TOWARDS GEOSPATIAL KNOWLEDGE GRAPH INFUSED NEURO-SYMBOLIC AI FOR REMOTE SENSING SCENE UNDERSTANDING

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ABSTRACT

Deep learning has proven its effectiveness in numerous tasks for remote sensing scene understanding. However there is an increasing interest to explore fusion of domain-specific background information to the deep neural network to further improve its performance. Remote sensing researchers are also working towards developing models that generalize and adapt to multiple applications. Generalization challenges coupled with the scarcity of large corpora of high-quality noise-free labelled data, have together fueled an interest for leveraging background information. Knowledge graphs serve as excellent choice to represent domain-specific information in a structured, standardized and extensible manner. Integrating symbolic knowledge representations in the form of Knowledge Graph Embedding (KGE) to perform neuro-symbolic reasoning is an emerging research direction promising significant impacts. This vision paper seeks to position ideas and provoke early thoughts toward advancing neuro-symbolic artificial intelligence in the context of geospatial challenges. Specifically, it conceptualizes and elaborates on an architecture for infusing geospatial knowledge from knowledge graph in a deep neural network pipeline. As guiding case studies - land-use land-cover classification, object detection and instance segmentation can benefit from infusing spatio-contextual information with remote sensing imagery. The discussion further reflects on and articulates the challenges and explainable AI opportunities anticipated when scaling and maintaining large-scale geospatial knowledge graphs.

***Index Terms*—** geospatial knowledge graphs, neuro-symbolic, knowledge-infused learning, remote sensing, scene understanding, deep learning, representation learning, knowledge graph embedding

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1. INTRODUCTION

The remote sensing research community has made significant progress by leveraging neural networks for a wide variety of applications. In particular, deep neural networks have enabled researchers to automatically extract features from earth observation (EO) data, without having to explicitly hand-craft features. Remote sensing applications for humanitarian mapping such as monitoring of natural and man-made disasters including earthquakes, forest fires, landslides, etc., demand speedy response and have greatly benefited due to the rapid inferencing that deep learning entails. Technological advancements in High Performance Computing (HPC), by developing high-compute capable systems, have also contributed to this widespread adoption of deep neural networks for EO data analysis.

Although deep learning has proven its efficacy in numerous domains including remote sensing, it is largely dependent on huge corpora of data for the model to effectively learn from. Large repositories of high-quality, noise-free, labeled data require significant man-hours for curation and thus are not easy to consolidate. Also it is difficult to interpret and trace the reasoning that a deep neural network employed during inferencing. This raises trust concerns when relying on deep neural networks as traceability and explainability of predictions is uncertain. There is also significant interest towards transfer learning - attempting to generalize and develop models that could potentially adapt themselves to specific domains and hypothetically yield significant performance improvements but with few training examples. The scarcity of high-quality training data, combined with increasing expectations to further improve the deep learning model performance in addition to efforts towards efficient domain adaptation, have collectively led researchers to explore an alternate research direction that rather ingests domain-specific background information. The background information to be consumed by a deep neural network is required to be structured and extensible. The graph-based representation consisting of entities and their relations - collectively termed as Knowledge Graph serve as an excellent candidate.

Across numerous domains, Knowledge Graphs (KGs) continue to revolutionize data integration using a graph-structured model. Knowledge graphs being utilized for repre-

