

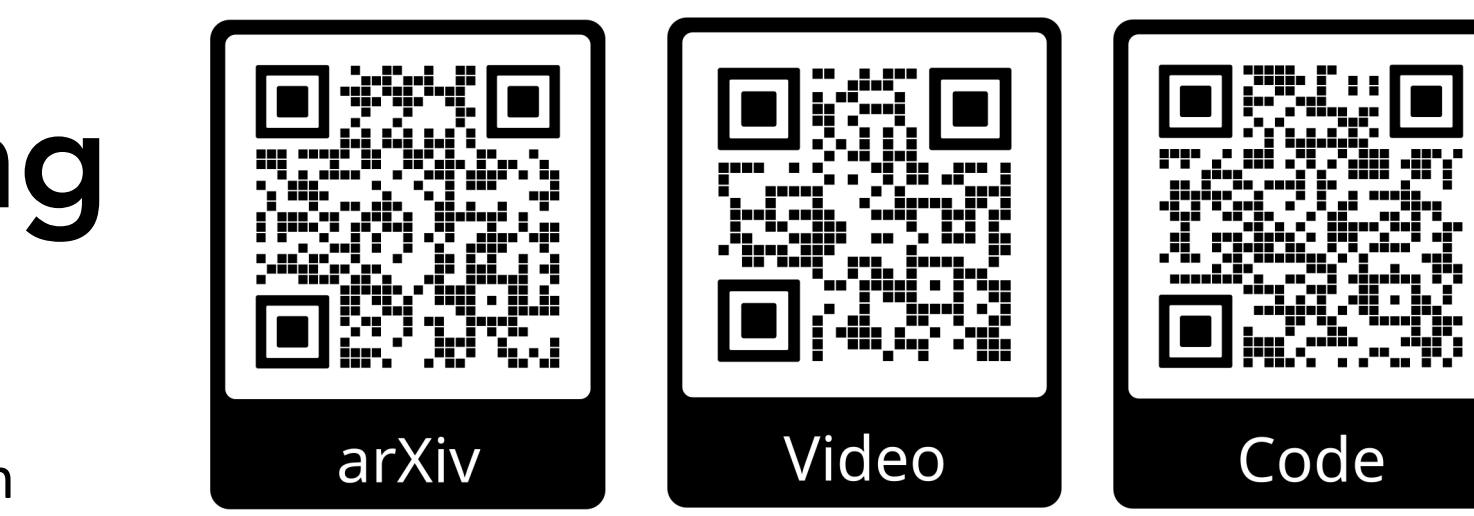
Chasing Ghosts

Chasing Ghosts : Instruction Following as Bayesian State Tracking

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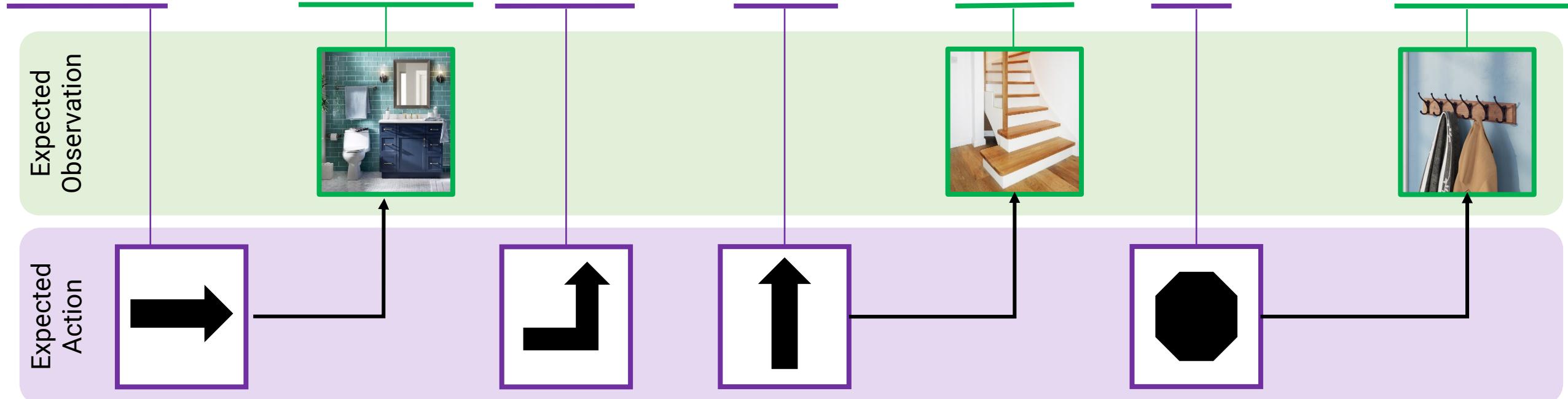
^{*} denotes equal contribution



1 INTUITION: UNPACKING A NAVIGATION INSTRUCTION

A visually-grounded navigation instruction can be interpreted as a sequence of expected **observations** and **actions** an agent following the correct trajectory would encounter and perform.

