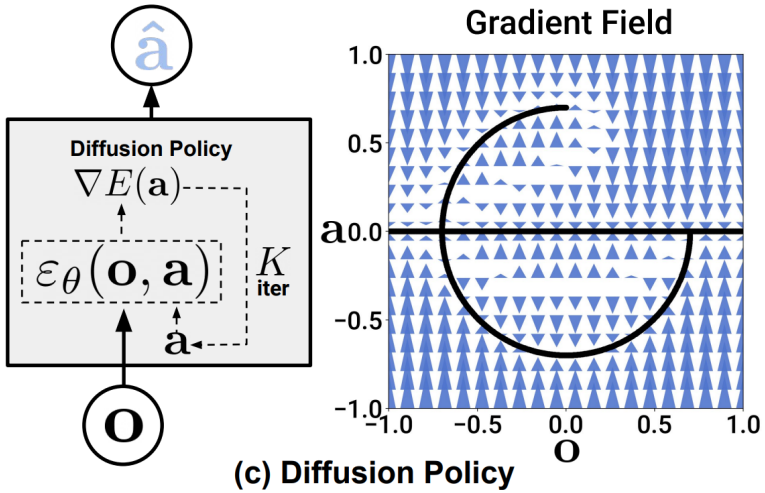
Diffusion Policy

Visuomotor Policy Learning via Action Diffusion

A. Buynitsky

Nov 7, 2024



(c) Diffusion Policy

Outline

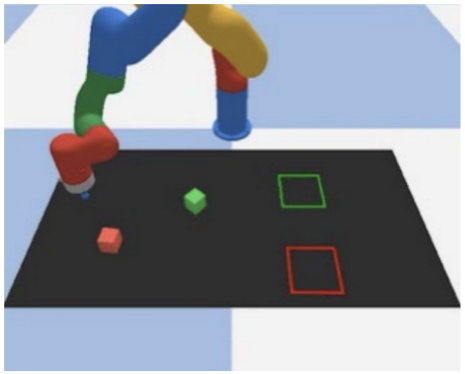
1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

Outline

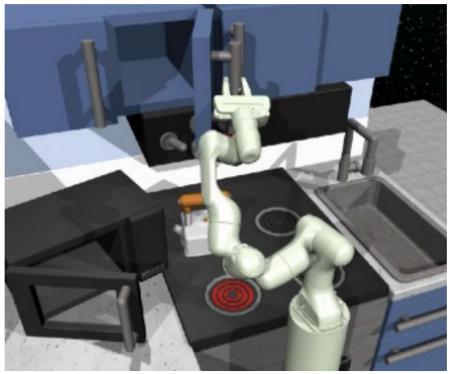
1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

TLDR

High Level: Learn visuomotor policy through a diffusion process
Results: 46.9% average improvement across 12 tasks (sim + real life)



Block Push

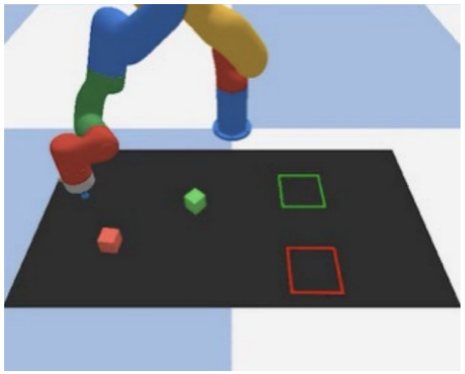


Kitchen

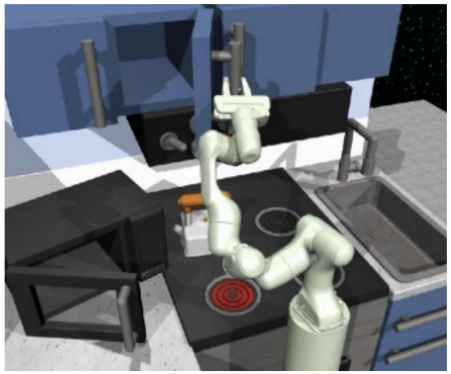
	BlockPush		Kitchen			
	p1	p2	p1	p2	p3	p4
LSTM-GMM [29]	0.03	0.01	**1.00**	0.90	0.74	0.34
IBC [12]	0.01	0.00	0.99	0.87	0.61	0.24
BET [42]	0.96	0.71	0.99	0.93	0.71	0.44
DiffusionPolicy-C	0.36	0.11	**1.00**	**1.00**	**1.00**	**0.99**
DiffusionPolicy-T	**0.99**	**0.94**	**1.00**	0.99	0.99	0.96

TLDR

High Level: Learn visuomotor policy through a diffusion process
Results: 46.9% average improvement across 12 tasks (sim + real life)



Block Push



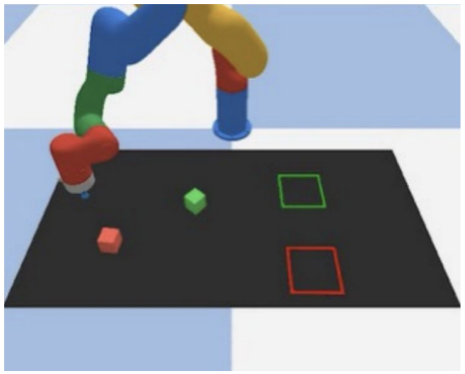
Kitchen

	BlockPush		Kitchen			
	p1	p2	p1	p2	p3	p4
LSTM-GMM [29]	0.03	0.01	**1.00**	0.90	0.74	0.34
IBC [12]	0.01	0.00	0.99	0.87	0.61	0.24
BET [42]	0.96	0.71	0.99	0.93	0.71	0.44
DiffusionPolicy-C	0.36	0.11	**1.00**	**1.00**	**1.00**	**0.99**
DiffusionPolicy-T	**0.99**	**0.94**	**1.00**	0.99	0.99	0.96

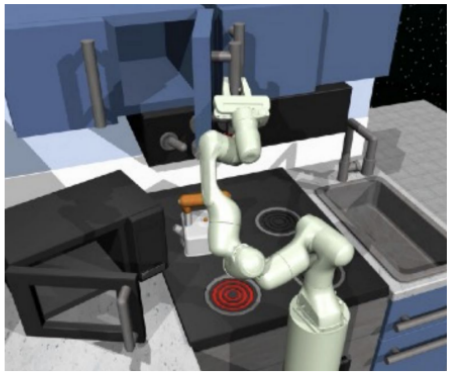
Research Group: Shuran Song; MIT, Columbia and Toyota Research Institute (TRI)

TLDR

High Level: Learn visuomotor policy through a diffusion process
Results: 46.9% average improvement across 12 tasks (sim + real life)



Block Push



Kitchen

	BlockPush		Kitchen			
	p1	p2	p1	p2	p3	p4
LSTM-GMM [29]	0.03	0.01	**1.00**	0.90	0.74	0.34
IBC [12]	0.01	0.00	0.99	0.87	0.61	0.24
BET [42]	0.96	0.71	0.99	0.93	0.71	0.44
DiffusionPolicy-C	0.36	0.11	**1.00**	**1.00**	**1.00**	**0.99**
DiffusionPolicy-T	**0.99**	**0.94**	**1.00**	0.99	0.99	0.96

Research Group: Shuran Song; MIT, Columbia and Toyota Research Institute (TRI)
Future Work:

- Apply Diffusion Policy to RL to avoid suboptimal data
- Accelerate inference time + decrease computational costs with advancements from modern diffusion methods

Outline

1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

BC-RNN / LSTM-RNN

Behavioral Cloning learns a policy $\pi_\theta(s)$ to clone actions from a set of demonstrations:

$$\arg\min_\theta \mathbb{E}_{(s,a)\sim D} ||\pi_\theta(s) - a||^2$$

BC-RNN / LSTM-RNN

Behavioral Cloning learns a policy $\pi_\theta(s)$ to clone actions from a set of demonstrations:

$$\arg\min_\theta \mathbb{E}_{(s,a)\sim D}||\pi_\theta(s) - a||^2$$

Method:

- RNN models temporal dependencies $(s_t, a_t, \ldots, s_{t+T}, a_{t+T})$ via hidden state
- predicts the sequence of action and is unrolled one step at a time:

$$a_t, h_{t+1} = \pi_\theta(s_t, h_t)$$

BC-RNN / LSTM-RNN

Behavioral Cloning learns a policy $\pi_\theta(s)$ to clone actions from a set of demonstrations:

$$\arg\min_\theta \mathbb{E}_{(s,a)\sim D}||\pi_\theta(s) - a||^2$$

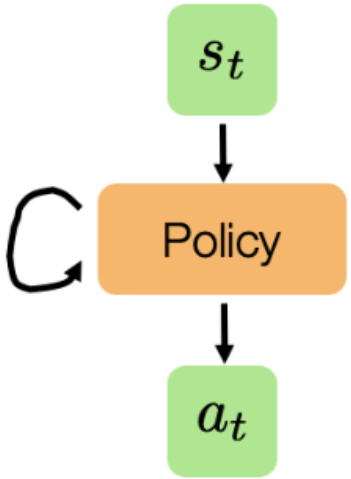
Method:

