基于深度学习的中文分词技术

Neural Models for Chinese Word Segmentation

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Direction: Natural Language Processing

What is Chinese word segmentation (CWS) ?

中国官员应邀到美国开会
中国/官员/应邀/到/美国/开会

大学生活好，还是中学生活好
大学/生活/好，还是/中学/生活/好

如果你饿了，我就下面给你吃
如果/你/饿/了，我/就/下/面/给/你/吃

Why CWS is important ?

- Parsing
- Text classification
- IR
- Translation
- QA
- ……

Why CWS is hard ?

- Low out-of-vocabulary (OOV) word recall rate
- Disambiguate
- Evaluation
  - Criteria & granularity
  - New Evaluation Metric[1]

1. A New Psychometric-inspired Evaluation Metric for Chinese Word Segmentation. ACL2016. Peng Qian et al.

OOV

人名、地名、机构名：
刘德华 长坂坡 耀华路

网名：
你是我的谁 旺仔小馒头

公司名、产品名
摩托罗拉 谷歌 爱国者 腾讯 网易 新浪
诺基亚C5 尼康D700

Disambiguate

这样/的/**人/才**能/经受住/考验
这样/的/**人才**/能/经受住/考验

学生**会/写**/文章
学生**/会/写**/文章

乒乓球**拍/卖**/完了
乒乓球**/拍卖**/完了

Evaluation

$$R = \frac{c}{N}$$

$$P = \frac{c}{c+e}$$

$$F = \frac{2 \times P \times R}{P+R}$$

N： 黄金标准分割的单词数
e： 分词器错误标注的单词数
c： 分词器正确标注的单词数

Granularity

上海市
上海/市

江泽民
江/泽民

Prevalent Approaches

- 基于规则的分词
- **基于统计的分词**

基于统计的分词

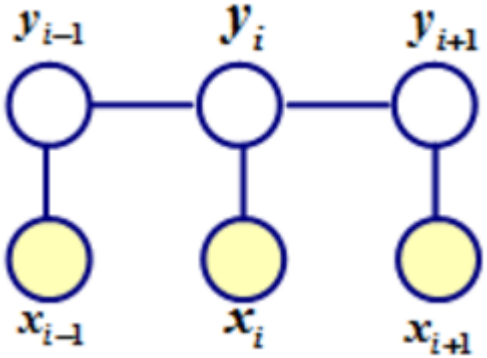
- 基于词的方法
- **基于字的序列标注方法[1]**
- 基于词和基于字的方法的结合

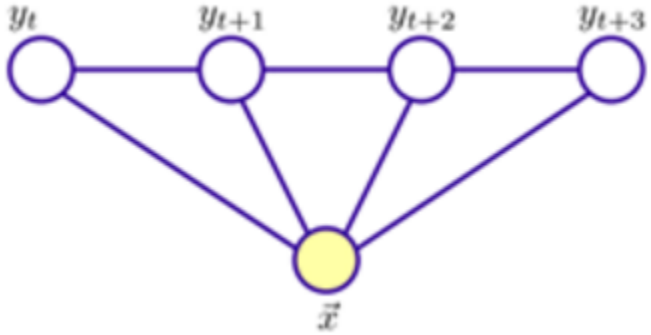
1. N. Xue. 2003. Chinese word segmentation as character tagging. *Computational Linguistics and Chinese Language Processing* 8(1):29–48.

基于字的序列标注方法

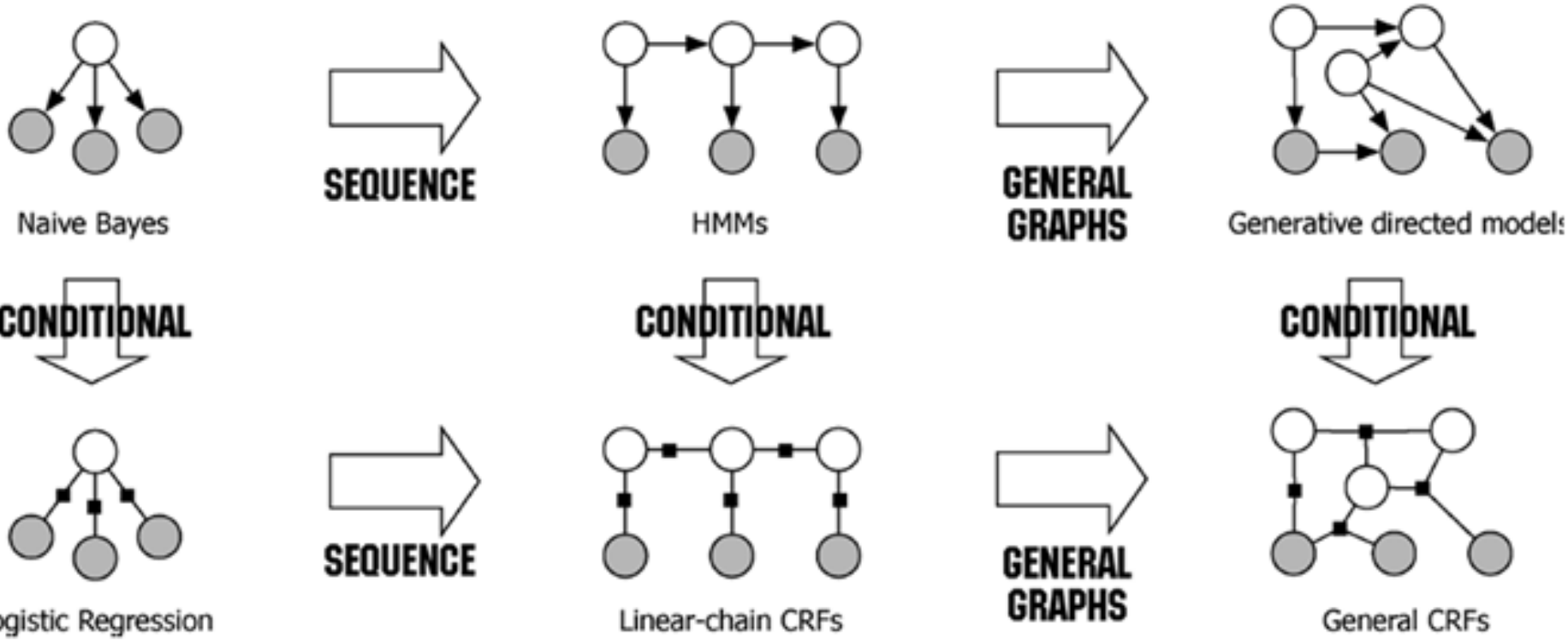
- HMM (隐马模型)
- MEMM (最大熵隐马模型)
- **CRF (条件随机场模型)**

Conditional Random Fields (Linear-chain CRFs)





Conditional Random Fields (Linear-chain CRFs)



CRF++实现中文分词

```
每    k    B
日    k    I
新    k    I <== 扫描到这一行，代表当前位置
聞    k    I
社    k    I
特    k    B
別    k    I
顧    k    B
問    k    I
4     n    B
```

```
1   # Unigram
2   U00:%x[-2,0]    ==> 每
3   U01:%x[-1,0]    ==> 日
4   U02:%x[0,0]     ==> 新
5   U03:%x[1,0]     ==> 聞
6   U04:%x[2,0]     ==> 社
7   U05:%x[-2,0]/%x[-1,0]/%x[0,0]    ==> 每/日/新
8   U06:%x[-1,0]/%x[0,0]/%x[1,0]     ==> 日/新/聞
9   U07:%x[0,0]/%x[1,0]/%x[2,0]      ==> 新/聞/社
10  U08:%x[-1,0]/%x[0,0]             ==> 日/新
11  U09:%x[0,0]/%x[1,0]              ==> 新/聞
12
13  # Bigram
14  B
```

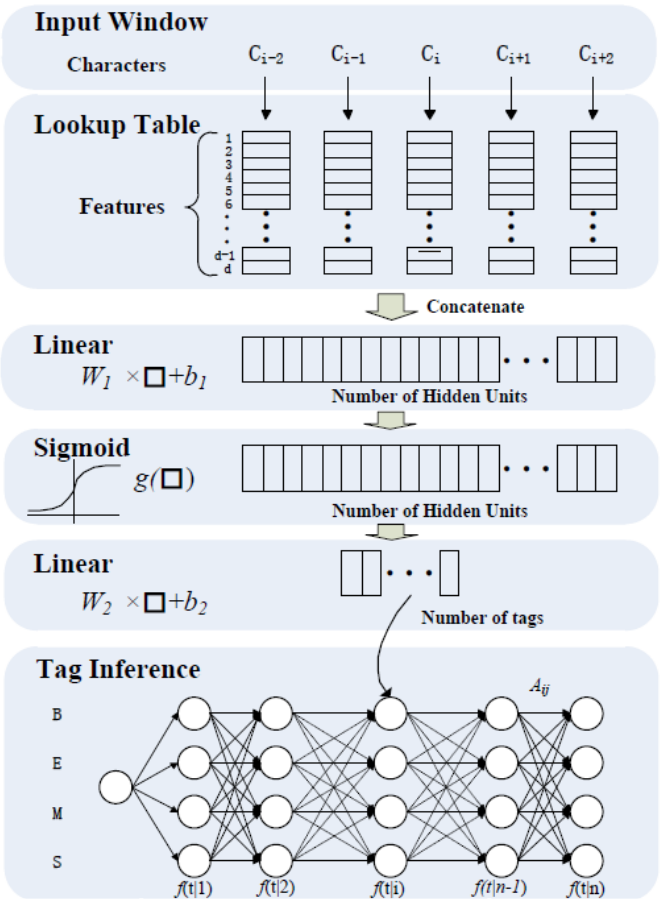
Neural Chinese Word Segmentation

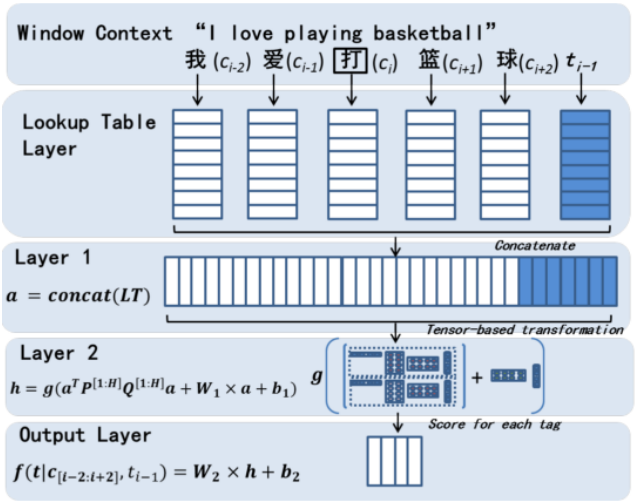
- 建模复杂的特征
  - Gated Recursive Neural Network
- 建模长距离的依赖
  - Long Short-Term Memory Neural Network
- 利用不同标准语料
  - Adversarial Multi-Criteria Learning for CWS

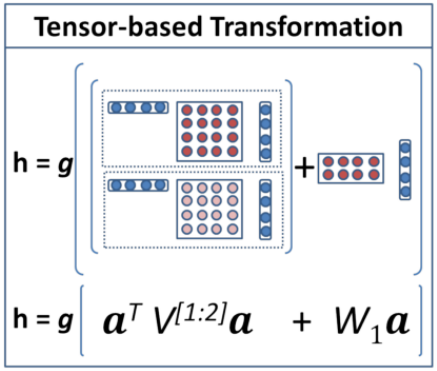
Neural network based CWS

Feature Template
$C_i\ (i = -2..2)$
$C_iC_{i+1}\ (i = -2..1)$
$C_{-1}C_1$
$Pu(C_0)$
$T(C_{-2})T(C_{-1})T(C_0)T(C_1)T(C_2)$

