

Implicit Argument Prediction as Reading Comprehension

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Introduction

Twice in the late 1980s *Gillingham* came close to winning promotion to the second tier of English football, but a **decline** then set in...

- We are interested in predicting implicit predicate-argument relations, where the *arguments* are not syntactically connected to the *predicate* and may not even be in the same sentence.
- We recently (Cheng & Erk, 2018) proposed a neural model and additional training / testing data for the task.

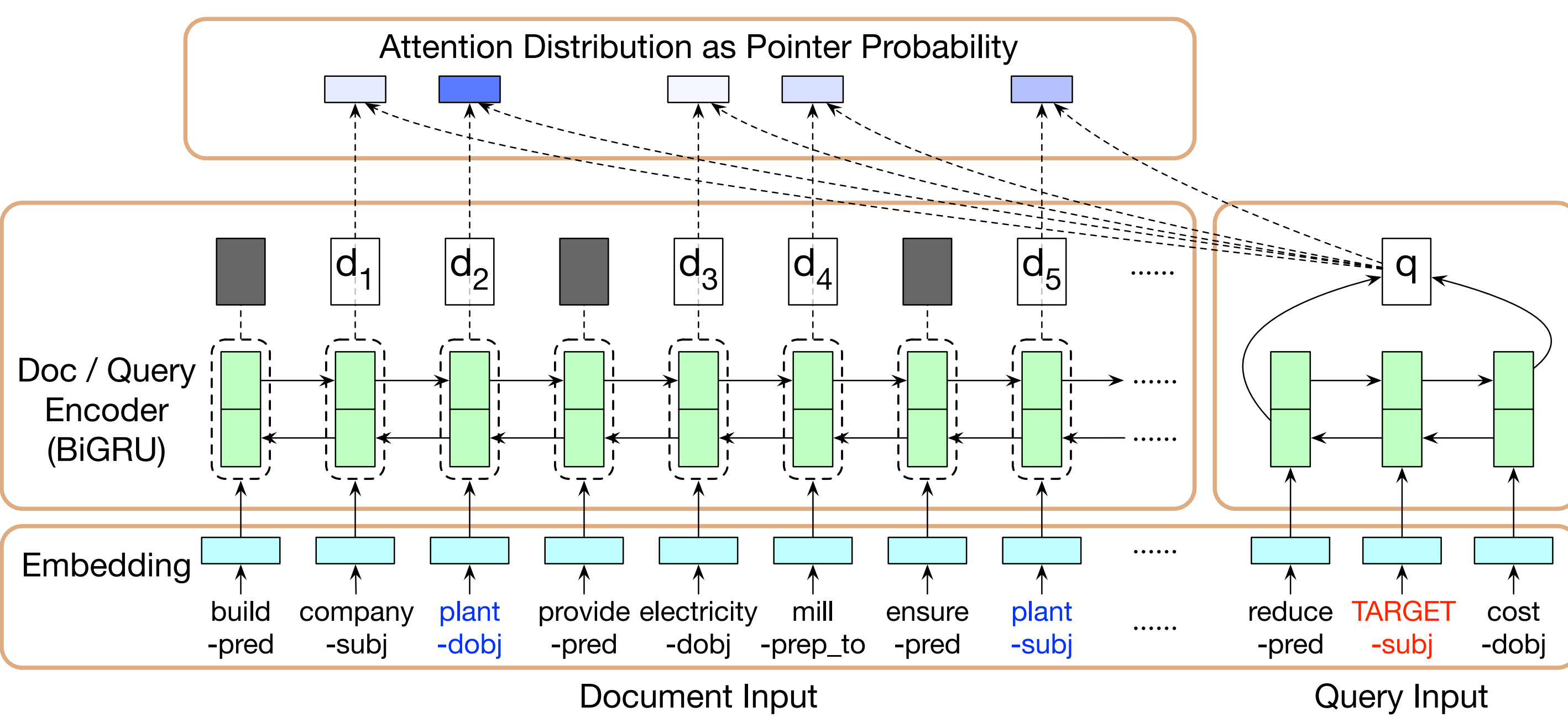
Task

- We view the task as **reading comprehension**.
 - A predicate-argument tuple with the **missing argument** is a **query**.
 - The **answer** to the query has to be located in the **document**.

