Boundary Smoothing for Named Entity Recognition

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Outline

Named Entity Recognition: Task Definition

Input text:

- The White House is in Washington D.C.

Named entities in text:

- The $\boxed{\text{White House}}_{\texttt{ORG}}$ is in $\boxed{\text{Washington D.C.}}_{\texttt{LOC}}$

Named entities as a set of tuples:

- { (ORG, 1, 2), (LOC, 5, 6) }

Named Entity Recognition: Task Definition

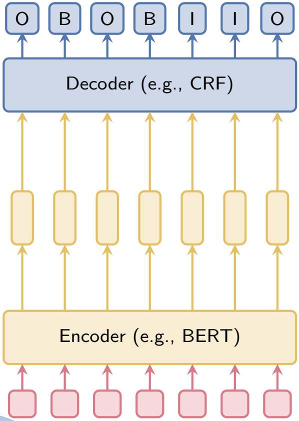
Input: A piece of raw text

- A T-length sequence of tokens: $x_1, x_2, \ldots, x_T$

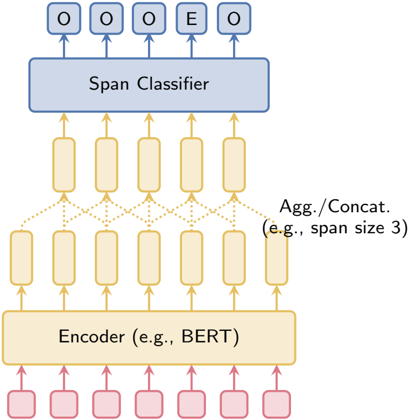
Output: A set of entities

- $\{(type_i, start_i, end_i) \mid type_i \in S, 0 \leq start_i \leq end_i < T\}$, where S is the set of entity types
- Each entity is specified by its type and boundaries (start and end positions)

Named Entity Recognition: Existing Methods



Sequence Tagging



Span Classification

Boundary Annotation Is Ambiguous

Take CoNLL 2003 Annotation Guidelines as the example:

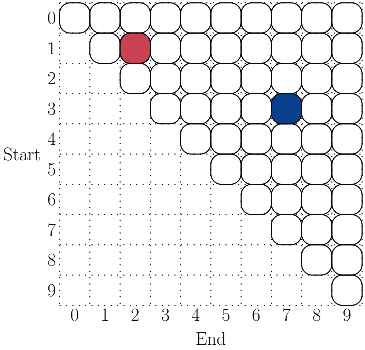
- Entity types are clear and easily distinguishable
  - PER, LOC, ORG, MISC
- Entity boundaries may be ambiguous for "boundary words"

Text	Boundary words
[The [White House]ORG]ORG	Article
[The [Godfather]PER]PER	Article
[[Clinton]PER government]ORG	Modifier
[Mr. [Harry Schearer]PER]PER	Person title
[[John Doe]PER, Jr.]PER	Name appositive

Sharpness in Classification Targets

The fitting targets of neural span-based NER models

- The annotated spans are assigned with full probability
- All other spans are assigned with zero probability



Over-Confidence

Over-confidence: The confidence of a predicted entity is much higher than its correctness probability

A manifestation: Disconnect between dev. loss and F_1 score

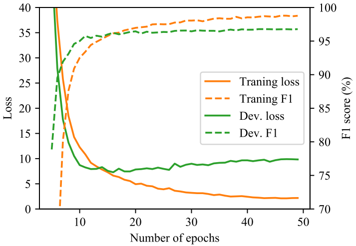


Figure: Cross entropy loss

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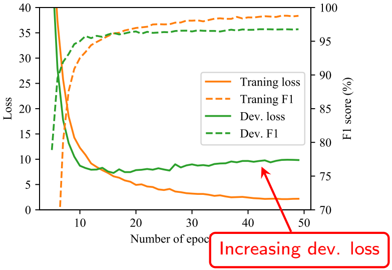