Unigram
Bigram
A*A* （一心一意）
A*B*（朝三暮四）
*A*B（朝三暮四）







Models	PKU	MSRA	CTB6
Conventional	**96.1**	**97.4**	**95.7**
Zheng et al. (EMNLP 2013)	92.8	93.9	93.7
Pei et al. (ACL 2014)	95.2	97.2	-

Optimization

- Max Margin
- CRFs

Max Margin

- For a given training instance (xi , yi), we search for the tag sequence with the highest score:

$$y^* = \arg\max_{\hat{y} \in Y(x)} s(x_i, \hat{y}, \theta)$$

- The object of Max-Margin training is that the highest scoring tag sequence is the correct one: y ∗ = yi and its score will be larger up to a margin to other possible tag sequences

$$s(x, y_i, \theta) \geq s(x, \hat{y}, \theta) + \triangle(y_i, \hat{y})$$

$$\triangle(y_i, \hat{y}) = \sum_{j}^{n} \kappa \mathbf{1}\{y_{i,j} \neq \hat{y}_j\}$$

Max Margin

- This leads to the regularized objective function for m training examples:

$$
\begin{aligned}
J(\theta) &= \frac{1}{m}\sum_{i=1}^{m} l_i(\theta) + \frac{\lambda}{2}||\theta||^2 \\
l_i(\theta) &= \max_{\hat{y}\in Y(x_i)} (s(x_i, \hat{y}, \theta) + \triangle(y_i, \hat{y})) \\
&\quad -s(x_i, y_i, \theta))
\end{aligned}
$$

- The subgradient of equation is:

$$
\frac{\partial J}{\partial \theta} = \frac{1}{m}\sum_{i}(\frac{\partial s(x_i, \hat{y}_{max}, \theta)}{\partial \theta} - \frac{\partial s(x_i, y_i, \theta)}{\partial \theta}) + \lambda\theta
$$

CRFs

Specifically, given a sequence with n characters $X = \{x_1, \ldots, x_n\}$, the aim of CWS task is to figure out the ground truth of labels $Y^* = \{y_1^*, \ldots, y_n^*\}$:

$$Y^* = \arg\max_{Y \in \mathcal{L}^n} p(Y|X), \tag{1}$$

where $\mathcal{L} = \{B, M, E, S\}$.

CRFs

$$p(Y|X) = \frac{\Psi(Y|X)}{\sum_{Y' \in \mathcal{L}^n} \Psi(Y'|X)}.$$

Here, $\Psi(Y|X)$ is the potential function, and we only consider interactions between two successive labels (first order linear chain CRFs):

$$\Psi(Y|X) = \prod_{i=2}^{n} \psi(X, i, y_{i-1}, y_i),$$

$$\psi(\mathbf{x}, i, y', y) = \exp(s(X, i)_y + \mathbf{b}_{y'y}),$$

$$s(X, i) = \mathbf{W}_s^\top \mathbf{h}_i + \mathbf{b}_s,$$

Feed-forward Neural Network for CWS
[Xiaoqing Zheng, Hanyang Chen, Tianyu Xu; EMNLP15]

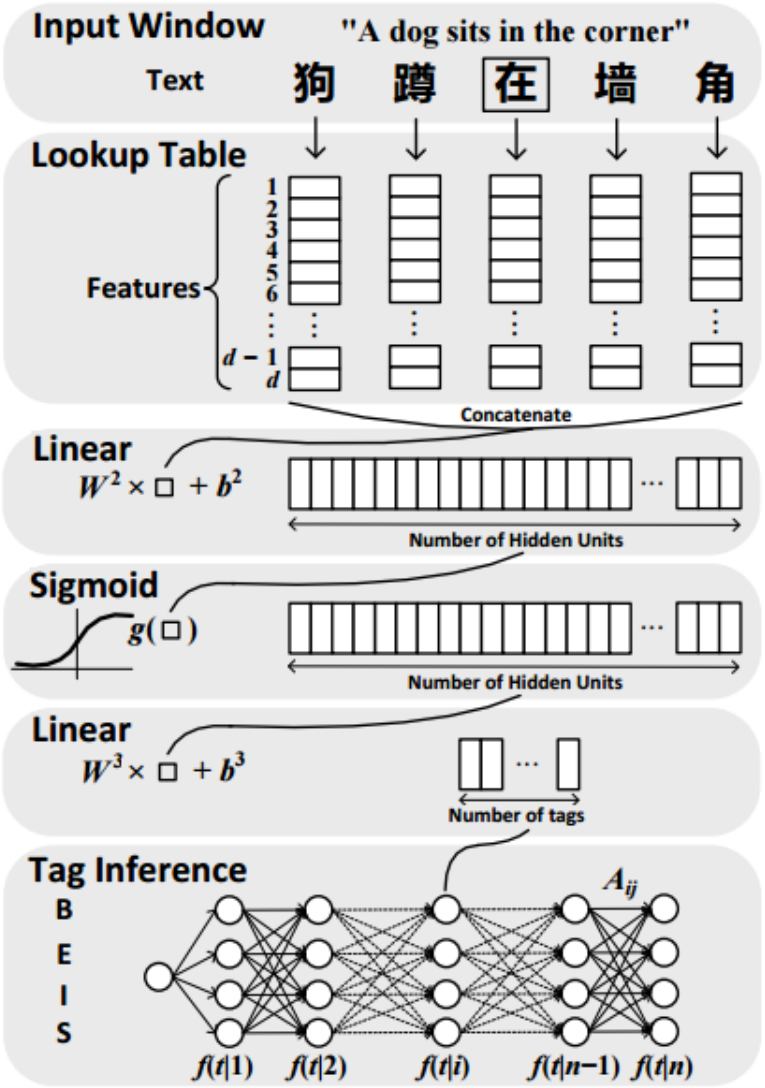
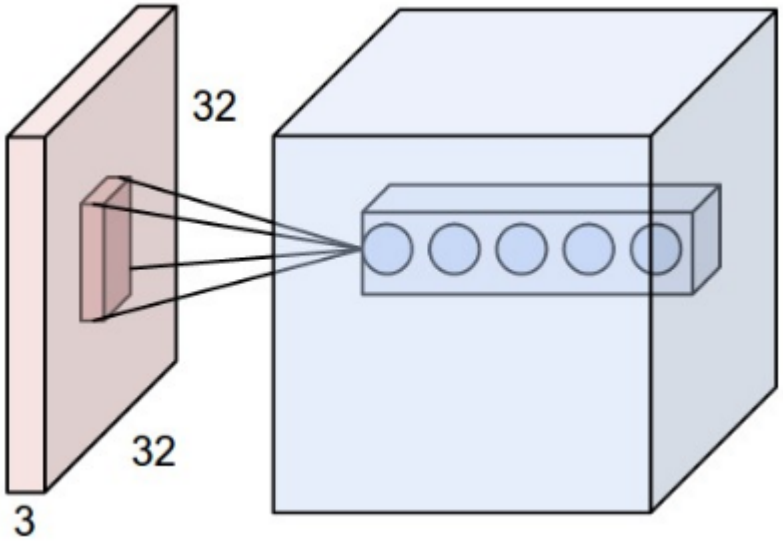
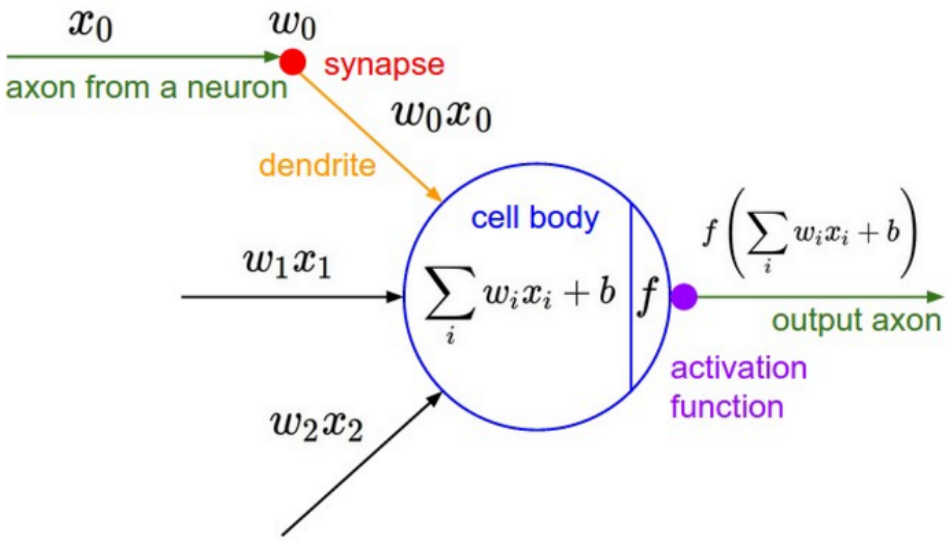
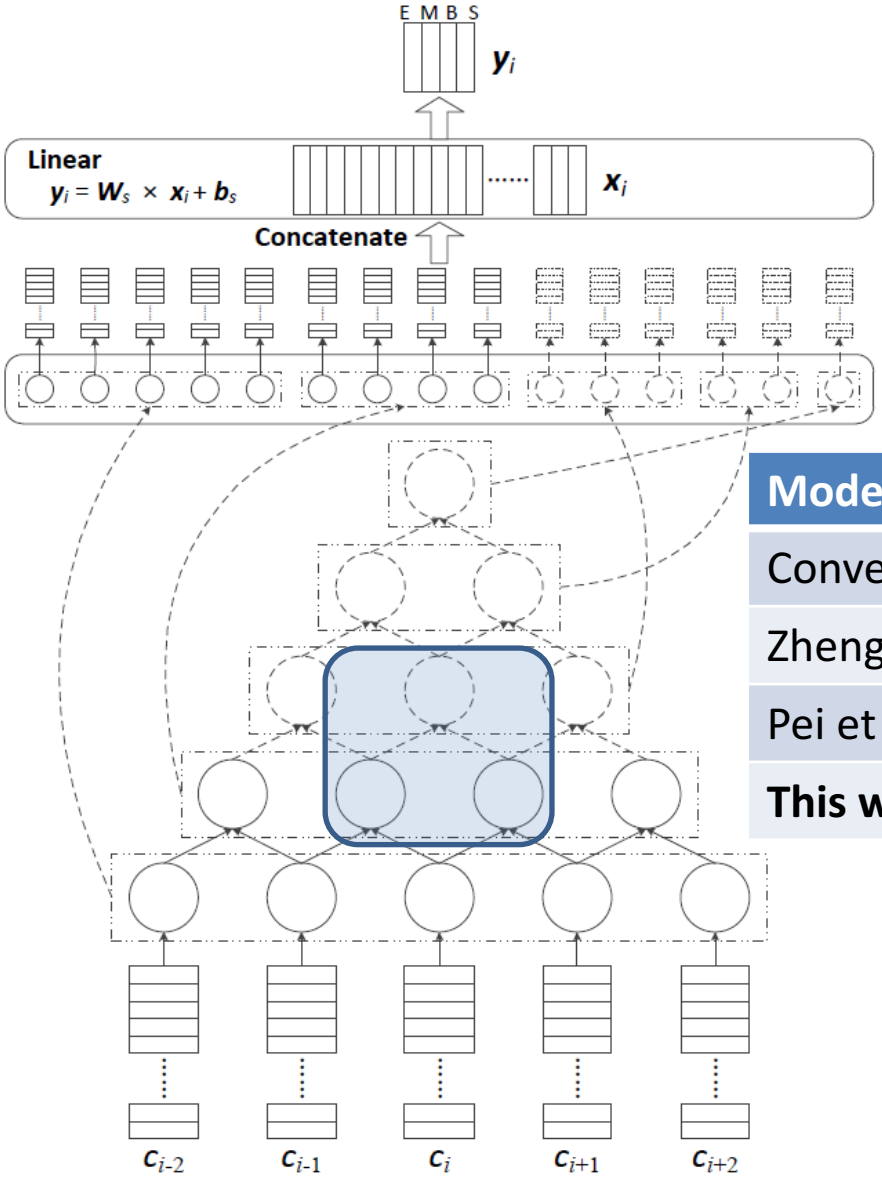


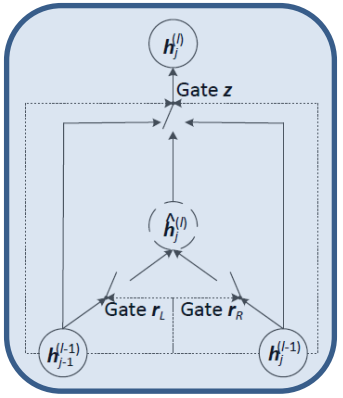
Figure 1: The neural network architecture.





