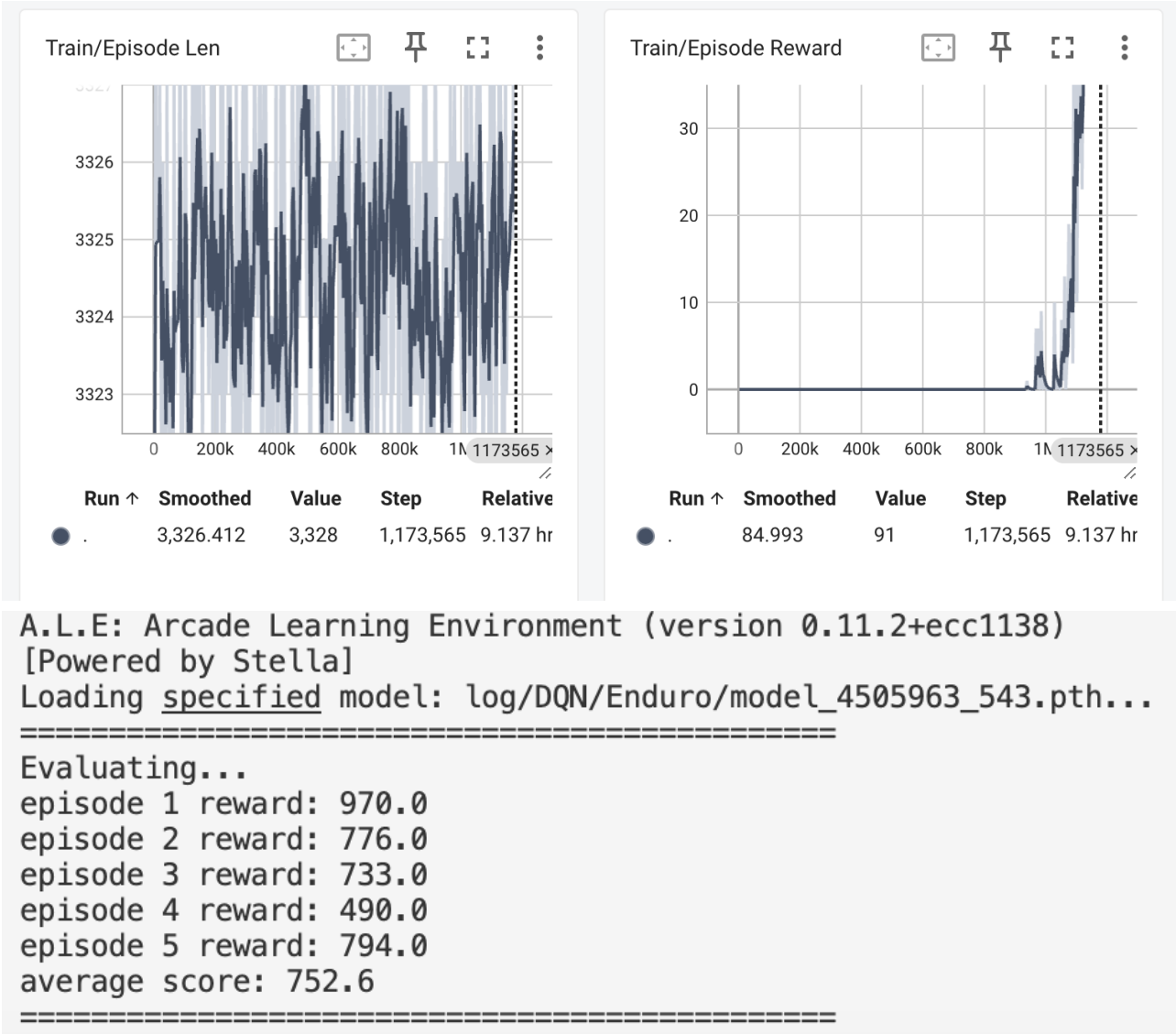