From raw text	Extract entities and events	Construct document-query pair
<p>Manville Corp. said it will build a \$ 24 million power plant to provide electricity to its Igaras pull and paper mill in Brazil.</p> <p>The company said the plant will ensure that it has adequate energy for the mill and will reduce the mill's energy costs.</p>	<p>$x_0 = \text{company}$ $x_1 = \text{mill}$ $x_2 = \text{power plant}$</p> <p>$e_0: (\text{build-pred}, x_0\text{-subj}, x_2\text{-dobj}, -)$</p> <p>$e_1: (\text{provide-pred}, -, \text{electricity-dobj}, x_1\text{-prep_to})$</p> <p>$e_2: (\text{ensure-pred}, x_2\text{-subj}, -, -)$</p> <p>$e_3: (\text{has-pred}, x_0\text{-subj}, \text{energy-dobj}, x_1\text{-prep_for})$</p> <p>$e_4: (\text{reduce-pred}, x_2\text{-subj}, \text{cost-dobj}, -)$</p>	<p>Document ($e_0 \sim e_3$):</p> <p>build-pred company-subj plant-dobj provide-pred electricity-dobj mill-prep_to ensure-pred plant-subj has-pred company-subj energy-dobj mill-prep_for</p> <p>Query (e_4):</p> <p>reduce-pred TARGET-subj cost-dobj</p>

Model

- We draw on the Attentive Reader [1] and Pointer Networks [2].

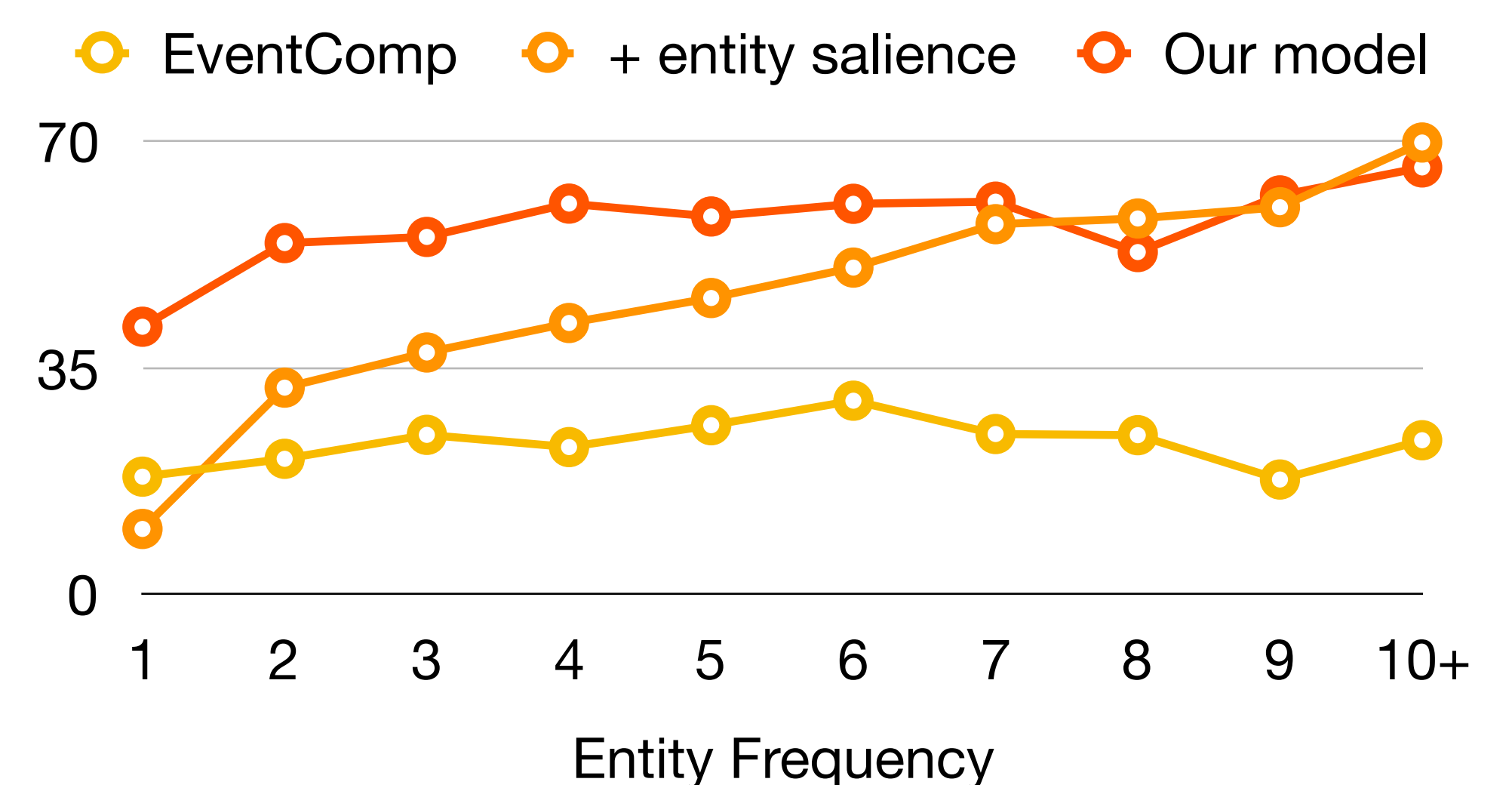


Results on OntoNotes

- Comparing to the previous EVENTCOMP model (Cheng & Erk, 2018).
- Our model does much better on the harder ON-LONG dataset with longer documents.

