

Learning Cross-lingual Distributed Logical Representations for Semantic Parsing

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Outline

- ✓ Background & Motivation
- ✓ Method
- ✓ Experiments & Analysis
- ✓ Conclusion

Semantic Parsing

Goal: Map natural languages into semantic representations.

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Natural
Language

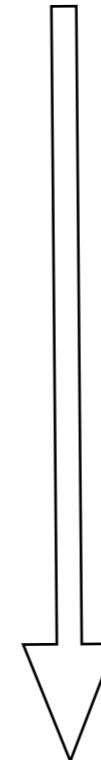
English: what states have no bordering state ?

Semantic Parsing

Goal: Map natural languages into semantic representations.

Natural
Language

English: what states have no bordering state ?



Logical
Form

answer(exclude(state(all), next_to(state(all))))

Semantic Parsing

Goal: Map natural languages into semantic representations.

Natural
Language

English: what states have no bordering state ?



QUERY : *answer* (STATE)

STATE: *exclude* (STATE, STATE)

STATE : *state* (all) STATE : *next_to* (STATE)

STATE : *state* (all)



answer(exclude(state(all), next_to(state(all))))

Logical
Form

Joint Representations

Proposed in previous works:

- ✓ Synchronous CFG derivation trees
Wong and Mooney (2006, 2007)
- ✓ CCG derivation trees
Zettlemoyer and Collins (2005, 2007)
- ✓ Bayesian tree transducers
Jones, Goldwater and Johnson (2012)
- ✓ Hybrid Trees
Lu, Ng, Lee, Zettlemoyer (2008)

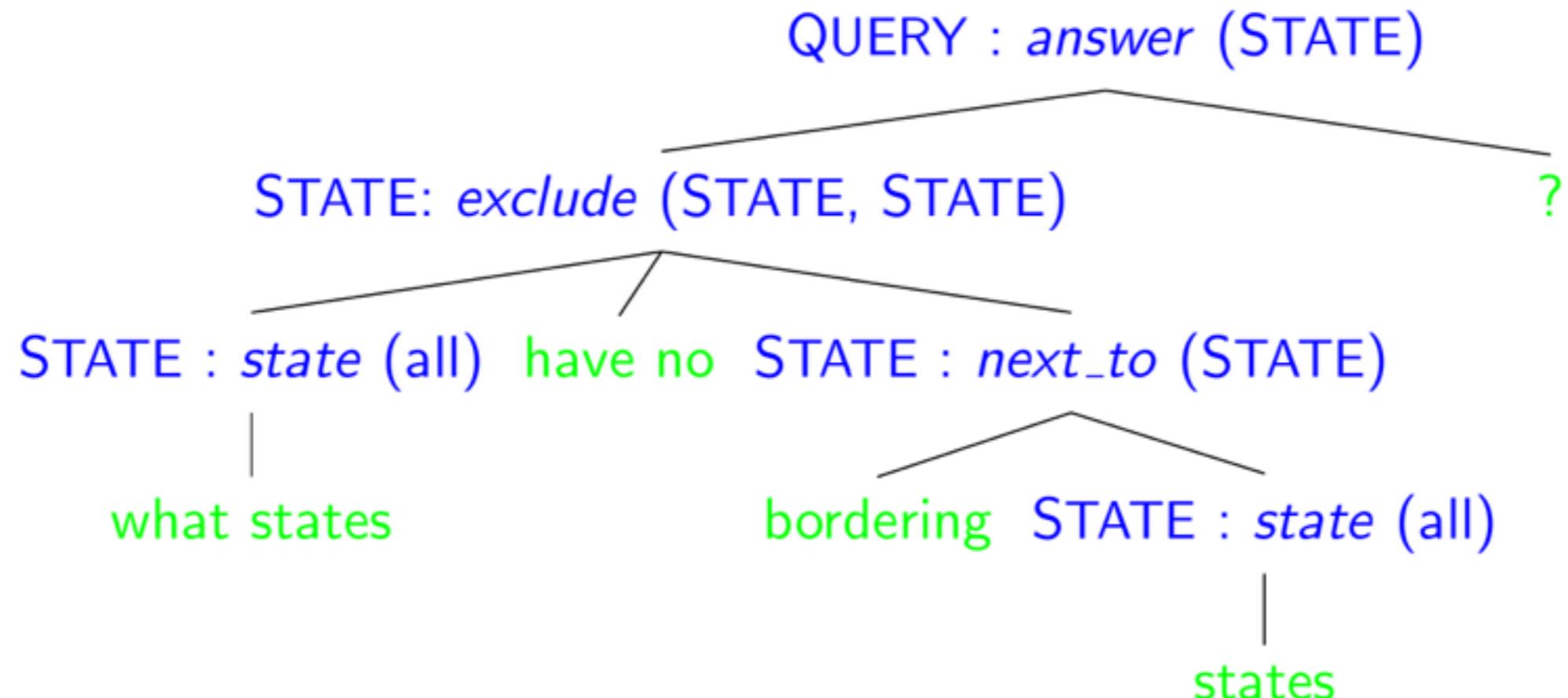


Hybrid Tree

Input: what states have no bordering states?

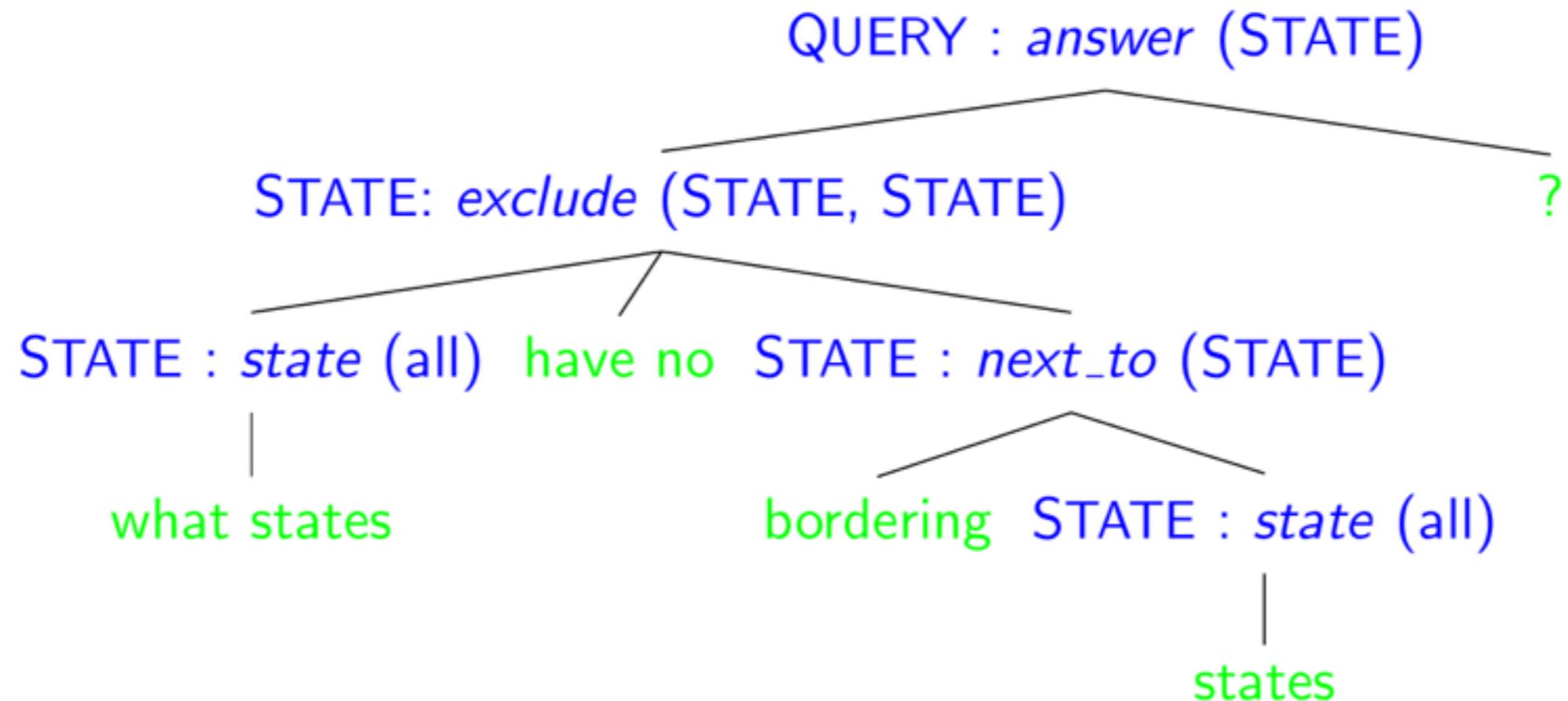
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Hybrid Tree

