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Rewards Prediction-Based Credit Assignment for Reinforcement Learning With Sparse Binary Rewards ——hoho

论文试图解决什么问题？

credit assignment 问题

这是否是一个新的问题？

否

这篇文章要验证一个什么科学假设？

只要识别出哪个动作是关键动作（key-action），还有其前后的相邻关键动作（adjacent-key-actions），然后将adjacent-key-actions也赋予奖励，则采样效率和模型收敛速度也会加快

有哪些相关研究？如何归类？谁是这一课题在领域内值得关注的研究员？

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论文中提到的解决方案之关键是什么？

核心：搭建额外的模型来预测每一步的奖励，识别出key-action。

总体流程如下图：

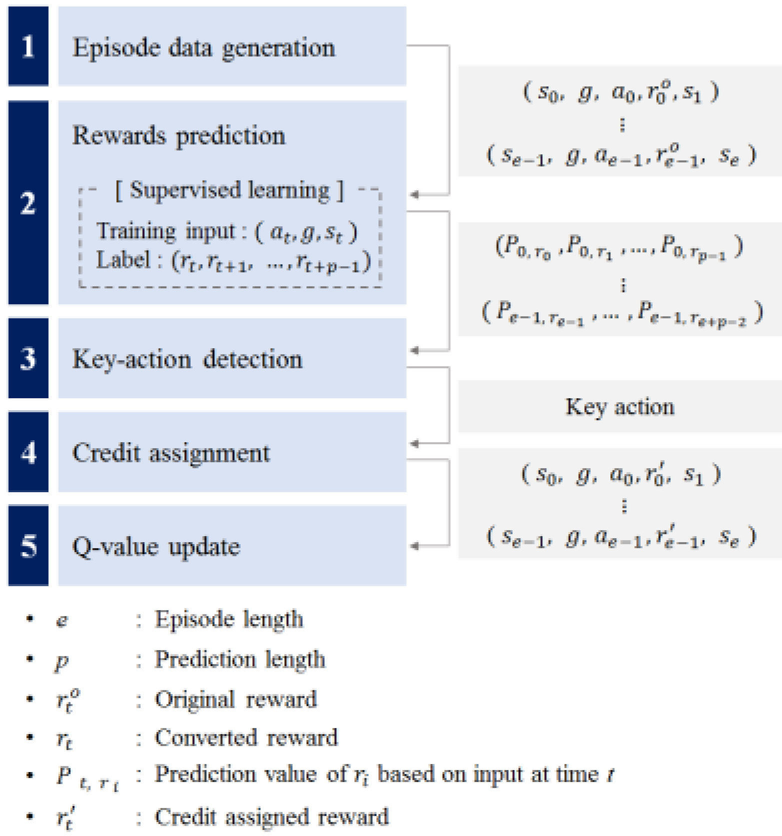


FIGURE 1. Process flow of the proposed method.

具体流程：

1. 用off-policy方式，agent与环境交互，生成回合数据$(s_{t-1}, g, a_{t-1}, r_{t-1}^o, s_t)$，g表示任务最后的目标
2. 使用1的数据进行奖励预测：

