Neural sequential transfer learning for relation extraction

Christoph Alt

November 30, 2020

Chair: Prof. Dr. Klaus Obermayer
Supervisor: Prof. Dr.-Ing. Sebastian Möller
Reviewer: Prof. Dr. Hans Uszkoreit
Prof. Dr.-Ing. Alan Akbik

Outline

- Motivation & background
- Problem statement
- Objectives and contributions
- Sequential transfer learning for neural relation extraction
  - Approach
  - Evaluation
  - Experiments
- Conclusion
- Outlook

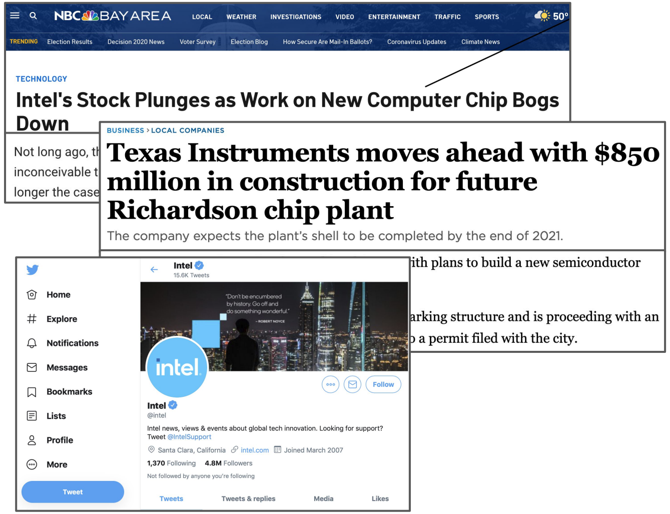
Information extraction

Information extraction

Information extraction

company	located in	...
Intel	Santa Clara	...
Texas Instruments	Dallas	...
...	...	...

Information extraction



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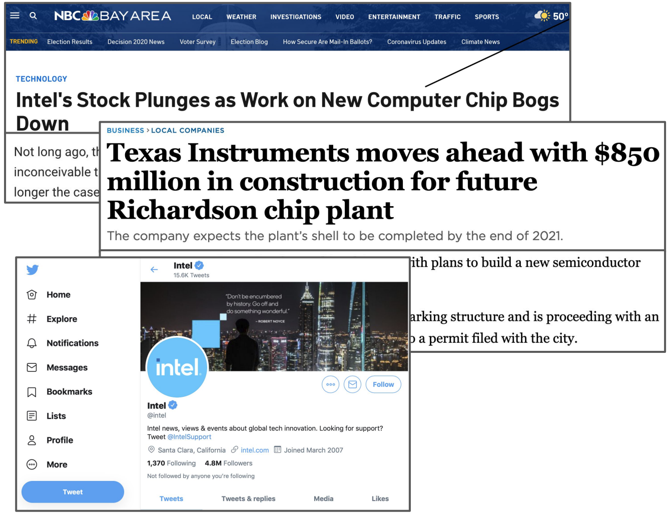

(Texas Instruments, located in, Dallas)

(Intel, located in, Santa Clara)

company	located in	…
Intel	Santa Clara	…
Texas Instruments	Dallas	…
…	…	…

Relation extraction

Relation extraction

- detect and retrieve relational information from unstructured text

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Intel is based in Santa Clara .

Relation extraction

- detect and retrieve relational information from unstructured text

$$\underbrace{\text{Intel}}_{\textit{organization}} \text{ is based in } \underbrace{\text{Santa Clara}}_{\textit{location}} \text{ .}$$

Relation extraction

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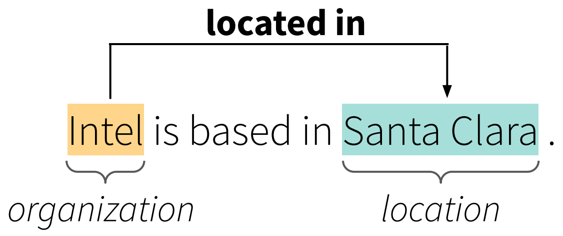


Relation extraction

- detect and retrieve relational information from unstructured text

located in

Intel is based in Santa Clara .

organization *location*

vs.

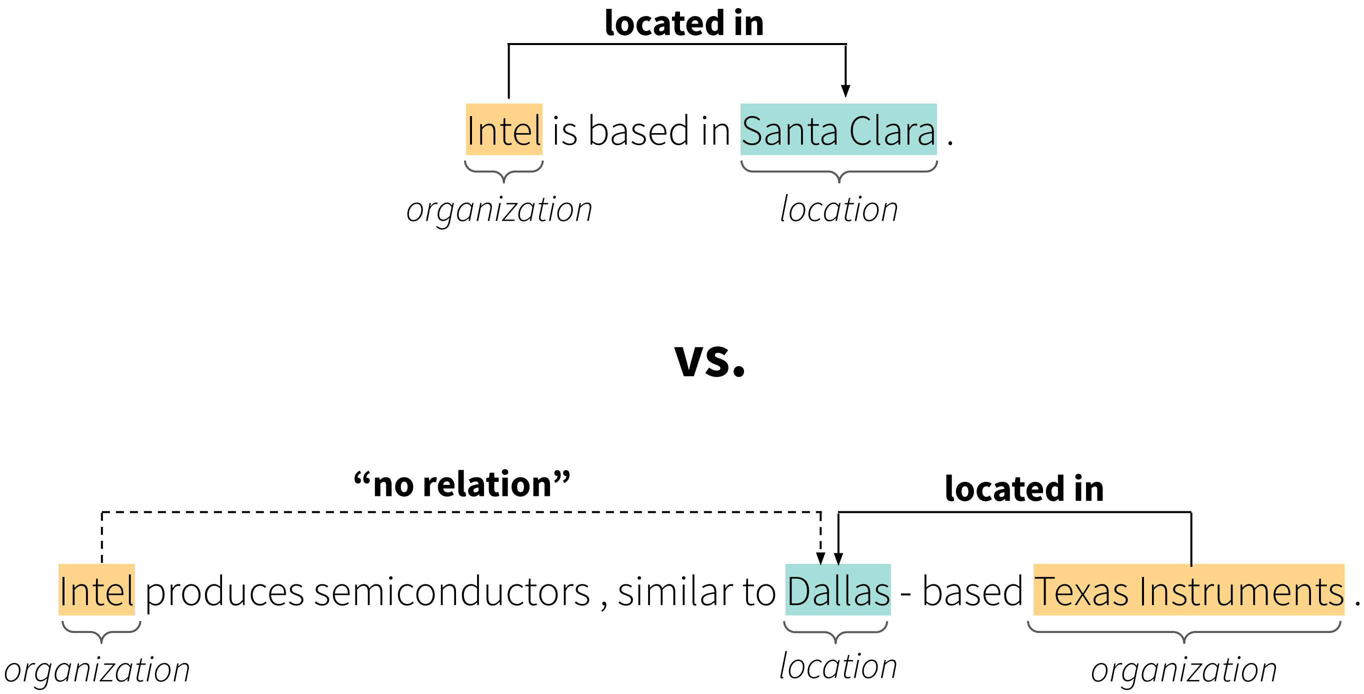
located in

Intel produces semiconductors , similar to Dallas - based Texas Instruments .

organization *location* *organization*

Relation extraction

- detect and retrieve relational information from unstructured text



Machine-learning-based relation extraction

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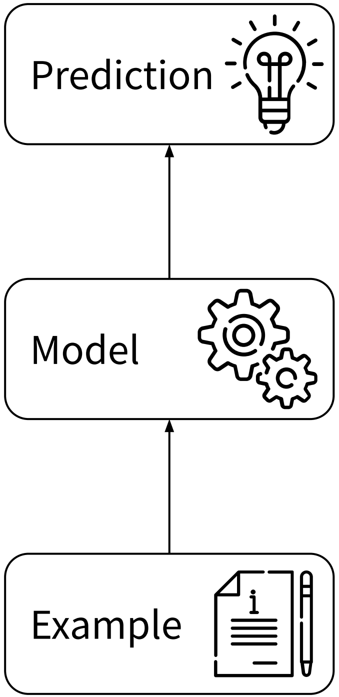

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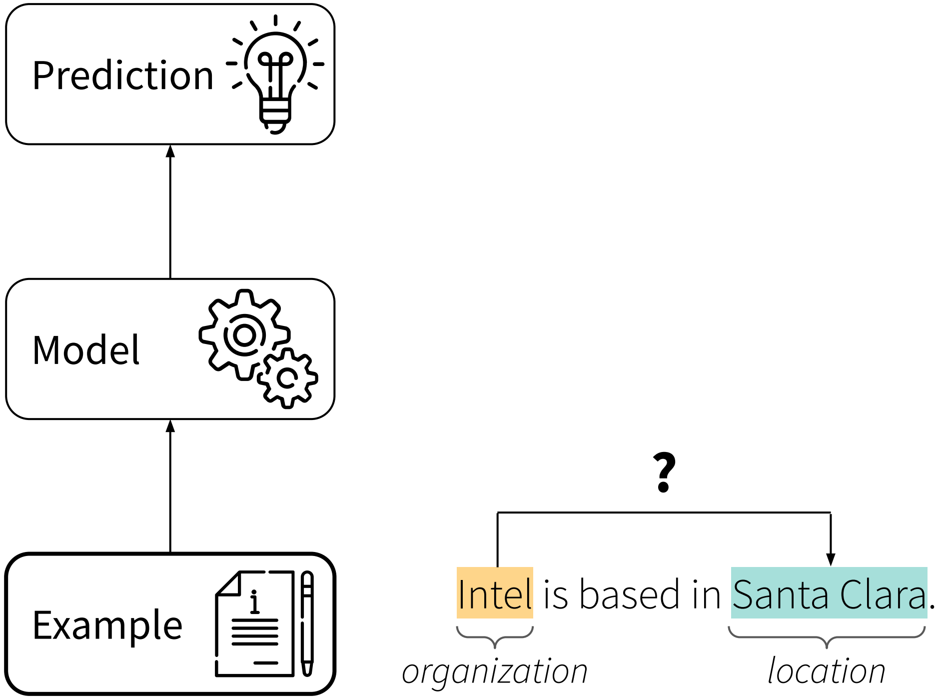

