Abstract

Recent BIO-tagging-based neural semantic role labeling models are very high performing, but assume gold predicates as part of the input and cannot incorporate span-level features. We propose an end-to-end approach for jointly predicting all predicates, arguments spans, and the relations between them. The model makes independent decisions about what relationship, if any, holds between every possible word-span pair, and learns contextualized span representations that provide rich, shared input features for each decision. Experiments demonstrate that this approach sets a new state of the art on PropBank SRL without gold predicates.

1 Introduction

Semantic role labeling (SRL) captures predicate-argument relations, such as “who did what to whom.” Recent high-performing SRL models (He et al., 2017; Marcheggiani et al., 2017; Tan et al., 2018) are BIO-taggers, labeling argument spans for a single predicate at a time (as shown in Figure 1). They are typically only evaluated with gold predicates, and must be pipelined with error-prone predicate identification models for deployment.

We propose an end-to-end approach for predicting all the predicates and their argument spans in one forward pass. Our model builds on a recent coreference resolution model (Lee et al., 2017), by making central use of learned, contextualized span representations. We use these representations to predict SRL graphs directly over text spans. Each edge is identified by independently predicting which role, if any, holds between every possible pair of text spans, while using aggressive beam pruning for efficiency. The final graph is simply the union of predicted SRL roles (edges) and their associated text spans (nodes).

Our span-graph formulation overcomes a key limitation of semi-markov and BIO-based models (Kong et al., 2016; Zhou and Xu, 2015; Yang and Mitchell, 2017; He et al., 2017; Tan et al., 2018): it can model overlapping spans across different predicates in the same output structure (see Figure 1). The span representations also generalize the token-level representations in BIO-based models, letting the model dynamically decide which spans and roles to include, without using previously standard syntactic features (Punyakanok et al., 2008; FitzGerald et al., 2015).

To the best of our knowledge, this is the first span-based SRL model that does not assume that predicates are given. In this more realistic setting, where the predicate must be predicted, our model achieves state-of-the-art performance on PropBank. It also reinforces the strong performance of similar span embedding methods for coreference (Lee et al., 2017), suggesting that this style of models could be used for other span-span relation tasks, such as syntactic parsing (Stern et al., 2017), relation extraction (Miwa and Bansal, 2016), and QA-SRL (FitzGerald et al., 2018).

1Code and models: https://github.com/luheng/lsgn
2 Model

We consider the space of possible predicates to be all the tokens in the input sentence, and the space of arguments to be all continuous spans. Our model decides what relation exists between each predicate-argument pair (including no relation).

Formally, given a sequence \( X = w_1, \ldots, w_n \), we wish to predict a set of labeled predicate-argument relations \( Y \subseteq \mathcal{P} \times \mathcal{A} \times \mathcal{L} \), where \( \mathcal{P} = \{w_1, \ldots, w_n\} \) is the set of all tokens (predicates), \( \mathcal{A} = \{(w_i, \ldots, w_j) \mid 1 \leq i \leq j \leq n\} \) contains all the spans (arguments), and \( \mathcal{L} \) is the space of semantic role labels, including a null label \( \epsilon \) indicating no relation. The final SRL output would be all the non-empty relations \( \{(p, a, l) \in Y \mid l \neq \epsilon\} \).

We then define a set of random variables, where each random variable \( y_{p,a} \) corresponds to a predicate \( p \in \mathcal{P} \) and an argument \( a \in \mathcal{A} \), taking value from the discrete label space \( \mathcal{L} \). The random variables \( y_{p,a} \) are conditionally independent of each other given the input \( X \):

\[
P(Y \mid X) = \prod_{p \in \mathcal{P}, a \in \mathcal{A}} P(y_{p,a} \mid X) \tag{1}
\]

\[
P(y_{p,a} = l \mid X) = \frac{\exp(\phi(p, a, l))}{\sum_{l' \in \mathcal{L}} \exp(\phi(p, a, l'))} \tag{2}
\]

Where \( \phi(p, a, l) \) is a scoring function for a possible (predicate, argument, label) combination. \( \phi \) is decomposed into two unary scores on the predicate and the argument (defined in Section 3), as well as a label-specific score for the relation:

\[
\phi(p, a, l) = \Phi_a(a) + \Phi_p(p) + \Phi_{rel}^{(l)}(a, p) \tag{3}
\]

The score for the null label is set to a constant: \( \phi(p, a, \epsilon) = 0 \), similar to logistic regression.

