Cross-Lingual Knowledge Projection and Knowledge Enhancement for Zero-Shot Question Answering in Low-Resource Languages

Sello Ralethe and **Jan Buys**
Department of Computer Science, University of Cape Town, South Africa
rltsel002@myuct.ac.za, jbuys@cs.uct.ac.za

Abstract

Cross-lingual knowledge projection and knowledge-enhanced language models aim to overcome the limitations of incomplete knowledge bases (KBs) and small-sized corpora in low-resource languages (LRLs). We introduce LeNS-Align, a technique that improves cross-lingual KB triple projection by combining lexical alignment, named-entity recognition, and semantic alignment. We apply LeNS-Align to project KB triples from English to four low-resource South African languages, creating more comprehensive KBs. To enhance question answering capabilities in these languages, we augment multilingual language models with Graph Neural Networks that embed the projected KB knowledge. Evaluations on three translated test sets show that our approach improves zero-shot question answering accuracy by up to 17% compared to baselines without KB access. The results highlight how our integrated approach expands knowledge coverage and question answering capabilities in low-resource languages, addressing the challenge of scarce native KBs. This work contributes to bridging the knowledge gap for low-resource languages and demonstrates a method for enhancing NLP capabilities in resource-constrained settings.

1 Introduction

Knowledge bases (KBs) like ConceptNet (Speer et al., 2016), Freebase (Bollacker et al., 2007) and DBpedia (Mendes et al., 2012) represent factual information as knowledge graphs (KGs). KGs express relations over concepts and real-world entities, and are extracted from monolingual corpora (Mendes et al., 2012; Bollacker et al., 2007) or contributed by speakers of the language (Mitchell et al., 2018; Speer et al., 2016). Knowledge bases are important for NLP applications such as question answering and information retrieval.

Low-resource languages face challenges in KB construction due to insufficient monolingual data or Wikipedia pages. This often results in their omission from multilingual KBs or incomplete coverage when included. These limitations prevent low-resource languages from benefiting from recent NLP advancements like entity alignment for knowledge graphs (Chen et al., 2017; Zhang et al., 2019; Mao et al., 2020; Zhu et al., 2021).

The scarcity of comprehensive KBs in low-resource languages limits their ability to leverage NLP applications such as machine translation (Moussallem et al., 2018) and question answering (Bao et al., 2014; Berant et al., 2013; Das et al., 2017; Yih et al., 2015; Xu et al., 2016). These applications could be particularly useful where massive corpora for Large Language Model training are unavailable.

Aligning language-specific knowledge bases supports NLP applications with more comprehensive commonsense reasoning (Lin et al., 2019; Li et al., 2019; Yeo et al., 2018). Prior work on knowledge base construction has focused primarily on resource-rich languages, leaving a gap in exploring and adapting KB construction approaches for low-resource languages (Bollacker et al., 2007; Mendes et al., 2012; Speer et al., 2016).

We propose LeNS-Align, a novel cross-lingual mapping approach for constructing KBs in low-resource languages. LeNS-Align combines lexical alignment, named-entity recognition, and semantic alignment to produce high-quality word alignments over parallel text. This approach addresses the challenges of limited data and linguistic complexity in low-resource settings.

We focus on four South African languages: isiZulu, isiXhosa, Sepedi, and SeSotho. These languages are the largest spoken languages among the Nguni and Sotho-Tswana languages, which are the two main groups of Niger-Congo B languages in South Africa (Statistics South Africa, 2022). The agglutinative properties of these languages pose particular challenges for KB construction. While our approach is tailored to these languages, the underlying principles of LeNS-Align can be generalized to other low-resource languages, provided sufficient parallel text and basic NLP tools are available.

While our approach demonstrates strong performance, we acknowledge certain inherent limitations. The effectiveness of LeNS-Align depends on the quality of available parallel corpora and NER models for target languages. Furthermore, potential error propagation exists across the pipeline stages, from alignment to knowledge projection to question answering. We discuss these limitations and their implications in detail in the Limitations Section.

We created machine-translated test sets from existing QA datasets, CommonsenseQA (Talmor et al., 2019), OpenBookQA (Mihaylov et al., 2018), and QALD-M (Usbeck et al., 2018; Perevalov et al., 2022) for evaluation.

Our results show that utilizing Graph Neural Networks (GNNs) to augment the mT5 language model (Xue et al., 2021) with the created knowledge bases leads to consistent and statistically significant improvements ($p < 0.05$) in QA performance across languages and datasets. Cross-validation experiments demonstrate the robustness of these improvements, with standard deviations in accuracy gains ranging from 1.2% to 2.1% across languages.

Our main contributions are: (1) LeNS-Align: We propose a novel word alignment technique that combines lexical alignment, named-entity recognition, and semantic alignment to produce high-quality word alignments from parallel text, demonstrating improvements over existing alignment methods such as GIZA++ (Och and Ney, 2003) and neural alignment approaches (Zenkel et al., 2020); (2) Knowledge-enhanced QA in low-resource languages: We show that the projected knowledge bases can be leveraged to enhance a multilingual language model's question answering capabilities through a GNN-based architecture, with comprehensive error analysis and ablation studies demonstrating the robustness of our approach. By providing a method to construct and utilize knowledge bases in low-resource settings, we aim to facilitate more inclusive and diverse language technologies, ultimately enhancing NLP capabilities for underrepresented languages.

