Dependency and Span,
Cross-Style Semantic Role Labeling on PropBank and NomBank

Zuchao Li\textsuperscript{1,2,3}, Shexia He\textsuperscript{1,2,3}, Junru Zhou\textsuperscript{1,2,3}, Hai Zhao\textsuperscript{1,2,3,\ast},
Kevin Parnow\textsuperscript{1,2,3}, Rui Wang\textsuperscript{4}

\textsuperscript{1}Department of Computer Science and Engineering, Shanghai Jiao Tong University
\textsuperscript{2}Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
\textsuperscript{3}MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
\textsuperscript{4}National Institute of Information and Communications Technology (NICT), Kyoto, Japan

Abstract

The latest developments in neural semantic role labeling (SRL), including both dependency and span representation formalisms, have shown great performance improvements. Although the two styles share many similarities in linguistic meaning and computation, most previous studies focus on a single style. In this paper, we define a new cross-style semantic role label convention and propose a new cross-style joint optimization model designed according to the linguistic meaning of semantic role, which provides an agreed way to make the results of two styles more comparable and let both types of SRL enjoy their natural connection on both linguistics and computation. Our model learns a general semantic argument structure and is capable of outputting optional style alone. Additionally, we propose a syntax aided method to enhance the learning of both dependency and span representations uniformly. Experiments show that the proposed methods are effective on both span (CoNLL-2005) and dependency (CoNLL-2009) SRL benchmarks.

1 Introduction

Semantic role labeling (SRL) aims to derive linguistic meaning representations, such as the predicate-argument structure for a given sentence. The currently popular formalisms for representing the semantic predicate-argument structure are dependency-based or span-based. While dependency SRL annotates the syntactic heads of arguments, span-style annotates entire argument spans.

Both dependency and span are effective formal representations for semantics, though which is superior has been uncertain for a long time. Furthermore, researchers have suspected that these two SRL models may benefit from being developed together rather than separately. This topic has been roughly discussed by Johansson and Nugues (2008) and Li et al. (2019), who both concluded that the (best) dependency SRL system at the time clearly outperformed the (best) span-based system through gold syntactic structure transformation. Besides, Peng et al. (2018) integrated dependency and span-style SRL into a model for frame-semantic parsing by a multi-task learning approach, which enabled the model to learn the internal relationship between dependency- and span-styles from multiple datasets.

In general, current research is limited to the existing datasets and argument representations, which adopt constituent-to-dependency head-rule transformation or multi-task joint learning methods to make the results of dependency and span SRL more comparable. Therefore, in this work, we create a new SRL dataset with a more general style of argument structure. Additionally, we take a new argument structure formulization, which enables our model to use a single decoder to implement two semantic formalisms. To verify the effectiveness and applicability of the proposed method, we evaluate the model on CoNLL-2005 and CoNLL-2009 datasets, which achieves new state-of-the-art results for both. Experimental results, therefore, show that the proposed general argument structure is effective for two SRL formalisms.

2 Dataset

There are two styles of semantic role labeling since PropBank (Palmer et al., 2005) style semantic annotation was applied to Pen Treebank.
(PTB) (Marcus et al., 1993): span-based and dependency-based. Early semantic role labeling (CoNLL-2004, CoNLL-2005 shared task) on the Peen Treebank was span-based (Carreras and Màrquez, 2004, 2005), with spans corresponding to syntactic constituents. However, as in syntactic parsing, there are sometimes theoretical or practical reasons to prefer dependency graphs. To this end, the CoNLL-2008 shared task (Surdeanu et al., 2008) proposed a unified dependency-based formalism, which models both syntactic dependencies and semantic roles in addition to introduce nominal predicate-argument structure from NomBank (Meyers et al., 2004). The CoNLL-2009 shared task (Hajič et al., 2009) further built on the CoNLL-2008 shared task by providing six more language annotations in addition to the original English. So far, CoNLL-2005 and CoNLL-2009 have become the benchmark datasets for span-based and dependency-based SRL, respectively. Although both CoNLL-2005 and CoNLL-2009 followed the same PropBank or NomBank semantic, due to the different labeling and conversion time and standard, there are large differences between the two data sets. Therefore, there is a bifurcation in semantic role labeling research that the results cannot be directly compared, let alone enjoying the benefits from a joint semantic learning.

