JBNU at MRP 2020: AMR Parsing using a Joint State Model for Graph-Sequence Iterative Inference

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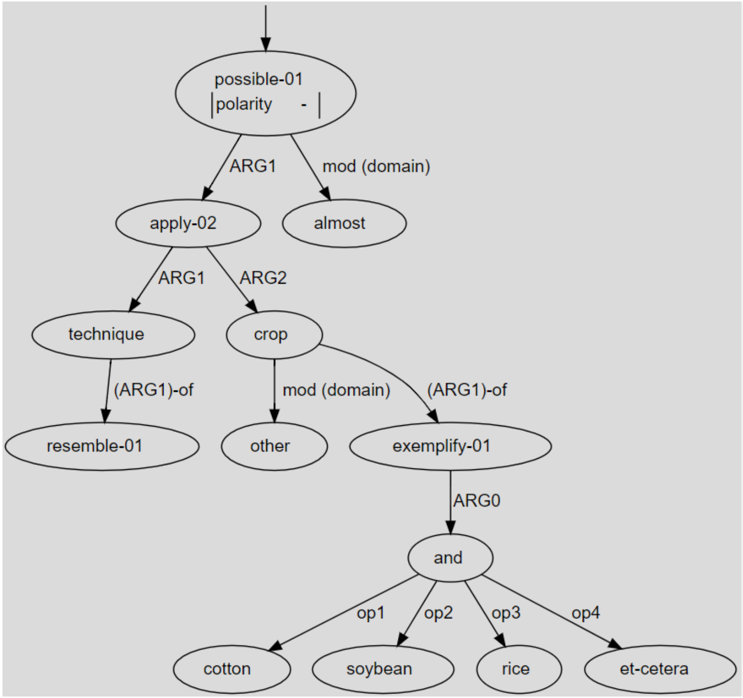
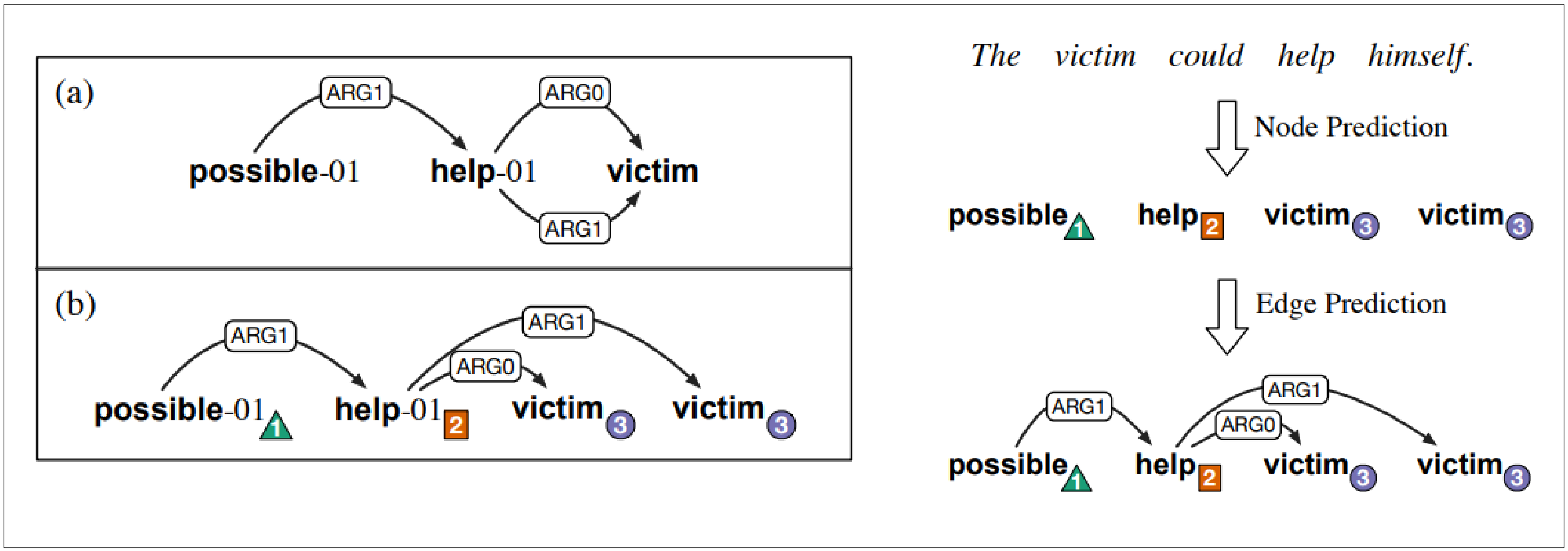
Introduction

