Ultra-Fine Entity Typing

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Entity Typing

1. Bill robbed John, and he was arrested shortly afterwards.
2. Nvidia hands out Titan V for free to AI researchers.

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Entity Typing

PER PER

1. Bill robbed John, and he was arrested shortly afterwards.
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ORG OBJ

- Information extraction [Ling 12, YY17]
- Coreference resolution [Durrett 14]
- Entity linking [Durrett 14, Raiman 18]
- Question answering [Yavuz 16]

Scaling Up Entity Typing: Mention Coverage

PER PER

1. Bill robbed John, and he was arrested shortly afterwards.
2. Nvidia hands out Titan V for free to AI researchers.

ORG OBJ

Prior Work

Bill
Nvidia
Titan V
John

This Work

Bill
Nvidia
Titan V
John
He
AI researchers

Scaling Up Entity Typing: Mention Coverage

1. Bill (PER) robbed John (PER), and he was arrested shortly afterwards.
2. Nvidia (ORG) hands out Titan V (OBJ) for free to AI researchers.

Challenge 1 :

Reasoning over diverse, challenging mention strings

Scaling Up Entity Typing: Type Coverage

1. Bill robbed John, and he was arrested shortly afterwards.
2. Nvidia hands out Titan V for free to AI researchers.

PER PER ORG OBJ

Scaling Up Entity Typing: Type Coverage

PER, Victim | PER, Criminal | PER, Criminal

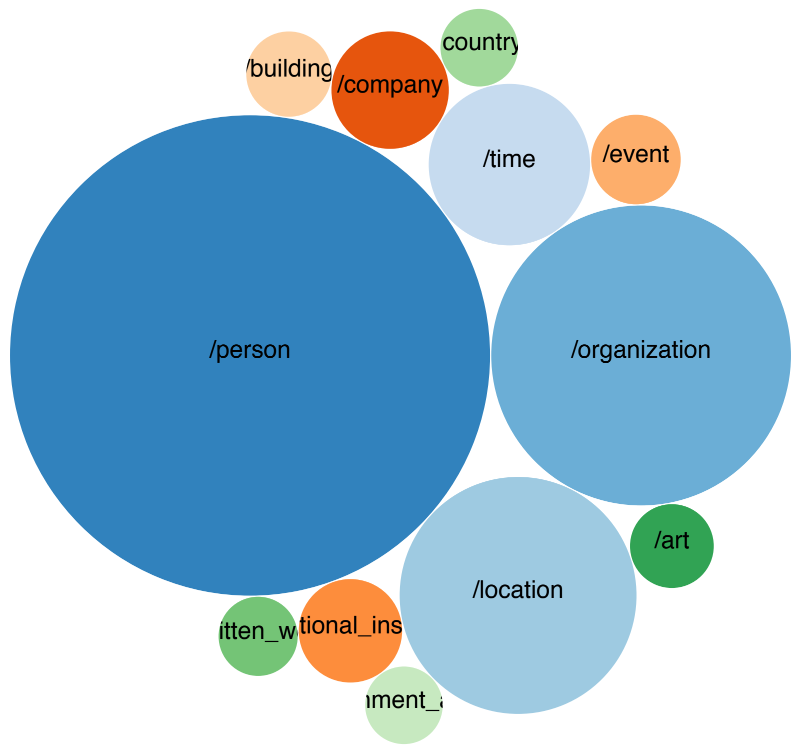
1. Bill robbed John, and he was arrested shortly afterwards.
2. Nvidia hands out Titan V for free to AI researchers.

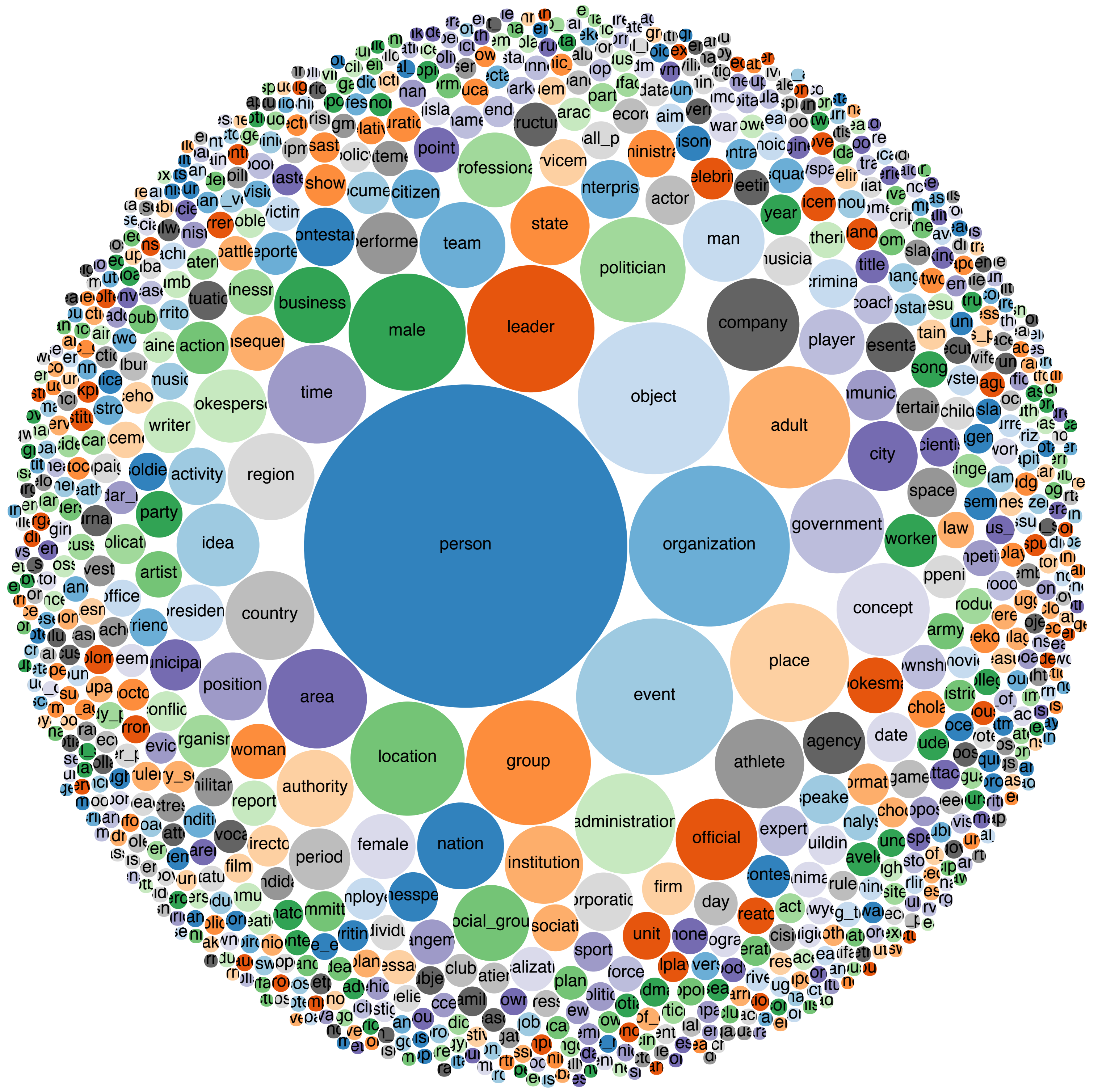
ORG, Company | OBJ, Product, Electronics | PER, Researcher, Professional

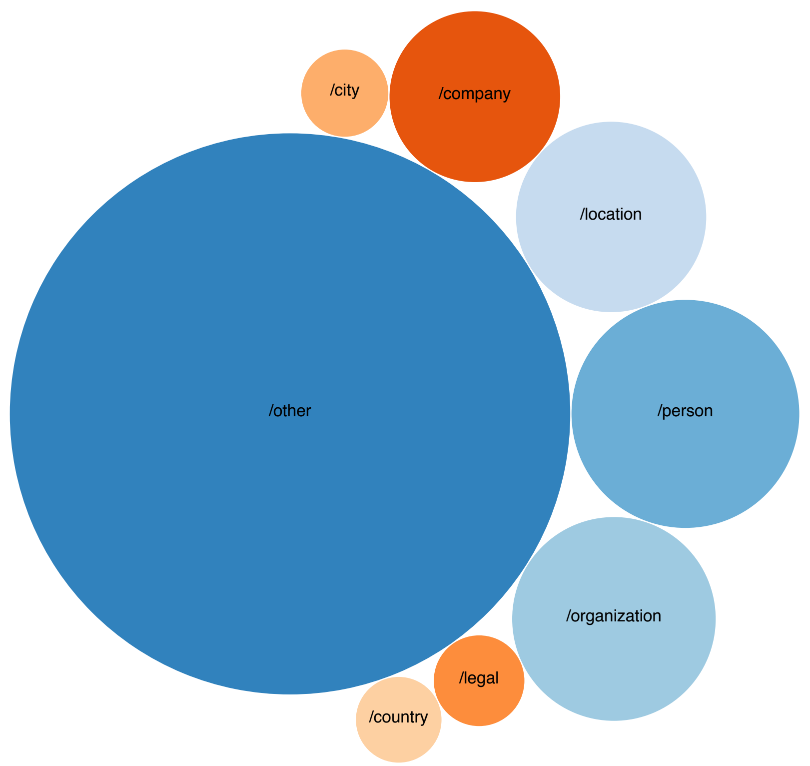
Any frequent nouns from dictionary is allowed as a type (10K vocabulary)

