

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

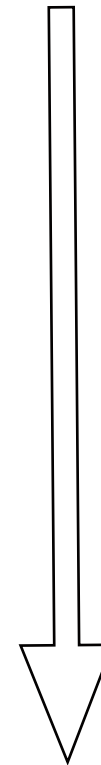
English: what states have no bordering state ?

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)

Semantic Tree

STATE: *exclude* (STATE, STATE)

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



STATE : *state* (all)

Logical Form

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

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)

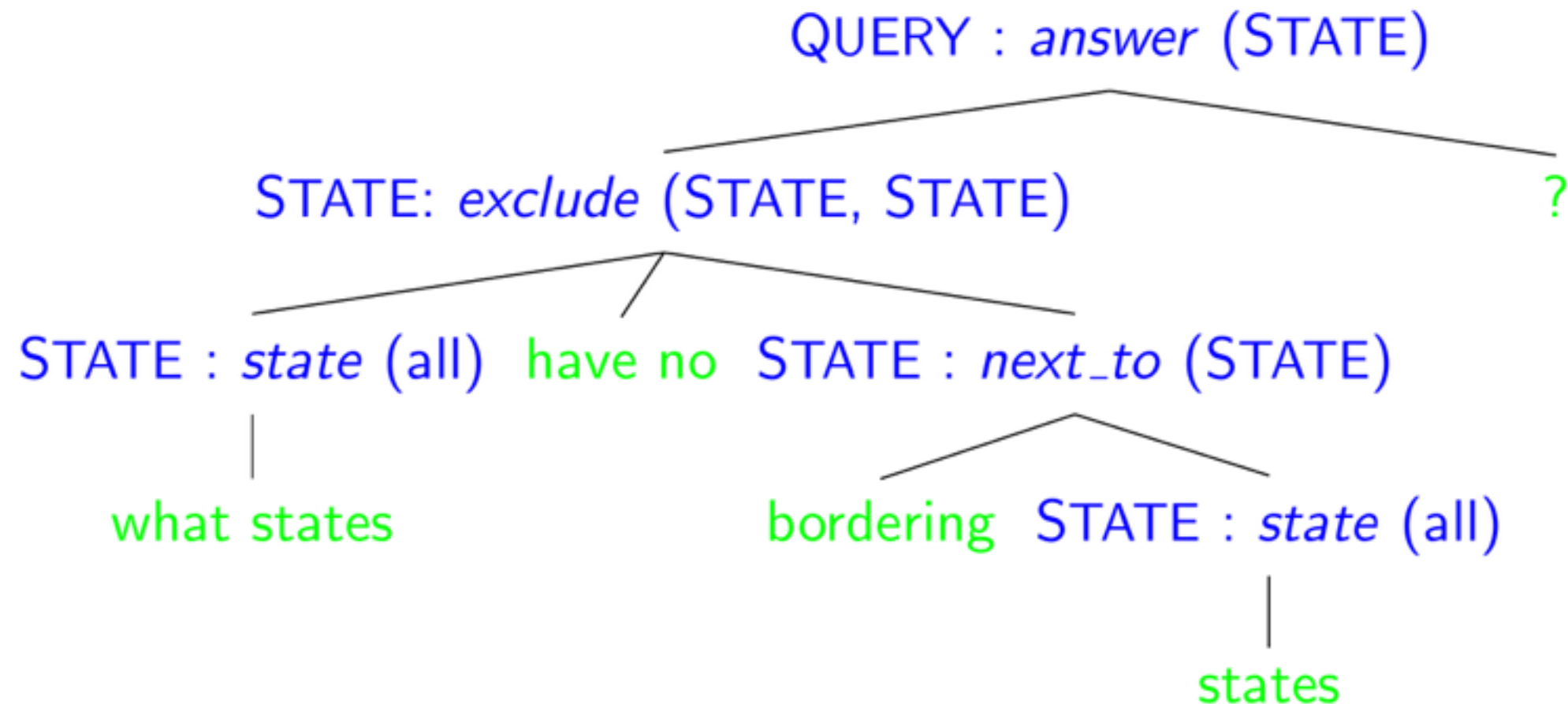


Hybrid Tree

Input: what states have no bordering states?