- RNN models temporal dependencies $(s_t, a_t, \ldots, s_{t+T}, a_{t+T})$ via hidden state
- predicts the sequence of action and is unrolled one step at a time:

$$a_t, h_{t+1} = \pi_\theta(s_t, h_t)$$

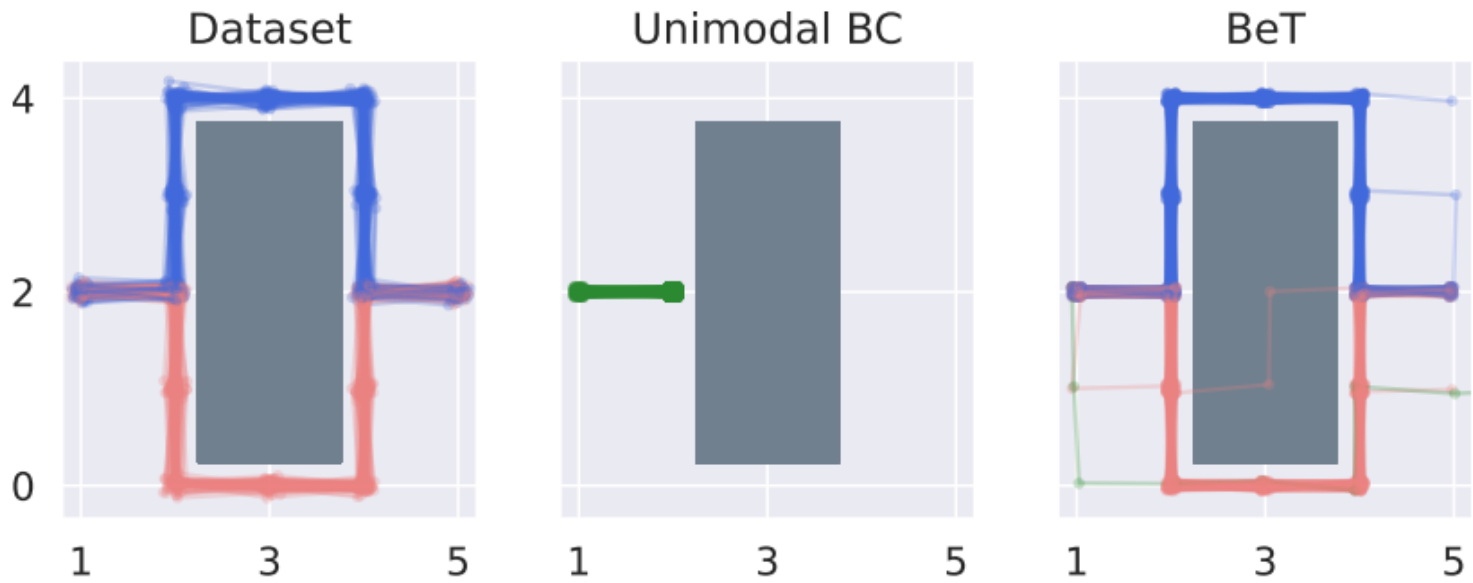
Limitation

1. Biased towards one mode
2. Brittle performance due to changes in observation space and hyperparameters



Behavior Transformer (BET)

Large Scale human datasets have wide variances with multiple modes

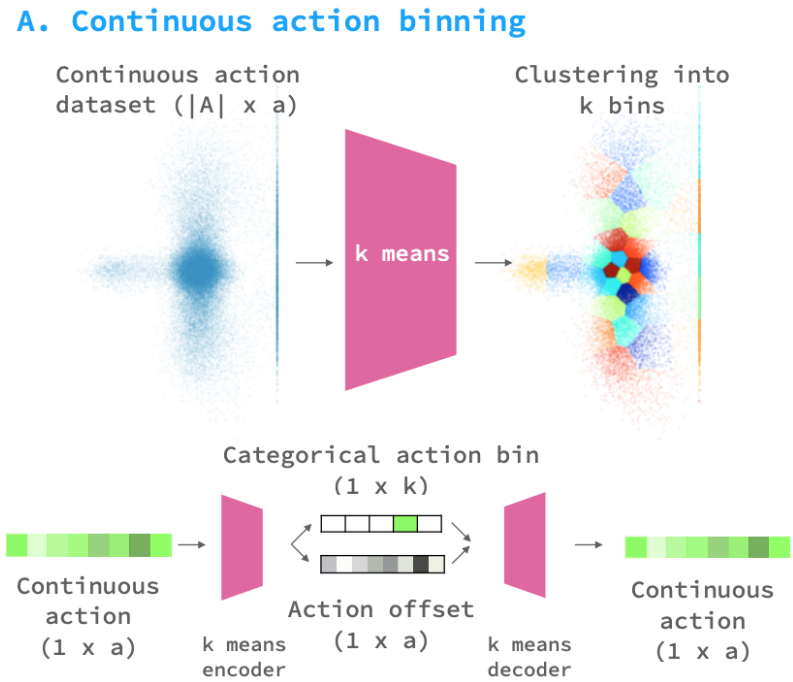


Limitation of BC: Current bc assumes that data is drawn from unimodal experts solving a single task

Behavior Transformer (BET)

Proposed Solution:

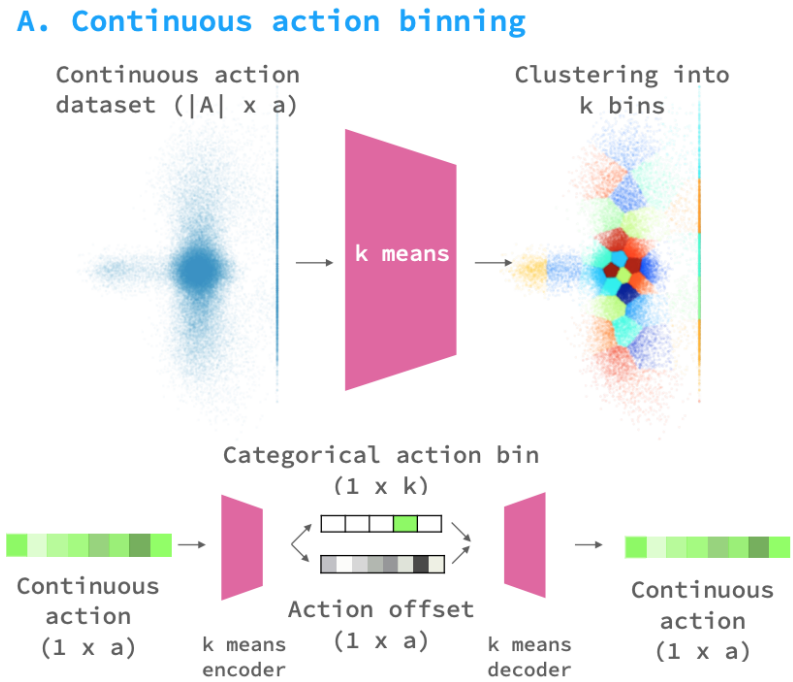
1. Descretize action dataset into k bins with k-means with offset
2. Train a transformer with two heads to predict an action bin and an offset for that bin



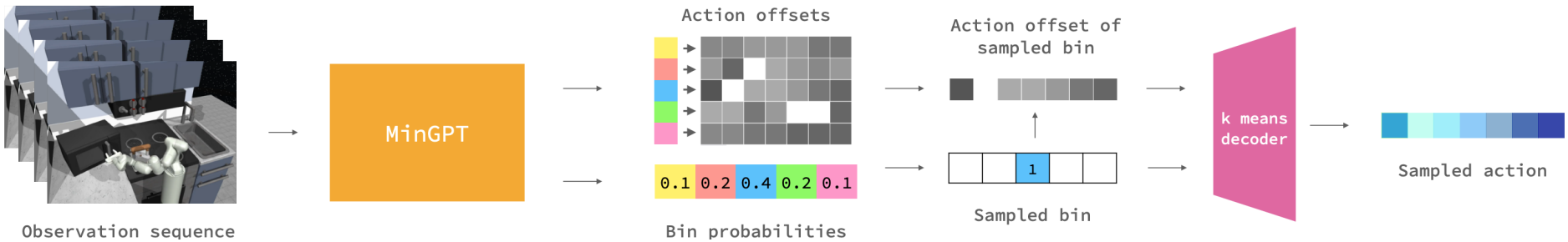
Behavior Transformer (BET)

Proposed Solution:

1. Descretize action dataset into k bins with k-means with offset
2. Train a transformer with two heads to predict an action bin and an offset for that bin



