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

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Main Work

• The latest developments in neural semantic role labeling (SRL), including both **dependency** and **span** representation formalisms.

- we define a new cross-style semantic role label convention and propose a new cross-style joint optimization model
- 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

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.

S: lifted_{PRED} [the minimum wage of working]_{ARG1},

D: $lifted_{PRED}$ $(wage)_{ARG1}$,

U: lifted_{PRED} [the minimum wage

of working] $(wage)_{ARG1}$.

Model NULL softmax-ARG0 Jointly Span SRL Dependency SRL ARG1 (Many tourists, meet) (tourists, meet) Score C-ARG1 Objective Span Argument Dependency Argument Predicate_Predicate AM-LOC Representation AM-TMP tourists visit Disney Disney to meet their favorite favorite carto on characters Many tourists to meet Span Representation Disney characters tourists favorite visit meet Head Representation **BiLSTM** Encoder Word & character Representation visit Many tourists Disney their favorite characters to meet cartoon

Figure 4: Overall architecture of our proposed SRL model.

Encoder

• Contextualized representation x_i

$$x_i = BiLSTM([e_i^{word}; e_i^{char}; e_i^{lm}])$$

Objective Representation Layer

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

$$\alpha_{span} = \mathbf{softmax}(\mathbf{w}_s^T x_{\mathsf{START}(a):\mathsf{END}(a)})$$

$$x_{span} = x_{START(a):END(a)} \cdot \alpha_{span}$$

Semantic Aided

Dependency Syntax Aided (DSA)

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

$$e_t^{dsa} = \begin{cases} 1, & w_t \in headset \\ 0, & w_t \notin headset \end{cases}$$
 (6)

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

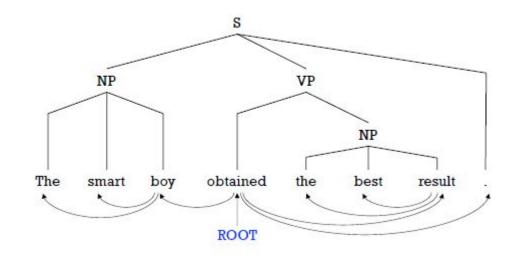
$$\alpha_{span} = \mathbf{softmax}(\mathbf{w}_s^T[x_{\mathsf{START}(a):\mathsf{END}(a)}; e_{\mathsf{START}(a):\mathsf{END}(a)}^{dsa}])$$

Semantic Aided

Constituency Syntax Aided (CSA)

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 $boundaryset = \{(S_{TART}(c), E_{ND}(c))\}$. We also define an indicator embedding e_{csa} on the constituent boundaries set boundaryset input to calculate the span representation.

$$e_t^{csa} = \begin{cases} 1, & span_t \in boundaryset \\ 0, & span_t \notin boundaryset \end{cases}$$
 (8)



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

$$x_{arg} = [x_{START(a)}; x_{END(a)}; x_{span}; e^{width}; e^{csa}].$$

Train

Scorer with biaffine attention

$$\Phi_r(p,a) = \{h_p\}^T \mathbf{W}_1 h_a + \mathbf{W}_2^T (h_p \oplus h_a) + \mathbf{b}.$$

Training Objectives

$$P_{\theta}(Y|X) = \prod_{p \in \mathcal{P}, a \in \mathcal{A}} P_{\theta}(y_{p,a}|X),$$

$$P_{\theta}(y_{p,a} = r|X) = \frac{\exp(\Phi_r(p, a))}{\sum_{r' \in \mathcal{R}} \exp(\Phi_{r'}(p, a))},$$

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

Result

Gold predicates	CoNLL05 WSJ		CoNLL05 Brown		CoNLL09 WSJ		CoNLL09 Brown					
	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F ₁
wo/LM												
FitzGerald et al. (2015)*	82.3	76.8	79.4	73.8	68.8	71.2	- -3	-	87.3	_	-	75.2
Li et al. (2019)	-		83.0	-	-	-			85.1	-	T	- 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

Result

End-to-end		WSJ		Brown		
Life to one	P	R	F_1	P	R	F ₁
CoNLL-2005						
He et al. (2017)	80.2	82.3	81.2	67.6	69.6	68.5
He et al. (2018a)	84.8	87.2	86.0	73.9	78.4	76.1
Strubell et al. (2018)	87.1	86.7	86.9	79.0	77.5	78.3
Li et al. (2019)	85.2	87.5	86.3	74.7	78.1	76.4
w/ELMo						
Ours	86.7	86.1	86.4	75.3	78.1	76.7
+Predicted Syntax	86.7	86.7	86.7	76.4	78.2	77.3
+Gold Syntax	88.6	88.0	88.3	78.0	78.2	78.1
w/BERT						
Ours	88.1	86.3	87.2	79.7	79.5	79.6
+Predicted Syntax	88.1	87.5	87.8	79.8	80.2	80.0
+Gold Syntax	88.4	89.6	89.0	80.3	83.9	82.1
CoNLL-2009						
He et al. (2018b)	83.9	82.7	83.3	_	_	<u>2002</u>
Cai et al.(2018)	84.7	85.2	85.0	N-0	_	72.5
Li et al. (2019)	84.5	86.1	85.3	74.6	73.8	74.2
w/ELMo						
Ours	85.0	86.2	85.6	74.6	74.0	74.3
+Predicted Syntax	86.1	85.9	86.0	75.0	74.8	74.9
+Gold Syntax	88.6	88.9	88.7	75.7	75.3	75.5
w/BERT						
Ours	87.9	86.3	87.1	77.1	74.9	76.0
+Predicted Syntax	87.8	88.0	87.9	77.1	75.5	76.3
+Gold Syntax	88.6	90.4	89.5	76.0	80.5	78.2