   2.1 预测模型的输入数据与标签构建：

   - 输入为：(a_t, g, s_t)
   - 标签构建：

     定义一个超参p：预测奖励的时间步长度，即基于当前时间步，要预测接下来多长的时间步

converted reward：本文以二分奖励为例（失败奖励为-1，成功奖励为0）,将原来的reward为-1的转为0，原来为0的转为1

extended reward：对最后一步而言，因为要预测p步，所以最后一步之后的p步的奖励赋值为跟最后一步的奖励相同

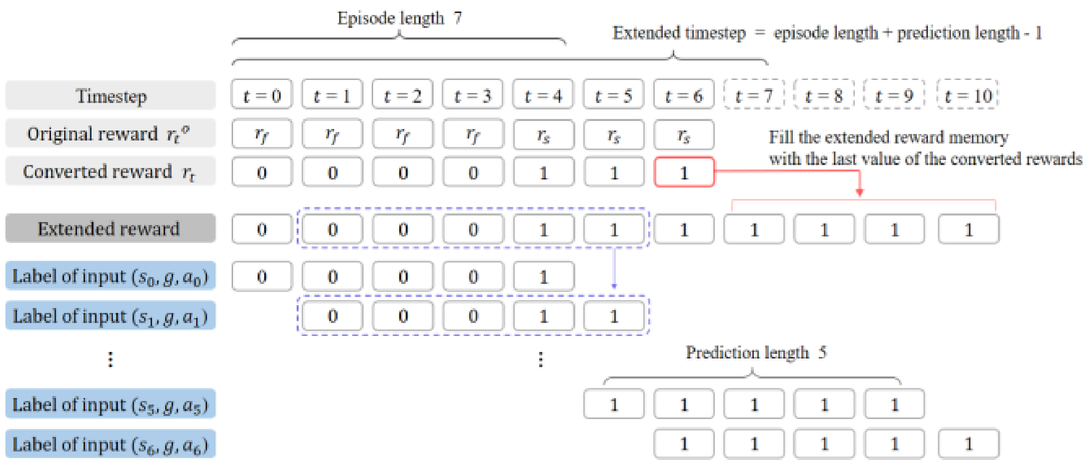
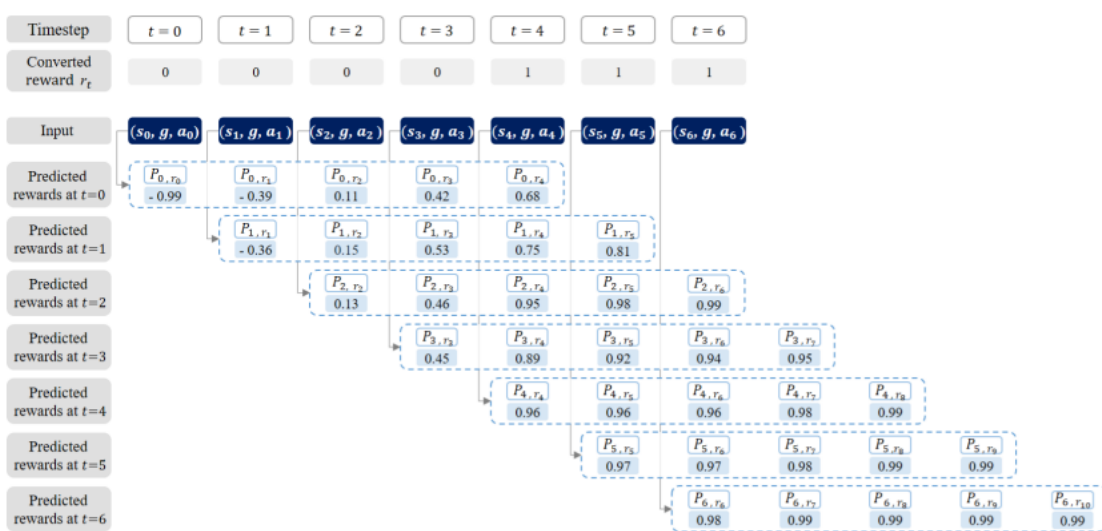


FIGURE 4. Framework for supervised learning of rewards prediction model.