Walk out of the **bathroom**, turn left, and go on to the **stairs** and wait near the **coat rack**.

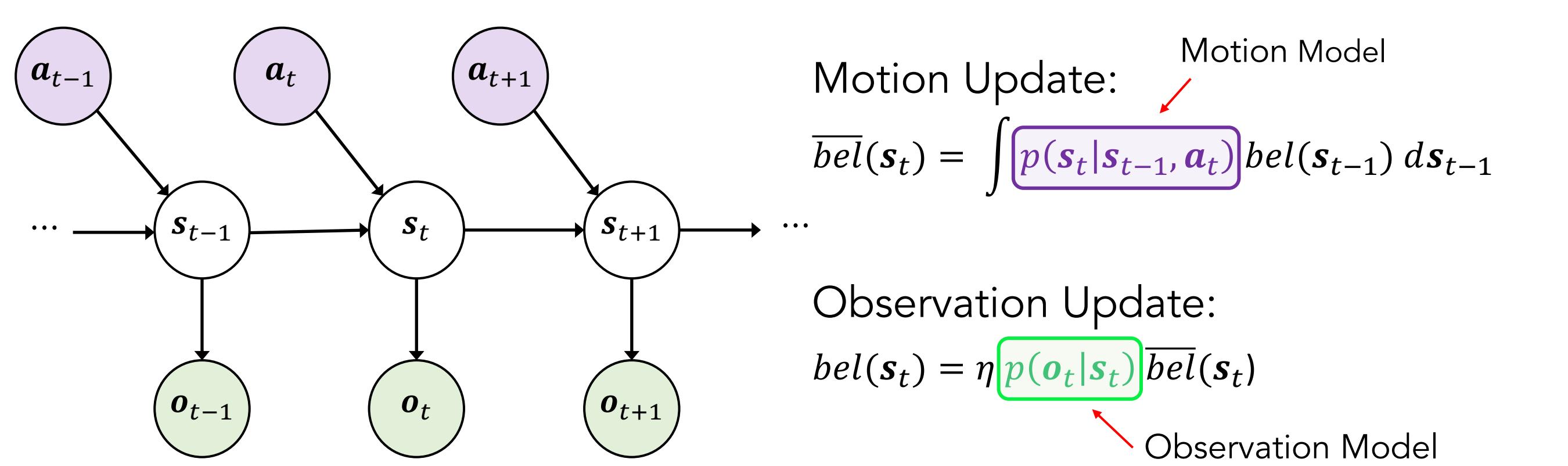


2 BACKGROUND: BAYESIAN STATE TRACKING

Given a sequence of **observations** $\mathbf{o}_{1:T}$ and **actions** $\mathbf{a}_{1:T}$ extracted from a natural language instruction, how should we determine the final (goal) location \mathbf{s}_T ?

Key idea: Use a **Bayes filter** to track the trajectory to goal, maintaining a probability distribution over the location state \mathbf{s}_t from start \mathbf{s}_0 to goal \mathbf{s}_T

i.e. at each time step t , compute $bel(\mathbf{s}_t) = p(\mathbf{s}_t | \mathbf{a}_{1:t}, \mathbf{o}_{1:t})$ also called **belief**.