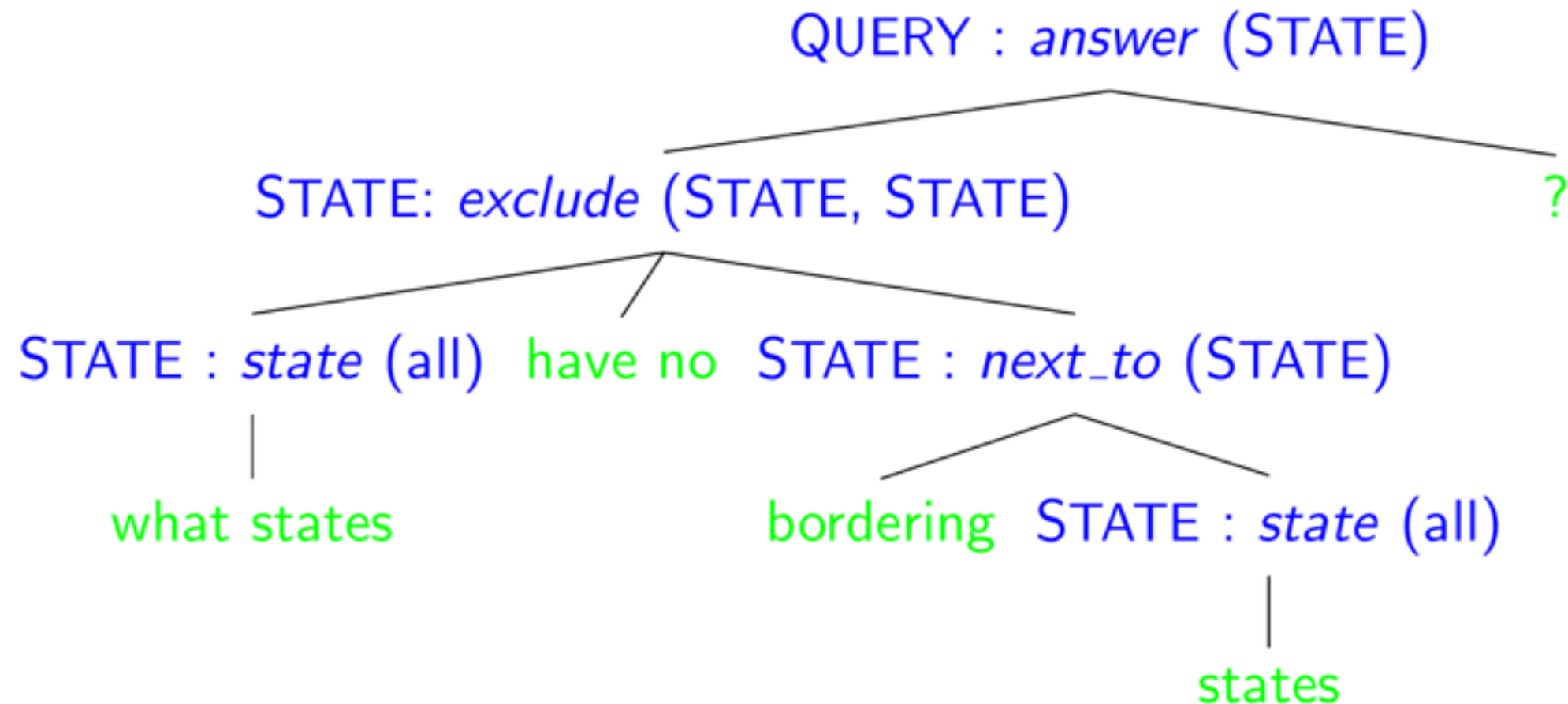
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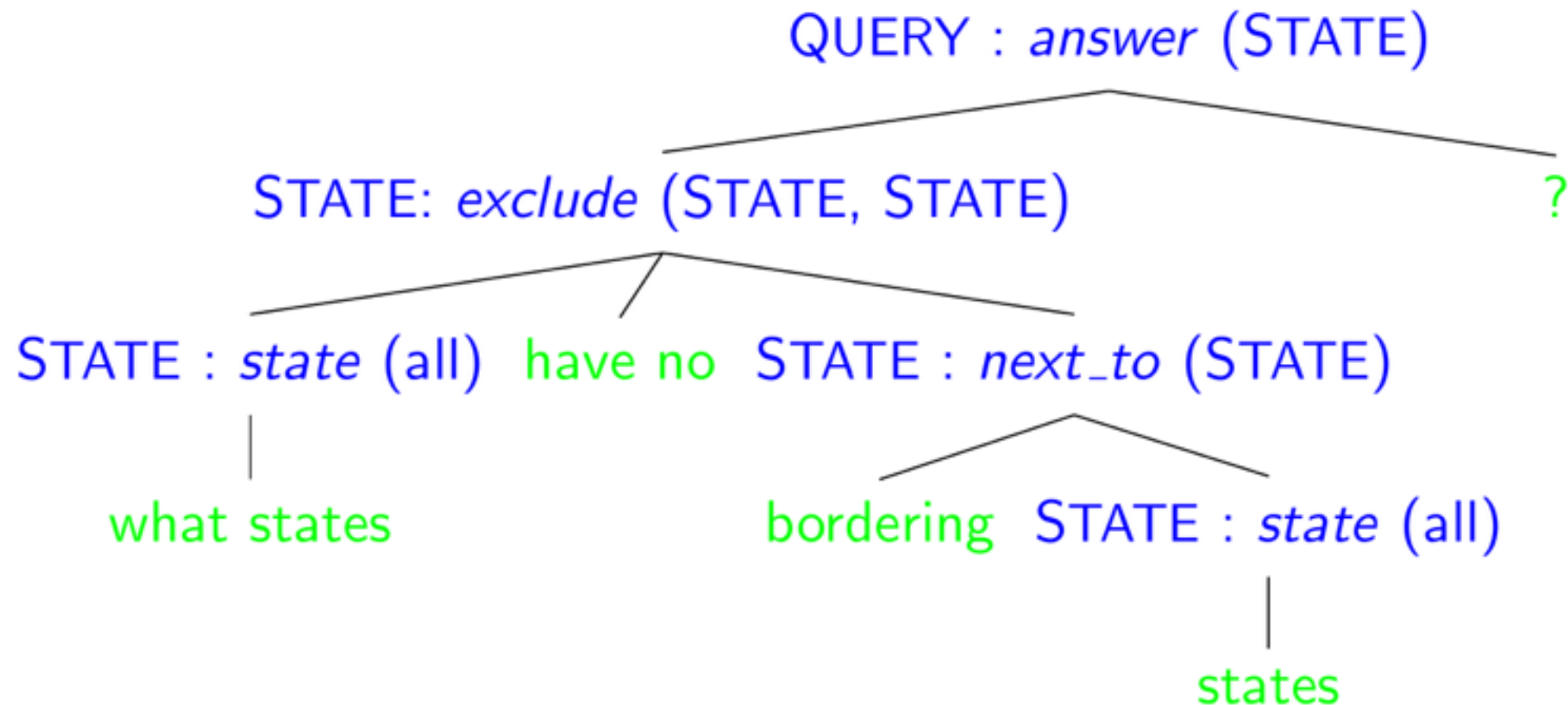


Output: `answer(exclude(state(all), next_to(state(all))))`



Generative Hybrid Tree

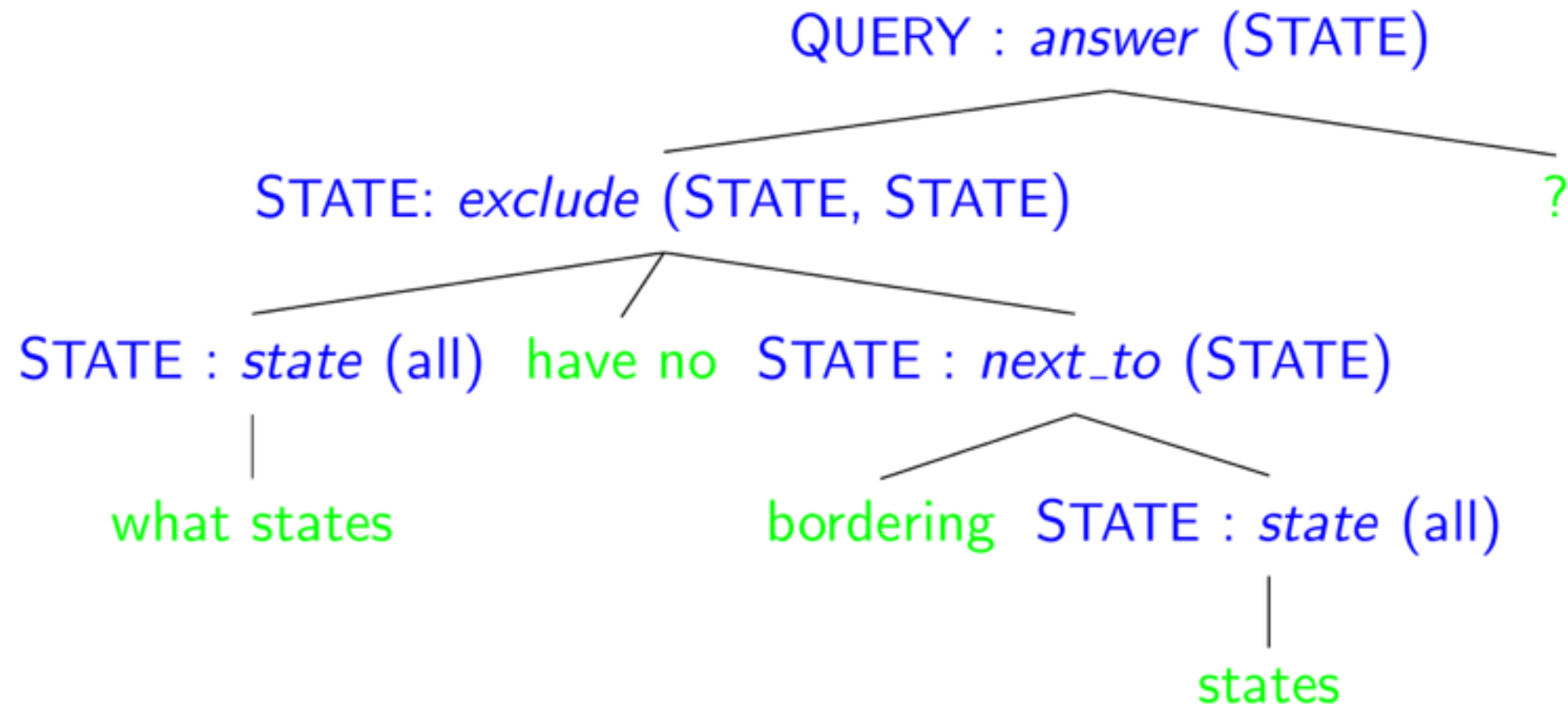
Input: what states have no bordering states?



