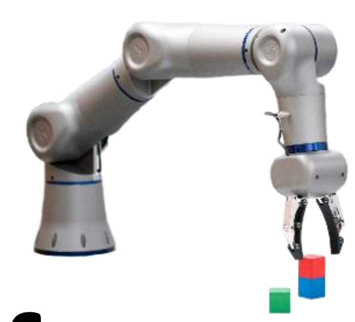
Cognitive Neurorobotics Research Unit
認知脳ロボティクス研究ユニット



Goal-Directed Planning for Habituated Agents by Active Inference Using a Variational Recurrent Neural Network

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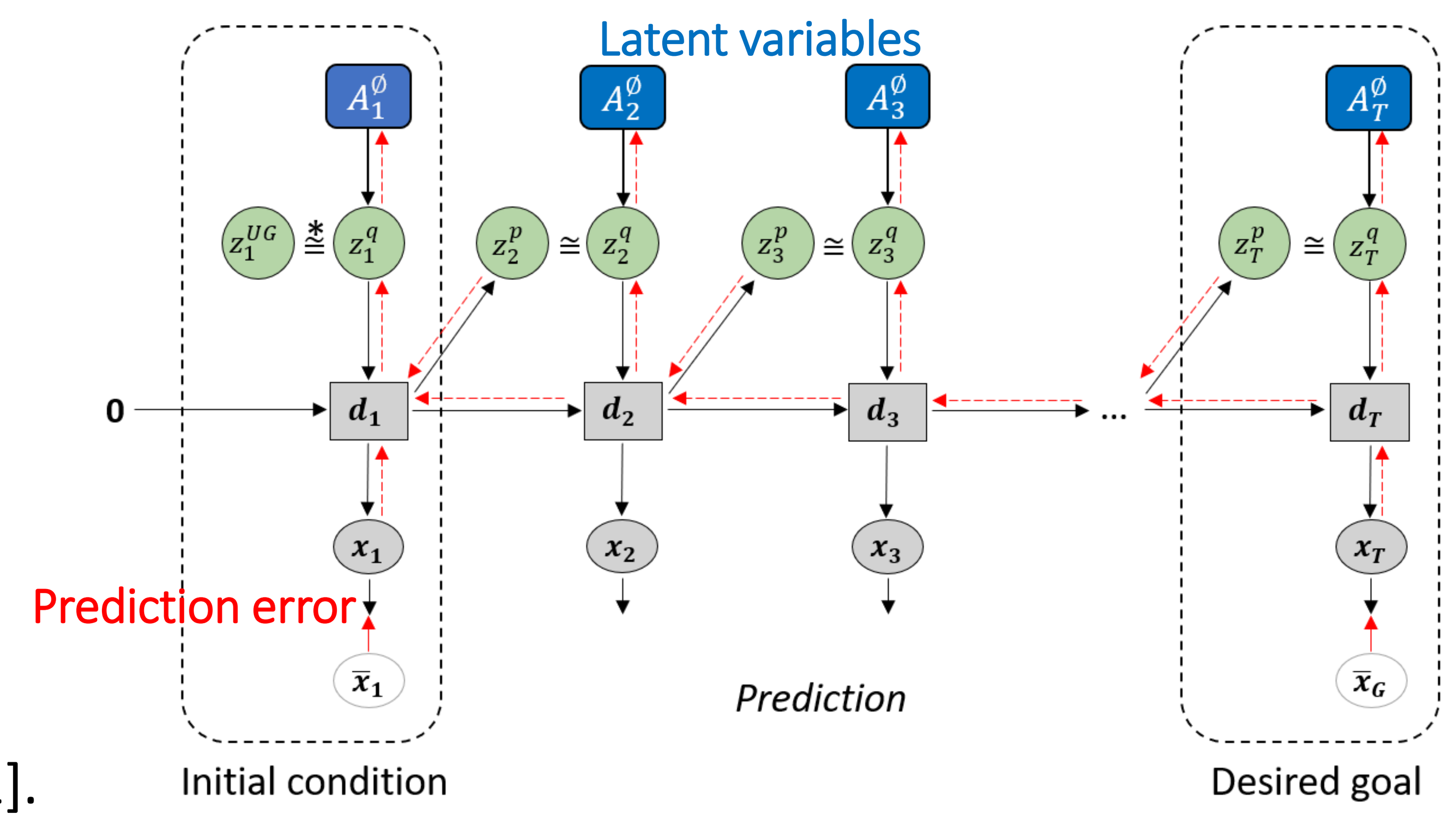
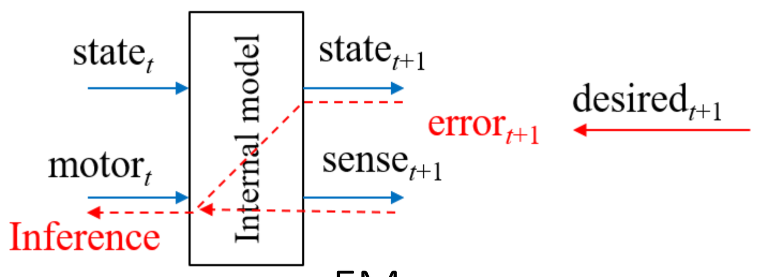
Motivation