Recursive neural network based CWS
[X Chen, X Qiu, C Zhu, X Huang; ACL 2015]

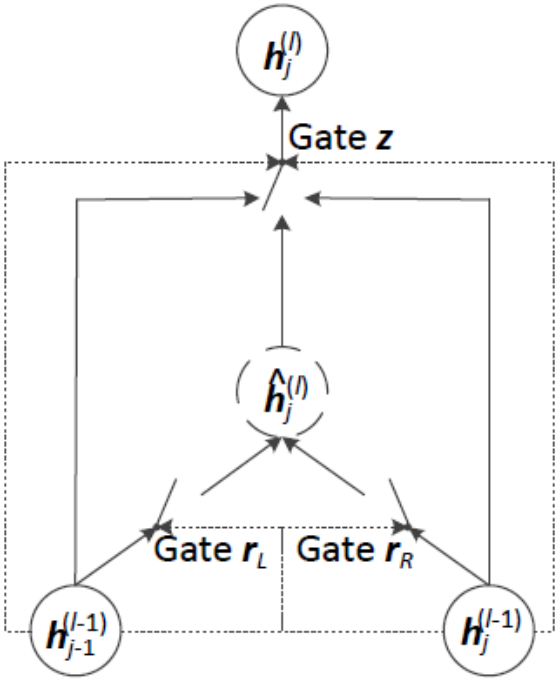




Models	PKU	MSRA	CTB6
Conventional	96.1	97.4	95.7
Zheng et al. (EMNLP 2013)	92.8	93.9	93.7
Pei et al. (ACL 2014)	95.2	97.2	-
This work (ACL 2015)	**96.4**	**97.6**	**95.8**

State-of-the-art

Gate mechanism



$$\mathbf{h}_j^{(l)} = \begin{cases} \mathbf{z}_N \odot \hat{\mathbf{h}}_j^l + \mathbf{z}_L \odot \mathbf{h}_{j-1}^{l-1} + \mathbf{z}_R \odot \mathbf{h}_j^{l-1}, & l > 1, \\ \mathbf{c}_j, & l = 1, \end{cases}$$

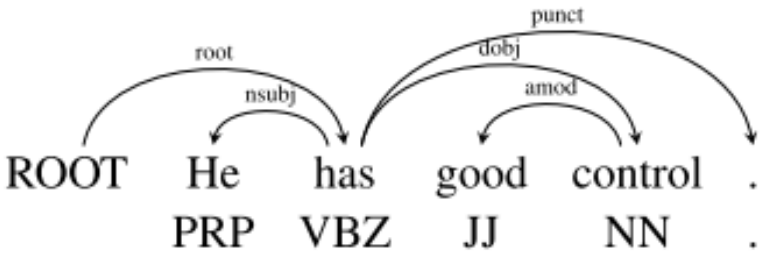
$$\hat{\mathbf{h}}_j^l = \tanh(\mathbf{W}_{\hat{\mathbf{h}}} \begin{bmatrix} \mathbf{r}_L \odot \mathbf{h}_{j-1}^{l-1} \\ \mathbf{r}_R \odot \mathbf{h}_j^{l-1} \end{bmatrix})$$

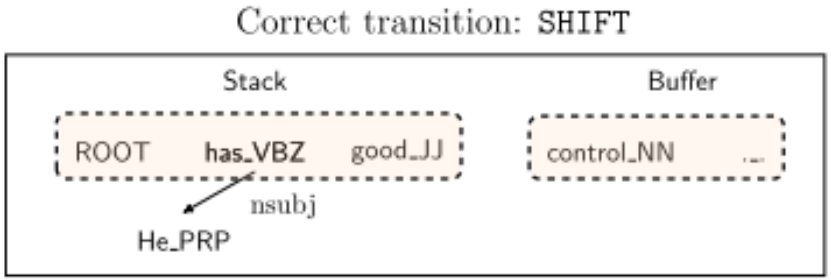
$$\begin{bmatrix} \mathbf{r}_L \\ \mathbf{r}_R \end{bmatrix} = \sigma(\mathbf{G} \begin{bmatrix} \mathbf{h}_{j-1}^{l-1} \\ \mathbf{h}_j^{l-1} \end{bmatrix}),$$

$$\mathbf{z} = \begin{bmatrix} \mathbf{z}_N \\ \mathbf{z}_L \\ \mathbf{z}_R \end{bmatrix} = \begin{bmatrix} 1/Z \\ 1/Z \\ 1/Z \end{bmatrix} \odot \exp(\mathbf{U} \begin{bmatrix} \hat{\mathbf{h}}_j^l \\ \mathbf{h}_{j-1}^{l-1} \\ \mathbf{h}_j^{l-1} \end{bmatrix})$$

- **Transition-based Dependency Parsing [EMNLP 2015]**
- **Sentence Modeling [EMNLP 2015]**

