



COS 484: Natural Language Processing

LI 9: Language Grounding - 2

Spring 2022

Logistics

- ▶ Sign up for project meetings on April 19
 - ▶ Mandatory for every team to meet with your staff guide
- ▶ Fill up preference form for poster session on April 21

Some grounding tasks

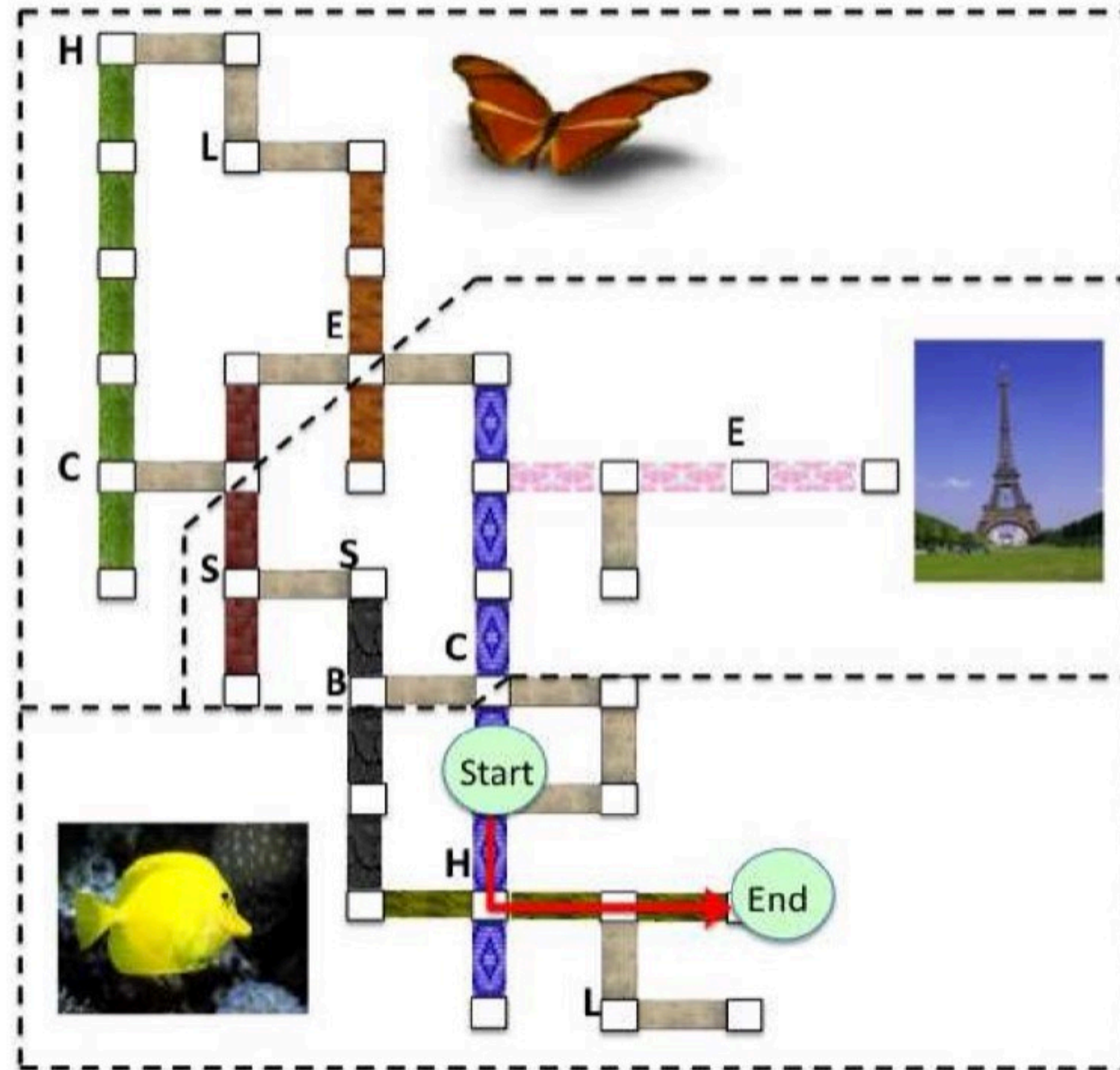
- ▶ **Vision**

- ▶ Captioning
- ▶ Visual question answering (VQA)
- ▶ Spatial reasoning

- ▶ **Interaction**

- ▶ Instruction following
- ▶ Text-based games
- ▶ RL for NLP

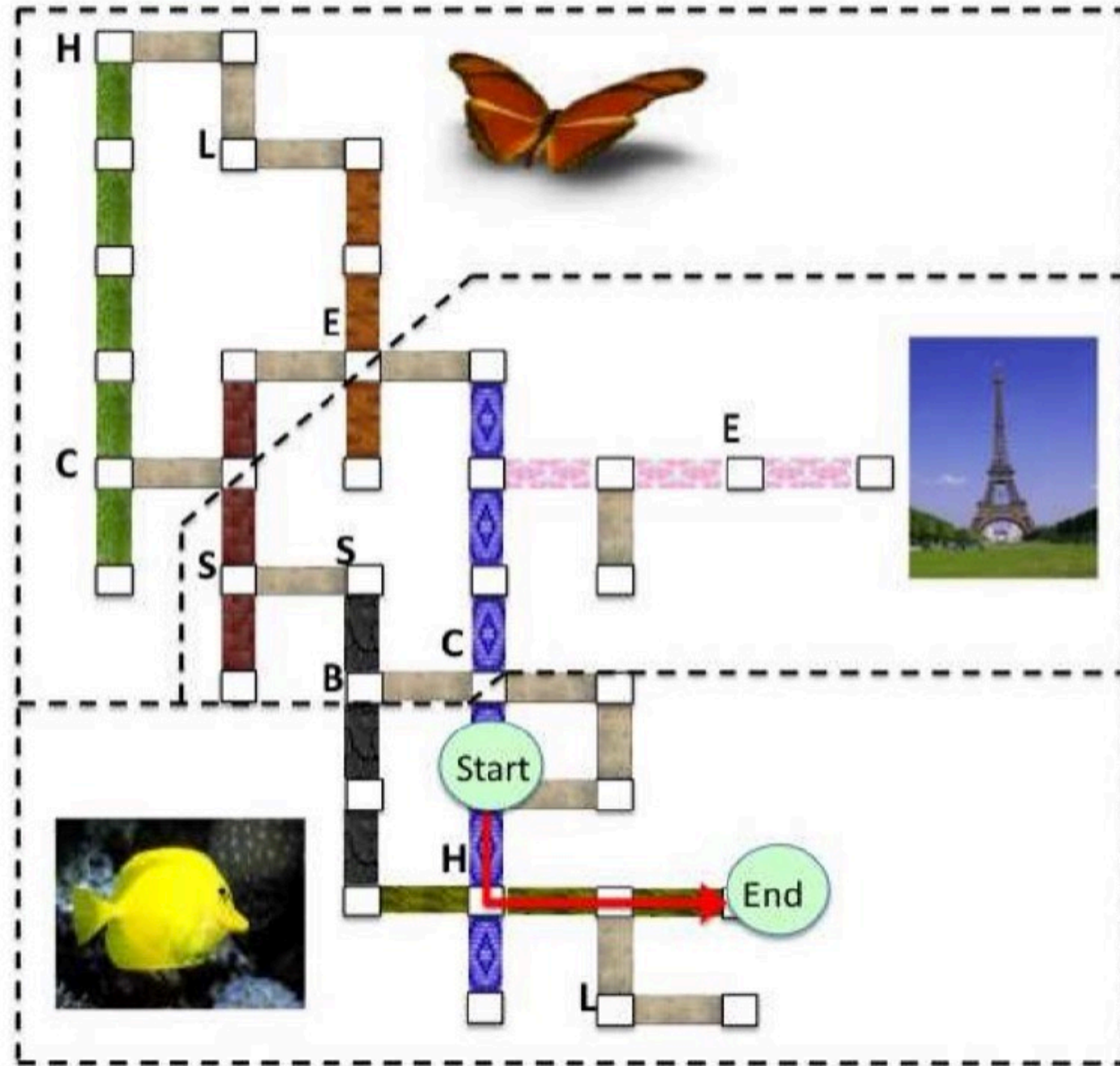
Instruction Following



- ▶ Want to be able to follow instructions in a virtual environment
- ▶ “Go along the blue hall, then turn left away from the fish painting and walk to the end of the hallway”

Grounding language to actions

Instruction Following



Instruction: "Go away from the lamp to the intersection of the red brick and wood"

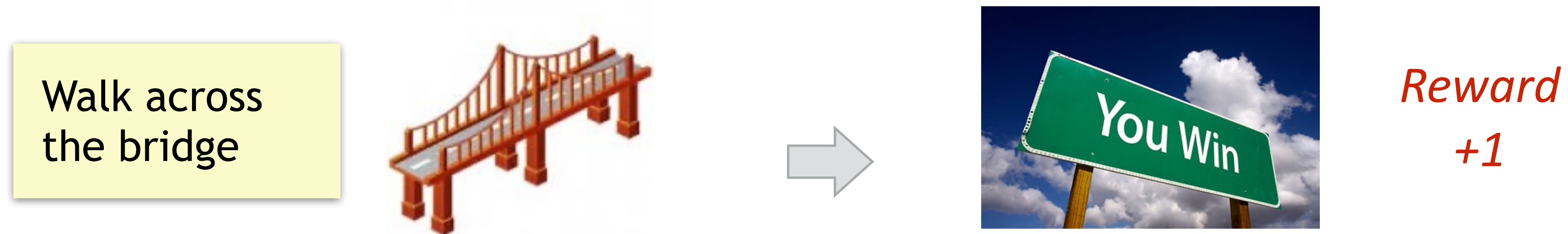
Basic: Turn (),
Travel (steps: 1)

Landmarks: Turn (),
Verify (left: WALL , back: LAMP , back: HATRACK , front: BRICK HALL) ,
Travel (steps: 1) ,
Verify (side: WOOD HALL)

