RICH PUNCTUATIONS PREDICTION USING LARGE-SCALE DEEP LEARNING

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Motivation

- **Rich punctuations paly important roles in many NLP tasks.**
- **ASR systems provide plain word streams.**
- **Small-scale models are hard to guarantee performance and generalization ability.**
- **We need data and model with larger scale to adapt to various genres of text.**

Data Comparison

- **Data used in previous research**
  - PTB, CTB
  - Manual speech transcripts

☹ small, out-of-date
☹ limited, expensive

- **Features used in previous research**
  - Syntax information
  - Prosodic cues
- **What we used**
  - 😃 abundant diversity
  - 😃 large scale
  - 😃 formal/informal

Dataset		Contents	Size (Byte)
formal corpus	training	Sina News, Wikipedia	1.4G
	in-domain	Sina News, Wikipedia	7.5M
	out-of-domain	People's Daily, Articles	12M
informal corpus	training	Weibo	1.5G
	in-domain	Weibo	4.5M
	out-of-domain	Speech Transcriptions	1.2M

Task Formulation

- **Punctuation Symbols → Labels**

Original Symbols	Unified	Punctuation	Label
, 、 ; ； —— ： : “ ” ‘ ’	,	Comma	CO
。 . …	。	Period	PE
! ！	！	Exclamation Mark	EX
? ？	？	Question Mark	QU
Space, None		None	EM

middle stop; full stop → sentence boundary denoted by SE

- **Sequence Labeling**

你知道吗？水稻、小麦、玉米，都是中国的主要农作物。

Preprocessing

你	知道	吗	水稻	小麦	玉米	都是	中国	的	主要	农作物
EM	EM	QU	CO	CO	CO	EM	EM	EM	EM	PE

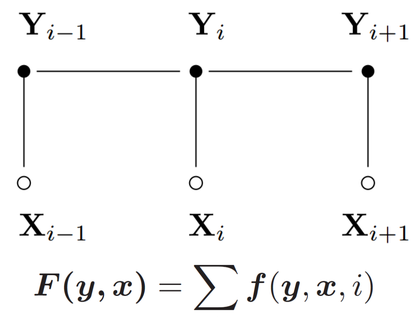
- **Evaluation Metrics**
  - **Precision** (denoted by **P**), **Recall** (denoted by **R**) and **F1-score** (the harmonic mean of precision and recall, denoted by **F**)
  - Only evaluate for **CO, PE, EX, QU,** and **SE**

Methods

- **CRF-based Model**

No.	Feature	Definition
W0	w_{i-4}	The fourth word before the current word.
...	...	...
W8	w_{i+4}	The fourth word after the current word.
P01	$p_{i-4}p_{i-3}$	The fourth and third POS tags before the current POS tags.
...	...	...
P67	$p_{i+3}p_{i+4}$	The fourth and third POS tags after the current POS tags.
P012	$p_{i-4}p_{i-3}p_{i-2}$	The fourth, third and second POS tags before the current POS tags.
...	...	...
P567	$p_{i+2}p_{i+3}p_{i+4}$	The fourth, third and second POS tags after the current POS tags.

CRF Feature-Templates



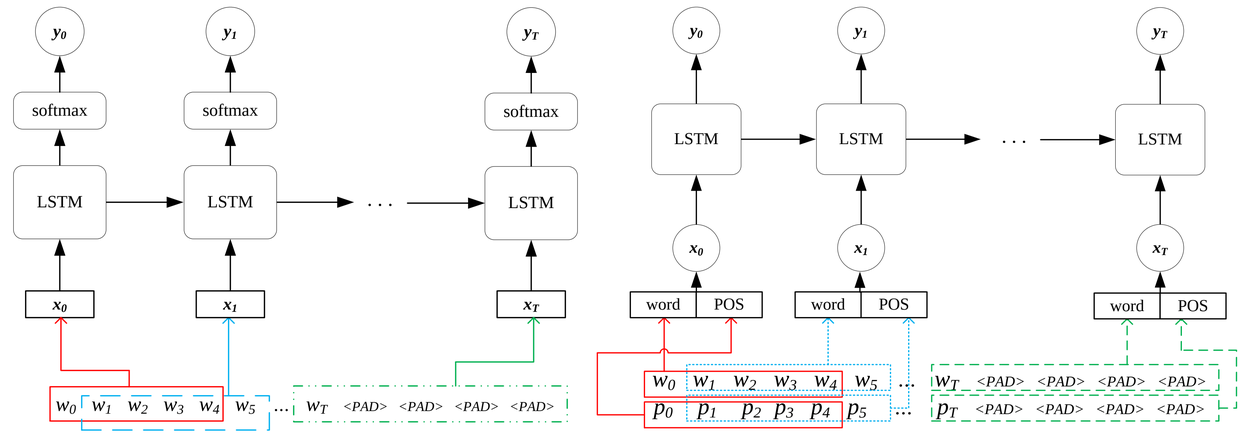
$$\boldsymbol{F}(\boldsymbol{y},\boldsymbol{x}) = \sum_{i} \boldsymbol{f}(\boldsymbol{y},\boldsymbol{x},i)$$

$$p_{\boldsymbol{\lambda}}(\boldsymbol{Y}|\boldsymbol{X}) = \frac{\exp(\boldsymbol{\lambda}\cdot\boldsymbol{F}(\boldsymbol{Y},\boldsymbol{X}))}{Z_{\boldsymbol{\lambda}}(\boldsymbol{X})}$$

$$Z_{\boldsymbol{\lambda}}(\boldsymbol{X}) = \sum_{\boldsymbol{y}} \exp(\boldsymbol{\lambda}\cdot\boldsymbol{F}(\boldsymbol{Y},\boldsymbol{X}))$$

