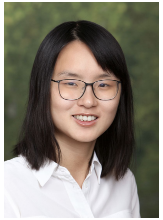
PRINCETON NLP

A Frustratingly Easy Approach for Entity and Relation Extraction

Zexuan Zhong



Danqi Chen

Princeton University

Entity and Relation Extraction: Problem Definition

Input

Bill Smith was in the hotel room

Named Entity Recognition

Bill Smith	hotel	room
PER	FAC	FAC

Relation Extraction

Bill Smith (PER) $\xrightarrow{\text{PHYS}}$ room (FAC)

hotel (FAC) $\xleftarrow{\text{PART-WHOLE}}$ room (FAC)

Entity and Relation Extraction: Problem Definition

Input: a piece of unstructured text

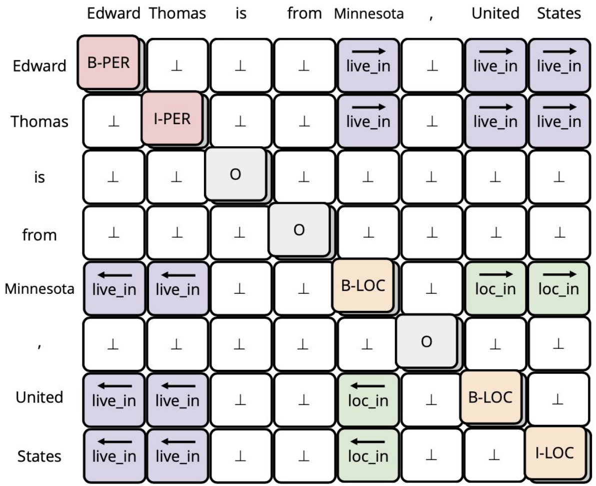
- A sequence of tokens $X = x_1, \ldots, x_n$
  - a set of spans $S = \{s_1, \ldots, s_m\}$

Output:

- A set of entities: $Y_e = \{(s_i, e) : s_i \in S, e \in \mathcal{E}\}$
  - *s*: span, *e*: entity type
- A set of relations: $Y_r = \{(s_i, s_j, r) : s_i, s_j \in S, r \in \mathcal{R}\}$
  - *s*: subject/object span, *r*: relation type

Existing Approaches (2014+)

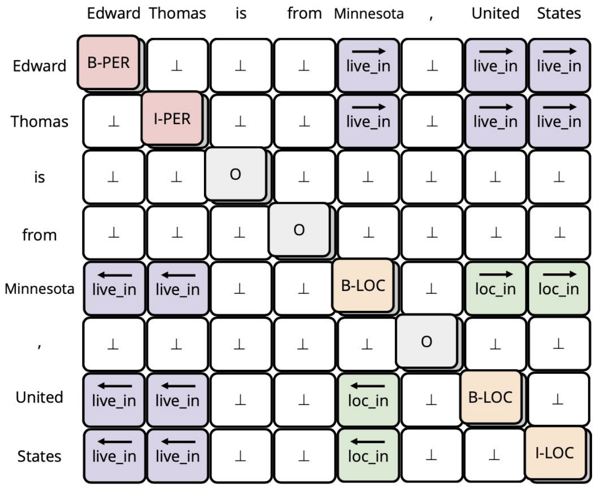
Existing Approaches (2014+)



Structured Prediction

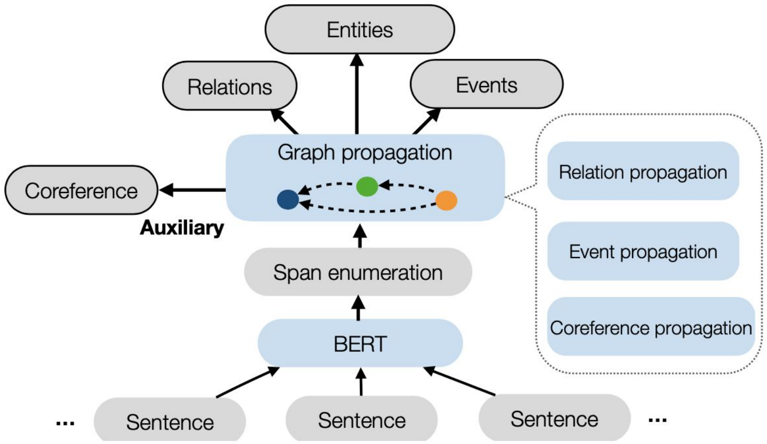
Li and Ji, 2014; Zhang et al., 2017; Katiyar and Cardie, 2017;
Li et al., 2019; Wang and Lu, 2020

Existing Approaches (2014+)



Structured Prediction

Li and Ji, 2014; Zhang et al., 2017; Katiyar and Cardie, 2017;
Li et al., 2019; Wang and Lu, 2020



Multi-task Learning

Miwa and Bansal, 2016; Bekoulis et al., 2018; Luan et al., 2019;
Wadden et al., 2019; Lin et al., 2020

This Work

1. **Our model: PURE**
    - A **pipelined** approach outperforming all previous joint models!
2. **Why does it work well?**
    - **Understanding** modeling choices between entity and relation extraction
3. **An efficient approximation model w/ large speedup**

This Work

1. **Our model: PURE**
    - A **pipelined** approach outperforming all previous joint models!
2. **Why does it work well?**
    - **Understanding** modeling choices between entity and relation extraction
3. **An efficient approximation model w/ large speedup**

