ASPER: Answer Set Programming Enhanced Neural Network Models for Joint Entity-Relation Extraction

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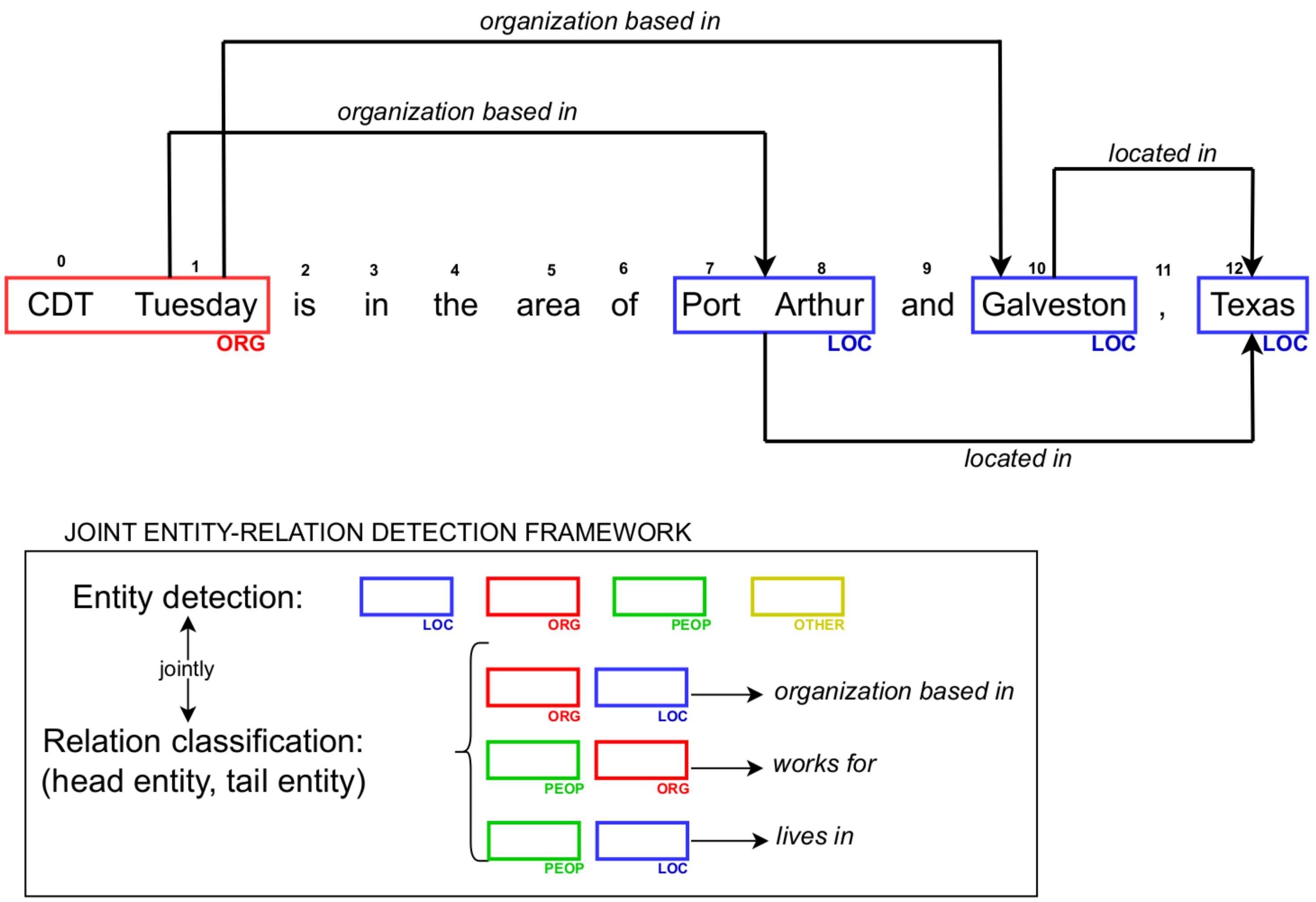
Joint Entity-relation Extraction

