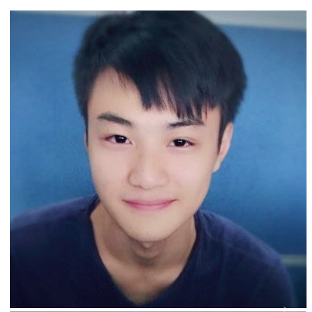
# AMR Parsing via Graph⇆Sequence Iterative Inference





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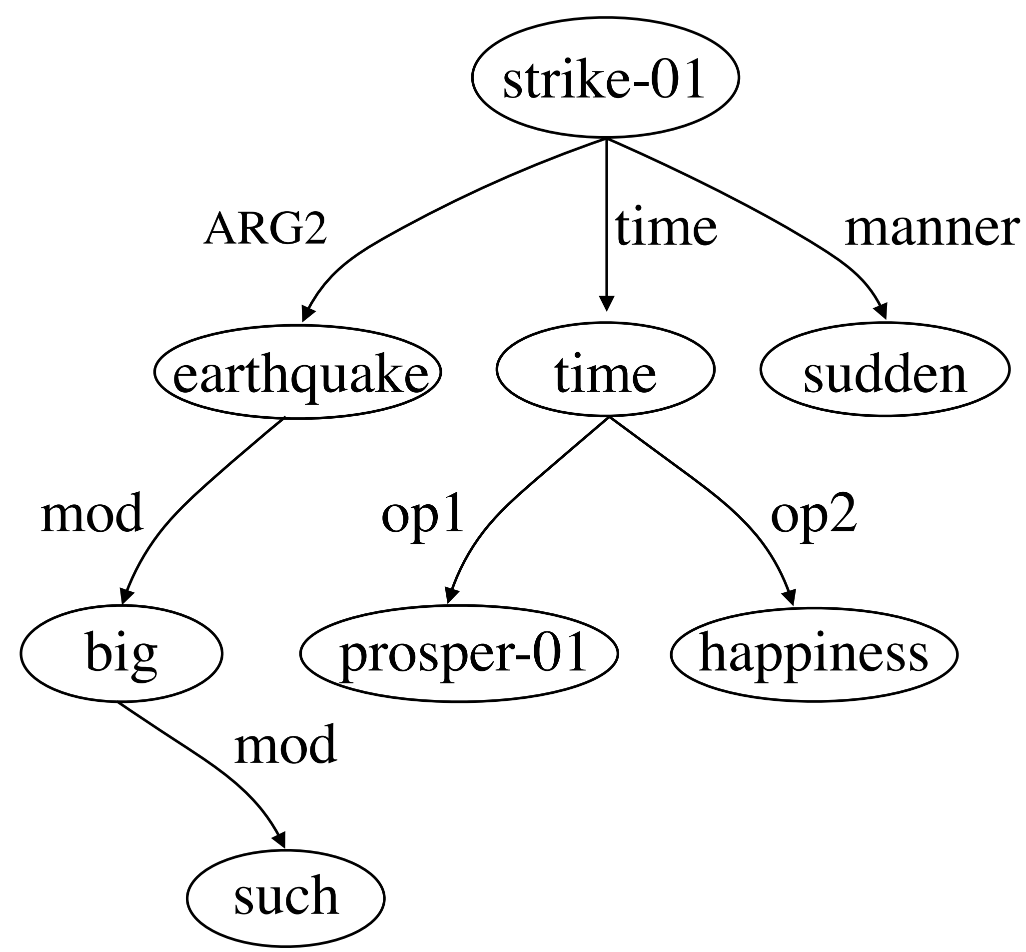
ACL2020

# Background

Natural Language ⟷ Meaning Representation (AMR)

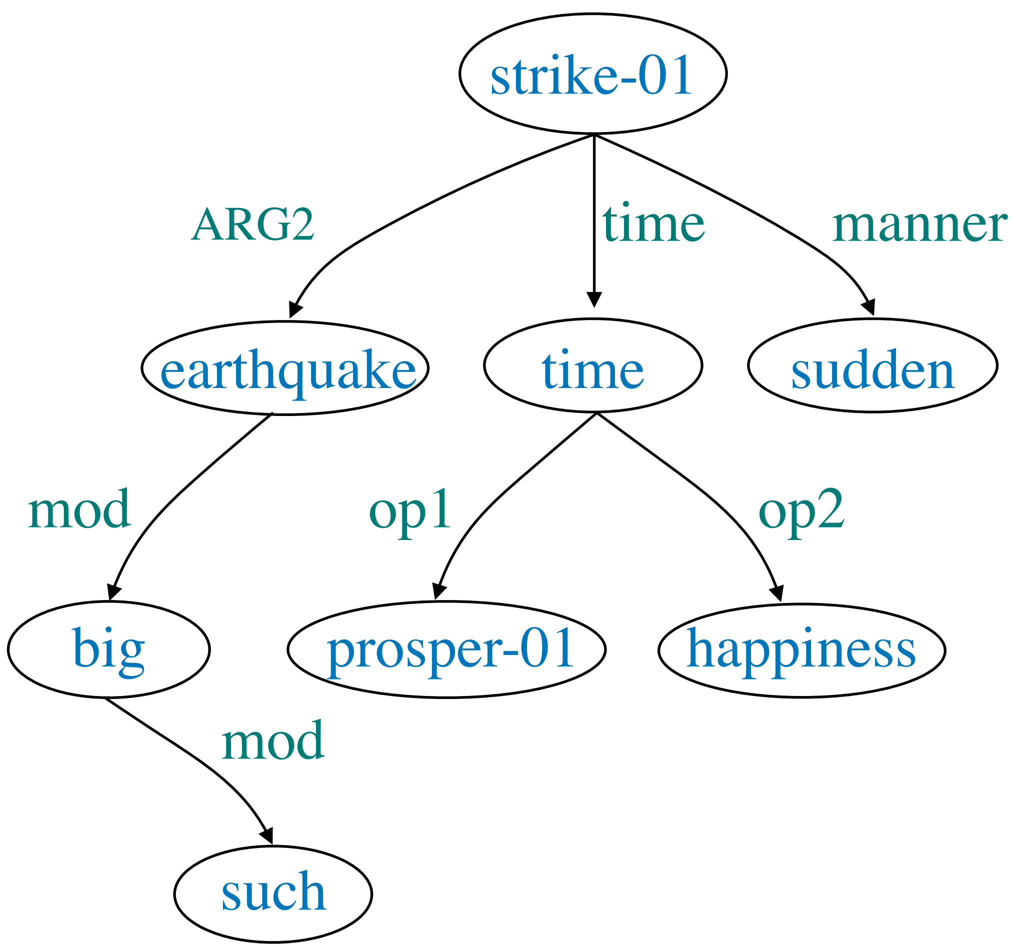
*During a time of prosperity and happiness, such a big earthquake suddenly struck.*



# Background

- Abstract Meaning Representation (AMR)
  - rooted, labeled, and directed acyclic graph
  - nodes represent concepts
  - edges represent relations

*During a time of prosperity and happiness, such a big earthquake suddenly struck.*



# Background

- Abstract Meaning Representation (AMR)
  - Named Entity Recognition
  - Word Sense Disambiguation
  - Semantic Role Labeling
  - Coreference Resolution
  - …