We seek to reduce style-specific “balkanization” in the field of semantic role labeling. Our goals, therefore, include (a) a unifying formal model over different-style semantic role labeling treebanks, (b) uniform representations and scoring, (c) systematic contrastive evaluation across styles, and (d) increased cross-fertilization via transfer and multi-task learning. We hope to uniform the representations of different styles, including from two types of prior style-specific semantic role labeling tasks at the CoNLL-2004, CoNLL-2005, CoNLL-2008 and CoNLL-2009. Owing to the scarcity of semantic annotations across different styles, the shared tasks were regrettably limited to parsing English on PTB text for the time being. For the first time, this work combines formally and linguistically different approaches to semantic role labeling representation in the uniform form with the same training and evaluation setup. We motivate to develop parsing systems that support two distinct semantic role labeling styles which encode all core predicate-argument structure, among other things – in the same implementation. Learning from multiple styles of semantic role labeling representation in tandem has seldom been explored (with notable exceptions, e.g., the parser of Peng et al., 2018 on FrameNet).

In order to achieve the above goals, the semantic bank used in this paper were generated through a process that merges several source treebanks and converts them from the constituent-based and dependency-based formalisms to a new uniform formalism. In this section, we will introduce our uniform format, the treebanks used, and describe the conversion process.

2.1 Uniform Format

For span-based SRL, the format of the predicate-argument structure is a quadruple consisting of the predicate, the start of argument span, the end of argument span, and the corresponding predicate-argument relation. For dependency SRL, the structure is a triple consisting of the predicate, the syntactic head of the argument span, and their relationship. To handle both of the representations uniformly, we design a uniform format to represent the two styles, which is a quintuple consisting of the predicate, the start of argument span, the end of argument span, the syntactic head of argument span, and the predicate-argument relation.

For example, given an input text The bill would have lifted the minimum wage of working to $4.55 an hour by late 1991, one of the predicate is lifted. In the span-based SRL, the ARG1 argument is [the minimum wage of working], while in the dependency-based SRL, the argument is (wage) which is the dependency head of the argument span in span-based SRL.

\[
\begin{align*}
S: & \quad \text{lifted}_{\text{PRED}} [\text{the minimum wage of working}]_{\text{ARG1}} \\
D: & \quad \text{lifted}_{\text{PRED}} (\text{wage})_{\text{ARG1}} \\
U: & \quad \text{lifted}_{\text{PRED}} [\text{the minimum wage of working}]_{\text{ARG1}} (\text{wage})_{\text{ARG1}}
\end{align*}
\]

We combine the two span-based (S) and dependency-based (D) to a new uniform SRL format (U) to predict the goal of span-based argument and dependency-based argument in the same time. This is also of sufficient linguistic significance. Compared with the span-based SRL, we not only focus on the boundary of the argument, but also on the center of the argument (dependency
head). Compared to the dependency-based SRL, not only the center has received attention, but also the range of constituent in the sentence has been considered. For the application of downstream tasks, this uniform format can extract the argument range and core components without the help of syntactic parse, which is more conducive to use with less potential error-propagation.

2.2 Source Treebank and Banks

Similar to the merging procedures in CoNLL-2008 shared task, source treebanks for our conversion process also includes the PTB, PropBank, and NomBank.

**Penn Treebank 3 (PTB)** The Penn Treebank 3 (Marcus et al., 1993) consists of hand-coded parses of the Wall Street Journal (training, development, and test) and a small subset of the Brown corpus (Francis and Kucera, 1979) (out-of-domain, test only). The Penn Treebank syntactic annotation includes phrases, part-of-speech (POS), empty category representations of various filler/gap constructions and other phenomena, based on a theoretical perspective similar to that of Government and Binding Theory (Chomsky, 1993). We follow the standard partition used in syntactic parsing: sections 02-21 for training, section 24 for development, and section 23 for test. In addition, three sections (ck01-03) from Brown corpus are used in out-of-domain evaluation setting.

