A Pseudocode

Algorithm 1 Subtask Decomposition and Virtual Training (SDVT)

Initialize Encoder q_ϕ, decoder p_θ, policy π_ψ, set of training tasks $\mathcal{M}_{\text{train}}$, virtual ratio p_v, GMVAE buffer $\mathcal{B}_{\text{VAE}}$, policy buffer $\mathcal{B}_{\text{pol}}$, total number of meta-episodes to train on n_{meta}, number of rollout episodes per meta-episode n_{roll}, running mean of subtask composition $\bar{y}$.

for meta-episode $k = 0, \ldots, n_{\text{meta}} - 1$ **do**
  Sample a training task $M_k \sim p(\mathcal{M}_{\text{train}})$
  Sample a virtual meta-episode flag $V \sim \text{Bernoulli}(p_v)$
  if $V = 1$ **then**
    Sample an imaginary subtask composition $\tilde{y} \sim \text{Dirichlet}(\bar{y})$
  end if
  Reset $h_0, y_0, \mathcal{B}_{\text{pol}}$
  for timestep $t = 0, \ldots, n_{\text{roll}} \times H - 1$ **do**
    if $t \mod H = 0$ **then**
      Reset rollout episode $s_t \sim T_{0,k}(\cdot)$
    end if
    Sample an action $a_t \sim \pi_\psi(\cdot|s_t, \mu_{\phi_z}(h_t, y_t), \sigma_{\phi_z}(h_t, y_t), \omega_{\phi_y}(h_t))$
    Take an environment step
      $s_{t+1} \sim T_k(\cdot|s_t, a_t)$
      $r_{t+1} \leftarrow R_k(s_t, a_t, s_{t+1})$
    if $V = 1$ **then**
      $\tilde{z}_t \sim \mathcal{N}(\mu_{\phi_z}(h_t, \tilde{y}), \sigma^2_{\phi_z}(h_t, \tilde{y}))$
      $\tilde{\hat{h}}_t = p_{\theta_{\hat{h}}}(\tilde{z}_t)$
      $\tilde{r}_{t+1} \sim p_{\theta_R}(\cdot|\text{DO}\left[s_t, a_t, s_{t+1}\right], \tilde{\hat{h}}_t)$
      Replace $r_{t+1} \leftarrow \tilde{r}_{t+1}$
    else
      Add the transition $(s_t, a_t, s_{t+1}, r_{t+1})$ to $\mathcal{B}_{\text{VAE}}$ $\cdots$ VAE NOT TRAINED WITH VIRTUAL DYNAMICS
    end if
    Add the transition $(s_t, a_t, s_{t+1}, r_{t+1})$ to $\mathcal{B}_{\text{pol}}$
    Update hidden embedding $h_{t+1} = q_{\phi_h}(\tau_{:t+1})$
    Update subtask composition $y_{t+1} \sim \text{Cat}\left(\omega_{\phi_y}(h_{t+1})\right)$
    Update the running mean of subtask composition $\bar{y} \leftarrow \text{RunningMeanUpdate}(\bar{y}, y_{t+1})$
  end for
  Update GMVAE $\{\phi, \theta\} \leftarrow \{\phi, \theta\} + \nabla_{\{\phi,\theta\}} \sum_{t=0}^{H^+} \text{ELBO}_t$ with samples from $\mathcal{B}_{\text{VAE}}$
  Update policy $\psi \leftarrow \psi + \nabla_\psi \mathcal{J}^+_{\text{pol}}$ with samples from $\mathcal{B}_{\text{pol}}$
  Anneal virtual ratio $p_v \leftarrow p_v + \Delta p_v$
end for

B ELBO Derivation

The GMVAE's ELBO objective is derived as follows.

$$
\begin{aligned}
\mathbb{E}_{d(M_k,\tau_{:H^+})}\left[\log p_\theta(\tau_{:H^+})\right] &= \mathbb{E}_{d(M_k,\tau_{:H^+})}\left[\log \mathbb{E}_{q_\phi(y_t,z_t|h_t)}\left[\frac{p_\theta(\tau_{:H^+}, y_t, z_t)}{q_\phi(y_t, z_t|h_t)}\right]\right] \\
&\geq \mathbb{E}_{d(M_k,\tau_{:H^+})}\left[\mathbb{E}_{q_\phi(y_t,z_t|h_t)}\left[\log \frac{p_\theta(\tau_{:H^+}, y_t, z_t)}{q_\phi(y_t, z_t|h_t)}\right]\right] \\
&= \mathbb{E}_{d(M_k,\tau_{:H^+})}\left[\mathbb{E}_{q_\phi(y_t,z_t|h_t)}\left[\log \frac{p_\theta(\tau_{:H^+}|y_t, z_t) p_\theta(z_t|y_t) p(y_t)}{q_\phi(y_t|h_t) q_\phi(z_t|h_t, y_t)}\right]\right] \\
&= \mathbb{E}_{d(M_k,\tau_{:H^+})}\left[\mathbb{E}_{q_\phi(y_t,z_t|h_t)}\left[\log p_\theta(\tau_{:H^+}|z_t) + \frac{p_\theta(z_t|y_t)}{q_\phi(z_t|h_t, y_t)} + \log \frac{p(y_t)}{q_\phi(y_t|h_t)}\right]\right].
\end{aligned}
\tag{8}
$$

Eq. (8) is equivalent to the ELBO objective in Eq. (3) without weighting coefficients. We assume that the reconstruction $\tau_{:H^+}$ is conditionally independent of the subtask composition y_t given z_t.

C Implementation Details

C.1 Reference Implementations

MAML, RL^2, and PEARL To replicate the results of MAML [12], RL^2 [8], and PEARL [44] as reported in the Meta-World paper [69], we utilize the exact version[2] of the Garage repository [14] without any modifications. For their hyperparameters, please refer to Appendix D.7, D.8, and D.9 of the Meta-World paper. MAML is the only baseline that has the advantage to take gradient updates during the test.

SDVT, SD, LDM, VariBAD Task-inference-based methods (SDVT, SD, LDM [33], and VariBAD [72]) are adapted to the Meta-World benchmark based on the VariBAD's implementation.[3] We begin with VariBAD's hyperparameter configuration for MuJoCo [56] Ant-goal and modify certain hyperparameters to accommodate the Meta-World benchmark (e.g., batch size, network capacity, etc.). In line with VariBAD and LDM, we train SDVT's policy using PPO [47]. The GMVAE is based on an implementation[4] that employs the Gumbel-Softmax reparameterization trick [22] when sampling the categorical subtask variable. The virtual training processes of SDVT and LDM require agent-environment interaction since they use states from the real environment. Therefore, the virtual training steps are also added when counting the total number of training steps. For a comprehensive list of SDVT hyperparameters, shared among SD, LDM, and VariBAD to ensure a fair comparison, please refer to Appendix C.3 and the supplementary material's source code.

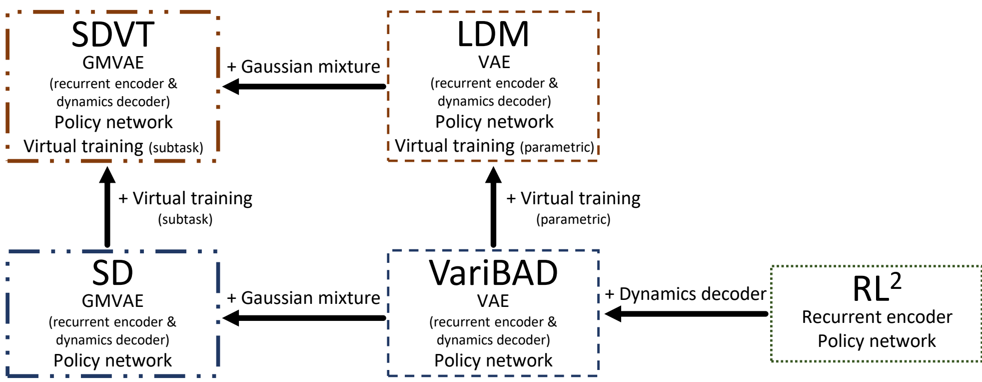


Figure 5: **Schematic overview of algorithms.** SDVT without a Gaussian mixture reduces to LDM, LDM without virtual training reduces to VariBAD, and VariBAD without a VAE decoder reduces to RL^2. MAML and PEARL use fully connected networks.