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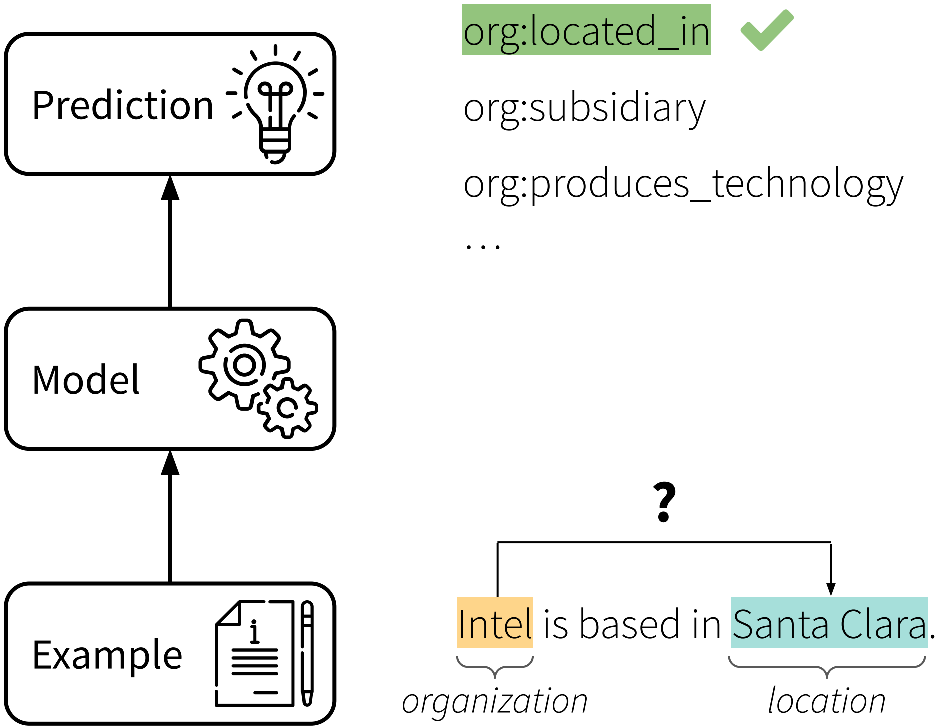

Relation extraction: Problems

- Quality and accuracy of extracted relations critical
- Neural-network-based methods achieve state-of-the-art results
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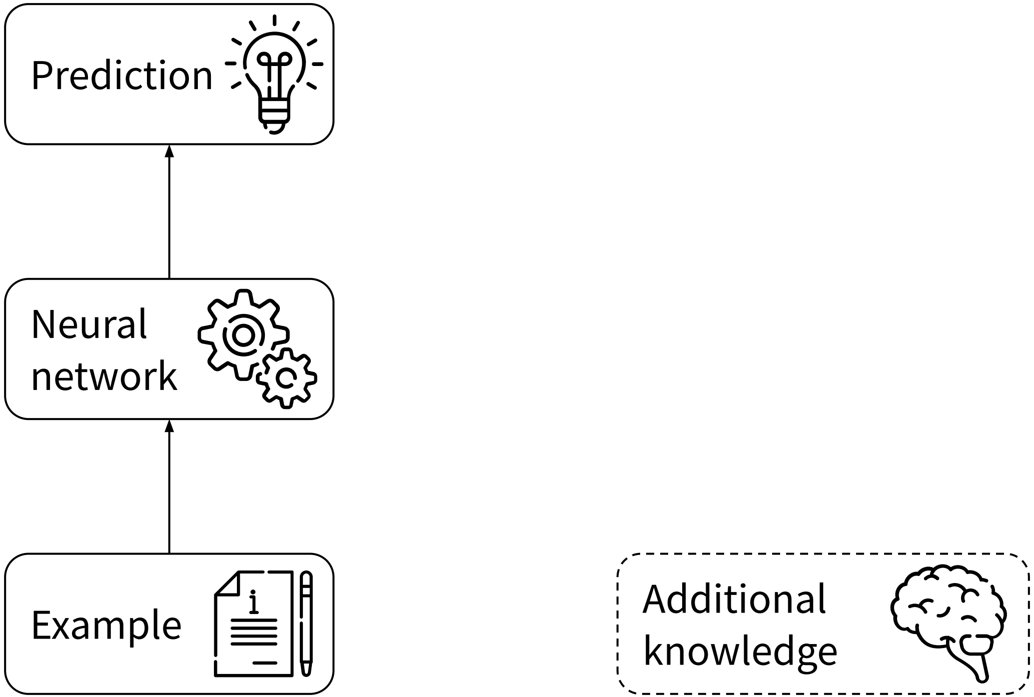
Issue

- Insufficient data to reliably model robust patterns

→ Poor generalization

State-of-the-art: Improve generalization with explicit features



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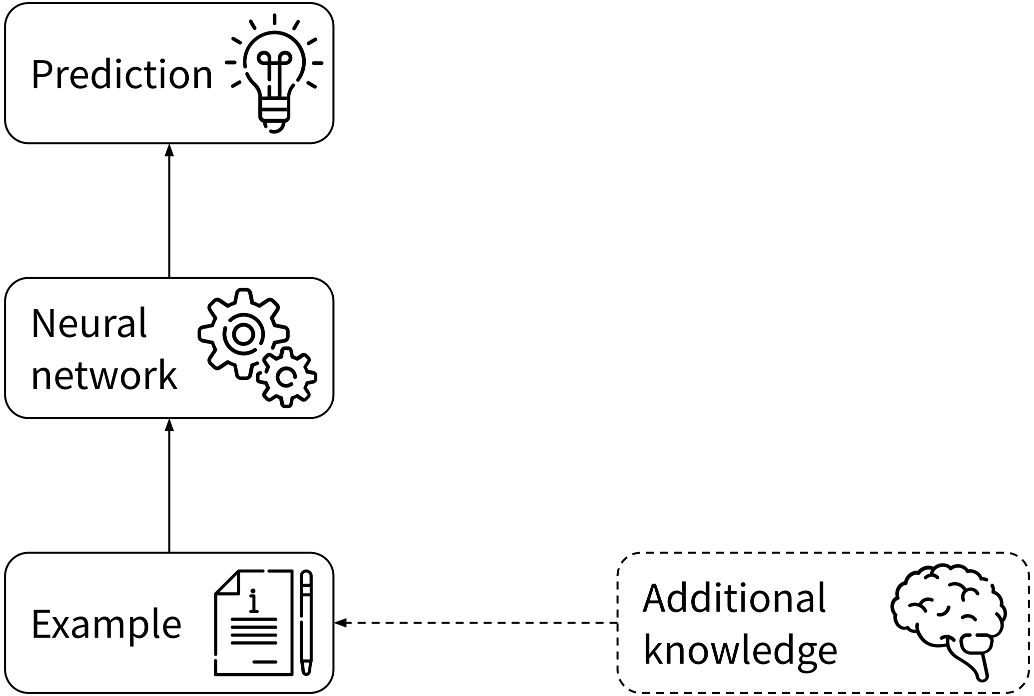

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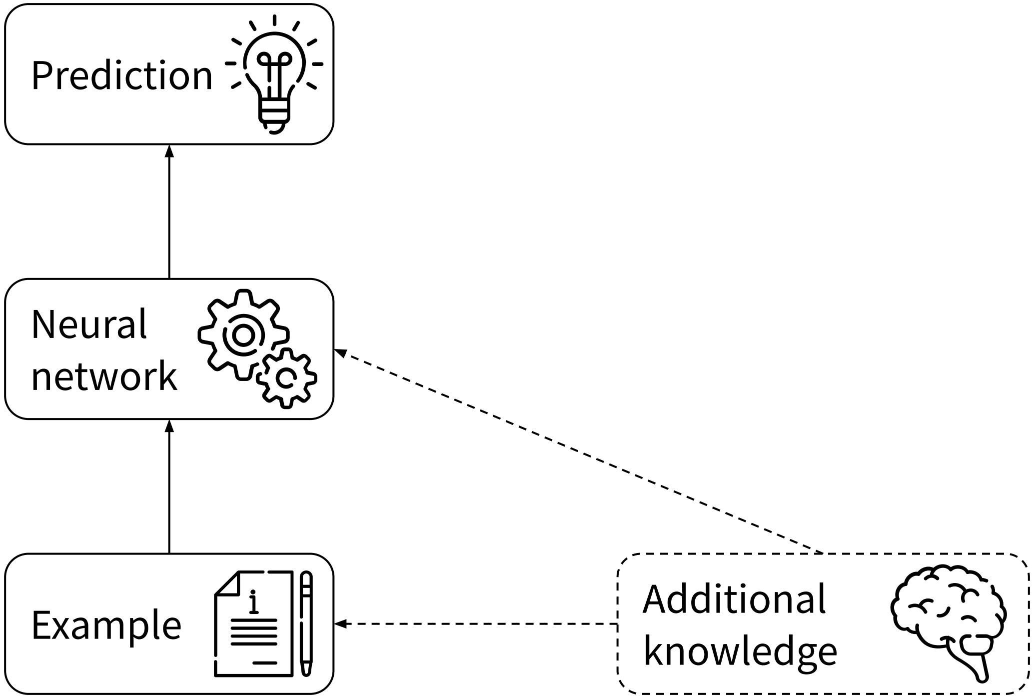

