上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

Syntax for Semantic Role Labeling, To Be, Or Not To Be

Shexia He[1,2], **Zuchao Li**[1,2], Hai Zhao[1,2,*], Hongxiao Bai[1,2]

[1]Department of Computer Science and Engineering, Shanghai Jiao Tong University

[2]Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, China

Semantic Role Labeling (SRL)

- SRL - a shallow **semantic parsing** task: recognize the **predicate-argument** structure, such as *who* did *what* to *whom*, *where* and *when*, etc.
- **Four subtasks**
  - – Predicate identification and disambiguation
  - – **Argument identification and classification**
- Applications:
  - – Machine Translation
  - – Information Extraction
  - – Question Answering, etc.

SRL - Example

Two formulizations of predicate-argument structure:

- Span-based (i.e., phrase or constituent)

	Marry	**borrowed**	a	book	from	john	last	week
borrow.01	A0		A1		A2		AM-TMP	

- **Dependency-based:** head of arguments

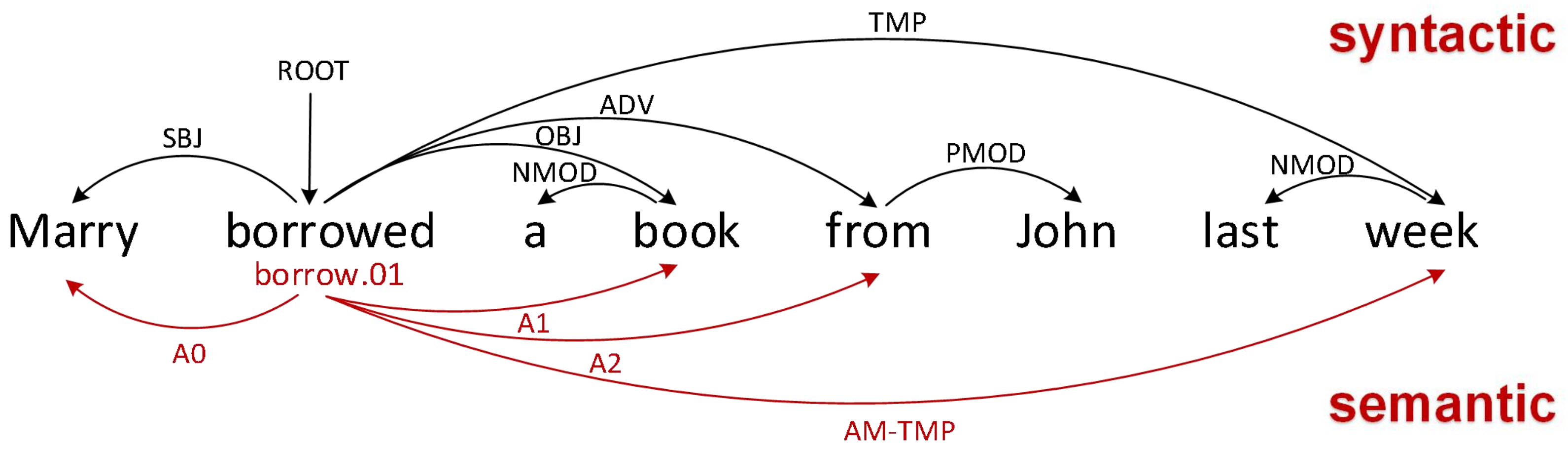
	Marry	**borrowed**	a	book	from	john	last	week
borrow.01	A0			A1	A2			AM-TMP

Related Work

- Previous methods

Traditional	Neural network
Pradhan et al. (2005) utilized a SVM classifier **Roth and Yih (2005)** employed CRF with integer linear programming **Punyakanok et al. (2008)** enforced global consistency with ILP **Zhao et al. (2009)** proposed a huge feature engineering method	**Zhou and Xu (2015)** introduced deep bi-directional RNN model **Roth and Lapata (2016)** proposed PathLSTM modeling approach **He et al. (2017)** used deep highway BiLSTM with constrained decoding **Marcheggiani et al. (2017)** presented a simple BiLSTM model **Marcheggiani and Titov (2017)** proposed a GCN-based SRL model

