Deep Learning on Graphs for Natural Language Processing

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CCS CONCEPTS

• **Computing methodologies → Natural language processing**; **Neural networks**.

KEYWORDS

Natural Language Processing, Deep Learning, Graph Learning, Graph Neural Networks

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1 BRIEF DESCRIPTION

This tutorial of **D**eep **L**earning on **G**raphs for **N**atural **L**anguage **P**rocessing (DLG4NLP) will cover relevant and interesting topics on applying deep learning on graph techniques to NLP, including automatic graph construction for NLP, graph representation learning for NLP, advanced GNN based models (e.g., graph2seq, graph2tree, and graph2graph) for NLP, and the applications of GNNs in various NLP tasks (e.g., machine translation, natural language generation, information extraction and semantic parsing). In addition, a hands-on demonstration session will be included to help the audience gain practical experience on applying GNNs to solve challenging NLP problems using our recently developed open source library – Graph4NLP, the first library for researchers and practitioners for easy use of GNNs for various NLP tasks.

2 MOTIVATION

Deep learning has become the dominant approach in Natural Language Processing (NLP) research today, especially when applied on large scale corpora. Conventionally, sentences are typically considered as a sequence of tokens in NLP tasks. Hence, popular deep learning techniques such as recurrent neural networks (RNN) and convolutional neural networks (CNN) have been widely applied for modeling text sequence.

However, there is a rich variety of NLP problems that can be best expressed with a graph structure. For instance, the structural and semantic information in sequence data (e.g., various syntactic parsing trees like dependency parsing trees and semantic parsing graphs like abstract meaning representation (AMR) graphs) can be exploited to augment original sequence data by incorporating the task-specific knowledge. As a result, these graph-structured data can encode complicated pairwise relationships between entity tokens for learning more informative representations. However, it is well-known that deep learning techniques that were disruptive for Euclidean data such as images or sequence data such as text are not immediately applicable to graph-structured data. Therefore, this gap has driven a tide in research for deep learning on graphs, especially in development of graph neural networks (GNN).

This wave of research at the intersection of deep learning on graphs and NLP has influenced a variety of NLP tasks. There has seen a surge of interests in applying/developing various types of GNNs and achieved considerable success in many NLP tasks, ranging from classification tasks like text classification and relation extraction, to generation tasks like machine translation, question generation and summarization. Despite these successes, deep learning on graphs for NLP still face many challenges, namely,

- Automatically transforming original text sequence data into highly graph-structured data. Such challenges are profound in NLP since most of the NLP tasks use the text sequence as the original inputs. Automatic graph construction from the text sequence to take into account underlying structural information is a critical step in the use of graph neural network models for NLP problems.
- Effectively modeling complex data that involves mapping between graph-based inputs and other highly structured output data such as sequences, trees, and graph data with multi-types in both nodes and edges. Many generation tasks in NLP such as SQL-to-Text, Text-to-AMR, Text-to-KB are emblematic of such challenges.

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3 OBJECTIVES

This tutorial aims to motivate and explain a topic of emerging importance for AI. After attending the tutorial, the audience are expected to 1) have a comprehensive understanding of basic concepts of deep learning on graphs for NLP; 2) learn major recent advances of research in the intersection of NLP and GNNs; and 3) explore novel research opportunities of GNNs for NLP, and learn how to use or even design novel algorithms with GNNs for effectively coping with various NLP tasks.

4 DETAILED DESCRIPTION

This tutorial of **D**eep **L**earning on **G**raphs for **N**atural **L**anguage **P**rocessing (DLG4NLP) is timely for the computational linguistics community, and covers relevant and interesting topics, including automatic graph construction for NLP, graph representation learning for NLP, various advanced GNN based models (e.g., graph2seq, graph2tree, and graph2graph) for NLP, and the applications of GNNs in various NLP tasks (e.g., machine translation, natural language generation, information extraction and semantic parsing). In addition, a hands-on demonstration session will be included to help the audience gain practical experience on applying GNNs to solve challenging NLP problems using our recently developed open source library – Graph4NLP, the first library for researchers and practitioners for easy use of graph neural networks for various NLP tasks.

