

1. Distantly-Labeled Data

Pros: Useful to scale up training data for data-hungry statistical models such as neural networks.

Cons: Typically *noisy* and that noise can vary with the distant labeling technique.

Examples:

(a) Wrong labels

No matter whom they buy from, users blame [Amazon].

location ✗
Company, business ✓

(b) Missing labels

The Minnesota Lynx play their home games at Target Center in [Minneapolis].

location, city, place, area, seat

How to fix these *noisy* labels produced by distant supervision?

2. Our Framework

Manually-Annotated Data

Example 1
According to the Rotten Tomatoes, 89% of critics gave [the film] positive reviews.

film
movie
art

1 We have **manually-annotated data** and **noisy data** (from distant supervision).

2 To train **Filtering/Relabeling models**, we construct synthetic training data.

Noisy Data

Example 2
No matter whom they buy from, users blame [Amazon].

location

Example 3
The Minnesota Lynx play their home games at Target Center in [Minneapolis].

location

Filtering Model

Relabeling Model

✓ location
✗ company
✓ city
✗ business
✓ place

Cleaned Data

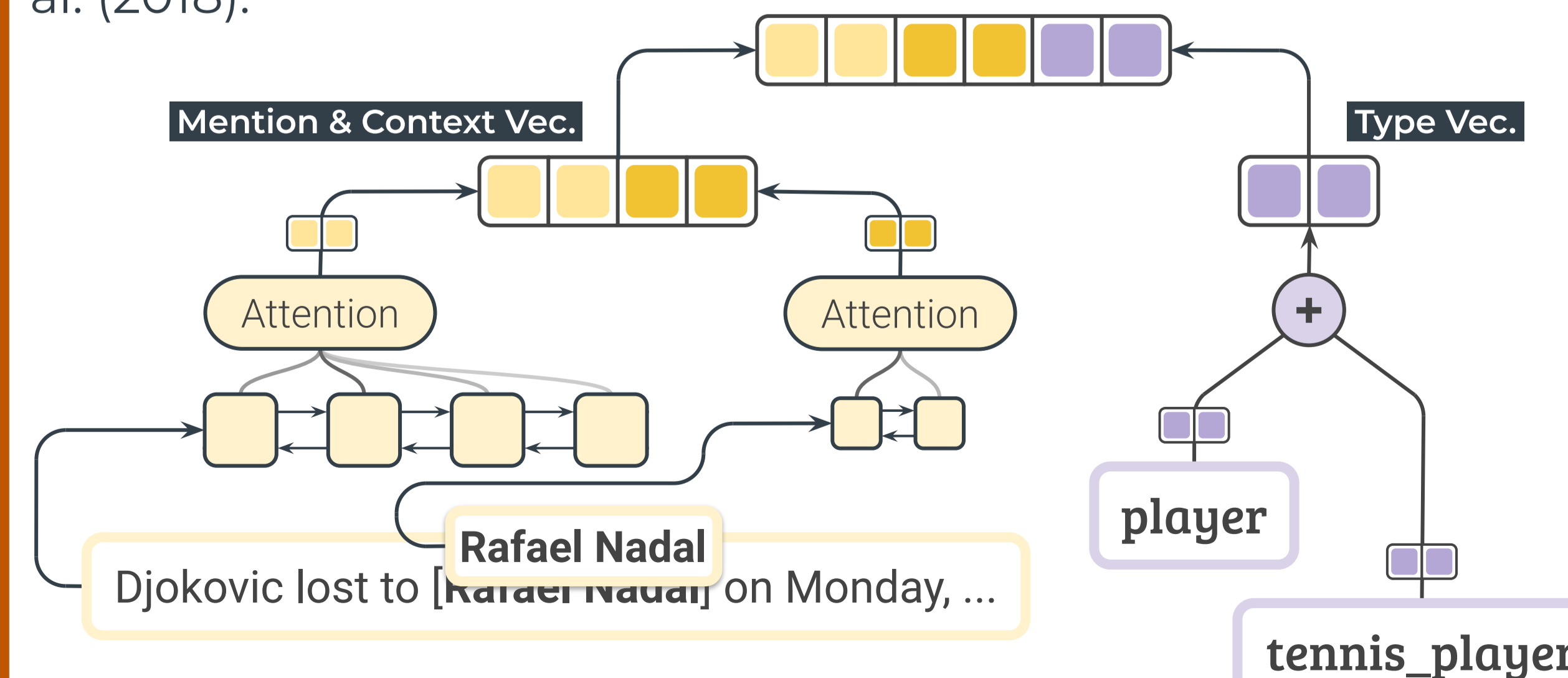
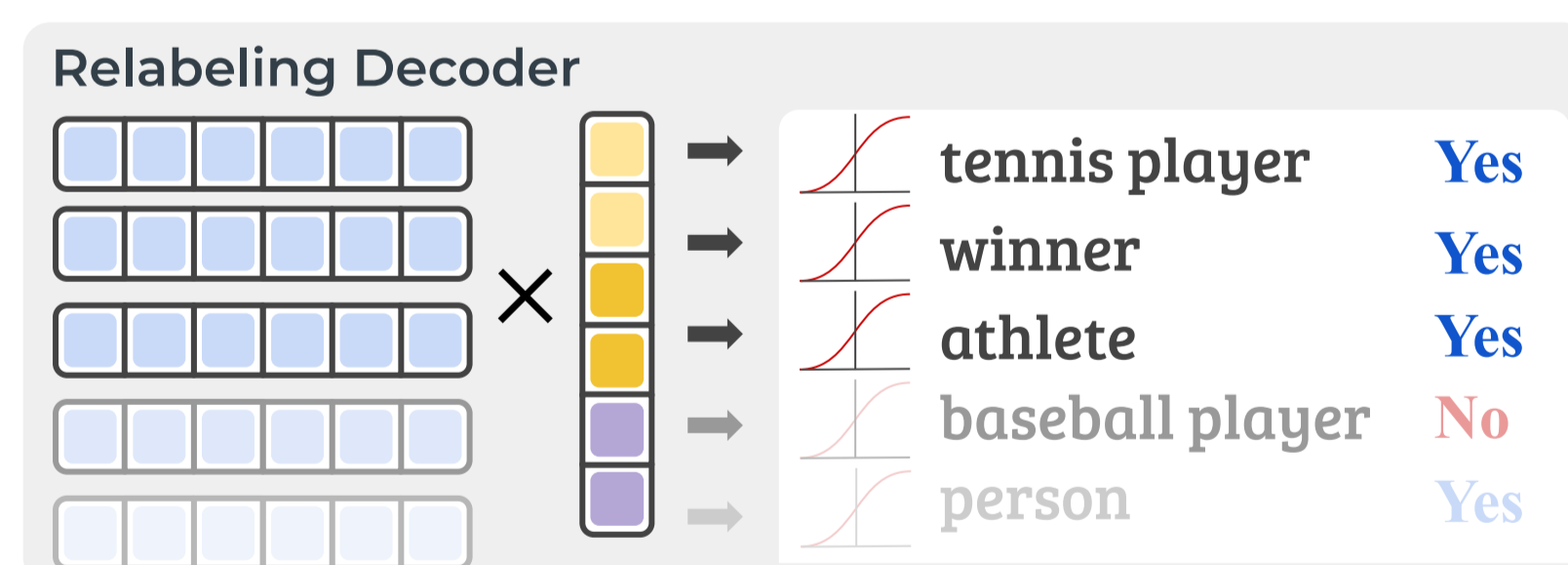
Example 3
The Minnesota Lynx play their home games at Target Center in [Minneapolis].

location
city
place
area
seat

4 Our final training data combines the **manually-annotated data** and **cleaned data** produced by this procedure.

3. Model

The figure shows the **Relabeling Model**. Our final entity typing model uses the mention & context vector only, which follows Choi et al. (2018).



We encode the mention in context as well as its noisy observed types, and predict the true type set based on these signals.

