## Algorithm 1 Action-Free Guide

Input: states s, returns-to-go  $\hat{R}$ , time steps t# get positional embedding for each time step  $f_t = \operatorname{Embed}_t(t)$ # compute the state and return-to-go embeddings  $f_s$ ,  $f_{\hat{R}} = \operatorname{Embed}_s(s) + f_t$ ,  $\operatorname{Embed}_R(\hat{R}) + f_t$ # send to transformer in the order  $(s_0, \hat{R}_0, s_1, \hat{R}_1, ...)$   $f_{output} = \operatorname{Transformer}(\operatorname{stack}(f_s, f_{\hat{R}}))$ # predict the state change  $\Delta s = \operatorname{Pred}_s(\operatorname{unstack}(f_{output}.\operatorname{states}))$ Output:  $\Delta s + s$ 

Embed<sub>t</sub>: a single-layer temporal encoder Embed<sub>t</sub>: a single-layer state encoder Embed<sub>R</sub>: a single-layer return-to-go encoder stack: operation to stack state features  $f_s$  and return-to-go features  $f_{\hat{R}}$  Pred<sub>s</sub>: state decoder converting output state features to the state change  $\Delta s$ 

Algorithm 2 Compute Guiding Reward

**Input:** states  $s_{1:t}$ , return-to-go  $\hat{R}_{1:t}$ , policy  $\pi$ , state standard deviation  $\sigma_s$ , environment env, AFDT with context length K repeat # get AFDT's prediction of the next state  $\widetilde{s}_{t+1} = AFDT(s_{t-K+1:t}, R_{t-K+1:t})$ # apply the policy in the environment for one step  $a_t = \pi(s_t)$  $s_{t+1}, r_e = env.step(a_t)$ # compute current guiding reward using Eq.4  $r_q = -\|\frac{1}{\sigma} \odot (\widetilde{s}_{t+1} - s_{t+1})\|_2$ # update return-to-go (same as DT) and time step  $\hat{R}_{t+1} = \hat{R}_t - r_e$ t = t + 1until Episode is finished

 $ilde{s}_{t+1}$ : planned next state from AFDT  $r_e$ : environment reward  $r_g$ : intrinsic guiding reward