.99
Hits@10	90.00 $\pm$ 2.36	**96.28** $\pm$ 1.37
Hits@20	100.00 $\pm$ 0.00	100.00 $\pm$ 0.00
Hits@50	100.00 $\pm$ 0.00	100.00 $\pm$ 0.00
AUC	95.32	**96.33**

Table 3: Ablation on Node Duplication module

Indic languages improves LLM performance compared to direct prompting, highlighting the flexibility of our approach. 2) Gemma2 9B consistently performs well in inter-Indic translation settings, significantly outperforming other LLMs. 3) Interestingly, in some language pairs like hi-xx and ta-xx, IndicTrans2 achieves strong results, even surpassing other models. Overall, IdiomCE demonstrates significant improvements in LLM evaluation, with a 12.5% performance gain for hi-xx, 11.2% for bn-xx, 17.5% for ta-xx, and 19.9% for te-xx translations over `Direct` prompting.

Ablation Studies To justify the use of the Node Duplication procedure (see Sec 3.2), we conduct an ablation experiment comparing performance with and without the NodeDup module in Table 3. We report Hits@k (Chen et al., 2020) for the en-hi translation task, which includes 8,233 nodes (4.6K Hindi target nodes), with 1.1K cold target nodes. Our results show that incorporating the NodeDup module improves Hits@k by 4.85% for $k = 5$ and 6.97% for $k = 10$, demonstrating its effectiveness in enhancing target node retrieval.

6 Conclusion

In this work, we addressed the challenges of idiomatic translation by introducing IdiomCE, an adaptive GNN-based approach that effectively captures the complex relationships between idiomatic expressions across languages. Our method generalizes to seen and unseen idioms, improves translation quality even in smaller models, and enables translation via a pivot language through the GNN framework. Experimental results across multiple Indian languages demonstrate that our approach outperforms traditional static knowledge graphs and prompt-based methods, significantly improving idiomatic translation. By leveraging GPT-4 as an evaluation metric, we show that our model better preserves meaning and cultural nuances in translation. Future work can extend this approach to more languages and richer contextual signals.

Limitations

While our work shows significant improvements in idiomatic translation, we mention some of the limitations of our work. Our approach heavily depends on the synthetically generated cultural elements (features). Noisy features, especially in low-resource languages, might affect the performance of our method. Secondly, as mentioned before, although our model captures idiomatic mappings, some idioms rely heavily on a deep contextual understanding of the surrounding sentences and not just on the training data used, which can limit the model's performance.

Acknowledgments

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A Prompt used in Experiment

A.1 Direct Prompt

```
Translate the Following {src_lang}
Sentence to {tgt_lang}. Only provide
final translation as output, Do not
provide any explainations.
{src_lang} Sentence: {sent}
```

A.2 Selection Prompt

```
You are a linguistic researcher on
idioms and good at {tgt_lang} and
{src_lang}. Choose the best
{tgt_lang} idiom matching the
{src_lang} idiom and Context of
Source Sentence in which it is used
in. Only Provide Best macthing
{tgt_lang} Idiom Do not provide any
explaination.
{src_lang} idiom: {en_idm}
Source Sentence: {sent}
Options: {tgt_lang idioms}
```

A.3 Translation Prompt

```
You are a linguistic researcher on
idioms and are good at {tgt_lang} and
{src_lang}. {en_idm} means {hi_idm}.
Given the above knowledge, translate
the following sentence to {tgt_lang}:
{sent}.
Only provide final translation as
output, Do not provide any
Explainations.
```

A.4 Cultural element generation prompt

```
You are a linguistic expert with deep
knowledge of {tgt_lang} idioms,
including their cultural and socio-
cultural contexts. For the given
idiom, provide a detailed analysis
covering the following key aspects.
Ensure each point has only a brief,
single-sentence description:
1. **Idiom:** - {idiom}
2. **Concepts:** - Explain the basic
meaning and underlying concepts of
the idiom.
3. **Values:** - Describe the beliefs
or desirable outcomes that the idiom
reflects.
4. **Situational Context:** -
Describe typical scenarios where the
idiom is used.
5. **Historical Context:** - Provide
any relevant historical background
influencing the idiom's usage.
```

Training Details: We train the GNN using a 2-layer SAGEConv architecture, mapping input states from 768 to a hidden dimension of 64. The hidden representation then passes through an MLP with two linear layers and ReLU activation. The model is trained for 50 epochs over 5 runs. For Node Duplication Augmentation, each target node is duplicated twice, and the distinction threshold (δ) between cold and warm nodes is set to 3. α used as margin for Contrastive Training is set to 1

B Examples

B.1 Translation Example en-hi direction

Source: **Close call**, though.
Direct: करीब से निकल गया।
IdiomCE: पीछा छुड़ा, हालाँकि...