Entity Model

Input

Bill Smith was in the hotel room

Output

Bill Smith — PER

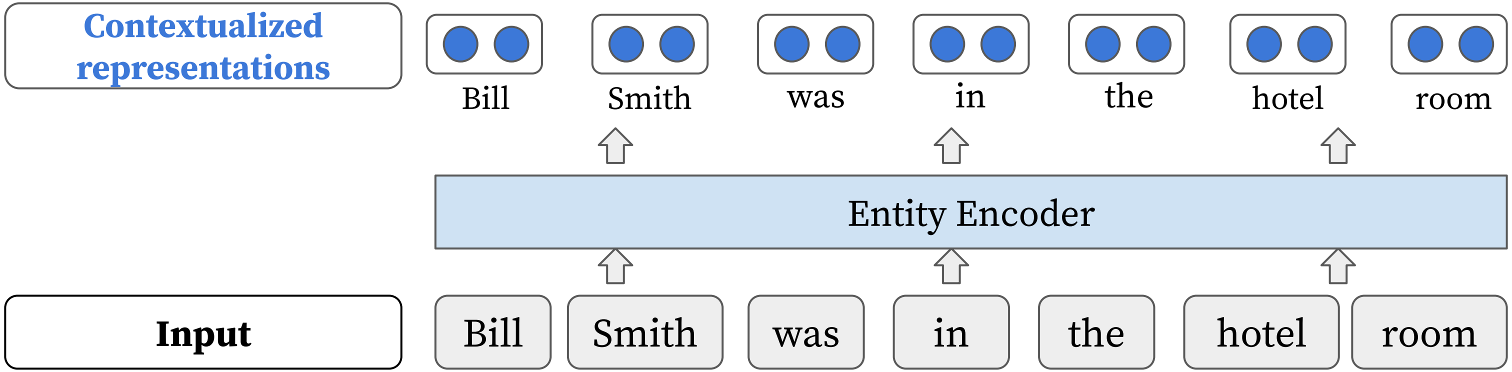
hotel — FAC

room — FAC

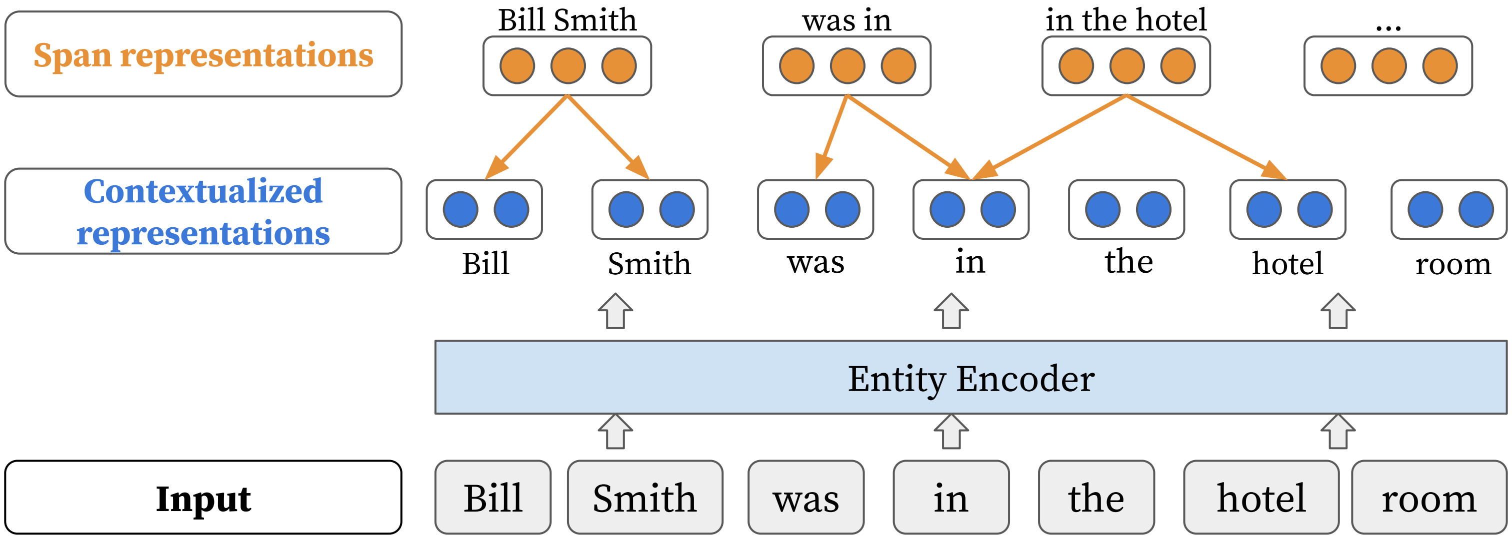
Entity Model

Input Bill Smith was in the hotel room

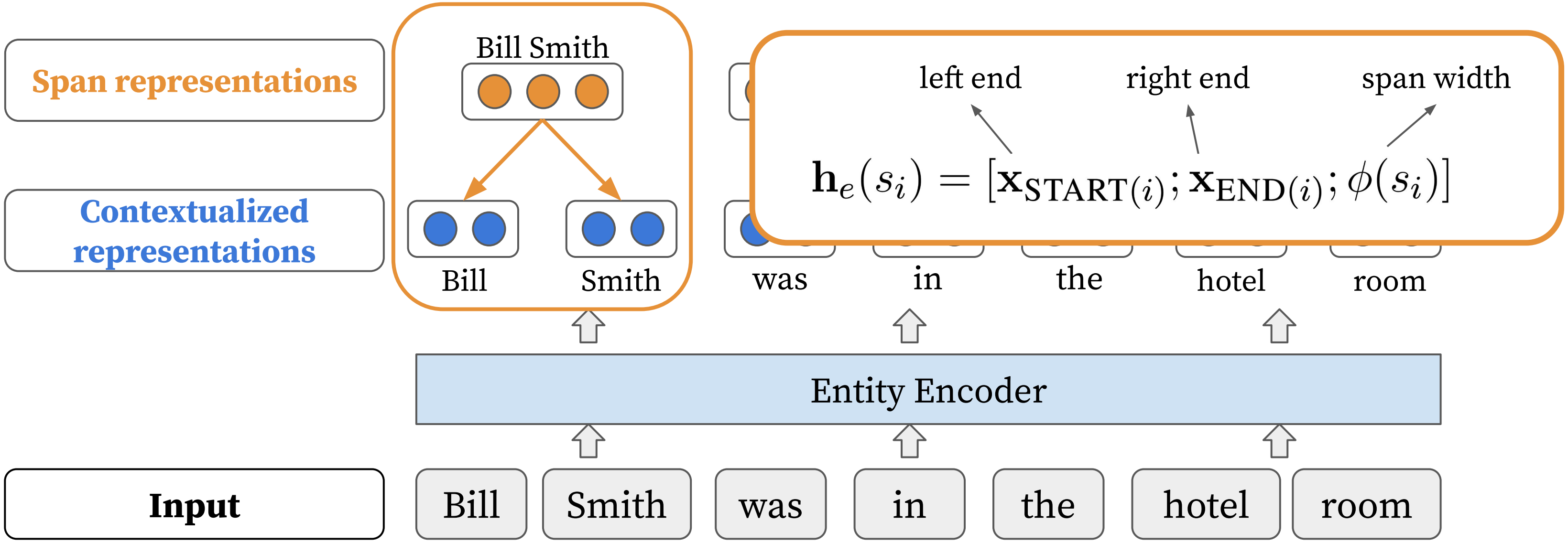
Entity Model



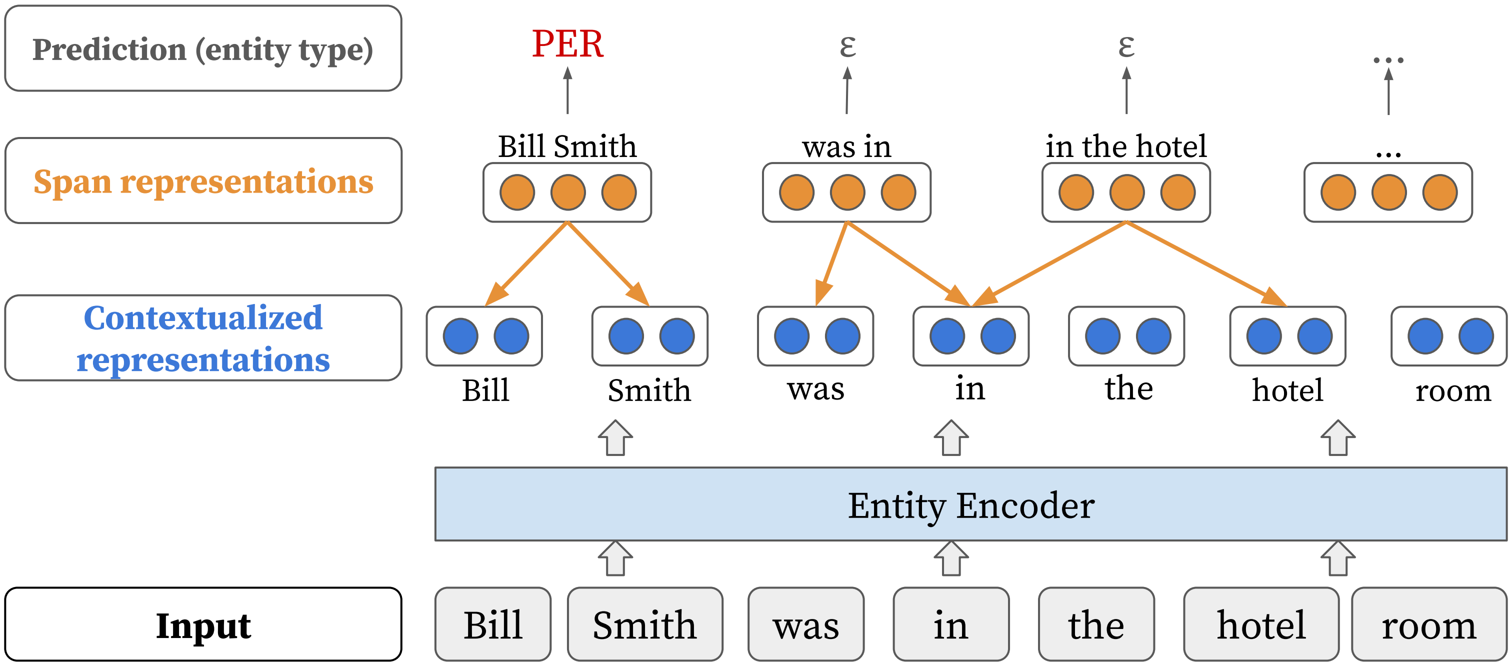
Entity Model



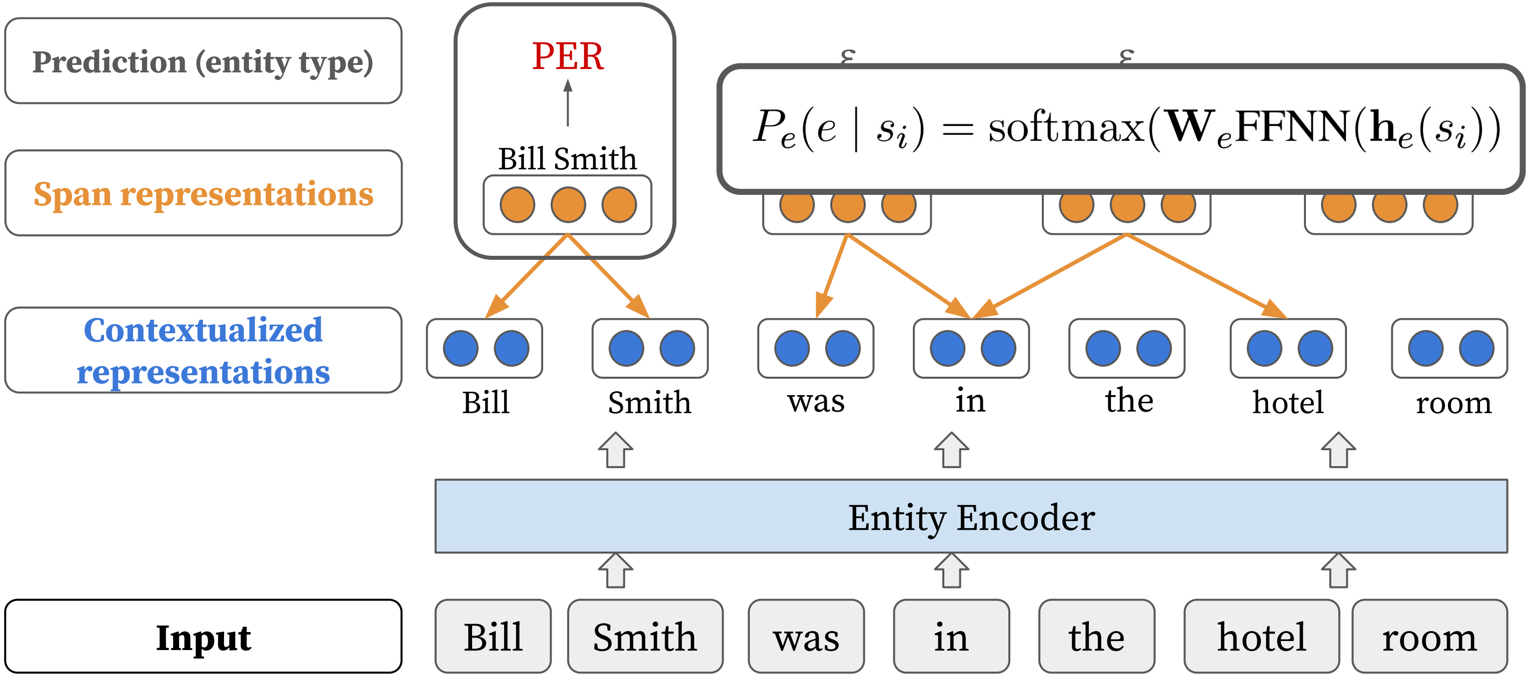
Entity Model



Entity Model

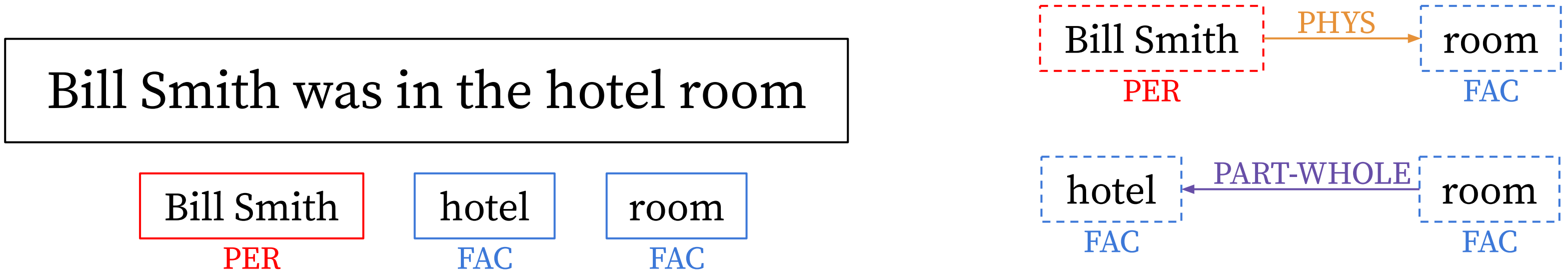


Entity Model



Relation Model

Input **Output**



Relation Model: Inserting Markers

Bill Smith was in the hotel room

PER FAC FAC

Bill Smith hotel

PER FAC

Relation Model: Inserting Markers