Figure: Cross entropy loss

Outline

Boundary Smoothing: Motivation

Our observations

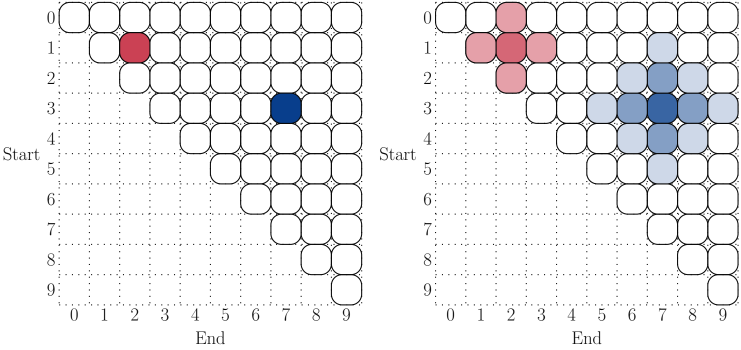
- Entity boundary annotation may be ambiguous
- Sharpness exists in the targets of span-based NER models (which should not, given the ambiguity of boundaries)
- Span-based NER models encounter over-confidence issue

Our Solution: **Boundary Smoothing**

- Re-allocate entity probabilities from annotated spans to the surrounding ones
- A regularization technique
- Inspired by label smoothing [Szegedy et al., 2016]

Boundary Smoothing

Re-allocate entity probabilities from annotated spans to the surrounding ones



(a) Hard boundary (b) Smoothed boundary

Outline

Experimental Settings

Backbone

- RoBERTa-base (English); BERT-base-wwm (Chinese)
- BiLSTM

Decoder

- Biaffine [Yu et al., 2020]
- Fuse representations of start and end tokens
- Simple but powerful

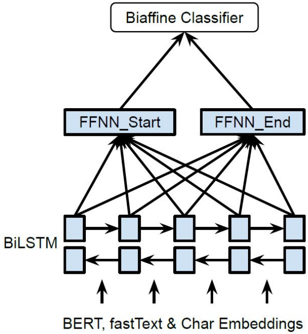


Figure: Biaffine Decoder.
Source: [Yu et al., 2020].

Experimental Settings

Eight datasets

- English corpora with flat entities
  - CoNLL 2003; OntoNotes 5
- English corpora with nested entities
  - ACE 2004; ACE 2005
- Chinese corpora with flat entities
  - OntoNotes 4; MSRA; Resume NER; Weibo NER

Evaluation

- Exact match of entity type and boundaries
- Precision, recall, F_1 score

Outline

Main Results: English Datasets

Compared with baseline: +0.2% to +0.6% F_1 score

CoNLL 2003			
Model	Prec.	Rec.	F1
Lample et al. (2016)	–	–	90.94
Chiu and Nichols (2016)†	91.39	91.85	91.62
Peters et al. (2018)	–	–	92.22
Akbik et al. (2018)†	–	–	93.07
Devlin et al. (2019)	–	–	92.8
Straková et al. (2019)†	–	–	93.38
Wang et al. (2019)†	–	–	93.43
Li et al. (2020b)	92.33	94.61	93.04
Yu et al. (2020)†	93.7	93.3	93.5
Baseline	92.93	94.03	93.48
Baseline + BS	93.61	93.68	**93.65**

+0.17%

OntoNotes 5			
Model	Prec.	Rec.	F1
Chiu and Nichols (2016)	86.04	86.53	86.28
Li et al. (2020b)	92.98	89.95	91.11
Yu et al. (2020)	91.1	91.5	91.3
Baseline	90.31	92.13	91.21
Baseline + BS	91.75	91.74	**91.74**

+0.53%

ACE 2004			
Model	Prec.	Rec.	F1
Katiyar and Cardie (2018)	73.6	71.8	72.7
Straková et al. (2019)†	–	–	84.40
Li et al. (2020b)	85.05	86.32	85.98
Yu et al. (2020)	87.3	86.0	86.7
Shen et al. (2021)	87.44	87.38	87.41
Baseline	86.67	88.42	87.54
Baseline + BS	88.43	87.53	**87.98**