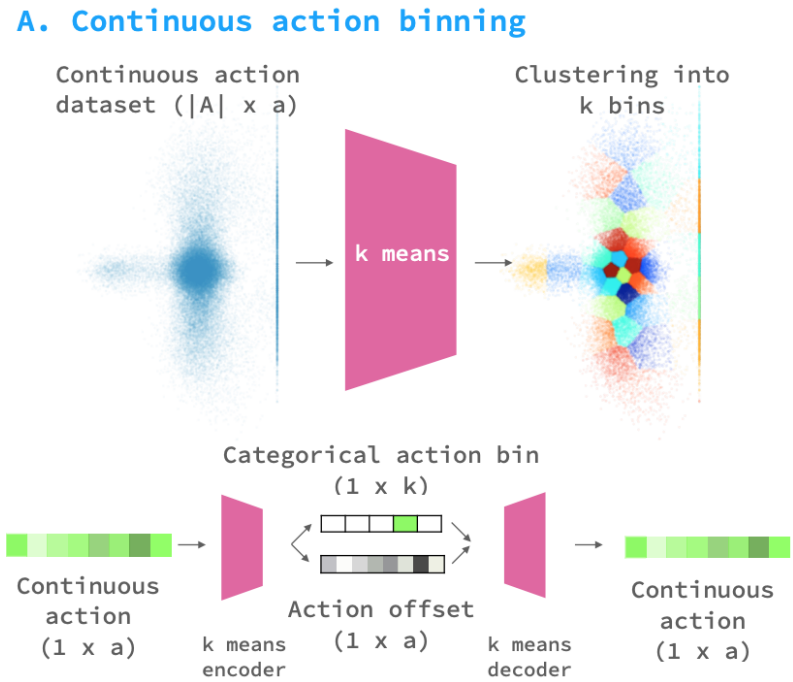
Inference:



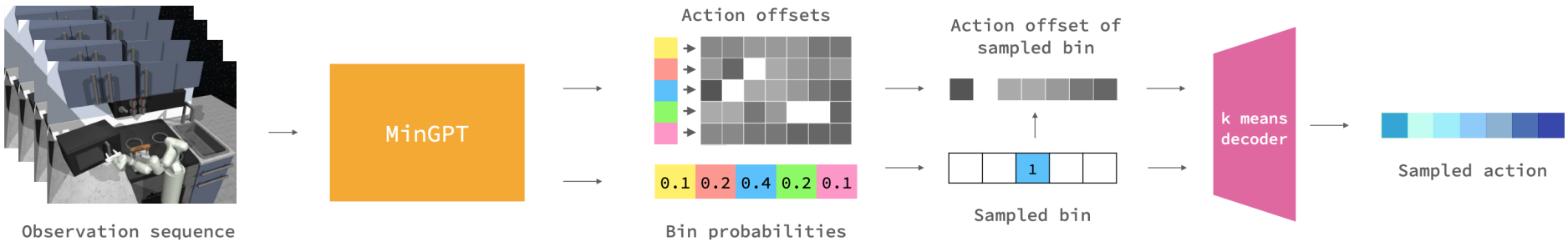
Behavior Transformer (BET)

Proposed Solution:

1. Descretize action dataset into k bins with k-means with offset
2. Train a transformer with two heads to predict an action bin and an offset for that bin



Inference:

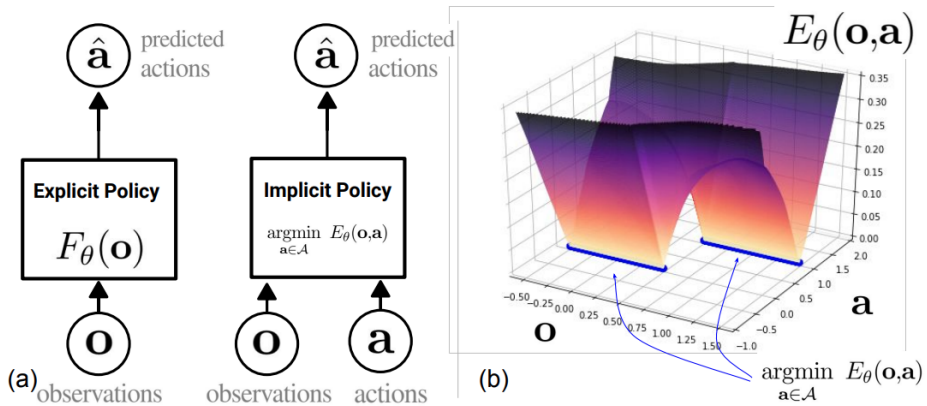


Limitation: Inconsistent sampling from action bins

Implicit BC

BC Reformulation: Use Energy-Based models instead of explicit policies

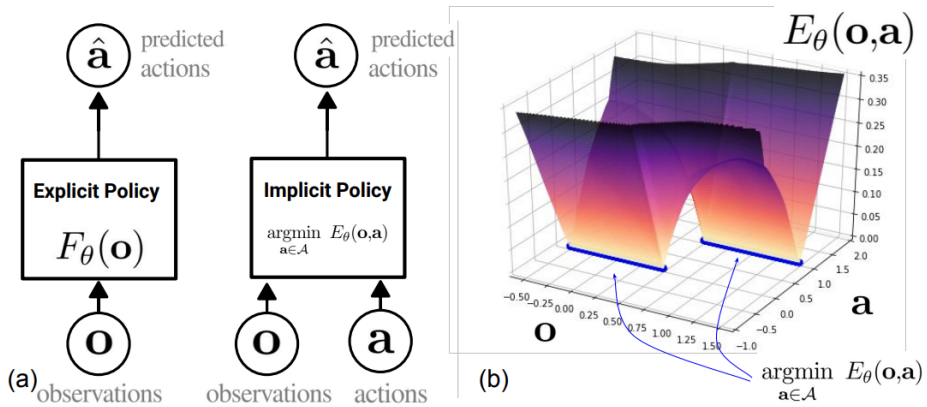
Energy Models: Scalar energy function captures the relationship between states and actions



Implicit BC

BC Reformulation: Use Energy-Based models instead of explicit policies

Energy Models: Scalar energy function captures the relationship between states and actions



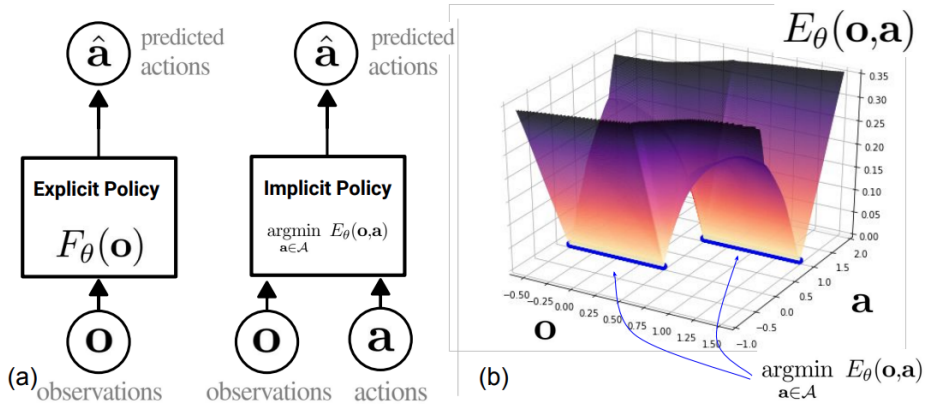
Inference: solve optimization problem (i.e. with gradient descent) for:

$$\hat{a} = \arg\min_{a \in A} \mathbf{E}(o, a)$$

Implicit BC

BC Reformulation: Use Energy-Based models instead of explicit policies

Energy Models: Scalar energy function captures the relationship between states and actions



Inference: solve optimization problem (i.e. with gradient descent) for:

$$\hat{a} = \arg\min_{a \in A} \mathbf{E}(o, a)$$

Limitation: Increases complexity, training and inference time, and computational cost