Source: Well, **it's all Greek to me**, but so long as it keeps him happy.
Direct: अच्छा, यह मेरे लिए सब ग्रीक है, लेकिन जब तक यह उसे खुश रखता है।
IdiomCE: चाहे वो मुझे समझ न आए, पर जब तक उसे खुश रखता है।

Source: Other women took one look at them, and went **green with envy**.
Direct: दूसरी महिलाओं ने उन्हें एक झलक में देखा और ईर्ष्या से हरा रंग हो गया।
IdiomCE: दूसरी महिलाओं ने उन्हें एक झलक में देखा और जल भून गईं।

Source: You're **chasing** an impossible **rainbow**.
Direct: आप असंभव इंद्रधनुष का पीछा कर रहे हैं।
IdiomCE: तुम खयाली पुलाव पका रहे हो।

Source: And for God's sake **bury the hatchet**.
Direct: और भगवान की आज्ञा से, तलवारों को दफना दो।
IdiomCE: और भगवान के लिए शत्रुता खत्म कर दो।

B.2 Translation Example en-bn direction

Source: A bottom drain is something which has **stood the test of time** too.
Direct: একটি বটম ড্রেনও বহুকাল ধরিয়া বিদ্যমান।
IdiomCE: একটি বটম ড্রেনও সময়ের প্রতিবাদে স্থিতিশীল।

Source: I hope you will soon **find your feet** again.
Direct: আমি আশা করি তুমি শীঘ্রই পা পাতা নেওয়া।
IdiomCE: আমি আশা করি, তুমি শীঘ্রই আবার তোমার আধার পেয়ে যাবে।

Source: We are not **joined at the hip**, Cabochon said, and smiled bitterly.
Direct: আমরা হাতের কাছে হাত বাড়িয়ে নেওয়া নই, ক্যাবোচন বলেছিল, এবং ক্ষুব্ধ হাসি দিয়ে।
IdiomCE: আমরা হিপে যুক্ত নই, ক্যাবোচন বলেছিল, এবং ক্ষুব্ধ হাসি দিয়ে।

Source: After all, **charity begins at home**.
Direct: অবশ্যই, দান নিজের ঘরের দেখা তারপর পরের ঘর।
IdiomCE: অবশেষে, দান বাড়ির থেকে শুরু হয়।

Source: Youd both have **got on like a house on fire**.
Direct: আপনারা উভয় খুব বাড় বাড়া হয়েছিল।
IdiomCE: আপনি দুজনেই খুব ভালো মিলেত।

B.3 Translation Example en-ta direction

Source: I had to **face the music**, I had to face myself.

Direct: நான் இசையை எதிர்கொள்ள வேண்டியிருந்தது, நான் என்னைத் தானே எதிர்கொள்ள வேண்டியிருந்தது.

IdiomCE: நான் படாத பாடு படுவதற்கு ஆக வேண்டியிருந்தது, நான் என்னை சந்திக்க வேண்டியிருந்தது.

Source: If I had to **sweat blood** it would be done.

Direct: எனக்கு இரத்தம் சிந்தினாலும், இது முடிந்துவிடும்.

IdiomCE: உயிரைக் கொடுத்து உழைத்தாலும் முடித்துவிடுவேன்.

Source: As Crilly is taken back into the cells, he **catches my eyes**.

Direct: கிரிலி செல் மீண்டும் கொண்டு செல்லப்படும் போது, என் கண்களைப் பிடித்துக்கொள்கிறார்.

IdiomCE: கிரில்லி மீண்டும் சிறைச்சாட்டிற்கு அழைத்துச் செல்லும் போது, அவர் என் கவனத்தை ஈர்க்குகிறார்.

Source: Why should he suddenly have materialized **out of the blue**?

Direct: அவன் திடீரென்று எப்படி மறைந்து போனான்?

IdiomCE: அவன் திடீரென்று எப்படி தோன்ற முடியும்?

Source: In a nutshell Yes.

Direct: சொல்லப்போனால், ஆம்.

IdiomCE: சுருக்கமாக சொல்வதென்றால் ஆம்.

B.4 Translation Example en-te direction

Source: You just have to try to **keep your head above water**.

Direct: నీవు కేవలం నీ తల నీటిపై ఉంచుకోవడానికి ప్రయత్నించాలి.

IdiomCE: తావు తీవ్రంగా ప్రయత్నం చేయాలి.

Source: In every country, intellectuals, too, have **jumped on the nationalist bandwagon**.

Direct: ప్రతి దేశంలో, మాకు

IdiomCE: ప్రతి దేశంలో, విద్వాంసులు కూడా జాతీయవాద బండిపై గోల గోల చేస్తున్నారు.