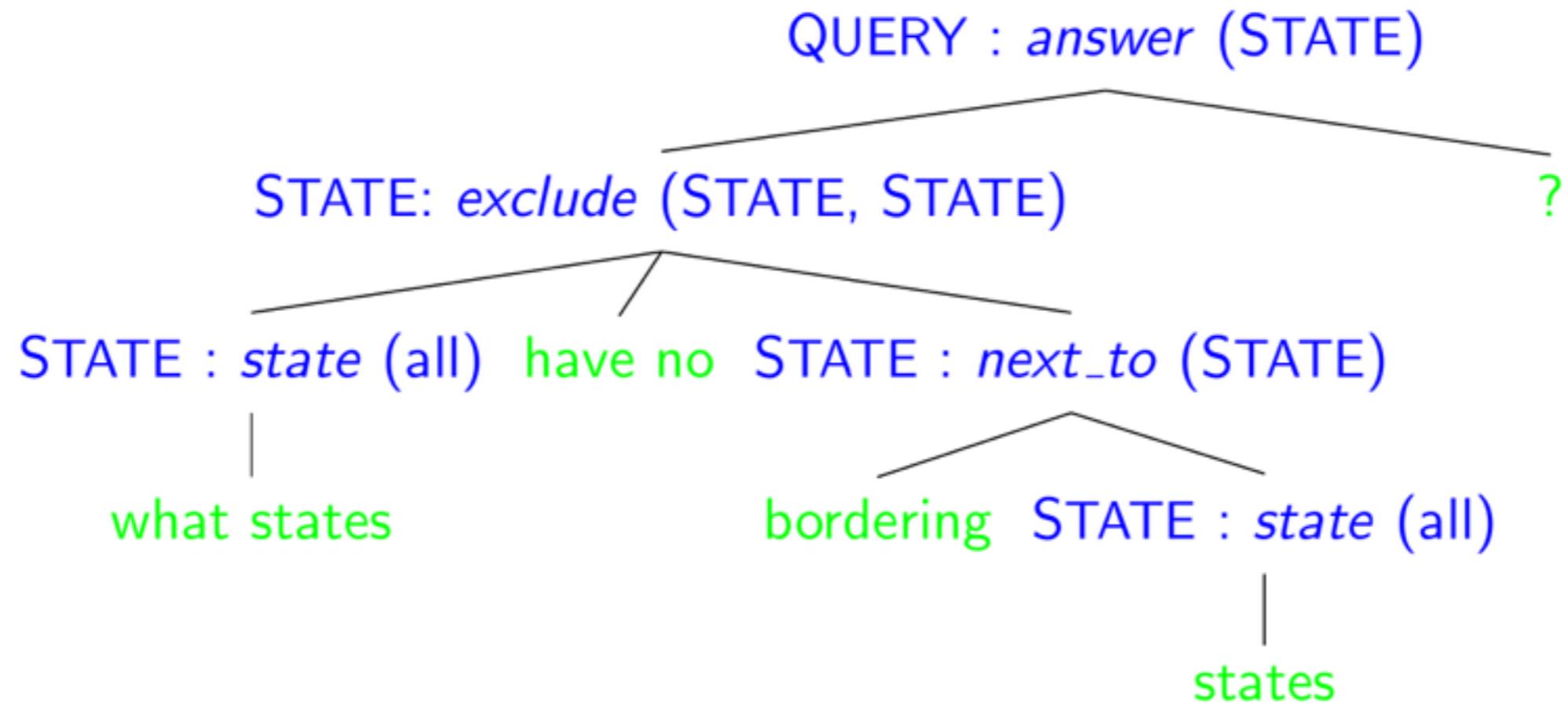
Input: what states have no bordering states?



Output: $\text{answer}(\text{exclude}(\text{state}(\text{all})), \text{next_to}(\text{state}(\text{all})))$

Generative Hybrid Tree

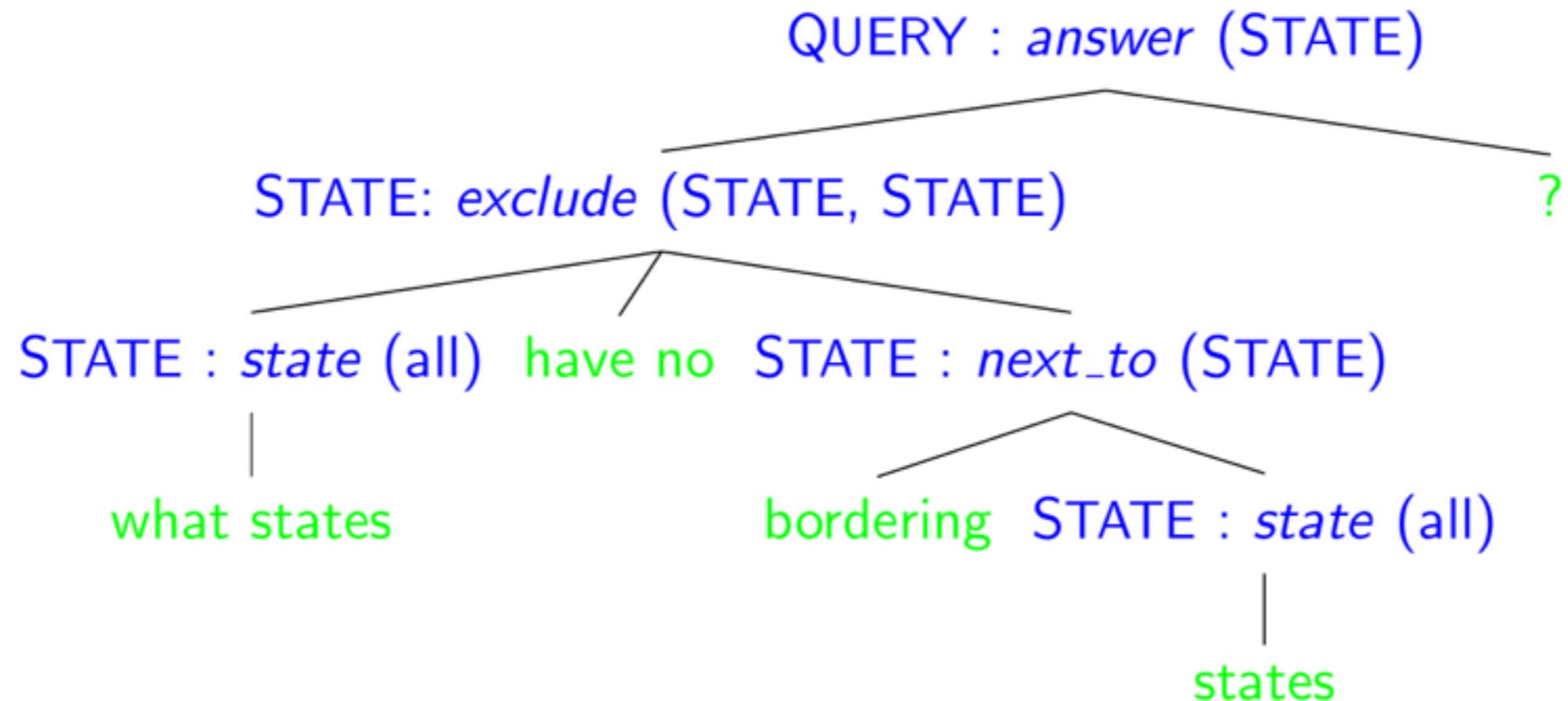
Input: what states have no bordering states?