Outline

1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

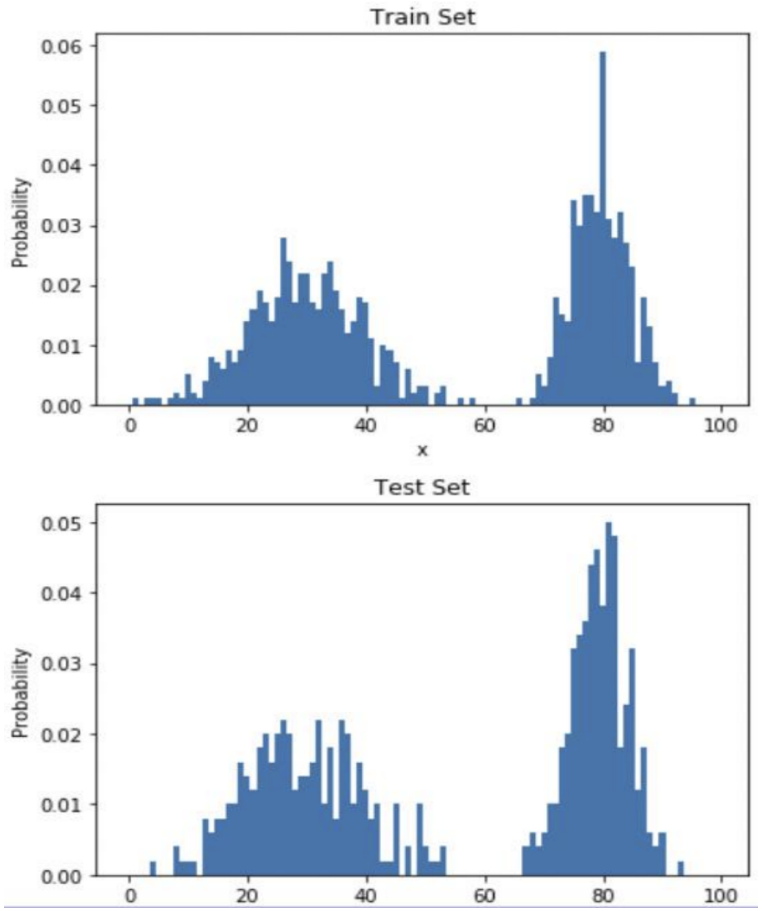
Learning

Assume that all Data (image, speech, etc.) is sampled from a distribution

Learning

Assume that all Data (image, speech, etc.) is sampled from a distribution

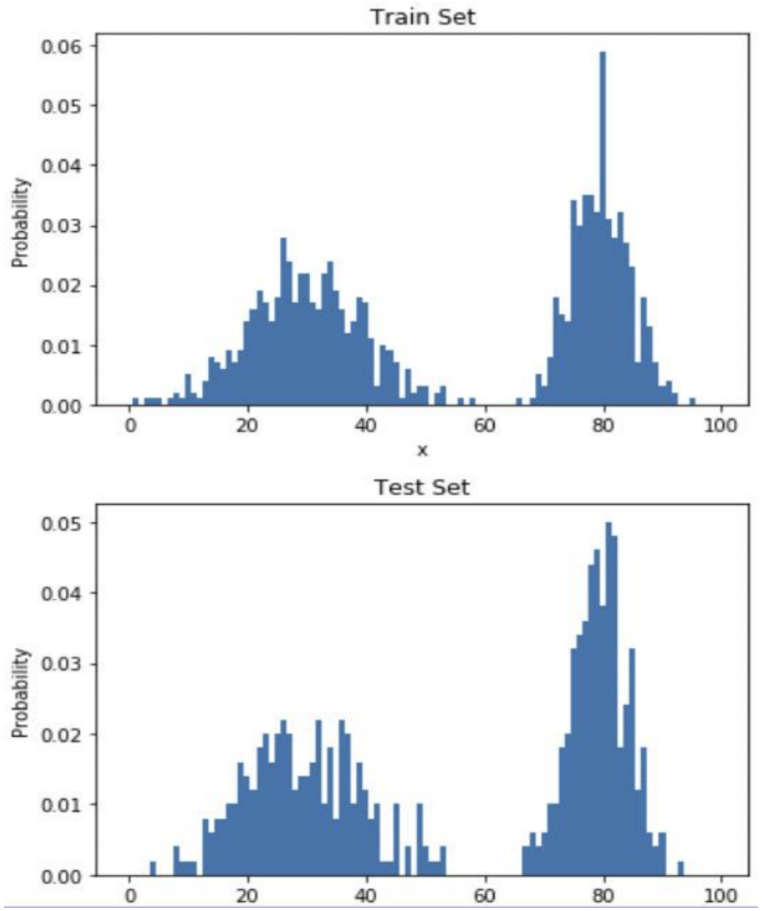
Generative Model: learn training distribution $P_\theta(x)$ from dataset



Learning

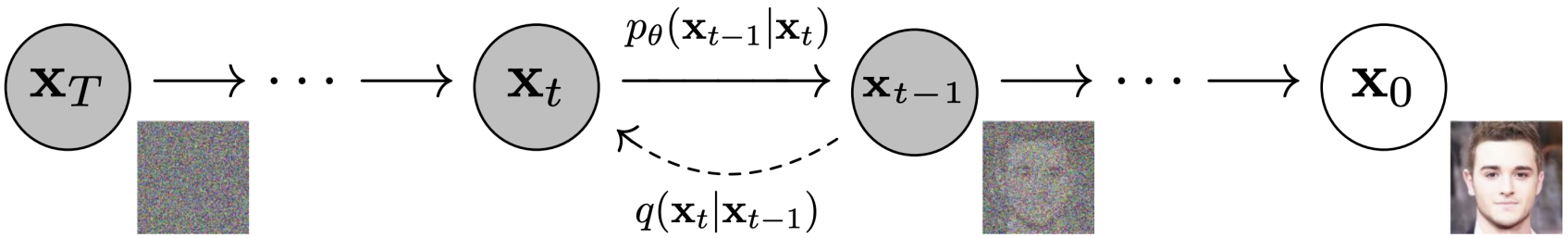
Assume that all Data (image, speech, etc.) is sampled from a distribution

Generative Model: learn training distribution $P_\theta(x)$ from dataset



Diffusion Models model the output as a denoising process, performing T denoising steps to produce a series of intermediate actions with decreasing noise levels.

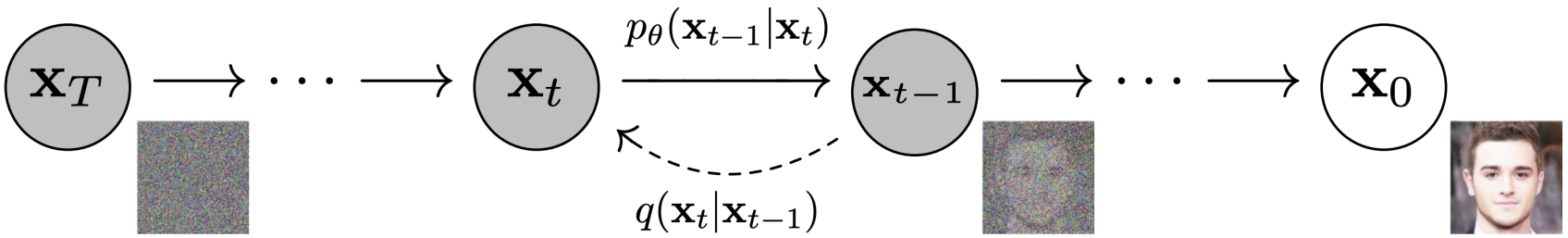
Diffusion Overview (Forward Process)



Forward Process ($q(x_t \mid x_{t-1})$): Markov chain that gradually adds Gaussian Noise according to variance schedule $\beta_t \in [\beta_1, \ldots, \beta_T]$

$$q(x_{1:T} \mid x_0) := \prod_{t=1}^{T} q(x_t \mid x_{t-1}), \quad q(x_t \mid q_{t-1}) := \mathbf{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_T \mathbf{I})$$

Diffusion Overview (Forward Process)



Forward Process ($q(x_t \mid x_{t-1})$): Markov chain that gradually adds Gaussian Noise according to variance schedule $\beta_t \in [\beta_1, \ldots, \beta_T]$

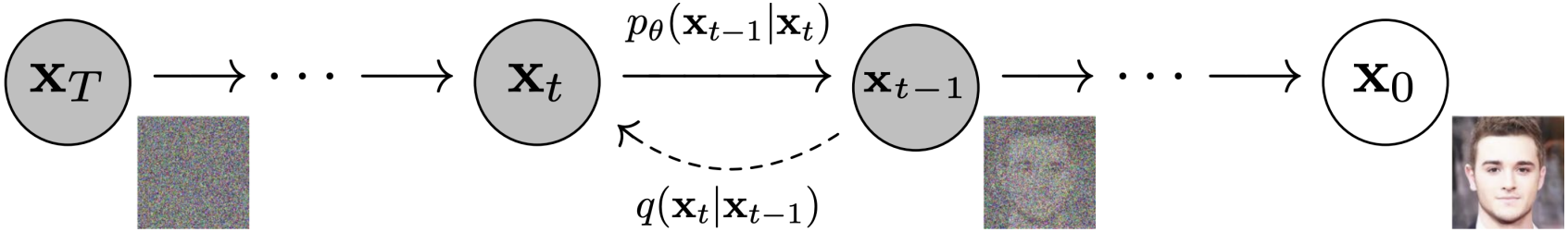
$$q(x_{1:T} \mid x_0) := \prod_{t=1}^{T} q(x_t \mid x_{t-1}), \quad q(x_t \mid q_{t-1}) := \mathbf{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_T \mathbf{I})$$

Reparametrization for $q(x_t \mid x_0)$ allows for sampling x_t at arbitrary t:

$$q(x_t \mid x_0) = N(x_t; \sqrt{\bar{\alpha}_t}x_0, (1-\bar{\alpha}_t)\mathbf{I}) \quad \text{where:}$$

$$\bar{\alpha}_t := \prod_{s=1}^{t} \alpha_s \quad \text{and} \quad \alpha_s = 1 - \beta_t$$