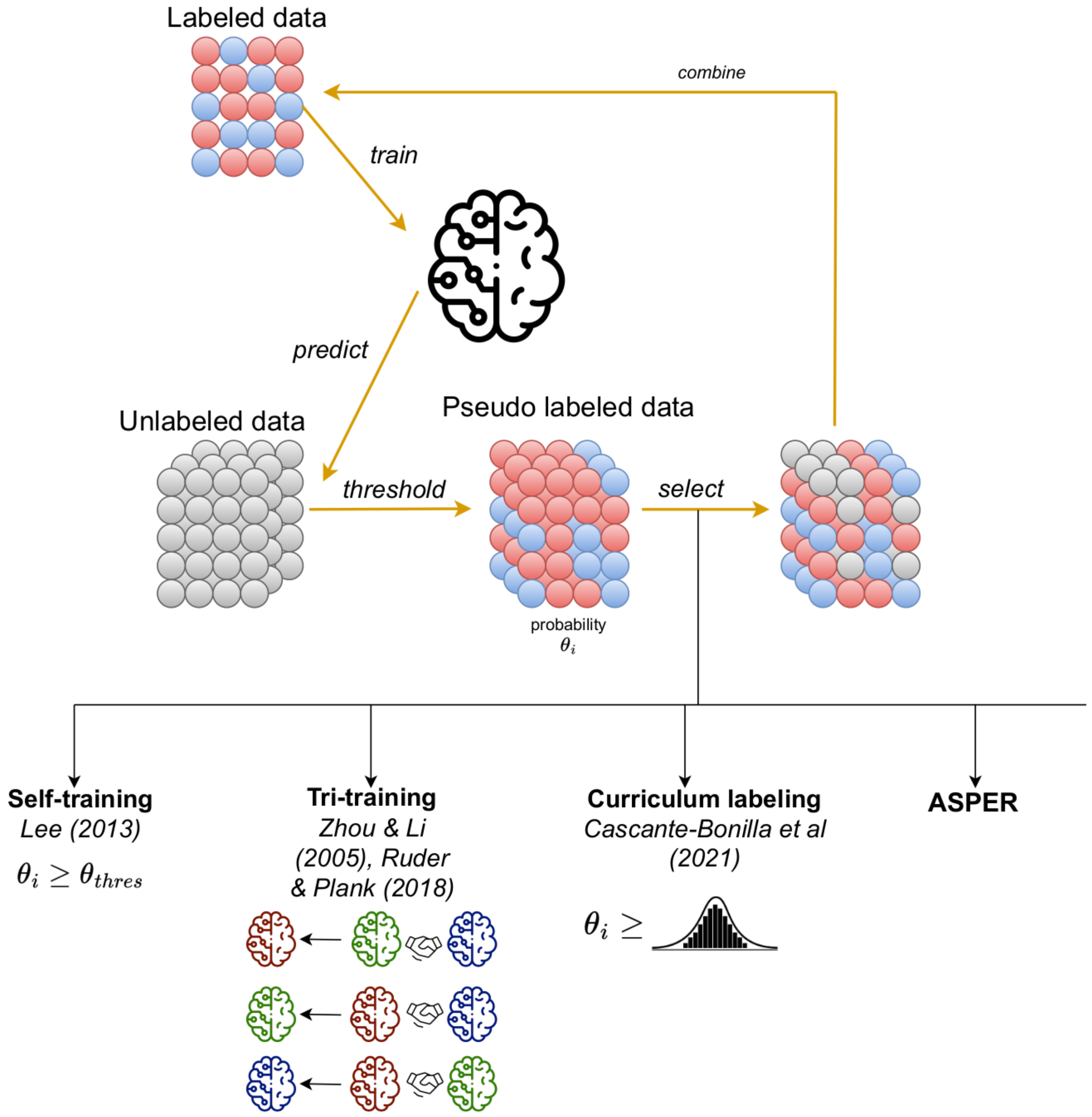


Semi-supervised learning

While **Labeled** data is expensive.

Unlabeled data is cheap and plentiful (e.g. Wikipedia dump).

Semi supervised learning (SSL): utilizes both labeled and unlabeled data to improve predictions.



