Sequence-to-Action: End-to-End Semantic Graph Generation for Semantic Parsing

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Task: Semantic Parsing

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Semantic Parsing

Logical form：$\lambda x.City(x) \wedge PlaceOfBirth($Barack_Obama，$x)$

Outline

- Motivation
- Sequence-to-Action
- Experiments & Conclusion

Two Lines of Work in Semantic Parsing

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Semantic Graph Based

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Sequence-to-Sequence Based

- **Strengths**
  - End-to-end
  - Powerful prediction ability
- **Challenges**
  - Hard to capture structure information
  - Ignore the relatedness to KB

Seq2Act: synthesizes their advantages

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- Use semantic graphs to represent sentence meanings
  - tight-coupling with knowledge bases

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- Use semantic graphs to represent sentence meanings
  - tight-coupling with knowledge bases
- Leverage the powerful prediction ability of RNN models
  - End-to-End

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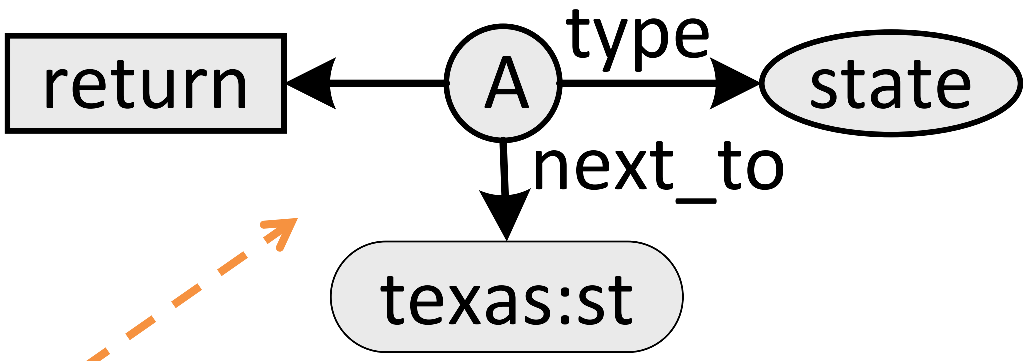
Which states border Texas?

sentence

Seq2Act: end-to-end semantic graph generation



semantic graph

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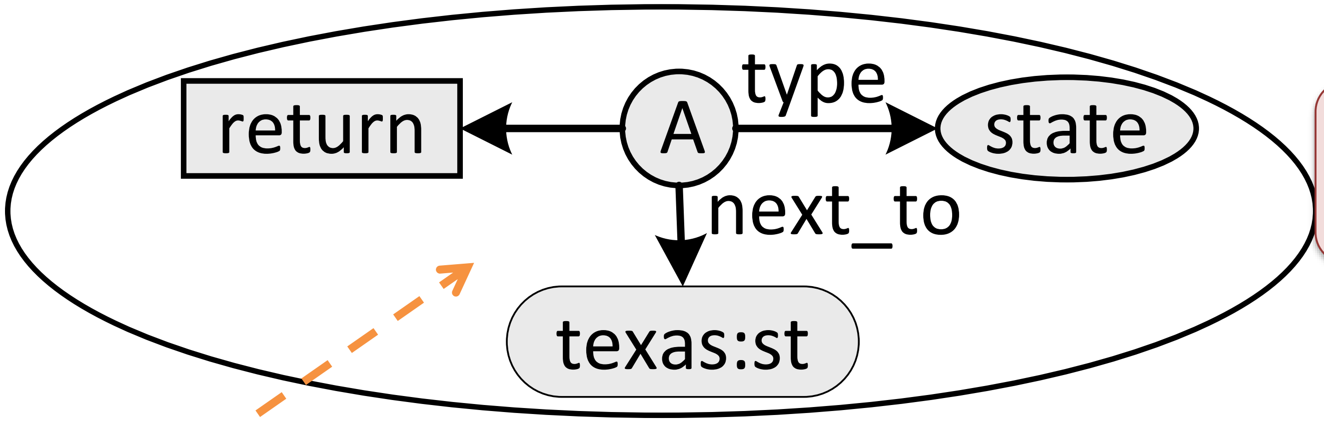

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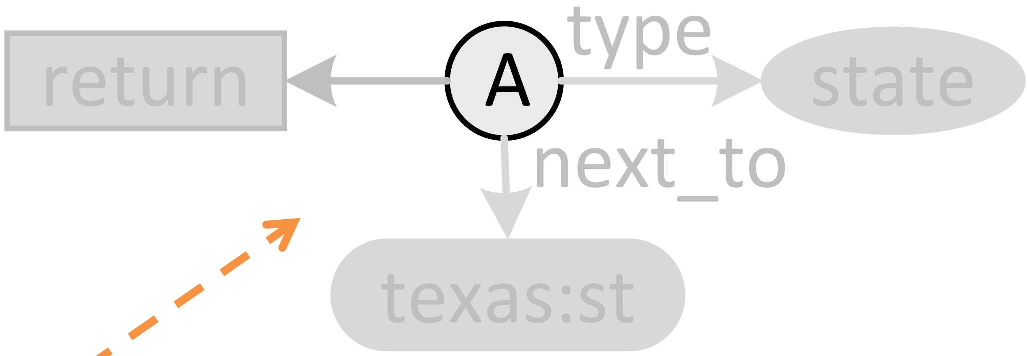


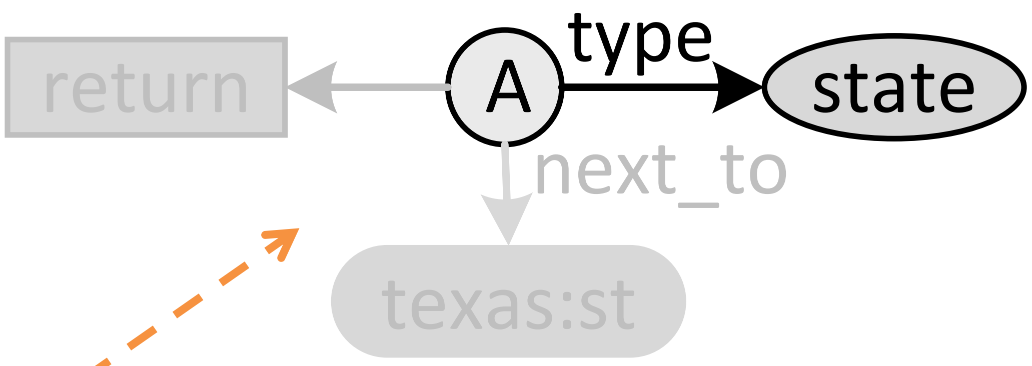
semantic graph

Action 1: add node A

Which states border Texas?

sentence

Seq2Act: end-to-end semantic graph generation



semantic graph

Action 1: add node A

Action 2: add type state

Which states border Texas?

sentence

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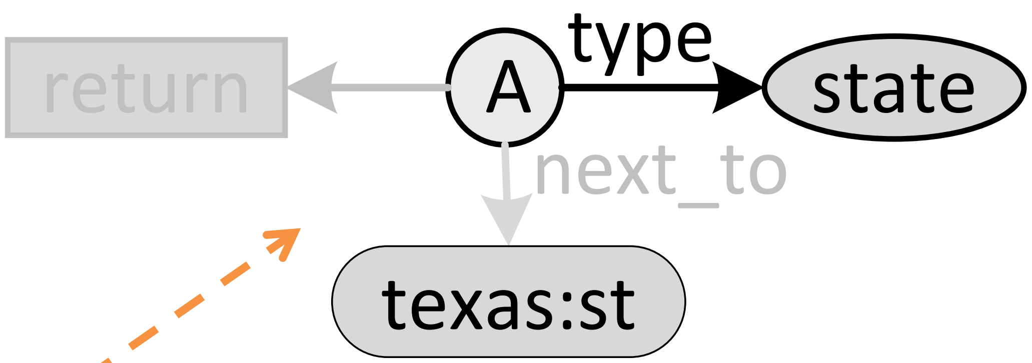

semantic graph

Action 1: add node A
Action 2: add type state
Action 3: add node texas:st

Which states border Texas?

sentence

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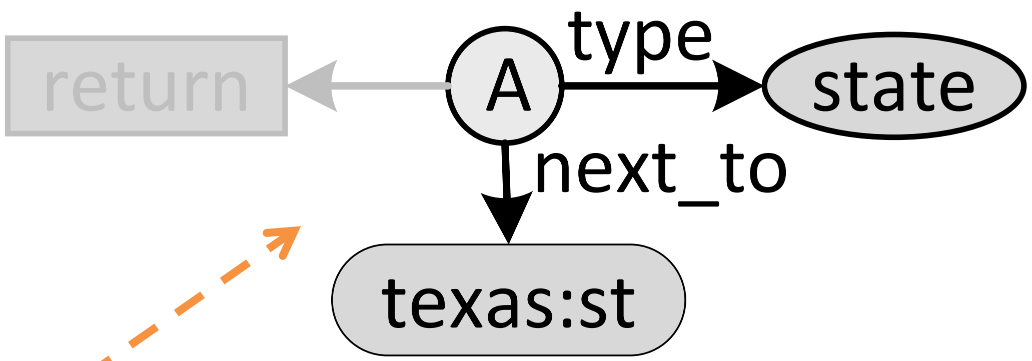

semantic graph

Action 1: add node A
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Action 3: add node texas:st
Action 4: add edge next_to

Which states border Texas?

sentence

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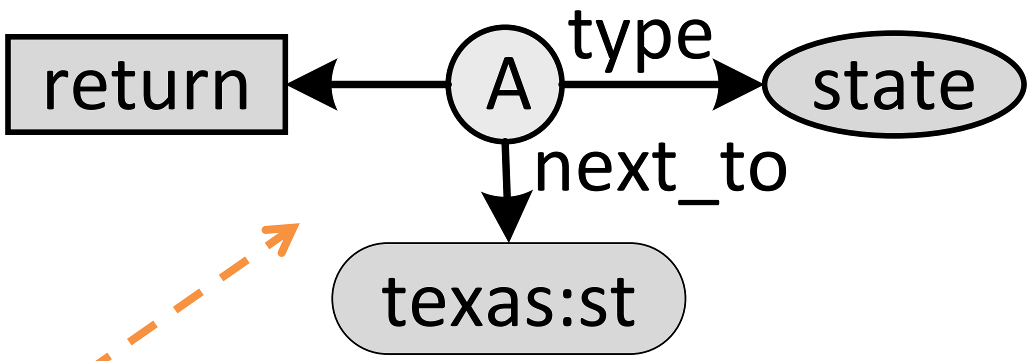

semantic graph

Action 1: add node A
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Action 3: add node texas:st
Action 4: add edge next_to
Action 5: return

Which states border Texas?

sentence

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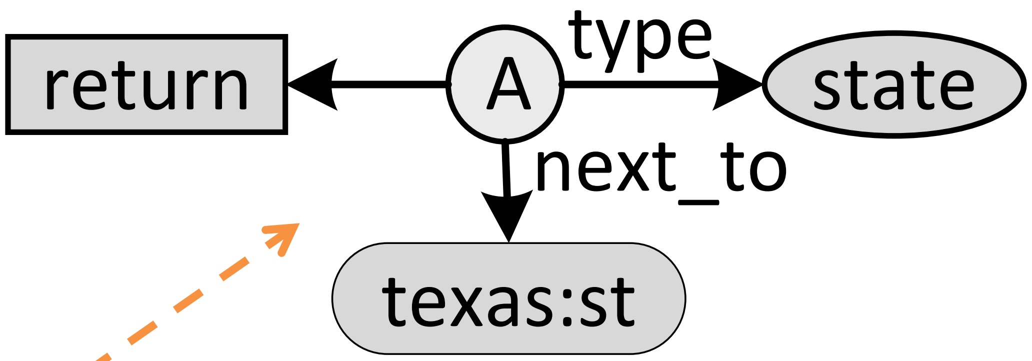