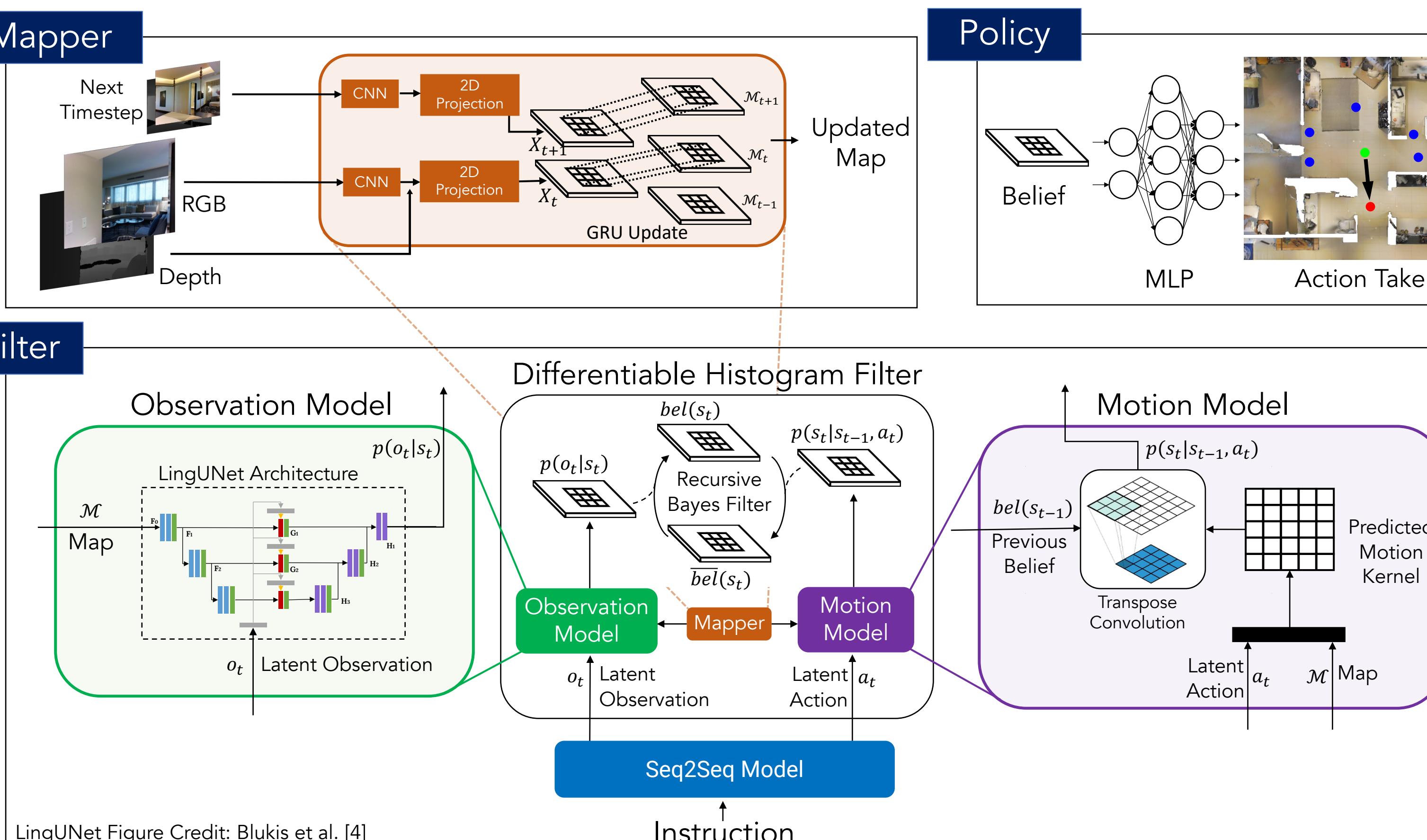
Recent work [1-3] show Bayes filter can be embedded into deep neural networks.