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

Discriminative Hybrid Tree

Input: what states have no bordering states?

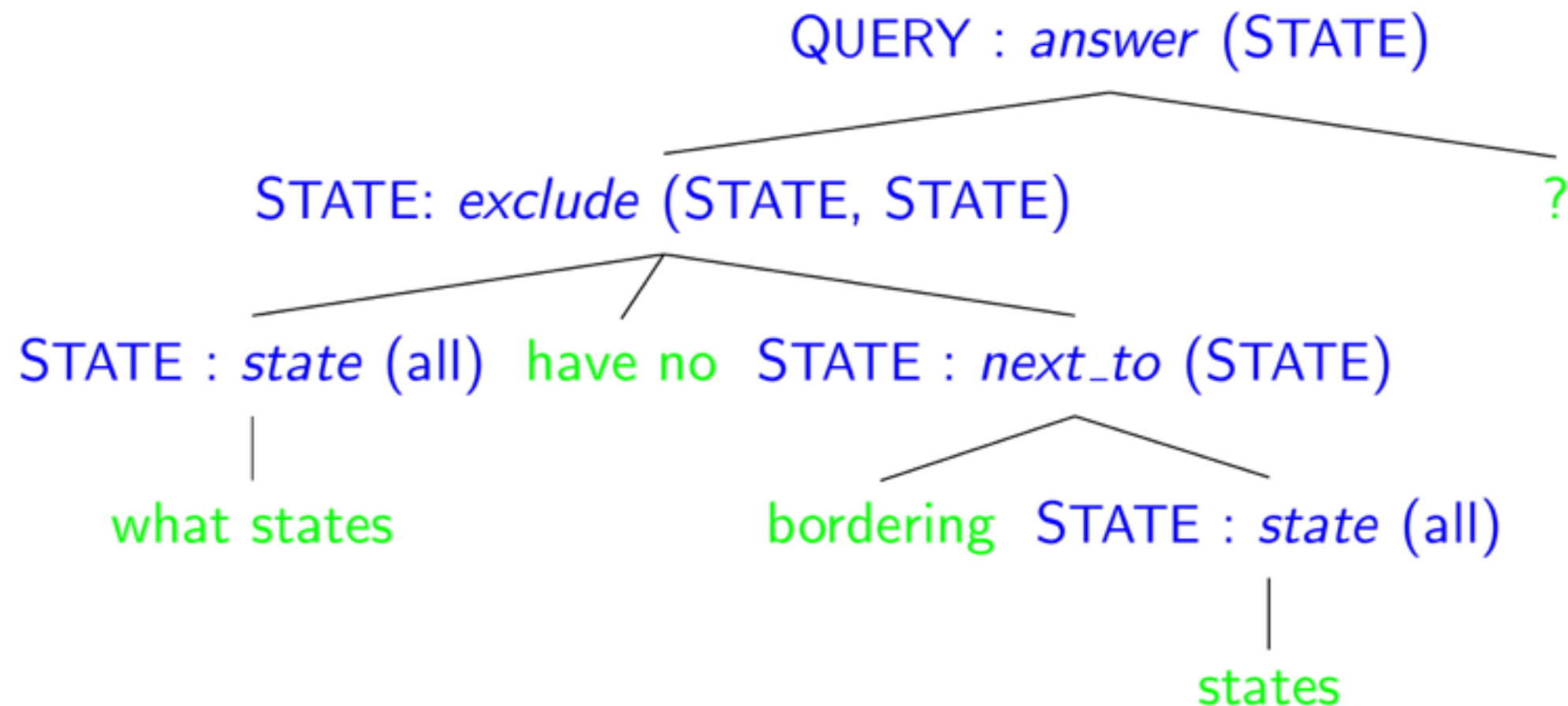


$$p(\mathbf{m}|\mathbf{n}) = \sum_{\mathbf{h} \in \mathcal{H}(\mathbf{n}, \mathbf{m})} p(\mathbf{m}, \mathbf{h}|\mathbf{n})$$