Source: **Keep your chin up**, girl, were not lost yet.

Direct: ముఖం ఎత్తు, అమ్మాయి, మాకు ఇంకా కోల్పోయలేదు.

IdiomCE: తల ఎత్తుకుని ఉండు, అమ్మాయి, మాకు ఇంకా కోల్పోయలేదా.

Source: Poor old British Rail were **between the devil and the deep blue sea**.

Direct: బాధపడిన పాత బ్రిటిష్ రైల్ దెవదాంబుల మధ్య ఉంది.

IdiomCE: గట్టిగా పోరాడిన బ్రిటిష్ రైల్ ముందు నుయ్యి వెనక గొయ్యిలో ఉన్నారు.

Source: **Close, but no cigar**.

Direct: సమీపంలో ఉన్నా, కానీ సిగారు కాదు.

IdiomCE: దగ్గరకు వచ్చినా దక్కలేదు.

Language	Hits@5	Hits@10	Hits@20	Hits@50	AUC
hindi	85.28 ± 2.99	96.28 ± 1.37	100.00 ± 0.00	100.00 ± 0.00	96.33 ± 0.28
Telugu	82.50 ± 8.54	95.83 ± 2.95	100.00 ± 0.00	100.00 ± 0.00	95.32 ± 0.37
Tamil	76.06 ± 3.98	88.45 ± 2.09	98.59 ± 1.00	100.00 ± 0.00	93.27 ± 0.73
Bengali	79.29 ± 5.30	95.00 ± 4.07	99.29 ± 1.60	100.00 ± 0.00	96.10 ± 0.12

Table 4: Performance on GNN Link Prediction task for each language

Model	Methods	en-hi		en-bn		en-ta		en-te	
		GPT-4	**COMET**	**GPT-4**	**COMET**	**GPT-4**	**COMET**	**GPT-4**	**COMET**
NLLB-200	Direct	1.34	0.70	1.45	0.77	1.21	0.69	1.14	0.64
Indictrans2	Direct	1.24	0.74	1.27	0.78	1.26	0.76	1.21	0.74
LLama-3.2-3B	IdiomCE	1.42	0.58	1.26	0.59	1.15	0.52	1.24	0.51
	Direct	1.12	0.62	1.06	0.60	1.03	0.51	1.09	0.54
	IdiomKB	1.25	0.61	1.05	0.59	1.07	0.52	1.11	0.52
Gemma2-9b-it	IdiomCE	2.08	0.69	1.84	0.69	1.76	0.68	1.68	0.63
	Direct	1.63	0.73	1.50	0.71	1.60	0.72	1.45	0.68
	IdiomKB	1.875	0.70	1.64	0.70	1.65	0.68	1.50	0.64
LLama-3.1-8B	IdiomCE	1.89	0.62	1.54	0.63	1.29	0.57	1.41	0.53
	Direct	1.27	0.68	1.22	0.67	1.16	0.62	1.14	0.58
	IdiomKB	1.40	0.67	1.19	0.67	1.20	0.60	1.21	0.59
GPT-4o	IdiomCE	2.48	0.71	2.30	0.69	1.90	0.69	1.89	0.68
	Direct	2.17	0.74	2.059	0.77	1.72	0.73	1.73	0.72
	IdiomKB	2.38	0.711	2.19	0.74	1.83	0.68	1.80	0.67

Table 5: Performance Metrics of Various Models on Seen Dataset; COMET range [0,1]

Model	Methods	en-hi		en-bn		en-ta		en-te	
		LLM-eval	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**	**LLM-eval**	**COMET**
NLLB-200	Direct	1.26	0.70	1.41	0.77	1.17	0.69	1.06	0.64
Indictrans2	Direct	1.25	0.74	1.28	0.78	1.22	0.76	1.27	0.74
LLama-3.2-3B	IdiomCE	1.25	0.58	1.14	0.59	1.06	0.52	1.13	0.51
	Direct	1.12	0.62	1.05	0.60	1.05	0.51	1.05	0.53
Gemma2-9b-it	IdiomCE	1.68	0.68	1.56	0.67	1.50	0.68	1.49	0.66
	Direct	1.57	0.72	1.39	0.70	1.53	0.72	1.4	0.68
LLama-3.1-8B	IdiomCE	1.42	0.63	1.27	0.62	1.21	0.59	1.19	0.53
	Direct	1.28	0.68	1.23	0.67	1.16	0.62	1.11	0.55
GPT-4o	IdiomCE	2.31	0.72	2.01	0.74	1.72	0.68	1.70	0.67
	Direct	2.12	0.74	1.92	0.77	1.76	0.73	1.61	0.71

Table 6: Performance Metrics of Various Models on Unseen Dataset; COMET range [0,1]