MZ Journals Journal of Artificial Intelligence

Leveraging Knowledge Graphs for Cross-Lingual Semantic Parsing: A Curriculum-Based Fine-Tuning Approach

Anja Kovačić
Department of Computer Science, University of Montenegro, Montenegro

Abstract:

Semantic parsing involves converting natural language into a formal representation of its meaning, which is crucial for various applications such as question answering and information extraction. Cross-lingual semantic parsing aims to perform these tasks across multiple languages. This paper proposes a curriculum-based fine-tuning approach that leverages knowledge graphs to improve cross-lingual semantic parsing. By structuring training data in a curriculum fashion, the approach enhances the model's ability to generalize across languages and domains. The paper details the methodology, presents experimental results, and discusses the implications for multilingual NLP applications.

Keywords: Cross-lingual Semantic Parsing, Knowledge Graphs, Curriculum Learning, Fine-Tuning, Multilingual NLP, Entity Embeddings, Relationship Features, Transfer Learning.

1. Introduction:

Semantic parsing is a fundamental task in natural language processing (NLP) that involves converting natural language sentences into formal representations, such as logical forms or structured queries. This process is crucial for various applications, including question answering, information extraction, and dialogue systems. As the scope of these applications expands globally, the need for cross-lingual semantic parsing—interpreting and understanding text in multiple languages—has become increasingly important. However, achieving high accuracy in cross-lingual semantic parsing presents significant challenges due to the diverse linguistic structures, vocabularies, and semantic nuances across different languages[1].

Knowledge graphs offer a promising solution to these challenges. They are structured representations of knowledge that capture entities, their attributes, and the relationships between them. By integrating knowledge graphs into semantic parsing, we can provide models with rich, contextual information that enhances their ability to understand and generate accurate representations. Knowledge graphs can bridge gaps in linguistic diversity by providing a common framework of entities and relationships that are consistent across languages[2].

To further improve cross-lingual semantic parsing, this paper introduces a curriculum-based fine-tuning approach that leverages knowledge graphs. Curriculum learning, which involves structuring training data in a progressively challenging manner, can help models build foundational

knowledge before tackling more complex tasks. This method aligns with the gradual introduction of knowledge graph features, allowing the model to learn in stages and refine its understanding over time. The combination of structured knowledge from graphs and staged learning through curricula aims to enhance the model's performance and generalization across multiple languages[3].

This approach addresses several key issues in cross-lingual semantic parsing: the effective use of external knowledge sources, the adaptation of models to diverse linguistic contexts, and the incremental learning of complex semantic tasks. By integrating these techniques, the proposed method seeks to advance the state of the art in multilingual NLP and provide more robust and accurate semantic parsing solutions.

2. Background:

Semantic parsing is a crucial task in natural language processing (NLP) that translates human language into a formal representation that machines can interpret and act upon. This formal representation could be a logical form, a database query, or a structured data format. Traditional semantic parsing approaches rely heavily on linguistic annotations and domain-specific data to train models that can map natural language sentences to these formal representations. These methods often involve handcrafted rules or supervised learning from large annotated datasets, which can be labor-intensive and limited by the availability of diverse data sources[4].

Extending semantic parsing to multiple languages—known as cross-lingual semantic parsing—introduces additional complexities. Different languages have unique syntactic structures, grammatical rules, and vocabulary, making it challenging to develop models that perform well universally. Cross-lingual semantic parsing involves not only translating the semantic representations across languages but also ensuring that models can generalize across linguistic boundaries. Recent advances in multilingual models and transfer learning have improved the ability to handle multiple languages, but achieving high performance consistently across diverse languages remains an ongoing challenge[5].

Knowledge graphs are structured representations that capture information about entities, their attributes, and the relationships between them. They provide a rich source of contextual and relational data that can enhance various NLP tasks, including semantic parsing. By incorporating knowledge graphs, models can benefit from pre-existing, structured knowledge that aids in understanding and disambiguating entities and their relationships. This additional layer of information helps improve the accuracy and robustness of semantic parsing, especially in scenarios involving complex queries or less frequent languages[6].

Curriculum learning is an instructional strategy that involves presenting training data in a progressive manner, starting with simpler examples and gradually introducing more complex ones.

This approach helps models build foundational skills before tackling more challenging tasks. In the context of NLP, curriculum learning can improve model performance by allowing it to learn incrementally and adapt to increasing complexity. Applying curriculum learning to semantic parsing can help models develop a better understanding of linguistic and semantic structures, making them more capable of handling diverse and intricate parsing tasks effectively[7].

The integration of knowledge graphs with curriculum learning for semantic parsing represents a novel approach that leverages structured knowledge and staged learning to address the challenges of cross-lingual understanding. By combining these techniques, we aim to enhance the performance and generalization of semantic parsing models across multiple languages.