- **Concentrate on Abstract Meaning Representation (AMR) frameworks**



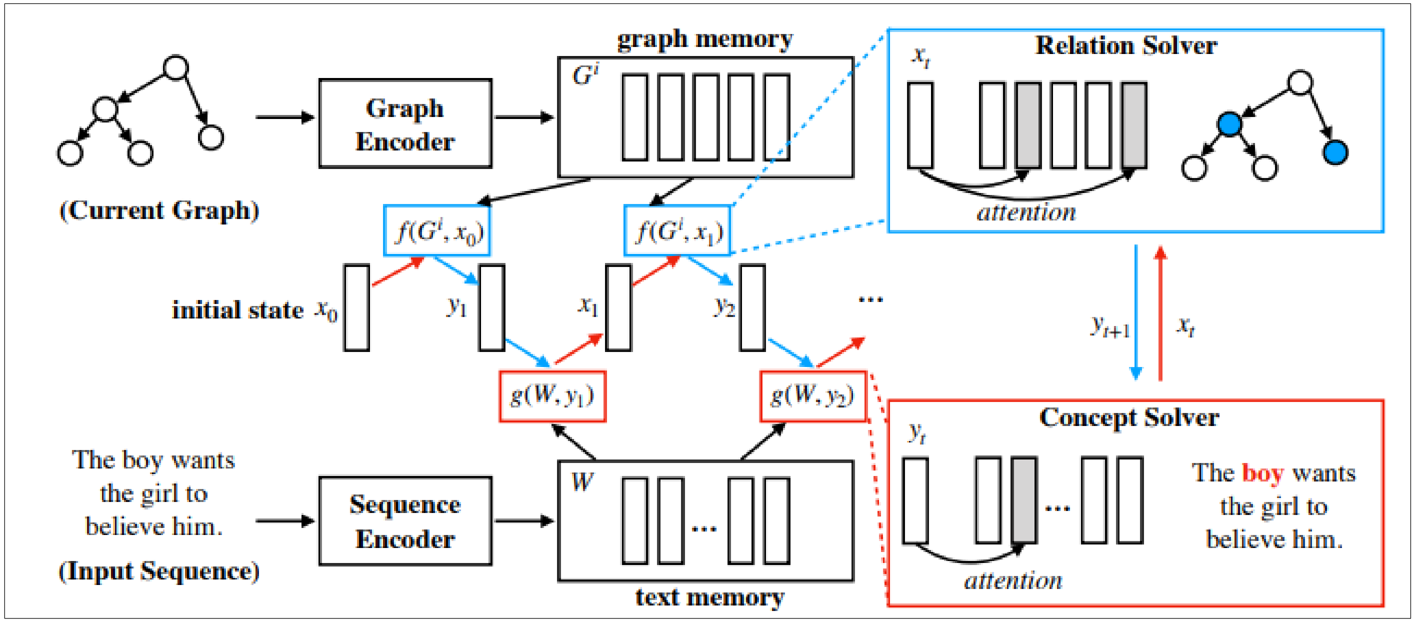
- Models
  - **Joint State Vector**: we propose a joint state model for the graph-sequence iterative inference of (Cai and Lam, 2020)