**Proposition Bank I (PropBank)** The PropBank annotation (Palmer et al., 2005) classifies the arguments of all the main verbs in PTB. Arguments are numbered (ARG0, ARG1, . . .) based on lexical entries or frames. Different sets of arguments are assumed for different rolesets. Dependent constituents that fall into categories independent of the lexical entries are classified as various types of ARG: (a) a word in a dictionary (COMLEX Syntax or any of the dictionaries available on the NOMLEX website); (b) part of a markable Named Entity; or (c) a prefix from the list: co, pre, post, un, anti, ante, ex, extra, fore, non, over, pro, re, super, sub, tri, bi, uni, ultra. For example, McGraw-Hill was split into 3 segments: McGraw-, -,-, and Hill. This step is consistent with the CoNLL-2008 shared task.

**NomBank** NomBank annotation (Meyers et al., 2004) uses essentially the same framework as PropBank to annotate arguments of nouns. Differences between PropBank and NomBank stem from (1) differences between noun and verb argument structure; (2) differences in treatment of nouns and verbs in PTB; and (3) differences in the sophistication of previous research about noun and verb argument structure.

2.3 Processing Steps

**Re-tokenization** Since NomBank uses a sub-word analysis in some hyphenated words, such as [finger]ARG-[pointing]PRED, we need to re-tokenize the words provided in the original PTB. Specifically, we split the Treebank tokens at a hyphen (-) or a forward slash (/) if the segments on either side of these delimiters are: (a) a word in a dictionary (COMLEX Syntax or any of the dictionaries available on the NOMLEX website); (b) part of a markable Named Entity; or (c) a prefix from the list: co, pre, post, un, anti, ante, ex, extra, fore, non, over, pro, re, super, sub, tri, bi, uni, ultra. For example, McGraw-Hill was split into 3 segments: McGraw, -, and Hill. This step is consistent with the CoNLL-2008 shared task.

**Lemma and Part-of-Speech** For ease of use, refer to the CoNLL-2009 shared task data, we provide the same gold-standard lemma, automatically predicted lemma, gold-standard POS tag and automatically predicted POS tag.

**Constituent Syntactic Tree** The golden syntactic trees are provided in the PTB. However, due to the re-tokenization, we need to change the span of constituent. For the predicted syntactic tree, we use the parser of (Kitaev and Klein, 2018) to obtain a full-parses.

**Dependency Syntactic Tree** Since the dependency syntax trees are not provided on PTB, we thus have to convert the dependency trees automatically from the PTB. The dependency syntax represents grammatical structure by means of labeled binary head-dependent relations rather than phrases. The idea underpinning constituent-to-dependency conversion algorithms (Magerman, 1994; Collins, 2003; Yamada and Matsumoto, 2003; De Marneffe et al., 2006) is that head-dependent pairs are created from constituent by selecting one word in each phrase as the head and setting all other as its dependents. The
dependency labels are then inferred from the phrase-subpharse or phrase-word relations. There are three typical different conversion rules and tools on PTB: (1) Penn2Malt and the head rules of Yamada and Matsumoto (2003), noted as PTB-Y&M; (2) dependency converter in Stanford parser v3.3.0 with Stanford Basic Dependencies (De Marneffe et al., 2006), noted as PTB-SD; (3) LTH Constituent-to-Dependency Conversion Tool (Johansson and Nugues, 2007), noted as PTB-LTH. In order to make the results on our corpora as comparable as possible to the one on CoNLL-2009 shared task, we use the same PTB-LTH conversion method to convert the golden and predicted constituent trees into dependency trees.

**Predicate** We transform all annotated semantic arguments in PropBank and NomBank not just a subset and address propositions centered around both verbal (PropBank) and nominal (NomBank) predicates.

**Uniform Argument** In order to obtain the uniform argument representation, the first step is to convert the underlying constituent analysis of PropBank and NomBank similar to the practice of CoNLL-2008 and CoNLL-2009. The same to the idea in syntax constituent-to-dependency conversion algorithms, find the dependency argument is to find the head of the span on the dependency tree. In order to avoid replicating effort and to ensure compatibility between syntactic and semantic dependencies, we use only the span argument boundaries and the golden dependency tree. We identify the head of an argument span by the following heuristic:

*The head of a semantic argument is assigned to the token inside the argument boundaries whose dependency head is token outside the argument boundaries (Surdeanu et al., 2008).*

For example, consider the following annotated text: `[visited]PRED [12 attractions]ARG1 [in the U.S.]ARGM-LOC`, whose syntax tree is shown in Figure 1. According to the heuristic, the head of ARG1 argument is set to `attractions` due to the dependency head of `attractions` is `visited` which is outside of span `[12 attractions]`. Similarly, the head of `ARGM-LOC` is set to `in`.