- ▶ Train semantic parser on (utterance, action) pairs

Grounding semantics in control applications

1. Use feedback from task to understand language

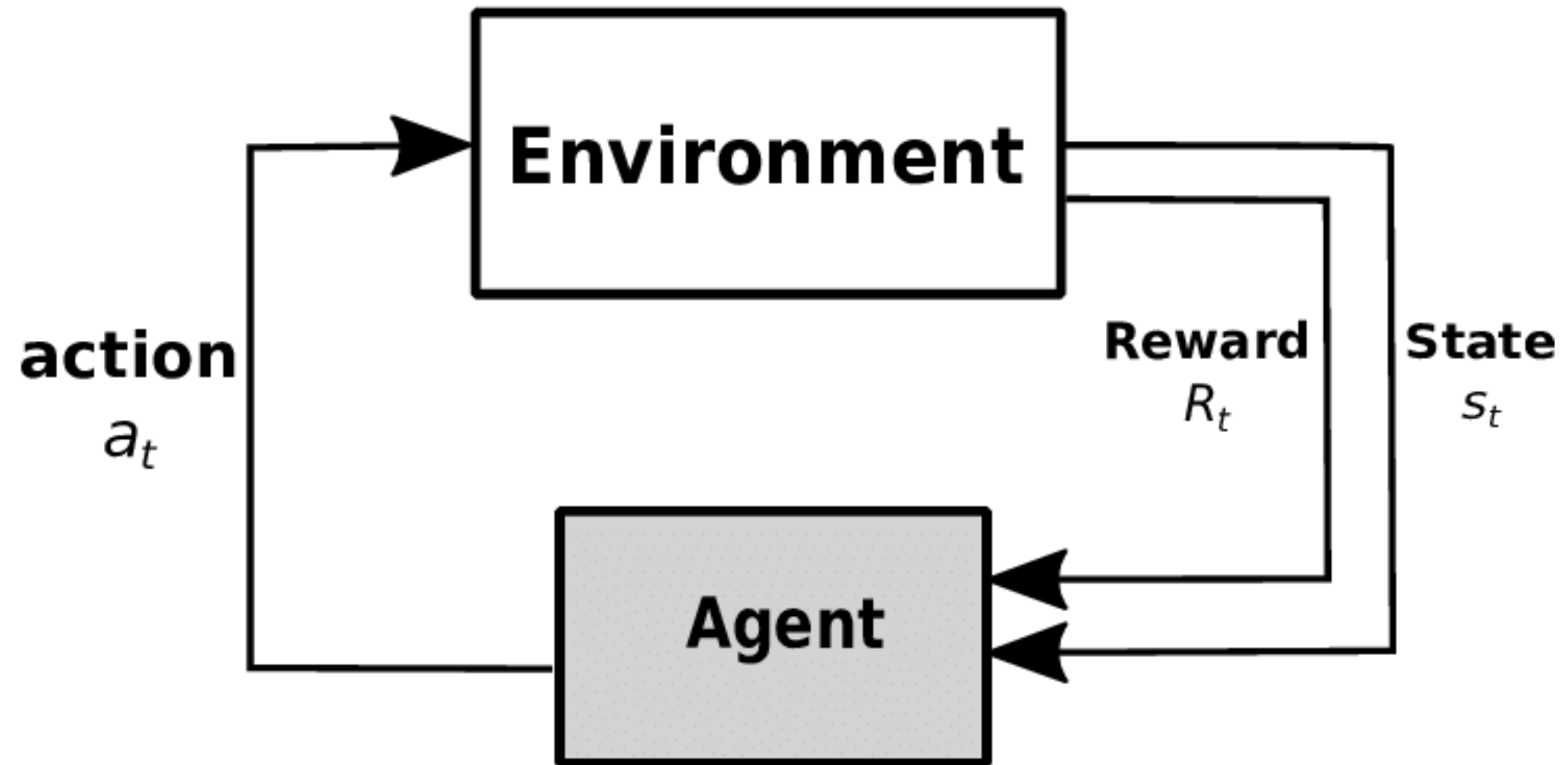


Alleviate dependence on supervised annotation

2. Use language to improve performance in control applications



Reinforcement learning



Reinforcement Learning

- Delayed feedback



⇒ *How to perform credit assignment for individual actions*

- Large number of possible action sequences

⇒ *Need for effective exploration*

Improved language understanding translates
to improved task performance

Playing Civilization by reading game manuals

Relevant text: "Use settlers to irrigate land near your city"
 Predicted action words: "irrigate", "settler"
 Predicted state words: "land", "near", "city"

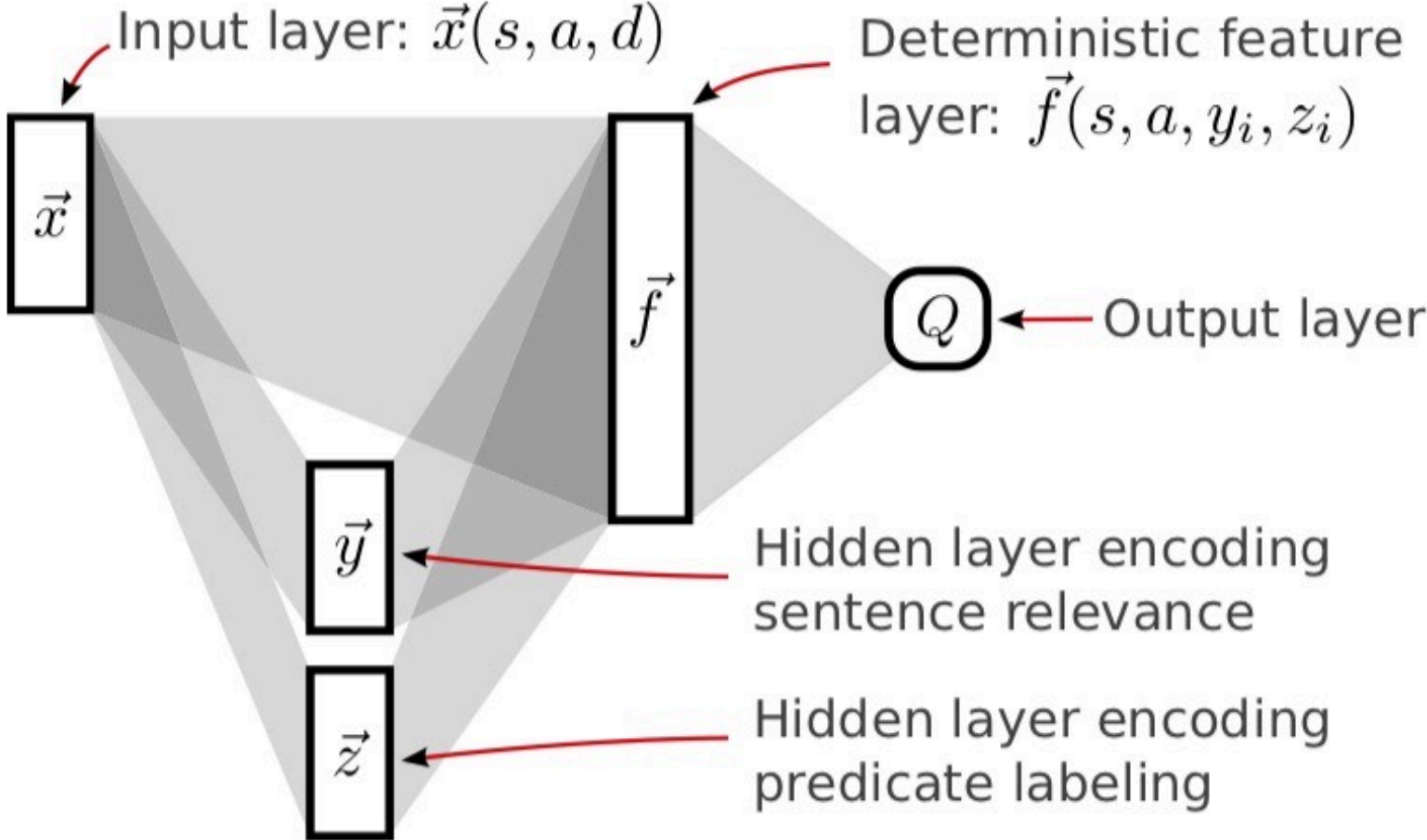
Settlers unit, candidate action 1: **irrigate**

Features:
 action = **irrigate** and action-word = "irrigate"
 action = **irrigate** and state-word = "land"
 action = **irrigate** and terrain = plains
 action = **irrigate** and unit-type = settler
 state-word = "city" and near-city = true

Settlers unit, candidate action 2: **build-city**

Features:
 action = **build-city** and action-word = "irrigate"
 action = **build-city** and state-word = "land"
 action = **build-city** and terrain = plains
 action = **build-city** and unit-type = settler
 state-word = "city" and near-city = true

Neural network for policy



Method	% Win	% Loss	Std. Err.
Random	0	100	—
Built-in AI	0	0	—
Game only	17.3	5.3	± 2.7
Latent variable	26.1	3.7	± 3.1
Full model	53.7	5.9	± 3.5
Randomized text	40.3	4.3	± 3.4

(Branavan et al., 2012)

Learning a grounding



*The **dangerous enemy** is the **alien** that is **inching** near you.*

*The **wolf** is **running from** you while holding a **secret message**.*



*The **bear** that is **coming near** you is the **crucial goal**.*

*The **dragon** which is **running away** is a **adversary** and the **adversary** is **deadly**.*

- How do we map symbols in language (i.e. words) to entities and concepts in the world?
- Can an agent learn grounding through interaction

[Grounding Language to Entities and Dynamics for Generalization in Reinforcement Learning.


Austin W. Hanjie, Victor Zhong, Karthik Narasimhan; ICML 2021]



GAME 1 MANUAL

1. at a particular locale, there exists a motionless mongrel that is a formidable adversary.
2. the top-secret paperwork is in the crook's possession, and he's heading closer and closer to where you are.
3. the crucial target is held by the wizard and the wizard is fleeing from you.
4. the mugger rushing away is the opposition posing a serious threat.
5. the thing that is not able to move is the mage who possesses the enemy that is deadly.
6. *the vital goal is found with the canine, but it is running away from you.*

Messenger

- Agent can move around and interact in a simulated environment
- Receives global state observations, rewards
- Has access to a text "manual" describing entities and dynamics, throughout an episode
- Agent is not provided any prior mapping between the observations () and symbols in text (*wizard, mage*) to help it "read" the manual.

[Grounding Language to Entities and Dynamics for Generalization in Reinforcement Learning.

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- Multi-game benchmark with separate train and test splits
- In each game, agent has to first pick up a *message*, and deliver it to *goal* entity, while avoiding an *enemy*
- Each game has different entities, each with different roles and different dynamics
 - *There may be multiple entities of the same type! (e.g. mage in game 1)*
- The agent must consult a natural language manual in order to consistently win
 - *Manual may contain extraneous/incorrect information (e.g. point 6 here).*

Messenger: Statistics



GAME 1 MANUAL

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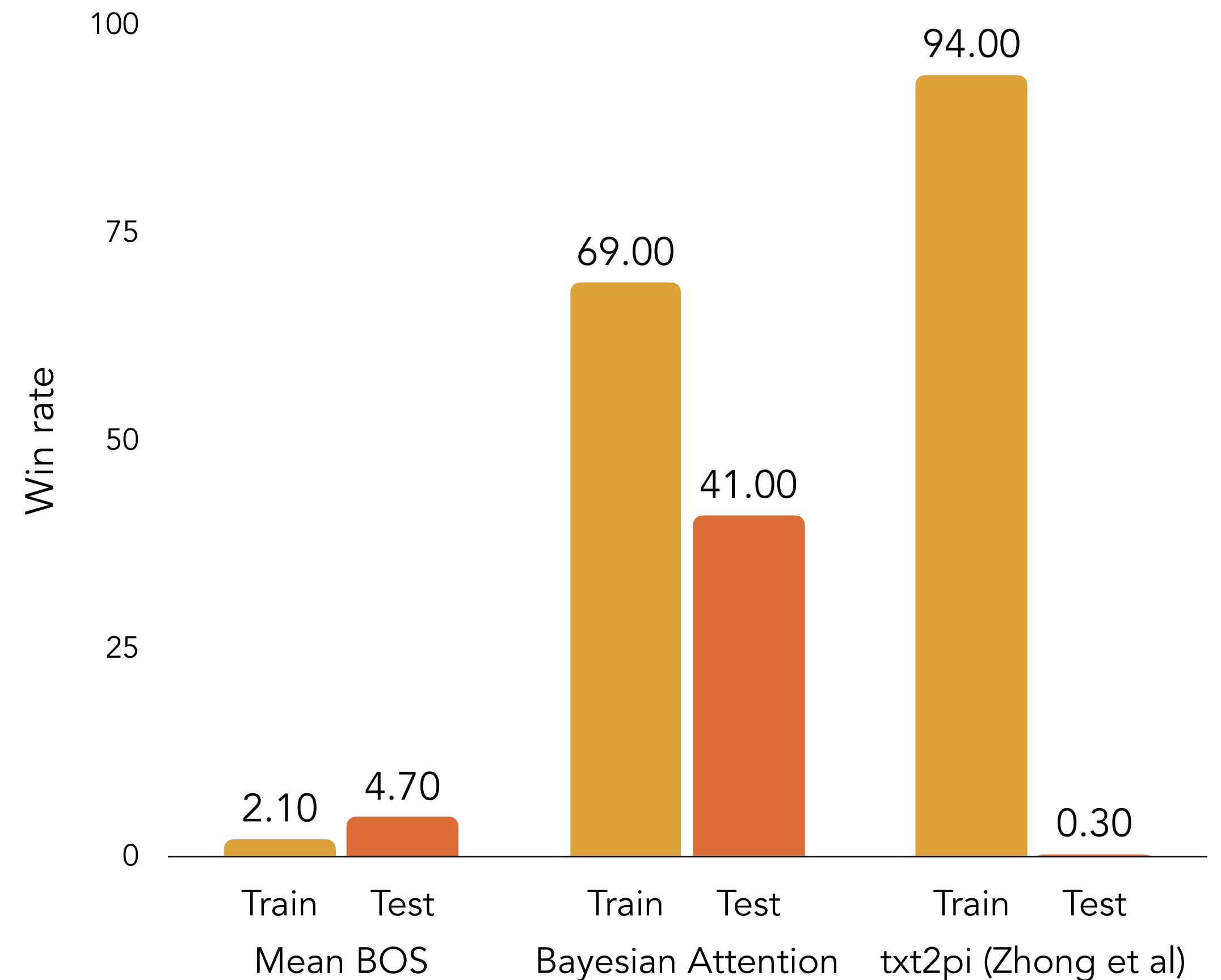
- Random instantiation of roles each time
- 44/32/32 train/val/test game variants
- 5000+ textual descriptions, vocabulary size of 1125
- 30-60 words/manual, completely human written (crowdsourced)

Why is Messenger challenging?