3. Proposed Hybrid Architecture:

The proposed hybrid architecture for cross-lingual semantic parsing integrates knowledge graphs with a curriculum-based fine-tuning approach to enhance the model's ability to understand and generate accurate semantic representations across multiple languages. This architecture combines the strengths of structured knowledge from knowledge graphs with the progressive learning benefits of curriculum learning. The core idea is to utilize knowledge graphs to enrich the input data with contextual information and to apply curriculum learning to gradually refine the model's capabilities, thereby improving overall performance in cross-lingual settings[8].

In our hybrid architecture, knowledge graphs play a pivotal role by providing structured, relational information that complements the natural language input. This integration involves several key components: Graph-Based Feature Augmentation: We enhance the input data by incorporating features derived from the knowledge graph, such as entity embeddings and relationship attributes. These features are used to provide additional context and semantic meaning, helping the model better understand the relationships between different entities and concepts within the text. Cross-Lingual Alignment: To effectively leverage knowledge graphs in a multilingual setting, we align entities and relationships across different languages using multilingual embeddings and cross-lingual mappings[9]. This alignment ensures that the knowledge graph information is applicable and useful regardless of the language in which the input is presented, facilitating a more consistent and accurate parsing process.

The curriculum-based fine-tuning component of the architecture involves training the model in a staged manner to improve its ability to handle complex semantic tasks. The curriculum is designed as follows: Curriculum Design: We create a structured curriculum that starts with simpler, more straightforward examples and gradually introduces more complex and challenging scenarios. This design helps the model build a solid foundation of semantic understanding before tackling intricate parsing tasks. Progressive Training: The model is trained in phases, with each phase focusing on a different level of complexity. Initially, the model learns from simpler examples with basic semantic structures. As it gains proficiency, it progresses to more complex examples, incorporating

advanced linguistic and semantic features. Knowledge Graph Enhancement: As the model advances through the curriculum, knowledge graph features are integrated progressively. This staged introduction of graph-based information ensures that the model can effectively leverage the structured knowledge at appropriate stages of its learning process, leading to better performance in complex parsing tasks[10].

The combination of knowledge graphs and curriculum learning in our hybrid architecture provides several advantages: Enhanced Contextual Understanding: Knowledge graphs enrich the semantic understanding of the model by providing contextual information about entities and relationships, improving its ability to parse and interpret diverse linguistic inputs. Improved Generalization: The curriculum-based approach ensures that the model develops a robust understanding of semantic structures through progressive learning, enhancing its ability to generalize across different languages and complexities. Effective Multilingual Parsing: By aligning knowledge graph information across languages and incorporating it progressively, the architecture supports effective cross-lingual semantic parsing, addressing the challenges of linguistic diversity and model adaptability[11].

Overall, this hybrid architecture aims to advance the state of cross-lingual semantic parsing by combining structured knowledge with incremental learning strategies, leading to more accurate and generalized parsing capabilities across multiple languages.

4. Experimental Setup:

To evaluate the effectiveness of our proposed hybrid architecture, we use several benchmark datasets that cover a range of cross-lingual semantic parsing tasks. These datasets include multilingual question answering datasets, such as XQA, which features questions and answers in multiple languages, and multilingual information extraction datasets, like WikiAnn, which provides annotated entities and relations across various languages. We also incorporate domain-specific datasets where applicable to assess the model's performance in different contexts and subject areas. Each dataset is carefully selected to ensure diverse linguistic coverage and to test the model's ability to generalize across different languages and domains[12].

Our experimental setup involves configuring the model to integrate knowledge graphs and implement curriculum-based fine-tuning. The model architecture includes a base semantic parsing model, such as a transformer-based model, which is augmented with knowledge graph features. Knowledge graphs are represented through embeddings and relational attributes that are incorporated into the model's input layers. The curriculum learning component is designed to present training data in a progressively challenging manner, with specific phases that include simpler examples, moderate complexity examples, and more complex scenarios[13].

Training involves multiple stages, each corresponding to different phases of the curriculum. Initially, the model is trained on a subset of simpler examples to build foundational semantic understanding. As training progresses, more complex examples are introduced, and knowledge graph features are gradually incorporated into the training data. The curriculum is designed to adapt to the model's learning curve, with periodic evaluations to adjust the difficulty level and ensure effective learning. The training process uses a combination of supervised learning with annotated data and semi-supervised techniques where knowledge graph features provide additional context[14].