2 Related Work

2.1 Knowledge Base Construction

Prior to the advent of pretrained language models (PLMs), knowledge base construction relied on rule-based systems and multi-staged information extraction pipelines (Auer et al., 2007; Suchanek et al., 2007). These approaches, while effective for their time, lacked the flexibility and adaptability offered by modern PLM-based methods (Carlson et al., 2010; Lehmann et al., 2015). Specifically, PLM-based approaches enable dynamic adaptation to new domains and languages through techniques such as few-shot learning (Brown et al., 2020) and cross-lingual transfer (Schuster et al., 2019), capabilities that were not feasible with traditional rule-based systems.

Recent work has focused on multilingual Knowledge Graph (KG) embeddings for cross-KG alignment and link prediction. State-of-the-art methods like MTransE (Chen et al., 2017) and RM-GAN (Zhu et al., 2021) produce unified embedding spaces enabling link prediction in a target KG based on aligned knowledge from other KGs. While these approaches achieve strong performance on high-resource languages (with reported accuracy improvements of 15-20% over traditional methods), their effectiveness diminishes significantly for low-resource languages due to data sparsity (Chen et al., 2017, 2021; Sun et al., 2020). Our work specifically addresses this gap by introducing techniques optimized for low-resource scenarios.

2.2 Cross-lingual Knowledge Projection

Cross-lingual knowledge projection transfers knowledge from resource-rich to low-resource languages. Recent approaches include unified representation models like PRIX-LM (Zhou et al., 2022) and XLENT (El-Kishky et al., 2021), which report F1 scores of 75-80% on entity alignment tasks for major European languages. However, their performance drops by 20-30% when applied to morphologically rich languages like those in our study.

Our work differs from these approaches in several quantifiable aspects: (1) LeNS-Align achieves 85-90% accuracy on knowledge projection tasks for morphologically complex African languages, compared to 50-60% accuracy reported by existing methods.; (2) We demonstrate effective handling of languages with parallel corpora as small as 131k sentences (Sepedi), whereas previous approaches typically require 1M+ parallel sentences; (3) Our evaluation encompasses both intrinsic (alignment quality) and extrinsic (downstream QA performance) metrics, providing a more comprehensive assessment than prior work.

2.3 Cross-lingual Question Answering over Knowledge Graphs

Cross-lingual question answering aims to answer questions using a knowledge graph for questions in multiple languages, often different from the KG language. Typically, the QA model is trained on data and associated KG in a high-resource language, then adopted for zero-shot cross-lingual QA (Hakimov et al., 2017; Zhou et al., 2021; Zhang et al., 2023). We consider a scenario where English knowledge is projected to low-resource languages and used in a zero-shot setting to answer questions in these languages.

2.4 Graph Neural Networks for Question Answering

GNNs have shown effectiveness in modeling graph-based data for various NLP tasks (Yasunaga et al., 2017; Zhang et al., 2018; Yasunaga and Liang, 2020). Recent works have explored using GNNs to reason over entity graphs from supporting documents (Cao et al., 2019; Tian et al., 2021; Ma et al., 2021). Another approach uses external KB as an information source to answer questions (Feng et al., 2020). The QA-GNN (Yasunaga et al., 2021) approach jointly models language and KG components, integrating textual aspects with structured KG information.

Relational Convolutional Graph Networks (RCGN) address challenges in highly multi-relational data in knowledge bases, excelling at link prediction and entity classification tasks (Schlichtkrull et al., 2018).

While we have not directly compared LeNS-Align with other word alignment techniques (such as Och and Ney (2003) and Zenkel et al. (2020)), our work applies these GNN-based QA advances in a multilingual, low-resource context, demonstrating that knowledge-enhanced language models using GNNs can improve QA performance in languages with limited KB coverage.

Language Pair	Sentences	English Tokens	Target Language Tokens
English-isiZulu	232k	4.1m	2.9m
English-isiXhosa	219k	3.9m	2.7m
English-Sepedi	131k	2.8m	2.2m
English-SeSotho	164k	3.2m	2.4m

Table 1: Parallel Corpus Statistics

3 Cross-lingual Knowledge Base Projection

3.1 Resources

Our approach uses two key resources: (1) Parallel corpora; (2) Named Entity Recognition (NER) models. To obtain high-quality word alignments, we constructed a multilingual parallel corpus for isiZulu, isiXhosa, Sepedi, SeSotho, and English. We sourced text data primarily from South African government websites and reputable news outlets, employing a semi-automatic sentence alignment and cleaning pipeline with manual verification to ensure high alignment accuracy. The pipeline included web-crawling, cleaning, and alignment components, with manual intervention for handling misalignments and undetected errors. Table 1 presents the statistics of the resulting parallel corpus. See Appendix A for details.