Diffusion Overview (Backward Process)



Backward Process ($p_\theta(x_{t-1} \mid x_t)$): Markov chain with learned Gaussian transitions initialized with $p(x_T) = \mathbf{N}(x_T; 0, \mathbf{I})$

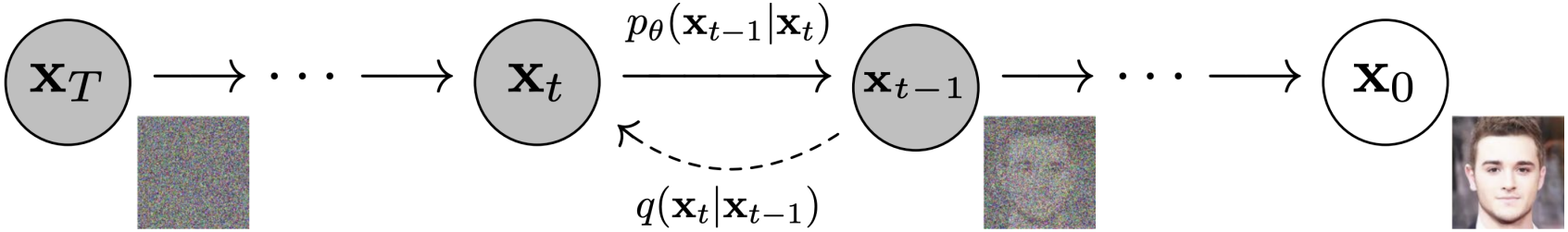
$$p_\theta(x_{0:T}) := p(x_t) \prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t) \tag{1}$$

$$p_\theta(x_{t-1} \mid x_t) := \mathbf{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{2}$$

$\Sigma_\theta(x_t, t) = \sigma_t^2 \mathbf{I}$: Fix to untrained time dependent constants (i.e. $\sigma_t^2 = \beta_t$)

$\mu_\theta(x_t, t)$: Reparametrize to predict the noise at step t with $\epsilon_\theta(x_t, t)$

Diffusion Overview (Backward Process)



Backward Process ($p_\theta(x_{t-1} \mid x_t)$): Markov chain with learned Gaussian transitions initialized with $p(x_T) = \mathbf{N}(x_T; 0, \mathbf{I})$

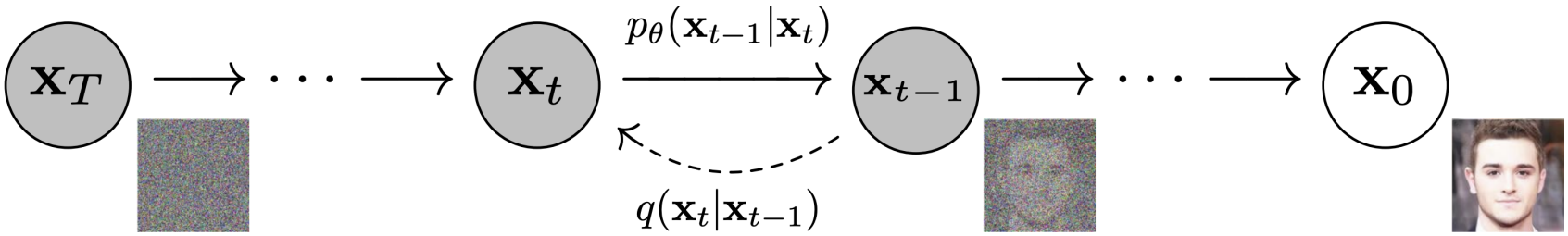
$$p_\theta(x_{0:T}) := p(x_t) \prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t) \tag{1}$$

$$p_\theta(x_{t-1} \mid x_t) := \mathbf{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{2}$$

$\Sigma_\theta(x_t, t) = \sigma_t^2 \mathbf{I}$: Fix to untrained time dependent constants (i.e. $\sigma_t^2 = \beta_t$)

$\mu_\theta(x_t, t)$: Reparametrize to predict the noise at step t with $\epsilon_\theta(x_t, t)$

Diffusion Overview (Backward Process)



Backward Process ($p_\theta(x_{t-1} \mid x_t)$): Markov chain with learned Gaussian transitions initialized with $p(x_T) = \mathbf{N}(x_T; 0, \mathbf{I})$

T Denoising iterations performed with decreasing levels of noise producing: $x_T, x_{T-1}, \ldots, x_0$ following:

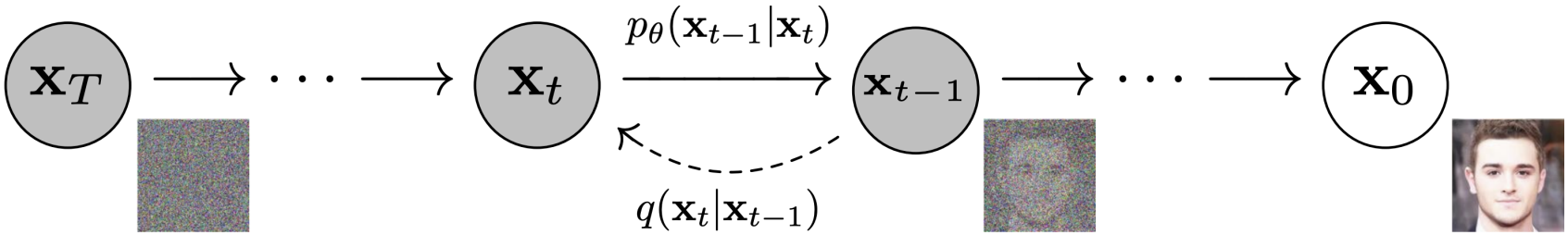
$$x_{t-1} = \alpha(x_t - \gamma\epsilon_\theta(x_t, t) + \mathbf{N}(0, \sigma^2, I)) \tag{3}$$

Above can be interpreted as a single noisy gradient step:

$$x' = x - \gamma\nabla E(x)$$

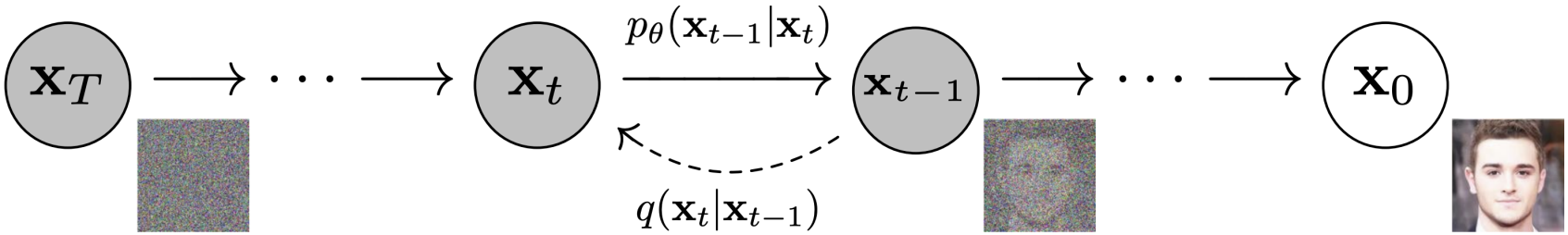
Where $\epsilon_\theta(x, t)$ predicts $E(x)$ with learning rate γ and parameters α and σ^2

Diffusion Training



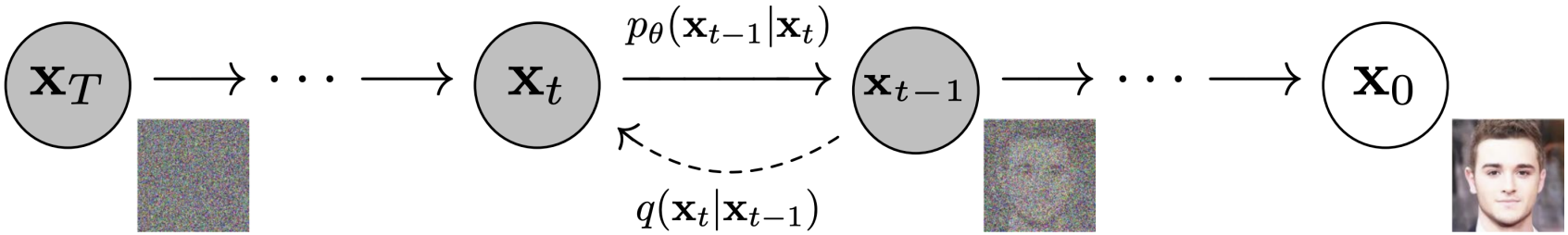
1. Randomly sampling examples x_0 from training dataset

Diffusion Training



1. Randomly sampling examples x_0 from training dataset
2. For each sample randomly select denoising iteration $k \in [1, \ldots, T]$ and noise ϵ_k with appropriate variance for k