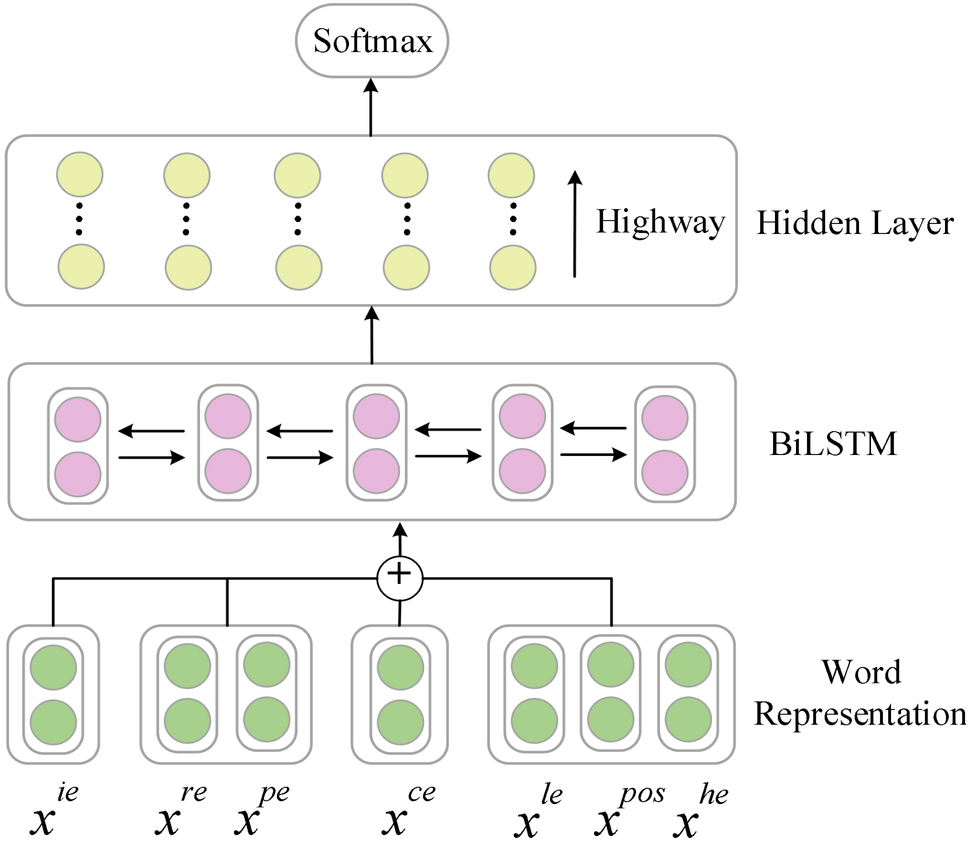
Focus - Dependency SRL



- Syntax-aware:
  - Maximum entropy model (Zhao et al., 2009)
  - Path embedding (Roth and Lapata, 2016)
  - Graph convolutional network (Marcheggiani and Titov, 2017)
- Syntax-agnostic:
  - The simple BiLSTM (Marcheggiani et al., 2017)

