Learning from Visual Observation via Offline Pretrained State-to-Go Transformer

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Motivation

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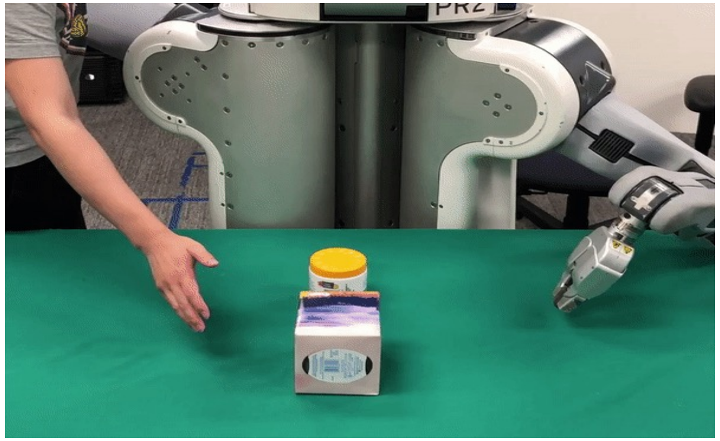
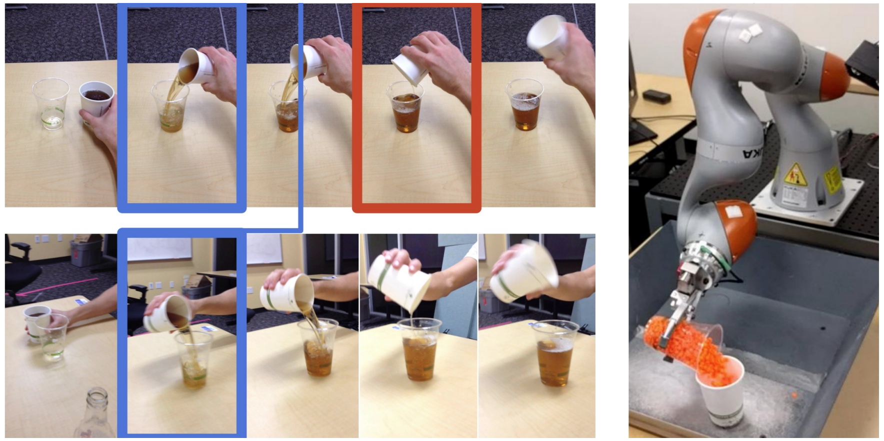


Learning from Demonstrations
(LfD)



Learning from Visual Observations
(LfVO)

+ Easy to learn
− Hard & expensive annotations
− Human-level upper bound

+ No actions or rewards
+ Intuitive like humans
+ An ocean of Internet videos
+ Explore unknown expert policy
− Hard to extract useful experience

From LfD to LfVO

- ✓ **Less Supervision**
- ✓ **Enlarging resource**
- ✓ **Biologically reasonable**

Previous work

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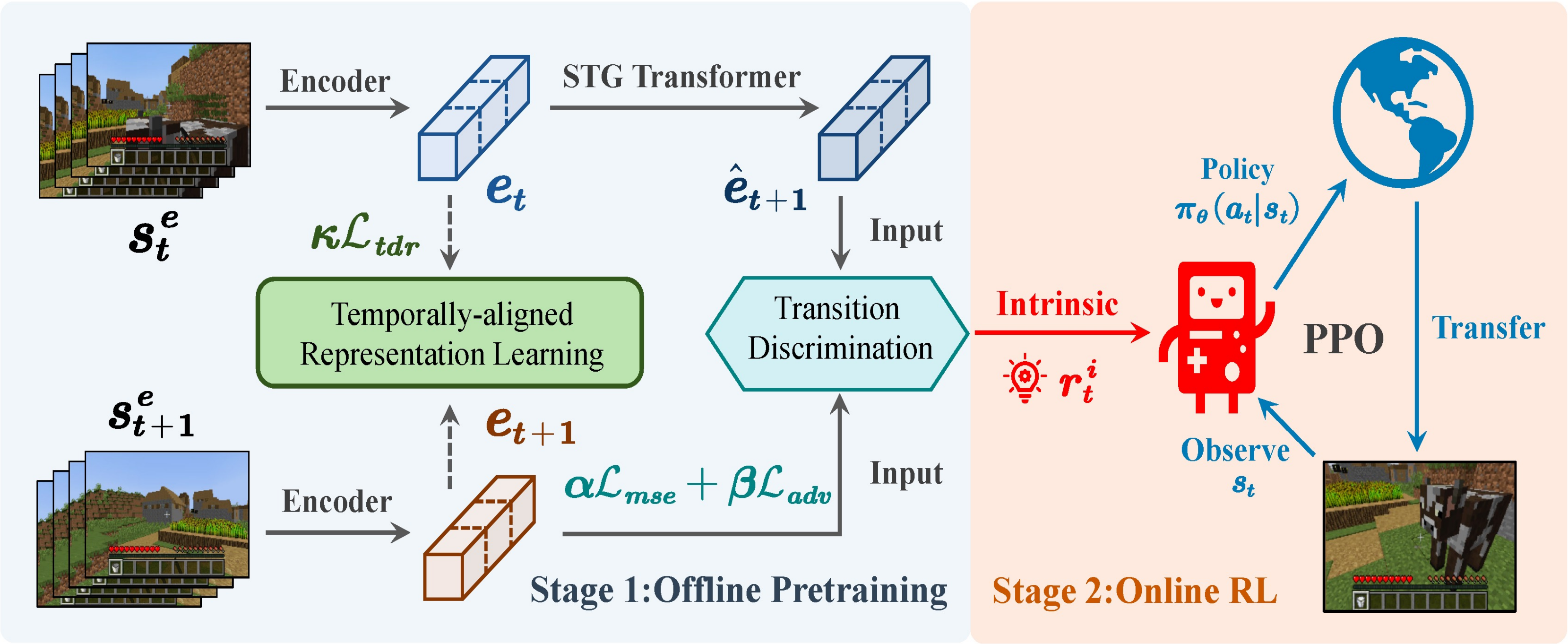
- **IDM-based methods – extra component, compounding error**
- **Adversarial methods – sample-inefficient online learning schemes**
- **Representation-learning-based methods – over-optimistic estimation**
- **Goal-oriented methods – extra task-specific information**

