Learning with Structured Representations for Negation Scope Extraction

Hao Li and Wei Lu
Singapore University of Technology and Design
hao_li@mymail.sutd.edu.sg luwei@sutd.edu.sg

SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

Task

Negation Scope Detection

Recognize the negation scope, the parts of the sentence being negated, given the negation cue.

Motivation

3 types of useful features that can be explicitly and implicitly captured and modelled

- **Cue-level features**
- **Long Distance Dependencies**
- **Implicit Patterns**.

Approach

Linear CRF for Cue-level features

- the negation cue type features (c)
- relative position with respect to the cue (r)

Semi CRF for Long Distance Dependencies

- partial scopes as spans (Semi i)
- gaps as spans (Semi o)
- both as spans (Semi io)

Latent CRF – Implicit Patterns

- implicit patterns on partial scopes (Latent i)
- implicit patterns on gaps (Latent o)
- implicit patterns on both (Latent io)

Main Result

System	Token-Level $P.$	$R.$	F_1	Scope-Level (Exact Scope Match) $P_A.$	$R_A.$	F_{1A}	$P_B.$	$R_B.$	F_{1B}
Read et al. (2012)	-	-	-	98.8	64.3	77.9	-	-	-
Packard et al. (2014)	86.1	**90.4**	88.2	98.8	65.5	78.7	-	-	-
Fancellu et al. (2016)	92.6	85.1	88.7	99.4	63.9	77.8	-	-	-
Linear (-c -r)	84.7	73.9	78.6	99.2	49.4	65.6	51.5	49.4	50.4
Linear (-r)	90.6	78.4	84.1	100	60.6	75.5	61.4	60.6	61.0
Linear (-c)	91.0	78.9	84.5	99.3	56.6	72.1	60.0	56.6	58.3
Linear	94.4	82.6	88.1	100	67.9	80.9	69.3	67.9	68.6
Semi *i*	95.0	84.1	89.2	100	67.5	80.6	69.4	67.5	68.4
Semi *o*	94.0	85.3	**89.4**	100	69.1	81.7	**71.1**	69.1	**70.1**
Semi *io*	94.5	84.1	89.0	100	68.3	81.2	70.3	68.3	69.3
Latent *i*	94.4	83.4	88.6	99.4	67.9	80.7	69.6	67.9	68.7
Latent *o*	90.4	83.9	87.1	99.4	65.5	78.9	66.3	65.5	65.9
Latent *io*	**94.8**	83.2	88.6	100	**69.5**	**82.0**	70.6	**69.5**	70.0

CDS-CO (English)

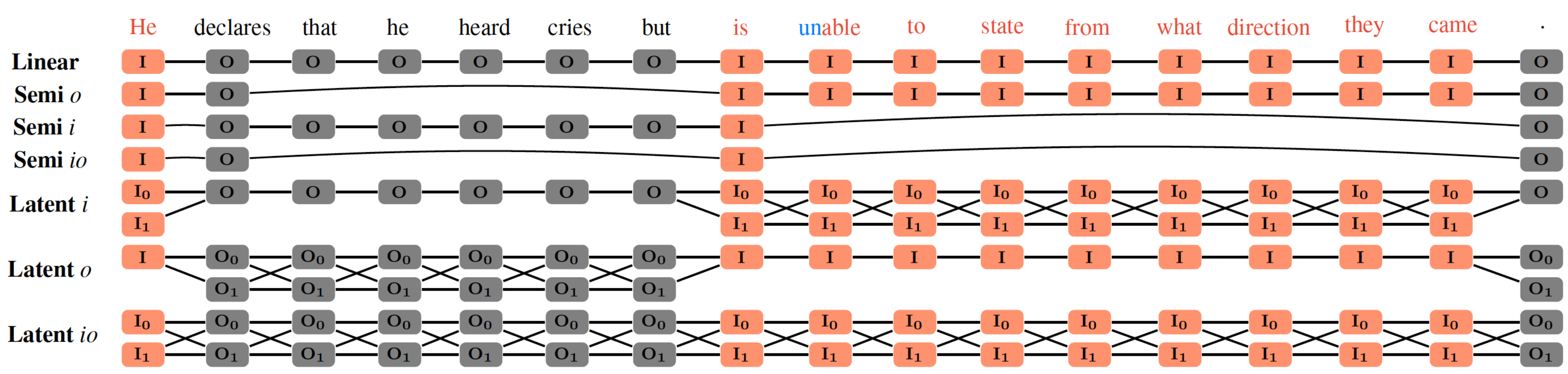
Example

He declares that he heard cries but **is unable to state from what direction they came** .

There is neither money nor credit in it , and yet one would wish to tidy it up .

Negation scope (partial scopes) in orange, negation cue in blue, gaps as non-orange spans

Model



Analysis

Semi is better on recovering discontinuous partial scopes

This person is alone and **can not** **<u>be approached by letter without a breach of that absolute secrecy .</u>**

He has been there for ten days, and **neither Mr. Warren, nor I, nor** **<u>the girl has once set eyes upon him</u>** .

*The incorrect predictions by **Linear** model are underlined*

Latent tends to make more accurate predications

- We found that there is only 1 incorrect prediction from the **Latent** *io* that is corrected by the Linear model. This indicates that the **Latent** *io* model is able to fix errors for the **Linear** model without producing other wrong predictions.

Characteristics of our models

- Higher scope-level recall compared to previous works
- Tend to recognize shorter partial scopes
- 45% of top 200 features related to POS bigram

Model Robustness

System	*Abstract* F_{1T}	F_{1A}	PCS	*Full Paper* F_{1T}	F_{1A}	PCS	*Clinical* F_{1T}	F_{1A}	PCS
Li et al. (2010)	-	-	81.8	-	-	**64.0**	-	-	89.8
Velldal et al. (2012)	-	74.4	-	-	70.2	-	-	90.7	-
Zou et al. (2013)	-	-	76.9	-	-	61.2	-	-	85.3
Qian et al. (2016)	89.9	-	77.1	**83.5**	-	55.3	94.4	-	89.7
Linear	90.3	90.3	82.3	80.8	74.0	58.8	96.4	96.6	93.3
Semi *io*	**92.1**	**91.3**	**84.1**	**83.1**	**75.1**	60.1	**97.5**	**97.1**	**94.4**
Latent *io*	91.5	90.8	83.2	79.5	71.0	55.1	97.3	97.0	94.1

BioScope (English)

System	*Product Review* F_{1T}	F_{1A}	F_{1B}	PCS
(Zou et al., 2015)	-	-	-	60.93
Linear	89.60	81.86	69.39	69.39
Semi *io*	**90.78**	83.49	71.69	71.69
Latent *io*	90.60	**83.95**	**72.43**	**72.43**

CNeSp (Chinese)