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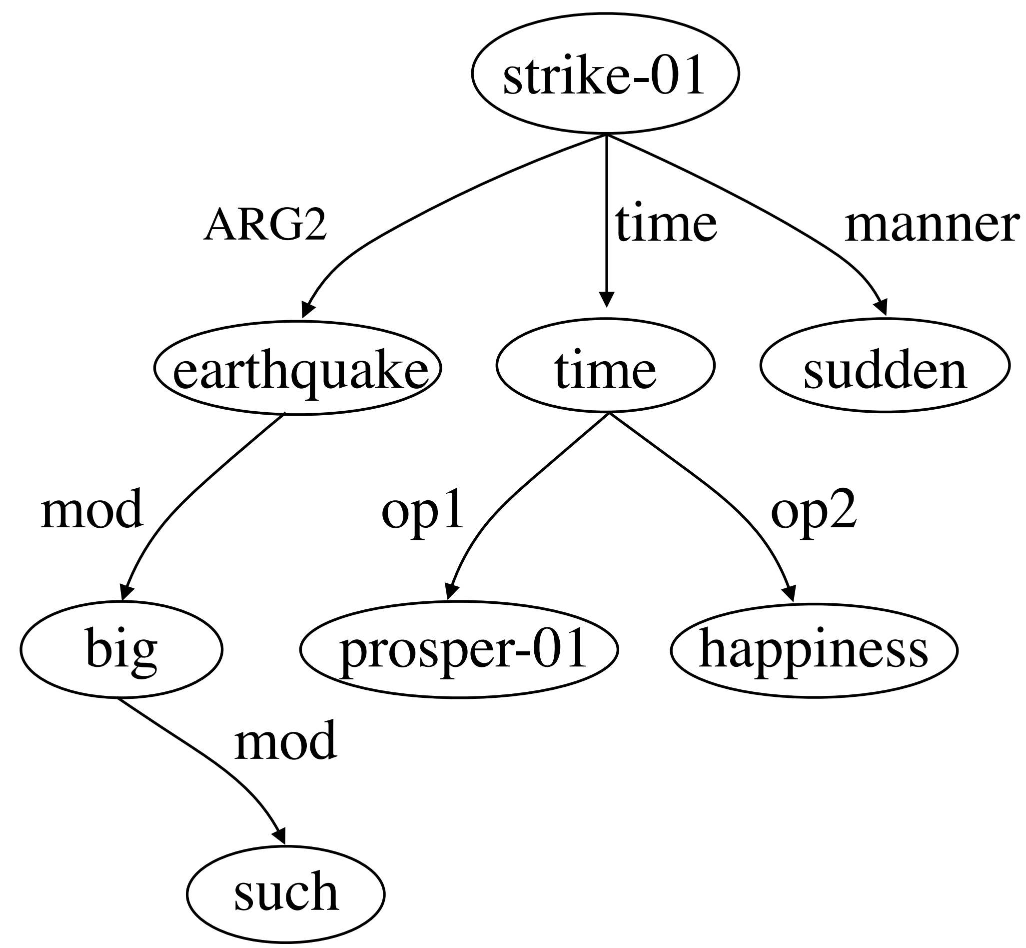
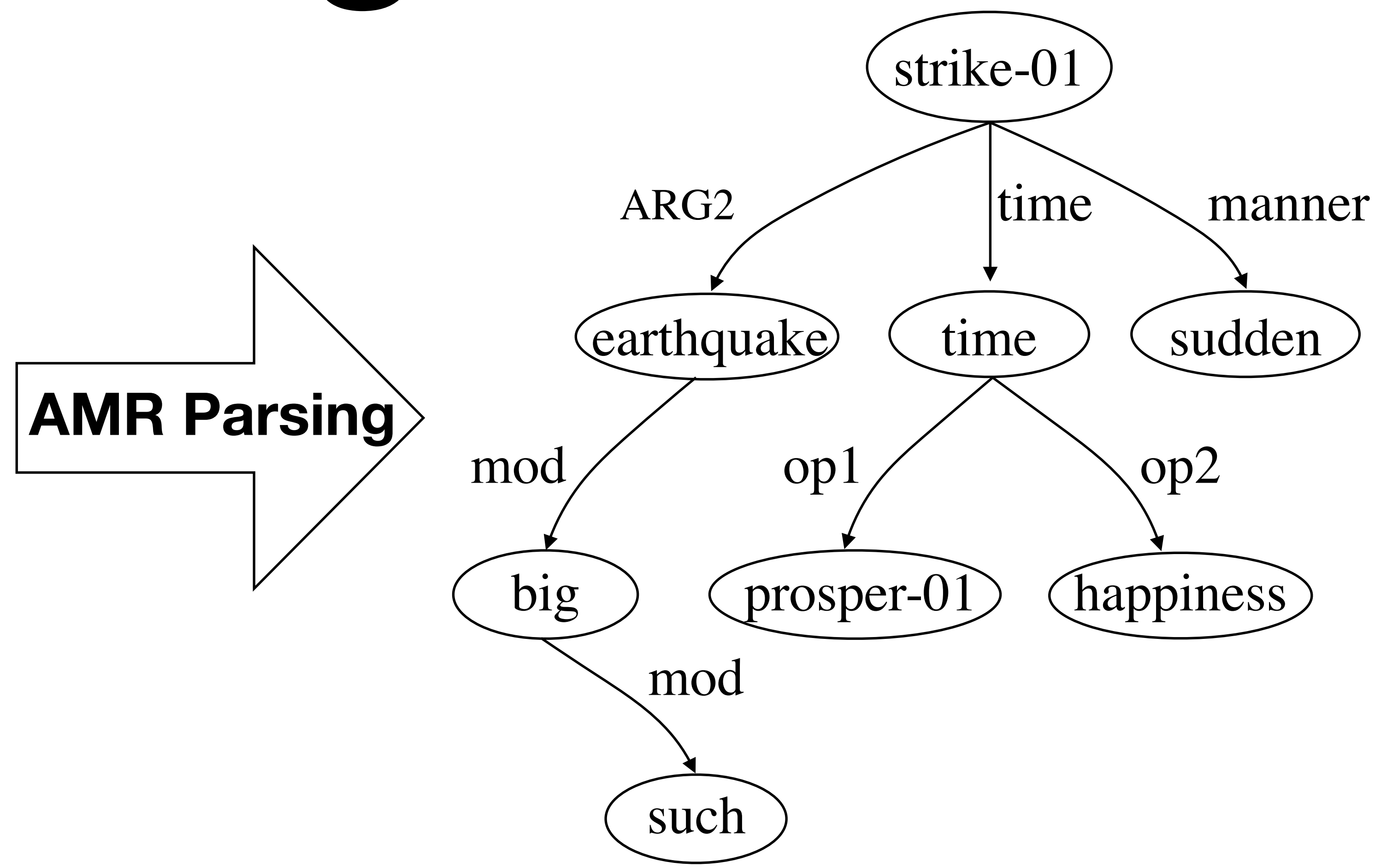


# Challenges

*During a time of prosperity and happiness, such a big earthquake suddenly struck.*




- Concept Prediction:
  - No explicit alignment of graph nodes and sentence tokens
  - Large and sparse concept vocabulary vs. Limited training data
- Relation Prediction:
  - Frequent reentrancies and non-projective arcs

# Existing Work

- Two-stage Parsing (Flanigan et al., 2014; Lyu and Titov, 2018; Zhang et al., 2019a)
  - first predict all concepts
  - then predict all relations

- One-stage Parsing (Wang et al., 2016; Damonte et al., 2017; Ballesteros and Al-Onaizan, 2017; Peng et al., 2017; Guo and Lu, 2018; Liu et al., 2018; Wang and Xue, 2017; Naseem et al., 2019; Barzdins and Gosko, 2016; Konstas et al., 2017; van Noord and Bos, 2017; Peng et al., 2018; Cai and Lam, 2019; Zhang et al., 2019b)
  - Construct a parse graph incrementally

- Grammar-based Parsing (Peng et al., 2015;Pust et al., 2015;Artzi et al., 2015; Groschwitz et al., 2018; Lindemann et al., 2019)