Abundant **video-only** data contain useful behavior patterns. How can we leverage them to effectively and efficiently tackle downstream **reward-free** visual control tasks?

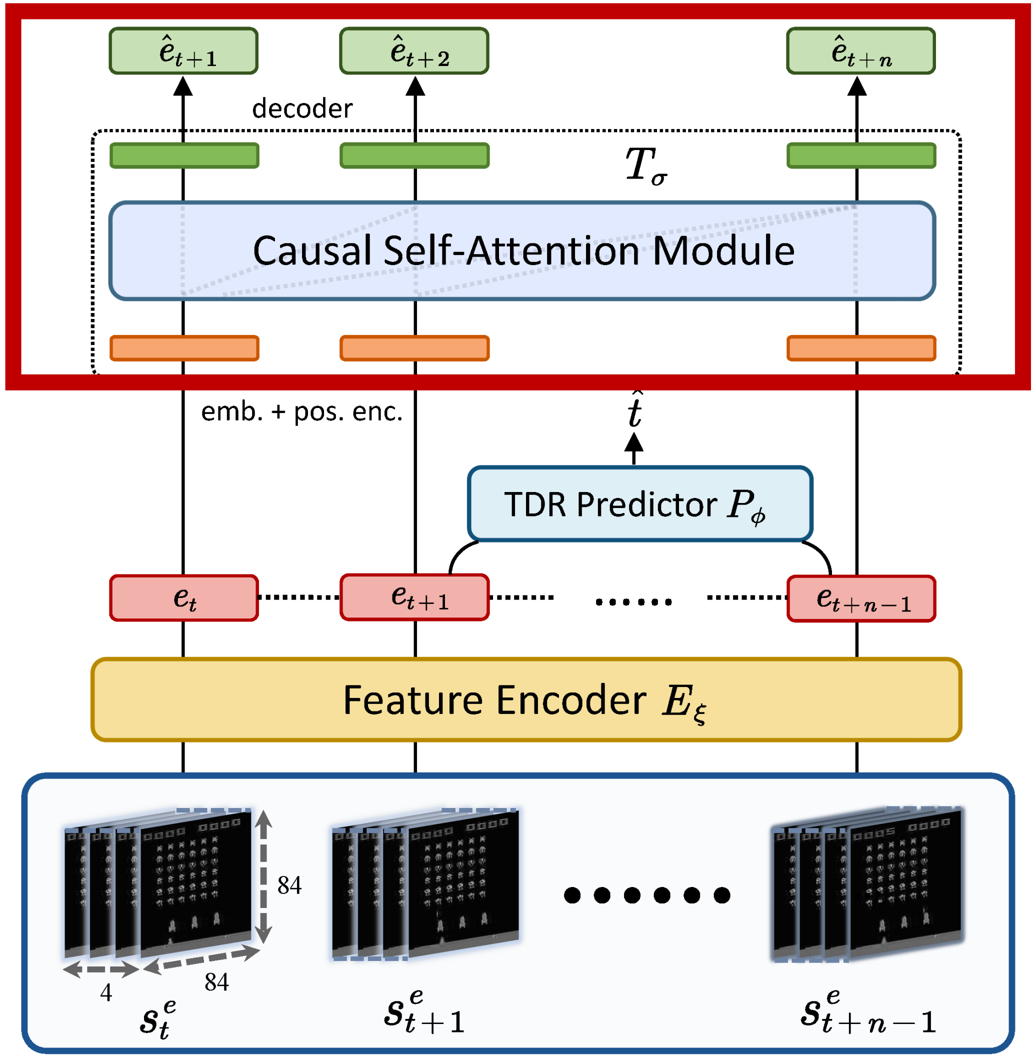
Starting Point!

Two-stage framework



- **Pretraining stage**: we simultaneously learn a **GPT** for latent transition prediction, an expert transition **discriminator** for intrinsic rewards and a temporal distance regressor (**TDR**) for temporally-aligned representations.
- **Reinforcecment learning stage**: agents **merely** learn from generated rewards from discriminator without environmental reward signals.