Diffusion Training



1. Randomly sampling examples x_0 from training dataset
2. For each sample randomly select denoising iteration $k \in [1, \ldots, T]$ and noise ϵ_k with appropriate variance for k
3. Noise Prediction Network ϵ_θ predicts noise from noisy data:

$$\mathcal{L} = MSE(\epsilon_k, \epsilon_\theta(x_0 + \epsilon_k, k)) \tag{4}$$

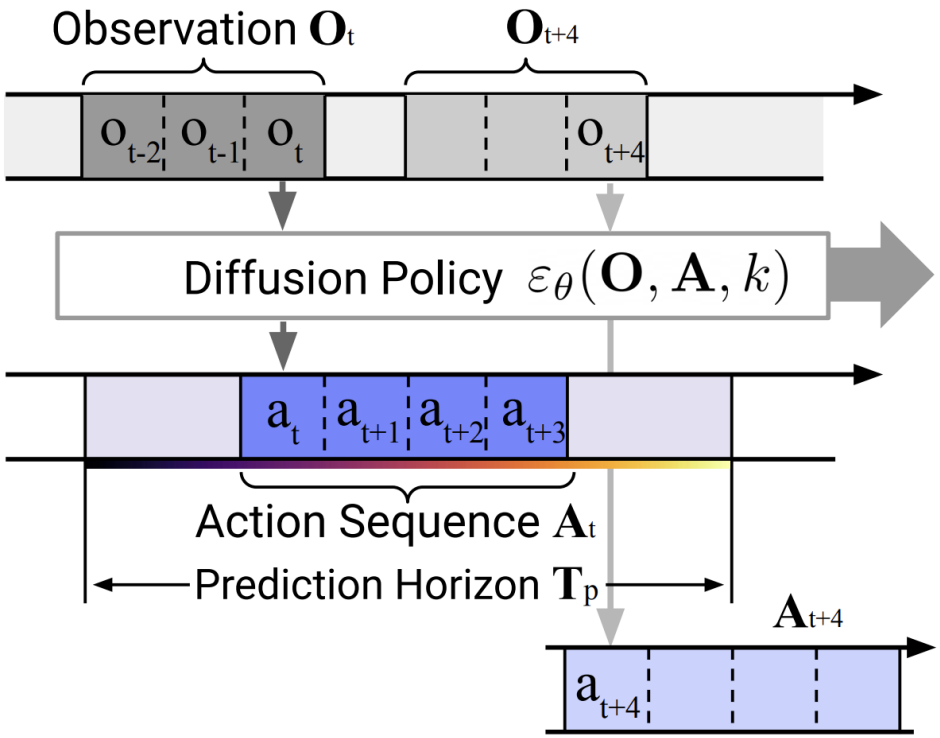
Outline

1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

Modifying Image Diffusion to Robotic Diffusion

Action Sequence Prediction:

- At step t policy takes latest T_o steps of observation data O_t
- Policy predicts T_p action steps
- The first T_a of T_p steps are executed



Modifying Image Diffusion to Robotic Diffusion

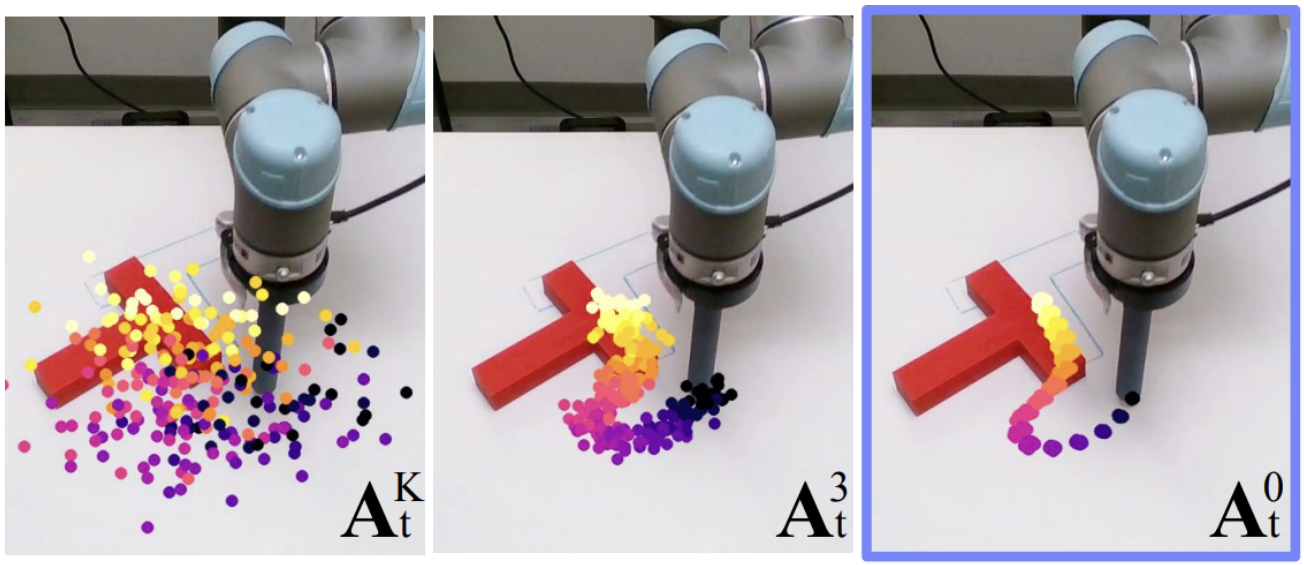
Visual Observation Conditioning: Learn conditional distribution $p(A_t \mid O_t)$ instead of joint distribution $p(A_t, O_t)$

Modify denoising iterations (3) to:

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

Modify MSE Loss (4) to:

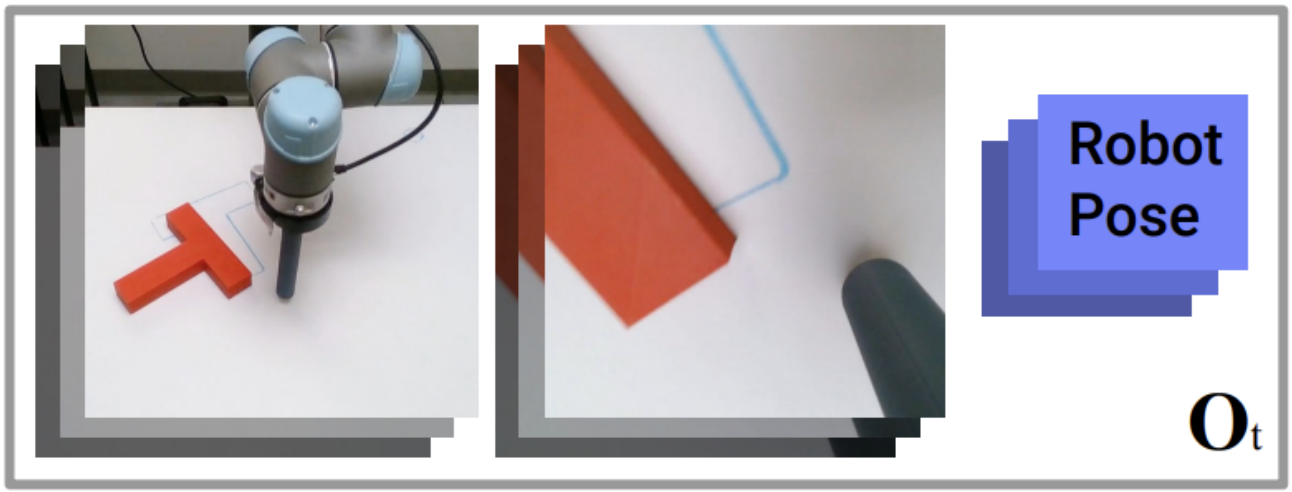
$$\mathcal{L} = MSE(\epsilon_k, \epsilon_\theta(O_t, A_t^0 + \epsilon^k, k))$$



Vision Encoder

Choice of noise prediction network ϵ_θ is **independent** of visual encoders
Vision encoder maps raw image sequence to latent embedding O_t from multiple camera views
Use a standard **Resnet-18** with the following modifications:

- Replace global average pooling with spatial softmax pooling
- Replace BatchNorm with GroupNorm



End-to-end performs better than pre-trained vision encoders.