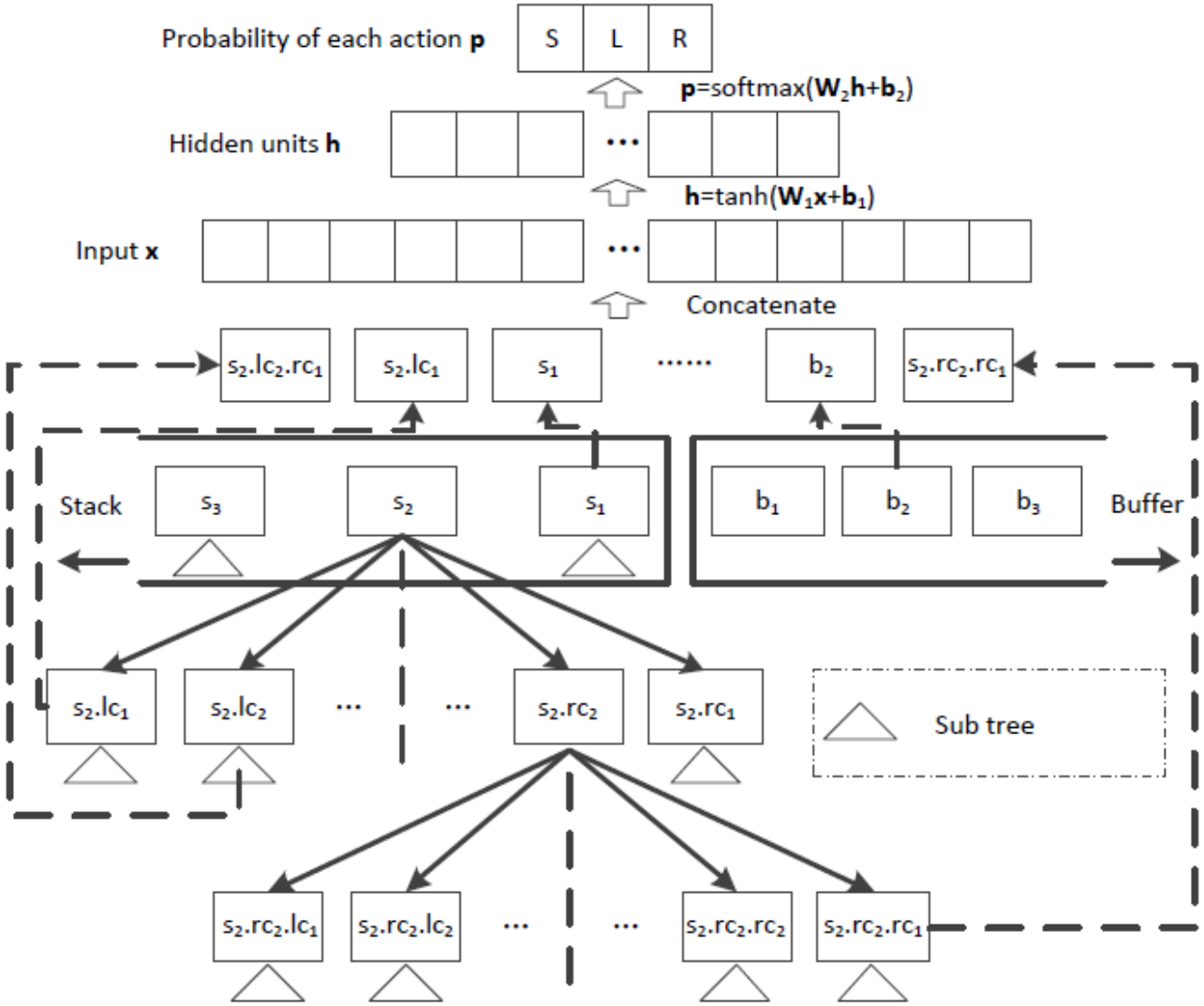
Transition based Dependency Parsing





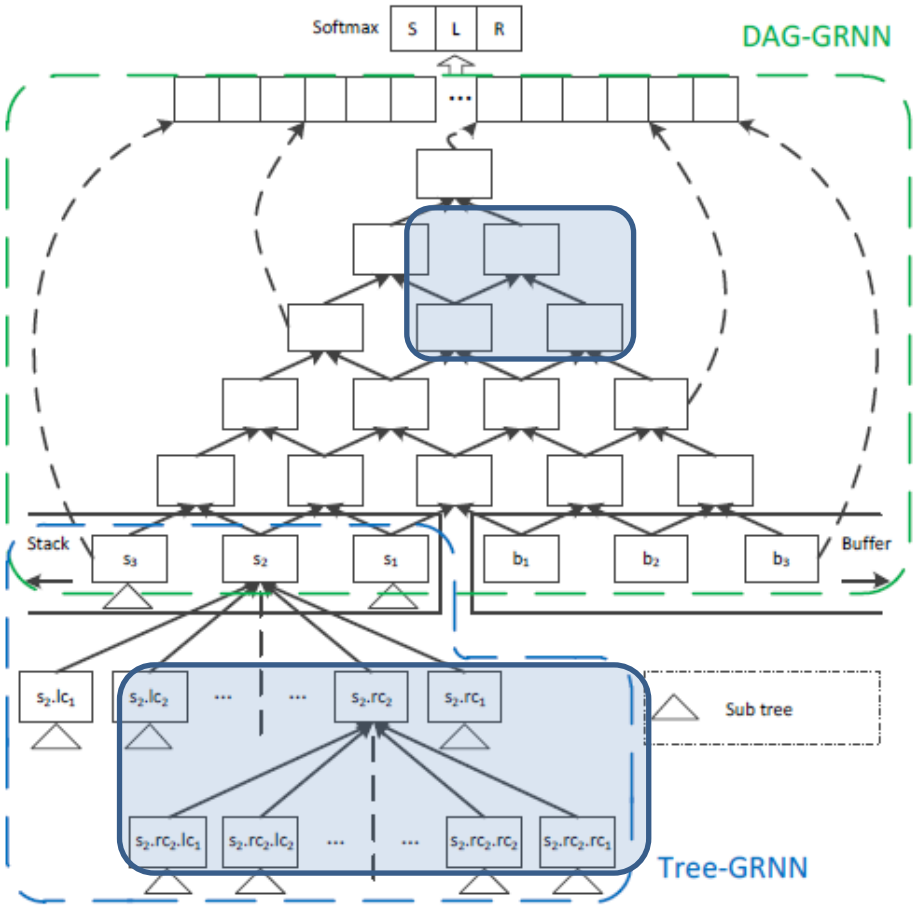
Transition	Stack	Buffer	A
	[ROOT]	[He has good control .]	$\emptyset$
SHIFT	[ROOT He]	[has good control .]	
SHIFT	[ROOT He has]	[good control .]	
LEFT-ARC(nsubj)	[ROOT has]	[good control .]	$A \cup$ nsubj(has,He)
SHIFT	[ROOT has good]	[control .]	
SHIFT	[ROOT has good control]	[.]	
LEFT-ARC(amod)	[ROOT has control]	[.]	$A \cup$amod(control,good)
RIGHT-ARC(dobj)	[ROOT has]	[.]	$A \cup$ dobj(has,control)
...	...	...	...
RIGHT-ARC(root)	[ROOT]	[]	$A \cup$ root(ROOT,has)

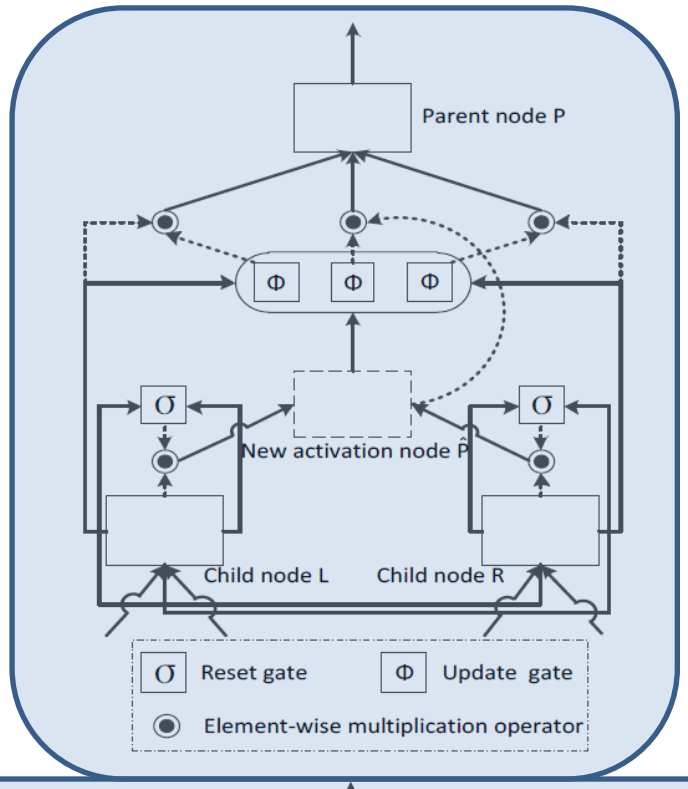
基于神经网络的依存句法模型

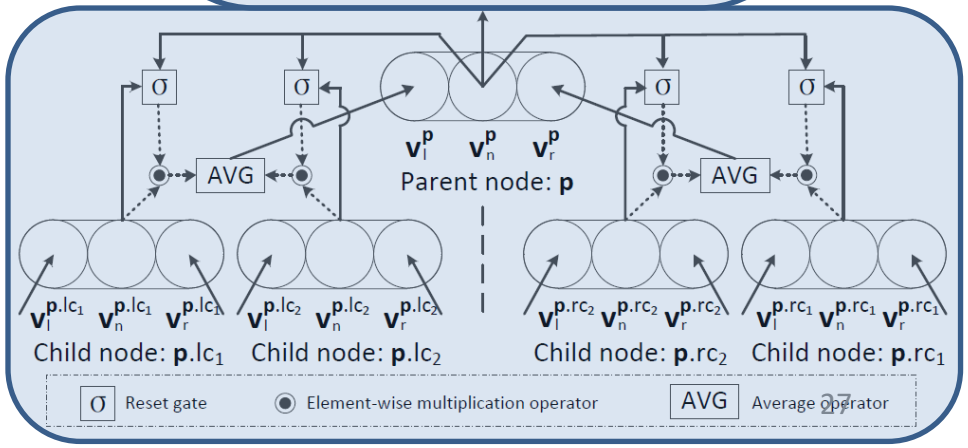


Transition-based Dependency Parsing Using Two Heterogeneous G… Recursive Neural Networks

[X Chen, Y Zhou, C Zhu, X Qiu, X Huang; EMNLP 2015]







Experiments

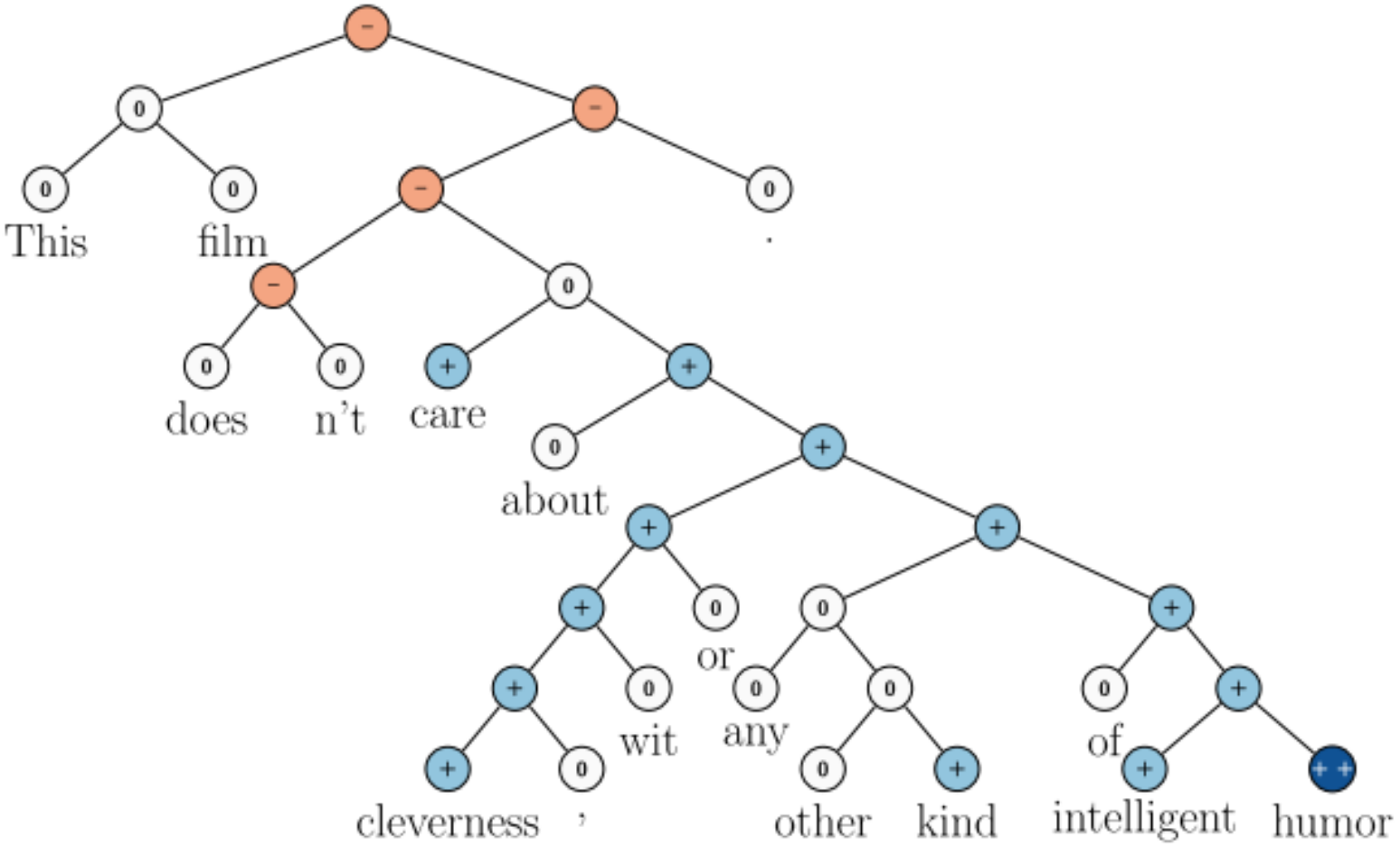
models	Dev		Test	
	UAS	LAS	UAS	LAS
Malt:standard	90.0	88.8	89.9	88.5
Malt:eager	90.1	88.9	90.1	88.7
MSTParser	92.1	90.8	92.0	90.5
Chen's Parser	92.2	91.0	92.0	90.7
Plain	91.1	90.0	91.2	89.7
Tree-RNN	92.4	91.0	92.1	90.8
Tree-GRNN	92.6	91.1	92.4	91.0
Tree-RNN+DAG-GRNN	**92.8**	**91.9**	92.4	91.5
Tree-GRNN+DAG-GRNN	92.6	**91.9**	**92.6**	**91.6**

Table 2: Performance of different models on PTB3 dataset. UAS: unlabeled attachment score. LAS: labeled attachment score.

models	Dev		Test	
	UAS	LAS	UAS	LAS
Malt:standard	82.4	80.5	82.4	80.6
Malt:eager	91.2	79.3	80.2	78.4
MSTParser	84.0	82.1	83.0	81.2
Chen's Parser	84.0	82.4	83.9	82.4
Plain	81.6	79.3	81.1	78.8
Tree-RNN	83.5	82.5	83.8	82.7
Tree-GRNN	84.2	82.5	84.3	83.1
Tree-RNN+DAG-GRNN	84.5	83.3	84.5	83.1
Tree-GRNN+DAG-GRNN	**84.6**	**83.6**	**84.7**	**83.7**

Table 3: Performance of different models on CTB5 dataset. UAS: unlabeled attachment score. LAS: labeled attachment score.