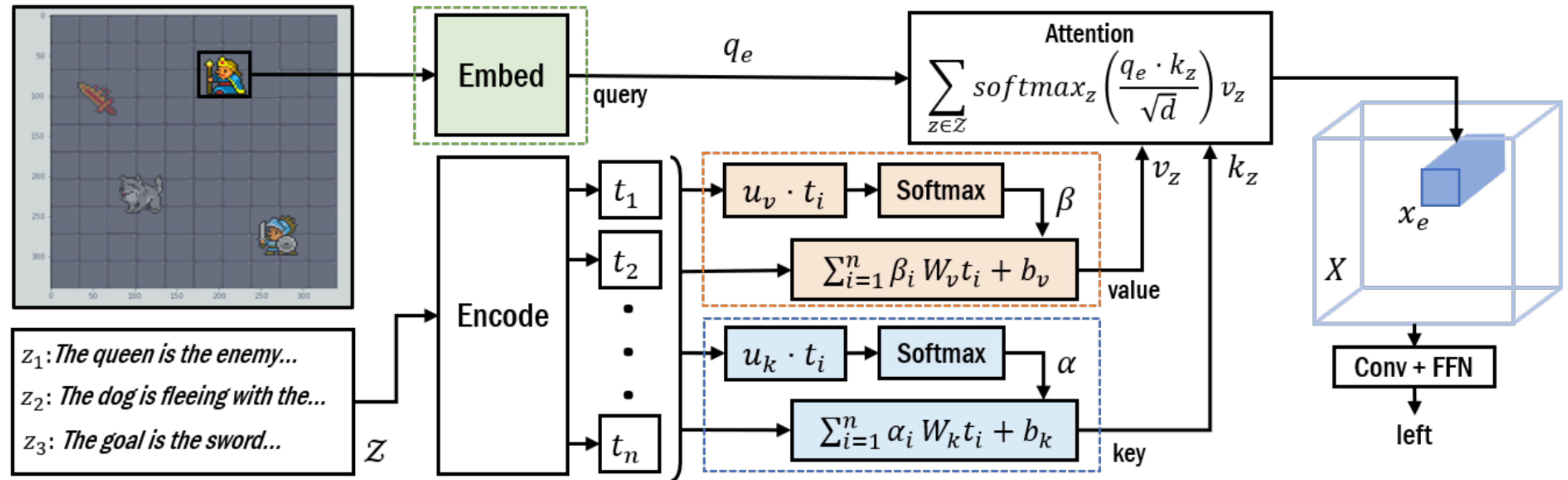
“The top-secret paperwork is in the crook’s possession, and he’s heading closer and closer to where you are”

- Agent has to learn an accurate grounding purely through interaction
- Wide variation in how an entity is described - e.g. use of multiple synonyms (*crook, thief*), non-templated freeform text
- No overlap in terms of entity-role-dynamics combinations between train and test games

Win rates on stage 2 of Messenger for baselines



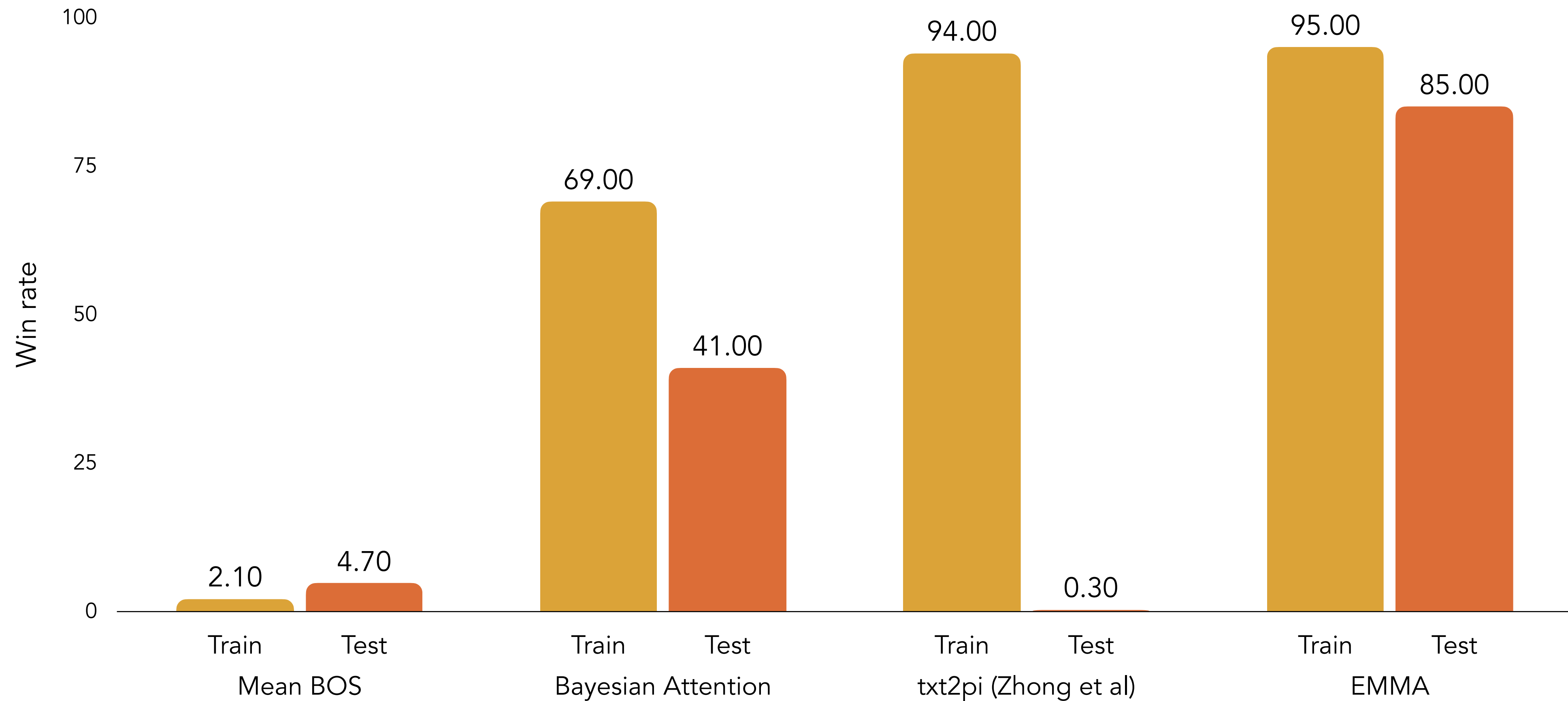
Our model: Entity Mapper with Multimodal Attention (EMMA)



Jointly process observations with text manual for control policy

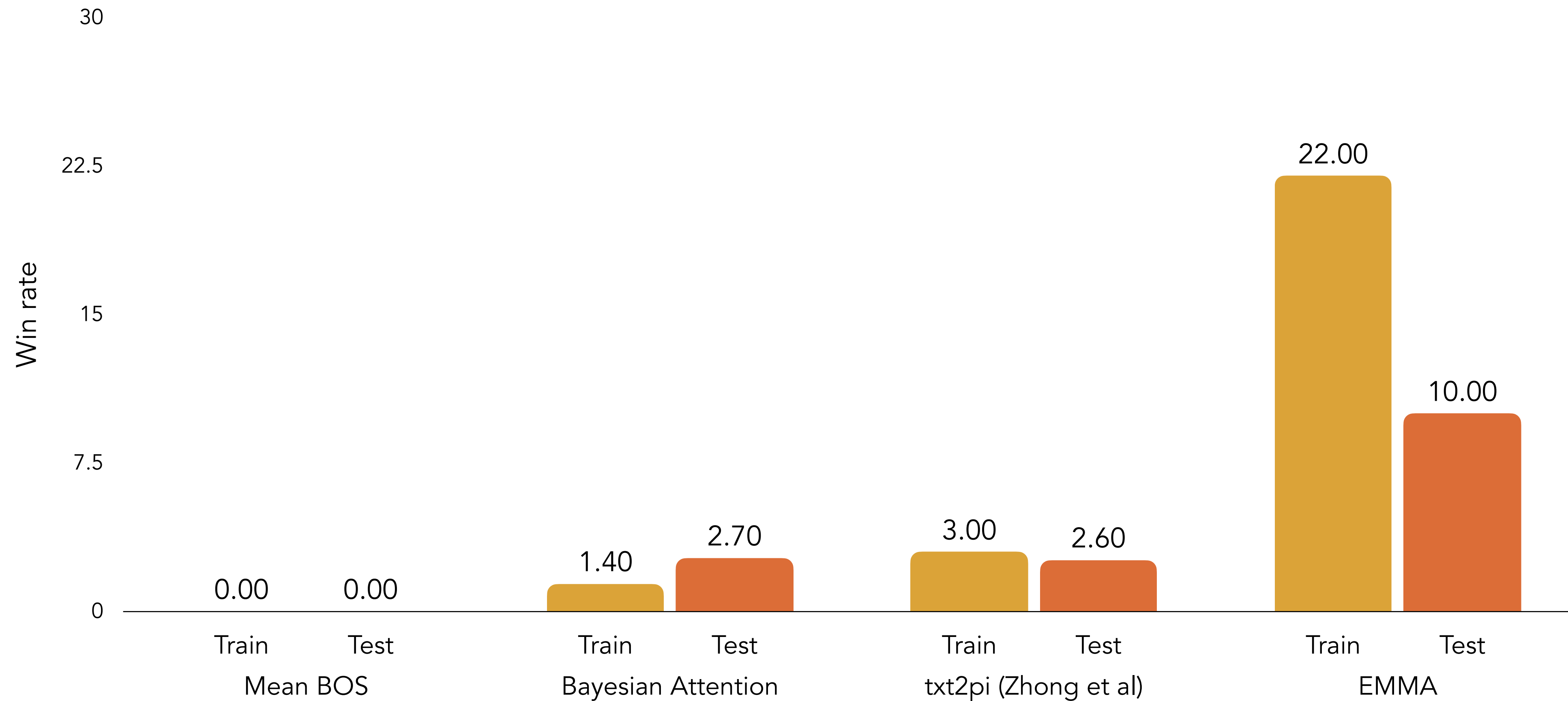
EMMA does better on Messenger...