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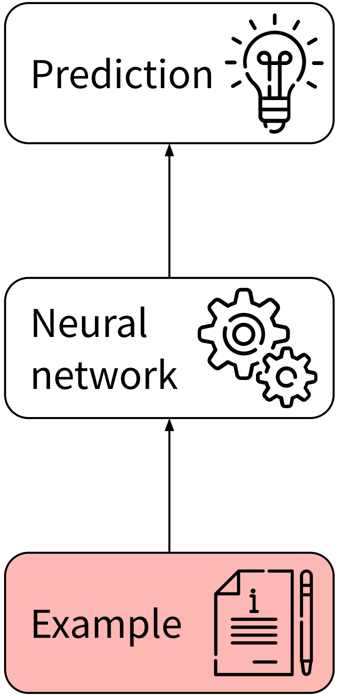

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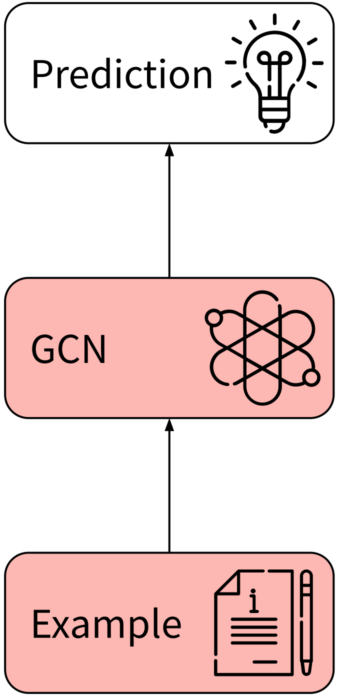

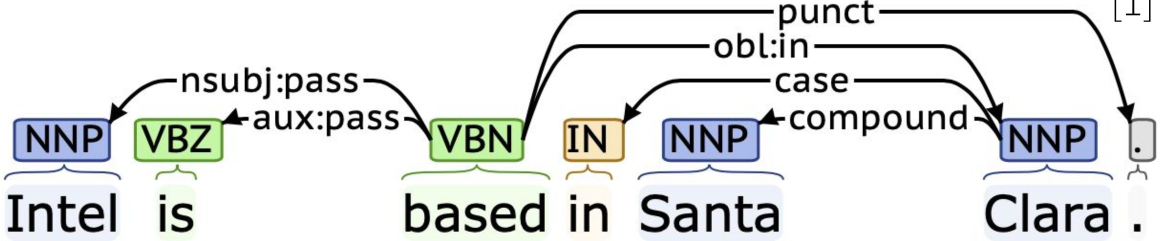

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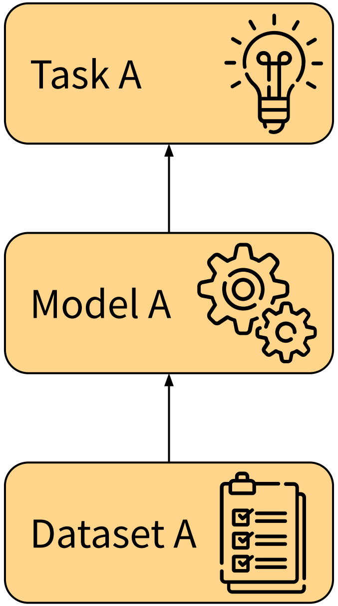
- **Complexity:** multiple systems (feature extractors), task-specific model architecture
- **Error propagation:** errors can propagate and accumulate
- **Limited portability:** domain and language dependence
- **A-priori feature selection:** features selected before training

Transfer learning



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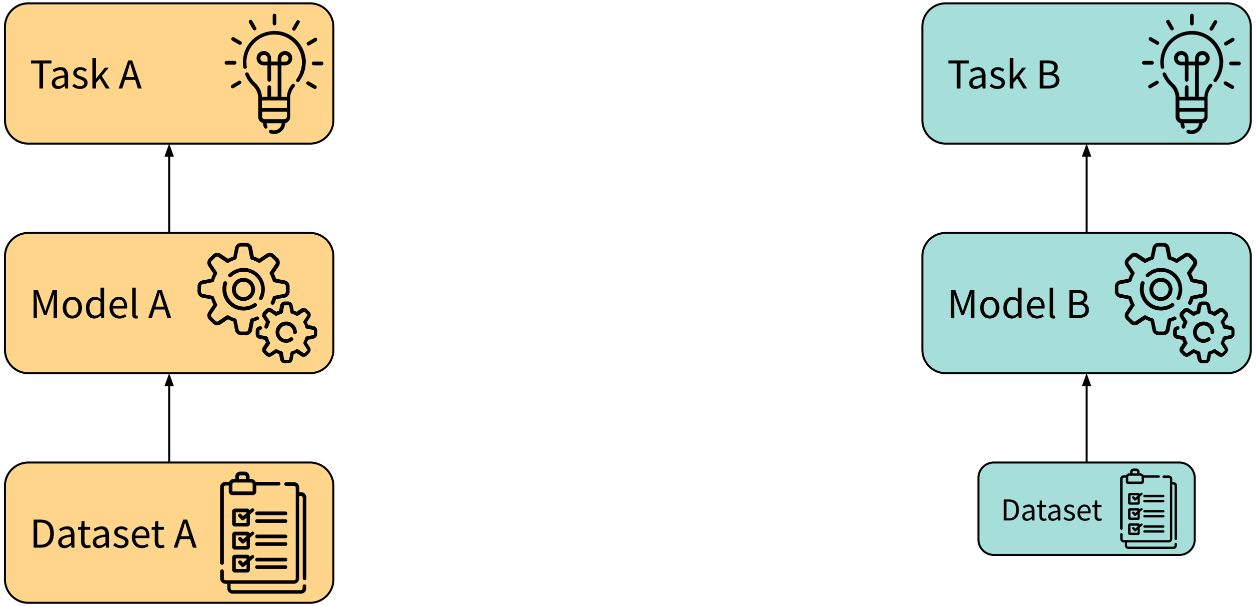
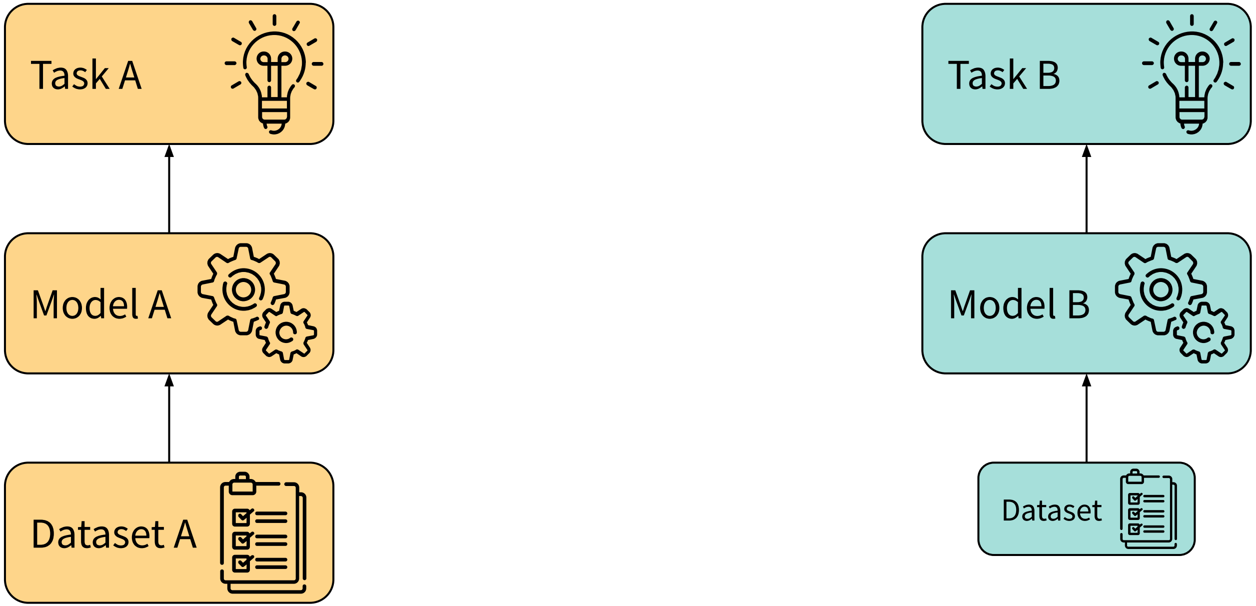


Transfer learning

1 build model on task A
(pre-training)



