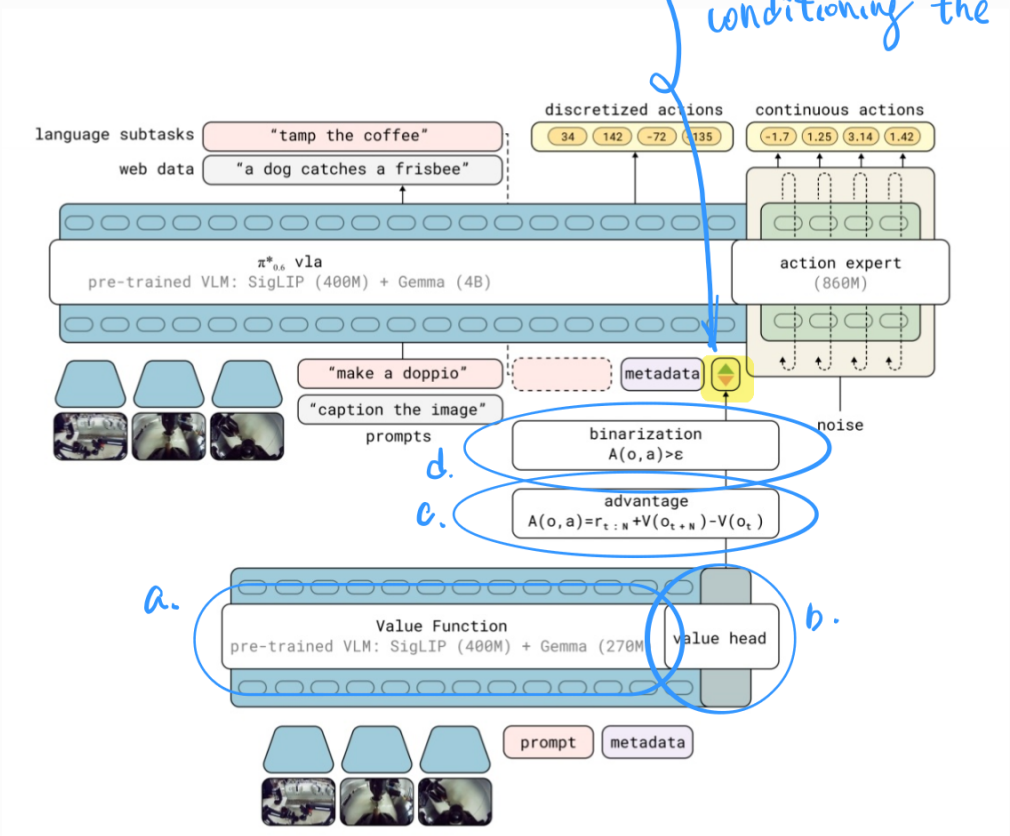
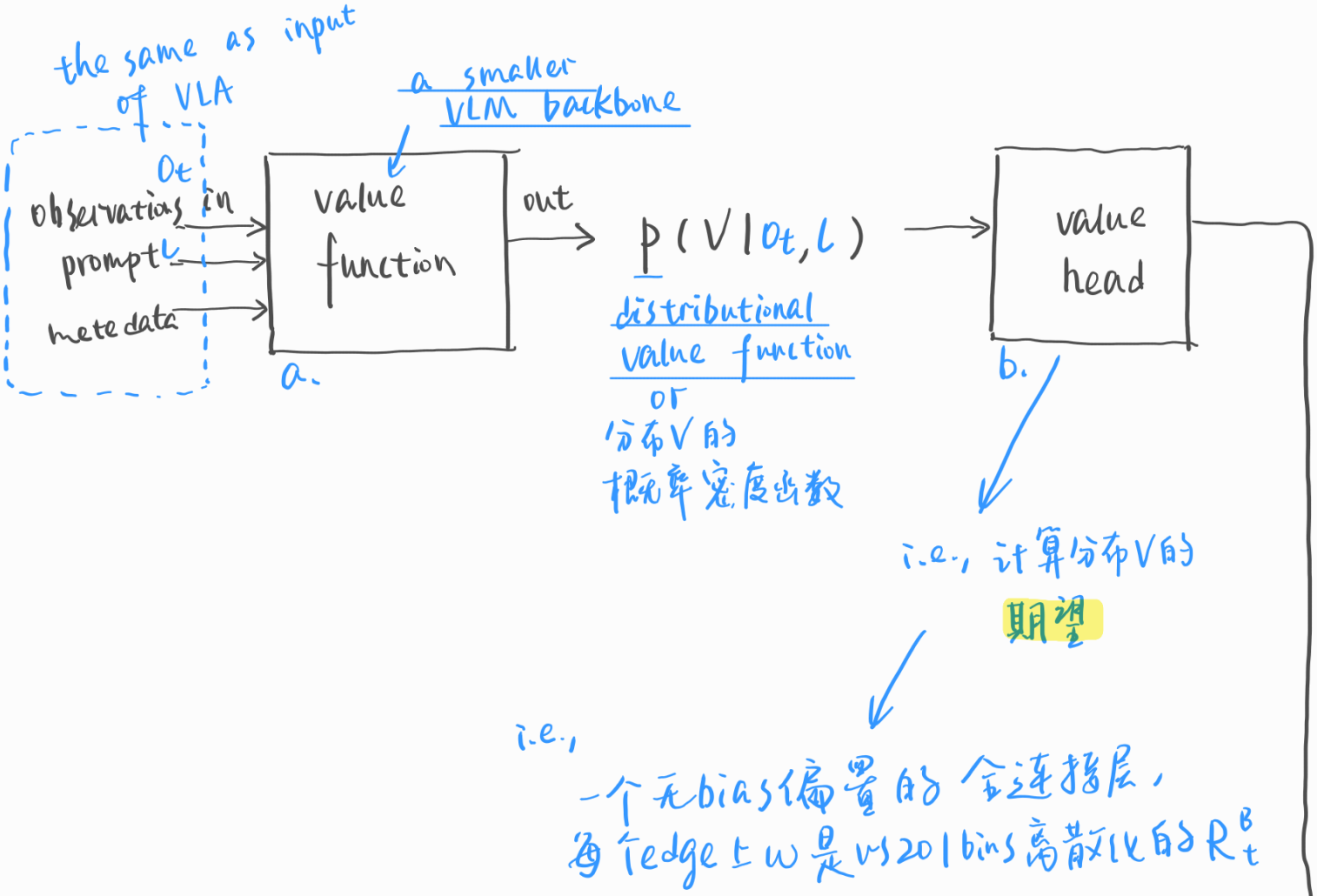