- **AMR Parsing as Sequence-to-Graph Transduction (Sheng Zhang, ACL '19)**



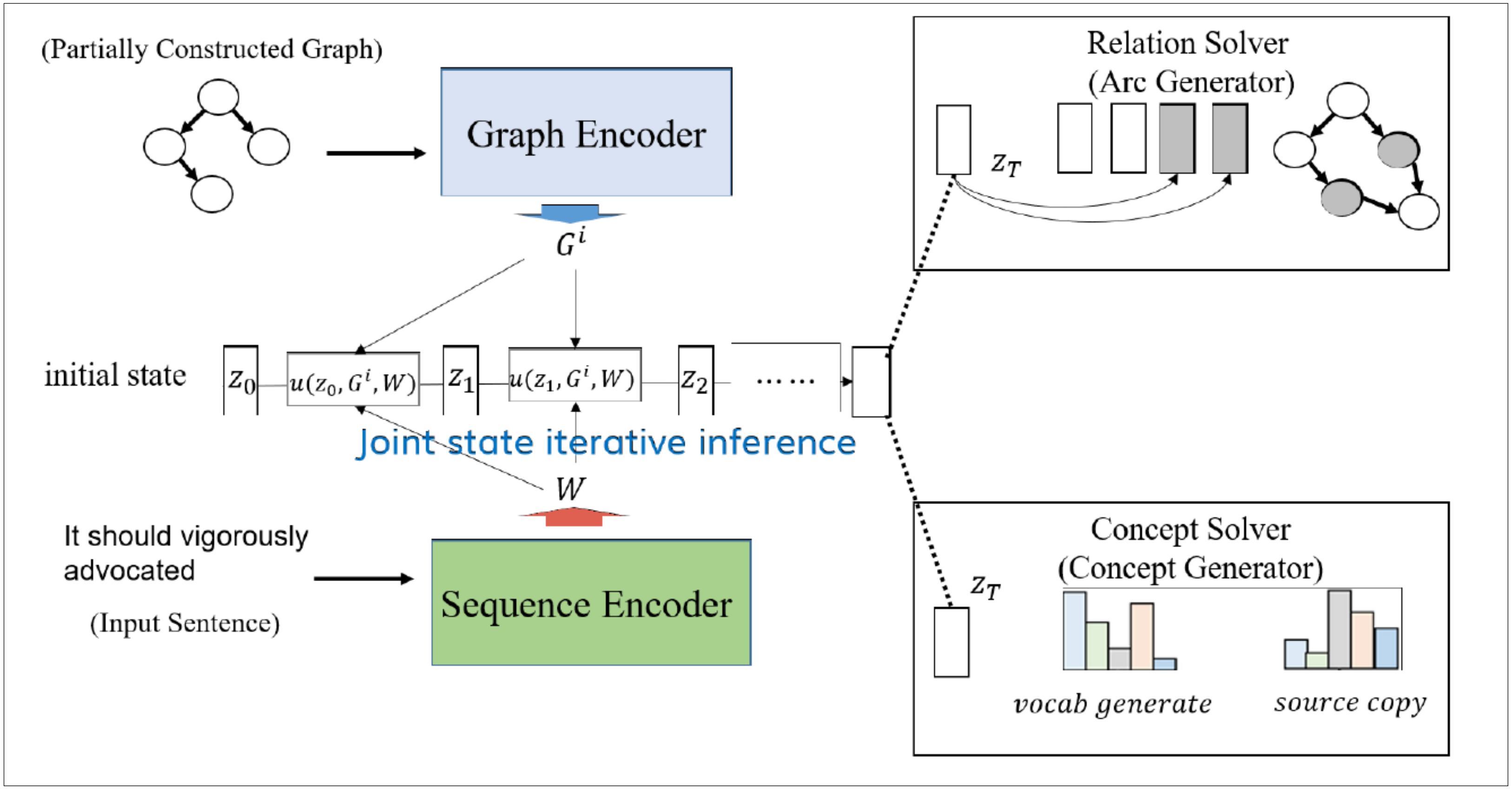
  - **Two Stage(Node Prediction, Edge Prediction)**
    - Propose the extended Pointer generator(add target attention from exsting nodes)
    - apply biaffine attention for edge Prediction

- **AMR Parsing via Graph ⇋ Sequence Iterative Inference(Cai and Lam, 2020)**



- **Iterative Inference(dual decision)**
  - To gradually expand the graph, iterative inference is applied at each expansion step.
  - concept solver and the relation solver are conceptually two attention mechanisms over the sequence and graph respectively.

AMR Parsing using a Joint State Model for Graph-Sequence Iterative Inference



- **Simplified Iterative Inference Model**
  - Using joint state vector z_t, we generate new concepts and determine relations new concept and partially Constructed graph

Encoder

- **Multi Layer Transformer(Vaswani at al., 2017)**
  - Sentence Encoder : multi Layer transformer Encoder
    - Input features
      - Input words, CNN based char-level word features, POS tags, NER tags
      - BERT-based Features