2.2 奖励的预测：

以下的每一行表示每一步对之后p步的奖励预测：



P_{t,r_e} 表示基于第t步预测的第e步的奖励

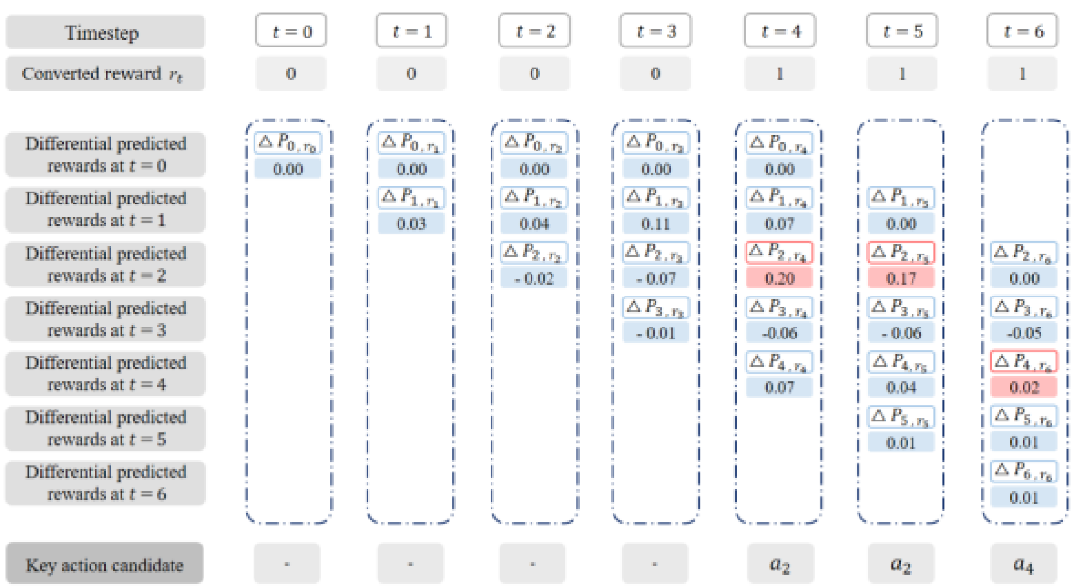
3. key-actions识别

   基于以下规则进行对前后奖励计算差分（这同一列中进行）：

$$\Delta P_{t,r_i} = \begin{cases} 0, & \text{if } P_{t-1,r_i} \text{ does not exist} \\ P_{t,r_i} - P_{t-1,r_i}, & \text{if } P_{t-1,r_i} \text{ exists} \end{cases} \quad ($$

因为奖励变化大的地方极有可能跟关键奖励相关（Since abrupt change of the predicted rewards according to input over timesteps is our concern）

于是得到如下统计数据：



取出差分值大的时间步(以上红框)对应的action作为候选key-actions：

Key action

Action	a_0	a_1	a_2	a_3	a_4	a_5	a_6
Nomination frequency	0	0	2	0	1	0	0

统计候选action的频次，可选频次大的为key-action（本文选两个频次最大的actions作为key-actions）

4. credit assignment

本文采用两种CA策略：

- CA_1: 分配key-action之前的action为adjacent-key-action

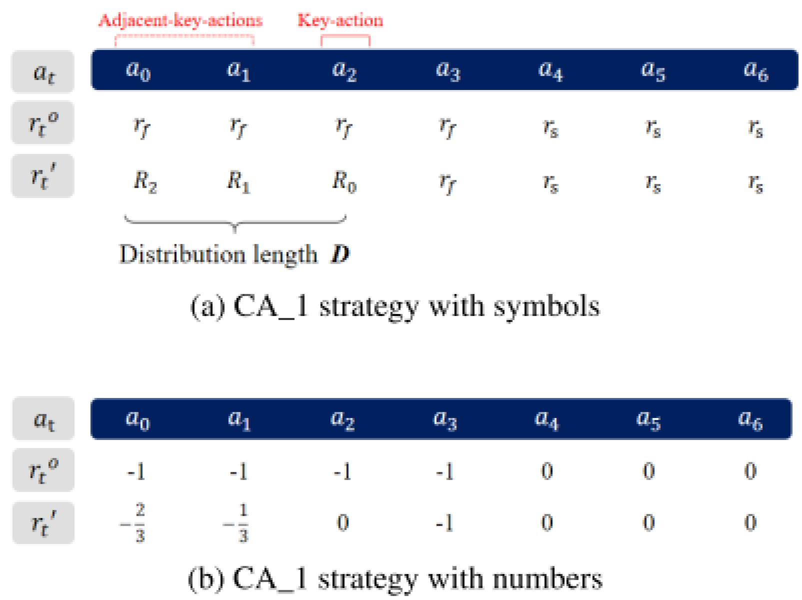


FIGURE 7. Credit assignment strategy CA_1.