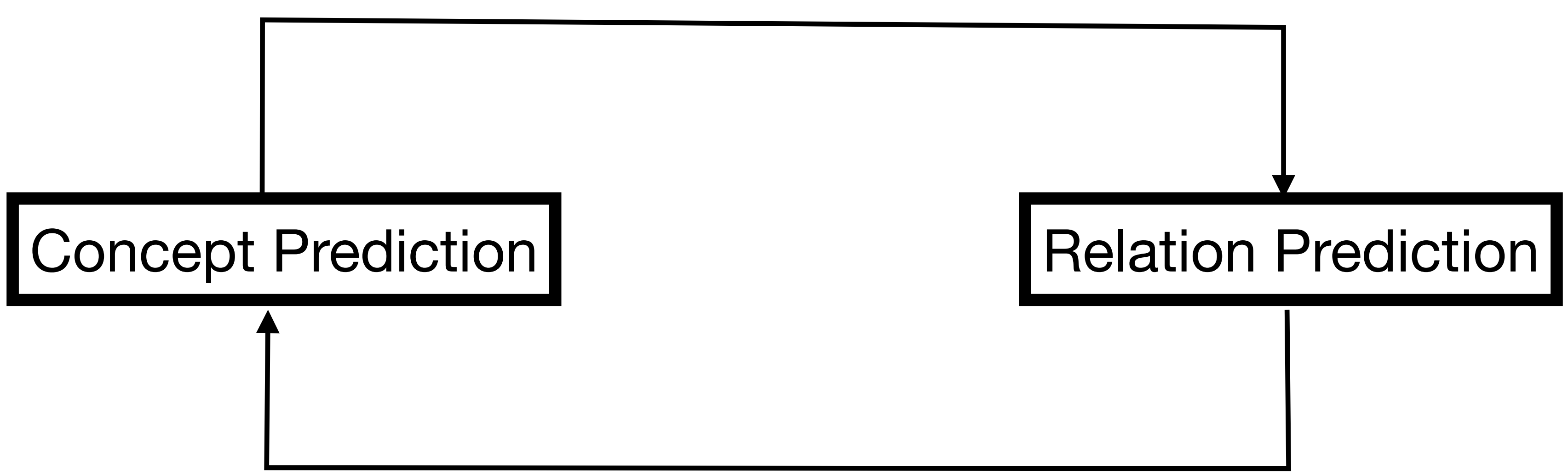
# Existing Work

- Two-stage Parsing (Flanigan et al., 2014; Lyu and Titov, 2018; Zhang et al., 2019a)
    - Pipeline: concept prediction -> relation prediction
- One-stage Parsing
    - Transition-based (Wang et al., 2016; Damonte et al., 2017; Ballesteros and Al-Onaizan, 2017; Peng et al., 2017; Guo and Lu, 2018; Liu et al., 2018; Wang and Xue, 2017; Naseem et al., 2019)
        - Insert node and build edge sequentially
    - Seq2seq-based (Barzdins and Gosko, 2016; Konstas et al., 2017; van Noord and Bos, 2017; Peng et al., 2018)
        - Nodes and edges are mixed in the same output space
    - Graph-based (Cai and Lam, 2019; Zhang et al., 2019b)
        - A new node and its connections to existing nodes are jointly decoded in order or in parallel.

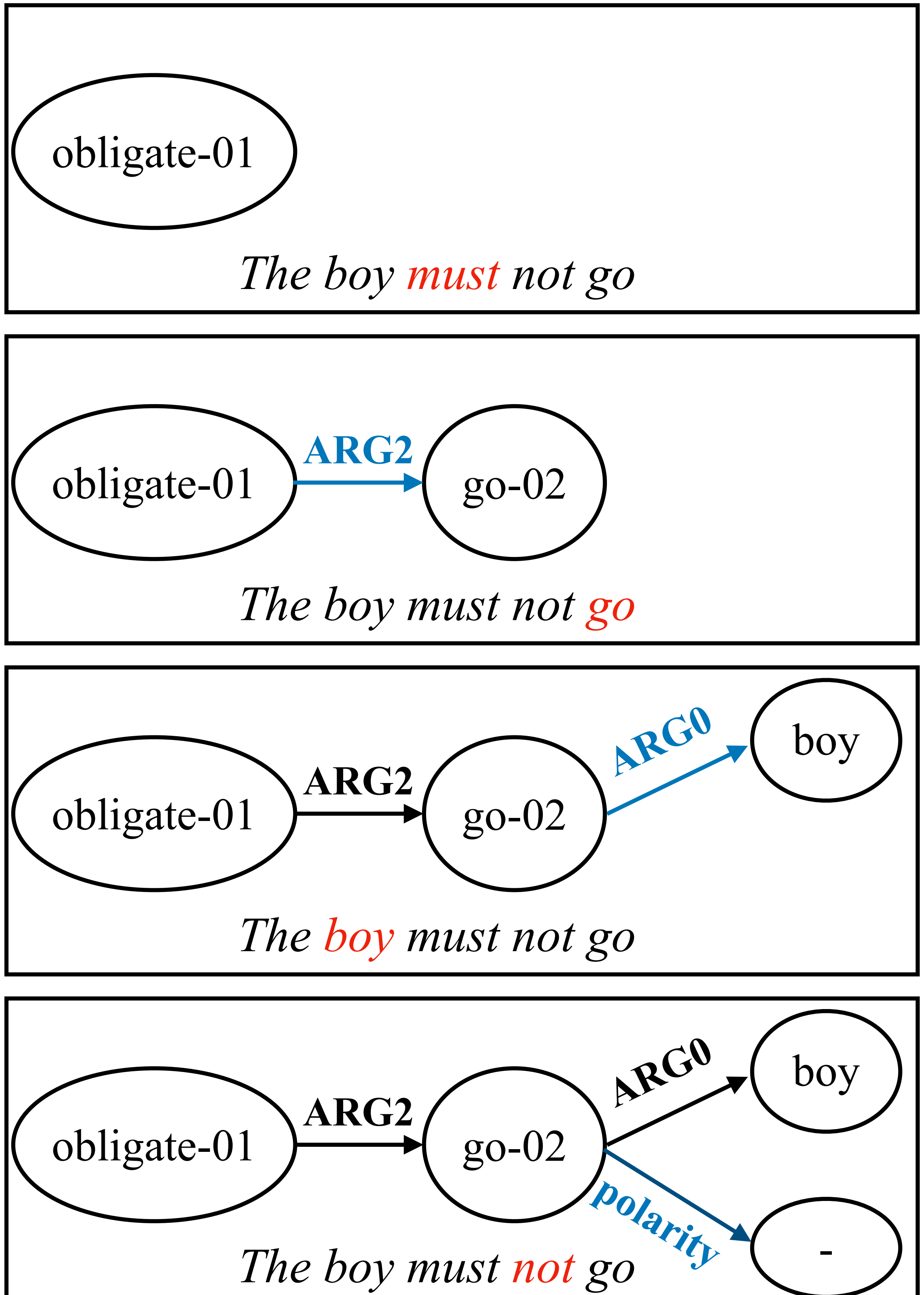
# Motivation

Our hypothesis for unsatisfactory parsing accuracy:

The lack of the modeling capability of the **interactions between concept prediction and relation prediction**



# Model Overview




**Step1**

- Which part of the input sequence to abstract?
- Where in the output graph to construct the new concept?

**Step2**

- Which part of the input sequence to abstract?
- Where in the output graph to construct the new concept?

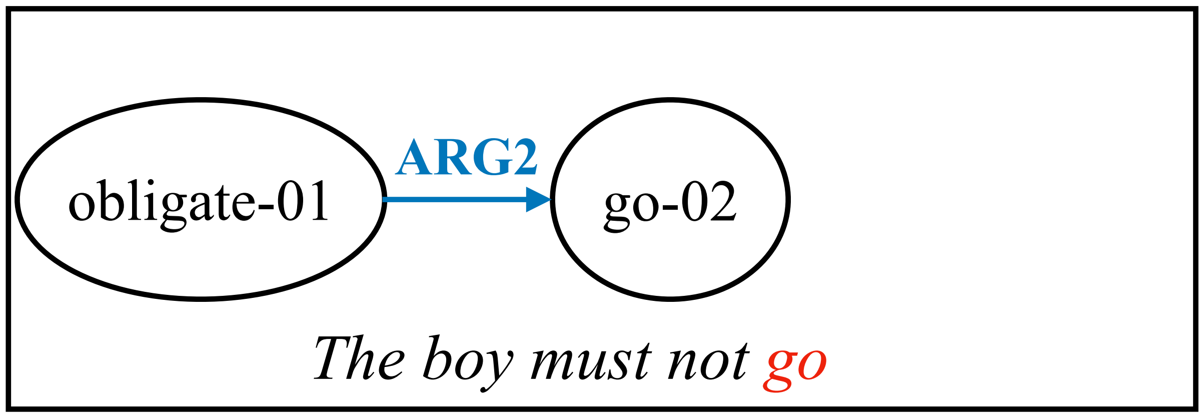
**Step3**

- Which part of the input sequence to abstract?
- Where in the output graph to construct the new concept?

**Step4**

- Which part of the input sequence to abstract?
- Where in the output graph to construct the new concept?