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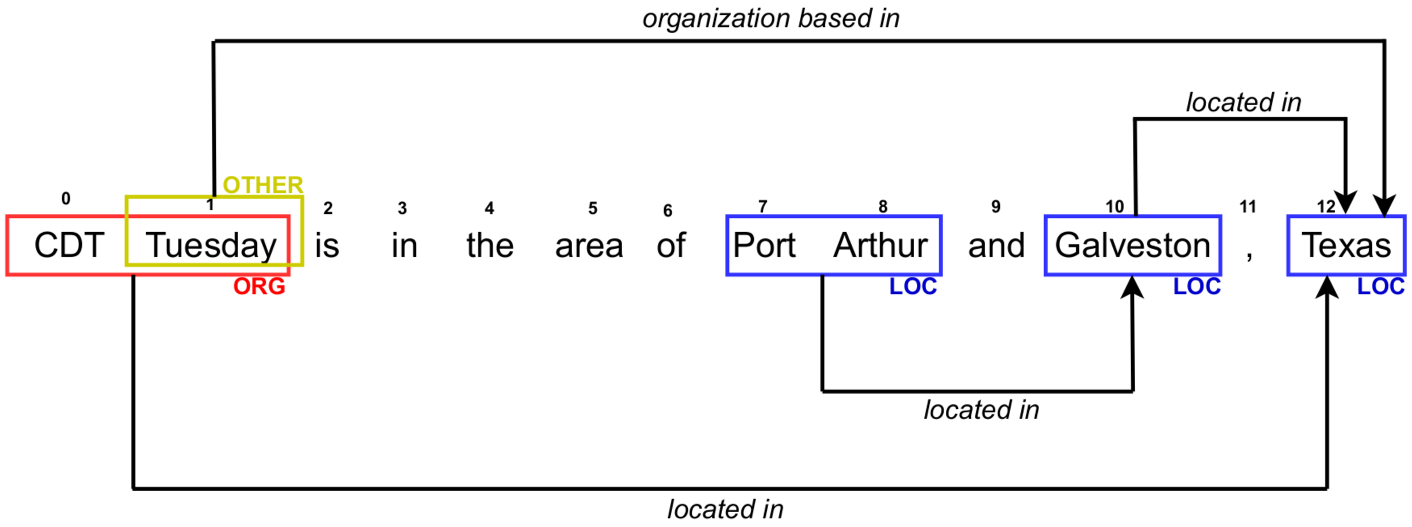
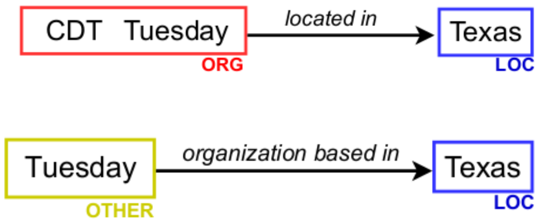
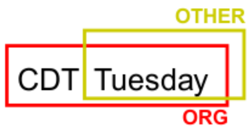


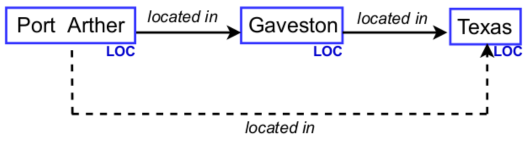
- Inconsistencies:



- Overlapped entities:



- Hidden relations:

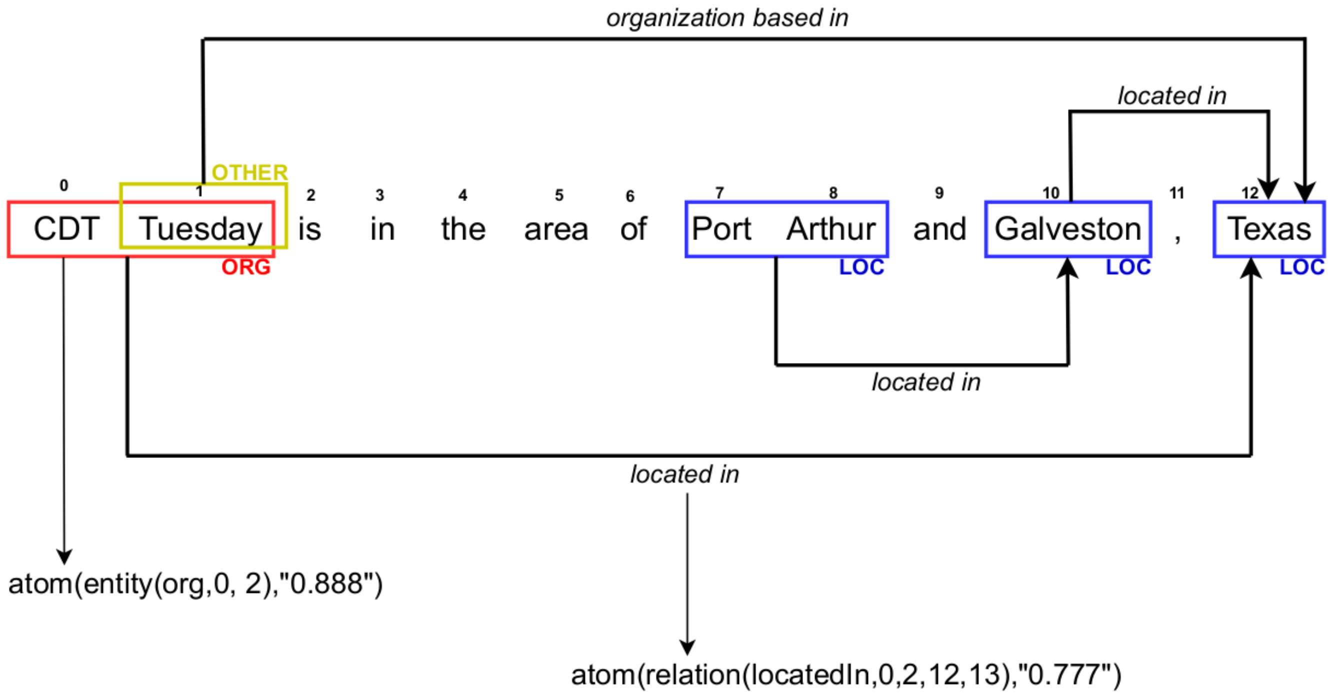


There are many consistent sets of pseudo labels.

1. How to find all of them?
2. Which set is "the best" to include in the training set?

ASPER

- Pseudo labels as atoms
- Three special predicates:
  - ok(X): accept X
  - nok(X): rejects X
  - pi(X): X could be rejected



- Knowledge are encoded as rules:

type_def(liveIn, peop, loc).
type_def(locatedIn, peop, loc).
type_def(orgbasedIn, org, loc).
type_def(workFor, peop, org).
type_def(kill, peop, peop).

2{pi(relation(R,B,E,B',E');pi(entity(N,B,E))}<- type_def(R,N1,N2), atom(relation(R,B,E,B',E')), atom(N,B,E)),N1 != N.
<- ok(relation(R,B,E,_,_)), ok(entity(N,B,E)), type_de(R,N',_), N!= N'.

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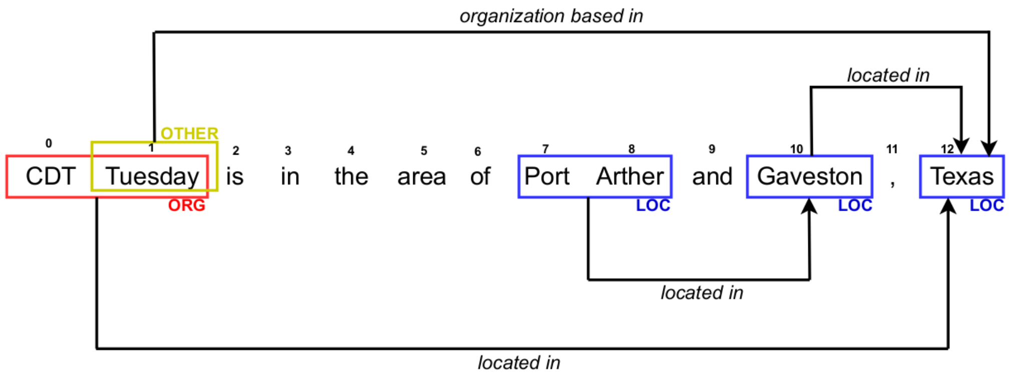
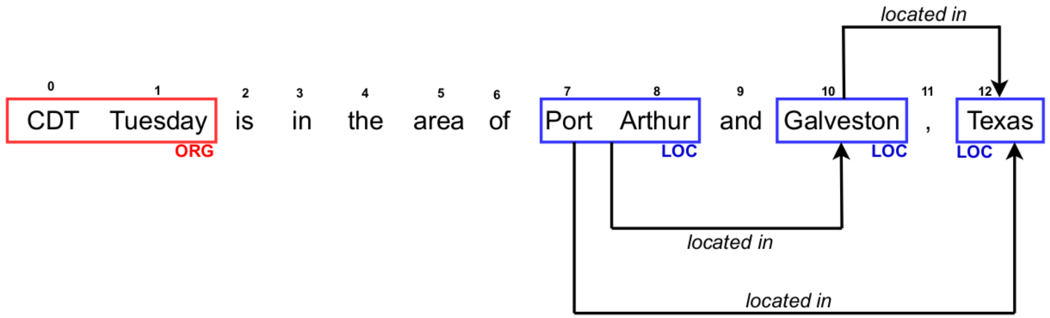