Offline Pretraining



1. Predicting Latent Transition

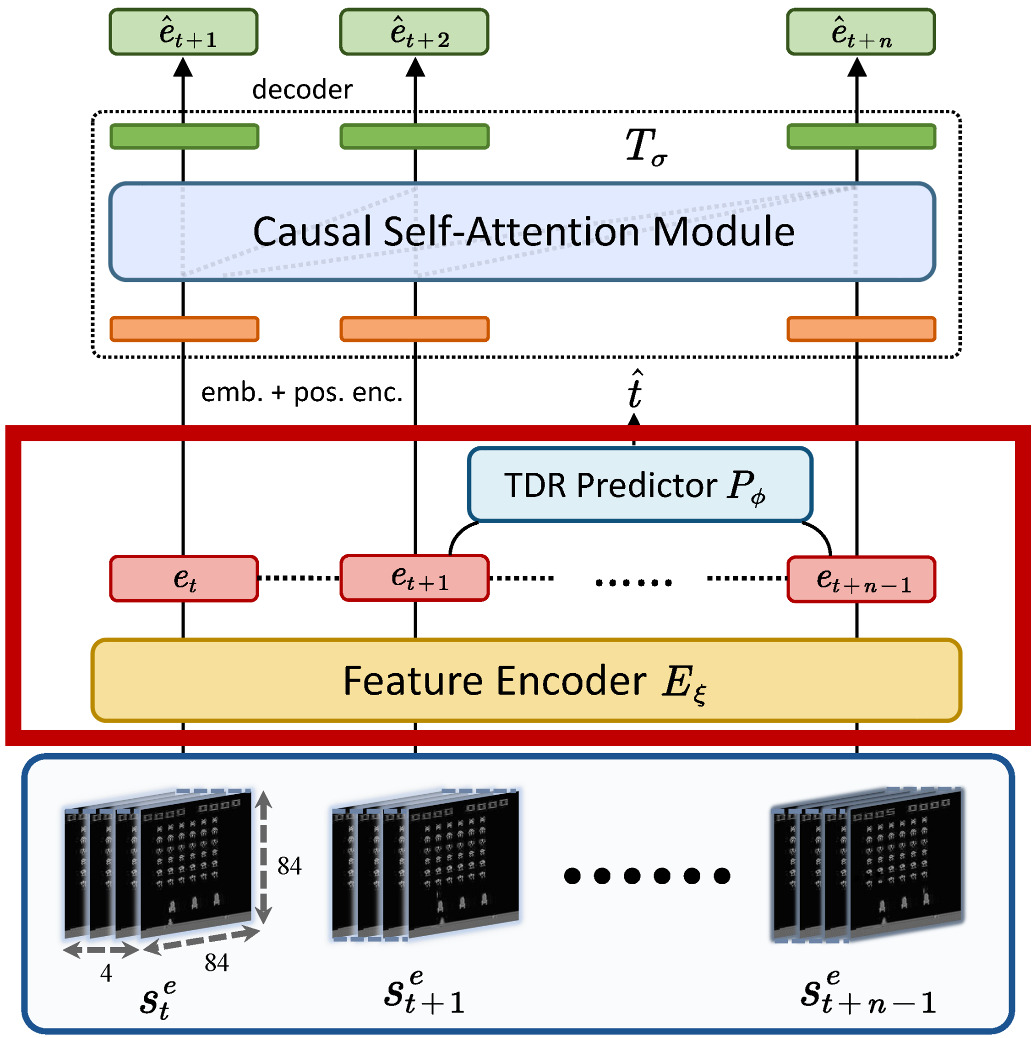
Adversarially learn transition module with L2 regularization as well as a WGAN discriminator

$$e_t = E_\xi(s_t),\ \hat{e}_{t+1} = T_\sigma(e_t)$$

$$\text{for } D_\omega:\ \min_{w\in\mathcal{W}} \mathbb{E}_{\mathcal{D}^e}\left[D_\omega(e_t,\hat{e}_{t+1}) - D_\omega(e_t,e_{t+1})\right]$$

$$\text{for } T_\sigma:\ \min_{\xi,\sigma} \mathbb{E}_{\mathcal{D}^e}\left[-D_\omega(e_t,\hat{e}_{t+1}) + \|\hat{e}_{t+1} - e_{t+1}\|_2^2\right]$$