C.2 Computational Complexity

Table 2: **Computational complexity.** The total wall-clock time required to generate the results for the ML-10, averaged across all eight random seeds.

	SDVT	SDVT-LW	SD	SD-LW	RL^2	MAML	PEARL	VariBAD	LDM
Wall-clock time (hours)	142	140	138	135	192	17	258	126	131

Our experiments were conducted using an Nvidia TITAN Xp. Due to the considerably larger variety of tasks compared to standard meta-RL benchmarks, non-parametric benchmarks require significantly more computational resources and time. In Table 2, we detail the total wall-clock time expended by our methods and baselines during the training and evaluation of the ML-10 benchmark. This time includes the environmental interaction time for 250M training steps, roughly 100M steps dedicated to evaluations, and the time taken to train the neural networks. Despite incorporating the GMVAE and virtual training, our method's computational demand does not substantially surpass that of VariBAD.

[2]`https://github.com/rlworkgroup/garage/pull/2287`
[3]`https://github.com/lmzintgraf/varibad`
[4]`https://github.com/jariasf/GMVAE`

C.3 Hyperparameters

Table 3: **Hyperparameters of SDVT and SD.** Hyperparameters of SDVT used for Meta-World ML-10 and ML-45 along with the notations in the manuscript and the argument names in the source code. SD shares the same hyperparameters except without those of virtual training. Different hyperparameters of our lightweight variant are denoted as (-LW).

Category	Description	Notation	Value (ML-10, 45)	Argument Name
General	Rollout episode horizon	H	500	`max_episode_steps`
	Number of rollout episodes	n_{roll}	10	`max_rollouts_per_task`
	Discount factor	γ	0.99	`policy_gamma`
	Number of parallel processes		10	`num_processes`
	Total Environment Steps		$2.5e8, 4.0e8$	`num_frames`
GMVAE	Optimizer		Adam	`optimiser_vae`
	Learning rate		$1e-3$	`lr_vae`
	Subsample ELBO		100	`vae_subsample_elbos`
	Subsample decodes		100	`vae_subsample_decodes`
	Buffer size (meta-episodes)	$\lvert\mathcal{B}_{\text{VAE}}\rvert$	1000	`size_vae_buffer`
	ELBO categorical coefficient	α_c	1.0	`cat_loss_coeff`
	ELBO categorical coefficient (-LW)	α_c	0.5	`cat_loss_coeff`
	ELBO Gaussian coefficient	α_g	1.0	`gauss_loss_coeff`
	ELBO reward coefficient	α_R	10	`rew_loss_coeff`
	ELBO transition coefficient	α_T	1000	`state_loss_coeff`
	ELBO occupancy coefficient	α_o	1.0	`occ_loss_coeff`
	ELBO occupancy coefficient (-LW)	α_o	0	`occ_loss_coeff`
	Gumbel softmax temperature		1	`gumbel_temperature`
	Number of updates per epoch		$10, 20$	`num_vae_updates`
	Subtask dimension	$K = N_{\text{train}}$	$10, 45$	`vae_mixture_num`
	Subtask dimension (-LW)	K	5	`vae_mixture_num`
	Gaussian dimension	$\dim(z)$	$5, 10$	`latent_dim`
	Dropout rate	p_{drop}	0.7	`dropout_rate`
	Reward reconstruction objective		MSE	`rew_pred_type`
	State reconstruction objective		MSE	`state_pred_type`
Policy	Algorithm		PPO	`policy`
	Optimiser		Adam	`policy_optimiser`
	Learning rate		$7e-4$	`lr_policy`
	Optimizer epsilon		$10e-8$	`policy_eps`
	PPO update epochs		5	`ppo_num_epochs`
	Steps per policy update	$\frac{\lvert\mathcal{B}_{\text{pol}}\rvert}{\texttt{num\_processes}}$	5000	`policy_num_steps`
	Number of minibatches		10	`ppo_num_minibatch`
	PPO clipping parameter		0.1	`ppo_clip_param`
	GAE λ		0.9	`policy_tau`
	Initial standard deviation		1.0	`policy_init_std`
	Minimum standard deviation		0.5	`policy_min_std`
	Maximum standard deviation		1.5	`policy_max_std`
	Entropy coefficient		$1e-3$	`policy_entropy_coef`
Virtual training	Initial virtual ratio		0.0	`virtual_ratio`
	Virtual ratio increment per step	Δp_v	$5e-8, 2.5e-8$	`virtual_ratio_increment`
	ELBO dispersion coefficient	α_d	10	`ext_loss_coeff`

Table 4: **Hyperparameters of VariBAD and LDM.** VariBAD and LDM employ identical hyperparameters for the general and policy categories of SDVT and SD, as shown in Table 3. The sole distinction lies in the structural variation resulting from the utilization of GMVAE and VAE. We choose the Gaussian dimension that yielded the most favorable outcomes among 5, 10, 15, and 20.

Category	Description	Notation	Value (ML-10, 45)	Argument Name
VAE	Optimizer		Adam	`optimiser_vae`
	Learning rate		$1e-3$	`lr_vae`
	Subsample ELBO		100	`vae_subsample_elbos`
	Subsample decodes		100	`vae_subsample_decodes`
	Buffer size (meta-episodes)	$\lvert\mathcal{B}_{\text{VAE}}\rvert$	1000	`size_vae_buffer`
	ELBO KL coefficient		0.1	`kl_weight`
	ELBO reward coefficient	α_R	10	`rew_loss_coeff`
	ELBO transition coefficient	α_T	1000	`state_loss_coeff`
	Number of updates per epoch		$10, 20$	`num_vae_updates`
	Gaussian dimension	$\dim(z)$	$5, 10$	`latent_dim`
	Dropout rate (VariBAD)	p_{drop}	0.0	`dropout_rate`
	Dropout rate (LDM)	p_{drop}	0.7	`dropout_rate`
	Reward reconstruction objective		MSE	`rew_pred_type`
	State reconstruction objective		MSE	`state_pred_type`

C.4 Network Architecture

The network architectures comprising our method are described in Table 5. Prior to being input into the encoder or decoder, all state, action, and reward inputs pass through embedding networks. The values of $K = \dim(y)$ and $\dim(z)$ differ for the ML-10 and ML-45, as indicated in Table 3.

Table 5: **Network architecture.** Details of the network architecture composing the GMVAE. The numbers in the Layers column represent the dimension of the hidden layers and the output.

Network	Notation	Architecture	Layers	Activations (last layer)
State embedding		MLP	[32]	(Tanh)
Reward embedding		MLP	[16]	(Tanh)
Action embedding		MLP	[16]	(Tanh)
Recurrent encoder	q_{ϕ_h}	GRU	[256]	(None)
Categorical parameter	ω_{ϕ_y}	MLP	$[512, 512, K]$	ReLU (Softmax)
Gaussian parameters	$\mu_{\phi_z}, \sigma^2_{\phi_z}$	MLP	$[512, 512, \dim(z)]$	ReLU (None, SoftPlus)
Gaussian regularization parameters	$\mu_{\theta_z}, \sigma^2_{\theta_z}$	MLP	$[\dim(z)]$	(None, SoftPlus)
Latent context dispersion	$p_{\theta_{\hat{h}}}$	MLP	$[256, 256, 256]$	ReLU (None)
Reward decoder	p_{θ_R}	MLP	$[64, 64, 32, 1]$	ReLU (None)
Transition decoder	p_{θ_T}	MLP	$[64, 64, 32, 40]$	ReLU (None)
Policy	π_ψ	MLP	$[256, 256, 4]$	Tanh (Tanh)

C.5 Aggregation method for the Success Rate

The main results in the Meta-World paper (Table 1 and Figure 6 of Yu et al. [69]) present the average of the *maximum* success rate for each task, diverging from the raw scores in their Figure 17 and 18. For instance, if an agent achieves a 90% success rate on "Door-close" in one evaluation during training and scores 10% in all other evaluations at different times, the reported success rate for "Door-close" is 90%. The mean of these maximum scores across tasks is reported as the aggregated success rate.

This unconventional aggregation method does not accurately represent the meta-RL objective, which aims to train a single agent capable of solving multiple tasks. Meta-World calculates success rates for various tasks at distinct time points during training, even though the agent might specialize in different tasks at various stages. As a result, the agent may excel at specific tasks by chance. Consequently, evaluating the agent more frequently could yield higher *maximum* scores. We report the conventional final performance, which better reflects the meta-RL objective.

