

Zero-Shot Open Entity Typing as Type-Compatible Grounding



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1. Goal

Given **mention** in its **context**, assign **a set of types** that the mention belongs to.

In this work, we extend this goal to type with an **open** type set, without reliance on task specific supervision (**zero-shot**).

2. Motivation

Most previous works focus on using supervision for typing, which often rely on costly annotation, do not generalize to unseen types or out-of-domain data.

Unlike previous systems, we propose an approach that is both **open** and **zero-shot**.

- **Open**: Not limited to a fixed label set
- **zero-shot**: No need for typing-specific annotation

To achieve zero-shot, we equip our model with **understanding** of the labels. We propose the notion of **type-compatible**, which transforms the typing problem to approximating type-compatibility, by mapping an input mention to a set of type-compatible entities, then inferring their types.

- **Understanding**: Each type is implicitly defined by entities that share that type.
- **Type-compatible**: Two mentions are type-compatible if they share at least one type.

3. Model

In order to compute type-compatibility between mention and entities, we propose a notion called **context-consistency**.

- **Context-consistency**: two mentions are context-consistent if they are interchangeable in some context. In other words, it represents the contextual similarity between two mentions.

We approximate the **type-compatibility** between a mention and an entity (represented by its mentions) through computing **context-consistency**.

A significant advantage of using context-consistency is that it relies mostly on context, which overcomes the issue of *polysemy* or *rare* mention surface forms. (see Figure 1)

Acknowledgements

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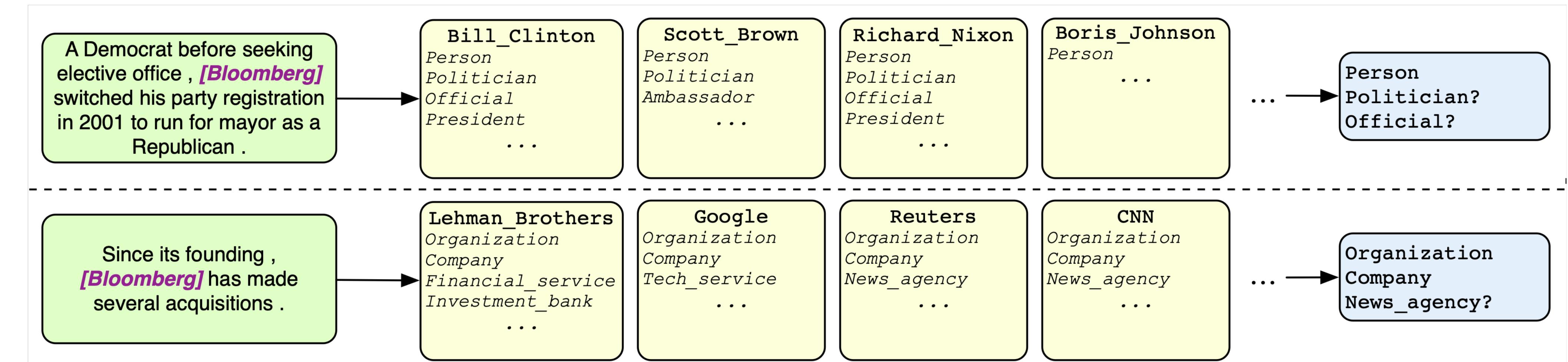


Figure 1: Example inputs, corresponding compatible entities and output

4. Details

We use **ESA** to generate a relatively large set of initial concepts.

Then we use **ELMo** representations to approximate context-consistency between a mention and a concept. A concept's representation is the averaged representations of its mentions in **WikiLinks**.

We take a small set of concepts with top context-consistency, then use **Priors** to add highly confident concepts based on surface form (if any) to this set.

Then we map the concepts in the small set to target taxonomy using **FreeBase** as a proxy (see figure 2), by defining each target type in terms of logical expressions of **FreeBase** types. The final process is a voting based **Inference** over types in target taxonomy.

- **A WikiLinks**: A dataset containing contextual examples for Wikipedia concepts.
- **B ESA**: Generated by treating each WikiLinks sentence as a document. It enables quick retrieval of topically relevant concepts given a sentence.
- **C ELMo**: A SOTA contextualized representation, which generates a representation for word in its context.
- **D Priors**: $P(\text{concept}/\text{surface})$ table, generated from Wikipedia text and anchor links.
- **E FreeBase**: A large taxonomy that each Wikipedia concept has a mapping to.
- **F Inference**: An algorithm that infers the types of the input mention, by taking into account the agreement among the types of the contextually similar concepts.

