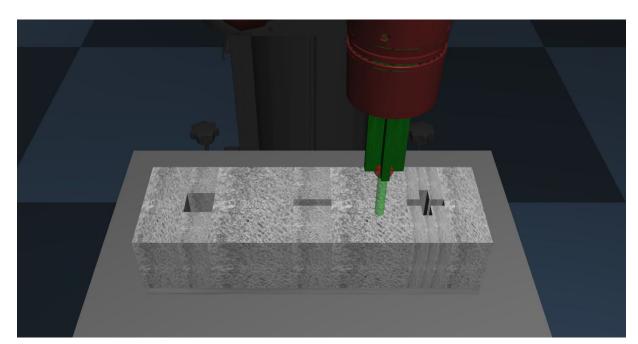
Learning Latent Space Dynamics Models for Planning in Robotics



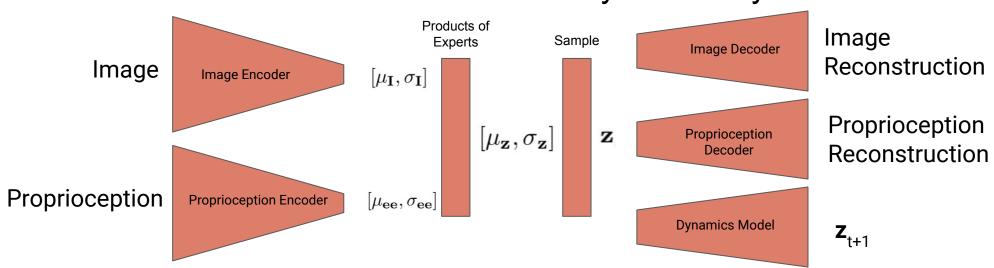
Peg Insertion: Mujoco Simulation Environment

Data collection Method:

- Collected using a heuristic waypoint following policy which accomplished the task of peg insertion
- Each data point (of ~600,000) includes an image, force-torque reading, 6DOF end-effector position and velocity and the action taken at that step in the trajectory

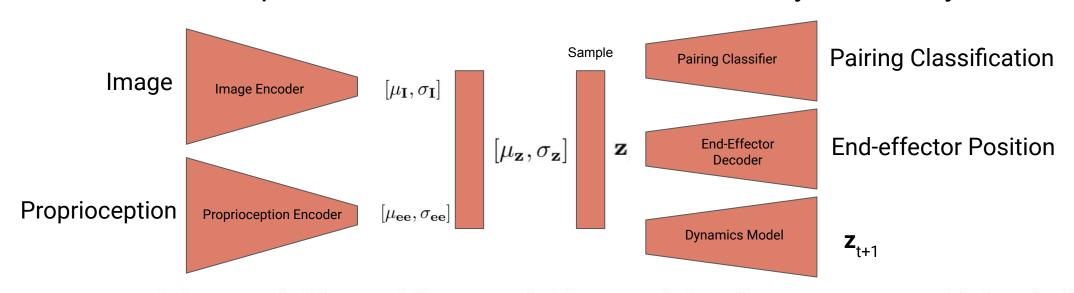
Joint Representation and Dynamics model Learning Method

Model 1: Variational Autoencoder with 6 layer MLP Dynamics Model



 $Loss = \log(p(image_{pred}|z_t)) + \log(p(prop_{pred}|z_t)) - D_{KL}(q(z_{t+1}|image_{t+1}, prop_{t+1})|p(z_{t+1}|z_t))$