Bill Smith was in the hotel room

PER FAC FAC

Bill Smith hotel

PER FAC

[S:PER] Bill Smith [/S:PER] was in [O:FAC] hotel [/O:FAC] room

Relation Model: Inserting Markers

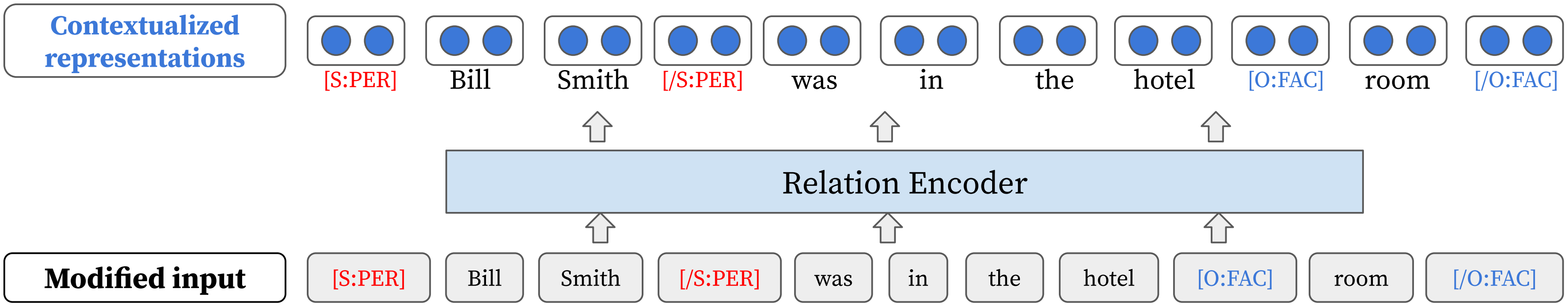
Bill Smith (PER) was in the hotel (FAC) room (FAC)

Bill Smith (PER)	hotel (FAC)	[S:PER] Bill Smith [/S:PER] was in [O:FAC] hotel [/O:FAC] room
Bill Smith (PER)	room (FAC)	[S:PER] Bill Smith [/S:PER] was in hotel [O:FAC] room [/O:FAC]
hotel (FAC)	room (FAC)	Bill Smith was in [S:FAC] hotel [/S:FAC] [O:FAC] room [/O:FAC]
…		…

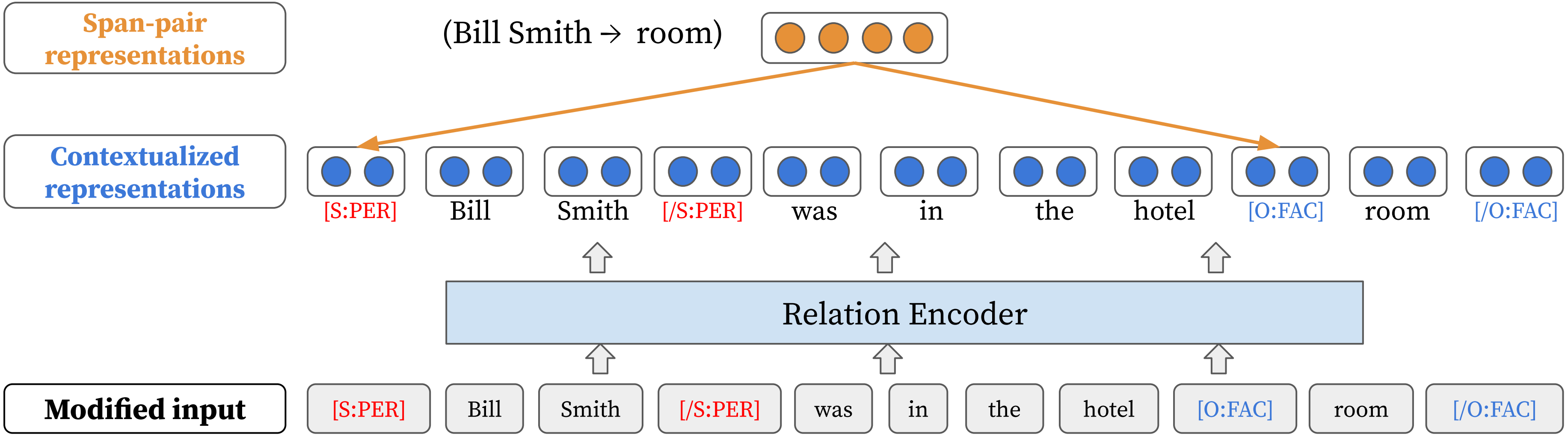
Relation Model

Modified input [S:PER] Bill Smith [/S:PER] was in the hotel [O:FAC] room [/O:FAC]