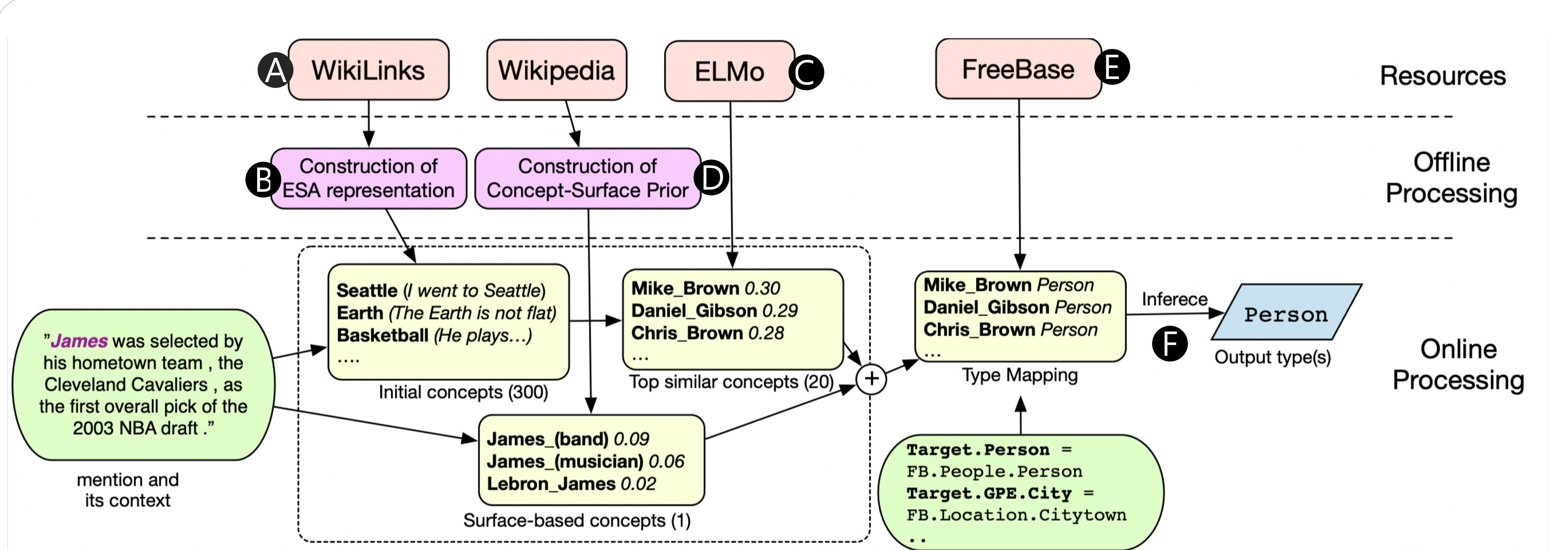
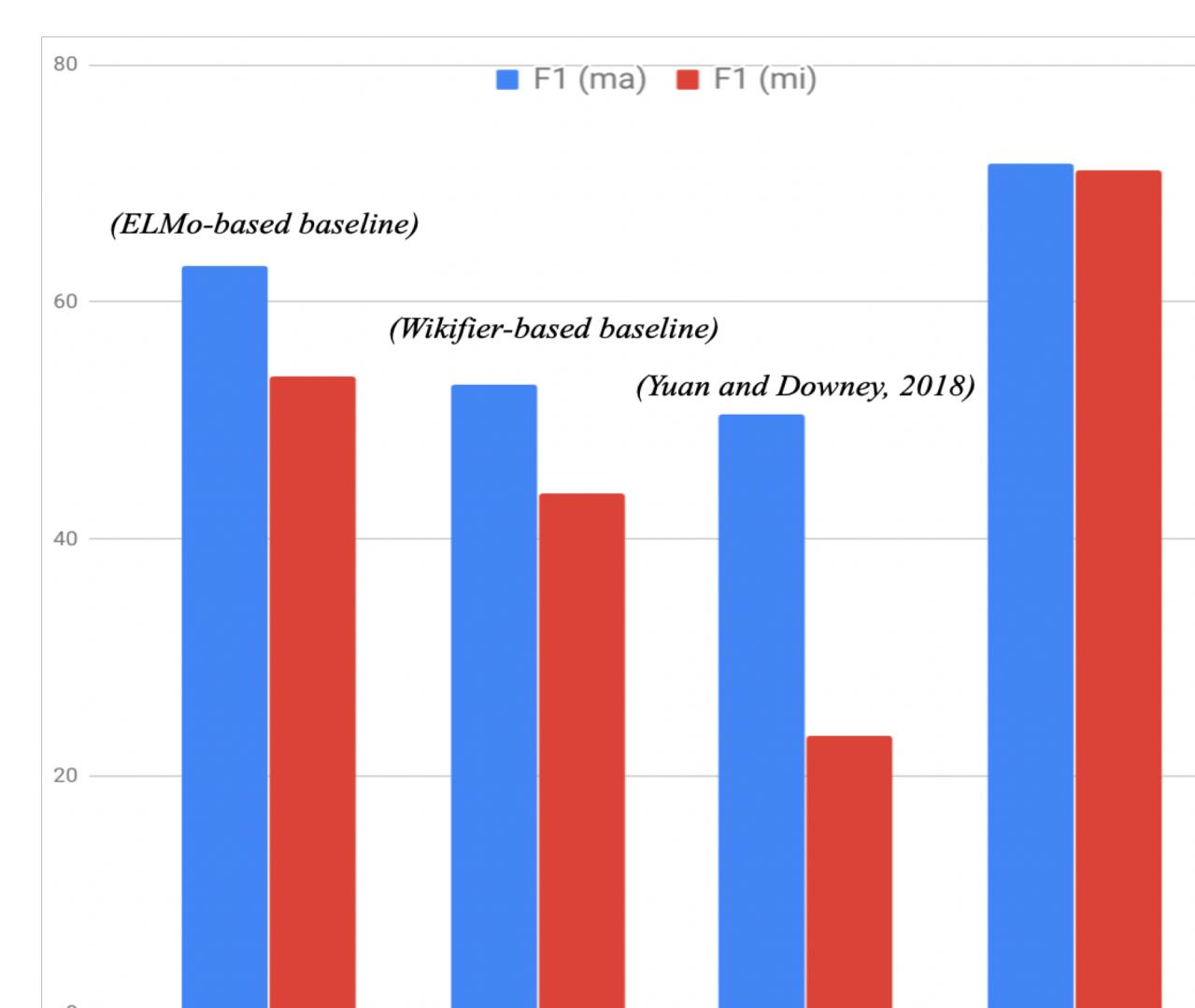