- Each answer set contains ok(…) atoms.

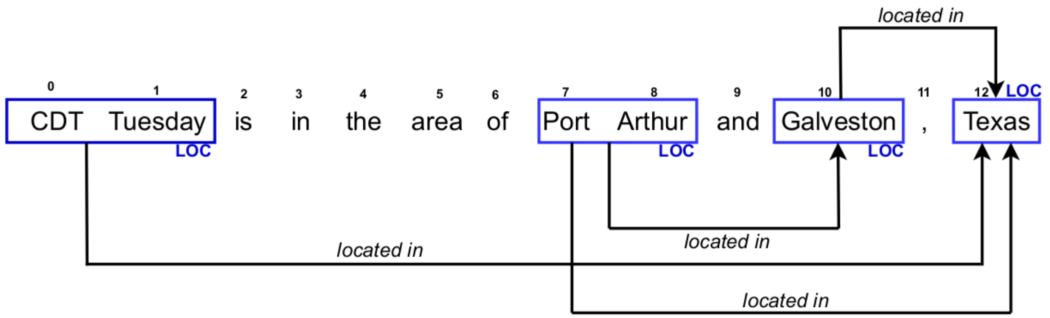
ok(entity(org,0,2))
ok(entity(loc,7,9))
ok(entity(loc,10,11))
ok(entity(loc,12,13))

ok(relation(locatedIn,7,9,10,11))
ok(relation(locatedIn,10,11,12,13))
ok(relation(locatedIn,7,9,12,13))



ok(entity(loc,7,9))
ok(entity(loc,10,11))
ok(entity(loc,12,13))
ok(entity(loc,0,2))

ok(relation(locatedIn,7,9,10,11))
ok(relation(locatedIn,10,11,12,13))
ok(relation(locatedIn,7,9,12,13))
ok(relation(locatedIn,0,2,12,13))