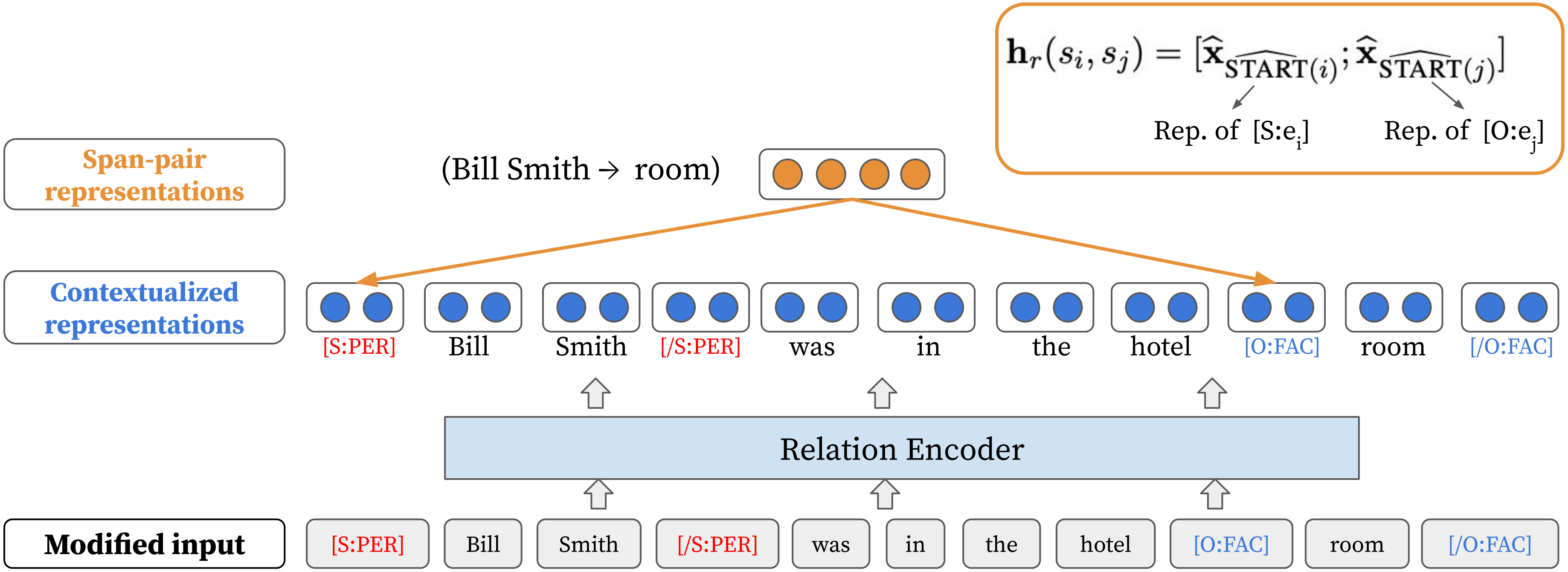
Relation Model



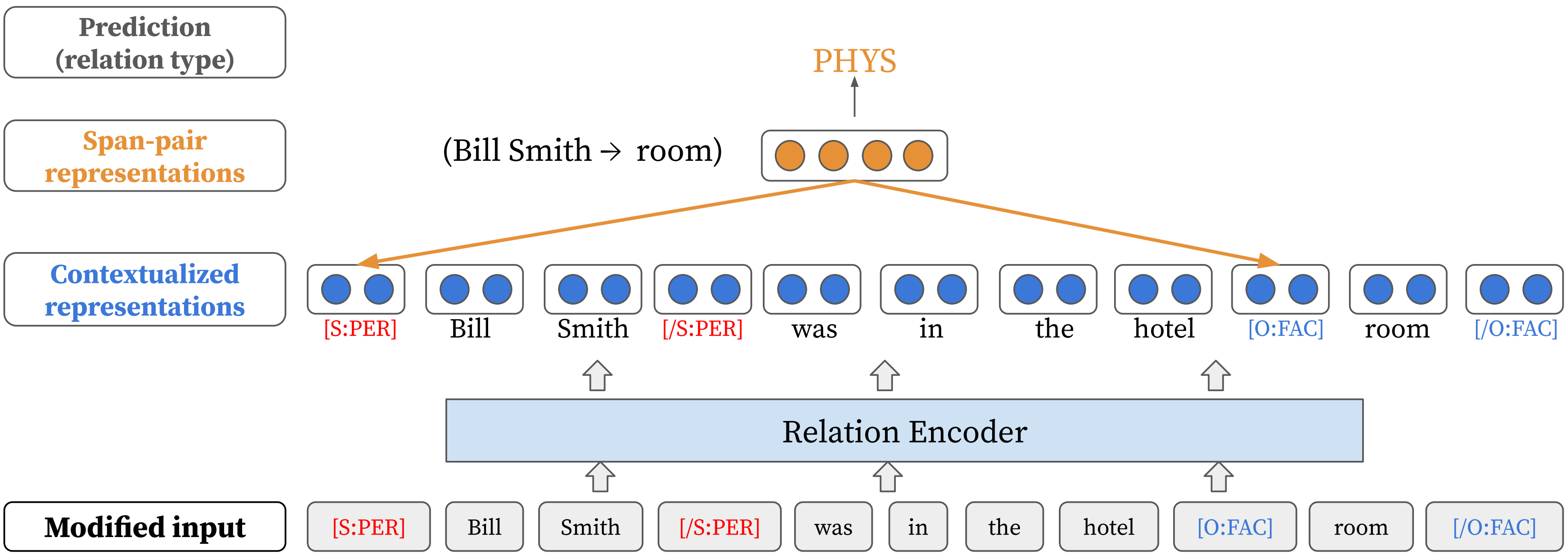
Relation Model



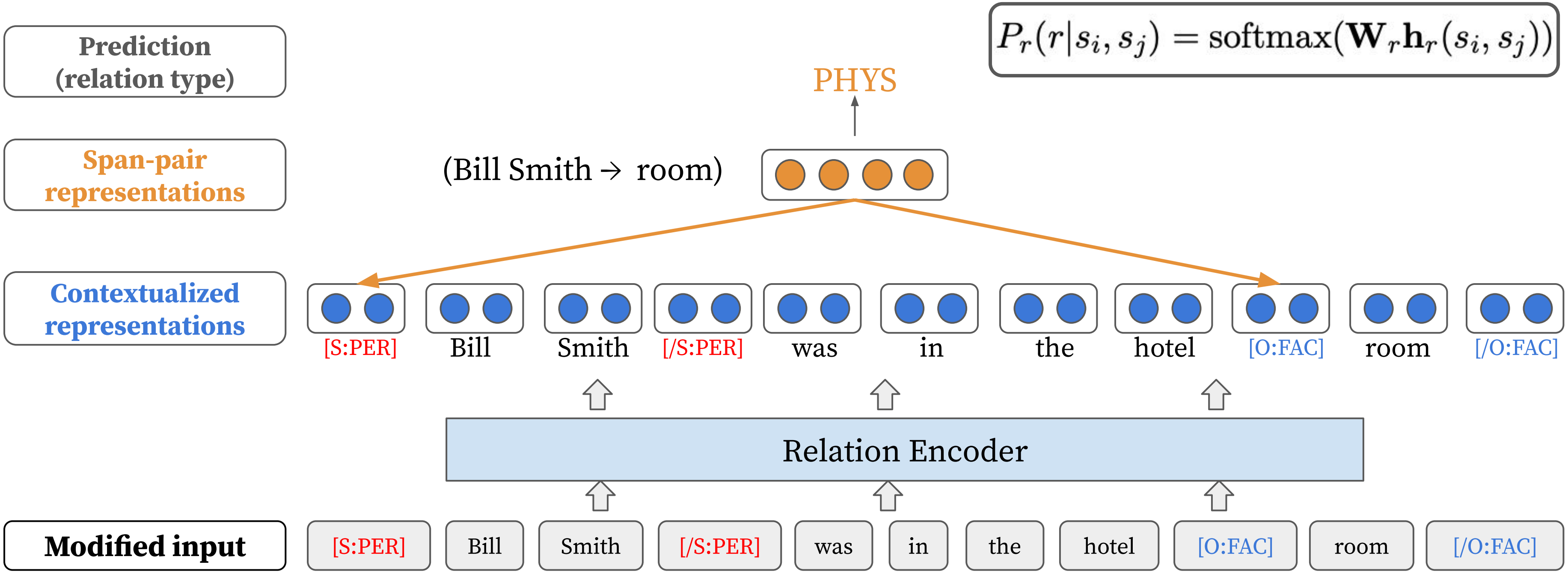
Relation Model



Relation Model



Relation Model



Experimental Settings

Datasets

- ACE04, ACE05: newswire, online forums
- SciERC: scientific articles

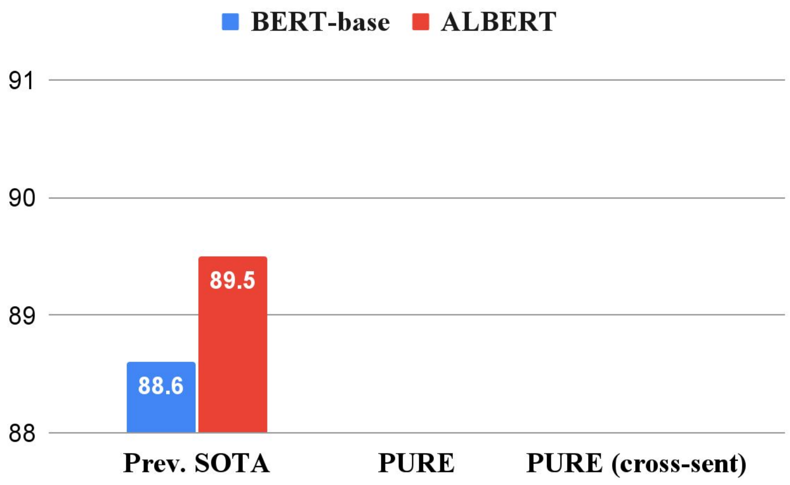
Evaluation metrics

- Entity F1
- Relation F1

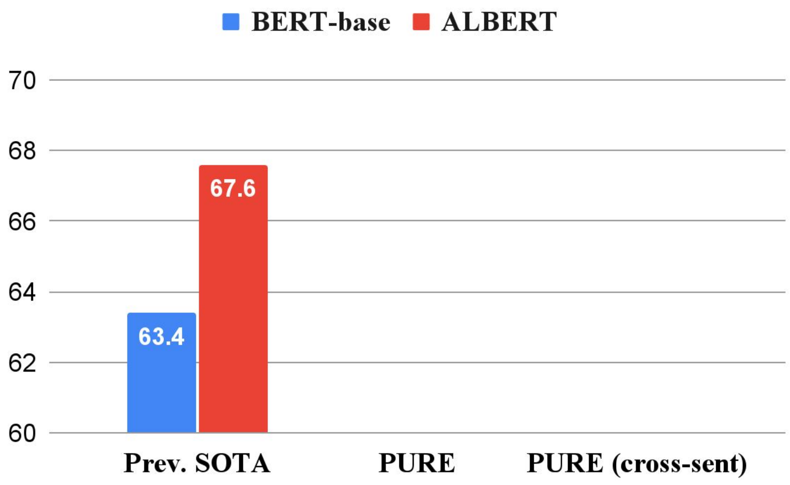