Model 2: Self-Supervised Variational Encoder with 6 layer MLP Dynamics Model

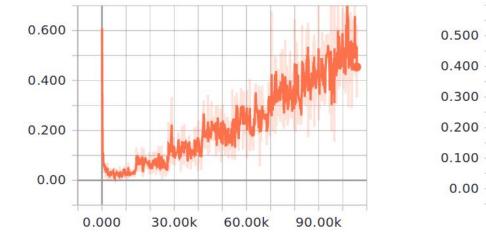


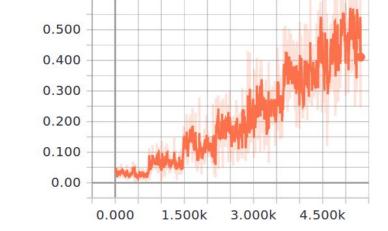
 $Loss = \log(p(pair_{class}|z_t)) + \log(p(eepos_{pred}|z_t)) - D_{KL}(q(z_{t+1}|image_{t+1}, prop_{t+1})|p(z_{t+1}|z_t))$

Training Details and Results:

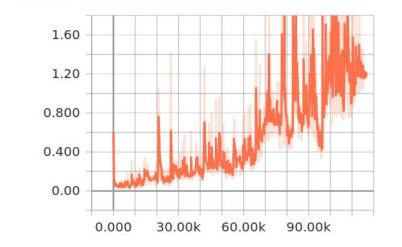
- Optimization Algorithm: ADAM
- Curriculum: 1 -10 step prediction, 3 epochs per number of steps

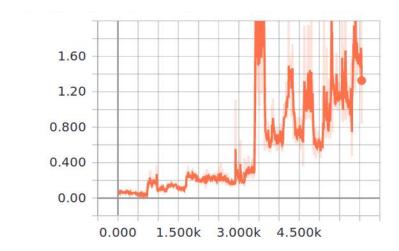
Model 1 - KL divergence Loss Term (ordering: Train, Val)



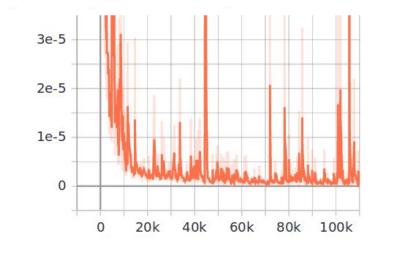


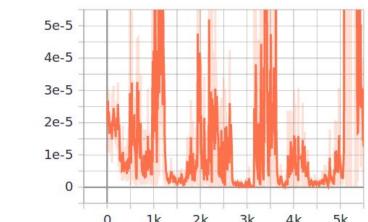
Model 2 - KL divergence Loss Term





Model 3 - Mean Square Error Dynamics Loss





Latent Space Planning Method

- 1. Sample a random 5 step action sequence and move away from a goal position by following that action sequence
- 2. Solve

$$\min_{a_{1:5}}||z_{goal} - z_{final}||_2$$

s.t.
$$z_{init} = z_{current}$$
 $z_{t+1} = learned model(z_t)$

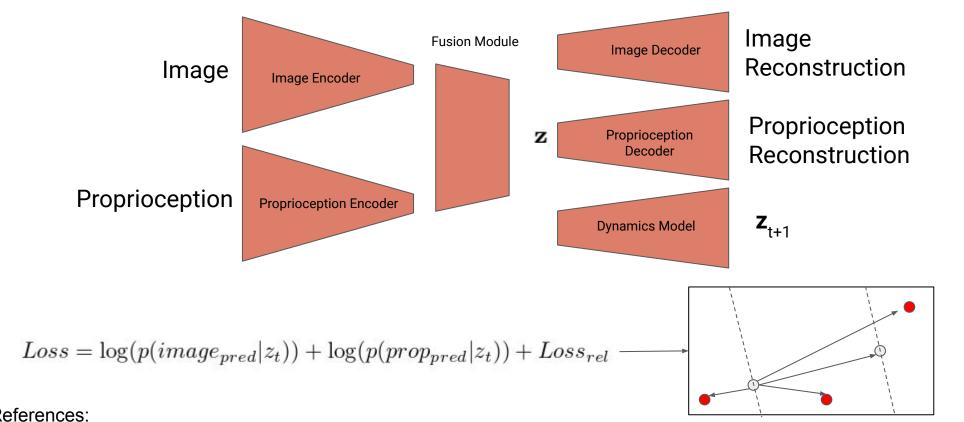
To solve this optimization the Cross Entropy Method was used along with the learned dynamics model.