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sentence

action sequence

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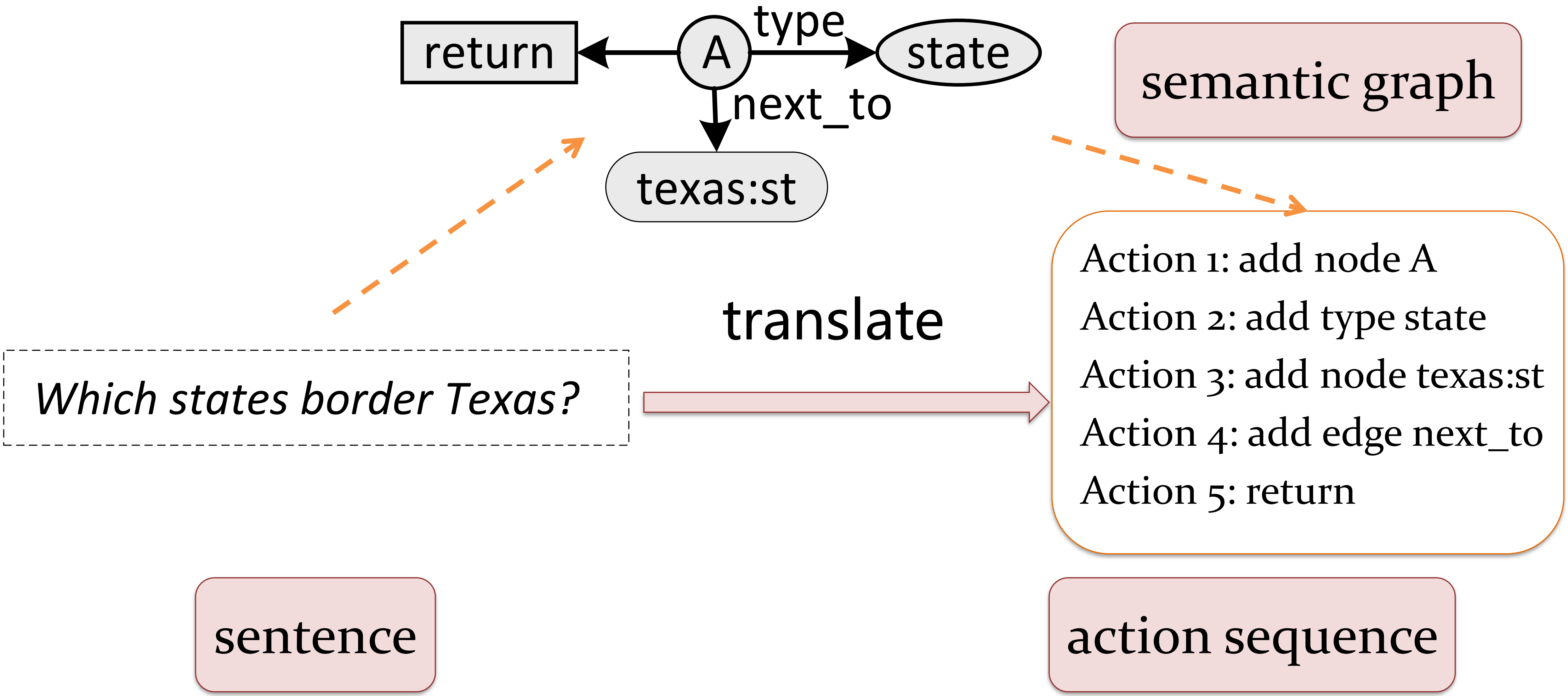

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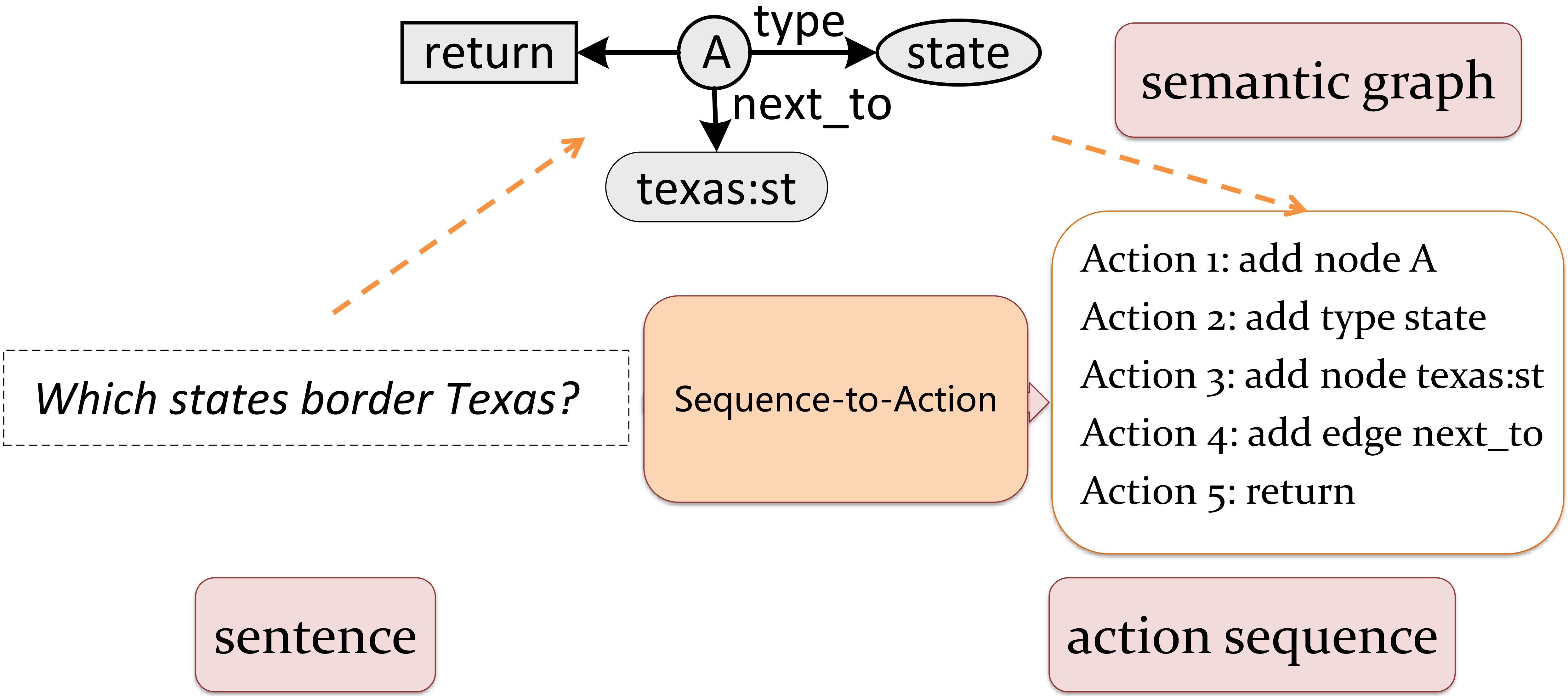

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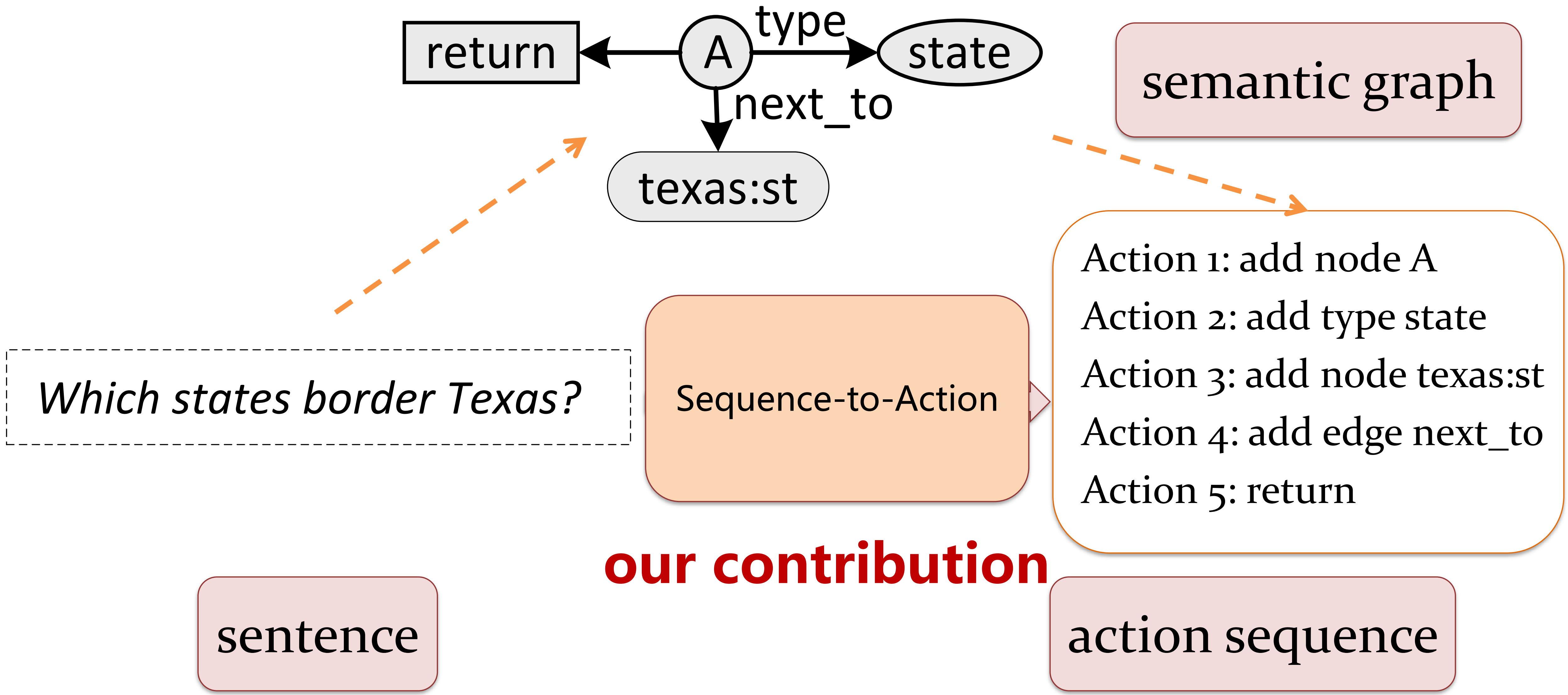

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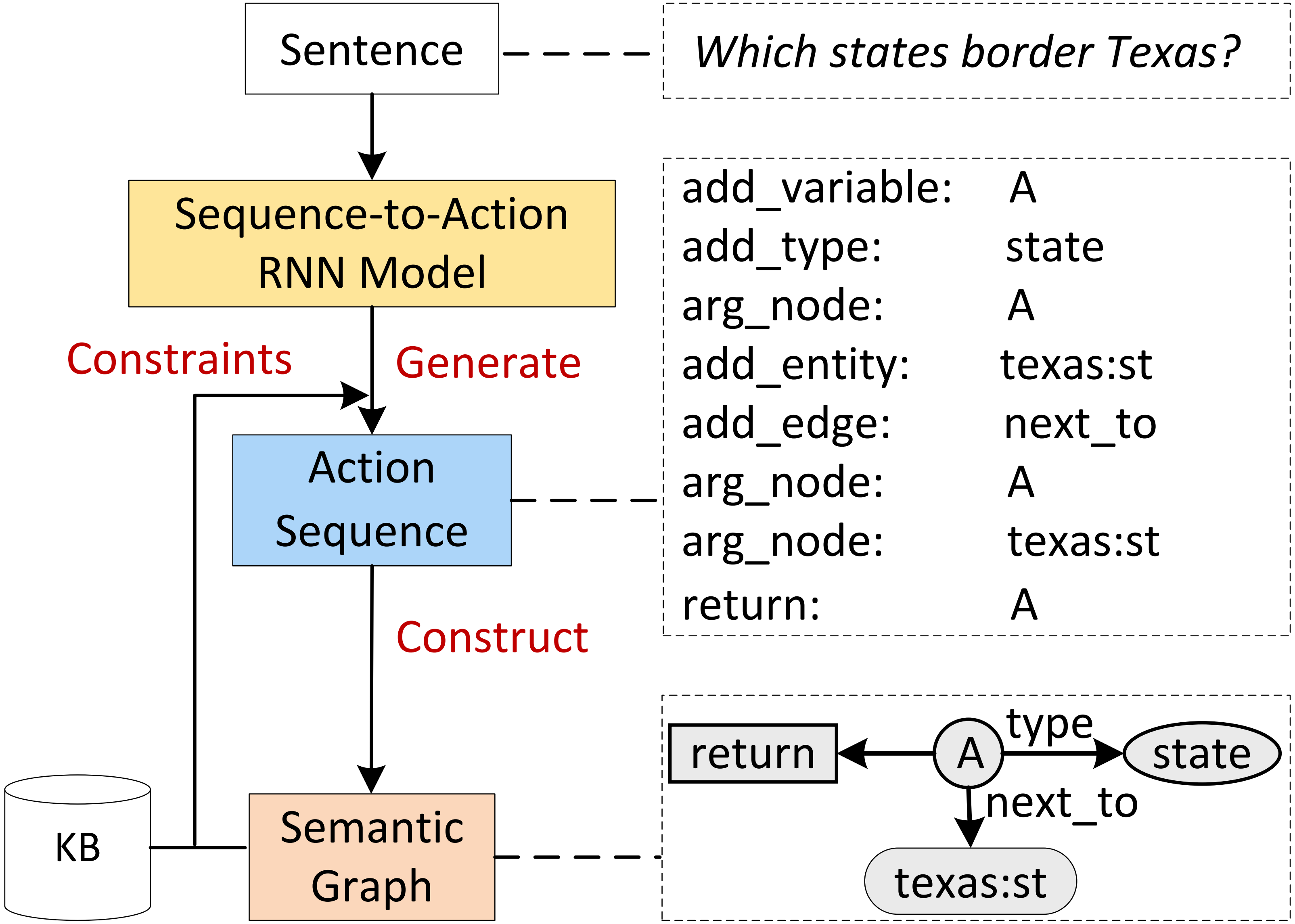

