Span-Based Semantic Role Labeling with Argument Pruning and Second-Order Inference

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1. Motivation
We study span-based semantic role labeling with high-order inference.
Advantages of span-based SRL:
- Capable of handling multiple predicates.
- Better utilization of span-level features.
Disadvantages of span-based SRL:
- $O(n^3)$ complexity of enumerating predicate-argument pairs.
- High degree of imbalance between positive and negative samples.
Advantage of high-order inference:
- Capture interactions between multiple arguments and predicates.
Disadvantage of high-order inference:
- Exact high-order inference is intractable, even for second-order inference, there are already $O(n^5)$ parts.

2. Our approach

Step 1: Pruning (corresponding to PAPN model)
Predicate-agnostic pruning reduces candidate arguments from $O(n^2)$ to $O(n)$.

Step 2: Identification (corresponding to SRLN Identifier)
Semantic Role Labeling Network with optional high-order decoder, which identifies the candidate arguments of each predicate.

Step 3: Classification (corresponding to SRLN Classifier)
Semantic Role Labeling Network, which labeled arguments of each predicate.

3. Our Model

A. PAPN
- We score every possible span by its start and end tokens, pick top-k spans as candidate arguments.
- We train PAPN by optimizing the loss as follows:
  \[ \text{Loss} = \sum_{i,j} \text{CrossEntropy} (y_{ij}, \text{Sigmoid} (s_{ij})) \]
  \[ s_{ij} : \text{score of span } (i,j) \]
  \[ y_{ij} = \begin{cases} 1 & \text{if span}(i,j) \text{ is an argument of some predicate} \\ 0 & \text{otherwise} \end{cases} \]

B. SRLN Identifier
- With candidate arguments $O(n)$ from PAPN, SRLN identifier considers the interaction between each pair of potential pred-arg pairs that share the same predicate.
- We use Mean Field Variational Inference to get the posterior probability of all possible pred-arg pairs.
- Dynamic programming is then used to identify all the pred-arg pairs under the constraint that there are no overlapping arguments for each predicate.

C. SRLN Classifier
- With the result of identified pred-arg pairs from SRLN identifier, we score each pred-arg pair and get its distribution over the SRL label set.

4. Experiment Settings

1. Datasets

2. Evaluation
Micro-average F1 score for correctly predicted (predicate, argument span, label) tuples.

3. Two SRL settings
predicted predicates setting and gold predicates setting.

5. Experiment Results

<table>
<thead>
<tr>
<th>Predicted predicates</th>
<th>WSJ</th>
<th>Brown</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoNLL2005</td>
<td>F1</td>
<td>86.0</td>
</tr>
<tr>
<td>CoNLL2012</td>
<td>F1</td>
<td>86.3</td>
</tr>
</tbody>
</table>

6. Experiment Analysis

1. Error correction of our second-order model over our first-order model.

2. Independent and joint learning of PAPN and SRLN

- With the result of identified pred-arg pairs from SRLN identifier, we score each pred-arg pair and get its distribution over the SRL label set.

3. Comparison results are from previous SOTA models which perform joint training of pruning and SRL model.
- Our experiments show that results of independent learning is better than the results of joint learning.

7. Conclusion
- We propose a novel graph-based approach to span-based SRL which consists of a predicate-agnostic argument pruning network and an SRL network.
- The pruning network reduces the number of candidate arguments to $O(n)$.
- The SRL network can perform both first-order decoding and second-order decoding using recurrent neural networks unfolded from mean-field variational inference.
- Experiments show effectiveness of our model and The second-order decoding achieves better result than the first-order.