Learning For each input \( X \), we minimize the negative log likelihood of the gold structure \( Y^* \):

\[
\mathcal{J}(X) = -\log P(Y^* \mid X) \tag{4}
\]

Beam pruning As our model deals with \( O(n^2) \) possible argument spans and \( O(n) \) possible predicates, it needs to consider \( O(n^3 |\mathcal{L}|) \) possible relations, which is computationally impractical. To overcome this issue, we define two beams \( B_a \) and \( B_p \) for storing the candidate arguments and predicates, respectively. The candidates in each beam are ranked by their unary score (\( \Phi_a \) or \( \Phi_p \)). The sizes of the beams are limited by \( \lambda_a \) and \( \lambda_p \). Elements that fall out of the beam do not participate in computing the edge factors \( \Phi_{rel}^{(l)} \), reducing the overall number of relational factors evaluated by the model to \( O(n^2 |\mathcal{L}|) \). We also limit the maximum width of spans to a fixed number \( W \) (e.g. \( W = 30 \)), further reducing the number of computed unary factors to \( O(n) \).

3 Neural Architecture

Our model builds contextualized representations for argument spans \( a \) and predicate words \( p \) based on BiLSTM outputs (Figure 2) and uses feed-forward networks to compute the factor scores in \( \phi(p, a, l) \) described in Section 2 (Figure 3).

Word-level contexts The bottom layer consists of pre-trained word embeddings concatenated with character-based representations, i.e. for each token \( w_i \), we have \( x_i = [\text{WORD}EMB(w_i); \text{CHAR}CNN(w_i)] \). We then contextualize each \( x_i \), using an \( m \)-layered bidirectional LSTM with highway connections (Zhang et al., 2016), which we denote as \( \bar{x}_i \).

Argument and predicate representation We build contextualized representations for all candidate arguments \( a \in \mathcal{A} \) and predicates \( p \in \mathcal{P} \). The argument representation contains the following: end points from the BiLSTM outputs \( \bar{x}_{\text{START}(a)}, \bar{x}_{\text{END}(a)} \), a soft head word \( \bar{x}_h(a) \), and embedded span width features \( f(a) \), similar to Lee et al. (2017). The predicate representation is simply the BiLSTM output at the position INDEX \( (p) \):

\[
g(a) = [\bar{x}_{\text{START}(a)}; \bar{x}_{\text{END}(a)}; \bar{x}_h(a); f(a)] \tag{5}
\]

\[
g(p) = \bar{x}_{\text{INDEX}(p)} \tag{6}
\]

The soft head representation \( \bar{x}_h(a) \) is an attention mechanism over word inputs \( \bar{x} \) in the argument span, where the weights \( e(a) \) are computed via a linear layer over the BiLSTM outputs \( \bar{x} \):

\[
\bar{x}_h(a) = \bar{x}_{\text{START}(a); \text{END}(a)} e(s)^T \tag{7}
\]

\[
e(a) = \text{SOFTMAX}(\bar{w}^T \bar{x}_{\text{START}(a); \text{END}(a)}) \tag{8}
\]

\( \bar{x}_{\text{START}(a); \text{END}(a)} \) is a shorthand for stacking a list of vectors \( \bar{x}_t \), where \( \text{START}(a) \leq t \leq \text{END}(a) \).

Scoring The scoring functions \( \Phi \) are implemented with feed-forward networks based on the predicate and argument representations \( g \):

\[
\Phi_a(a) = \bar{w}_a^T \text{MLP}_a(g(a)) \tag{9}
\]

\[
\Phi_p(p) = \bar{w}_p^T \text{MLP}_p(g(p)) \tag{10}
\]

\[
\Phi_{rel}^{(l)}(a, p) = \bar{w}_{rel}^{(l)} \text{MLP}_r([g(a); g(p)]) \tag{11}
\]
Many tourists visit Disney to meet their favorite cartoon characters.

```
Many tourists
visit Disney to
meet their favorite
favorite cartoon characters
```

Figure 2: Building the argument span representations \( g(a) \) from BiLSTM outputs. For clarity, we only show one BiLSTM layer and a small subset of the arguments.

Figure 3: The span-pair classifier takes in predicate and argument representations as inputs, and computes a softmax over the label space \( \mathcal{L} \).

4 Experiments

We experiment on the CoNLL 2005 (Carreras and Márquez, 2005) and CoNLL 2012 (OntoNotes 5.0, (Pradhan et al., 2013)) benchmarks, using two SRL setups: end-to-end and gold predicates. In the end-to-end setup, a system takes a tokenized sentence as input, and predicts all the predicates and their arguments. Systems are evaluated on the micro-averaged F1 for correctly predicting (predicate, argument span, label) tuples. For comparison with previous systems, we also report results with gold predicates, in which the complete set of predicates in the input sentence is given as well. Other experimental setups and hyperparameters are listed in Appendix A.1.