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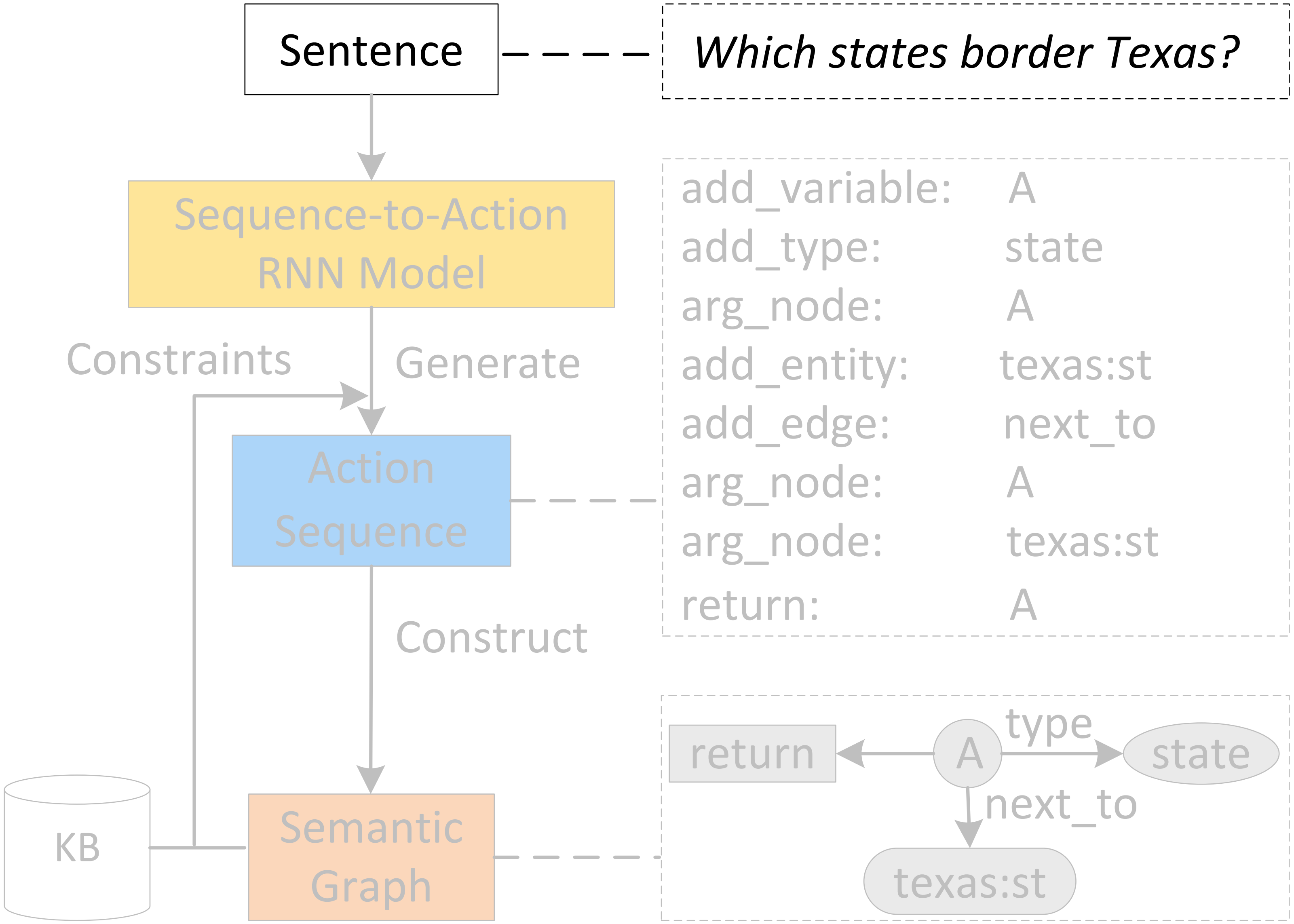

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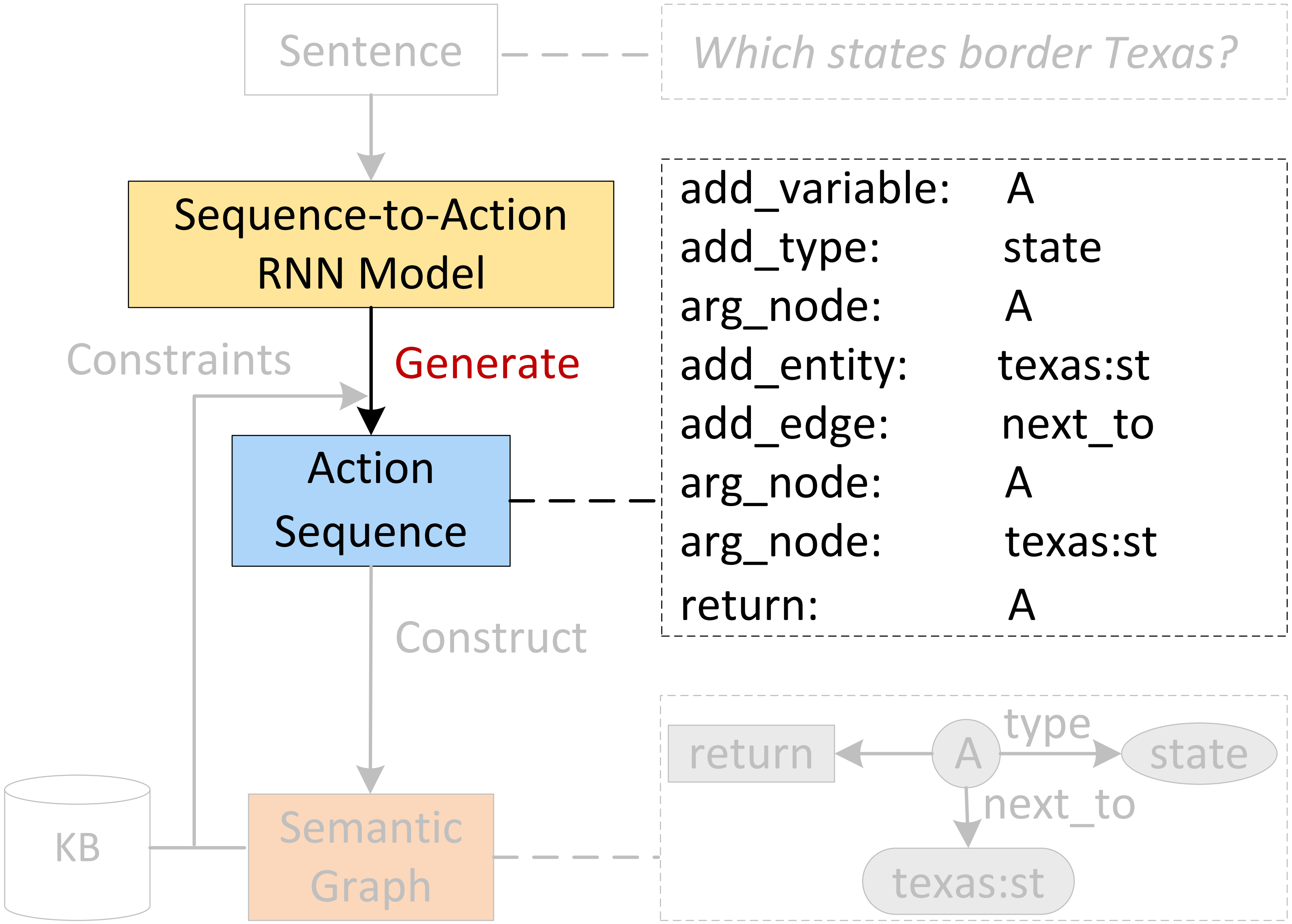

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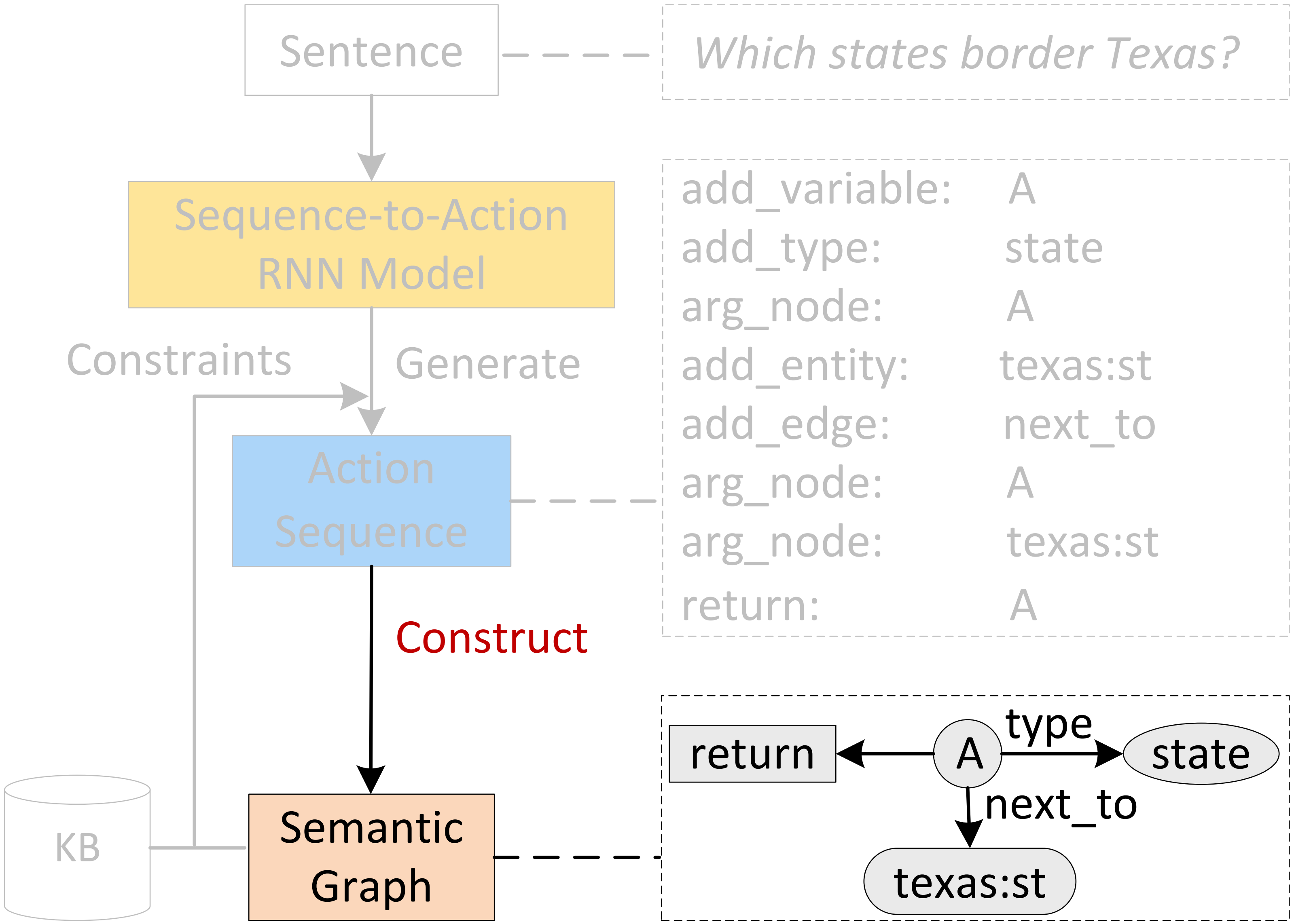