- 3. Perform first action in the optimal action sequence and repeat 2.
- 4. The process ends when you have performed 5 actions

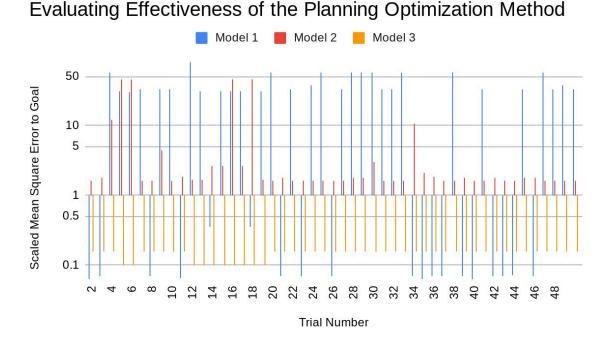
Requirements for Effective Distance **Based Latent Space Planning**

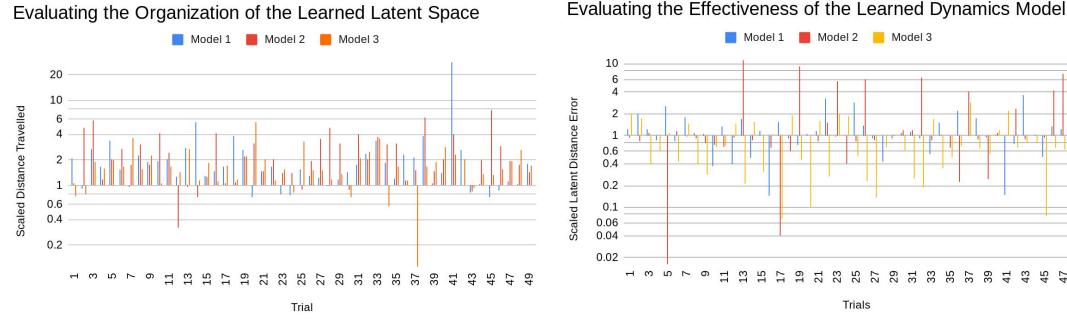
- Points in latent space in between z and z_goal correspond to points in the environment between x and x goal and from which x_goal is reachable
- The dynamics model can accurately predict effect of action on the environment

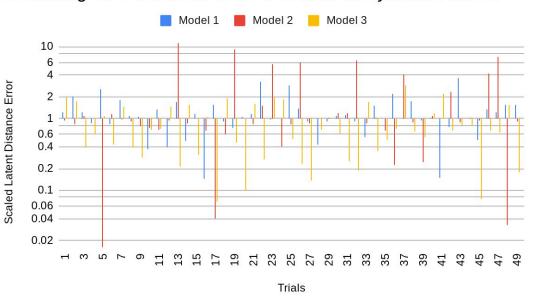
Model 3: Relational Autoencoder with 6 layer MLP Dynamics Model



Latent Space Planning Results







Acknowledgement:

Thank you for the mentorship from Michelle Lee and Jeannette Bohg in the Interactive Perception and Robotic Learning Lab as Stanford

1. Kingma, D. P. and Welling, M. Auto-encoding variational bayes. CoRR, abs/1312.6114, 2013. 2. Lee, M. A. Making sense of vision and touch: Self-supervised learning of multimodal representations for contact-rich tasks CoRR, abs/1810.10191, 2018. 3. Rubinstein, R. The cross-entropy method for combinatorial and continuous optimization. Methodology And Computing In Applied Probability, 1(2):127–190, Sep 1999. ISSN 1573-7713. doi: 10.1023/A:1010091220143 4. Wu, M. and Goodman, N. Multimodal generative models for scalable weakly-supervised learning. CoRR abs/1802.05335, 2018