Knowledgebot: Neuroknowledge based Complimentary Learning Model for Question Answering Systems

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***Abstract*—It is well known that two complementary learning modules are important to achieve human-level language understanding: one gradually acquires structured representations of knowledge from language, the other quickly learns the episodic memory composed of individual knowledge. In this paper, we suggest a new machine learning model which combines symbolic and neuronal approaches to construct the complementary learning model. The suggested model extracts symbolic knowledge from natural language sentences, then the symbolic knowledge is embedded into a real-valued continuous vector space, a neural representation. The neural representation implies the meaning and the correlations between the symbolic knowledge, also generalize the patterns among the knowledge. At the same time, the model rapidly learns to predict a specific knowledge which is supposed to be based on the reasoning. As an application of the suggested method, we conduct a challenging problem, a question and answering, which needs to understand the context of the language input and reason answer for the given question based on the context.**

Complementary learning system (CLS) is a great theoretical base to understand the mechanism of human learning and memory. According to the theory, in neocortex, semantic knowledge is gradually constructed using information from episodic memory. At the same time, in hippocampus, the episodic memory is rapidly constructed using semantic knowledge structure[**?**], [**?**], [**?**]. Getting intuitions from the CLS theory, we consider a model combining a symbolic approach (from Artificial intelligence) and a neural representation approach (from the recent machine learning) to build complementary system for learning human language.

In this paper, we suggest a new model to construct the neuroknowledge based complementary learning architecture to understand and reason about knowledge written in human language. For demonstration, we will show a novel challenging problem, question and answering task which needs reasoning answer from the text input and question.

A. Model description

The suggested model consists of four parts: a symbolic knowledge extraction module, a neuroknowledge representation module, an episodic memory module, an answer module. In the symbolic knowledge extraction module, the symbolic knowledge triplet, <subject, relation, object>, is automatically extracted from the input text. Then the neuroknowledge representation module learns generalized neural representation of each knowledge triplet. The episodic memory module learns to predict to pick specific knowledge from a trigger, question for example, then finally output will be comes out from the answer module. A high-level illustration of the model is shown in Figure **??**.

1) Symbolic knowledge extraction module: To extract symbolic knowledge automatically from the text, we use open information extraction (OpenIE) which can identify entities (subject and object) and relations from natural sentences [**?**]. For example, given the sentence, "McCain, fought hard against Obama, but finally lost the election," an OpenIE system may extract two triplets, <McCain, fought against Obama>, and <McCain, lost, the election>. Using this technique, multiple symbolic knowledge triplet are obtained from natural text input.

2) Neuroknowledge representation module: From the symbolic knowledge triplet, the neuroknowledge representation module learns generalized neural representations of each symbolic knowledge triplet. There are several approaches embedding knowledge triplets to neural representation, but most of them more focused on entity embedding which toward to reflected relation in a fixed number of relation environment [**?**], [**?**]. In the suggested model, we use factored high-order Boltzmann machine to learn neural representation of knowledge triplets. The factored high-order Boltzmann machine is shown to have nature of capturing correlational structure among inputs [**?**], [**?**]. Using this property, we feed Word2Vec [**?**] representation of <subject, relation, object> triplet as an input, and use hidden representation as neuroknowledge representation. Specifically, to obtain neuroknowledge representation, we firstly embed each component of a triplet, to continuous vector space using word2vec as follows.

$$\begin{aligned} e_s &= word2vec(subject) \\ e_r &= word2vec(relation) \qquad (1) \\ e_o &= word2vec(object) \end{aligned}$$