Neural Hybrid Tree

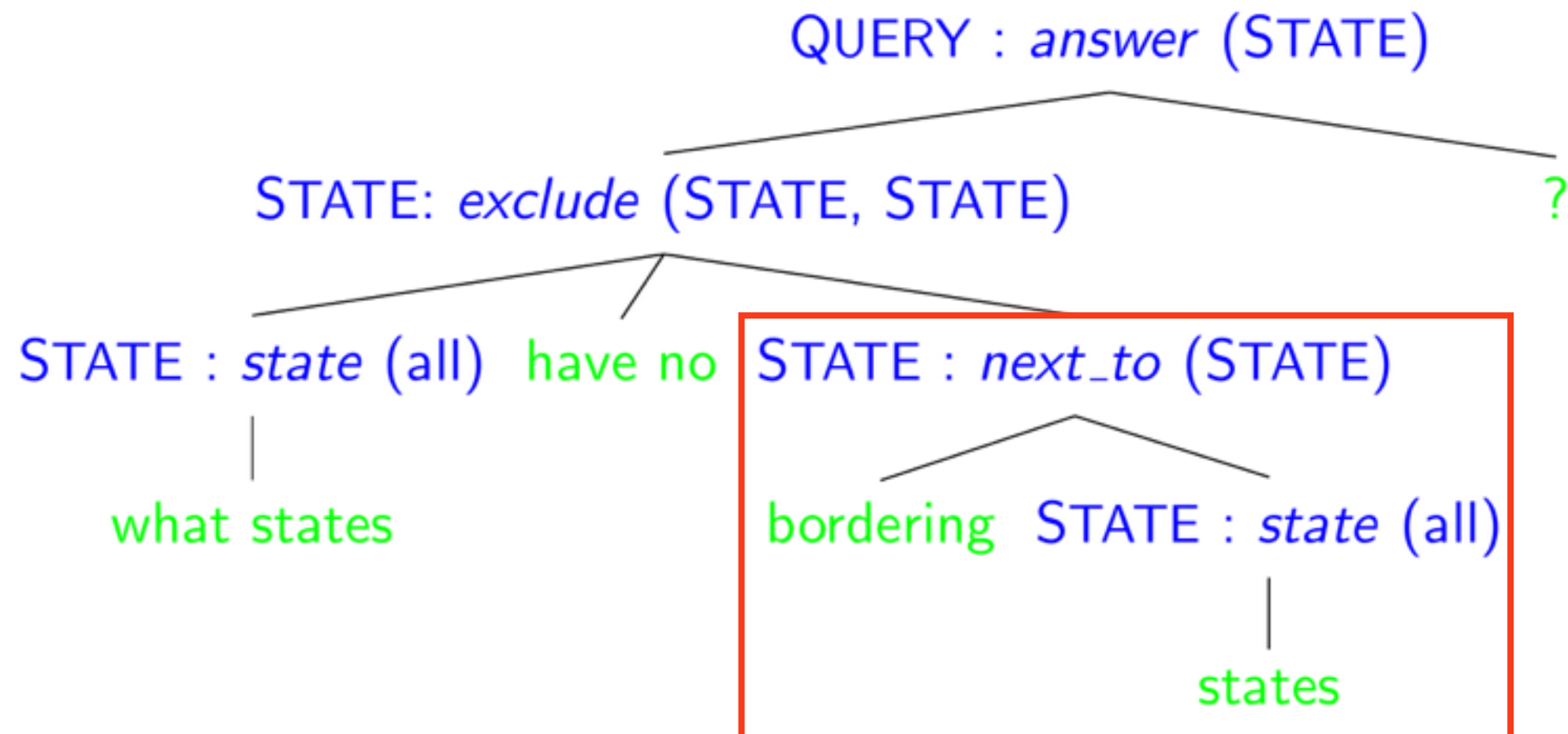
Input: what states have no bordering states?



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

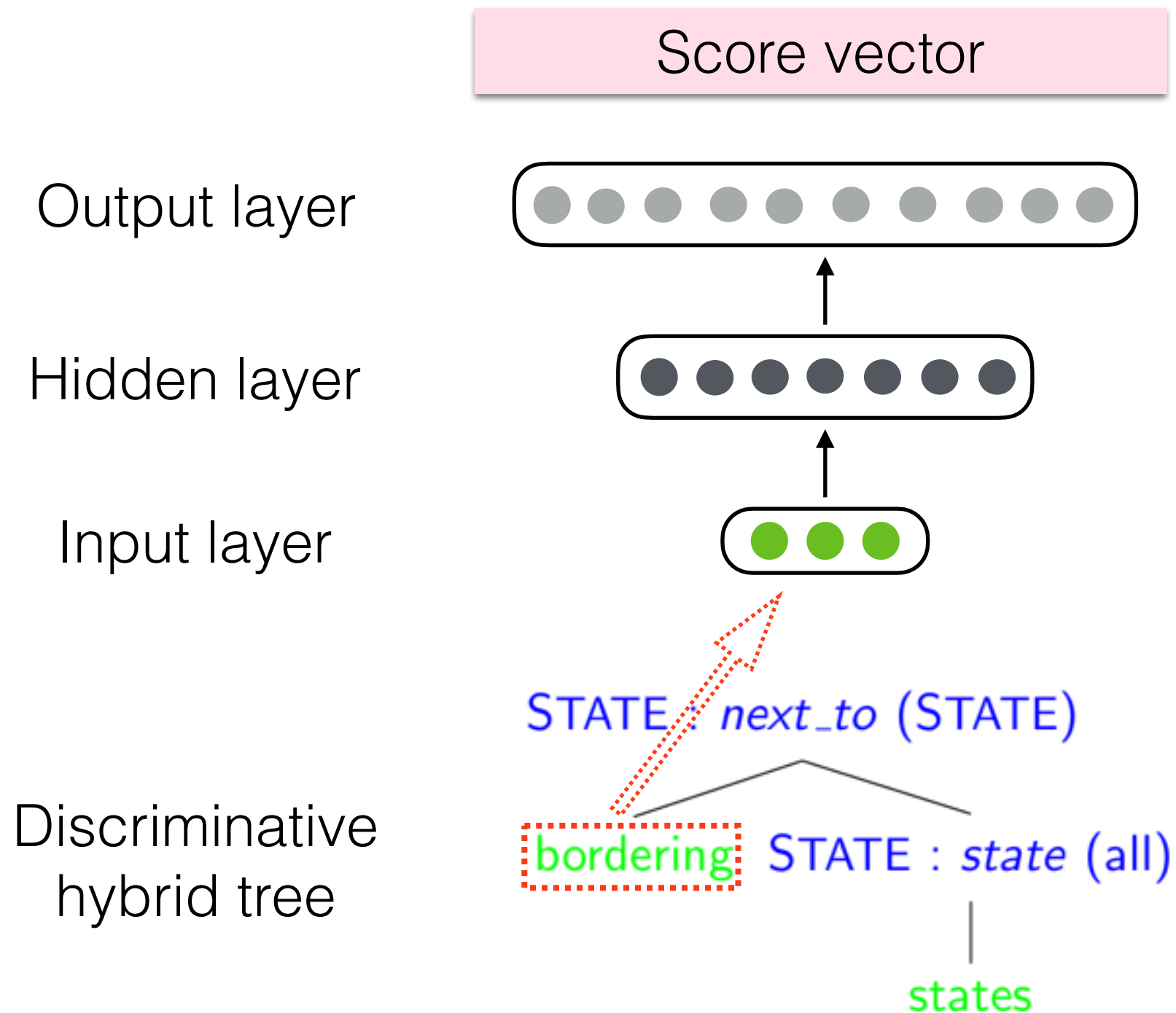
Neural Hybrid Tree

Input: what states have no bordering states?



