Filtered Semi-Markov CRF

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Introduction

PER						LOC		
Input sentence:	Alain	Farley	works	at	McGill	University	in	Montreal
	÷	÷	÷	*	*	÷	*	÷
BIO Tags:	B-PER	I-PER	0	0	B-ORG	I-ORG	0	B-LOC

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Spans: (0,1,PER) (4,5,ORG) (7,7,LOC) (0,0,0) (1,1,0) (1,3,0) (3,3,0) ...
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Entity Spans	Non-entity spans (null)
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Background

1) Probabilistic Structured Prediction

Probability of a structure y given an input x.

$$p_{ heta}(oldsymbol{y}|oldsymbol{x}) = rac{\exp oldsymbol{S}_{ heta}(oldsymbol{y}|oldsymbol{x})}{\sum_{oldsymbol{y}'\in\mathcal{Y}(oldsymbol{x})} \exp oldsymbol{S}_{ heta}(oldsymbol{y}'|oldsymbol{x})}$$

 $\mathcal{L}(\boldsymbol{x}, \boldsymbol{y}) = -\log p_{\theta}(\boldsymbol{y}|\boldsymbol{x})$

Filtered Semi-CRF

Main idea:

- Filter spans/segments using a lightweight classifier (easily parallelizable)
- Run Semi-CRF on the filtered spans
- Filtering is learned jointly with the Semi-CRF during training (multitask learning)
- No redundancy problem / Linear complexity (decoding)
- Strong performance (a variant our model won Arabic NER shared task)

Results

• We conducted experiments on flat NER datasets using BERT for token representation.

Models	CoNLL-2003	OntoNotes 5.0	
WIGUCIS	CONLL-2005	Unionoles J.U	

Loss function (NLL)

$$= - oldsymbol{S}_{ heta}(oldsymbol{y}|oldsymbol{x}) + \log \mathcal{Z}_{ heta}(oldsymbol{x})$$

Inference: produce the most likely structure

$$oldsymbol{y}^* = rg\max_{oldsymbol{y}\in\mathcal{Y}(oldsymbol{x})}oldsymbol{S}_{ heta}(oldsymbol{y}|oldsymbol{x})$$

2) Conditional Random Field (CRF) [1]

$$m{S}(m{y}|m{x}) = \sum_{i=1}^{|m{x}|} m{\psi}(y_i|m{x}) + \sum_{i=2}^{|m{x}|} m{T}[y_{i-1},y_i]$$

- Token-level modelling + 1st order markov transition between tags
- Linear complexity
- Limited to modeling relationships between individual tokens

3) Semi-Markov CRF [2]

$$oldsymbol{S}(oldsymbol{y}|oldsymbol{x}) = \sum^M oldsymbol{\phi}(s_k|oldsymbol{x}) + oldsymbol{T}[l_{k-1},l_k]$$

	Р	R	F	P	R	F	P	R	F	
Yu et al. (2020)	93.7	93.3	93.5	91.1	91.5	91.3	-	-	-	
Yan et al. (2021)	92.61	93.87	93.24	89.99	90.77	90.38	-	-	-	
Zhu and Li (2022)	93.61	93.68	93.65	91.75	91.74	91.74	-	-	-	
Shen et al. (2022)	93.29	92.46	92.87	91.43	90.73	90.96	-	-	-	
Zaratiana et al. (2022a)	94.29	93.33	93.81	90.21	91.21	90.71	85.35	83.64	84.49	
El Khbir et al. (2022)	-	-	-	-	-	-	84.42	84.05	84.23	

Our experiments

CRF	93.29	92.21	92.75	89.00	90.16	89.57	82.79	84.44	83.61
Semi-CRF	92.37	90.49	91.42	88.91	89.78	89.34	82.97	84.24	83.60
+ Unit size null [†]	92.08	91.41	91.74	89.17	89.76	89.47	83.35	83.62	83.48
FSemiCRF	94.72	93.09	93.89	90.69	91.31	91.00	83.43	85.51	84.46
- w/o \mathcal{L}_{global} (14) [†]	94.24	92.70	93.46	90.85	89.57	90.21	83.73	83.56	83.64

Inference speed

• Walll clock time

	CoNLL-2003 (Y = 4)			Oi	ntoNotes 5.0 (Y = 18)	Arabic ACE $(Y = 7)$			
	CRF	Semi-CRF	FSemiCRF	CRF	Semi-CRF	FSemiCRF	CRF	Semi-CRF	FSemiCRF	
Scoring	3.9	3.9	3.9	4.8	4.9	4.9	8.1	8.3	8.3	
Decoding	2.7	3.7	0.2	4.4	27.5	0.2	6.0	10.1	0.3	
Decoding Speedup	1.3x	1.0x	18.5x	6.2x	1.0x	137x	1.7x	1.0x	33.7x	

 $k{=}1$

- (Span) segment-level modelling
 - y completely should cover the input sequence without overlapping
 - non-entity segments ('O' or null segments) have unit length
 - x = Alain Farley works at McGill University
 y = (1,2,PER) (3,3,0) (4,4,0) (5,6,ORG)
- Higher-level segment features
- Slow training and inference
- Multiple valid paths (redundancy problem)
- Poor performance in practice

Overall	6.6	7.6	4.1	9.2	32.4	5.1	14.1	18.4	8.6
Overall Speedup	1.1x	1.0x	1.8 x	3.5x	1.0x	6.3x	1.30x	1.0x	2.1 x

• Graph size after training



[1] Lafferty et al. (2003) Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data

[2] Sarawagi & Cohen (2004) Semi-Markov Conditional Random Fields for Information Extraction



Arabic ACE