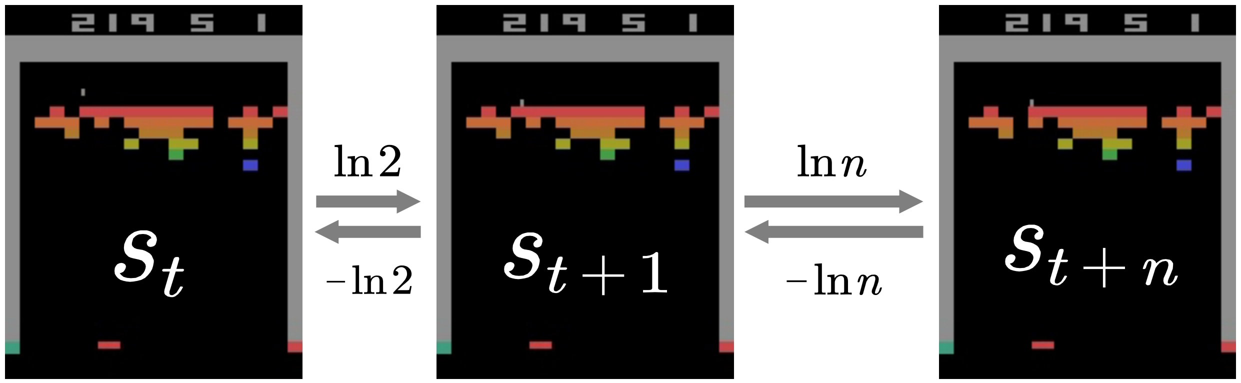
Offline Pretraining



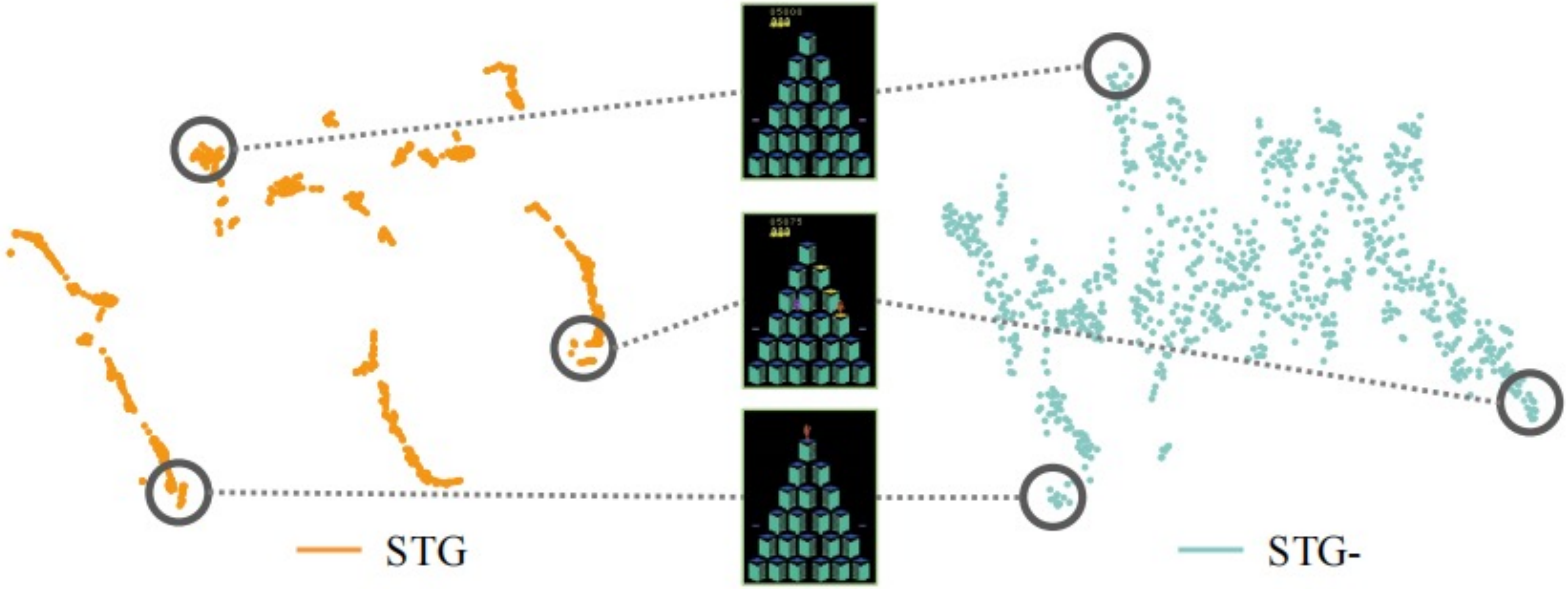
2. Learning Temporally-Aligned Representation

Apply symlog temporal distance prior in low-dimensional representation space

$$\min_{\xi,\phi} \mathbb{E}_{\mathcal{D}^e} \| P_\phi(e_t, e_{t+j}) - \mathrm{sign}(j)\ln(1+|j|) \|$$



TDR Representation



Sampled Atari Qbert Trajectory

Algo: STG Pretraining

Algorithm 1 STG Transformer Offline Pretraining

Input: STG Transformer T_σ, feature encoder E_ξ, discriminator D_ω, expert dataset $D^e = \{\tau^1, \tau^2, \ldots, \tau^m\}, \tau^i = \{s_1^i, s_2^i, \ldots\}$, buffer $\mathcal{B}$, loss weights α, β, κ .

Initialize parametric network $E_\xi, T_\sigma, D_\omega$ randomly.
for $e \leftarrow 0, 1, 2 \ldots$ **do** ▷ epoch
    Empty buffer $\mathcal{B}$.
    for $b \leftarrow 0, 1, 2 \ldots |\mathcal{B}|$ **do** ▷ batchsize
        Stochastically sample state sequence τ^i from D^e.
        Stochastically sample timestep t and n adjacent states $\{s_t^i, \ldots, s_{t+n-1}^i\}$ from τ^i.
        Store $\{s_t^i, \ldots, s_{t+n-1}^i\}$ in $\mathcal{B}$.
    end for
    Update D_ω: $\omega \leftarrow \text{clip}(\omega - \epsilon \nabla_\omega \mathcal{L}_{dis}, -0.01, 0.01)$.
    Update E_ξ and T_σ concurrently by minimizing total loss $\alpha \mathcal{L}_{mse} + \beta \mathcal{L}_{adv} + \kappa \mathcal{L}_{tdr}$.
end for

Algo: Online RL

Pretrained WGAN discriminator works as reward function:

$$r_t^i = -\left[D_\omega\Big(E_\xi\left(s_t\right), T_\sigma\left(E_\xi\left(s_t\right)\right)\Big) - D_\omega\Big(E_\xi\left(s_t\right), E_\xi\left(s_{t+1}\right)\Big) \right]$$

Algorithm 2 Online Reinforcement Learning with Intrinsic Rewards

Input: pretrained $E_\xi, T_\sigma, D_\omega$, policy π_θ, MDP $\mathcal{M}$, intrinsic coefficient η.