Accuracy (%)	ON-SHORT	ON-LONG
EVENTCOMP	36.90	21.26
+ entity salience	46.06	31.43
Our model	58.12	51.52

- Our model performs well on both frequent and infrequent entities out of the box.

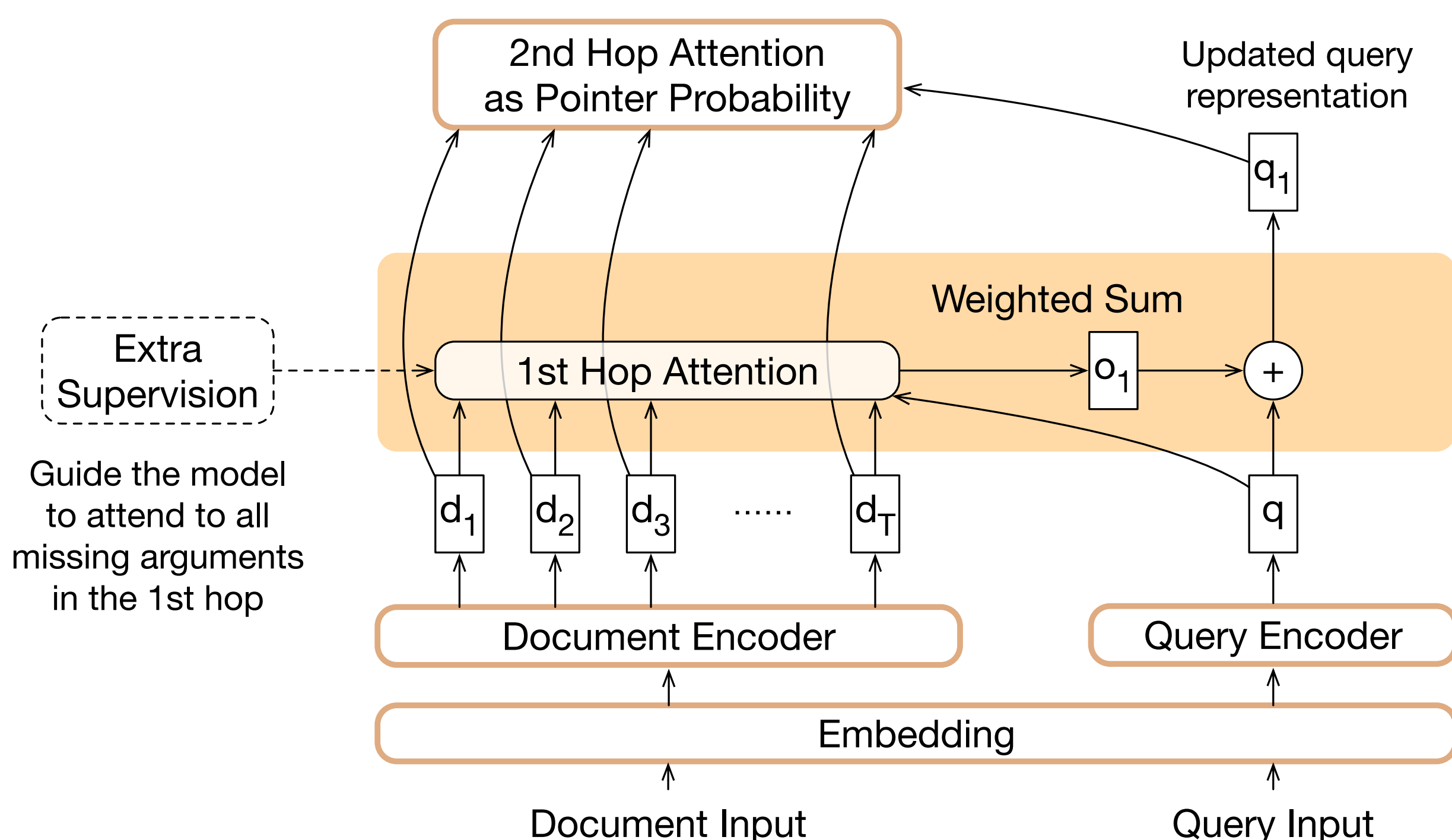


Multi-hop Inference

- A single predicate can have more than one implicit arguments.
- Occurred in over 30% of the G&C dataset (Gerber & Chai, 2010).