Challenge 2 :

Very large label space







This Talk

- Task: Ultra-Fine Entity Typing
    - Covers all entity mentions
    - Allows all concepts as types
- New Data:
    - Crowdsourcing ultra fine-grained typing data
    - New source of distant supervision
- New Results:
    - Multitask loss for predicting ultra-fine types
    - Sets state-of-the-art results on existing benchmark

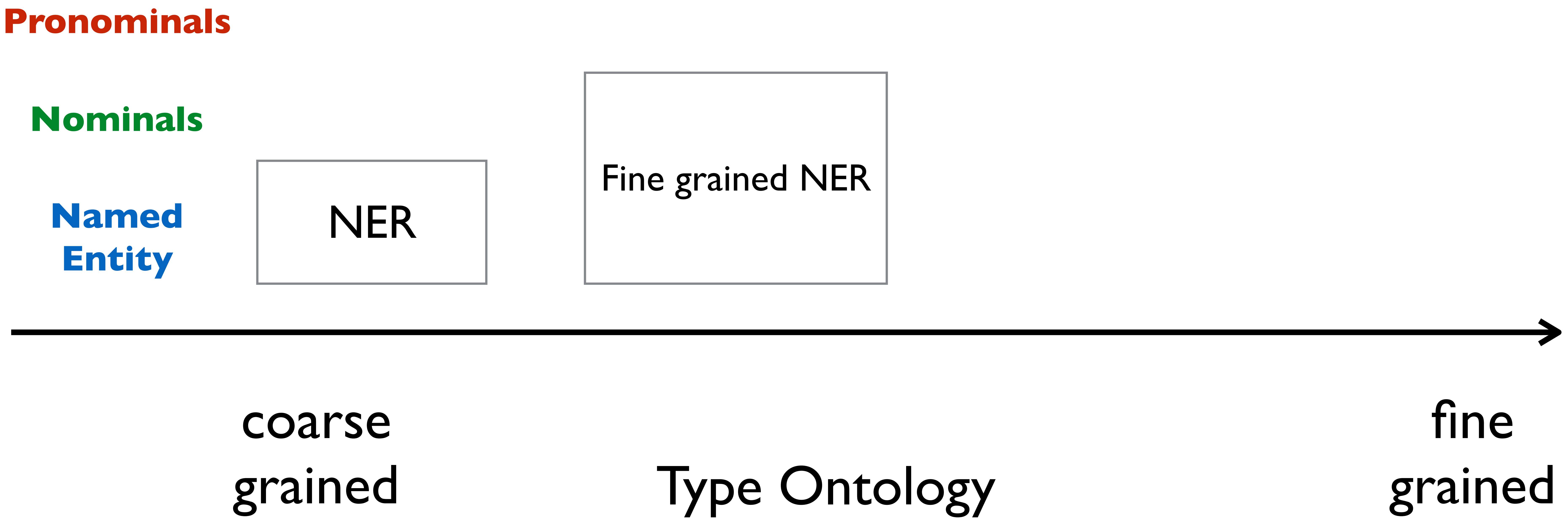
Outline

- New Task: Ultra-Fine Entity Typing
- **Related Work**
- Crowdsourcing Ultra-Fine labels
- Distant Supervision
- Model and Experiments

Fine grained NER

He was elected over John McCain

Person, Politician



Fine grained NER

He was elected over John McCain

FIGER [Ling 12]	OntoNotes [Gillick 14]	TypeNet [next talk]	Ours
112 types 2 hierarchy level	89 types 3 hierarchy level	2K types 14 hierarchy level	10K types No hierarchy

coarse grained → fine grained

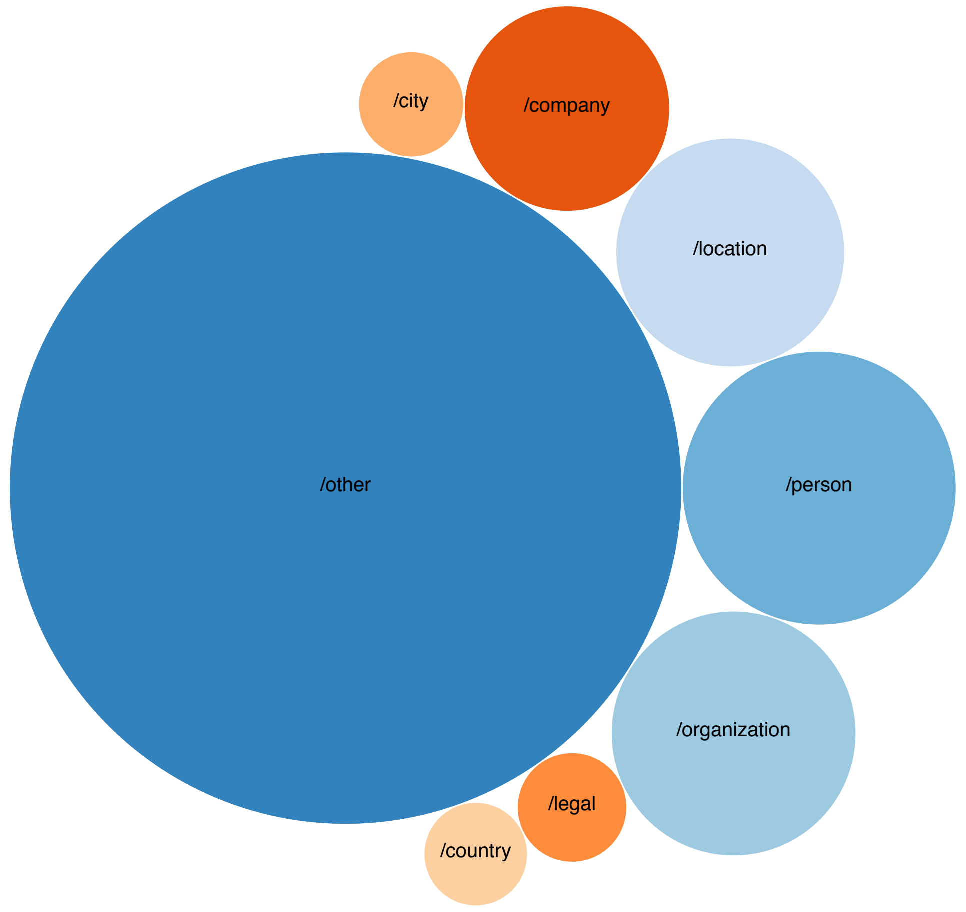
Type Ontology

Label Coverage Problem

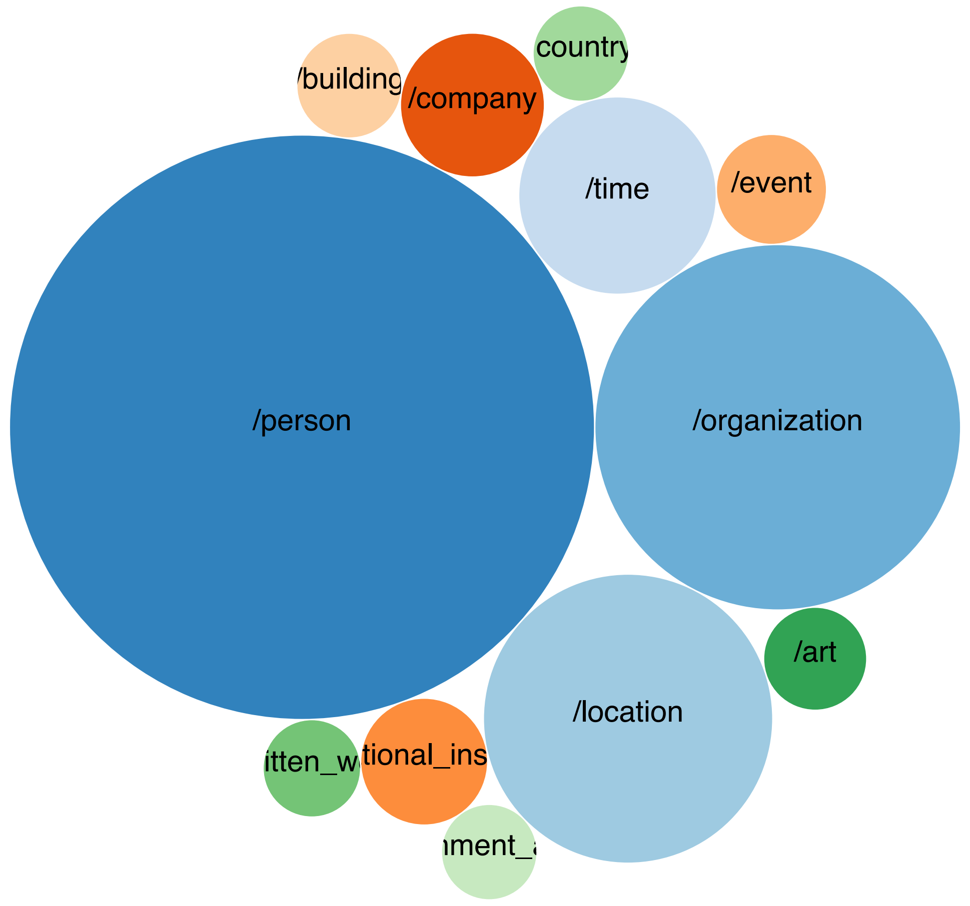
- In both, top 9 types covers over 80% of the evaluation data.
- In OntoNotes, 52% of mentions was marked as “Other”.

