Robust Subgraph Generation Improves Abstract Meaning Representation Parsing

Parsing

IIP lab
정남규

Summary

- Title : Robust Subgraph Generation Improves Abstract Meaning Representation Parsing
- Journal Name : **Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing**
- Published in, Year : **2015**
- Authors : Keenon Werling, Gabor Angeli, Christopher D. Manning

Abstract Meaning Representation

Graph-based language for expressing semantics over a broad domain

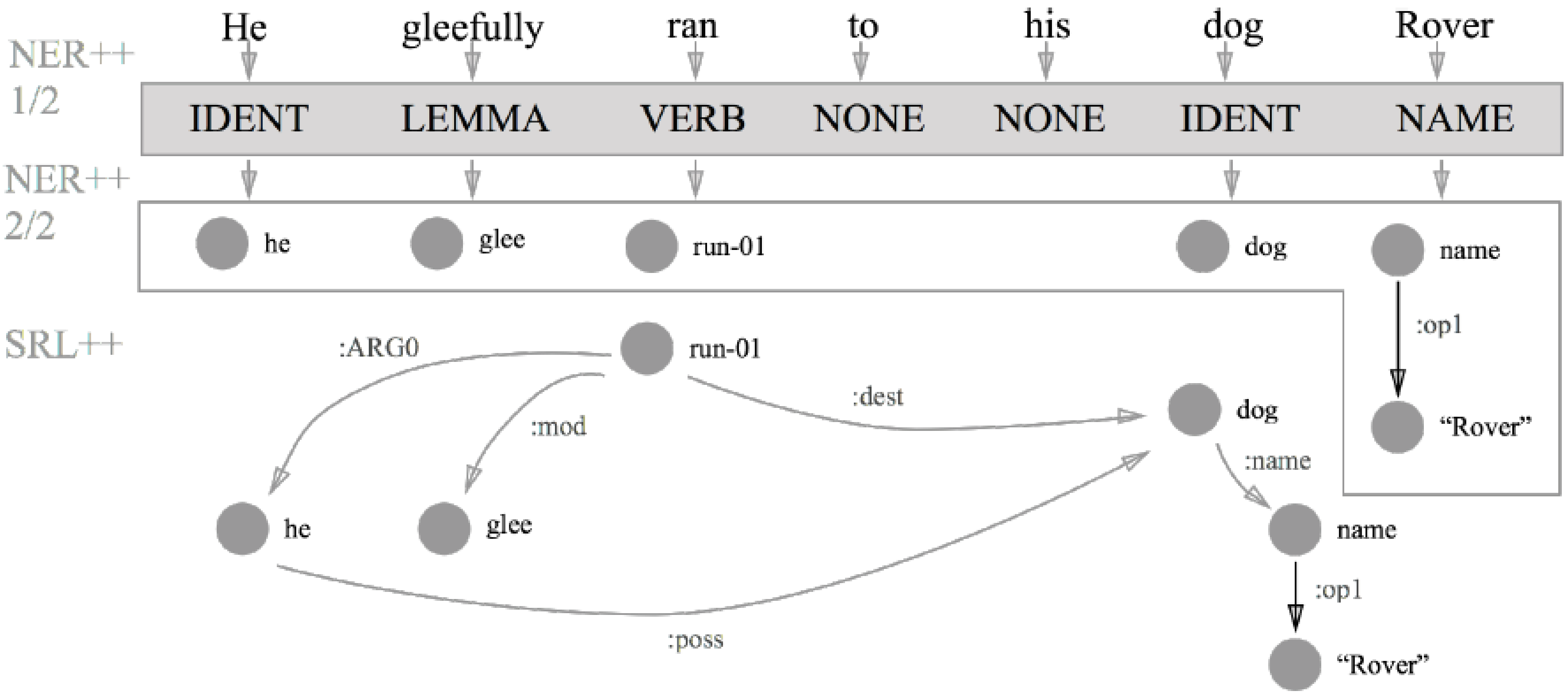
AMR Parsing

The task of mapping a natural language sentence into an AMR graph

JAMR Parser

Only published end-to-end AMR parser

1. NER++ : Concept identification
2. SRL ++ : Relation identification



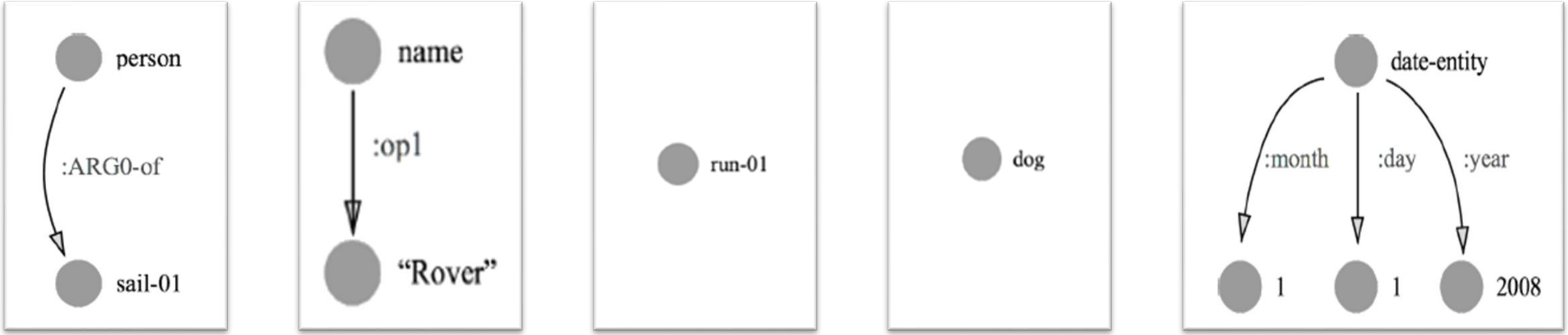
NER++

Generates a disjoint set of subgraphs that represent abstract meanings in a sentence.

We Partition the AMR sub-graph space into a set of 9 actions.