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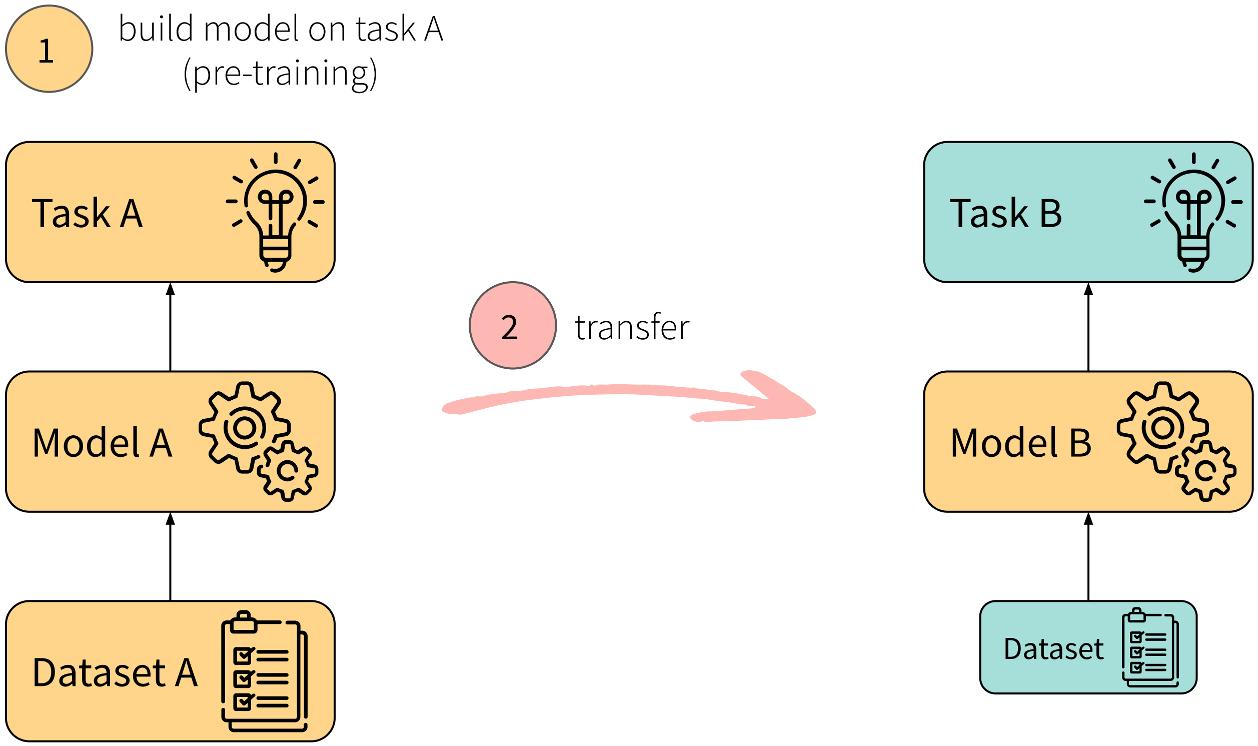

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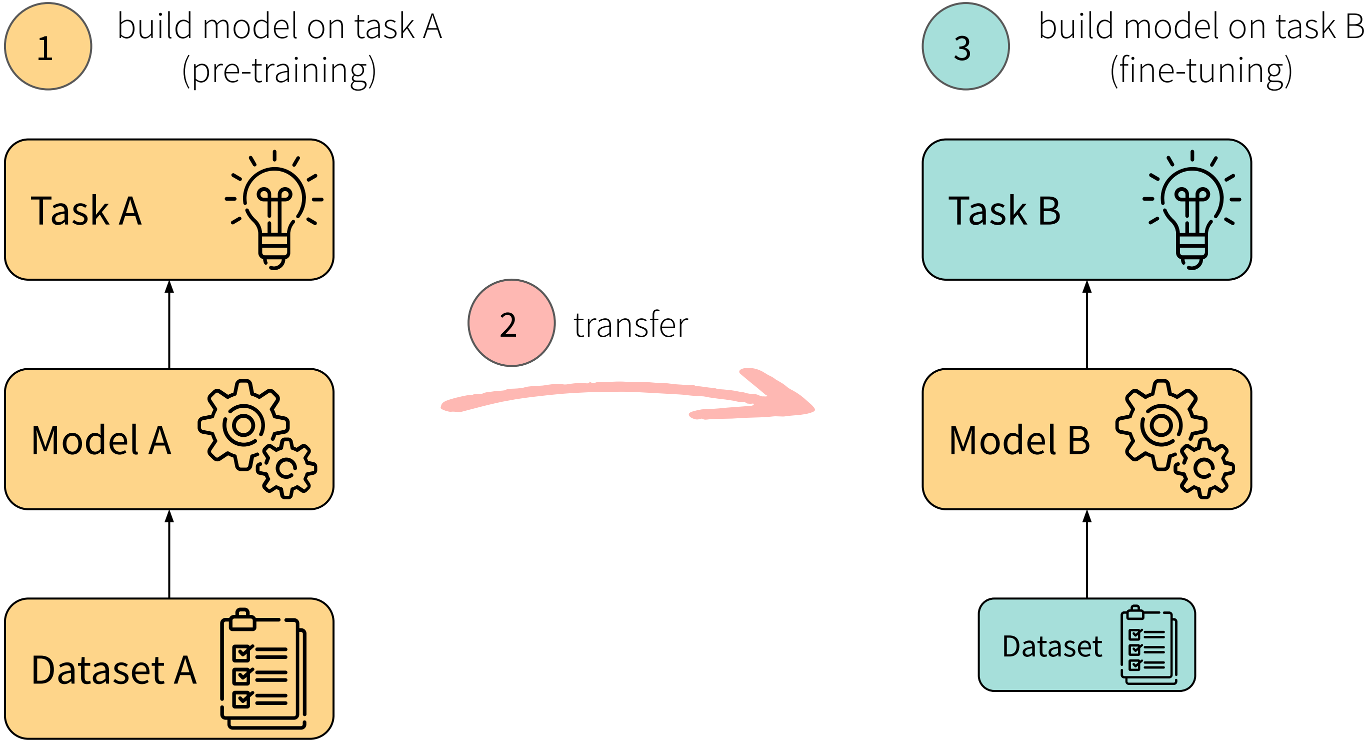

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Develop better performing and more data-efficient neural relation extraction methods

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Main contributions

Sequential transfer learning for supervised relation extraction

C. Alt*, M. Hübner*, L. Hennig. *"Improving Relation Extraction by Pre-trained Language Representations"*. **AKBC 2019**.

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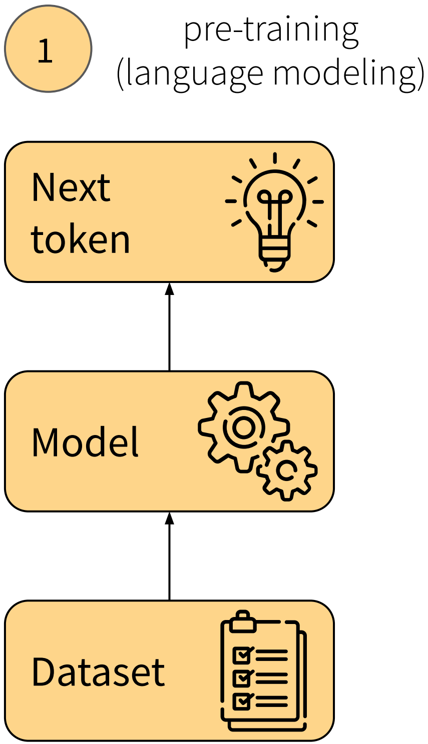