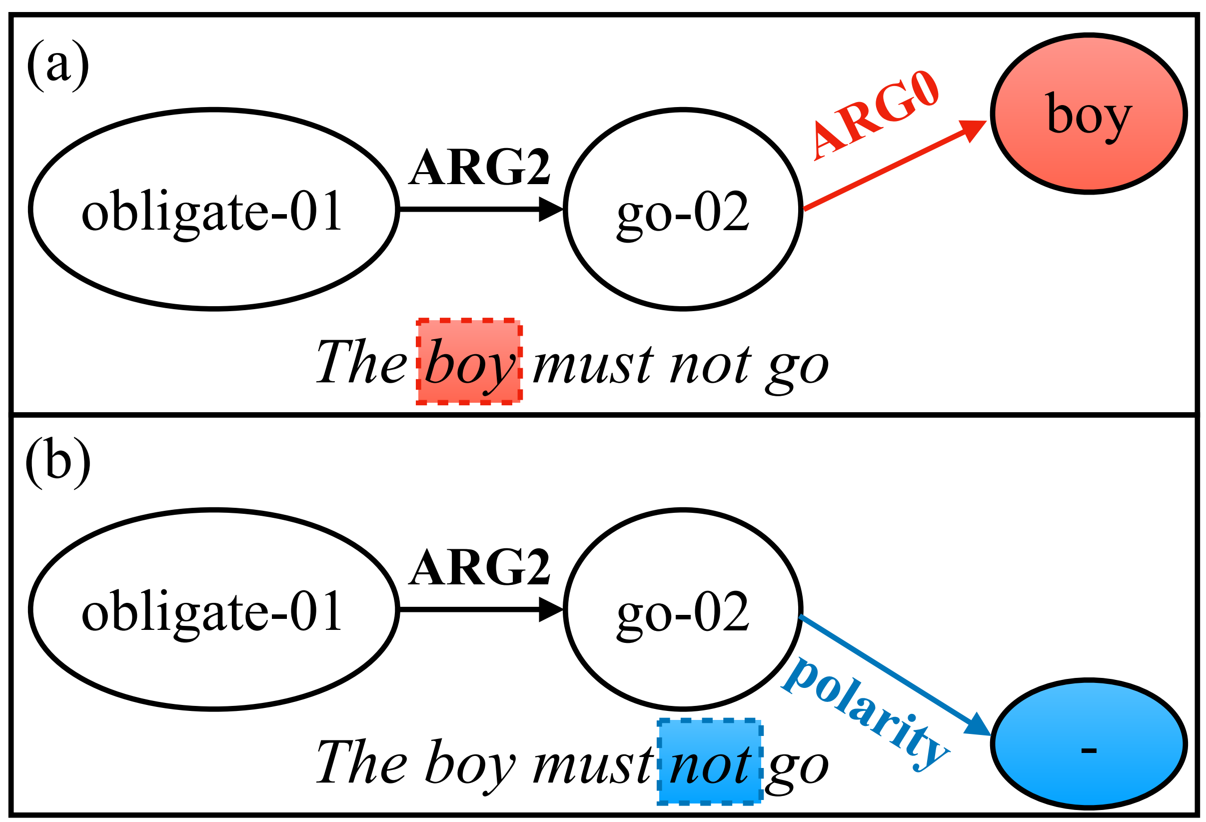
# Model Overview




**Step2**

Which part of the input sequence to abstract?

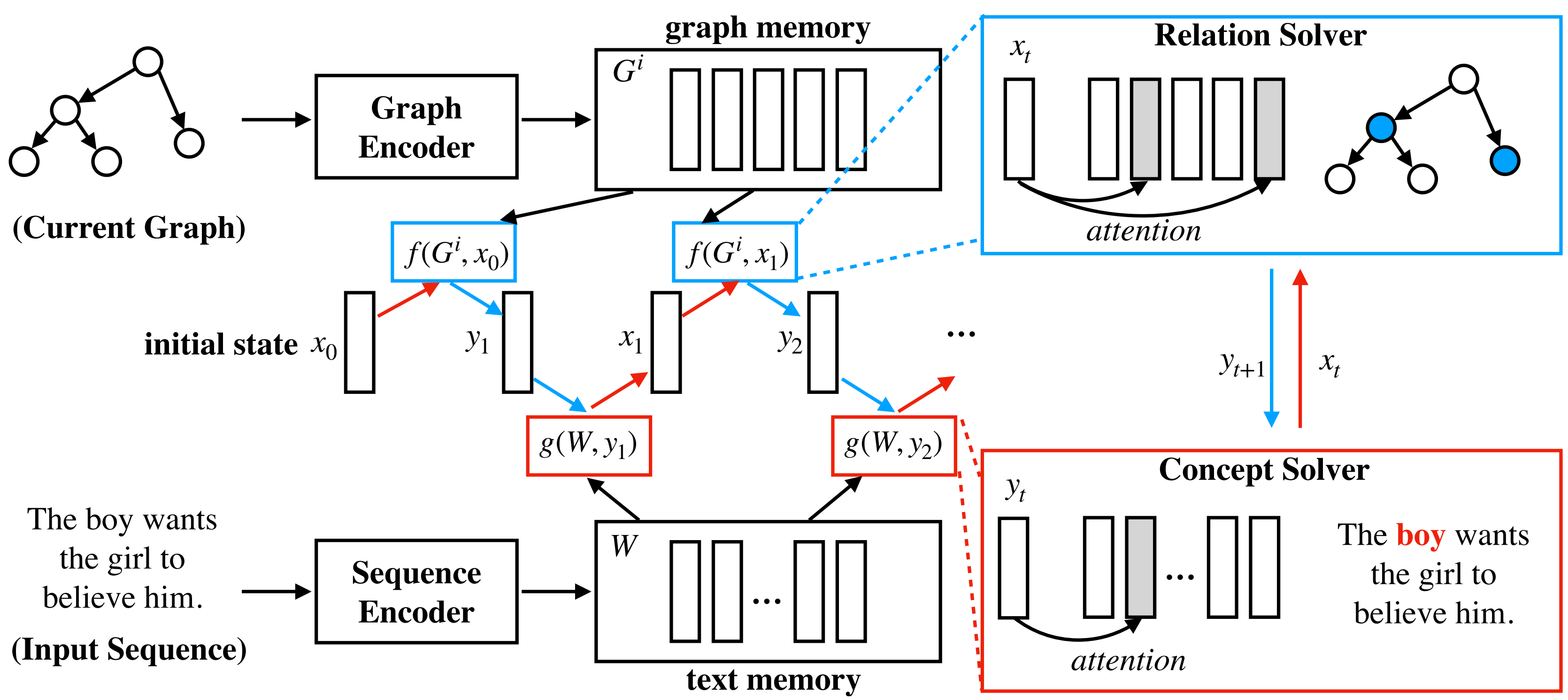
Where in the output graph to construct the new concept?



# Model Overview

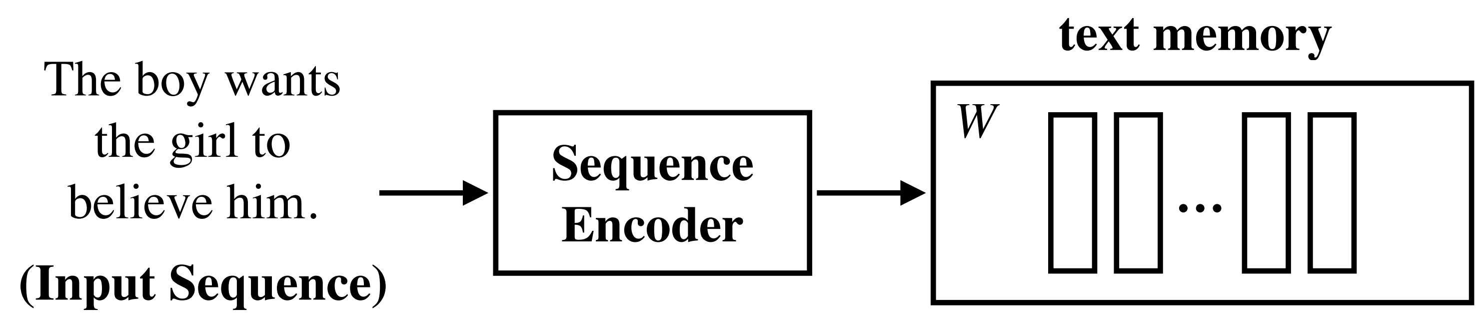
$W$: the input sentence
$G^i$: the current graph
$x_t$: the $t$-th hypothesis for where to construct (relation prediction)
$y_t$: the $t$-th hypothesis for what to abstract (concept prediction)