4. Experiments

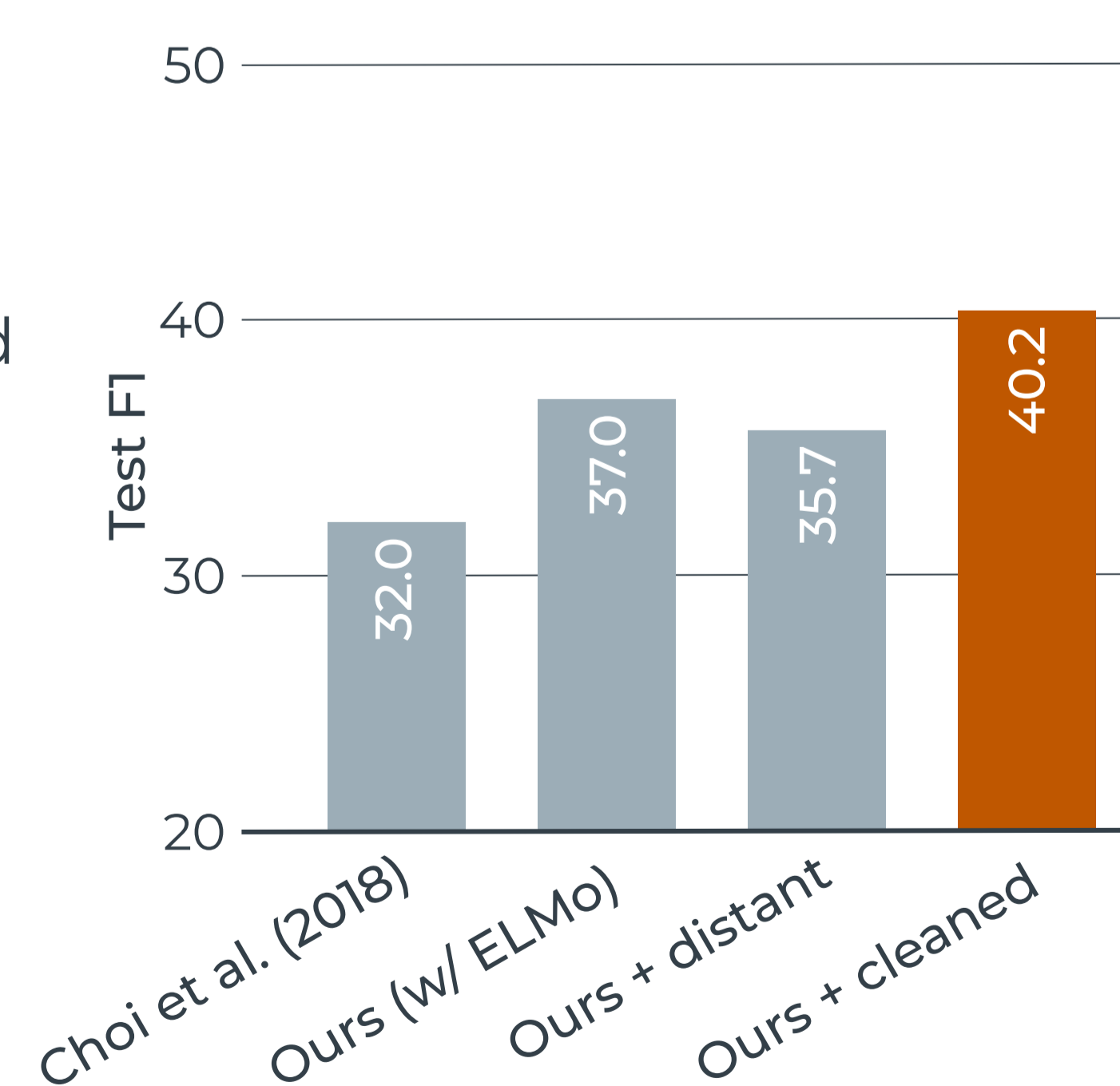
Dataset: Ultra-Fine Entity Typing (Choi et al. 2018)

1 Does denoising help?

■ We compare the performance of our model without data augmentation and with/without denoising. Also, we compare with the current SOTA model (Choi et al. 2018).