Win rates on stage 2 of Messenger for baselines



... but some stages continue to prove challenging

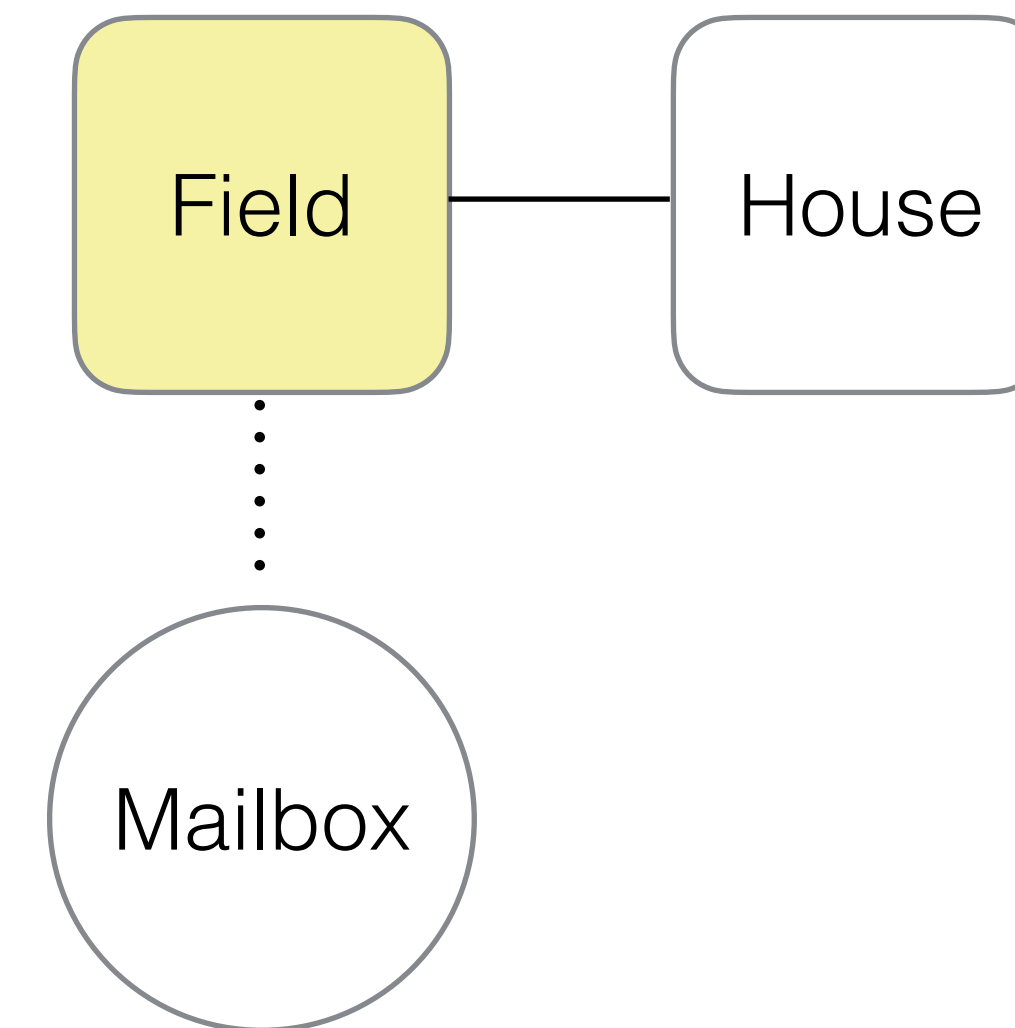
Win rates on stage 3 of Messenger for baselines



Text-based games

You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.

- ◆ open mailbox
- ◆ go east
- ◆ search field

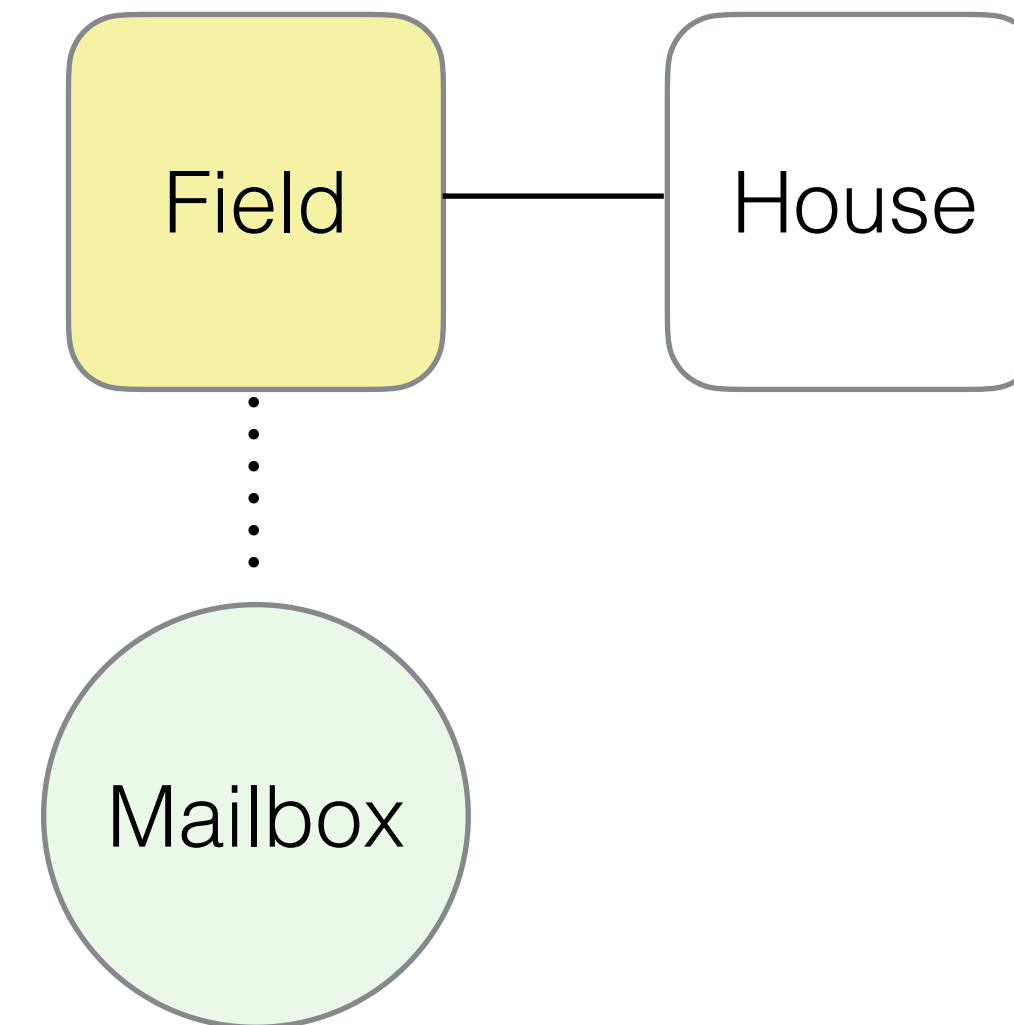


Underlying game state (h1)

Text-based games

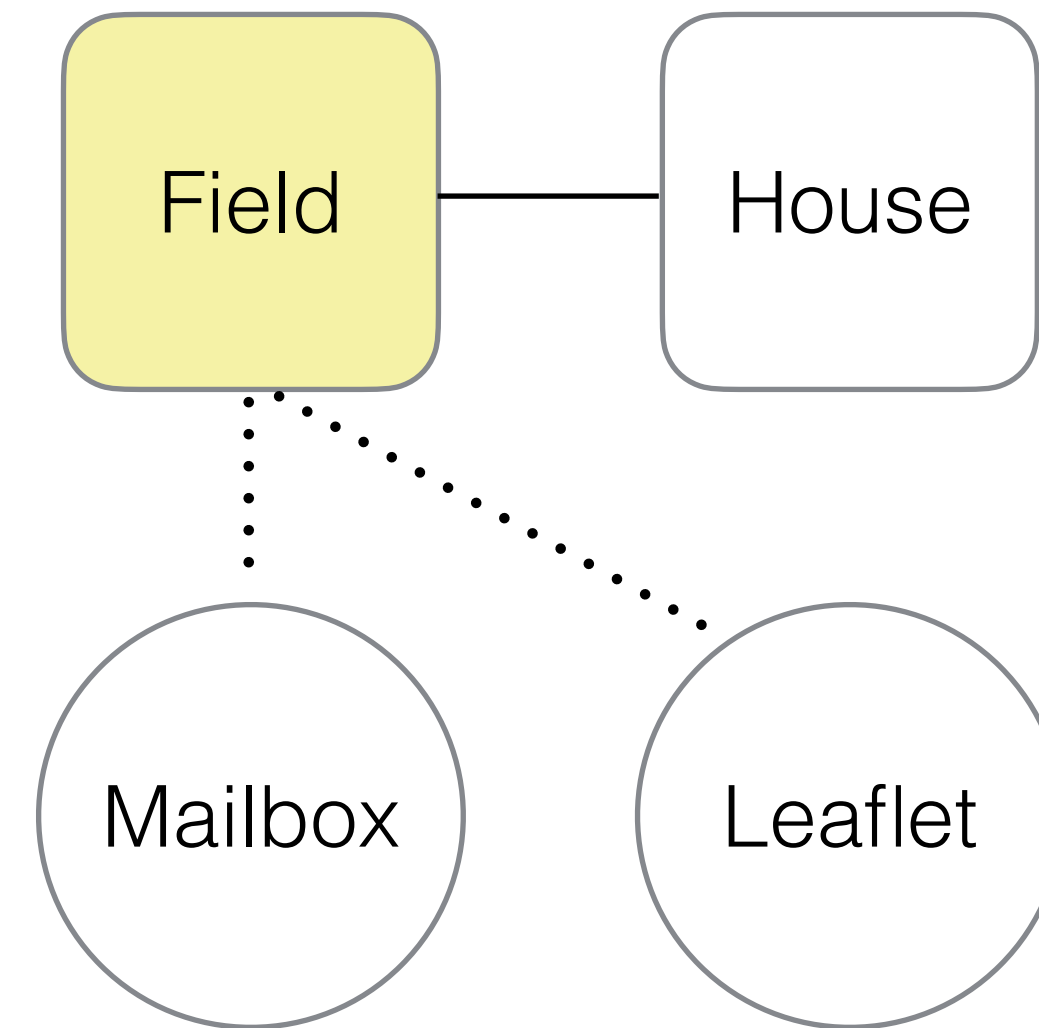
You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.

◆ open mailbox



Text-based games

Opening the mailbox reveals a leaflet.



Underlying game state (h2)

No symbolic representation available

You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.

~~Location: Field~~

~~Wind level: 3~~

~~Time: 12pm~~

Varying text descriptions

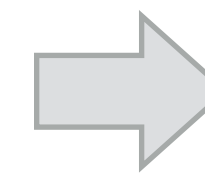
You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.

You are in an open field next to a white house. The house's front door is boarded shut. You see a small mailbox here.

Opportunity

Grounded language learning

You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.



