CS520

Knowledge Graphs

What should AI Know ?

How do Knowledge Graphs Relate to AI?

1. Introduction

In this concluding chapter, we will discuss different ways in which the knowledge graphs intersect with Artificial Intelligence (AI). As we noted in the opening chapter, use of labeled directed graphs for knowledge representation has been around since the early days of AI. Our focus for discussion in this chapter is on the use of knowledge graphs in the recent developments. Consequently, we have chosen three themes for further elaboration: knowledge graphs as a test bed for AI algorithms, emerging new specialty area of graph data science, and knowledge graphs in the broader context of achieving the ultimate vision of AI.

2. Knowledge Graphs as a Test-Bed for Current Generation AI Algorithms

Knowledge graphs have a two way relationship with AI algorithms. On one hand, knowledge graphs enable many of the current AI applications, and on the other, many of the current AI algorithms are used in creating the knowledge graphs. We will consider this symbiotic synergy in both directions.

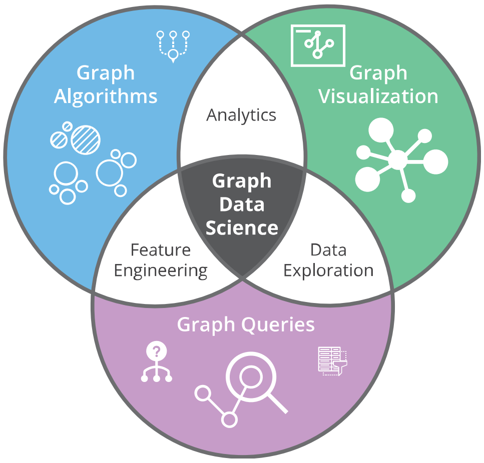
Personal assistants, recommender systems, and search engines are applications that exhibit intelligent behavior and have billions of users. It is now widely accepted that these applications behave better if they can leverage knoweldge graphs. A personal assistant using a knowledge graph can get more things done. A recommender system with a knowledge graph can make better recommendations. Similarly, a search engine can return better results when it has access to a knowledge graph. Thus, these applications provide a compelling context and a set of requirements for knowledge graphs to have an impact on immediate product offerings.

To create a knowledge graph, we must absorb knowledge from multiple information sources, align that information, distill key pieces of knowledge from the sea of information, and mine that knowledge to extract the wisdom that would influence the intelligent behavior. The AI techniques play an important role at each step of knowledge graph creation and exploitation. For extracting information from sources, we considered entity and relation extraction techniques. For aligning information across multiple sources, we used techniques such as schema mapping and entity linking. To distill the extracted information, we can use techniques such as data cleaning and anamaly detection. Finally, to extract the wisdom from the graph we used inference algorithms, natural language question answering, etc.

Hence, knowledge graphs enable AI systems, which provide motivation and a set of requirements for them. AI techniques are also fueling our ability to create the knowledge graph economically and at scale.

3. Knowledge Graphs and Graph Data Science

Graph data science is an emerging discipline that aims to derive knowledge by leveraging structure in the data. Organizations typically have access to huge amount of data, but their ability to leverage this data has been limited by a collection of preset reports that are generated using that data. The discipline of graph data science is transforming that experience by combining graph algorithms, graph queries and visualizations into products that significantly speedup the process of gaining insights.



As we saw in the analytics-oriented use cases for financial industry, businesses are keen to exploit the relational structure in their data to make predictions about risk, new market opportunities, etc. For making predictions, it is common to use machine learning algorithms that rely on careful feature engineering. As machine learning algorithms are now becoming a commodity and can be used as off-the-shelf products, there is emerging a distinct skill of feature engineering. Feature engineering requires a deep understanding of the domain as well as understanding of the workings of machine learning algorithms.

It is this synergy among the traditional graph-based system and the availability of machine learning to identify and predict relational properties in data, that has catalyzed the creation of the sub-discipline of graph data science. Because of the high impact use cases possible through graph data science, it is becoming an increasingly sought after software skill in the industry today.