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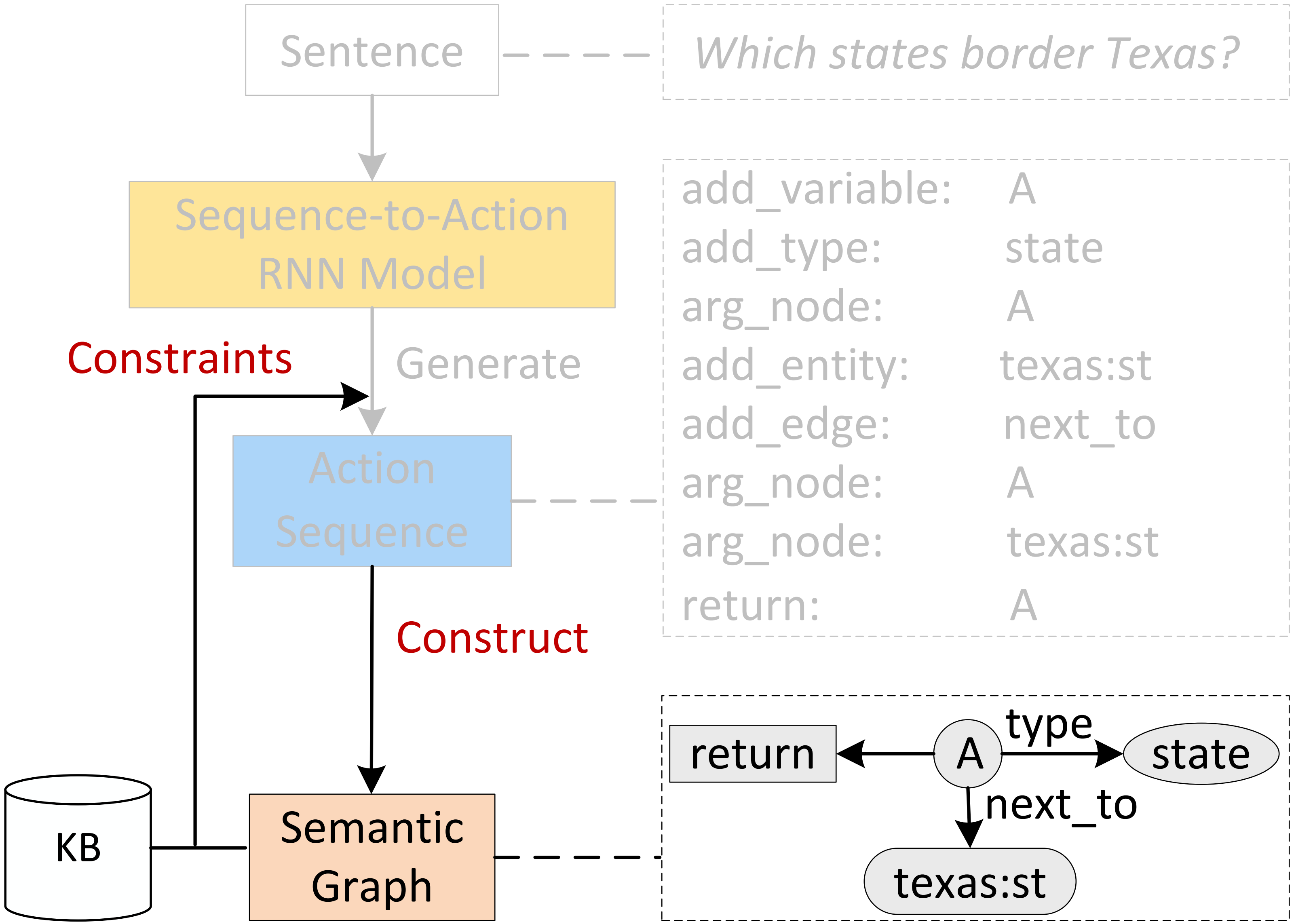
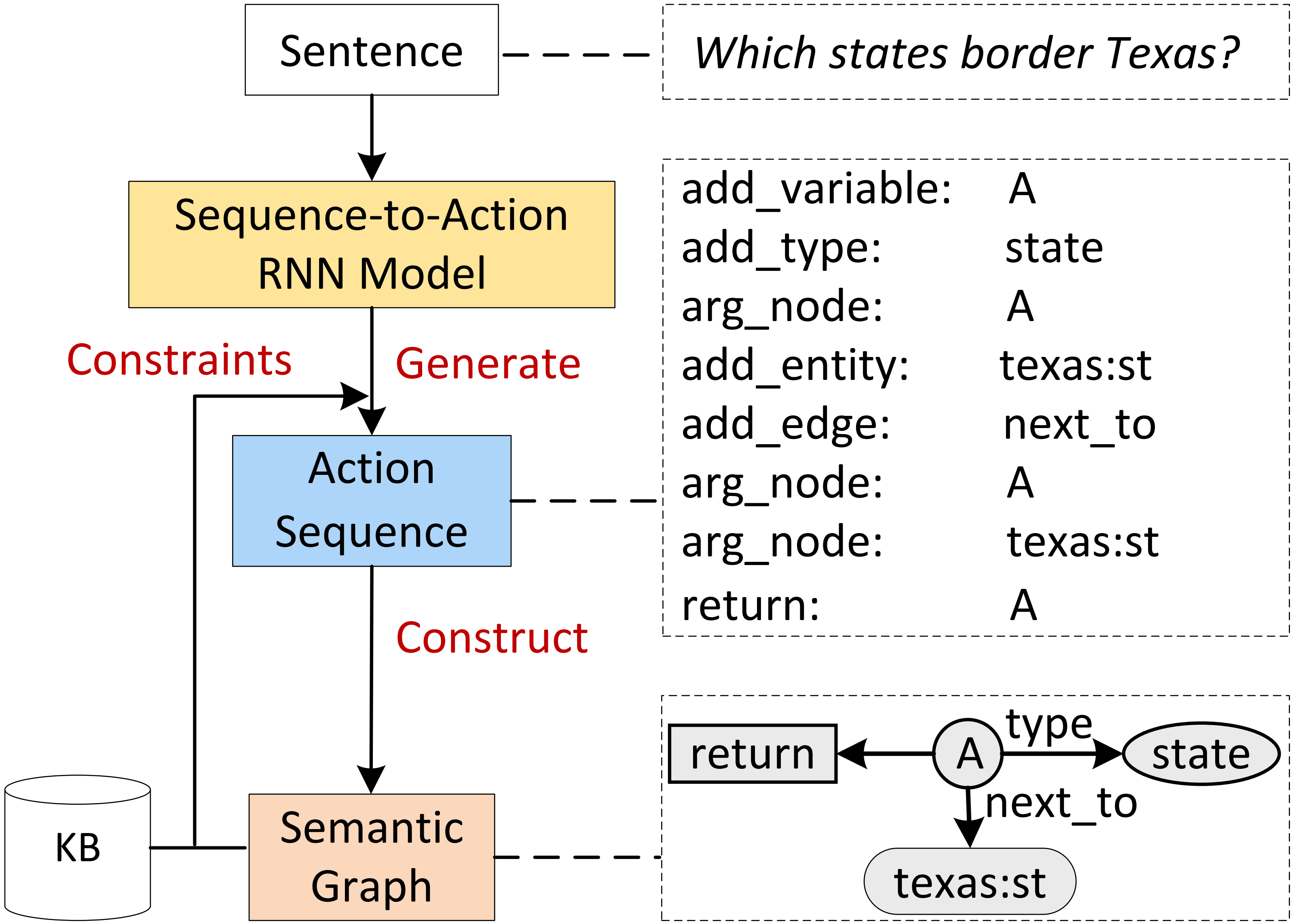
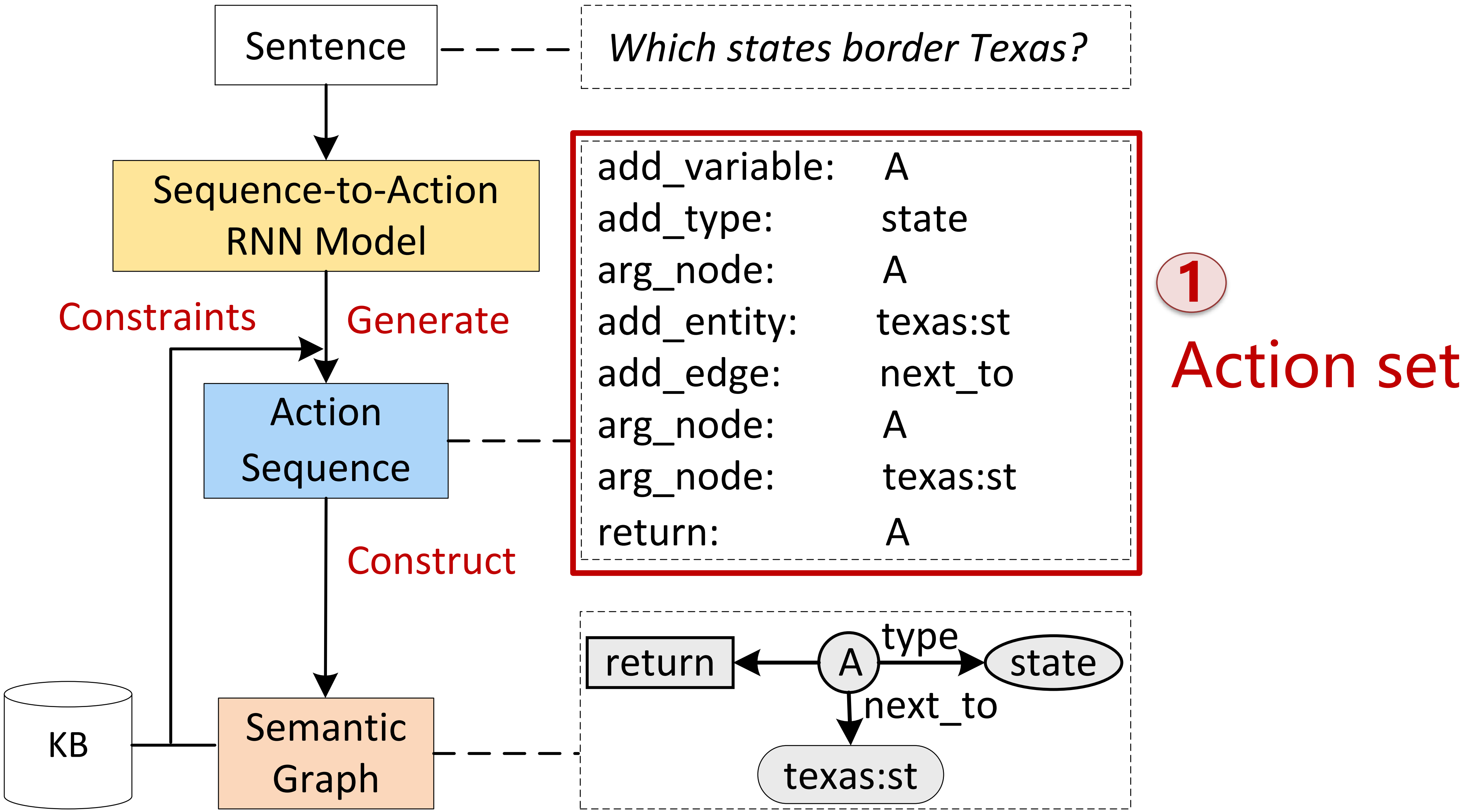


