AMR Parsing as Graph Prediction with Latent Alignment

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Abstract Meaning Representations

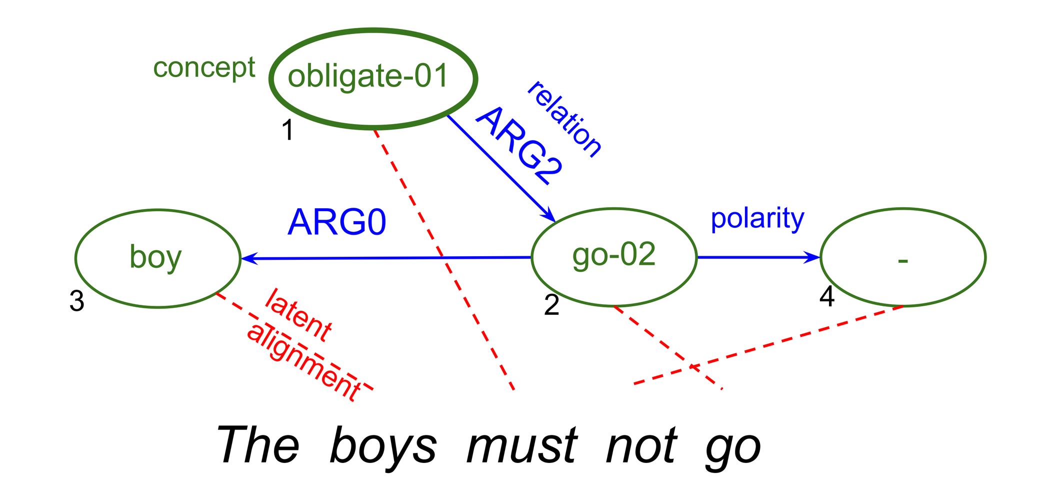


Fig. 1. An example of AMR, the dashed lines denote latent alignments, obligate-01 is the root.

Main Contributions

- Lack of gold alignment -> **AMR parsing with a joint probabilistic model for alignment, concept and relation identification.**
- Seq2seq model could work well for semantic parsing ? -> **our non-autoregressive model achieves the best reported results (+3.4% over previous state of the art).** Sequence tagging does not suffer from exposure bias.