Context information

- Single-sentence
- Cross-sentence

Results on ACE05

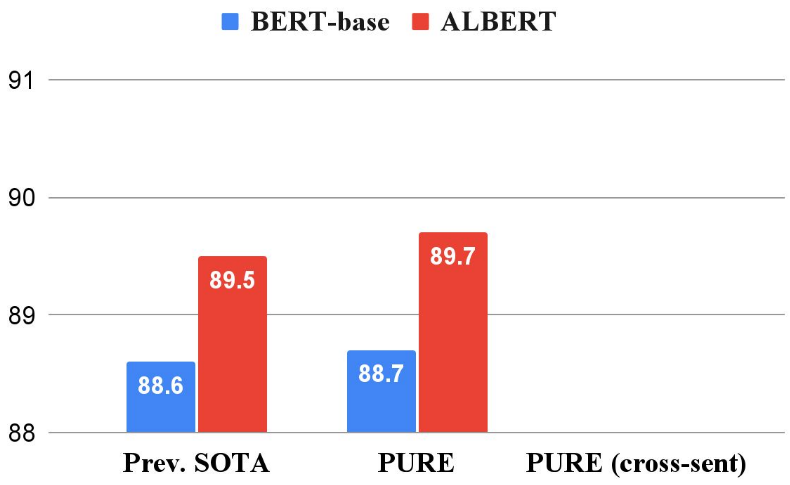


Entity F1

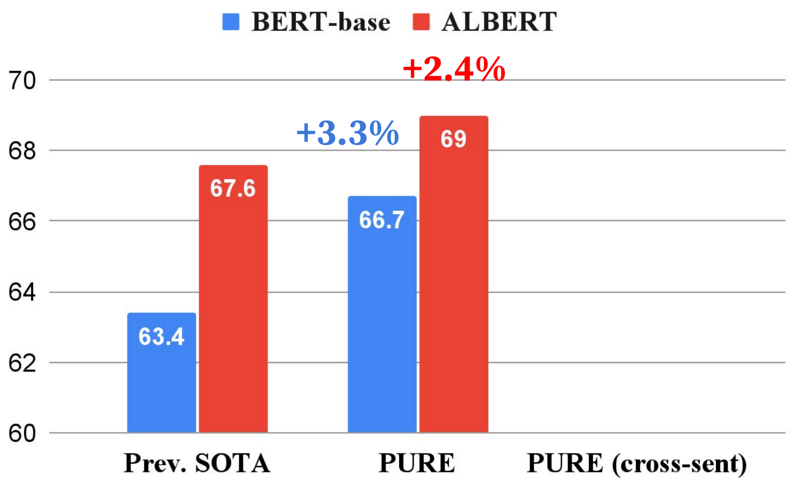


Relation F1

Results on ACE05



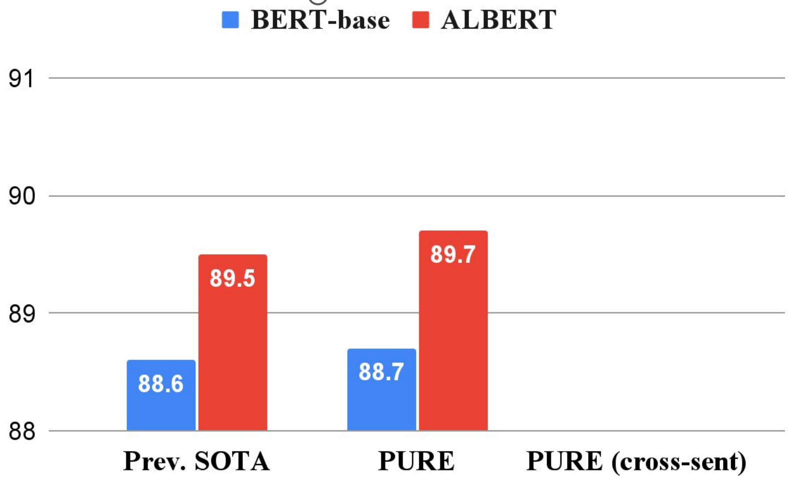
Entity F1



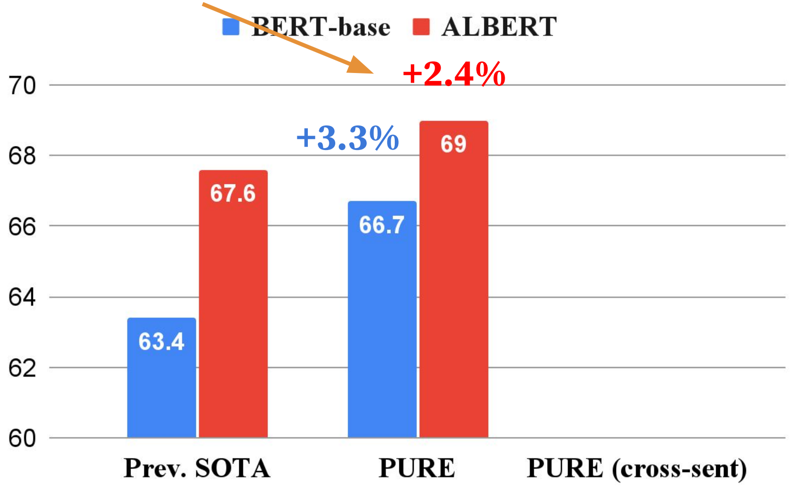
Relation F1

Results on ACE05

With the same pre-trained encoder, PURE significantly outperforms previous SOTA.