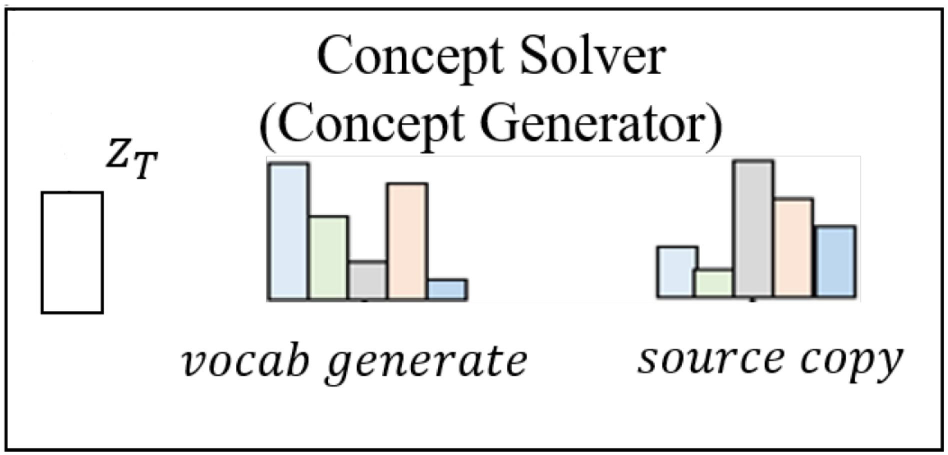
$$h_0, h_1, \cdots, h_n = \mathrm{SequenceEncoder}((BOS, w_1, \cdots, w_N))$$

  - Graph Encoder: multi Layer transformer Decoder
    - Masked Self Attention & Source Attention
    - Input features
      - Input nodes, CNN based char-level node features

$$s_0, s_1, \cdots, s_i = \mathrm{GraphEncoder}(G = \{c_1, \cdots, c_i\})$$

Concept Solver

- **Generates a new concept using pointer generator**
  - Pointer generator[See et al., 2017]
  - Using joint State Vector z_t

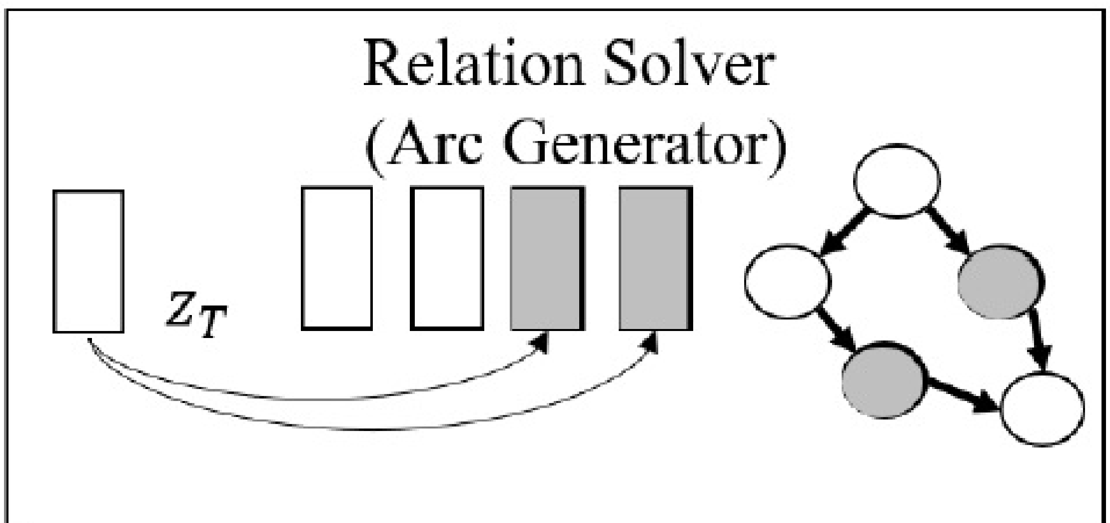


$$
\begin{aligned}
q_t &= W^Q z_t \\
k_{1:n} &= W^K h_{1:n} \\
v_{1:n} &= W^V h_{1:n} \\
[\alpha_t, r_t] &= Attention(q_t, k_{1:n}, v_{1:n}) \\
z'_t &= z_t + r_t
\end{aligned}
$$

$$
\begin{aligned}
P^{(vocab)} &= softmax\left(W^{(vocab)} z'_t + b^{(vocab)}\right) \\
[p_1, p_2, p_3] &= softmax\left(W^{(switch)} z'_t\right) \\
P(c) &= p_0 \cdot P^{(vocab)}(c) + \\
& \quad p_1 \cdot \left(\sum_{i \in L(c)} \alpha_t[i]\right) + p_2 \cdot \left(\sum_{i \in T(c)} \alpha_t[i]\right)
\end{aligned}
$$

Relation Solver

- **Determine relations new node and existing nodes**
  - Using joint State Vector z_t
  - To solve reentrancies problem, we use multi-head attention. for each head h, we calculate an attention distribution over all existing node.
  - If no relationship exists, it will point to the dummy node