Paris Agreement | Security Mortgages | Oil

Label Distribution In Evaluation Data

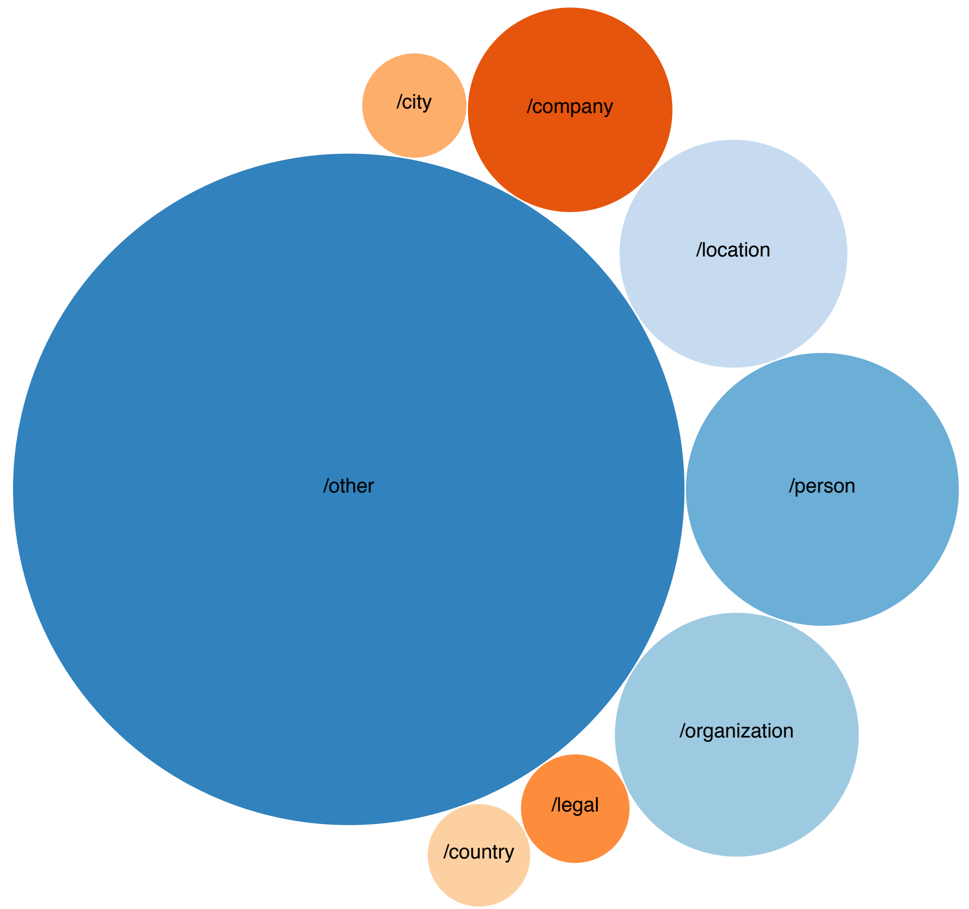


OntoNotes [Gillick 14]

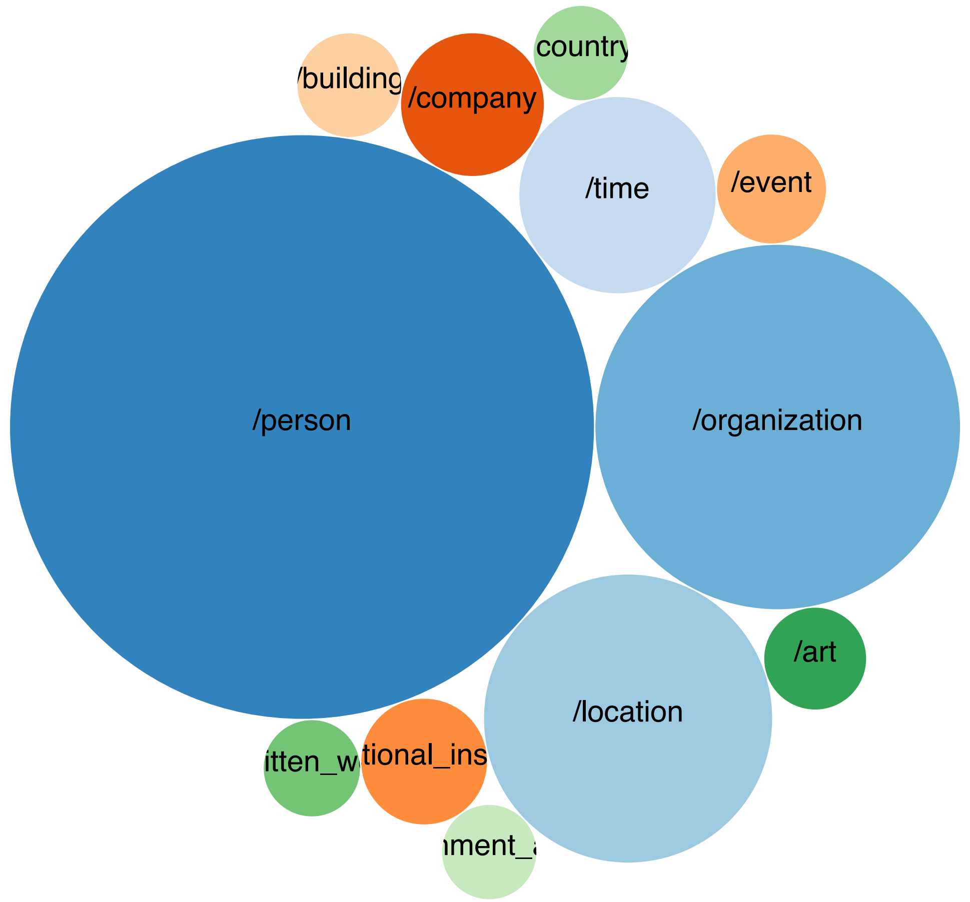


FIGER [Ling 12]