3 REFERENCES

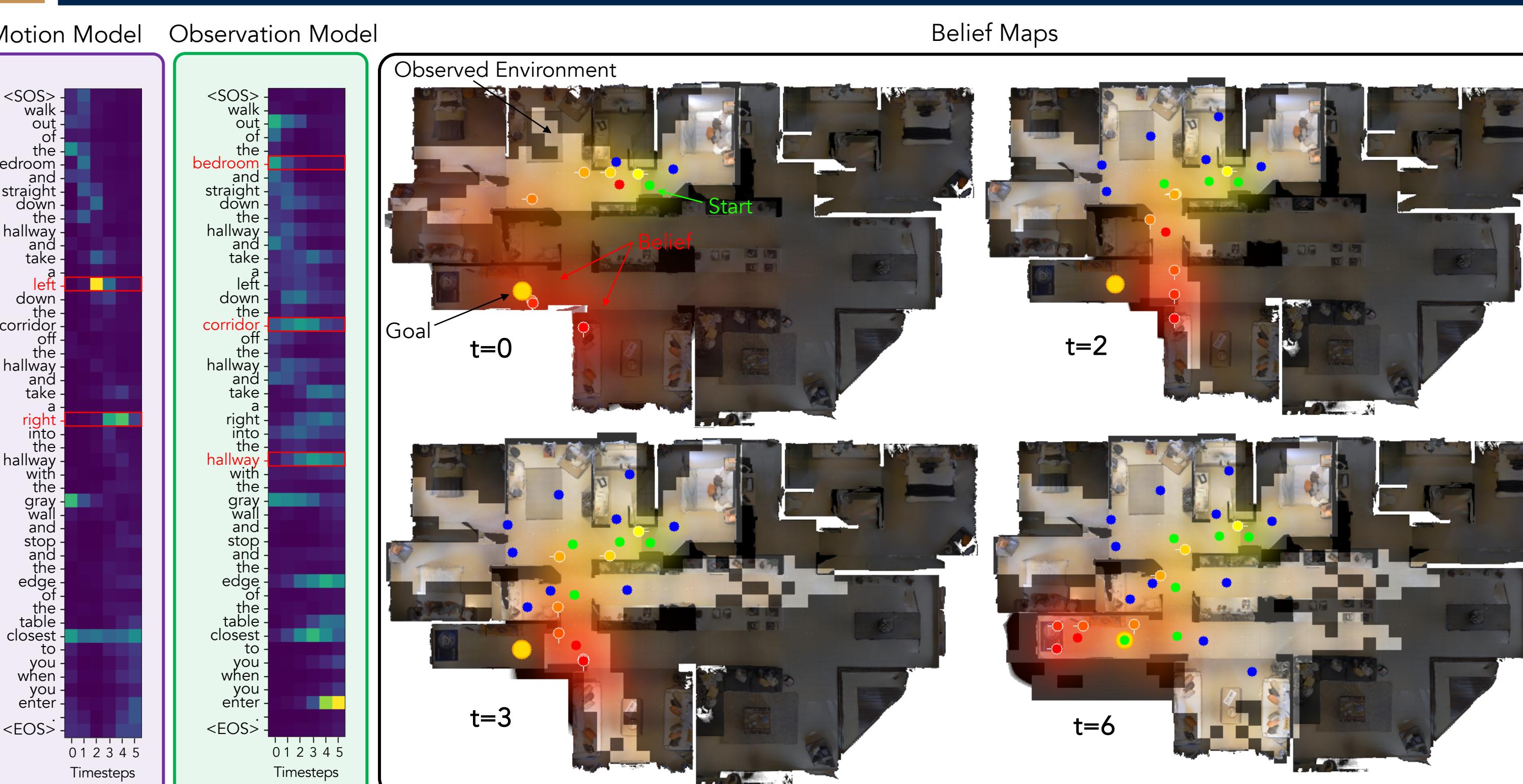
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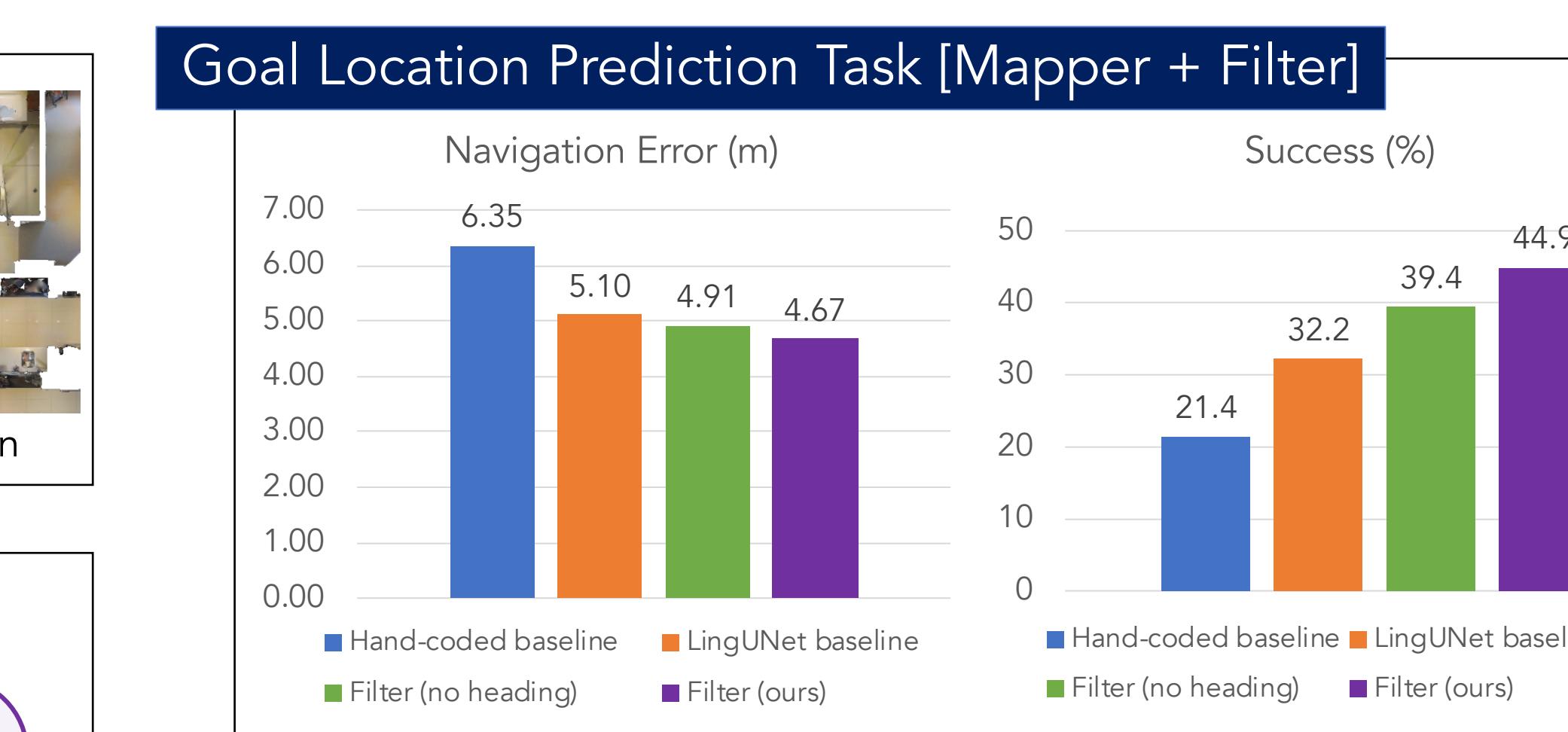
4 AGENT MODEL