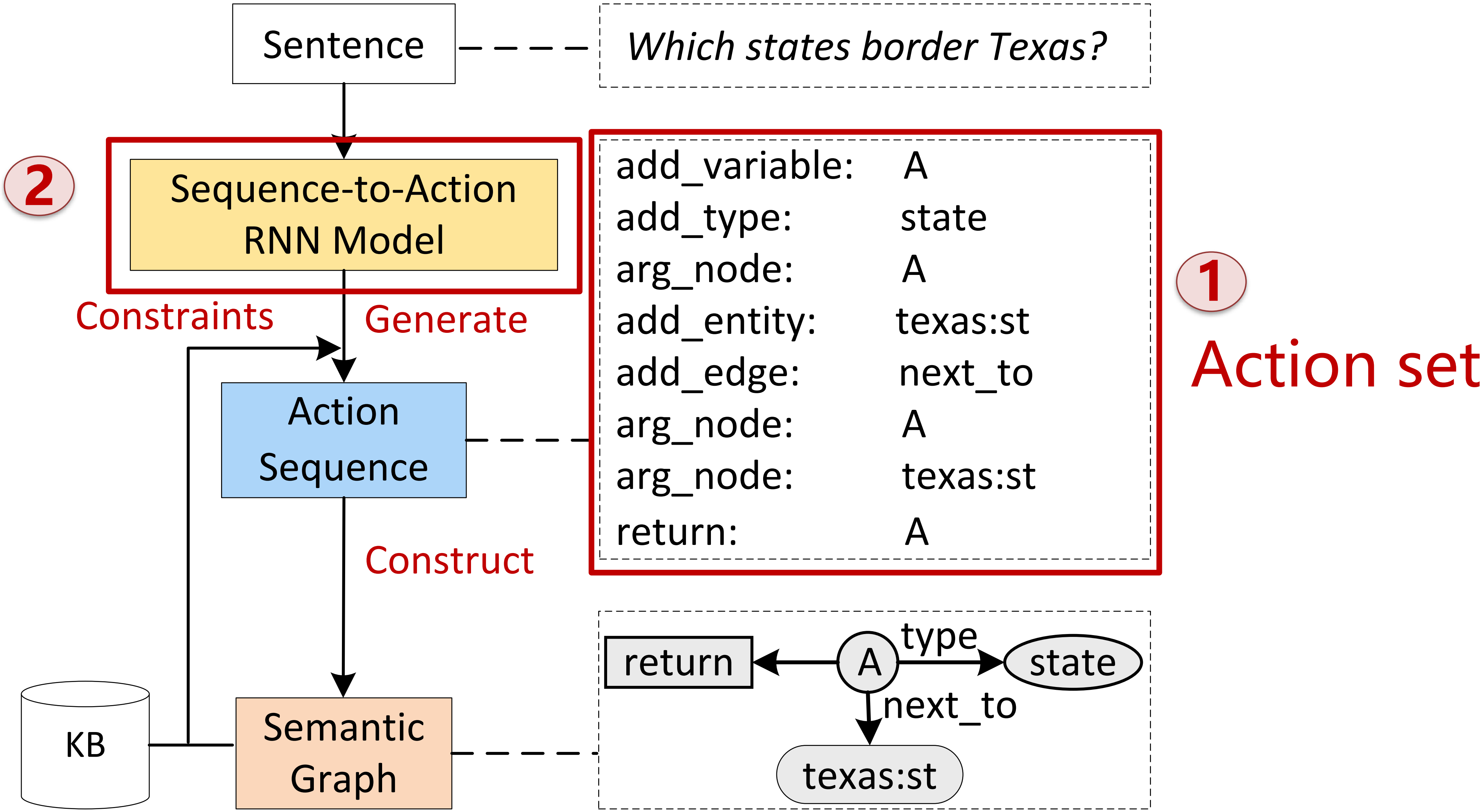
Major components of Our Model



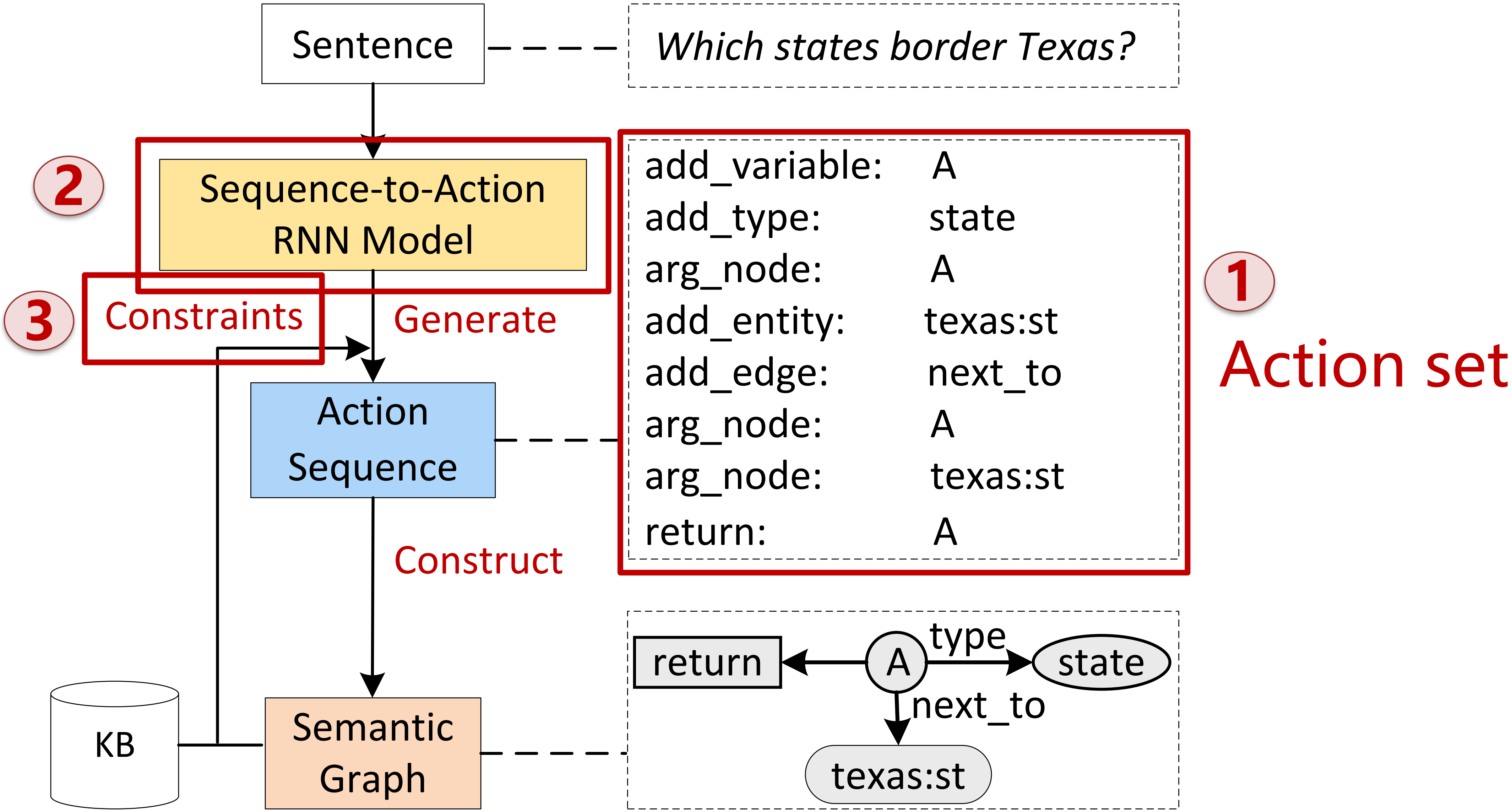
Major components of Our Model (1)



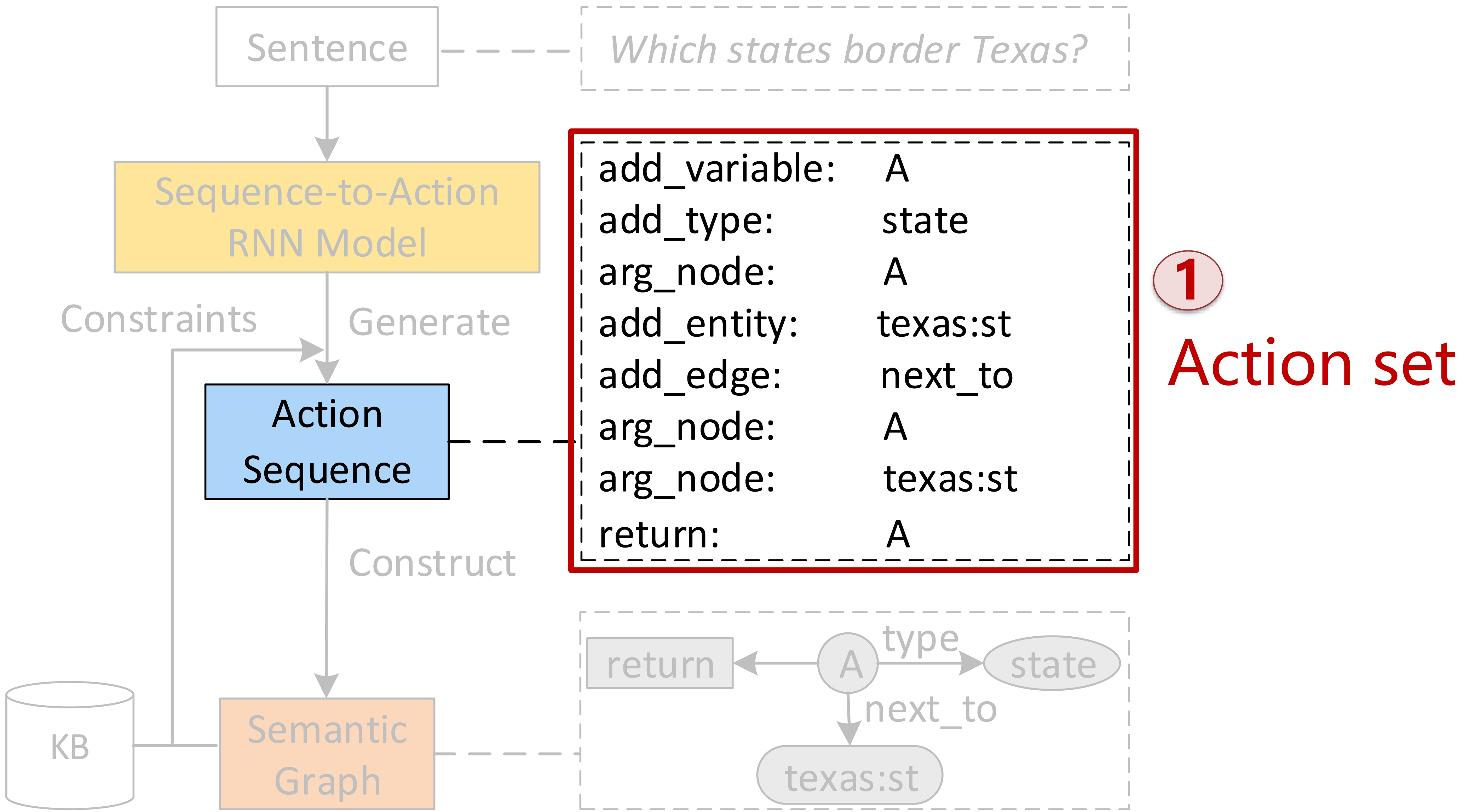
Major components of Our Model (2)



Major components of Our Model (3)



Action Set


Sentence
Which states border Texas?
Sequence-to-Action RNN Model
Constraints
Generate
Action Sequence
add_variable: A
add_type: state
arg_node: A
add_entity: texas:st
add_edge: next_to
arg_node: A
arg_node: texas:st
return: A
1
Action set
Construct
KB
Semantic Graph
return
A
type
state
next_to
texas:st

Action Set

- Define atom actions involved in semantic graph construction

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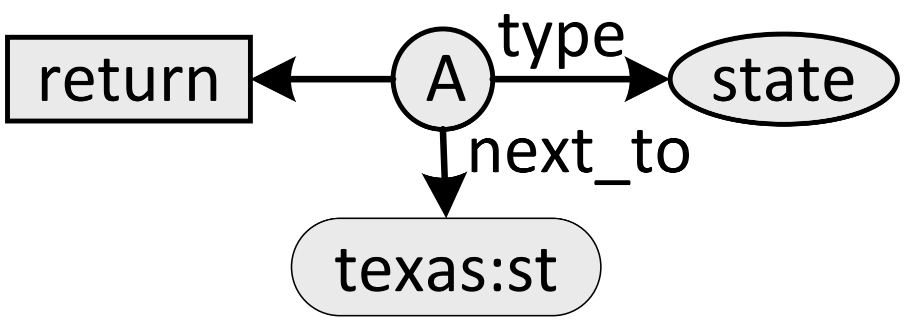
Which states border Texas?