◆ open mailbox

Opportunity

Grounded language learning

In-game rewards provide unstructured feedback



+10 gold



+5 health

Opportunity



Learn language through gamifying tasks

In-game rewards provide structured feedback to learn

duolingo

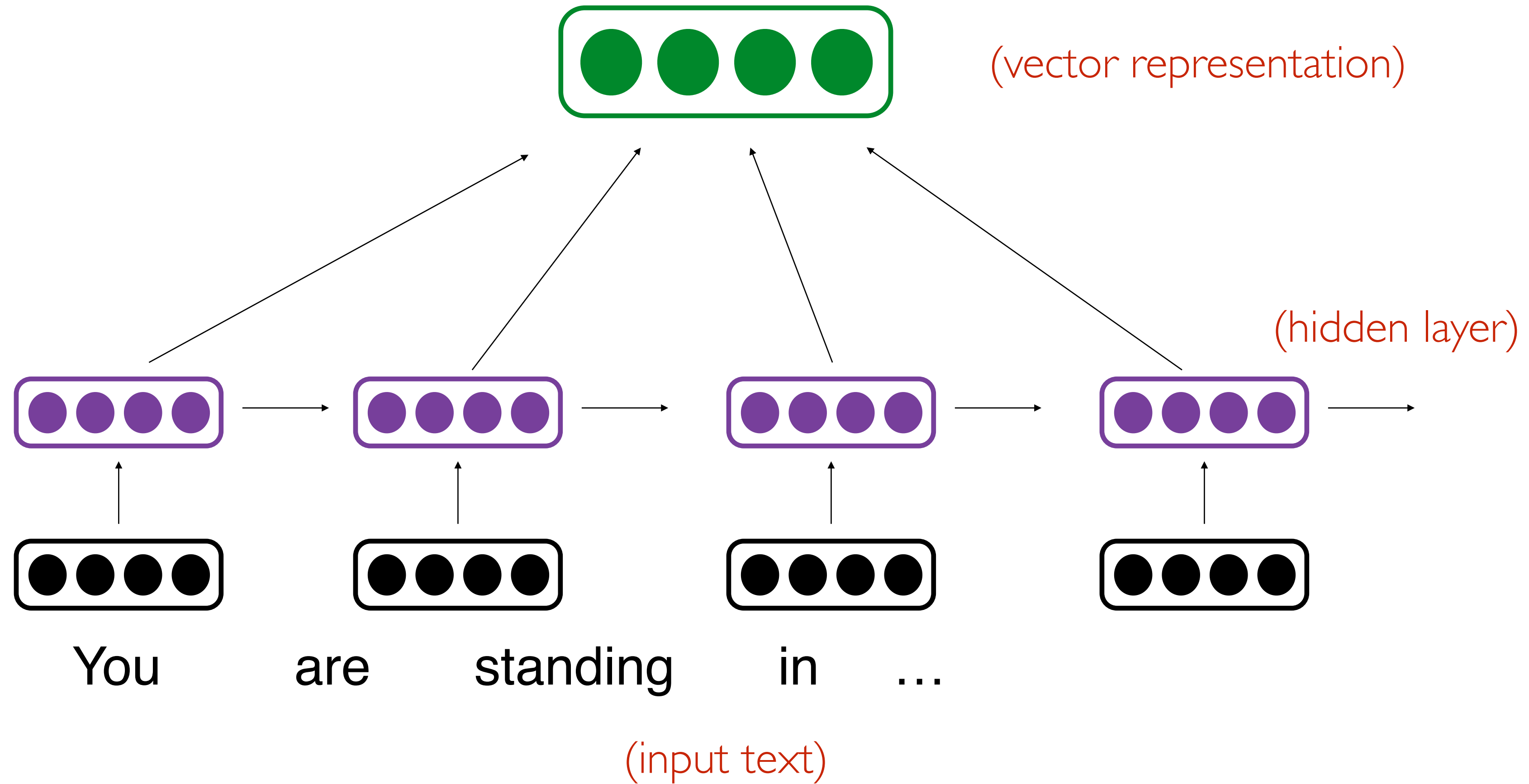


+10 gold

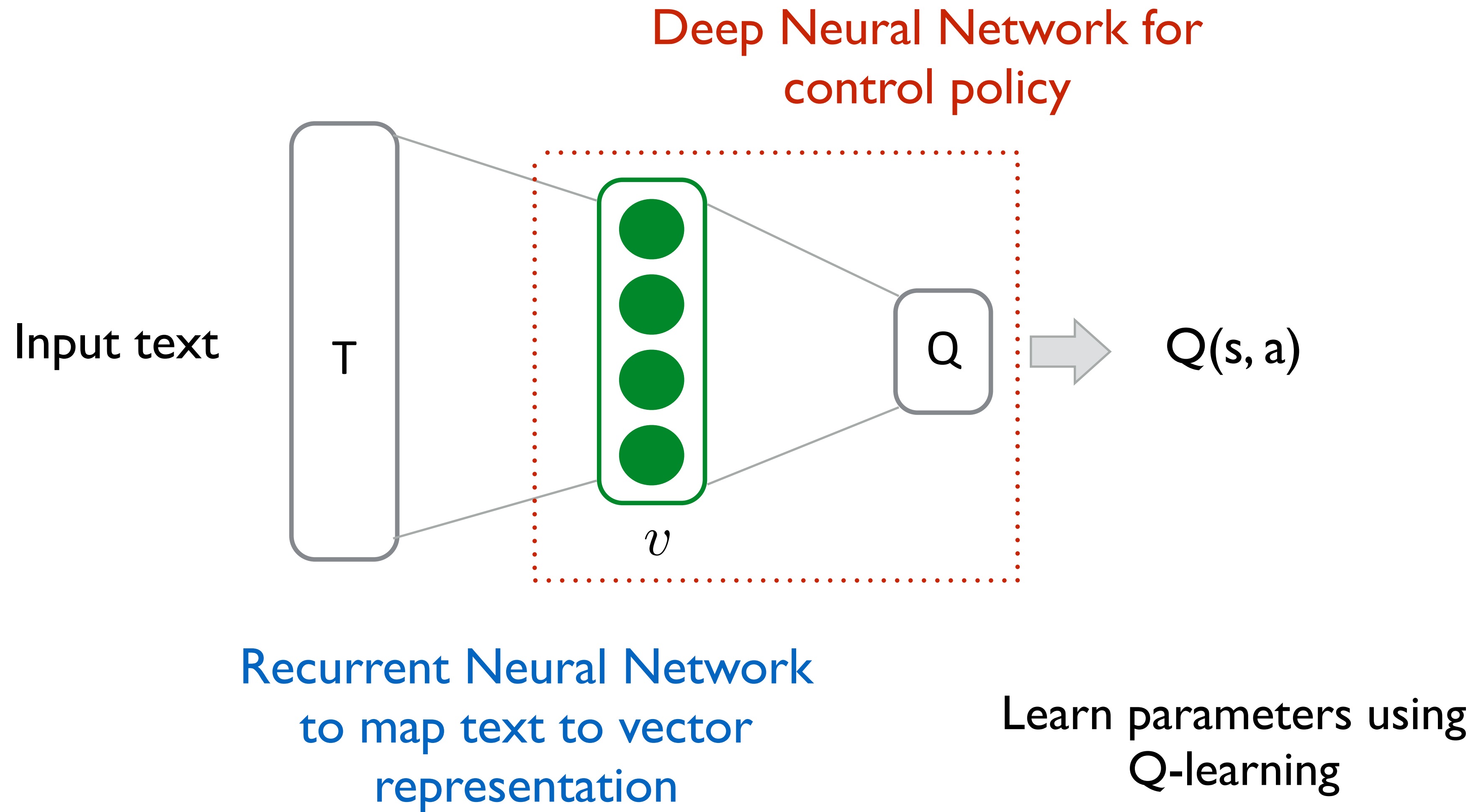


+5 health

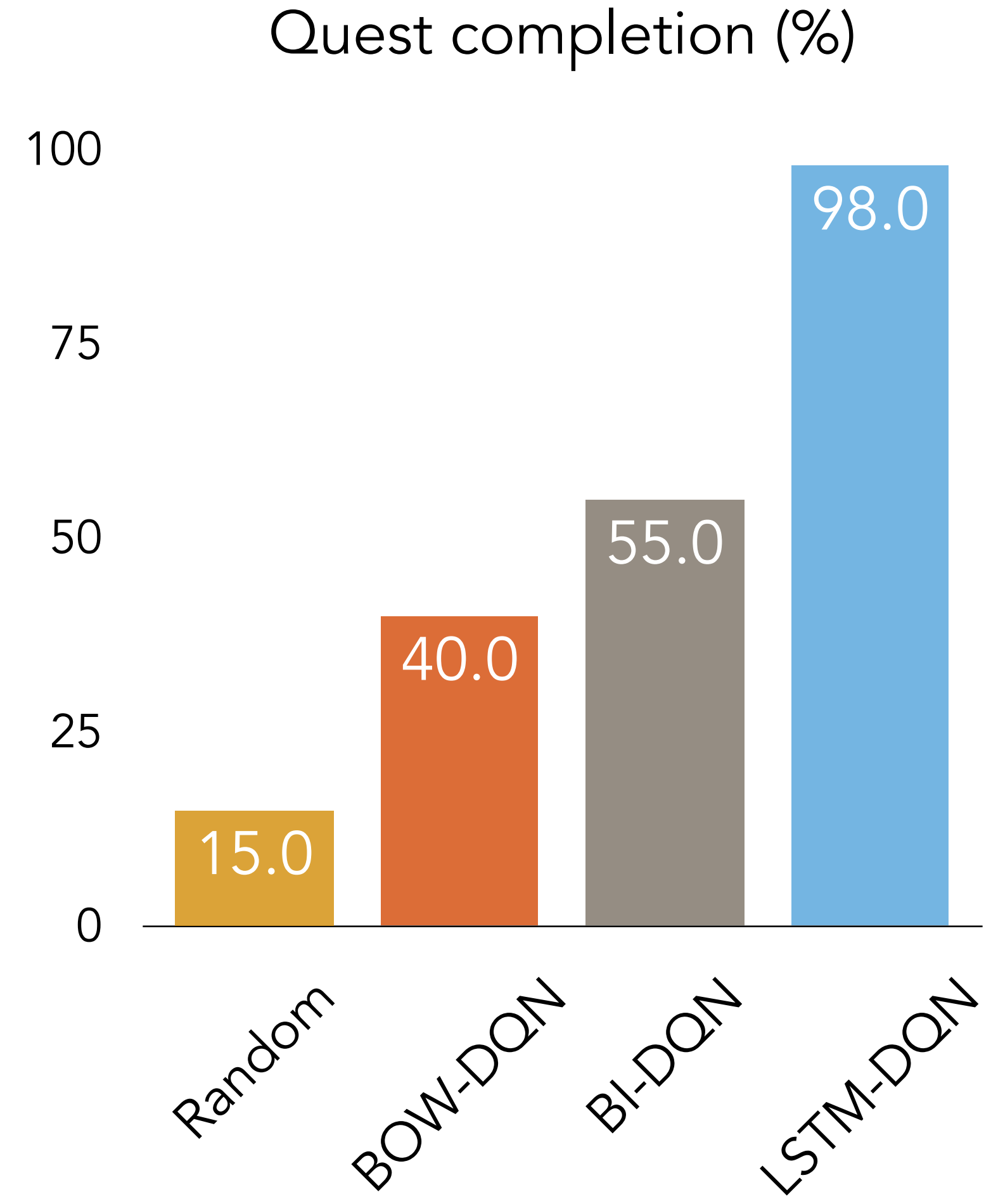
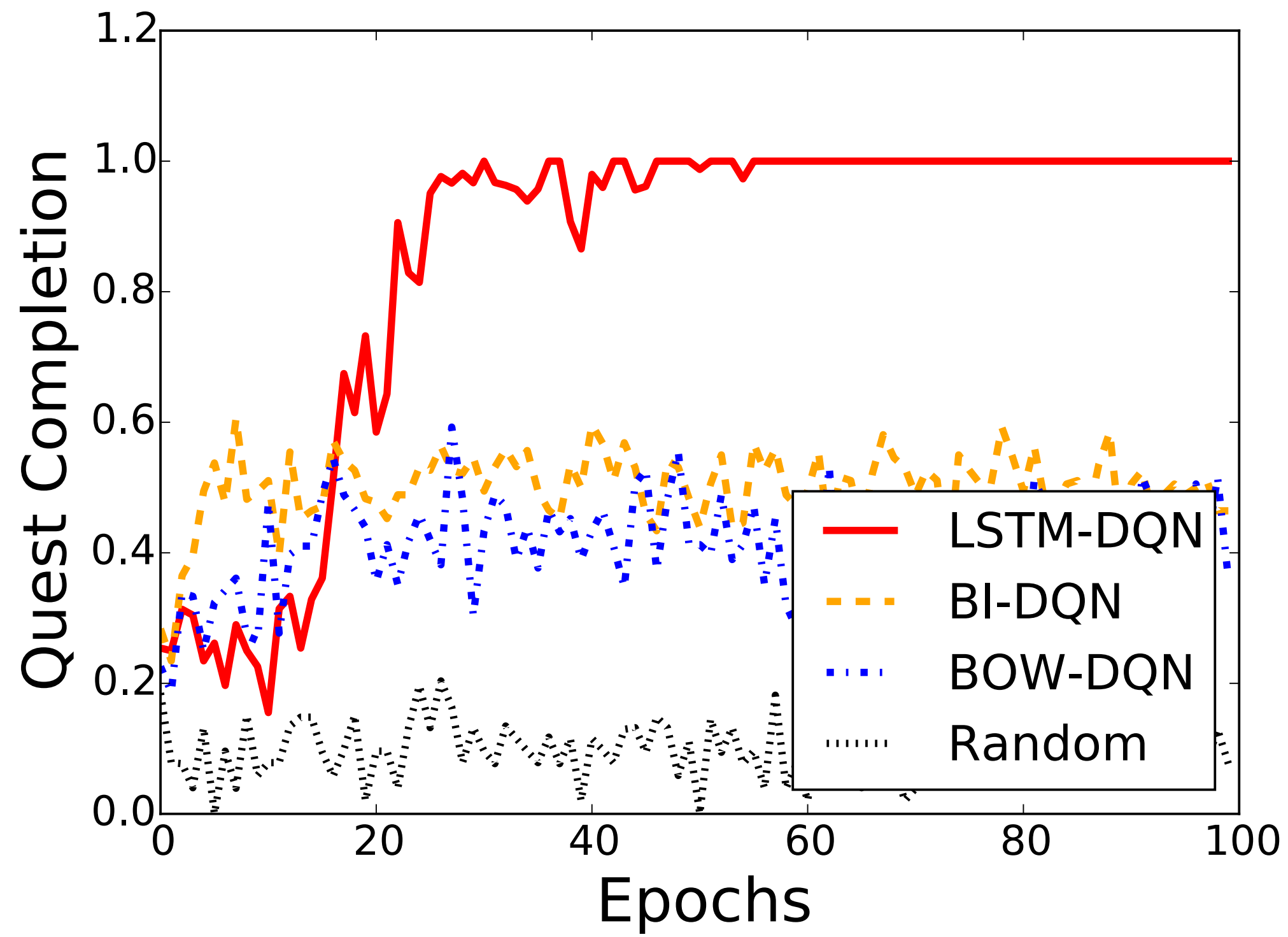
Recurrent Neural Network