We will start with a broad overview of various NLP problems that deal with graph structured data, and highlight some challenges of modeling graph-structured data in the field of NLP with traditional graph-based algorithms (e.g., random walk methods, spectral graph clustering, graph kernels). We will then introduce the general idea as well as some commonly used models of GNNs, which have been an emerging popular tool to deal with graph structured data. After the introduction of NLP tasks on graph data and graph neural networks, we will describe some important yet challenging techniques for deep learning on graphs for NLP, including automatic graph construction for NLP, graph representation learning for NLP and various advanced GNN based models (e.g., graph2seq, graph2tree, and graph2graph) for NLP. Some representative NLP applications are introduced following the methods. When introducing the NLP applications, we also include a hands-on demonstration session on how to quickly build GNN-based models for solving NLP tasks using our recently developed open source library Graph4NLP, which was designed for the easy use of GNNs for NLP. We will summarize the tutorial and highlight some open directions in the end of this tutorial. The Introduction, Methodologies, Applications, and Conclusion and Open Directions form the four segments of this tutorial.

5 TUTORIAL OUTLINE

The intended duration of this tutorial is half-day (i.e., 3 hours plus breaks).

(1) (20 minutes) Introduction
- (a) Natural Language Processing: A Graph Perspective
- (b) Graph Based Algorithms for Natural Language Processing
- (c) Deep Learning on Graphs: Graph Neural Networks
  - (i) Foundations
  - (ii) Methodologies
  - (iii) Applications in Natural Language Processing: An Overview
  - (iv) High-level DLG4NLP Roadmap

(2) (70 minutes) Methodologies
- (a) Automatic Graph Construction from Text
  - (i) Static Graph Construction
  - (ii) Dynamic Graph Construction
- (b) Graph Representation Learning for NLP
  - (i) Graph Neural Networks for Improved Text Representation
  - (ii) Graph Neural Networks for Joint Text & Knowledge Representation
  - (iii) Graph Neural Networks for Various Graph Types
- (c) GNN Based Encoder-Decoder Models
  - (i) Graph-to-Sequence Models
  - (ii) Graph-to-Tree Models

(3) (60 minutes) Applications
- (a) Semantic Parsing
- (b) Machine Reading Comprehension
- (c) Information Extraction
- (d) Natural Language Generation
- (e) Machine Translation

(4) (20 minutes) Hands-on Demonstration
- (a) A Brief Overview of the Graph4NLP Library
- (b) Live Demo

(5) (10 minutes) Conclusion and Open Directions

6 READING LIST

We aim to make the tutorial self-contained. For trainees interested in reading important studies before the tutorial, we recommend the following papers regarding GNNs [6, 7, 9], automatic graph construction for NLP [1–3, 11], joint text and knowledge representation learning [5, 10], modeling directed graphs [3, 12] and heterogeneous graphs [1, 4], and GNN based encoder-decoder models [3, 8, 12].

7 RELEVANCE TO THE INFORMATION RETRIEVAL COMMUNITY

This new wave of GNN research has achieved great success in various applications such as Natural Language Processing, Computer Vision, recommender systems, drug discovery and so on. This tutorial introduces he broad and successful applications of GNNs in the NLP field which could inspire and spur the research on GNNs in the IR community because the NLP community and IR community share many common interests such as text/knowledge representation, information extraction, content analysis and question answering. We believe that audience from the IR community will find this tutorial helpful and inspiring.

8 SIMILAR TUTORIALS

We have identified two related previous tutorials as follows:

(1) A tutorial titled "Graph Neural Networks for Natural Language Processing" was presented by other researchers at EMNLP 2019. Different from this tutorial, our tutorial pinpoints several important and unique challenges of applying GNNs to NLP. Specifically, we propose a new taxonomy, which systematically organizes GNN for NLP approaches

along three axes: graph construction, graph representation learning, encoder-decoder models. For each challenge, we summarize and categorize the recent technical advances, and highlight remaining challenges and future directions. Finally, our tutorial includes a hands-on demonstration session, which is based on our recently developed open source library- Graph4NLP.

(2) A tutorial titled "Deep Graph Learning: Foundations, Advances and Applications" was presented by our lead tutor and other researchers at KDD 2020. However, this tutorial mainly focuses on 1) training deep GNNs; 2) robustness of GNNs; 3) scalability of GNNs; and 4) self-supervised and unsupervised learning of GNNs. This tutorial pays very little attention on NLP domain. Differently, our tutorial pinpoints several important and unique challenges of applying GNNs to NLP, which is a very fastgrowing direction attracting many researchers and practitioners from the ML/DM and NLP domains. This tutorial is designed to fill this gap.

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