ELMo embeddings To further improve performance, we also add ELMo word representations (Peters et al., 2018) to the BiLSTM input (in the +ELMo rows). Since the contextualized representations ELMo provides can be applied to most previous neural systems, the improvement is orthogonal to our contribution. In Table 1 and 2, we organize all the results into two categories: the comparable single model systems, and the models augmented with ELMo or ensembling (in the POE rows).

End-to-end results As shown in Table 1,2 our joint model outperforms the previous best pipeline system (He et al., 2017) by an F1 difference of anywhere between 1.3 and 6.0 in every setting. The improvement is larger on the Brown test set, which is out-of-domain, and the CoNLL 2012 test set, which contains nominal predicates. On all datasets, our model is able to predict over 40% of the sentences completely correctly.

Results with gold predicates To compare with additional previous systems, we also conduct experiments with gold predicates by constraining our predicate beam to be gold predicates only. As shown in Table 2, our model significantly out-performs He et al. (2017), but falls short of Tan et al. (2018), a very recent attention-based (Vaswani et al., 2017) BIO-tagging model that was developed concurrently with our work. By adding the contextualized ELMo representations, we are able to out-perform all previous systems, including Peters et al. (2018), which applies ELMo to the SRL model introduced in He et al. (2017).

5 Analysis

Our model’s architecture differs significantly from previous BIO systems in terms of both input and decision space. To better understand our model’s strengths and weaknesses, we perform three analyses following Lee et al. (2017) and He et al. (2017), studying (1) the effectiveness of beam...
Table 1: End-to-end SRL results for CoNLL 2005 and CoNLL 2012, compared to previous systems. CoNLL 05 contains two test sets: WSJ (in-domain) and Brown (out-of-domain).

| End-to-End          | CoNLL 05 In-domain (WSJ) | CoNLL 2012 (OntoNotes) |
|---------------------|---------------------------|-------------------------|
|                     | Dev. F1 | P | R | F1 | Dev. F1 | P | R | F1 |
| Ours+ELMo           | 85.3    | 84.8 | 87.2 | 86.0 | 73.9    | 78.4 | 76.1 | 76.0 |
| He et al. (2017)    | 81.5    | 82.0 | 83.4 | 82.7 | 69.7    | 70.5 | 70.1 | 71.5 |
| Ours                | 81.6    | 81.2 | 83.9 | 82.5 | 69.7    | 71.9 | 70.8 | 71.4 |
| He et al. (2017)    | 80.3    | 80.2 | 82.3 | 81.2 | 67.6    | 69.6 | 68.5 | 69.3 |

Table 2: Experiment results with gold predicates.

|                     | WSJ | Brown | OntoNotes |
|---------------------|-----|-------|-----------|
| Ours+ELMo           | 87.4 | 80.4 | 85.5 |
| Peters et al. (2018) | 86.1 | 74.8 | 83.9 |
| Tan et al. (2018)   | 84.6 | 73.6 | 83.4 |
| He et al. (2017)    | 80.3 | 72.2 | 80.1 |
| Ours                | 83.9 | 73.7 | 82.1 |
| Tan et al. (2018)   | 84.8 | 74.1 | 82.7 |
| He et al. (2017)    | 83.1 | 72.1 | 81.7 |
| Yang and Mitchell (2017) | 81.9 | 72.0 | - |
| Zhou and Xu (2015)  | 82.8 | 69.4 | 81.1 |

Effectiveness of beam pruning Figure 4 shows the candidate arguments and predicates kept in the argument beam, sorted with their unary scores. Our model efficiently prunes unlikely argument spans and predicates, significantly reducing the number of edges it needs to consider. Figure 5 shows the recall of predicate words on the CoNLL 2012 development set. By retaining $\lambda_p = 0.4$ predicates per word, we are able to keep over 99.7% argument-bearing predicates. Compared to having a part-of-speech tagger (POS:X in Figure 5), our joint beam pruning allowing the model to have a soft trade-off between efficiency and recall.

Long-distance dependencies Figure 6 shows the performance breakdown by binned distance between arguments to the given predicates. Our model is better at accurately predicting arguments that are farther away from the predicates, even compared to an ensemble model (He et al., 2017) that has a higher overall F1. This is very likely due to architectural differences; in a BIO tagger, predicate information passes through many LSTM timesteps before reaching a long-distance argument, whereas our architecture enables direct connections between all predicates-arguments pairs.

