

# Vision Based Pendulum Control using Diffusion Policy

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# Image to control inverted pendulum swing up

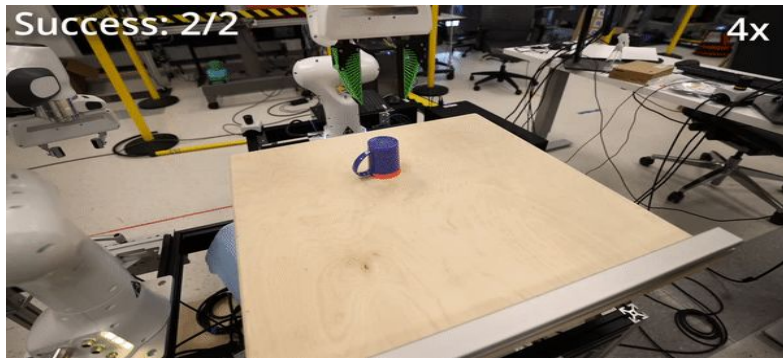
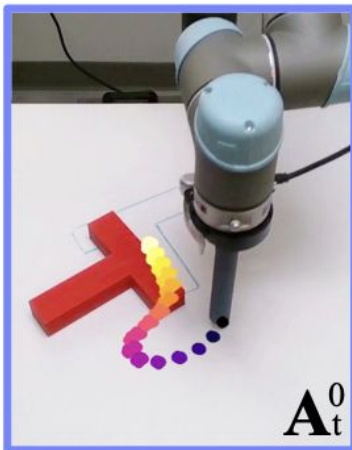
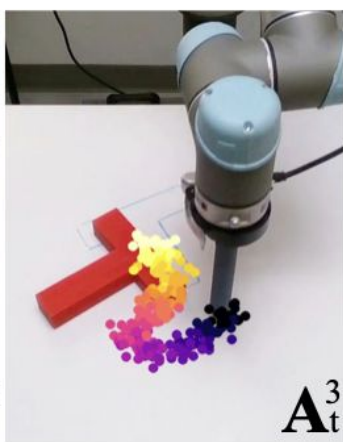
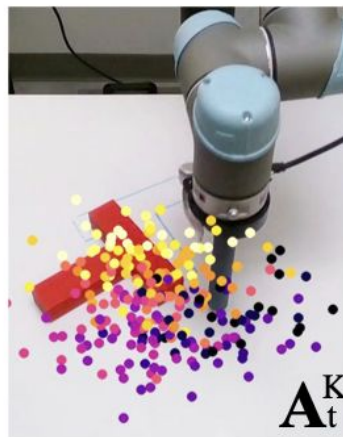
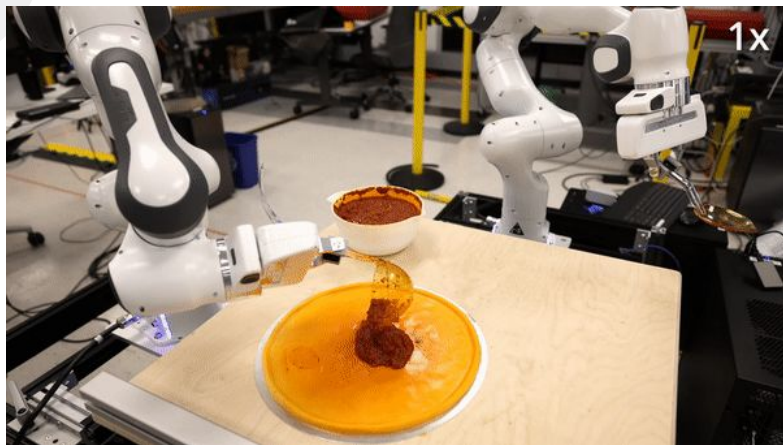
$$r = -(\theta^2 + 0.1 * \dot{\theta}^2 + 0.001 * \tau^2)$$



Action Torque	1d, -2 to 2
Observation Shape	(3,) + rgb
Observation High	[1. 1. 8.]
Observation Low	[-1. -1. -8.]
Import	<code>gym.make("Pendulum-v1")</code>



# Diffusion Policy in Robotics



- High Dimensional Action Space
- Multiple Trajectories
- Closed Loop Action Sequences
- Very complicated tasks