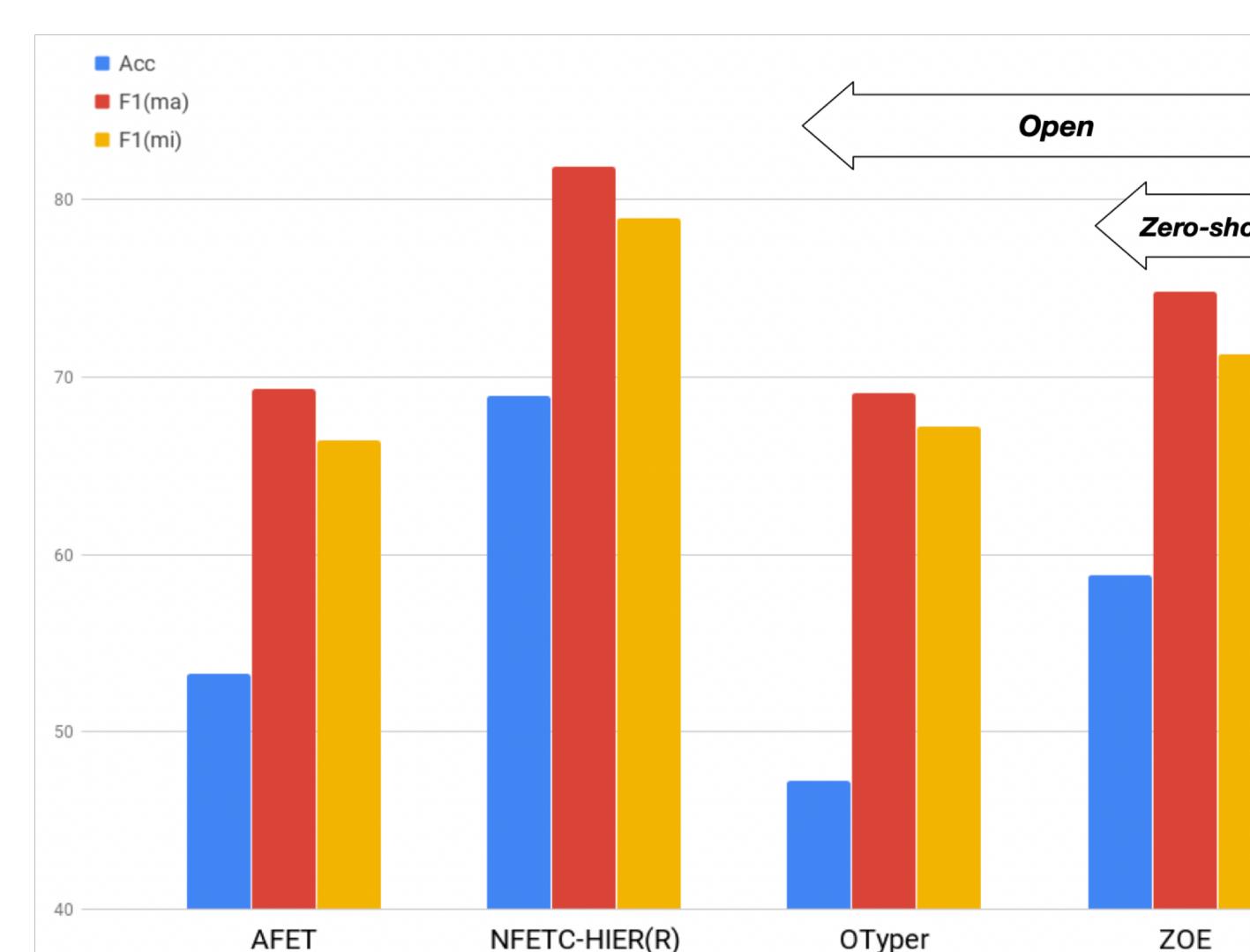
Figure 2: Overview of the system through an example