D Detailed Experimental Results

D.1 Performance on Individual Tasks

Table 6: **Meta-World V2 ML-10 success rate.** We report the final success rates (%) of baselines and our methods for training tasks and test tasks of the Meta-World ML-10 benchmark. All results are reported as the mean success rate $\pm$ 95% confidence interval of 8 seeds at 250M steps.

Index. Task	SDVT	SDVT-LW	SD	SD-LW	RL^2	MAML	PEARL	VariBAD	LDM
1. Reach	50.0±11.0	22.0±3.5	53.8±11.5	56.2±9.1	27.5±19.8	50.0±34.6	**70.0±11.9**	28.5±5.0	28.5±4.1
2. Push	57.5±18.6	25.2±16.5	61.2±7.3	**68.8±10.6**	60.0±13.0	0.0±0.0	0.0±0.0	25.8±12.9	25.5±12.8
3. Pick-place	47.5±9.6	39.0±5.4	52.5±7.6	**55.0±13.9**	42.5±21.0	0.0±0.0	0.0±0.0	24.8±13.3	27.2±13.3
4. Door-open	**100.0±0.0**	60.5±31.9	**100.0±0.0**	63.8±32.5	93.8±9.1	79.5±22.1	10.2±11.9	86.8±22.7	62.5±33.5
5. Drawer-close	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	98.8±2.3	99.5±1.1	86.8±5.6	**100.0±0.0**	**100.0±0.0**
6. Button-press	98.8±2.3	98.8±1.8	96.2±6.9	**100.0±0.0**	87.5±8.3	93.0±8.3	46.0±11.2	98.5±0.9	99.5±0.9
7. Peg-insert-side	31.2±13.2	24.5±10.2	**50.0±19.9**	36.2±11.5	45.0±21.6	0.0±0.0	0.0±0.0	19.8±14.0	21.8±15.3
8. Window-open	**100.0±0.0**	**100.0±0.0**	98.8±2.3	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	19.2±11.5	**100.0±0.0**	**100.0±0.0**
9. Sweep	**96.2±4.8**	72.2±29.0	83.8±22.2	83.8±15.1	75.0±17.3	0.0±0.0	0.0±0.0	60.2±32.4	61.2±32.9
10. Basketball	**91.2±6.4**	78.8±9.8	73.8±14.3	91.2±8.8	43.8±16.6	0.0±0.0	0.0±0.0	37.2±26.0	40.5±28.9
Train mean	**77.2±3.0**	62.1±4.1	77.0±5.9	75.5±5.5	67.4±4.4	42.2±4.5	23.2±1.9	58.2±8.9	56.7±12.3
11. Drawer-open	**65.0±19.9**	30.5±12.9	48.8±23.4	45.0±24.0	2.2±1.9	15.8±19.3	1.5±1.1	12.8±12.8	21.8±12.0
12. Door-close	7.5±9.0	**81.2±19.0**	33.8±25.4	18.8±24.1	8.2±7.3	3.2±6.0	1.2±1.5	27.0±21.8	30.2±28.2
13. Shelf-place	0.0±0.0	**1.0±1.2**	0.0±0.0	0.0±0.0	0.2±0.2	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
14. Sweep-into	**90.0±8.5**	51.2±18.9	71.2±14.9	55.0±21.6	64.5±8.3	0.0±0.0	0.8±1.0	30.5±22.0	46.5±21.8
15. Lever-pull	1.2±2.3	3.2±2.7	0.0±0.0	**12.5±10.2**	0.5±0.8	0.5±0.9	0.5±0.9	0.2±0.5	0.5±0.9
Test mean	32.8±3.9	**33.4±5.0**	30.8±7.7	26.2±8.7	15.1±2.7	3.9±3.7	0.8±0.5	14.1±6.1	19.8±6.0

Table 7: **Meta-World V2 ML-10 return.** We report the final return of baselines and our methods at the last rollout episode on the Meta-World ML-10 analogous to the success rate in Table 6. Results are reported as the mean $\pm$ 95% confidence intervals of 8 seeds at 250M steps.

Index. Task	SDVT	SDVT-LW	SD	SD-LW	RL^2	MAML	PEARL	VariBAD	LDM
1. Reach	3565±132	3681±115	3708±228	3806±220	2291±276	**3899±560**	3841±554	3829±153	3740±59
2. Push	**3923±339**	3493±469	3636±628	3579±870	815±133	17±1	15±2	2609±990	2470±1220
3. Pick-place	**2257±239**	2241±300	2131±441	2156±593	501±137	6±0	5±1	1395±759	1561±861
4. Door-open	4441±37	3171±825	**4447±106**	3530±831	1249±115	3561±753	1064±254	4051±780	3249±1134
5. Drawer-close	4813±71	4850±10	4850±13	**4854±9**	2193±336	4804±55	4081±314	4841±18	4837±18
6. Button-press	3392±59	**3437±133**	3257±265	3423±209	1189±151	2574±274	956±300	3246±161	3252±140
7. Peg-insert-side	1903±430	1919±348	**2634±588**	2225±592	682±157	7±0	7±1	1148±761	1237±825
8. Window-open	**4486±39**	4371±77	4349±165	4398±79	1230±112	3271±732	784±390	4483±32	4458±42
9. Sweep	**4235±202**	3617±682	3823±702	3557±634	906±223	79±38	51±14	2807±1260	2789±1333
10. Basketball	3549±292	**3759±307**	3466±511	3726±331	532±116	7±1	6±2	2141±1119	2035±1256
Train mean	**3656±62**	3454±137	3630±241	3525±297	1159±83	1822±136	1081±77	3055±466	2963±626
11. Drawer-open	**2558±165**	2280±271	2305±298	2310±280	1649±100	1737±270	1130±87	2336±340	2389±386
12. Door-close	566±335	**3030±857**	1068±740	638±670	568±137	263±278	321±221	1121±689	1343±1214
13. Shelf-place	501±77	550±138	494±102	434±154	**578±70**	0±0	0±0	211±144	328±204
14. Sweep-into	**2221±764**	1455±615	1359±632	1532±721	490±46	41±3	48±33	658±358	1509±889
15. Lever-pull	279±38	318±45	**335±45**	300±48	291±66	156±49	200±58	271±26	260±48
Test mean	1225±160	**1527±214**	1112±190	1043±234	715±33	439±78	340±54	919±143	1166±264

Table 8: **Meta-World V2 ML-45 success rate.** We report the final success rates (%) of baselines and our methods for training tasks and test tasks of the Meta-World ML-45 benchmark. All results are reported as the mean success rate ± 95% confidence interval of 8 seeds at 400M steps.