Agreement with syntax As mentioned in He et al. (2017), their BIO-based SRL system has good agreement with gold syntactic span boundaries (94.3%) but falls short of previous syntax-based systems (Punyakanok et al., 2004). By directly modeling span information, our model achieves comparable syntactic agreement (95.0%) to Punyakanok et al. (2004) without explicitly modeling syntax.

Global consistency On the other hand, our model suffers from global consistency issues. For example, on the CoNLL 2005 test set, our model has lower complete-predicate accuracy (62.6%) than the BIO systems (He et al., 2017; Tan et al., 2018) (64.3%-66.4%). Table 3 shows its viola-
Figure 5: Recall of gold argument-bearing predicates on the CoNLL 2012 development data as we increase the number of predicates kept per word. POS:X shows the gold predicate recall from using certain pos-tags identified by the NLTK part-of-speech tagger (Bird, 2006).

Figure 6: F1 by surface distance between predicates and arguments, showing degrading performance on long-range arguments.

Table 3: Comparison on the CoNLL 05 development set against previous systems in terms of unlabeled agreement with gold constituency (Syn%) and each type of SRL-constraints violations (Unique core roles, Continuation roles and Reference roles).

| Model/Oracle | SRL F1 | Syn % | U | C | R |
|--------------|--------|-------|---|---|---|
| Gold         | 100.0  | 98.7  | 24 | 0 | 61|
| Ours+decode  | 82.4   | 95.1  | 0  | 8 | 104|
| Ours         | 82.3   | 95.0  | 69 | 7 | 105|
| He (PoE)     | 82.7   | 94.3  | 37 | 3 | 68 |
| He           | 81.6   | 94.0  | 48 | 4 | 73 |
| Punyakanok   | 77.4   | 95.3  | 0  | 0 | 0 |

6 Conclusion and Future Work

We proposed a new SRL model that is able to jointly predict all predicates and argument spans, generalized from a recent coreference system (Lee et al., 2017). Compared to previous BIO systems, our new model supports joint predicate identification and is able to incorporate span-level features. Empirically, the model does better at long-range dependencies and agreement with syntactic boundaries, but is weaker at global consistency, due to our strong independence assumption.

In the future, we could incorporate higher-order inference methods (Lee et al., 2018) to relax this assumption. It would also be interesting to combine our span-based architecture with the self-attention layers (Tan et al., 2018; Strubell et al., 2018) for more effective contextualization.

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References

Steven Bird. 2006. Nltk: the natural language toolkit. In ACL.
Xavier Carreras and Lluís Márquez. 2005. Introduction to the conll-2005 shared task: Semantic role labeling. In CoNLL.

Nicholas FitzGerald, Julian Michael, Luheng He, and Luke Zettlemoyer. 2018. Large-scale qa-srl parsing. In ACL.

Nicholas FitzGerald, Oscar Täckström, Kuzman Ganchev, and Dipanjan Das. 2015. Semantic role labeling with neural network factors. In EMNLP.

Yarin Gal and Zoubin Ghahramani. 2016. A theoretically grounded application of dropout in recurrent neural networks. In NIPS.

Luheng He, Kenton Lee, Mike Lewis, and Luke S. Zettlemoyer. 2017. Deep semantic role labeling: What works and what’s next. In ACL.

Diederik Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In ICLR.

Lingpeng Kong, Chris Dyer, and Noah A Smith. 2016. Segmental recurrent neural networks. In ICLR.

Kenton Lee, Luheng He, Mike Lewis, and Luke S. Zettlemoyer. 2017. End-to-end neural coreference resolution. In EMNLP.

Kenton Lee, Luheng He, and Luke Zettlemoyer. 2018. Higher-order coreference resolution with coarse-to-fine inference. In NAACL.

Diego Marcheggiani, Anton Frolov, and Ivan Titov. 2017. A simple and accurate syntax-agnostic neural model for dependency-based semantic role labeling. In CoNLL.

Makoto Miwa and Mohit Bansal. 2016. End-to-end relation extraction using lstms on sequences and tree structures. In ACL.

Vinod Nair and Geoffrey E Hinton. 2010. Rectified linear units improve restricted boltzmann machines. In ICML.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. Glove: Global vectors for word representation. In EMNLP.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In NAACL.

Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Hwee Tou Ng, Anders Björkelund, Olga Uryupina, Yuchen Zhang, and Zhi Zhong. 2013. Towards robust linguistic analysis using ontonotes. In CoNLL.