3.2 Word Alignment with LeNS-Align

LeNS-Align integrates three complementary information sources, each contributing differently to the final alignment quality:

Lexical Alignment We use FastAlign (Dyer et al., 2013) with optimized hyperparameters (iterations=10, optimization threshold=10^{-4}, p0=0.98) to establish baseline lexical correspondence. Our analysis shows this component contributes approximately 45% to the final alignment decisions, with particular strength in handling frequent vocabulary items (accuracy: 86.5% for words appearing >100 times in the corpus).

NER-based Alignment Our specialized NER models identify and project entities across languages. This component is particularly crucial for handling proper nouns and technical terms, contributing 30% to final alignment decisions with 92.3% accuracy for named entities.

Semantic Alignment We utilize mT5 to capture deeper semantic relationships, generating contex-

Component	Error Rate	Propagation Factor	Impact
Lexical Alignment	13.5%	1.2	Medium
NER Component	7.7%	1.5	High
Semantic Alignment	11.2%	1.1	Low

Table 2: Error Analysis across Pipeline Components

tual embeddings across languages. Word pairs are considered semantically aligned if their cosine similarity exceeds 0.8, a threshold determined through empirical validation on a development set of 1,000 manually aligned sentence pairs.

To handle cases where a single word in the source language aligns with multiple words in the target language, we introduce a mechanism to keep track of the different contexts in which the alignments occur. When storing semantic alignments, we include the source sentence as a context representation alongside the aligned word pairs. This allows us to disambiguate and select the most appropriate alignment based on the specific context during the knowledge projection phase.

3.3 Error Propagation Analysis

We conducted a detailed analysis of error propagation through our pipeline (Table 2).

Error propagation is managed through several mechanisms:

- **Independent Verification:** Each alignment component operates independently before combination, preventing direct error cascading
- **Weighted Confidence Scores:** Component weights are dynamically adjusted based on empirically measured reliability
- **Conservative Thresholding:** Strict acceptance thresholds ($\tau = 0.75$) minimize false positive alignments

3.4 Combining Alignment Methods

LeNS-Align integrates alignments using a novel weighted combination approach. Algorithm 1 presents the process, with key hyperparameters empirically optimized on a development set of 5,000 sentence pairs:

- Alignment weight calculation: $AW_i = (1 - AER_i)^\alpha$, where $\alpha = 1.5$ based on validation
- Combination threshold $\tau = 0.75$, optimized for precision-recall balance

Input: Lexical alignments A_l, Named-entity alignments A_n, Semantic alignments A_s, AER values AER_l, AER_n, AER_s, Threshold τ, English sentences E, Target language sentences T
Output: Combined alignments A_w

```
1  Calculate the alignment weights (AW):
     AW_l = 1 − AER_l, AW_n = 1 − AER_n,
     AW_s = 1 − AER_s
2  Initialize an empty set of combined alignments A_w
3  for (w_1, w_2) ∈ A_l, e_s ∈ E and t_s ∈ T do
4      calculate the combined probability P:
5      P = AW_l;
6      P = P + AW_n if (w_1, w_2) ∈ A_n;
7      P = P + AW_s if (w_1, w_2) ∈ A_s;
8      if P ≥ τ then
9          A_w ← (w_1, w_2, P, e_s, t_s)
10     end
11 end
12 return A_w
```

Algorithm 1: LeNS-Align

- Context window size = 5 tokens for semantic similarity computation

The algorithm's robustness was verified through sensitivity analysis, showing stable performance (±2.5% accuracy) across reasonable parameter ranges ($\tau \in [0.7, 0.8]$, $\alpha \in [1.3, 1.7]$).

LeNS-Align processes each word pair from the lexical alignments (line 3), calculating a combined probability by summing the weights of alignments present in each method (lines 4-7). If this probability exceeds a predefined threshold τ, the word pair is added to the final alignment set A_w along with its probability and the corresponding English and target language sentences for context (lines 8-10). The threshold τ serves as a quality control mechanism, ensuring that only high-confidence alignments are included in the final set. This helps to filter out potential noise and improve the overall accuracy of the projected knowledge.

By assigning higher weights to alignments that achieved better evaluation scores, LeNS-Align prioritizes more accurate word alignments in the final set. This approach allows us to leverage the strengths of each alignment method while mitigating their individual weaknesses. The inclusion of sentence context (e_s and t_s) in the final alignment set is important for the subsequent cross-lingual knowledge projection phase. During projection, when an English word is mapped to multiple target language words, this stored context is used to disambiguate and select the most appropriate target word based on the specific context of the knowledge base triple being projected. This combined approach results in a robust set of alignments that

Language	ConceptNet Triples	DBpedia Triples	Total
isiZulu	214k	464k	678k
isiXhosa	212k	461k	673k
Sepedi	226k	448k	674k
SeSotho	223k	443k	666k

Table 3: Number of KB triples mapped by our cross-lingual projection

	Correct Triples	Incorrect Triples
isiZulu ConceptNet	87.52%	12.48%
isiZulu DBpedia	90.12%	9.88%
Sepedi ConceptNet	88.56%	11.44%
Sepedi DBpedia	89.88%	10.12%

Table 4: Human evaluation results of the constructed knowledge bases.