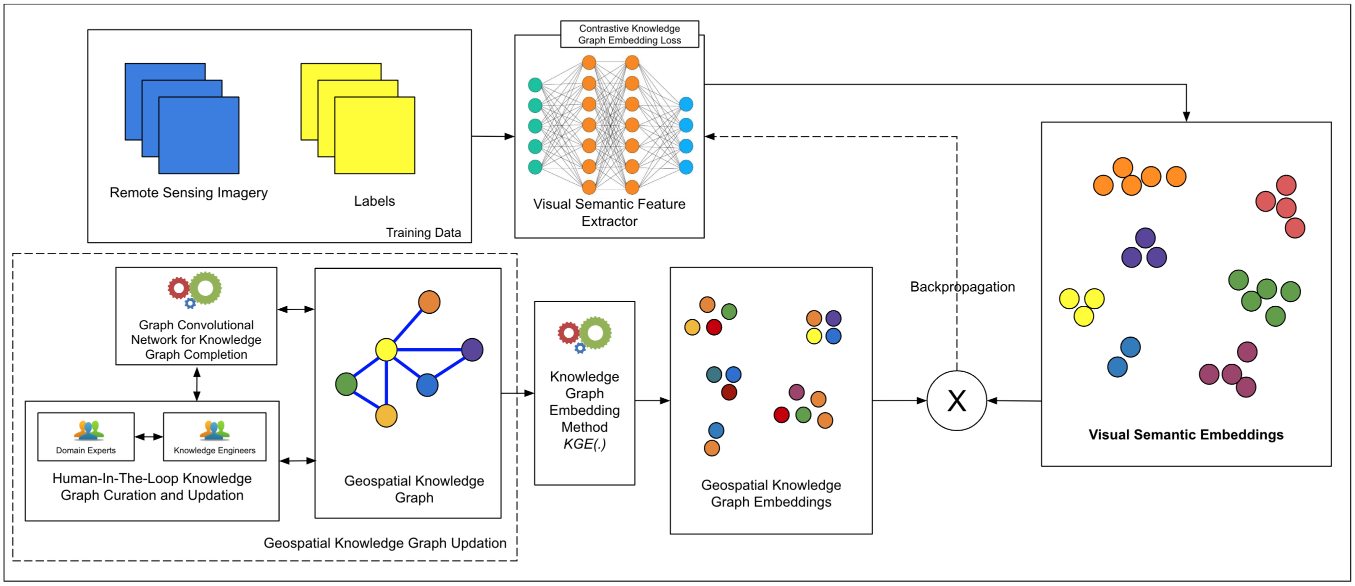

Fig. 1. Conceptual Architecture of Geospatial Knowledge Graphs Infused Neuro-Symbolic AI for Remote Sensing Scene Understanding Tasks, adapted from [1]

senting domain-specific background information with DNNs also opens up opportunities for the DNNs to learn relations between the entities in the KG.

This vision paper analyses and discusses on early works in the research area of knowledge-infused learning. It seeks to position ideas towards advancing the emerging research area of neuro-symbolic GeoAI. It conceptualizes and puts forth a conceptual architecture for knowledge-infused neuro-symbolic AI for remote sensing scene understanding tasks, by leveraging spatial and contextual relations between land-use land cover classes embedded in a geospatial knowledge graph of remote sensing scenes. It further elaborates on the core components of the proposed architecture. It also reflects upon and highlights the anticipated challenges and opportunities for research in the area of geospatial knowledge graph infused learning.

2. KNOWLEDGE-INFUSED LEARNING

Neuro-symbolic AI[2][3][4][5] is an emerging class of AI that seeks to combine - (1) data-driven and (2) knowledge-driven strategies that have so far been utilized individually for building AI systems. Deep Neural Networks - (a data-driven strategy) are excellent at learning from huge corpus of data, however they do not entail traceability and interpretabiltiy and also lack methods for integration of external knowledge. Knowledge-based reasoning (a knowledge-driven strategy)[6][7] utilizes axioms to infer and make explicit the otherwise implicit knowledge, however scalability and performance remain a bottleneck for this strategy.

Neuro-symbolic AI seeks to combine the strengths of these two strategies by leveraging symbolic knowledge representations to guide the learning process of deep neural networks. This specific research direction within the paradigm of neuro-symbolic reasoning is termed as ”Knowledge-infused Learning”. The research paradigm of knowledge-infused learning has begun to receive significant attention especially from the computer vision community. The research [1] discusses the strategy of using KG as a Trainer where the visual-semantic embedding is learned using contrastive loss for reproducing the semantic embedding using visual information. Research studies [8] and [9] have proposed leveraging KG embedding for qualitative spatio-temporal reasoning and zero-shot learning respectively. The survey [10] highlights different methods for translating knowledge graphs into their corresponding vector representations termed as knowledge graph embedding (KGE) and further elaborates on the different approaches for integrating a KG with a deep neural network pipeline. Along similar lines, [9] proposes a novel Deep Alignment Network (DAN) with custom optimizations for cross-modal matching of visual and semantic features, targeting the problem of Zero Shot Learning (ZSL).

3. GEOSPATIAL KG-INFUSED LEARNING FOR RS SCENE UNDERSTANDING

This paper proposes a conceptual architecture depicted in Figure 1, for integrating Geospatial Knowledge Graphs in a Deep Neural Network pipeline for the tasks of remote sensing scene understanding. In that regard, it envisions to improve the performance of down-stream tasks such as land-use land-cover classification, object detection, instance segmentation among

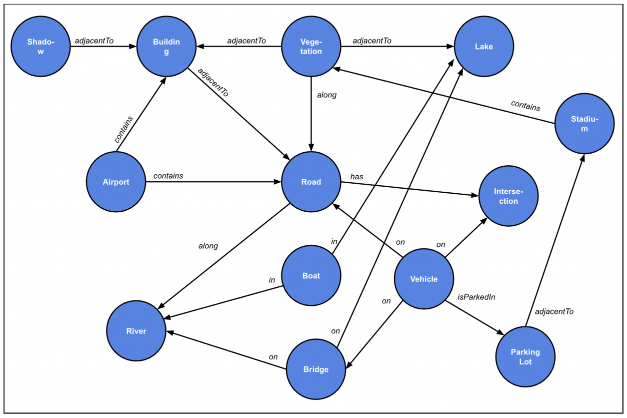

Fig. 2. Geospatial knowledge graph depicting the objects and their spatial relations in a remote sensing scene adapted from the Remote Sensing Scene Ontology[11]

others by fusing geospatial knowledge with state-of-art neural approaches.