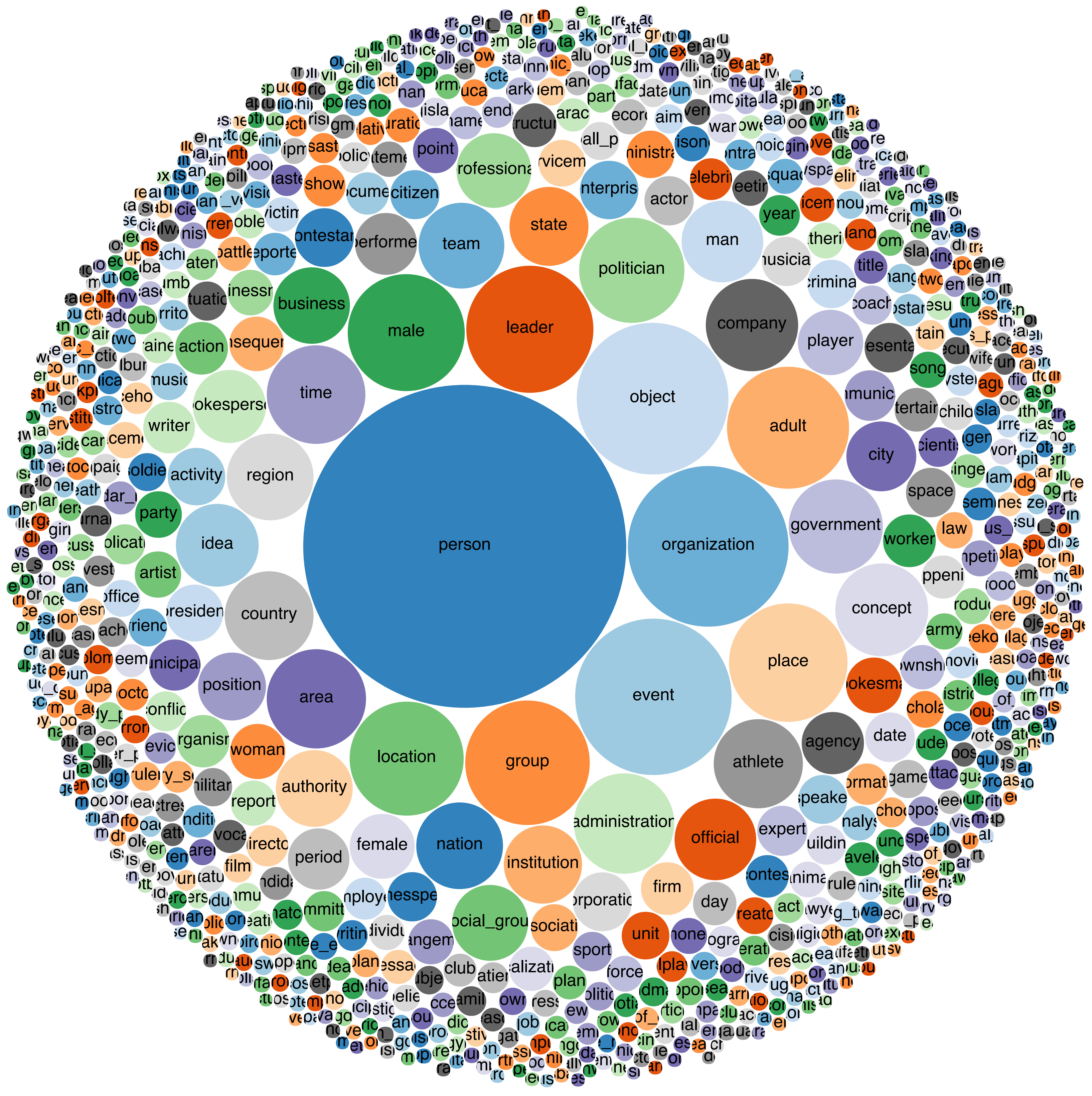
Label Distribution In Evaluation Data



OntoNotes [Gillick 14]



FIGER [Ling 12]



Ours

This Talk

- New Task: Ultra-Fine Entity Typing
- Related Work
- **Crowdsourcing Ultra-Fine labels**
- Distant Supervision
- Model and Experiments

Automatic Mention Detection

- Maximal noun phrases from the constituency parser (Manning et al 14)
- Mentions from the co-reference resolution system (Lee et al 17)

In 1817, in collaboration with David Hare, he set up the Hindu College.

In [1817], in [collaboration with David Hare], [he] set up [the Hindu College].

Crowdsourcing Type Labels

Context	General	Specific	
Michael Buble putting career ‘on hold’ after son’s cancer diagnosis	Person	Parent	Professional

- Label space: **10K** most common nouns from Wiktionary
- Five crowd workers provide labels per each example

Crowdsourcing Type Labels

Context	General	Specific	
Michael Buble putting career ‘on hold’ after son’s cancer diagnosis	Person	Parent	Professional

- Label space: **10K** most common nouns from Wiktionary
- Five crowd workers provide labels per each example
- Collected 6K examples, 5.2 labels per example.
  - On average, 1 general type, 4 fine types

Diverse Fine-grained Types

town, company, space, mountain, work, murderer, journalist, army, outcome, politician, duty, document, general_of_the_army, women, employment, community, ballot, stage, host, son, friend, investigator, inflation, film, injection, album, music_group, food, milestone, chancellor, village, philosopher, military, medicine, river, health, incident, male, actor, citizenship, language, prisoner, exhibition, cricketer, attack, singer, battle, religious_leader, economy, vice_president, man, benefit, agency, deity, painting, bread, effect, university, power, direction, competition, civilian, reviewer, worker, member, cinema, talk, thinker, contract, landmark, fashion_designer, citizen, investor, territory, train, moss, concert, team, troglodyte, consequence, staff, subject, professor, use, tournament, planet, city, coach, date, curator, poet, rule, goddess, symptom, senator, month, weapon, parent, crime, hiding, general, position, protegee, political, religion, cell, business, designation, computer_game, promotion, disaster, historian, poll, institution, transportation, painter, free, official, traveller, year, player, beverage, performer, biographer, priest, wind, cash, race, guest, area, agreement, prison, analyst, draw, love, police, actress

Diverse Fine-grained Types

town, company, space, mountain, work, murderer, journalist, army, outcome, politician, duty, document, women, **employment**, community, ballot, stage, host, son, friend, investigator, inflation, film, injection, album, music_group, food, milestone, chancellor, village, philosopher, military, medicine, river, health, incident, male, actor, citizenship, **language**, prisoner, exhibition, cricketer, attack, singer, battle, **religious_leader,** economy, vice_president, man, benefit, agency, deity, painting, bread, effect, university, power, direction, competition, civilian, reviewer, worker, member, cinema, talk, thinker, contract, landmark, fashion_designer, citizen, investor, territory, train, moss, concert, team, troglodyte, consequence, staff, subject, professor, use, tournament, planet, city, coach, date, curator, poet, rule, goddess, symptom, senator, month, weapon, parent, crime, hiding, general, position, political, religion, cell, business, designation, **computer_game**, promotion, disaster, historian, poll, institution, transportation, painter, free, official, traveller, year, player, beverage, performer, biographer, priest, wind, cash, race, guest, area, agreement, prison, analyst, draw, love, police, actress

Diverse Fine-grained Types

town, company, space, mountain, work, murderer, journalist, army, outcome, politician,
duty, docu ... on, friend,
investigat ... chancellor,
village, ph ... tizenship,
languag ... **_leader,**
economy, ... university,
power, di ... alk, thinker,
contract, ... s, concert,
team, tro ... lanet, city,
coach, da ... n, parent,
crime, hic
comput ... portation,
painter, free, official, traveller, year, player, beverage, performer, biographer, priest,
wind, cash, race, guest, area, agreement, prison, analyst, draw, love, police, actress

- 2,300 unique types for 6K examples
- To cover 80% of labels, 429 types are needed

Data Validation

town, company, space, mountain, work, murderer, journalist, army, outcome, politician,
duty, docu… …on, friend,
investigat… …chancellor,
village, ph… …izenship,
languag… **…_leader,**
economy… …university,
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contract, … …, concert,
team, tro… …lanet, city,
coach, da… …, parent,
crime, hic…
comput… …portation,
painter, free, official, traveller, year, player, beverage, performer, biographer, priest,
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- 86% binary agreement
- Only collects labels that majority of validators (3/5) agreed

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- Related Work
- Crowdsourcing Ultra-Fine labels
- **Distant Supervision**
- Model and Experiments

1. Knowledge Base Supervision

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

1. Knowledge Base Supervision

Entity linking

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

1. Knowledge Base Supervision

Entity linking

Freebase

{ person, politician, athlete, businessman, artist, actor, author }

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

1. Knowledge Base Supervision

Types: { person, politician, athlete, businessman, artist, actor, author }

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

1. Knowledge Base Supervision

person, politician, athlete,
Types: { businessman, artist, actor, author }

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

Not context sensitive!

2. Wikipedia Supervision

Entity linking

WIKIPEDIA
The Free Encyclopedia

Arnold Alois Schwarzenegger is an Austrian-American actor, producer, businessman, investor, author, philanthropist, activist, politician and former professional body-builder.

[Arnold Schwarzenegger] gives a speech at Mission Serve's service project on Veterans Day 2010.

2. Wikipedia Supervision

Entity linking

Types: { actor, producer, businessman, investor, author, philanthropist, activist, politician }

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Still Context Insensitive

2. Wikipedia Supervision

- 4.6K unique types on 3.1M entities

Entity Name	**Type**
Pille Raadik	defender
Byco Petroleum	company
Třebešov	village, municipality
Mexican National Championship	competition
Palestinian Interest Committee	movement
Giovanni Paolo Lancelotti	canonist

Supervision Summary

Source	Preprocessing	Type Granularity	Context Dependent	Entity Coverage
Knowledge base	Entity linking	Fine	X	Good
Wikipedia	Entity linking, Parser	Finer	X	Better

3. Head Word Supervision

- [Controversial judge James Pickles] sentences Tracey Scott to six months in prison after she admitted helping shoplifter.

Using a head word from original noun phrase as a source of supervision.

3. Head Word Supervision

Types: { Judge }

- [Controversial judge James Pickles] sentences Tracey Scott to six months in prison after she admitted helping shoplifter.

  Using a head word from original noun phrase as a source of supervision.