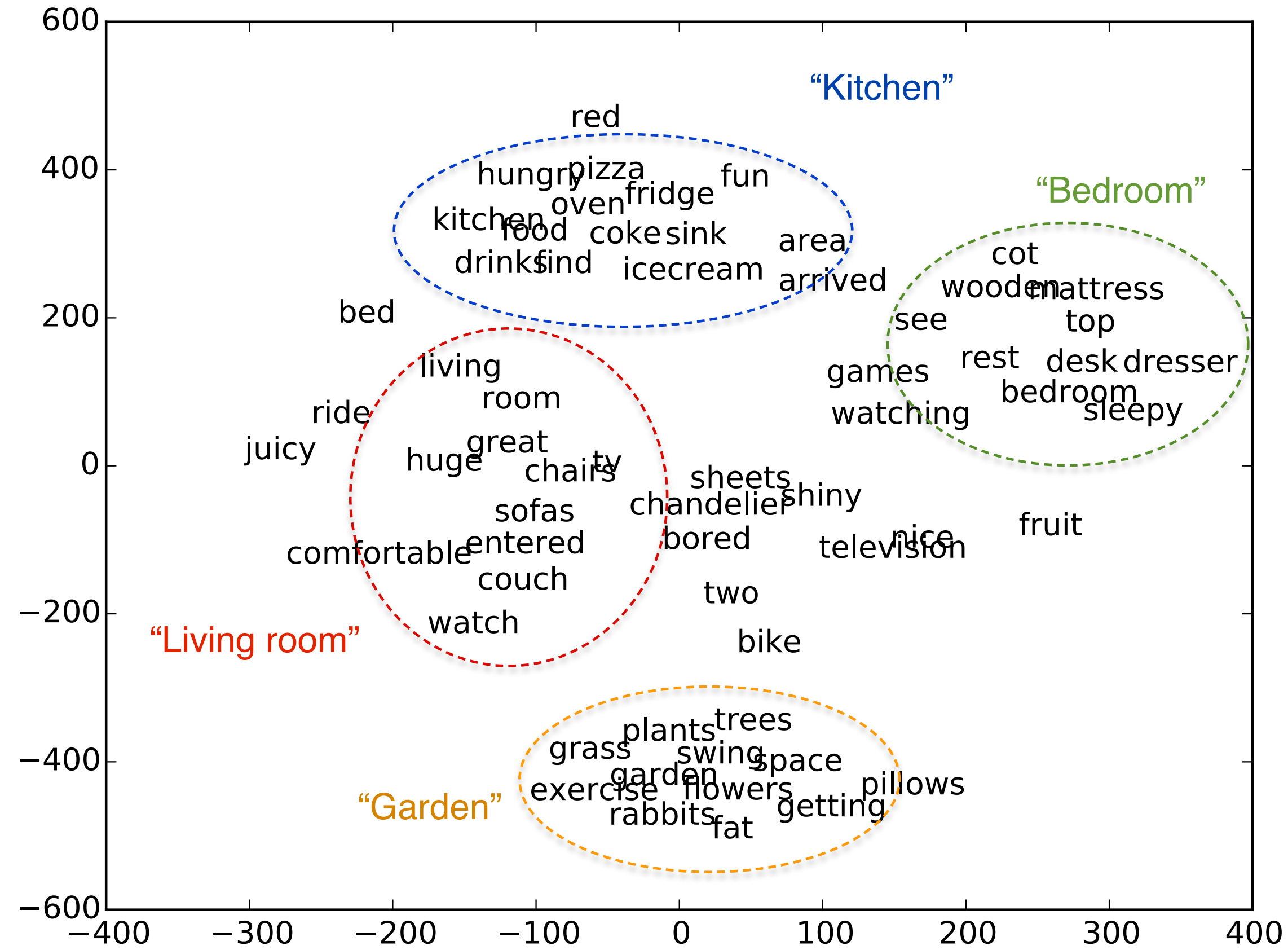
LSTM-DQN: Action Scorer



Results



Visualizing Learnt Representations



t-SNE visualization of vectors learnt by agent

Contextual Action Language Model (CALM)

- **Want:** Generate sensible action commands
- **Idea:** Train a *single* language model to generate action candidates for any game
- Actions are subsequently reranked by an RL agent using game-specific rewards

Observation: You are in the living room. There is a doorway to the east, a wooden door with strange gothic lettering to the west, which appears to be nailed shut, a trophy case, and a large oriental rug in the center of the room. You are carrying: A brass lantern ...

Random Actions:

close door, north a, eat troll with egg, ...

CALM (n-gram) Actions:

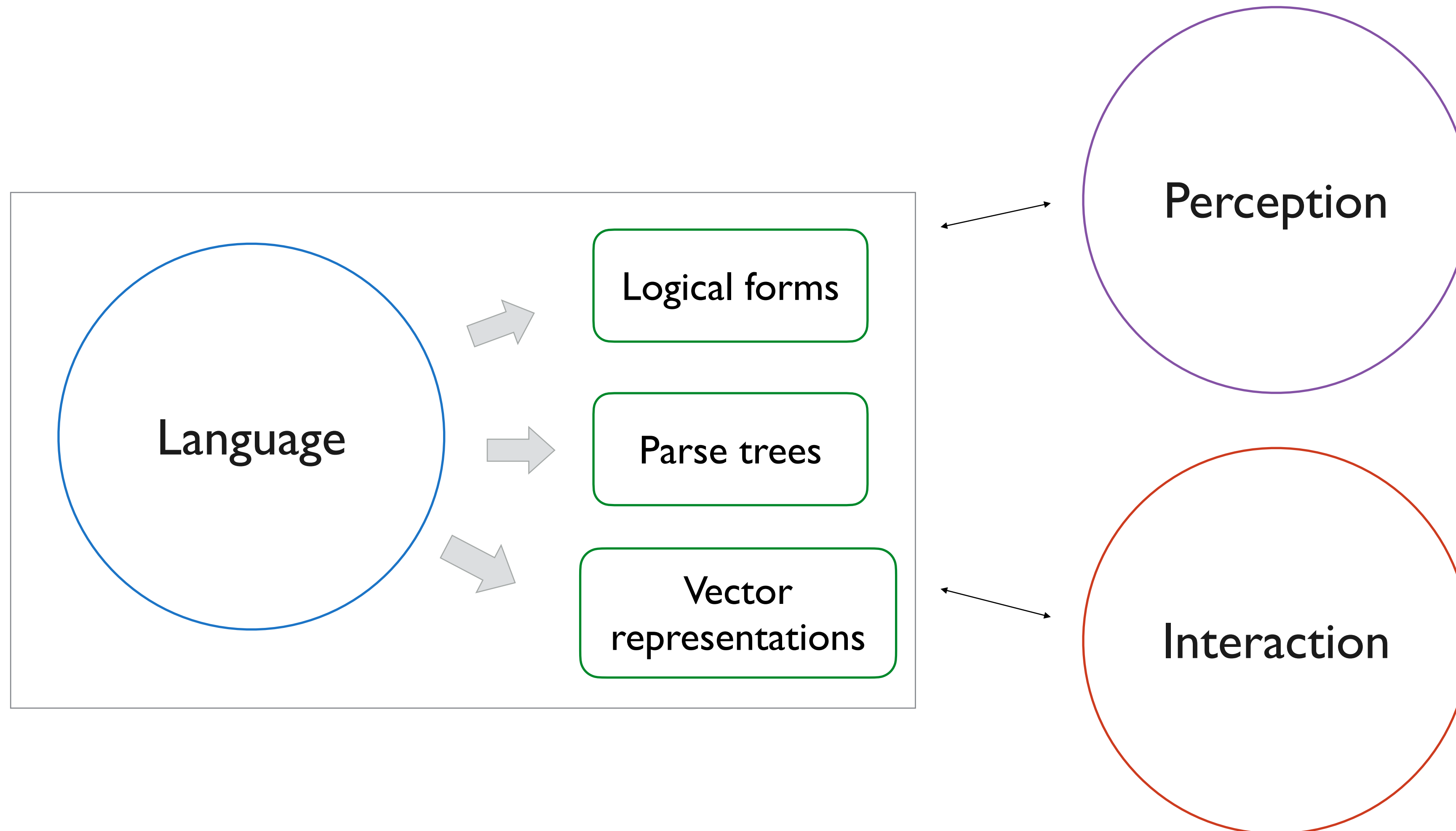
enter room, leave room, lock room, open door, close door, knock on door, ...

CALM (GPT-2) Actions:

east, open case, get rug, turn on lantern, move rug, unlock case with key, ...

Next Observation: With a great effort, the rug is moved to one side of the room, revealing the dusty cover of a closed trap door...

Semantics does not exist in isolation



Is coffee a carcinogen?

Coffee significantly reduced ER and cyclin D I abundance in ER(+) cells

...

Coffee reduced the pAkt levels in both ER(+) and ER(-) cells.

Hard to understand!

Information Extraction: State of the Art

Dependence on large training sets

ACE: 300K words

Freebase: 24M relations

Not available for many domains (ex. medicine, crime)

Even large corpora do not guarantee high performance

~ 75% F1 on relation extraction (ACE)

~ 58% F1 on event extraction (ACE)

IE: A hard reading task for machines

Extraction
(NumWounded)

© CBS Chicago.com

A 2 year old girl and four other people were wounded in a shooting in West Englewood Thursday night, police said

four 

IE: A hard reading task (not always!)

Extraction
(NumWounded)



A 2 year old girl and four other people were wounded in a shooting in West Englewood Thursday night, police said

four 



The last shooting left five people wounded.

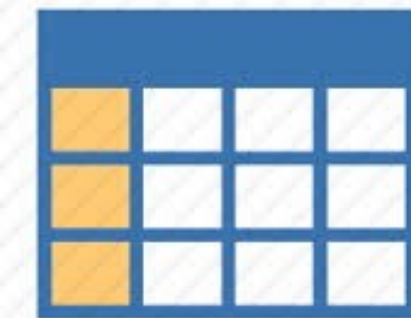
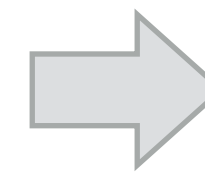
five 

Incorporate external evidence

Traditional formulation



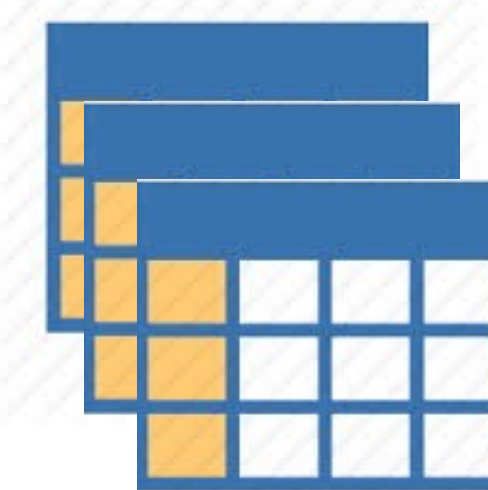
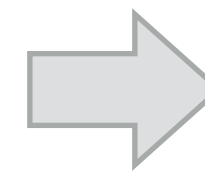
extract + reason



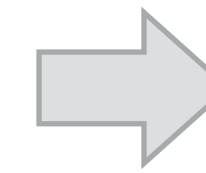
[Narasimhan et al. 2016]



extract



aggregate



extract



find extra articles

Challenges

I. Event Coreference

4 adults, 1 teenager shot in west Baltimore

All News Shopping Images Videos More Search tools

About 16,200,000 results (0.63 seconds)

4 adults, 1 teenager shot in west Baltimore | Maryland News ...
www.wbaltv.com/news/...shot-in-west-baltimore/32156116 ▾ WBAL-TV ▾
Apr 3, 2015 - Five people were **shot** Thursday afternoon in **west Baltimore**.