$$p(\mathbf{m}, \mathbf{n}) = \sum_{\mathbf{h} \in \mathcal{H}(\mathbf{n}, \mathbf{m})} p(\mathbf{m}, \mathbf{h}, \mathbf{n})$$

Discriminative Hybrid Tree

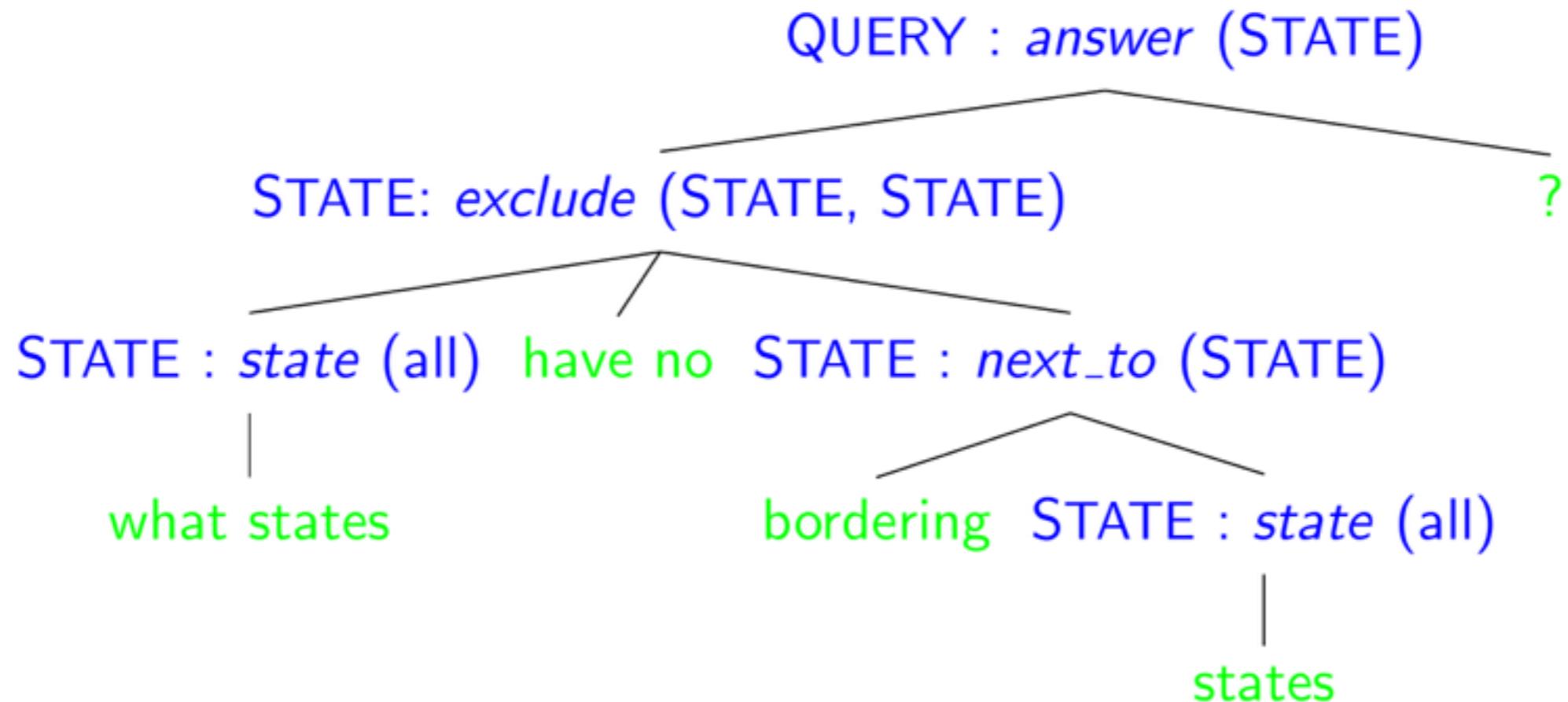
Input: what states have no bordering states?



$$p(\mathbf{m}|\mathbf{n}) = \sum_{\mathbf{h} \in \mathcal{H}(\mathbf{n}, \mathbf{m})} p(\mathbf{m}, \mathbf{h}|\mathbf{n})$$