AMR Parsing as Graph Prediction

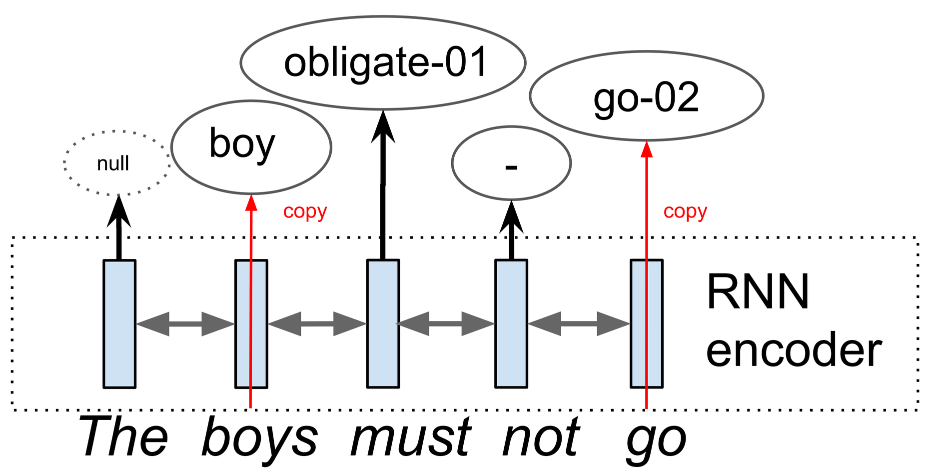


Fig. 2. Concept Identification

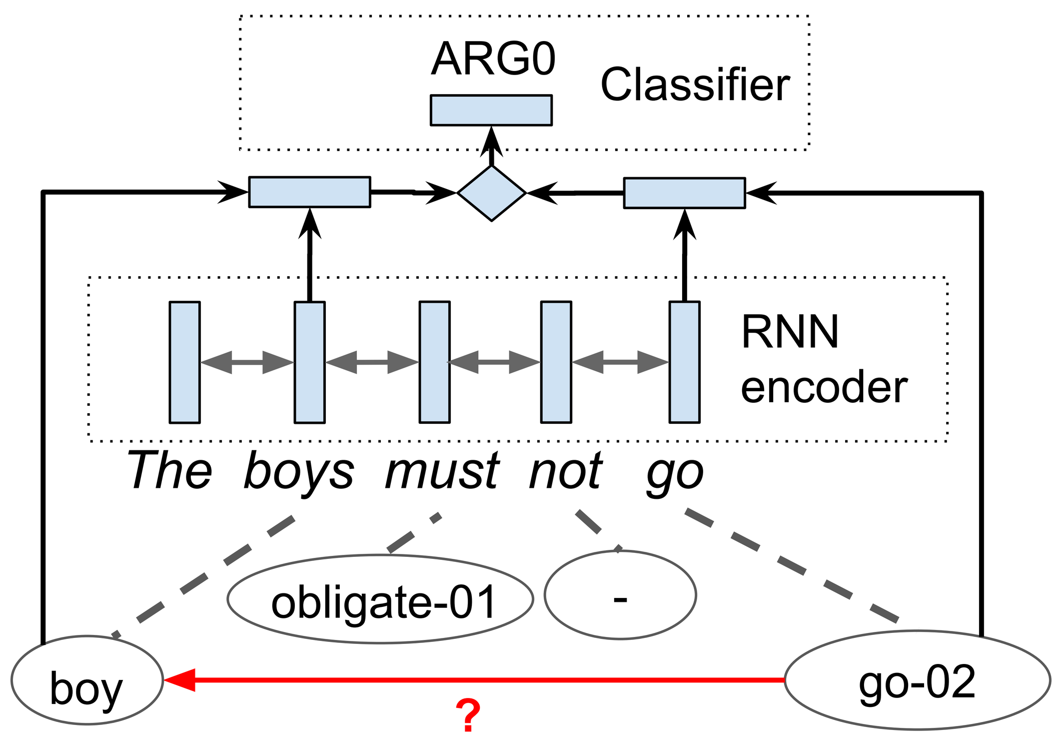


Fig. 3. Relation Identification:

Variational Auto-Encoder

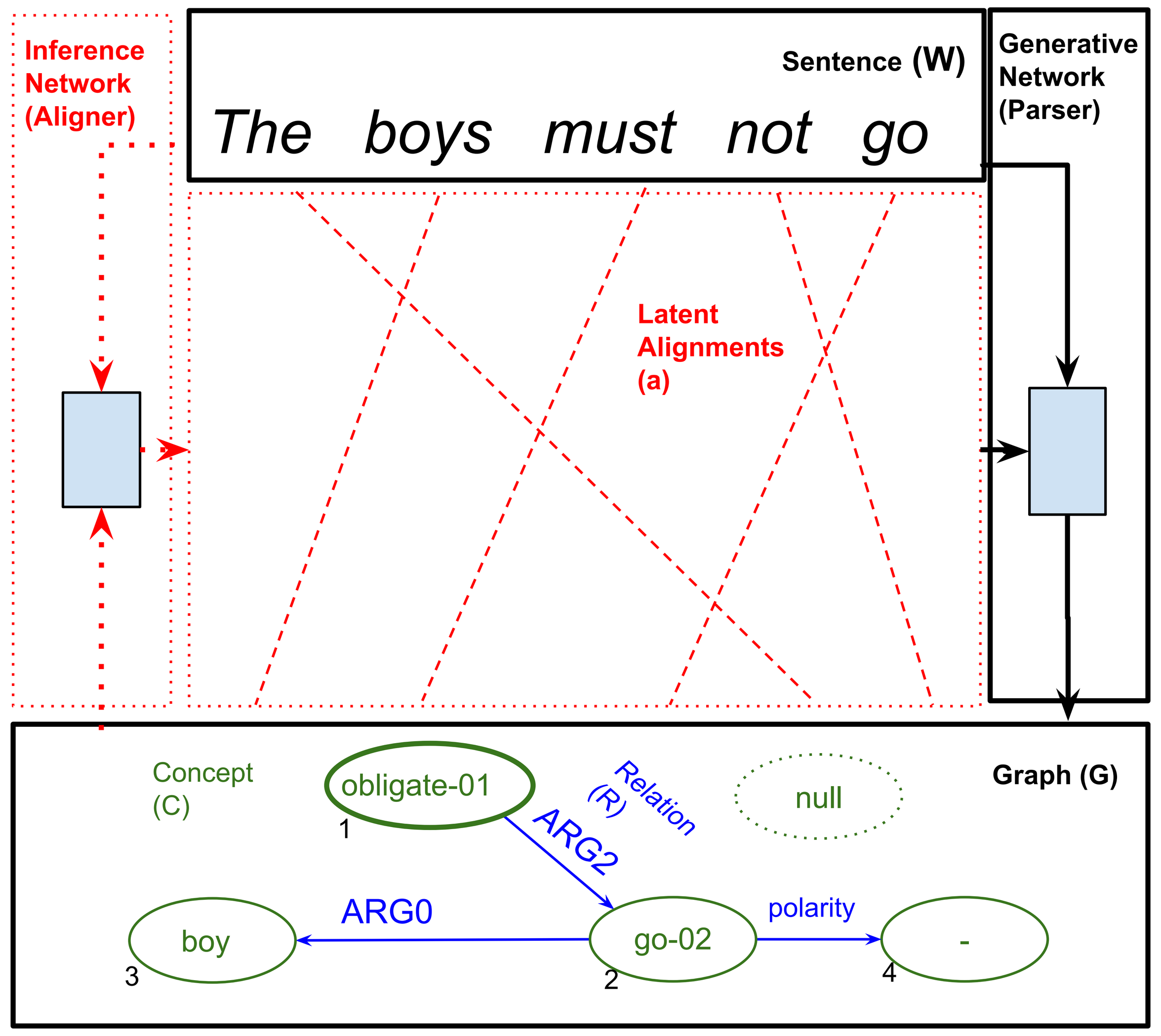


Fig. 4. Joint Training for AMR parsing

Joint Training Objective

$P_{\theta,\phi}(\mathbf{c}, R|\mathbf{w})$ Conditional probability needs marginalizing over bi-jective alignment

$$= \sum_{\mathbf{a} \in Perm} P(\mathbf{a}) P_\theta(\mathbf{c}|\mathbf{a}, \mathbf{w}) P_\phi(R|\mathbf{a}, \mathbf{w}, \mathbf{c})$$

Further conditional independence

$$= \sum_{\mathbf{a} \in Perm} P(\mathbf{a}) \prod_{i=1}^{m} P(c_i|\mathbf{h}_{a_i}) \prod_{i,j=1}^{m} P(r_{ij}|\mathbf{h}_{a_i}, \mathbf{c}_i, \mathbf{h}_{a_j}, \mathbf{c}_j)$$

- marginalization is intractable

-> variational inference

Variational Lower Bound

$\log P_{\theta,\phi}(\mathbf{c}, R|\mathbf{w})$ Log of marginalized probability

$\geq E_Q[\log P_\theta(\mathbf{c}|\mathbf{a}, \mathbf{w}) P_\phi(R|\mathbf{a}, \mathbf{w}, \mathbf{c})]$ Expected likelihood

$-D_{KL}(Q_\psi(\mathbf{a}|\mathbf{c}, R, \mathbf{w}) || P(\mathbf{a})),$ KL regularizer

- Sampling over permutation is still intractable

-> For permutation, Gumbel-Sinkhorn provides relaxed sample from approximate Perturb-and-MAP

(Mena Et all. 2018)

Gumbel-Sinkhorn Relaxation

$\Sigma_{ij} \sim \mathcal{G}(0, 1)$ Generate Gumbel noise for each concept word pair

$\Phi_{ij} = \mathbf{c}_i^T B \mathbf{w}_j$ Compute bilinear score based on RNN encoding

$\hat{\mathbf{a}} = S_t(\Phi, \Sigma)$ Apply Sinkhorn operator to get soft alignment

$S_0(\Phi, \Sigma) = \exp(\Phi + \Sigma)$ Sinkhorn initialize with exponential

$S_t(\Phi, \Sigma) = \mathcal{N}_r(\mathcal{N}_c(S_{t-1}(\Phi, \Sigma)))$ Iteratively normalize across columns and rows

$E_{\Sigma \sim \mathcal{G}(0,1)}[\log P_\theta(c|S_t(\Phi_\psi, \Sigma), \mathbf{w})$
$+ \log P_\phi(R|S_t(\Phi_\psi, \Sigma), \mathbf{w}, \mathbf{c})]$ Feed soft alignment to neural model

$-D_{KL}(\frac{\Phi_\psi + \Sigma}{t} || \frac{\Sigma}{t_0})$ Reparemetrized KL to be computable

- Soft alignment can not be used directly

-> Model relaxation is needed

Model Relaxation

For concept identification model , treat soft alignment as prior

$$\log P_\theta(c_i|\hat{\mathbf{a}}_\mathbf{i}, \mathbf{w}) \approx \log \sum_{k=1}^{n} \hat{\mathbf{a}}_{ik} P_\theta(c_i|a_i = k, \mathbf{w})$$