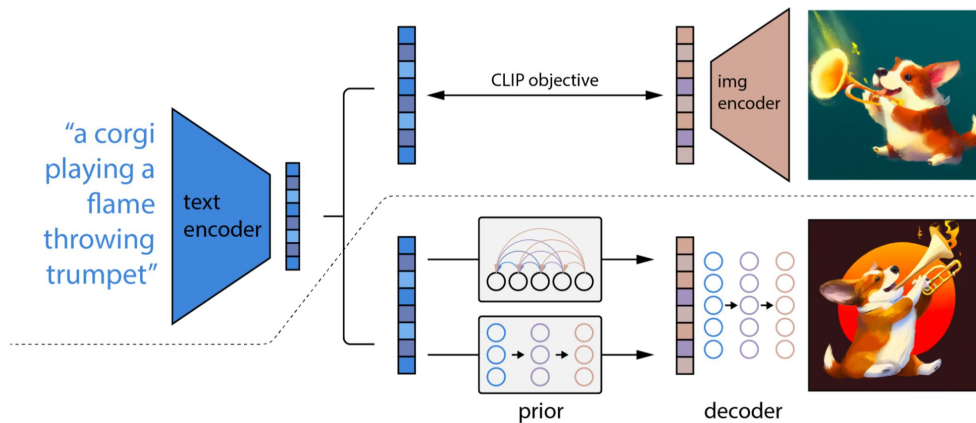


# Does a Diffusion Policy work for simple, one dimensional action space, unimodal, nonlinear control problems?

Intuition: **yes!**



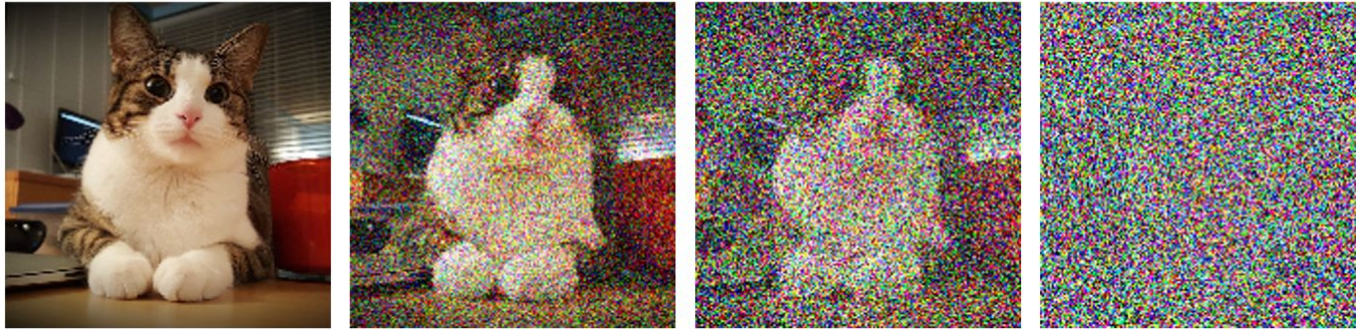
# What is Diffusion ??