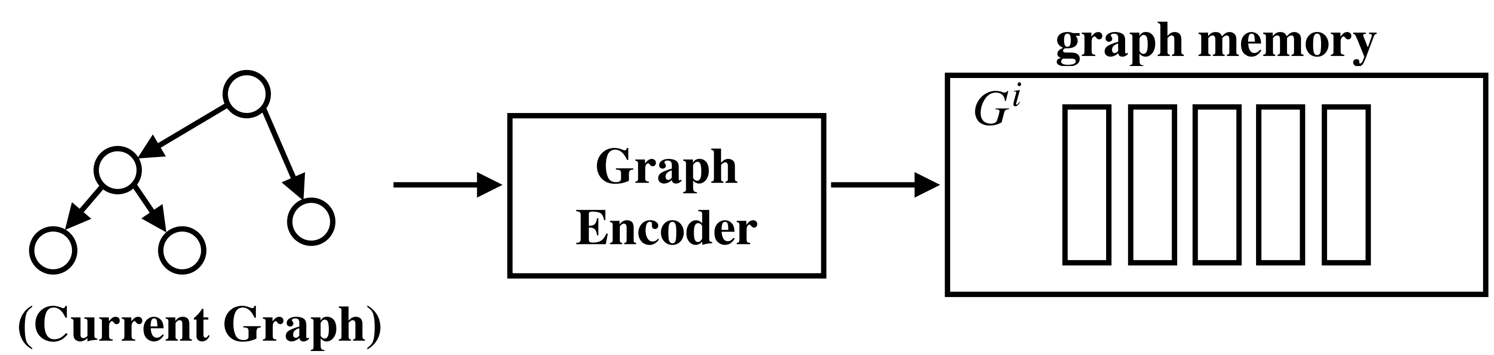
$$x_0 \rightarrow f(G^i, x_0) \rightarrow y_1 \rightarrow g(W, y_1) \rightarrow x_1 \rightarrow f(G^i, x_1) \rightarrow y_2 \rightarrow g(W, y_2) \rightarrow \cdots$$



# Model Components

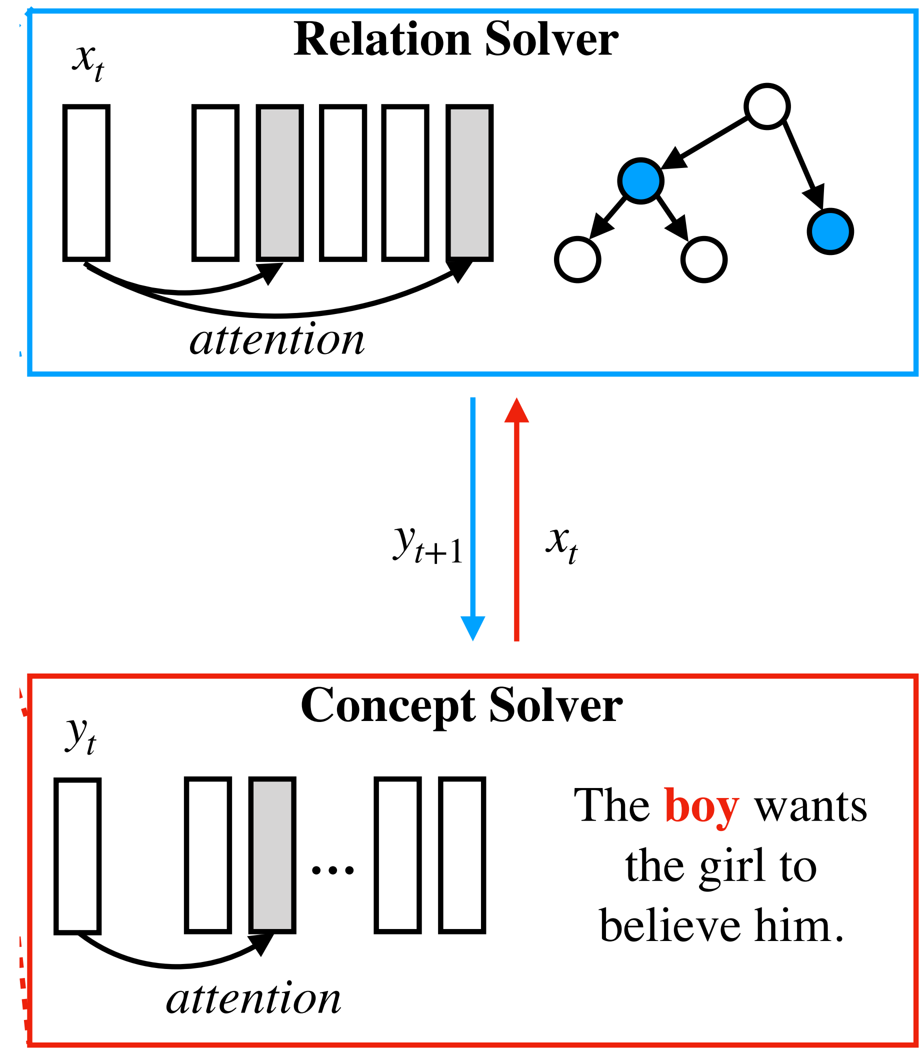
- Sequence Encoder
- Graph Encoder
- Relation Solver
- Concept Solver



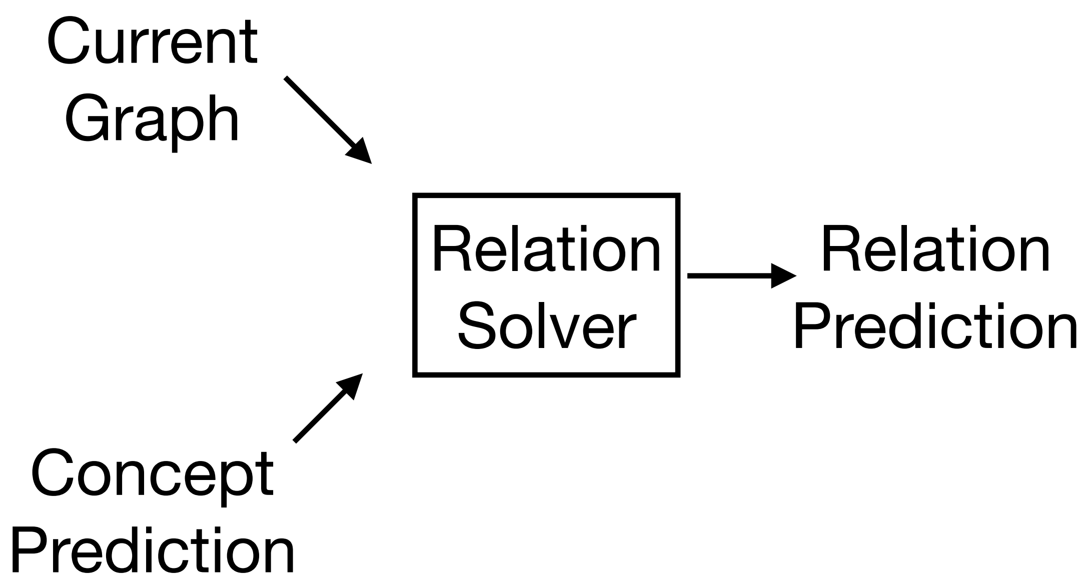
# Model Components

- Sequence Encoder
- Graph Encoder
- Relation Solver $\to f(\cdot)$
- Concept Solver $\to g(\cdot)$




$$x_0 \to f(G^i, x_0) \to y_1 \to g(W, y_1) \to x_1 \to f(G^i, x_1) \to y_2 \to g(W, y_2) \to \cdots$$