While the heuristic works well on the majority of arguments which guarantees a one-to-one relationship between the span argument and the head. Due to the special structure of some dependency syntactic trees, some span arguments have multiple heads, which affects this one-to-one relationship, so we need to deal with these cases individually.

For 0.7% of the span arguments, multiple syntactic heads are detected inside the span boundary. For example, `[allow]PRED [executives to report exercises of options later and less often]ARG1`. Under our rule set defined by our processing script, two syntactic heads `executives` and `to` are assigned ARG1. Therefore, we split the original span argument into a sequence of discontinuous sub-spans, set the first sub-span to the original argument role `role`, the rest to C-role, e.g., the ARG1 argument becomes `[allow]PRED [executives]ARG1 [to report exercises of options later and less often]C-ARG1.

Due to the existence of the non-projective dependency tree, all the children of a head cannot form a continuous span, so it is necessary to continue iterative splitting of the discontinuous span until all sub-spans have only one head, and all children of each head compose a continuous span. For example, `[says]PRED [if you drink more, you get more]ARG1. In the first iteration, two syntactic heads `you` and `get` are detected, the original span argument is split into two sub-spans `[you]ARG1 [if you drink more, get more]C-ARG1. Since the second sub-span `[if you drink more, get more]C-ARG1 is not continuous, it cannot be used as a constituent. Therefore, further splitting is required until each span is continuous and has a unique syntax head. We use the recursive partitioning method and finally get the span as follows: `[if you drink more]ARG1 (if). [.]C-ARG1 (.), [you]C-ARG1 (you), and [get more]C-ARG1 (get).

**3 Model**

Given a sentence, the SRL task can be decomposed into four classification subtasks: predicate.
3.2 Objective Representation Layer

Formally, for each candidate argument \( a \in \mathcal{A} \), the representation contains four features: the boundary hidden state of argument span (start position \( \text{START}(\cdot) \) and end position \( \text{END}(\cdot) \)) from HBiLSTM outputs \( (x_{\text{START}(a)}, x_{\text{END}(a)}) \), the attention-based span representation \( x_{\text{span}} \), and the embedded span width features \( e^{\text{width}} \). The argument representation \( x_{\text{arg}} \) can thus be described as follows:

\[
x_{\text{arg}} = [x_{\text{START}(a)}; x_{\text{END}(a)}; x_{\text{span}}; e^{\text{width}}],
\]

(2)

\[
\alpha_{\text{span}} = \text{softmax}(w^T x_{\text{START}(a)}; \text{END}(a)),
\]

(3)

\[
x_{\text{span}} = x_{\text{START}(a)}; \text{END}(a) \cdot \alpha_{\text{span}}
\]

(4)

where \( x_{\text{START}(a)}; \text{END}(a) \) is a shorthand for stacking a list of vectors \( x_t (\text{START}(a) \leq t \leq \text{END}(a)) \), \( \alpha_{\text{span}} \) is the span attention weight. In addition, the predicate representation \( x_{p} \) is simply the HBiLSTM output at the candidate’s position \( p \). At the same time, \( \alpha_{\text{span}} \) is not only used to obtain the attention-based representation of the span \( x_{\text{span}} \), it can also be used to train to obtain the dependency head position \( h \) of the span:

\[
h = \arg \max(\alpha_{\text{span}}).
\]

(5)

3.3 Candidates Pruning

The number of all possible candidate arguments for a sentence of length \( n \) is \( O(n^2) \) for span SRL, and \( O(n) \) for dependency; however, when we adopt a unified goal, the number is \( O(n^2) \). As the model deals with \( O(n) \) possible predicates, the overall computational complexity is \( O(n^3) \), which is too computationally expensive and why we perform candidate pruning. Following (He et al., 2018a), we adopt two unary scorers to choose the most probable candidate arguments and predicates to reduce the overall number of candidate tuples to \( O(n^2) \). Furthermore, for arguments, we set the maximum width of argument to \( L \), which may decrease the number of candidate arguments to only \( O(n) \).