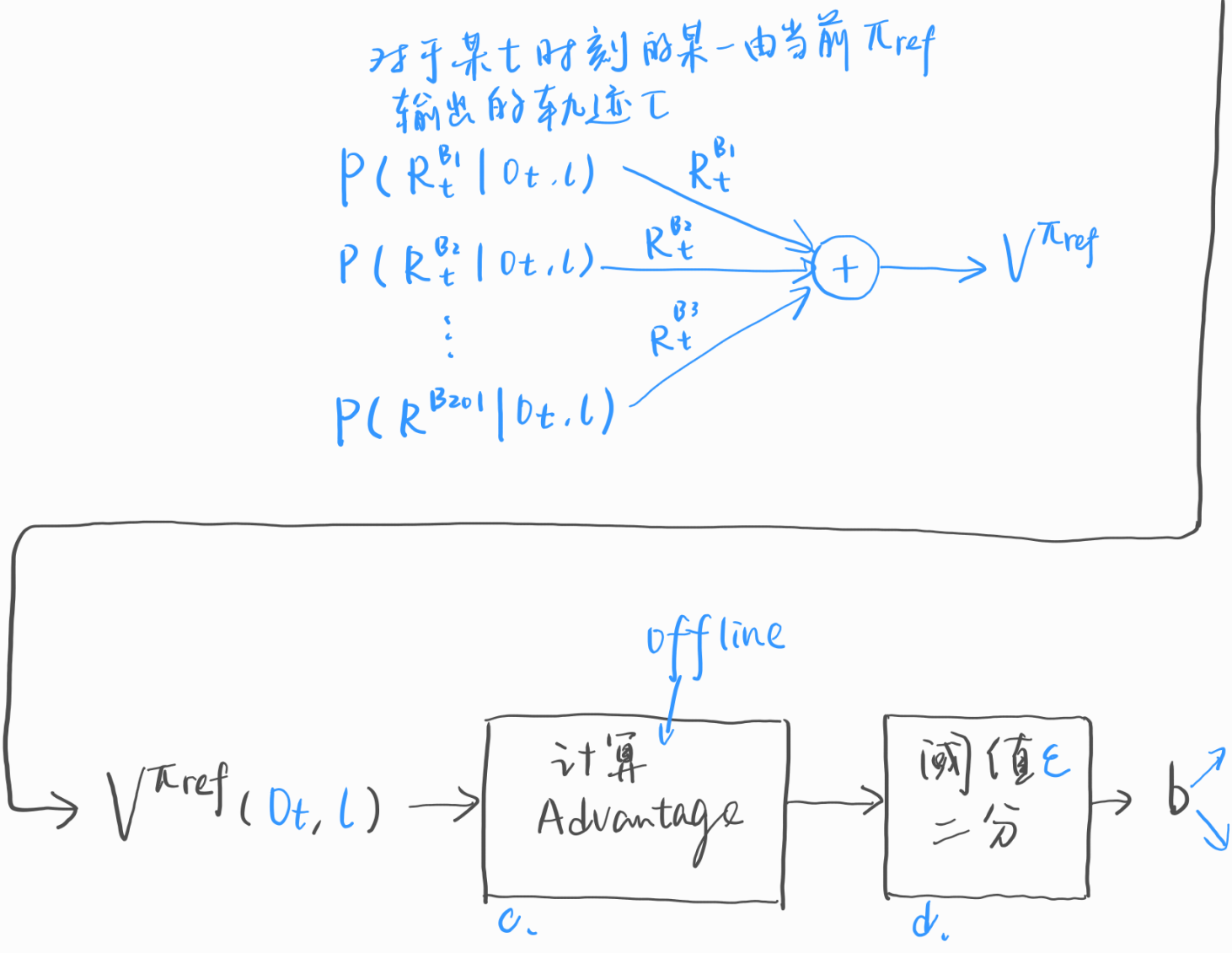
RECAP - RL with Experience and Corrections via Advantage-conditioned Policies