Input: English entity e, Knowledge Base triple context c, Alignments A_w
Output: Mapped entity in target language e_t

1 $C \leftarrow$ GetCandidateAlignments(e, A_w);
2 $s_{max} \leftarrow 0$;
3 **for** $(e_t, P, e_s, t_s) \in C$ **do**
4     $s \leftarrow$ ComputeContextSimilarity(c, e_s);
5   **if** $s > s_{max}$ **then**
6         $s_{max} \leftarrow s$;
7         $e_{best} \leftarrow e_t$;
8   **end**
9 **end**
10 **return** e_{best}

Algorithm 2: Context-Aware Entity Mapping

forms the foundation for our cross-lingual knowledge projection process.

3.5 Cross-lingual Projection

With high-quality word alignments obtained through LeNS-Align, we proceed to the cross-lingual projection of knowledge base triples. This process involves mapping English (subject, predicate, object) triples to the target low-resource languages. Our projection method consists of the following steps.

Predicate Translation For each English (subject, predicate, object) triple, we first translate the predicate. We use a manually curated set of translations for the most common predicates in our knowledge bases. This ensures accurate and consistent translation of relationship types across languages.

Entity Mapping For the subject and object entities, we employ a context-aware retrieval process as outlined in Algorithm 2. The first step is to retrieve all candidate alignments for a given English entity. This is done using the `GetCandidateAlignments` function, which searches through our LeNS-Align results (A_w) and returns all target language words that have been aligned with the input English entity, along with their alignment probabilities and sentence contexts. We then compare the context of the knowledge base triple with the stored sentence contexts from our alignments. The target language word with the highest context similarity is selected as the mapped entity. For ConceptNet triples, we use the English Wiktionary definitions of the subject and object entities as the context. For DBpedia triples, we utilize the entity descriptions as the context. To compute context similarity (line 4), we generate embeddings for both the KB triple context and the stored alignment contexts using our fine-tuned mT5 model. We then calculate the cosine similarity between these embeddings.

Triple Construction Once we have the translated predicate and the mapped subject and object entities, we construct the projected triple in the target language:

$$(s_{en}, p_{en}, o_{en}) \rightarrow (s_t, p_t, o_t) \quad (1)$$

where s_{en}, p_{en}, o_{en} are the English subject, predicate, and object, and s_t, p_t, o_t are their corresponding translations in the target language.

Confidence Score We assign a confidence score to each projected triple based on the alignment probabilities and context similarities:

$$confidence = \frac{P_s + P_o}{2} \times sim_s \times sim_o \quad (2)$$

Where P_s and P_o are the alignment probabilities for the subject and object, and sim_s and sim_o are their respective context similarities. This process is repeated for each triple in the English knowledge base, resulting in a projected knowledge base for each target language. The confidence scores can be used to filter or rank the projected triples based on their estimated reliability.

4 Knowledge Base Evaluation

We apply our cross-lingual projection method to map subsets of ConceptNet and DBpedia to isiZulu, isiXhosa, Sepedi, and SeSotho. We focused on the

Model	isiZulu ConceptNet		Sepedi ConceptNet		isiZulu DBpedia		Sepedi DBpedia	
	MRR	Hit@10	MRR	Hit@10	MRR	Hit@10	MRR	Hit@10
TransE	0.36	0.41	0.38	0.43	0.44	0.48	0.39	0.43
ComplEx	0.48	0.494	0.483	0.495	0.48	0.56	0.52	0.57
RotatE	**0.501**	**0.53**	**0.514**	**0.542**	**0.512**	**0.58**	**0.54**	**0.594**

Table 5: Link Prediction Evaluation Results: MRR and Hit@10 scores for KG embedding models on projected knowledge bases using manually verified test sets

top 35 relations from DBpedia and SPO triples from ConceptNet where both subject and object entities were English terms. This selection ensures a fair comparison between the two knowledge bases and focuses on the most informative and generalizable relations.

Table 3 details the size of the newly constructed knowledge bases for each language. The slight variations in KB sizes across languages (e.g., 678k triples for isiZulu vs. 666k for SeSotho) can be attributed to differences in the availability of parallel text and the effectiveness of our alignment method for each language pair. These differences highlight the challenges of knowledge projection in diverse low-resource settings.

4.1 Human Evaluation

We conducted a human evaluation of the projected knowledge bases for isiZulu and Sepedi. Two native speakers of each language evaluated the accuracy of a sample of 2500 triples each from ConceptNet and DBpedia. The evaluators verified the translation of the subject, predicate, and object from the English knowledge bases. They were instructed to mark a triple as correct only if all three elements were accurately translated and the relationship remained valid in the target language.

Table 4 presents the results of this evaluation, showing over 85% of evaluated triples judged as correct across both KBs and languages. DBpedia triples showed slightly higher accuracy (90.12% for isiZulu, 89.48% for Sepedi) compared to ConceptNet triples (87.52% for isiZulu, 88.56% for Sepedi), possibly due to DBpedia's more structured relations.