For relation identification , weight representation with soft alignment

$$\hat{\mathbf{h}_{a_i}} := \sum_{k=1}^{n} \hat{\mathbf{a}}_{ik} \mathbf{h}_k$$

Recategorization

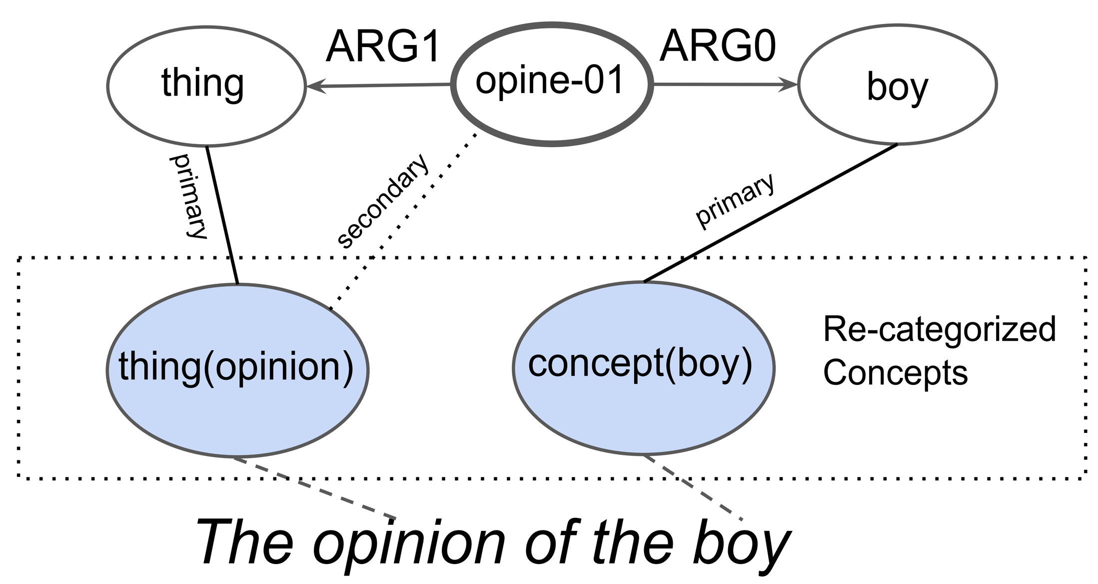
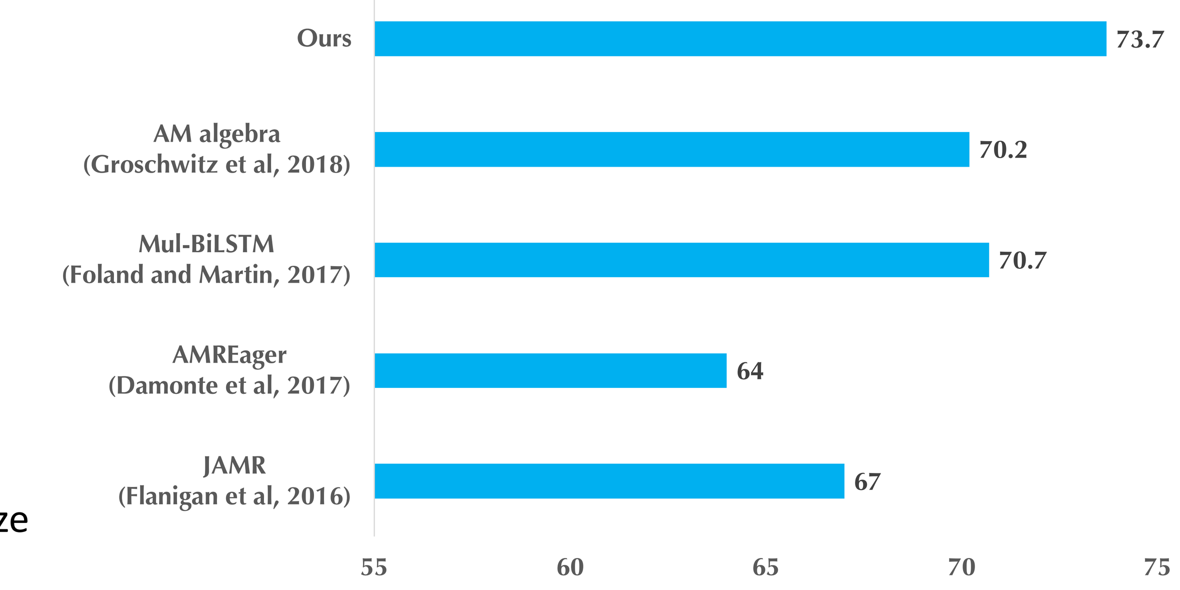
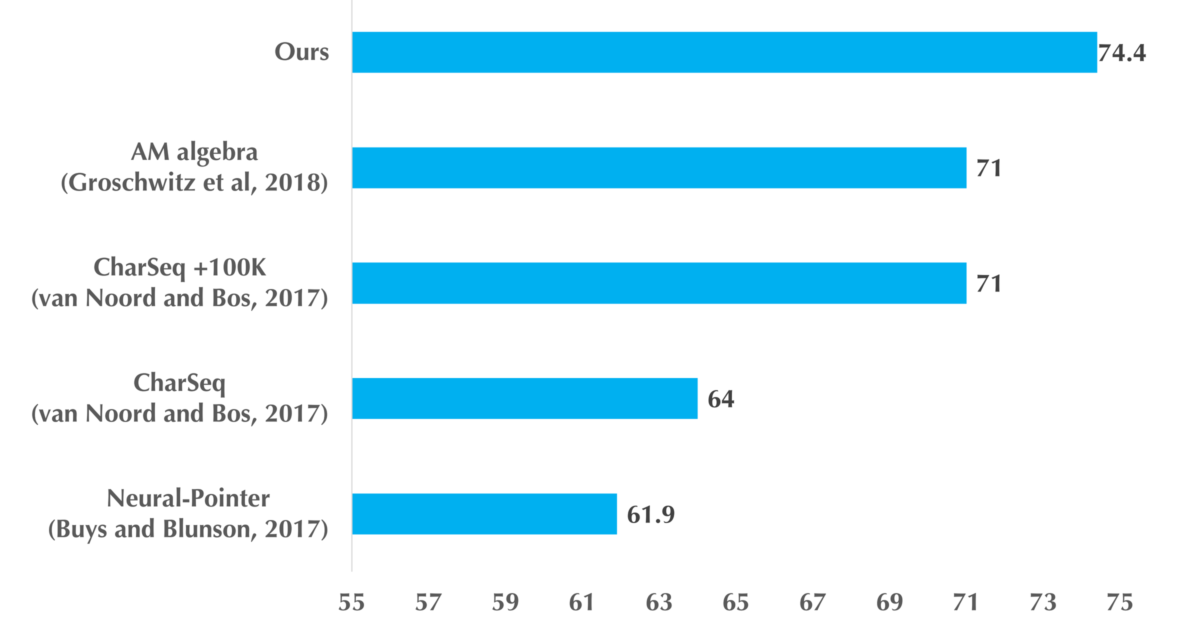