KEY FOCUS

1. How to get the binarized indicator?



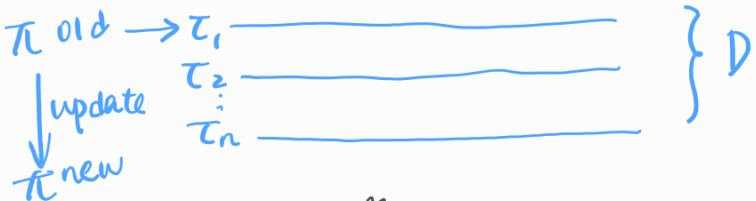




2. 如何训练 value function 即 $P(V|O_t,l)$?

1) Receipt

step1 用当前 policy π_{ref} rollout 得到多段轨迹的集合 D



step2 对集合 D Monte Carlo 抽样，通过交叉熵 loss 更新 value function

$$\min_{\phi} \mathbb{E}_{\tau \in \mathcal{D}} \left[\sum_{\mathbf{o}_t \in \tau} H(R_t^B(\tau), p_\phi(V|\mathbf{o}_t, \ell)) \right]. \quad (1)$$

Q: Equation 1 表达了什么?

传统的交叉熵公式 $H(P,Q)$ 中两个变量均为分布，但 Equation 1 中 $R_t^B(\tau)$ 是一个 constant，$P(V|o_t,\ell)$ 是概率密度函数

A (by Gemini):

、应该将 $R_t^B(\tau)$ 视为一个 One-Hot Encoding (像脉冲信号) 分布，即

$$P(b) = \begin{cases} 1, & b = R_t^B(\tau) \\ 0, & b \neq R_t^B(\tau) \end{cases}$$

、因此，展开 Equation (1) 得到，

Step 1: Substitute the definition of H We treat $R_t^B(\tau)$ as the target distribution P and p_ϕ as the predicted distribution Q:

$$\min_\phi \mathbb{E}_{\tau\in\mathcal{D}}\left[\sum_{\mathbf{o}_t\in\tau}\left(-\sum_{b=0}^{B} P(b)\log p_\phi(V=b|\mathbf{o}_t,\ell)\right)\right]$$

Step 2: Apply the One-Hot logic Since $P(b)=1$ only when $b=R_t^B(\tau)$ and is 0 otherwise, the inner summation collapses. All terms where $b\neq R_t^B(\tau)$ become zero:

$$\min_\phi \mathbb{E}_{\tau\in\mathcal{D}}\left[\sum_{\mathbf{o}_t\in\tau}\left(-1\cdot\log p_\phi(V=R_t^B(\tau)|\mathbf{o}_t,\ell)\right)\right]$$

Step 3: Final Expanded Form The simplified objective function, which is what is actually implemented in code (often called the **Negative Log-Likelihood**), is:

$$\min_\phi \mathbb{E}_{\tau\in\mathcal{D}}\left[\sum_{\mathbf{o}_t\in\tau} -\log p_\phi(V=R_t^B(\tau)|\mathbf{o}_t,\ell)\right]$$

Note:

1. 随机变量 $V\in[\min R_t^B(\tau), \max R_t^B(\tau)]$，

与当前轨迹τ有关（不同τ R的离散结果不同）

2. 分布V的随机密度函数用VLM建模

附，

Standard Definition of Cross-Entropy

For two discrete probability distributions P (the ground truth) and Q (the prediction) over the same set of outcomes $\mathcal{X}$, the Cross-Entropy $H(P, Q)$ is defined as:

$$H(P, Q) = -\sum_{x \in \mathcal{X}} P(x) \log Q(x)$$

2) On-policy learning

、value function(部分)通过π_{ref}选择的D更新，

(部分)通过人类逐条采数据更新，始终只存在一个π

While this on-policy estimator is less optimal than a more classic off-policy Q-function estimator, we found it to be simple and highly reliable, while still allowing for substantial improvement over imitation learning. Our method could be extended to accommodate off-policy estimators in future work.