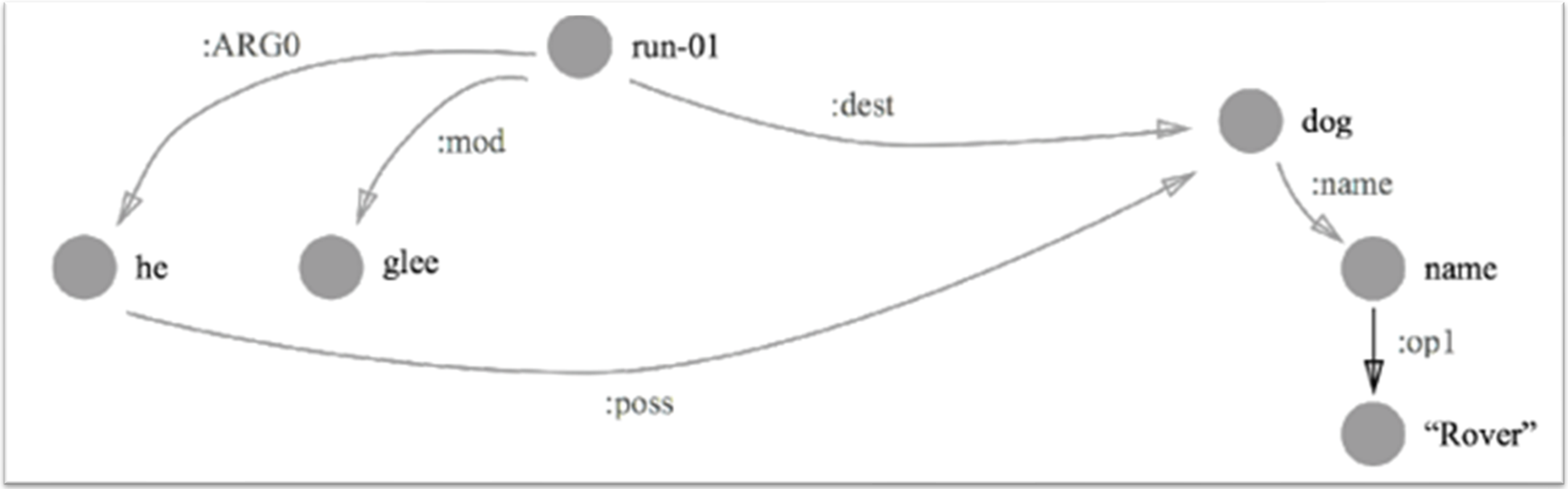
PERSON | IDENTITY | NAME | NONE | LEMMA | VALUE | VERB | DATE | DICT

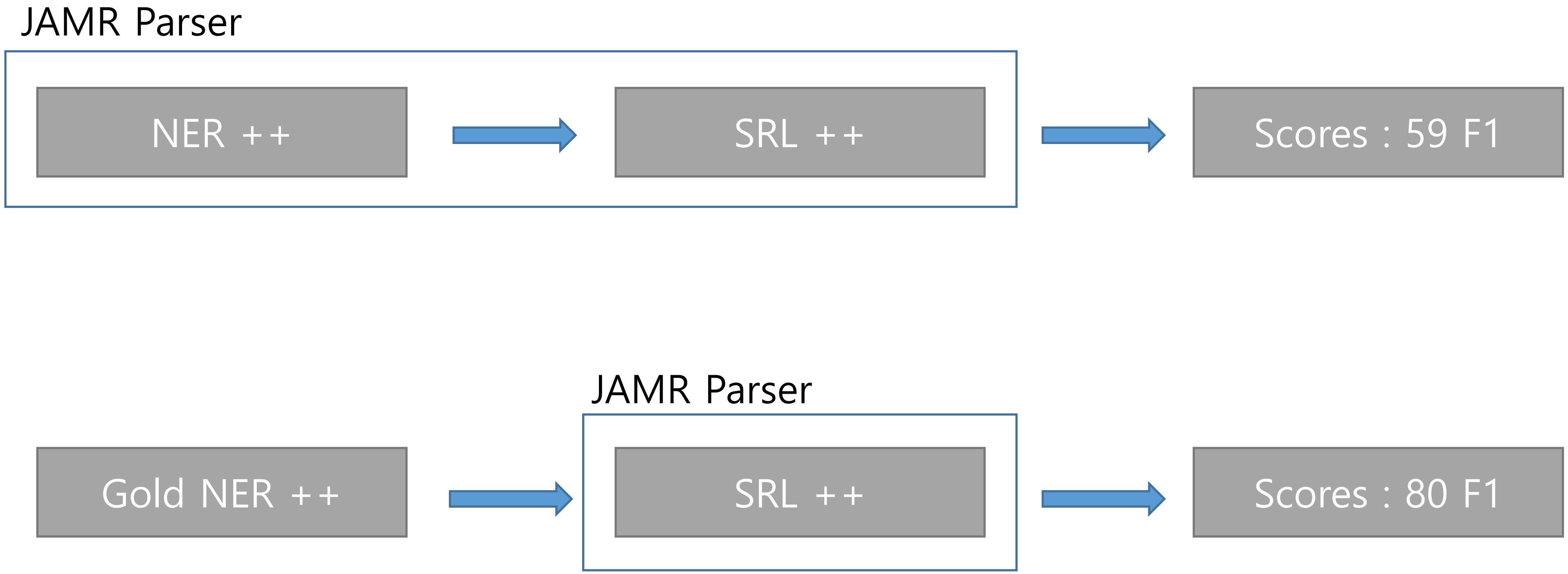
Verb : use PropBank



SRL++

Generates a coherent graph from the set of disjoint subgraphs.




JAMR Parser
NER ++
SRL ++
Scores : 59 F1
JAMR Parser
Gold NER ++
SRL ++
Scores : 80 F1

A Novel NER++ Method

38% of the words in the LDC2014E113 dev set are unseen during training time.