3.4 Dependency Syntax Aided (DSA)

Dependency syntax provides binary asymmetric relations (e.g., modifications and arguments) between words. It is represented by a tree structure with words as nodes, and relations as edges. As can be seen from the data conversion process,
the dependency syntax provides the location information of the head token in the argument span. Therefore, this motivate us to use the dependency tree structure to aid the semantic role labeling.

To utilize such dependency tree structures, for each candidate span \( \text{span} = \{w_j, w_{j+1}, \ldots, w_{j+L}\} \), we get the dependency syntax heads set \( \text{headset} = \{w_h\}, h \in [j : j + L] \) from the span by the heuristic defined in previous section. We define an indicator embedding \( e_{dsa} \) on the dependency syntax heads set \( \text{headset} \) input to calculate the span representation \( x_{span} \) and head position \( h \).

\[
e_{dsa}^t = \begin{cases} 1, & w_t \in \text{headset} \\ 0, & w_t \notin \text{headset} \end{cases} \tag{6}
\]

After we add the indicator embedding \( e_{dsa} \) into Eq. (3), the equation becomes:

\[
\alpha_{\text{span}} = \text{softmax}(w_s^T [x_{\text{START}(a)}; x_{\text{END}(a)}; e_{\text{width}}; e_{\text{csa}}]) \tag{7}
\]

### 3.5 Constituency Syntax Aided (CSA)

Constituency syntax breaks a sentence into constituents (e.g., phrases), which naturally forms a constituency tree in a top-down fashion. In contrast with the dependency syntax tree, words can only be the terminals in a constituency tree, while the non-terminals are phrases with types. In SRL, each argument corresponds to a constituent in constituency trees, which can be used to generate span argument candidates given the predicates (Xue and Palmer, 2004; Carreras and Márquez, 2005). Punyakanok et al. (2005) showed that the constituency tree offer high-quality argument boundaries.

In order to utilize such constituent boundaries in the constituency tree and use it to help decide the argument candidates, we extract all the constituent \( c \) boundaries to form a set \( \text{boundaryset} = \{\text{START}(c), \text{END}(c)\} \). We also define an indicator embedding \( e_{csa} \) on the constituent boundaries set \( \text{boundaryset} \) input to calculate the span representation.

\[
e_{csa}^t = \begin{cases} 1, & \text{span}_t \in \text{boundaryset} \\ 0, & \text{span}_t \notin \text{boundaryset} \end{cases} \tag{8}
\]

After we add the indicator embedding \( e_{csa} \) into Eq. (2), the equation becomes:

\[
x_{\text{arg}} = [x_{\text{START}(a)}; x_{\text{END}(a)}; x_{\text{span}}; e_{\text{width}}; e_{\text{csa}}]. \tag{9}
\]

### 3.6 Scorer

As mentioned above, our model treats SRL task as predicate-argument pair classification problem, handling argument identification and classification in one shot. To label semantic roles, we employ a scorer with biaffine attention (Dozat and Manning, 2017) as a role classifier on top of the
Thus, for each input $X$, our model minimizes the negative log likelihood of the span $Y^*_{\text{span}}$ and dependency $Y^*_{\text{dep}}$ structure:

$$\mathcal{J}(X) = \lambda (- \log P_\theta(Y^*_{\text{span}}|X)) + (1 - \lambda) (- \log P_\theta(Y^*_{\text{dep}}|X)),$$

where $\lambda$ is to balance the two formalisms training.