R_i的计算方法：

$$R_i = r_s + \left(\frac{r_f - r_s}{D}\right) i,$$

r_f为原来的失败奖励值，r_s为原来的成功的奖励值

(图b为例子)

- CA_2：分配key-action和首次获得成功奖励的action之间的步骤为adjacent-key-action

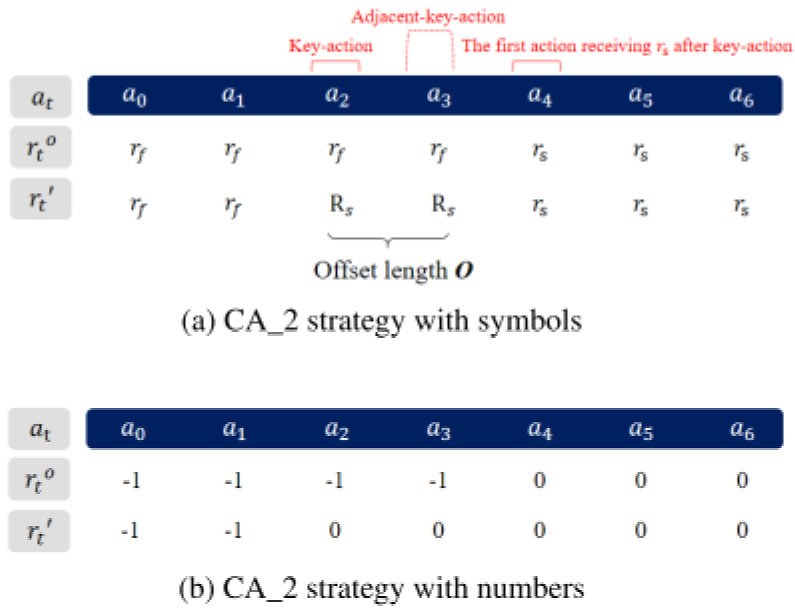


FIGURE 8. Credit assignment strategy CA_2.

key-action和adjacent-key-actions都赋予成功的奖励值。

论文中的实验是如何设计的？

设计了Fetch push（机器人推箱子到目的地）和Fethc slide（机器人滑动撞击滑块到目标点）实验

用于定量评估的数据集是什么？代码有没有开源？

都无

论文中的实验及结果有没有很好地支持需要验证的科学假设？

CA_1和CA_2收敛都比普通的DDPG+HER方法快

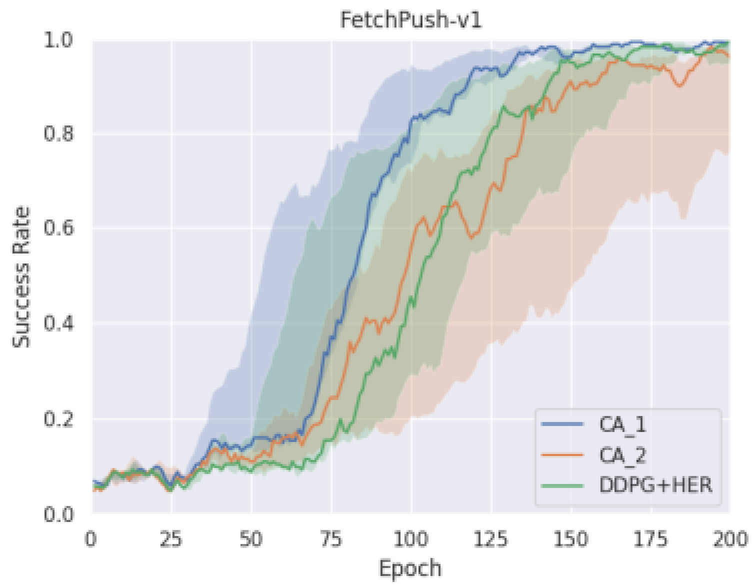


FIGURE 10. **Success rate obtained by proposed method and DDPG+HER for the Fetch push task. Results show that proposed method achieves similar performance to that of DDPG+HER over 200 epochs. Success rates of CA_1 strategy, CA_2 strategy, DDPG+HER are 100%, 98%, 98%, respectively. It is seen that CA_1 strategy converges faster as compared to others.**

