

Modeling Context-sensitive Selectional Preference with Distributed Representations

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Introduction

- What is Context-sensitive Selectional Preference (CSP)?

CSP = predicate slot preference + **contextual fitness**

John shot a woman.
Police arrested _____

Arg.	SP	CSP
John	😊	😊
watch	😞	😞
woman	😊	😞

“obj. of arrest should be person”

+ “someone who is shot is unlikely to be arrested”

Results

- Pseudo-disambiguation test (480k tuples from ClueWeb 2012)

Observed:
(police, arrest, man who shot woman)
versus random negative:
(police, arrest, apple which is delicious)

Van de Cruys 2014	Proposed
0.8635	0.8947

- Coreference cluster ranking

(12k pronouns in OntoNotes 5.0 [Hovy et al. 2006])

In his_(i) 40-minute speech_(j), Chen_(i) declared the determination_(k) of the people_(l) ... he_(?) made a statement...

Van de Cruys 2014	Proposed
0.7420	0.8265

- Distributed representations successfully model context-sensitivity!

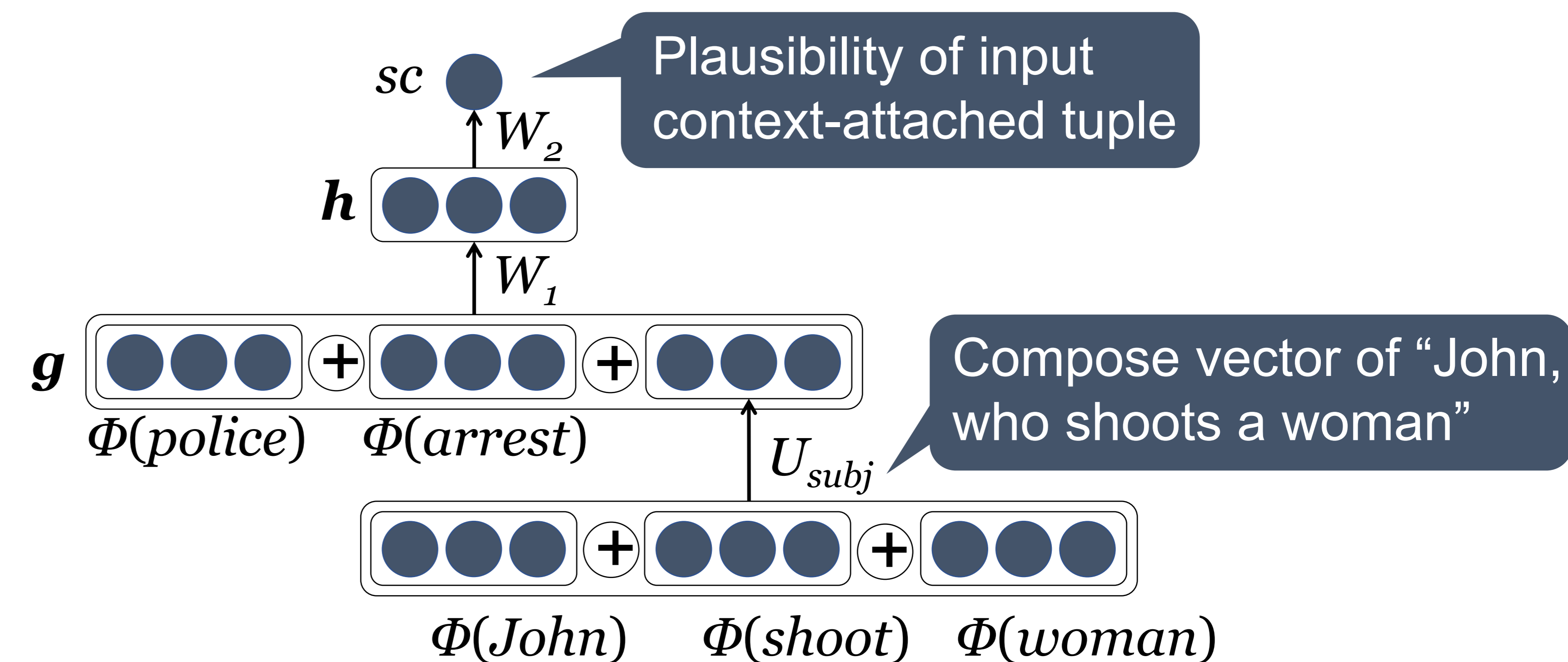
Contacts / Acknowledgement

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Proposed Model for CSP

Architecture

- Key challenge: how to effectively model context-attached tuples?
- Leverage distributed representations to solve the sparsity issue
- Extend Van de Cruys (2014)’s Neural SP model for CSP



Training

- Generate positive/negative context-attached tuples from ClueWeb12 with coreference resolver (similarly to Chambers & Jurafsky (2008))



- 4,824,394 instances (2,912,624 types) are extracted
- Learn parameters W_* , U_* , Φ via max-margin training:

$$L = \max(0, 1 - sc(s^+, v^+, o^+) + sc(s^-, v^+, o^+)) + \max(0, 1 - sc(s^+, v^+, o^+) + sc(s^+, v^+, o^-)) + \max(0, 1 - sc(s^+, v^+, o^+) + sc(s^-, v^+, o^-))$$

s^-, v^-, o^- : randomly-generated negative example