Sentence Segmentation for Ancient Chinese Texts Based on RNN

一种基于循环神经网络的古文断句方法

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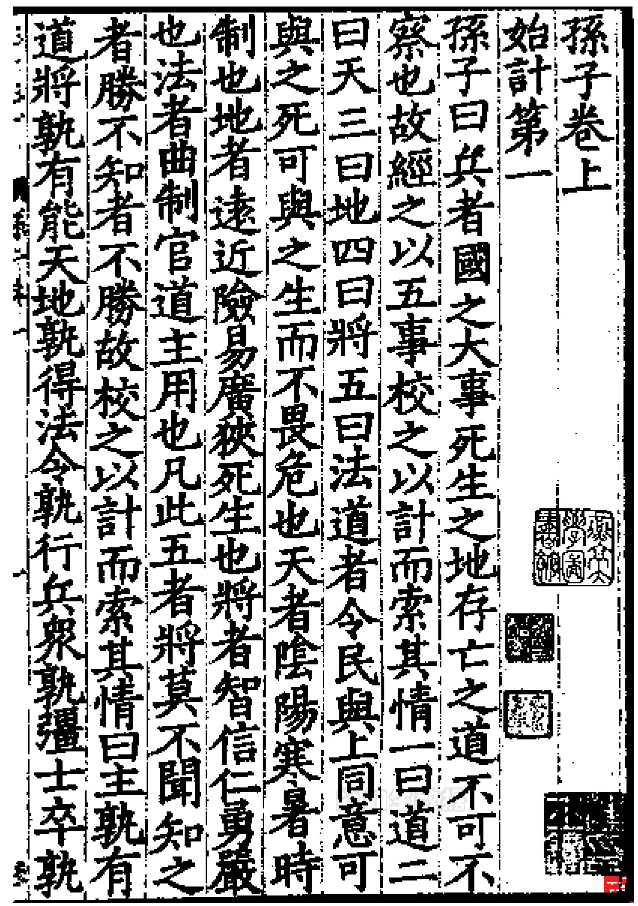
Introduction

- Ancient Chinese texts
  - No punctuations



孫子卷上
始計第一
孫子曰兵者國之大事死生之地存亡之道不可不
察也故經之以五事校之以計而索其情一曰道二
曰天三曰地四曰將五曰法道者令民與上同意可
與之死可與之生而不畏危也天者陰陽寒暑時
制也地者遠近險易廣狹死生也將者智信仁勇嚴
也法者曲制官道主用也凡此五者將莫不聞知之
者勝不知者不勝故校之以計而索其情曰主孰有
道將孰有能天地孰得法令孰行兵衆孰彊士卒孰

Introduction

- Ancient Chinese texts
  - No punctuations
- Ju Dou (句读)
  - Rely on language expertise
  - Time-consuming

汗 汗 吐 吐 下

而下者有醫用藥汗之下之者中間節目頗多汗藥宜早
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張仲景曰凡發汗服三劑若汗不出者死病也
千金曰熱病脉躁盛而不得汗者此陽極之極脉也死
王三陽曰亦有黄耆建中補之而後汗出者若服三劑發
汗藥汗復不出其死必矣宜仔細候脉消息之毋妄治也
華佗曰傷寒三日四日邪在胸中者宜吐之凡吐用瓜蒂
散或温茶湯乘熱與之以指探喉中即吐也
張仲張景曰大法春宜吐中病即止不欲過也誤吐則損
人上焦元氣

金匱玉函曰虛者十補勿一瀉之虛家下之為重虛內竭
津液故令大渴求水者陽氣未竭而猶可愈惡水者陽氣
已竭則難可制
難經曰實實虛虛損不足益有餘此中工所害也
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若表已解而內不消非大滿尤生寒熱則病不除言表雖罷非大堅滿者
亦未可下之若表已解而內不消大滿大實堅滿燥屎自可除下
之若不宜不下而便攻之內虛熱入協熱遂利煩燥諸變
不可勝數輕者困篤重者必死矣

Introduction

- Ancient Chinese texts
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- Ju Dou (句读)
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- Digitalized ancient Chinese texts
  - Segmented: only about 4000

- Automatic sentence segmentation

Related work

- Rule-based Methods
  - RegExp (Huang, 2008)
- Statistical Methods
  - N-gram (Chen, 2007)
  - CRF (H. Zhang, 2009) (K. Zhang, 2009) (Huang, 2010)
    - Handcrafted local context features
    - State-of-the-art
- NN-based Methods
  - Sequence generation: RNNLM (Wang, 2016)
    - Underperform CRF
    - High time complexity