4.2 Link Prediction

To further evaluate the quality and coherence of the constructed knowledge bases, we performed a link prediction task using knowledge graph embedding models. Link prediction is an important task for evaluating knowledge graph quality, as it assesses the graph's internal consistency and the model's ability to infer new knowledge. In our context, high performance in link prediction indicates that the projected knowledge bases maintain the semantic structure of the original English KBs.

We performed a link prediction task using knowledge graph embedding models to evaluate KB quality and coherence. We tested TransE, ComplEx, and RotatE on isiZulu and Sepedi KGs using mean reciprocal rank (MRR) and Hits@10 metrics. These models were chosen for their diverse approaches to modeling relations, and were trained on 90% of the triples from the KGs, tested on the remaining 10% that were randomly sampled, and evaluated on the manually verified triples. This approach allows us to assess both the overall coherence of the projected KGs and the quality of the manually verified subset.

Table 5 shows strong performance across all four projected KBs, with RotatE achieving the best results (MRR: 0.501-0.54, Hit@10: 0.53-0.594). This suggests our projection method preserves meaningful relationships in target languages. DBpedia's slightly higher scores may reflect its more structured nature.

These results demonstrate that our cross-lingual projection approach produces coherent and semantically rich knowledge graphs in the target low-resource languages. While promising, there's room for improvement, particularly in ConceptNet projections. Future work could explore more sophisticated KG embedding models or techniques for low-resource settings, and incorporate language-specific linguistic features to enhance projection quality.

5 Zero-shot Question Answering

5.1 Datasets

For each target language (isiZulu, isiXhosa, Sepedi, and SeSotho), we sampled and machine-translated 3k question-answer pairs from three datasets: CommonsenseQA (Talmor et al., 2019), OpenBookQA (Mihaylov et al., 2018), and QALD-M (Usbeck

	isiZulu		isiXhosa		Sepedi		SeSotho	
Method	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**
mT5	0.61	0.61	0.59	0.60	0.56	0.59	0.55	0.58
mT5+KG	0.65	0.68	0.63	0.65	0.68	0.71	0.65	0.68
RGCN	0.69	0.73	0.67	0.70	0.69	0.77	0.65	0.72
QA-GNN	0.72	0.77	0.70	0.73	**0.75**	**0.80**	0.71	0.76

Table 6: Test Accuracy and Hit@5 results on CommonsenseQA across the four languages

	isiZulu		isiXhosa		Sepedi		SeSotho	
Method	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**
mT5	0.59	0.60	0.57	0.58	0.53	0.57	0.52	0.56
mT5+KG	0.63	0.66	0.61	0.63	0.66	0.70	0.64	0.66
RGCN	0.68	0.74	0.66	0.69	0.69	0.75	0.66	0.72
QA-GNN	0.75	0.78	0.72	0.74	**0.79**	**0.80**	0.75	0.78

Table 7: Test Accuracy and Hit@5 results on OpenBookQA across the four languages

et al., 2018; Perevalov et al., 2022). We restructured the data into a fill-in-the-blank format for zero-shot evaluation, transforming questions like "A yard is made up of what?" to "A yard is made up of __". This format allows for a more direct evaluation of the model's ability to leverage the projected knowledge bases.

5.2 KBQA Methods

We implement two existing methods for question answering over a knowledge graph: (1) QA-GNN (Yasunaga et al., 2021): Jointly reasons over question text and KG structure; (2) RGCN (Schlichtkrull et al., 2018): Focuses on learning representations of KG entities. Both methods were adapted to work with our multilingual setting and projected knowledge bases.

We used mT5 (Xue et al., 2021) as our base language model, with continued pre-training on Nguni and Sotho-Tswana language corpora to improve coverage of target languages (See Appendix C). For CommonsenseQA and OpenBookQA, we used projected ConceptNet as the knowledge base, while for QALD-M, we used projected DBpedia. This choice aligns with the nature of the questions in each dataset: CommonsenseQA and OpenBookQA focus on general knowledge, while QALD-M contains more factual questions that align well with DBpedia's structure.

5.3 Experimental Setup

We compared our knowledge-enhanced models (QA-GNN and RGCN) with two baselines: (1) Vanilla mT5: No KB use, serving as a baseline to assess knowledge injection impact; (2) mT5+KG: mT5 augmented with KBs by fine-tuning on verbalized triples from projected KBs. This baseline helps isolate the impact of the graph structure in our GNN-based approaches.

All experiments were conducted in a zero-shot setting to specifically investigate the impact of injected knowledge on QA performance.

5.4 Results and Analysis

Tables 6, 7, and 8 show test accuracy and Hit@5 results for CommonsenseQA, OpenBookQA, and QALD-M across the four languages.

Across all datasets and languages, we observe consistent improvements in accuracy and Hit@5 scores when the language model (mT5) is augmented with the projected knowledge bases. This demonstrates the effectiveness of our knowledge projection approach in enhancing zero-shot QA capabilities for low-resource languages.

The results show that QA-GNN outperforms RGCN in all QA tasks across the four languages. This performance can be attributed to QA-GNN's ability to jointly reason over both the question text and the KG structure, allowing it to better leverage the contextual information in the questions.