| Gold predicates | CoNLL05 WSJ | CoNLL05 Brown | CoNLL09 WSJ | CoNLL09 Brown |
|----------------|------------|--------------|------------|--------------|
|                | P  | R | F₁   | P  | R | F₁   | P  | R | F₁   | P  | R | F₁   |
| **wo/LM**      |    |   |      |    |   |      |    |   |      |    |   |      |
| FitzGerald et al. (2015)' | 82.3 | 76.8 | 79.4 | 73.8 | 68.8 | 71.2 | -  | -  | 87.3  | -  | -  | 75.2  |
| Li et al. (2019) | -  | -  | 83.0 | -  | -  | -  | -  | -  | -  | 85.1 | -  | -  |
| Ours            | 83.9 | 83.5 | 83.7 | 73.5 | 69.1 | 71.2 | 86.7 | 86.9 | 86.8 | 75.2 | 75.4 | 75.3 |
| Ours + Predicted Syntax | 85.0 | 86.0 | 85.5 | 74.0 | 70.8 | 72.3 | 87.8 | 88.0 | 87.9 | 77.0 | 76.8 | 76.9 |
| Ours + Gold Syntax | 88.0 | 86.4 | 87.2 | 76.6 | 71.2 | 73.8 | 89.1 | 88.7 | 88.9 | 78.9 | 76.7 | 77.8 |
| **w/ELMo**     |    |   |      |    |   |      |    |   |      |    |   |      |
| Li et al. (2019) | 87.9 | 87.5 | 87.7 | 80.6 | 80.4 | 80.5 | 89.6 | 91.2 | 90.4 | 81.7 | 81.4 | 81.5 |
| Ours            | 88.2 | 87.6 | 87.9 | 81.0 | 80.8 | 80.9 | 90.0 | 91.2 | 90.6 | 81.7 | 81.5 | 81.6 |
| Ours + Predicted Syntax | 88.5 | 88.1 | 88.3 | 81.3 | 81.1 | 81.2 | 90.5 | 92.1 | 91.3 | 81.7 | 81.9 | 81.8 |
| Ours + Gold Syntax | 89.6 | 90.1 | 89.8 | 82.4 | 82.6 | 82.5 | 90.8 | 93.5 | 92.2 | 82.0 | 83.4 | 82.7 |
| **w/BERT**     |    |   |      |    |   |      |    |   |      |    |   |      |
| Ours            | 87.9 | 89.7 | 88.8 | 81.4 | 81.6 | 81.5 | 91.2 | 91.4 | 91.3 | 82.8 | 82.2 | 82.5 |
| Ours + Predicted Syntax | 88.9 | 89.1 | 89.0 | 81.6 | 82.0 | 81.8 | 91.4 | 91.4 | 91.4 | 82.4 | 82.8 | 82.6 |
| Ours + Gold Syntax | 90.2 | 91.8 | 91.0 | 83.2 | 84.0 | 83.6 | 92.4 | 93.0 | 92.7 | 82.8 | 84.8 | 83.8 |

Table 1: Joint SRL results on CoNLL-2005 and CoNLL-2009 test sets with gold predicates. The whole converted predicate and dependency argument are comparable to the CoNLL-2005 results.

4 Experiments

We experimented on the dataset converted from PropBank and NomBank on PTB, using the two common evaluation setups: end-to-end and gold predicates. The model was evaluated on the micro-averaged $F_1$ for correctly predicting tuples (predicate, argument span, argument head, and label). For the predicate disambiguation task in dependency SRL, following Marcheggiani and Titov (2017), we used the off-the-shelf disambiguator from Roth and Lapata (2016) and converted the $F_1$ score to CoNLL-2009 official $F_1$ score. Although we used our own converted dataset, the results of predicate we converted in PropBank and the span argument can be compared with CoNLL-2005. The whole converted predicate and dependency argument are comparable to the CoNLL-2009 results.

4.1 Setup

In our experiments, the pre-trained word embedding is 100-dimensional GloVe vectors (Pennington et al., 2014). The dimension of ELMo (Peters et al., 2018) or BERT (Devlin et al., 2018) language model feature embedding is 1024. Besides, we used 3 layers BiLSTM with 400-dimensional hidden states, applying dropout with an 80% keep probability between time-steps and layers. For biaffine scorer, we employed two 300-dimensional affine transformations with the ReLU non-linear activation, also setting the dropout probability to 0.2. All models were trained for up to 500 epochs.
4.2 Main Results

Table 1 presents the joint test results with gold predicates setup on the CoNLL-2005 and CoNLL-2009 test dataset. In contrast to previous methods, we used a single model (instead of two independent models) to optimize the joint objectives. It shows that our model yields an absolute improvement on dependency (+1.7) and span (+0.7). With the help of the pretrained language model features (ELMo, BERT), the performance can be further improve and the improvement is orthogonal to our contributions.

