Incrementally Learning Structured Knowledge for Question Answering

Contact: Debjit Paul | debjit.paul@epfl.ch

Motivation: Humans learn and understand new concepts by building on our own memories and applying prior knowledge. On the other hand, machines don't possess prior knowledge. Hence, several works (ConceptNet, ATOMIC, WordNet, WebChild) focused on building knowledge graphs (KGs) from scratch. We have also seen that training state-of-the-art language models on a KG can learn the structure of knowledge (COMET). However, most current knowledge graphs are incomplete. Therefore, when additional knowledge is included in a knowledge graph, one needs to train the NLP system from scratch.

Recently, with the advancement in transfer learning[1] methods, researchers have focused on addressing continual learning [2] for NLP tasks. However, studies have shown when a model is incrementally fine-tuned on new data distribution; it risks forgetting (concept drift, catastrophic forgetting) how to treat instances of the previously learned ones.

Goal: We want to build NLP systems that are environmentally friendly (less training time); we think continual learning will be an important research direction. We will focus on two different kinds of continual learning (a) **class incremental learning** for knowledge graphs (b) **task incremental learning** for NLP tasks. In this project, we are interested in the research questions: (a) how to design a method that can incrementally learn about new structures in a knowledge graph without forgetting? and (b) how to evaluate the incrementally learned knowledge on different Question Answering tasks incrementally? We expect the method will create a knowledge model that can be incrementally used to address different NLP downstream tasks.

Steps:

1. Read the related work papers and blog posts [1-3] to learn about continual learning.
2. Familiarize yourself with the existing datasets which require NLP models to perform reasoning [4-7] and knowledge integration models [8-10].
3. Implement some existing SOTA class incremental learning methods for knowledge graphs like ConceptNet, ATOMIC, and Aristo Tuple KB.
4. Propose a new knowledge integration method to address the different reasoning datasets incrementally.

Requirements:

1. Strong Knowledge in Machine Learning and NLP.
2. Interested in working with state-of-the-art NLP models.
3. Efficient in PyTorch or Tensorflow.
4. Being motivated and ready to produce publishable work.
5. (Optional) experienced with HuggingFace Transformers library.

[1] Transfer learning method deals with transferring knowledge from a source task to a target task to improve the performance of the target task
[2] Continual Learning is building complicated skills on top of those already developed.

Related Works:

[1] *Lifelong Graph Learning*, Link: https://arxiv.org/pdf/2009.00647.pdf
[2] Summary Paper on class incremental learning : https://arxiv.org/pdf/2010.15277.pdf
[3] Blog Post :
(a)https://www.deepmind.com/blog/enabling-continual-learning-in-neural-networks
(b)https://developpaper.com/technology-blog-on-continuous-learning
[4] Commonsense Reasoning 2.0 Dataset Link:
https://leaderboard.allenai.org/csqa2/submissions/get-started
[5] eQASC: Multihop Explanations for QASC Link: https://allenai.org/data/eqasc
[6] DREAM: Improving Situational QA by First Elaborating the Situation
https://arxiv.org/pdf/2112.08656.pdf
[7] Rainbow: A Commonsense Reasoning Benchmark Link : https://allenai.org/data/rainbow
[8] KagNet: Knowledge-Aware Graph Networks for Commonsense Reasoning
https://aclanthology.org/D19-1282.pdf
[9] GreaseLM: Graph REASoning Enhanced Language Models for Question Answering Link:
https://arxiv.org/pdf/2201.08860.pdf
[10] Social Commonsense Reasoning with Multi-Head Knowledge Attention
https://aclanthology.org/2020.findings-emnlp.267.pdf