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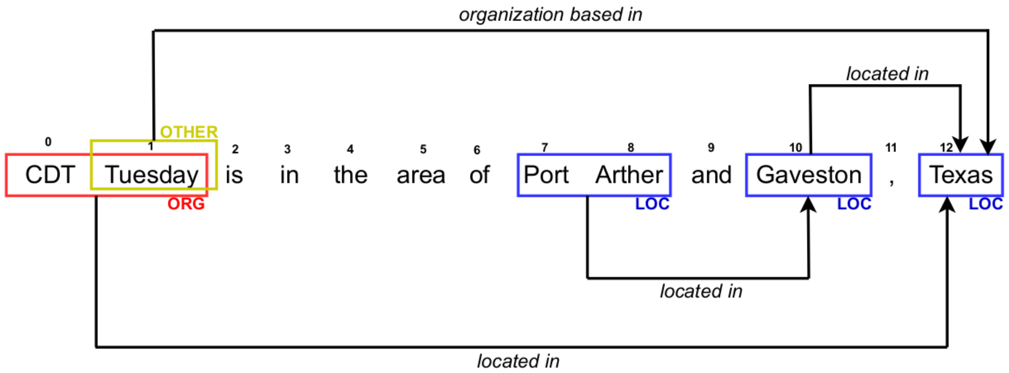
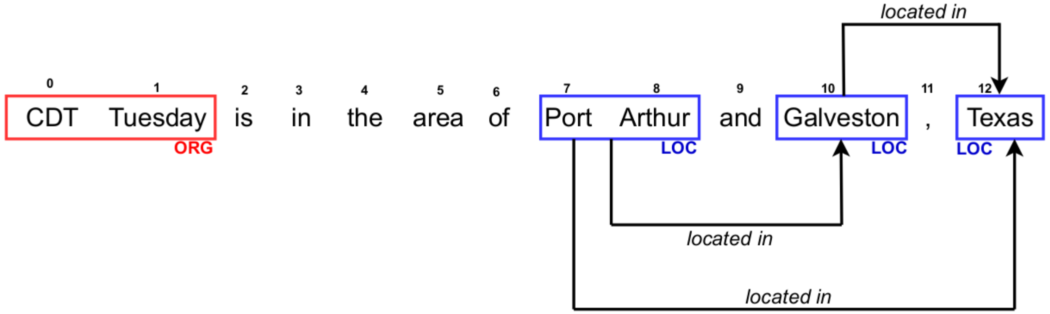
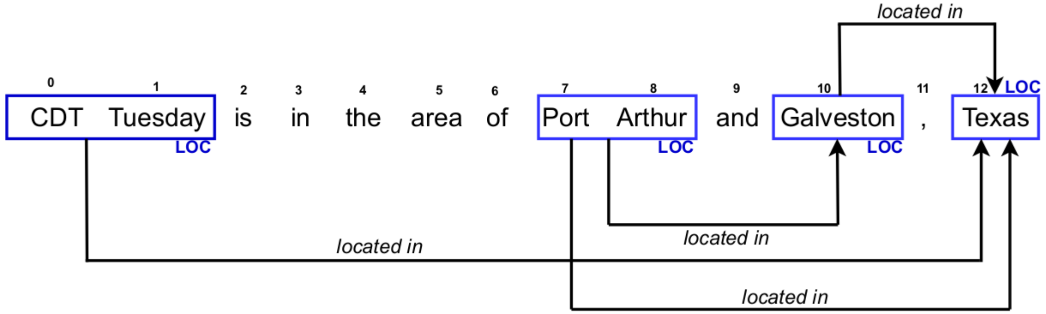
- **Which** answer set is better?







While **both** are **consistent** 2nd **seems** to be **better** because it keeps as much as what the model **originally predicted**.

ASPER

- Selection of consistent pseudo labels

  prob(X,P) <- atom(X,P), ok(X)

  invprob(X,P) <- atom(X,P), nok(X).