Index. Task	SDVT	SDVT-LW	SD	SD-LW	RL^2	MAML	PEARL	VariBAD	LDM
1. Assembly	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	**2.2±0.4**	0.0±0.0	0.0±0.1	0.0±0.0	0.0±0.0
2. Basketball	**24.8±17.7**	3.0±3.6	23.8±19.2	24.2±13.6	21.0±9.8	0.0±0.0	0.0±0.0	19.8±13.7	10.2±8.9
3. Button-press -topdown	95.0±7.6	94.5±0.6	**100.0±0.0**	98.0±1.7	98.8±1.0	78.2±21.2	7.5±8.6	99.5±0.6	82.5±18.7
4. Button-press -topdown-wall	94.0±7.9	96.5±0.6	99.0±1.4	99.5±0.6	98.5±1.5	78.2±21.6	9.5±10.6	**99.8±0.5**	86.2±15.6
5. Button-press	93.2±3.3	96.5±0.6	89.0±8.1	**99.0±0.7**	84.2±3.2	95.5±1.9	26.8±11.3	98.0±1.0	93.5±8.0
6. Button-press -wall	**86.0±11.6**	68.0±4.0	80.5±8.7	75.5±9.4	67.0±4.8	71.2±10.6	20.2±8.3	74.5±8.3	56.0±11.3
7. Coffee-button	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	97.5±2.3	97.5±1.6	92.0±4.9	2.8±1.3	78.0±14.7	**100.0±0.0**
8. Coffee-pull	37.2±19.1	33.2±12.2	45.5±23.4	46.5±22.0	**65.0±4.3**	0.5±0.3	0.0±0.1	52.5±10.5	48.8±12.9
9. Coffee-push	64.8±6.5	37.0±15.8	56.8±2.7	67.8±12.6	60.8±9.0	22.0±10.6	3.0±2.4	76.5±10.8	**81.8±5.8**
10. Dial-turn	**87.2±4.4**	86.2±2.9	82.8±7.9	67.2±11.9	14.5±8.3	81.2±8.8	9.8±7.7	44.0±13.9	60.8±5.9
11. Disassemble	59.5±32.0	32.0±14.7	**87.8±6.2**	74.0±10.9	23.2±27.1	0.0±0.1	0.2±0.2	44.5±21.8	65.5±18.5
12. Door-close	**100.0±0.0**	**100.0±0.0**	99.5±0.6	97.0±3.6	98.2±1.2	**100.0±0.0**	52.2±21.2	**100.0±0.0**	99.2±1.0
13. Door-open	56.2±31.2	56.0±24.3	**99.8±0.5**	64.8±26.9	54.0±23.8	6.8±11.9	0.5±0.3	98.0±1.4	96.2±3.6
14. Drawer-close	**100.0±0.0**	99.0±1.2	97.2±2.2	**100.0±0.0**	98.5±0.5	100.0±0.1	96.5±2.9	99.2±0.7	96.5±4.0
15. Drawer-open	96.5±1.1	83.8±16.3	96.0±4.8	87.2±13.8	83.5±8.4	0.0±0.0	2.5±1.3	**100.0±0.0**	93.2±6.6
16. Faucet-open	99.5±0.6	82.5±21.0	99.2±1.0	**100.0±0.0**	86.8±9.7	70.5±19.1	28.8±11.7	95.5±1.7	98.2±1.5
17. Faucet-close	97.0±5.5	77.0±18.3	99.2±0.7	97.0±2.3	56.8±16.8	52.8±22.5	15.0±6.3	**99.5±0.6**	99.2±1.0
18. Hammer	2.0±3.7	0.0±0.0	0.0±0.0	1.5±1.8	**12.8±15.4**	6.8±5.8	2.2±1.3	0.0±0.0	0.0±0.0
19. Handle-press -side	97.8±4.1	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	99.8±0.1	83.2±12.2	12.8±11.8	**100.0±0.0**	99.8±0.5
20. Handle-press	98.5±1.1	99.0±1.2	**100.0±0.0**	**100.0±0.0**	99.8±0.1	72.0±20.2	66.8±19.8	**100.0±0.0**	**100.0±0.0**
21. Handle-pull -side	40.0±22.3	5.2±5.2	50.5±25.2	39.5±24.1	**83.2±4.3**	13.8±15.5	0.8±0.7	41.2±23.3	31.8±28.5
22. Handle-pull	0.0±0.0	1.0±1.2	35.2±31.5	3.8±2.6	0.2±0.2	**49.0±18.9**	0.8±0.4	1.0±0.7	1.0±1.0
23. Lever-pull	10.0±9.8	16.0±4.4	11.5±6.8	**23.2±16.6**	1.0±0.8	3.2±3.9	0.0±0.0	20.0±11.3	6.0±3.9
24. Peg-insert -side	1.0±0.7	0.0±0.0	0.8±0.7	0.5±0.6	**19.5±5.8**	0.0±0.0	0.0±0.0	0.0±0.0	2.2±2.7
25. Pick-place -wall	30.0±16.7	29.5±9.8	**48.5±3.7**	41.2±11.7	42.5±4.0	6.5±6.0	0.0±0.0	35.5±4.6	31.2±15.9
26. Pick-out -of-hole	26.8±16.4	23.2±12.0	**53.0±7.0**	43.8±8.4	5.5±2.7	0.0±0.0	0.0±0.0	32.0±20.8	34.0±11.4
27. Reach	31.5±6.7	13.5±4.0	36.0±8.7	25.5±6.7	**45.8±8.4**	18.8±10.6	13.5±7.2	27.0±4.7	28.5±3.2
28. Push-back	40.8±21.3	31.0±11.9	76.0±5.3	44.5±9.3	**77.8±4.6**	0.0±0.0	0.0±0.0	41.5±24.1	49.5±10.5
29. Push	50.5±5.7	**62.8±5.1**	36.2±14.3	29.2±18.3	58.5±1.6	16.8±14.9	1.8±1.4	45.0±9.5	35.2±11.7
30. Pick-place	28.2±13.5	26.2±6.5	**57.5±9.1**	36.8±3.9	43.5±1.8	4.8±5.3	0.0±0.0	34.8±3.9	44.0±5.2
31. Plate-slide	**75.8±5.7**	56.5±6.9	58.2±10.8	60.2±10.4	20.5±14.4	17.0±15.2	9.5±10.6	55.2±6.8	57.0±7.3
32. Plate-slide -side	81.8±0.8	1.0±0.7	**97.0±3.6**	87.0±3.2	70.8±5.1	2.0±3.6	0.2±0.3	89.5±13.6	59.5±24.2
33. Plate-slide -back	82.0±6.2	86.0±9.7	83.5±4.2	76.5±10.8	**90.0±3.9**	0.0±0.0	0.8±0.8	84.0±6.1	80.2±7.9
34. Plate-slide -back-side	71.8±5.6	59.0±4.5	60.8±11.2	73.5±10.8	**81.5±1.9**	5.5±5.7	0.5±0.6	73.5±2.4	80.8±8.0
35. Peg-unplug -side	40.0±17.2	50.8±12.0	54.0±5.1	47.8±17.8	54.0±3.7	13.0±3.4	3.5±2.1	**60.5±5.8**	48.8±9.1
36. Soccer	29.8±7.2	25.5±8.8	16.0±2.7	24.5±16.9	**37.8±4.7**	14.5±12.7	2.5±1.8	20.2±5.4	15.2±2.5
37. Stick-push	0.0±0.0	47.5±32.9	0.0±0.0	20.5±24.6	**88.2±3.4**	0.0±0.1	0.0±0.0	0.0±0.0	0.0±0.0
38. Stick-pull	0.0±0.0	**15.0±10.4**	0.0±0.0	12.0±14.4	4.5±3.6	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
39. Push-wall	51.0±4.9	50.0±25.4	62.8±21.7	27.5±20.8	**72.5±5.4**	18.2±16.5	0.2±0.2	63.8±15.7	44.0±20.5
40. Reach-wall	16.2±5.9	7.0±4.9	27.0±8.1	28.0±7.3	**65.0±5.6**	35.2±20.2	15.0±6.9	18.0±3.6	13.8±9.1
41. Shelf-place	0.0±0.0	0.5±0.6	0.8±0.7	0.0±0.0	3.8±2.9	0.0±0.0	0.0±0.0	**4.5±4.6**	0.8±1.0
42. Sweep-into	92.8±3.2	91.0±2.9	90.5±5.8	90.2±8.6	87.5±1.5	23.8±21.3	4.8±3.2	97.8±2.6	**98.5±1.3**
43. Sweep	11.8±10.1	27.0±17.4	33.0±17.7	20.0±23.2	**41.5±21.1**	0.0±0.0	0.0±0.0	40.5±28.1	5.5±6.5
44. Window-open	99.5±0.6	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	97.8±1.0	91.5±6.6	27.5±11.4	98.2±1.6	98.8±2.3
45. Window-close	**100.0±0.0**	99.0±1.2	**100.0±0.0**	**100.0±0.0**	95.2±3.3	97.0±1.9	27.2±11.0	**100.0±0.0**	99.8±0.5
Train mean	55.6±4.2	50.4±4.1	**61.0±1.7**	56.7±1.5	58.0±0.4	32.0±1.4	10.3±2.4	57.0±1.2	54.1±0.9
46. Bin-picking	0.0±0.0	1.5±1.8	**2.2±1.1**	1.2±1.0	1.2±0.9	0.0±0.0	0.0±0.0	1.8±1.1	0.5±0.9
47. Box-close	0.5±0.6	0.0±0.0	0.5±0.6	0.0±0.0	0.5±0.3	0.0±0.0	0.0±0.0	**5.5±4.6**	0.0±0.0
48. Hand-insert	2.2±2.3	3.8±3.1	1.0±1.2	1.5±1.8	5.2±3.0	**23.0±15.8**	0.0±0.0	1.5±1.1	0.8±1.0
49. Door-lock	59.2±9.1	**74.8±7.5**	49.8±15.5	51.5±9.5	14.0±8.2	11.2±10.5	8.2±10.0	37.5±20.3	59.2±9.6
50. Door-unlock	**78.5±7.9**	75.8±9.1	61.8±10.2	72.5±9.5	38.0±11.3	64.5±19.2	25.0±19.2	64.2±4.3	63.2±6.9
Test mean	28.1±3.2	**31.2±1.2**	23.0±5.1	25.4±2.9	11.8±3.2	19.8±6.3	6.7±3.3	22.1±3.5	24.8±2.9

Table 9: **Meta-World V2 ML-45 return.** We report the final return of baselines and our methods at the last rollout episode on the Meta-World ML-45 analogous to the success rate in Table 8. Results are reported as the mean $\pm$ 95% confidence intervals of 8 seeds at 400M steps.