How can agents achieve goals given only partial knowledge of the world? It is generally assumed that agents can never have complete knowledge of their environment because the experience that can be gained in a finite amount of time is limited. However, some agents such as humans are able to generalize from experience to form action plans that accomplish unfamiliar tasks.

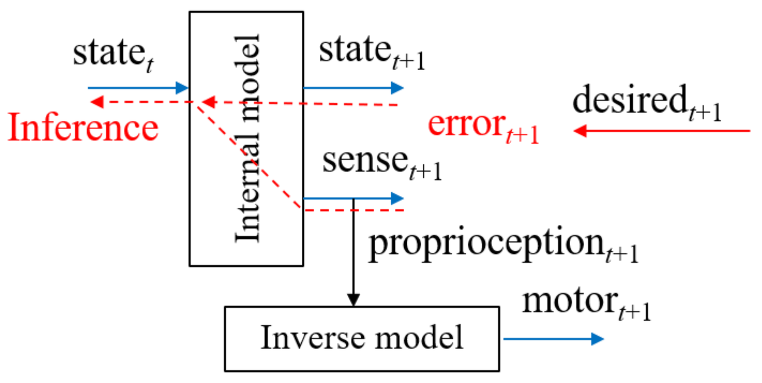
In our proposed model, generalization is achieved by learning probabilistic patterns from well habituated sensory-motor trajectories. These prior distributions are stored in a low dimensional latent state space. Goal-directed planning is accomplished by inferring latent variables which maximizes the estimated lower bound, following the principle of Free Energy Minimization [1].



Goal directed planning using PV-RNN



FM



PC + AIF

Method

Our proposed model (GLean) uses the frameworks of predictive coding (PC) [2] and active inference (AIF) [3], and leverages the PV-RNN architecture [4] to learn probabilistic patterns as a prior distribution z^p. For plan generation, given z^p, a known initial condition and desired goal, we use an estimate of the evidence based lower bound to infer a posterior distribution z^q that leads to generation of a plausible action plan and sensory prediction.

In comparison, the forward model (FM) [5] is a conventional approach for sensory-motor systems and uses the current state and motor command to predict the next state and associated sensory state. In theory it is possible to infer a sequence of optimal motor commands to reach a desired goal state, however in practice it is impractical to learn such a combination with limited training.

