Graph-based Multi-Hop Commonsense Knowledge

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Understanding narrative and argumentative text often requires knowledge beyond the text. While reading such texts, as humans, we are competent in distilling and performing inference by applying commonsense knowledge. Although there has been significant progress in neural machine reading and understanding (using powerful language models), there is still a performance gap between machines and humans, especially when it requires implicit knowledge (Talmor et al., 2018). One of the reasons being that commonsense knowledge is not often explicitly stated in natural language text (Gordon and Van Durme, 2013). We aim to solve this issue by leveraging knowledge from resources such as ConceptNet (Speer and Havasi, 2012). However, identifying contextually relevant information from such a large knowledge base is a non-trivial task. In this work, we propose an effective two-step method to extract relevant multi-hop knowledge paths from the chosen knowledge resource that associate concepts in a given textual sequence: (i) collect all potentially relevant knowledge relations among concepts that appear in the text in a subgraph; (ii) rank, filter and select high-quality multi-hop paths using graph-based local measures and graph centrality algorithms. Further, we propose a neural model that uses a gated attention mechanism to incorporate relevant multi-hop commonsense knowledge paths. We evaluate our model on two different task: (i) Argumentation relation classification (task of determining *support or attack* relations that hold between two arguments) (Stab and Gurevych, 2014), (ii) determining the human needs (multi-label classification task) of story characters given a narrative story (Rashkin et al., 2018). We show considerable improvement above strong knowledge-agnostic baselines (Table 1, 2). Our model offers interpretability through the learned attention map over commonsense knowledge paths (Fig. 1).

Context: Liv was a budding artist and she loved painting. She wanted to go to art classes, but her school didn't offer any!, So Liv got together with her friends and began brainstorming. They decided to form their own art group at the high school.
Sentence: They made an after-school art club and named Liv president!
True Label: *Independent, Curiosity, Contact*
Predicted without Knowledge: *Contact*
Predicted with Knowledge : *Independent, Curiosity, Contact*

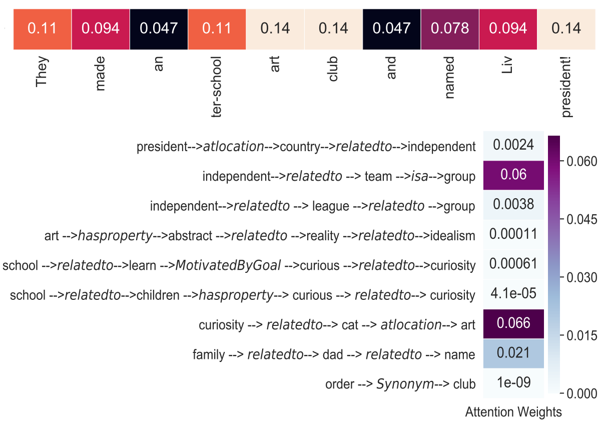

Figure 1: Example where including knowledge paths helps the model to predict the correct human need category. Attention weights on sentence representation and selected commonsense paths enhance interpretability.

		Human Need			Arg Classification		
Model	**WE**	**P**	**R**	$F1_{micro}$	**P**	**R**	$F1_{macro}$
Bi-ATT	ELMo	29.50	**44.28**	35.41	56.44	54.77	55.16
Bi-ATT+K	ELMo	**31.74**	43.51	**36.70**	58.22	58.64	**58.25**

Table 1: Results: Bi-ATT: BiLSTM+Self-Att.; +K:w/ knowledge. (Paul and Frank, 2019; Paul et al., 2020)

Path	**Ranking**	**P**	**R**	**F1**
S+M	None	32.51	42.70	36.90
S+M	Random	31.63	43.35	36.57
Single Hop	GBR	33.00	44.63	37.94
S+M	GBR	**36.76**	42.53	**39.44**

Table 2: Results for different path selection strategies on (Rashkin et al., 2018) dataset; S+M: Single+Multi hop, GBR: top-k paths our Graph-based Ranking Method, None: All paths, Random: Randomly selecting top-k paths from all paths

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