Fine-Grained Entity Typing for Domain Independent Entity Linking

Yasumasa Onoe and Greg Durrett, {yasumasa, gdurrett}@cs.utexas.edu

TEXAS
The University of Texas at Austin
TAUR LAB

1. Motivation

Here is an example from the CoNLL-YAGO dataset.

The Irish took a 4-0 lead within 20 minutes.

What does "Irish" mean here?

Irish people or **Ireland national football team**?

Entity linking training data contains mostly this…

…so linking model will never predict this

2. Our Approach

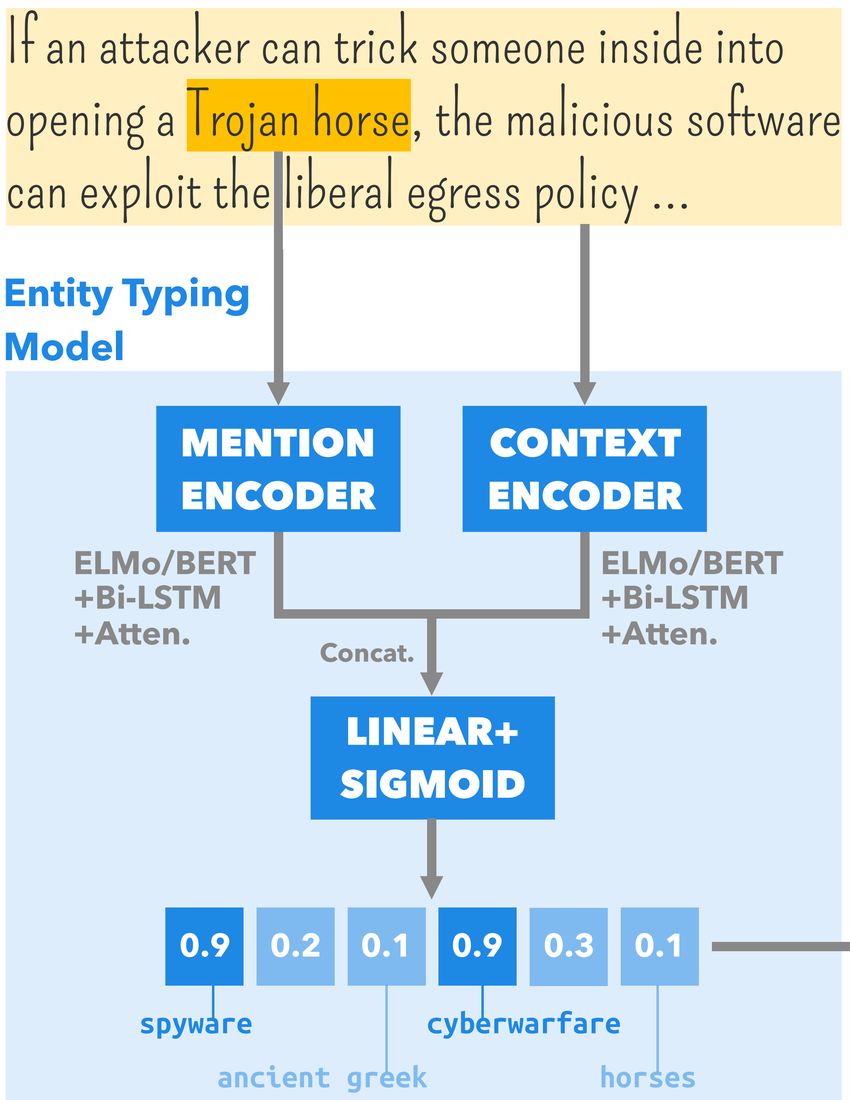
Our model predicts **fine-grained entity types** of "Irish" that make sense in this context. Supervision comes from mention-types, and this way prevents a model from memorizing mention-entity pairs. As a result, our model **generalizes well to new domains**.