Neural Hybrid Tree

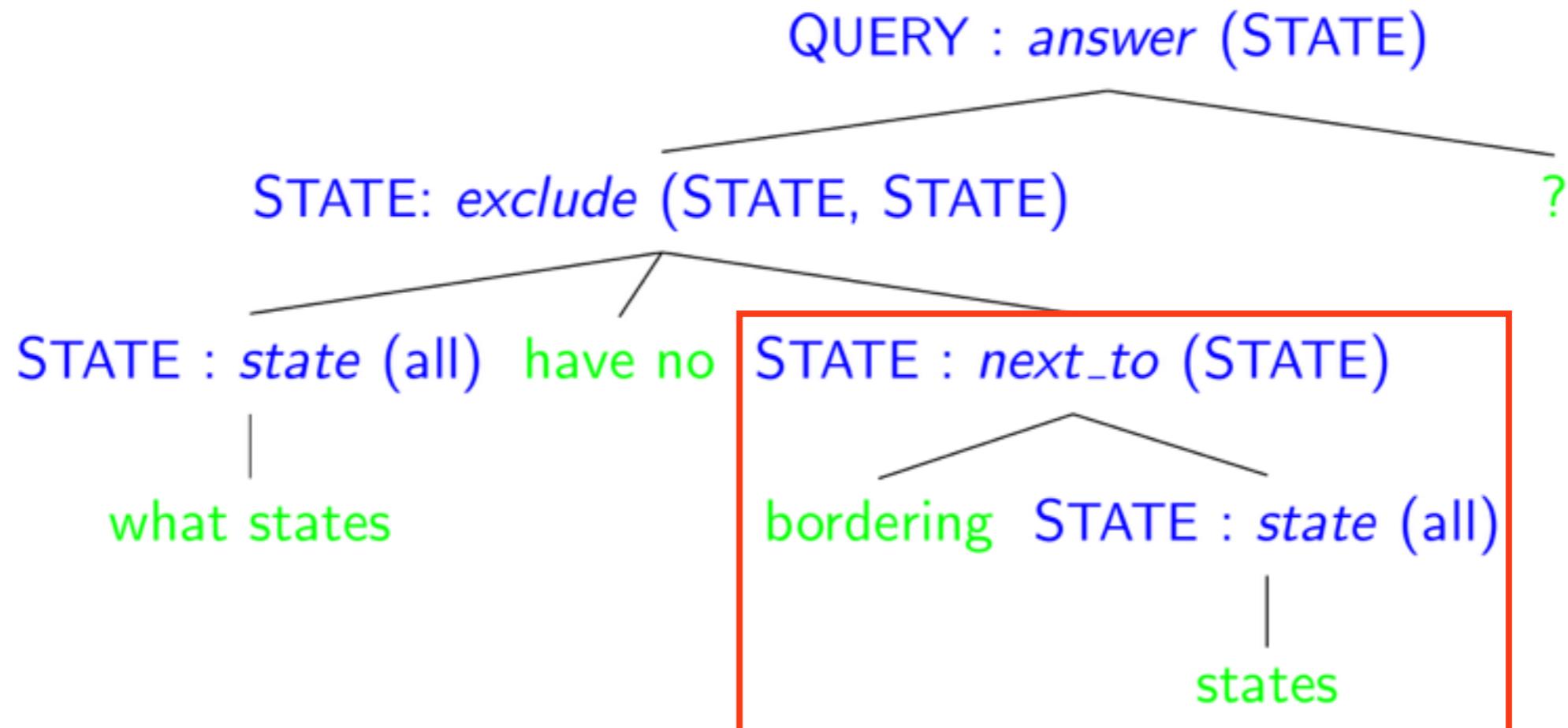
Input: what states have no bordering states?



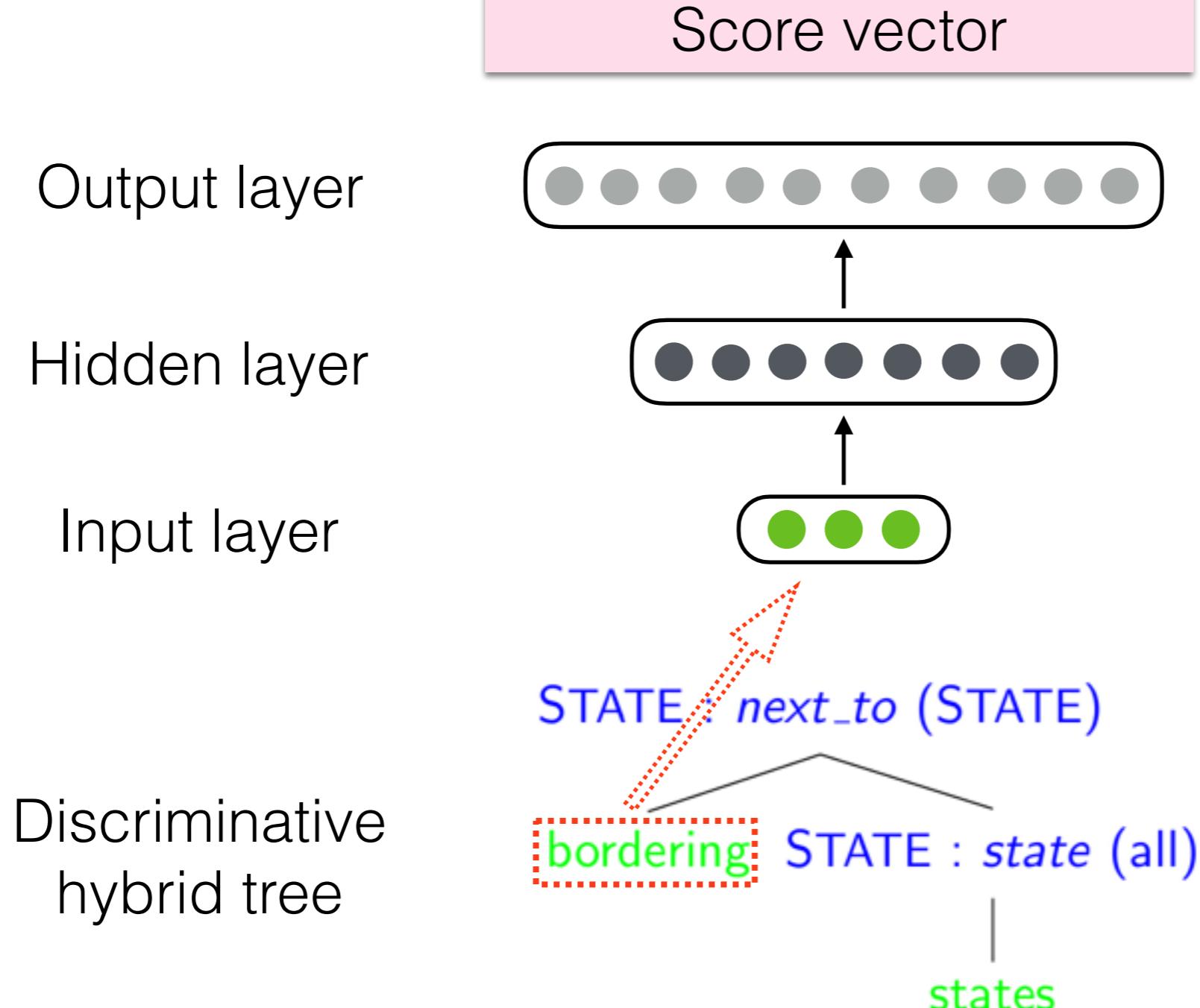
- Neural hybrid tree is an extension of discriminative hybrid tree.