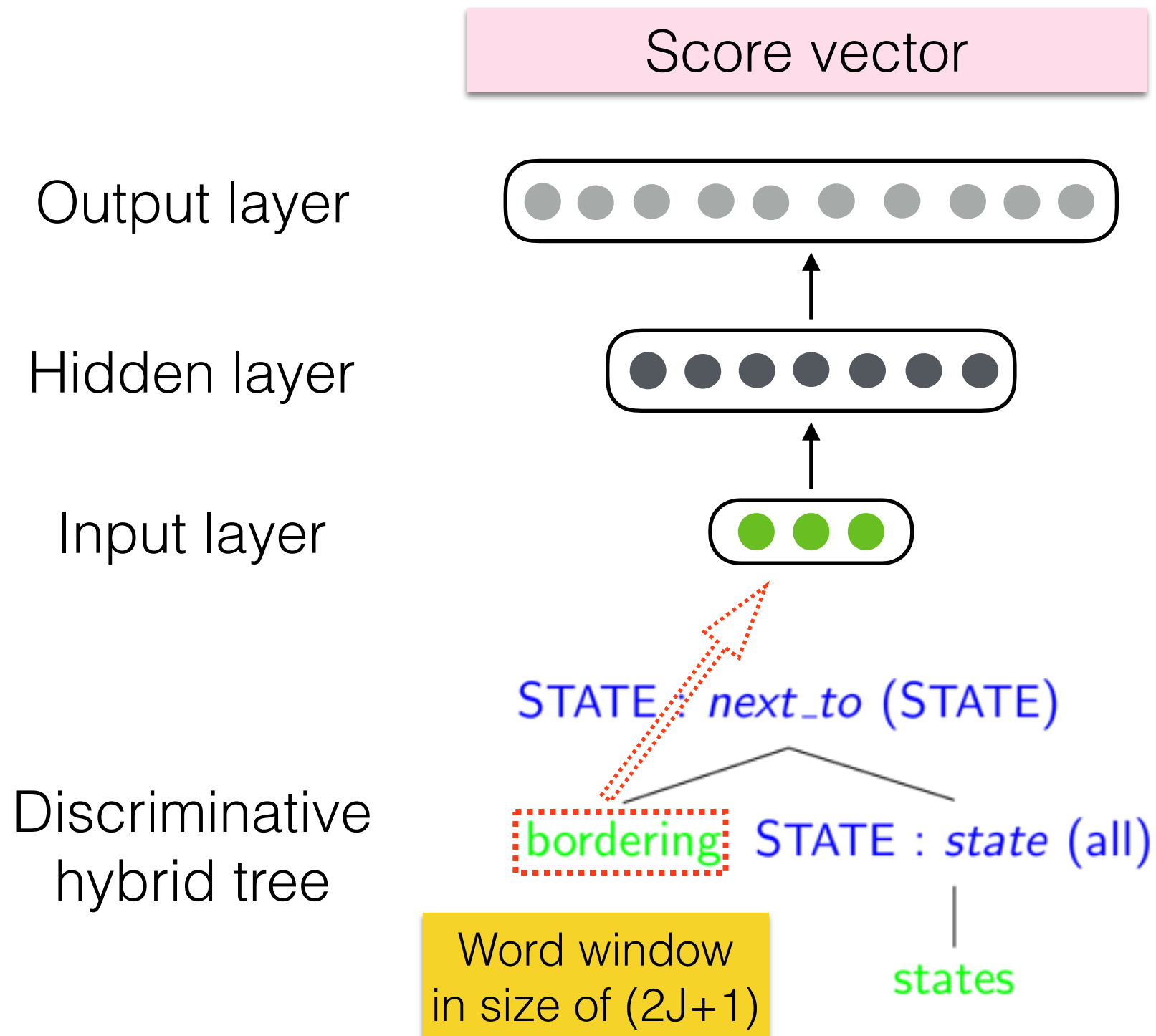


Neural Hybrid Tree

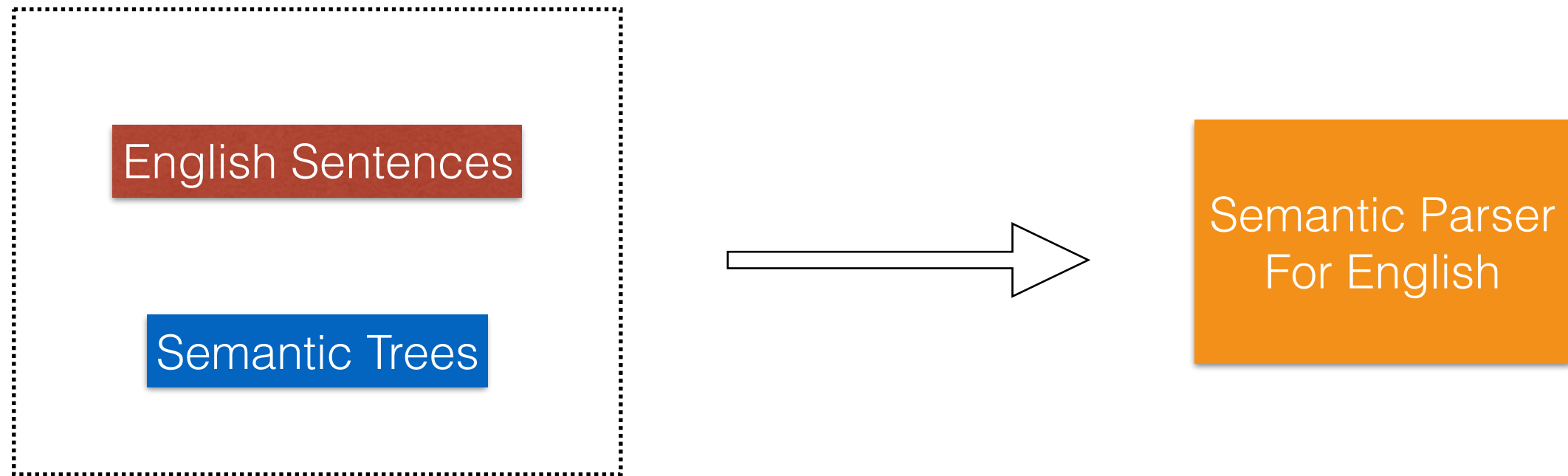




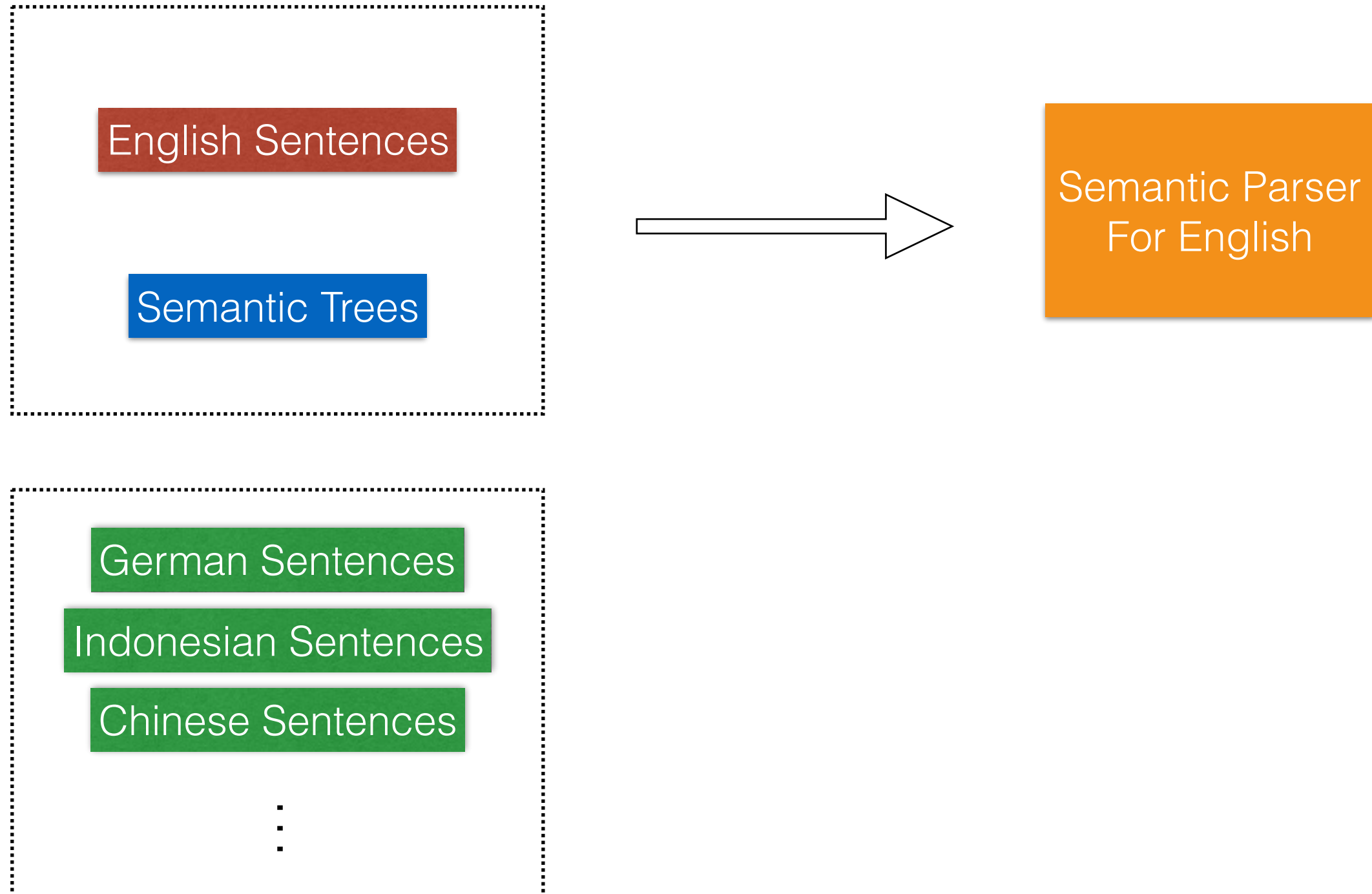
Neural Hybrid Tree



What do we have?



What do we have?



What do we have?

English Sentences

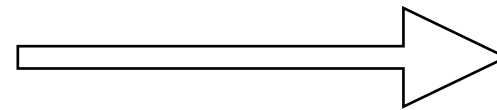
Semantic Trees

German Sentences