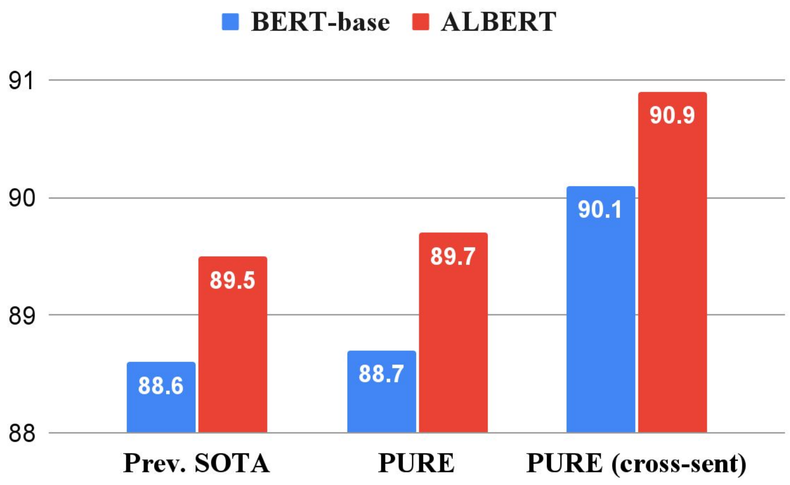


Entity F1

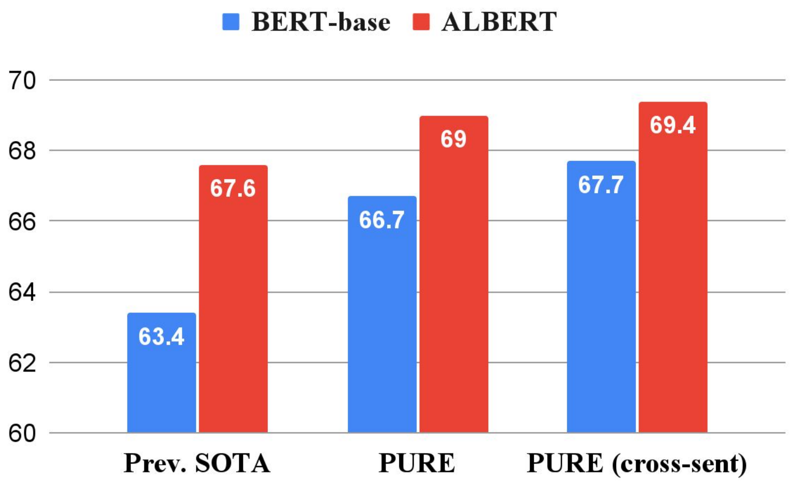


Relation F1

Results on ACE05



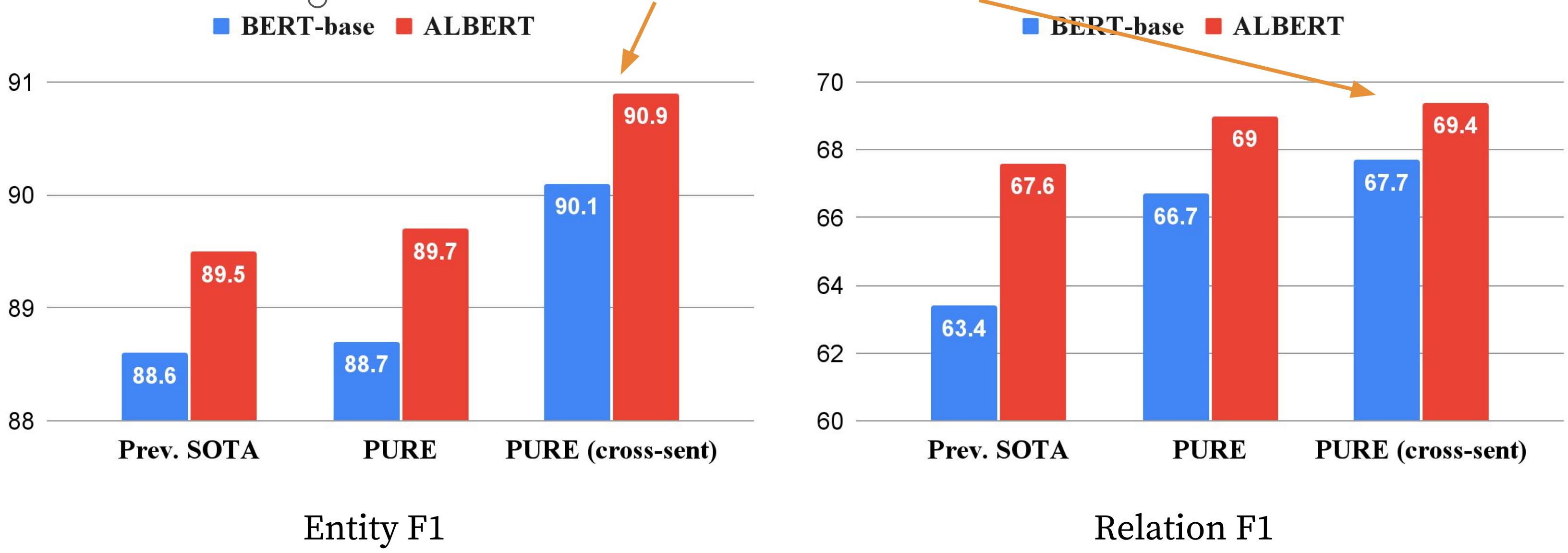
Entity F1



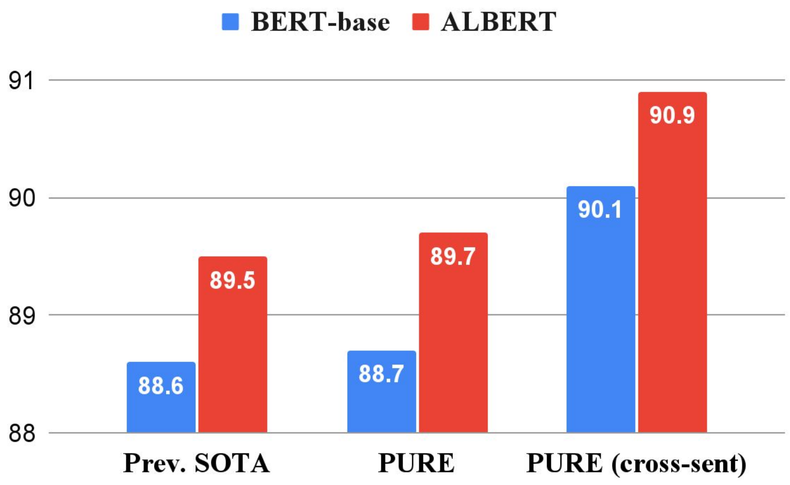
Relation F1

Results on ACE05

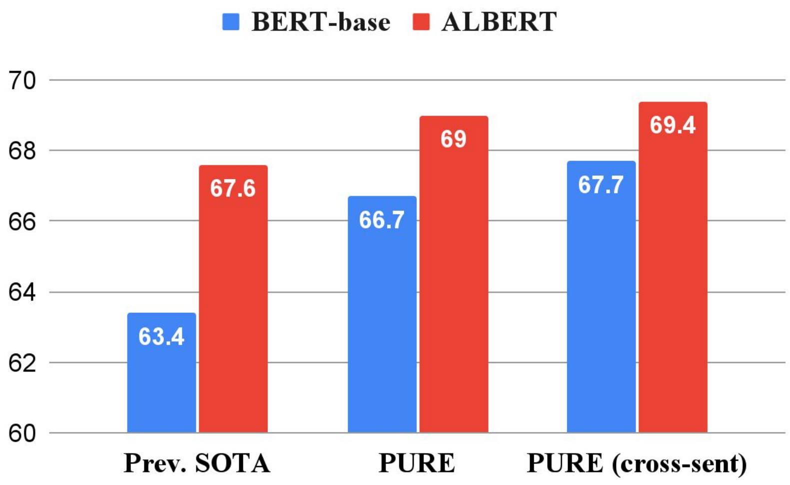
Incorporating cross-sentence information can further improve the performance.