Neural Hybrid Tree

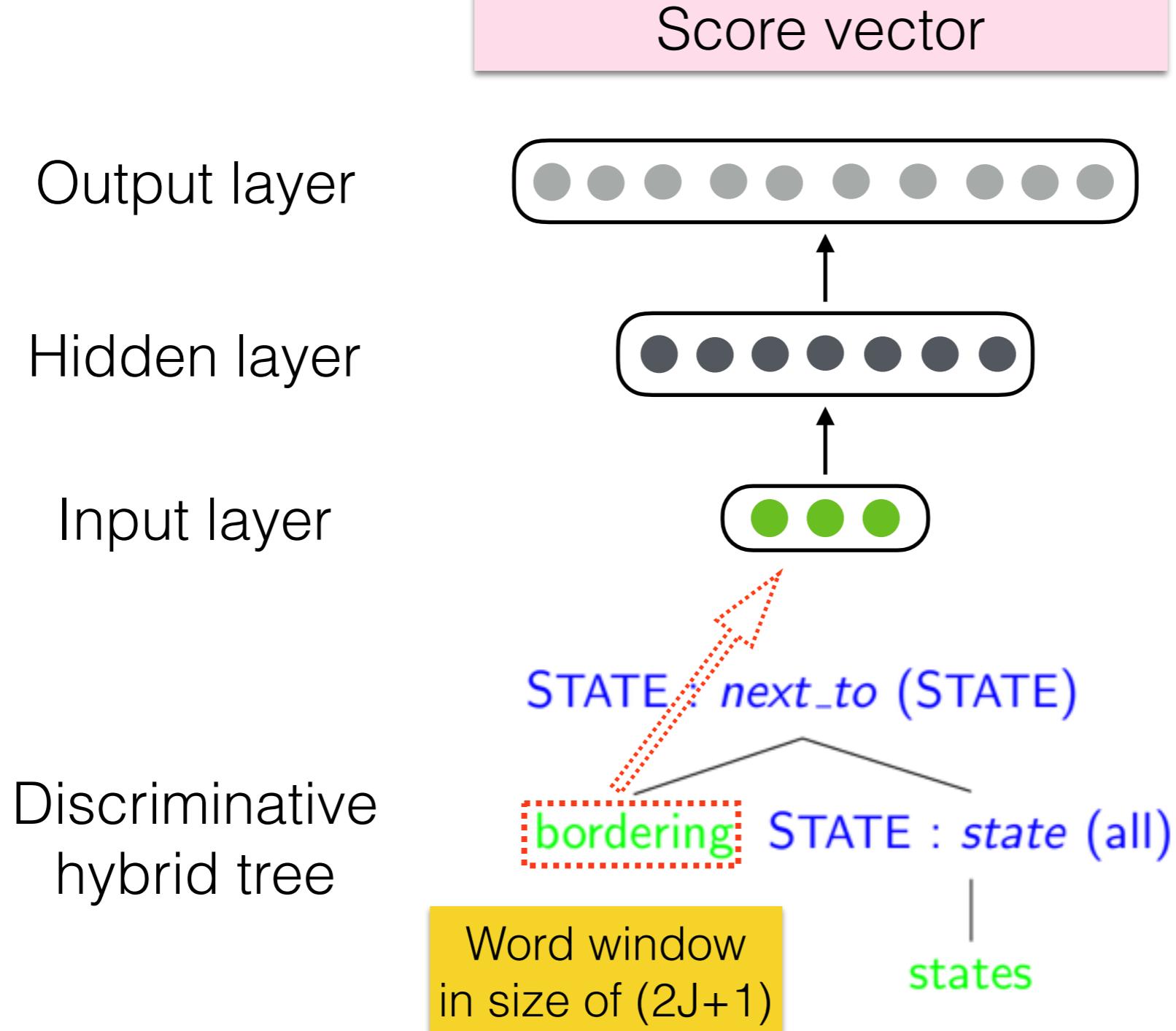
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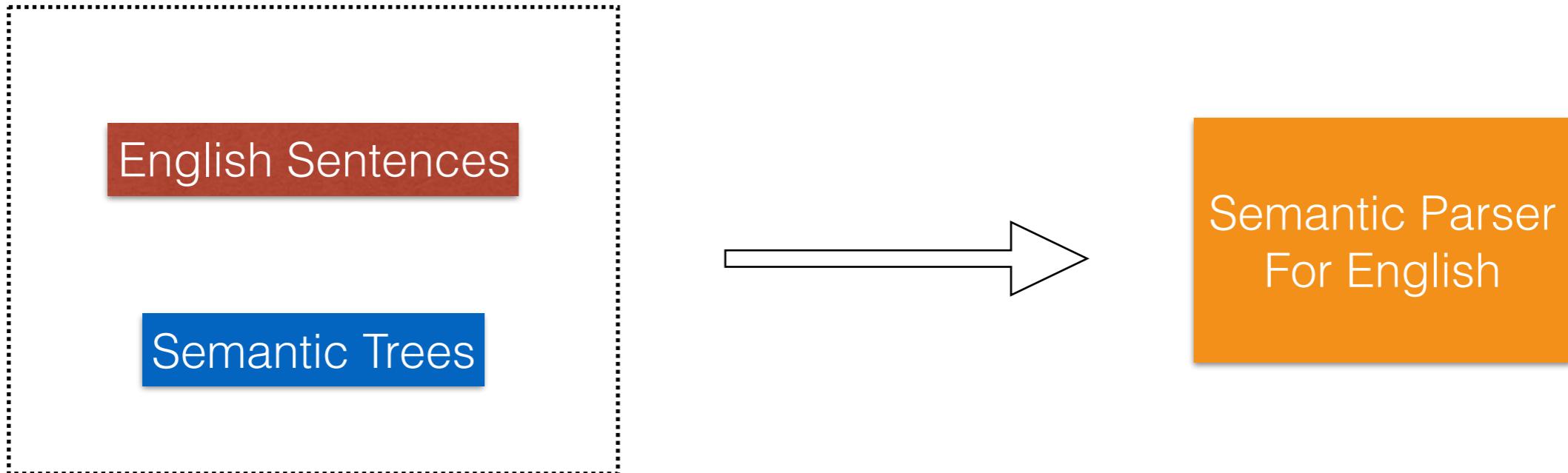
Neural Hybrid Tree



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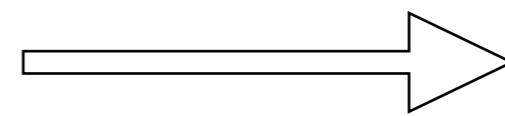
What do we have?



What do we have?

English Sentences

Semantic Trees



Semantic Parser
For English

German Sentences

Indonesian Sentences

Chinese Sentences

:

What do we have?

English Sentences

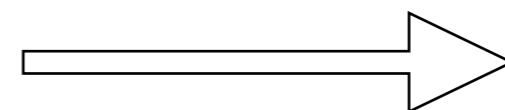
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Semantic Parser
For English

Can we leverage multi-lingual resources to improve the performance of a monolingual semantic parser?

What do we have?