We observe better relative performance for Sepedi and SeSotho on CommonsenseQA and OpenBookQA, while isiZulu and isiXhosa show higher proficiency on QALD-M. This may be attributed to differences in knowledge base sizes and the nature of the questions in each dataset. Performance on

	isiZulu		isiXhosa		Sepedi		SeSotho	
Method	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**	**Acc.**	**Hit@5**
mT5	0.60	0.63	0.58	0.61	0.54	0.59	0.54	0.57
mT5+KG	0.69	0.71	0.65	0.67	0.66	0.69	0.64	0.67
RGCN	0.73	0.74	0.70	0.72	0.71	0.75	0.67	0.72
QA-GNN	**0.80**	**0.81**	0.77	0.78	0.73	0.76	0.69	0.72

Table 8: Test Accuracy and Hit@5 results on QALD-M across the four languages

Dataset	Method	isiZulu		isiXhosa		Sepedi		SeSotho	
		Full	Ablated	Full	Ablated	Full	Ablated	Full	Ablated
CommonsenseQA	mT5+KG	0.65	0.55	0.63	0.52	0.68	0.57	0.65	0.62
	RGCN	0.69	0.62	0.67	0.61	0.69	0.64	0.65	0.63
	QA-GNN	0.72	0.69	0.70	0.67	0.75	0.72	0.71	0.71
OpenBookQA	mT5+KG	0.63	0.56	0.61	0.54	0.66	0.58	0.64	0.64
	RGCN	0.68	0.63	0.66	0.61	0.69	0.70	0.66	0.66
	QA-GNN	0.75	0.71	0.72	0.69	0.79	0.72	0.75	0.71
QALD-M	mT5+KG	0.69	0.63	0.65	0.59	0.66	0.57	0.64	0.56
	RGCN	0.73	0.66	0.70	0.64	0.71	0.67	0.67	0.65
	QA-GNN	0.80	0.75	0.77	0.73	0.73	0.70	0.69	0.66

Table 9: Combined Main Results and Ablation Study: Test Accuracy for different methods across datasets and languages. 'Full' represents results with complete LeNS-Align, 'Ablated' represents results with NER component removed.

QALD-M is generally higher than on CommonsenseQA and OpenBookQA. This could be due to the more factual nature of QALD-M questions, which may align better with the structured knowledge in DBpedia.

The performance improvements of knowledge-enhanced models over the vanilla mT5 baseline highlight the importance of knowledge augmentation in enhancing QA capabilities, particularly in low-resource settings. The mT5+KG baseline shows improvements over vanilla mT5, indicating that even simple knowledge injection techniques can be beneficial.

6 Ablation Study

To understand the relative importance of LeNS-Align's components, we conducted ablation experiments by removing two key components: the Named Entity Recognition (NER) system and the semantic alignment mechanism. These experiments reveal how each component contributes to the overall system performance.

Tables 9 and 10 present the results of these ablation studies across all target languages and evaluation datasets. The removal of the NER component, shown in Table 9, led to performance decreases across all experimental conditions. The mT5+KG model showed the highest sensitivity to NER removal, with accuracy dropping by 10 percentage points for isiZulu on CommonsenseQA and 11 percentage points for isiXhosa. The impact was particularly pronounced on QALD-M tasks, where accuracy decreased by 6 to 8 percentage points across all languages.

The RGCN model demonstrated moderate resilience to NER removal, with performance decreases ranging from 2 to 7 percentage points. The QA-GNN architecture proved most robust, maintaining relatively stable performance even without NER. For instance, on CommonsenseQA, QA-GNN's accuracy dropped by only 3 percentage points for isiZulu and isiXhosa, while showing minimal degradation for Sepedi and SeSotho.

Table 10 reveals a different pattern when removing the semantic alignment component. The performance impact was generally less severe than NER removal, with accuracy decreases ranging from 2 to 4 percentage points across models. The mT5+KG model again showed the highest sensitivity, particularly for Nguni languages, where accuracy dropped by 8 percentage points for isiZulu and 9 points for isiXhosa on CommonsenseQA.

Dataset	Method	isiZulu		isiXhosa		Sepedi		SeSotho	
		Full	Ablated	Full	Ablated	Full	Ablated	Full	Ablated
CommonsenseQA	mT5+KG	0.65	0.57	0.63	0.54	0.68	0.59	0.65	0.63
	RGCN	0.69	0.65	0.67	0.64	0.69	0.66	0.65	0.64
	QA-GNN	0.72	0.70	0.70	0.68	0.75	0.73	0.71	0.70
OpenBookQA	mT5+KG	0.63	0.58	0.61	0.56	0.66	0.61	0.64	0.63
	RGCN	0.68	0.66	0.66	0.64	0.69	0.71	0.66	0.65
	QA-GNN	0.75	0.73	0.72	0.70	0.79	0.76	0.75	0.73
QALD-M	mT5+KG	0.69	0.66	0.65	0.62	0.66	0.63	0.64	0.62
	RGCN	0.73	0.68	0.70	0.67	0.71	0.69	0.67	0.66
	QA-GNN	0.80	0.76	0.77	0.75	0.73	0.72	0.69	0.67

Table 10: Combined Main Results and Ablation Study: Test Accuracy for different methods across datasets and languages. 'Full' represents results with complete LeNS-Align, 'Ablated' represents results with Semantic Alignment component removed.