1: Initialize parametric policy π_θ with random θ randomly and reset $\mathcal{M}$.
2: **while** updating π_θ **do** ▷ policy improvement
3: Execute π_θ and store the resulting n state transitions $\{(s, s')\}_t^{t+n}$.
4: Use E_ξ to obtain n real latent transitions $\{(e, e')\}_t^{t+n}$.
5: Use T_σ to obtain n predicted latent transitions $\{(e, \hat{e}')\}_t^{t+n}$.
6: Use D_ω to calculate intrinsic rewards: $\Delta_t^{t+n} = \{D_\omega(e, \hat{e}')\}_t^{t+n} - \{D_\omega(e, e')\}_t^{t+n}$.
7: Perform PPO update to improve π_θ with respect to $r^i = -\eta\Delta$.
8: **end while**

Atari Experiments

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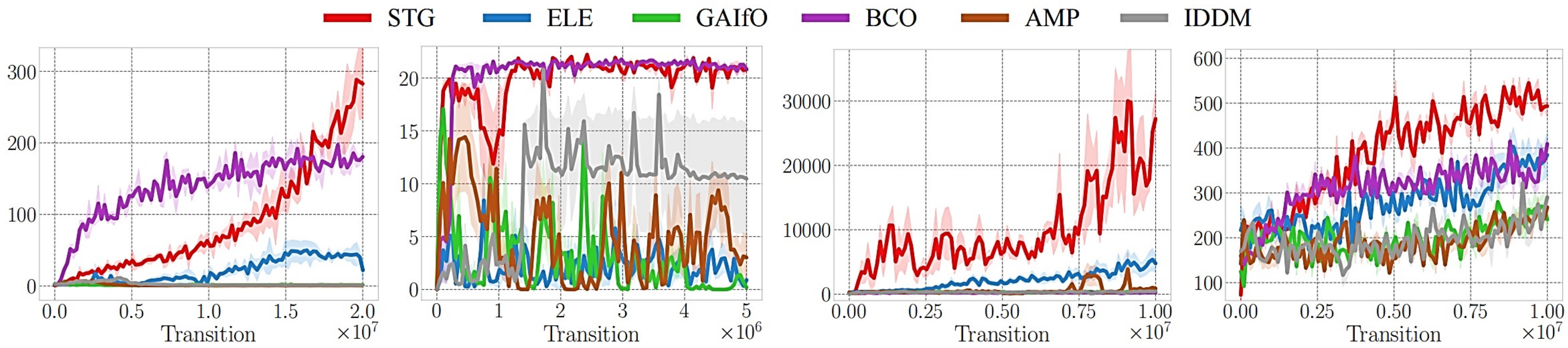


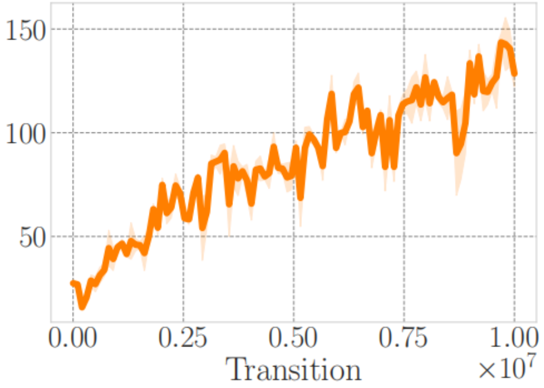
(a) Breakout **(b)** Freeway **(c)** Qbert **(d)** Space Invaders

Environment	**GAIfO**	**AMP**	**IDDM**	**ELE**	**BCO**	**STG**	**Expert**	**PPO**
Breakout	1.5	0.6	1.2	22.0	180.4	**288.8**	212.5	274.8
Freeway	0.6	3.0	10.5	2.7	21.6	21.8	31.9	32.5
Qbert	394.4	874.9	423.3	4698.6	234.1	**27234.1**	15620.7	14293.3
Space Invaders	260.2	268.1	290.4	384.6	402.2	502.1	1093.9	942.5

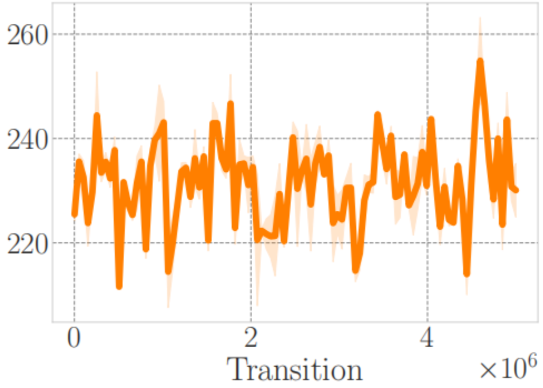
Learning from **50** trajectories for each task, STG demonstrates **superiority among baselines** and even **surpass expert level**.

