A Deep Sequential Model for Discourse Parsing on Multi-Party Dialogues

Zhouxing Shi, Minlie Huang

Department of Computer Science & Technology, Tsinghua University, Beijing, China

Introduction

Task definition

- **Discourse parsing on a multi-party dialogue**: to identify dependency links and the corresponding relation types $\{(u_j, u_i, r_{ji}) \mid j \neq i\}$ from a given dialogue segmented into a sequence of Elementary Discourse Units(EDUs) $u_1, u_2, \cdots, u_n$.

Motivation

- Parse the discourse structure of a *multi-party dialogue* which is different from written text.
- Construct a discourse structure incrementally by predicting dependency relations and building the structure *jointly and alternately*.
- Predict dependency relations with not only *local* information, but also *global* information that encodes the EDU sequence and the discourse structure that is already built at the current step.
- Build the discourse structure incrementally with a *structured encoder*, using the predicted links and relation types.

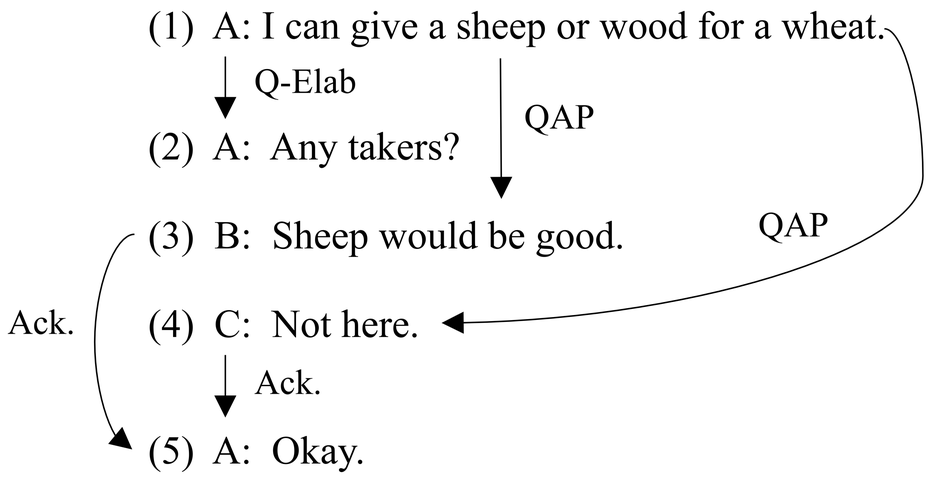

Figure 1: A multi-party dialogue example with its discourse structure from the STAC Corpus.

Framework

- The overall process:
  1. Compute the non-structured representations of the EDUs with hierarchical Gated Recurrent Unit (GRU) encoders, denoted as $\boldsymbol{h}_i$ and $\boldsymbol{g}_i^{NS}$.
  2. Make a sequential scan of the EDUs, predicting dependency relations and constructing the discourse structure.
- Three steps when handling u_i:
  1. Link prediction: predict the parent node p_i of EDU u_i with a link predictor.
  2. Relation classification: predict the relation type between p_i (assume $p_i = u_j$) and u_i with a relation classifier.
  3. Structured representation encoding: compute the structured representation of u_i with a structured representation encoder.
- Compute the structured representation of u_i: apply a structured encoder to the path from the root to u_i. In practice, it is computed incrementally.
- Speaker highlighing mechanism (SHM): compute $|\mathcal{A}|$ different structured representations for each EDU such that each one highlights a specific speaker.

$$\boldsymbol{g}_{i,a}^S = \begin{cases} \boldsymbol{0} & i = 0 \\ \textbf{GRU}_{hl}(\boldsymbol{g}_{j,a}^S, \boldsymbol{h}_i \oplus \boldsymbol{r}_{ji}) & a_i = a, i > 0 \\ \textbf{GRU}_{gen}(\boldsymbol{g}_{j,a}^S, \boldsymbol{h}_i \oplus \boldsymbol{r}_{ji}) & a_i \neq a, i > 0 \end{cases}$$