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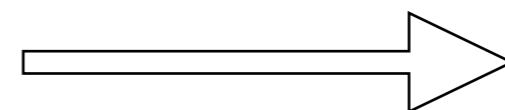
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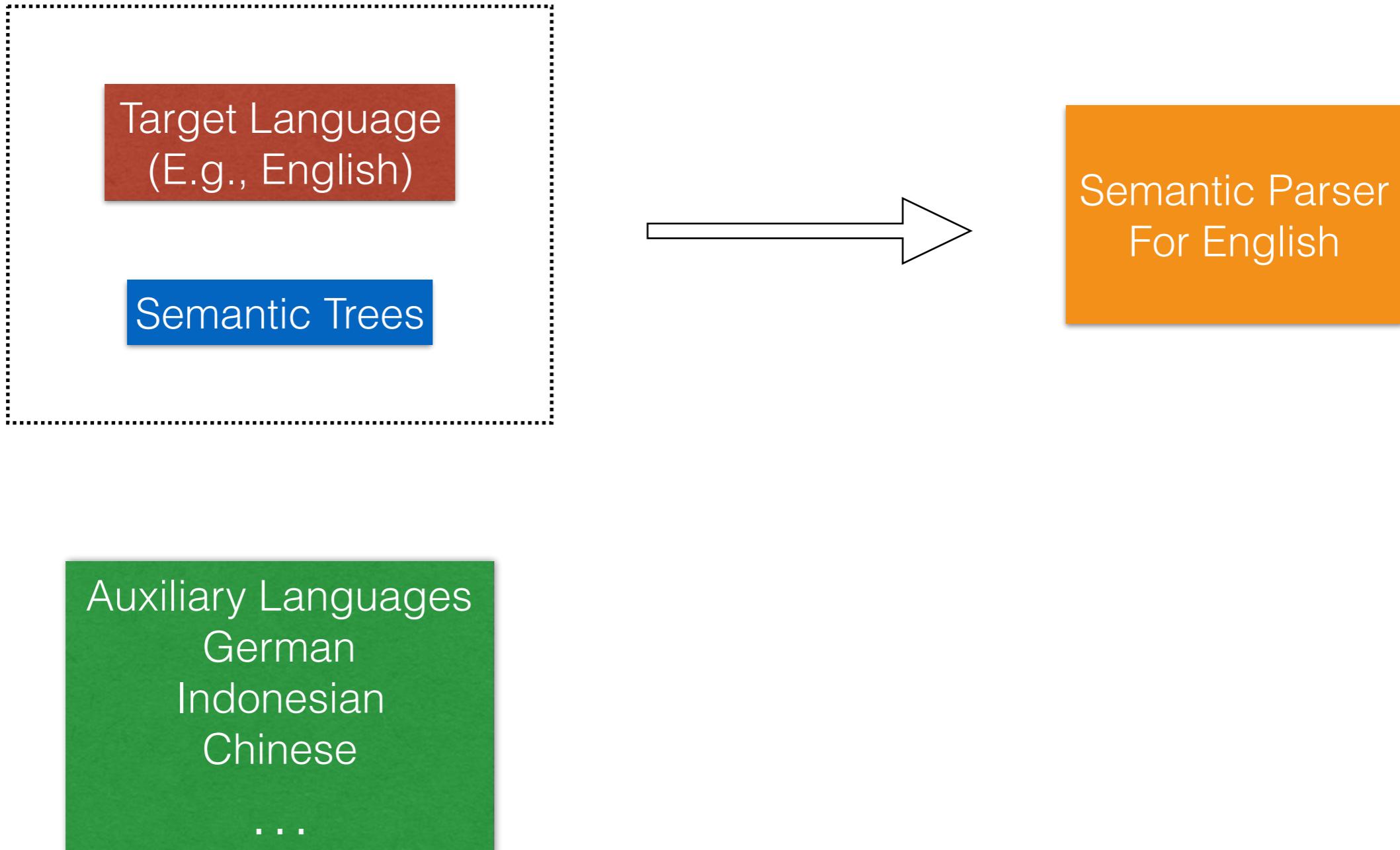


Semantic Parser
For English

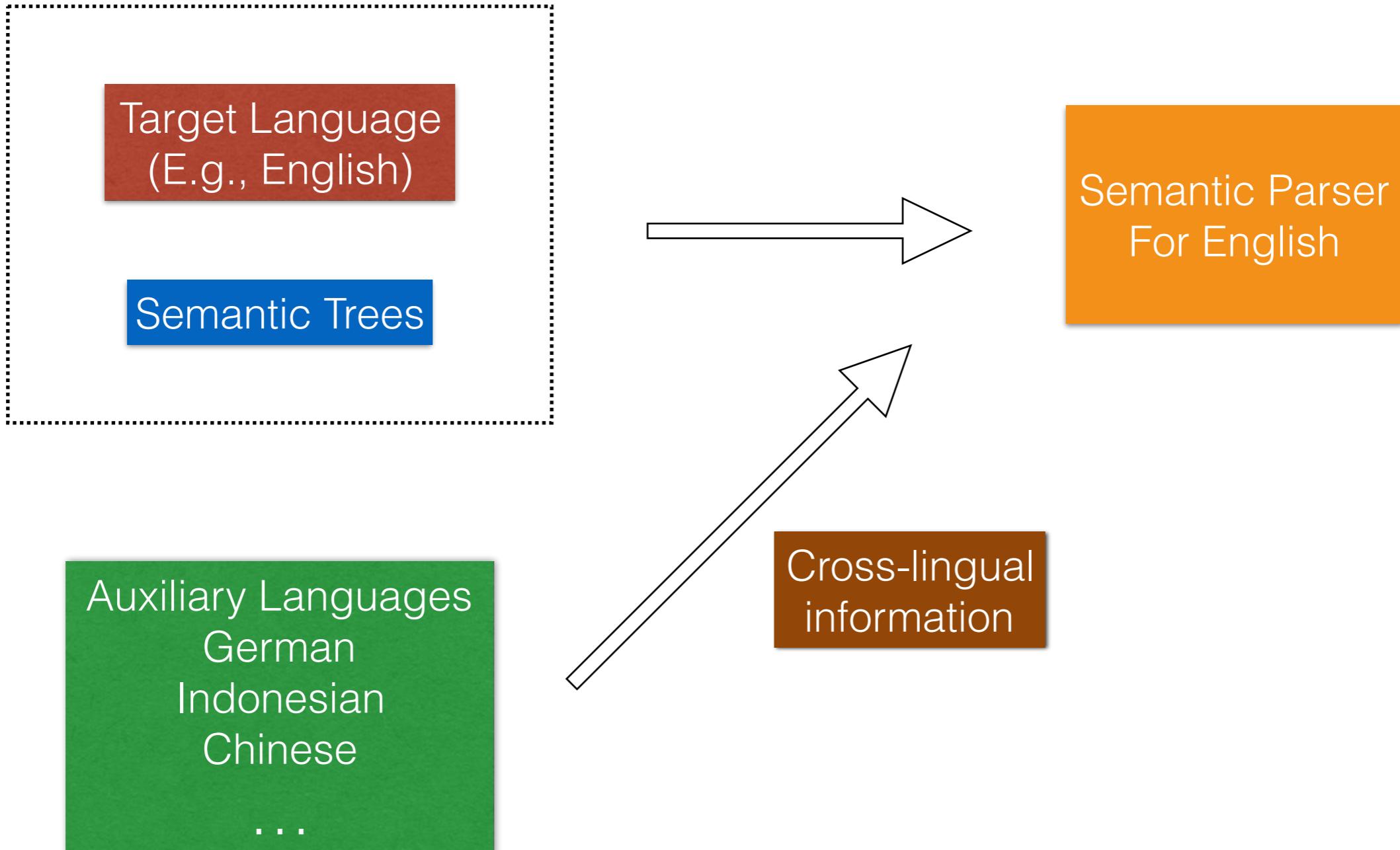
Can we leverage multi-lingual resources to improve the performance of a monolingual semantic parser?

The answer is Yes!!!