Sentence Modeling with Gated Recursive Neural Networ
[X Chen, X Qiu, C Zhu, S Wu, X Huang]



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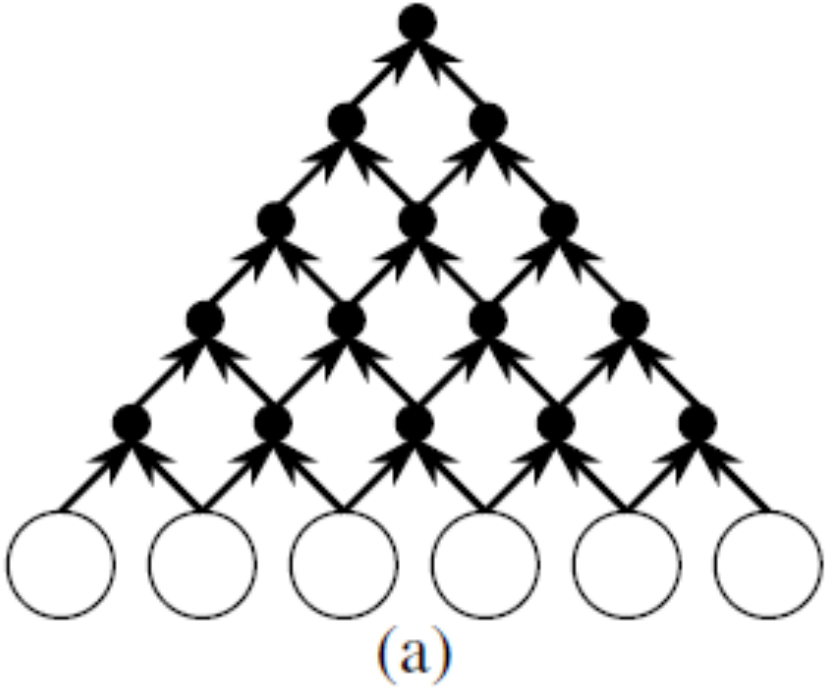

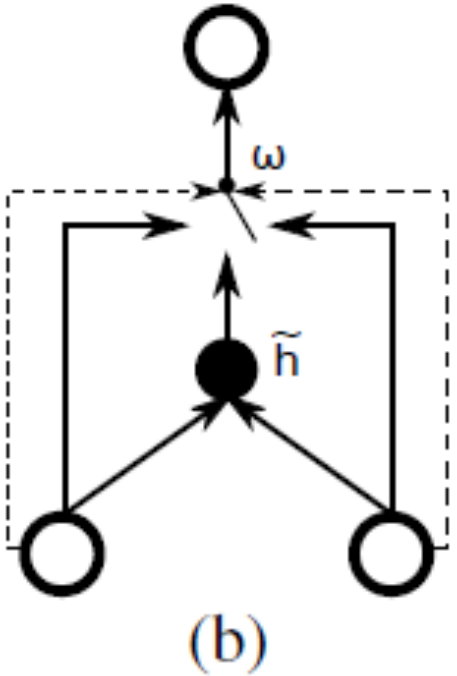

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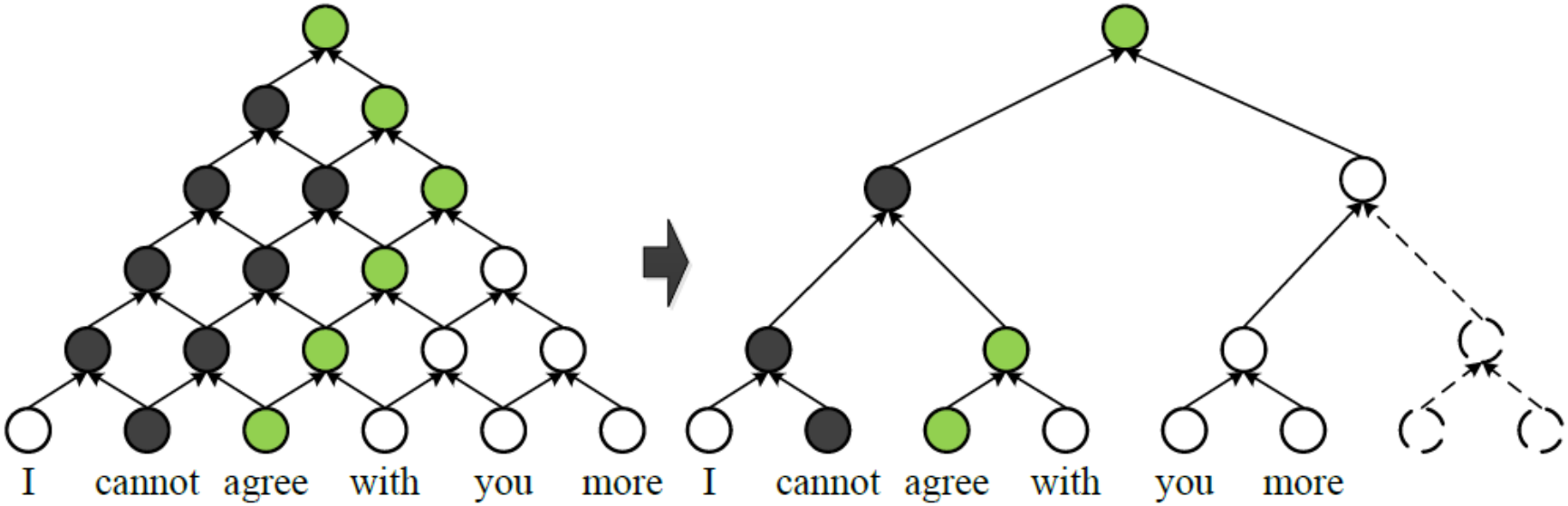


Sentence Modeling with Gated Recursive Neural Networ
[X Chen, X Qiu, C Zhu, S Wu, X Huang]

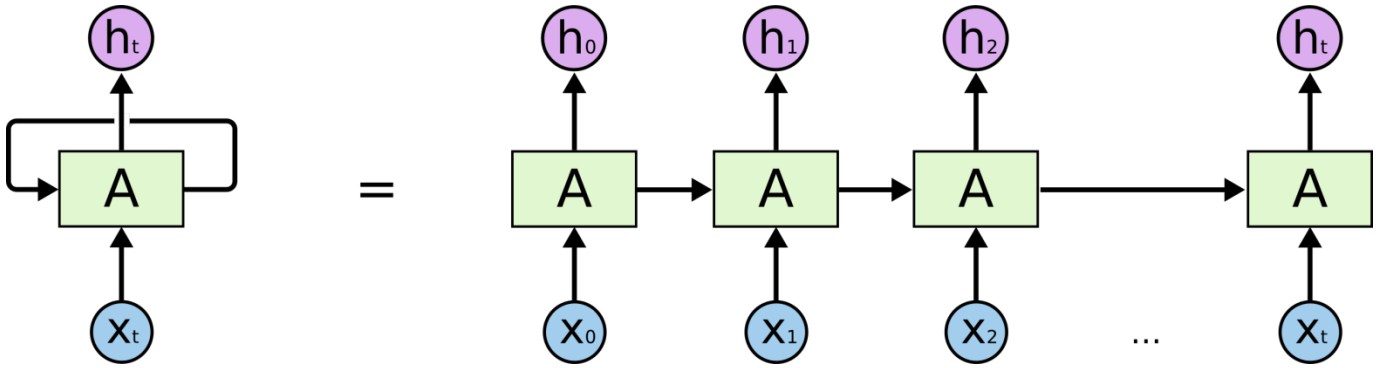
Methods	SST-1	SST-2	QC
NBoW (Kalchbrenner et al., 2014)	42.4	80.5	88.2
PV (Le and Mikolov, 2014)	44.6*	82.7*	91.8*
CNN-non-static (Kim, 2014)	48.0	87.2	93.6
CNN-multichannel (Kim, 2014)	47.4	**88.1**	92.2
MaxTDNN (Collobert and Weston, 2008)	37.4	77.1	84.4
DCNN (Kalchbrenner et al., 2014)	**48.5**	86.8	93.0
RecNTN (Socher et al., 2013b)	45.7	85.4	-
RAE (Socher et al., 2011)	43.2	82.4	-
MV-RecNN (Socher et al., 2012)	44.4	82.9	-
AdaSent (Zhao et al., 2015)	-	-	92.4
GRNN (our approach)	47.5	85.5	**93.8**

Long Short-term Neural Network based CWS
[X Chen, X Qiu, C Zhu, P Liu, X Huang; EMNLP 2015]

冬天(winter)， 能(can) 穿(wear) 多少(amount) 穿(wear) 多少(amount)；

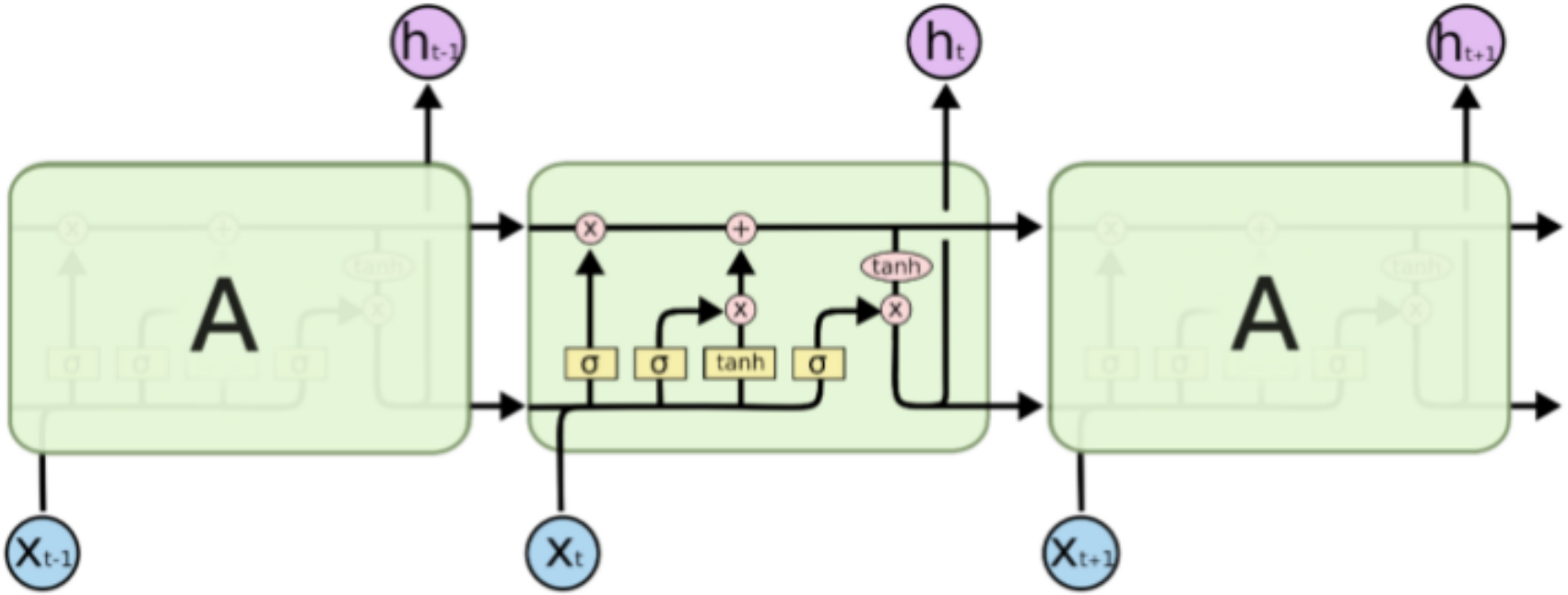
夏天(summer)，能(can) 穿(wear) 多(more) 少(little) 穿(wear) 多(more) 少(little)。

Recurrent Neural Networks

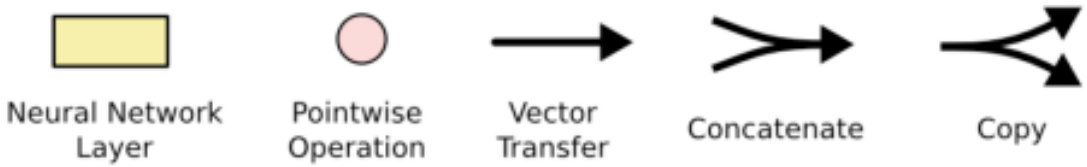


$$\mathbf{h}^{(t)} = g(\mathbf{U}\mathbf{h}^{(t-1)} + \mathbf{W}\mathbf{x}^{(t)} + \mathbf{b}),$$

Long Short-Term Memory Neural Networks [J Schmidhuber ; 1997]



The repeating module in an LSTM contains four interacting layers.