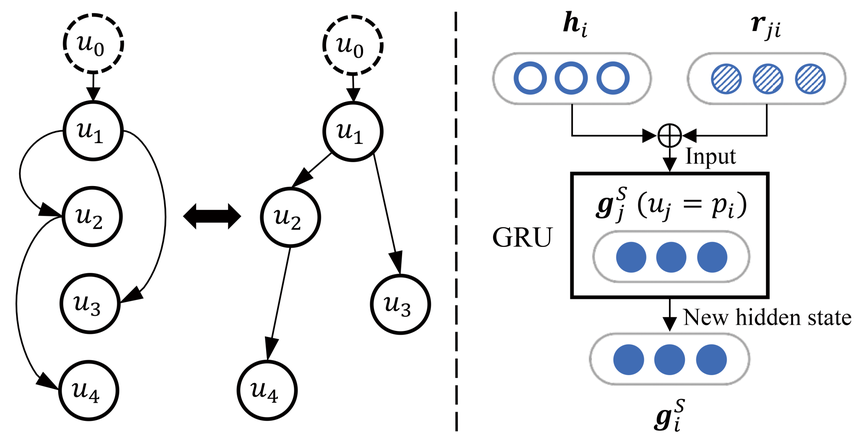

Figure 2: An example dependency tree (left) and the structured encoder (right).

- Input for link prediction and relation classification:

$$\boldsymbol{H}_{i,j} = \boldsymbol{h}_i \oplus \boldsymbol{g}_i^{NS} \oplus \boldsymbol{g}_j^{NS} \oplus \boldsymbol{g}_{j,a_i}^S$$

Experiments

Model	Link	Link & Rel
MST	68.8	50.4
ILP	68.6	52.1
Deep+MST	69.6	52.1
Deep+ILP	69.0	53.1
Deep+Greedy	69.3	51.9
Deep Sequential (shared)	72.1	54.7
Deep Sequential	**73.2**	**55.7**

Table 1: F_1 scores (%) for different models.

Model	Link	Link & Rel
Deep+Greedy	69.3	51.9
Deep Sequential (NS)	71.0	53.7
Deep Sequential (Random)	71.8	53.7
Deep Sequential (w/o SHM)	71.7	54.5
Deep Sequential	**73.2**	**55.7**

Table 2: F_1 scores (%) for different models.

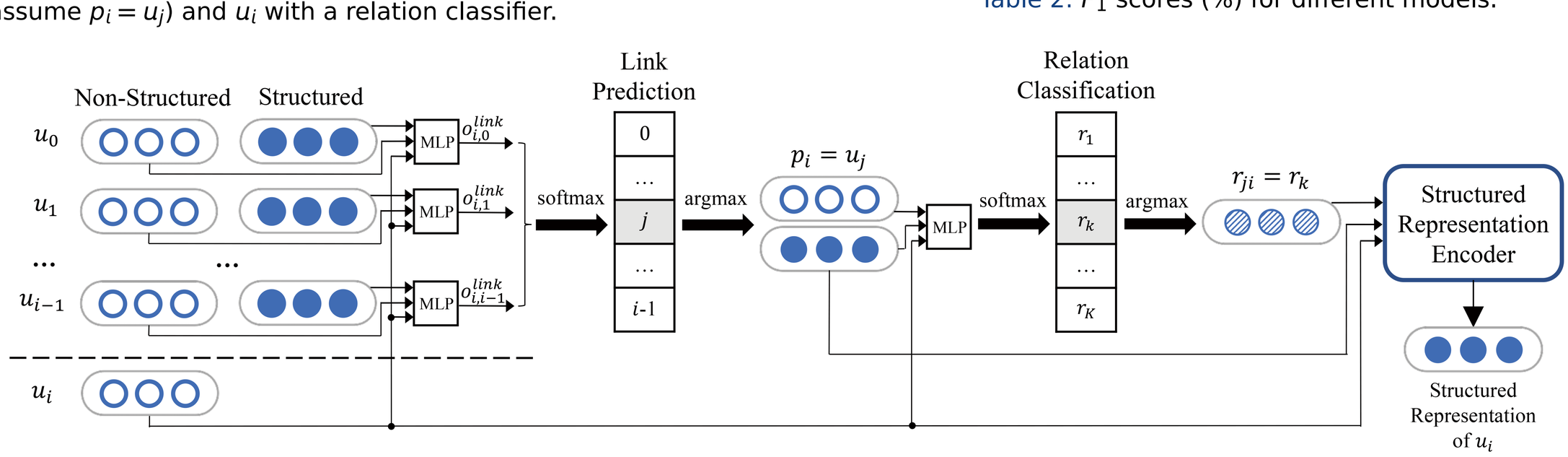

Figure 3: Illustration of the model which consists of modules for link prediction, relation classification, and structured representation encoding.

 Contact: zhouxingshichn@gmail.com, aihuang@tsinghua.edu.cn