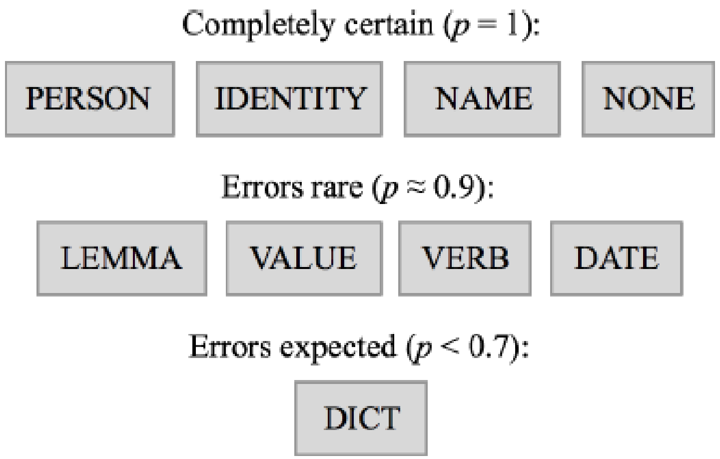
Old Approach : memorization-based approach

New Approach : reliability action-based approach

Action Reliability

Action Reliability as the probability of deriving the correct.

We can therefore construct a hierarchy of reliability.



We prefer to generate actions from higher in the hierarchy.
They are more likely to produce the correct subgraph.

Training the action classifier

Given a set of AMR training data, in the form of (graph, sentence) pairs.

For every node n_i in the AMR graph,
alignment gives us some token s_j (jth index in the sentence) that we believe generated the node n_i

Inducing the most reliable action for every token in the training corpus provides a supervised training set

Input token; word embedding
Left+right token / bigram
Token length indicator
Token starts with "non"
POS; Left+right POS / bigram
Dependency parent token / POS
Incoming dependency arc
Bag of outgoing dependency arcs
Number of outgoing dependency arcs
Max Jaro-Winkler to any lemma in PropBank
Output tag of the **VERB** action if applied
Output tag of the **DICT** action if applied
NER; Left+right NER / bigram
Capitalization
Incoming prep_* or appos + parent has NER
Token is pronoun
Token is part of a coref chain
Token pronoun and part of a coref chain

< Maxent classifier >

Automatic Alignment of Training Data

We formulate this objective as a Boolean LP problem.

Let Q be a matrix in $\{0,1\}^{|N|\times|S|}$ of Boolean constrained variables, where N are the nodes in an AMR graph, and S are the tokens in the sentence.

Let V be a matrix in $T^{|N|\times|S|}$, where T is the set of actions in the NER++.

Let the function $REL(l)$ be the reliability of action l.

Our objective :

$$\max_{\mathbf{Q}} \sum_{i,j} \mathrm{Q}_{i,j}\left[\log(\mathrm{REL}(\mathrm{V}_{i,j})) + \alpha\mathcal{E}_{i,j}\right]$$

$$\text{s.t.} \quad \sum_{j} \mathrm{Q}_{i,j} = 1 \quad \forall i \qquad (2)$$

$$\mathrm{Q}_{k,j} + \mathrm{Q}_{l,j} \leq 1 \quad \forall k, l, j;\ n_k \nleftrightarrow n_l \qquad (3)$$

Where ε is the Jaro-Winkler similarity between the title of the node i and the token j, α is a hyper-parameter

Results

Dataset	System	P	R	F1
2014T12	JAMR	**67.1**	53.2	59.3
	Our System	66.6	**58.3**	**62.2**
2013E117	JAMR	**66.9**	52.9	59.1
	Our System	65.9	**59.0**	**62.3**

Conclusion

We address a key challenge in AMR parsing: the task of generating subgraphs for AMR.

Our work improves end-to-end recall for AMR parsing with only a small drop in precision.

We hope our decomposition provides a useful framework to guide future work in AMR in general.

Thank you

Parsing