Fig. 5 An example of re-categorized AMR

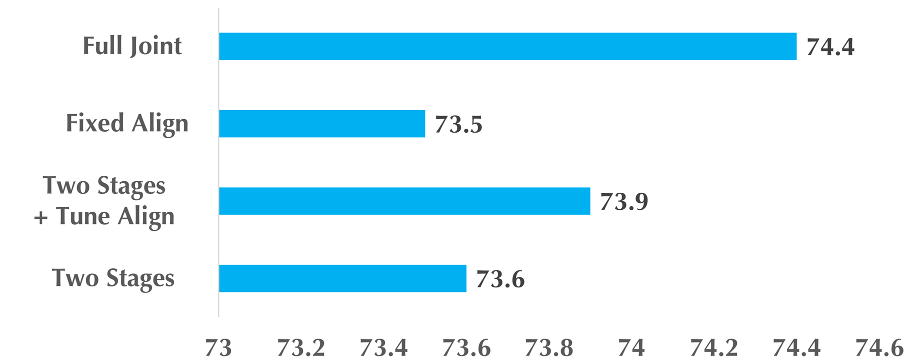
Results





Models	A'17	J'16	Ch'17	AM	Ours
Dataset		R1			R2
Smatch	64	67	71	71	***74.4±0.16***
Unlabeled	69	69	74	74	***77.1±0.10***
No WSD	65	68	72	72	***75.5±0.12***
Concepts	83	83	82	84	***85.9±0.11***
NER	83	79	79	78	***86.0±0.46***
Negations	48	45	***62***	57	58.4±1.32
SRL	56	60	66	64	***69.8±0.24***

Table 1. F1 scores on individual phenomena. A'17 is AMREager, J'16 is JAMR, Ch'17 is CharSeq+100K, AM is AM algebra.



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