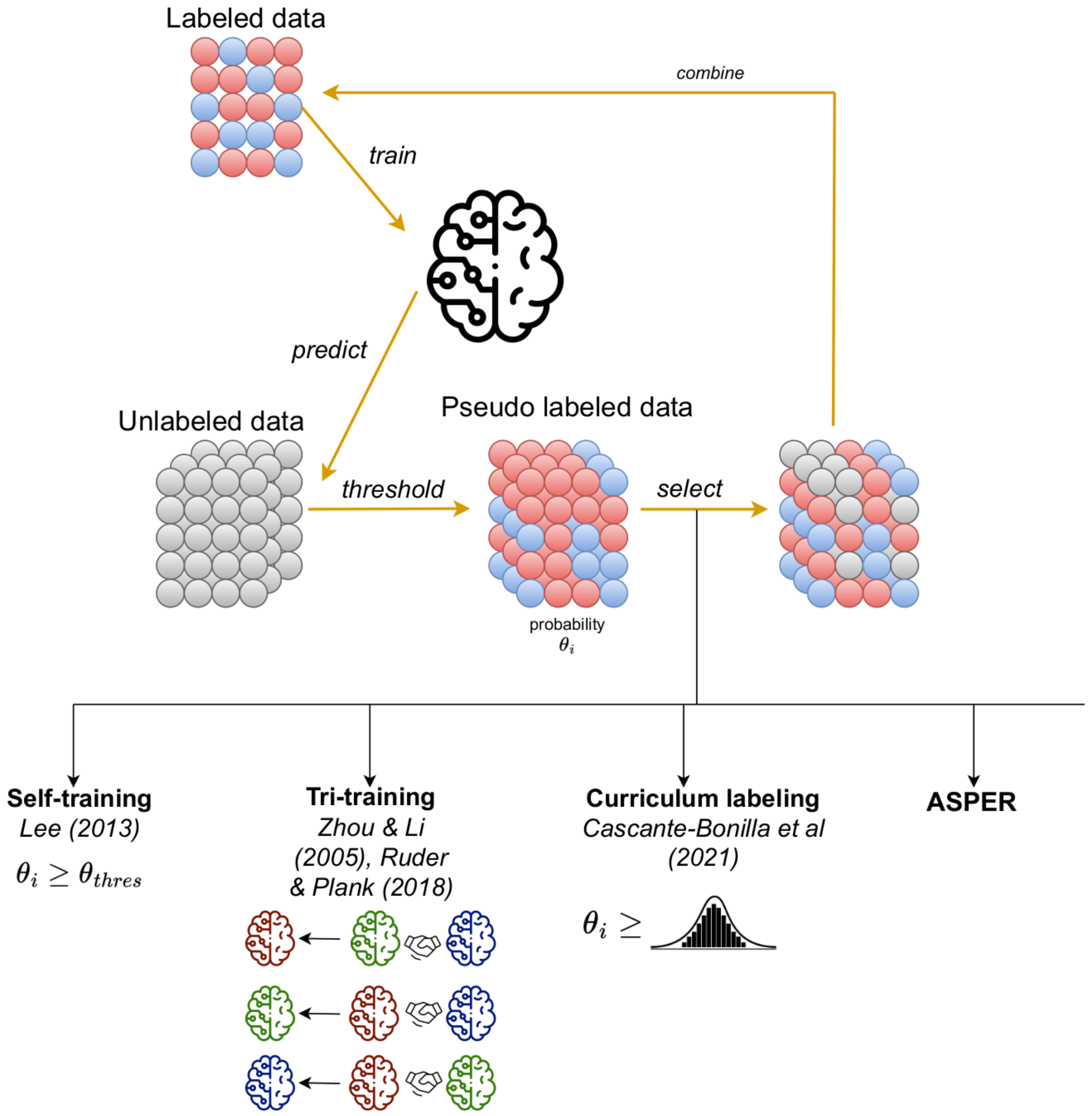
- Each answer set has two scores
  - Preference:

    $\prod_{prob(a,p) \in W} p \times \prod_{invprob(a,p) \in W} (1-p)$

  - Confidence:

    min{p | prob(l,p) ∈ W}

- Answer sets are selected based on preference.
- Sentences are selected based on confidence.



Experiments

- We use two datasets, **CoNLL04** and **SciERC** which have been utilized in other entity/relation extraction work.
- The **CoNLL04** dataset extracted from **newspapers** with train/dev/test split as **922/231/288** sentences.
- The **SciERC** dataset extracted from **artificial intelligence research papers** with train/dev/test split as **1861/275/551** sentences.
- We use a portion of training set (10%) as labeled data and the rest as unlabeled data.
- To get stable results, we randomly choose **five subsets** from the training data and train five models and report the average result.
- Comparison methods: **Self-training** (Lee 2013), **Curriculum labeling** (Cascante-Bonilla et al 2021) and **Tri-training** (Zhou&Li 2005, Ruder and Plank 2018).