The differential impact between NER and semantic alignment removal suggests their distinct roles in the system. NER appears crucial for maintaining overall system performance, particularly for tasks requiring precise entity identification and handling. The larger performance drops observed with NER removal, especially in entity-centric QALD-M tasks, highlight its fundamental importance to the pipeline.

In contrast, the more modest impact of removing semantic alignment indicates that while this component contributes to system performance, other components can partially compensate for its absence. The graph-based architectures (RGCN and QA-GNN) showed particular resilience to both types of ablation, suggesting their ability to leverage graph structure helps maintain performance even with reduced input quality.

These findings reveal the complementary yet distinct roles of LeNS-Align's components. While both NER and semantic alignment contribute to system performance, NER plays a more critical role in enabling accurate cross-lingual knowledge projection and question answering.

7 Conclusion

This paper introduced LeNS-Align, a novel approach for constructing knowledge bases in low-resource languages through the integration of lexical alignment, named entity recognition, and semantic alignment techniques. Our work demonstrates the effectiveness of combining these complementary approaches for cross-lingual knowledge projection, particularly for morphologically complex African languages.

The empirical results validate LeNS-Align's effectiveness across multiple evaluation dimensions. Human evaluation demonstrated over 85% accuracy in projected triples, while link prediction results indicated strong semantic coherence in the projected knowledge bases. In downstream question answering tasks, our approach improved accuracy by up to 17% over baseline methods across all target languages and datasets. The ablation studies revealed the important role of named entity recognition in producing high-quality cross-lingual alignments, with its removal leading to performance drops of up to 11 percentage points, particularly affecting entity-centric tasks.

Our analysis revealed several key insights about cross-lingual knowledge projection for low-resource languages. The effectiveness of different components varies by language family, with Nguni languages showing higher sensitivity to component removal compared to Sotho-Tswana languages. This finding suggests the need for language-family-specific adaptations in cross-lingual knowledge projection systems.

The demonstrated success of LeNS-Align in projecting knowledge bases to four South African languages opens new possibilities for expanding NLP capabilities in low-resource settings. By providing a method to construct and utilize knowledge bases in low-resource settings, this work contributes to bridging the digital divide in language technologies. Our results demonstrate that combining multiple alignment strategies with neural architectures can significantly improve cross-lingual knowledge projection and question answering capabilities for underserved languages.

Limitations

In this section, we discuss key limitations of our approach and potential areas for future work. The effectiveness of LeNS-Align is constrained by several factors:

- **Resource Dependencies:** The quality of our method depends heavily on the availability of parallel corpora and the performance of NER models in target languages. Languages with very limited parallel data or lacking robust NER systems may see reduced performance.
- **Error Propagation:** Our pipeline architecture means that errors can cascade through multiple stages. Alignment errors may lead to incorrect knowledge projection, which in turn affects QA performance. While our weighted combination approach helps mitigate this, it cannot completely eliminate such error propagation.
- **Morphological Complexity:** The agglutinative nature of the target languages poses particular challenges for alignment and knowledge projection. Our current approach may not fully capture all morphological variations, potentially missing some valid knowledge relationships.
- **Scalability:** The manual verification steps in our pipeline, while ensuring quality, may limit scalability to a larger number of languages or larger knowledge bases.

Future work could address these challenges through several avenues. The development of more robust alignment techniques that require minimal parallel data would expand the approach's applicability to more resource-constrained languages. Integrating morphological analysis tools could improve handling of agglutinative languages, while end-to-end architectures might help reduce error propagation. Additionally, exploring methods for maintaining cultural and contextual accuracy during knowledge projection represents an important direction for future research.

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A Parallel Corpus Creation

Existing parallel datasets for the four low-resource languages are mostly automatically constructed by scrapping webpages and then using a language identification model to align sentences across the languages. This approaches is fiddled with errors and also depends on the accuracy of the language identification model.

In order to obtain high-quality word alignments, we constructed a multilingual parallel corpus for isiZulu, isiXhosa, Sepedi, SeSotho and English using text data sourced from mostly South African government websites[1] and news websites. We employed a semi-automatic sentence alignment and cleaning pipeline with manual verification to ensure high alignment accuracy. The pipeline includes a web-crawling component to scrape text data from identified websites, and a cleaning and alignment component with manual intervention for handling cases of sentence misalignment and undetected errors.

Sentence alignment was performed on a per-web page basis, with manual intervention utilized to correct errors that arose from inconsistent sentence counts. We implemented a verification process by randomly selecting sentence pairs and comparing them across languages, ensuring that they were semantically equivalent. In cases where errors were identified, we implemented manual correc-

[1] https://www.gov.za/

tions through minor edits or adding missing sentences in one or more languages.

Table 1 shows the statistics of the parallel corpus for the four different language pairs, giving the number of sentences and number of words for each language pair.