Long Short-Term Memory Neural Networks [J Schmidhuber ; 1997]

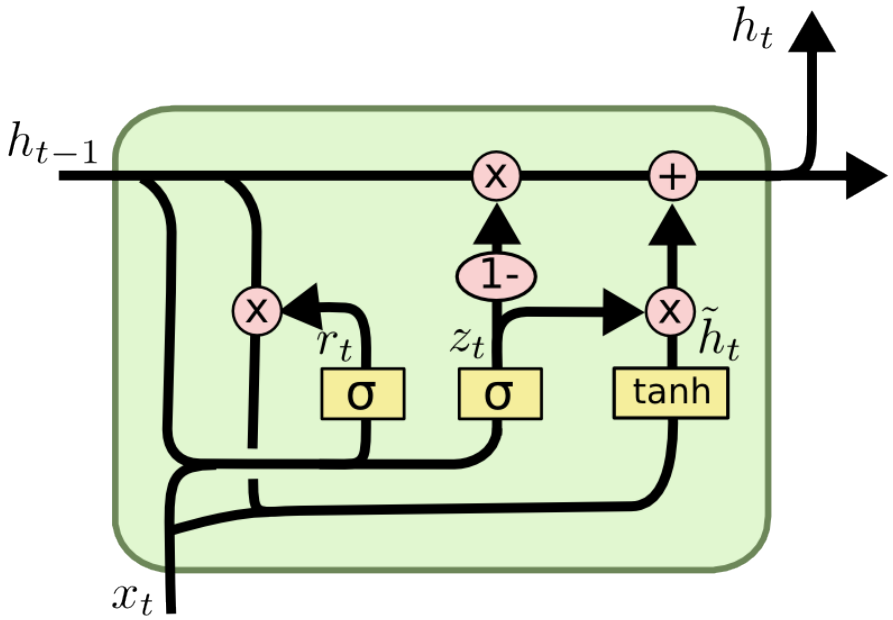
$$\begin{bmatrix} \mathbf{i}_i \\ \mathbf{o}_i \\ \mathbf{f}_i \\ \tilde{\mathbf{c}}_i \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \phi \end{bmatrix} \left(\mathbf{W}_g{}^{\intercal} \begin{bmatrix} \mathbf{e}_{x_i} \\ \mathbf{h}_{i-1} \end{bmatrix} + \mathbf{b}_g \right),$$

$$\mathbf{c}_i = \mathbf{c}_{i-1} \odot \mathbf{f}_i + \tilde{\mathbf{c}}_i \odot \mathbf{i}_i,$$

$$\mathbf{h}_i = \mathbf{o}_i \odot \phi(\mathbf{c}_i),$$

Gated Recurrent Neural Networks

[Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling]



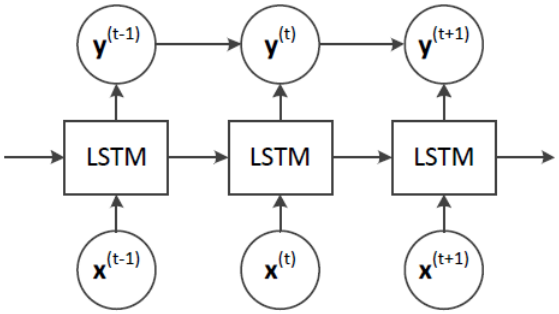
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

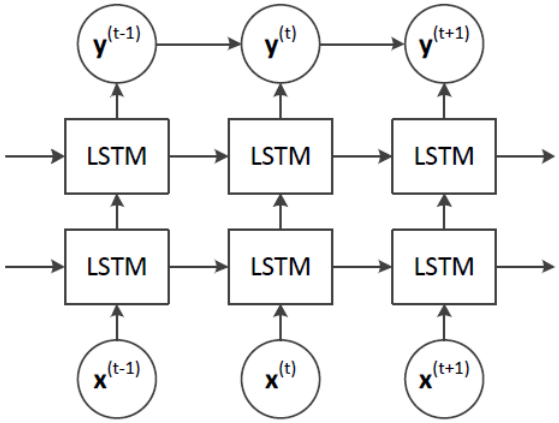
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

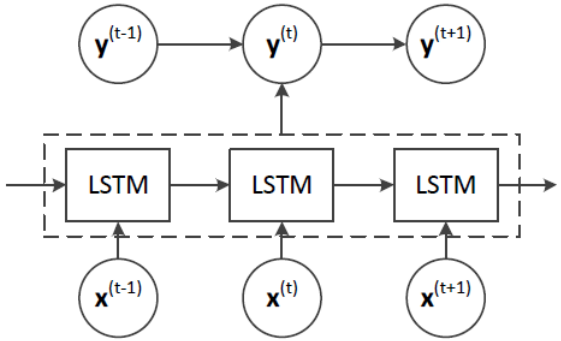
Long Short-term Neural Network based CWS
[X Chen, X Qiu, C Zhu, P Liu, X Huang; EMNLP 2015]



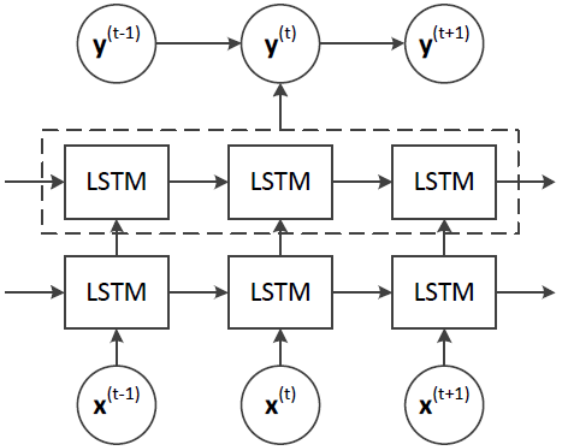
(a) LSTM-1



(b) LSTM-2



(c) LSTM-3



(d) LSTM-4

Long Short-term Neural Network based CWS
[X Chen, X Qiu, C Zhu, P Liu, X Huang; EMNLP 2015]

Models	PKU	MSRA	CTB6
Conventional	96.1	97.4	95.7
Zheng et al. (EMNLP 2013)	92.8	93.9	93.7
Pei et al. (ACL 2014)	95.2	97.2	-
GRNN(ACL 2015)	96.4	**97.6**	95.8
This work (EMNLP 2015)	**96.5**	97.4	**96.0**

Adversarial Multi-Criteria Learning for Chinese Word Segmentation [X Chen, Zhan Shi, X Qiu, X Huang; ACL 2017]

Corpora	Yao	Ming	reaches	the final	
CTB	姚明		进入	总决赛	
PKU	姚	明	进入	总	决赛

Table 1: Illustration of the different segmentation criteria.

Formally, assume that there are M corpora with heterogeneous segmentation criteria. We refer $\mathcal{D}_m$ as corpus m with N_m samples:

$$\mathcal{D}_m = \{(X_i^{(m)}, Y_i^{(m)})\}_{i=1}^{N_m}, \quad (2)$$

where X_i^m and Y_i^m denote the i-th sentence and the corresponding label in corpus m.

Adversarial Multi-Criteria Learning for Chinese Word Segmentation [X Chen, Zhan Shi, X Qiu, X Huang; ACL 2017]

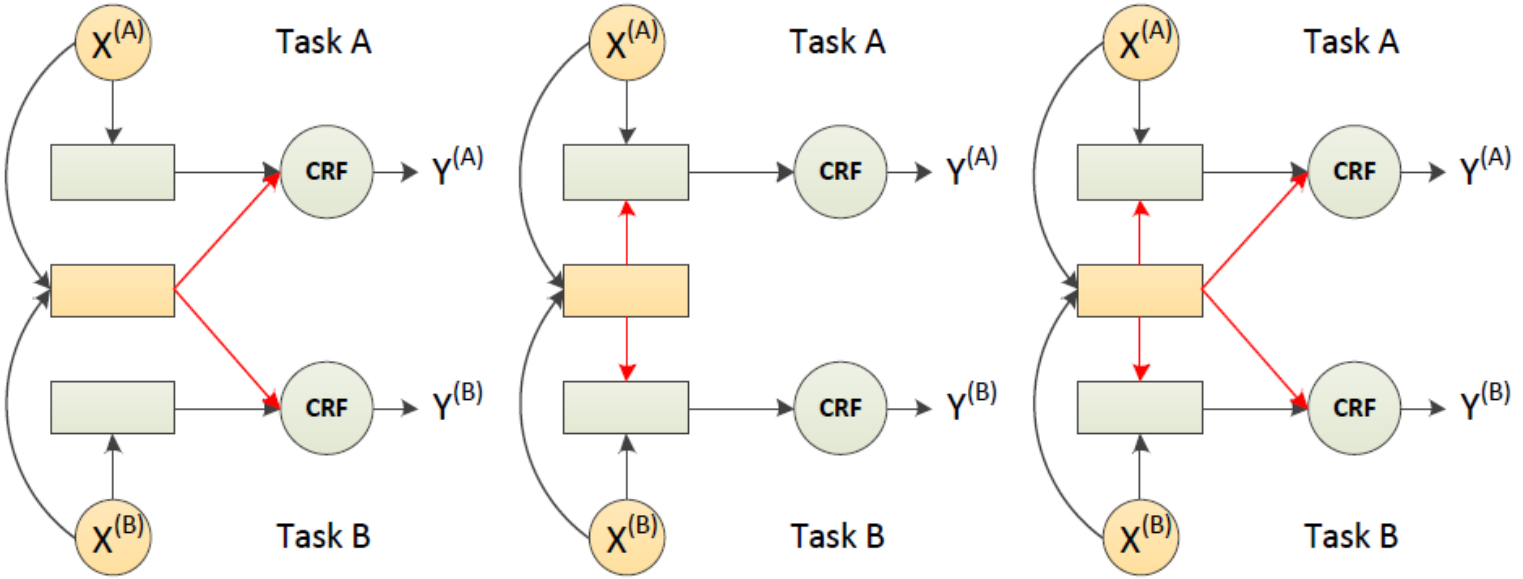


Figure: Three shared-private models for multi-criteria learning. The yellow blocks are the shared Bi-LSTM layer, while the gray block are the private Bi-LSTM layer. The yellow circles denote the shared embedding layer. The red information flow indicates the difference between three models.

