

1. Motivation

- The large majority of commonsense is generally recognized to be **implicitly expressed** in unstructured text or **human interactions** in everyday life.
- The ways of combining knowledge into deep learning architectures are far from satisfaction, and it is an issue to balance the tradeoff between **noise** and the amount of incorporated **commonsense** from knowledge base such as **ConceptNet**.
- Some pilot experiments have shown **inference** remains a challenging problem in natural language understanding.

2. Data description

Task	Examples
	Which statement of the two is against commonsense?
Subtask A	S1: he put an elephant into the fridge. × S2: he put a turkey into the fridge. ✓
	Why is “he put an elephant into the fridge” against commonsense?
Subtask B	A. an elephant is much bigger than a fridge. ✓ B. elephants are usually gray while fridges are usually white. × C. an elephant cannot eat a fridge. ×

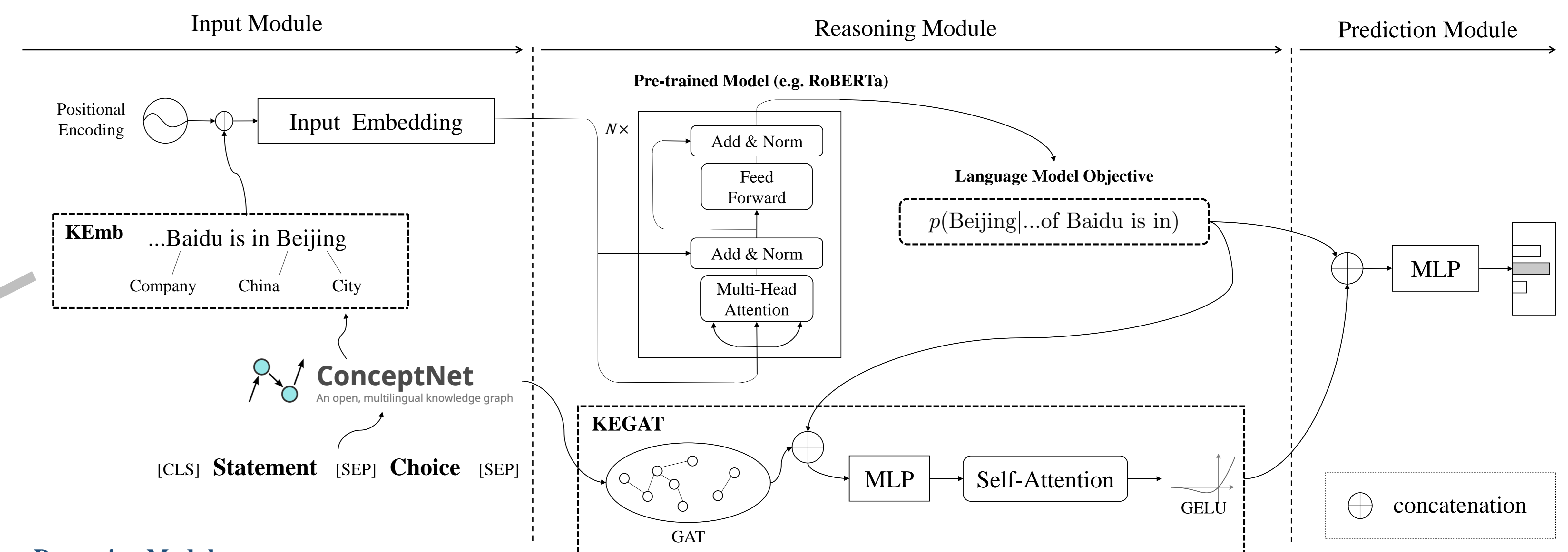
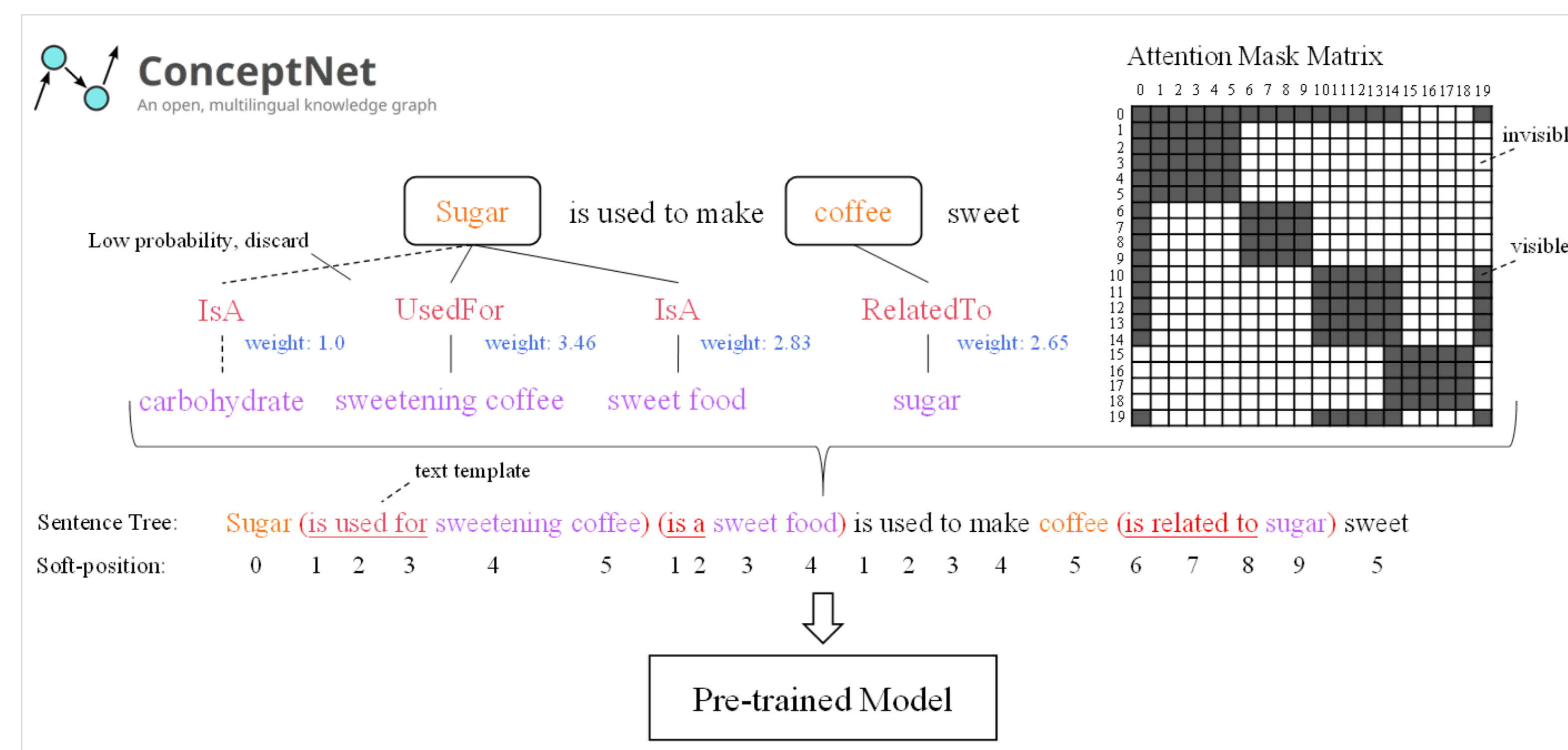
3. Contributions