Indonesian Sentences

Chinese Sentences

⋮



Semantic Parser
For English



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

What do we have?

English Sentences

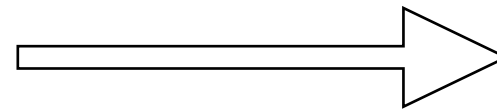
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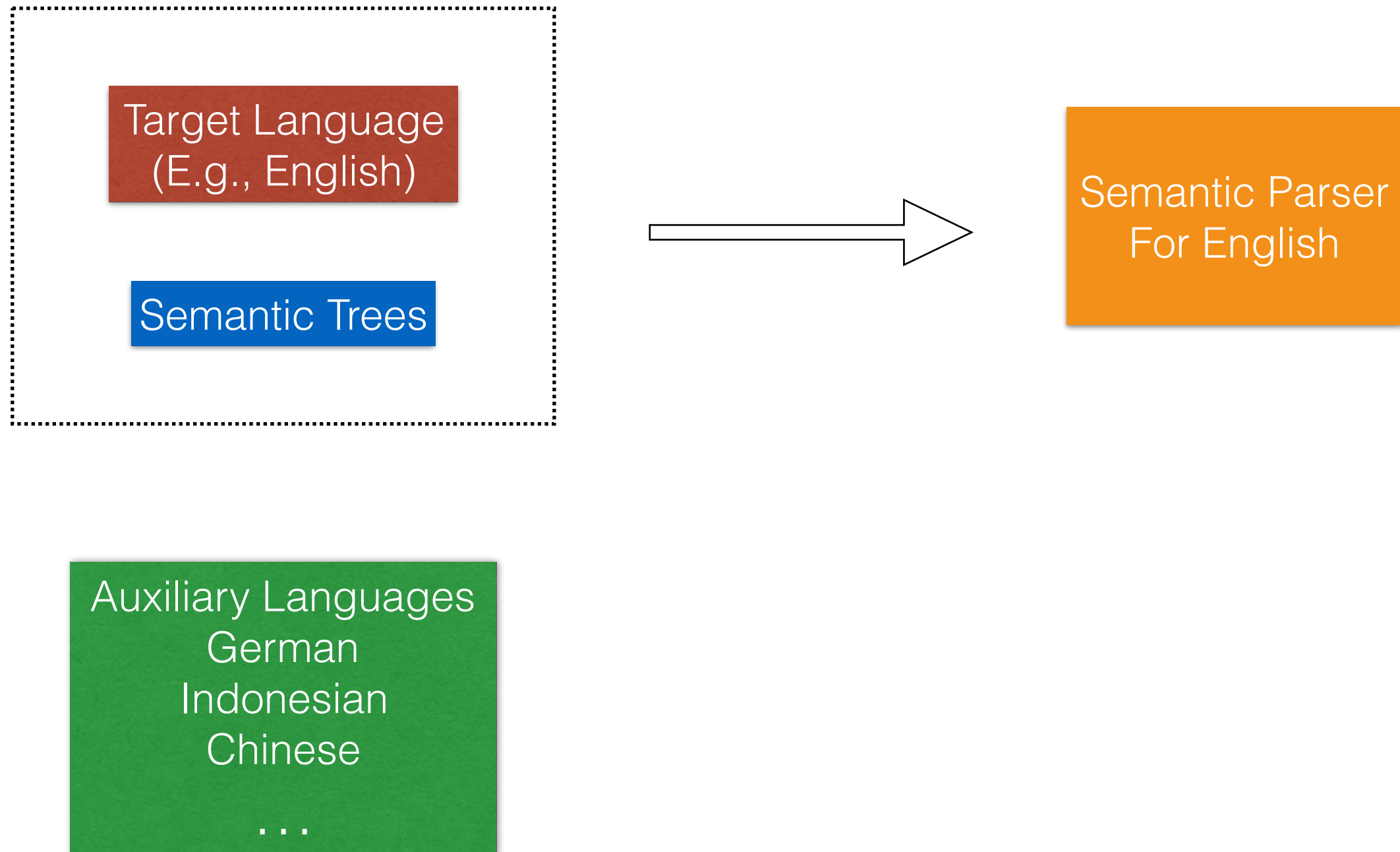