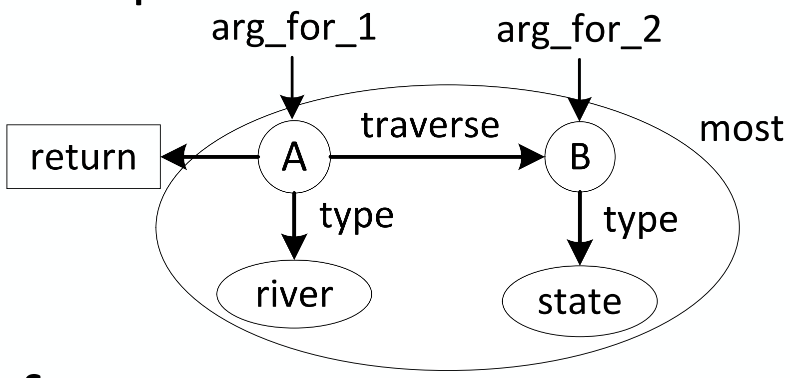
Node: A (variable), texas:st (entity), state (type)
Edge: next_to
Return node: A

Action Set

- Add variable node
  - E.g., A
- Add entity node
  - E.g., texas:st
- Add type node
  - E.g., state
- Add edge
  - E.g., next_to
- Operation action
  - E.g., argmax, argmin, count
- Argument action
  - For type node, edge and operation

Sentence: *Which river runs through the most states?*

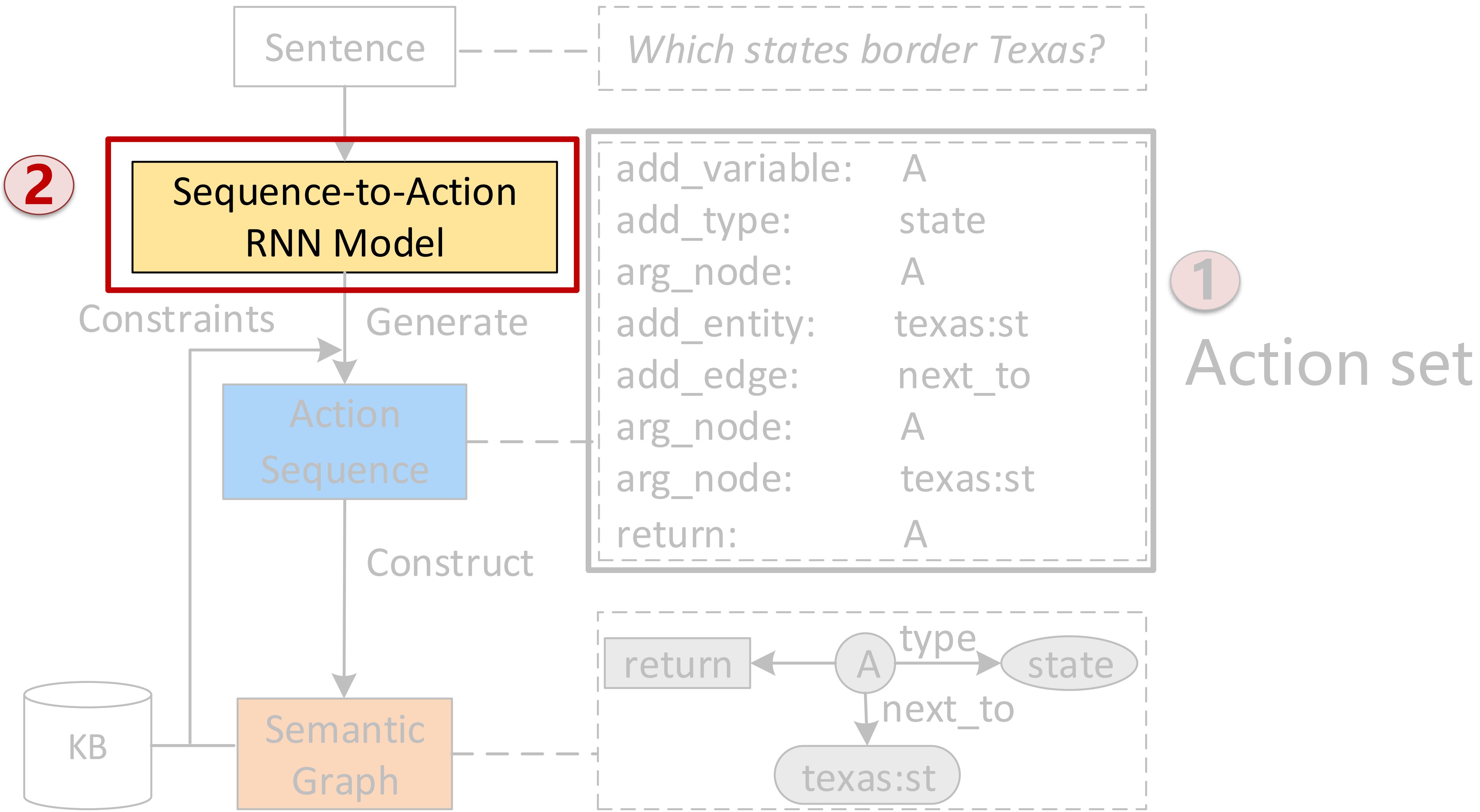
Semantic Graph:



Action Sequence:

Structure	Semantic	Arg
add_operation	most	
add_variable	A	
add_type	river	A
add_variable	B	
add_type	state	B
add_edge	traverse	A, B
end_operation	most	A, B
return	A	

Encoder-Decoder Model



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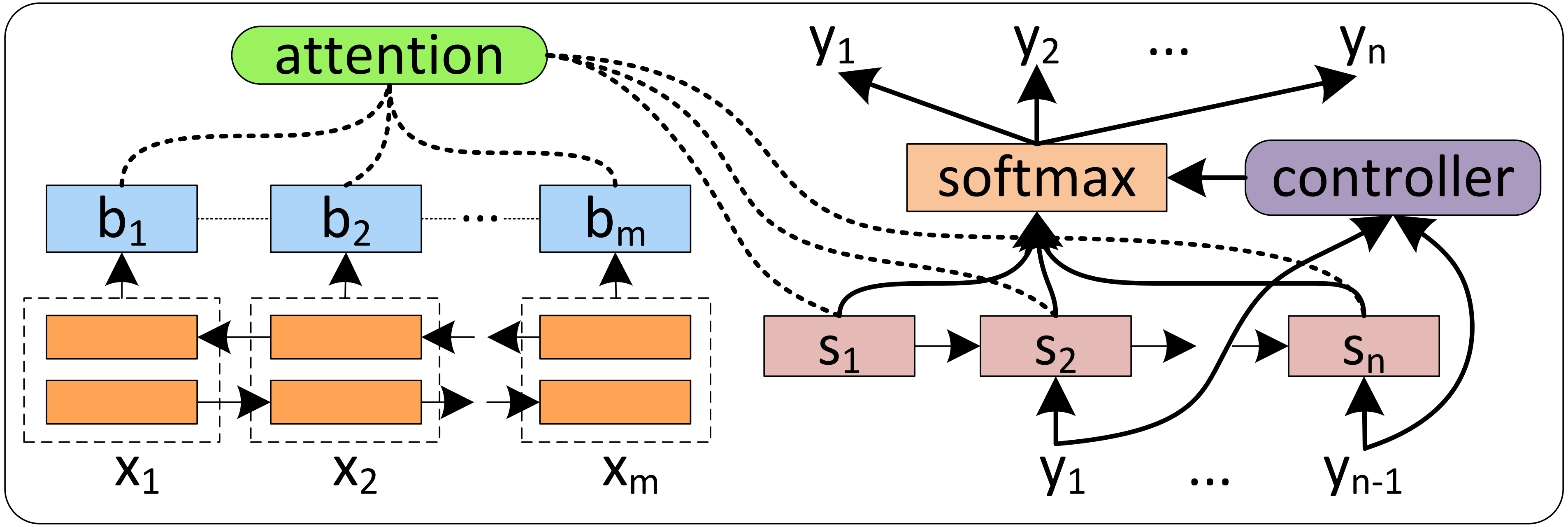

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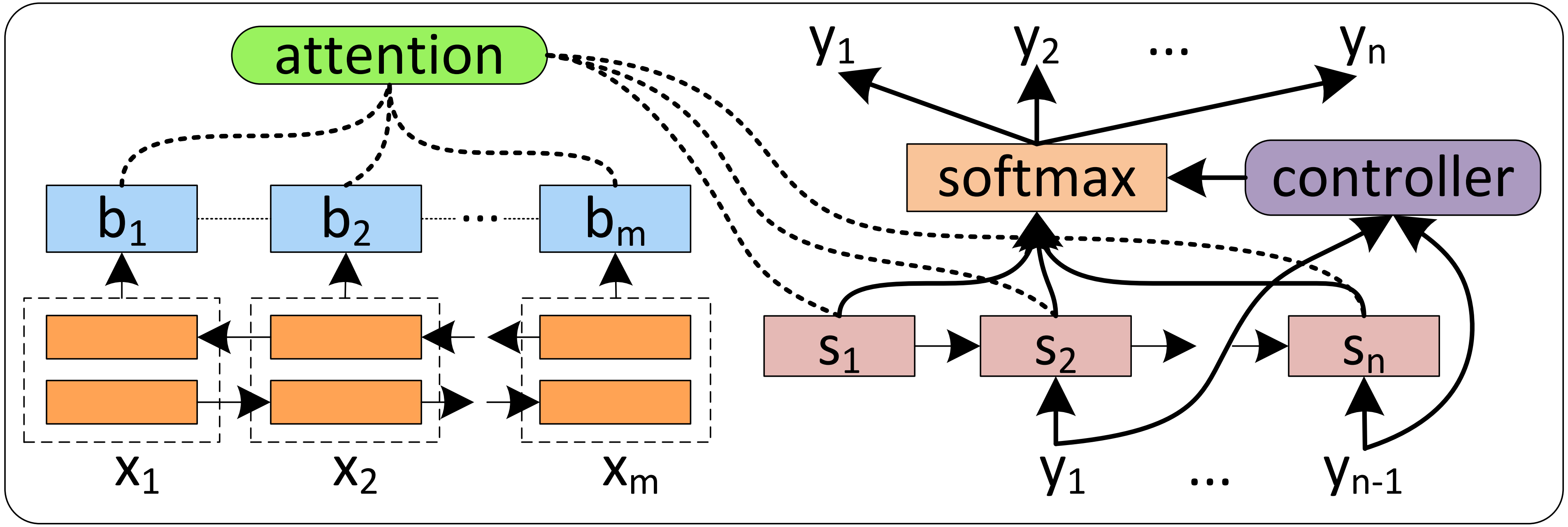

Typical encoder-decoder model (bi-LSTM with attention)

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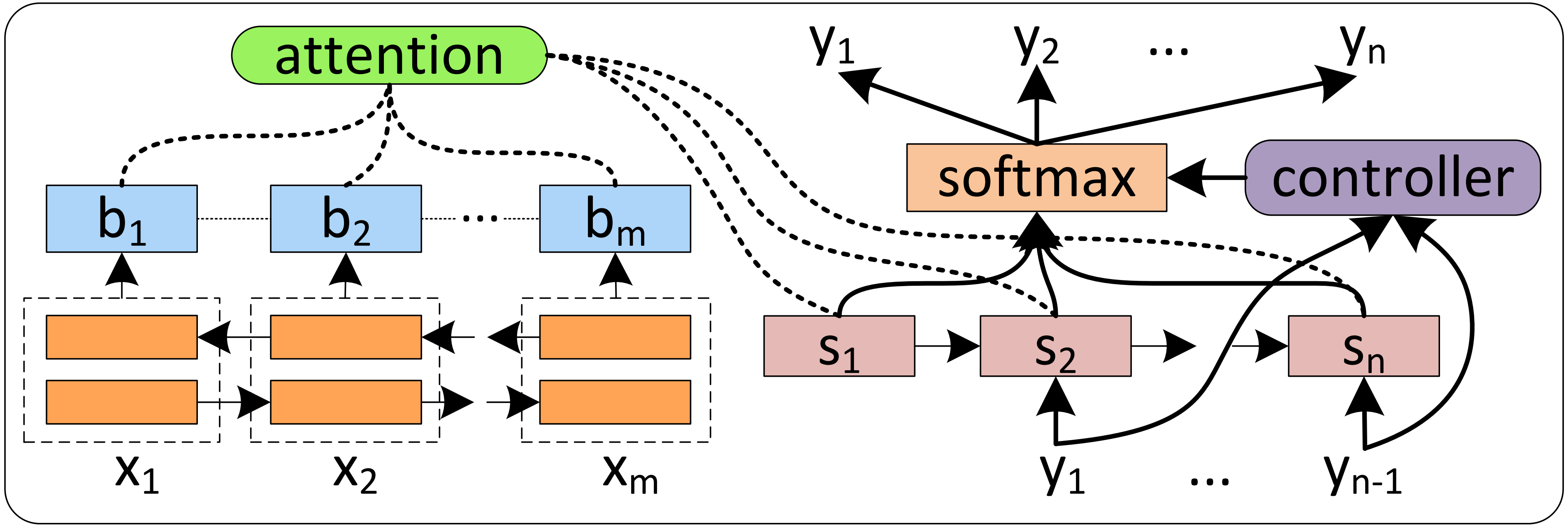