CA_1和CA_2最后的Q值都和普通的DDPG+HER几乎一样

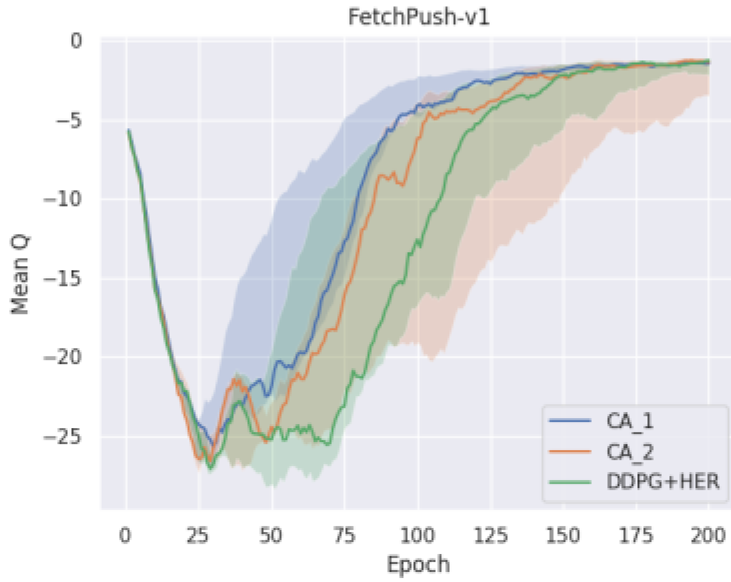


FIGURE 11. **Variation of mean Q value during training with DDPG+HER and proposed method (CA_1 and CA_2 strategies) for the Fetch push task. At epoch index 200, the mean Q value is approximately −2 with DDPG+HER and proposed method. It is seen that CA_1 and CA_2 strategies converge to the optimum mean Q value −2 faster, which means more efficient exploration during training.**

至于成功率CA_1较高

TABLE 1. **Comparison between the proposed method and DDPG+HER for the Fetch push task.**

Algorithm	Push succ %
DDPG+HER	$97.67\% \pm 1.5\%$
CA_1 strategy	$\mathbf{99.17\% \pm 0.15\%}$
CA_2 strategy	$88.83\% \pm 7.25\%$

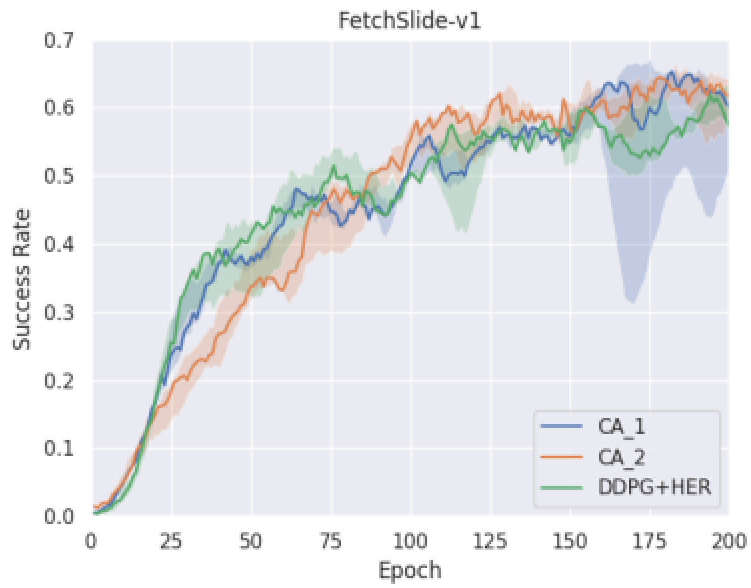


FIGURE 12. **Success rate obtained by proposed method and DDPG+HER for Fetch slide task. Results show that the proposed method achieves similar performance to that of DDPG+HER over 200 epochs. Success rates of CA_2 strategy, CA_1 strategy, DDPG+HER are 62%, 60%, 57%, respectively. This success rate accounts for the Fetch slide task in near zone as well, which conceals higher success rate in far zone with the CA_2 strategy. The higher success rate in far zone is referred to Fig. 14.**

这篇论文到底有什么贡献？

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下一步呢？有什么工作可以继续深入？

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