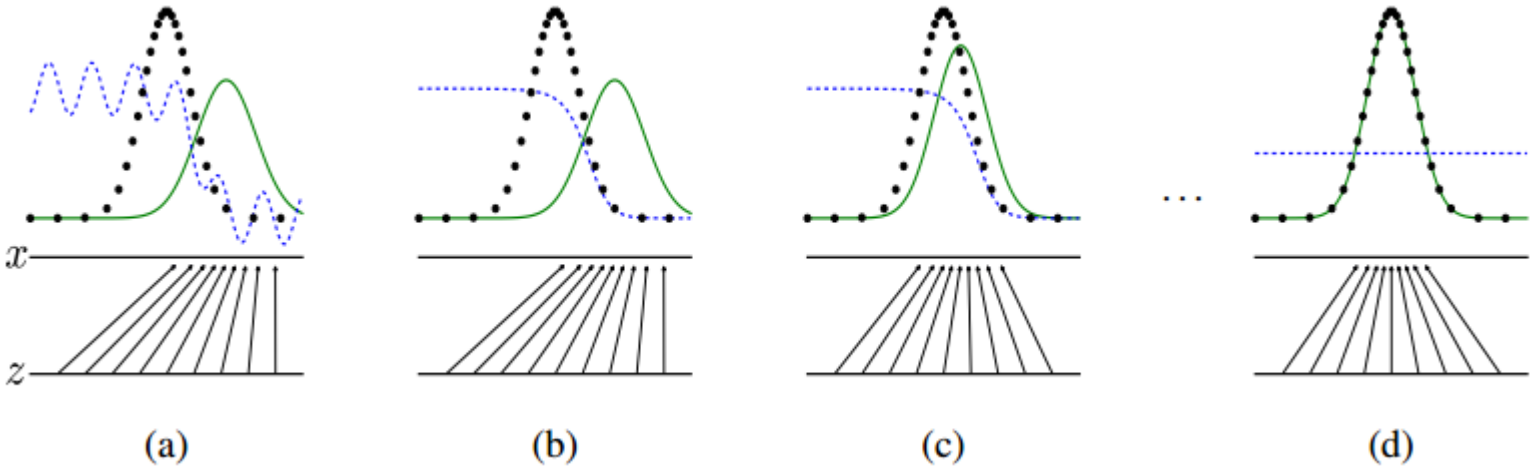
Objective function

The parameters of the network are trained to maximize the log conditional likelihood of true labels on all the corpora. The objective function $\mathcal{J}_{seg}$ can be computed as:

$$\mathcal{J}_{seg}(\Theta^m, \Theta^s) = \sum_{m=1}^{M} \sum_{i=1}^{N_m} \log p(Y_i^{(m)} | X_i^{(m)}; \Theta^m, \Theta^s), \tag{18}$$

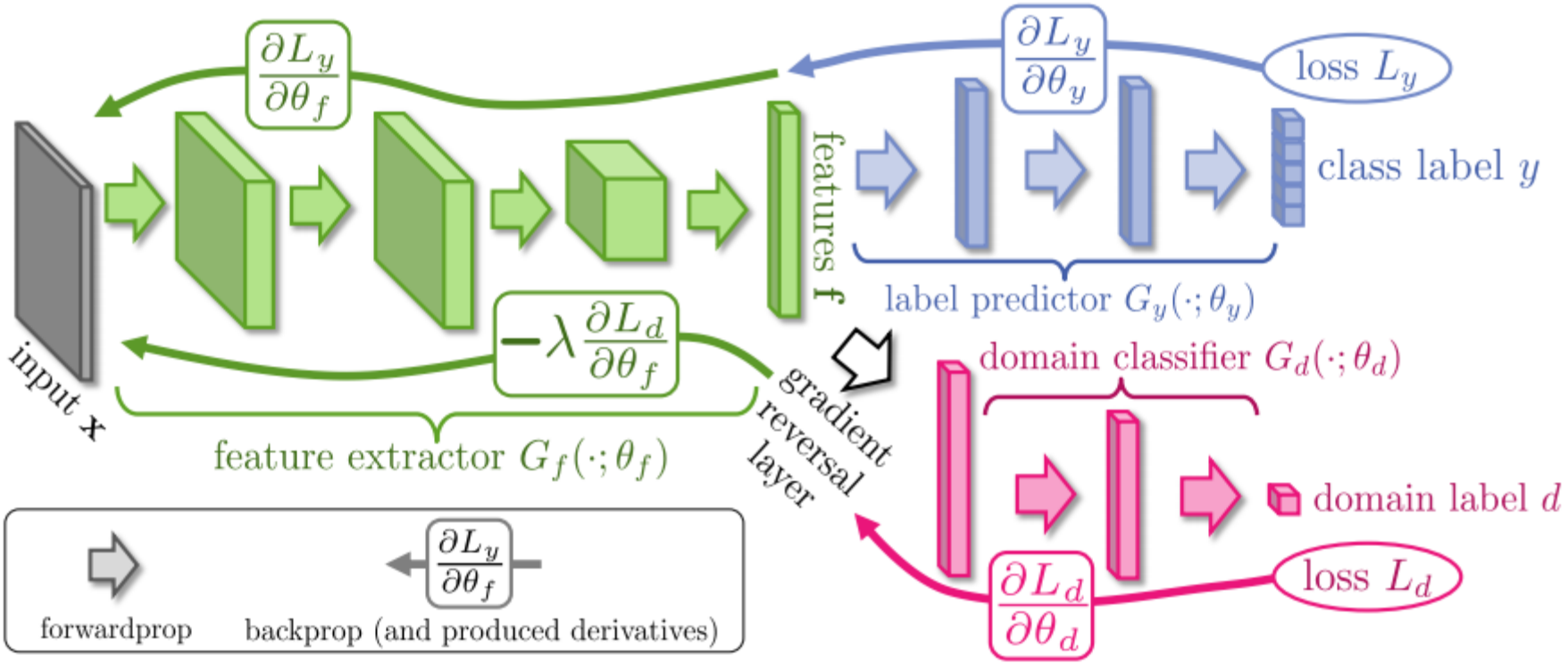
where Θ^m and Θ^s denote all the parameters in private and shared layers respectively.

Generative Adversarial Networks [IJ Goodfellow - 2014]

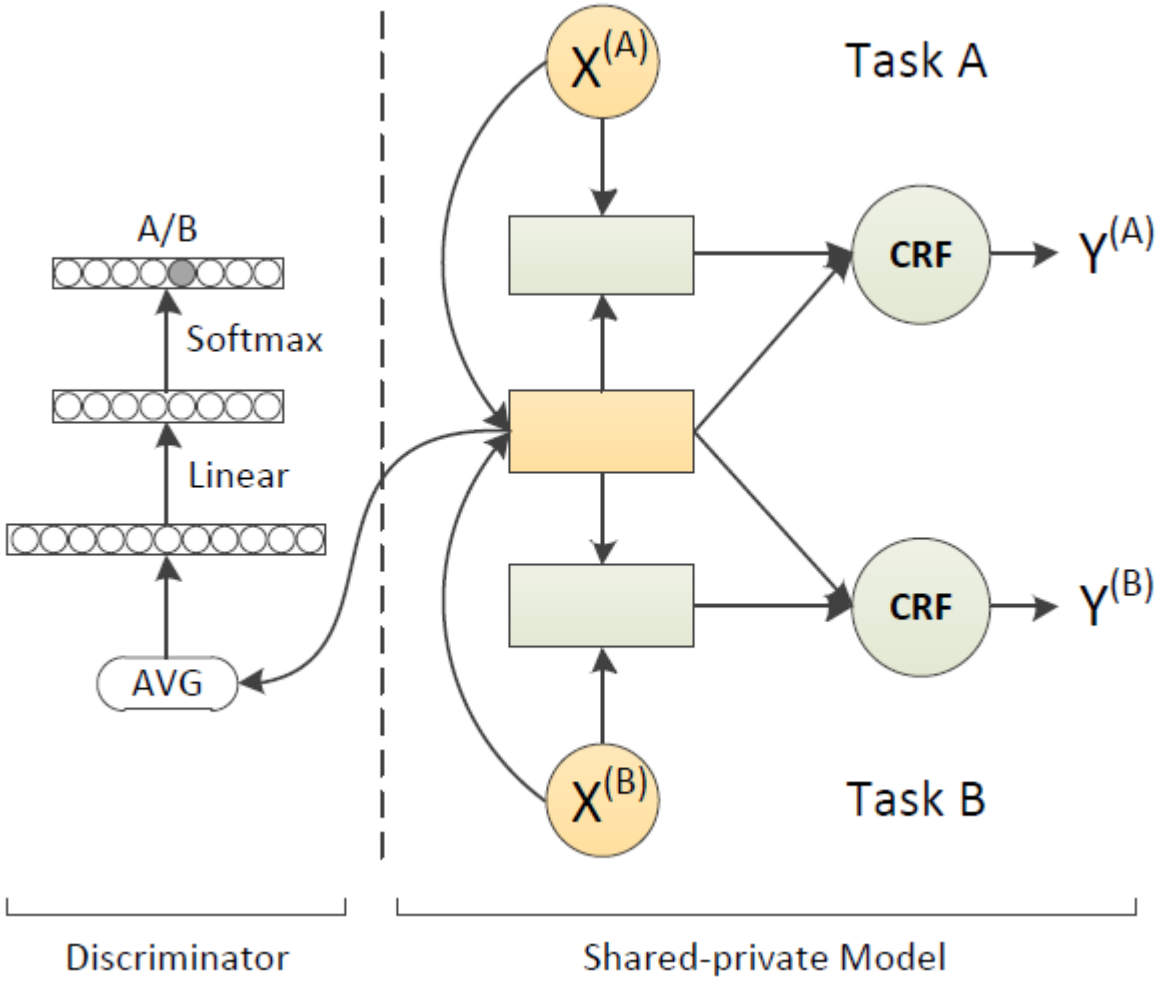


$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Unsupervised Domain Adaptation by Backpropagation [Yaroslav Ganin, et al.]



Adversarial Multi-Criteria Learning for Chinese Word Segmentation [X Chen, Zhan Shi, X Qiu, X Huang; ACL 2017]



Adversarial loss function

- The criterion discriminator maximizes the cross-entropy of predicted criterion distribution $p(\ |X)$ and true criterion.

$$\max_{\Theta^d} \mathcal{J}^1_{adv}(\Theta^d) = \sum_{m=1}^{M} \sum_{i=1}^{N_m} \log p(m|X_i^{(m)}; \Theta^d, \Theta^s). \quad (20)$$

- An adversarial loss aims to produce shared features, such that a criterion discriminator cannot reliably predict the criterion by using these shared features. Therefore, we maximize the entropy of predicted criterion distribution when training shared parameters.

$$\max_{\Theta^s} \mathcal{J}^2_{adv}(\Theta^s) = \sum_{m=1}^{M} \sum_{i=1}^{N_m} \mathrm{H}\left(p(m|X_i^{(m)}; \Theta^d, \Theta^s)\right),$$

Training

$$\mathcal{J}(\Theta;\mathcal{D}) = \mathcal{J}_{seg}(\Theta^m, \Theta^s) + \lambda \mathcal{J}^1_{adv}(\Theta^d) + \lambda \mathcal{J}^2_{adv}(\Theta^s),$$

Algorithm 1 Adversarial multi-criteria learning for CWS task.

for $i = 1; i <= n\_epoch; i++$ **do**
  # Train tag predictor for CWS
  for $m = 1; m <= M; m++$ **do**
    # Randomly pick data from corpus m
    $\mathcal{B} = \{X, Y\}_1^{b_m} \in \mathcal{D}^m$
    $\Theta^s \mathrel{+}= \alpha \nabla_{\Theta^s} \mathcal{J}(\Theta; \mathcal{B})$
    $\Theta^m \mathrel{+}= \alpha \nabla_{\Theta^m} \mathcal{J}(\Theta; \mathcal{B})$
  end for
  # Train criterion discriminator
  for $m = 1; m <= M; m++$ **do**
    $\mathcal{B} = \{X, Y\}_1^{b_m} \in \mathcal{D}^m$
    $\Theta^d \mathrel{+}= \alpha \nabla_{\Theta^d} \mathcal{J}(\Theta; \mathcal{B})$
  end for
end for