# Relation Solver



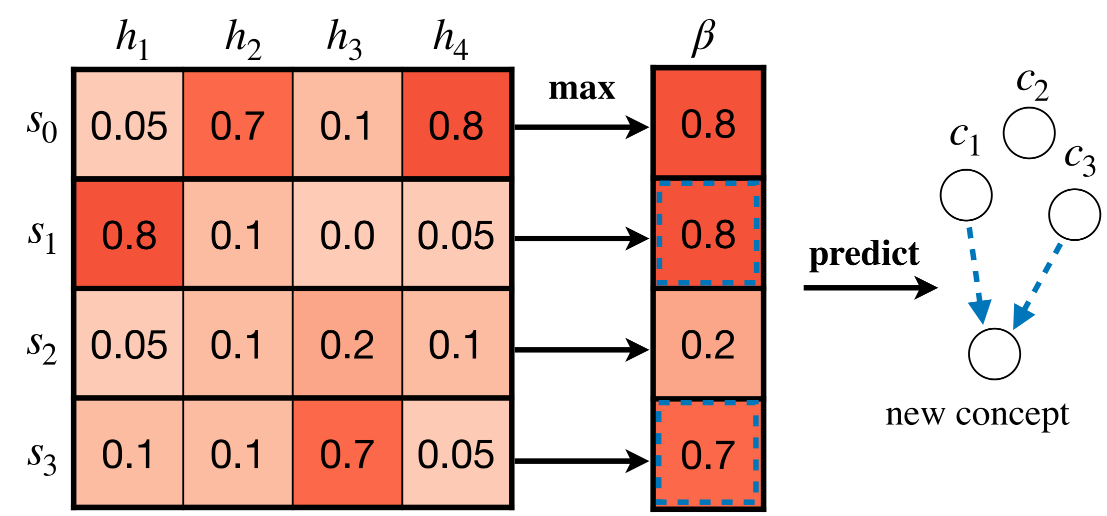
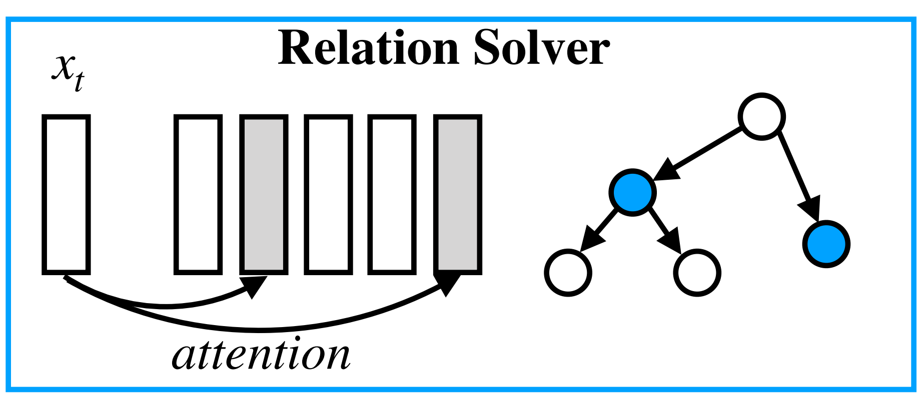
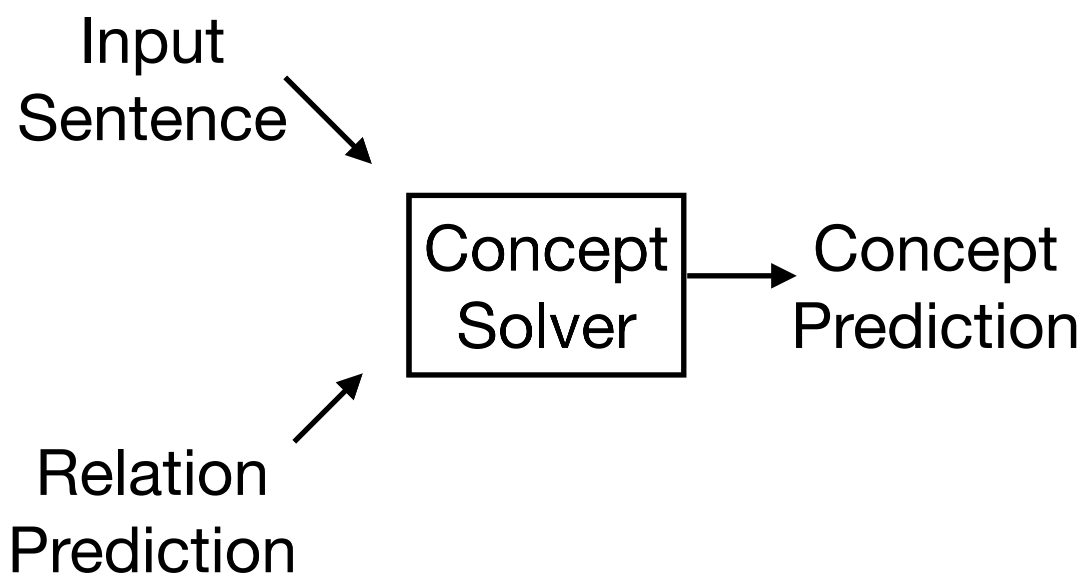




Figure 3: Multi-head attention for relation identification. At left is the attention matrix, where each column corresponds to a unique attention head, and each row corresponds to an existing node.



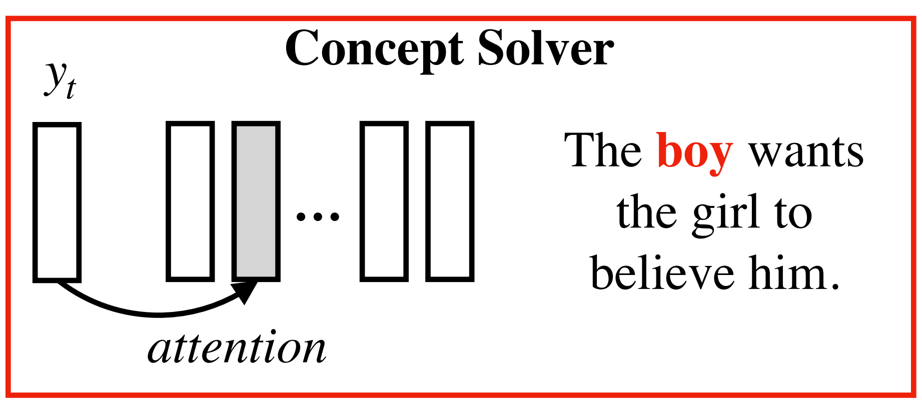
# Concept Solver




**Copy mechanisms**
0: generate from the concept vocabulary
1: copy the lemma
2: copy the token string

$$P(c) = p_0 \cdot P^{(\text{vocab})}(c) + p_1 \cdot (\sum_{i \in L(c)} \alpha_t[i]) + p_2 \cdot (\sum_{i \in T(c)} \alpha_t[i]),$$

where $[i]$ indexes the $i$-th element and $L(c)$ and $T(c)$ are index sets of lemmas and tokens respectively that have the surface form as $c$.



# Experiment Setup

- AMR2.0 (LDC2017T10)
  - The latest AMR sembank
  - ~37K, ~1K, and ~1K sentences in the training, development, and testing sets respectively
- AMR1.0 (LDC2014T12)
  - Same dev and test with AMR2.0, ~10K training sentences
  - good testbed to evaluate our model’s sensitivity for data size