Table 2: The SRL results on CoNLL-2005 and CoNLL-2009 test sets with the end-to-end setup.

|        | WSJ | Brown |
|--------|-----|-------|
|        | P   | R    | F1  |
| CoNLL-2005 |     |      |     |
| He et al. (2017) | 80.2 | 82.3 | 81.2 |
| He et al. (2018a) | 84.8 | 87.2 | 86.0 |
| Strubell et al. (2018) | 87.1 | 86.7 | 86.9 |
| Li et al. (2019) | 85.2 | 87.5 | 86.3 |

Table 3: The different syntactic contribution to span-based and dependency-based SRL with end-to-end setup using predicted syntax and BERT pretrained LM features.

Although the gold syntax is not available in practical applications, it can still be used to draw some conclusions. The group using gold syntax in the experiment has achieved a significant increase in recall, indicating that the boundary and head position indicator embeddings is useful to identify the arguments.

5 Ablation

In order to assess the effect of our proposed two syntax aided methods to the span-based SRL and dependency-based SRL respectively, we conducted an ablation study on WSJ test set with end-to-end setup using predicted syntax and BERT pretrained language model (LM) features to explore how the different syntax (constituency and dependency) impact our model. As the results shown in Table 3, in our joint model, CSA (constituent syntax) has a more impact than DSA (dependency syntax), because CSA affects the argument span decision and the DSA affects the head position and also contributes to the representation of span. This shows that our two syntactic enhancements are effective.

6 Related Work

In early work of semantic role labeling, most of researchers were dedicated to feature engineering (Xue and Palmer, 2004; Pradhan et al., 2005; Punyakanok et al., 2008). The first neural SRL model was proposed by Collobert et al. (2011), which used convolutional neural network but their efforts fell short. Later, Foland and Martin (2015) effectively extended their work by using syntactic features as input. Roth and Lapata (2016) introduced syntactic paths to guide neural architectures for dependency SRL. In the meantime, putting syntax aside has sparked much research interest since Zhou and Xu (2015) employed deep BiLSTMs for span SRL. A series of neural SRL
models without syntactic inputs were proposed. Marcheggiani et al. (2017) applied a simple LSTM model with effective word representation, achieving encouraging results on English, Chinese, Czech and Spanish. Cai et al. (2018) built a full end-to-end SRL model with biaffine attention and provided strong performance on English and Chinese. Li et al. (2019) also proposed an end-to-end model for both dependency and span SRL with a unified argument representation, obtaining favorable results on English.

Despite the success of syntax-agnostic SRL models, more recent work attempts to further improve performance by integrating syntactic information. Marcheggiani and Titov (2017) used graph convolutional network to encode syntax into dependency SRL. He et al. (2018b) proposed an extended $k$-order argument pruning algorithm based on syntactic tree and boosted SRL performance. Li et al. (2018) presented a unified neural framework to provide multiple methods for syntactic integration. While the above models only considered dependency syntax, an alternative syntax representation available to use is constituency syntax. He et al. (2017) treated constituency syntax tree as an indication of argument boundary. However, they only used these boundary information during sequence decoding. Besides, all the above models only individually consider either of dependency or span SRL formalism, even though the latest work (Li et al., 2019) which use two separated models though with the similar model design to handle the two formalisms, respectively. Instead, we propose a joint SRL formalism for both dependency and span style representations.

7 Conclusion

We build a new cross-style SRL dataset that for the first time jointly considers dependency and span SRL formalisms from a linguistic motivation. Furthermore, with a new cross-style joint syntactic-agnostic model and syntax-aided features, our model achieves new state-of-the-art results on the benchmark settings, which verifies the proposed cross-style SRL convention is also helpful for computational purpose.

References

Jiaxun Cai, Shexia He, Zuchao Li, and Hai Zhao. 2018. A full end-to-end semantic role labeler, syntactic-agnostic over syntactic-aware? In COLING.

Xavier Carreras and Lluís Màrquez. 2004. Introduction to the conll-2004 shared task: Semantic role labeling. In NAACL:HLT.

Xavier Carreras and Lluís Màrquez. 2005. Introduction to the CoNLL-2005 shared task: Semantic role labeling. In CoNLL.

Noam Chomsky. 1993. Lectures on government and binding: The Pisa lectures. Walter de Gruyter.