4. Knowledge Graphs and Longer-Term Objectives of AI

Early work in AI focused on explicit representation of knowledge and initiated the field of knowledge graphs through representations such as semantic networks. As the field evolved, semantic networks were formalized, and led to several generations of representation languages such as description logics, logic programs, and graphical models. Along with the development of these languages, an equally important challenge of authoring the knowledge in the chosen formalism was addressed. The techniques for authoring knowledge have ranged from knowledge engineering, inductive learning, and more recently deep learning methods.

To realize the vision of AI, an explicit knowledge representation of a domain that matches human understanding and enables reasoning with it is essential. While in some performance tasks such as search, recommendation, translation, etc., human understanding and precision are not hard requirements, but there are numerous domains where these requirements are essential. Examples of such domains include knowledge of law for income tax calculations, knowledge of a subject domain for teaching it to a student, knowledge of a contract so that a computer can automatically execute it, etc. Furthermore, it is being increasingly recognized that for many situations where we can achieve intelligent behavior without explicit knowledge representation, the behavior still needs to be explainable so that humans can understand the rationale for it. For this reason, we believe, that an explicit representation is essential.

There is narrative in the research community that knowledge engineering does not scale, and that the natural language processing, and machine learning methods scale. Such claims are based on an incorrect characterization of the tasks addressed by natural language processing. For example, using language models, one may be able to calculate word similarity, but the language model gives us no information on the reason for that similarity. In contrast, when we use a resource such as Wordnet for calculating word similarity, we know exactly the basis for that similarity. A language model might have achieved scale, but at the cost of human understandability of its conclusions. The success of web-scale methods is crucially dependent on the human input in the form of hyperlinks, click data, or explicit user feedback. Leveraging these scalable and automated methods to create human understandable knowledge graphs, and using them to achieve intelligent behavior truly addresses how an AI system should function.

It is well-known that a simple labeled graph representation is insufficient for many of the performance tasks desired from AI. That was precisely the reason for developing more expressive representation formalisms. Due to a need to address the economics and the scale of creating such representation, expressive formalisms are less commonly used, but it does not imply that the problems such formalisms address have been solved by the newer deep learning and NLP methods. Some examples of such problems include self-awareness, commonsense reasoning, model-based reasoning, experimental design, etc. A self-aware system can recognize and express the limits of its own knowledge. Commonsense understanding of the world gives a system ability to recognize obviously nonsensical situations, e.g., a coin that has a date stamp of 1800 B.C., could not be a real coin. Current language models can generate sentences that make sense only up to a certain length, but they lack an overall model of the narrative to generate longer coherent texts. Creating AI programs that can master a domain, formulate a hypothesis, design an experiment, and analyze its results is a challenge that is out of reach of any of the current generation systems.

5. Summary

We considered three different ways the work on knowledge graphs intersect with AI: as a test-bed for evaluating machine learning and NLP algorithms, as an enabler of the emerging discipline of graph data science, and as a core ingredient to realizing the long-term vision of AI. We hope that this volume will inspire many to leverage what is possible through the scalable creation of knowledge graphs and their exploitation. And yet, we should not let go a longer-term vision of creating expressive, and human understandable representations that can also be created scalably.

Exercises

Exercise 10.1. Which of the following statements is false?

- (*a*) Knowledge graphs have been an essential ingredient to the success of personal assistants.
- (*b*) Machine learning is indispensable for creating large-scale modern knowledge graphs.
- (*c*) Knowledge graphs will eventually be unnecessary for the success of AI applications.
- (*d*) Knowledge graphs significantly expand the inferences possible using natural language.
- (*e*) Technology is now available to create rudimentry knowledge graphs from images.

Exercise 10.2. Which of the following is out of scope of graph data science?

- (*a*) Transaction management
- (*b*) Feature engineering
- (*c*) Visual Analytics
- (*d*) Block Chain
- (*e*) Semantic transformation of logical expressions

Exercise 10.3. Which of the following is true about how knowledge graphs might relate to the future of AI?

- (*a*) Property graphs provide a sufficient representation for us to build future intelligent applications.
- (*b*) Expressive logic-based representations are what we need for future intelligent applications.
- (*c*) Some explicit representation similar to knowledge graphs is required, but exactly what is needed, is open for future research.
- (*d*) Future techniques of AI will have reducing reliance on explicit representation.
- (*e*) The goal of AI should be to eliminate the need for any representation.