Atari Visualization

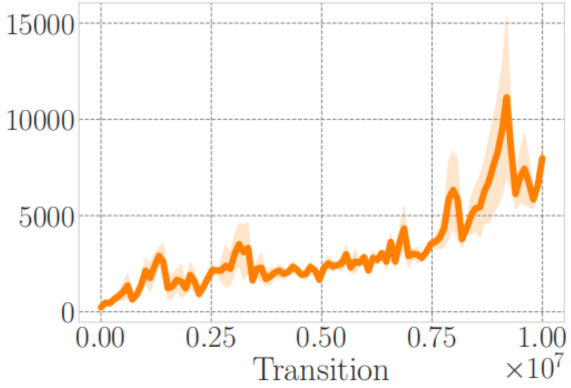
$$\mathbb{E}_{(s,s')\sim\tau^i}\mathrm{D}_f\left[\mu^\pi(s,s')\,\|\,\mu^e(s,s')\right]$$



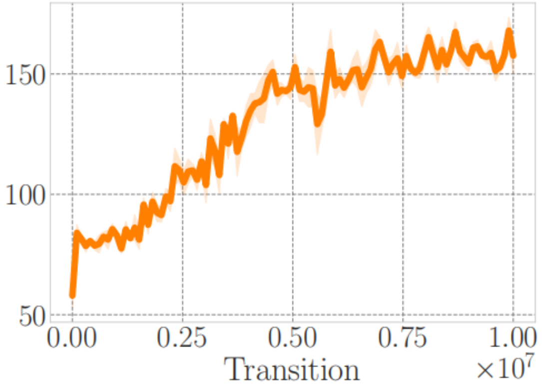
(a) Breakout



(b) Freeway



(c) Qbert



(d) Space Invaders

The rising trend of **intrinsic return** proves that online collected observation distribution is getting **closer** to expert observation distribution during training.

Minecraft Experiments

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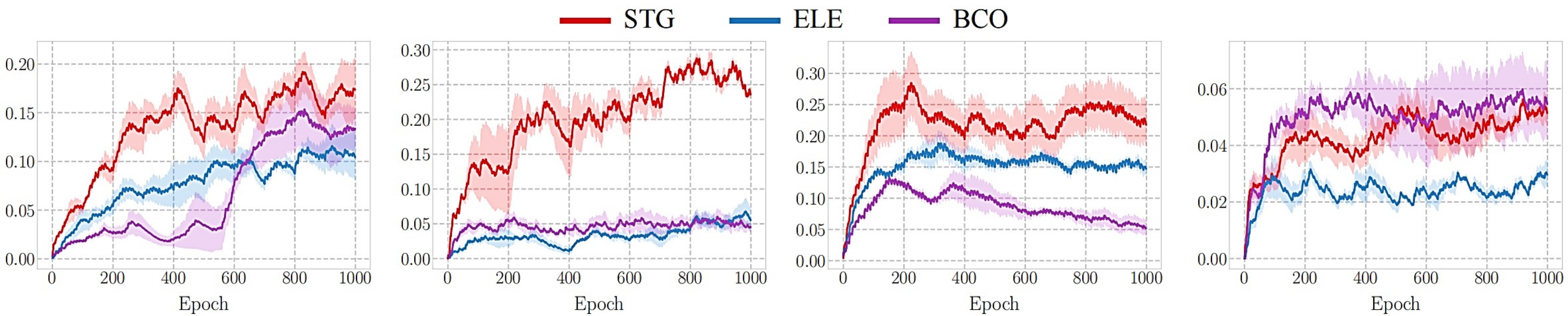
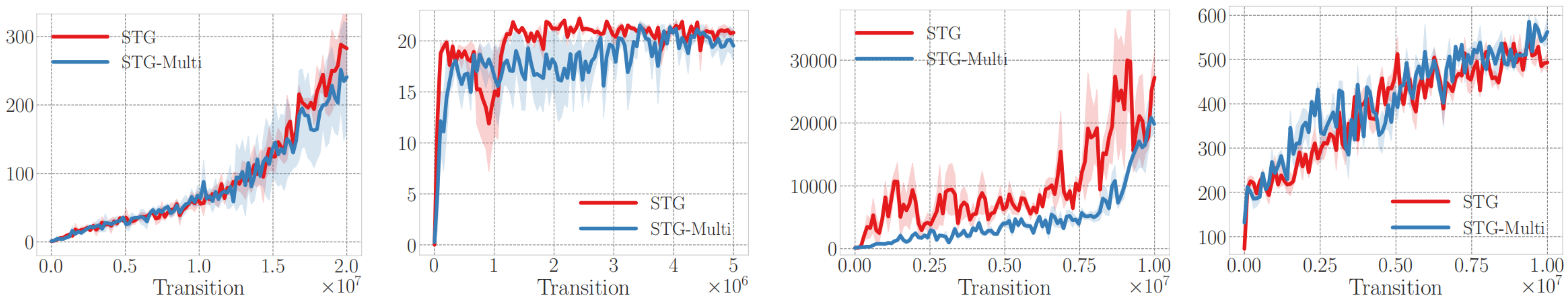


(a) Pick a flower **(b)** Milk a cow **(c)** Harvest tallgrass **(d)** Gather wool

In challenging **open-ended** Minecraft tasks,
STG shows superiority over baselines!