- **This paper**: seq-to-seq

Our approach

– Sequence labeling: $o_t^{[i]} = \mathrm{P}(y_t = i | x_1 x_2 \dots x_N)$

– Punctuations: 。？！，；：

曰：“朕此衣已三浣矣。”

曰/S 朕/B 此/M 衣/M
已/M 三/E3 浣/E2 矣/E

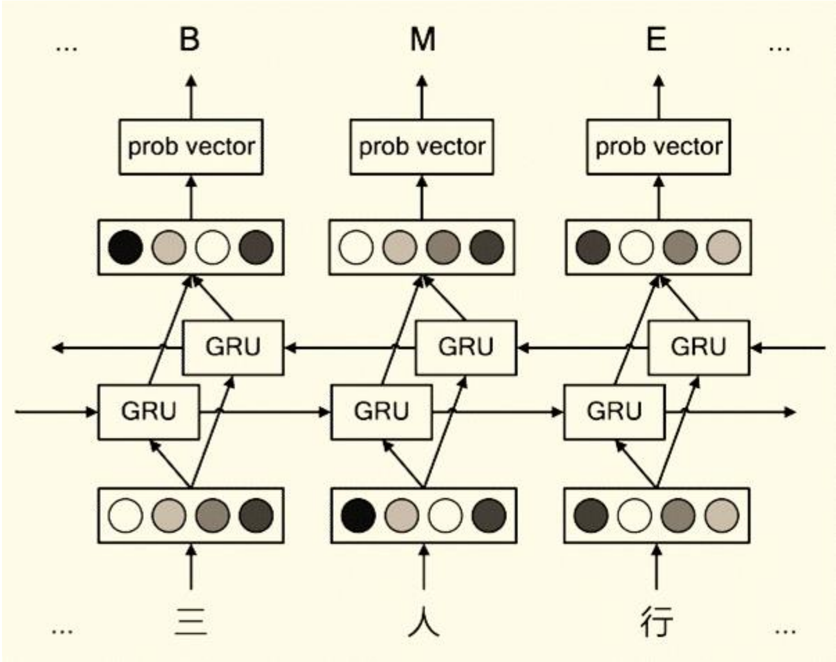
– 6-tag set (H. Zhang, 2009)

$$T = \{B, M, E3, E2, E, S\}$$

B – the first character of a clause
M – the middle character of a clause
E3 – the last 3rd character of a clause
E2 – the last 2nd character of a clause
E – the last character of a clause
S – a single character forming a clause

Our approach

- Model: RNN
  - Input layer
    Character embedding: $x_t \rightarrow e_t$
  - Hidden layer:
    Bi-directional GRU
    $\overrightarrow{h}_t = f(e_t, \overrightarrow{h}_{t-1}) \quad \overleftarrow{h}_t = f(e_t, \overleftarrow{h}_{t+1})$
  - Output layer: softmax

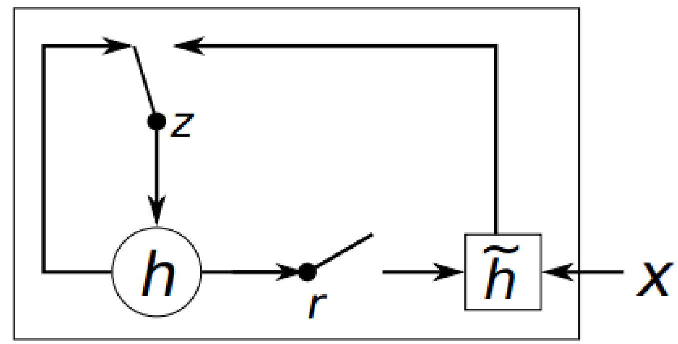


$$o_t^{[i]} = \frac{exp(W^{[i]}_{\overrightarrow{h}o} \overrightarrow{h}_t + W^{[i]}_{\overleftarrow{h}o} \overleftarrow{h}_t + b_o)}{\sum_{j \in T} exp(W^{[j]}_{\overrightarrow{h}o} \overrightarrow{h}_t + W^{[j]}_{\overleftarrow{h}o} \overleftarrow{h}_t + b_o)}$$