Vasin Punyakanok, Dan Roth, Wen-tau Yih, Dav Zimak, and Yuancheng Tu. 2004. Semantic role labeling via generalized inference over classifiers. In CoNLL.

Vasin Punyakanok, Dan Roth, and Wen-tau Yih. 2008. The importance of syntactic parsing and inference in semantic role labeling. Computational Linguistics.

Andrew M Saxe, James L McClelland, and Surya Ganguli. 2014. Exact solutions to the nonlinear dynamics of learning in deep linear neural networks. arXiv preprint.

Mitchell Stern, Jacob Andreas, and Dan Klein. 2017. A minimal span-based neural constituency parser. In ACL.

Emma Strubell, Patrick Verga, Daniel Andor, David Weiss, and Andrew McCallum. 2018. Linguistically-Informed Self-Attention for Semantic Role Labeling. arXiv preprint.

Oscar Täckström, Kuzman Ganchev, and Dipanjan Das. 2015. Efficient inference and structured learning for semantic role labeling. Transactions of the Association for Computational Linguistics.

Zhixing Tan, Mingxuan Wang, Jun Xie, Yidong Chen, and Xiaodong Shi. 2018. Deep semantic role labeling with self-attention. In AAAI.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS.

Bishan Yang and Tom M. Mitchell. 2017. A joint sequential and relational model for frame-semantic parsing. In EMNLP.

Yu Zhang, Guoguo Chen, Dong Yu, Kaisheng Yaco, Sanjeev Khudanpur, and James Glass. 2016. Highway long short-term memory rnns for distant speech recognition. In ICASSP.

Jie Zhou and Wei Xu. 2015. End-to-end learning of semantic role labeling using recurrent neural networks. In ACL.

A Supplemental Material

A.1 Hyperparameters

Representation sizes The word embeddings are fixed 300-dimensional GloVe embeddings (Pennington et al., 2014) (context window size of 2 for head word embeddings, and window size of 10 for LSTM inputs), normalized to be unit vectors. Out-of-vocabulary words are represented by a vector of zeros. In the character CNN, characters are represented as learned 8-dimensional embeddings. The convolutions have window sizes of 3, 4, and 5 characters, each consisting of 50 filters.

Network sizes We use 3 stacked bidirectional LSTMs with highway connections and 200 dimensional hidden states. Each MLP consists of two hidden layers with 150 dimensions and rectified linear units (Nair and Hinton, 2010).
|               | CoNLL 2012 |               | OntoNotes5 |
|---------------|------------|---------------|------------|
|               | Train | Dev | Test | Train | Dev |
| Docs          | 2.8   | 0.3  | 0.3  | 11    | 1.5  |
| Sentences     | 75    | 9.6  | 9.5  | 116   | 16   |
| Predicates    | 189   | 24   | 24   | 253   | 35   |

Table 4: Data statistics (in number of thousands) for the CoNLL 2012 split and the train/dev split of OntoNotes5.

**Inference** We model spans up to length 30. We use $\lambda_a = 0.8$ for pruning arguments, $\lambda_p = 0.4$ for pruning predicates. At decoding time, we use dynamic programming (a simplified version of Täckström et al. (2015)) to predict a set of non-overlapping arguments for each predicate.

**Training** We use Adam (Kingma and Ba, 2015) with initial learning rate 0.001 and decay rate of 0.1% every 100 steps. The LSTM weights are initialized with random orthonormal matrices (Saxe et al., 2014). We apply 0.5 dropout to the word embeddings and character CNN outputs and 0.2 dropout to all hidden layers and feature embeddings. In the LSTMs, we use variational dropout masks that are shared across timesteps (Gal and Ghahramani, 2016), with 0.4 dropout rate.

**Batching** At training time, we randomly shuffle all the documents and then batch at sentence level. Each batch contains at most 40 sentences and 700 words. All models are trained for at most 320,000 steps with early stopping on the development set, which takes less than 48 hours on a single Titan X GPU.

**A.2 OntoNotes Data Statistics**

Table 4 shows the data statistics on various splits of OntoNotes. We found that some sentences in the OntoNotes 5.0 train/dev split have missing predicates, which is unsuitable for training end-to-end SRL systems. Therefore, our end-to-end SRL models are trained on the smaller but cleaner CoNLL 2012 splits. For experiments with gold predicates, we use the full OntoNotes 5.0 train/dev split and the CoNLL 2012 test set, following previous work.

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7This is mainly a constraint enforced by the official CoNLL evaluation script.