# Evaluation Metrics

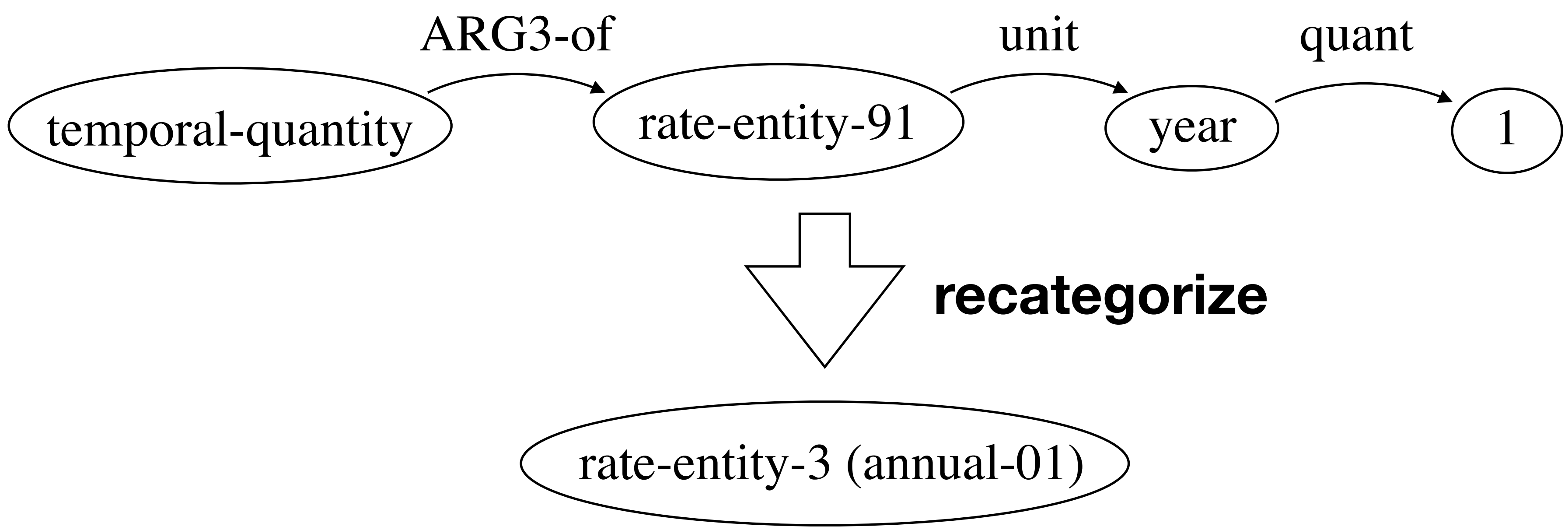
- Smatch (Cai and Knight, 2013) : seeks the maximum overlap after transforming graph into relation triples.
- Fine-grained metrics (Damonte et al, 2017) for individual sub-tasks.
    - NER, SRL, reentrancies, …

# Ablation

## (settings)

- Graph Re-categorization
- BERT

# Graph Re-categorization




- Non-trivial. It requires exhaustive screening and expert-level manual efforts.
- The precise set of re-categorization rules differs among different models.

# BERT

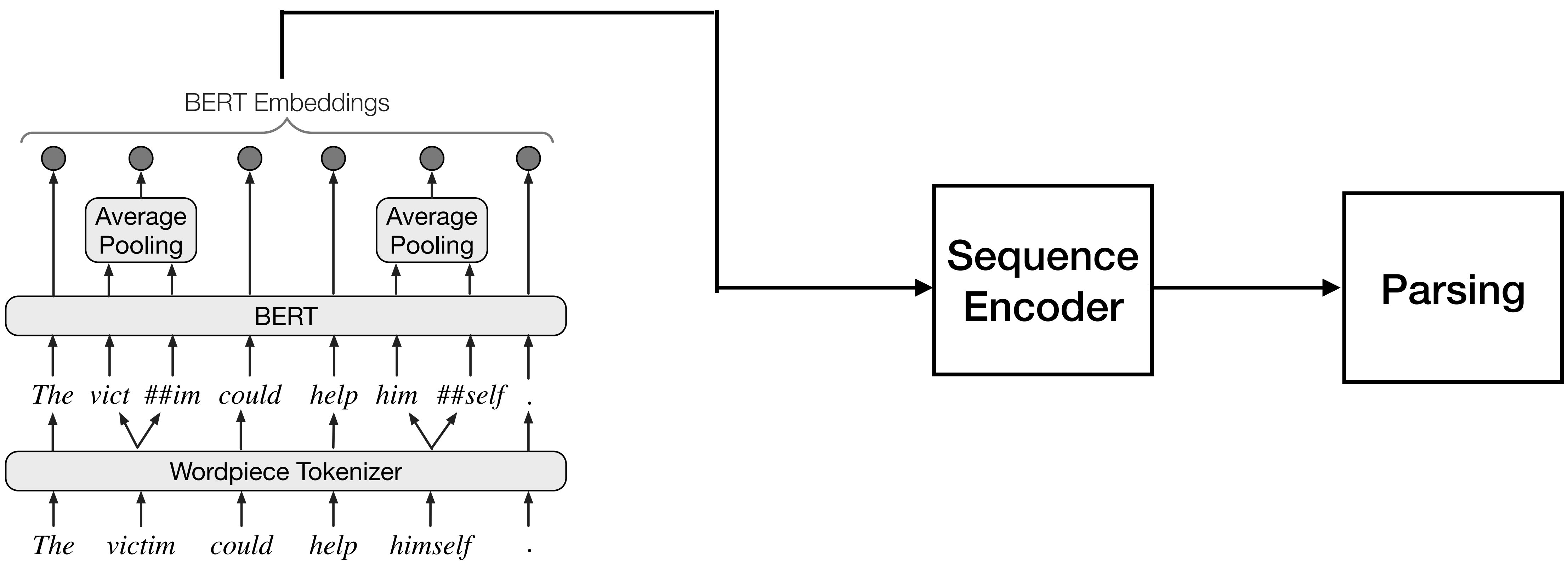



Figure 4: Word-level embeddings from BERT.

** left figure is from (Zhang et al., 2019a)*

# Settings

| Model | G. R. | BERT | SMATCH |
|---|---|---|---|
| van Noord and Bos (2017) | × | × | 71.0 |
| Groschwitz et al. (2018) | ✓ | × | 71.0 |
| Lyu and Titov (2018) | ✓ | × | 74.4 |
| Cai and Lam (2019) | × | × | 73.2 |
| Lindemann et al. (2019) | ✓ | ✓ | 75.3 |
| Naseem et al. (2019) | ✓ | ✓ | 75.5 |
| Zhang et al. (2019a) | ✓ | × | 74.6 |
| Zhang et al. (2019a) | ✓ | ✓ | 76.3 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 |

Table 1: SMATCH scores on the test set of AMR 2.0.

| Model | G. R. | BERT | SMATCH |
|---|---|---|---|
| Flanigan et al. (2016) | × | × | 66.0 |
| Pust et al. (2015) | × | × | 67.1 |
| Wang and Xue (2017) | ✓ | × | 68.1 |
| Guo and Lu (2018) | ✓ | × | 68.3 |
| Zhang et al. (2019a) | ✓ | ✓ | 70.2 |
| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |

Table 2: SMATCH scores on the test set of AMR 1.0.

# Settings

| Model | G. R. | BERT | SMATCH |
|---|---|---|---|
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| Zhang et al. (2019a) | ✓ | ✓ | 76.3 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 |
| Ours | × | × | |
| | ✓ | × | |
| | × | ✓ | |
| | ✓ | ✓ | |

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| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |
| Ours | × | × | |
| | ✓ | × | |
| | × | ✓ | |
| | ✓ | ✓ | |

Table 2: SMATCH scores on the test set of AMR 1.0.

# Main Results

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| Zhang et al. (2019a) | ✓ | × | 74.6 |
| Zhang et al. (2019a) | ✓ | ✓ | 76.3 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 |
| Ours | × | × | 74.5 |
| | ✓ | × | 77.3 |
| | × | ✓ | 78.7 |
| | ✓ | ✓ | **80.2** |

+3.2

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| Model | G. R. | BERT | SMATCH |
|---|---|---|---|
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| Guo and Lu (2018) | ✓ | × | 68.3 |
| Zhang et al. (2019a) | ✓ | ✓ | 70.2 |
| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |
| Ours | × | × | 68.8 |
| | ✓ | × | 71.2 |
| | × | ✓ | 74.0 |
| | ✓ | ✓ | **75.4** |

Table 2: SMATCH scores on the test set of AMR 1.0.

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| Ours | × | × | 74.5 |
| | ✓ | × | 77.3 |
| | × | ✓ | 78.7 |
| | ✓ | ✓ | **80.2** |

Table 1: SMATCH scores on the test set of AMR 2.0.

+0.3 w/o BERT

| Model | G. R. | BERT | SMATCH |
|---|---|---|---|
| Flanigan et al. (2016) | × | × | 66.0 |
| Pust et al. (2015) | × | × | 67.1 |
| Wang and Xue (2017) | ✓ | × | 68.1 |
| Guo and Lu (2018) | ✓ | × | 68.3 |
| Zhang et al. (2019a) | ✓ | ✓ | 70.2 |
| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |
| Ours | × | × | 68.8 |
| | ✓ | × | 71.2 |
| | × | ✓ | 74.0 |
| | ✓ | ✓ | **75.4** |

Table 2: SMATCH scores on the test set of AMR 1.0.