Experiments

Datasets			N_w	N_c	$\lvert\mathcal{D}_w\rvert$	$\lvert\mathcal{D}_c\rvert$	N_s
Sighan05	MSRA	Train	2.4M	4.1M	88.1K	5.2K	86.9K
		Test	0.1M	0.2M	12.9K	2.8K	4.0K
	AS	Train	5.4M	8.4M	141.3K	6.1K	709.0K
		Test	0.1M	0.2M	18.8K	3.7K	14.4K
Sighan08	PKU	Train	1.1M	1.8M	55.2K	4.7K	47.3K
		Test	0.2M	0.3M	17.6K	3.4K	6.4K
	CTB	Train	0.6M	1.1M	42.2K	4.2K	23.4K
		Test	0.1M	0.1M	9.8K	2.6K	2.1K
	CKIP	Train	0.7M	1.1M	48.1K	4.7K	94.2K
		Test	0.1M	0.1M	15.3K	3.5K	10.9K
	CITYU	Train	1.1M	1.8M	43.6K	4.4K	36.2K
		Test	0.2M	0.3M	17.8K	3.4K	6.7K
	NCC	Train	0.5M	0.8M	45.2K	5.0K	18.9K
		Test	0.1M	0.2M	17.5K	3.6K	3.6K
	SXU	Train	0.5M	0.9M	32.5K	4.2K	17.1K
		Test	0.1M	0.2M	12.4K	2.8K	3.7K

Models		MSRA	AS	PKU	CTB	CKIP	CITYU	NCC	SXU	Avg.
Bi-LSTM	P	95.70	93.64	93.67	95.19	92.44	94.00	91.86	95.11	93.95
	R	95.99	94.77	92.93	95.42	93.69	94.15	92.47	95.23	94.33
	F	**95.84**	94.20	93.30	**95.30**	**93.06**	**94.07**	92.17	95.17	**94.14**
	OOV	66.28	70.07	66.09	76.47	72.12	65.79	59.11	71.27	68.40
Stacked Bi-LSTM	P	95.69	93.89	94.10	95.20	92.40	94.13	91.81	94.99	94.03
	R	95.81	94.54	92.66	95.40	93.39	93.99	92.62	95.37	94.22
	F	95.75	**94.22**	**93.37**	**95.30**	92.89	94.06	**92.21**	**95.18**	94.12
	OOV	65.55	71.50	67.92	75.44	70.50	66.35	57.39	69.69	68.04
Multi-Criteria Learning										
Model-I	P	95.67	94.44	94.93	95.95	93.99	95.10	92.54	96.07	94.84
	R	95.82	95.09	93.73	96.00	94.52	95.60	92.69	96.08	94.94
	F	95.74	94.76	**94.33**	95.97	**94.26**	95.35	**92.61**	96.07	**94.89**
	OOV	69.89	74.13	72.96	81.12	77.58	80.00	64.14	77.05	74.61
Model-II	P	95.74	94.60	94.82	95.90	93.51	95.30	92.26	96.17	94.79
	R	95.74	95.20	93.76	95.94	94.56	95.50	92.84	95.95	94.94
	F	95.74	**94.90**	94.28	95.92	94.03	95.40	92.55	96.06	94.86
	OOV	69.67	74.87	72.28	79.94	76.67	81.05	61.51	77.96	74.24
Model-III	P	95.76	93.99	94.95	95.85	93.50	95.56	92.17	96.10	94.74
	R	95.89	95.07	93.48	96.11	94.58	95.62	92.96	96.13	94.98
	F	**95.82**	94.53	94.21	**95.98**	94.04	**95.59**	92.57	**96.12**	94.86
	OOV	70.72	72.59	73.12	81.21	76.56	82.14	60.83	77.56	74.34
Adversarial Multi-Criteria Learning										
Model-I+ADV	P	95.95	94.17	94.86	96.02	93.82	95.39	92.46	96.07	94.84
	R	96.14	95.11	93.78	96.33	94.70	95.70	93.19	96.01	95.12
	F	**96.04**	94.64	**94.32**	**96.18**	**94.26**	**95.55**	**92.83**	96.04	**94.98**
	OOV	71.60	73.50	72.67	82.48	77.59	81.40	63.31	77.10	74.96
Model-II+ADV	P	96.02	94.52	94.65	96.09	93.80	95.37	92.42	95.85	94.84
	R	95.86	94.98	93.61	95.90	94.69	95.63	93.20	96.07	94.99
	F	95.94	**94.75**	94.13	96.00	94.24	95.50	92.81	95.96	94.92
	OOV	72.76	75.37	73.13	82.19	77.71	81.05	62.16	76.88	75.16
Model-III+ADV	P	95.92	94.25	94.68	95.86	93.67	95.24	92.47	96.24	94.79
	R	95.83	95.11	93.82	96.10	94.48	95.60	92.73	96.04	94.96
	F	95.87	94.68	94.25	95.98	94.07	95.42	92.60	**96.14**	94.88
	OOV	70.86	72.89	72.20	81.65	76.13	80.71	63.22	77.88	74.44

Traditional & Simplified Chinese

	AS	CKIP	CITYU	Avg.
Base line	**94.20**	93.06	94.07	93.78
This work	94.12	**93.24**	**95.20**	**94.19**

Table 5: Performance on 3 traditional Chinese datasets with shared parameters fixed shared. The shared parameters are trained on 5 simplified Chinese datasets. Here, we conduct Model-I without incorporating adversarial training strategy.

Error Analysis

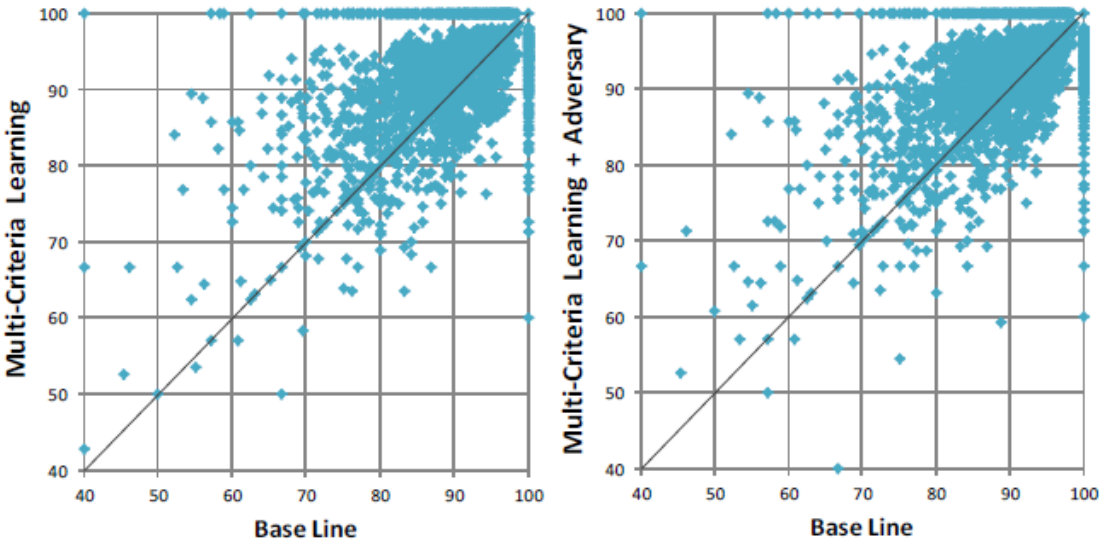


Figure 5: F-measure scores on test set of CITYU dataset. Each point denotes a sentence, with the (x, y) values of each point denoting the F-measure scores of the two models, respectively. (a) is comparison between Bi-LSTM and Model-I. (b) is comparison between Bi-LSTM and Model-I with adversarial training.

Case Study

Models	PKU-2333		MSRA-89	
Golds	Lu 卢	Wu Xuan 武铉	Mu Ling Ying 穆玲英	
Base Line	卢武铉		穆	玲英
Model-I	卢武铉		穆	玲英
Modell-I+ADV	卢	武铉	穆玲英	

Table 6: Segmentation cases of personal name.

Other Neural Models

1. Jianqiang Ma and Erhard W Hinrichs. 2015. **Accurate linear-time chinese word segmentation via embedding matching**. In *ACL (1)*. pages 1733–1743.
2. Deng Cai and Hai Zhao. 2016. **Neural word segmentation learning for chinese**. *arXiv preprint arXiv:1606.04300.*
3. Xu Sun, Yaozhong Zhang, Takuya Matsuzaki, Yoshimasa Tsuruoka, and Jun'ichi Tsujii. 2009. **A discriminative latent variable chinese segmenter with hybrid word/character information.** NAACL. pages 56–64.
4. Yijia Liu, Wanxiang Che, Jiang Guo, Bing Qin, and Ting Liu. 2016. **Exploring segment representations for neural segmentation models**. *arXiv preprint arXiv:1604.05499* .
5. ……

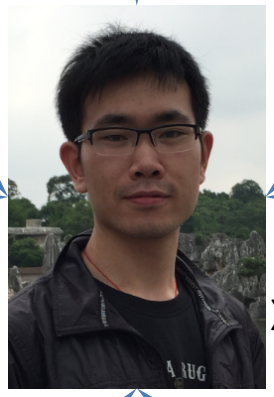
Team work

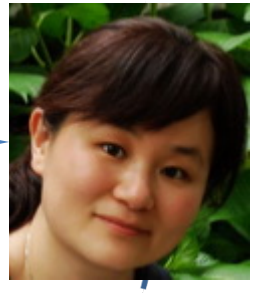

Xipeng Qiu


Xuanjing Huang

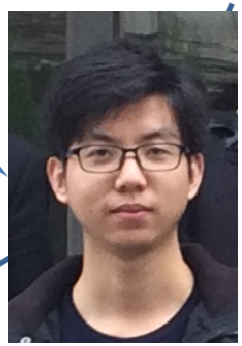

Qi Zhang


Lide Wu


Xinchi Chen


Yaqian Zhou


Chenxi Zhu


Pengfei Liu

Publications

- **Xinchi Chen**, Xipeng Qiu, Chenxi Zhu & Xuanjing Huang, **Gated Recursive Neural Network For Chinese Word Segmentation**, In Proceedings of Annual Meeting of the Association for Computational Linguistics **(ACL), 2015**.
- **Xinchi Chen**, Xipeng Qiu, Chenxi Zhu, Pengfei Liu & Xuanjing Huang, **Long Short-Term Memory Neural Networks for Chinese Word Segmentation**, In Proceedings of the Conference on Empirical Methods in Natural Language Processing **(EMNLP), 2015**.
- **Xinchi Chen**, Yaqian Zhou, Chenxi Zhu, Xipeng Qiu & Xuanjing Huang, **Transition-based Dependency Parsing Using Two Heterogeneous Gated Recursive Neural Networks**, In Proceedings of the Conference on Empirical Methods in Natural Language Processing **(EMNLP), 2015**.
- **Xinchi Chen**, Xipeng Qiu, Chenxi Zhu, Shiyu Wu & Xuanjing Huang, **Sentence Modeling with Gated Recursive Neural Network**, In Proceedings of the Conference on Empirical Methods in Natural Language Processing **(EMNLP), 2015 [short]**.
- Chenxi Zhu, Xipeng Qiu, **Xinchi Chen** & Xuanjing Huang, **A Re-Ranking Model For Dependency Parser With Recursive Convolutional Neural Network**, In Proceedings of Annual Meeting of the Association for Computational Linguistics **(ACL), 2015**.
- PengFei Liu, Xipeng Qiu, **Xinchi Chen**, Shiyu Wu & Xuanjing Huang, **Multi-Timescale Long Short-Term Memory Neural Network for Modelling Sentences and Documents**, In Proceedings of the Conference on Empirical Methods in Natural Language Processing **(EMNLP), 2015**.
- **Xinchi Chen**, Zhan Shi, Xipeng Qiu & Xuanjing Huang, **Adversarial Multi-Criteria Learning for Chinese Word Segmentation**, In Proceedings of Annual Meeting of the Association for Computational Linguistics **(ACL), 2017**.

Thank you for your attention!

Thank you for your attention!

Xinchi Chen (Fudan University)
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Direction: Natural Language Processing