+0.44%

ACE 2005			
Model	Prec.	Rec.	F1
Katiyar and Cardie (2018)	70.6	70.4	70.5
Straková et al. (2019)†	–	–	84.33
Li et al. (2020b)	87.16	86.59	86.88
Yu et al. (2020)	85.2	85.6	85.4
Shen et al. (2021)	86.09	87.27	86.67
Baseline	84.29	88.97	86.56
Baseline + BS	86.25	88.07	**87.15**

+0.59%

Main Results: English Datasets

Compared with previous SOTA: +0.2% to +0.6% F_1 score

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+0.57%

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Li et al. (2020b)	87.16	86.59	86.88
Yu et al. (2020)	85.2	85.6	85.4
Shen et al. (2021)	86.09	87.27	86.67
Baseline	84.29	88.97	86.56
Baseline + BS	86.25	88.07	**87.15**

+0.27%

Main Results: Chinese Datasets

Compared with baseline: +0.3% to +1.2% F_1 score

OntoNotes 4			
Model	Prec.	Rec.	F1
Zhang and Yang (2018)	76.35	71.56	73.88
Ma et al. (2020)	83.41	82.21	82.81
Li et al. (2020a)	–	–	81.82
Li et al. (2020b)	82.98	81.25	82.11
Chen and Kong (2021)	79.25	80.66	79.95
Wu et al. (2021)	–	–	82.57
Baseline	82.79	81.27	82.03
Baseline + BS	81.65	84.03	**82.83**

+0.80%

MSRA			
Model	Prec.	Rec.	F1
Zhang and Yang (2018)	93.57	92.79	93.18
Ma et al. (2020)	95.75	95.10	95.42
Li et al. (2020a)	–	–	96.09
Li et al. (2020b)	96.18	95.12	95.75
Wu et al. (2021)	–	–	96.24
Baseline	95.82	95.78	95.80
Baseline + BS	96.37	96.15	**96.26**

+0.46%

Weibo NER			
Model	Prec.	Rec.	F1
Zhang and Yang (2018)	–	–	58.79
Ma et al. (2020)	–	–	70.50
Li et al. (2020a)	–	–	68.55
Shen et al. (2021)	70.11	68.12	69.16
Chen and Kong (2021)	–	–	70.14
Wu et al. (2021)	–	–	70.43
Baseline	68.65	74.40	71.41
Baseline + BS	70.16	75.36	**72.66**

+1.25%

Resume NER			
Model	Prec.	Rec.	F1
Zhang and Yang (2018)	94.81	94.11	94.46
Ma et al. (2020)	96.08	96.13	96.11
Li et al. (2020a)	–	–	95.86
Wu et al. (2021)	–	–	95.98
Baseline	95.81	96.87	96.34
Baseline + BS	96.63	96.69	**96.66**

+0.32%

Main Results: Chinese Datasets

Compared with previous SOTA: +0.02% to +2.1% F_1 score

OntoNotes 4				
Model	Prec.	Rec.	F1	
Zhang and Yang (2018)	76.35	71.56	73.88	
Ma et al. (2020)	83.41	82.21	82.81	
Li et al. (2020a)	–	–	81.82	
Li et al. (2020b)	82.98	81.25	82.11	
Chen and Kong (2021)	79.25	80.66	79.95	
Wu et al. (2021)	–	–	82.57	
Baseline	82.79	81.27	82.03	
Baseline + BS	81.65	84.03	**82.83**	+0.02%

MSRA				
Model	Prec.	Rec.	F1	
Zhang and Yang (2018)	93.57	92.79	93.18	
Ma et al. (2020)	95.75	95.10	95.42	
Li et al. (2020a)	–	–	96.09	
Li et al. (2020b)	96.18	95.12	95.75	
Wu et al. (2021)	–	–	96.24	
Baseline	95.82	95.78	95.80	
Baseline + BS	96.37	96.15	**96.26**	+0.02%

Weibo NER				
Model	Prec.	Rec.	F1	
Zhang and Yang (2018)	–	–	58.79	
Ma et al. (2020)	–	–	70.50	
Li et al. (2020a)	–	–	68.55	
Shen et al. (2021)	70.11	68.12	69.16	
Chen and Kong (2021)	–	–	70.14	
Wu et al. (2021)	–	–	70.43	
Baseline	68.65	74.40	71.41	
Baseline + BS	70.16	75.36	**72.66**	+2.16%

