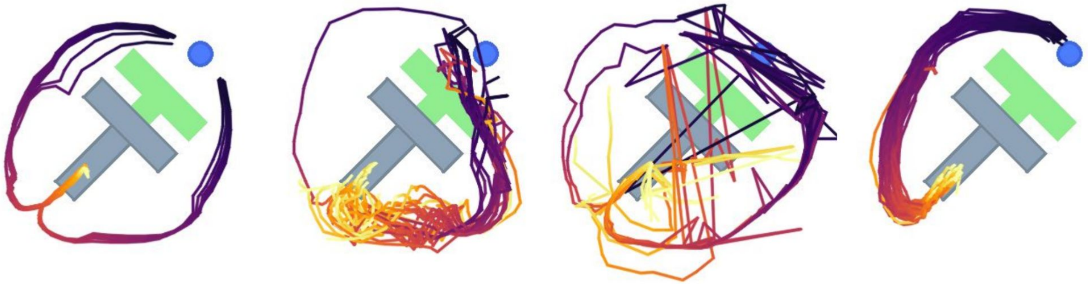
Diffusion Policy

Diffusion Policy

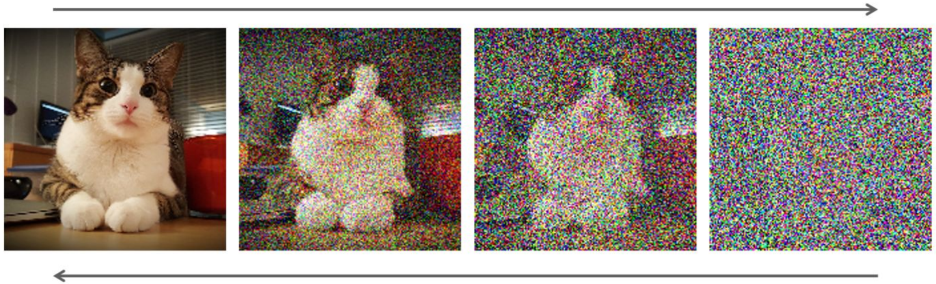
- It can account for the different ways a task can be performed as demonstrated by various users
- Diffusion Policy achieves an average improvement of 46% with a smaller number of demonstrations and in a variety of simulated and real-world benchmarks

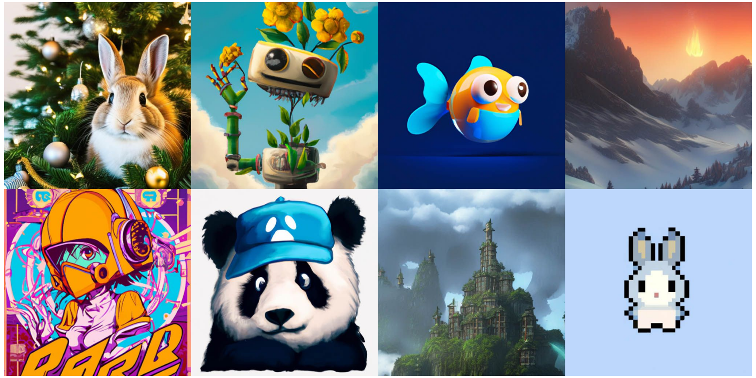


Diffusion Policy LSTM-GMM BET IBC

Diffusion

Generative model that can learn the distribution of a dataset and create new data points from this distribution

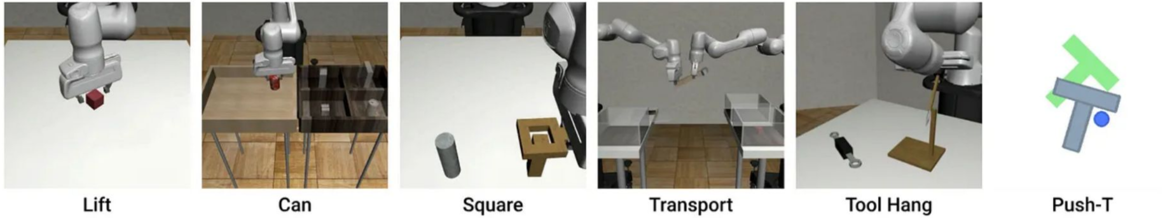




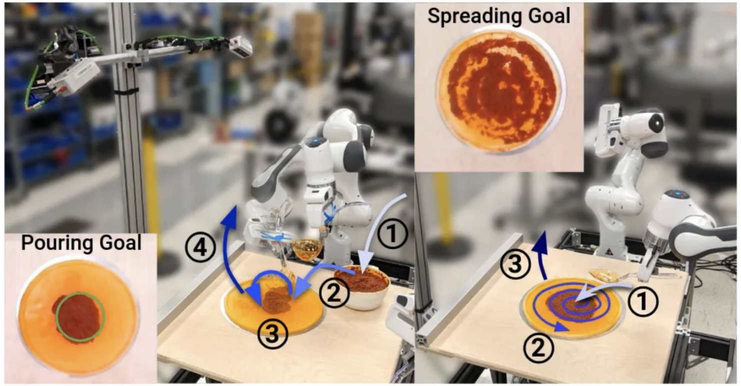
How Does Diffusion Policy Work

- A forward process to gradually add noise to a sampled action sequence and then a backward process to learn how to remove the noise
- Sample an action from the learned distribution by injecting random noise into the model and gradually denoising it up to a noiseless action
- Also, conditioning the denoising (reverse diffusion) processes on the observations
- The neural network learns a score function for the actions
    - Essentially, the score function acts as a guide that quantifies the most probable direction to adjust data points during the generative process
- During the reverse diffusion process, the model sculpts the noisy data back into coherent, structured actions

Does it Work?



Simulated Environments



Sauce Pouring and Spreading