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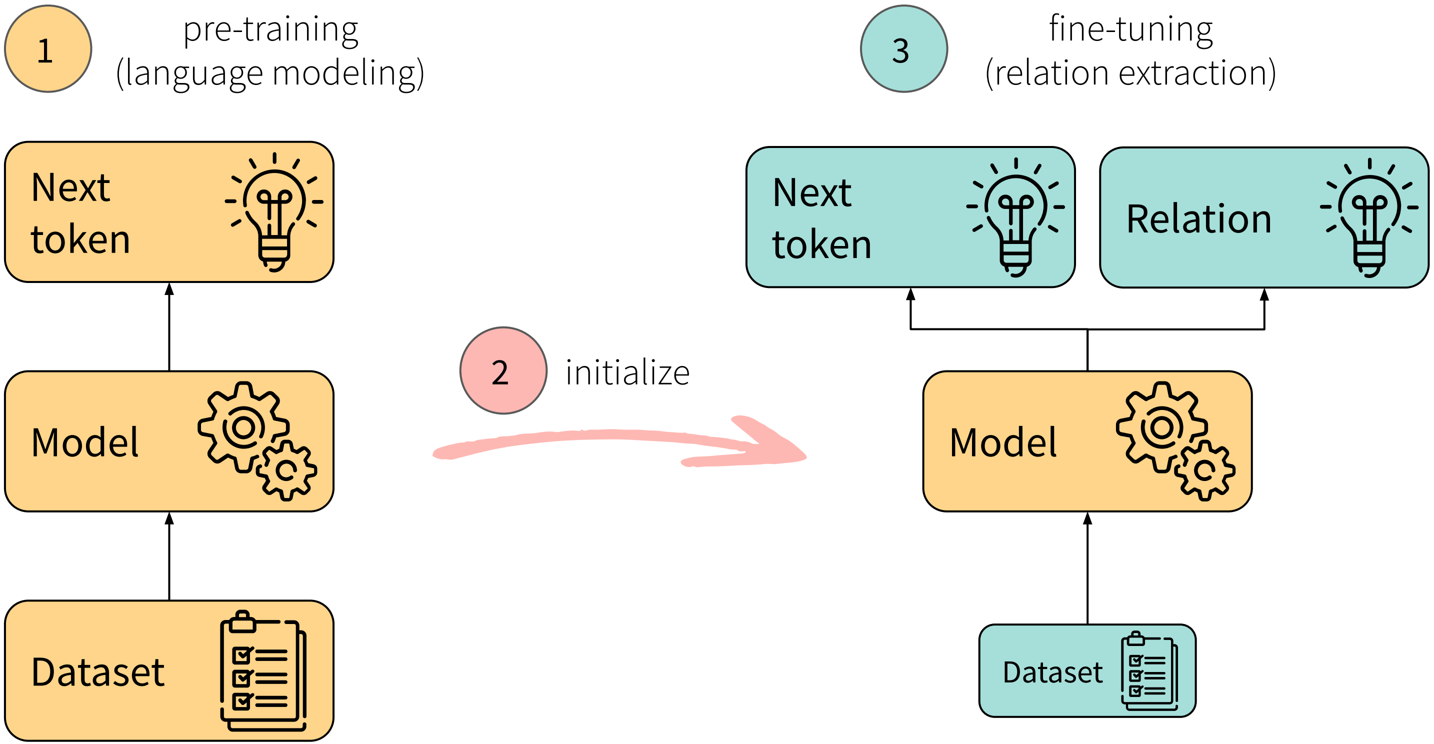
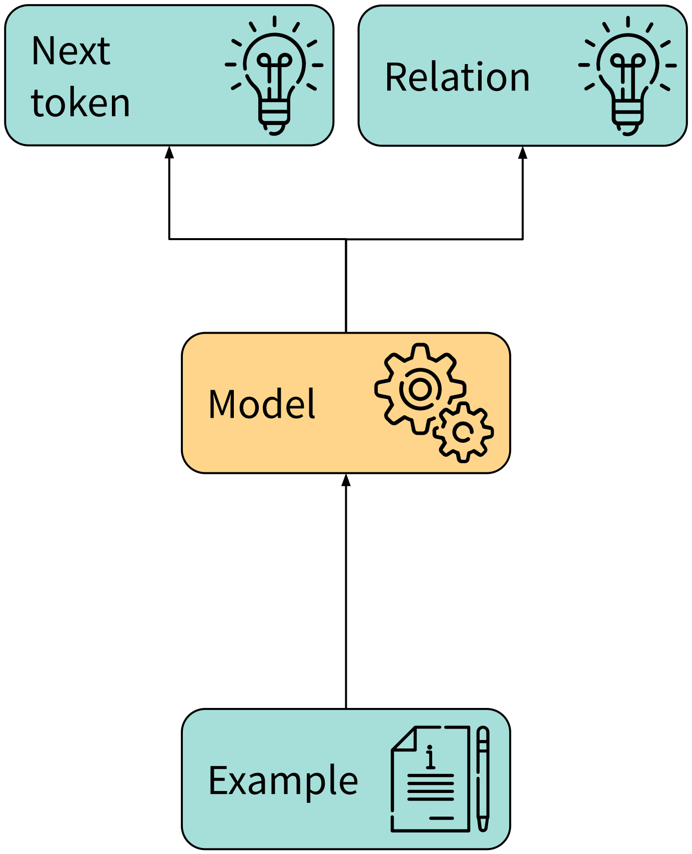

1
pre-training
(language modeling)
Next token
Model
Dataset
2
initialize
3
fine-tuning
(relation extraction)
Next token
Relation
Model
Dataset

Model architecture



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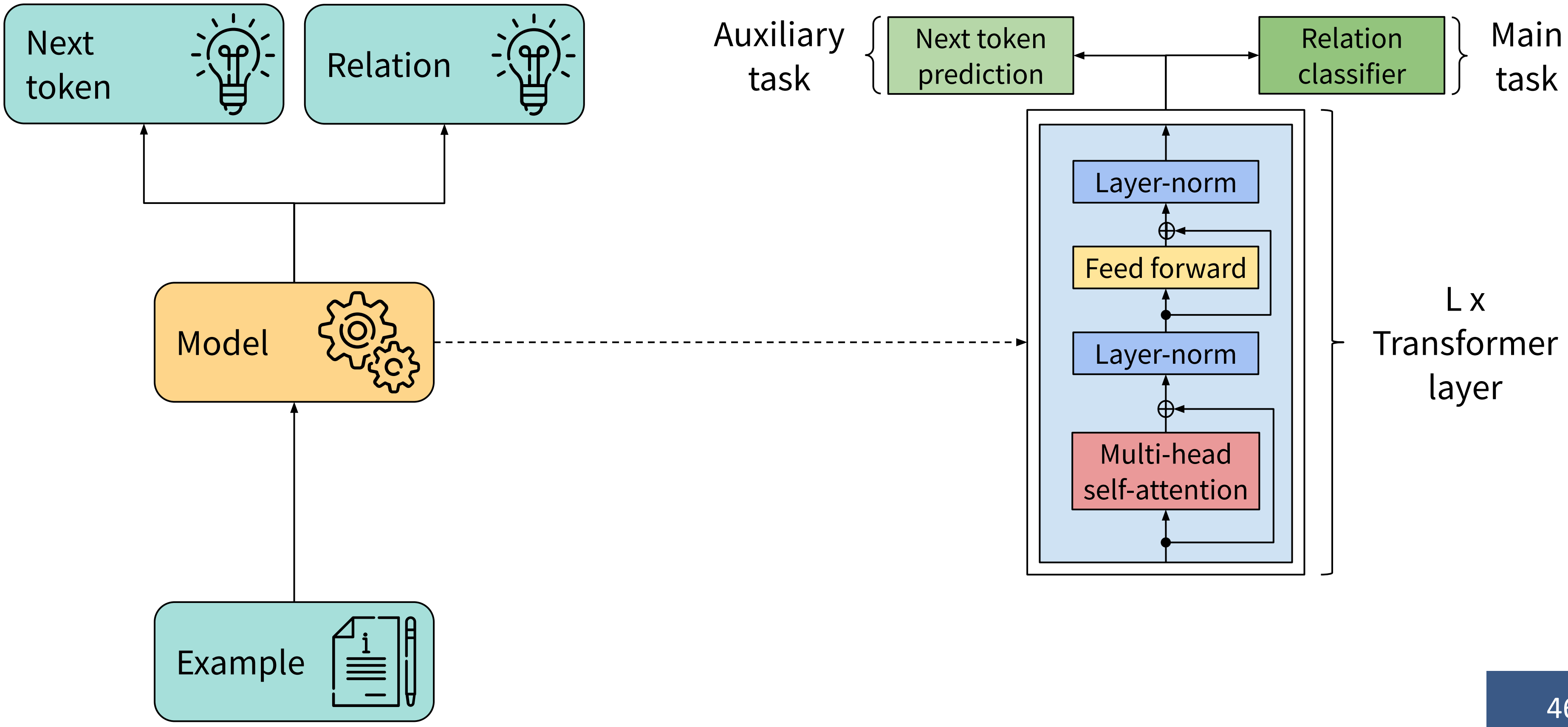