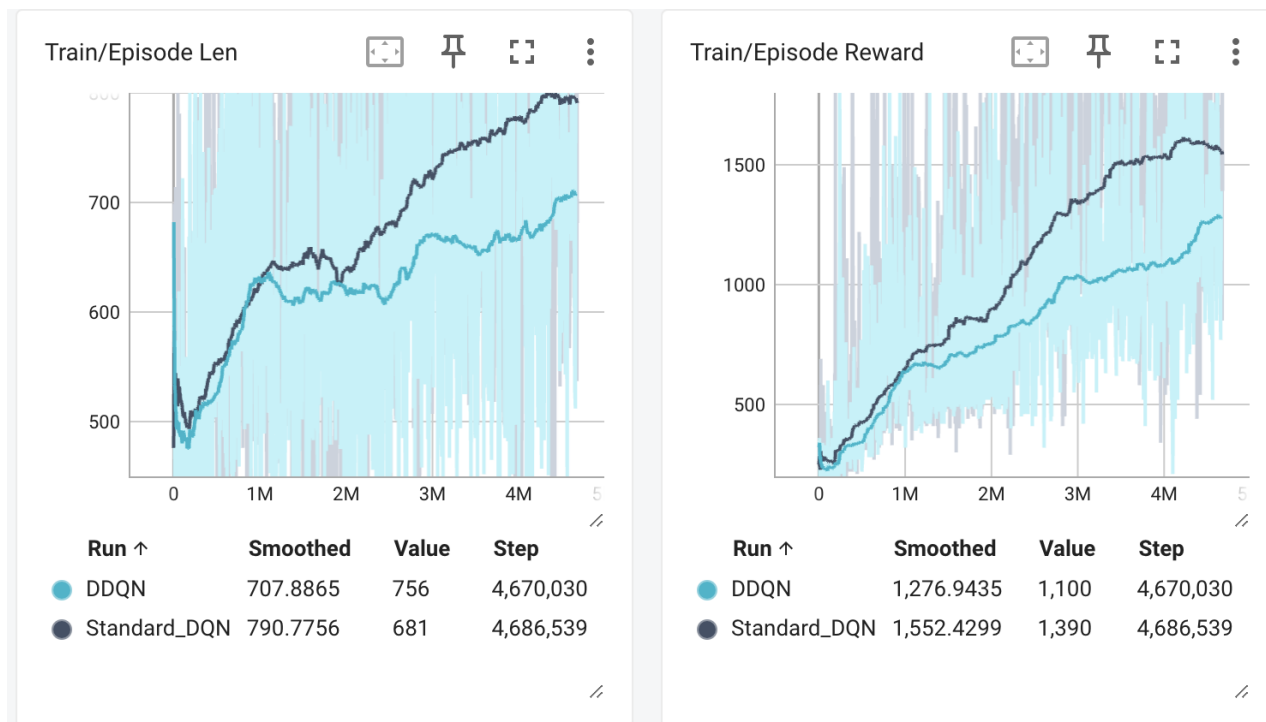