Michael Collins. 2003. Head-driven statistical models for natural language parsing. CL.

Ronan Collobert, Jason Weston, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. JMLR.

Marie-Catherine De Marneffe, Bill MacCartney, Christopher D Manning, et al. 2006. Generating typed dependency parses from phrase structure parses. In LREC.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Timothy Dozat and Christopher D Manning. 2017. Deep biaffine attention for neural dependency parsing. In ICLR.

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

William Foland and James Martin. 2015. Dependency-based semantic role labeling using convolutional neural networks. In JCLCS.

W Nelson Francis and Henry Kucera. 1979. Brown corpus manual: Manual of information to accompany a standard corpus of present-day edited american english for use with digital computers.

Jan Hajíč, Massimiliano Ciaramita, Richard Johansson, Daisuke Kawahara, Maria Antònia Martí, Lluís Màrquez, Adam Meyers, Joakim Nivre, Sebastian Padó, Jan Štěpánek, et al. 2009. The conll-2009 shared task: Syntactic and semantic dependencies in multiple languages. In CoNLL.

Luheng He, Kenton Lee, Omer Levy, and Luke Zettlemoyer. 2018a. Jointly predicting predicates and arguments in neural semantic role labeling. In ACL.

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

Shexia He, Zuchao Li, Hai Zhao, Hongxiao Bai, and Gongshen Liu. 2018b. Syntax for semantic role labeling, to be, or not to be. In ACL.
Richard Johansson and Pierre Nugues. 2007. Extended constituent-to-dependency conversion for english. In *NODALIDA*.

Richard Johansson and Pierre Nugues. 2008. Dependency-based syntactic-semantic analysis with propbank and nombank. In *CoNLL*.

Nikita Kitaev and Dan Klein. 2018. Constituency parsing with a self-attentive encoder. In *ACL*.

Zuchao Li, Shexia He, Jiaxun Cai, Zhuosheng Zhang, Hai Zhao, Gongshen Liu, Linlin Li, and Luo Si. 2018. A unified syntax-aware framework for semantic role labeling. In *EMNLP*.

David M Magerman. 1994. Natural language parsing as statistical pattern recognition.

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

Diego Marcheggiani and Ivan Titov. 2017. Encoding sentences with graph convolutional networks for semantic role labeling. In *EMNLP*.

Mitchell Marcus, Beatrice Santorini, and Mary Ann Marcinkiewicz. 1993. Building a large annotated corpus of english: The penn treebank.

A Meyers, R Reeves, C Macleod, R Szekely, V Zielinska, B Young, and R Grishman. 2004. The nombank project: An interim report. *NAACL:HLT*.

Martha Palmer, Daniel Gildea, and Paul Kingsbury. 2005. The proposition bank: An annotated corpus of semantic roles. *CL*.

Hao Peng, Sam Thomson, Swabha Swayamdipta, and Noah A Smith. 2018. Learning joint semantic parsers from disjoint data. In *NAACL:HLT*.

Jeffrey Pennington, Richard Socher, and Christopher 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:HLT*.

Sameer Pradhan, Wayne Ward, Kadri Hacioglu, James Martin, and Daniel Jurafsky. 2005. Semantic role labeling using different syntactic views. In *ACL*.

Vasin Punyakanok, Dan Roth, and Wen-tau Yih. 2005. The necessity of syntactic parsing for semantic role labeling. In *IJCAI*.

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

Michael Roth and Mirella Lapata. 2016. Neural semantic role labeling with dependency path embeddings. In *ACL*.

Emma Strubell, Patrick Verga, Daniel Andor, David Weiss, and Andrew McCallum. 2018. Linguistically-informed self-attention for semantic role labeling. In *EMNLP*.

Mihai Surdeanu, Richard Johansson, Adam Meyers, Luís Marquez, and Joakim Nivre. 2008. The conll-2008 shared task on joint parsing of syntactic and semantic dependencies. In *CoNLL*.

Nianwen Xue and Martha Palmer. 2004. Calibrating features for semantic role labeling. In *EMNLP*.

Hiroyasu Yamada and Yuji Matsumoto. 2003. Statistical dependency analysis with support vector machines. In *IWPT*.

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