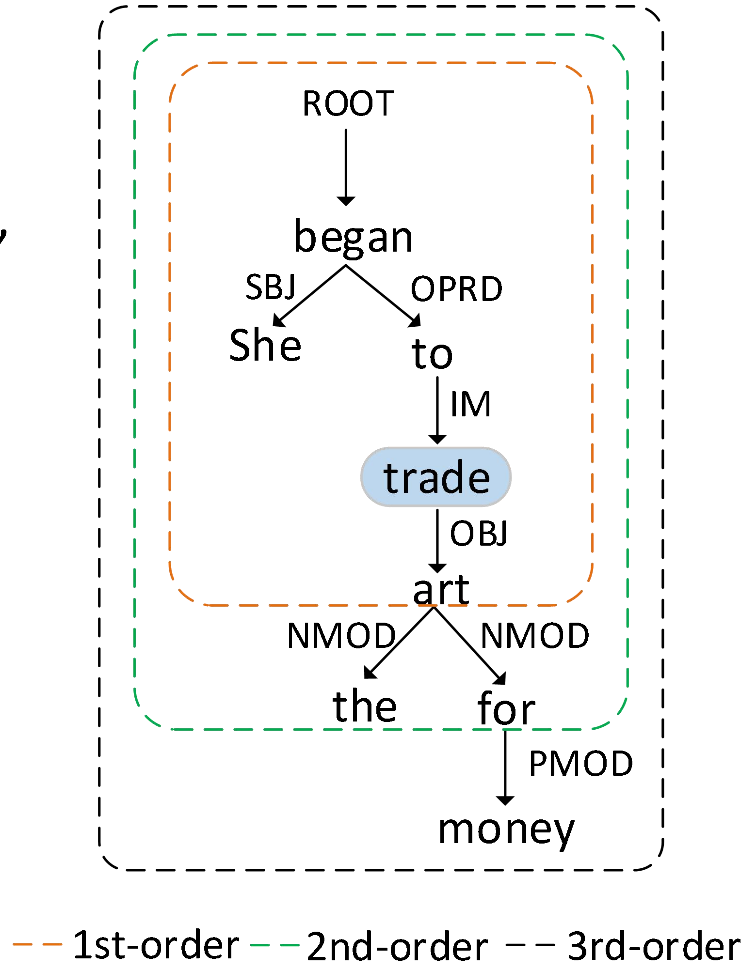
Method - Overview

- Pipeline
  - Predicate Disambiguation & Argument Labeling
  - Sequence labeling: BiLSTM - MLP
  - Enhanced representation: ***ELMo***
  - Argument Labeling Model
    - Preprocessing: *k*-order pruning