1. Screenshot of Tensorboard training curve and testing results on DQN.(Enduro)



2. Screenshot of Tensorboard training curve and testing results on DDQN, and discuss the difference between DQN and DDQN.



Loading specified model: log/DDQN/Pacman/model_5187918_1414.pth...

=====

Evaluating...

episode 1 reward: 2130.0

episode 2 reward: 1740.0

episode 3 reward: 1430.0

episode 4 reward: 920.0

episode 5 reward: 1190.0

average score: 1482.0

=====

$$Y_t^Q = r_{t+1} + \gamma \max_a Q(S_{t+1}, a | \theta^-)$$



$$Y_t^{DoubleQ} = r_{t+1} + \gamma Q(S_{t+1}, \underset{a}{\operatorname{argmax}} Q(S_{t+1}, a | \theta^-) | \theta^-)$$

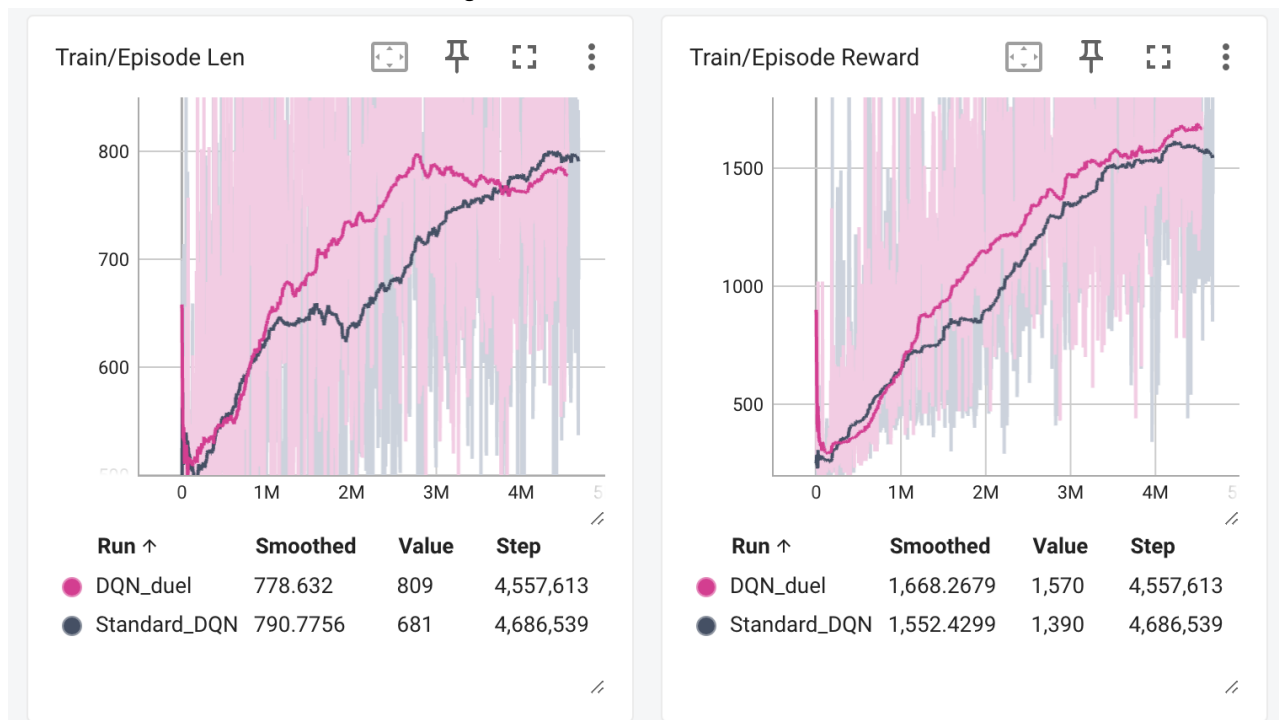
- 主要差別是DDQN用 behavior_net來選action，用target_net來評估該action的Q值，DQN只使用同一個target_net來選action與評估Q值。

在理論上，DDQN透過action selection (behavior network) 與 evaluation (target network) 分開，可以有效減少DQN中常見的Q-value overestimation的問題，因此通常能得到更好的結果。

但我目前DQN的表現反而優於DDQN。可能原因如下：

- DDQN的更新較保守，在訓練初期收斂速度較慢，後期可能DDQN會較好也說不定。
- Preprocessing 或 hyperparameter 設定差異（例如 frame skip、normalization 或 epsilon decay）造成輸入資料分佈與網路更新步調不一致。

3. Screenshot of Tensorboard training curve and testing results on Dueling DQN, and discuss the difference between DQN and Dueling DQN.



Loading specified model: log/DQN_duel/Pacman/model_5153273_1980.pth...

=====

Evaluating...

episode 1 reward: 1760.0
 episode 2 reward: 2240.0
 episode 3 reward: 2110.0
 episode 4 reward: 1450.0
 episode 5 reward: 1690.0
 average score: 1850.0