Our approach

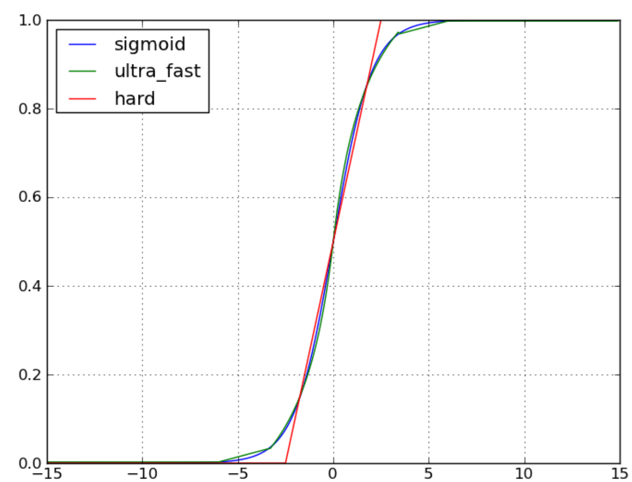
- Gated Recurrent Unit (Cho, 2014)

$$r_t = sigmoid(W_r x_t + U_r h_{t-1} + b_r),$$
$$\tilde{h}_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h),$$
$$z_t = sigmoid(W_z x_t + U_z h_{t-1} + b_z),$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t,$$



- Our implementation
  - using **hard_sigmoid**

$$\text{hard\_sigmoid}(x) = \begin{cases} 0, & x < -2.5 \\ 0.2x + 0.5, & -2.5 \le x < 2.5 \\ 1, & x \ge 2.5 \end{cases}$$



Our approach

- Training
  - Maximum-likelihood estimation

$$Loss(\theta) = -\sum_i log(P(y_i|x_i, \theta))$$

  - Mini-batch gradient descent
    - Back-Propagation Through Time (Werbos, 1990)
    - RMSProp (Tieleman, 2012)
    - Gradient Re-normalization (Salimans, 2016)
    - Early Stopping (Yao, 2007)

- Pre-training: using a GRU-RNNLM

Our approach

- Decoding
  - Given a char sequence $x_{1:N}$
  - Goal: find $y_{1:N}$ to maximize $s(x_{1:N}, y_{1:N})$

$$s(x_{1:N}, y_{1:N}) = \sum_{i=1}^{N} (o_i^{[y_i]} + \alpha \cdot \underline{A_{y_{i-1} y_i}} + \beta \cdot \underline{C(y_{i:N})})$$

state transition probability

length penalty (# of sents)

  - Tag inference: beam search

Experiments

- Datasets

Dataset	Number of characters	Charset size	Source
Training Set	237M	23905	STCC
Development Set	0.01M	1890	HDST
Test Set 1	0.32M	6188	4HN
Test Set 2	0.36M	5755	HDST&4HN

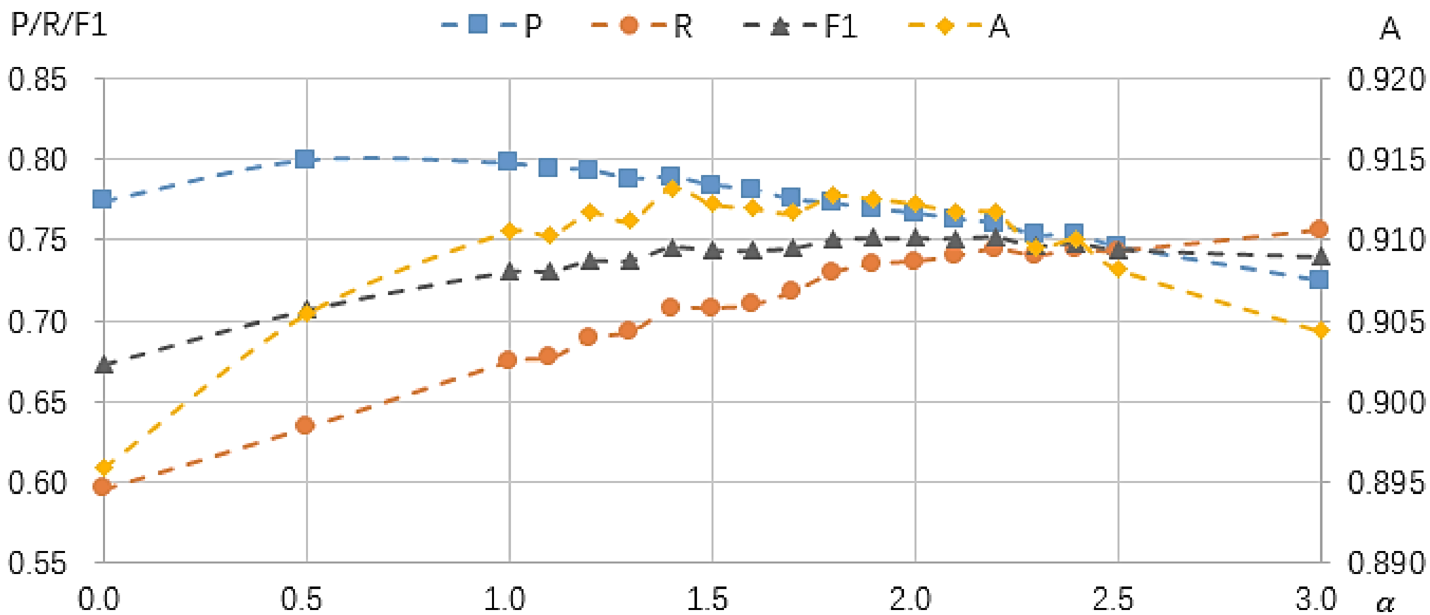
  - Superfection Traditional Chinese Corpus
    http://cloudtranslation.cc/corpus_tc.html