Index. Task	SDVT	SDVT-LW	SD	SD-LW	RL^2	MAML	PEARL	VariBAD	LDM
1. Assembly	1813±485	**2573±117**	2414±233	2285±195	1202±19	268±70	208±9	2434±161	2572±56
2. Basketball	1929±688	1443±524	2215±148	**2581±129**	489±38	100±90	6±2	1311±651	2227±236
3. Button-press -topdown	3120±447	3297±328	**3580±87**	3343±176	1344±14	2660±633	543±273	3348±227	3208±354
4. Button-press -topdown-wall	3217±384	3386±246	**3614±110**	3392±185	1359±18	2664±638	604±314	3337±279	3218±319
5. Button-press	**3100±270**	2977±199	2833±208	2938±193	1165±29	2942±178	434±195	2878±74	2745±205
6. Button-press -wall	**3401±220**	2916±94	3148±157	3165±92	1378±17	2589±341	327±183	3040±136	2991±108
7. Coffee-button	1605±678	2196±430	2517±296	2420±303	1348±40	**3342±157**	80±20	2253±303	2610±271
8. Coffee-pull	1032±307	916±323	1010±338	**1305±395**	572±35	38±7	21±5	1292±260	1244±220
9. Coffee-push	1424±443	889±455	1254±137	1687±497	504±41	111±47	20±10	1901±413	**2175±491**
10. Dial-turn	1821±478	1704±520	**1835±414**	1825±484	944±70	1553±254	449±407	680±130	1101±571
11. Disassemble	2451±1226	897±350	**3387±382**	2840±485	2642±1397	130±58	150±25	1564±749	2268±688
12. Door-close	4178±204	**4404±22**	4375±17	4251±93	1231±20	4265±158	2430±965	4181±105	4067±174
13. Door-open	3086±761	2215±430	**4134±151**	2833±517	1312±216	1095±316	469±142	3741±333	3857±325
14. Drawer-close	4310±274	4544±54	4392±307	4680±80	1626±25	**4725±28**	4539±225	4515±112	4506±206
15. Drawer-open	3964±96	3624±334	**4265±106**	4035±221	2169±118	2259±235	1288±367	4180±114	3876±270
16. Faucet-open	4572±68	4057±692	4582±81	**4674±21**	1925±193	3757±540	1810±497	4338±155	4479±118
17. Faucet-close	4166±351	3656±471	**4457±194**	4300±95	1662±115	3298±561	1470±414	4267±57	4401±196
18. Hammer	466±60	465±17	469±5	459±16	**738±233**	649±135	420±20	476±4	384±115
19. Handle-press -side	4676±192	4722±14	4767±38	**4797±17**	2276±43	3696±522	652±524	4772±19	4737±51
20. Handle-press	4601±74	4355±183	4480±147	**4789±14**	2239±86	2902±791	3036±958	4728±22	4747±55
21. Handle-pull -side	853±523	83±30	**1507±832**	907±731	565±43	199±300	12±5	991±576	917±826
22. Handle-pull	1469±153	1491±110	**2260±666**	1541±100	2048±86	2001±597	29±19	1549±57	1612±170
23. Lever-pull	446±84	496±74	483±39	**500±106**	305±21	264±60	119±38	457±32	345±27
24. Peg-insert -side	767±408	757±48	**1106±186**	1067±192	640±77	33±24	7±2	778±101	962±232
25. Pick-place -wall	1647±893	2011±717	**2765±64**	2570±543	491±22	389±359	0±0	2042±501	1873±854
26. Pick-out -of-hole	809±435	1015±365	1319±183	**1385±310**	270±26	20±1	8±1	1129±261	1247±392
27. Reach	2682±225	2448±313	3048±238	**3116±182**	2273±49	2447±829	2466±1079	2843±147	3085±183
28. Push-back	674±362	514±154	**1438±156**	1218±334	433±42	11±7	8±3	871±372	1404±324
29. Push	3130±290	3139±655	2961±253	2581±530	945±32	634±555	34±13	3427±185	**3524±200**
30. Pick-place	1221±650	1582±433	**2145±159**	1992±122	576±23	247±222	5±1	2034±48	2128±144
31. Plate-slide	**3526±161**	2950±232	3022±196	2828±303	2863±1349	1043±789	561±490	2858±251	2801±231
32. Plate-slide -side	3058±289	1362±37	**3471±258**	2761±317	949±20	322±249	56±35	3107±167	2351±462
33. Plate-slide -back	3783±204	3790±239	3844±128	3754±272	1544±10	581±364	655±259	**3900±155**	3720±325
34. Plate-slide -back-side	3732±91	3764±149	3755±256	3987±228	1561±7	676±420	133±56	**4099±72**	4094±130
35. Peg-unplug -side	982±390	971±331	1187±111	1079±464	401±36	62±26	45±28	**1523±142**	1087±282
36. Soccer	1374±169	**1566±207**	1311±129	1348±332	671±31	439±359	98±60	1399±90	1486±82
37. Stick-push	47±70	786±533	11±2	291±333	**955±14**	128±212	6±1	17±2	10±4
38. Stick-pull	25±23	**905±616**	14±3	600±702	730±46	39±52	7±1	19±3	11±4
39. Push-wall	2547±426	2197±668	**3291±421**	2496±639	877±85	597±532	20±7	2813±716	2744±549
40. Reach-wall	1871±157	1889±412	2447±462	2741±456	2303±89	**2802±1052**	1741±641	2102±128	1836±569
41. Shelf-place	608±308	657±195	920±55	**1056±165**	623±61	9±8	0±0	795±186	725±167
42. Sweep-into	3755±333	3847±400	3869±214	3584±495	793±67	623±541	148±82	3750±159	**4151±185**
43. Sweep	1148±98	1433±477	**1905±449**	1415±623	872±230	160±82	36±9	1865±799	1219±325
44. Window-open	3789±249	4004±190	4138±56	4121±53	1163±37	2463±1004	705±184	**4177±123**	3986±154
45. Window-close	4201±166	4333±135	4293±209	**4496±29**	1152±109	3215±425	990±417	4346±111	4450±33
Train mean	2379±214	2294±202	**2672±79**	2578±64	1411±22	1388±104	597±121	2492±47	2515±67
46. Bin-picking	114±44	113±56	**322±70**	140±72	265±73	37±6	12±5	127±27	90±29
47. Box-close	190±49	128±2	143±5	137±9	**820±159**	215±26	176±40	243±83	151±10
48. Hand-insert	299±64	465±101	386±25	392±64	**467±48**	337±188	6±2	377±61	398±39
49. Door-lock	1694±302	**1973±160**	1359±262	1427±289	995±303	821±243	960±149	1358±445	1573±168
50. Door-unlock	**1898±158**	1792±225	1721±132	1870±245	769±108	1880±426	1374±537	1707±324	1627±169
Test mean	839±74	**894±27**	786±69	793±49	663±100	658±96	506±122	762±40	768±63

D.2 Learning Curves

In Figures 6 through 9, the mean training and test success rates are represented by solid and dashed lines respectively, with the shaded region indicating the 95% confidence interval. All results are compiled from 8 random seeds. The data corresponding to the final training steps in these plots (250M steps for ML-10 and 400M steps for ML-45) are used to present the main results in Table 1.