3. Head Word Supervision

- Parse Errors:

  [Consent **forms** , Institutional Review Boards,] peer review committees and data safety committees did not exist decades ago.

- Idiomatic Usages:

  In [**addition**] there's an USB 1.1 port that can be used to attach to a printer.

Supervision Summary 1

Source	Preprocessing	Type Granularity	Context Dependent	Entity Coverage
KB	Entity linking	Fine	X	Good
Wikipedia	Entity linking, Parser	Finer	X	Better
Headword	Dependency Parser	Finest	O	Best

Supervision Summary II

Source	Cover	Accuracy*	Scale
KB	Named Entities	80%	2.5 M
Wikipedia	Named Entities	77%	2.7 M
Headword	Nominals	77%	20 M

* Manual examination on 200 examples

This Talk

- New Task: Ultra-Fine Entity Typing
- Related Work
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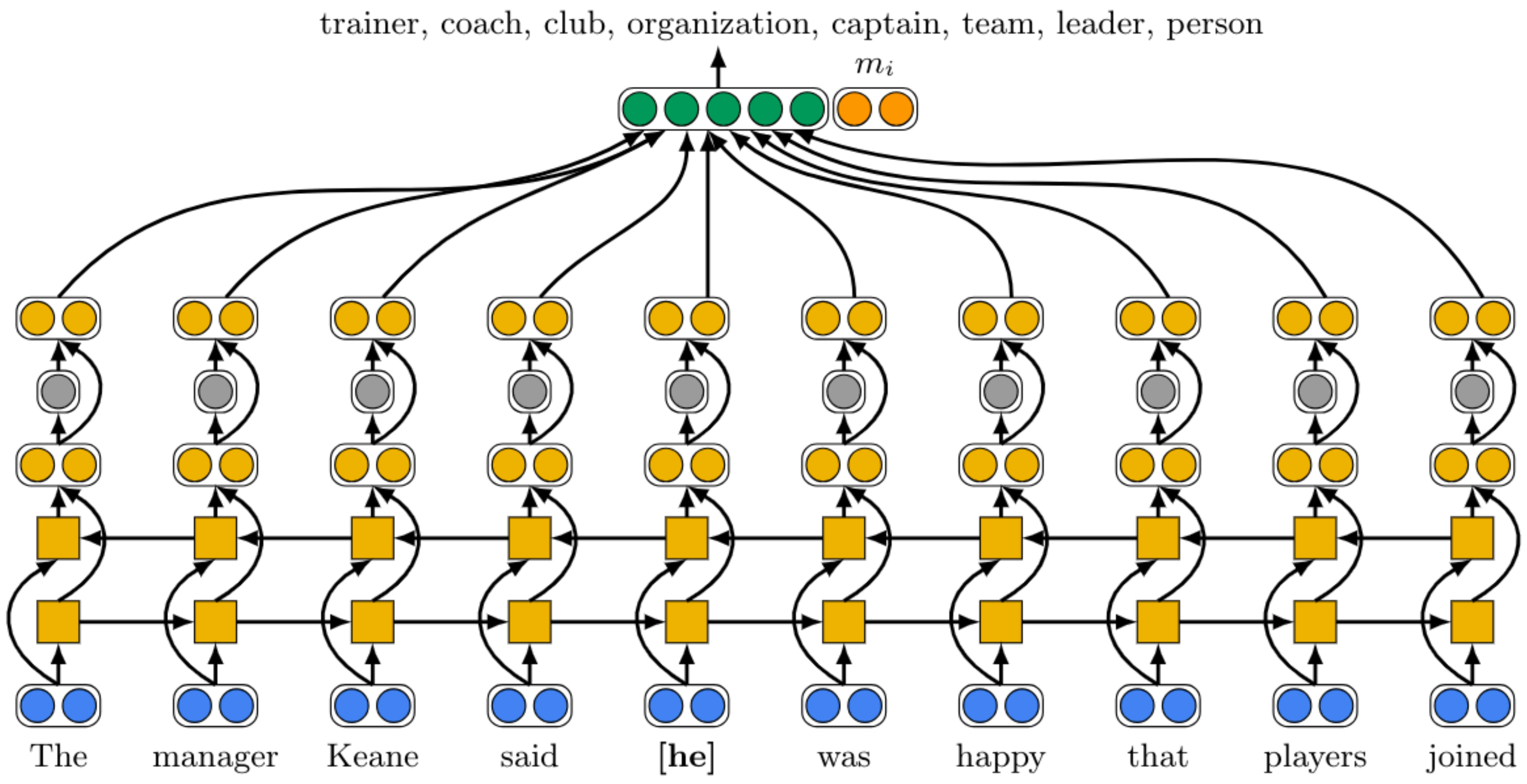
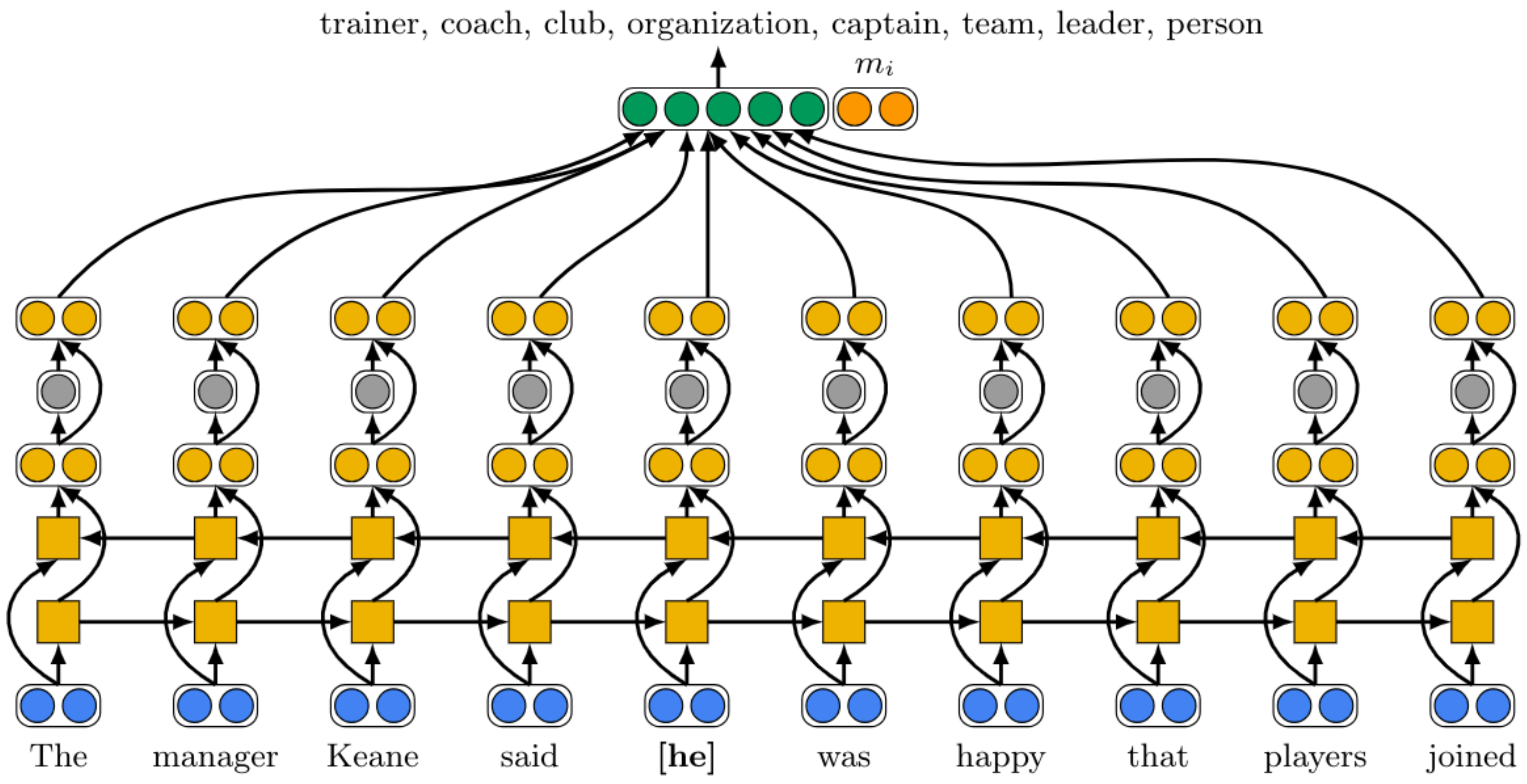
- Distant Supervision
- **Model and Experiments**

Bidirectional RNN Model



- Closely follow previous model for fine-grained NER [Shimaoka 17]
- Improved Mention Representation (with character-level CNN)
- Single LSTM to cover left, right context and mention

Bidirectional RNN Model



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- Improved Mention Representation (with character-level CNN)
- Single LSTM to cover left, right context and mention