B Named Entity Recognition Models

For the Named Entity Recognition (NER) component of LeNS-Align, we developed specialized NER models for each target language (isiZulu, isiXhosa, Sepedi, and SeSotho) as well as English. These models play a crucial role in identifying and aligning named entities across languages, enhancing our knowledge projection process.

B.1 Model Architecture

We implemented a Bidirectional Long Short-Term Memory (Bi-LSTM) architecture for our NER models. This choice was motivated by the Bi-LSTM's ability to capture contextual information from both directions in a sequence, which is particularly useful for NER tasks.

The model architecture consists of:

1. An embedding layer to convert input tokens into dense vector representations
2. A Bi-LSTM layer to process the embedded sequences
3. A time-distributed dense layer with softmax activation for entity classification

B.2 Training Data

We used the NCHLT Text Resource Development dataset (Eiselen and Puttkammer, 2014) for training our NER models. This dataset provides annotated text for several South African languages, including our target languages. The dataset includes annotations for person names, organization names, and location names.

B.3 Training Process

The models were trained using the following hyperparameters:

- Embedding dimension: 100
- LSTM hidden units: 100
- Batch size: 32
- Number of epochs: 10
- Optimizer: Adam with learning rate 0.001

We used an 80-10-10 split for training, validation, and test sets.

B.4 Model Performance

The performance of our NER models on the test set for each language is summarized in Table 11.

Language	Precision	Recall	F1-Score
English	0.92	0.90	0.91
isiZulu	0.83	0.81	0.82
isiXhosa	0.82	0.80	0.81
Sepedi	0.81	0.79	0.80
SeSotho	0.79	0.77	0.78

Table 11: NER Model Performance

These results demonstrate the performance of our NER models across all target languages, with English showing the highest performance. The slightly lower performance for the African languages can be attributed to the more complex morphological structures and less training data compared to English.

B.5 Integration with LeNS-Align

The NER models were integrated into the LeNS-Align pipeline to identify named entities in both the source (English) and target language texts. This information was then used to improve the alignment of named entities across languages, contributing to more accurate knowledge projection.

C mT5 Continued Pre-training

To enhance the performance of our question answering system for low-resource South African languages, we performed continued pre-training of the multilingual T5 (mT5) model (Xue et al., 2021). This process involved further training the pre-trained model on our target languages to better capture their linguistic nuances and structures.

C.1 Model Selection and Hardware

We chose the mT5-large model as our starting point due to its strong performance on multilingual tasks and its capacity to capture complex linguistic patterns. The mT5-large model has approximately 1.2 billion parameters, offering a good balance between model capacity and computational feasibility for continued pre-training.

For our computational infrastructure, we utilized a Google Cloud Compute Engine instance with the following specifications:

- Machine Type: a2-ultragpu-2g
- GPUs: 2 x NVIDIA A100 80GB
- Memory: 340GB

C.2 Pre-training Data

We compiled a diverse corpus for each target language:

- News articles from major South African news websites
- Government documents and reports
- Wikipedia articles (where available)
- Multilingual Educational materials
- Multilingual short stories

The size of the pre-training corpora varied by language, as shown in Table 12.

Language	Tokens (millions)	Unique Words
isiZulu	87	1.9M
isiXhosa	83	1.5M
Sepedi	45	0.3M
SeSotho	51	0.6M

Table 12: Size of Continued Pre-training Corpora

C.3 Pre-processing

We applied the following pre-processing steps:

- Text cleaning (removing HTML tags, standardizing punctuation)
- Tokenization using the SentencePiece model from the original mT5
- Removal of sentences with more than 50% non-alphabetic characters
- Deduplication at the document level

C.4 Continued Pre-training Process

We continued pre-training using the original mT5 objective: a denoising task where the model must reconstruct randomly masked spans of input text. The training was performe d on a Google Cloud Compute Engine instance with two NVIDIA A100 80GB GPUs.

- Batch size: 16 per GPU (32 total, with gradient accumulation steps of 8, resulting in an effective batch size of 256)
- Learning rate: 5e-5 with linear decay and 2000 warmup steps
- Number of epochs: 3 (approximately 75,000 steps)
- Maximum sequence length: 512 tokens
- Masked span length: Average of 3 tokens, determined by a Poisson distribution ($\lambda = 3$)
- Masking probability: 15% of all tokens
- Optimizer: AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 1e - 8$
- Weight decay: 0.01
- Gradient clipping: 1.0

We implemented several techniques to maximize the use of our dual-GPU setup:

- Mixed precision training (FP16) to reduce memory usage and speed up computations
- Data parallelism across the two GPUs to effectively double our processing capacity
- Gradient accumulation to fine-tune our effective batch size

C.5 Integration with LeNS-Align

The continued pre-trained mT5 model was integrated into the LeNS-Align pipeline for two main purposes:

1. Generating contextual word embeddings for semantic alignment
2. Providing a strong baseline for the question answering task, which was further enhanced by the knowledge graph integration

This continued pre-trained model played an important role in bridging the gap between the original pre-trained multilingual model and the specific requirements of our low-resource language task.