3.1. Proposed Conceptual Architecture

The architecture proposed in this paper seeks to learn the joint visual-semantic embedding by fusing the symbolic knowledge from knowledge graphs with the visual features from the remote sensing scenes. In that regard, the core components of the architecture are discussed as follows:

3.1.1. Geospatial Knowledge Graph

A knowledge graph refers to a data structure that houses information structured in a node-edge form where an edge denotes a relation and a node denotes an entity or a concept. A geospatial knowledge graph can refer to a knowledge graph conveying geospatial information and may include spatial, temporal and contextual attributes and relations. The research works [11] and [12] put forth the Remote Sensing Scene Ontology (RSSO) to represent a remote sensing scene in the form of a geospatial knowledge graph. Figure 2 depicts a geospatial knowledge graph for an urban remote sensing scene consisting of land-use land-cover regions represented as nodes and their spatial relations with each other as edges. The Corine Land Cover (CLC)[1], WorldKG [13] and KnowWhere [14] are relevant examples of geospatial knowledge graphs that can be potentially leveraged for infusion with a deep neural network to further improve its performance for down-stream tasks. To address the challenge posed for scaling and maintaining the GeoKG, we posit the use of Graph Neural Networks for KG completion in tandem with a Human-In-The-Loop strategy for timely curation and updates.

[1]https://land.copernicus.eu/pan-european/corine-land-cover

3.1.2. Knowledge Graph Embedding

Knowledge Graph Embedding (KGE) refers to the semantically meaningful vector representation of nodes and edges of a knowledge graph in a lower dimensional vector space. A KGE method translates a given knowledge graph to its corresponding vector representation. The primary design rationale underlying a KGE method is to effectively capture from the KG, the patterns of - symmetry, asymmetry, inversion and composition in addition to conforming to hierarchies, type constraints, transitivity and long-range dependencies. The survey [15] analyses and documents some of different KGE methods, commenting on their performance. A recent research study [8] proposed HyperQuaternionE - a novel hyperbolic knowledge graph embedding model focusing on qualitative spatial and temporal reasoning to capture the properties of a geospatial knowledge graph. Graph Neural Networks (GNNs) as a method to learn Knowledge Graph Embedding (KGE)[16] are also receiving significant attention. The conceptual architecture proposed in this work, is designed to be KGE-method agnostic, thus enabling to leverage any state-of-art KGE method suitable for geospatial knowledge graphs.

3.1.3. Visual Semantic Features Extractor

This component is structured to learn the joint visual-semantic embedding by enabling the Knowledge Graph Embedding (KGE) to supervise the training of the deep neural network. The contrastive knowledge embedding loss as proposed in [1], compares the output of the visual feature extractor with the knowledge graphs embedding (KGE) to learn a visual-semantic embedding space. This strategy of leveraging *Knowledge Graph as a Trainer* has proven to outperform a conventional visual deep neural network trained with cross-entropy loss for the problem of road sign recognition[1]. This component would thus enable infusion of explicit geospatial knowledge extracted using Knowledge Graph Embedding (KGE) from the geospatial KG into the deep neural network. The trained feature extractor can then be fine-tuned for a specific down-stream task such as land-use land-cover classification that would potentially benefit from learning the explicitly defined spatial and contextual axioms from the GeoKG.

4. DISCUSSION

In the background of neuro-symbolic AI for geospatial applications, structured information consisting of explicit spatial relations between land-use land-cover regions, objects of interest, along with contextual axioms can be of great significance for remote sensing scene understanding tasks such as semantic segmentation, classification, object detection and information retrieval. Towards advancing the thrust area of neuro-symbolic GeoAI, this vision paper discussed early works in this area and put forth a conceptual architecture for infusing geospatial knowledge from GeoKG in a deep neural network pipeline. The primary challenges identified towards Geospatial Knowledge Graph Infused Learning include - *(1) Knowledge Graph Creation and Interoperability:* Formalization and subsequent standardization of domain-specific information in the form of concepts, attributes and relations pertaining to an application; and *(2) Scalability and Updation of GeoKG:* As more knowledge is iteratively infused into the KG, the graph would need to be continuously monitored for consistency and correctness. As the GeoKG would expand, scalability challenges pertaining to disk storage, query latency and retrieval are expected to manifest. In addition to these, manual update and maintenance of very large-scale KGs is not feasible and would subsequently require automated solutions such as graph neural networks based KG completion and Human-In-The-Loop strategies. It is envisaged that Geospatial KG-Infused Neuro-Symbolic AI would consequently reinforce explainability, traceability and trustworthiness in AI in addition to advancing the generalization capabilities and performance of deep neural network based GeoAI workflows.

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