Preface (CSSA)

Since the beginning of the 2000s, there has been an increasing number of studies and standards proposed for generating large scale symbolic representations of knowledge (known as Knowledge Graphs (KGs)) out of heterogeneous resources such as text, images, etc. Moreover, there have been many advances in symbolic reasoning, as well as their applications to various fields. Recently, sub-symbolic methods have gained momentum. These methods aim at generating distributed representations from several resources such as text or symbolic representations (Graph Neural Networks, KG embeddings, etc.). These sub-symbolic methods for symbolic representations mainly focus on the task of KG completion. However, they have also recently been used for various tasks, e.g., in Natural Language Processing (NLP). The future perspective for these methods would be a combination of these approaches, leading to a form of neurosymbolic reasoning. Advances in the real world applications related to these methods will also serve as a stepping stone in the proving their practicality.

Overview (KGRL)

Knowledge Graphs are becoming the standard for storing, retrieving, and querying structured data. In academia and industry, they are increasingly used to provide background knowledge. Over the last years, several research contributions were made which show that machine learning, especially representation learning, can be successfully applied to knowledge graphs enabling inductive inference about facts with unknown truth values.
Brief Introduction

Several of these approaches encode the graph structure that can be used for tasks such as link prediction, node classification, entity resolution, recommendation, dialogue systems, and many more. Although proposed graph representations can capture the complex relational patterns over multiple hops, they are still insufficient to solve more complex tasks such as relational reasoning .For this kind of tasks, we envision a need for representations with more expressive power, which could include representation in non-Euclidean space. This starts by capturing e.g., type constrained, transitive or hierarchical relations in an embedding up to learning expressive knowledge representations languages like first-order logic rules.

Furthermore, most approaches for learning representations for knowledge graphs focus on transductive settings, i.e., all entities and relations need to be seen during training, not allowing predictions for unseen elements. For evolving graphs, approaches are required that generalize to unseen entities and relations. One avenue of research to address inductiveness is to employ multimodal approaches that compensate for missing modalities, and recently meta-learning approaches have successfully been applied

Lately, the generalization of deep neural network models to non-Euclidean domains such as graphs and manifolds is explored They study the fundamental aspects that influence the underlying geometry of structured data for building graph representations Recent advances in graph representation learning led to novel approaches such as convolutional neural networks for graphs attention-based graph networketc. Most graphs here are either undirected or directed with both discrete and continuous node and edge attributes representing types of spatial or spectral data.

In this workshop, we want to see novel representation learning methods, approaches that can be applied to inductive learning and to (logical) reasoning and works that shed insights into the expressive power, interpretability, and generalization of graph representation learning methods.
Also, we want to bring together researchers from different disciplines but united by their adoption of earlier mentioned techniques from machine learning.