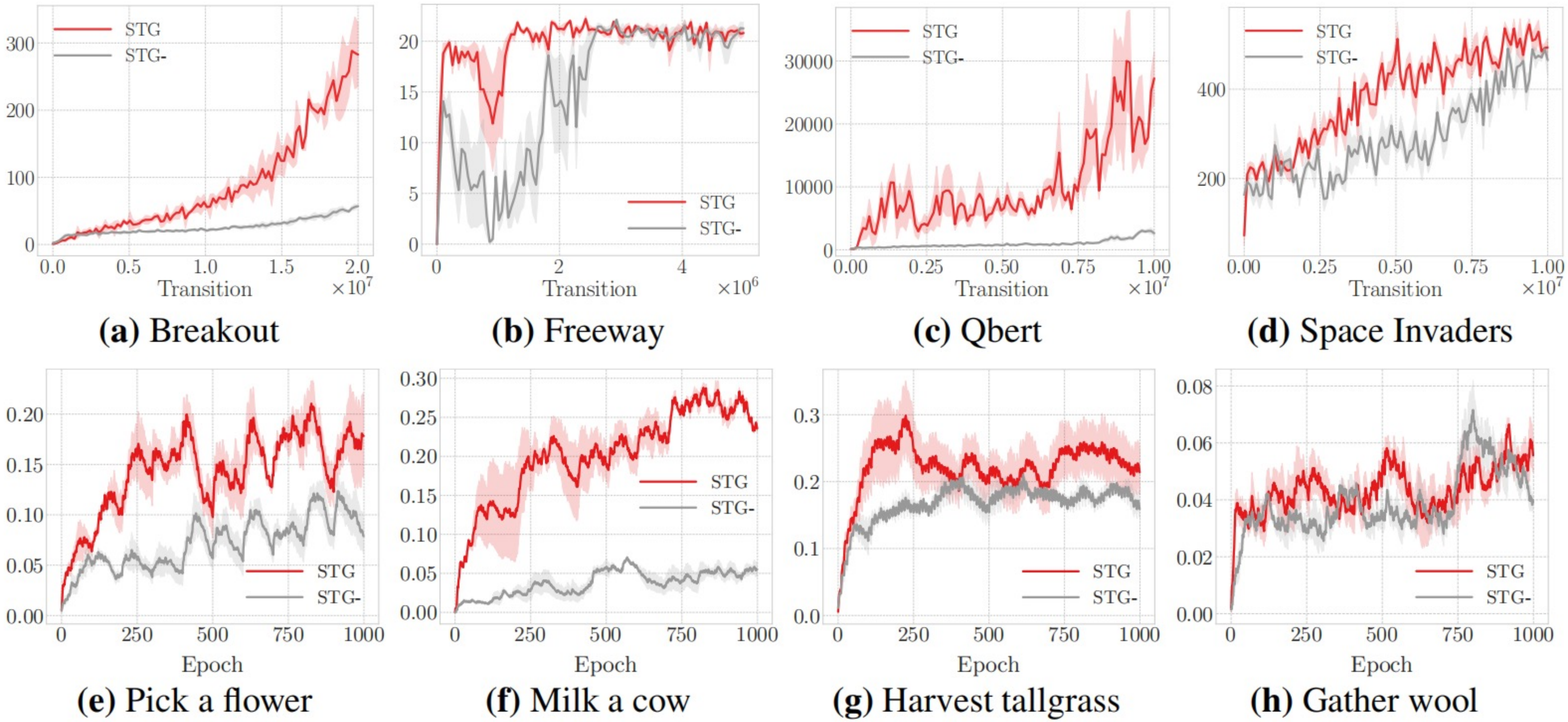
Multi-Task STG



(a) Breakout (b) Freeway (c) Qbert (d) Space Invaders

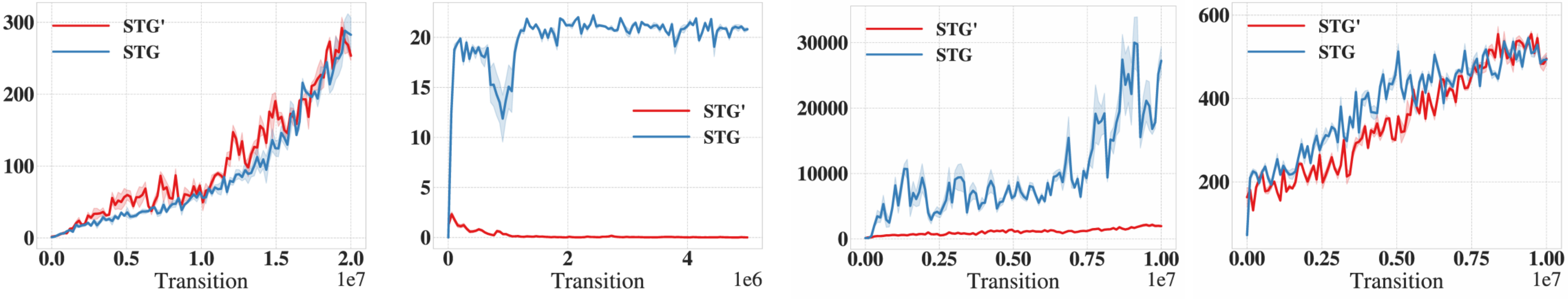
Pretrained on whole Atari datasets, STG-Multi shows comparable performance.