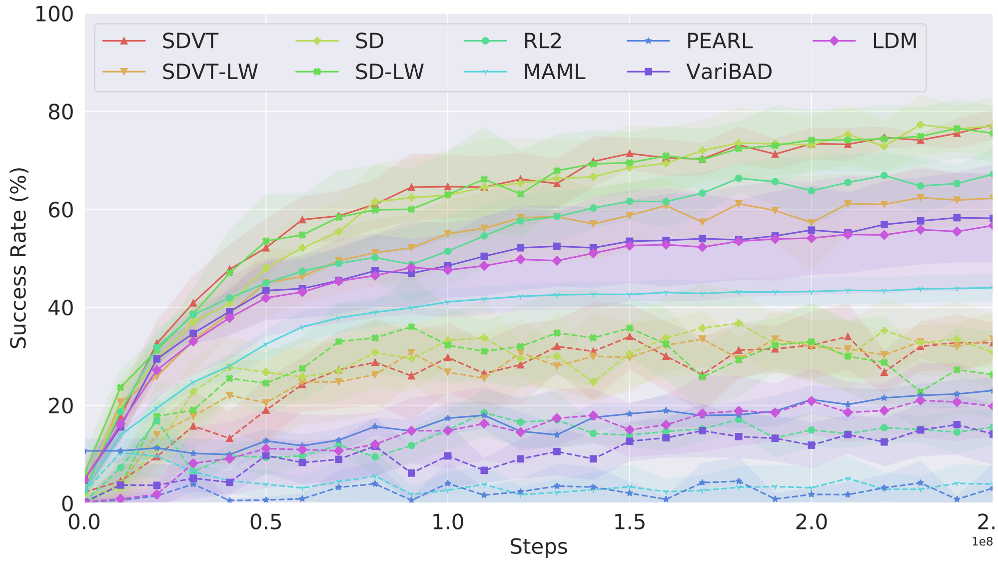


Figure 6: **Learning curve on ML-10 – success rate.**

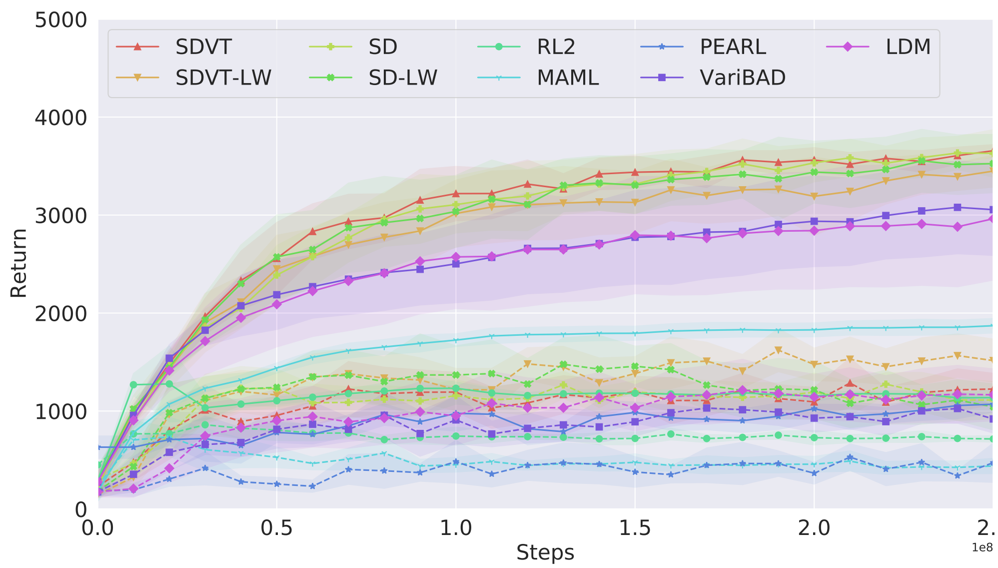


Figure 7: **Learning curve on ML-10 – return.**

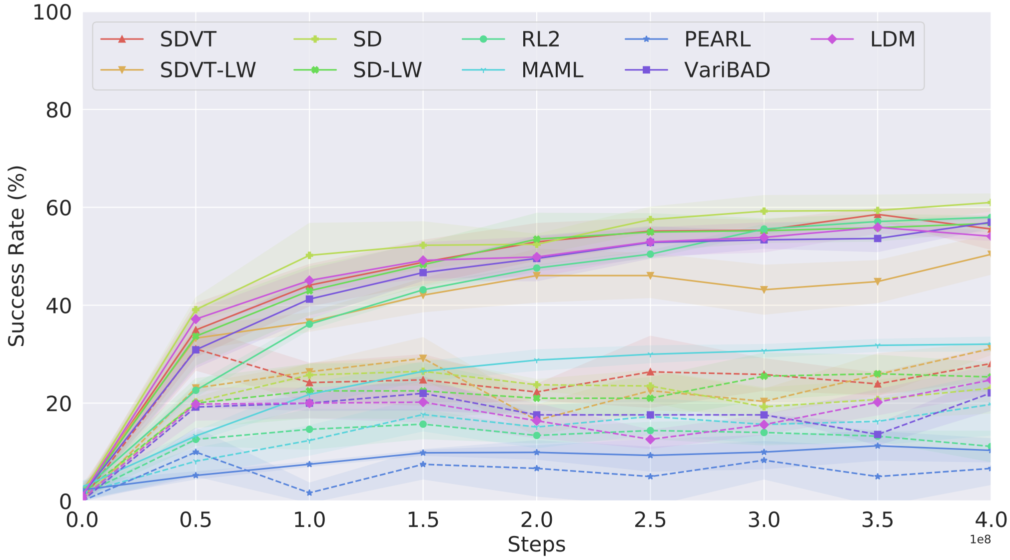


Figure 8: **Learning curve on ML-45 – success rate.**

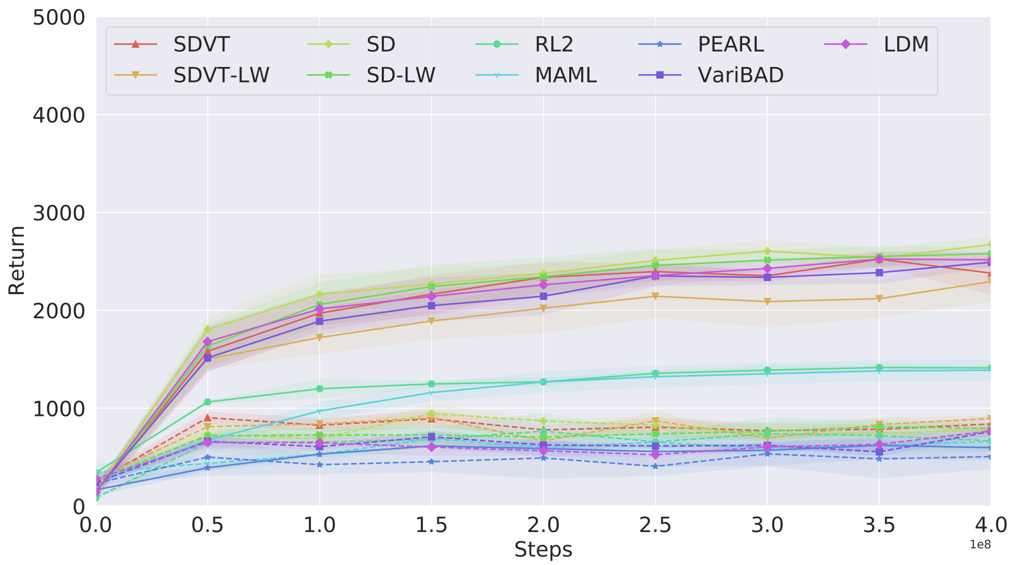
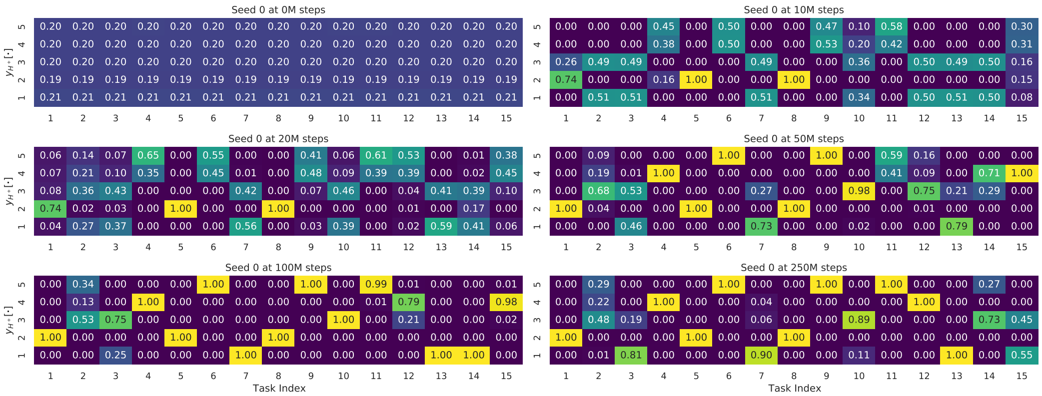
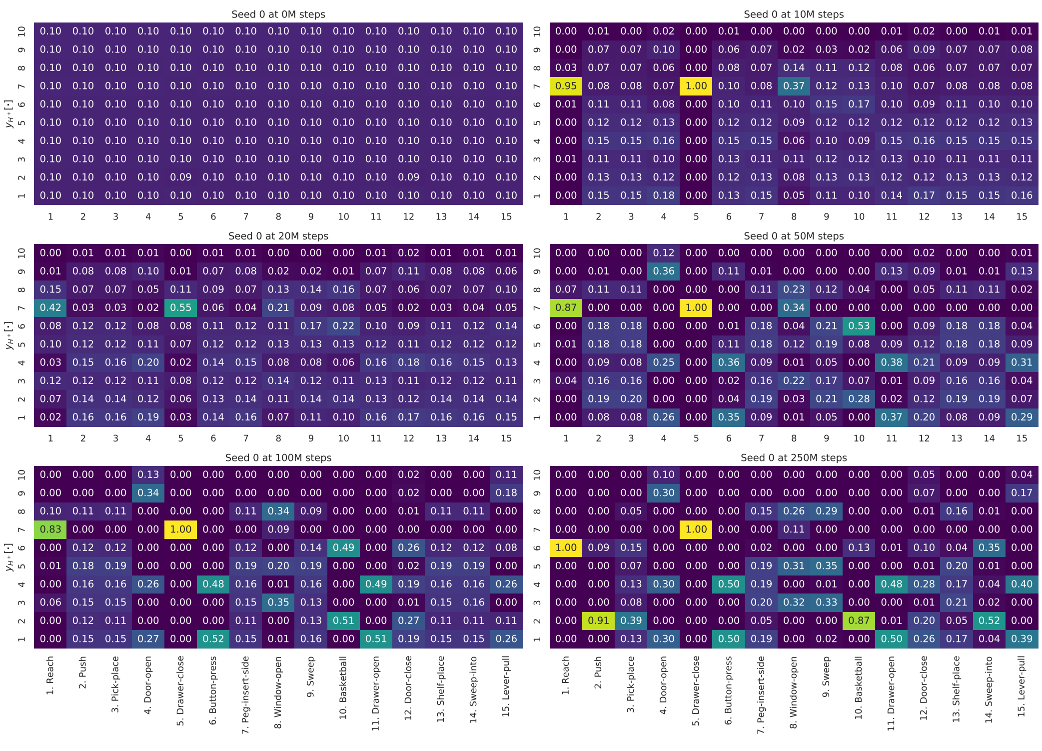