Multitask Objective

- Binary classification log likelihood objective for each label

$$J = -\sum_i t_i \cdot \log(y_i) + (1 - t_i) \cdot \log(1 - y_i)$$

- Sum loss at different type granularities

$$\begin{aligned} J_{\text{all}} &= J_{\text{general}} \cdot \mathbb{1}_{\text{general}}(t) \\ &+ J_{\text{fine}} \cdot \mathbb{1}_{\text{fine}}(t) \\ &+ J_{\text{ultra}} \cdot \mathbb{1}_{\text{ultra}}(t) \end{aligned}$$

Experiments

- Datasets
  - Ultra-Fine Entity Typing Dataset
  - OntoNotes Fine-Grained Typing Dataset (Gillick et al 14)
- Evaluation Measure
  - Macro-averaged Precision, Recall, F1
  - Mean Reciprocal Rank

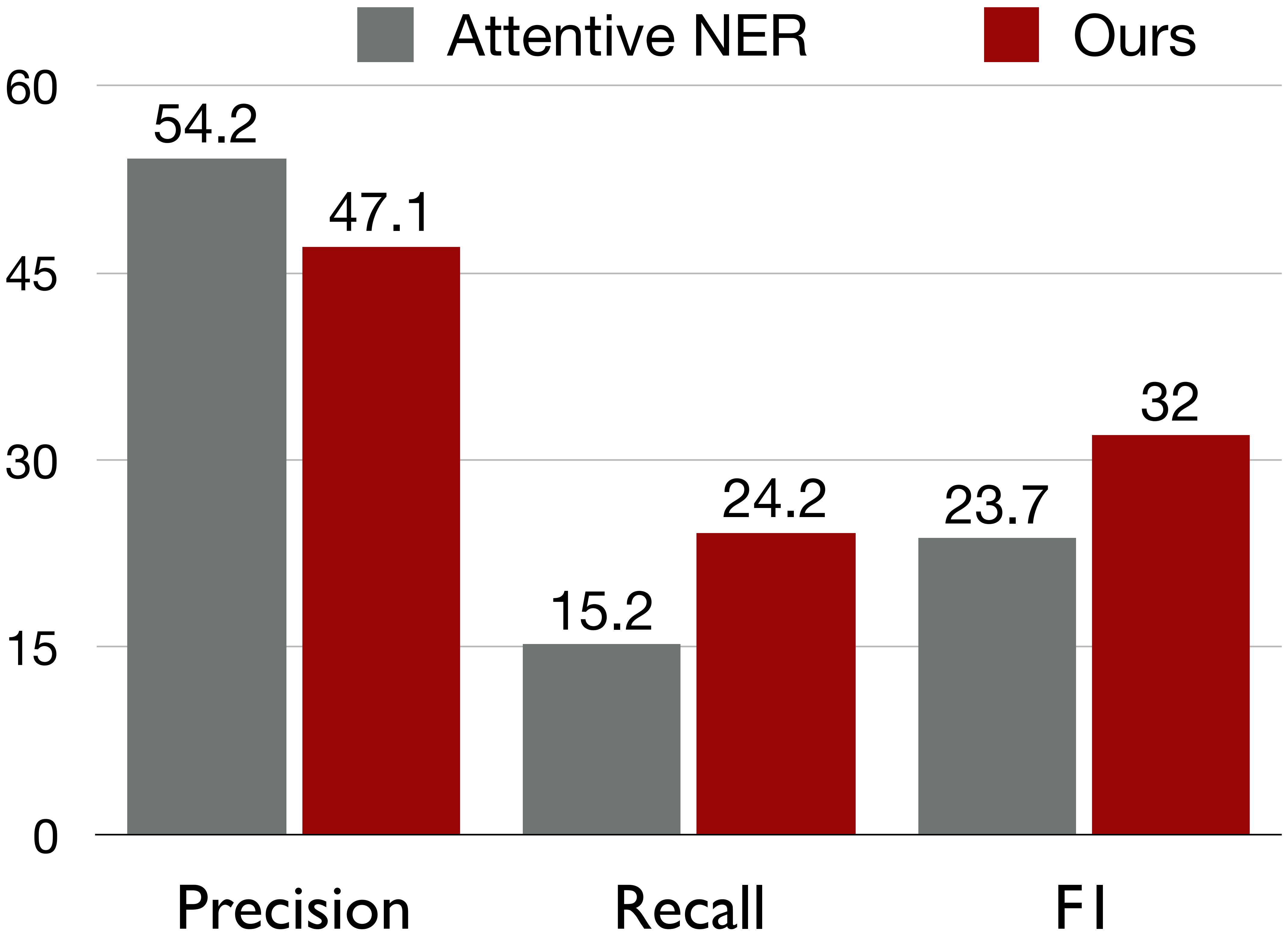
Data Setup

	Ultra-Fine Entity Typing Benchmark	OntoNotes Dataset (Gillick et al 14)
Train	2K crowdsourced	2.69M KB supervision
	20M Headword	2.1M Headword supervision
	5M Entity Linking	0.6M Wikipedia supervision
Dev	2K crowdsourced	2K crowdsourced
Test	2K crowdsourced	8K crowdsourced

Comparison Systems

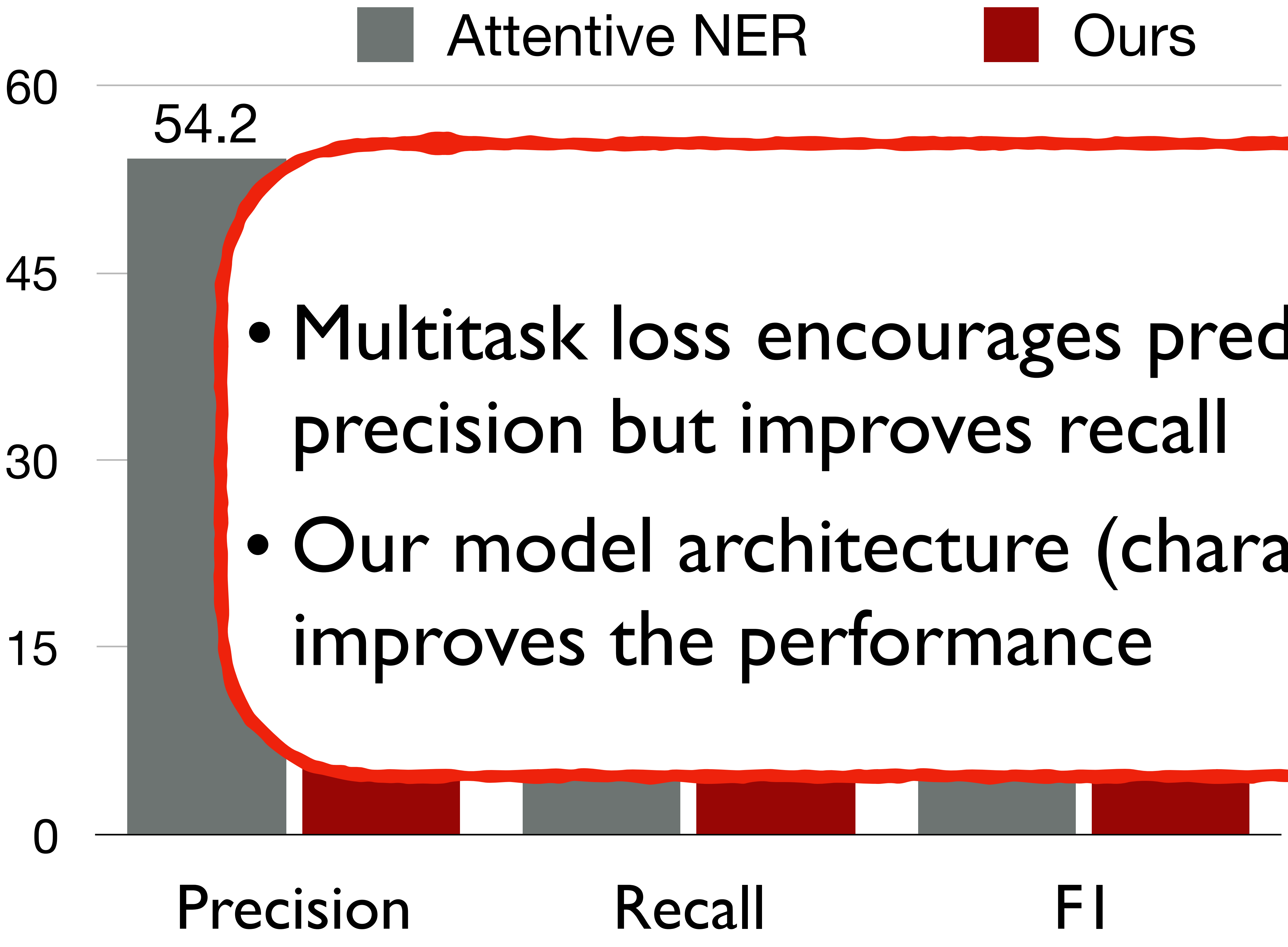
- AttentiveNER Model [Shimaoka et al., 2017]
- Our model
  - Ablation on the different sets of supervision