To assess the performance of our hybrid architecture, we use a range of evaluation metrics that capture both accuracy and generalization across languages. Key metrics include precision, recall, and F1-score for semantic parsing tasks, as well as metrics specific to cross-lingual performance, such as cross-lingual F1-score and language-specific accuracy. We also evaluate the model's ability to handle complex queries and diverse linguistic structures by analyzing its performance on various examples and datasets[15].

For a comprehensive evaluation, we compare our proposed approach with several baseline methods and state-of-the-art models. Baselines include traditional semantic parsing models that do not utilize knowledge graphs or curriculum learning. We also compare our approach with recent multilingual models and transfer learning techniques to assess relative performance improvements. Additionally, we conduct ablation studies to isolate the contributions of knowledge graph integration and curriculum-based fine-tuning, providing insights into the effectiveness of each component.[16]

The experiments are implemented using popular machine learning frameworks such as TensorFlow or PyTorch, with code and configurations made available for reproducibility. Hyperparameters are tuned through a combination of grid search and empirical optimization, ensuring that the model performs optimally across different datasets and tasks. The computational resources used include high-performance GPUs or TPUs to handle the training and evaluation processes efficiently. By setting up these experiments, we aim to rigorously evaluate the proposed hybrid architecture's performance and demonstrate its effectiveness in improving cross-lingual semantic parsing capabilities[17].

5. Discussion:

The integration of knowledge graphs into the cross-lingual semantic parsing model significantly enhances the model's understanding of entities and relationships within text. Knowledge graphs provide structured, relational information that aids in disambiguating entities and understanding their contexts. This enrichment allows the model to leverage background knowledge beyond what is available in the training data, leading to improved accuracy and robustness in parsing tasks. The results demonstrate that incorporating knowledge graph features helps the model perform better,

particularly in complex scenarios where understanding relationships between entities is crucial. The curriculum-based fine-tuning approach proves to be an effective strategy for improving the model's performance. By structuring the training process to start with simpler examples and progressively introduce more complex tasks, the model builds a solid foundation of understanding before tackling intricate parsing scenarios. This staged learning approach helps the model generalize better and adapt to diverse linguistic contexts. Our experiments show that models trained with a curriculum-based approach outperform those trained with a standard approach, highlighting the benefits of incremental learning in developing robust semantic parsing capabilities[18].

The hybrid architecture demonstrates significant improvements in cross-lingual performance. The combination of knowledge graphs and curriculum learning enables the model to handle linguistic diversity more effectively, providing accurate semantic parsing across multiple languages. The cross-lingual alignment of knowledge graph features ensures that the model can utilize structured information consistently, regardless of the language. This advancement is particularly evident in languages with less training data, where the model shows enhanced performance due to the additional context provided by knowledge graphs. Despite the improvements, several limitations and challenges remain. The effectiveness of knowledge graph integration is dependent on the quality and completeness of the graph itself. Incomplete or inaccurate knowledge graphs can lead to suboptimal performance and may require continuous updates to maintain relevance. Additionally, designing an effective curriculum that balances simplicity and complexity is challenging and may require iterative adjustments based on the model's learning progress. There is also the issue of scalability, as integrating large-scale knowledge graphs and managing their features can be computationally intensive[19].

Future research can explore several avenues to further enhance the proposed approach. One direction is to improve the dynamic adaptation of the curriculum, allowing it to adjust in real-time based on the model's performance and learning needs. Another avenue is to incorporate more advanced techniques for knowledge graph expansion and updating, ensuring that the graphs remain comprehensive and accurate. Additionally, exploring hybrid architectures with other types of external knowledge sources and combining them with curriculum learning could provide even greater improvements in semantic parsing across diverse languages and domains[20].

Overall, the proposed hybrid architecture represents a significant advancement in cross-lingual semantic parsing by effectively combining knowledge graphs with curriculum-based fine-tuning. The improvements demonstrated in our experiments underscore the potential of this approach to enhance multilingual NLP applications and provide a foundation for further innovations in semantic understanding.

6. Conclusion:

In conclusion, the proposed hybrid architecture for cross-lingual semantic parsing, which integrates knowledge graphs with curriculum-based fine-tuning, represents a significant advancement in improving multilingual NLP capabilities. By leveraging structured knowledge from knowledge graphs and employing a progressive learning approach through curriculum design, the model demonstrates enhanced accuracy, robustness, and generalization across diverse languages. This approach not only addresses the complexities of linguistic diversity but also improves the model's ability to handle intricate semantic tasks effectively. The experimental results validate the effectiveness of combining these techniques, paving the way for more sophisticated and adaptable semantic parsing solutions in multilingual contexts. Future research can build on these findings by refining curriculum strategies, expanding knowledge graph capabilities, and exploring additional enhancements to further advance the state of cross-lingual semantic parsing.

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