Figure 9: **Learning curve on ML-45 – return.**

D.3 Subtask Compositions Learned over Training



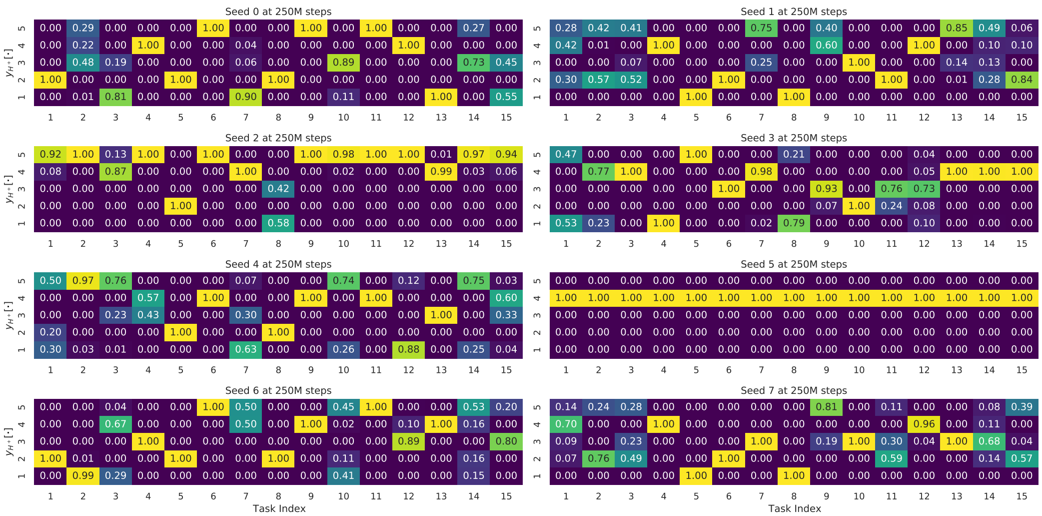
(a) SDVT-LW ($K = 5, \alpha_c = 0.5, \alpha_o = 0.0$).



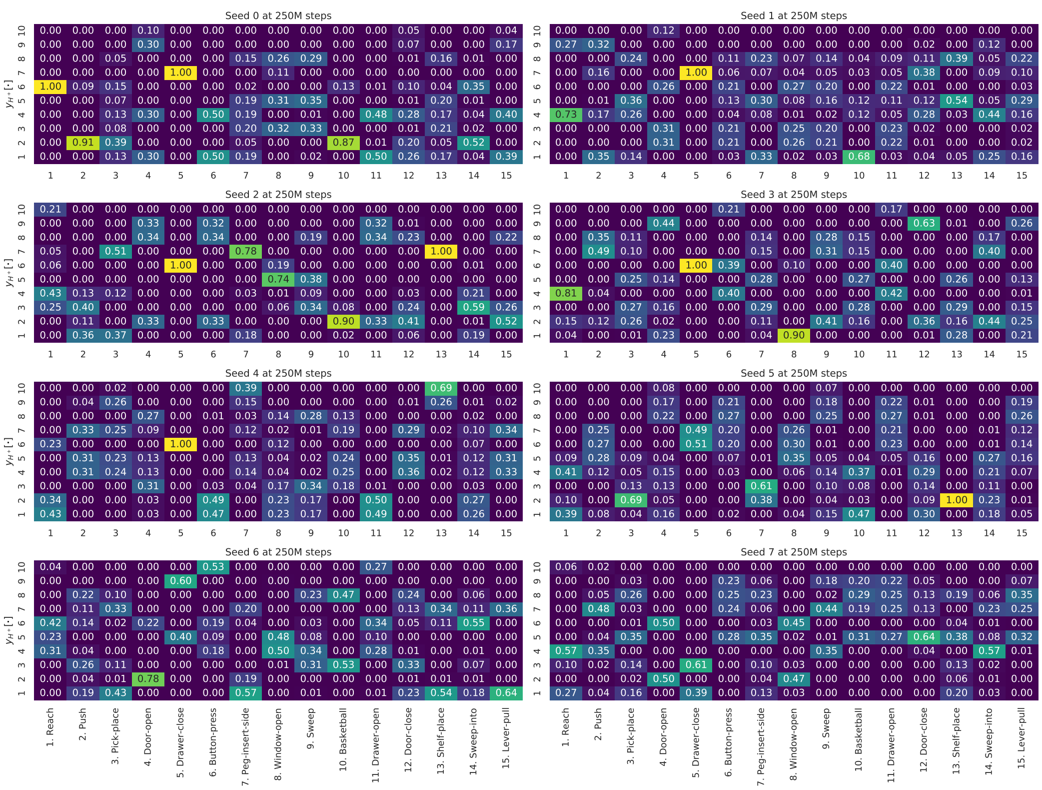
(b) SDVT ($K = 10, \alpha_c = 1.0, \alpha_o = 1.0$).

Figure 10: **Subtask compositions learned over training.** We visualize the development of subtask compositions for **(a)** SDVT-LW and **(b)** SDVT during training on ML-10. Similar to Figure 4, each column represents the terminal subtask composition (y_{H^+}) averaged across 50 parametric variants. **(a)** As training progresses, subtask compositions of (4) "Door-open" and (12) "Door-close" merge due to shared transition dynamics, which may cause the "Door-close" policy to keep the door open during testing without virtual training, underscoring the crucial role that virtual training can play in these scenarios. **(b)** With occupancy regularization, as the training progresses, the decomposition process prioritizes occupying lower indices over higher ones in the subtask compositions.

D.4 Subtask Compositions of all Seeds



(a) SDVT-LW ($K = 5, \alpha_c = 0.5, \alpha_o = 0.0$).