Ablation: TDR removal



Ablation: Reward design

$$r_t^i = D_\omega\left(E_\xi\left(s_t\right), E_\xi\left(s_{t+1}\right)\right) - D_\omega\left(E_\xi\left(s_t\right), T_\sigma\left(E_\xi\left(s_t\right)\right)\right) = r_t^{guide} - r_t^{base}$$



(a) Breakout (b) Freeway (c) Qbert (d) Space Invaders

Figure 4: Atari experiments comparing using r^{guide} (STG') and r^i (STG) as intrinsic reward.

Ablation: Reward design

$$\begin{cases} \text{discrimination reward: } D_\omega(e_t, e_{t+1}) - D_\omega(e_t, \hat{e}_{t+1}) \\ \text{progression reward: } P_\phi(e_t, e_{t+k}),\ k=1 \end{cases}$$

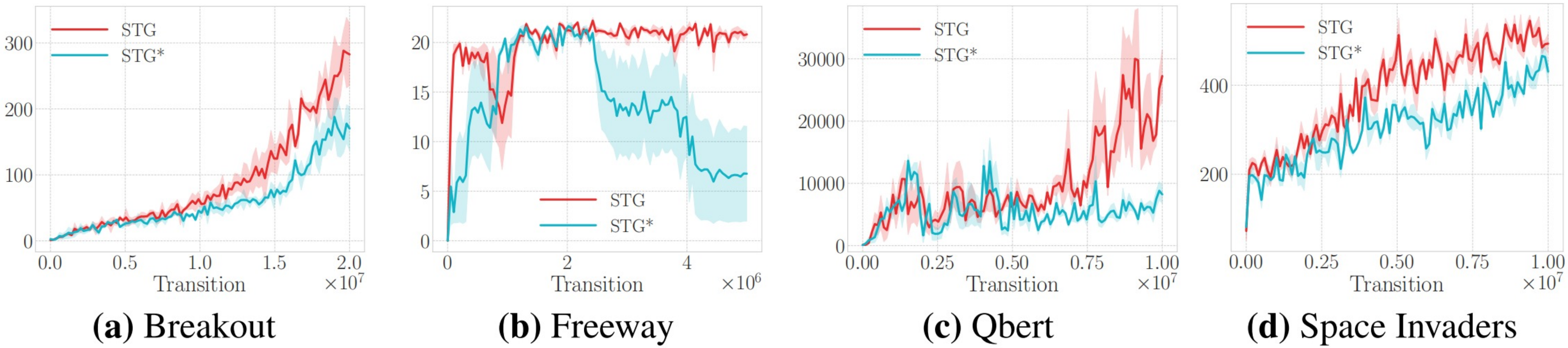


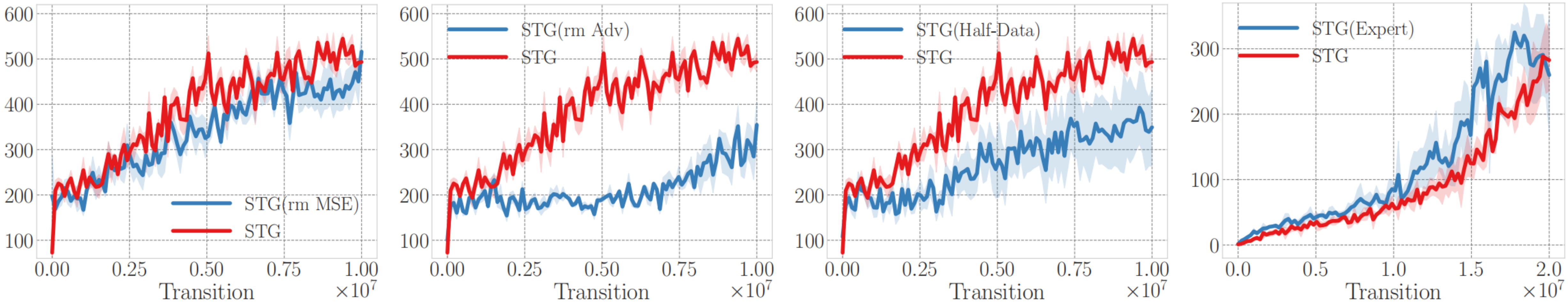
Figure 9: Atari experiments comparing using discriminative rewards (STG) and using both discriminative rewards and progression rewards (STG*).

Ablation : Loss and Dataset

$\alpha\mathcal{L}_{mse} + \beta\mathcal{L}_{adv} + \kappa\mathcal{L}_{tdr}$

25 trajectories

High-return trajectories



(a) Ablate removing $\mathcal{L}_{mse}$ **(b)** Ablate removing $\mathcal{L}_{adv}$ **(c)** Ablate dataset size **(d)** Ablate dataset quality

Figure 8: Learning curves of four pre-training ablations: (a) removing $\mathcal{L}_{mse}$ in SpaceInvaders; (b) removing $\mathcal{L}_{adv}$ in SpaceInvaders; (c) using half dataset to train STG in SpaceInvaders; (d) using expert dataset to train STG in Breakout.

Extensions

STG offers a pretraining solution in situations with **plentiful video demonstrations**, **limited environment interactions**, and **inaccessible labeled action or rewards**.

In future work, STG is likely to benefit from:

- More powerful **large-scale vision foundation** models to facilitate generalization across a broader range of related tasks, domains or embodiments.
- **Hierarchical framework** where one-step predicted rewards can be employed for training low-level policies and multi-step rewards for a high-level policy to tackle long-horizon tasks.

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Thanks

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