Results on ACE05

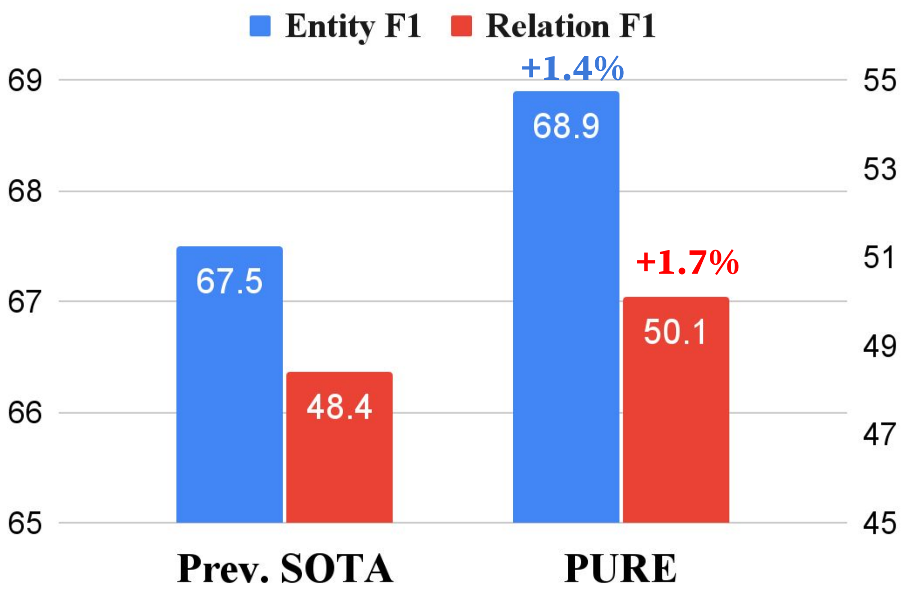


Entity F1



Relation F1

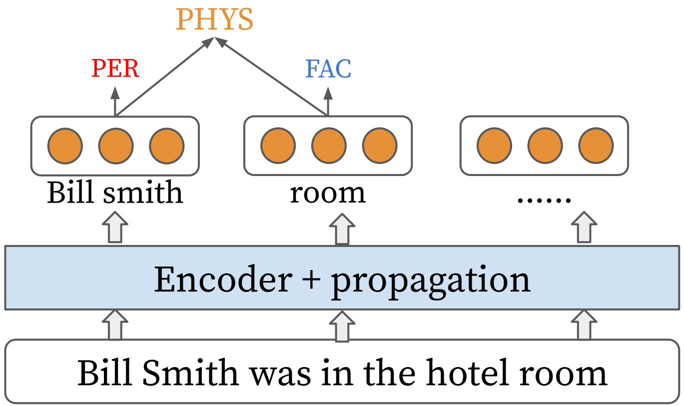
Results on SciERC



This Work

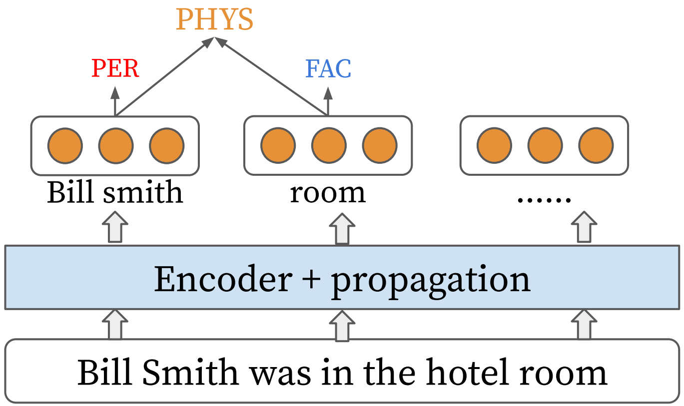
1. **Our model: PURE**
    - A **pipelined** approach outperforming all previous joint models!
2. **Why does it work well?**
    - **Understanding** modeling choices between entity and relation extraction
3. **An efficient approximation model w/ large speedup**

Comparison: Our Approach vs Joint Models

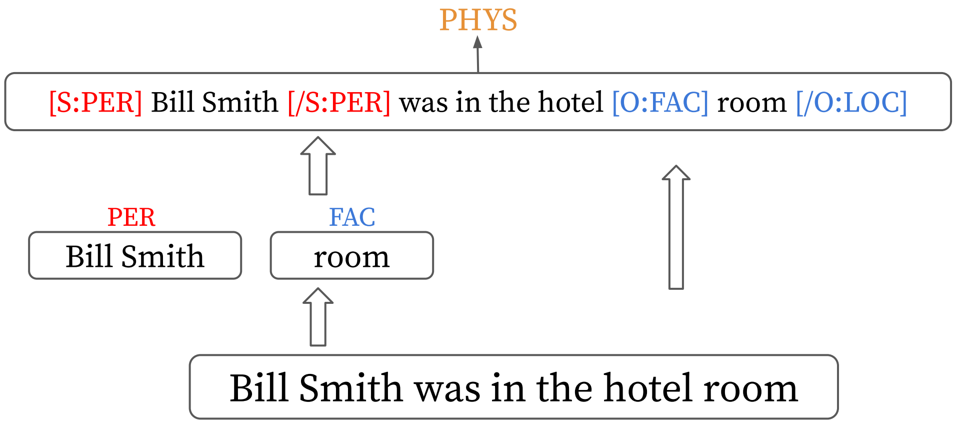


DYGIE++
(Wadden et al. 2019)

Comparison: Our Approach vs Joint Models



DYGIE++
(Wadden et al. 2019)



PURE (ours)

Importance of Typed Markers

Importance of Typed Markers

No marker

PHYS

Bill Smith was in the hotel room

Typed markers

PHYS

[S:PER] Bill Smith [/S:PER] was in the hotel [O:FAC] room [/O:FAC]

Importance of Typed Markers

No marker

PHYS

Bill Smith was in the hotel room

Untyped markers

PHYS

[S] Bill Smith [/S] was in the hotel [O] room [/O]

Typed markers

PHYS

[S:PER] Bill Smith [/S:PER] was in the hotel [O:FAC] room [/O:FAC]

Importance of Typed Markers

No marker

PHYS

Bill Smith was in the hotel room

Untyped markers

PHYS

[S] Bill Smith [/S] was in the hotel [O] room [/O]

Markers + entity auxiliary loss

PER PHYS FAC

[S] Bill Smith [/S] was in the hotel [O] room [/O]

Typed markers

PHYS

[S:PER] Bill Smith [/S:PER] was in the hotel [O:FAC] room [/O:FAC]

Importance of Typed Markers

Relation F1

No marker 67.6%

PHYS

Bill Smith was in the hotel room

Untyped markers 70.5%

PHYS

[S] Bill Smith [/S] was in the hotel [O] room [/O]

Markers + entity auxiliary loss 70.7%

PER PHYS FAC

[S] Bill Smith [/S] was in the hotel [O] room [/O]

Typed markers <u>**72.6%**</u>

PHYS

[S:PER] Bill Smith [/S:PER] was in the hotel [O:FAC] room [/O:FAC]

Why Pipelined Model?

Why Pipelined Model?

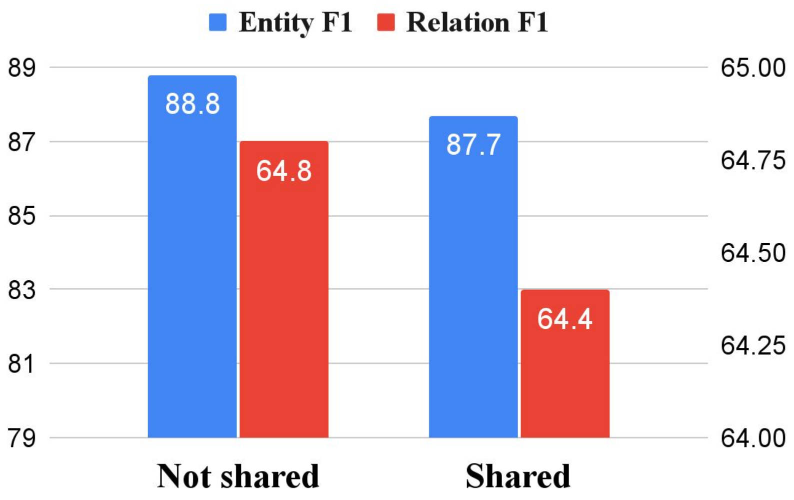
1. Two encoders capture distinct information!

   Does **sharing encoders** help?

Why Pipelined Model?

1. Two encoders capture distinct information!

Does **sharing encoders** help? **No!**



Why Pipelined Model?

2. Modeling entity-relation interaction

Why Pipelined Model?

2. Modeling entity-relation interaction

Entity → Relation? 🙂

- Use typed markers!

Why Pipelined Model?

2. Modeling entity-relation interaction

Entity → Relation? 🙂

- Use typed markers!

Relation → Entity? 🙁

- Adding a relation auxiliary in the entity model does not help!

Why Pipelined Model?

3. Error propagation?

Why Pipelined Model?

3. Error propagation?

- Both **jackknifing** and **beam pruning** (Lee et al., 2017; Luan et al., 2018) didn't improve performance!