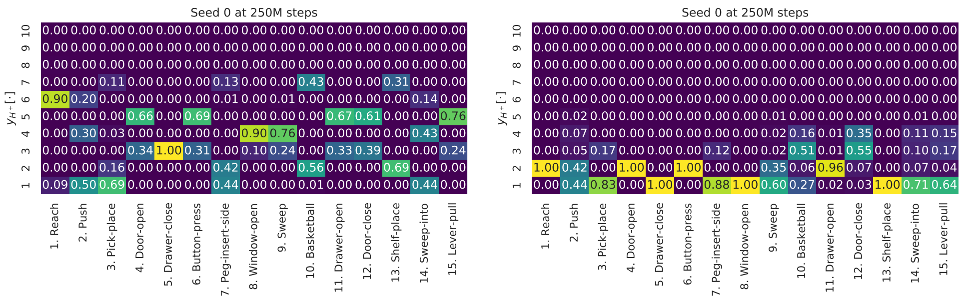
(b) SDVT ($K = 10, \alpha_c = 1.0, \alpha_o = 1.0$).

Figure 11: **Subtask compositions of all seeds.** We visualize the subtask compositions of **(a)** SDVT-LW and **(b)** on ML-10 after 250M training steps for all seeds. Decomposition processes differ among random seeds due to varying initialization and sample tasks during meta-training. One subtask can be interpreted as a combination of multiple subtasks and vice versa, depending on the seed and the dimension K. We rarely have a collapse to a single Gaussian as in **(a)** Seed 5, which lowers the average performance. **(b)** With occupancy regularization, we find that the 10th element of the composition is rarely occupied, whereas the first element is occupied by many tasks.

E Ablation Results

In order to confirm the source of the gain obtained from the proposed method, we conduct an extensive ablation study based on SDVT and SDVT-LW on ML-10.

E.1 Occupancy Regularization



(a) SDVT ($\alpha_o = 5.0$).

(b) SDVT ($\alpha_o = 10.0$).

Figure 12: **Occupancy ablation.** We report the learned subtask compositions of SDVT ($K = 10, \alpha_c = 1.0$) for different occupancy coefficients analogous to Figure 4a.

Figures 4a and 12 indicate that our occupancy regularization effectively constrains the use of higher indices as intended. We fix the default choice of $\alpha_o = 1.0$ that we found to work well on ML-10. Our default SDVT with $\alpha_o = 1.0$ scores a test success rate of 32.8%, which scored the best among $\alpha_o \in \{0.0, 5.0, 10.0\}$ that scored 22.8%, 25.5%, and 21.0%, respectively.

E.2 Dropout and Dispersion

Table 10: **Ablation results.** We report the mean success rate (%) and the difference caused by the changes made from the default SDVT-LW ($K = 5, \alpha_c = 0.5, \alpha_o = 0.0$) on ML-10 in parenthesis.

SDVT-LW	without		K			α_c		
	Dropout	Dispersion	3	7	10	0.1	1.0	2.0
ML-10 Train	65.6 (+3.5)	73.0 (+10.9)	60.1 (-2.0)	69.5 (+7.4)	70.8 (+8.7)	59.8 (-2.3)	70.3 (+8.2)	66.3 (+4.2)
ML-10 Test	16.5 (-16.9)	21.5 (-11.9)	25.0 (-8.4)	22.0 (-11.4)	21.1 (-12.3)	20.5 (-12.9)	16.1 (-17.3)	17.9 (-15.5)

Table 10 demonstrates the significant roles played by both dropout and dispersion in generating extrapolated dynamics during virtual training, thereby enhancing the test success rate. As outlined in Appendix E.1 of the LDM paper [33], virtual training without dropout does not exhibit a significant improvement due to decoder overfitting on the state and action inputs of the training tasks. In fact, virtual training without dropout can even lead to a decrease in test performance.

However, it is important to note that these factors are not the primary contributors to the empirical gains of our method. Dropout is specifically essential for virtual training, but not necessarily for other methods that do not employ virtual training, such as VariBAD and RL2 (as discussed in Appendix E.2 of the LDM paper). We verified this in our ML-10 experiment using VariBAD with dropout. The inclusion of dropout marginally improves the training success rate of vanilla VariBAD from 58.2% to 63.0% and the test success rate from 14.1% to 16.5%. However, the performance enhancement achieved through dropout is not as substantial for VariBAD as it is for SDVT-LW's virtual training.

E.3 Decomposition Distribution

Table 10 emphasizes the significance of hyperparameters such as subtask dimension K and categorical coefficient α_c in determining subtask compositions. It is crucial to carefully set these hyperparameters based on the number of training tasks and their correlations. In our lightweight (LW) approach, we have selected $K = 5$ and $\alpha_c = 0.5$, which effectively distributes subtasks across the ML-10 tasks. When α_c is set to a small value, task classification collapses into a few subtasks, as depicted in Figure 4b. Conversely, with a large value of α_c, the entropy of the composition is maximized, and all tasks exhibit a uniform probability distribution, as illustrated in Figure 4d. However, it is noteworthy that SDVT-LW outperforms VariBAD and LDM in test success rate, regardless of the specific values chosen for K, such as $K = 3, 7, 10$. To alleviate the burden of hyperparameter tuning in our LW methods, we introduce the occupancy regularization.

E.4 Number of parameters

Table 11: **Number of parameters and success rates.** We report the number of parameters used by our methods and baselines. We demonstrate that our gain is not from the increased capacity.

	Number of Parameters				ML-10 Success Rate (%)	
Methods	Encoder	Decoder	Policy	Sum	Train	Test
SDVT-LW	1,047,455	174,821	235,401	1,457,677	62.1	33.4
SD-LW	1,047,455	25,637	235,401	1,308,493	75.5	26.2
LDM	502,580	25,577	202,249	730,406	56.7	19.8
VariBAD	251,290	25,577	202,249	479,116	58.2	14.1
VariBAD (hidden $\times$2)	894,362	25,577	663,305	1,583,244	62.4	12.0

Table 11 indicates that SDVT-LW employs 3 and 2 times more parameters compared to VariBAD and LDM, respectively. The encoder of our method has more parameters than VariBAD due to the added categorical layer. The decoder of SDVT-LW includes the parameters of the dispersion layers. However, we find that the model's improvement is not mainly attributed to the increased capacity. Generally, a larger capacity does not necessarily guarantee better generalization. While selecting encoder (GRU) and policy hidden sizes, we experimented with 128, 256, and 512, discovering that 256 works best for all task-inference methods (LDM, SD only, and SDVT). Notably, VariBAD with hidden dimensions of 512 possesses more parameters than SDVT but exhibits an even lower test success rate than the vanilla VariBAD.

E.5 Conditioning policy on belief

Table 12: **Masking contexts.** We present the success rates (%) on ML-10, achieved by ablating the contexts fed into the policy, to illustrate the effective utilization of learned contexts by the policy.

	SDVT-LW	SDVT-LW masked (ω_{ϕ_y})	SDVT-LW masked $(\mu_{\phi_z}, \sigma_{\phi_z})$	SDVT-LW masked $(\omega_{\phi_y}, \mu_{\phi_z}, \sigma_{\phi_z})$
ML-10 Train	62.1	58.6	36.9	34.8
ML-10 Test	33.4	33.6	25.8	24.5

We employ VariBAD's stop gradient architecture to avoid the instability that may arise from the concurrent training of policy and ELBO objectives. This may lead to a potential vulnerability where the policy neglects contexts. However, in Meta-World, identical observations could belong to different tasks, such as "Reach" and "Pick-place." Therefore, the agent must rely on the inferred context. To confirm this, we evaluate SDVT by masking either (ω_{ϕ_y}) or $(\mu_{\phi_z}, \sigma_{\phi_z})$ in the policy input.

Our findings reveal that masking the contexts severely damages the training and test success rates. Especially, masking the Gaussian parameters of z is more critical than masking the categorical parameter of y. However, this does not suggest that y is redundant, given that the continuous context z is trained to include y's information. Interestingly, the test success rate, with all contexts masked (i.e., solely relying on the current state s_t), achieves a success rate of 24.5%, surpassing all baseline scores. Although the policy does not directly employ the context learned by the GMVAE, it can still be effectively trained in the imaginary task generated by the learned GMVAE to prepare for tests with unseen compositions of subtasks.