5 INTERPRETABILITY OF MODEL



6 RESULTS



- Trained/eval'ed without Policy
- Fixed trajectories move towards goal with 50% probability
- Adding Bayes filter structure improves over just using LingUNet [4]
- Including heading in the state is important for modeling oriented instructions (e.g., "pass the kitchen on your left")

Vision and Language Navigation (VLN) Task [Mapper + Filter + Policy]

Model	Val-Seen					Val-Unseen						
	RL	Aug	TL	NE	OS	SR	SPL	TL	NE	OS	SR	SPL
Speaker-Follower	✓	-	3.36	0.74	0.66	-	-	6.62	0.45	0.36	-	-
RCM	✓	-	10.65	3.53	0.75	0.67	-	11.46	6.09	0.50	0.43	-
Regretful Agent	✓	-	3.23	0.77	0.69	0.63	-	5.32	0.59	0.50	0.41	-
FAST	✓	-	-	-	-	-	-	21.1	4.97	-	0.56	0.43
Back Translation	✓	✓	11.0	3.99	-	0.62	0.59	10.7	5.22	-	0.52	0.48
Speaker-Follower	-	-	4.86	0.63	0.52	-	-	7.07	0.41	0.31	-	-
Back Translation	-	-	10.3	5.39	-	0.48	0.46	9.15	6.25	-	0.44	0.40
Ours	-	-	10.15	7.59	0.42	0.34	0.30	9.64	7.20	0.44	0.35	0.31

- Training trajectories: Sampled from Policy with 50% probability, otherwise GT
- Credible performance on the full VLN task compared to existing models with no RL and no data augmentation
- Improved generalization from seen to unseen environments

7 CONCLUSION

- Instruction following can be formulated as **Bayesian State Tracking** with observations and actions extracted from the instruction.
- Advantages of this approach:
 - **Uncertainty:** an explicit probability for every trajectory the agent could take (naturally handles multimodal hypotheses)
 - **Interpretability:** inspect the predicted goal location distribution
 - **Performance:** Improved goal location prediction
- Ideas for future work:
 - More sophisticated policy module, RL training and data augmentation
 - Reasoning about unseen map regions