End-to-end	S_1	pan SR	EL.	Depedency SRL			
	P	R	F_1	P	R	F ₁	
Baseline	88.1	87.5	87.8	87.8	88.0	87.9	
-DSA	88.0	87.4	87.7	88.1	86.5	87.3	
-CSA	87.9	86.7	87.3	88.3	86.5	87.4	
-Both	88.1	86.3	87.2	87.9	86.3	87.1	

Dev / Test

- -- items are TAB-separated, first two items are 0s
- -- 3rd item: number of annotations for this predicate (frame and role annotations: "2" means 1 frame and 1 role are annotated)
- -- 4th item: Frame label of predicate
- -- 5th item: lemma.POS of predicate
- -- 6th item: index of predicate word in sentence (as tokenized in *.lemma.tags file, index starting with 0), multiwords separated by "_"
- -- 7th item: predicate word
- -- 8th item: index of sentence belonging to this predicate (sentences found in *.lemma.tags file
- -- 9th/10th item (optional): first pair of role label and index of argument word in the sentence (multiword spans separated by ":")
- -- further pairs of items (optional): additional pairs of role label and index of argument word

Text

- -- the first column marks the number of tokens in a sentence (n)
- -- the next n items contain the WORDS (tokens)
- -- the next n items contain the corresponding POS tags
- -- the next n items contain the dependency labels
- -- the next n items contain the dependency heads
- -- the next n items are 0
- -- the next n items contain the LEMMA

Dev

• size: 1000

• frame: 268

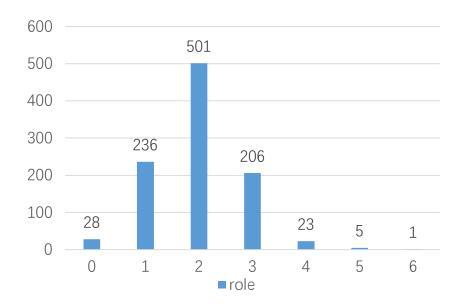
• role_avg= 2.979

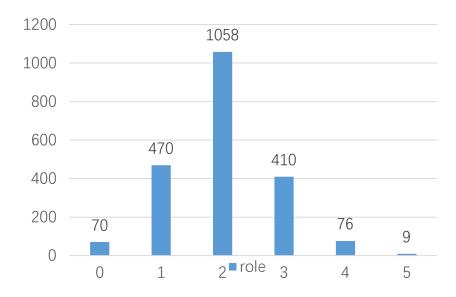
Test

• size: 2093

• frame: 363

• role_avg=2.98





YAGS
• example

```
Personal_relationship boyfriend.n 3 boyfriend
                                             1007
Intentionally_act do.v 5 did 1007
                                     Agent
                                             2:3 Act
Capability able.a 15 able
                            1007
                                   Degree 13
                                             Event
```

• Frame-frame Relations:

Frame-frame Relations:

Inherits from: Physical_entity

Is Inherited by: Perspective on: Is Perspectivized in:

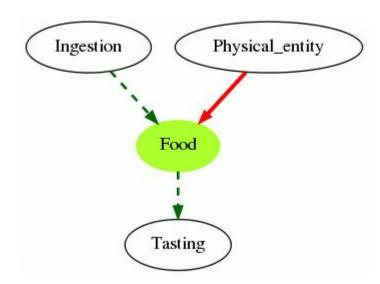
Uses: <u>Ingestion</u>

Is Used by: <u>Tasting</u> Subframe of:

Has Subframe(s):

Precedes:

Is Preceded by: Is Inchoative of: Is Causative of:



ImsituVQA

IMAGE about cooking



QUESTION	ANSWER	FRAME ELEMENT
Who is cooking?	boy	AGENT
What does the boy cook with spatula?	meat	FOOD
What is the boy doing?	cooking	VERB
What does the boy use to cook in wok?	spatula	TOOL
Where does the boy cook meat in wok?	kitchen	PLACE

IMAGE about buying



QUESTION	ANSWER	FRAME ELEMENT
Who is buying shoes?	woman	AGENT
What is the woman doing?	buying	VERB
What item does the woman buy	shoe	GOODS
with credit card? who does the woman buy shoe from? where does the woman buy shoe?	person shoe store	SELLER PLACE