=====

Dueling DQN 將 Q-value 拆解為「狀態價值 (Value)」與「動作優勢 (Advantage)」：

- Value：估計當前狀態的整體價值 $V(s)$ ，代表該狀態本身的好壞。
- Advantage：估計在該狀態下各動作的相對優勢 $A(s,a)$ 。

$$A(s_t, a_t) = Q(s_t, a_t) - V(s_t)$$

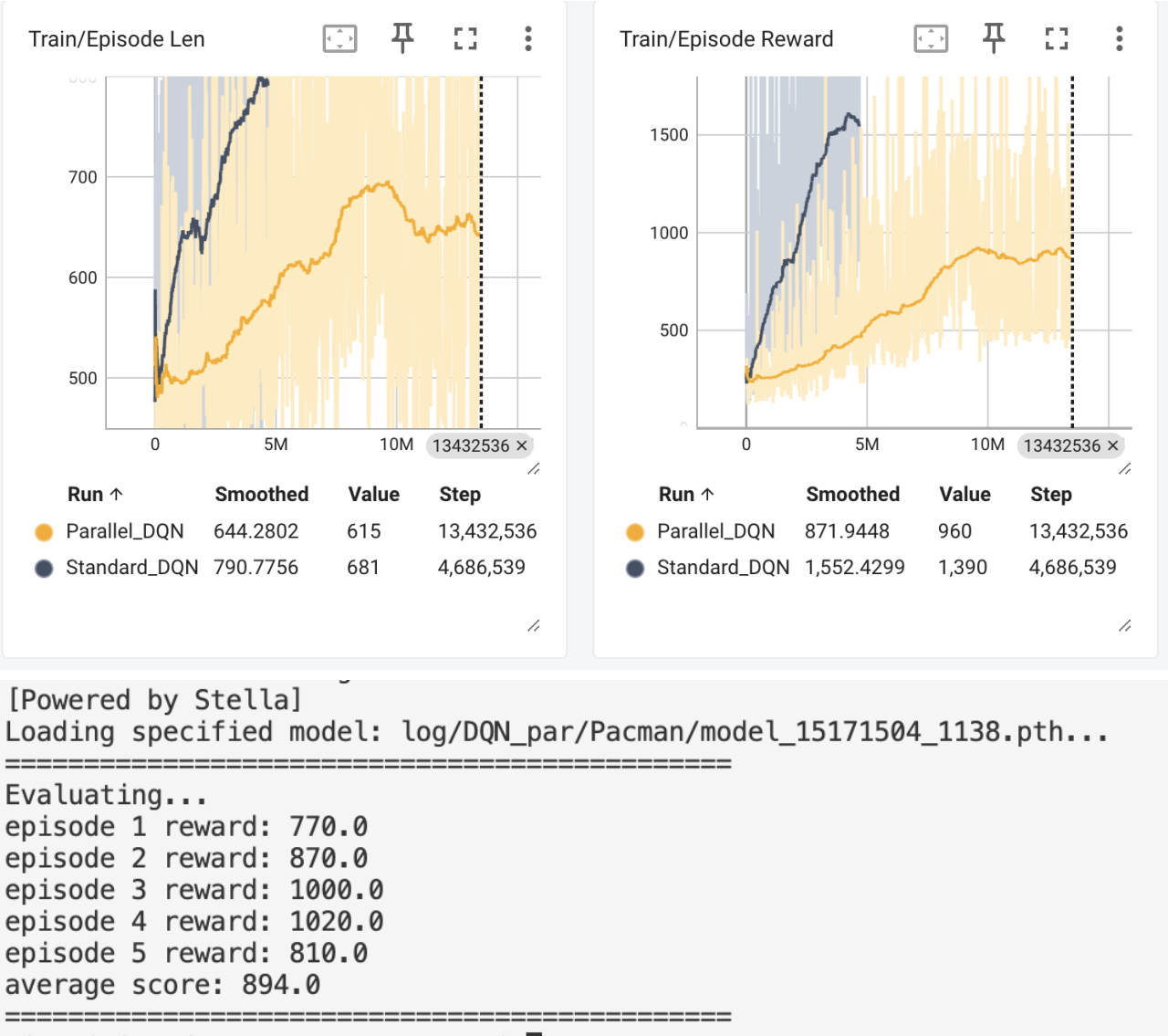
$$\rightarrow Q(s_t, a_t) = A(s_t, a_t) + V(s)$$

- Constrain the value of A:

$$Q(s_t, a_t) = V(s) + (A(s_t, a_t) - \frac{1}{|A|} \sum_{a'_t} A(s_t, a'_t))$$

我的結果看來 Dueling DQN 也略好。

4. Screenshot of Tensorboard training curve and testing results on DQN with parallelized rollout, and discuss the difference between DQN and DQN with parallelized rollout.



DQN with Parallelized Rollout 同時啟動多個環境（例如 4 或 8 個環境）並行收集經驗。每個環境獨立與 agent 互動，產生各自的 (state, action, reward, next_state) transition，再一起存入 replay buffer。