- Baselines
  - RNNLM: CLM1 / CLM6 (Wang, 2016)
  - CRF: reproduce (H. Zhang, 2009) with CRF++

Experiments

- Parameter Selection
  - Weight of transition score $\boldsymbol{\alpha}$

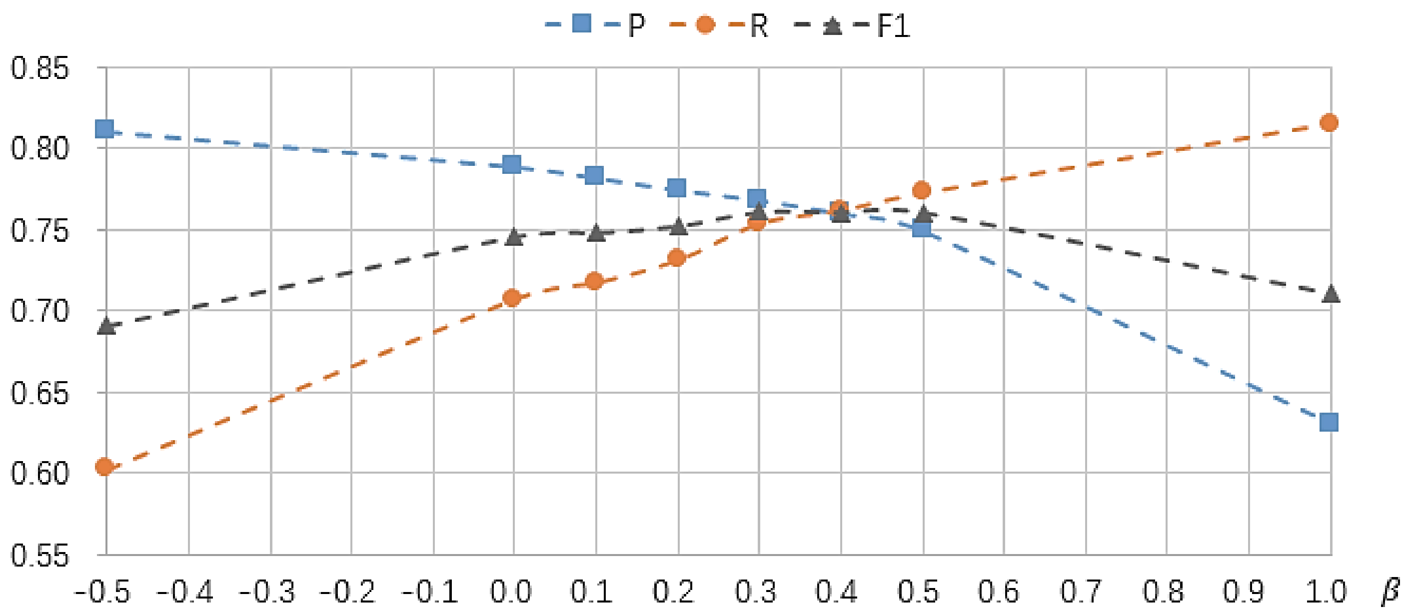
    Fix $\boldsymbol{beam = 50}$, $\boldsymbol{\beta = 0}$ => highest accuracy when $\boldsymbol{\alpha = 1.4}$