interesting

Q：如何规避过拟合？

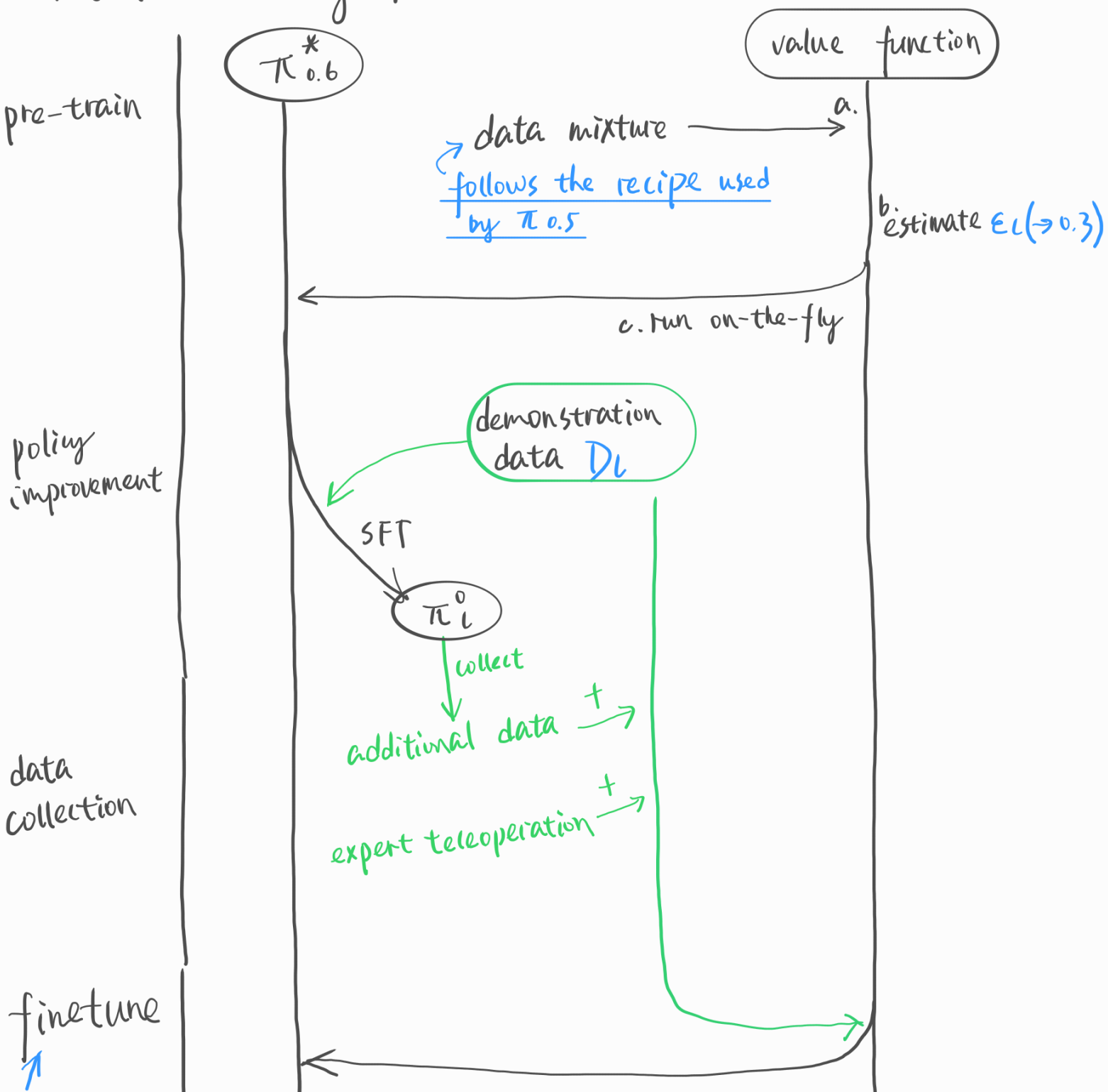
传统on-policy方法易陷入过拟合，

需要引入exploration，e.g. greedy → ε-greedy

A: co-train with web data

The value function takes as input the same language inputs as the $\pi^*_{0.6}$ VLA, and uses the same architecture design, with a smaller 670M parameter VLM backbone that is also initialized from Gemma 3 (see Figure 3). To prevent overfitting, we also co-train the value function on a small mixture of multi-modal web data. Figure 4 show visualizations of the value function on some examples of successful and failure episodes, with additional visualizations in Figure 13 in Appendix B.

3. Overall training process



using the same procedure as in pre-training

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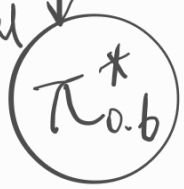

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