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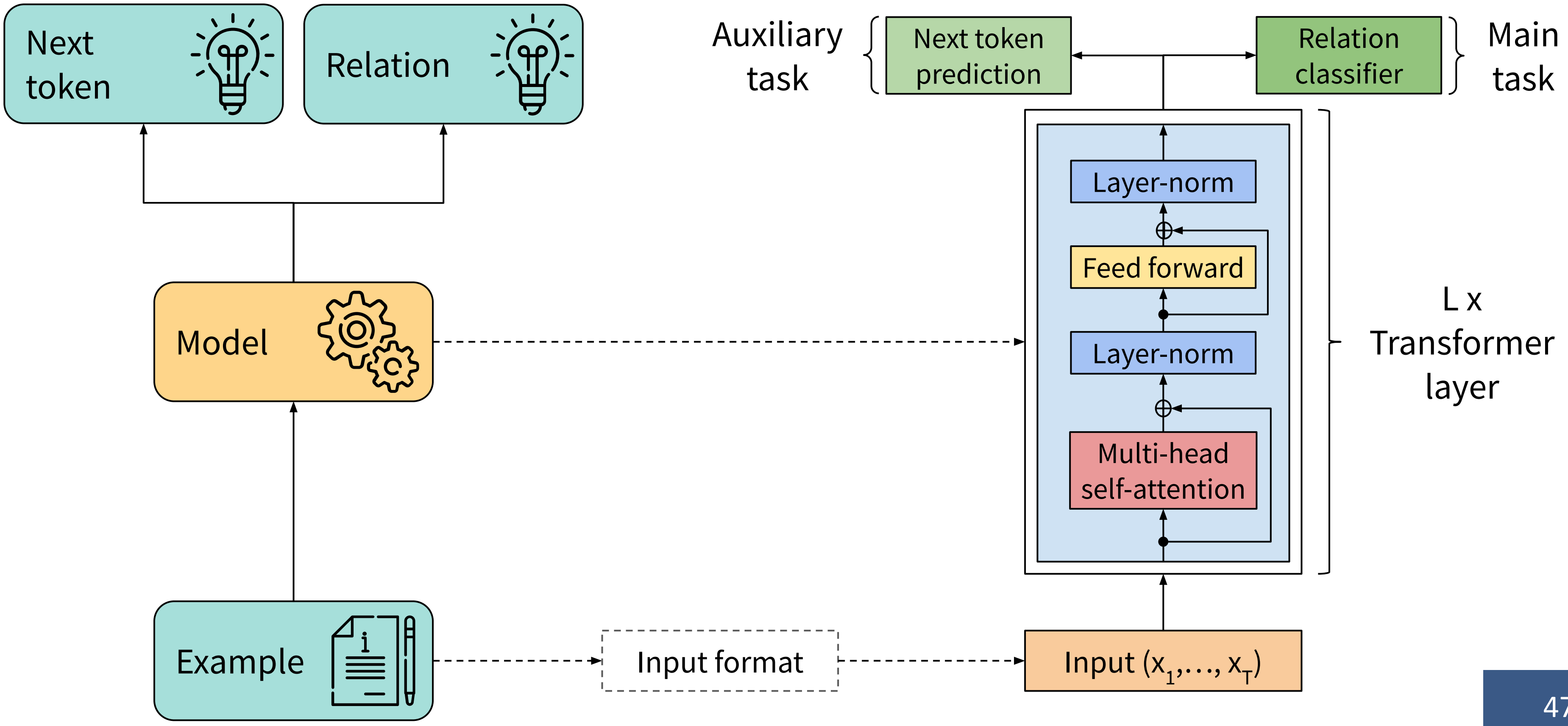
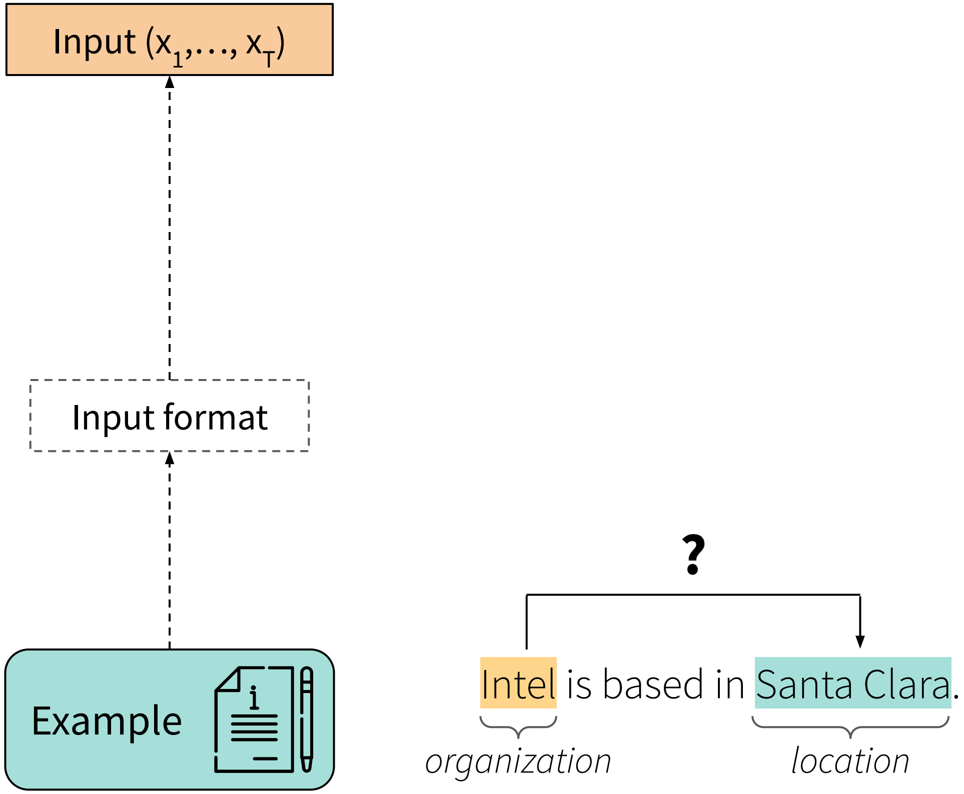


Input format



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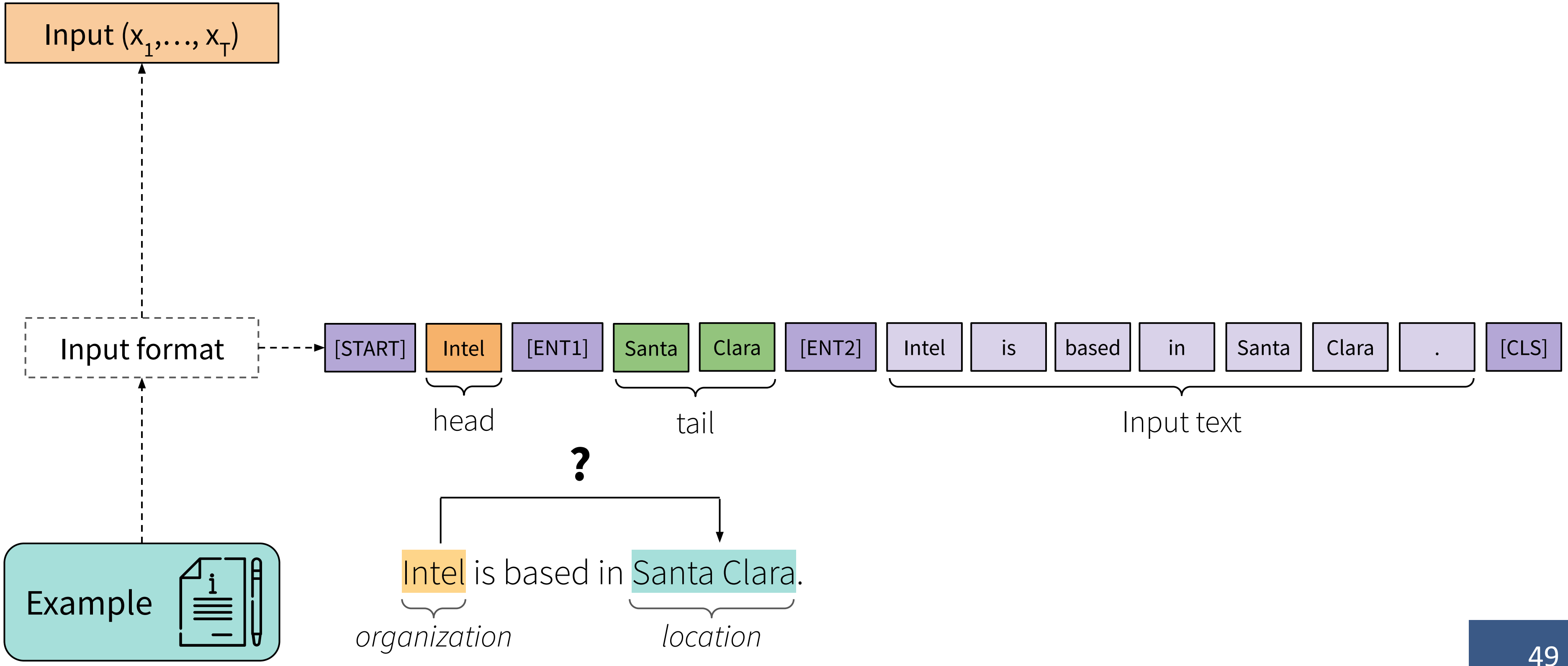

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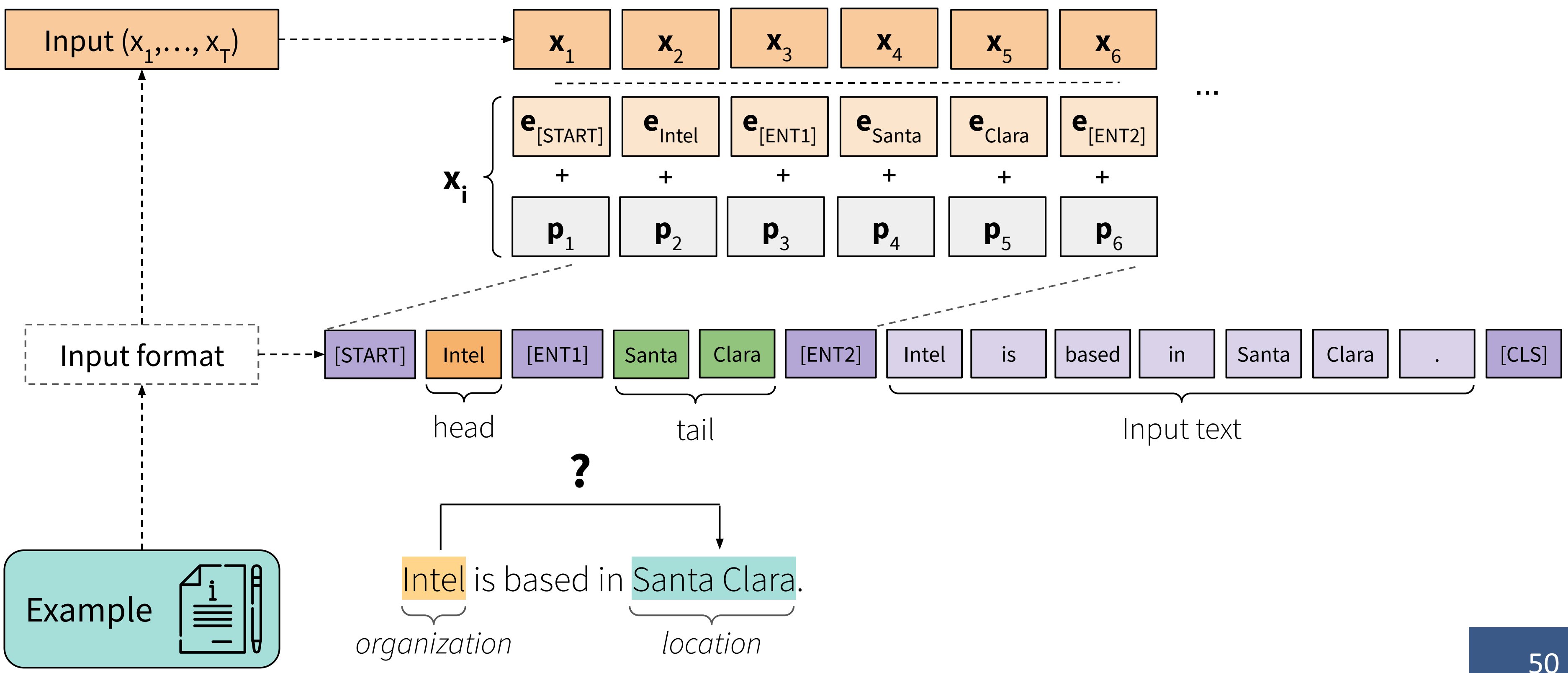