The average interest rate rose to 8.3875% at *[Citicorp]*_{subj}'s \$50 million weekly auction of *[91-day commercial paper]*_{obj}, or corporate IOUs, from 8.337% at last week's *[sale]*_{pred}.

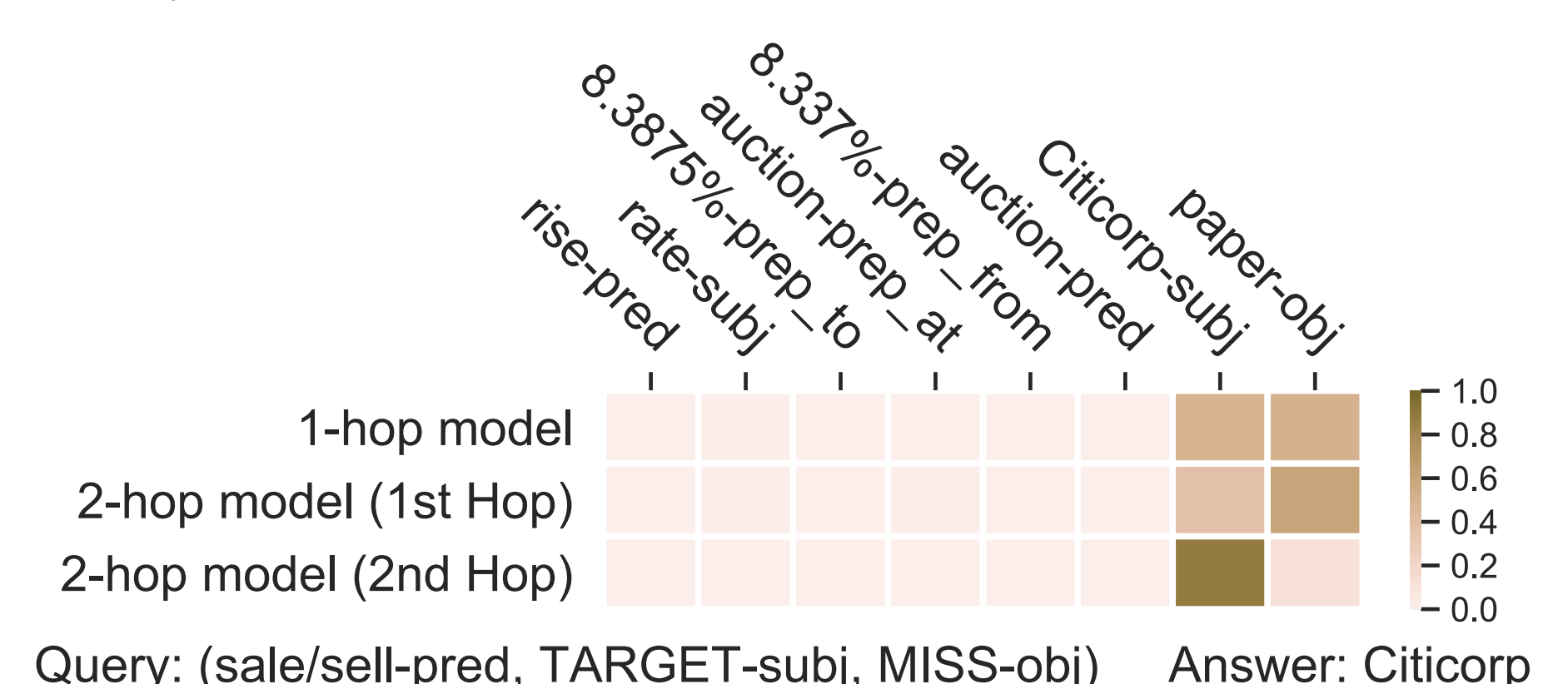
- We strengthen the model by multi-hop attention computation [3].



Results on G&C

Model	F1	
Gerber & Chai (2012)	50.3	* GCAUTO is a re-implementation of Gerber & Chai (2012) by removing gold features for a fair comparison.
GCAUTO*	44.5	
EVENTCOMP	48.3	
Our model	44.4	
+ 2-hop attention	46.2	
+ extra supervision	48.3	

The average interest rate rose to 8.3875% at Citicorp's \$50 million weekly auction of 91-day commercial paper, or corporate IOUs, from 8.337% at last week's sale.



References

- Hermann, Karl Moritz, et al. "Teaching machines to read and comprehend." *NIPS*. 2015.
- Vinyals, Oriol, Meire Fortunato, and Navdeep Jaitly. "Pointer networks." *NIPS*. 2015.
- Sukhbaatar, Sainbayar, Jason Weston, and Rob Fergus. "End-to-end memory networks." *NIPS*. 2015.