Ultra-Fine Entity Typing



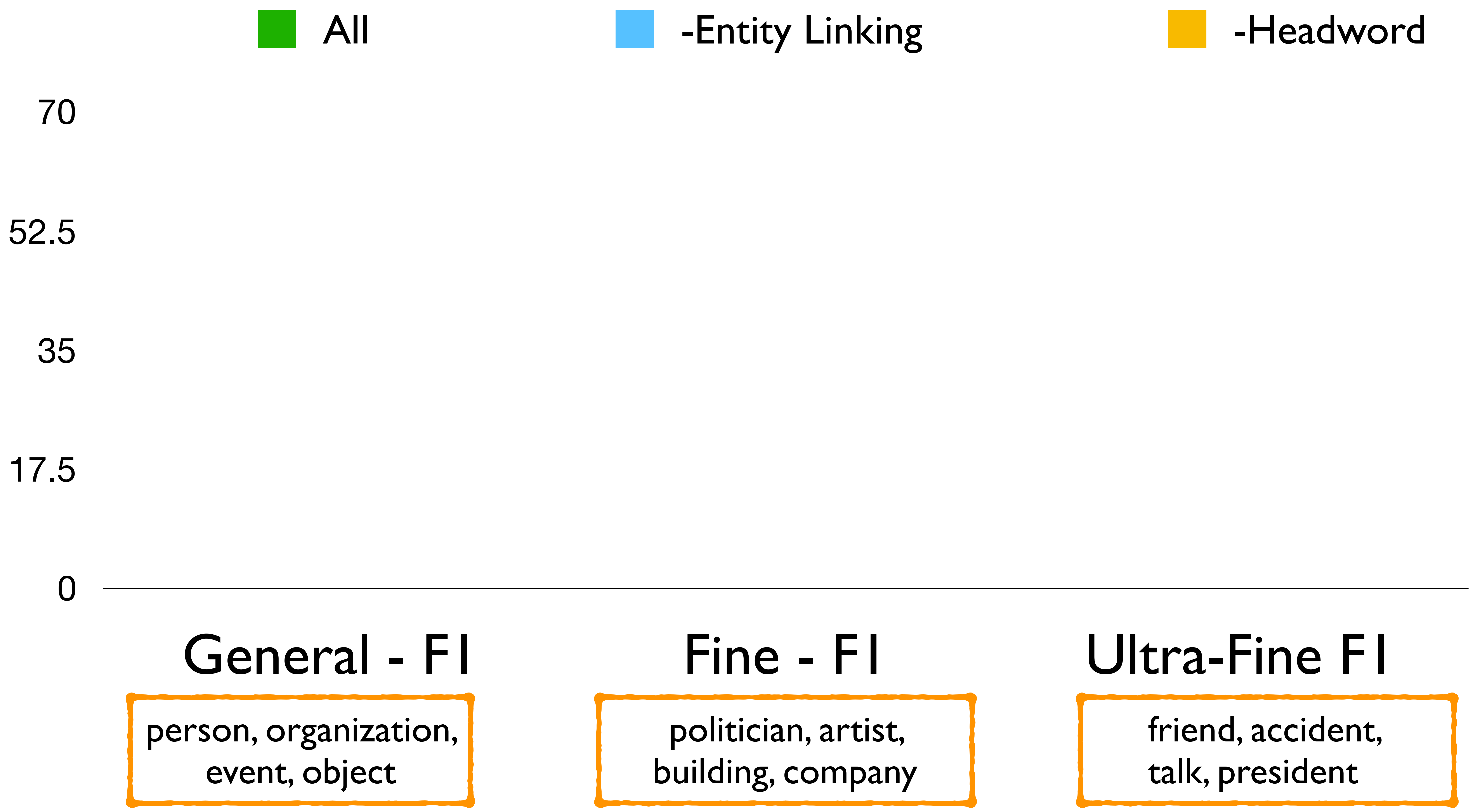
	Mean Reciprocal Rank (MRR)
AttentiveNER	0.223
Ours	0.234

Ultra-Fine Entity Typing

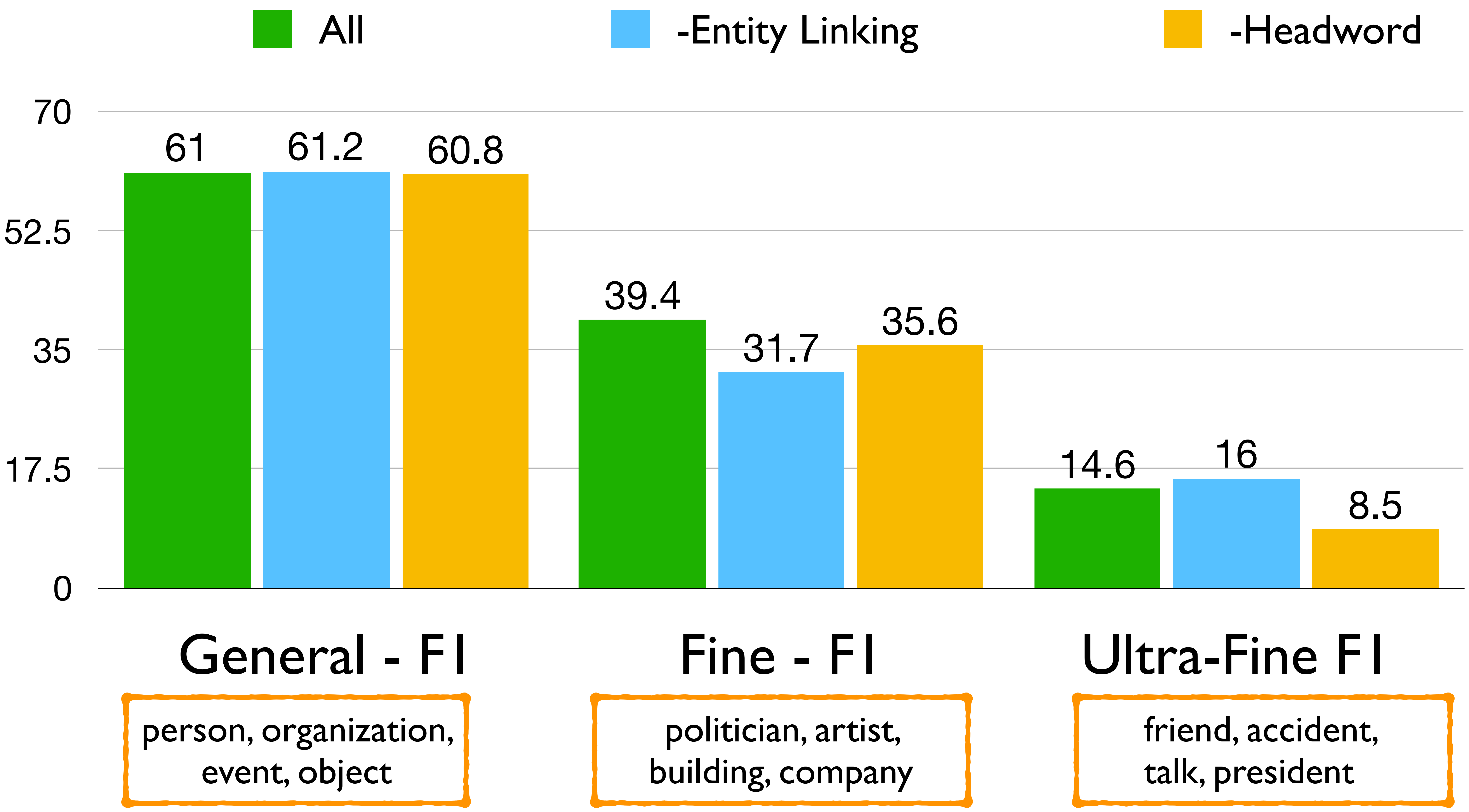


- Multitask loss encourages prediction on fine-grained labels, hurting precision but improves recall
- Our model architecture (character-level CNN, single LSTM) improves the performance