Resume NER				
Model	Prec.	Rec.	F1	
Zhang and Yang (2018)	94.81	94.11	94.46	
Ma et al. (2020)	96.08	96.13	96.11	
Li et al. (2020a)	–	–	95.86	
Wu et al. (2021)	–	–	95.98	
Baseline	95.81	96.87	96.34	
Baseline + BS	96.63	96.69	**96.66**	+0.55%

Outline

Ablation Study: Smoothing Parameters

The effect of boundary smoothing remains robust
Standard label smoothing does not have such effect

	CoNLL 2003	ACE 2005	Resume NER
Baseline	93.48	86.56	96.34
BS ($\epsilon = 0.1$, $D = 1$)	93.50	86.65	96.63
BS ($\epsilon = 0.2$, $D = 1$)	93.56	86.96	**96.66**
BS ($\epsilon = 0.3$, $D = 1$)	**93.65**	86.81	96.50
BS ($\epsilon = 0.1$, $D = 2$)	93.45	**87.15**	96.33
BS ($\epsilon = 0.2$, $D = 2$)	93.39	86.99	96.62
BS ($\epsilon = 0.3$, $D = 2$)	93.57	86.71	96.28
LS ($\alpha = 0.1$)	93.43	86.31	96.31
LS ($\alpha = 0.2$)	93.37	86.17	96.38
LS ($\alpha = 0.3$)	93.26	85.65	96.26

Ablation Study: Backbone

Boundary smoothing works regardless of PLM and BiLSTM
RoBERTa outperforms original BERT on English NER

- RoBERTa is trained on much more data
- RoBERTa focuses on MLM by removing NSP

	CoNLL 2003	ACE 2005	Resume NER
Baseline	93.48	86.56	96.34
+ BS	**93.65**	**87.15**	**96.66**
Baseline w/ BERT-base	91.84	84.51	
+ BS	**92.05**	**84.95**	
Baseline w/ BERT-large	92.92	85.83	
+ BS	**93.08**	**86.33**	
Baseline w/ RoBERTa-large	93.66	87.82	
+ BS	**93.77**	**88.02**	
Baseline w/ MacBERT-base			96.41
+ BS			**96.75**
Baseline w/ MacBERT-large			96.46
+ BS			**96.75**
Baseline w/o BiLSTM	93.13	86.22	96.24
+ BS	**93.30**	**86.58**	**96.56**

Outline

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Model Calibration

Calibration: Do prediction confidences well reflect accuracy?

	Confidence	Correctness Probability
Well calibrated	80% (−)	80%
Over confident	90% (↑)	80%
Under confident	60% (↓)	80%

How to measure model calibration?

- Expected calibration error (ECE) [Guo et al., 2017]
  - Group samples into confidence bins $I_m = \left(\frac{m-1}{M}, \frac{m}{M}\right]$
  - Lower ECE suggests better calibration

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} \left|\mathrm{acc}(B_m) - \mathrm{conf}(B_m)\right|$$

Model Calibration

How to measure model calibration?

- Reliability diagram [Guo et al., 2017]
  - Plot accuracy against confidence
  - Being closer to the diagonal suggests better calibration

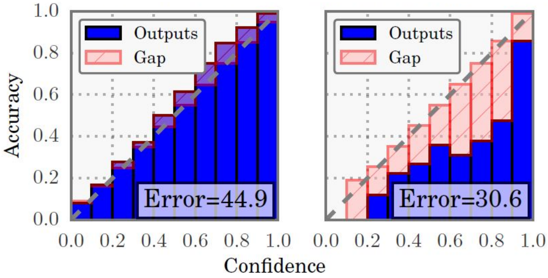
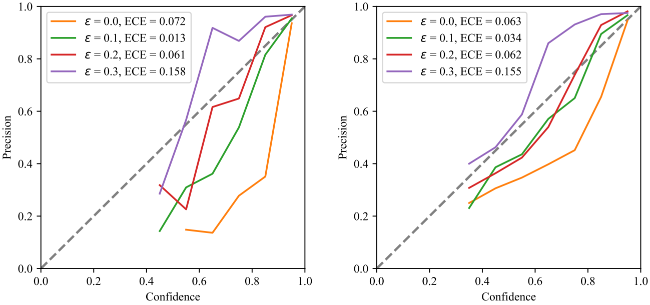


Figure: Reliability diagrams. Source: [Guo et al., 2017].