It can be used  
for a lot more than just  
image generation



# How does Diffusion Work? Forward Pass



$$q(x_t|x_{t-1}) = \mathcal{N}(x_t, \sqrt{1 - \beta_t}x_{t-1}, \beta_t I)$$

normal distribution

mean

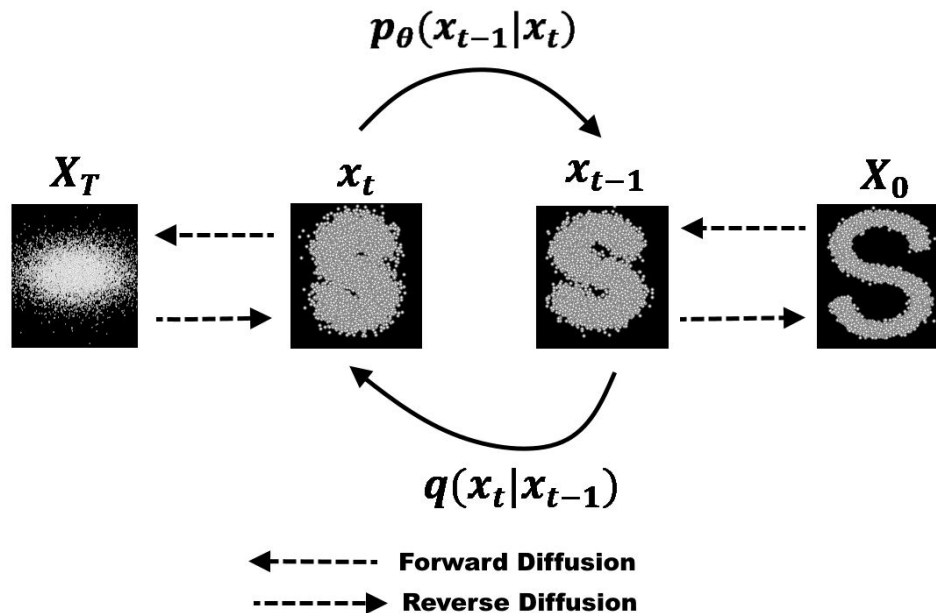
output

variance





# Backward Pass

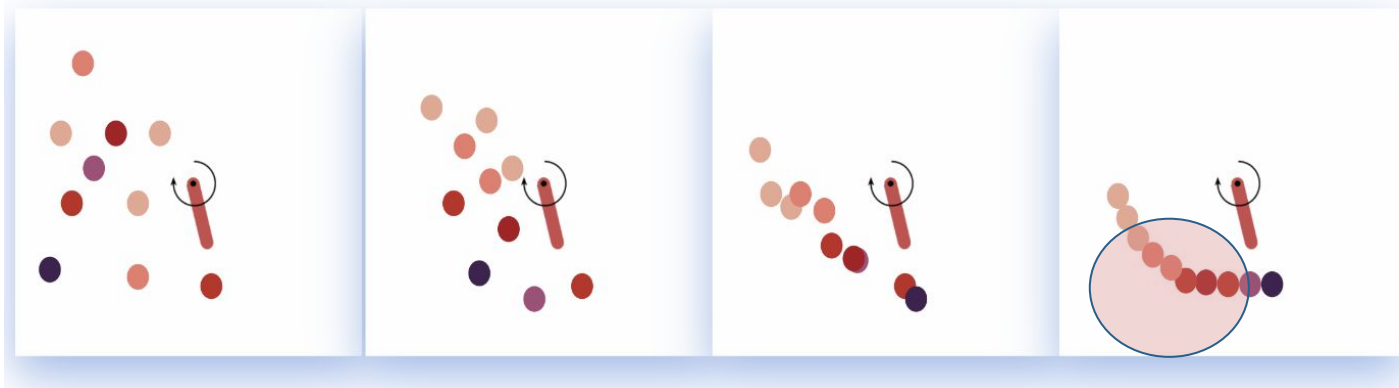


$$p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_{\theta}(\mathbf{x}_t, t), \Sigma_{\theta}(\mathbf{x}_t, t))$$



# How do we adapt this for control?

## We just denoise actions instead!

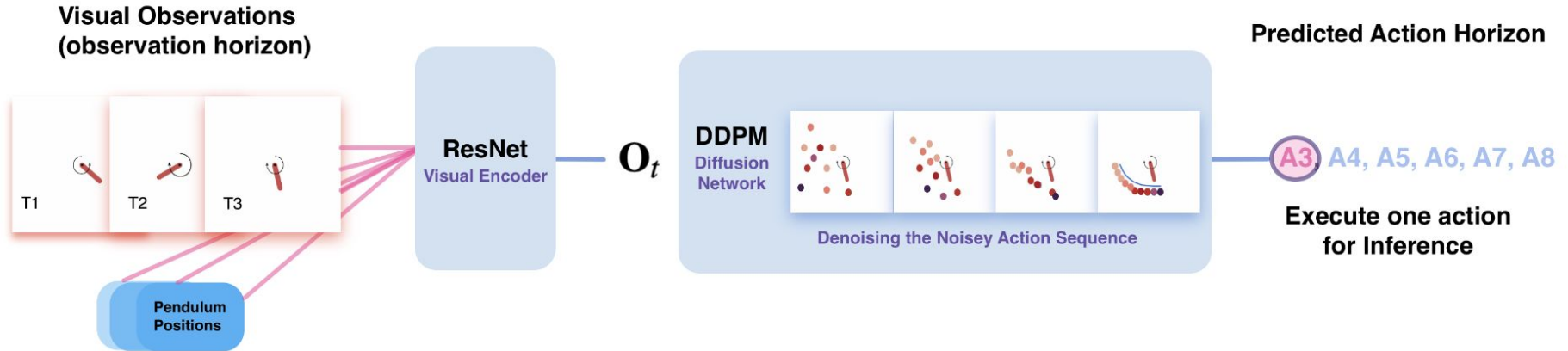


$$\mathbf{x}^{k-1} = \alpha(\mathbf{x}^k - \gamma \epsilon_{\theta}(\mathbf{x}^k, k) + \mathcal{N}(0, \sigma^2 I))$$





# The Architecture



# Training - Dataset



Solved DQN



# Model Training

**500** Episodes, **100** steps each  
**Observation Horizon: 8**  
**Prediction Horizon: 16**  
**Action Horizon: 2**

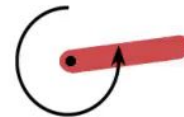


# Results (best model from 450 runs)

Model 1 ( $\theta$  - not given,  $\dot{\theta}$  dot not given)



Model 2 ( $\theta$  - given,  $\dot{\theta}$  dot not given)



# Is diffusion a good policy for simple, nonlinear control problems?

**Computational Expense**

**Fine Tuning**

**Does not converge easily**



**If I had more time, I would test...**

**Transformer Model (more  
robust for velocity)**

**Other control problems**

**Different Diffusion Models**

**Other ways to concatenate  
observations**



# Why not? (open question)

## Stability/Target