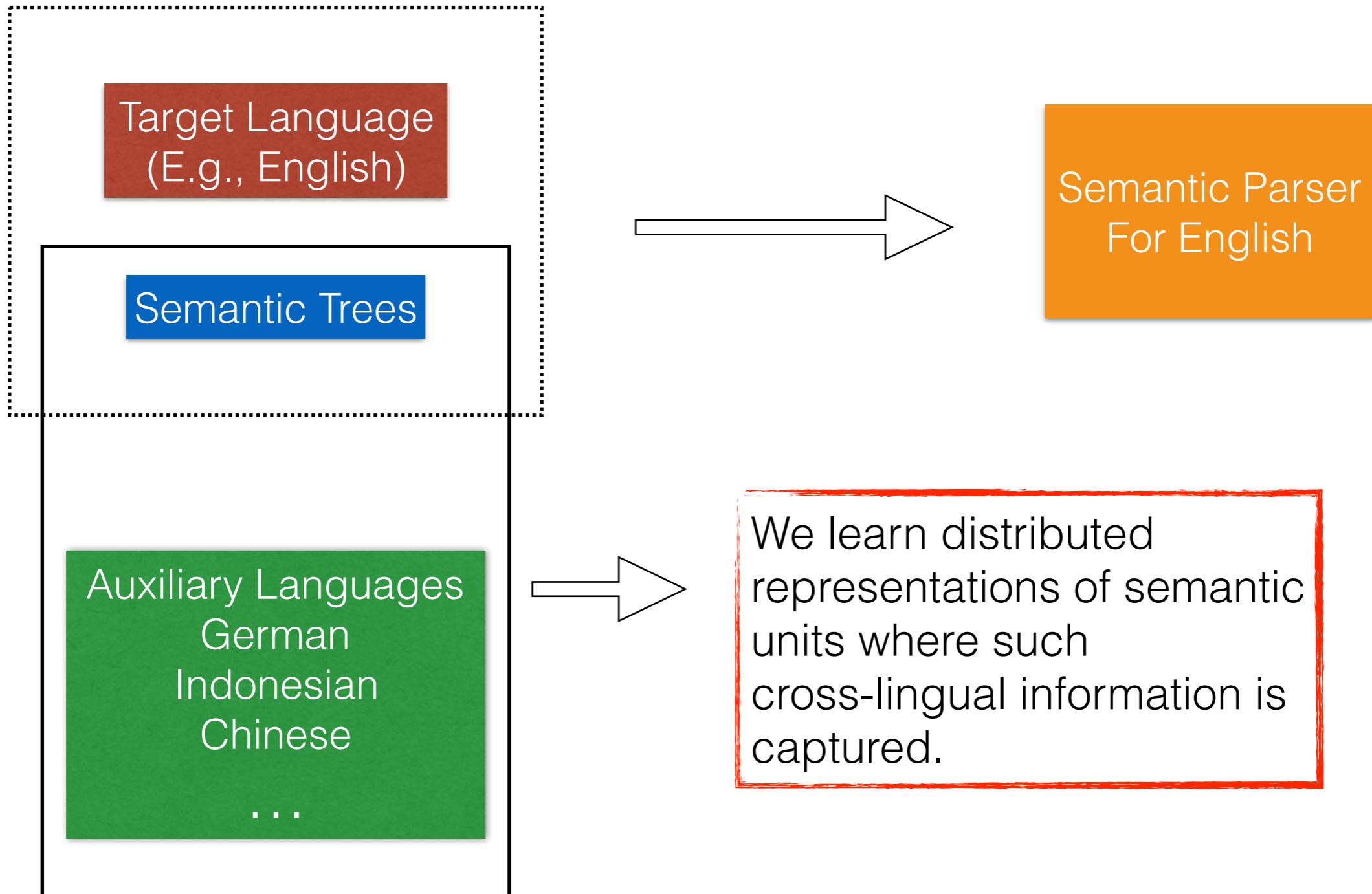
Setup



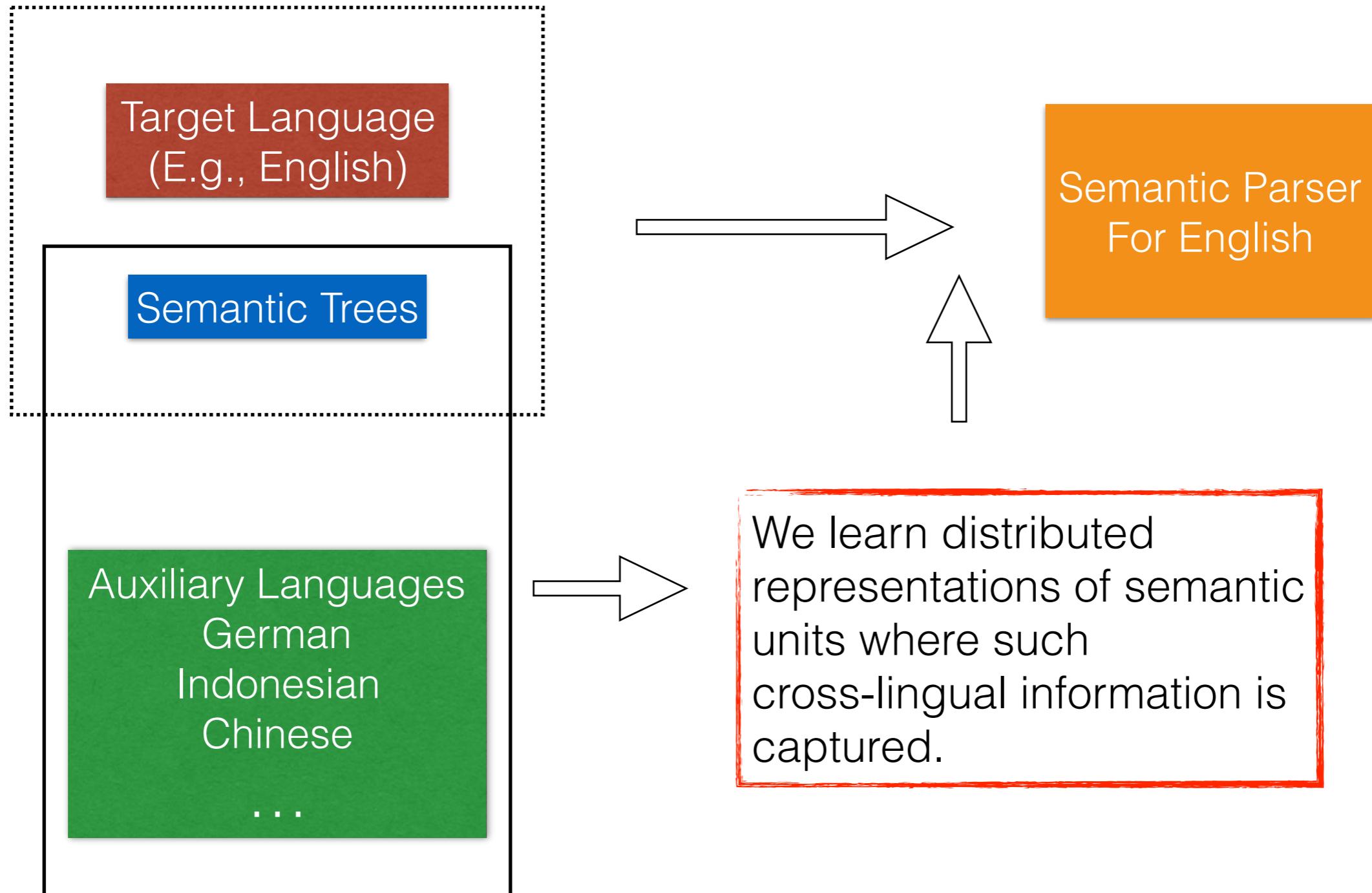
Setup



Setups



Setups



Cross-lingual Representations

We construct a semantics-word co-occurrence matrix $C \in R^{m \times n}$ based on auxiliary languages and semantic trees.



$$\rightarrow C = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{bmatrix}$$

Cross-lingual Representations

The singular value decomposition (SVD) is then applied to the co-occurrence matrix, leading to

$$C = U\Sigma V^*$$

We truncate the diagonal matrix Σ and left multiply it with U :

$$R = U\tilde{\Sigma}$$

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The learned representations are considered as features for discriminative and neural hybrid tree models.