Calibration of Entities

Entity calibration: How well do the entity confidence reflect its probability to be a true entity?

- Models encounter over-confidence without BS
- BS improves calibration; $\epsilon = 0.1$ achieves the lowest ECE

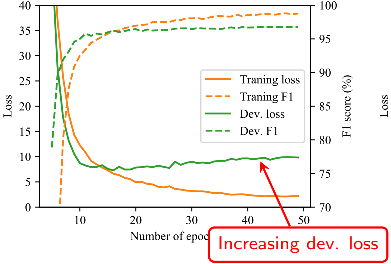


(a) CoNLL 2003 (b) OntoNotes 5

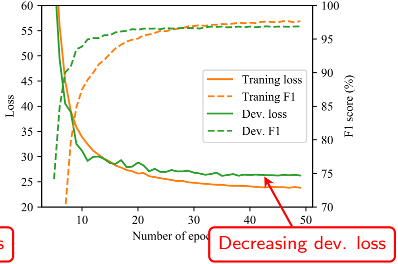
Over-Confidence

Over-confidence: The confidence of a predicted entity is much higher than its correctness probability

Boundary smoothing alleviates the disconnect between dev. loss and F_1 score



(a) Cross entropy loss



(b) Boundary smoothing loss

Outline

Why Does It Improve Performance?

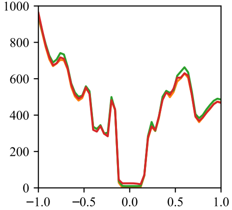
How does boundary smoothing improve the performance?

- Recall: Sharpness exists in the targets of span-based NER models
- Neural networks may prefer continuous solutions [Hornik et al., 1989]
- It is intuitively hard to optimize the neural models given the sharpness
- Boundary smoothing mitigates the sharpness

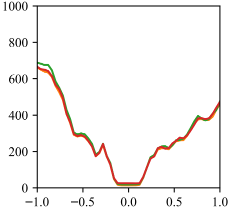
Loss Landscape Visualization

- Flatter minima and less chaotic loss landscapes result in better generalization and trainability [Hochreiter and Schmidhuber, 1997, Li et al., 2018]
- Many techniques improve loss landscapes, e.g., residual connection, small batch size [Li et al., 2018]

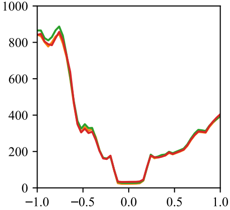
Loss Landscape Visualization



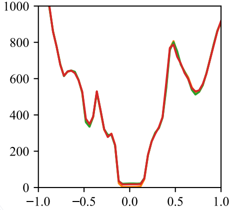
(a) CoNLL 2003



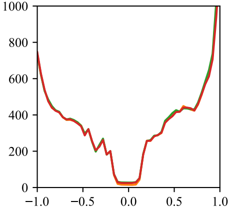
(b) CoNLL 2003 ($\epsilon = 0.1$)



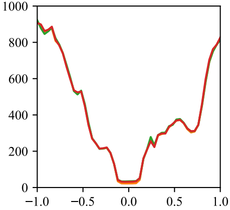
(c) CoNLL 2003 ($\epsilon = 0.2$)



(d) OntoNotes 5



(e) OntoNotes 5 ($\epsilon = 0.1$)



(f) OntoNotes 5 ($\epsilon = 0.2$)

Conclusions

We propose boundary smoothing for span-based neural NER models

Boundary smoothing re-assigns entity probabilities from annotated spans to the surrounding ones

With the help of boundary smoothing, our model:

- Achieves SOTA performance on eight well-known NER benchmarks
- Presents better entity calibration, less over-confidence
- Arrives at flatter neural minima and more smoothed loss landscapes

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