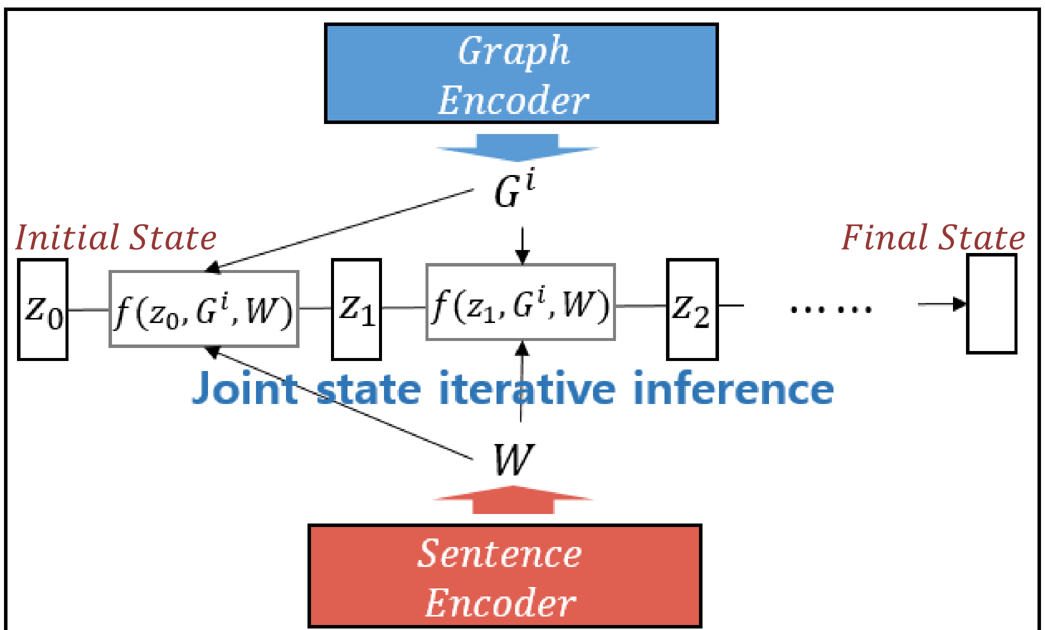


$$
\begin{aligned}
q_t^h &= W_h^Q z_t \\
k_{0:i}^h &= W_h^K s_{0:i} \\
v_{0:i}^h &= W_h^V s_{0:i} \\
\left[\beta_t^h, r_t^h\right] &= Attention(q_t^h, k_{0:i}^h, v_{0:i}^h)
\end{aligned}
$$

$$\beta_t[i] = max_{h=1}^{H} \beta_t^h[i]$$

Iterative inference : Joint State Model

- **Simplified Iterative Inference**
  - define joint State Vector z_t
  - After selectively sum the information of sequence and partially constructed graph using a gate, we Iteratively updates the state vector z_t.



$$
\begin{aligned}
z_0 &= fusion(h_0, s_i) \\
g_t &= \sigma(z_t) \\
[\_, z_t^{seq}] &= Attention(z_t, h_{1:n}, h_{1:n}) \\
\left[\_, z_t^{graph}\right] &= Attention(z_t, s_{0:i}, s_{0:i}) \\
z_{t+1} &= z_t + (1 - g_t) z_t^{seq} + g_t z_t^{graph}
\end{aligned}
$$

Official Results

method		tops			labels			properties			edges			all		
		P	R	F	P	R	F	P	R	F	P	R	F	P	R	F
Hitachi	lpps	0.84	0.84	0.84	0.83	0.85	0.84	0.86	0.77	0.81	0.71	0.73	0.72	0.78	0.79	0.79
	all	0.86	0.86	0.86	0.88	0.86	0.87	0.83	0.81	0.82	0.77	0.74	0.76	0.83	0.80	0.82
ÚFAL	lpps	0.86	0.86	0.86	0.85	0.87	0.86	0.78	0.71	0.75	0.69	0.71	0.70	0.77	0.79	0.78
	all	0.84	0.84	0.84	0.88	0.87	0.87	0.86	0.85	0.85	0.73	0.70	0.71	0.81	0.79	0.80
Graph-Sequence+Joint	lpps	0.86	0.86	0.86	0.79	0.80	0.79	0.54	0.45	0.49	0.68	0.67	0.68	0.74	0.73	0.74
	all	0.84	0.84	0.84	0.79	0.73	0.76	0.68	0.39	0.50	0.61	0.54	0.57	0.71	0.62	0.66

- **Official Results**
  - compares the results of the top-2 systems
  - Overall, our system ranks between 3rd and 4th place among all participants which submitted to the AMR framework.
- **Future Works**
  - joint state models by reformulating an iterative inference based on attention results from the concept and relation solvers.