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Action embedding

Action Embedding

add_edge	:	next_to
add_edge	:	loc

Action Embedding

add_edge : next_to

add_edge : loc

Structure part

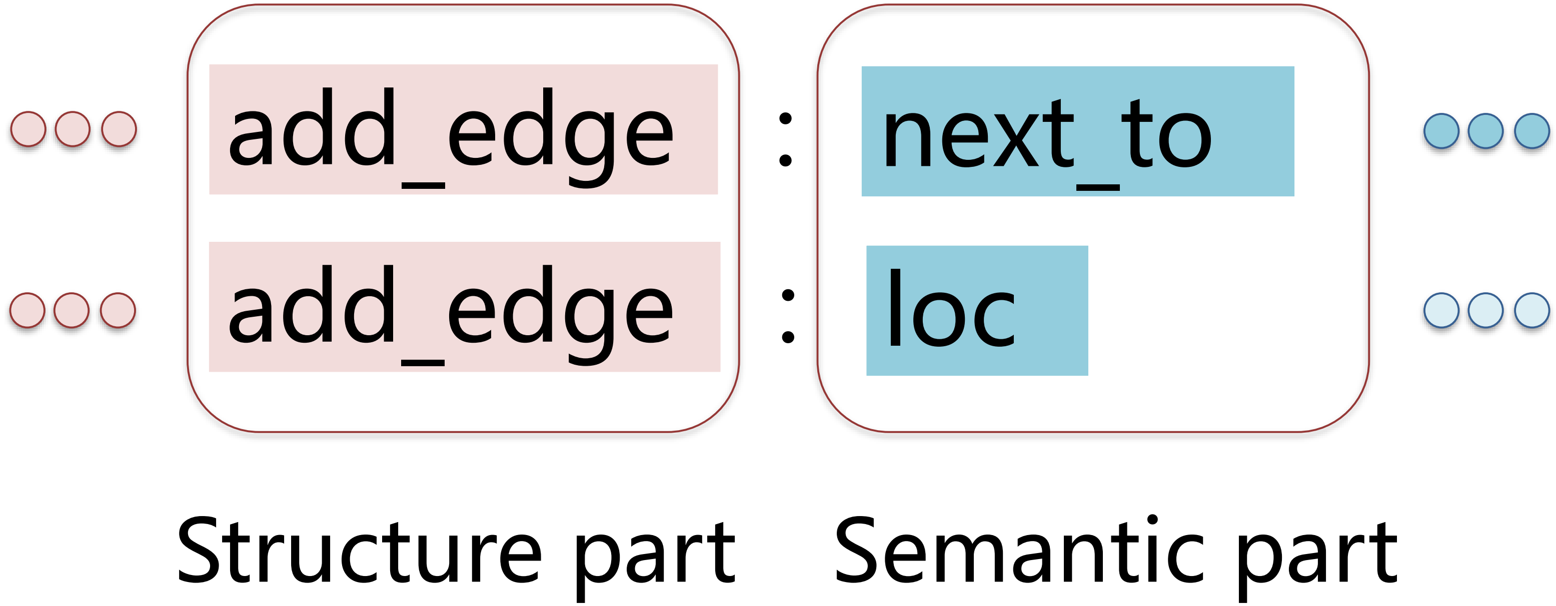
Action Embedding

add_edge : next_to

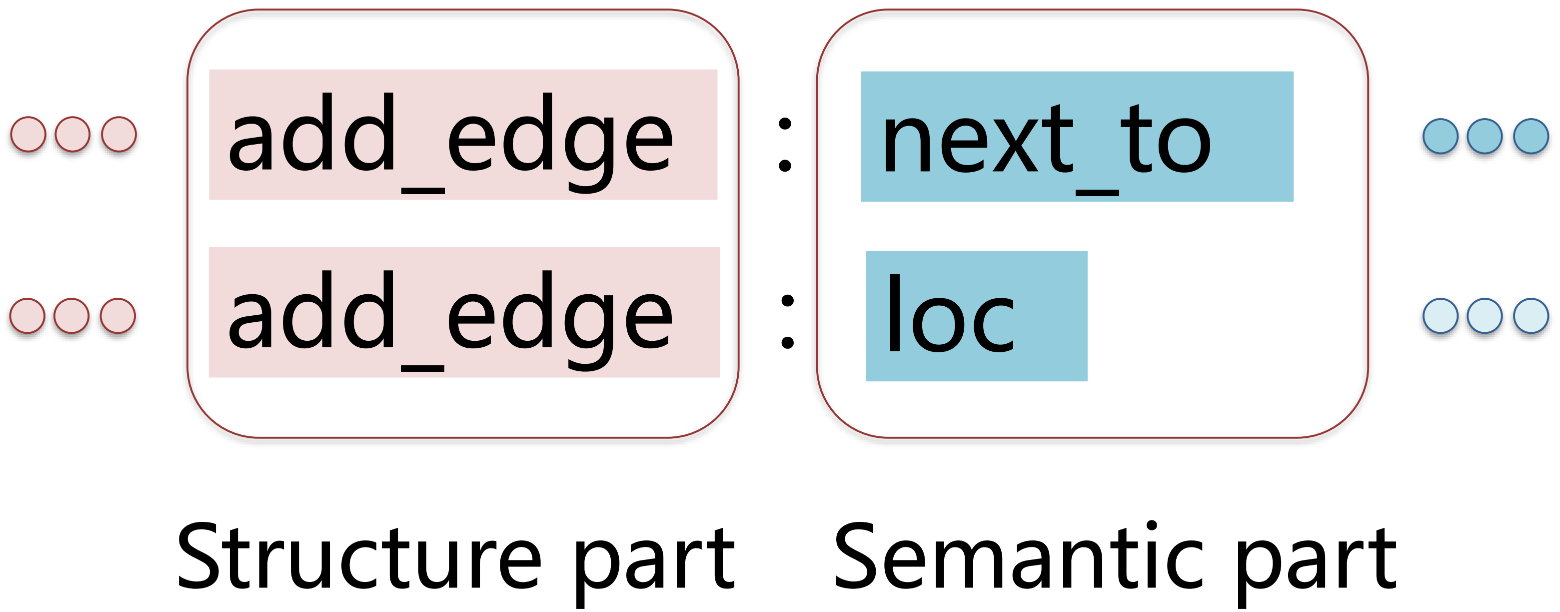
add_edge : loc

Structure part　Semantic part

Action Embedding

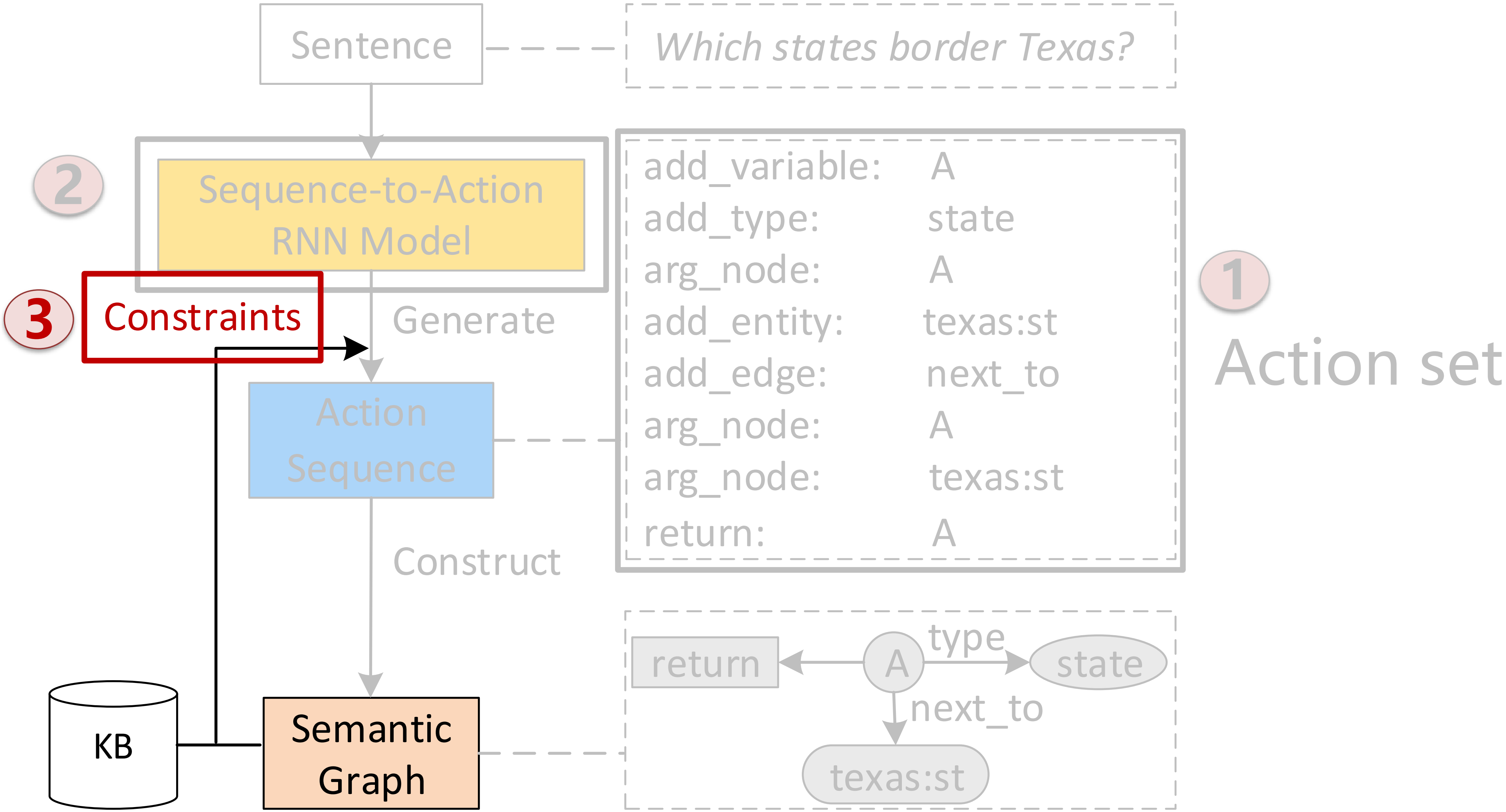


Action Embedding



Φ (add_edge:next to) = [Φ (add_edge); Φ (next_to)]

Structure & Semantic Constraints



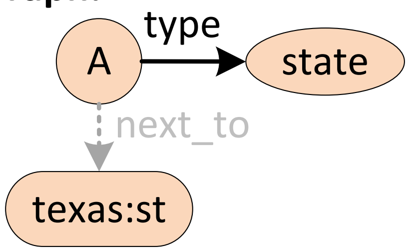
Structure & Semantic Constraints

- Structure constraints
  - Ensure action sequence will form a connected acyclic graph
- Semantic constraints
  - Ensure the constructed graph must follow the schema of knowledge bases

Structure & Semantic Constraints

Sentence: *Which states border Texas?*

Partial Semantic Graph:



	Structure	Semantic	Arg	Validity
Generated Actions	add_variable	A		
	add_type	state	A	
	add_entity	texas:st		
Candidate Next Action	add_type	city	texas:st	✗
	add_edge	loc	A, texas:st	✗
	add_edge	next_to	A, A	✗
	add_edge	next_to	A, texas:st	✓
	⋮	⋮	⋮	⋮

Action 1: violate type conflict

Action 2: violate selectional preference constraint

Action 3: structure constraint

Action 4: YES

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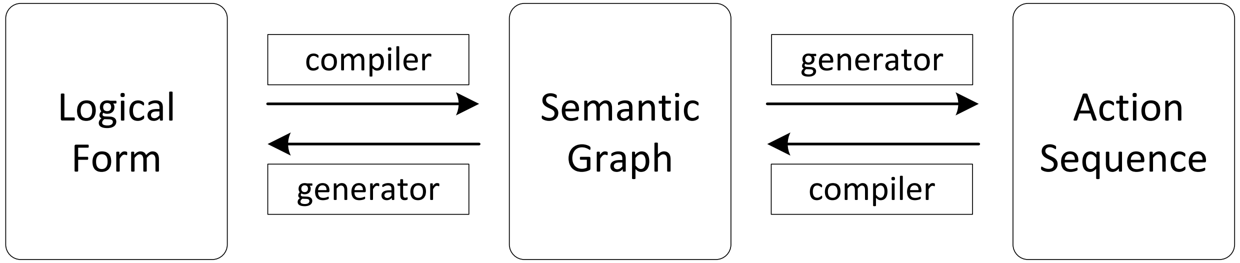
Experiments

- Datasets: GEO[Zelle and Mooney, 1996], ATIS[He and Young, 2005], OVERNIGHT[Wang et al., 2015b]
- We generate the action sequences from logical forms automatically.



what is the population of illinois ?

add_node:-:B add_node:-:A add_edge:-:_population arg_node:-:B arg_node:-:A add_entity_node:-:illinois:=:state arg_node:-:B return:-:A

Baselines

- **Traditional Methods**
  - Zettlemoyer and Collins, 2005
  - Zettlemoyer and Collins, 2007
  - Liang et al., 2011
  - Zhao et al., 2015
  - Wang et a., 2015
- **Sequence-to-Sequence Models**
  - Dong and Lapata, 2016
  - Jia and Liang, 2016
  - Xiao et al., 2016
  - Rabinovich et al., 2017

Competitive performance on three datasets

	SOTA	SOTA without extra resources	Our full model
GEO	91.1 [Liang et al., 2011]	89.9 [zhao et al., 2015]	89.9
ATIS	85.9 [Rabinovich et al., 2017]	85.9 [Rabinovich et al., 2017]	85.5
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Seq2Act outperforms Seq2Seq