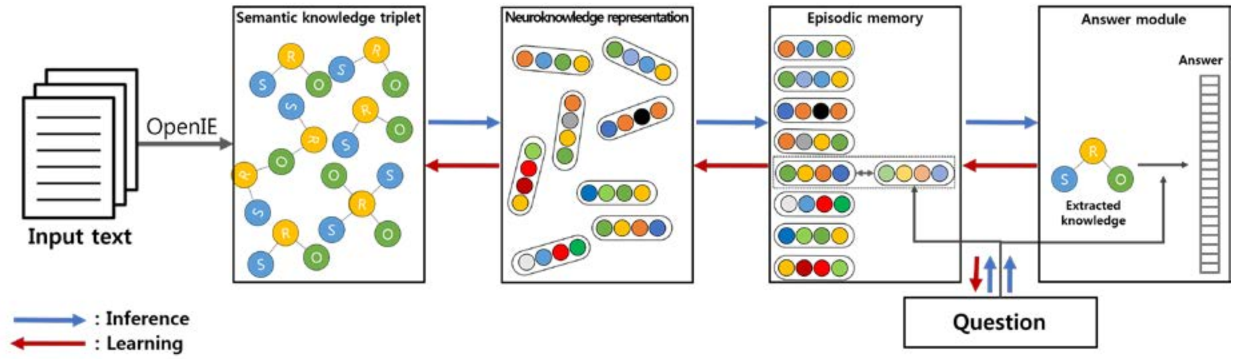

Fig. 1. Overview of suggested framework. The blue arrow indicates flow of inference and the red arrow indicates back-propagation learning. Briefly, the suggested model extract semantic knowledge triplet from input text, then learn neuroknowledge representation of each triplet. In the episodic memory, all knowledge is stored in a form of neuroknowledge representation and key for predicting appropriate knowledge to be learned. using this key, specific knowledge for question is extracted and based on that knowledge, the answer to be predicted.

The $word2vec()$ is the word2vec function. After that, the neuroknowledge representation h_n of specific $< e_s, e_r, e_o >$ triplet is determined by

$$h_n = \sigma\left(W_{nf}^{\top} \cdot (W_{sf}^{\top} \cdot e_s) \circ (W_{rf}^{\top} \cdot e_r) \circ (W_{of}^{\top} \cdot e_o) + bias\right) \quad (2)$$

Here, W_{nf}, W_{sf}, W_{rf} and W_{of} are weight matrices, h_n, e_s, e_r, e_o and $bias$ are vector and σ is an activation function. Also, $\cdot$ is the dot product and $\circ$ is the element-wise multiplication.

3) Episodic memory module: In the episodic memory module, the set of symbolic knowledge embedded in neuroknowledge representation is stored sequentially and retrieved based on the trigger, such as questions. The episodic memory module rapidly learns to predict appropriate knowledge to be retrieved corresponding to the question. This process imitate the pattern completion process in hippocampus of brain and is done by two steps. First, a knowledge-key $k_{knowledge}$ is generated by

$$k_{knowledge} = f_{knowledgekey}(e_q) \quad (3)$$

Here, e_q is an embedding vector of a question and the function $f_{knowledge}$ is the multilayer perceptron (MLP). This function can be replaced by any other differential functions. Using the generated knowledge-key $k_{knowledge}$, a key-value look-up over the neuroknowledge in episodic memory is performed to retrieve appropriate neuroknowledge h_n^t,

$$\begin{aligned} P(h_n^t|e_q) &= \frac{exp(k_{knowledgekey}^{\top} \cdot h_n^t)}{\sum_{t'} exp(k_{knowledgekey}^{\top} \cdot h_n^{t'})} \\ h_n^t &= \underset{h_n^t}{\operatorname{argmax}} P(h_n^t|e_q) \end{aligned} \quad (4)$$

4) Answer module: To generate an answer for a question, we first extract <subject (e_s), relation (e_r), object (e_o)> triplet again from the retrieved neuroknowledge h_n^t. Then the answer a is determined by

$$a = f_{answer}([e_s||e_r||e_o||e_q]) \quad (5)$$

The notation $[a||b||c||d]$ denote the concatenation of vector a, b, c and d. The function f_{answer} used here is the softmax function. Also, f_{answer} can be replaced by other functions.

B. Expected experimental results

To demonstrate the performance of the suggested model, the Q/A experiment will be conducted based on two different dataset: the Facebook bAbI dataset & educational video Q/A dataset. The bAbI dataset is well-known dataset for testing a model's ability to reason over facts. educational video Q/A dataset is collected questions and answers based on video contents mad by Pinkfong. With these experiments, we will show better results compared with other existing approach.

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