Distant supervision

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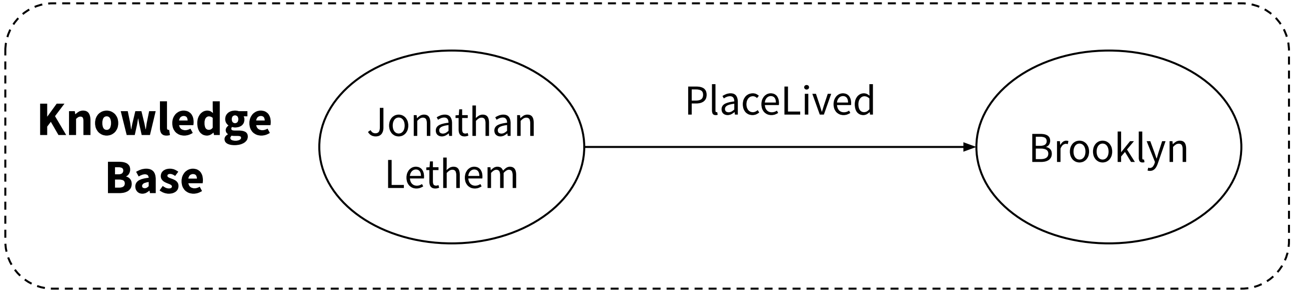
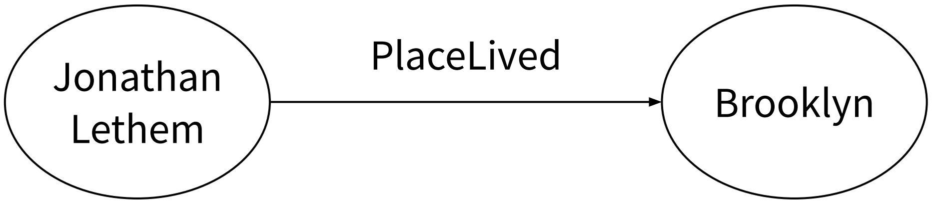


Distant supervision

Knowledge Base



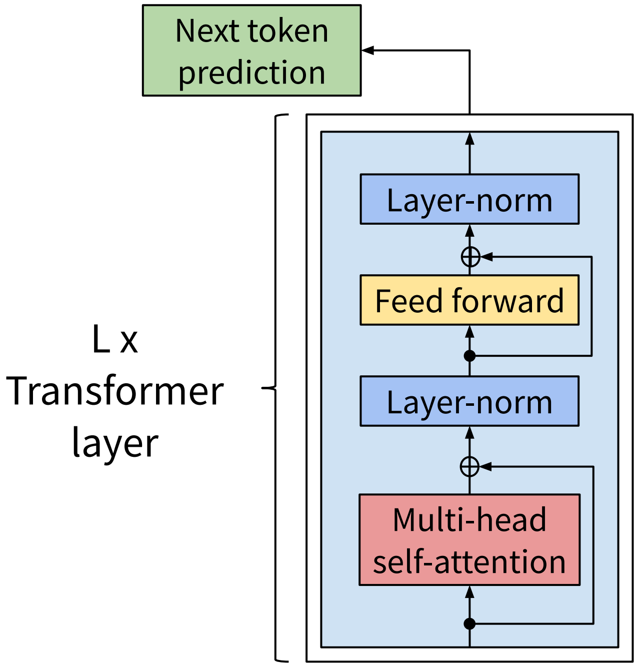
Data

You could say that only the dead, and Jonathan Lethem, know Brooklyn. ✗

“Non-connectivity becomes a commodity , something to cherish, '' said Jonathan Lethem, a Brooklyn novelist and a new MacArthur fellow. ✓

In Brooklyn, they ask when you're going on Charlie Rose and if you know Jonathan Lethem. ✗

Extension to distantly supervised data



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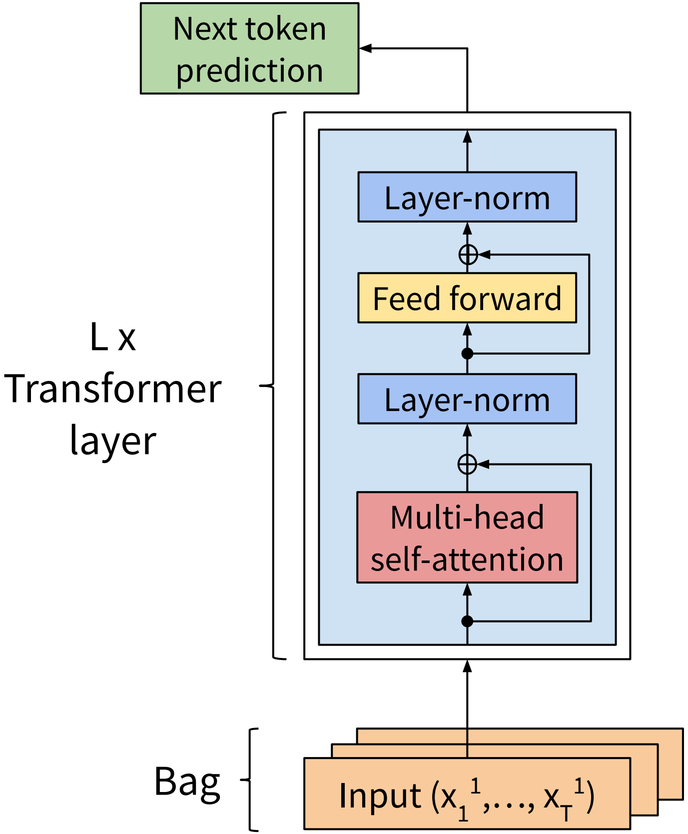

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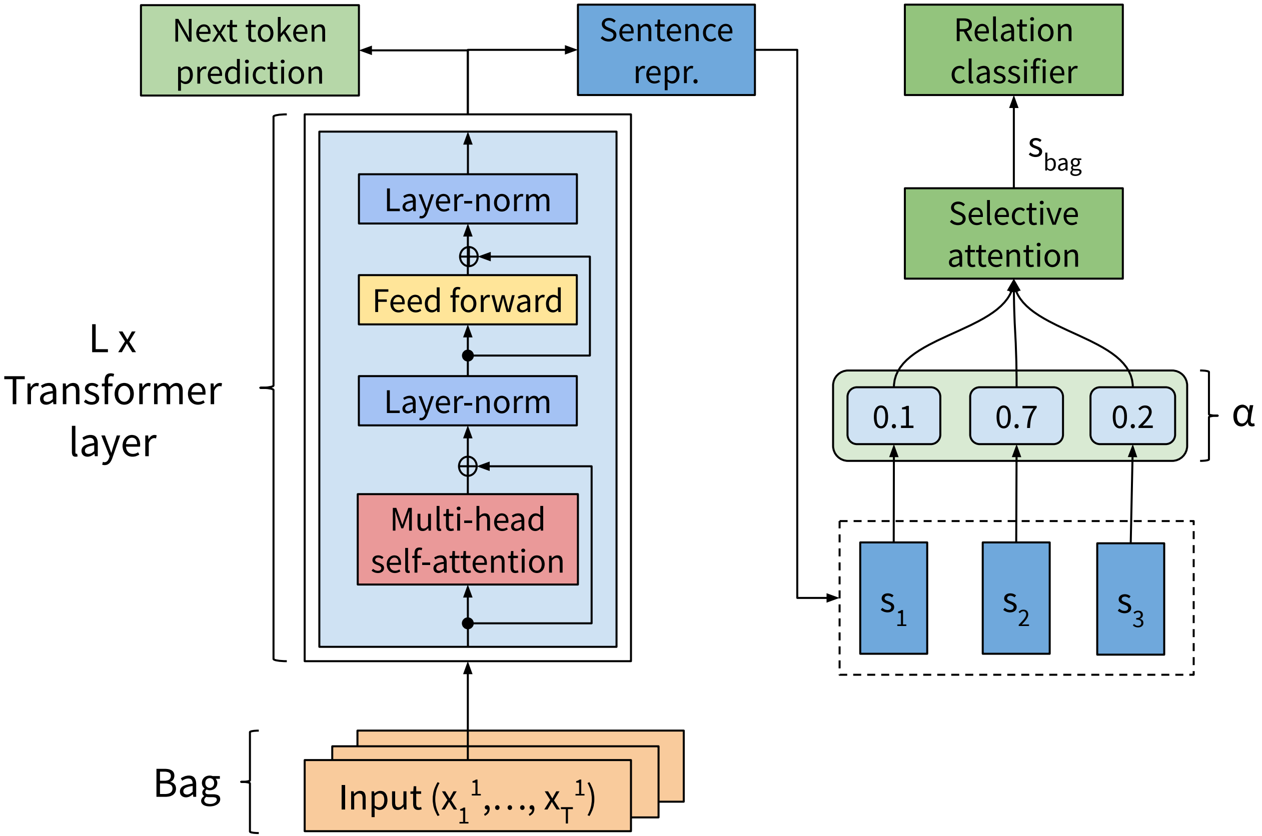