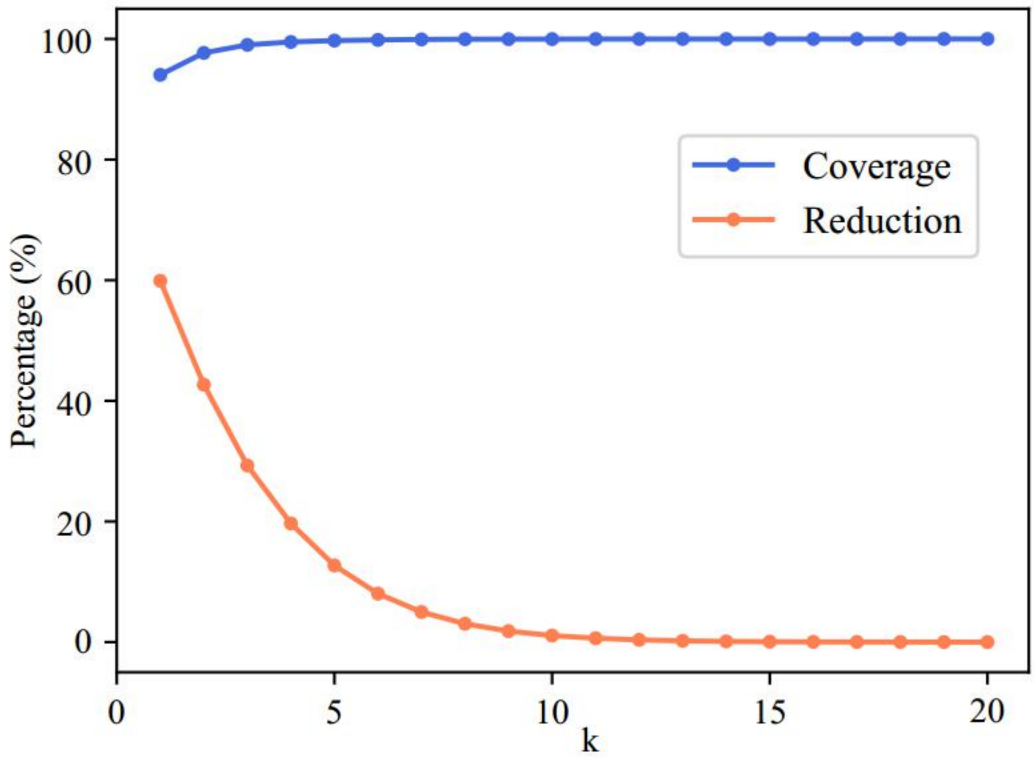
k-order argument pruning

- **Initialization**: Set the marked predicate as the current node;
- 1. Collect all its descendant node as argument candidates, which is at most ***k*** syntactically distant from the current node.
- 2. Reset the current node to its syntactic head and repeat step 1 until the root is reached.
- 3. Collect the root and stop.