Experiments

- Parameter Selection
  - Weight of length penalty $\boldsymbol{\beta}$

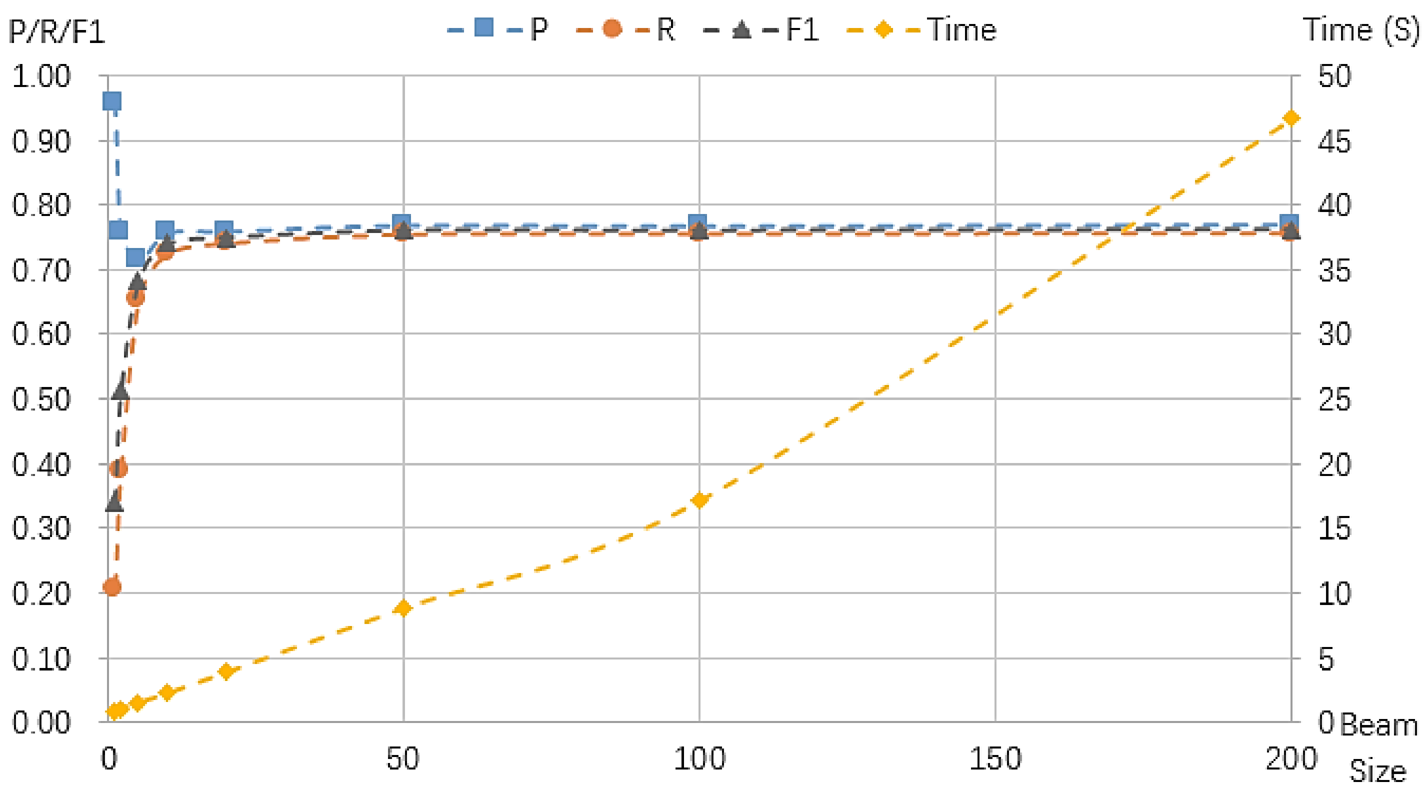
    Fix $\boldsymbol{beam = 50}$, $\boldsymbol{\alpha = 1.4}$ => highest F1 when $\boldsymbol{\beta = 0.3}$



Experiments

- Parameter Selection
  - Size of beam

    Fix $\alpha = 1.4$, $\beta = 0.3$



Experiments

- Results

Models	Test Set 1			Test Set 2		
	P	**R**	**F1**	**P**	**R**	**F1**
CLM6	0.782	0.577	0.664	0.728	0.636	0.679
CLM6+0.65LP	0.749	0.673	0.709	0.686	0.721	0.703
CLM1+0.65LP	0.721	0.733	0.727	0.639	**0.769**	0.698
CRF	**0.816**	0.662	0.731	**0.786**	0.710	0.746
GRU-RNN	0.755	0.677	0.714	0.734	0.633	0.680
GRU-RNN+1.4ST[50]	0.785	0.720	0.751	0.760	0.719	0.739
GRU-RNN+1.4ST+0.3LP[50]	0.761	0.746	0.753	0.735	0.753	0.744
GRU-RNN+1.4ST+0.3LP[200]	0.763	**0.748**	**0.755**	0.738	0.756	**0.747**

Conclusion

- Bi-directional GRU-RNN outperform CRF and RNNLM methods.
- Integrations of transition score and length penalty are effective.

- Future works
  - Classify texts by ages and train sub-models
  - Segmentation → punctuation

Thank you!

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