3. Entity Typing for Entity Linking

Mention & Context

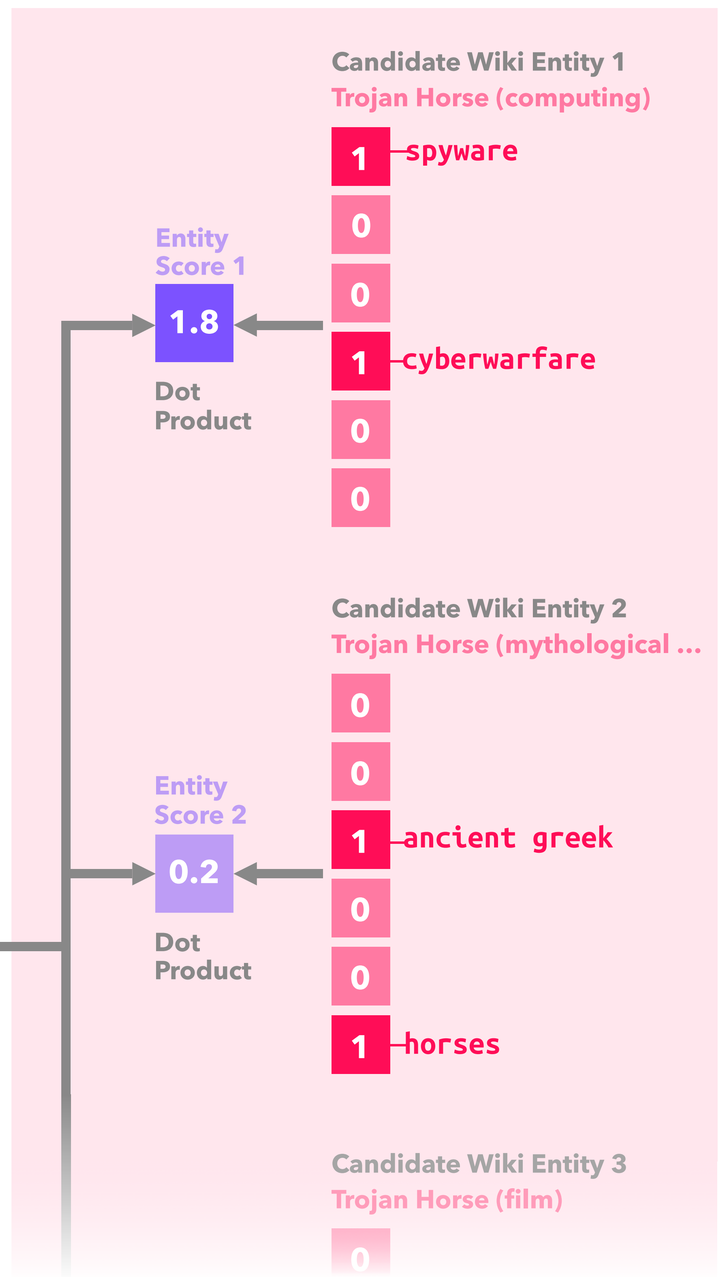
If an attacker can trick someone inside into opening a Trojan horse, the malicious software can exploit the liberal egress policy …

Entity Typing Model



Typing model **encodes mention and context** and **predicts types independently** using binary classification from a shared representation.

Entity Ranking Module



4. Training

Entity Typing Training Data

For each hyperlink in Wikipedia, treat the text (**New York City**) as a mention and the destination page's Wiki categories (**Cities**, **Populated places**, …) as gold entity types.

Type Set

We derive a type set from Wikipedia categories. To obtain more coarse-grained types, we split each category using several rules. We use a vocabulary of 60,000 types in our experiments.

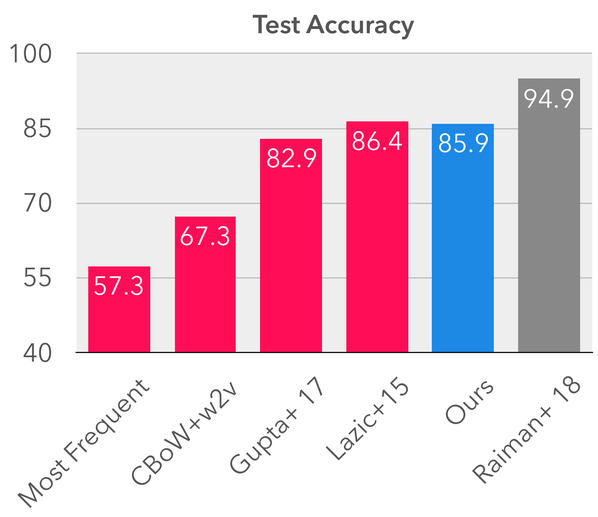
5. Experiments

CoNLL-YAGO (standard benchmark dataset)

■ Significant entity overlap between standard training and standard test set

Baselines: Popularity prior baseline (Most Frequent); neural baseline trained on Wikipedia (CBoW+w2v); SOTA models that do not use in-domain training data (Gupta+ 17, Lazic+ 15).

Results: Without using the in-domain training data, our approach shows strong performance on this dataset. Supervised systems (Raimain+) still achieve stronger performance, but much of this is due to entity memorization.

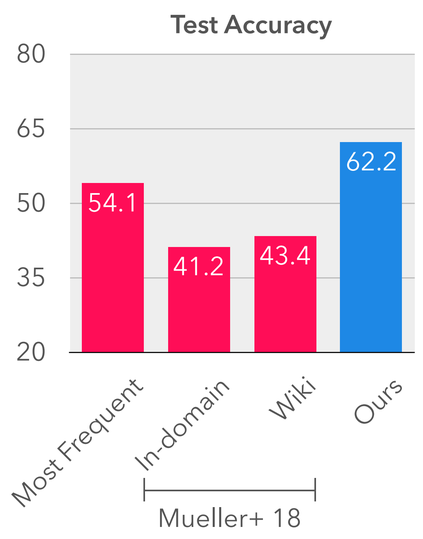


WikilinksNED: Unseen-Mentions (challenging setting)

■ All mentions in development set do not occur in test set

Baselines: Popularity prior baseline (Most Frequent); SOTA neural EL model (Mueller+ 18) trained on either WikilinksNED or Wikipedia data.

Results: Our approach handles unseen mention-entity pairs better. State-of-the-art models do poorly when generalization to new entities is required.



Code & data available at https://github.com/yasumasaonoe/ET4EL