5. Experiments

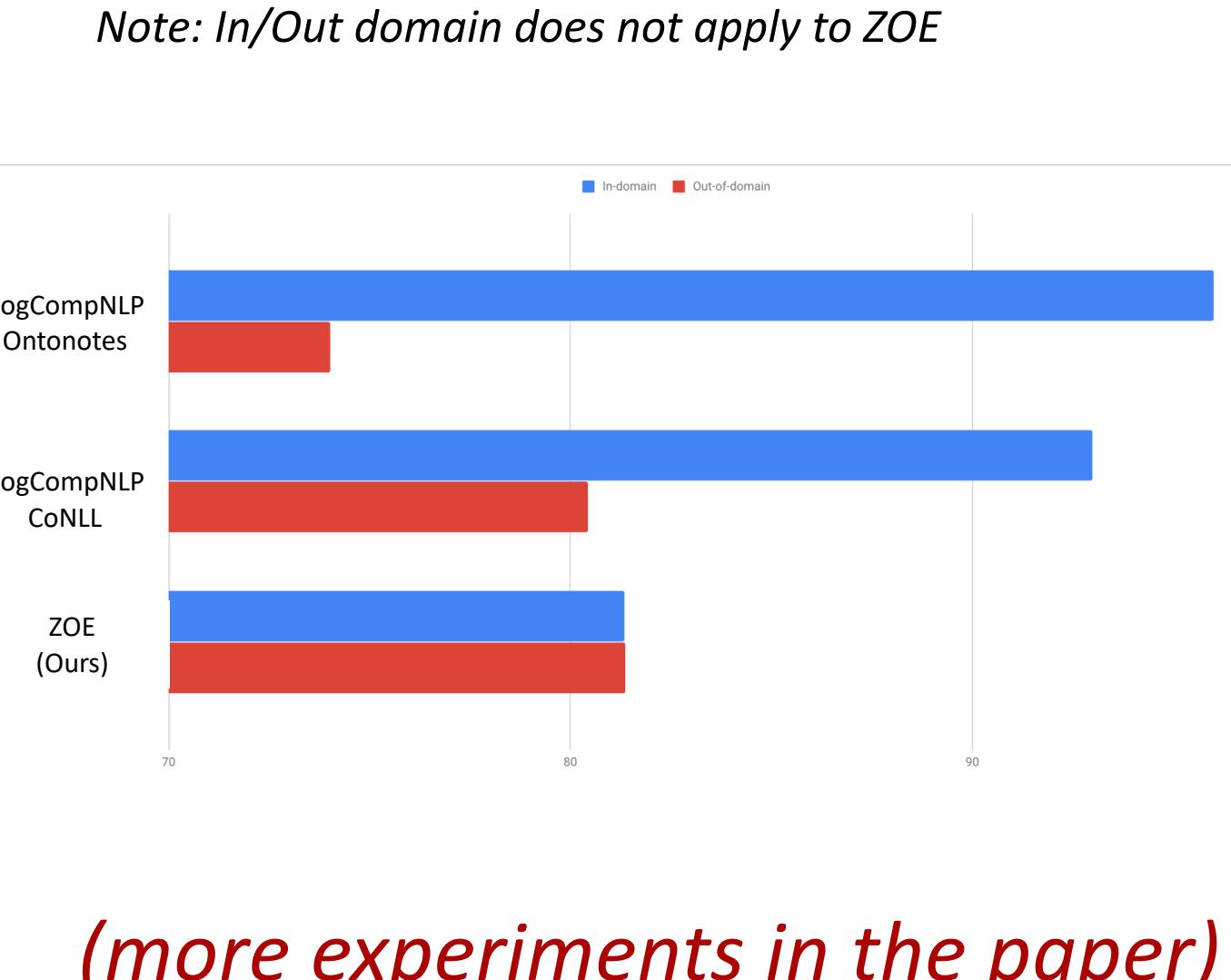
Significantly outperforms SOTA open typing system and baselines:



Comparable results with supervised systems on fine typing:



Outperforms supervised system in cross-domain settings
Note: In/Out domain does not apply to ZOE



(more experiments in the paper)