- We propose the **Knowledge-enhanced Graph Attention Network (KEGAT)** to solve Commonsense Validation and Explanation, leveraging heterogeneous knowledge resources for better commonsense reasoning.
- Our system utilizes an **elegant embedding module (KEmb)** to well incorporate commonsense from structured knowledge bases, and design novel approaches to alleviate the noise caused by external knowledge.
- Our system gains valuable commonsense knowledge based on a large amount of unstructured text via a novel data augmentation technique, which also improves the robustness of our model.
- Last but not the least, this system uses an **internal sharing mechanism** to indirectly guide the reasoning process, which greatly avoids insufficient and excessive commonsense inference.

4. Networks and Training Process

Input Module:

- For all entities in every sentences, we extract their adjacent entities from **ConceptNet** and add the corresponding relations to form a new **tree-structured form**.
- We use **soft-position** instead of **positional encoding**, and use a **custom attention mask matrix** to make irrelevant words **invisible**.



Reasoning Module:

- We propose a **Knowledge-enhanced Graph Attention Network (KEGAT)** component to reason based on all relevant entities and the high-level representation of the entire statements or explanations from the pre-trained model.
- The **internal sharing mechanism** utilizes some processed outputs of pre-trained models to assist the KEGAT module in reasoning with a right direction, aiming to avoid insufficient or excessive inferences.

5. Leaderboard and Ablation study

- It outperforms the baseline (**BERT base**) model (Wang et al., 2019a) with a relative improvement of **52.98%** and achieves a relative improvement of **15.43%** compared with **fine-tuned BERT base**.

Rank	Subtask A		Subtask B	
	Team Name	Accuracy	Rank	Team Name
1	hit itnlp	97.00	1	ECNU ICA (Ours)
2	ECNU ICA (Ours)	96.70	2	hit itnlp
3	iie-nlp-NUT	96.40	3	iie-nlp-NUT
4	nlpX	96.40	4	Solomon
5	Solomon	96.00	5	NEUKG
Baseline				
-	BERT base	71.20	-	BERT base
-	fine-tuned BERT base	89.10	-	fine-tuned BERT base

Model	Dev Acc.(%)	Test Acc.(%)
Random guess	33.33	33.33
fine-tuned BERT base	-	82.30
RoBERTa-large	91.13	92.90
+ LM	92.18	93.70
+ KEmb	92.37	91.90
+ KEGAT	92.78	93.30
+ LM + KEmb	91.27	91.90
+ LM + KEGAT	92.68	93.00
+ KEmb + KEGAT	91.57	92.30
+ LM + KEmb + KEGAT	91.98	91.80
+ CommonsenseQA pre-trained	93.58	93.60
RoBERTa-large + ALBERT-xxlarge	94.08	94.00
RoBERTa-large LM + ALBERT-xxlarge	94.38	94.60
RoBERTa-large LM + RoBERTa-large + ALBERT-xxlarge	94.68	95.00
Human Performance (Wang et al., 2019a)	-	97.80

6. Feature Works

- Research how to make the model have powerful **multi-hop reasoning ability**.
- Research how to make the model **truly** understand commonsense knowledge.

7. Contact



GitHub Profile



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