Option 1: CNN-Based Diffusion Policy

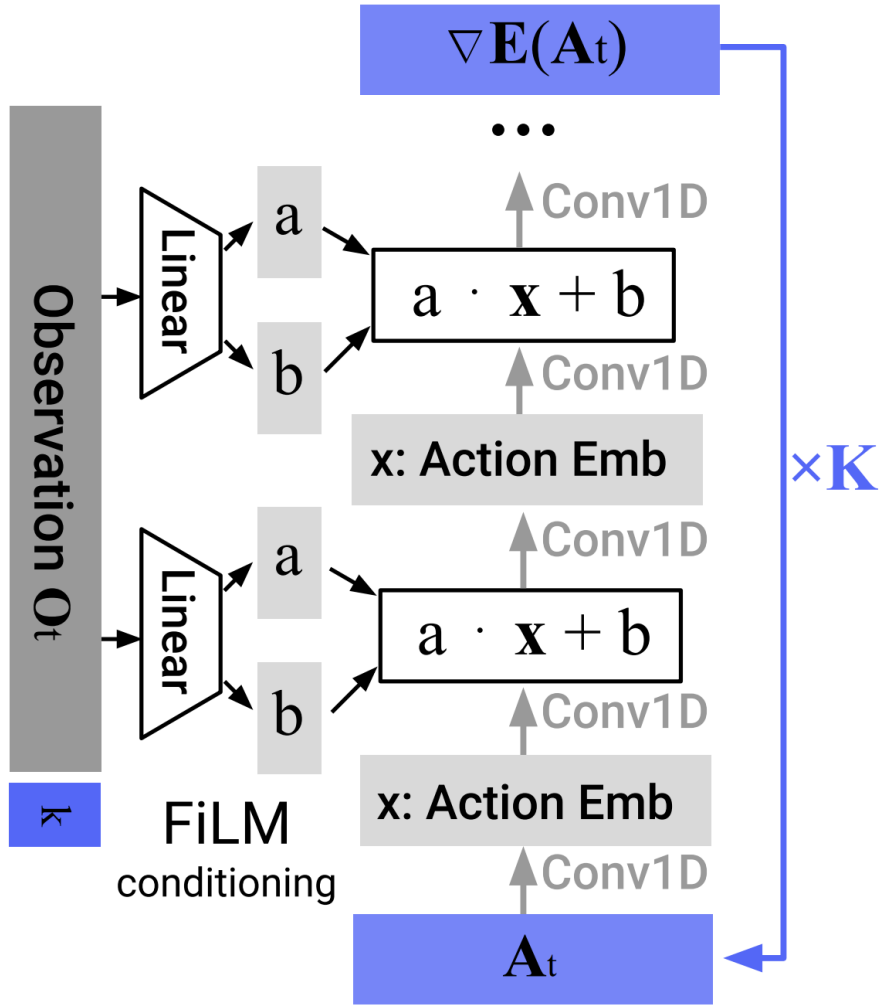
1D temporal CNN: learn training distribution $P_\theta(x)$ from dataset

Method:

- Condition on O_t using FiLM layers
- Only Predict Action Trajectory

Result:

- Ok performance on most tasks
- Poor performance when desired action sequence changes rapidly



Option 2: Time-series Diffusion Transformer

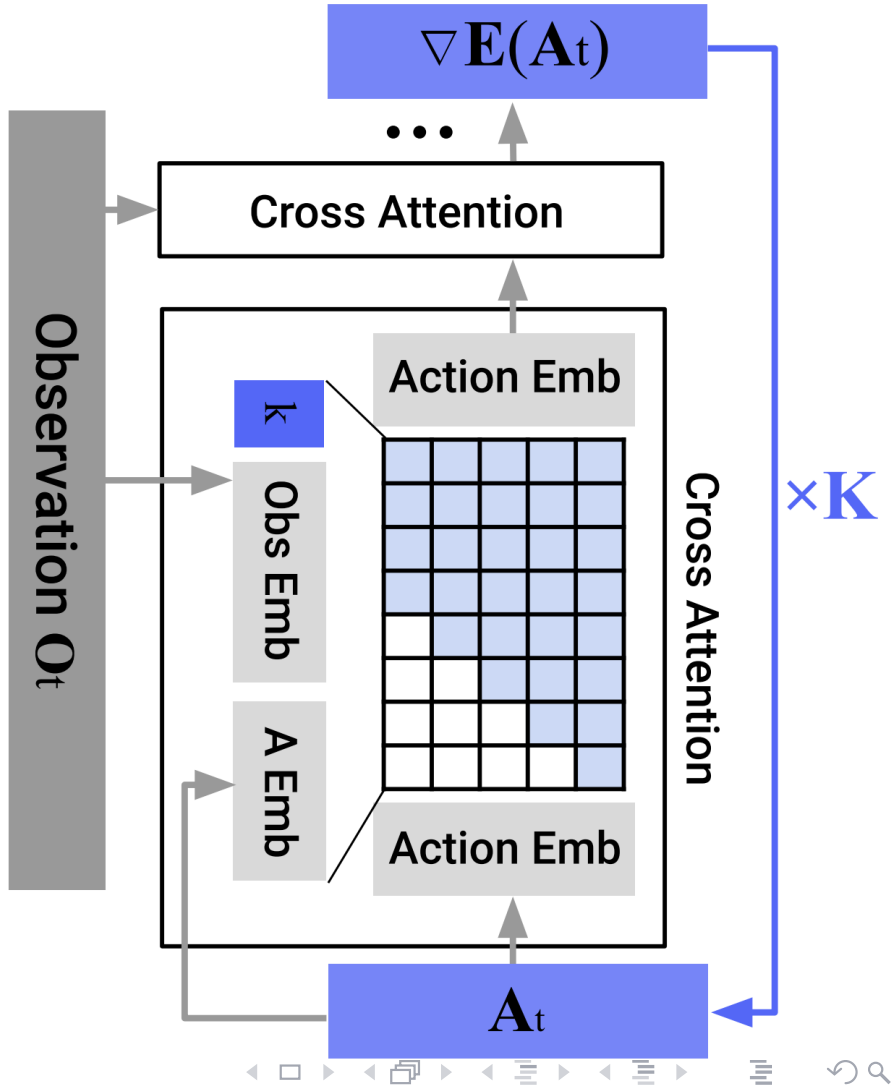
Time-Series Transformer: Adopted from MinGPT

Transformer Input:

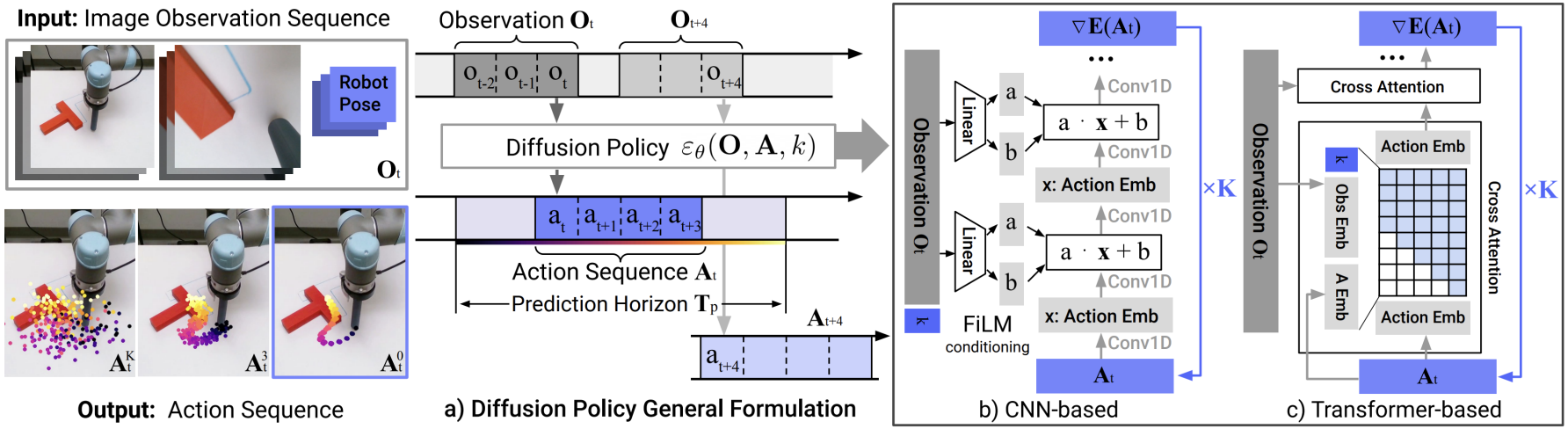
- Noisy Actions A_t^k
- Embedding for diffusion iteration k
- Observations O_t transformed into input tokens by MLP

Result:

- Best performing policy on even complicated tasks
- Sensitive to hyperparameter tuning



Final Result:



Outline

1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

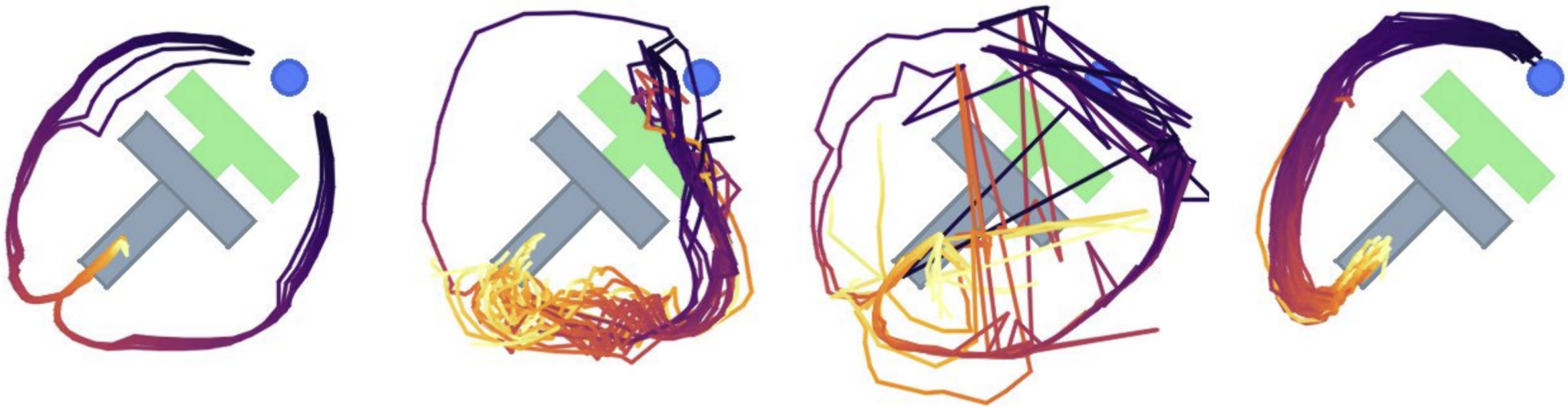
Convergence Basins

A_t^K **is stochastically initialized**:

- Help specify different convergence basins for final action prediction A_t^0

A_t^K **is stochastically pertubated**:

- K iterations enable individual action samples to converge and move between differnet action basins.



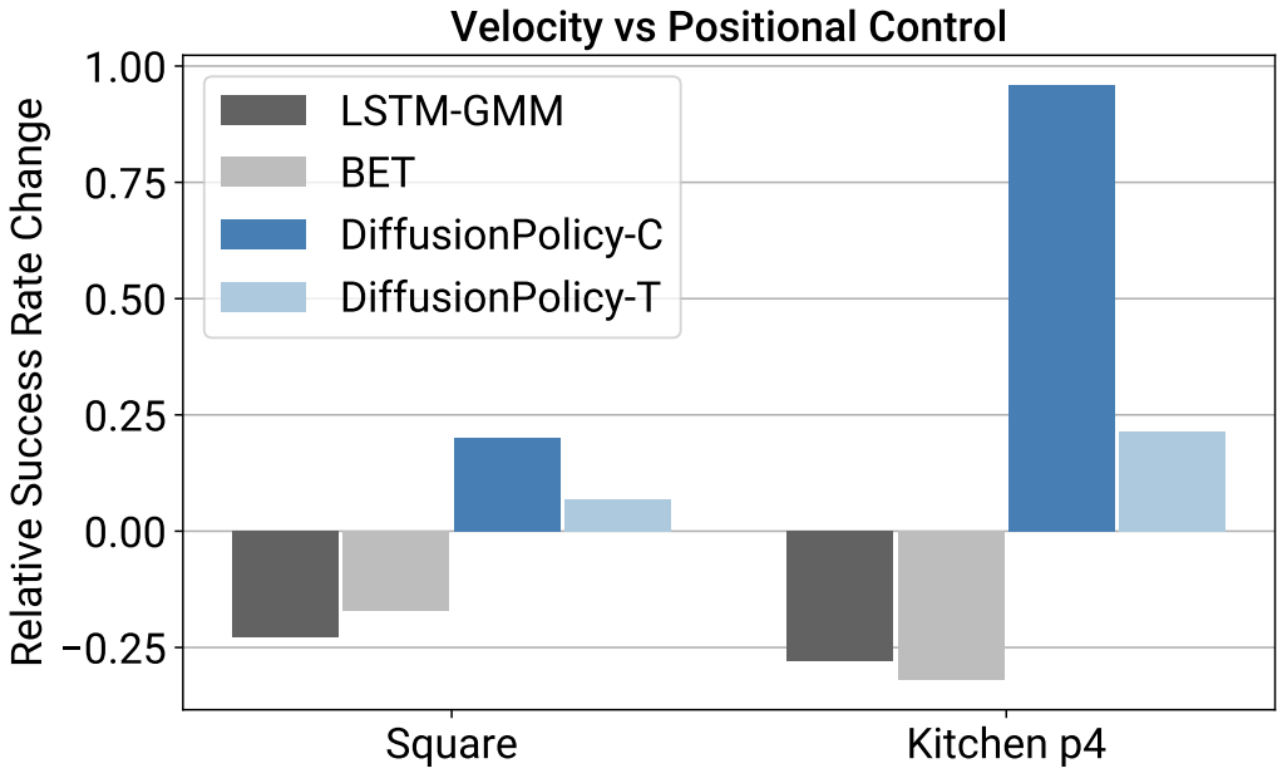
Diffusion Policy LSTM-GMM BET IBC

Robotic Control

Diffusion Policy with position control outperforms velocity-control

Reasoning:

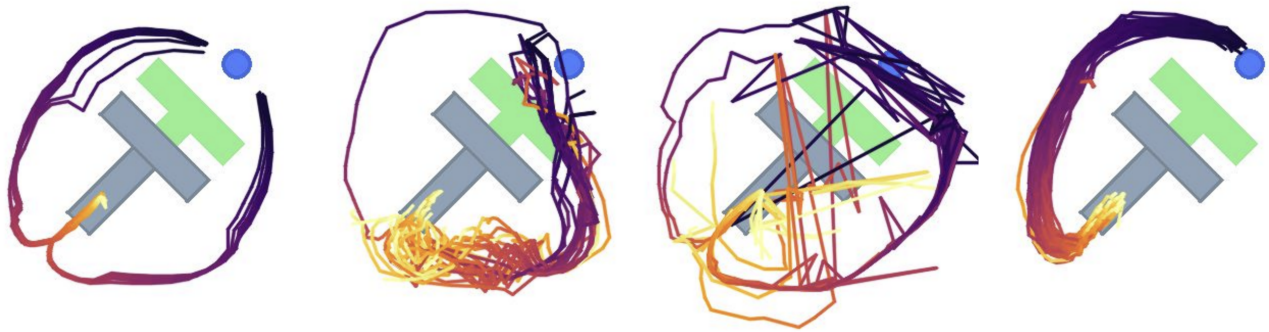
- action multimodality more pronounced in position-control
- position control suffers less from compounding errors than velocity control



Benefits of Action Prediction

Temporal Action Consistency: DDPM represents action in a high-dimensional action sequence overcoming:

1. **Temporal Action Consistency**: Alternate approach (BC-RNN / BET) represents actions as independent multimodal distributions leading to jittery actions
2. **Robustness to Idle Actions**: Single step policies overfit to pausing behavior (BC-RNN + IBC get stuck)



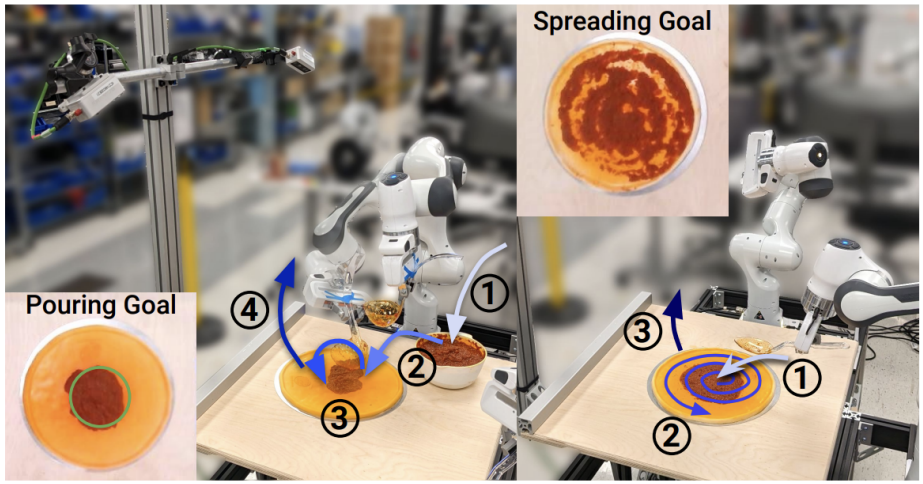
Outline

1. TLDR
2. Related Work
3. Background & Intuition
4. Diffusion for Visuomotor Policies
5. Diffusion Properties
6. Key Findings

Diffusion Policy Benefits

Diffusion policy ...

1. expresses short and long-horizon multimodality
2. better leverages position control
   - Baseline methods work better with velocity control
3. has a better action horizon tradeoff
   - Horizon > 1 help policy predict consistent actions
   - Compensate for idle portions
   - Optimal action horizon of 8 steps



	Pour		Spread	
	IoU	Succ	Coverage	Succ
Human	0.79	1.00	0.79	1.00
LSTM-GMM	0.06	0.00	0.27	0.00
Diffusion Policy	**0.74**	**0.79**	**0.77**	**1.00**

Thank you!

Have a great rest of your Day!!!