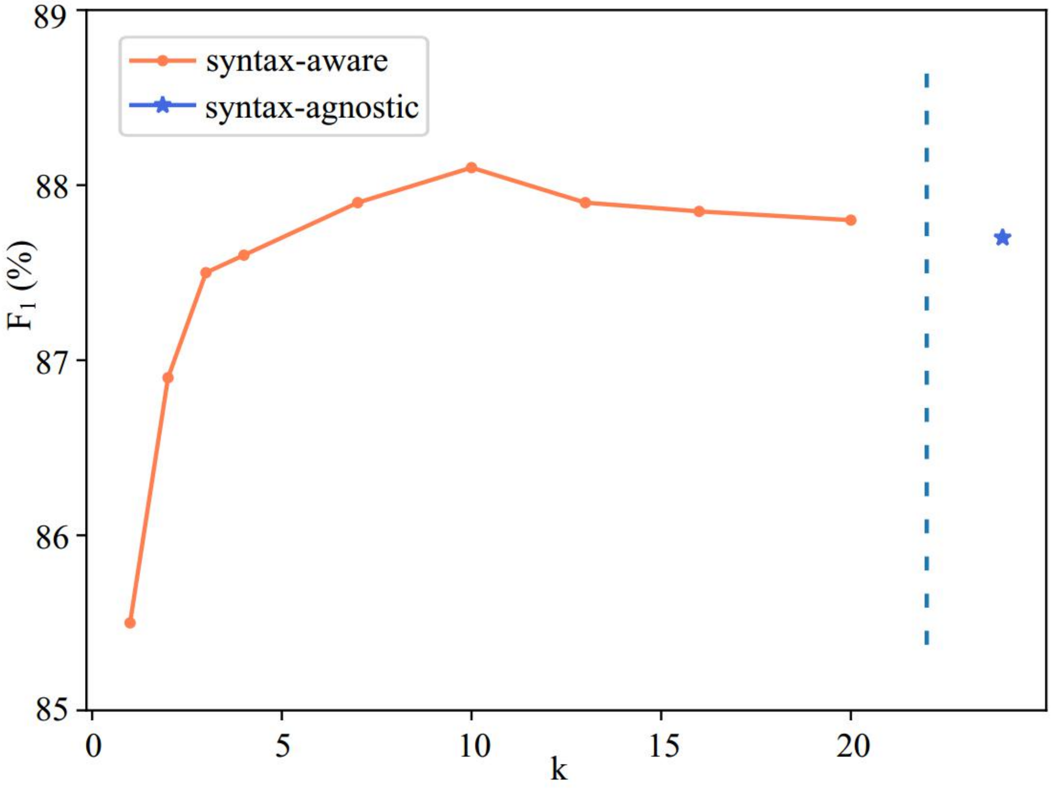


Reference: Zhao et al., 2009

syntax-aware → syntax-agnostic



CoNLL-2009 English training set



CoNLL-2009 English development set

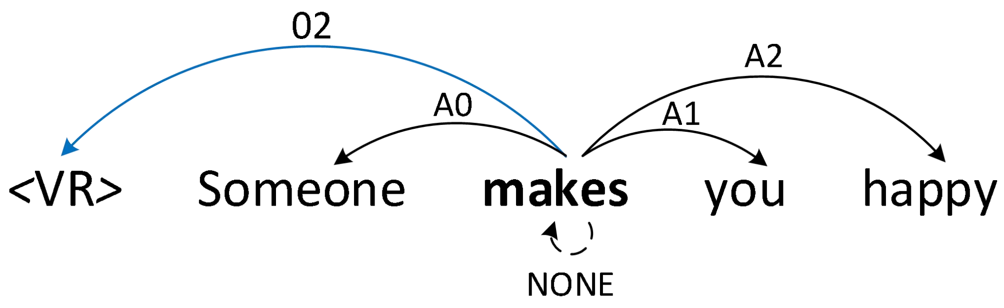
CoNLL-2009 Results

	Models	English	Chinese	OOD
Non-NN	Zhao et al., 2009	86.2	77.7	74.6
	Bjorkelund et al., 2010	85.8	78.6	73.9
NN syntax-aware	Lei et al., 2015	86.6	-	75.6
	FitzGerald et al., 2015	86.7	-	75.2
	Roth and Lapata, 2016	86.7	79.4	75.3
	Marcheggiani and Titov, 2017	88.0	82.5	77.2
	Ours	89.5	82.8	79.3
NN syntax-agnostic	Marcheggiani et al., 2017	87.7	81.2	77.7
	Ours	88.7	81.8	78.8

Results on CoNLL-2009 English, Chinese and out-of-domain (OOD) test set.

End-to-end SRL

- Integrate predicate disambiguation and argument labeling



- CoNLL-2009 results

	Models	F1
syntax-agnostic	end-to-end	88.4
	pipeline	88.7
syntax-aware	end-to-end	89.0
	pipeline	89.5

Results of end-to-end model on the CoNLL-2009 data.

CoNLL-2008 Results

- Indispensable task: predicate identification

Models	LAS	Sem-F1
Johansson and Nugues, 2008	90.13	81.75
Zhao and Kit, 2008	87.52	77.67
Zhao et al, 2009	88.39	82.1
	89.28	82.5
Zhao et al, 2013	88.39	82.5
	89.28	82.4
Ours (syntax-agnostic)	-	82.9
Ours (syntax-aware)	86.0	83.3

Results on the CoNLL-2008 in-domain test set.

Syntactic Role

- Different syntax-aware SRL models may adopt different syntactic parser
  - PathLSTM SRL (Roth and Lapata, 2016): **mate-tools**
  - GCN-based SRL (Marcheggiani and Titov, 2017): **BIST Parser**
- How to quantitatively evaluate the syntactic contribution to SRL?
  - Evaluation Measure: **the Sem-F_1 / LAS ratio**
  - Sem-F_1: the labeled F_1 score for semantic dependencies
  - LAS: the labeled attachment score for syntactic dependencies

Reference: Surdeanu et al., CoNLL-2008 Shared Task

Performance Comparison

Models	LAS	Sem-F1	Sem-F1/LAS
Zhao et al, 2009 [CoNLL SRL-only]	86.0	85.4	99.3
Zhao et al, 2009 [CoNLL Joint]	89.2	86.2	96.6
Bjorkelund et al, 2010	89.8	85.8	95.6
Lei et al, 2015	90.4	86.6	95.8
Roth and Lapata, 2016	89.8	86.7	96.5
Marcheggiani and Titov, 2017	90.3	88.0	97.5
Ours + CoNLL-2009 predicted	86.0	89.5	104.0
Ours + Auto syntax	90.0	89.9	99.9
Ours + Gold syntax	100.0	90.3	90.3