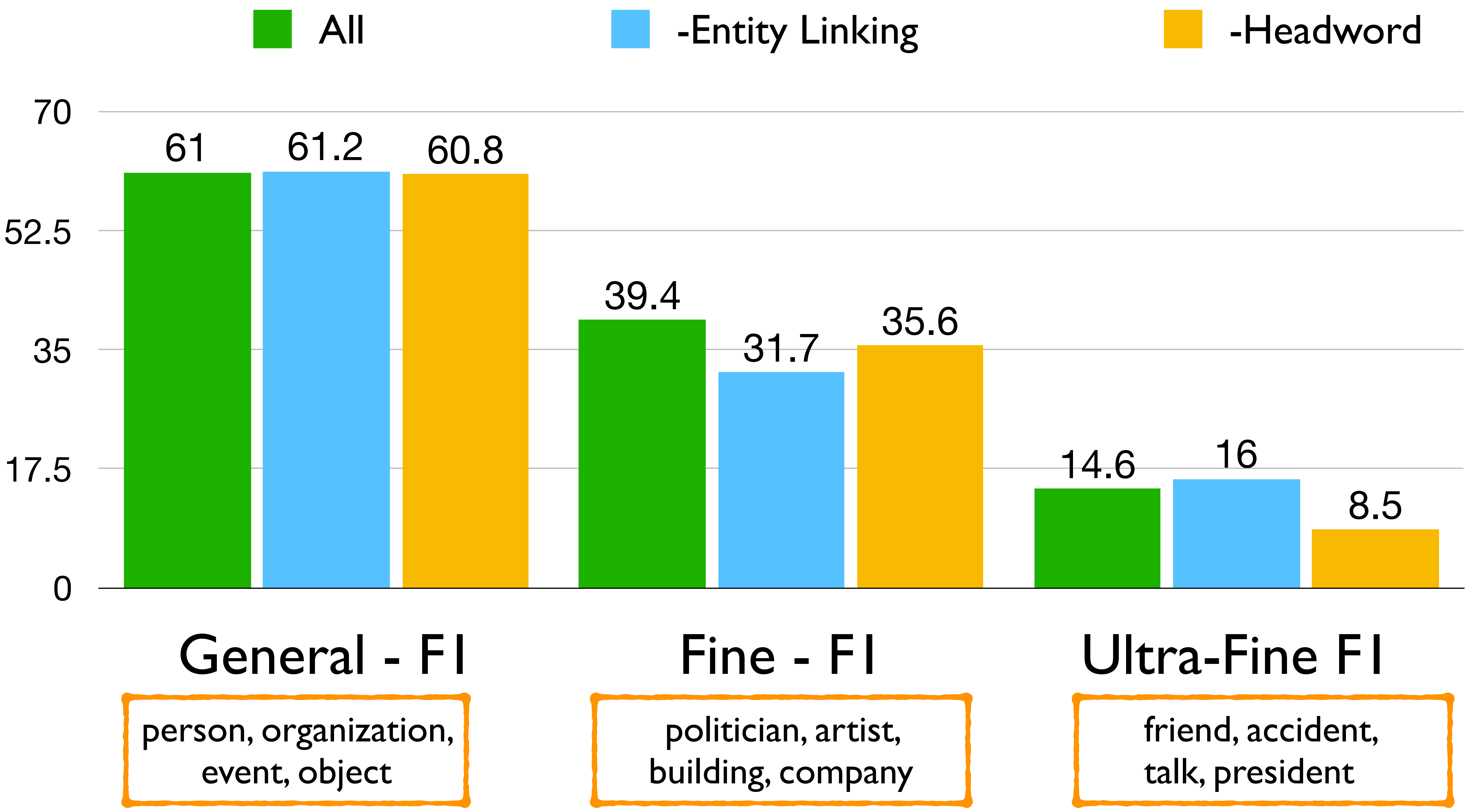
Ablation Study



Ablation Study

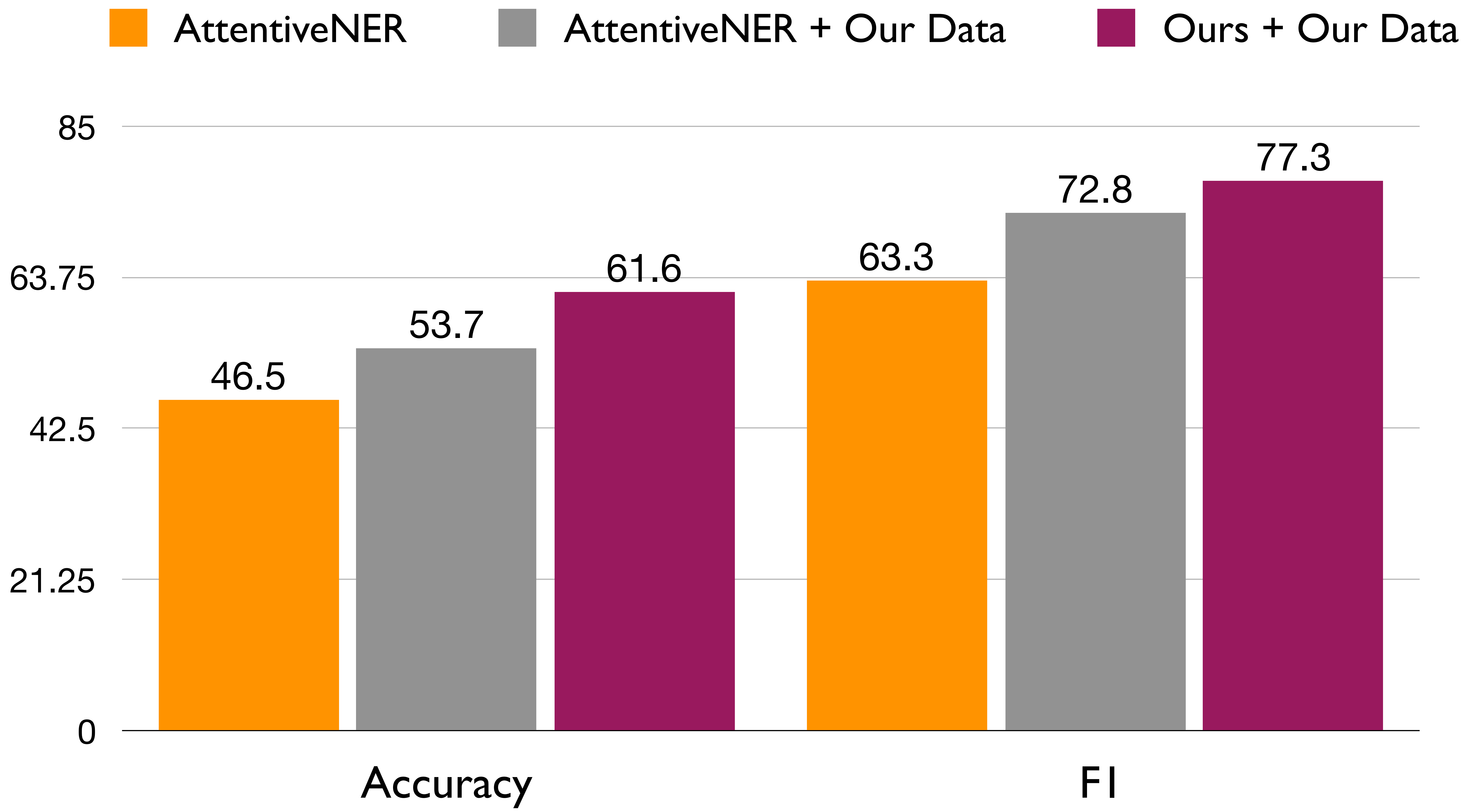


Ablation Study



- Finer types are harder to predict
- Headword is more important for ultra-fine types, entity linking for fine types.

OntoNotes Fine-grained Types



Example Outputs

Example Annotation	Bruguera said {**he**} had problems with his left leg and had grown tired early during the match . **person, athlete, player, adult, male, contestant**
Prediction	**person, athlete, player, adult, male, contestant**, defendant, man
Example Annotation	{**The explosions**} occurred on the night of October 7 , against the Hilton Taba and campsites used by Israelis in Ras al-Shitan. **event** *calamity, attack, disaster*
Prediction	**event,** accident
Example Annotation	Similarly , Enterprise was considered for refit to replace Challenger after {**the latter**} was destroyed , but Endeavour was built from structural spares instead . *object, spacecraft, rocket, thing, vehicle, shuttle*
Prediction	event
Context Annotation	“ There is a wealth of good news in this report , and I ’m particularly encouraged by the progress {**we**} are making against AIDS , ” HHS Secretary Donna Shalala said in a statement. **government, group,** *organization,hospital,administration,socialist*
Prediction	**government, group**, person

More Examples at: **https://homes.cs.washington.edu/~eunsol/_site/acl18_sample_output.html**

Example Outputs

Example Annotatio	Bruguera said {**he**} had problems with his left leg and had grown tired early during the match .
Predictio	
Exampl Annotati	by
Predictio	
Exampl Annotati	d ,
Predictio	
Contex Annotatio	e}
Prediction	**government, group**, person

- Evaluation is still challenging : annotation coverage can be improved
- Model suffers from recall problem
- Joint modeling of type labels would be helpful

More Examples at: **https://homes.cs.washington.edu/~eunsol/_site/acl18_sample_output.html**

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Thank you!

Any Questions?

Data & Code at the project website