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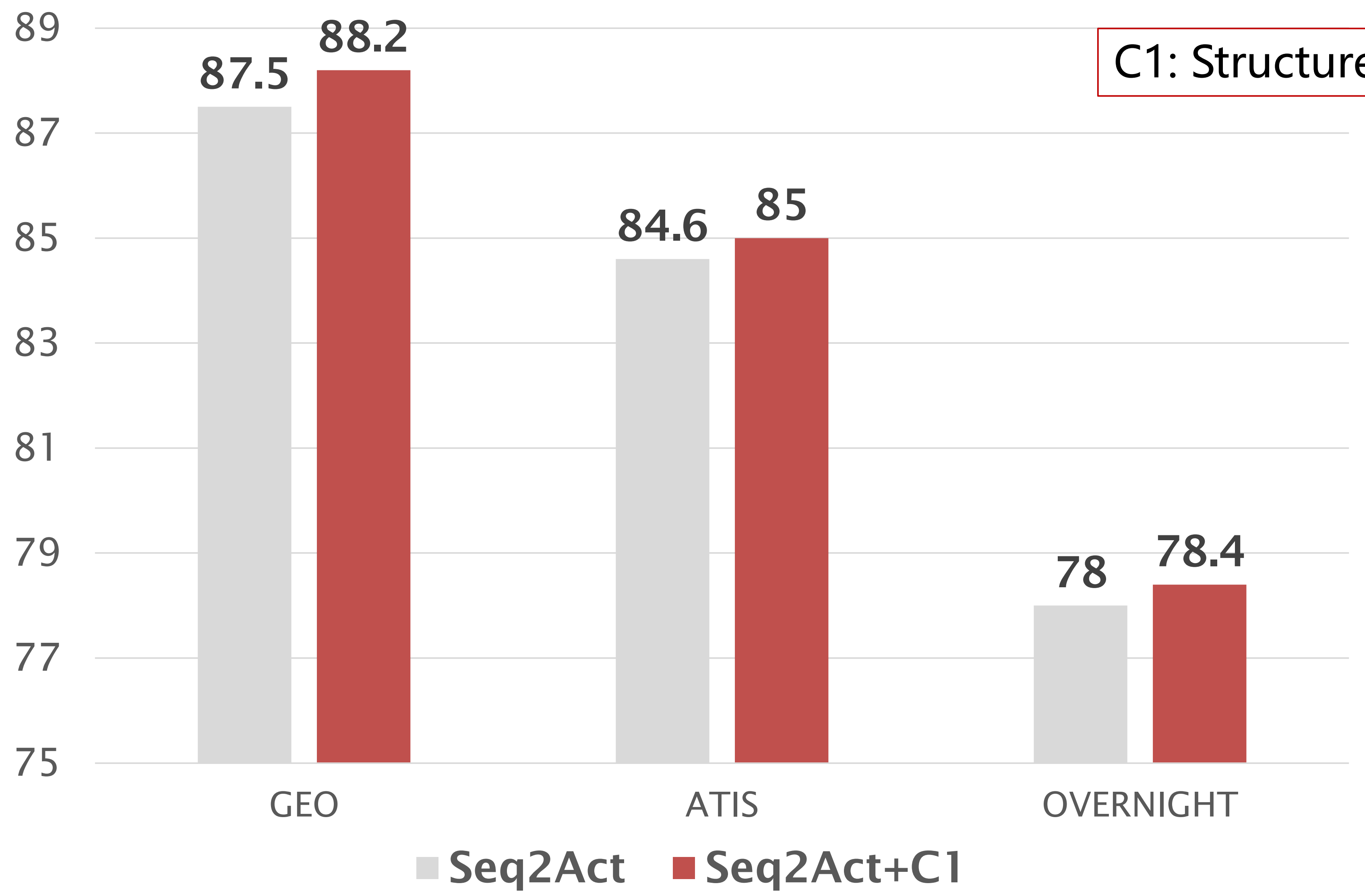
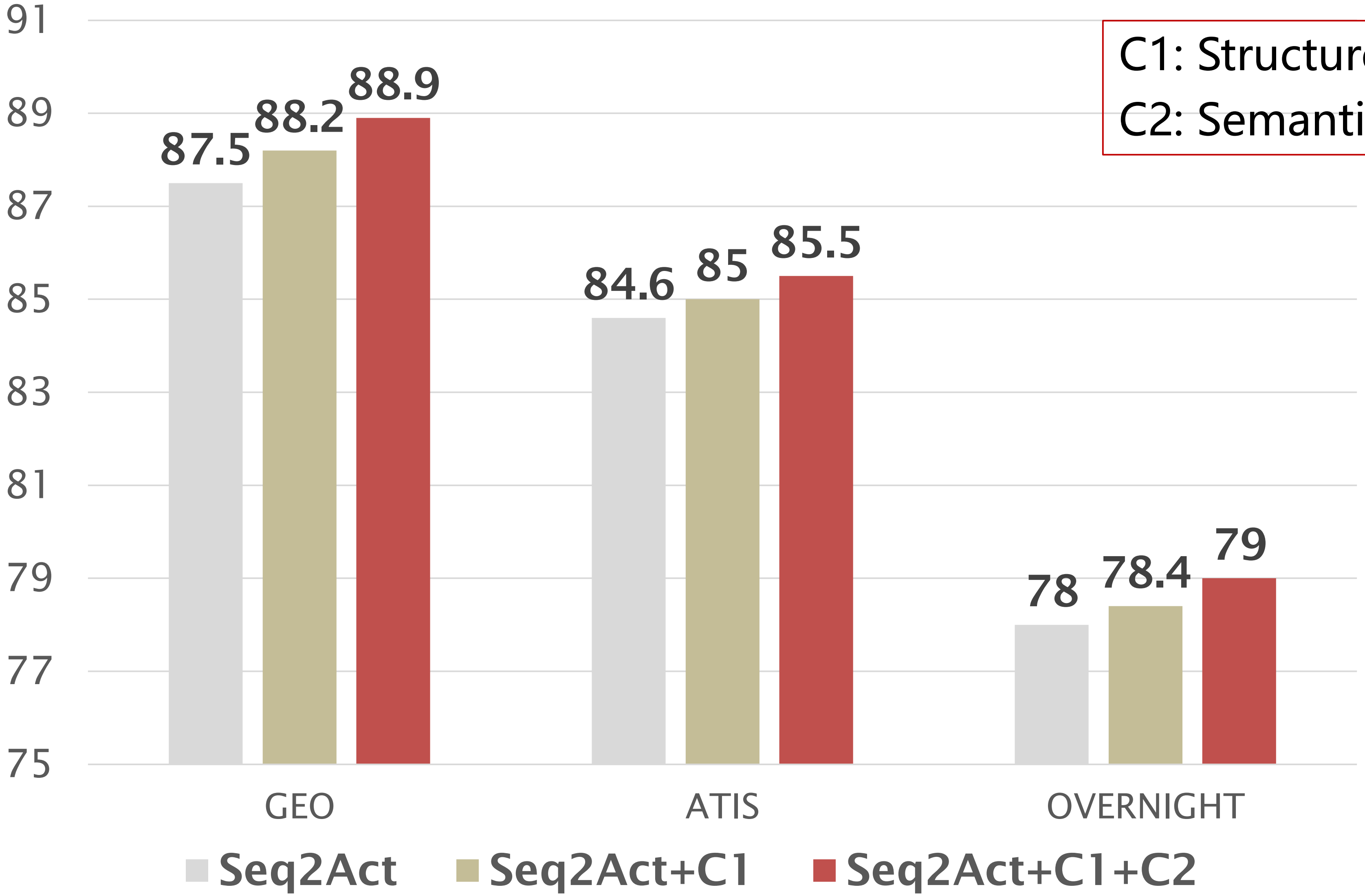
Seq2Act+C1 outperforms Seq2Act

C1: Structure Constraints



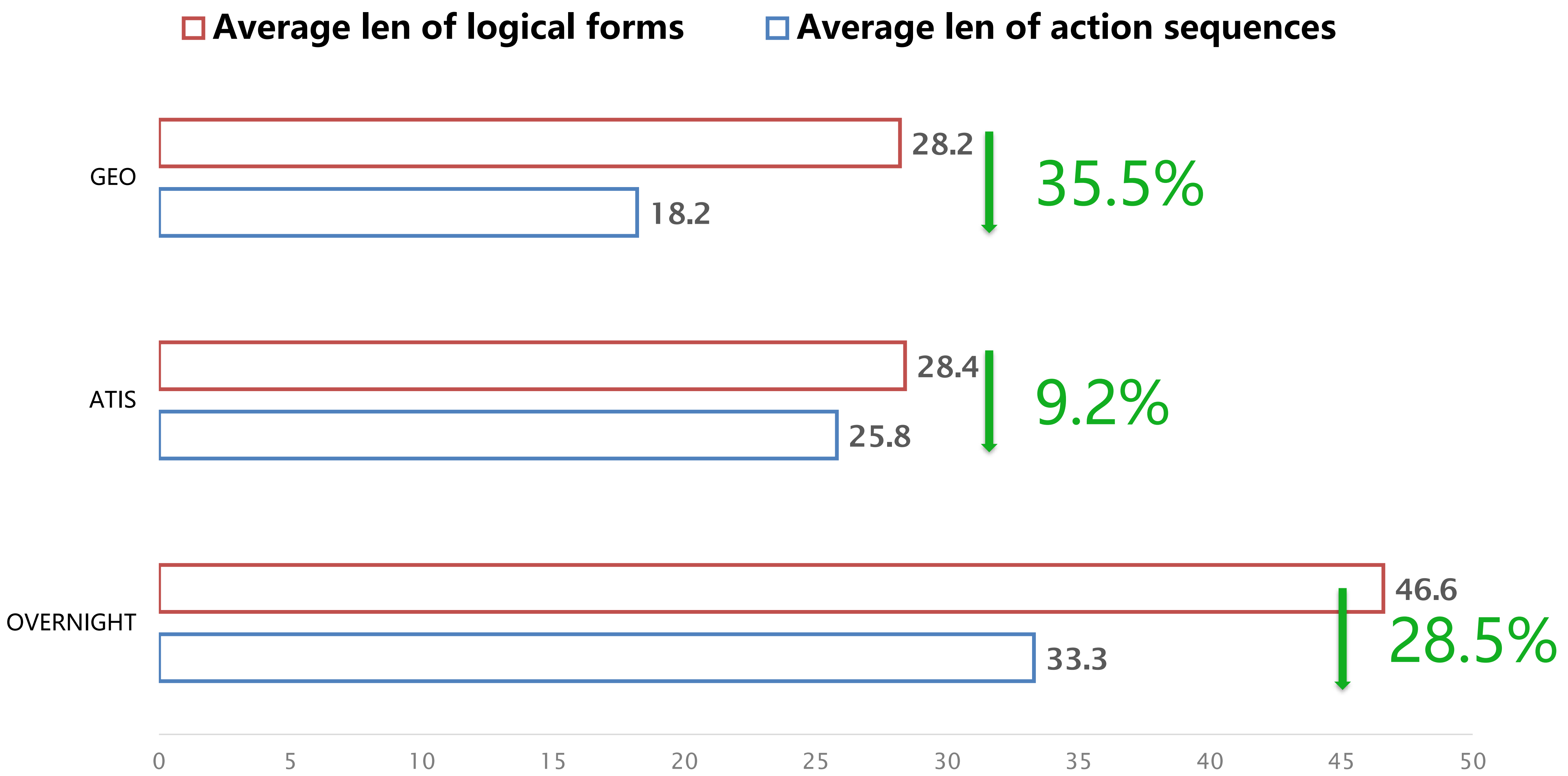
Seq2Act+C1+C2 outperforms Seq2Act+C1



C1: Structure Constraints

C2: Semantic Constraints

Average Length of Logical Forms and Action Sequences



Error Analysis

- Un-covered Sentence Structure
  - *Iowa borders how many states?* (Formal Form: *How many states does Iowa border?*)

- Under Mapping
  - *Please show me first class flights from indianapolis to memphis one way leaving before 10am*

Conclusion

- Sequence-to-Action: End-to-End Semantic Graph Generation
  - Representation ability of semantic graphs
  - Sequence prediction ability of RNN models
- Achieve competitive results on GEO, ATIS and OVERNIGHT

Future work

- Weak supervised learning algorithm for Seq2Act
  – So our method can be applied to (q, a) pair datasets such as WebQuestions
- Apply Seq2Act model to other parsing tasks (e.g., AMR parsing)

Thanks!

Data and code available:

https://github.com/dongpobeyond/Seq2Act

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