This Work

1. **Our model: PURE**
    - A **pipelined** approach outperforming all previous joint models!
2. **Why does it work well?**
    - **Understanding** modeling choices between entity and relation extraction
3. **An efficient approximation model w/ large speedup**

Improving Runtime Efficiency of PURE

Bill Smith was in the hotel room

PER FAC FAC

M predicted entities

Improving Runtime Efficiency of PURE

M predicted entities

Bill Smith was in the hotel room

PER FAC FAC

$O(M^2)$ entity pairs!

[S:PER] Bill Smith [/S:PER] was in [O:FAC] hotel [/O:FAC] room

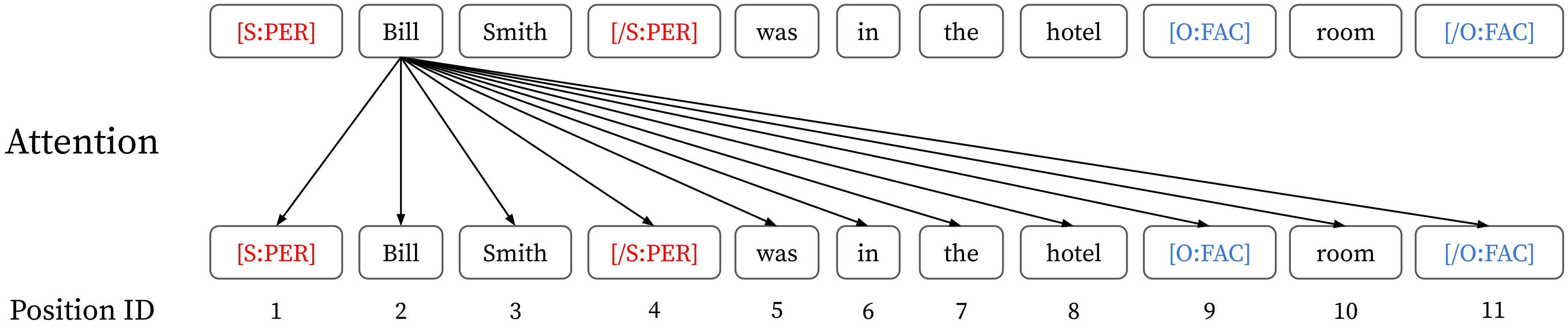
[S:PER] Bill Smith [/S:PER] was in hotel [O:FAC] room [/O:FAC]

Bill Smith was in [S:FAC] hotel [/S:FAC] [O:FAC] room [/O:FAC]

...

Addressing the Efficiency Issue

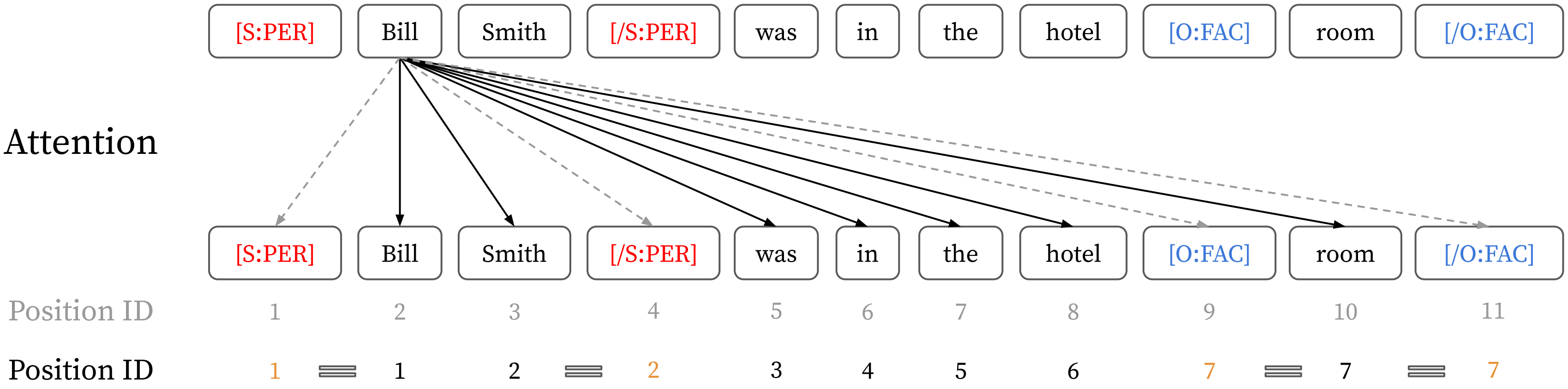
Key idea: re-use computations for different pairs of spans in the same sentence



Original Model

Addressing the Efficiency Issue

Key idea: re-use computations for different pairs of spans in the same sentence



Approximation Model

Approximation Model with Batch Computations

#1: [S:PER] Bill Smith [/S:PER] was in [O:FAC] hotel [/O:FAC] room

#2: [S:PER] Bill Smith [/S:PER] was in hotel [O:FAC] room [/O:FAC]

Bill Smith was in the hotel room [S:PER] [/S:PER] [O:FAC] [/O:FAC]

Bill Smith was in the hotel room [S:PER] [/S:PER] [O:FAC] [/O:FAC]

Bill Smith was in the hotel room [S:PER] [/S:PER] [O:FAC] [/O:FAC] [S:PER] [/S:PER] [O:FAC] [/O:FAC]

Re-use computations

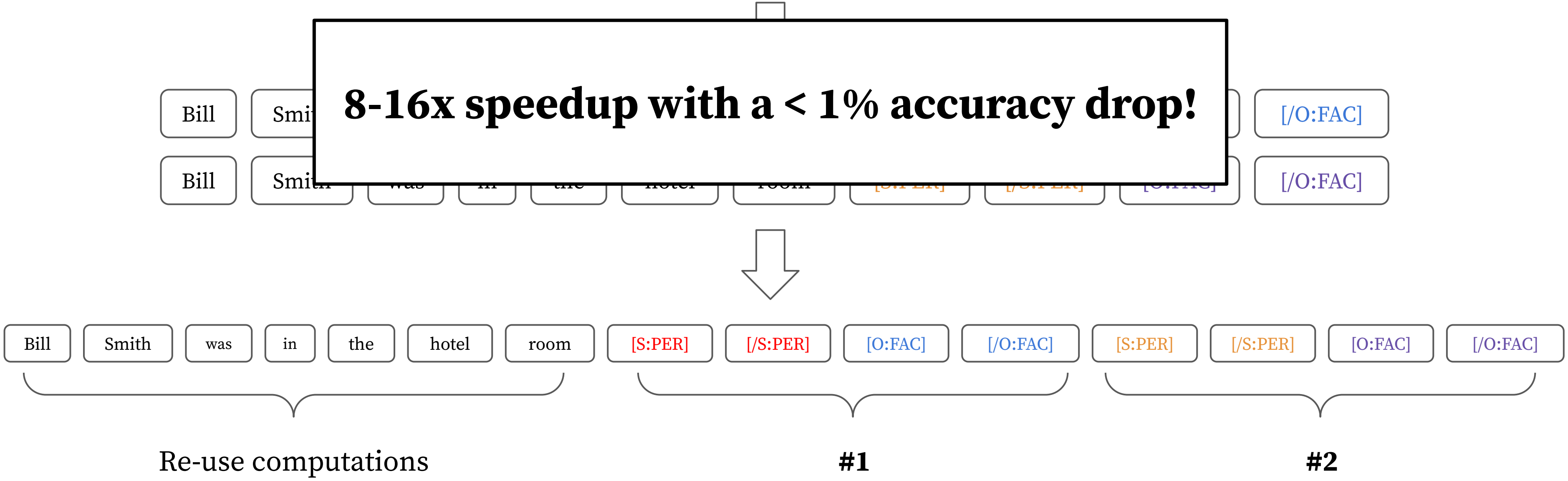
#1

#2

Approximation Model with Batch Computations

#1: [S:PER] Bill Smith [/S:PER] was in [O:FAC] hotel [/O:FAC] room

#2: [S:PER] Bill Smith [/S:PER] was in hotel [O:FAC] room [/O:FAC]



8-16x speedup with a < 1% accuracy drop!

Conclusions

PURE: A simple and effective approach for entity and relation extraction

- Learns two independent encoders
- Outperforms all previous joint model on three datasets
- An efficient approximation: 8-16x speedup with a small accuracy drop

Conclusions

PURE: A simple and effective approach for entity and relation extraction

- Learns two independent encoders
- Outperforms all previous joint model on three datasets
- An efficient approximation: 8-16x speedup with a small accuracy drop

Let's rethink the value of joint training in entity and relation extraction!

Thank You!

Paper: https://arxiv.org/pdf/2010.12812.pdf

Code: https://github.com/princeton-nlp/PURE