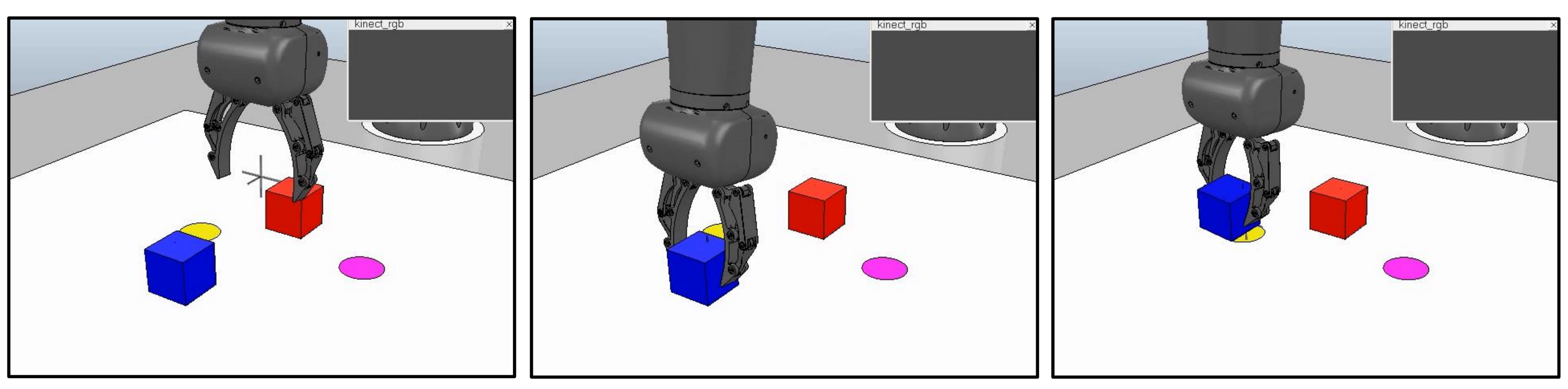
Experimental Results

Our model (GLean) was evaluated with simulated robot tasks in probabilistic settings and demonstrated generalization with limited training data by setting an appropriate regularization coefficient.

GLean also outperformed both a conventional forward model (FM), and a model with stochasticity only in the initial state (SI) [6] in goal-directed planning, due to the learned prior directing the search of motor plans within the range of habituated trajectories.

Model	Success rate	Avg. error at goal
GLean	**86.0%**	**1.52±0.07cm**
Stochastic initial state (SI)	68.0%	2.02cm±0.14cm
Forward model (FM)	0.0%	-

Success rate and error for GLean and two alternative methods



Simulated robot arm grasping a block and moving it to the goal

Accuracy at t=1 (start) and t=T (goal)

$$L_e(\theta,\phi) = E_{q_\phi(z_1|e_1,e_T)}\left[p_{\theta_x}(x_1|z_1)\right] + E_{q_\phi(z_T|e_T)}\left[p_{\theta_x}(x_T|z_{1:T})\right] - \left(D_{KL}\left[q_\phi(z_1|e_1)||p_{\theta_z}(z_1)\right] + \sum_{t=2}^{T} D_{KL}\left[q_\phi(z_t|e_T)||p_{\theta_z}(z_t|z_{1:t-1})\right]\right)$$

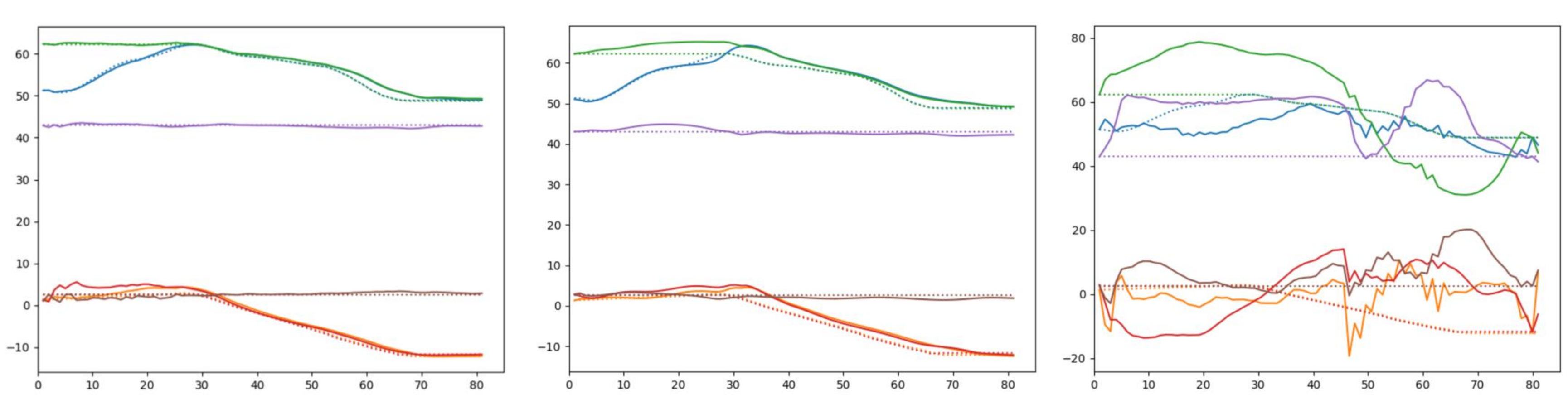
Complexity at t=1 (start) and t=T (goal)

Estimated lower bound

Conclusion & Ongoing Work

This work demonstrates our approach to generating action plans and sensory predictions for a robot to achieve untrained goals by generalizing from limited experience.

We are currently working on real time planning using physical robot hardware, with the robot able to dynamically alter its plan in response to changes in its environment.



Sensory state predictions (solid) compared to ground truth (dotted)

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