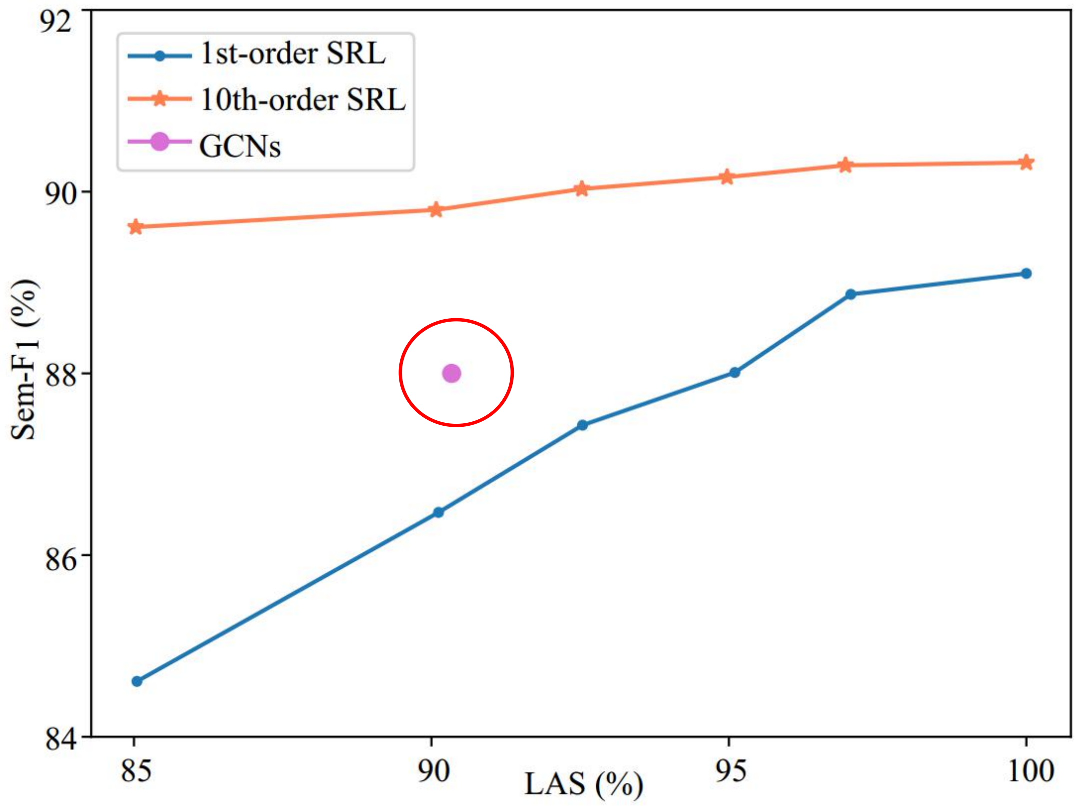
Sem-F1/LAS ratio on CoNLL-2009 English test set.

Faulty Syntactic Tree Generator

- How to obtain syntactic input of different quality?
  - **A Faulty Syntactic Tree Generator** (STG)
  - Produce random errors in the output parse tree
- **STG implementation**
  - Given an input error probability distribution
  - Modify the syntactic heads of nodes

Sem-F1 - LAS Curve

- Syntactic inputs generated from STG
- The 10th-order SRL gives quite stable results regardless of syntactic quality
- The 1st-order SRL model yields overall lower performance
- Better syntax could result in better SRL



1st and 10th-order SRL on CoNLL-2009 English test set.

Conclusion and Future Work

- We present an effective model for dependency SRL with extended *k*-order pruning.
- The gap between syntax-enhanced and -agnostic SRL has been greatly reduced, from as high as **10%** to only **1-2%** performance loss.
- High-quality syntactic parses indeed enhance SRL.

- Future work:
  - Develop a more effective syntax-agnostic SRL system.
  - Explore syntactic integration method based on high-quality syntax.

Thank You!

{heshexia, charlee}@sjtu.edu.cn

Code is publicly available at:

https://github.com/bcmi220/srl_syn_pruning