# Main Results

| Model | G. R. | BERT | SMATCH |
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| Groschwitz et al. (2018) | ✓ | × | 71.0 |
| Lyu and Titov (2018) | ✓ | × | 74.4 |
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| Zhang et al. (2019a) | ✓ | × | 74.6 |
| Zhang et al. (2019a) | ✓ | ✓ | 76.3 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 |
| Ours | × | × | 74.5 |
| | ✓ | × | 77.3 |
| | × | ✓ | 78.7 |
| | ✓ | ✓ | **80.2** |

Table 1: SMATCH scores on the test set of AMR 2.0.

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| Wang and Xue (2017) | ✓ | × | 68.1 |
| Guo and Lu (2018) | ✓ | × | 68.3 |
| Zhang et al. (2019a) | ✓ | ✓ | 70.2 |
| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |
| Ours | × | × | 68.8 |
| | ✓ | × | 71.2 |
| | × | ✓ | 74.0 |
| | ✓ | ✓ | **75.4** |

Table 2: SMATCH scores on the test set of AMR 1.0.

**comparable with models on AMR2.0**

**+4.1**

# Main Results

| Model | G. R. | BERT | SMATCH |
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| van Noord and Bos (2017) | × | × | 71.0 |
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| Naseem et al. (2019) | ✓ | ✓ | 75.5 |
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| Zhang et al. (2019a) | ✓ | ✓ | 76.3 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 |
| Ours | × | × | 74.5 |
| | ✓ | × | 77.3 |
| | × | ✓ | 78.7 |
| | ✓ | ✓ | **80.2** |

Table 1: SMATCH scores on the test set of AMR 2.0.

| Model | G. R. | BERT | SMATCH |
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| Zhang et al. (2019b) | ✓ | ✓ | 71.3 |
| Ours | × | × | 68.8 |
| | ✓ | × | 71.2 |
| | × | ✓ | 74.0 |
| | ✓ | ✓ | **75.4** |

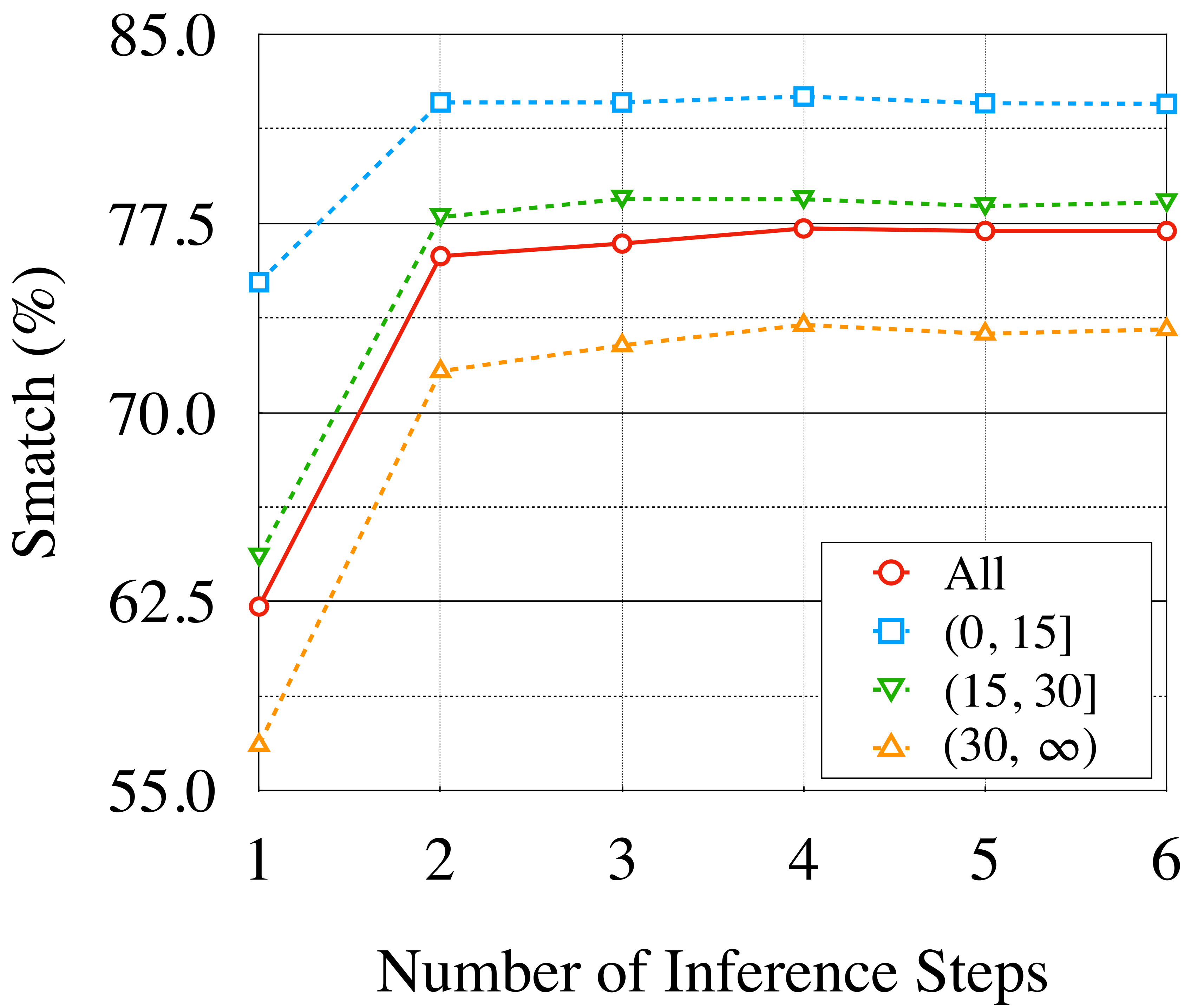
Table 2: SMATCH scores on the test set of AMR 1.0.

# Fine-grained Results

| Model | G. R. | BERT | SMATCH | fine-grained evaluation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Unlabeled | No WSD | Concept | SRL | Reent. | Neg. | NER | Wiki |
| van Noord and Bos (2017) | × | × | 71.0 | 74 | 72 | 82 | 66 | 52 | 62 | 79 | 65 |
| Groschwitz et al. (2018) | ✓ | × | 71.0 | 74 | 72 | 84 | 64 | 49 | 57 | 78 | 71 |
| Lyu and Titov (2018) | ✓ | × | 74.4 | 77.1 | 75.5 | 85.9 | 69.8 | 52.3 | 58.4 | 86.0 | 75.7 |
| Cai and Lam (2019) | × | × | 73.2 | 77.0 | 74.2 | 84.4 | 66.7 | 55.3 | 62.9 | 82.0 | 73.2 |
| Lindemann et al. (2019) | ✓ | ✓ | 75.3 | - | - | - | - | - | - | - | - |
| Naseem et al. (2019) | ✓ | ✓ | 75.5 | 80 | 76 | 86 | 72 | 56 | 67 | 83 | 80 |
| Zhang et al. (2019a) | ✓ | × | 74.6 | - | - | - | - | - | - | - | - |
| Zhang et al. (2019a) | ✓ | ✓ | 76.3 | 79.0 | 76.8 | 84.8 | 69.7 | 60.0 | 75.2 | 77.9 | 85.8 |
| Zhang et al. (2019b) | ✓ | ✓ | 77.0 | 80 | 78 | 86 | 71 | 61 | 77 | 79 | 86 |
| Ours | × | × | 74.5 | 77.8 | 75.1 | 85.9 | 68.5 | 57.7 | 65.0 | 82.9 | 81.1 |
| | ✓ | × | 77.3 | 80.1 | 77.9 | 86.4 | 69.4 | 58.5 | 75.6 | 78.4 | 86.1 |
| | × | ✓ | 78.7 | 81.5 | 79.2 | 88.1 | **74.5** | 63.8 | 66.1 | **87.1** | 81.3 |
| | ✓ | ✓ | **80.2** | **82.8** | **80.8** | **88.1** | 74.2 | **64.6** | **78.9** | 81.1 | **86.3** |

Table 3 : Fine-grained results on the test set of AMR 2.0.

# Effect of Iterative Inference



# AMR Parsing via Graph⇆Sequence Iterative Inference

# Thanks!

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*thisisjcykcd@gmail.com*