Experiments

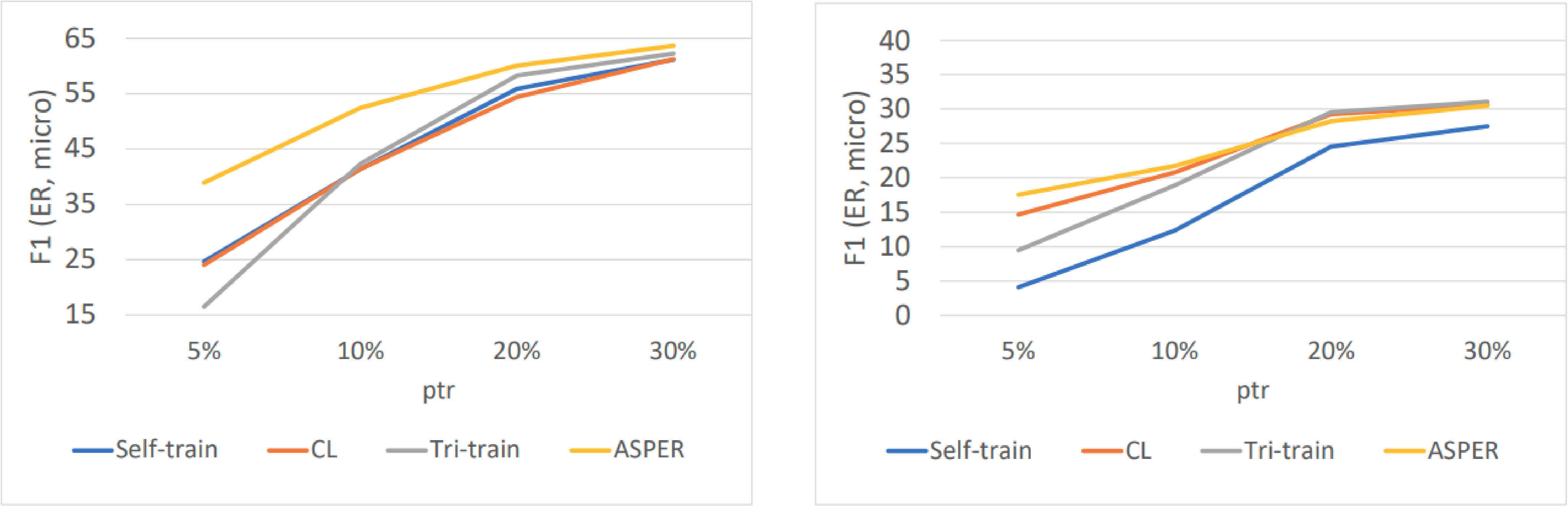
Performance of ASPER with 10% labeled data

	CoNLL04 dataset					
	F_1 (micro)			F_1 (macro)		
method	E	R	ER	E	R	ER
Self-train	77.74±1.7	41.76±5.7	41.39±5.7	72.50±1.9	43.19±6.0	42.82±6.0
CL	77.49±1.1	41.61±3.0	41.35±3.2	72.03±1.6	43.07±3.8	42.77±4.0
Tri-train	78.63±2.4	42.60±6.7	42.29±6.7	72.49±2.5	42.99±7.1	42.64±7.2
ASPER	**81.25**±1.2	**52.47**±3.6	**52.41**±3.6	**75.90**±1.7	**53.32**±4.0	**53.27**±4.0

	SciERC dataset					
	F_1 (micro)			F_1 (macro)		
method	E	R	ER	E	R	ER
Self-train	56.72±1.2	18.60±2.6	12.36±1.7	54.43±1.4	11.07±3.7	6.98±2.3
CL	60.75±0.8	31.00±2.1	20.81±1.0	59.19±0.4	22.00±3.8	15.55±1.8
Tri-train	**60.99**±0.7	27.43±1.9	18.94±1.4	**59.52**±0.4	17.09±3.6	11.59±2.7
ASPER	60.34±0.6	**32.30**±1.2	**21.73**±1.2	59.10±0.4	**22.72**±3.1	**16.06**±2.3

Experiments

ASPER's performance when we vary the portion of labeled data



(a) CoNLL04

(b) SciERC

Conclusions

- ASPER leverages ASP to improve NN models in the joint recognition of entities and relation task when limited amount of training data is available.
- The ASP program encodes different types of commonsense rules by taking advantage of the commonsense domain knowledge.
- The experiments on two real datasets show that ASPER can report significantly better results than the other baselines in most cases.
- ASPER is a framework that can be extended for Semi-supervised learning when pseudo labels have clear semantic.

References

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3. RUDER, S. AND PLANK, B. 2018. Strong baselines for neural semi-supervised learning under domain shift. In ACL 2018. Association for Computational Linguistics, 1044–1054.

4. CASCANTE-BONILLA, P., TAN, F., QI, Y., AND ORDONEZ, V. 2021. Curriculum labeling: Revisiting pseudo-labeling for semi-supervised learning. In AAAI. AAAI Press, 6912–6920.