1 killed, 3 injured in Baltimore shooting, police say ... - WBAL
www.wbaltv.com/news/...shot-in-west-baltimore.../36588266 ▾ WBAL-TV ▾
Nov 21, 2015 - **2 teens**, **2 adults** **shot** on Stricker Street ... man was **killed** and three others were injured in a **shooting** Saturday morning in **west Baltimore**, police said. ... Mom tries to buy baby for her 14-year-old daughter; WBALTV.com. Undo.

10-year-old boy shot in West Baltimore - Baltimore Sun
www.baltimoresun.com/.../baltimore.../bs-md-ci-shoot... ▾ The Baltimore Sun ▾
Sep 3, 2015 - A 10-year-old boy was **shot** Thursday night, along with two **adult** ... **Baltimore** police report 6 shootings, including one of a **teenage** boy. ... The homicide occurred about 4:30 p.m. at Ninth and East Jeffrey streets in Brooklyn, police said. ... At 1:20 a.m., officers found a 32-year-old **Baltimore** man **shot** in the ...

Several irrelevant articles!

2. Reconciling Predictions

Shooter: Scott Westerhuis
NumKilled: 4
Location: S.D

Shooter: Scott Westerhuis
NumKilled: 6
Location: Platte

Inconsistent extractions

Learning through reinforcement

original



extract

Shooter: Scott Westerhuis
NumKilled: 4
Location: S.D

Start with traditional extraction system

Learning through reinforcement

original



extract

Shooter: Scott Westerhuis

NumKilled: 4

Location: S.D

query



extract

Shooter: Scott Westerhuis

NumKilled: 6

Location: Platte

Perform a query and extract from a new article

Learning through reinforcement

original



query



extract



Shooter: Scott Westerhuis
NumKilled: 4
Location: S.D

extract



Shooter: Scott Westerhuis
NumKilled: 6
Location: Platte

Current

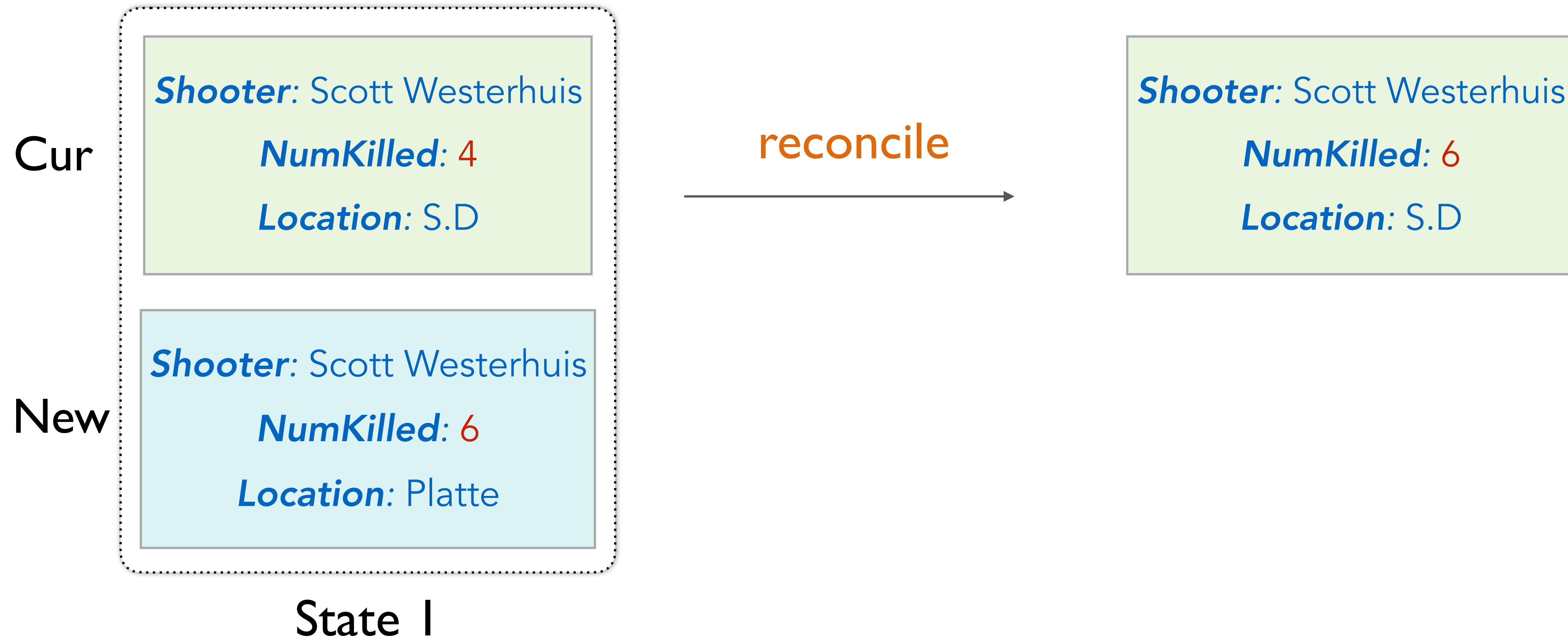


State

New

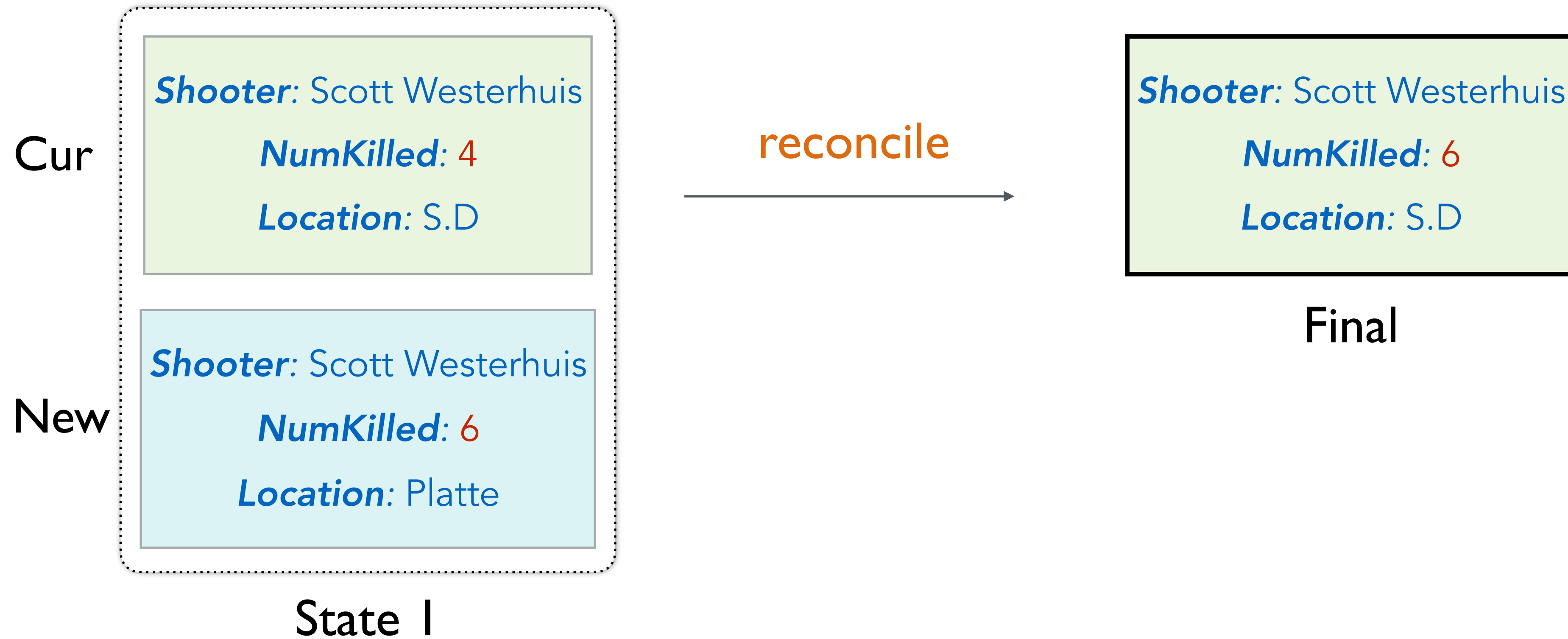


RL: Actions



- I. **Reconcile (d)** old values and new values.
 - ✦ Pick a single value, all values or no value from new set