■ **Adding the distantly-labeled data lowers the performance, but denoising makes the distantly-labeled data useful.**

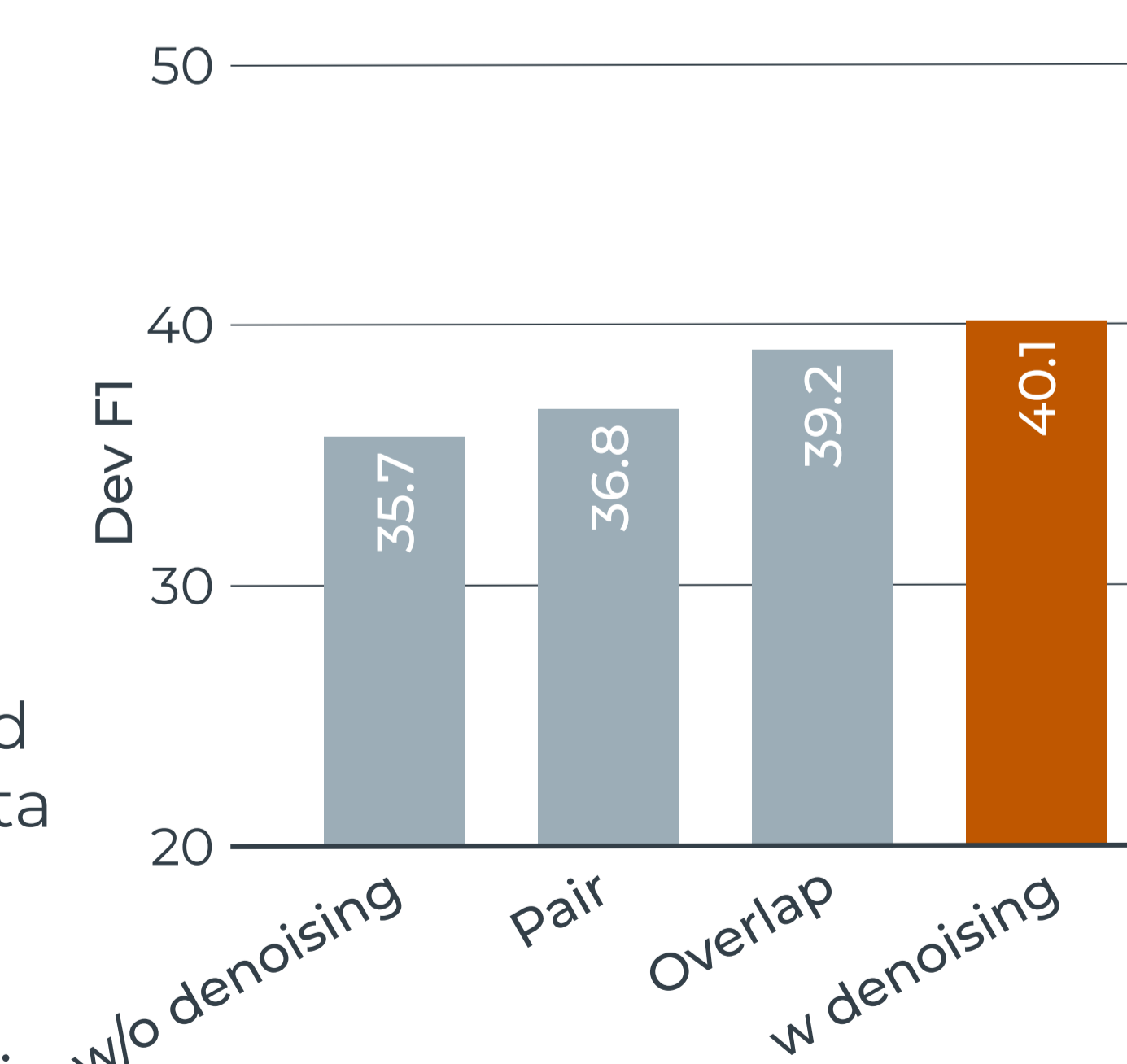
* **BERT:** BERT without data augmentation achieves 40.2 F1. BERT performs well on OntoNotes but not as well as our model with augmented training data. Using the distant data in BERT was challenging due to instability in training.



2 Comparing Denoising Models

■ We compare with simple denoising heuristics: **Pair:** look at type pair cooccurrences and use a heuristic to add types. **Overlap:** use a model trained on the manually-labeled data to predict types, treat those types as gold when they overlap with the noisy types.

■ **Our learned denoising techniques outperform heuristic baselines.**



See our paper for results on the OntoNotes dataset