Semantic Parser
For English

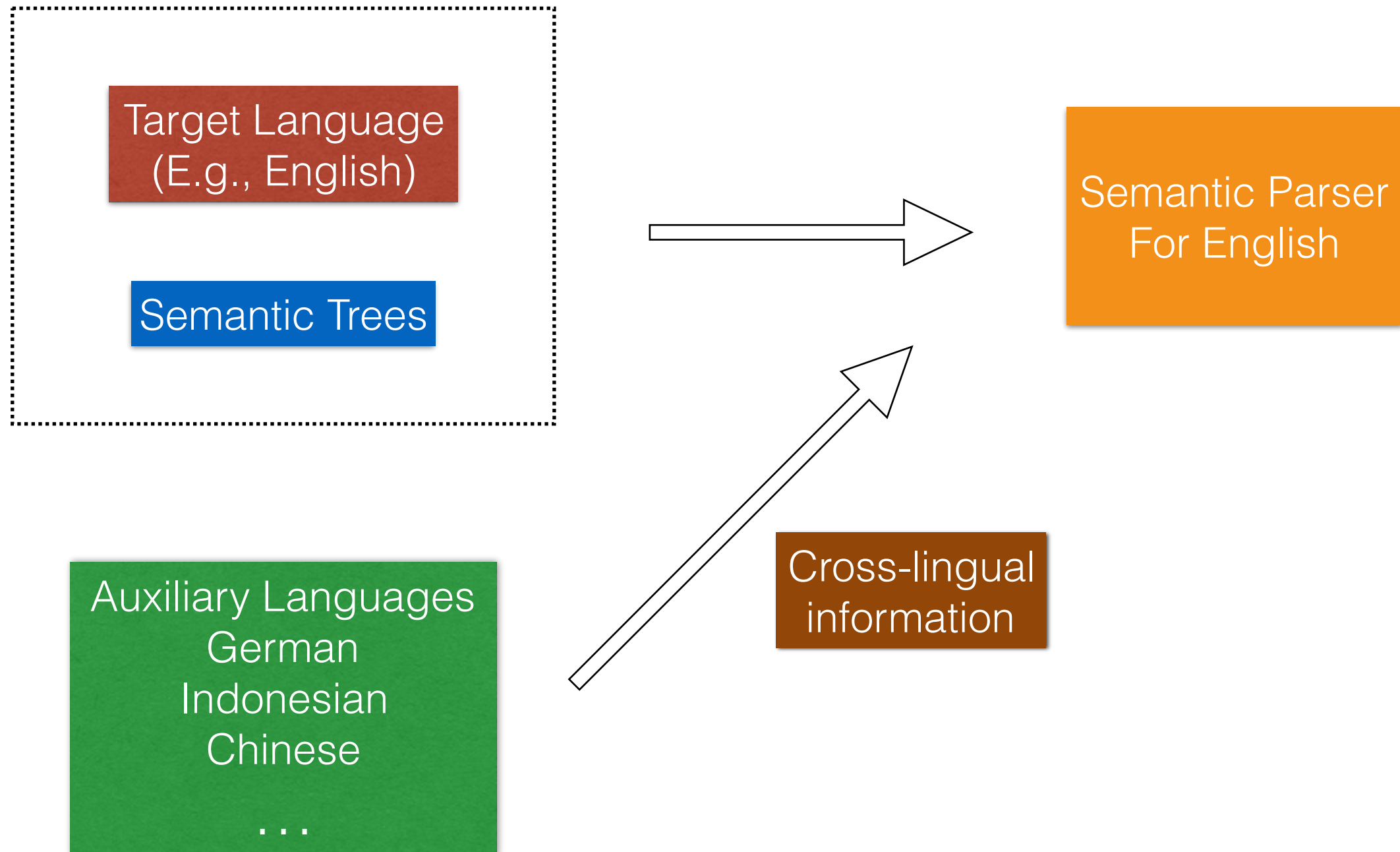
Can we leverage multi-lingual resources to improve the performance of a monolingual semantic parser?

The answer is Yes!!!