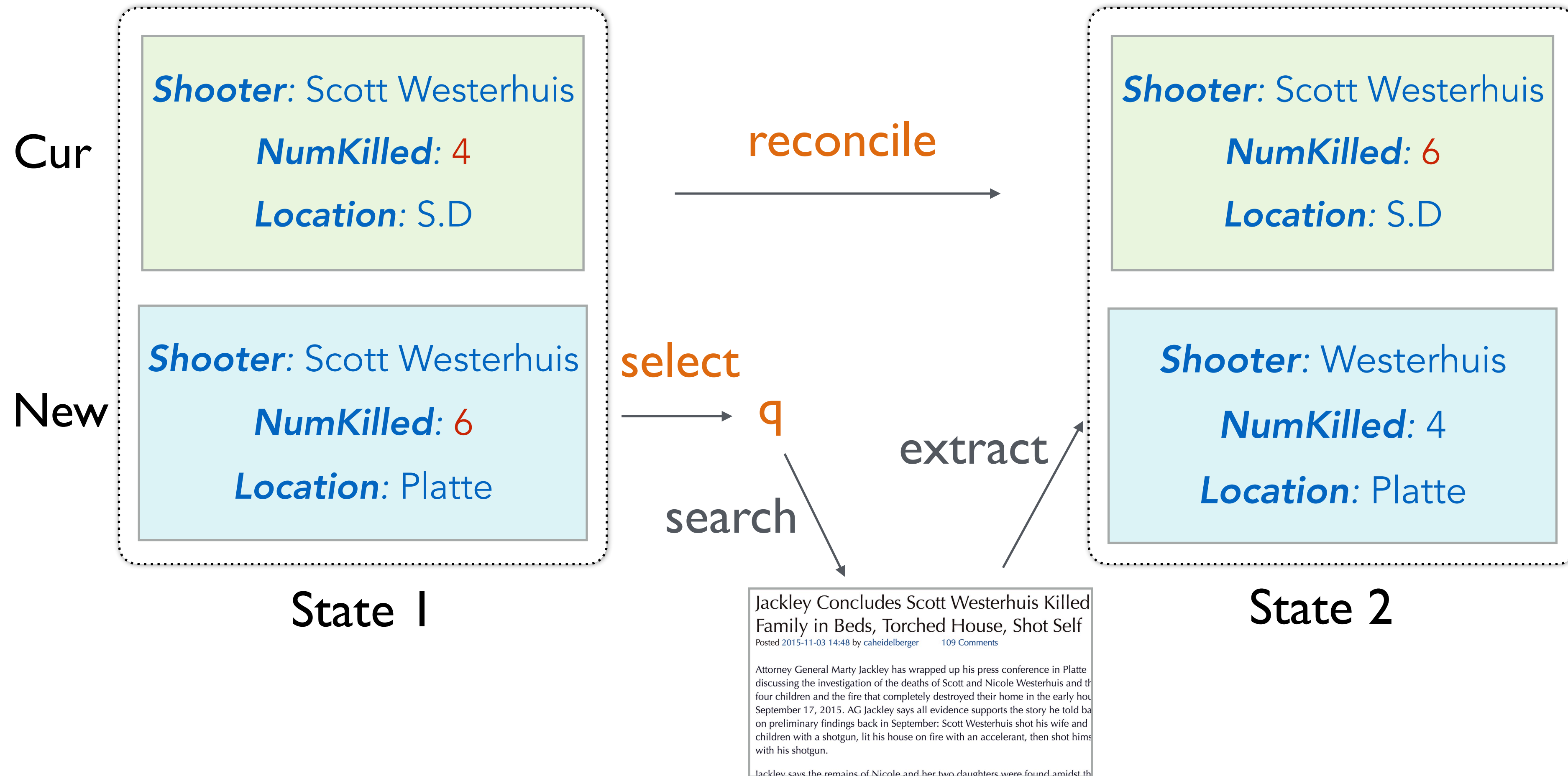
RL: Actions



2. Decide how to proceed:

✦ **Stop**

RL: Actions



2. Decide how to proceed:
- ♦ **Select next query (q)**

Acquiring external evidence

1. Select a query to search for articles on the same event



2. Use base extractor to obtain values for entities of interest



extract

Shooter: Scott Westerhuis
NumKilled: 6
Location: Platte

3. Reconcile old and new extractions

Shooter: Scott Westerhuis
NumKilled: 4
Location: S.D

Shooter: Scott Westerhuis
NumKilled: 6
Location: Platte



Learning from rewards

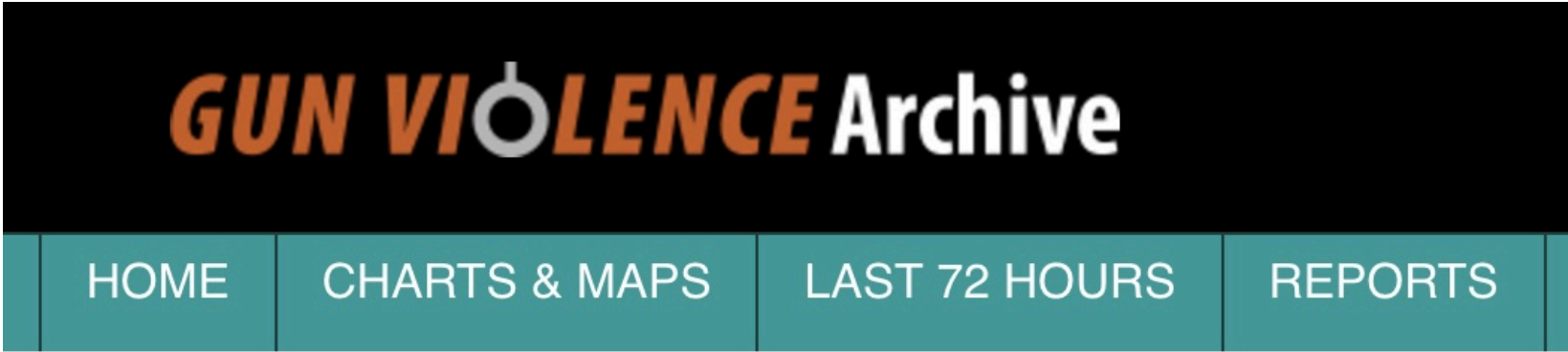
- Change in accuracy

	Previous Values	Current Values
✓	<i>Shooter:</i> Scott Westerhuis	✓ <i>Shooter:</i> Scott Westerhuis
✓	<i>NumKilled:</i> 6	✓ <i>NumKilled:</i> 6
✗	<i>NumWounded:</i> 1	✓ <i>NumWounded:</i> 0
✓	<i>Location:</i> Platte	✓ <i>Location:</i> Platte

$$R(s, a) = \sum_{\text{entity } j} \text{Acc}(e_{cur}^j) - \text{Acc}(e_{prev}^j) = 1$$

- Small penalty for each transition

Mass shootings in the United States



- Shooter Name
- Num Killed
- Num Wounded
- City

~300 training instances

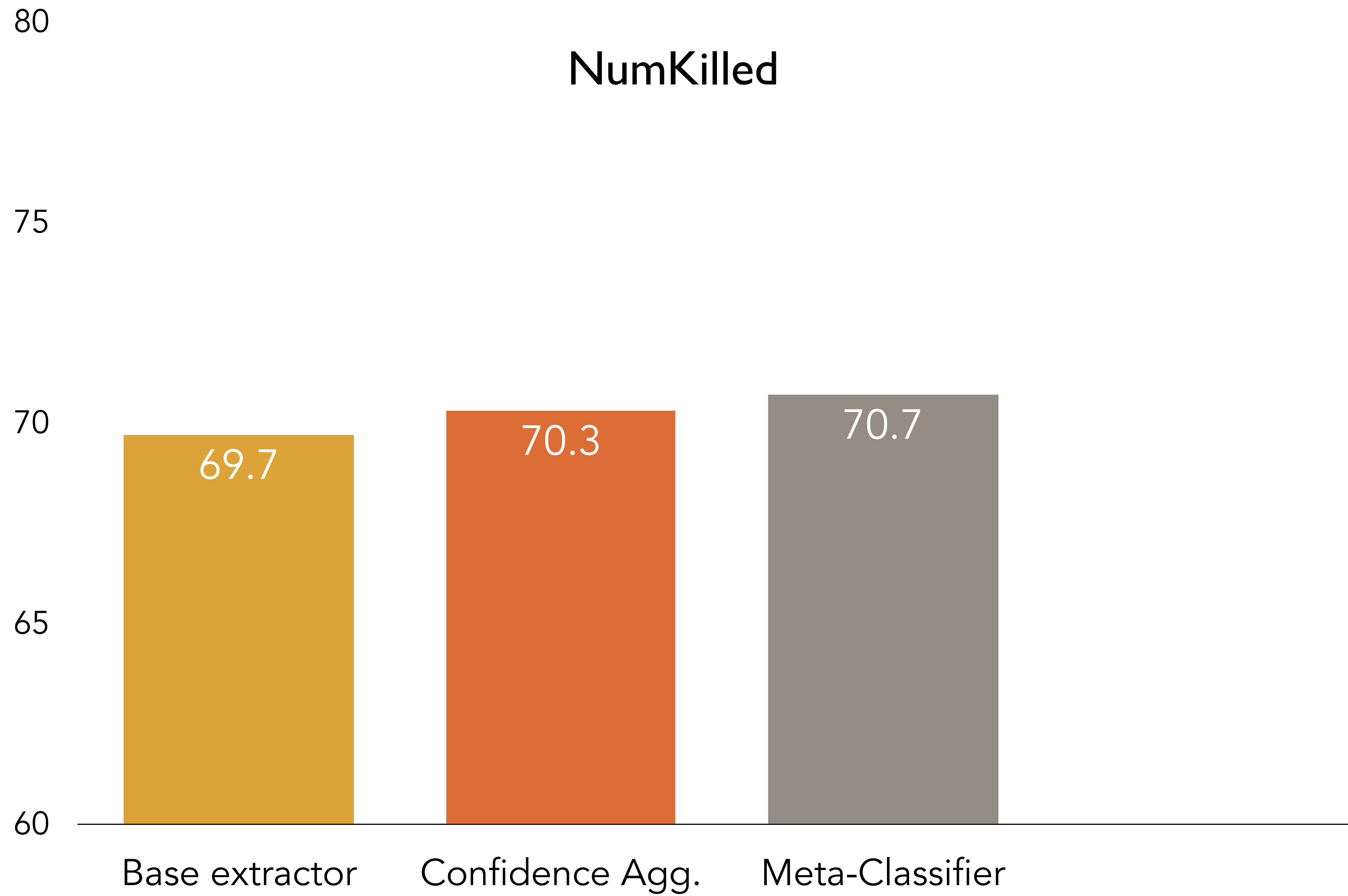
Adulteration incidents from Foodshield EMA



- Food
- Adulterant
- Location

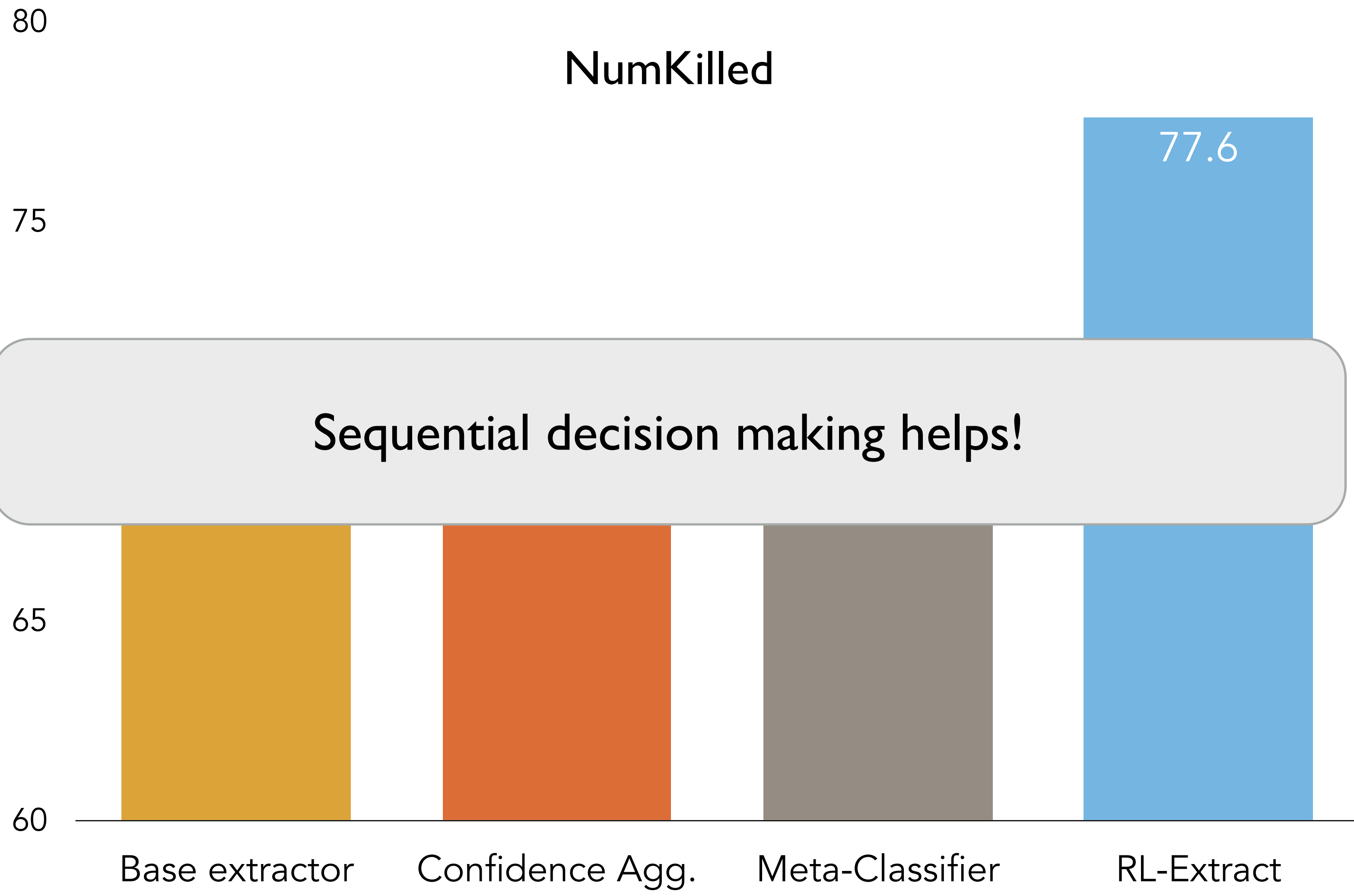
Accuracy

NumKilled



Accuracy

NumKilled



Sequential decision making helps!