Parameter estimation

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Relation extraction objective

$$L_{rel}(\mathcal{D}) = \sum_{i=1}^{|\mathcal{D}|} \log P(r_i | t_i^1, \ldots, t_i^{|T_i|}, head_i, tail_i)$$

Parameter estimation

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$$L_{rel}(\mathcal{D}) = \sum_{i=1}^{|\mathcal{D}|} \log P(r_i | t_i^1, \ldots, t_i^{|T_i|}, head_i, tail_i) \rightarrow f_R(f_M(\ldots;\theta_M);\theta_R)$$

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Language model objective

$$L_{lang}(\mathcal{D}) = \sum_{i=1}^{|D|} \sum_{j=1}^{|T_i|} \log P(t_j | t_{j-1}, \ldots, t_1)$$

Parameter estimation

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Parameter estimation

Relation extraction objective

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Maximum likelihood estimate

$$L(\mathcal{D}) = L_{rel}(\mathcal{D}) + \lambda * L_{lang}(\mathcal{D})$$

$$\hat{\theta} = \arg\max_{\theta} L(\mathcal{D}; \theta), with\ \theta = \{\theta_M, \theta_R, \theta_L\}$$

Datasets

Dataset	Examples	Neg. examples (%)	Relations	Supervision
SemEval 2010 Task 8	10,717	17.4%	19	traditional
TACRED	106,264	79.5%	42	traditional
NYT-10	522,611	-	53	distant

Examples

SemEval 2010

content-container

The key was in a chest.

TACRED

org:subsidiary

The measure included Aerolineas's domestic subsidiary, Austral.

Evaluation

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Hypothesis:

The proposed method performs equal or better than baselines that rely on explicit features.

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Experiment setup:

- Initialize the model (with parameters from OpenAI GPT [Radford et al., 2018])
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Metrics:

- Performance: Precision, Recall, F1 score, P-R curve, area under the curve
- Data efficiency: F1 score over percentage of training data

Supervised RE: Results

TACRED

System	P	R	F1
LR	72.0	47.8	57.5
CNN	72.1	50.3	59.2
PCNN	**73.6**	53.4	61.9
Tree-LSTM	66.0	59.2	62.4
PA-LSTM	65.7	64.5	65.1
C-GCN	69.9	63.3	66.4
TRE	70.1	**65.0**	**67.4**

SemEval 2010

System	P	R	F1
SVM	–	–	82.2
PA-LSTM	–	–	82.7
C-GCN	–	–	84.8
DRNN	–	–	86.1
BRCNN	–	–	86.3
PCNN	86.7	86.7	86.6
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Baselines: LR, SVM
State-of-the-art systems: PCNN, C-GCN, PA-LSTM

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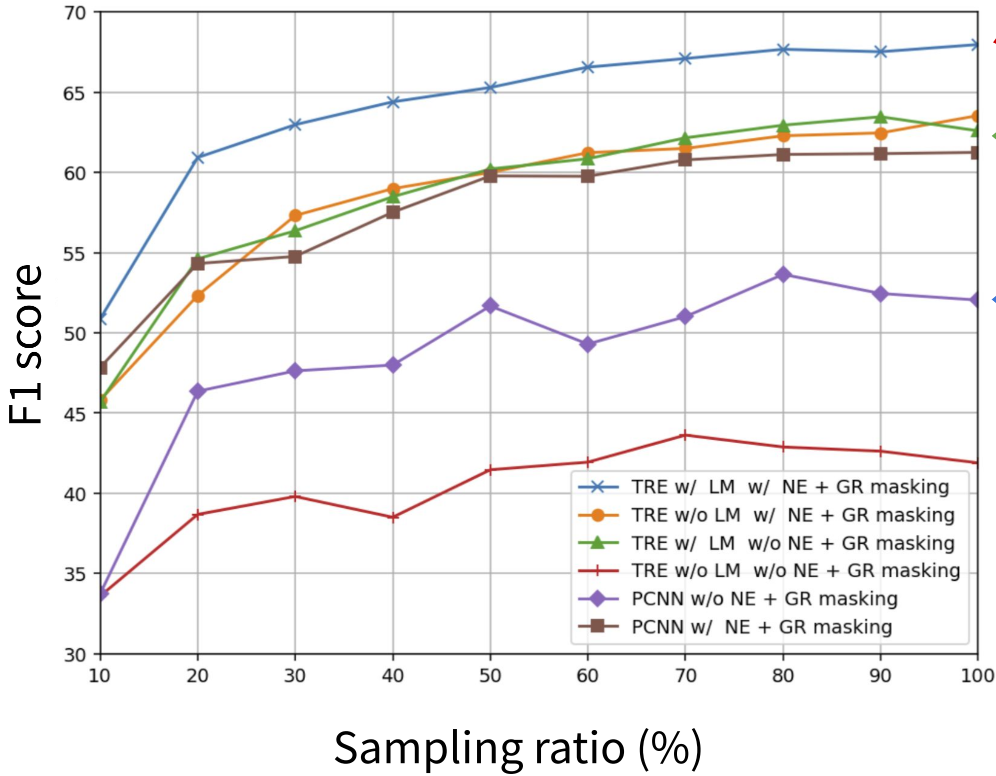
TACRED: Data efficiency

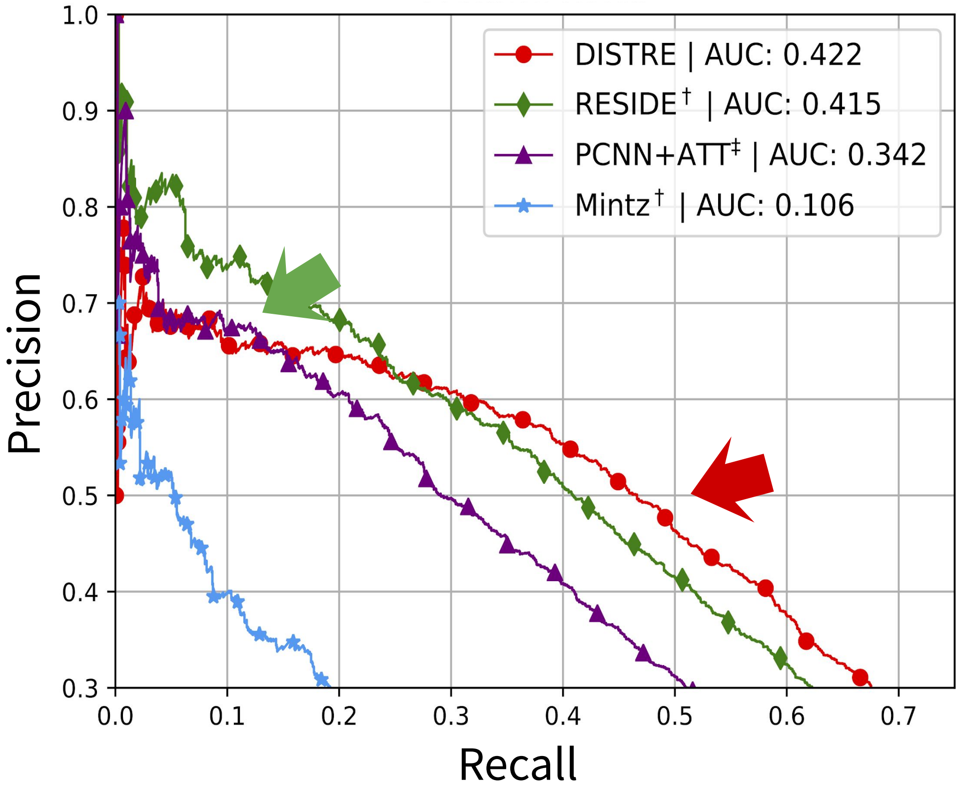


transfer learning with entity masking

transfer learning w/o entity masking
baseline with entity masking

baseline

Distantly supervised RE: Results



Baselines: Mintz

State-of-the-art system: RESIDE

Conclusion

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- State-of-the-art sequential transfer learning systems for RE
- Language models capture more syntactic than semantic knowledge
- Improved performance on infrequently observed relations (long-tail)

Outlook

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- Improve acquisition and reuse of relevant knowledge

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- Improve acquisition and reuse of relevant knowledge
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- Further improvements require better understanding of models, datasets, and the task

Thank you!

Publications

- *Improving Relation Extraction by Pre-trained Language Representations.* Christoph Alt*, Marc Hübner* and Leonhard Hennig. **AKBC 2019**
- *Fine-tuning Pre-Trained Transformer Language Models to Distantly Supervised Relation Extraction.* Christoph Alt, Marc Hübner and Leonhard Hennig. **ACL 2019**
- *Probing Linguistic Features of Sentence-Level Representations in Neural Relation Extraction.* Christoph Alt, Aleksandra Gabryszak and Leonhard Hennig. **ACL 2020**
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References

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