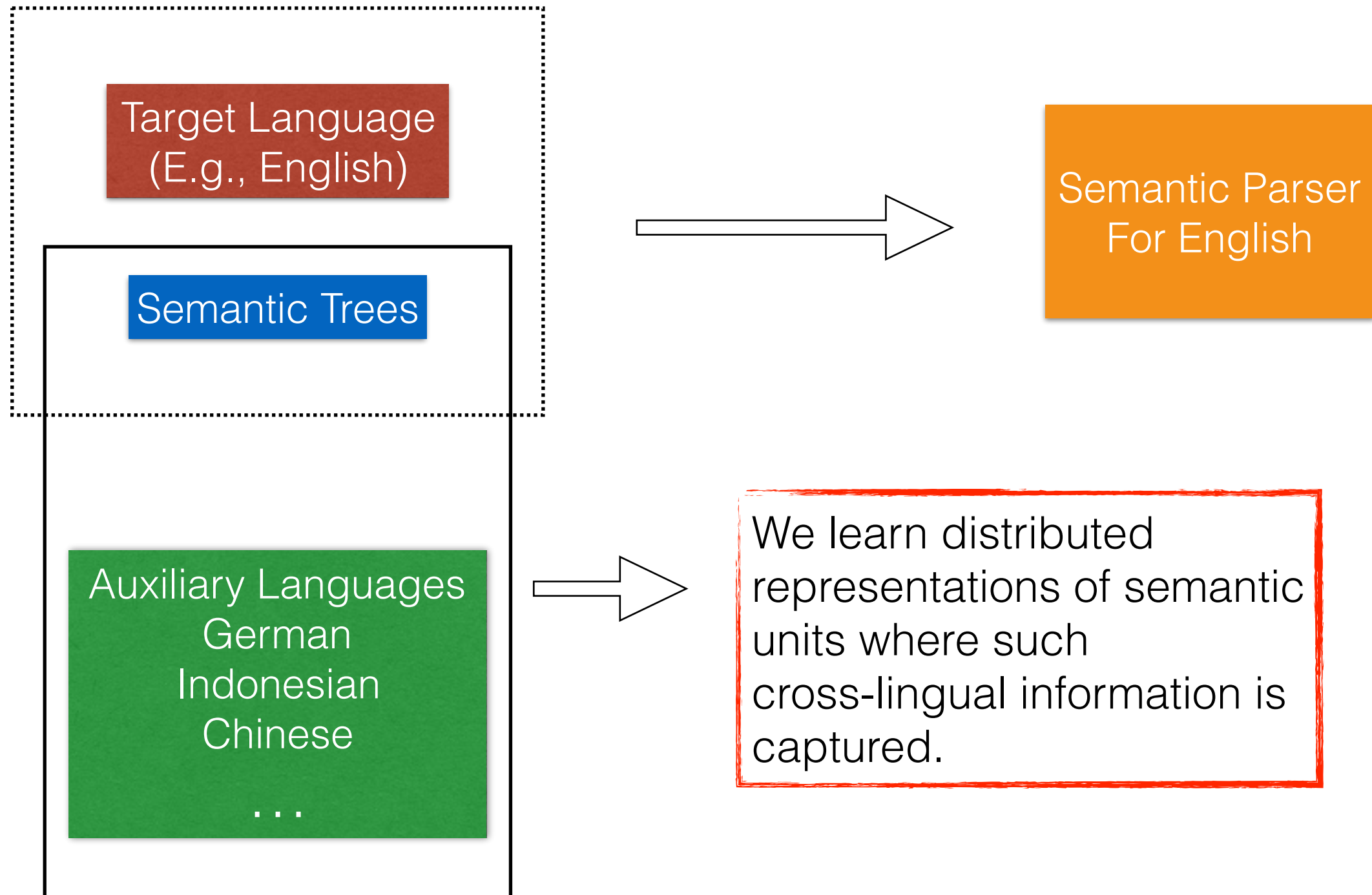
Setup



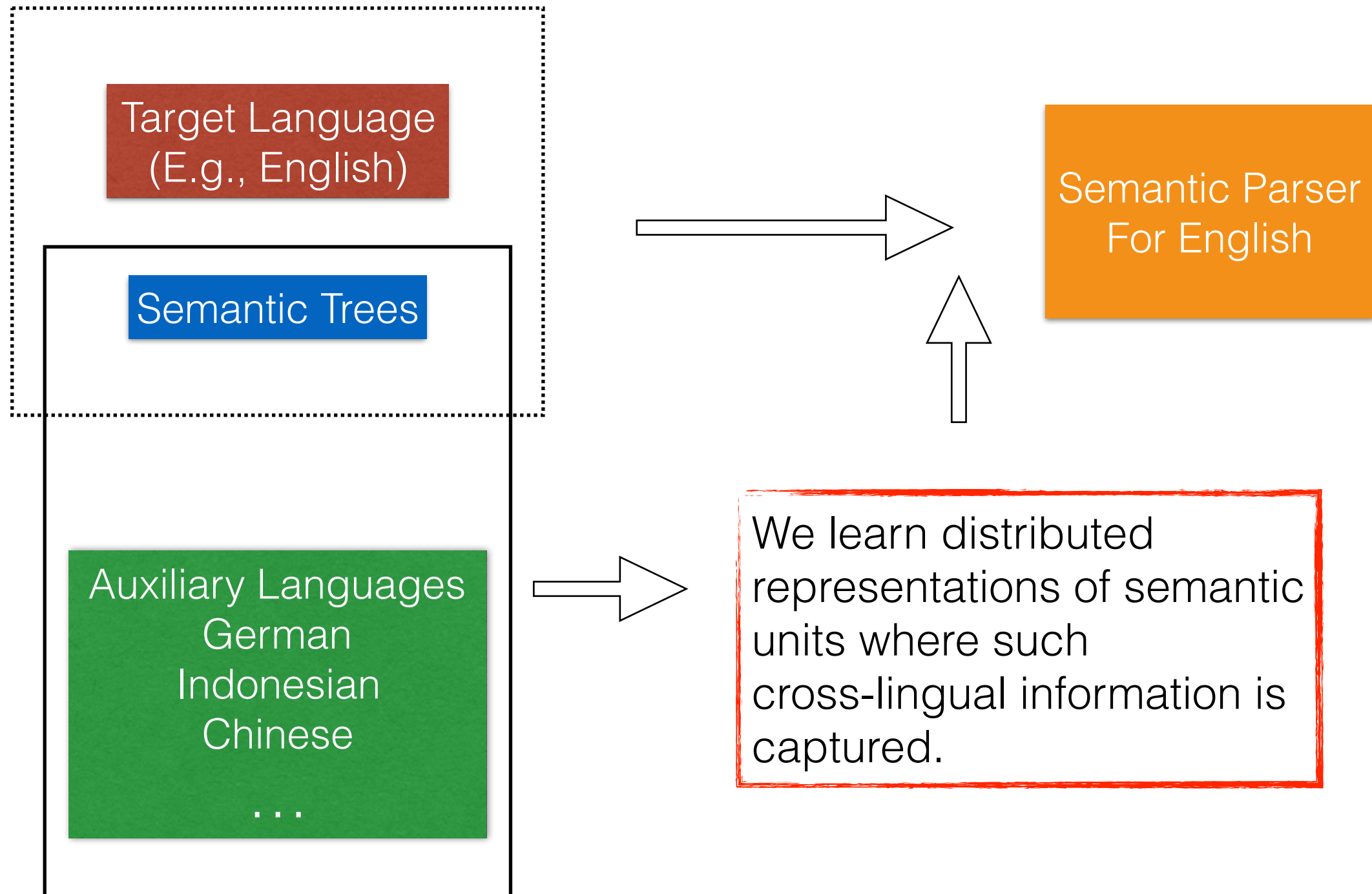
Setup



Setups

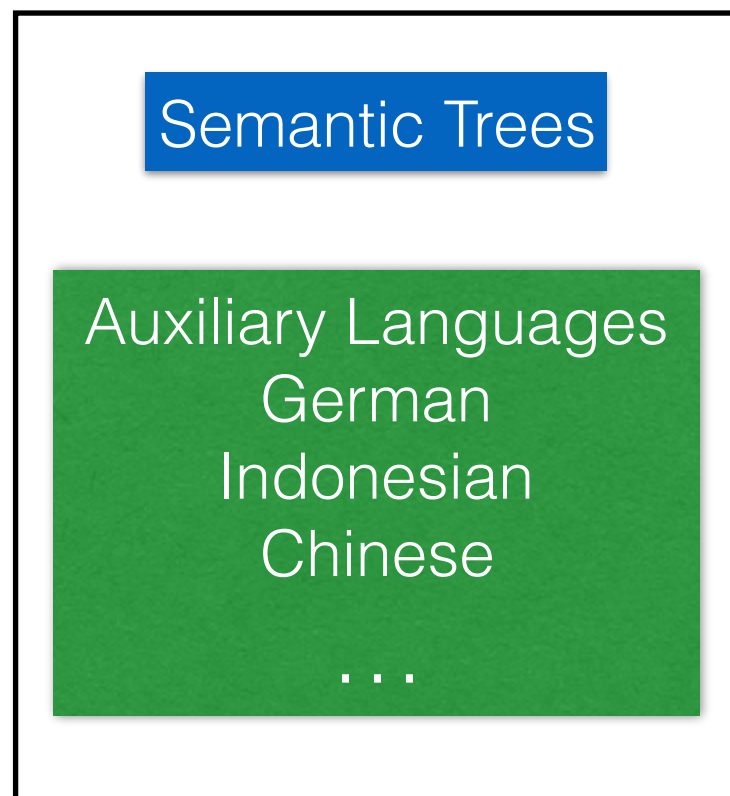


Setups



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	
	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
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=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

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5 out of 8 languages get improved

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.

Conclusions

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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
Grazie Danke Ευχαριστίες Dalu Obrigado
Thank You Köszönöm
Спасибо Dank Gracias
谢谢 Merci Seé
ありがとう

Questions?