Results

Data: Multilingual Geoquery

Results without Neural Features

Data: Multilingual Geoquery

Baselines: (Lu et al., 2008) (Lu, 2015)

	English		Thai		German		Greek		Chinese		Indonesian		Swedish		Farsi	
	Acc.	F.	Acc.	F.	Acc.	F.	Acc.	F.	Acc.	F.	Acc.	F.	Acc.	F.	Acc.	F.
HT-G	76.8	81.0	73.6	76.7	62.1	68.5	69.3	74.6	56.1	58.4	66.4	72.8	61.4	70.5	51.8	58.6
HT-D	86.8	86.8	80.7	80.7	75.7	75.7	79.3	79.3	76.1	76.1	75.0	75.0	79.3	79.3	73.9	73.9

Results without Neural Features

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(+o): models with distributed representations of semantic units.

	English		Thai		German		Greek		Chinese		Indonesian		Swedish		Farsi	
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HT-D (+O)	86.1	86.1	81.1	81.1	73.6	73.6	81.4	81.4	77.9	77.9	79.6	79.6	79.3	79.3	75.7	75.7

Results with Neural Features

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HT-D (+O)	86.1	86.1	81.1	81.1	73.6	73.6	81.4	81.4	77.9	77.9	79.6	79.6	79.3	79.3	75.7	75.7
HT-D (NN) J=0	87.9	87.9	82.1	82.1	75.7	75.7	81.1	81.1	76.8	76.8	76.1	76.1	81.1	81.1	75.0	75.0
HT-D (NN) J=1	88.6	88.6	84.6	84.6	76.8	76.8	79.6	79.6	75.4	75.4	78.6	78.6	82.9	82.9	76.1	76.1
HT-D (NN) J=2	90.0	90.0	82.1	82.1	73.9	73.9	80.7	80.7	81.1	81.1	81.8	81.8	83.9	83.9	74.6	74.6

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HT-D (NN+O) J=1	86.1	86.1	86.1	86.1	72.5	72.5	80.4	80.4	81.4	81.4	82.5	82.5	82.5	82.5	75.7	75.7
HT-D (NN+O) J=2	89.6	86.1	84.6	84.6	72.1	72.1	83.2	83.2	82.1	82.1	83.9	83.9	83.6	83.6	76.8	76.8

Results with Neural Features

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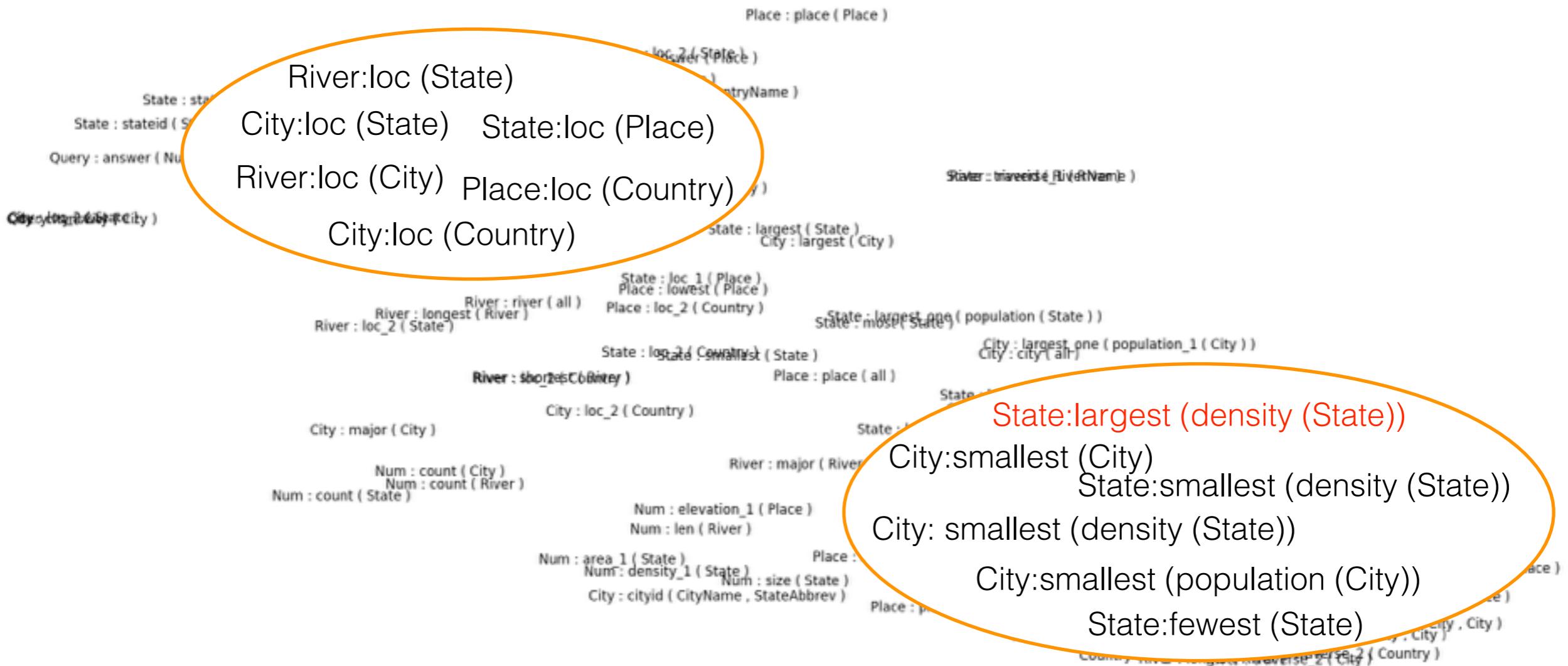
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5 out of 8 languages get improved

Cross-Lingual Representations



- Semantic units with similar meanings gather together.
 - Occasionally, semantic units conveying opposite meanings are grouped together.

Conclusions

✓ Summary

- ✓ Presented a novel method to learning distributed representations of semantic units containing cross-lingual information.

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✓ Future work

✓ Learn representations and semantic parsers in a joint manner.

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✓ Future work

✓ Learn representations and semantic parsers in a joint manner.
✓ Investigate which languages from auxiliary corpus are the leading sources of performance gains.

Code available at: <http://statnlp.org/research/sp/>

감사합니다 Natick
Danke Eυχαριστίες Dalu
Thank You Köszönöm
Grazie Tack
Спасибо Dank Gracias
谢谢 Merci Seé ありがとう
Obrigado

Questions?