- **Rule Settings**
  - **Conjunction**: insert **comma** before a conjunction.
  - **Parenthesis**: insert **comma** or **period** to the front and rear of parenthesis.
  - **Interrogative sentence**: insert **question mark** after the tone word if interrogative indicator is detected.
  - **Exclamatory sentence**: insert **exclamation mark** after the tone word if exclamatory indicator is detected.

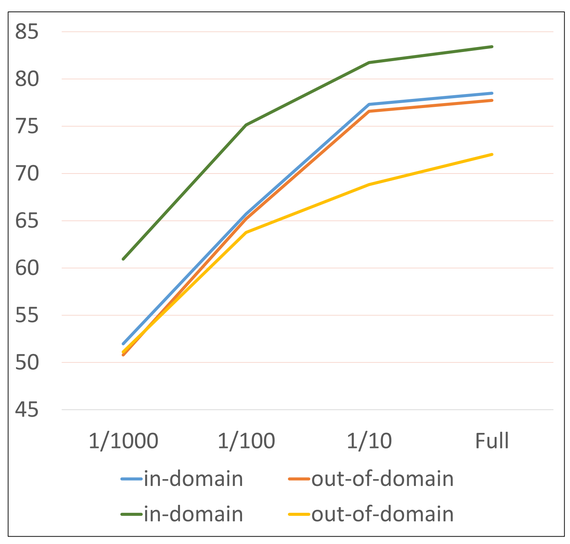
- **LSTM Model and Multiview-LSTM Model**
  - **Words** $x_t = [w_t, w_{t+1}, w_{t+2}, w_{t+3}, w_{t+4}]$
  - **POS-tag / Chunking-tag**
    $v_t = [k_t, k_{t+1}, k_{t+2}, k_{t+3}, k_{t+4}]$ $v_t = [p_t, p_{t+1}, p_{t+2}, p_{t+3}, p_{t+4}]$
  - **Multiview:** concatenate $\boldsymbol{x}_t$ and $\boldsymbol{v}_t/\boldsymbol{v}_t$



Experiments

- **CRF-based Model vs. LSTM Model (left, F1-score of each label)**
  - LSTM significantly outperform CRF-based model.
  - LSTM model knows better about *when to stop*.
  - In Chinese, the selection of punctuations relies more on long-term context. It's hard to **distinguish comma** and **period**.
- **Scale vs. Performance (right, F1-score of sentence boundary)**
  - Increasing data scale helps improves model performance
  - Low model complexity may limits the potential of large data

Training	Testing	Label	CRF-based	LSTM
formal corpus	in-domain	CO	47.43	**66.15**
		PE	55.78	**66.63**
		QU	43.03	**52.98**
		EX	**7.91**	2.79
		SE	55.99	**78.49**
	out-of-domain	CO	47.75	**66.60**
		PE	60.33	**68.05**
		QU	45.51	**52.58**
		EX	4.95	**11.41**
		SE	56.98	**77.74**
informal corpus	in-domain	CO	54.96	**69.57**
		PE	37.76	**58.78**
		QU	53.63	**57.36**
		EX	67.66	**62.97**
		SE	59.58	**83.42**
	out-of-domain	CO	30.52	**48.11**
		PE	37.07	**52.62**
		QU	49.02	**61.66**
		EX	7.09	**32.99**
		SE	41.87	**72.02**



Corpus	testing	1/1000	1/100	1/10	Full
formal corpus	in-domain	51.98	65.71	77.32	78.49
	out-of-domain	50.79	65.2	76.58	77.74
informal corpus	in-domain	60.94	75.14	81.74	83.42
	out-of-domain	51.12	63.76	68.83	72.02

- **Multiview-LSTM**
  - F1-score of SE on different training scales using **words**, **words+POS tags** and **words+chunking**.
  - When the sizes of corpora are small, extra information helps improve performance.
  - When the sizes become larger, the promotion will vanish.

Testing	Formal Corpus	Words	+POS	+chunking
in-domain	1/1000	51.98	**55.51**	54.96
	1/100	65.71	**67.25**	65.81
	1/10	**77.32**	77.06	76.70
out-of-domain	1/1000	51.50	**56.26**	56.16
	1/100	65.20	**67.25**	65.07
	1/10	76.58	**76.75**	75.87

Conclusion

- **Long-term dependency matters!**
- **The more data, the higher performance! (even though there are some noise)**
- **Syntax information can boost the model when using small corpora.**
- **Need more design of both architecture and algorithm.**

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